Transparency and Interpretability

Responsible Data Science
DS-UA 202 and DS-GA 1017

Compiled by Julia Stoyanovich

This reader contains selected articles on responsibility transparency and interpretability. For convenience, the readings are organized by course week. Some articles include additional materials in an appendix. Appendices are not part of required reading.

Week 7: Auditing black-box models

“Why Should I Trust You?” Explaining the Predictions of Any Classifier

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ABSTRACT

Despite widespread adoption, machine learning models remain mostly black boxes. Understanding the reasons behind predictions is, however, quite important in assessing *trust*, which is fundamental if one plans to take action based on a prediction, or when choosing whether to deploy a new model. Such understanding also provides insights into the model, which can be used to transform an untrustworthy model or prediction into a trustworthy one.

In this work, we propose LIME, a novel explanation technique that explains the predictions of *any* classifier in an interpretable and faithful manner, by learning an interpretable model locally around the prediction. We also propose a method to explain models by presenting representative individual predictions and their explanations in a non-redundant way, framing the task as a submodular optimization problem. We demonstrate the flexibility of these methods by explaining different models for text (e.g. random forests) and image classification (e.g. neural networks). We show the utility of explanations via novel experiments, both simulated and with human subjects, on various scenarios that require trust: deciding if one should trust a prediction, choosing between models, improving an untrustworthy classifier, and identifying why a classifier should not be trusted.

1. INTRODUCTION

Machine learning is at the core of many recent advances in science and technology. Unfortunately, the important role of humans is an oft-overlooked aspect in the field. Whether humans are directly using machine learning classifiers as tools, or are deploying models within other products, a vital concern remains: *if the users do not trust a model or a prediction, they will not use it.* It is important to differentiate between two different (but related) definitions of trust: (1) *trusting a prediction*, i.e. whether a user trusts an individual prediction sufficiently to take some action based on it, and (2) *trusting a model*, i.e. whether the user trusts a model to behave in reasonable ways if deployed. Both are directly impacted by how much the human understands a model's behaviour, as opposed to seeing it as a black box.

Determining trust in individual predictions is an important problem when the model is used for decision making. When using machine learning for medical diagnosis [6] or terrorism detection, for example, predictions cannot be acted upon on blind faith, as the consequences may be catastrophic.

Apart from trusting individual predictions, there is also a need to evaluate the model as a whole before deploying it "in the wild". To make this decision, users need to be confident that the model will perform well on real-world data, according to the metrics of interest. Currently, models are evaluated using accuracy metrics on an available validation dataset. However, real-world data is often significantly different, and further, the evaluation metric may not be indicative of the product's goal. Inspecting individual predictions and their explanations is a worthwhile solution, in addition to such metrics. In this case, it is important to aid users by suggesting which instances to inspect, especially for large datasets.

In this paper, we propose providing explanations for individual predictions as a solution to the "trusting a prediction" problem, and selecting multiple such predictions (and explanations) as a solution to the "trusting the model" problem. Our main contributions are summarized as follows.

- LIME, an algorithm that can explain the predictions of *any* classifier or regressor in a faithful way, by approximating it locally with an interpretable model.
- SP-LIME, a method that selects a set of representative instances with explanations to address the "trusting the model" problem, via submodular optimization.
- Comprehensive evaluation with simulated and human subjects, where we measure the impact of explanations on trust and associated tasks. In our experiments, non-experts using LIME are able to pick which classifier from a pair generalizes better in the real world. Further, they are able to greatly improve an untrustworthy classifier trained on 20 newsgroups, by doing feature engineering using LIME. We also show how understanding the predictions of a neural network on images helps practitioners know when and why they should not trust a model.

2. THE CASE FOR EXPLANATIONS

By "explaining a prediction", we mean presenting textual or visual artifacts that provide qualitative understanding of the relationship between the instance's components (e.g. words in text, patches in an image) and the model's prediction. We

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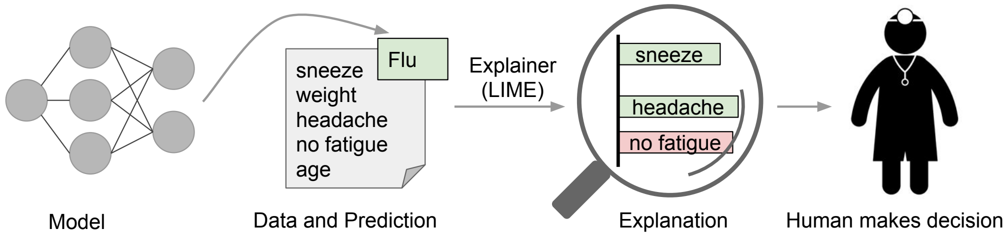


Figure 1: Explaining individual predictions. A model predicts that a patient has the flu, and LIME highlights the symptoms in the patient's history that led to the prediction. Sneeze and headache are portrayed as contributing to the "flu" prediction, while "no fatigue" is evidence against it. With these, a doctor can make an informed decision about whether to trust the model's prediction.

argue that explaining predictions is an important aspect in getting humans to trust and use machine learning effectively, if the explanations are faithful and intelligible.

The process of explaining individual predictions is illustrated in Figure 1. It is clear that a doctor is much better positioned to make a decision with the help of a model if intelligible explanations are provided. In this case, an explanation is a small list of symptoms with relative weights – symptoms that either contribute to the prediction (in green) or are evidence against it (in red). Humans usually have prior knowledge about the application domain, which they can use to accept (trust) or reject a prediction if they understand the reasoning behind it. It has been observed, for example, that providing explanations can increase the acceptance of movie recommendations [12] and other automated systems [8].

Every machine learning application also requires a certain measure of overall trust in the model. Development and evaluation of a classification model often consists of collecting annotated data, of which a held-out subset is used for automated evaluation. Although this is a useful pipeline for many applications, evaluation on validation data may not correspond to performance "in the wild", as practitioners often overestimate the accuracy of their models [21], and thus trust cannot rely solely on it. Looking at examples offers an alternative method to assess truth in the model, especially if the examples are explained. We thus propose explaining several representative individual predictions of a model as a way to provide a global understanding.

There are several ways a model or its evaluation can go wrong. Data leakage, for example, defined as the unintentional leakage of signal into the training (and validation) data that would not appear when deployed [14], potentially increases accuracy. A challenging example cited by **(author?)** [14] is one where the patient ID was found to be heavily correlated with the target class in the training and validation data. This issue would be incredibly challenging to identify just by observing the predictions and the raw data, but much easier if explanations such as the one in Figure 1 are provided, as patient ID would be listed as an explanation for predictions. Another particularly hard to detect problem is dataset shift [5], where training data is different than test data (we give an example in the famous 20 newsgroups dataset later on). The insights given by explanations are particularly helpful in identifying what must be done to convert an untrustworthy model into a trustworthy one – for example, removing leaked data or changing the training data to avoid dataset shift.

Machine learning practitioners often have to select a model from a number of alternatives, requiring them to assess the relative trust between two or more models. In Figure

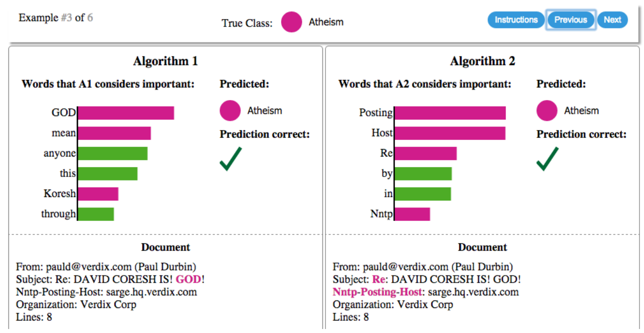


Figure 2: Explaining individual predictions of competing classifiers trying to determine if a document is about "Christianity" or "Atheism". The bar chart represents the importance given to the most relevant words, also highlighted in the text. Color indicates which class the word contributes to (green for "Christianity", magenta for "Atheism").

2, we show how individual prediction explanations can be used to select between models, in conjunction with accuracy. In this case, the algorithm with higher accuracy on the validation set is actually much worse, a fact that is easy to see when explanations are provided (again, due to human prior knowledge), but hard otherwise. Further, there is frequently a mismatch between the metrics that we can compute and optimize (e.g. accuracy) and the actual metrics of interest such as user engagement and retention. While we may not be able to measure such metrics, we have knowledge about how certain model behaviors can influence them. Therefore, a practitioner may wish to choose a less accurate model for content recommendation that does not place high importance in features related to "clickbait" articles (which may hurt user retention), even if exploiting such features increases the accuracy of the model in cross validation. We note that explanations are particularly useful in these (and other) scenarios if a method can produce them for *any* model, so that a variety of models can be compared.

Desired Characteristics for Explainers

We now outline a number of desired characteristics from explanation methods.

An essential criterion for explanations is that they must be **interpretable**, i.e., provide qualitative understanding between the input variables and the response. We note that interpretability must take into account the user's limitations. Thus, a linear model [24], a gradient vector [2] or an additive model [6] may or may not be interpretable. For example, if hundreds or thousands of features significantly contribute to a prediction, it is not reasonable to expect any user to comprehend why the prediction was made, even if individual weights can be inspected. This requirement further implies that explanations should be easy to understand, which is not necessarily true of the features used by the model, and thus the "input variables" in the explanations may need to be different than the features. Finally, we note that the notion of interpretability also depends on the target audience. Machine learning practitioners may be able to interpret small Bayesian networks, but laymen may be more comfortable with a small number of weighted features as an explanation.

Another essential criterion is **local fidelity**. Although it is often impossible for an explanation to be completely faithful unless it is the complete description of the model itself, for an explanation to be meaningful it must at least be *locally faithful*, i.e. it must correspond to how the model behaves in the vicinity of the instance being predicted. We note that local fidelity does not imply global fidelity: features that are globally important may not be important in the local context, and vice versa. While global fidelity would imply local fidelity, identifying globally faithful explanations that are interpretable remains a challenge for complex models.

While there are models that are inherently interpretable [6, 17, 26, 27], an explainer should be able to explain *any* model, and thus be **model-agnostic** (i.e. treat the original model as a black box). Apart from the fact that many state-of-the-art classifiers are not currently interpretable, this also provides flexibility to explain future classifiers.

In addition to explaining predictions, providing a **global perspective** is important to ascertain trust in the model. As mentioned before, accuracy may often not be a suitable metric to evaluate the model, and thus we want to *explain the model*. Building upon the explanations for individual predictions, we select a few explanations to present to the user, such that they are representative of the model.

3. LOCAL INTERPRETABLE MODEL-AGNOSTIC EXPLANATIONS

We now present Local Interpretable Model-agnostic Explanations (**LIME**). The overall goal of LIME is to identify an **interpretable** model over the *interpretable representation* that is **locally faithful** to the classifier.

3.1 Interpretable Data Representations

Before we present the explanation system, it is important to distinguish between features and interpretable data representations. As mentioned before, **interpretable** explanations need to use a representation that is understandable to humans, regardless of the actual features used by the model. For example, a possible *interpretable representation* for text classification is a binary vector indicating the presence or absence of a word, even though the classifier may use more complex (and incomprehensible) features such as word embeddings. Likewise for image classification, an *interpretable representation* may be a binary vector indicating the "presence" or "absence" of a contiguous patch of similar pixels (a super-pixel), while the classifier may represent the image as a tensor with three color channels per pixel. We denote $x \in \mathbb{R}^d$ be the original representation of an instance being explained, and we use $x' \in \{0,1\}^{d'}$ to denote a binary vector for its interpretable representation.

3.2 Fidelity-Interpretability Trade-off

Formally, we define an explanation as a model $g \in G$, where G is a class of potentially *interpretable* models, such as linear models, decision trees, or falling rule lists [27], i.e. a model $g \in G$ can be readily presented to the user with visual or textual artifacts. The domain of g is $\{0,1\}^{d'}$, i.e. g acts over absence/presence of the *interpretable components*. As not every $g \in G$ may be simple enough to be interpretable - thus we let $\Omega(g)$ be a measure of *complexity* (as opposed to *interpretability*) of the explanation $g \in G$. For example, for decision trees $\Omega(g)$ may be the depth of the tree, while for linear models, $\Omega(g)$ may be the number of non-zero weights.

Let the model being explained be denoted $f : \mathbb{R}^d \to \mathbb{R}$. In classification, $f(x)$ is the probability (or a binary indicator) that x belongs to a certain class[1]. We further use $\pi_x(z)$ as a proximity measure between an instance z to x, so as to define locality around x. Finally, let $\mathcal{L}(f, g, \pi_x)$ be a measure of how unfaithful g is in approximating f in the locality defined by π_x. In order to ensure both **interpretability** and **local fidelity**, we must minimize $\mathcal{L}(f, g, \pi_x)$ while having $\Omega(g)$ be low enough to be interpretable by humans. The explanation produced by **LIME** is obtained by the following:

$$\xi(x) = \operatorname*{argmin}_{g \in G} \ \mathcal{L}(f, g, \pi_x) + \Omega(g) \tag{1}$$

This formulation can be used with different explanation families G, fidelity functions $\mathcal{L}$, and complexity measures Ω. Here we focus on sparse linear models as explanations, and on performing the search using perturbations.

3.3 Sampling for Local Exploration

We want to minimize the locality-aware loss $\mathcal{L}(f, g, \pi_x)$ without making any assumptions about f, since we want the explainer to be **model-agnostic**. Thus, in order to learn the local behavior of f as the interpretable inputs vary, we approximate $\mathcal{L}(f, g, \pi_x)$ by drawing samples, weighted by π_x. We sample instances around x' by drawing nonzero elements of x' uniformly at random (where the number of such draws is also uniformly sampled). Given a perturbed sample $z' \in \{0,1\}^{d'}$ (which contains a fraction of the nonzero elements of x'), we recover the sample in the original representation $z \in R^d$ and obtain $f(z)$, which is used as a *label* for the explanation model. Given this dataset $\mathcal{Z}$ of perturbed samples with the associated labels, we optimize Eq. (1) to get an explanation $\xi(x)$. The primary intuition behind LIME is presented in Figure 3, where we sample instances both in the vicinity of x (which have a high weight due to π_x) and far away from x (low weight from π_x). Even though the original model may be too complex to explain globally, LIME presents an explanation that is locally faithful (linear in this case), where the locality is captured by π_x. It is worth noting that our method is fairly robust to sampling noise since the samples are weighted by π_x in Eq. (1). We now present a concrete instance of this general framework.

3.4 Sparse Linear Explanations

For the rest of this paper, we let G be the class of linear models, such that $g(z') = w_g \cdot z'$. We use the locally weighted square loss as $\mathcal{L}$, as defined in Eq. (2), where we let $\pi_x(z) = exp(-D(x,z)^2/\sigma^2)$ be an exponential kernel defined on some

[1]For multiple classes, we explain each class separately, thus $f(x)$ is the prediction of the relevant class.

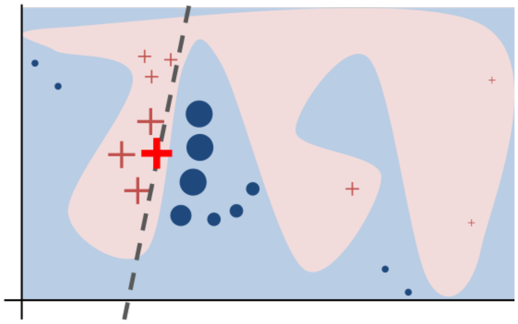


Figure 3: Toy example to present intuition for LIME. The black-box model's complex decision function f (unknown to LIME) is represented by the blue/pink background, which cannot be approximated well by a linear model. The bold red cross is the instance being explained. LIME samples instances, gets predictions using f, and weighs them by the proximity to the instance being explained (represented here by size). The dashed line is the learned explanation that is locally (but not globally) faithful.

distance function D (e.g. cosine distance for text, $L2$ distance for images) with width σ.

$$\mathcal{L}(f, g, \pi_x) = \sum_{z, z' \in \mathcal{Z}} \pi_x(z) \left(f(z) - g(z')\right)^2 \tag{2}$$

For text classification, we ensure that the explanation is **interpretable** by letting the *interpretable representation* be a bag of words, and by setting a limit K on the number of words, i.e. $\Omega(g) = \infty \mathbb{1}[\|w_g\|_0 > K]$. Potentially, K can be adapted to be as big as the user can handle, or we could have different values of K for different instances. In this paper we use a constant value for K, leaving the exploration of different values to future work. We use the same Ω for image classification, using "super-pixels" (computed using any standard algorithm) instead of words, such that the interpretable representation of an image is a binary vector where 1 indicates the original super-pixel and 0 indicates a grayed out super-pixel. This particular choice of Ω makes directly solving Eq. (1) intractable, but we approximate it by first selecting K features with Lasso (using the regularization path [9]) and then learning the weights via least squares (a procedure we call K-LASSO in Algorithm 1). Since Algorithm 1 produces an explanation for an individual prediction, its complexity does not depend on the size of the dataset, but instead on time to compute $f(x)$ and on the number of samples N. In practice, explaining random forests with 1000 trees using scikit-learn (http://scikit-learn.org) on a laptop with $N = 5000$ takes under 3 seconds without any optimizations such as using gpus or parallelization. Explaining each prediction of the Inception network [25] for image classification takes around 10 minutes.

Any choice of interpretable representations and G will have some inherent drawbacks. First, while the underlying model can be treated as a black-box, certain interpretable representations will not be powerful enough to explain certain behaviors. For example, a model that predicts sepia-toned images to be *retro* cannot be explained by presence of absence of super pixels. Second, our choice of G (sparse linear models) means that if the underlying model is highly non-linear even in the locality of the prediction, there may not be a faithful explanation. However, we can estimate the faithfulness of the explanation on $\mathcal{Z}$, and present this information to the user. This estimate of faithfulness can also be used for selecting an appropriate family of explanations from a set of multiple interpretable model classes, thus adapting to the given dataset and the classifier. We leave such exploration for future work, as linear explanations work quite well for multiple black-box models in our experiments.

Algorithm 1 Sparse Linear Explanations using LIME

Require: Classifier f, Number of samples N
Require: Instance x, and its interpretable version x'
Require: Similarity kernel π_x, Length of explanation K
  $\mathcal{Z} \leftarrow \{\}$
  for $i \in \{1, 2, 3, ..., N\}$ **do**
    $z'_i \leftarrow sample\_around(x')$
    $\mathcal{Z} \leftarrow \mathcal{Z} \cup \langle z'_i, f(z_i), \pi_x(z_i)\rangle$
  end for
  $w \leftarrow$ K-Lasso($\mathcal{Z}, K$) ▷ with z'_i as features, $f(z)$ as target
  return w

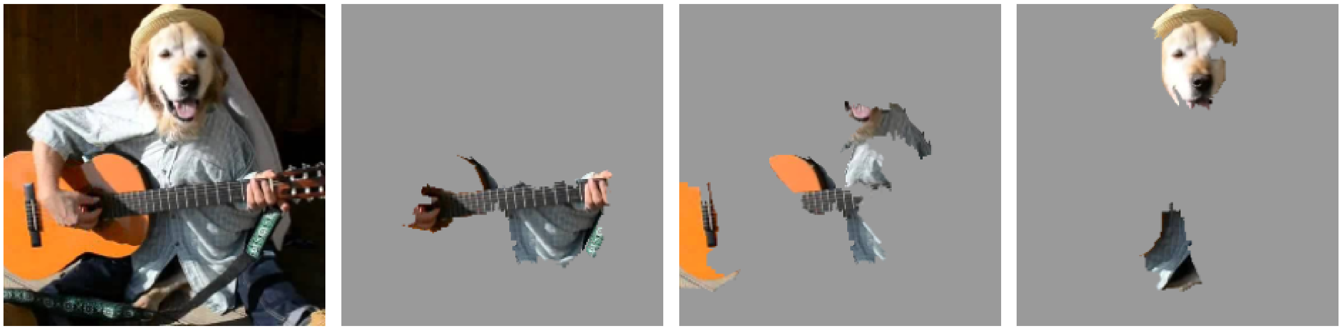
3.5 Example 1: Text classification with SVMs

In Figure 2 (right side), we explain the predictions of a support vector machine with RBF kernel trained on unigrams to differentiate "Christianity" from "Atheism" (on a subset of the 20 newsgroup dataset). Although this classifier achieves 94% held-out accuracy, and one would be tempted to trust it based on this, the explanation for an instance shows that predictions are made for quite arbitrary reasons (words "Posting", "Host", and "Re" have no connection to either Christianity or Atheism). The word "Posting" appears in 22% of examples in the training set, 99% of them in the class "Atheism". Even if headers are removed, proper names of prolific posters in the original newsgroups are selected by the classifier, which would also not generalize.

After getting such insights from explanations, it is clear that this dataset has serious issues (which are not evident just by studying the raw data or predictions), and that this classifier, or held-out evaluation, cannot be trusted. It is also clear what the problems are, and the steps that can be taken to fix these issues and train a more trustworthy classifier.

3.6 Example 2: Deep networks for images

When using sparse linear explanations for image classifiers, one may wish to just highlight the super-pixels with positive weight towards a specific class, as they give intuition as to why the model would think that class may be present. We explain the prediction of Google's pre-trained Inception neural network [25] in this fashion on an arbitrary image (Figure 4a). Figures 4b, 4c, 4d show the superpixels explanations for the top 3 predicted classes (with the rest of the image grayed out), having set $K = 10$. What the neural network picks up on for each of the classes is quite natural to humans - Figure 4b in particular provides insight as to why acoustic guitar was predicted to be electric: due to the fretboard. This kind of explanation enhances trust in the classifier (even if the top predicted class is wrong), as it shows that it is not acting in an unreasonable manner.



(a) Original Image (b) Explaining *Electric guitar* (c) Explaining *Acoustic guitar* (d) Explaining *Labrador*

Figure 4: Explaining an image classification prediction made by Google's Inception neural network. The top 3 classes predicted are "Electric Guitar" ($p = 0.32$), "Acoustic guitar" ($p = 0.24$) and "Labrador" ($p = 0.21$)

4. SUBMODULAR PICK FOR EXPLAINING MODELS

Although an explanation of a single prediction provides some understanding into the reliability of the classifier to the user, it is not sufficient to evaluate and assess trust in the model as a whole. We propose to give a global understanding of the model by explaining a set of individual instances. This approach is still model agnostic, and is complementary to computing summary statistics such as held-out accuracy.

Even though explanations of multiple instances can be insightful, these instances need to be selected judiciously, since users may not have the time to examine a large number of explanations. We represent the time/patience that humans have by a budget B that denotes the number of explanations they are willing to look at in order to understand a model. Given a set of instances X, we define the **pick step** as the task of selecting B instances for the user to inspect.

The pick step is not dependent on the existence of explanations - one of the main purpose of tools like Modeltracker [1] and others [11] is to assist users in selecting instances themselves, and examining the raw data and predictions. However, since looking at raw data is not enough to understand predictions and get insights, the pick step should take into account the explanations that accompany each prediction. Moreover, this method should pick a diverse, representative set of explanations to show the user – i.e. non-redundant explanations that represent how the model behaves globally.

Given the explanations for a set of instances X ($|X| = n$), we construct an $n \times d'$ *explanation matrix* $\mathcal{W}$ that represents the local importance of the interpretable components for each instance. When using linear models as explanations, for an instance x_i and explanation $g_i = \xi(x_i)$, we set $\mathcal{W}_{ij} = |w_{g_{ij}}|$. Further, for each component (column) j in $\mathcal{W}$, we let I_j denote the *global* importance of that component in the explanation space. Intuitively, we want I such that features that explain many different instances have higher importance scores. In Figure 5, we show a toy example $\mathcal{W}$, with $n = d' = 5$, where $\mathcal{W}$ is binary (for simplicity). The importance function I should score feature f2 higher than feature f1, i.e. $I_2 > I_1$, since feature f2 is used to explain more instances. Concretely for the text applications, we set $I_j = \sqrt{\sum_{i=1}^{n} \mathcal{W}_{ij}}$. For images, I must measure something that is comparable across the super-pixels in different images,

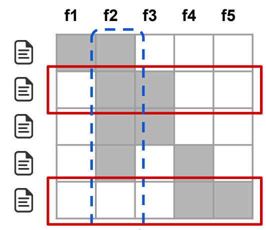


Figure 5: Toy example $\mathcal{W}$. Rows represent instances (documents) and columns represent features (words). Feature f2 (dotted blue) has the highest importance. Rows 2 and 5 (in red) would be selected by the pick procedure, covering all but feature f1.

Algorithm 2 Submodular pick (SP) algorithm

Require: Instances X, Budget B
  for all $x_i \in X$ **do**
    $\mathcal{W}_i \leftarrow$ **explain**(x_i, x'_i) ▷ Using Algorithm 1
  end for
  for $j \in \{1 \ldots d'\}$ **do**
    $I_j \leftarrow \sqrt{\sum_{i=1}^{n} |\mathcal{W}_{ij}|}$ ▷ Compute feature importances
  end for
  $V \leftarrow \{\}$
  while $|V| < B$ **do** ▷ Greedy optimization of Eq (4)
    $V \leftarrow V \cup \text{argmax}_i\, c(V \cup \{i\}, \mathcal{W}, I)$
  end while
  return V

such as color histograms or other features of super-pixels; we leave further exploration of these ideas for future work.

While we want to pick instances that cover the important components, the set of explanations must not be redundant in the components they show the users, i.e. avoid selecting instances with similar explanations. In Figure 5, after the second row is picked, the third row adds no value, as the user has already seen features f2 and f3 - while the last row exposes the user to completely new features. Selecting the second and last row results in the coverage of almost all the features. We formalize this non-redundant coverage intuition in Eq. (3), where we define coverage as the set function c that, given $\mathcal{W}$ and I, computes the total importance of the features that appear in at least one instance in a set V.

$$c(V, \mathcal{W}, I) = \sum_{j=1}^{d'} \mathbb{1}_{[\exists i \in V : \mathcal{W}_{ij} > 0]} I_j \qquad (3)$$

The pick problem, defined in Eq. (4), consists of finding the set $V, |V| \leq B$ that achieves highest coverage.

$$Pick(\mathcal{W}, I) = \underset{V, |V| \leq B}{\operatorname{argmax}}\, c(V, \mathcal{W}, I) \qquad (4)$$

The problem in Eq. (4) is maximizing a weighted coverage function, and is NP-hard [10]. Let $c(V \cup \{i\}, \mathcal{W}, I) - c(V, \mathcal{W}, I)$ be the marginal coverage gain of adding an instance i to a set V. Due to submodularity, a greedy algorithm that iteratively adds the instance with the highest marginal coverage gain to the solution offers a constant-factor approximation guarantee of $1 - 1/e$ to the optimum [15]. We outline this approximation in Algorithm 2, and call it **submodular pick**.

5. SIMULATED USER EXPERIMENTS

In this section, we present simulated user experiments to evaluate the utility of explanations in trust-related tasks. In particular, we address the following questions: (1) Are the explanations faithful to the model, (2) Can the explanations aid users in ascertaining trust in predictions, and (3) Are the explanations useful for evaluating the model as a whole. Code and data for replicating our experiments are available at https://github.com/marcotcr/lime-experiments.

5.1 Experiment Setup

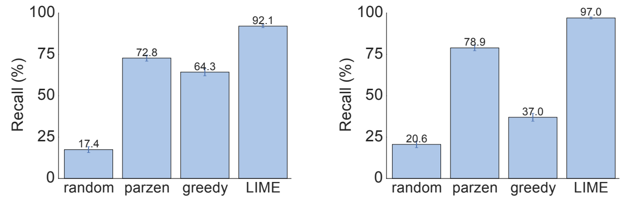
We use two sentiment analysis datasets (*books* and *DVDs*, 2000 instances each) where the task is to classify product reviews as positive or negative [4]. We train decision trees (**DT**), logistic regression with L2 regularization (**LR**), nearest neighbors (**NN**), and support vector machines with RBF kernel (**SVM**), all using bag of words as features. We also include random forests (with 1000 trees) trained with the average word2vec embedding [19] (**RF**), a model that is impossible to interpret without a technique like LIME. We use the implementations and default parameters of scikit-learn, unless noted otherwise. We divide each dataset into train (1600 instances) and test (400 instances).

To explain individual predictions, we compare our proposed approach (**LIME**), with **parzen** [2], a method that approximates the black box classifier globally with Parzen windows, and explains individual predictions by taking the gradient of the prediction probability function. For parzen, we take the K features with the highest absolute gradients as explanations. We set the hyper-parameters for parzen and LIME using cross validation, and set $N = 15,000$. We also compare against a **greedy** procedure (similar to **(author?)** [18]) in which we greedily remove features that contribute the most to the predicted class until the prediction changes (or we reach the maximum of K features), and a **random** procedure that randomly picks K features as an explanation. We set K to 10 for our experiments.

For experiments where the pick procedure applies, we either do random selection (random pick, **RP**) or the procedure described in §4 (submodular pick, **SP**). We refer to pick-explainer combinations by adding RP or SP as a prefix.

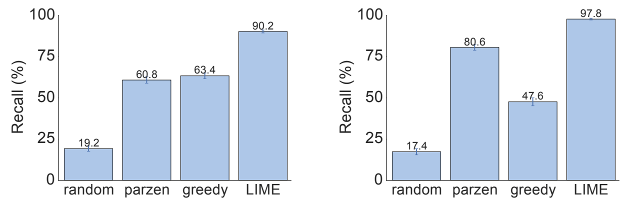
5.2 Are explanations faithful to the model?

We measure faithfulness of explanations on classifiers that are by themselves interpretable (sparse logistic regression



(a) Sparse LR (b) Decision Tree

Figure 6: Recall on truly important features for two interpretable classifiers on the books dataset.



(a) Sparse LR (b) Decision Tree

Figure 7: Recall on truly important features for two interpretable classifiers on the DVDs dataset.

and decision trees). In particular, we train both classifiers such that the maximum number of features they use for any instance is 10, and thus we know the *gold* set of features that the are considered important by these models. For each prediction on the test set, we generate explanations and compute the fraction of these *gold* features that are recovered by the explanations. We report this recall averaged over all the test instances in Figures 6 and 7. We observe that the greedy approach is comparable to parzen on logistic regression, but is substantially worse on decision trees since changing a single feature at a time often does not have an effect on the prediction. The overall recall by parzen is low, likely due to the difficulty in approximating the original high-dimensional classifier. LIME consistently provides $> 90\%$ recall for both classifiers on both datasets, demonstrating that LIME explanations are faithful to the models.

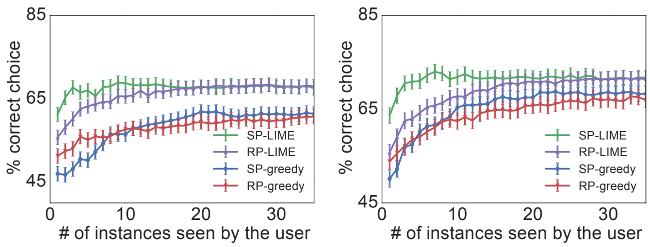
5.3 Should I trust this prediction?

In order to simulate trust in individual predictions, we first randomly select 25% of the features to be "untrustworthy", and assume that the users can identify and would not want to trust these features (such as the headers in 20 newsgroups, leaked data, etc). We thus develop *oracle* "trustworthiness" by labeling test set predictions from a black box classifier as "untrustworthy" if the prediction changes when untrustworthy features are removed from the instance, and "trustworthy" otherwise. In order to simulate users, we assume that users deem predictions untrustworthy from LIME and parzen explanations if the prediction from the linear approximation changes when all untrustworthy features that appear in the explanations are removed (the simulated human "discounts" the effect of untrustworthy features). For greedy and random, the prediction is mistrusted if any untrustworthy features are present in the explanation, since these methods do not provide a notion of the contribution of each feature to the prediction. Thus for each test set prediction, we can evaluate whether the simulated user trusts it using each explanation method, and compare it to the trustworthiness oracle.

Using this setup, we report the F1 on the trustworthy

Table 1: Average F1 of *trustworthiness* for different explainers on a collection of classifiers and datasets.

	Books				DVDs			
	LR	NN	RF	SVM	LR	NN	RF	SVM
Random	14.6	14.8	14.7	14.7	14.2	14.3	14.5	14.4
Parzen	84.0	87.6	94.3	92.3	87.0	81.7	94.2	87.3
Greedy	53.7	47.4	45.0	53.3	52.4	58.1	46.6	55.1
LIME	**96.6**	**94.5**	**96.2**	**96.7**	**96.6**	**91.8**	**96.1**	**95.6**



(a) Books dataset (b) DVDs dataset

Figure 8: Choosing between two classifiers, as the number of instances shown to a simulated user is varied. Averages and standard errors from 800 runs.

predictions for each explanation method, averaged over 100 runs, in Table 1. The results indicate that LIME dominates others (all results are significant at $p = 0.01$) on both datasets, and for all of the black box models. The other methods either achieve a lower recall (i.e. they mistrust predictions more than they should) or lower precision (i.e. they trust too many predictions), while LIME maintains both high precision and high recall. Even though we artificially select which features are untrustworthy, these results indicate that LIME is helpful in assessing trust in individual predictions.

5.4 Can I trust this model?

In the final simulated user experiment, we evaluate whether the explanations can be used for model selection, simulating the case where a human has to decide between two competing models with similar accuracy on validation data. For this purpose, we add 10 artificially "noisy" features. Specifically, on training and validation sets (80/20 split of the original training data), each artificial feature appears in 10% of the examples in one class, and 20% of the other, while on the test instances, each artificial feature appears in 10% of the examples in each class. This recreates the situation where the models use not only features that are informative in the real world, but also ones that introduce spurious correlations. We create pairs of competing classifiers by repeatedly training pairs of random forests with 30 trees until their validation accuracy is within 0.1% of each other, but their test accuracy differs by at least 5%. Thus, it is not possible to identify the *better* classifier (the one with higher test accuracy) from the accuracy on the validation data.

The goal of this experiment is to evaluate whether a user can identify the better classifier based on the explanations of B instances from the validation set. The simulated human marks the set of artificial features that appear in the B explanations as untrustworthy, following which we evaluate how many total predictions in the validation set should be trusted (as in the previous section, treating only marked features as untrustworthy). Then, we select the classifier with fewer untrustworthy predictions, and compare this choice to the classifier with higher held-out test set accuracy.

We present the accuracy of picking the correct classifier as B varies, averaged over 800 runs, in Figure 8. We omit SP-parzen and RP-parzen from the figure since they did not produce useful explanations, performing only slightly better than random. LIME is consistently better than greedy, irrespective of the pick method. Further, combining submodular pick with LIME outperforms all other methods, in particular it is much better than RP-LIME when only a few examples are shown to the users. These results demonstrate that the trust assessments provided by SP-selected LIME explanations are good indicators of generalization, which we validate with human experiments in the next section.

6. EVALUATION WITH HUMAN SUBJECTS

In this section, we recreate three scenarios in machine learning that require trust and understanding of predictions and models. In particular, we evaluate LIME and SP-LIME in the following settings: (1) Can users choose which of two classifiers generalizes better (§ 6.2), (2) based on the explanations, can users perform feature engineering to improve the model (§ 6.3), and (3) are users able to identify and describe classifier irregularities by looking at explanations (§ 6.4).

6.1 Experiment setup

For experiments in §6.2 and §6.3, we use the "Christianity" and "Atheism" documents from the 20 newsgroups dataset mentioned beforehand. This dataset is problematic since it contains features that do not generalize (e.g. very informative header information and author names), and thus validation accuracy considerably overestimates real-world performance.

In order to estimate the real world performance, we create a new *religion dataset* for evaluation. We download Atheism and Christianity websites from the DMOZ directory and human curated lists, yielding 819 webpages in each class. High accuracy on this dataset by a classifier trained on 20 newsgroups indicates that the classifier is generalizing using semantic content, instead of placing importance on the data specific issues outlined above. Unless noted otherwise, we use SVM with RBF kernel, trained on the 20 newsgroups data with hyper-parameters tuned via the cross-validation.

6.2 Can users select the best classifier?

In this section, we want to evaluate whether explanations can help users decide which classifier generalizes better, i.e., which classifier would the user deploy "in the wild". Specifically, users have to decide between two classifiers: SVM trained on the original 20 newsgroups dataset, and a version of the same classifier trained on a "cleaned" dataset where many of the features that do not generalize have been manually removed. The original classifier achieves an accuracy score of 57.3% on the *religion dataset*, while the "cleaned" classifier achieves a score of 69.0%. In contrast, the test accuracy on the original 20 newsgroups split is 94.0% and 88.6%, respectively – suggesting that the worse classifier would be selected if accuracy alone is used as a measure of trust.

We recruit human subjects on Amazon Mechanical Turk – by no means machine learning experts, but instead people with basic knowledge about religion. We measure their ability to choose the better algorithm by seeing side-by-side explanations with the associated raw data (as shown in Figure 2). We restrict both the number of words in each explanation (K) and the number of documents that each

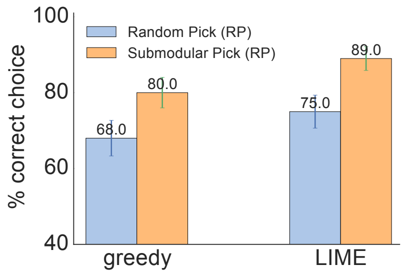


Figure 9: Average accuracy of human subject (with standard errors) in choosing between two classifiers.

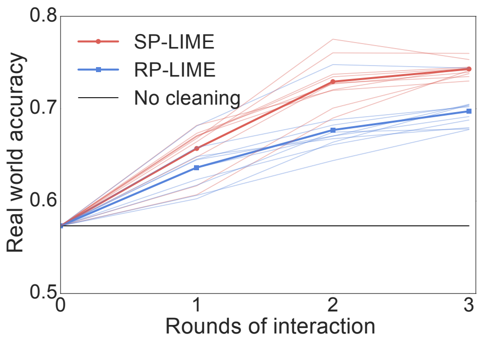


Figure 10: Feature engineering experiment. Each shaded line represents the average accuracy of subjects in a path starting from one of the initial 10 subjects. Each solid line represents the average across all paths per round of interaction.

person inspects (B) to 6. The position of each algorithm and the order of the instances seen are randomized between subjects. After examining the explanations, users are asked to select which algorithm will perform best in the real world. The explanations are produced by either greedy (chosen as a baseline due to its performance in the simulated user experiment) or LIME, and the instances are selected either by random (RP) or submodular pick (SP). We modify the greedy step in Algorithm 2 slightly so it alternates between explanations of the two classifiers. For each setting, we repeat the experiment with 100 users.

The results are presented in Figure 9. Note that all of the methods are good at identifying the better classifier, demonstrating that the explanations are useful in determining which classifier to trust, while using test set accuracy would result in the selection of the wrong classifier. Further, we see that the submodular pick (SP) greatly improves the user's ability to select the best classifier when compared to random pick (RP), with LIME outperforming greedy in both cases.

6.3 Can non-experts improve a classifier?

If one notes that a classifier is untrustworthy, a common task in machine learning is feature engineering, i.e. modifying the set of features and retraining in order to improve generalization. Explanations can aid in this process by presenting the important features, particularly for removing features that the users feel do not generalize.

We use the 20 newsgroups data here as well, and ask Amazon Mechanical Turk users to identify which words from the explanations should be removed from subsequent training, for the worse classifier from the previous section (§6.2). In each round, the subject marks words for deletion after observing $B = 10$ instances with $K = 10$ words in each explanation (an interface similar to Figure 2, but with a single algorithm). As a reminder, the users here are not experts in machine learning and are unfamiliar with feature engineering, thus are only identifying words based on their semantic content. Further, users do not have any access to the *religion* dataset – they do not even know of its existence. We start the experiment with 10 subjects. After they mark words for deletion, we train 10 different classifiers, one for each subject (with the corresponding words removed). The explanations for each classifier are then presented to a set of 5 users in a new round of interaction, which results in 50 new classifiers. We do a final round, after which we have 250 classifiers, each with a path of interaction tracing back to the first 10 subjects.

The explanations and instances shown to each user are produced by **SP-LIME** or **RP-LIME**. We show the average accuracy on the *religion* dataset at each interaction round for the paths originating from each of the original 10 subjects (shaded lines), and the average across all paths (solid lines) in Figure 10. It is clear from the figure that the crowd workers are able to improve the model by removing features they deem unimportant for the task. Further, **SP-LIME** outperforms **RP-LIME**, indicating selection of the instances to show the users is crucial for efficient feature engineering.

Each subject took an average of 3.6 minutes per round of cleaning, resulting in just under 11 minutes to produce a classifier that generalizes much better to real world data. Each path had on average 200 words removed with **SP**, and 157 with **RP**, indicating that incorporating coverage of important features is useful for feature engineering. Further, out of an average of 200 words selected with SP, 174 were selected by at least half of the users, while 68 by *all* the users. Along with the fact that the variance in the accuracy decreases across rounds, this high agreement demonstrates that the users are converging to similar *correct* models. This evaluation is an example of how explanations make it easy to improve an untrustworthy classifier – in this case easy enough that machine learning knowledge is not required.

6.4 Do explanations lead to insights?

Often artifacts of data collection can induce undesirable correlations that the classifiers pick up during training. These issues can be very difficult to identify just by looking at the raw data and predictions. In an effort to reproduce such a setting, we take the task of distinguishing between photos of Wolves and Eskimo Dogs (huskies). We train a logistic regression classifier on a training set of 20 images, hand selected such that all pictures of wolves had snow in the background, while pictures of huskies did not. As the features for the images, we use the first max-pooling layer of Google's pre-trained Inception neural network [25]. On a collection of additional 60 images, the classifier predicts "Wolf" if there is snow (or light background at the bottom), and "Husky" otherwise, regardless of animal color, position, pose, etc. We trained this *bad* classifier intentionally, to evaluate whether subjects are able to detect it.

The experiment proceeds as follows: we first present a balanced set of 10 test predictions (without explanations), where one wolf is not in a snowy background (and thus the prediction is "Husky") and one husky is (and is thus predicted as "Wolf"). We show the "Husky" mistake in Figure 11a. The other 8 examples are classified correctly. We then ask the subject three questions: (1) Do they trust this algorithm

(a) Husky classified as wolf

(b) Explanation

Figure 11: Raw data and explanation of a bad model's prediction in the "Husky vs Wolf" task.

	Before	After
Trusted the bad model	10 out of 27	3 out of 27
Snow as a potential feature	12 out of 27	25 out of 27

Table 2: "Husky vs Wolf" experiment results.

to work well in the real world, (2) why, and (3) how do they think the algorithm is able to distinguish between these photos of wolves and huskies. After getting these responses, we show the same images with the associated explanations, such as in Figure 11b, and ask the same questions.

Since this task requires some familiarity with the notion of spurious correlations and generalization, the set of subjects for this experiment were graduate students who have taken at least one graduate machine learning course. After gathering the responses, we had 3 independent evaluators read their reasoning and determine if each subject mentioned snow, background, or equivalent as a feature the model may be using. We pick the majority to decide whether the subject was correct about the insight, and report these numbers before and after showing the explanations in Table 2.

Before observing the explanations, more than a third trusted the classifier, and a little less than half mentioned the snow pattern as something the neural network was using – although all speculated on other patterns. After examining the explanations, however, almost all of the subjects identified the correct insight, with much more certainty that it was a determining factor. Further, the trust in the classifier also dropped substantially. Although our sample size is small, this experiment demonstrates the utility of explaining individual predictions for getting insights into classifiers knowing when not to trust them and why.

7. RELATED WORK

The problems with relying on validation set accuracy as the primary measure of trust have been well studied. Practitioners consistently overestimate their model's accuracy [21], propagate feedback loops [23], or fail to notice data leaks [14]. In order to address these issues, researchers have proposed tools like Gestalt [20] and Modeltracker [1], which help users navigate individual instances. These tools are complementary to LIME in terms of explaining models, since they do not address the problem of explaining individual predictions. Further, our submodular pick procedure can be incorporated in such tools to aid users in navigating larger datasets.

Some recent work aims to anticipate failures in machine learning, specifically for vision tasks [3, 29]. Letting users know when the systems are likely to fail can lead to an increase in trust, by avoiding "silly mistakes" [8]. These solutions either require additional annotations and feature engineering that is specific to vision tasks or do not provide insight into why a decision should not be trusted. Furthermore, they assume that the current evaluation metrics are reliable, which may not be the case if problems such as data leakage are present. Other recent work [11] focuses on exposing users to different kinds of mistakes (our pick step). Interestingly, the subjects in their study did not notice the serious problems in the 20 newsgroups data even after looking at many mistakes, suggesting that examining raw data is not sufficient. Note that **(author?)** [11] are not alone in this regard, many researchers in the field have unwittingly published classifiers that would not generalize for this task. Using LIME, we show that even non-experts are able to identify these irregularities when explanations are present. Further, LIME can complement these existing systems, and allow users to assess trust even when a prediction seems "correct" but is made for the wrong reasons.

Recognizing the utility of explanations in assessing trust, many have proposed using interpretable models [27], especially for the medical domain [6, 17, 26]. While such models may be appropriate for some domains, they may not apply equally well to others (e.g. a supersparse linear model [26] with $5-10$ features is unsuitable for text applications). Interpretability, in these cases, comes at the cost of flexibility, accuracy, or efficiency. For text, EluciDebug [16] is a full human-in-the-loop system that shares many of our goals (interpretability, faithfulness, etc). However, they focus on an already interpretable model (Naive Bayes). In computer vision, systems that rely on object detection to produce candidate alignments [13] or attention [28] are able to produce explanations for their predictions. These are, however, constrained to specific neural network architectures or incapable of detecting "non object" parts of the images. Here we focus on general, model-agnostic explanations that can be applied to any classifier or regressor that is appropriate for the domain - even ones that are yet to be proposed.

A common approach to model-agnostic explanation is learning a potentially interpretable model on the predictions of the original model [2, 7, 22]. Having the explanation be a gradient vector [2] captures a similar locality intuition to that of LIME. However, interpreting the coefficients on the gradient is difficult, particularly for confident predictions (where gradient is near zero). Further, these explanations approximate the original model *globally*, thus maintaining local fidelity becomes a significant challenge, as our experiments demonstrate. In contrast, LIME solves the much more feasible task of finding a model that approximates the original model *locally*. The idea of perturbing inputs for explanations has been explored before [24], where the authors focus on learning a specific *contribution* model, as opposed to our general framework. None of these approaches explicitly take cognitive limitations into account, and thus may produce non-interpretable explanations, such as a gradients or linear models with thousands of non-zero weights. The problem becomes worse if the original features are nonsensical to humans (e.g. word embeddings). In contrast, LIME incorporates interpretability both in the optimization and in our notion of *interpretable representation*, such that domain and task specific interpretability criteria can be accommodated.

8. CONCLUSION AND FUTURE WORK

In this paper, we argued that trust is crucial for effective human interaction with machine learning systems, and that explaining individual predictions is important in assessing trust. We proposed LIME, a modular and extensible approach to faithfully explain the predictions of *any* model in an interpretable manner. We also introduced SP-LIME, a method to select representative and non-redundant predictions, providing a global view of the model to users. Our experiments demonstrated that explanations are useful for a variety of models in trust-related tasks in the text and image domains, with both expert and non-expert users: deciding between models, assessing trust, improving untrustworthy models, and getting insights into predictions.

There are a number of avenues of future work that we would like to explore. Although we describe only sparse linear models as explanations, our framework supports the exploration of a variety of explanation families, such as decision trees; it would be interesting to see a comparative study on these with real users. One issue that we do not mention in this work was how to perform the pick step for images, and we would like to address this limitation in the future. The domain and model agnosticism enables us to explore a variety of applications, and we would like to investigate potential uses in speech, video, and medical domains, as well as recommendation systems. Finally, we would like to explore theoretical properties (such as the appropriate number of samples) and computational optimizations (such as using parallelization and GPU processing), in order to provide the accurate, real-time explanations that are critical for any human-in-the-loop machine learning system.

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Algorithmic Transparency via Quantitative Input Influence:
Theory and Experiments with Learning Systems

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***Abstract*—Algorithmic systems that employ machine learning play an increasing role in making substantive decisions in modern society, ranging from online personalization to insurance and credit decisions to predictive policing. But their decision-making processes are often opaque—it is difficult to explain why a certain decision was made. We develop a formal foundation to improve the transparency of such decision-making systems. Specifically, we introduce a family of *Quantitative Input Influence (QII)* measures that capture the degree of influence of inputs on outputs of systems. These measures provide a foundation for the design of transparency reports that accompany system decisions (e.g., explaining a specific credit decision) and for testing tools useful for internal and external oversight (e.g., to detect algorithmic discrimination).**

Distinctively, our *causal* QII measures carefully account for correlated inputs while measuring influence. They support a *general* class of transparency queries and can, in particular, explain decisions about individuals (e.g., a loan decision) and groups (e.g., disparate impact based on gender). Finally, since single inputs may not always have high influence, the QII measures also quantify the *joint influence* of a set of inputs (e.g., age and income) on outcomes (e.g. loan decisions) and the *marginal influence* of individual inputs within such a set (e.g., income). Since a single input may be part of multiple influential sets, the average marginal influence of the input is computed using principled aggregation measures, such as the Shapley value, previously applied to measure influence in voting. Further, since transparency reports could compromise privacy, we explore the transparency-privacy tradeoff and prove that a number of useful transparency reports can be made differentially private with very little addition of noise.

Our empirical validation with standard machine learning algorithms demonstrates that QII measures are a useful transparency mechanism when black box access to the learning system is available. In particular, they provide better explanations than standard associative measures for a host of scenarios that we consider. Further, we show that in the situations we consider, QII is efficiently approximable and can be made differentially private while preserving accuracy.

I. Introduction

Algorithmic decision-making systems that employ machine learning and related statistical methods are ubiquitous. They drive decisions in sectors as diverse as Web services, healthcare, education, insurance, law enforcement and defense [1], [2], [3], [4], [5]. Yet their decision-making processes are often opaque. *Algorithmic transparency* is an emerging research area aimed at explaining decisions made by algorithmic systems.

The call for algorithmic transparency has grown in intensity as public and private sector organizations increasingly use large volumes of personal information and complex data analytics systems for decision-making [6]. Algorithmic transparency provides several benefits. First, it is essential to enable identification of harms, such as discrimination, introduced by algorithmic decision-making (e.g., high interest credit cards targeted to protected groups) and to hold entities in the decision-making chain accountable for such practices. This form of accountability can incentivize entities to adopt appropriate corrective measures. Second, transparency can help detect errors in input data which resulted in an adverse decision (e.g., incorrect information in a user's profile because of which insurance or credit was denied). Such errors can then be corrected. Third, by explaining why an adverse decision was made, it can provide guidance on how to reverse it (e.g., by identifying a specific factor in the credit profile that needs to be improved).

Our Goal. While the importance of algorithmic transparency is recognized, work on computational foundations for this research area has been limited. This paper initiates progress in that direction by focusing on a concrete algorithmic transparency question:

How can we measure the influence of inputs (or features) on decisions made by an algorithmic system about individuals or groups of individuals?

Our goal is to inform the design of transparency reports, which include answers to transparency queries of this form. To be concrete, let us consider a predictive policing system that forecasts future criminal activity based on historical data; individuals high on the list receive visits from the police. An individual who receives a visit from the police may seek a transparency report that provides answers to *personalized transparency queries* about the influence of various inputs (or features), such as race or recent criminal history, on the system's decision. An oversight agency or the public may desire a transparency report that provides answers to *aggregate transparency queries*, such as the influence of sensitive inputs (e.g., gender, race) on the system's decisions concerning the entire population or about systematic differences in decisions

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among groups of individuals (e.g., discrimination based on race or age). These reports can thus help identify harms and errors in input data, and provide guidance on what input features to work on to modify the decision.

Our Model. We focus on a setting where a *transparency report* is generated with black-box access to the decision-making system[1] and knowledge of the input dataset on which it operates. This setting models the kind of access available to a private or public sector entity that pro-actively publishes transparency reports. It also models a useful level of access required for internal or external oversight of such systems to identify harms introduced by them. For the former use case, our approach provides a basis for design of transparency mechanisms; for the latter, it provides a formal basis for testing. Returning to our predictive policing system, the law enforcement agency that employs it could proactively publish transparency reports, and test the system for early detection of harms like race-based discrimination. An oversight agency could also use transparency reports for post hoc identification of harms.

Our Approach. We formalize transparency reports by introducing a family of *Quantitative Input Influence (QII)* measures that capture the degree of influence of inputs on outputs of the system. Three desiderata drove the definitions of these measures.

First, we seek a formalization of a *general* class of transparency reports that allows us to answer many useful transparency queries related to input influence, including but not limited to the example forms described above about the system's decisions about individuals and groups.

Second, we seek input influence measures that appropriately account for *correlated inputs*—a common case for our target applications. For example, consider a system that assists in hiring decisions for a moving company. Gender and the ability to lift heavy weights are inputs to the system. They are positively correlated with each other and with the hiring decisions. Yet transparency into whether the system uses the weight lifting ability or the gender in making its decisions (and to what degree) has substantive implications for determining if it is engaging in discrimination (the business necessity defense could apply in the former case [7]). This observation makes us look beyond correlation coefficients and other associative measures.

Third, we seek measures that appropriately quantify input influence in settings where any input by itself does not have significant influence on outcomes but a set of inputs does. In such cases, we seek measures of *joint influence* of a set of inputs (e.g., age and income) on a system's decision (e.g., to serve a high-paying job ad). We also seek measures of *marginal influence* of an input within such a set (e.g., age) on the decision. This notion allows us to provide finer-grained transparency about the relative importance of individual inputs within the set (e.g., age vs. income) in the system's decision.

We achieve the first desideratum by formalizing a notion of a *quantity of interest*. A transparency query measures the influence of an input on a quantity of interest. A quantity of interest represents a property of the behavior of the system for a given input distribution. Our formalization supports a wide range of statistical properties including probabilities of various outcomes in the output distribution and probabilities of output distribution outcomes conditioned on input distribution events. Examples of quantities of interest include the conditional probability of an outcome for a particular individual or group, and the ratio of conditional probabilities for an outcome for two different groups (a metric used as evidence of disparate impact under discrimination law in the US [7]).

We achieve the second desideratum by formalizing *causal* QII measures. These measures (called *Unary QII*) model the difference in the quantity of interest when the system operates over two related input distributions—the real distribution and a hypothetical (or counterfactual) distribution that is constructed from the real distribution in a specific way to account for correlations among inputs. Specifically, if we are interested in measuring the influence of an input on a quantity of interest of the system behavior, we construct the hypothetical distribution by retaining the marginal distribution over all other inputs and sampling the input of interest from its prior distribution. This choice breaks the correlations between this input and all other inputs and thus lets us measure the influence of this input on the quantity of interest, independently of other correlated inputs. Revisiting our moving company hiring example, if the system makes decisions only using the weightlifting ability of applicants, the influence of gender will be zero on the ratio of conditional probabilities of being hired for males and females.

We achieve the third desideratum in two steps. First, we define a notion of joint influence of a set of inputs (called *Set QII*) via a natural generalization of the definition of the hypothetical distribution in the Unary QII definition. Second, we define a family of *Marginal QII* measures that model the difference on the quantity of interest as we consider sets with and without the specific input whose marginal influence we want to measure. Depending on the application, we may pick these sets in different ways, thus motivating several different measures. For example, we could fix a set of inputs and ask about the marginal influence of any given input in that set on the quantity of interest. Alternatively, we may be interested in the average marginal influence of an input when it belongs to one of several different sets that significantly affect the quantity of interest. We consider several marginal influence aggregation measures from cooperative game theory originally developed in the context of influence measurement in voting scenarios and discuss their applicability in our setting. We also build on that literature to present an efficient approximate algorithm for computing these measures.

Recognizing that different forms of transparency reports may be appropriate for different settings, we generalize our QII measures to be parametric in its key elements: the intervention

[1]By "black-box access to the decision-making system" we mean a typical setting of software testing with complete control of inputs to the system and full observability of the outputs.

used to construct the hypothetical input distribution; the quantity of interest; the difference measure used to quantify the distance in the quantity of interest when the system operates over the real and hypothetical input distributions; and the aggregation measure used to combine marginal QII measures across different sets. This generalized definition provides a structure for exploring the design space of transparency reports.

Since transparency reports released to an individual, regulatory agency, or the public might compromise individual privacy, we explore the possibility of answering transparency queries while protecting differential privacy [8]. We prove bounds on the sensitivity of a number of transparency queries and leverage prior results on privacy amplification via sampling [9] to accurately answer these queries.

We demonstrate the utility of the QII framework by developing two machine learning applications on real datasets: an income classification application based on the benchmark `adult` dataset [10], and a predictive policing application based on the National Longitudinal Survey of Youth [11]. Using these applications, we argue, in Section VII, the need for causal measurement by empirically demonstrating that in the presence of correlated inputs, observational measures are not informative in identifying input influence. Further, we analyze transparency reports of individuals in our dataset to demonstrate how Marginal QII can provide insights into individuals' classification outcomes. Finally, we demonstrate that under most circumstances, QII measures can be made differentially private with minimal addition of noise, and can be approximated efficiently.

In summary, this paper makes the following contributions:

- A formalization of a specific algorithmic transparency problem for decision-making systems. Specifically, we define a family of Quantitative Input Influence metrics that accounts for correlated inputs, and provides answers to a general class of transparency queries, including the absolute and marginal influence of inputs on various behavioral system properties. These metrics can inform the design of transparency mechanisms and guide proactive system testing and posthoc investigations.
- A formal treatment of privacy-transparency trade-offs, in particular, by construction of differentially private answers to transparency queries.
- An implementation and experimental evaluation of the metrics over two real data sets. The evaluation demonstrates that (a) the QII measures are *informative*; (b) they remain *accurate* while preserving differential privacy; and (c) can be *computed* quite quickly for standard machine learning systems applied to real data sets.

II. Unary QII

Consider the situation discussed in the introduction, where an automated system assists in hiring decisions for a moving company. The input features used by this classification system are : *Age*, *Gender*, *Weight Lifting Ability*, *Marital Status* and *Education*. Suppose that, as before, weight lifting ability is strongly correlated with gender (with men having better overall lifting ability than woman). One particular question that an analyst may want to ask is: "What is the influence of the input *Gender* on positive classification for women?". The analyst observes that 20% of women are approved according to his classifier. Then, he replaces every woman's field for gender with a random value, and notices that the number of women approved does not change. In other words, an *intervention* on the *Gender* variable does not cause a significant change in the classification outcome. Repeating this process with *Weight Lifting Ability* results in a 20% increase in women's hiring. Therefore, he concludes that for this classifier, *Weight Lifting Ability* has more influence on positive classification for women than *Gender*.

By breaking correlations between gender and weight lifting ability, we are able to establish a causal relationship between the outcome of the classifier and the inputs. We are able to identify that despite the strong correlation between a negative classification outcome for women, the feature gender was not a cause of this outcome. We formalize the intuition behind such causal experimentation in our definition of Quantitative Input Influence (QII).

We are given an algorithm $\mathcal{A}$. $\mathcal{A}$ operates on inputs (also referred to as *features* for ML systems), $N = \{1, \ldots, n\}$. Every $i \in N$, can take on various *states*, given by X_i. We let $\mathcal{X} = \prod_{i \in N} \mathcal{X}_i$ be the set of possible feature state vectors, let $\mathcal{Z}$ be the set of possible outputs of $\mathcal{A}$. For a vector $\mathbf{x} \in \mathcal{X}$ and set of inputs $S \subseteq N$, $\mathbf{x}|_S$ denotes the vector of inputs in S. We are also given a probability distribution π on $\mathcal{X}$, where $\pi(\mathbf{x})$ is the probability of the input vector $\mathbf{x}$. We can define a marginal probability of a set of inputs S in the standard way as follows:

$$\pi_S(\mathbf{x}|_S) = \sum_{\{\mathbf{x}' \in \mathcal{X} | \mathbf{x}'|_S = \mathbf{x}|_S\}} \pi(\mathbf{x}') \tag{1}$$

When S is a singleton set $\{i\}$, we write the marginal probability of the single input as $\pi_i(x)$.

Informally, to quantify the influence of an input i, we compute its effect on some *quantity of interest*; that is, we measure the difference in the quantity of interest, when the feature i is changed via an intervention. In the example above, the quantity of interest is the fraction of positive classification of women. In this paper, we employ a particular interpretation of "changing an input", where we replace the value of every input with a random independently chosen value. To describe the replacement operation for input i, we first define an expanded probability space on $\mathcal{X} \times \mathcal{X}$, with the following distribution:

$$\tilde{\pi}(\mathbf{x}, \mathbf{u}) = \pi(\mathbf{x})\pi(\mathbf{u}). \tag{2}$$

The first component of an expanded vector $(\mathbf{x}, \mathbf{u})$, is just the original input vector, whereas the second component represents an independent random vector drawn from the same distribution π. Over this expanded probability space, the random variable $X(\mathbf{x}, u_i) = \mathbf{x}$ represents the original feature vector.

The random variable $X_{-i}U_i(\mathbf{x}, \mathbf{u}) = \mathbf{x}|_{N\setminus\{i\}}u_i$, represents the random variable with input i replaced with a random sample. Defining this expanded probability space allows us to switch between the original distribution, represented by the random variable X, and the *intervened distribution*, represented by $X_{-i}U_i$. Notice that both these random variables are defined from $\mathcal{X} \times \mathcal{X}$, the expanded probability space, to $\mathcal{X}$. We denote the set of random variables of the type $\mathcal{X} \times \mathcal{X} \to \mathcal{X}$ as $\mathfrak{R}(\mathcal{X})$.

