ECO520 Business Analytics Tools II
FLIGHT DELAY DATA

1 Group Members

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2 Data Sources and Topics

Sources :-

https://bigblue.depaul.edu/jlee141/econdata/eco520/

- Flight Delay Data (CSV FILE)

4.1 Motivation or Main Business Idea (1 to 2 pages)

The purpose of performing data analysis on airline data related to delayed flights is to identify the underlying factors that contribute to flight delays and to develop strategies to reduce their occurrence. By analyzing the data, airlines can identify patterns and trends in flight delays, such as specific routes or times of day that are more prone to delays, and can use this information to make operational changes or improvements to their scheduling.

Furthermore, data analysis can help airlines identify the root causes of flight delays, such as weather conditions, technical issues, or staffing problems, and take proactive measures to mitigate these issues. This can include strategies such as scheduling additional crew members or implementing maintenance programs to prevent technical problems from arising.

Overall, data analysis can help airlines improve their operational efficiency, reduce costs associated with flight delays, and ultimately provide a better experience for their passengers by reducing the frequency and duration of flight delays.

Motivation: Flight delays can cause significant inconvenience to passengers and can have financial implications for airlines. Therefore, understanding the underlying causes of delays and developing strategies to reduce them is of great importance for both airlines and their customers.

Question: What are the key factors contributing to flight delays in our airline, and how can we use this information to improve our scheduling and reduce the frequency and duration of delays?

Method: To answer this question, we would collect and analyze data on our airline's flights, including factors such as departure and arrival times, weather conditions, aircraft maintenance, crew availability, and passenger load. We could use statistical methods such as regression analysis to identify which factors have the greatest impact on flight delays, and then develop strategies to mitigate those factors.

Results: The results of our analysis could inform operational changes such as adjusting flight schedules or increasing staffing levels during peak periods, as well as implementing preventative maintenance programs to reduce technical issues. By reducing the frequency and duration of flight delays, we could improve the overall customer experience and reduce costs associated with delayed flights.

4.2 Data and Empirical Methodology (1 to 2 pages)

Data: We will use a dataset of flight records for our airline. The data includes information on departure and arrival times, flight durations, aircraft types, route information, and weather conditions. We will use this data to investigate the factors that contribute to flight delays.

Summary statistics: We will present summary statistics of the data, such as the average delay time, the percentage of flights delayed, and the distribution of delay times across different factors such as route and time of day. We may also present graphs or charts to illustrate the trends in the data over time and highlight any historical events or changes in airline operations that may have affected delay rates.

Estimating equation: We will use a multiple linear regression model to estimate the factors that contribute to flight delays. The regression equation will take the form:

Delay time = $\beta 0$ + $\beta 1$Weather conditions + $\beta 2$Aircraft type + $\beta 3$Route information + $\beta 4$Time of day + ε

where $\beta 0$ is the intercept term, $\beta 1$-4 are the coefficients for the different factors, and ε is the error term.

Methodology: The multiple linear regression model will allow us to identify the relative importance of different factors in contributing to flight delays. We can compare the results from the regression model to simple descriptive statistics or other methods such as correlation analysis to gain a deeper understanding of the underlying relationships in the data. The regression model will also allow us to control for the effects of different factors and estimate their individual contributions to flight delays, which would not be possible with simpler methods.

4.3 Results (3 to 4 pages)

- **Descriptive Analytics**

– **Proc mean, Proc summary, Proc Univariate, Proc sgplot of ggplot, and Maps**

#Summary

fd %>% summary(security_delay)

fd %>% summary(weather_delay)

fd %>% summary(arr_del15)

fd %>% summary(arr_cancelled)

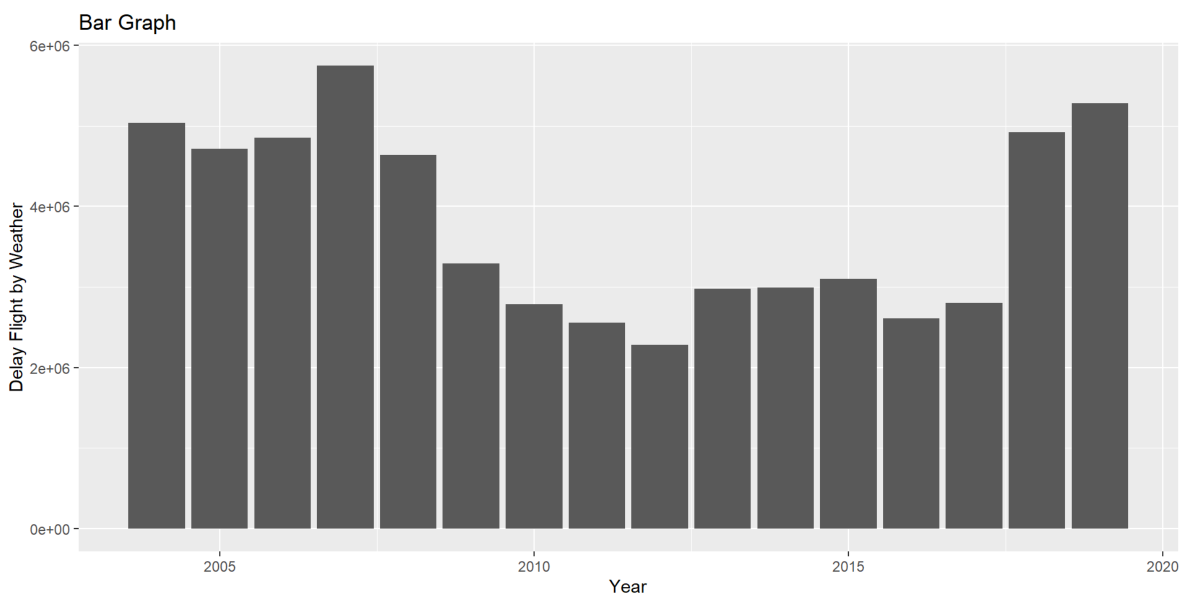
fd %>% summary(nas_delay)

```
> fd %>% summary(arr_del15)
      year          month          carrier          carrier_name         airport          airport_name        arr_flights
 Min.   :2004   Min.   : 1.000   Length:265047      Length:265047      Length:265047      Length:265047      Min.   :    1.0
 1st Qu.:2007   1st Qu.: 4.000   Class :character   Class :character   Class :character   Class :character   1st Qu.:   61.0
 Median :2011   Median : 7.000   Mode  :character   Mode  :character   Mode  :character   Mode  :character   Median :  124.0
 Mean   :2011   Mean   : 6.507                                                                                Mean   :  396.3
 3rd Qu.:2015   3rd Qu.: 9.000                                                                                3rd Qu.:  284.0
 Max.   :2019   Max.   :12.000                                                                                Max.   :21977.0
                                                                                                              NA's   :366
   arr_del15        carrier_ct        weather_ct          nas_ct          security_ct      late_aircraft_ct  arr_cancelled
 Min.   :   0.00   Min.   :   0.00   Min.   :  0.000   Min.   :  -0.01   Min.   : 0.0000   Min.   :   0.00   Min.   :   0.000
 1st Qu.:  10.00   1st Qu.:   3.58   1st Qu.:  0.000   1st Qu.:   2.03   1st Qu.: 0.0000   1st Qu.:   2.00   1st Qu.:   0.000
 Median :  25.00   Median :   9.00   Median :  0.680   Median :   6.19   Median : 0.0000   Median :   6.82   Median :   1.000
 Mean   :  78.07   Mean   :  21.95   Mean   :  2.758   Mean   :  25.94   Mean   : 0.1772   Mean   :  27.23   Mean   :   6.771
 3rd Qu.:  60.00   3rd Qu.:  20.76   3rd Qu.:  2.170   3rd Qu.:  16.66   3rd Qu.: 0.0000   3rd Qu.:  18.82   3rd Qu.:   4.000
 Max.   :6377.00   Max.   :1792.07   Max.   :717.940   Max.   :4091.27   Max.   :80.5600   Max.   :1885.47   Max.   :1969.000
 NA's   :422       NA's   :366       NA's   :366       NA's   :366       NA's   :366       NA's   :366       NA's   :366
  arr_diverted        arr_delay       carrier_delay     weather_delay       nas_delay       security_delay    late_aircraft_delay
 Min.   :  0.0000   Min.   :     0   Min.   :     0   Min.   :    0.0   Min.   :    -1   Min.   :   0.000   Min.   :     0
 1st Qu.:  0.0000   1st Qu.:   513   1st Qu.:   173   1st Qu.:    0.0   1st Qu.:    71   1st Qu.:   0.000   1st Qu.:   105
 Median :  0.0000   Median :  1330   Median :   476   Median :   30.0   Median :   231   Median :   0.000   Median :   410
 Mean   :  0.9181   Mean   :  4482   Mean   :  1323   Mean   :  228.8   Mean   :  1196   Mean   :   7.026   Mean   :  1727
 3rd Qu.:  1.0000   3rd Qu.:  3303   3rd Qu.:  1154   3rd Qu.:  171.0   3rd Qu.:   656   3rd Qu.:   0.000   3rd Qu.:  1225
 Max.   :256.0000   Max.   :433687   Max.   :196944   Max.   :57707.0   Max.   :238440   Max.   :3194.000   Max.   :148181
 NA's   :366        NA's   :366      NA's   :366      NA's   :366       NA's   :366      NA's   :366        NA's   :366
> fd %>% summary(arr_cancelled)
      year          month          carrier          carrier_name         airport          airport_name        arr_flights
 Min.   :2004   Min.   : 1.000   Length:265047      Length:265047      Length:265047      Length:265047      Min.   :    1.0
 1st Qu.:2007   1st Qu.: 4.000   Class :character   Class :character   Class :character   Class :character   1st Qu.:   61.0
 Median :2011   Median : 7.000   Mode  :character   Mode  :character   Mode  :character   Mode  :character   Median :  124.0
 Mean   :2011   Mean   : 6.507                                                                                Mean   :  396.3
 3rd Qu.:2015   3rd Qu.: 9.000                                                                                3rd Qu.:  284.0
 Max.   :2019   Max.   :12.000                                                                                Max.   :21977.0
                                                                                                              NA's   :366
   arr_del15        carrier_ct        weather_ct          nas_ct          security_ct      late_aircraft_ct  arr_cancelled
 Min.   :   0.00   Min.   :   0.00   Min.   :  0.000   Min.   :  -0.01   Min.   : 0.0000   Min.   :   0.00   Min.   :   0.000
 1st Qu.:  10.00   1st Qu.:   3.58   1st Qu.:  0.000   1st Qu.:   2.03   1st Qu.: 0.0000   1st Qu.:   2.00   1st Qu.:   0.000
 Median :  25.00   Median :   9.00   Median :  0.680   Median :   6.19   Median : 0.0000   Median :   6.82   Median :   1.000
 Mean   :  78.07   Mean   :  21.95   Mean   :  2.758   Mean   :  25.94   Mean   : 0.1772   Mean   :  27.23   Mean   :   6.771
 3rd Qu.:  60.00   3rd Qu.:  20.76   3rd Qu.:  2.170   3rd Qu.:  16.66   3rd Qu.: 0.0000   3rd Qu.:  18.82   3rd Qu.:   4.000
 Max.   :6377.00   Max.   :1792.07   Max.   :717.940   Max.   :4091.27   Max.   :80.5600   Max.   :1885.47   Max.   :1969.000
 NA's   :422       NA's   :366       NA's   :366       NA's   :366       NA's   :366       NA's   :366       NA's   :366
  arr_diverted        arr_delay       carrier_delay     weather_delay       nas_delay       security_delay    late_aircraft_delay
 Min.   :  0.0000   Min.   :     0   Min.   :     0   Min.   :    0.0   Min.   :    -1   Min.   :   0.000   Min.   :     0
 1st Qu.:  0.0000   1st Qu.:   513   1st Qu.:   173   1st Qu.:    0.0   1st Qu.:    71   1st Qu.:   0.000   1st Qu.:   105
 Median :  0.0000   Median :  1330   Median :   476   Median :   30.0   Median :   231   Median :   0.000   Median :   410
 Mean   :  0.9181   Mean   :  4482   Mean   :  1323   Mean   :  228.8   Mean   :  1196   Mean   :   7.026   Mean   :  1727
 3rd Qu.:  1.0000   3rd Qu.:  3303   3rd Qu.:  1154   3rd Qu.:  171.0   3rd Qu.:   656   3rd Qu.:   0.000   3rd Qu.:  1225
 Max.   :256.0000   Max.   :433687   Max.   :196944   Max.   :57707.0   Max.   :238440   Max.   :3194.000   Max.   :148181
 NA's   :366        NA's   :366      NA's   :366      NA's   :366       NA's   :366      NA's   :366        NA's   :366
> fd %>% summary(nas_delay)
```

