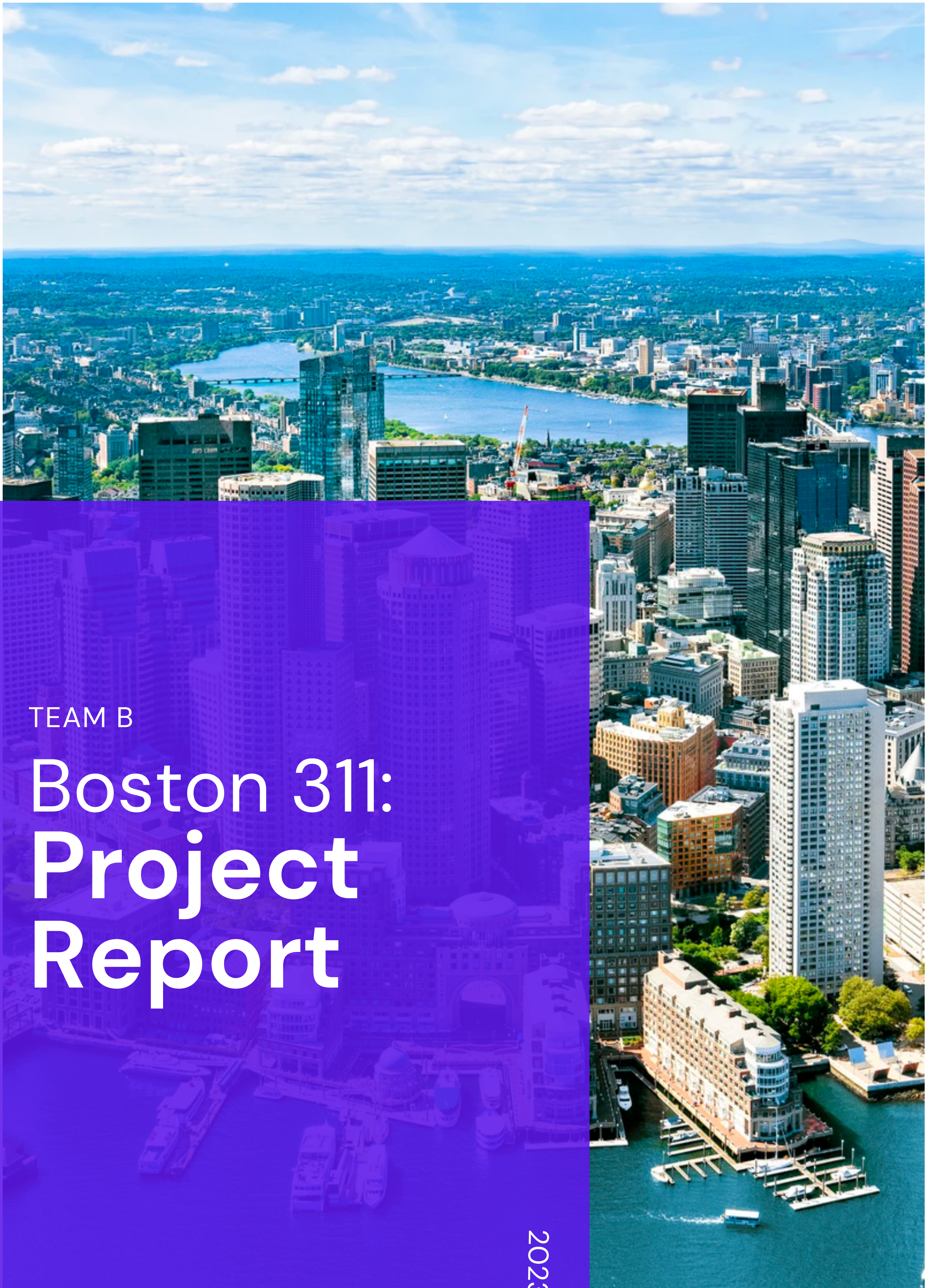

TEAM B

Boston 311: **Project Report**

2023

Boston 311 - Team B
BU Spark | CS 506
12/09/2023

Final Project Report

Team B: Rishi Shah, Ivanna Morales-Roman, Mark Maci, Arianit Balidemaj, Richard Buehling

I. Problem Statement, Data Collection and Cleaning

The 311 service connects users with constituent service representatives to solve non-emergency requests in Boston. We are using the data collected by the city of Boston from 2011-2023 to analyze how the service is being used and by who. The goal is to produce a comprehensive dashboard that reflects an annualized summary of the service's performance in terms of how requests are handled, who is making requests and how those requests are made, as well as if there are any disparities in service by region or population.

We have done some initial high-level analysis to answer the following base questions: What is the total volume of requests per year, or how many 311 requests is the city receiving per year? Which service requests are most common for the city overall and by neighborhood and how is this changing year over year by subject (department), reason_queue? How is the case volume changing by submission channel source? What is the average # of daily contacts by year? Volume of top 5 request types (type) Average goal resolution time by queue Average goal resolution time by QUEUE and neighborhood What % of service requests are closed vs. no data vs. unresolved?

For the data collection of 311 Boston cases, the data was collected by the city of Boston and we did not have to search for the data or collect the data in any sort. Importing the data and ensuring that the most up to date information is available to us, we created a script to pull the information from the 311 Boston website using the CKAN API made available to us. This ensures that the most up to date information is used when analyzing these reports.

For the cleaning of the data, we decided that for each base question, cleaning would be better on a case by case basis, fitting exactly towards the needs of the base question. We felt that this approach would be more effective because it does not run the risk that one question would have the necessary data available to it and not the other so by keeping the cleaning based on each question, it helps to keep accuracy in what we are concluding. Some aspects of data cleaning we have done are removing NA values when needed based on the question or sorting and arranging the data such that only columns required are used. Aggregating some of the data points into certain groups has also been another data cleaning/sorting method used to help us break down each data point and get certain plots that help go in depth with the base questions asked.

Our data collection method ensures that the most up to date data sources are used and the cleaning method for each question allows for optimal data quality when used for analyzing purposes.

II. Exploratory Data Analysis

For the initial exploratory data analysis, Arianit created a function to describe the columns in the dataset. We used this to extract the number of null and non-null values in each column, as well as the number of unique values. This helped to better understand the structure of the dataset and to get a sense of what kinds of analyses could be done for each section. We also individually did some surface level analysis to determine general patterns relevant to the base questions we were answering, such as determining outliers, and disparities in the data if any.

