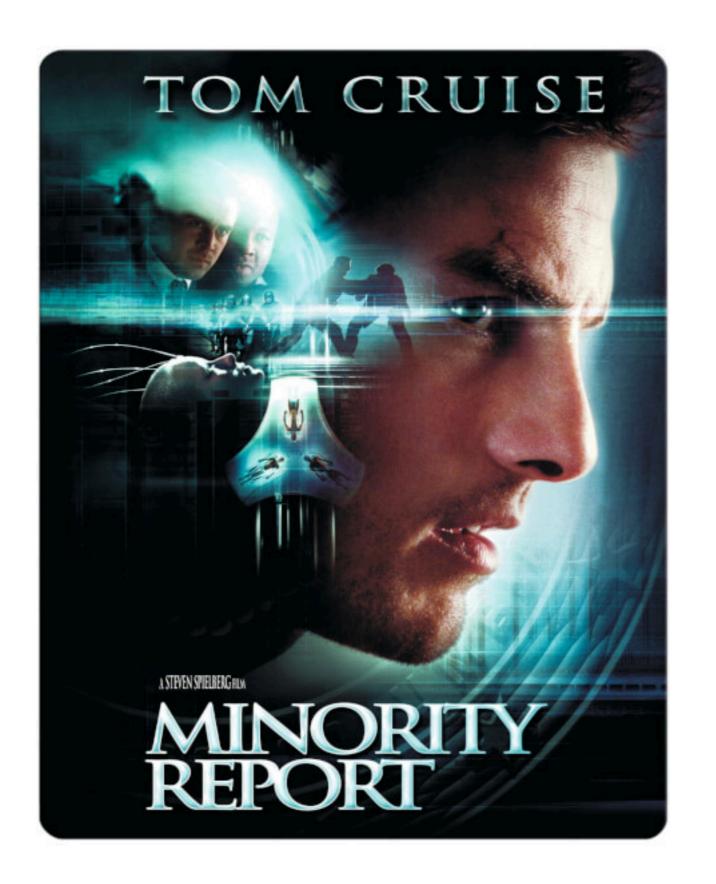
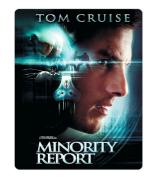
CS 520

Theory and Practice of Software Engineering Fall 2019

Software Fairness

September 5, 2019





Resilient cities Cities

Predicting crime, LAPD-style

Cutting edge data-driven analysis directs Los Angeles patrol officers to likely future crime scenes - but critics worry that decision-making by machine will bring 'tyranny of the algorithm'

• Join our live Q&A with Homicide Watch this Friday



▲ PredPol co-developer P Jeffrey Brantingham at the Unified Command Post in Los Angeles. 'This is not Minority Report,' he said. Photograph: Damian Dovarganes/AP



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- Toshiba Fights to Clear Way for Chip-Unit Sale

U.S. Politics Economy



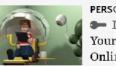
Samsung's Bixby Delayed as It Struggles With

Business Tech Markets Opinion Arts



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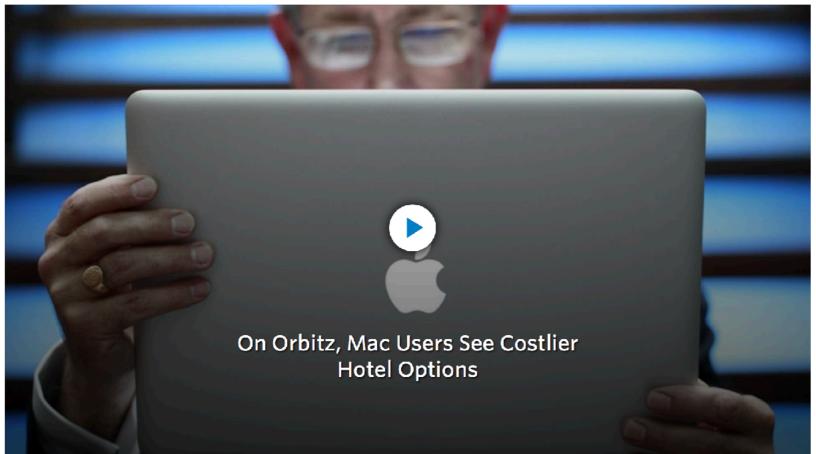




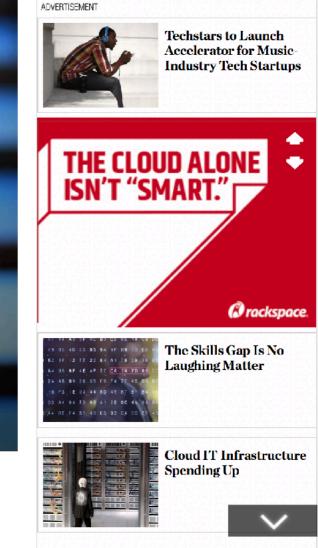




On Orbitz, Mac Users Steered to Pricier Hotels



Orbitz has found that Apple users spend as much as 30% more a night on hotels, so the online travel site is starting to show them different, and sometimes costlier, options than Windows visitors see. Dana Mattioli has details on The News Hub. Photo: Bloomberg.



b

The Algorithm That Beats Your Bank Manager

HAAS NEWS > NEWS CATEGORIES > RESEARCH NEWS

Minority homebuyers face widespread statistical lending discrimination, study finds

16,947 @

By Laura Counts NOVEMBER 13, 2018

Face-to-face meetings between mortgage officers and homebuyers have been rapidly replaced by online applications and algorithms, but lending discrimination hasn't gone away.

A new University of California, Berkeley study has found that both online and face-to-face lenders charge ıt higher interest rates to African American and Latino borrowers, earning 11 to 17 percent higher profits on such loans. All told, those homebuyers pay up to half a billion dollars more in interest every year than white LS borrowers with comparable credit scores do, researchers found.

The findings raise legal questions about the rise of statistical discrimination in the fintech era, and point to potentially widespread violations of U.S. fair lending laws, the researchers say. While lending discrimination 1 has historically been caused by human prejudice, pricing disparities are increasingly the result of algorithms that use machine learning to target applicants who might shop around less for higher-priced loans.

"The mode of lending discrimination has shifted from human bias to algorithmic bias," said study co-author Adair Morse, a finance professor at UC Berkeley's Haas School of Business. "Even if the people writing the

Wisconsin Supreme Court allows state to continue using computer program to assist in sentencing

KATELYN FERRAL | The Capital Times | kferral@madison.com | @katelynferral | Jul 13, 2016











Machine Bias

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

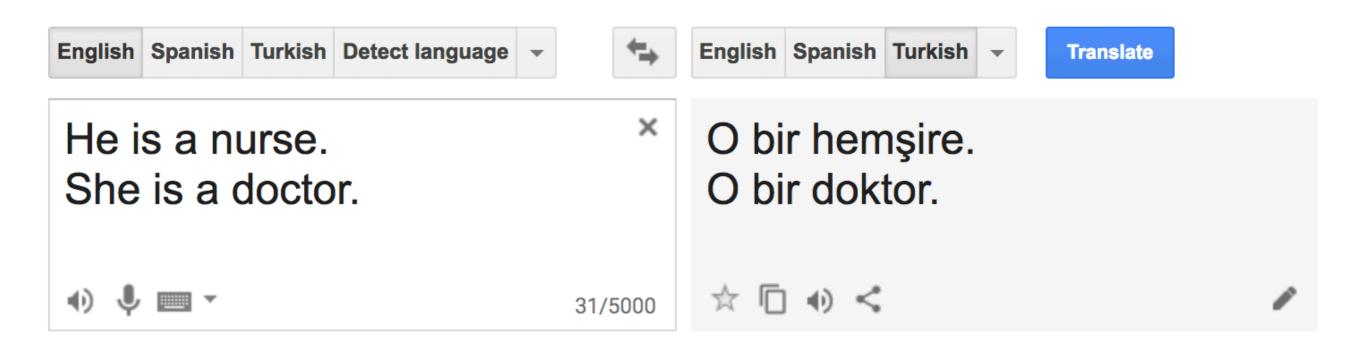
by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

