Fairness

Material from Berkeley's CS 294: Fairness in Machine Learning (https://fairmlclass.github.io)
and
N[eur]IPS2017 tutorial
(https://vimeo.com/248490141)
by Solon Barocas (Cornell)
and Moritz Hardt (Berkeley)

Massachusetts Institute of Technology

NASEM Committee on Science, Technology, and Law

March, 2018

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- Science Curriculum for Law School
- Emerging Issues in Science, Technology, and Law
- Using Litigation to Target Scientists
- Communicating Advances in the Life Sciences to a Skeptical Public

Algorithms and Justice

- Government use of decision automation for
  - determining eligibility for services
  - evaluating where to deploy health inspectors and law enforcement personnel
  - defining boundaries around voting districts
- In the law
  - “To the extent they inject clarity and precision into bail, parole, and sentencing decisions, algorithmic technologies may minimize harms that are the products of human judgment.”
  - “Conversely, the use of technology to determine whose liberty is deprived and on what terms raises significant concerns about transparency and interpretability.”

https://cyber.harvard.edu/sites/default/files/2018-07/2018-02-12_AIAlgorithmsJusticeOnePager.pdf

What is Fairness?

- *your ideas…*

Bias, Technically

The NEW ENGLAND JOURNAL of MEDICINE
n engl j med 375;7 nejm.org August 18, 2016

SPECIAL ARTICLE

Genetic Misdiagnoses and the Potential for Health Disparities

Arjun K. Manrai, Ph.D., Birgit H. Funke, Ph.D., Heidi L. Rehm, Ph.D., Morten S. Olesen, Ph.D., Bradley A. Maron, M.D., Peter Szolovits, Ph.D., David M. Margulies, M.D., Joseph Loscalzo, M.D., Ph.D., and Isaac S. Kohane, M.D., Ph.D.

- {Selection, Sampling, Reporting} bias
- Case of Hypertrophic Cardiomyopathy
  - … risk stratification for hypertrophic cardiomyopathy has been enhanced by targeted genetic testing
  - Multiple patients, all of whom were of African or unspecified ancestry, received positive reports, with variants misclassified as pathogenic on the basis of the understanding at the time of testing.
  - Subsequently, all reported variants were re-categorized as benign.
  - The mutations that were most common in the general population were significantly more common among black Americans than among white Americans ($P<0.001$).
  - Simulations showed that the inclusion of even small numbers of black Americans in control cohorts probably would have prevented these misclassifications.

SCIENTIFIC REPORTS

Article | OPEN | Published: 15 April 2019

Genetic risk factors identified in populations of European descent do not improve the prediction of osteoporotic fracture and bone mineral density in Chinese populations

Yu-Mei Li ✉, Cheng Peng, Ji-Gang Zhang, Wei Zhu, Chao Xu, Yong Lin, Xiao-Ying Fu, Qing Tian, Lei Zhang, Yang Xiang, Victor Sheng & Hong-Wen Deng ✉

Scientific Reports **9**, Article number: 6086 (2019) | Download Citation ↓

Bias, Technically

- {Selection, Sampling, Reporting} bias
- Bias of an Estimator
  - Generally, we have bias, variance, and noise
  - O = optimal possible model over all possible learners (model family)
  - L = best model learnable by this learner
  - A = actual model learned
  - Bias = O - L (limitation of learning method or target model)
  - Variance = L - A (error due to sampling of training cases)
    - Estimate significance by comparing against learning from randomly permuted data

- Inductive Bias — assumptions made by the learning algorithm about regularities that allow prediction on unseen cases

adapted from Solon Barocas

Aliferis, C. F., Statnikov, A., & Tsamardinos, I. (2006). Challenges in the analysis of mass-throughput data: a technical commentary from the statistical machine learning perspective. Cancer Informatics, 2, 133–162.

Isn’t Discrimination the Very Point of Machine Learning?

- *Unjustified* basis for differentiation
- Practical irrelevance
- Moral irrelevance

- Fairness focuses on ethical concerns

- Discrimination is
  - domain specific — how it influences people’s life chances
  - feature specific — socially salient qualities that have served as the basis for unjustified and systematically adverse treatment in the past

adapted from Solon Barocas

Legally recognized ‘protected classes’

- Race (Civil Rights Act of 1964)
- Color (Civil Rights Act of 1964)
- Sex (Equal Pay Act of 1963; Civil Rights Act of 1964)
- Religion (Civil Rights Act of 1964)
- National origin (Civil Rights Act of 1964)
- Citizenship (Immigration Reform and Control Act)
- Age (Age Discrimination in Employment Act of 1967)
- Pregnancy (Pregnancy Discrimination Act)
- Familial status (Civil Rights Act of 1968)
- Disability status (Rehabilitation Act of 1973; Americans with Disabilities Act of 1990)
- Veteran status (Vietnam Era Veterans' Readjustment Assistance Act of 1974; Uniformed Services Employment and Reemployment Rights Act); Genetic information (Genetic Information Nondiscrimination Act)
- *Sexual orientation* (in some jurisdictions)

adapted from Solon Barocas

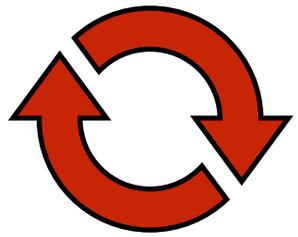
Two Doctrines of Discrimination Law

- Disparate Treatment
  - Formal — considering class membership
    - E.g., country club exclusion based on race or religion,
  - Intentional — without explicit reference to class, but with same effect
    - E.g., red-lining (mortgage availability based on geographic location)
- Disparate Impact
  - Unjustified, Avoidable
  - How to demonstrate: “4/5 rule” (20% difference establishes it)
  - How to defend: business necessity, job-related
  - Alternative practice: can we achieve the same goal but with less disparity?