We can now define probabilities over this expanded space. For example, the probability over X remains the same:

$$\begin{aligned}\Pr(X = \mathbf{x}) &= \sum_{\{(\mathbf{x}', \mathbf{u}') | \mathbf{x}' = \mathbf{x}\}} \tilde{\pi}(\mathbf{x}', \mathbf{u}') \\ &= \left(\sum_{\{\mathbf{x}' | \mathbf{x}' = \mathbf{x}\}} \pi(\mathbf{x}')\right)\left(\sum_{\mathbf{u}'} \pi(\mathbf{u}')\right) \\ &= \pi(\mathbf{x})\end{aligned}$$

Similarly, we can define more complex quantities. The following expression represents the expectation of a classifier c evaluating to 1, when i is randomly intervened on:

$$\mathbb{E}(c(X_{-i}U_i) = 1) = \sum_{\{(\mathbf{x}, \mathbf{u}) | c(\mathbf{x}_{N\setminus i}u_i) = 1\}} \tilde{\pi}(\mathbf{x}, u_i).$$

Observe that the expression above computes the probability of the classifier c evaluating to 1, when input i is replaced with a random sample from its probability distribution $\pi_i(u_i)$.

$$\begin{aligned}&\sum_{\{(\mathbf{x}, \mathbf{u}) | c(\mathbf{x}_{N\setminus i}u_i) = 1\}} \tilde{\pi}(\mathbf{x}, u_i) \\ &= \sum_{\mathbf{x}} \pi(\mathbf{x}) \sum_{\{u_i' | c(\mathbf{x}_{N\setminus i}u_i') = 1\}} \sum_{\{\mathbf{u} | u_i = u_i'\}} \pi(\mathbf{u}) \\ &= \sum_{\mathbf{x}} \pi(\mathbf{x}) \sum_{\{u_i' | c(\mathbf{x}_{N\setminus i}u_i') = 1\}} \pi_i(u_i')\end{aligned}$$

We can also define conditional distributions in the usual way. The following represents the probability of the classifier evaluating to 1 under the randomized intervention on input i of X, given that X belongs to some subset $\mathcal{Y} \subseteq \mathcal{X}$:

$$\mathbb{E}(c(X_{-i}U_i) = 1 \mid X \in \mathcal{Y}) = \frac{\mathbb{E}(c(X_{-i}U_i) = 1 \wedge X \in \mathcal{Y})}{\mathbb{E}(X \in \mathcal{Y})}.$$

Formally, for an algorithm $\mathcal{A}$, a *quantity of interest* $Q_{\mathcal{A}}(\cdot) : \mathfrak{R}(\mathcal{X}) \mapsto \mathbb{R}$ is a function of a random variable from $\mathfrak{R}(\mathcal{X})$.

Definition 1 (QII)**.** For a quantity of interest $Q_{\mathcal{A}}(\cdot)$, and an input i, the Quantitative Input Influence of i on $Q_{\mathcal{A}}(\cdot)$ is defined to be

$$\iota^{Q_{\mathcal{A}}}(i) = Q_{\mathcal{A}}(X) - Q_{\mathcal{A}}(X_{-i}U_i).$$

In the example above, for a classifier $\mathcal{A}$, the quantity of interest, the fraction of women (represented by the set $\mathcal{W} \subseteq \mathcal{X}$) with positive classification, can be expressed as follows:

$$Q_{\mathcal{A}}(\cdot) = \mathbb{E}(\mathcal{A}(\cdot) = 1 \mid X \in \mathcal{W}),$$

and the influence of input i is:

$$\iota(i) = \mathbb{E}(\mathcal{A}(X) = 1 \mid X \in \mathcal{W}) - \mathbb{E}(\mathcal{A}(X_{-i}U_i) = 1 \mid X \in \mathcal{W}).$$

When $\mathcal{A}$ is clear from the context, we simply write Q rather than $Q_{\mathcal{A}}$. We now instantiate this definition with different quantities of interest to illustrate the above definition in three different scenarios.

A. QII for Individual Outcomes

One intended use of QII is to provide personalized transparency reports to users of data analytics systems. For example, if a person is denied a job application due to feedback from a machine learning algorithm, an explanation of which factors were most influential for that person's classification can provide valuable insight into the classification outcome.

For QII to quantify the use of an input for individual outcomes, we define the quantity of interest to be the classification outcome for a particular individual. Given a particular individual $\mathbf{x}$, we define $Q^{\mathbf{x}}_{\text{ind}}(\cdot)$ to be $\mathbb{E}(c(\cdot) = 1 \mid X = \mathbf{x})$. The influence measure is therefore:

$$\iota^{\mathbf{x}}_{\text{ind}}(i) = \mathbb{E}(c(X) = 1 \mid X = \mathbf{x}) - \mathbb{E}(c(X_{-i}U_i) = 1 \mid X = \mathbf{x}) \tag{3}$$

When the quantity of interest is not the probability of positive classification but the classification that $\mathbf{x}$ actually received, a slight modification of the above QII measure is more appropriate:

$$\begin{aligned}\iota^{\mathbf{x}}_{\text{ind-act}}(i) &= \mathbb{E}(c(X) = c(\mathbf{x}) \mid X = \mathbf{x}) \\ &\quad - \mathbb{E}(c(X_{-i}U_i) = c(\mathbf{x}) \mid X = \mathbf{x}) \\ &= 1 - \mathbb{E}(c(X_{-i}U_i) = c(\mathbf{x}) \mid X = \mathbf{x}) \\ &= \mathbb{E}(c(X_{-i}U_i) \neq c(\mathbf{x}) \mid X = \mathbf{x})\end{aligned} \tag{4}$$

The above probability can be interpreted as the probability that feature i is pivotal to the classification of $c(\mathbf{x})$. Computing the average of this quantity over X yields:

$$\begin{aligned}&\textstyle\sum_{\mathbf{x} \in \mathcal{X}} \Pr(X = \mathbf{x}) \mathbb{E}(i \text{ is pivotal for } c(X) \mid X = \mathbf{x}) \\ =\ & \mathbb{E}(i \text{ is pivotal for } c(X)).\end{aligned} \tag{5}$$

We denote this average QII for individual outcomes as defined above, by $\iota_{\text{ind-avg}}(i)$, and use it as a measure for importance of an input towards classification outcomes.

B. QII for Group Outcomes

As in the running example, the quantity of interest may be the classification outcome for a set of individuals. Given a group of individuals $\mathcal{Y} \subseteq \mathcal{X}$, we define $Q^{\mathcal{Y}}_{\text{grp}}(\cdot)$ to be $\mathbb{E}(c(\cdot) = 1 \mid X \in \mathcal{Y})$. The influence measure is therefore:

$$\iota^{\mathcal{Y}}_{\text{grp}}(i) = \mathbb{E}(c(X) = 1 \mid X \in \mathcal{Y}) - \mathbb{E}(c(X_{-i}U_i) = 1 \mid X \in \mathcal{Y}) \tag{6}$$

C. QII for Group Disparity

Instead of simply classification outcomes, an analyst may be interested in more nuanced properties of data analytics systems. Recently, disparate impact has come to the fore as a measure of unfairness, which compares the rates of positive classification within protected groups defined by gender or race. The '80% rule' in employment which states that the rate of selection within a protected demographic should be at least 80% of the rate of selection within the unprotected demographic. The quantity of interest in such a scenario is the ratio in positive classification outcomes for a protected group $\mathcal{Y}$ from the rest of the population $\mathcal{X} \setminus \mathcal{Y}$.

$$\frac{\mathbb{E}(c(X) = 1 \mid X \in \mathcal{Y})}{\mathbb{E}(c(X) = 1 \mid X \notin \mathcal{Y})}$$

However, the ratio of classification rates is unstable at at low values of positive classification. Therefore, for the computations in this paper we use the difference in classification rates as our measure of group disparity.

$$Q^{\mathcal{Y}}_{\text{disp}}(\cdot) = |\mathbb{E}(c(\cdot) = 1 \mid X \in \mathcal{Y}) - \mathbb{E}(c(\cdot) = 1 \mid X \notin \mathcal{Y})| \tag{7}$$

The QII measure of an input group disparity, as a result is:

$$\iota^{\mathcal{Y}}_{\text{disp}}(i) = Q^{\mathcal{Y}}_{\text{disp}}(X) - Q^{\mathcal{Y}}_{\text{disp}}(X_{-i}U_i). \tag{8}$$

More generally, group disparity can be viewed as an association between classification outcomes and membership in a group. QII on a measure of such association (e.g., group disparity) identifies the variable that causes the association in the classifier. *Proxy variables* are variables that are associated with protected attributes. However, for concerns of discrimination such as *digital redlining*, it is important to identify which proxy variables actually introduce group disparity. It is straightforward to observe that features with high QII for group disparity are proxy variables, and also cause group disparity. Therefore, QII on group disparity is a useful diagnostic tool for determining discriminiation. The use of QII in identifying proxy variables is explored experimentally in Section VII-B. Note that because of such proxy variables, simply ensuring that protected attributes are not input to the classifier is not sufficient to avoid discrimination (see also [12]).

III. Set and Marginal QII

In many situations, intervention on a single input variable has no influence on the outcome of a system. Consider, for example, a two-feature setting where features are age (A) and income (I), and the classifier is $c(A, I) = (A = \mathit{old}) \wedge (I = \mathit{high})$. In other words, the only datapoints that are labeled 1 are those of elderly persons with high income. Now, given a datapoint where $A = \mathit{young}, I = \mathit{low}$, an intervention on either age or income would result in the same classification. However, it would be misleading to say that neither age nor income have an influence over the outcome: changing both the states of income and age would result in a change in outcome.

Equating influence with the *individual* ability to affect the outcome is uninformative in real datasets as well: Figure 1 is a histogram of influences of features on outcomes of individuals for a classifier learnt from the adult dataset [13][2]. For most individuals, all features have zero influence: changing the state of one feature alone is not likely to change the outcome of a classifier. Of the 19537 datapoints we evaluate, more than half have $\iota^{\mathbf{x}}(i) = 0$ for all $i \in N$, Indeed, changes to outcome are more likely to occur if we intervene on *sets of features*. In order to get a better understanding of the influence of a feature $i \in N$, we should measure its effect when coupled with interventions on other features. We define the influence of a set of inputs as a straightforward extension of the influence of individual inputs. Essentially, we wish the influence of a set of inputs $S \subseteq N$ to be the same as when the set of inputs is considered to be a single input; when intervening on S, we draw the states of $i \in S$ based on the joint distribution of the states of features in S, $\pi_S(\mathbf{u}_S)$, as defined in Equation (1).

We can naturally define a distribution over $\mathcal{X} \times \prod_{i \in S} \mathcal{X}_i$, naturally extending (2) as:

$$\tilde{\pi}(\mathbf{x}, u_S) = \pi(\mathbf{x})\pi_S(\mathbf{u}_S). \tag{9}$$

We also define the random variable $X_{-S}U_S(\mathbf{x}, \mathbf{u}_S) = \mathbf{x}|_{N \setminus S}\mathbf{u}_S$; $X_{-S}(\mathbf{x}, \mathbf{u}_S)$ has the states of features in $N \setminus S$ fixed to their original values in $\mathbf{x}$, but features in S take on new values according to $\mathbf{u}_S$.

Definition 2 (Set QII)**.** For a quantity of interest Q, and an input i, the Quantitative Input Influence of set $S \subseteq N$ on Q is defined to be

$$\iota^Q(S) = Q(X) - Q(X_{-S}U_S).$$

Considering the influence of a set of inputs opens up a number of interesting questions due to the interaction between inputs. First among these is how does one measure the *individual effect* of a feature, given the measured effects of interventions on sets of features. One natural way of doing so is by measuring the *marginal effect* of a feature on a set.

[2] The adult dataset contains approximately 31k datapoints of users' personal attributes, and whether their income is more than $50k per annum; see Section VII for more details.

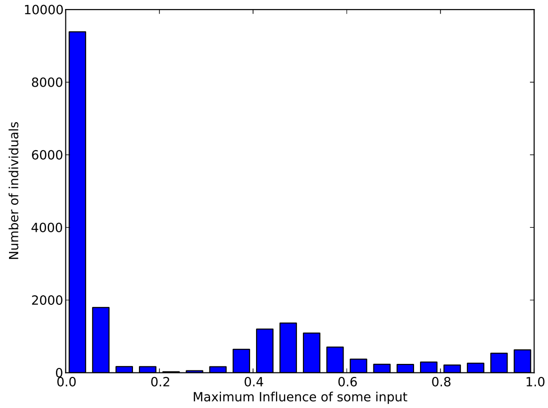


Fig. 1: A histogram of the highest specific causal influence for some feature across individuals in the adult dataset. Alone, most inputs alone have very low influence.

Definition 3 (Marginal QII)**.** For a quantity of interest Q, and an input i, the Quantitative Input Influence of input i over a set $S \subseteq N$ on Q is defined to be

$$\iota^Q(i, S) = Q(X_{-S}U_S) - Q(X_{-S\cup\{i\}}U_{S\cup\{i\}}).$$

Notice that marginal QII can also be viewed as a difference in set QIIs: $\iota^Q(S \cup \{i\}) - \iota^Q(S)$. Informally, the difference between $\iota^Q(S \cup \{i\})$ and $\iota^Q(S)$ measures the "added value" obtained by intervening on $S \cup \{i\}$, versus intervening on S alone.

The marginal contribution of i may vary significantly based on S. Thus, we are interested in the *aggregate marginal contribution* of i to S, where S is sampled from some natural distribution over subsets of $N \setminus \{i\}$. In what follows, we describe a few measures for aggregating the marginal contribution of a feature i to sets, based on different methods for sampling sets. The primary method of aggregating the marginal contribution is the Shapley value [14]. The less theoretically inclined reader can choose to proceed to Section V without a loss in continuity.

A. Cooperative Games and Causality

In this section, we discuss how measures from the theory of cooperative games define measures for aggregating marginal influence. In particular, we observe that the Shapley value [14] is characterized by axioms that are natural in our setting. However, other measures may be appropriate for certain input data generation processes.

Definition 2 measures the influence that an intervention on a set of features $S \subseteq N$ has on the outcome. One can naturally think of Set QII as a function $v : 2^N \to \mathbb{R}$, where $v(S)$ is the influence of S on the outcome. With this intuition in mind, one can naturally study influence measures using *cooperative game theory*, and in particular, prevalent influence measures in cooperative games such as the Shapley value, Banzhaf index and others. These measures can be thought of as *influence aggregation methods*, which, given an influence measure $v : 2^N \to \mathbb{R}$, output a vector $\phi \in \mathbb{R}^n$, whose i-th coordinate corresponds in some natural way to the aggregate influence, or aggregate causal effect, of feature i.

The original motivation for game-theoretic measures is *revenue division* [15, Chapter 18]: the function v describes the amount of money that each subset of players $S \subseteq N$ can generate; assuming that the set N generates a total revenue of $v(N)$, how should $v(N)$ be divided amongst the players? A special case of revenue division that has received significant attention is the measurement of voting power [16]. In voting systems with multiple agents with differing weights, voting power often does not directly correspond to the weights of the agents. For example, the US presidential election can roughly be modeled as a cooperative game where each state is an agent. The weight of a state is the number of electors in that state (i.e., the number of votes it brings to the presidential candidate who wins that state). Although states like California and Texas have higher weight, swing states like Pennsylvania and Ohio tend to have higher power in determining the outcome of elections.

A voting system is modeled as a cooperative game: players are voters, and the value of a coalition $S \subseteq N$ is 1 if S can make a decision (e.g. pass a bill, form a government, or perform a task), and is 0 otherwise. Note the similarity to classification, with players being replaced by features. The game-theoretic measures of revenue division are a measure of *voting power*: how much influence does player i have in the decision making process? Thus the notions of voting power and revenue division fit naturally with our goals when defining aggregate QII influence measures: in both settings, one is interested in measuring the aggregate effect that a single element has, given the actions of subsets.

A revenue division should ideally satisfy certain desiderata. Formally, we wish to find a function $\phi(N, v)$, whose input is N and $v : 2^N \to \mathbb{R}$, and whose output is a vector in $\mathbb{R}^n$, such that $\phi_i(N, v)$ measures some quantity describing the overall contribution of the i-th player. Research on fair revenue division in cooperative games traditionally follows an axiomatic approach: define a set of properties that a revenue division should satisfy, derive a function that outputs a value for each player, and argue that it is the unique function that satisfies these properties.

Several canonical fair cooperative solution concepts rely on the fundamental notion of *marginal contribution*. given a player i and a set $S \subseteq N \setminus \{i\}$, the marginal contribution of i to S is denoted $m_i(S, v) = v(S \cup \{i\}) - v(S)$ (we simply write $m_i(S)$ when v is clear from the context). Marginal QII, as defined above, can be viewed as an instance of a measure of marginal contribution. Given a permutation $\pi \in \Pi(N)$ of the elements in N, we define $P_i(\sigma) = \{j \in N \mid \sigma(j) < \sigma(i)\}$; this is the set of i's *predecessors* in σ. We can now similarly define the marginal contribution of i to a permutation $\sigma \in \Pi(N)$ as $m_i(\sigma) = m_i(P_i(\sigma))$. Intuitively, one can think of the players sequentially entering a room, according to some ordering σ; the value $m_i(\sigma)$ is the marginal contribution that i has to whoever is in the room when she enters it.

Generally speaking, game theoretic influence measures specify some reasonable way of aggregating the marginal contributions of i to sets $S \subseteq N$. That is, they measure a player's *expected marginal contribution* to sets sampled from some distribution $\mathcal{D}$ over 2^N, resulting in a payoff of

$$\mathbb{E}_{S \sim \mathcal{D}}[m_i(S)] = \sum_{S \subseteq N} \Pr_{\mathcal{D}}[S] m_i(S).$$

Thus, fair revenue division draws its appeal from the degree to which the distribution $\mathcal{D}$ is justifiable within the context where revenue is shared. In our setting, we argue for the use of the Shapley value. Introduced by the late Lloyd Shapley, the Shapley value is one of the most canonical methods of dividing revenue in cooperative games. It is defined as follows:

$$\varphi_i(N, v) = \mathbb{E}_\sigma[m_i(\sigma)] = \frac{1}{n!} \sum_{\sigma \in \Pi(N)} m_i(\sigma)$$

Intuitively, the Shapley value describes the following process: players are sequentially selected according to some randomly chosen order σ; each player receives a payment of $m_i(\sigma)$. The Shapley value is the expected payment to the players under this regime. The definition we use describes a distribution over permutations of N, not its subsets; however, it is easy to describe the Shapley value in terms of a distribution over subsets. If we define $p[S] = \frac{1}{n} \frac{1}{\binom{n-1}{|S|}}$, it is a simple exercise to show that

$$\varphi_i(N, v) = \sum_{S \subseteq N} p[S] m_i(S).$$

Intuitively, $p[S]$ describes the following process: first, choose a number $k \in [0, n-1]$ uniformly at random; next, choose a set of size k uniformly at random.

The Shapley value is one of many reasonable ways of measuring influence; we provide a detailed review of two others — the *Banzhaf index* [17], and the *Deegan-Packel index* [18] — in Appendix A.

B. Axiomatic Treatment of the Shapley Value

In this work, the Shapley value is our function of choice for aggregating marginal feature influence. The objective of this section is to justify our choice, and provide a brief exposition of axiomatic game-theoretic value theory. We present the axioms that define the Shapley value, and discuss how they apply in the QII setting. As we show, by requiring some desired properties, one arrives at a game-theoretic influence measure as the *unique* function for measuring information use in our setting.

The Shapley value satisfies the following properties:

Definition 4 (Symmetry (Sym))**.** We say that $i, j \in N$ are *symmetric* if $v(S \cup \{i\}) = v(S \cup \{j\})$ for all $S \subseteq N \setminus \{i, j\}$. A value ϕ satisfies *symmetry* if $\phi_i = \phi_j$ whenever i and j are symmetric.

Definition 5 (Dummy (Dum))**.** We say that a player $i \in N$ is a *dummy* if $v(S \cup \{i\}) = v(S)$ for all $S \subseteq N$. A value ϕ satisfies the *dummy* property if $\phi_i = 0$ whenever i is a dummy.

Definition 6 (Efficiency (Eff))**.** A value satisfies the *efficiency* property if $\sum_{i \in N} \phi_i = v(N)$.

All of these axioms take on a natural interpretation in the QII setting. Indeed, if two features have the same probabilistic effect, no matter what other interventions are already in place, they should have the same influence. In our context, the dummy axiom says that a feature that never offers information with respect to an outcome should have no influence. In the case of specific causal influence, the efficiency axiom simply states that the total amount of influence should sum to

$$\begin{aligned} &\Pr(c(X) = c(\mathbf{x}) \mid X = \mathbf{x}) - \Pr(c(X_{-N}) = c(\mathbf{x}) \mid X = \mathbf{x}) \\ =&1 - \Pr(c(X) = c(\mathbf{x})) = \Pr(c(X) \neq c(\mathbf{x})). \end{aligned}$$

That is, the total amount of influence possible is the likelihood of encountering elements whose evaluation is not $c(\mathbf{x})$. This is natural: if the vast majority of elements have a value of $c(\mathbf{x})$, it is quite unlikely that changes in features' state will have any effect on the outcome whatsoever; thus, the total amount of influence that can be assigned is $\Pr(c(X) \neq c(\mathbf{x}))$. Similarly, if the vast majority of points have a value different from $\mathbf{x}$, then it is likelier that a random intervention would result in a change in value, resulting in more influence to be assigned.

In the original paper by [14], it is shown that the Shapley value is the only function that satisfies (Sym), (Dum), (Eff), as well as the additivity (Add) axiom.

Definition 7 (Additivity (Add))**.** Given two games $\langle N, v_1 \rangle, \langle N, v_2 \rangle$, we write $\langle N, v_1 + v_2 \rangle$ to denote the game $v'(S) = v_1(S) + v_2(S)$ for all $S \subseteq N$. A value ϕ satisfies the *additivity* property if $\phi_i(N, v_1) + \phi_i(N, v_2) = \phi_i(N, v_1 + v_2)$ for all $i \in N$.

In our setting, the additivity axiom makes little intuitive sense; it would imply, for example, that if we were to multiply Q by a constant c, the influence of i in the resulting game should be multiplied by c as well, which is difficult to justify.

[19] offers an alternative characterization of the Shapley value, based on the more natural *monotonicity* assumption, which is a strong generalization of the dummy axiom.

Definition 8 (Monotonicity (Mono))**.** Given two games $\langle N, v_1 \rangle, \langle N, v_2 \rangle$, a value ϕ satisfies *strong monotonicity* if $m_i(S, v_1) \geq m_i(S, v_2)$ for all S implies that $\phi_i(N, v_1) \geq \phi_i(N, v_2)$, where a strict inequality for some set $S \subseteq N$ implies a strict inequality for the values as well.

Monotonicity makes intuitive sense in the QII setting: if a feature has consistently higher influence on the outcome in one setting than another, its measure of influence should increase. For example, if a user receives two transparency reports (say, for two separate loan applications), and in one report gender had a consistently higher effect on the outcome than in the other, then the transparency report should reflect this.

Theorem 9 ([19])**.** *The Shapley value is the only function that satisfies (Sym), (Eff) and (Mono).*

To conclude, the Shapley value is a *unique* way of measuring aggregate influence in the QII setting, while satisfying a set of very natural axioms.

IV. Transparency Schemas

We now discuss two generalizations of the definitions presented in Section II, and then define a transparency schema that map the space of transparency reports based on QII.

a) Intervention Distribution: In this paper we only consider randomized interventions when the interventions are drawn independently from the priors of the given input. However, depending on the specific causal question at hand, we may use different interventions. Formally, this is achieved by allowing an arbitrary intervention distribution π^{inter} such that

$$\tilde{\pi}(\mathbf{x}, \mathbf{u}) = \pi(\mathbf{x})\pi^{\text{inter}}(\mathbf{u}).$$

The subsequent definitions remain unchanged. One example of an intervention different from the randomized intervention considered in the rest of the paper is one held constant at a vector $\mathbf{x}_0$:

$$\pi^{\text{inter}}_{\mathbf{x}_0}(\mathbf{u}) = \begin{cases} 1 & \text{for } \mathbf{u} = \mathbf{x}_0 \\ 0 & \text{o.w.} \end{cases}$$

A QII measure defined on the constant intervention as defined above, measures the influence of being different from a default, where the default is represented by $\mathbf{x}_0$.

b) Difference Measure: A second generalization allows us to consider quantities of interest which are not real numbers. Consider, for example, the situation where the quantity of interest is an output probability distribution, as in the case in a randomized classifier. In this setting, a suitable measure for quantifying the distance between distributions can be used as a difference measure between the two quantities of interest. Examples of such difference measures include the KL-divergence [20] between distribution or distance metrics between vectors.

c) Transparency Schema: We now present a transparency schema that maps the space of transparency reports based on QII measures. It consists of the following elements:

- A *quantity of interest*, which captures the aspect of the system we wish to gain transparency into.
- An *intervention distribution*, which defines how a counterfactual distribution is constructed from the true distribution.
- A *difference measure*, which quantifies the difference between two quantities of interest.
- An *aggregation technique*, which combines marginal QII measures across different subsets of inputs (features).

For a given application, one has to appropriately instantiate this schema. We have described several instances of each schema element. The choices of the schema elements are guided by the particular causal question being posed. For instance, when the question is: "Which features are most important for group disparity?", the natural quantity of interest is a measure of group disparity, and the natural intervention distribution is using the prior as the question does not suggest a particular bias. On the other hand, when the question is: "Which features are most influential for person A's classification as opposed to person B?", a natural quantity of interest is person A's classification, and a natural intervention distribution is the constant intervention using the features of person B. A thorough exploration of other points in this design space remains an important direction for future work.

V. Estimation

While the model we propose offers several appealing properties, it faces several technical implementation issues. Several elements of our work require significant computational effort; in particular, both the probability that a change in feature state would cause a change in outcome, and the game-theoretic influence measures are difficult to compute exactly. In the following sections we discuss these issues and our proposed solutions.

A. Computing Power Indices

Computing the Shapley or Banzhaf values exactly is generally computationally intractable (see [21, Chapter 4] for a general overview); however, their probabilistic nature means that they can be well-approximated via random sampling. More formally, given a random variable X, suppose that we are interested in estimating some determined quantity $q(X)$ (say, $q(X)$ is the mean of X); we say that a random variable q^* is an ε-δ approximation of $q(X)$ if

$$\Pr[|q^* - q(X)| \geq \varepsilon] < \delta;$$

in other words, it is extremely likely that the difference between $q(X)$ and q^* is no more than ε. An *ε-δ approximation scheme* for $q(X)$ is an algorithm that for any $\varepsilon, \delta \in (0, 1)$ is able to output a random variable q^* that is an ε-δ approximation of $q(X)$, and runs in time polynomial in $\frac{1}{\varepsilon}, \log 1\delta$.

[22] show that when $\langle N, v\rangle$ is a *simple* game (i.e. a game where $v(S) \in \{0, 1\}$ for all $S \subseteq N$), there exists an ε-δ approximation scheme for both the Banzhaf and Shapley values; that is, for $\phi \in \{\varphi, \beta\}$, we can guarantee that for any $\varepsilon, \delta > 0$, with probability $\geq 1 - \delta$, we output a value ϕ_i^* such that $|\phi_i^* - \phi_i| < \varepsilon$.

More generally, [23] observe that the number of i.i.d. samples needed in order to approximate the Shapley value and Banzhaf index is parametrized in $\Delta(v) = \max_{S\subseteq N} v(S) - \min_{S\subseteq N} v(S)$. Thus, if $\Delta(v)$ is a bounded value, then an ε-δ approximation exists. In our setting, coalitional values are always within the interval $[0, 1]$, which immediately implies the following theorem.

Theorem 10. *There exists an ε-δ approximation scheme for the Banzhaf and Shapley values in the QII setting.*

B. Estimating Q

Since we do not have access to the prior generating the data, we simply estimate it by observing the dataset itself. Recall that $\mathcal{X}$ is the set of all possible user profiles; in this case, a dataset is simply a multiset (i.e. possibly containing multiple copies of user profiles) contained in $\mathcal{X}$. Let $\mathcal{D}$ be a finite multiset of $\mathcal{X}$, the input space. We estimate probabilities by computing sums over $\mathcal{D}$. For example, for a classifier c, the probability of $c(X)=1$.

$$\hat{\mathbb{E}}_{\mathcal{D}}(c(X)=1)=\frac{\sum_{\mathbf{x}\in\mathcal{D}}\mathbb{1}(c(\mathbf{x})=1)}{|\mathcal{D}|}. \tag{10}$$

Given a set of features $S\subseteq N$, let $\mathcal{D}|_S$ denote the elements of $\mathcal{D}$ truncated to only the features in S. Then, the intervened probability can be estimated as follows:

$$\hat{\mathbb{E}}_{\mathcal{D}}(c(X_{-S})=1)=\frac{\sum_{\mathbf{u}_S\in\mathcal{D}|_S}\sum_{\mathbf{x}\in\mathcal{D}}\mathbb{1}(c(\mathbf{x}|_{N\setminus S}\mathbf{u}_S)=1)}{|\mathcal{D}|^2}. \tag{11}$$

Similarly, the intervened probability on individual outcomes can be estimated as follows:

$$\hat{\mathbb{E}}_{\mathcal{D}}(c(X_{-S})=1|X=\mathbf{x})=\frac{\sum_{\mathbf{u}_S\in\mathcal{D}_S}\mathbb{1}(c(\mathbf{x}|_{N\setminus S}\mathbf{u}_S)=1)}{|\mathcal{D}|}. \tag{12}$$

Finally, let us observe group disparity:

$$\left|\hat{\mathbb{E}}_{\mathcal{D}}(c(X_{-S})=1\mid X\in\mathcal{Y})-\hat{\mathbb{E}}_{\mathcal{D}}(c(X_{-S})=1\mid X\notin\mathcal{Y})\right|$$

The term $\hat{\mathbb{E}}_{\mathcal{D}}(c(X_{-S})=1\mid X\in\mathcal{Y})$ equals

$$\frac{1}{|\mathcal{Y}|}\sum_{\mathbf{x}\in\mathcal{Y}}\sum_{\mathbf{u}_S\in\mathcal{D}_S}\mathbb{1}(c(\mathbf{x}|_{N\setminus S}\mathbf{u}_S)=1),$$

Thus group disparity can be written as:

$$\Big|\frac{1}{|\mathcal{Y}|}\sum_{\mathbf{x}\in\mathcal{Y}}\sum_{\mathbf{u}_S\in\mathcal{D}_S}\mathbb{1}(c(\mathbf{x}|_{N\setminus S}\mathbf{u}_S)=1) - \frac{1}{|\mathcal{D}\setminus\mathcal{Y}|}\sum_{\mathbf{x}\in\mathcal{D}\setminus\mathcal{Y}}\sum_{\mathbf{u}_S\in\mathcal{D}_S}\mathbb{1}(c(\mathbf{x}|_{N\setminus S}\mathbf{u}_S)=1)\Big|. \tag{13}$$

We write $\hat{Q}^{\mathcal{Y}}_{\text{disp}}(S)$ to denote (13).

If $\mathcal{D}$ is large, these sums cannot be computed efficiently. Therefore, we approximate the sums by sampling from the dataset $\mathcal{D}$. It is possible to show using the According to the Hoeffding bound [24], partial sums of n random variables X_i, within a bound Δ, can be well-approximated with the following probabilistic bound:

$$\Pr\left(\left|\frac{1}{n}\sum_{i=1}^{n}(X_i-\mathbb{E}X_i)\right|\geq\varepsilon\right)\leq 2\exp\left(\frac{-2n\varepsilon^2}{\Delta}\right)$$

Since all the samples of measures discussed in the paper are bounded within the interval $[0,1]$, we admit an ε-δ approximation scheme where the number of samples n can be chosen to be greater than $\log(2/\delta)/2\varepsilon^2$. Note that these bounds are independent of the size of the dataset. Therefore, given an efficient sampler, these quantities of interest can be approximated efficiently even for large datasets.

VI. Private Transparency Reports

One important concern is that releasing influence measures estimated from a dataset might leak information about individual users; our goal is providing accurate transparency reports, without compromising individual users' private data. To mitigate this concern, we add noise to make the measures differentially private. We show that the sensitivities of the QII measures considered in this paper are very low and therefore very little noise needs to be added to achieve differential privacy.

The *sensitivity* of a function is a key parameter in ensuring that it is differentially private; it is simply the worst-case change in its value, assuming that we change a single data point in our dataset. Given some function f over datasets, we define the sensitivity of a function f with respect to a dataset $\mathcal{D}$, denoted by $\Delta f(\mathcal{D})$ as

$$\max_{\mathcal{D}'}|f(\mathcal{D})-f(\mathcal{D}')|$$

where $\mathcal{D}$ and $\mathcal{D}'$ differ by at most one instance. We use the shorthand Δf when $\mathcal{D}$ is clear from the context.

In order to not leak information about the users used to compute the influence of an input, we use the standard Laplace Mechanism [8] and make the influence measure differentially private. The amount of noise required depends on the sensitivity of the influence measure. We show that the influence measure has low sensitivity for the individuals used to sample inputs. Further, due to a result from [9] (and stated in [25]), sampling amplifies the privacy of the computed statistic, allowing us to achieve high privacy with minimal noise addition.

The standard technique for making any function differentially private is to add Laplace noise calibrated to the sensitivity of the function:

Theorem 11 ([8])**.** *For any function f from datasets to $\mathbb{R}$, the mechanism $\mathcal{K}_f$ that adds independently generated noise with distribution $Lap(\Delta f(\mathcal{D})/\epsilon)$ to the k output enjoys ϵ-differential privacy.*

Since each of the quantities of interest aggregate over a large number of instances, the sensitivity of each function is very low.

Theorem 12. *Given a dataset $\mathcal{D}$,*

1) $\Delta\hat{\mathbb{E}}_{\mathcal{D}}(c(X)=1)=\frac{1}{|\mathcal{D}|}$
2) $\Delta\hat{\mathbb{E}}_{\mathcal{D}}(c(X_{-S})=1)\leq\frac{2}{|\mathcal{D}|}$
3) $\Delta\hat{\mathbb{E}}_{\mathcal{D}}(c(X_{-S})=1|X=\mathbf{x})=\frac{1}{|\mathcal{D}|}$
4) $\hat{Q}^{\mathcal{Y}}_{disp}(S)\leq\max\left\{\frac{1}{|\mathcal{D}\cap\mathcal{Y}|},\frac{1}{|\mathcal{D}\setminus\mathcal{Y}|}\right\}$

Proof. We examine some cases here. In Equation 10, if two datasets differ by one instance, then at most one term of the summation will differ. Since each term can only be either 0 or 1, the sensitivity of the function is

$$\Delta\hat{\mathbb{E}}_{\mathcal{D}}(c(X)=1)=\left|\frac{0}{|\mathcal{D}|}-\frac{1}{|\mathcal{D}|}\right|=\frac{1}{|\mathcal{D}|}.$$

Similarly, in Equation 11, an instance appears $2|\mathcal{D}| - 1$ times, once each for the inner summation and the outer summation, and therefore, the sensitivity of the function is

$$\Delta\hat{\mathbb{E}}_{\mathcal{D}}(c(X_{-S}) = 1) = \frac{2|\mathcal{D}| - 1}{|\mathcal{D}|^2} \leq \frac{2}{|\mathcal{D}|}.$$

For individual outcomes (Equation (12)), similarly, only one term of the summation can differ. Therefore, the sensitivity of (12) is $1/|\mathcal{D}|$.

Finally, we observe that a change in a single element $\mathbf{x}'$ of $\mathcal{D}$ will cause a change of at most $\frac{1}{|\mathcal{D}\cap\mathcal{Y}|}$ if $\mathbf{x}' \in \mathcal{D} \cap \mathcal{Y}$, or of at most $\frac{1}{|\mathcal{D}\setminus\mathcal{Y}|}$ if $\mathbf{x}' \in \mathcal{D} \setminus \mathcal{Y}$. Thus, the maximal change to (13) is at most $\max\left\{\frac{1}{|\mathcal{Y}|}, \frac{1}{|\mathcal{D}\setminus\mathcal{Y}|}\right\}$.

□

While the sensitivity of most quantities of interest is low (at most a $\frac{2}{|\mathcal{D}|}$), $\hat{Q}^{\mathcal{Y}}_{\text{disp}}(S)$ can be quite high when $|\mathcal{Y}|$ is either very small or very large. This makes intuitive sense: if $\mathcal{Y}$ is a very small minority, then any changes to its members are easily detected; similarly, if $\mathcal{Y}$ is a vast majority, then changes to protected minorities may be easily detected.

We observe that the quantities of interest which exhibit low sensitivity will have low influence sensitivity as well: for example, the local influence of S is $\mathbb{1}(c(\mathbf{x}) = 1) - \hat{\mathbb{E}}_{\mathcal{D}}(c(X_{-S}) = 1] \mid X = \mathbf{x})$; changing any $\mathbf{x}' \in \mathcal{D}$ (where $\mathbf{x}' \neq \mathbf{x}$ will result in a change of at most $\frac{1}{|\mathcal{D}|}$ to the local influence.

Finally, since the Shapley and Banzhaf indices are normalized sums of the differences of the set influence functions, we can show that if an influence function ι has sensitivity $\Delta\iota$, then the sensitivity of the indices are at most $2\Delta\iota$.

To conclude, all of the QII measures discussed above (except for group parity) have a sensitivity of $\frac{\alpha}{|\mathcal{D}|}$, with α being a small constant. To ensure differential privacy, we need only need add noise with a Laplacian distribution $\text{Lap}(k/|\mathcal{D}|)$ to achieve 1-differential privacy.

Further, it is known that sampling amplifies differential privacy.

Theorem 13 ([9], [25])**.** *If $\mathcal{A}$ is 1-differentially private, then for any $\epsilon \in (0, 1)$, $\mathcal{A}'(\epsilon)$ is 2ϵ-differentially private, where $\mathcal{A}'(\epsilon)$ is obtained by sampling an ϵ fraction of inputs and then running $\mathcal{A}$ on the sample.*

Therefore, our approach of sampling instances from $\mathcal{D}$ to speed up computation has the additional benefit of ensuring that our computation is private.

Table I contains a summary of all QII measures defined in this paper, and their sensitivity.

VII. Experimental Evaluation

We demonstrate the utility of the QII framework by developing two simple machine learning applications on real datasets. Using these applications, we first argue, in Section VII-A, the need for causal measurement by empirically demonstrating that in the presence of correlated inputs, observational measures are not informative in identifying which inputs were actually used. In Section VII-B, we illustrate the distinction between different quantities of interest on which Unary QII can be computed. We also illustrate the effect of discrimination on the QII measure. In Section VII-C, we analyze transparency reports of three individuals to demonstrate how Marginal QII can provide insights into individuals' classification outcomes. Finally, we analyze the loss in utility due to the use of differential privacy, and provide execution times for generating transparency reports using our prototype implementation.

We use the following datasets in our experiments:

- `adult` [10]: This standard machine learning benchmark dataset is a a subset of US census data that classifies the income of individuals, and contains factors such as age, race, gender, marital status and other socio-economic parameters. We use this dataset to train a classifier that predicts the income of individuals from other parameters. Such a classifier could potentially be used to assist credit decisions.
- `arrests` [11]: The National Longitudinal Surveys are a set of surveys conducted by the Bureau of Labor Statistics of the United States. In particular, we use the National Longitudinal Survey of Youth 1997 which is a survey of young men and women born in the years 1980-84. Respondents were ages 12-17 when first interviewed in 1997 and were subsequently interviewed every year till 2013. The survey covers various aspects of an individual's life such as medical history, criminal records and economic parameters. From this dataset, we extract the following features: age, gender, race, region, history of drug use, history of smoking, and history of arrests. We use this data to train a classifier that predicts history of arrests to aid in predictive policing, where socio-economic factors are used to decide whether individuals should receive a visit from the police. This application is inspired by a similar application in [26].

The two applications described above are hypothetical examples of decision-making aided by machine learning that use potentially sensitive socio-economic data about individuals, and not real systems that are currently in use. We use these classifiers to illustrate the subtle causal questions that our QII measures can answer.

We use the following standard machine learning classifiers in our dataset: Logistic Regression, SVM with a radial basis function kernel, Decision Tree, and Gradient Boosted Decision Trees. Bishop's machine learning text [27] is an excellent resource for an introduction to these classifiers. While Logistic Regression is a linear classifier, the other three are nonlinear and can potentially learn very complex models. All our experiments are implemented in Python with the numpy library, and the scikit-learn machine learning toolkit, and run on an Intel i7 computer with 4 GB of memory.

A. Comparison with Observational Measures

In the presence of correlated inputs, observational measures often cannot identify which inputs were causally influential. To illustrate this phenomena on real datasets, we train two

Name	Notation	Quantity of Interest	Sensitivity
QII on Individual Outcomes (3)	$\iota_{\text{ind}}(S)$	Positive Classification of an Individual	$1/\|\mathcal{D}\|$
QII on Actual Individual Outcomes (4)	$\iota_{\text{ind-act}}(S)$	Actual Classification of an Individual	$1/\|\mathcal{D}\|$
Average QII (5)	$\iota_{\text{ind-avg}}(S)$	Average Actual Classification	$2/\|\mathcal{D}\|$
QII on Group Outcomes (6)	$\iota^{\mathcal{Y}}_{\text{grp}}(S)$	Positive Classification for a Group	$2/\|\mathcal{D} \cap \mathcal{Y}\|$
QII on Group Disparity (8)	$\iota^{\mathcal{Y}}_{\text{disp}}(S)$	Difference in classification rates among groups	$2\max(1/\|\mathcal{D} \setminus \mathcal{Y}\|, 1/\|\mathcal{D} \cap \mathcal{Y}\|)$

TABLE I: A summary of the QII measures defined in the paper

classifiers: (A) where gender is provided as an actual input, and (B) where gender is not provided as an input. For classifier (B), clearly the input *Gender* has no effect and any correlation between the outcome and gender is caused via inference from other inputs. In Table II, for both the `adult` and the `arrests` dataset, we compute the following observational measures: Mutual Information (MI), Jaccard Index (Jaccard), Pearson Correlation (corr), and the Disparate Impact Ratio (disp) to measure the similarity between Gender and the classifiers outcome. We also measure the QII of Gender on outcome. We observe that in many scenarios the observational quantities do not change, or sometimes increase, from classifier A to classifier B, when gender is removed as an actual input to the classifier. On the other hand, if the outcome of the classifier does not depend on the input *Gender*, then the QII is guaranteed to be zero.

B. Unary QII Measures

In Figure 2, we illustrate the use of different Unary QII measures. Figures 2a, and 2b, show the Average QII measure (Equation 5) computed for features of a decision forest classifier. For the income classifier trained on the `adult` dataset, the feature with highest influence is *Marital Status*, followed by *Occupation*, *Relationship* and *Capital Gain*. Sensitive features such as *Gender* and *Race* have relatively lower influence. For the predictive policing classifier trained on the `arrests` dataset, the most influential input is *Drug History*, followed by *Gender*, and *Smoking History*. We observe that influence on outcomes may be different from influence on group disparity.

QII on group disparity: Figures 2c, 2d show influences of features on group disparity for two different settings. The figure on the left shows the influence of features on group disparity by Gender in the `adult` dataset; the figure on the right shows the influence of group disparity by Race in the `arrests` dataset. For the income classifier trained on the `adult` dataset, we observe that most inputs have negative influence on group disparity; randomly intervening on most inputs would lead to a reduction in group disparity. In other words, a classifier that did not use these inputs would be fairer. Interestingly, in this classifier, marital status and not sex has the highest influence on group disparity by sex.

For the `arrests` dataset, most inputs have the effect of increasing group disparity if randomly intervened on. In particular, *Drug history* has the highest positive influence on disparity in `arrests`. Although Drug history is correlated with race, using it reduces disparate impact by race, i.e. makes fairer decisions.

In both examples, features correlated with the sensitive attribute are the most influential for group disparity according to the sensitive attribute instead of the sensitive attribute itself. It is in this sense that QII measures can identify proxy variables that cause associations between outcomes and sensitive attributes.

QII with artificial discrimination: We simulate discrimination using an artificial experiment. We first randomly assign ZIP codes to individuals in our dataset. Then to simulate systematic bias, we make an f fraction of the ZIP codes discriminatory in the following sense: All individuals in the protected set are automatically assigned a negative classification outcome. We then study the change in the influence of features as we increase f. Figure 3a, shows that the influence of *Gender* increases almost linearly with f. Recall that *Marital Status* was the most influential feature for this classifier without any added discrimination. As f increases, the importance of *Marital Status* decreases as expected, since the number of individuals for whom *Marital Status* is pivotal decreases.

C. Personalized Transparency Reports

To illustrate the utility of personalized transparency reports, we study the classification of individuals who received potentially unexpected outcomes. For the personalized transparency reports, we use decision forests.

The influence measure that we employ is the Shapley value, with the underlying cooperative game defined over the local influence Q. In more detail, $v(S) = \iota^{Q_{\mathcal{A}}}(S)$, with $Q_{\mathcal{A}}$ being $\mathbb{E}[c(\cdot) = 1 \mid X = \mathbf{x}]$; that is, the marginal contribution of $i \in N$ to S is given by $m_i(S) = \mathbb{E}[c(X_{-S}) = 1 \mid X = \mathbf{x}] - \mathbb{E}[c(X_{-S\cup\{i\}}) = 1 \mid X = \mathbf{x}]$.

We emphasize that some features may have a negative Shapley value; this should be interpreted as follows: a feature with a high positive Shapley value often increases the certainty that the classification outcome is 1, whereas a feature whose Shapley value is negative is one that increases the certainty that the classification outcome would be zero.

Mr. X: The first example is of an individual from the `adult` dataset, who we refer to as Mr. X, and is described in Figure 4a. He is is deemed to be a low income individual, by an income classifier learned from the data. This result may be surprising to him: he reports high capital gains ($14k), and only 2.1% of people with capital gains higher than $10k are reported as low income. In fact, he might be led to believe that his classification may be a result of his ethnicity or country of origin. Examining his transparency report in Figure 4b, however, we find that the the most influential features that led

		logistic		kernel svm		decision tree		random forest	
		`adult`	`arrests`	`adult`	`arrests`	`adult`	`arrests`	`adult`	`arrests`
MI	A	0.045	0.049	0.046	0.047	0.043	0.054	0.044	0.053
MI	B	0.043	0.050	0.044	0.053	0.042	0.051	0.043	0.052
Jaccard	A	0.501	0.619	0.500	0.612	0.501	0.614	0.501	0.620
Jaccard	B	0.500	0.611	0.501	0.615	0.500	0.614	0.501	0.617
corr	A	0.218	0.265	0.220	0.247	0.213	0.262	0.218	0.262
corr	B	0.215	0.253	0.218	0.260	0.215	0.257	0.215	0.259
disp	A	0.286	0.298	0.377	0.033	0.302	0.335	0.315	0.223
disp	B	0.295	0.301	0.312	0.096	0.377	0.228	0.302	0.129
QII	A	0.036	0.135	0.044	0.149	0.023	0.116	0.012	0.109
QII	B	0	0	0	0	0	0	0	0

TABLE II: Comparison of QII with associative measures. For 4 different classifiers, we compute metrics such as Mutual Information (MI), Jaccard Index (JI), Pearson Correlation (corr), Group Disparity (disp) and Average QII between Gender and the outcome of the learned classifier. Each metric is computed in two situations: (A) when Gender is provided as an input to the classifier, and (B) when Gender is not provided as an input to the classifier.

to his negative classification were Marital Status, Relationship and Education.

Mr. Y: The second example, to whom we refer as Mr. Y (Figure 5), has even higher capital gains than Mr. X. Mr. Y is a 27 year old, with only Preschool education, and is engaged in fishing. Examination of the transparency report reveals that the most influential factor for negative classification for Mr. Y is his Occupation. Interestingly, his low level of education is not considered very important by this classifier.

Mr. Z: The third example, who we refer to as Mr. Z (Figure 6) is from the `arrests` dataset. History of drug use and smoking are both strong indicators of arrests. However, Mr. X received positive classification by this classifier even without any history of drug use or smoking. On examining his classifier, it appears that race, age and gender were most influential in determining his outcome. In other words, the classifier that we train for this dataset (a decision forest) has picked up on the correlations between race (Black), and age (born in 1984) to infer that this individual is likely to engage in criminal activity. Indeed, our interventional approach indicates that this is not a mere correlation effect: race is actively being used by this classifier to determine outcomes. Of course, in this instance, we have explicitly offered the race parameter to our classifier as a viable feature. However, our influence measure is able to pick up on this fact, and alert us of the problematic behavior of the underlying classifier. More generally, this example illustrates a concern with the black box use of machine learning which can lead to unfavorable outcomes for individuals.

D. Differential Privacy

Most QII measures considered in this paper have very low sensitivity, and therefore can be made differentially private with negligible loss in utility. However, recall that the sensitivity of influence measure on group disparity $\iota^{\mathcal{Y}}_{\text{disp}}$ depends on the size of the protected group in the dataset $\mathcal{D}$ as follows:

$$\iota^{\mathcal{Y}}_{\text{disp}} = 2\max\left(\frac{1}{|\mathcal{D}\setminus\mathcal{Y}|}, \frac{1}{|\mathcal{D}\cap\mathcal{Y}|}\right)$$

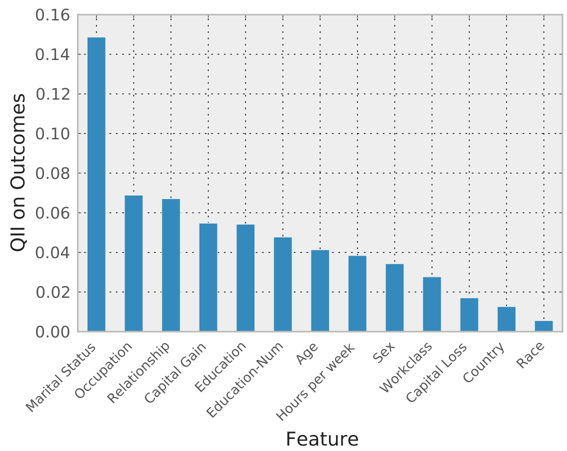
For sufficiently small minority groups, a large amount of noise might be required to ensure differential privacy, leading to a loss in utility of the QII measure. To estimate the loss in utility, we set a noise of 0.005 as the threshold of noise at which the measure is no longer useful, and then compute fraction of times noise crosses that threshold when Laplacian noise is added at $\epsilon = 1$. The results of this experiment are as follows:

$\mathcal{Y}$	Count	Loss in Utility
Race: White	27816	2.97×10^{-14}
Race: Black	3124	5.41×10^{-14}
Race: Asian-Pac-Islander	1039	6.14×10^{-05}
Race: Amer-Indian-Eskimo	311	0.08
Race: Other	271	0.13
Gender: Male	21790	3.3×10^{-47}
Gender: Female	10771	3.3×10^{-47}

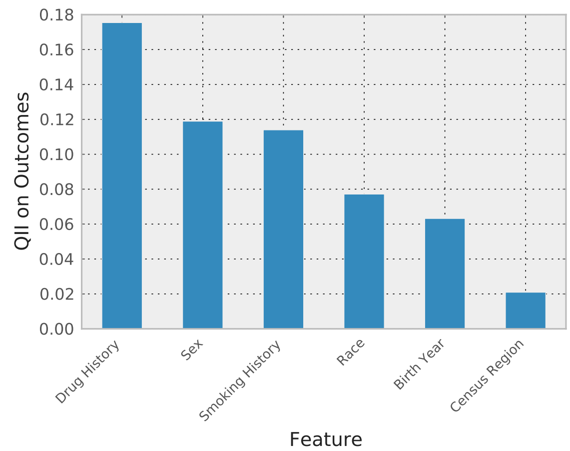
We note that for most reasonably sized groups, the loss in utility is negligible. However, the Asian-Pac-Islander, and the Amer-Indian-Eskimo racial groups are underrepresented in this dataset. For these groups, the QII on Group Disparity estimate needs to be very noisy to protect privacy.

E. Performance

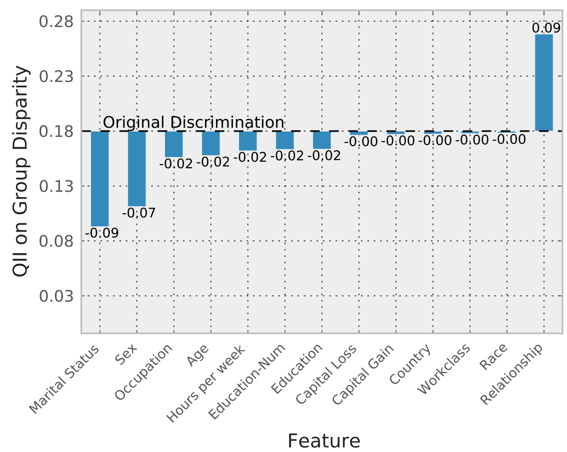
We report runtimes of our prototype for generating transparency reports on the `adult` dataset. Recall from Section VI that we approximate QII measures by computing sums over samples of the dataset. According to the Hoeffding bound to derive an (ϵ, δ) estimate of a QII measure, at $\epsilon = 0.01$, and $n = 37000$ samples, $\delta = 2\exp(-n\epsilon^2) < 0.05$ is an upper bound on the probability of the output being off by ϵ. Table III shows the runtimes of four different QII computations, for 37000 samples each. The runtimes of all algorithms except for kernel SVM are fast enough to allow real-time feedback for machine learning application developers. Evaluating QII metrics for Kernel SVMs is much slower than the other metrics because each call to the SVM classifier is very computationally intensive due to a large number of distance computations that it entails. We expect that these runtimes can be optimized significantly. We present them as proof of tractability.



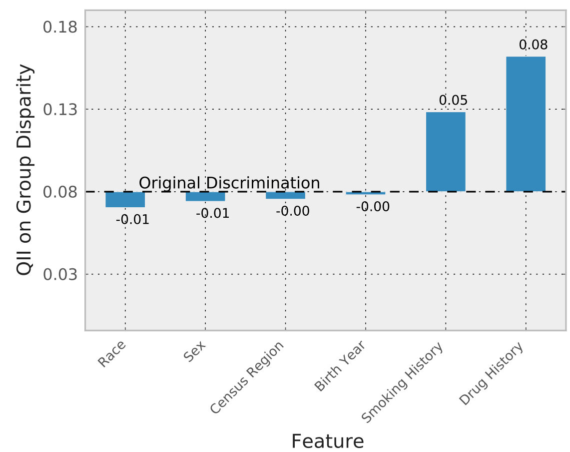
(a) QII of inputs on Outcomes for the `adult` dataset



(b) QII of inputs on Outcomes for the `arrests` dataset



(c) QII of Inputs on Group Disparity by Sex in the `adult` dataset



(d) Influence on Group Disparity by Race in the `arrests` dataset

Fig. 2: QII measures for the `adult` and `arrests` datasets

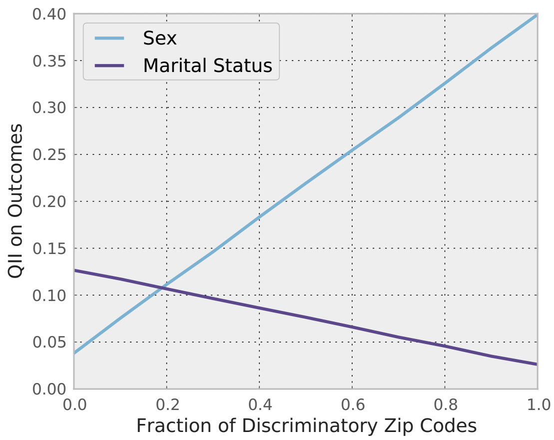
	logistic	kernel-svm	decision-tree	decision-forest
QII on Group Disparity	0.56	234.93	0.57	0.73
Average QII	0.85	322.82	0.77	1.12
QII on Individual Outcomes (Shapley)	6.85	2522.3	7.78	9.30
QII on Individual Outcomes (Banzhaf)	6.77	2413.3	7.64	10.34

TABLE III: Runtimes in seconds for transparency report computation

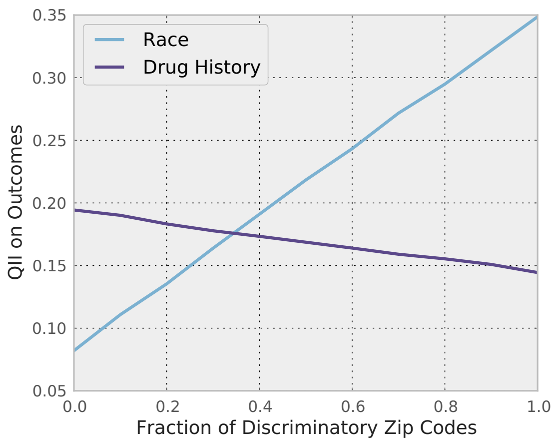
VIII. Discussion

A. *Probabilistic Interpretation of Power Indices*

In order to quantitatively measure the influence of data inputs on classification outcomes, we propose causal interventions on sets of features; as we argue in Section III, the aggregate marginal influence of i for different subsets of features is a natural quantity representing its influence. In order to aggregate the various influences i has on the outcome, it is natural to define some probability distribution over (or equivalently, a weighted sum of) subsets of $N \setminus \{i\}$, where $\Pr[S]$ represents the probability of measuring the marginal contribution of i to S; $\Pr[S]$ yields a value $\sum_{S \subseteq N \setminus \{i\}} m_i(S)$. For the Banzhaf index, we have $\Pr[S] = \frac{1}{2^{n-1}}$, the Shapley value has $\Pr[S] = \frac{k!(n-k-1)!}{n!}$ (here, $|S| = k$), and the Deegan-Packel Index selects minimal winning coalitions uniformly at random. These choices of values for $\Pr[S]$ are based on some natural assumptions on the way that players (features) interact, but they are by no means exhaustive. One can define other sampling methods that are more appropriate for the model at hand; for example, it is entirely possible that the only interventions that are possible in a certain setting are of size $\leq k + 1$, it is reasonable to aggregate the marginal influence



(a) Change in QII of inputs as discrimination by Zip Code increases in the `adult` dataset

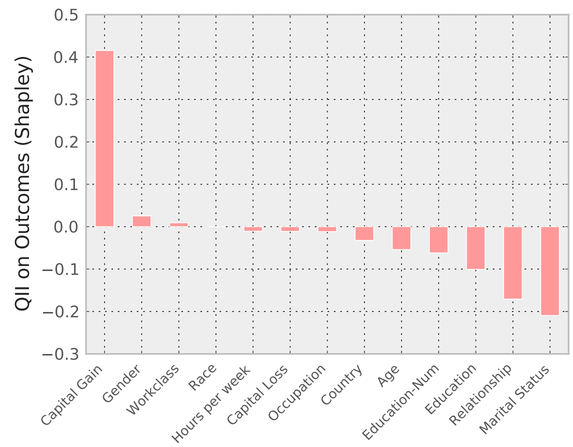


(b) Change in QII of inputs as discrimination by Zip Code increases in the `arrests` dataset

Fig. 3: The effect of discrimination on QII.

Age	23
Workclass	Private
Education	11th
Education-Num	7
Marital Status	Never-married
Occupation	Craft-repair
Relationship	Own-child
Race	Asian-Pac-Islander
Gender	Male
Capital Gain	14344
Capital Loss	0
Hours per week	40
Country	Vietnam

(a) Mr. X's profile



(b) Transparency report for Mr. X's negative classification

Fig. 4: Mr. X

of i over sets of size $\leq k$, i.e.

$$\Pr[S] = \begin{cases} \frac{1}{\binom{n-1}{|S|}} & \text{if } |S| \leq k \\ 0 & \text{otherwise.} \end{cases}$$

The key point here is that one must define *some* aggregation method, and that choice reflects some normative approach on how (and which) marginal contributions are considered. The Shapley and Banzhaf indices do have some highly desirable properties, but they are, first and foremost, *a-priori* measures of influence. That is, they do not factor in any assumptions on what interventions are possible or desirable.

One natural candidate for a probability distribution over S is some natural extension of the prior distribution over the dataset; for example, if all features are binary, one can identify a set with a feature vector (namely by identifying each $S \subseteq N$ with its indicator vector), and set $\Pr[S] = \pi(S)$ for all $S \subseteq N$. If features are not binary, then there is no canonical way to transition from the data prior to a prior over subsets of features.

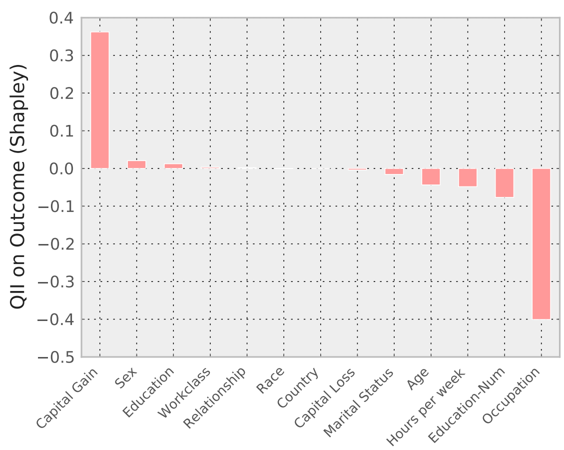
B. *Fairness*

Due to the widespread and black box use of machine learning in aiding decision making, there is a legitimate concern of algorithms introducing and perpetuating social harms such as racial discrimination [28], [6]. As a result, the algorithmic foundations of fairness in personal information processing systems have received significant attention recently [29], [30], [31], [12], [32]. While many of of the algorithmic approaches [29], [31], [32] have focused on group parity as a metric for achieving fairness in classification, Dwork et al. [12] argue that group parity is insufficient as a basis for fairness, and propose a similarity-based approach which prescribes that similar individuals should receive similar classification outcomes. However, this approach requires a similarity metric for individuals which is often subjective and difficult to construct.

