Learning Optimal Fair Policies

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Joint work with **Daniel Malinsky** and **Ilya Shpitser**

ICML-19: Thirty-sixth International Conference on Machine Learning

Fairness in automated decision-making

- Algorithms are increasingly prevalent in socially-impactful settings
  - Criminal justice, welfare policy, hiring, personal finance

- Data includes potentially sensitive attributes (and/or proxies)
  - Risk of perpetuating injustice:
    naively maximizing utility may maintain, reinforce, or even introduce unfair dependence between sensitive features, decisions, and outcomes

- Automated decisions should respect principles of fairness

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Objective

Want to make **optimal but fair** decisions, which “break the cycle of injustice" by correcting for the unfair dependence of both decisions and outcomes on sensitive features.

Child welfare example

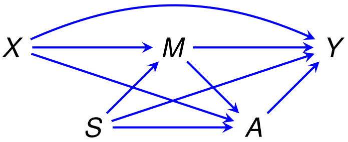
X: baseline factors

S: sensitive features

M: mediators

A: action/decision

Y: outcome/utility



- Child welfare hotline: decision A to dispatch case-worker may depend on all available information, and optimal decision would minimize negative outcomes (e.g. child separation and/or hospitalization).
- Concern that unconstrained optimal decision-making may lead to unacceptable racial disparities.
  - Ignoring race information is insufficient: dependence due to proxies

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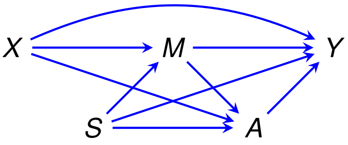

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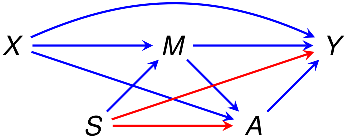

Our perspective:

- In a “fairer world,” certain (discriminatory or unjust) mechanisms would be absent.
- This corresponds to the absence of some path-specific causal effects; generalizing a view in (Nabi and Shpitser, 2018).
- Try to approximate the “nearest fair world” and learn optimal policies there.
- Must sacrifice some optimality to make decisions fairly.

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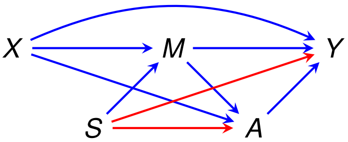

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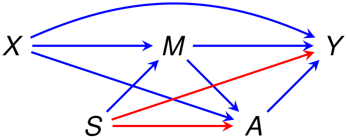

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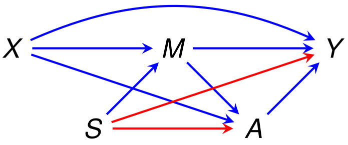

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Outline

Causal inference: preliminaries

- Data $\mathcal{D} \sim p(X, A, Y)$
- $Y(a)$: outcome Y had A been assigned to a
- Average causal effect: $\text{ACE} = \mathbb{E}[Y(A=1)] - \mathbb{E}[Y(A=0)]$
  - Randomized experiments: compare cases, $(A=1)$ and controls $(A=0)$
  - Observational data: people choose to smoke
- Identifiability under standard assumptions:
  - Consistency: $Y(A) = Y$,
  - Ignorability: $Y(a) \perp\!\!\!\perp A \mid X, \forall a$,
  - Positivity: $p(a|X) > 0, \forall a$.

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

Mediation analysis: preliminaries

- Causal mechanisms: how does A cause 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 $Y(a, M(a'))$
  - Outcome Y had A been assigned to a and M been assigned to whatever value it would have had under a'

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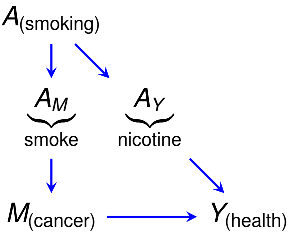


	a_Y **nicotine**	a_M **smoke**	potential outcome
$Y(1, M(0))$	1	0	nicotine patch

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

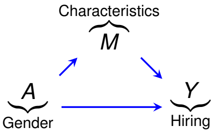
Unfair path-specific effects

Example: name-swapping experiments to evaluate gender bias in hiring

$Y(a')$: $Y(A = male, M(A = male)) = Y(A = male)$,

$Y(a, M(a'))$: $Y(A = female, M(A = male))$.

Direct effect: $\mathbb{E}[Y(a, M(a')) - \mathbb{E}[Y(a')]]$



- **Path-specific effects (PSEs)**
  - Along a set of paths, all nodes behave as if $A = a$,
  - Along all other paths, nodes behave as if $A = a'$.
- Some PSEs should be considered impermissible, depending on context.
  - Policymakers, (bio)ethicists, general public should determine which mechanisms are problematic in applied settings.

