

# Analysis on NYC Pedestrian Ramp Complaints: Final Presentation

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# Agenda

- Project Plan Recap
- Modeling Methods
- Findings
- Recommendations



# Executive Summary

## Context:

As part of a settlement between the City of New York and plaintiffs regarding ADA accessibility, the City agreed to invest \$1.55 Billion in the next decade. To make New York City more accessible.

## Problem:

Pedestrian ramps and corner complaints can pose safety and accessibility issues.

This project aims to answer:

How can the city of New York improve the efficiency and effectiveness of pedestrian ramp repairs to reduce complaint volumes and minimize repair times?

# Project Plan Recap

Deliverable	Due Date	Status
Data & EDA	3/25/25	Complete
Methods, Findings and Recommendations	4/1/25	Complete
Final Presentation	4/22/25	In Progress

# Data

# Dataset overview

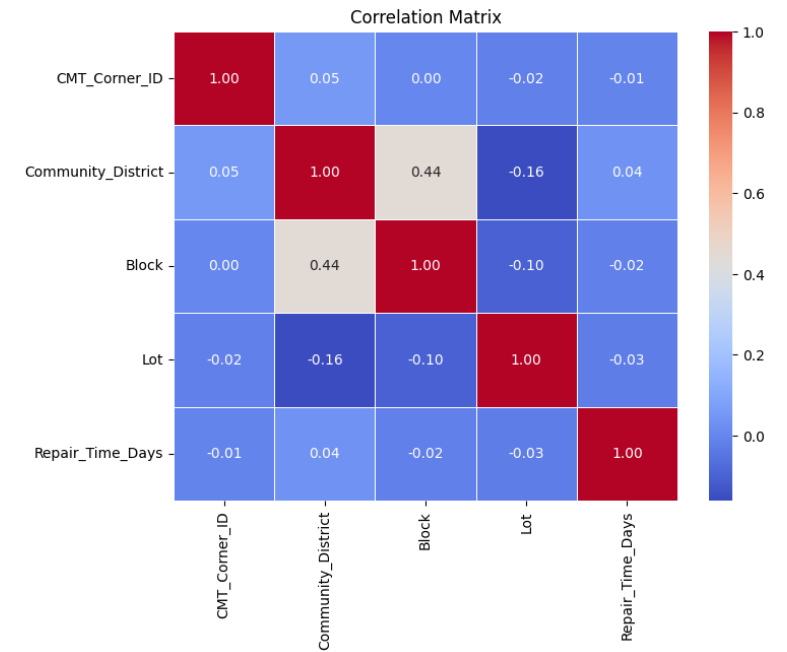
Pedestrian [Ramp Complaints Data Set](#) available on NYC Open Data:

- 4,583 rows. Each row is a complaint or represent a bulk complaint if more than one person made a report about the same corner ramp on the same day.
- Earliest Data point is from September 11, 2018
- Available data since 2018 last updated March 5, 2025
- Dataset was made public on June 20, 2024

# Exploratory Data Analysis

# Correlation

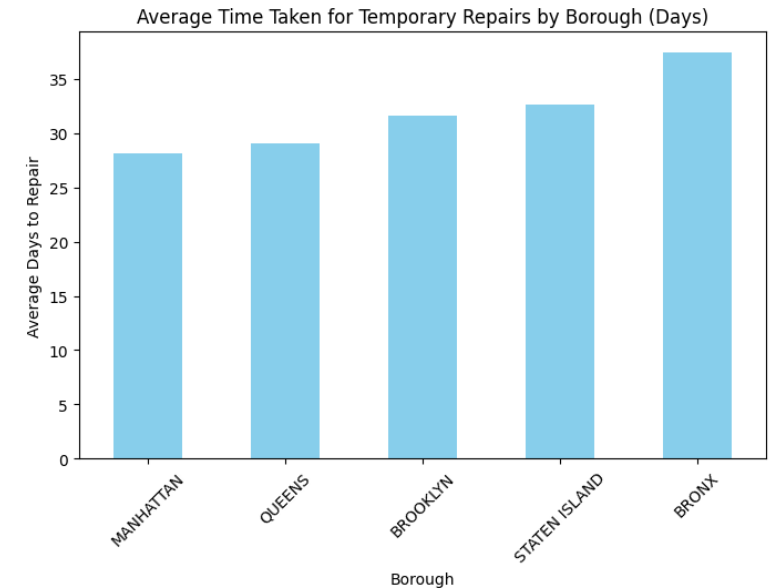
- What does this mean?
- The weak correlations indicate that relationships between variables are nonlinear or influenced by hidden factors.
- Key Takeaway:
  - For the purpose of this project, maybe a decision tree model will help to uncover hidden patterns.





