Fairness in Machine Learning and AI

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Outline

When machines replace humans

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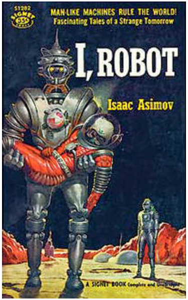
Isaac Asimov's three laws of robotics



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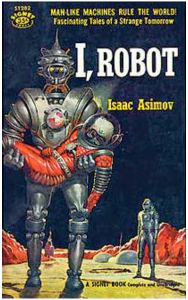

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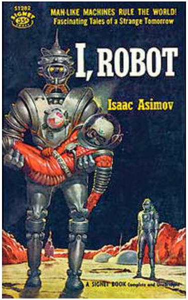

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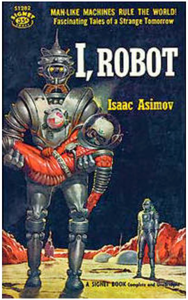

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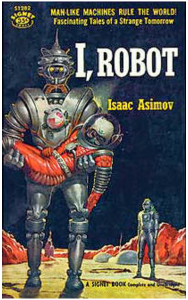

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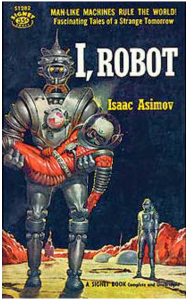

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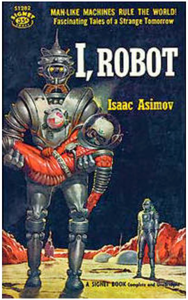

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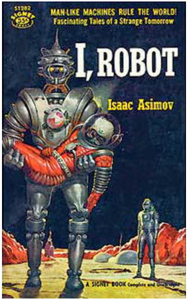

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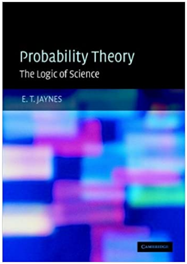

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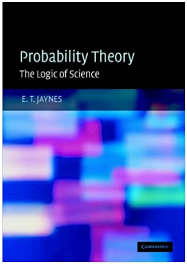

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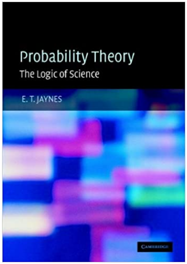

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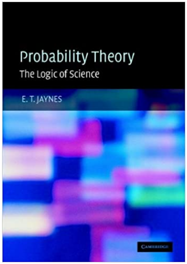

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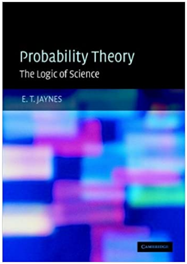

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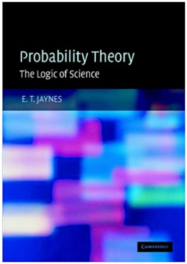

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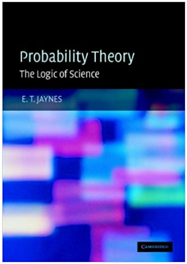

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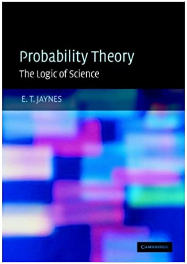

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Consequence: open door to unfair decisions, uncontrollable behavior, unseen biases.

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Consequence: clear example of undesired/uncontrolled discrimination:

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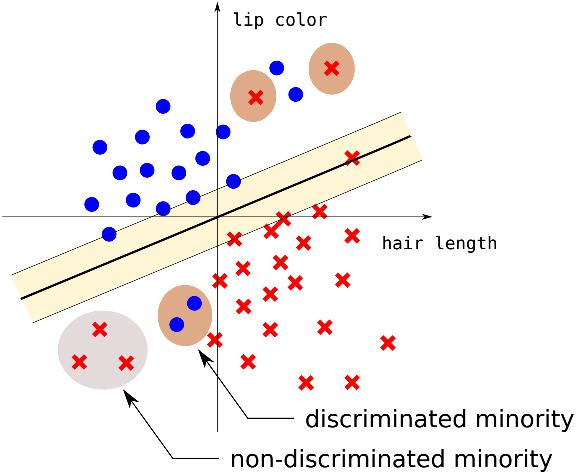
Under SVM formulation: in best effort strategy, minority groups excluded from optimization