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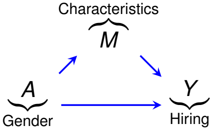

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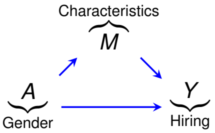

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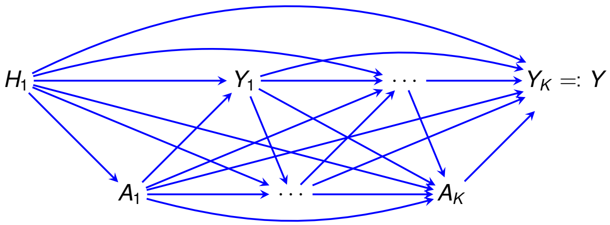
Sequential decision-making



- K decision points.
  - H_1: available information prior to the first decision A_1.
  - Y_k: intermediate outcome between k^{th} and $(k+1)^{th}$ decision points.
  - H_k: history prior to kth decision point.
- Policy $f_A = \{f_{A_1}, \ldots, f_{A_K}\}$ where $f_{A_k} : \mathcal{H}_k \mapsto \mathcal{A}_k, \forall k = 1, \ldots, K$.

Optimal policy in causal inference

- Counterfactual response under f_A is denoted by $Y(f_A(H))$
- **Optimal policy**:

$$f_A^* := \arg\max_{f_A} \mathbb{E}[Y(f_A)]$$

- Under certain **identification** assumptions (Shpitser, 2013):
- Fairness concerns arise since $H_1 = \{X, S, M\}$

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$$\mathbb{E}[Y(f_A)] = \sum_{h_1, y_1} p\big(Y|h_1, a_1 = f_{A_1}, y_1, a_2 = f_{A_2}\big)\ p(y_1|a_1 = f_{A_1}, h_1)\ p(h_1).$$

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Sources of bias

Consider the following effects impermissible:

- The effect of S on Y *not through M*

$$\begin{aligned} \text{PSE}^{sy} &= \mathbb{E}[Y(s, M(s')) - Y(s', M(s'))] \\ &\equiv g_1(Z) \end{aligned}$$

- The effect of S on A_k *not through M*

$$\begin{aligned} \text{PSE}^{sa_k} &= \mathbb{E}[A_k(s, M(s')) - A_k(s', M(s'))] \\ &\equiv g_k(Z) \end{aligned}$$

$$Z = \{X, S, M, A_1, ..., A_K, Y_1, ..., Y_K\}$$

The closest "fair world"

Given *a set of identified PSEs* $g_j(Z)\ \forall j \in \{1, ..., J\}$ and *lower/upper tolerance bounds* $\epsilon_j^-, \epsilon_j^+$, the fair distribution $p^*(Z)$ is defined:

$$p^*(Z) \equiv \arg\min_q \ D_{KL}(p||q)$$
$$\text{subject to} \ \ \epsilon_j^- \leq g_j(Z) \leq \epsilon_j^+, \ \ \forall j \in \{1, ..., J\},$$

Approximating the “fair world” in finite samples

Approximate $p^*(Z)$ by solving:

$$\widehat{\alpha} = \arg\max_{\alpha} \quad \mathcal{L}(Z;\alpha)$$

$$\text{s.t.} \quad \epsilon_j^- \leq \widehat{g}_j(Z) \leq \epsilon_j^+, j = 1, \ldots, J.$$

Consistent estimators of PSE^{sy} and PSE^{sa_k}:

$$\widehat{g}^{sy}(Z) = \frac{1}{N}\sum_{n=1}^{N}\left\{\frac{\mathbb{I}(S_n = s)}{p(S_n|X_n)}\,\frac{p(M_n|s', X_n)}{p(M_n|s, X_n)} - \frac{\mathbb{I}(S_n = s')}{p(S_n|X_n)}\right\} Y_n,$$

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Constraints involve $p(S|X;\alpha_s)$ and $p(M|S,X;\alpha_m)$ models.

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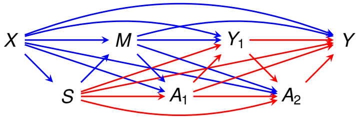

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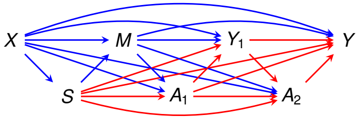

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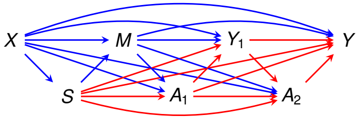

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Constraints involve $p(S|X;\alpha_s)$ and $p(M|S, X;\alpha_m)$ models.