Understanding the data structures of each column was very important for us to understand because it gave us a deeper understanding of how to approach this data and what routes we as a group can take to analyze each aspect of the dataset. We did not feel that going blindly into this dataset would have been the best bet because we could end up with many type errors and false understanding of the data. Being able to take apart each column of the dataset also helped us realize how certain columns were related to each other. This would be useful in our answers to the base questions for the project. Certain columns only had a set amount of variability in answers so it also helped us understand the restrictions that certain columns had as well.

For data regarding resolution times by QUEUE, it was important to do some visualizations of general trends given that there are 181 unique values within the QUEUE column. Figure 1.1 depicts the imbalance in resolution times by QUEUE; while the highest 20 times lie in the 5000-3500 hour range, the lowest 20 times lie in the 0-50 hour range. This helped us decide how to best approach the question of average resolution time by QUEUE and by QUEUE and neighborhood.

It was also useful to graph the number of requests submitted for each neighborhood in the dataset since imbalances in data for each neighborhood could impact patterns in our subsequent analysis. As shown on Figure 1.2, the number of requests vary greatly by neighborhood. This is important because the amount of data available for each neighborhood needs to be considered when conducting further data analysis, especially for the geographical base questions.

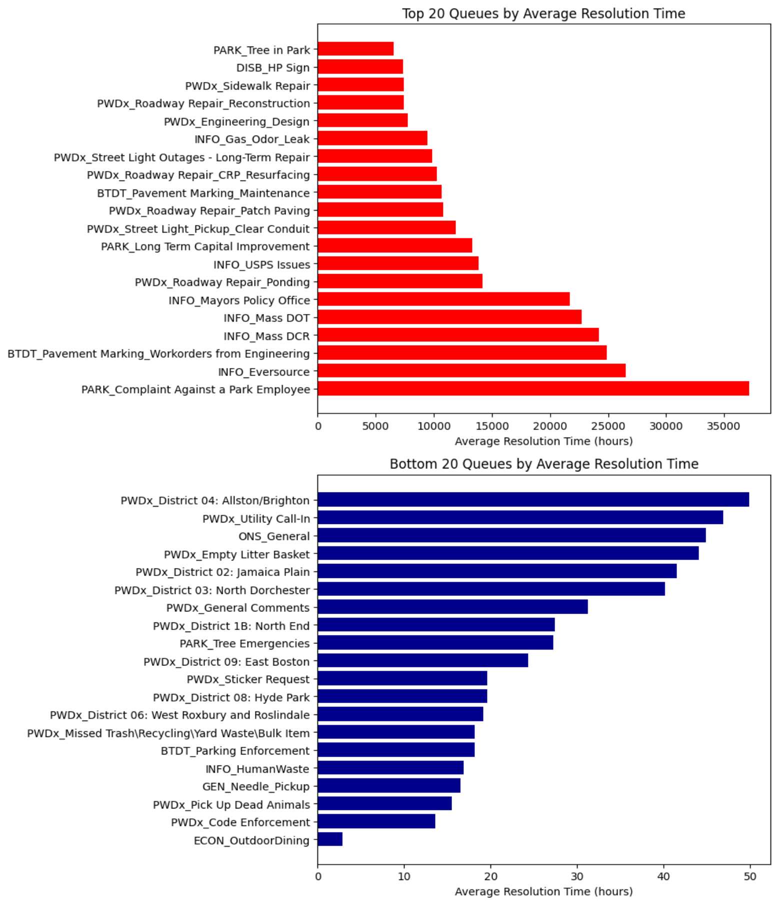

Figure 1.1 Graph of the average resolution time in hours for the queues with the 20 highest and 20 lowest times, not annualized.

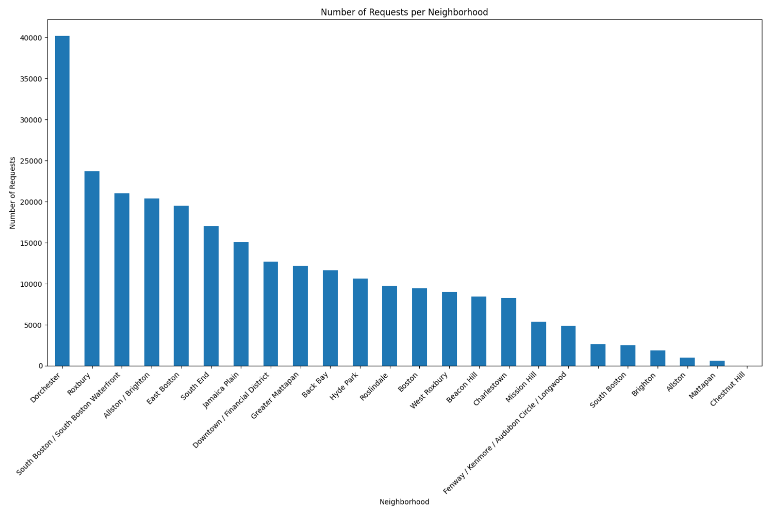

Figure 1.2 Graph of the number of requests of all time submitted for each neighborhood.

III. Visualizations and Methodologies

When examining the most common 311 requests for the city, parking enforcement is by far the most prominent reason to use the hotline, being nearly double the next highest call-reason, which is street cleaning. After these top 2, the request reasons follow a long tail distribution as expected. Figure 2.1, shown below, is for the entire lifespan of the 311 dataset (2011 - now).

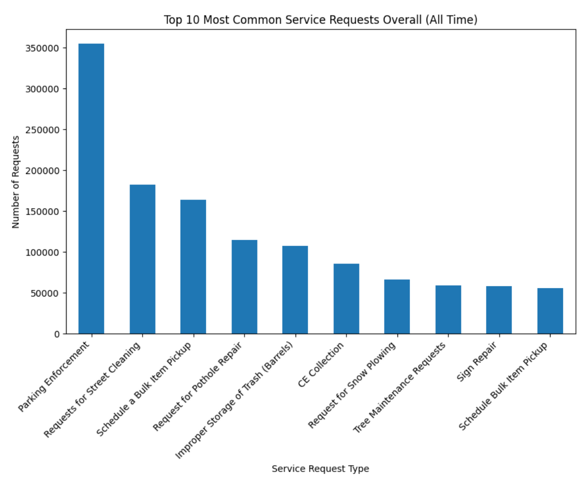

Figure 2.1 Graph of the 10 most common service requests of all time.

