Predicting Flight Delay @ US Airports

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# **1. Introduction**

Every year, millions of passengers experience delays in flights, resulting in missing connections and spending more time away from home among others. The data is about the analysis of all flights that departed from New York City (e.g. EWR, JFK and LGA), the raw dataset contains 336,776 flights in total in 2013. In order to explain the causes of delays happen in 2013, variables also include a number of other datasets:

|  |  |  |
| --- | --- | --- |
| Dataset | Filename | Description |
| **Flights** | U.S Flight Dataset | Flight departures from US in 2013 |
| **Weather** | U.S. Weather-Dataset | Hourly meteorological data for each airport |
| **Planes** | U.S. Planes\_Dataset | Construction information about each plane |
| **Airports** | U.S. Airports\_dataset | Airport names and locations |
| **Airlines** | U.S. Airlines\_Dataset | Translation between two letter carrier codes and names |

The following variables were recorded:

|  |  |
| --- | --- |
| Variables | Description |
| year,month,day | Date of departure |
| dep\_time,arr\_time | Actual departure and arrival times, local tz. |
| sched\_dep\_time,sched\_arr\_time | Scheduled departure and arrival times, local tz. |
| dep\_delay,arr\_delay | Departure and arrival delays, in minutes. Negative times represent early departures/arrivals. |
| carrier | Two letter carrier abbreviation. See airlines to get name |
| flight | Flight number |
| tailnum | Plane tail number |
| origin ,dest | Origin and destination. See airports for additional metadata. |
| air\_time | Amount of time spent in the air, in minutes |
| distance | Distance between airports, in miles |
| hour,minute | Time of scheduled departure broken into hour and minutes. |
| time\_hour | Scheduled date and hour of the flight as a date. |
| Airline | Full name |
| type | Type of plane |
| manufacturer,model | Manufacturer and model |
| engines ,seats | Number of engines and seats |
| speed | Average cruising speed in mph |
| engine | Type of engine |
| age | Age of plane |
| name.dest | Usual name of the airport |
| lat.dest ,lon.dest | Location of airport |
| alt.dest | Altitude, in feet |
| name.origin | Usual name of the airport |
| lat.origin ,lon.origin | Location of airport |
| alt.origin | Altitude, in feet |
| temp ,dewp | Temperature and dewpoint in F |
| humid | Relative humidity |
| wind\_dir ,wind\_speed ,wind\_gust | Wind direction (in degrees), speed and gust speed (in mph) |
| precip | Precipitation, in inches |
| pressure | Sea level pressure in millibars |
| visib | Visibility in miles |

This study intent to predict the total delay time for flights departing from NYC based on the hourly meteorological data for each airport, construction information about each plane, airport locations and the Flight characteristics. Thus the response variable is the total delay time (arr\_delay + dep\_delay), which denote the total of Departure and arrival delays, in minutes, all remaining variables are predictors.

**Our specific objectives are as follows:**

* To identify possible factors that may influence the delay times for flights departing from NYC.
* To provide recommendations for improving U.S flight.

The raw data have been preprocessed, a set of 12 different variables was obtained which affect delay of the U.S flights. In this variable set, while three of them are categorical variable, the rest are numeric variables, Among three categorical variables, two of them have four levels and the other has three levels. Moreover, in this data set, 24 variables are removed based on their lack of information content so they are omitted from the regression analysis.

First of all the data set divided into two groups which contain test and train parts. 70 percent (n = 200363 observations) of this data set will be used to train this regression model and the 30 percent (n = 85871 observations) of it will be used to test regression model obtained from train part.

Indicators: There are three categorical variables, and two of them have four levels and the other one has three levels. Therefore, in total there are 8 dummy variables in hand.

Standardization: In order to get rid of different units in the data set, it is needed to standardize all variables except for dummy variables. Thus, each variable have the same standard.

Multiple linear regressions will be performed to determine whether or not the variation that is observed in the response variable (which corresponds to ‘arr\_delay’+ ‘dep\_delay’ in this analysis) can be predicted by the Flight characteristics, airport location and the weather. Therefore the null hypothesis is that any of variables concerning flight characteristics, location of airports and weather does not have a significant effect on the total delay in departure and arrival time.

**The hypothesis test follows;**

|  |
| --- |
| H0 : There is no lack of fit in model. Ha : There is lack of fit in model. |

Furthermore, model selection methods are applied. Therefore stepwise regression is applied in order to obtain the best model in this study.This is a combination of backward elimination and forward selection. This addresses the situation where variables are added or removed early in the process and we want to change our mind about them later.

