Using Machine Learning to Predict Police Misconduct

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Executive Summary

Every year nearly 1,000 people are fatally shot by police in the US (Berman, Sullivan, Tate, & Jenkins, 2020). More often than not, police misconduct is predictable. Given thorough data collection on officer actions and an administration committed to following up, early intervention has been shown to reduce the number of adverse incidents between cops and civilians. The Chicago Police Department's current early warning system relies on arbitrary thresholds and supervisor discretion to flag officers for this sort of intervention. Our model seeks to provide a more data-driven approach. According to a report from the Police Accountability Task Force (PATF), "It is imperative that CPD have a system in place that allows for a 360-degree view of the activity and conduct of its officers. The system should allow CPD to identify problematic behaviors at the earliest possible instance so that it can get officers back on track or, if necessary, manage them out of the department before it is too late" (PATF Report, 2016). We believe we have taken preliminary steps to creating such a system.

We used data on formal complaint reports among other data on officer demographics and CPD paperwork from a database created and maintained by the Invisible Institute's Citizens Police Data Project (CPDP). Our observation period was January 2012- December 2014. For each complaint in this period, we considered the alleged action of the officer which we classified into one of six categories: excessive force with a weapon, excessive force without a weapon, racist/bigoted conduct, drug possession/D.U.I., non-violent civilian conduct like illegal searches, and unknown/other. We also considered whether the officer was formally disciplined for the complaint. We then created one row for each officer listing their total number of sustained complaints and the number of complaints they had in each category. Other officer features included the total amount of settlement dollars the officer had cost the city throughout the observation period, the percent of complaints they had from victims of various races and genders, the age, gender, and race of the officer, the number of years the officer served on the force, and the types of force the officer indicated using in any Tactical Response Reports from the observation period.

For all officers who had at least one complaint in the observation period, we looked at whether or not those officers engaged in serious misconduct in 2015. Serious misconduct was defined as one or more of the following:a complaint of use of force, a complaint of racist/bigoted behavior, a complaint involving officer drug use/possesion or D.U.I.,any complaint of illegal behavior related to civilian contact (e.g., an illegal search), or a complaint of any type that was sustained by the internal review process of the CPD. These features were applied to a random forest to perform a binary classification. Each officer was classified as either having or not having engaged in serious misconduct in the target period.

Our best-performing model had a balanced accuracy of .654. It was able to flag 58.6% of officers who do go on to commit serious misconduct, compared to the CPD's currency system which flags fewer than 1% of such officers. The model favors recall over precision, as 26.5% of flagged officers actually turn out to commit misconduct (compared to the current system's precision of 37.5%), a justifiable tradeoff in not wanting to let officers in need of intervention fall through the cracks.

Link to github repository:
https://mit.cs.uchicago.edu/aweinstein5/Police_Misconduct_ML_2020.git

Background and Overview of Solution

Though the city of Chicago has a long history of police misconduct, the issue galvanized widespread activism when former Chicago police officer Jason Van Dyke shot and killed 17-year-old Lacquan McDonald in October 2014. Van Dyke had 19 citizen complaints and two misconduct lawsuits pending against him, yet had not been flagged by the Chicago Police Department as at-risk of committing violent misconduct. Police misconduct has garnered unprecedented national attention in recent weeks (late May 2020) following a series of police murders of black individuals including George Floyd in Minneapolis and Breonna Taylor of Louisville. Similar to Van Dyke and other killer cops, Derek Chauvin, the cop who murdered Floyd, had at least 17 complaints filed against him including shooting a civilian and beating a civilian to death (Dewan & Kovaleski, 2020).

Data on complaints of police misconduct and CPD records of use of force collected by the Invisible Institute, a nonprofit devoted to making data public to uphold police accountability, revealed that 29% of police shootings between January 2004 and March 2016 were committed by a group of 130 officers, only 5% of the CPD's total officers (Arthur, 2018). Most of these officers had previous complaints against them, and repeat shootings by a single officer often occurred in patterns. It was also found that when officers exhibit use of force, nearly 90% of the time it is toward a person of color (Fan, 2018). All too often, police misconduct starts with racial profiling and results in the unjust loss of black and brown lives.

