# Responsible Data Science

## Transparency & Interpretability

Auditing black-box models

*April 12, 2023*

**Prof. Elisha Cohen**

Center for Data Science
New York University

NYU Center for Data Science

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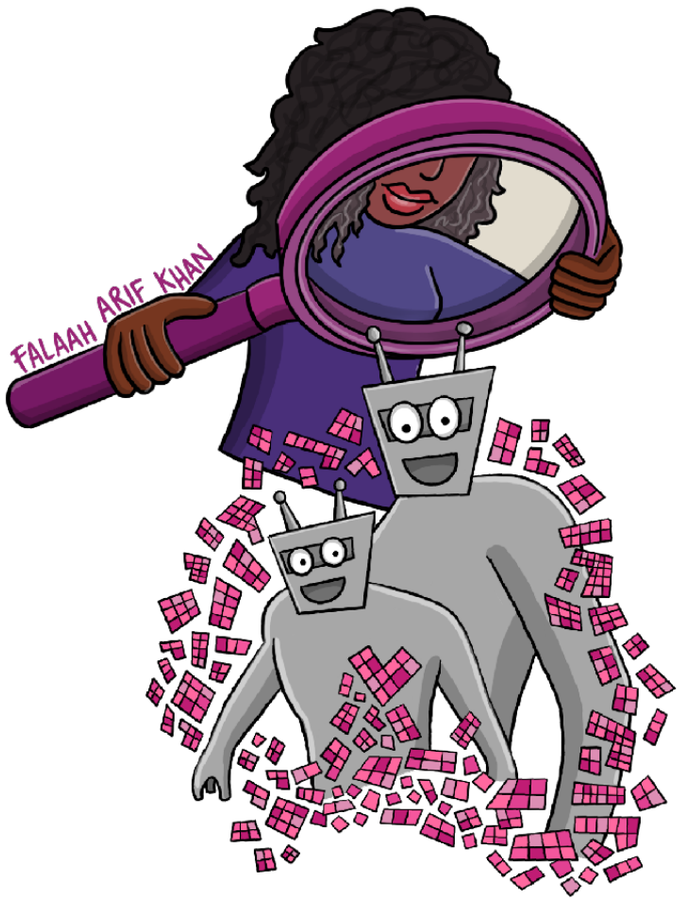
# Terminology & vision




transparency, interpretability,
explainability, intelligibility

responsible AI



agency, responsibility

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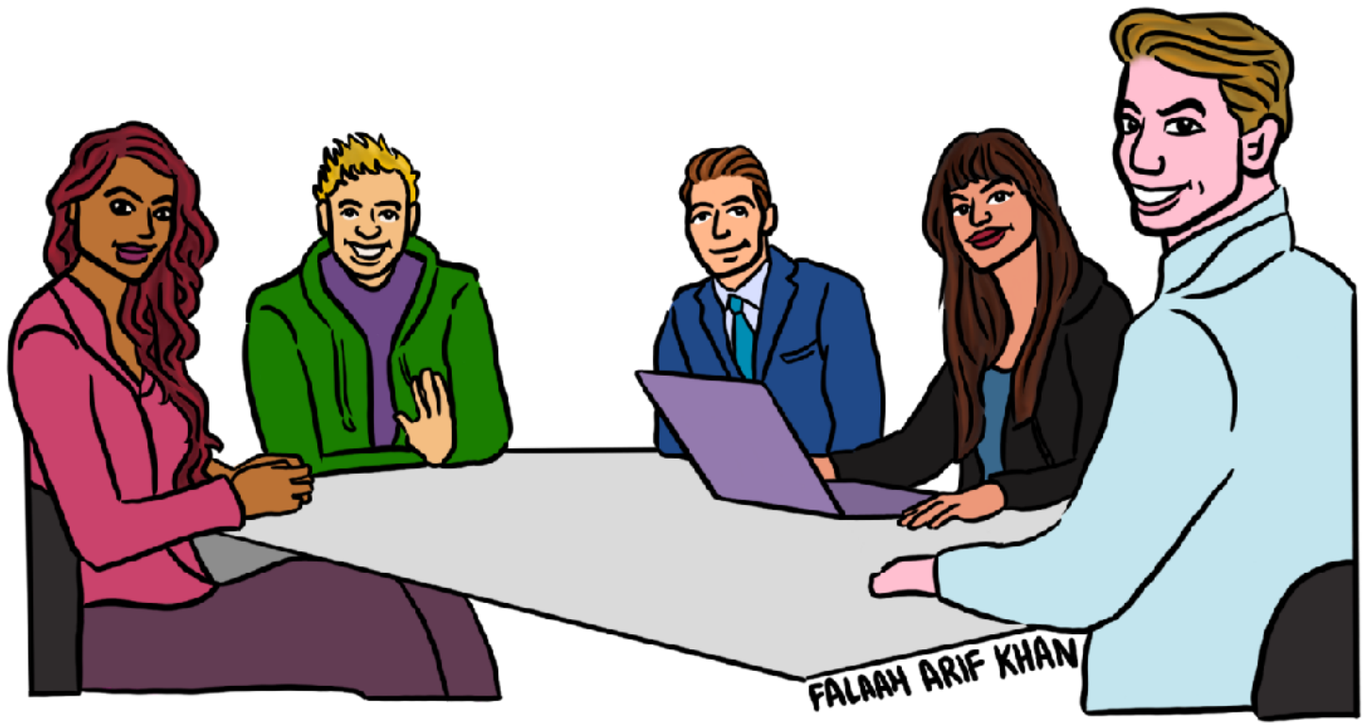
# Interpretability for different stakeholders




**What** are we explaining?

To **Whom** are we explaining?

**Why** are we explaining?

# Staples discounts

THE WALL STREET JOURNAL.

**December 2012**

WHAT THEY KNOW

## Websites Vary Prices, Deals Based on Users' Information

*By Jennifer Valentino-DeVries, Jeremy Singer-Vine and Ashkan Soltani*

December 24, 2012

WHAT PRICE WOULD YOU SEE?


It was the same Swingline stapler, on the same Staples.com website. But for Kim Wamble, the price was $15.79, while the price on Trude Frizzell's screen, just a few miles away, was $14.29.

A key difference: where Staples seemed to think they were located.

A Wall Street Journal investigation found that the Staples Inc. website displays different prices to people after estimating their locations. More than that, **Staples appeared to consider the person's distance from a rival brick-and-mortar store**, either OfficeMax Inc. or Office Depot Inc. If rival stores were within 20 miles or so, Staples.com usually showed a discounted price.

https://www.wsj.com/articles/SB10001424127887323772045781893918138815 34

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# Online job ads

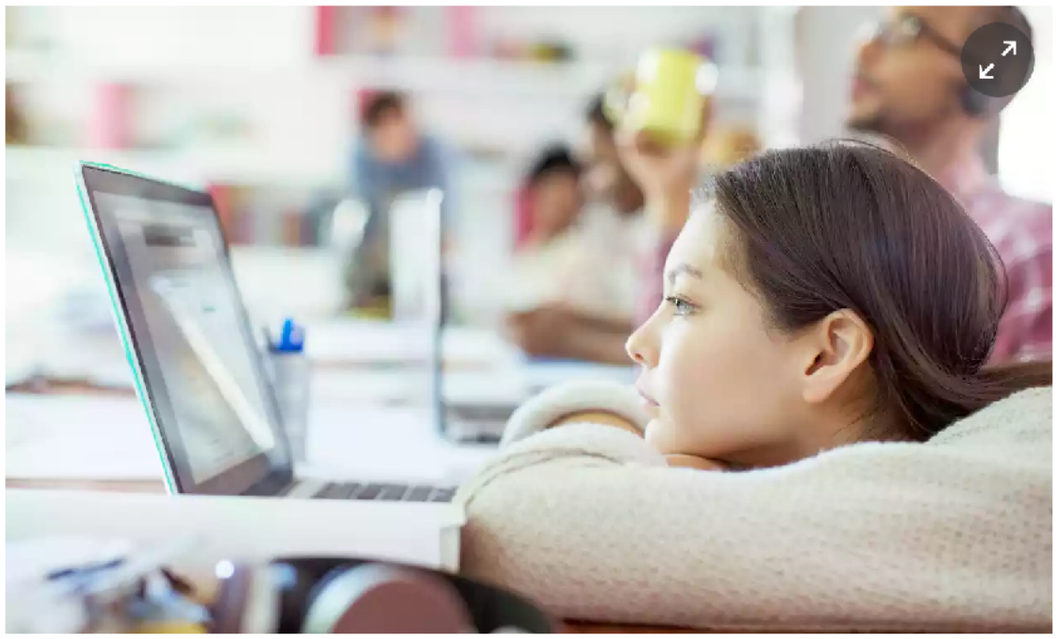
**July 2015**

theguardian

Samuel Gibbs

Wednesday 8 July 2015 11.29 BST

Automated testing and analysis of company's advertising system reveals male job seekers are shown far more adverts for high-paying executive jobs



One experiment showed that Google displayed adverts for a career coaching service for executive jobs 1,852 times to the male group and only 318 times to the female group. Photograph: Alamy

## Women less likely to be shown ads for high-paid jobs on Google, study shows

The AdFisher tool simulated job seekers that did not differ in browsing behavior, preferences or demographic characteristics, except in gender.

One experiment showed that Google displayed ads for a career coaching service for "$200k+" executive jobs **1,852 times to the male group and only 318 times to the female group**. Another experiment, in July 2014, showed a similar trend but was not statistically significant.

https://www.theguardian.com/technology/2015/jul/08/women-less-likely-ads-high-paid-jobs-google-study

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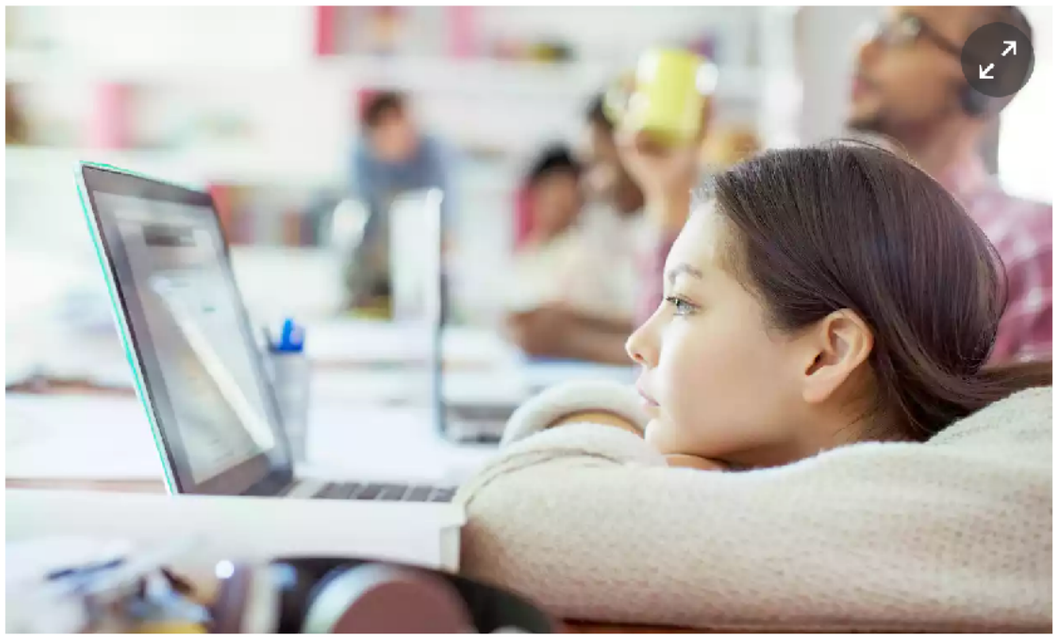

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executive job
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Another exp
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https://www.theguardian.com/technology/2015/jul/08/women-less-likely-ads-high-paid-jobs-google-study

