

Report: NYC 311 Service Requests Analysis and Resolution Prediction

Date: January 11, 2026

Project Overview: This analysis utilizes the NYC 311 Service Requests dataset to identify major urban pain points across New York City and to develop a predictive model that estimates the time required for various agencies to resolve these requests.

1. Dataset Characteristics & Data Quality

The analysis was performed on a dataset containing approximately **184,335 service requests**.

- **Data Integrity:** The dataset is largely robust, though certain fields like “resolution_description” and “incident_address” have missing values at rates of **2.9%** and **5.9%** respectively.
- **Variable Types:** The data includes a mix of categorical, and numerical variables.
- **Spatial Consistency:** Most requests are tied to specific ZIP codes, with a range between 10000 and 12345, covering all five boroughs.

2. Exploratory Findings: Complaint Trends

A significant portion of the project focused on understanding the distribution of complaints to identify which issues most frequently affect NYC residents.

- **Dominant Complaint Types:** "Noise - Residential" and "Heat/Hot Water" are the leading causes of 311 calls.
- **Geographic Hotspots:**
 - **Brooklyn** consistently reports the highest volume of service requests among all boroughs.
 - Specific neighborhoods like **Queens** show high activity for infrastructure-related issues, such as blocked driveways and street conditions.
- **Resolution Efficiency:** Analysis of the “request_closing_time” indicates significant variance depending on the complaint type. Noise complaints typically have a shorter lifecycle compared to complex housing maintenance issues.

3. Regression Learning Model

The Jupyter Notebook details a machine learning model designed to predict the number of days required to close a case.

- **Feature Engineering:**
 - Categorical features such as Complaint Type and Borough were transformed using vectorization techniques.
 - Temporal features were extracted to account for seasonal variations.
- **Model Architecture:** The project utilizes a **Regression model** built with scikit-learn to predict the numerical target `predicted_days`.
- **Training Environment:** The model was developed using a standard Python stack including pandas for data manipulation, matplotlib for visualization, and ydata-profiling for automated EDA.

4. Predictive Performance and Results

The model was tested using specific scenarios to evaluate its practical utility.

- **Test Case Result:** For a request involving **"HEAT/HOT WATER"** in **"QUEENS"** created in **"January 2010"**, the model successfully generated a predicted resolution time.
- **Handling New Inputs:** A custom function `input_transfrom()` was implemented to ensure that new user inputs are processed through the same vectorizers used during training, maintaining consistency between training and inference.

5. Conclusion

- **Resource Allocation:** The city should prioritize staffing for "Noise" and "Heating" issues, as these represent the bulk of the 311 workload.
- **Infrastructure Improvement:** High request volumes in specific ZIP codes (e.g., Brooklyn and Queens) suggest a need for targeted infrastructure audits.
- **Future Enhancements:** To improve the prediction model, incorporating external factors like daily temperature (for heating complaints) or public event schedules (for noise) could significantly increase accuracy.

6. References

- NYC-311-Service-Request-Analysis, GitHub repository link:
<https://github.com/AvonleaFisher/Analyzing-NYC-311-Service-Requests>
- Wang, L., Qian, C., Kats, P., Kontokosta, C. and Sobolevsky, S., 2017. Structure of 311 service requests as a signature of urban location. *PloS one*, 12(10), p.e0186314.
- Tussey, D. and Yan, J., 2025. Principles for Open Data Curation: A Case Study with the New York City 311 Service Request Data. *arXiv preprint arXiv:2502.08649*.
- Minkoff, S.L., 2016. NYC 311: A tract-level analysis of citizen–government contacting in New York City. *Urban Affairs Review*, 52(2), pp.211-246.