Due to the predictable nature of misconduct, a majority of cities have implemented computerized early warning systems to flag officers for additional counseling and intervention. Chicago developed a system that used neural network analysis in 1994, but it was scrapped almost immediately due to backlash from police unions (Arthur, 2016). CPD has a Performance Recognition System dashboard, which could potentially contain a wealth of information, and instead goes largely unused. A report states, "Supervisors are not required to input information to explain the data or take any action in response to the data they receive" (PATF Report, 2016). CPD currently employs two early intervention systems, called the Behavioral Intervention System and Personnel Concerns. Due to a contract with police unions, CPD does not consider full complaint histories when flagging officers for intervention.

The Behavioral Intervention System considers whether an officer had two sustained complaints or three excessive force complaints within the past year as well as features such as excessive tardiness, misuse of medical leave, and performance review scores (Newman, 2015). It also considers more subjective categories such as "significant deviation of normal behavior or the conduct expected of the member" (BIS Directive, 2017). Many officers who go on to commit serious misconduct, including Van Dyke, have no sustained complaints; in fact, fewer than 4% of complaints are sustained by CPD. Clearly we need to look at more than just sustained complaints to create an effective early warning system.

Police misconduct is also costly for the city. In 2018, Chicago spent $113 million on police misconduct settlement payments and lawyers, bringing the total from the previous 8 years to over $500 million. These are resources that could be put toward improving the safety and well-being of Chicagoans rather than to police penitence. With this in mind, we seek to develop a more sensitive algorithm that still does a good job of flagging officers who will go on to participate in adverse incidents without flagging an unmanageable number of total officers.

Our intended audience is the Chicago Police Department (CPD), as well as community stakeholders who seek to hold the CPD accountable. Our hope is that when officers are flagged for being at risk of adverse incidents, the CPD will be able to intervene accordingly, whether that means putting those officers in targeted trainings and counseling sessions or even removing them from patrol duty for some amount of time. These sorts of interventions are consistent with the consent decree issued by Illinois in January 2019, which gave the CPD two years to comply with a set of reforms. One of these reforms is that the CPD must redouble its efforts around de-escalation tactics, report when officers point firearms, and track/analyze use-of-force data (Chicago Police Department Consent Decree Fact Sheet, 2019). This sort of record-keeping naturally lends itself to a predictive system that attempts to identify officers most at "risk" of committing violence and illegal tactics against civilians. A machine learning algorithm is instrumental to this task of the CPD making best use of its data to achieve the goals laid out by the consent decree.

Our model uses the aforementioned inputs and applies a classification model on three years of data to construct a "profile" for each officer and use that profile to predict whether or not an officer will have an adverse event in the subsequent fourth year (the "target year"). We define that adverse incident, or "target," as whether an officer has any of the following within the target year: complaint of use of force, a complaint racist/bigoted behavior, a complaint of officer drug use/possession or D.U.I., any nonviolent civilian contact (e.g., illegal search) complaint, or any complaint sustained by the CPD's internal disciplinary process. This classification is binary, meaning it does not take into account how many of each sort of event the officer was involved in, only whether or not the officer was involved in any.

Our model is intended to be implemented in a system that flags officers who have risk profiles that suggest they are likely to have adverse events in the future. Officers with sufficiently high risk profiles should be mandated to undergo some level of intervention. Whether that intervention consists of a formal warning, counseling, or revoking some of that officer's responsibilities is ultimately up to the CPD, but we believe that having an accurate risk score is a part of an effective reform to reduce incidences of police misconduct.

Data

Our source of data is a series of files shared with us by the Invisible Institute's Citizens Police Data Project (CPDP). These files are organized into four broad categories: information about CPD officers, complaints filed to the Civilian Office of Police Accountability, data on settlements paid out by the city of Chicago, and records called Tactical Response reports that the CPD uses to track officer actions. Several files were merged to create a single dataframe wherein each row represents a single officer's complaint history and profile information from 2012-2014 as well as a binary column representing our target variable.

