Flight Delay Prediction

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October 11, 2019

Abstract

The Project aims to predict the whether a scheduled flight will be delayed or not based on various parameters that define the travel and also the environmental conditions. Dataset of flights departing and arriving at 15 different stations were used for this task. The weather details were collected at an interval of one hour for the years 2016 and 2017. Based on these data an attempt to predict weather the flight will be delayed or not (classification). If delayed predict the delay(regression). Out of various algorithms Extra Trees Classifier(0.8407,0.9428,0.9418) proved to be best for the classification task and Gradient Boosting Regressor(0.9422) proved to be working best for the regression task.

1 Introduction

Flight operators incur a considerable amount of loss due to flight delay. Delay in flight's departure or arrival can be related with various factors that define the scheduling of the flight and the environmental conditions. On a abstract level the flight delay prediction can be viewed a pipelined operation of two sequential tasks, first to predict whether a flight will be delayed or not(classification) and secondly, if the flight is delayed then to predict the delay(regression). For the classification task Logistic Regression, Random Forest Classifier, Support Vector Machine, Extra Trees Classifier and Extra Gradient Boost Classifier can be applied. For regression task Linear Regression, Extra Tree Regressor, Support Vector Regressor, and Extra Gradient Boosting Regressor can be applied.

2 Data Set

The flight data set, a comma separated value, contains the details the flight schedules in 15 airports of US. Each entry in the dataset is uniquely identified by the composite key (Flight ID, day of month, month, year). In total there are 18,77,667 datapoints the flight data set. The weather data set is a JSON file that contain weather data that is recorded periodically for every one hour over two years(2016-2017).

3 Pre-Processing

The following features were used from flight dataset.

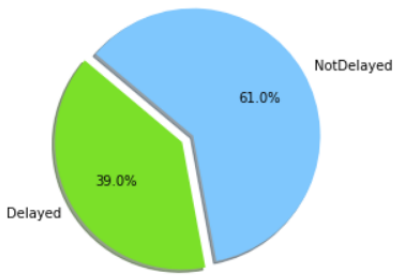
Feature	Value	Feature	Value
Quarter	[1-4]	Month	[1-12]
Day of month	[1-31]	Day of week	[1-7]
Flight Number	Integer	Origin	15 air stations in US
Scheduled Departure Time	Integer	Actual Departure Time	Integer
Departure Delay	Integer	Departure Delay > 15 minutes	Integer
Destination	15 air stations in US	Year	2016, 2017
Scheduled Arrival Time	Integer	Actual Arrival Time	Integer
Arrival Delay	Integer	Arrival Delay > 15 minutes	Integer

Out of these features 'Origin' and 'Destination' were label encoded to [1-15], each value representing each station.

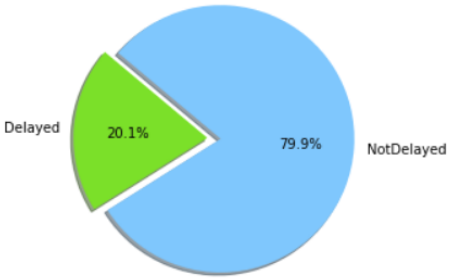
Thus there are $731 \times 24 \times 15 = 263160$ records in the weather data set. The following features were extracted from the weather dataset.

Feature	Value	Feature	Value
Quarter	[1-4]	Month	[1-12]
Day of month	[1-31]	Day of week	[1-7]
Time	Integer	Airport	15 air stations in US
Dew Point in Celsius	Float	Heat Index in Celsius	Float
Wind temperature (Celcius)	Float	Wind Speed (kmph)	Float
Percentage cloud cover	Float	Humidity	Float
Precipitation (mm)	Float	Pressure	Float
Average Temperature	Float	Visibility	Float
Wind Direction (Degree)	Float	Weather Code	Integer

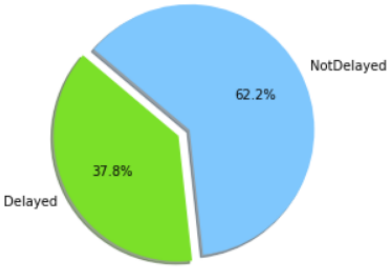
In ordered to merge these to dataset the fields time, day, month, year and airport code were used. Since the time in fight data set is not rounded off to the nearest hour time was rounded off to its nearest hour. Based on what field is chosen for the 'time' from the flight data set we can derive two different dataset, snapshot before departure and snapshot after the departure.



