LEVERAGING BIG DATA FOR MTA SUBWAY RIDERSHIP ANALYSIS

CSGY 6513 Fall 2024 Professor Juan Rodriguez

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INTRODUCTION AND PROBLEM STATEMENT

The Metropolitan Transportation Authority (MTA) is an integral part of New York City, serving as the backbone of daily commutes for millions of residents and visitors. MTA is essential to the city's economy and is what ties the city together.

As ridership has grown significantly since the pandemic, the demand for reliable, efficient, and accessible service has increased. This ever-growing demand brings its own set of challenges, from managing delays, maintaining service quality, and addressing rider satisfaction.

DATA SOURCES

Datasets Used: (Millions of Rows ~ 35 GB of size)

- MTA Customer Feedback Data (2014–2019): Contains feedback regarding service quality, complaints, and commendations.
- MTA Daily Ridership Data (Post-2020): Tracks daily ridership metrics for subways, buses, and other transit systems.
- MTA Key Performance Indicators (2008–2021): Evaluates performance metrics such as punctuality and safety.
- MTA Monthly Ridership Traffic Data: Aggregated monthly ridership data for trend analysis.
- MTA Service Alerts Data (Post-2020): Logs alerts and disruptions in transit services.
- MTA Subway Customer Journey Metrics: Provides details on journey times, delays, and passenger metrics.
- MTA Hourly Ridership Data (Post-July 2020): Hourly granular ridership data for subway systems.
- MTA Subway Major Incidents Data: Logs major incidents affecting service.
- MTA Subway Origin-Destination Data: Tracks passenger movement between stations.
- MTA Subway Stations: Metadata about station attributes such as location, accessibility, and facilities.
- MTA Subway Stations and Complexes: Details about station complexes and associated stations.
- MTA Subway Turnstile Usage Data: Data on subway entry and exit counts.
- MTA Subway and Bus Lost Time Data: Metrics on lost time due to accidents and other disruptions.

Sources:

- MTA Open Data Platform
- Official NYC Open Data API

WHY BIG DATA

- Volume - Handling large datasets from multiple sources (daily, monthly, hourly ridership, service alerts, station data)
- Variety - Diverse data types: numerical ridership figures, textual service alerts, geospatial station locations
- Velocity - Real-time data processing for timely insights and alerts.
- Veracity - Ensuring data quality and accuracy amidst vast and varied data sources.
- Value - Extracting actionable insights to drive strategic decisions.

DATA PROCESSING

Loading:

- Used PySpark for large dataset handling and sampling.
- Example: Sampled 1% of the "Hourly Ridership Data" for exploratory analysis.

Cleaning: Removed duplicates, handled missing values, standardized column names.

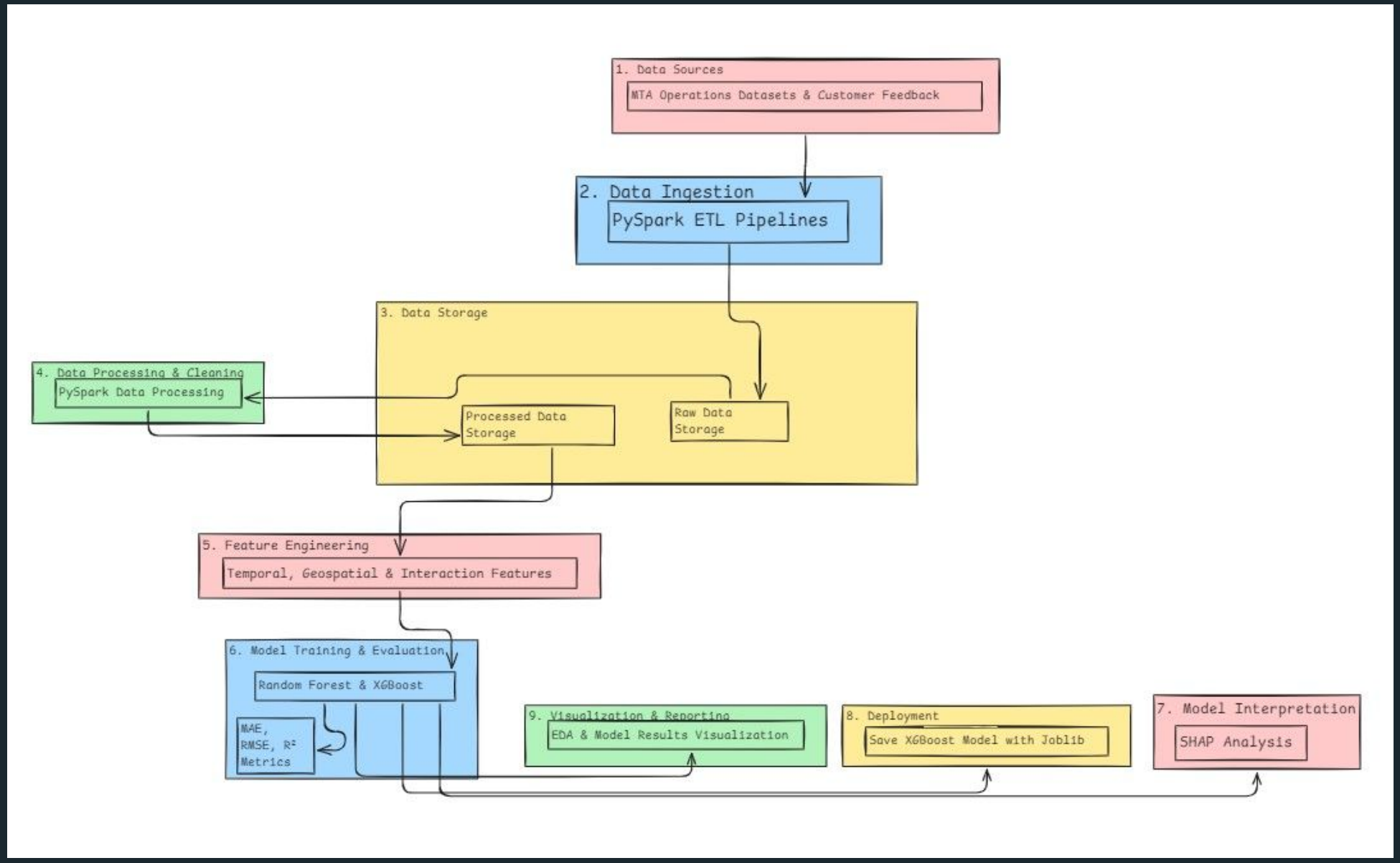
Transformation:

- Created a geosphere for mapping latitudes and longitudes.
- Calculated and added the distance parameter calculating it from the geosphere.
- Derived new features like "Day of Week" and "Hour of Day" for trend analysis.

Merging: Integrated multiple datasets on keys such as station_complex_id, transit_times, or agency.

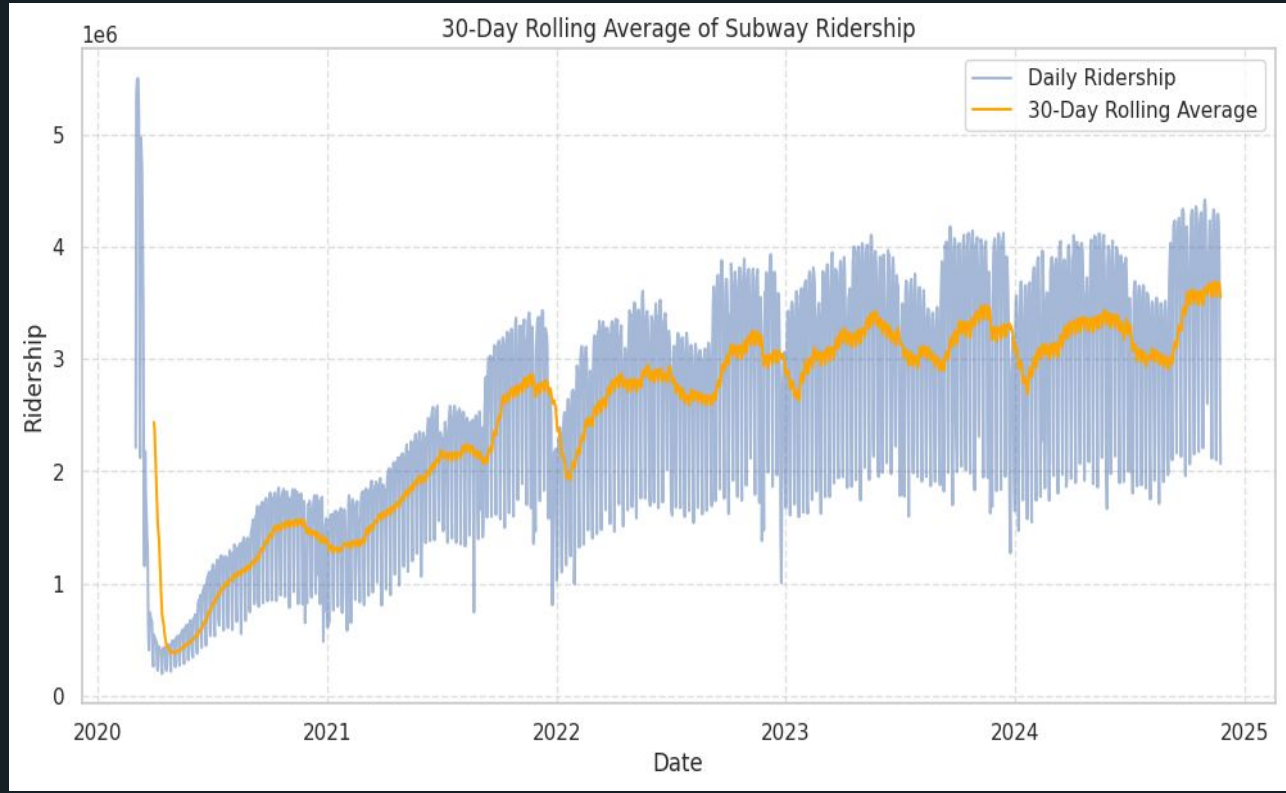
```python
import pandas as pd
import random
from pyspark.sql import SparkSession
from pyspark.sql.functions import rand

spark = SparkSession.builder \
    .appName("MTADataSampling") \
    .getOrCreate()

input_file = "/kaggle/input/mta-combined/MTA_Subway_Hourly_Ridership__Beginning_July_2020.csv"

sample_fraction = 0.01

# Read the CSV file using PySpark
try:
    # Load data into Spark DataFrame
    df = spark.read.csv(input_file, header=True, inferSchema=True)

    sampled_df = df.sample(withReplacement=False, fraction=sample_fraction, seed=42)

    sampled_df.coalesce(1).write.csv("sampled_output_temp", header=True, mode='overwrite')

    import shutil
    import glob
    import os

    part_file = glob.glob("sampled_output_temp/part-*.csv")[0]

    shutil.move(part_file, output_file)

    shutil.rmtree("sampled_output_temp")

    print(f"Sampled data saved to {output_file}")

except Exception as e:
    print(f"An error occurred: {e}")

# Stop the Spark session
spark.stop()
```