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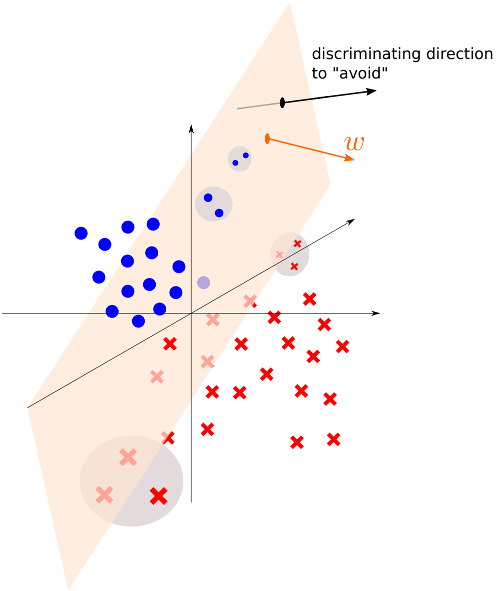
Under SVM formulation: possible counter-measure: force separating hyperplane against discriminating directions?



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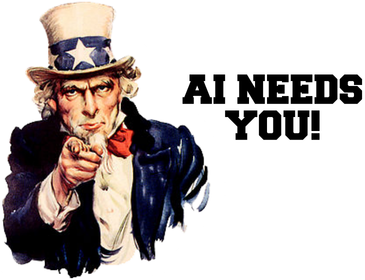
4. **Big problem**: three desiderata mutually incompatible!

Main objectives and messages of the class

. . . incomplete conclusion . . . : as future AI engineers, you will be the ambassadors of **a fair AI**



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Outline

Fairness: law and ethics

The question of discriminating data and information

The problem: algorithms reinforce human prejudices

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- algorithms written and maintained by people,

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  - indirect sensitive information inference is also unethical...

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discriminating data $\Leftrightarrow$ **disparate treatment**

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3. plaintiff may retort: live tests with modern construction site equipment has same effect, but is less discriminating.

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Consequence: Tension between disparate treatment and disparate outcomes!

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3. white people in turn complain: job chances have become unequal!

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- but still limited: exploits previous managers' biases

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3. understand causes of disparities: identify and eliminate proxies (correlated features).

Outline

Formalizing fairness in machine learning

Formal Setup

Probabilistic setup: (e.g., advertisement display for Software Engineer job position)

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  $\longrightarrow$ e.g., Bayes' optimal score for quadratic loss (MMSE):

$$R_{\text{Bayes}} = \mathbb{E}[Y|X = x, A = a].$$

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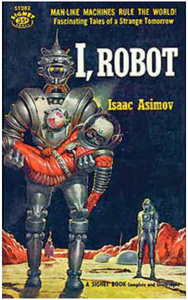

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Law 2. **Separation** (also called **predictive value parity**)

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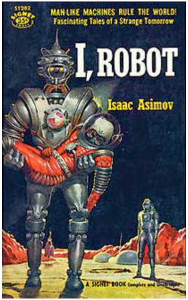

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Question: How would the "AI robot" apply the fairness rules?

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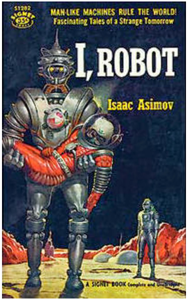

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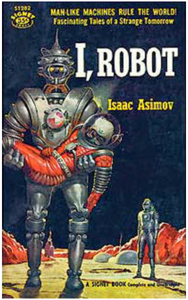

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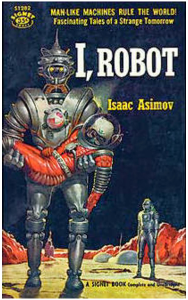

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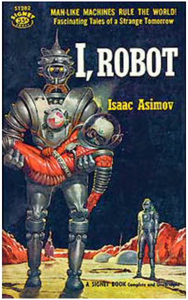