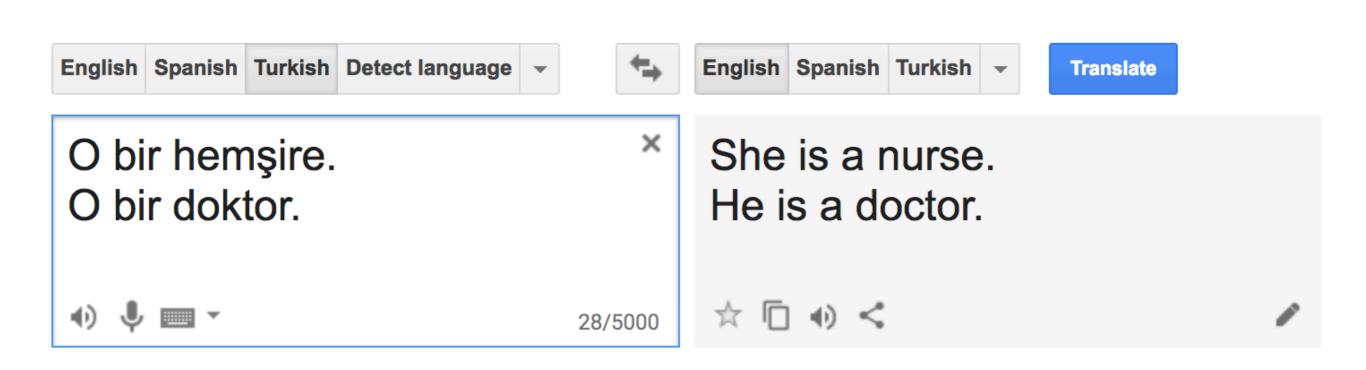
May 23, 2016

Software can make bad decisions. Software can discriminate!

Just as the 18-year-old girls were realizing they were too big for the tiny conveyances — which belonged to a 6-year-old boy — a woman came running after them saying, "That's my kid's stuff." Borden and her friend immediately dropped the bike and scooter and walked away.

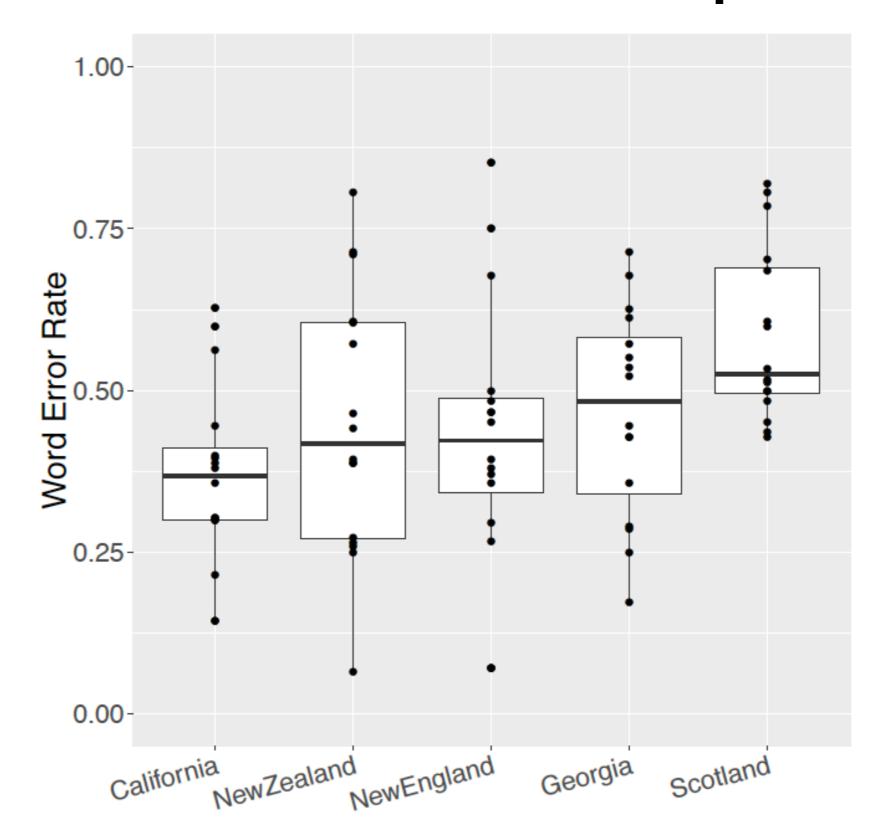
But it was too late — a neighbor who witnessed the heist had already called the police. Borden and her friend were arrested and charged with burglary and petty theft for the items, which were valued at a total of \$80.



