Fairness in Machine Learning and AI

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Motivation and basic concepts

Fairness: law and ethics

How machines learn to discriminate

Formalizing fairness in machine learning

Case study: loan granting

Conclusion... well, partial!

Outline

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When machines replace humans

The new era of machine learning:

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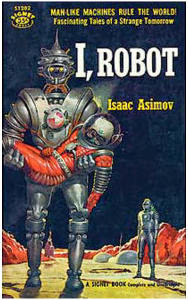

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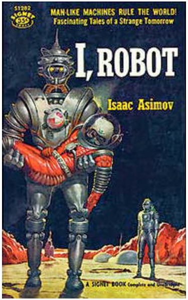

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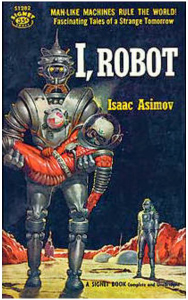

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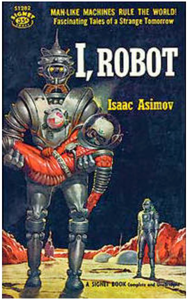

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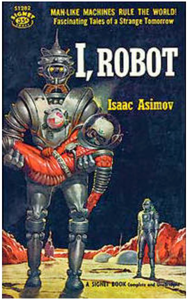

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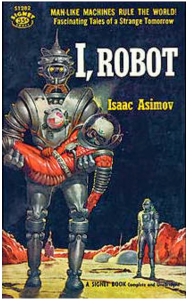

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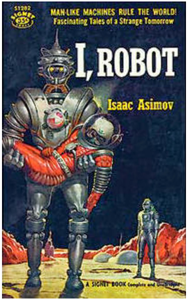

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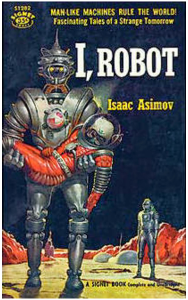

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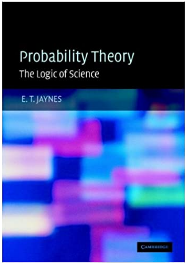

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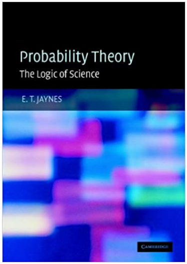

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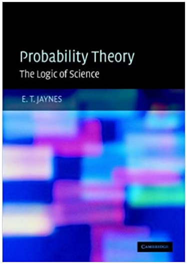

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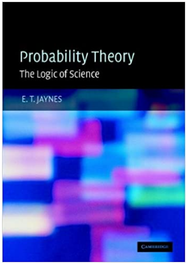

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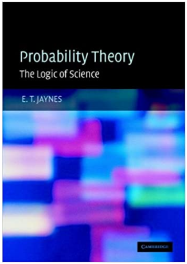

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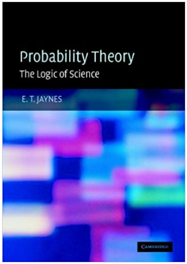

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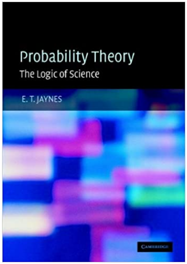

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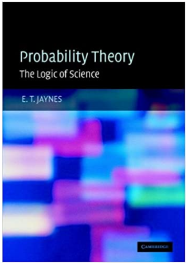

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Consequence: open door to unfair decisions, uncontrollable behavior, unseen biases.

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- inequity of information access in minority populations.

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3. Following people ill-classified: do not receive ad, job proposal

