final_project_draft

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Introduction

On Time Performance analysis of an airline network - This is an important metric for the airline which are delayed while the aircraft arrives at the gate. There are multiple reasons which contribute to the variation in OTP. An analysis of the OTP data breaking it down into its individual components namely different delay and historical delays can provide insights into how the OTP for an airline can be managed by operational/process changes. The Department of Transport releases the flight level, On Time Performance data. This dataset also has various other factors which affect the Arrival Delay of a flight. An exploratory analysis of this data with the Arrival Delay as the response variable analyzed against different dimensions provided in the dataset can reveal several insights to improve the OTP of an Airline.

What

As my Final Project, I am planning to use a subset of OTP data to perform analysis of delays on actual file arrivals focusing on one particular Station and Airline. Since airline operations are very complex, the arrival delays itself can be due to varying factors, like weather delay, carrier delays, security delays, Late aircraft delay. . . etc or any combinations of any of these in general. My focus is only on 2 types of delays so that I can minimize the complexities in data structures and limit any repeating processes or steps, and rather focus on how to explore data and do analysis/inference with few variables. Hence I will be considering only 5 years data ranging from year 2014 till 2018 and two types of delays "Weather Delays" and "Carrier Delays"

Why

I thought airline is an interesting business with lot of complex operation/data and business itself is most of us are familiar with. Also, with the time constraint we have, there were few sites like given below which gives a head start for this project. Kaggle and DOT On-Time_performance

This data is presented as yearly file in csv format, I have to merge different years data using dply bind command to append rows to build one master file for implementing different plots in base R as well as ggplot.

How

Use RMarkdown and explore R functions by utilizing some of the topics learned in the class. The following are steps which will be followed as part of the project

- Load data into R Markdown using R chunks.
- Merge Data using dplyr.

- Filter/melt/massage data using Tidyverse.
- Use sampling strategy for identifying sample observations.
- Use Stats function to determine mean, median, IQR,...
- Regression - Find any co-relation between total flights arriving at a particular airport and delays to identify if it's the airport operational/capacity issue or not.
- Cloud hosted data and R Markdown interface. Demonstrate on how to pull data from AWS S3 buckets than loading from local machine.

Body

This project perform analysis of flight arrival delays focusing on one particular Station and Airline. This analysis can be used to answer some of the questions on airline delays like how often a particular delay happens and if the process/schedule/operations can be enhanced or optimized to minimize delays and adjust future schedules.

Packages Required

```
library(knitr) ##for printing tables in R Markdown
library(dplyr) ##for data munging
library(ggplot2) ## for charts
library(infer) ## for rep_sample_n used for samplings
```

Below code loads data into R. Since this is a large data set, sampling/manipualting on all the observations is throwing memory error in my machine. So for ease of processing, I am considering a subset of data operated by Delta Air Lines(OP_CARRIER ==‘DL’).

```
library(readr)
flight.data.y2014 <- read_csv("Data/2014.csv") %>%
  filter(OP_CARRIER == 'DL') %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY, WEATHER_DELAY,
           CARRIER_DELAY, AIR_TIME, CRS_ARR_TIME))
# head(flight.data.y2014)

flight.data.y2015 <- read_csv("Data/2015.csv") %>%
  filter(OP_CARRIER == 'DL') %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY, WEATHER_DELAY,
           CARRIER_DELAY, AIR_TIME, CRS_ARR_TIME))
# head(flight.data.y2015)

flight.data.y2016 <- read_csv("Data/2016.csv") %>%
  filter(OP_CARRIER == 'DL') %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY, WEATHER_DELAY,
           CARRIER_DELAY, AIR_TIME, CRS_ARR_TIME))
# head(flight.data.y2016)

flight.data.y2017 <- read_csv("Data/2017.csv") %>%
  filter(OP_CARRIER == 'DL') %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY, WEATHER_DELAY,
           CARRIER_DELAY, AIR_TIME, CRS_ARR_TIME))
```

```
# head(flight.data.y2017)

flight.data.y2018 <- read_csv("Data/2018.csv") %>%
  filter(OP_CARRIER == 'DL') %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY, WEATHER_DELAY,
           CARRIER_DELAY, AIR_TIME, CRS_ARR_TIME))
  # head(flight.data.y2018)
```

As an alternate approach on loading data set, I used AWS S3 and have the following code to get data from AWS instead of loading from local machine. Most of the times, data will reside in a different system(cloud, different servers, mainframe, datawarehouse, operational data, streams...) so I thought of using an additional approach approach than downloading to local machine. Here i am considering a way to connect R markdown to AWS using package aws.s3 - For this approach first we need to install package 'aws.s3' using install.package

Below R chunk which I tested successfully, will access data from s3. I am commenting out this code since I have to mask the Secret Access Key before uploading to a public repo(github) else AWS will attach an "AWSCompromisedKeyQuarantineV2" policy to my AWS account to protect account key exposure...–>

library("aws.s3")

Sys.setenv(

"AWS_ACCESS_KEY_ID" = "***************", # access key id masked.

