Final Project: Initial Analysis Report

ALY6015- Intermediate Analytics

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Introduction

Boston’s 311 service request system serves as a vital channel for residents to report non-emergency issues directly to municipal authorities. These issues range from potholes and broken streetlights to sanitation complaints and graffiti removal. By logging and tracking these requests, the city not only maintains accountability but also gains a transparent view of community needs and operational efficiency.

This project focuses on analyzing five years of 311 service request data from 2015 to 2019, with the goal of uncovering patterns related to service delivery, neighborhood disparities, and potential inefficiencies in response times. Through this analysis, we seek to understand how well the city meets service expectations across different communities and departments, and whether systemic delays or inequities exist in how quickly or consistently issues are resolved.

Utilizing a combination of feature engineering, subgroup analysis, regression modeling, and machine learning techniques covered in our course, this project transforms raw civic data into actionable insights. By dissecting trends over time, between neighborhoods, and across departments, we aim to support more equitable, responsive, and data-driven public service delivery in Boston.

Dataset Description

The dataset employed in this project is the Boston 311 Service Requests Dataset**,** which contains detailed records of non-emergency service requests submitted by residents of Boston between the years 2015 and 2019. These service requests span a wide range of civic issues, including pothole repairs, graffiti removal, noise complaints, and public maintenance concerns, among others. Each entry includes key information such as the date and time the request was opened and closed, the target resolution date, the responsible department, request type, location (neighborhood), and status (open or closed), allowing for robust temporal, geographic, and departmental analysis.

The raw data files for each year were individually downloaded from the Boston Open Data Portal: https://data.boston.gov/dataset/311-service-requests. In R, each yearly file was first imported and stored as a separate dataframe. To create a unified dataset suitable for longitudinal analysis, the data was vertically concatenated using the bind_rows() function from the dplyr package. This method ensures that all rows are appended while preserving the structure and consistency of variables across years.

After preprocessing, the consolidated dataset contains over 1.5 million service request records**,** offering a comprehensive view of civic engagement and municipal response over a five-year period. The large volume and diversity of this dataset enable a range of analytical approaches, from descriptive summaries to predictive modeling, while also supporting subgroup analysis by time, location, and department.

This dataset forms the foundation for investigating patterns in service delivery, potential disparities between neighborhoods, response efficiency, and the impact of digital access on public engagement.

Research Questions

1. To what extent are service requests being completed by their target resolution date with respect to reason and type? (Service level agreements performance)

This research question focuses on evaluating the performance of Boston’s 311 service system in meeting its established Service Level Agreements (SLAs)—specifically, whether service requests are resolved on or before the assigned target completion date. SLAs are critical benchmarks set by municipal departments to ensure timely and efficient resolution of non-emergency issues reported by residents.

We compared the actual close date of each request to its corresponding target date. This allows us to create a derived binary variable indicating whether the request was resolved on time (On Time = 0) or delayed (Overdue = 1). This outcome serves as a key performance indicator for SLA adherence.

Understanding SLA performance provides valuable insight into the operational efficiency of various departments, identifies recurring delays, and can help inform process improvements and resource allocation. Moreover, tracking SLA compliance over time and across neighborhoods may uncover service inequities that warrant attention from city administrators and policymakers.

2. To what extent do response times for Boston 311 service requests from 2015 to 2019 vary across neighborhoods, and do these variations indicate potential inequities in service delivery? (Service equity and response time analysis)

This aims to investigate whether disparities exist in the response times of Boston's 311 service requests across different neighborhoods, particularly between North and South Boston. The objective is to assess if certain communities experience longer wait times for municipal services, which could indicate systemic inequities in service delivery.

Similar concerns have been raised in other cities. For instance, in Baltimore, significant disparities in 311 response times were identified between neighborhoods. A report highlighted that requests in wealthier, predominantly white areas were fulfilled more promptly compared to those in less affluent, minority-populated neighborhoods. This led to a city council hearing to address these inequities in service delivery.

By analyzing Boston's 311 data from 2015 to 2019, this research seeks to determine if similar patterns of inequity are present. The findings could inform policy decisions aimed at ensuring equitable municipal services across all neighborhoods.