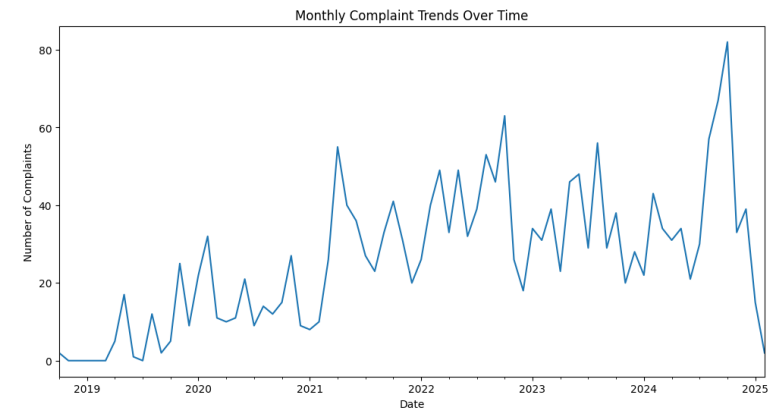
# How Long Does It Take To Repair a Ramp in Each Borough?

- Key Takeaway:
- Repairs in the Boroughs of Manhattan and Queens advance at a faster pace than the five-borough average of 31 days.
- Assumption:
- The boroughs of Brooklyn, the Bronx and Staten Island are caused by bureaucratic delays.
- 



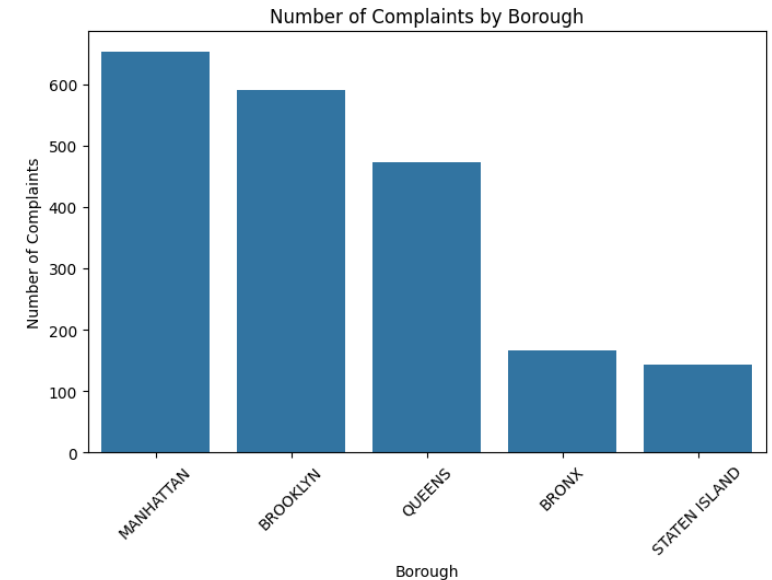
# Are Complaints Seasonal?

- Key Takeaway:
- This graph clearly shows there is a seasonality trend in the spikes and valleys of the complaints.
- Summer and Winters seasons are tied to spikes in complaints.
- Conclusion:
- The city should prepare in advance for the summer and winter to avoid complaints and repairs backlog.



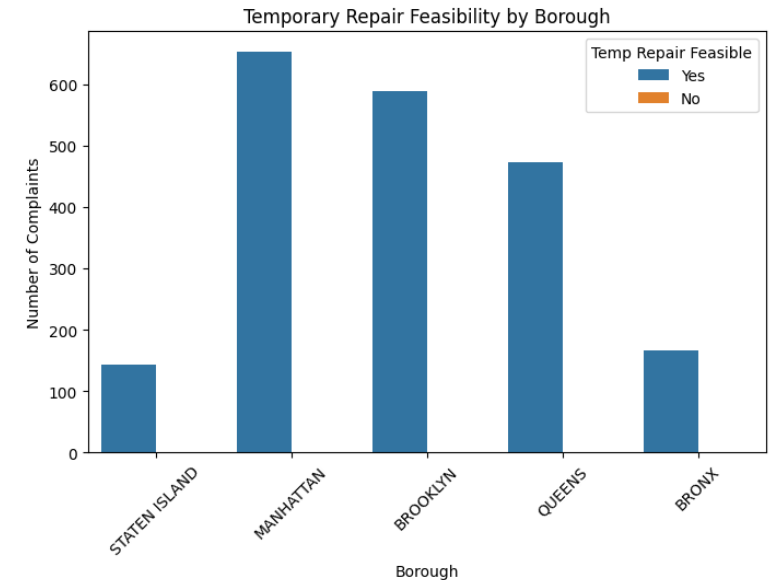
# Number of Complaints by Borough

- Key Takeaway:
- Manhattan and Brooklyn lead by number of complaints. Which means that higher amount of works needs to be done in these boroughs.
- Assumption:
- The high numbers of complaints in Manhattan, Brooklyn and Queens are a result of higher number of ramps, higher population and higher foot traffic.



