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CS 6923

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Flight Delay Predictions

**I. Introduction**

For this assignment, we were tasked with predicting flight delays based on a dataset of flights from 2017. Our training set has 4,911 examples and 21 features. Of those 21, several are redundant (e.g., Airline ID, Unique Carrier), and one is the label.

Before selecting algorithms to test, we did data pre-processing and dimensionality reduction. We then evaluated different algorithms to find the best performing two for our dataset. We used Tableau for initial dataset evaluation, and python with pandas, sci-kit learn and matplotlib for all subsequent steps, from data pre-processing to result visualization.

**II. Pre-processing and dimensionality reduction**

As we have discussed, some features of our dataset are clearly redundant, and some, such as flight number, we wish to discard to prevent overfitting. After removing such fields, we are left with the following features:

|  |  |
| --- | --- |
| **Feature Name** | **Type** |
| Day of Week | Continuous |
| Departure Time | Continuous |
| Taxi Out | Continuous |
| Taxi In | Continuous |
| Actual Elapsed Time | Continuous |
| Distance Group | Continuous |
| Day of Year | Continuous |
| Origin Airport\* | Categorical |
| Destination Airport\* | Categorical |
| Carrier\* | Categorical |

\*Note: The bottom three categories in the chart are categorical, so we one-hot encoded them.

To get to this list, we removed:

UID – removed to prevent overfit

Airline Id – redundant to Carrier field

Flight Number – removed to prevent overfit

Origin City Market – highly correlated with Origin Airport

Origin City Name – redundant to Origin Airport

Origin State – redundant to Origin Airport

Destination City Market – highly correlated with Origin Airport

Destination City Name – redundant to Destination Airport

Destination State – redundant to Destination Airport

Distance – redundant to Distance Group

First Departure Time – too sparse

Before we begin evaluating our features, we decided to add one additional feature: Flight Month. We believe that some pattern of flight delays may be seasonal, due to weather or high load related delays, but this may be more evident when looking at the month of travel rather than the specific day. We would normally at this point develop some meta features, such as flights per day of week, or flights per month, to examine the relationship between load and flight delay, but it appears that when this dataset was sampled from the database of flight delay data, the sample evened out the number of examples per day and month, so we do not expect such features would be meaningful.

When we evaluated Arrival Delay labels in our training set, we observed that our training data had a mean arrival delay of 4.3 minutes and the standard deviation of the arrival delays was 45.4 minutes. When visualizing the data, we noticed that there was a long tail of outliers of extremely delayed flights. We further noted that the median arrival delay was -6. Based on this, also we evaluated training our models with outliers (which we defined as examples with a delay greater than two standard deviations from the mean), and with outliers removed. We also tried limiting our search to flights within one standard deviation, but the differences were insignificant.

Of the algorithms we studied in class, Linear Regression, K-Nearest Neighbor, Decision Trees, Support Vector Machines, and Neural Networks can be used for regression. We decided to investigate the performance of Linear Regression and Neural Networks in depth, after initial investigations found those two methods to be promising and interesting.

**III. Results**

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