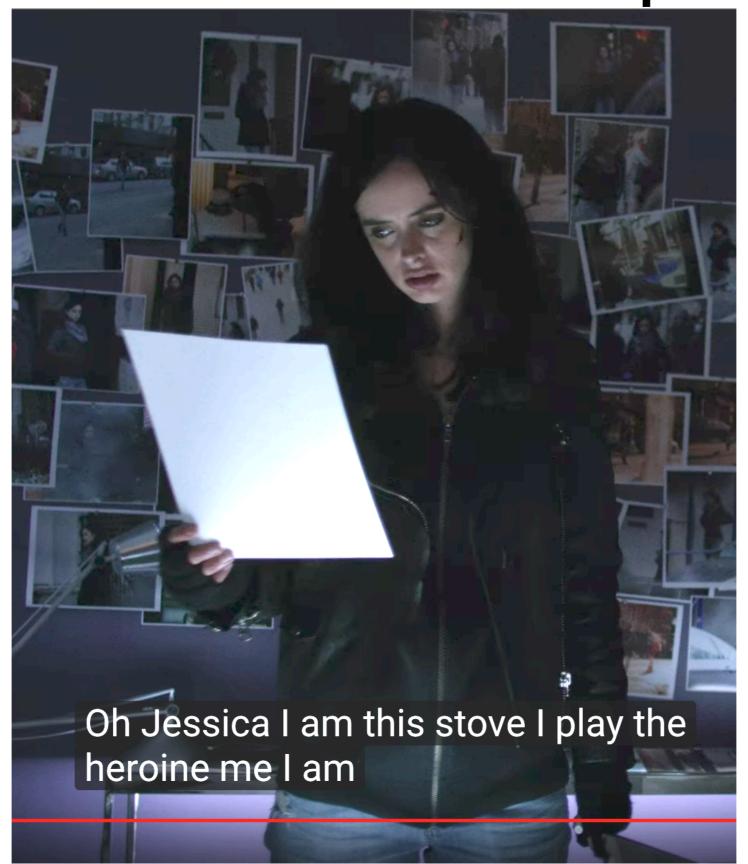


You Tube

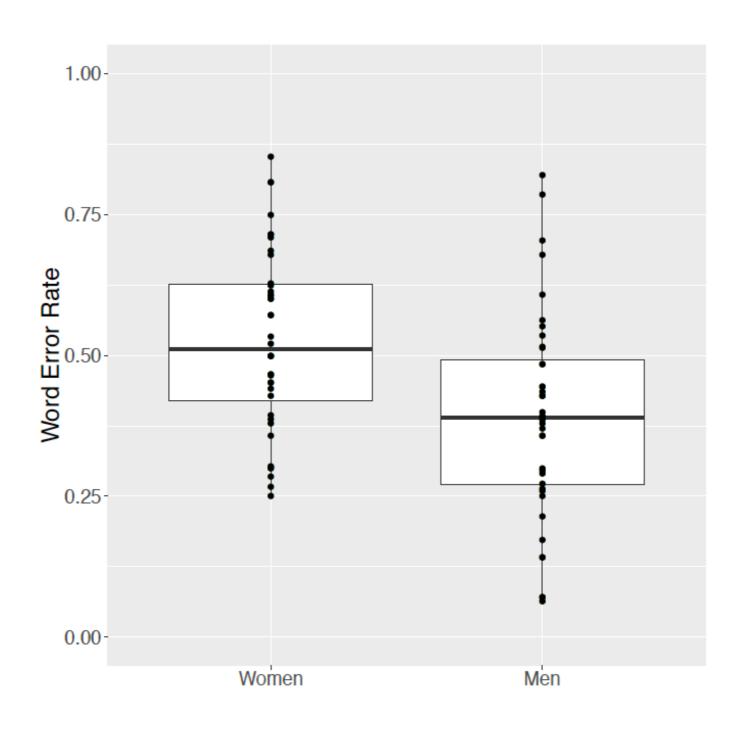
YouTube automatic captions



YouTube automatic captions



YouTube automatic captions





how people want to use vision software



how people want to use vision software

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today's goals

Define software discrimination.

Operationalize measuring discrimination through causal software testing.

Provide provable fairness guarantees.

Design software to be fair

2011 11th IEEE International Conference on Data Mining

Handling Conditional Discrimination

Bournemouth University, UK

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[stat.ML]

arXiv:1507.05259v5

TU Eindhoven, the Netherlands f.kamiran@tue.nl

TU Eindhoven, the Netherland t.calders@tue.nl

Fairness Constraints: Mechanisms for Fair Classification

Muhammad Bilal Zafar, Isabel Valer

Abstract

Algorithmic decision making systems ubiquitous across a wide variety of online well as offline services. These systems rely complex learning methods and vast amoun of data to optimize the service functionality satisfaction of the end user and profitab ity. However, there is a growing concern th these automated decisions can lead even the absence of intent, to a lack of fairner hurt (or, benefit) particular gro ple sharing one or more ser (e.g., race, sex). In this pa a flexible mechanism to by leveraging a novel i cision boundary (un) this mechanism with fiers, logistic regress machines, and show our mechanism allow trol on the degree of cost in terms of accur A Python implemen

1 INTRODUCTI

is available at fate-c

Algorithmic decision mak becoming automated and (e.g., spam filtering, prod as offline (e.g., pretrial ris provals) settings. Howeve sis replaces human superv the scale of the analyzed of growing concerns from ci 2016, governments Podes 2016, and researchers Sw loss of transparency, acco

Proceedings of the 20th Inte cial Intelligence and Statistic erdale, Florida, USA, JMI right 2017 by the author(s

Toon Calders , Faisal Kam Eindhoven University t.calders, f.kamin

with Prejudice Remover Regularizer

Building Classifiers with Independency Constraints

stract. 150 word abstract:

Fairness-aware Classifier

Toshihiro Kamishima¹, Shotaro Akaho¹, Hideki Asoh¹, and Jun Saku

Discrimination Aware Decision Tree Learning

Faisal Kamiran, Toon Calders and Mykola Pechenizkiy Email: {f.kamiran,t.calders,m.pechenizkiy}@tue.nl Eindhoven University of Technology, The Netherlands

 $\label{eq:Abstract} \textbf{--Recently, the following discrimination aware classification problem was introduced: given a labeled dataset and an attribute B, find a classifier with high predictive accuracy$

It can be argued that in many real-life cases discrimination can be explained; e.g., it may very well be that females in an employment dataset overall have less years of working

e, justifying a correlation between the gender and abel. Nevertheless, in this paper we assume this not ase. We assume that the data is already divided up based on acceptable explanatory attributes. Within gender discrimination can no longer be justified. wn in previous works [7], [3], simply removing ve attribute from the training data does not work, attributes may be correlated with the suppressed was observed that classifiers tend to pick up

Learning Fair Representations

Richard Zemel Yu (Ledell) Wu Toniann Pitass

University of Toronto, 10 King's College Rd., Toron

Cynthia Dwork

Microsoft Research, 1065 La Avenida Mountain Vie

We propose a learning algorithm for fair classification that achieves both group fairness (the proportion of members in a protected

2012 IEEE 12th International Conference on Data Mining

Decision Theory for Discrimination-aware Classification

Faisal Kamiran*, Asim Karim†, and Xiangliang Zhang* *King Abdullah University of Science and Technology (KAUST), The Kingdom of Saudi Arabia Email: faisal.kamiran, xiangliang.zhang@kaust.edu.sa Lahore University of Management Sciences, Pakistan Email: akarim@lums.edu.nk

Typically machine learning systems:

- Balance training sets
- Introduce training noise
- Constrain regression's loss function
- Split criteria on sensitive inputs

eds to be processed again. Being restricted to n-aware classifier (e.g., naive Bayes ee [2]) is also an issue because that classifier est performing classifier for a given dataset. we propose two flexible and easy-to-use imination-aware classification based on hesis: discriminatory decisions are often e decision boundary because of decision implement this hypothesis via decision of prediction confidence and ensemble first solution, called Reject Option based ensemble of probabilistic classifiers for ction. More specifically, ROC invokes and labels instances belonging to deprived s in a manner that reduces discrimination on, called Discrimination-Aware Ensemble the disagreement region of a classifier pel deprived and favored group instances ation. Our proposed solutions have fol over existing discrimination-aware clas-

are not restricted to a particular clasrst solution works with any probabilistic hile our second solution works with gen

require neither modification of learnin or preprocessing of historical data - pre on time. Thus, the change in the sensitive be handled easily by decision makers. as give better control and interpretability of n-aware classification to decision makers. tensive experimental evaluation of our world datasets. The results demonstrate discrimination and superior accuracy de-off, when compared to existing sate

II. RELATED WORK

edreschi et al. [3], [4], focusing on discover-

© computer society

Design alone is not enough

possible causes







unintended interactions and mismatched components



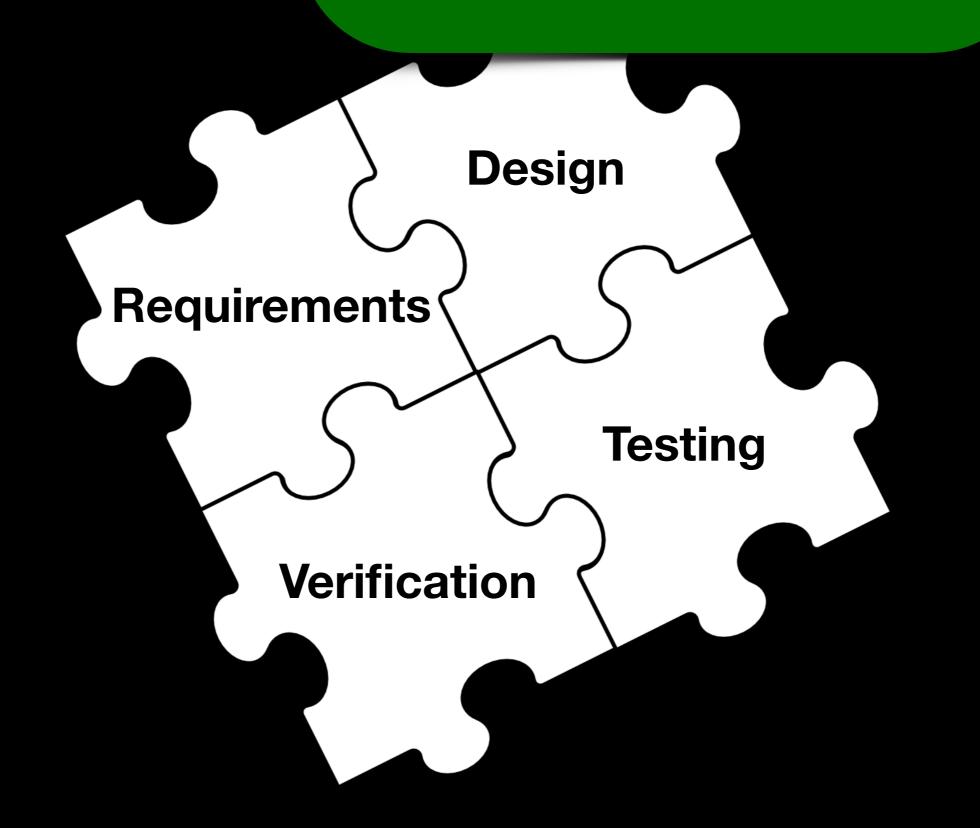
poor design

Fairness is just like quality and security

Fairness must be part of the software engineering lifecycle

Call to Action!

