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# Business analysis and modelling of flight delays using artificial intelligence

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**Abstract**---In the current day, with the growth of technology the number of people travelling by flights has increased. Consistently a significant number of flights are delayed or crossed out because of numerous of reasons. These delays bother travelers. These delays also cost a lot to the aircraft organization. Flight delays negatively affect carriers, air terminals and travelers. There are different methodologies used to manufacture flight delays expectation models from the Data Science point of view. The key resource of a flight includes aircraft, cockpit crew and cabin crew. For purposes of dispatching resources effectively, the three resources may be distributed independently. If

the initial flight of a flight plan is delayed due to bad weather or other factors, it may result in the delays of the directly downstream flights that need to await its resources. If the delays continue to spread to the lower downstream flights, it may result in large area delay propagation. The method proposed here introduces and summarizes the initiatives used to address the flight delay prediction problem, according to scope, data and computational methods, giving special attention to an increasing usage of machine learning methods. Besides, it also presents a timeline of major works that depicts relationship between flight delay prediction problems and research trends to address them. First of all, business analysis and modelling is provided, then the definitions of variables and algorithms are described, finally, the effectiveness of the model and algorithm is proved through simulation computing.

**Keywords**---Flight delay, Weather, Travelers, Aircraft.

## **Introduction**

Flight delays have negative effects, mainly economic, for travelers, aircrafts, and airports. Given the vulnerability of their event, travelers for the most part intend to plan to travel hours earlier for their arrangements, expanding their trip costs, to guarantee their arrival on time. On the other hand, carriers suffer punishments, fines and extra activity costs. Besides, from the manageability point of view, postponements may likewise cause ecological harm by increases of fuel utilization and gas emissions. Business aircrafts are a spine of the overall transportation framework, bringing huge financial utility by empowering less expensive and simpler long distance travel. After the greater part an era of standard appropriation (particularly in the US), carrier activities have seen real advancements, In any case, a traveler is troubled via flight delays, upsetting a generally demanding framework and causing huge wasteful aspects at scale in 2007, 23% of US flights were over 15 minutes late imposing a total cost of \$32.9bn on the US economy. Problematic climate conditions were the immediate reason for ~17% of those postponements. To better comprehend the whole flight environments, huge volumes of data from commercial aviation are gathered and stored in databases. Submerged in this huge data information created by experts and information researchers are escalating their computational and information administration abilities to separate valuable data from every datum. In this setting, the system of fathoming the space, overseeing information and applying a model is known as Data Science, a trend in solving challenging problems related to Big Data. This examination is directed by building up a flight delay look into scientific categorization, which organizes approaches as indicated by the kind of issue, scope, information issues, and computational methods. The paper additionally contributes by showing a course of events of real works assembled by the kind of flight delay prediction problem.

## **Related Background**

Consistently an extensive number of flights are deferred or wiped out because of a numerous of reasons. These delays result in bother to Airline companies and passengers, also it costs in large numbers to the carrier organizations. Flights are postponed because of an assortment of reasons extending from climate conditions, security etc. While numerous postponements are caused because of unanticipated conditions, a lot of these delays can be limited and anticipated by carrier information. Flight delays are a simple fact of life and affect most people at some time or another. Moreover if one has to link to a connecting flight or if an important meeting is missed then the issue is compounded. If the delay is small enough it can pass un-noticed but if it is significant it can have a cost attached to it. Personal costs would fall under accommodation costs or finding alternative travel arrangements, as for airlines it would include crew costs and passenger costs in having to re-obliging them alongside air terminal expenses and rescheduling expenses of flights. It is evaluated that postpones of flights cost the US economy in the locale of 16 Billion dollars per year due to the defers understanding via carrier and airplane terminal clients as carried by (NEXTOR, 2016). Flight delays additionally risks carriers marketing techniques, since aircrafts depend on client's faithfulness to help their long standing customer programs also the passenger's decision is likewise influenced. The estimation of flight postponements can enhance the strategic and operational choices of airplane terminals and carriers supervisors and caution travelers, so that they can rework on their plans.

