NYC Stop-and-frisk: a racial perspective

The New York Police Department is world-known for its interaction with the people of New York. During 2011 more than 600.000 stops were performed on the street. Most of the stopped people were innocent. But is there a racial bias in who is stopped? The NYPD provides data covering these stops. This project goes into the data to see if patterns of racial profiling can be found.

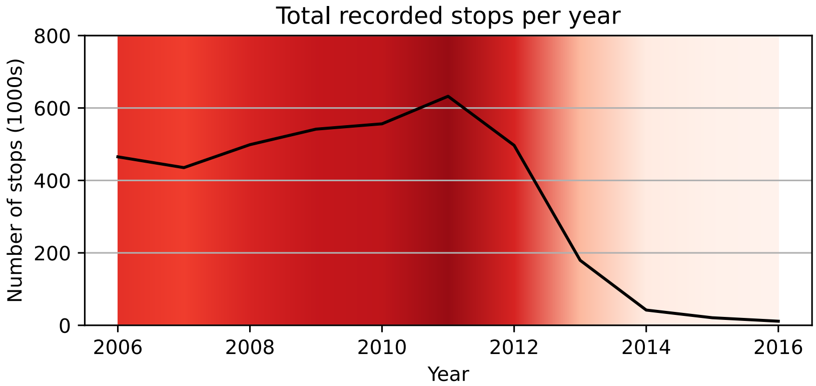
What is stop-and-frisk?

Terry v. Ohio, a U.S. Supreme Court decision from 1968, is the legal basis for stop-and-frisks. It held that the police stopping pedestrians for questioning and patting down for weapons or drugs without probable cause does not violate the Fourth Amendment. A suspicion based on gut feeling is all that is necessary for the police to have a legal reason to question and search individuals on the street.

Under Michael Bloomberg's time as mayor during the early 2000s, initiatives were put in place to fight crime in New York City. As part of this, the police were encouraged to perform focus on stop-and-frisks in New York City. This initiative has since been criticized in public media and research for being racially biased. Multiple studies find a racial imbalance in unsuccessful stops. Multiple studies have shown the stop-and-frisk initiative to have a limited effect in preventing crime. The negative effects of racial profiling have been argued to have done more harm than good, with documented increases of distrust in government among marginalized groups.