# Feasibility of Temporary Repairs

- Key Takeaway:
- Plan for quick and low on resources temporary repairs based on feasibility.
- Deploy more repair crews where temporary repairs will help reduce the complaint backlog.
- Assuming non-temporary repairs require more work and resources, assign “heavy duty” crews where permanent needed are high and aim for “a one and done repair”.



# Model Selection

# Model Selection

Initially we found out that the features are not linearly correlated.

## Key Takeaways:

### What it does:

- Flags complaints as “High Priority” if they match urgency signals like:
  - High community demand
  - Infeasible repairs
  - Bulk reporting

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Model Type: Transparent Decision Tree

Why this approach?

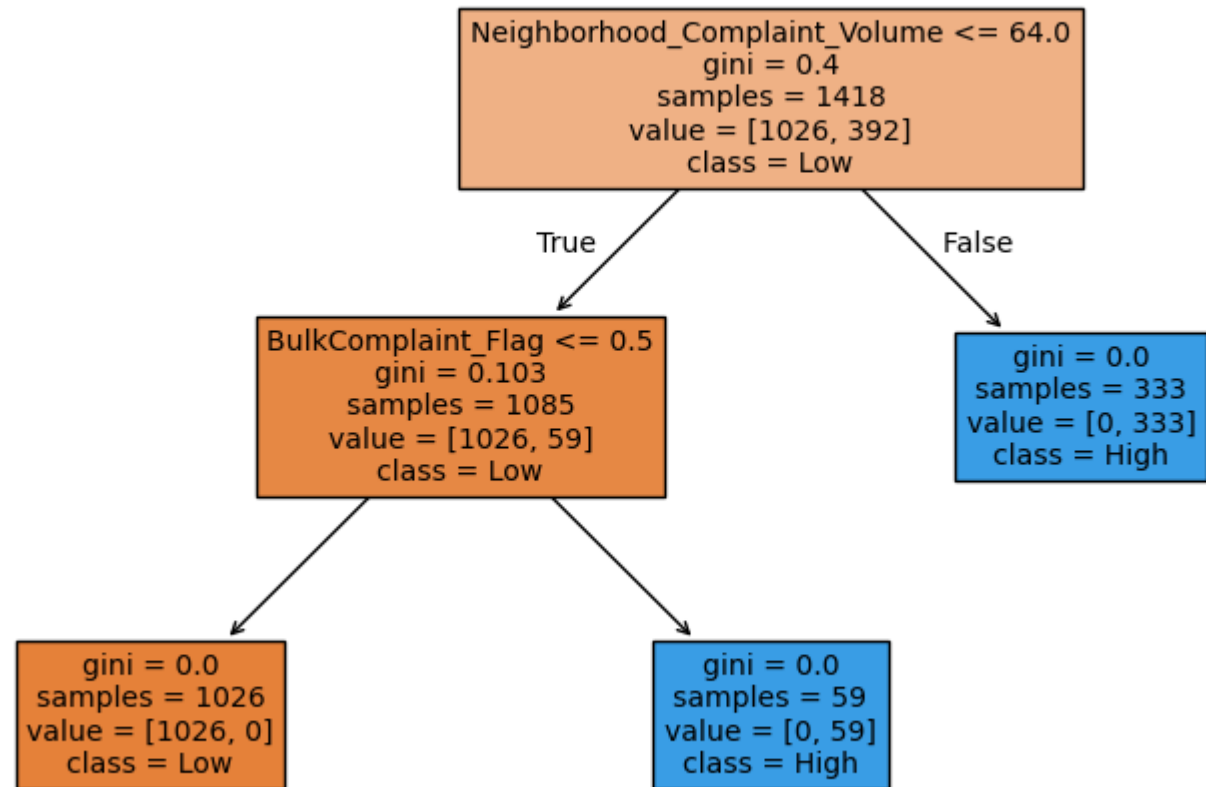
- Clear logic: The model works like a flowchart — anyone can follow it
- Fast decisions: Makes instant classifications using a simple “yes/no” rule path
- Fair and consistent: Ensures all complaints are evaluated by the same objective criteria
- Explainable: Helps operations teams understand why a complaint is considered high priority

# Model Selection

The model determined that a Neighborhood Complaint Volume of 64 is the cutoff between low and high priority

Bulk Complaint Flag can either have a value of 0 or 1 so the 0.5 is used to determine whether it is a bulk complaint or not.

