Trends in Stop-and-Frisk Visualization Project
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Accompaniment to Stop and Frisk Shiny App Project

Background on Stop and Frisk

Stop and frisk is an NYPD practice of temporarily detaining, questioning, and at times searching civilians on the street for weapons and other contraband. In 2013, a constitutional ruling established legal requirement of "reasonable suspicion" for stop and frisk, having found requirements were inconsistent and often not met in the current state of policing behavior and regulation pertaining to stop question and frisk (SQF). Recent studies examine racial disparities in SQF and much debate has concerned the policy, as some claim that stopping suspects effectively reduces gun violence in neighborhoods with high rates of gang violence, while others argue that SQF police practices violate just treatment of residents and do not effectively reduce possession of weapons, contraband or reduce crime. This debate centers around cases where criminal possession of a weapon (CPW) is suspected, and key to providing concrete numbers to inform the debate could involve examination of hit rate, which is the probability a weapon is found. Racial profiling, and characteristics of disproportionately stopped groups, as well as geographic areas insofar as they show proximity to crime level, poverty, and geographic areas, are also factors that could motivate further research questions on effective policing, racial profiling, and regulatory changes.

Study Motivation and Research Questions

With Stop and Frisk NYPD policing context in mind, I explore whether trends in stop and frisk frequency are evident before and after the 2013 constitutional ruling using data visualization. Also, I investigate whether there are differences in SQF rate based on individual characteristics of suspects, including questions such as whether black and Hispanic individuals are disproportionately stopped, what geographic trends exist, and what boroughs display lower thresholds for stopping individuals, holding factors like race constant. To do so, I assessed descriptive statistics of stop, question, frisk, and arrest rate separately and the type of force used by precinct, racial/ethnic subgroup, suspected crime and gender. Additionally, I built predictive models for the probability of being stopped, the probability of being frisked, and the probability of finding a weapon based on the characteristics of suspect and characteristics of the stop.

Data & Methods

Three data sources were used for this research: the NYC Open Data Portal SQF data, ACS Census Data population estimates, and John Keefe's WNYC crime series NY precinct geographic data crosswalks. The SQF data is available from 2003 to 2018 through the portal, which I subset to 2012 to 2016, and merge with five 5-year ACS estimates at the tract level, and decennial tract to precinct crosswalk data. SQF stop data is extremely rich, with over 150 variables per row at stop level, with information such as the characteristics of the individuals who were stopped, whether they were frisked or not, the reasons for being frisked, the suspected crime, the force used, and other items. The data range needed to span several years, since I am primarily interested in the change in SQF frequencies before and after the 2013 ruling. Using this data, I built a dashboard displaying the data on the NYC map that feeds into five plots with multiple widgets. Each of these plots utilize a reshaped version of this starting data which can be run start to finish using three programs included with this write up. Also, I included some visualizations of descriptive statistics, such as time trends in stop counts, and frisk and arrest rates by year in each borough. Finally, for the predictive modeling, I performed logistic regression to predict the probability of finding weapons among stops for individuals suspected of criminal possession of one.

Preliminary Results

From the map plot, I can distill several key spatial relationships over time. Time trends show considerable reductions in stop and frisk frequencies across all 5 boroughs between 2012 and 2016 with a steep drop after the 2013 ruling across all races. The full geographic layout allows us to view hot spots where majority of stops are white, or unknown race in Far Rockaway, Bay Ridge, and East downtown Manhattan, that are mostly hidden when I view averages at the borough or county level. Four small hot spots show majority Hispanic hotspots that span multiple precincts and would not appear as majority race ethnic groups by table also emerge. In addition to showing trends that do not ascribe to administrative regions, I can also see the relative density trends, such as the higher frequency and area covered by stops in Manhattan and Central Brooklyn compared to South Brooklyn and Staten Island.

