Visualizing Airfare Trends: A Data Analytics Approach to Airline Pricing

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1 Introduction

The airline industry significantly influences global connectivity, economic growth, and consumer mobility, making airfare prices an important area of study. Airline pricing strategies throughout history have not only determined the market for air travel, but have been indicative of worldwide events and problems.

This project aims to analyze and visualize historical airfare trends to uncover deeper insights into how external and long term factors influence pricing trends across various key domestic airline routes.

2 Problem Definition

Airline ticket prices have historically been subject to both periods of stagnation and volatility because of the number of different factors that go into pricing strategies. Factors like economic conditions, airline competition, political tensions, and global crises like pandemics, have been major factors into defining airline prices. Our project aims to use historical airfare data to clearly identify what factors most strongly influence ticket prices and to create models and visualizations to accurately display these trends.

3 Literature Survey

The literature review covers dominant forces influencing the airline industry for over three decades. We synthesize research on six significant dimensions that shape air travel demand and correlations.

3.1 Economic & Political Impacts

Blunk et al. [4] analyzed how policy changes after 2001 permanently altered United States air travel, illustrating that increased security measures raised the opportunity cost of air travel. This paper is valuable because it provides insights into how political events redesign route planning and pricing strategies after disruptions. It could be improved by distinguishing between low-cost carriers and legacy carriers. Kiracı [12] charted the historical evolution of airline fare pricing and examined how economic conditions and market competition shape pricing. This is valuable because it gives a basis for assessing economic impacts on fare structures. However, it would be further reinforced by incorporating more specific case studies that link economic events to price changes. Abdi et al. [1] demonstrated airline valuation sensitivities in response to worldwide pandemics through their COVID-19 research. This is important for giving empirical backing for our modeling effects on probability as well as pricing strategies. For further improvement, more complex econometric models would be able to quantify impacts more accurately.

3.2 Pandemic-Related Impacts

Bielecki et al. [2] quantified the effect of COVID-19 on global air travel via load factor decreases and profitability concerns. They provided valuable fare dynamics data in relation to our project; however, the focus was mainly for early pandemic phases and did not examine long-term recovery patterns. Poletto et al. [15] used mobility simulations to illustrate that flight cancellations due to Ebola only delayed disease transmission by weeks. This work is extremely valuable because it provides a methodology to correlate flight route cancellations with disease indicators. It could be further improved by incorporating an analysis of fare adjustments and shifts in consumer behavior. Gao and Zhang [8] studied COVID-19's local impacts on air traffic and revenues. They offer valuable insights for our planned spatial analysis of route network changes. A more in-depth passenger behavior analysis would make their results more comprehensive.

3.3 Airline Competition

Smith et al. [16] documented American Airlines' pioneering hub-and-spoke system and their yield management systems post-deregulation. This work is valuable because it shows how pricing optimization underlies airline economics. It could be further improved with a more comprehensive and up-to-date analysis. Borenstein [6] analyzed how deregulation reformed the U.S. airline industry. His work is important in highlighting initial market concentrations as carriers expanded their networks, which our project will seek to track across markets. Again, this work could be improved with a modern analysis. Oum et al. [14] found that liberation measures in air transport led to higher traffic growth, competition, and fare decrease. They demonstrated something we aim to visualize: liberalization can enable market domination by major carriers. Their work could be made more comprehensive with our visualizations.

3.4 Environmental Impacts

Bombelli and Sallan [5] revealed how weather disruptions spread across the air network using a delay and cancellation propagation approach. Their work provides us with a methodological approach to visualize environmental impacts on route planning and pricing. It could be further improved with interactive visualizations. Gratton et al. [9] looked at the influence of climate change on flight routes, fuel use, and infrastructure demands. Our analysis will factor their work regarding growing impact into long-term route and price trends. Gratton et al. could further improve their analysis by discussing the influence of climate change on prices. Voskaki et al. [17] uncovered airport exposure to climate risks and evaluated adaptation strategies. This will inform our modeling of the impact of environmental factors on airline planning. Their work could be further improved by breaking down various types of risks.

