

Exploring the data

I wrote a python script to look at the data and clean if necessary. Here are the priliminary check results.

```
Index(['year', ' month', 'carrier', 'carrier_name', 'airport', 'airport_name',  
      'arr_flights', 'arr_del15', 'carrier_ct', ' weather_ct', 'nas_ct',  
      'security_ct', 'late_aircraft_ct', 'arr_cancelled', 'arr_diverted',  
      ' arr_delay', ' carrier_delay', 'weather_delay', 'nas_delay',  
      'security_delay', 'late_aircraft_delay', 'Unnamed: 21'],  
      dtype='object')  
year                : 175915  
 month              : 175915  
 carrier            : 175915  
 carrier_name       : 175915  
 airport            : 175915  
 airport_name       : 175915  
 arr_flights        : 175663  
 arr_del15          : 175460  
 carrier_ct         : 175663  
  weather_ct        : 175663  
 nas_ct             : 175663  
 security_ct        : 175663  
 late_aircraft_ct   : 175663  
 arr_cancelled      : 175663  
 arr_diverted       : 175663  
  arr_delay         : 175663  
  carrier_delay     : 175663  
 weather_delay      : 175663  
 nas_delay          : 175663  
 security_delay     : 175663  
 late_aircraft_delay : 175663  
 Unnamed: 21        :      0
```

As seen above there were over 200 rows with missing values. For this project, I dropped those rows as it was not significant in the analysis that I was working on. There were over 175663 valid data rows for an effective analysis.

Evaluating the dataset

I used carrier_ct as the prediction factor. I created a new variable to evaluate if there was a carrier delay (1) or not (0) based on the values of carrier_ct. If carrier_ct was not null and a valid value greater than 0, the carrier delay variable was set to 1 else 0. The numeric variables of interest were arr_del15 (delay over 15 minutes as reported to RITA), weather_ct (delays caused by extreme weather conditions), nas_ct (delays caused by NAS directives), security_ct (delays caused by security issues), late_aircraft_ct (delays caused by the airline carrier)

A simple decision tree classifier is used to train and test the data. Based on the output below we can say the most important feature to determine flight delays is the variable arr_del15. Another variable that affects flight delay are nas_ct and late_aircraft_ct. Weather and Security do not play a significant part in the delay times. Thus we can conclude that our analysis is on the right track to determine trends with airports and airlines to determine the pain points for a particular carrier. At some airports our selected carrier experienced considerable delays. We will focus our visualizations on this aspect. If we can pinpoint the delay times and location, we might be able to do further research to eliminate the delays for the airline.

```
training time for all data: 0.425 s
Decision Tree Accuracy on All the data: 1.0
training time: 0.184 s
prediction time: 0.008 s
no. positive predictions: 82060
F1 Score: 0.996
Precision score: 0.996
Recall score: 0.996
Decision Tree Classifier Accuracy: 0.992
output: [0, 1, 2, 3, 4]
importance: of arr_del15 is 0.716
importance: of weather_ct is 0.053
importance: of nas_ct is 0.12
importance: of security_ct is 0.004
importance: of late_aircraft_ct is 0.107
```

PCA Fit

Using the PCA Fit we come to the similar conclusion. Weather and Security are not the leading causes for flight delays. The features we have used are the same as above. The numeric variables of interest were arr_del15 (delay over 15 minutes as reported to RITA), weather_ct (delays caused by extreme weather conditions), nas_ct (delays caused by NAS directives), security_ct (delays caused by security issues), late_aircraft_ct (delays

caused by the airline carrier)

PCA Fit confirms that the Decision Tree Classifier is the best fit for this data set.

```
Prediction accuracy for the normal test dataset with PCA using the Decision Tree Classifier
```

```
99.01%
```

```
Prediction accuracy for the standardized test dataset with PCA using the Gaussian Naive Bayes Classifier
```

```
66.76%
```

```
PC 1 without scaling:
```

```
[0.86776321 0.20001608 0.02510475 0.30166796 0.00134976 0.33962471]
```

```
PC 1 with scaling:
```

```
[0.45851309 0.44154183 0.39242163 0.42110894 0.26603731 0.43897976]
```

```
Carrier Delay: [0.93628354 0.91977291 0.92658247 ... 0.92730209 1.02254084 0.92235982]
```

```
slope: [-0.04989449 0.05111411 0.0497768 0.04979733 0.04961322 0.04960349]
```

```
intercept: 0.9199668519849167
```

```
##### stats on test dataset #####
```

```
r-squared score: 0.015727406648427977
```

```
##### stats on training dataset #####
```

```
r-squared score: 0.015813212459995896
```

Tuning Decision Tree Parameters

I adjusted the decision tree parameters, in the first run, I let the classifier traverse all the nodes till the tree was completed. In the second case, I limited the depth to 3 levels.

