

Fides: Towards responsible data management

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data RESPONSIBLY

Online price discrimination

THE WALL STREET JOURNAL.

WHAT THEY KNOW

Websites Vary Prices, Deals Based on Users' Information

By JENNIFER VALENTINO-DEVRIES,
JEREMY SINGER-VINE and ASHKAN SOLTANI

December 24, 2012

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.

WHAT PRICE WOULD YOU SEE?



lower prices offered to buyers who live in more affluent neighborhoods

<https://www.wsj.com/articles/SB10001424127887323777204578189391813881534>

Online job ads

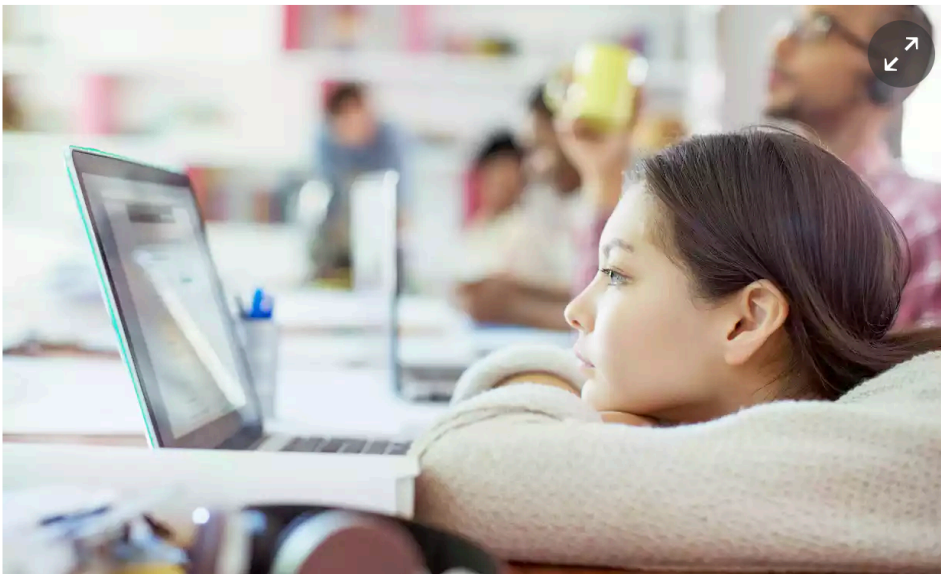
theguardian

Samuel Gibbs

Wednesday 8 July 2015 11.29 BST

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

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

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>

Job-screening personality tests

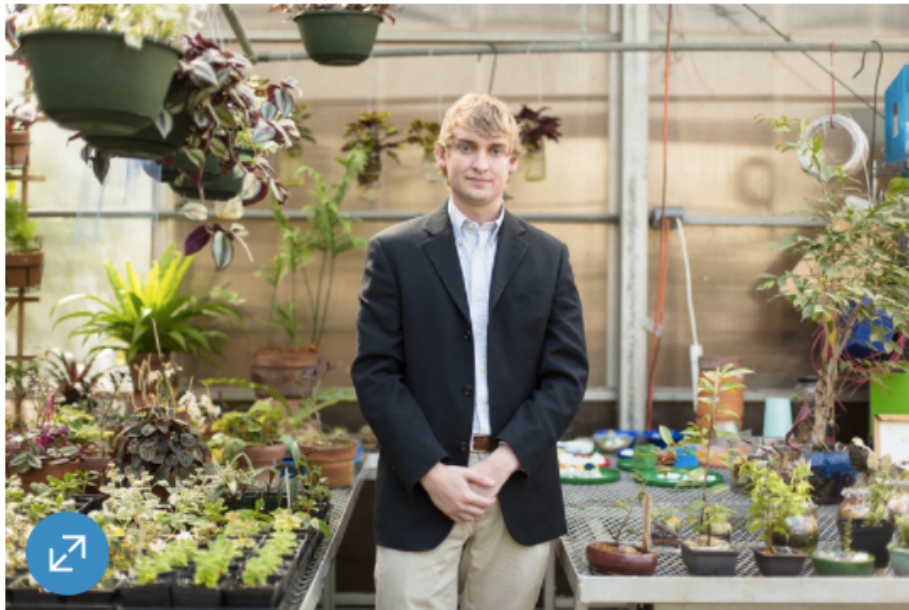
THE WALL STREET JOURNAL.