A similar database of complaints to the Civilian Office of Policy Accountability (COPA) of the CPD is maintained by the city. We chose to use the CPDP data as our primary source because it has unique identifying information on the police officer committing the misconduct, which is vital to our model design of creating a prediction for particular cops. The COPA data does not have descriptions of complaints, so complaints in the CPDP data labeled as "miscellaneous" could not be more accurately identified through cross-checking.

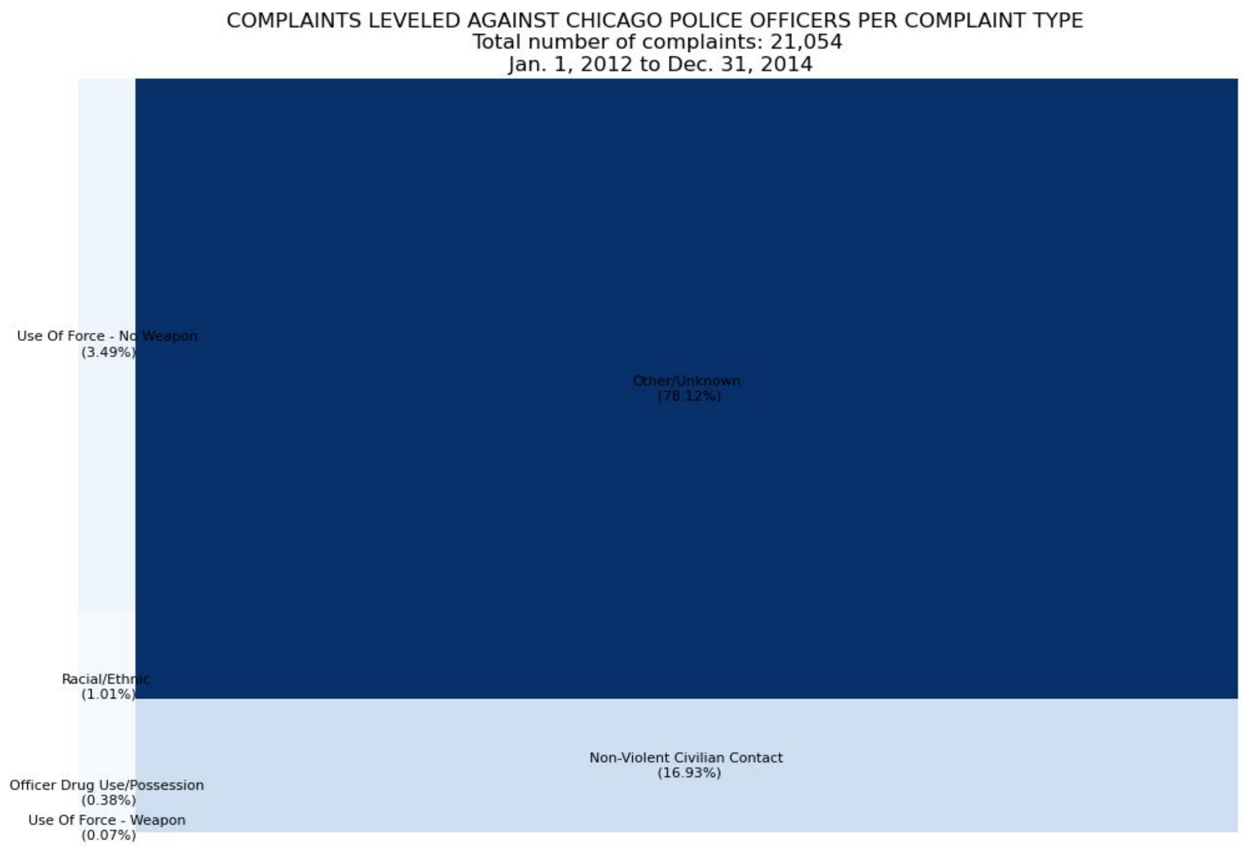
We extracted the following features from the files to include in our model:

Complaint history. We binned complaints into the following supercategories, and each officer was given a count of how many of that type of complaint they had filed against them during the observation period. *Use of force - weapon*. Category description contained "taser" or "firearm." *Use of force - no weapon*. Category description contained "kicked," "choked," "grab," "stomp," "assault," "punch," "take down," "unnecessary physical contact," or "excessive force" without the mention of a taser or firearm. *Officer Drug Use/Possession*. Category description contained "drug," "intoxicated," "D.U.I," or "alcohol." *Racial/Ethnic*. Category description contained "racial"

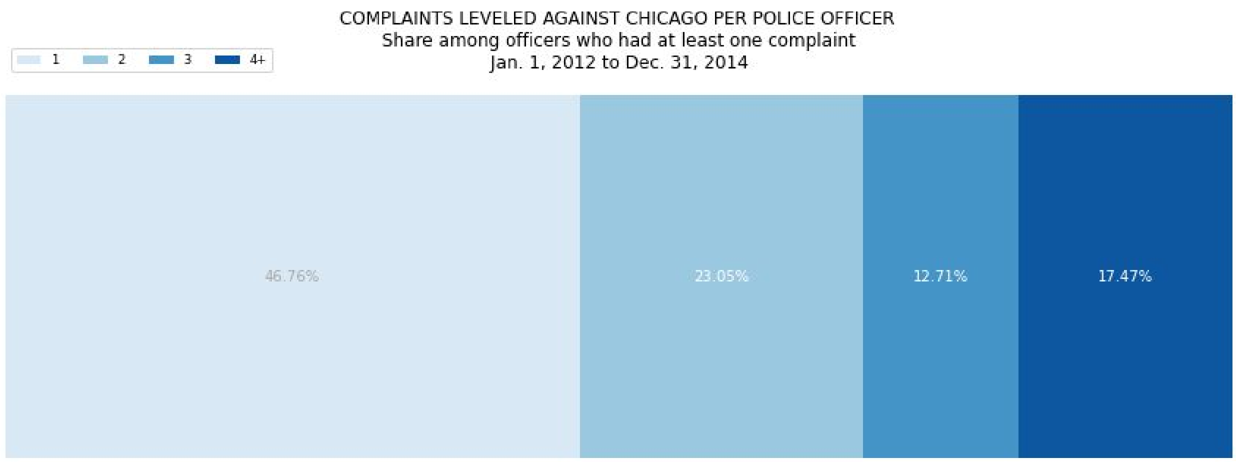
or “ethnic.” *Non-Violent Civilian Contact.* Category contained “illegal arrest,” “detention,” “altercation,” or “warrant.” *Other/Unknown*. Category did not contain any of the above or was labeled “unknown.”
Count sustained. Number of complaints against the officer sustained by the CPD.
Suspension length*.* Total number of days an officer was suspended in the observation period.
Tactical Response Report (TRR). When an officer exercises use of force or pulls out a weapon, they are required to fill out a TRR detailing any actions they took. These reports include descriptions of discrete “actions,” ranging from verbal commands to physically restraining a civilian to use of weapons. These reports also include the cop’s assessment of how much the civilian was resisting, ranging from not following orders to physically fighting back against arrest. We engineered the following features from this data.
TRR Total: total number of tactical response reports an officer filed
TRR actions were divided into the following categories, and each officer was given a count for the number of times they reported each type of action. *Firearm* - use of firearm. *Non-Lethal Weapon* - use of taser or chemicals. *Physical Force* - any use of physical restraint or use of an “impact weapon.” *Other* - member presence, verbal commands, and taser display.
Reports of civilian resistance were folded down into “passive” vs. “active” for each action. The final feature was a combination of these categories, so each officer gets a count for Passive - Physical Force or Active - Firearm for example.
Officer profile information - *Birth year; Race; Gender; Start date.* This data was also used to remove officers who resigned before our target year started.
Salary *- average salary, change in salary.* Change in salary is the difference between first and last year in the observation period.
Settlement Total. The total amount of money the officer cost the city in settlements throughout the observation period.
Complainant Demographics *- percent complaints alleged by race and by gender*
Target. To identify our target, we used the same binning process as in complaints section
We initially set out to use sustained complaints as our final target, but found the percent of officers that would have y = 1 which was too small to make good predictions with our data. The table below shows how the share of officers increased as we widened the net of complaint types for which we flagged officers. Because activists also seek to hold police accountable for illegal searches and related actions, we decided it was worthwhile adding nonviolent civilian contact complaints to our target, which expanded our set of y = 1 to 13.96%. Thus, the target is “severe complaints,” a binary variable indicating whether an officer had any of the following in the target period: a sustained complaint, a use of force complaint, a racial complaint, a drug-related complaint, or a nonviolent civilian contact complaint. Complaints in the unknown/other category were not included in our target variable.