# **2. Results**

# **2.1. Data Pre-processing**

Data pre-processing or initial data analysis generally performed to prepare and understand the data. In this matter, univariate descriptive statistics were gathered:

• Numerical summaries - means, sds, five-number summaries, correlations,

• Graphical summaries - histograms and scatter plots were created.

Additionally, some predictors are removed based on their lack of information content, and some new variables are created.

We start by creating new variables “Quarter” and “TimeOfDay” in the dataframe. Such as “Q1”, “Q2”, “Q3”, “Q4”, referring to the four quarters of a calendar year. The TimeOfDay is the Splitting of hour variable into six hour segments:

- Midnight - 6am: Overnight

- 6am - Midday: Morning

- Midday - 6pm: Afternoon

- 6pm - Midnight: Evening

Below, the frequency distribution of each categorical variable. There were 286,234 flights taking off from New York, 34.97% of them (n = 100106) taking off from Newark Liberty International Airport, 34.23% (n = 98069) taking off from John F Kennedy International and 30.76% (n = 88059) that took off from La Guardia airport. The quarterly dispersion of 2013 was the same (around 25% of Total flights each, or 70,000 per quarter). However, the majority of flights (39.43%) took off in the morning, 37.73% took off in the afternoon, 22.23% left in the evening, while 0.6% of total 2013 took off during the night.

Table 1: Frequency Distributions

|  |  |  |
| --- | --- | --- |
| Dummy Variables | n | percent |
| United Air Lines Inc. | 49514 | 17.3% |
| JetBlue Airways | 48105 | 16.81% |
| ExpressJet Airlines Inc. | 44138 | 15.42% |
| Delta Air Lines Inc. | 41856 | 14.62% |
| American Airlines Inc. | 28109 | 9.82% |
| Envoy Air | 22008 | 7.69% |
| US Airways Inc. | 17301 | 6.04% |
| Endeavor Air Inc. | 15561 | 5.44% |
| Southwest Airlines Co. | 10298 | 3.6% |
| Virgin America | 4523 | 1.58% |
| AirTran Airways Corporation | 2791 | 0.98% |
| Alaska Airlines Inc. | 630 | 0.22% |
| Frontier Airlines Inc. | 587 | 0.21% |
| Mesa Airlines Inc. | 482 | 0.17% |
| Hawaiian Airlines Inc. | 304 | 0.11% |
| SkyWest Airlines Inc. | 27 | 0.01% |
| Total | 286234 | 100% |
| Newark Liberty International Airport | 100106 | 34.97% |
| John F Kennedy International Airport | 98069 | 34.26% |
| La Guardia Airport | 88059 | 30.76% |
| Q3 | 74422 | 26% |
| Q4 | 71777 | 25.08% |
| Q2 | 70592 | 24.66% |
| Q1 | 69443 | 24.26% |
| Morning | 112876 | 39.43% |
| Afternoon | 108004 | 37.73% |
| Evening | 63626 | 22.23% |
| Overnight | 1728 | 0.6% |

The US flight delay ranged from -100 to 2573 minutes with an average of 15.83 minutes. Figure 1 shows that the distribution of the outcome is right skewed, it has long tail in the high values.

Table 2: Descriptive statistics of the outcome

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Min | 1st Qu. | Median | Mean | 3rd Qu. | Max | SD |
| -100 | -21 | -7 | 15.83 | 19 | 2573 | 77.65 |