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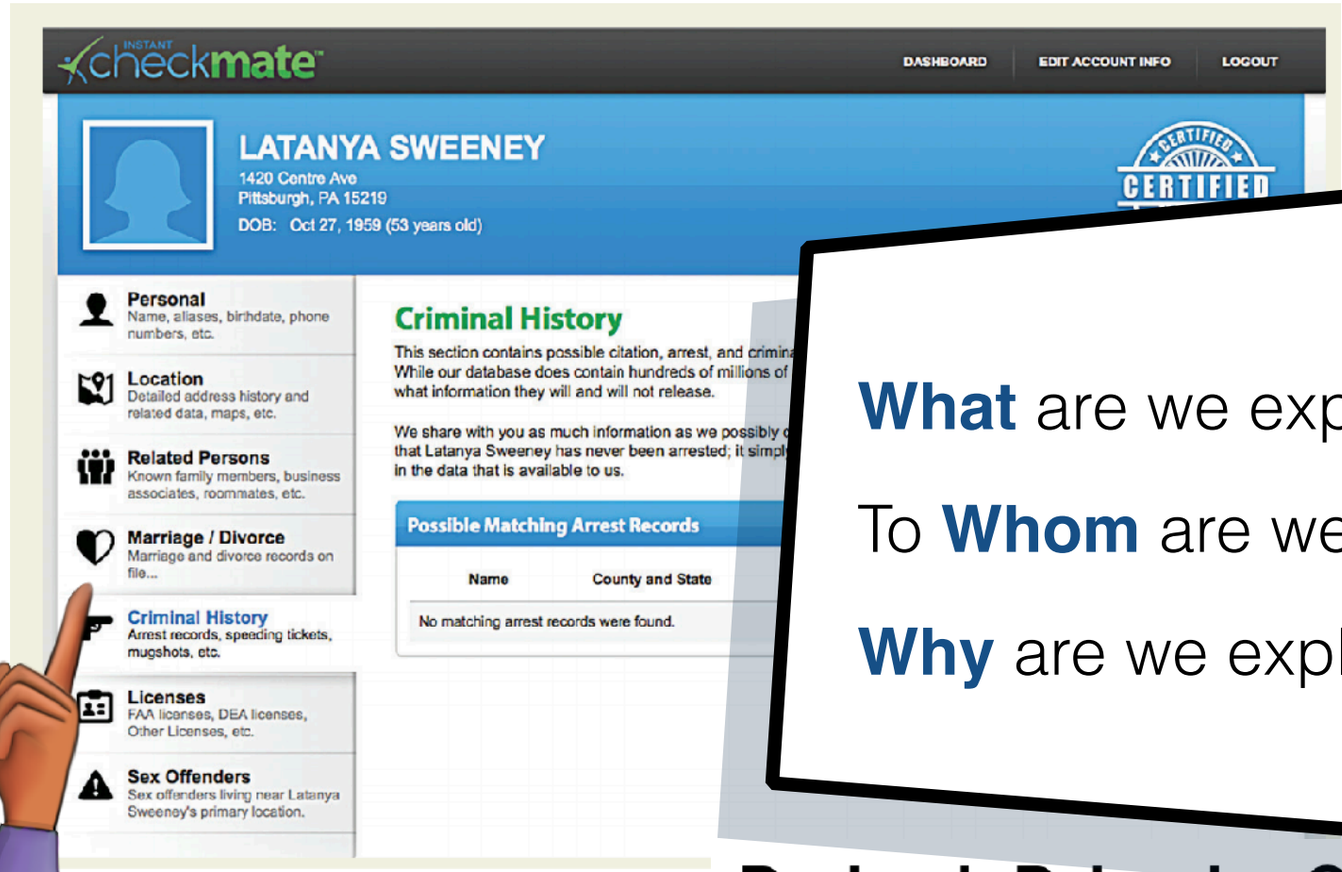
# Instant Checkmate

Google
AdSense


**February 2013**

**What** are we explaining?

To **Whom** are we explaining?

**Why** are we explaining?

## Racism is Poisoning Online Ad Delivery, Says Harvard Professor

Google searches involving black-sounding names are more likely to serve up ads suggestive of a criminal record than white-sounding names, says computer scientist

https://www.technologyreview.com/s/510646/racism-is-poisoning-online-ad-delivery-says-harvard-professor/

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# Nutritional labels

**What** are we explaining?

To **Whom** are we explaining?

**Why** are we explaining?

SIDE-BY-SIDE COMPARISON

| Original Label | | New Label | |
|---|---|---|---|
| **Nutrition Facts** | | **Nutrition Facts** | |
| Serving Size 2/3 cup (55g) | | 8 servings per container | |
| Servings Per Container About 8 | | **Serving size** | **2/3 cup (55g)** |
| **Amount Per Serving** | | **Amount per serving** | |
| **Calories** 230 | Calories from Fat 72 | **Calories** | **230** |
| | % Daily Value* | | % Daily Value* |
| **Total Fat** 8g | 12% | **Total Fat** 8g | 10% |
| Saturated Fat 1g | 5% | Saturated Fat 1g | 5% |
| *Trans* Fat 0g | | *Trans* Fat 0g | |
| **Cholesterol** 0mg | 0% | **Cholesterol** 0mg | 0% |
| **Sodium** 160mg | 7% | **Sodium** 160mg | 7% |
| **Total Carbohydrate** 37g | 12% | **Total Carbohydrate** 37g | 13% |
| Dietary Fiber 4g | 16% | Dietary Fiber 4g | 14% |
| Sugars 1g | | Total Sugars 12g | |
| **Protein** 3g | | Includes 10g Added Sugars | 20% |
| | | **Protein** 3g | |
| Vitamin A | 10% | Vitamin D 2mcg | 10% |
| Vitamin C | 8% | Calcium 260mg | 20% |
| Calcium | 20% | Iron 8mg | 45% |
| Iron | 45% | Potassium 235mg | 6% |

* Percent Daily Values are based on a 2,000 calorie diet. Your daily value may be higher or lower depending on your calorie needs.

| Calories: | 2,000 | 2,500 |
|---|---|---|
| Total Fat | Less than 65g | 80g |
| Sat Fat | Less than 20g | 25g |
| Cholesterol | Less than 300mg | 300mg |
| Sodium | Less than 2,400mg | 2,400mg |
| Total Carbohydrate | | 300g 375g |
| Dietary Fiber | | 25g 30g |

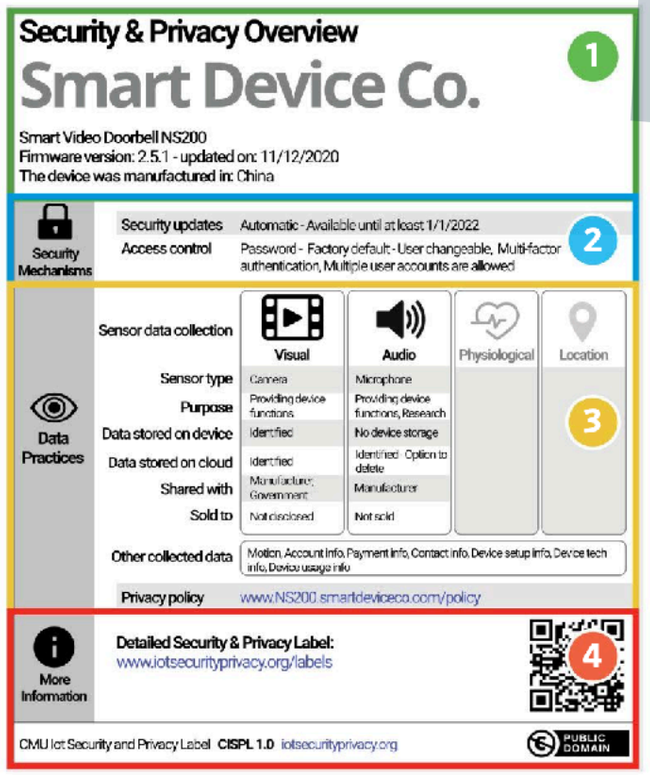
* The % Daily Value (DV) tells you how much a nutrient in a serving of food contributes to a daily diet. 2,000 calories a day is used for general nutrition advice.

**Note:** The images above are meant for illustrative purposes to show how the new Nutrition Facts label might look compared to the old label. Both labels represent fictional products. When the original hypothetical label was developed in 2014 (the image on the left-hand side), added sugars was not yet proposed so the "original" label shows 1g of sugar as an example. The image created for the "new" label (shown on the right-hand side) lists 12g total sugar and 10g added sugar to give an example of how added sugars would be broken out with a % Daily Value.

An example of the old nutrition labels, left, and the new one. The new nutrition labels will display calories and serving size more prominently, and include added sugars for the first time.

PHOTO: FOOD AND DRUG ADMINISTRATION/ASSOCIATED PRESS

https://www.wsj.com/articles/why-the-labels-on-your-food-are-changing-or-



Security & Privacy Overview

Smart Device Co.

Smart Video Doorbell NS200
Firmware version: 2.5.1 - updated on: 11/12/2020
The device was manufactured in: China

**Security Mechanisms**

| | |
|---|---|
| Security updates | Automatic - Available until at least 1/1/2022 |
| Access control | Password - Factory default - User changeable, Multi-factor authentication, Multiple user accounts are allowed |

**Data Practices**

| | Visual | Audio | Physiological | Location |
|---|---|---|---|---|
| Sensor type | Camera | Microphone | | |
| Purpose | Providing device functions | Providing device functions, Research | | |
| Data stored on device | Identified | No device storage | | |
| Data stored on cloud | Identified | Identified Option to delete | | |
| Shared with | Manufacturer, Government | Manufacturer | | |
| Sold to | Not disclosed | Not sold | | |

Other collected data: Motion, Account Info, Payment Info, Contact Info, Device setup info, Device tech info, Device usage info

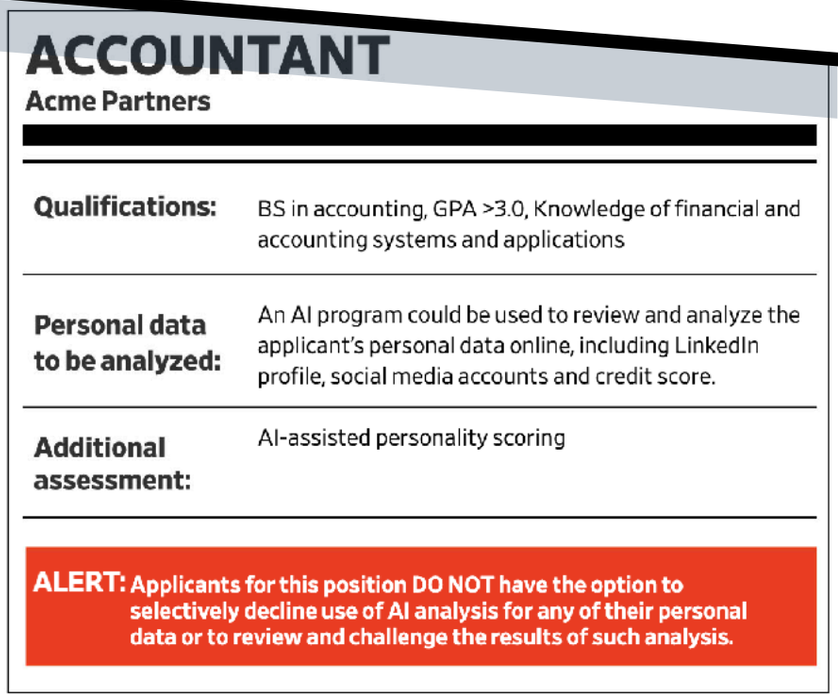
Privacy policy: www.NS200.smartdeviceco.com/policy

**More Information**

Detailed Security & Privacy Label:
www.iotsecurityprivacy.org/labels

CMU Iot Security and Privacy Label CISPL 1.0 iotsecurityprivacy.org PUBLIC DOMAIN

https://www.wsj.com/articles/imagine-a-nutrition-labelfor-



**ACCOUNTANT**

**Acme Partners**

| | |
|---|---|
| **Qualifications:** | BS in accounting, GPA >3.0, Knowledge of financial and accounting systems and applications |
| **Personal data to be analyzed:** | An AI program could be used to review and analyze the applicant's personal data online, including LinkedIn profile, social media accounts and credit score. |
| **Additional assessment:** | AI-assisted personality scoring |

**ALERT: Applicants for this position DO NOT have the option to selectively decline use of AI analysis for any of their personal data or to review and challenge the results of such analysis.**

https://www.wsj.com/articles/hiring-job-candidates-ai-11632244313

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# This week's reading

2016 IEEE Symposium on Security and Privacy

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

Anupam Datta Shayak Sen Yair Zick
Carnegie Mellon University, Pittsburgh, USA
{danupam, shayaks, yairzick}@cmu.edu

***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


DOI 10.1109/SP.2016.42


## "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


*KDD 2016 San Francisco, CA, USA*

ISBN 978-1-4503-4232-2/16/08…$15.00
DOI: http://dx.doi.org/10.1145/2939672.2939778

## 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

31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.