By **LAUREN WEBER** and **ELIZABETH DWOSKIN**

Sept. 29, 2014 10:30 p.m. ET

Are Workplace Personality Tests Fair?

Growing Use of Tests Sparks Scrutiny Amid Questions of Effectiveness and Workplace Discrimination



Kyle Behm accused Kroger and six other companies of discrimination against the mentally ill through their use of personality tests. *TROY STAINS FOR THE WALL STREET JOURNAL*

The Equal Employment Opportunity commission is **investigating whether personality tests discriminate against people with disabilities.**

As part of the investigation, officials are trying to determine if the tests **shut out people suffering from mental illnesses** such as depression or bipolar disorder, even if they have the right skills for the job.

<http://www.wsj.com/articles/are-workplace-personality-tests-fair-1412044257>

Racial bias in criminal sentencing

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

May 23, 2016



A commercial tool COMPAS automatically predicts some categories of future crime to assist in bail and sentencing decisions. It is used in courts in the US.

The tool correctly predicts recidivism **61% of the time.**

Blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend.

The tool makes **the opposite mistake among whites:** They are much more likely than blacks to be labeled lower risk but go on to commit other crimes.

<https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing>

Lack of diversity in data and methods

The New York Times

Artificial Intelligence's White Guy Problem

By KATE CRAWFORD JUNE 25, 2016



Like all technologies before it, artificial intelligence will reflect the values of its creators. So **inclusivity matters** — from who designs it to who sits on the company boards and which ethical perspectives are included.

Otherwise, **we risk constructing machine intelligence that mirrors a narrow and privileged vision of society**, with its old, familiar biases and stereotypes.

<http://www.nytimes.com/2016/06/26/opinion/sunday/artificial-intelligences-white-guy-problem.html>

Mayor de Blasio Scrambles to Curb Homelessness After Years of Not Keeping Pace

By J. DAVID GOODMAN and NIKITA STEWART JAN. 13, 2017



Volunteers during the homeless census in February 2015. In a decision made by Mayor Bill de Blasio, New York City stopped opening shelters for much of that year. Stephanie Keith for The New York Times

The New York Times

<https://www.nytimes.com/2017/01/13/nyregion/mayor-de-blasio-scrambles-to-curb-homelessness-after-years-of-not-keeping-pace.html>

Ms. Glen emphasized that the construction of new housing takes several years, a long-term solution whose effect on homelessness could not yet be evaluated.

Homeless Young People of New York, Overlooked and Underserved

By NIKITA STEWART FEB. 5, 2016



Abdul, 23, at Safe Horizon in Harlem, has been homeless since 2010. Jake Naughto

The New York Times

<https://www.nytimes.com/2016/02/06/nyregion/young-and-homeless-in-new-york-overlooked-and-underserved.html>

