

# Final Project Data Exploration

2023-05-31

## R Markdown

```
library(magrittr)
library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union

library(ggplot2)

SuperClean<-read.csv('SuperClean2019.csv')

# Check if there are any NA values in the entire dataframe 'FreshStart_clean'
has_na <- any(is.na(SuperClean))

# Print the result
if (has_na) {
  print("There are NA values in the dataframe.")
} else {
  print("There are no NA values in the dataframe.")
}

## [1] "There are no NA values in the dataframe."

range(SuperClean$ARR_DELAY)

## [1] -94 2649

fivenum(SuperClean$ARR_DELAY)

## [1] -94 -16 -6 9 2649

quantile(SuperClean$ARR_DELAY, probs = c(0.01,0.05,0.1,0.25,.5,.75,.90,.95,.99))

## 1% 5% 10% 25% 50% 75% 90% 95% 99%
## -39 -29 -24 -16 -6 9 39 76 202

mean(SuperClean$ARR_DELAY >= 60)
```

```
## [1] 0.06575714

MajorAirports<-c("ATL","DFW","DEN","ORD","LAX","CLT","MCO","SEA","MIA","JFK",
"PHX","IAH","SFO","EWR","BOS",
"DTW","SLC","PHL","BWI","FLL","MSP","TPA","SAN","LGA","MDW",
"BNA","IAD","DCA","AUS","DAL",
"HNL","PDX","HOU","RSW")
SuperCleanMajorAirports<-subset(SuperClean,DEST %in% MajorAirports)

Q3 <- function(x) { quantile(x,probs=.75) }
SuperClean %>% group_by(SuperClean$DEST) %>%
  summarize(n=n(),med_d = median(ARR_DELAY),Q3_d = Q3(ARR_DELAY), max_d = max
(ARR_DELAY)) %>%
  arrange(desc(Q3_d)) %>% head(10)

## # A tibble: 10 × 5
##   `SuperClean$DEST`      n med_d  Q3_d max_d
##   <chr>                <int> <dbl> <dbl> <int>
## 1 PIB                  106  0.5   62    961
## 2 MEI                  160 -1     43.8  477
## 3 EAU                   88 -6.5   43.2  720
## 4 ALO                   79  3     35.5  126
## 5 MKG                   88  3     35.5  134
## 6 ASE                  1443  0     35    967
## 7 LWB                   81 -6     35    319
## 8 MMH                  120  4     34.8  497
## 9 HGR                   18  2.5   30.8  143
## 10 CMI                 326  2     27.8  900

SuperCleanMajorAirports %>% group_by(SuperCleanMajorAirports$DEST) %>%
  summarize(n=n(),med_d = median(ARR_DELAY),Q3_d = Q3(ARR_DELAY), max_d = max
(ARR_DELAY)) %>%
  arrange(desc(Q3_d)) %>% head(36)

## # A tibble: 34 × 5
##   `SuperCleanMajorAirports$DEST`      n med_d  Q3_d max_d
##   <chr>                <int> <dbl> <dbl> <int>
## 1 LGA                  23631  -6    22   2649
## 2 EWR                  17906  -5   21.8  1594
## 3 SFO                  22677  -4    21   1447
## 4 ORD                  42118  -3    20   2050
## 5 BOS                  18906  -7    13   1113
## 6 DFW                  40236  -4    11   1652
## 7 LAX                  31089  -5    11   1442
## 8 FLL                  15030  -6    10   1288
## 9 SAN                  13047  -4    10    680
## 10 DCA                 20030  -7     9   1313
## # i 24 more rows

SuperClean %>% group_by(SuperClean$OP_UNIQUE_CARRIER) %>%
  summarize(n=n(),med_d = median(ARR_DELAY),Q3_d = Q3(ARR_DELAY), max_d = max
```

```

(ARR_DELAY)) %>%
  arrange(desc(Q3_d)) %>% head(17)

## # A tibble: 17 × 5
##   `SuperClean$OP_UNIQUE_CARRIER`      n med_d  Q3_d max_d
##   <chr>                <int> <dbl> <dbl> <int>
## 1 B6                  40878    -6    16  1313
## 2 MQ                  42013    -3    16  2649
## 3 EV                  21370    -5    14  1594
## 4 G4                  12987    -3    14  1478
## 5 F9                  15974    -6    13  1020
## 6 OO                 110349    -6    13  1498
## 7 AS                   34996    -5    11   816
## 8 YX                   43594    -7    10  1353
## 9 AA                 132935    -5     9  1638
## 10 YV                  31473    -4     9  2206
## 11 UA                  81619    -7     8  1398
## 12 HA                  12017    -2     7  1507
## 13 OH                   39798    -6     7  1145
## 14 WN                 184748    -6     7   566
## 15 9E                   34634   -11     6  1464
## 16 NK                   26099    -7     5  1429
## 17 DL                 128948    -9     3  1241

SuperClean %>% group_by(SuperClean$ORIGIN, SuperClean$OP_UNIQUE_CARRIER) %>%
  summarize(n=n(), med_d = median(ARR_DELAY), Q3_d = Q3(ARR_DELAY), max_d = max
(ARR_DELAY)) %>%
  arrange(desc(Q3_d)) %>% head(10)

## `summarise()` has grouped output by 'SuperClean$ORIGIN'. You can override
## using
## the `.groups` argument.

## # A tibble: 10 × 6
## # Groups:   SuperClean$ORIGIN [9]
##   `SuperClean$ORIGIN` `SuperClean$OP_UNIQUE_CARRIER`      n med_d  Q3_d ma
x_d
##   <chr>                <chr>                <int> <dbl> <dbl> <i
nt>
## 1 FAR                  EV                  2 214.  315.
416
## 2 CWA                  OO                  1 161  161
161
## 3 BHM                  UA                  3 131  148
165
## 4 FAR                  YX                  9  18  140
888
## 5 RAP                  9E                  1 132  132
132
## 6 CID                  YX                  5  83  110
118

```

```
## 7 ALB          YX          6 39.5 98.8
181
## 8 BTV          EV        117 20 97
959
## 9 MLI          EV        36 30.5 92.2
208
## 10 EVV         EV         1 89 89
89
```

```
SuperClean %>% group_by(SuperClean$DEST, SuperClean$OP_UNIQUE_CARRIER) %>%
  summarize(n=n(), med_d = median(ARR_DELAY), Q3_d = Q3(ARR_DELAY), max_d = max
(ARR_DELAY)) %>%
  arrange(desc(Q3_d)) %>% head(10)
```

