

Experimental Evaluation of Computer-Assisted Human Decision Making

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Rise of the Machines



- Statistics, machine learning, artificial intelligence in our daily lives
- Nothing new but accelerated due to technological advances
- Examples: factory assembly lines, ATM, home appliances, autonomous cars and drones, games (Chess, Go, Shogi), ...

Motivation

- But, humans still make many consequential decisions
 - this is true even when human decisions can be suboptimal
 - we may want to hold *someone*, rather than *something*, accountable
- **Computer-assisted human decision making**
 - humans make decisions with the aid of machine recommendations
 - routine decisions made by individuals in daily lives
 - consequential decisions made by judges, doctors, etc.
- How do machine recommendations influence human decisions?
 - Do they help human decision-makers achieve a goal?
 - Do they help humans improve the fairness of their decisions?
- Many have studied the accuracy and fairness of machine recommendations rather than their impacts on human decisions
- We develop a set of statistical methodology for experimentally evaluating computer-assisted human decision making

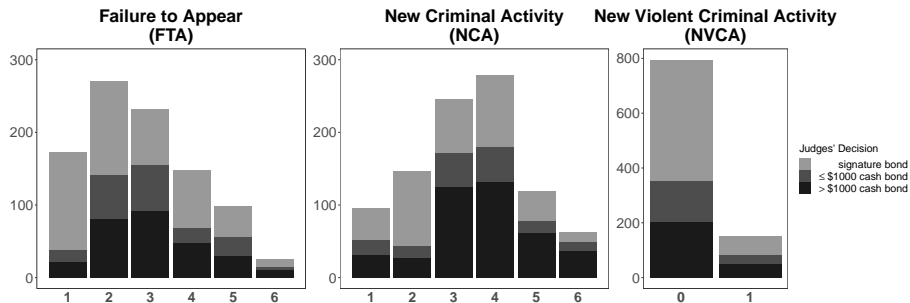
Application: Pretrial Risk Assessment Instrument (PRAI)

- Machine recommendations often used in US criminal justice system
- At the **first appearance hearing**, judges primarily make two decisions
 - ① whether to release an arrestee pending disposition of criminal charges
 - ② what conditions (e.g., bail and monitoring) to impose if released
- Goal: avoid predispositional incarceration while preserving public safety
- Judges are required to consider three risk factors along with others
 - ① arrestee may fail to appear in court (FTA)
 - ② arrestee may engage in new criminal activity (NCA)
 - ③ arrestee may engage in new violent criminal activity (NVCA)
- **PRAI** as a machine recommendation to judges
 - classifying arrestees according to FTA and NCA/NVCA risks
 - derived from an application of a machine learning algorithm or a statistical model to a training data set based on past observations
- Controversy over the potential racial bias of COMPAS score
 - Propublica's analysis and Northpointe's rebuttal
 - Almost all existing work focus on the accuracy and fairness of PRAI

A Field Experiment for Evaluating a PRAI

- An anonymous (for now) county
- PRAI
 - 1 based on criminal history (prior convictions and FTA) and age
 - 2 two separate ordinal risk scores for FTA and NCA
 - 3 one binary risk score for new violent criminal activity (NVCA)
- Judges have other information about an arrestee
 - affidavit by a police officer about the arrest
 - defense attorney may inform about the arrestee's connections to the community (e.g., family, employment)
 - assistant district attorney may provide additional information
- Field experiment
 - clerk assigns case numbers sequentially as cases enter the system
 - PRAI is calculated for each case using a computer system
 - if the first digit of case number is even, PRAI is given to the judge

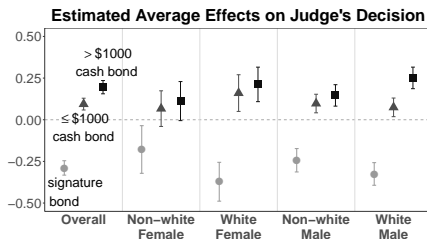
(Somewhat Empirically Informed) Synthetic Data Set



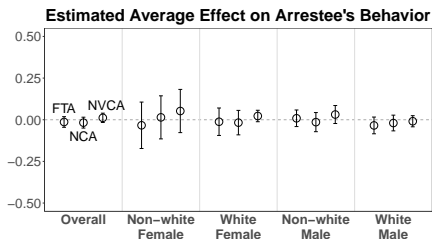
- PRAI
 - 1 6-point scale for FTA and NCA
 - 2 binary flag for NVCA
- Trichotomized ordinal decisions
 - 1 signature bond
 - 2 ≤ \$1,000 cash bond
 - 3 > \$1,000 cash bond

Intention-to-Treat Analysis of PRAI Provision

(a) Estimated effects on judges' decisions



(b) Estimated effects on outcomes



- Large effects on judges' decisions
- But little effects on outcomes
 - Do judges' decisions have no effect on outcomes? \rightsquigarrow unlikely
 - Are the heterogeneous effects being masked?

