Final Report: Investigating Police Misconduct in North vs. South Sides of Chicago

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Introduction

Staggering investigation results show that people of color in Chicago suffer from police violence significantly more than White residents of the city (Fan, 2018). Furthermore, Chicago Police Department has a history of justifying police misconduct, which leads to a lack of accountability (Rivera, n.d.). Furthermore, in light of targeted police violence and lack of proper accountability for such actions, we cannot omit the stigma surrounding the North and South sides of the city. The North is viewed as more affluent and populated by majority-White communities – the good side of the city. On the other hand, the South is perceived as the less affluent and populated by the people-of-color-majority communities – the more dangerous, problematic one. The combination of these factors, excessive use of force by the Chicago police, a disturbing trend of targeted racial violence, and the surrounding stigma sparked our interest in the subject. Therefore, in this research paper, we will investigate the chronological patterns and correlations in the allegations of procedural misconduct by police officers on Chicago's North vs. South sides. We will also focus on the racial and economic factors impacting them.

Methodology and Dataset

We used the data available in Chicago Police Database (CPDB) as our dataset to conduct our research. To retrieve, clean, and manipulate this data, we primarily used PostgreSQL. We had two definitions for North and South: by communities and police districts. We used the one that best suited the needs of the question we were answering. For our data visualizations, we first produced the dataset we needed using PostgreSQL and CPDB. Then, we used the D3.js framework to allow for interactivity. We used the community split for the first question, whereas for the second, we used the police district split. For this task, our IDE of choice was Observable, which allows for efficient online collaboration in real-time. For the machine learning component of our project, we used Python and relevant libraries and frameworks, such as sklearn, pandas, NumPy, and others. For this part of the project, we used a community-level split. Similarly, we used Google Colab as our IDE to collaborate efficiently.

Results

Checkpoint 1: SQL

We performed a quantitative analysis of police complaints data from the North and South sides to investigate the correlation between income, racial differences, and police violence. The questions we answered:

Q1. How many complaint reports are filed per capita on the north and south sides annually?

This question sheds light on a trend in the magnitude of police misconduct. As we can observe in Figure 1, for every year from 2000 to 2018, there were more registered per-capita complaints in South Chicago than in North Chicago.

	year	south_per_capita_perc	north_per_capita_perc
1	2000	0.00274822260122106887	0.00239711960876545454
2	2001	0.00192289008744869327	0.00151407153458941631
3	2002	0.0017237714040560572	0.00138805922770808624
4	2003	0.00143423167603101634	0.00124280840069220195
5	2004	0.00151503346059614402	0.00107158557149466949
6	2005	0.00150156649650195688	0.00111283392058916044
7	2006	0.00159294946714108857	0.00112545342787142127
8	2007	0.002099884472686592	0.00158910176311417773
9	2008	0.00196040520171107398	0.00154581509281143076
10	2009	0.00210180832470004742	0.00154389124079797534
11	2010	0.00209603676865968116	0.00141787893391664526
12	2011	0.00193924282956306435	0.00132745788928424848
13	2012	0.00186325067503157522	0.00119375017434908872
14	2013	0.0017699438523789873	0.00113218690991851525
15	2014	0.00147270871630012476	0.00086380955404148402
16	2015	0.00114084424397906464	0.00083976140387329126
17	2016	0.00102829890119192251	0.00077146465739562381
18	2017	0.00094268748659315628	0.00065891931460848169
19	2018	0.00051078270957241427	0.00030781632215286736

Figure 1: Per Capita Complaint Reports Rates in South (Left) vs. North (Right)

Q2. What is the racial distribution of each side of Chicago? What is this distribution for complainants in the database?

Answering these questions helped us understand the racial trends in filing complaints in Chicago's north vs. south sides. From Figure 2, In the north, we observed that despite the number of black people being only roughly 12.5% that of white people, the number of police misconduct complaints against black people is 50% that of white people.

