

The background image shows the wing and tail of an airplane flying through a clear blue sky with scattered white clouds.

# Flight Price Prediction

Big Project Progress Presentation

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# Introduction & Motivation

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## Motivation:

Flight prices seem to change rapidly and for no reason

- Even refreshing a page can show a change in the price of a flight

Predicting flight prices could help consumers save hundreds per flight

## Research Question:

What factors influence the price of a flight, and can we predict the price of a flight with machine learning?

# Data Source

- Amadeus
  - Provides tech solutions for the travel industry
  - API access for free
- API Details:
  - Provides prices & features for bookable flights given airport codes for route and a date
  - Limited to 2,000 calls per month
  - 1 API call = all flights for 1 day between two specified airports





# Data Collection

- Scope:
    - Limited to cross-country flights
    - Limited to 6 major airports (3 east coast, 3 west coast)
    - Limited to 14 days in advance
  - API Scheduler
    - Runs .py script with API calls 2x per day (12:00 am & pm UTC)
    - 252 API calls per run (18 routes x 14 days)
    - Uses multiple API keys to avoid call limit
    - ~12,000 flight observations per run
    - Each run returns a .csv file and uploads to Dropbox
    - Scheduling done via GitHub workflows ([link](#))
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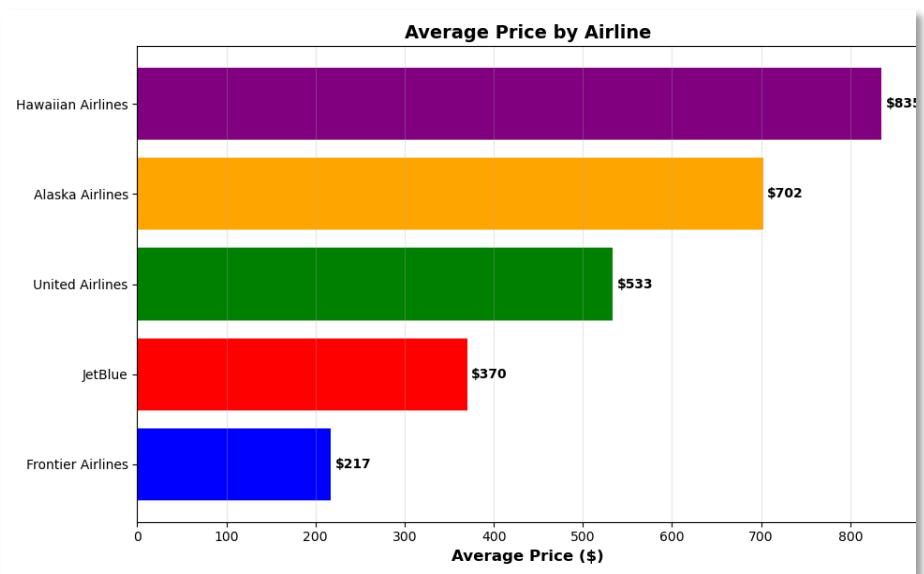
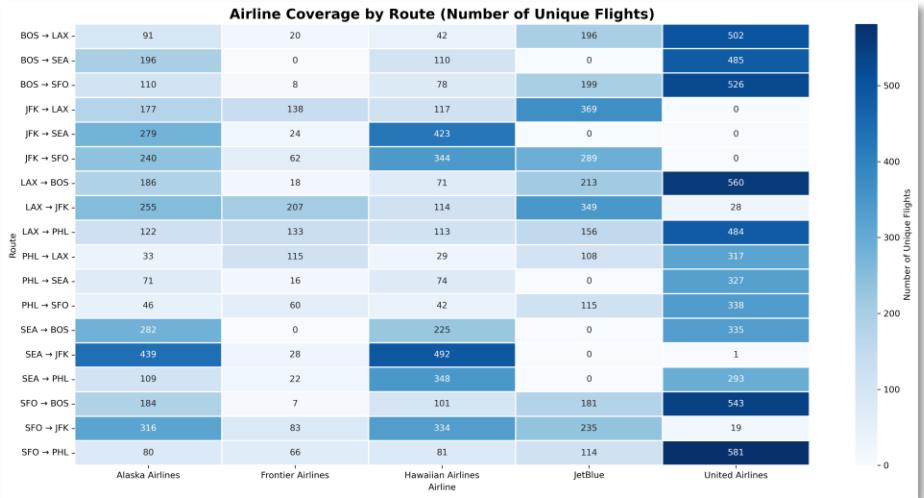
# Final Dataset