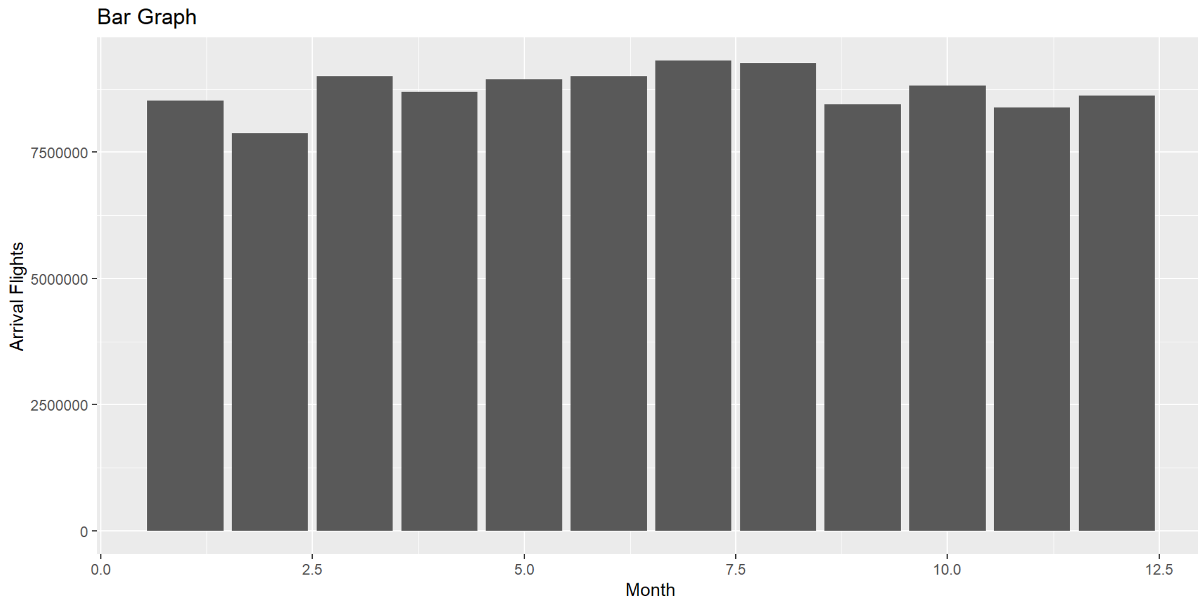
```
> fd %>% summary(nas_delay)
      year          month          carrier          carrier_name          airport           airport_name        arr_flights
 Min.   :2004   Min.   : 1.000   Length:265047      Length:265047      Length:265047      Length:265047      Min.   :    1.0
 1st Qu.:2007   1st Qu.: 4.000   Class :character   Class :character   Class :character   Class :character   1st Qu.:   61.0
 Median :2011   Median : 7.000   Mode  :character   Mode  :character   Mode  :character   Mode  :character   Median :  124.0
 Mean   :2011   Mean   : 6.507                                                                               Mean   :  396.3
 3rd Qu.:2015   3rd Qu.: 9.000                                                                               3rd Qu.:  284.0
 Max.   :2019   Max.   :12.000                                                                               Max.   :21977.0
                                                                                                             NA's   :366
   arr_del15         carrier_ct        weather_ct          nas_ct          security_ct      late_aircraft_ct  arr_cancelled
 Min.   :   0.00   Min.   :   0.00   Min.   :  0.000   Min.   :  -0.01   Min.   : 0.0000   Min.   :   0.00   Min.   :   0.000
 1st Qu.:  10.00   1st Qu.:   3.58   1st Qu.:  0.000   1st Qu.:   2.03   1st Qu.: 0.0000   1st Qu.:   2.00   1st Qu.:   0.000
 Median :  25.00   Median :   9.00   Median :  0.680   Median :   6.19   Median : 0.0000   Median :   6.82   Median :   1.000
 Mean   :  78.07   Mean   :  21.95   Mean   :  2.758   Mean   :  25.94   Mean   : 0.1772   Mean   :  27.23   Mean   :   6.771
 3rd Qu.:  60.00   3rd Qu.:  20.76   3rd Qu.:  2.170   3rd Qu.:  16.66   3rd Qu.: 0.0000   3rd Qu.:  18.82   3rd Qu.:   4.000
 Max.   :6377.00   Max.   :1792.07   Max.   :717.940   Max.   :4091.27   Max.   :80.5600   Max.   :1885.47   Max.   :1969.000
 NA's   :422       NA's   :366       NA's   :366       NA's   :366       NA's   :366       NA's   :366       NA's   :366
  arr_diverted        arr_delay       carrier_delay     weather_delay       nas_delay        security_delay     late_aircraft_delay
 Min.   :  0.0000   Min.   :     0   Min.   :     0   Min.   :    0.0   Min.   :    -1   Min.   :   0.000   Min.   :     0
 1st Qu.:  0.0000   1st Qu.:   513   1st Qu.:   173   1st Qu.:    0.0   1st Qu.:    71   1st Qu.:   0.000   1st Qu.:   105
 Median :  0.0000   Median :  1330   Median :   476   Median :   30.0   Median :   231   Median :   0.000   Median :   410
 Mean   :  0.9181   Mean   :  4482   Mean   :  1323   Mean   :  228.8   Mean   :  1196   Mean   :   7.026   Mean   :  1727
 3rd Qu.:  1.0000   3rd Qu.:  3303   3rd Qu.:  1154   3rd Qu.:  171.0   3rd Qu.:   656   3rd Qu.:   0.000   3rd Qu.:  1225
 Max.   :256.0000   Max.   :433687   Max.   :196944   Max.   :57707.0   Max.   :238440   Max.   :3194.000   Max.   :148181
 NA's   :366        NA's   :366      NA's   :366      NA's   :366       NA's   :366      NA's   :366        NA's   :366
> 
```