Outcome Variables

To assess the efficiency and timeliness of municipal responses to service requests, we extracted and engineered several outcome variables from the Boston 311 dataset. These variables serve as the primary metrics for evaluating performance across different departments, time periods, and geographic areas.

1. Response Time (in Hours)

This continuous variable represents the total time taken to resolve a service request, calculated as the difference between the open_dt (the date and time when the request was initiated) and the close_dt (the date and time when the request was marked as completed). The value is expressed in hours, providing a standardized measure for comparison across all types of service requests. This variable forms the basis for analyzing resolution efficiency and identifying bottlenecks in the service pipeline.

2. Binary Timeliness Indicator (On Time vs. Overdue)

To facilitate classification analysis and policy evaluation, we constructed a binary variable that flags whether a service request was completed on time. This indicator is derived by comparing the close_dt with the target_dt (the target resolution deadline assigned to the request).

A value of 0 denotes that the request was completed on or before the target date (On Time).

A value of 1 indicates that the request was completed after the target date (Overdue).

3. Temporal Indicators (Year, Month, Hour)

To enable time-based analysis, we extracted several components from the open_dt timestamp:

Year: Useful for identifying long-term trends and changes in service delivery over the five-year period.

Month: Allows for seasonal trend analysis and comparison across different times of the year.

Hour: Captures the time of day the request was submitted, which may influence response prioritization and resolution speed.

These temporal features not only support exploratory analysis but also act as control variables in our statistical models, helping to isolate the effects of time-related patterns on response outcomes.

Together, these outcome variables provide a comprehensive framework for evaluating the timeliness and equity of service delivery in Boston's 311 system.

Predictor Variables

To build robust analytical and predictive models, a set of ten predictor variables was extracted and engineered from the Boston 311 Service Requests dataset. These predictors were selected based on their potential to influence or explain variations in the outcome variable—whether a service request was resolved on time or overdue. Each variable was chosen for its relevance to operational performance, temporal trends, or spatial dynamics.

Open DateTime
This variable captures the exact date and time when a service request was initially submitted. It serves as a baseline for calculating response time and deriving other temporal features such as month, day of the week, and hour of the request.

Close DateTime
This records when the service request was officially closed or marked as resolved. It is essential for determining total resolution time and assessing whether the request met the targeted service level agreement (SLA).

SLA Target DateTime
The SLA target represents the deadline by which the department is expected to resolve the issue. Comparing this value with the actual close time helps assess performance compliance and enables the creation of the binary on-time/overdue indicator.

Department (Subject)
This categorical variable indicates which city department was responsible for addressing the request (e.g., Public Works, Sanitation, Parks). Different departments may exhibit varying levels of efficiency or prioritization, making this a critical predictor.

Neighborhood
This spatial variable identifies the geographic location within Boston where the request originated. Including this variable enables neighborhood-level equity analysis and detection of any regional disparities in service delivery.

Case Status (Open/Closed)
The current status of the request helps distinguish between active and resolved cases. For modeling purposes, only closed cases were included in time-based performance evaluations to ensure accuracy in response time calculations.

On Time Flag
A binary indicator derived from the SLA comparison. It is set to **1** if the request was completed within the target date and **0** if it was resolved late. This is both a useful predictor and a key intermediate variable in feature engineering.

Month and Season (from Open DateTime)
The request's month and season were derived from the Open DateTime variable. These temporal features help uncover seasonal patterns in request volume or service delays, which could inform resource allocation strategies.

Request Type or Reason
This variable categorizes the nature of the complaint or issue (e.g., pothole, snow removal, noise complaint). Different request types may inherently require more or less time to resolve, making this a strong categorical predictor.

Response Time (in Hours)
Calculated as the difference between the Open and Close DateTimes, this numeric variable quantifies the total duration it took to resolve a request. While it can be considered an outcome in some analyses, it also serves as an explanatory variable when modeling binary SLA compliance or neighborhood-level delays.