Figure 3 shows an interesting case in the South. The percentage of total black people and the percentage of total white people filing police misconduct is almost similar (4% for black people and 5% people for white people). This finding further made us wonder if any other factors contributed to the disparity of police misconduct in North vs. South. Finally, there is an alarming rate of police misconduct against the "Other/Unknown" race section in the south (almost 1 out of every 7).

	racial_distribution.race	1	population	complainant_distribution.race	complainants
1	White		550086	White	6538
2	Other/Unknown		26170	Other/Unknown	1385
3	Hispanic		326498	Hispanic	2600
4	Black		63957	Black	3619
5	Asian/Pacific Islander		83944	Asian/Pacific Islander	343
6	<null>		<null>	Native American/Alaskan Native	31

Figure 2: Racial Distribution by total population and total civilian complainants (North)

	racial_distribution.race	population	complainant_distribution.race	complainants
1	Black	351617	Black	14887
2	White	78993	White	3712
3	Hispanic	58751	Hispanic	841
4	Asian/Pacific Islander	10807	Asian/Pacific Islander	84
5	Other/Unknown	7338	Other/Unknown	1216
6	<null>	0	Native American/Alaskan Native	11

Figure 3: Racial Distribution by total population and total civilian complainants (South)

Q3. What is the distribution of complaint categories on the north and south sides?

	category	count
1	Operation/Personnel Violations	7902
2	Use Of Force	6375
3	Verbal Abuse	2188
4	Illegal Search	1816
5	Traffic	1585
6	Lockup Procedures	1222
7	Conduct Unbecoming (Off-Duty)	1004
8	Domestic	709
9	Criminal Misconduct	585
10	False Arrest	440
11	Supervisory Responsibilities	386
12	Drug / Alcohol Abuse	166
13	Bribery / Official Corruption	130
14	Unknown	8
15	First Amendment	6
16	Medical	5
17	Money / Property	5
18	Excessive Force	2

	category	count
1	Operation/Personnel Violations	10241
2	Use Of Force	6730
3	Illegal Search	2521
4	Verbal Abuse	1956
5	Lockup Procedures	1552
6	Traffic	1392
7	Conduct Unbecoming (Off-Duty)	1288
8	Domestic	871
9	False Arrest	789
10	Criminal Misconduct	573
11	Supervisory Responsibilities	526
12	Drug / Alcohol Abuse	287
13	Bribery / Official Corruption	84
14	Unknown	14
15	Medical	10
16	First Amendment	8
17	Money / Property	7
18	Racial Profiling	7
19	Excessive Force	3

Figure 4: Distribution of allegation category North (Left) and South (Right)

Answering this question revealed the most frequent police misconduct types in the north vs. south sides of Chicago (Figure 4). In both cases, *Operation/Personnel violations* and *Use of Force* were the top two. Overall, our findings showed that the distribution of complaint categories across the city is similar, except for a few categories with swapped places.

4. What is the median income of the north and south sides?

Knowing the median income of the north and south sides helps put into perspective whether there is potentially more police misconduct in the city's less affluent areas. In Figure 5, we observed the drastic difference in median income between the north and south side. On average, a resident of North Chicago earns 1.4 times more than a resident of South Chicago.

	north_median_income	south_median_income
1	51713	37084

Figure 5: Median Income North and South

Checkpoint: D3 Data Visualization

Q1. What is the distribution of complaint categories across the North and South of the city? In those categories, how many complaints involved using weapons or firearms by police officers?

We inspected that most police misconduct incidents did not involve using weapons or firearms by police officers, as seen in Figures 6 and 7. However, not surprisingly, the only category with significant firearms incidents was "Use of Force," as evidenced by Figures 8 and 9. Overall, we can observe similar patterns across both sides of the city.