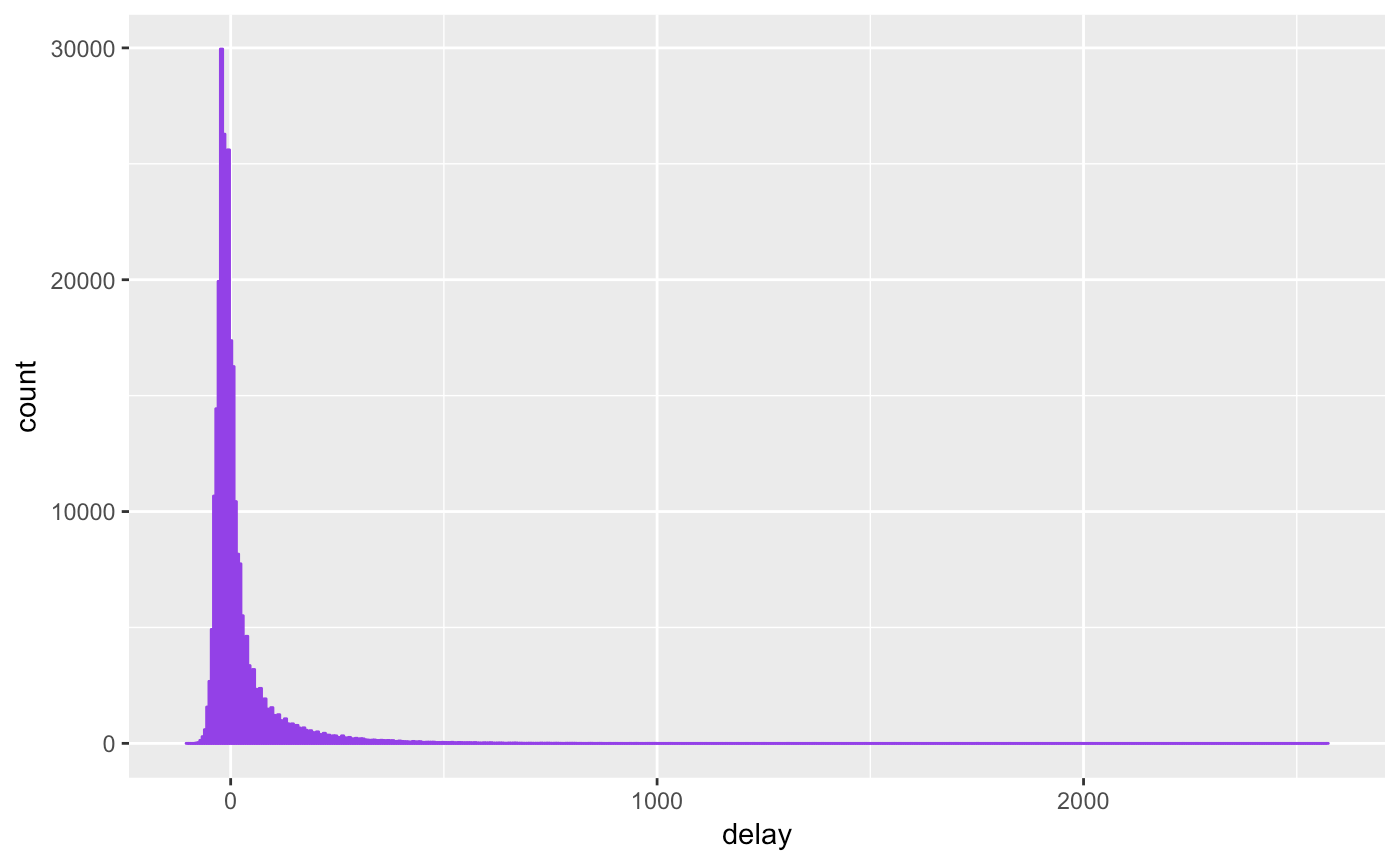


Figure 1: Distribution of the flight delay at NYC Airports

Here, some predictors are removed based on their lack of information content, the caret package function nearZeroVar is used in order to filter all predictors with near zero variance. In our data, there are three problematic predictors that should be removed from the data.

Similarly, ***findCorrelation*** function from the caret package is used in order to filter on high absolute pairwise between-predictor correlations:

The Figure below helps up to visually examine the between-predictor of the data:

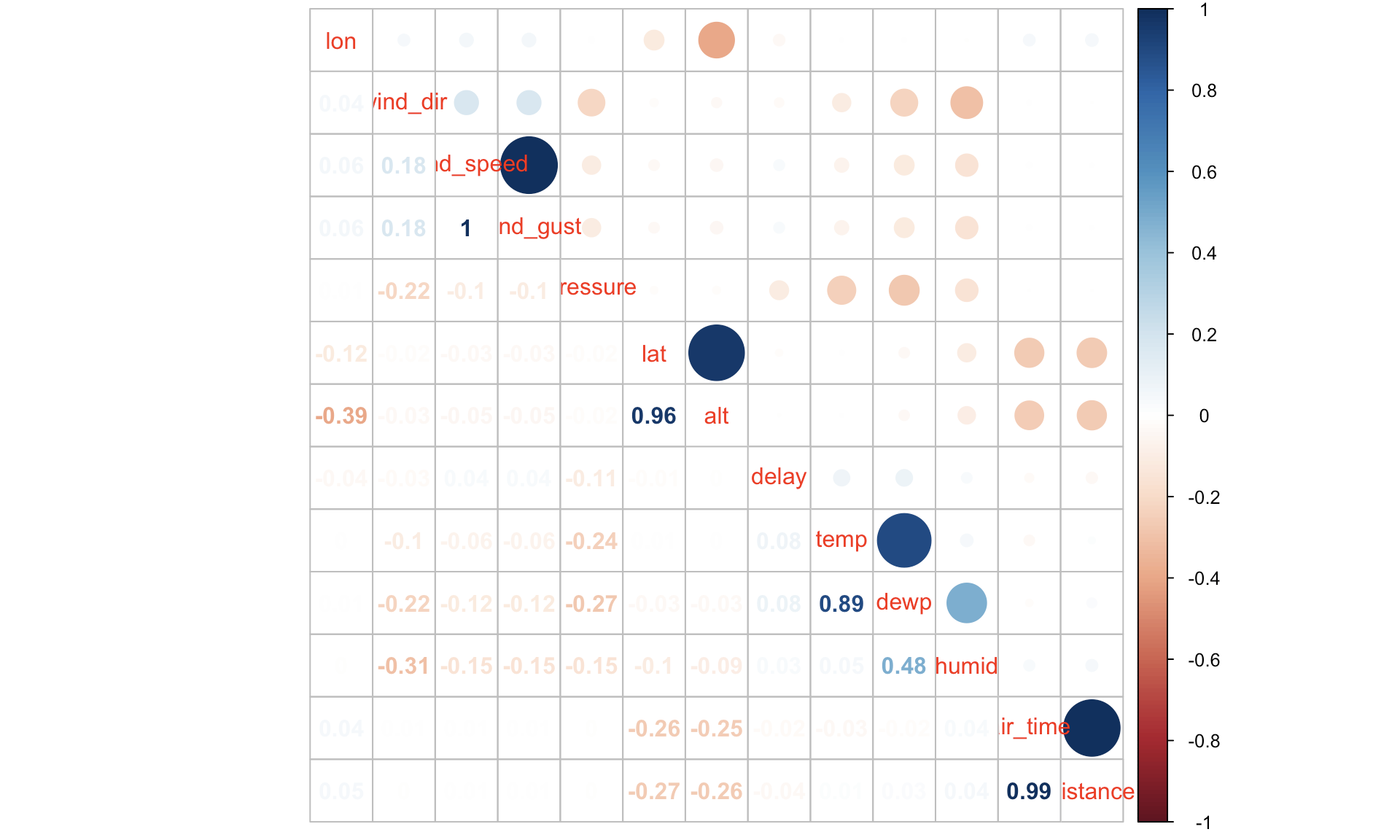


Figure 2: Correlation Matrix of the Flights NYC Airports

As shown in the Figure above, the pairs, (air\_time and distance), (wind\_speed and wind\_gust) and (alt and lat) have a strong positive correlation, respectively.

Now, let us reduce the four predictors identified as collinear that have an absolute pairwise correlation above 0.75:

The variables *dewp*, alt, *wind\_gust*, *distance* are highly correlated with others predictors.

Moving on, we can evaluate the continuous predictors for skewness. The skewness statistic ranges from a minimum of -0.5 to a maximum of 66.52, indicating that most of our predictors are right skewed. To correct for this skewness, a Box-Cox transformation was applied to all predictors.

Table 3: skewness statistic

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| air\_time | temp | humid | wind\_dir | wind\_speed | pressure | lat | lon | delay |
| 1.061 | -0.0007674 | 0.1504 | -0.5233 | 66.53 | 0.0885 | 0.3601 | -0.4783 | 4.673 |

Figure 3 shows scatter plots of the predictors against the outcome along with a regression line from a flexible “smoother” model. According to these two figures, we can assume that the relationship between the predictors and the outcome is linear.



Figure 3: Graphical Representation of flights.2013 dataset

# **2.2. Data Splitting**

To allocate data to model building and evaluating performance: let’s split the *flights.2013* dataset into two parts: training and test data. 70% of the 2013 U.S flights will belong to the training set, and the other 30% to the test set:

Allocate *training* dataset to model building, which contains 200363 cases, and *test* dataset to evaluating performance, which contains 200363 cases.

# **2.3. Model Building**

The regression line can be written in the form:

Where:

• : mean of the dependent variable when all (Center)

• Binary X = “dummy variable” for group

– :i=1,.., total groups -1: mean difference in outcome between groups

• Continuous X

– difference in mean outcome corresponding to a 1-unit increase in X

delay of fights is the response, and the remaining variables are the predictors. we have 9 continuous variables, eight dummy variables and no missing data.