QII does not suggest any normative definition of fairness. Instead, we view QII as a diagnostic tool to aid fine-grained fairness determinations. In fact, QII can be used in the spirit of the similarity based definition of [12]. By comparing the personalized privacy reports of individuals who are *perceived*

Age	27
Workclass	Private
Education	Preschool
Education-Num	1
Marital Status	Married-civ-spouse
Occupation	Farming-fishing
Relationship	Other-relative
Race	White
Gender	Male
Capital Gain	41310
Capital Loss	0
Hours per week	24
Country	Mexico

(a) Mr. Y's profile

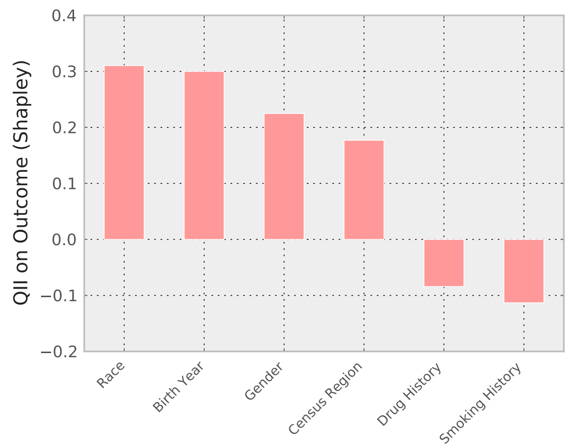


(b) Transparency report for Mr. Y's negative classification

Fig. 5: Mr. Y.

Birth Year	1984
Drug History	None
Smoking History	None
Census Region	West
Race	Black
Gender	Male

(a) Mr. Z's profile



(b) Transparency report for Mr. Z's positive classification

Fig. 6: Mr. Z.

to be similar but received different classification outcomes, and identifying the inputs which were used by the classifier to provide different outcomes. Additionally, when group parity is used as a criteria for fairness, QII can identify the features that lead to group disparity, thereby identifying features being used by a classifier as a proxy for sensitive attributes.

The determination of whether using certain proxies for sensitive attributes is discriminatory is often a task-specific normative judgment. For example, using standardized test scores (e.g., SAT scores) for admissions decisions is by and large accepted, although SAT scores may be a proxy for several protected attributes. In fact, several universities have recently announced that they will not use SAT scores for admissions citing this reason [33], [34]. Our goal is not to provide such normative judgments. Rather we seek to provide fine-grained transparency into input usage (e.g., what's the extent to which SAT scores influence decisions), which is useful to make determinations of discrimination from a specific normative position.

Finally, we note that an interesting question is whether providing a sensitive attribute as an input to a classifier is fundamentally discriminatory behavior, even if QII can show that the sensitive input has no significant impact on the outcome. Our view is that this is a policy question and different legal frameworks might take different viewpoints on it. At a technical level, from the standpoint of information use, the two situations are identical: the sensitive input is not really used although it is supplied. However, the very fact that it was supplied might be indicative of an intent to discriminate even if that intended goal was not achieved. No matter what the policy decision is on this question, QII remains a useful diagnostic tool for discrimination because of the presence of proxy variables as described earlier.

IX. Related Work

A. *Quantitative Causal Measures*

Causal models and probabilistic interventions have been used in a few other settings. While the form of the interventions in some of these settings may be very similar, our generalization to account for different quantities of interests enables us to reason about a large class of transparency queries for data analytics systems ranging from classification outcomes of individuals to disparity among groups. Further, the notion of marginal contribution which we use to compute responsibility does not appear in this line of prior work.

Janzing et al. [35] use interventions to assess the causal importance of relations between variables in causal graphs; in order to assess the causal effect of a relation between two variables, $X \to Y$ (assuming that both take on specific values $X = x$ and $Y = y$), a new causal model is constructed, where the value of X is replaced with a prior over the possible values of X. The influence of the causal relation is defined as the KL-

Divergence of the joint distribution of all the variables in the two causal models with and without the value of X replaced. The approach of the intervening with a random value from the prior is similar to our approach of constructing X_{-S}.

Independently, there has been considerable work in the machine learning community to define importance metrics for variables, mainly for the purpose of feature selection (see [36] for a comprehensive overview). One important metric is called Permutation Importance [37], which measures the importance of a feature towards classification by randomly permuting the values of the feature and then computing the difference of classification accuracies before and after the permutation. Replacing a feature with a random permutation can be viewed as a sampling the feature independently from the prior.

There exists extensive literature on establishing causal relations, as opposed to quantifying them. Prominently, Pearl's work [38] provides a mathematical foundation for causal reasoning and inference. In [39], Tian and Pearl discuss measures of causal strength for individual binary inputs and outputs in a probabilistic setting. Another thread of work by Halpern and Pearl discusses actual causation [40], which is extended in [41] to derive a measure of responsibility as degree of causality. In [41], Chockler and Halpern define the responsibility of a variable X to an outcome as the amount of change required in order to make X the counterfactual cause. As we discuss in Appendix A-B, the Deegan-Packel index is strongly related to causal responsibility.

B. *Quantitative Information Flow*

One can think of our results as a causal alternative to *quantitative information flow*. Quantitative information flow is a broad class of metrics that quantify the information leaked by a process by comparing the *information* contained before and after observing the outcome of the process. Quantitative Information Flow traces its information-theoretic roots to the work of Shannon [42] and Rényi [43]. Recent works have proposed measures for quantifying the security of information by measuring the amount of information leaked from inputs to outputs by certain variables; we point the reader to [44] for an overview, and to [45] for an exposition on information theory. Quantitative Information Flow is concerned with information leaks and therefore needs to account for correlations between inputs that may lead to leakage. The dual problem of transparency, on the other hand, requires us to destroy correlations while analyzing the outcomes of a system to identify the causal paths for information leakage.

C. *Interpretable Machine Learning*

An orthogonal approach to adding interpretability to machine learning is to constrain the choice of models to those that are interpretable by design. This can either proceed through regularization techniques such as Lasso [46] that attempt to pick a small subset of the most important features, or by using models that structurally match human reasoning such as Bayesian Rule Lists [47], Supersparse Linear Integer Models [48], or Probabilistic Scaling [49]. Since the choice of models in this approach is restricted, a loss in predictive accuracy is a concern, and therefore, the central focus in this line of work is the minimization of the loss in accuracy while maintaining interpretability. On the other hand, our approach to interpretability is forensic. We add interpretability to machine learning models after they have been learnt. As a result, our approach does not constrain the choice of models that can be used.

D. *Experimentation on Web Services*

There is an emerging body of work on systematic experimentation to enhance transparency into Web services such as targeted advertising [50], [51], [52], [53], [54]. The setting in this line of work is different since they have restricted access to the analytics systems through publicly available interfaces. As a result they only have partial control of inputs, partial observability of outputs, and little or no knowledge of input distributions. The intended use of these experiments is to enable external oversight into Web services without any cooperation. Our framework is more appropriate for a transparency mechanism where an entity proactively publishes transparency reports for individuals and groups. Our framework is also appropriate for use as an internal or external oversight tool with access to mechanisms with control and knowledge of input distributions, thereby forming a basis for testing.

E. *Game-Theoretic Influence Measures*

Recent years have seen game-theoretic influence measures used in various settings. Datta et al. [55] also define a measure for quantifying feature influence in classification tasks. Their measure does not account for the prior on the data, nor does it use interventions that break correlations between sets of features. In the terminology of this paper, the quantity of interest used by [55] is the ability of changing the outcome by changing the state of a feature. This work greatly extends and generalizes the concepts presented in [55], by both accounting for interventions on sets, and by generalizing the notion of influence to include a wide range of system behaviors, such as group disparity, group outcomes and individual outcomes.

Game theoretic measures have been used by various research disciplines to measure influence. Indeed, such measures are relevant whenever one is interested in measuring the marginal contribution of variables, and when sets of variables are able to cause some measurable effect. Lindelauf et al. [56] and Michalak et al. [57] use game theoretic influence measures on graph-based games in order to identify key members of terrorist networks. Del Pozo et al. [58] and Michalak et al. [59] use similar ideas for identifying important members of large social networks, providing scalable algorithms for influence computation. Bork et al. [60] use the Shapley value to assign importance to protein interactions in large, complex biological interaction networks; Keinan et al. [61] employ the Shapley value in order to measure causal effects in neurophysical models. The novelty in our use of the game theoretic power indices lies in the conception of a cooperative game via a valuation function $\iota(S)$, defined by an randomized intervention on inputs S. Such an intervention breaks correlations and allows us to compute marginal causal influences on a wide range of system behaviors.

X. Conclusion & Future Work

In this paper, we present QII, a general family of metrics for quantifying the influence of inputs in systems that process personal information. In particular, QII lends insights into the behavior of opaque machine learning algorithms by allowing us to answer a wide class of transparency queries ranging from influence on individual causal outcomes to influence on disparate impact. To achieve this, QII breaks correlations between inputs to allow causal reasoning, and computes the marginal influence of inputs in situations where inputs cannot affect outcomes alone. Also, we demonstrate that QII can be efficiently approximated, and can be made differentially private with negligible noise addition in many cases.

An immediate next step in this line of work is to explore adoption strategies in the many areas that use personal information to aid decision making. Areas such as healthcare [3], predictive policing [1], education [4], and defense [5] all have a particularly acute need for transparency in their decision making. It is likely that specific applications will guide us in our choice of a QII metric that is appropriate for that scenario, which includes a choice for our game-theoretic power index.

We have not considered situations where inputs do not have well understood semantics. Such situations arise often in settings such as image or speech recognition, and automated video surveillance. With the proliferation of immense processing power, complex machine learning models such as deep neural networks have become ubiquitous in these domains. Defining transparency and developing analysis techniques in such settings is important future work.

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Appendix A
Alternative Game-Theoretic Influence Measures

In what follows, we describe two alternatives to the Shapley value used in this work. The Shapley value makes intuitive sense in our setting, as we argue in Section III-B. However, other measures may be appropriate for certain input data generation processes. In what follows we revisit the Banzhaf index, briefly discussed in Section III-A, and introduce the readers to the *Deegan-Packel index*, a game-theoretic influence measure with deep connections to a formal theory of responsibilty and blame [41].

A. The Banzhaf Index

Recall that the Banzhaf index, denoted $\beta_i(N, v)$ is defined as follows:

$$\beta_i(N, v) = \frac{1}{2^{n-1}} \sum_{S \subseteq N \setminus \{i\}} m_i(S).$$

The Banzhaf index can be thought of as follows: each $j \in N \setminus \{i\}$ will join a work effort with probability $\frac{1}{2}$ (or, equivalently, each $S \subseteq N \setminus \{i\}$ has an equal chance of forming); if i joins as well, then its expected marginal contribution to the set formed is exactly the Banzhaf index. Note the marked difference between the probabilistic models: under the Shapley value, we sample *permutations* uniformly at random, whereas under the regime of the Banzhaf index, we sample sets uniformly at random. The different sampling protocols reflect different normative assumptions. For one, the Banzhaf index is not guaranteed to be efficient; that is, $\sum_{i \in N} \beta_i(N, v)$ is not necessarily equal to $v(N)$, whereas it is always the case that $\sum_{i=1}^{n} \varphi_i(N, v) = v(N)$. Moreover, the Banzhaf index is more biased towards measuring the marginal contribution of i to sets of size $\frac{n}{2} \pm O(\sqrt{n})$; this is because the expected size of a randomly selected set follows a binomial distribution $B(n, \frac{1}{2})$. On the other hand, the Shapley value is equally likely to measure the marginal contribution of i to sets of any size $k \in \{0, \dots, k\}$, as i is equally likely to be in any one position in a randomly selected permutation σ (and, in particular, the the set of i's predecessors in σ is equally likely to have any size $k \in \{0, \dots, n-1\}$).

Going back to the QII setting, the difference in sampling procedure is not merely an interesting anecdote: it is a significant modeling choice. Intuitively, the Banzhaf index is more appropriate if we assume that large sets of features would have a significant influence on outcomes, whereas the Shapley value is more appropriate if we assume that even small sets of features might cause significant effects on the outcome. Indeed, as we mention in Section VIII, aggregating the marginal influence of i over sets is a significant modeling choice; while using the measures proposed here is perfectly reasonable in many settings, other aggregation methods may be applicable in others.

Unlike the Shapley value, the Banzhaf index is not guaranteed to be efficient (although it does satisfy the symmetry and dummy properties). Indeed, [62] shows that replacing the efficiency axiom with an alternative axiom, uniquely characterizes the Banzhaf index; the axiom, called *2-efficiency*, prescribes the behavior of an influence measure when two players merge. First, let us define a *merged game*; given a game $\langle N, v \rangle$, and two players $i, j \in N$, we write $T = \{i, j\}$. We define the game $\bar{v}$ on $N \setminus T \cup \{\bar{t}\}$ as follows: for every set $S \subseteq N \setminus \{i, j\}$, $\bar{v}(S) = v(S)$, and $\bar{v}(S \cup \{\bar{t}\}) = v(S \cup \{i, j\})$, note that the added player $\bar{t}$ represents the two players i and j who are now acting as one. The 2-Efficiency axiom states that influence should be invariant under merges.

Definition 14 (2-Efficiency (2-EFF))**.** Given two players $i, j \in N$, let $\bar{v}$ be the game resulting from the merge of i and j into a single player $\bar{t}$; an influence measure ϕ satisfies 2-Efficiency if $\phi_i(N, v) + \phi_j(N, v) = \phi_{\bar{t}}(N \setminus \{i, j\} \cup \{\bar{t}\}, \bar{v})$.

Theorem 15 ([62])**.** *The Banzhaf index is the only function to satisfy (Sym), (D), (Mono) and (2-EFF).*

In our context, 2-Efficiency can be interpreted as follows: suppose that we artificially treat two features i and j as one, keeping all other parameters fixed; in this setting, 2-efficiency means that the influence of merged features equals the influence they had as separate entities.

B. The Deegan-Packel Index

Finally, we discuss the *Deegan-Packel index* [18]. While the Shapley value and Banzhaf index are well-defined for any coalitional game, the Deegan-Packel index is only defined for *simple games*. A cooperative game is said to be simple if $v(S) \in \{0, 1\}$ for all $S \subseteq N$. In our setting, an influence measure would correspond to a simple game if it is binary (e.g. it measures some threshold behavior, or corresponds to a binary classifier). The binary requirement is rather strong; however, we wish to draw the reader's attention to the Deegan-Packel index, as it has an interesting connection to *causal responsibility* [41], a variant of the classic Pearl-Halpern causality model [40], which aims to measure the degree to which a single variable causes an outcome.

Given a simple game $v : 2^N \to \{0, 1\}$, let $\mathcal{M}(v)$ be the set of *minimal winning coalitions*; that is, for every $S \in \mathcal{M}(v)$, $v(S) = 1$, and $v(T) = 0$ for every strict subset of S. The Deegan-Packel index assigns a value of

$$\delta_i(N, v) = \frac{1}{|\mathcal{M}(v)|} \sum_{S \in \mathcal{M}(v) : i \in S} \frac{1}{|S|}.$$

The intuition behind the Deegan-Packel index is as follows: players will not form coalitions any larger than what they absolutely have to in order to win, so it does not make sense to measure their effect on non-minimal winning coalitions. Furthermore, when a minimal winning coalition is formed, the benefits from its formation are divided equally among its members; in particular, small coalitions confer a greater benefit for those forming them than large ones. The Deegan-Packel index measures the expected payment one receives, assuming that every minimal winning coalition is equally likely to form. Interestingly, the Deegan-Packel index corresponds nicely to the notion of responsibility and blame described in [41].

Suppose that we have a set of variables $X_1, \ldots, X_n$ set to $x_1, \ldots, x_n$, and some binary effect $f(x_1, \ldots, x_n)$ (written as $f(\mathbf{x})$) occurs (say, $f(\mathbf{x}) = 1$). To establish a causal relation between the setting of X_i to x_i and $f(\mathbf{x}) = 1$, [40] require that there is some set $S \subseteq N \setminus \{i\}$ and some values $(y_j)_{j \in S \cup \{i\}}$ such that $f(\mathbf{x}_{-S \cup \{i\}}, (y_j)_{j \in S \cup \{i\}}) = 0$, but $f(\mathbf{x}_{-S}, (y_j)_{j \in S}) = 1$. In words, an intervention on the values of both S and i may cause a change in the value of f, but performing the same intervention just on the variables in S would not cause such a change. This definition is at the heart of the marginal contribution approach to interventions that we describe in Section III-A. [41] define the responsibility of i for an outcome as $\frac{1}{k+1}$, where k is the size of the smallest set S for which the causality definition holds with respect to i. The Deegan-Packel index can thus be thought of as measuring a similar notion: instead of taking the overall minimal number of changes necessary in order to make i a direct, counterfactual cause, we observe all minimal sets that do so. Taking the average responsibility of i (referred to as *blame* in [41]) according to this variant, we obtain the Deegan-Packel index.

Example 16. Let us examine the following setup, based on Example 3.3 in [41]. There are $n = 2k + 1$ voters (n is an odd number) who must choose between two candidates, Mr. B and Mr. G ([41] describe the setting with $n = 11$). All voters elected Mr. B, resulting in an n-0 win. It is natural to ask: how responsible was voter i for the victory of Mr. B? According to [41], the degree of responsibility of each voter is $\frac{1}{k+1}$. It will require that i and k additional voters change their vote in order for the outcome to change. Modeling this setup as a cooperative game is quite natural: the voters are the players $N = \{1, \ldots, n\}$; for every subset $S \subseteq N$ we have

$$v(S) = \begin{cases} 1 & \text{if } |S| \geq k + 1 \\ 0 & \text{otherwise.} \end{cases}$$

That is, $v(S) = 1$ if and only if the set S can change the outcome of the election. The minimal winning coalitions here are the subsets of N of size $k + 1$, thus the Deegan-Packel index of player i is

$$\begin{aligned} \delta_i(N, v) &= \frac{1}{|\mathcal{M}(v)|} \sum_{S \in \mathcal{M}(v) : i \in S} \frac{1}{|S|} \\ &= \frac{1}{\binom{n}{k+1}} \binom{n}{k} \frac{1}{k+1} = \frac{1}{n-k} = \frac{1}{k+1} \end{aligned}$$

We note that if one assumes that all voters are equally likely to prefer Mr. B over Mr. G, then the blame of voter i would be computed in the exact manner as the Deegan-Packel index.

A Unified Approach to Interpreting Model Predictions

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Abstract

Understanding why a model makes a certain prediction can be as crucial as the prediction's accuracy in many applications. However, the highest accuracy for large modern datasets is often achieved by complex models that even experts struggle to interpret, such as ensemble or deep learning models, creating a tension between *accuracy* and *interpretability*. In response, various methods have recently been proposed to help users interpret the predictions of complex models, but it is often unclear how these methods are related and when one method is preferable over another. To address this problem, we present a unified framework for interpreting predictions, SHAP (SHapley Additive exPlanations). SHAP assigns each feature an importance value for a particular prediction. Its novel components include: (1) the identification of a new class of additive feature importance measures, and (2) theoretical results showing there is a unique solution in this class with a set of desirable properties. The new class unifies six existing methods, notable because several recent methods in the class lack the proposed desirable properties. Based on insights from this unification, we present new methods that show improved computational performance and/or better consistency with human intuition than previous approaches.

1 Introduction

The ability to correctly interpret a prediction model's output is extremely important. It engenders appropriate user trust, provides insight into how a model may be improved, and supports understanding of the process being modeled. In some applications, simple models (e.g., linear models) are often preferred for their ease of interpretation, even if they may be less accurate than complex ones. However, the growing availability of big data has increased the benefits of using complex models, so bringing to the forefront the trade-off between accuracy and interpretability of a model's output. A wide variety of different methods have been recently proposed to address this issue [5, 8, 9, 3, 4, 1]. But an understanding of how these methods relate and when one method is preferable to another is still lacking.

Here, we present a novel unified approach to interpreting model predictions.[1] Our approach leads to three potentially surprising results that bring clarity to the growing space of methods:

1. We introduce the perspective of viewing *any* explanation of a model's prediction as a model itself, which we term the *explanation model*. This lets us define the class of *additive feature attribution methods* (Section 2), which unifies six current methods.

[1] https://github.com/slundberg/shap

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2. We then show that game theory results guaranteeing a unique solution apply to the *entire class* of additive feature attribution methods (Section 3) and propose *SHAP values* as a unified measure of feature importance that various methods approximate (Section 4).

3. We propose new SHAP value estimation methods and demonstrate that they are better aligned with human intuition as measured by user studies and more effectually discriminate among model output classes than several existing methods (Section 5).

2 Additive Feature Attribution Methods

The best explanation of a simple model is the model itself; it perfectly represents itself and is easy to understand. For complex models, such as ensemble methods or deep networks, we cannot use the original model as its own best explanation because it is not easy to understand. Instead, we must use a simpler *explanation model*, which we define as any interpretable approximation of the original model. We show below that six current explanation methods from the literature all use the same explanation model. This previously unappreciated unity has interesting implications, which we describe in later sections.

Let f be the original prediction model to be explained and g the explanation model. Here, we focus on *local methods* designed to explain a prediction $f(x)$ based on a single input x, as proposed in LIME [5]. Explanation models often use *simplified inputs* x' that map to the original inputs through a mapping function $x = h_x(x')$. Local methods try to ensure $g(z') \approx f(h_x(z'))$ whenever $z' \approx x'$. (Note that $h_x(x') = x$ even though x' may contain less information than x because h_x is specific to the current input x.)

Definition 1 Additive feature attribution methods *have an explanation model that is a linear function of binary variables:*

$$g(z') = \phi_0 + \sum_{i=1}^{M} \phi_i z'_i, \tag{1}$$

where $z' \in \{0, 1\}^M$, M is the number of simplified input features, and $\phi_i \in \mathbb{R}$.

Methods with explanation models matching Definition 1 attribute an effect ϕ_i to each feature, and summing the effects of all feature attributions approximates the output $f(x)$ of the original model. Many current methods match Definition 1, several of which are discussed below.

2.1 LIME

The *LIME* method interprets individual model predictions based on locally approximating the model around a given prediction [5]. The local linear explanation model that LIME uses adheres to Equation 1 exactly and is thus an additive feature attribution method. LIME refers to simplified inputs x' as "interpretable inputs," and the mapping $x = h_x(x')$ converts a binary vector of interpretable inputs into the original input space. Different types of h_x mappings are used for different input spaces. For bag of words text features, h_x converts a vector of 1's or 0's (present or not) into the original word count if the simplified input is one, or zero if the simplified input is zero. For images, h_x treats the image as a set of super pixels; it then maps 1 to leaving the super pixel as its original value and 0 to replacing the super pixel with an average of neighboring pixels (this is meant to represent being missing).

To find ϕ, LIME minimizes the following objective function:

$$\xi = \underset{g \in \mathcal{G}}{\arg\min} \; L(f, g, \pi_{x'}) + \Omega(g). \tag{2}$$

Faithfulness of the explanation model $g(z')$ to the original model $f(h_x(z'))$ is enforced through the loss L over a set of samples in the simplified input space weighted by the local kernel $\pi_{x'}$. Ω penalizes the complexity of g. Since in LIME g follows Equation 1 and L is a squared loss, Equation 2 can be solved using penalized linear regression.

2.2 DeepLIFT

DeepLIFT was recently proposed as a recursive prediction explanation method for deep learning [8, 7]. It attributes to each input x_i a value $C_{\Delta x_i \Delta y}$ that represents the effect of that input being set to a reference value as opposed to its original value. This means that for DeepLIFT, the mapping $x = h_x(x')$ converts binary values into the original inputs, where 1 indicates that an input takes its original value, and 0 indicates that it takes the reference value. The reference value, though chosen by the user, represents a typical uninformative background value for the feature.

DeepLIFT uses a "summation-to-delta" property that states:

$$\sum_{i=1}^{n} C_{\Delta x_i \Delta o} = \Delta o, \tag{3}$$

where $o = f(x)$ is the model output, $\Delta o = f(x) - f(r)$, $\Delta x_i = x_i - r_i$, and r is the reference input. If we let $\phi_i = C_{\Delta x_i \Delta o}$ and $\phi_0 = f(r)$, then DeepLIFT's explanation model matches Equation 1 and is thus another additive feature attribution method.

2.3 Layer-Wise Relevance Propagation

The *layer-wise relevance propagation* method interprets the predictions of deep networks [1]. As noted by Shrikumar et al., this menthod is equivalent to DeepLIFT with the reference activations of all neurons fixed to zero. Thus, $x = h_x(x')$ converts binary values into the original input space, where 1 means that an input takes its original value, and 0 means an input takes the 0 value. Layer-wise relevance propagation's explanation model, like DeepLIFT's, matches Equation 1.

2.4 Classic Shapley Value Estimation

Three previous methods use classic equations from cooperative game theory to compute explanations of model predictions: Shapley regression values [4], Shapley sampling values [9], and Quantitative Input Influence [3].

Shapley regression values are feature importances for linear models in the presence of multicollinearity. This method requires retraining the model on all feature subsets $S \subseteq F$, where F is the set of all features. It assigns an importance value to each feature that represents the effect on the model prediction of including that feature. To compute this effect, a model $f_{S\cup\{i\}}$ is trained with that feature present, and another model f_S is trained with the feature withheld. Then, predictions from the two models are compared on the current input $f_{S\cup\{i\}}(x_{S\cup\{i\}}) - f_S(x_S)$, where x_S represents the values of the input features in the set S. Since the effect of withholding a feature depends on other features in the model, the preceding differences are computed for all possible subsets $S \subseteq F \setminus \{i\}$. The Shapley values are then computed and used as feature attributions. They are a weighted average of all possible differences:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} \left[f_{S\cup\{i\}}(x_{S\cup\{i\}}) - f_S(x_S) \right]. \tag{4}$$

For Shapley regression values, h_x maps 1 or 0 to the original input space, where 1 indicates the input is included in the model, and 0 indicates exclusion from the model. If we let $\phi_0 = f_\varnothing(\varnothing)$, then the Shapley regression values match Equation 1 and are hence an additive feature attribution method.

Shapley sampling values are meant to explain any model by: (1) applying sampling approximations to Equation 4, and (2) approximating the effect of removing a variable from the model by integrating over samples from the training dataset. This eliminates the need to retrain the model and allows fewer than $2^{|F|}$ differences to be computed. Since the explanation model form of Shapley sampling values is the same as that for Shapley regression values, it is also an additive feature attribution method.

Quantitative input influence is a broader framework that addresses more than feature attributions. However, as part of its method it independently proposes a sampling approximation to Shapley values that is nearly identical to Shapley sampling values. It is thus another additive feature attribution method.

3 Simple Properties Uniquely Determine Additive Feature Attributions

A surprising attribute of the class of additive feature attribution methods is the presence of a single unique solution in this class with three desirable properties (described below). While these properties are familiar to the classical Shapley value estimation methods, they were previously unknown for other additive feature attribution methods.

The first desirable property is *local accuracy*. When approximating the original model f for a specific input x, local accuracy requires the explanation model to at least match the output of f for the simplified input x' (which corresponds to the original input x).

Property 1 (Local accuracy)

$$f(x) = g(x') = \phi_0 + \sum_{i=1}^{M} \phi_i x'_i \tag{5}$$

The explanation model $g(x')$ matches the original model $f(x)$ when $x = h_x(x')$, where $\phi_0 = f(h_x(\mathbf{0}))$ represents the model output with all simplified inputs toggled off (i.e. missing).

The second property is *missingness*. If the simplified inputs represent feature presence, then missingness requires features missing in the original input to have no impact. All of the methods described in Section 2 obey the missingness property.

Property 2 (Missingness)

$$x'_i = 0 \implies \phi_i = 0 \tag{6}$$

Missingness constrains features where $x'_i = 0$ to have no attributed impact.

The third property is *consistency*. Consistency states that if a model changes so that some simplified input's contribution increases or stays the same regardless of the other inputs, that input's attribution should not decrease.

Property 3 (Consistency) *Let $f_x(z') = f(h_x(z'))$ and $z' \setminus i$ denote setting $z'_i = 0$. For any two models f and f', if*

$$f'_x(z') - f'_x(z' \setminus i) \geq f_x(z') - f_x(z' \setminus i) \tag{7}$$

for all inputs $z' \in \{0,1\}^M$, then $\phi_i(f', x) \geq \phi_i(f, x)$.

Theorem 1 *Only one possible explanation model g follows Definition 1 and satisfies Properties 1, 2, and 3:*

$$\phi_i(f, x) = \sum_{z' \subseteq x'} \frac{|z'|!(M - |z'| - 1)!}{M!} \left[f_x(z') - f_x(z' \setminus i) \right] \tag{8}$$

where $|z'|$ is the number of non-zero entries in z', and $z' \subseteq x'$ represents all z' vectors where the non-zero entries are a subset of the non-zero entries in x'.

Theorem 1 follows from combined cooperative game theory results, where the values ϕ_i are known as Shapley values [6]. Young (1985) demonstrated that Shapley values are the only set of values that satisfy three axioms similar to Property 1, Property 3, and a final property that we show to be redundant in this setting (see Supplementary Material). Property 2 is required to adapt the Shapley proofs to the class of additive feature attribution methods.

Under Properties 1-3, for a given simplified input mapping h_x, Theorem 1 shows that there is only one possible additive feature attribution method. This result implies that methods not based on Shapley values violate local accuracy and/or consistency (methods in Section 2 already respect missingness). The following section proposes a unified approach that improves previous methods, preventing them from unintentionally violating Properties 1 and 3.

4 SHAP (SHapley Additive exPlanation) Values

We propose SHAP values as a unified measure of feature importance. These are the Shapley values of a conditional expectation function of the original model; thus, they are the solution to Equation

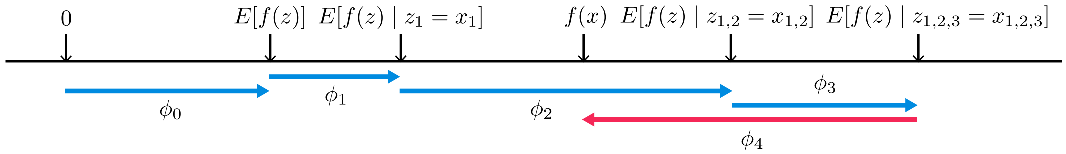

Figure 1: SHAP (SHapley Additive exPlanation) values attribute to each feature the change in the expected model prediction when conditioning on that feature. They explain how to get from the base value $E[f(z)]$ that would be predicted if we did not know any features to the current output $f(x)$. This diagram shows a single ordering. When the model is non-linear or the input features are not independent, however, the order in which features are added to the expectation matters, and the SHAP values arise from averaging the ϕ_i values across all possible orderings.

8, where $f_x(z') = f(h_x(z')) = E[f(z) \mid z_S]$, and S is the set of non-zero indexes in z' (Figure 1). Based on Sections 2 and 3, SHAP values provide the unique additive feature importance measure that adheres to Properties 1-3 and uses conditional expectations to define simplified inputs. Implicit in this definition of SHAP values is a simplified input mapping, $h_x(z') = z_S$, where z_S has missing values for features not in the set S. Since most models cannot handle arbitrary patterns of missing input values, we approximate $f(z_S)$ with $E[f(z) \mid z_S]$. This definition of SHAP values is designed to closely align with the Shapley regression, Shapley sampling, and quantitative input influence feature attributions, while also allowing for connections with LIME, DeepLIFT, and layer-wise relevance propagation.

The exact computation of SHAP values is challenging. However, by combining insights from current additive feature attribution methods, we can approximate them. We describe two model-agnostic approximation methods, one that is already known (Shapley sampling values) and another that is novel (Kernel SHAP). We also describe four model-type-specific approximation methods, two of which are novel (Max SHAP, Deep SHAP). When using these methods, feature independence and model linearity are two optional assumptions simplifying the computation of the expected values (note that $\bar{S}$ is the set of features not in S):

$$\begin{aligned} f(h_x(z')) &= E[f(z) \mid z_S] && \text{SHAP explanation model simplified input mapping} && (9) \\ &= E_{z_{\bar{S}} \mid z_S}[f(z)] && \text{expectation over } z_{\bar{S}} \mid z_S && (10) \\ &\approx E_{z_{\bar{S}}}[f(z)] && \text{assume feature independence (as in [9, 5, 7, 3])} && (11) \\ &\approx f([z_S, E[z_{\bar{S}}]]). && \text{assume model linearity} && (12) \end{aligned}$$

4.1 Model-Agnostic Approximations

If we assume feature independence when approximating conditional expectations (Equation 11), as in [9, 5, 7, 3], then SHAP values can be estimated directly using the Shapley sampling values method [9] or equivalently the Quantitative Input Influence method [3]. These methods use a sampling approximation of a permutation version of the classic Shapley value equations (Equation 8). Separate sampling estimates are performed for each feature attribution. While reasonable to compute for a small number of inputs, the Kernel SHAP method described next requires fewer evaluations of the original model to obtain similar approximation accuracy (Section 5).

Kernel SHAP (Linear LIME + Shapley values)

Linear LIME uses a linear explanation model to locally approximate f, where local is measured in the simplified binary input space. At first glance, the regression formulation of LIME in Equation 2 seems very different from the classical Shapley value formulation of Equation 8. However, since linear LIME is an additive feature attribution method, we know the Shapley values are the only possible solution to Equation 2 that satisfies Properties 1-3 – local accuracy, missingness and consistency. A natural question to pose is whether the solution to Equation 2 recovers these values. The answer depends on the choice of loss function L, weighting kernel $\pi_{x'}$ and regularization term Ω. The LIME choices for these parameters are made heuristically; using these choices, Equation 2 does not recover the Shapley values. One consequence is that local accuracy and/or consistency are violated, which in turn leads to unintuitive behavior in certain circumstances (see Section 5).

Below we show how to avoid heuristically choosing the parameters in Equation 2 and how to find the loss function L, weighting kernel $\pi_{x'}$, and regularization term Ω that recover the Shapley values.

Theorem 2 (Shapley kernel) *Under Definition 1, the specific forms of $\pi_{x'}$, L, and Ω that make solutions of Equation 2 consistent with Properties 1 through 3 are:*

$$\Omega(g) = 0,$$

$$\pi_{x'}(z') = \frac{(M-1)}{(M\ choose\ |z'|)|z'|(M-|z'|)},$$

$$L(f, g, \pi_{x'}) = \sum_{z' \in Z} \left[f(h_x(z')) - g(z')\right]^2 \pi_{x'}(z'),$$

where $|z'|$ is the number of non-zero elements in z'.

The proof of Theorem 2 is shown in the Supplementary Material.

It is important to note that $\pi_{x'}(z') = \infty$ when $|z'| \in \{0, M\}$, which enforces $\phi_0 = f_x(\varnothing)$ and $f(x) = \sum_{i=0}^{M} \phi_i$. In practice, these infinite weights can be avoided during optimization by analytically eliminating two variables using these constraints.

Since $g(z')$ in Theorem 2 is assumed to follow a linear form, and L is a squared loss, Equation 2 can still be solved using linear regression. As a consequence, the Shapley values from game theory can be computed using weighted linear regression.[2] Since LIME uses a simplified input mapping that is equivalent to the approximation of the SHAP mapping given in Equation 12, this enables regression-based, model-agnostic estimation of SHAP values. Jointly estimating all SHAP values using regression provides better sample efficiency than the direct use of classical Shapley equations (see Section 5).

The intuitive connection between linear regression and Shapley values is that Equation 8 is a difference of means. Since the mean is also the best least squares point estimate for a set of data points, it is natural to search for a weighting kernel that causes linear least squares regression to recapitulate the Shapley values. This leads to a kernel that distinctly differs from previous heuristically chosen kernels (Figure 2A).

4.2 Model-Specific Approximations

While Kernel SHAP improves the sample efficiency of model-agnostic estimations of SHAP values, by restricting our attention to specific model types, we can develop faster model-specific approximation methods.

Linear SHAP

For linear models, if we assume input feature independence (Equation 11), SHAP values can be approximated directly from the model's weight coefficients.

Corollary 1 (Linear SHAP) *Given a linear model $f(x) = \sum_{j=1}^{M} w_j x_j + b$: $\phi_0(f, x) = b$ and*

$$\phi_i(f, x) = w_j(x_j - E[x_j])$$

This follows from Theorem 2 and Equation 11, and it has been previously noted by Štrumbelj and Kononenko [9].

Low-Order SHAP

Since linear regression using Theorem 2 has complexity $O(2^M + M^3)$, it is efficient for small values of M if we choose an approximation of the conditional expectations (Equation 11 or 12).

[2] During the preparation of this manuscript we discovered this parallels an equivalent constrained quadratic minimization formulation of Shapley values proposed in econometrics [2].

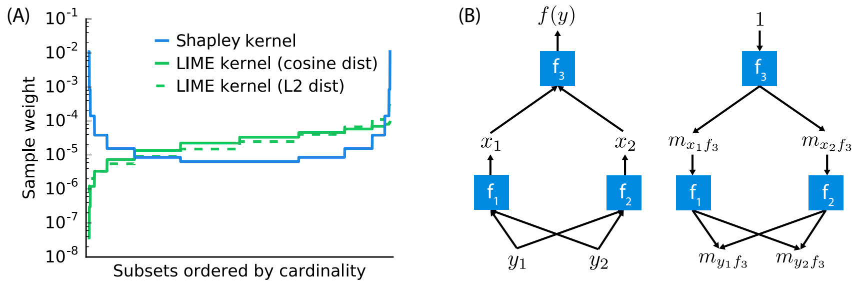

Figure 2: (A) The Shapley kernel weighting is symmetric when all possible z' vectors are ordered by cardinality there are 2^{15} vectors in this example. This is distinctly different from previous heuristically chosen kernels. (B) Compositional models such as deep neural networks are comprised of many simple components. Given analytic solutions for the Shapley values of the components, fast approximations for the full model can be made using DeepLIFT's style of back-propagation.

Max SHAP

Using a permutation formulation of Shapley values, we can calculate the probability that each input will increase the maximum value over every other input. Doing this on a sorted order of input values lets us compute the Shapley values of a max function with M inputs in $O(M^2)$ time instead of $O(M2^M)$. See Supplementary Material for the full algorithm.

Deep SHAP (DeepLIFT + Shapley values)

While Kernel SHAP can be used on any model, including deep models, it is natural to ask whether there is a way to leverage extra knowledge about the compositional nature of deep networks to improve computational performance. We find an answer to this question through a previously unappreciated connection between Shapley values and DeepLIFT [8]. If we interpret the reference value in Equation 3 as representing $E[x]$ in Equation 12, then DeepLIFT approximates SHAP values assuming that the input features are independent of one another and the deep model is linear. DeepLIFT uses a linear composition rule, which is equivalent to linearizing the non-linear components of a neural network. Its back-propagation rules defining how each component is linearized are intuitive but were heuristically chosen. Since DeepLIFT is an additive feature attribution method that satisfies local accuracy and missingness, we know that Shapley values represent the only attribution values that satisfy consistency. This motivates our adapting DeepLIFT to become a compositional approximation of SHAP values, leading to Deep SHAP.

Deep SHAP combines SHAP values computed for smaller components of the network into SHAP values for the whole network. It does so by recursively passing DeepLIFT's multipliers, now defined in terms of SHAP values, backwards through the network as in Figure 2B:

$$m_{x_j f_3} = \frac{\phi_i(f_3, x)}{x_j - E[x_j]} \tag{13}$$

$$\forall_{j \in \{1,2\}} \quad m_{y_i f_j} = \frac{\phi_i(f_j, y)}{y_i - E[y_i]} \tag{14}$$

$$m_{y_i f_3} = \sum_{j=1}^{2} m_{y_i f_j} m_{x_j f_3} \qquad \text{chain rule} \tag{15}$$

$$\phi_i(f_3, y) \approx m_{y_i f_3}(y_i - E[y_i]) \qquad \text{linear approximation} \tag{16}$$

Since the SHAP values for the simple network components can be efficiently solved analytically if they are linear, max pooling, or an activation function with just one input, this composition rule enables a fast approximation of values for the whole model. Deep SHAP avoids the need to heuristically choose ways to linearize components. Instead, it derives an effective linearization from the SHAP values computed for each component. The max function offers one example where this leads to improved attributions (see Section 5).

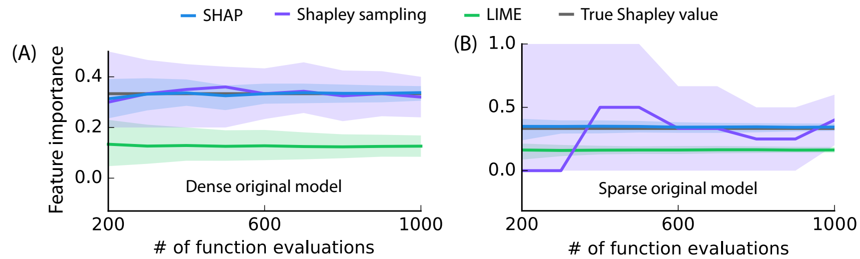

Figure 3: Comparison of three additive feature attribution methods: Kernel SHAP (using a debiased lasso), Shapley sampling values, and LIME (using the open source implementation). Feature importance estimates are shown for one feature in two models as the number of evaluations of the original model function increases. The 10th and 90th percentiles are shown for 200 replicate estimates at each sample size. (A) A decision tree model using all 10 input features is explained for a single input. (B) A decision tree using only 3 of 100 input features is explained for a single input.

5 Computational and User Study Experiments

We evaluated the benefits of SHAP values using the Kernel SHAP and Deep SHAP approximation methods. First, we compared the computational efficiency and accuracy of Kernel SHAP vs. LIME and Shapley sampling values. Second, we designed user studies to compare SHAP values with alternative feature importance allocations represented by DeepLIFT and LIME. As might be expected, SHAP values prove more consistent with human intuition than other methods that fail to meet Properties 1-3 (Section 2). Finally, we use MNIST digit image classification to compare SHAP with DeepLIFT and LIME.

5.1 Computational Efficiency

Theorem 2 connects Shapley values from game theory with weighted linear regression. Kernal SHAP uses this connection to compute feature importance. This leads to more accurate estimates with fewer evaluations of the original model than previous sampling-based estimates of Equation 8, particularly when regularization is added to the linear model (Figure 3). Comparing Shapley sampling, SHAP, and LIME on both dense and sparse decision tree models illustrates both the improved sample efficiency of Kernel SHAP and that values from LIME can differ significantly from SHAP values that satisfy local accuracy and consistency.

5.2 Consistency with Human Intuition

Theorem 1 provides a strong incentive for all additive feature attribution methods to use SHAP values. Both LIME and DeepLIFT, as originally demonstrated, compute different feature importance values. To validate the importance of Theorem 1, we compared explanations from LIME, DeepLIFT, and SHAP with user explanations of simple models (using Amazon Mechanical Turk). Our testing assumes that good model explanations should be consistent with explanations from humans who understand that model.

We compared LIME, DeepLIFT, and SHAP with human explanations for two settings. The first setting used a sickness score that was higher when only one of two symptoms was present (Figure 4A). The second used a max allocation problem to which DeepLIFT can be applied. Participants were told a short story about how three men made money based on the maximum score any of them achieved (Figure 4B). In both cases, participants were asked to assign credit for the output (the sickness score or money won) among the inputs (i.e., symptoms or players). We found a much stronger agreement between human explanations and SHAP than with other methods. SHAP's improved performance for max functions addresses the open problem of max pooling functions in DeepLIFT [7].

5.3 Explaining Class Differences

As discussed in Section 4.2, DeepLIFT's compositional approach suggests a compositional approximation of SHAP values (Deep SHAP). These insights, in turn, improve DeepLIFT, and a new version

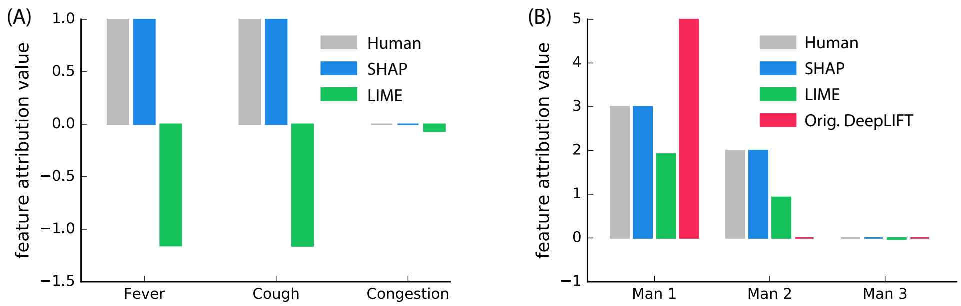

Figure 4: Human feature impact estimates are shown as the most common explanation given among 30 (A) and 52 (B) random individuals, respectively. (A) Feature attributions for a model output value (sickness score) of 2. The model output is 2 when fever and cough are both present, 5 when only one of fever or cough is present, and 0 otherwise. (B) Attributions of profit among three men, given according to the maximum number of questions any man got right. The first man got 5 questions right, the second 4 questions, and the third got none right, so the profit is \$5.

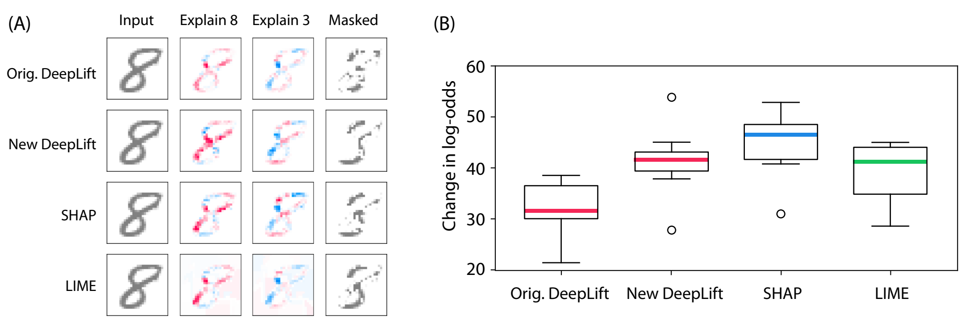

Figure 5: Explaining the output of a convolutional network trained on the MNIST digit dataset. Orig. DeepLIFT has no explicit Shapley approximations, while New DeepLIFT seeks to better approximate Shapley values. (A) Red areas increase the probability of that class, and blue areas decrease the probability. Masked removes pixels in order to go from 8 to 3. (B) The change in log odds when masking over 20 random images supports the use of better estimates of SHAP values.

includes updates to better match Shapley values [7]. Figure 5 extends DeepLIFT's convolutional network example to highlight the increased performance of estimates that are closer to SHAP values. The pre-trained model and Figure 5 example are the same as those used in [7], with inputs normalized between 0 and 1. Two convolution layers and 2 dense layers are followed by a 10-way softmax output layer. Both DeepLIFT versions explain a normalized version of the linear layer, while SHAP (computed using Kernel SHAP) and LIME explain the model's output. SHAP and LIME were both run with 50k samples (Supplementary Figure 1); to improve performance, LIME was modified to use single pixel segmentation over the digit pixels. To match [7], we masked 20% of the pixels chosen to switch the predicted class from 8 to 3 according to the feature attribution given by each method.

6 Conclusion

The growing tension between the accuracy and interpretability of model predictions has motivated the development of methods that help users interpret predictions. The SHAP framework identifies the class of additive feature importance methods (which includes six previous methods) and shows there is a unique solution in this class that adheres to desirable properties. The thread of unity that SHAP weaves through the literature is an encouraging sign that common principles about model interpretation can inform the development of future methods.

We presented several different estimation methods for SHAP values, along with proofs and experiments showing that these values are desirable. Promising next steps involve developing faster model-type-specific estimation methods that make fewer assumptions, integrating work on estimating interaction effects from game theory, and defining new explanation model classes.

Acknowledgements

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ShaRP: Explaining Rankings with Shapley Values

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Abstract

Algorithmic decisions in critical domains such as hiring, college admissions, and lending are often based on rankings. Because of the impact these decisions have on individuals, organizations, and population groups, there is a need to understand them: to know whether the decisions are abiding by the law, to help individuals improve their rankings, and to design better ranking procedures.

In this paper, we present ShaRP (Shapley for Rankings and Preferences), a framework that explains the contributions of features to different aspects of a ranked outcome, and is based on Shapley values. Using ShaRP, we show that even when the scoring function used by an algorithmic ranker is known and linear, the weight of each feature does not correspond to its Shapley value contribution. The contributions instead depend on the feature distributions, and on the subtle local interactions between the scoring features. ShaRP builds on the Quantitative Input Influence framework, and can compute the contributions of features for multiple Quantities of Interest, including score, rank, pair-wise preference, and top-k. Because it relies on black-box access to the ranker, ShaRP can be used to explain both score-based and learned ranking models. We show results of an extensive experimental validation of ShaRP using real and synthetic datasets, showcasing its usefulness for qualitative analysis.

1 Introduction

Algorithmic rankers are broadly used to support decision-making in critical domains, including critical domains such as hiring and employment, school and college admissions, credit and lending, and college ranking. Because of the impact rankers have on individuals, organizations, and population groups, there is a need to understand them: to know whether the decisions are abiding by the law, to help individuals improve their rankings, and to design better ranking procedures. In this paper, we present ShaRP (Shapley for Rankings and Preferences), a framework that explains the contributions of features to different aspects of a ranked outcome.

name	gpa	sat	essay	f	g
Bob	4	5	5	4.6	5
Cal	4	5	5	4.6	5
Dia	5	4	4	4.4	4
Eli	4	5	3	4.2	3
Fay	5	4	3	4.2	3
Kat	5	4	2	4.0	2
Leo	4	4	3	3.8	3
Osi	3	3	3	3.0	3

(a)

$r_{\mathcal{D},f}$
Bob
Cal
Dia
Eli
Fay
Kat
Leo
Osi

(b)

$r_{\mathcal{D},g}$
Bob
Cal
Dia
Eli
Fay
Leo
Osi
Kat

(c)

Figure 1: (a) Dataset $\mathcal{D}$ of college applicants, scored on gpa, sat, and $essay$. (b) Ranking $r_{\mathcal{D},f}$ of $\mathcal{D}$ on $f = 0.4 \times gpa + 0.4 \times sat + 0.2 \times essay$; the highlighted top-4 candidates will be interviewed and potentially admitted. (c) Ranking $r_{\mathcal{D},g}$ on $g = 1.0 \times essay$; the top-4 coincides with that of $r_{\mathcal{D},f}$, signifying that $essay$ has the highest importance for f, despite carrying the lowest weight.

There are two types of rankers: score-based and learned. In score-based ranking, a given set of candidates is sorted on a score, which is typically computed using a simple formula, such as a sum of attribute values with non-negative weights Zehlike *et al.* [2022a]. In supervised learning-to-rank, a preference-enriched set of candidates is used to train a model that predicts rankings of unseen candidates Li [2014]. To motivate our work, let us start with score-based rankers that are often preferred in critical domains, based on the premise that they are easier to design, understand, and justify than complex learning-to-rank models Berger *et al.* [2019]. In fact, score-based rankers are a prominent example of the so-called "interpretable models" Rudin [2019]: the scoring function, such as $Y_1 = 0.4 \times gpa + 0.4 \times sat + 0.2 \times essay$ in a college admissions scenario, is based on a (normative) a priori understanding of what makes for a good candidate.

And yet, despite being syntactically "interpretable", score-based rankers may not be "explainable," in the sense that the designer of the ranker or the decision-maker who uses it, may be unable to accurately predict and understand their output (Miller [2019]; Molnar [2020]). We now illustrate this with a simple example.

Example 1. *Consider a dataset $\mathcal{D}$ of college applicants in Figure 1, with scoring features gpa, sat, and essay. Very different scoring functions $f = 0.4 \times gpa + 0.4 \times sat + 0.2 \times essay$ and $g = 1.0 \times essay$ induce very similar rankings $r_{\mathcal{D},f}$ and $r_{\mathcal{D},g}$, with the same top-4 items appearing in the*

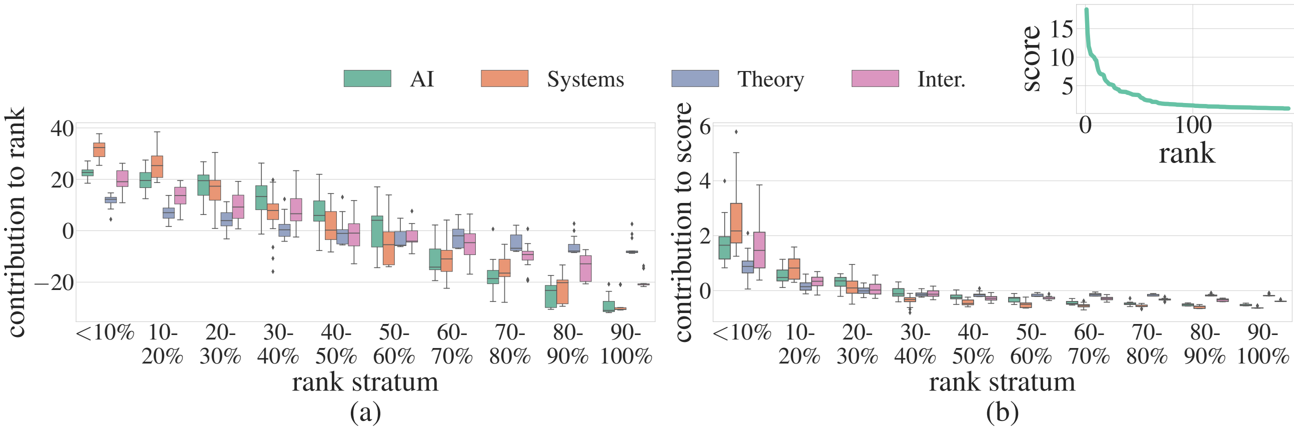


Figure 2: Feature contributions to rank and score for the CSRankings dataset, aggregated over 10% strata. In this ranking, 189 computer science departments are ranked based on a normalized publication count of the faculty across 4 research areas: AI (green), Systems (orange), Theory (purple), and Interdisciplinary (pink). (a) Systems is the most important feature for an item's rank in the top-20%, followed by AI. AI becomes more important for the rest of the ranking strata. (b) Feature contributions to score are less informative than to rank: both capture the same relative feature importance for the top 20%; however, feature contributions become small and very similar as more items are tied for their score. (See rank vs. score plot on the top-right.)

same order, apparently because essay *is the feature that is best able to discriminate between the top-*4 *and the rest, and — regardless of its weight — determines the relative order among the top-*4.

This example shows that the weight of a scoring feature may not be indicative of its impact on the ranked outcome. Intuitively, this happens because rankings are, by definition, relative, while feature values, and scores computed from them, are absolute. That is, knowing the score of an item says little about the position of that item in the ranking *relative to other items*. The key insight then is that the impact of the scoring features on the ranking must be measured in a way that captures the *lack of independence between per-item outcomes*.

There has been substantial work on quantifying *feature importance for classification* (Covert *et al.* [2020]; Datta *et al.* [2016]; Guidotti *et al.* [2019]; Lundberg and Lee [2017]; Mohler *et al.* [2020]; Ribeiro *et al.* [2016]; Strumbelj and Kononenko [2010]), and one may be tempted to think that these methods can be reused to explain ranking. Unfortunately, this is not the case, because in classification, predictions are being made independently for each item. For example, in binary classification, if all points happen to fall on the positive side of the decision boundary, then all will receive the positive outcome. In contrast, in ranking, an outcome for some item $\mathbf{v}$ is not independent of the outcomes for items $\mathcal{D} \setminus \{\mathbf{v}\}$. For example, only one item can occupy a specific rank position, and exactly k items can appear at the top-k. This lack of independence has profound implications for how rankings are generated and explained.

Rankings have been treated differently from classification in predictive contexts, as evidenced by the rich literature on learning-to-rank (Li [2014]). Rankings have also been treated differently to quantify fairness (Zehlike *et al.* [2022a,b]). Similarly, interpretability methods have to be customized for rankings, as we do in this work. We use the Quantitative Input Influence (QII) framework by Datta *et al.* [2016] as the starting point and augment it with several Quantities of Interest (QoI) that are appropriate for ranking, including score, rank, pair-wise preference, and top-k. We preview two of these QoIs in Figure 2, showing that they surface different insights about feature importance.

Summary of approach and contributions. We build on the Quantitative Input Influence (QII) framework by Datta *et al.* [2016] to quantify the influence of features on the ranked outcome. We use QII as the starting point because this framework flexibly and naturally accommodates local, group-wise, and global explanations. This flexibility is essential for expressing new quantities of interest for ranking, because of the need to accommodate the lack of independence between per-item outcomes, as already discussed.

QII produces explanations of the features based on Shapley values Shapley and others [1953]. Shapley value is a canonical method of dividing revenue in cooperative games based on the expected payment. QII uses Shapley values to explain the influence of an item's features (players) on the classification outcome for that item (cooperative game).

QII was proposed in the context of predictive classification, and extend it for ranking. *Our first contribution is a formalization of several natural quantities of interest (QoI) that are appropriate for ranking*, expressing feature contributions to an item's score or rank, to its presence or absence at the top-k, and to the relative order between a pair of items.

QII has not been seeing much adoption because, unlike in the case of LIME Ribeiro *et al.* [2016] and SHAP Lundberg and Lee [2017], only a preliminary implementation of QII is publicly available. *Our second contribution is a robust and extensible open-source ShaRP library that implements QII*, making this powerful framework — including also its functionality for explaining classification outcomes — available to others in the community.[1]

[1] We will make ShaRP publicly available following peer review.

Ultimately, explanations are only useful if they help uncover important insights about the decision-making process. *Our third contribution is an extensive experimental evaluation of Shapley-based explanations for ranking, in score-based and learning-to-rank settings.* We present results with numerous synthetic datasets, showing that feature importance for all QoIs depends on the properties of the data distribution even when the scoring function remains fixed. Further, we show that the quantities of interest we define bring interesting — and complementary — insights about the data that cannot be captured simply by the relationship between the scores and the ranks. Finally, we conduct a qualitative evaluation of ShaRP for CSRankings — a real dataset that ranks 189 Computer Science departments in the US based on a normalized publication count of the faculty across 4 research areas: AI, Systems, Theory, and Interdisciplinary (Berger [2023]). Our results, previewed in Figure 2, show that ShaRP surfaces subtle and valuable insights about the importance of specific research areas. We observe that Systems is the most important feature for attaining a high rank, followed by AI.

2 Related work

We are aware of several other lines of work on *interpretability in ranking*. Yang *et al.* [2018] proposed a "nutritional label" for score-based rankers that includes two visual widgets that explain the ranking methodology and outcome: "Recipe" shows scoring feature weights and "Ingredients" shows the features (scoring or not) that have the strongest (global) Spearman's rank correlation with the score. The authors observed that the weight of a feature in the "Recipe" rarely corresponds to how well it correlates with the score.

Gale and Marian [2020] developed "participation metrics" for score-based rankers that measure the contributions of scoring features to whether an item $\mathbf{v}$ is among the top-k. Their most important metric, "weighted participation," attributes the fact that $\mathbf{v}$ is included among the top-k to the values of its scoring features, the weight of these features in the scoring function, the distance of $\mathbf{v}$'s feature values from the maximum possible values, and to whether these values exceed the k^{th} highest values for each feature among all items in $\mathcal{D}$. Unlike this work, we use Shapley values to measure the average marginal contribution of a feature, aggregated over all feature subsets, weighted by subset size. Our QoI that is most similar to weighted participation is the top-k QoI, which expresses the probability that intervening on a subset of features will land an item in the top-k, computed for all strata (not only for the items that are actually among the top-k).

Yuan and Dasgupta [2023] designed an interface for sensitivity analysis of ranked synthetic datasets using Shapley values. Their methods are designed specifically for linear weighted scoring functions with two Gaussian features, and compute feature contributions for custom quantiles of a ranking. They define ranking-specific quantities of interest. Our methods are more general and more flexible, accommodating a variety of feature distributions, real datasets, quantities of interest, and scoring functions.

Anahideh and Mohabbati-Kalejahi [2022] provide local explanations of feature importance in the immediate neighborhood of an item. They consider multiple methods including Shapley values, and conclude that it is the best method for local explanations. To apply Shapley values and calculate the local contributions using only the surrounding neighborhood, they fit a linear model and use a subset of the features per coalition. Like Anahideh and Mohabbati-Kalejahi [2022], we show that feature importance differs significantly per rank stratum. However, in contrast to the findings of Anahideh and Mohabbati-Kalejahi [2022], we find that slight changes in feature values can move an item significantly in the ranks, far beyond the local neighborhood (e.g., see Figure 7).

Finally, Hu *et al.* [2022] developed PrefSHAP, a method for explaining pairwise preference data from learned rankers. They calculate the Shapley value contributions for pairwise preferences on a new quantity they propose: They create artificial items from the pair of items simultaneously for each coalition, and then evaluate how the preference changes. While this quantity can be applied to any preferential function, they introduce PrefSHAP specifically for functions that use the generalized preferential kernel defined in Chau *et al.* [2022] for running time efficiency. They compare their results with an adaptation of SHAP for preference models and show that this adaptation does not capture the contributions properly. We work with score-based rankers, not learned pairwise preferences, but, also argue that ranking-specific quantities of interest are needed to explain rankings.

In summary, we share motivation with these lines of work, but take a leap, describing the first comprehensive Shapley-value-based framework for rankings and preferences.