"AWS_SECRET_ACCESS_KEY" = "***************************", # secret access key masked.

"AWS_DEFAULT_REGION" = "us-east-1"

)

bucketlist(bucket='seis631-final-project')

s3.2014 <- s3read_using(FUN = read.csv, bucket = "seis631-final-project", object = "2014.csv")

head(s3.2014)

dim(s3.2014)

Merge data sets and convert all missing values in Delays to 0

```
flight.data.y2014.y2018 <-
  dplyr::bind_rows(flight.data.y2014,
                   flight.data.y2015,
                   flight.data.y2016,
                   flight.data.y2017,
                   flight.data.y2018,
                   )
dim(flight.data.y2014.y2018)
```

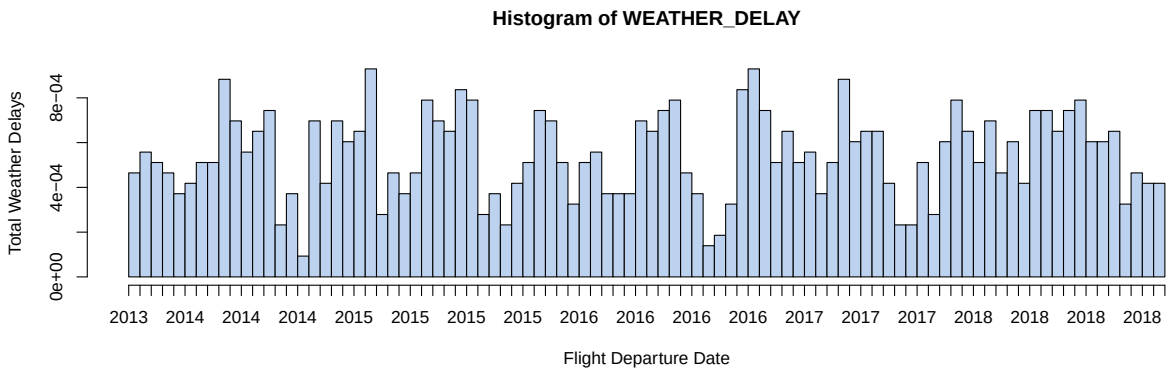
```
## [1] 4471845       6
```

```
flight.data.y2014.y2018$WEATHER_DELAY <-
  flight.data.y2014.y2018$WEATHER_DELAY %>%
  replace(is.na(.), 0)

flight.data.y2014.y2018$CARRIER_DELAY <-
  flight.data.y2014.y2018$CARRIER_DELAY %>%
```

```
  replace(is.na(.), 0)

flight.data.y2014.y2018$AIR_TIME <-
  flight.data.y2014.y2018$AIR_TIME %>%
  replace(is.na(.), 0)
```

Plot delays from the given data set. Just giving weather dealy here to show ploting. Different combinations between delays(like carrier delays and weather dealys) is given in later sections.

```
flight.data.y2014.y2018.wd <- flight.data.y2014.y2018 %>%
  filter(WEATHER_DELAY > 0) %>%
  filter(DEST == 'MSP') %>%
  group_by(FL_DATE) %>%
  summarize(countDelay = n())

hist(flight.data.y2014.y2018.wd$FL_DATE,
    flight.data.y2014.y2018.wd$countDelay,
     main = paste("Histogram of WEATHER_DELAY" ),
     xlab = 'Flight Departure Date',
     ylab = 'Total Weather Delays',
     breaks = 100,
     col='lightsteelblue2')
```