PROJECT ARCHITECTURE



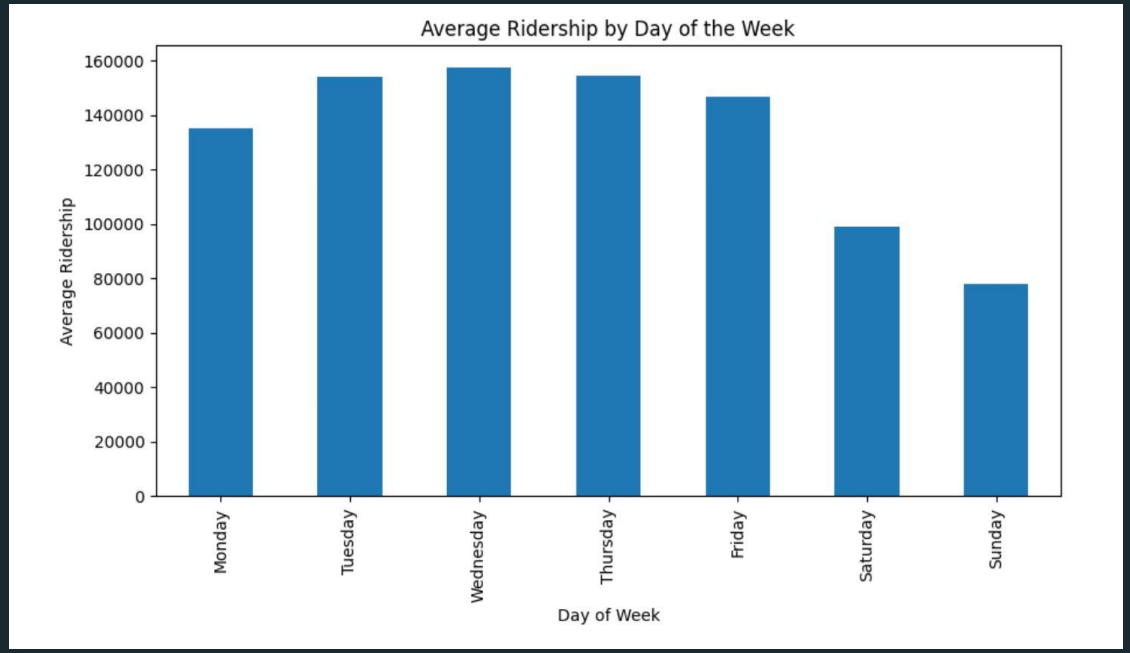
EXPLORING RIDERSHIP: DAILY TRENDS

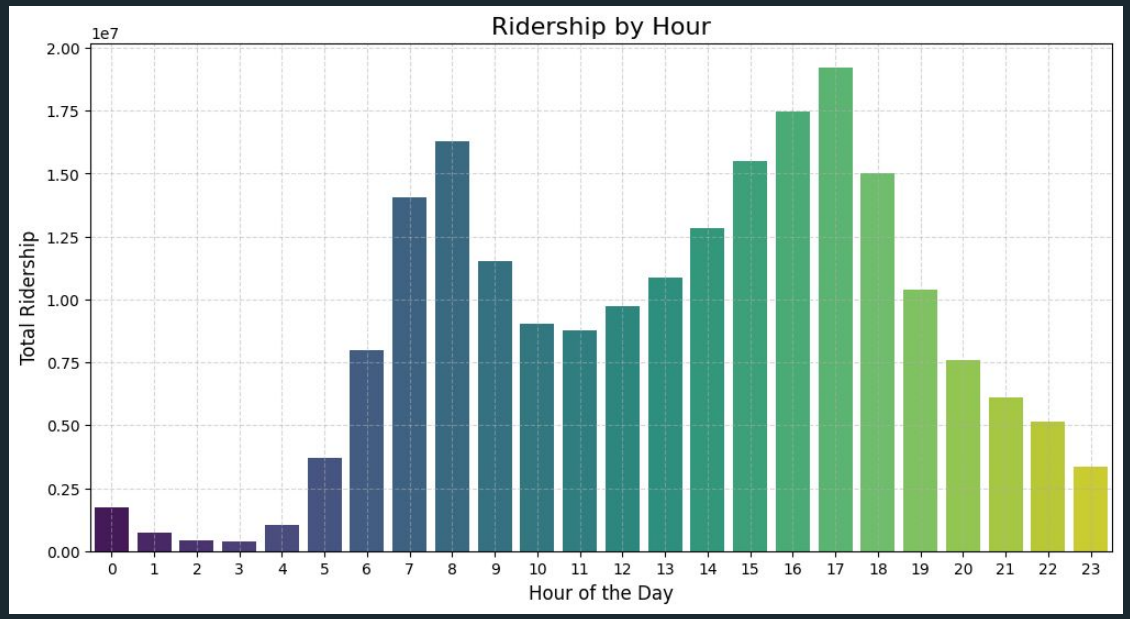
- MTA ridership experienced about 140% growth from 2020 pandemic to 2024 November
- Daily ridership has yet to return to pre-pandemic levels. Additionally, as more and more jobs demand return-to-office, the need to placate the growing demands of reliability becomes more important
- We'll examine deeper into overall trends and where there are gaps in MTA's service that impact riders' sentiment



EXPLORING RIDERSHIP: WEEKDAY PEAKS

- Ridership is the highest on weekdays, peaking on Wednesdays, reflecting typical work week commuting.
- This underscores the importance of on weekdays and hours when commuters travel from and to work as critical ridership periods, driven by work and business needs.