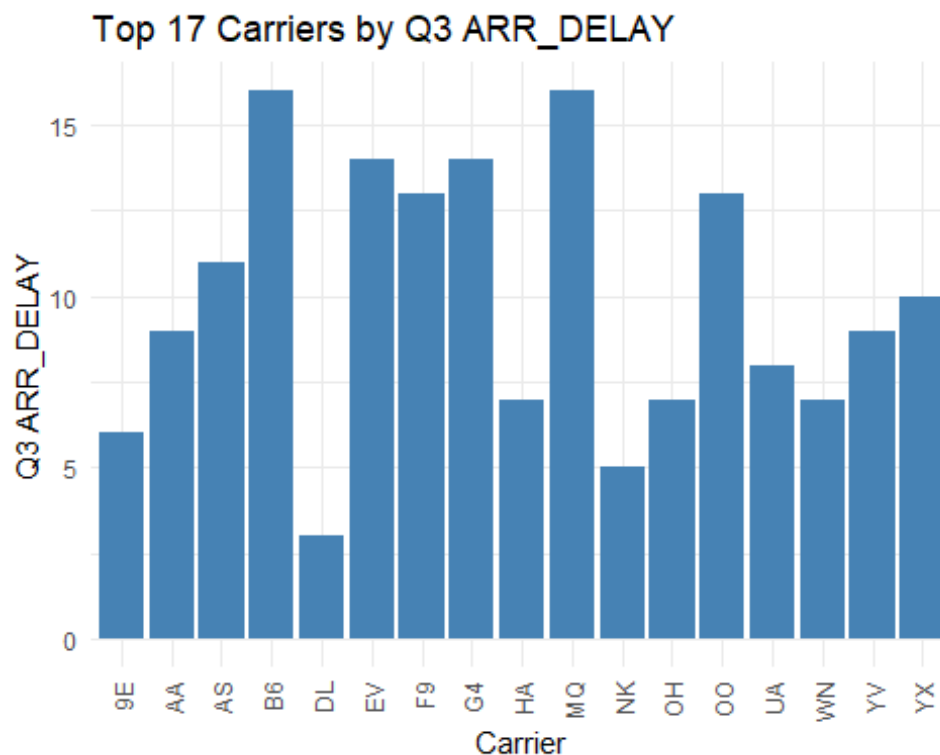
```
## `summarise()` has grouped output by 'SuperClean$DEST'. You can override us
ing
## the `.groups` argument.
```

```
## # A tibble: 10 × 6
## # Groups:   SuperClean$DEST [10]
##   `SuperClean$DEST` `SuperClean$OP_UNIQUE_CARRIER`      n med_d  Q3_d max_
d
##   <chr>          <chr>          <int> <dbl> <dbl> <int>
>
## 1 EVV          EV              1 99 99 9
9
## 2 MLI          EV            38 25.5 95.2 23
6
## 3 SYR          EV            41 8 92 23
8
## 4 HOU          EV             4 38 74.2 11
4
## 5 ABE          EV            68 10.5 72.8 32
3
## 6 CID          YX             5 34 67 13
6
## 7 CRP          OO            10 23 65.8 12
4
## 8 CLT          EV            28 6 65 15
6
## 9 RAP          YX            10 11.5 63 12
2
## 10 COU         EV            45 -2 62 32
6
```

```
summary_data <- SuperClean %>%
  group_by(OP_UNIQUE_CARRIER) %>%
  summarize(n = n(), med_d = median(ARR_DELAY), Q3_d = quantile(ARR_DELAY, 0.
75), max_d = max(ARR_DELAY)) %>%
  arrange(desc(Q3_d)) %>%
  head(17)
```

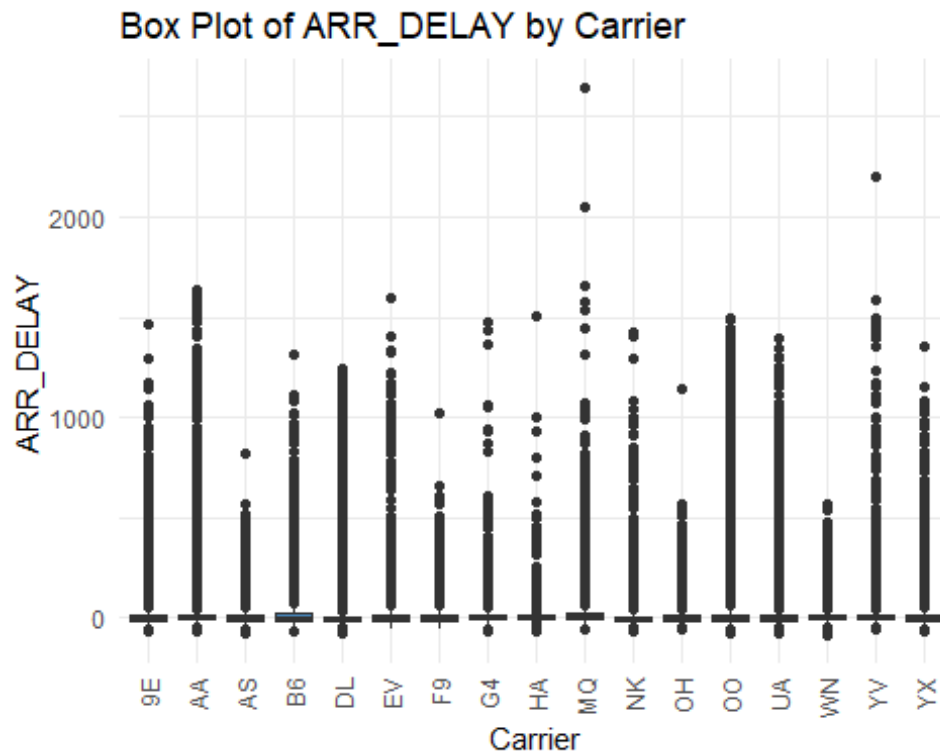
```
# Create a bar plot
bar_plot <- ggplot(summary_data, aes(x = OP_UNIQUE_CARRIER, y = Q3_d)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  labs(x = "Carrier", y = "Q3 ARR_DELAY", title = "Top 17 Carriers by Q3 ARR_
DELAY") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))

# Display the bar plot
print(bar_plot)
```



```
# Create a box plot
box_plot <- ggplot(SuperClean, aes(x = OP_UNIQUE_CARRIER, y = ARR_DELAY)) +
  geom_boxplot(fill = "steelblue") +
  labs(x = "Carrier", y = "ARR_DELAY", title = "Box Plot of ARR_DELAY by Carr
ier") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))

# Display the box plot
print(box_plot)
```

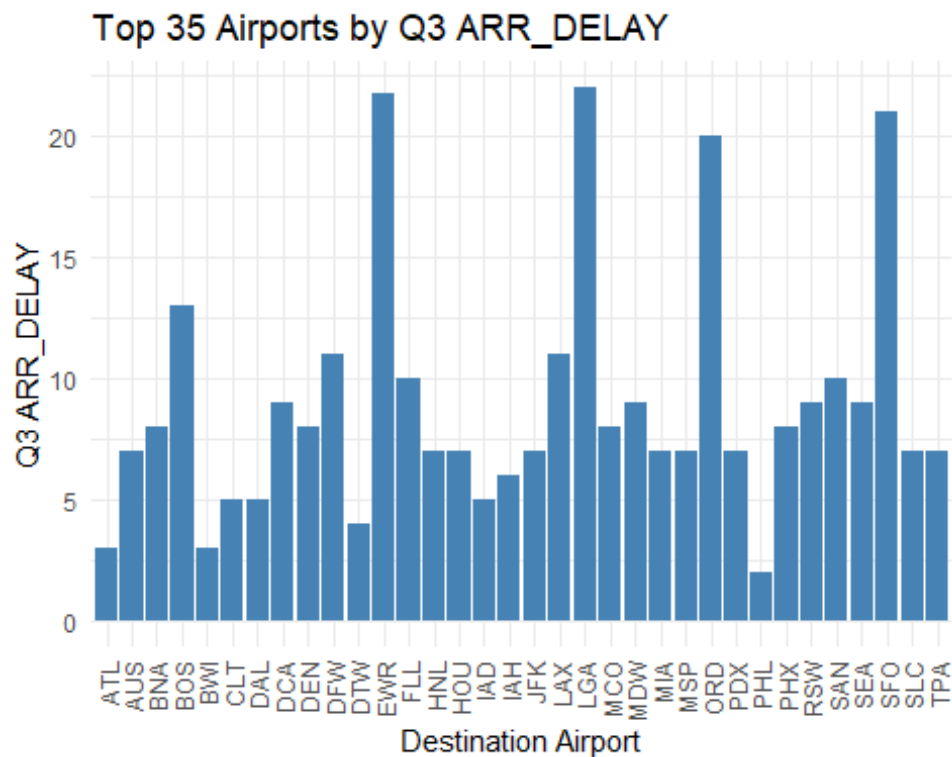


```
library(ggplot2)

# Summarize the data
summary_data2 <- SuperCleanMajorAirports %>%
  group_by(DEST) %>%
  summarize(n = n(), med_d = median(ARR_DELAY), Q3_d = quantile(ARR_DELAY, 0.
75), max_d = max(ARR_DELAY)) %>%
  arrange(desc(Q3_d)) %>%
  head(346)

# Create a bar plot
bar_plot <- ggplot(summary_data2, aes(x = DEST, y = Q3_d)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  labs(x = "Destination Airport", y = "Q3 ARR_DELAY", title = "Top 35 Airport
s by Q3 ARR_DELAY") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 1))

# Display the bar plot
print(bar_plot)
```



```
SuperClean %>% group_by(SuperClean$FL_DATE) %>%
  summarize(n=n(), med_d = mean(ARR_DELAY), max_d = max(ARR_DELAY)) %>%
  arrange(desc(med_d)) %>% head(10)
```

```
## # A tibble: 10 × 4
##   `SuperClean$FL_DATE`      n med_d max_d
##   <chr>                <int> <dbl> <int>
## 1 2/20/2019             17477  30.8  1479
## 2 2/12/2019             16340  18.2  1200
## 3 1/24/2019             19040  17.7  1143
## 4 1/21/2019             18381  15.5  1186
## 5 1/23/2019             18000  13.6  1270
## 6 2/25/2019             10782  13.1  1498
## 7 2/17/2019             16656  12.9  2649
## 8 2/18/2019             19434  12.7  1209
## 9 2/22/2019             19579  12.0  1464
## 10 1/22/2019            17051  11.8  1431
```

```
library(ggplot2)
```