Boston 311 - Team B
BU Spark | CS 506
12/09/2023

<u>Which service requests are most common for the city overall AND by NEIGHBORHOOD and how is this changing year over year by SUBJECT (department), REASON,QUEUE?</u>

Examining the top request reasons by neighborhood reveals some stark differences in how often 311 is used by different parts of the city, and for which reasons. To illustrate these disparities, we compiled the top 5 request issues for various 3 neighborhood combinations and looked for patterns among requests, as seen in Figure 2.2. Just by sheer number of requests, it is abundantly clear that 311 is not used in Chestnut Hill as it is in Roxbury and Dorchester, nor is it used for similar reasons. Over the past decade, the latter 2 neighborhoods have requested totals in the tens of thousands, with Chestnut hill not even having a reason that scratches 30.

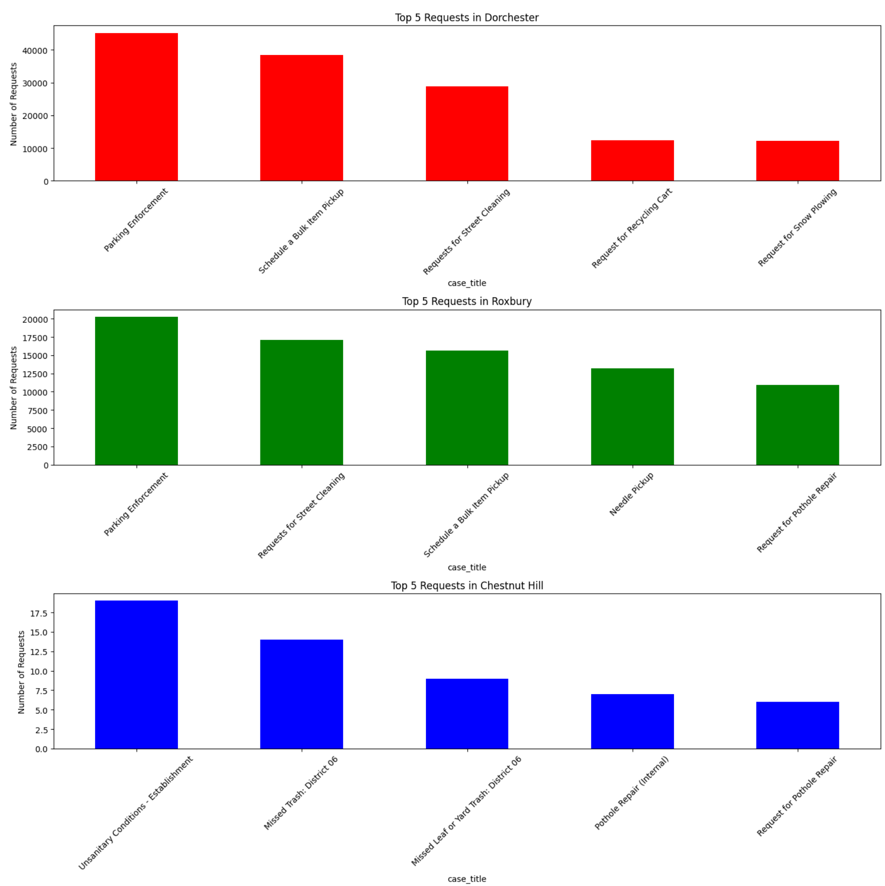

Figure 2.2 The graphs show the top 5 most common requests by neighborhood for Dorchester, Roxbury and Chestnut Hill.

For instance, the types of requests prevalent in Chestnut Hill—unsanitary conditions, missed trash collection, and leaf pickup—contrast sharply with those in Dorchester and Roxbury, where street cleaning, parking enforcement, needle pickup, and snow plowing are prevalent. This distinction not only highlights varying neighborhood priorities but also underscores deeper socio-economic differences. A higher standard of living indicates a lower bar for calling 311, should you ever have to.

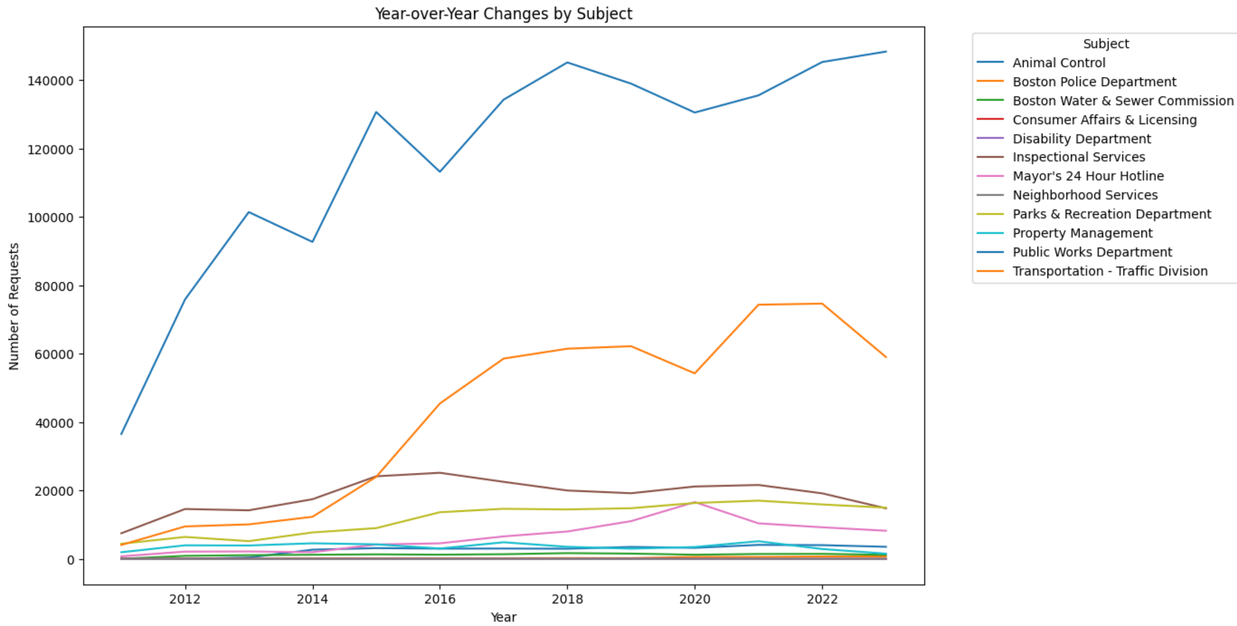

Figure 2.3 The graph the year over year changes by subject for number requests of such subjects.

