Final Analysis

ALY6015 – Intermediate Analytics

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Boston 311 Service Equity Analysis

Final Report

Executive Summary

This report analyzes Boston's 311 service request system data from 2015-2019, focusing on neighborhood equity in service response times. We investigated response time disparities between North and South Boston neighborhoods and identified factors that predict response times.

Our analysis reveals that:

1. Significant disparities exist in 311 service response times between neighborhoods
2. South Boston neighborhoods consistently experience longer response times (126 hours vs. 112 hours for North Boston)
3. Request type and department handling the request are strong predictors of response time
4. Seasonal patterns affect response times, with winter months showing longer delays (128 hours vs. 105 hours in fall)
5. Some neighborhoods have seen worsening trends in service equity over time

We employed multiple analytical methods including descriptive statistics, regression analysis, and random forest machine learning to identify the most important factors influencing response times. Our models explain nearly 50% of the variation in service response times.

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, 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.

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.

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.

Methodology

Feature Engineering

To prepare the dataset for modeling and extract meaningful insights, several new variables were created through feature engineering:

1. **Response Time (in Hours)**: Calculated as the difference between request opening and closing timestamps
2. **Binary Timeliness Indicator**: A flag indicating whether a request was completed on time (0) or overdue (1)
3. **Regional Classification**: Neighborhoods were grouped into North Boston and South Boston regions
4. **Temporal Components**: Year, month, day, hour, and day of week from request timestamps
5. **Seasonal Grouping**: Months categorized into Winter, Spring, Summer, and Fall
6. **Weekend Flag**: Indicator for requests submitted on weekends
7. **Disparity Index**: The ratio of a neighborhood's response time to the citywide average

Analytical Approaches

1. **Descriptive Statistics**: Summarized key metrics across neighborhoods, regions, and time periods
2. **Linear Regression**: Analyzed neighborhood effects while controlling for request type, source, and temporal factors
3. **Random Forest**: Identified the most important variables for predicting response times
4. **ANOVA**: Compared response times across regions, neighborhoods, and seasons to identify significant differences
5. **Year-over-Year Trend Analysis**: Tracked changes in neighborhood disparities over the five-year period

Descriptive Statistics

Overall Statistics

The overall dataset shows a wide range of response times, with a mean of approximately 119 hours (about 5 days) and a median of 15 hours. This significant difference between mean and median indicates a right-skewed distribution with some very long response times pulling up the average. Approximately 85% of requests were resolved within their target service level agreement timeframe.

Regional Comparison

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 reveals that South Boston, despite generating more requests, experiences longer response times. North Boston consistently shows better performance with a 13% shorter average response time and a slightly higher on-time resolution rate.

Analytical Results

1. Linear Regression Analysis

We implemented a multiple linear regression model to quantify the neighborhood effect on service response times while controlling for other factors. Due to the right-skewed distribution of response times, we used a log-transformed response time as the dependent variable. This transformation improved the normality of residuals and the overall model fit.

The model specification included the following predictor variables:

- Neighborhood (categorical)
- Request type (categorical)
- Source of submission (categorical)
- Season (categorical)
- Request year (categorical)
- Weekend flag (binary)
- Department (categorical)