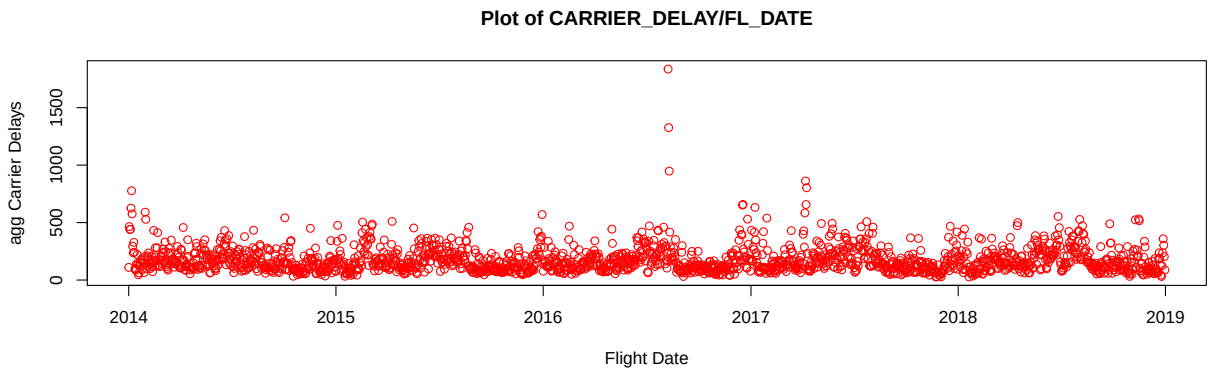



```
summary(flight.data.y2014.y2018.wd)
```

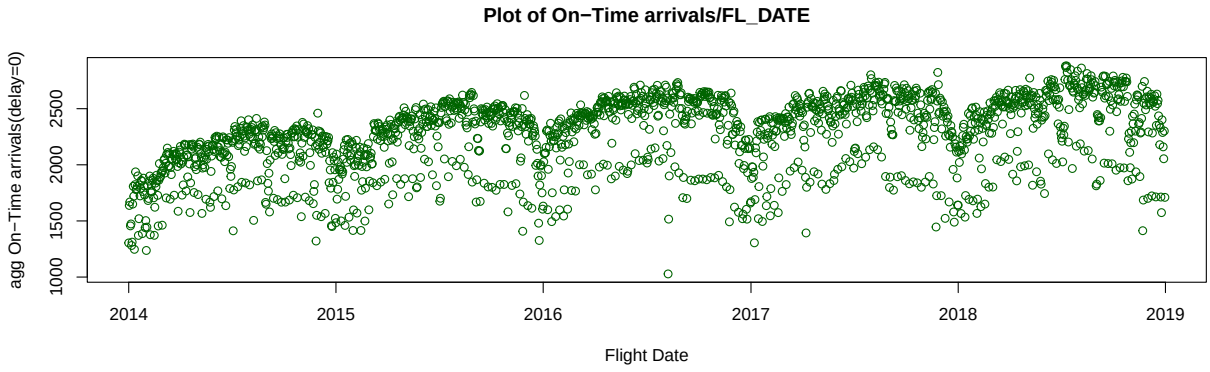
```
##     FL_DATE             countDelay
##  Min.   :2014-01-01   Min.   : 1.000
##  1st Qu.:2015-04-08   1st Qu.: 1.000
##  Median :2016-07-18   Median : 2.000
##  Mean   :2016-07-09   Mean   : 2.812
##  3rd Qu.:2017-10-27   3rd Qu.: 3.000
##  Max.   :2018-12-31   Max.   :24.000
```

Below I am just doing Base R plot for Carrier Delays and no-delay. Over the years the performance on on-time arrival has improved. But we cannot infer too much on this given data since it can be due to more flights added into the schedule.

```
flight.data.y2014.y2018$year <- format(flight.data.y2014.y2018$FL_DATE, "%Y")

agg_counts <- aggregate(cbind(countDelay=CARRIER_DELAY>0,
                              countOntime=CARRIER_DELAY==0) ~ FL_DATE,
                        data = flight.data.y2014.y2018, FUN = sum,
                        na.rm = TRUE)

plot(agg_counts$FL_DATE,
      main = paste("Plot of CARRIER_DELAY/FL_DATE" ),
      xlab = 'Flight Date',
      ylab = 'agg Carrier Delays',
      agg_counts$countDelay, col = "red")
```




```
plot(agg_counts$FL_DATE,
      main = paste('Plot of On-Time arrivals/FL_DATE'),
      xlab = 'Flight Date',
      ylab = 'agg On-Time arrivals(delay=0)',
      agg_counts$countOntime, col = "darkgreen")
```



