

Safe Policy Learning through Extrapolation: Application to Pre-trial Risk Assessment

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Motivation

- Widespread use of algorithmic recommendation and decisions
- Fast growing literature on policy learning
- **High-stake** algorithmic recommendations/decisions in medicine and public policy
 - need for transparency and accountability
 - simple and deterministic rules
- Question: How can we learn new and better policies using the data based on existing **deterministic** policies?
- Prior policy learning methods require existing policies to be **stochastic**
- Goal: Develop a **safe** approach to policy learning through **extrapolation**

Pretrial Public Safety Assessment (PSA)

- Algorithmic 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)
- **PSA** as an algorithmic recommendation to judges
 - classifying arrestees according to FTA and NCA/NVCA risks
 - derived from an application of a machine learning algorithm to a training data set based on past observations
 - different from COMPAS score

A Field Experiment for Evaluating the PSA

- Dane County, Wisconsin
- PSA = weighted indices of ten factors
 - age as the single demographic factor: no gender or race
 - nine factors drawn from criminal history (prior convictions and FTA)
- PSA scores and recommendation
 - 1 two separate ordinal six-point risk scores for FTA and NCA
 - 2 one binary risk score for new violent criminal activity (NVCA)
 - 3 aggregate recommendation: signature bond, small and large cash bond
- Judges may 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)
- Field experiment
 - clerk assigns case numbers sequentially as cases enter the system
 - PSA is calculated for each case using a computer system
 - if the first digit of case number is even, PSA is given to the judge
 - mid-2017 – 2019 (randomization), 2-year follow-up for half sample



DANE COUNTY CLERK OF COURTS

Public Safety Assessment – Report

215 S Hamilton St #1000
Madison, WI 53703
Phone: (608) 266-4311

Name: [REDACTED]

Spillman Name Number: [REDACTED]

DOB: [REDACTED]

Gender: Male

Arrest Date: 03/25/2017

PSA Completion Date: 03/27/2017

New Violent Criminal Activity Flag

No

New Criminal Activity Scale

1	2	3	4	5	6
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Failure to Appear Scale

1	2	3	4	5	6
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Charge(s):

961.41(1)(D)(1) MFC DELIVER HEROIN <3 GMS F 3

Risk Factors:

Responses:

- | | |
|--|-------------|
| 1. Age at Current Arrest | 23 or Older |
| 2. Current Violent Offense | No |
| a. Current Violent Offense & 20 Years Old or Younger | No |
| 3. Pending Charge at the Time of the Offense | No |
| 4. Prior Misdemeanor Conviction | Yes |
| 5. Prior Felony Conviction | Yes |
| a. Prior Conviction | Yes |
| 6. Prior Violent Conviction | 2 |
| 7. Prior Failure to Appear Pretrial in Past 2 Years | 0 |
| 8. Prior Failure to Appear Pretrial Older than 2 Years | Yes |
| 9. Prior Sentence to Incarceration | Yes |

Recommendations:

Release Recommendation - Signature bond

Conditions - Report to and comply with pretrial supervision

PSA Scoring Rule

Risk factor		FTA	NCA	NVCA
Current violent offense	> 20 years old			2
	≤ 20 years old			3
Pending charge at time of arrest		1	3	1
Prior conviction	misdemeanor or felony	1	1	1
	misdemeanor and felony	1	2	1
Prior violent conviction	1 or 2		1	1
	3 or more		2	2
Prior sentence to incarceration			2	
Prior FTA in past 2 years	only 1	2	1	
	2 or more	4	2	
Prior FTA older than 2 years		1		
Age	22 years or younger		2	

- FTA: $\{0 \rightarrow 1, 1 \rightarrow 2, 2 \rightarrow 3, (3, 4) \rightarrow 4, (5, 6) \rightarrow 5, 7 \rightarrow 6\}$
- NCA: $\{0 \rightarrow 1, (1, 2) \rightarrow 2, (3, 4) \rightarrow 3, (5, 6) \rightarrow 4, (7, 8) \rightarrow 5, (9, 10, 11, 12, 13) \rightarrow 6\}$
- NVCA: $\{(0, 1, 2, 3) \rightarrow 0, (4, 5, 6, 7) \rightarrow 1\}$

