

The Daily Challenge of NYC Transit

Why This Matters

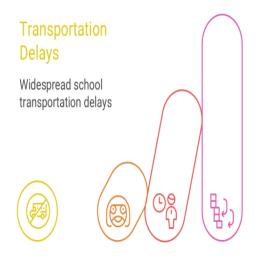
•NYC's massive school transportation system causes frequent delays.

These delays impact everyone:

- Students miss crucial learning time.
- Parents are often late for work.
- Schools face daily logistical chaos.

Our Goal: Use data to find patterns that improve communication and resource management.

School Transportation Delays Impact NYC



Missed Learning

Students lose crucial time

Parental Tardiness

Parents are late for work

Logistical Chaos

Schools face daily chaos



Five Core Research Questions

Project Scope

Five Core Research Questions

This project utilizes integrated data to provide a comprehensive analysis of public transit performance in NYC, focusing on the following core areas:



Causes of Delays

What are the leading operational causes of bus delays and breakdowns?



Weekly Trends

Is there a statistically significant link between the day of the week and bus delay frequency or duration?



Geographic Variation

How do delay times differ across specific bus companies and New York City boroughs?

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Weather Impact

What is the quantifiable impact of various weather conditions on average delay duration?



Predictive Power

Can an integrated, machine learning model accurately predict the severity of bus delays?

Data Sources

1. NYC Bus Operations Data 🚒

- A decade of operational history from NYC Open Data.
- Contains over 700,000 individual bus incidents

2. Daily Weather Intelligence 🥽



- Comprehensive daily weather metrics from NOAA.
- Monitoring everything from snowfall and fog to temperature and wind speed.

Our Final Analytical Dataset

By fusing these two sources, I have created a robust, model-ready dataset with:

- 711,939 Enriched Rows
- 68+ Predictive Features

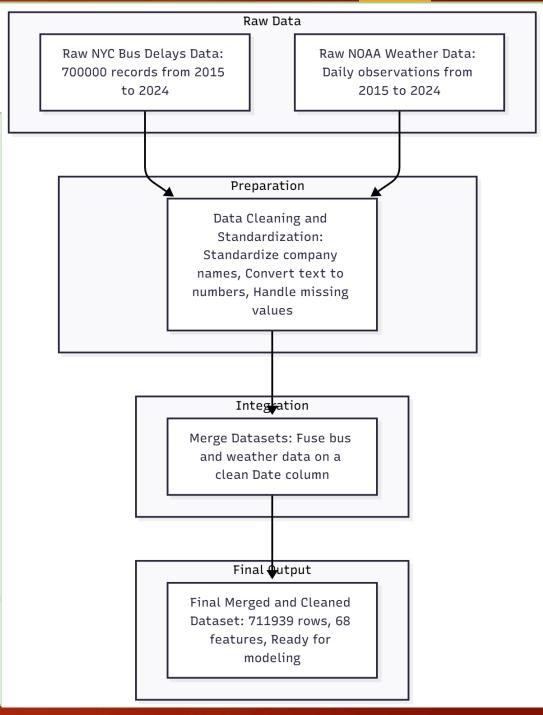


Data Cleaning & Preparation

I executed a rigorous data overhaul to forge a pristine, model-ready dataset.

- Merged and cleaned 700,000+ records from NYC Bus and NOAA Weather datasets.
- Standardized formats, removed duplicates/outliers, and filled missing values.
- Streamlined the final dataset by eliminating all irrelevant columns and metadata.
- Achieved a final, flawless dataset of over 711,000 rows with zero missing values.

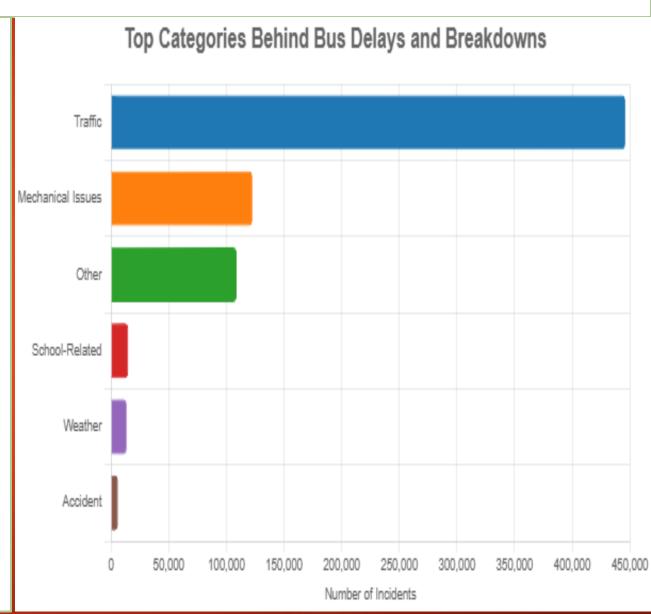




Research Question 1: What are the leading causes of delays and breakdowns?

