311 Service Requests Analysis & Predictive Modeling

Capstone Final Report: Springboard

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July 06, 2025

NYC receives millions of 311 service requests every year from noise complaints to public safety. However, not all of the requests receive equal attention and treatment. There are inefficiencies and response time disparities across boroughs, complaint types and agencies that need to be identified and addressed. This project aimed to analyze NYC 311 Service Request data to understand complaint resolution delays and build a predictive model to identify which complaints are likely to experience delays. Through exploratory analysis and a logistic regression model, we identified complaint types and agencies with the highest likelihood of delay, achieving an accuracy of 87%. Based on the findings, recommendations are made to improve responsiveness and allocate resources more effectively.

Problem Statement: NYC's 311 service request data offers a depiction of how effectively the city addresses residents' concerns. However, delays in resolution times, disparities across boroughs, and inconsistent agency performance make it difficult to ensure equitable and efficient service delivery. This project aims to uncover patterns in complaint types, geographic trends, and agency response times to identify underserved areas and systemic inefficiencies. The ultimate goal is to inform data-driven recommendations that can help city planners and agency leaders improve responsiveness, optimize resource allocation, and enhance resident satisfaction.

Data Overview: 311 Service Requests from 2010 to Present data was taken from NYC Open Data: https://data.cityofnewyork.us/Social-Services/NYC-311-Data/jrb2-thup/about_data. It was downloaded in CSV form and cleaned with Python.

The steps that were followed to complete this project are:

- Data cleaning and wrangling
- Exploratory Data Analysis through Tableau
- Preprocessing and Modeling using Train-Test Split
- Insights and recommendations.

Tools that were used:

- Python + Pandas for data wrangling
- Tableau for EDA
- Python + Machine Learning for Preprocessing and Modeling

Data Wrangling: The data wrangling process began with importing the necessary libraries and loading the NYC 311 Service Request dataset. Initial exploration was performed using head(), info(), shape, columns, and describe() to understand the structure, size, and summary statistics of the data. Unnecessary columns such as 'Created Date', 'Closed Date', 'Status', 'Incident Zip', 'Latitude', 'Longitude', and others did not contribute to the modeling or analysis goals, hence they were dropped to reduce noise and improve efficiency. Datetime columns were then converted to datetime objects to enable the calculation of time-based features.

Two new columns were added:

- **Response Time (Hours):** The time difference between the creation and closure of a complaint.