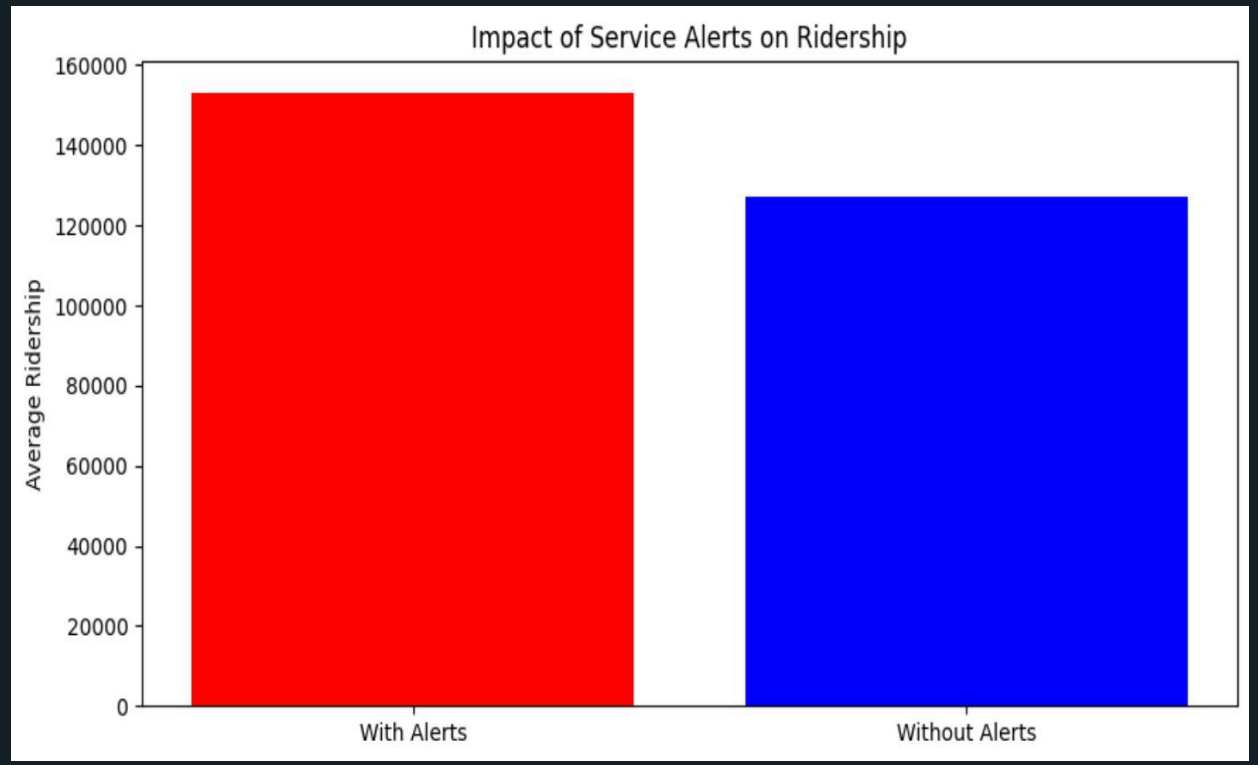




EXPLORING RIDERSHIP: DELAYS AND ALERTS

- Despite New York's reliance on MTA services, riders are more likely to experience disruptions than not
- Delays are the most prevalent alert, indicating that delays are regular and recurring issue
- Addressing the root causes of these delays, such as infrastructure inefficiencies, could have a meaningful impact on overall service reliability

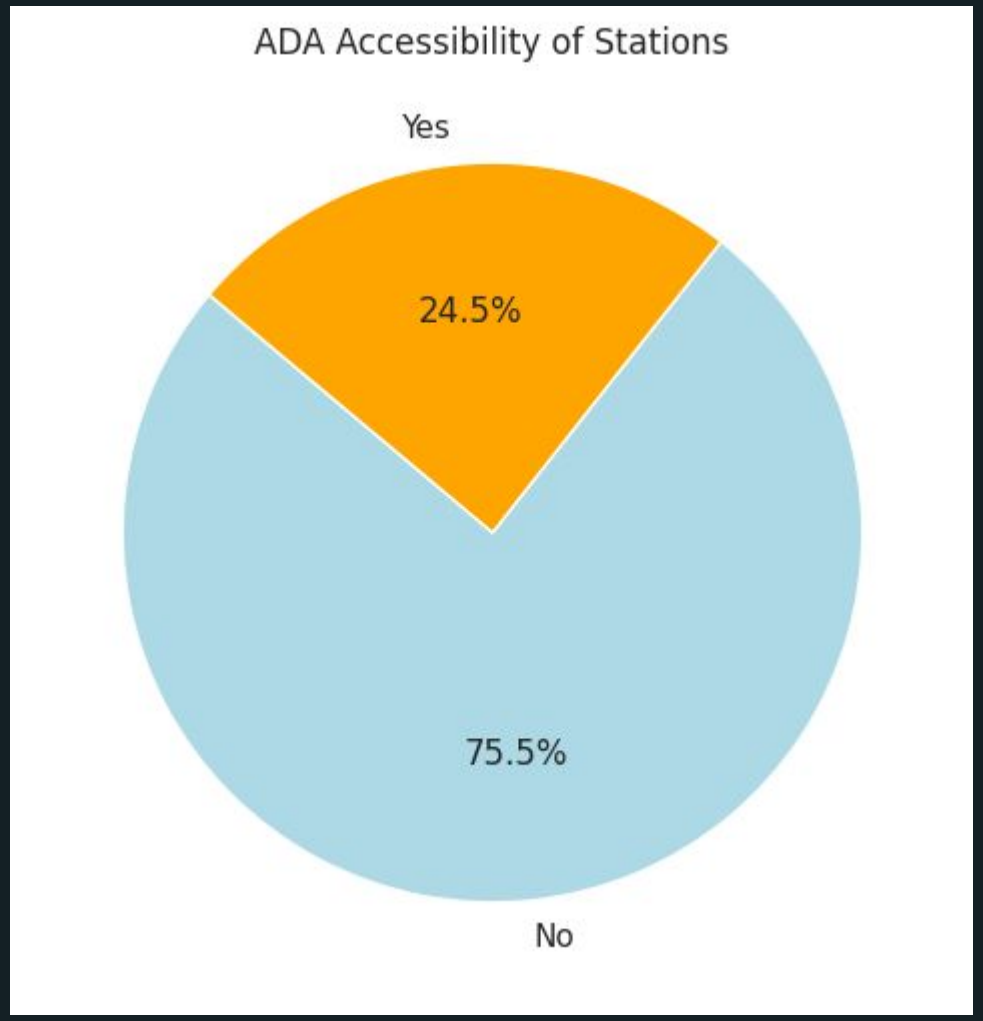
Status Alerts	Frequency
Delays	173,711
Some-Delays	48,120
Buses-Detoured	16,901
Weekday-Service	16,850
Essential-Service	8,219