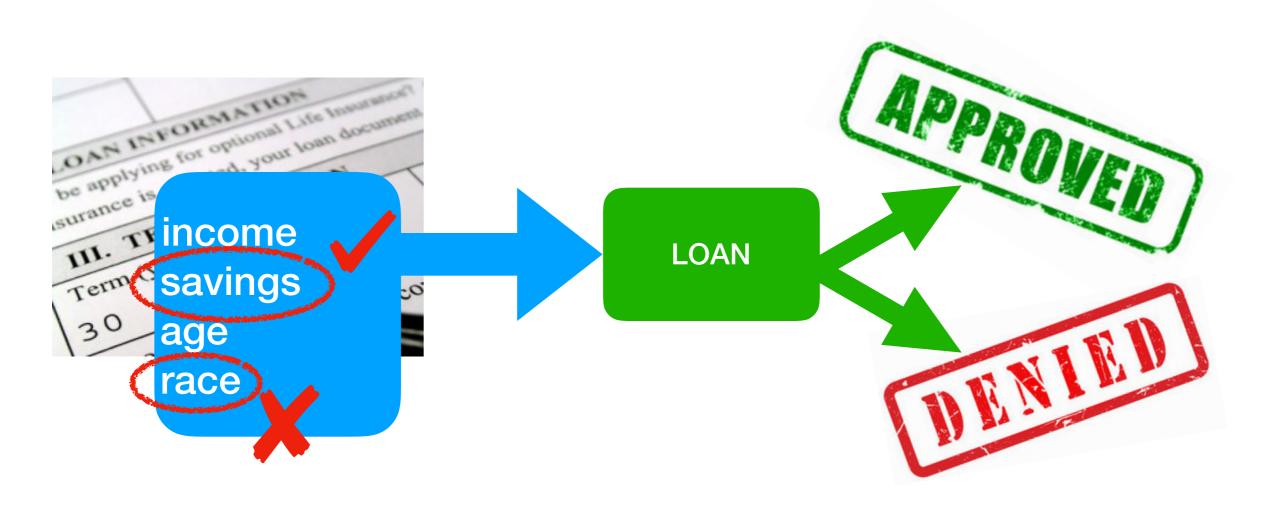
Fairness must be part of the software engineering lifecycle



Let's talk about requirements.

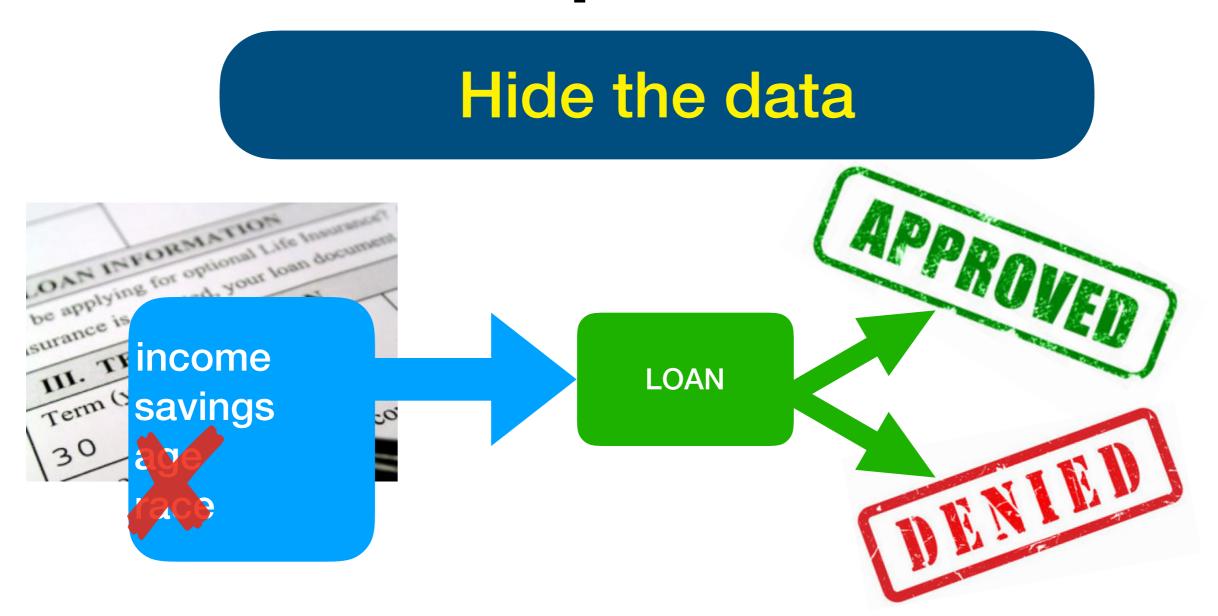
What does it mean for software to discriminate?

LOAN program



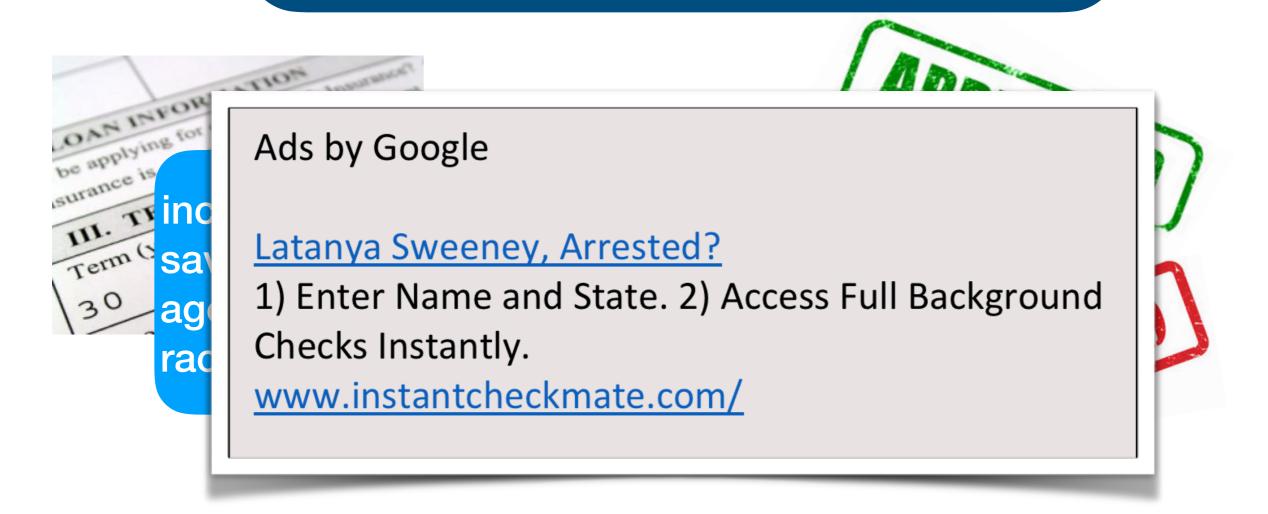
This talk is not about policy.

