Data Science for Good: Policing and Census

EPFL Project Report: Applied Data Analysis

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1 Introduction

Justice is a difficult concept to grasp, let alone to measure. Since the XVIIIth century, justice has indeed been understood to be an inherent right to man, however it's somewhat paradoxical that it requires the swift hand of the law as a deterrent to maintain it. This statement naturally begs the question of who is to make these law enforcement agencies accountable.

In the summer of 2014, the fatal police shooting of unarmed teenager Michael Brown ignited a series of protests and riot in Ferguson, Missouri [9, 7]. Now, the incident in Ferguson didn't stay isolated for long. It sparked protests across the country with polarizing reactions and intensified scrutiny of past and present police behaviour and response, particularly when it comes to detaining and arresting black people. Many similar incidents have taken on hashtags of their own, often referred to as #LivingWhileBlack and #BlackLivesMatter [10]. Through this project, we expand upon the issue of racial bias in police behaviour by relying on The Police Data Initiative which promotes the use of open data to encourage joint problem solving, innovation, enhanced understanding, and accountability between communities and the law enforcement agencies that serve them. To that end, we construct a joint dataset of census information and police stop information for the city of Boston from 2011 to 2015. From it, we aim to study whether racial bias can be detected in police actions and , in case it were, how demographics and spatio-temporal patterns are intertwined with it.

2 Data Description

One of the main achievements of our study was the construction of a combined dataset for the analysis of police actions as a function of the socioeconomic status of the inhabitants of the location where the stop took place as well as other information such as, the geographic location itself and the date when it happened.

2.1 Boston Police Stops (2011-2015)

This first dataset [5] encompasses a wide range of interactions between the Boston Police Department (BPD) and private individuals. Specifically, this corpus records 152,230 every stop made by Boston Police officers between January 2011 and June 2015 . Among the contained information, we dispose of the officer's ID (unanonymised), his supervisor's, the race of the stopped citizen, the time and address where the stop was made and the actions that followed the stops (observation,interrogation, frisk, or search).
In terms of geographical information, the dataset provides us with the textual address where the stop took place as well as the corresponding street's identification number (ID). In order to obtain the precise coordinates of the event, the provided ID of the street was matched with the geographical center of the street segment provided by the Boston Street Catalog [4]. Given that the average street in Boston is half a kilometer long, the spatial granularity of the data is roughly restricted to that level.

2.2 American Census Survey (2008-2012)

This data corpus [2] contains a set of socio-demographic aggregated indicators for all the US mainland territory as well as the corresponding geostatistical framework needed for our study. Using these indicators, one can estimate the distribution of the average socioeconomic status of people with the spatial resolution of the used census track. In the case of Boston, the whole metropolitan area is covered by an irregular grid of 204 census tracks with a median track area of 1.52 km^2. Out of this dense dataset, we extract the the percentage of citizens per race per census track as well as other meaningful socioeconomic variables such as the median income and unemployment rate per race and track. By doing so, we will be able to assess bias in police activities despite the demographic inequalities that are contained within the population (such as the for instance the fact that when aggregating per track, white people earn roughly twice as much as black people).

2.3 Combined dataset: Police data enriched with census

In the last step, both datasets were merged by placing each stop within the corresponding census track. By doing so we obtain a joint dataset providing unrivaled opportunities to study police actions in terms of the underlying population demographics where they take place. In doing so, we focus respectively on 143,963 and 84,442 stops for the data analysis and data visualization.

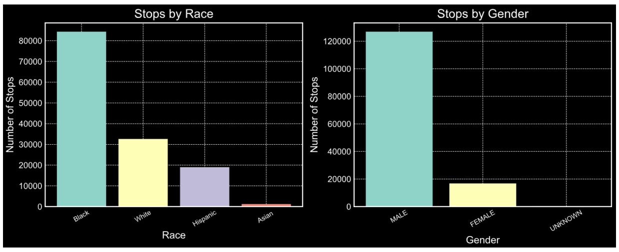

Figure 1: Univariate stop distribution per race and gender

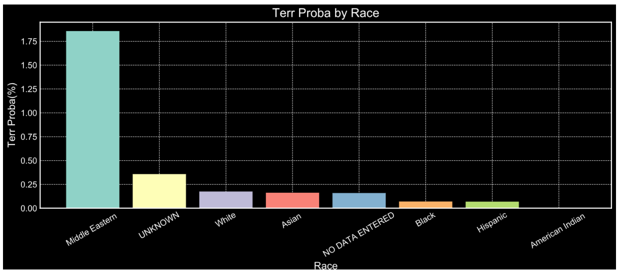

Figure 2: Percentage of stops for which terrorism is the basis for the stop.