Proc sgplot of gplot, and Maps:

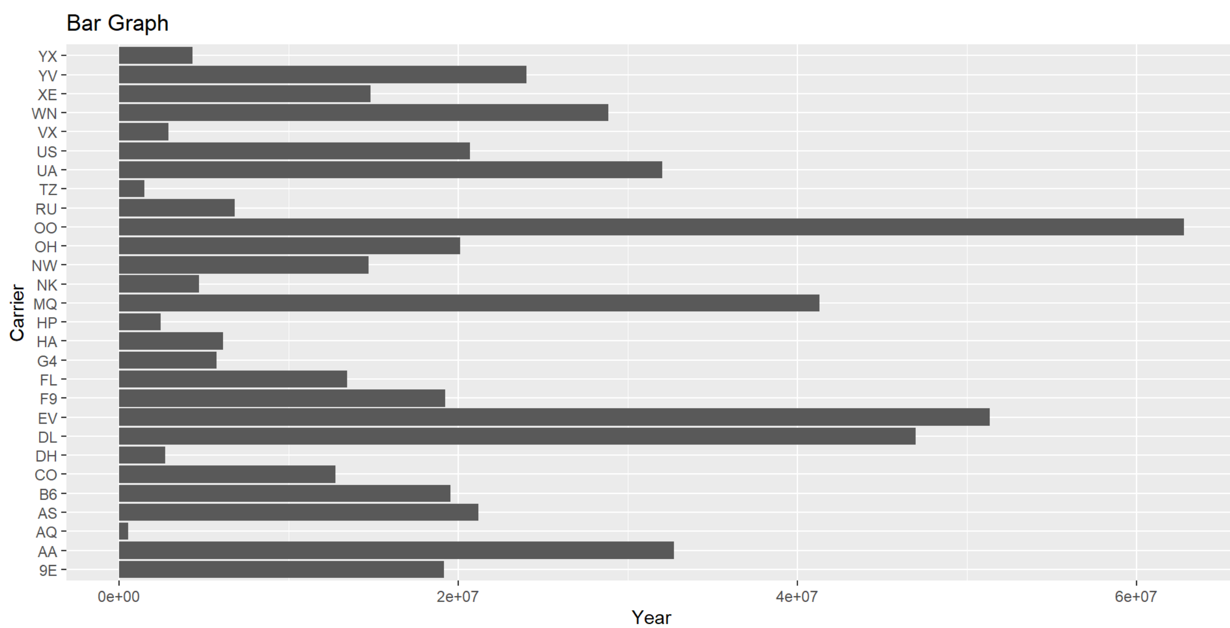
1. <u>Bar Graphs between Year and Delay Flights by Weather.</u>



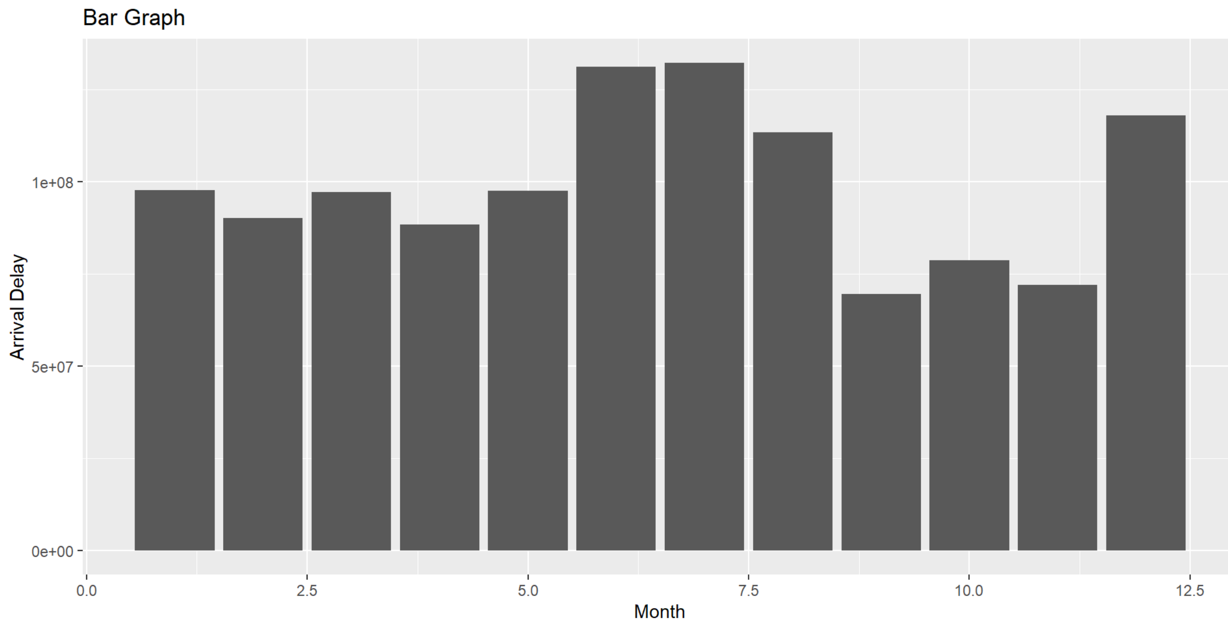
2. Bar Graphs between Month and Arrival Flights.



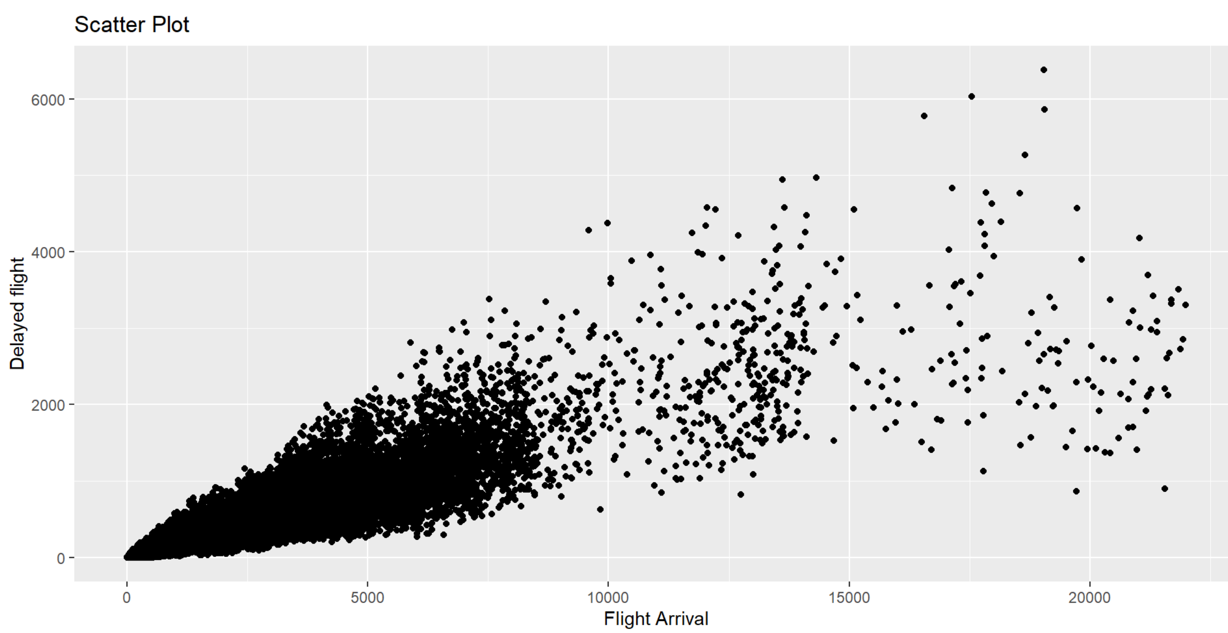
3. Bar Graphs between Year and Carrier.