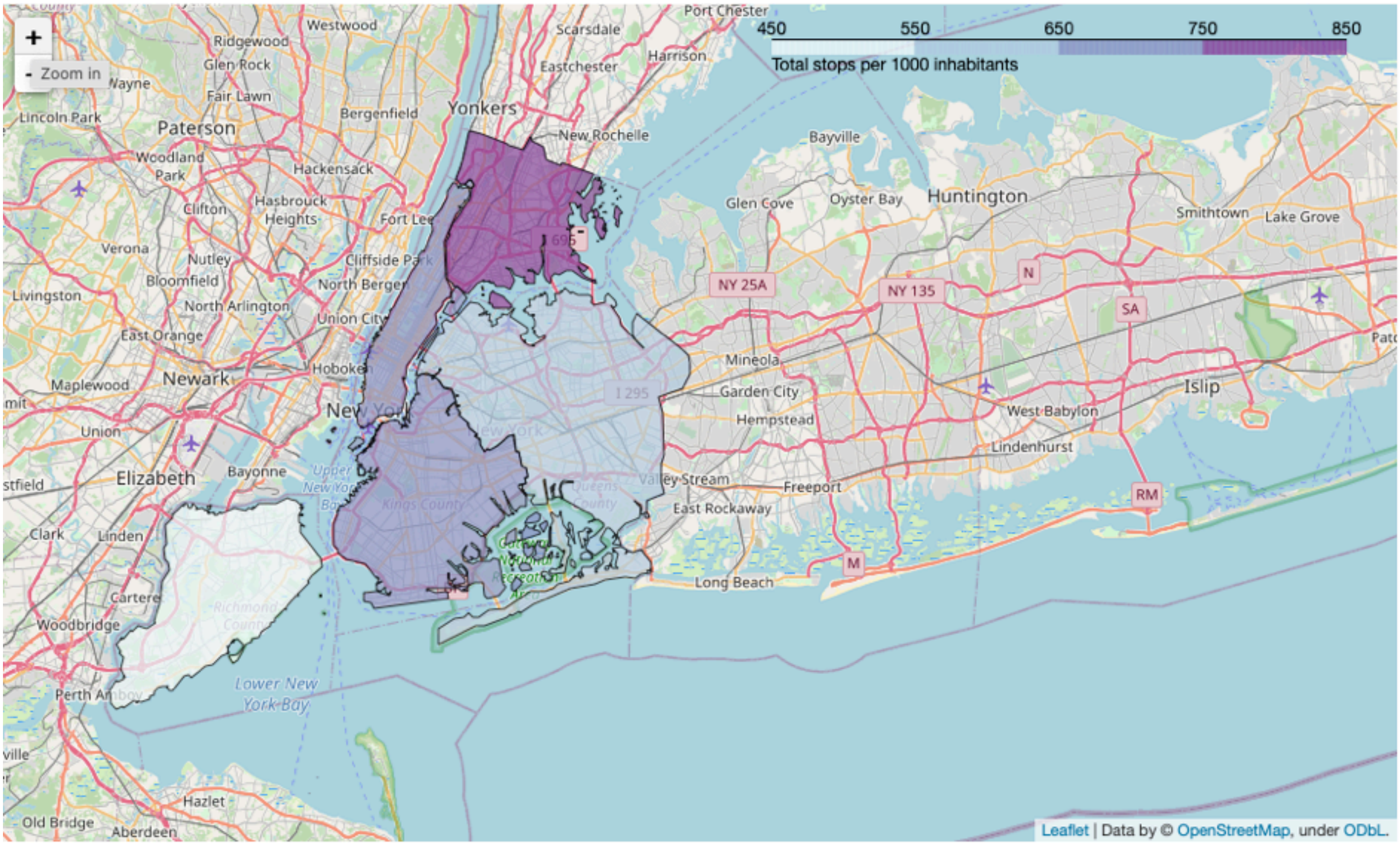
Data

This project evolves around a dataset covering all recorded stops from 2006 up to and including 2016. During these 11 years of data, the NYPD performed more than 5 million stops in total. Studies suggest that the true number is higher, with estimates up towards 15 million stops, the discrepancy caused by limited registration by officers. For each stop, an array of attributes are recorded, such as spatio-temporal data (time, year, precinct, city), personal data (age, sex, race) and criminal data (was force used, did it result in arrest, did the officer find weapons on the suspect). To simplify the analysis, only stops with the race designation black, white and Hispanic are used, and only a subset of attributes were kept. The cleaned dataset constitutes 3.880.159 entries with 12 attributes. The kept attributes are: year, precinct, arrested, frisked, searched, was a pistol found, was force used, sex, age, race, city and criminal clothing.