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

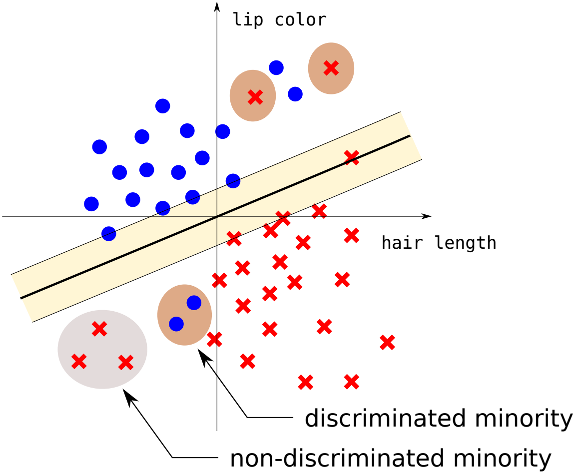
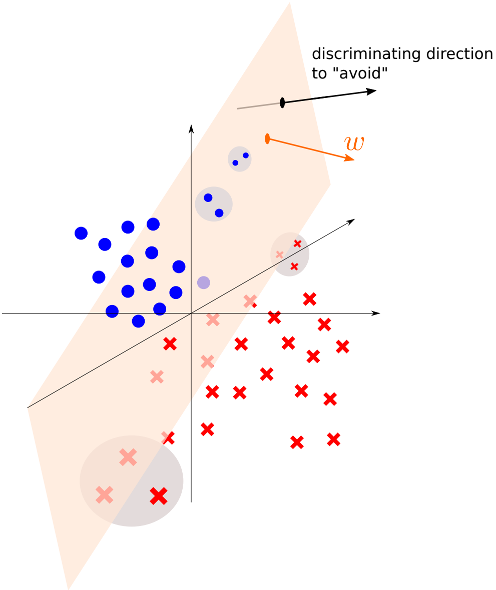


Illustration: gender discrimination

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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  - indirect sensitive information inference is also unethical...

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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!

Illustrating 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

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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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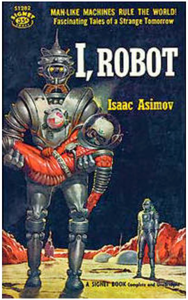

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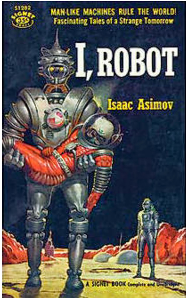

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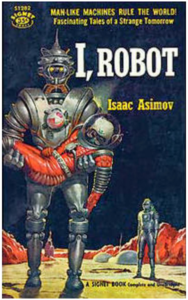

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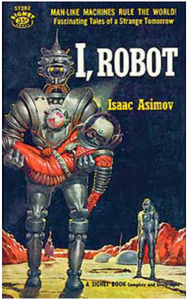

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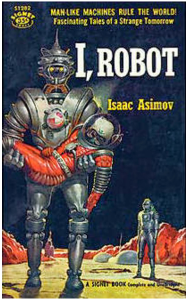

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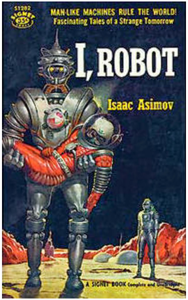

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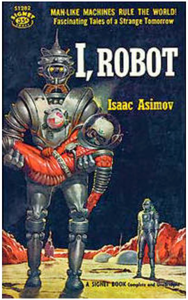

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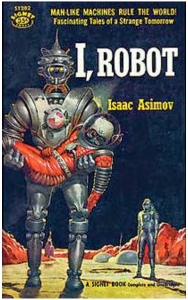

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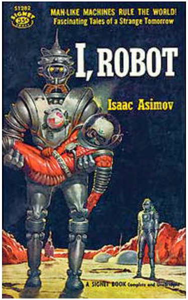

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e.g., the 20% discrimination rule!

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- promotes **algorithm laziness!**

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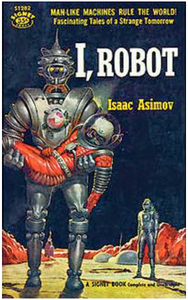

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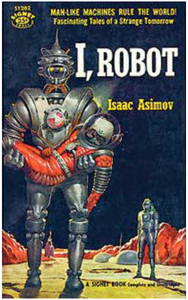

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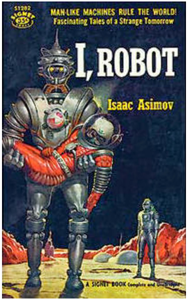

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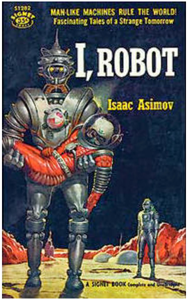

