Lecture 7:
AI Fairness

CMSC 25910

Winter 2026

The University of Chicago

THE UNIVERSITY OF CHICAGO

Algorithmic Decision Making

Proposal: Algorithmic Grading in 25910

- The data we have:

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Idea 1

- Let's extrapolate from the Assignment 1 grade

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Idea 1

- Small data! We also advertised something different!

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Idea 2

- Let's extrapolate from the CS 144 grade

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Idea 2

- Is this just? Does Jane get a grade?

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Idea 3

- Let's use Department and the Grade in CS 144

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Idea 3

- Why should these matter?

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Idea 4

- Let's use all demographics and the Grade in CS 144

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Idea 4

- Why?!?! (Also, age and gender are protected classes)

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Idea 4

- Also consider the mutability of characteristics / recourse

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Idea 5

- Everyone gets an A!

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Idea 6

- Everyone gets an F!

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Idea 6

- Societal notions of justice may imply that failing everyone is bad

Name	Age	Department	Gender	Grade in CS 144	Grade on Assignment 1
Jack	55	CS	M	B+	100
Jill	23	Econ	F	A	95
Josh	32	Bio	M	B	50
Jenn	44	Bio	F	A-	98
Jane	27	Stats	F	---	80

Bias in Algorithmic Decision Making

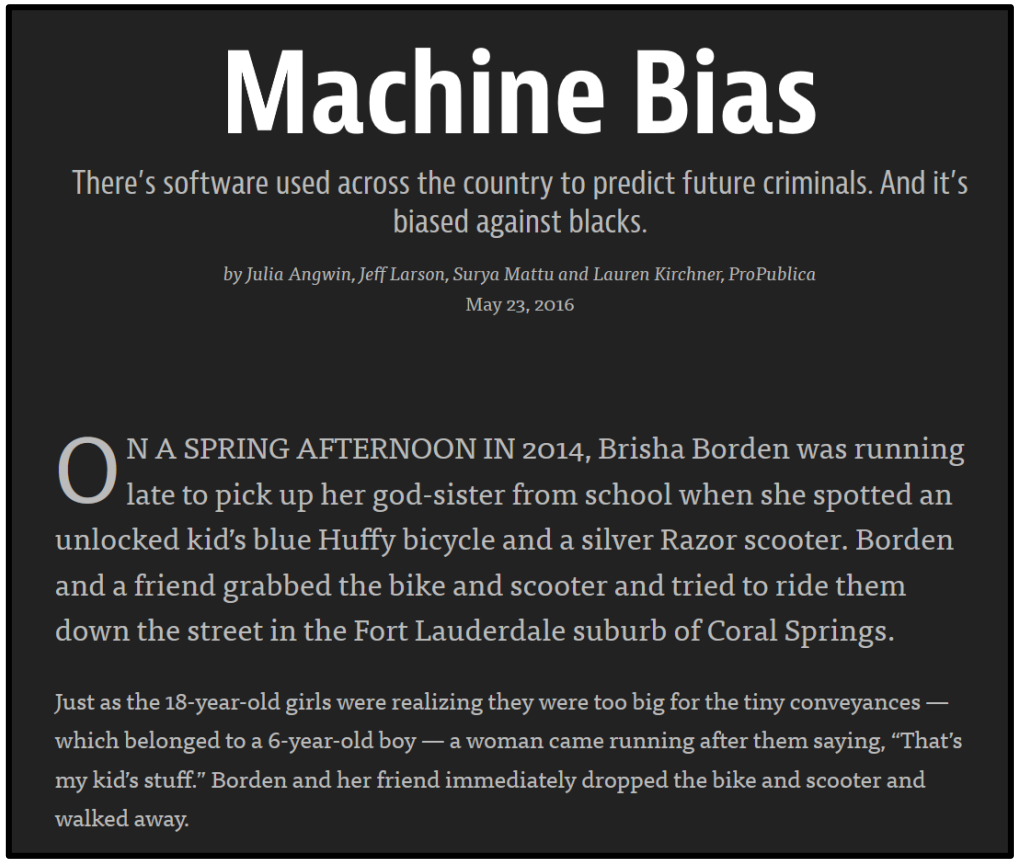
Machine Bias (ProPublica)

- COMPAS System for risk assessment
- Based on answers to 137 questions
- ProPublica obtained data:
  - Broward County, Florida

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

Machine Bias (ProPublica)

- COMPAS System for risk assessment
- Based on answers to 137 questions
- ProPublica obtained data:
  - Broward County, Florida
- “And it’s biased against blacks.”
  - Northpointe: It’s equally accurate across demographic groups!



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

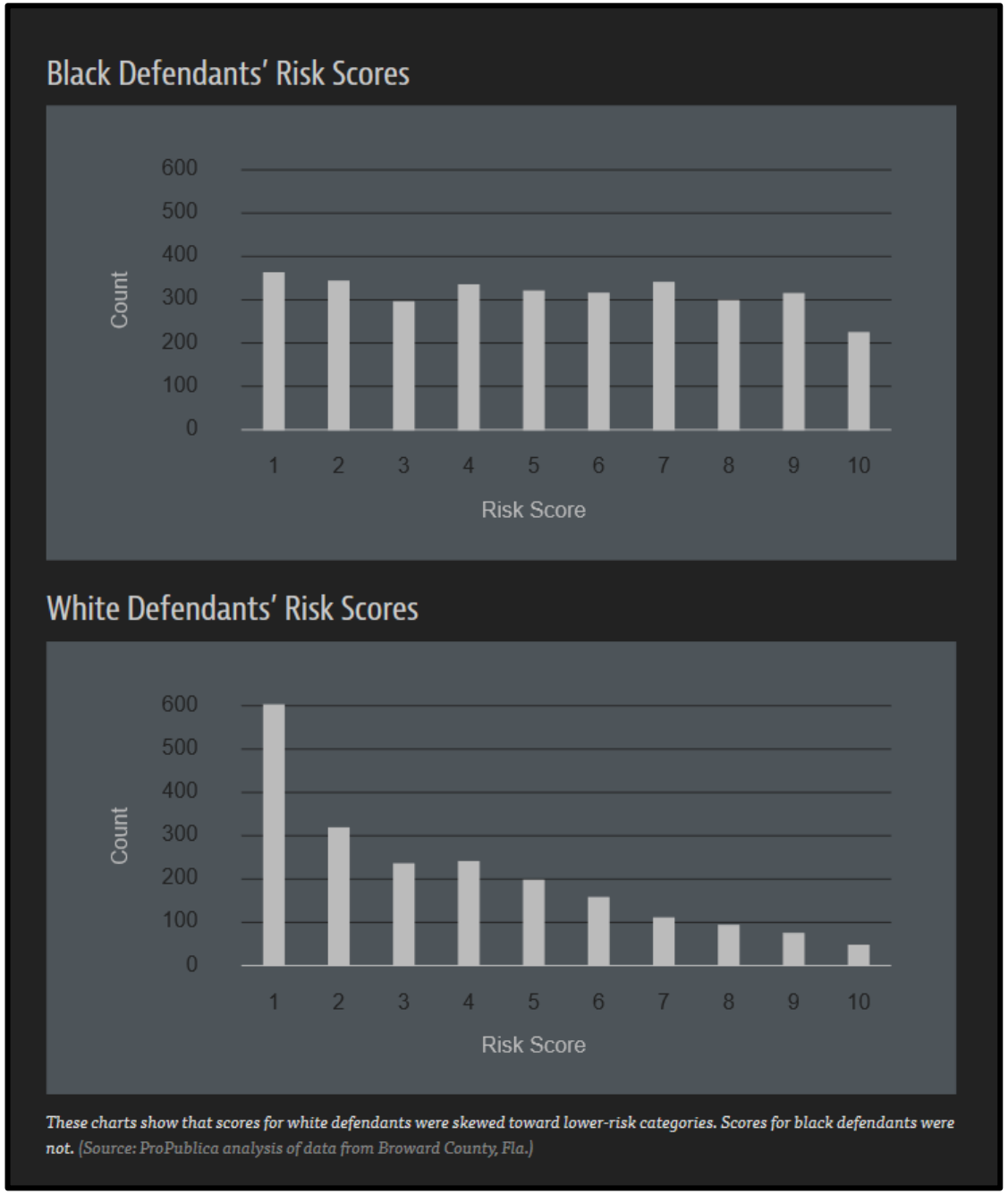
ON A SPRING AFTERNOON IN 2014, Brisha Borden was running late to pick up her god-sister from school when she spotted an unlocked kid’s blue Huffy bicycle and a silver Razor scooter. Borden and a friend grabbed the bike and scooter and tried to ride them down the street in the Fort Lauderdale suburb of Coral Springs.

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.

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

COMPAS

- Evidence of discrimination?



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

COMPAS

- Evidence of discrimination?