adapted from Solon Barocas

Goals of (Anti-)Discrimination Law

- Disparate Treatment
  - Procedural fairness
  - Equality of opportunity
- Disparate Impact
  - Distributive justice
  - Minimize inequality of outcome



Conflict

E.g., affirmative action

- Non-discrimination:
  - ensuring that decision-making treats similar people similarly on the basis of relevant features, given their current degree of similarity
- Equality of opportunity:
  - organizing society in such a way that people of equal talents and ambition can achieve equal outcomes over the course of their lives
- Equality of outcome:
  - treat seemingly dissimilar people similarly, on the belief that their current dissimilarity is the result of past injustice

adapted from Solon Barocas

Discrimination Persists in Many Areas

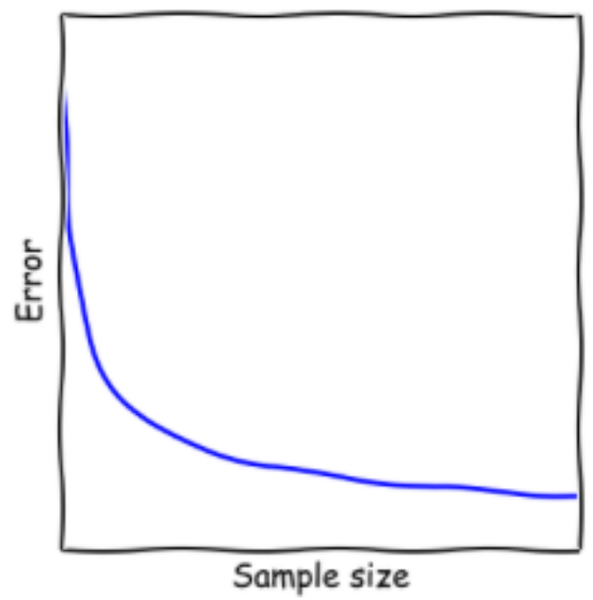
- Criminal justice — “Predictive Policing”
  - Police records measure “some complex interaction between criminality, policing strategy, and community-policing relations”
  - Future observations of crime confirm predictions
  - Fewer opportunities to observe crime that contradicts predictions
  - Initial bias may compound over time
- Housing
- Employment
- Health care
- …

adapted from Solon Barocas

https://hrdag.org/2016/10/10/predictive-policing-reinforces-police-bias/

Ongoing Problems

- Limited features
  - Features may be less informative or less reliably collected for certain parts of the population
  - A feature set that supports accurate predictions for the majority group may not for a minority group
  - Different models with the same reported accuracy can have a very different distribution of error across population
- Sample size disparity
- Leakage
  - With rich data, protected class membership will be unavoidably encoded across other features
  - No self-evident way to determine when a relevant attribute is too correlated with proscribed features



adapted from Solon Barocas

Formalizing Fairness Discussion

- Hardt's example: advertising for a software engineer, question of gender bias

- Notation:
  $\mathbb{P}_a\{E\} = \mathbb{P}\{E \mid A=a\}$

$\boldsymbol{X}$	features of an individual (browsing history)
$\boldsymbol{A}$	sensitive attribute (gender)
$\boldsymbol{R} = r(\boldsymbol{X}, \boldsymbol{A})$ $\boldsymbol{C} = c(\boldsymbol{X}, \boldsymbol{A})$	score/predictor (show ad) [classify by thresholding score]
$\boldsymbol{Y}$	hire software engineer

adapted from Moritz Hardt

https://fairmlbook.org/index.html

Proposed Criteria of Fairness

- **Independence** of scoring function from sensitive attributes
  - $R \perp A$
- **Separation** of score and sensitive attribute given outcome
  - $R \perp A \mid Y$
- **Sufficiency**
  - $Y \perp A \mid R$

adapted from Moritz Hardt

https://fairmlbook.org/demographic.html

Independence
R ⊥ A

- Also called demographic parity, statistical parity, group fairness, disparate impact
- $P\{R = 1 \mid A = a\} = P\{R = 1 \mid A = b\}$ for all groups A
- thus, unfair if
  - $|P\{R = 1 \mid A = a\} - P\{R = 1 \mid A = b\}| > \epsilon$
  - $\left|\frac{P\{R = 1 \mid A = a\}}{P\{R = 1 \mid A = b\}} - 1\right| \geq \epsilon$
  - ε = 0.2 relates to 4/5 rule

adapted from Moritz Hardt

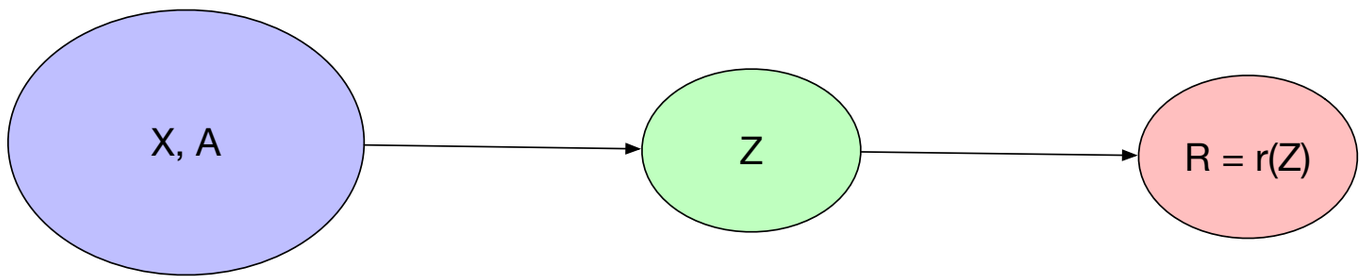
Problems with Independence

- Only requires equal rates of decisions (hiring, liver transplants, etc.)
  - But, what if hiring is based on a good score in group a, but random in b, though with same probability?
  - Outcomes will (most likely) be better for group a, establishing problems for the future!
    - Could be caused by malice, or by better information about group a.
- What if A is a perfect predictor of Y?
  - … or at least is strongly correlated?
  - How much are you willing to decrease the effectiveness of the predictor to achieve fairness?