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explaining black box models

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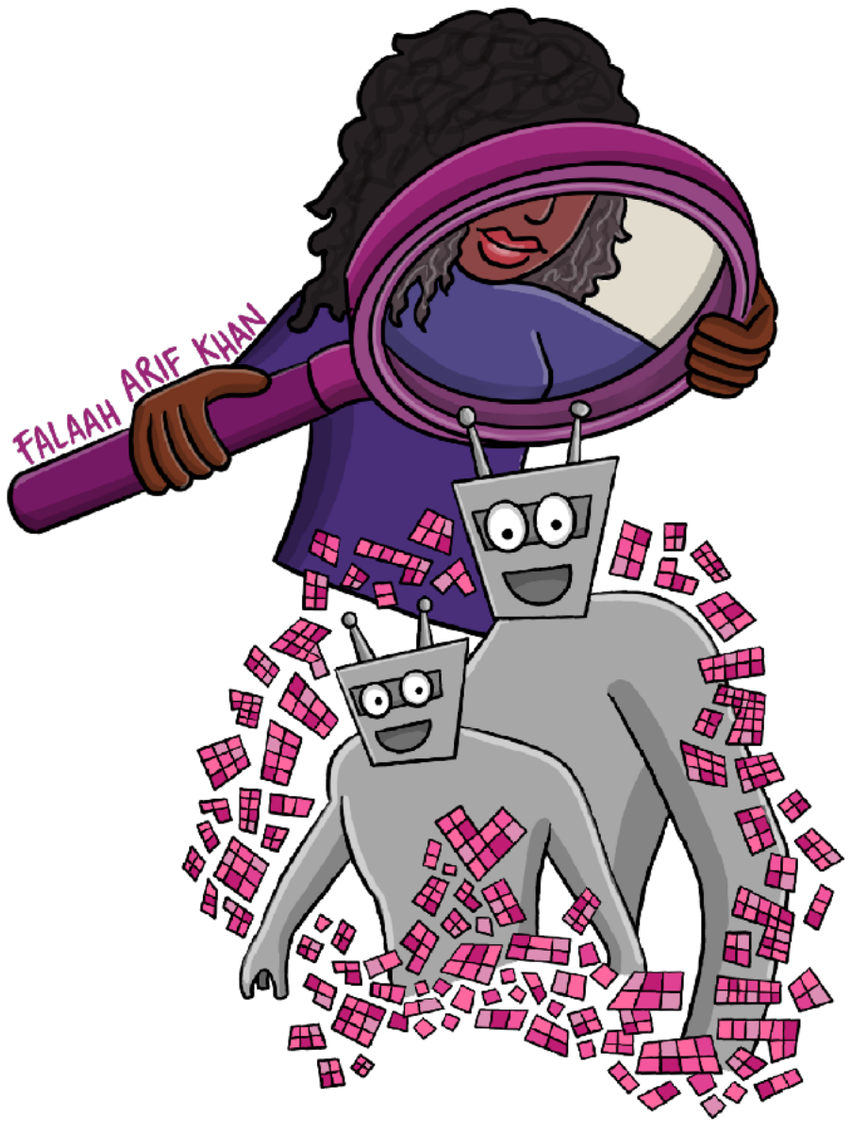
# What are we explaining?




How does a system work?

How **well** does a system work?

What does a system do?

Why was I ___ (mis-diagnosed / not offered a discount / denied credit) ?

Are a system's decisions discriminatory?

Are a system's decisions illegal?

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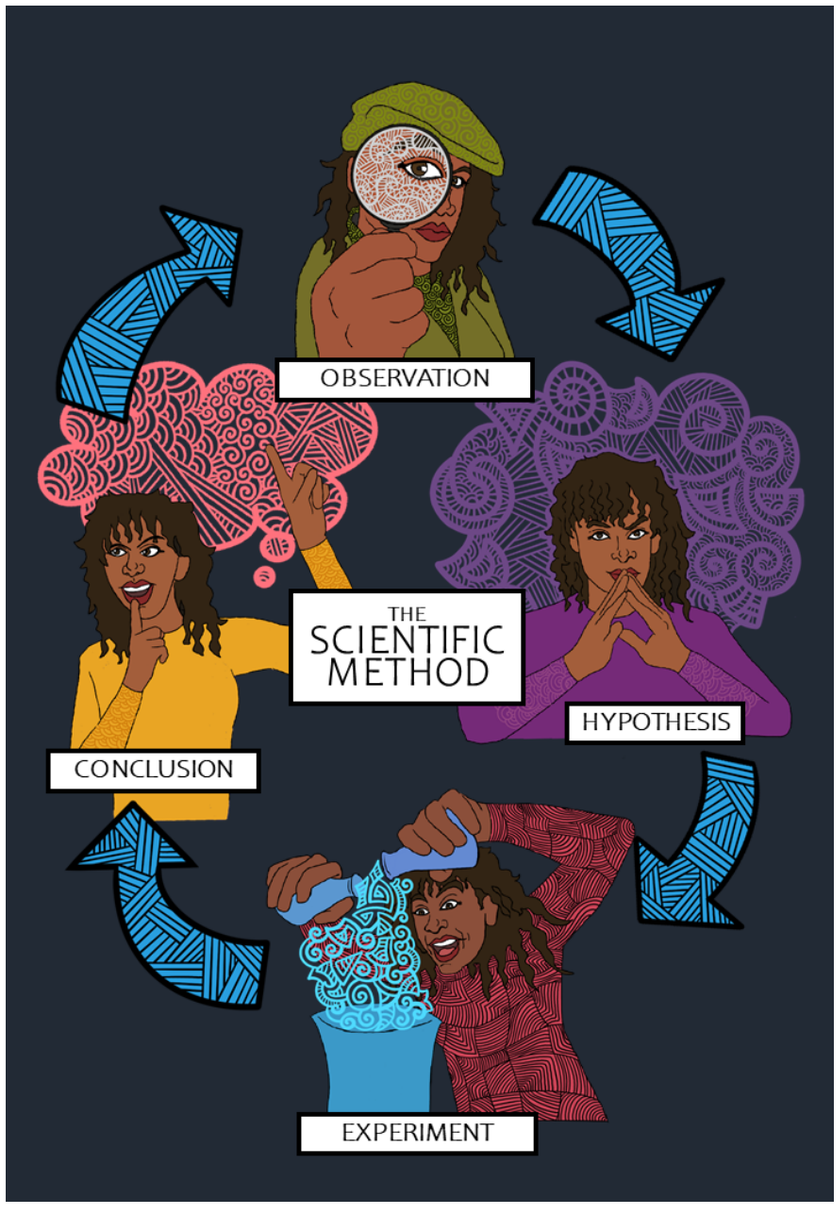
# But isn’t accuracy sufficient?




How is accuracy measured?  FPR / FNR / …

Accuracy for whom: over-all or in sub-populations?

Accuracy over which data?

There is never 100% accuracy.  Mistakes for what reason?

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# Facebook's real-name policy

Shane Creepingbear is a member of the Kiowa Tribe of Oklahoma

**October 13, 2014**

Tweet

**Shane Creepingbear** @Creepingbear · Oct 13, 2014

Hey yall today I was kicked off of Facebook for having a fake name. Happy Columbus Day great job #facebook #goodtiming #racist #ColumbusDay

17

TIME

## Facebook Thinks Some Native American Names Are Inauthentic

BY JOSH SANBURN FEBRUARY 14, 2015

**February 14, 2015**

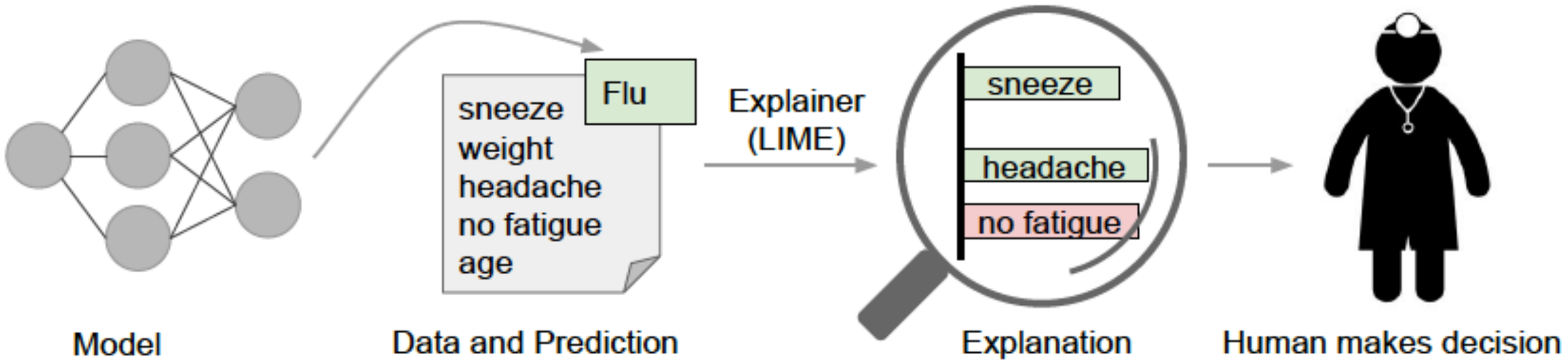
If you're Native American, Facebook might think your name is fake.

The social network has a history of telling its users that the names they're attempting to use aren't real. Drag queens and overseas human rights activists, for example, have experienced error messages and problems logging in in the past.

The latest flap involves Native Americans, including Dana Lone Hill, who is Lakota. Lone Hill recently wrote in a blog post that Facebook told her her name was not "authentic" when she attempted to log in.

# Explanations based on features

- **LIME** (Local Interpretable Model-Agnostic Explanations): to help users trust a prediction, explain individual predictions
- **SP-LIME**: to help users trust a model, select a set of representative instances for which to generate explanations




features in green ("sneeze", "headache") support the prediction ("Flu"), while features in red ("no fatigue") are evidence against the prediction

**what if patient id appears in green in the list? - an example of "data leakage"**

[Ribeiro, Singh & Guestrin, 2016]

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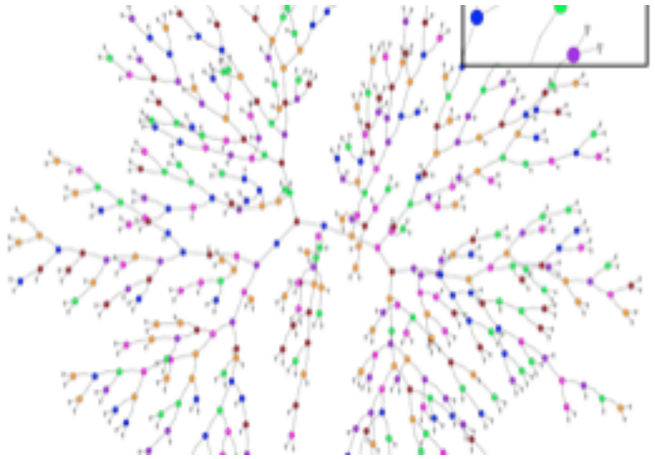
# LIME: Local explanations of classifiers

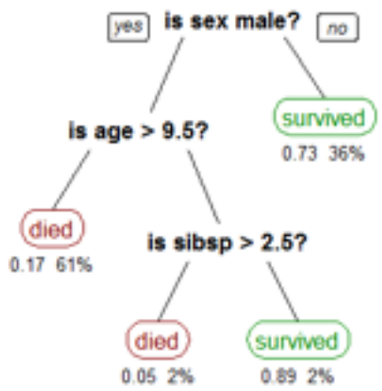
## Three must-haves for a good explanation