3.5 Terrorism-Related Impacts

Blalock et al. [3] found that post-9/11, the screening of baggage reduced the number of passengers by 6% on all flights and 9% at major airports. This analysis is valuable in that it shows the differential effects of security on travel behavior. The work could be further supported with a more long-term analysis. Ito and Lee [10] documented the immediate 30% fall in demand and continued 7.4% years after the 9/11 attacks. This is valuable in that it provides proofs of long-term structural shifts in customer demand, which our model will be able to explain. Again, a more recent and long-term analysis would provide further improvements. Cornwell and Roberts [7] found that after 9/11, travel to the U.S. declined precipitously. This research is helpful in that it reveals the persistent impact of security policies on different classes of travels. The study would be more robust if it isolated the impact of security policies from overall economic trends.

3.6 Technological Advancements

Kim et al. [11] investigated how digital amenities and AI customer reshaped passenger expectations during COVID-19. This source is valuable because it reveals how modern amenities change demand. This work could be further improved by accounting for overall airline demand during COVID-19. La et al. [13] highlighted how digitization enhances customer satisfaction and operational efficiency along the process of traveling. This is valuable because it provides a basis for examining how digital innovation shapes route planning. The source could be further improved by diving deeper into how digitization improves efficiency. Yas et al. [19] emphasized travelers' increasing demand for custom-tailored, high-quality services. Our project will account for this by modeling relationships between airline quality and price. The source could be further improved by diving deeper into "no-go's" for passengers.

4 Proposed Method

4.1 Intuition

Airline pricing methods currently rely heavily on short-term, demand-based pricing models, which utilize algorithms to adjust ticket prices based on booking timelines, seat availability, and historical demand trends. While effective for maximizing revenue in the short run, these models often lack the ability to integrate broader signals dramatically impact pricing behavior. These include economic conditions, global crises, or shifting policy environments.

Our project addresses this gap by creating a hybrid pricing model that not only considers traditional pricing dynamics but also incorporates macroeconomic indicators and external events. This allows for a more forward-looking analysis of airfare trends. For example, users can simulate how airline pricing would shift in the face of a recession, oil price spike, or pandemic-induced travel restrictions. This capability is especially valuable for travelers planning future trips, policymakers evaluating market resilience, or airline analysts seeking competitive insights.

By combining machine learning techniques with long-term historical data, our solution goes beyond static dashboards. We deliver interactive, dynamic visualizations and predictive models that empower users to explore route, carrier, and time specific pricing behavior. The end result is a system designed to support decisions and further the understanding of how prices are formed. The new model will allow for more informed and strategic planning to all stakeholders.

4.2 Description of Approaches

4.2.1 *Base-level analysis in Tableau*

We began by conducting a base-level analysis in Tableau for 20 years of historical data to understand the most popular flight routes and airlines based on the number of passengers that travel. This analysis allowed us to uncover initial insights about route popularity, airline dominance, and seasonal passenger flows. We were able to note down potential limitations to this data, such as the dataset not fully capturing international routes and thereby potentially changing airline rankings, but we decided to continue the project within the scope of this dataset due to its robustness and availability. To ensure we focused on routes with significant historical data and market impact, we made the decision to use the top 50 routes and the top 20 airlines that service those routes to use in our analysis. This filtered focus helped ensure more accurate and generalizable results later in our pipeline.

4.2.2 *Cleaning using Pandas/NumPy*

After we identified our criteria, we filtered that data in Tableau to get an understanding of the steps we would need to take to clean that data. We identified NaN values present in many rows and columns throughout the data, as well as some significant outliers, such as extremely high or low fares or improbable passenger counts. With this information, we developed a comprehensive data cleaning and processing model using Python. Our model would utilize the Pandas and NumPy libraries to clean up NaN values in the data, handle outliers through IQR filtering, and then filter the dataset to only provide the routes and airlines we had chosen. Finally, the prepossessing model would select past years of data and output a clean CSV file we could use for our analysis and modeling in subsequent steps.

4.2.3 Incorporating macroeconomic and event data

To conclude our data-cleaning process, we incorporate data for other relevant indicators that have meaningful impact on airline pricing based on our literature survey and domain understanding. We did this by finding and cleaning datasets that contained indicators such as GDP, national oil prices, and unemployment data, and matching them to the relevant quarters from our original dataset to ensure consistency. Additionally, we also accounted for significant external events we could factor into our models, such as pandemics, market crashes, as well as geopolitical conflicts. These event-driven features were included as binary or categorical variables to assess their impact on pricing. This concluded our data collection and cleaning stage and ensured our dataset was both diverse and analytically rich.

