Optimize Intervention Allocation

Machine Learning on Voter Mobilization Experiments

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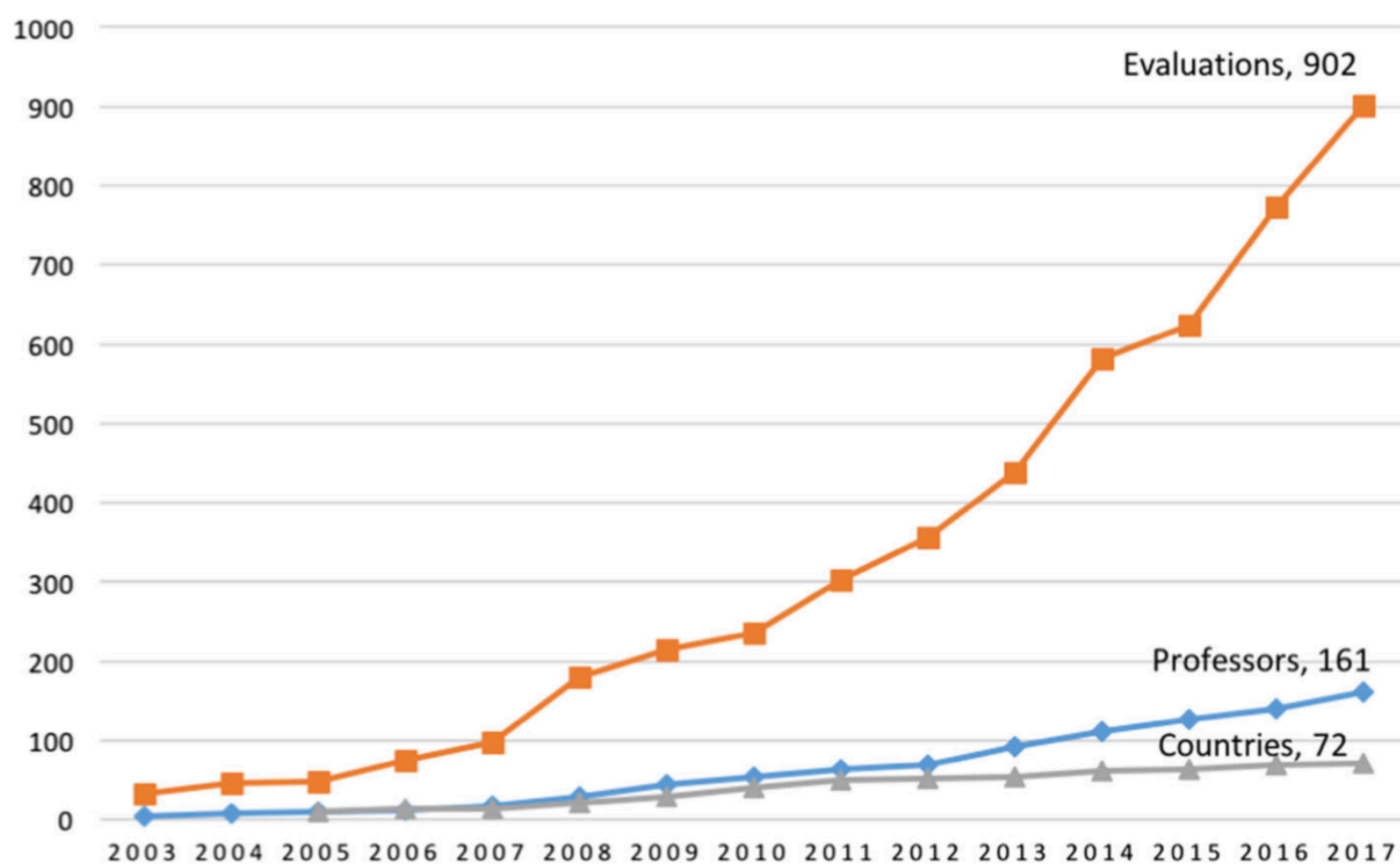
Topic Statement

Background

- Randomized Control Trials (RCT) has been the “gold standard” to draw causal inference and program evaluation.
- Recent Nobel laureates in economics also been awarded because of their study on global poverty via experimental approach .



