# Commercial Aircraft Trajectory Weather and Fuel Analysis

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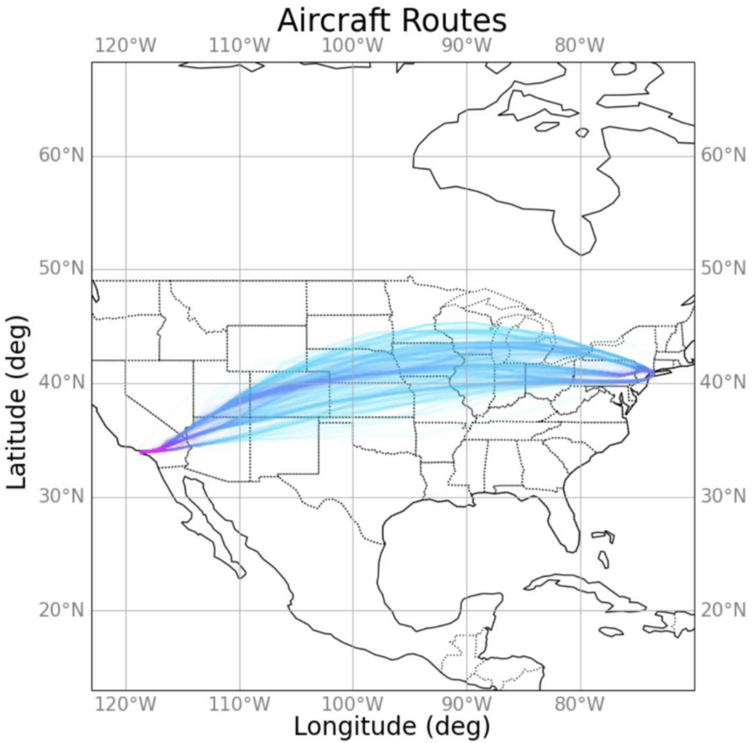
https://github.com/Flight-Path-Analysis/FlightPathAnalysis

# Objectives:

- **Data Collection**
  - Download, clean and organize Flight Data and Weather Data
- **Data Analysis**
  - Estimate fuel consumption
  - Estimate weather conditions on the paths of each flight
  - Analyze flight paths and carry out EDA
- **Machine Learning**
  - Identify how weather might affect flight paths and/or fuel consumption
  - Train a predictive model to estimate fuel consumption given the forecasted weather pattern

# Flight and Weather Data Collection

- **Flight Data** - OpenSky Network
  - **Icao24**, **callsign**
  - **longitude**, **latitude**, **altitude**, **heading**, **etc**
- **Weather Data -** The Iowa Environmental Mesonet (IEM)
  - **Temperature**, **wind speed**, **relative humidity**, **etc**.
  - Using interpolation and weather models to estimate the weather at any point in space and time