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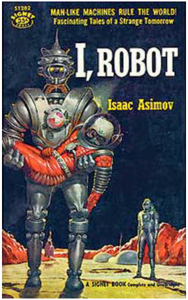

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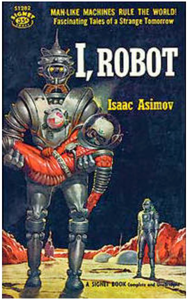

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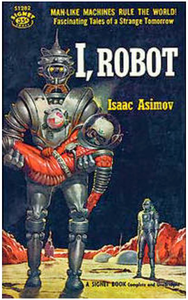

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e.g., the 20% discrimination rule!

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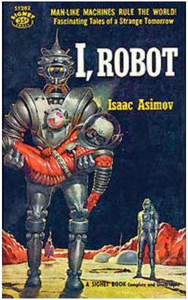

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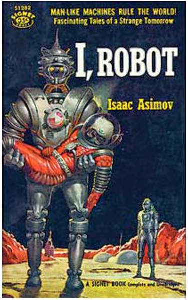

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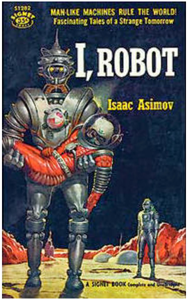

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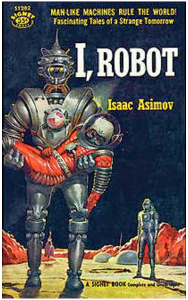

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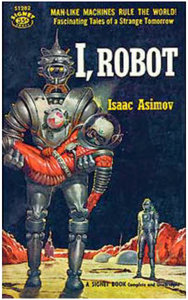

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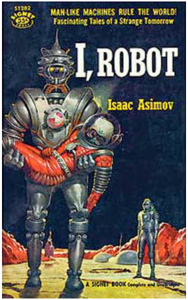

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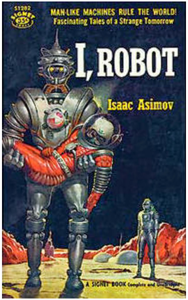

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- postprocessing ($R \to \hat{Y}$): any thresholding allowed!

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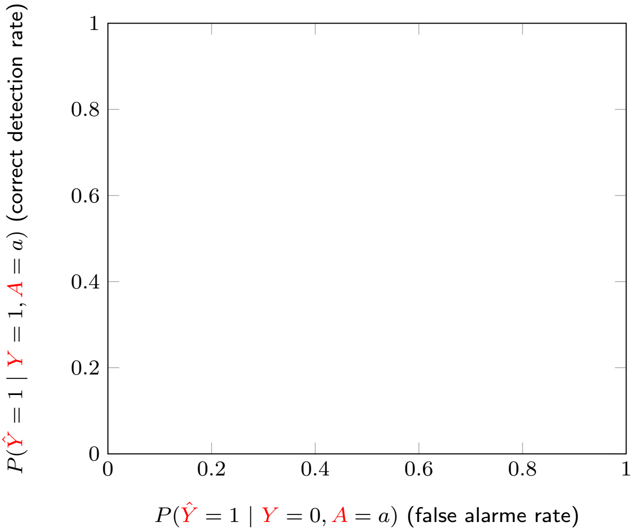

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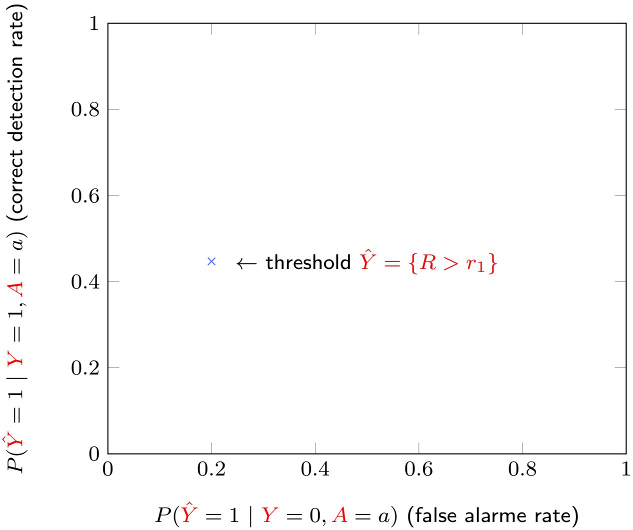