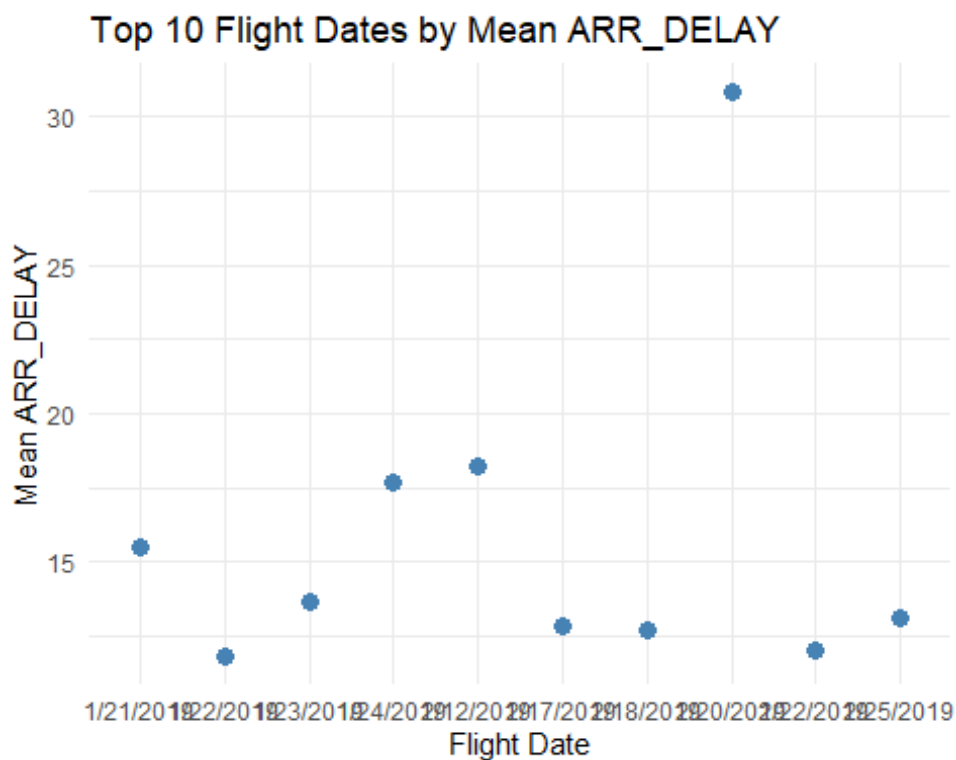
```
# Summarize the data
summary_data3 <- SuperClean %>%
  group_by(FL_DATE) %>%
  summarize(n = n(), med_d = mean(ARR_DELAY), max_d = max(ARR_DELAY)) %>%
  arrange(desc(med_d)) %>%
  head(10)
```

```
# Create a Line plot
line_plot <- ggplot(summary_data3, aes(x = FL_DATE, y = med_d)) +
  geom_line(color = "steelblue", size = 1) +
  geom_point(color = "steelblue", size = 3) +
  labs(x = "Flight Date", y = "Mean ARR_DELAY", title = "Top 10 Flight Dates
by Mean ARR_DELAY") +
  theme_minimal()

## Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use `linewidth` instead.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning was
## generated.

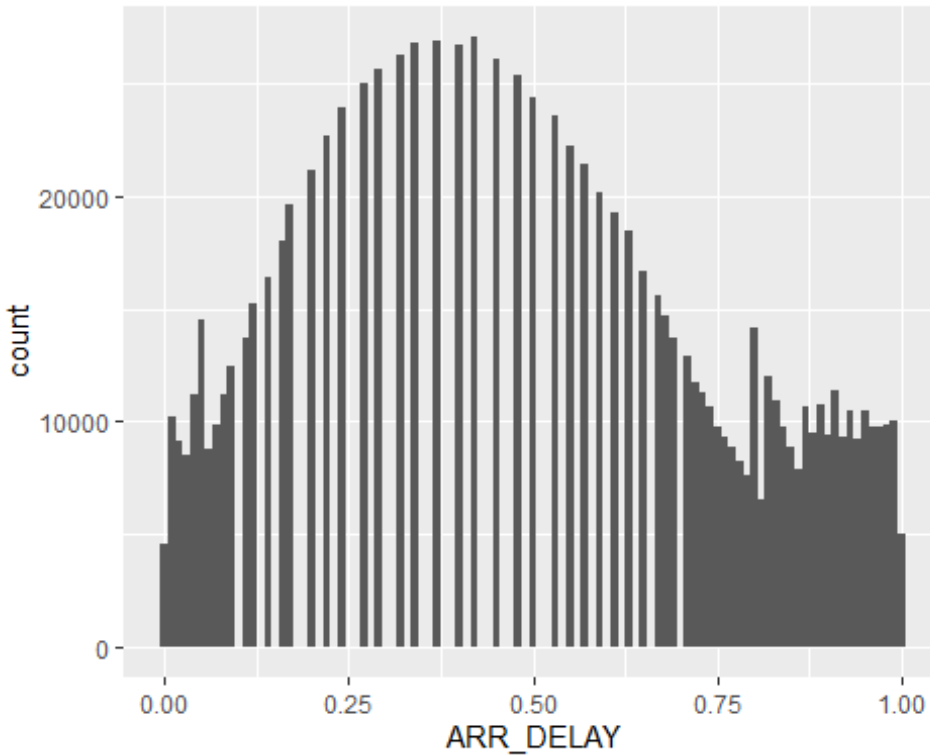
# Display the Line plot
print(line_plot)

## `geom_line()`: Each group consists of only one observation.
## i Do you need to adjust the group aesthetic?
```



```
den <- nrow(SuperClean)+1
SuperCleanMutated <- SuperClean %>% mutate(ARR_DELAY = rank(ARR_DELAY)/den)
ggplot(SuperCleanMutated, aes(x=ARR_DELAY)) + geom_histogram(binwidth=.01)
```





```
ggplot(SuperClean,aes(x=SuperClean$FL_DATE,y=SuperClean$ARR_DELAY)) + geom_point(alpha=.05) + geom_smooth()
```

