Investigating Bias & Demographic Distribution of Crime Prediction Models on Historically Red-Lined Communities

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Abstract

This paper aims to quantify the effect of predictive policing tactics in Los Angeles County. Since 2008, the PredPol algorithm has been in effect in determining police activity, and has been a hot topic for debate in its usage of historical data to generate potential crime hotspots. To quantify this, our group used the Los Angeles County Sheriff's Office 2017 and 2018 federal crime dataset to train the PredPol algorithm on drug data. We used the results to generate simulations for the year 2018, and generated distributions of fairness against demographic Census data and geographic redlining data.

1 Introduction

Visibility is a trap. Communities built by systematic racism experience free space as surveilled and controlled space — where their bodies are not their own but perpetually disciplined, fragmented, and examined by the eyes of artificial intelligence.

Since 2008, the Los Angeles Police Department has begun utilizing a tool called Predpol (now known as Geolitica), a predictive-policing software that uses spatio-temporal modeling to predict crime before it happens, mapping police to patrol areas deemed high risk. However, because the data fed into Predpol's algorithm is based on reported crime, critics argue that the program would lead to aggressive policing in communities of color, where crime reporting tends to be higher. However, the LAPD and Predpol argue that because the algorithm does not factor demographic characteristics, it could not possibly be racist — unlike other racially-motivated algorithms like COMPAS, which predicts incarcerated individuals' recidivism likelihood using race as a factor.

"It is math, not magic, and it is not racist," LAPD spokesman Josh Rubenstein wrote in an email.

Many social scientists and historians understand the dark connection between policing and historic crime data, citing past (and present) racially-biased policing campaigns against protected communities for the past 200 years as a means for skewing historic crime data. However, because there are no explicit numbers proving the bias, it is difficult to show this relationship to those unaware.

In this paper, we investigate Predpol's algorithm to show the connection between historic crime data and racially-biased predictive policing, using Los Angeles County as a case study. Furthermore, because historically Red-Lined zones with low grades were typical targets for racially-biased policing campaigns, we show how Predpol's use of historic crime data still targets these communities today, despite the banning of red-lining decades ago.

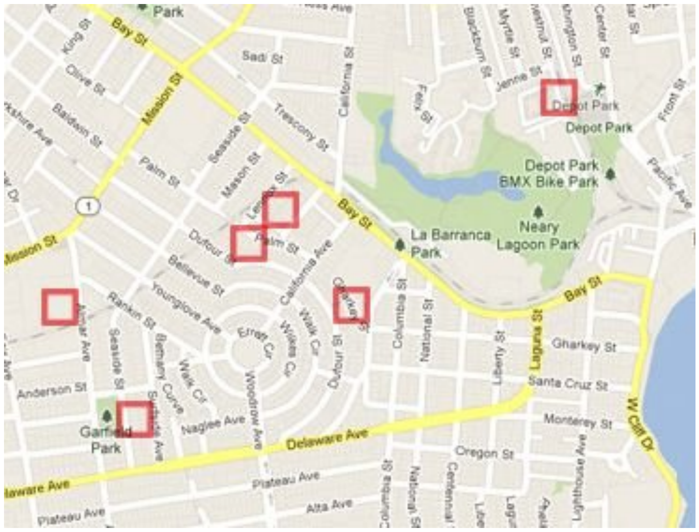

Figure 1: Sample Dashboard of Predpol Platform

2 Overview of goals and approaches

Our report is divided into two subdivisions: (1) We format an existing and publicly available algorithm that simulates Predpol, training on data from 2018, and show the proportions of Police Deployments among historically-redlined zones with different grades. (2) Using our Predpol Simulation and Census Data, we calculate proportions of demographics that are policed when above different "risk" thresholds. Then, combining actual crime data from 2019 with the Predpol's predictions, we determine the success rate of policing for different demographics.

3 Background and related work

Some previous research has been done on investigating the impact of predictive policing tools on different communities. According to the Stanford Open Policing Project's 2020 research into racial bias of traffic stops across the United States, Black and Latino/a communities are disproportionately stopped and searched for suspicion of contraband [5].