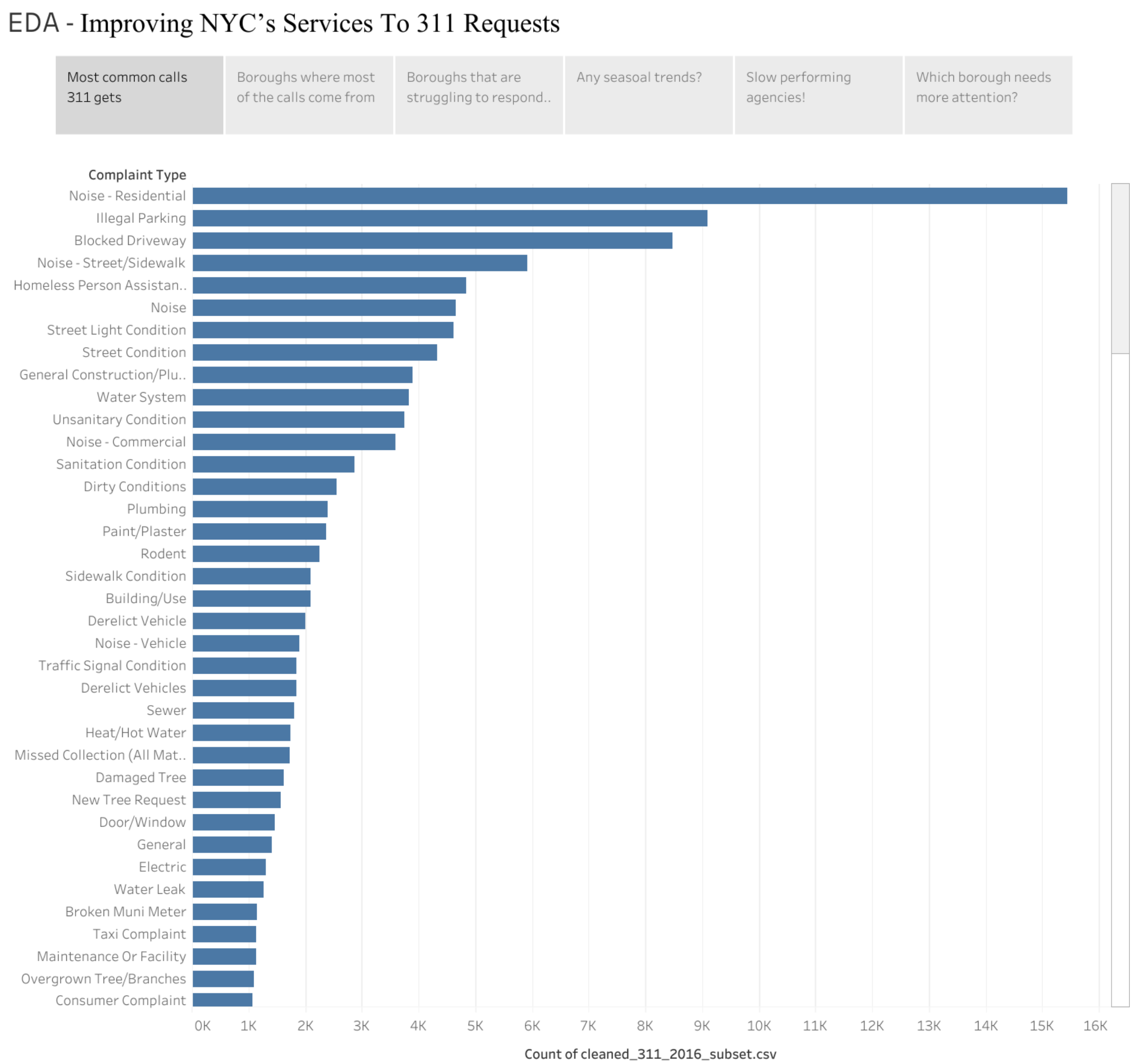
- **Is Closed:** A binary indicator of whether a complaint was closed (used as the target variable for modeling).

Categorical values such as 'Agency', 'Borough', and 'Complaint Type' were standardized for consistency and easier grouping. The data was further refined by identifying the top five boroughs with the highest complaint volume and narrowing focus to the most active 2-3 boroughs for modeling. Duplicate records were also removed to ensure data integrity.

Finally, the cleaned dataset was saved and prepared for the next phase: exploratory data analysis and modeling.