Fairness: Disparate Treatment



Fairness: Disparate Treatment

Hide the data



Ineffective because of data correlation.

[Latanya Sweeney. Discrimination in online ad delivery. CACM 2013]

1 1 1

\equiv Business Insider

Amazon just showed us that 'unbiased' algorithms can be inadvertently racist



f FACEBOOK in LINKEDIN

A Bloomberg report
Thursday revealed that
Amazon's same-day
delivery service offered to
Prime users around
major US cities seems to
routinely, if
unintentionally, exclude
black neighborhoods.

The maps, which you should check out on Bloomberg's site, show that in cities like Chicago, New York, and Atlanta, same-day code at this point — except the maps, which you Should check out on Chi Bloomberg's site, show that in cities like Chicago,

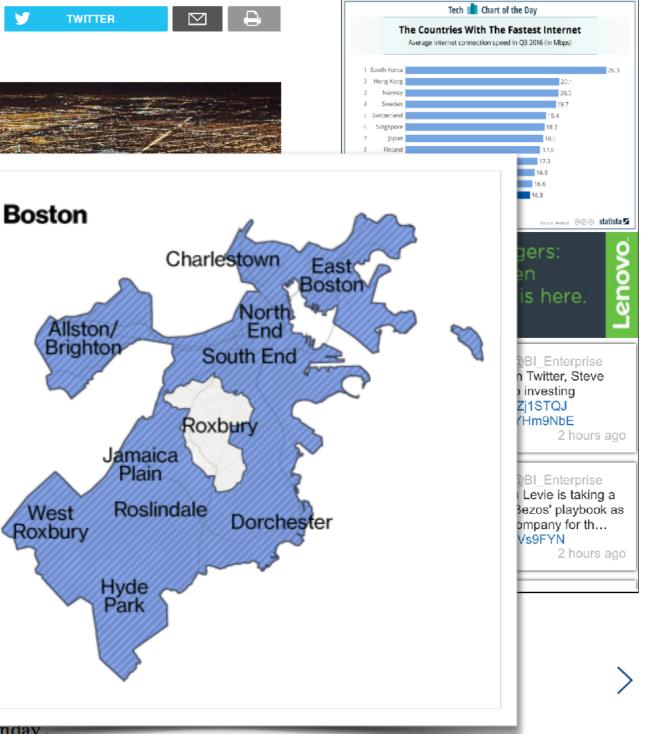
But the thing is that Amazon's de of PR Scott Stanzel wrote in an e

There are a number of factor deliver same-day. Those includenter, local demand in an ararea, as well as the ability of to 9:00 pm every single day, even Sunday

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'None of it makes much sense': Experts are baffled by Comey's use of a fake Russian document to skirt the DOJ



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Amazon built an AI tool to hire people but had to shut it down because it was discriminating against women

Isobel Asher Hamilton 4h

- Amazon tried building an artificial-intelligence tool to help with recruiting, but it showed a bias against women, Reuters reports.
- Engineers reportedly found the AI was unfavorable toward female candidates because it had combed through maledominated résumés to accrue its data.
- Amazon reportedly abandoned the project at the beginning of 2017.



Amazon wo

disparate treatment: still not fair

Fairness: Demographic Parity

Compare subpopulation proportions



Fails to identify discrimination against individuals.

How group discrimination can fail

Europe Asia

Asia

approve loans to all green deny loans to all purple applicants

approve loans to all **purple** deny loans to all **green** applicants

European and Asian discriminations cancel each other out, and the group discrimination measure can be 0.

Fairness: Disparate Impact

Prohibits using a facially neutral practice that has an unjustified adverse impact on members of a protected class.

80% rule: Employer's hiring rates for protected groups may not differ by more than 80%.

Fairness: Delayed Impact

Making seemingly fair decisions can (but shouldn't), in the long term, produce unfair consequences

Liu et al., Delayed impact of fair machine learning. ICML 2018

Fairness: Predictive Equality

False positive rates should not differ

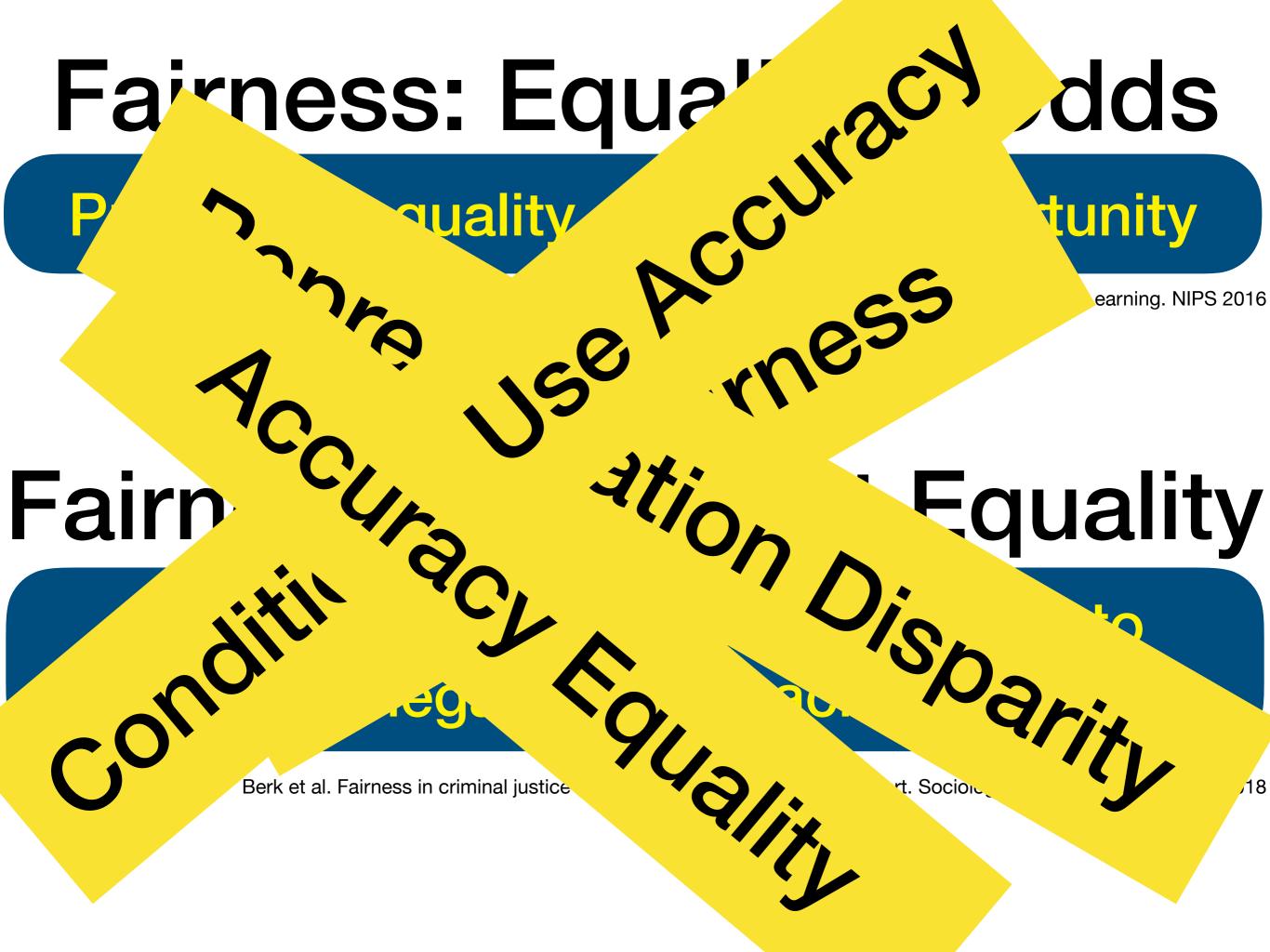
Chouldechova. Fair prediction with disparate impact: A study of bias in recidivism prediction instruments. FATML 2016
Corbett-Davies. Algorithmic decision making and the cost of fairness. KDD 2017

Fairness: Equal Opportunity

False negative rates should not differ

Hardt et al. Equality of Opportunity in Supervised Learning. NIPS 2016

Chouldechova. Fair prediction with disparate impact: A study of bias in recidivism prediction instruments FATML 2016



HOW STANDARDS PROLIFERATE: (SEE: A/C CHARGERS, CHARACTER ENCODINGS, INSTANT MESSAGING, ETC.)