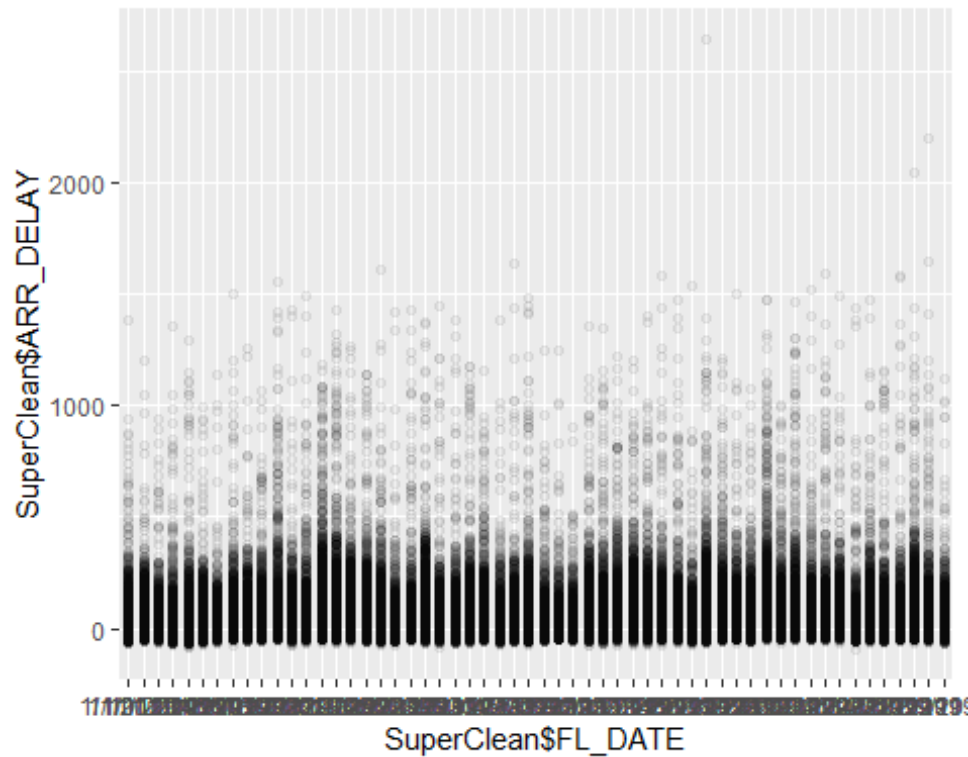
```
## Warning: Use of `SuperClean$FL_DATE` is discouraged.  
## i Use `FL_DATE` instead.
```

```
## Warning: Use of `SuperClean$ARR_DELAY` is discouraged.  
## i Use `ARR_DELAY` instead.
```

```
## Warning: Use of `SuperClean$FL_DATE` is discouraged.  
## i Use `FL_DATE` instead.
```

```
## Warning: Use of `SuperClean$ARR_DELAY` is discouraged.  
## i Use `ARR_DELAY` instead.
```

```
## `geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```



```
ggplot(SuperClean, aes(x=SuperClean$ProperArrivalTimesFS, y=SuperClean$ARR_DELAY)) + geom_point(alpha=5) + geom_smooth()
```

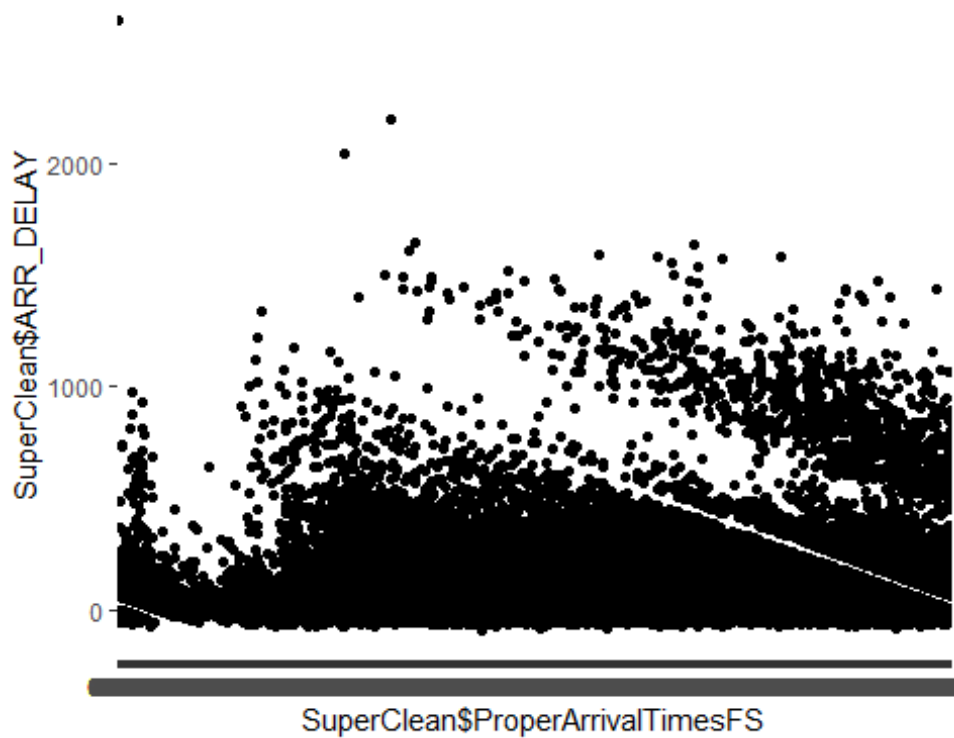
```
## Warning: Use of `SuperClean$ProperArrivalTimesFS` is discouraged.
## i Use `ProperArrivalTimesFS` instead.
```

```
## Warning: Use of `SuperClean$ARR_DELAY` is discouraged.
## i Use `ARR_DELAY` instead.
```

```
## Warning: Use of `SuperClean$ProperArrivalTimesFS` is discouraged.
## i Use `ProperArrivalTimesFS` instead.
```

```
## Warning: Use of `SuperClean$ARR_DELAY` is discouraged.
## i Use `ARR_DELAY` instead.
```