4.2.4 SARIMA baseline and performance

We began by creating a framework for our machine learning model based on the cleaned data. We thought it would be useful to experiment with various types of predictive models (e.g., ARIMA, random forest, binary trees) to get an understanding of what would be best for our data and the features we wanted to incorporate. We began by implementing a SARIMA model, as we believed this would be able to accurately capture seasonal trends due to its integrated seasonal components. However, SARIMA underperformed in our initial tests, with an R^2 of just 0.41 and a mean absolute error exceeding \$20, indicating it failed to generalize well across routes or handle macroeconomic variability. It also lacked flexibility in incorporating categorical variables such as event indicators. Eventually, we settled on utilizing a Ridge Regression model to capture our baseline relationships, and a Random Forest model to capture the more complex and nonlinear interactions among features.

4.2.5 Ridge Regression for linear features

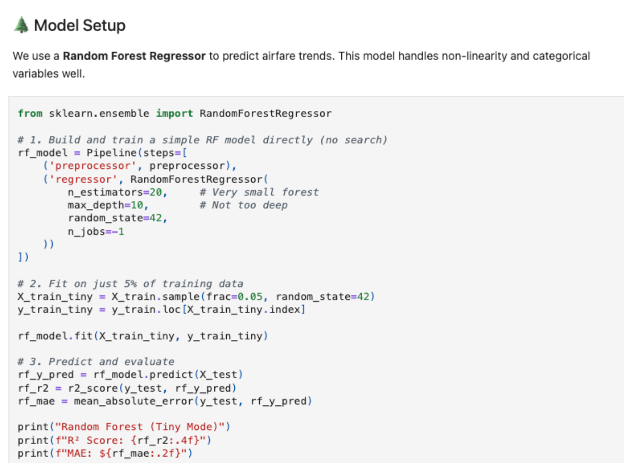
For our Ridge Regression Model, we aimed to better understand the linear relationships between airline pricing and continuous variables such as GDP, oil prices, and unemployment rates. Ridge Regression helped us manage multicollinearity while offering interpretable coefficients that reveal directionality and strength of macroeconomic effects. Through our model, we were not only able to compare airfare data to these external macroeconomic factors, but also understand trends between fare prices, distances, passenger counts, and airline market shares. This analysis helped us gather meaningful insights into linear dependencies, and also proved useful for the base-level data analysis that we wanted to include in our project. It also served as a reliable benchmark for evaluating the performance of more complex models.

4.2.6 Random Forest for nonlinear interaction

In order to capture some of the more nonlinear interactions among our factors that influenced airfare prices, we implemented a Random Forest regression model. This model takes into account the features discussed in step (1), such as route popularity and macroeconomic indicators. The model pre-processes the relevant data, and then builds multiple decision trees, each of which independently predicts airfares that will later be averaged for a final prediction. In order to tune our decision tree to avoid overfitting and not reach computational constraints, we used a selected 5% subset of our data to train the model. Combining this with a refined 20 trees with a maximum depth of 10 for our Random Forest model ensures that our program runs both effectively and accurately, while still delivering strong predictive power across diverse routes and economic scenarios.

4.2.7 Hybrid Model combining stability and performance

To wrap up our machine learning phase, we created a hybrid model that predicts the price based both on the Random Forest and Ridge Regression models through utilizing an average to maintain predictive stability and accuracy. This method leverages the interpretability of linear models and the flexibility of tree-based methods. Using carefully selected portions of training data also allowed us to implement functionality into our model that would simulate the impact of external events (e.g., pandemics, recessions, conflicts...) on future airfare prices. These simulations were built by adjusting macroeconomic indicators and event flags, allowing users to forecast in "what-if" scenarios. With a thorough analysis and an unbiased approach, this concludes step 2 of our approach and sets the foundation for interactive forecasting.



Model Setup

We use a **Random Forest Regressor** to predict airfare trends. This model handles non-linearity and categorical variables well.

```
from sklearn.ensemble import RandomForestRegressor

# 1. Build and train a simple RF model directly (no search)
rf_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', RandomForestRegressor(
        n_estimators=20,      # Very small forest
        max_depth=10,         # Not too deep
        random_state=42,
        n_jobs=-1
    ))
])

# 2. Fit on just 5% of training data
X_train_tiny = X_train.sample(frac=0.05, random_state=42)
y_train_tiny = y_train.loc[X_train_tiny.index]

rf_model.fit(X_train_tiny, y_train_tiny)

# 3. Predict and evaluate
rf_y_pred = rf_model.predict(X_test)
rf_r2 = r2_score(y_test, rf_y_pred)
rf_mae = mean_absolute_error(y_test, rf_y_pred)

print("Random Forest (Tiny Mode)")
print(f"R² Score: {rf_r2:.4f}")
print(f"MAE: ${rf_mae:.2f}")
```