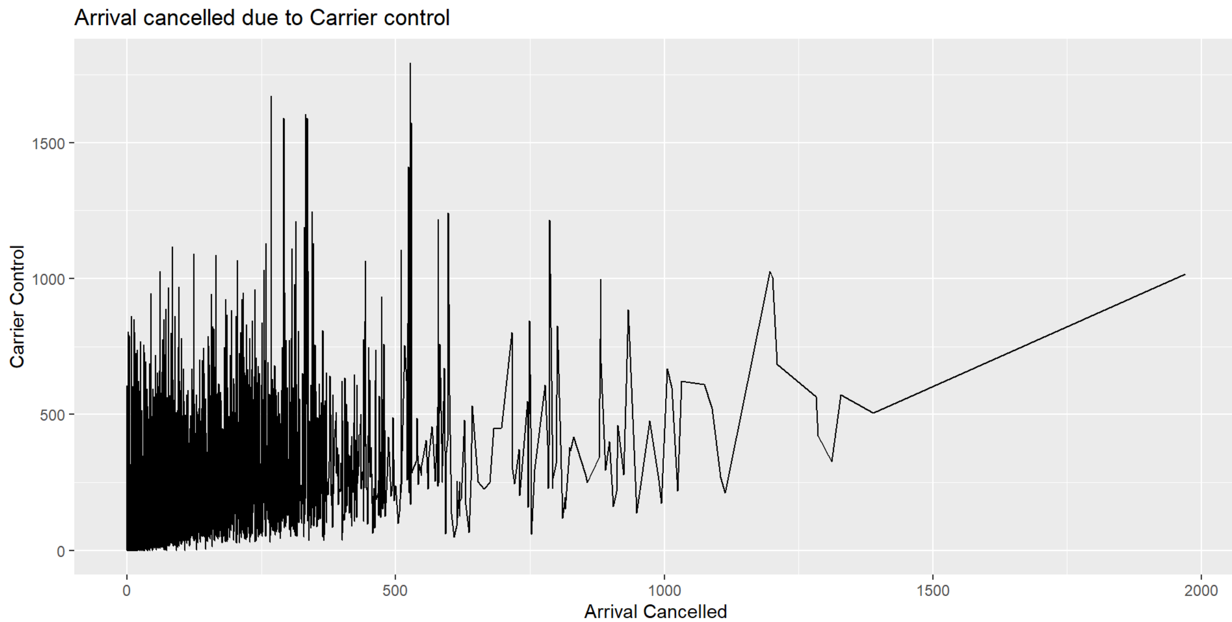
4. Bar Graphs between Month and Arrival Delay.



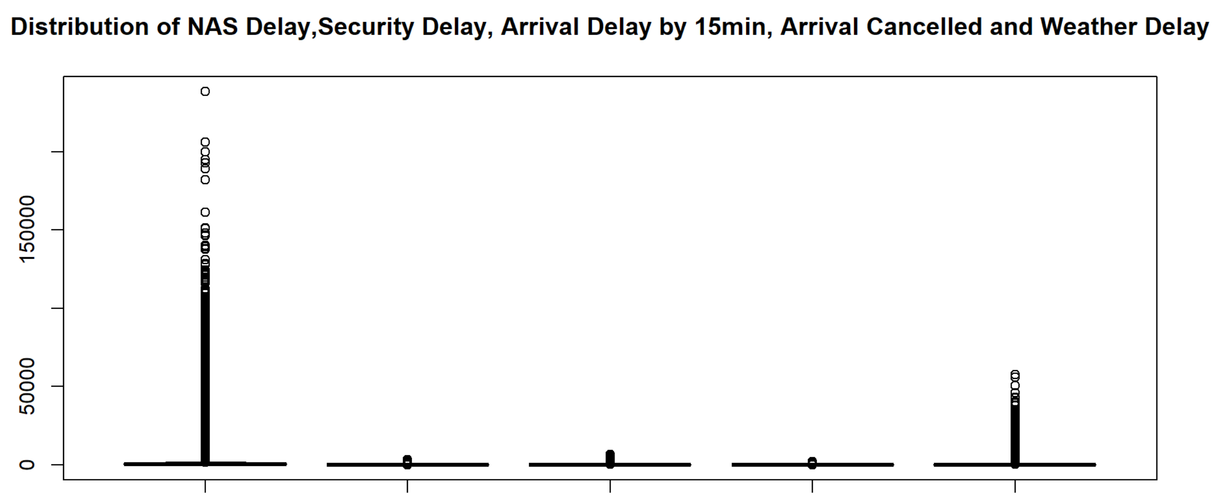
5. Scatter Plot between Flight Arrival and Delayed Flight.



6. Line Graphs between Arrival Canceled and Carrier Control.



7. Boxplot between NAS Delay, Security Delay, Arrival Delay by 15 min, Arrival Canceled and Weather Delay(To Find Outliers).



– **Correlation analysis and Analysis of Variance (ANOVA)**

# Correlation
# Select relevant columns for analysis
relevant_cols <- c("weather_delay","arr_del15")
# Create a correlation matrix for the relevant columns
cor_mat <- cor(fd[,relevant_cols], use = "complete.obs")
Cor_mat

```
> cor_mat
              weather_delay arr_del15
weather_delay     1.0000000 0.6847649
arr_del15         0.6847649 1.0000000
>
```

relevant_cols1 <- c("arr_del15","security_ct")

cor_mat1 <- cor(fd[,relevant_cols1], use = "complete.obs")

cor_mat1

```
> cor_mat1
            arr_del15 security_ct
arr_del15   1.0000000   0.4902167
security_ct 0.4902167   1.0000000
>
```

– Other relative analyses including histograms and statistics

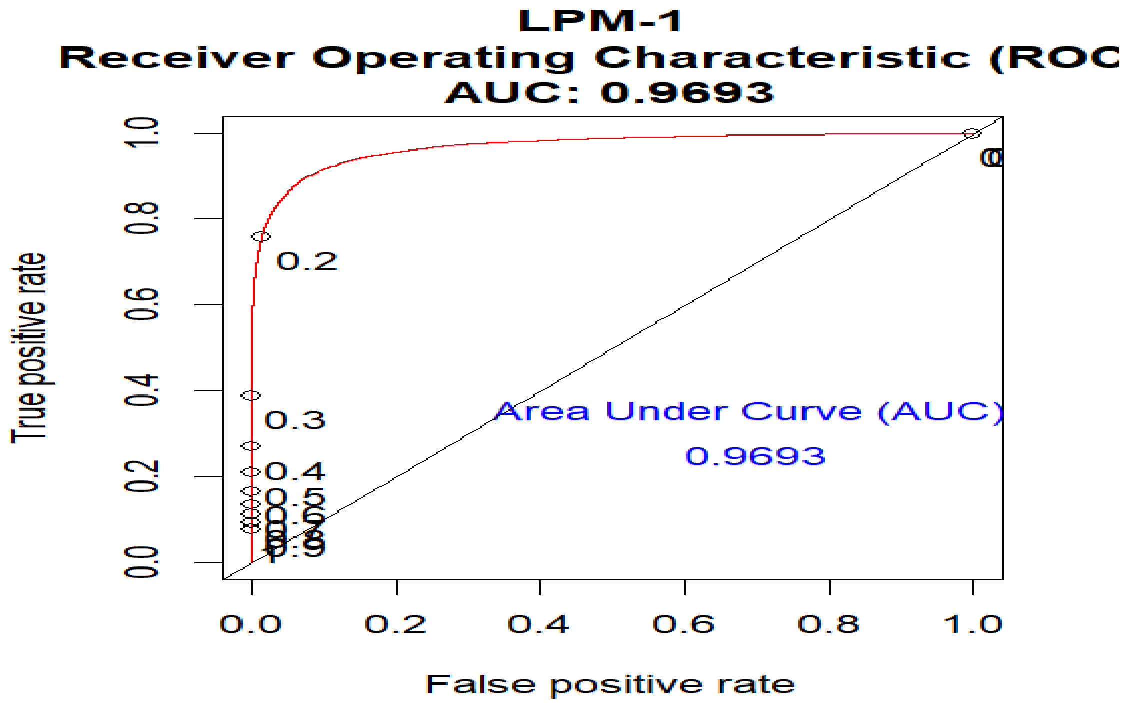
- **Simple, Multiple Regression on linear or nonlinear models**
- **Linear Regression Model :**