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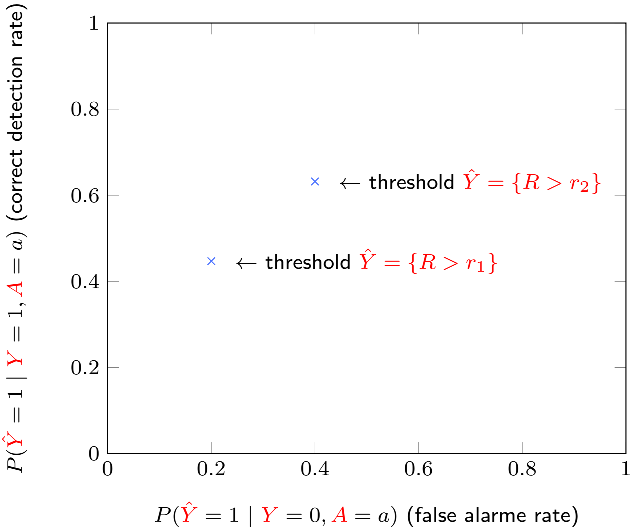

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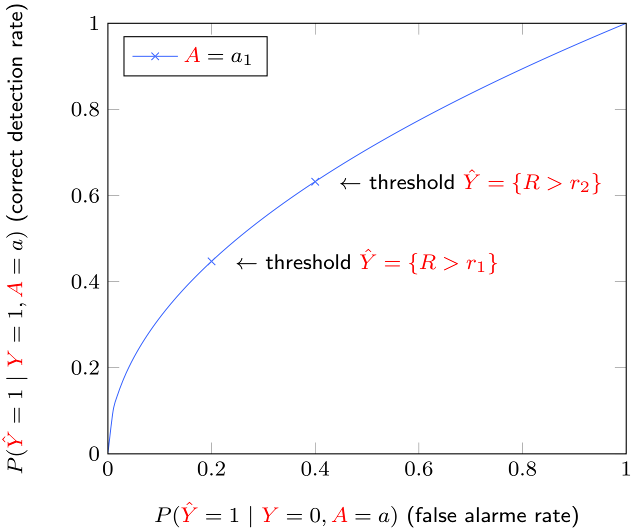

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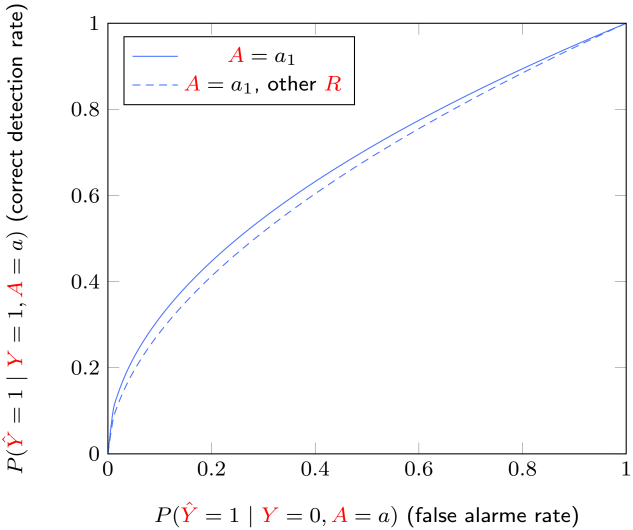

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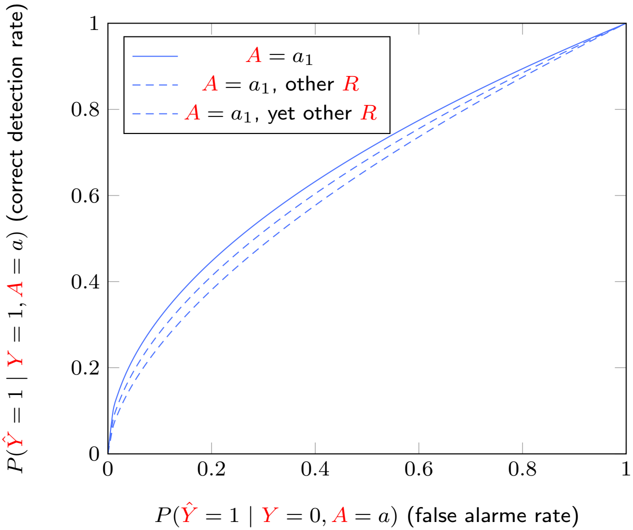