The Setup of the Proposed Methodology

- Notation:

- $i = 1, 2, \dots, n$: cases
- Z_i : whether PRAI is presented to the judge ($Z_i = 1$) or not ($Z_i = 0$)
- D_i : judge's binary decision to release ($D_i = 1$) or detain ($D_i = 0$)
- Y_i : binary outcome (NCA, FTA, or NVCA)
- X_i : observed (by researchers) pre-treatment covariates

- Potential outcomes:

- $D_i(z)$: potential value of the release decision when $Z_i = z$
- $Y_i(z, d)$: potential outcome when $Z_i = z$ and $D_i = d$
- Relationship to observed data: $D_i = D_i(Z_i)$ and $Y_i = Y_i(Z_i, D_i(Z_i))$
- No interference across cases: we analyze the first arrest cases only

- Assumptions maintained throughout our analysis:

- 1 Randomized treatment assignment: $\{D_i(z), Y_i(z, d), X_i\} \perp\!\!\!\perp Z_i$
- 2 Exclusion restriction: $Y_i(z, d) = Y_i(d)$
- 3 Monotonicity: $Y_i(0) \leq Y_i(1)$

Causal Quantities of Interest

- Principal stratification (Frangakis and Rubin 2002)
 - $(Y_i(1), Y_i(0)) = (1, 0)$: preventable cases
 - $(Y_i(1), Y_i(0)) = (1, 1)$: risky cases
 - $(Y_i(1), Y_i(0)) = (0, 0)$: safe cases
 - ~~$(Y_i(1), Y_i(0)) = (0, 1)$: eliminated by monotonicity~~
- **Average principal causal effects** of PRAI on judge's decisions:

$$\text{APCEp} = \mathbb{E}\{D_i(1) - D_i(0) \mid Y_i(1) = 1, Y_i(0) = 0\},$$

$$\text{APCEr} = \mathbb{E}\{D_i(1) - D_i(0) \mid Y_i(1) = 1, Y_i(0) = 1\},$$

$$\text{APCEs} = \mathbb{E}\{D_i(1) - D_i(0) \mid Y_i(1) = 0, Y_i(0) = 0\}.$$

- If PRAI is helpful, we should have $\text{APCEp} < 0$ and $\text{APCEs} > 0$
- The desirable sign of APCEr depends on various factors
- **Partial identification** (e.g., the signs of APCE) is possible under the assumptions of randomization, exclusion restriction, and monotonicity

Point Identification under Unconfoundedness

- Unconfoundedness:

$$Y_i(d) \perp\!\!\!\perp D_i \mid X_i, Z_i = z$$

for $z = 0, 1$ and all d .

- Violated if judges base their decision on additional information they have about arrestees \rightsquigarrow sensitivity analysis
- Principal scores (Ding and Lu 2017)

$$e_P(x) = \Pr\{Y_i(1) = 1, Y_i(0) = 0 \mid X_i = x\}$$

$$e_R(x) = \Pr\{Y_i(1) = 1, Y_i(0) = 1 \mid X_i = x\}$$

$$e_S(x) = \Pr\{Y_i(1) = 0, Y_i(0) = 0 \mid X_i = x\}$$

Identification Results

Under the assumptions of randomization, monotonicity, exclusion restriction, and unconfoundedness, we can identify causal effects as

$$\text{APCE}_P = \mathbb{E}\{w_P(X_i)D_i \mid Z_i = 1\} - \mathbb{E}\{w_P(X_i)D_i \mid Z_i = 0\},$$

$$\text{APCE}_R = \mathbb{E}\{w_R(X_i)D_i \mid Z_i = 1\} - \mathbb{E}\{w_R(X_i)D_i \mid Z_i = 0\},$$

$$\text{APCE}_S = \mathbb{E}\{w_S(X_i)D_i \mid Z_i = 1\} - \mathbb{E}\{w_S(X_i)D_i \mid Z_i = 0\},$$