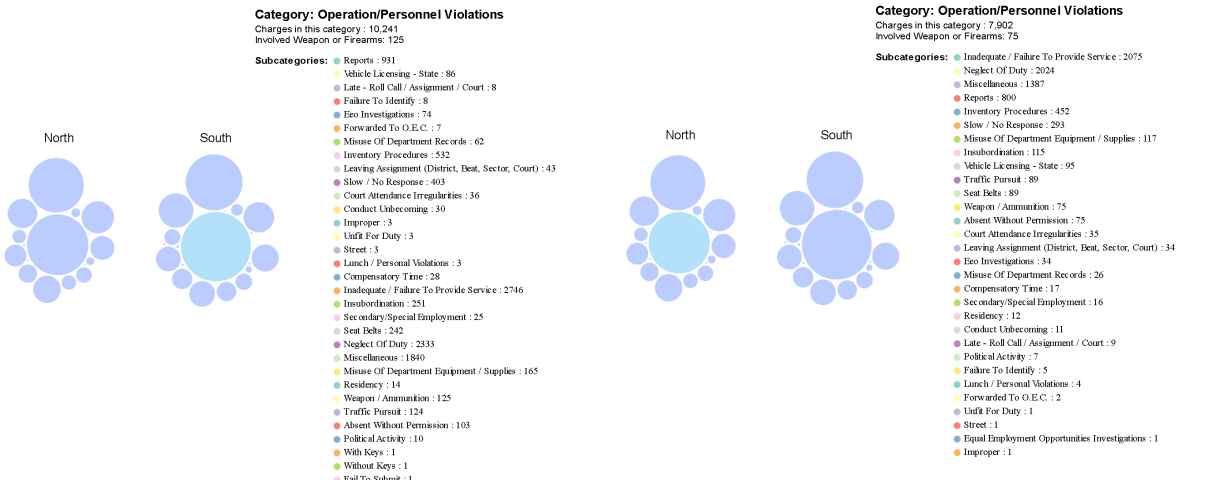

Figure 6, 7: Bubble chart depicting Operation/Personnel Violations in South (Left) and North (Right)

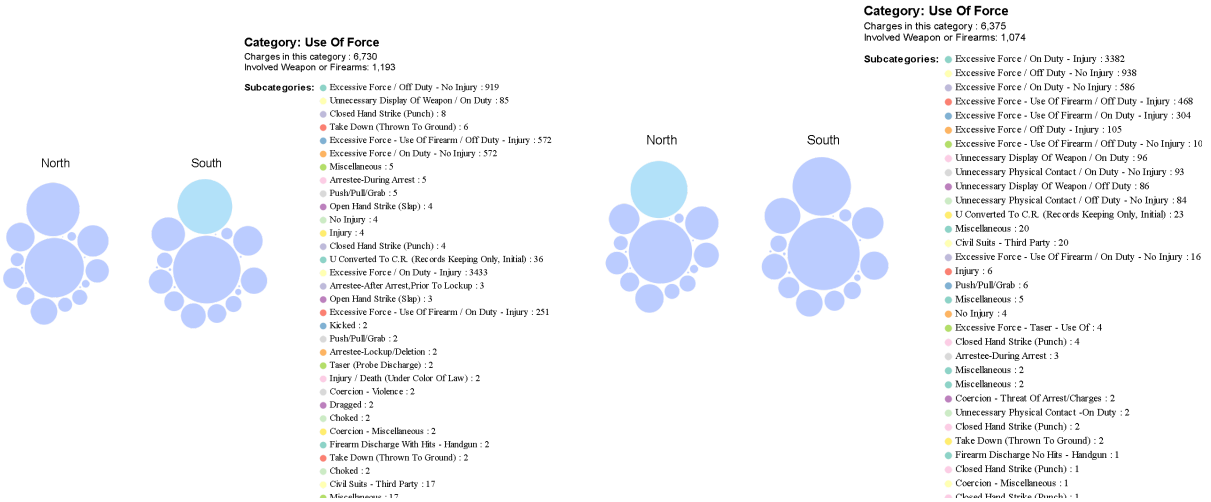

Figure 8, 9: Bubble chart depicting Use of Force in South (Left) and North (Right)

Q2. What is the distribution of police misconduct allegations (total count and per capita values) per police district across the North and South of the city? Then, what is the racial distribution of the civilian community and police officers per given police district?

Figures 11 and 12 show that there are more police misconduct allegations (both total count and per capita values) in the South side as opposed to the North. Furthermore, it was interesting to see the racial distribution of the police officers in the majority of police districts of the North side (such as in Figures

13 and 14), roughly matched that of the civilian community. Predominantly White districts had more white police officers, predominantly Hispanic districts had more Hispanic police officers, etc.