Over the course of the 311 data's lifespan, the subject of requests (the entity or service called upon to help the caller) has 2 YoY significantly increasing parties, being Animal Control and BUPD. When examining the YoY changes by reason, Enforcement and Abandoned Vehicles experiences a volatile increase from 2015 to 2021, ending currently as the most prominent reason for 311 calls. For queue, Parking and Code Enforcement experience a similar increase in this 2015-2017 time-frame, peaking during COVID. The supplementary graphs for YoY changes by queue and reason can be found in the project repository's notebooks.

<u>What is the total volume of requests per year, or how many 311 requests is the city receiving per year?</u>

For the total volume of requests per year, it was simply shown to be the total count of cases reported and through using pandas functions, we were able to get that amount of requests cases for the years. Figure 2.4 shows the number of requests per year reported by the analysis done by us.

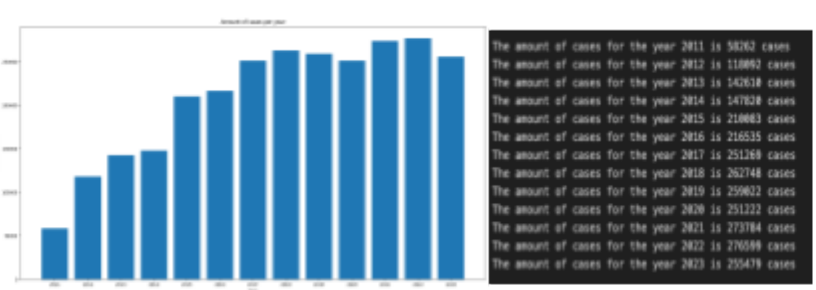

Figure 2.4: Reported # cases per year

Boston 311 - Team B
BU Spark | CS 506
12/09/2023

<u>What % of service requests are closed (CLOSED_DT or CASE_STATUS) vs. no data (CASE_STATUS = null) vs. unresolved (CASE_STATUS = open)?</u>

The percent of service requests that were closed was around 92.74% and the percent of requests that were still open/unresolved was around 7.26% and finally the amount of null case status requests was 0%. This was for all the requests from 2011-2023. Going further into the analysis it was important to understand what percentage of cases remained open and closed per year so we took it one step further and showed the proportion per year for the open vs closed vs null case status (Figure 2.5). We can see that the percentage of closed cases each year goes up some years and down the other years. This could be due to varying types of cases being unable to close like in other years and thus could be a possible explanation for it.

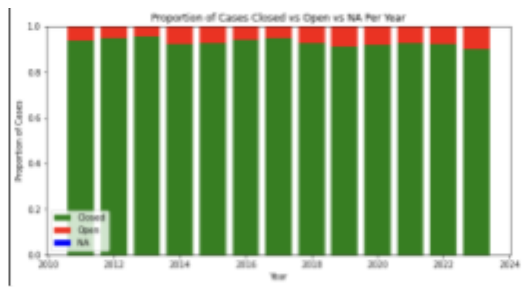

Figure 2.5: Proportion of cases closed vs open vs null per year

<u>What is the average goal resolution time by QUEUE , as well as by both QUEUE and neighborhood?</u>

We also looked at the average resolution times by QUEUE and by neighborhood to get a sense of how cases are handled in terms of time efficiency. When considering the average resolution time for the most common QUEUEs of each year, there is a decreasing trend in average resolution time after the year 2020, as well as a peak in 2017. This trend is also visible, as seen on Figure 2.6, when considering the average resolution times for the most common QUEUEs in the 5 neighborhoods with the most requests submitted.

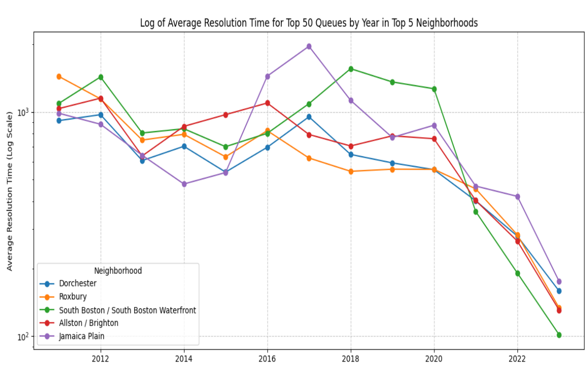

Figure 2.6

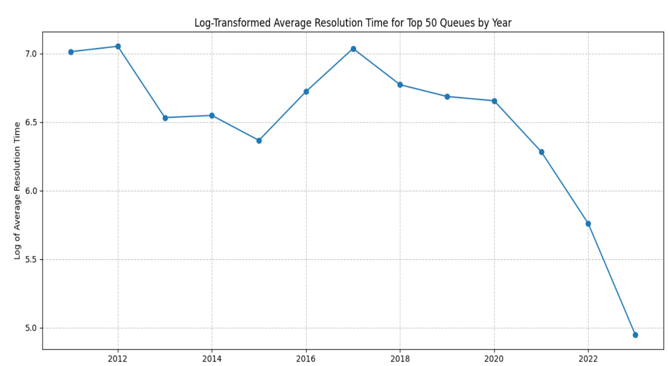

Figure 2.7

<u>What is the average # of daily contacts by year?</u>

Analyzing Boston's 311 average daily contacts per year reveals interesting insights. Initially, there's a noticeable upward trend in average daily contacts, potentially reflecting a growing population or increased service awareness. However, fluctuations are evident, possibly due to city policy changes or infrastructure improvements. Additionally, linear regression predicts a continued rise in contacts, though this assumes a consistent pattern, not accounting for unexpected societal or technological shifts.