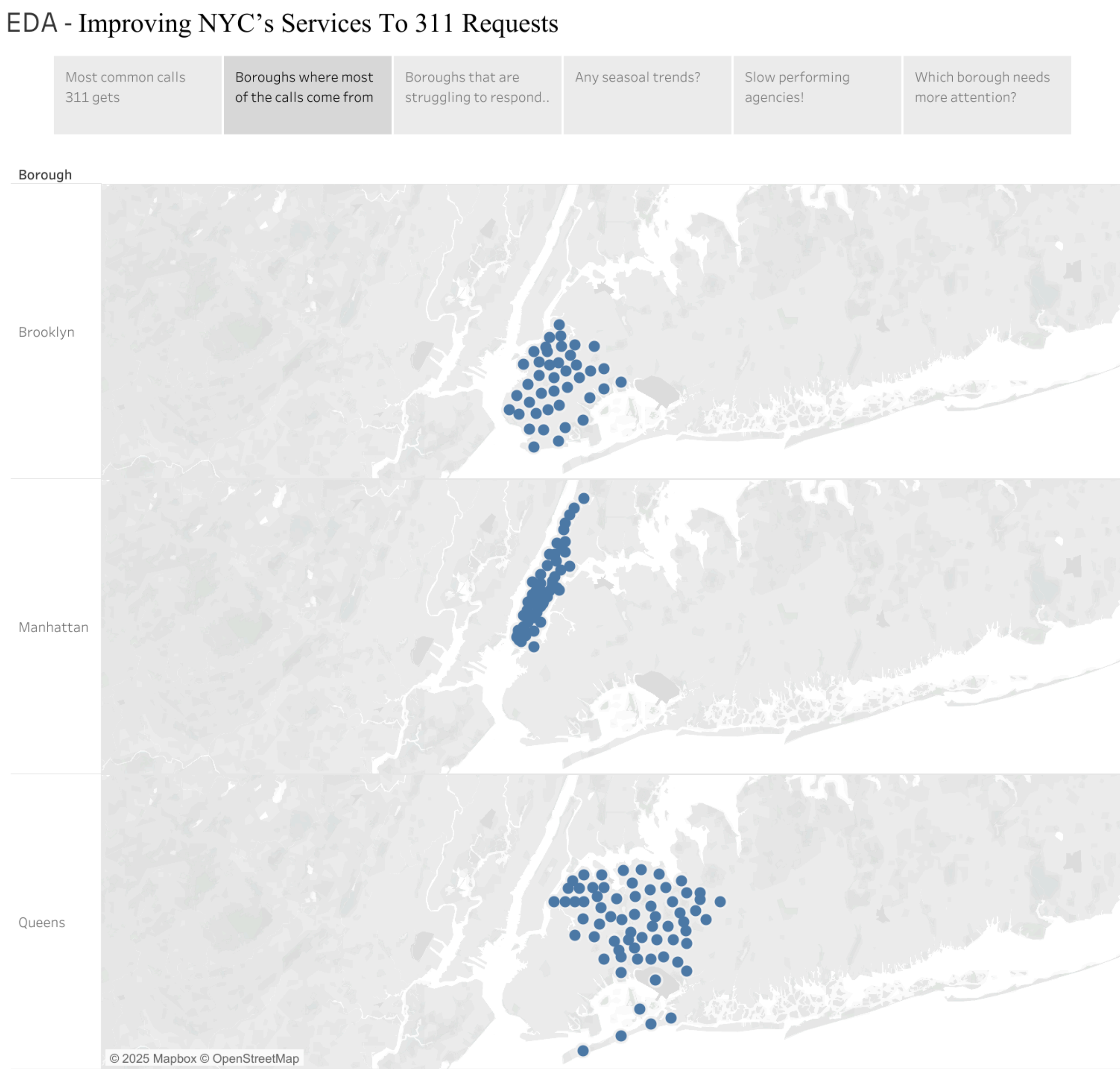
EDA: To better understand the patterns in 311 service requests, I used Tableau for interactive and visual analysis. The key questions driving the EDA were:

What are the most common complaint types received by 311?