Temporal evolution of stops

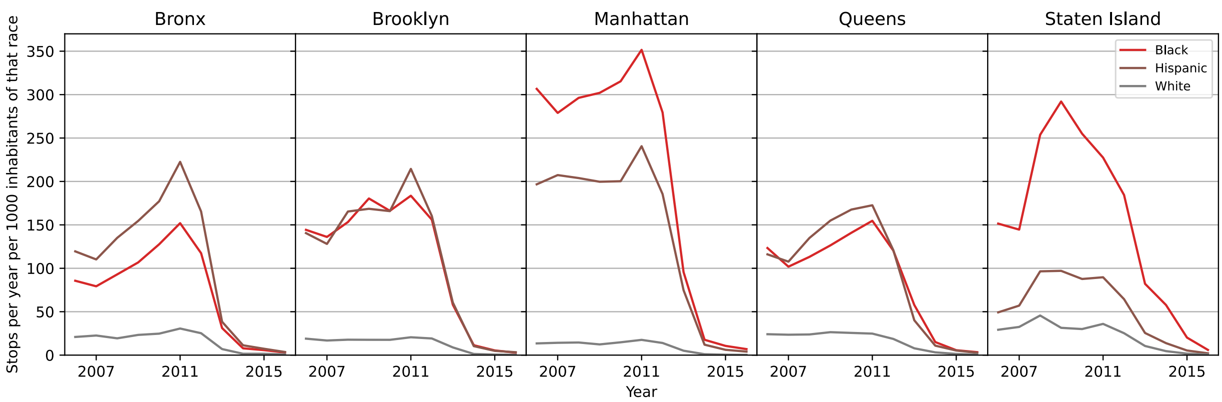
The total number of stops peaks in 2011, where more than 600.000 stops were performed. Since then, it has been steadily decreasing with a new administration taking the mayors office. As of 2016, the number of stops is negligible compared to earlier years, with a total of 11.338 stops. How has this significant decrease in total stops affected the performed stops? Is a higher proportion being searched and arrested, and has the rate of innocent people being stopped decreased? Are there any changes to the racial statistics in the data? And are there changes in how these parameters have changed in space?