where

$$w_P(x) = \frac{e_P(x)}{\mathbb{E}\{e_P(X_i)\}}, \quad w_R(x) = \frac{e_R(x)}{\mathbb{E}\{e_R(X_i)\}}, \quad w_S(x) = \frac{e_S(x)}{\mathbb{E}\{e_S(X_i)\}}.$$

and

$$e_P(x) = \Pr\{Y_i = 1 \mid D_i = 1, X_i = x\} - \Pr\{Y_i = 1 \mid D_i = 0, X_i = x\},$$

$$e_R(x) = \Pr\{Y_i = 1 \mid D_i = 0, X_i = x\},$$

$$e_S(x) = \Pr\{Y_i = 0 \mid D_i = 1, X_i = x\}.$$

Extension to Ordinal Decision

- Judge's decision is typically ordinal (e.g., bail amount)
 - $D_i = 0, 1, \dots, k$: a bail of increasing amount
 - **Monotonicity**: $Y_i(d_1) \geq Y_i(d_2)$ for $d_1 \leq d_2$
- Principal strata based on an ordinal measure of risk

$$R_i = \begin{cases} \min\{d : Y_i(d) = 0\} & \text{if } Y_i(k) = 0 \\ k + 1 & \text{if } Y_i(k) = 1 \end{cases}$$

- Least amount of bail that keeps an arrestee from committing NCA
- Example with $k = 2$: risky cases ($R_i = 3$), preventable cases ($R_i = 2$ and $R_i = 1$), safe cases ($R_i = 0$)
- **Causal quantities of interest**: reduction in the proportion of NCA attributable to the PRAI within each principal strata $r = 1, \dots, k$

$$\text{APCEp}(r) = \Pr\{D_i(1) \geq r \mid R_i = r\} - \Pr\{D_i(0) \geq r \mid R_i = r\}$$

- Nonparametric identification under unconfoundedness

Sensitivity Analysis

- Judges may use additional information when making decisions
- Bounds: avoid the unconfoundedness assumption
- Sensitivity analysis: How robust are one's empirical results to the potential violation of the key assumption?
- Ordinal probit models for $D_i(z)$ and R_i with latent variables

$$\begin{aligned}D_i^*(z) &= \beta_z + \mathbf{X}_i^\top \gamma_z + \epsilon_{i1}, \\R_i^* &= \mathbf{X}_i^\top \alpha + \epsilon_{i2},\end{aligned}$$

where $\begin{pmatrix} \epsilon_{i1} \\ \epsilon_{i2} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right)$.

- Identified under unconfoundedness (i.e., $\rho = 0$)

Principal Fairness (Imai and Jiang, 2020)

- Literature focuses on the fairness of machine-recommendations/PRAI
- We focus on the fairness of human decision
- Problems with the existing definitions and methods:
 - ① protected attributes should not be used as inputs
↪ may still depend on these attributes through other variables
 - ② equality of classification accuracy between different groups
↪ censoring may bias the results
 - ③ counterfactual fairness: what if one belongs to a different group
↪ many attributes cannot be manipulated
- **Principal fairness:** decision should not (statistically) depend on a protected attribute A_i (e.g., race and gender) within a principal strata

$$D_i \perp\!\!\!\perp A_i \mid R_i = r \quad \text{for all } r \in \{-1, 0, 1, \dots, k\}$$

Measuring and Estimating the Degree of Fairness

- How fair are the judges' decisions?

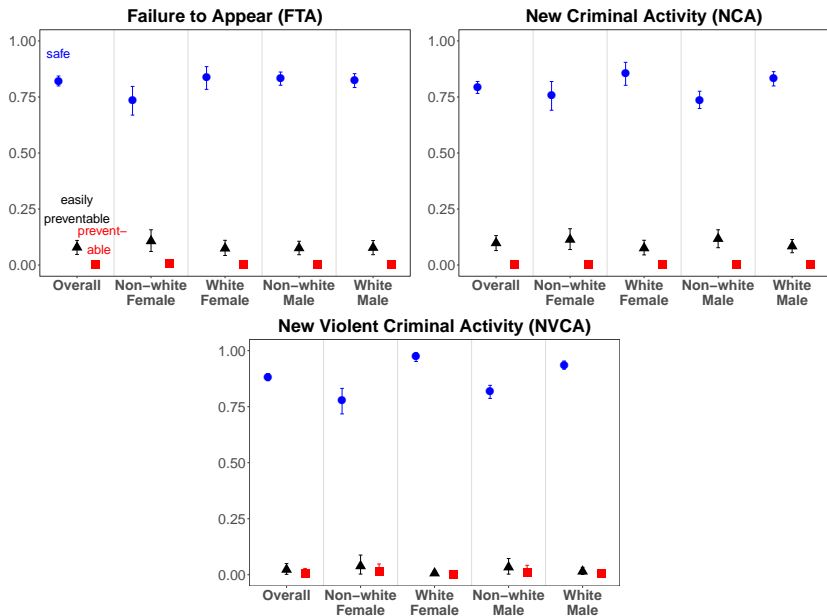
$$\Delta_r(z) = \max_{a, a', d} |\Pr\{D_i(z) \geq d \mid A_i = a, R_i = r\} \\ - \Pr\{D_i(z) \geq d \mid A_i = a', R_i = r\}|$$