Target	True labels	False Labels	Percentage True
Sustained complaints	184	6990	2.56
Sustained and force complaints	344	6830	4.79
Sustained, force and drug complaints	357	6817	4.97
Sustained, force drug and racial complaints	399	6775	5.56
Severe complaints	1002	6172	13.96

In our 2012-2014 observation period, we analyzed 21,054 records of individual complaints. We organized these complaints into six main categories based on the type of misconduct alleged, where the majority of complaints (78.12%) were classified as “Other or Unknown”. Of the remaining 21.88%, Non-Violent Civilian Contact is the most frequent complaint, with 77.6%, followed by Use of Force with No Weapon complaints with 15.9%. One out of 100 cases turned out to be related to Racial or Ethnic complaints, nearly 3 out of 1,000 cases were related to Officer Drug Use or Possession and 7 out of 10,000 were Use of Force with Weapon complaints.

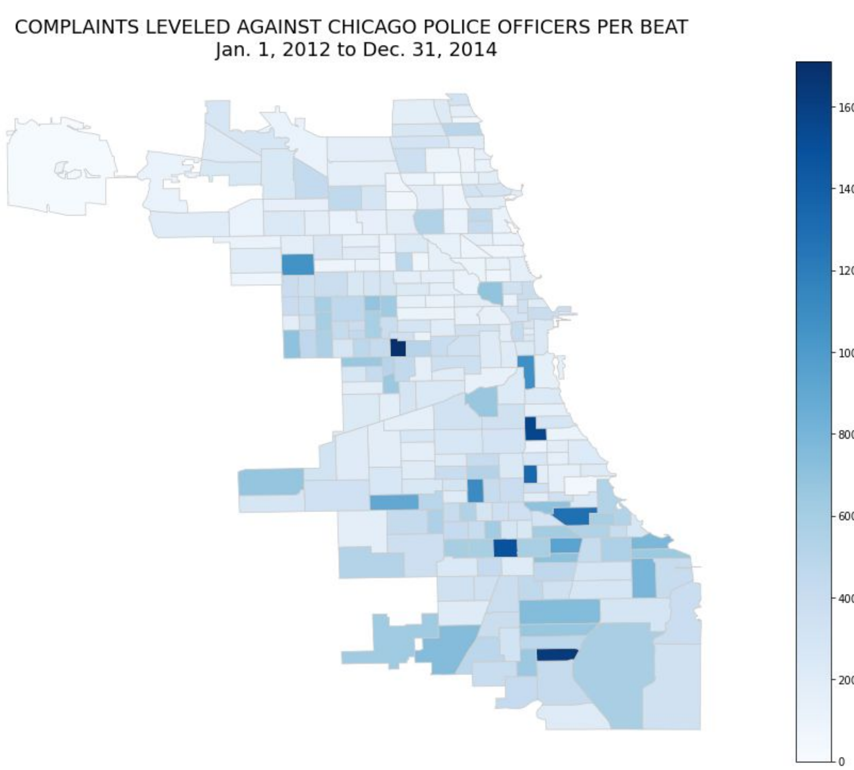


Of those officers with complaints during our observation period of 2012-2014, almost half of those cops had only one complaint against them, 23% of them had 2 complaints leveled, 12.71% reported 3 complaints and, finally, the officers with more than 4 complaints in the period of interest represented 17.47% of the population in our data. The maximum amount of complaints registered by one officer was 23.



Some limitations of the data are that it only went until 2017, and data from 2016 on tended to be more incomplete. Thus, we decided to use 2012-2014 as our observation period and 2015 as our prediction period. Even these years had a significant amount of missing data, particularly in complaint outcomes (i.e., whether or not a complaint was sustained by CPD). We marked these unknowns as not sustained, but if this is not the case our model may be less reliable.