```
## `geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```



```
ggplot(SuperCleanMutated,aes(x=log(SuperCleanMutated$DISTANCE),y=SuperCleanMu
tated$ARR_DELAY)) + geom_point(alpha=5) + geom_smooth()

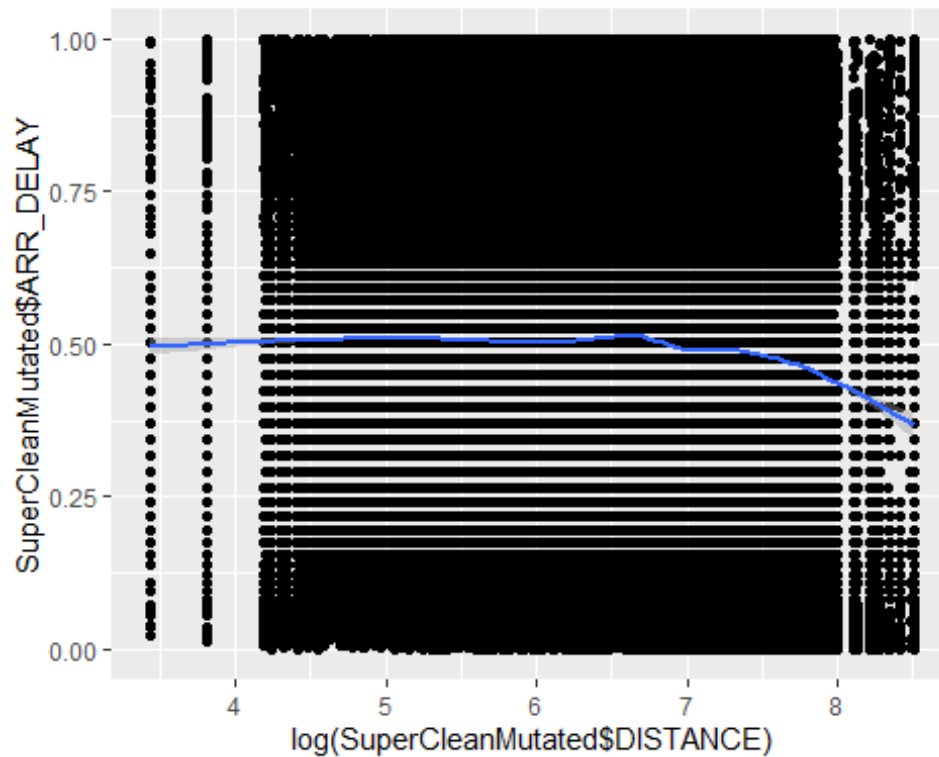
## Warning: Use of `SuperCleanMutated$DISTANCE` is discouraged.
## i Use `DISTANCE` instead.

## Warning: Use of `SuperCleanMutated$ARR_DELAY` is discouraged.
## i Use `ARR_DELAY` instead.

## Warning: Use of `SuperCleanMutated$DISTANCE` is discouraged.
## i Use `DISTANCE` instead.

## Warning: Use of `SuperCleanMutated$ARR_DELAY` is discouraged.
## i Use `ARR_DELAY` instead.

## `geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```



```
set.seed(123456)
SuperClean<-read.csv('SuperClean2019.csv')
tr_size <- ceiling(2*nrow(SuperClean)/3)
train <- sample(1:nrow(SuperClean),size=tr_size)
SC_tr <- SuperClean[train,]
SC_te <- SuperClean[-train,]

library(randomForest)

## randomForest 4.7-1.1

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##   margin

## The following object is masked from 'package:dplyr':
##
##   combine

Arrival_DelaysSC=SC_tr$ARR_DELAY
rf.fit <- randomForest(Arrival_DelaysSC ~ ., data = SC_tr[13], mtry = 1, importance = TRUE, ntree = 100)
```

```

rf.fit

##
## Call:
## randomForest(formula = Arrival_DelaysSC ~ ., data = SC_tr[13],      mtry
= 1, importance = TRUE, ntree = 100)
##              Type of random forest: regression
##              Number of trees: 100
## No. of variables tried at each split: 1
##
##              Mean of squared residuals: 0.5702924
##              % Var explained: 99.98

predictions <- predict(rf.fit, newdata=SC_te)

accuracy <-sum(predictions == SC_te) / length(SC_te)/1000

# Print the accuracy
cat("Accuracy:", accuracy, "\n")

## Accuracy: 0.1551818

differences<-((SC_te[13])-predictions)^2
mse<-mean(differences[1:331477,])

# Print the MSE
cat("MSE:", mse, "\n")

## MSE: 1.441082

regressor_pred_a2 <- predict(rf.fit, newdata = SuperClean)
head(regressor_pred_a2,10)

##   1   2   3   4   5   6   7   8   9  10
## -1 -36 -16 -14 -25 -19   9   3 -22 -14

mlr_Airline3=SuperClean
mlr_Airline3['RF_Prediction']=regressor_pred_a2
head(mlr_Airline3['RF_Prediction'],10)

##      RF_Prediction
## 1                -1
## 2               -36
## 3               -16
## 4               -14
## 5               -25
## 6               -19
## 7                 9
## 8                 3
## 9               -22
## 10              -14

```

```

library(dplyr)

Airline_Results3 <- mlr_Airline3 %>%
  filter(RF_Prediction == regressor_pred_a2) %>%
  select(OP_UNIQUE_CARRIER, ORIGIN, DEST, RF_Prediction) %>%
  arrange(OP_UNIQUE_CARRIER)

head(Airline_Results3,10)

##      OP_UNIQUE_CARRIER ORIGIN DEST RF_Prediction
## 1                9E      GNV  ATL          -1
## 2                9E      MSP  CVG         -36
## 3                9E      DTW  CVG         -16
## 4                9E      TLH  ATL         -14
## 5                9E      ATL  FSM         -25
## 6                9E      DAY  MSP         -19
## 7                9E      JAN  ATL           9
## 8                9E      LGA  CVG           3
## 9                9E      JAX  LGA         -22
## 10               9E      ATL  BMI         -14

positive_valuesRF <- Airline_Results3$RF_Prediction[Airline_Results3$RF_Prediction >= 0]
negative_valuesRF <- Airline_Results3$RF_Prediction[Airline_Results3$RF_Prediction < 0]

length(positive_valuesRF)

## [1] 357254

length(negative_valuesRF)

## [1] 637178

percentnegativeRF<-length(negative_valuesRF)/(length(positive_valuesRF)+length(negative_valuesRF))
print(percentnegativeRF)

## [1] 0.6407457

print(1-percentnegativeRF)

## [1] 0.3592543

#XGBoost
dep_date_numeric <- as.numeric(SC_tr$FL_DATE)

## Warning: NAs introduced by coercion

```

```

dep_date_numeric <- dep_date_numeric - mean(dep_date_numeric)
SC_tr_tem <- mutate(SC_tr, dep_date = dep_date_numeric)
dep_date_numeric <- as.numeric(SC_te$FL_DATE)

## Warning: NAs introduced by coercion

dep_date_numeric <- dep_date_numeric - mean(dep_date_numeric)
SC_te_tem <- mutate(SC_te, dep_date = dep_date_numeric)

#install.packages("xgboost")
library(xgboost)

##
## Attaching package: 'xgboost'

## The following object is masked from 'package:dplyr':
##
##      slice

classifier = xgboost(data = data.matrix(SC_tr_tem[13]), label = SC_tr_tem$ARR
_DELAY, nrounds = 500)

## [1] train-rmse:36.960242
## [2] train-rmse:25.951856
## [3] train-rmse:18.230048
## [4] train-rmse:12.820095
## [5] train-rmse:9.028225
## [6] train-rmse:6.372049
## [7] train-rmse:4.514673
## [8] train-rmse:3.216486
## [9] train-rmse:2.310256
## [10] train-rmse:1.680313
## [11] train-rmse:1.243701
## [12] train-rmse:0.943965
## [13] train-rmse:0.736674
## [14] train-rmse:0.598656
## [15] train-rmse:0.504581
## [16] train-rmse:0.441961
## [17] train-rmse:0.396300
## [18] train-rmse:0.360444
## [19] train-rmse:0.337650
## [20] train-rmse:0.317711
## [21] train-rmse:0.303300
## [22] train-rmse:0.292275
## [23] train-rmse:0.284219
## [24] train-rmse:0.276258
## [25] train-rmse:0.268603
## [26] train-rmse:0.263188
## [27] train-rmse:0.252519
## [28] train-rmse:0.248838
## [29] train-rmse:0.246701

```