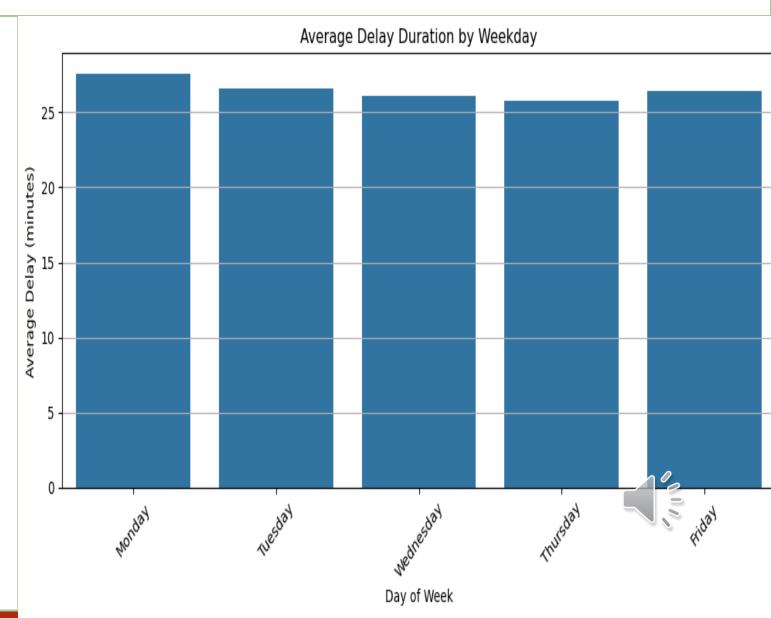
- Traffic delays: 62% of incidents (446K+ cases), the primary cause.
- Mechanical issues: 17% (122K cases), the second major factor.
- Other causes: 15% (109K cases), needs further exploration.
- School & Weather: ~4% combined (14.8K & 13.6K cases).
- Accidents: <1% (5.9K cases), low impact.





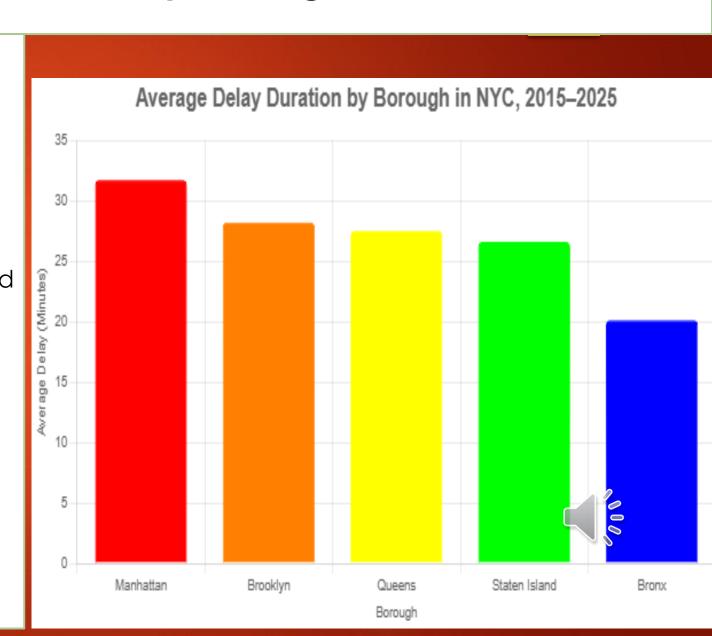
Research Question 2: Does the Day of the Week Impact Delay Durations?

- Monday delays peak: Highest average,
 likely due to weekend resets or traffic.
- Midweek (Tue-Thu) stable: Slightly lower, more consistent delays.
- Friday uptick: Minor increase, possibly from congestion or fatigue.
- This pattern suggests that day-of-week scheduling may affect operational efficiency.



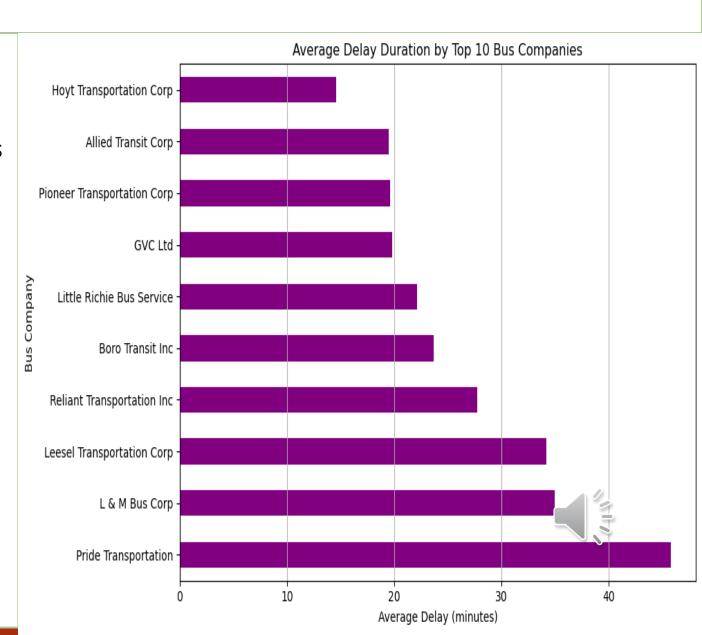
Research Question 3: Do Delays Differ by Borough?