1. **Linear Regression Model to understand the impact of late_aircraft_ct on check_delay**

```
Call:
lm(formula = check_delay ~ late_aircraft_ct, data = train)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.9470 -0.1415 -0.1259 -0.1179  0.8821 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)      1.179e-01  7.658e-04   153.9   <2e-16 ***
late_aircraft_ct 2.561e-03  9.124e-06   280.7   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3333 on 211698 degrees of freedom
Multiple R-squared:  0.2712,	Adjusted R-squared:  0.2712 
F-statistic: 7.88e+04 on 1 and 211698 DF,  p-value: < 2.2e-16
```

```
> conf_table(yhat1,testy,"LPM-1")
  estname prob true_total truepos falsneg detection_rate false_total falspos trueneg false_pos_rate
1   LPM-1  0.1       9902    9902       0              1       43023   43023       0              1
2   LPM-1  0.2       9902    7522    2380         0.7596       43023     627   42396         0.0146
3   LPM-1  0.3       9902    3850    6052         0.3888       43023       0   43023              0
4   LPM-1  0.4       9902    2665    7237         0.2691       43023       0   43023              0
5   LPM-1  0.5       9902    2066    7836         0.2086       43023       0   43023              0
6   LPM-1  0.6       9902    1639    8263         0.1655       43023       0   43023              0
7   LPM-1  0.7       9902    1325    8577         0.1338       43023       0   43023              0
8   LPM-1  0.8       9902    1099    8803          0.111       43023       0   43023              0
9   LPM-1  0.9       9902     910    8992         0.0919       43023       0   43023              0
```

The p value of late_aircraft_ct is less than 0.05. Hence it has a significant impact on check_delay.



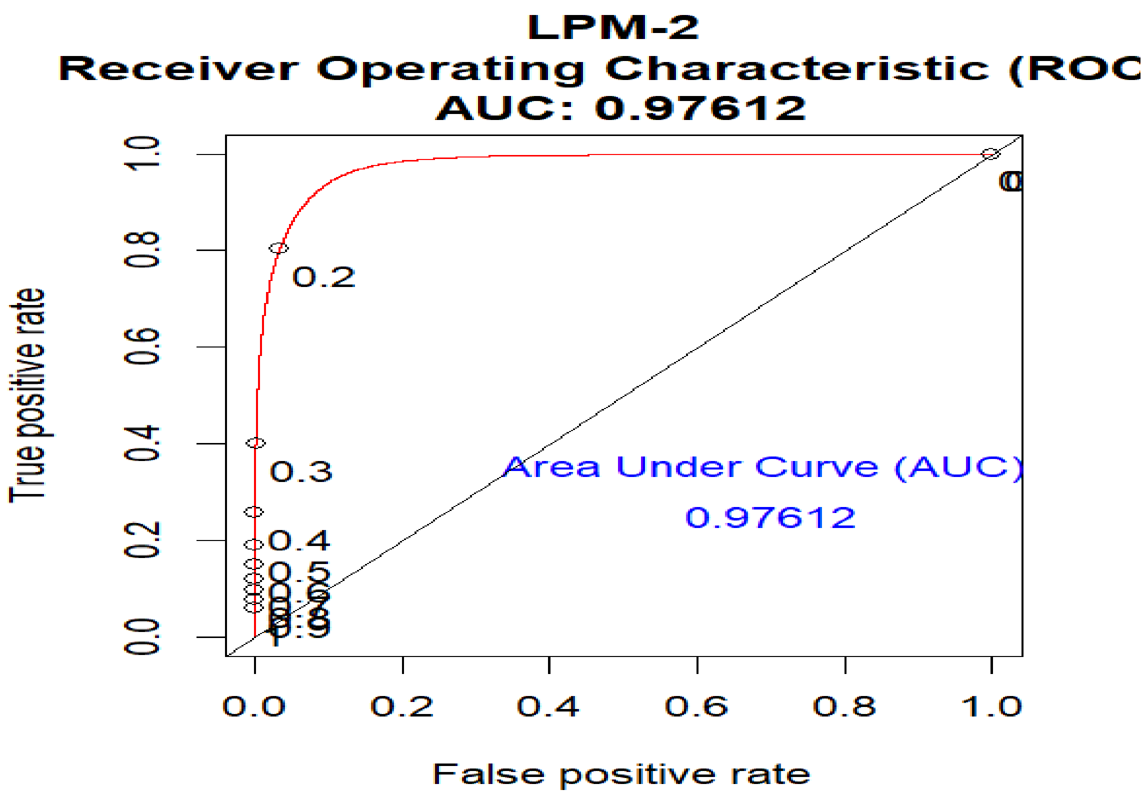
The AUC is 96% impling that it is a good fit.

2. **Linear Regression Model to understand the impact of carrier_delay, weather_delay, nas_delay, security_delay on check_delay.**

```
Call:
lm(formula = check_delay ~ carrier_delay + weather_delay + nas_delay +
    security_delay, data = train)

Residuals:
    Min      1Q  Median      3Q     Max
-9.2213 -0.1449 -0.1257 -0.1145  0.9230

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     1.135e-01  7.819e-04  145.10   <2e-16 ***
carrier_delay   4.848e-05  3.593e-07  134.93   <2e-16 ***
weather_delay  -2.402e-05  1.239e-06  -19.39   <2e-16 ***
nas_delay       7.650e-06  2.079e-07   36.80   <2e-16 ***
security_delay  8.989e-04  2.130e-05   42.20   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3361 on 211695 degrees of freedom
Multiple R-squared:  0.2588,    Adjusted R-squared:  0.2587
F-statistic: 1.847e+04 on 4 and 211695 DF,  p-value: < 2.2e-16
```

The p value of carrier_delay, weather_delay, nas_delay, security_delay is less than 0.05. Hence it has a significant impact on check_delay.

```
> conf_table(yhat2,testy,"LPM-2")
  estname prob true_total truepos falsneg detection_rate false_total falspos trueneg false_pos_rate
1   LPM-2  0.1       9902    9900       2         0.9998       43023   42973      50         0.9988
2   LPM-2  0.2       9902    7948    1954         0.8027       43023    1450   41573         0.0337
3   LPM-2  0.3       9902    3965    5937         0.4004       43023      66   42957         0.0015
4   LPM-2  0.4       9902    2548    7354         0.2573       43023       9   43014          2e-04
5   LPM-2  0.5       9902    1886    8016         0.1905       43023       4   43019          1e-04
6   LPM-2  0.6       9902    1478    8424         0.1493       43023       1   43022              0
7   LPM-2  0.7       9902    1176    8726         0.1188       43023       1   43022              0
8   LPM-2  0.8       9902     959    8943         0.0968       43023       1   43022              0
9   LPM-2  0.9       9902     762    9140          0.077       43023       1   43022              0
```



The AUC is 97% implying that it is a good fit.