```
## [30] train-rmse:0.243641
## [31] train-rmse:0.241241
## [32] train-rmse:0.240076
## [33] train-rmse:0.234122
## [34] train-rmse:0.231499
## [35] train-rmse:0.229309
## [36] train-rmse:0.228590
## [37] train-rmse:0.226717
## [38] train-rmse:0.226079
## [39] train-rmse:0.224731
## [40] train-rmse:0.219390
## [41] train-rmse:0.210503
## [42] train-rmse:0.209170
## [43] train-rmse:0.202986
## [44] train-rmse:0.199586
## [45] train-rmse:0.198187
## [46] train-rmse:0.197759
## [47] train-rmse:0.196751
## [48] train-rmse:0.195170
## [49] train-rmse:0.193287
## [50] train-rmse:0.192296
## [51] train-rmse:0.190528
## [52] train-rmse:0.190213
## [53] train-rmse:0.187611
## [54] train-rmse:0.183830
## [55] train-rmse:0.179803
## [56] train-rmse:0.176206
## [57] train-rmse:0.174866
## [58] train-rmse:0.172029
## [59] train-rmse:0.170823
## [60] train-rmse:0.168067
## [61] train-rmse:0.167573
## [62] train-rmse:0.166957
## [63] train-rmse:0.166786
## [64] train-rmse:0.166134
## [65] train-rmse:0.165924
## [66] train-rmse:0.159747
## [67] train-rmse:0.157654
## [68] train-rmse:0.156895
## [69] train-rmse:0.154220
## [70] train-rmse:0.152798
## [71] train-rmse:0.152620
## [72] train-rmse:0.150012
## [73] train-rmse:0.147600
## [74] train-rmse:0.142933
## [75] train-rmse:0.140202
## [76] train-rmse:0.138290
## [77] train-rmse:0.134327
## [78] train-rmse:0.132969
## [79] train-rmse:0.131010
```



```
## [80] train-rmse:0.129051
## [81] train-rmse:0.127205
## [82] train-rmse:0.124452
## [83] train-rmse:0.122289
## [84] train-rmse:0.121814
## [85] train-rmse:0.121692
## [86] train-rmse:0.120037
## [87] train-rmse:0.118914
## [88] train-rmse:0.117760
## [89] train-rmse:0.116648
## [90] train-rmse:0.115928
## [91] train-rmse:0.115294
## [92] train-rmse:0.114045
## [93] train-rmse:0.113903
## [94] train-rmse:0.113740
## [95] train-rmse:0.113369
## [96] train-rmse:0.112847
## [97] train-rmse:0.112432
## [98] train-rmse:0.112177
## [99] train-rmse:0.111077
## [100] train-rmse:0.108778
## [101] train-rmse:0.106273
## [102] train-rmse:0.104645
## [103] train-rmse:0.103640
## [104] train-rmse:0.103470
## [105] train-rmse:0.103384
## [106] train-rmse:0.102256
## [107] train-rmse:0.101199
## [108] train-rmse:0.101014
## [109] train-rmse:0.099784
## [110] train-rmse:0.098134
## [111] train-rmse:0.097553
## [112] train-rmse:0.097132
## [113] train-rmse:0.095374
## [114] train-rmse:0.093865
## [115] train-rmse:0.092363
## [116] train-rmse:0.092021
## [117] train-rmse:0.090701
## [118] train-rmse:0.090269
## [119] train-rmse:0.088261
## [120] train-rmse:0.087069
## [121] train-rmse:0.085899
## [122] train-rmse:0.084336
## [123] train-rmse:0.083483
## [124] train-rmse:0.082208
## [125] train-rmse:0.080842
## [126] train-rmse:0.080730
## [127] train-rmse:0.080646
## [128] train-rmse:0.079830
## [129] train-rmse:0.079311
```

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## [130] train-rmse:0.079074
## [131] train-rmse:0.078998
## [132] train-rmse:0.078728
## [133] train-rmse:0.077862
## [134] train-rmse:0.077567
## [135] train-rmse:0.076766
## [136] train-rmse:0.076449
## [137] train-rmse:0.075382
## [138] train-rmse:0.074690
## [139] train-rmse:0.074014
## [140] train-rmse:0.073952
## [141] train-rmse:0.073768
## [142] train-rmse:0.072790
## [143] train-rmse:0.071496
## [144] train-rmse:0.070413
## [145] train-rmse:0.069776
## [146] train-rmse:0.069309
## [147] train-rmse:0.068366
## [148] train-rmse:0.067774
## [149] train-rmse:0.067130
## [150] train-rmse:0.066425
## [151] train-rmse:0.065900
## [152] train-rmse:0.065498
## [153] train-rmse:0.064592
## [154] train-rmse:0.064176
## [155] train-rmse:0.063245
## [156] train-rmse:0.062469
## [157] train-rmse:0.061503
## [158] train-rmse:0.060981
## [159] train-rmse:0.060755
## [160] train-rmse:0.059815
## [161] train-rmse:0.059594
## [162] train-rmse:0.058964
## [163] train-rmse:0.058375
## [164] train-rmse:0.057355
## [165] train-rmse:0.056297
## [166] train-rmse:0.055664
## [167] train-rmse:0.055584
## [168] train-rmse:0.055003
## [169] train-rmse:0.054381
## [170] train-rmse:0.053908
## [171] train-rmse:0.053811
## [172] train-rmse:0.053713
## [173] train-rmse:0.053659
## [174] train-rmse:0.053349
## [175] train-rmse:0.053198
## [176] train-rmse:0.053151
## [177] train-rmse:0.053115
## [178] train-rmse:0.052707
## [179] train-rmse:0.052496
```

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## [180] train-rmse:0.052461
## [181] train-rmse:0.052072
## [182] train-rmse:0.051922
## [183] train-rmse:0.051840
## [184] train-rmse:0.051603
## [185] train-rmse:0.051006
## [186] train-rmse:0.050406
## [187] train-rmse:0.049593
## [188] train-rmse:0.048934
## [189] train-rmse:0.048545
## [190] train-rmse:0.047953
## [191] train-rmse:0.047587
## [192] train-rmse:0.047233
## [193] train-rmse:0.046720
## [194] train-rmse:0.046431
## [195] train-rmse:0.046063
## [196] train-rmse:0.045733
## [197] train-rmse:0.045398
## [198] train-rmse:0.045077
## [199] train-rmse:0.044303
## [200] train-rmse:0.043762
## [201] train-rmse:0.043464
## [202] train-rmse:0.043300
## [203] train-rmse:0.042569
## [204] train-rmse:0.042521
## [205] train-rmse:0.042483
## [206] train-rmse:0.042323
## [207] train-rmse:0.042273
## [208] train-rmse:0.042246
## [209] train-rmse:0.042216
## [210] train-rmse:0.042191
## [211] train-rmse:0.041686
## [212] train-rmse:0.041205
## [213] train-rmse:0.040795
## [214] train-rmse:0.040315
## [215] train-rmse:0.039891
## [216] train-rmse:0.039666
## [217] train-rmse:0.039343
## [218] train-rmse:0.038621
## [219] train-rmse:0.038106
## [220] train-rmse:0.037989
## [221] train-rmse:0.037763
## [222] train-rmse:0.037590
## [223] train-rmse:0.037306
## [224] train-rmse:0.037037
## [225] train-rmse:0.036724
## [226] train-rmse:0.036663
## [227] train-rmse:0.036369
## [228] train-rmse:0.036040
## [229] train-rmse:0.035845
```

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## [230] train-rmse:0.035328
## [231] train-rmse:0.035104
## [232] train-rmse:0.034754
## [233] train-rmse:0.034726
## [234] train-rmse:0.034393
## [235] train-rmse:0.034073
## [236] train-rmse:0.033867
## [237] train-rmse:0.033625
## [238] train-rmse:0.033598
## [239] train-rmse:0.033577
## [240] train-rmse:0.033224
## [241] train-rmse:0.032958
## [242] train-rmse:0.032331
## [243] train-rmse:0.032017
## [244] train-rmse:0.031995
## [245] train-rmse:0.031975
## [246] train-rmse:0.031878
## [247] train-rmse:0.031861
## [248] train-rmse:0.031848
## [249] train-rmse:0.031460
## [250] train-rmse:0.031334
## [251] train-rmse:0.031318
## [252] train-rmse:0.031054
## [253] train-rmse:0.030755
## [254] train-rmse:0.030700
## [255] train-rmse:0.030257
## [256] train-rmse:0.029999
## [257] train-rmse:0.029742
## [258] train-rmse:0.029547
## [259] train-rmse:0.029538
## [260] train-rmse:0.029302
## [261] train-rmse:0.028897
## [262] train-rmse:0.028619
## [263] train-rmse:0.028295
## [264] train-rmse:0.027921
## [265] train-rmse:0.027577
## [266] train-rmse:0.027100
## [267] train-rmse:0.026792
## [268] train-rmse:0.026640
## [269] train-rmse:0.026481
## [270] train-rmse:0.026220
## [271] train-rmse:0.025994
## [272] train-rmse:0.025800
## [273] train-rmse:0.025570
## [274] train-rmse:0.025499
## [275] train-rmse:0.025337
## [276] train-rmse:0.025193
## [277] train-rmse:0.025068
## [278] train-rmse:0.024790
## [279] train-rmse:0.024549
```