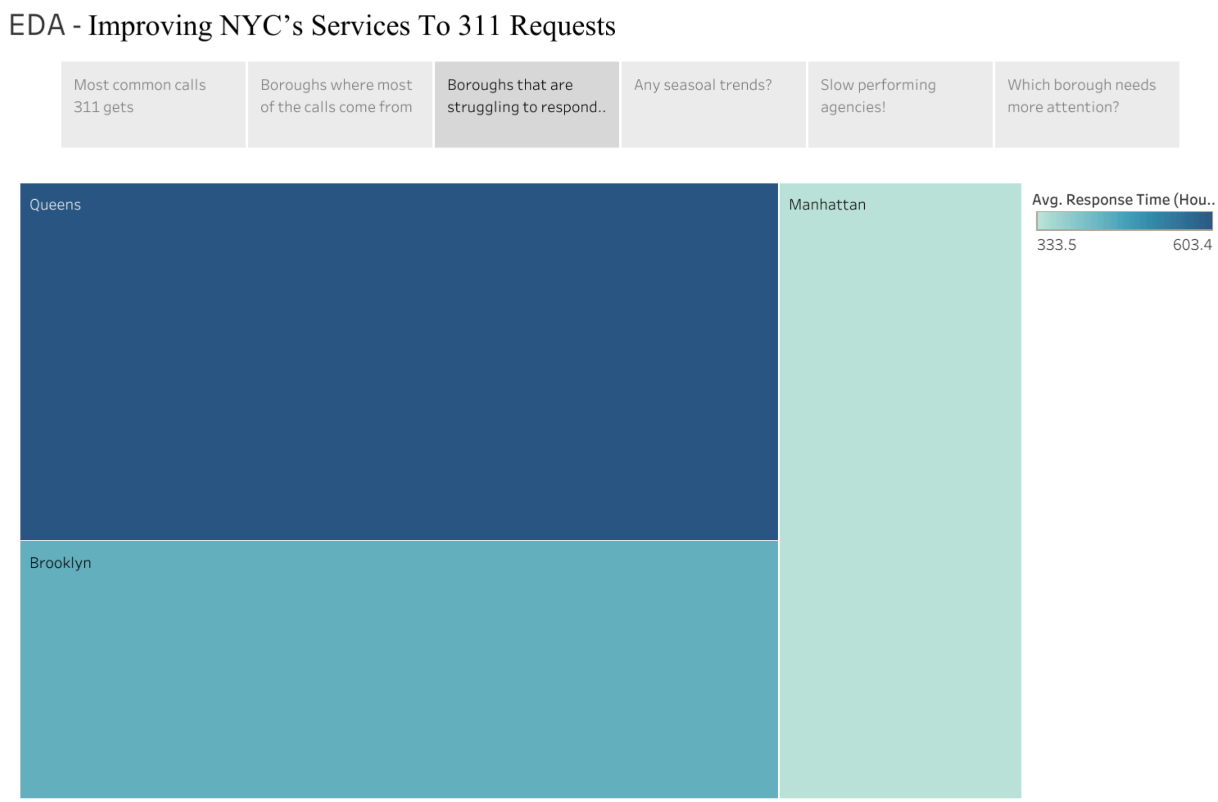
The most frequently reported complaint was Noise - Residential with over 15,000 complaints, followed by Illegal Parking, Blocked Driveway, Noise - Sidewalk, Homeless Person Assistance, and Street Light Conditions. This indicates that noise and parking issues are dominant public concerns across the city.

Which boroughs generate the most 311 calls?