SITUATION: THERE ARE 14 COMPETING STANDARDS.

14?! RIDICULOUS! WE NEED TO DEVELOP ONE UNIVERSAL STANDARD THAT COVERS EVERYONE'S USE CASES. YEAH!

SOON:

SITUATION: THERE ARE 15 COMPETING STANDARDS.

Fairness: Correlation

Correlation does not measure causation

What is fairness?

Sensitive inputs should not affect software behavior.

We want to measure causality!

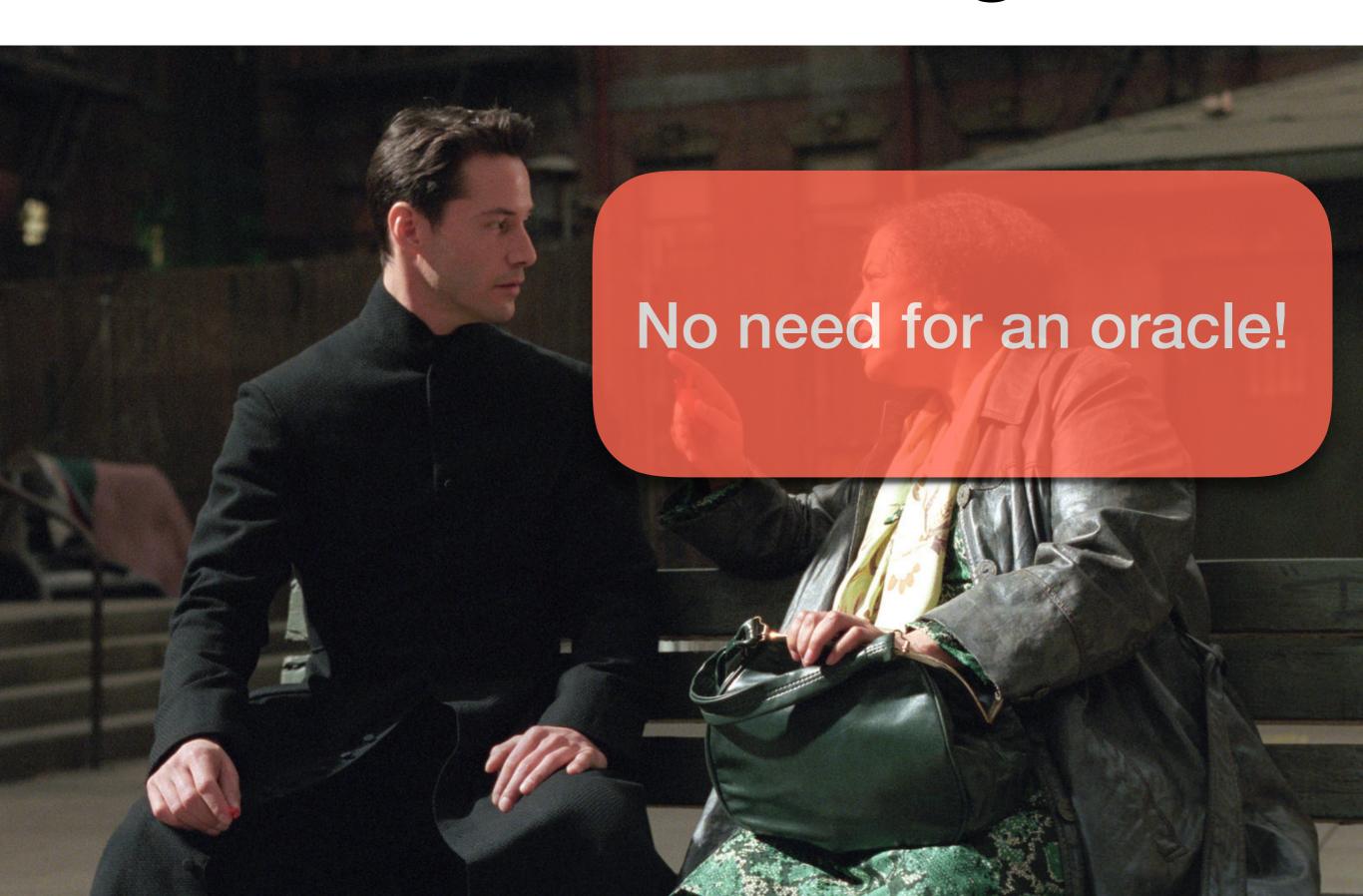
causal testing

Sensitive inputs should not affect software behavior.

hypc testing:



causal testing



causal testing



Themis

automated test-suite generator



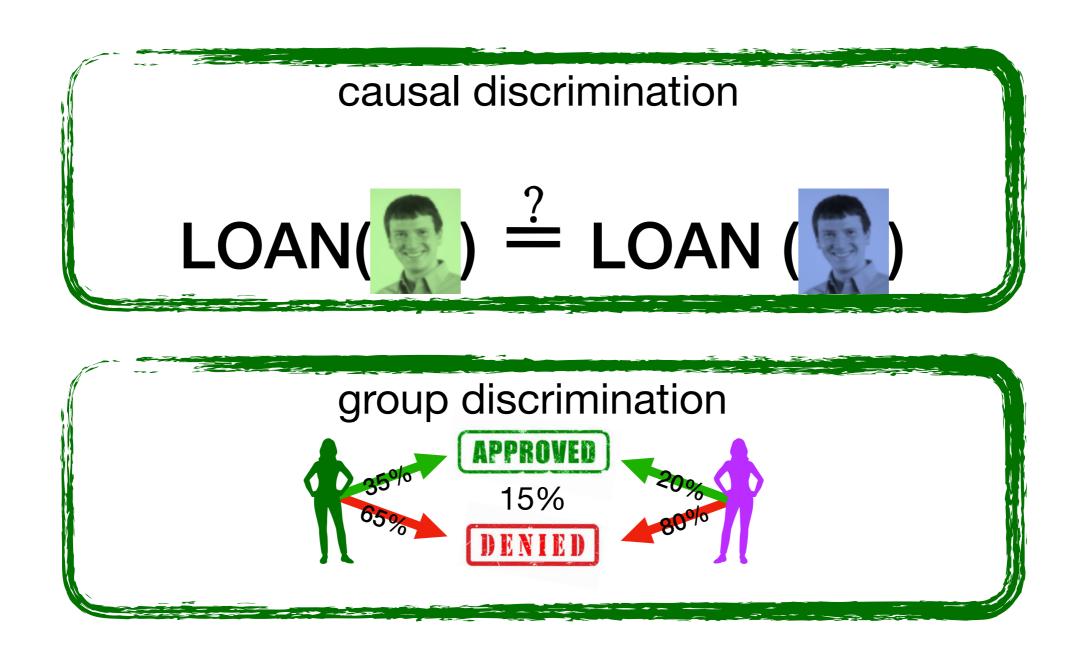
How much does my software discriminate with respect to ...?