Prediction Fails Differently for Black Defendants

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

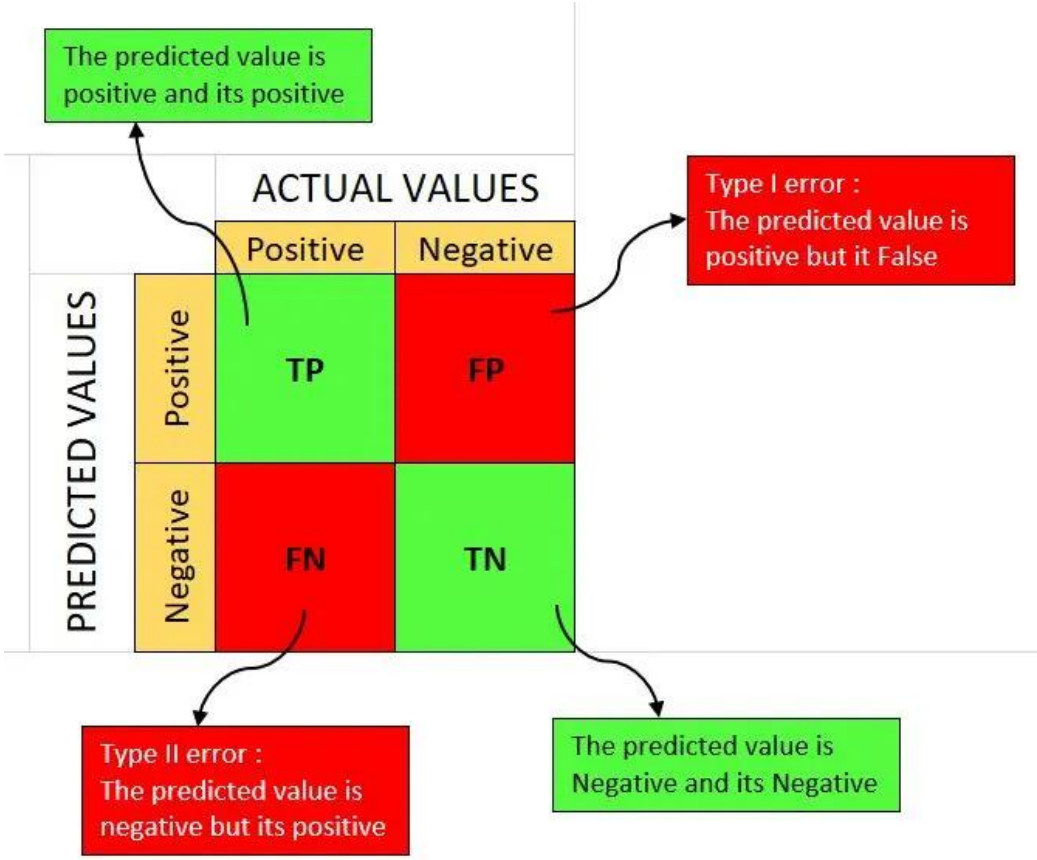
Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. (Source: ProPublica analysis of data from Broward County, Fla.)

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

ML Metrics (And Their Connection to Fairness)

Some Possible Metrics (Classifiers)

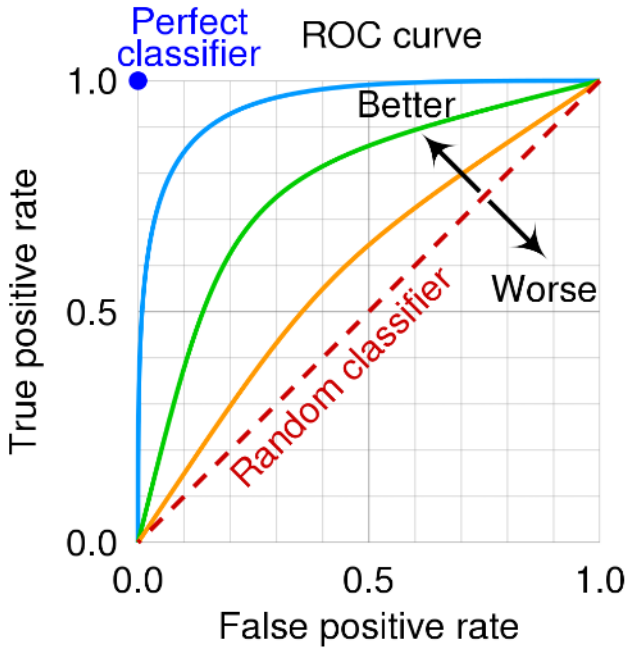
- Accuracy: # correct / # total
- Confusion matrix (TP/FP/TN/FN)
  - Binary classifier
  - Positive and negative classes
  - True = prediction matched ground truth
  - **T**rue **P**ositive
  - **T**rue **N**egative
  - **F**alse **P**ositive
  - **F**alse **N**egative



See https://medium.com/analytics-vidhya/performance-metrics-for-machine-learning-models-80d7666b432e
https://www.tutorialspoint.com/machine_learning_with_python/machine_learning_algorithms_performance_metrics.htm
https://www.justintodata.com/machine-learning-model-evaluation-metrics/ or many more!
Confusion matrix image taken from https://medium.com/analytics-vidhya/what-is-a-confusion-matrix-d1c0f8feda5

Some Possible Metrics (Classifiers)

- Receiver Operating Characteristic (ROC) Curve
  - True Positive Rate (TPR) = TP / P = TP / (TP + FN)
  - False Positive Rate (FPR) = FP / N = FP / (FP + TN)
  - ROC curve plots TPR vs. FPR at various thresholds
  - Area under the ROC curve (AUC) is a common metric



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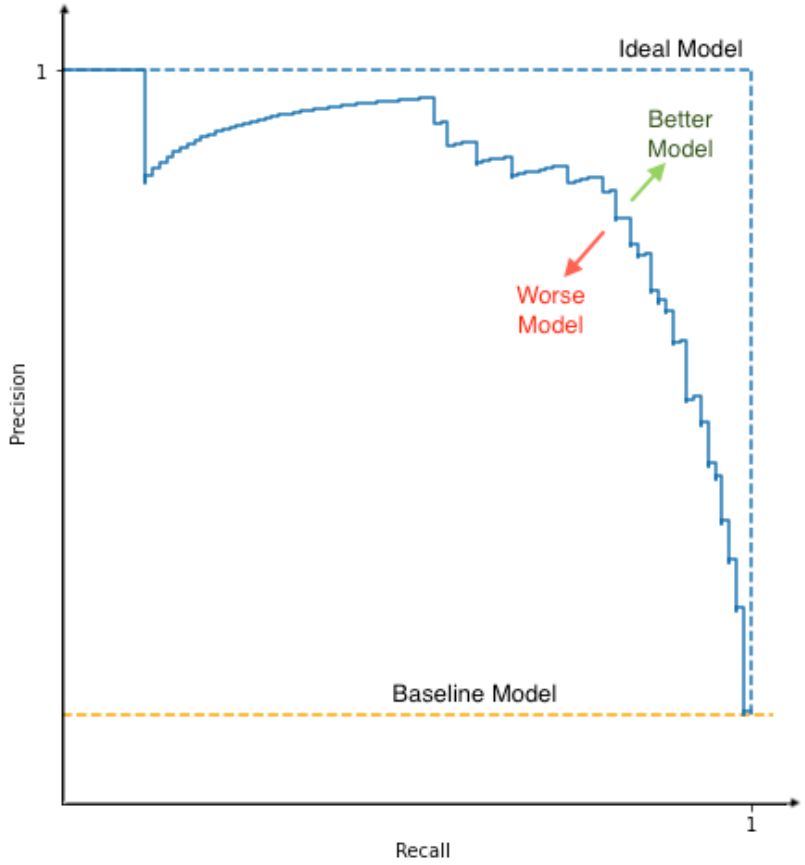
https://www.justintodata.com/machine-learning-model-evaluation-metrics/ or many more!
ROC curve image taken from https://en.wikipedia.org/wiki/Receiver_operating_characteristic#/media/File:Roc_curve.svg

Some Possible Metrics (Classifiers)

- Precision: TP / (TP + FP)
- Recall: TP / (TP + FN)
- Precision-Recall Curve



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https://www.tutorialspoint.com/machine_learning_with_python/machine_learning_algorithms_performance_metrics.htm
https://www.justintodata.com/machine-learning-model-evaluation-metrics/ or many more!
Precision-recall curve image taken from https://towardsai.net/p/l/precision-recall-curve

Some Possible Metrics (Regressions)

- Mean Squared Error
- Mean Absolute Error

See https://medium.com/analytics-vidhya/performance-metrics-for-machine-learning-models-80d7666b432e
https://www.tutorialspoint.com/machine_learning_with_python/machine_learning_algorithms_performance_metrics.htm
https://www.justintodata.com/machine-learning-model-evaluation-metrics/ or many more!

Some Possible Metrics (Performance)

- Model training time
- Frequency of model re-training
- Model size
- Classification time
- Privacy issues of the model
- “Security” (future lecture)

Some Possible Metrics **Revisited**

- Do these metrics capture the **relationship** between **errors?**
- Do these metrics capture the **impact of errors?**
- Do these metrics capture the **differential** impact of **particular types of errors?**
- Do these metrics break down **errors by group**?
- We calculate errors on our **test set**; what about **in practice**?
  - Do we have enough data in different sub-groups?
  - Do we have representative data? How do we define representative?
- Where is the data even coming from? How accurate is it?

Defining Fairness

The Difficulty of Defining Fairness

- Terminology is conflated across disciplines
  - Political philosophy
  - Employment law
  - Computer science

- See: Deirdre K. Mulligan, Joshua A. Kroll, Nitin Kohli, Richmond Y. Wong. This Thing Called Fairness: Disciplinary Confusion Realizing a Value in Technology. PACM HCI (CSCW), 2019.

Individual Fairness

- One of the early definitions of fairness
- **Individual fairness:** Similar people should be treated equally

Statistical Non-Discrimination

- Basis in employment and housing law (e.g., Fair Housing Act)
- Primarily considers *protected classes*
  - Race, gender, sex, national origin, religion, marital status, etc.
- In this approach to fairness, we want to approximately equalize some quantities across demographic groups (**group fairness**)
  - Mainly focuses on **disparate impact** (treating different groups differently)

Group Fairness (Just a Few Approaches)

- Demographic parity (**equal outcomes**)
  - Equalize the chance of positive classifications across groups

Group Fairness (Just a Few Approaches)

- **Equalized accuracy** across groups?

