Optimal and Fair Encouragement Policy Evaluation and Learning

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- "Program evaluation view of algorithmic accountability"
- Two settings
 - Encouragement designs
 i.e. targeted interventions to improve service delivery
 - Algorithmic recommendations
- Contributions:

Modeling using "off-policy learning", methodology Applied context:

Targeted service delivery interventions to reduce disparities

Setting 1: Encouragement Designs



Encouragement



Setting 2: Algorithmic Recommendations



"High-risk", "low-risk", etc.

Decision Making Framework Matrix									
	NCA 1	NCA 2	NCA 3	NCA 4	NCA 5	NCA 6			
FTA 1	Release with No Conditions	Release with No Conditions							
FTA 2	Release with No Conditions	Release with PM	Release with PM	PSL I	PSL II				
FTA 3		Release with PM	PSL I	PSL II	PSL III with Curfew	Release Not Recommended			
FTA 4		PSL I	PSL I	PSL III	Release with Sheriff's EM	Release Not Recommended			
FTA 5		PSL I	PSL III	Release with Sheriff's EM	Release Not Recommended	Release Not Recommended			
FTA 6				Release Not Recommended	Release Not Recommended	Release Not Recommended			

Algorithmic recommendations need a human in the loop in consequential domains: social services, medicine, law ...



Usual algorithmic auditing focuses on recommendations only, or assumes recs = treatment!

Optimal encouragement designs



- Goal: A data-driven optimal decision rule $\pi(X)$... recommend treatment
 - ... to optimize population expected utility

... subject to policy-relevant concerns (parity in beneficial resources)

 $\max \mathbb{E}[u(\pi, T(\pi), Y(\pi))]$ $\mathbb{E}[T(\pi) \mid A = a] - \mathbb{E}[T(\pi) \mid A = b] \le \epsilon$ $\mathbb{E}[T(\pi)] \le \kappa$

Case study: Oregon insurance study



Figure 1: Distribution of lift in treatment probabilities $p_{1|1,a} - p_{1|0,a} = P(T = 1 | R = 1, A = a, X) - P(T = 1 | R = 0, A = a, X)$, and plot of $p_{1|1,a} - p_{1|0,a}$ vs. τ .



Figure 2: Policy value $V(\pi^{\lambda})$, treatment value $\mathbb{E}[T(\pi^{\lambda}) \mid A = a]$, for A = race, gender.

Case study: Supervised release

- Pretrial risk assessment in criminal justice
 R: Recommendation for supervised release
 - **T**: Electronic monitoring (EM)
 - Y: Failure to appear (FTA)
 - **Y(t(r))**: does someone FTA when T=t,R=r?
- Causal impact of *electronic monitoring* (EM) on reducing failure to appear for court date Heterogeneity: EM could mean *beneficial services* or *burdensome surveillance* (paying for EM, losing job)

Decision Making Framework Matrix											
	NCA 1	NCA 2	NCA 3	NCA 4	NCA 5	NCA 6					
FTA 1	Release with	Release with									
	No Conditions	No Conditions									
FTA 2	Release with	Release with	Release with	I I2G	II IZA						
	No Conditions	PM	PM	I SL I	I SL II						
ETA 3		Release with		wole of	PSL III with	Release Not					
FIAS		PM	Supony		Curfew	Recommended					
ETA 4		DSI I	Supervised release		Release with	Release Not					
FIA4		FSL I			Sheriff's EM	Recommended					
FTA 5		DELT	PSL III	Release with	Release Not	Release Not					
		FSL I		Sheriff's EM	Recommended	Recommended					
ETA 6				Release Not	Release Not	Release Not					
FIAO				Recommended	Recommended	Recommended					

Exhibit 2: Decision Making Framework

PSA-DMF *(Coarsened) data from Chicago

Source: Cook County Sheriff's Office, Sheriff's Justice Institute, Central Bond Court Report, April 2016, p. 7,

- "Program evaluation view of algorithmic accountability"
- Contributions: modeling, methodology

Applied context: Targeted service delivery interventions to reduce disparities