Together, these predictors provide a comprehensive view of operational performance, enabling both descriptive and inferential analysis.

Feature Engineering

To prepare the dataset for modeling and extract meaningful insights, several new variables were created through feature engineering. These transformations were designed to enhance the predictive power of the dataset and allow for deeper subgroup analysis. The engineered features are described below:

Binary Response Variable: A new binary target variable was generated to represent service timeliness. Based on the existing `On Time` flag in the dataset, requests that were resolved within the expected timeframe were assigned a value of **0 (On Time)**, while those that exceeded the target date were assigned a value of **1 (Overdue)**. This transformation enabled classification modeling techniques such as logistic regression and decision trees.

Response Time (Numeric Variable): To quantify the duration taken to resolve each request, a continuous variable was created by calculating the time difference between the `open_dt` (request initiation date) and `close_dt` (request resolution date). This value, expressed in hours, allows for granular analysis of response efficiency and supports both statistical modeling and visualization.

Neighborhood Grouping: A new categorical feature was constructed to represent broader geographic regions by grouping individual neighborhoods into two categories: **North Boston** and **South Boston**. This grouping facilitates regional comparison and is particularly useful for analyzing service equity and response time disparities across different parts of the city.

Temporal Variables: Several time-based features were extracted from the `open_dt` timestamp to capture potential temporal trends and cyclical patterns in service requests. These include

Year: For tracking changes in service performance over time.

Month: To identify monthly or seasonal demand cycles.

Hour of Day: To evaluate request timing and municipal response based on time of day.

Season: Requests were classified into four seasons (Winter, Spring, Summer, Fall) based on their submission month, allowing for seasonal performance comparison.

Sub-Group Analysis

To better understand potential disparities and variations in service delivery across the city, we conducted a sub-group analysis by dividing the dataset into meaningful categories. This approach allows for a more granular examination of response patterns and helps identify whether certain communities or types of requests experience systematic differences in outcomes.

Region-Based Comparison: North Boston vs. South Boston:

Geographic disparities in municipal service delivery have been a topic of concern in many urban centers. To explore this issue in the context of Boston, we created a regional variable that classifies service requests into two broad geographic categories: North Boston and South Boston. This classification was derived by grouping neighborhoods based on their spatial location relative to the city center. By comparing average response times, the proportion of on-time versus overdue cases, and the frequency of requests between these two regions, we aim to uncover any evidence of inequity in how services are dispatched and resolved across the city.

Performance-Based Comparison: On-Time vs. Overdue Cases:

To evaluate the operational efficiency of the 311 system, we also categorized requests based on whether they were resolved on time (i.e., by or before the target resolution date) or overdue. This binary classification enables us to compare various features—such as request type, responsible department, time of day, and neighborhood—between cases that met their service-level agreements (SLAs) and those that did not. This sub-grouping is particularly useful in identifying factors that may contribute to delays or bottlenecks in service delivery.

By analyzing these sub-groups, we aim to address critical questions related to service equity and performance consistency. The insights gained from these comparisons will be essential in evaluating whether all neighborhoods receive equitable service and in identifying opportunities for improving operational practices within Boston's 311 system.

Descriptive Statistics

Descriptive statistics provide a foundational understanding of the dataset by summarizing its key characteristics across all records. These summaries help to uncover initial patterns, detect any potential anomalies, and support the formulation of further analysis strategies.

Table 1: Summary Statistics for All Samples

The following table summarizes the composition of the dataset across multiple dimensions:

Year: Requests were evenly distributed across five years, from 2015 to 2019, with each year contributing 20% of the sample (3 requests per year out of 15 total records in the demonstration subset).

Department (Subject): Requests were also evenly split among three major city departments—Boston Police Department, Boston Water & Sewer Commission, and the Public Works Department—each accounting for 33% of the total records.

Response Time: The dataset included an average response time of 1,298,448 hours, with a wide range indicated by the first and third quartiles (Q1 = 7,247 hours; Q3 = 58,023,448 hours), suggesting the presence of extreme values or potential data quality issues.

Median Value: The median value of the response time variable is 15, with an interquartile range of 0 to 97.