Another limitation of our data is the lack of socio-demographic information related to the specific beat in which police officers work at. The socio-demographic information of the beat could include population density, median income, level of education or race share. These factors could play an important role in predicting misconduct of police officers since South Chicago has a bigger number of complaints leveled against police officers per beat than North Chicago.



Machine Learning and Details of Solution

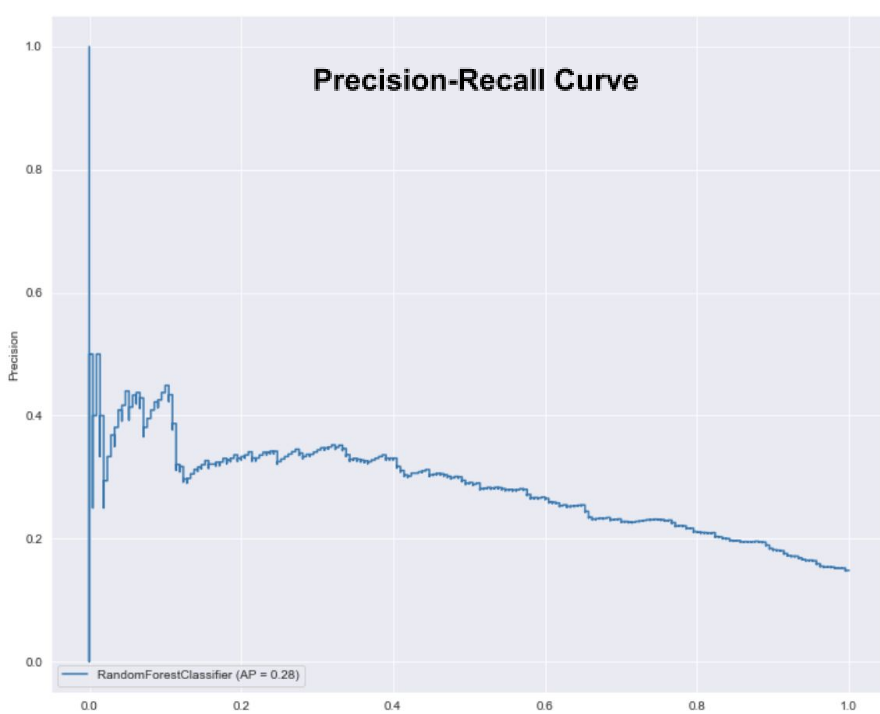
Since we seek to develop a more sensitive algorithm that helps the CPD flagging officers who will go on to participate in adverse incidents, our problem is a classification one with binary output. The model is intended to learn from past incidents of police misconduct in order to flag officers that could be involved in serious misconduct. Given the complexity and sensitivity of our output, we explored a few different models to predict officer's misconduct.

We started our analysis by using a **logistic regression** for two reasons: the simplicity of the model and its interpretability, and that it allows the understanding of the relationship between different features with the target. Nevertheless, logistic regression predicts the likelihood of occurrence of a particular event and works well when the classes are almost separable but not completely. We then employed **decision tree** modeling which used training data to produce a sequence of rules that can be used to classify test data. This model had two main advantages: it is simple to understand and able to handle categorical data as features. We also tried a **Naive Bayes** model which was never able to get comparable predictive power to the other models. This suggests that interactions between features and non-linear relationships between features and the target play an important role in establishing patterns that provide predictive power.

Finally, due to potential instability because of different trees being generated with small variations in the data, we decided to use a **random forest** as our fourth predictive model, which ultimately gave us the best results. The main advantage of the random forest was that it favors accuracy over interpretability, and in our project it is important to minimize the number of false positive cases in the prediction. In more detail, random forests have the power to handle large data, estimate effectively for missing data and balance errors when classes are imbalanced.