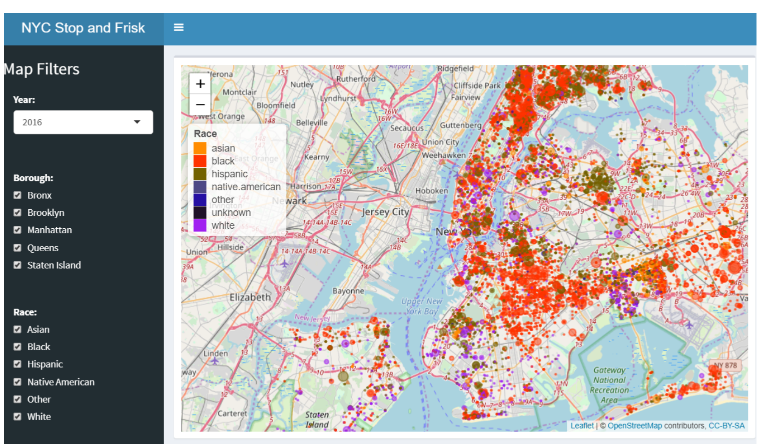

Image 1: SQF data visualization on the R Shiny dashboard

As the map displays spatial data intuitively, the three bar chart plots illuminate comparative relationships in the data alongside magnitudes. Grouped and stacked bar charts facilitate viewing time trends and provide a sense of the absolute levels of a given outcome, namely stops, stop and frisks, and arrests, by racevand by borough. The axis alongside data visuals provides absolute values in terms of stops and rates and offers a viewer to contextualize this number alongside any other estimates they have about New York City populations, crime rates, or otherwise. I can see from this data that the share of individuals experiencing SQF are consistently mostly black in Manhattan and central Brooklyn, Hispanic in Queens, and white in southwest Brooklyn. I also see rate of frisk and arrest increase over time, perhaps suggesting that fewer stops have occurred alongside higher level intervention.

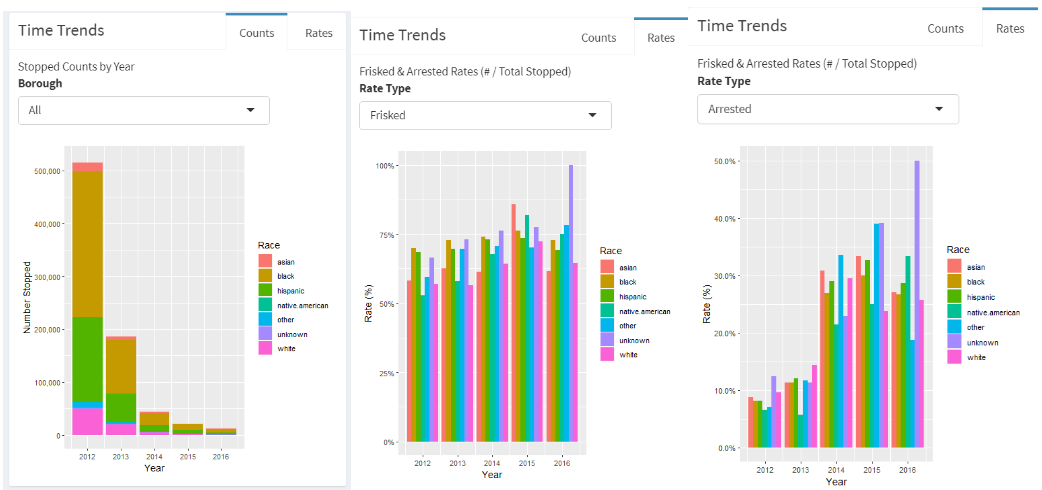

Image 2: Descriptive statistics visualization

The result of the logistic regression model shows statistically significant coefficients on age, build and weight, but the insignificant coefficients on height and sex. The exponentiated coefficients (odds) on weight and age are rather marginal, at 1.001 and 1.021, while that on suspect build is considerably higher. Suspect.build ‘muscular’ has odds of 1.49, suggesting that it is 49% more likely to find a weapon when frisking someone who appears muscular, compared to someone who as a heavy build. Similarly, suspect.build ‘medium’ and ‘thin’ have odds of 0.83 and 0.92, suggesting that it is 17% and 8% less likely to find a weapon from frisking someone with medium and thin build compared to someone with heavy build. Full results can be found in appendix, under table 1.