## Data Collection Metrics:

- Total observations: 229,924
- Unique flights tracked: 15,224
- Flights with price changes: 13,500
- Average price change: \$154.67
- Collection period: 2025-11-10 to 2025-11-19

- Currently 229,924 observations & growing
- Screenshot below shows the features given by the API

origin	destination	departure_date	days_until_departure	price	currency	airline	number_of_stops	departure_time	arrival_time	total_duration	aircraft_type	cabin_class	bookable_seats
JFK	LAX	2025-11-11	1	144.27	EUR	F9	1	2025-11-11 06:25:00	2025-11-11T12:25:00	PT9H	32Q,32Q	ECONOMY	4
JFK	LAX	2025-11-11	1	149.13	EUR	F9	1	2025-11-11 07:59:00	2025-11-11T19:53:00	PT14H54M	32Q,32Q	ECONOMY	4
JFK	LAX	2025-11-11	1	149.13	EUR	F9	1	2025-11-11 07:59:00	2025-11-11T20:42:00	PT15H43M	32Q,32N	ECONOMY	4
JFK	LAX	2025-11-11	1	210.02	EUR	F9	0	2025-11-11 11:29:00	2025-11-11T14:32:00	PT6H3M	32Q	ECONOMY	4
JFK	LAX	2025-11-11	1	256.07	EUR	AS	1	2025-11-11 07:00:00	2025-11-11T15:17:00	PT11H17M	73H,73J	ECONOMY	7