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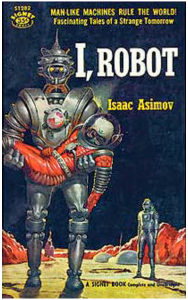

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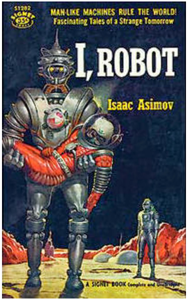

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$$A - Y - R$$

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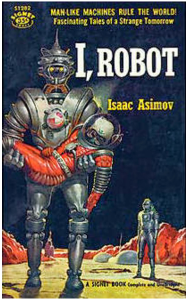

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  $$\textcircled{A} — \textcircled{Y} — \textcircled{R}$$

  (i.e., Y "sits" between A and R.)

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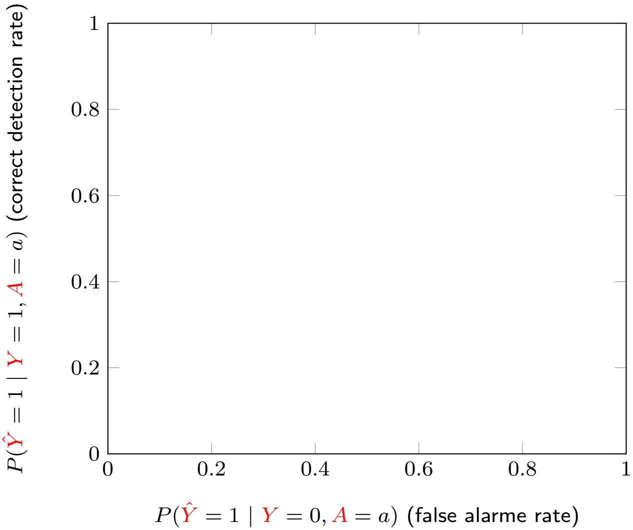

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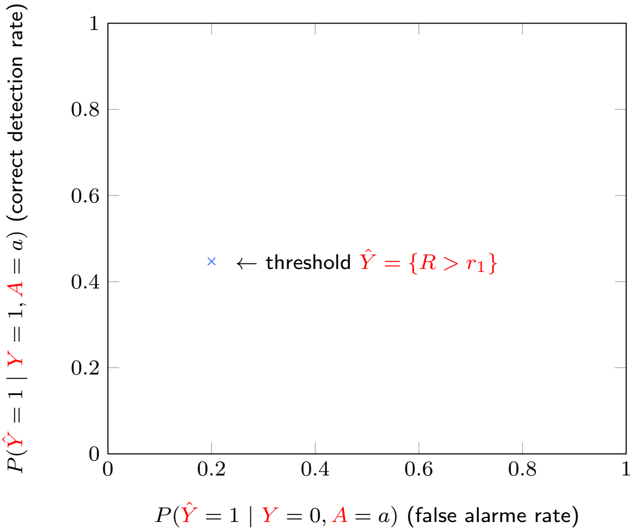

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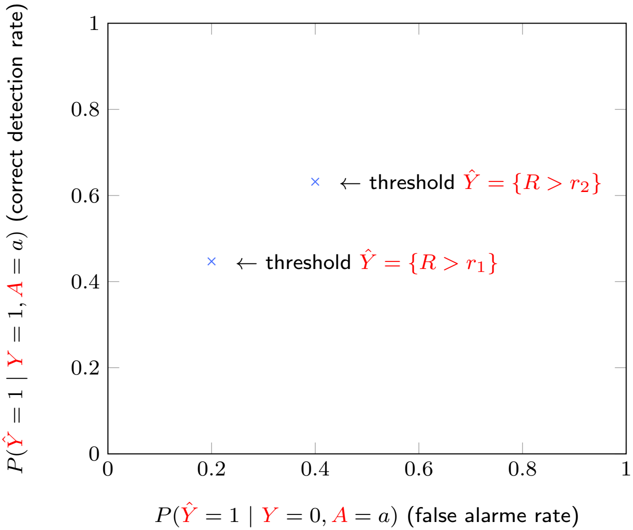