EXPLORING RIDERSHIP: ADA ACCESSIBILITY

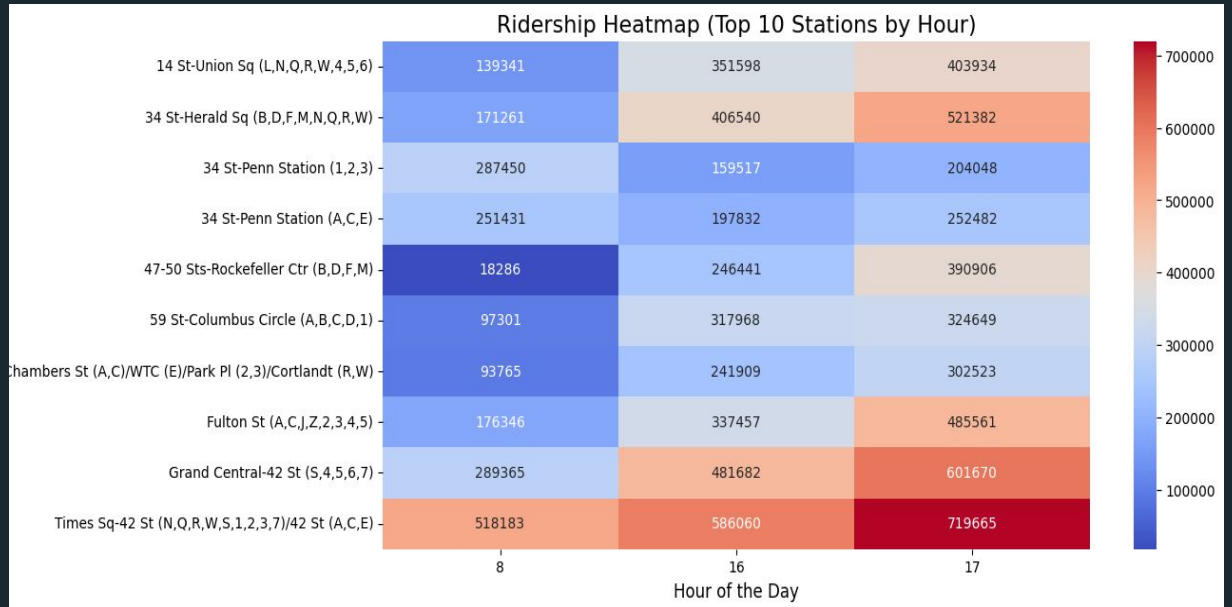
- As only 24.5% are compliant with ADA, the majority of the stations are left without accessibility features, a significant gap in inclusivity for individuals with disabilities.

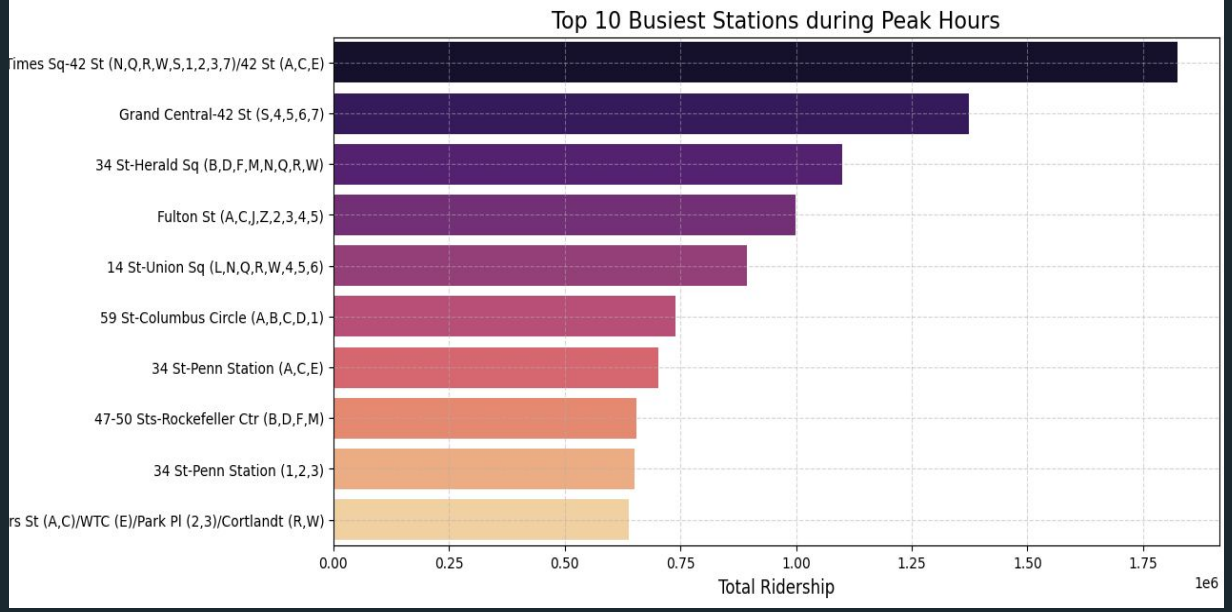
- Low ADA-accessible stations discourage potential ridership among people who rely on these features, which is limiting for a diverse and touristy city like NYC.