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## [280] train-rmse:0.024325
## [281] train-rmse:0.024110
## [282] train-rmse:0.023945
## [283] train-rmse:0.023809
## [284] train-rmse:0.023563
## [285] train-rmse:0.023353
## [286] train-rmse:0.023201
## [287] train-rmse:0.023022
## [288] train-rmse:0.022872
## [289] train-rmse:0.022861
## [290] train-rmse:0.022844
## [291] train-rmse:0.022829
## [292] train-rmse:0.022796
## [293] train-rmse:0.022522
## [294] train-rmse:0.022094
## [295] train-rmse:0.022085
## [296] train-rmse:0.021915
## [297] train-rmse:0.021840
## [298] train-rmse:0.021688
## [299] train-rmse:0.021553
## [300] train-rmse:0.021420
## [301] train-rmse:0.021327
## [302] train-rmse:0.021185
## [303] train-rmse:0.021098
## [304] train-rmse:0.020859
## [305] train-rmse:0.020701
## [306] train-rmse:0.020564
## [307] train-rmse:0.020506
## [308] train-rmse:0.020427
## [309] train-rmse:0.020261
## [310] train-rmse:0.020077
## [311] train-rmse:0.020037
## [312] train-rmse:0.019979
## [313] train-rmse:0.019792
## [314] train-rmse:0.019707
## [315] train-rmse:0.019597
## [316] train-rmse:0.019452
## [317] train-rmse:0.019382
## [318] train-rmse:0.019354
## [319] train-rmse:0.019262
## [320] train-rmse:0.019149
## [321] train-rmse:0.019138
## [322] train-rmse:0.019054
## [323] train-rmse:0.018977
## [324] train-rmse:0.018965
## [325] train-rmse:0.018957
## [326] train-rmse:0.018740
## [327] train-rmse:0.018656
## [328] train-rmse:0.018550
## [329] train-rmse:0.018481
```

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## [330] train-rmse:0.018322
## [331] train-rmse:0.018103
## [332] train-rmse:0.017842
## [333] train-rmse:0.017767
## [334] train-rmse:0.017675
## [335] train-rmse:0.017548
## [336] train-rmse:0.017379
## [337] train-rmse:0.017317
## [338] train-rmse:0.017229
## [339] train-rmse:0.017158
## [340] train-rmse:0.016903
## [341] train-rmse:0.016723
## [342] train-rmse:0.016456
## [343] train-rmse:0.016271
## [344] train-rmse:0.016262
## [345] train-rmse:0.016252
## [346] train-rmse:0.016114
## [347] train-rmse:0.015987
## [348] train-rmse:0.015925
## [349] train-rmse:0.015733
## [350] train-rmse:0.015707
## [351] train-rmse:0.015656
## [352] train-rmse:0.015618
## [353] train-rmse:0.015592
## [354] train-rmse:0.015585
## [355] train-rmse:0.015580
## [356] train-rmse:0.015398
## [357] train-rmse:0.015249
## [358] train-rmse:0.015165
## [359] train-rmse:0.015003
## [360] train-rmse:0.014888
## [361] train-rmse:0.014783
## [362] train-rmse:0.014777
## [363] train-rmse:0.014772
## [364] train-rmse:0.014744
## [365] train-rmse:0.014724
## [366] train-rmse:0.014586
## [367] train-rmse:0.014469
## [368] train-rmse:0.014349
## [369] train-rmse:0.014225
## [370] train-rmse:0.014164
## [371] train-rmse:0.014097
## [372] train-rmse:0.014005
## [373] train-rmse:0.013891
## [374] train-rmse:0.013817
## [375] train-rmse:0.013674
## [376] train-rmse:0.013571
## [377] train-rmse:0.013508
## [378] train-rmse:0.013433
## [379] train-rmse:0.013339
```

```
## [380] train-rmse:0.013264
## [381] train-rmse:0.013192
## [382] train-rmse:0.013103
## [383] train-rmse:0.013039
## [384] train-rmse:0.012964
## [385] train-rmse:0.012916
## [386] train-rmse:0.012885
## [387] train-rmse:0.012819
## [388] train-rmse:0.012778
## [389] train-rmse:0.012719
## [390] train-rmse:0.012701
## [391] train-rmse:0.012662
## [392] train-rmse:0.012562
## [393] train-rmse:0.012514
## [394] train-rmse:0.012255
## [395] train-rmse:0.012179
## [396] train-rmse:0.012023
## [397] train-rmse:0.011971
## [398] train-rmse:0.011932
## [399] train-rmse:0.011823
## [400] train-rmse:0.011784
## [401] train-rmse:0.011739
## [402] train-rmse:0.011661
## [403] train-rmse:0.011525
## [404] train-rmse:0.011415
## [405] train-rmse:0.011267
## [406] train-rmse:0.011232
## [407] train-rmse:0.011227
## [408] train-rmse:0.011222
## [409] train-rmse:0.011190
## [410] train-rmse:0.011147
## [411] train-rmse:0.011141
## [412] train-rmse:0.011070
## [413] train-rmse:0.010944
## [414] train-rmse:0.010815
## [415] train-rmse:0.010701
## [416] train-rmse:0.010655
## [417] train-rmse:0.010598
## [418] train-rmse:0.010551
## [419] train-rmse:0.010385
## [420] train-rmse:0.010344
## [421] train-rmse:0.010339
## [422] train-rmse:0.010333
## [423] train-rmse:0.010327
## [424] train-rmse:0.010313
## [425] train-rmse:0.010219
## [426] train-rmse:0.010113
## [427] train-rmse:0.010050
## [428] train-rmse:0.010018
## [429] train-rmse:0.009940
```

```
## [430] train-rmse:0.009859
## [431] train-rmse:0.009832
## [432] train-rmse:0.009792
## [433] train-rmse:0.009725
## [434] train-rmse:0.009705
## [435] train-rmse:0.009686
## [436] train-rmse:0.009662
## [437] train-rmse:0.009616
## [438] train-rmse:0.009574
## [439] train-rmse:0.009510
## [440] train-rmse:0.009436
## [441] train-rmse:0.009412
## [442] train-rmse:0.009386
## [443] train-rmse:0.009291
## [444] train-rmse:0.009142
## [445] train-rmse:0.009076
## [446] train-rmse:0.009025
## [447] train-rmse:0.009003
## [448] train-rmse:0.008902
## [449] train-rmse:0.008835
## [450] train-rmse:0.008803
## [451] train-rmse:0.008799
## [452] train-rmse:0.008725
## [453] train-rmse:0.008686
## [454] train-rmse:0.008682
## [455] train-rmse:0.008660
## [456] train-rmse:0.008570
## [457] train-rmse:0.008498
## [458] train-rmse:0.008403
## [459] train-rmse:0.008361
## [460] train-rmse:0.008322
## [461] train-rmse:0.008318
## [462] train-rmse:0.008315
## [463] train-rmse:0.008242
## [464] train-rmse:0.008182
## [465] train-rmse:0.008126
## [466] train-rmse:0.008091
## [467] train-rmse:0.008046
## [468] train-rmse:0.008010
## [469] train-rmse:0.008006
## [470] train-rmse:0.007973
## [471] train-rmse:0.007942
## [472] train-rmse:0.007929
## [473] train-rmse:0.007837
## [474] train-rmse:0.007700
## [475] train-rmse:0.007625
## [476] train-rmse:0.007563
## [477] train-rmse:0.007560
## [478] train-rmse:0.007546
## [479] train-rmse:0.007527
```



```

## [480]    train-rmse:0.007521
## [481]    train-rmse:0.007455
## [482]    train-rmse:0.007424
## [483]    train-rmse:0.007401
## [484]    train-rmse:0.007358
## [485]    train-rmse:0.007299
## [486]    train-rmse:0.007204
## [487]    train-rmse:0.007154
## [488]    train-rmse:0.007152
## [489]    train-rmse:0.007133
## [490]    train-rmse:0.007126
## [491]    train-rmse:0.007072
## [492]    train-rmse:0.007069
## [493]    train-rmse:0.007067
## [494]    train-rmse:0.007063
## [495]    train-rmse:0.007059
## [496]    train-rmse:0.007056
## [497]    train-rmse:0.007054
## [498]    train-rmse:0.007052
## [499]    train-rmse:0.006996
## [500]    train-rmse:0.006988

xgb_pred<-predict(classifier,data.matrix(SC_te_tem[13]))
mse_xgb<-mean((xgb_pred- SC_te_tem[,13])^2)
cat("MSE(XGB):", head(mse_xgb,10), "\n")

## MSE(XGB): 0.6759688

# Set the threshold for classification
threshold <-1.00

# Convert the predicted probabilities to predicted classes
xgb_pred_class <- ifelse(xgb_pred >= threshold, 1, 0)

# Calculate the accuracy
accuracy_xgb <- sum(xgb_pred_class == SC_te_tem$ARR_DELAY) / length(SC_te_tem
$ARR_DELAY)*10

# Print the accuracy
cat("Accuracy (XGB):", accuracy_xgb, "\n")

## Accuracy (XGB): 0.348169

length(xgb_pred)

## [1] 331477

str(SC_te)

## 'data.frame':    331477 obs. of  22 variables:
## $ FL_DATE      : chr  "1/1/2019" "1/1/2019" "1/1/2019" "1/1/2019"