Additionally, the predicted probability plot created based on this model provides an explicit question and answer, offering the viewer the possibility of adjusting factors for stratification in a mostly pre-set modeling structure. While many such plots could be generated with relative ease, this one approaches the question of what share of stops due to a suspected criminal possession of a weapon results in seizing of such a weapon. The predictive model shows the probability of finding a weapon has increased since 2012, and that the rate varies visibly by race and ethnic group. This could suggest that the probability of finding a weapon from white suspects who were stopped because of suspected criminal possession of weapon is much higher than that of any other ethnic subgroups, which may suggest a higher threshold of suspicion to be frisked. Questions such as this one arise frequently in the SQF debate, and a dashboard with multiple levers could be particularly well suited to informing policy in an area where relevant factors are themselves up for debate.

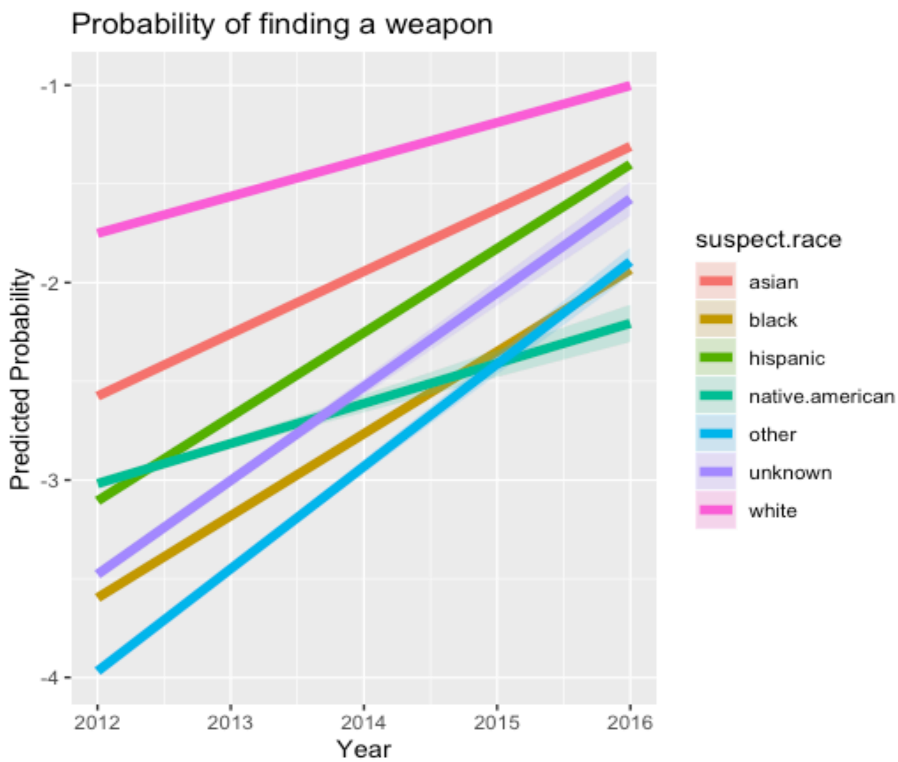

Image 3: Predicted Probability of Finding a Weapon

Static and non-visual descriptive statistics can also be displayed using Shiny, generating tables or static plots, however these were not within the goals of this project, and were generated by the team for exploratory analysis and for presentation purposes only.

Path Forward

The RShiny SQF Dashboard created by this project served as a data visualization tool for social science researchers to use to display trends with a variety of stratification variables. Future social science and policy research could base hypotheses from these visualized trends. Examples of policy research that could be extended from these findings include questions about policing contexts, such as changes in NYPD procedural requirements by borough following the constitutional ruling. Examples of research using different methodological approaches that could be extended from these findings could apply different inference types, such as causal inference, spatial statistics, or network analysis.