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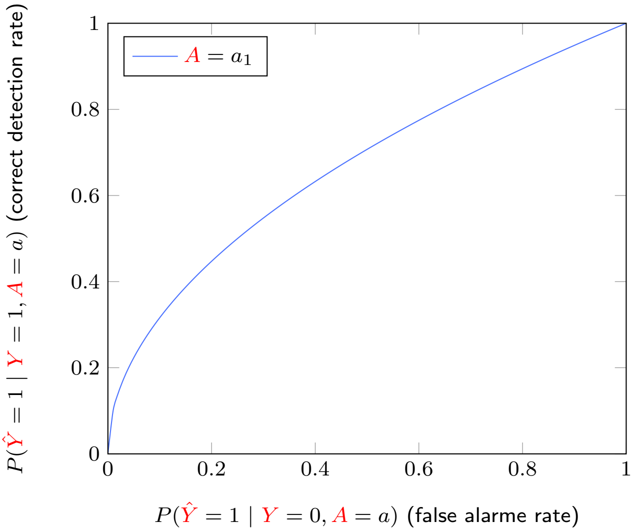

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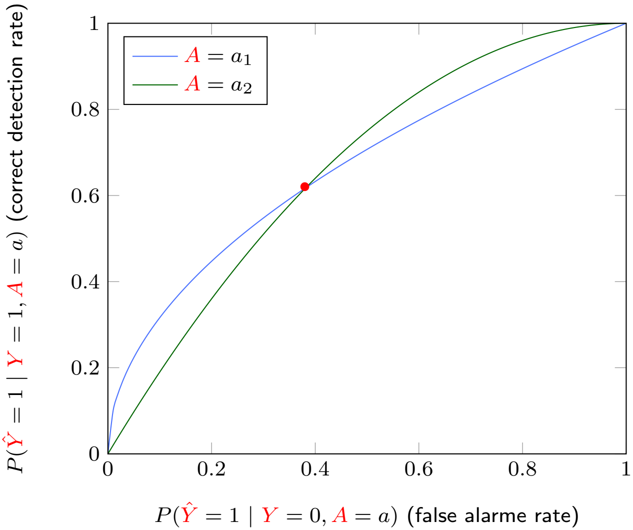

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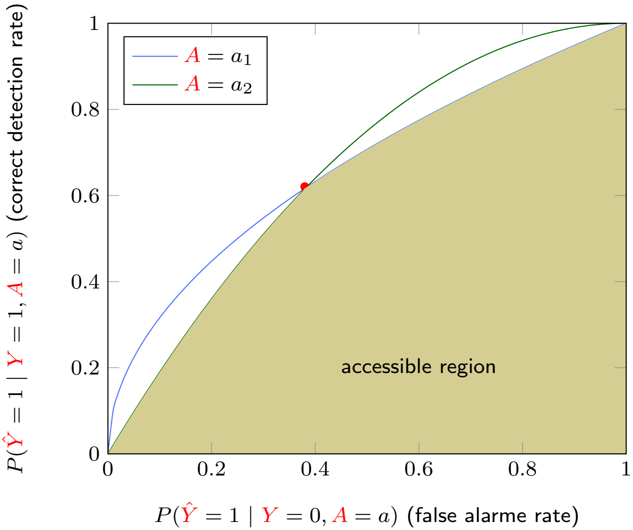