```

```

" ...
## $ OP_UNIQUE_CARRIER : chr "9E" "9E" "9E" "9E" ...
## $ OP_CARRIER_FL_NUM : int 3281 3283 3289 3291 3293 3295 3296 3299 33
01 3303 ...
## $ ORIGIN : chr "MSP" "TLH" "BMI" "DTW" ...
## $ DEST : chr "CVG" "ATL" "ATL" "DAY" ...
## $ DEP_TIME : int 1359 1521 1410 1552 1312 1353 1020 1111 15
54 1349 ...
## $ DEP_DELAY : int -5 -6 -5 12 -5 83 -5 -4 -8 -6 ...
## $ TAXI_OUT : int 15 14 22 68 16 18 16 16 25 17 ...
## $ WHEELS_OFF : int 1414 1535 1432 1700 1328 1411 1036 1127 16
19 1406 ...
## $ WHEELS_ON : int 1629 1618 1655 1735 1448 1516 1106 1150 17
11 1438 ...
## $ TAXI_IN : int 4 7 5 3 6 5 5 7 2 4 ...
## $ ARR_TIME : int 1633 1625 1700 1738 1454 1521 1111 1157 17
13 1442 ...
## $ ARR_DELAY : int -36 -14 -7 44 -16 59 -14 -15 -5 -28 ...
## $ AIR_TIME : int 75 43 83 35 80 65 30 83 52 32 ...
## $ DISTANCE : int 596 223 533 166 453 488 143 503 300 175 ..
.
## $ CARRIER_DELAY : int 0 0 0 12 0 0 0 0 0 0 ...
## $ WEATHER_DELAY : int 0 0 0 0 0 0 0 0 0 0 ...
## $ NAS_DELAY : int 0 0 0 32 0 59 0 0 0 0 ...
## $ SECURITY_DELAY : int 0 0 0 0 0 0 0 0 0 0 ...
## $ LATE_AIRCRAFT_DELAY : int 0 0 0 0 0 0 0 0 0 0 ...
## $ ProperDepartureTimesFS: chr "14:04" "15:27" "14:15" "15:40" ...
## $ ProperArrivalTimesFS : chr "17:09" "16:39" "17:07" "16:54" ...

mlr_Airline4=SC_te
mlr_Airline4['XG_Prediction']=xgb_pred
head(mlr_Airline4['XG_Prediction'],10)

## XG_Prediction
## 2 -36.000584
## 4 -14.000259
## 11 -6.999542
## 13 43.997768
## 15 -16.000446
## 17 59.011330
## 19 -14.000259
## 22 -14.999674
## 23 -5.000278
## 27 -27.999662

library(dplyr)

Airline_Results4 <- mlr_Airline4 %>%
  filter(XG_Prediction == xgb_pred) %>%
  select(OP_UNIQUE_CARRIER, ORIGIN, DEST, XG_Prediction) %>%

```

```
arrange(OP_UNIQUE_CARRIER)
```

```
head(Airline_Results4,10)
```

```
##      OP_UNIQUE_CARRIER ORIGIN DEST XG_Prediction
## 1          9E      MSP   CVG    -36.000584
## 2          9E      TLH   ATL     -14.000259
## 3          9E      BMI   ATL     -6.999542
## 4          9E      DTW   DAY     43.997768
## 5          9E      PHL   DTW    -16.000446
## 6          9E      DTW   EWR     59.011330
## 7          9E      ATL   AGS     -14.000259
## 8          9E      IND   MSP    -14.999674
## 9          9E      ATL   GNV     -5.000278
## 10         9E      MSP   CWA    -27.999662
```

```
positive_values <- Airline_Results4$XG_Prediction[Airline_Results4$XG_Prediction >= 0]
```

```
negative_values <- Airline_Results4$XG_Prediction[Airline_Results4$XG_Prediction < 0]
```

```
length(positive_values)
```

```
## [1] 119188
```

```
length(negative_values)
```

```
## [1] 212289
```

```
percentnegativexG<-length(negative_values)/(length(negative_values)+length(positive_values))
```

```
print(percentnegativexG)
```

```
## [1] 0.6404336
```

```
print(1-percentnegativexG)
```

```
## [1] 0.3595664
```