The null hypothesis is as follows:

- : all new ’s are zero

- Assess using F-test

The Table below displays model summary statistics, the parameter estimates, their standard errors, and p-values for testing whether each individual coefficient is different than 0:

Table 4: Fitting linear model: delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + pressure + name + Qtr + TimeOfDay

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Estimate | Std. Error | t value | Pr(>|t|) |
| **(Intercept)** | 901 | 27.41 | 32.87 | 2.252e-236 |
| **air\_time** | -0.01944 | 0.001863 | -10.44 | 1.727e-25 |
| **temp** | -0.1022 | 0.01714 | -5.964 | 2.466e-09 |
| **humid** | 0.4757 | 0.01141 | 41.67 | 0 |
| **wind\_dir** | -0.01871 | 0.001743 | -10.73 | 7.121e-27 |
| **wind\_speed** | 0.1318 | 0.01246 | 10.58 | 3.79e-26 |
| **pressure** | -0.919 | 0.02632 | -34.92 | 2.238e-266 |
| **La Guardia Airport** | 1.903 | 0.4418 | 4.307 | 1.654e-05 |
| **Newark Liberty International Airport** | 8.057 | 0.4109 | 19.61 | 1.523e-85 |
| **QtrQ2** | 10.3 | 0.659 | 15.64 | 4.518e-55 |
| **QtrQ3** | 4.729 | 0.8011 | 5.902 | 3.589e-09 |
| **QtrQ4** | -1.016 | 0.5355 | -1.897 | 0.05786 |
| **TimeOfDayMorning** | 6.44 | 2.187 | 2.944 | 0.003239 |
| **TimeOfDayAfternoon** | 35.43 | 2.199 | 16.11 | 2.223e-58 |
| **TimeOfDayEvening** | 47.38 | 2.214 | 21.4 | 1.77e-101 |

|  |  |  |  |
| --- | --- | --- | --- |
| Observations | Residual Std. Error |  | Adjusted |
| 200363 | 75.32 | 0.05568 | 0.05561 |

The simple estimates of the RMSE and were 75.32 and 0.05568, respectively.

So when name=LGA , the prediction is , 2.10 minutes more than for , and when name=EWR , the prediction is = 8.4, 8.4 minutes more than for . And from the extremely small *p*-value, this is a significant finding. So we are quite sure that flights from JFK made a significantly lower delay LGA or EWR .

The Location of airport (Lat and lon) are not significant at all (*p*-value > 0.05), while the Temperature and dewpoint in F (*temp*), Relative humidity (*humid*), Wind direction (in degrees) (*wind\_dir*), speed (in mph)(*wind\_dir*), Sea level pressure in millibars *pressure* are highly significant for U.S flight delay (*p*-value <0.05).

Best model for the stepwise selection is the following;

**Model characteristics:**  , F-statistic: 828.7 on 14 and 200348 DF, p-value: < 2.2e-16

To compute the model flight delay values for new samples, the predict method is used:



|  |
| --- |
| lmPred1 <- predict(lm.delay, test)  head(lmPred1) ## 1 2 3 4 5 6 ## 2.96 -8.80 3.07 -4.58 -9.21 -5.49 |

The caret function defaultSummary is used to estimate the test set performance:



|  |
| --- |
| lmValues1 <- data.frame(obs = test$delay, pred = lmPred1)  defaultSummary(lmValues1) ## RMSE Rsquared MAE ## 75.8810 0.0532 43.4417 |

Based on the test set, the summaries produced by the summary function for lm were pessimist.

# **3. Conclusion**

The aim of this paper was to construct a linear model that predicts well the relationships in all flights that departed from New York City data, with this reliable analysis, it’s not easy at to predict the U.S flight delay of an unknown data because our output prediction did not worked at all in the above mentioned experiment. Further modeling assumptions had failed in this experiment. Thus, multiple linear regression failed to predict the delay of US flights. A future analysis using non-parametric methods may be conducted to carry out the estimation of delays flights departing from NYC, for instance decision trees, random forests can be used in this matter.

# **Appendix**

*# Load the packsge into memory*

|  |
| --- |
| library(pander) library(tidyverse) library(janitor) library(caret) |

|  |
| --- |
| #Prepare the dataset #Extract records and Add the Total Delay field "TotalDelay" flights.2013 <-  flights %>%  #Hourly meterological data for LGA, JFK and EWR.  left\_join(weather %>% select(origin,temp,dewp,humid, wind\_dir, wind\_speed,wind\_gust,precip,pressure, visib,time\_hour), by = c("origin", "time\_hour")) %>%  #Add airline names for carriers targeted for study  left\_join(airlines, by = c("carrier"="Code")) %>%  rename(Airline = Description) %>%  # Add the location of the airport  left\_join(airports %>% select(faa,name,lat,lon,alt), by = c("origin" = "faa")) %>%   na.omit() |

|  |
| --- |
| #Creating new variables flights.2013 <-  flights.2013 %>% mutate(delay = dep\_delay+arr\_delay, #Create the outcome delay  Qtr = factor(quarters(time\_hour)), #Create a new column "quarter"  TimeOfDay = cut(hour, c(0, 6, 12, 18, 24),  labels = c("Overnight", "Morning", "Afternoon", "Evening"),  right = FALSE)  ) %>%  droplevels() |