for $1 \leq d \leq k$ and $0 \leq r \leq k$

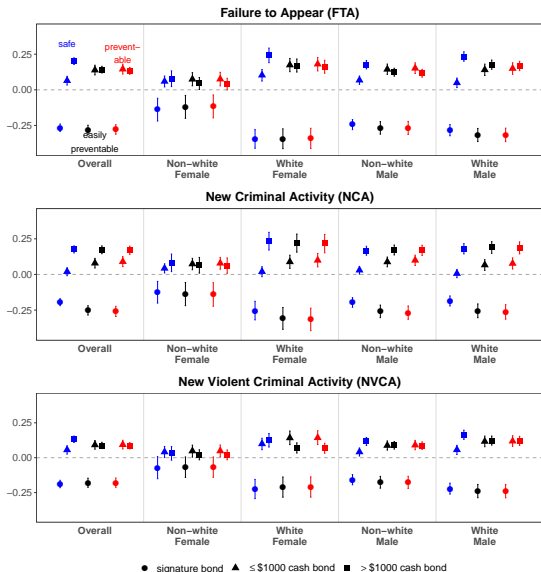
- Does the provision of PRAI improve the fairness of judges' decision?

$$\Delta_r(1) - \Delta_r(0)$$

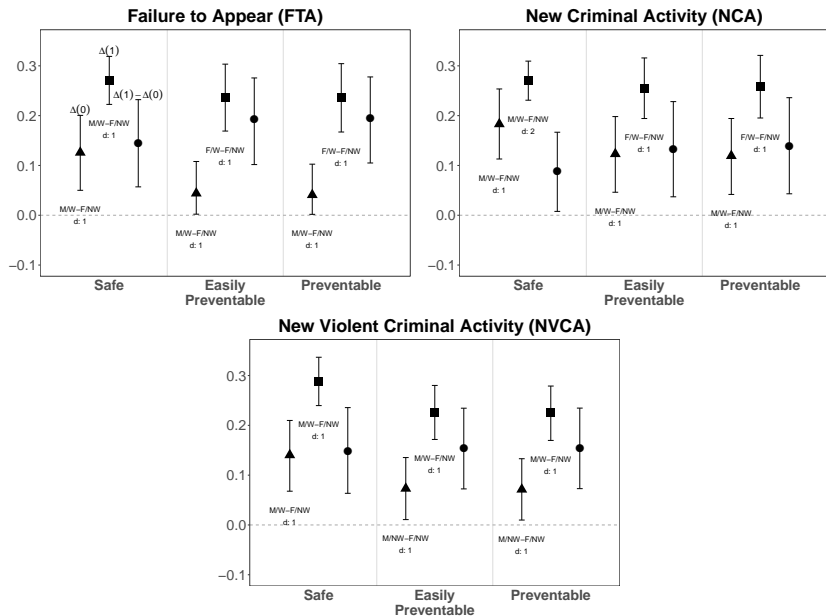
Estimated Proportion of Principal Strata



Estimated Average Principal Causal Effects



Principal Fairness



Concluding Remarks

- We offer a set of statistical methods for experimentally evaluating computer-assisted human decision making
- Application to pretrial risk assessment instrument
 - first field experiment since the 1981–82 Philadelphia experiment
 - actual empirical results will be made public in the future
- Future research
 - extension to multi-dimensional decision
 - optimal PRAI provision vs. optimal PRAI
 - effects of PRAI on judges and arrestees over time
- Paper available at
<https://imai.fas.harvard.edu/research/PRAI.html>