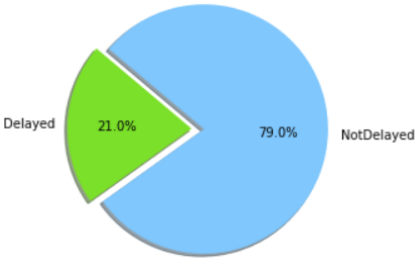
(a) Departure Delay



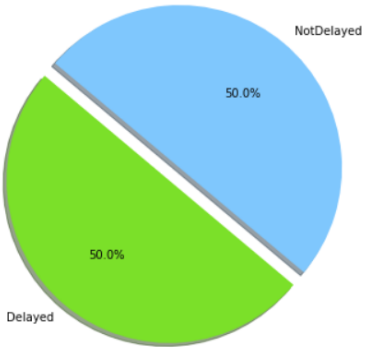
(b) Departure Delay > 15



(c) Arrival Delay



(d) Arrival Delay > 15



(e) Dataset after Sampling

Figure 1: Delay Analysis

4 Dataset Analysis

Based on the pie-chart($fig.1$) We observe that the dataset is skewed towards the class 'Not-Delayed'. This skew can lead to incorrect learning because the information is biased to one class. Thus we perform sampling to reduce this skew. The are two method to make the dataset even, Over-sampling or Under-sampling. In order to preserve the existing data and make full use of it, Over-sampling was employed to balance the dataset. Synthetic Minority Over-sampling Technique(SMOTE)was used to sample the dataset as it synthesises data-points that has smooth variation and high correlation with existing dataset.

5 Classification Metrics

The following metrics are used for evaluating a classification model

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

$$f1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

6 Classification

Classification task is done to predict whether a scheduled flight will be delayed or not. Three kinds of classification were performed on the dataset obtained.

- Prediction of departure delay based on the weather data obtained during scheduled departure time.
- Prediction of arrival delay based on the weather data obtained during scheduled departure time
- Prediction of arrival delay based on the weather data obtained during actual departure time.

Random Forest Classifier, Gradient Boosting Classifier, Extra Trees Classifier, Support Vector Machine and Extra Gradient Boosting Classifier were used to perform the classification. The results obtained are as as follows,

Table 1: Departure Delay

Algorithm	Precision	Recall	f1 score	Accuracy
Random Forest Classifier	0.38	0.20	0.27	0.7728
Extra Tree Classifier	0.35	0.26	0.29	0.7525
Gradient Boosting Classifier	0.66	0.22	0.31	0.7389
XGB Classifier	0.66	0.08	0.14	0.8065

Table 2: Arrival Delay based on the weather data before departure

Algorithm	Precision	Recall	f1 score	Accuracy
Random Forest Classifier	0.89	0.68	0.77	0.9151
Extra Tree Classifier	0.84	0.66	0.74	0.9020
Gradient Boosting Classifier	0.74	0.78	0.76	0.8952
XGB Classifier	0.78	0.75	0.77	0.9043

Table 3: Arrival Delay based on the weather data after departure

Algorithm	Precision	Recall	f1 score	Accuracy
Random Forest Classifier	0.85	0.71	0.77	0.9122
Extra Tree Classifier	0.89	0.62	0.73	0.9044
Gradient Boosting Classifier	0.90	0.68	0.77	0.9162
XGB Classifier	0.90	0.69	0.78	0.9198

We note that though all the model perform with accuracy more than 0.9 the individual class score for the 'Delayed' class is less. Thus the model is poorly trained on a dataset that is skewed to one class. To correct this we perform oversampling. The results of model that is trained over sampled dataset is as follows,