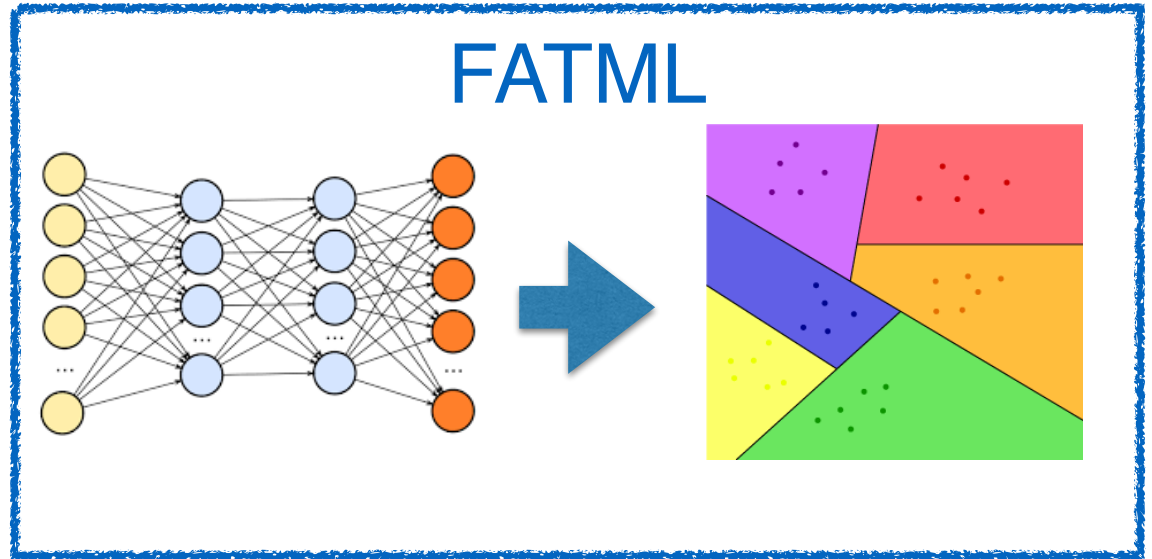
Last year, the total number of sheltered and unsheltered homeless people in the city was 75,323, which included 1,706 people between ages 18 and 24. The actual number of young people is significantly higher, according to the service providers, who said the census mostly captured young people who received social services. The census takers were not allowed to enter private businesses, including many of the late-night spots where young people often create an ad hoc shelter by pretending to be customers.

Ending urban homelessness

- A variety of **services**: rapid rehousing, transitional housing, emergency shelter, permanent supportive housing
- A variety of **support mechanisms**: substance abuse treatment, mental health treatment, protection for victims of domestic violence
- Challenges
 - **recommend** pathways through the system
 - **evaluate** effectiveness of interventions
 - **measure** performance of the coordinated system of homeless assistance

Piece of cake!

#	A	B	C	D	E	F	G	H	
1	UID	sex	race	MarriageSta	DateOfBirth	age	juv fel	cour decile	score
2	1	0	1	1	4/18/47	69	0	1	
3	2	0	2	1	1/22/82	34	0	3	
4	3	0	2	1	5/14/91	24	0	4	
5	4	0	2	1	1/21/93	23	0	8	
6	5	0	1	2	1/22/73	43	0	1	
7	6	0	1	3	8/22/71	44	0	1	
8	7	0	3	1	7/23/74	41	0	6	
9	8	0	1	2	2/25/73	43	0	4	
10	9	0	3	1	6/10/94	21	0	3	
11	10	0	3	1	6/1/88	27	0	4	
12	11	1	3	2	8/22/78	37	0	1	
13	12	0	2	1	12/2/74	41	0	4	
14	13	1	3	1	6/14/68	47	0	1	
15	14	0	2	1	3/25/85	31	0	3	
16	15	0	4	4	1/25/79	37	0	1	
17	16	0	2	1	6/22/90	25	0	10	
18	17	0	3	1	12/24/84	31	0	5	
19	18	0	3	1	1/8/85	31	0	3	
20	19	0	2	3	6/28/51	64	0	6	
21	20	0	2	1	11/29/94	21	0	9	
22	21	0	3	1	8/6/88	27	0	2	
23	22	1	3	1	3/22/95	21	0	4	
24	23	0	4	1	1/23/92	24	0	4	
25	24	0	3	3	1/10/73	43	0	1	
26	25	0	1	1	8/24/83	32	0	3	
27	26	0	2	1	2/8/89	27	0	3	
28	27	1	3	1	9/3/79	36	0	3	
...	



done?