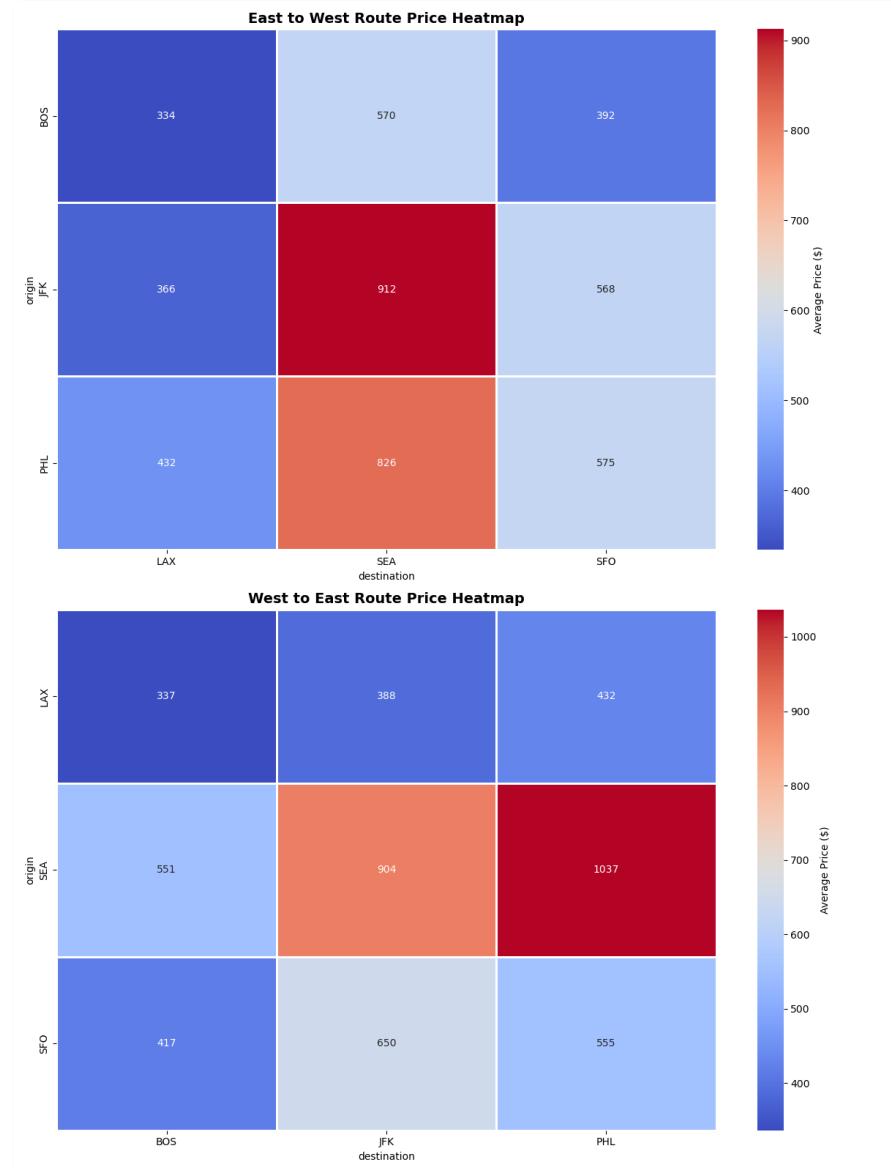


# EDA: Airline-Level Analysis

- United: highest route coverage; moderate prices
- Frontier: few flights, very low prices
- Alaska & Hawaiian: specialize in low-competition routes -> charge premium for tickets

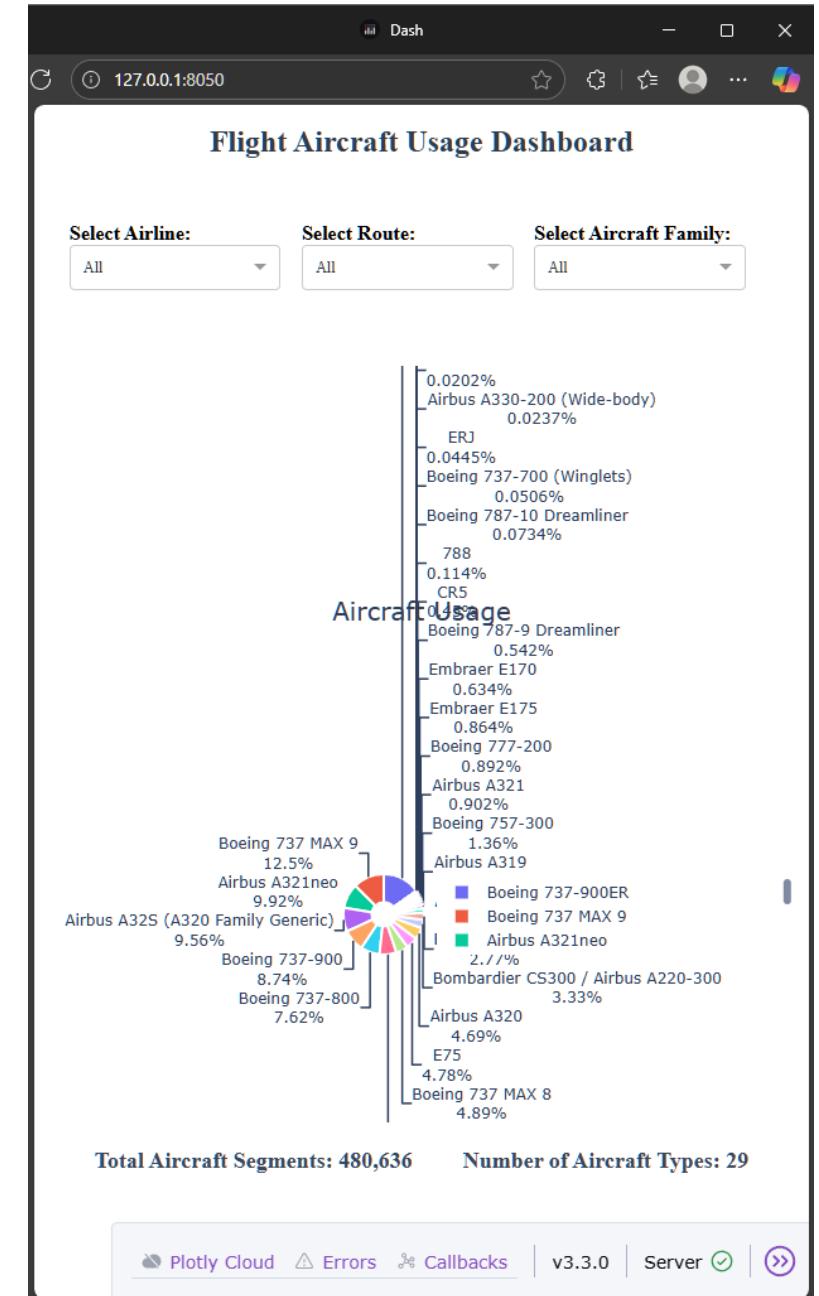
# EDA: Route-Level Analysis

- Most Routes: East -> West is cheaper than West -> East
- Flights to & from Seattle are most expensive
  - Dominated by Hawaiian Airlines & Alaska Airlines (less low-cost offerings)
- Cheaper routes have more competition between major low- and mid-cost airlines