- Manhattan: ~31.7 minutes delay.
- Brooklyn: ~28.2 minutes
- Queens: ~27.5 minutes
- Staten Island: ~26.6 minutes
- Bronx: ~20.1 minutes
- The 11.6-minute gap between Manhattan and Bronx suggests targeting Manhattan traffic interventions.



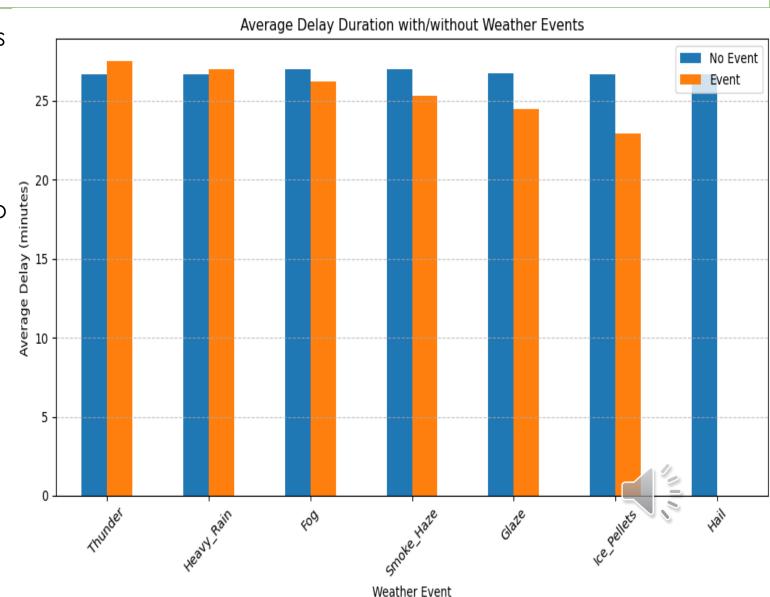
Research Question 3: Do Delays Differ by Bus Company?

- Pride Transportation: Highest delay, over 45 minutes.
- Hoyt Transportation: Lowest delay, ~14 minutes
- Wide performance gap: Over 30-minute spread, hinting at inefficiencies.
- Use data for contract oversight and targeted improvements.



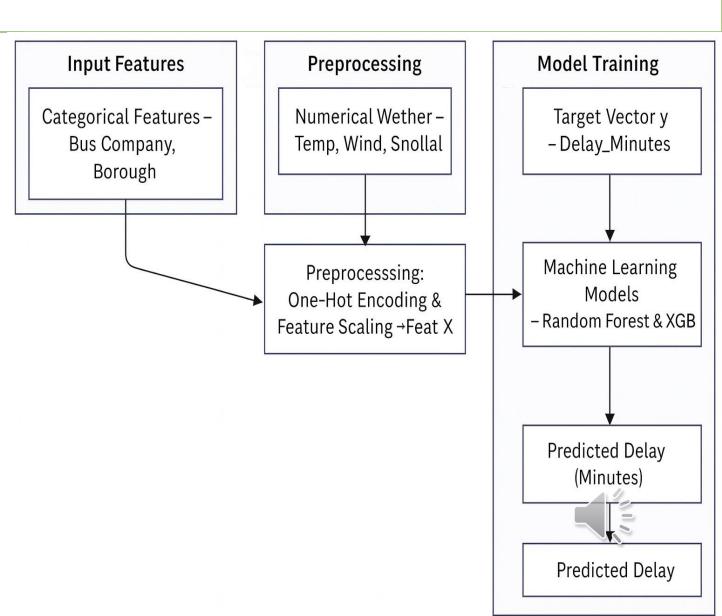
Research Question 4: Impact of Weather Events on Bus Delays

- Thunderstorms: Highest delay, dangerous driving conditions.
- Heavy Rain & Fog: Moderate delays, reduced visibility, and traffic.
- Ice Pellets, Glaze, Smoke/Haze, low or no delay, rerouting, or closures.
- Hail: no impact, rare in NYC.



Research Question 5: Can Delays or Breakdowns Be Forecasted Using Predictive Models?