Decision Tree for High Priority Complaints



# Feature Engineering

Why? The dataset didn't contain optimal features, but combining some features allowed us to create new features to work on.

Key Takeaways:

More complaints = higher attention needed

Feature: Neighborhood\_Complaint\_Volume

- Counted how many complaints came from each Community\_District.

- Why:

High complaint volume may signal:

- Systemic infrastructure issues
- Greater public demand
- Potential equity gaps in service delivery

Business Insight: More complaints = higher attention needed



# Feature Engineering

## Key Takeaways:

Business Insight: Bulk = potentially higher operational urgency.

Feature: BulkComplaint\_Flag (1 = Yes, 0 = No)

- Converted the text field BulkComplaint ("Yes"/"No") into a binary numeric value.

- Why:

Assumed Bulk complaints typically come from citywide audits or coordinated community efforts.

- Represent many problem sites
- Often require faster and more strategic responses

# Feature Engineering

## Key Takeaways:

Business Insight: No temp fix = high impact = higher urgency.

Feature: Temp\_Repair\_Feasible\_Flag (1 = Yes, 0 = No)

- Converted Temp\_Repair\_Feasible from text to binary numeric.

- Why:

If a temporary repair is not feasible, it usually means:

- The ramp is inaccessible until full repair
- The situation is more urgent and impactful for residents with disabilities

# Feature Engineering

## Key Takeaways:

Technical Insight: Prevents large values from dominating the model.

Feature: Normalized\_Volume (scaled between 0 and 1)

- Applied min-max scaling to Neighborhood\_Complaint\_Volume to normalize it for modeling.

### •Why:

Some models (especially scoring or regression-based) perform better when numeric values are scaled evenly.

# Feature Engineering

## Key Takeaways:

This simulates real-world prioritization using measurable features.

- It allows us to train the model to learn patterns from known high-priority complaints.
- Once trained, the model can be used to predict  $\text{High\_Priority} = 1$  for new complaints, helping prioritize them automatically

Feature: Priority\_Score (custom formula)

- Combined all engineered features into a scoring formula. Ultimately this is the outcome variable of the model
- Why: This formula reflects business intuition about what makes a complaint more urgent.
- Each factor is weighted based on perceived importance.