Using the given data set, let's do samplings for further analysis.

```
simple.sampling <- dplyr::sample_n(flight.data.y2014.y2018, 1000, replace=FALSE)
# View(simple.sampling)
head(simple.sampling)
```

```
## # A tibble: 6 x 7
##   FL_DATE    DEST  CARRIER_DELAY WEATHER_DELAY AIR_TIME CRS_ARR_TIME year
##   <date>     <chr>         <dbl>         <dbl>    <dbl>        <dbl> <chr>
## 1 2017-03-19 MKE               0             0       99         1756 2017
## 2 2017-03-01 ATL               0             0       44         1702 2017
## 3 2018-11-09 MSP               0             0      131         1635 2018
## 4 2018-04-02 ATL               0             0       42          942 2018
## 5 2015-12-04 SEA               0             0      248         1045 2015
## 6 2017-12-07 SEA               0             0      327         1906 2017
```

```
strata.MSP <- flight.data.y2014.y2018[flight.data.y2014.y2018$DEST %in% 'MSP',]
strata.ATL <- flight.data.y2014.y2018[flight.data.y2014.y2018$DEST %in% 'ATL',]
strata.JFL <- flight.data.y2014.y2018[flight.data.y2014.y2018$DEST %in% 'JFK',]
strata.LAX <- flight.data.y2014.y2018[flight.data.y2014.y2018$DEST %in% 'LAX',]

stratified.sampling <- dplyr::sample_n((strata.MSP), 100000, replace=FALSE)
head(stratified.sampling)
```

```
## # A tibble: 6 x 7
##   FL_DATE    DEST  CARRIER_DELAY WEATHER_DELAY AIR_TIME CRS_ARR_TIME year
##   <date>     <chr>         <dbl>         <dbl>    <dbl>        <dbl> <chr>
## 1 2014-02-04 MSP               0             0       49         1633 2014
## 2 2015-06-13 MSP               0             0      165         1031 2015
## 3 2018-09-21 MSP               0             0       65          749 2018
## 4 2015-01-24 MSP               0             0      124         1640 2015
## 5 2017-11-04 MSP               0             0      118          916 2017
## 6 2018-08-09 MSP               0             0      105         1839 2018
```

```
#randomly choose 10 groups out of the n
clusters <-
  sample(unique(flight.data.y2014.y2018$DEST), size=10, replace=FALSE)

#define sample as all observations belonging to one of the 10 airports
clustered_by_airport <-
  flight.data.y2014.y2018[flight.data.y2014.y2018$DEST %in% clusters, ]

#view how many observations came from each airport codes
table(clustered_by_airport$DEST)
```

```
##
##     ABQ     ATL     AVP     BHM     FAY     LAS     MSO     PHX     PVD     RNO
##    6843 1204159    1333   15962    2223   62948    3114   37655    7895    4396
```

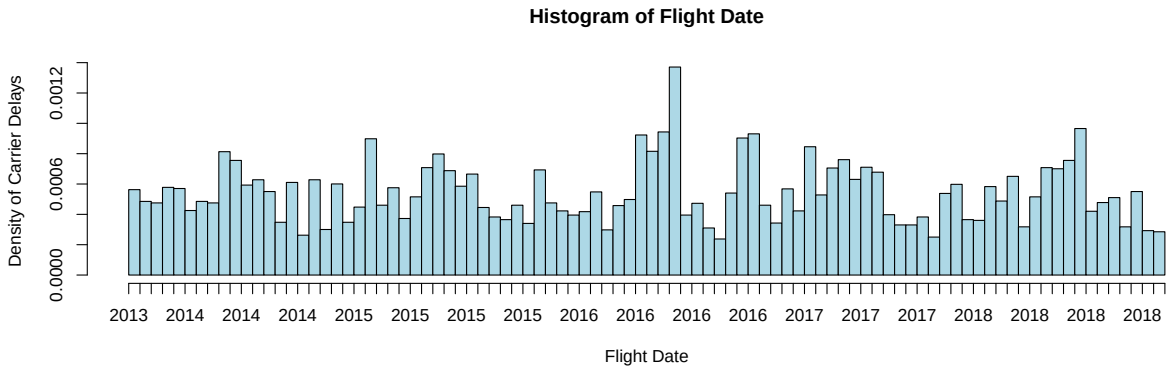
```
head(clustered_by_airport)
```

```
## # A tibble: 6 x 7
##   FL_DATE    DEST  CARRIER_DELAY WEATHER_DELAY AIR_TIME CRS_ARR_TIME year
##   <date>     <chr>         <dbl>         <dbl>    <dbl>        <dbl> <chr>
## 1 2014-01-01 ATL               0             0      171         1521 2014
## 2 2014-01-01 ATL               0             0      203         1844 2014
## 3 2014-01-01 ATL               0             0       61         1500 2014
## 4 2014-01-01 ATL               0             0       48         1425 2014
```

```
## 5 2014-01-01 ATL               0             0       84         1830 2014
## 6 2014-01-01 ATL               0             0       62         1603 2014
```