goal: responsible data science

Data, Responsibly

fairness



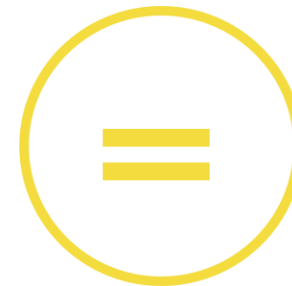
diversity



data protection

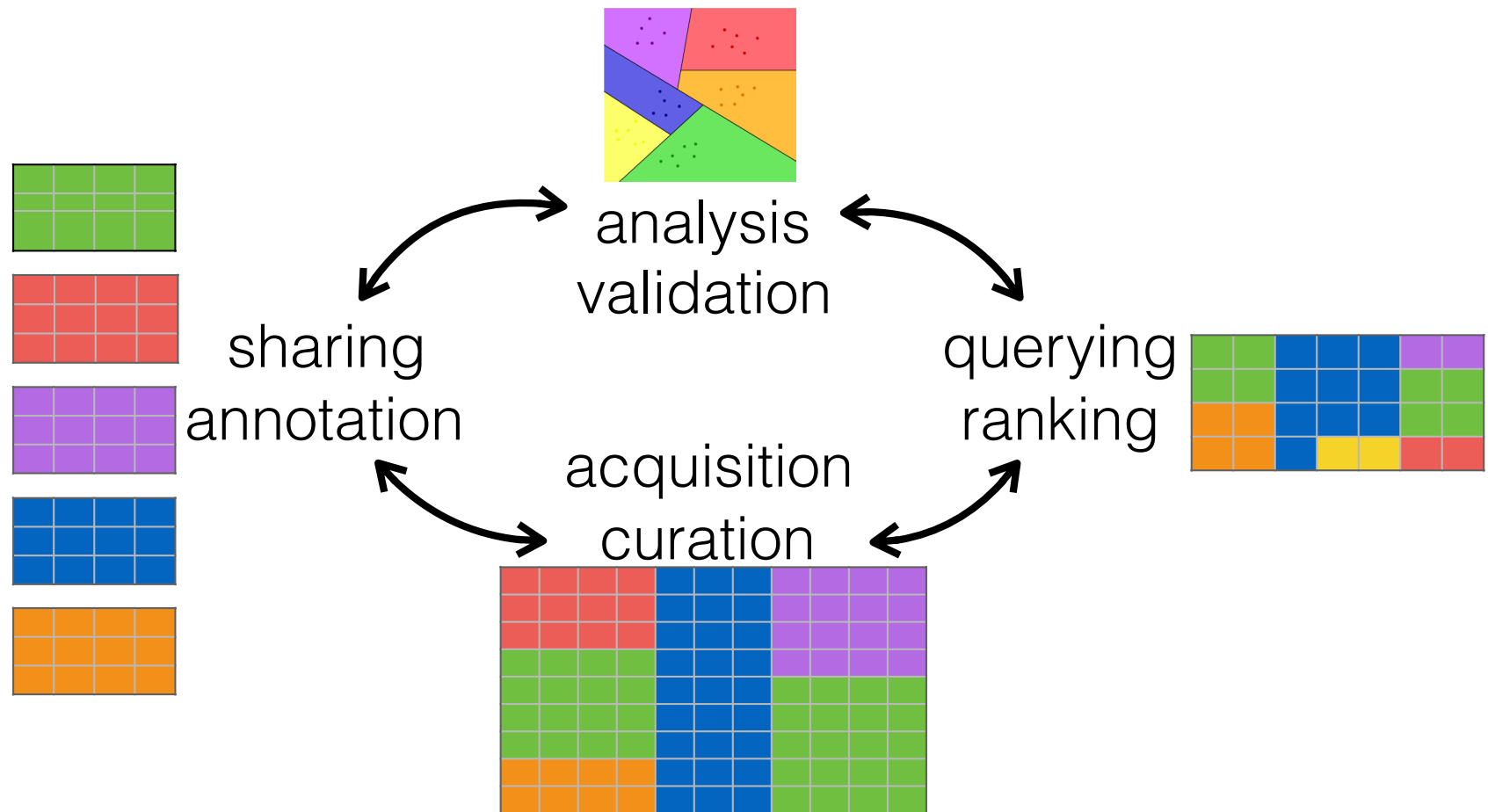


transparency



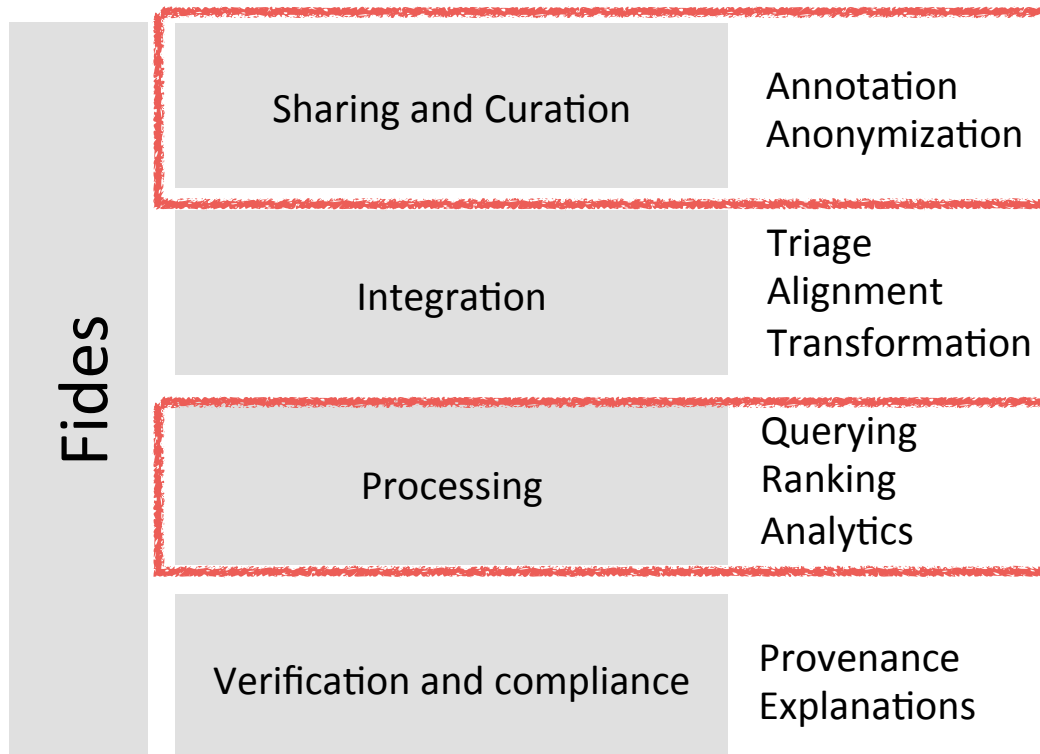
neutrality

Data science lifecycle



responsible data science starts with responsible data collection, sharing, integration, querying, ranking - with **responsible data management!**

Systems support for responsible data science



Fides: A responsible data science platform.

Responsibility by design, managed at all stages of the lifecycle of data-intensive applications.

Application: DS for social good / urban homelessness

key point: holistic view of the lifecycle, information about both data and process, allow us to do much more!

DataSynthesizer (demo)

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Julia Stoyanovich
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Bill Howe