Setup

- For each individual i , observe
 - Covariates $X_i \in \mathcal{X}$
 - Action taken $A_i \in \mathcal{A}$
 - **Binary** outcome $Y_i \in \{0, 1\}$
- Potential outcome under action a , $Y(a)$
- Conditional expectation

$$m(a, x) = \mathbb{E}[Y(a) \mid X = x]$$

- **Deterministic baseline policy** $\tilde{\pi}$
 - Observed outcomes are $Y_i = Y_i(\tilde{\pi}(X_i))$
 - Partitions the covariate space $\mathcal{X}_a = \{x \in \mathcal{X} \mid \tilde{\pi}(x) = a\}$
- Cost of actions and utility of outcomes

$$\underbrace{c(a)}_{\text{cost}} + \underbrace{u}_{\text{utility}} Y(a)$$

Identification Problem

- Goal: Find a policy with high expected utility (value/welfare)

$$V(\pi) = \mathbb{E} \left[\sum_{a \in \mathcal{A}} \pi(a | X) (c(a) + u \cdot m(a, X)) \right]$$

where $\pi(a | X) = 1\{\pi(X) = a\}$

- But how do we identify the **counterfactuals**?

$$\text{When } \tilde{\pi}(x) = a \quad \mathbb{E}[Y(a) | X = x] = \mathbb{E}[Y | X = x]$$

$$\text{When } \tilde{\pi}(x) \neq a \quad \mathbb{E}[Y(a) | X = x] = ?$$

- Existing work uses **stochastic policies** for identification
 - inverse probability weighting

$$\mathbb{E}[Y(a) | X = x] = \mathbb{E} \left[\frac{Y 1\{A = a\}}{P(A = a | X = x)} \mid X = x \right]$$

- outcome model imputation, and double robust methods as well

Decomposition and Maxmin Principle

- Decompose the value into **identifiable** and **unidentifiable** components

$$\begin{aligned} V(\pi, m) = & \underbrace{\mathbb{E} \left[\sum_{a \in \mathcal{A}} \pi(a | X) c(a) \right]}_{\text{cost}} + \underbrace{\mathbb{E} \left[\sum_{a \in \mathcal{A}} \pi(a | X) \tilde{\pi}(a | X) u Y \right]}_{\pi \text{ and } \tilde{\pi} \text{ agree}} \\ & + \underbrace{\mathbb{E} \left[\sum_{a \in \mathcal{A}} \pi(a | X) (1 - \tilde{\pi}(a | X)) u \cdot m(a, X) \right]}_{\pi \text{ and } \tilde{\pi} \text{ disagree}} \end{aligned}$$

- Partially identify** $m \in \mathcal{M}$, then find the best policy in the worst case

$$\pi^{\text{inf}} \in \operatorname{argmax}_{\pi \in \Pi} \min_{m \in \mathcal{M}} V(\pi, m) \iff \pi^{\text{inf}} \in \operatorname{argmin}_{\pi \in \Pi} \max_{m \in \mathcal{M}} \underbrace{V(\tilde{\pi}) - V(\pi, m)}_{\text{regret relative to baseline}}$$

- This is a **safe** policy based on robust optimization
 - Conservative, “pessimistic” principle
 - Falls back on the status quo policy if there is too much uncertainty

Partial Identification

- To partially identify the conditional expectation $\mathbb{E}[Y(a) \mid X = x]$
 - ① Put restrictions on the class of possible models
 - ② Compute the set of functions f in the selected model class that agree with the observable data

$$\mathcal{M} = \{f \in \mathcal{F} \mid f(\tilde{\pi}(x), x) = \mathbb{E}[Y \mid X = x] \ \forall x \in \mathcal{X}\}$$

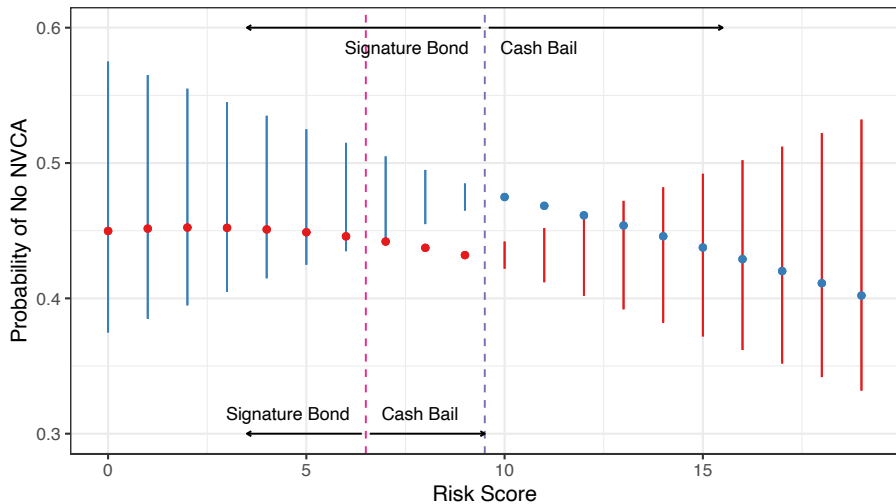
- Many model classes result in **pointwise bounds**

$$B_\ell(a, x) \leq m(a, x) \leq B_u(a, x)$$

- Examples: Lipschitz functions, additive models, linear models
- Use the worst-case bound in place of the missing counterfactual:

$$\Upsilon(a) = \tilde{\pi}(a \mid X)Y + (1 - \tilde{\pi}(a \mid X))B_\ell(a, X)$$