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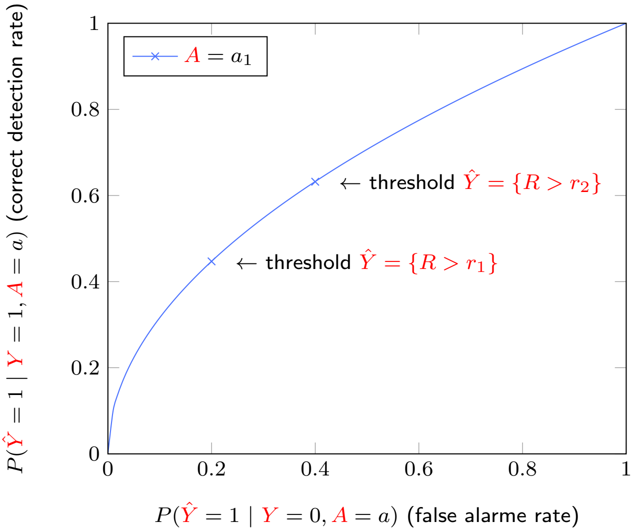

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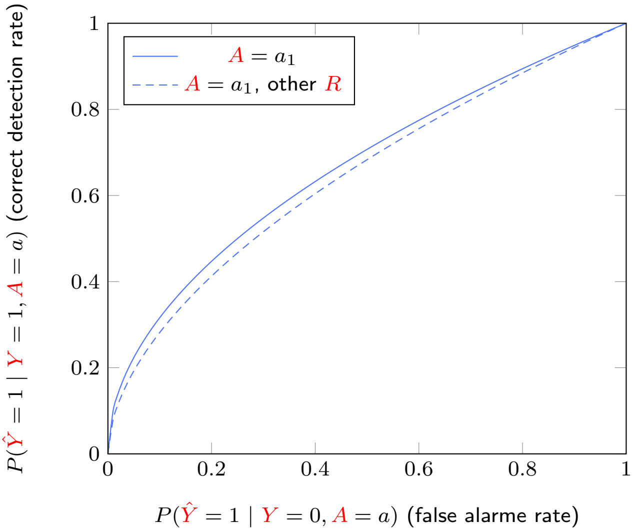

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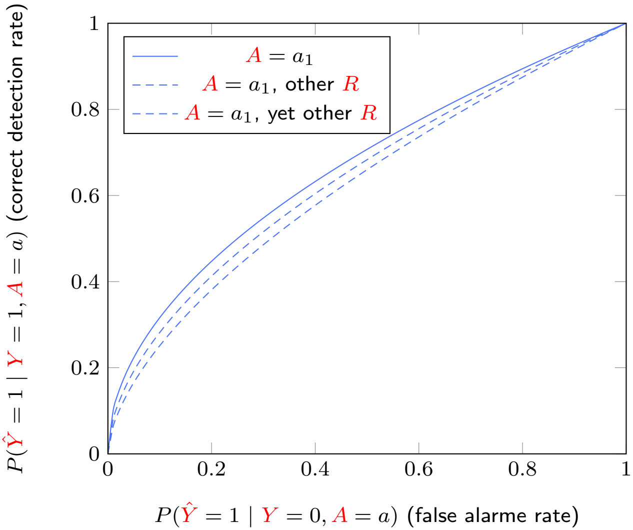

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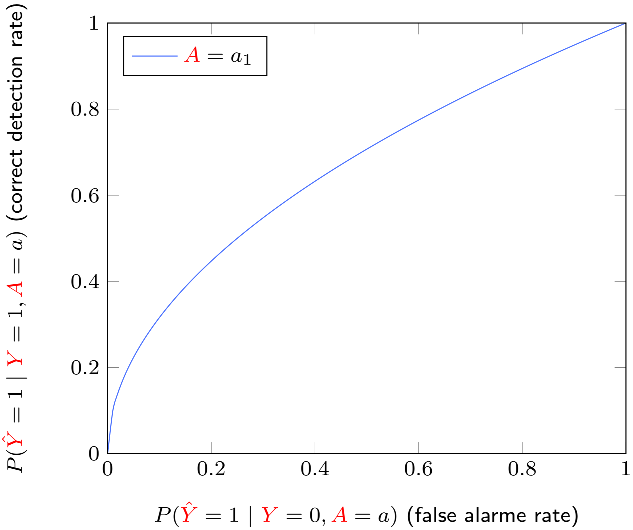