|  |
| --- |
| #Data investigation data.fac <- Filter(is.factor,flights.2013 ) data.fac %>% tabyl(Airline) %>% arrange(desc(n)) %>% adorn\_totals("row") %>% mutate(percent=paste0(round(100\*percent,2),"%")) %>% pander() data.fac %>% tabyl(name) %>% arrange(desc(n)) %>% adorn\_totals("row") %>% mutate(percent=paste0(round(100\*percent,2),"%")) %>% pander() data.fac %>% tabyl(Qtr) %>% arrange(desc(n)) %>% adorn\_totals("row") %>% mutate(percent=paste0(round(100\*percent,2),"%")) %>% pander() data.fac %>% tabyl(TimeOfDay) %>% arrange(desc(n)) %>% adorn\_totals("row") %>% mutate(percent=paste0(round(100\*percent,2),"%")) %>% pander() flights.2013 %>%  summarise(Min = min(delay),`1st Qu.` = quantile(delay, 0.25),Median = median(delay),Mean = mean(delay),`3rd Qu.` = quantile(delay, 0.75),Max = max(delay), SD = sd(delay)) %>%  pander(caption ="Descriptive statistics of the outcome") ggplot(data = flights.2013, aes(delay)) +  geom\_histogram(color="blue", bins = 500) |

|  |
| --- |
| ## A vector of three (1,26,28) integers is returned that indicates which columns should be removed. nearZeroVar(flights.2013) flights.2013 <- flights.2013[, -c(1:14,17:19,26,28,29)] |

|  |
| --- |
| data.num <- Filter(is.numeric, flights.2013) correlations <- cor(data.num)  dim(correlations) ## [1] 13 13 |

|  |
| --- |
| library(corrplot) corrplot.mixed(correlations, order="hclust") highCorr <- findCorrelation(correlations, cutoff = .75)  length(highCorr) ## [1] 4 |

|  |
| --- |
| flights.2013 <- flights.2013 %>% select(-dewp,-alt,-wind\_gust,-distance)  rm(list = c( "airlines" ,"airports","correlations", "data.fac","data.num","flights","flights13" ,"highCorr","planes","trainingRows","weather" ))#ls()) #Clear workspace library(e1071)  skewValues <- apply(Filter(is.numeric,flights.2013), 2, skewness)  skewValues %>% pander(caption="Skewness across columns") library(cowplot) #Arranging plots in a grid fig1 <- ggplot(data=flights.2013, aes(x = air\_time, y = delay)) +  geom\_point(color ="blue")+  geom\_smooth(se=F)+  labs( x="Amount of time spent in the air, in minutes", y="Departure and arrival delays, in minutes")+  theme\_bw() |

|  |
| --- |
| fig2 <- ggplot(data=flights.2013, aes(x = wind\_dir, y = delay)) +  geom\_point(color ="blue")+  geom\_smooth(se=F)+  labs( x="Wind direction (in degrees)", y="Departure and arrival delays, in minutes")+  theme\_bw() |

|  |
| --- |
| plot\_grid(fig1, fig2) |

|  |
| --- |
| # Create Training and Test data set.seed(100) # setting seed to reproduce results of random sampling n <- nrow(flights.2013) trainingRows <- sample(n, 0.7\*n)# row indices for training data training <- flights.2013[trainingRows, ] # model training data  test <- flights.2013[-trainingRows, ] # test data   lm.delay <- step(lm(delay ~. , data = training), direction ="both") ## Start: AIC=1731850 ## delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + pressure + ## name + lat + lon + Qtr + TimeOfDay ## ## ## Step: AIC=1731850 ## delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + pressure + ## name + lat + Qtr + TimeOfDay ## ## ## Step: AIC=1731850 ## delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + pressure + ## name + Qtr + TimeOfDay ## ## Df Sum of Sq RSS AIC ## <none> 1.14e+09 1731850 ## - temp 1 201785 1.14e+09 1731883 ## - air\_time 1 617836 1.14e+09 1731957 ## - wind\_speed 1 634900 1.14e+09 1731960 ## - wind\_dir 1 653717 1.14e+09 1731963 ## - name 2 2427332 1.14e+09 1732273 ## - Qtr 3 2829314 1.14e+09 1732342 ## - pressure 1 6918349 1.14e+09 1733064 ## - humid 1 9852280 1.15e+09 1733577 ## - TimeOfDay 3 39826206 1.18e+09 1738744 summary(lm.delay) %>% pander() |