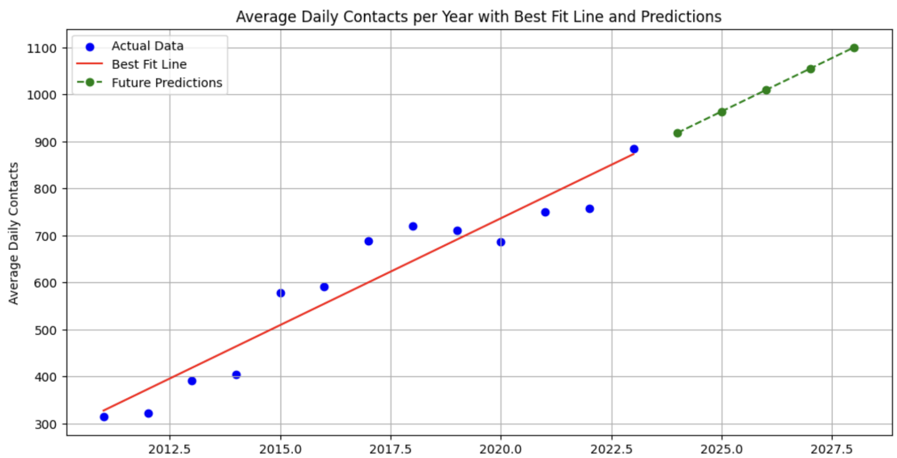

Figure 2.8 Graph of the average daily contacts by year, including predictions for years 2024-2027 using linear regression.

Top 5 request types:

Analyzing the top 5 request types for Boston's 311 calls displays a clear hierarchy in the volume of different service requests. Parking Enforcement leads significantly, suggesting either a high level of enforcement activity or a prevalent issue with parking violations. This is followed by Requests for Street Cleaning, indicating a prioritization of cleanliness in public spaces. Schedule a Bulk Item Pickup and Request for Pothole Repair represent other common concerns, pointing to active civic engagement in maintaining the cleanliness and infrastructure of the area.

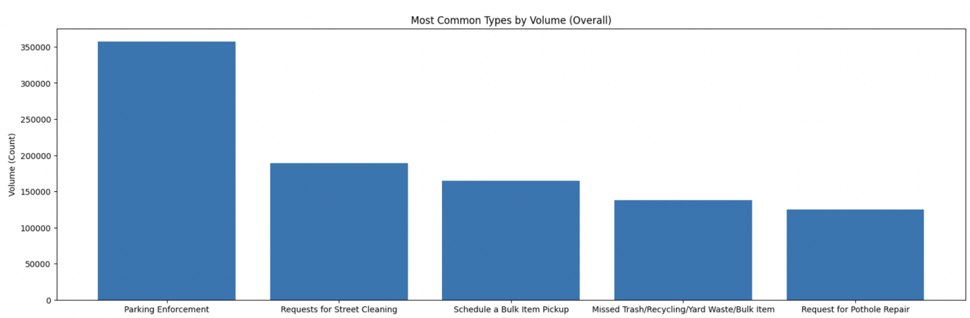

Figure 2.9 Graph of the top 5 request types, across all years.

<u>How is the case volume changing by submission channel SOURCE?</u>

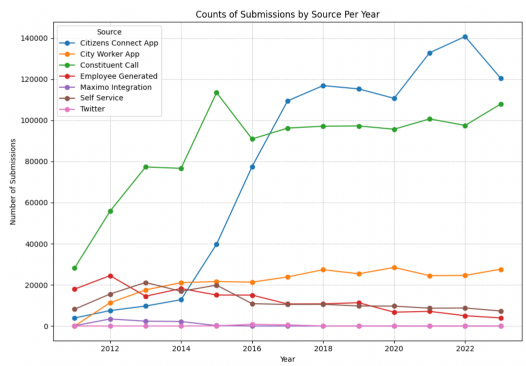

Figure 2.10 - Submission source by year

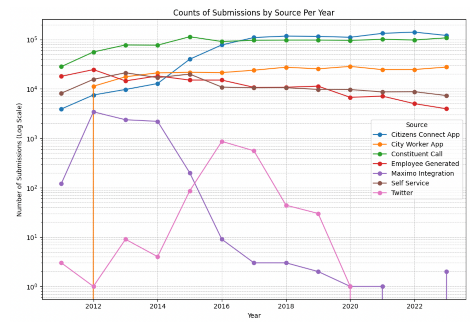

Figure 2.11 - Submission source by year (different view)

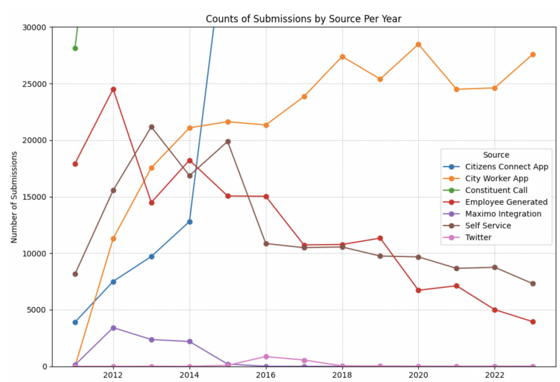

Figure 2.12 - Submission source by year (different view)

When analyzing trends in submission sources, Figure 2.9 clearly indicates that the Citizens Connect App has experienced the most robust growth in submission counts compared to other channels. Notably, it has surpassed Constituent Calls, becoming the predominant source of submissions in recent years. This trend is reflective of a broader shift towards digital platforms for civic engagement. Figure 2.10 reveals a net decline in submissions through Twitter and Maximo Integration, despite observing significant spikes in usage — Twitter between 2014 and

2016, and Maximo Integration between 2012 and 2014. However, both channels have seen a steep fall in popularity, with their submission counts nearly dwindling to zero in recent times. This pattern suggests that these channels might be becoming obsolete or have been systematically phased out. Additionally, Figure 2.12 presents a discernible decrease in employee-generated and self-serviced submissions. Conversely, there is a notable uptick in the utilization of the City Worker App. This data supports the inference that Boston's residents are increasingly reliant on app-based platforms for lodging reports. Collectively, this analysis not only underscores a notable shift in the modalities through which civic issues are reported, but also highlights a possible growing tendency among the community to engage in reporting via 311 services independently. The diminishing employee-generated reports further reinforces this trend. These trends can be visualized in the animation in Figure 2.13.