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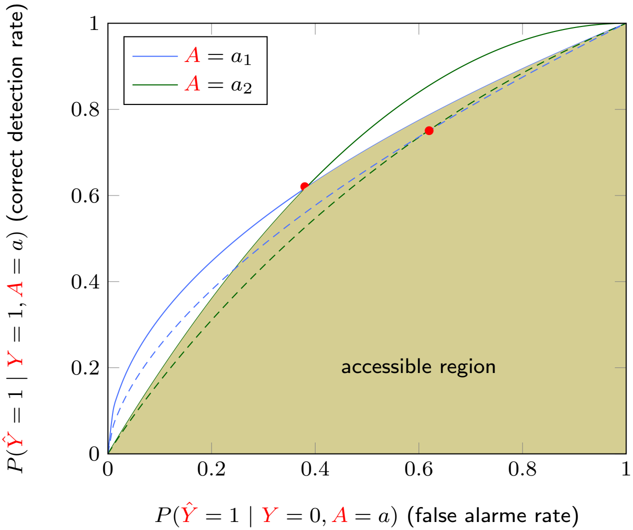

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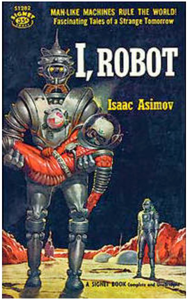

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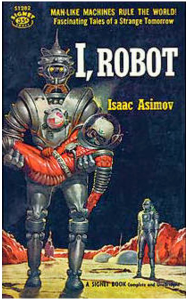

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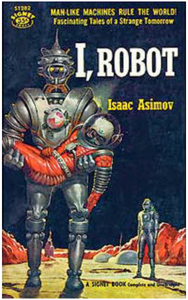

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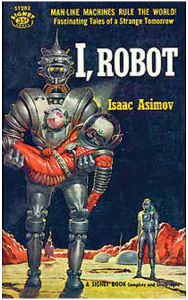

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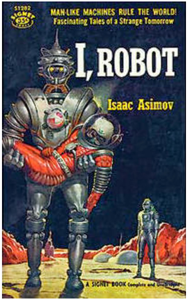

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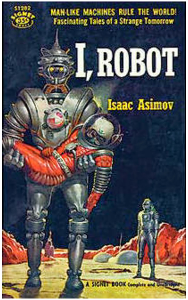

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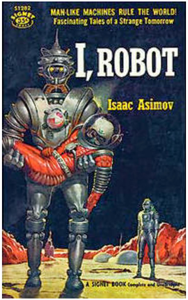

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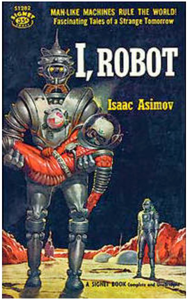

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- since cross-entropy loss unknown, calibration performed on **training dataset** $\{(y_i, r_i)\}_{i=1}^n$:

$$\min_{\alpha,\beta} - \sum_{i=1}^{n} y_i \log s_i + (1 - y_i) \log(1 - s_i) \quad \text{where} \quad s_i = \frac{1}{1 + \exp(\alpha r_i + \beta)}.$$

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- which optimal balancing of desiderata for each given situation, ML problem?

MAJOR PROBLEM

Any two of the **3 desiderata are mutually exclusive**! (except in trivial cases)

Consequences:

- in practice, **trade-offs** must be performed
- this explains **(theoretically!)** why lawsuits can be endless!
- which optimal balancing of desiderata for each given situation, ML problem?
- more philosophically: **is fairness accessible to mathematics, and thus machines?**

The three desiderata

Independence vs. sufficiency:

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Independence vs. sufficiency:

Proposition

If $Y \not\perp A$, then **either independence holds or sufficiency, but not both**.

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If $Y \not\perp A$ (non trivial case) and $Y \perp A \mid R$ (sufficiency), then $R \not\perp A$ (no independence).

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If $Y \not\perp A$ (non trivial case) and $Y \perp A \mid R$ (sufficiency), then $R \not\perp A$ (no independence).

So, conversely, if $R \perp A$ (independence), then $Y \not\perp A \mid R$ (not sufficiency) or $Y \perp A$ (trivial case).

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If $R \perp A$ and $R \perp A \mid Y$, then $A \perp Y$ or $R \perp Y$.

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If $R \perp A$ and $R \perp A \mid Y$, then $A \perp Y$ or $R \perp Y$.

So, conversely, if $A \not\perp Y$ and $R \not\perp Y$, then either $R \not\perp A$ (not independence) or $R \not\perp A \mid Y$ (not separation).