Table 4: Departure Delay

Algorithm	Precision	Recall	f1 score	Accuracy
Random Forest Classifier	0.89	0.80	0.84	0.8514
Extra Tree Classifier	0.85	0.82	0.84	0.8407
Gradient Boosting Classifier	0.93	0.72	0.81	0.8296
XGB Classifier	0.93	0.72	0.81	0.8317

Table 5: Arrival Delay based on the weather data before departure

Algorithm	Precision	Recall	f1 score	Accuracy
Random Forest Classifier	0.96	0.91	0.94	0.9386
Extra Tree Classifier	0.96	0.92	0.94	0.9428
Gradient Boosting Classifier	0.96	0.91	0.94	0.8955
XGB Classifier	0.96	0.92	0.94	0.9413

Table 6: Arrival Delay based on the weather data after departure

Algorithm	Precision	Recall	f1 score	Accuracy
Random Forest Classifier	0.96	0.91	0.94	0.9392
Extra Tree Classifier	0.96	0.92	0.94	0.9418
Gradient Boosting Classifier	0.96	0.91	0.94	0.8944
XGB Classifier	0.90	0.69	0.78	0.9197

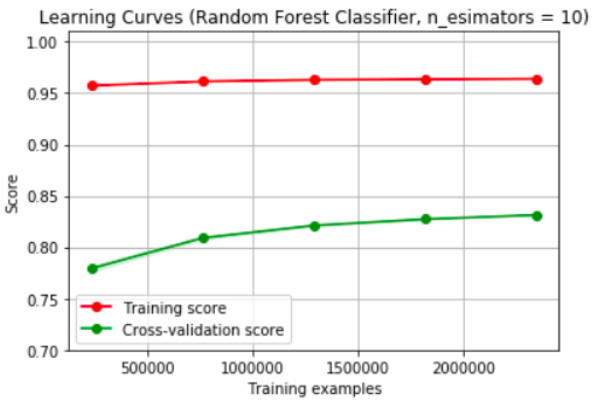


Figure 2: Learning history of the Random Forest Classifier

7 Regression - Metrics

The following metrics were used to evaluate the regression model,

$$MSE = \sum_{i=1}^{n} \frac{(y_i - \bar{y})^2}{n}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \bar{y})^2}{n}}$$

$$MAE = \sum_{i=1}^{n} \frac{|y_i - \bar{y}|}{n}$$

$$R^2(y, \hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

8 Regression

Regression algorithm have a continuous output unlike the classification task which produce discrete output. Arrival delay of the flight at destination was predicted based on the weather data of the origin airport during the actual departure time. Linear regression, Support Vector Machine, Extra Tree Regression and Gradient Boosting regression were used for the task. The performance for each algorithm is shown as below.

Table 7: Arrival delay prediction based on weather data after departure at the origin airport

Algorithm	MSE	RMSE	MAE	R2-score
Linear Regressor	415.9970	20.3960	15.1254	0.9178
Support Vector Machine	2485.3669	49.8535	16.9795	0.5057
Extra Tree Regressor	326.9334	18.0813	12.7911	0.9349
Gradient Boosting Regressor	292.9988	17.1172	11.8265	0.9422

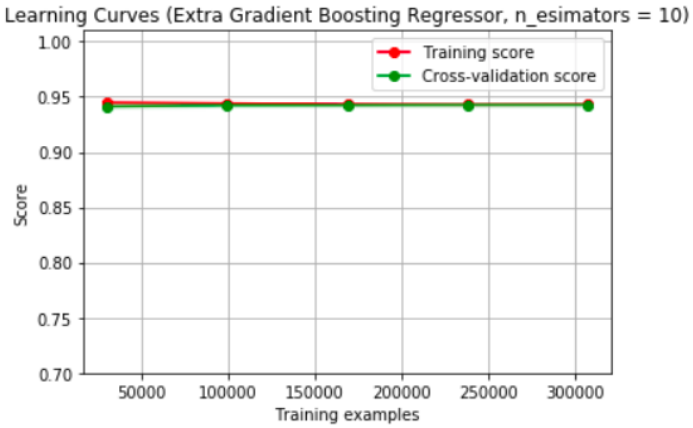


Figure 3: Learning History of XGB Regressor

9 Regression Testing

As we analyse the arrival delay value in the dataset we observe that, though the delay value range from 0 to 2142, only values in the range 0-200 occur with maximum frequency. The frequency distribution graph of the arrival delay is shown as below.