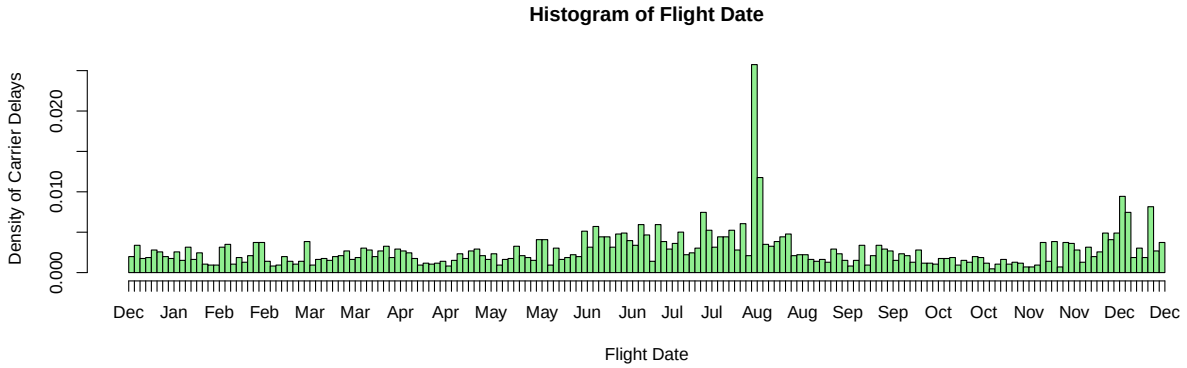
Below I am ploting Carrier delay using one of the strata identified in prior step

```
delay_by_airport <-
  strata.MSP %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY)) %>%
  filter(CARRIER_DELAY > 0)

hist(delay_by_airport$FL_DATE,
    delay_by_airport$CARRIER_DELAY,
    breaks = 100,
    xlab = 'Flight Date',
    ylab = 'Density of Carrier Delays',
    col = "lightblue")
```



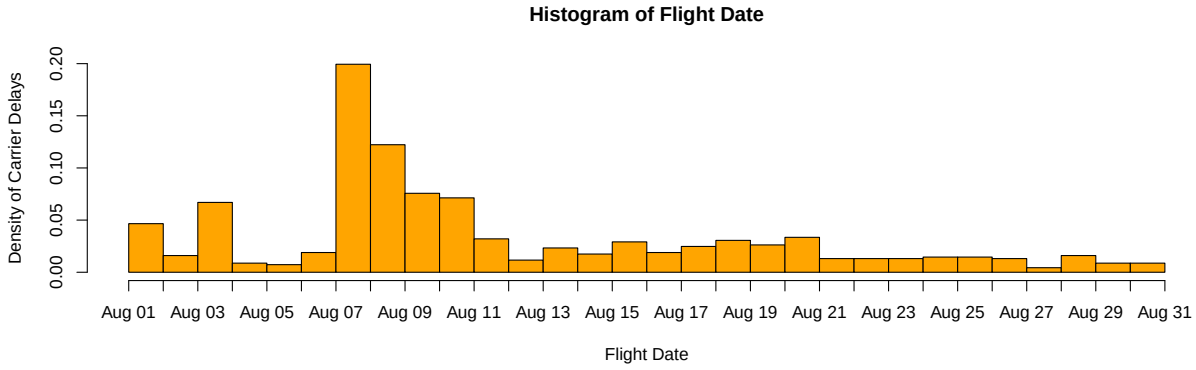
Identify the surge in 2016 from above plot. Drill down to months in year 2016

```
delay_by_airport_2016 <-
  delay_by_airport

delay_by_airport_2016$YEAR <-
  format(delay_by_airport$FL_DATE, "%Y")

delay_by_airport_2016 <-
  delay_by_airport_2016 %>%
  filter(YEAR == '2016')

delay_by_airport_2016$MONTH <-
  format(delay_by_airport_2016$FL_DATE, "%m")

hist(delay_by_airport_2016$FL_DATE,
      delay_by_airport_2016$CARRIER_DELAY,
      breaks =200,
      xlab = 'Flight Date',
      ylab = 'Density of Carrier Delays',
      col = "lightgreen")
```



From the above plotting we can come to conclusion that August2016 has an increase in carrier delay. The following code will plot by Days in Aug2016 to determine which day have an surge in Carrier Delays.

```
delay_by_airport_2016_AUG <-
  delay_by_airport_2016

delay_by_airport_2016_AUG <-
  delay_by_airport_2016_AUG %>%
  filter(MONTH == '08')

delay_by_airport_2016_AUG$DAY <-
  format(delay_by_airport_2016_AUG$FL_DATE,
         "%d")

hist(delay_by_airport_2016_AUG$FL_DATE,
      delay_by_airport_2016_AUG$CARRIER_DELAY,
      xlab = 'Flight Date',
      ylab = 'Density of Carrier Delays',
      breaks =40,
      col = "orange")
```




```
summary(delay_by_airport_2016_AUG$CARRIER_DELAY)
```