Examples of analyses that could be inspired by these visualizations or scaffolded by them include predicted probability, significant associations, and natural experiments. Ravi Shroff's machine learning research on minimalist decision models to optimize seizing weapons with higher hit rates was simulated to reduce inequality of SQF tactics. This work involved modeling data based on specific characteristics of a stop. If a borough decided to adopt such a decision procedure model, a visualization like the RShiny SQF dashboard could both monitor the progress of such a behavior change, and then evaluate changes in outcomes (I would not call them "impacts" unless the model incorporated causal inference techniques). If one borough or precinct was found to have implemented another such intervention uniformly at a specific time in the history of SQF, activity in a borough or precinct of similar characteristics could be used for a difference in difference. Difference in difference studies over the threshold constitutional ruling could also be used assess impacts, not just on the regulations put into place about requirements of suspicion for SQF to take place, but further implications for other outcomes, such as found contraband. These are examples of research questions that could be inspired by the trends illustrated by RShiny.

This RShiny SQF Dashboard could also be useful for direct observation of data by a variety of stakeholders. Precinct chiefs, corrections agencies, civil rights organizations, journalists, or other public servants or member of civil society could use such a dashboard to generate analyses, report to the public, intervene meaningfully in day to day operations, or strategize on course corrections or new initiatives for the future. At smaller geographic levels, the map size can either be made specific to the precinct, for example, or maintain displays for all New York City and serve as a comparison. Dashboards like this could be further integrated with crime data to test theories. In industry, CEO's use API linked data dashboards for strategic innovation, middle managers use them for accountability at various levels of command, and financial journalist technologists like Bloomberg use them to generate news content. Such dashboards could be put in place, if they are not already, within NYPD and New York City government, and serve as automatic reporting for others with vested interests in policing policies like SQF. Data dashboards like RShiny SQF can be used for monitoring, implementation, strategy and evaluation for both routine operations and strategic assessment of policing activity.

Another future use of such an RShiny SQF Dashboard is for transparency and automation of reporting more broadly. Visualizations, while capable of hiding many assumptions within their data management processes, also have the power to make trends widely understandable. Because RShiny can be shared with code alongside it, is open source and free to any user or server system, and can easily be placed online and made to automatically scrape data from the public databases that feed it, it offers a method of transparent dissemination of data to the public. Dashboards for SQF data that combine information from other relevant datasets, including the Census data used in this dashboard, have the opportunity to integrate with other public datasets such as health, crime, and geographic datasets showing low income housing and public park data. These far reaching contextual determinants could be overlaid in interesting ways. RShiny SQF Dashboards and others made by open source software that link easily to API's such as Census and can render on html provide unique opportunities for public consumption.

Primarily, I have used the dashboard generated trends to explore associations in the data and generate hypotheses for further research. In particular, I focused on differences in "hit rates" of found weapons by racial/ethnic discrepancies over time as the basis of logistic regression modeling questions. Further questions could examine covariate factors such as suspected crime, suspect characteristics, geographic location, or incidence of specific NYPD operations. Specific to this project's next steps, and in particular with regards to the logistic regression model I have incorporated into the dashboard, adding interactive features with which users can select predictors to include in the model would be useful. Following feedback from the presentation, log-transforming the Y axis of the predictive probability plot would provide additional insights on how and at what point in time ethnic group trends diverge.

References

Goel, Sharad, Justin M. Rao, and Ravi Shroff. "Precinct or prejudice? Understanding racial disparities in New York City's stop-and-frisk policy." The Annals of Applied Statistics 10, no. 1 (2016): 365-394.

Stop and Frisk. https://en.wikipedia.org/wiki/Stop-and-frisk_in_New_York_City

"The Real History of Stop-and-Frisk ". NY Daily News. Ed. Ernie Naspretto. 3 June 2012. Web. 06 May 2014.

New York City Police Precinct and Census Data https://johnkeefe.net/nyc-police-precinct-and-census-data

"Stop, Question and Frisk in New York Neighborhoods." The New York Times. 11 July 2010. https://archive.nytimes.com/www.nytimes.com/interactive/2010/07/11/nyregion/20100711-stop-and-frisk.html?ref=newyorkcitypolicedepartment.