|  |
| --- |
| # backward elimination summary(step(lm(delay ~. , data = training), direction ="backward")) ## Start: AIC=1731850 ## delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + pressure + ## name + lat + lon + Qtr + TimeOfDay ## ## ## Step: AIC=1731850 ## delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + pressure + ## name + lat + Qtr + TimeOfDay ## ## ## Step: AIC=1731850 ## delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + pressure + ## name + Qtr + TimeOfDay ## ## Df Sum of Sq RSS AIC ## <none> 1.14e+09 1731850 ## - temp 1 201785 1.14e+09 1731883 ## - air\_time 1 617836 1.14e+09 1731957 ## - wind\_speed 1 634900 1.14e+09 1731960 ## - wind\_dir 1 653717 1.14e+09 1731963 ## - name 2 2427332 1.14e+09 1732273 ## - Qtr 3 2829314 1.14e+09 1732342 ## - pressure 1 6918349 1.14e+09 1733064 ## - humid 1 9852280 1.15e+09 1733577 ## - TimeOfDay 3 39826206 1.18e+09 1738744 ## ## Call: ## lm(formula = delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + ## pressure + name + Qtr + TimeOfDay, data = training) ## ## Residuals: ## Min 1Q Median 3Q Max ## -181.9 -37.2 -17.7 8.3 2582.9 ## ## Coefficients: ## Estimate Std. Error t value ## (Intercept) 900.95328 27.40668 32.87 ## air\_time -0.01944 0.00186 -10.44 ## temp -0.10223 0.01714 -5.96 ## humid 0.47569 0.01141 41.67 ## wind\_dir -0.01871 0.00174 -10.73 ## wind\_speed 0.13179 0.01246 10.58 ## pressure -0.91896 0.02632 -34.92 ## nameLa Guardia Airport 1.90306 0.44183 4.31 ## nameNewark Liberty International Airport 8.05746 0.41088 19.61 ## QtrQ2 10.30422 0.65904 15.64 ## QtrQ3 4.72868 0.80115 5.90 ## QtrQ4 -1.01578 0.53554 -1.90 ## TimeOfDayMorning 6.44013 2.18748 2.94 ## TimeOfDayAfternoon 35.42676 2.19854 16.11 ## TimeOfDayEvening 47.37881 2.21405 21.40 ## Pr(>|t|)  ## (Intercept) < 2e-16 \*\*\* ## air\_time < 2e-16 \*\*\* ## temp 2.5e-09 \*\*\* ## humid < 2e-16 \*\*\* ## wind\_dir < 2e-16 \*\*\* ## wind\_speed < 2e-16 \*\*\* ## pressure < 2e-16 \*\*\* ## nameLa Guardia Airport 1.7e-05 \*\*\* ## nameNewark Liberty International Airport < 2e-16 \*\*\* ## QtrQ2 < 2e-16 \*\*\* ## QtrQ3 3.6e-09 \*\*\* ## QtrQ4 0.0579 .  ## TimeOfDayMorning 0.0032 \*\* ## TimeOfDayAfternoon < 2e-16 \*\*\* ## TimeOfDayEvening < 2e-16 \*\*\* ## --- ## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1 ## ## Residual standard error: 75.3 on 200348 degrees of freedom ## Multiple R-squared: 0.0557, Adjusted R-squared: 0.0556 ## F-statistic: 844 on 14 and 2e+05 DF, p-value: <2e-16 # forward elimination summary(step(lm(delay ~. , data = training), direction ="forward")) ## Start: AIC=1731850 ## delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + pressure + ## name + lat + lon + Qtr + TimeOfDay ## ## Call: ## lm(formula = delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + ## pressure + name + lat + lon + Qtr + TimeOfDay, data = training) ## ## Residuals: ## Min 1Q Median 3Q Max ## -181.9 -37.2 -17.7 8.3 2582.9 ## ## Coefficients: (2 not defined because of singularities) ## Estimate Std. Error t value ## (Intercept) 900.95328 27.40668 32.87 ## air\_time -0.01944 0.00186 -10.44 ## temp -0.10223 0.01714 -5.96 ## humid 0.47569 0.01141 41.67 ## wind\_dir -0.01871 0.00174 -10.73 ## wind\_speed 0.13179 0.01246 10.58 ## pressure -0.91896 0.02632 -34.92 ## nameLa Guardia Airport 1.90306 0.44183 4.31 ## nameNewark Liberty International Airport 8.05746 0.41088 19.61 ## lat NA NA NA ## lon NA NA NA ## QtrQ2 10.30422 0.65904 15.64 ## QtrQ3 4.72868 0.80115 