**Interpretable**

- Humans can easily interpret reasoning



Definitely
not interpretable




Potentially
interpretable

slide by Marco Tulio Ribeiro, KDD 2016

[Ribeiro, Singh & Guestrin, 2016]

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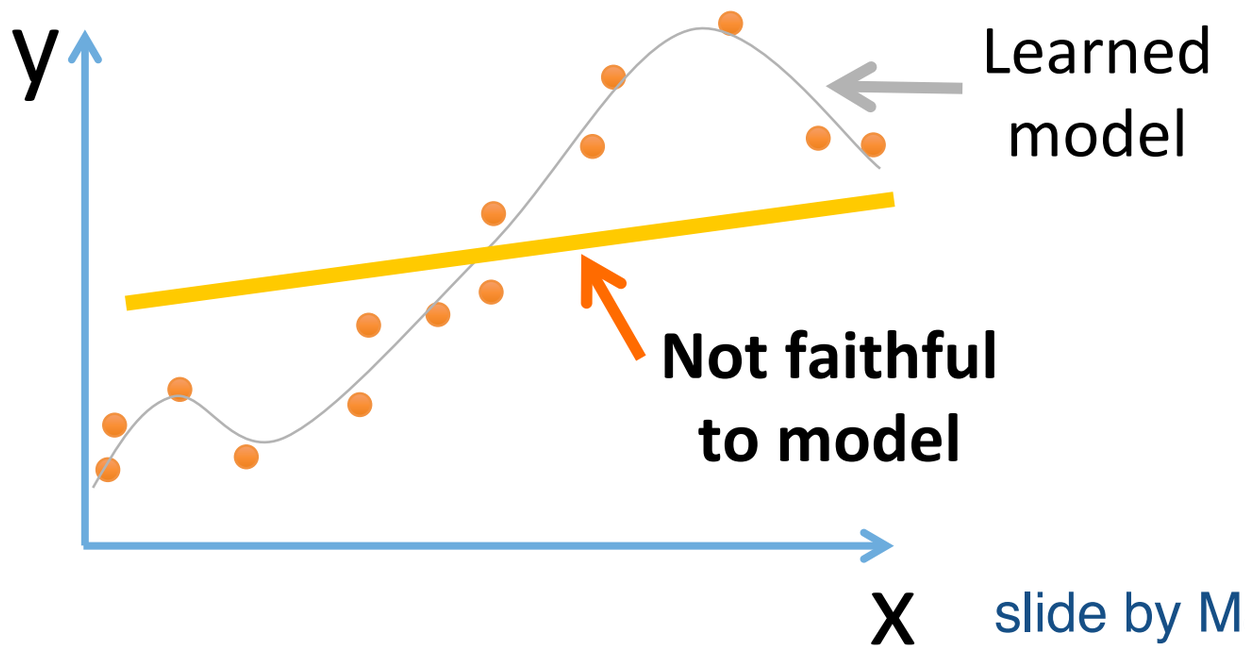
# Explanations based on features

## Three must-haves for a good explanation

| | |
|---|---|
| Interpretable | • Humans can easily interpret reasoning |
| Faithful | • Describes how this model actually behaves |




slide by Marco Tulio Ribeiro, KDD 2016

[Ribeiro, Singh & Guestrin, 2016]

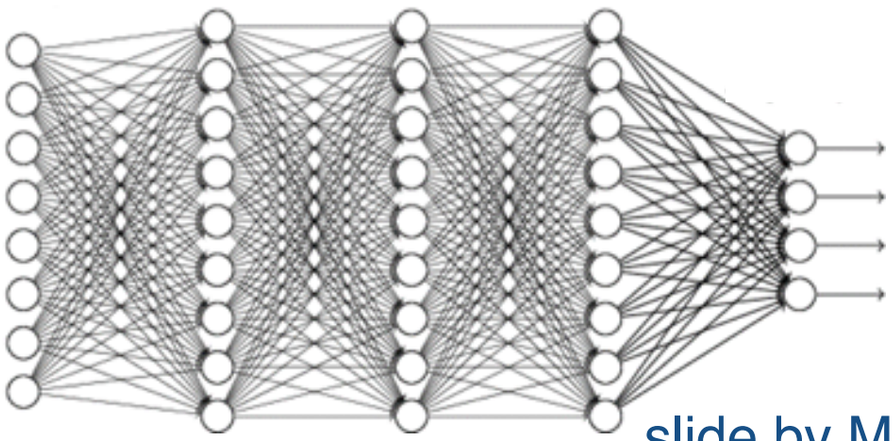
r/ai

# Explanations based on features

## Three must-haves for a good explanation

| | |
|---|---|
| Interpretable | • Humans can easily interpret reasoning |
| Faithful | • Describes how this model actually behaves |
| Model agnostic | • Can be used for *any* ML model |

Can explain this mess ☺



slide by Marco Tulio Ribeiro, KDD 2016

[Ribeiro, Singh & Guestrin, 2016]

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# Key idea: Interpretable representation

"The overall goal of LIME is to identify an **interpretable** model over the *interpretable representation* that is **locally faithful** to the classier."

- LIME relies on a distinction between **features** and **interpretable data representations**; examples:
  - In text classification features are word embeddings; an interpretable representation is a vector indicating the presence of absence of a word
  - In image classification features encoded in a tensor with three color channels per pixel; an interpretable representation is a binary vector indicating the presence or absence of a contiguous patch of similar pixels
- **To summarize**: we may have some ***d*** features and ***d'*** interpretable components; interpretable models will act over domain $\{0, 1\}^{d'}$ - denoting the presence of absence of each of d' interpretable components

[Ribeiro, Singh & Guestrin, 2016]

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# Fidelity-interpretability trade-off

"The overall goal of LIME is to identify an **interpretable** model over the *interpretable representation* that is **locally faithful** to the classier."

$$f : \mathbb{R}^d \rightarrow \mathbb{R} \qquad g \in G, dom(g) = \{0,1\}^{d'} \qquad \Omega(g)$$

classifier **model being explained**

**explanation model**

some class of interpretable models

measure of complexity of explanation ***g***

$f(x)$ denotes the probability that ***x*** belongs to some class

$\pi_x$ is a **proximity measure** relative to ***x***

we make no assumptions about ***f*** to remain model-agnostic: draw samples weighted by $\pi_x$

**explanation**

measures how unfaithful is ***g*** to ***f*** in the locality around ***x***

$$\xi(x) = \text{argmin}_{g \in G} L(f, g, \pi_x) + \Omega(g)$$

[Ribeiro, Singh & Guestrin, 2016]

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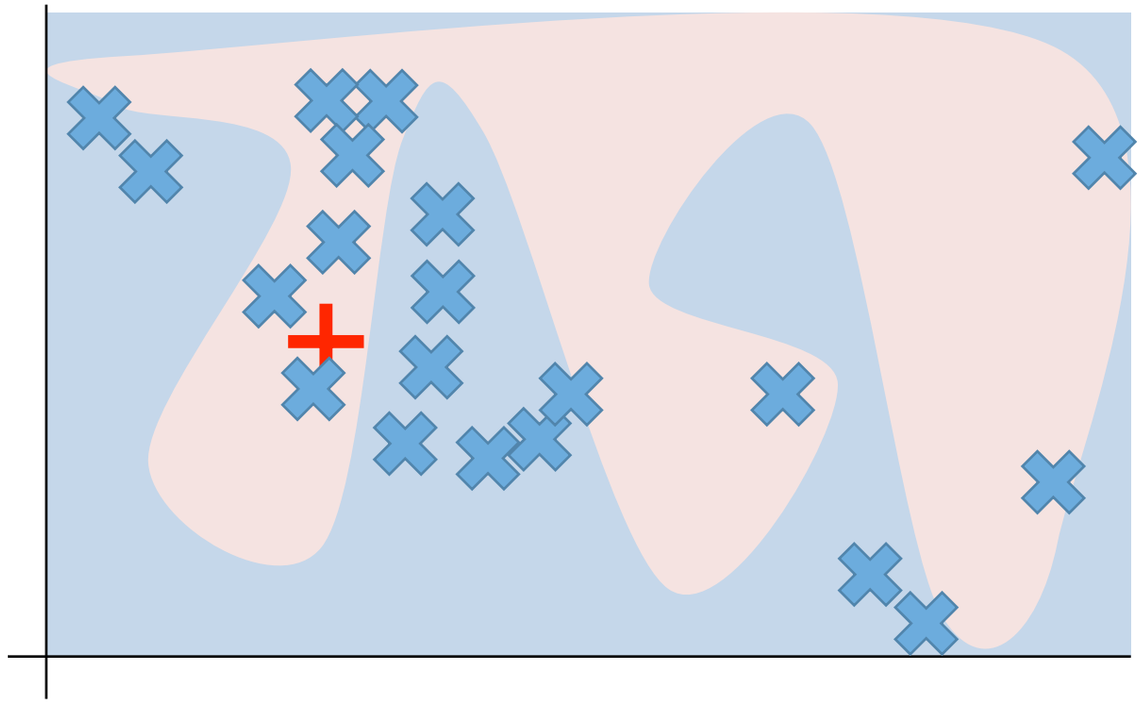
# Fidelity-interpretability trade-off

"The overall goal of LIME is to identify an **interpretable** model over the *interpretable representation* that is **locally faithful** to the classier."

1. sample points around +



based on a slide by Marco Tulio Ribeiro, KDD 2016

[Ribeiro, Singh & Guestrin, 2016]

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# Fidelity-interpretability trade-off

"The overall goal of LIME is to identify an **interpretable** model over the *interpretable representation* that is **locally faithful** to the classier."

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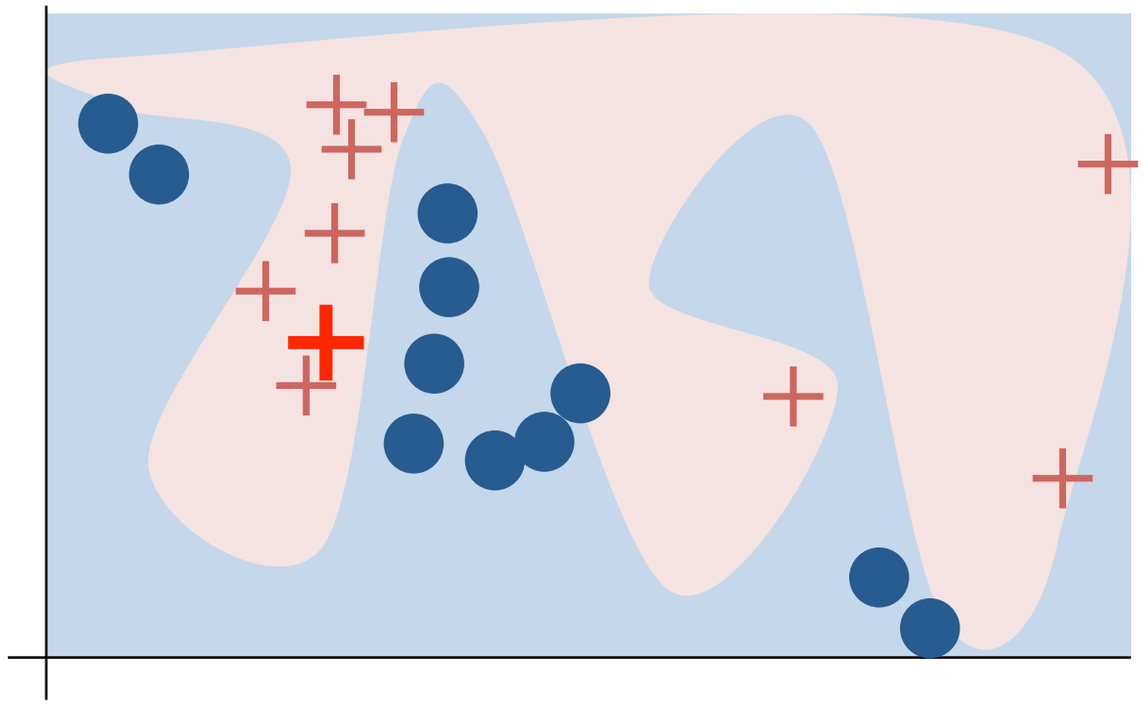
2. use complex model ***f*** to assign class labels



based on a slide by Marco Tulio Ribeiro, KDD 2016

[Ribeiro, Singh & Guestrin, 2016]