Source: Poverty Action Lab at MIT (J-PAL)

However, field experiments are prohibitively expensive in terms of time and money.

Research Question

- Beyond the crude estimand Average Treatment Effect (ATE) across the subject pool, can we learn the variability of treatment effect over certain covariates?

- If we know a subgroup is more persuadable, we could use this information to refine our intervention allocation in the future program to lift overall campaign effect.

Data

Three Field Experiments Datasets

Three text-messaging voter mobilization experiments conducted before 2016 general election.

Experiment	Treatment Group	Control Group
One Arizona Campaign	200,442	50,187
NextGen Climate Campaign	94,257	94,229
Vote.org	905,396	301,920

Questions

How to estimate heterogeneous treatment effects (HTE) given the voting history?

- Is the text-messaging intervention more efficacious on those who voted in the past or those who seldom vote?
- After we know the HTE, how we can allocate the text-messaging to boost the mobilization effect?

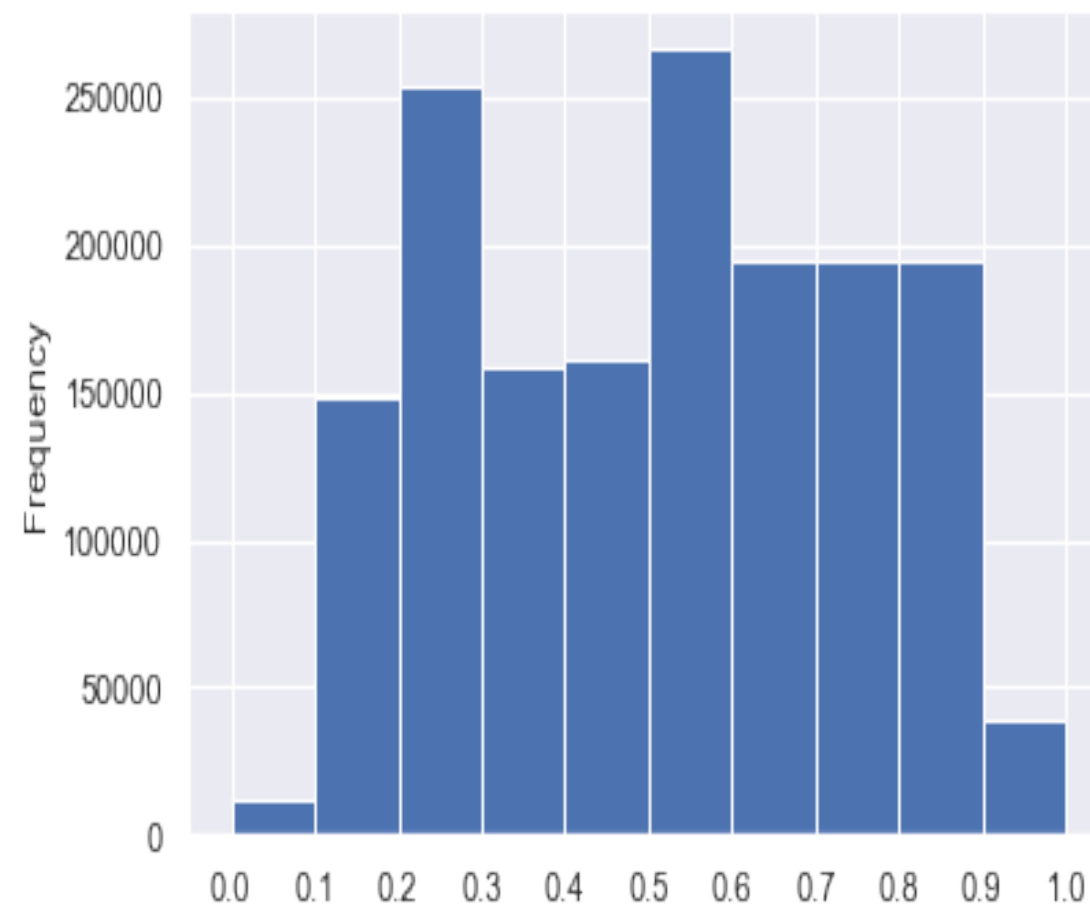
Exploratory Analysis

Data Dimension Reduction

Compress Past Vote History Covariates into a Single Variable