# Findings

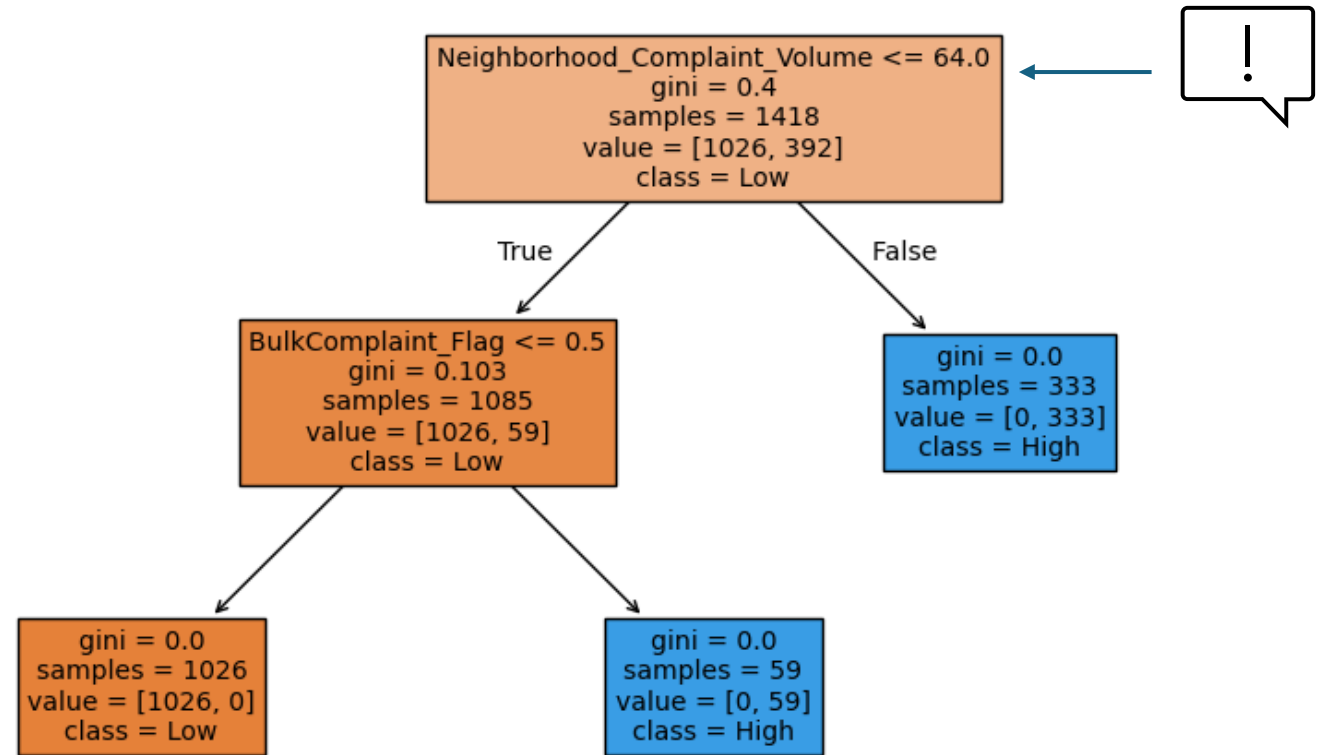
# Neighborhood Volume Drives Urgency

## Key Takeaways:

Complaint clusters signal widespread infrastructure problems:

The model prioritizes areas where multiple residents are raising concerns

Decision Tree for High Priority Complaints



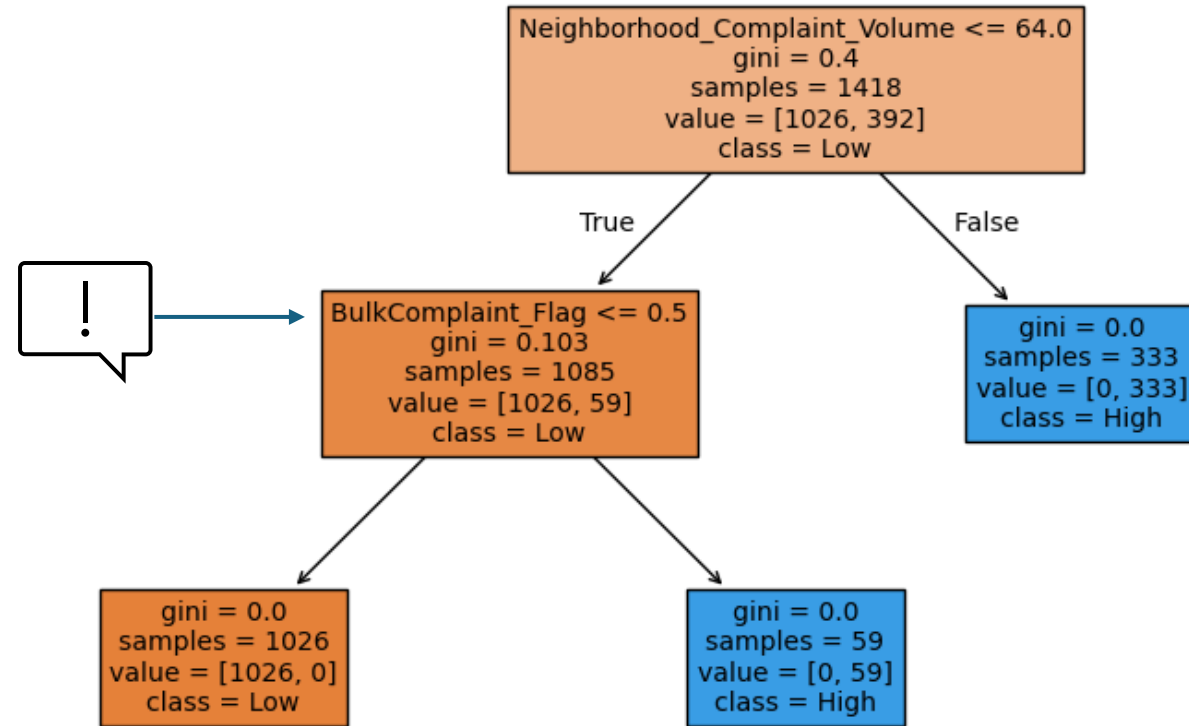
- The first and most important split in the tree was based on total complaints in a community district
- Neighborhoods with more than 64 complaints were automatically flagged high-priority

# Bulk Complaints Drive Action

## Key Takeaways:

The city can improve efficiency by addressing grouped complaints first: Maximize impact with less resources.