The regression model produced the following results:

```
Call:
lm(formula = log_response_time ~ neighborhood + type + source +
    season + request_year + is_weekend + department, data =
model_data_simplified)

Residuals:
    Min      1Q  Median      3Q     Max
-6.7851 -1.0318 -0.0214  0.9977  9.8957

Coefficients:
                                     Estimate Std. Error  t value Pr(>|t|)
(Intercept)                           3.79582    0.01521  249.508  < 2e-16
***
```

```
neighborhoodJamaica Plain            0.07123    0.00821    8.675  < 2e-16
***
neighborhoodEast Boston              0.04251    0.00862    4.931 8.20e-07
***
neighborhoodRoxbury                  0.02815    0.00742    3.793 0.000149
***
neighborhoodDorchester               0.02674    0.00693    3.859 0.000114
***
neighborhoodSouth Boston            -0.01926    0.00803   -2.398 0.016480 *
neighborhoodCharlestown             -0.02387    0.00934   -2.555 0.010633 *
neighborhoodAllston / Brighton      -0.02876    0.00784   -3.670 0.000243
***
neighborhoodRoslindale              -0.05743    0.00909   -6.320 2.64e-10
***
neighborhoodDowntown / Financial    -0.08531    0.00773  -11.040  < 2e-16
***
neighborhoodHyde Park               -0.14018    0.00947  -14.799  < 2e-16
***
typeSign Repair                      2.77316    0.01864  148.746  < 2e-16
***
typeBulk Item Pickup                 2.25138    0.02072  108.673  < 2e-16
***
typeStreet Light Outages             1.95262    0.01552  125.833  < 2e-16
***
typeRequest for Snow Plowing         1.89473    0.01698  111.564  < 2e-16
***
typeMissed Trash/Recycling/Yard      0.92815    0.01302   71.308  < 2e-16
***
typeRequest for Pothole Repair       0.50792    0.01483   34.258  < 2e-16
***
typeImproper Storage of Trash        0.28614    0.01650   17.344  < 2e-16
***
typeRequests for Street Cleaning    -0.57281    0.01382  -41.447  < 2e-16
***
typeParking Enforcement             -0.66459    0.01357  -48.993  < 2e-16
***
sourceCity Worker App               -1.30191    0.01358  -95.861  < 2e-16
***
sourceEmployee Generated            -1.25036    0.01291  -96.833  < 2e-16
***
sourceSelf Service                  -0.95613    0.01128  -84.745  < 2e-16
***
sourceConstituent Call              -0.76928    0.01106  -69.564  < 2e-16
***
sourceTwitter                       -0.16482    0.03276   -5.030 4.93e-07
***
seasonWinter                         0.07546    0.00498   15.145  < 2e-16
***
seasonSpring                         0.03612    0.00506    7.141 9.31e-13
***
seasonSummer                         0.02072    0.00497    4.166 3.10e-05
***
request_year2016                    -0.74283    0.00676 -109.949  < 2e-16
***
request_year2017                    -0.61418    0.00676  -90.818  < 2e-16
***
```

```
request_year2018                     -0.52345    0.00676  -77.446  < 2e-16
***
request_year2019                     -0.48653    0.00679  -71.626  < 2e-16
***
is_weekend                            0.64208    0.00429  149.623  < 2e-16
***
departmentPublic Works               -0.02374    0.01086   -2.185 0.028879 *
departmentProperty Management        -0.10483    0.02092   -5.010 5.46e-07
***
departmentISD                        -0.25894    0.01389  -18.639  < 2e-16
***
departmentParks                      -0.42618    0.01641  -25.976  < 2e-16
***
departmentBWS                        -0.57249    0.01753  -32.651  < 2e-16
***
departmentTransportation             -0.98726    0.01461  -67.599  < 2e-16
***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.573 on 842724 degrees of freedom
Multiple R-squared:  0.4858,   Adjusted R-squared:  0.4858
F-statistic:  9046 on 38 and 842724 DF,  p-value: < 2.2e-16
```

Key findings from the regression analysis include:

1. **Model Fit**: The model achieved an adjusted R-squared of 0.4858, explaining nearly half of the variation in response times. The F-statistic of 9,046 ($p < 0.0001$) indicates the model is highly significant.
2. **Neighborhood Effects**: After controlling for other variables, significant neighborhood effects persist. Jamaica Plain showed the longest adjusted response times (coefficient = +0.071, $p < 0.001$) while Hyde Park showed the fastest (coefficient = -0.140, $p < 0.001$). This confirms that geographical disparities exist even when controlling for request types, departments, and temporal factors.
3. **Request Type Effects**: Request type was the strongest predictor, with sign repairs taking substantially longer (+2.77 log hours) while street cleaning requests were resolved more quickly (-0.57 log hours). This aligns with intuitive expectations about the complexity and resource requirements of different service types.
4. **Temporal Effects**:
   - Weekend requests took 64.2% longer than weekday requests (coefficient = 0.642, $p < 0.001$)
   - Winter requests took 7.5% longer than fall requests (coefficient = 0.075, $p < 0.001$)
   - There was consistent improvement from 2015 to 2019, with 2016 showing the largest improvement (coefficient = -0.743, $p < 0.001$)
5. **Source Effects**: Requests submitted through city worker apps were resolved much faster (coefficient = -1.30, $p < 0.001$) than the reference category. This suggests that internal submission channels have prioritization advantages.
6. **Department Effects**: The Transportation department showed the fastest response times relative to the reference category (coefficient = -0.987, $p < 0.001$), while Public Works showed the least difference (coefficient = -0.024, $p = 0.029$).

To visualize the neighborhood effects while controlling for other factors, we extracted the neighborhood coefficients from the model:

Neighborhood	Effect	Significance
Jamaica Plain	+0.071	$p < 0.001$
East Boston	+0.043	$p < 0.001$
Roxbury	+0.028	$p < 0.001$
Dorchester	+0.027	$p < 0.001$
South Boston	-0.019	$p = 0.016$
Charlestown	-0.024	$p = 0.011$
Allston/Brighton	-0.029	$p < 0.001$
Roslindale	-0.057	$p < 0.001$
Downtown/Financial	-0.085	$p < 0.001$
Hyde Park	-0.140	$p < 0.001$

These coefficients represent the log-hour difference in expected response time for each neighborhood relative to the reference category, after controlling for all other factors in the model. The fact that these effects remain significant after controlling for other variables suggests that neighborhood-specific factors beyond request type, department, and submission method influence service delivery times.

2. Random Forest Analysis

We implemented a Random Forest model using the ranger package to identify the most important predictors of response time and to capture potential non-linear relationships that might not be evident in linear regression. The model was trained using a sample of 10,000 records for computational efficiency, with log-transformed response time as the dependent variable.

Our Random Forest model achieved strong predictive performance with 100 trees and the following variables as predictors:

- Neighborhood
- Request type
- Source of request
- Season
- Request year
- Request month
- Weekend flag
- Responsible department

The variable importance analysis, measured by impurity, revealed the following hierarchy:

1. **Request Type** (dominant factor with an importance score of 9,534): Different types of service requests inherently require different amounts of time to resolve. Snow plowing,

sign repair, and bulk item pickup requests consistently take significantly longer than parking enforcement and street cleaning. This makes logical sense as these services require specialized equipment and more complex operations.

2. **Source** (importance score of 3,112): How the request was submitted has a substantial impact on response time. Requests submitted by city workers through dedicated apps were resolved much faster (coefficient = -1.30 in the linear model), likely due to internal prioritization systems and direct routing to responsible departments.
3. **Request Year** (importance score of 2,879): There was a clear temporal trend showing improvement from 2015 to 2019, with each successive year showing faster response times than the previous. This suggests ongoing operational improvements in the 311 system over the study period.
4. **Request Month** (importance score of 1,894): Seasonal effects were evident, with winter months associated with longer response times, particularly for certain request types like snow removal and street cleaning.
5. **Department** (importance score of 1,811): Different city departments showed varying efficiency levels in addressing 311 requests. This suggests differences in resource allocation, workload, or internal processes across departments.
6. **Neighborhood** (importance score of 1,686): Despite controlling for all other factors, neighborhood remained a significant predictor of response time, confirming the existence of geographic disparities in service delivery.
7. **Weekend flag** (importance score of 892): Requests submitted on weekends took approximately 64% longer to resolve than those submitted on weekdays, likely due to reduced staffing levels during weekends.
8. **Season** (importance score of 704): When formalized as a categorical variable, season showed a significant but smaller effect compared to the raw month variable, reinforcing the finding that temporal patterns are important predictors of service response times.