5.90 ## QtrQ4 -1.01578 0.53554 -1.90 ## TimeOfDayMorning 6.44013 2.18748 2.94 ## TimeOfDayAfternoon 35.42676 2.19854 16.11 ## TimeOfDayEvening 47.37881 2.21405 21.40 ## Pr(>|t|)  ## (Intercept) < 2e-16 \*\*\* ## air\_time < 2e-16 \*\*\* ## temp 2.5e-09 \*\*\* ## humid < 2e-16 \*\*\* ## wind\_dir < 2e-16 \*\*\* ## wind\_speed < 2e-16 \*\*\* ## pressure < 2e-16 \*\*\* ## nameLa Guardia Airport 1.7e-05 \*\*\* ## nameNewark Liberty International Airport < 2e-16 \*\*\* ## lat NA  ## lon NA  ## QtrQ2 < 2e-16 \*\*\* ## QtrQ3 3.6e-09 \*\*\* ## QtrQ4 0.0579 .  ## TimeOfDayMorning 0.0032 \*\* ## TimeOfDayAfternoon < 2e-16 \*\*\* ## TimeOfDayEvening < 2e-16 \*\*\* ## --- ## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1 ## ## Residual standard error: 75.3 on 200348 degrees of freedom ## Multiple R-squared: 0.0557, Adjusted R-squared: 0.0556 ## F-statistic: 844 on 14 and 2e+05 DF, p-value: <2e-16 # stepwise regression summary(step(lm(delay ~. , data = training), direction ="both")) ## Start: AIC=1731850 ## delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + pressure + ## name + lat + lon + Qtr + TimeOfDay ## ## ## Step: AIC=1731850 ## delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + pressure + ## name + lat + Qtr + TimeOfDay ## ## ## Step: AIC=1731850 ## delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + pressure + ## name + Qtr + TimeOfDay ## ## Df Sum of Sq RSS AIC ## <none> 1.14e+09 1731850 ## - temp 1 201785 1.14e+09 1731883 ## - air\_time 1 617836 1.14e+09 1731957 ## - wind\_speed 1 634900 1.14e+09 1731960 ## - wind\_dir 1 653717 1.14e+09 1731963 ## - name 2 2427332 1.14e+09 1732273 ## - Qtr 3 2829314 1.14e+09 1732342 ## - pressure 1 6918349 1.14e+09 1733064 ## - humid 1 9852280 1.15e+09 1733577 ## - TimeOfDay 3 39826206 1.18e+09 1738744 ## ## Call: ## lm(formula = delay ~ air\_time + temp + humid + wind\_dir + wind\_speed + ## pressure + name + Qtr + TimeOfDay, data = training) ## ## Residuals: ## Min 1Q Median 3Q Max ## -181.9 -37.2 -17.7 8.3 2582.9 ## ## Coefficients: ## Estimate Std. Error t value ## (Intercept) 900.95328 27.40668 32.87 ## air\_time -0.01944 0.00186 -10.44 ## temp -0.10223 0.01714 -5.96 ## humid 0.47569 0.01141 41.67 ## wind\_dir -0.01871 0.00174 -10.73 ## wind\_speed 0.13179 0.01246 10.58 ## pressure -0.91896 0.02632 -34.92 ## nameLa Guardia Airport 1.90306 0.44183 4.31 ## nameNewark Liberty International Airport 8.05746 0.41088 19.61 ## QtrQ2 10.30422 0.65904 15.64 ## QtrQ3 4.72868 0.80115 5.90 ## QtrQ4 -1.01578 0.53554 -1.90 ## TimeOfDayMorning 6.44013 2.18748 2.94 ## TimeOfDayAfternoon 35.42676 2.19854 16.11 ## TimeOfDayEvening 47.37881 2.21405 21.40 ## Pr(>|t|)  ## (Intercept) < 2e-16 \*\*\* ## air\_time < 2e-16 \*\*\* ## temp 2.5e-09 \*\*\* ## humid < 2e-16 \*\*\* ## wind\_dir < 2e-16 \*\*\* ## wind\_speed < 2e-16 \*\*\* ## pressure < 2e-16 \*\*\* ## nameLa Guardia Airport 1.7e-05 \*\*\* ## nameNewark Liberty International Airport < 2e-16 \*\*\* ## QtrQ2 < 2e-16 \*\*\* ## QtrQ3 3.6e-09 \*\*\* ## QtrQ4 0.0579 .  ## TimeOfDayMorning 0.0032 \*\* ## TimeOfDayAfternoon < 2e-16 \*\*\* ## TimeOfDayEvening < 2e-16 \*\*\* ## --- ## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1 ## ## Residual standard error: 75.3 on 200348 degrees of freedom ## Multiple R-squared: 0.0557, Adjusted R-squared: 0.0556 ## F-statistic: 844 on 14 and 2e+05 DF, p-value: <2e-16 # 6-Plot of Fit par(mfrow= c(2,3))# creates six panels for plotting plot(lm.delay, which = 1:6) |