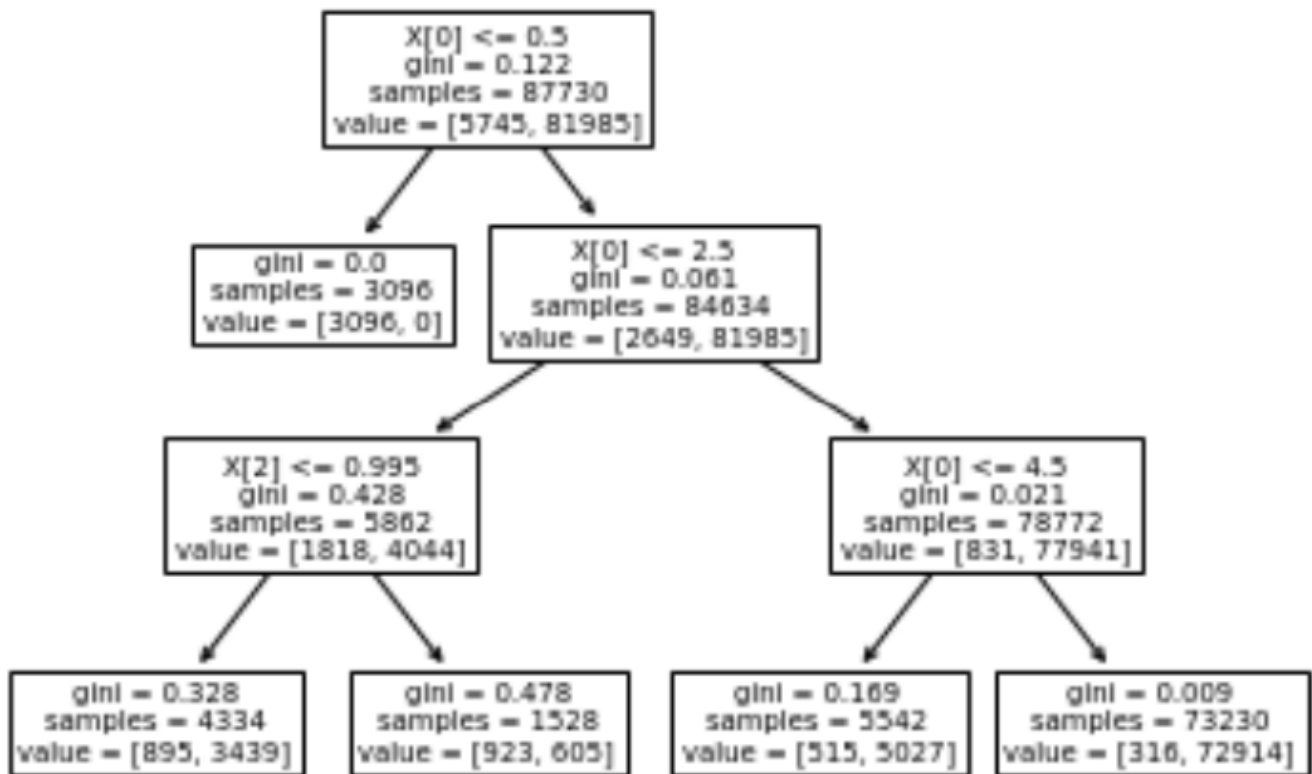
```
In [1]: runfile('C:/Users/maya_/datasets/D195/e
training time for all data: 0.514 s
Decision Tree Accuracy on All the data: 1.0
training time: 0.225 s
prediction time: 0.004 s
no. postive predictions: 82049
F1 Score: 0.996
Precision score: 0.996
Recall score: 0.996
Decision Tree Classifier Accuracy: 0.993
output: [0, 1, 2, 3, 4]
importance: of arr_del15 is 0.715
importance: of weather_ct is 0.053
importance: of nas_ct is 0.121
importance: of security_ct is 0.004
importance: of late_aircraft_ct is 0.106
```

Figures now render in the Plots pane by default
Plots pane options menu.

```
In [2]: runfile('C:/Users/maya_/datasets/D195/c
Reloaded modules: readdata, classifyDT
```

```
In [3]: runfile('C:/Users/maya_/datasets/D195/e
training time for all data: 0.418 s
Decision Tree Accuracy on All the data: 1.0
training time: 0.079 s
prediction time: 0.006 s
no. postive predictions: 83198
F1 Score: 0.986
Precision score: 0.979
Recall score: 0.993
Decision Tree Classifier Accuracy: 0.973
output: [0, 2]
importance: of arr_del15 is 0.949
importance: of nas_ct is 0.051
```

The tree visualization is given below



Changing the test size to 20% did not yield different results for the F1 score, precision or recall. I chose to leave it at 50%.

The two parameters I tuned were the `max_depth=10` and `min_samples_split=10`. I saw an improvement in the positive predictions with these values.

The features we have used in this project to analyse the flight delays have been verified as appropriate according to the statistics and algorithms seen above.