University of Washington



data RESPONSIBLY

Privacy-preserving synthetic data



input

id	sex	race	MarriageStatus	DaysOfWeek	age	no.	no.	no.
1	1	0	1	1	45/3/47	49	0	1
2	2	0	2	1	1/2/9/2	34	0	3
3	3	0	2	1	1/2/4/9/2	24	0	4
4	4	0	2	1	1/2/1/9/2	23	0	8
5	4	0	1	2	1/2/2/7/3	43	0	1
6	5	0	1	3	4/2/2/7/1	44	0	1
7	6	0	1	3	4/2/2/7/1	44	0	1
8	7	0	1	3	1/2/2/7/4	41	0	6
9	8	0	1	2	2/2/5/7/3	43	0	4
10	9	0	3	1	4/2/5/9/4	21	0	3
11	10	0	3	1	4/2/5/9/4	27	0	4
12	11	1	3	2	4/2/5/7/8	37	0	1
13	12	0	2	1	1/2/2/7/4	41	0	4
14	13	1	3	1	4/2/4/8/8	47	0	1
15	14	0	2	1	1/2/5/9/1	31	0	3
16	15	0	4	4	1/2/5/7/9	37	0	10
17	16	0	2	1	4/2/2/9/2	25	0	10
18	17	0	3	1	1/2/4/8/4	31	0	5
19	18	0	3	1	1/2/8/5	31	0	9
20	19	0	2	3	4/2/8/1	44	0	6
21	20	0	3	1	1/2/2/9/4	21	0	6
22	21	0	3	1	4/2/8/8	27	0	2
23	22	1	3	1	1/2/2/9/1	27	0	4
24	23	0	4	1	1/2/5/9/2	24	0	4
25	24	0	3	3	1/2/2/7/1	43	0	1
26	25	0	1	1	4/2/4/8/3	32	0	3
27	26	0	2	1	2/3/8/9	27	0	3
28	27	1	3	1	4/2/7/9	36	0	3