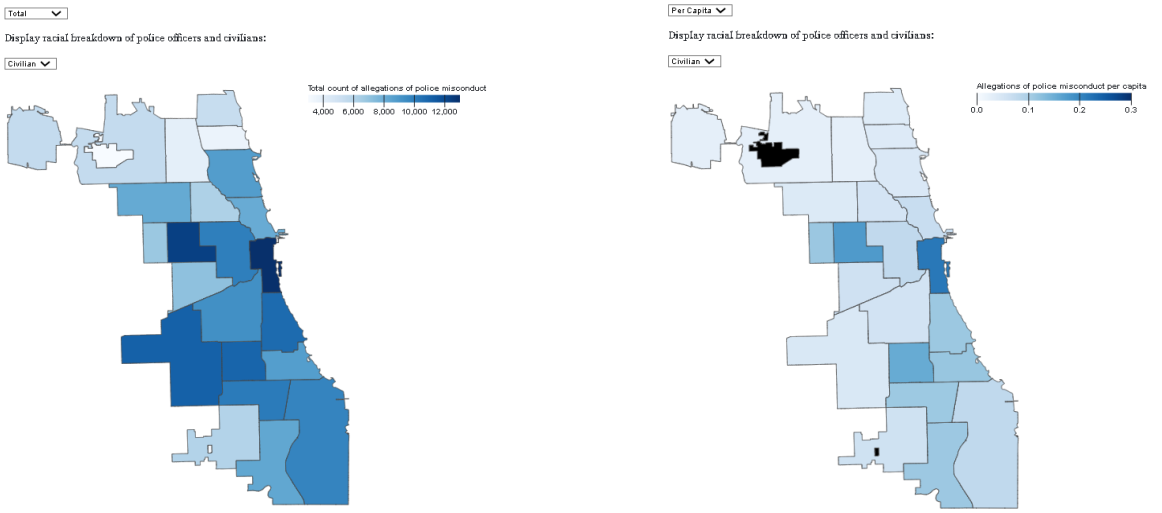

Figure 11, 12: Choropleth map of Chicagoshowing allegation count for total and per capita population

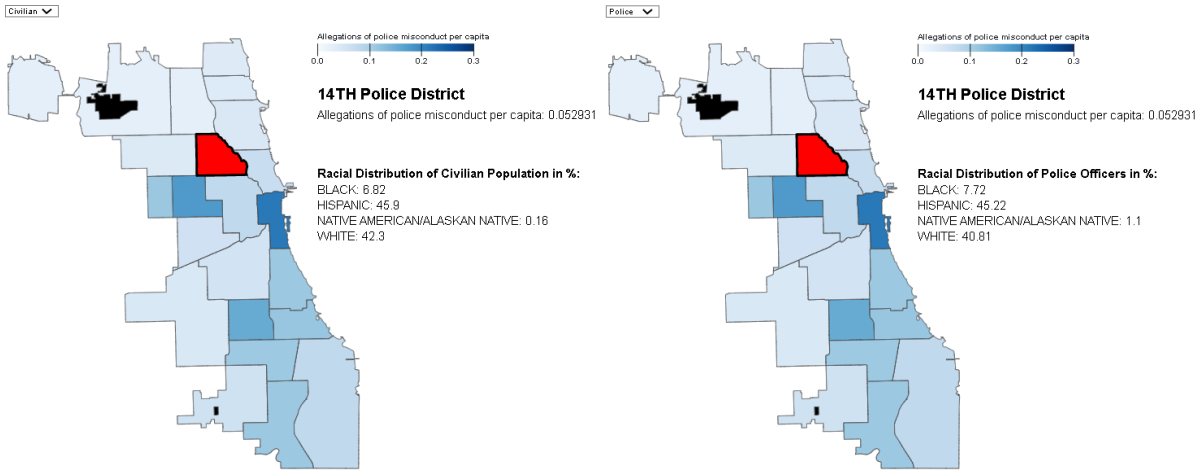

Figure 13, 14: Civilian (left) and police (right) racial distribution per capita for 14th Police District

However, the 25th police district is an exception. Despite it being populated predominantly by the Hispanic community (66.37%), with the White community being a minority (14.66%), the police force of this district was dominated by White police officers and accounted for 56.25% of the force.

When it comes to the police districts in the South of Chicago, the situation looks slightly different. The disparities between the racial distribution of civilian communities differ drastically from that of the police force. For instance, in Figures 17 and 18, we see the 7th Police district, which has reported one of the highest per capita values of police misconduct allegations, is predominantly populated by the Black community (96.79%), with the White community being a tiny one (0.37%).