3 Stop distribution and citizen demographics

A first question that naturally comes to mind when focusing solely on police data, is how are the stops distributed among the population. To that end, we show the count data of stops per race and gender through the 4 years time window in Fig. 1. It seems that BPD officers stopped in greater African-Americans (particularly males seeing the numbers). Whites and Hispanics follow ,even though any close comparison is far from possible. This result is already quite shocking since the black community barely represents 21.59 % of the whole population of the Boston Metropolitan Area while concentrating roughly 60% of all stops. This racial disparity in police actions is not however unique to the African-American community. For instance, if we are to look at stops per race again, we see that Middle Easterners were stopped the most (1.75%) on the basis of suspicion of terrorism by the officer (see Fig. 2). So far, we have been able to show that there is some dependency of the number of police stops on the race of the stopped citizen. This tendency is however not yet a clear sign of bias since this analysis completely ignores the real composition of the population. Indeed, if the rate at which African Americans are stopped is higher than for any other race couldn't it be related to the fact that most of the population in economically deprived neighborhoods is of that ethnicity and thus, because of the situation of the neighborhood, crime is more likely to happen? For that matter, we now turn to our combined dataset in order to study whether bias can be detected through police activities.

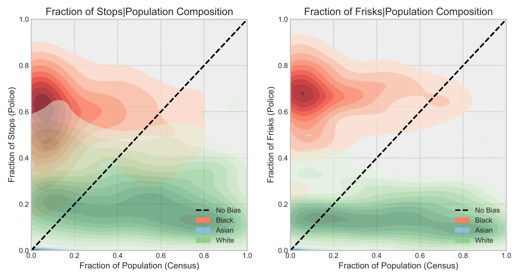

Figure 3: Kernel Density Estimation plots for $p(\text{stop}|race)$ (left) $p(\text{frisk}|race)$ (right)

4 Detecting bias on census-enriched stop data

A maybe naive hypothesis to discard the possibility of police actions being biased would be that the fraction of stops per race should follow the rate at which that population is present. Should this happen, then the probability distribution $p(\text{stop}|race)$ should follow closely the identity line in the $(\%\,\text{population}, \%\,\text{stops})$ plane. We thus aggregate stopped data per race and census track and plot the aforementioned distribution for actions where the target was black, white or asian (see Fig. 3)

The situation seems far from the no-bias scenario. In the density plots of stops (left), we see that African Americans are distributed well above the non-bias line, i.e, residents of that ethnicity are being stopped at a significantly greater rate than the rate at which they are present (live) in that given area. An inverse trend occurs for residents of Asian ethnicity that are consistently under the no-bias line at different concentrations. White residents living in areas where they are the minority seem to also be over-stopped nonetheless, as they become present in rates greater than 20% of the whole population, the center of mass of the distribution seems to shift well under the no-bias line. More interestingly perhaps, is that the aforementioned trends seem to be accentuated when the stopped is followed by a more aggressive follow-up such as frisks (see right plot).

There is nonetheless a clear distinction to make though. While the above plot clearly indicates the disparity of treatment by police of citizens of different race, this argument cannot be extended so far as to really indicate whether law enforcement actions is solely responsible for it. Indeed, as was previously stated this treatment despair is clearly entangled with the socioeconomic inequalities splitting up Bostonians by race. Therefore, one might argue that the reason why Blacks concentrate stops unevenly with respect to the size of their communities is exactly because they suffer from economic disenfranchisement which in turn might lead to higher rates of crimes justifying all-in-all the followed procedure. In order to control for that scenario, we repeat the above analysis while only studying stops in census tracks where both the

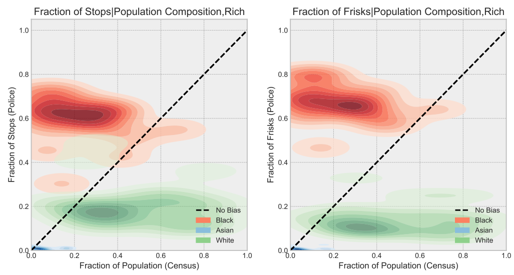

Figure 4: Kernel Density Estimation plots for $p(\text{stop}|race, rich)$ (left) $p(\text{frisk}|race, rich)$ (right)