A recent study has shown that the differential victim crime reporting rates across geographical areas often leads to outcome disparities in the common crime hot spot prediction models such as Predpol [6]. The paper specifically suggests that relying on victims crime reporting data as the training data for the predictive models leads to hot spot prediction bias towards areas with high crime and high reporting areas which would lead to over policing these areas and neglecting areas with high crime rate and low crime report rates [6].

A variety of predictive tools have been used for crime prediction. The most popular method is the Self-Exciting Spatio-Temporal Point Process (SEPP) model which uses the temporal and spatial features of previous crime data to predict distribution of future crimes. Some other studies have relied on simpler time series models to predict crime count. A study has been done using simple time-series analysis to predict crime count in small spatial units of Pittsburgh using moving average of crime counts [7].

A recent paper by Lum and Isaac has investigated the use of Predpol in predicting drug related crime in the Oakland area. Our project is an extension of this paper and relies on the implementation of the Predpol algorithm as a predictive policing tool. Lum and Isaac (2016) studied the effect of predictive policing tools on low-income and POC communities [4].

The paper focused on the Oakland drug related crimes in 2010. The paper first assessed how the police reported crimes are actually overrepresenting low-income and POC communities. The researchers used the National Survey on Drug Use and and Health (NSDUH) data combined with the census demographic data of Oakland population to predict the probability of drug use (as an estimate of drug crime probability) for each individual in a synthetic population of Oakland. The paper fit a model on the data gathered from the 2011 National Survey on Drug Use and and Health (NSDUH) to predict the probability of a person with certain demographic characteristics, i.e. age, race, etc. to commit drug related crimes. The paper showed that the drug crime probability is shown to be distributed uniformly among different neighborhoods of Oakland. However, the police reported data (i.e. Predpol's training data) often over-represent low-income and POC neighborhoods. They used these predicted probabilities as the baseline measure of true crime statistics of the Oakland city. Then by implementing Predpol as their predictive model they compared the prediction of the drug related crime's count trained the police reported crimes vs estimated true crimes. They also used the police reported crime data from 2010 as input to the Predpol (a Predictive Policing tool) to predict the drug crime hotspots for every day in 2011 [4].

Inspired by Lum and Isaac paper, we first looked at how Los Angeles reported crimes are distributed across different categories in the Los Angeles area. We then implemented the Predpol algorithm to combine simulation and Census Data to calculate proportions of demographics that are policed when above different "risk" thresholds. Then, combining actual crime data from 2019 with the Predpol's predictions, we determined the success rate of policing for different demographics.
For the specific implementation of Predpol, we also used the research paper on Predpol's algorithm, titled "Randomized Controlled Field Trials of Predictive Policing" by Mohler and Malinowski [2]. The paper uses ETAS to predict crime hotspots based on data from three divisions of Los Angeles Police Department to compare the results with the hotspot prediction of the analysts. This paper helped us understand Predpol parameters and how to preprocess our dataset to fit the input of the Predpol algorithm.

4 Data

The first dataset that we used for this project is the 2017,2018, and 2019 Los Angeles County Sheriff's Department's records of federal crimes within their jurisdiction [1]. Within this dataset, individual rows describe a single federal crime that occurred within the jurisdiction of Los Angeles County. Descriptors of the crimes include the date of the crime, the type of crime committed, the exact location of the crime in longitude, latitude, and address, and specific details about the crime.

For the Census Analysis, we used the American Community Survey (ACS) 2019 5-year count from the U.S. Census Bureau. Specifically, we selected a survey for Table B03002, which details Hispanic or Latino Origin by race. We also download it in terms of Census tracts in Los Angeles. We use this table to find distributions for White, Black, and Latina/o populations, used in our bias analysis section.

Finally, a dataset that we used is the Living Atlas redlining data, which contains information about which neighborhoods in Los Angeles were given which HOLC ratings in the 1940s. We can use this information to determine if the HOLC rating of a district has any impact now on whether the policing areas are recommended.