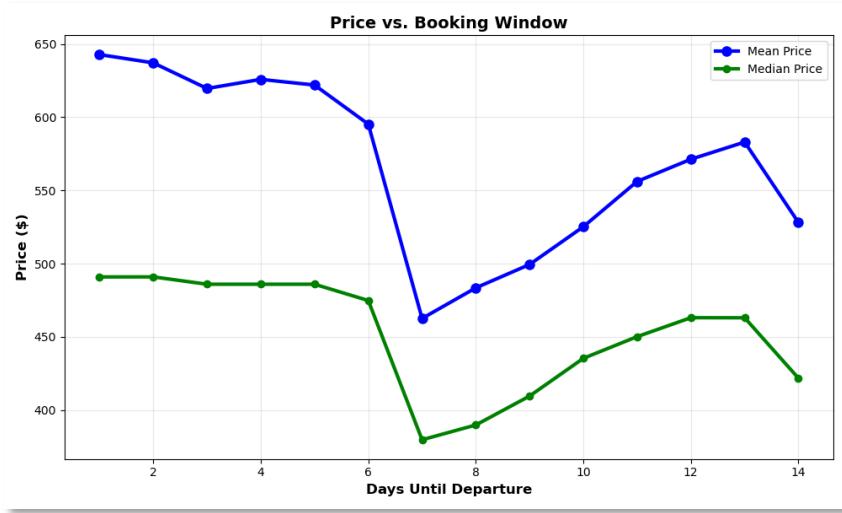


# EDA: Aircraft Usage Analysis

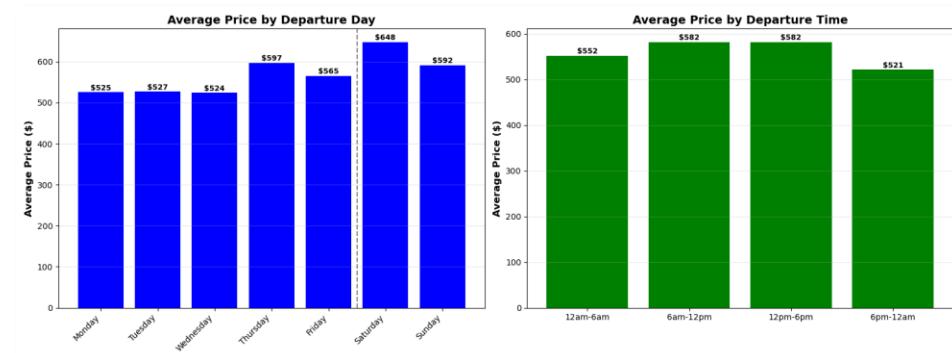
- Most popular type: Boeing 737-900ER
  - Most popular family: 737 NG & MAX, then A320ceo & A320neo
    - Full-cost airlines (United, Hawaiian, Alaska) go for 737
      - Still have A320 & A321s
    - Low-cost (Frontier, JetBlue) go for Airbus (A320/A321) only