Decision Tree for High Priority Complaints



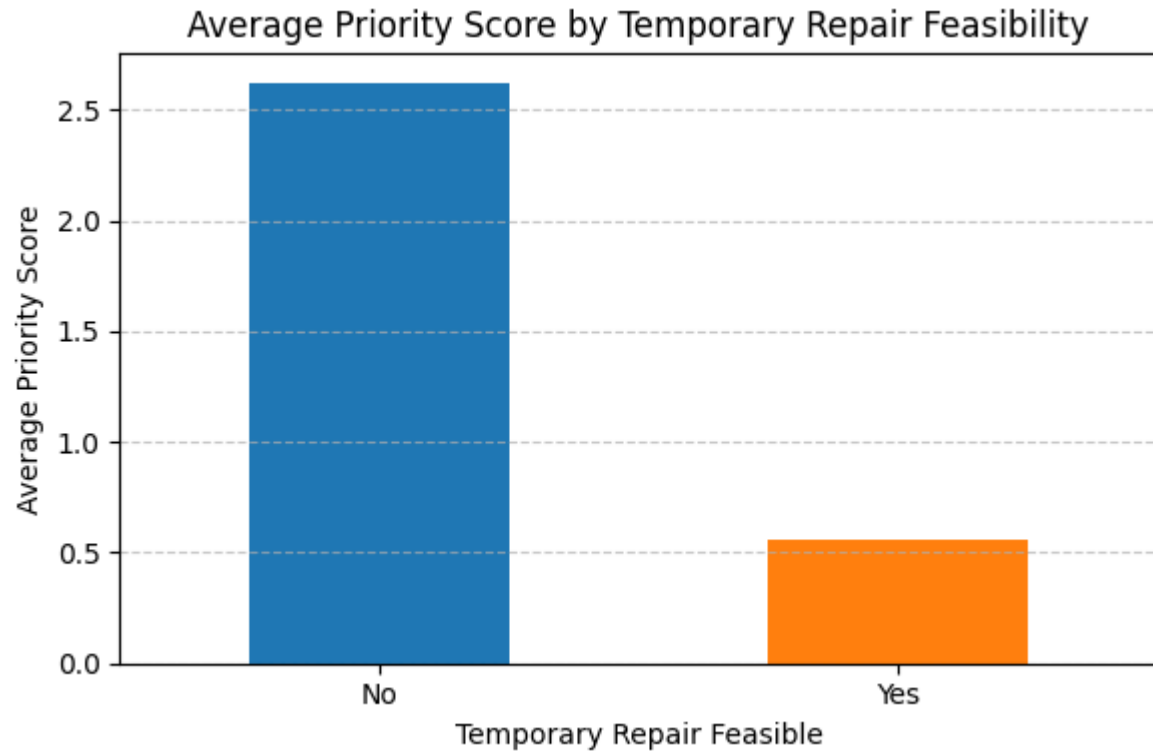
- In quieter districts ( $\leq 64$  complaints), only complaints flagged as bulk were labeled high-priority
- Complaints not part of bulk reports were deprioritized

# Temporary Repairs Not Feasible = Greater Urgency

## Key Takeaways:

If a sidewalk ramp can't be fixed temporarily, this means these ramp locations will remain inaccessible and present compliance risks.

Important to fix it with enough time to avoid compliance risk during the yearly Summer and Winter spike in complaints.



- Complaints where temporary repairs were not feasible had significantly higher priority scores
- These complaints were more likely to result in long-term inaccessibility