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Hence, $A \not\perp Y$ implies either $A \not\perp R \mid Y$ or $A \not\perp Y \mid R$.

So, conversely, separation **and** sufficiency imply $A \perp Y$ which is forbidden (trivial setting).

Outline

Case study: loan granting

Loan granting: the setup

Borrowed from:

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

Setup:

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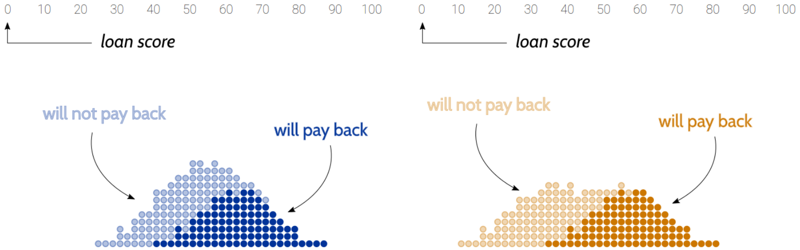
- expected output $Y =$"will pay back".

Output for the bank:

- successful loan: $\$300$,
- unsuccessful loan: $-\$700$,
- credit score in $(0, 100)$.

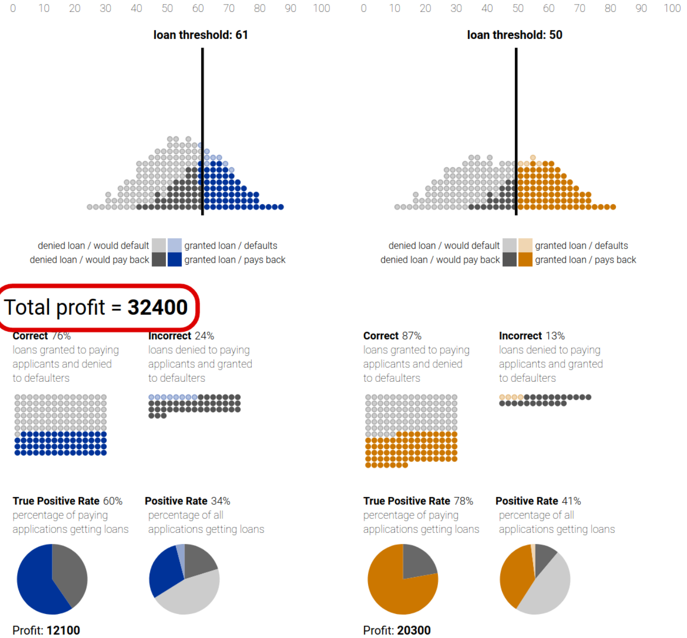
Loan granting: the setup

Populations and credit score:



Loan granting: Max profit

No fairness case: max profit for bank (assuming bank knows statistics)



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- disparate positive rates $\hat{Y} \mid A$ (34% vs. 41%)
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- disparate true positives $\mathbb{P}(\hat{Y} = 1 \mid Y = 1, A = a)$ (60% vs. 78%)

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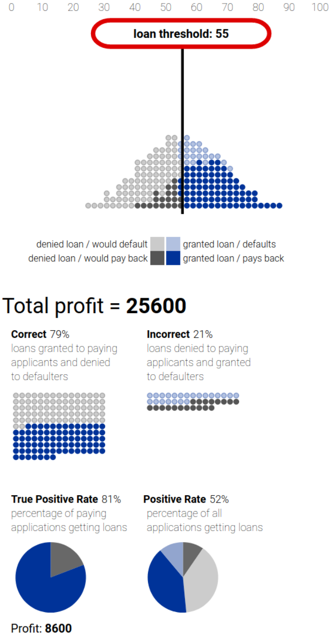
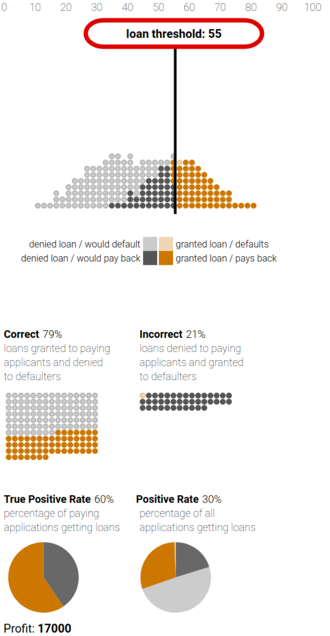
"**The most profitable, since there are no constraints**"