This small summary subset illustrates the structure of the larger dataset and highlights variables that may be further investigated through regression or machine learning models.

Statistics table for All Samples (n = 15)

Characteristic	N = 15
Year	
2015	3 (20%)
2016	3 (20%)
2017	3 (20%)
2018	3 (20%)
2019	3 (20%)
Subject	
Boston Police Department	5 (33%)
Boston Water & Sewer Commission	5 (33%)
Public Works Department	5 (33%)
AVG_Response_time	1,298,448 (7,247, 58,023,448)
Median	15 (0, 97)

Table 2: Summary by Group

Comparison between North and South Boston Regions:

This provides a comparative breakdown of key performance metrics between North Boston and South Boston. This regional subgroup analysis helps assess service equity, efficiency, and common request patterns between the two areas.

The table includes metrics such as the number of requests, average and median response times, percentage of requests resolved on time, and the most frequent service request category. South Boston accounts for a larger proportion of requests (61.3%), yet exhibits a longer average and median response time when compared to North Boston. Interestingly, North Boston demonstrates slightly better performance in terms of timeliness, with 86.6% of requests resolved on time versus 84.7% in South Boston.

Region	Total Requests	% of All Requests	Avg Response Time (hrs)	Median Response Time (hrs)	% Resolved On Time	Most Common Request
South Boston	639,641	61.3%	126.4	17.4	84.7%	Parking Enforcement
North Boston	350,110	33.6%	111.7	13.0	86.6%	Parking Enforcement

This comparison suggests that while both regions commonly report parking violations, North Boston may benefit from slightly more efficient response patterns. These disparities raise potential questions regarding operational logistics, staffing allocation, or neighborhood-specific service prioritization.

Comparison between On-Time vs. Overdue Requests:

While the prior subgroup analysis focused on geographic regions, this section explores operational performance by comparing on-time vs. overdue service requests. Understanding these differences is essential for identifying process inefficiencies and predicting factors that impact service delivery effectiveness.

Requests completed on time are associated with substantially lower average response times and make up the majority of the dataset. In contrast, overdue requests tend to take longer to resolve and may signal areas for improvement in service capacity or prioritization protocols.

Request Type	Total Requests	% of All Requests	Avg Response Time (hrs)	Median Response Time (hrs)
On Time	950,000+	~85%	~1,200	Lower than overdue group
Overdue	166,000+	~15%	Higher than on-time group	Higher than on-time group

Analytical plans and methods

Linear Regression Analysis:
The multiple linear regression model examining factors influencing 311 service response times produced a robust model with strong explanatory power ($R^2 = 0.4858$, $F = 9046$, $p < 0.0001$). After controlling for other variables, significant neighborhood effects persist, with Jamaica Plain showing the longest adjusted response times (coefficient = +0.071, $p < 0.001$) and Hyde Park showing the fastest (coefficient = -0.140, $p < 0.001$). Request type was a particularly influential predictor, with sign repairs taking substantially longer (+2.77 log hours) while street cleaning requests were resolved more quickly (-0.57 log hours). Temporal factors were also significant, with requests made on weekends taking 64% longer than weekday requests, and winter requests taking 7.5% longer than fall requests. The source of the request significantly impacted response times, with requests from city worker apps being resolved much faster (coefficient = -1.30). Year effects showed consistent improvement from 2015 to 2019, with each year showing faster response times than the previous year. Below is the table for linear regression.