- A logistic regression model on control group: the independent variables are available vote history, and all possible interaction terms between those vote history covariates, the dependent variable is the vote turnout in the 2016 general election.

- Use this logistic model to predict the probability of voting.



Estimate HTE by OLS

The interaction term in the regression results demonstrate that overall the vote propensity is negatively correlated with the treatment effect.

	Dependent variable:			
	Pooled	One Arizona	NextGen Climate	Vote.org
	(1)	(2)	(3)	(4)
Intercept	-0.0007	-0.0051	-0.0008	-0.0008
	(0.0015)	(0.0102)	(0.0025)	(0.002)
Propensity	1.0004***	1.008***	1.0024***	1.0001***
	(0.0028)	(0.0155)	(0.0066)	(0.0035)
Treatment	0.0106***	0.113***	0.0141***	0.0042*
	(0.0018)	(0.0112)	(0.0036)	(0.0023)
Treatment:Propensity	-0.0165***	-0.169***	-0.0364***	-0.0055
	(0.0033)	(0.0171)	(0.0094)	(0.004)
Observations	1622800.0	226998.0	188486.0	1207316.0
R2	0.2125	0.0733	0.189	0.2122
Adjusted R2	0.2125	0.0733	0.189	0.2122
Residual Std. Error	0.4435(df = 1622796.0)	0.4612(df = 226994.0)	0.4214(df = 188482.0)	0.4433(df = 1207312.0)
F Statistic	145963.7908*** (df = 3.0; 1622796.0)	5988.0838*** (df = 3.0; 226994.0)	14644.4877*** (df = 3.0; 188482.0)	108386.6704*** (df = 3.0; 1207312.0)