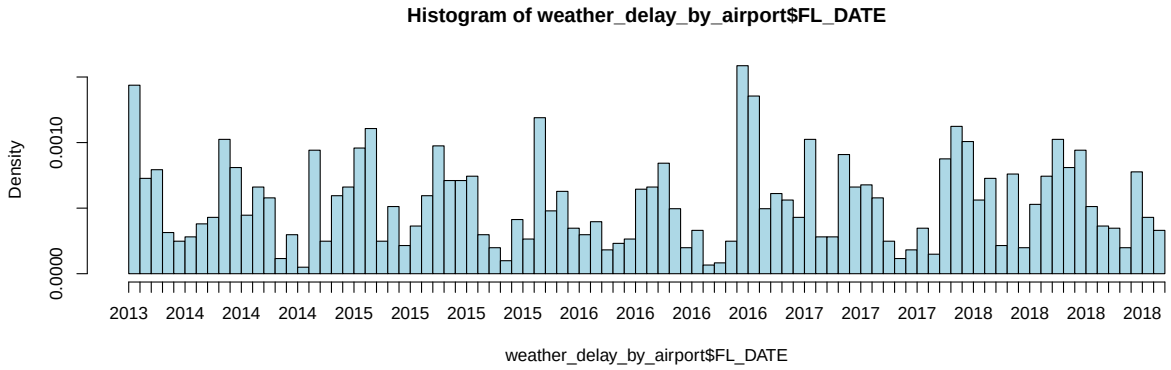
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    9.00   22.00   70.74   76.00 1167.00
```

From the news archives from that day we can conclude that there was a system outage which caused massive delay/cancellations and the plotting above matches with that conclusion. Delta System Outage - Aug2016

WEATHER DELAY.

Let's do similar analysis on weather delay and see which month/day have most weather delays.

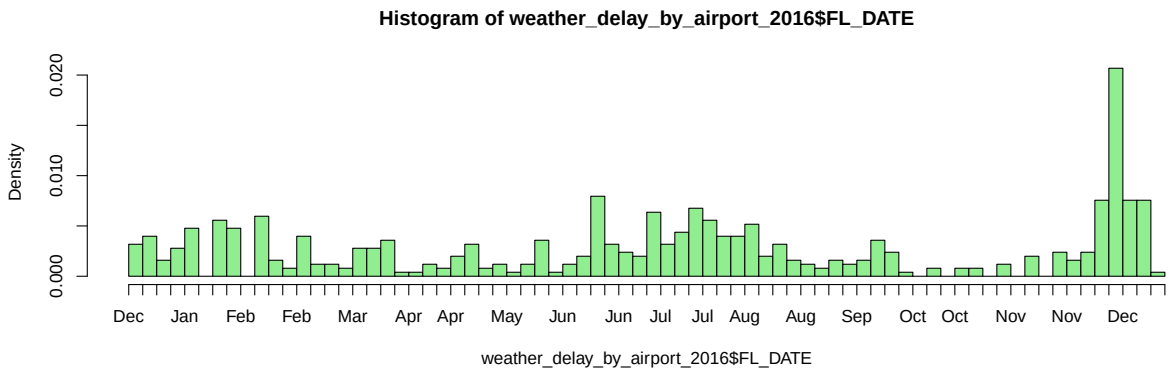
```
# First select the sub-vectors which contains only he coulums we are interested in
weather_delay_by_airport <-
  strata.MSP %>%
  select(c(FL_DATE,
           WEATHER_DELAY)) %>%
  filter(WEATHER_DELAY > 0
         )

hist(weather_delay_by_airport$FL_DATE,
     weather_delay_by_airport$WEATHER_DELAY,
     breaks = 100,
     col = "lightblue")
```



From the above chart it was apparant that in 2016 there was an increase in weather delay. The following RChunks will further drill down the data and analyze to find out approximately during which month in 2016 we had delay issue.