# EDA – Temporal Analysis

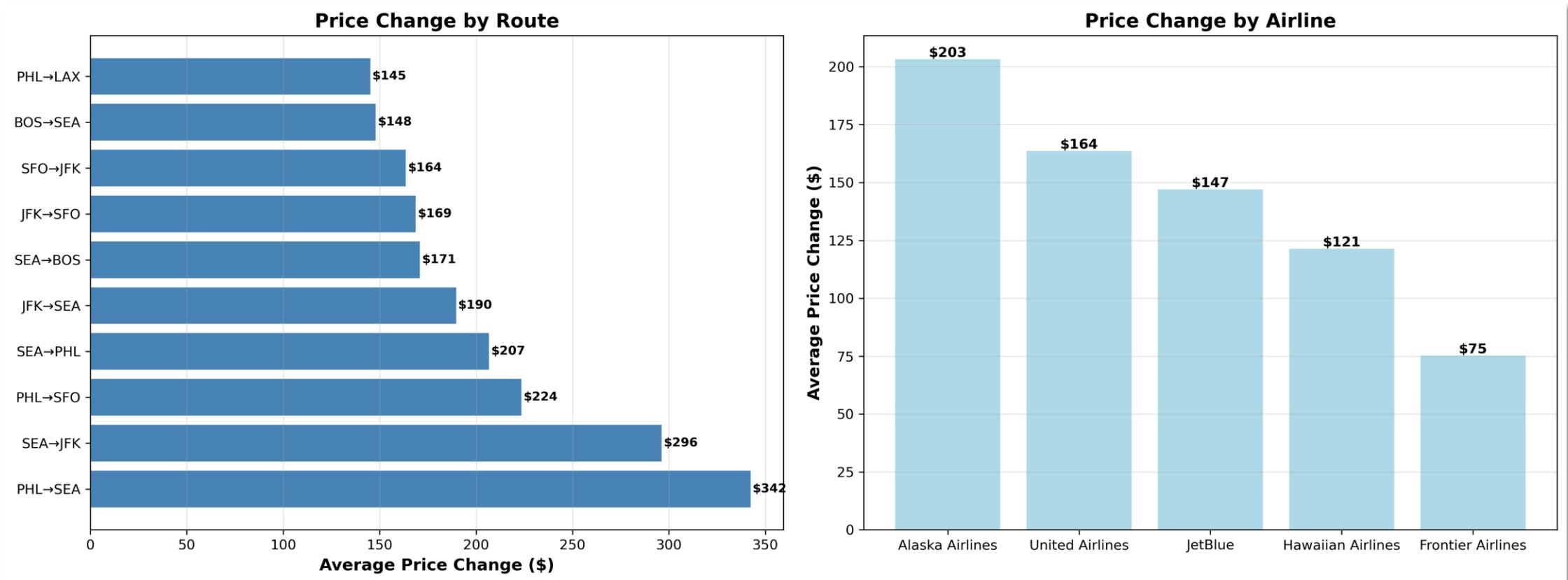


- Prices peak closest to departure
- Significant drop in price 7 days out
- Likely Reason:
  - Airlines price higher for last-minute bookers AND for bookers who plan far in advance
- Cheapest flights depart Monday through Wednesday
- Cheapest time to fly is at night (red-eye flights priced cheaply)