Note: *p<0.1; **p<0.05; ***p<0.01

Machine Learning

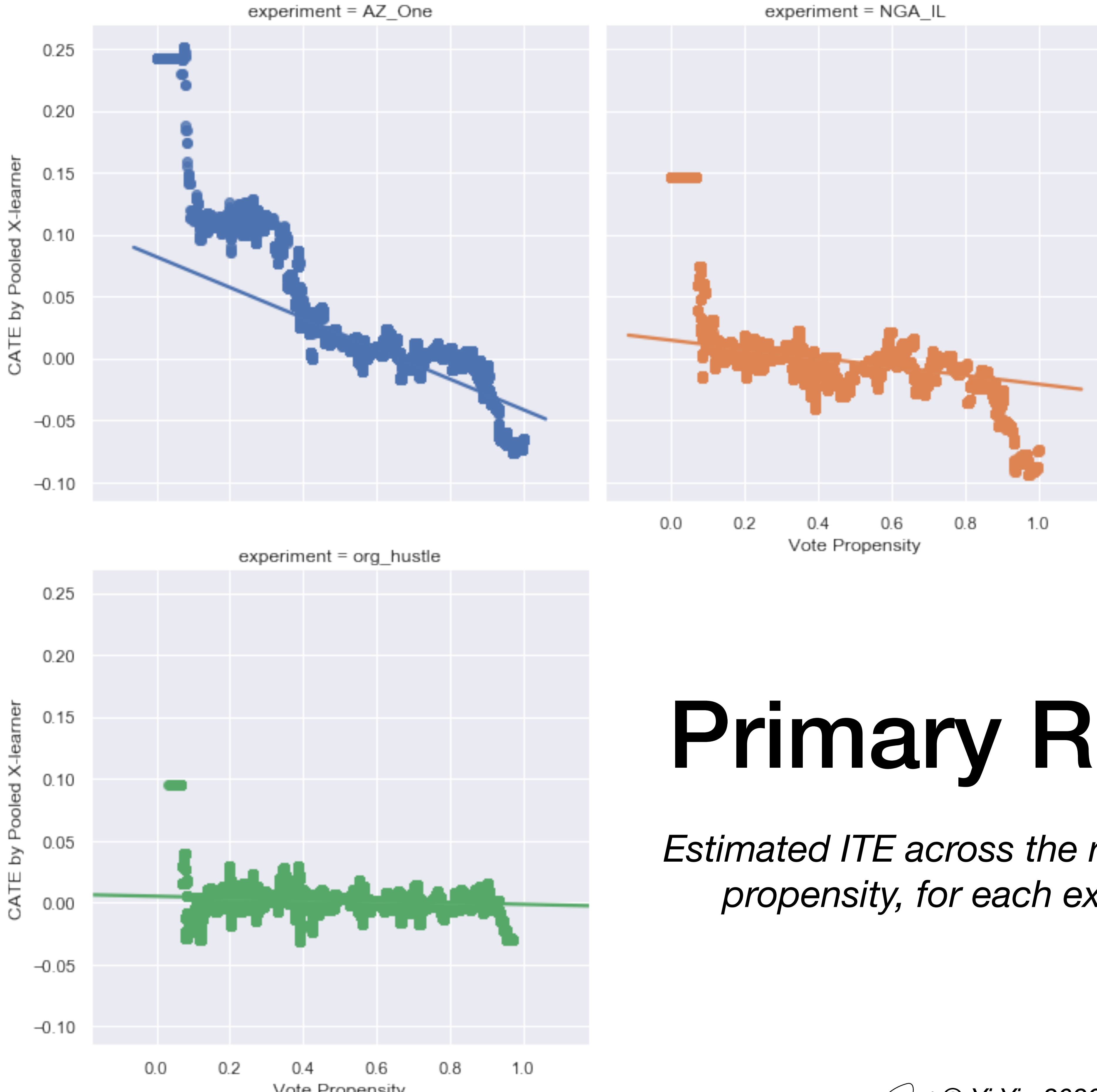
Machine learning Framework

Estimate Individual Treatment Effect (ITE)

- Base Algorithm: Model the outcome (in this study is the vote turnout in 2016 general election) for control and treatment group respectively

- Using base algorithm, for treatment group, impute the untreated outcomes; for control group, impute the treated outcome