4.1 Pre-Processing Predpol

To initially pre-process our data, we had to transform the data so it would fit the PredPol model. To do this, we first needed to divide Los Angeles into 150m x 150m sections. This is the way that the PredPol algorithm originally divides up cities, and offers recommendations for where to go. In order to do this, we needed to implement a translation between longitude and latitude with a numbered bin, and create a new dataset accordingly. We used the following calculations to determine the meter offset between two coordinates:

$$Y_m(a_1, a_2) = 111{,}111(a_1 - a_2)$$
$$X_m(o_1, o_2, a) = 111{,}111\ (o_1 - o_2)\ cos(a)$$

where Y_m is the distance in the y axis in meters between two different latitudes, a_1 and a_2, and X_m is the distance in the x-axis in meters between two different longitudes, o_1 and o_2, at latitude a. In order to determine how many bins we need, we built code in order to detect the minimum and maximum latitude and longitude to form a box around Los Angeles, and indexed each latitude and longitude in boxes by detecting how far away a point was from the initial minimum latitude and longitude. By repeating this for every point, we were able to determine the PredPol boxes that each crime occurred in, and add this as a feature.

After generating the bins that each data point occurred in, we filtered by the "NARCOTICS" category to only expand upon drug data. This is because as Lum and Isaac wrote [4], drug usage is mostly equal across race categorizations, so any differences in crime predictions on drug data in the distribution of race is evidence of bias. In addition, we filtered our dataset down to only clean examples. The raw dataset contained 331,905 crimes over the span of 2017 and 2018, and after filtering only on the drug crimes we had a dataset of 32,229 crimes. Finally, only 30,563 data points were entered correctly enough to feed into the PredPol algorithm, which is the final amount of crimes that we used in order to generate the PredPol results.

4.2 Preprocessing Census Data

The census data we downloaded was in geojson format, meaning that our data was formatted geographically, per census tract in LA county. For each polygon, it contained information from the ACS 5-year table able B03002. This table included a number of race characteristics, but for the small-scale of this project, we formatted our polygons to contain: 'geoid', 'name', 'Total', 'White', 'Black', 'Hispanic', and 'geometry'.

While the Predpol simulation makes its predictions according to 150 x 150 bins, the 'geometry' tag within each census polygon referred to census tracts, which differed greatly in size. Our first step was to map each census tract to its respective 150 x 150 bin because our demographic distributions from the Census data were divided by tracts ranging in different sizes, and the policing predictions were divided by bins, we had to first map each bin to a census tract. We did this by generating the centroid of each bin and checking which census tract multipolygon it belonged to. Although this process works enough for generating some distribution understanding, it is not completely accurate as it doesn't map bins perfectly to centrus tracts. Furthermore, some tracts were smaller than the 150 x 150 bins, which skewed the demographic distribution even more.

After mapping bins to their respective census tracts, the next step was to normalize the demographic distribution between 150 x 150 square meter bins and the sizes of their respectively mapped census tracts. For each of the White, Black, and Latina/o populations within each census tract, we found the normalized target demographic distribution for each bin using:

$$TargetDemographic_b = \frac{150 * 150m^2}{Area_c} * TargetDemographicPopulation_c$$

where b is the chosen bin, c is the respective census tract. Once we successfully mapped and normalized the demographic distributions for each bin, we finally had the policing frequencies for White, Black, and Latina/o populations.

4.3 Crime data visualization and exploration

Through investigating the data, we are able to produce spatial mappings of crimes that occured in the Los Angeles area through the LACSD data [1]. Through this, we are able to see where crimes have taken place throughout the year. These graphs provide an understanding of the population and crime distribution of the Los Angeles area, and help to provide a geographic intuition of the area.