EXPLORING RIDERSHIP: WHERE RIDERS ARE CONCENTRATED

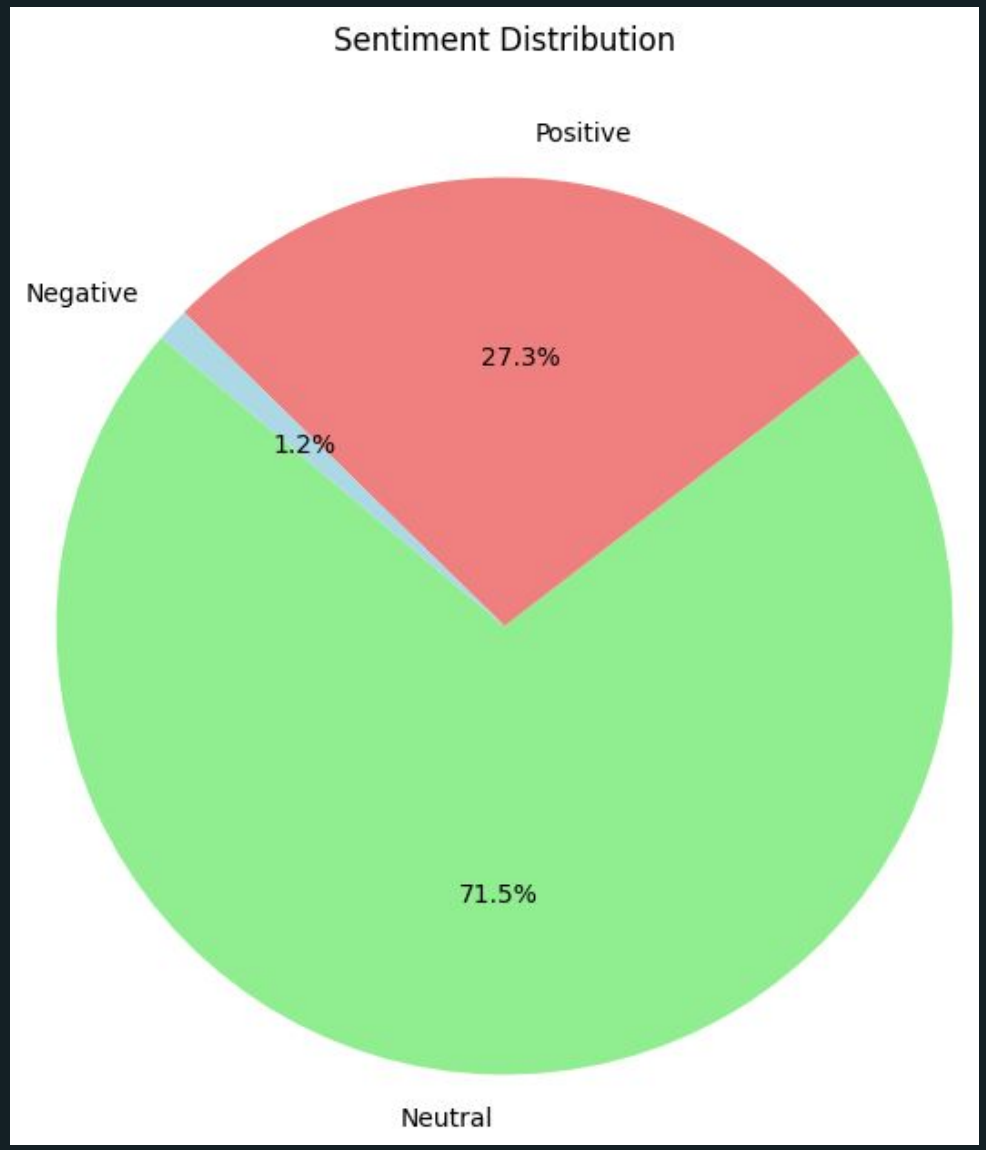
- Stations in Manhattan, like 42nd St and 34th St, remain critical focal points for managing crowd control and optimizing service during peak hours.
- Stations like Rockefeller Center and Chambers St have notable spikes in ridership, indicating there are localized surges that MTA can strategically allocate resources to.