Breaking the cycle of injustice

- Let $p^*(M|S,X;\alpha_m)$ and $p^*(S|X;\alpha_s)$ be the constrained models chosen to satisfy $\text{PSE}^{sy} = 0$ and $\text{PSE}^{sa_k} = 0$,
- Let $\widetilde{p}(Z)$ be the joint distribution induced by $p^*(M|S,X;\alpha_m)$ and $p^*(S|X;\alpha_s)$:

$$\widetilde{p}(Z) \equiv p(X) p^*(S|X;\alpha_s)\, p^*(M|S,X;\alpha_m) \prod_{k=1}^{K} p(A_k|H_k) p(Y_k|A_k,H_k).$$

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- Then PSE^{sy} and PSE^{sa_k} taken wrt $\widetilde{p}(Z)$ are also zero.

  $\implies$ constraining the S and M models induces a “fair distribution” no matter how A_k or Y_k are determined.

Three strategies for policy estimation

In the paper, we consider three strategies for estimating the optimal policy:

- Q-learning
- Value search
- G-estimation

In each case, we must modify these procedures to operate wrt the fair distribution.

We focus on Q-learning in this talk.

Optimal fair policy: Q-learning

- **Unfair world**: expectations wrt to $p(Z)$

$\mathrm{H_1, A_1}$ $\longleftarrow$ $\mathrm{H_k, A_k}$ $\longleftarrow$ $\mathrm{H_K, A_K}$

$$Q_1(H_1, A_1) = E[V_2(H_2, a_1) | H_1] \quad \ldots \quad Q_k(H_k, A_k) = E[V_{k+1}(H_{k+1}, a_k) | H_k] \quad \ldots \quad Q_K(H_K, A_K) = E[Y(a_K) | H_K]$$

$$V_1(H_1) = \max_{a_1} Q_1(H_1, A_1) \qquad V_k(H_k) = \max_{a_k} Q_k(H_k, A_k) \qquad V(H_K) = \max_{a_K} Q_K(H_K, A_K)$$

- **Optimal policy**: $f^*_{A_k} = \arg\max_{a_k} Q_k(H_k, a_k; \beta_k)$

- **Fair world** expectations wrt to $p^*(Z)$

Optimal fair policy: Q-learning

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- **Fair world** expectations wrt to $p^*(Z)$

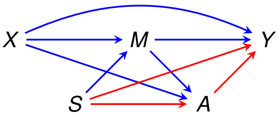
$$\widetilde{Q}_k(H_k \setminus \{M, S\}, A_k) = \frac{1}{Z_k} \sum_{m,s} Q^*_k(H_k, A_k)\, p^*(m | X, s; \alpha_m)\, p^*(s | X; \alpha_s),$$

for $k = 1, \ldots, K$.

COMPAS data

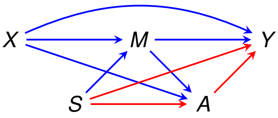
- COMPAS is a criminal justice risk assessment tool created by the company Northpointe (now Equivant)
- Used across the US to determine whether to release or detain a defendant before their trial
- COMPAS scores: recidivism score

COMPAS application



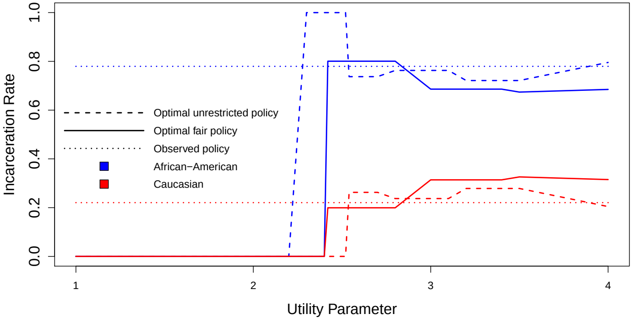
- S: race, X: other demographics, M: prior convictions
- A: incarceration (based on risk of recidivism)
- Heuristic utility: $Y \equiv (1 - A) \times \{\theta R + (1 - R)\} - A$
  - R: whether or not recidivism occurred in a span of two years
  - Negative utility (social, economical costs) associated with incarceration $A = 1$.
  - Some cost to releasing individuals who go on to reoffend (i.e., for whom $A = 0$ and $R = 1$) controlled by θ
  - Positive utility associated with releasing individuals who do not go on to recidivate (i.e., for whom $A = 0$ and $R = 0$)

COMPAS application



- S: race, X: other demographics, M: prior convictions
- A: incarceration (based on risk of recidivism)
- Heuristic utility: $Y \equiv (1 - A) \times \{\theta R + (1 - R)\} - A$
  - R: whether or not recidivism occurred in a span of two years
  - Negative utility (social, economical costs) associated with incarceration $A = 1$.
  - Some cost to releasing individuals who go on to reoffend (i.e., for whom $A = 0$ and $R = 1$) controlled by θ
  - Positive utility associated with releasing individuals who do not go on to recidivate (i.e., for whom $A = 0$ and $R = 0$)

COMPAS application



Question: What would be the resulting difference in pre-trial incarceration rate under a “fair” vs. unconstrained optimal policy?