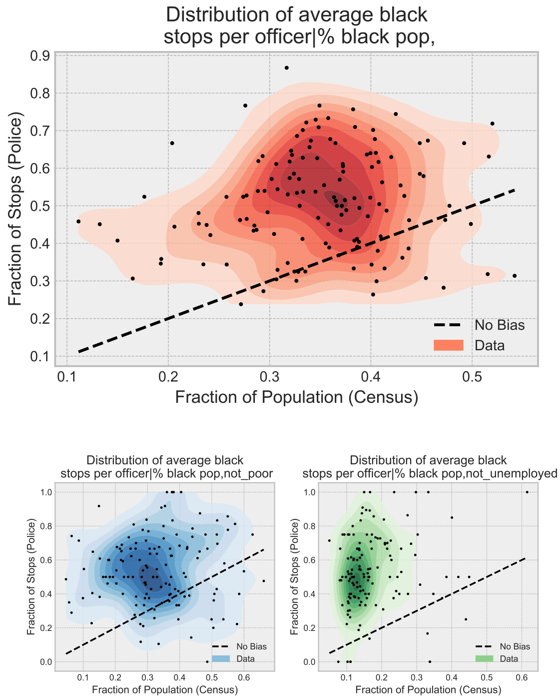

Figure 5: KDE plots for $p(\text{stop}|\text{officer}, race)$ (top), $p(\text{stop}|\text{officer}, race, rich)$ (bottom, left), and $p(\text{stop}|\text{officer}, race, employed)$ (bottom, right)

median income for African Americans and Caucasians is above the median income for the whole population within the metropolitan area (58710 \$). The resulting plots are shown in Fig. 4

The results are quite astonishing: When controlling for socioeconomic welfare, we see that citizens of African American ethnicity are still being stopped to a greater extent than what would correspond to a non-biased scenario while the stop distributions for the two other ethnicities are now below the no-bias curve. We hence conclude that police activities are therefore biased even when controlling for socioeconomic inequalities. Similar behaviour was seen when economic welfare was defined by both races having an unemployment rate lower than the city average (estimated from the census at 9%). At which level within the hierarchical structure of the police department is however this bias encoded?

5 Police Department Structure and Bias

One of the main counter-arguments yielded by law enforcement agencies when these issues are addressed is that bias is less an institutional problem than it is an individual one (this is usually referred to as the ”bad apples” problem [8]).

Bringing back this argument to the analysis carried out so far, if this hypothesis were to hold, we would expect that the bias observed so far is a result of a reduced set of officers which actions shift the aforementioned distributions above the no-bias line. In order to study this, we now focus on stops involving Caucasian or African-American citizens and aggregate them by the officer that carried them out. In order to obtain officer data from which to compute reliable statistics, we focus on individuals that were in the upper 25% of the distribution of stops per officer (i.e which performed more than 71 stops from 2011 to 2015). By doing so, we avoid having to deal with law enforcers not having performed enough stops to be able to assess whether bias is observable from their activities. We then perform an analysis identical to the one previously conducted (see Fig. 5). Note that now the distribution studied now is $p(\text{stop}|\text{officer}, race)$ where each black dot in the KDE plot is an individual officer. Furthermore, in order to obtain the individual coordinates of each officer in $(\%\ \text{population}, \%\ \text{stops})$ plane, his x-coordinate was obtained by performing an average of the rate of black people living in a given census track weighted by the number of stops performed in that track (respectively, weighted average of the the rate of stops of black individuals for the y-coordinate).

We hence observe again that most officers do stop African-American citizens at a greater rate than they are actually present within the population Fig 5, (top). This trend is furthermore observed when considering only stops made by officers within census tracks where both population hold above median income Fig 5, (bottom-left) and below average unemployment rate Fig 5, (bottom-right).

What this information suggests is that the bias is encoded at the finest grained level of the judicial system, that is at the officer level. However, these calculations do not account solely for cognitive biases in the way police officers carry out their stops (implicit bias) as other systemic issues are also masked within these distributions (explicit bias). For instance, in Fig. 6, we plotted the probability that a stopped individual has prior arrest records given his race. We see that more than 85% of stopped individuals of African-American ethnicity actually hold a prior judicial record. Hence what this data suggests relates not only to issues in how police treat differently citizens according to their race but also to recursive issues in America's justice system as a whole: indeed, after contact with the criminal justice system, citizens are denied employment, college education, voting rights or housing and are excluded from public benefits which in turn makes them more likely to