adapted from Moritz Hardt

Potential Fixes to Achieve Independence

- Pre-processing:
  - Adjust the feature space to be uncorrelated with the sensitive attribute
    - Domain-specific
  - Representation learning



max I(X; Z)
min I(A; Z)

Zemel, R. S., Wu, Y., Swersky, K., Pitassi, T., & Dwork, C. (2013). Learning Fair Representations. ICML.

- Impose independence constraints at training time (for a given data set)
  E.g., include dependence in the loss function, differential sampling, …

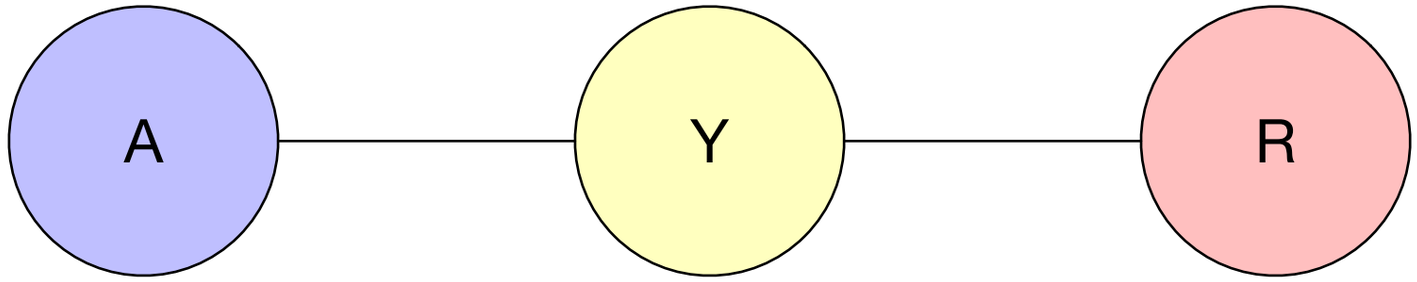
Calders, T., Kamiran, F., & Pechenizkiy, M. (2010). Building Classifiers with Independency Constraints (pp. 13–18). Presented at the 2009 IEEE International Conference on Data Mining Workshops (ICDMW), IEEE. http://doi.org/10.1109/ICDMW.2009.83

- Post-processing
  - Create a new classifier F, $\hat{Y} = F(R, A)$
  - minimize cost of misclassification, perhaps more strongly for protected A