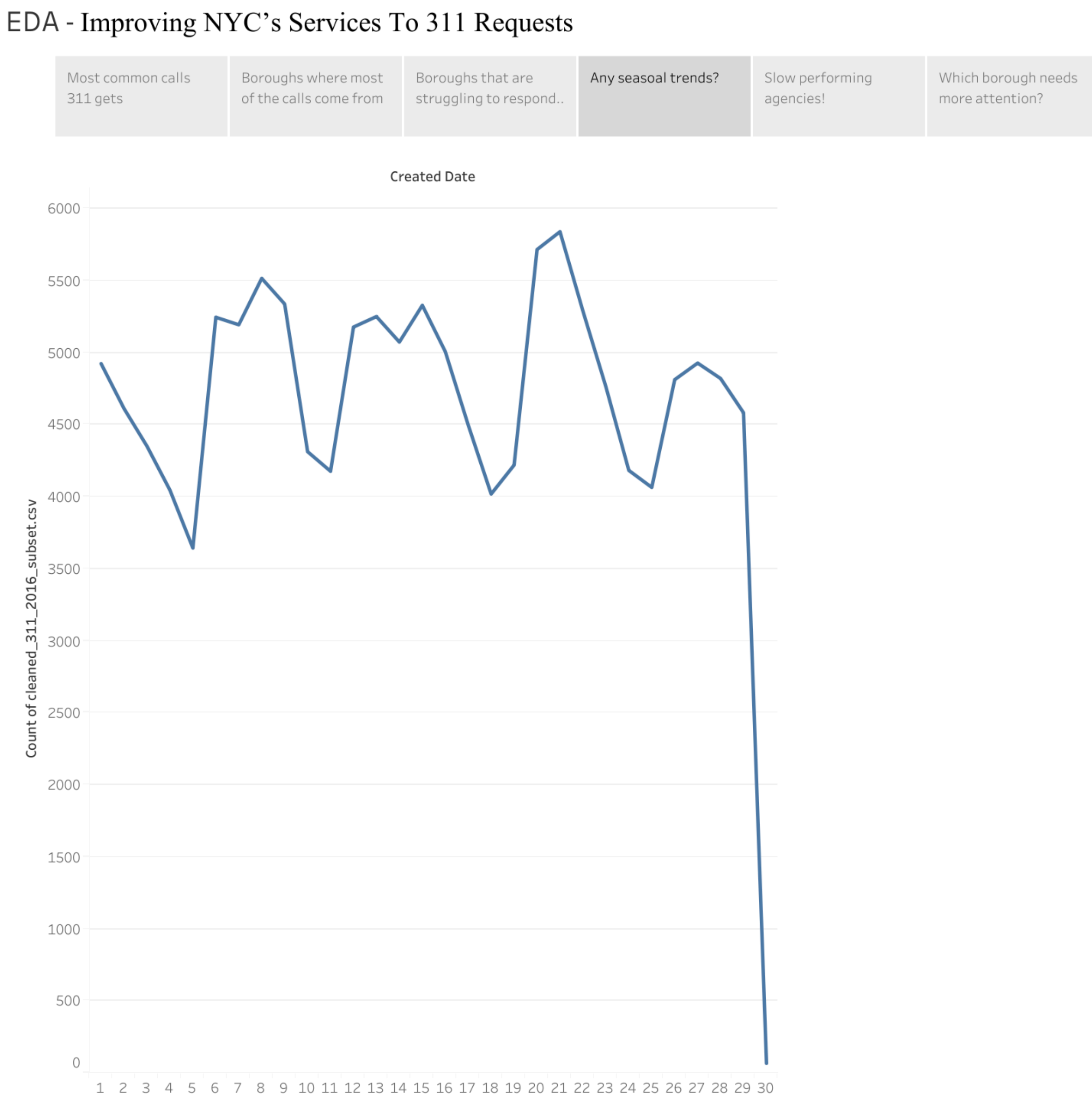
Queens accounted for the highest number of service requests. While this may reflect population size and density, it also signals the need for targeted service optimization in that borough.

Which boroughs are struggling to respond in time?