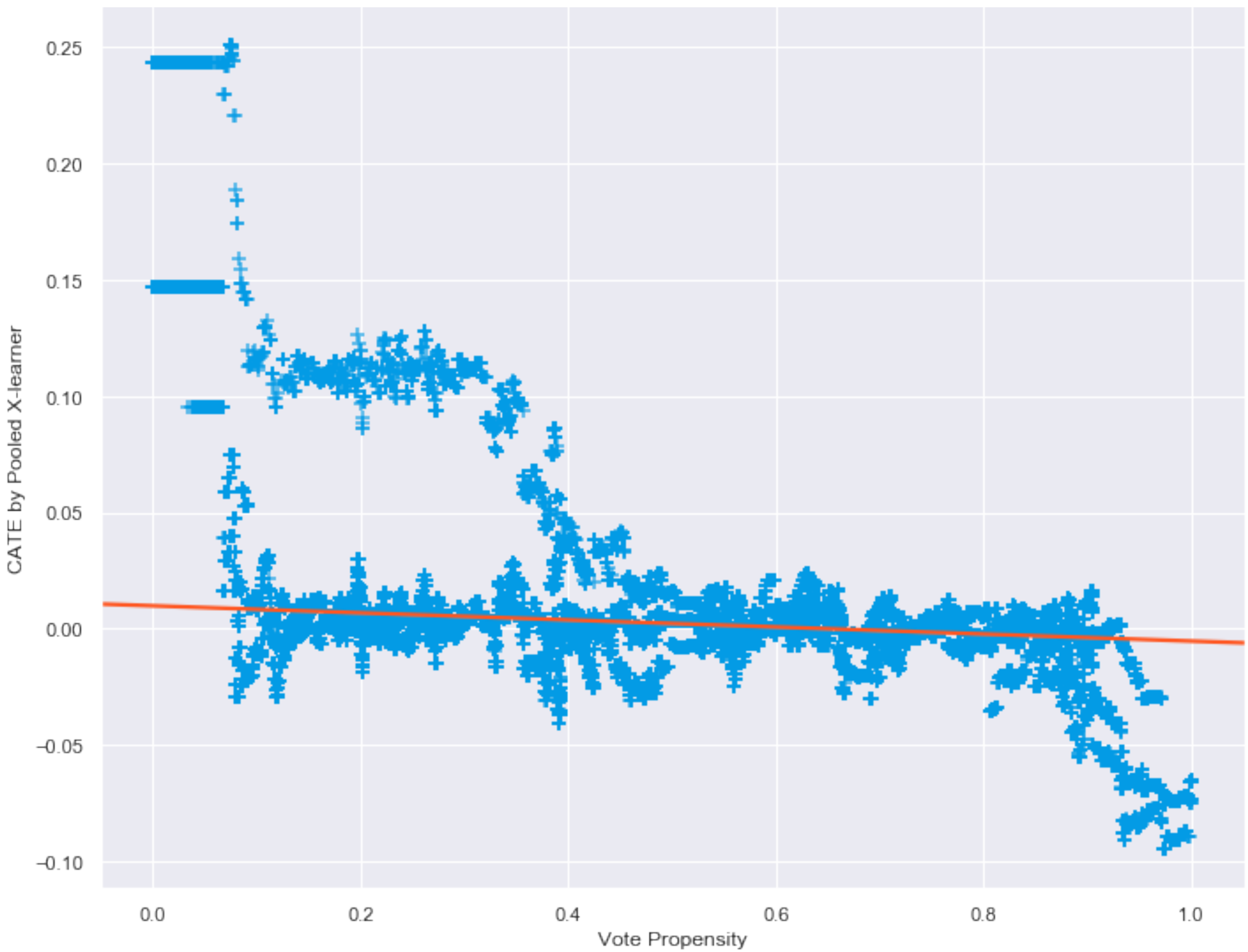
- Obtain the ITE by simply subtracting the untreated outcome from treated outcome



Primary Result

Estimated ITE across the range of vote propensity, for each experiment

Estimated ITE over Vote Propensity (Pooled)



Next Steps

Cross-Validation

Is the ITE information really helpful to lift the intervention result ?

- Simulate the allocation of one experiment based on the information gain in another experiment.

- Using such training-and-test design, we could measure the uplift effect of targeting impressionable subjects via simulating allocation

- Comparing the different simulation for the same experiment, we are able to check the robustness of the Machine Learning framework

Extrapolation and Limitation

How informative and/or misleading this study is ?

- Based on the machine learning and simulation, we could advise future voter mobilization experiments using text-messaging.
- This machine learning framework to estimate ITE is generalizable to other binary treatment experiments
- *We do not address more complex intervention design which is not binary,*
- *How to maximize the intervention effect by customizing the dosage of treatment on individual subject remain an open question.*

References

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- Künzel, S. R., Sekhon, J. S., Bickel, P. J., & Yu, B. (2019). Metalearners for estimating heterogeneous treatment effects using machine learning. Proceedings of the National Academy of Sciences, 116(10), 4156–4165. https://doi.org/10.1073/pnas.1804597116

- Exploratory analysis and primary machine learning implemented in python language.
- Data Obtained from Dr. Donald Green (Advisor of this thesis).

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