Flight Delay Forecasting using Machine Learning

Team SG (Team Number 109)

Kiki Ang (kang30), Ho Wei Sin (who46), Jorge Almeyda (jalmeyda3),
Joel Quek (jquek7), Ahmed Elsemary (aelsemary3)

Motivation and Introduction

Problem: Flight delays are disruptive, impacting passenger satisfaction and costing airlines billions annually in increased labor and maintenance costs. Predicting delays can enhance planning and operational efficiency, benefiting both travelers and airlines.

Importance: Reliable flight delay predictions can enhance traveler experiences by reducing stress and improving operational decision-making for airlines. Early insights allow passengers to adjust plans, while airlines can optimise resource allocation and mitigate disruptions.

Data

Source: The team sourced data from the Kaggle Flight Delay and Cancellation Dataset (2019-2023), covering millions of United States flight records (Flight Delay and Cancellation Dataset (2019-2023) (kaggle.com))

Characteristics: The dataset is substantial (~2.9 million), containing temporal data points such as flight schedules and delays, weather, and airport information. The size and scope enable comprehensive analyses.

Approach

Algorithms & Visualizations: The team employed multiple machine learning algorithms: XGBoost, Random Forest, Support Vector Machine and logistic regression to predict delays.

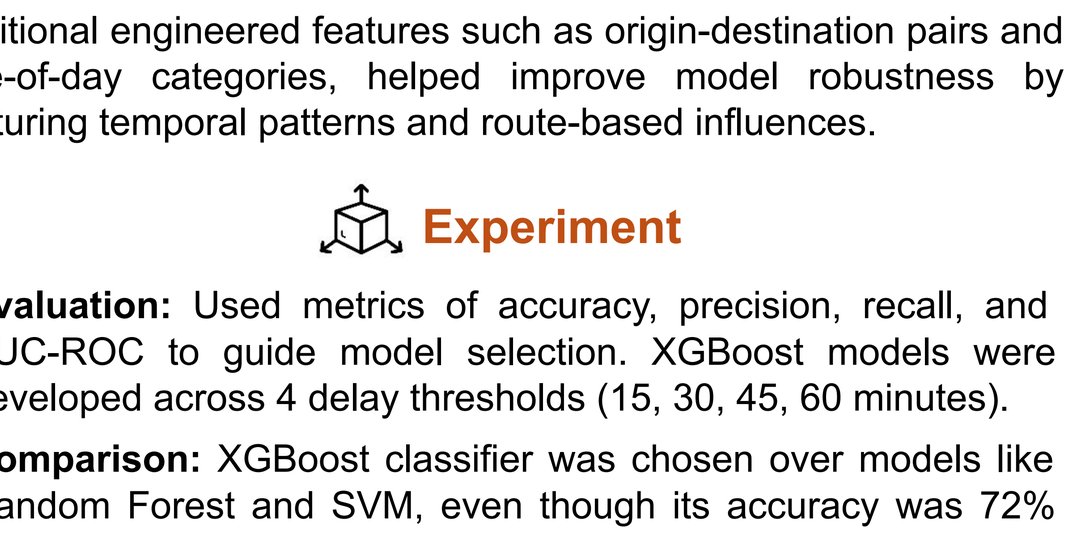
Methodology: XGBoost was chosen for its efficiency in training large datasets and flexibility with mixed data types, achieving highest accuracy among the tested models.

Additional engineered features such as origin-destination pairs and time-of-day categories, helped improve model robustness by capturing temporal patterns and route-based influences.

Experiment

- **Evaluation:** Used metrics of accuracy, precision, recall, and AUC-ROC to guide model selection. XGBoost models were developed across 4 delay thresholds (15, 30, 45, 60 minutes).
- **Comparison:** XGBoost classifier was chosen over models like Random Forest and SVM, even though its accuracy was 72% because its recall was the best at 42%. It also effectively captured complex interactions within the dataset compared with other models.
- Feature importance analysis highlighted critical predictors of temporal factors (month, day of week), route-based features, and operational data.