However, its police force consists mainly of White officers (46.34%). These results make us ponder how such a huge disparity is possible in the first place, and whether there is any correlation between the racial factor and police misconduct. Therefore, this relationship should be further researched.

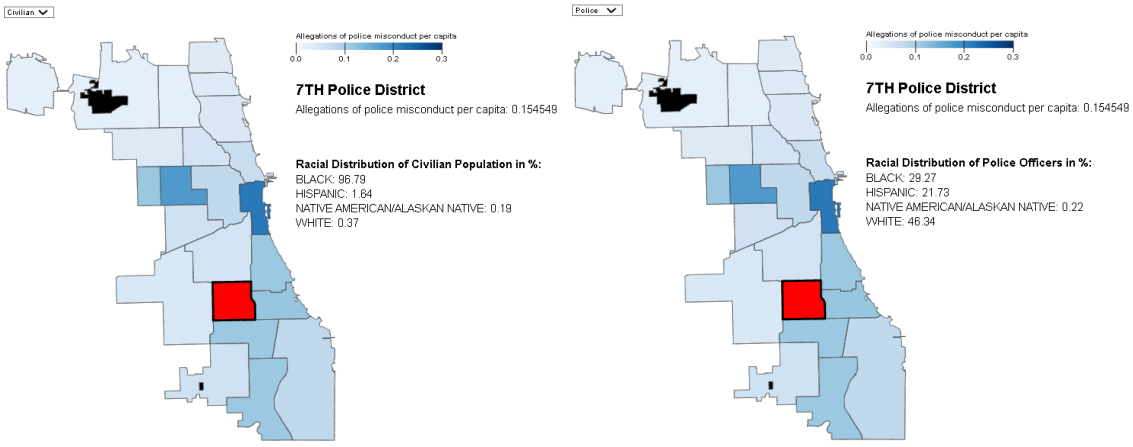

Figure 17, 18: Civilian (left) and Police (right) racial distribution per capita for 7th Police District

Checkpoint: ML

Q1. Two time-series predictive models that predict the number of police officers for the North and South side of Chicago, respectively, while accounting for the number of allegations per 10,000 people.

We trained a Ridge regression model that predicts the number of police officers for a given set of features. For this part, we constructed a different dataset which consisted of several numerical features (officer count, racial distribution of officers, civilian count, racial distribution of the civilian community, and the per capita number of allegations) and categorical variables ('years,' 'unit_name,' 'race'). Surprisingly, this model scored exceptionally well, the R^2 was close to 1 on both train and test datasets.

Figure 19, 20: Train, Test values and associated predictions for North (Left) and South (Right)

Before training the model, we normalized the distribution of variables with skewness > 0.5 with coxblox transformation, transformed categorical variables with dummy variables, scaled the values, and finally

performed Recursive Feature Elimination to select the most impactful predictors out of the resulting 48 and avoid the curse of dimensionality. However, unfortunately, despite all the pre-processing, the plot for the distribution of residuals between actual and predicted values shows that said distribution is slightly right-skewed. Therefore, further parameter tuning and pre-processing are required. With regard to our research question, RFE has determined that per capita allegation numbers are less impactful predictors than other features.

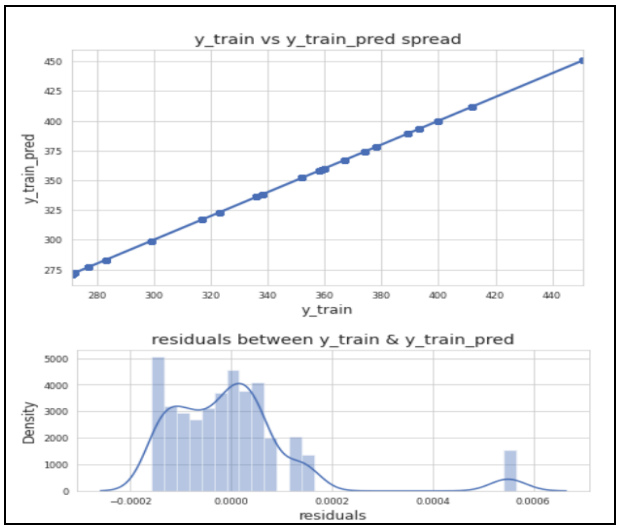

Figure 21: Assessing for Linear Regression Assumptions

Q2. A machine learning model predicting the number of TRRs per year in the north and south sides of Chicago, accounting for such features as demographics of the officers and the communities we serve.