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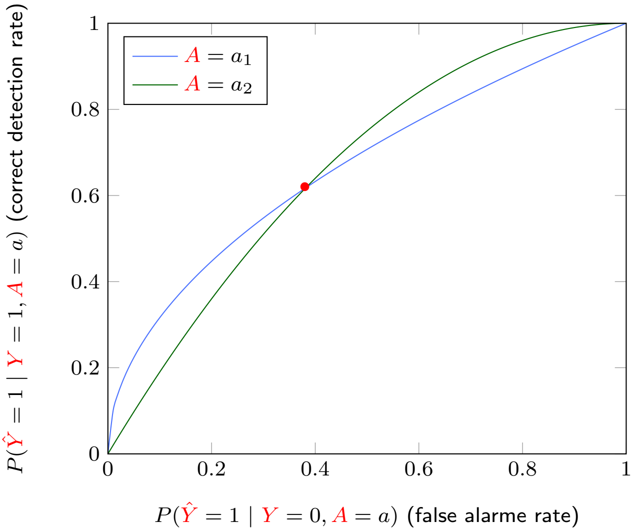

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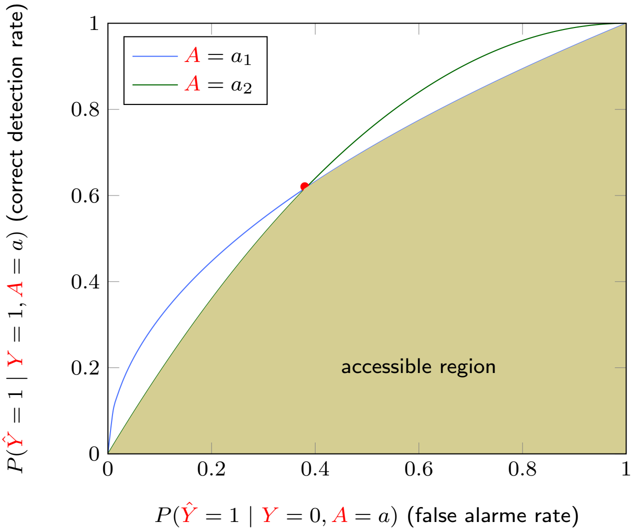

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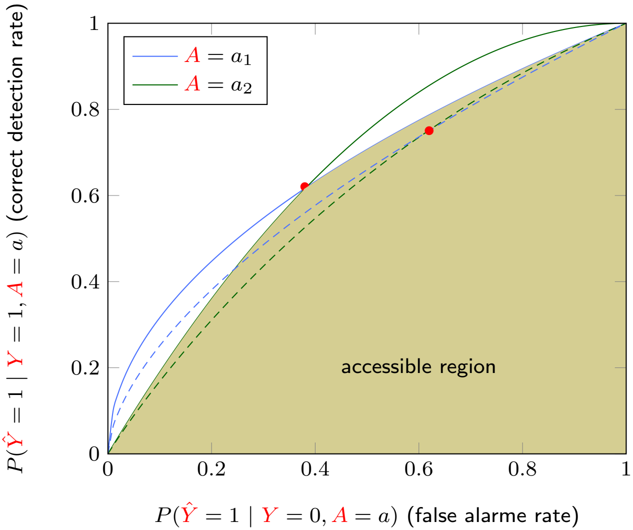

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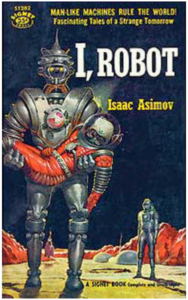

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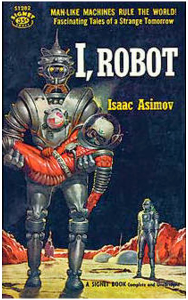

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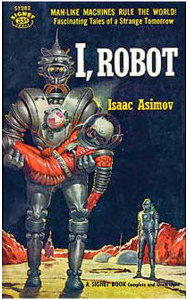

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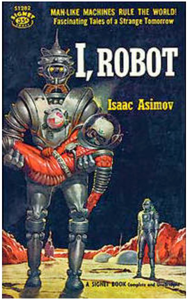