The analysis highlights a need for the city's infrastructure to adapt to increasing demands, suggesting a boost in resources or more efficient systems. It is crucial to remember that these predictions, based on past data, don't consider variables like seasonality or unforeseen events, which could significantly alter future trends. Further investigation into the causes behind these trends is necessary for targeted improvements. Overall, the data suggests a growing reliance on Boston's 311 services, calling for proactive planning to maintain effectiveness and efficiency.

IV. Extension Analysis

We have done some preliminary research into the rate of closure for 311 requests across various geographical bounds within the city. This extension path for the project aims to answer the question of “if I call 311 in my location, what is my rate of service relative to everyone else?” In order to extract patterns that could help provide answers to the aforementioned, we cross analyzed the 311 dataset with neighborhood, precinct, and zip code geoJSON data. This also comes straight from the city of Boston and was used to create folium heatmaps for TTC (time-to-close) for cases across these city lines (controlling for request reason).

In regards to the technical aspects of mapping, we use Python and the Folium library to merge the city's 311 service request data with geoJSON files representing precincts, neighborhoods, and zip codes. Our code calculates average service closure times for each precinct and visualizes these on a map, using color intensity to indicate variations in service rates. The map is interactive, with tooltips providing details like district names and average closure times, allowing for an easy understanding of the spatial distribution and efficiency of public services across the city.

By visualizing the 311 geographical data according to various city bounds, we can better convey the differences in service among regions, and identify where certain public resources can be deployed to make the largest impact in TTC. Moreover, the heatmaps for various call reasons can be overlaid to get an aggregated picture of 311 service variance based on location. This process of cross-analyzing the original dataset with other socio-economic indicators could be applied to various methodologies. We could look at how this map overlays with social vulnerability, income-per-household, crime, food deserts, or any other metric that is used to obtain an idea of a communities prosperity/lack thereof.

Therefore for the extension project we are going to answer in depth which requests are most common for census tracts defined as high social vulnerability based on the city's social vulnerability index while also exploring what patterns/ differences do you see between the 311 requests and service by high vulnerability groups vs. the rest of Boston? Being able to explore both of these questions is crucial in helping the city of Boston which areas need more designated help allocated towards it, whether it is financially or with other services.

It's important to explore these extension projects because of how in depth we are able to go into this portion of the data and report conclusions that are even more definitive and support not only the city but the communities as a whole. 311 service hotline data can be mutated to find better relationships and trends that are not seen with simple analysis. Visual representations are also a key aspect in how a person can understand and interpret the 311 cases data.

V. Visualization and Insights for Extension

The following are figures from the early stages in our extension research with folium maps and cross analyzing 311 calls with geoJSON data for city lines via neighborhood, precinct, and zip-code (maps follow that order).

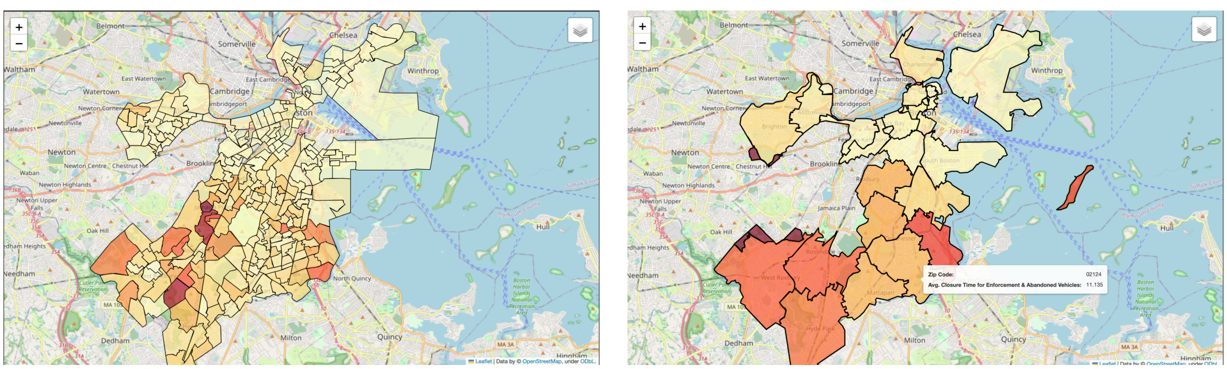

Figure 3.1 - Average Closure Time for Boston Neighborhoods

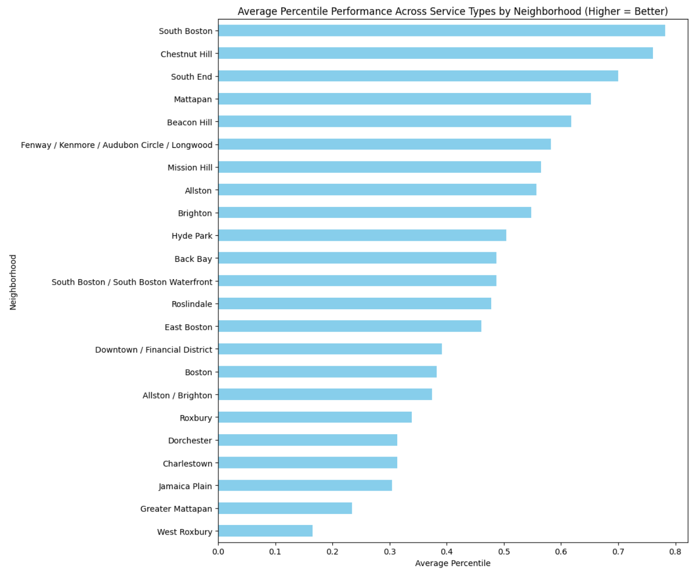

Figure 3.2 - 311 Percentile Performance for Boston Neighborhoods

After analyzing the data, we can see distinguishable patterns in the closure time of the same type of service request across different geographic areas. Certain precincts of Roxbury, West Roxbury, and Jamaica Plain, especially precincts 19-08, 19-09 and 19-10 have much higher closure times for service requests relating to abandoned vehicles and sanitation. These types of disparities can be noticed in many regions and call reasons by layering the maps of service call types. This reflects what we see in the aggregated (all 5 reasons) analysis where these three neighborhoods rank among the bottom 6 in service percentiles. A hypothesis for why abandoned cars and trash are not being picked up in these at rates of other neighborhoods is that these neighborhoods are less affluent with public services already spread thin.