Factor	Key Finding	Statistical Significance
Neighborhood Effects	Jamaica Plain (+0.071) and East Boston (+0.043) had significantly slower response times; Hyde Park (-0.140) and Downtown/Financial District (-0.085) had significantly faster response times	All significant at $p < 0.001$ except Roxbury ($p > 0.05$)
Request Type	Sign Repair (+2.77), Bulk Item Pickup (+2.25), and Street Light Outages (+1.95) took significantly longer; Street Cleaning (-0.57) and Parking Enforcement (-0.66) were resolved faster	All significant at $p < 0.001$
Source Effects	City Worker App (-1.30) and Employee Generated (-1.25) requests were resolved much faster	All source variables significant at $p < 0.01$
Seasonal Effects	Winter (+0.075) had the longest response times, followed by Spring (+0.036) and Summer (+0.021), with Fall as the reference season	All significant at $p < 0.001$
Weekend Effect	Weekend requests took 64.2% longer to resolve than weekday requests	$p < 0.001$
Year Effects	Consistent improvement from 2015-2019, with 2016 (-0.74), 2017 (-0.61), 2018 (-0.52), and 2019 (-0.49) all faster than 2015	All significant at $p < 0.001$
Model Fit	Adjusted $R^2 = 0.4858$, explaining nearly half of the variation in response times	$F = 9046$, $p < 0.0001$

ANOVA Analysis:
The ANOVA tests revealed statistically significant differences in 311 service response times across all examined factors, with all p-values <0.0001. Response times differed significantly between North and South Boston regions (F=2754.27), with South Boston experiencing consistently longer mean response times (126 hours vs. 112 hours for North Boston). Significant variations also appeared among the top 10 neighborhoods (F=807.04), with Downtown/Financial District having the fastest responses (mean=94.7 hours) and Dorchester the slowest (mean=136

hours). Tukey's post-hoc tests confirmed that all neighborhood pairwise comparisons showed statistically significant differences. Seasonal effects were pronounced (F=453.91), with Fall showing the shortest response times (mean=105 hours) and Winter the longest (mean=128 hours). The significant region-season interaction (F=55.30) indicates that seasonal patterns affect regions differently, with South Boston experiencing more pronounced seasonal variation. Levene's tests indicated heterogeneity of variance for all factors, but Welch's robust ANOVA confirmed the significant findings. Below is the ANOVA table.

Comparison	F-statistic	p-value	Significant	Key Finding
North vs. South Boston Regions	2,754.27	<0.0001	Yes	South Boston has significantly longer response times (126 hrs vs. 112 hrs)
Top 10 Neighborhoods	807.04	<0.0001	Yes	Downtown/Financial District fastest (94.7 hrs), Dorchester slowest (136 hrs)
Seasonal Effects	453.91	<0.0001	Yes	Fall fastest (105 hrs), Winter slowest (128 hrs); Summer-Spring difference not significant
Region-Season Interaction	55.30	<0.0001	Yes	South Boston experiences greater seasonal variation in response times

Conclusion

This analysis of Boston's 311 service requests from 2015 to 2019 offers valuable insights into the patterns, predictors, and disparities in municipal response times. Using multiple linear regression, we identified several statistically significant factors influencing service delivery efficiency. Neighborhood characteristics had a notable impact, with areas like Jamaica Plain and East Boston experiencing longer response times, while neighborhoods such as Hyde Park and the Downtown/Financial District showed faster service. Request type emerged as a strong predictor, where certain maintenance tasks like sign repairs and bulk pickups required substantially more time, whereas street cleaning and parking enforcement were resolved more efficiently. Furthermore, the mode of request submission played a critical role—requests generated through city worker apps and internal employee systems were fulfilled much faster, suggesting that technological integration and internal prioritization improve response performance. Temporal patterns also shaped outcomes, as weekend and winter requests consistently took longer to address. Year-over-year improvements from 2015 to 2019 highlight the city's positive trajectory in operational efficiency.

The ANOVA results reinforced these findings, revealing significant disparities in response times across regions, seasons, and neighborhoods. South Boston experienced longer delays on average compared to North Boston, and seasonal effects were substantial, with winter months associated with the longest delays. The interaction between region and season further indicated that geographic areas are differently impacted by seasonal factors—South Boston, for instance, displayed more pronounced seasonal variation in response performance. The robustness of these results, confirmed through post-hoc and Welch's ANOVA tests, underscores the importance of tailoring municipal service strategies based on neighborhood-specific needs, request type, and time-sensitive conditions. Together, these findings can guide Boston city planners and policymakers in allocating resources more equitably, optimizing service delivery channels, and refining operational protocols to ensure that all residents receive timely and fair access to city services.

References

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