TRR is the abbreviation for Tactical Response Reports. Usually, an event has one complaint with a unique id (CRID) linked to it. But in cases when an event has one or more use-of-force reports linked to it, it comes under TRR data. Let's check out the TRR counts from each year. First, we will visualize the TRR count by year distinguished by north and south sides in Figure 22.

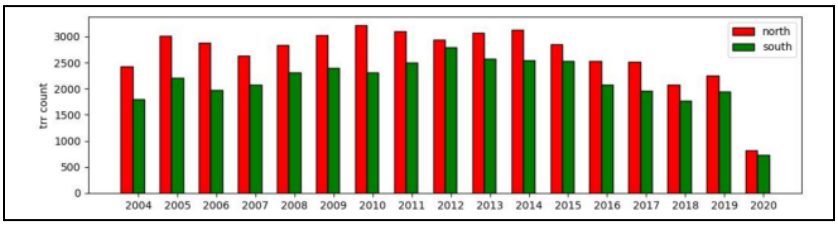

Figure 22: Actual yearly side-distinguished TRR counts from 2004 to 2020

	model	best hparams	... 1
9	KernelRidge()	No tuning	0.86726…
3	Ridge()	No tuning	0.86620…
7	SGDRegressor()	No tuning	0.86540…
1	LinearRegressio…	No tuning	0.86404…
8	KernelRidge()	{'kreg__alpha': 5e-05, 'kreg__kernel': 'rbf'}	0.60424…
0	LinearRegressio…	{'lreg__positive': False}	-0.3751…
4	GammaRegressor()	{'greg__alpha': 0.01, 'greg__warm_start': True}	-0.4646…
2	Ridge()	{'rreg__alpha': 1, 'rreg__positive': False}	-0.5450…
6	SGDRegressor()	{'sgdreg__learning_rate': 'invscaling', 'sgdreg__max_iter': 10000, 'sg…	-0.7350…
5	GammaRegressor()	No tuning	-0.9582…

Figure 23: Model comparisons

Initially, we tested several models as shown in Figure 23. We performed grid search and hyperparameter tuning to find the best-performing models for this task. Regardless, among the simple models, Kernel Ridge remained the one with the better performance (> 86%). Even though 86% is somewhat good, we need a better model to understand which factors are crucial in the trr_count trend. So we used XGBoost for the best performance (99% score when trr_count is predicted by sides and 92% where trr_count is predicted by beats) as it operates on a powerful gradient-boosting framework. We can see that the performance of this model is very good from the regplot in Figure 24.

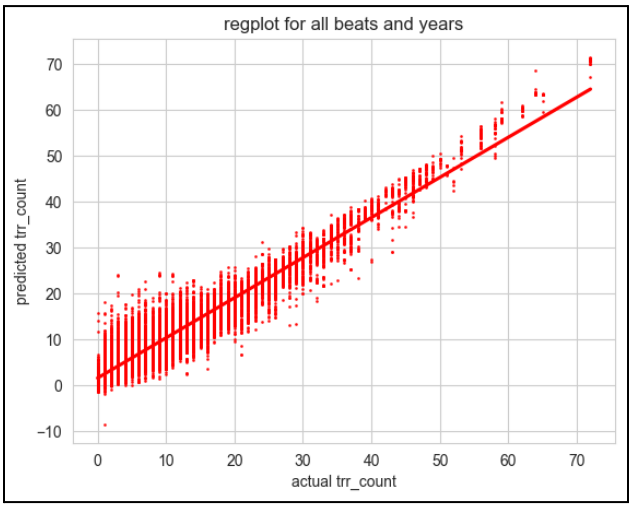

Figure 24: Actual vs predicted TRR count for XGBoost

Figure 25 shows the feature importance values for these predictions. From this figure, we can interpret that factors like civilian allegation percentile, complaint percentile, honorable mention count, beat, and allegation count have a higher correlation with trr_count. Moreover, we can interpret that higher civilian allegations, beats (a higher value of beat implies more north side) and complaint percentiles motivate higher trr_counts.