RIDER SENTIMENT: MOSTLY NEUTRAL, ROOM FOR IMPROVEMENT

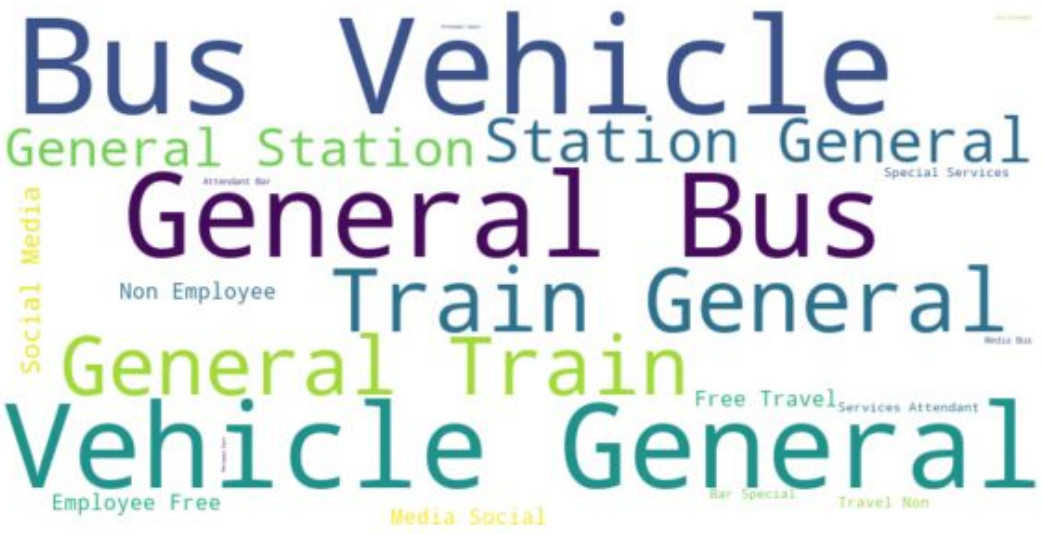
- Most riders express a neutral sentiment, indicating that while they are not dissatisfied, their experiences are not exceeding expectations.
- Negative sentiment at 1.2% shows that outright dissatisfaction is relatively rare.
- However, the overwhelming neutrality highlights opportunities to improve aspects of MTA to move more neutral riders toward positive experiences.



RIDER SENTIMENT: THEMES IN FEEDBACK

- Within the positive word cloud, “Bus”, “Vehicle”, and “General” dominate could suggest riders feel that MTA do provide basic service reliability and functionality.
- Negative feedback is concentrated on issues of cleanliness, customer service, and operational inefficiencies, pointing to areas that MTA put more attention to improve.

Positive Feedback Word Cloud



Negative Feedback Word Cloud

RECOMMENDATIONS FOR IMPROVEMENT

Operational Efficiency

Focus on reducing delays and efficiencies during peak hours and weekdays that reflect normal commuting times, especially in the busiest stations such as Times Square-42nd St and Grand Central-42nd St

Cleanliness and Maintenance

Invest more into waste management and general maintenance to improve daily commutes; enforce basic etiquette and rules to discourage unauthorized activities such as merchandise sales

Communication and Alerts

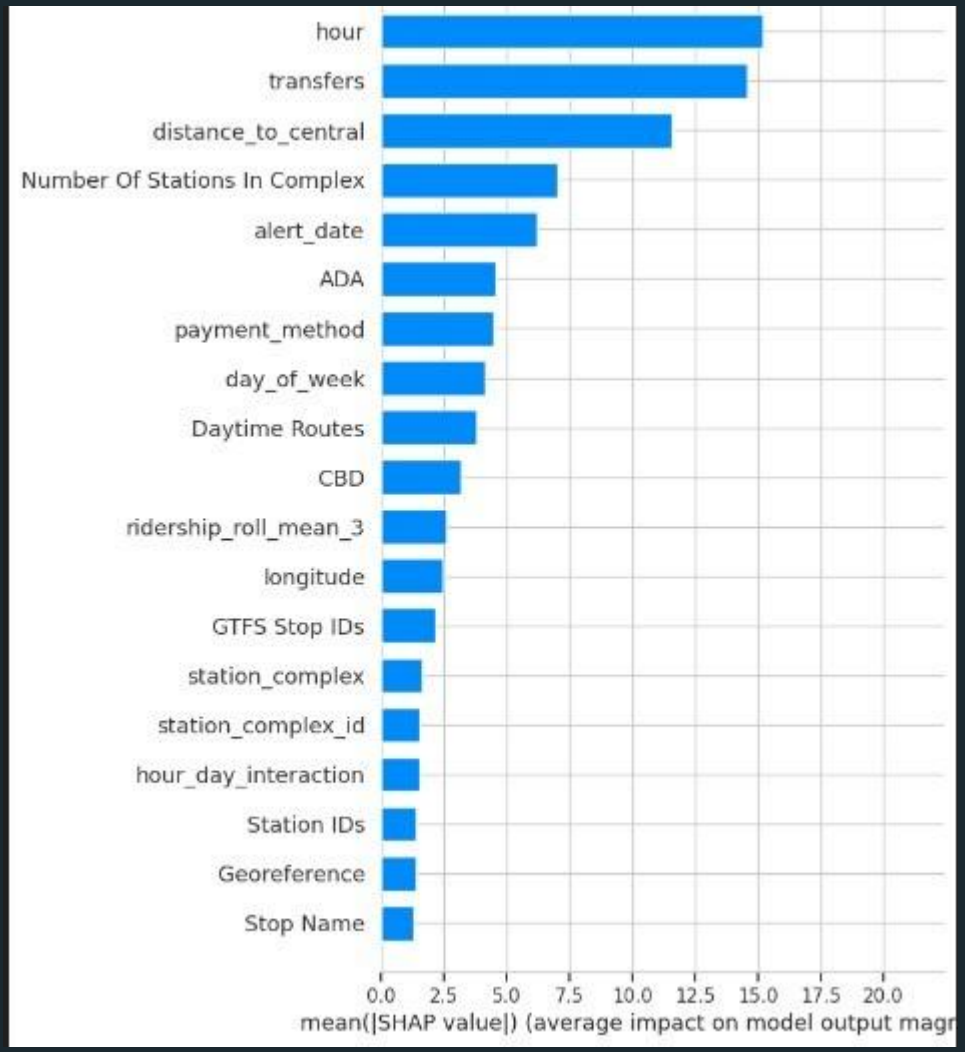
Improve real-time communication about delays and disruptions by leveraging mobile apps, digital signages to keep riders informed and reduce frustration