```
weather_delay_by_airport_2016 <-
  weather_delay_by_airport

weather_delay_by_airport_2016$YEAR <-
  format(weather_delay_by_airport$FL_DATE, "%Y")

weather_delay_by_airport_2016 <-
  weather_delay_by_airport_2016 %>%
  filter(YEAR == '2016')

weather_delay_by_airport_2016$MONTH <-
  format(weather_delay_by_airport_2016$FL_DATE, "%m")

hist(weather_delay_by_airport_2016$FL_DATE,
```

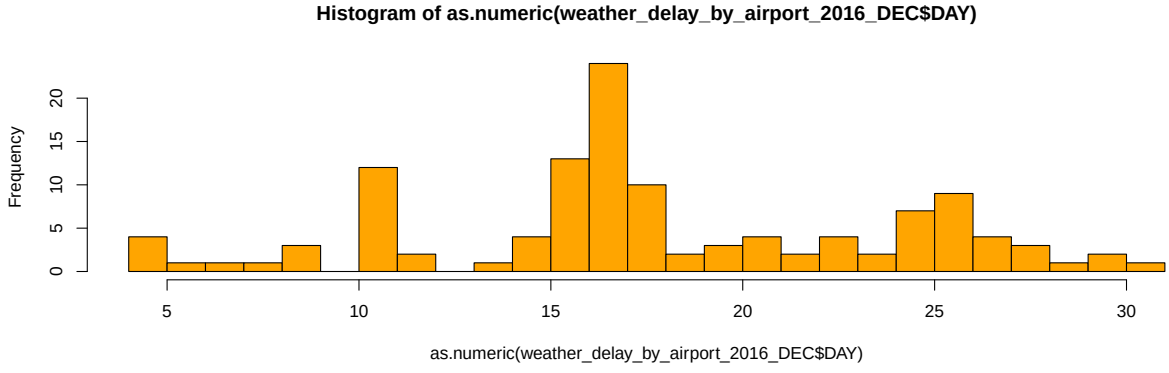
```
     weather_delay_by_airport_2016$WEATHER_DELAY,
     breaks =120, col = "lightgreen")
```



The above histogram shows that whether delays are more in December month in MSP airport. This could be explained by winter storm related delays.

```
weather_delay_by_airport_2016_DEC <-
  weather_delay_by_airport_2016 %>%
  filter(MONTH == '12')

weather_delay_by_airport_2016_DEC$DAY <-
  format(weather_delay_by_airport_2016_DEC$FL_DATE, "%d")

hist(as.numeric(weather_delay_by_airport_2016_DEC$DAY),
     weather_delay_by_airport_2016_DEC$WEATHER_DELAY,
     breaks =30, col = "orange")
```

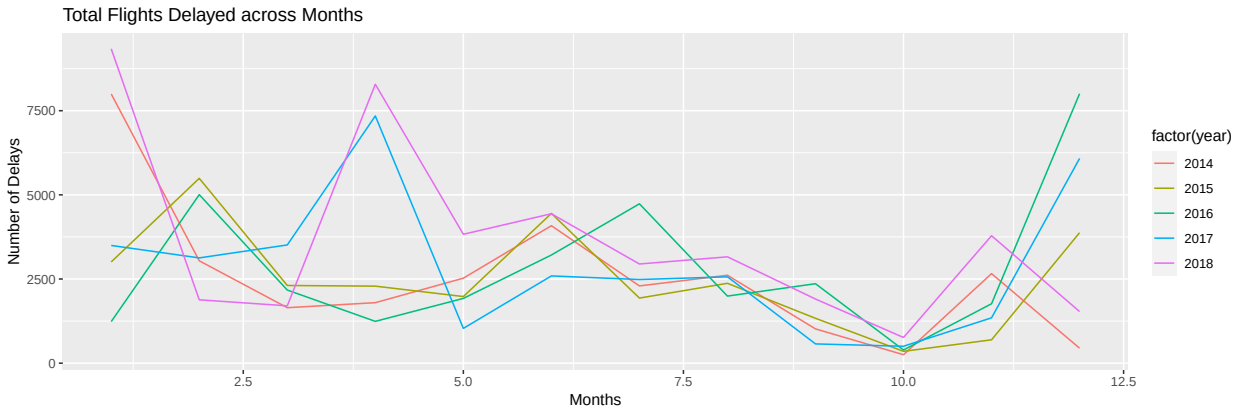
```
## Warning in if (freq) x$counts else x$density: the condition has length > 1 and
## only the first element will be used

## Warning in if (!freq) "Density" else "Frequency": the condition has length > 1
## and only the first element will be used
```



Below code generates weather delay plot for each year using ggplot