Group Fairness (Just a Few Approaches)

- **Equalized odds** (true positive rate and false positive rate are equal across groups)?
  - True Positive Rate (TPR) = TP / P = TP / (TP + FN)
  - False Positive Rate (FPR) = FP / N = FP / (FP + TN)

The Need to Make Tough Trade-offs

- A. Chouldechova. “Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments.” *Big Data 2017*.
- J. Kleinberg, S. Mullainathan, M. Raghavan. “Inherent Trade-Offs in the Fair Determination of Risk Scores.” *ITCS 2017*.
  - “Recent discussion in the public sphere about algorithmic classification has involved tension between competing notions of what it means for a probabilistic classification to be fair to different groups. We formalize three fairness conditions that lie at the heart of these debates, and we prove that except in highly constrained special cases, there is no method that can satisfy these three conditions simultaneously. Moreover, even satisfying all three conditions approximately requires that the data lie in an approximate version of one of the constrained special cases identified by our theorem. These results suggest some of the ways in which key notions of fairness are incompatible with each other, and hence provide a framework for thinking about the trade-offs between them.”

Blindness to Protected Classes

- Should we just intentionally not collect data about whether or not data subjects belong to a protected class?
  - The answer is very complicated. It's often (but not always!) "no"… why not?

Process Fairness

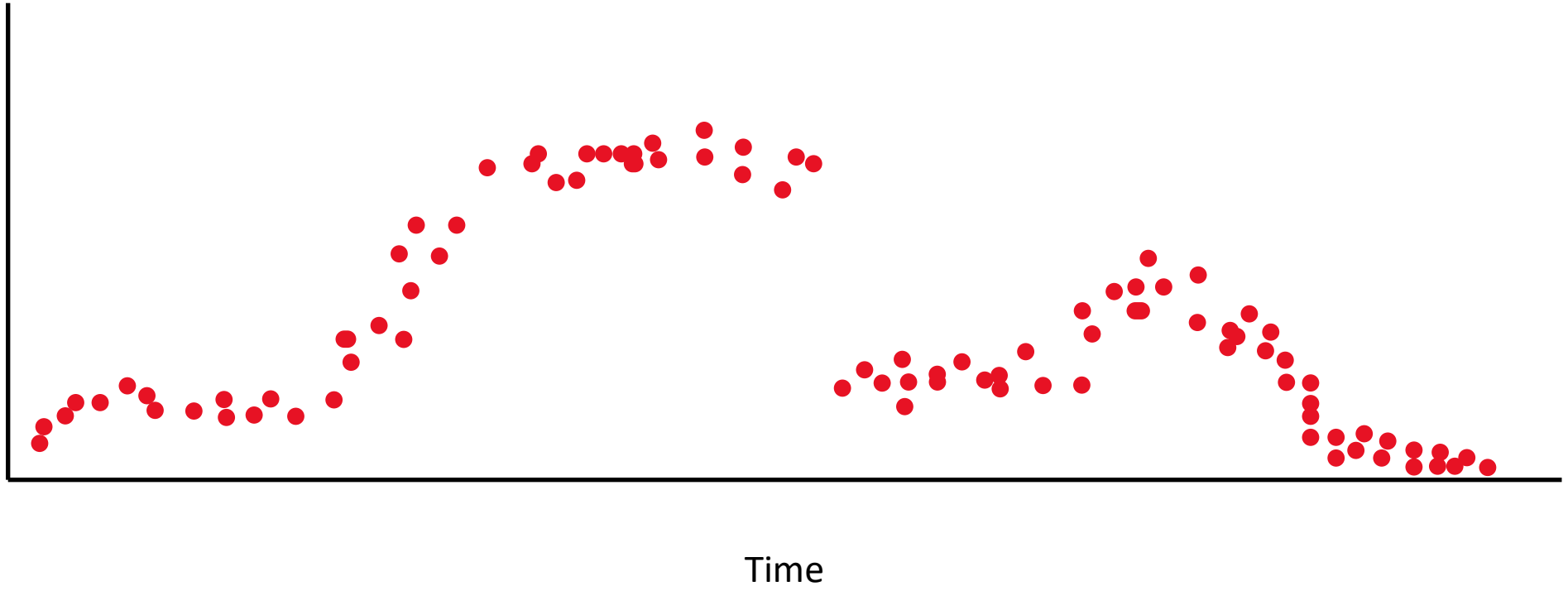
- How do we decide what predictor variables to include?
- **Process fairness**: Exclude from the model predictor variables that are *deemed to be* unfair for the classification task
- Should we just crowdsource perceptions?
  - Grgic-Hlaca et al. Human Perceptions of Fairness in Algorithmic Decision Making: A Case Study of Criminal Risk Prediction. In *Proc. WWW*, 2018.
  - Important question: Who gets to decide what is fair? Is it majoritarian voting? Should it be experts in law/technology?

How Does Sampling Impact Fairness?

- What if our sample is unbalanced? Can that cause problems?
- What if our sample is not representative?
- What if we collect the wrong features?

Concept Drift – The Passage of Time

- Can we be embedding historical biases?



Reconceptualizing Fairness as Justice

- Should we follow Rawls and consider justice as fairness?
- Should we start thinking about fairness in terms of trolley problems? https://en.wikipedia.org/wiki/Trolley_problem
- How might our societal notions of what is just change how we build a classifier, **as well as whether we use ML at all**?
- How do we think about due process within fairness?
- Returning to the COMPAS example: How did **human judges** use (or choose not to use) COMPAS risk scores? Is this just?
- Accountability? Transparency? Explanations?

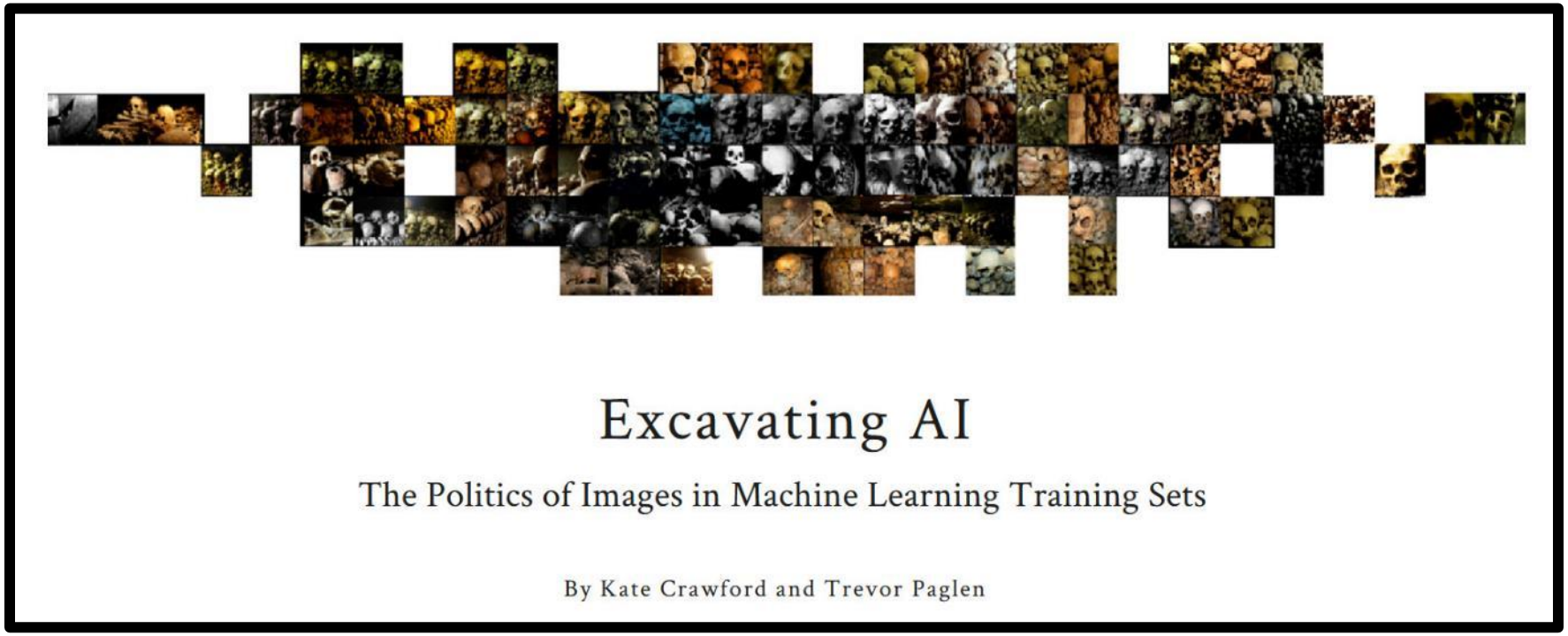
Training Data

Training Datasets and Benchmarks

- Standardization of training datasets and benchmarks have arguably pushed the field of ML forward
  - Not without pitfalls
- If everyone is testing against the same datasets, what does that say about the ML model's generalizability?
  - Are results practically significant?
  - Do we notice errors that occur for data **excluded** from reference sets?
- There are more serious problems than a lack of progress!

What Datasets Include/Exclude

- *Kate Crawford and Trevor Paglen, "Excavating AI: The Politics of Training Sets for Machine Learning (September 19, 2019)*
- https://excavating.ai



What Datasets Include/Exclude

- “The automated interpretation of images is an inherently social and political project, rather than a purely technical one”
- “What work do images do in AI systems? What are computers meant to recognize in an image and what is misrecognized or even completely invisible?”
- “How do humans tell computers which words will relate to a given image? And what is at stake in the way AI systems use these labels to classify humans, including by race, gender, emotions, ability, sexuality, and personality?”
- “As the fields of information science and science and technology studies have long shown, all taxonomies or classificatory systems are political.”