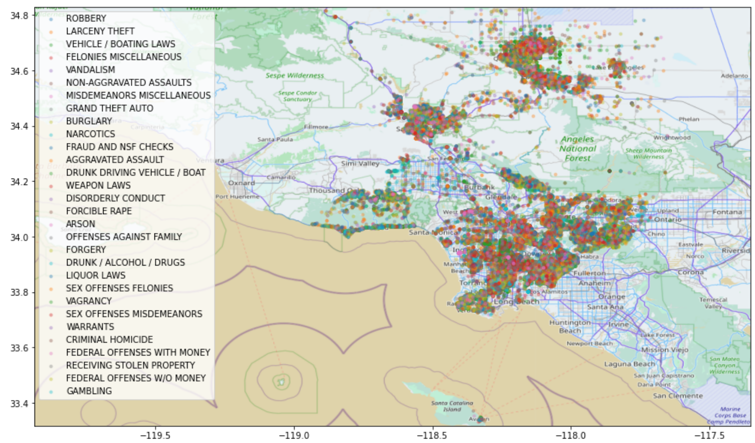

Figure 2: Mapping of all crime in 2017

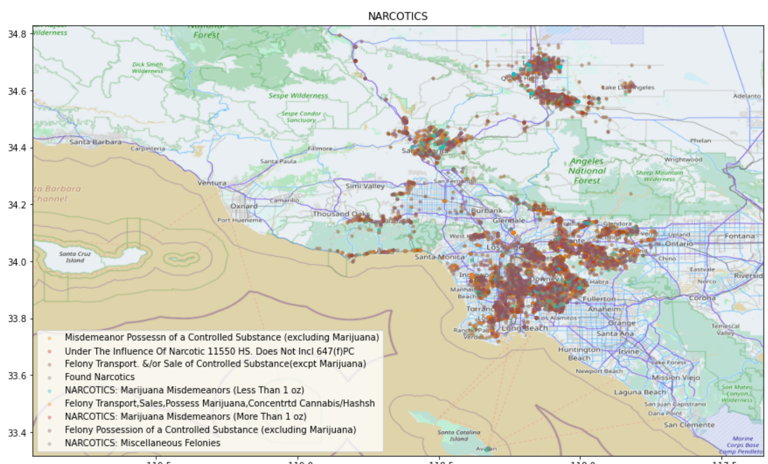

Figure 3: Mapping of 2017 crime in the “Narcotics” category

Because ETAS will be using this data to make crime predictions, we can already see small correlation with historically-redlined zones (Figure 5) without even having to make any quantitative analysis.

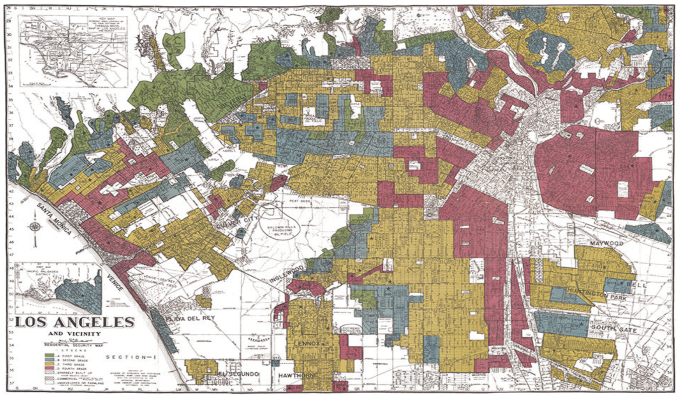

Figure 4: Redlining in Los Angeles

5 Tasks

In this section, we walk through each task and its respective results. This includes our Predpol Model and Redlining Analysis, and Bias Assessment.

5.1 PredPol

The PredPol algorithm is based on an Epidemic-Type Aftershock Sequence (ETAS) point process model. This style of model was initially developed for seismology and predicting earthquakes, and was refactored for the context of policing by Mohler et al [2]. After discretizing the space of prediction into 150 x 150 m boxes, the probability of a crime occurring within a given bin on a certain date is generated using the following equation:

$$\lambda_n(t) = \mu_n + \sum_{t_n^i < t} \theta\omega e^{-\omega(t - t_n^i)}$$

Eq. 1: ETAS Algorithm

This algorithm outputs $\lambda_n(t)$, which is a measure of the likelihood of a crime in bin n on day t. The equation is parameterized by the variables μ_n, θ, and ω, where μ_n represents the rate at which first-generation events occur, and θ and ω represent the parameters of a Poisson random variable.
To optimize the model, the PredPol algorithm applies expectation-maximization (EM) to converge each parameter. During the E-step, the following expectations are generated:

$$p_n^{ij} = \frac{\theta\omega e^{-\omega(t_n^j - t_n^i)}}{\lambda_n(t_n^j)}$$
$$p_n^j = \frac{\mu_n}{\lambda_n(t_n^j)}$$