- **Honorable mentions and awards**: Interestingly, a higher honorable mention and award count are also motivating factors for higher trr_counts.

- **Ranks**: Less "Police Officers" have a high trr_count, while a higher number of "Sergeant of Police" is a motivating factor towards a higher predicted trr_count.
- **Gender:** More female officers have less predicted trr_count, however, there are some outlier cases.
- **Race:** Similarly, more Black officers contribute to lower TRR counts but there is a significant amount of outliers here.

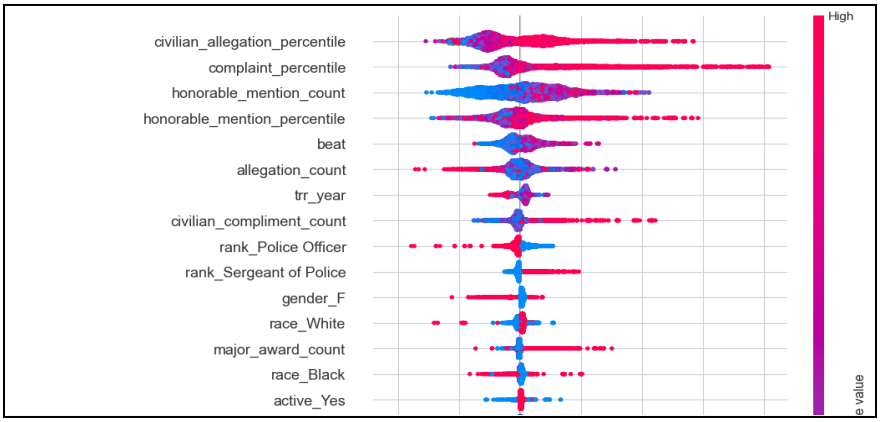

Figure 25: Beeswarm plot of SHAP values of predictions

Discussion

Through our experiments, we discovered that there are differences between police misconduct rates in the North and South sides of Chicago, albeit subtle. We did confirm that the North of Chicago is populated by predominantly White communities, whereas the South – is by Black and other POC communities. Furthermore, an average resident of the North side earns significantly more than a resident of the South. Unfortunately, we observe a consistent trend where year after year, residents of the South side of Chicago do, indeed, suffer from higher per capita rates of police misconduct. However, the rate differences are not high enough to indicate a critical level of severity. Furthermore, It was interesting to see that complaint categories frequencies were similar for both the North and South sides. Unfortunately, we discovered that Use of Force is the second most frequent complaint category across both sides of the city; the use of weapons by police rate was alarmingly high in this category.

When we delved deeper into the racial aspect of police misconduct in Chicago, we found that for the majority of police districts, the racial distribution of the civilian community and the police officers roughly matched. For instance, majority-White communities were policed by majority-White police units. The 7th police district is an interesting outlier, however. Being a district with the highest rate of police misconduct allegations, it is also almost exclusively populated by Black people (~97%) and

is policed by majority-White police units. Hence, for future work, we should pay special attention to this district to better understand these dynamics. Given that our Machine Learning models predicted that over time the number of police officers in the North will stabilize and decrease in the South, future research could investigate these trends. Our models also show that female officers tend to have fewer TRR counts on average compared to their counterparts. If the City of Chicago were to implement a police reform aimed at reducing police violence, these conclusions would potentially benefit policy-making by inviting more women to join the police force. Similarly, higher-ranking officers who are on the field are predicted to have a higher TRR count. This could also be used for policy-making and conclude in creating de-escalation training sessions for higher-rank police officers.

Conclusions

To conclude, our preliminary research shows that the residents of the South side of Chicago suffer from higher rates of police misconduct than residents of the North. However, it is important to clarify that although our results show a systemically higher level of police misconduct in the low-income communities in South Chicago – predominantly by Black and POC communities, further research is needed for more definitive answers. To further our analysis in the future, we should narrow down the scope of the research, pre-process data more efficiently, check for model constraint satisfaction more strictly, and perform hypothesis testing.

Bibliography

Fan, A. (2018, August 16). *Chicago Police Are 14 Times More Likely to Use Force Against Young Black Men Than Against Whites*.

Rivera, R. (n.d.). *Chicago Police Superintendent Eddie Johnson's Long Record of Justifying Police Misconduct and Shootings*.