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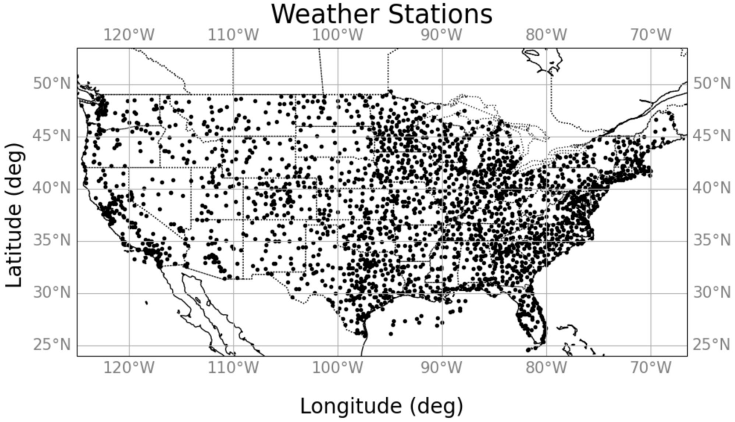
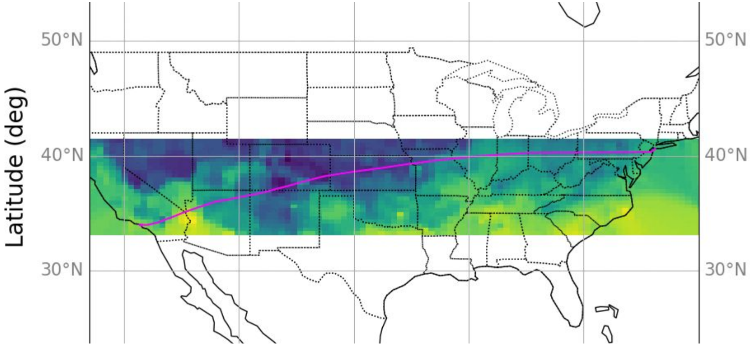
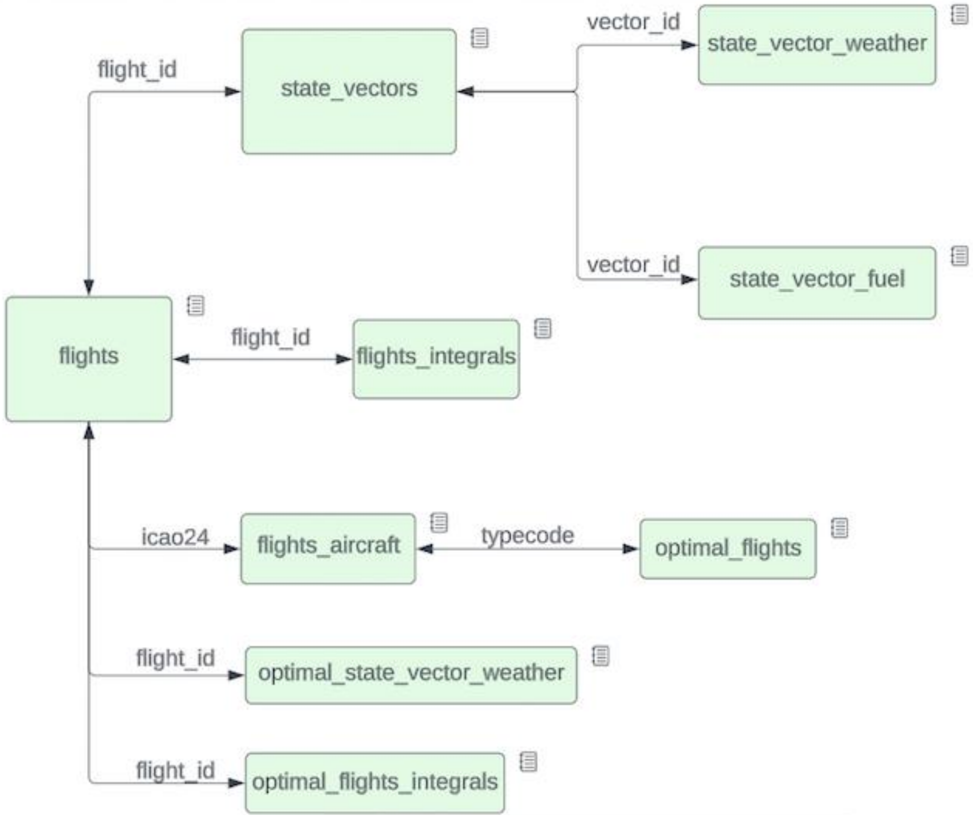
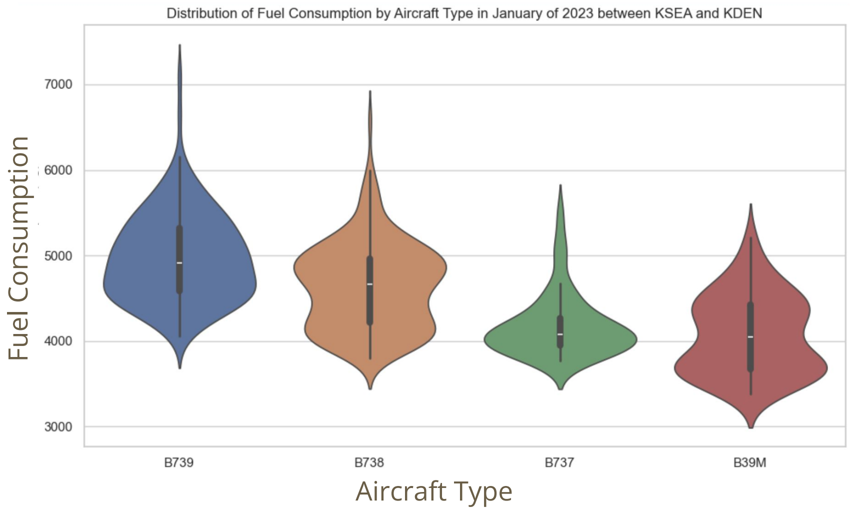


