Project Proposal

Machine Learning for Public Policy

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Project goals

To increase the trust in the police, ensure the proper use of the public force, and decrease the risk of public officers, our group aims to strengthen the Early Intervention System for the Charlotte-Mecklenburg Police Department (CMPD) through machine learning algorithms.

Problem definition

Besides efforts to prevent officers' incidents, there is still room for improvement to increase the security system and ensure that best application of law.

Recently, the advent of social media has placed the actions of police officers under severe scrutiny. There has been videos and pictures of police officers performing adverse actions to civilians circulating online. This media coverage has increased the incentives of the police department to improve their procedures to ensure that the public trust in them.

Importance and Impact

Security is required for civilians, and it is the goal of the police force. The importance of this measure is regarding two different dimensions. On the one hand, to ensure the best rule of law, it is required to develop the better procedures for police officers. On the other hand, this action can increase the trust in the policy, given that incidents can be reduced.

Who cares

The White House has placed public safety, law enforcement and community relations as one of its top priorities. Also, civil society has expressed its concern in many different forums.

Who will take action based on your work

The Charlotte-Mecklenburg Police Department (CMPD) would apply our recommendations based on machine learning algorithms to improve on their existing Early Intervention System. By detecting police officers at risk of adverse events prior to them committing the action, the CMPD can direct these officers to retrain programmes to extract them from high-stress environments, and improve their capacity to deal with such situations.

What are the policy goals you care about?

Improve the Early Intervention System to better identify police officers at risk, increase internal accountability and reduce inappropriate uses of force.

Other secondary goals are achieve a safer public-facing CMPD, without compromising law enforcement; ease the existing tensions; foster stronger trust between the community and the CMPD.

Data

The data consists of a detailed event record of each police officer and the officer's demographic information. This extensive dataset has been collected by the CMPD to manage their daily operations. Our outcome variable, adverse events conducted by police officers, is extracted from the incident records when an incident is ruled by the Internal Affairs to be preventable, unjustified and sustained. Other useful variables for the analysis include officer dispatch events, criminal complaints made by citizens, traffic stops and arrests made by officers, employee records, secondary employment and neighborhood.

Analysis

We are looking to identify a risk ranking score (our dependent variable) that determines the probability that police officers will engage in adverse event/misconduct behavior[1].

We will implement Machine Learning techniques, with features such as number of resisted arrests, number of injuries, number of criminals who assaulted an officer, number of crime related events, average weight of suspects, the average height of suspects. All that measures at the officer level in a defined time period, which we will define through empirical testing. With that information, we will predict a risk ranking score which could be used, at different thresholds, to obtain a dummy output variable $0, 1$ for a top-N list, that indicate if an officer is likely to misbehave in a period of time.

For this endeavor, we will look to implement three different binary classification models: Logistic Regression, Support Vector Machine (SVM's) and Random Forests. We expect to estimate the probability assigned to class C_i from the three proposed models with distinct parameters settings.

What actions will this enable or improve?

The objective of police departments is to train and retain the very highest quality police force. As budget constraints exists, police officers need to train and mentor those that needed the most. In this sense, the objective is to better identify police officers that are riskier to misconduct. By the provision of a score (probability) to each police officer, we could rank police officers by the risk of adverse behavior controlling for precision-recall tradeoffs that can give more control and flexibility to police departments to make interventions such as training, counselling or mentorship that can improve their quality services to the society. As there are limited resources to intervene all the police force, the ranking allows to the police department to adjust the risk threshold depending on their resources and their capacity to intervene police officers. To sum up, our recommendations will allow the CMPD to enhance its allocation of resources due to a ranking approach that identifies the riskiest officers, which will allow prioritizing in the enrollment of early intervention programs.

Evaluation

We will train our data for a fixed period of time, likely 2013-2014, to test in 2015. However, we will look to different approaches to cross-validation and testing to identify if information of other years is useful for the final model.

[1] We refer to adverse events or misconduct behavior for the following criteria: (1) officer's improper use of force, (2) citizen or officer injury or accident and (3) any sustained serious complaint from a citizen or colleague.

As we expect that our class of interest is the minority class (incidents), accuracy and performance on the majority class are not the right metrics to optimize. For this reason, for assessing the classification performance, we will use precision (true negative rate), the proportion of actual positives among the predicted positives.[2]. We will evaluate the process with a N-fold cross validation in order to compare the models. The N will be defined through practical considerations.

Policy recommendations.

Kind of recommendations we hope to give to policymakers

We aim to generate a public policy recommendation for the CMPD. For instance, the objective will be to improve the current system for early interventions.

The design of this plan will take care that the proposal will be: 1) feasible, within a moderate budget range; 2) better that the actual system (if not, the recommendation is meaningless); 3) political viable, that is to say, that its implementation is realistic given the political constraints.

In specific, the recommendations will be rules to improve their daily operations. For instance, practices like if an officer has been injured two times in the last six months, and has been in two resisted arrests during the past 12 months, assign him to a low-risk area for the next three months. Also, given the limited scope of the project, the recommendations can be design a particular policy for certain officers that we know are at risk. For example, maybe police officers, who are white, between 40 and 50 years old, married, and with more than three arrests related to drugs in the last six months need a particular policy because we know they are at high risk. Specific recommendations need to be discussed with people closer to the daily-basis operations to avoid implausible public policies.

Validate that our policy will have the desired impact

We can verify our policy in two stages. The first one, before the implementation phase, is run computer simulations with our model to assess the possible results of our recommendations. Then, modify and simplify our recommendation until we produce one with two characteristics: 1) maximize positive results, 2) be feasible and straightforward to operationalize (or the closest to that). At the same time of computer simulations, it will be clue to talk with experts in the field to find reasonable possible outcomes. The effects can be dramatically different of the simulations if we omit key behaviours that experts will know better than us.

The second one is after the application of our public policy. We will validate or implementation against historical data and possible future trends with and without our policy. For instance, one of the methods to evaluate our program will be regression discontinuity to detect structural changes in the patterns before and after the policy. Another way can be, limited to operational and political constraints, make a randomized control experiment with this plan. That is to say, implement the policy in some small subsamples of the population and compare its outcomes with the general ones through econometrics. Then, it will be possible to find it out if the new proposed methodology has the desired impact. Finally, other simple approaches can be implemented, such as compare historical data of the same month, or analyze correlations of incident indicators and relevant variables, like temperature, festivals, vacations days, snow days, or others that can affect the probability of officer's adverse events.

[2]Flach, Peter. Machine learning: the art and science of algorithms that make sense of data. Cambridge University Press, 2012