Taken from Kate Crawford and Trevor Paglen, “Excavating AI: The Politics of Training Sets for Machine Learning (September 19, 2019)

What Datasets Include/Exclude

“There is much at stake in the architecture and contents of the training sets used in AI. They can promote or discriminate, approve or reject, render visible or invisible, judge or enforce. And so we need to examine them—because they are already used to examine us—and to have a wider public discussion about their consequences, rather than keeping it within academic corridors. As training sets are increasingly part of our urban, legal, logistical, and commercial infrastructures, they have an important but underexamined role: the power to shape the world in their own images.”

Taken from Kate Crawford and Trevor Paglen, “Excavating AI: The Politics of Training Sets for Machine Learning (September 19, 2019)

Imagenet: Computer Vision dataset

- 15 million images
  - Each image is annotated with a noun from Wordnet
    - Wordnet -> hierarchy of concepts
- Instrumental dataset to advance computer vision
- Where did these images come from?

Trevor Paglen's Art About ImageNet

- Trevor Paglen, "From 'Apple' to 'Abomination'" (2023)
- "This work is composed of more than 13,000 images from ImageNet, a training set with more than 20,000 categories totaling over 14 million images… The work spotlights the systems commonly inherent in such software and affecting us all, questioning the arbitrary connections between images and words, and the problems they create."

Taken from Trevor Paglen, "From 'Apple' to 'Abomination'" (2023), photographed by me at the Louisiana Museum of Modern Art, Denmark

Trevor Paglen's Art About ImageNet

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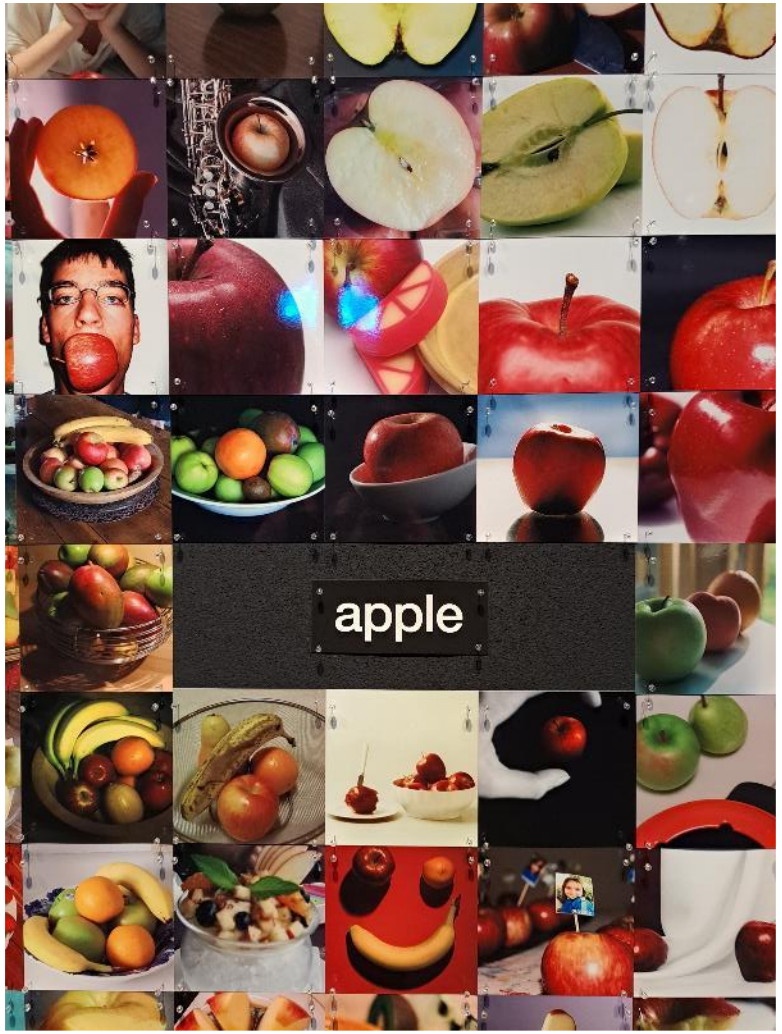
Trevor Paglen's Art About ImageNet



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Where Do Labels Come From?

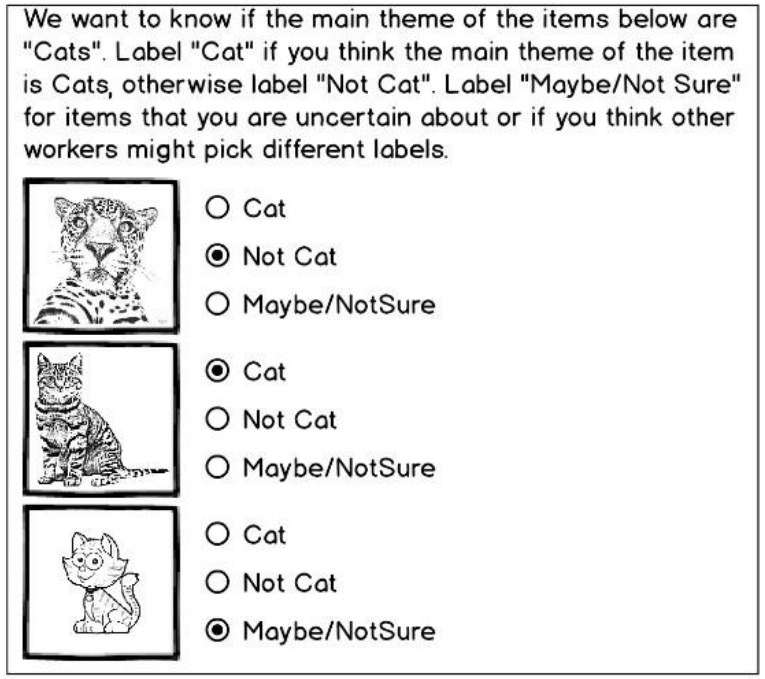


Figure 3. Human Intelligence Task (HIT) interface for the Vote Stage. In addition to the predefined labels, crowdworkers can also select *Maybe/NotSure* when they were uncertain about the item.

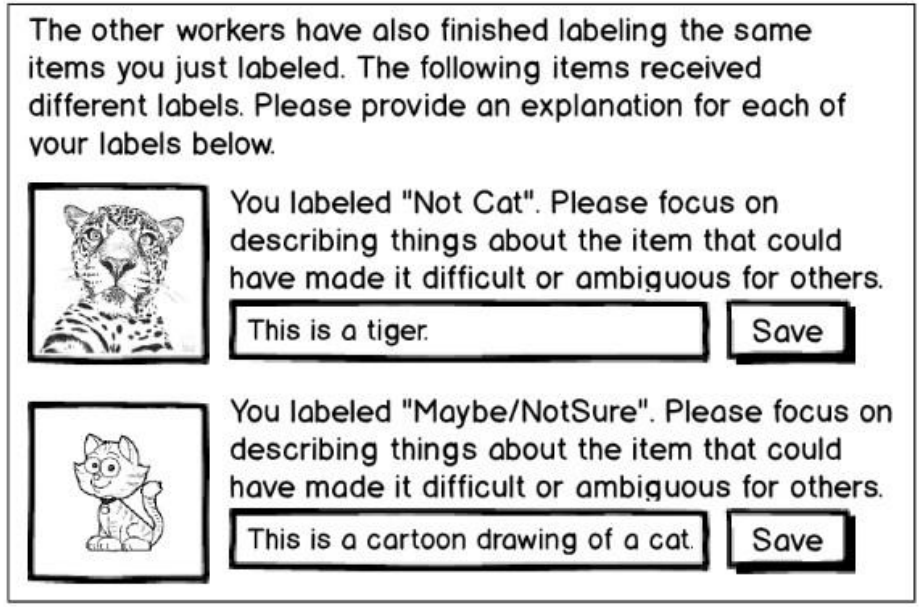


Figure 4. Human Intelligence Task (HIT) interface for the Explain Stage. Crowdworkers enter a short description for each item that was labeled differently in the Vote Stage. They were informed that disagreement occurred, but not the distribution of different labels used.

Chang et al. Revolt: Collaborative Crowdsourcing for Labeling Machine Learning Datasets. CHI 2017
https://dl.acm.org/doi/pdf/10.1145/3025453.3026044

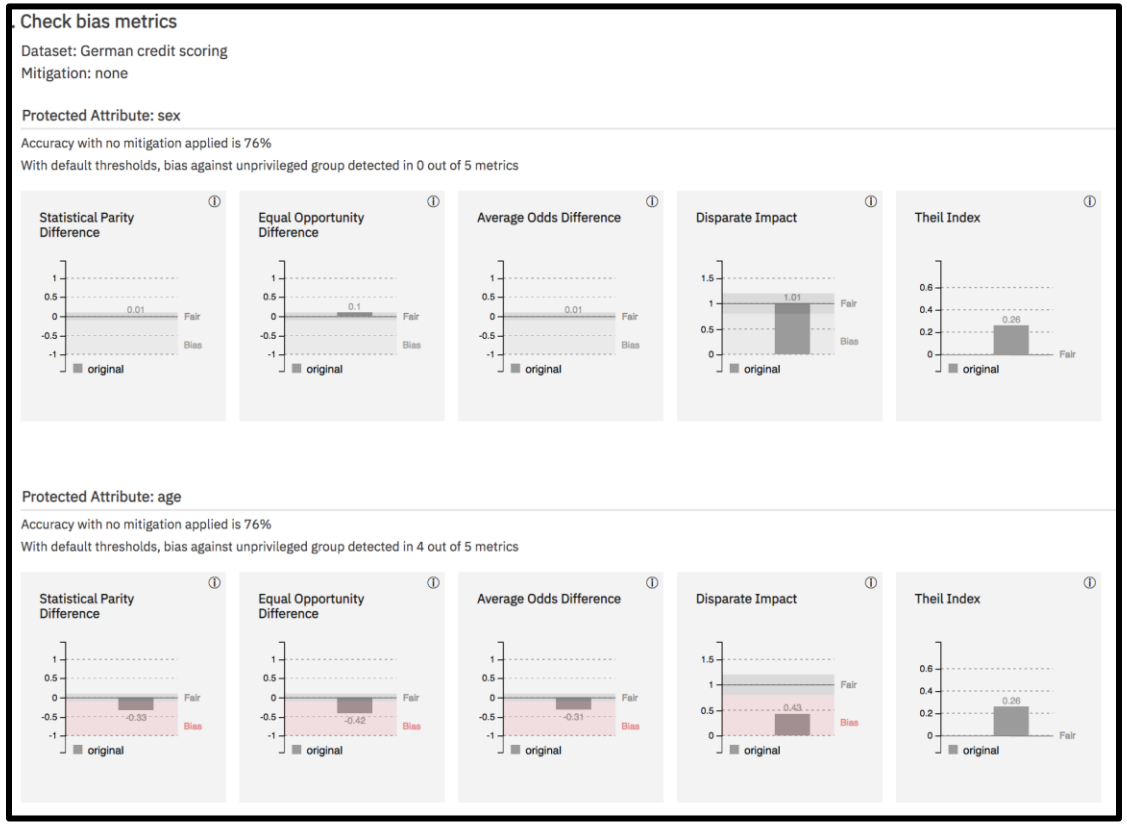
Attempts at Mitigating Fairness Concerns

