Team 094 Progress Report

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Introduction:

Currently, the commercial airline industry relies on simple statistics about on-time arrival/departures that are sometimes provided to passengers alongside their airline reservation. In addition, certain internet based real time flight tracking services provide the same statistical data [1]. Some flight delay information can be derived indirectly from FAA's National Airspace System which provides information on airport events in real time [2]. At present, there appear to be no commercially available services which are able to provide prediction or probability of delay for a specific flight. There is no commercial usage of any ML models in the airline industry to assist consumers in predicting flight delays.

Problem definition:

Our objective is to provide highly transparent delay prediction information to the air travelers in the US. To accomplish this, we propose to develop a visualization application that leverages the power of machine learning to predict domestic flight delays in the country. The application will feature an interactive user interface enabling the user to furnish flight particulars and obtain an estimate of the expected delay. This objective is critical since customers anticipate three levels of service quality: desired, adequate, and predicted [3], where customers not only want to know if their schedule is delayed, but also want to know the anticipated estimation on their schedule.

Literature Survey:

In academia, there has been considerable work done on building and applying ML based models to analyze flight delays. Some studies have focused on certain specific aspects of aviation to predict delays. For example, use of Markov chain algorithm to model some processes (like baggage handling) which are critical to flight punctuality and then using these models to predict flight delays [4] or focusing on meteorological data and using Dual-channel Neural Networks to predict delays caused by weather factors [5]. These were useful studies but were lacking in that they did not wholistically look at flight and weather specific information together in their models. Other studies utilized a much wider array of parameters to model aircraft delay and used a variety of modeling techniques including but not limited to deep learning and neural networks ([6], Random Forest [7], Support Vector ([8], LinearR, ExtraRT ([9], extreme gradient boosting algorithms ([10] and Stacking algorithms [11]. Some studies expanded their datasets available for modeling by incorporating communication and surveillance data from air traffic management systems [12]. Although these studies were more detailed, as discussed later, they are not consumable commercially at their current stage. Some experts used as many as 10 ML algorithms to model and evaluate flight operations data and identify the features most suited for optimum prediction accuracy for each model [13]. One study by Stanford on pre-flight data compared Decision Tree, Logistic Regression and Neural Network and was able to show that all 3 of the techniques were able to produce comparable accuracies. The limitations observed was on the training data size [14]. This is a useful result for us because it emphasizes the importance of the datasets rather than the actual modeling method used.

Considerable non-commercial work has been done on the back end to build ML models for flight delay prediction. However, none of these are accessible to general consumer because they are lacking in one crucial aspect which is a user-friendly front end where a consumer or future traveler can navigate through an interactive interface and access flight delay prediction or forecast. Thus, even if adequate ML based models exist to accurately predict flight delays, they are inaccessible to an average consumer.

Proposed Method:

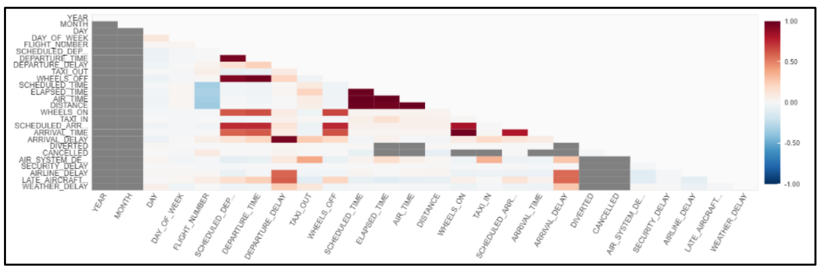
We intend to use Python and R for tasks pertaining to feature selection, feature analysis and building models. In order to solve a problem related to flight delays, multiple datasets will be used, and essential features will be identified to create an optimal model. Feature selection techniques such as correlation coefficient matrices, stepwise regression, and ANOVA will be used to identify the most significant features. The data will then be split into training and test sets to fit and evaluate multiple models such as decision trees, logistic regression, and neural networks. Evaluation metrics such as accuracy, recall, f1 score, and precision will be used, and k-fold cross-validation will be performed to evaluate the performance of the models. Once the best performing model is identified, hyperparameters will be tuned to improve its accuracy, and the selected model will be used to predict flight delays when passengers enter airline information [15].

The team intends to develop a visualization tool that presents delay prediction information to travelers in the United States in a transparent and comprehensible manner. This visualization will include an interactive graphical user interface (GUI) that employs various visualization techniques such as geographical maps, bar charts, and kanban boards...etc. The GUI will enable traveler to input their flight information and receive output information regarding their flight. To accomplish this, the team plans to integrate the model output mentioned earlier with the IOS mobile apps. The team have also done initial testing and validation and proven the feasibility of embedding such models inside the mobile apps; the team also determined that IOS mobile apps have the best usability and visual effectiveness.