Eq. 2 and 3: Iterative expectation generation

p_n^{ij} represents the probability of an event j at time t_n^j at bin n being a direct offspring of event i, and p_n^j represents the probability of an event j at time t_n^j at bin n being the probability that the event was generated by μ_n. Finally, during the M-step, the expectations are used to generate updated parameters:

$$\omega = \frac{\sum_n \quad \sum_{i<j} \quad p_n^{ij}}{\sum_n \quad \sum_{i<j} \quad p_n^{ij}(t_n^j - t_n^i)}$$

$$\theta = \frac{\sum_n \quad \sum_{i<j} \quad p_n^{ij}}{\sum_n \quad \sum_j \quad 1}$$

$$\mu = \frac{\sum_n \quad \sum_j \quad p_n^j}{T}$$

Eq. 4, 5, and 6: Iterative maximization of ETAS parameters

This two-step iterative process is used to generate the model parameters, where T is the number of days of crime information that we are using to inform the model. By using a rolling window of T = 365 days of crime data, we are able to generate optimal parameters for $\lambda_n(t)$, and use the generated model to estimate likelihood of crime within each bin n for that day. By including two years of data, we had 365 sliding windows, so we were able to use that information to determine the probability of a narcotics crime happening at each bin for every day of 2018.

5.1.1 Predpol simulation

Once we had the probabilities of crimes, we were able to simulate the response of LAPD for each day. In order to do this, we determined a probability threshold that the police would use to send additional units, and use this information to accumulate frequencies of additional police visits per bin.

By reverse-engineering the bin number to its respective real-world longitude and latitude, we can accumulate frequencies based on varying geographic distributions. Within the scope of our work, we accumulated frequencies based on HOLC-rating redlining categories.

5.1.2 Policing deployment distributions per HOLC rating

Below are the distributions of HOLC rating vs. policing. For each of the distributions, we divide by the sum total of the distribution in order to generate a proportion for each of the thresholds.

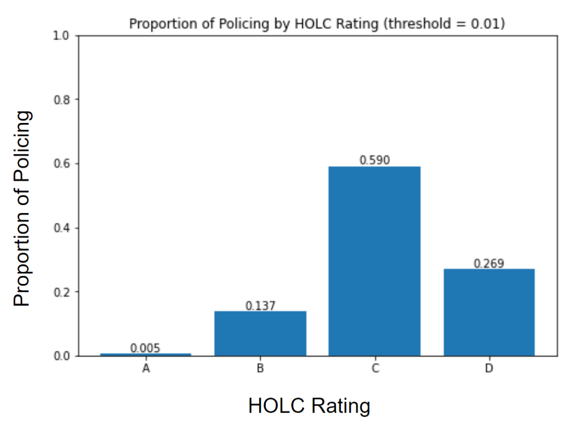

Figure 5: Distribution of of HOLC rating vs. policing for the threshold of 0.01

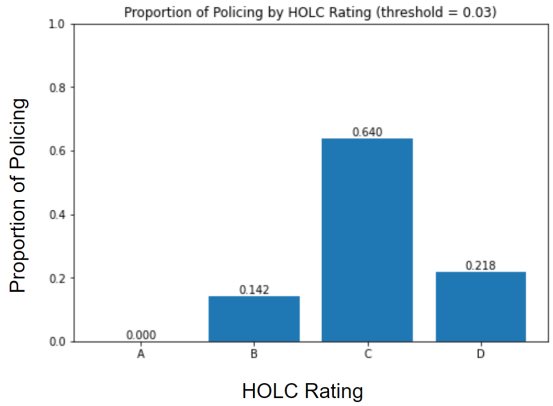

Figure 6: Distribution of of HOLC rating vs. policing for the threshold of 0.03

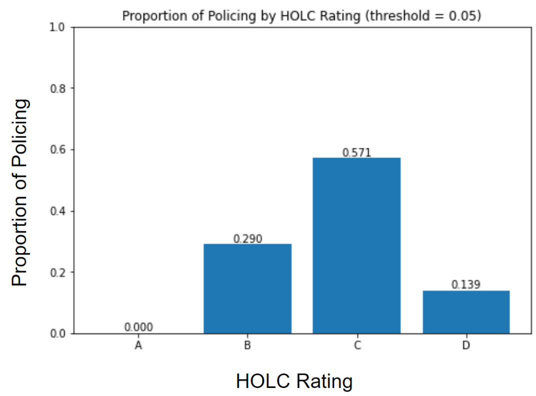

Figure 7: Distribution of of HOLC rating vs. policing for the threshold of 0.05

5.2 Predpol bias analysis

Using the Predpol simulation from the previous section, we used the distributions of its ratings to make two conclusions about its effect toward White, Black, and Latino/a populations in Los Angeles County. First, following the path of the Lum and Isaac's [4] analysis of Oakland, we find the distributions of police deployment based on White, Black, and Latina/a populations. After we find those distributions, we use crime data in 2019 to check the validity of Predpol's predictions, and compare the success rate per demographic to show if Predpol truly overpolices specific demographics.