Some Attempted Fairness Mitigations

- Transform the training data features and/or labels
- Change the weights in the model produced
- Adversarial de-biasing
  - e.g., using a discriminator from a Generative Adversarial Network

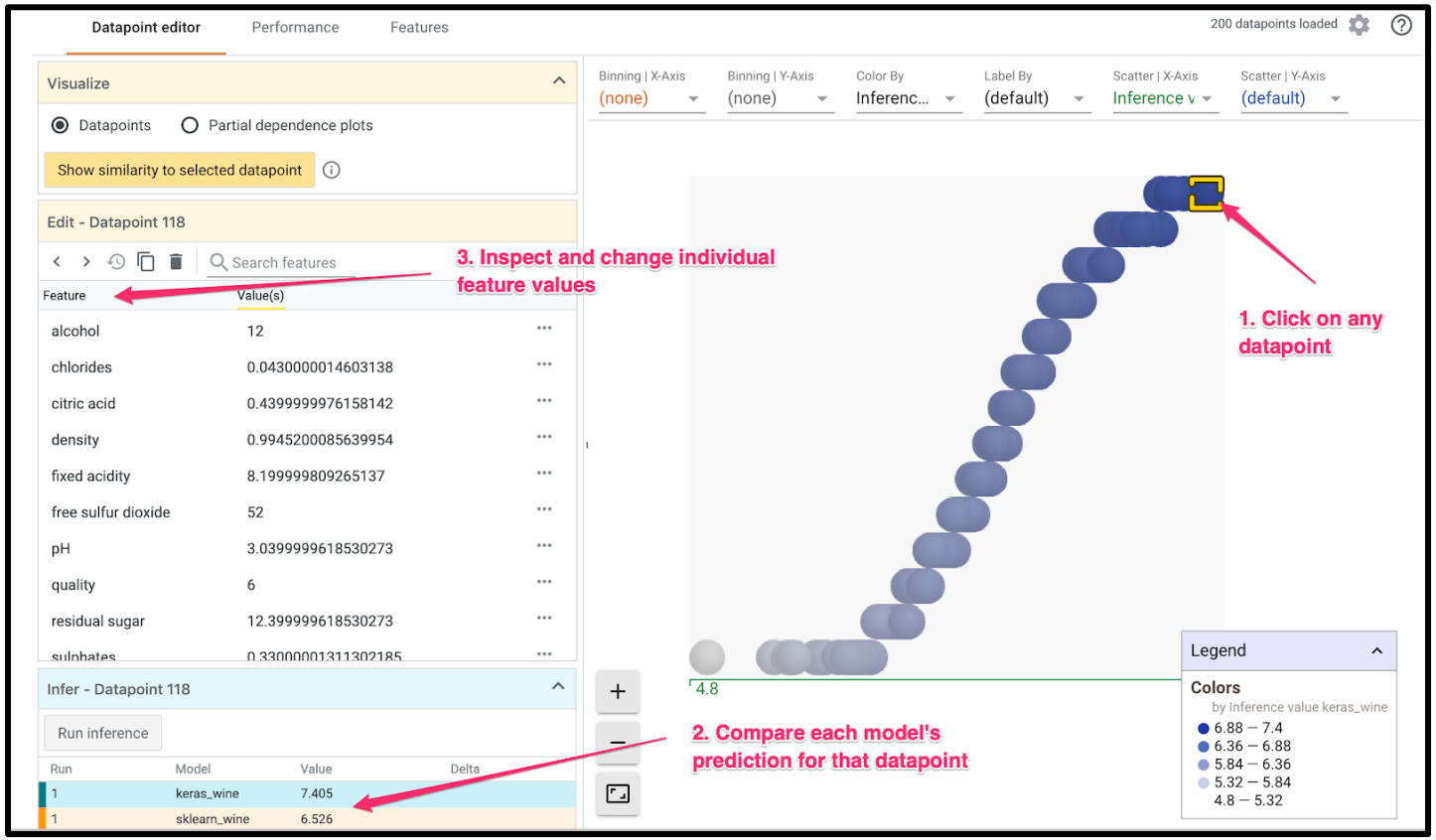
AI Fairness 360

- IBM open source project: https://aif360.mybluemix.net/
- Online demo: https://aif360.mybluemix.net/data

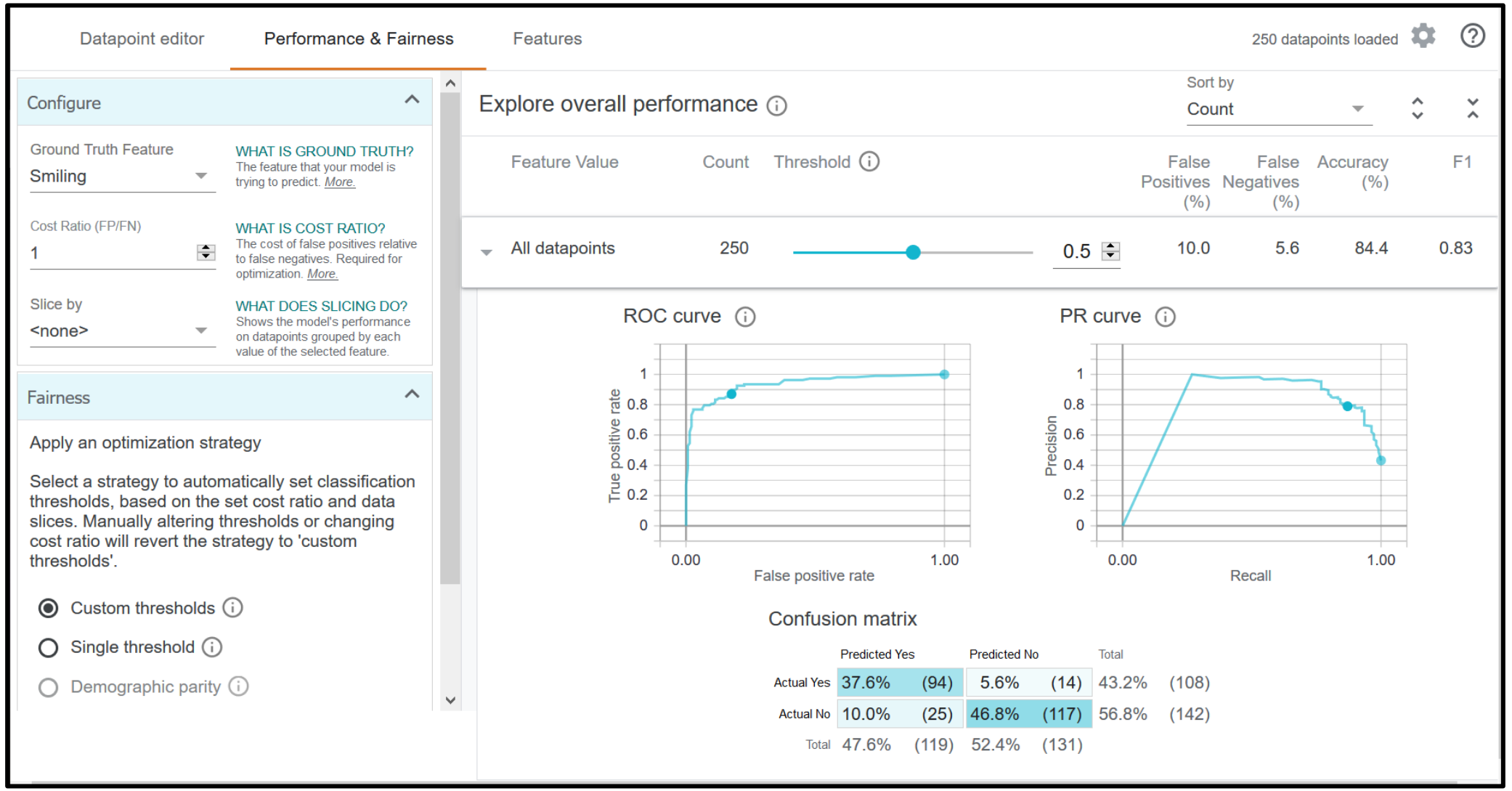


What-If Tool

- Google open source project: https://pair-code.github.io/what-if-tool/
- Online demo: https://pair-code.github.io/what-if-tool/image.html