Illustration with Single Discrete Covariate



Population Safe Policy

The value of the safe policy is at least as high as the baseline policy

$$\underbrace{V(\tilde{\pi}) - V(\pi^{\text{inf}})}_{\text{regret relative to baseline}} \leq 0$$

- **Safety** comes at the cost of a potentially suboptimal policy
- Compare to **oracle policy** $\pi^* \in \operatorname{argmax}_{\pi \in \Pi} V(\pi)$

Optimality gap controlled by the size of the model class $\mathcal{M}$

$$\underbrace{V(\pi^*) - V(\pi^{\text{inf}})}_{\text{regret relative to oracle}} \leq u \mathbb{E} \left[\max_{a \in \mathcal{A}} \{ B_u(a, X) - B_\ell(a, X) \} \right]$$

- The tighter the **partial identification**, the smaller the optimality gap

Empirical Safe Policy

- Construct a **larger** empirical model class $\widehat{\mathcal{M}}_n(\alpha)$

$$P\left(\mathcal{M} \in \widehat{\mathcal{M}}_n(\alpha)\right) \geq 1 - \alpha$$

- Using simultaneous confidence bands for $\mathbb{E}[Y \mid X = x]$, get pointwise bounds

$$\widehat{B}_{\alpha\ell}(a, x) \leq m(a, x) \leq \widehat{B}_{\alpha u}(a, x)$$

- Impute missing counterfactuals from bound

$$\widehat{\Upsilon}_i(a) = \tilde{\pi}(a \mid X)Y + (1 - \tilde{\pi}(a \mid X))\widehat{B}_{\alpha\ell}(a, X)$$

- Solve an empirical welfare maximization problem

$$\hat{\pi} \in \operatorname{argmax}_{\pi \in \Pi} \frac{1}{n} \sum_{i=1}^n \sum_{a \in \mathcal{A}} \pi(a \mid X_i) (c(a) + u \widehat{\Upsilon}_i(a))$$

Statistical Properties

- Conservative approach gives a **statistical safety** guarantee with level α

Value is probably, approximately at least as high as baseline

$$V(\tilde{\pi}) - V(\hat{\pi}) \lesssim \text{Complexity}(\Pi)$$

with probability at least $\gtrsim 1 - \alpha$

- If policy class Π is complex, need more samples to avoid overfitting

Empirical optimality gap controlled by the size of the empirical model class and the complexity of policy class

$$V(\pi^*) - V(\hat{\pi}) \lesssim \frac{u}{n} \sum_{i=1}^n \max_{a \in \mathcal{A}} \{ \hat{B}_{\alpha u}(a, X_i) - \hat{B}_{\alpha \ell}(a, X_i) \} + \text{Complexity}(\Pi)$$

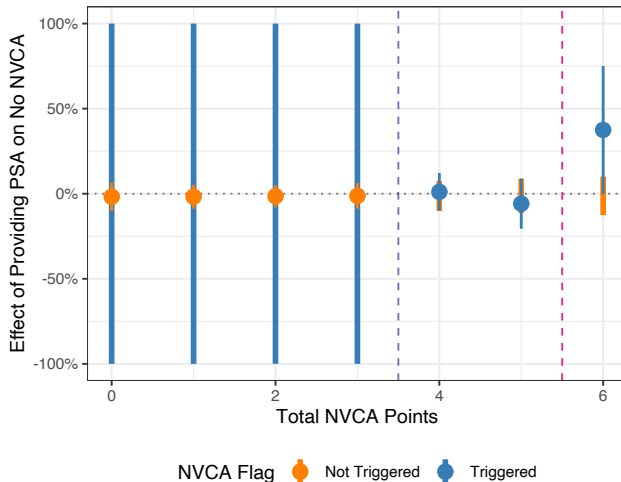
with probability at least $\gtrsim 1 - \alpha$