Figure 1: *Feature Importance showing the most significant predictors*

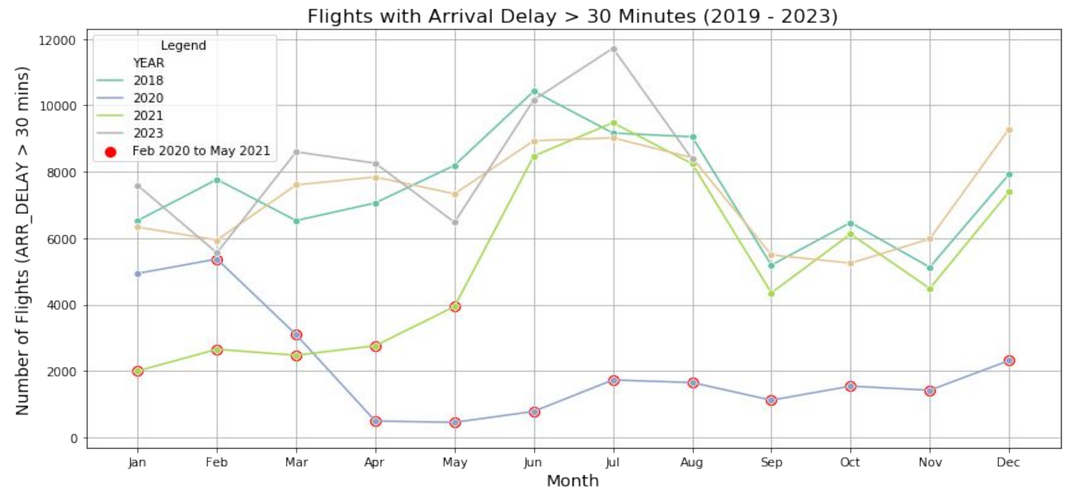


Results

Results: Temporal features such as month and day of week effectively capture seasonal and weekly delay patterns, while interaction terms enhance the model's ability to account for complex relationships. Additionally, network centrality metrics highlight the impact of airport connectivity on delays.

Future work may enhance predictions by integrating other real-time data like weather and operational bottlenecks.

Figure 2: *This graph shows seasonality of flights with arrival delays by month*



Interactive Visualization:

- **Web-Based Interface App:** Our intuitive, web-based interface provides detailed and customizable flight delay predictions tailored to individual flights. This interface combines ease of use with rich map visualization, enhancing accessibility and interaction (Figure 3).
- **Browser Plug-In:** Our plug-in provides quick and convenient delay predictions by seamless integration with travel platforms. The plug-in is embedded into the browsing experience, allowing users to directly check delay predictions without navigating to an external website. (Figure 4).

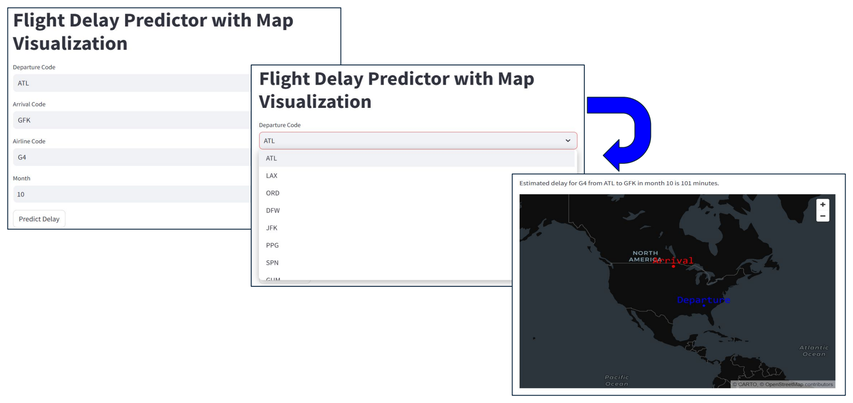


Figure 3*: This Streamlit web-based application enables users to enter key fields to predict and visualise flight delay time.*

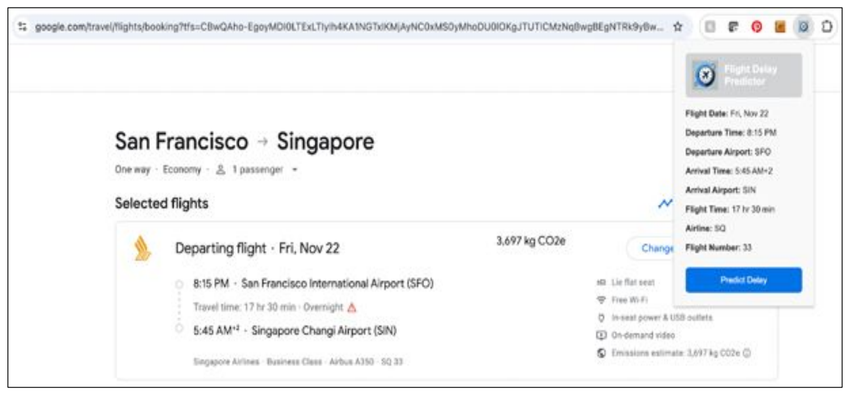


Figure 4*: One-click action by user to automatically extract flight details with estimated delay prediction from browser plug-in*

Intuition and Innovation:

- **Advanced Predictors:** Combines traditional factors with network-based features, including route interactions.
- **Real-Time Integration**: Seamlessly embedded into travel websites for instant, browser-based predictions.
- **Engineered Insights**: Tailored features address key delay factors, ensuring precise and reliable forecasts.