Loan granting: Group unaware

Group unaware case: max profit by considering all groups as one (unique threshold r_0)





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- disparate positive rates $\hat{Y} \mid A$ (52% vs. 30%)

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- disparate positive rates $\hat{Y} \mid A$ (52% vs. 30%)
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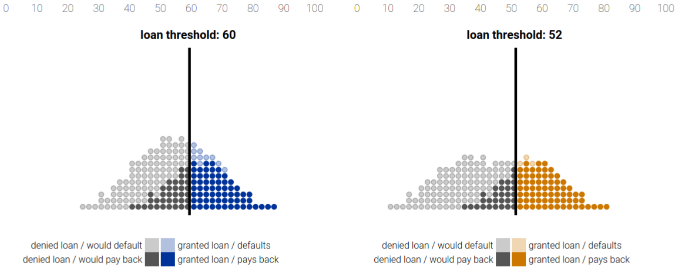
"**Both groups have the same threshold**"

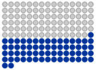
Loan granting: Demographic parity

Demographic parity case: Independence $\hat{Y} \perp A$ (law 1)



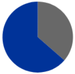
Total profit = **30800**

Correct 77%
loans granted to paying applicants and denied to defaulters



Incorrect 23%
loans denied to paying applicants and granted to defaulters

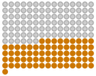
True Positive Rate 64%
percentage of paying applications getting loans



Positive Rate 37%
percentage of all applications getting loans

Profit: **11900**

Correct 84%
loans granted to paying applicants and denied to defaulters



Incorrect 16%
loans denied to paying applicants and granted to defaulters

True Positive Rate 71%
percentage of paying applications getting loans

Positive Rate 37%
percentage of all applications getting loans

Profit: **18900**

Loan granting: Demographic parity

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- equal positive rates $\hat{Y} \mid A$ (37% vs. 37%)
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- disparate true positives $\mathbb{P}(\hat{Y} = 1 \mid Y = 1, A = a)$ (64% vs. 71%)

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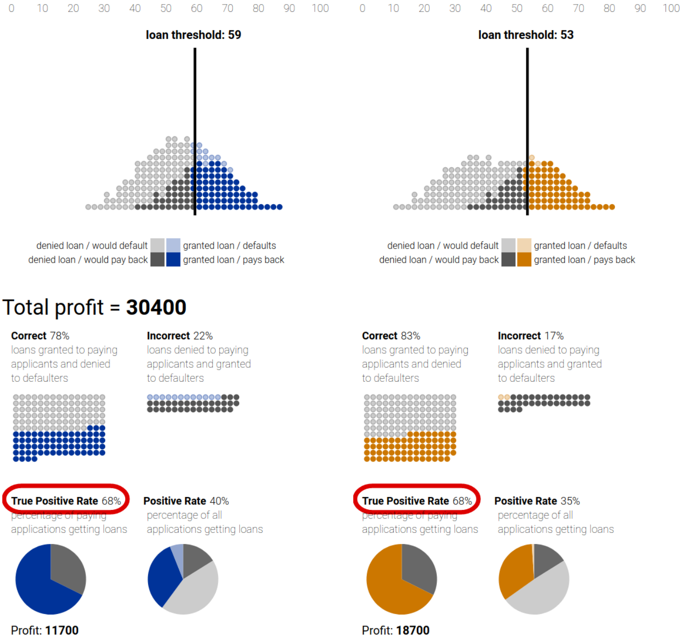
"**The number of loans given to each group is the same**"

Loan granting: Equal opportunity

Equal opportunity case: Separation $R \perp A \mid Y$ (law 2)



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"**Among people who would pay back a loan, blue and orange groups do equally well**"

Outline

Conclusion. . . well, partial!

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what about AI and ethics? should we (as AI experts) become philosophers again?