3 Preliminaries and Notation

Ranking. Let $\mathcal{A}$ denote an ordered collection of features (equiv. attributes), and let $\mathcal{D}$ denote a set of items (equiv. points or candidates). An item $\mathbf{v} = (v_1, \ldots, v_d) \in \mathbb{R}^d$ assigns values to $|\mathcal{A}| = d$ features, and may additionally be associated with a score. Score-based rankers use a scoring function $f(\mathbf{v})$ to compute the score of $\mathbf{v}$. For example, using $f_1(\mathbf{v}) = 0.4 \times gpa + 0.4 \times sat + 0.2 \times essay$, we compute $f(\texttt{Bob}) = 4.6$ and $f(\texttt{Leo}) = 3.8$.

A *ranking* $r_{\mathcal{D}}$ is a permutation over the items in $\mathcal{D}$. Letting $n = |\mathcal{D}|$, we denote by $r_{\mathcal{D}} = \langle \mathbf{v}_1, \ldots, \mathbf{v}_n \rangle$ a ranking that places item $\mathbf{v}_i$ at rank i. We denote by $r_{\mathcal{D}}(i)$ the item at rank i, and by $r_{\mathcal{D}}^{-1}(\mathbf{v})$ the rank of item $\mathbf{v}$ in $r_{\mathcal{D}}$. In score-based ranking, we are interested in rankings induced by some scoring function f. We denote these rankings $r_{\mathcal{D},f}$. For example, in Figure 1(b), $r_{\mathcal{D},f}(1) = \texttt{Bob}$, $r_{\mathcal{D},f}^{-1}(\texttt{Leo}) = 7$. We assume that $r_{\mathcal{D},f}^{-1}(\mathbf{v}_1) < r_{\mathcal{D},f}^{-1}(\mathbf{v}_2) < \cdots < r_{\mathcal{D},f}^{-1}(\mathbf{v}_n)$, where a smaller rank means a better position in the ranking.

We are often interested in a sub-ranking of $r_{\mathcal{D},f}$ containing its best-ranked k items, for some integer $k \leq n$; this sub-ranking is called the top-k. The top-4 of the ranking in Figure 1(b) is $\langle \texttt{Bob}, \texttt{Cal}, \texttt{Dia}, \texttt{Eli} \rangle$.

Our goal is to explain the importance of features $\mathcal{A}$ to the ranking $r_{\mathcal{D},f}$. We will do so using Shapley values.

Shapley values and quantities of interest. For a subset of features $\mathcal{S} \subseteq \mathcal{A}$, let $\mathbf{v}_{\mathcal{S}}$ denote a projection of $\mathbf{v}$ onto $\mathcal{S}$. Continuing with the example in Figure 1, $(\texttt{Bob}, 4, 5, 2)_{\{name, gpa\}} = (\texttt{Bob}, 4)$. Let $\mathbf{U} =$

Algorithm 1 Feature importance for per-item outcomes

Input: Dataset $\mathcal{D}$, item $\mathbf{v}$, number of samples m, $\iota()$
Output: Shapley values $\phi(\mathbf{v})$ of $\mathbf{v}$'s features

$\phi(\mathbf{v}) = \langle 0, \ldots, 0 \rangle$
for $i \in \mathcal{A}$ **do**
  for $\mathcal{S} \subseteq \mathcal{A} \setminus \{i\}$ **do**
    $\mathbf{U} \sim \mathcal{D} \backslash \mathbf{v}, m$
    $\mathbf{U}_1 = \mathbf{v}_{\mathcal{A} \backslash \mathcal{S}} \mathbf{U}_{\mathcal{S}}$
    $\mathbf{U}_2 = \mathbf{v}_{\mathcal{A} \backslash \{\mathcal{S} \cup i\}} \mathbf{U}_{\mathcal{S} \cup i}$
    $\phi_{i_{\mathcal{S}}}(\mathbf{v}) = \iota(\mathbf{U}_1, \mathbf{U}_2)$
    $\phi_i(\mathbf{v}) = \phi_i(\mathbf{v}) + \frac{1}{d} \frac{1}{\binom{d-1}{|\mathcal{S}|}} \phi_{i_{\mathcal{S}}}(\mathbf{v})$
  end for
end for
return $\phi(\mathbf{v})$

$\langle \mathbf{u}_1, \ldots, \mathbf{u}_m \rangle$ denote a vector of m items, sampled from $\mathcal{D}$ using some sampling mechanism. For a subset of features $\mathcal{S} \in \mathcal{A}$, let $\mathbf{v}_{\mathcal{A} \backslash \mathcal{S}} \mathbf{U}_{\mathcal{S}} = \langle \mathbf{v}_{\mathcal{A} \backslash \mathcal{S}}(\mathbf{u}_1)_{\mathcal{S}}, \ldots, \mathbf{v}_{\mathcal{A} \backslash \mathcal{S}}(\mathbf{u}_m)_{\mathcal{S}} \rangle$ denote a vector of items in which each item $\mathbf{v}_{\mathcal{A} \backslash \mathcal{S}}(\mathbf{u}_i)_{\mathcal{S}}$ takes on the values of the features in $\mathcal{S}$ from $\mathbf{u}_i$, and the values of the remaining $\mathcal{A} \setminus \mathcal{S}$ features from $\mathbf{v}$.

Algorithm 1 presents the computation of feature importance — in the form of a vector of Shapley values $\phi(\mathbf{v})$ — to QoIs that can be specified for a single item $\mathbf{v}$, independently of other items. The algorithm relies on black-box access to the model that generates the outcomes (i.e., specifying an input to the model and observing the output).

The algorithm takes as input a dataset $\mathcal{D}$, an item $\mathbf{v}$ for which the explanation is generated, the number of samples to draw m, and the QoI function $\iota()$ based on which we quantify the feature importance. Note that m is user-defined and controls the quality of approximation. Passing in the full set of items $\mathcal{D}$ and setting $m = |\mathcal{D} - 1|$ results in the exact computation of the Shapley values (i.e., the item $\mathbf{v}$'s features are quantified against every other item in $\mathcal{D}$). Passing in $\mathcal{D}' \subset \mathcal{D}$ that corresponds to a specific group (e.g., women) computes group-specific feature importance for the given QoI.

For every feature $i \in \mathcal{A}$, the algorithm computes every coalition of the remaining features $\mathcal{S} \subseteq \mathcal{A} \setminus \{i\}$. For each coalition $\mathcal{S}$, it draws m samples from $\mathcal{D}$. Two vectors of items are created based on this sample: $\mathbf{U}_1$, in which feature values of the coalition vary as in $\mathbf{U}$ and the remaining features are fixed to their values in $\mathbf{v}$; and $\mathbf{U}_2$, in which features in the coalition *and* the feature of interest i vary as in $\mathbf{U}$, and the remaining features are fixed to their values of $\mathbf{v}$. The importance of the coalition, $\phi_{i_{\mathcal{S}}}(\mathbf{v})$, is computed by invoking the function $\iota()$, which computes the difference in QoI between the two vectors of items $\mathbf{U}_1$ and $\mathbf{U}_2$. This value is added to the contribution of feature i, $\phi_i(\mathbf{v})$ weighted by the number of coalitions of this size $\binom{d-1}{|\mathcal{S}|}$, and the total number of possible coalition sizes d.

4 Quantities of Interest for Ranking

We use Algorithm 1 as a starting point for computing feature importance for ranked outcomes. We will define different QoIs with the help of the $\iota()$ function.

Algorithm 2 ι_{Rank}

Input: Dataset $\mathcal{D}$, scoring function f, item $\mathbf{v}$, $\mathbf{U}_1$, $\mathbf{U}_2$, number of samples m
Output: ϕ

$\phi = 0$
for $i \in \{1, \ldots, m\}$ **do**
  $\mathbf{u}_1 = \mathbf{U}_1(i)$
  $\mathbf{u}_2 = \mathbf{U}_2(i)$
  $\mathcal{D}_1 = \mathcal{D} \setminus \{\mathbf{v}\} \cup \{\mathbf{u}_1\}$
  $\mathcal{D}_2 = \mathcal{D} \setminus \{\mathbf{v}\} \cup \{\mathbf{u}_2\}$
  $\phi = \phi + r^{-1}_{\mathcal{D}_2, f}(\mathbf{u}_2) - r^{-1}_{\mathcal{D}_1, f}(\mathbf{u}_1)$
end for
return $\phi / |\mathbf{U}_1|$

Score QoI. Recall that f denotes the scoring function. We overload notation and denote by $f(\mathbf{U})$ the computation of the score for each item in $\mathbf{U}$, and return these scores as a vector. Since $\mathbf{U}_1$ and $\mathbf{U}_2$ are vectors of items constructed from the same vector $\mathbf{U}$, they are of the same size. To quantify feature importance to an item's score, we define ι_{Score} as the mean of the (per-element) difference of $f(\mathbf{U}_1)$ and $f(\mathbf{U}_2)$:

$$\iota_{Score}(\mathbf{U}_1, \mathbf{U}_2, f) = \mathbb{E}\left[f(\mathbf{U}_1) - f(\mathbf{U}_2) \right]$$

This ι_{Score} is commonly used for Shapley value feature importance, and we use it as a qualitative baseline for comparison with the other QoIs we propose.

Rank QoI. An item's rank is computed with respect to all other items in the sample. For this reason, to quantify the impact of $\mathbf{v}$'s features on its rank, we must compute the ranking of each intervened-upon instantiation of $\mathbf{v}$ in $\mathcal{D}'$. This adds two steps to calculating this QoI compared to the score QoI. The item we are explaining needs to be removed from $\mathcal{D}'$, and the score of each item $\mathbf{u}_i \in \mathbf{U}_1$ (and equivalently $\mathbf{u}_j \in \mathbf{U}_2$) needs to be compared to the scores of all items in $\mathcal{D}'$.

The computation of ι_{Rank} is summarized in Algorithm 2. We consider each a pair of corresponding (i.e., at the same position in their respective vector) samples $\mathbf{u}_1 \in \mathbf{U}_1$ and $\mathbf{u}_2 \in \mathbf{U}_2$, and compute $\mathcal{D}_1 = \mathcal{D} \setminus \{\mathbf{v}\} \cup \{\mathbf{u}_1\}$ and $\mathcal{D}_2 = \mathcal{D} \setminus \{\mathbf{v}\} \cup \{\mathbf{u}_2\}$. Next, we rank $\mathcal{D}_1$ and $\mathcal{D}_2$ on f, and compute the difference in ranks $r^{-1}_{\mathcal{D}_2, f}(\mathbf{u}_2) - r^{-1}_{\mathcal{D}_1, f}(\mathbf{u}_1)$. Note that we are subtracting the rank of $\mathbf{u}_1$ from the rank of $\mathbf{u}_2$, since a lower rank corresponds to a higher (better) position in the ranking. We return the average (expected) rank-difference as ι.

Top-k QoI. To compute feature importance that explains whether an item appears at the top-k, for some given k, we use a similar method as for rank QoI. The difference is that, rather than computing the difference in rank positions for a given pair of items $\mathbf{u}_1$ and $\mathbf{u}_2$, we instead check whether one, both, or neither of them are at the top-k. As in Algorithm 2, we work with $\mathcal{D}_1 = \mathcal{D} \setminus \{\mathbf{v}\} \cup \{\mathbf{u}_1\}$ and $\mathcal{D}_2 = \mathcal{D} \setminus \{\mathbf{v}\} \cup \{\mathbf{u}_2\}$ for each sample. We increase the contribution to ϕ by 1 if only $\mathbf{u}_1$ is in the top-k, and decrease it by 1 if only $\mathbf{u}_2$ is in the top-k. We omit pseudocode due to space constraints.

Pairwise QoI. We developed a method for computing feature importance for the relative order between a pair of items $\mathbf{u}$ and $\mathbf{v}$, to answer the question of why $\mathbf{u}$ is ranked higher

Algorithm 3 Feature importance for preference $\mathbf{u} \succ \mathbf{v}$

Input: Item $\mathbf{v}$, item $\mathbf{u}$, $\iota()$
Output: Shapley values $\phi(\mathbf{u} \succ \mathbf{v})$ that explain why $\mathbf{u}$ is ranked higher than $\mathbf{v}$

```
φ(u ≻ v) = ⟨0, ..., 0⟩
for i ∈ A do
    for S ⊆ A \ {i} do
        U_1 = ⟨v_{A\S} u_S⟩
        U_2 = ⟨v_{A\{S∪i}} u_{S∪i}⟩
        φ_{i_S}(u ≻ v) = ι(U_1, U_2)
        φ_i(u ≻ v) = φ_i(u ≻ v) + (1/d) · 1/C(d−1, |S|) · φ_{i_S}(u ≻ v)
    end for
end for
return φ(u ≻ v)
```

than $\mathbf{v}$ (i.e., $\mathbf{u} \succ \mathbf{v}$). In Algorithm 3, we create feature coalitions as in Algorithm 1 and then, instead of sampling from $\mathcal{D}$, we create $\mathbf{U}_1$ and $\mathbf{U}_2$ as vectors of 1 element each, based on the values of the items being compared. We then invoke the $\iota()$ function to compute the feature importance with respect to the difference in score, or rank, or the presence/absence at the top-k, as described earlier in this section.

5 Experimental Evaluation

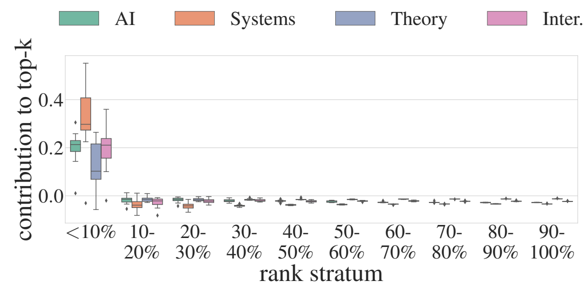
In this section, we showcase the versatility of the ShaRP framework for explaining rankings.

Datasets and rankers. We present results for CS Rankings, a real dataset that ranks 189 Computer Science departments in the US based on a normalized publication count of the faculty across 4 research areas (Berger [2023]). We use the scoring formula provided by csrankings.org: a geometric mean of the adjusted counts per area, $f = \sqrt[27]{(AC^5_{AI}+1)(AC^{12}_{Sys}+1)(AC^3_{Th}+1)(AC^7_{Int}+1)}$.

We also generate synthetic datasets in which items have 2 features, x_1 and x_2, distributed according to the uniform, Gaussian, or Bernoulli distributions, with varying parameters. We experiment with both independent and correlated features. Each synthetic dataset consists of $2,000$ items. We use three linear scoring functions: $f_1 = 0.8 \times x_1 + 0.2 \times x_2$, $f_2 = 0.5 \times x_1 + 0.5 \times x_2$, and $f_3 = 0.2 \times x_1 + 0.8 \times x_2$. We sample $m = 1,999$ for each QoI computation that requires sampling (all except pairwise QoI). For the top-k QoI, we set $k = 200$ (10% of the data).

Finally, we use a benchmark dataset of 2000 candidates who are applying for a position at a fictional moving company from Yang *et al.* [2021], with an LGBM ranker, for our learning-to-rank experiment.

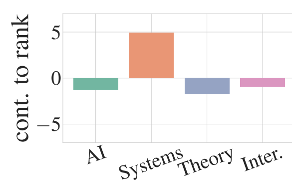
Visualizing feature importance. We use three methods for visualizing experimental results. The first, used in Figures 4a and 4b, is a waterfall visualization that presents feature importance for a single item (as in Lundberg and Lee [2017]). The second visualization, used in Figures 2, 3a, 5, 6, and 7, is a box-and-whiskers plot that aggregates local feature importance across ranking strata, each covering 10% of the range.



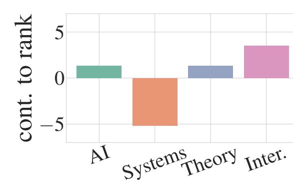
(a) Feature contribution to the top-k QoI, for $k = 10\%$. Systems is the most important feature, followed by Interdisciplinary and AI, while Theory is least important.

Institution	AI	Systems	Theory	Inter.	Rank
`Georgia Tech`	28.5	7.8	6.9	10.2	5
`Stanford`	36.7	5.4	13.3	11.5	6
`UMich`	30.4	9.0	9.3	5.9	7

(b) Feature values and rank of three highly ranked departments: Georgia Tech, Stanford, and UMich.



(c) Pairwise QoI explaining that Georgia Tech ranks higher than Stanford because of its relative strength in Systems.



(d) Pairwise QoI explaining that Stanford ranks higher than UMich despite Stanford's relative weakness in Systems.

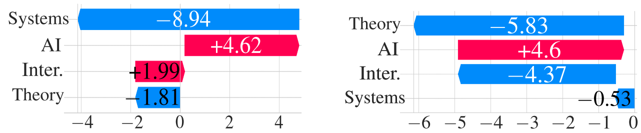
Figure 3: Feature importance for the top-k QoI for CS Rankings, with further analysis of 3 departments using Pairwise QoI.

This visualization allows us to see both the median contribution of each feature to a stratum and the variance in that feature's contribution across the items in the stratum. The third visualization, used in Figures 3c and 3d, is a bar graph that presents feature contributions for pairwise QoI.

5.1 Qualitative Analysis of CS Ranking

We already previewed the compelling results of Figure 2 in the Introduction. In that figure, we show feature contributions to rank and score QoI for the CS Rankings dataset, aggregated over 10% strata. According to rank QoI in Figure 2(a), Systems is the most important feature in all strata, followed closely by AI. Both features have the most positive contributions in the top strata and the most negative in the bottom strata. Further, we observe that *feature contributions to score are less informative than to rank*: both capture the same relative feature importance for the top 20%; however, feature contributions become small and very similar as more items are tied or nearly-tied for their scores, making it nearly impossible to quantify feature importance across strata.

Figure 3a presents the top-k QoI for this dataset. The feature importance it shows is consistent with Figure 2(a) (score QoI), but the high positive impact of Systems on an department's presence at the top-k is even stronger pronounced.



(a) South Carolina, ranked 101 (b) Wayne State, ranked 102

Figure 4: Feature contributions to rank QoI for two departments.

Additionally, unlike the score QoI, this top-k QoI shows that Theory is impactful for getting into the top-k. Further, both top-k and rank QoIs show that Systems and AI swap places in terms of importance, while score QoI does not detect this.

In Figure 3(b)-(d), we continue our analysis of the top-k and consider the relative ranking of three universities: Georgia Tech in rank 5, Stanford in rank 6, and UMich in rank 7. We wish to understand why Georgia Tech is ranked higher than Stanford (Figure 3c), and why Stanford is ranked higher than UMich (Figure 3d). In both cases, Georgia Tech and UMich have lower values for all features except Systems. The Systems value of Georgia Tech is high enough to overcome the contributions of other features and rank it higher than Stanford. However, for UMich, we see that, while Systems is the most important feature in the top-10% stratum, it is not important enough to move UMich above Stanford. Note that adding the contributions for each feature adds up to the total difference in rank between each pair.

In Figure 4, we present the rank QoI for The University of South Carolina (rank 101) and Wayne State University (rank 102), using the waterfall visualization. These universities are ranked consecutively, but for different reasons. For South Carolina, Systems and Theory have negative contributions, while AI and Interdisciplinary have positive contribution. For Wayne State, only AI has a positive contribution, while other features have negative contributions.

5.2 Score-based Ranking with Synthetic Data

Fixed scoring function, varying data distribution. In this experiment, we illustrate that feature importance is impacted by the data distribution of the scoring features to a much greater extent than by the feature weights in the scoring function. Further, we show that feature importance varies by rank stratum. In Figure 5, we show rank QoI for 4 synthetic datasets, using the same scoring function, f_2.

We observe that, while the features have equal scoring function weights, their contributions to rank QoI differ for most datasets. In D_1, the Bernoulli-distributed x_2 determines whether the item is in the top or the bottom half of the ranking, while the Gaussian-distributed x_1 is responsible for the ranking inside each half. For D_2, the uniform x_1 has higher importance because it often takes on larger values than the Gaussian x_2. In D_4, x_1 and x_2 are negatively correlated, so when one contributes positively, the other contributes negatively. Only for D_3, with two uniform identically distributed features, the median contributions of both features are approximately the same within each stratum.

Additionally, we see that feature contributions differ per rank stratum. For example, for D_3, the medians show a downward trajectory across strata. This is because they quantify the expected change (positive or negative) in the number of rank positions to which the current feature values contribute. Also for D_3, feature contributions have higher variance in the middle of the range, because a 40-60% rank corresponds to many combinations of feature values.

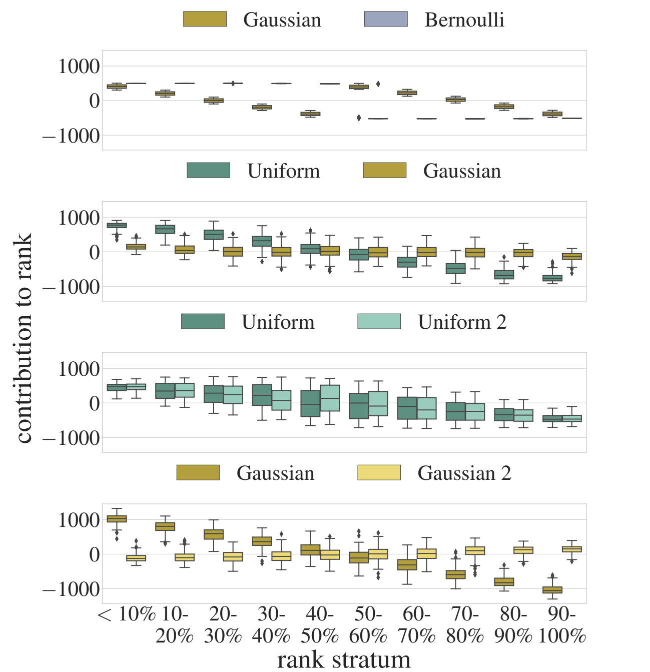


Figure 5: The rank QoI using $f_2 = 0.5 \times x_1 + 0.5 \times x_2$ for four datasets; D_1: $x_1 \sim N(0.5, 0.1)$, $x_2 \sim Bern(0.5)$; D_2: $x_1 \sim [0,1]$, $x_2 \sim N(0.5, 0.1)$; D_3: $x_1 \sim [0,1]$, $x_2 \sim [0,1]$; D_4: $x_1 \sim N(0.5, 0.05)$, $x_2 \sim N(0.75, 0.016)$, with -0.8 correlation. Feature contributions are different per rank stratum and data distribution.

Fixed data distribution, varying scoring function. In this experiment, we investigate the impact of the scoring function on rank and top-k QoI for two datasets. In Figure 6, we use D_3 and see that the contributions to rank QoI vary depending on the scoring function. For f_1, x_1 is the only important feature (although it carries 0.8 — and not 1.0 — of the weight). This can be explained by the compounding effect of the higher scoring function weight and higher variance of the distribution from which x_1 is drawn. Between f_2 and f_3, features x_1 and x_2 switch positions in terms of importance, and show a similar trend, despite being associated with different scoring function weights (0.5 & 0.5 vs. 0.2 & 0.8). This, again, can be explained by the higher variance of x_1, hence, x_2 needs a higher scoring function weight to compensate for lower variance and achieve similar importance.

Access to the top-k is determined by the interaction between the scoring feature weights and the distributions of these features. The higher the weight of the less important feature, the higher the likelihood for an item to move to the top-k by changing the other feature. Figure 7 illustrates this for dataset D_3. Under f_1, items in the lower strata have a nonzero probability to move to the top-k by changing the second feature, as indicated by the variance. In contrast, under f_2, with equal scoring feature weights, items in the bottom strata

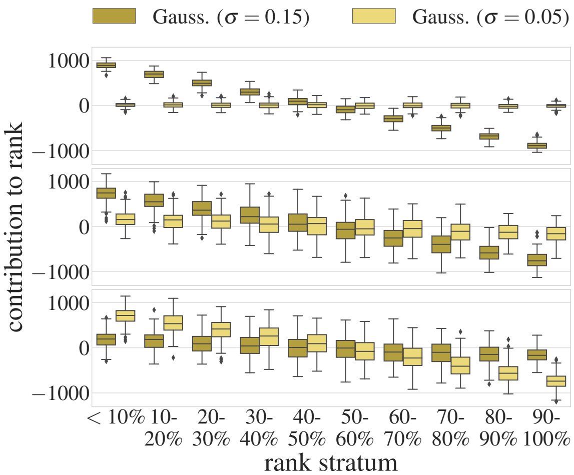


Figure 6: Rank QoI for D_5: $x_1 \sim N(0.5, 0.1)$, $x_2 \sim N(0.5, 0.05)$. Subplots correspond to different scoring functions: $f_1 = 0.8 \times x_1 + 0.2 \times x_2$ (top), $f_2 = 0.5 \times x_1 + 0.5 \times x_2$ (middle), $f_3 = 0.2 \times x_1 + 0.8 \times x_2$ (bottom).

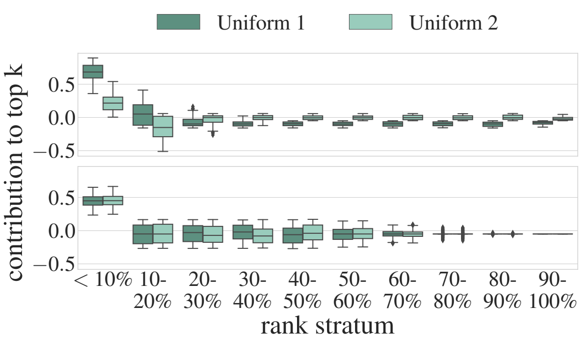


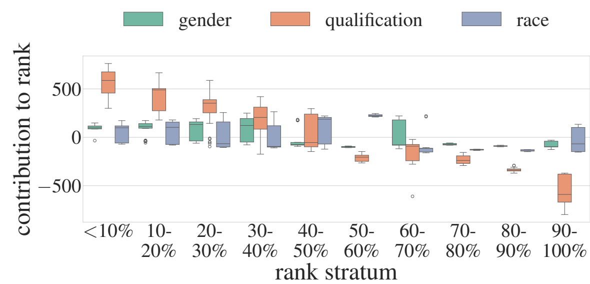
Figure 7: Top-k QoI for $k = 10\%$ and D_3: $x_1 \sim [0, 1]$, $x_2 \sim [0, 1]$. Subplots correspond to different scoring functions: $f_1 = 0.8 \times x_1 + 0.2 \times x_2$ (top), $f_2 = 0.5 \times x_1 + 0.5 \times x_2$ (bottom).

cannot change either feature sufficiently to move into the top-k, while items in the middle strata have a higher probability of moving to the top-k compared to f_1, by changing either feature. Evidence that items from lower strata can move to the top-k under some scoring functions and feature distributions counters the assumption of Anahideh and Mohabbati-Kalejahi [2022] that changes in rank are localized.

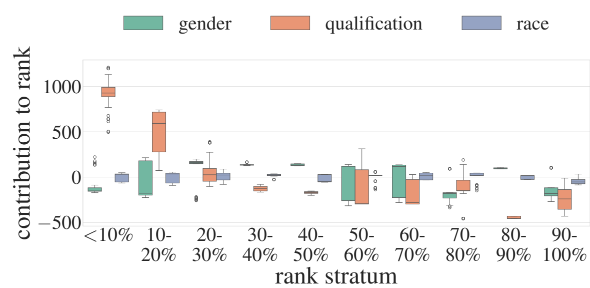
5.3 Learning-to-rank

In our final set of experiments, we showcase the use of ShaRPin a learning-to-rank (LtR) setting. For this, we use a benchmark dataset of 2000 candidates who are applying for a position at a fictional moving company from Yang *et al.* [2021]. The dataset contains three features: gender, qualification score (i.e., weight lifting ability) and race, along with the final score Y. The score Y is computed by causal model $\mathcal{M}_1$ and used to rank the job applicants. The score Y is then withheld, and an LGBM Ranker (Ke *et al.* [2017]) with the LambdaRank objective (Burges *et al.* [2006]) is trained on 80% of the data, with 20% reserved for testing.

Figure 8 shows the rank QoI for the test dataset, under two conditions. In Figure 8a, we show the rank QoI for a test set, using an LtR model trained on a dataset in which both race and, to some extent, gender, impact the final ranking, in addition to the qualification score. In Figure 8b, we show feature importance for a test set, but with an LtR model that is trained on a counterfactually fair data (per Yang *et al.* [2021]), in which the impact of race is reduced. Observe that the impact of the race feature is also lower in Figure 8b (after intervention) compared to Figure 8a (before intervention), as expected. Furthermore, the impact of the qualification feature is higher in Figure 8b, as expected, since the importance of race is now reduced.



(a) Qualification is the most important feature, but gender and race also impact the rank.



(b) Feature importance of race is lower when learning-to-rank model is trained on counterfactually fair data.

Figure 8: Rank QoI for two versions of the moving company hiring task from Yang *et al.* [2021], with learning-to-rank. Qualification is the most important feature, but gender and race also impact the rank. Feature importance differs across strata in both experiments.

6 Conclusions, Limitations, and Future Work

In this paper, we presented ShaRP, a comprehensive framework for quantifying feature importance for rankings. We used the Quantitative Influence (QII) framework as a starting point, and augmented it with several natural quantities of interest that can be used to explain the contributions of features to an item's score or rank, to the relative order between a pair of items, and to the presence or absence of an item at the top-k. We implemented ShaRP in a software library, which we will contribute to the open source following publication.

We showcased the usefulness of ShaRP for qualitative analysis of an impactful real dataset and task — the ranking of Computer Science departments. We augmented this analysis with a thorough evaluation of our methods on numerous synthetic datasets, showing that the quantities of interest we define bring interesting — and complementary — insights about the data that cannot be captured simply by the relationship between the scores and the ranks. We showed that feature importance depends on the properties of the data distribution *even if* the scoring function remains fixed, and, further, that feature importance exhibits locality: it changes substantially depending on where in the ranking one looks.

Limitations and future work. The most important limitation is that our evaluation of the usefulness of explainability methods did not include a user study. Understanding how humans make sense of feature importance in ranking and act on their understanding, is in our immediate plans.

An important technical limitation, which we share with QII, is that we require black-box access to the ranker. Recently, methods have been proposed to fit a ranker to the data and treat it as a surrogate black-box model. Developing methods for learning low-complexity black-box models is part of our future work. We also plan to support additional quantities of interest, accommodate a broader class of preferences in addition to ranking (e.g., partial orders), and develop a comprehensive benchmark that compares feature importance methods for rankings in terms of their usability, expressiveness, and performance.

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BY LATANYA SWEENEY

Discrimination in Online Ad Delivery

DO ONLINE ADS suggestive of arrest records appear more often with searches of black-sounding names than white-sounding names? What is a black-sounding name or white-sounding name, anyway? How do you design technology to reason about societal consequences like structural racism? Let's take a scientific dive into online ad delivery to find answers.

"Have you ever been arrested?" Imagine this question appearing whenever someone enters your name in a search engine. Perhaps you are in competition for an award or a new job, or maybe you are in a position of trust, such as a professor or a volunteer. Perhaps you are dating or engaged in any one of hundreds of circumstances for which someone wants to learn more about you online. Appearing alongside your accomplishments is an advertisement implying you may have a criminal record, whether you actually have one or not. Worse, the ads may not appear for your competitors.

Employers frequently ask whether applicants have ever been arrested or charged with a crime, but if an employer disqualifies a job applicant based solely upon information indicating an arrest record, the company may face legal consequences. The U.S. Equal Employment Opportunity Commission (EEOC) is the federal agency charged with enforcing Title VII of the Civil Rights Act of 1964, a law that applies to most employers, prohibiting employment discrimination based on race, color, religion, sex, or national origin, and extended to those having criminal records.[5,11] Title VII does not prohibit employers from obtaining criminal background information, but a blanket policy of excluding applicants based solely upon information indicating an arrest record can result in a charge of discrimination.

To make a determination, the EEOC uses an adverse impact test that measures whether certain practices, intentional or not, have a disproportionate effect on a group of people whose defining characteristics are covered by Title VII. To decide, you calculate the percentage of people affected in each group and then divide the smaller value by the larger to get the ratio and compare the result to 80. If the ratio is less than 80, then the EEOC considers the effect disproportionate and may hold the employer responsible for discrimination.[6]

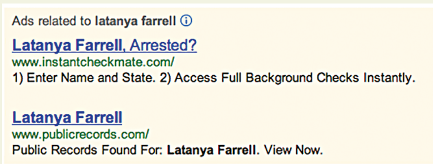
What about online ads suggesting someone with your name has an arrest record? Title VII only applies if you have an arrest record and can prove the employer inappropriately used the ads.

Are the ads commercial free speech—a constitutional right to display the ad associated with your name? The First Amendment of the U.S. Constitution protects advertising, but the U.S. Supreme Court set out a test for assessing restrictions on commercial speech, which begins by determining whether the speech is misleading.[3] Are online ads suggesting the existence of an arrest record misleading if no one by that name has an arrest record?

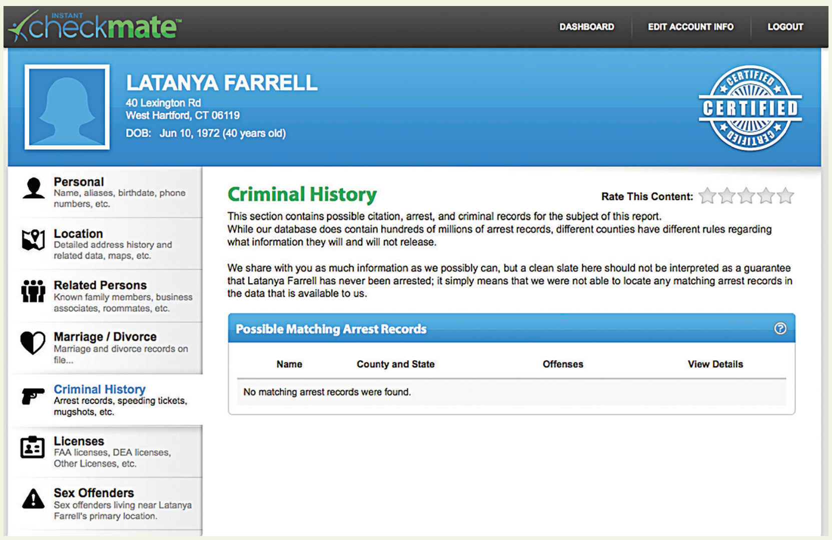
ILLUSTRATION BY ALEX WILLIAMSON


80
72
69
70
66
60

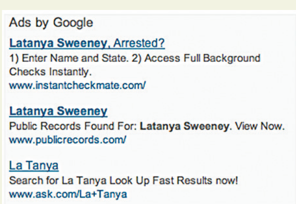
Figure 1. Ads from a Google search of three different names beginning with first name "Latanya."



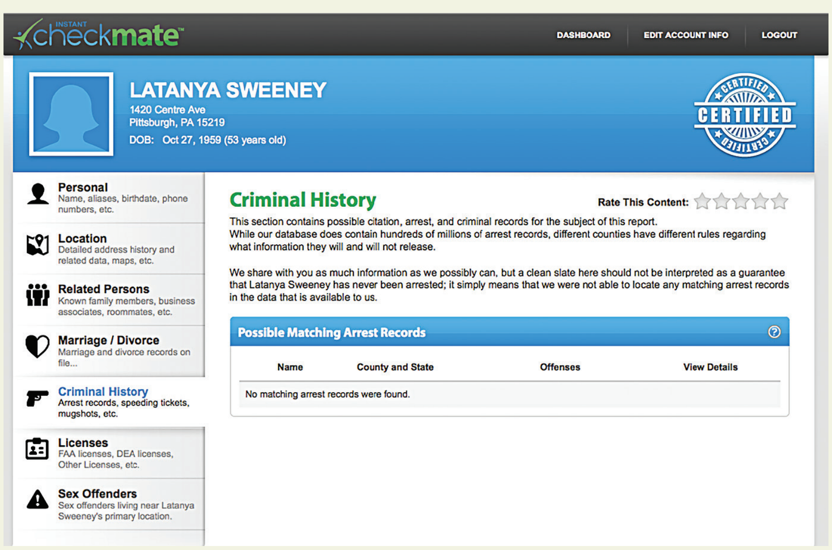
(a)



(b)



(c)



(d)

Assume the ads are free speech: what happens when these ads appear more often for one racial group than another? Not everyone is being equally affected by free speech. Is that free speech or racial discrimination?

Racism, as defined by the U.S. Commission on Civil Rights, is "any attitude, action, or institutional structure which subordinates a person or group because of their color."[16] *Racial discrimination* results when a person or group of people is treated differently based on their racial origins, according to the Panel on Methods for Assessing Discrimination of the National Research Council.[12] Power is a necessary precondition, for it depends on the ability to give or withhold benefits, facilities, services, and opportunities from someone who should be entitled to them and is denied on the basis of race. *Institutional or structural racism*, as defined in *The Social Work Dictionary*, is a system of procedures/patterns whose effect is to foster discriminatory outcomes or give preferences to members of one group over another.[1]

These considerations frame the relevant socio-legal landscape. Now we turn to whether online ads suggestive of arrest records appear more often for one racial group than another among a sample of racially associated names, and if so, how technology can solve the problem.

The Pattern

What is the suspected pattern of ad delivery? Here is an overview using real-world examples.

Earlier this year, a Google search for *Latanya Farrell*, *Latanya Sweeney*, and *Latanya Lockett* yielded ads and criminal reports like those shown in Figure 1. The ads appeared on Google.com (Figure 1a, 1c) and on a news website, Reuters.com, to which Google supplies ads (Figure 1c), All the ads in question linked to instantcheckmate.com (Figure 1b, 1d). The first ad implied *Latanya Farrell* might have been arrested. Was she? Clicking on the link and paying the requisite fee revealed the company had no arrest record for her or *Latanya Sweeney*, but there is a record for *Latanya Lockett*.

In comparison, searches for *Kristen Haring*, *Kristen Sparrow*, and *Kristen Lindquist* did not yield any instantcheckmate.com ads, even though the company's database reported having records for all three names and arrest records for *Sparrow* and *Lindquist*.

Searches for *Jill Foley*, *Jill Schneider*, and *Jill James* displayed instantcheckmate.com ads with neutral copy; the word *arrest* did not appear in the ads even though arrest records for all three names appeared in the company's database. Figure 2 shows ads appearing on Google.com and Reuters.com and criminal reports from instantcheckmate.com for the first two names.

Finally, we considered a proxy for race associated with these names. Figure 3 shows racial distinction in Google image search results for *Latanya*, *Latisha*, *Kristen*, and *Jill*, respectively. The faces associated with *Latanya* and *Latisha* tend to be black, while white faces dominate the images of *Kristen* and *Jill*.

These handpicked examples describe the suspected pattern: ads suggesting arrest tend to appear with names associated with blacks, and neutral or no ads appear with names associated with whites, regardless of whether the company placing the ad has an arrest record associated with the name.

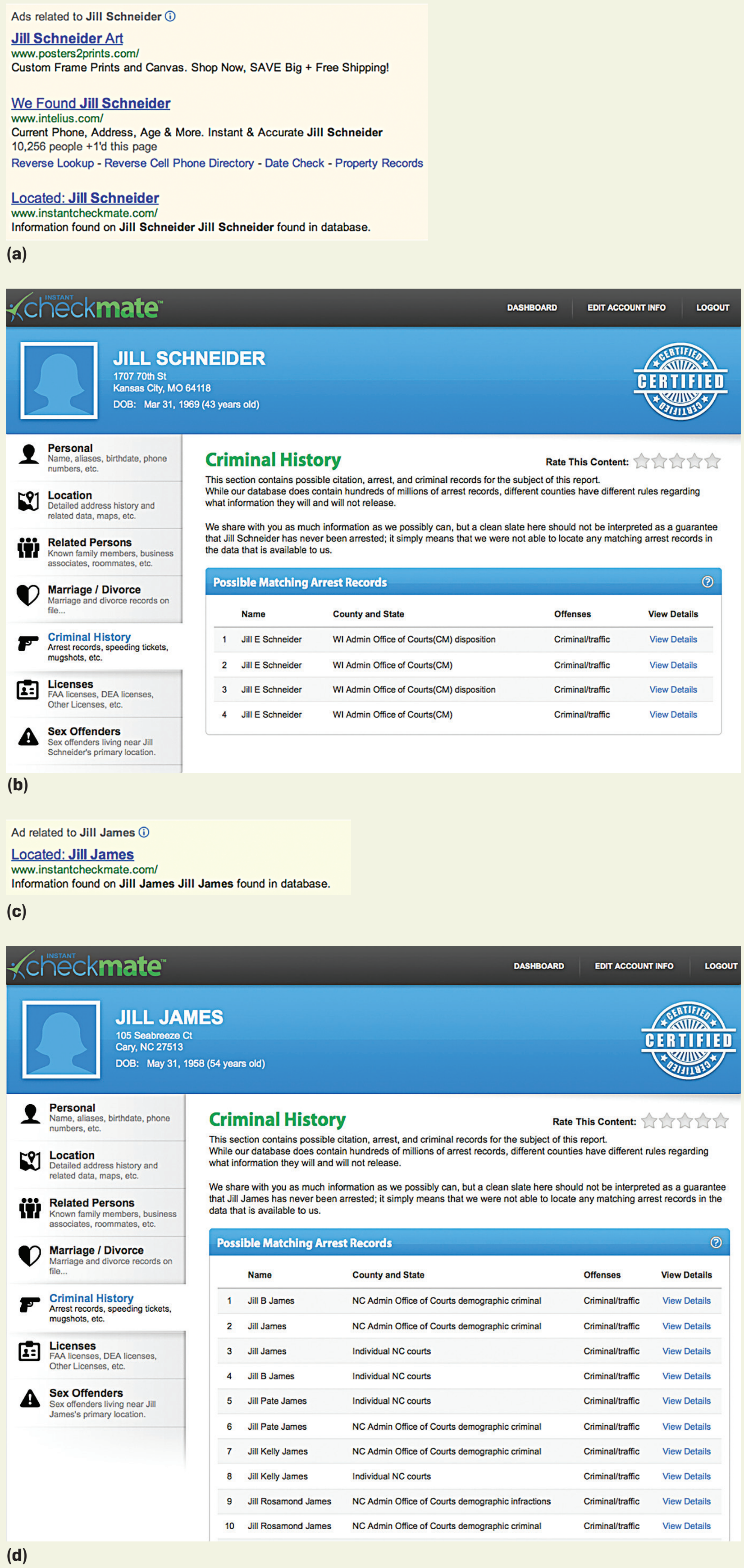
Google Adsense

Who generates the ad's text? Who decides when and where an ad will appear? What is the relationship among Google, a news website such as Reuters, and Instant Checkmate in the previous examples? An overview of Google AdSense, the program that delivered the ads, provides the answers.

In printed newspapers, everyone who reads the publication sees the same ad in the same space. Online ads can be tailored to the reader's search criteria, interests, geographical location, and so on. Any two readers (or even the same reader returning to the same website) might view different ads.

Google AdSense is the largest provider of dynamic online advertisements, placing ads for millions of sponsors on millions of websites.[9] In the first quarter of 2011, Google earned $2.43 billion through Google AdSense.[10] Several different advertising arrangements exist, but for simplicity this article describes only those features of Google AdSense specific to the Instant Checkmate ads in question.

Figure 2. Ad from a search of three different names beginning with the first name "Jill."



When a reader enters search criteria in an enrolled website, Google AdSense embeds into the Web page of results ads believed to be relevant to the search. Figures 1 and 2 show ads delivered by Google AdSense in response to various *firstname lastname* searches.

An advertiser provides Google with search criteria, copies of possible ads to deliver, and a bid to pay if a reader clicks the delivered ad. (For convenience, this article conflates Google AdSense with the related Google Adwords.) Google operates a real-time auction across bids for the same search criteria based on a "quality score" for each bid. A quality score includes many factors such as the past performance of the ad and characteristics of the company's website.[10] The ad having the highest quality score appears first, the second-highest second, and so on, and Google may elect not to show any ad if it considers the bid too low or if showing the ad exceeds a threshold (For example, a maximum account total for the advertiser). The Instant Checkmate ads in figures 1 and 2 often appeared first among ads, implying Instant Checkmate ads had the highest quality scores.

A website owner wanting to "host" online ads enrolls in AdSense and modifies the website to send a user's search criteria to Google and to display returning ads under a banner "Ads by Google" among search results. For example, Reuters.com hosts AdSense, and entering *Latanya Sweeney* in the search bar generated a new Web page with ads under the banner "Ads by Google" (Figure 1c).

There is no cost for displaying an ad, but if the user actually clicks on the ad, the advertiser pays the auction price. This may be as little as a few pennies, and the amount is split between Google and the host. Clicking the *Latanya Sweeney* ad on Reuters.com (Figure 1c) would cause Instant Checkmate to pay its auction amount to Google, and Google would split the amount with Reuters.

Search Criteria

What search criteria did Instant Checkmate specify? Will ads be delivered for made-up names? Ads displayed on Google.com allow users to learn why a specific ad appeared. Clicking the circled "i" in the ad banner (for example, Figure 1c) leads to a Web page explaining the ads. Doing so for ads in figures 1 and 2 reveals that the ads appeared because the search criteria matched the exact first- and last-name combination searched.

So, the search criteria must consist of both first and last names; and the names should belong to real people because a company presumably bids on records it sells.

The next steps describe the systematic construction of a list of racially associated first and last names for real people to use as search criteria. Neither Instant Checkmate nor Google are presumed to have used such a list. Rather, the list provides a qualified sample of names to use in testing ad-delivery systems.

Black- and White-Identifying Names

Black-identifying and white-identifying first names occur with sufficiently higher frequency in one race than the other.

In 2003 Marianne Bertrand and Sendhil Mullainathan of the National Bureau of Economic Research (NBER) conducted an experiment in which they provided resumes to job posts that were virtually identical, except some of the resumes had black-identifying names and others had white-identifying names. Results showed white names received 50% more interviews.[2]

The study used names given to black and white babies in Massachusetts between 1974 and 1979, defining black-identifying and white-identifying names as those that have the highest ratio of frequency in one racial group to frequency in the other racial group.

In the popular book *Freakonomics*, Steven Levitt and Stephen Dubner report the top 20 whitest- and blackest-identifying girl and boy names. The list comes from earlier work by Levitt and Roland Fryer, which shows a pattern change in the way blacks named their children starting in the 1970s.[7] It was compiled from names given to black and white children recorded in California birth records from 1961–2000 (more than 16 million births).

To test ad delivery, I combined the lists from these prior studies and added two black female names, *Latanya* and *Latisha*. Table 1 lists the names used here, consisting of eight for each of the categories: white female, black female, white male, and black male from the Bertrand and Mullainathan study (first row in Table 1); and the first eight names for each category from the Fryer and Levitt work (second row in Table 1). Emily, a white female name, Ebony, a black female name, and Darnell, a black male name, appear in both rows. The third row includes the observation shown in Figure 3. Removing duplicates leaves a total of 63 distinct first names.

Table 1. Black-identifying names and white-identifying first names.

	White Female	Black Female	White Male	Black Male
(a)	Allison	Aisha	Brad	Darnell
	Anne	Ebony	Brendan	Hakim
	Carrie	Keisha	Geoffrey	Jermaine
	Emily	Kenya	Greg	Kareem
	Jill	Latonya	Brett	Jamal
	Laurie	Lakisha	Jay	Leroy
	Kristen	Latoya	Matthew	Rasheed
	Meredith	Tamika	Neil	Tremayne
(b)	Molly	Imani	Jake	DeShawn
	Amy	Ebony*	Connor	DeAndre
	Claire	Shanice	Tanner	Marquis
	Emily*	Aaliyah	Wyatt	Darnell*
	Katie	Precious	Cody	Terrell
	Madeline	Nia	Dustin	Malik
	Katelyn	Deja	Luke	Trevon
	Emma	Diamond	Jack	Tyrone
(c)		Latanya		
		Latisha		

Full Names of Real People

Web searches provide a means of locating and harvesting a real person's first and last name (full name) by sampling names of professionals appearing on the Web; and sampling names of people active on social media sites and blogs (netizens).

Professionals often have their own Web pages that list positions and describe prior accomplishments. Several professions have degree designations (for example, Ph.D., M.D., J.D., or MBA) associated with people in that profession. A Google search for a first name and a degree designation can yield lists of people having that first name and degree.

The next step is to visit the Web page associated with each full name, and if an image is discernible, record whether the person appears black, white, or other.

Here are two examples from my test. A Google search for *Ebony PhD* revealed links for real people having *Ebony* as a first name—specifically, *Ebony Bookman*, *Ebony Glover*, *Ebony Baylor*, and *Ebony Utley*. I harvested the full names appearing on the first three pages of search results, using searches with other degree designations to find at least 10 full names for *Ebony*. Clicking on the link associated with *Ebony Glover* displayed an image.[8] The *Ebony Glover* in this study appeared black.

Similarly, search results for *Jill PhD* listed professionals whose first name is *Jill*. Visiting links yielded Web pages with more information about each person. For example, *Jill Schneider*'s Web page had an image showing that she is white.[14]

PeekYou searches were used to harvest a sample of full names of netizens having racially associated first names. The website peekyou.com compiles online and offline information on individuals—thereby connecting residential information with Facebook and Twitter users, bloggers, and others—then assigns its own rating to reflect the size of each person's online footprint. Search results from peekyou.com list people having the highest score first, and include an image of the person.

A PeekYou search of *Ebony* listed *Ebony Small*, *Ebony Cams*, *Ebony King*, *Ebony Springer*, and *Ebony Tan*. A PeekYou search for *Jill* listed *Jill Christopher*, *Jill Spivack*, *Jill English*, *Jill Pantozzi*, and *Jill Dobson*. After harvesting these and other full names, I reported the race of the person if discernible.

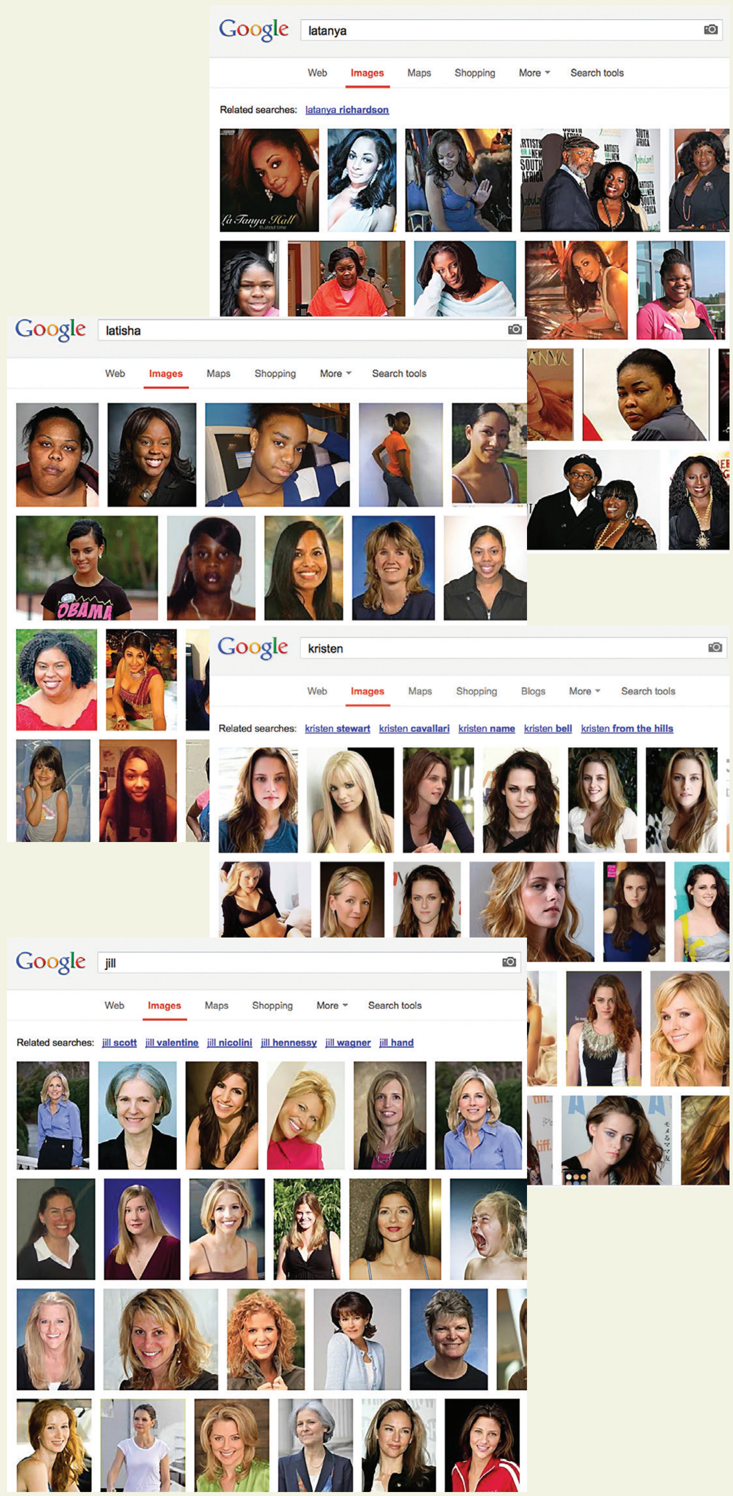
Figure 3. Image search results for first names Latanya, Latisha, Kirsten, and Jill.

(a)

(b)

(c)

(d)



Armed with the approach just described, I harvested 2,184 racially associated full names of people with an online presence from September 24 through October 22, 2012. Most images associated with black-identifying names were of black people (88%), and an even greater percentage of images associated with white-identifying names were of white people (96%).[15]

Google searches of first names and degree designations were not as productive as first name lookups on PeekYou. On Google, white male names, *Cody*, *Connor*, *Tanner*, and *Wyatt* retrieved results with those as last names rather than first names; the black male name, *Kenya*, was confused with the country; and black names *Aaliyah*, *Deja*, *Diamond*, *Hakim*, *Malik*, *Marquis*, *Nia*, *Precious*, and *Rasheed* retrieved fewer than 10 full names. Only *Diamond* posed a problem with PeekYou searches, seemingly confused with other online entities. *Diamond* was therefore excluded from further consideration.

Some black first names had perfect predictions (100%): *Aaliyah*, *DeAndre*, *Imani*, *Jermaine*, *Lakisha*, *Latoya*, *Malik*, *Tamika*, and *Trevon*. The worst predictors of blacks were *Jamal* (48%) and *Leroy* (50%). Among white first names, 12 of 31 names made perfect predictions: *Brad*, *Brett*, *Cody*, *Dustin*, *Greg*, *Jill*, *Katelyn*, *Katie*, *Kristen*, *Matthew*, *Tanner*, and *Wyatt*; the worst predictors of whites were *Jay* (78%) and *Brendan* (83%). These findings strongly support the use of these names as racial indicators in this study.

Sixty-two full names appeared in the list twice even though the people were not necessarily the same. No name appeared more than twice. Overall, Google and PeekYou searches tended to yield different names.

Ad Delivery

With this list of names suggestive of race, I was ready to test which ads appear when these names are searched. To do this, I examined ads delivered on two sites, Google.com and Reuters.com, in response to searches of each full name, once at each site. The browser's cache and cookies were cleared before each search, and copies of Web pages received were preserved. Figures 1, 2, 5, and 6 provide examples.

From September 24 through October 23, 2012, I searched 2,184 full names on Google.com and Reuters.com. The searches took place at different times of day, different days of the week, with different IP and machine addresses operating in different parts of the United States using different browsers. I manually searched 1,373 of the names and used automated means[17] for the remaining 812 names. Here are nine observations.

1. *Fewer ads appeared on Google.com than Reuters.com*—about five times fewer. When ads did appear on Google.com, typically only one ad showed, compared with three ads routinely appearing on Reuters.com. This suggests Google may be sensitive to the number of ads appearing on Google.com.

2. *Of 5,337 ads captured, 78% were for government-collected information (public records) about the person whose name was searched.* Public records in the U.S. often include a person's address, phone number, and criminal history. Of the more than 2,000 names searched, 78% had at least one ad for public records about the person being searched.

3. *Four companies had more than half of all the ads captured.* These companies were Instant Checkmate, PublicRecords (which is owned by Intelius), PeopleSmart, and PeopleFinders, and all their ads were selling public records. Instant Checkmate ads appeared more than any other: 29% of all ads. Ad distribution was different on Google's site; Instant Checkmate still had the most ads (50%), but Intelius.com, while not in the top four overall, had the second most ads on Google.com. These companies dominate the advertising space for online ads selling public records.

4. *Ads for public records on a person appeared more often for those with black-associated names than white-associated names, regardless of company.* PeopleSmart ads appeared disproportionately higher for black-identifying names—41% as opposed to 29% for white names. PublicRecords ads appeared 10% more often for those with black first names than white. Instant Checkmate ads displayed only slightly more often for black-associated names (2% difference). This is an interesting finding and it spawns the question: Public records contain information on everyone, so why more ads for black-associated names?

5. *Instant Checkmate ads dominated the topmost ad position.* They occupied that spot in almost half of all searches on Reuters.com. This suggests Instant Checkmate offers Google more money or has higher quality scores than do its competitors.

6. *Instant Checkmate had the largest percentage of ads in virtually every first-name category, except for Kristen, Connor, and Tremayne.* For those names, Instant Checkmate had uncharacteristically fewer ads (less than 25%). Pub-

Of the more than 2,000 names searched, 78% had at least one ad for public records about the person being searched.

licRecords had ads for 80% of names beginning with *Tremayne*, and *Connor*, and 58% for *Kristen*, compared to 20% and less for Instant Checkmate. Why the underrepresentation in these first names? During a conference call with company's representatives, they asserted that Instant Checkmate gave the same ad text to Google for groups of last names (not first names).

7. *Almost all ads for public records included the name of the person, making each ad virtually unique, but beyond personalization, the ad templates showed little variability.* The only exception was Instant Checkmate. Almost all PeopleFinder ads appearing on Reuters.com used the same personalized template. PublicRecords used five templates and PeopleSmart seven, but Instant Checkmate used 18 different ad templates on Reuters.com. Figure 4 enumerates ad templates for frequencies of 10 or more for all four companies (replace fullname with the person's first and last name).

While Instant Checkmate's competitors also sell criminal history information, only Instant Checkmate ads used the word arrest.

8. *A greater percentage of Instant Checkmate ads using the word "arrest" appeared for black-identifying first names than for white first names.* More than 1,100 Instant Checkmate ads appeared on Reuters.com, with 488 having black-identifying first names; of these, 60% used *arrest* in the ad text. Of the 638 ads displayed with white-identifying names, 48% used *arrest*. This difference is statistically significant, with less than a 0.1% probability that the data can be explained by chance (chi-square test: $X^2(1)=14.32$, $p < 0.001$). The EEOC's and U.S. Department of Labor's adverse impact test for measuring discrimination is 77 in this case, so if this were an employment situation, a charge of discrimination might result. (The adverse impact test uses the ratio of neutral ads, or 100 minus the percentages given, to compute disparity: 100-60=40 and 100-48=52; dividing 40 by 52 equals 77.)

The highest percentage of neutral ads (where the word *arrest* does not appear in ad text) on Reuters.com were those for *Jill* (77%) and *Emma* (75%), both white-identifying names. Names receiving the highest percentage of ads with *arrest* in the text were *Darnell* (84%), *Jermaine* (81%), and *DeShawn* (86%), all black-identifying first names. Some names appeared counter to this pattern: *Dustin*, a white-identifying name, generated *arrest* ads in 81% of searches; and *Imani*, a black-identifying name, resulted in neutral ads in 75% of searches.

9. *Discrimination results on Google's site were similar, but, interestingly, ad text and distributions were different.* While the same neutral and *arrest* ads having dominant appearances on Reuters.com also appeared frequently on Google.com, Instant Checkmate ads on Google included an additional 10 templates, all using the word *criminal* or *arrest*.

More than 400 Instant Checkmate ads appeared on Google, and 90% of these were suggestive of *arrest*, regardless of race. Still, a greater percentage of Instant Checkmate ads suggestive of arrest displayed for black-associated first names than for whites. Of the 366 ads that appeared for black-identifying names, 92% were suggestive of arrest. Far fewer ads displayed for white-identifying names (66 total), but 80% were suggestive of arrest. This difference in the ratios 92 and 80 is statistically significant, with less than a 1% probability that the data can be explained by chance (chi-square test: X2(1)=7.71, p < 0.01). The EEOC's adverse impact test for measuring discrimination is 40%, so if this were employment, a charge of discrimination might result. (The adverse impact test gives 100-92=8 and 100-80=20; dividing 8 by 20 equals 40.)

A greater percentage of Instant Checkmate ads having the word *arrest* in ad text appeared for black-identifying first names than for white-identifying first names within professional and netizen subsets, too. On Reuters.com, which hosts Google AdSense ads, a black-identifying name was 25% more likely to generate an ad suggestive of an arrest record.

Figure 4. Template for ads for public records on Reuters for frequencies less than 10. Full list is available.[15]

instantcheckmate		**Peoplesmart**	
382	**Located:** ***fullname*** Information found on *fullname* *fullname* found in database.	87	**We found:** ***fullname*** 1) Get Aisha's Background Report 2) Current Contact Info—Try Free!
96	**We found** ***fullname*** Search Arrests, Address, Phone, etc. Search records for *fullname*.	105	**We found:** ***fullname*** 1) Contact *fullname*—Free Info! 2) Current Address, Phone & More.
40	**Background of** ***fullname*** Search Instant Checkmate for the Records of *fullname*	348	**We found:** ***fullname*** 1) Contact *fullname*—Free Info! 2) Current Phone, Address & More.
17	***fullname's*** **Records** 1) Enter Name and State. 2) Access Full Background Checks Instantly.	**Publicrecords**	
195	***fullname*****: Truth** Arrests and Much More. Everything About *fullname*	570	***fullname*** Public Records Found For: *fullname*. View now.
67	***fullname*** **Truth** Looking for *fullname*? Check *fullname*'s Arrests	128	***fullname*** Public Records Found For: *fullname*. Search now.
176	***fullname*****, Arrested?** 1) Enter Name and State. 2) Access Full Background Checks Instantly.	13	**Records:** ***fullname*** Database of all lastname's in the Country. Search now.
55	***fullname*** **Located** Background Check, Arrest Records, Phone, & Address. Instant, Accurate	56	***fullname*** We have Public Records For: *fullname*. Search Now.
62	**Looking for** ***fullname*****?** Comprehensive Background Report and More on *fullname*	**Peoplefinders**	
		523	**We found** ***fullname*** Current Address, Phone and Age. Find *fullname*, Anywhere.