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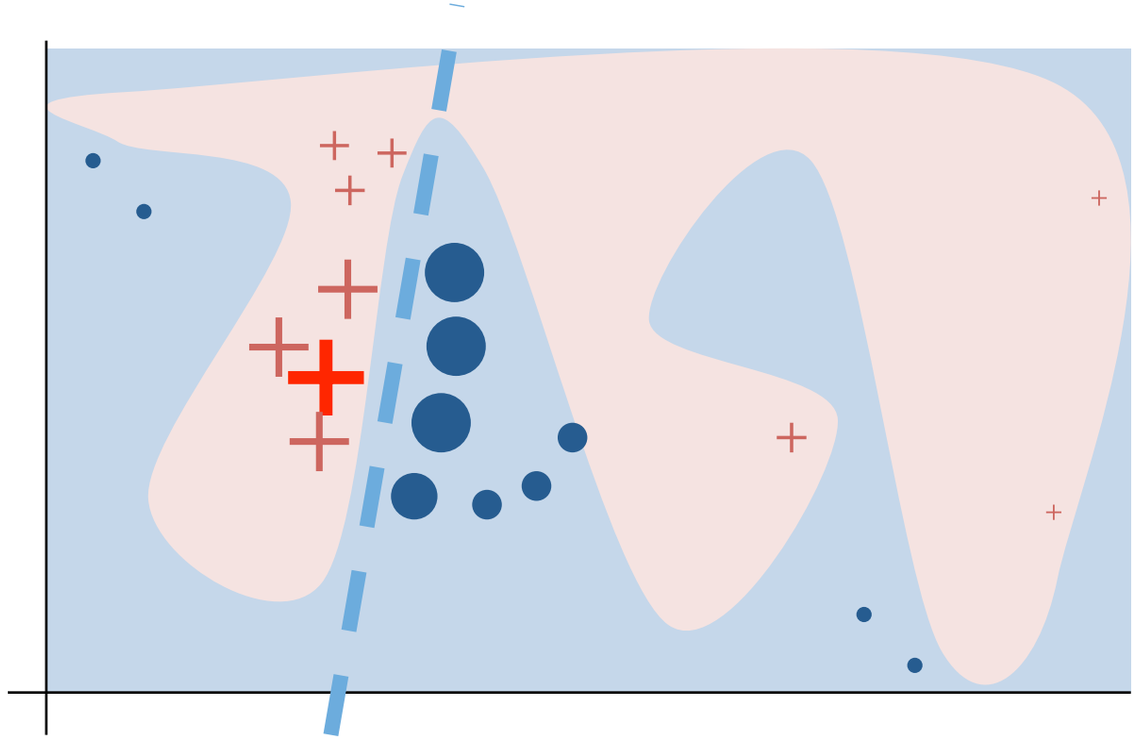
# Fidelity-interpretability trade-off

"The overall goal of LIME is to identify an **interpretable** model over the *interpretable representation* that is **locally faithful** to the classier."

1. sample points around +
2. use complex model ***f*** to assign class labels
3. weigh samples according to $\pi_x$
4. learn simple model ***g*** according to samples



based on a slide by Marco Tulio Ribeiro, KDD 2016

[Ribeiro, Singh & Guestrin, 2016]

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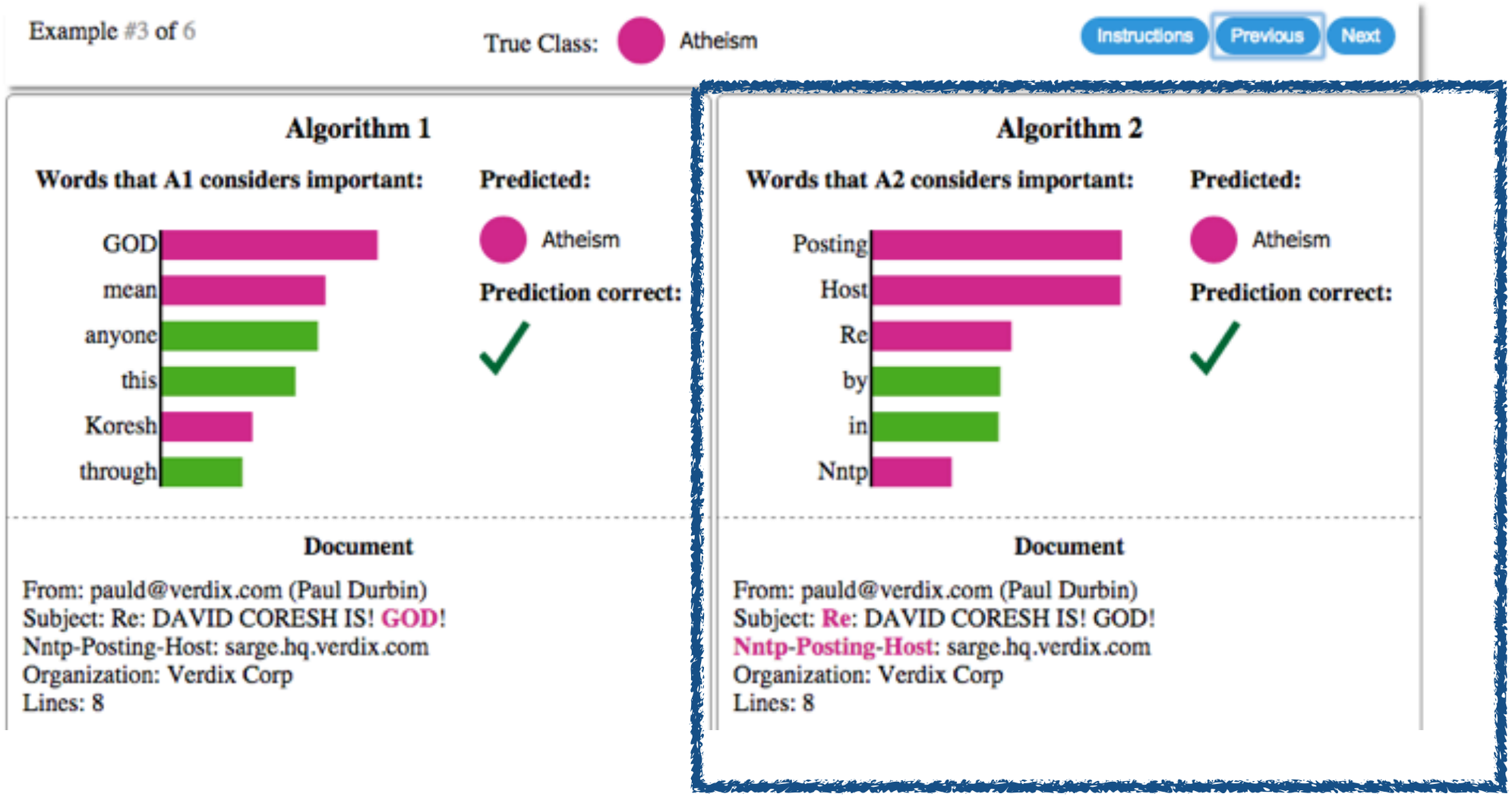
# Example: text classification with SVMs




**94% accuracy, yet we shouldn't trust this classifier!**

[Ribeiro, Singh & Guestrin, 2016]

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# When accuracy is not enough

## Explaining Google's Inception NN

probabilities of the top-3 classes
and the super-pixels predicting each

P( ) = 0.32

Electric guitar - incorrect but reasonable, similar fretboard

P( ) = 0.24

Acoustic guitar

P( ) = 0.21

Labrador

[Ribeiro, Singh & Guestrin, 2016]

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# When accuracy is not enough

Train a neural network to predict wolf v. husky


Only 1 mistake!!!

Do you trust this model?
How does it distinguish between huskies and wolves?

slide by Marco Tulio Ribeiro, KDD 2016

[Ribeiro, Singh & Guestrin, 2016]

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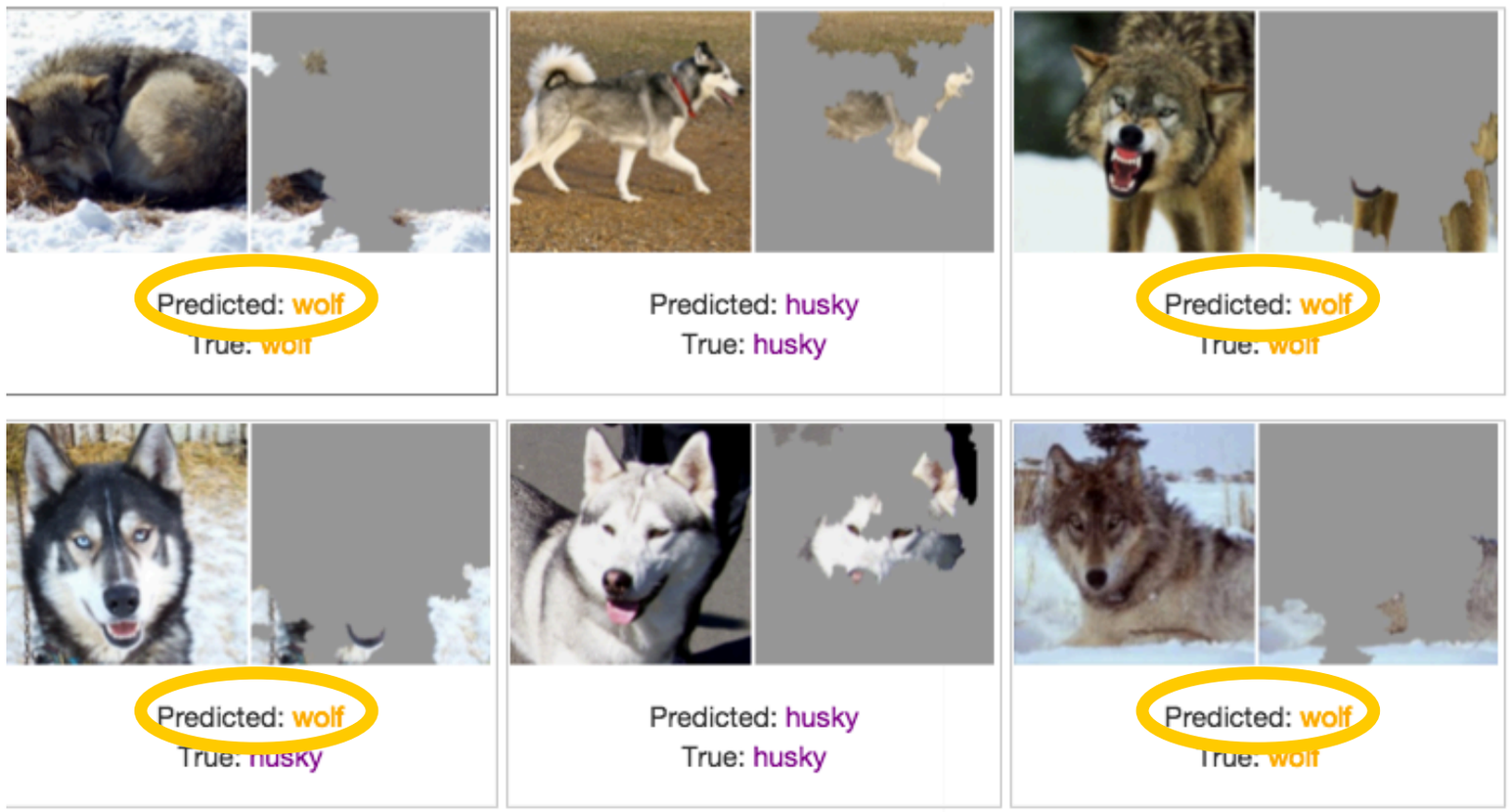
# When accuracy is not enough

