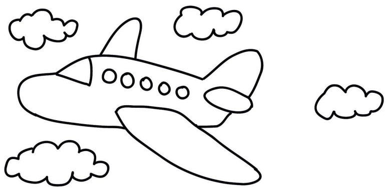


Flight Delays And Cancellations

A Classification Analysis

By Adina Steinman

Business Problem

- Our team of strategy consultants has been hired by the FAA, Federal Aviation Administration, to optimize efficiency across US airports and minimize flight delays as much as possible
- Our goal is to create a model that is able to predict whether a flight will be delayed or not and see which features are most useful in determining our predictions
- We will build a model that optimizes **recall**. We want to ensure that all delayed flights are classified correctly and that none are mistakenly classified as non-delayed. It is important to ensure that the model classifies delayed flights as correctly as possible so the FAA can effectively strategize to minimize these delays

Datasets

- Kaggle's "2015 Flight Delays and Classifications" dataset consisting of 3 csv files; information on flights, airports, and airlines
- Data has 39 columns containing information on delay/arrival times, reason for delays, location of airport, airlines, etc.
- Data has 5,819,079 rows; a random sample of 10,000 was used for this analysis

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 39 columns):
YEAR                          10000 non-null int64
MONTH                         10000 non-null int64
DAY                           10000 non-null int64
DAY_OF_WEEK                   10000 non-null int64
AIRLINE_CODE                  10000 non-null object
FLIGHT_NUMBER                 10000 non-null int64
TAIL_NUMBER                   9981 non-null object
ORIGIN_AIRPORT_CODE           10000 non-null object
DESTINATION_AIRPORT_CODE      10000 non-null object
SCHEDULED_DEPARTURE           10000 non-null int64
DEPARTURE_TIME                9862 non-null float64
DEPARTURE_DELAY               9862 non-null float64
TAXI_OUT                      9852 non-null float64
WHEELS_OFF                    9852 non-null float64
SCHEDULED_TIME                10000 non-null float64
ELAPSED_TIME                  9828 non-null float64
AIR_TIME                      9828 non-null float64
DISTANCE                      10000 non-null int64
WHEELS_ON                     9847 non-null float64
TAXI_IN                       9847 non-null float64
SCHEDULED_ARRIVAL             10000 non-null int64
ARRIVAL_TIME                  9847 non-null float64
ARRIVAL_DELAY                 9828 non-null float64
DIVERTED                      10000 non-null int64
CANCELLED                     10000 non-null int64
CANCELLATION_REASON           148 non-null object
AIR_SYSTEM_DELAY              1890 non-null float64
SECURITY_DELAY                1890 non-null float64
AIRLINE_DELAY                 1890 non-null float64
LATE_AIRCRAFT_DELAY           1890 non-null float64
WEATHER_DELAY                 1890 non-null float64
AIRLINE                       10000 non-null object
AIRPORT_CODE                  9184 non-null object
AIRPORT                       9184 non-null object
CITY                          9184 non-null object
STATE                         9184 non-null object
COUNTRY                       9184 non-null object
LATITUDE                      9173 non-null float64
LONGITUDE                     9173 non-null float64
dtypes: float64(18), int64(10), object(11)
memory usage: 3.0+ MB
```

Class Imbalance

- From our sampled dataset, 64% of data was classified as non-delayed and 36% as delayed
- SMOTE technique was applied to handle this imbalance, and the synthetic dataset split was 50% delayed and 50% non-delayed. These resampled values were used to fit all our future models

```
Original class distribution:

0    6384
1    3616
Name: DELAYED, dtype: int64
----------------------------------------
Synthetic sample class distribution:

1    4795
0    4795
Name: DELAYED, dtype: int64
```

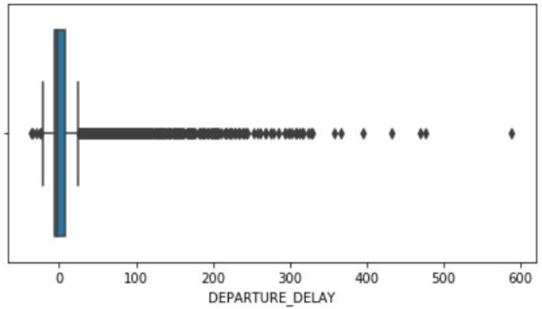
Exploratory Data Analysis

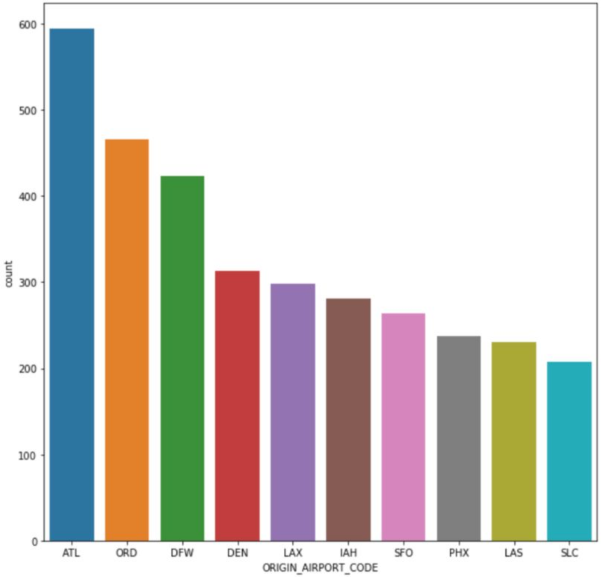
- Replaced NaNs with 0s or median values, then one-hot-encoding was applied to Months, Days of Week, Airlines and Airports

- Some extreme outliers in the target variable, departure delay, indicating that there could be some extreme cases/unique situations that caused certain flights to be delayed

- Feature engineering: created variable that binned airports based on flight traffic; heavy, medium, light and very light

- Certain airports are busier than others; particularly ATL, ORD, and DFW have the most air traffic, which makes sense as they are all hubs for Delta, United and American Airlines, respectively





Vanilla Model Results

	train_accuracy	train_precision	train_recall	train_f1	test_accuracy	test_precision	test_recall	test_f1
model								
knn	0.792	0.699	0.746	0.721	0.617	0.475	0.492	0.483
bayes	0.789	0.965	0.432	0.597	0.782	0.979	0.412	0.580
decisiontree	1.000	1.000	1.000	1.000	0.758	0.666	0.671	0.668
bagging	0.996	0.999	0.991	0.995	0.801	0.773	0.643	0.702
randomforest	1.000	1.000	1.000	1.000	0.813	0.805	0.643	0.715
Adaboost	0.815	0.768	0.695	0.730	0.802	0.765	0.661	0.709
XGBoost	0.835	0.819	0.696	0.752	0.821	0.804	0.672	0.732
SVM	0.863	0.887	0.710	0.789	0.785	0.773	0.581	0.663

Final Model

model	train_accuracy	train_precision	train_recall	train_f1	test_accuracy	test_precision	test_recall	test_f1
decisiontree	1.000	1.000	1.000	1.000	0.758	0.666	0.671	0.668
Decision Tree Tuned	0.792	0.687	0.779	0.730	0.774	0.672	0.739	0.704
XGBoost	0.835	0.819	0.696	0.752	0.821	0.804	0.672	0.732
XGBoost Tuned	1.000	1.000	1.000	1.000	0.785	0.718	0.676	0.696

- Decision Tree and XGBoost were tuned as their test_recall scores were the highest amongst the vanilla models
- Decision Tree final model included hyperparameters for criterion, max depth, minimum samples split and minimum split leaf. The result improved test_recall from 0.671 in vanilla model to 0.739 in final model
- XGBoost final model included hyperparameters for max depth, learning rate, subsample, minimum split loss, and number of estimators. The result improved test_recall from 0.672 to 0.676
- Resulting models will still misclassify some delayed flights as non-delayed (false negatives)

Conclusions and Recommendations

- While XGBoost increased our test recall score, it was only marginally, and the resulting model was overfit to our train data
- In future models, we should look to remove features that are not correlated with our target variable, as well as remove features that have low feature importances. Future work with more data cleaning could potentially lead us to stronger recall scores, without producing a model that is overfit
- FAA should allocate resources to improve the efficiencies of Late Aircraft Delay, Arrival Delay and Airline Delay, as these types of delays had the highest feature importances in our models

Thank You!

- Kaggle Dataset: https://www.kaggle.com/usdot/flight-delays
- GitHub: https://github.com/adinas94/phase3_project
- Contact Information
  - Email: adinasteinman@gmail.com
  - Linkedin: https://www.linkedin.com/in/adinasteinman/