- Data Processing: Cleaned 700,000+ records from transit and weather datasets for accuracy.
- Class Removal: Excluded delay classes with
 <2 entries (<1% of data) for robust training.
- Data Split: Used stratified sampling for an 80/20 train-test split
- Feature Prep: Applied one-hot encoding to categorical data and normalized numerical variables.
- Model Building: Developed ML models to predict delays, achieving RMSE ~17.6 minutes.



Model Selection and Comparison – Random Forest vs. XGBoost

- Tree-based models capture complex patterns & handle missing values well
- Built-in feature importance supports interpretability
- Ideal for large, real-world datasets
- Chosen for performance and interpretability over linear or SVM models

Model	RMSE	R2
Random Forest	17.62 mins	0.26
XGBoost	17.58 mins	0.26

Interpretation:

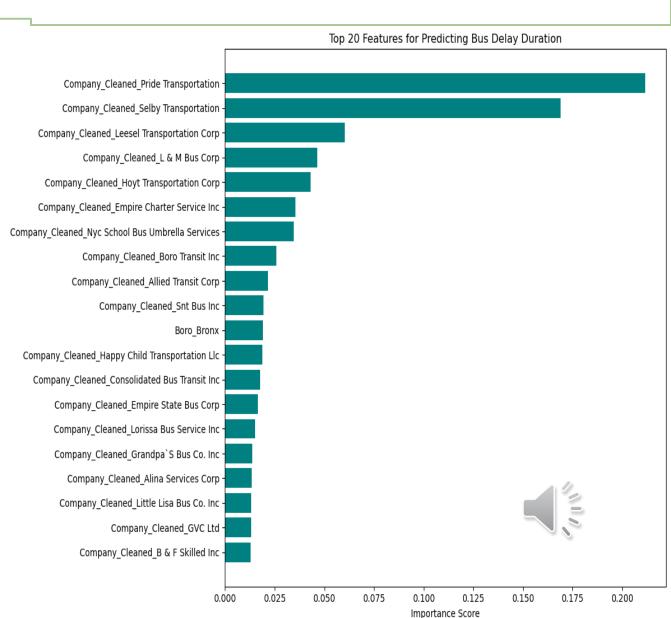
- Both models perform similarly, suggesting diminishing returns with added model complexity.
- RMSE of \sim 17.6 minutes means the average prediction error is about 17 minutes.
 - R² of 0.26 indicates modest predictive power; external factors likely influence delays.



What Drives Bus Delays? Top Predictive Features

Key Takeaways from Feature Importance Analysis(based on XGBoost model)

- Company identity key: Pride and Selby show unique delay patterns.
- Bus companies dominate: 8 of the top 10 predictors, highlighting internal impact.
- Bronx challenges: Top 20 ranking reveals location issues.
- Model success: Confirms learning of operational and regional patterns.
- Target underperforming companies for improvements.



Recommendation: Actionable Insights & Recommendations

- Target high-delay bus companies, e.g., Pride & Selby Transportation, to prioritize audits, retraining, or contract review.
- Address borough-specific issues. Manhattan exhibits longer delays when exploring traffic coordination or rerouting options.
- Focus on Monday operations. Delay durations peak on Mondays, which suggests a need for improved weekend-to-weekday transition planning.
- Weather has a modest influence. Thunder slightly increases delays; most events are not affected significantly by weather, so weather-resilient planning may not require a significant overhaul.
- Leverage ML predictions for daily operations. Use delay risk scoring by company, day, and weather to proactively manage dispatching and communication.

Conclusion & Key Takeaways

- Analyzed over 700,000 NYC school bus incidents. Cleaned, merged, and enriched with weather data to uncover delay patterns.
- Identified major causes of delays: "Heavy Traffic" is by far the most common, accounting for over 60% of all reports.
- Delay duration varies by weekday, borough, and bus company. Manhattan and Mondays experienced the most extended average delays.
- Built and compared ML models (Random Forest & XGBoost). XGBoost performed slightly better with an RMSE of 17.58 minutes and R² of 0.26.
- Top predictive features revealed company-level trends. Some bus companies are consistently linked to longer delays, offering actionable focus areas.
- Project demonstrates how data science can drive more innovative transportation planning, from cuditing vendors to improving scheduling and communication with parents.

Tools and Libraries used

- Numpy: Python fundamental package for scientific computing
- Pandas: Python data wrangling library
- Scikit-Learn: For Machine Learning and Vectorization
- Seaborn: Statistical visualization too built on top of matplotlib.
- Matplotlib: Foundational library for visualizations.
- Jupyter Notebook: Interactive Python Programming server-client interface.



Thank You & Questions

Thank You! I appreciate your time and attention.



Questions? I am happy to answer any questions or discuss insights further.