As mentioned in section 3.1, we use the ACS 5-year report for Los Angeles County's census tracts, limiting to race data specifically. We also use this data in a geojson format so that we can distribute the information spatially as multipolygons, and also have a simpler time comparing it with various geographic crime predictions given by our Predpol model.

5.2.1 Policing deployment distributions per demographic

After mapping lat/long bins to their respective census tracts, and normalizing the demographic distributions within them, our next step was to simply find the policing frequency distribution per demographic population in LA County for a specific threshold. For each bin and its corresponding demographic distributions, we aggregated the demographic populations based on whether their policing frequencies fell above the threshold, and then divided the groups based on their total populations for LA County:

$$\frac{\Sigma_b\ (score_b\ \geq threshold) * TargetDemographic_b}{TotalTargetDemographicPopulationforLACounty}$$

Given the frequency distribution for White, Black, and Latina/o populations, we compared the results for a threshold of .05 in Figure 8 below.

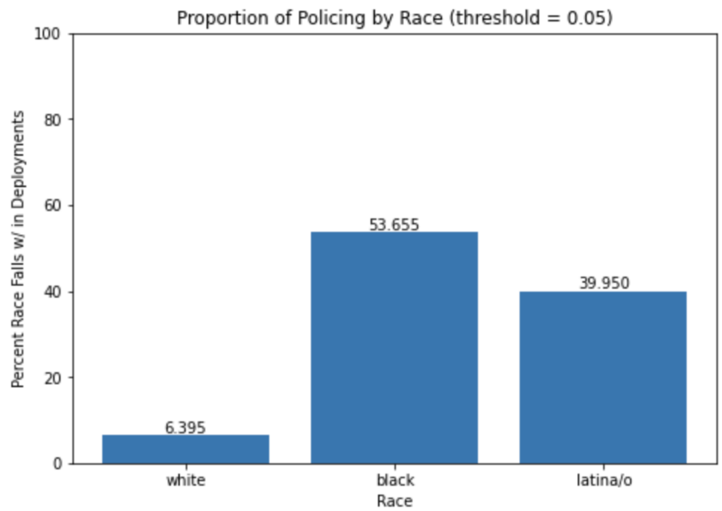

Figure 8: Drug crime prediction distribution for White, Black, and Latina/o populations in LA county

This graph tells us that out of the total White, Black and Latina/o population in LA County, 54% of Predpol's predictions are within an area that contains a Black population, 40% Latina/o population, and 6.4% White population. Although this graph definitely shows some discrepancy between Predpol's predictions for each demographic, it does not necessarily show any bias by Predpol.

5.2.2 Success rate of prediction per demographic

The results of Figure 8 show the demographic distribution of Predpol's predictions, but do not tell us if they are a result of racial bias. That is the question we explore in this section.

Using the same normalized demographic distribution per bin, we apply the same formula as used in section 4.3.1, except this time we aggregate based on the success rate of Predpol's predictions for each demographic instead of threshold.

$$\frac{\Sigma \frac{crimes_b}{crimeprediction_b} * TargetDemographic_b}{TotalTargetDemographicPopulationforLACounty}$$

When finding the total number of drug-related crimes for each bin, we used all crime data coordinates gathered from 2019 for LA County, and mapped each point to a respective census tract that was mapped to a bin. Because the predictions were trained on 2018, 2019 crime data was a respective decision. This is in reference to the same crime data used from the LA Sheriff's county office — the exact database used for the preprocessing and running of our Predpol algorithm.

Then, just like in the previous section, we map each of the demographics against each other, giving us the results in Figure 9 below.