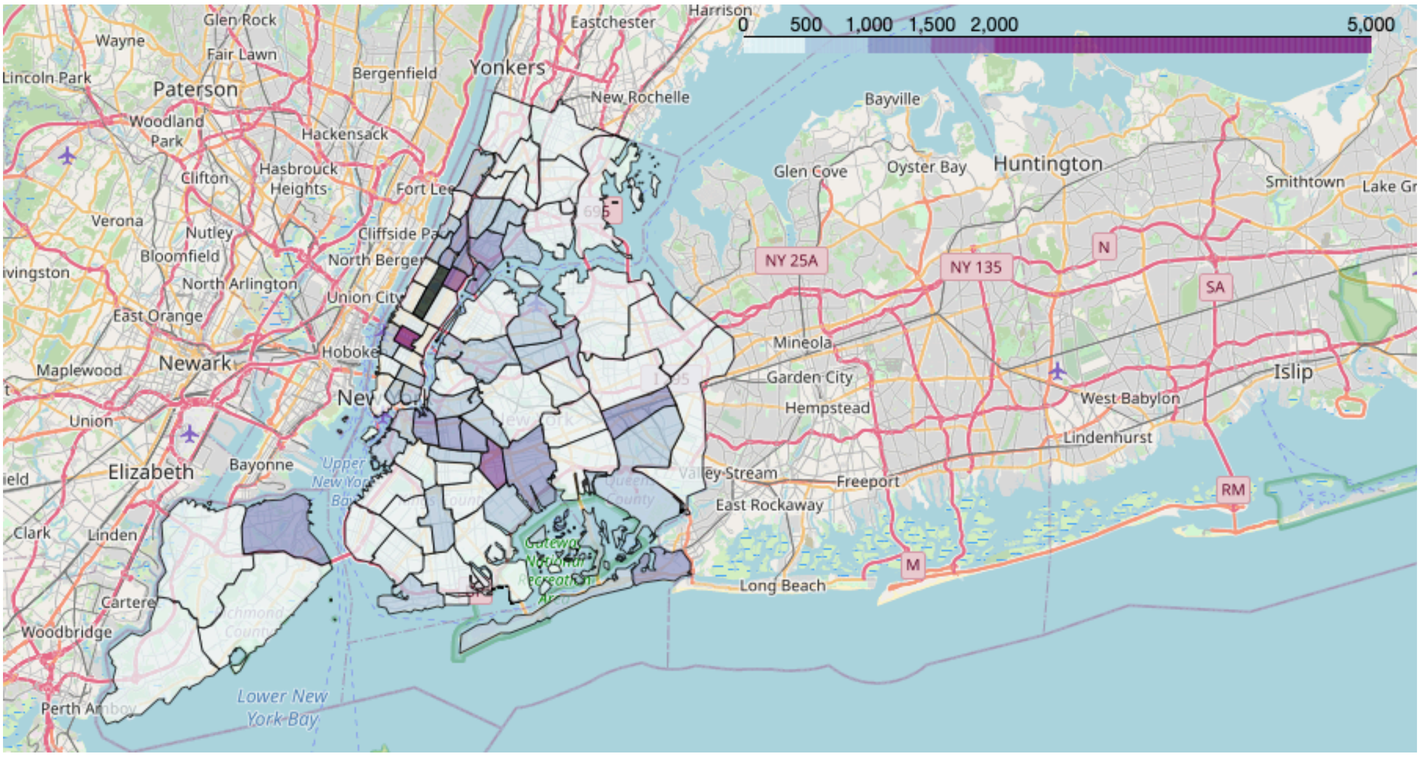


Borough distribution

New York City covers five cities: Bronx, Brooklyn, Manhattan, Queens and Staten Island. Their extent is shown on the map above, coloured by the total number of stops per 1000 inhabitants over 11 years. Clicking the image takes you to a more detailed view. In all the boroughs, there were between 450 and 850 stops per 1000 inhabitants. In particular the Bronx in the north has a higher stop rate than the other boroughs.

Below, a more detailed look into the different boroughs is presented. The graphs depict the number of stops for each race, normalized to the population of each race in each city. There is a remarkable racial signal in these data. The extreme was in Manhattan in 2011 when 350 black people were stopped for every 1000 black people residing in Manhattan. For white people, the number is around 30, and thus the difference is of an order of magnitude. In the other boroughs, there are similar patterns, while the contrasts are smaller.





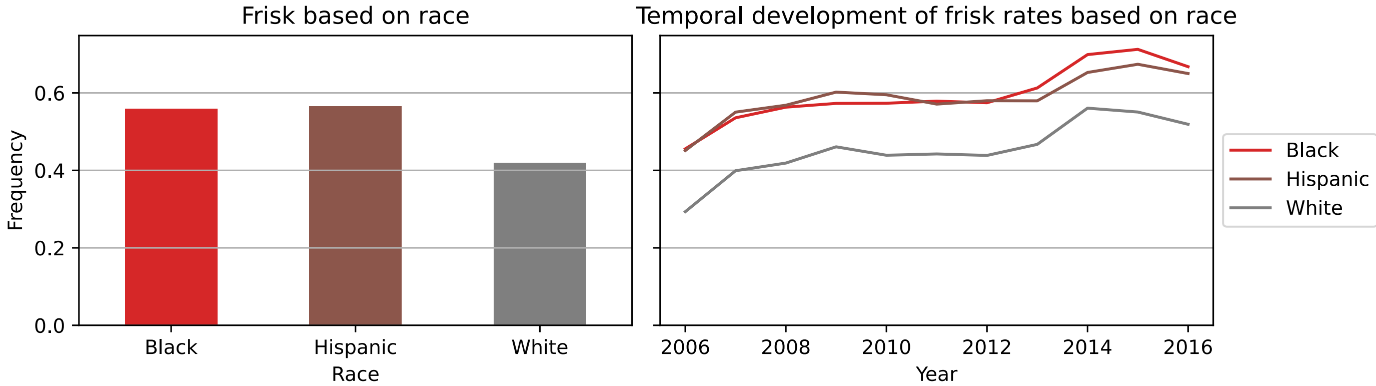
Precinct distribution

On the map above, a more detailed geographical breakdown of crime prevalence is shown, here split into the different precincts of New York (precinct are a division of NYC into smaller segments used in policing. In this view, the differences are more pronounced, with a few high concentration areas. Note that Central Park is not included, as the number of crimes registered there does not reflect the census count (25 in 2010). Clicking the map enables interactive exploration of the data.