## **Proposed Method**

The proposed method considers a dataset. The dataset for this issue was taken from the Bureau of the Transportation Statistics which consists of all business flight tasks from the year 1987 to 2017. To reduce the size of the dataset, a subset of dataset is taken for analysis as follows:

- For the project the flight activities was considered i.e flight activities for the period of May (2016) is been considered.
- Additionally flight activities from December 2016 have additionally been considered with the goal of comparison and analysis.
- This venture thinks about all flight activities (inbound and outbound) from the province of California, United States, though it is among the busiest air terminals. This has reduced the datasets to 2, 00,020 records. The dataset is arranged in order considering the months. So the main screen shot consists the records of May (5).

YEAR	MONTH	DAY_OF_MONTH	CARRIER	ORIGIN_CITY_NAME	DEST_CITY_NAME	DELTA	ARR_DELAY	DEPART_DELAY	DISTANCE	CARRIER	WEATHER	NAS_DELT	SECURITY	LATE_AIRCRAFT	DELAY
2015	5	1	AA	San Francisco	Dallas/Fort Worth	0	0	0	1684						
2015	5	2	AA	San Francisco	Dallas/Fort Worth	0	0	0	1684						
2015	5	3	AA	San Francisco	Dallas/Fort Worth	0	0	0	1684						
2015	5	4	AA	San Francisco	Dallas/Fort Worth	52	1	0	1684	50	0	2	0	0	
2015	5	5	AA	San Francisco	Dallas/Fort Worth	0	0	0	1684						
2015	5	6	AA	San Francisco	Dallas/Fort Worth	11	0	0	1684						
2015	5	7	AA	San Francisco	Dallas/Fort Worth	0	0	0	1684						
2015	5	8	AA	San Francisco	Dallas/Fort Worth	0	0	0	1684						
2015	5	9	AA	San Francisco	Dallas/Fort Worth	0	0	0	1684						
2015	5	10	AA	San Francisco	Dallas/Fort Worth	0	0	0	1684						
2015	5	11	AA	San Francisco	Dallas/Fort Worth	0	0	0	1684						
2015	5	12	AA	San Francisco	Dallas/Fort Worth	0	0	0	1684						
2015	5	13	AA	San Francisco	Dallas/Fort Worth	48	1	0	1684	48	0	0	0	0	
2015	5	14	AA	San Francisco	Dallas/Fort Worth	0	0	0	1684						
2015	5	15	AA	San Francisco	Dallas/Fort Worth	0	0	0	1684						
2015	5	16	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	17	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	18	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	19	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	20	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	21	AA	Dallas/Fort Worth	San Diego	2	0	0	1173						
2015	5	22	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	23	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	24	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	25	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	26	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	27	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	28	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	29	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						
2015	5	30	AA	Dallas/Fort Worth	San Diego	0	0	0	1173						

Figure 1. Snapshot of Original Dataset (MAY\_2016)

Keeping in mind the aim construct the predictive model, the attributes considered are timeslot, Carrier, Distance, Month. Since the above components are assumed to be the most vital part in deciding Delays, different variables have not been considered to keep up accuracy level. With the purpose of this task, 3 sorts of models have been built and accuracy of the two models have been made to compared. The algorithms utilized to do so are:

- Naive Bayes Classification Algorithm
- Random Forest Algorithm
- Cluster Analysis
- K-Means Method

With the aim to construct a predictive model, 80% of the data information is taken as a training data (to prepare the classifier) and the remaining 20% of the data information is considered as test data information. Initially analysis is done with a training set whereas the test set and validation set are used for evaluating the relationships hold between them. Implementation methods and data processing techniques to develop a predictive model are following :

- First we check whether all the attribute names are correctly given, in order to avoid any confusion during analysis. This will also make our data set presentable.
- Import the dataset to R and store it with a suitable name.
- Now we perform the descriptive analysis of our dataset to find out the mean, median, mode, maxima, minima, 1st quartile, 3rd quartile.
- The results for every important attributes are noted for analysis purpose.
- Now that we have all the necessary details and since our aim is to analyse the delay of airplanes so we now group the delay into two major categories- minor delay and major delay according to the mean obtained from the descriptive analysis of the delay column of the dataset. We put major delay for any delay greater than mean delay and minor delay for delay less than mean delay.
- Now, individually analyse every attribute of the dataset with respect to delays with the help of graphs and other mathematical tools and note the

results.