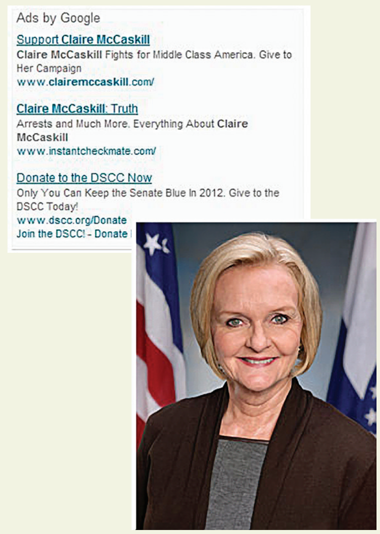


Figure 5. Senator Claire McCaskill's campaign ad appeared next to an ad using the word "arrest."

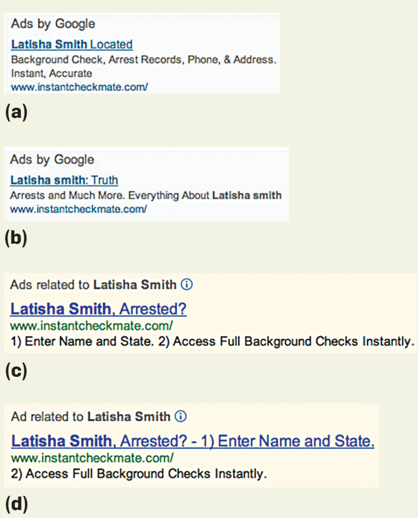


Figure 6. An assortment of ads appearing for Latisha Smith.

These findings reject the hypothesis that no difference exists in the delivery of ads suggestive of an arrest record based on searches of racially associated names.

Additional Observations

The people behind the names used in this study are diverse. Political figures included Maryland State Representatives Aisha Braveboy (arrest ad) and Jay Jacobs (neutral ad); Jill Biden (neutral ad), wife of U.S. Vice President Joe Biden; and Claire McCaskill, whose campaign ad for the U.S. Senate in Missouri appeared alongside an Instant Checkmate ad using the word *arrest* (Figure 5). Names mined from academic websites included graduate students, staff, and accomplished academics, such as Amy Gutmann, president of the University of Pennsylvania. Dustin Hoffman (arrest ad) was among names of celebrities used. A smorgasbord of athletes appeared, from local to national fame (assorted neutral and arrest ads). The youngest person whose name was used in the study was a missing 11-year-old black girl.

More than 1,100 of the names harvested for this study were from PeekYou, with scores estimating the name's overall presence on the Web. As expected, celebrities get the highest scores of 10s and 9s. Only four names used here had a PeekYou score of 10, and 12 had a score of 9, including Dustin Hoffman. Only two ads appeared for these high-scoring names; an abundance of ads appeared across the remaining spectrum of PeekYou scores. We might presume that the bid price needed to display an ad is greater for more popular names with higher PeekYou scores. Knowing that very few high-scoring people were in the study and that ads appeared across the full spectrum of PeekYou scores reduces concern about variations in bid prices.

Different Instant Checkmate ads sometimes appeared for the same person. About 200 names had Instant Checkmate ads on both Reuters.com and Google.com, but only 42 of these names received the same ad. The other 82% of names received different ads across the two sites. At most, three distinct ads appeared across Reuters.com and Google.com for the same name. Figure 6 shows the assortment of ads appearing for *Latisha Smith*. Having different possible ad texts for a name reminds us that while Instant Checkmate provided the ad texts, Google's technology selected among the possible texts in deciding which to display. Figure 6 shows ads both suggestive of arrest and not, though more ads appear suggestive of arrest than not.

More About the Problem

Why is this discrimination occurring? Is Instant Checkmate, Google, or society to blame? We do not yet know. Google understands that an advertiser may not know which ad copy will work best, so the advertiser may provide multiple templates for the same search string, and the "Google algorithm" learns over time which ad text gets the most clicks from viewers. It does this by assigning weights (or probabilities) based on the click history of each ad. At first, all possible ad texts are weighted the same and are equally likely to produce a click. Over time, as people tend to click one ad copy over others, the weights change, so the ad text getting the most clicks eventually displays more frequently.

Did Instant Checkmate provide ad templates suggestive of arrest disproportionately to black-identifying names? Or did Instant Checkmate provide roughly the same templates evenly across racially associated names but users clicked ads suggestive of arrest more often for black-identifying names? As mentioned earlier, during a conference call with the founders of Instant Checkmate and their lawyer, the company's representatives asserted that Instant Checkmate gave the same ad text to Google for groups of last names (not first names) in its database; they expressed no other criteria for name and ad selection.

This study is a start, but more research is needed. To preserve research opportunities, I captured additional results for 50 hits on 2,184 names across 30 Web sites serving Google Ads to learn the underlying distributions of ad occurrences per name. While analyzing the data may prove illuminating, in the end the basic message presented in this study does not change: there is discrimination in delivery of these ads.

Technical Solutions

How can technology solve this problem? One answer is to change the quality scores of ads to discount for unwanted bias. The idea is to measure real-time bias in an ad's delivery and then adjust the weight of the ad accordingly at auction. The general term for Google's technology is *ad exchange*. This approach generalizes to other ad exchanges (not just Google's); integrates seamlessly into the way ad exchanges operate, allowing minimal modifications to harmonize ad deliveries with societal norms; and, works regardless of the cause of the discrimination—advertiser bias in placing ads or society bias in selecting ads.

Discrimination, however, is at the heart of online advertising. Differential delivery is the very idea behind it. For example, if young women with children tend to purchase baby products and retired men with bass boats tend to purchase fishing supplies, and you know the viewer is one of these two types, then it is more efficient to offer ads for baby products to the young mother and fishing rods to the fisherman, not the other way around.

On the other hand, not all discrimination is desirable. Societies have identified groups of people to protect from specific forms of discrimination. Delivering ads suggestive of arrest much more often for searches of black-identifying names than for white-identifying names is an example of unwanted discrimination, according to American social and legal norms. This is especially true because the ads appear regardless of whether actual arrest records exist for the names in the company's database.

The good news is that we can use the mechanics and legal criteria described earlier to build technology that distinguishes between desirable and undesirable discrimination in ad delivery. Here I detail the four key components:

1. *Identifying Affected Groups.* A set of predicates can be defined to identify members of protected and comparison groups. Given an ad's search string and text, a predicate returns *true* if the ad can impact the group that is the subject of the predicate and returns *false* otherwise. Statistics of baby names can identify first names for constructing race and gender groups and last names for grouping some ethnicities. Special word lists or functions that report degree of membership may be helpful for other comparisons.

In this study, ads appeared on searches of full names for real people, and first names assigned to more black or white babies formed groups for testing. These *black* and *white* predicates evaluate to *true* or *false* based on the first name of the search string.

2. *Specifying the Scope of Ads to Assess.* The focus should be on those ads capable of impacting a protected group in a form of discrimination prohibited by law or social norm. Protection typically concerns the ability to give or withhold benefits, facilities, services, employment, or opportunities. Instead of lumping all ads together, it is better to use search strings, ad texts, products, or URLs that display with ads to decide which ads to assess.

Discrimination is at the heart of online advertising. Differential delivery is the very idea behind it.

This study assessed search strings of first and last names of real people, ads for public records, and ads having a specific display URL (instantcheckmate.com), the latter being the most informative because the adverse ads all had the same display URL.

Of course, the audience for the ads is not necessarily the people who are the subject of the ads. In this study, the audience is a person inquiring about the person whose name is the subject of the ad. This distinction is important when thinking about the identity of groups that might be impacted by an ad. Group membership is based on the ad's search string and text. The audience may resonate more with a distinctly positive or negative characterization of the group.

3. *Determining Ad Sentiment.* Originally associated with summarizing product and movie reviews, sentiment analysis is an area of computer science that uses natural-language processing and text analytics to determine the overall attitude of a writing.[13] Sentiment analysis can measure whether an ad's search string and accompanying text has positive, negative, or neutral sentiment. A literature search does not find any prior application to online ads, but a lot of research has been done assessing sentiment in social media (sentiment140.com, for example, reports the sentiment of tweets, which like advertisements have limited words).

In this study, ads containing the word *arrest* or *criminal* were classified as having negative sentiment; ads without those words were classified as neutral.

4. *Testing for Adverse Impact.* Consider a table where columns are comparative groups, rows are sentiment, and values are the number of ad impressions (the number of times an ad appears, though the ad is not necessarily clicked). Ignore neutral ads. Comparing the percentage of ads having the same positive or negative sentiment across groups reveals the degree to which one group may be impacted more or less by the ad's sentiment.

Table 2. Negative and neutral sentiments of black and white groups.

	Black		White	
Negative	291	60%	308	48%
Neutral	197	40%	330	52%
Positive				
Totals	**488**		**638**	

A chi-square test can determine statistical significance, and the adverse impact test used by the EEOC and the U.S. Department of Labor can alert whether in some circumstances legal risks may result.

In this study the groups are black and white, and the sentiments are negative and neutral. Table 2 shows a summary chart. Of the 488 ads that appeared for the black group, 291 (or 60%) had negative sentiment. Of the 638 ads displayed for the white group, 308 (or 48%) had negative sentiment. The difference is statistically significant ($X^2(1)=14.32$, $p < 0.001$) and has an adverse impact measure of (40/52), or 77%.

An easy way of incorporating this analysis into an ad exchange is to decide which bias test is critical (for example, statistical significance or adverse impact test) and then factor the test result into the quality score for the ad at auction. For example, if we were to modify the ad exchange not to display any ad having an adverse impact score of less than 80, which is the EEOC standard, then arrest ads for blacks would sometimes appear, but would not be overly disproportionate to whites, regardless of advertiser or click bias.

Though this study served as an example throughout, the approach generalizes to many other forms of discrimination and combats other ways ad exchanges may foster discrimination.

Suppose female names tend to get neutral ads such as "Buy now," while male names tend to get positive ads such as "Buy now. 50% off!" Or suppose black names tend to get neutral ads such as "Looking for Ebony Jones," while white names tend to get positive ads such as "Meredith Jones. Fantastic!" Then the same analysis would suppress some occurrences of the positive ads so as not to foster a discriminatory effect.

This approach does not stop the appearance of negative ads for a store placed by a disgruntled customer or ads placed by competitors on brand names of the competition, unless these are deemed to be protected groups.

Nonprotected marketing discrimination can continue even to protected groups. For example, suppose search terms associated with blacks tend to get neutral ads for some music artists, while those associated with whites tend to get neutral ads for other music artists. All ads would appear regardless of the disproportionate distribution because the ads are not subject to suppression.

As a final example, this approach allows everyone to be negatively impacted as long as the impact is approximately the same. Suppose all ads for public records on all names, regardless of race, were equally suggestive of arrest and had almost the same number of impressions; then no ads suggestive of arrest would be suppressed.

Computer scientist Cynthia Dwork and her colleagues have been working on algorithms that assure racial fairness.[4] Their general notion is to ensure similar groups receive similar ads in proportions consistent with the population. Utility is the critical concern with this direction because not all forms of discrimination are bad, and unusual and outlier ads could be unnecessarily suppressed. Still, their research direction looks promising.

In conclusion, this study demonstrates that technology can foster discriminatory outcomes, but it also shows that technology can thwart unwanted discrimination.

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Automated Experiments on Ad Privacy Settings

A Tale of Opacity, Choice, and Discrimination

Abstract: To partly address people's concerns over web tracking, Google has created the Ad Settings webpage to provide information about and some choice over the profiles Google creates on users. We present AdFisher, an automated tool that explores how user behaviors, Google's ads, and Ad Settings interact. AdFisher can run browser-based experiments and analyze data using machine learning and significance tests. Our tool uses a rigorous experimental design and statistical analysis to ensure the statistical soundness of our results. We use AdFisher to find that the Ad Settings was opaque about some features of a user's profile, that it does provide some choice on ads, and that these choices can lead to seemingly discriminatory ads. In particular, we found that visiting webpages associated with substance abuse changed the ads shown but not the settings page. We also found that setting the gender to female resulted in getting fewer instances of an ad related to high paying jobs than setting it to male. We cannot determine who caused these findings due to our limited visibility into the ad ecosystem, which includes Google, advertisers, websites, and users. Nevertheless, these results can form the starting point for deeper investigations by either the companies themselves or by regulatory bodies.

Keywords: blackbox analysis, information flow, behavioral advertising, transparency, choice, discrimination

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1 Introduction

Problem and Overview. With the advancement of tracking technologies and the growth of online data aggregators, data collection on the Internet has become a serious privacy concern. Colossal amounts of collected data are used, sold, and resold for serving targeted content, notably advertisements, on websites (e.g., [1]). Many websites providing content, such as news, outsource their advertising operations to large third-party ad networks, such as Google's DoubleClick. These networks embed tracking code into webpages across many sites providing the network with a more global view of each user's behaviors.

People are concerned about behavioral marketing on the web (e.g., [2]). To increase transparency and control, Google provides Ad Settings, which is "a Google tool that helps you control the ads you see on Google services and on websites that partner with Google" [3]. It displays inferences Google has made about a user's demographics and interests based on his browsing behavior. Users can view and edit these settings at

http://www.google.com/settings/ads

Yahoo [4] and Microsoft [5] also offer personalized ad settings.

However, they provide little information about how these pages operate, leaving open the question of how completely these settings describe the profile they have about a user. In this study, we explore how a user's behaviors, either directly with the settings or with content providers, alter the ads and settings shown to the user and whether these changes are in harmony. In particular, we study the degree to which the settings provides transparency and choice as well as checking for the presence of discrimination. Transparency is important for people to understand how the use of data about them affects the ads they see. Choice allows users to control how this data gets used, enabling them to protect the information they find sensitive. Discrimination is an increasing concern about machine learning systems and one reason people like to keep information private [6, 7].

To conduct these studies, we developed AdFisher, a tool for automating randomized, controlled experiments for studying online tracking. Our tool offers a combination of automation, statistical rigor, scalability, and explanation for determining the use of information by web advertising algorithms and by personalized ad settings, such as Google Ad Settings. The tool can simulate having a particular interest or attribute by visiting web-

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pages associated with that interest or by altering the ad settings provided by Google. It collects ads served by Google and also the settings that Google provides to the simulated users. It automatically analyzes the data to determine whether statistically significant differences between groups of agents exist. AdFisher uses machine learning to automatically detect differences and then executes a test of significance specialized for the difference it found.

Someone using AdFisher to study behavioral targeting only has to provide the behaviors the two groups are to perform (e.g., visiting websites) and the measurements (e.g., which ads) to collect afterwards. AdFisher can easily run multiple experiments exploring the causal connections between users' browsing activities, and the ads and settings that Google shows.

The advertising ecosystem is a vast, distributed, and decentralized system with several players including the users consuming content, the advertisers, the publishers of web content, and ad networks. With the exception of the user, we treat the entire ecosystem as a blackbox. We measure simulated users' interactions with this blackbox including page views, ads, and ad settings. Without knowledge of the internal workings of the ecosystem, we cannot assign responsibility for our findings to any single player within it nor rule out that they are unintended consequences of interactions between players. However, our results show the presence of concerning effects illustrating the existence of issues that could be investigated more deeply by either the players themselves or by regulatory bodies with the power to see the internal dynamics of the ecosystem.

Motivating Experiments. In one experiment, we explored whether visiting websites related to substance abuse has an impact on Google's ads or settings. We created an experimental group and a control group of agents. The browser agents in the experimental group visited websites on substance abuse while the agents in the control group simply waited. Then, both groups of agents collected ads served by Google on a news website.

Having run the experiment and collected the data, we had to determine whether any difference existed in the outputs shown to the agents. One way would be to intuit what the difference could be (e.g. more ads containing the word "alcohol") and test for that difference. However, developing this intuition can take considerable effort. Moreover, it does not help find unexpected differences. Thus, we instead used machine learning to automatically find differentiating patterns in the data. Specifically, AdFisher finds a classifier that can predict which group an agent belonged to, from the ads shown to an agent. The classifier is trained on a subset of the data. A separate test subset is used to determine whether the classifier found a statistically significant difference between the ads shown to each group of agents. In this experiment, AdFisher found a classifier that could distinguish between the two groups of agents by using the fact that only the agents that visited the substance abuse websites received ads for Watershed Rehab.

We also measured the settings that Google provided to each agent on its Ad Settings page after the experimental group of agents visited the webpages associated with substance abuse. We found no differences (significant or otherwise) between the pages for the agents. Thus, information about visits to these websites is indeed being used to serve ads, but the Ad Settings page does not reflect this use in this case. Rather than providing transparency, in this instance, the ad settings were *opaque* as to the impact of this factor.

In another experiment, we examined whether the settings provide *choice* to users. We found that removing interests from the Google Ad Settings page changes the ads that a user sees. In particular, we had both groups of agents visit a site related to online dating. Then, only one of the groups removed the interest related to online dating. Thereafter, the top ads shown to the group that kept the interest were related to dating but not the top ads shown to the other group. Thus, the ad settings do offer the users a degree of choice over the ads they see.

We also found evidence suggestive of *discrimination* from another experiment. We set the agents' gender to female or male on Google's Ad Settings page. We then had both the female and male groups of agents visit webpages associated with employment. We established that Google used this gender information to select ads, as one might expect. The interesting result was how the ads differed between the groups: during this experiment, Google showed the simulated males ads from a certain career coaching agency that promised large salaries more frequently than the simulated females, a finding suggestive of discrimination. Ours is the first study that provides statistically significant evidence of an instance of discrimination in online advertising when demographic information is supplied via a transparency-control mechanism (i.e., the Ad Settings page).

While neither of our findings of opacity or discrimination are clear violations of Google's privacy policy [8] and we do not claim these findings to generalize or imply widespread issues, we find them concerning and warranting further investigation by those with visibility into the ad ecosystem. Furthermore, while our finding of discrimination in the non-normative sense of the word is on firm statistical footing, we acknowledge that people may disagree about whether we found discrimination in the normative sense of the word. We defer discussion of whether our findings suggest unjust discrimination until Section 7.

Contributions. In addition to the experimental findings highlighted above, we provide AdFisher, a tool for *automating* such experiments. AdFisher is structured as a Python API providing functions for setting up, running, and analyzing experiments. We use Selenium to drive Firefox browsers and the scikit-learn library [9] for implementations of classification algorithms. We use the SciPy library [10] for implementing the statistical analyses of the core methodology.

AdFisher offers *rigor* by performing a carefully designed experiment. The statistical analyses techniques applied do not make questionable assumptions about the collected data. We base our design and analysis on a prior proposal that makes no assumptions about the data being independent or identically distributed [11]. Since advertisers update their behavior continuously in response to unobserved inputs (such as ad auctions) and the experimenters' own actions, such assumptions may not always hold. Indeed, in practice, the distribution of ads changes over time and simulated users, or *agents*, interfere with one another [11].

Our automation, experimental design, and statistical analyses allow us to *scale* to handling large numbers of agents for finding subtle differences. In particular, we modify the prior analysis of Tschantz et al. [11] to allow for experiments running over long periods of time. We do so by using *blocking* (e.g., [12]), a nested statistical analysis not previously applied to understanding web advertising. The blocking analysis ensures that agents are only compared to the agents that start out like it and then aggregates together the comparisons across blocks of agents. Thus, AdFisher may run agents in batches spread out over time while only comparing those agents running simultaneously to one another.

AdFisher also provides *explanations* as to how Google alters its behaviors in response to different user actions. It uses the trained classifier model to find which features were most useful for the classifier to make its predictions. It provides the top features from each group to provide the experimenter/analyst with a qualitative understanding of how the ads differed between the groups.

To maintain statistical rigor, we carefully circumscribe our claims. We only claim statistical soundness of our results: if our techniques detect an effect of the browsing activities on the ads, then there is indeed one with high likelihood (made quantitative by a p-value). We do not claim that we will always find a difference if one exists, nor that the differences we find are typical of those experienced by users. Furthermore, while we can characterize the differences, we cannot assign blame for them since either Google or the advertisers working with Google could be responsible.

Contents. After covering prior work next, we present, in Section 3, privacy properties that our tool AdFisher can check: nondiscrimination, transparency, and choice. Section 4 explains the methodology we use to ensure sound conclusions from using AdFisher. Section 5 presents the design of AdFisher. Section 6 discusses our use of AdFisher to study Google's ads and settings. We end with conclusions and future work.

Raw data and additional details about AdFisher and our experiments can be found at

http://www.cs.cmu.edu/~mtschant/ife/

AdFisher is freely available at

https://github.com/tadatitam/info-flow-experiments/

2 Prior Work

We are not the first to study how Google uses information. The work with the closest subject of study to ours is by Wills and Tatar [13]. They studied both the ads shown by Google and the behavior of Google's Ad Settings (then called the "Ad Preferences"). Like us, they find the presence of opacity: various interests impacted the ads and settings shown to the user and that ads could change without a corresponding change in Ad Settings. Unlike our study, theirs was mostly manual, small scale, lacked any statistical analysis, and did not follow a rigorous experimental design. Furthermore, we additionally study choice and discrimination.

Other related works differ from us in both goals and methods. They all focus on how visiting webpages change the ads seen. While we examine such changes in our work, we do so as part of a larger analysis of the interactions between ads and personalized ad settings, a topic they do not study.

Barford et al. come the closest in that their recent study looked at both ads and ad settings [14]. They do so in their study of the "adscape", an attempt to understand each ad on the Internet. They study each ad individually and cast a wide net to analyze many ads from many websites while simulating many different interests. They only examine the ad settings to determine whether they successfully induced an interest. We rigorously study how the settings affects the ads shown (choice) and how behaviors can affect ads without affecting the settings (transparency). Furthermore, we use focused collections of data and an analysis that considers all ads collectively to find subtle causal effects within Google's advertising ecosystem. We also use a randomized experimental design and analysis to ensure that our results imply causation.

The usage study closest to ours in statistical methodology is that of Tschantz et al. [11]. They developed a rigorous methodology for determining whether a system like Google uses information. Due to limitations of their methodology, they only ran small-scale studies. While they observed that browsing behaviors could affect Ad Settings, they did not study how this related to the ads received. Furthermore, while we build upon their methodology, we automate the selection of an appropriate test statistic by using machine learning whereas they manually selected test statistics.

The usage study closest to ours in terms of implementation is that of Liu et al. in that they also use machine learning [15]. Their goal is to determine whether an ad was selected due to the content of a page, by using behavioral profiling, or from a previous webpage visit. Thus, rather than using machine learning to select a statistical test for finding causal relations, they do so to detect whether an ad on a webpage matches the content on the page to make a case for the first possibility. Thus, they have a separate classifier for each interest a webpage might cover. Rather than perform a statistical analysis to determine whether treatment groups have a statistically significant difference, they use their classifiers to judge the ratio of ads on a page unrelated to the page's content, which they presume indicates that the ads were the result of behavioral targeting.

Lécuyer et al. present XRay, a tool that looks for correlations between the data that web services have about users and the ads shown to users [16]. While their tool may check many changes to a type of input to determine whether any of them has a correlation with the frequency of a single ad, it does not check for causation, as ours does.

Englehardt et al. study filter bubbles with an analysis that assumes independence between observations [17], an assumption we are uncomfortable making. (See Section 4.4.)

Guha et al. compare ads seen by three agents to see whether Google treats differently the one that behaves differently from the other two [18]. We adopt their suggestion of focusing on the title and URL displayed on ads when comparing ads to avoid noise from other less stable parts of the ad. Our work differs by studying the ad settings in addition to the ads and by using larger numbers of agents. Furthermore, we use rigorous statistical analyses. Balebako et al. run similar experiments to study the effectiveness of privacy tools [19].

Sweeney ran an experiment to determine that searching for names associated with African-Americans produced more search ads suggestive of an arrest record than names associated with European-Americans [20]. Her study required considerable insight to determine that suggestions of an arrest was a key difference. AdFisher can automate not just the collection of the ads, but also the identification of such key differences by using its machine learning capabilities. Indeed, it found on its own that simulated males were more often shown ads encouraging the user to seek coaching for high paying jobs than simulated females.

3 Privacy Properties

Motivating our methodology for finding causal relationships, we present some properties of ad networks that we can check with such a methodology in place. As a fundamental limitation of science, we can only prove the existence of a causal effect; we cannot prove that one does not exist (see Section 4.5). Thus, experiments can only demonstrate violations of nondiscrimination and transparency, which require effects. On the other hand, we can experimentally demonstrate that effectful choice and ad choice are complied with in the cases that we test since compliance follows from the existence of an effect. Table 1 summarizes these properties.

3.1 Discrimination

At its core, *discrimination* between two classes of individuals (e.g., one race vs. another) occurs when the attribute distinguishing those two classes causes a change in behavior toward those two classes. In our case, discrimination occurs when membership in a class causes a change in ads. Such discrimination is not always bad (e.g., many would be comfortable with men and women receiving different clothing ads). We limit our discus-

Property Name	Requirement	Causal Test	Finding
Nondiscrimination	Users differing only on protected attributes are treated similarly	Find that presence of protected attribute causes a change in ads	Violation
Transparency	User can view all data about him used for ad selection	Find attribute that causes a change in ads, not in settings	Violation
Effectful choice	Changing a setting has an effect on ads	Find that changing a setting causes a change in ads	Compliance
Ad choice	Removing an interest decreases the number ads related to that interest	Find setting causes a decease in relevant ads	Compliance

Table 1. Privacy Properties Tested on Google's Ad Settings

sion of whether the discrimination we found is unjust to the discussion section (§7) and do not claim to have a scientific method of determining the morality of discrimination.

Determining whether class membership causes a change in ads is difficult since many factors not under the experimenter's control or even observable to the experimenter may also cause changes. Our experimental methodology determines when membership in certain classes causes significant changes in ads by comparing many instances of each class.

We are limited in the classes we can consider since we cannot create actual people that vary by the traditional subjects of discrimination, such as race or gender. Instead, we look at classes that function as surrogates for those classes of interest. For example, rather than directly looking at how gender affects people's ads, we instead look at how altering a gender setting affects ads or at how visiting websites associated with each gender affects ads.

3.2 Transparency

Transparency tools like Google Ad Settings provide online consumers with some understanding of the information that ad networks collect and use about them. By displaying to users what the ad network may have learned about the interests and demographics of a user, such tools attempt to make targeting mechanisms more transparent.

However the technique for studying transparency is not clear. One cannot expect an ad network to be *completely transparent* to a user. This would involve the tool displaying all other users' interests as well. A more reasonable expectation is for the ad network to display any inferred interests about that user. So, if an ad network has inferred some interest about a user and is serving ads relevant to that interest, then that interest should be displayed on the transparency tool. However, even this notion of transparency cannot be checked precisely as the ad network may serve ads about some other interest correlated with the original inferred interest, but not display the correlated interest on the transparency tool.

Thus, we only study the extreme case of the lack of transparency — *opacity*, and leave complex notions of transparency open for future research. We say that a transparency tool has opacity if some browsing activity results in a significant effect on the ads served, but has no effect on the ad settings. If there is a difference in the ads, we can argue that prior browsing activities must have been tracked and used by the ad network to serve relevant ads. However, if this use does not show up on the transparency tool, we have found at least one example which demonstrates a lack of transparency.

3.3 Choice

The Ad Settings page offers users the option of editing the interests and demographics inferred about them. However, the exact nature of how these edits impact the ad network is unclear. We examine two notions of choice.

A very coarse form is *effectful choice*, which requires that altering the settings has some effect on the ads seen by the user. This shows that altering settings is not merely a "placebo button": it has a real effect on the network's ads. However, effectful choice does not capture whether the effect on ads is meaningful. For example, even if a user adds interests for cars and starts receiving *fewer* ads for cars, effectful choice is satisfied. Moreover, we cannot find violations of effectful choice. If we find no differences in the ads, we cannot conclude that users do not have effectful choice since it could be the result of the ad repository lacking ads relevant to the interest.

Ideally, the effect on ads after altering a setting would be meaningful and related to the changed setting. One way such an effect would be meaningful, in the case of removing an inferred interest, is a decrease in the number of ads related to the removed interest. We call this requirement *ad choice*. One way to judge whether an ad is relevant is to check it for keywords associated with the interest. If upon removing an interest, we find a statistically significant decrease in the number of ads containing some keywords, then we will conclude that the choice was respected. In addition to testing for compliance in ad choice, we can also test for a violation by checking for a statistically significant increase in the number of related ads to find egregious violations. By requiring the effect to have a fixed direction, we can find both compliance and violations of ad choice.

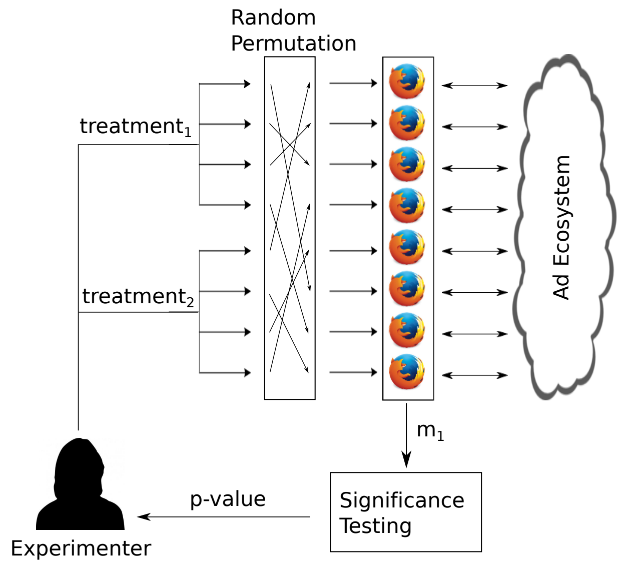

Fig. 1. Experimental setup to carry out significance testing on eight browser agents comparing the effects of two treatments. Each agent is randomly assigned a treatment which specifies what actions to perform on the web. After these actions are complete, they collect measurements which are used for significance testing.

4 Methodology

The goal of our methodology is to establish that a certain type of input to a system causes an effect on a certain type of output of the system. For example, in our experiments, we study the system of Google. The inputs we study are visits to content providing websites and users' interactions with the Ad Settings page. The outputs we study are the settings and ads shown to the users by Google. However, nothing in our methodology limits ourselves to these particular topics; it is appropriate for determining I/O properties of any web system. Here, we present an overview of our methodology; Appendix B provides details of the statistical analysis.

4.1 Background: Significance Testing

To establish causation, we start with the approach of Fisher (our tool's namesake) for significance testing [21] as specialized by Tschantz et al. for the setting of online systems [11]. Significance testing examines a *null hypothesis*, in our case, that the inputs do not affect the outputs. To test this hypothesis the experimenter selects two values that the inputs could take on, typically called the *control* and *experimental treatments*. The experimenter applies the treatments to *experimental units*. In our setting, the units are the browser agents, that is, simulated users. To avoid noise, the experimental units should initially be as close to identical as possible as far as the inputs and outputs in question are concerned. For example, an agent created with the Firefox browser should not be compared to one created with the Internet Explorer browser since Google can detect the browser used.

The experimenter randomly applies the experimental (control) treatment to half of the agents, which form the experimental (control) group. (See Figure 1.) Each agent carries out actions specified in the treatment applied to it. Next, the experimenter takes measurements of the outputs Google sends to the agents, such as ads. At this point, the experiment is complete and data analysis begins.

Data analysis starts by computing a *test statistic* over the measurements. The experimenter selects a test statistic that she suspects will take on a high value when the outputs to the two groups differ. That is, the statistic is a measure of distance between the two groups. She then uses the *permutation test* to determine whether the value the test statistic actually took on is higher than what one would expect by chance unless the groups actually differ. The permutation test randomly permutes the labels (control and experimental) associated with each observation, and recomputes a hypothetical test statistic. Since the null hypothesis is that the inputs have no effect, the random assignment should have no effect on the value of the test statistic. Thus, under the null hypothesis, it is unlikely that the actual value of the test statistic is larger than the vast majority of hypothetical values.

The *p-value* of the permutation test is the proportion of the permutations where the test statistic was greater than or equal to the actual observed statistic. If the value of the test statistic is so high that under the null hypothesis it would take on as high of a value in less than 5% of the random assignments, then we conclude that the value is *statistically significant* (at the 5% level) and that causation is likely.

4.2 Blocking

In practice, the above methodology can be difficult to use since creating a large number of nearly identical agents might not be possible. In our case, we could only run ten agents in parallel given our hardware and network limitations. Comparing agents running at different times can result in additional noise since ads served to an agent change over time. Thus, with the above methodology, we were limited to just ten comparable units. Since some effects that the inputs have on Google's outputs can be probabilistic and subtle, they might be missed looking at so few agents.

To avoid this limitation, we extended the above methodology to handle varying units using *blocking* [12]. To use blocking, we created *blocks* of nearly identical agents running in parallel. These agents differ in terms their identifiers (e.g., process id) and location in memory. Despite the agents running in parallel, the operating system's scheduler determines the exact order in which the agents operate. Each block's agents were randomly partitioned into the control and experimental groups. This randomization ensures that the minor differences between agents noted above should have no systematic impact upon the results: these differences become noise that probably disappears as the sample size increases. Running these blocks in a staged fashion, the experiment proceeds on block after block. A modified permutation test now only compares the actual value of the test statistic to hypothetical values computed by reassignments of agents that respect the blocking structure. These reassignments do not permute labels across blocks of observations.

Using blocking, we can scale to any number of agents by running as many blocks as needed. However, the computation of the permutation test increases exponentially with the number of blocks. Thus, rather than

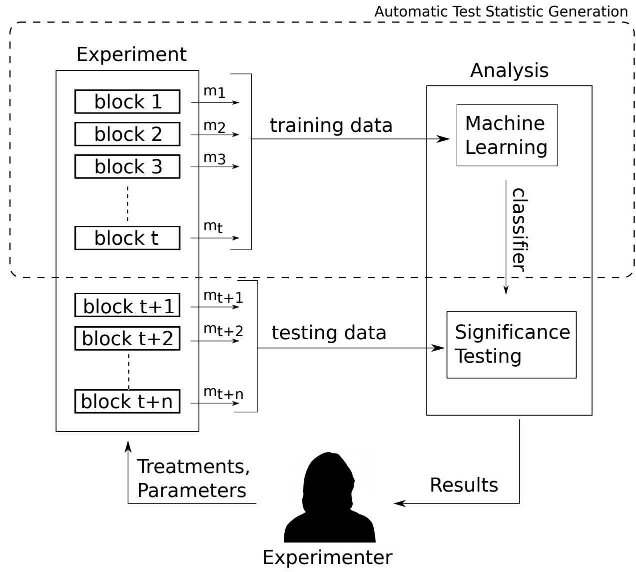

Fig. 2. Our experimental setup with training and testing blocks. Measurements from the training blocks are used to build a classifier. The trained classifier is used to compute the test statistic on the measurements from the testing blocks for significance testing.

compute the exact p-value, we estimate it by randomly sampling the possible reassignments. We can use a confidence interval to characterize the quality of the estimation [12]. The p-values we report are actually the upper bounds of the 99% confidence intervals of the p-values (details in Appendix B).

4.3 Selecting Test Statistics

The above methodology leaves open the question of how to select the test statistic. In some cases, the experimenter might be interested in a particular test statistic. For example, an experimenter testing ad choice could use a test statistic that counts the number of ads related to the removed interest. In other cases, the experimenter might be looking for *any* effect. AdFisher offers the ability to automatically select a test statistic. To do so, it partitions the collected data into training and testing subsets, and uses the training data to train a classifier. Figure 2 shows an overview of AdFisher's workflow.

To select a classifier, AdFisher uses 10-fold cross validation on the training data to select among several possible parameters. The classifier predicts which treatment an agent received, only from the ads that get served to that agent. If the classifier is able to make this prediction with high accuracy, it suggests a systematic difference between the ads served to the two groups that the classifier was able to learn. If no difference exists, then we would expect the number to be near the guessing rate of 50%. AdFisher uses the accuracy of this classifier as its test statistic.

To avoid the possibility of seeing a high accuracy due to overfitting, AdFisher evaluates the accuracy of the classifier on a testing data set that is disjoint from the training data set. That is, in the language of statistics, we form our hypothesis about the test statistic being able to distinguish the groups before seeing the data on which we test it to ensure that it has predictive power. AdFisher uses the permutation test to determine whether the degree to which the classifier's accuracy on the test data surpasses the guessing rate is statistically significant. That is, it calculates the p-value that measures the probability of seeing the observed accuracy given that the classifier is just guessing. If the p-value is below 0.05, we conclude that it is unlikely that classifier is guessing and that it must be making use of some difference between the ads shown to the two groups.

4.4 Avoiding Pitfalls

The above methodology avoids some pitfalls. Most fundamentally, we use a statistical analysis whose assumptions match those of our experimental design. Assumptions required by many statistical analyses appear unjustifiable in our setting. For example, many analyses assume that the agents do not interact or that the ads are independent and identically distributed (e.g., [14, 17]). Given that all agents receive ads from the same pool of possible ads governed by the same advertisers' budgets, these assumptions appear unlikely to hold. Indeed, empirical evidence suggests that it does not [11]. The permutation test, which does not require this assumption, allows us to ensure statistical soundness of our analysis without making these assumptions [22].

Our use of randomization implies that many factors that could be confounding factors in an unrandomized design become noise in our design (e.g., [12]). While such noise may require us to use a large sample size to find an effect, it does not affect the soundness of our analysis.

Our use of two data sets, one for training the classifier to select the test statistic and one for hypothesis testing ensures that we do not engage in overfitting, data dredging, or multiple hypothesis testing (e.g., [23]). All these problems result from looking for so many possible patterns that one is found by chance. While we look for many patterns in the training data, we only check for one in the testing data.

Relatedly, by reporting a p-value, we provide a quantitative measure of the confidence we have that the observed effect is genuine and not just by chance [24]. Reporting simply the classifier accuracy or that some difference occurred fails to quantify the possibility that the result was a fluke.

4.5 Scope

We restrict the scope of our methodology to making claims that an effect exists with high likelihood as quantified by the p-value. That is, we expect our methodology to only rarely suggest that an effect exists when one does not.

We do not claim "completeness" or "power": we might fail to detect some use of information. For example, Google might not serve different ads upon detecting that all the browser agents in our experiment are running from the same IP address. Despite this limitation in our experiments, we found interesting instances of usage.

Furthermore, we do not claim that our results generalize to all users. To do so, we would need to a take a random sample of all users, their IP addresses, browsers, and behaviors, which is prohibitively expensive. We cannot generalize our results if for example, instead of turning off some usage upon detecting our experiments, Google turns it on. While our experiments would detect this usage, it might not be experienced by normal users. However, it would be odd if Google purposefully performs questionable behaviors only with those attempting to find it.

While we use webpages associated with various interests to simulate users with those interests, we cannot establish that having the interest itself caused the ads to change. It is possible that other features of the visited webpages causes change - a form of confounding called "profile contamination" [14], since the pages cover other topics as well. Nevertheless, we have determined that visiting webpages associated with the interest does result in seeing a change, which should give pause to users visiting webpages associated with sensitive interests.

Lastly, we do not attempt to determine how the information was used. It could have been used by Google directly for targeting or it could have been used by advertisers to place their bids. We cannot assign blame. We hope future work will shed light on these issues, but given that we cannot observe the interactions between Google and advertisers, we are unsure whether it can be done.

5 AdFisher

In this section, we describe AdFisher - a tool implementing our methodology. AdFisher makes it easy to run experiments using the above methodology for a set of treatments, measurements, and classifiers (test statistics) we have implemented. AdFisher is also extensible allowing the experimenter to implement additional treatments, measurements, or test statistics. For example, an experimenter interested in studying a different online platform only needs to add code to perform actions and collect measurements on that platform. They need not modify methods that randomize the treatments, carry out the experiment, or perform the data analysis.

To simulate a new person on the network, AdFisher creates each agent from a fresh browser instance with no browsing history, cookies, or other personalization. AdFisher randomly assigns each agent to a group and applies the appropriate treatment, such as having the browser visit webpages. Next, AdFisher makes measurements of the agent, such as collecting the ads shown to the browser upon visiting another webpage. All of the agents within a block execute and finish the treatments before moving on to collect the measurements to remove time as a factor. AdFisher runs all the agents on the same machine to prevent differences based on location, IP address, operating system, or other machine specific differences between agents.

Next, we detail the particular treatments, measurements, and test statistics that we have implemented in AdFisher. We also discuss how AdFisher aids an experimenter in understanding the results.

Treatments. A treatment specifies what actions are to be performed by a browser agent. AdFisher automatically applies treatments assigned to each agent. Typically, these treatments involve invoking the Selenium WebDriver to make the agent interact with webpages.

AdFisher makes it easy to carry out common treatments by providing ready-made implementations. The simplest stock treatments we provide set interests, gender, and age range in Google's Ad Settings. Another stock treatment is to visit a list of webpages stored on a file.

To make it easy to see whether websites associated with a particular interest causes a change in behavior, we have provided the ability to create lists of webpages associated with a category on Alexa. For each category, Alexa tracks the top websites sorted according to their traffic rank measure (a combination of the number of users and page views) [25]. The experimenter can use AdFisher to download the URLs of the top webpages Alexa associates with an interest. By default, it downloads the top 100 URLs. A treatment can then specify that agents visit this list of websites. While these treatments do not correspond directly to having such an interest, it allows us to study how Google responds to people visiting webpages associated with those interests.

Often in our experiments, we compared the effects of a certain treatment applied to the experimental group against the *null treatment* applied to the control group. Under the null treatment, agents do nothing while agents under a different treatment complete their respective treatment phase.

Measurements. AdFisher can currently measure the values set in Google's Ad Settings page and the ads shown to the agents after the treatments. It comes with stock functionality for collecting and analyzing text ads. Experimenters can add methods for image, video, and flash ads.

To find a reasonable website for ad collection, we looked to news sites since they generally show many ads. Among the top 20 news websites on alexa.com, only five displayed text ads served by Google: theguardian.com/us, timesofindia.indiatimes.com, bbc.com/news, reuters.com/news/us and bloomberg.com. AdFisher comes with the built-in functionality to collect ads from any of these websites. One can also specify for how many reloads ads are to collected (default 10), or how long to wait between successive reloads (default 5s). For each page reload, AdFisher parses the page to find the ads shown by Google and stores the ads. The experimenter can add parsers to collect ads from other websites.

We run most of our experiments on Times of India as it serves the most (five) text ads per page reload. We repeat some experiments on the Guardian (three ads per reload) to demonstrate that our results are not specific to one site.

Classification. While the experimenter can provide AdFisher with a test statistic to use on the collected data, AdFisher is also capable of automatically selecting a test statistic using machine learning. It splits the entire data set into training and testing subsets, and examines a training subset of the collected measurements to select a classifier that distinguishes between the measurements taken from each group. From the point of view of machine learning, the set of ads collected by an agent corresponds to an *instance* of the concept the classifier is attempting to learn.

Machine learning algorithms operate over sets of *features*. AdFisher has functions for converting the text ads seen by an agent into three different feature sets. The *URL feature set* consists of the URLs displayed by the ads (or occasionally some other text if the ad displays it where URLs normally go). Under this feature set, the feature vector representing an agent's data has a value of n in the ith entry iff the agent received n ads that display the ith URL where the order is fixed but arbitrary.

The *URL+Title feature set* looks at both the displayed URL and the title of the ad jointly. It represents an agent's data as a vector where the ith entry is n iff the agent received n ads containing the ith pair of a URL and title.

The third feature set AdFisher has implemented is the *word feature set*. This set is based on word stems, the main part of the word with suffixes such as "ed" or "ing" removed in a manner similar to the work of Balebako et al. [19]. Each word stem that appeared in an ad is assigned a unique id. The ith entry in the feature vector is the number of times that words with the ith stem appeared in the agent's ads.

We explored a variety of classification algorithms provided by the scikit-learn library [9]. We found that logistic regression with an L2 penalty over the URL+title feature set consistently performed well compared to the others. At its core, logistic regression predicts a class given a feature vector by multiplying each of the entries of the vector by its own weighting coefficient (e.g., [26]). It then takes a the sum of all these products. If the sum is positive, it predicts one class; if negative, it predicts the other.

While using logistic regression, the training stage consists of selecting the coefficients assigned to each feature to predict the training data. Selecting coefficients requires balancing the training-accuracy of the model with avoiding overfitting the data with an overly complex model. We apply 10-fold cross-validation on the training data to select the regularization parameter of the logistic regression classifier. By default, AdFisher splits the data into training and test sets by using the last 10% of the data collected for testing.

Explanations. To explain how the learned classifier distinguished between the groups, we explored several methods. We found the most informative to be the model produced by the classifier itself. Recall that logistic regression weighted the various features of the instances with coefficients reflecting how predictive they are of each group. Thus, with the URL+title feature set, examining the features with the most extreme coefficients identifies the URL+title pair most used to predict the group to which agents receiving an ad with that URL+title belongs.

We also explored using simple metrics for providing explanations, like ads with the highest frequency in each group. However, some generic ads gets served in huge numbers to both groups. We also looked at the proportion of times an ad was served to agents in one group to the total number of times observed by all groups. However, this did not provide much insight since the proportion typically reached its maximum value of 1.0 from ads that only appeared once. Another choice we explored was to compute the difference in the number of times an ad appears between the groups. However, this metric is also highly influenced by how common the ad is across all groups.

6 Experiments

In this section, we discuss experiments that we carried out using AdFisher. In total, we ran 21 experiments, each of which created its own testing data sets using independent random assignments of treatments to agents. We analyze each test data set only once and report the results of each experiment separately. Thus, we do not test multiple hypotheses on any of our test data sets ensuring that the probability of false positives (p-value) are independent with the exception of our analyses for ad choice. In that case, we apply a Bonferroni correction.

Each experiment examines one of the properties of interest from Table 1. We found violations of nondiscrimination and data transparency and cases of compliance with effectful and ad choice. Since these summaries each depend upon more than one experiment, they are the composite of multiple hypotheses. To prevent false positives for these summaries, for each property, we report p-values adjusted by the number of experiments used to explore that property. We use the Holm-Bonferroni method for our adjustments, which is uniformly more powerful than the commonly used Bonferroni correction [27]. This method orders the component hypotheses by their unadjusted p-values applying a different correction to each until reaching a hypothesis whose adjusted value is too large to reject. This hypothesis and all remaining hypotheses are rejected regardless of their p-values. Appendix C provides details.

Table 2 in Appendix A summarizes our findings.

6.1 Nondiscrimination

We use AdFisher to demonstrate a violation in the nondiscrimination property. If AdFisher finds a statistically significant difference in how Google treats two experimental groups, one consisting of members having a protected attribute and one whose members do not, then the experimenter has strong evidence that Google discriminates on that attribute. In particular, we use AdFisher's ability to automatically select a test statistic to check for possible differences to test the null hypothesis that the two experimental groups have no differences in the ads they receive.

As mentioned before, it is difficult to send a clear signal about any attribute by visiting related webpages since they may have content related to other attributes. The only way to send a clear signal is via Ad Settings. Thus, we focus on attributes that can be set on the Ad Settings page. In a series of experiments, we set the gender of one group to female and the other to male. In one of the experiments, the agents went straight to collecting ads; in the others, they simulated an interest in jobs. In all but one experiment, they collected ads from the Times of India (TOI); in the exception, they collected ads from the Guardian. In one experiment, they also visited the top 10 websites for the U.S. according to alexa.com to fill out their interests.[1] Table 3 in Appendix A summarizes results from these experiments.

AdFisher found a statistically significant difference in the ads for male and female agents that simulated an interest in jobs in May, 2014. It also found evidence of discrimination in the nature of the effect. In particular, it found that females received fewer instances of an ad encouraging the taking of high paying jobs than males. AdFisher did not find any statistically significant differences among the agents that did not visit the job-related pages or those operating in July, 2014. We detail the experiment finding a violation before discussing why we think the other experiments did not result in significant results.

Gender and Jobs. In this experiment, we examine how changing the gender demographic on Google Ad Settings affects the ads served and interests inferred for agents browsing employment related websites. We set up AdFisher to have the agents in one group visit the Google Ad Settings page and set the gender bit to female while agents in the other group set theirs to male. All the agents then visited the top 100 websites listed under the Employment category of Alexa [2]. The agents then collect ads from Times of India.

AdFisher ran 100 blocks of 10 agents each. (We used blocks of size 10 in all our experiments.) AdFisher used the ads of 900 agents (450 from each group) for training a classifier using the URL+title feature set, and used the remaining 100 agents' ads for testing. The learned classifier attained a test-accuracy of 93%, suggesting that Google did in fact treat the genders differently. To test whether this response was statistically significant, AdFisher computed a p-value by running the permutation test on a million randomly selected block-respecting permutations of the data. The significance test yielded an adjusted p-value of < 0.00005.

We then examined the model learned by AdFisher to explain the nature of the difference. Table 4 shows the five URL+title pairs that the model identifies as the strongest indicators of being from the female or male group. How ads for identifying the two groups differ is concerning. The two URL+title pairs with the highest coefficients for indicating a male were for a career coaching service for "$200k+" executive positions. Google showed the ads 1852 times to the male group but just 318 times to the female group. The top two URL+title pairs for the female group was for a generic job posting service and for an auto dealer.

The found discrimination in this experiment was predominately from a pair of job-related ads for the same service making the finding highly sensitive to changes in the serving of these ads. A closer examination of the ads from the same experimental setup ran in July, 2014, showed that the frequency of these ads reduced from 2170 to just 48, with one of the ads completely disappearing. These 48 ads were only shown to males, continuing the pattern of discrimination. This pattern was recognized by the machine learning algorithm, which selected the ad as the second most useful for identifying males. However, they were too infrequent to establish statistical significance. A longer running experiment with more blocks might have succeeded.

1 http://www.alexa.com/topsites/countries/US

2 http://www.alexa.com/topsites/category/Top/Business/Employment

6.2 Transparency

AdFisher can demonstrate violations of individual data use transparency. AdFisher tests the null hypothesis that two groups of agents with the same ad settings receives ads from the same distribution despite being subjected to different experimental treatments. Rejecting the null hypothesis implies that some difference exists in the ads that is not documented by the ad settings.

In particular, we ran a series of experiments to examine how much transparency Google's Ad Settings provided. We checked whether visiting webpages associated with some interest could cause a change in the ads shown that is not reflected in the settings.

We ran such experiments for five interests: substance abuse, disabilities, infertility[3], mental disorders[4], and adult websites[5]. Results from statistical analysis of these experiments are shown in Table 5 of Appendix A.

We examined the interests found in the settings for the two cases where we found a statistically significant difference in ads, substance abuse and disability. We found that settings did not change at all for substance abuse and changed in an unexpected manner for disabilities. Thus, we detail these two experiments below.

Substance Abuse. We were interested in whether Google's outputs would change in response to visiting webpages associated with substance abuse, a highly sensitive topic. Thus, we ran an experiment in which the experimental group visited such websites while the control group idled. Then, we collected the Ad Settings and the Google ads shown to the agents at the Times of India. For the webpages associated with substance abuse, we used the top 100 websites on the Alexa list for substance abuse[6].

AdFisher ran 100 blocks of 10 agents each. At the end of visiting the webpages associated with substance abuse, none of the 500 agents in the experimental group had interests listed on their Ad Settings pages. (None of the agents in the control group did either since the settings start out empty.) If one expects the Ad Settings page to reflect all learned inferences, then he would not anticipate ads relevant to those website visits given the lack of interests listed.

Fig. 3. Screenshot of an ad with the top URL+title for identifying agents that visited webpages associated with substance abuse

However, the ads collected from the Times of India told a different story. The learned classifier attained a test-accuracy of 81%, suggesting that Google did in fact respond to the page visits. Indeed, using the permutation test, AdFisher found an adjusted p-value of < 0.00005. Thus, we conclude that the differences are statistically significant: Google's ads changed in response to visiting the webpages associated with substance abuse. Despite this change being significant, the Ad Settings pages provided no hint of its existence: the transparency tool is opaque!

We looked at the URL+title pairs with the highest coefficients for identifying the experimental group that visited the websites related to substance abuse. Table 6 provides information on coefficients and URL+titles learned. The three highest were for "Watershed Rehab". The top two had URLs for this drug and alcohol rehab center. The third lacked a URL and had other text in its place. Figure 3 shows one of Watershed's ads. The experimental group saw these ads a total of 3309 times (16% of the ads); the control group never saw any of them nor contained any ads with the word "rehab" or "rehabilitation". None of the top five URL+title pairs for identifying the control group had any discernible relationship with rehab or substance abuse.

These results remain robust across variations on this design with statistical significance in three variations. For example, two of these ads remain the top two ads for identifying the agents that visited the substance abuse websites in July using ads collected from the Guardian.

One possible reason why Google served Watershed's ads could be *remarketing*, a marketing strategy that encourages users to return to previously visited websites [28]. The website thewatershed.com features among the top 100 websites about substance-abuse on Alexa, and agents visiting that site may be served Watershed's ads as part of remarketing. However, these users cannot see any changes on Google Ad Settings despite Google having learnt some characteristic (visited thewatershed.com) about them and serving ads relevant to that characteristic.

Disabilities. This experiment was nearly identical in setup but used websites related to disabilities instead of

3 http://www.alexa.com/topsites/category/Top/Health/Reproductive_Health/Infertility

4 http://www.alexa.com/topsites/category/Top/Health/Mental_Health/Disorders

5 http://www.alexa.com/topsites/category/Top/Adult

6 http://www.alexa.com/topsites/category/Top/Health/Addictions/Substance_Abuse substance abuse. We used the top 100 websites on Alexa on the topic.[7]

For this experiment, AdFisher found a classifier with a test-accuracy of 75%. It found a statistically significant difference with an adjusted p-value of less than 0.00005.

Looking at the top ads for identifying agents that visited the webpages associated with disabilities, we see that the top two ads have the URL www.abilitiesexpo.com and the titles "Mobility Lifter" and "Standing Wheelchairs". They were shown a total of 1076 times to the experimental group but never to the control group. (See Table 7.)

This time, Google did change the settings in response to the agents visiting the websites. None of them are directly related to disabilities suggesting that Google might have focused on other aspects of the visited pages. Once again, we believe that the top ads were served due to remarketing, as abilitiesexpo.com was among the top 100 websites related to disabilities.

6.3 Effectful Choice

We tested whether making changes to Ad Settings has an effect on the ads seen, thereby giving the users a degree of choice over the ads. In particular, AdFisher tests the null hypothesis that changing some ad setting has no effect on the ads.

First, we tested whether opting out of tracking actually had an effect by comparing the ads shown to agents that opted out after visiting car-related websites to ads from those that did not opt out. We found a statistically significant difference.

We also tested whether removing interests from the settings page actually had an effect. We set AdFisher to have both groups of agents simulate some interest. AdFisher then had the agents in one of the groups remove interests from Google's Ad Settings related to the induced interest. We found statistically significant differences between the ads both groups collected from the Times of India for two induced interests: online dating and weight loss. We describe one in detail below.

Online Dating. We simulated an interest in online dating by visiting the website www.midsummerseve.com/, a website we choose since it sets Google's ad setting for "Dating & Personals" (this site no longer affects the setting). AdFisher then had just the agents in the experimental group remove the interest "Dating & Personals" (the only one containing the keyword "dating"). All the agents then collected ads from the Times of India.

AdFisher found statistically significant differences between the groups with a classifier accuracy of 74% and an adjusted p-value of < 0.00003. Furthermore, the effect appears related to the interests removed. The top ad for identifying agents that kept the romantic interests has the title "Are You Single?" and the second ad's title is "Why can't I find a date?". None of the top five for the control group that removed the interests were related to dating (Table 9). Thus, the ad settings appear to actually give users the ability to avoid ads they might dislike or find embarrassing. In the next set of experiments, we explicitly test for this ability.

We repeated this experiment in July, 2014, using the websites relationshipsurgery.com and datemypet.com, which also had an effect on Ad Settings, but did not find statistically significant differences.

6.4 Ad Choice

Whereas the other experiments tested merely for the presence of an effect, testing for ad choice requires determining whether the effect is an increase or decrease in the number of relevant ads seen. Fortunately, since AdFisher uses a one-sided permutation test, it tests for either an increase or a decrease, but not for both simultaneously, making it usable for this purpose. In particular, after removing an interest, we check for a decrease to test for compliance using the null hypothesis that either no change or an increase occurred, since rejecting this hypothesis would imply that a decrease in the number of related ads occurred. To check for a violation, we test for the null hypothesis that either no change or a decrease occurred. Due to testing two hypotheses, we use an adjustment to the p-value cutoff considered significant to avoid finding significant results simply from testing multiple hypotheses. In particular, we use the standard Bonferroni correction, which calls for multiplying the p-value by 2 (e.g., [29]).

We ran three experiments checking for ad choice. The experiments followed the same setup as the effectful choice ones, but this time we used all the blocks for testing a given test statistic. The test statistic counted the number of ads containing keywords. In the first, we again test online dating using relationshipsurgery.com and datemypet.com. In particular, we found that re-

7 http://www.alexa.com/topsites/category/Top/Society/Disabled moving online dating resulted in a significant decrease (p-value adjusted for all six experiments: 0.0456) in the number of ads containing related keywords (from 109 to 34). We detail the inconclusive results for weight loss below.

Weight Loss. We induced an interest in weight loss by visiting dietingsucks.blogspot.com. Afterwards, the agents in the experimental group removed the interests "Fitness" and "Fitness Equipment and Accessories", the only ones related to weight loss. We then used a test statistic that counted the number of ads containing the keyword "fitness". Interestingly, the test statistic was higher on the group with the interests removed, although not to a statistically significant degree. We repeated the process with a longer keyword list and found that removing interests decreased test statistic this time, but also not to a statistically significant degree.

7 Discussion and Conclusion

Using AdFisher, we conducted 21 experiments using 17,370 agents that collected over 600,000 ads. Our experiments found instances of discrimination, opacity, and choice in targeted ads of Google. Discrimination, is at some level, inherent to profiling: the point of profiling is to treat some people differently. While customization can be helpful, we highlight a case where the customization appears inappropriate taking on the negative connotations of discrimination. In particular, we found that males were shown ads encouraging the seeking of coaching services for high paying jobs more than females (§6.1).

We do not, however, claim that any laws or policies were broken. Indeed, Google's policies allow it to serve different ads based on gender. Furthermore, we cannot determine whether Google, the advertiser, or complex interactions among them and others caused the discrimination (§4.5). Even if we could, the discrimination might have resulted unintentionally from algorithms optimizing click-through rates or other metrics free of bigotry. Given the pervasive structural nature of gender discrimination in society at large, blaming one party may ignore context and correlations that make avoiding such discrimination difficult. More generally, we believe that no scientific study can demonstrate discrimination in the sense of *unjust discrimination* since science cannot demonstrate normative statements (e.g., [30])

Nevertheless, we are comfortable describing the results as "discrimination". From a strictly scientific view point, we have shown discrimination in the non-normative sense of the word. Personally, we also believe the results show discrimination in the normative sense of the word. Male candidates getting more encouragement to seek coaching services for high-paying jobs could further the current gender pay gap (e.g., [31]). Thus, we do not see the found discrimination in our vision of a just society even if we are incapable of blaming any particular parties for this outcome.

Furthermore, we know of no justification for such customization of the ads in question. Indeed, our concern about this outcome does not depend upon how the ads were selected. Even if this decision was made solely for economic reasons, it would continue to be discrimination [32]. In particular, we would remain concerned if the cause of the discrimination was an algorithm ran by Google and/or the advertiser automatically determining that males are more likely than females to click on the ads in question. The amoral status of an algorithm does not negate its effects on society.

However, we also recognize the possibility that no party is at fault and such unjust effects may be inadvertent and difficult to prevent. We encourage research developing tools that ad networks and advertisers can use to prevent such unacceptable outcomes (e.g., [33]).

Opacity occurs when a tool for providing transparency into how ads are selected and the profile kept on a person actually fails to provide such transparency. Our experiment on substance abuse showed an extreme case in which the tool failed to show any profiling but the ad distributions were significantly different in response to behavior (§6.2). In particular, our experiment achieved an adjusted p-value of < 0.00005, which is 1000 times more significant than the standard 0.05 cutoff for statistical significance. This experiment remained robust to variations showing a pattern of such opacity.

Ideally, tools, such as Ad Settings, would provide a complete representation of the profile kept on a person, or at least the portion of the profile that is used to select ads shown to the person. Two people with identical profiles might continue to receive different ads due to other factors affecting the choice of ads such as A/B testing or the time of day. However, systematic differences between ads shown at the same time and in the same context, such as those we found, would not exist for such pairs of people.

In our experiments testing transparency, we suspect that Google served the top ads as part of remarketing, but our blackbox experiments do not determine whether this is the case. While such remarketing may appear less concerning than Google inferring a substance abuse issue about a person, its highly targeted nature is worrisome particularly in settings with shared computers or shoulder surfing. There is a need for a more inclusive transparency/control mechanism which encompasses remarketed ads as well. Additionally, Google states that "we prohibit advertisers from remarketing based on sensitive information, such as health information" [28]. Although Google does not specify what they consider to be "health information", we view the ads as in violation of Google's policy, thereby raising the question of how Google should enforce its policies.