Data
Describer



summary

age	int	min=23	32%	40
		max=60	mis	0
name	str	length	no	
		10 to 98	mis	
sex	str	cat	10%	60
			mis	0

Data
Generator



output

id	sex	race	MarriageStatus	DaysOfWeek	age	no.	no.	no.
1	1	0	1	1	41/4/47	49	0	1
2	2	0	2	1	1/2/2/9/2	34	0	3
3	3	0	2	1	1/2/4/9/2	24	0	4
4	4	0	2	1	1/2/1/9/2	23	0	8
5	4	0	1	2	1/2/2/7/3	43	0	1
6	5	0	1	3	4/2/2/7/1	44	0	1
7	6	0	1	3	1/2/2/7/4	41	0	6
8	7	0	1	2	2/2/5/7/3	43	0	4
9	8	0	3	1	4/2/5/9/4	21	0	3
10	9	0	3	1	4/2/5/9/4	27	0	4
11	10	1	3	2	4/2/5/7/8	37	0	1
12	11	1	3	1	1/2/2/7/4	41	0	4
13	12	0	2	1	4/2/4/8/8	47	0	1
14	13	0	3	1	1/2/5/9/1	31	0	3
15	14	0	4	4	1/2/5/7/9	37	0	10
16	15	0	2	1	4/2/2/9/2	25	0	10
17	16	0	3	1	1/2/4/8/4	31	0	5
18	17	0	3	1	1/2/8/5	31	0	9
19	18	0	2	3	4/2/8/1	44	0	6
20	19	0	3	1	1/2/2/9/4	21	0	6
21	20	0	3	1	1/2/2/9/1	27	0	2
22	21	1	3	1	1/2/2/9/5	24	0	4
23	22	0	4	1	1/2/5/9/2	24	0	4
24	23	0	3	3	1/2/2/7/1	43	0	1
25	24	0	1	1	4/2/4/8/3	32	0	3
26	25	0	2	1	2/3/8/9	27	0	3
27	26	1	3	1	4/2/7/9	36	0	3