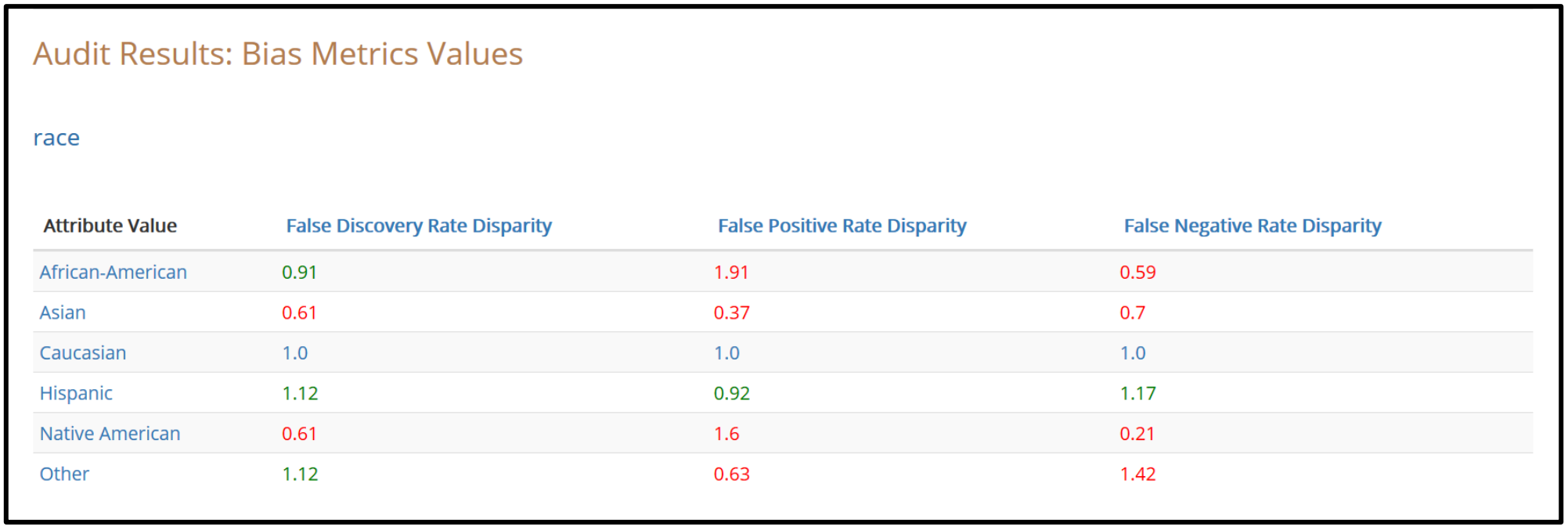


What-If Tool


Datapoint editor
Performance & Fairness
Features
250 datapoints loaded
Configure
Ground Truth Feature
Smiling
WHAT IS GROUND TRUTH?
The feature that your model is trying to predict. More.
Cost Ratio (FP/FN)
1
WHAT IS COST RATIO?
The cost of false positives relative to false negatives. Required for optimization. More.
Slice by
<none>
WHAT DOES SLICING DO?
Shows the model's performance on datapoints grouped by each value of the selected feature.
Fairness
Apply an optimization strategy
Select a strategy to automatically set classification thresholds, based on the set cost ratio and data slices. Manually altering thresholds or changing cost ratio will revert the strategy to 'custom thresholds'.
Custom thresholds
Single threshold
Demographic parity
Explore overall performance
Sort by
Count
Feature Value
Count
Threshold
False Positives (%)
False Negatives (%)
Accuracy (%)
F1
All datapoints
250
0.5
10.0
5.6
84.4
0.83
ROC curve
True positive rate
False positive rate
0.00
1.00
PR curve
Precision
Recall
Confusion matrix
Predicted Yes
Predicted No
Total
Actual Yes
37.6% (94)
5.6% (14)
43.2% (108)
Actual No
10.0% (25)
46.8% (117)
56.8% (142)
Total
47.6% (119)
52.4% (131)

Aequitas Tool

- Formerly a UChicago open source project: http://www.datasciencepublicpolicy.org/projects/aequitas/
- Online demo: http://aequitas.dssg.io/example.html

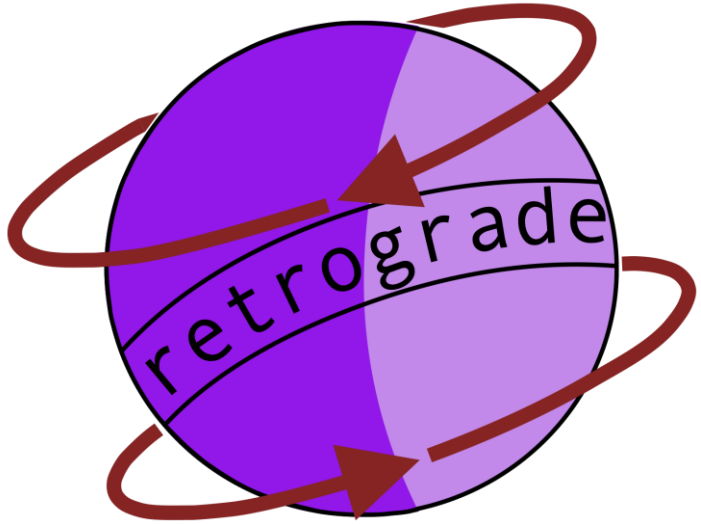


Audit Results: Bias Metrics Values

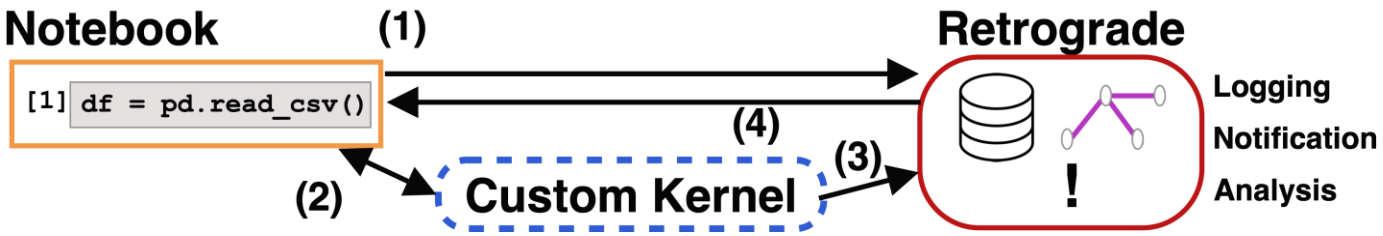
race

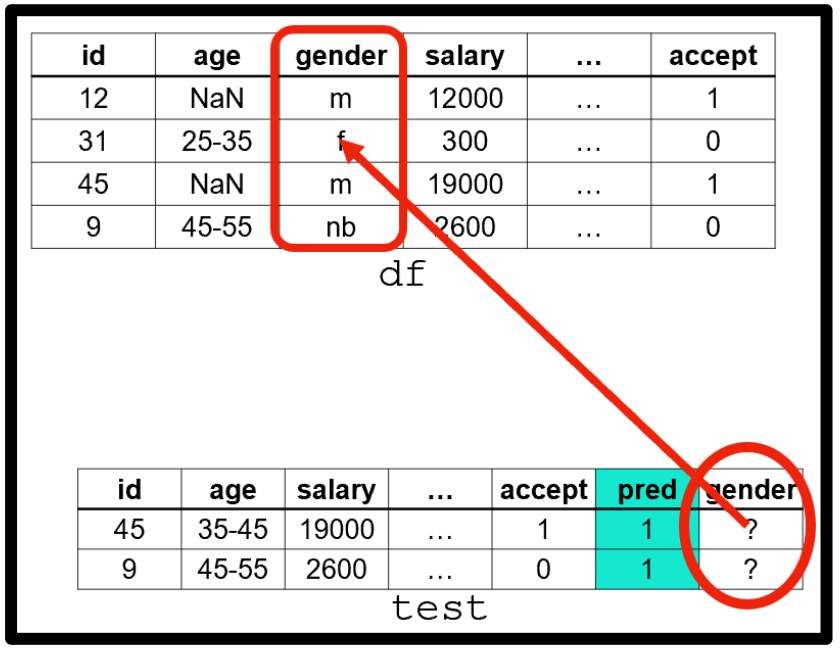
Attribute Value	False Discovery Rate Disparity	False Positive Rate Disparity	False Negative Rate Disparity
African-American	0.91	1.91	0.59
Asian	0.61	0.37	0.7
Caucasian	1.0	1.0	1.0
Hispanic	1.12	0.92	1.17
Native American	0.61	1.6	0.21
Other	1.12	0.63	1.42