Conversely, in the case of code enforcement, closure time varies much less across neighborhoods. This is likely because code enforcement is a more serious issue that is not as dependent on the resources of the neighborhood. An officer/public servant is most likely dispatched to these calls ASAP, while sanitation and abandoned vehicles are less of a priority, especially in marginalized neighborhoods, regions, and zip codes. Sanitation map layers also show that the City of Boston is very keen on keeping its most tourist-heavy areas clean, as the precincts of Boston Common, the North End, and Fenway have the lowest closure times for sanitation calls. As you get further from these areas, closure time typically increases.

While not a perfect picture of the city, these layered maps and subsequent aggregated graphs illustrate some overarching disparities between certain regions within Boston, as well as the city's priorities in terms of public services.

Boston 311 - Team B
BU Spark | CS 506
12/09/2023

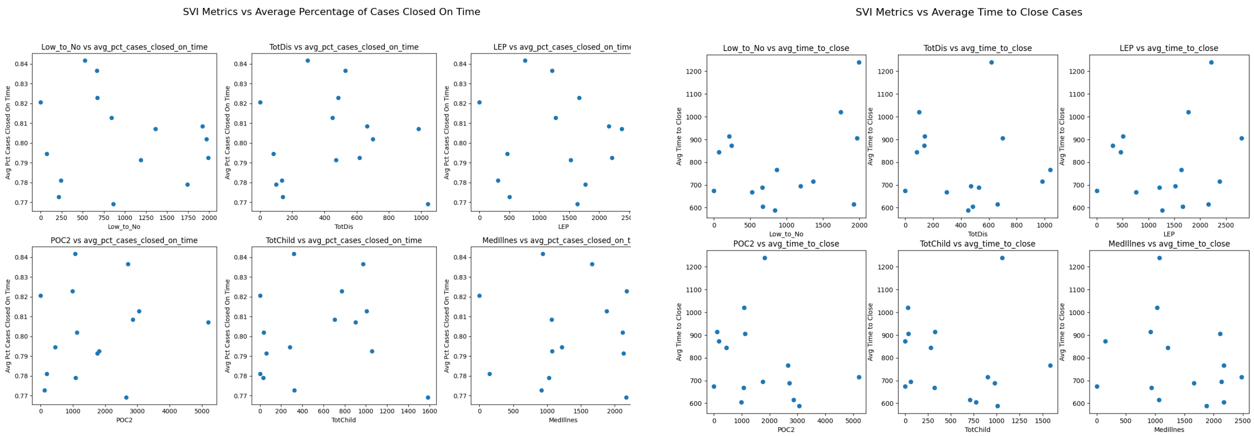

Figure 3.2 - SVI Metrics vs 311 Case Closure/Response Time

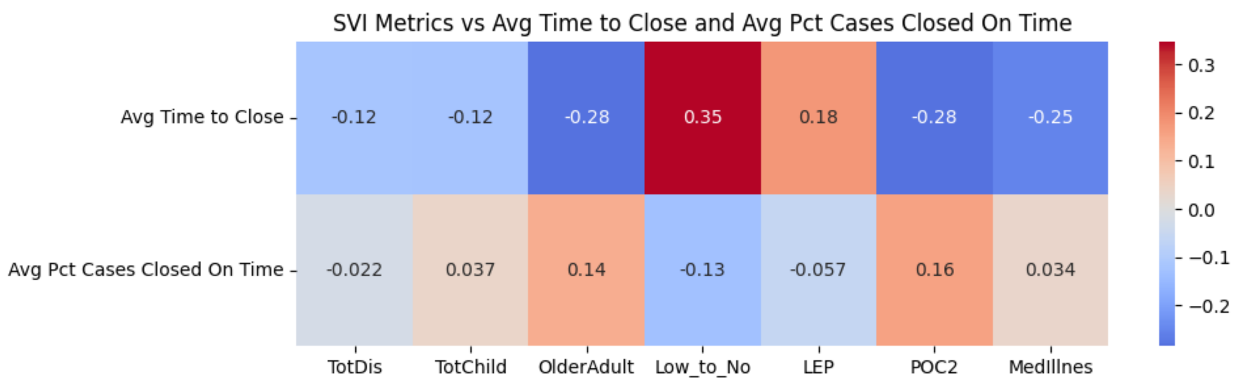

Figure 3.3 - Correlatory Heatmap of SVI Metrics vs 311 Case Closure/Response Time

Plotting SVI metrics vs on-time closure frequency and average response time reveals more insight. Figure 3.2 reveals a few notable conclusions. First, the on-time closure percentage decreases as the number of low income residents increases. Consistent with this observation is the average time to close a service case increases and closing time percentage decreases as the population size of low english proficient individuals increases. Interestingly the population of children increases, the average time to close decreases and the on-time closure percentage increases. Another insightful observation is that higher populations of people of color and people with mental illness are correlated with improved outcomes for 311 services.

These conclusions are reinforced in Figure 3.3 where we can see that older populations, people of color and people with medical illness are all marked with a negative correlation coefficient of over -0.25 for time to close. We also see that low to no income populations have the largest positive correlation coefficient among all the metrics. This analysis suggests that low income communities are experiencing disproportionally slower closure times, such that there are inequities by SVI in the city of Boston, which should be addressed further.

In order to examine the interactions of SVI and 311 performance, we performed PCA on the SVI metrics and 311 performance, reducing our dimensionality to 2 principal components. Then, k-means clustering was performed on the resulting principal components plot (k=3) (Figure 3.4).

Figure 3.4 - PCA on SVI and 311 Performance

The clustering reveals interesting insights from our unsupervised analysis. Typically lower-income neighborhoods, such as West Roxbury, Hyde Park, and Mattapan are clustered in the same region, and more affluent neighborhoods such as Back Bay and Allston are clustered in a different region. In conjunction with the correlatory analysis and the discussion of 311 percentile performance, this reinforces earlier conclusions that neighborhoods of Boston that are more socially vulnerable are also receiving lower quality 311 services.

