From: Cassandra Bayer
To: California Policy Lab
Sub: Analysis of Treatment on Re-Arrest Rates
Date: July 25 2018

Research Question

Does the program treatment decrease the likelihood of a defendant's probability to get arrested prior to their disposition?

Methodology

Because the variable of interest (re_arrest) and the primary independent variable (treat) are both binary, I developed a logit regression using the forward-stepwise model selection. I developed four different models and used model validation to select the most accurate model. (Figure 1). I then applied the model to the training set of data and measured its ratio of false positive to true positive classification using the ROC curve to further validate the model. Finally, I employed propensity scores to measure the effect of the treatment between two balanced treatment and control groups to isolate the effect of the treatment.

Findings

The model revealed that, while prior arrests and age significantly predict whether a defendant will be arrested prior to their disposition, the treatment explains much less of the variance in the probability. In fact, the treatment was associated with a rise in the probability of a defendant's re-arrest. Other factors outside of treatment status seem to affect the defendants re-arrest status, such as age. As a defendant gets older, the likelihood of re-arrests drop. The model also revealed that there is an exponential impact of prior-arrests on the likelihood of re-arrests, which means that one prior arrest may not be as detrimental as two or more. When controlling for a defendant's propensity to get arrested prior to their disposition, there was no statistically significant difference between the probability for re-arrest between the treatment and control groups.

Analysis

The findings suggest that the treatment had no significant impact on recipients. However, the treatment was likely not assigned at random given the imbalance between treatment and control groups. The results indicate that there may be systematic differences between those who received treatment and those who did not. Because the treatment was initially associated with a higher probability for re-arrest, the treatment was likely given to those disproportionately more likely to getting arrested prior to disposition. While is is unclear what actions the program took, the treatment should look closely at the strong relationship that prior arrests have with the likelihood of rearrest, especially amongst younger defendants.

Recommendation

It is recommended that the treatment be assigned by propensity score for re-arrest and then be reevaluated. Due to lack of random assignment, the efficacy of the treatment is unclear.

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Appendix

$$re\_arrest = \alpha + \beta1prior\_arrest_i + \beta2treat + \beta3age_i +_i \beta4male_i + \beta3prior\_arrests\text{^}2_i + \beta4prior\_arrests*age_i$$

Figure 1: Model 2

	Likelihood of Re-Arrest			
	B (CI)	*p*		
(Intercept)	-2.01 (-2.15 – -1.86)	**<.001**	-1.99 (-2.31 – -1.67)	**<.001**
Prior Arrests	0.14 (0.12 – 0.16)	**<.001**	0.39 (0.33 – 0.45)	**<.001**
Treatment	-0.06 (-0.13 – 0.01)	.085	-0.09 (-0.16 – -0.02)	**.011**
Age	0.01 (0.01 – 0.02)	**<.001**	-0.02 (-0.03 – -0.01)	**.006**
Male			0.06 (-0.02 – 0.15)	.135
Prior Arrests Squared			-0.05 (-0.06 – -0.04)	**<.001**
Age * Prior Arrests			0.01 (0.00 – 0.01)	**<.001**
Observations	18750		18750	
R^2 / adj. R^2	.023 / .035		.033 / .050	

Figure 2: Comparison of model 1 (left) and model 2 (right)