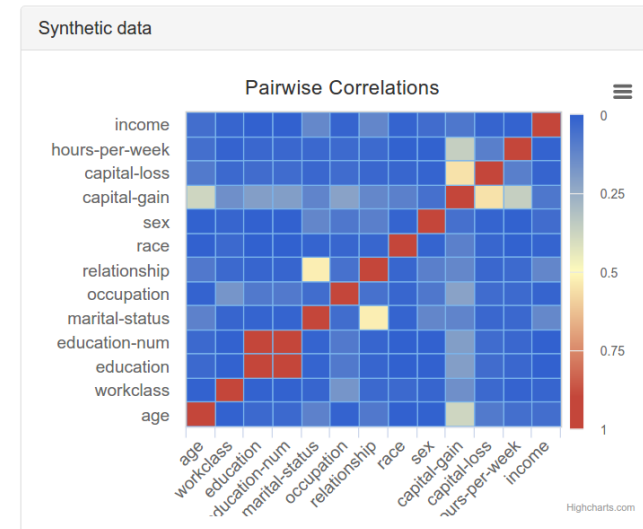
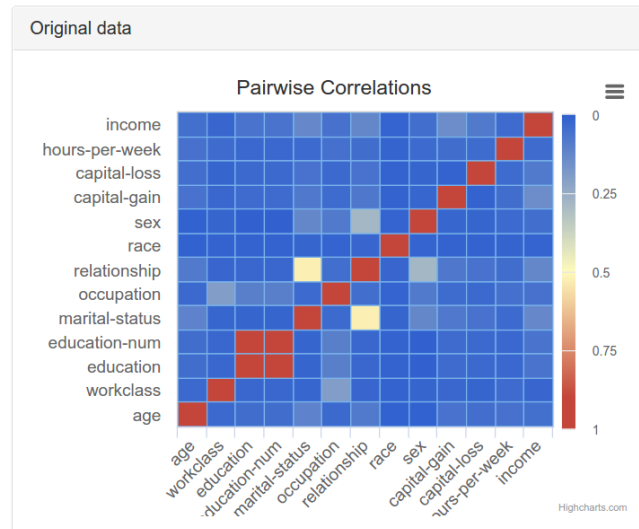
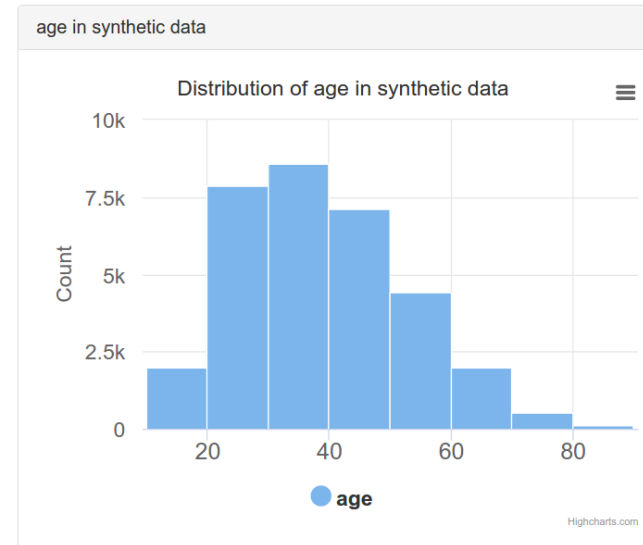
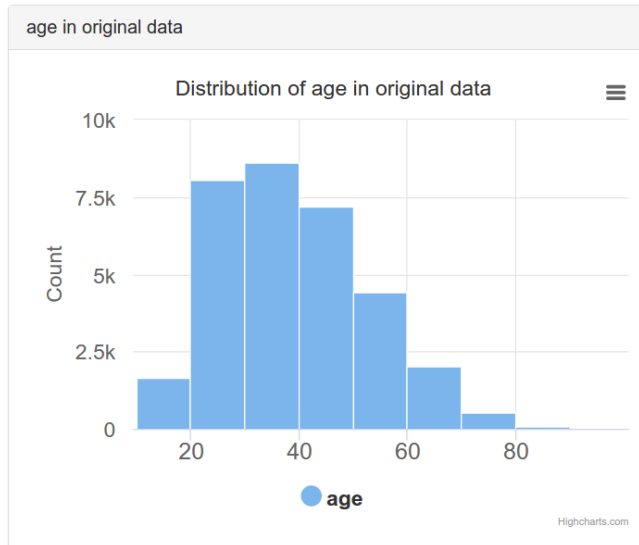
Model
Inspector



comparison

	before	after
age	int min=23 32% max=60 mis	int min=23 32% max=60 mis
name	str length 10 to 98 no mis	str length 10 to 98 no mis
sex	str cat 10% mis	str cat 10% mis

Privacy-preserving synthetic data



Measuring fairness in ranked outputs (poster)

Ke Yang
Drexel University

Julia Stoyanovich
Drexel University



data *RESPONSIBLY*

Fairness in classification

Group fairness (aka **statistical parity**)

demographics of the individuals receiving any outcome are the same as demographics of the underlying population



Fairness in ranking

Input: database of items (individuals, colleges, cars, ...)

Score-based ranker: computes the score of each item using a known formula, e.g., monotone aggregation, then sorts items on score

Output: permutation of the items (complete or top-k)

id	sex	race	age	cat
a	F	W	25	T
b	F	B	23	S
c	M	W	27	T
d	M	B	45	S
e	M	W	60	U



ranker



What is a positive outcome in a ranking?

idea: rankings are relative, fairness measures should be rank-aware

Thank you!



data *RESPONSIBLY*