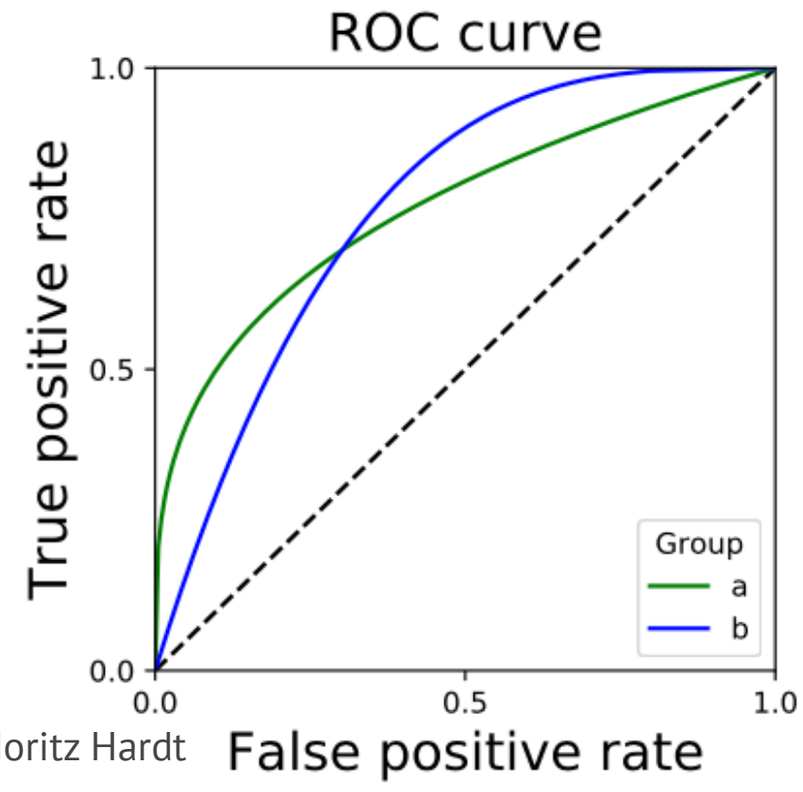
adapted from Moritz Hardt

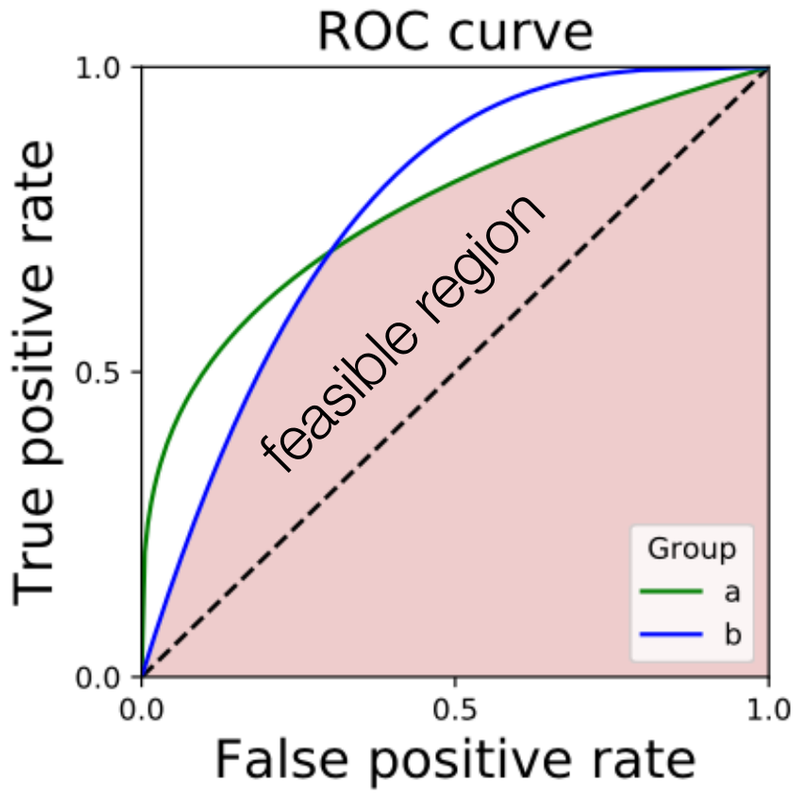
Feldman, M., Friedler, S. A., Moeller, J., Scheidegger, C., & Venkatasubramanian, S. (2015). Certifying and Removing Disparate Impact. KDD : Proceedings / International Conference on Knowledge Discovery & Data Mining. International Conference on Knowledge Discovery & Data Mining, 259–268. http://doi.org/10.1145/2783258.2783311

Separation
$R \perp A \mid Y$



- Recognizes that A may be correlated with the target variable
  - E.g., different success rates in a drug trial for different ethnic populations
- $P\{R = 1 \mid Y = 1, A = a\} = P\{R = 1 \mid Y = 1, A = b\}$
  $P\{R = 1 \mid Y = 0, A = a\} = P\{R = 1 \mid Y = 0, A = b\}$
  - i.e., true and false positive rates for both classes must be the same
- Can choose any true positive/false positive tradeoff in the feasible region, depending on relative costs





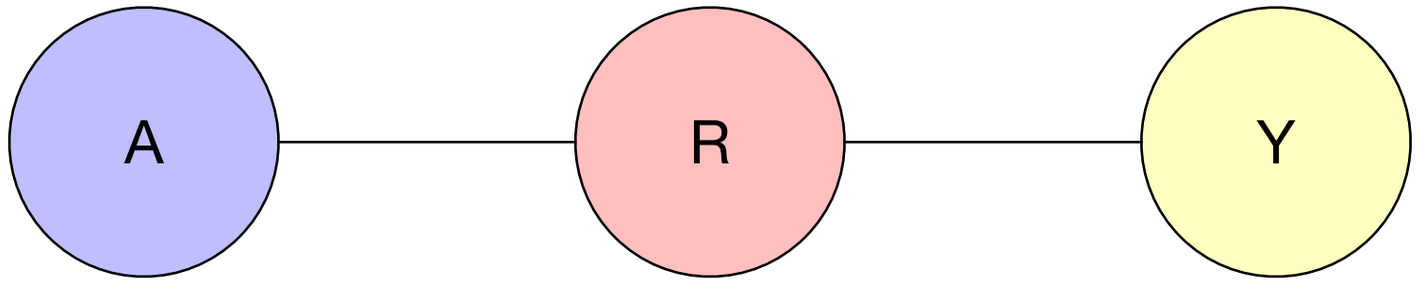
adapted from Moritz Hardt

Advantages of Separation over Independence

- Allows correlation between R and Y (even perfect predictor)
- Incentive to reduce errors uniformly in all groups