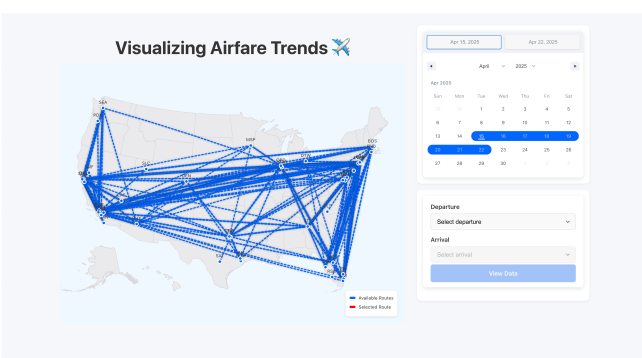
4.2.8 Visualization types (fares, routes, economics)

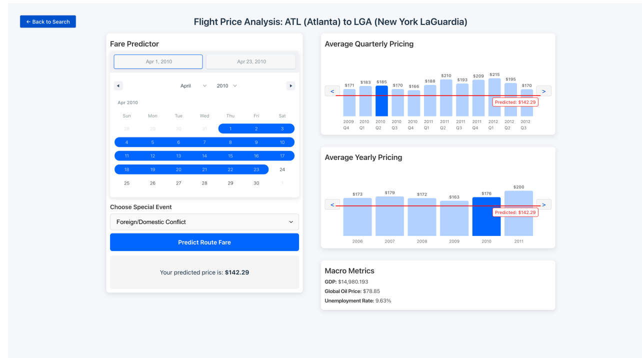
Now that we effectively cleaned our data and developed a machine learning model for complex data analysis, we wanted to also provide users with a way to understand more foundational insights into airline pricing. To do this, we focused on a set of interactive visualizations that include route-level and macroeconomic trends. These included:

- **Average Fare Over Time:** Displays how fare has changed quarterly for selected routes and airlines, allowing users to depict seasonal trends, pricing volatility, and responses to major global events.
- **Route Popularity Metrics:** Based on the number of passengers and airlines that fly a given route, users can visualize which routes are most traveled, giving insights into demand-driven pricing. We also incorporate a map here to visualize *all* the most popular routes traveled within our data, enhancing geographic context.
- **Economic Indicator Tracking:** Highlights how changes in relevant macroeconomic indicators such as GDP, oil prices, and unemployment rates help shape pricing trends over longer periods of time, providing users with a view of external market forces.

4.2.9 React.js frontend, Flask backend

To effectively present our models and analysis, we developed an interactive analytical interface using React.js for front end development, and Flask for our backend needs. Our choices made it so that users can dynamically choose departure airports, arrival airports, and travel dates. The interface visualizes route-specific trends that show predicted airfares prices and present other factors to help users understand pricing for a given selection. We implemented filters and drop downs to allow for customized insights, and our front-end solutions allowed for smooth integration of interactive charts and geographic maps for highly effective data presentation. This structure also allows for future scalability and real-time enhancements.





4.2.10 Scalable, real-time API with SQLite

The backend API we built with Flask also proves to be a strategic decision as it integrates our machine learning models in order to provide real-time airfare predictions based on any front-end user inputs. Flask is also crucial to many other key functions such as our historical data comparison and event filtering. The API allows users to send queries involving route, date, and external conditions, and retrieves model predictions within milliseconds. Flask allows almost immediate retrieval of historical average fares from an inputted time period, which is helpful for either when a user selects a date range or a date range is automatically selected when a user is trying to visualize the impact of an event on airfare. Since Flask uses SQLite, we are able to quickly pull data from large datasets, making our API both quick as well as scalable. With the conclusion of the website development phase, we concluded the final step of our project and prepared for deployment.

5 Evaluation

5.1 Description of Testbed & Questions Answered

To evaluate the effectiveness of our predictive airfare model, we conducted a series of experiments designed to assess both the accuracy and capacity of our approach across multiple routes, timeframes, and conditions. These experiments aimed not only to validate our model performance numerically, but also to understand how well it generalizes across different types of flights and reacts to unpredictable historical conditions.