Does my software discriminate more than 10% of the time, and against what?

Themis generates a test suite or can use a manually written one

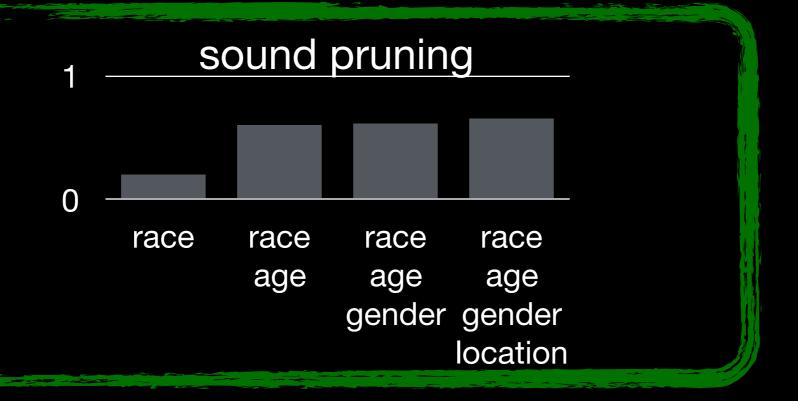
http://fairness.cs.umass.edu

discrimination measures



How does Themis work?

adaptive, confidence-driven sampling input schema confidence error bound $\underbrace{\text{error} = z^* \sqrt{\frac{p(1-p)}{r}}}_{\text{error}}$



Evaluation

Eight open-source decision systems trained on two public data sets

discrimination-aware logistic regression	[88]
discrimination-aware decision tree	[40]
discrimination-aware naive Bayes	[18]
discrimination-aware decision tree	[91]
naive Bayes	scikit- learn
decision tree	
logistic regression	
SVM	

- Census income dataset: financial data
 45K people income > \$50K?
- Statlog German credit dataset: credit data
 1K people
 "good" or "bad" credit?

findings

Group discrimination is not enough.

More than 11% of the individuals had the output flipped just by altering the individual's gender.

Decision tree trained not to group discriminate against gender causal discriminated against gender: 0.11.

findings

Trying to avoid group discrimination may introduce other discrimination.

Training a decision tree not to discriminate against gender made it discriminate against race 38.4% of the time.

findings

Pruning is highly effective.

- The more a system discriminates, the more efficient Themis is.
- On average, pruning reduced test suites by 148x for causal and 2,849x for group discrimination. Best improvement was 13,000x.





Amazon's Face Recognition Falsely Matched 28 Members of Congress With Mugshots



By Jacob Snow, Technology & Civil Liberties Attorney, ACLU of Northern California JULY 26, 2018 | 8:00 AM

TAGS: Face Recognition Technology, Surveillance Technologies, Privacy & Technology











"The false matches were disproportionately of people of color, including six members of the Congressional Black Caucus, among them civil rights legend Rep. John Lewis (D-Ga.)."

nationwide, and today, there are 28 more causes for concern. In a test the ACLU recently conducted of the facial recognition tool, called "Rekognition," the software incorrectly matched 28 members of Congress, identifying them as other people who have been arrested for a crime.

The members of Congress who were falsely matched with the mugshot



What are we doing now?

ACLU V

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Amazon's Face Recognition Falsely Matched 28 Members of Congress With Mugshots



By Jacob Snow, Technology & Civil Liberties Attorney, ACLU of Northern California JULY 26, 2018 | 8:00 AM

TAGS: Face Recognition Technology, Surveillance Technologies, Privacy & Technology

() ♥ ◎ ⊠ ⊜

Amazon's face surveillance technology is the target of growing opposition nationwide, and today, there are 28 more causes for concern. In a test the ACLU recently conducted of the facial recognition tool. called "Rekognition."









What are we doing now?

ACLU V

Amazon's Face Recognition Falsely Matched 28 Members of Congress With Mugshots



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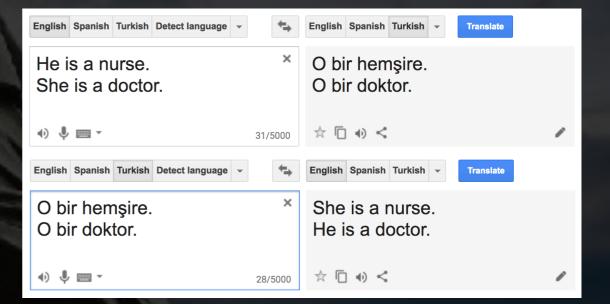
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The members of Congress who were



Fair natural language processing

Fair computer vision

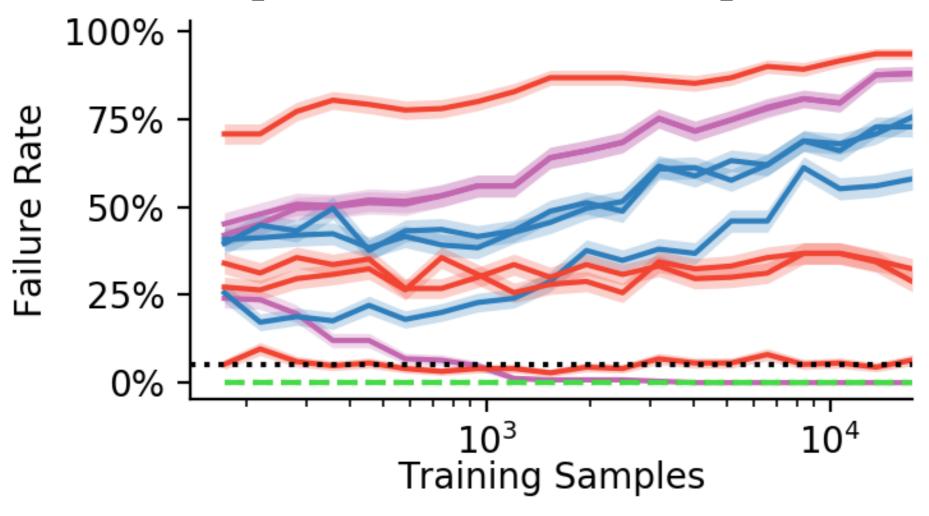


But what's the holy grail?

Provably fair machine learning:

Provide (high-probability) guarantees that the classifier is fair on unseen data.