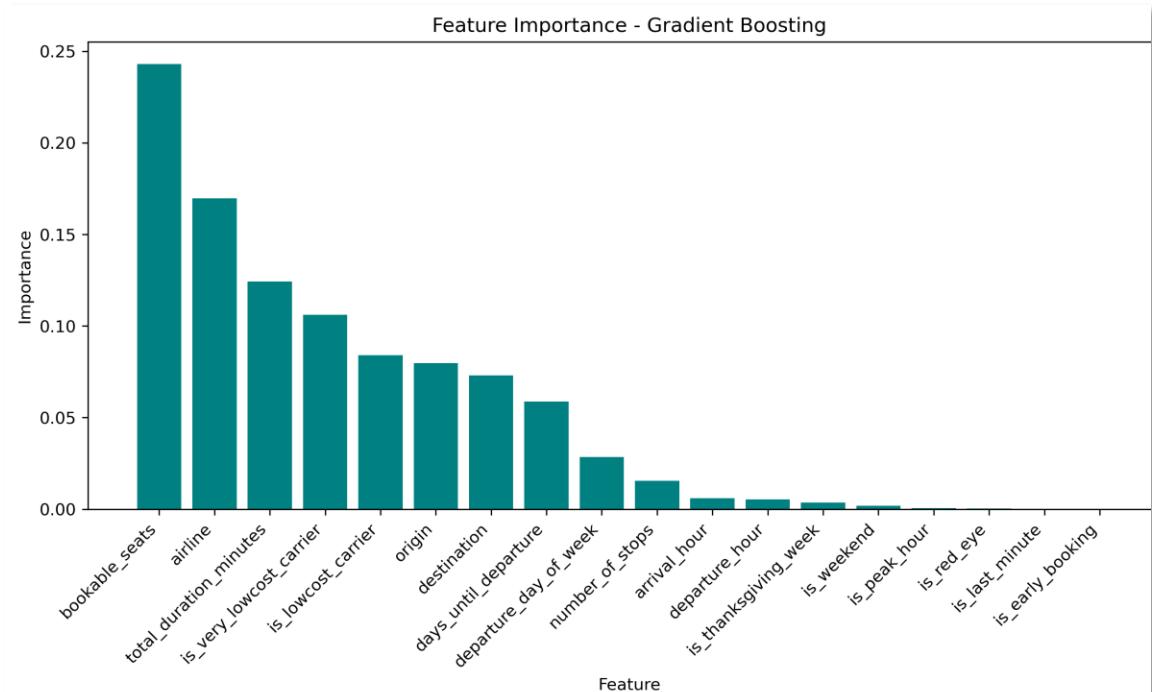
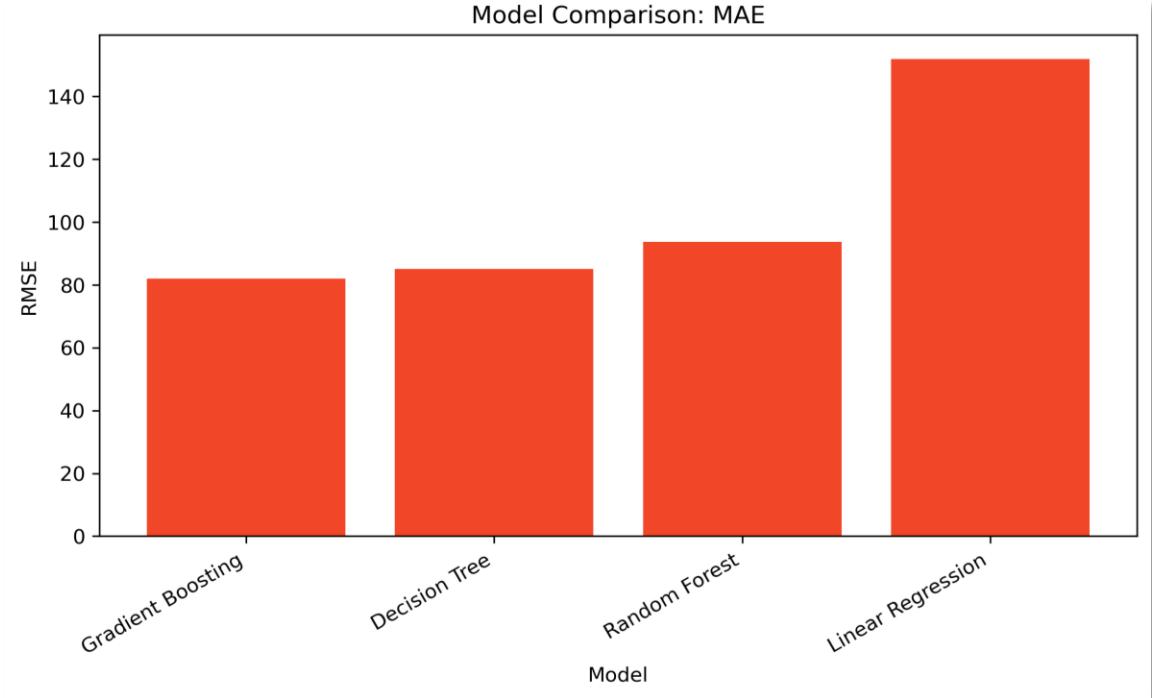
# EDA – Price Change Analysis

- Because of the scheduled API calls, we can track the same flight's price over time
- Below shows the average change in price for a specific flight (max listed price – min listed price)