## Explanations for neural network prediction




We've built a great snow detector… ☹

slide by Marco Tulio Ribeiro, KDD 2016

[Ribeiro, Singh & Guestrin, 2016]

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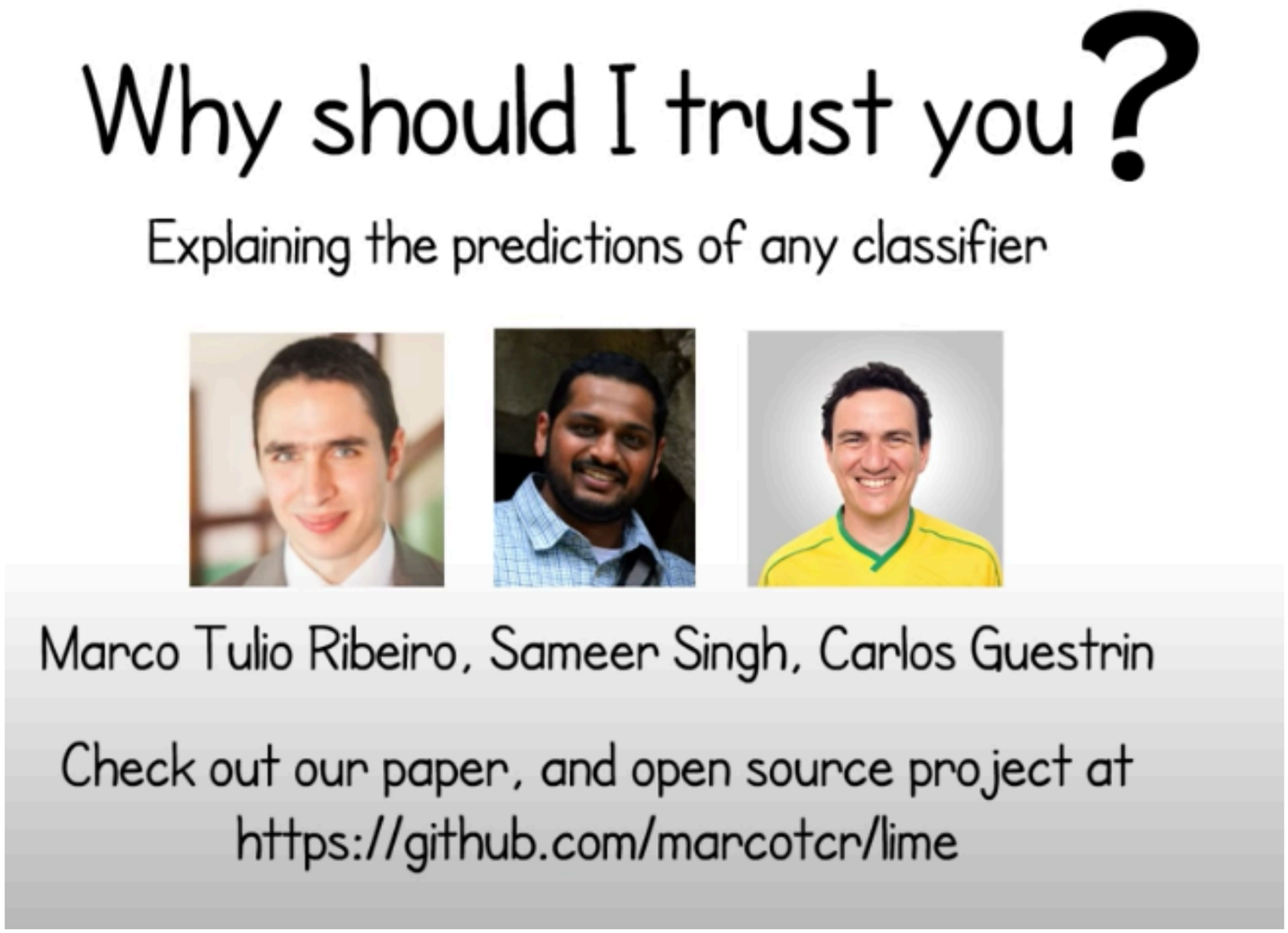
# LIME: Recap




https://www.youtube.com/watch?v=hUnRCxnydCc

[Ribeiro, Singh & Guestrin, 2016]

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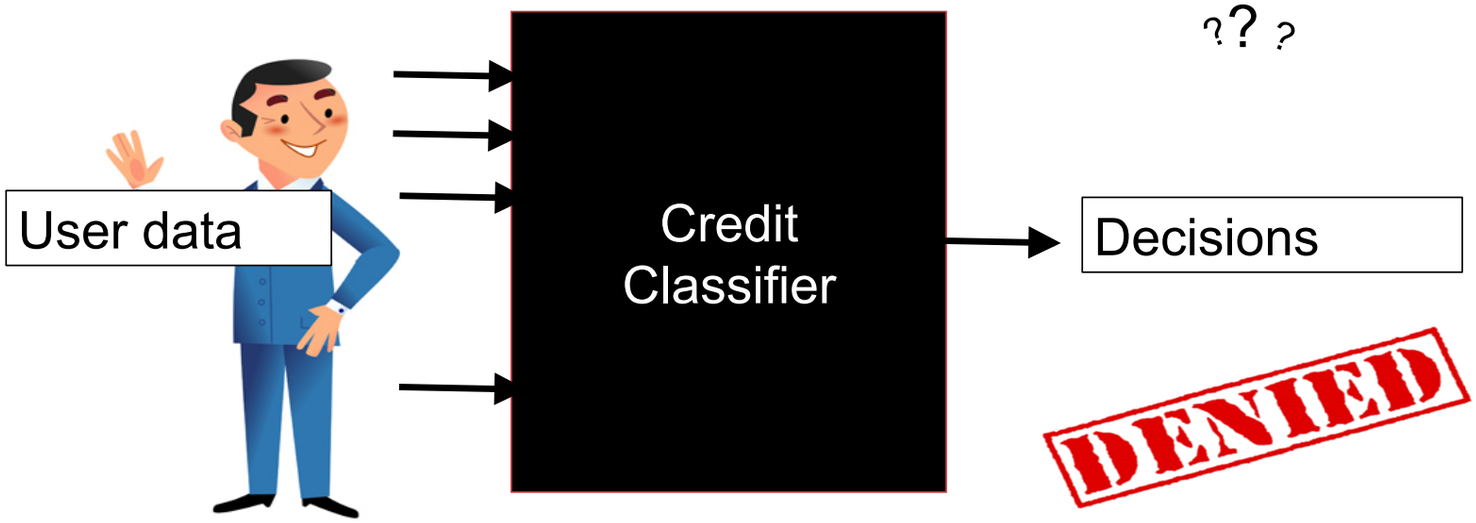
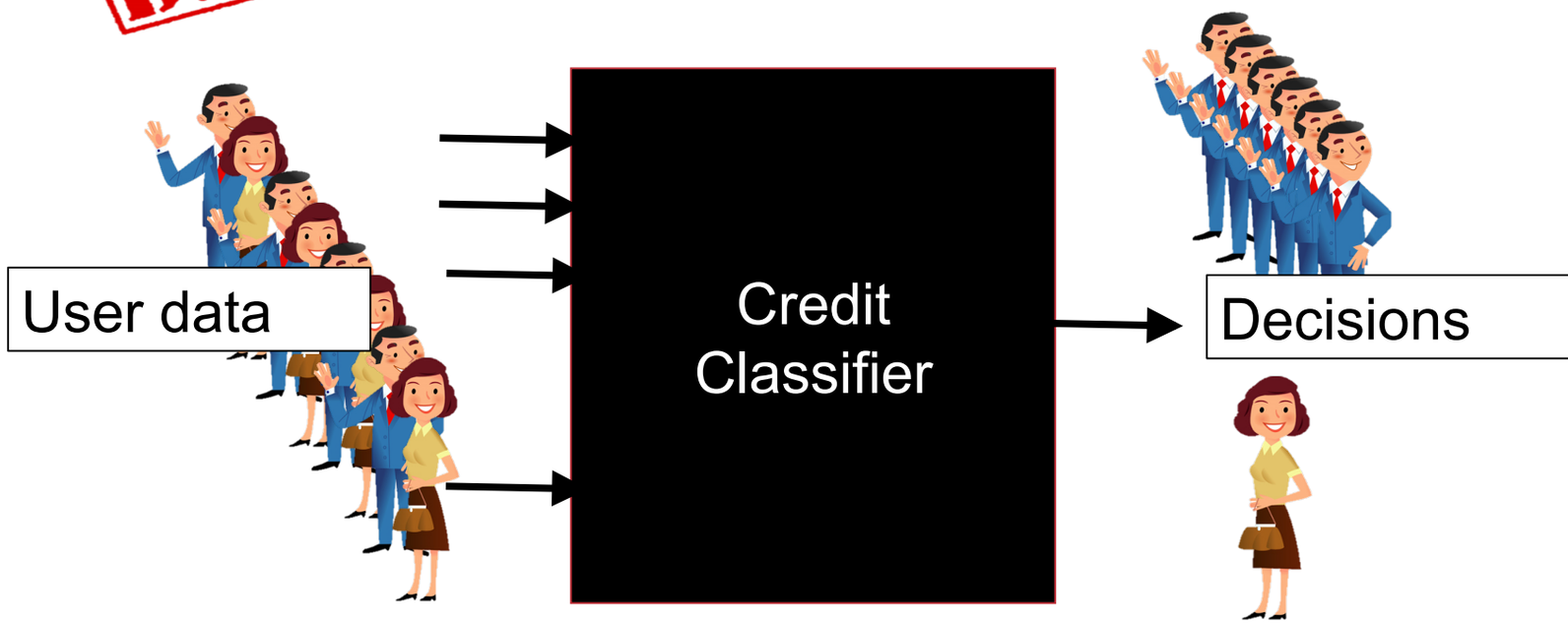
# Auditing black-box models




images by Anupam Datta

[Datta, Sen & Zick, 2016]

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# QII: Quantitative Input Influence

Goal: determine how much influence an input, or a set of inputs, has on a **classification outcome** for an individual or a group

**Transparency queries / quantities of interest**

**Individual:** Which inputs have the most influence in my credit denial?

**Group:** Which inputs have the most influence on credit decisions for women?

**Disparity:** Which inputs influence men getting more positive outcomes than women?

[Datta, Sen & Zick, 2016]

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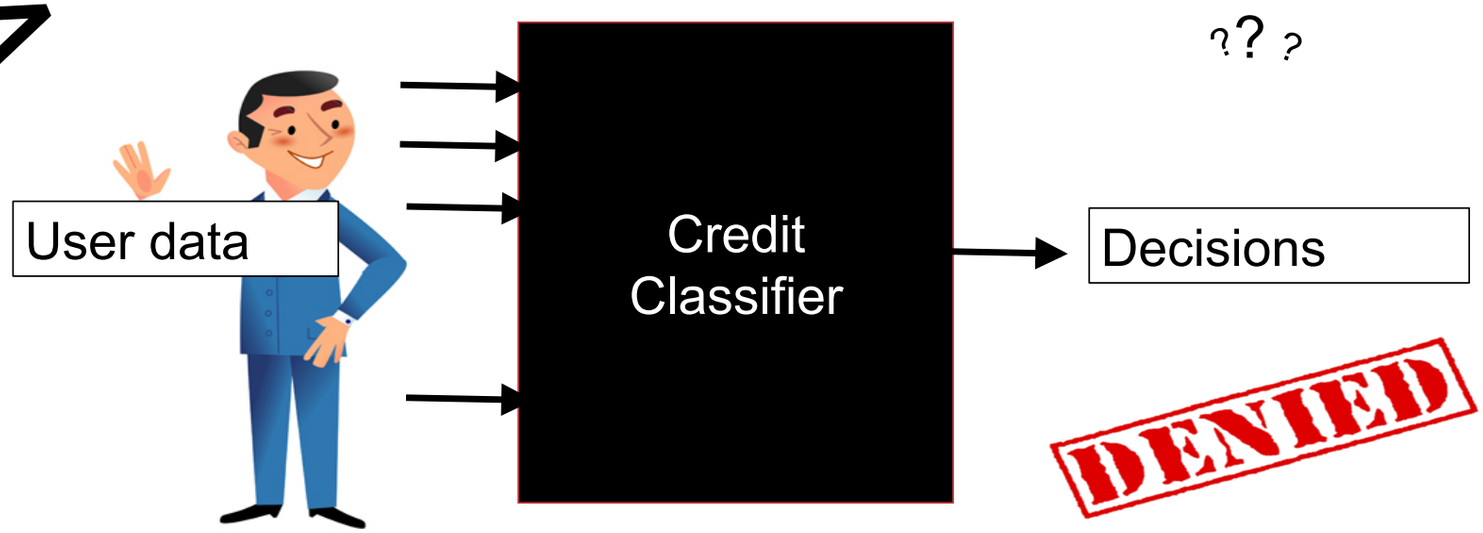
# QII: Quantitative Input Influence

For a quantity of influence *Q* and an input feature *i*, the QII of *i* on *Q* is the difference in *Q* when *i* is changed via an **intervention**.