VI. Limitations and Challenges

The dataset may have inherent limitations in capturing the full spectrum of service needs, as it likely reflects only those issues that are formally reported. Our analysis also assumes that the service request data accurately reflects the true nature and frequency of neighborhood issues, which may not account for unreported or misclassified requests. Furthermore, temporal variations in service requests, influenced by factors such as seasonal changes or specific local events, might skew the understanding of long-term trends or needs (take snow plowing for example). Lastly, the analysis assumes a consistent classification and handling of service requests across neighborhoods, which may not always be the case.

Some challenges faced throughout the project was being able to get the proper API keys for the script to pull the data from the website. This was because the 311 dataset is such a large dataset and it was not easy to go through and grab every single data point. Eventually we were able to find the keys corresponding to each year and then created a script that takes around 3 hours to pull data from the 311 website. Another script was created to overcome the limitation that the current 2023 date is different from the future 2023 date so there could be more cases added to the dataset. That script only updates the 2023 dataset making it better in keeping current information.

Another challenge that was faced was the visualization of our complex questions and managing our messaging. The questions that we explored often were in-depth and hard to visualize. We spent a lot of time in our reports and our presentations finding ways to streamline our visualization and messaging.

A possible limitation affecting our cross-examination of TTC (Time to Close) and geographical bounds via geoJSON data is the inherent variance and outlier skewing potential of certain regions. For instance, affluent areas like Chestnut Hill might have fewer service requests but with higher efficiency, leading to a skewed perception of overall service quality. Conversely, in more densely populated and economically challenged areas like Roxbury, a higher volume of requests with varied resolution times could mask systemic inefficiencies or specific challenges faced by such neighborhoods. This contrast in service dynamics between different areas highlights the need for careful interpretation of data to avoid misleading conclusions about service distribution and efficiency across the city.

VII. Conclusion

This data-driven analysis has provided valuable insights into the usage and performance of Boston's 311 service system. Through reasoned data collection, cleaning, exploratory analysis, and cross examination, our team has successfully addressed several key questions regarding the volume and nature of 311 requests, the disparities across the city's demographics, evolving trends in submission channels, and more.

The project's findings reveal significant variations in the types of requests and service efficiency across neighborhoods, highlighting underlying socio-economic disparities. The analysis of service request data from 2011 to 2023 has shown that issues like parking enforcement and street cleaning dominate city-wide, but neighborhoods like Chestnut Hill, Roxbury, and Dorchester exhibit distinct patterns in their service needs regarding these request reasons. Conversely, neighborhoods such as Chestnut Hill and Beacon Hill have much quicker service times and call 311 for less severe reasons. This disparity not only reflects the diverse challenges faced by different neighborhoods but also underscores the necessity for tailored city services.

Moreover, the shift towards digital platforms, particularly the Citizens Connect App, as the primary mode of service request submissions, indicates a broader trend in civic engagement. This digital transition, while enhancing accessibility, also poses challenges for equitable service delivery, especially in communities with limited digital access.

Our team's extension proposal involving the crossanalyzing of geoJSON data from the city's geographic bounds, and Social Vulnerability Index data allowed us to better understand and illustrate these aforementioned insights from the nature of 311 calls depending on who, where, and why of the calling party. Through interactive maps and plots generated by this analysis, city leaders could make more informed decisions regarding where Boston's public resources should be going in efforts to reach a state where every citizen, regardless of location or predisposed factors, receives proper service.

In conclusion, this project has not only provided a detailed analysis of Boston's 311 service system but also laid the groundwork for future research and policy-making. The insights gained from this study can assist city administrators in identifying areas that require focused attention and in developing strategies to ensure equitable access to city services. As urban populations continue to grow and diversify, such data-driven approaches will be crucial in addressing the complex challenges of urban management and in promoting inclusive and sustainable city living.

VIII. Individual Contributions

Arianit: I worked on answering my portion of the base questions to the best of my ability and furthering the analysis with test ideas for the extension projects and aiding with the coding and file structure of the github repository. I also ensured that all deliverables were submitted with everything that would be necessary for project completion. Helped with the creation of the slides for presentation and the creation of the report and its figures on it as well. Used many types of libraries to help break down the 311 data to its elementary parts for extensive analysis. Created the python scripts for the API calls to the 311 website so that the most updated data is available with the use of a script.

Rishi: I first created a bash script to easily download all our data for the 311 project. I also worked on answering the base question about 311 submission source through plotting submission counts by time and visualizing the relationships with line graphs and an animated bar chart. I also conducted preliminary correlation analysis through creating scatter plots and multidimensional unsupervised analysis by PCA and k-means clustering to create an interactive plot for the extension project. As with every team member, I helped with preparing the slides for the deliverables and producing the final report.

Ivanna: I did some exploratory data analysis concerning the average resolution times and submission counts for the QUEUEs in the dataset to reveal any imbalances, as well as some visualizations of the count of submissions in the dataset for each neighborhood. This helped to figure out some of the limitations in the nature of the data like which neighborhoods and job requests were underrepresented in the dataset. I then explored the base questions regarding average resolution times both by QUEUE and by QUEUE and neighborhood. I used the Pandas and Matplot libraries to conduct the analysis and create some visualizations of the trends present regarding this question. For the extension portion, I worked on determining correlations between the SVI metrics and rate of closure/closure times. I used the seaborn library to create a correlation matrix of these relationships.

Mark: I first went about answering my base question by getting a grasp of which parts of the dataset will need to be preprocessed and analyzed. Since my question involved the commonality of service requests, I created a top 10 of 311 call reasons since 2011. I also examined how call quantities varied across neighborhoods, with certain examples serving as dichotomous for how 311 is used i.e. Chestnut Hill and Roxbury. The latter part of the base question involved how the subject of calls is changing year-over-year, so I generated a line graph to illustrate its evolution. I then moved on to the extension project, where I messed around with folium and geoJSON data to create the maps above and get some insights on how the geography of 311 calls overlaid with the city's various borders can illustrate what a user's experience is like when using the hotline.

Richard: I explored my base questions of the top 5 request types per year and drew some conclusions on trends in those request volumes. Additionally, I also explored the base question about average daily contacts and drew some conclusions as seen in the report. Also, I used linear regression techniques to predict the rate of increase for the contacts and what an increased contact volume will mean for The City of Boston. I also explored the base question that investigates top 5 request types; adding my graph and analysis as well. Lastly, I helped format the report and also helped out with the design of the slides for the presentations.