Lastly, we found that Google Ad Settings does provide the user with a degree of choice about the ads shown. In this aspect, the transparency/control tool operated as we expected.

Our tool, AdFisher, makes it easy to run additional experiments exploring the relations between Google's ads and settings. It can be extended to study other systems. It's design ensures that it can run and analyze large scale experiments to find subtle differences. It automatically finds differences between large data sets produced by different groups of agents and explains the nature of those differences. By completely automating the data analysis, we ensure that an appropriate statistical analysis determines whether these differences are statistically significant and sound conclusions.

AdFisher may have cost advertisers a small sum of money. AdFisher never clicked on any ads to avoid per click fees, which can run over $4 [34]. Its experiments may have caused per-impression fees, which run about $0.00069 [35]. In the billion dollar ad industry, its total effect was about $400.

8 Future Work

We would like to extend AdFisher to study information flow on other advertising systems like Facebook, Bing, or Gmail. We would also like to analyze other kinds of ads like image or flash ads. We also plan to use the tool to detect price discrimination on sites like Amazon or Kayak, or find differences in suggested posts on blogs and news websites, based on past user behavior. We have already mentioned the interesting problem of how ad networks can ensure that their policies are respected by advertisers (§7).

We also like to assign blame where it is due. However, doing so is often difficult. For example, our view on blame varies based on why females were discriminated against in our gender and jobs experiment. If Google allowed the advertiser to easily discriminate, we would blame both. If the advertiser circumvented Google's efforts to prevent such discrimination by targeting correlates of gender, we would blame just the advertiser. If Google decided to target just males with the ad on its own, we would blame just Google. While we lack the access needed to make this determination, both Google and the advertiser have enough information to audit the other with our tool.

As another example, consider the results of opacity after visiting substance abuse websites. While we suspect, remarketing is the cause, it is also possible that Google is targeting users without the rehab center's knowledge. In this case, it would remain unclear as to whether Google is targeting users as substance abusers or due to some other content correlated with the webpages we visited to simulate an interest in substance abuse. We would like to find ways of controlling for these confounding factors.

For these reasons, we cannot claim that Google has violated its policies. In fact, we consider it more likely that Google has lost control over its massive, automated advertising system. Even without advertisers placing inappropriate bids, large-scale machine learning can behave in unexpected ways. With this in mind, we hope future research will examine how to produce machine learning algorithms that automatically avoid discriminating against users in unacceptable ways and automatically provide transparency to users.

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A Tables

Table 2 summarizes the results. Table 3 covers the discrimination experiments with Table 4 showing the top ads for experiment on gender and jobs. Table 5 covers the opacity experiments with Table 6 showing the top ads for the substance-abuse experiment and Table 7 showing them for the disability experiment. Table 8 show the experiments for effectful choice with Table 9 showing the tops ads for online dating. Tables 10 and 11 cover ad choice.

B Details of Methodology

Let the units be arranged in a vector $\vec{u}$ of length n. Let $\vec{t}$ be a *treatment vector*, a vector of length n whose entries are the treatments that the experimenter wants to apply to the units. In the case of just two treatments, $\vec{t}$ can be half full of the first treatment and half full of the second. Let a be an *assignment* of units to treatments, a bijection that maps each entry of $\vec{u}$ to an entry in $\vec{t}$. That is, an assignment is a permutation on the set of indices of $\vec{u}$ and $\vec{t}$.

The result of the experiment is a vector of observations $\vec{y}$ where the ith entry of $\vec{y}$ is the response measured for the unit assigned to the ith treatment in $\vec{t}$ by the assignment used. In a randomized experiment, such as those AdFisher runs, the actual assignment used is selected at random uniformly over some set of possible assignments $\mathcal{A}$.

Let s be a test statistic of the observations of the units. That is $s : \mathcal{Y}^n \to \mathcal{R}$ where $\mathcal{Y}$ is the set of possible observations made over units, n is the number of units, and $\mathcal{R}$ is the range of s. We require $\mathcal{R}$ to be ordered numbers such as the natural or real numbers. We allow s to treat its arguments differently, that is, the order in which the observations are passed to s matters.

If the null hypothesis is true, then we would expect the value of s to be the same under every permutation of the arguments since the assignment of units to treatments should not matter under the null hypothesis. This reasoning motivates the permutation test. The value produced by a (one-tailed signed) permutation test given observed responses $\vec{y}$ and a test statistic s is

$$\frac{|\{\, a \in \mathcal{A} \mid s(\vec{y}) \leq s(a(\vec{y}))\,\}|}{|\mathcal{A}|} = \frac{1}{|\mathcal{A}|} \sum_{a\in\mathcal{A}} I[s(\vec{y}) \leq s(a(\vec{y}))] \tag{1}$$

where the assignments in $\mathcal{A}$ only swaps nearly identical units and $I[\cdot]$ returns 1 if its argument is true and 0 otherwise.

Blocking. For the blocking design, the set of units $\mathcal{U}$ is partitioned into k blocks $\mathcal{B}_1$ to $\mathcal{B}_k$. In our case, all the blocks have the same size. Let $|\mathcal{B}_i| = m$ for all i. The set of assignments $\mathcal{A}$ is equal to the set of functions from $\mathcal{U}$ to $\mathcal{U}$ that are permutations not mixing up blocks. That is, a such that for all i and all u in $\mathcal{B}_i$, $a(u) \in \mathcal{B}_i$. Thus, we may treat $\mathcal{A}$ as k permutations, one for each $\mathcal{B}_i$. Thus, $\mathcal{A}$ is isomorphic to $\times_{i=1}^{k}\Pi(\mathcal{B}_i)$ where $\Pi(\mathcal{B}_i)$ is the set of all permutations over $\mathcal{B}_i$. Thus, $|\times_{i=1}^{k}\Pi(\mathcal{B}_i)| = (m!)^k$. Thus, (1) can be computed as

$$\frac{1}{(m!)^k} \sum_{a\in\times_{i=1}^{k}\Pi(\mathcal{B}_i)} I[s(\vec{y}) \leq s(a(\vec{y}))] \tag{2}$$

Sampling. Computing (2) can be difficult when the set of considered arrangements is large. One solution is to randomly sample from the assignments $\mathcal{A}$. Let $\mathcal{A}'$ be a random subset of $\mathcal{A}$. We then use the approximation

$$\frac{1}{|\mathcal{A}'|} \sum_{a\in\mathcal{A}'} I[s(\vec{y}) \leq s(a(\vec{y}))] \tag{3}$$

Confidence Intervals. Let $\hat{P}$ be this approximation and p be the true value of (2). p can be understood as the frequency of arrangements that yield large values of the test statistic where *largeness* is determined to be at least as large as the observed value $s(\vec{y})$. That is, the probability that a randomly selected arrangement will yield a large value is p. $\hat{P}$ is the frequency of seeing large values in the $|\mathcal{A}'|$ sampled arrangements. Since the arrangements in the sample were drawn uniformly at random from $\mathcal{A}$ and each draw has probability p of being large, the number of large values will obey the binomial distribution. Let us denote this value as L. and $|\mathcal{A}'|$ as n. Since $\hat{P} = L/n$, $\hat{p} * n$ also obeys the binomial distribution. Thus,

$$\Pr[\hat{P} = \hat{p} \,|\, n, p] = \binom{n}{\hat{p}n} p^{\hat{p}n}(1-p)^{(1-\hat{p})n} \tag{4}$$

Thus, we may use a binomial proportion confidence interval. We use the Clopper-Pearson interval [36].

Test Statistic. The statistic we use is based on a classifier c. Let $c(y_i) = 1$ mean that c classifiers the ith observation as having come from the experimental group and $c(y_i) = 0$ as from the control group. Let $\neg(0) = 1$ and $\neg(1) = 0$. Let $\vec{y}$ be ordered so that all of the exper-

Property	Treatment	Other Actions	Source	When	Length (hrs)	# ads	Result
Nondiscrimination	Gender	-	TOI	May	10	40,400	Inconclusive
	Gender	Jobs	TOI	May	45	43,393	Violation
	Gender	Jobs	TOI	July	39	35,032	Inconclusive
	Gender	Jobs	Guardian	July	53	22,596	Inconclusive
	Gender	Jobs & Top 10	TOI	July	58	28,738	Inconclusive
Data use transparency	Substance abuse	-	TOI	May	37	42,624	Violation
	Substance abuse	-	TOI	July	41	34,408	Violation
	Substance abuse	-	Guardian	July	51	19,848	Violation
	Substance abuse	Top 10	TOI	July	54	32,541	Violation
	Disability	-	TOI	May	44	43,136	Violation
	Mental disorder	-	TOI	May	35	44,560	Inconclusive
	Infertility	-	TOI	May	42	44,982	Inconclusive
	Adult websites	-	TOI	May	57	35,430	Inconclusive
Effectful choice	Opting out	-	TOI	May	9	18,085	Compliance
	Dating interest	-	TOI	May	12	35,737	Compliance
	Dating interest	-	TOI	July	17	22,913	Inconclusive
	Weight loss interest	-	TOI	May	15	31,275	Compliance
	Weight loss interest	-	TOI	July	15	27,238	Inconclusive
Ad choice	Dating interest	-	TOI	July	1	1,946	Compliance
	Weight loss interest	-	TOI	July	1	2,862	Inconclusive
	Weight loss interest	-	TOI	July	1	3,281	Inconclusive

Table 2. Summary of our experimental results. Ads are collected from the Times of India (TOI) or the Guardian. We report how long each experiment took, how many ads were collected for it, and what result we concluded.

Treatment	Other visits	Measurement	Blocks	# ads (# unique ads)		Accuracy	Unadj. p-value	Adj. p-value
				female	male			
Gender	Jobs	TOI, May	100	21,766 (545)	21,627 (533)	93%	0.0000053	0.0000265*
Gender	Jobs	Guardian, July	100	11,366 (410)	11,230 (408)	57%	0.12	0.48
Gender	Jobs & Top 10	TOI, July	100	14,507 (461)	14,231 (518)	56%	0.14	n/a
Gender	Jobs	TOI, July	100	17,019 (673)	18,013 (690)	55%	0.20	n/a
Gender	-	TOI, May	100	20,137 (603)	20,263 (630)	48%	0.77	n/a

Table 3. Results from the discrimination experiments sorted by unadjusted p-value. TOI stands for Times of India. * denotes statistically significant results under the Holm-Bonferroni method.

Title	URL	Coefficient	appears in agents		total appearances	
			female	male	female	male
Top ads for identifying the simulated female group						
Jobs (Hiring Now)	www.jobsinyourarea.co	0.34	6	3	45	8
4Runner Parts Service	www.westernpatoyotaservice.com	0.281	6	2	36	5
Criminal Justice Program	www3.mc3.edu/Criminal+Justice	0.247	5	1	29	1
Goodwill - Hiring	goodwill.careerboutique.com	0.22	45	15	121	39
UMUC Cyber Training	www.umuc.edu/cybersecuritytraining	0.199	19	17	38	30
Top ads for identifying agents in the simulated male group						
$200k+ Jobs - Execs Only	careerchange.com	−0.704	60	402	311	1816
Find Next $200k+ Job	careerchange.com	−0.262	2	11	7	36
Become a Youth Counselor	www.youthcounseling.degreeleap.com	−0.253	0	45	0	310
CDL-A OTR Trucking Jobs	www.tadrivers.com/OTRJobs	−0.149	0	1	0	8
Free Resume Templates	resume-templates.resume-now.com	−0.149	3	1	8	10

Table 4. Top URL+titles for the gender and jobs experiment on the Times of India in May.

Treatment	Other visits	Measurement	# ads (# unique ads)		Accuracy	Unadj. p-value	Adj. p-value
			experimental	control			
Substance abuse	-	TOI, May	20,420 (427)	22,204 (530)	81%	0.0000053	0.0000424*
Substance abuse	-	TOI, July	16,206 (653)	18,202 (814)	98%	0.0000053	0.0000371*
Substance abuse	Top 10	TOI, July	15,713 (603)	16,828 (679)	65%	0.0000053	0.0000318*
Disability	-	TOI, May	19,787 (546)	23,349 (684)	75%	0.0000053	0.0000265*
Substance abuse	-	Guardian, July	8,359 (242)	11,489 (319)	62%	0.0075	0.03*
Mental disorder	-	TOI, May	22,303 (407)	22,257 (465)	59%	0.053	0.159
Infertility	-	TOI, May	22,438 (605)	22,544 (625)	57%	0.11	n/a
Adult websites	-	TOI, May	17,670 (602)	17,760 (580)	52%	0.42	n/a

Table 5. Results from transparency experiments. TOI stands for Times of India. Every experiment for this property ran with 100 blocks. * denotes statistically significant results under the Holm-Bonferroni method.

Title	URL	Coefficient	appears in agents		total appearances	
			control	experi.	control	experi.
Top ads for identifying agents in the experimental group (visited websites associated with substance abuse)						
The Watershed Rehab	www.thewatershed.com/Help	−0.888	0	280	0	2276
Watershed Rehab	www.thewatershed.com/Rehab	−0.670	0	51	0	362
The Watershed Rehab	Ads by Google	−0.463	0	258	0	771
Veteran Home Loans	www.vamortgagecenter.com	−0.414	13	15	22	33
CAD Paper Rolls	paper-roll.net/Cad-Paper	−0.405	0	4	0	21
Top ads for identifying agents in control group						
Alluria Alert	www.bestbeautybrand.com	0.489	2	0	9	0
Best Dividend Stocks	dividends.wyattresearch.com	0.431	20	10	54	24
10 Stocks to Hold Forever	www.streetauthority.com	0.428	51	44	118	76
Delivery Drivers Wanted	get.lyft.com/drive	0.362	22	6	54	14
VA Home Loans Start Here	www.vamortgagecenter.com	0.354	23	6	41	9

Table 6. Top URL+titles for substance abuse experiment on the Times of India in May.

Title	URL	Coefficient	appears in agents		total appearances	
			control	experi.	control	experi.
Top ads for identifying agents in the experimental group (visited websites associated with disability)						
Mobility Lifter	www.abilitiesexpo.com	−1.543	0	84	0	568
Standing Wheelchairs	www.abilitiesexpo.com	−1.425	0	88	0	508
Smoking MN Healthcare	www.stillaproblem.com	−1.415	0	24	0	60
Bike Prices	www.bikesdirect.com	−1.299	0	24	0	79
$19 Car Insurance - New	auto-insurance.quotelab.com/MN	−1.276	0	6	0	9
Top ads for identifying agents in control group						
Beautiful Women in Kiev	anastasiadate.com	1.304	190	46	533	116
Melucci DDS	AdsbyGoogle	1.255	4	2	10	6
17.2% 2013 Annuity Return	advisorworld.com/CompareAnnuities	1.189	30	5	46	6
3 Exercises To Never Do	homeworkoutrevolution.net	1.16	1	1	3	1
Find CNA Schools Near You	cna-degrees.courseadvisor.com	1.05	22	0	49	0

Table 7. Top URL+titles for disability experiment on the Times of India in May.

Experiment	blocks	# ads (# unique ads)			accuracy	Unadj. p-value	Adj. p-value
		removed/opt-out	keep/opt-in	total			
Opting out	54	9,029 (139)	9,056 (293)	18,085 (366)	83%	0.0000053	0.0000265*
Dating (May)	100	17,975 (518)	17,762 (457)	35,737 (669)	74%	0.0000053	0.0000212*
Weight Loss (May)	83	15,826 (367)	15,449 (427)	31,275 (548)	60%	0.041	0.123
Dating (July)	90	11,657 (727)	11,256 (706)	22,913 (1,014)	59%	0.070	n/a
Weight Loss (July)	100	14,168 (917)	13,070 (919)	27,238 (1,323)	52%	0.41	n/a

Table 8. Results from effectful choice experiments using the Times of India sorted by unadjusted p-value. * denotes statistically significant results under the Holm-Bonferroni method.

Title	URL	Coefficient	appears in agents		total appearances	
			kept	removed	kept	removed
Top ads for identifying the group that kept dating interests						
Are You Single?	www.zoosk.com/Dating	1.583	367	33	2433	78
Top 5 Online Dating Sites	www.consumer-rankings.com/Dating	1.109	116	10	408	13
Why can't I find a date?	www.gk2gk.com	0.935	18	3	51	5
Latest Breaking News	www.onlineinsider.com	0.624	2	1	6	1
Gorgeous Russian Ladies	anastasiadate.com	0.620	11	0	21	0
Top ads for identifying agents in the group that removed dating interests						
Car Loans w/ Bad Credit	www.car.com/Bad-Credit-Car-Loan	−1.113	5	13	8	37
Individual Health Plans	www.individualhealthquotes.com	−0.831	7	9	21	46
Crazy New Obama Tax	www.endofamerica.com	−0.722	19	31	22	51
Atrial Fibrillation Guide	www.johnshopkinshealthalerts.com	−0.641	0	6	0	25
Free $5 - $25 Gift Cards	swagbucks.com	−0.614	4	11	5	32

Table 9. Top URL+titles for the dating experiment on Times of India in May.

Experiment	Keywords	# ads (# unique ads)		appearances	
		removed	kept	removed	kept
Dating	dating, romance, relationship	952 (117)	994 (123)	34	109
Weight Loss (1)	fitness	1,461 (259)	1,401 (240)	21	16
Weight Loss (2)	fitness, health, fat, diet, exercise	1,803 (199)	1,478 (192)	2	15

Table 10. Setup for and ads from ad choice experiments. All experiments used 10 blocks. The same keywords are used to remove ad interests, as well as create the test statistic for permutation test.

Experiment	Unadjusted p-value	Bonferroni p-value	Holm-Bonferroni p-value	Unadjusted flipped p-value	Bonferroni flipped p-value	Holm-Bonferroni flipped p-value
Dating	0.0076	0.0152	0.0456*	0.9970	1.994	n/a
Weight Loss (2)	0.18	0.36	0.9	0.9371	1.8742	n/a
Weight Loss (1)	0.72	1.44	n/a	0.3818	0.7636	n/a

Table 11. P-values from ad choice experiments sorted by the (unflipped) p-value. The Bonferroni adjusted p-value is only adjusted for the two hypotheses tested within a single experiment (row). The Holm-Bonferroni adjusts for all 6 hypotheses. * denotes statistically significant results under the Holm-Bonferroni method.

imental group comes first. The statistic we use is

$$s(\vec{y}) = \sum_{i=1}^{n/2} c(y_i) + \sum_{i=n/2+1}^{n} \neg c(y_i)$$

This is the number correctly classified.

C Holm-Bonferroni Correction

The Holm-Bonferroni Correction starts by ordering the hypotheses in a family from the hypothesis with the smallest (most significant) p-value p_1 to the hypothesis with the largest (least significant) p-value p_m [27]. For a hypothesis H_k, its unadjusted p-value p_k is compared to an adjusted level of significance $\alpha'_k = \frac{\alpha}{m+1-k}$ where α is the unadjusted level of significance (0.05 in our case), m is the total number of hypotheses in the family, and k is the index of hypothesis in the ordered list (counting from 1 to m). Let $k^\dagger$ be the lowest index k such that $p_k > \alpha'_k$. The hypotheses H_k where $k < k^\dagger$ are accepted as having statistically significance evidence in favor of them (more technically, the corresponding null hypotheses are rejected). The hypotheses H_k where $k \geq k^\dagger$ are not accepted as having significant evidence in favor of them (their null hypotheses are not rejected).

We report adjusted p-values to give an intuition about the strength of evidence for a hypothesis. We let $p'_k = p(m + 1 - k)$ be the adjusted p-value for H_k provided $k < k^\dagger$ since $p_k > \alpha'_k$ iff $p'_k > \alpha$. Note that the adjusted p-value depends not just upon its unadjusted value but also upon its position in the list. For the remaining hypotheses, we provide no adjusted p-value since their p-values are irrelevant to the correction beyond how they order the list of hypotheses.

Discrimination through Optimization: How Facebook's Ad Delivery Can Lead to Biased Outcomes

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The enormous financial success of online advertising platforms is partially due to the precise targeting features they offer. Although researchers and journalists have found many ways that advertisers can target—or exclude—particular groups of users seeing their ads, comparatively little attention has been paid to the implications of the platform's *ad delivery* process, comprised of the platform's choices about which users see which ads.

It has been hypothesized that this process can "skew" ad delivery in ways that the advertisers do not intend, making some users less likely than others to see particular ads based on their demographic characteristics. In this paper, we demonstrate that such skewed delivery occurs on Facebook, due to market and financial optimization effects as well as the platform's own predictions about the "relevance" of ads to different groups of users. We find that both the advertiser's budget and the content of the ad each significantly contribute to the skew of Facebook's ad delivery. Critically, we observe significant skew in delivery along gender and racial lines for "real" ads for employment and housing opportunities despite neutral targeting parameters.

Our results demonstrate previously unknown mechanisms that can lead to potentially discriminatory ad delivery, even when advertisers set their targeting parameters to be highly inclusive. This underscores the need for policymakers and platforms to carefully consider the role of the ad delivery optimization run by ad platforms themselves—and not just the targeting choices of advertisers—in preventing discrimination in digital advertising.[1]

CCS Concepts: • **Information systems** → **Social advertising**; • **Human-centered computing** → *Empirical studies in HCI*; • **Applied computing** → Law;

Keywords: online advertising; ad delivery; bias; fairness; policy

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[1]The delivery statistics of ad campaigns described in this work can be accessed at https://facebook-targeting.ccs.neu.edu/
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1 INTRODUCTION

Powerful digital advertising platforms fund most popular online services today, serving ads to billions of users daily. At a high level, the functionality of these advertising platforms can be divided into two phases: *ad creation*, where advertisers submit the text and images that comprise the content of their ad and choose targeting parameters, and *ad delivery*, where the platform delivers ads to specific users based on a number of factors, including advertisers' budgets, their ads' performance, and the predicted relevance of their ads to users.

One of the underlying reasons for the popularity of these services with advertisers is the rich suite of *targeting* features they offer during ad creation, which allow advertisers to precisely specify which users (called the *audience*) are eligible to see the advertiser's ad. The particular features that advertisers can use for targeting vary across platforms, but often include demographic attributes, behavioral information, users' personally identifiable information (PII), mobile device IDs, and web tracking pixels [11, 73].

Due to the wide variety of targeting features—as well as the availability of sensitive targeting features such as user demographics and interests—researchers have raised concerns about discrimination in advertising, where groups of users may be excluded from receiving certain ads based on advertisers' targeting choices [69]. This concern is particularly acute in the areas of credit, housing, and employment, where there are legal protections in the U.S. that prohibit discrimination against certain protected classes in advertising [1–3]. As ProPublica demonstrated in 2016 [33], this risk is not merely theoretical: ProPublica investigators were able to run housing ads that explicitly excluded users with specific "ethnic affinities" from receiving them.[2] Recently, the U.S. Department of Housing and Urban Development (HUD) sued Facebook over these concerns and others, accusing Facebook's advertising platform of "encouraging, enabling, and causing" violations of the Fair Housing Act [32].

The role of ad delivery in discrimination Although researchers and investigative journalists have devoted considerable effort to understanding the potential discriminatory outcomes of ad targeting, comparatively little effort has focused on ad delivery, due to the difficulty of studying its impacts without internal access to ad platforms' data and mechanisms. However, there are several potential reasons why the ad delivery algorithms used by a platform may open the door to discrimination.

First, consider that most platforms claim their aim is to show users "relevant" ads: for example, Facebook states "we try to show people the ads that are most pertinent to them" [68]. Intuitively, the goal is to show ads that particular users are likely to engage with, even in cases where the advertiser does not know a priori which users are most receptive to their message. To accomplish this, the platforms build extensive user interest profiles and track ad performance to understand how different users interact with different ads. This historical data is then used to steer future ads towards those users who are most likely to be interested in them, and to users like them. However, in doing so, the platforms may inadvertently cause ads to deliver primarily to a skewed subgroup of the advertiser's selected audience, an outcome that the advertiser may not have intended or be aware of. As noted above, this is particularly concerning in the case of credit, housing, and employment, where such skewed delivery might violate antidiscrimination laws.

Second, market effects and financial optimization can play a role in ad delivery, where different desirability of user populations and unequal availability of users may lead to skewed ad delivery [25].

[2] In response, Facebook banned the use of certain attributes for housing ads, but many other, un-banned, mechanisms exist for advertisers that achieve the same outcome [69]. Facebook agreed as part of a lawsuit settlement stemming from these issues to go further by banning age, gender, and certain kinds of location targeting—as well as some related attributes—for housing, employment, or credit ads [22].

For example, it is well-known that certain users on advertising platforms are more valuable to advertisers than others [48, 55, 65]. Thus, advertisers who choose low budgets when placing their ads may be more likely to lose auctions for such "valuable" users than advertisers who choose higher budgets. However, if these "valuable" user demographics are strongly correlated with protected classes, it could lead to discriminatory ad delivery due to the advertiser's budget alone. Even though a low budget advertiser may not have intended to exclude such users, the ad delivery system may do just that because of the higher demand for that subgroup.

Prior to this work, although hypothesized [25, 52, 72], it was not known whether the above factors resulted in skewed ad delivery in real-world advertising platforms. In fact, in response to the HUD lawsuit [32] mentioned above, Facebook claimed that the agency had "no evidence" of their ad delivery systems' role in creating discrimination [45].

Contributions In this paper, we aim to understand whether ads could end up being shown in a skewed manner—i.e., where some users are less likely than others to see ads based on their demographic characteristics—due to the ad delivery phase alone. In other words, we determine whether the ad delivery could cause skewed delivery *that an advertiser did not cause by their targeting choices and may not even be aware of*. We focus on Facebook—as it is the most mature platform offering advanced targeting features—and run dozens of ad campaigns, hundreds of ads with millions of impressions, spending over $8,500 as part of our study.

Answering this question—especially without internal access to the ad delivery algorithm, user data, and advertiser targeting data or delivery statistics—involves overcoming a number of challenges. These include separating market effects from optimization effects, distinguishing ad delivery adjustments based on the ad's performance measured through user feedback from initial ad classification, and developing techniques to determine the racial breakdown of the delivery audience (which Facebook does not provide). The difficulty of solving these without the ad platform's cooperation in a rigorous manner may at least partially explain the lack of knowledge about the potential discriminatory effects due to ad delivery to date. After addressing these challenges, we find the following:

First, we find that *skewed delivery can occur due to market effects alone*. Recall the hypothesis above concerning what may happen if advertisers in general value users differently across protected classes. Indeed, we find this is the case on Facebook: when we run identical ads targeting the same audience but with varying budgets, the resulting audience of users who end up seeing our ad can range from over 55% men (for ads with very low budgets) to under 45% men (for ads with high budgets).

Second, we find that *skewed delivery can occur due to the content of the ad itself* (i.e., the ad headline, text, and image, collectively called the *ad creative*). For example, ads targeting the same audience but that include a creative that would stereotypically be of the most interest to men (e.g., bodybuilding) can deliver to over 80% men, and those that include a creative that would stereotypically be of the most interest to women (e.g., cosmetics) can deliver to over 90% women. Similarly, ads referring to cultural content stereotypically of most interest to Black users (e.g., hip-hop) can deliver to over 85% Black users, and those referring to content stereotypically of interest to white users (e.g., country music) can deliver to over 80% white users, even when targeted identically by the advertiser. Thus, despite placing the same bid on the same audience, the advertiser's ad delivery can be heavily skewed based on the ad creative alone.

Third, we find that *the ad image itself has a significant impact on ad delivery*. By running experiments where we swap different ad headlines, text, and images, we demonstrate that the differences in ad delivery can be significantly affected by the image alone. For example, an ad whose headline and text would stereotypically be of the most interest to men with the image that would stereotypically be of the most interest to women delivers primarily to women at the same rate as when all three ad creative components are stereotypically of the most interest to women.

Fourth, we find that *the ad image is likely automatically classified by Facebook*, and that this classification can skew delivery from the beginning of the ad's run. We create a series of ads where we add an alpha channel to stereotypically male and female images with over 98% transparency; the result is an image with all of the image data present, but that looks like a blank white square to humans. We find that there are statistically significant differences in how these ads are delivered depending on the image used, despite the ads being visually indistinguishable to a human. This indicates that the image classification—and, therefore, relevance determination—is likely an automated process, and that the skew in ad delivery can be due in large part to skew in Facebook's automated estimate of relevance, rather than ad viewers' interactions with the ad.

Fifth, we show that *real-world employment and housing ads can experience significantly skewed delivery*. We create and run ads for employment and housing opportunities, and use our methodology to measure their delivery to users of different races and genders. When optimizing for clicks, we find that ads with the same targeting options can deliver to vastly different racial and gender audiences depending on the ad creative alone. In the most extreme cases, our ads for jobs in the lumber industry reach an audience that is 72% white and 90% male, our ads for cashier positions in supermarkets reach an 85% female audience, and our ads for positions in taxi companies reach a 75% Black audience, even though the targeted audience specified by us as an advertiser is identical for all three. We run a similar suite of ads for housing opportunities, and find skew there as well: despite the same targeting and budget, some of our ads deliver to an audience of over 72% Black users, while others delivery to over 51% Black users. While our results only speak to how our particular ads are delivered (i.e., we cannot say how housing or employment ads *in general* are delivered), the significant skew we observe even on a small set of ads suggests that real-world housing and employment ads are likely to experience the same fate.

Taken together, our results paint a distressing picture of heretofore unmeasured and unaddressed skew that can occur in online advertising systems, which have significant implications for discrimination in targeted advertising. Specifically, due to platforms' optimization in the ad delivery stage together with market effects, ads can unexpectedly be delivered to skewed subsets of the advertiser's specified audience. For certain types of ads, such skewed delivery might implicate legal protections against discriminatory advertising. For example, Section 230 of the U.S. Communications Decency Act (CDA) protects publishers (including online platforms) from being held responsible for third-party content. Our results show Facebook's integral role in shaping the delivery mechanism and might make it more difficult for online platforms to present themselves as neutral publishers in the future. We leave a full exploration of these implications to the legal community. However, our results indicate that regulators, lawmakers, and the platforms themselves need to think carefully when balancing the optimization of ad platforms against desired societal outcomes, and remember that ensuring that individual advertisers do not discriminate in their targeting is insufficient to achieve non-discrimination goals sought by regulators and the public.

Ethics All of our experiments were conducted with careful consideration of ethics. We obtained Institutional Review Board review of our study at Northeastern University (application #18-11-13), with our protocol being marked as "Exempt". We minimized harm to Facebook users when we were running our ads by always running "real" ads (in the sense that if people clicked on our ads, they were brought to real-world sites relevant to the topic of the ad). While running our ads, we never intentionally chose to target ads in a discriminatory manner (e.g., we never used discriminatory targeting parameters). To further minimize the potential for discrimination, we ran most of our experimental ads in categories with no legal salience (such as entertainment and lifestyle); we only ran ad campaigns on jobs and housing to verify whether the effects we observed persist in these domains. We minimized harm to the Facebook advertising platform by paying for ads and using the ad reporting tools in the same manner as any other advertiser. The particular sites we advertised were unaffiliated with the study, and our ads were not defamatory, discriminatory, or suggestive of discrimination.

2 BACKGROUND

Before introducing our methodology and analyses, we provide background on online display advertising, describe Facebook's advertising platform's features, and detail related work.

2.1 Online display advertising

Online display advertising is now an ecosystem with aggregate yearly revenues close to $100 billion [21]. The web advertising ecosystem is a complex set of interactions between ad publishers, ad networks, and ad exchanges, with an ever-growing set of entities involved at each step allowing advertisers to reach much of the web. In contrast, online services such as Facebook and Twitter run advertising platforms that primarily serve a single site (namely, Facebook and Twitter themselves). In this paper, we focus on single-site advertising platforms, but our results may also be applicable to more general display advertising on the web; we leave a full investigation of the extent to which this is the case to future work.

The operation of platforms such as Facebook and Twitter can be divided into two phases: *ad creation* and *ad delivery*. We provide more details on each below.

Ad creation Ad creation refers to the process by which the advertiser submits their ad to the advertising platform. At a high level, the advertiser has to select three things when doing so:

(1) *Ad contents*: Advertisers will typically provide the ad headline, text, and any images/videos. Together, these are called the *ad creative*. They will also provide the link where the platform should send users who click.
(2) *Audience Selection/Targeting*: Advertisers need to select which platform users they would like to see the ad (called the *audience*).
(3) *Bidding strategy*: Advertisers need to specify how much they are willing to pay to have their ads shown. This can come in the form of a per-impression or per-click bid, or the advertiser can simply place an overall *bid cap* and allow the platform to bid on their behalf.

Once the advertiser has entered all of the above information, they submit the ad for review;[3] once it is approved, the ad will move to the ad delivery phase.

Ad delivery Ad delivery refers to the process by which the advertising platform shows ads to users. For every opportunity to show a user an ad (e.g., an *ad slot* is available as the user is browsing the service), the ad platform will run an *ad auction* to determine, from among all of the ads that include the current user in the audience, which ad should be shown.

In practice, however, the ad delivery process is somewhat more complicated. *First*, the platforms try to avoid showing ads from the same advertiser repeatedly in quick succession to the same user; thus, the platforms will sometimes disregard bids for recent winners of the same user. *Second*, the platforms often wish to show users relevant ads; thus, rather than relying solely on the bid to determine the winner of the auction, the platform may incorporate a relevance score into consideration, occasionally allowing ads with lower bids but more relevance to win over those

[3]Most platforms have a review process to prevent abuse or violations of their platforms' advertising policies [8, 77].

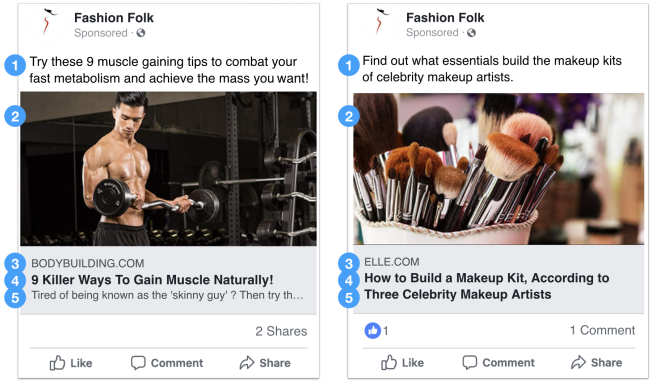


Fig. 1. Each ad has five elements that the advertiser can control: (1) the ad text, entered manually by the advertiser, (2) the images and/or videos, (3) the domain, pulled automatically from the HTML `meta` property `og:site_name` of the destination URL, (4) the title, pulled automatically from the HTML `meta` property `og:title` of the destination URL, and (5) the description from `meta` property `og:description` of the destination URL. The title and description can be manually customized by the advertiser if they wish.

with higher bids. *Third*, the platforms may wish to evenly spread the advertiser budget over their specified time period, rather than use it all at once, which introduces additional complexities as to which ads should be considered for particular auctions. The exact mechanisms by which these issues are addressed are not well-described or documented by the platforms.

Once ads enter the ad delivery phase, the advertising platforms give advertisers information on how their ads are performing. Such information may include detailed breakdowns (e.g., along demographic or geographic lines) of the characteristics of users to whom their ad is being shown and those who click on the ad.

2.2 Facebook's advertising platform

In this paper, we focus on Facebook's advertising platform as it is one of the most powerful and feature-rich advertising platforms in use today. As such, we provide a bit more background here about the specific features and options that Facebook provides to advertisers.

Ad contents Each ad placed on Facebook must be linked to a *Page*; advertisers are allowed to have multiple Pages and run ads for any of them. Ads can come in multiple forms, such as promoting particular posts on the page. However, for typical ads, the advertiser must provide (a) the headline and text to accompany the ad, and (b) one or more images or videos to show to the user. Optionally, the advertiser can provide a *traffic destination* to send the user to if they click (e.g., a Facebook Page or an external URL); if the advertiser provides a traffic destination, the ad will include a brief description (auto-generated from the HTML `meta` data) about this destination. Examples showing all of these elements are presented in Figure 1.

Audience selection Facebook provides a wide variety of audience selection (or *targeting*) options [10, 11, 38, 69]. In general, these options fall into a small number of classes:

- *Demographics and attributes*: Similar to other advertising platforms [39, 71], Facebook allows advertisers to select audiences based on demographic information (e.g., age, gender, and location), as well as profile information, activity on the site, and data from third-parties. Recent work has shown that Facebook offers over 1,000 well-defined attributes and hundreds of thousands of free-form attributes [69].

- *Personal information*: Alternatively, Facebook allows advertisers to specify *the exact users* who they wish to target by either (a) uploading the users' personally identifiable information including names, addresses, and dates of birth [34, 73, 74], or (b) deploying web tracking pixels on third-party sites [27]. On Facebook, audiences created using either mechanism are called *Custom Audiences*.[4]
- *Similar users*: Advertisers may wish to find "similar" users to those who they have previously selected. To do so, Facebook allows advertisers to create *Lookalike Audiences*[5] by starting with a source Custom Audience they had previously uploaded; Facebook then "identif[ies] the common qualities of the people in it" and creates a new audience with other people who share those qualities [28].

Advertisers can often combine many of these features together, for example, by uploading a list of users' personal information and then using attribute-based targeting to further narrow the audience.

Objective and bidding Facebook provides advertisers with a number of *objectives* to choose from when placing an ad [6], where each tries to maximize a different *optimization event* the advertiser wishes to occur. These include "Awareness" (simply optimizing for the most *impressions*, a.k.a. views), "Consideration" (optimizing for clicks, engagement, etc.), and "Conversion" (optimizing for sales generated by clicking the ad). For each objective, the advertiser bids on the objective itself (e.g., for "Awareness", the advertiser would bid on ad impressions). The bid can take multiple forms, and includes the start and end time of the ad campaign and either a lifetime or a daily budget cap. With these budget caps, Facebook places bids in ad auctions on the advertisers' behalf. Advertisers can optionally specify a per-bid cap as well, which will limit the amount Facebook would bid on their behalf for a single optimization event.

Facebook's ad auction When Facebook has ad slots available, it runs an ad auction among the active advertisements bidding for that user. However, the auction does not just use the bids placed by the advertisers; Facebook says [29]:

> The ad that wins an auction and gets shown is the one with the highest *total value* [emphasis added]. Total value isn't how much an advertiser is willing to pay us to show their ad. It's combination of 3 major factors: (1) Bid, (2) Estimated action rates, and (3) Ad quality and relevance.

Facebook defines "Estimated action rates" as "how well an ad performs", meaning whether or not *users in general* are engaging with the ad [5]. They define "Ad quality and relevance" as "how interesting or useful we think a given user is going to find a given ad", meaning how much *a particular user* is likely to be interested in the ad [5].

Thus, it is clear that Facebook attempts to identify the users within an advertiser's selected audience who they believe would find the ad most useful (i.e., those who are most likely to result in an optimization event) and shows the ad preferentially to those users. Facebook says exactly as such in their documentation [4]:

> During ad set creation, you chose a target audience ... and an optimization event ... We show your ad to people in that target audience who are likely to get you that optimization event

[4]Google, Twitter, and Pinterest all provide similar features; these are called *Customer Match* [7], *Tailored Audiences*, and *Customer Lists* [61], respectively.
[5]Google and Pinterest offer similar features: on Google it is called *Similar Audiences* [40], and on Pinterest it is called *Actalike Audiences* [63].

Facebook provides advertisers with an overview of how well-matched it believes an ad is with the target audience using a metric called *relevance score*, which ranges between 1 and 10. Facebook says [68]:

> Relevance score is calculated based on the positive and negative feedback we expect an ad to receive from its target audience.

Facebook goes on to say [68]:

> Put simply, the higher an ad's relevance score, the less it will cost to be delivered. This is because our ad delivery system is designed to show the right content to the right people, and a high relevance score is seen by the system as a positive signal.

Statistics and reporting Facebook provides advertisers with a feature-rich interface [30] as well as a dedicated API [56] for both launching ads and monitoring those ads as they are in ad delivery. Both the interface and the API give semi-live updates on delivery, showing the number of impressions and optimization events as the ad is running. Advertisers can also request this data be broken down along a number of different dimensions, including age, gender, and location (Designated Market Area [58], or DMA, region). Notably, the interface and API *do not* provide a breakdown of ad delivery along racial lines; thus, analyzing delivery along racial lines necessitates development of a separate methodology that we describe in the next section.

Anti-discrimination rules In response to issues of potential discrimination in online advertising reported by researchers and journalists [33], Facebook currently has several policies in place to avoid discrimination for certain types of ads. Facebook also recently built tools to automatically detect ads offering housing, employment, and credit, and pledged to prevent the use of certain targeting categories with those ads. [46]. Additionally, Facebook relies on advertisers to self-certify [15] that they are not in violation of Facebook's advertising policy prohibitions against discriminatory practices [31]. More recently, in order to settle multiple lawsuits stemming from these reports, Facebook no longer allows age, gender, or ZIP code-based targeting for housing, employment or credit ads, and blocks other detailed targeting attributes that are "describing or appearing to relate to protected classes" [22, 44, 60].

2.3 Related work

Next, we detail related work on algorithm auditing, transparency, and discriminatory ad targeting.

Auditing algorithms for fairness Following the growing ubiquity of algorithms in daily life, a community formed around investigating their societal impacts [66]. Typically, the algorithms under study are not available to outside auditors for direct examination; thus, most researchers treat them as "black boxes" and observe their reactions to different inputs. Among most notable results, researchers have shown price discrimination in online retail sites [42], gender discrimination in job sites [16, 43], stereotypical gender roles re-enforced by online translation services [12] and image search [47], disparate performance on gender classification for Black women [13], and political partisanships in search [20, 51, 64]. Although most of the work focused exclusively on the algorithms themselves, recently researchers began to point out that auditors should consider the entire socio-technical systems that include the users of those algorithms, an approach referred to as "algorithm-in-the-loop" [41, 67]. Furthermore, recent work has demonstrated that fairness is not necessarily composable, i.e., for several notions of fairness such as individual fairness [24], a collection of classifiers that are fair in isolation do not necessarily result in a fair outcome when they are used as part of a larger system [25].

Advertising transparency In parallel to the developments in detecting and correcting unfairness, researchers have conducted studies and introduced tools with the aim of increasing transparency and explainability of algorithms and their outcomes. For example, much attention has been dedicated to shedding light on the factors that influence the targeting of a particular ad on the web [26, 53, 54, 62] and on specific services [19, 78].

Focusing on Facebook, Andreou et al. investigated the transparency initiative from Facebook that purportedly tells users why they see particular targeted ads [11]. They found that the provided explanations are incomplete and, at times, misleading. Venkatadri et al. introduced the tool called "TREADS" that attempts to close this gap by providing Facebook users with detailed descriptions of their inferred attributes using the ads themselves as a vehicle [75]. Further, they investigated how data from third-party data brokers is used in Facebook's targeting features and—for the first time—revealed those third-party attributes to the users themselves using TREADS [76]. Similar to other recent work [59], Venkatadri et al. found that the data from third-party data brokers had varying accuracy [76].

Discrimination in advertising As described above, Facebook has some policies and tools in place to prevent discriminatory ad targeting. However, advertisers can still exclude users based on a variety of interests that are highly correlated with race by using custom audiences [69], or by using location [37, 50]. Separately, Sweeney [70] and Datta et al. [19] have studied discrimination in Google's advertising system.

The work just described deals with identifying possibilities for the advertisers to run discriminatory ads using the platform's features. In contrast, other researchers, as well as and HUD's recent complaint, have suggested that discrimination may be introduced by the ad platform itself, rather than by a malicious advertiser [19, 45, 52, 72]. For example, Lambrecht et al. ran a series of ads for STEM education and found they were consistently delivered more to men than to women, even though there are more female users on Facebook, and they are known to be more likely to click on ads and generate conversions [52]. Datta et al. explored ways that discrimination could arise in the targeting and delivery of job-related ads, and analyzed how different parties might be liable under existing law [18]. Our work explores these findings in depth, separating market effects from optimization effects and exploring the mechanisms by which ads are delivered in a skewed manner.

3 METHODOLOGY

We now describe our methodology for measuring the delivery of Facebook ads. At a high level, our goal is to run groups of ads where we vary a particular feature, with the goal of then measuring how changing that feature skews the set of users the Facebook platform delivers the ad to. To do so, we need to carefully control which users are in our target audience. We also need to develop a methodology to measure the ad delivery skew along racial lines, which, unlike gender, is not provided by Facebook's existing reporting tools. We detail how we achieve that in the following sections.

3.1 Audience selection

When running ads, we often wish to control exactly which ad auctions we are participating in. For example, if we are running multiple instances of the same ad (e.g., to establish statistical confidence), we do not want the instances to be competing against each other. To this end, we use random PII-based custom audiences, where we randomly select U.S. Facebook users to be included in mutually-exclusive audiences. By doing so, we can ensure that our ads are only competing against each other in the cases where we wish them to. We also replicate some of the experiments while targeting all U.S. users to ensure that the effects do not only exist when custom audiences are

DMA(s) [58]	# Records (A)		# Records (B)		# Records (C)	
	White	Black	White	Black	White	Black
Wilmington, Raleigh–Durham	400,000	0	0	400,000	900,002	0
Greenville-Spartanburg, Greenville-New Bern, Charlotte, Greensboro	0	400,000	400,000	0	0	892,097

Table 1. Overview of the North Carolina custom audiences used to measure racial delivery. We divide the most populated DMAs in the state into two sets, and create three audiences each with one race per DMA set. Audiences A and B are disjoint from each other; audience C contains the voters from A with additional white voters from the first DMA set and Black voters from the second DMA set. We then use the statistics Facebook reports about delivery by DMAs to infer delivery by race.

targeted. As we show later in Section 4, we observe equivalent skews in these scenarios, which leads us to believe that preventing internal competition between our own ads is not crucial to measure the resulting skews.

Generating custom audiences We create each custom audience by randomly generating 20 lists of 1,000,000 distinct, valid North American phone numbers (`+1 XXX XXX XXXX`, using known-valid area codes). Facebook reported that they were able to match approximately 220,000 users on each of the 20 lists we uploaded.

Initially, we used these custom audiences directly to run ads, but while conducting the experiments we noticed that—even though we specifically target only North American phone numbers—many ads were delivered to users outside of North America. This could be caused by users traveling abroad, users registering with fake phone numbers or with online phone number services, or for other reasons, whose investigation is outside the scope of this paper. Therefore, for all the experiments where we target custom audiences, we additionally limit them to people located in the U.S.

3.2 Data collection

Once one of our ad campaigns is run, we use the Facebook Marketing API to obtain the delivery performance statistics of the ad every two minutes. When we make this request, we ask Facebook to break down the ad delivery performance according to the attribute of study (age, gender, or location). Facebook's response to each query features the following fields, among others, for each of the demographic attributes that we requested:

- `impressions`: The number of times the ad was shown
- `reach`: The number of unique users the ad was shown to
- `clicks`: The number of clicks the ad has received
- `unique_clicks`: The number of unique users who clicked

Throughout the rest of the paper, we use the `reach` value when examining delivery; thus, when we report "Fraction of men in the audience" we calculate this as the `reach` of men divided by the sum of the `reach` of men and the `reach` of women (see Section 3.5 for discussion on using binary values for gender).

3.3 Measuring racial ad delivery

The Facebook Marketing API allows advertisers to request a breakdown of ad delivery performance along a number of axes but it does not provide a breakdown based on race. However, for the purposes of this work, we are able to measure the ad delivery breakdown along racial lines by using location (Designated Market Area, or DMA[6]) as a proxy.

Similar to prior work [69], we obtain voter records from North Carolina; these are publicly available records that have the name, address, race, and often phone number of each registered voter in the state. We partition the most populated North Carolina DMAs into two sets; for the exact DMAs, please see Table 1. We ensure that each racial group (white and Black) from a set of DMAs has a matching number of records of the other group in the other set of DMAs. We sample three audiences (*A*, *B*, and *C*) that fit these constraints from the voter records and upload as separate Custom Audiences to Facebook.[7] Audiences *A* and *B* are disjoint from each other; audience *C* contains the voters from *A* with additional white voters from the first DMA set and Black voters from the second DMA set. We create audiences in this way to be able to test both "flipped" versions of the audiences (*A* and *B*), as well as large audiences with as many users as possible (*C*); we created audience *B* as large as possible (exhausting all voters who fit the necessary criteria), and sampled audience *A* to match its size. The details of the resulting audiences are shown in Table 1.

When we run ads where we want to examine the ad delivery along racial lines, we run the ads to one audience (*A*, *B*, or *C*). We then request that Facebook's Marketing API deliver us results broken down by DMA. Because we selected DMAs to be a proxy for race, we can use the results to infer which custom audience they were originally in, allowing us to determine the racial makeup of the audience who saw (and clicked on) the ad. Note that in experiments that involve measuring racial skew all ads target the same target audience. The limited number of registered voters does not allow us to create many large, disjoint custom audiences like we do in other experiments. However, as we show with ads targeting all U.S. users, internal competition does not appear to influence the results.

3.4 Ad campaigns

We use the Facebook Ad API described in Section 2.2 to create all ads for our experiments and to collect data on their delivery. We carefully control for any time-of-day effects that might be present due to different user demographics using Facebook at different times of the day: for any given experiment, we run all ads at the same time to ensure that any such effects are experienced equally by all ads. Unless otherwise noted, we used the following settings:

- *Objective:* Consideration⟶Traffic[8]
- *Optimization Goal:* Link Clicks
- *Traffic destination:* An external website (that depends on the ads run)
- *Creative:* All of our ads had a single image and text relevant to the ad.
- *Audience selection:* We use custom audiences for many of our ads, as described in Section 3.1, and further restrict them to adult (18+) users of all genders residing in the United States. For other ads, we target all U.S. users age 18 or older.

[6]Designated Market Areas [58] are groups of U.S. counties that Neilson defines as "market areas"; they were originally used to signify a region where users receive similar broadcast television and radio stations. Facebook reports ad delivery by location using DMAs, so we use them here as well.

[7]Unfortunately, Facebook does not report the number of these users who match as we use multiple PII fields in the upload file [73].

[8]This target is defined as: Send more people to a destination on or off Facebook such as a website, app, or Messenger conversation.

- *Budget:* We ran most ads with a budget of \$20 per day, and stopped them typically after six hours.

3.5 Measuring and comparing audiences

We now describe the measurements we make during our experiments and how we compute their confidence intervals.

Binary values of gender and race Facebook's marketing API reports "female", "male", and "uncategorized" as the possible values for gender. Facebook's users self-report their gender, and the available values are "female", "male", and "custom". The latter allows the user to manually type in their gender (with 60 predefined gender identities suggested through auto-complete functionality) and select the preferred pronoun from "female - her", "male - him", and "neutral - them". Across our experiments, we observe that up to 1% of the audiences are reported as "uncategorized" gender. According to Facebook's documentation this represents the users who did not not list their gender.[9] We do not know whether the "uncategorized" gender also features users with self-reported "custom" gender. Thus, in this work we only consider the self-reported binary gender values of "female" and "male".

Further, when considering racial bias, we use the self-reported information from voter records. The data we obtained has 7,560,885 individuals, with 93% reporting their race as either Black or White. Among those, less than 1% report their ethnicity as "Hispanic/Latino". Thus, in this work, we only target the individuals with self-reported race of White or Black. However, when running our experiments measuring race (and targeting specific DMAs), we observe that a fraction (∼10%) of our ads are delivered to audiences outside of our predefined DMAs, thus making it impossible for us to infer their race. This fraction remains fairly consistent across our experiments regardless of what we advertise, thus introducing the same amount of noise across our measurements. This is not entirely unexpected, as we are targeting users directly, and those users may be traveling, may have moved, may have outdated information in the voter file, etc.

We do not claim that gender or race are binary, but choose to focus the analysis on users who self-reported their gender as "female" or "male" and race as "Black" or "White". This way, we report the observable skew in delivery only along these axes. We recognize that delivery can be *further* skewed with respect to gender of non-binary users and/or users of other races in a way that remains unreported in this work.

Measuring statistical significance Using the binary race and gender features, throughout this work, we describe the audiences by the fraction of male users and the fraction of white users. We calculate the lower and upper limits of the 99% confidence interval around this fraction using the method recommended by Agresti and Coull [9], defined in Equation 1:

$$
\begin{aligned}
L.L. &= \frac{\hat{p} + \frac{z^2_{\alpha/2}}{2n} - z_{\alpha/2}\sqrt{\frac{\hat{p}(1-\hat{p})}{n} + \frac{z^2_{\alpha/2}}{4n^2}}}{1 + z^2_{\alpha/2}/n}, \\
U.L. &= \frac{\hat{p} + \frac{z^2_{\alpha/2}}{2n} + z_{\alpha/2}\sqrt{\frac{\hat{p}(1-\hat{p})}{n} + \frac{z^2_{\alpha/2}}{4n^2}}}{1 + z^2_{\alpha/2}/n},
\end{aligned}
\tag{1}
$$

where $L.L.$ is the lower confidence limit, $U.L.$ is the upper confidence limit, $\hat{p}$ is the observed fraction of the audience with the attribute (here: male), n is the size of the audience reached by the

[9] https://www.facebook.com/business/help/151999381652364

ad. To obtain the 99% interval we set $z_{\alpha/2} = 2.576$. The advantage of using this calculation instead of the more frequently used normal approximation

$$p \pm z_{\alpha/2}\sqrt{\frac{\hat{p}(1-\hat{p})}{n}} \tag{2}$$

is that the resulting intervals fall in the $(0, 1)$ range. Whenever the confidence intervals around these fractions for two audiences are non-overlapping, we can make a claim that the gender or racial makeups of two audiences are significantly different [17]. However, the converse is not true: overlapping confidence intervals do not necessarily mean that the means are not different (see Figure 4 in [17] for explanation). In this work we report all the results of our experiments but for easier interpretation emphasize those where the confidence intervals are non-overlapping. We further confirm that the non-overlapping confidence intervals represent statistically significant differences, using the difference of proportion test as shown in Equation 3:

$$Z = \frac{(\hat{p_1} - \hat{p_2}) - 0}{\sqrt{\hat{p}(1-\hat{p})(\frac{1}{n_1} + \frac{1}{n_2})}} \tag{3}$$

where $\hat{p_1}$ and $\hat{p_2}$ are the fractions of men (white users) in the two audiences that we compare, n_1 and n_2 are sizes of these audiences, and $\hat{p}$ is the fraction of men (white users) in the two delivery audiences combined. All the results we refer to as statistically significant are significant in this test with a Z-score of at least 2.576. Finally, as we present in the Appendix, the comparisons presented are statistically significant also after the application of Bonferroni correction [14] for multiple hypotheses testing.

Note that in experiments where we run multiple instances of an ad targeting disjoint custom audiences, the values of $\hat{p}$ and n are calculated from the sums of reached audiences.

4 EXPERIMENTS

In this section, we explore how an advertiser's choice of ad creative (headline, text, and image) and ad campaign settings (bidding strategy, targeted audience) can affect the demographics (gender and race) of the users to whom the ad is ultimately delivered.

4.1 Budget effects on ad delivery

We begin by examining the impact that market effects can have on delivery, aiming to test the hypothesis put forth by Lambrecht et al. [52]. In particular, they observed that their ads were predominantly shown to men even though women had consistently higher click through rates (CTRs). They then hypothesized that the higher CTRs led to women being more expensive to advertise to, meaning they were more likely to lose auctions for women when compared to auctions for men.

We test this hypothesis by running the same ad campaign with different budgets; our goal is to measure the effect that the daily budget alone has on the makeup of users who see the ads. When running these experiments, we keep the ad creative and targeted audience constant, only changing the bidding strategy to give Facebook different daily limits (thus, any ad delivery differences can be attributed to the budget alone). We run an ad with daily budget limits of \$1, \$2, \$5, \$10, \$20, and \$50, and run multiple instances at each budget limit for statistical confidence. Finally, we run the experiment twice, once targeting our random phone number custom audiences, and once targeting all users located in U.S.; we do so to verify that any effect we see is not a function of our particular target audience, and that it persists also when non-custom audiences are targeted.

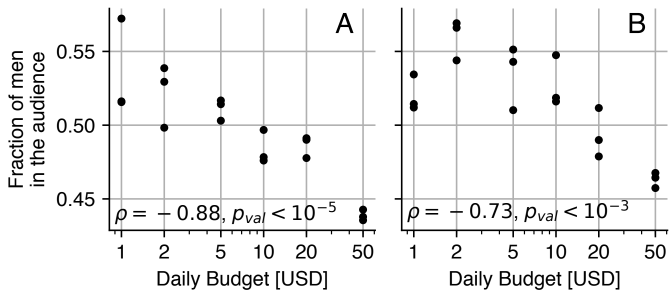


Fig. 2. Gender distributions of the audience depend on the daily budget of an ad, with higher budgets leading to a higher fraction of women. The left graph shows an experiment where we target all users located in the U.S.; the right graph shows an experiment where we target our random phone number custom audiences.

Figure 2 presents the results, plotting the daily budget we specify versus the resulting fraction of men in the audience. The left graph shows the results when we target all users located in the U.S., and the right graph shows the results when we target the random phone number custom audiences. In both cases, we observe that changes in ad delivery due to differences in budget are indeed happening: the higher the daily budget, the smaller the fraction of men in the audience, with the Pearson's correlation of $\rho = -0.88$, $p_{val} < 10^{-5}$ for all U.S. users and $\rho = -0.73$, $p_{val} < 10^{-3}$ for the custom audiences.

The stronger effect we see when targeting all U.S. users may be due to the additional freedom that the ad delivery system has when choosing who to deliver to, as this is a significantly larger audience.

To eliminate the impact that market effects can have on delivery in our following experiments, we ensure that all runs of a given experiment use the same bidding strategy and budget limit. Typically we use a daily budget of $20 per campaign.

4.2 Ad creative effects on ad delivery

Now we examine the effect that the ad creative (headline, text, and image) can have on ad delivery. To do so, we create two stereotypical ads that we believe would appeal primarily to men and women, respectively: one ad focusing on *bodybuilding* and another on *cosmetics*. The actual ads themselves are shown in Figure 1. We run each of the ads at the same time and with the same bidding strategy and budget. For each variable we target different custom audiences, i.e., the "base" level ads target one audience, "text" level ads target another, etc. *Note that we do not explicitly target either ad based on gender; the only targeting restrictions we stipulate are 18+ year old users in the U.S.*

We observe dramatic differences in ad delivery, even though the bidding strategy is the same for all ads, and each pair of ads target the same gender-agnostic audience. In particular, the bodybuilding ad ended up being delivered to over 75% men on average, while the cosmetics ad ended up being delivered to over 90% women on average. Again, this skewed delivery is despite the fact that we—the advertiser—did not specify difference in budget or target audience.

Individual components' impact on ad delivery With the knowledge that the ad creative can skew delivery, we dig deeper to determine *which* of the components of the ad creative (headline, text, and image) have the greatest effect on ad delivery. To do so, we stick with the bodybuilding and cosmetics ads, and "turn off" various features of the ad creative by replacing them with empty strings or blank images. For example, the bodybuilding experiment listed as "base" includes an empty headline, empty ad text, and a blank white image; it does however link to the domain

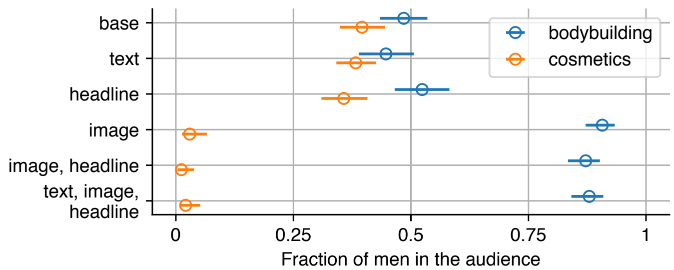


Fig. 3. "Base" ad contains a link to a page about either bodybuilding or cosmetics, a blank image, no text, or headline. There is a small difference in the fraction of male users for the base ads, and adding the "text" only decreases it. Setting the "headline" sets the two ads apart but the audience of each is still not significantly different than that of the base version. Finally, setting the ad "image" causes drastic changes: the bodybuilding ad is shown to a 91% male audience, the cosmetics ad is shown to a 5% male audience, despite the same target audience.

`bodybuilding.com`. Similarly, the cosmetics experiment listed as "base" includes no headline, text, or image, but does link to the domain `elle.com`. We then add back various parts of the ad creative, as shown in Figure 1.

The results of this experiment are presented in Figure 3. Error bars in the figure correspond to 99% confidence intervals as defined in Equation 1. All results are shown relative to that experiment's "base" ad containing only the destination URL. We make a number of observations. *First*, we can observe an ad delivery difference due to the destination URL itself; the base bodybuilding ad delivers to 48% men, while the base cosmetics ad delivers to 40% men. *Second*, as we add back the title and the headline, the ad delivery does not appreciably change from the baseline. However, once we introduce the image into the ad, the delivery changes dramatically, returning to the level of skewed delivery discussed above (over 75% male for bodybuilding, and over 90% female for cosmetics). When we add the text and/or the headline back alongside the image, the skew of delivery does not change significantly compared to the presence of image only. Overall, our results demonstrate that the choice of ad image can have a dramatic effect on which users in the audience ultimately are shown the ad.

Swapping images To further explore how the choice of image impacts ad delivery, we continue using the bodybuilding and cosmetics ads, and test how ads with incongruent images and text are delivered. Specifically, we swap the images between the two ads, running an ad with the bodybuilding headline, text, and destination link, but with the image from cosmetics (and vice versa). We also run the original ads (with congruent images and text) for comparison.