The Linear Regressor model was tested on various ranges of input. It was obsewrved that as the range

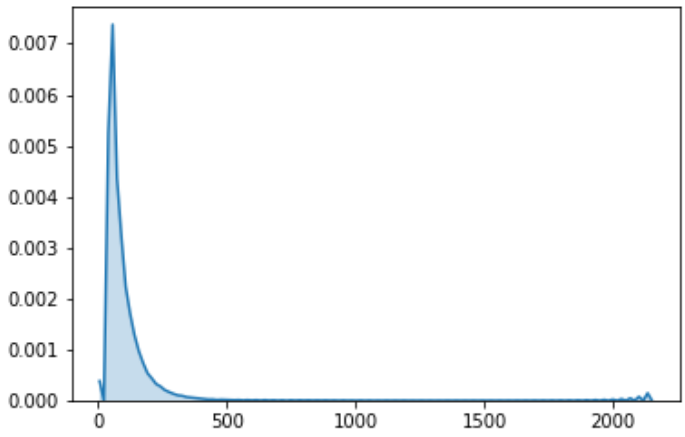


Figure 4: Frequency distribution of arrival delay

of input approached the maxima of the distribution plot the errors reduced. The testing information is as follows

Table 8: Testing of Linear Regression Model

Range	MSE	RMSE	MAE
$>$ 2000 minutes	26194.1169	161.8460	161.7119
$>$ 1000 minutes	9286.1945	96.3649	92.4357
$<$ 200 minutes	379.2796	19.4751	14.7297
$<$ 100 minutes	329.5595	18.1538	14.3314

The histogram plot in $fig.4$ indicates that the number of datapoints with delay in the range 0-100 is relatively high. Thus we see that the model perform better as we approach the point of maxima in the plot. This is reflected in the MSE,RMSE and MAE score of the predicted values.

10 Pipelining

In order to test the whole model a pipelined architecture was followed. The data was preprocessed to perform classification using Random Forest Classifier. The data points that were predicted to be delayed were selected to perform the regression. Linear regressor was used to perform the prediction. The overall flow of the program can be depicted as below.

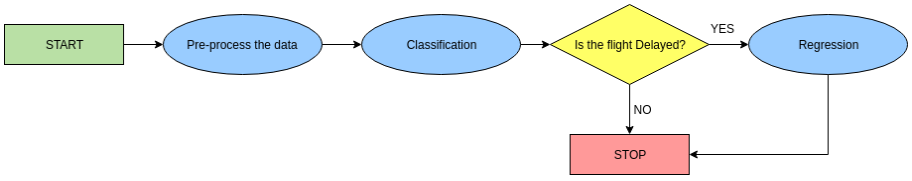


Figure 5: Flow the pipelined program

The model performed with a r^2 score of 0.9272. The Mean Squared Error was 408.9991, The Root Mean Squared Error was 20.2237 and the Mean Absolute Error was 14.9275.

11 Conclusions

The flight and weather datasets were preprocessed and merged in to one comma separated value file. We see that learning process of the model can be significantly affected by the skewness of the dataset. The algorithm tend to give less importance to the classes that are less dominant in the dataset. Thus to improve the performance of the algorithm the dataset was over-sampled to reduce the skew. Out of all classification algorithm employed **Extra Tree Classifier** proved to be better performing on compared based on the validation accuracy(0.8407,0.9428,0.9418) for the test dataset and precision(0.85,0.96,0.96), recall(0.82,92,92) and f1-score(0.81,94,94) of the class 'Delayed'. **Gradient Boosting Regressor** was found to be performing best when evaluated based on the MSE(292.99), RMSE(17.11), MAE(11.82) and R^2(0.9422) score. The pipelined model constructed using the Random Forest Classifier and linear regressor was useful in evaluating the overall performance of the system.