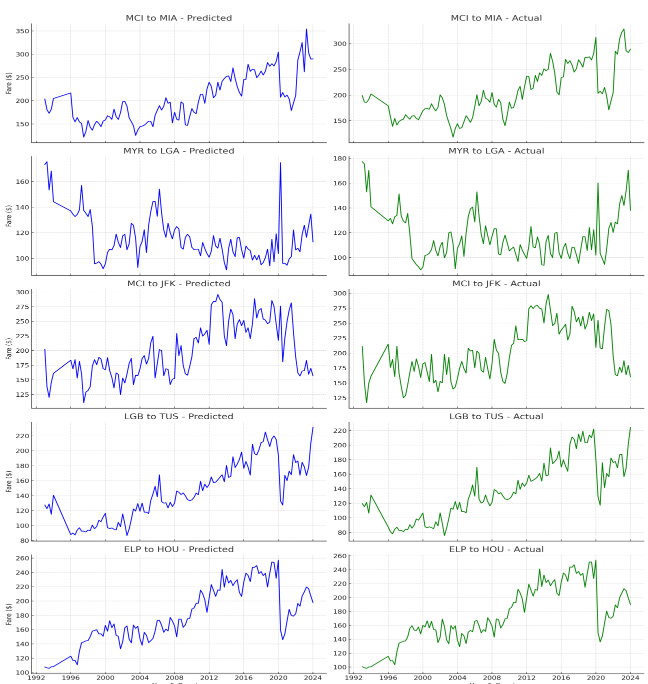
These experiments were intended to answer key questions such as:

- How close are our predicted fares to actual historical fares?
- What is the error distribution across different routes and time periods?
- How reliable is our model in capturing both long-term trends and short-term fluctuations?
- Can we use this model to simulate the effects of external disruptions?

These guiding questions helped structure our evaluation methodology to ensure it was both comprehensive and focused. In addition, our testbed reflects a mix of highly and moderately used routes, ensuring the model performs across varied levels of data density and complexity.

5.2 Experiments, Results, and Observations

We selected five representative domestic flight routes from our dataset: *MCI to MIA, MYR to LGA, MCI to JFK, LGB to TUS, and ELP to HOU.* These routes were intentionally chosen to span various geographic regions and demand levels, covering both hub-to-hub and point-to-point connections. We then visualized their predicted versus actual fares from 1993 to 2024. This route-level analysis allowed us to observe how the model handled seasonal variation, fare spikes, and long-term pricing shifts. For example, we saw consistent alignment in fare increases during holiday periods, and accurate depressions in fare data during crises like COVID-19 and the 2008 recession. These visual comparisons revealed that the model was able to closely track real-world fare trends in both shape and scale over time. The model captured both the macro-level price trends and route-specific fare behavior, strengthening confidence in its forecasting capability, especially for use in decision-making tools.

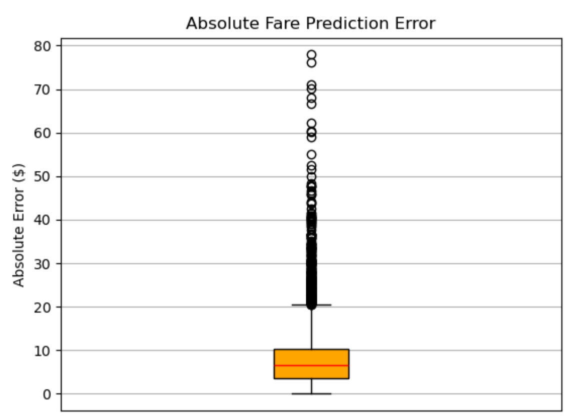


To quantify performance, we computed several accuracy metrics, shown in Table 1. These results indicate a high level of accuracy. On average, our model predicted fares within \$8.46 of the true price, which is particularly promising given the natural variability and complexity of airfare pricing. The low RMSE reinforces this conclusion, suggesting that extreme errors are well-contained and do not significantly distort predictions. Our MAPE value translates to a prediction accuracy of **95.60%**, meaning predicted values are within 95% of actual fares, on average. This level of accuracy is rarely seen in public airfare forecasting models and speaks to the strength of our hybrid approach. The R^2 value of 0.963 suggests that our model captures the majority of fare variability and explains it effectively with the features selected. Benchmarked traditional models (e.g., linear regression) show significantly lower performance (R^2 = 0.61), validating our approach's improved accuracy and justifying the decision to combine Ridge Regression with Random Forest models [18].