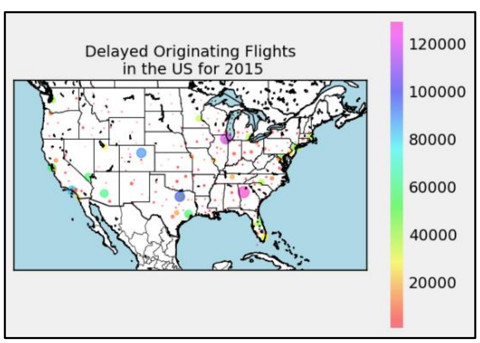
Experiments/Evaluation:

Exploration Data Analysis: We started our phase of experiments and evaluations with some basic data exploration. We first analyzed our data at a high level looking at some basic statistical parameters for example, correlation matrix between variables.

Dataset Statistics	
Number of Variables	31
Number of Rows	165843
Missing Cells	783826
Missing Cells (%)	15.2%
Duplicate Rows	0
Duplicate Rows (%)	0.0%
Total Size in Memory	76.3 MB
Average Row Size in Memory	482.6 B
Variable Types	Categorical: 10 Numerical: 21



The next step in our data exploration was to look at some individual variables that we think are important and their impact on total flight delay separately from other variables.



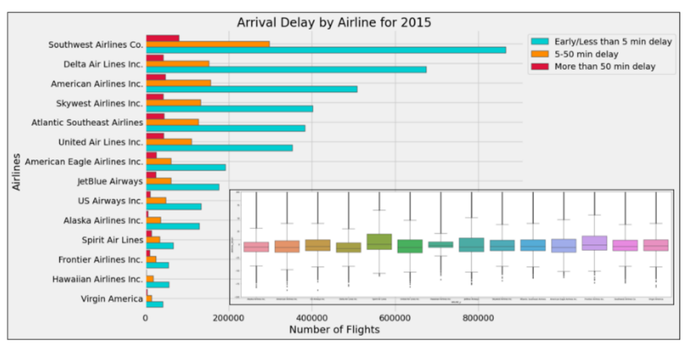


Figure 2a) Arrival delays by airport of origin *2b) Arrival delays by airline*

For example, if we look at the average daily delay throughout the year of 2015 with date, we can see some trends (Figure 3a). We decided to analyze at the 7 day (weekly) rolling averge of the daily delays to reduce noise. Clear spikes can be observed around Dec/Jan, Feb/March and Nov/Dec. These correspond to the Christmas holidays, spring break and thanksgiving. In addition, we can also observe a series of spikes between Jun-Aug which corresponds to summer vacations for schools in the US.

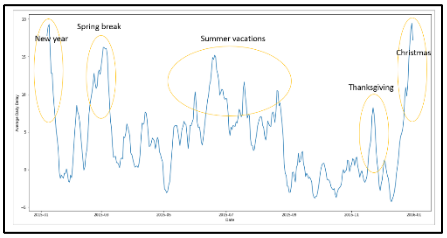
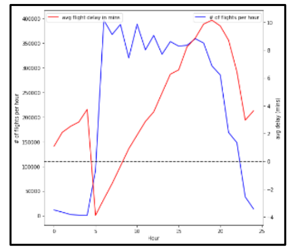
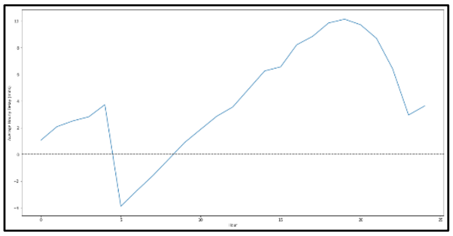


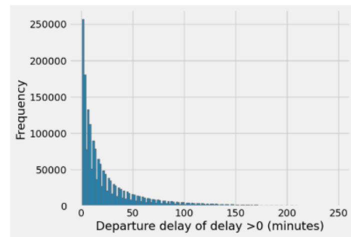
Figure 3a) 7 day (weekly) rolling average of the daily delays vs date



3b)Daily average delays vs hour of departure



3c) Daily average delays vs # of flights in a hour



3d) Frequency of delays per bucket of delay time

In order to analyze if the time of the day at which a flight is scheduled to depart has any impact on delay, we created a scatter plot of the scheduled departure time vs delay in arrival in mins (Figure 3b). To provide more clarity, we decided to group flights by hours of scheduled departure.

