A History of Algorithmic Fairness

Mingle Presentation

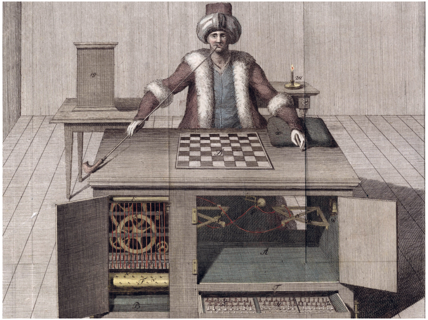
Dom Owens

University of Bristol

September 2020

Contents

Introduction: Algorithmic Fairness



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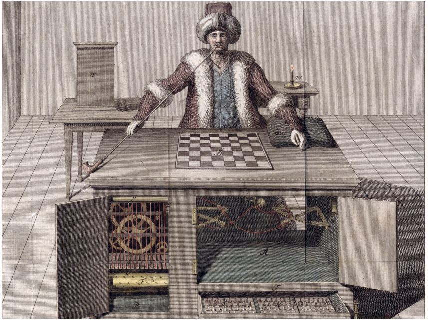

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- Some of these affect humans: Parole decisions, hiring, credit scores...
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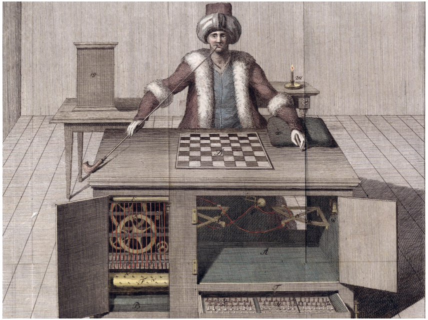

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- Some of these affect humans: Parole decisions, hiring, credit scores...
- Algorithms *should* make decisions better than humans: More data, much faster, **less biased?**
- Often, algorithms show same biases as humans - why?

Definitions and Measures: What are we dealing with?

Disparate Treatment: **intentionally** treating an individual differently based on his/her membership in a protected class

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For some yes/no decision ($Y \in \{0, 1\}$), with class membership $S \in \{0, 1\}$, consider ratio

$$R = \frac{P(\hat{Y} = 1|S = 0)}{P(\hat{Y} = 1|S = 1)}$$

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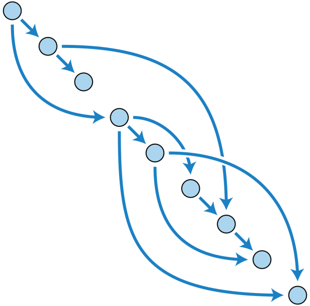
$$R = \frac{P(\hat{Y} = 1 | S = 0)}{P(\hat{Y} = 1 | S = 1)}$$

If $R \leq 1 - \epsilon$, we have evidence of discrimination ($\epsilon = 0.2$ for "80% rule")

Causes: Where does this come from?



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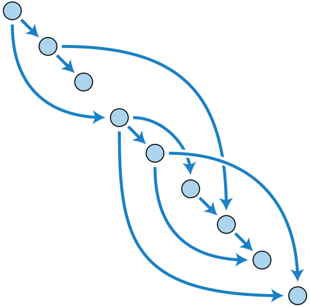

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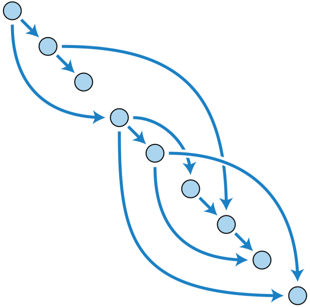
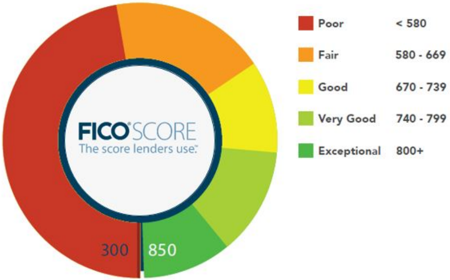


- **"Optimality"** - algorithm aims for accuracy for majority groups
- **Reconstructing** protected characteristics from correlated features
- **Biases in data set** (bad measurements, historical decisions...)

1989: FICO Credit Scoring



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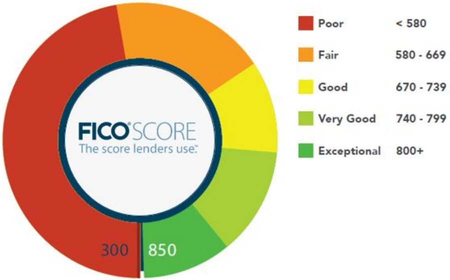

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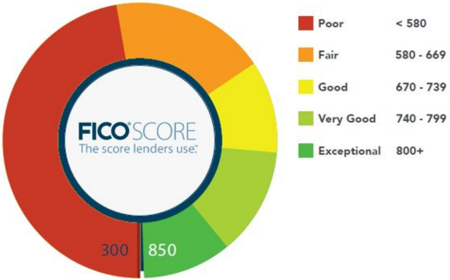

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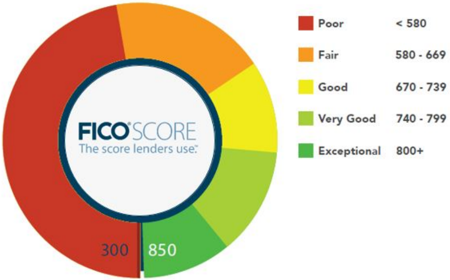

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- **Reconstructs** from address, university, web activity...

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- Learned e.g. gender through choice of language

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- Were schools on a **fair footing?** Resources, class sizes, student backgrounds...
- Small classes not re-evaluated by algorithm

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- Used unwisely, algorithms can discriminate
- This can have potentially very unfair outcomes
- **Don't despair!** Ongoing research, increased awareness