Fair Inference on Outcomes

Razieh Nabi
rnabiab1@jhu.edu

Ilya Shpitser
ilyas@cs.jhu.edu

Computer Science Department

JOHNS HOPKINS UNIVERSITY

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Bias and Discrimination

- ML algorithms are making making influential decisions in people's lives
  - Insurance approval, hiring decision, recidivism prediction
  - Based on complicated regression or classification algorithms $\mathbb{E}[Y \mid \mathbf{X}; \alpha]$ or $p(Y \mid \mathbf{X}; \alpha)$, ($Y$: outcome, $\mathbf{X}$: features, α: model parameters)
- Algorithms can reinforce human prejudices
  - Data is collected from the "unfair" world
    - Example: racial profiling (police officers vs African-Americans)
  - No (default) correction for discriminatory biases in statistical models
    - Selection bias is not the same as statistical bias
- How to define and measure discrimination/fairness?
- How to make statistical inference "fair"?

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Fairness in Machine Learning

- Problem setup:
  - **X**: a set of covariates, A: sensitive variable, Y: outcome variable
  - Given data on $(\mathbf{X}, A, Y)$, are predictions of Y from **X** and A discriminatory (with respect to A)?
- A mathematical definition **+** "analytic philosophy" argument
  - Define "discrimination" as X
  - Why is X a good definition?
- Fairness is something rooted in **human intuition**
- Our approach is inspired by causal inference
  - Causal inference: move from a *factual* to a *counterfactual* world
  - Fair inference: move from an *"unfair"* to a *"fair world"*
- Discrimination wrt A for Y is the presence of an effect of A on Y along "unfair causal paths."

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Intuitions for Defining Discrimination

- Gender discrimination and hiring:
  - Data: features $\mathbf{X}$ (collected from resumes), gender A, hiring decision Y
  - Title VII of the Civil Rights Act of 1964 forbids employment discrimination on the basis of gender, race, national origin, etc
  - Is there hiring discrimination wrt A?
- Intuition: hypothetical experiments

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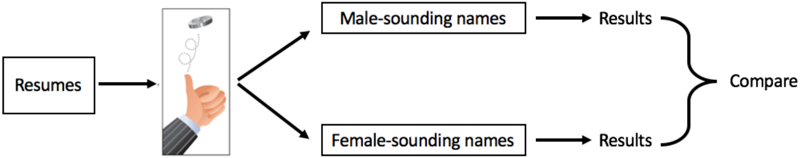

Intuitions in Defining Discrimination

- 7th circuit court case (Carson versus Bethlehem Steel Corp, 1996):

  “The central question in any employment-discrimination case is whether the employer would have taken the same action had the employee been of a different gender (age, race, religion, national origin etc.) and everything else had been the same"

- Intuitive definitions of fairness are **counterfactual**
  - Causal inference: study of hypothetical experiments and counterfactuals
  - “Fairness” is a causal inference problem

- Mediation analysis: study of causal mechanisms
  - Our approach to fairness uses tools from mediation analysis

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Causal Inference: preliminaries

- Data $\mathcal{D} \sim p(\mathbf{X}, A, Y)$, $\mathbf{X}$ baselines, A treatment, Y outcome
- $Y(a)$: outcome Y had A been assigned to a
- Average causal effect: $\text{ACE} = \mathbb{E}[Y(a)] - \mathbb{E}[Y(a')]$
  - Randomized experiments: compare cases $(A = a)$ and controls $(A = a')$
  - Observational data: people choose to smoke
- Consistency $(Y(A) = Y)$ and ignorability $(Y(a) \perp\!\!\!\perp A \mid \mathbf{X}, \forall a)$

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$$\text{ACE} = \sum_{\mathbf{X}} \{\mathbb{E}[Y \mid A = 1, \mathbf{X}] - \mathbb{E}[Y \mid A = 0, \mathbf{X}]\} p(\mathbf{X})$$

Mediation Analysis: preliminaries

- Causal mechanisms: how A causes Y?
- ACE = Direct effect ($A \rightarrow Y$) + Indirect effect ($A \rightarrow M \rightarrow Y$)
  - $\mathcal{D} = \{\mathbf{X}, A, M, Y\}$. M mediates the effect of A on Y
- Nested counterfactuals $Y(a, M(a'))$
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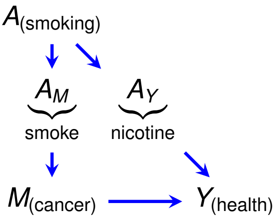

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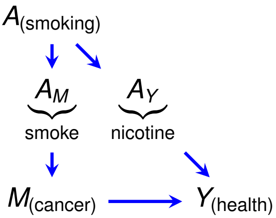

	a_Y **nicotine**	a_M **smoke**	potential outcome in:
$Y(1, M(0))$	1	0	nicotine patch

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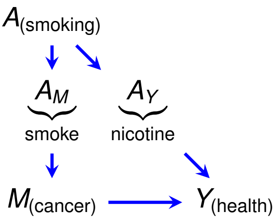