Some patterns can easily be observed. For example, the flights departing between 10 AM and 10 PM are prone to most delays. Flights departing between midnight and 9 AM are mostly on time as the average flight delays are 0 or below. This intuitively makes sense as most US airports are in urban areas and shut down or reduce flight operations at night. This means the air traffic congestion is greatly reduced and with it, flight delays. To further prove this, we plot the number of flights in an hour and the average flight delay on the same plot (Figure 3c). It is interesting to note that the flight delays do not increase or decrease immediately with the increase or decrease with the number of departing flights. There is a lag effect where the flight delays increase gradually and build up as the as the day goes on and more and more flights are added to the air traffic system, increasing the congestion and load on the system.

<u>ML Models:</u> Initially, we tried to model flight delay as a continuous variable, however, we soon found that our models were inadequate in modeling the variability of the data resulting in extremely low R-squared values. Therefore, we decided to divide our response variable into bins or buckets. These bins will vary in size ranging from a few mins for shorter delays to a few hours in case of longer delays. We decided to use random forest classifier to classify the flights (data points) into one of the many delay categories based on various predictors.

To start off with a simple model, we used a handful of predictors including airline, origin and destination airports, scheduled duration of flight, day of week, month, time of day of the flight and the distance between the two airports to categorize the expected delay. Our RFC model is able to achieve >70% accuracy, precision, recall and f1 score for early or on-time flights. However, these performance metrics for the delayed categories are relatively low.

In order to improve on that, we're working on increasing the model complexity to capture the variability in our data. One facet that we're currently exploring is how weather conditions relate to a particular flight's delay. For example, the effect of features like dew point, humidity, pressure, cloud cover, precipitation, snowfall, windspeed etc. on a flight's timeliness.

<u>Building an app as the front-end interface:</u> While building the actual ML models, we were also looking into finding an appropriate method to provide a front end for these models. We looked at several options including d3 and python-based toolkits (PyQT, wxPython etc) but finally decided to go with an

app style front interface & developing an iOS app that visualizes flight delays through a user-friendly interface. To achieve this, we plan to convert our trained Python model into a CoreML model format, which will be integrated into the app. The app will feature a map display of flight locations, allowing users to select a specific flight and view its predicted delay. Alternatively, users can input flight information such as flight number, date, source, and destination to obtain the predicted delay for their desired flight. Both methods will provide users with valuable information about potential flight delays. The app will be available for both iPhone and iPad users. Attached are few screenshots of our in-progress app work:

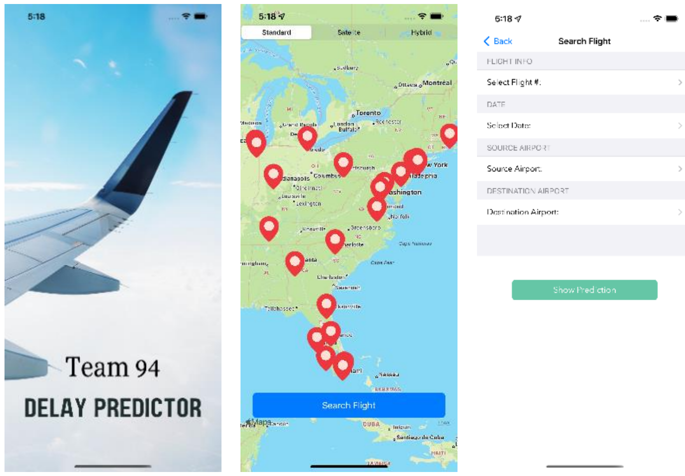


Figure 4a) Delay Predictor Launch screen 4b)Map view 4c) User defined inputs

<u>Conclusions and discussions:</u>

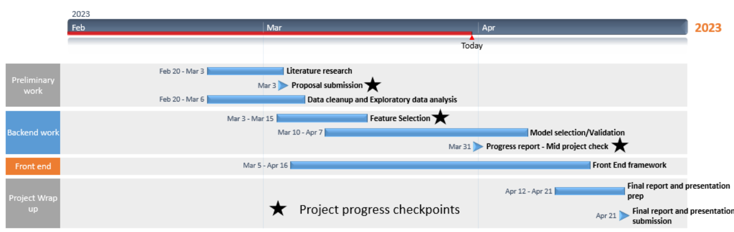


Fig 5: Revised plan

From data exploration phase, some predictors like data and time of the flight, airline, origin and destination airports and the distance between them, have a very clear impact on fight delay. We also conclude that delays increase as the number of planes in the air traffic system increases.

In terms of the models, we are able to conclude that RFC based models seem to be much better than others and this is in line with observations in literature. [16]

Finally, all team members have contributed a similar amount of effort and this project will be prepared for commercial development for members who wish to proceed. In addition to the progress evaluation, the team plans to conduct further assessments on the model mentioned in the preceding section. Importantly, as pointed out in the HAL Open Science's paper, "Evaluation should be representative of how the model would perform when deployed in a real-life setting." [17] Therefore, the team intends to incorporate this perspective into the final product to ensure its suitability for real-world applications.

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