FEATURE ANALYSIS USING SHAPE ANALYSIS

The bar chart presents the mean absolute SHAP values for each feature, ranked in descending order. This shows the average contribution of each feature to the model's output.

- hour: The time of day also significantly affects the model's decision.
- transfers: The number of transfers contributes substantially to the predictions.
- Features such as Geo-fence, Stop Name, and Station IDs have minimal impact on the model's output.

By quantifying the importance of features, SHAP values provide transparency to a typically "black-box" model like XGBoost.



XGBOOST RIDERSHIP PREDICTION

- Leveraged the XGBoost machine learning model to forecast daily estimated ridership for the MTA subway system with high accuracy.
- Integrated big data sources such as ridership statistics, service alerts, customer feedback, and operational metrics to capture influencing factors.
- Designed the model to identify complex patterns and provide actionable predictions using efficient large-scale data processing.
- Enabled the MTA to optimize train schedules, allocate resources, and enhance service reliability based on forecasted demand.

```
from sklearn.metrics import r2_score

# Evaluate R² Score
r2 = r2_score(y_test_cv, y_pred_cv)
print(f"XGBoost R²: {r2:.4f}")
```

```
XGBoost R²: 0.7727
```

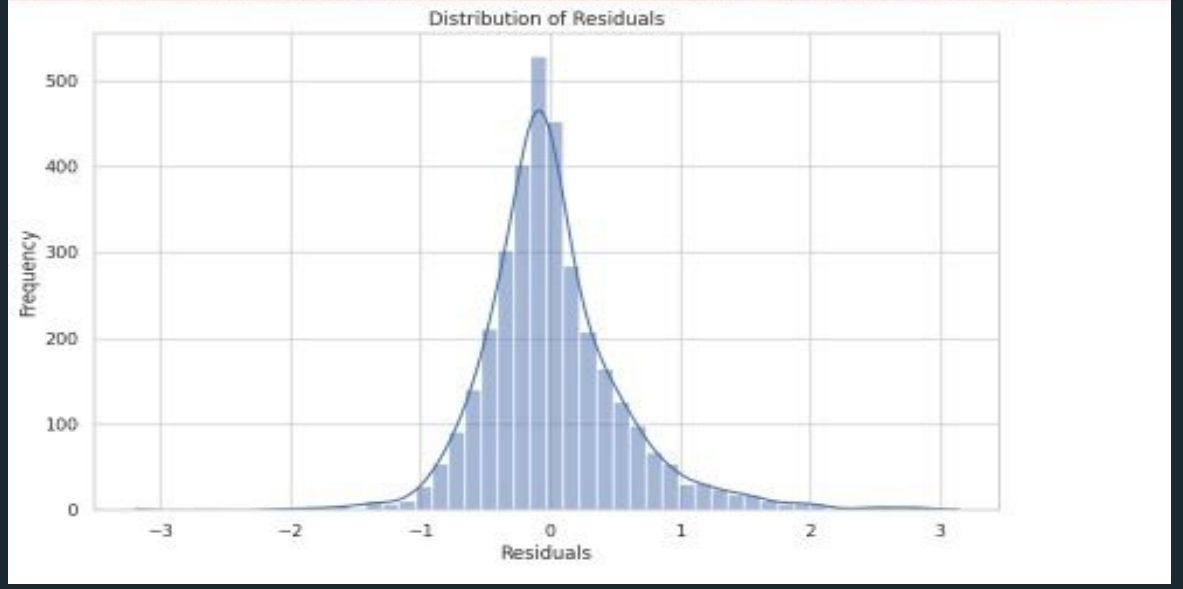
DISTRIBUTION

- A normal distribution of residuals indicates that the errors are unbiased and randomly distributed, suggesting the model is well-fitted.

- There are no major skewness or outliers visible in the distribution.

```python
import matplotlib.pyplot as plt
import seaborn as sns

# Calculate Residuals
residuals = y_test_cv - y_pred_cv

# Plot Residual Distribution
plt.figure(figsize=(10,6))
sns.histplot(residuals, bins=50, kde=True)
plt.title('Distribution of Residuals')
plt.xlabel('Residuals')
plt.ylabel('Frequency')
plt.show()

# Residuals vs Predictions Plot
plt.figure(figsize=(10,6))
sns.scatterplot(x=y_pred_cv, y=residuals)
plt.axhline(0, color='red', linestyle='--')
plt.title('Residuals vs. Predictions')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.show()
```

```
use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
```



HOW CAN WE IMPROVE THE ANALYSIS FURTHER

- Incorporating real-time data streams for dynamic forecasting directly through an API.
- Sampling a larger set of data and training the model on a much larger training dataset.
- Extending analysis to include additional factors like weather, events, and economic indicators.
- Implement Reinforcement Learning by analyzing their predictions and connecting it to the MTA data stream API.

THANK YOU!