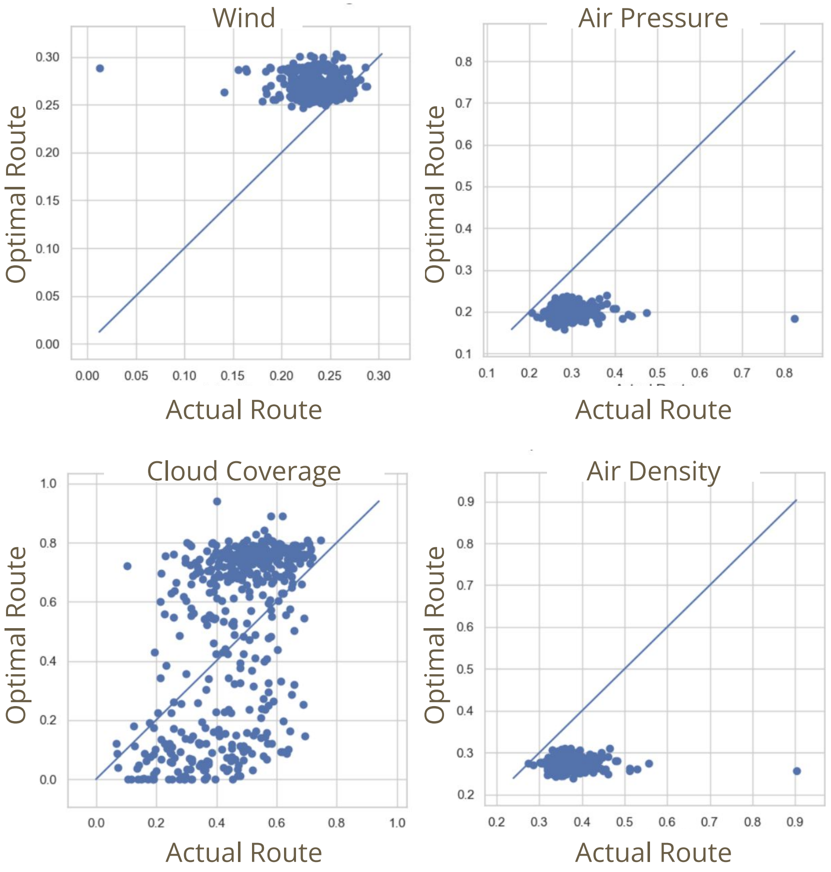



# Data Treatment and Metric Calculations



# Data Analysis - Key Findings

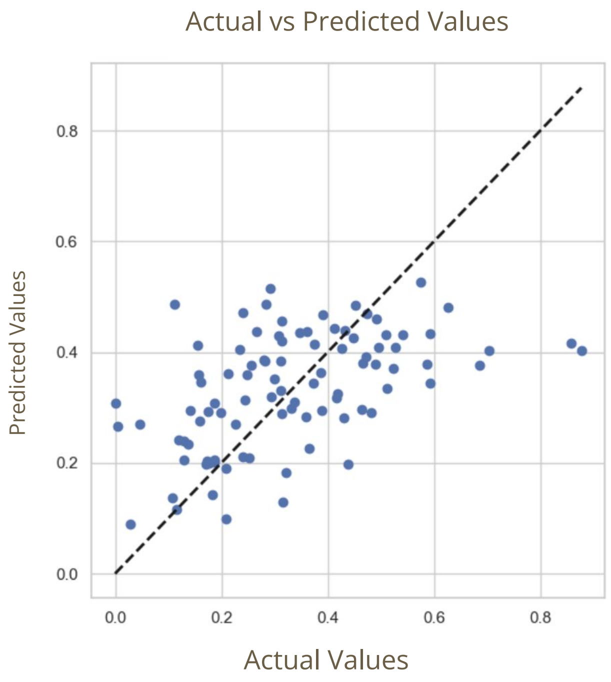


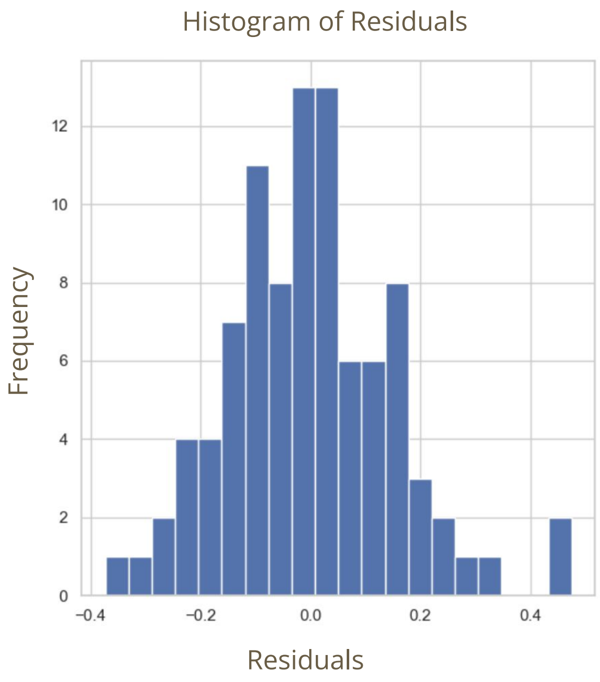



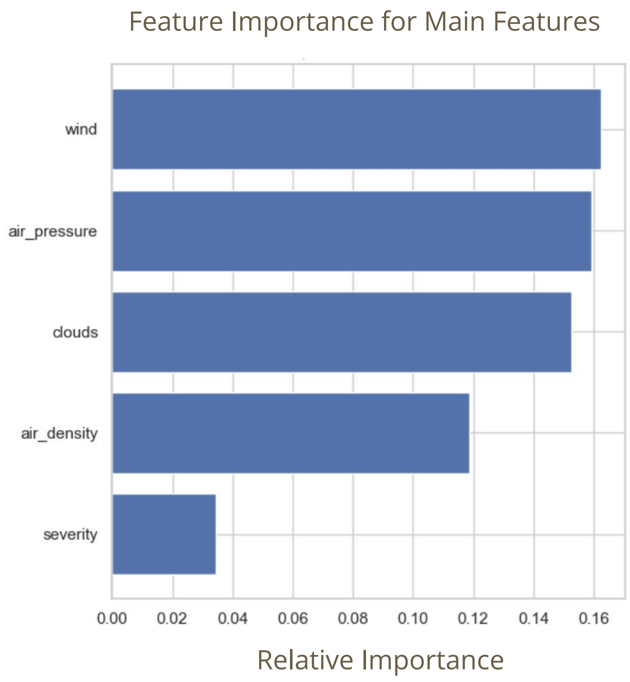
# Our Predictive Model

- Machine Learning
    - Model: **Random Forest Regressor**
    - Features: **Air Density**, **Air Pressure**, **Wind Speed**, **Cloud Coverage**, **Weather Severity**, and **Aircraft Type**
    - Predicted Value: **Fuel Consumption**
- Feature importance
    - **Gini importance:** A measure on how much each feature lowers the data variance on each node of a decision tree