- From the above results, identify the major causes of delay.
- Now since we have all the necessary results, we will now build a predictive model with the help of two very prominent algorithms “Naïve byes algorithm and Random forest algorithm”.
- The accuracy of the two algorithms is compared and the best one is used to predict further delays.
- Now cluster analysis is performed to know about the carriers that have the most delays.
- Number of clusters is decided by the elbow method as deciding number of clusters manually can be very cumbersome task.
- Now that we know the appropriate number of clusters, we draw the graph and find out the carriers which have the most delays and the carriers which have the least delay.

Once the dataset has been extracted and integrated, the next step involves exploring the dataset for general trends, missing values and other information. Considering the large size of the data, exploring the data manually would be a tedious and time consuming task. To avoid this, the summary method in R is used to explore the variables in the dataset in order to detect specific trends or outliers and even missing values. The summary of the entire dataset gives the following result :

```
##      YEAR      timeslot  CRS_DEP_TIME  MONTH
## Min.   :2014  AFTERNOON:70696  Min.   : 5  Min.   : 5.000
## 1st Qu.:2014  EVENING   :46443  1st Qu.: 915  1st Qu.: 5.000
## Median :2015  MORNING   :76562  Median :1320  Median : 5.000
## Mean   :2015  OVERNIGHT: 6319  Mean   :1341  Mean   : 8.468
## 3rd Qu.:2015                3rd Qu.:1740  3rd Qu.:12.000
## Max.   :2015                Max.   :2359  Max.   :12.000
##                                     NA's   :1
## DAY_OF_WEEK  CARRIER  ORIGIN_CITY_NAME
## Min.   :1.000  WN       :54321  Los Angeles, CA : 35779
## 1st Qu.:2.000  OO       :39322  San Francisco, CA: 27359
## Median :4.000  UA       :31114  San Diego, CA   : 12924
## Mean   :3.932  AA       :19664  Oakland, CA     : 7551
## 3rd Qu.:6.000  DL       :15442  Phoenix, AZ     : 7465
## Max.   :7.000  AS       :11709  San Jose, CA    : 7097
## (Other):28448 (Other) :101845
## DEST_CITY_NAME ARR_DELAY_NEW DELAY
## Los Angeles, CA : 35800 Min. : 0.00 NO :108396
## San Francisco, CA: 27347 1st Qu.: 0.00 YES: 91624
## San Diego, CA : 12934 Median : 0.00
## Oakland, CA : 7550 Mean : 15.95
## Phoenix, AZ : 7476 3rd Qu.: 15.00
## San Jose, CA : 7096 Max. :1707.00
## (Other) :101817 NA's :3583
## DELAYCAT ARR_DEL15 DISTANCE
## FALSE :108396 Min. :0.000 Min. : 56 ## MAJOR
## DELAY: 48364 1st Qu.:0.000 1st Qu.: 386
## MINOR DELAY: 43260 Median :0.000 Median : 846 ##
## Mean :0.256 Mean :1111
```

Figure 2. Extracted Dataset Summary

Since the clusters are to be formed based on the delay times of all flights, the delay time (minutes) was extracted for all flights in the dataset. Since all missing values and outliers had been dealt with at the beginning of the data transformation phase, there was no need to check for missing values again. Now for clustering the extracted data is explored and a dataset is prepared with a view of deciding optimal number of clusters. It is a visual method used to identify the optimal number of clusters. The idea is to start with  $K=2$ , and keep increasing it in each step by 1, calculating the clusters and the cost, that comes with the training. At some value for  $K$  the cost drops dramatically. Elbow method is used and The results of the elbow method implementation has the following result:

### Assessing the Optimal Number of Clusters with the Elbow Method

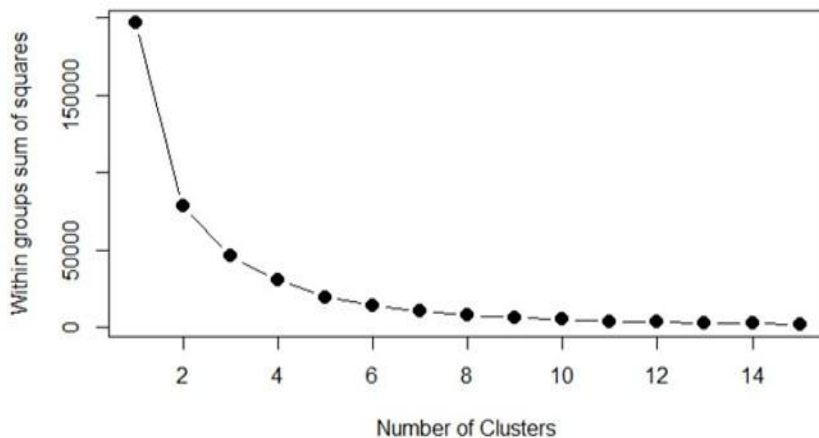


Figure 3. Graph to find the number of clusters

As observed from the above graph, the graph shows very little variation in the within cluster sum of squares when cluster size exceeds 6. Therefore the optimal number of clusters is assumed to be 6 for the purpose of this study.

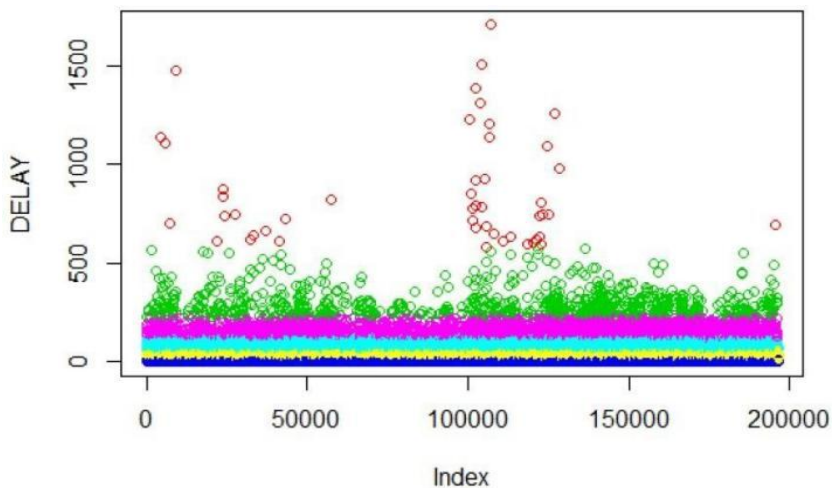


Figure 4. Clustering graph

As observed from the above plot the points colored in red, green, and purple represent clusters with flights that have been delayed by over 200 minutes. A detailed study into the causes of delays of these flights may reveal some interesting information from the perspective of the airline companies. On the other hand, it could be of great use for passengers as well in selecting their flights. Flights which are delayed share a few common characteristics. The bottom 3 clusters (dark blue, yellow and light blue) have been delayed the least and are not considered important to serve the purpose of this project. To determine the efficiency of the model we used Naive Bayes Classification Algorithm and Random Forest Algorithm. The Naïve Bayes Classification Algorithm gives error of 0.404915. It shows that about 40% of the flights have been incorrectly classified. The Random Forest algorithm the model predicts a flight to be on time with much higher accuracy of 73%. On the other hand the model predicts a flight to correctly delayed only 46% of the times. Such behavior is expected since the dataset being studied has a much higher number of on time flights as compared to delayed flights. In order to achieve higher and similar accuracy for both “delayed” and “on-time” flights we must apply the above model to a dataset consisting of an equal proportion of delayed and on time flights. The overall accuracy of the random forest model was observed to be similar to the Naïve Bayes model of about 60%.

### **Simulation and Results**

Using the month of the flight departure, a comparison was made between the flight delays in the month of May and December. The graph of the same is depicted below in fig 5. The results show that most flight delays occurred on business days i.e. Monday to Friday, whereas delays were considerably lesser on weekends i.e. Saturday and Sunday. The possible explanation can be, people plan holidays such that on weekends they reach their destination, so most of the travelling part is done on Friday and you can check that from the graph above. This is depicted in fig 6. The airline or the carrier could also play a major role in determining delays. The graph in fig 7 shows percentage of flights delayed in some of the major airline carriers in UnitedStates.