The results of this experiment are presented in Figure 4, showing the skew in delivery of the ads over time. The color of the lines indicates the image that is shown in the ad; solid lines represent the delivery of ads with images consistent with the description, while dotted lines show the delivery for ads where image was replaced. We make a number of observations. *First*, when using congruent ad text and image (solid lines), we observe the skew we observed before. However, we can now see clearly that this delivery skew appears to exist from the very beginning of the ad delivery, i.e., before users begin viewing and interacting with our ads. We will explore this further in the following section. *Second*, we see that when we switch the images—resulting in incongruent ads (dotted lines)—the skew still exists but to a lesser degree. Notably, we observe that the ad with an image of bodybuilding but cosmetics text delivers closest to 50:50 across genders, but the ad with the image of cosmetics but bodybuilding text does not. The exact mechanism by which Facebook

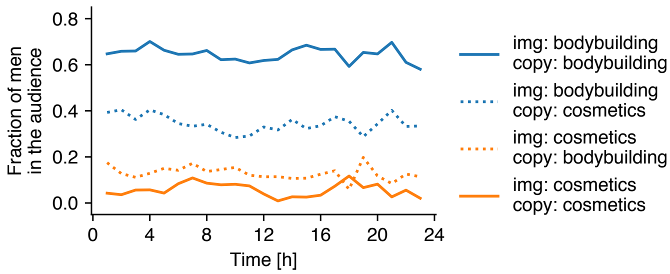


Fig. 4. Ad delivery of original bodybuilding and cosmetics ads, as well as the same ads with incongruent images. Skew in delivery is observed from the beginning. Using incongruent images skews the delivery to a lesser degree, indicating that the image is not the only element of the ad that drives the skew in delivery.

decides to use the ad text and images in influencing ad delivery is unknown, and we leave a full exploration to future work.

Swapping images mid-experiment Facebook allows advertisers to change their ad while it is running, for example, to update the image or text. As a final point of analysis, we examine how changing the ad creative mid-experiment—after it has started running—affects ad delivery. To do so, we begin the experiment with the original congruent bodybuilding and cosmetics ads; we let these run for over six hours. We then swap the images on the running ads, thereby making the ads incongruent, and examine how ad delivery changes.

Figure 5 presents the results of this experiment. In the top graph, we show the instantaneous ad delivery skew: as expected, the congruent ads start to deliver in a skewed manner as we have previously seen. After the image swap at six hours, we notice a very rapid change in delivery with the ads almost completely flipping in ad delivery skew in a short period of time. Interestingly, we do not observe a significant change in users' behavior to explain this swap: the bottom graph plots the click through rates (CTRs) for both ads by men and women over time. Thus, our results suggest that the change in ad delivery skew is unlikely to be due to the users' responses to the ads.

4.3 Source of ad delivery skew

We just observed that ads see a significant skew in ad delivery due to the contents of the ad, despite the bidding strategy and targeting parameters being held constant. However, we observed that the ad delivery skew was present from the very beginning of ad delivery, and that swapping the image in the middle of a run resulted in a very rapid change in ad delivery that could not be explained by how frequently users click on our ads. We now turn to explore the mechanism that may be leading to this ad delivery skew.

Almost-transparent images We begin with the hypothesis that Facebook itself is automatically classifying the ad creative (including the image), and using the output of this classification to calculate a predicted relevance score to users. In other words, we hypothesize that Facebook is running automatic text and image classification, rather than (say) relying on the ad's initial performance, which would explain (a) the delivery skew being present from the beginning of ad delivery, and (b) how the delivery changes rapidly despite no significant observable change in user behavior. However, validating this hypothesis is tricky, as we are not privy to all of Facebook's ad performance data.

To test this hypothesis, we take an alternate approach. We use the *alpha channel* that is present in many modern image formats; this is an additional channel that allows the image to encode the

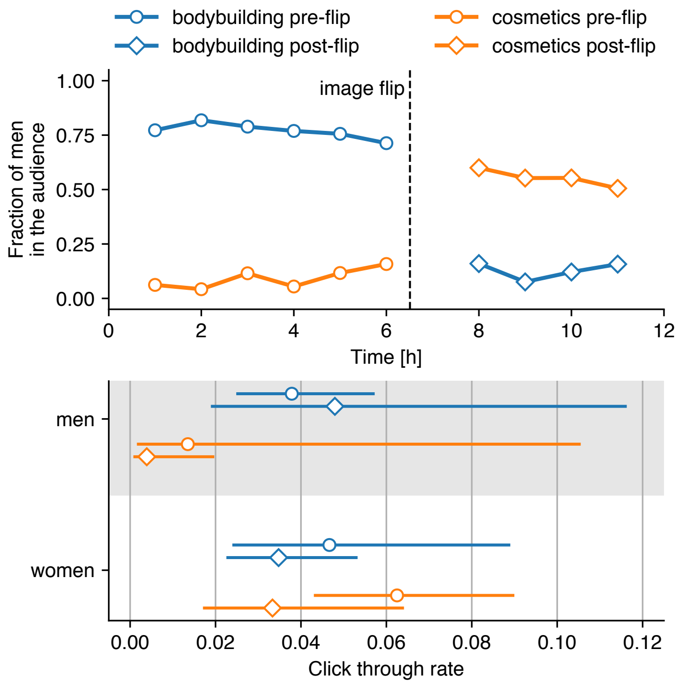


Fig. 5. When we flip the image in the middle of the campaign, the ad is reclassified and shown to an updated audience. Here, we start bodybuilding and cosmetics ads with corresponding descriptions and after 6 hours and 32 minutes we flip the images. Within an hour of the change, the gender proportions are reversed, while there is no significant difference between the click through rates per gender pre and post flipping of the images.

transparency of each pixel. Thus, if we take an image and add an alpha channel with (say) 99% opacity, all of the image data will still be present in the image, but any human who views the image would not be able to see it (as the image would show almost completely transparent). However, if an automatic classifier exists, and if that classifier is not properly programmed to handle the alpha channel, it may continue to classify the image.

Test images To test our hypothesis, we select five images that would stereotypically be of interest to men and five images that would stereotypically be of interest to women; these are shown in the second and fourth columns of Table 2.[10, 11] We convert them to PNG format add an alpha channel with 98% opacity[12] to each of these images; these are shown in the third and fifth columns of Table 2. Because we cannot render a transparent image without a background, the versions in the paper are rendered on top of a white background. As the reader can see, these images are not discernible to the human eye.

We first ran a series of tests to observe how Facebook's ad creation phase handled us uploading such transparent images. If we used Reach as our ad objective, we found that Facebook "flattened"

[10] All of these images were cropped from images posted to `pexels.com`, which allow free non-commercial use.

[11] We cropped these images to the Facebook-recommended resolution of 1,080×1,080 pixels to reduce the probability Facebook would resample the image.

[12] We were unable to use 100% transparency as we found that Facebook would run an image hash over the uploaded images and would detect different images with 100% opacity to be the same (and would refuse to upload it again). By using 98% transparency, we ensure that the images were still almost invisible to humans but that Facebook would not detect they were the same image.

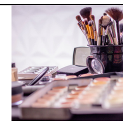
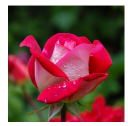
No.	Masculine Visible	Masculine Invisible	Feminine Visible	Feminine Invisible
1				
2				
3				
4				
5				

Table 2. Diagram of the images used in the transparency experiments. Shown are the five stereotypical masculine and feminine images, along with the same images with a 98% alpha channel, denoted as invisible. The images with the alpha channel are almost invisible to humans, but are still delivered in a skewed manner.

these images onto a white background in the ad preview.[13] By targeting ourselves with these Reach ads, we verified that when they were shown to users on the Facebook mobile app or in the desktop Facebook web feed, the images did indeed show up as white squares. Thus, we can use this methodology to test whether there is an automatic image classifier present by examining whether running different transparent white ads results in different delivery.

Results We run ads with all twenty of the images in Table 2, alongside ads with five truly blank white images for comparison. For all 25 of these ads, we hold the ad headline, text, and destination link constant, run them all at the same time, and use the same bidding strategy and target custom audiences in a way that each user is potentially exposed to up to three ads (one masculine image, one feminine image, and one blank image). We then record the differences in ad delivery of these 25 images along gender lines. The results are presented in Figure 6A, with all five images in each of the five groups aggregated together. We can observe that ad delivery is, in fact, skewed, with the ads with stereotypically masculine images delivering to over 43% men and the ads with feminine images delivering to 39% men in the experiment targeting custom audiences as well as 58% and 44% respectively in the experiment targeting all U.S. users. Error bars in the plot correspond to the 99% confidence interval calculated using Equation 1.

[13]Interestingly, we found that if we instead used Traffic as our ad objective, Facebook would both "flatten" these images onto a white background *and then normalize the contrast*. This caused the ads to be visible to humans—simply with less detail that the original ads—thus defeating the experiment. We are unsure of why Facebook did not choose to normalize images with the objective for Reach.

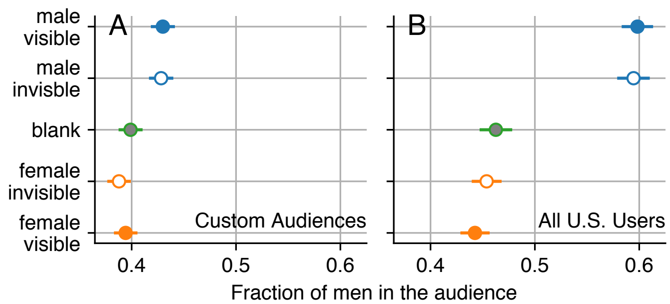


Fig. 6. Fraction of reached men in the audiences for ads with the images from Table 2, targeting random phone number custom audience (A) and US audience (B). The solid markers are visible images, and the hollow markers are the same images with 98% opacity. Also shown is the delivery to truly white images ("blank"). We can observe that a difference in ad delivery exists, and that that difference is statistically significant between the masculine and feminine invisible images. This suggests that automated image classification is taking place.

Interestingly, we also observe that the masculine invisible ads appear to be indistinguishable in the gender breakdown of their delivery from the masculine visible ads, and the feminine invisible ads appear to be indistinguishable in their delivery from the feminine visible ads.

As shown in Figure 6A, we verify that the fraction of men in the delivery of the male ads is significantly higher than in female-centered and neutral ads, as well as higher in neutral ads than in female-centered ads. We also show that we cannot reject the null hypothesis that the fraction of men in the two versions of each ad (one visible, one invisible) are the same. Thus, we can conclude that the difference in ad delivery of our invisible male and female images is statistically significant, despite the fact that humans would not be able to perceive any differences in these ads. This strongly suggests that our hypothesis is correct: that Facebook has an automated image classification mechanism in place that is used to steer different ads towards different subsets of the user population.[14]

To confirm this finding, we re-run the same experiment except that we change the target audience from our random phone number custom audiences (hundreds of thousands of users) to all U.S. users (over 320 million users). Our theory is that if we give Facebook's algorithm a larger set of auctions to compete in, any effect of skewed delivery would be amplified as they may be able to find more users for whom the ad is highly "relevant". In Figure 6B we observe that the ad delivery differences are, indeed, even greater: the male visible and invisible images deliver to approximately 60% men, while the female visible and invisible images deliver to approximately 45% men. Moreover, the statistical significance of this experiment is even stronger, with a Z value over 10 for the ad delivery difference between the male invisible and female invisible ads.

4.4 Impact on real ads

We have observed that differences in the ad headline, text, and image can lead to dramatic difference in ad delivery, despite the bidding strategy and target audience of the advertiser remaining the same. However, all of our experiments thus far were on test ads where we typically changed only

[14]It is important to note we not know exactly how the classification works. For example, the classifier may also be programmed to take in the "flattened" images that appear almost white, but there may sufficient data present in the images for the classification to work. We leave a full exploration of how exactly the classifier is implemented to future work.

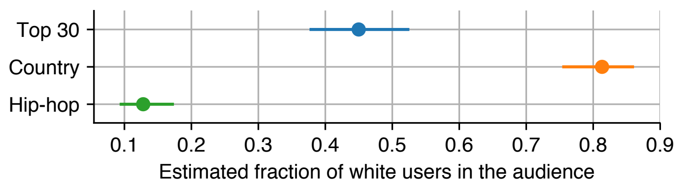


Fig. 7. We run three campaigns about the best selling albums. *Top 30* is neutral, targeting all. *Country* implicitly targets white users, and *Hip-hop* implicitly targets Black users. Facebook classification picks up on the implicit targeting and shows it to the audience we would expect.

a single variable. We now turn to examine the impact that ad delivery can have on realistic ads, where all properties of the ad creative can vary.

Entertainment ads We begin by constructing a series of benign entertainment ads that, while holding targeting parameters fixed (targeting custom audience C from Table 1, are stereotypically of interest to different races. Namely, we run three ads leading to lists of best albums in the previous year: general top 30 (neutral), top country music (stereotypically of interest mostly to white users), and top hip-hop albums (stereotypically of interest mostly to Black users). We find that Facebook ad delivery follows the stereotypical distribution, despite all ads being targeted in the same manner and using the same bidding strategy. Figure 7 shows the fraction of white users in the audience in the three different ads, treating race as a binary (Black users constitute the remaining fraction). Error bars represent 99% confidence intervals calculated using Equation 1.

Neutral ads are seen by a relatively balanced, 45% white audience, while the audiences receiving the country and hip-hop ads are 80% and 13% white, respectively. Assuming significant population level differences of preferences, it can be argued that this experiment highlights the "relevance" measures embedded in ad delivery working as intended. Next, we investigate cases where such differences may not be desired.

Employment ads Next, we advertise eleven different generic job types: artificial intelligence developer, doctor, janitor, lawyer, lumberjack, nurse, preschool teacher, restaurant cashier, secretary, supermarket clerk, and taxi driver. For each ad, we customize the text, headline, and image as a real employment ad would. For example, we advertise for taxi drivers with the text "Begin your career as a taxi driver or a chauffeur and get people to places on time." For each ad, we link users to the appropriate category of job listings on a real-world job site.

When selecting the ad image for each job type, we select five different stock photo images: one that has a white male, one that has a white female, one that has a black male, one that has a black female, and one that is appropriate for the job type but has no people in it. We run each of these five independently to test a representative set of ads for each job type, looking to see how they are delivered along gender and racial lines (targeting custom audience C from Table 1). We run these ads for 24 hours, using the objective of Traffic, all targeting the same audience with the same bidding strategy.

The results of this experiment are presented in Figure 8, plotting the distribution of each of our ads along gender (left graph) and racial (right graph) lines. As before, the error bars represent the 99% confidence interval calculated using Eq. 1. We can immediately observe drastic differences in ad delivery across our ads along both racial and gender lines: our five ads for positions in the lumber industry deliver to over 90% men and to over 70% white users in aggregate, while our five ads for janitors deliver to over 65% women and over 75% black users in aggregate. Recall that the

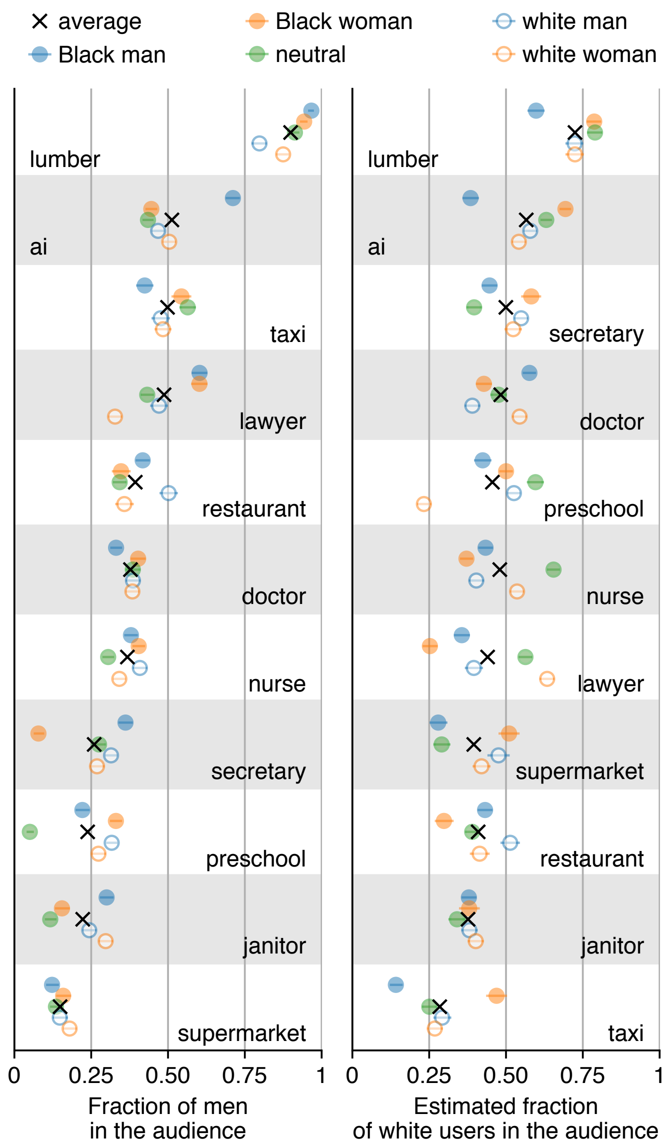


Fig. 8. Results for employment ads, showing a breakdown of ad delivery by gender (left figure) and race (right figure) in the ultimate delivery audience. The labels refer to the race/gender of the person in the ad image (if any). The jobs themselves are ordered by the average fraction of men or white users in the audience. Despite the same bidding strategy, the same target audience, and being run at the same time, we observe significant skew along on both racial and gender lines due to the content of the ad alone.

only difference between these ads are the ad creative and destination link; we (the advertiser) used the same bidding strategy and target audience, and ran all ads at the same time.

Furthermore, we note that the skew in delivery cannot merely be explained by possibly different levels of competition from other advertisers for white and Black users or for male and female users. Although it is the case that each user may be targeted by a different number of advertisers with varying bid levels, by virtue of running all of our job ads at the same time, targeting the same users, with the same budget, we are ensuring that our ads are experiencing competition from other

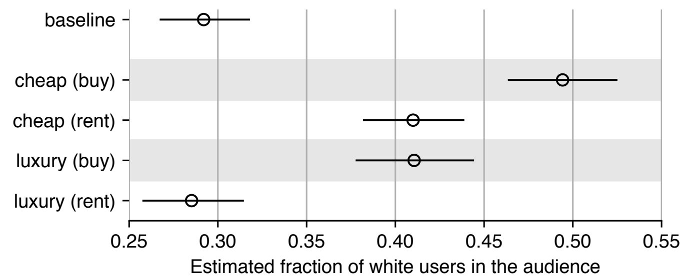


Fig. 9. Results for housing ads, showing a breakdown in the ad delivery audience by race. Despite being targeted in the same manner, using the same bidding strategy, and being run at the same time, we observe significant skew in the makeup of the audience to whom the ad is delivered (ranging from estimated 27% white users for luxury rental ads to 49% for cheap house purchase ads).

advertisers identically. In other words, our ad targeting asks that every user who is considered for our "lumberjack" job ad should also be considered for our taxi driver job ad, so these ads should be competing with each other and facing identical competition from other advertisers at auction time. If the content of the ad was not taken into account by the delivery optimization system, then the ads would be expected to have similar—though not necessarily even—breakdowns by race and gender at delivery. Our experiment demonstrates that this is not the case, and thus, aspects of ad delivery optimization, rather than merely advertiser competition, influence the skew in the delivery outcome.

Housing ads Finally, we create a suite of ads that advertise a variety of housing opportunities, as discrimination in online housing ads has recently been a source of concern [32]. We vary the type of property advertised (rental vs. purchase) and the implied cost (fixer-upper vs. luxury). In each ad, the cost is implied through wording of the ad as well as the accompanying image. Each ad points to a listing of houses for sale or rental apartments in North Carolina on a real-world housing site. Simultaneously, we ran a baseline ad with generic (non-housing) text that simply links to `google.com`. All of the ads ran for 12 hours, using the objective of Traffic, all targeting the same North Carolina audiences and using the same bidding strategy. We construct the experiment such that each particular ad is run twice: once targeting audience A and once targeting audience B (see Table 1) This way we eliminate any potential geographical effects (for example, users in Wilmington could be interested in cheap houses to buy, and users in Charlotte could be interested in luxury rentals regardless of their ethnicity, but if we only used audience C that effect could appear as racial skew).

We present the results in Figure 9 (we found little skew for the housing ads along gender lines, and we omit those results). We observe significant ad delivery skew along racial lines in the delivery of our ads, with certain ads delivering to an audience of over 72% Black users (comparable to the baseline results) while others delivering to an audience of as little as 51% Black users.

As with the employment ads, we cannot make claims about what particular properties of our ads lead to this skew, or about how housing ads in general are delivered. However, given the significant skew we observe with our suite of ads, it indicates the further study is needed to understand how real-world housing ads are delivered.

5 CONCLUDING DISCUSSION

To date, the public debate and ad platform's comments about discrimination in digital advertising have focused heavily on the targeting features offered by advertising platforms, and the ways that advertisers can misuse those features [23].

In this paper, we set out to investigate a different question: *to what degree and by what means may advertising platforms themselves play a role in creating discriminatory outcomes?*

Our study offers an improved understanding of the mechanisms behind and impact of ad delivery, a process distinct from ad creation and targeting. While ad targeting is facilitated by an advertising platform—but nominally controlled by advertisers—ad delivery is conducted and controlled by the advertising platform itself. We demonstrate that, during the ad delivery phase, advertising platforms can play an independent, central role in creating skewed, and potentially discriminatory, outcomes. More concretely, we have:

- Replicated and affirmed prior research suggesting that market and pricing dynamics can create conditions that lead to differential outcomes, by showing that the lower the daily budget for an ad, the fewer women it is delivered to.
- Shown that Facebook's ad delivery process can significantly alter the audience the ad is delivered to compared to the one intended by the advertiser based on the content of the ad itself. We used public voter record data to demonstrate that broadly and inclusively targeted ads can end up being differentially delivered to specific audience segments, even when we hold the budget and target audience constant.
- Demonstrated that skewed ad delivery can start at the beginning of an ad's run. We also showed that this process is likely automated on Facebook's side, and is not a reflection of the early feedback received from users in response to the ad, by using transparent images in ads that appear the same to humans but are distinguishable by automatic image classification tools, and showing they result in skewed delivery.
- Confirmed that skewed delivery can take place on real-world ads for housing and employment opportunities by running a series of employment ads and housing ads with the same targeting parameters and bidding strategy. Despite differing only in the ad creative and destination link, we observed skewed delivery along racial and gender lines.

We briefly discuss some limitations of our work and touch on the broader implications of our findings.

Limitations It is important to note that while we have revealed certain aspects of how ad delivery is accomplished, and the effects it had on our experimental ad campaigns, we cannot make broad conclusions about how it impacts ads more generally. For example, we observe that all of *our ads* for lumberjacks deliver to an audience of primarily white and male users, but that may not hold true of *all ads* for lumberjacks. However, the significant ad delivery skew that we observe for our employment and housing ads strongly suggests that such skew is present for such ads run by real-world advertisers.

Skew vs. discrimination Throughout this paper we refer to differences in the demographics of reached audience as "skew" in delivery. We do not claim any observed skew *per se* is necessarily wrong or should be mitigated. Without making value judgements on skew in general, we do emphasize the distinct case of ads for housing and employment. In particular, the skew we observe in the delivery of ads for cosmetics or bodybuilding might be interpreted as reinforcing gender stereotypes but is unlikely to have legal implications. On the other hand, the skew in delivery of employment and housing ads is potentially discriminatory in a legal sense.

Further, for the experiments involving ethnicity, we attempted to create equally sized audiences (50% white and 50% Black). However, solely the fact that ads are not delivered to an evenly split audience does not indicate skew, as there might be differences in matching rates (what fraction of registered voters are active Facebook users) per ethnicity, or the groups could have different temporal usage patterns. Only when we run two or more ads at the same time, targeting the same audience, and these ads are delivered with different proportions to white and Black users, do we claim we observe skew in delivery.

Our focus lies in understanding the extent to which the ad platform's delivery optimization, rather than merely its targeting tools and their use as implied by Facebook [23], determine the outcomes of ad delivery, and on highlighting that demographic skews presently arise for certain legally protected categories in Facebook, even when the advertiser targets broadly and inclusively.

Skew in traditional media Showing ads to individuals most likely to engage with them is one of the cornerstone promises of online ad platforms. While in traditional media—such as newspapers and television—advertisers can also place their ads strategically to reach particular kinds of readers or viewers, there are three significant differences with implications for fairness and discrimination when compared to advertising on Facebook.

First, when advertising in traditional media, *the advertiser* has the ability to purposefully advertise to a wide and diverse audience, and be assured that their ads will reach that audience. As we show in this work, this is not the case for advertising on Facebook. Even if the advertiser intends to reach a general and diverse audience, their ad can be steered to a narrow slice within that specified audience, that is skewed in unexpected or undesirable ways.

Second, *the individual's* agency to see ads targeted at groups they do not belong to is more severely limited in the hyper-targeted and delivery-optimized scenario of online ad platforms. In traditional media, an individual interested in seeing ads targeted to a different demographic than they belong to has to merely watch programming or read a newspaper that they are not usually a target demographic for. On Facebook, finding out what ads one may be missing out on due to gender, race, or other characteristic inferred or predicted by Facebook is more challenging. A particularly motivated user could change their self-reported gender but might find themselves discouraged from doing so because the account's gender information is always public. Other characteristics, such as race and net worth, are inferred by Facebook (or accessed via third-party companies [76]) rather than obtained through user's self-reported data, which makes them challenging to alter for the purposes of seeing ads. Moreover, although users can remove some of their inferred interests using ad controls on Facebook, they have no ability to control *negative inferences* Facebook may be making about them. For example, Facebook may infer that a particular user is "not interested in working at a lumber yard", and therefore, not show this user ads for a lumberjack job even if the employer is trying to reach them. As a result, Facebook would be excluding them from an opportunity in ways unbeknownst to the user and to the advertiser.

Third, *public interest scrutiny* of the results of advertising is much more difficult in online delivery-optimized systems than in traditional media. Advertising in traditional media can be easily observed and analyzed by many members of society, from individuals to journalists, and targeting and delivery outside the expectation norms can be detected and called out by many. In the case of hyper-targeted online advertising whose delivery is controlled by the platform, such scrutiny is currently outside reach for most ads [36, 57].

Policy implications Our findings underscore the need for policymakers and platforms to carefully consider the role of the optimizations run by the platforms themselves—and not just the targeting choices of advertisers—in seeking to prevent discrimination in digital advertising.

First, because discrimination can arise in ad delivery independently from ad targeting, limitations on ad targeting—such as those currently deployed by Facebook to limit the targeting features that can be used—will not address discrimination arising from ad delivery. On the contrary, to the extent limiting ad targeting features prompts advertisers to rely on larger target audiences, the mechanisms of ad delivery will have an even greater practical impact on the ads that users see.

Second, regulators, lawmakers, and platforms themselves will need to more deeply consider whether and how longstanding civil rights laws apply to modern advertising platforms in light of ad delivery dynamics. At a high level, U.S. federal law prohibits discrimination in the marketing of housing, employment and credit opportunities. A detailed consideration of these legal regimes is beyond the scope of this paper. However, our findings show that ad platforms themselves can shape access to information about important life opportunities in ways that might present a challenge to equal opportunity goals.

Third, in the U.S., Section 230 of the Communications Decency Act (CDA) provides broad legal immunity for internet platforms acting as publishers of third-party content. This immunity was a central issue in recently-settled litigation against Facebook, who argued its ad platform should be protected by CDA Section 230 in part because its advertisers are "wholly responsible for deciding where, how, and when to publish their ads." [35] Our research shows that this claim is misleading, particularly in light of Facebook's role in determining the ad delivery outcomes. Even absent unlawful behavior by advertisers, our research demonstrates that Facebook's own, independent actions during the delivery phase are crucial to determining how, when, and to whom ads are shown, and might produce unlawful outcomes. These effects can be invisible to, and might even create liability for, Facebook's advertisers.

Thus, the effects we observed could introduce new liability for Facebook. In determining whether Section 230 protections apply, courts consider whether an internet platform "materially contributes" to the alleged illegal conduct. Courts have yet to squarely consider how the delivery mechanisms described in this paper might affect an ad platform's immunity under Section 230.

Fourth, our results emphasize the need for increased transparency into advertising platforms, particularly around ad delivery algorithms and statistics for real-world housing, credit, or employment ads. Facebook's existing ad transparency efforts are not yet sufficient to allow researchers to analyze the impact of ad delivery in the real world.

Potential mitigations Given the potential impact that discriminatory ad delivery can have on exposure to opportunities available to different populations, a natural question is how ad platforms such as Facebook may mitigate these effects. This is not straightforward, and is likely to require increased commitment and transparency from ad platforms as well as development of new algorithmic and machine learning techniques. For instance, as we have demonstrated empirically in Section 4.1 (and as [25] have shown theoretically), skewed ad delivery can occur even if the ad platform refrains from refining the audience supplied by the advertisers according to the predicted relevance of the ad to individual users. This happens because different users are valued differently by advertisers, which, in a setting of limited user attention, leads to a tension between providing a useful service for users and advertisers, fair ad delivery, and the platform's own revenue goals.[15]

Thus, more advanced and nuanced approaches to addressing the potential issues of discrimination in digital advertising are necessary. Developing them is beyond the scope of this paper; however, we can imagine several different options, each with their own pros and cons. First, Facebook and similar platforms could disable optimization altogether for some ads, and deliver them to a random sample of users within an advertiser's target audience (with or without market considerations).

[15] A formal statement of this claim for the theoretical notions of individual fairness [24] and its generalization, preference-informed fairness, can be found in [49].

Second, platforms could remove ads in protected categories from their normal ad flows altogether, and provide those listings in a separate kind of marketing product (e.g., , a user-directed listing service like `craigslist.org`). Third, the platforms could allow the advertisers to enforce their own demographic outcomes so long as those desired outcomes don't themselves violate anti-discrimination laws. Finally, the platforms could seek to constrain their delivery optimization algorithms to satisfy chosen fairness criteria (some candidates for such criteria from the theoretical computer science community are individual fairness [24] and preference-informed fairness [49], but a broader discussion of appropriate criteria involving policymakers is needed).

Digital advertising increasingly influences how people are exposed to the world and its opportunities, and helps keep online services free of monetary cost. At the same time, its potential for negative impacts, through optimization due to ad delivery, is growing. Lawmakers, regulators, and the ad platforms themselves need to address these issues head-on.

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APPENDIX

Multiple hypotheses testing. In the experiment described in the main paper we ran ads for 11 different job postings, each with five variations of the accompanying image. Here, we confirm that the apparent differences are not an effect of testing multiple hypotheses. We do so by aggregating the five variants for each ad and comparing the fraction of men and the estimated fraction of white users between each for pairs of jobs. This results in 55 tests, so rather than using the Z value corresponding to $p_{val} = 0.01$, we use the Bonferroni correction [14], a statistical technique used to address the problem of making multiple comparisons. In Figure 10 we show that the majority of comparisons remain statistically significant, each at the Z value corresponding to corrected $p_{val} = \frac{0.01}{55} \approx 0.0002$.

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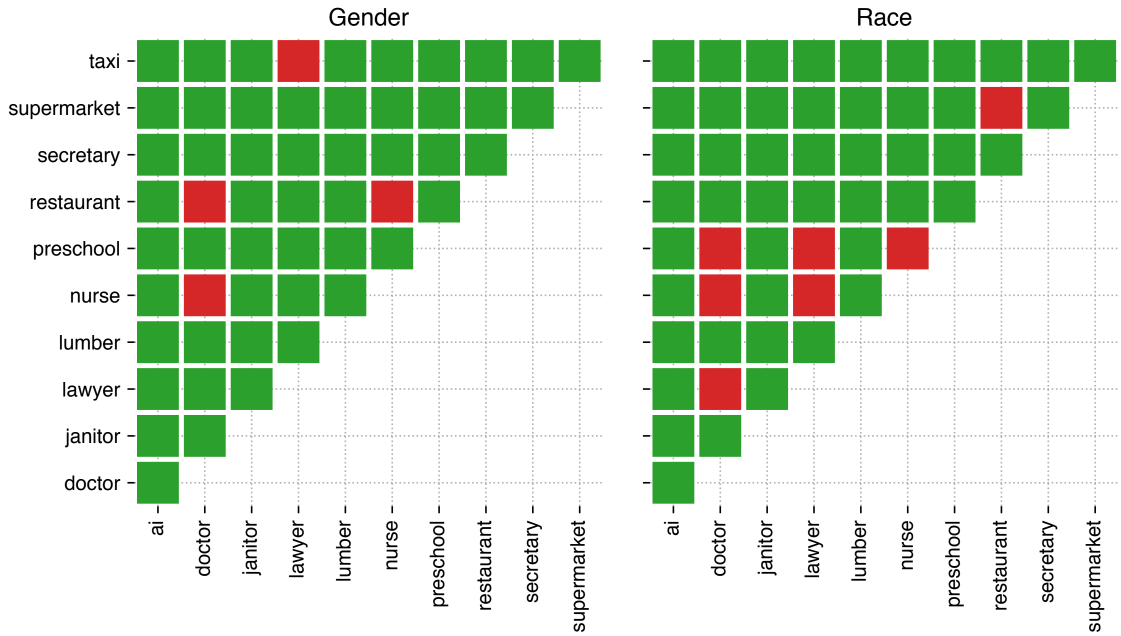

Fig. 10. The demographic differences in ad delivery both in terms of gender and race are statistically significant after introducing Bonferroni correction with N tests of 55. Green squares mark statistically significant differences, red squares indicate insignificant differences.

Weeks 9: Interpretability

The imperative of interpretable machines

As artificial intelligence becomes prevalent in society, a framework is needed to connect interpretability and trust in algorithm-assisted decisions, for a range of stakeholders.

Julia Stoyanovich, Jay J. Van Bavel and Tessa V. West

We are in the midst of a global trend to regulate the use of algorithms, artificial intelligence (AI) and automated decision systems (ADS). As reported by the *One Hundred Year Study on Artificial Intelligence*[1]: "AI technologies already pervade our lives. As they become a central force in society, the field is shifting from simply building systems that are intelligent to building intelligent systems that are human-aware and trustworthy." Major cities, states and national governments are establishing task forces, passing laws and issuing guidelines about responsible development and use of technology, often starting with its use in government itself, where there is, at least in theory, less friction between organizational goals and societal values.

In the United States, New York City has made a public commitment to opening the black box of the government's use of technology: in 2018, an ADS task force was convened, the first of such in the nation, and charged with providing recommendations to New York City's government agencies for how to become transparent and accountable in their use of ADS. In a 2019 report, the task force recommended using ADS where they are beneficial, reduce potential harm and promote fairness, equity, accountability and transparency[2]. Can these principles become policy in the face of the apparent lack of trust in the government's ability to manage AI in the interest of the public? We argue that overcoming this mistrust hinges on our ability to engage in substantive multi-stakeholder conversations around ADS, bringing with it the imperative of interpretability — allowing humans to understand and, if necessary, contest the computational process and its outcomes.

Remarkably little is known about how humans perceive and evaluate algorithms and their outputs, what makes a human trust or mistrust an algorithm[3], and how we can empower humans to exercise agency — to adopt or challenge an algorithmic decision. Consider, for example, scoring and ranking — data-driven algorithms that prioritize entities such as individuals, schools, or products and services. These algorithms may be used to determine credit worthiness, and desirability for college admissions or employment. Scoring and ranking are as ubiquitous and powerful as they are opaque. Despite their importance, members of the public often know little about why one person is ranked higher than another by a résumé screening or a credit scoring tool, how the ranking process is designed and whether its results can be trusted.

As an interdisciplinary team of scientists in computer science and social psychology, we propose a framework that forms connections between interpretability and trust, and develops actionable explanations for a diversity of stakeholders, recognizing their unique perspectives and needs. We focus on three questions (Box 1) about making machines interpretable: (1) what are we explaining, (2) to whom are we explaining and for what purpose, and (3) how do we know that an explanation is effective? By asking — and charting the path towards answering — these questions, we can promote greater trust in algorithms, and improve fairness and efficiency of algorithm-assisted decision making.

Box 1 | Research questions

- **What are we explaining?** Do people trust algorithms more or less than they would trust an individual making the same decisions? What are the perceived trade-offs between data disclosure and the privacy of individuals whose data are being analysed, in the context of interpretability? Which potential sources of bias are most likely to trigger distrust in algorithms? What is the relationship between the perceptions about a dataset's fitness for use and the overall trust in the algorithmic system?
- **To whom are we explaining and why?** How do group identities shape perceptions about algorithms? Do people lose trust in algorithmic decisions when they learn that outcomes produce disparities? Is this only the case when these disparities harm their in-group? Are people more likely to see algorithms as biased if members of their own group were not involved in algorithm construction? What kinds of transparency will promote trust, and when will transparency decrease trust? Do people trust the moral cognition embedded within algorithms? Does this apply to some domains (for example, pragmatic decisions, such as clothes shopping) more than others (for example, moral domains, such as criminal sentencing)? Are certain decisions taboo to delegate to algorithms (for example, religious advice)?
- **Are explanations effective?** Do people understand the label? What kinds of explanations allow individuals to exercise agency: make informed decisions, modify their behaviour in light of the information, or challenge the results of the algorithmic process? Does the nutrition label help create trust? Can the creation of nutrition labels lead programmers to alter the algorithm?

What are we explaining?

Existing legal and regulatory frameworks, such as the US's Fair Credit Reporting Act and the EU's General Data Protection Regulation, differentiate between two kinds of explanations. The first concerns the outcome: what are the results for an individual, a demographic group or the population as a whole? The second concerns the logic behind the decision-making process: what features help an individual or group get a higher score, or, more generally, what are the rules by which the score is computed? Selbst and Barocas[4] argue for an additional kind of an explanation that considers the justification: why are the rules what they are? Much has been written about explaining outcomes[5], so we focus on explaining and justifying the process.

Procedural justice aims to ensure that algorithms are perceived as fair and legitimate. Research demonstrates that, as long as a process is seen as fair, people will accept outcomes that may not benefit them. This finding is supported in numerous domains, including hiring and employment, legal dispute resolution and citizen reactions to police and political leaders[6], and it remains relevant when decisions are made with the assistance of algorithms. A recent lawsuit against Harvard University, filed by Students for Fair Admissions, stems, at least in part, from a lack of transparency and sense of procedural justice among some applicant groups. Similar allegations of injustice were levelled against the New York City Department of Education when only seven black students (out of 895 spots) had been admitted into New York's most selective high school[7]. To increase feelings of procedural justice, interests of different stakeholders should be taken into account when building and evaluating algorithms, prior to observing any outcomes[8].

Data transparency is a dimension of explainability unique to algorithm-assisted — rather than purely human — decision making. In applications involving predictive analytics, data are used to customize generic algorithms for specific situations: algorithms are trained using data. The same algorithm may exhibit radically different behaviour — making different predictions and different kinds of mistakes — when trained on two different datasets. Without access to the training data, it is impossible to know how an algorithm will behave. For example, predictive policing algorithms often reproduce the systemic historical bias towards poor or black neighbourhoods because of their reliance on historical policing data. This can amplify historical patterns of discrimination, rather than provide insight into crime patterns[9]. Transparency of the algorithm alone is insufficient to understand and counteract these particular errors.

The requirement for data transparency is in keeping with the justification dimension of interpretability: if the rules derived by the algorithm are due to the data on which it was trained, then justifying these rules must entail explaining the rationale behind the data selection and collection process. Why was this particular dataset used, or not used? It is also important to make statistical properties of the data available and interpretable, along with the methodology that was used to produce it, substantiating the fitness for use of the data for the task at hand[10].

To whom are we explaining and why?

Different stakeholder groups take on distinct roles in algorithm-assisted decision making, and so have different interpretability requirements. While much important work focuses on interpretability for computing professionals[5] — those who design, develop and test technical solutions — less is known about the interpretability needs of others. These include members of the public who are affected by algorithmic decisions: doctors, judges and college admissions officers who make — and take responsibility for — these decisions; and auditors, policymakers and regulators who assess the systems' legal compliance and alignment with societal norms.

Social identity is key to understanding the values, beliefs and interpretations of the world held by members of a group[11]. People tend to trust in-group members more than out-group members, and if their group is not represented during decision making, they will not trust the system to make judgments that are in their best interest[12]. Numerous identities may play a critical role in how algorithms are evaluated and whether the results they produced should be trusted. One recent case that highlights the contentious role of group identity is the effect of political ideology on search engines and news feeds. Liberal and conservative politicians both demand that technology platforms like Facebook become 'neutral'[13], and have repeatedly criticized Google for embedding bias into its algorithms[14]. In this case, the identity of the programmers can overshadow more central features, such as the accuracy of the news source.

Moral cognition is concerned with how people determine whether an action or outcome is morally right or wrong. Moral cognition is influenced by intuitions, and therefore is often inconsistent with reasoning[15]. A large body of evidence suggests that people evaluate decisions made by humans differently from those made by computers (although this may be changing, see ref. [16]); as such, they may be uncomfortable delegating certain types of decisions to algorithms. Consider the case of driverless vehicles. Even though people approve of autonomous vehicles that might sacrifice passengers to save a larger number of non-passengers, they would prefer not to ride in such vehicles[17]. Thus, utilitarian algorithms designed to minimize net harm may ironically increase harm by making objectively safer technology aversive to consumers. Failing to understand how people evaluate the moral programming of algorithms could thus unwittingly cause harm to large groups of people. The problem is compounded by the fact that moral preferences for driverless vehicles vary dramatically across cultures[18]. Solving these sorts of problems will require an understanding of social dilemmas, since self-interest might come directly in conflict with collective interest[19].

Are explanations effective?

A promising approach for interpretability is to develop labels for data and models analogous to nutritional labels used in the food industry, where simple, standard labels convey information about the ingredients and nutritional value. Nutritional labels are designed to inform specific decisions rather than provide exhaustive information. Proposals for hand-designed labels for data, models or both have been suggested in the literature[20,21]. We advocate instead for generating such labels automatically or semi-automatically as a part of the computational process itself, embodying the paradigm of interpretability by design[10,22].

We expect that data and model labels will inform different design choices by computer scientists and data scientists who implement algorithms and deploy them in complex multi-step decision-making processes. These processes typically use a combination of proprietary and third-party algorithms that may encode hidden assumptions, and rely on datasets that are often repurposed (used outside of the original context for which they were intended). Labels will help determine the 'fitness for use' of a given model or dataset, and assess the methodology that was used to produce it.

Information disclosure does not always have the intended effect. For instance, nutritional and calorie labelling for food are in broad use today. However, the information conveyed in the labels does not always affect calorie consumption[23]. A plausible explanation is that "When comparing a $3 Big Mac at 540 calories with a similarly priced chicken sandwich with 360 calories, the financially strapped consumer [...] may well conclude that the Big Mac is a better deal in terms of calories per dollar"[23]. It is therefore important to understand, with the help of experimental studies, what kinds of disclosure are effective, and for what purpose.

Conclusion

The integration of expertise from behavioural science and computer science is essential to making algorithmic systems interpretable by a wide range of stakeholders, allowing people to exercise agency and ultimately building trust. Individuals and groups who distrust algorithms may be less likely to harness the potential benefits of new technology, and, in this sense, interpretability intimately relates to equity. Education is an integral part of making explanations effective. Recent studies found that individuals who are more familiar with AI fear it less, and are more optimistic about its potential societal impacts[24]. We share this cautious optimism, but predicate it on helping different stakeholders move beyond the extremes of unbounded techno-optimism and techno-criticism, and into a nuanced and productive conversation about the role of technology in society. ❐

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Competing interests

The authors declare no competing interests.

Nutritional Labels for Data and Models *

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Abstract

An essential ingredient of successful machine-assisted decision-making, particularly in high-stakes decisions, is interpretability — allowing humans to understand, trust and, if necessary, contest, the computational process and its outcomes. These decision-making processes are typically complex: carried out in multiple steps, employing models with many hidden assumptions, and relying on datasets that are often used outside of the original context for which they were intended. In response, humans need to be able to determine the "fitness for use" of a given model or dataset, and to assess the methodology that was used to produce it.

To address this need, we propose to develop interpretability and transparency tools based on the concept of a nutritional label, drawing an analogy to the food industry, where simple, standard labels convey information about the ingredients and production processes. Nutritional labels are derived automatically or semi-automatically as part of the complex process that gave rise to the data or model they describe, embodying the paradigm of interpretability-by-design. In this paper we further motivate nutritional labels, describe our instantiation of this paradigm for algorithmic rankers, and give a vision for developing nutritional labels that are appropriate for different contexts and stakeholders.

1 Introduction

An essential ingredient of successful machine-assisted decision-making, particularly in high-stakes decisions, is interpretability — allowing humans to understand, trust and, if necessary, contest, the computational process and its outcomes. These decision-making processes are typically complex: carried out in multiple steps, employing models with many hidden assumptions, and relying on datasets that are often repurposed — used outside of the original context for which they were intended.[1] In response, humans need to be able to determine the "fitness for use" of a given model or dataset, and to assess the methodology that was used to produce it.

To address this need, we propose to develop interpretability and transparency tools based on the concept of a *nutritional label*, drawing an analogy to the food industry, where simple, standard labels convey information about the ingredients and production processes. Short of setting up a chemistry lab, the consumer would otherwise

Bulletin of the IEEE Computer Society Technical Committee on Data Engineering

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[1]See Section 1.4 of Salganik's "Bit by Bit" [24] for a discussion of data repurposing in the Digital Age, which he aptly describes as "mixing readymades with custommades."

have no access to this information. Similarly, consumers of data products cannot be expected to reproduce the computational procedures just to understand fitness for their use. Nutritional labels, in contrast, are designed to support specific decisions by the consumer rather than completeness of information. A number of proposals for hand-designed nutritional labels for data, methods, or both have been suggested in the literature[9, 12, 17]; we advocate deriving such labels automatically or semi-automatically as a side effect of the computational process itself, embodying the paradigm of *interpretability-by-design*.

Interpretability means different things to different stakeholders, including individuals being affected by decisions, individuals making decisions with the help of machines, policy makers, regulators, auditors, vendors, data scientists who develop and deploy the systems, and members of the general public. Designers of nutritional labels must therefore consider *what* they are explaining, *to whom*, and *for what purpose*. In the remainder of this section, we will briefly describe two regulatory frameworks that mandate interpretability of data collection and processing to members of the general public, auditors, and regulators, where nutritional labels offer a compelling solution (Section 1.1). We then discuss interpretability requirements in data sharing, particularly when data is altered to protect privacy or mitigate bias (Section 1.2).

1.1 Regulatory Requirements for Interpretability

The European Union recently enacted a sweeping regulatory framework known as the General Data Protection Regulation, or the GDPR [30]. The regulation was adopted in April 2016, and became enforceable about two years later, on May 25, 2018. The GDPR aims to protect the rights and freedoms of natural persons with regard to how their personal data is processed, moved, and exchanged (Article 1). The GDPR is broad in scope, and applies to "the processing of personal data wholly or partly by automated means" (Article 2), both in the private sector and in the public sector. Personal data is broadly construed, and refers to any information relating to an identified or identifiable natural person, called the *data subject* (Article 4).

According to Article 4, lawful processing of data is predicated on the data subject's *informed consent*, stating whether their personal data can be used, and for what purpose (Articles 6, 7). Further, data subjects have *the right to be informed* about the collection and use of their data. [2] Providing insight to data subjects about the collection and use of their data requires technical methods that support interpretability.

Regulatory frameworks that mandate interpretability are also starting to emerge in the US. New York City was the first US municipality to pass a law (Local Law 49 of 2018) [32], requiring that a task force be put in place to survey the current use of "automated decision systems" (ADS) in city agencies. ADS are defined as "computerized implementations of algorithms, including those derived from machine learning or other data processing or artificial intelligence techniques, which are used to make or assist in making decisions." The task force is developing recommendations for enacting algorithmic transparency by the agencies, and will propose procedures for: (i) requesting and receiving an explanation of an algorithmic decision affecting an individual (Section 3 (b) of Local Law 49); (ii) interrogating ADS for bias and discrimination against members of legally protected groups, and addressing instances in which a person is harmed based on membership in such groups (Sections 3 (c) and (d)); (iii) and assessing how ADS function and are used, and archiving the systems together with the data they use (Sections 3 (e) and (f)).

Other government entities in the US are following suit. Vermont is convening an Artificial Intelligence Task Force to "... make recommendations on the responsible growth of Vermont's emerging technology markets, the use of artificial intelligence in State government, and State regulation of the artificial intelligence field." [33]. Idaho's legislature has passed a law that eliminates trade secret protections for algorithmic systems used in criminal justice [31]. In early April 2019, Senators Booker and Wyden introduced the Algorithmic Accountability Act of 2019 to the US Congress [6]. The Act, if passed, would use "automated decision systems impact assessment" to address and remedy harms caused by algorithmic systems to federally protected classes of people. The act

[2] `https://gdpr-info.eu/issues/right-to-be-informed/`

empowers the Federal Trade Commission to issue regulations requiring larger companies to conduct impact assessments of their algorithmic systems.

The use of nutritional labels in response to these and similar regulatory requirements can benefit a variety of stakeholders. The designer of a data-driven algorithmic method may use them to validate assumptions, check legal compliance, and tune parameters. Government agencies may exchange labels to coordinate service delivery, for example when working to address the opioid epidemic, where at least three sectors must coordinate: health care, criminal justice, and emergency housing, implying a global optimization problem to assign resources to patients effectively, fairly and transparently. The general public may review labels to hold agencies accountable to their commitment to equitable resource distribution.

1.2 Interpretability with Semi-synthetic Data

A central issue in machine-assisted decision-making is its reliance on historical data, which often embeds results of historical discrimination, also known as *structural bias*. As we have seen time and time again, models trained on data will appear to work well, but will silently and dangerously reinforce discrimination [1, 7, 13]. Worse yet, these models will legitimize the bias — "the computer said so." Nutritional labels for data and models are designed specifically to mitigate the harms implied by these scenarios, in contrast to the more general concept of "data about data."

Good datasets drive research: they inform new methods, focus attention on important problems, promote a culture of reproducibility, and facilitate communication across discipline boundaries. But research-ready datasets are scarce due to the high potential for misuse. Researchers, analysts, and practitioners therefore too often find themselves compelled to use the data they have on hand rather than the data they would (or should) like to use. For example, aggregate usage patterns of ride hailing services may overestimate demand in early-adopter (i.e., wealthy) neighborhoods, creating a feedback loop that reduces service in poorer neighborhoods, which in turn reduces usage. In this example, and in many others, there is a need to alter the input dataset to achieve specific properties in the output, while preserving all other relevant properties. We refer to such altered datasets as *semi-synthetic*.

Recent examples of methods that produce semi-synthetic data include database repair for causal fairness [25], database augmentation for coverage enhancement [4], and privacy-preserving and bias-correcting data release [21, 23]. A semi-synthetic datasets may be altered in different ways. Noise may be added to it to protect privacy, or statistical bias may be removed or deliberately introduced. When a dataset of this kind is released, its composition and the process by which it was derived must be made interpretable to a data scientist, helping determine fitness for use. For example, datasets repaired for racial bias are unsuitable for studying discrimination mitigation methods, while datasets with bias deliberately introduced are less appropriate for research unrelated to fairness. This gives another compelling use case for nutritional labels.

2 Nutritional Labels for Algorithmic Rankers

To make our discussion more concrete, we now describe Ranking Facts, a system that automatically derives nutritional labels for rankings [36]. Algorithmic decisions often result in scoring and ranking individuals — to determine credit worthiness, desirability for college admissions and employment, and compatibility as dating partners. Algorithmic rankers take a collection of items as input and produce a ranking – a sorted list of items – as output. The simplest kind of a ranker is a score-based ranker, which computes a score for each item independently, and then sorts the items on their scores. While automatic and seemingly objective, rankers can discriminate against individuals and protected groups [5], and exhibit low diversity at top ranks [27]. Furthermore, ranked results are often unstable — small changes in the input or in the ranking methodology may lead to drastic changes in the output, making the result uninformative and easy to manipulate [11]. Similar concerns apply in cases where

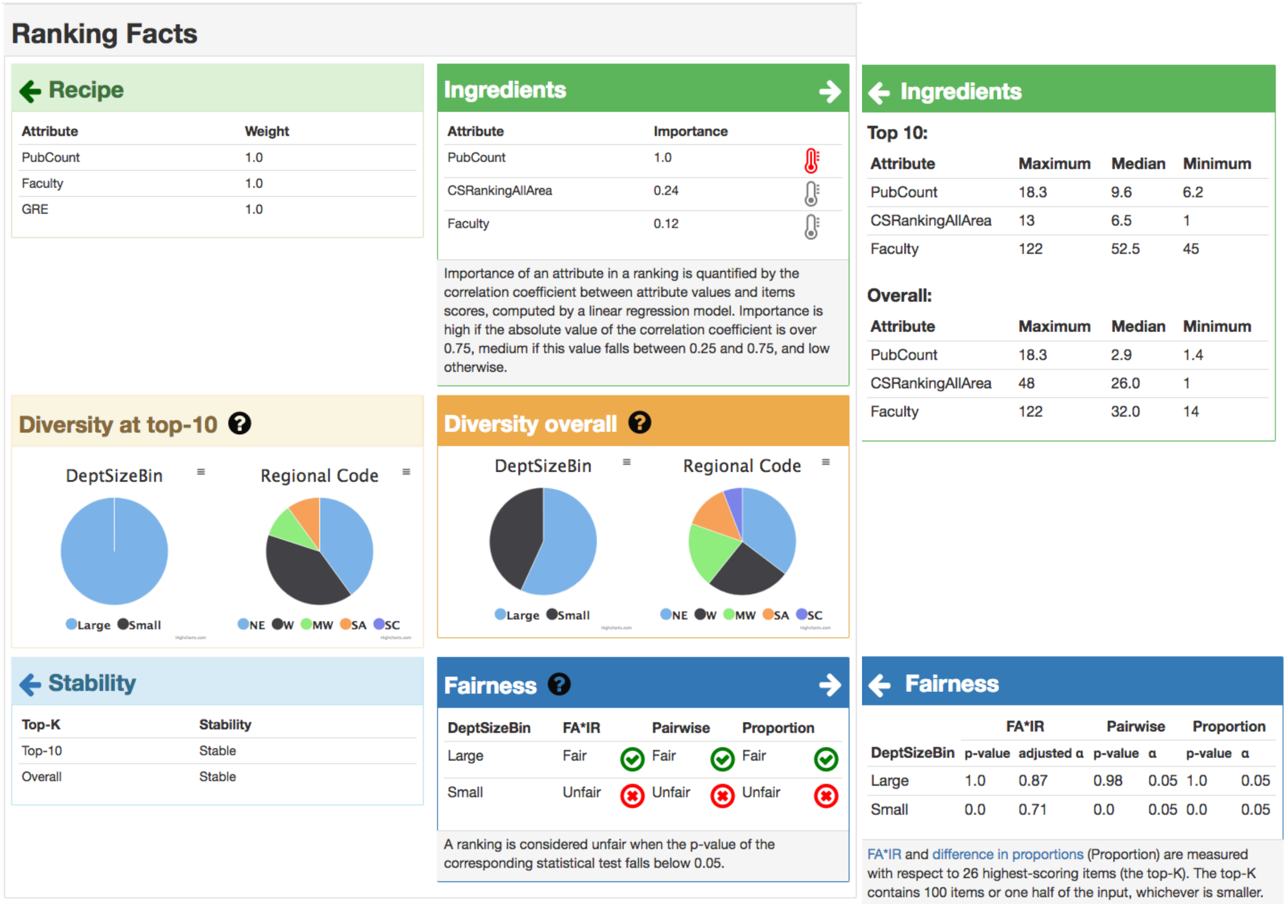

Figure 1: Ranking Facts for the CS departments dataset. The Ingredients widget (green) has been expanded to show the details of the attributes that strongly influence the ranking. The Fairness widget (blue) has been expanded to show the computation that produced the fair/unfair labels.

items other than individuals are ranked, including colleges, academic departments, and products.

In a recent work, we developed Ranking Facts, a nutritional label for rankings [36]. Ranking Facts is available as a Web-based tool[3], and its code is available in the open source [4]. Figure 1 presents Ranking Facts that explains a ranking of Computer Science departments. The data in this example was obtained from CS Rankings[5], augmented with attributes from the NRC dataset [6]. Ranking Facts is made up of a collection of visual widgets, each with an overview and a detailed view. Each widget addresses an essential aspect of transparency and interpretability, and is based on our recent technical work on fairness [3, 35], diversity [8, 27, 28, 34], and stability [2] in algorithmic rankers. We now describe each widget in some detail.

2.1 Recipe and Ingredients

These two widgets help to explain the ranking methodology. The Recipe widget succinctly describes the ranking algorithm. For example, for a linear scoring formula, each attribute would be listed together with its weight. The

[3] http://demo.dataresponsibly.com/rankingfacts/
[4] https://github.com/DataResponsibly/RankingFacts
[5] https://github.com/emeryberger/CSRankings
[6] http://www.nap.edu/rdp/

Ingredients widget lists attributes most material to the ranked outcome, in order of importance. For example, for a linear model, this list could present the attributes with the highest learned weights. Put another way, the explicit intentions of the designer of the scoring function about which attributes matter, and to what extent, are stated in the Recipe, while Ingredients may show attributes that are actually associated with high rank. Such associations can be derived with linear models or with other methods, such as rank-aware similarity in our prior work [27]. The detailed Recipe and Ingredients widgets list statistics of the attributes in the Recipe and in the Ingredients: minimum, maximum and median values at the top-10 and over-all.

2.2 Stability

The Stability widget explains whether the ranking methodology is robust on this particular dataset. An unstable ranking is one where slight changes to the data (e.g., due to uncertainty and noise), or to the methodology (e.g., by slightly adjusting the weights in a score-based ranker) could lead to a significant change in the output. This widget reports a stability score, as a single number that indicates the extent of the change required for the ranking to change. As with the widgets above, there is a detailed Stability widget to complement the overview widget.

An example is shown in Figure 2, where the stability of the ranking is quantified as the slope of the line that is fit to the score distribution, at the top-10 and over-all. A score distribution is unstable if scores of items in adjacent ranks are close to each other, and so a very small change in scores will lead to a change in the ranking. In this example the score distribution is considered unstable if the slope is 0.25 or lower. Alternatively, stability can be computed with respect to each scoring attribute, or it can be assessed using a model of uncertainty in the data. In these cases, stability quantifies the extent to which a ranked list will change as a result of small changes to the underlying data. A complementary notion of stability quantifies the magnitude of change as a result of small changes to the ranking model. We explored this notion in our recent work, briefly discussed below.

In [2] we develped methods for quantifying the stability of a score-based ranker with respect to a given dataset. Specifically, we considered rankers that specify non-negative weights, one for each item attribute, and compute the score as a weighted sum of attribute values. We focused on a notion of stability that quantifies whether the output ranking will change due to a small change in the attribute weights. This notion of stability is natural for consumers of a ranked list (i.e., those who use the ranking to prioritize items and make decisions), who should be able to assess the magnitude of the *region in the weight space* that produces the observed ranking. If this region is large, then the same ranked order would be obtained for many choices of weights, and the ranking is stable. But if this region is small, then we know that only a few weight choices can produce the observed ranking. This may suggest that the ranking was engineered or “cherry-picked” by the producer to obtain a specific outcome.

2.3 Fairness

The Fairness widget quantifies whether the ranked output exhibits statistical parity (one interpretation of fairness) with respect to one or more sensitive attributes, such as gender or race of individuals [35]. We denote one or several values of the sensitive attribute as a protected feature. For example, for the sensitive attribute gender, the assignment gender=F is a protected feature.

A variety of fairness measures have been proposed in the literature [38], with a primary focus on classification or risk assessment tasks. One typical fairness measure for classification compares the proportion of members of a protected group (e.g., female gender or minority race) who receive a positive outcome to their proportion in the overall population. For example, if the dataset contains an equal number of men and women, then among the individuals invited for a job interview, one half should be women. A measure of this kind can be adapted to rankings by quantifying the proportion of members of a protected group in some selected set of size k (treating the top-k as a set).

In [35], we were the first to propose a family of *fairness measures specifically for rankings*. Our measures are based on a generative process for rankings that meet a particular fairness criterion (fairness probability f) and

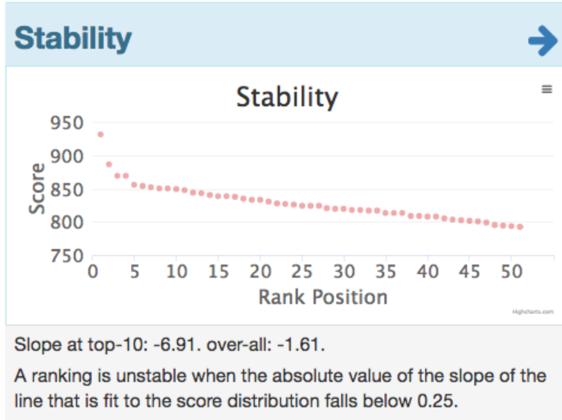

Figure 2: Stability: detailed widget.

are drawn from a dataset with a given proportion of members of a binary protected group (p). This method was subsequently used in FA*IR [37] to quantify fairness in every prefix of a top-k list. We also developed a pairwise measure that directly models the probability that a member of a protected group is preferred to a member of the non-protected group.

Let us now return to the Fairness widget in Figure 1. We select a binary version of the department size attribute DeptSizeBin from the CS departments dataset as the sensitive attribute, and treat the value and "small" as the protected feature. The summary view of the Fairness widget in our example presents the output of three fairness measures: FA*IR [37], proportion [38], and our own pairwise measure. All these measures are statistical tests, and whether a result is fair is determined by the computed p-value. The detailed Fairness widget provides additional information about the tests and explains the process.