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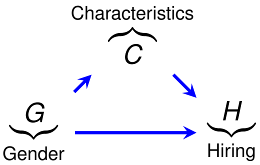
- **Direct Effect** $= \mathbb{E}[Y(1, M(0))] - \mathbb{E}[Y(0)]$ $(A \rightarrow Y)$
- **Indirect Effect** $= \mathbb{E}[Y(1)] - \mathbb{E}[Y(1, M(0))]$ $(A \rightarrow M \rightarrow Y)$

Direct Effect and Path-Specific Effect

- Compare resumes of men and **same** resumes with names switched to female ones:

$$Y(a') : H(G = male, C(G = male)) = H(G = male)$$

$$Y(a, M(a')) : H(G = female, C(G = male))$$



1. **Path-specific effect (PSE)**
   - Along a path, all nodes behave as if $A = a$,
   - Along all other paths, nodes behave as if $A = a'$
2. Discrimination as the presence of effect along unfair causal pathways
3. Fairness is a domain specific issue!

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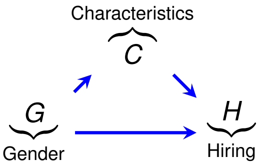

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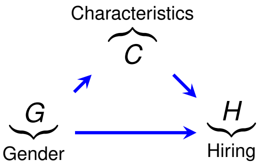

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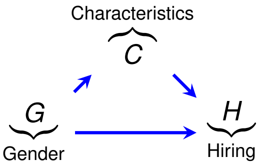

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Our Approach

- Predict Y from $\mathbf{X}, A, \mathbf{M}$ in a fair way:
  - Consider all causal paths from A to Y
  - Mark "unfair" causal paths and
  - Compute PSE along those paths: $g(\mathcal{D})$
  - If there is PSE, then $p(\mathbf{X}, A, \mathbf{M}, Y)$ is "unfair"
  - Find a "fair world" p^* close to p where there is no PSE
    - Close in Kullback-Leibler divergence sense (use data as well as possible while remaining fair)
    - $(\epsilon_l; \epsilon_u)$: discrimination tolerance
- Approximate "Fair World" p^*:
  - Likelihood function: $\mathcal{L}(\mathcal{D}; \alpha)$

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- Approximate "Fair World" p^*:
  - Likelihood function: $\mathcal{L}(\mathcal{D}; \boldsymbol{\alpha})$

$$\hat{\boldsymbol{\alpha}} = \arg\max_{\boldsymbol{\alpha}} \quad \mathcal{L}(\mathcal{D}; \boldsymbol{\alpha})$$
$$\text{subject to} \quad \epsilon_l \leq g(\mathcal{D}) \leq \epsilon_u.$$

Inference on New Instances

- Inference on new instances $(\mathbf{x}, a, \mathbf{m})$:
  - New instances are drawn from unfair p
  - Cannot classify/regress new instances using $p^*(Y \mid \mathbf{x}, a, \mathbf{m}, \hat{\alpha})$
  - Use only shared information between p and p^*
    - If $p^*(\mathbf{X}, A, \mathbf{M}, Y) = p(\mathbf{X})p^*(A, \mathbf{M}, Y \mid \mathbf{X})$, use $\mathbb{E}[Y \mid \mathbf{X}; \hat{\alpha}]$.
    - Depends on $g(\mathcal{D})$: inverse weighting, g-formula, semi-parametric

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Application: COMPAS

Machine Bias (ProPublica)

COMPAS: risk assessments in criminal sentencing (developed by Northpointe)

Experiment 1: Bias in Data

- Is there any **bias in the data** wrt race in predicting recidivism?

  Y: recidivism

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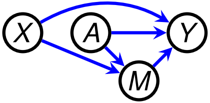

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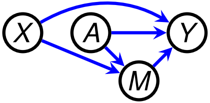

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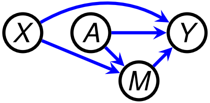

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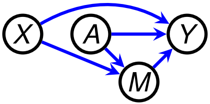

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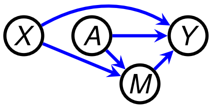

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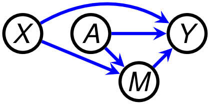

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	Direct Effect (odds ratio scale, null = 1)	Accuracy %
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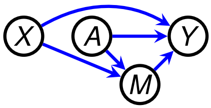

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- Do not have access to Northpointe's model
- Best we can do:
  - Try to learn $\tilde{\mathbb{E}}[Y \mid M, \mathbf{X}]$ with what we have
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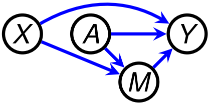

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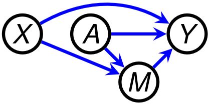

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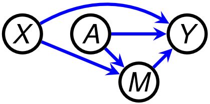

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Summary

- An approach to fair inference based on mediation analysis.
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- Fairness may be characterized as the absence (or dampening) of a path-specific effect (PSE).
- Restriction of a PSE is expressed as a likelihood maximization problem that features constraining the magnitude of the undesirable PSE.
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Thank you for listening.

Razieh Nabi, `rnabi@jhu.edu`
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