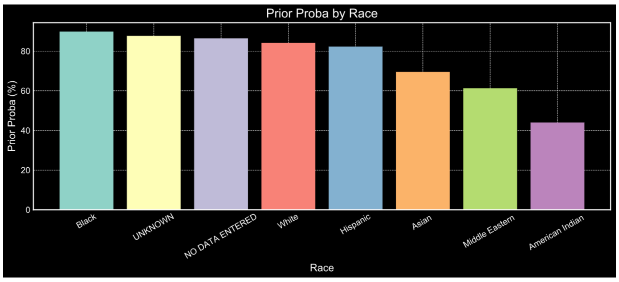

Figure 6: Probability that stopped individual has prior arrest records per race

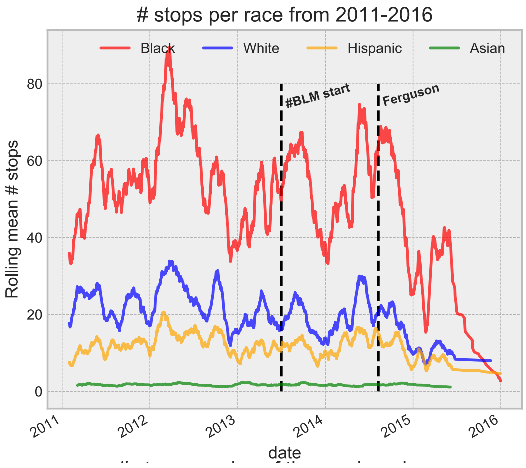

Figure 7: Probability that stopped individual has prior arrest records per race

be re-incarcerated [6].

6 A Temporal View of Stops

Despite the volume of public discourse these problems have attracted, there is still no sign on whether these issues have been addressed and if they have, on whether there has been any significant change in police attitude towards communities that are affected by biased behaviour. In order to shed some light on this, we wondered if any change point in the timeseries of police activities could be detected around events when bias was on the public spotlight. Specifically, we were interested in observing whether social movements such as #BLM(#BlackLivesMatter) or the Ferguson protests had led to any major change in the way police conducted stops in the Boston metropolitan area. For that purpose, we started by studying the stops per race timeseries (Fig. 7) We clearly see that the disparities in the number of stops per races observed previously (ignoring when the stop happened actually) is sustained throughout all the recording period with African-Americans concentrating most of the stops followed loosely by Caucasian and Hispanics. In order to study whether any significant change was detected around the time periods of interest, we look for any events that might have been behind sudden variations (change points) in the number of stops of both African-Americans and Caucasians. For that matter, we rely on a state-of-the-art change point detection algorithm [11]. Once individual dates around which the timeseries changes are detected, we crawl the NYTimes API in a two weeks time-window around the yielded date for articles posted at that time by the U.S. news desk. and mentioning the Boston Police. The results are shown in Fig. 8 Though no major change was picked up around dates during which social protest where taking place, surprisingly, we were able to link 2 changes in the number of stops for both races to events taking place around the date of the change. Specifically, the algorithm was able to pick up, major upheavals such as the Boston Marathon bombing [1] on 2013-04-15 or a search for suspicious backpacks [3] one year after that date. Those events were probably followed by an increase in police activity which might explain why they were caught. These findings clearly don't hold any relationship to the bias analysis previously carried out but rather highlight how spontaneous events might induce temporal breakpoints in the studied timeseries. The events that were picked up were nonetheless limited by the available source of news as well as the querying terms.

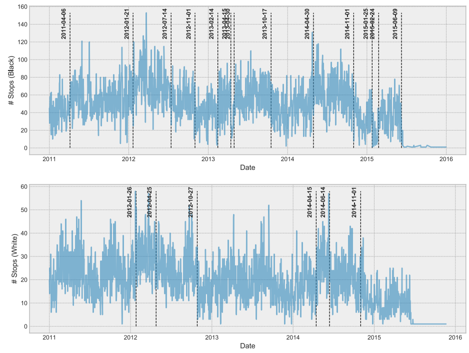

Figure 8: Evolution of stops of black and white people and detected change points (dashed lines)

Furthermore an STL decomposition of the time series of the black-to-white ratio of stops (shown in notebook), seems to suggest that despite all public discourse, no major change in terms of bias correction seems to have taken place at the observed dates.

7 Conclusion

The overall goal of this study was to show the presence of racial bias in police actions. To do so, we relied on a combined dataset of census and police records to study how unevenly stops in the city of Boston were taking place. When analyzed, this dataset revealed that African-Americans where being stopped consistently through time at rates greater than the ones at which they were present in the census area and that they took place despite African-Americans earning more than the median income or being employed at higher rates than the metropolitan average. Despite these issues being in the public spotlight, we were not able to see observe significant sign of change in the observed trends.

References

[1] Blasts at boston marathon kill 3 and injure 100. *The New York Times*, 2018 (accessed December 16, 2018).

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[11] Charles Truong, Laurent Oudre, and Nicolas Vayatis. A review of change point detection methods, 2018.