# SEA ↔ DEN (January 2023)



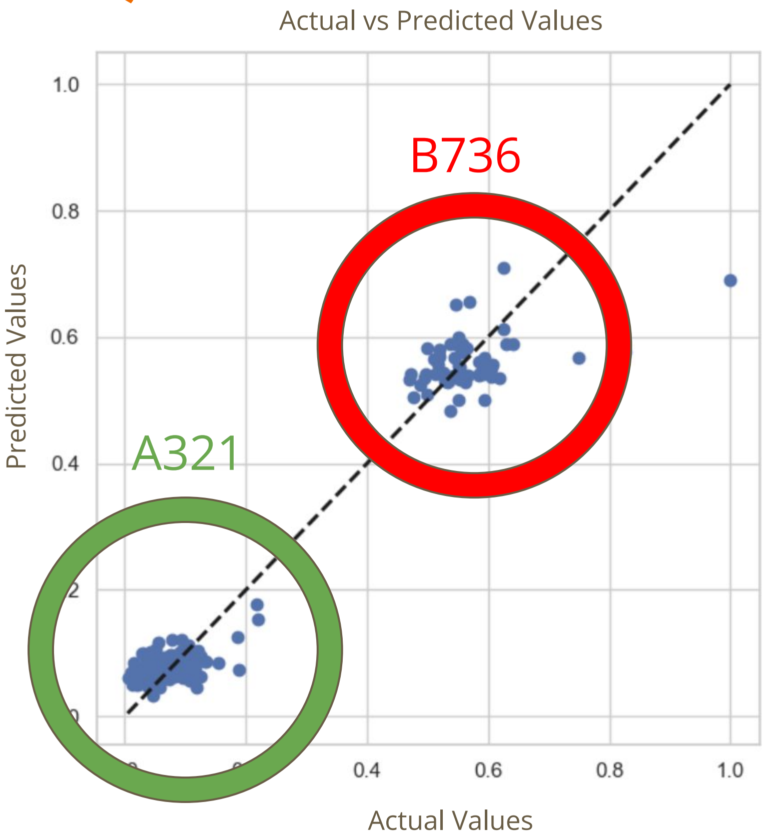



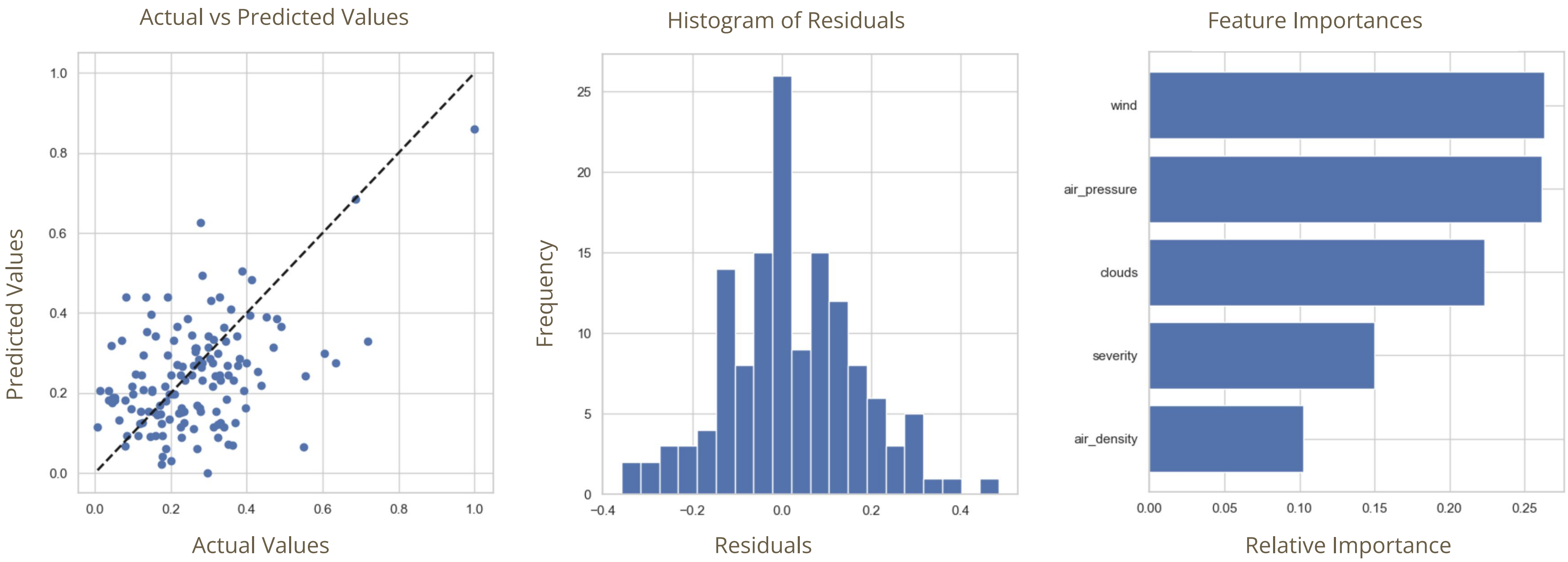
# LAX → JFK (January + July 2023)

- Values clustered by aircraft type

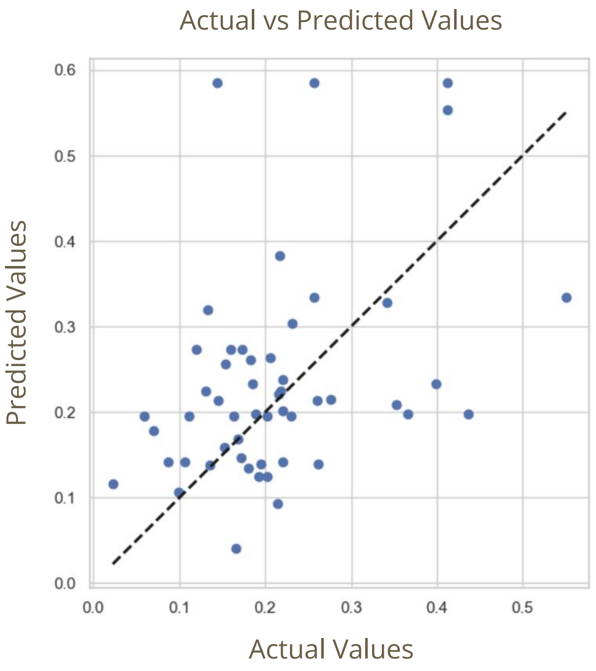
- Not predictive due to aircraft type having stronger influence than weather