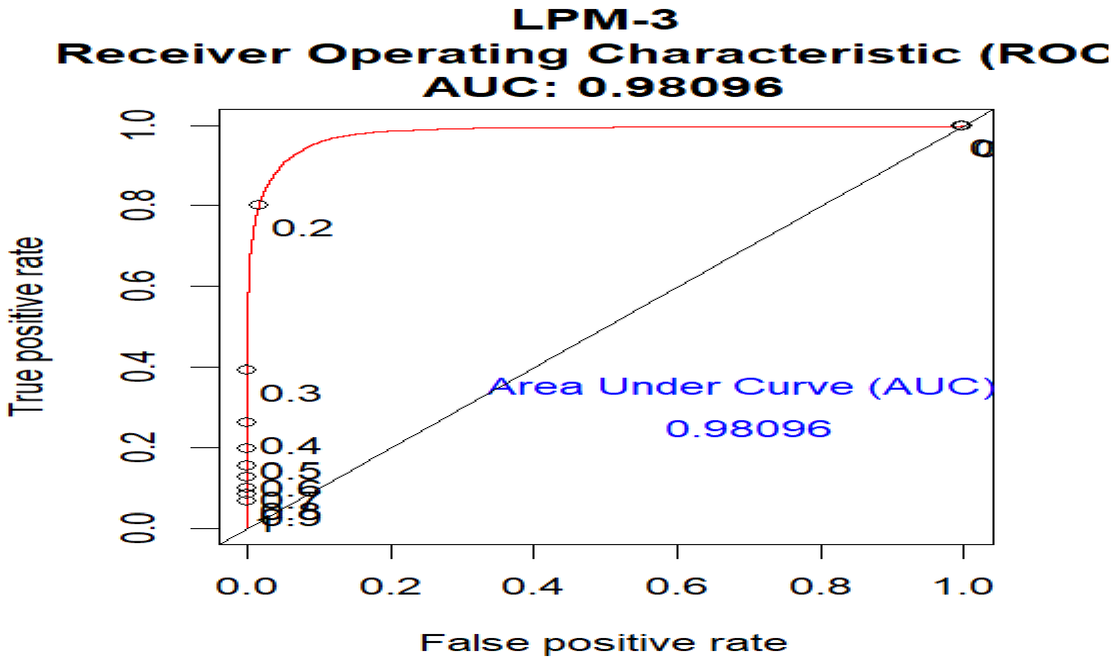
3. **Linear Regression Model to understand the impact of arr_cancelled, arr_diverted, arr_delay, late_aircraft_delay on check_delay.**

```
Call:
lm(formula = check_delay ~ arr_cancelled + arr_diverted + arr_delay +
    late_aircraft_delay, data = train)

Residuals:
    Min      1Q  Median      3Q     Max
-5.2143 -0.1428 -0.1268 -0.1183  1.2532

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          1.180e-01  7.682e-04  153.62   <2e-16 ***
arr_cancelled       -5.922e-04  3.599e-05  -16.46   <2e-16 ***
arr_diverted        -7.631e-03  2.524e-04  -30.23   <2e-16 ***
arr_delay            9.891e-06  1.797e-07   55.03   <2e-16 ***
late_aircraft_delay  2.100e-05  4.088e-07   51.37   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.334 on 211695 degrees of freedom
Multiple R-squared:  0.2681,    Adjusted R-squared:  0.2681
F-statistic: 1.939e+04 on 4 and 211695 DF,  p-value: < 2.2e-16
```

```
> conf_table(yhat3,testy,"LPM-3")
```

	estname	prob	true_total	truepos	falsneg	detection_rate	false_total	falspos	trueneg	false_pos_rate
1	LPM-3	0.1	9902	9882	20	0.998	43023	42830	193	0.9955
2	LPM-3	0.2	9902	7941	1961	0.802	43023	726	42297	0.0169
3	LPM-3	0.3	9902	3888	6014	0.3926	43023	0	43023	0
4	LPM-3	0.4	9902	2592	7310	0.2618	43023	0	43023	0
5	LPM-3	0.5	9902	1965	7937	0.1984	43023	0	43023	0
6	LPM-3	0.6	9902	1541	8361	0.1556	43023	0	43023	0
7	LPM-3	0.7	9902	1254	8648	0.1266	43023	0	43023	0
8	LPM-3	0.8	9902	986	8916	0.0996	43023	0	43023	0
9	LPM-3	0.9	9902	829	9073	0.0837	43023	0	43023	0

The p value of arr_cancelled, arr_diverted, arr_delay, late_aircraft_delay is less than 0.05. Hence it has a significant impact on check_delay.



The AUC is 98% implying that it is a good fit.

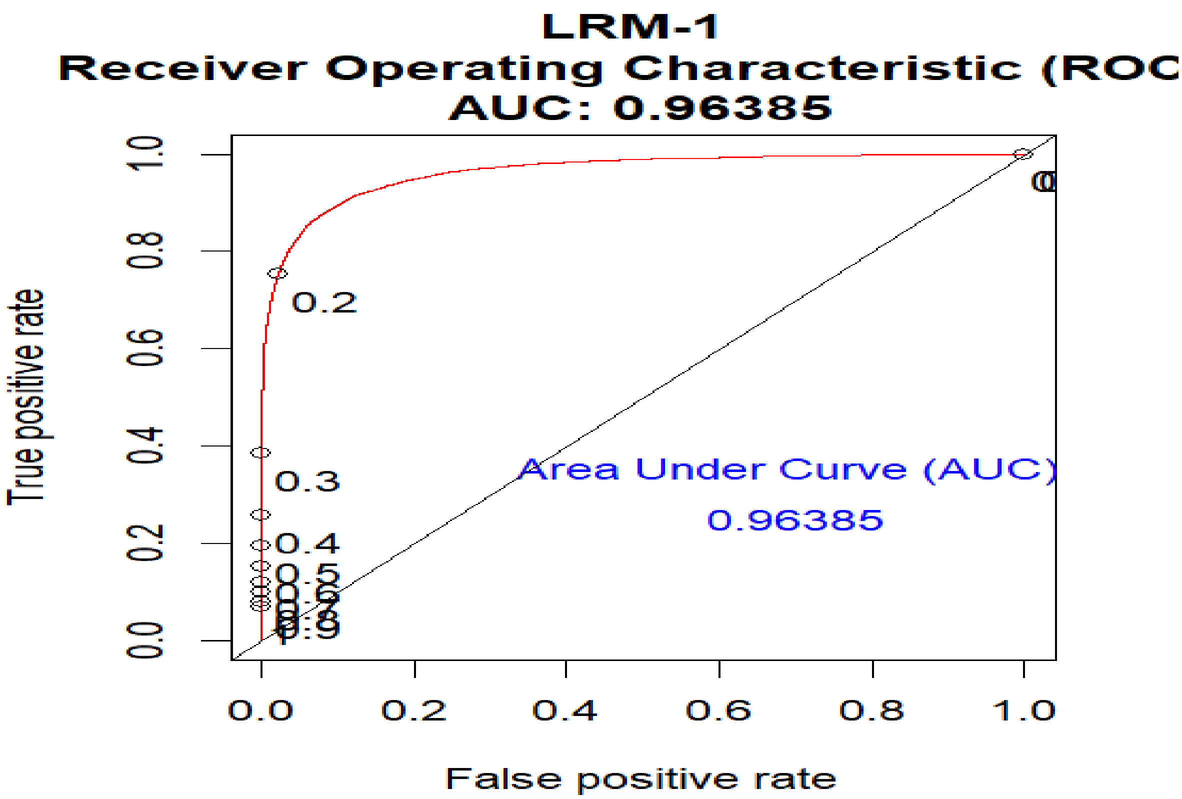
– **Discrete Probability Model : Logistic Model**

1. **Logistic Regression Model to understand the impact of late_aircraft_ct on check_delay**

```
Call:
glm(formula = check_delay ~ late_aircraft_delay, data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-4.7968  -0.1433  -0.1281  -0.1215   0.8785

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)         1.215e-01  7.714e-04   157.5   <2e-16 ***
late_aircraft_delay 3.830e-05  1.416e-07   270.4   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.1133011)

    Null deviance: 32269  on 211699  degrees of freedom
Residual deviance: 23986  on 211698  degrees of freedom
AIC: 139762

Number of Fisher Scoring iterations: 2
```

```
> conf_table(yhat4,testy,"LRM-1")
  estname prob true_total truepos falsneg detection_rate false_total falspos trueneg false_pos_rate
1   LRM-1  0.1       9902    9902       0              1       43023   43023       0              1
2   LRM-1  0.2       9902    7464    2438         0.7538       43023     962   42061         0.0224
3   LRM-1  0.3       9902    3805    6097         0.3843       43023       3   43020          1e-04
4   LRM-1  0.4       9902    2539    7363         0.2564       43023       0   43023              0
5   LRM-1  0.5       9902    1921    7981          0.194       43023       0   43023              0
6   LRM-1  0.6       9902    1514    8388         0.1529       43023       0   43023              0
7   LRM-1  0.7       9902    1193    8709         0.1205       43023       0   43023              0
8   LRM-1  0.8       9902     980    8922          0.099       43023       0   43023              0
9   LRM-1  0.9       9902     791    9111         0.0799       43023       0   43023              0
```

The p value of late_aircraft_ct is less than 0.05. Hence it has a significant impact on check_delay.