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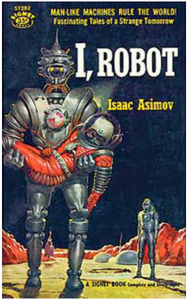

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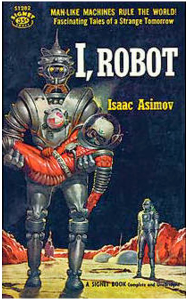

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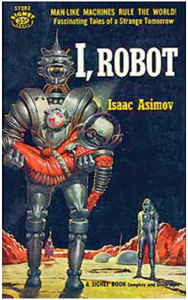

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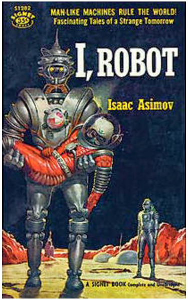

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- since cross-entropy loss unknown, calibration performed on **training dataset** $\{(y_i, r_i)\}_{i=1}^{n}$:

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

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- in practice, **trade-offs** must be performed
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- 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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Proposition

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

The three desiderata

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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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It can be shown that $A \perp R \mid Y$ and $A \perp Y \mid R$ implies $A \perp (R, Y)$ (which implies $A \perp Y$).

Hence, $A \not\perp Y$ implies either $A \not\perp R \mid Y$ (no separation) or $A \not\perp Y \mid R$ (no sufficiency).

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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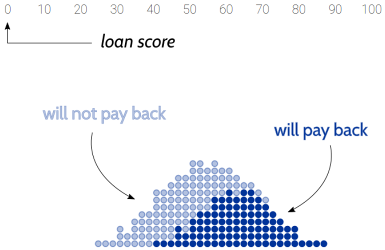
  - $\hat{Y} \in \{0, 1\} =$ "gets the loan or not"
- expected output $Y =$ "will pay back".

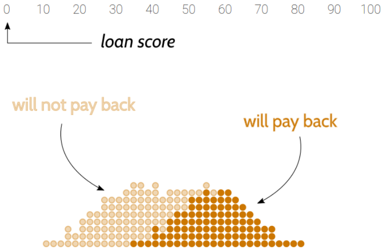
Output for the bank:

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

Loan granting: the setup

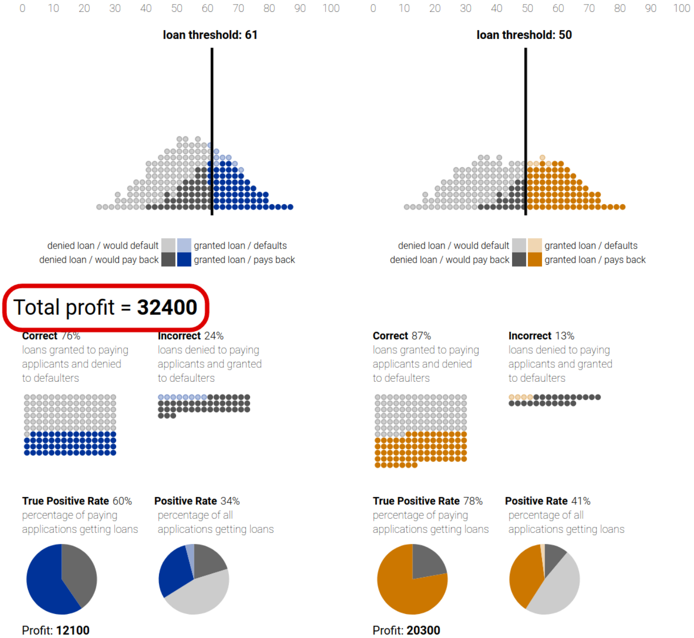
Populations and credit score:





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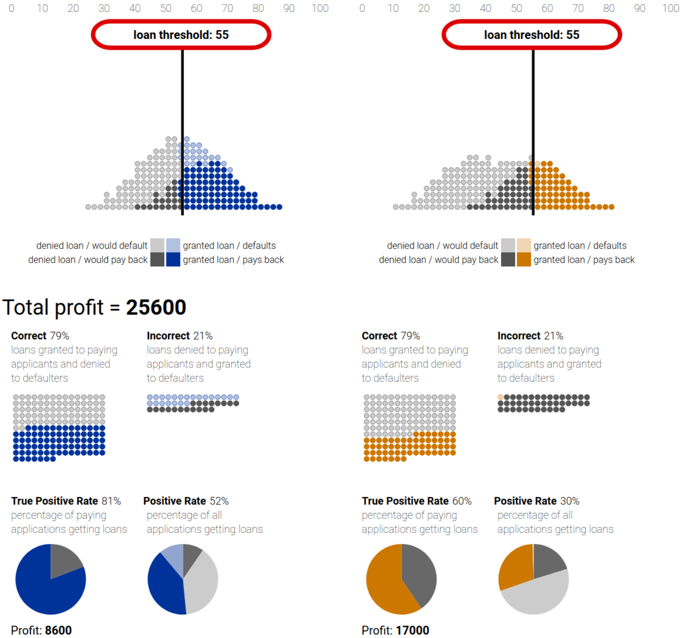
"**The most profitable, since there are no constraints**"

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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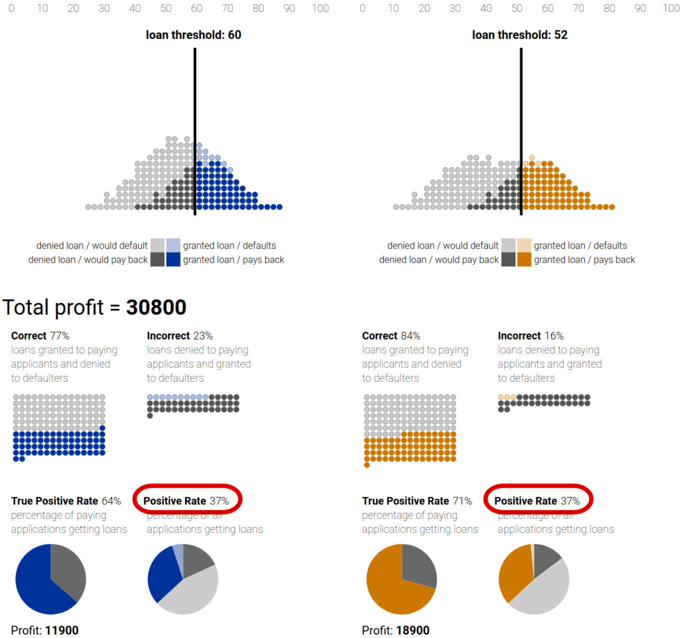
"**Both groups have the same threshold**"

Loan granting: Demographic parity

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



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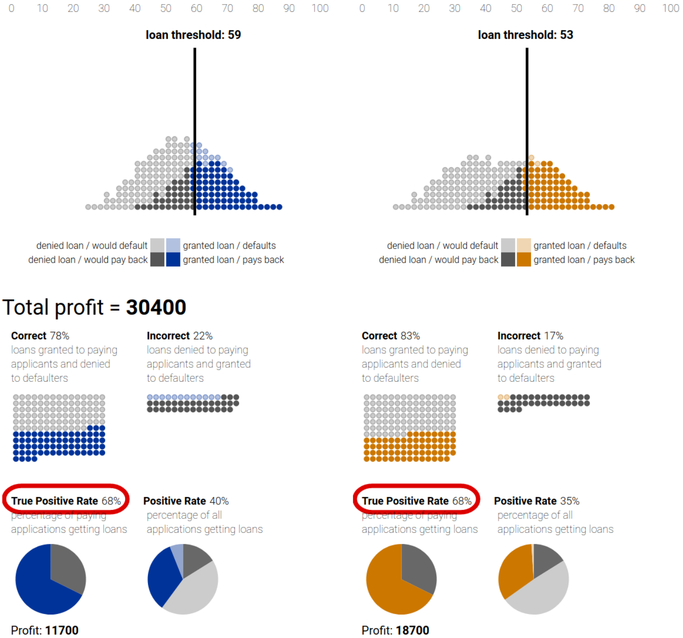
"**The number of loans given to each group is the same**"

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!

Conclusion: fairness in AI

Not a classical course: (you may have noticed!)

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