**Key ideas**

**intervene** on an input feature, measure its **importance**

aggregate feature importance using its **Shapley value**




images by Anupam Datta

[Datta, Sen & Zick, 2016]

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# Running example

Consider lending decisions by a bank, based on gender, age, education, and income. **Does gender influence lending decisions?**

- Observe that 20% of women receive the positive classification.
- To check whether gender impacts decisions, take the input dataset and replace the value of gender in each input profile by drawing it from the uniform distribution: set gender in 50% of the inputs to female and 50% to male.
- If we still observe that 20% of female profiles are positively classified **after the intervention** - we conclude that gender does not influence lending decisions.
- Do a similar test for other features, one at a time. This is known as **Unary QII**

[Datta, Sen & Zick, 2016]

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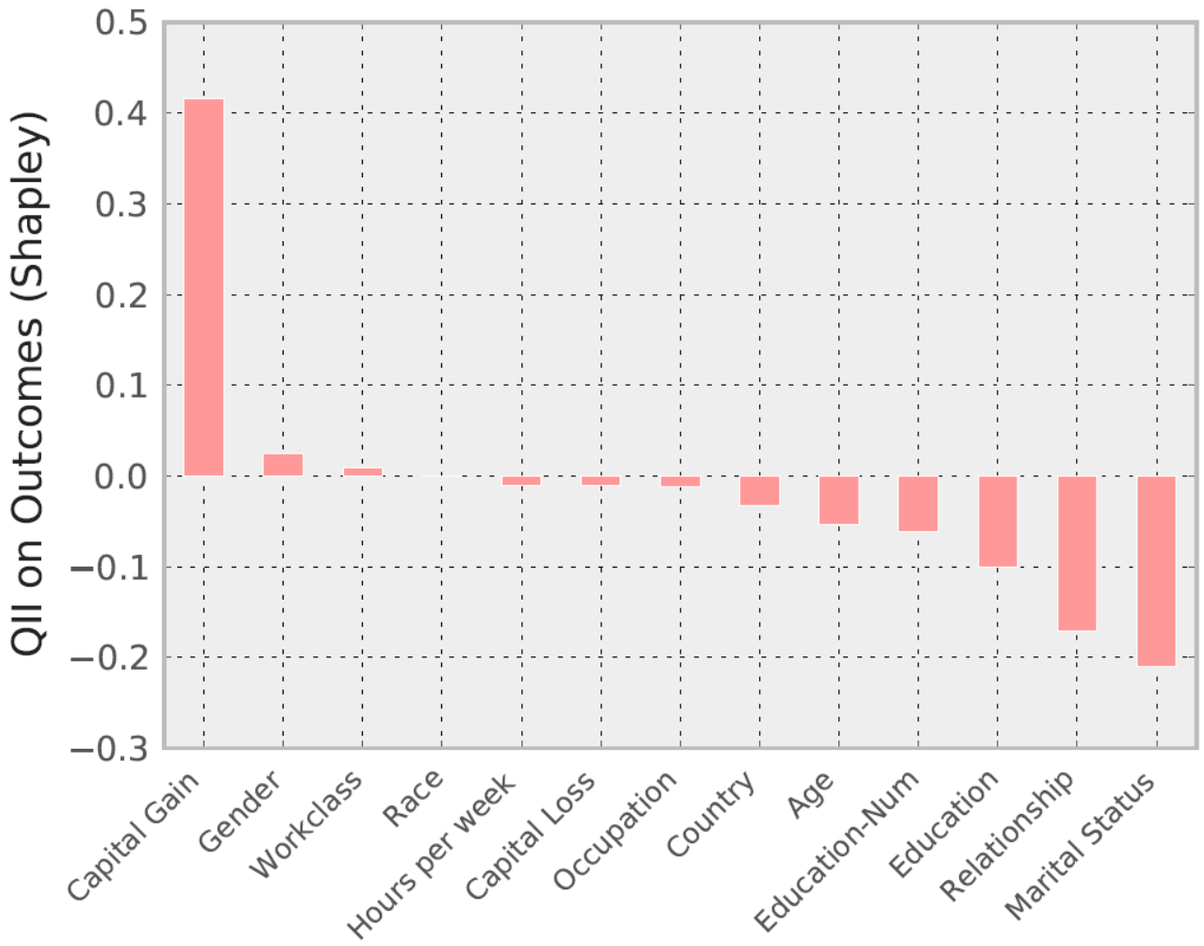
# Transparency report: Mr. X

How much influence do individual features have a given classifier's decision about an individual?




DENIED

| | |
|---|---|
| Age | 23 |
| Workclass | Private |
| Education | 11th |
| Marital Status | Never married |
| Occupation | Craft repair |
| Relationship to household income | Child |
| Race | Asian-Pac Island |
| Gender | Male |
| Capital gain | $14344 |
| Capital loss | $0 |
| Work hours per week | 40 |
| Country | Vietnam |

income

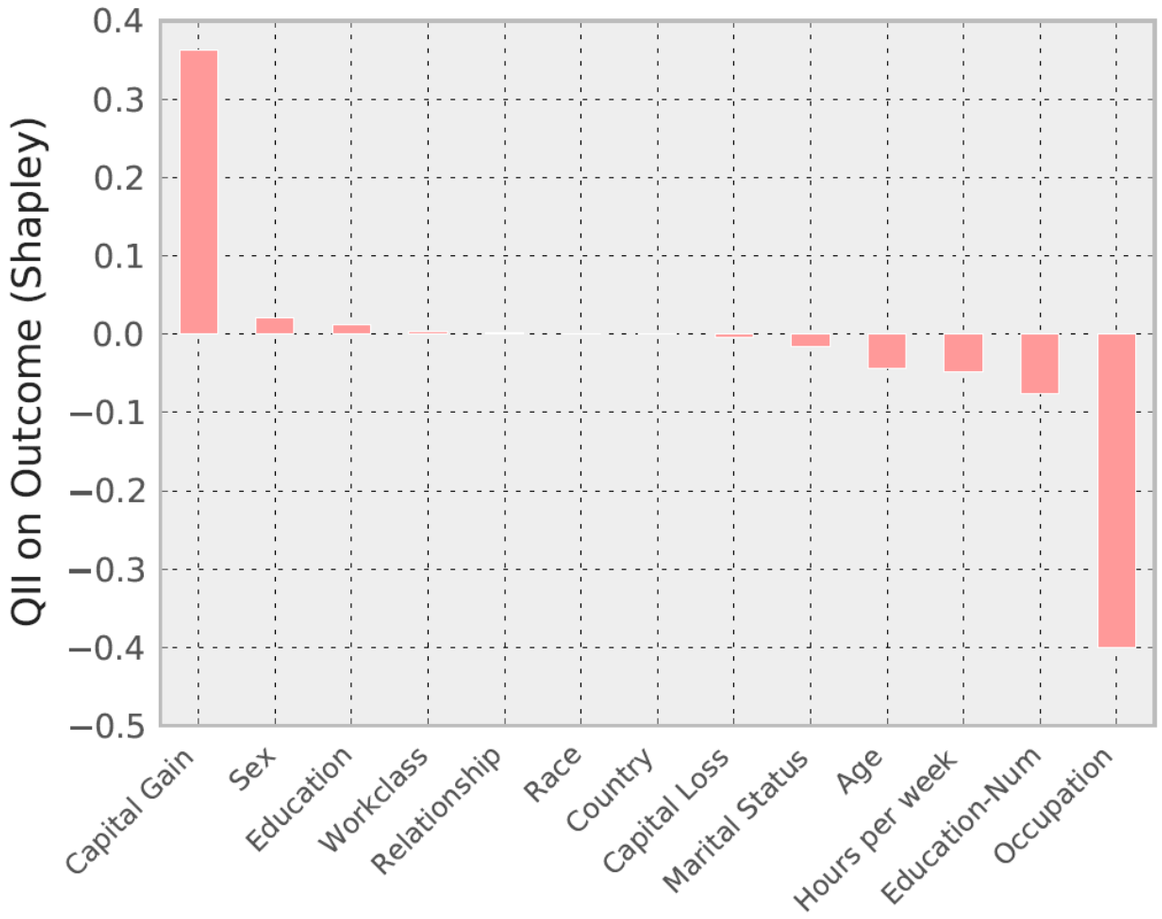
images by Anupam Datta

[Datta, Sen & Zick, 2016]

r/ai

# Transparency report: Mr. Y

## Explanations for superficially similar individuals can be different

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| | |
|---|---|
| Age | 27 |
| Workclass | Private |
| Education | Preschool |
| Marital Status | Married |
| Occupation | Farming-Fishing |
| Relationship to household income | Other Relative |
| Race | White |
| Gender | Male |
| Capital gain | $41310 |
| Capital loss | $0 |
| Work hours per week | 24 |
| Country | Mexico |

income

images by Anupam Datta

[Datta, Sen & Zick, 2016]

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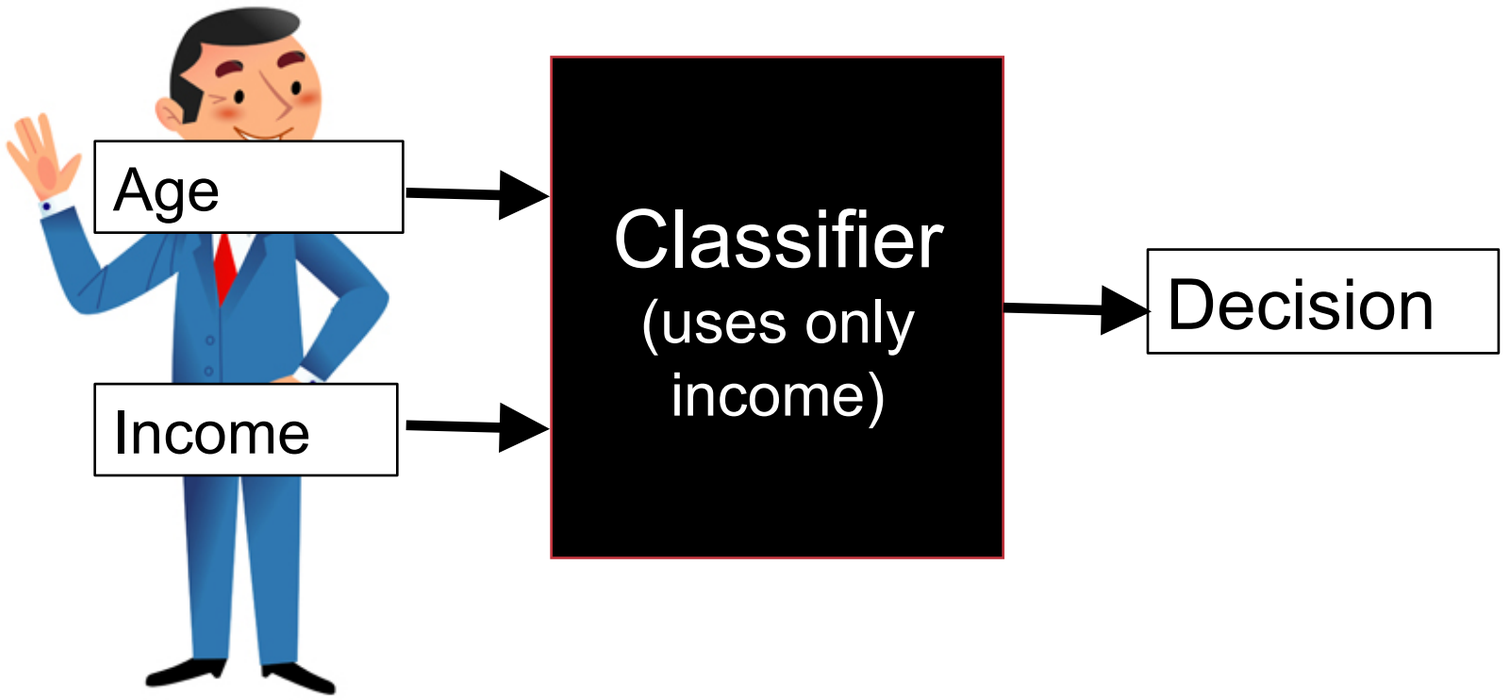
# Unary QII

images by Anupam Datta

For a quantity of influence *Q* and an input feature *i*, the QII of *i* on *Q* is the difference in *Q* when *i* is changed via an **intervention**.