Evaluation and Results

We chose balanced accuracy as our main evaluation metric because of our unbalanced target. Originally we considered using recall with the thought that it's better to cast a wide net and flag many officers as long as you catch most of those at high risk, but settled on balanced accuracy as it became clear that we could achieve a reasonable balance between precision and



recall. The best-performing random forest model had a precision score of .265, a recall score of .586, and a balanced accuracy score of .654.

Table of Feature Importances

	Gini ImporFeaturetance
Percent of all Complaints Against Male Victims	0.10807
Count of Other/Unknown Complaints	0.09238
Count of times Officer Reported using Physical Force (without a weapon) against a Civilian “Actively” Resisting Arrest	0.08960
Count of times Officer Reported Using Verbal Commands towards a Civilian “Passively” Resisting Arrest	0.08466
Date Officer Started Working for CPD	0.08149
Birth Year	0.07281
Total Tactical Response Reports Officer Filled out	0.06877
Average Salary over Study Period	0.06186
Change in Salary from beginning to end of Study Period	0.04606
Count of Complaints of Non-Violent Civilian Contact	0.04235
Officer Gender	0.04033
Count of times Officer Reported Passively” Resisting Arrest	0.03575
Percent of Total Complaints Against White Civilians	0.03534
Percent of Total Complaints Against Black Civilians	0.03510
Percent of Total Complaints Against Hispanic Civilians	0.01225
Count of Complaints of Use of Force against Civilians without a Weapon	0.01142
Count of times Officer Reported using a non-lethal Weapon against a Civilian “Actively” Resisting Arrest	0.01103
Count of Complaints against Officer filed by another CPD Officer	0.01014
Total Dollars Paid out in Settlements that Name Cop as Defendant	0.00949
Total Days Officer was Suspended from CPD for Disciplinary Reasons	0.00920
Percent of Total Complaints Against Asian Civilians	0.00788
Count of Complaints against Officer Sustained by CPD	0.00619
Whether Officer is White	0.00522

Policy Recommendations

The superiority of our model over the flagging system the CPD currently employs is clear. The CPD’s system for flagging officers at high risk of committing misconduct uses some data we do not have access to, which makes a full comparison in this report impossible. However, it does use two metrics included in our data: any officer with three or more complaints of excessive use of force or two or more sustained complaints gets flagged. To compare this system against our model, we looked for officers that met this criteria in 2014. We found eight officers with two or more sustained complaints and none with three complaints of excessive use of force (that the CPD's stated tolerance for violence is higher than what any officer actually met in 2014 is striking). We observe that three of these eight officers went on to commit serious misconduct in 2015. With 1002 total officers committing serious misconduct in 2015, the existing system identifies 0.3% of total officers who go on to commit misconduct (recall), and of all officers it flags for concern, 37.5% actually turn out to commit serious misconduct (precision). By comparison, our final model used data from 2012-2014 to flag officers in our smaller test set. We were able to flag 58.6% of total officers who did go on to commit serious misconduct (recall), and of all officers who were flagged for concern, 26.5% went on to commit serious misconduct (precision). Thus, our model is able to identify a group of at-risk officers around 195 times larger than the group flagged by the current system, at the cost of approximately an 11% reduction in precision.

It's important to consider the broader impacts within departments and communities of allowing repeat offenders to stay on the beat. As Invisible Institute founder Jamie Kalven points out in an interview, "within the department, repeaters might normalize misconduct toward residents, pushing other cops toward wrongdoing." (Arthur, 2015). Thus, not only for the safety of entire communities, flagged officers must be taken seriously. To make the early warning system as robust as possible, our first policy recommendation is that data be thoroughly collected and consolidated into one place. Demographic information about the victim is a useful feature in our current model, so we also stress the importance of gathering correct information on complainants and those subjected to police violence generally. In accordance with recommendations made by the Police Accountability Task Force, we propose the following implementation of the Early Intervention System (EIS).