Temporal development of rates

How many people are frisked and searched, how often do the police use force, and how many stops end in arrests? Below, the temporal rates for each race are depicted for NYC as a whole. Click through the tabs to see the temporal development of each rate. Common for all rates is that the trends are very similar for all three races and that from 2013 and onwards, all rates increase drastically. This coincides with the fact that the total number of stops is significantly decreasing from 2013 and onwards, leading to fewer irrelevant stops.

Arrests Frisks Force uses Searches



Frisk rates

White people have a significantly lower frequency of being frisked, at around 42% of all stops, compared to around 57-58% for both Black and Hispanics. The offset is also present in the temporal developments. The frisk rates increase less than, e.g. the arrest rates from 2013 and onwards.

[Click here for interactive Bokeh plot of for frisk rates]()

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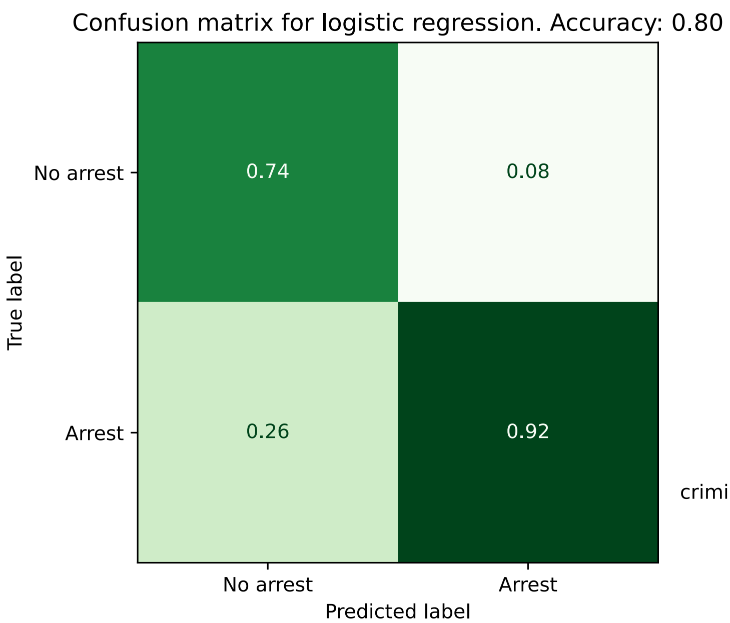
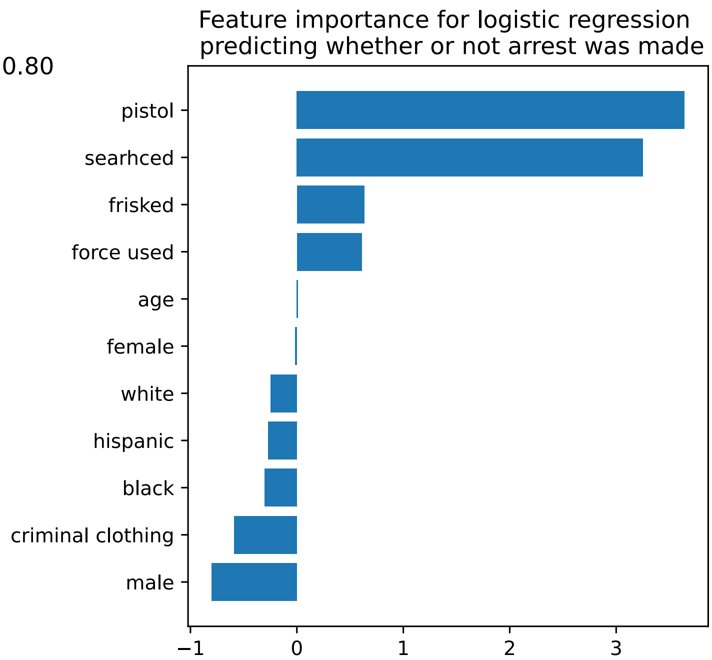
This website presents the final project in DTU course Social data analysis and visualization 2021. The background code can be accessed on the link below, where the data analysis process is presented, along with a brief overview of methodology and discussion.