adapted from Moritz Hardt

Sufficiency
$Y \perp A \mid R$

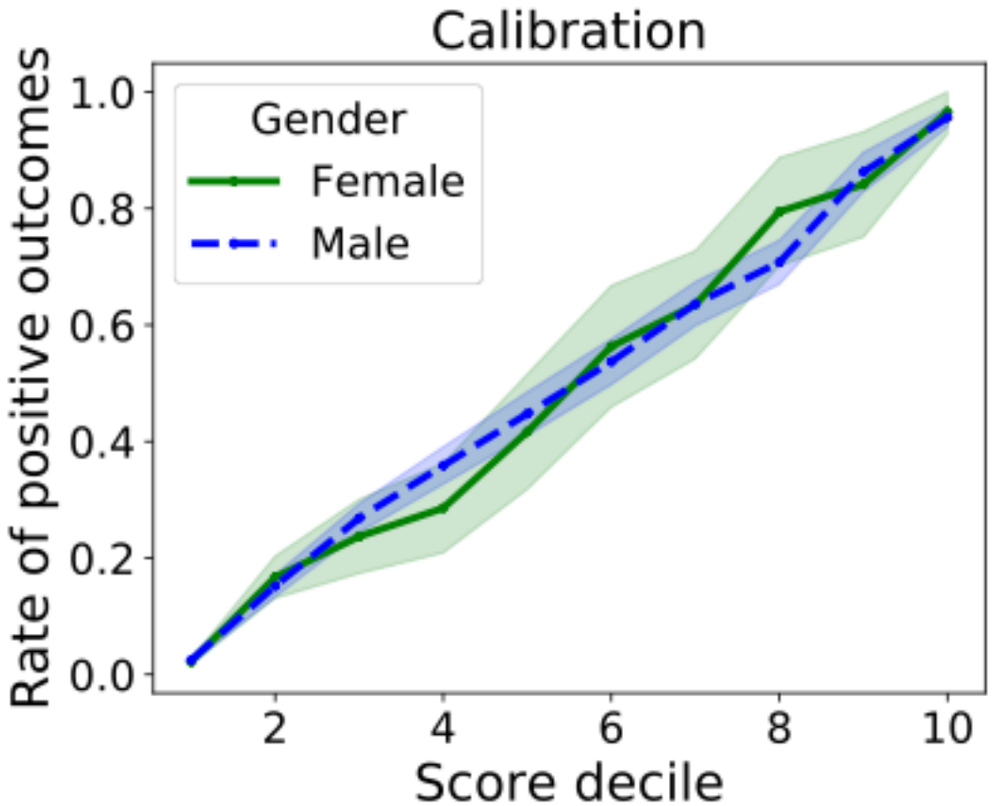


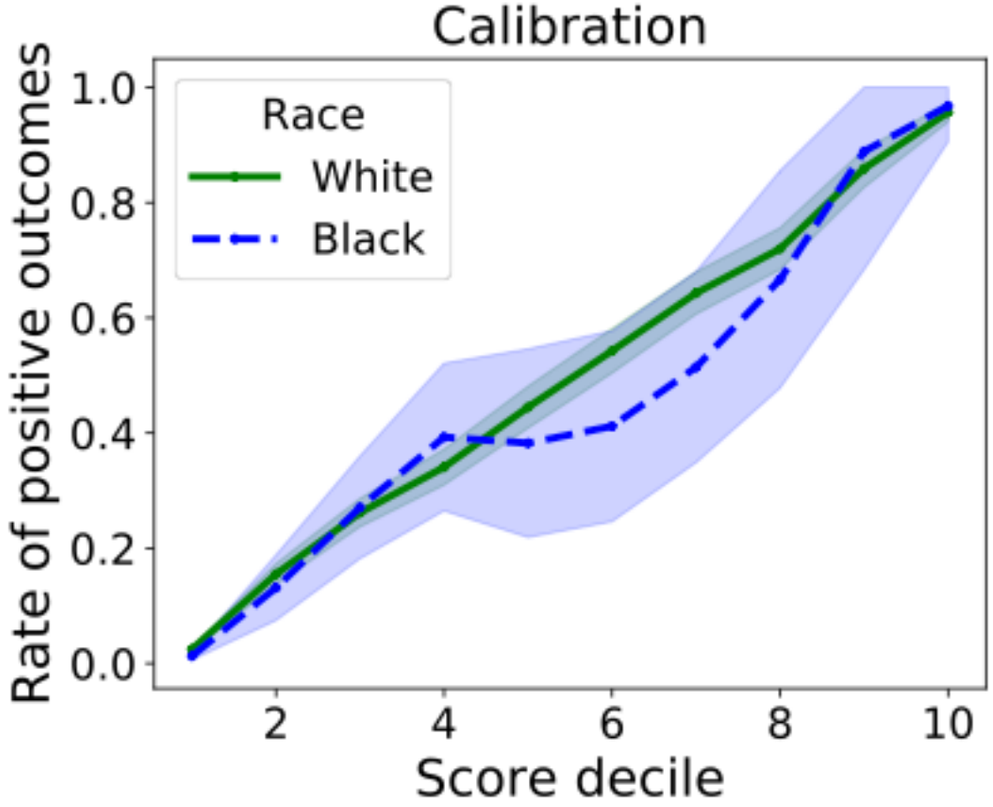
- $P\{Y = 1 \mid R = r, A = a\} = P\{Y = 1 \mid R = r, A = b\}$
- Requires parity of positive and negative predictive values across groups
- R is *calibrated* if $P\{Y = 1 \mid R = r, A = a\} = r$
  - I.e., if the scoring function is a probability of outcome, or
  - “the set of all instances assigned a score value *r* has an *r* fraction of positive instances among them”
- Can recalibrate a scoring function R by fitting a sigmoid
  - $S = \frac{1}{1 + e^{aR+b}}$
  - and optimizing log loss $-\mathbb{E}[Y \log S + (1 - Y) \log(1 - S)]$
- Calibration by group implies sufficiency

adapted from Moritz Hardt

Calibration Can be Good Without Even Trying

- E.g., UCI census data set, predicting income > $50,000/year for those over 16yo with some income
- Features (14): age, type of work, weight of sample, education, marital status, occupation, military service, race, sex, capital gain/loss, hours per week of work, native country, …





https://fairmlbook.org/demographic.html
https://archive.ics.uci.edu/ml/datasets/adult

Bad News!

- It is not possible to jointly achieve any pair of these conditions
  - Independence *xor* Separation
  - Independence *xor* Sufficiency
  - Separation *xor* Sufficiency

- Nice illustration at
  - https://research.google.com/bigpicture/attacking-discrimination-in-ml/

Modeling Mistrust in End-of-Life Care

Willie Boag [1] Harini Suresh [1] Leo Anthony Celi [1] Peter Szolovits [1] Marzyeh Ghassemi [1 2 3 4]

Based on Boag, W. (2018, June). Quantifying Racial Disparities in End-of-Life Care. Master's Thesis, MIT EECS. Cambridge, MA.