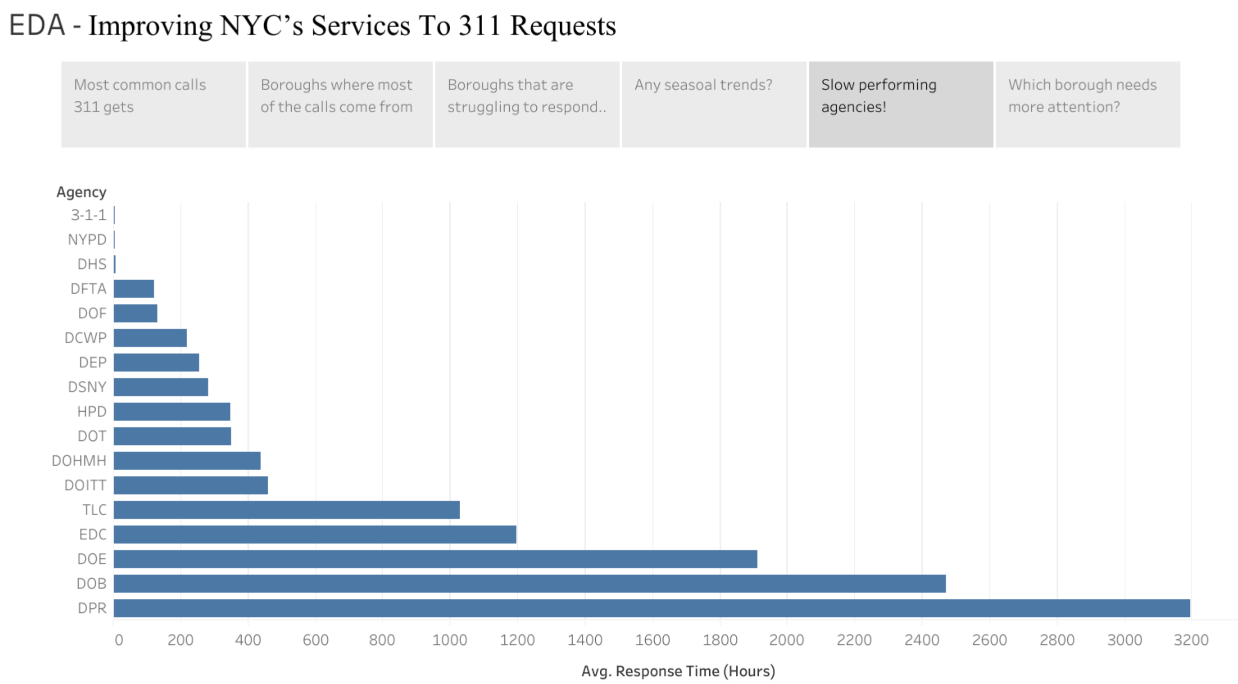
Analyzing resolution time by borough revealed that Queens had the highest share of delayed responses, suggesting possible operational bottlenecks or resource shortages.

Are there any seasonal or weekly trends?



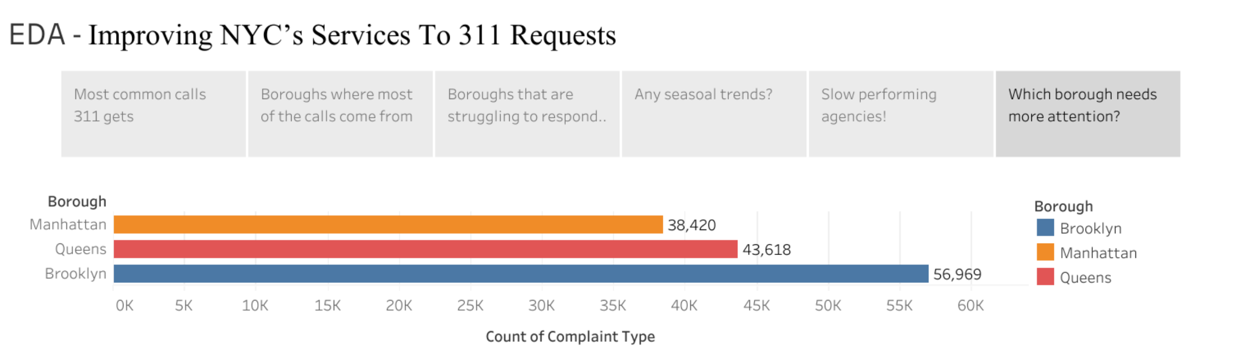
Request volume showed noticeable peaks during mid-week (Tuesday to Thursday) and drops on Fridays and weekends, which may reflect both service usage patterns and agency staffing schedules.

Which agencies are slowest in responding to complaints?



The NYPD emerged as the slowest performing agency, particularly for noise related complaints, with a high rate of delayed resolutions.

Which boroughs need more attention based on response performance?



While Queens generated the most complaints and had many delays, Brooklyn also stood out with high volumes of unresolved or slower solving complaints, signaling that both boroughs may benefit from additional oversight or reallocation of agency resources.