2.4 Diversity

Fairness is related to diversity: ensuring that different kinds of objects are represented in the output of an algorithmic process [8]. Diversity has been considered in search and recommender systems, but in a narrow context, and was rarely applied to profiles of individuals. The Diversity widget shows diversity with respect to a set of demographic categories of individuals, or a set of categorical attributes of other kinds of items [8]. The widget displays the proportion of each category in the top-10 ranked list and over-all, and, like other widgets, is updated as the user selects different ranking methods or sets different weights. In our example in Figure 1, we quantify diversity with respect to department size and to the regional code of the university. By comparing the pie charts for top-10 and over-all, we observe that only large departments are present in the top-10.

This simple diversity measure that is currently included in Ranking Facts can be augmented by, or replaced with, other measures, including, for example, those we developed in our recent work [28, 34].

3 Learning Labels

The creation of nutritional labels is often cast as a design problem rather than a computational problem [9, 12]. Standard labels with broad applicability can amortize the cost of design, but the diversity of datasets, methods, and desirable properties for nutritional labels suggest a learning approach to help develop labels for a variety of situations. Since opaque automation is what motivated the need for labels in the first place, automating their creation may seem like a step backwards. But there are several benefits:

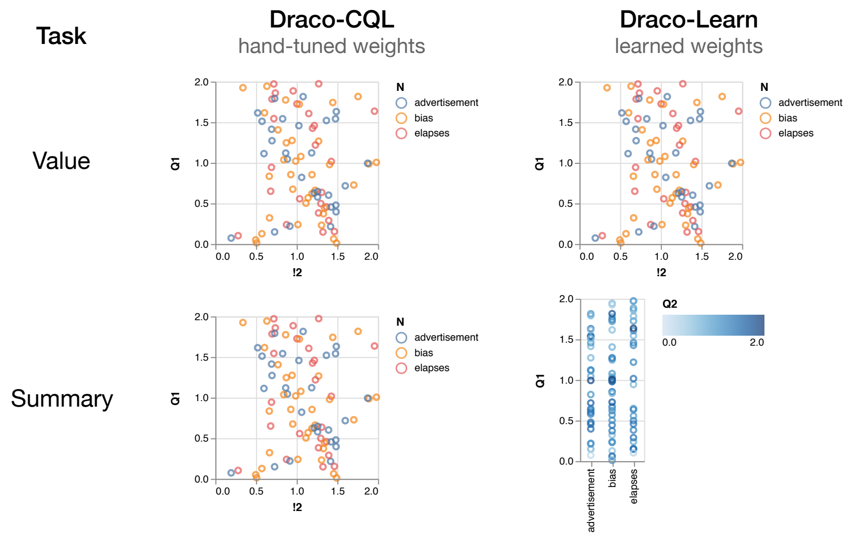

Figure 3: Draco can be used to re-implement existing visualization systems like CQL by hand-tuning weights (left) or be used to learn weights automatically from preference data (right). The visualizations selected can vary significantly, affording customization for specific applications. A similar approach can be used when generating nutritional labels for data and models.

- Coverage: *some* information provided in (nearly) *all* cases is preferable to *all* information provided in *some* cases, as there are many models and datasets being deployed.
- Correctness: Hand-designed labels imply human metadata attachment, but curation of metadata is essentially an unsolved problem. Computable labels reduce reliance on human curation efforts.
- Retroactivity: Some information can only be manually collected at the time of data collection (e.g., demographics of authors in a speech corpus to control for nationality bias). This opportunity is lost for existing datasets. However, inferring relevant properties based on the content of the data may be "better than nothing."

We now consider two approaches to the problem of learning labels, one based on the visualization recommendation literature, and one based on bin-packing optimization.

3.1 Learning as Visualization Recommendation

Moritz et al. proposed Draco [19], a formal model that represents visualizations as sets of logical facts, and represents design guidelines as a collection of hard and soft constraints over these facts, following an earlier proposal for the VizDeck system [14]. Draco enumerates the visualizations that do not violate the hard constraints and finds the most preferred visualizations according to the weights of the soft constraints. Formalized visualization descriptions are derived from the Vega-Lite grammar [26] extended with rules to encode expressiveness criteria [16], preference rules validated in perception experiments, and general visualization design best practices. Hard constraints *must* be satisfied (e.g., shape encodings cannot express quantitative values), whereas soft constraints express a preference (e.g., temporal values should use the x-axis by default). The weights associated with soft constraints can be learned from preference or utility data, when available (see example in Figure 3).

Draco implements the constraints using Answer Set Programming (ASP) semantics, and casts the problem of finding appropriate encodings as finding optimal answer sets [10]. Draco has been extended to optimize for constraints over multiple visualizations [22], and adapted for use in specialized domains.

Using Draco (or similar formalizations), the specialized constraints governing the construction of nutritional labels can be developed in the general framework of ASP, while borrowing the foundational constraints capturing general visualization design principles. This approach can help reduce the cost of developing hundreds of application-specific labels by encoding common patterns, such as including descriptive statistics in all labels, or only showing fairness visualizations when bias is detected.

3.2 Learning as Optimization

Sun et al. proposed MithraLabel [29], focusing on generating task-specific labels for datasets to determine fitness for specific tasks. Considering the dataset as a collection of items over a set of attributes, each widget provides specific information (such as functional dependencies) about the whole dataset or some selected part of it. For example, if a data scientist is considering the use of a number-of-prior-arrests attribute to predict likelihood of recidivism, she should know that the number of prior arrests is highly correlated with the likelihood of re-offending, but it introduces bias as the number of prior arrests is higher for African Americans than for other races due to policing practices and segregation effects in poor neighborhoods. Widgets that might appear in the nutritional label for prior arrests include the count of missing values, correlation with the predicted attribute or a protected attribute, and the distribution of values.

4 Properties of a nutritional label

The database and cyberinfrastructure communities have been studying systems and standards for metadata, provenance, and transparency for decades [20, 18]. We are now seeing renewed interest in these topics due to the proliferation of data science applications that use data opportunistically. Several recent projects explore these concepts for data and algorithmic transparency, including the Dataset Nutrition Label project [12], Datasheets for Datasets [9], and Model Cards [17]. All these method rely on manually constructed annotations. In contrast, our goal is to *generate labels automatically or semi-automatically*.

To differentiate a nutritional label from more general forms of metadata, we articulate several properties:

- **Comprehensible**: The label is not a complete (and therefore overwhelming) history of every processing step applied to produce the result. This approach has its place and has been extensively studied in the literature on scientific workflows, but is unsuitable for the applications we target. The information on a nutritional label must be short, simple, and clear.

- **Consultative**: Nutritional labels should provide actionable information, rather than just descriptive metadata. For example, universities may invest in research to improve their ranking, or consumers may cancel unused credit card accounts to improve their credit score.

- **Comparable**: Nutritional labels enable comparisons between related products, implying a standard. The IEEE is developing a series of ethics standards, known as the IEEE P70xx series, as part of its Global Initiative on Ethics of Autonomous and Intelligent Systems.[7] These standards include “IEEE P7001: Transparency of Autonomous Systems” and “P7003: Algorithmic Bias Considerations” [15]. The work on nutritional labels is synergistic with these efforts.

- **Concrete**: The label must contain more than just general statements about the source of the data; such statements do not provide sufficient information to make technical decisions on whether or not to use the data.

Data and models are chained together into complex automated pipelines — computational systems “consume” datasets at least as often as people do, and therefore also require nutritional labels! We articulate additional properties in this context:

[7] https://ethicsinaction.ieee.org/

- **Computable**: Although primarily intended for human consumption, nutritional labels should be machine-readable to enable specific applications: data discovery, integration, automated warnings of potential misuse.
- **Composable**: Datasets are frequently integrated to construct training data; the nutritional labels must be similarly integratable. In some situations, the composed label is simple to construct: the union of sources. In other cases, the biases may interact in complex ways: a group may be sufficiently represented in each source dataset, but underrepresented in their join.
- **Concomitant**: The label should be carried with the dataset; systems should be designed to propagate labels through processing steps, modifying the label as appropriate, and implementing the paradigm of transparency by design.

5 Conclusions

In this paper we discussed work on transparency and interpretability for data and models based on the concept of a nutritional label. We presented Ranking Facts, a system that automatically derives nutritional labels for rankings, and outlined directions for ongoing research that casts the creation of nutritional labels as a computational problem, rather than as purely a design problem.

We advocate interpretability tools for a variety of datasets and models, for a broad class of application domains, and to accommodate the needs of a variety of stakeholders. These tools must be informed by an understanding of how humans perceive algorithms and the decisions they inform, including issues of trust and agency to challenge or accept an algorithm-informed decision. These tools aim to reduce bias and errors in deployed models by preventing the use of an inappropriate dataset or model at design time. Although the extent of data misuse is difficult to measure directly, we can design experiments to show how well nutritional labels inform usage decisions, and design the tools accordingly. More broadly, we see the review of human-curated and machine-computed metadata as a critical step for interpretability in data science, which can lead to lasting progress in the use of machine-assisted decision-making in society.

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Documentation to facilitate communication between dataset creators and consumers.

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Datasheets for Datasets

DATA PLAYS A critical role in machine learning. Every machine learning model is trained and evaluated using data, quite often in the form of static datasets. The characteristics of these datasets fundamentally influence a model's behavior: a model is unlikely to perform well in the wild if its deployment context does not match its training or evaluation datasets, or if these datasets reflect unwanted societal biases. Mismatches like this can have especially severe consequences when machine learning models are used in high-stakes domains, such as criminal justice,[1,13,24] hiring,[19] critical infrastructure,[11,21] and finance.[18] Even in other domains, mismatches may lead to loss of revenue or public relations setbacks. Of particular concern are recent examples showing that machine learning models can reproduce or amplify unwanted societal biases reflected in training datasets.[4,5,12] For these and other reasons, the World Economic Forum suggests all entities should document the provenance, creation, and use of machine learning datasets to avoid discriminatory outcomes.[25]

Although data provenance has been studied extensively in the databases community,[3,8] it is rarely discussed in the machine learning community. Documenting the creation and use of datasets has received even less attention. Despite the importance of data to machine learning, there is currently no standardized process for documenting machine learning datasets.

To address this gap, we propose *datasheets for datasets*. In the electronics industry, every component, no matter how simple or complex, is accompanied with a datasheet describing its operating characteristics, test results, recommended usage, and other information. By analogy, we propose that every dataset be accompanied with a datasheet that documents its motivation, composition, collection process, recommended uses, and so on. Datasheets for datasets have the potential to increase transparency and accountability within the machine learning community, mitigate unwanted societal biases in machine learning models, facilitate greater reproducibility of machine learning results, and help researchers and practitioners to select more appropriate datasets for their chosen tasks.

After outlining our objectives, we describe the process by which we developed datasheets for datasets. We then provide a set of questions designed to elicit the information that a datasheet for a dataset might contain, as well as a workflow for dataset creators to use when answering these questions. We conclude with a summary of the impact to date of datasheets for datasets and a discussion of implementation challenges and avenues for future work.

Objectives. Datasheets for datasets are intended to address the needs of two key stakeholder groups: dataset creators and dataset consumers. For dataset creators, the primary objective is to encourage careful reflection on the process of creating, distributing, and maintaining a dataset, including any underlying assumptions, potential risks or harms, and implica-

tions of use. For dataset consumers, the primary objective is to ensure they have the information they need to make informed decisions about using a dataset. Transparency on the part of dataset creators is necessary for dataset consumers to be sufficiently well informed that they can select appropriate datasets for their chosen tasks and avoid unintentional misuse.[a]

Beyond these two key stakeholder groups, datasheets for datasets may be valuable to policy makers, consumer advocates, investigative journalists, individuals whose data is included in datasets, and individuals who may be impacted by models trained or evaluated using datasets. They also serve a secondary objective of facilitating greater reproducibility of machine learning results: researchers and practitioners without access to a dataset may be able to use the information in its datasheet to create alternative datasets with similar characteristics.

Although we provide a set of questions designed to elicit the information a datasheet for a dataset might contain, these questions are not intended to be prescriptive. Indeed, we expect that datasheets will necessarily vary depending on factors such as the domain or existing organizational infrastructure and workflows. For example, some the questions are appropriate for academic researchers publicly releasing datasets for the purpose of enabling future research, but less relevant for product teams

a We note that in some cases, the people creating a datasheet for a dataset may not be the dataset creators, as was the case with the example datasheets that we created as part of our development process.

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key insights

- There are currently no industry standards for documenting machine learning datasets.
- Datasheets address this gap by documenting the contexts and contents of datasets: from their motivation, composition, collection process, and recommended uses.
- Datasheets for datasets can increase transparency and accountability within the machine learning community, mitigate unwanted biases in machine learning models, facilitate greater reproducibility of machine learning results, and help researchers and practitioners to choose the right dataset.
- Datasheets enable dataset creators to be intentional throughout the dataset creation process.
- Iterating on the design of datasheets with practitioners and legal experts helped improve the questions.
- Datasheets and other forms of data documentation are increasingly commonly released along with datasets.

creating internal datasets for training proprietary models. As another example, Bender and Friedman[2] outline a proposal similar to datasheets for datasets specifically intended for language-based datasets. Their questions may be naturally integrated into a datasheet for a language-based dataset as appropriate.

We emphasize that the process of creating a datasheet is not intended to be automated. Although automated documentation processes are convenient, they run counter to our objective of encouraging dataset creators to carefully reflect on the process of creating, distributing, and maintaining a dataset.

Development Process

Here, we refined the questions and workflow provided over a period of approximately two years, incorporating many rounds of feedback.

First, leveraging our own experiences as researchers with diverse backgrounds working in different domains and institutions, we drew on our knowledge of dataset characteristics, unintentional misuse, unwanted societal biases, and other issues to produce an initial set of questions designed to elicit information about these topics. We then "tested" these questions by creating example datasheets for two widely used datasets: Labeled Faces in the Wild[16] and Pang and Lee's polarity dataset.[22] We chose these datasets in large part because their creators provided exemplary documentation, allowing us to easily find the answers to many of the questions. While creating these example datasheets, we found gaps in the questions, as well as redundancies and lack of clarity. We therefore refined the questions and distributed them to product teams in two major U.S.-based technology companies, in some cases helping teams to create datasheets for their datasets and observing where the questions did not achieve their intended objectives. Contemporaneously, we circulated an initial draft of this article to colleagues through social media and on arXiv (draft posted Mar. 23, 2018). Via these channels we received extensive comments from dozens of researchers, practitioners, and policy makers. We also worked with a team of lawyers to review the questions from a legal perspective.

We incorporated this feedback to yield the questions and workflow provided in the next section: We added and removed questions, refined the content of the questions, and reordered the questions to better match the key stages of the dataset life cycle. Based on our experiences with product teams, we reworded the questions to discourage yes/no answers, added a section on "Uses," and deleted a section on "Legal and Ethical Considerations." We found that product teams were more likely to answer questions about legal and ethical considerations if they were integrated into sections about the relevant stages of the dataset lifecycle rather than grouped together. Finally, following feedback from the team of lawyers, we removed questions that explicitly asked about compliance with regulations, and introduced factual questions intended to elicit relevant information about compliance without requiring dataset creators to make legal judgments.

Questions and Workflow

In this section, we provide a set of questions designed to elicit the information that a datasheet for a dataset might contain, as well as a workflow for dataset creators to use when answering these questions. The questions are grouped into sections that approximately match the key stages of the dataset lifecycle: motivation, composition, collection process, preprocessing/cleaning/labeling, uses, distribution, and maintenance. This grouping encourages dataset creators to reflect on the process of creating, distributing, and maintaining a dataset, and even alter this process in response to their reflection. We note that not all questions will be applicable to all datasets; those that do not apply should be skipped.

To illustrate how these questions might be answered in practice, we produced an appendix that includes an example datasheet for Pang and Lee's polarity dataset.[22] (The appendix is available online at https://dl.acm.org/doi/10.1145/3458723.) We answered some of the questions with "Unknown to the authors of the datasheet." This is because we did not create the dataset ourselves and could not find the answers to these questions in the available documentation. For an example of a datasheet that was created by the creators of the corresponding dataset, please see that of Cao and Daumé.[6,b] We note that even dataset creators may be unable to answer all the questions provided here. We recommend answering as many questions as possible rather than skipping the datasheet creation process entirely.

Motivation. The following questions are primarily intended to encourage dataset creators to clearly articulate their reasons for creating the dataset and to promote transparency about funding interests. The latter may be particularly relevant for datasets created for research purposes.

1. **For what purpose was the dataset created?** Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.
2. **Who created the dataset (for example, which team, research group) and on behalf of which entity (for example, company, institution, organization)?**
3. **Who funded the creation of the dataset?** If there is an associated grant, please provide the name of the grantor and the grant name and number.
4. **Any other comments?**

Composition. Dataset creators should read through these questions prior to any data collection and then provide answers once data collection is complete. Most of the questions here are intended to provide dataset consumers with the information they need to make informed decisions about using the dataset for their chosen tasks. Some of the questions are designed to elicit information about compliance with the EU's General Data Protection Regulation (GDPR) or comparable regulations in other jurisdictions.

Questions that apply only to datasets that relate to people are grouped together at the end of the

b See https://github.com/TristaCao/into_inclusivecoref/blob/master/GICoref/datasheet-gicoref.md.

section. We recommend taking a broad interpretation of whether a dataset relates to people. For example, any dataset containing text that was written by people relates to people.

5. **What do the instances that comprise the dataset represent (for example, documents, photos, people, countries)?** Are there multiple types of instances (for example, movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.

6. **How many instances are there in total (of each type, if appropriate)?**

7. **Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set?** If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (for example, geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (for example, to cover a more diverse range of instances, because instances were withheld or unavailable).

8. **What data does each instance consist of?** "Raw" data (for example, unprocessed text or images) or features? In either case, please provide a description.

9. **Is there a label or target associated with each instance?** If so, please provide a description.

10. **Is any information missing from individual instances?** If so, please provide a description, explaining why this information is missing (for example, because it was unavailable). This does not include intentionally removed information, but might include, for example, redacted text.

11. **Are relationships between individual instances made explicit (for example, users' movie ratings, social network links)?** If so, please describe how these relationships are made explicit.

12. **Are there recommended data splits (for example, training, development/validation, testing)?** If so, please provide a description of these splits, explaining the rationale behind them.

13. **Are there any errors, sources of noise, or redundancies in the dataset?** If so, please provide a description.

Datasheets for datasets have the potential to increase transparency and accountability within the ML community, mitigate unwanted societal biases in ML models, facilitate greater reproducibility of ML results, and help researchers and practitioners select more appropriate datasets for their chosen tasks.

14. **Is the dataset self-contained, or does it link to or otherwise rely on external resources (for example, websites, tweets, other datasets)?** If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (that is, including the external resources as they existed at the time the dataset was created); c) are there any restrictions (for example, licenses, fees) associated with any of the external resources that might apply to a dataset consumer? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.

15. **Does the dataset contain data that might be considered confidential (for example, data that is protected by legal privilege or by doctor–patient confidentiality, data that includes the content of individuals' non-public communications)?** If so, please provide a description.

16. **Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety?** If so, please describe why.

If the dataset does not relate to people, you may skip the remaining questions in this section.

17. **Does the dataset identify any subpopulations (for example, by age, gender)?** If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.

18. **Is it possible to identify individuals (that is, one or more natural persons), either directly or indirectly (that is, in combination with other data) from the dataset?** If so, please describe how.

19. **Does the dataset contain data that might be considered sensitive in any way (for example, data that reveals race or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)?** If so, please provide a description.

20. **Any other comments?**

Collection process. As with the questions in the previous section, dataset creators should read through these questions prior to any data collection to flag potential issues and then provide answers once collection is complete. In addition to the goals outlined earlier, the following questions are designed to elicit information that may help researchers and practitioners to create alternative datasets with similar characteristics. Again, questions that apply only to datasets that relate to people are grouped together at the end of the section.

21. **How was the data associated with each instance acquired? Was the data directly observable (for example, raw text, movie ratings), reported by subjects (for example, survey responses), or indirectly inferred/derived from other data (for example, part-of-speech tags, model-based guesses for age or language)?** If the data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.

22. **What mechanisms or procedures were used to collect the data (for example, hardware apparatuses or sensors, manual human curation, software programs, software APIs)?** How were these mechanisms or procedures validated?

23. **If the dataset is a sample from a larger set, what was the sampling strategy (for example, deterministic, probabilistic with specific sampling probabilities)?**

24. **Who was involved in the data collection process (for example, students, crowdworkers, contractors) and how were they compensated (for example, how much were crowdworkers paid)?**

25. **Over what timeframe was the data collected?** Does this timeframe match the creation timeframe of the data associated with the instances (for example, recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.

26. **Were any ethical review processes conducted (for example, by an institutional review board)?** If so, please provide a description of these review processes, including the outcomes, as well as a link or other access point to any supporting documentation.

The process of creating a datasheet is not intended to be automated. Although automated documentation processes are convenient, they run counter to our objective of encouraging dataset creators to carefully reflect on the process of creating, distributing, and maintaining a dataset.

If the dataset does not relate to people, you may skip the remaining questions in this section.

27. **Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (for example, websites)?**

28. **Were the individuals in question notified about the data collection?** If so, please describe (or show with screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself.

29. **Did the individuals in question consent to the collection and use of their data?** If so, please describe (or show with screenshots or other information) how consent was requested and provided, and provide a link or other access point to, or otherwise reproduce, the exact language to which the individuals consented.

30. **If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses?** If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate).

31. **Has an analysis of the potential impact of the dataset and its use on data subjects (for example, a data protection impact analysis) been conducted?** If so, please provide a description of this analysis, including the outcomes, as well as a link or other access point to any supporting documentation.

32. **Any other comments?**

Preprocessing/cleaning/labeling. Dataset creators should read through these questions prior to any preprocessing, cleaning, or labeling and then provide answers once these tasks are complete. The questions in this section are intended to provide dataset consumers with the information they need to determine whether the "raw" data has been processed in ways that are compatible with their chosen tasks. For example, text that has been converted into a "bag-of-words" is not suitable for tasks involving word order.

33. **Was any preprocessing/clean-**

ing/labeling of the data done (for example, discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? If so, please provide a description. If not, you may skip the remaining questions in this section.

34. **Was the "raw" data saved in addition to the preprocessed/cleaned/labeled data (for example, to support unanticipated future uses)?** If so, please provide a link or other access point to the "raw" data.

35. **Is the software that was used to preprocess/clean/label the data available?** If so, please provide a link or other access point.

36. **Any other comments?**

Uses. The following questions are intended to encourage dataset creators to reflect on the tasks for which the dataset should and should not be used. By explicitly highlighting these tasks, dataset creators can help dataset consumers to make informed decisions, thereby avoiding potential risks or harms.

37. **Has the dataset been used for any tasks already?** If so, please provide a description.

38. **Is there a repository that links to any or all papers or systems that use the dataset?** If so, please provide a link or other access point.

39. **What (other) tasks could the dataset be used for?**

40. **Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses?** For example, is there anything that a dataset consumer might need to know to avoid uses that could result in unfair treatment of individuals or groups (for example, stereotyping, quality of service issues) or other risks or harms (for example, legal risks, financial harms)? If so, please provide a description. Is there anything a dataset consumer could do to mitigate these risks or harms?

41. **Are there tasks for which the dataset should not be used?** If so, please provide a description.

42. **Any other comments?**

Distribution. Dataset creators should provide answers to these questions prior to distributing the dataset either internally within the entity on behalf of which the dataset was created or externally to third parties.

43. **Will the dataset be distributed to third parties outside of the entity (for example, company, institution, organization) on behalf of which the dataset was created?** If so, please provide a description.

44. **How will the dataset be distributed (for example, tarball on website, API, GitHub)?** Does the dataset have a digital object identifier (DOI)?

45. **When will the dataset be distributed?**

46. **Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)?** If so, please describe this license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.

47. **Have any third parties imposed IP-based or other restrictions on the data associated with the instances?** If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.

48. **Do any export controls or other regulatory restrictions apply to the dataset or to individual instances?** If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.

49. **Any other comments?**

Maintenance. As with the previous questions, dataset creators should provide answers to these questions prior to distributing the dataset. The questions in this section are intended to encourage dataset creators to plan for dataset maintenance and communicate this plan to dataset consumers.

50. **Who will be supporting/hosting/maintaining the dataset?**

51. **How can the owner/curator/manager of the dataset be contacted (for example, email address)?**

52. **Is there an erratum?** If so, please provide a link or other access point.

53. **Will the dataset be updated (for example, to correct labeling errors, add new instances, delete instances)?** If so, please describe how often, by whom, and how updates will be communicated to dataset consumers (for example, mailing list, GitHub)?

54. **If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (for example, were the individuals in question told that their data would be retained for a fixed period of time and then deleted)?** If so, please describe these limits and explain how they will be enforced.

55. **Will older versions of the dataset continue to be supported/hosted/maintained?** If so, please describe how. If not, please describe how its obsolescence will be communicated to dataset consumers.

56. **If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so?** If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to dataset consumers? If so, please provide a description.

57. **Any other comments?**

Impact and Challenges

Since circulating an initial draft of this article in March 2018, datasheets for datasets have already gained traction in a number of settings. Academic researchers have adopted our proposal and released datasets with accompanying datasheets.[7,10,23,26] Microsoft, Google, and IBM have begun to pilot datasheets for datasets internally within product teams. Researchers at Google published follow-up work on *model cards* that document machine learning models[20] and released a *data card* (a lightweight version of a datasheet) along with the Open Images dataset.[17] Researchers at IBM proposed *factsheets*[14] that document various characteristics of AI services, including whether the datasets used to develop the services are accompanied with datasheets. The Data Nutrition Project incorporated some of the questions provided in the previous section into the latest release of their Dataset Nutrition Label.[9] Finally, the Partnership on AI, a multi-stakeholder organization focused on studying and formulating best practices for developing and deploying AI technologies, is working on industry-wide documentation guidance that builds on datasheets for datasets, model cards, and factsheets.[c]

These initial successes have also revealed implementation challenges that may need to be addressed to support wider adoption. Chief among them is the need for dataset creators to modify the questions and workflow provided earlier based on their existing organizational infrastructure and workflows. We also note that the questions and workflow may pose problems for dynamic datasets. If a dataset changes only infrequently, we recommend accompanying updated versions with updated datasheets.

Datasheets for datasets do not provide a complete solution to mitigating unwanted societal biases or potential risks or harms. Dataset creators cannot anticipate every possible use of a dataset, and identifying unwanted societal biases often requires additional labels indicating demographic information about individuals, which may not be available to dataset creators for reasons including those individuals' data protection and privacy.[15]

When creating datasets that relate to people, and hence their accompanying datasheets, it may be necessary for dataset creators to work with experts in other domains such as anthropology, sociology, and science and technology studies. There are complex and contextual social, historical, and geographical factors that influence how best to collect data from individuals in a manner that is respectful.

Finally, creating datasheets for datasets will necessarily impose overhead on dataset creators. Although datasheets may reduce the amount of time that dataset creators spend answering one-off questions about datasets, the process of creating a datasheet will always take time, and organizational infrastructure and workflows—not to mention incentives—will need to be modified to accommodate this investment.

Despite these implementation challenges, there are many benefits to creating datasheets for datasets. In addition to facilitating better communication between dataset creators and dataset consumers, datasheets provide an opportunity for dataset creators to distinguish themselves as prioritizing transparency and accountability. Ultimately, we believe that the benefits to the machine learning community outweigh the costs.

c https://www.partnershiponai.org/about-ml/

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Watch the authors discuss this work in the exclusive *Communications* video. https://cacm.acm.org/videos/datasheets-for-datasets

Model Cards for Model Reporting

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ABSTRACT

Trained machine learning models are increasingly used to perform high-impact tasks in areas such as law enforcement, medicine, education, and employment. In order to clarify the intended use cases of machine learning models and minimize their usage in contexts for which they are not well suited, we recommend that released models be accompanied by documentation detailing their performance characteristics. In this paper, we propose a framework that we call model cards, to encourage such transparent model reporting. Model cards are short documents accompanying trained machine learning models that provide benchmarked evaluation in a variety of conditions, such as across different cultural, demographic, or phenotypic groups (e.g., race, geographic location, sex, Fitzpatrick skin type [15]) and intersectional groups (e.g., age and race, or sex and Fitzpatrick skin type) that are relevant to the intended application domains. Model cards also disclose the context in which models are intended to be used, details of the performance evaluation procedures, and other relevant information. While we focus primarily on human-centered machine learning models in the application fields of computer vision and natural language processing, this framework can be used to document any trained machine learning model. To solidify the concept, we provide cards for two supervised models: One trained to detect smiling faces in images, and one trained to detect toxic comments in text. We propose model cards as a step towards the responsible democratization of machine learning and related artificial intelligence technology, increasing transparency into how well artificial intelligence technology works. We hope this work encourages those releasing trained machine learning models to accompany model releases with similar detailed evaluation numbers and other relevant documentation.

CCS CONCEPTS

• **General and reference** → **Evaluation**; • **Social and professional topics** → *User characteristics*; • **Software and its engineering** → **Use cases**; *Documentation*; *Software evolution*; • **Human-centered computing** → *Walkthrough evaluations*;

KEYWORDS

datasheets, model cards, documentation, disaggregated evaluation, fairness evaluation, ML model evaluation, ethical considerations

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1 INTRODUCTION

Currently, there are no standardized documentation procedures to communicate the performance characteristics of trained machine learning (ML) and artificial intelligence (AI) models. This lack of documentation is especially problematic when models are used in applications that have serious impacts on people's lives, such as in health care [14, 42, 44], employment [1, 13, 29], education [23, 45] and law enforcement [2, 7, 20, 34].

Researchers have discovered systematic biases in commercial machine learning models used for face detection and tracking [4, 9, 49], attribute detection [5], criminal justice [10], toxic comment detection [11], and other applications. However, these systematic errors were only exposed after models were put into use, and negatively affected users reported their experiences. For example, after MIT Media Lab graduate student Joy Buolamwini found that commercial face recognition systems failed to detect her face [4], she collaborated with other researchers to demonstrate the disproportionate errors of computer vision systems on historically marginalized groups in the United States, such as darker-skinned women [5, 41]. In spite of the potential negative effects of such reported biases, documentation accompanying trained machine learning models (if supplied) provide very little information regarding model performance characteristics, intended use cases, potential pitfalls, or other information to help users evaluate the suitability of these systems to their context. This highlights the need to have detailed documentation accompanying trained machine learning models, including metrics that capture bias, fairness and inclusion considerations.

As a step towards this goal, we propose that released machine learning models be accompanied by short (one to two page) records we call model cards. Model cards (for model reporting) are complements to "Datasheets for Datasets" [21] and similar recently proposed documentation paradigms [3, 28] that report details of the datasets used to train and test machine learning models. Model cards are also similar to the TRIPOD statement proposal in medicine [25]. We provide two example model cards in Section 5: A smiling detection model trained on the CelebA dataset [36] (Figure 2), and a public toxicity detection model [32] (Figure 3). Where Datasheets highlight characteristics of the data feeding into the model, we

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focus on trained model characteristics such as the type of model, intended use cases, information about attributes for which model performance may vary, and measures of model performance.

We advocate for measures of model performance that contain quantitative evaluation results to be broken down by individual cultural, demographic, or phenotypic groups, domain-relevant conditions, and intersectional analysis combining two (or more) groups and conditions. In addition to model evaluation results, model cards should detail the motivation behind chosen performance metrics, group definitions, and other relevant factors. Each model card could be accompanied with Datasheets [21], Nutrition Labels [28], Data Statements [3], or Factsheets [27], describing datasets that the model was trained and evaluated on. Model cards provide a way to inform users about what machine learning systems can and cannot do, the types of errors they make, and additional steps that could create more fair and inclusive outcomes with the technology.

2 BACKGROUND

Many mature industries have developed standardized methods of benchmarking various systems under different conditions. For example, as noted in [21], the electronic hardware industry provides datasheets with detailed characterizations of components' performances under different test conditions. By contrast, despite the broad reach and impact of machine learning models, there are no standard stress tests that are performed on machine learning based systems, nor standardized formats to report the results of these tests. Recently, researchers have proposed standardized forms of communicating characteristics of datasets used in machine learning [3, 21, 28] to help users understand the context in which the datasets should be used. We focus on the complementary task for machine learning models, proposing a standardized method to evaluate the performance of human-centric models: Disaggregated by unitary and intersectional groups such as cultural, demographic, or phenotypic population groups. A framework that we refer to as "Model Cards" can present such evaluation supplemented with additional considerations such as intended use.

Outside of machine learning, the need for population-based reporting of outcomes as suggested here has become increasingly evident. For example, in vehicular crash tests, dummies with prototypical female characteristics were only introduced after researchers discovered that women were more likely than men to suffer serious head injuries in real-world side impacts [18]. Similarly, drugs developed based on results of clinical trials with exclusively male participants have led to overdosing in women [17, 50]. In 1998, the U.S. Food and Drug Administration mandated that clinical trial results be disaggregated by groups such as age, race and gender [16].

While population-based analyses of errors and successes can be provided for unitary groups such as "men", "women", and "nonbinary" gender groups, they should also be provided intersectionally, looking at two or more characteristics such as gender and age simultaneously. Intersectional analyses are linked to intersectionality theory, which describes how discrete experiences associated with characteristics like race or gender in isolation do not accurately reflect their interaction [8]. Kimberlé Crenshaw, who pioneered intersectional research in critical race theory, discusses the story of Emma DeGraffenreid, who was part of a failed lawsuit against General Motors in 1976, claiming that the company's hiring practices discriminated against Black women. In their court opinion, the judges noted that since General Motors hired many women for secretarial positions, and many Black people for factory roles, they could not have discriminated against Black women. However, what the courts failed to see was that only White women were hired into secretarial positions and only Black men were hired into factory roles. Thus, Black women like Emma DeGraffenreid had no chance of being employed at General Motors. This example highlights the importance of intersectional analyses: empirical analyses that emphasize the interaction between various demographic categories including race, gender, and age.

Before further discussing the details of the model card, it is important to note that at least two of the three characteristics discussed so far, race and gender, are socially sensitive. Although analyzing models by race and gender may follow from intersectionality theory, how "ground truth" race or gender categories should be labeled in a dataset, and whether or not datasets should be labeled with these categories at all, is not always clear. This issue is further confounded by the complex relationship between gender and sex. When using cultural identity categories such as race and gender to subdivide analyses, and depending on the context, we recommend either using datasets with self-identified labels or with labels clearly designated as *perceived* (rather than self-identified). When this is not possible, datasets of public figures with known public identity labels may be useful. Further research is necessary to expand how groups may be defined, for example, by automatically discovering groups with similarities in the evaluation datasets.

3 MOTIVATION

As the use of machine learning technology has rapidly increased, so too have reports of errors and failures. Despite the potentially serious repercussions of these errors, those looking to use trained machine learning models in a particular context have no way of understanding the systematic impacts of these models before deploying them.

The proposal of "Model Cards" specifically aims to standardize ethical practice and reporting - allowing stakeholders to compare candidate models for deployment across not only traditional evaluation metrics but also along the axes of ethical, inclusive, and fair considerations. This goes further than current solutions to aid stakeholders in different contexts. For example, to aid policy makers and regulators on questions to ask of a model, and known benchmarks around the suitability of a model in a given setting.

Model reporting will hold different meaning to those involved in different aspects of model development, deployment, and use. Below, we outline a few use cases for different stakeholders:

- **ML and AI practitioners** can better understand how well the model might work for the intended use cases and track its performance over time.
- **Model developers** can compare the model's results to other models in the same space, and make decisions about training their own system.
- **Software developers** working on products that use the model's predictions can inform their design and implementation decisions.

- **Policymakers** can understand how a machine learning system may fail or succeed in ways that impact people.
- **Organizations** can inform decisions about adopting technology that incorporates machine learning.
- **ML-knowledgeable individuals** can be informed on different options for fine-tuning, model combination, or additional rules and constraints to help curate models for intended use cases without requiring technical expertise.
- **Impacted individuals** who may experience effects from a model can better understand how it works or use information in the card to pursue remedies.

Not only does this practice improve model understanding and help to standardize decision making processes for invested stakeholders, but it also encourages forward-looking model analysis techniques. For example, slicing the evaluation across groups functions to highlight errors that may fall disproportionately on some groups of people, and accords with many recent notions of mathematical fairness (discussed further in the example model card in Figure 2). Including group analysis as part of the reporting procedure prepares stakeholders to begin to gauge the fairness and inclusion of future outcomes of the machine learning system. Thus, in addition to supporting decision-making processes for determining the suitability of a given machine learning model in a particular context, model reporting is an approach for responsible transparent and accountable practices in machine learning.

People and organizations releasing models may be additionally incentivized to provide model card details because it helps potential users of the models to be better informed on which models are best for their specific purposes. If model card reporting becomes standard, potential users can compare and contrast different models in a well-informed way. Results on several different evaluation datasets will additionally aid potential users, although evaluation datasets suitable for disaggregated evaluation are not yet common. Future research could include creating robust evaluation datasets and protocols for the types of disaggregated evaluation we advocate for in this work, for example, by including differential privacy mechanisms [12] so that individuals in the testing set cannot be uniquely identified by their characteristics.

4 MODEL CARD SECTIONS

Model cards serve to disclose information about a trained machine learning model. This includes how it was built, what assumptions were made during its development, what type of model behavior different cultural, demographic, or phenotypic population groups may experience, and an evaluation of how well the model performs with respect to those groups. Here, we propose a set of sections that a model card should have, and details that can inform the stakeholders discussed in Section 3. A summary of all suggested sections is provided in Figure 1.

The proposed set of sections below are intended to provide relevant details to consider, but are not intended to be complete or exhaustive, and may be tailored depending on the model, context, and stakeholders. Additional details may include, for example, interpretability approaches, such as saliency maps, TCAV [33], and Path-Integrated Gradients [38, 43]); stakeholder-relevant explanations (e.g., informed by a careful consideration of philosophical, psychological, and other factors concerning what is as a good explanation in different contexts [22]); and privacy approaches used in model training and serving.

Model Card

- **Model Details**. Basic information about the model.
  - Person or organization developing model
  - Model date
  - Model version
  - Model type
  - Information about training algorithms, parameters, fairness constraints or other applied approaches, and features
  - Paper or other resource for more information
  - Citation details
  - License
  - Where to send questions or comments about the model
- **Intended Use**. Use cases that were envisioned during development.
  - Primary intended uses
  - Primary intended users
  - Out-of-scope use cases
- **Factors**. Factors could include demographic or phenotypic groups, environmental conditions, technical attributes, or others listed in Section 4.3.
  - Relevant factors
  - Evaluation factors
- **Metrics**. Metrics should be chosen to reflect potential real-world impacts of the model.
  - Model performance measures
  - Decision thresholds
  - Variation approaches
- **Evaluation Data**. Details on the dataset(s) used for the quantitative analyses in the card.
  - Datasets
  - Motivation
  - Preprocessing
- **Training Data**. May not be possible to provide in practice. When possible, this section should mirror Evaluation Data. If such detail is not possible, minimal allowable information should be provided here, such as details of the distribution over various factors in the training datasets.
- **Quantitative Analyses**
  - Unitary results
  - Intersectional results
- **Ethical Considerations**
- **Caveats and Recommendations**

Figure 1: Summary of model card sections and suggested prompts for each.

4.1 Model Details

This section of the model card should serve to answer basic questions regarding the model version, type and other details.

Person or organization developing model: What person or organization developed the model? This can be used by all stakeholders to infer details pertaining to model development and potential

conflicts of interest.
Model date: When was the model developed? This is useful for all stakeholders to become further informed on what techniques and data sources were likely to be available during model development.
Model version: Which version of the model is it, and how does it differ from previous versions? This is useful for all stakeholders to track whether the model is the latest version, associate known bugs to the correct model versions, and aid in model comparisons.
Model type: What type of model is it? This includes basic model architecture details, such as whether it is a Naive Bayes classifier, a Convolutional Neural Network, etc. This is likely to be particularly relevant for software and model developers, as well as individuals knowledgeable about machine learning, to highlight what kinds of assumptions are encoded in the system.
Paper or other resource for more information: Where can resources for more information be found?
Citation details: How should the model be cited?
License: License information can be provided.
Feedback on the model: E.g., what is an email address that people may write to for further information?

There are cases where some of this information may be sensitive. For example, the amount of detail corporations choose to disclose might be different from academic research groups. This section should not be seen as a requirement to compromise private information or reveal proprietary training techniques; rather, a place to disclose basic decisions and facts about the model that the organization can share with the broader community in order to better inform on what the model represents.

4.2 Intended Use

This section should allow readers to quickly grasp what the model should and should not be used for, and why it was created. It can also help frame the statistical analysis presented in the rest of the card, including a short description of the user(s), use-case(s), and context(s) for which the model was originally developed. Possible information includes:
Primary intended uses: This section details whether the model was developed with general or specific tasks in mind (e.g., plant recognition worldwide or in the Pacific Northwest). The use cases may be as broadly or narrowly defined as the developers intend. For example, if the model was built simply to label images, then this task should be indicated as the primary intended use case.
Primary intended users: For example, was the model developed for entertainment purposes, for hobbyists, or enterprise solutions? This helps users gain insight into how robust the model may be to different kinds of inputs.
Out-of-scope uses: Here, the model card should highlight technology that the model might easily be confused with, or related contexts that users could try to apply the model to. This section may provide an opportunity to recommend a related or similar model that was designed to better meet that particular need, where possible. This section is inspired by warning labels on food and toys, and similar disclaimers presented in electronic datasheets. Examples include "not for use on text examples shorter than 100 tokens" or "for use on black-and-white images only; please consider our research group's full-color-image classifier for color images."

4.3 Factors

Model cards ideally provide a summary of model performance across a variety of relevant factors including *groups*, *instrumentation*, and *environments*. We briefly describe each of these factors and their relevance followed by the corresponding prompts in the model card.

4.3.1 Groups. "Groups" refers to distinct categories with similar characteristics that are present in the evaluation data instances. For human-centric machine learning models, "groups" are people who share one or multiple characteristics. Intersectional model analysis for human-centric models is inspired by the sociological concept of intersectionality, which explores how an individual's identity and experiences are shaped not just by unitary personal characteristics – such as race, gender, sexual orientation or health – but instead by a complex combination of many factors. These characteristics, which include but are not limited to cultural, demographic and phenotypic categories, are important to consider when evaluating machine learning models. Determining which groups to include in an intersectional analysis requires examining the intended use of the model and the context under which it may be deployed. Depending on the situation, certain groups may be more vulnerable than others to unjust or prejudicial treatment.

For human-centric computer vision models, the visual presentation of age, gender, and Fitzpatrick skin type [15] may be relevant. However, this must be balanced with the goal of preserving the privacy of individuals. As such, collaboration with policy, privacy, and legal experts is necessary in order to ascertain which groups may be responsibly inferred, and how that information should be stored and accessed (for example, using differential privacy [12]).

Details pertaining to groups, including who annotated the training and evaluation datasets, instructions and compensation given to annotators, and inter-annotator agreement, should be provided as part of the data documentation made available with the dataset. See [3, 21, 28] for more details.

4.3.2 Instrumentation. In addition to groups, the performance of a model can vary depending on what instruments were used to capture the input to the model. For example, a face detection model may perform differently depending on the camera's hardware and software, including lens, image stabilization, high dynamic range techniques, and background blurring for portrait mode. Performance may also vary across real or simulated traditional camera settings such as aperture, shutter speed and ISO. Similarly, video and audio input will be dependent on the choice of recording instruments and their settings.

4.3.3 Environment. A further factor affecting model performance is the environment in which it is deployed. For example, face detection systems are often less accurate under low lighting conditions or when the air is humid [51]. Specifications across different lighting and moisture conditions would help users understand the impacts of these environmental factors on model performance.

4.3.4 Card Prompts. We propose that the Factors section of model cards expands on two prompts:

Relevant factors: What are foreseeable salient factors for which model performance may vary, and how were these determined?
Evaluation factors: Which factors are being reported, and why were these chosen? If the relevant factors and evaluation factors are different, why? For example, while Fitzpatrick skin type is a relevant factor for face detection, an evaluation dataset annotated by skin type might not be available until reporting model performance across groups becomes standard practice.

4.4 Metrics

The appropriate metrics to feature in a model card depend on the type of model that is being tested. For example, classification systems in which the primary output is a class label differ significantly from systems whose primary output is a score. In all cases, the reported metrics should be determined based on the model's structure and intended use. Details for this section include:
Model performance measures: What measures of model performance are being reported, and why were they selected over other measures of model performance?
Decision thresholds: If decision thresholds are used, what are they, and why were those decision thresholds chosen? When the model card is presented in a digital format, a threshold slider should ideally be available to view performance parameters across various decision thresholds.
Approaches to uncertainty and variability: How are the measurements and estimations of these metrics calculated? For example, this may include standard deviation, variance, confidence intervals, or KL divergence. Details of how these values are approximated should also be included (e.g., average of 5 runs, 10-fold cross-validation).

4.4.1 Classification systems. For classification systems, the error types that can be derived from a confusion matrix are *false positive rate*, *false negative rate*, *false discovery rate*, and *false omission rate*. We note that the relative importance of each of these metrics is system, product and context dependent.

For example, in a surveillance scenario, surveillors may value a low false negative rate (or the rate at which the surveillance system fails to detect a person or an object when it should have). On the other hand, those being surveilled may value a low false positive rate (or the rate at which the surveillance system detects a person or an object when it should not have). We recommend listing all values and providing context about which were prioritized during development and why.

Equality between some of the different confusion matrix metrics is equivalent to some definitions of fairness. For example, equal false negative rates across groups is equivalent to fulfilling Equality of Opportunity, and equal false negative and false positive rates across groups is equivalent to fulfilling Equality of Odds [26].

4.4.2 Score-based analyses. For score-based systems such as pricing models and risk assessment algorithms, describing differences in the distribution of measured metrics across groups may be helpful. For example, reporting measures of central tendency such as the mode, median and mean, as well as measures of dispersion or variation such as the range, quartiles, absolute deviation, variance and standard deviation could facilitate the statistical commentary necessary to make more informed decisions about model development. A model card could even extend beyond these summary statistics to reveal other measures of differences between distributions such as cross entropy, perplexity, KL divergence and pinned area under the curve (pinned AUC) [11].

There are a number of applications that do not appear to be score-based at first glance, but can be considered as such for the purposes of intersectional analysis. For instance, a model card for a translation system could compare BLEU scores [40] across demographic groups, and a model card for a speech recognition system could compare word-error rates. Although the primary outputs of these systems are not scores, looking at the score differences between populations may yield meaningful insights since comparing raw inputs quickly grows too complex.

4.4.3 Confidence. Performance metrics that are disaggregated by various combinations of instrumentation, environments and groups makes it especially important to understand the confidence intervals for the reported metrics. Confidence intervals for metrics derived from confusion matrices can be calculated by treating the matrices as probabilistic models of system performance [24].

4.5 Evaluation Data

All referenced datasets would ideally point to any set of documents that provide visibility into the source and composition of the dataset. Evaluation datasets should include datasets that are publicly available for third-party use. These could be existing datasets or new ones provided alongside the model card analyses to enable further benchmarking. Potential details include:
Datasets: What datasets were used to evaluate the model?
Motivation: Why were these datasets chosen?
Preprocessing: How was the data preprocessed for evaluation (e.g., tokenization of sentences, cropping of images, any filtering such as dropping images without faces)?

To ensure that model cards are statistically accurate and verifiable, the evaluation datasets should not only be representative of the model's typical use cases but also anticipated test scenarios and challenging cases. For instance, if a model is intended for use in a workplace that is phenotypically and demographically homogeneous, and trained on a dataset that is representative of the expected use case, it may be valuable to evaluate that model on two evaluation sets: one that matches the workplace's population, and another set that contains individuals that might be more challenging for the model (such as children, the elderly, and people from outside the typical workplace population). This methodology can highlight pathological issues that may not be evident in more routine testing.

It is often difficult to find datasets that represent populations outside of the initial domain used in training. In some of these situations, synthetically generated datasets may provide representation for use cases that would otherwise go unevaluated [35]. Section 5.2 provides an example of including synthetic data in the model evaluation dataset.

4.6 Training Data

Ideally, the model card would contain as much information about the training data as the evaluation data. However, there might be cases where it is not feasible to provide this level of detailed information about the training data. For example, the data may be proprietary, or require a non-disclosure agreement. In these cases, we advocate for basic details about the distributions over groups in the data, as well as any other details that could inform stakeholders on the kinds of biases the model may have encoded.

4.7 Quantitative Analyses

Quantitative analyses should be *disaggregated*, that is, broken down by the chosen factors. Quantitative analyses should provide the results of evaluating the model according to the chosen metrics, providing confidence interval values when possible. Parity on the different metrics across disaggregated population subgroups corresponds to how *fairness* is often defined [37, 48]. Quantitative analyses should demonstrate the metric variation (e.g., with error bars), as discussed in Section 4.4 and visualized in Figure 2.
The disaggregated evaluation includes:
Unitary results: How did the model perform with respect to each factor?
Intersectional results: How did the model perform with respect to the intersection of evaluated factors?

4.8 Ethical Considerations

This section is intended to demonstrate the ethical considerations that went into model development, surfacing ethical challenges and solutions to stakeholders. Ethical analysis does not always lead to precise solutions, but the process of ethical contemplation is worthwhile to inform on responsible practices and next steps in future work.

While there are many frameworks for ethical decision-making in technology that can be adapted here [19, 30, 46], the following are specific questions you may want to explore in this section:
Data: Does the model use any sensitive data (e.g., protected classes)?
Human life: Is the model intended to inform decisions about matters central to human life or flourishing – e.g., health or safety? Or could it be used in such a way?
Mitigations: What risk mitigation strategies were used during model development?
Risks and harms: What risks may be present in model usage? Try to identify the potential recipients, likelihood, and magnitude of harms. If these cannot be determined, note that they were considered but remain unknown.
Use cases: Are there any known model use cases that are especially fraught? This may connect directly to the intended use section of the model card.

If possible, this section should also include any additional ethical considerations that went into model development, for example, review by an external board, or testing with a specific community.

4.9 Caveats and Recommendations

This section should list additional concerns that were not covered in the previous sections. For example, did the results suggest any further testing? Were there any relevant groups that were not represented in the evaluation dataset? Are there additional recommendations for model use? What are the ideal characteristics of an evaluation dataset for this model?

5 EXAMPLES

We present worked examples of model cards for two models: an image-based classification system and a text-based scoring system.

5.1 Smiling Classifier

To show an example of a model card for an image classification problem, we use the public CelebA dataset [36] to examine the performance of a trained "smiling" classifier across both age and gender categories. Figure 2 shows our prototype.

These results demonstrate a few potential issues. For example, the false discovery rate on older men is much higher than that for other groups. This means that many predictions incorrectly classify older men as smiling when they are not. On the other hand, men (in aggregate) have a higher false negative rate, meaning that many of the men that are in fact smiling in the photos are incorrectly classified as not smiling.

The results of these analyses give insight into contexts the model might not be best suited for. For example, it may not be advisable to apply the model on a diverse group of audiences, and it may be the most useful when detecting the presence of a smile is more important than detecting its absence (for example, in an application that automatically finds 'fun moments' in images). Additional finetuning, for example, with images of older men, may help create a more balanced performance across groups.

5.2 Toxicity Scoring

Our second example provides a model card for Perspective API's TOXICITY classifier built to detect 'toxicity' in text [32], and is presented in Figure 3. To evaluate the model, we use an intersectional version of the open source, synthetically created Identity Phrase Templates test set published in [11]. We show two versions of the quantitative analysis: one for TOXICITY v. 1, the initial version of the this model, and one for TOXICITY v. 5, the latest version.

This model card highlights the drastic ways that models can change over time, and the importance of having a model card that is updated with each new model release. TOXICITY v. 1 has low performance for several terms, especially "lesbian", "gay", and "homosexual". This is consistent with what some users of the initial TOXICITY model found, as reported by the team behind Perspective API in [47]. Also in [47], the Perspective API team shares the bias mitigation techniques they applied to the TOXICITY v. 1 model, in order to create the more equitable performance in TOXICITY v. 5. By making model cards a standard part of API launches, teams like the Perspective API team may be able to find and mitigate some of these biases earlier.

6 DISCUSSION & FUTURE WORK

We have proposed frameworks called model cards for reporting information about what a trained machine learning model is and how well it works. Model cards include information about the context of the model, as well as model performance results disaggregated by different unitary and intersectional population groups. Model

Model Card - Smiling Detection in Images

Model Details

- Developed by researchers at Google and the University of Toronto, 2018, v1.
- Convolutional Neural Net.
- Pretrained for face recognition then fine-tuned with cross-entropy loss for binary smiling classification.

Intended Use

- Intended to be used for fun applications, such as creating cartoon smiles on real images; augmentative applications, such as providing details for people who are blind; or assisting applications such as automatically finding smiling photos.
- Particularly intended for younger audiences.
- Not suitable for emotion detection or determining affect; smiles were annotated based on physical appearance, and not underlying emotions.

Factors

- Based on known problems with computer vision face technology, potential relevant factors include groups for gender, age, race, and Fitzpatrick skin type; hardware factors of camera type and lens type; and environmental factors of lighting and humidity.
- Evaluation factors are gender and age group, as annotated in the publicly available dataset CelebA [36]. Further possible factors not currently available in a public smiling dataset. Gender and age determined by third-party annotators based on visual presentation, following a set of examples of male/female gender and young/old age. Further details available in [36].

Metrics

- Evaluation metrics include **False Positive Rate** and **False Negative Rate** to measure disproportionate model performance errors across subgroups. **False Discovery Rate** and **False Omission Rate**, which measure the fraction of negative (not smiling) and positive (smiling) predictions that are incorrectly predicted to be positive and negative, respectively, are also reported. [48]
- Together, these four metrics provide values for different errors that can be calculated from the confusion matrix for binary classification systems.
- These also correspond to metrics in recent definitions of "fairness" in machine learning (cf. [6, 26]), where parity across subgroups for different metrics correspond to different fairness criteria.
- 95% confidence intervals calculated with bootstrap resampling.
- All metrics reported at the .5 decision threshold, where all error types (FPR, FNR, FDR, FOR) are within the same range (0.04 - 0.14).

Training Data

- CelebA [36], training data split.

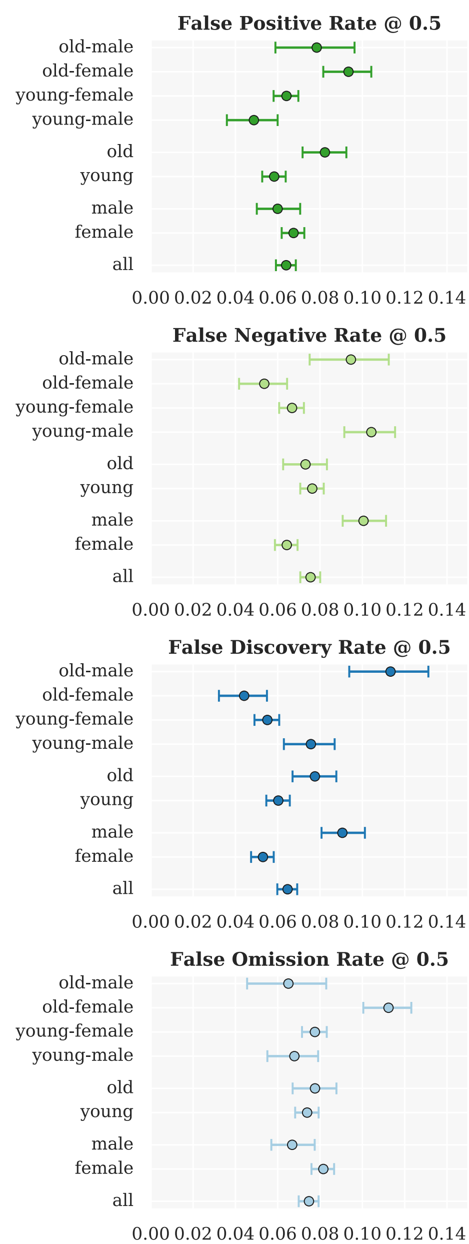
Evaluation Data

- CelebA [36], test data split.
- Chosen as a basic proof-of-concept.

Ethical Considerations

- Faces and annotations based on public figures (celebrities). No new information is inferred or annotated.

Quantitative Analyses



Caveats and Recommendations

- Does not capture race or skin type, which has been reported as a source of disproportionate errors [5].
- Given gender classes are binary (male/not male), which we include as male/female. Further work needed to evaluate across a spectrum of genders.
- An ideal evaluation dataset would additionally include annotations for Fitzpatrick skin type, camera details, and environment (lighting/humidity) details.

Figure 2: Example Model Card for a smile detector trained and evaluated on the CelebA dataset.

Model Card - Toxicity in Text

Model Details

- The TOXICITY classifier provided by Perspective API [32], trained to predict the likelihood that a comment will be perceived as toxic.
- Convolutional Neural Network.
- Developed by Jigsaw in 2017.

Intended Use

- Intended to be used for a wide range of use cases such as supporting human moderation and providing feedback to comment authors.
- Not intended for fully automated moderation.
- Not intended to make judgments about specific individuals.

Factors

- Identity terms referencing frequently attacked groups, focusing on sexual orientation, gender identity, and race.

Metrics

- Pinned AUC, as presented in [11], which measures threshold-agnostic separability of toxic and non-toxic comments for each group, within the context of a background distribution of other groups.

Ethical Considerations

- Following [31], the Perspective API uses a set of values to guide their work. These values are Community, Transparency, Inclusivity, Privacy, and Topic-neutrality. Because of privacy considerations, the model does not take into account user history when making judgments about toxicity.

Training Data

- Proprietary from Perspective API. Following details in [11] and [32], this includes comments from a online forums such as Wikipedia and New York Times, with crowdsourced labels of whether the comment is "toxic".
- "Toxic" is defined as "a rude, disrespectful, or unreasonable comment that is likely to make you leave a discussion."

Evaluation Data

- A synthetic test set generated using a template-based approach, as suggested in [11], where identity terms are swapped into a variety of template sentences.
- Synthetic data is valuable here because [11] shows that real data often has disproportionate amounts of toxicity directed at specific groups. Synthetic data ensures that we evaluate on data that represents both toxic and non-toxic statements referencing a variety of groups.

Caveats and Recommendations

- Synthetic test data covers only a small set of very specific comments. While these are designed to be representative of common use cases and concerns, it is not comprehensive.

Quantitative Analyses

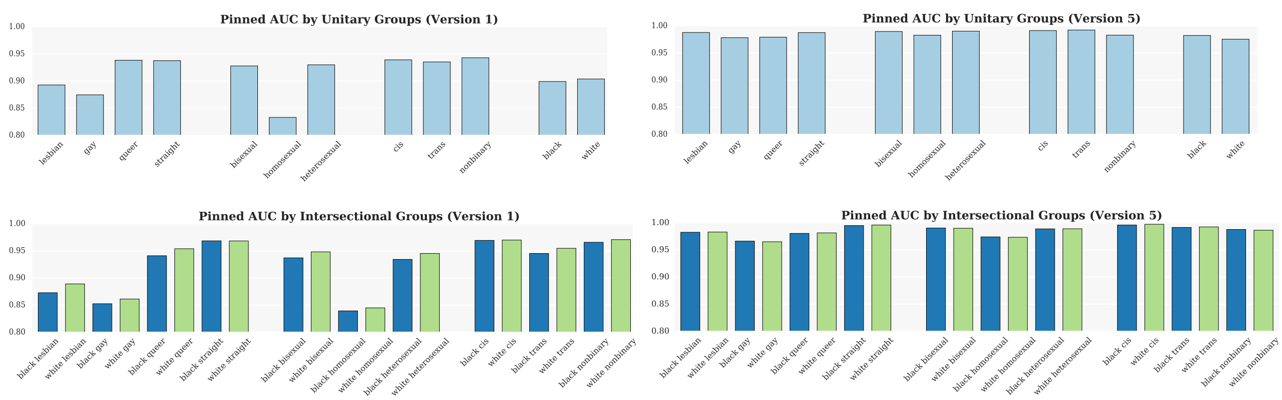


Figure 3: Example Model Card for two versions of Perspective API's toxicity detector.

cards are intended to accompany a model after careful review has determined that the foreseeable benefits outweigh the foreseeable risks in the model's use or release.

To demonstrate the use of model cards in practice, we have provided two examples: A model card for a smiling classifier tested on the CelebA dataset, and a model card for a public toxicity detector tested on the Identity Phrase Templates dataset. We report confusion matrix metrics for the smile classifier and Pinned AUC for the toxicity detector, along with model details, intended use, pointers to information about training and evaluation data, ethical considerations, and further caveats and recommendations.

The framework presented here is intended to be general enough to be applicable across different institutions, contexts, and stakeholders. It also is suitable for recently proposed requirements for analysis of algorithmic decision systems in critical social institutions, for example, for models used in determining government benefits, employment evaluations, criminal risk assessment, and criminal DNA analysis [39].

Model cards are just one approach to increasing transparency between developers, users, and stakeholders of machine learning models and systems. They are designed to be flexible in both scope and specificity in order to accommodate the wide variety of machine learning model types and potential use cases. Therefore the usefulness and accuracy of a model card relies on the integrity of the creator(s) of the card itself. It seems unlikely, at least in the near term, that model cards could be standardized or formalized to a degree needed to prevent misleading representations of model results (whether intended or unintended). It is therefore important to consider model cards as one transparency tool among many, which could include, for example, algorithmic auditing by third-parties (both quantitative and qualitative), "adversarial testing" by technical and non-technical analysts, and more inclusive user feedback mechanisms. Future work will aim to refine the methodology of creating model cards by studying how model information is interpreted and used by different stakeholders. Researchers should also explore how model cards can strengthen and complement other transparency methods

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