- Replicate in MIMIC Racial Disparities expectation from previous studies
- Model Mistrust Algorithmically
- Compare Racial and Mistrust Disparities

slide from Willie Boag

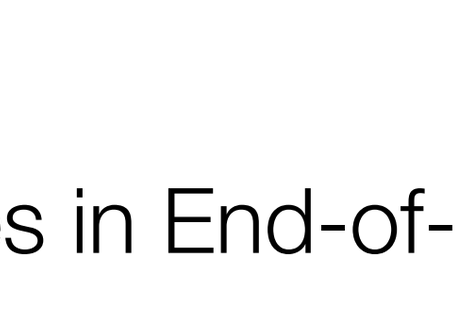
,
W Boag, H Suresh, L Celi, P Szolovits, and M Ghassemi (2018). Racial Disparities and Mistrust in End-of-Life Care, In Proceedings of the 3rd Machine Learning for Healthcare Conference, PMLR, Palo Alto, California, 85, pages 587-602, 17--18 Aug, 2018. URL: http://proceedings.mlr.press/v85/boag18a.html.

Racial Disparities in End-of-Life Care

African American patients receive longer durations of aggressive treatment during end-of-life care

Figure 3-1: **Mechanical Ventilation:** CDF of ventilation duration by race, where dotted lines represent the median duration treatment for a population. In multiple datasets, the median black patient receives statistically significant longer ventilation durations than the median white patient.

(a) *MIMIC Mechanical Ventilation*
White: 4810 patients
Black: 510 patients
p=0.005



(b) *eICU Mechanical Ventilation*
White: 4911 patients
Black: 655 patients
$p < 0.001$

Figure 3-2: **Vasopressors:** In both datasets, the median black patient receives a longer duration of vasopressors than the median white patient. This trend is not statistically significant in either dataset..

(a) *MIMIC Vasopressors*
White: 4458 patients
Black: 453 patients
p=0.122

(b) *eICU Vasopressors*
White: 3479 patients
Black: 464 patients
p=0.422

Could this be the result of mistrust?

(e.g. If your doctor recommends hospice, do you accept their advice?)

slide from Willie Boag

Clues of Mistrust

Noncompliance in Clinical Notes

Social: Pt refused to sign ICU consent and expressed wishes to be DNR/DNI, seemingly very frustrated and mistrusting of healthcare system in relation to [redacted]. Also, w/ hx of poor medication compliance and follow-up

Autopsy Rates

Table 4.3: Autopsy rates by race in MIMIC III.

population	consent	decline	% consent
Asian	2	23	8.0%
White	161	505	24.2%
Other	56	102	32.9%
Black	32	51	38.6%
Hispanic	9	11	45.0%
ALL	260	692	27.3%

Problem: Not every patient has an “obvious” label.

Can we use the obvious examples as labels and train a model to interpolate every patient’s “mistrust” score onto the scale?

slide from Willie Boag

Chart Events Give Clues About Patient State Relevant to True

Table 4.1: Coded interpersonal feature types from chartevents.

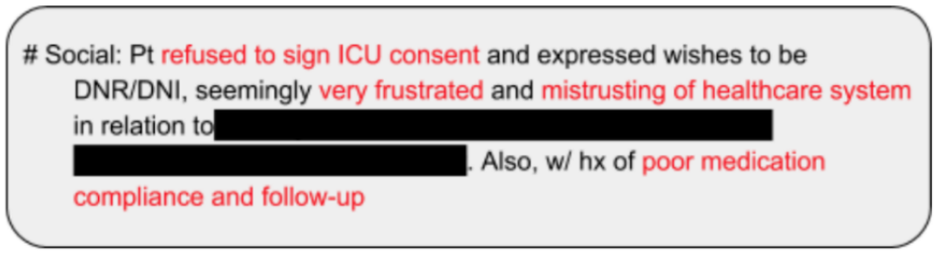
1:1 sitter present?	baseline pain level (0 to 10)	received bath?	bedside observer
behavioral intervent	currently experiencing pain	disease state	consults
education barrier	education learner	education method	feamily meeting?
education readiness	harm by partner?	education topic	judgement
follows commands?	family communication method	gcs - verbal response	informed?
hair washed?	goal richmond-ras scale	headache?	health care proxy?
pain management	non-violent restraints?	orientation	pain (0 to 10)
pain assess method	understand & agree with plan?	pain level acceptable?	reason for restraint
restraint device	richmond-ras scale (-5 to +4)	rsbi deferred	riker-sas scale
safety measures	violent restraints ordered?	security	security guard
side rails	status and comfort	sitter	skin care?
spiritual support	behavior during application	support systems	stress
verbal response	teaching directed toward	wrist restraints?	social work consult?