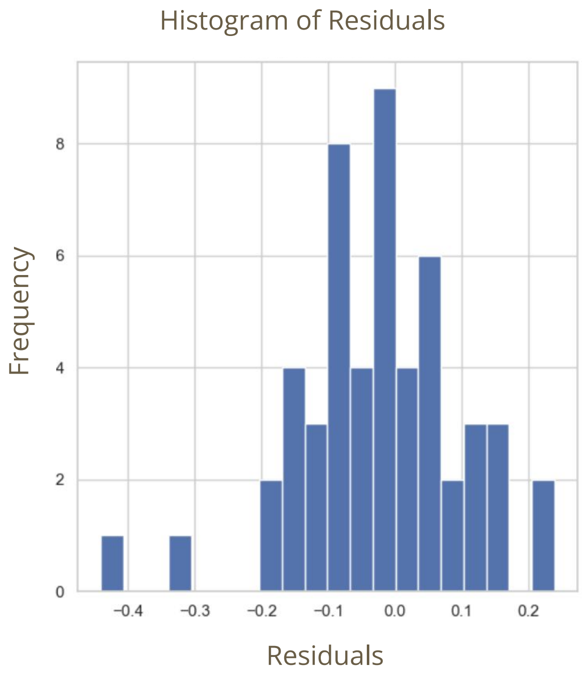


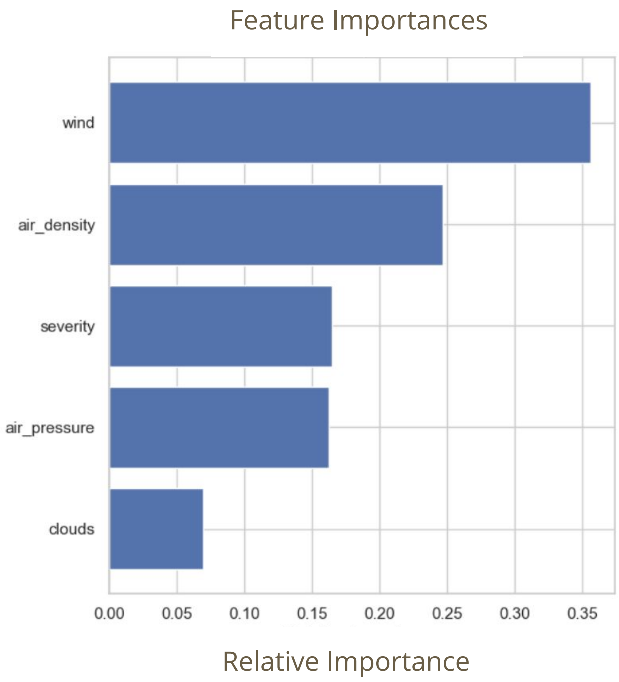
# LAX → JFK (January + July 2023) Airbus 321



# LAX → JFK (January + July 2023) Boeing 736



# Key Findings

- Model works reasonably well for shorter duration flights, not as reliable for longer durations
    - Higher discrepancy of fuel consumption
    - Higher variance of weather influences to be summarized in a single value
- Wind is consistently the most impactful feature, followed by either Air Pressure or Air Density
- Limitations:
    - Learning curves might indicate issues with fit
    - Relies on long computation times for weather influence on flight paths
    - Weather computations accumulate large errors quickly
    - Small dataset

# Next Steps

- **Improvements and Future Directions:**
    - Collect more data
        - Diversify flight locations and times
    - Improve on estimation of weather conditions
        - Experiment with other weather models
        - Parallelize the processing
    - Understand and improve upon the traffic module used to calculate fuel consumption
    - Experiment with different definitions of *Optimal Path*
    - Experiment with different ML models
    - Carbon footprint calculations and optimization

# Thank You

# EXTRA SLIDES

# Data Analysis - Key Findings