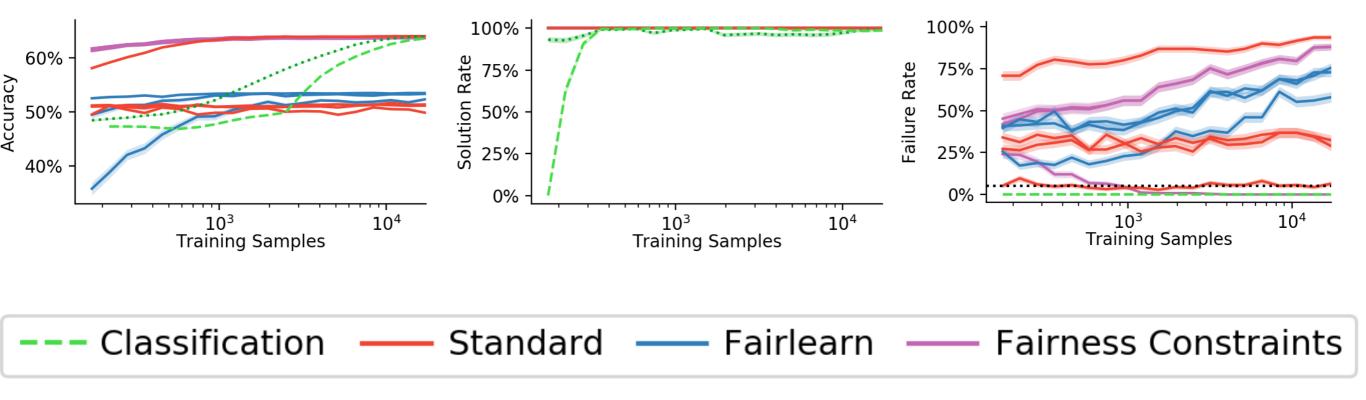
Disparate Impact





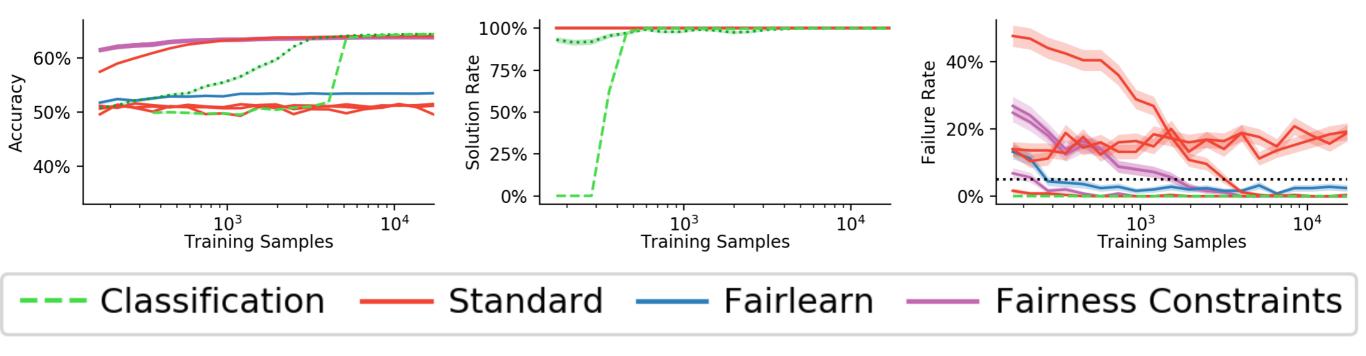
Fairlearn: Agarwal et al. A reductions approach to fair classification. ICML 2018. Fairness Constraints: Zafar et al., Fairness Constraints: A Mechanism for Fair Classification. FATML 2015.

Disparate Impact

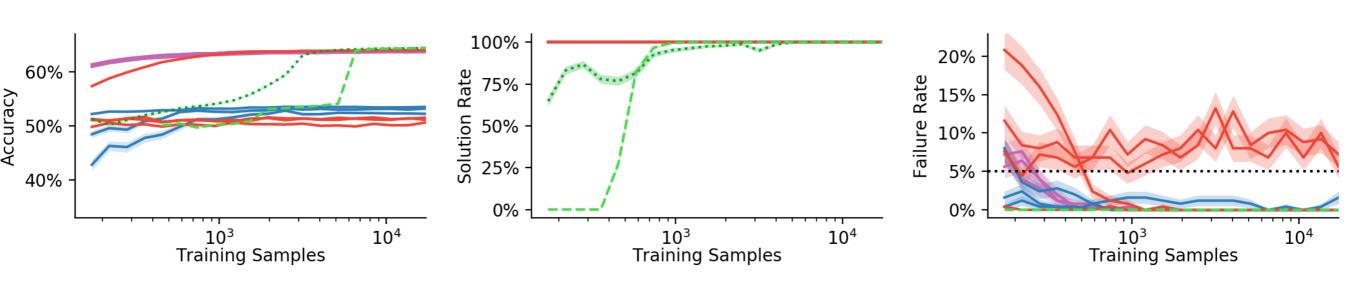


Fairlearn: Agarwal et al. A reductions approach to fair classification. ICML 2018. Fairness Constraints: Zafar et al., Fairness Constraints: A Mechanism for Fair Classification. FATML 2015.

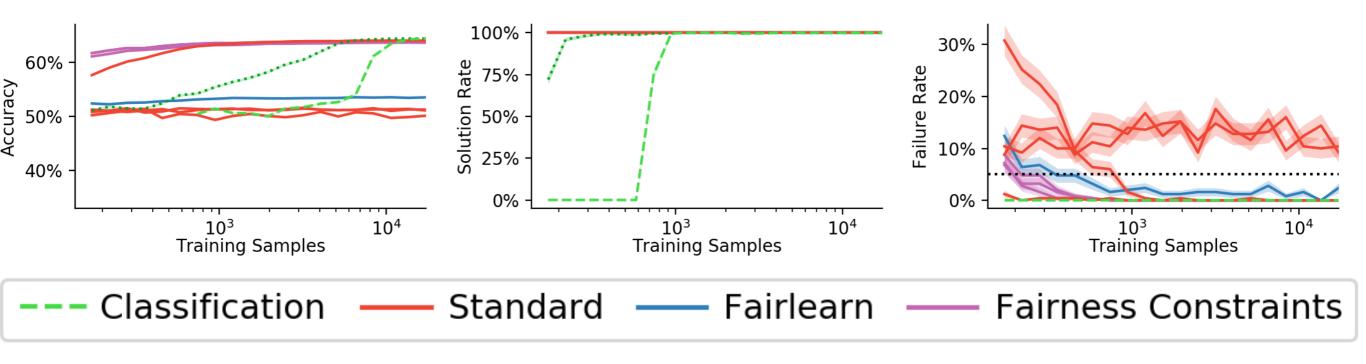
Demographic Parity



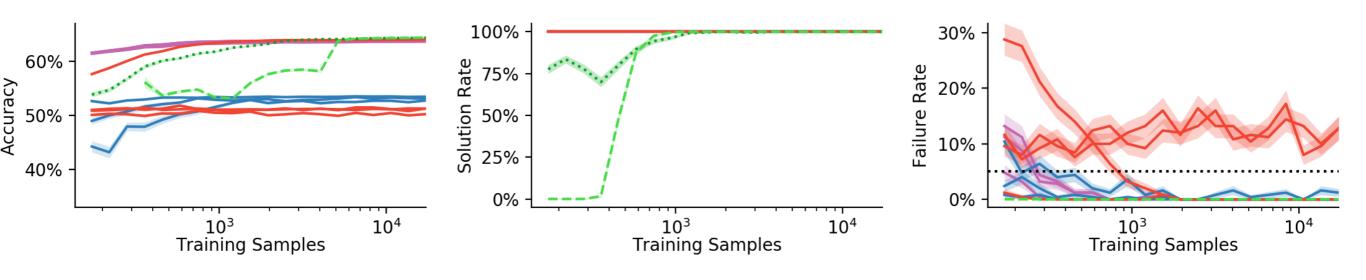
Equal Opportunity



Equalized Odds



Predictive Equality



Contributions

http://fairness.cs.umass.edu



- Causality-based definition and method for measuring software fairness
- Themis, an automated test-suite generator for fairness testing
- Evaluation on real-world software, demonstrating software is biased and our methods can catch it
- Provable guarantees on fairness in machine learning



Rico Angell



Brittany Johnson



Stephen Giguere



Sarah Brockman



Blossom Metevier



Sainyam Galhotra



Alexandra Meliou



Andy Barto



Bruno Castro da Silva



Emma Brunskill



Philip Thomas



Yuriy Brun

http://fairness.cs.umass.edu

https://tinyurl.com/FairnessPaper



UMassAmherst



Contributions

http://fairness.cs.umass.edu



- Causality-based definition and method for measuring software fairness
- Themis, an automated test-suite generator for fairness testing
- Evaluation on real-world software, demonstrating software is biased and our methods can catch it
- Provable guarantees on fairness in machine learning

Homework 1

- Due September 17, 9AM
- Will be posted shortly (you'll get an email)
- Learn some machine learning! Learn to use tools that help evaluate and mitigate bias in machine learning.
- Requires downloading a 5GB file, so do that early.