replace features with random values from the population, examine the distribution over outcomes

[Datta, Sen & Zick, 2016]

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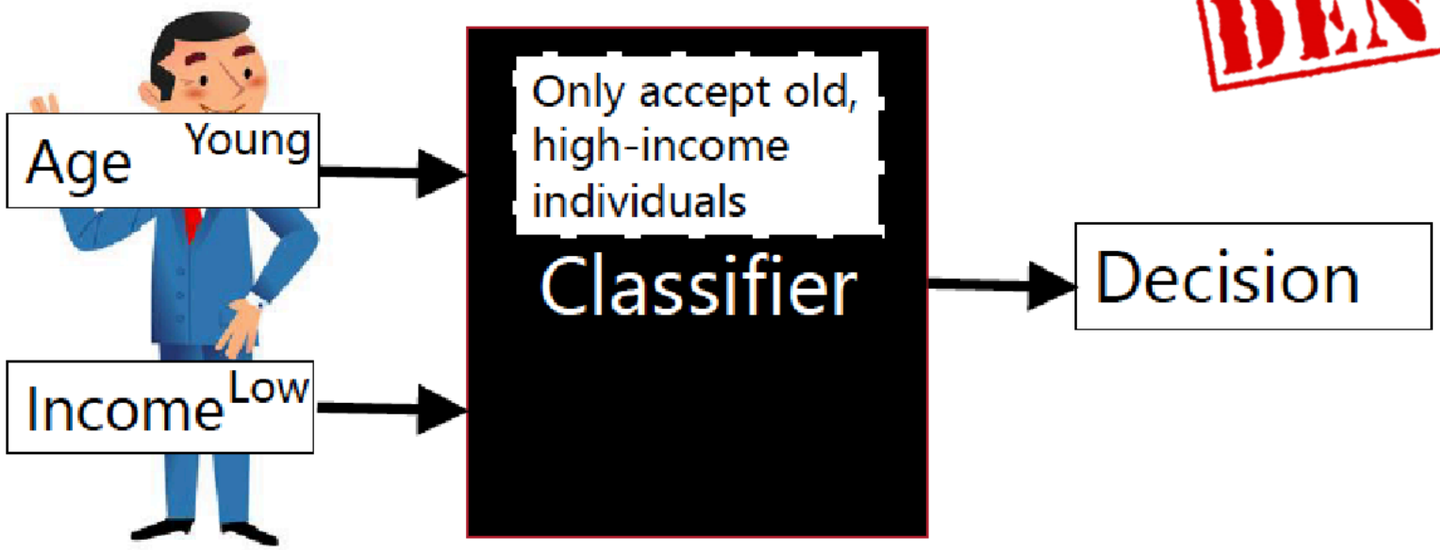
# Unary QII

For a quantity of influence *Q* and an input feature *i*, the QII of *i* on *Q* is the difference in *Q* when *i* is changed via an **intervention**.




**intervening on one feature at a time will not have any effect**

images by Anupam Datta

[Datta, Sen & Zick, 2016]

# Marginal QII

- Not all features are equally important within a set.

- *Marginal QII*: Influence of age and income over only income.

$$\iota(\{\text{age}, \text{income}\}) - \iota(\{\text{income}\})$$

**Need to aggregate Marginal QII across all sets**

- But age is a part of many sets!

$$\iota(\{\text{age}\}) - \iota(\{\})$$

$$\iota(\{\text{age}, \text{job}\}) - \iota(\{\text{job}\})$$

$$\iota(\{\text{age}, \text{gender}, \text{income}\}) - \iota(\{\text{gender}, \text{income}\})$$

$$\iota(\{\text{age}, \text{gender}, \text{job}\}) - \iota(\{\text{gender}, \text{job}\})$$

$$\iota(\{\text{age}, \text{gender}\}) - \iota(\{\text{gender}\})$$

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$$\iota(\{\text{age}, \text{gender}, \text{income}, \text{job}\}) - \iota(\{\text{gender}, \text{income}, \text{job}\})$$

[Datta, Sen & Zick, 2016]

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# Aggregating influence across sets

**Idea:** Use game theory methods: voting systems, revenue division

*"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."*

This paper uses the **Shapley value** as the aggregation mechanism

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

[Datta, Sen & Zick, 2016]

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# Aggregating influence across sets

**Idea:** Use game theory methods: voting systems, revenue division

This paper uses the **Shapley value** as the aggregation mechanism

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

$v : 2^N \to \mathbb{R}$ influence of a set of features ***S*** on the outcome

$\varphi_i(N,v)$ influence of feature ***i***, given the set of features ***N*** = {***1***,…, ***n***}

$\sigma \in \Pi(N)$ a permutation over the features in set ***N***

$m_i(\sigma)$ payoff corresponding to this permutation

[Datta, Sen & Zick, 2016]

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# QII summary

- A principled (and beautiful!) framework for determining the influence of a feature, or a set of features, on a decision
- Works for black-box models, with the assumption that the full set of inputs is available
- Accounts for correlations between features
- “Parametrizes” on what quantity we want to set (QII), how we intervene, how we aggregate the influence of a feature across sets
- Experiments in the paper: interesting results
- Also in the paper: a discussion of **transparency under differential privacy**

[Datta, Sen & Zick, 2016]

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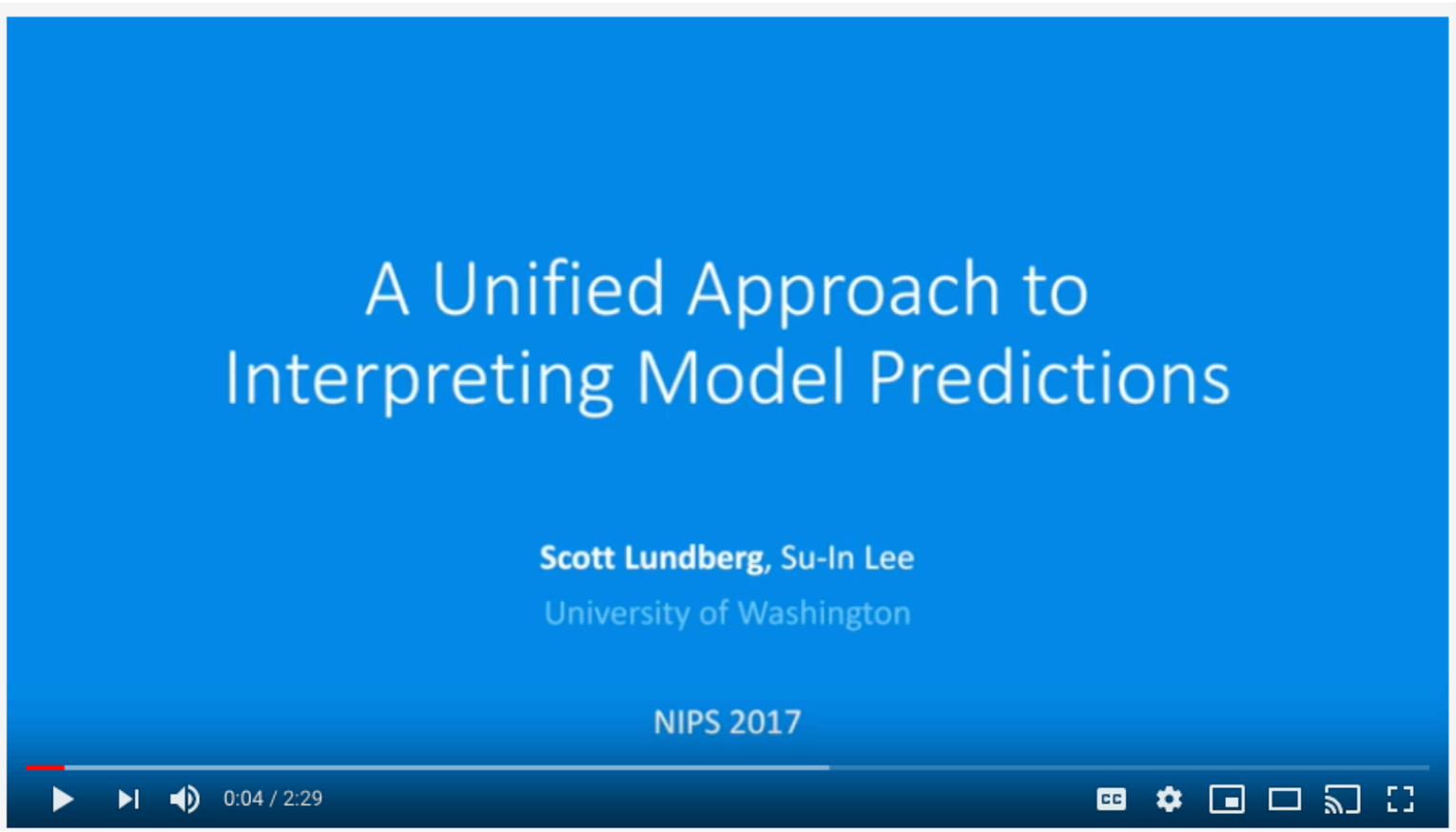
# SHAP: Shapley Additive Explanations

A unifying framework for interpreting predictions with “additive feature attribution methods”, including LIME and QII, for **local explanations**




https://www.youtube.com/watch?v=wjd1G5bu_TY

[Lundberg & Lee, 2017]

# SHAP: Shapley Additive Explanations

A unifying framework for interpreting predictions with "**additive feature attribution methods**", including LIME and QII, for **local explanations**

- The best explanation of a **simple model** is the model itself: the explanation is both accurate and interpretable. For complex models we must use a simpler **explanation model** — an interpretable approximation of the original model.

$$f : \mathbb{R}^d \rightarrow \mathbb{R}$$

**model being explained**

$$g \in G, dom(g) = \{0,1\}^{d'}$$

**explanation model** from a class of interpretable models, over a set of **simplified features**

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

[Lundberg & Lee, 2017]

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# Additive feature attribution methods

**Additive feature attribution methods** have an explanation model that is a linear function of binary variables (simplified features)

$$g(x') = \phi_0 + \sum_{i=1}^{d'} \phi_i x'_i \quad \text{where } x' \in \{0,1\}^{d'}, \text{and } \phi_i \in \mathbb{R}$$

Three properties guarantee a single unique solution — a unique allocation of Shapley values to each feature

1. **Local accuracy**: ***g(x')*** matches the original model ***f(x)*** when ***x'*** is the **simplified input** corresponding to x.

2. **Missingness**: if $x'_i$ — the $i^{th}$ feature of simplified input **x'**— is missing, then it has no attributable impact for ***x***

3. **Consistency** (**monotonicity**): if toggling off feature ***i*** makes a bigger (or the same) difference in model ***f'(x)*** than in model ***f(x)***, then the weight (attribution) of ***i*** should be no lower in ***f'(x)*** than in ***f(x)***

[Lundberg & Lee, 2017]

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# Additive feature attribution methods

README.md

SHAP


https://github.com/slundberg/shap

[Lundberg & Lee, 2017]

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