Retrograde



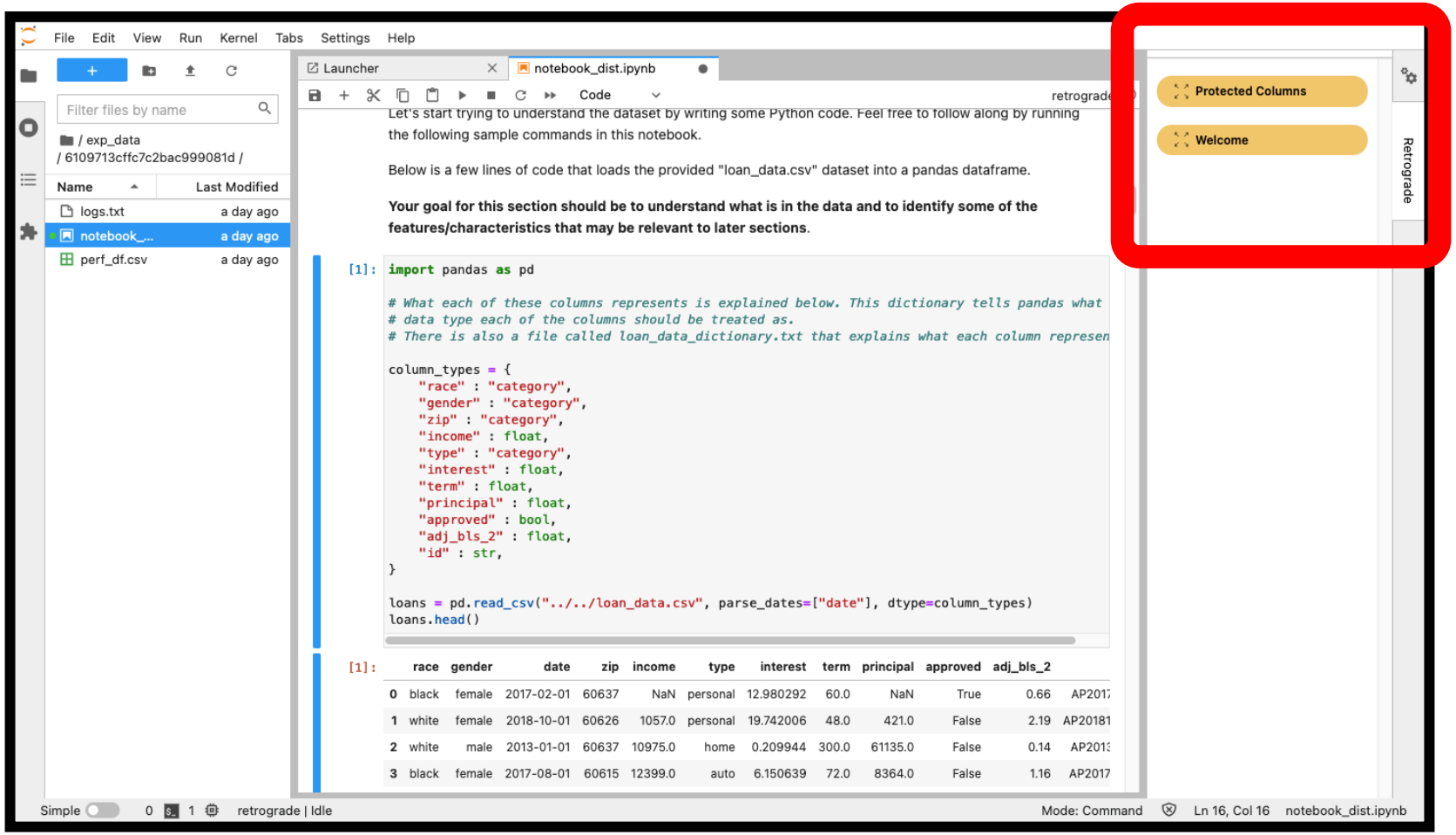
- Improved techniques for tracking provenance in computational notebooks (JupyterLab)
- Design of data-driven contextual nudges
- Evaluation study (51 data scientists)





Galen Harrison, Kevin Bryson, Ahmad Bamba, Luca Dovichi, Alek Binion, Arthur Borem, and Blase Ur. JupyterLab in Retrograde: Contextual Notifications that Highlight Fairness and Bias Issues for Data Scientists. In *Proc. CHI*, 2024

Retrograde



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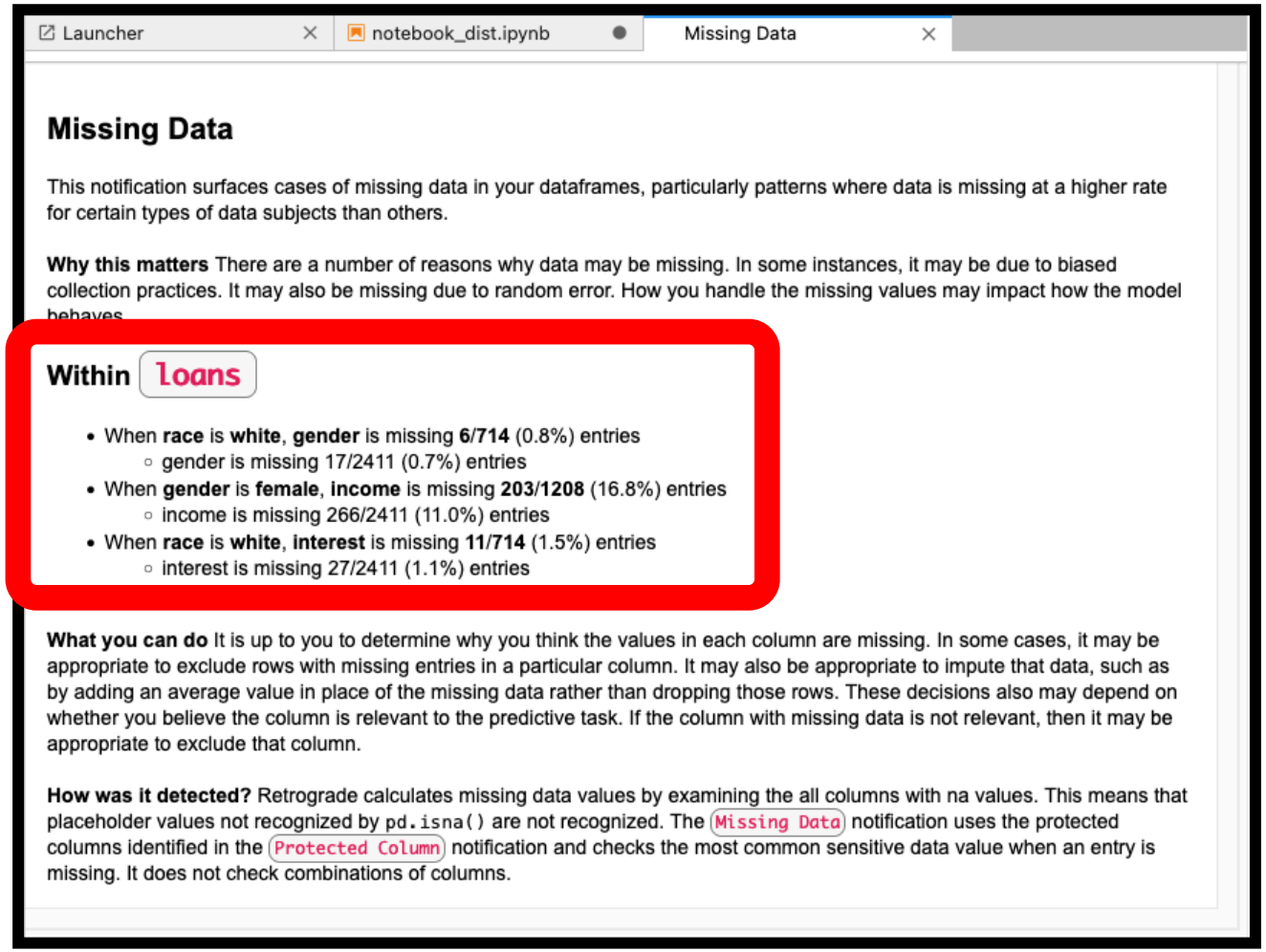

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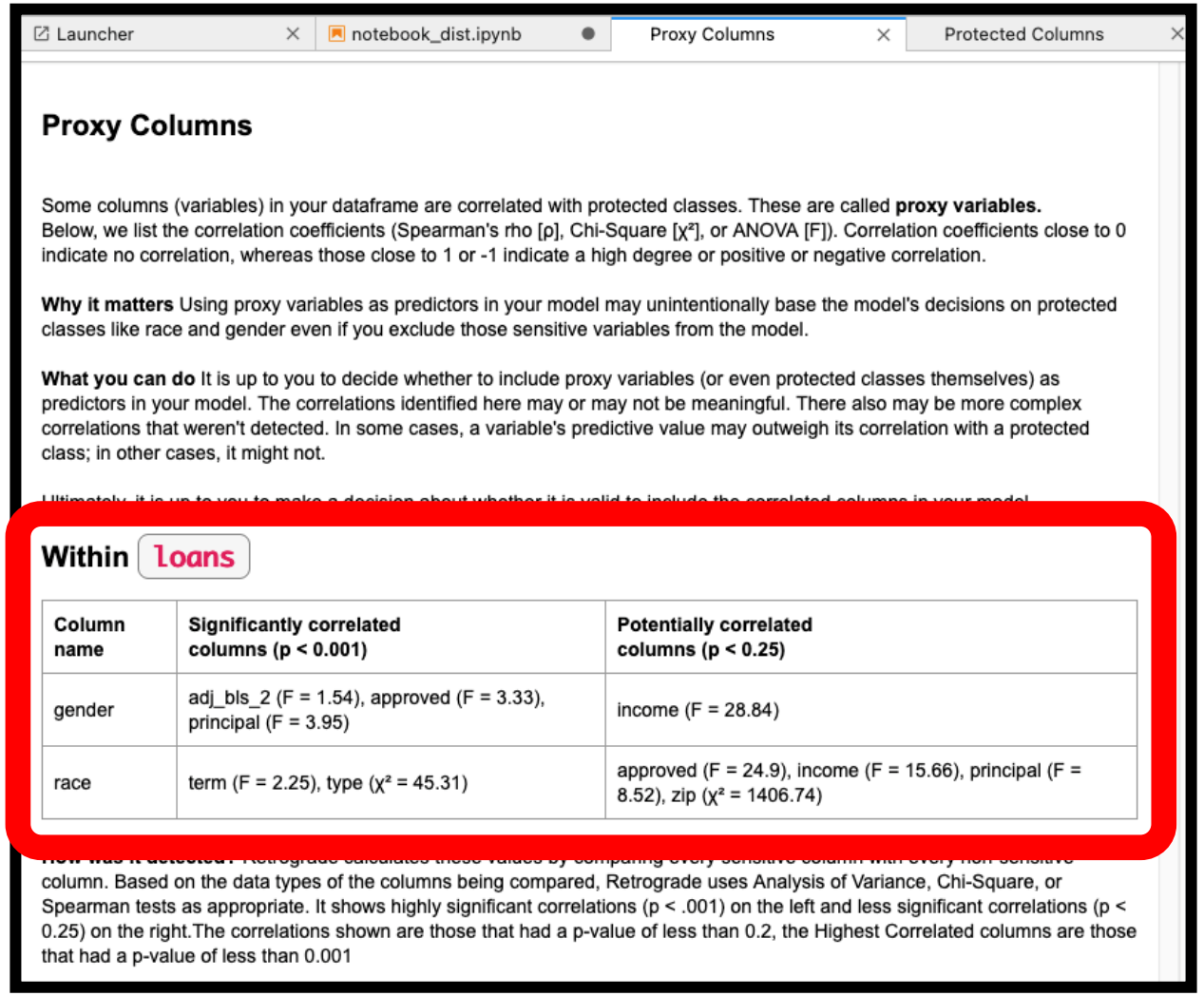