Structured data in the EHR documenting interpersonal variables, including:

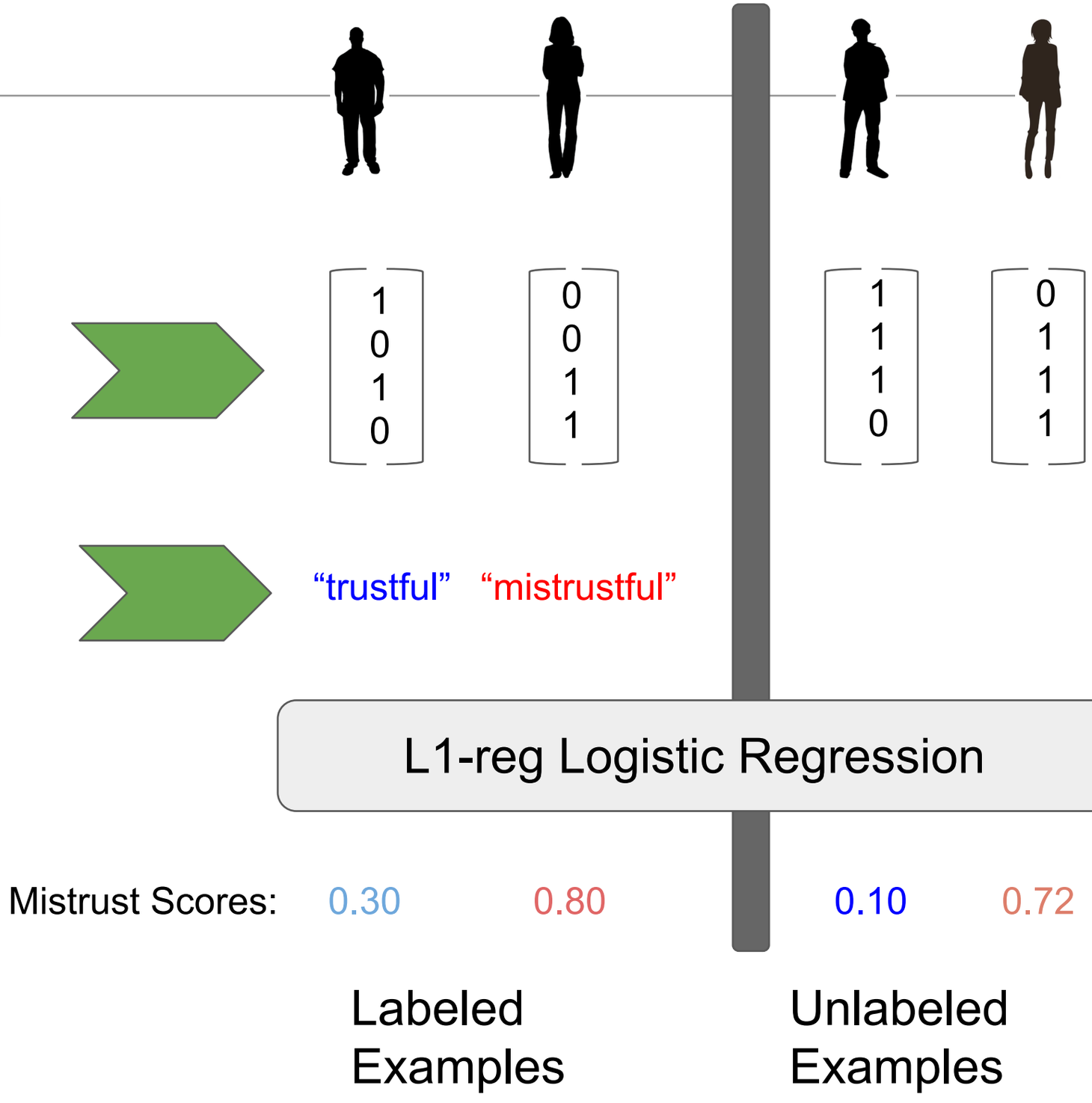
- Is the patient's comfort being taken seriously?
- Is the patient being treated as a threat?
- Is the patient's pain being managed?
- Are there good communication between staff and the family?

slide from Willie Boag

Modeling Mistrust



620 binary indicators of trust
indication of family meetings
patient education engagement
patient needed to be restrained
pain is being monitored and treate
healthcare literacy
has a healthcare proxy
has a support system (such as family, social workers, and religion)
agitation scales (Riker-SAS and Richmond-RAS)



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Inspecting the Mistrust Metrics

Mistrustful patients: Agitated & in pain
Trustful patients: No pain & calm

Feature	Weight
state: alert	-1.0156
riker-sas scale: agitated	0.7013
pain: none	-0.5427
richmond-ras scale: 0 alert and calm	-0.3598
education readiness: no	0.2540
pain level: 7-mod to severe	0.2168

(a) Noncompliance-derived Mistrust

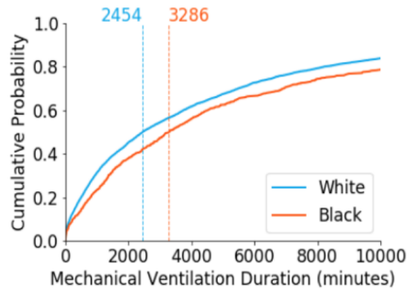
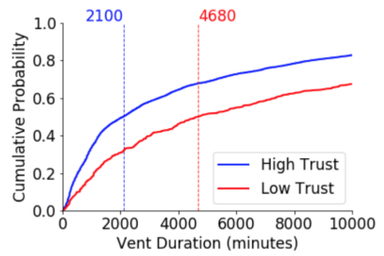
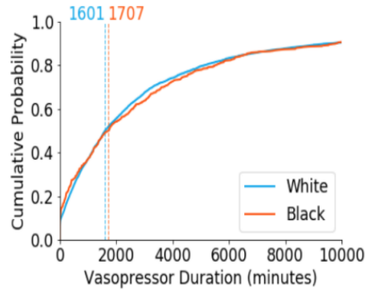
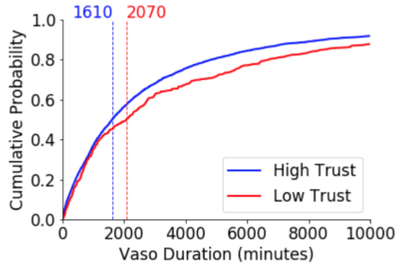
Mistrustful patients: Restrained
Trustful patients: No pain & healthcare literacy

Feature	Weight
pain present: no	-0.2689
spokesperson is healthcare proxy	-0.2271
family communication: talked to m.d.	-0.1184
reapplied restraints	0.1153
restraint type: soft limb	0.0980
orientation: oriented 3x	0.0363

(b) Autopsy-derived Mistrust

slide from Willie Boag

Treatment Disparities are much larger across trust cohorts than race.