**FLIGHTS DELAYED BY MONTH**

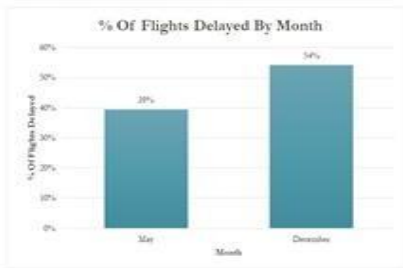


Fig 5 Percentage of delays by month

**Flight Delayed by Carrier**



Fig 7 percentage of flight delayed by carrier

**Flights Delayed By Day**



Fig 6 Percentage of flight delayed by week

**Flight Delays by Timeslot**

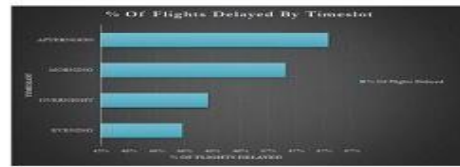


Fig 8 Percentage of flight delay by timeslot

Analysis shows some major causes of delay, as it is important to analyze the major causes of flight delays in order to minimize them. Although delays caused due to certain factors such as weather cannot be averted, some factors can be minimized based on the results obtained from this study.

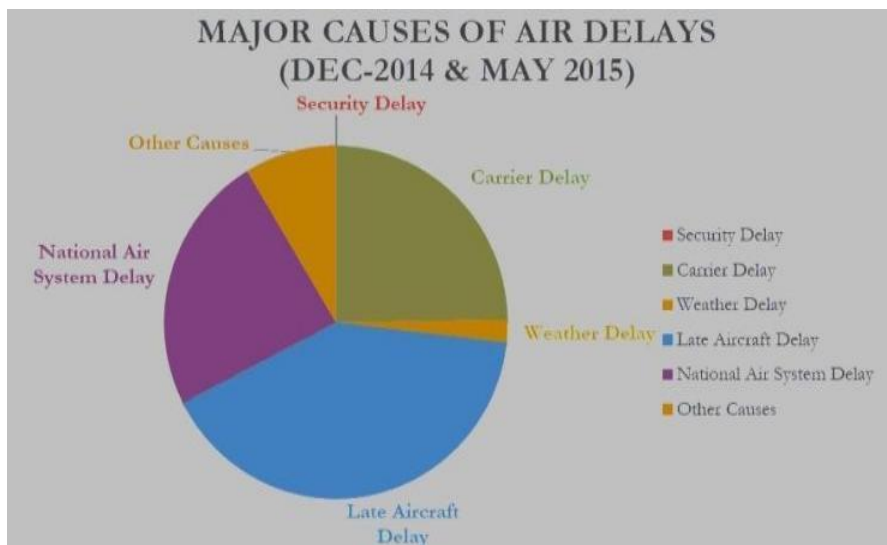


Fig 9. Major causes of delay

As observed from the above graph Late Aircraft Delay, National Air System Delay, and Carrier delays have played a major role in causing most flight delays. If the above causes of delays are minimized, airlines may have a greater proportion of on time flights.

## Conclusion

The proposed method successfully implements and will replace a traditional system. This method covers many activities not least starting with the search for a suitable data set to work on. A way of analyzing the data is formulated which will bring about a Requirements Specification on what would be required in order to carry out the analysis. The results and findings of this project can be summarized as follows:

- Flight delays in December, 2014 (54%) were much more than flight delays in the month of May, 2015(39%).
- Most flight delays occurred on business days i.e. Monday to Friday, whereas delays were considerably lesser on weekends i.e. Saturday and Sunday.
- Flights to Honolulu and Pittsburgh have seen the most delays when the origin state was California.
- Most number of flight delays were observed with Spirit Airline flights and the least delays were observed when travelling with Delta Airlines flights.
- Although there was not much variation observed in the percentage of delays.
- Depending on the timeslot, it was observed that overnight and evening flights had seen a lesser percentage of delays as compared to morning and afternoon flights.

Late Aircraft Delay, National Air System Delay, and Carrier delays have played a major role in causing most flight delays. Subsequent to this the components required to carry out the activities involved need to be gathered together. A system to support the analysis will then be built and the data will be loaded. With all this in place the building of the reports to analyze the data can be developed and made available for use. Looking at the results of a number of reports, will lead to the following insights. It is interesting to see that over the number of parameters that can be filtered on, choosing to filter by airline or airport seems to only affect the numbers of the delays but not the percentage of spread of delays for each airline. So it seems that there is very little difference between each airline in terms of percentage of flights that are late.

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