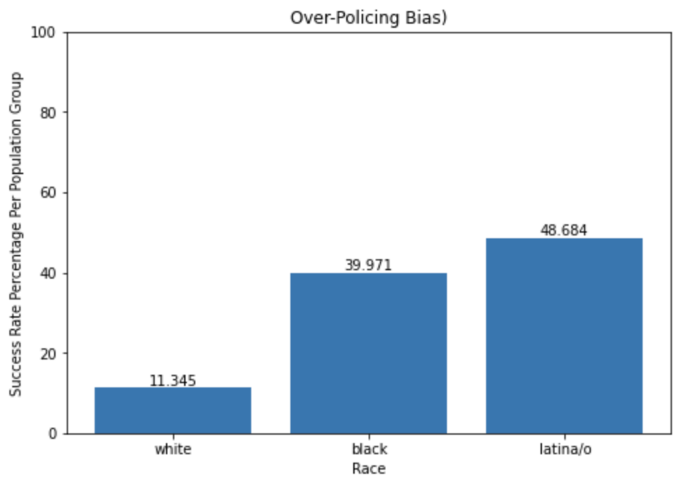

Figure 9: Success rate of Prepol's drug crime predictions per White, Black, and Latina/o populations in LA county

This figure shows that Predpol, indeed, predicts crimes successfully at higher rates for Black and Latino/a populations than for White populations in Los Angeles country. More specifically, this figure tells us that Predpol does not necessarily over-predict for each demographic, but under-predicts crime rates for certain populations. For White populations in LA County, crime assessment is under-predicted roughly four times less than for Black populations. This not only shows Predpol's bias toward Black populations, but it undermines Predpol's goal of successfully predicting crime in general.

6 Conclusion

Over-policing and surveillance of BIPOC communities is a product of both and historical systematic racism. According to the Stanford Open Policing Project's 2020 research into racial bias of traffic stops across the United States [5], Black and Latino/a communities are disproportionately stopped and searched for suspicion of contraband. However, over-policing of protected communities is not unique to the 21st century, but rather a product of a long-running campaign of separation and mass incarceration that spans centuries. By using Predpol, The Los Angeles Police Department plays an important role in this crusade.

These are the main takeaways:

1. Predpol's crime predictions are unequally distributed among White, Black, and Latina/o populations, as well as historically red-lined areas. Although this is not a direct result of bias, it shows the connection between racially skewed historic crime data, and its effects on protected groups today.
2. The analysis of the Policing deployment distributions per HOLC rating shows that for a low threshold (odds of police being sent to an area) a very small percentage of police forces get sent to the Green Zones (indicated by letter A). And as we increase the threshold, the number of times the police get sent to the green zones becomes close to zero. This shows that an unproportionate number of police forces get sent to the areas with a HOLC rating of C or lower.
3. Predpol unsuccessfully predicts crimes for White populations at higher rates than for Black and Latina/o populations. Not only does this mean that Predpol is biased against BIPOC groups, but it fails in its overall goal of crime prediction.

6.1 Limitations

There are still several limitations in our predictions and analysis that are subject to more inspection:

1. In analyzing demographic distribution from our census tracts, there was some discrepancy between White and Latina/o populations. Because the two are not mutually-exclusive, and the confusing labeling of the two demographics, it was difficult to correctly divide the two populations. Therefore, we focused purely on single race labeling, disregarding categories of two or more races.

6.2. Possible applications and extensions

An extension to our project would be to use various anonymous citizen reported survey data to predict true crime count estimates as a separate source of crime statistics from the police reported data. This synthetic data can be fed into Predpol to run simulations and assess how the bias towards low-income or POC communities can be improved. In some recent studies, GAN-based data augmentation techniques have been used to debias predictive models [8]. Similar techniques could be used to generate a well-distributed synthetic dataset that has a more uniform distribution of crime across different areas. These synthetic population data can be used as a supplement to the real crime data to perform bias correction and improve the crime hot spot predictions.

Another possible future work would be to assess the effect of over policing on future crime statistics. Our project and several other papers reviewed in this paper have been built on the assumption that over policing leads to higher crime reporting within an area. However, as an extension to this project the effect of over-policing on the hotspot areas in Los Angeles or other cities can be analyzed to test the hypothesis of the crime rate going down. The long term effect of over-policing on crime count in different areas can be further analyzed. Another extension would be to use several other predictive models -other than Predpol- that similarly rely only on the temporal and spatial features to assess how they perform on synthetic vs. real crime data.

Acknowledgments

We want to thank Professor Bistra Dilkina for her tremendous effort and patience in helping us navigate this project, and for answering our many emails ˘◡˘

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