Preprocessing and Modeling: Following the data wrangling and exploratory analysis phases, this stage focuses on preparing the dataset for predictive modeling to better understand patterns in NYC's 311 service response times. Preprocessing involves transforming categorical variables into machine readable formats using one hot encoding, standardizing feature scales, and splitting the dataset into training and testing subsets to ensure valid model evaluation.

We started with light data wrangling and then did feature engineering followed by one hot encoding, standardized feature scales and train test split. We trained the model for logistic regression and evaluated the model.

```
              precision    recall  f1-score   support

           0       0.92      0.92      0.92     17198
           1       0.82      0.82      0.82      7896

    accuracy                           0.89     25094
   macro avg       0.87      0.87      0.87     25094
weighted avg       0.89      0.89      0.89     25094

Confusion Matrix:
 [[15787  1411]
 [ 1391  6505]]
ROC AUC Score: 0.9539899022211413
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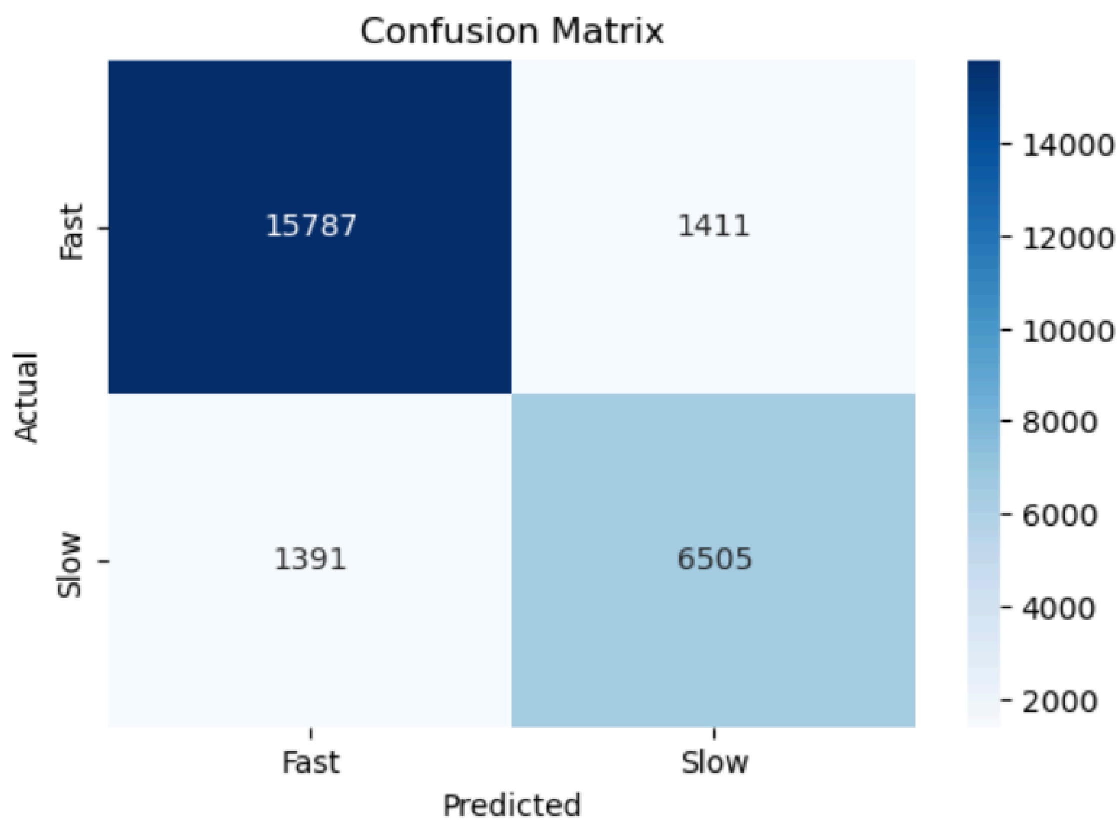
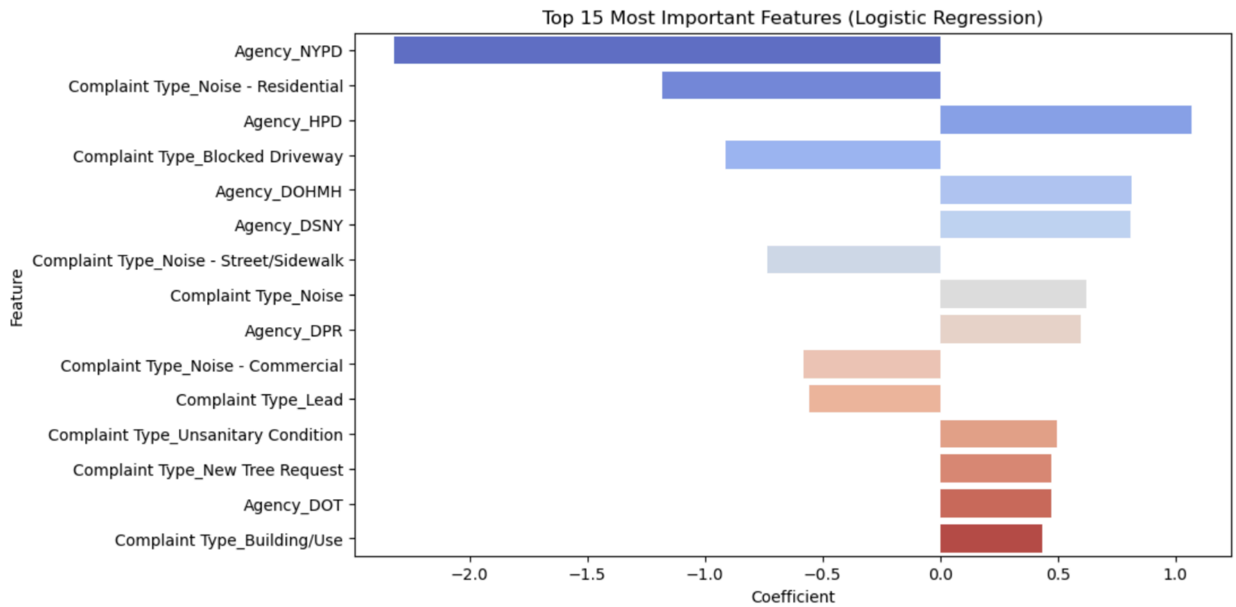
The logistic regression model continued to perform strongly in classifying whether a 311 service request would receive a slow or fast response, showing improvements after data cleaning. It achieved an accuracy of 89% and an excellent ROC AUC score of 0.95, reflecting its strong ability to distinguish between fast and slow complaints. The model achieved a precision of 0.82 and a recall of 0.82 for slow responses, meaning it correctly identified the majority of delayed cases while keeping false alarms relatively low. The F1-score for slow responses was 0.82, demonstrating a strong balance between precision and recall. According to the confusion matrix, out of 7,896 actual slow complaints, the model correctly predicted 6,505 and misclassified 1,391 as fast. Similarly, it correctly identified 15,787 out of 17,198 fast complaints, misclassifying only 1,411. These results indicate that the model is a reliable tool for flagging service delays in NYC's 311 system, offering valuable support for improving agency responsiveness and prioritizing high risk complaint types.





This project leveraged NYC 311 service request data to uncover meaningful trends in complaint types, geographic distribution, and agency performance. Through a combination of Tableau based exploratory analysis and predictive modeling, we identified key challenges such as noise-related complaints, slow response times by the NYPD, and Queens and Brooklyn as boroughs requiring increased attention. The logistic regression model helped surface which complaints are most likely to experience delays, offering a data driven approach to improving operational efficiency. By integrating these insights into decision making processes, city officials and agency leaders can better allocate resources, monitor key performance indicators, and improve response times ultimately enhancing resident satisfaction and trust in public services.