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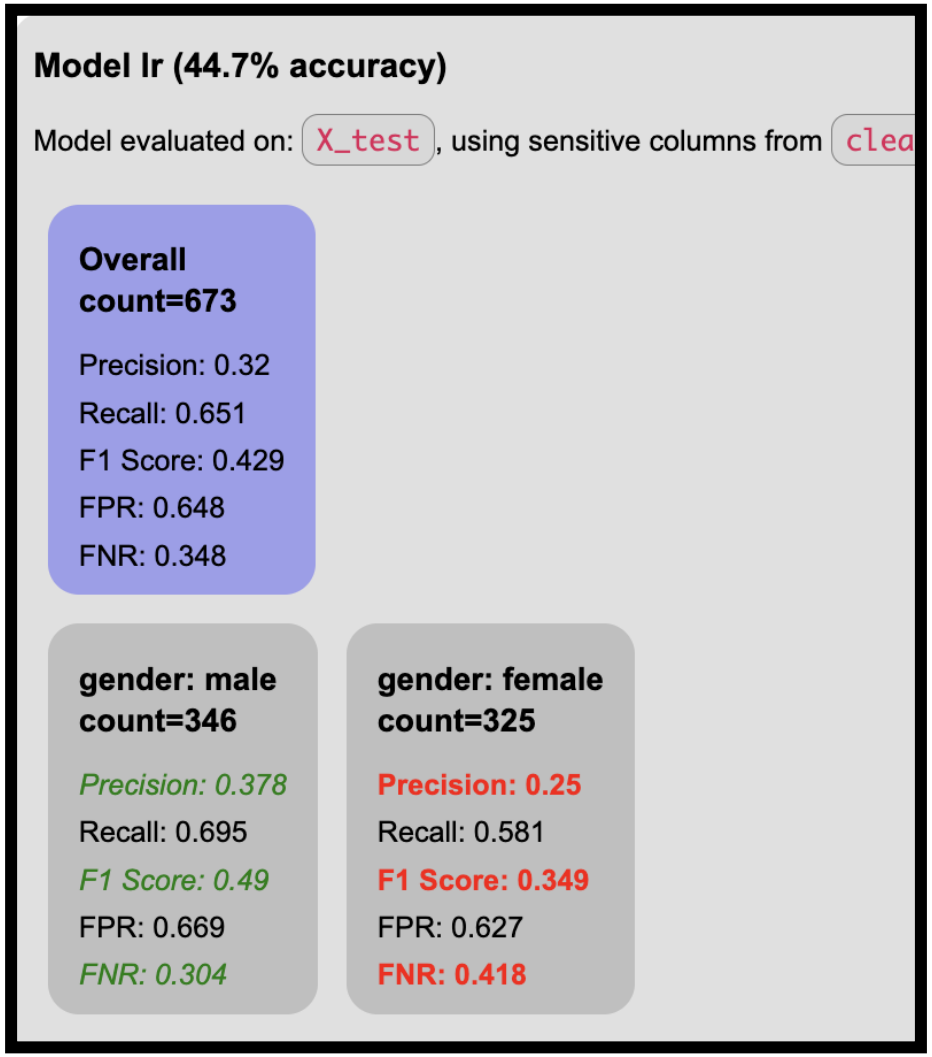

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Retrograde

Modifications Table

Select columns to modify

prediction	index	gender	income	race	type
~~1~~ → 0	1781	~~female~~ → non-binary	-0.402	white	~~home~~ → personal
~~1~~ → 0	1854	~~male~~ → non-binary	-0.132	asian	~~personal~~ → auto
~~0~~ → 1	1646	~~male~~ → female	0.62	other	~~auto~~ → personal
~~1~~ → 0	1126	~~male~~ → female	0.097	hispanic	~~auto~~ → home
~~0~~ → 1	1872	~~female~~ → male	1.289	white	~~home~~ → personal
~~1~~ → 0	389	~~female~~ → male	-0.031	other	~~home~~ → auto
~~1~~ → 0	1387	~~male~~ → non-binary	0.451	white	~~personal~~ → auto
~~1~~ → 0	2288	~~female~~ → non-binary	0.82	white	~~home~~ → personal
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~~1~~ → 0	1602	~~female~~ → non-binary	0.227	black	~~home~~ → auto

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Retrograde: Key Results

- In-context notifications impacted data scientists' actions
- Continuous participants less likely to use protected attributes
- Continuous participants' models had fewer disparities
- Continuous participants more nuanced about missing data
- Nobody in None or Post-facto replicated Retrograde's analyses

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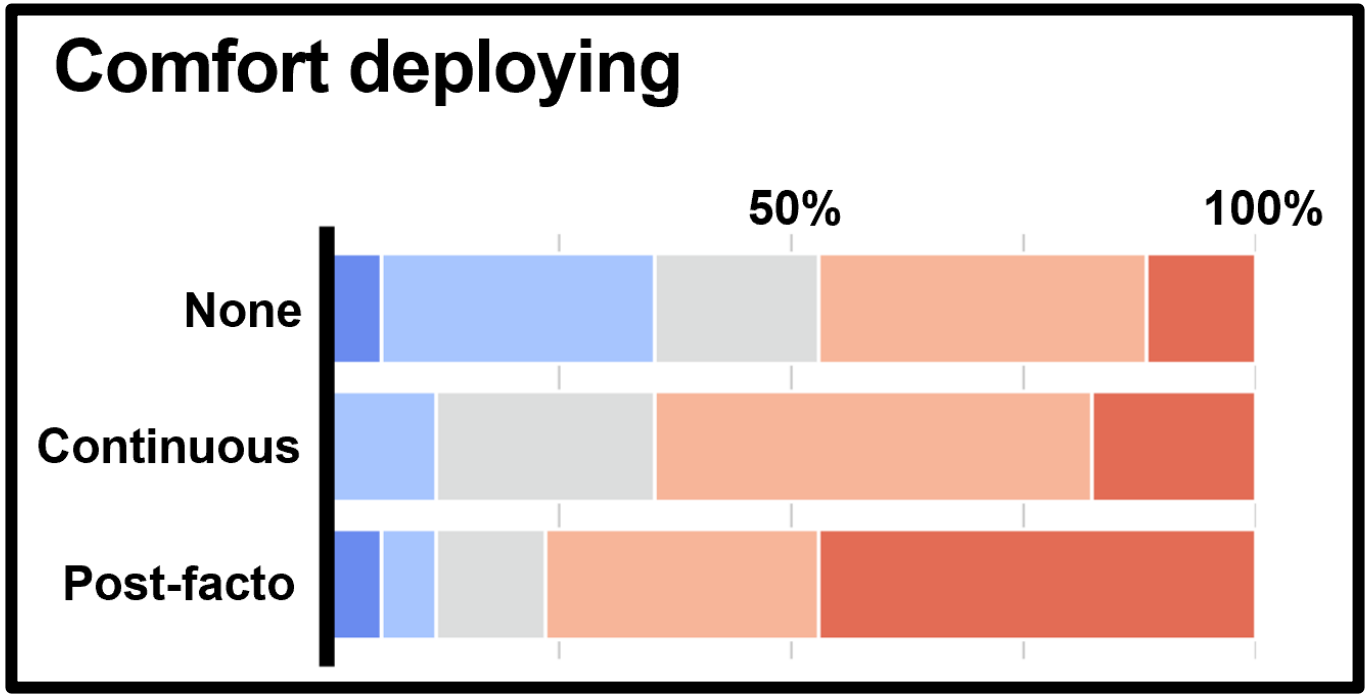
Retrograde: Comfort Deploying Model



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Algorithmic Decision Making (Revisited)

The Application Context Matters Greatly

Hiring

Online Advertising

Student Admissions

Criminal Justice

Health Insurance Markets

Creditworthiness

Selbst et al.’s Five Pitfalls

- Framing Trap
  - “Failure to model the entire system over which a social criterion, such as fairness, will be enforced“
- Portability Trap
  - “Failure to understand how repurposing algorithmic solutions designed for one social context may be misleading, inaccurate, or otherwise do harm when applied to a different context”
- Formalism Trap
  - “Failure to account for the full meaning of social concepts such as fairness, which can be procedural, contextual, and contestable, and cannot be resolved through mathematical formalisms”
- Ripple Effect Trap
  - “Failure to understand how the insertion of technology into an existing social system changes the behaviors and embedded values of the pre-existing system”
- Solutionism Trap
  - “Failure to recognize the possibility that the best solution to a problem may not involve technology”

Selbst et al. Fairness and Abstraction in Sociotechnical Systems. FAT*, 2019. https://dl.acm.org/doi/pdf/10.1145/3287560.3287598

What Does Accountability Mean Here?

- Who’s accountable for the consequences of an ML model?
  - Those who deployed it?
  - Those who built it and trained it?
  - The owners of the training data?
  - Those who listened to the algorithm?