	Race-based Disparity	Trust-based Disparity
Mechanical ventilation	 (a) *MIMIC Mechanical Ventilation* **White**: 4810 patients **Black**: 510 patients p=0.005	 (a) **Mechanical Ventilation** **High Trust**: 4810 patients **Low Trust**: 510 patients $p < 0.001$
Vasopressors	 (a) *MIMIC Vasopressors* **White**: 4458 patients **Black**: 453 patients p=0.122	 (b) **Vasopressors** **High Trust**: 4456 patients **Low Trust**: 453 patients p=0.001

slide from Willie Boag

Mistrust is Not Just a Proxy for Severity

Table 4: Pairwise Pearson correlation coefficients between scores.

	OASIS	SAPS II	Noncompliance	Autopsy	Sentiment
OASIS	1.0	0.679	0.050	-0.012	0.075
SAPS II	0.679	1.0	0.013	-0.013	0.086
Noncompliance	0.050	0.013	1.0	0.262	0.058
Autopsy	-0.012	-0.013	0.262	1.0	0.044
Sentiment	0.075	0.086	0.058	0.044	1.0

slide from Willie Boag

Population Mistrust

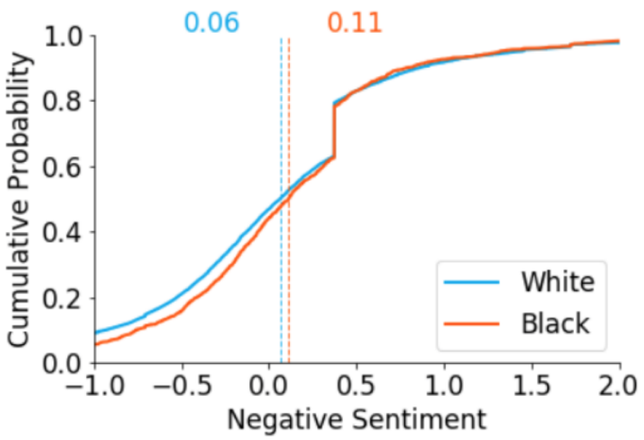


Figure 4-4: Racial disparity in (negative) sentiment.
White: 9669 patients
Black: 1173 patients
p=0.007

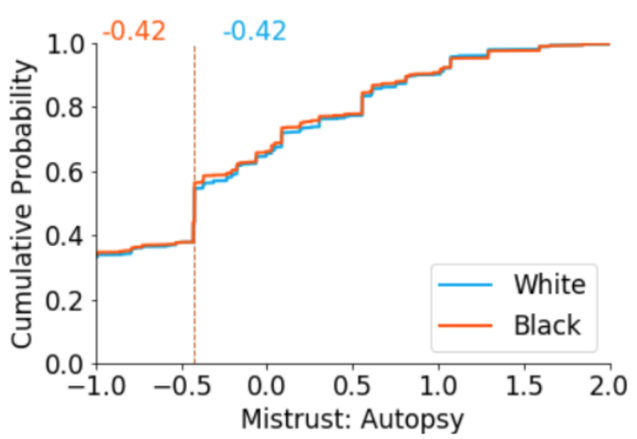


Figure 4-3: Racial disparity in autopsy-derived mistrust metric.
White: 9923 patients
Black: 1202 patients
p=0.126

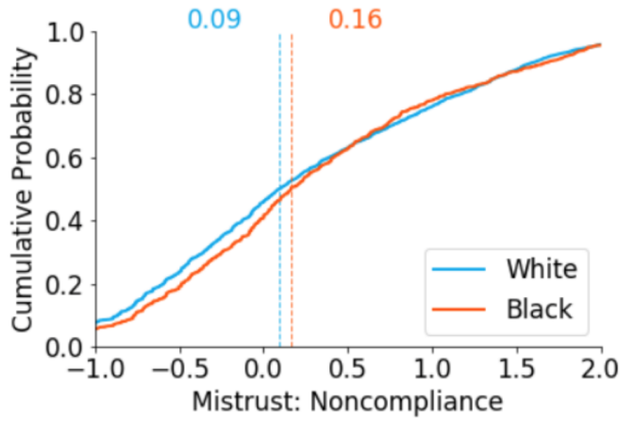


Figure 4-2: Racial disparity in noncompliance-derived mistrust metric.
White: 9923 patients
Black: 1202 patients
$p < 0.001$

For 2/3 metrics, the median black patient has a statistically significantly higher mistrust score than the median white patient.

slide from Willie Boag

Much Work and Education to be Done

- Conferences and Workshops
  - Fairness, Accountability, and Transparency in Machine Learning (FAT/ML) Workshop
  - ACM Conference on Fairness, Accountability, and Transparency (ACM FAT*)
  - Machine Learning for Healthcare Conference (MLHC)
  - ACM CHI Conference on Human Factors in Computing Systems (CHI)
- Popular Press
- Classes
  - Berkeley CS 294: Fairness in Machine Learning
  - U. Penn CIS 399 The Science of Data Ethics