Result: “fair” vs. unconstrained policies differ, and incarceration rates depend crucially on the utility function.

Summary

- We extended a formalization of algorithmic fairness from Nabi and Shpitser (2018) to the setting of learning optimal policies under fairness constraints.
- We showed how to constrain a set of statistical models and learn a policy that induces high-quality outcomes while satisfying the specified fairness constraints in the induced joint distribution.
- We investigated the performance of our proposals on synthetic and real data.
- We hope to develop and implement more sophisticated constrained optimization methods, to use information as efficiently as possible while satisfying the desired theoretical guarantees.

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Thank you for listening.

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Appendix A: mapping instances to $p^*(Z)$

- A new instance Z is not drawn from the "fair world" $p^*(Z)$, but from "unfair world" $p(Z)$.
  - Map new instances from p to p^*
- Assume $Z = \{Z_1, Z_2\}$ such that $p^*(Y, Z) = p^*(Y, Z_1 | Z_2) p(Z_2)$.
  - Z_2 is shared between p and p^*, i.e. $p^*(Z_2) = p(Z_2)$ but $p^*(Z_1|Z_2) \neq p(Z_1|Z_2)$.
- There is no obvious principled way of knowing exactly what values of Z_1 the "fair version" of the new instance would attain.
  - All such possible values are averaged out, weighted appropriately by how likely they are according to the estimated p^*.
  - This entails predicting Y as the expected value $E^*[Y|Z_2]$ (with respect to the distribution $\sum_{Z_1} p^*(Y, Z_1|Z_2)$).

Appendix B: value search

- **Optimal policy**: $f_A^* = \arg\max_{f_A} \mathbb{E}[Y(f_A)]$
- **Unfair world**: expectations wrt to $p(Z)$

$$\mathbb{E}[Y(f_A)] = \mathbb{E}\left[\frac{\mathbb{I}(A_1 = f_{A_1}(H_1))}{p(A_1 | H_1; \psi)} \times \frac{\mathbb{I}(A_2 = f_{A_2}(H_2))}{p(A_2 | H_2; \psi)} \times Y\right],$$

- **Fair world**: expectations wrt to $p^*(Z)$

$$\widetilde{\mathbb{E}}[Y(f_A)] = \frac{1}{Z} \sum_{m,s} \mathbb{E}[Y(f_A)] \, p^*(m | X, s; \alpha_m) \, p^*(s | X; \alpha_s)$$

Appendix C: synthetic data

	Unfair Policy	**Fair Policy**
Q-learning	7.219 ± 0.005	6.104 ± 0.006

Table: Comparison of population outcomes $\mathbb{E}[Y]$

- For observed policy, the value is 4.82 ± 0.007
- $(X, Y) \sim$ Normal, $(M, A) \sim$ Logistic, $S \sim$ Bernoulli.

Appendix D: additional COMPAS results

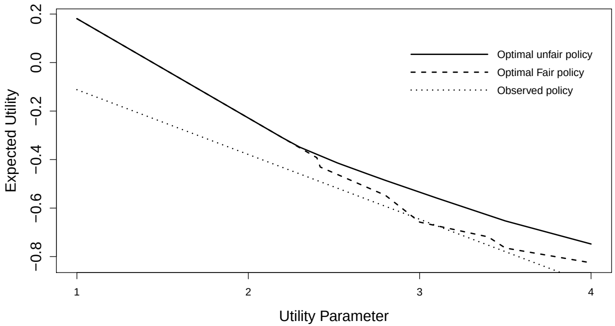
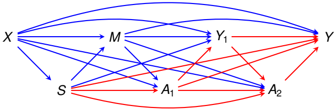
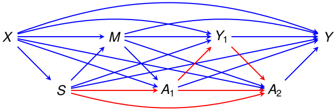


Figure: Relative expected utilities for policies as function of θ

Appendix E: sources of bias





- **Retrospective bias**: bias in historical data used as input to learning procedure.

  Example: unfair paths from S to Y:
  $\{S \to Y,$
  $S \to A_1 \to \ldots \to Y,$
  $S \to A_2 \to \ldots \to Y\}.$

  $$\text{PSE}^{sy} = g_1(Z)$$

- **Prospective bias**: functional form of policy depends on sensitive features.

  Example: unfair paths from S to A_1, A_2:
  $\{S \to A_1\}$,
  and
  $\{S \to A_2, \quad S \to A_1 \to \ldots \to A_2\}$

  $$\text{PSE}^{sa_k} = g_k(Z)$$

- **Confounding bias**: spurious associations between sensitive features, decisions, and outcomes.

- **Statistical bias**: reliance on misspecified statistical models.