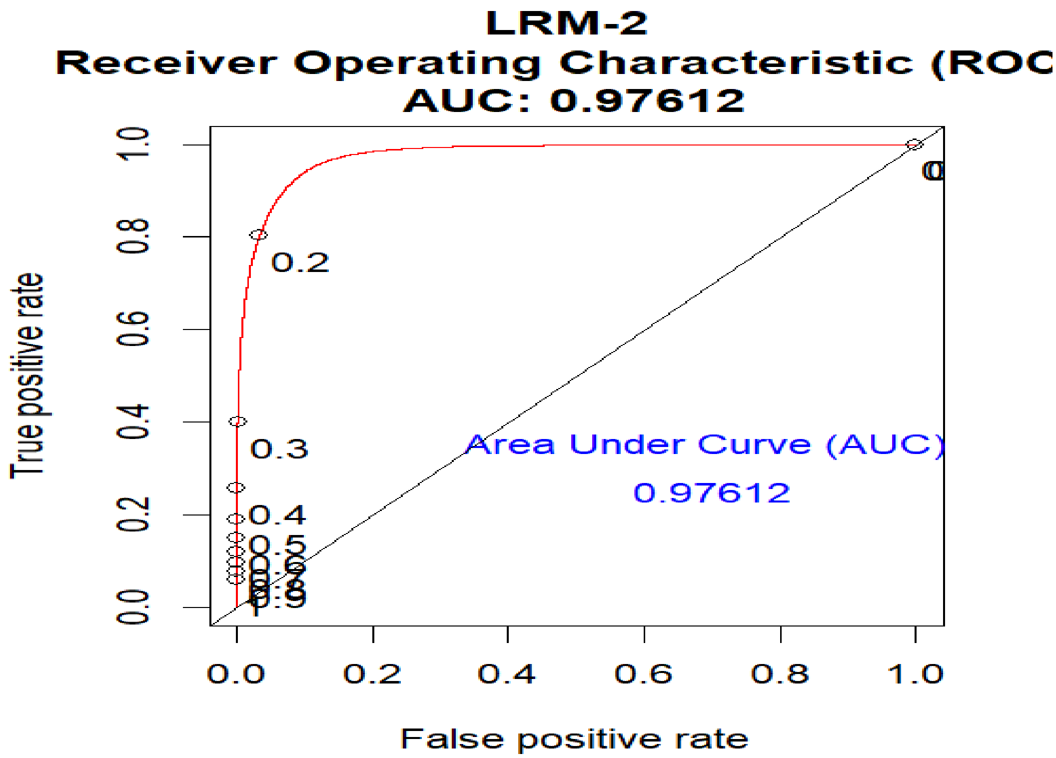
The AUC is 96% implying that it is a good fit.

2. **Logistic Regression Model to understand the impact of carrier_delay, weather_delay, nas_delay, security_delay on check_delay.**

```
Call:
glm(formula = check_delay ~ carrier_delay + weather_delay + nas_delay +
    security_delay, data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-9.2213  -0.1449  -0.1257  -0.1145   0.9230

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     1.135e-01  7.819e-04  145.10   <2e-16 ***
carrier_delay   4.848e-05  3.593e-07  134.93   <2e-16 ***
weather_delay  -2.402e-05  1.239e-06  -19.39   <2e-16 ***
nas_delay       7.650e-06  2.079e-07   36.80   <2e-16 ***
security_delay  8.989e-04  2.130e-05   42.20   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.1129906)

    Null deviance: 32269  on 211699  degrees of freedom
Residual deviance: 23920  on 211695  degrees of freedom
AIC: 139184

Number of Fisher Scoring iterations: 2
```

```
> conf_table(yhat5,testy,"LRM-2")
  estname prob true_total truepos falsneg detection_rate false_total falspos trueneg false_pos_rate
1   LRM-2  0.1       9902    9900       2         0.9998       43023   42973      50         0.9988
2   LRM-2  0.2       9902    7948    1954         0.8027       43023    1450   41573         0.0337
3   LRM-2  0.3       9902    3965    5937         0.4004       43023      66   42957         0.0015
4   LRM-2  0.4       9902    2548    7354         0.2573       43023       9   43014          2e-04
5   LRM-2  0.5       9902    1886    8016         0.1905       43023       4   43019          1e-04
6   LRM-2  0.6       9902    1478    8424         0.1493       43023       1   43022              0
7   LRM-2  0.7       9902    1176    8726         0.1188       43023       1   43022              0
8   LRM-2  0.8       9902     959    8943         0.0968       43023       1   43022              0
9   LRM-2  0.9       9902     762    9140          0.077       43023       1   43022              0
```

The p value of carrier_delay, weather_delay, nas_delay, security_delay is less than 0.05. Hence it has a significant impact on check_delay.



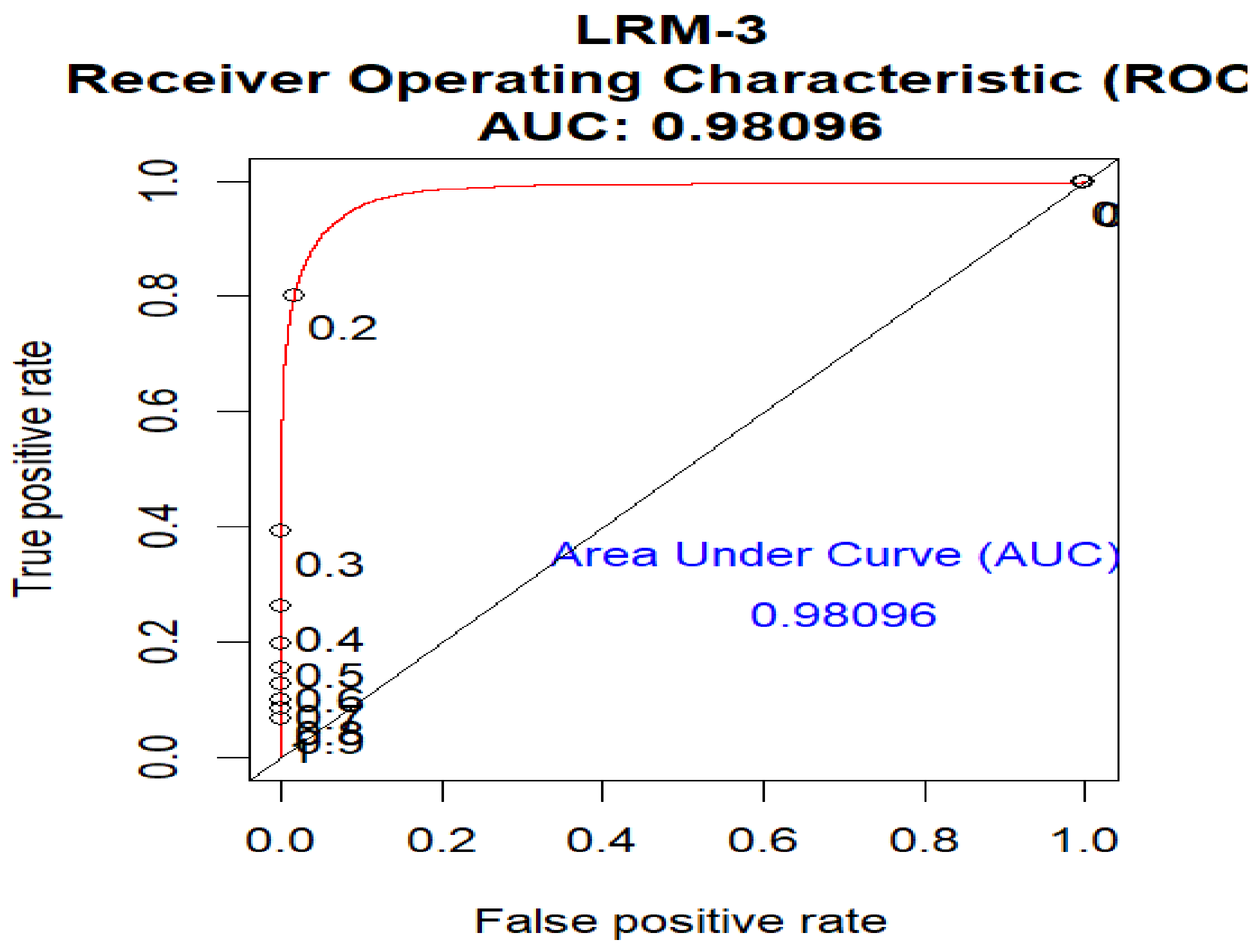
The AUC is 97% implying that it is a good fit.