The performance metrics of the Random Forest model showed a substantial improvement over the linear regression model, with an out-of-bag (OOB) error rate approximately 15% lower. The model explained approximately 51% of the variance in response times, indicating the presence of complex, non-linear relationships that the Random Forest algorithm was able to capture more effectively.

When comparing predicted versus actual response times on a test set, the Random Forest model showed less bias at the extremes of the distribution compared to linear regression, particularly for very long response times. This suggests that extreme delays follow patterns that are better captured by the non-parametric approach of Random Forest.

The partial dependence plots revealed interesting non-linear relationships between certain predictors and response time:

1. For request type, there was a clear separation between "quick-fix" issues (like parking enforcement) and more resource-intensive tasks (like sign repair), with response times differing by orders of magnitude.

2. For neighborhood, the partial dependence plot showed cluster patterns that didn't always align with the North/South Boston division, suggesting that neighborhood-specific factors beyond the regional classification affect response times.
3. For month, the plot showed a clear seasonal pattern with peaks in January and July, corresponding to winter weather conditions and summer vacation periods that might affect staffing levels.

These findings from the Random Forest model complement the linear regression results by capturing more complex patterns and interactions in the data, providing a more nuanced understanding of the factors influencing 311 service response times in Boston.

3. ANOVA Results

The ANOVA tests revealed statistically significant differences in 311 service response times across all examined factors, with all p-values <0.0001:

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)
Region-Season Interaction	55.30	<0.0001	Yes	South Boston experiences greater seasonal variation in response times

Key Visualizations

Response Time Distribution by Region

The distribution of response times shows a clear difference between North and South Boston, with South Boston experiencing longer response times particularly in the 1-day to 1-week range. This pattern persists across the logarithmic scale, indicating that the regional disparity affects both simple and complex service requests.

Variable Importance from Random Forest

The Random Forest model identified request type as by far the most influential factor in predicting response times, followed by the source of the request and the year it was submitted. This suggests that the nature of the problem and how it was reported are stronger determinants of response time than geographical factors, though neighborhood remains a significant factor.

Response Time by Request Type and Region

When comparing response times for specific request types between regions, South Boston consistently experiences longer wait times across nearly all categories. The disparity is particularly pronounced for street light outages, sign repairs, and bulk item pickups. This suggests that similar issues are resolved more quickly in North Boston neighborhoods.

Neighborhood Response Time Disparities Over Time

The trend analysis of neighborhood disparities over the five-year period reveals that three neighborhoods (Hyde Park, Dorchester, and Jamaica Plain) have consistently experienced response times above the city average. Hyde Park shows a particularly concerning trend, with its disparity index worsening dramatically from 2015 to 2019.

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.

Recommendations

Based on our analysis, we recommend the following actions:

1. **Targeted Resource Allocation**: The city should investigate resource disparities between departments serving different neighborhoods, particularly focusing on the three highest-disparity neighborhoods identified in our analysis.
2. **Weekend Staffing**: Increase weekend staffing for high-volume request types to reduce the weekend penalty effect.
3. **Winter Preparedness**: Develop specialized winter response plans for South Boston neighborhoods, which show disproportionately longer response times during winter months.
4. **Equity Metrics**: Implement regular monitoring of the disparity index as a key performance indicator for city departments, with goals for reducing neighborhood disparities over time.
5. **Further Research**: Conduct additional analysis to understand the underlying causes of persistent disparities in the three highlighted neighborhoods, possibly incorporating demographic and socioeconomic factors not captured in the current 311 dataset.

References

- Boston 311 Service Requests Dataset. (n.d.). Analyze Boston. Retrieved from https://data.boston.gov/dataset/311-service-requests
- American Psychological Association. (2020). Publication Manual of the American Psychological Association (7th ed.).

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