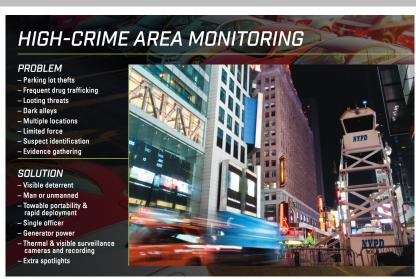
Making Decisions that Reduce Discriminatory Impact

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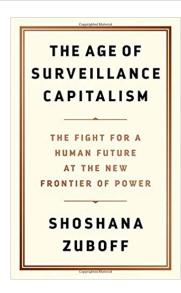
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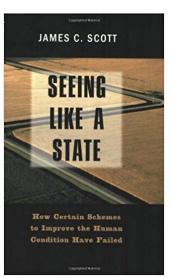
Data-driven processes: not necessarily fair by default



Source: flir.com "SkyWatch"

Maybe closer to the opposite of fair by default...





This.paper()

- ► Propose to formalize the **impact problem**
- ▶ Design fair(er) interventions under causal interference

Defining impact

An **impact** is an event caused jointly by the decisions under our control and other real world factors. *Decisions about one individual* can impact another individual.

Fair predictions/decisions do not imply fair impacts, since other downstream factors can make the impact unfair (possibly to different individuals than the subjects of the original prediction/decision)

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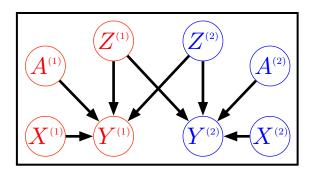
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See also Liu et al. (ICML 2018), Green & Chen (FAT* 2019)

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Causal interference: decisions affect multiple individuals

We use the structural causal model (SCM) framework



Z is the intervention or policy we want to optimize, **A** the protected attribute, **X** other predictors, and **Y** the outcome (higher values are desirable), superscript for observation index

School example

- Budget to pay for calculus classes in highschools (that do not already have them)
- ▶ Intervention: $\mathbf{Z}^{(i)} = 1$ if school i receives funding for a class and 0 otherwise
- Outcome: $\mathbf{Y}^{(i)}$ percent of students at school i taking the SAT (planning to go to college)
- Protected attribute: $\mathbf{A}^{(i)}$ encodes whether school i is majority black, Hispanic, or white
- ► Interference: students at school *i may be able to take a calculus class at nearby schools*

Given causal model and data, design the best fair intervention Z

Predictions or decisions should be the same in the actual world and in a counterfactual world where the value of the protected attribute had been different

- Changing a to a' also changes descendents of A in the SCM graph (model-based counterfactuals)
- ► Counterfactual fairness (Kusner et al, NeuRIPs 2017) is the property of invariance to those specific changes
- In this paper we instead bound counterfactual privilege

$$\mathbb{E}[\widehat{\mathbf{Y}}(\mathbf{a},\mathbf{Z})] - \mathbb{E}[\widehat{\mathbf{Y}}(\mathbf{a}',\mathbf{Z})] < \tau$$

▶ In practice these asymmetric constraints will only be active for privileged values of a (actual, left term), and inactive otherwise

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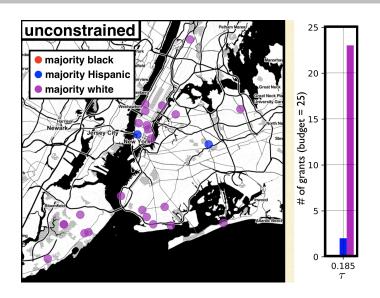
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Our goal is to design optimal interventions or policies Z subject to a budget constraint, e.g.

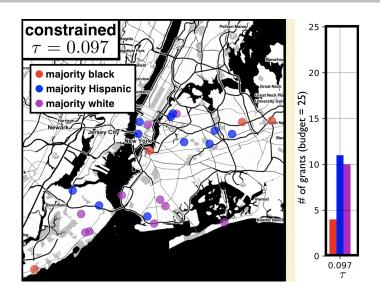
$$\mathbf{Z} = \arg \max \sum_{i} \mathbb{E} \left[\widehat{\mathbf{Y}}^{(i)}(a^{(i)}, \mathbf{Z}) | \mathbf{A}^{(i)}, \mathbf{X}^{(i)} \right] \quad s.t. \quad \sum_{i} \mathbf{Z}^{(i)} \leq b$$

- ▶ Interference means Y⁽ⁱ⁾ is potentially a function of all of Z and not just Z⁽ⁱ⁾
- Next two slides: optimal interventions with and without counterfactual privilege constraint

School resource allocation without fairness constraint



School resource allocation bounded counterfactual privilege



Matt Kusner

Chris Russell

Ricardo Silva















The Alan Turing Institute