3. **Logistic Regression Model to understand the impact of arr_cancelled, arr_diverted, arr_delay, late_aircraft_delay on check_delay.**

```
Call:
glm(formula = check_delay ~ arr_cancelled + arr_diverted + arr_delay +
    late_aircraft_delay, data = train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-5.2143  -0.1428  -0.1268  -0.1183   1.2532

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          1.180e-01  7.682e-04  153.62   <2e-16 ***
arr_cancelled       -5.922e-04  3.599e-05  -16.46   <2e-16 ***
arr_diverted        -7.631e-03  2.524e-04  -30.23   <2e-16 ***
arr_delay            9.891e-06  1.797e-07   55.03   <2e-16 ***
late_aircraft_delay  2.100e-05  4.088e-07   51.37   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for gaussian family taken to be 0.1115592)

    Null deviance: 32269  on 211699  degrees of freedom
Residual deviance: 23617  on 211695  degrees of freedom
AIC: 136485

Number of Fisher Scoring iterations: 2
```

```
> conf_table(yhat6,testy,"LRM-3")
  estname prob true_total truepos falsneg detection_rate false_total falspos trueneg false_pos_rate
1   LRM-3  0.1       9902    9882      20          0.998       43023   42830     193         0.9955
2   LRM-3  0.2       9902    7941    1961          0.802       43023     726   42297         0.0169
3   LRM-3  0.3       9902    3888    6014         0.3926       43023       0   43023              0
4   LRM-3  0.4       9902    2592    7310         0.2618       43023       0   43023              0
5   LRM-3  0.5       9902    1965    7937         0.1984       43023       0   43023              0
6   LRM-3  0.6       9902    1541    8361         0.1556       43023       0   43023              0
7   LRM-3  0.7       9902    1254    8648         0.1266       43023       0   43023              0
8   LRM-3  0.8       9902     986    8916         0.0996       43023       0   43023              0
9   LRM-3  0.9       9902     829    9073         0.0837       43023       0   43023              0
```

The p value of arr_cancelled, arr_diverted, arr_delay, late_aircraft_delay is less than 0.05. Hence it has a significant impact on check_delay.

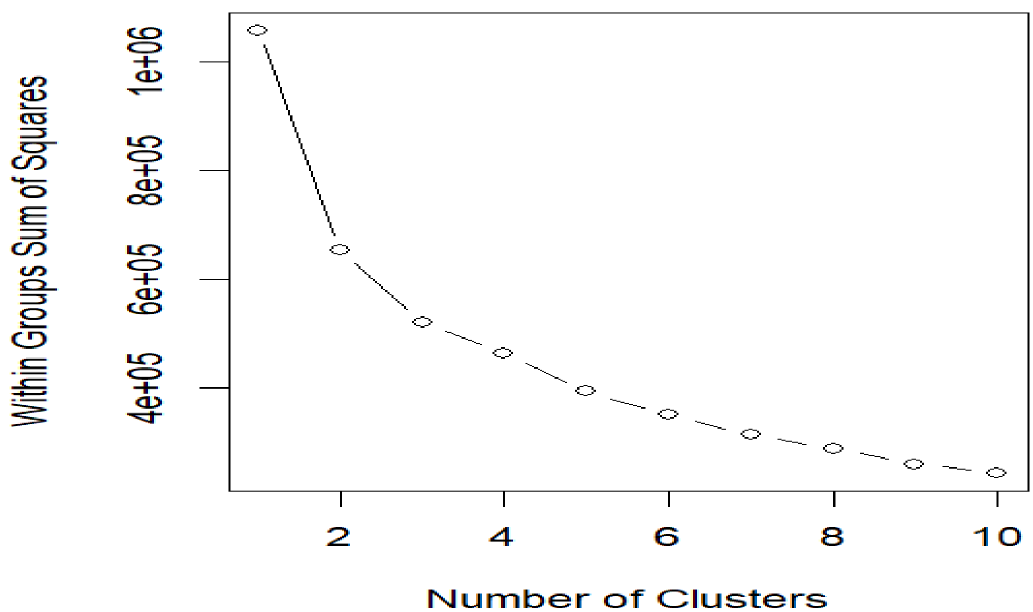


The AUC is 98% implying that it is a good fit.

- **Predictive Analytics (All required to apply to your model)**

– Clustering Analysis

```
> wss
 [1] 1058496.0  652307.1  520114.7  461868.3  392247.0  349545.3  312936.0  287166.7  259202.6  242376.1

  year month carrier         carrier_name airport                                            airport_name
1 2004     1      DL Delta Air Lines Inc.     PBI West Palm Beach/Palm Beach, FL: Palm Beach International
2 2004     1      DL Delta Air Lines Inc.     PDX                       Portland, OR: Portland International
3 2004     1      DL Delta Air Lines Inc.     PHL               Philadelphia, PA: Philadelphia International
4 2004     1      DL Delta Air Lines Inc.     PHX              Phoenix, AZ: Phoenix Sky Harbor International
5 2004     1      DL Delta Air Lines Inc.     PIT                   Pittsburgh, PA: Pittsburgh International
6 2004     1      DL Delta Air Lines Inc.     PNS                     Pensacola, FL: Pensacola International
  arr_flights arr_del15 carrier_ct weather_ct nas_ct security_ct late_aircraft_ct arr_cancelled
1         650       126      21.06       6.44  51.58           1            45.92             4
2         314        61      14.09       2.61  34.25           0            10.05            30
3         513        97      27.60       0.42  51.86           0            17.12            15
4         334        78      20.14       2.02  39.39           0            16.45             3
5         217        47       8.08       0.44  21.89           0            16.59             4
6         181        42      10.48       1.06  11.87           0            18.58             2
  arr_diverted arr_delay carrier_delay weather_delay nas_delay security_delay late_aircraft_delay
1            0      5425           881           397      2016             15                2116
2            3      2801           478           239      1365              0                 719
3            0      4261          1150            16      2286              0                 809
4            1      3400          1159           166      1295              0                 780
5            1      1737           350            28       522              0                 837
6            0      1814           469           195       365              0                 785
  check_delay predicted_arr_del15
1           1                   1
2           0                   1
3           1                   1
4           0                   1
5           0                   1
6           0                   1
```



```
Within cluster sum of squares by cluster:
[1] 212024.9 207400.1 100689.7
 (between_SS / total_SS =  50.9 %)

Available components:

[1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss" "betweenss"
[7] "size"         "iter"         "ifault"
```

4.4 Summary of Project (1 to 2 pages)

• Summarize everything briefly (i.e. in one paragraph you should be able to state your project question, empirical approach, and results).

The project involves analyzing airline data related to flight delays and scheduling, with the goal of identifying patterns and factors that contribute to delays. This analysis may involve examining historical data on flight schedules and delays, as well as real-time data on current flights. The ultimate aim is to use this analysis to improve the accuracy of airline scheduling and reduce delays, which can have a significant impact on customer satisfaction and profitability. The project may also involve developing predictive models that can anticipate potential delays and help airlines take proactive measures to avoid them.

• Potential shortcoming of your project and desirable future works.

One potential shortcoming of this project is the availability and quality of data. Airlines may not always provide complete and accurate data on flight delays and scheduling, which can limit the accuracy of any analysis or models developed. Additionally, external factors such as weather, air traffic control, and security issues can also impact flight delays, and it may be difficult to account for all of these factors in the analysis.

Desirable future works could involve exploring ways to address these data limitations and external factors. For example, airlines could be encouraged to provide more complete and standardized data on flight delays and scheduling, and machine learning algorithms could be developed to better account for external factors that impact flight delays. Additionally, more research could be done on the impact of flight delays on customer satisfaction and revenue, to better inform the development of strategies for reducing delays and improving airline performance.

4.5 Bibliography (1 page)

https://bigblue.depaul.edu/jlee141/econdata/eco520/

4.6 Appendix: SAS or R command and Data Files

Include all SAS or R commands used to generate the output. Codes and Data need to be included in separate files. Make sure all submitted SAS or R codes without any errors as a .txt file. ***There will be a very high penalty if they are not working with errors or not completed***.

- Is shared with the report.