[Explainer notebook]()

Machine learning approach

The approach until now has been centred around summing, counting and dividing to get insight into the data. Machine learning is a different approach to answer some of the same questions. The idea here is to feed certain attributes to logistic regression and train it to predict whether or not a stop resulted in an arrest. This is a crude approximation of whether or not an innocent person was stopped or not. Using logistic regression provides insight into what variables contribute to whether or not an individual was arrested.





The **confusion matrix** for the trained model is shown above, along with the **coefficients** of the logistic regressor. The confusion matrix is a visualization and quantization of how well the model is at predicting the outcome of an arrest based on the 11 attributes fed to it. The diagonal elements are the true positives and true negatives - thus, for 74% of the predictions of no arrest, the model was correct, with the same true for 92% of the model's predictions of arrest. Based on this and the accuracy of 80%, the model is accepted for further analysis.

This leads us to the learned coefficients. A high coefficient value for a given attribute means that if this attribute is true, then the model will be more likely to predict an arrest. This is the case for the attribute pistol, which indicates whether or not a pistol was found on the suspect. The same can be said for searched, which is whether or not a suspect was searched. These are obvious characteristics - if a stop ends in a search, and in particular, if a pistol is found on the subject, there is a higher probability of an arrest being made, compared to a stop where no search is performed, and no pistol is found. These are *not* the interesting coefficients. They do, however, support the use of the model, as its coefficients follow along with the expected outcome.

Looking towards the bottom three attributes, we find here negative values for black, criminal clothing (short for the official attribute "reason for stop - wearing clothes commonly used in a crime". This is not a joke.), and male. The fact that these are negative means that if one or more of these attributes are true for the stopped individual, there is a higher probability that you will be subject to a stop with no arrest. Thus, a black male wearing "clothes commonly used in a crime" are more likely than others to be stopped with no resulting arrestation. The interpretation of this is that there is a selection bias in police stops, which is *not* supported by statistical evidence in this dataset.

Discussion and outlook

These data cover only recorded stops and thus does not cover who was *not* stopped. Further, out of the scope of this project is a thorough statistical analysis that covers the significance of the results found. Finally, causality is not investigated in any way, and no judgements of criminal traits of races, nor judgments of structural racism among police officers are made.

With that said, the data supports that for black people, there is a higher frequency of frisks and use of force from police officers. Further, the logistic regression shows that for stops with registered black males with criminal looking clothing, there is a lower probability of being arrested. This suggests that there is some unjustified racial profiling is who is getting stopped by police.

In the light of political movements in 2020, this is a highly sensitive topic, and while these data do not cover the most recent years, there data suggests unfair treatment of individuals suffering from being targeted by police, for just being who they are.

Further work with this type of data could include a deeper investigation of the individual precincts to see if other patterns emerged here. Are there certain precincts where people of a particular race are more often stopped with no following arrest? Are there temporal trends in, e.g. frisk rates that are different in certain neighbourhoods? Including theory from sociology and criminology would allow going into causality and the effect of these stops, and within the framework of law, it might even be possible to find evidence of illegal structural racism and racial profiling in police work. With the use of more advanced software and coding, the dataset could be made more open for exploration by the user, which could allow new insights to be had. Further machine learning work could discover other connections among variables in the data, shedding more light on who is getting stopped. Finally, an actionable outcome could be a framework for police officers to help them decide whether or not an individual should be stopped based on observable traits prior to stopping. This could potentially lead to decreasing the amount of innocent people being stopped on the street. The effects of this might be an increased trust in police and government among groups subject to profiling based on their personal traits. This, however, is out of the scope of this project and will be left as an option for the reader.

Sources

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