A box-and-whisker plot of absolute error further confirmed that most predictions fall within a tight range, with most values having an error between \$3.59 and \$10.36. These margins are well within an acceptable range for policy and consumer-level applications. Outliers were rare and typically occurred during disruptive periods such as the 2008 financial crisis and the COVID-19 pandemic. These anomalies are expected, as even sophisticated models may struggle during black-swan events where pricing deviates dramatically from historical patterns.

Table 1: Model Accuracy Metrics

Metric	Value
Mean Absolute Error (MAE)	\$8.46
Root Mean Squared Error (RMSE)	\$11.59
R^2 Score	0.963
Mean Absolute Percentage Error (MAPE)	4.40%



To test model strength, we tuned our Random Forest with 20 trees and a maximum depth of 10 and trained on a 5% subset of the data to ensure scalability and avoid overfitting. These hyper-parameters were selected with a grid search, balancing training time with prediction accuracy. The Ridge Regression model provided stable trend baselines, particularly for features like GDP, unemployment, and oil prices, which showed strong linear correlation with long-term pricing trends. These two models, when averaged, allowed us to capture both smooth macro patterns and jagged micro fluctuations without requiring complex deep learning architectures or large-scale GPU acceleration.

While we initially explored SARIMA for capturing seasonality, we found it struggled to model the effects of external major economic or geopolitical events. This was mainly due to SARIMA's limitations in handling non-stationary external regressors and its sensitivity to missing data. Our hybrid Ridge + Random Forest approach ultimately proved more flexible and accurate, combining linear interpretability with nonlinear complexity. This hybrid approach is particularly valuable when simulating counterfactual scenarios such as "What if another oil crisis occurs?" or "How would pricing be impacted by a temporary spike in unemployment?"

In summary, our experiments show that the model is both quantitatively accurate and qualitatively interpretable. It can reliably forecast airfare trends while providing insights into how external events impact pricing over time. The combination of statistical and machine learning techniques has allowed our system to outperform traditional methods while retaining interpretability. This is a critical requirement for stakeholders like airline analysts, regulators, and end consumers alike. Future work will explore expanding the model to international routes and incorporating daily or hourly granularity as more refined datasets become available.

6 Conclusions and Discussion

6.1 Final Analysis

This project began with the goal to investigate how data analytics and machine learning can be used to forecast and analyses airfare pricing across many major US domestic routes and airlines. Through using over 20 years of data, and the most popular routes we selected using surface level data analysis we were able to build a framework that integrates statistical modeling, macroeconomic indicators, and interactive visualizations to make it accessible for users to explore and predict airline pricing trends.

After cleaning and filtering the data with Python, we merged it with quarterly macroeconomic indicators such as GDP, oil prices, and unemployment rates. From here we built a machine learning model with a prediction tool to attempt to predict airfare prices based on these indicators. This model was also developed with features that would allow users to select from major world events such as pandemics, terror attacks, and recession and understand how pricing fluctuated during these times.

In order to effectively implement our machine learning model, we utilize a hybrid of 2 models: a Random Forest model and a Ridge Regression model. We then optimized this model to get preferable outputs, and the result was a strong performance with an R^2 value of 0.963, and a mean absolute error of $8.46. This overall displayed our model is highly accurate at predicting pricing trends.

In addition to machine learning, we also implemented a set of useful analytics from our data to promote better user decision making. These metrics include items such as the average fare over time, fare prices by route and airline, and economic indicator tracking.

To present our results effectively, we developed a full stack web application using React.js and Flask. This allows all users of the platform to visualize fare trends and receive real time pricing predictions, making our analysis quick and easy to use.

While our scope and models are currently limited to domestic flights, the platform we have built has a lot of room for scaling. In the future we may be able to incorporate international flight data alongside global macroeconomic indicators and other major factors. Alongside this we can develop more visualizations and include more metrics for better user decision making in the context of airline pricing trends. Overall, our tool as presented is a very powerful method for gaining meaningful insights into airline pricing for travelers, analysts, and airline strategists alike.

6.2 Team Effort Statement

Ishan worked on the frontend, backend, and integrated the model with the system. Sristi created the poster, ran experiments, and tested the model. Juntae developed the model. Ved worked on the report.

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