Our model features better recall than precision, which means that it successfully identified most officers who would go on to commit serious misconduct at the cost of incorrectly flagging some officers who would not. In terms of implementation, this model is generally not appropriate for determining which officers should receive discipline, but rather additional supervision and resources. Similar to the Seattle Police Department, we recommend designated staff to oversee the EIS. When an officer is flagged, their profile should be reviewed by their supervisor to determine the appropriate course of action. All flagged officers should be required to partake in intensive de-escalation training, regardless of the supervisor's recommendations. The supervisor should determine further training and counseling based on the officer's history and submit a written plan to be reviewed and approved by EIS oversight staff. In alignment with the task force, "CPD's EIS should use a structured, tiered program where interventions are appropriate, escalated proportionally and are timely… Intervention options should include, but not be limited to, meeting with a direct supervisor, meeting with a commander, training, referral to employee assistance resources and/or reassignment or relief from duty " (PATF Report, 2016). Supervisors should be trained, held accountable, and robustly supported in creating intervention plans for flagged officers. Further recommendations to the EIS system include that if an officer is transferred, their data is also transferred and reviewed and that community members be invited to meetings to discuss EIS data and outcomes.

Ethics

Using data on formally-filed officer complaints carries its own biases. Most individuals who are victims of police misconduct don't file complaints and often are unaware that a formal process exists to do so. Citizens in a predominantly white neighborhood may file undue complaints against minority officers. More analysis is needed to reveal biases in this process.

We recognize that there are limitations to using a prediction tool of this kind to target interventions designed to reduce police misconduct. A model that produces false negatives would allow officers who present a high risk for misconduct to continue working without necessary intervention which puts citizens at risk and makes the city more likely to be liable for damages. On the other hand, a model that flags too many officers as potential dangers risks losing credibility in the eyes of decision makers.

A model that takes into account the demographics of the victim/complainant could conceivably assign a higher “penalty” to complaints from a certain demographic group or neighborhood. This opens the possibility of an officer being punished more severely for beating a white civilian than a black one. Similarly, our model considers variables such as the officer’s race, age, and gender. The tradeoff between predictive power and fairness is a common element of these machine learning algorithms. While there is clearly a civil rights imperative to get the best predictions possible, there is also a question of fairness in using data on anything more than an officer’s complaint history in flagging an officer as at risk of misconduct.

Limitations, Caveats, and Suggestions for Future Work

One limitation of our model is that it requires three years of officer history to flag officers. This means officers who have served for fewer than three years may not get accurate risk scores. Furthermore, our model only considers officers with complaints against them in the observation period as candidates for engaging in serious misconduct in the target period. Our model therefore has no way of predicting officers who engage in serious misconduct in the target year if they do not have any complaints in the previous three years. Ideally, we’d like to have a model that can take in each officer’s entire history, be that one year or 20 years, and flag officers based on any existing patterns. We could benefit by incorporating data used in a similar project such as number of arrests, tickets/citations written by cops, which cops work second jobs as security at sports games or businesses, and paperwork about “field interviews” cops must complete when they talk to civilians in certain settings (Helsby et al., 2018).

We didn’t develop a way to engineer features based on which units/beats officers were assigned to, as these assignments change regularly and thus the beat an officers works during the 3-year period when the profile is constructed would not mean anything if the officer changes assignments in the fourth year when we observe our target. Future models could engineer features around which beats officers were assigned to during which dates.

Additionally, even a system that could perfectly identify officers who would be involved in serious misconduct would be rendered useless if police departments do not take it seriously and follow up with flagged officers. As Rob Arthur said, “For all the complexity of policing, there is a clear signal in the data of who the bad actors are, and to a lesser extent, whether they are going to commit misconduct. Whether police departments will make use of that signal is another, trickier matter” (Arthur, 2015).

Our model classifies officers on a binary of either being at risk or not at risk of misconduct, which limits policy recommendations it can inform. Future iterations could assign each officer a severity score based on the number of misconduct instances or severity of misconduct instances in which they are likely to engage. Then, based on their assigned scores, officers could be placed into different intervention programs, and those with more severe scores would receive more intensive training. This could also allow officers to receive training specific to the types of misconduct they are more likely to commit.

We were also limited by our late discovery of police “actions” from the tactical response reports; with more time we suspect we could have done more with this information. Finally, because research suggests police misconduct has a contagion effect, future expansions of this project might consider the number of violent officer/repeat offenders in an officer’s beat when making predictions for that officer (Wu, 2019).

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