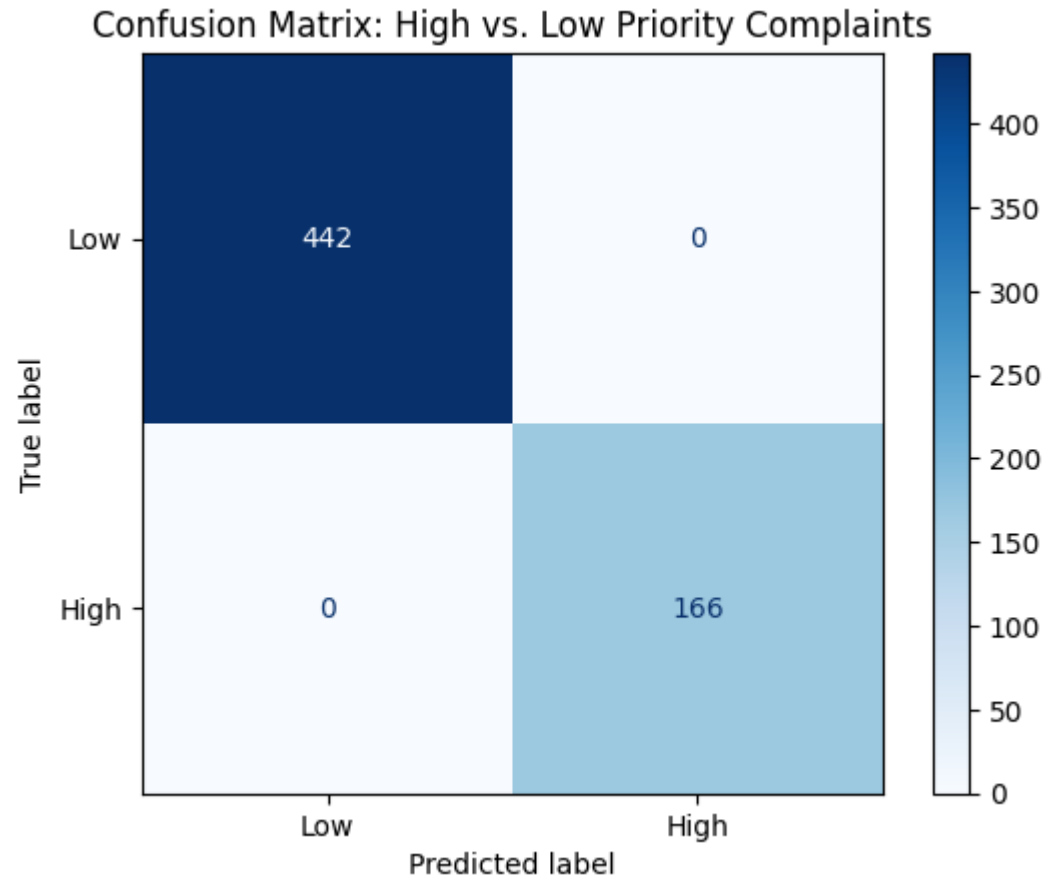
# Model Summary: Transparent, Accurate, Actionable

## Key Takeaways:

This model offers a fast, fair, and transparent way to label new complaints based on historical urgency.

With an F1 Score of 1.0, which means it had perfect recall.

It allows for an easy to explain and transparent process.



- The model correctly classified all high-priority and standard-priority complaints in the test set
- Built with just three engineered features which are fully explainable and reproducible ([BulkComplaint\\_Flag](#), [Temp\\_Repair\\_Feasible\\_Flag](#), [Neighborhood\\_Complaint\\_Volume](#))

# Recommendations

# Integrate Spatial and Demographic Data

## Key Takeaways:

This would help the city target underserved, vulnerable areas, not just areas with high complaint volume.



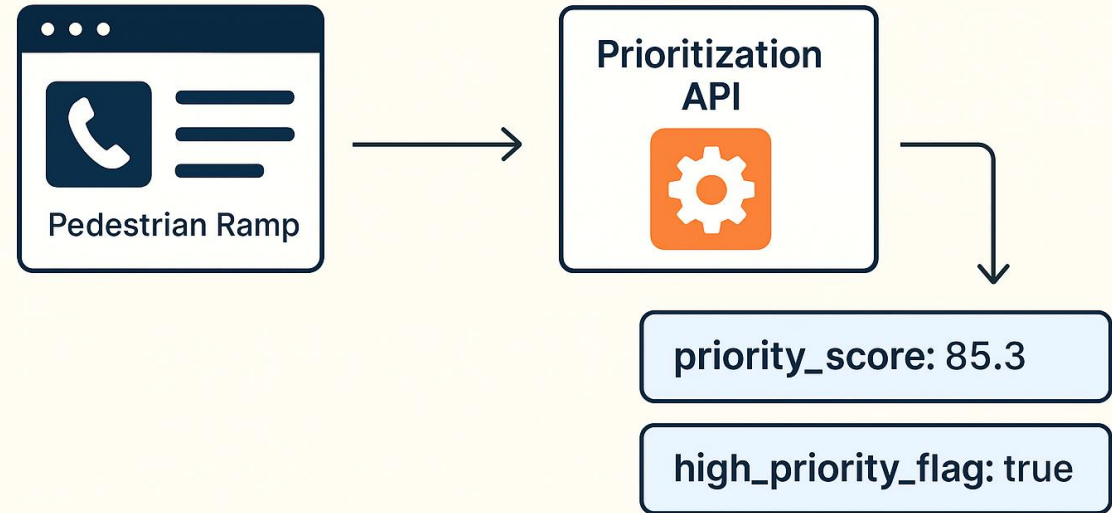
- Add spatial joins to link each complaint to:
- **Census data** (e.g. % of population with disabilities, income levels)
- **Sidewalk accessibility scores** or known infrastructure gaps

# Integrate Spatial and Demographic Data

## Key Takeaways:

Enables instant, data-driven labeling:  
Allowing field crews, repair  
schedulers, and accessibility teams  
can act faster and smarter.