Appendix

Table 1: Logistic regression result

term	estimate	std.error	statistic	p.value
(Intercept)	-2.8269526	0.2545900	-11.1039426	0.0000000
suspect.age	0.0216363	0.0009722	22.2546692	0.0000000
suspect.height	0.0404861	0.0471230	0.8591572	0.3902538
suspect.weight	0.0014748	0.0004644	3.1758251	0.0014941
suspect.buildmedium	-0.1867395	0.0406768	-4.5908149	0.0000044
suspect.buildmuscular	0.3969835	0.1132355	3.5058220	0.0004552
suspect.buildthin	-0.0816102	0.0462582	-1.7642306	0.0776932
suspect.buildunknown	-0.2202334	0.1113126	-1.9785118	0.0478710
suspect.sexmale	0.0529179	0.0584250	0.9057404	0.3650733
suspect.sexunknown	-0.7107538	0.1660068	-4.2814737	0.0000186
year.f2013	0.3347534	0.0682226	4.9067840	0.0000009
year.f2014	0.5356125	0.1015018	5.2768763	0.0000001
year.f2015	0.3000535	0.1355283	2.2139551	0.0268319
year.f2016	0.6290143	0.1620244	3.8822189	0.0001035
suspect.raceblack	-1.7586625	0.0453441	-38.7847796	0.0000000
suspect.raceasian	-0.8233429	0.1041905	-7.9022868	0.0000000
suspect.racehispanic	-1.2840410	0.0472377	-27.1825668	0.0000000
suspect.racenative.american	-1.0425824	0.2688576	-3.8778238	0.0001054
suspect.raceother	-1.8207184	0.1647713	-11.0499702	0.0000000
suspect.raceunknown	-1.5551439	0.1906134	-8.1586284	0.0000000
year.f2013:suspect.raceblack	0.1644586	0.0771691	2.1311450	0.0330772
year.f2014:suspect.raceblack	0.3433942	0.1142541	3.0055309	0.0026512
year.f2015:suspect.raceblack	1.0154989	0.1472063	6.8984737	0.0000000
year.f2016:suspect.raceblack	0.8433482	0.1778807	4.7410897	0.0000021
year.f2013:suspect.raceasian	0.2932896	0.1630927	1.7983003	0.0721294
year.f2014:suspect.raceasian	0.2361603	0.2364446	0.9987977	0.3178927
year.f2015:suspect.raceasian	0.7306407	0.2660505	2.7462486	0.0060281
year.f2016:suspect.raceasian	0.5375032	0.2992066	1.7964281	0.0724265
year.f2013:suspect.racehispanic	0.1847952	0.0811991	2.2758280	0.0228563
year.f2014:suspect.racehispanic	0.4987754	0.1195500	4.1721080	0.0000302
year.f2015:suspect.racehispanic	1.0681385	0.1543267	6.9212819	0.0000000
year.f2013:suspect.racenative.american	-0.9273607	0.5778101	-1.6049577	0.1085031
year.f2014:suspect.racenative.american	0.7187963	0.5702479	1.2604980	0.2074898
year.f2015:suspect.racenative.american	-8.9897382	52.4388224	-0.1714329	0.8638834
year.f2016:suspect.racenative.american	0.3339733	1.1301926	0.2955013	0.7676110
year.f2013:suspect.raceother	0.3364246	0.2622915	1.2826363	0.1996195
year.f2014:suspect.raceother	0.4080108	0.3618190	1.1276656	0.2594612
year.f2015:suspect.raceother	1.4576479	0.4513389	3.2296080	0.0012396
year.f2016:suspect.raceother	1.2075665	0.5804751	2.0803070	0.0374974
year.f2013:suspect.raceunknown	0.3512130	0.3328706	1.0551038	0.2913779
year.f2014:suspect.raceunknown	0.2294031	0.5109415	0.4489812	0.6534452
year.f2015:suspect.raceunknown	0.8374564	0.5773342	1.4505574	0.1469031
year.f2016:suspect.raceunknown	1.0134350	0.6072682	1.6688423	0.0951486