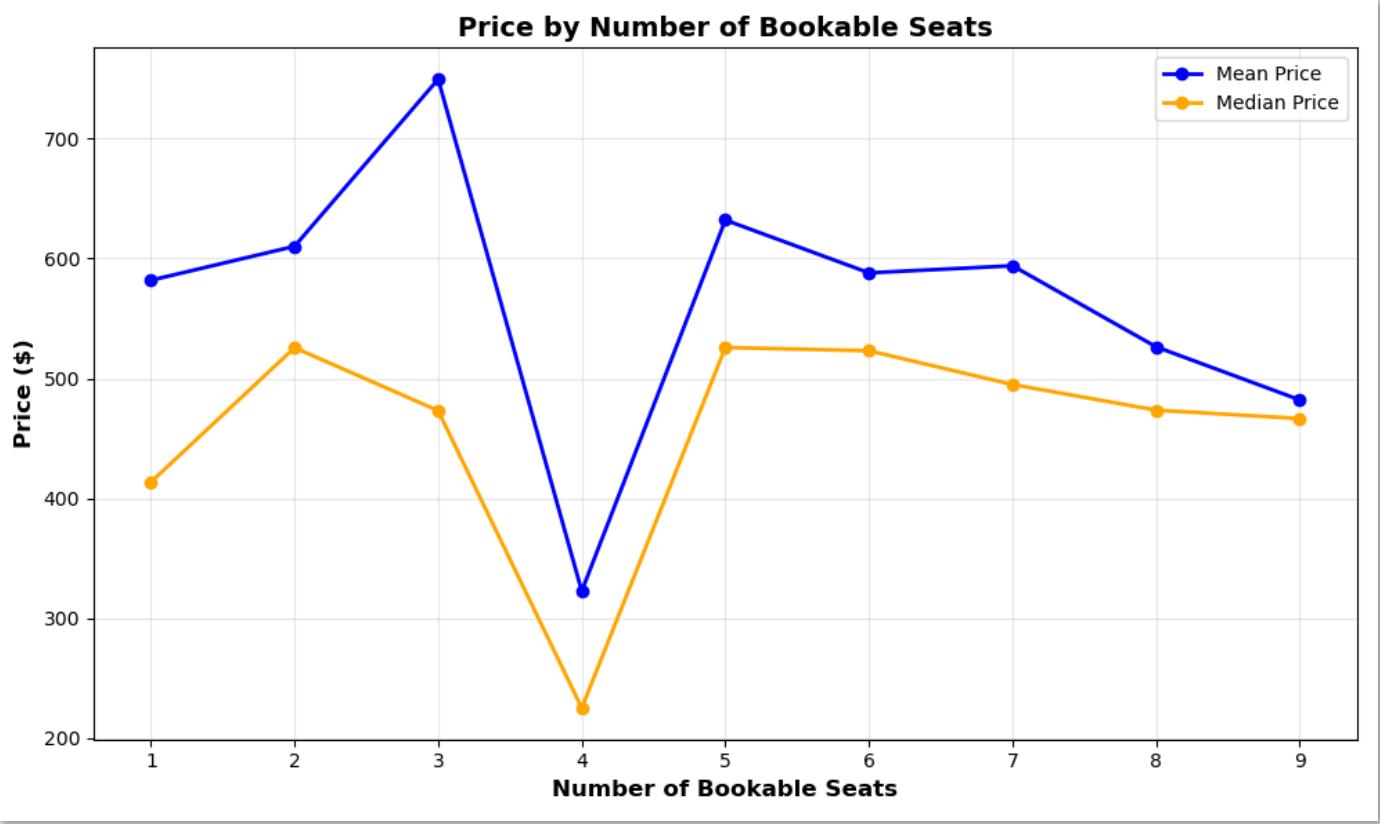


# Preliminary Machine Learning Results

- Tested 4 initial models:
  - Linear Regression
  - 3 Tree Models (Decision Tree, Random Forest, & Gradient Boosting)
- Tree models outperformed linear regression
- Lowest MAE (Gradient Boosting) ~ 82 (~16% mean error assuming \$500 average price)
- Number of bookable seats, airline, and flight duration most important features
- Temporal features have less predictive power



# Note On Bookable Seats



- Non-linear relationship
- Drop in mean & median price at 4 bookable seats
  - Data issue or intentional pricing strategy?

# Future Work

- Enhanced Machine Learning Models
  - Neural Networks, XGBoost, etc.
  - Adding further hyperparameter tuning
  - Adding more engineered features
- Added Data Sources
  - Features about airlines
  - Features about weather/climate

# Implications & Limitations

- Limitations:
  - Data availability (6 airports, select airlines)
  - Limited date range
  - Limited features from API (had to create *flight\_id* separately, etc)
- Ethical, Economic, & Social Implications:
  - Predicting prices could help consumers save money and protect consumers against confusing or exploitative pricing strategies
  - Pricing strategies are kept secret by airlines, secrets could be discovered