- Same tradeoff between safety and optimality

Learning a New NVCA Flag Threshold

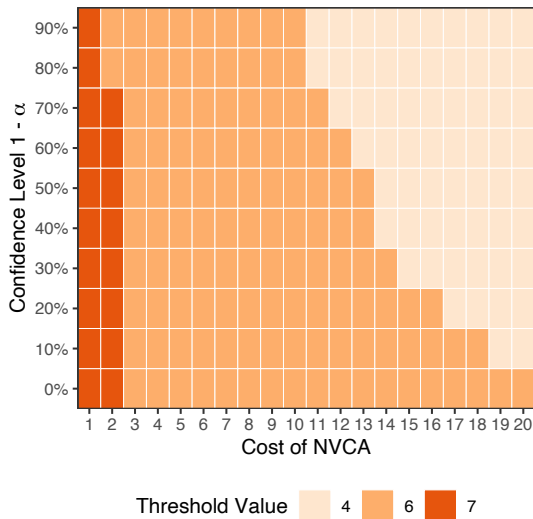
- Find an improved NVCA flag threshold using the same risk factors
 - Status quo policy: $\tilde{\pi}(x_{\text{nvca}}) = 1\{x_{\text{nvca}} \geq 4\}$ where $x_{\text{nvca}} \in \{0, 1, \dots, 6\}$
 - Policy class: $\Pi_{\text{thresh}} = \{\pi(x) = 1\{x_{\text{nvca}} \geq \eta\} \mid \eta \in \{0, \dots, 7\}\}$
- Lipschitz constraint on the CATE $\tau(a, x_{\text{nvca}})$
- The Working–Hotelling–Scheffé simultaneous confidence intervals
- Cost of triggering the NVCA flag is 1: $c(0) = 0$ and $c(1) = -1$
- Monetary cost is zero, but fiscal costs on jurisdiction and socioeconomic costs on individuals and community
- Equal utility $u(1) = u(0) = u$: cost of an NVCA is $-u$

Extrapolating the CATE



- More information when extrapolating the CATE for the case that the NVCA flag is *not triggered*

New NVCA Thresholds



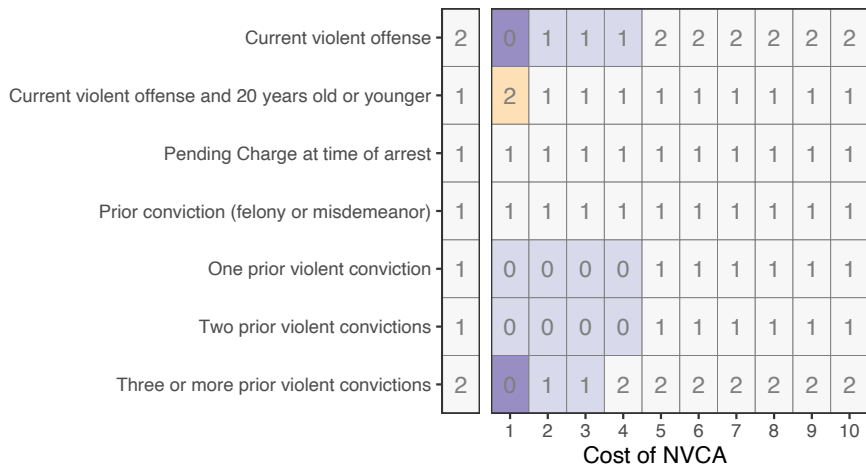
- Higher cost of NVCA and greater confidence $\rightsquigarrow$ fall back on the status quo policy

Learning a New NVCA Flag Point System

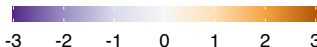
- Changing the integer weights applied to 7 binary risk factors
 - Status quo policy: $\tilde{\pi}(x) = 1 \left\{ \sum_{j=1}^7 \tilde{\theta}_j x_j \geq 4 \right\}$ where $x \in \{0, 1\}^7$
 - Policy class: $\Pi_{\text{int}} = \left\{ \pi(x) = 1 \left\{ \sum_{j=1}^7 \theta_j x_j \geq 4 \right\} \mid \theta_j \in \mathbb{Z} \right\}$
- Two model classes:
 - 1 additive models
 - 2 second-order interactive models
- For the outcome $m(a, x)$ as well as for the CATE $m(a, x) - m(\emptyset, x)$

Changes in the NVCA Flag Weights

(additive effect model; confidence level = 80%)



Difference from original weights



Concluding Remarks

- Deterministic decisions and recommendation algorithms are ubiquitous
 - government policies and medical treatment decisions
 - transparency and simplicity
- Proposed methodology: extrapolate and use robust optimization to learn a new policy
 - Partially identify the counterfactuals and find the policy that is the best in the worst case
 - Gives a statistical safety guarantee relative to the status quo
- Some evidence we can improve the PSA, but noisy. Need more data!
- Potential applications:
 - Policy learning with asymmetric utility functions
 - Optimizing for long term outcomes using short term outcomes