## Build a Real-Time Scoring API for 311 Intake



Right now, the model is static and used retrospectively. Turning it into a live tool would prioritize complaints as they come in.

How to do it:

- Wrap the model into an API that takes in 311 complaint data
- Have it return a `priority_score` + `high_priority_flag`
- Integrate this into the city's 311 or DOT complaint triage system

# Appendix

# Model Selection

## Key Takeaways:

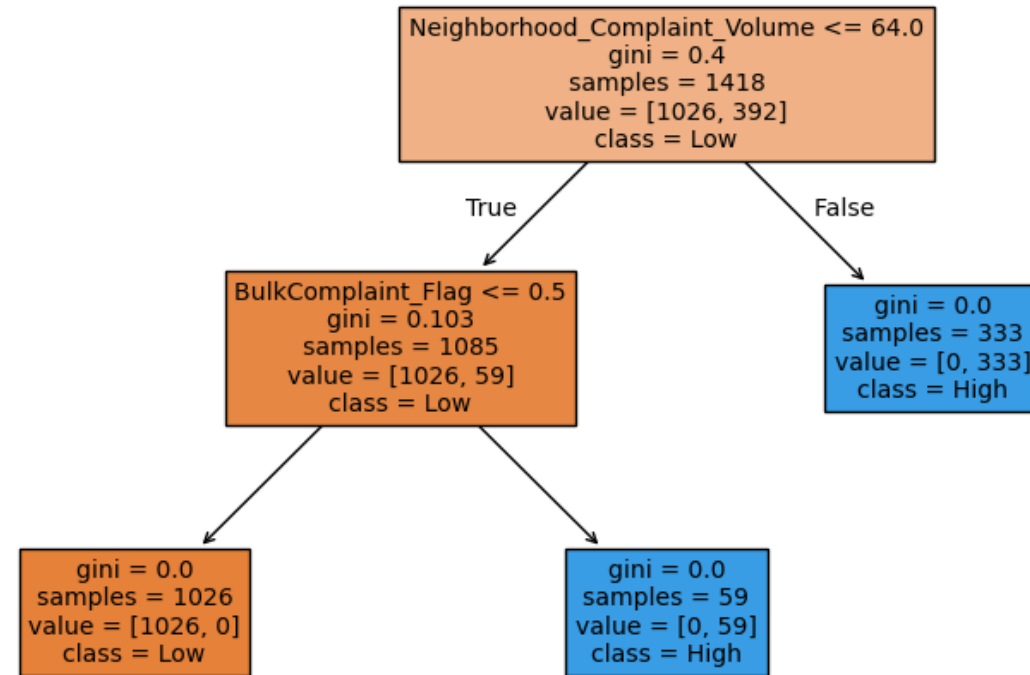
### Used For:

- Binary classification:  
High\_Priority = 1 (Top 25% of complaints by urgency score)

### Why not more complex models?

- Transparency is essential for public trust and decision-making
- Avoids “black box” concerns from city stakeholders. The “if-then” logic is transparent, and the model is defensible and equitable.

Decision Tree for High Priority Complaints



## Why this model?

- It is easy to understand and visualize, ideal for public-sector applications
- Non-linear: Captures complex interactions between features like complaint volume and repair feasibility
- Fast & Lightweight: Works well with small datasets and doesn't require heavy computational power
- Deterministic Rules: Produces repeatable logic that aligns with operational policies

# GitRepo Link

<https://github.com/cjcorrea12/NYC-Ramp>

# Dataset Source

[https://data.cityofnewyork.us/Transportation/Pedestrian-Ramp-Complaints/jagj-gttd/about\\_data](https://data.cityofnewyork.us/Transportation/Pedestrian-Ramp-Complaints/jagj-gttd/about_data)



# PDF of Settlement for the Class Lawsuit

The settlement between the City of New York and the CENTER FOR INDEPENDENCE OF THE DISABLED, NEW YORK can be found at:

- <https://www.nycpedramps.info/sites/default/files/2019-07/Pedestrian%20Ramp%20Settlement%20Agreement--Final%20Approved%207-23-2019.pdf>