```
airport = c('MSP')

weather_delay_by_airport_2014.gorupby <-
  flight.data.y2014 %>%
  select(c(FL_DATE, DEST, WEATHER_DELAY)) %>%
  filter(DEST == airport) %>%
  filter(WEATHER_DELAY > 0) %>%
  group_by(as.numeric(format(FL_DATE, "%m"))) %>%
  summarize(total_delayed=sum(WEATHER_DELAY)) %>%
  mutate(year=2014)

weather_delay_by_airport_2015.gorupby <-
  flight.data.y2015 %>%
  select(c(FL_DATE, DEST, WEATHER_DELAY)) %>%
  filter(DEST == airport) %>%
  filter(WEATHER_DELAY > 0) %>%
  group_by(as.numeric(format(FL_DATE, "%m"))) %>%
  summarize(total_delayed=sum(WEATHER_DELAY)) %>%
  mutate(year=2015)

weather_delay_by_airport_2016.gorupby <-
  flight.data.y2016 %>%
  select(c(FL_DATE, DEST, WEATHER_DELAY)) %>%
  filter(DEST == airport) %>%
  filter(WEATHER_DELAY > 0) %>%
  group_by(as.numeric(format(FL_DATE, "%m"))) %>%
  summarize(total_delayed=sum(WEATHER_DELAY)) %>%
  mutate(year=2016)

weather_delay_by_airport_2017.gorupby <-
  flight.data.y2017 %>%
  select(c(FL_DATE, DEST, WEATHER_DELAY)) %>%
  filter(DEST == airport) %>%
  filter(WEATHER_DELAY > 0) %>%
  group_by(as.numeric(format(FL_DATE, "%m"))) %>%
  summarize(total_delayed=sum(WEATHER_DELAY)) %>%
  mutate(year=2017)

weather_delay_by_airport_2018.gorupby <-
  flight.data.y2018 %>%
  select(c(FL_DATE, DEST, WEATHER_DELAY)) %>%
  filter(DEST == airport) %>%
  filter(WEATHER_DELAY > 0) %>%
  group_by(as.numeric(format(FL_DATE, "%m"))) %>%
  summarize(total_delayed=sum(WEATHER_DELAY)) %>%
  mutate(year=2018)

month_Delay<-rbind(weather_delay_by_airport_2014.gorupby,
                   weather_delay_by_airport_2015.gorupby,
                   weather_delay_by_airport_2016.gorupby,
                   weather_delay_by_airport_2017.gorupby,
                   weather_delay_by_airport_2018.gorupby)
```

```
ggplot(month_Delay,
       aes(x = `as.numeric(format(FL_DATE, "%m"))`,
           y = total_delayed,
           color = factor(year), group = factor(year))) +
geom_line(linetype = 1) +
  labs(title="Total Flights Delayed across Months",
       y = 'Number of Delays',x = 'Months', fill='YEAR')
```

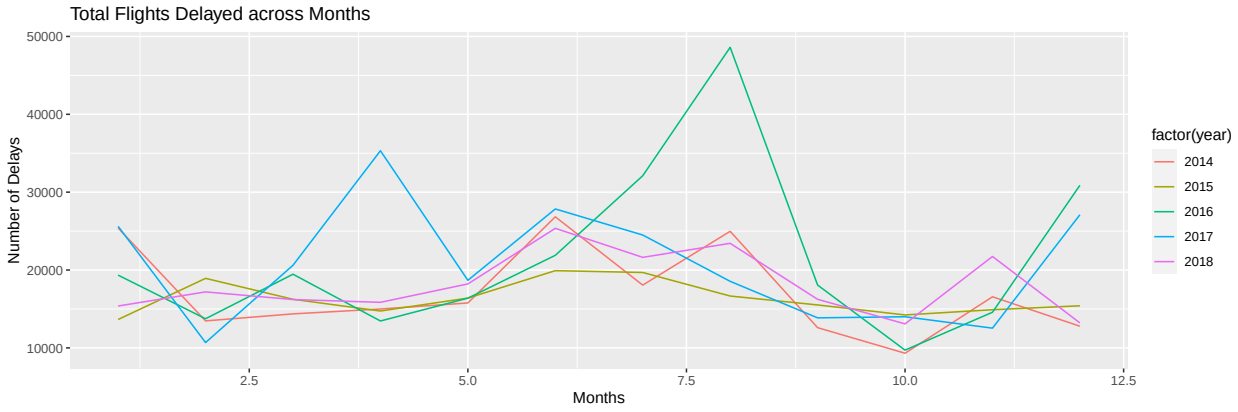


The above plot shows weather delays during 2014-2018 and it's clear that most of the weather delays happens during year start/end.

Below code generates carrier delay plot for each year using ggplot

```
airport = c('MSP')

weather_delay_by_airport_2014.gorupby <-
  flight.data.y2014 %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY)) %>%
  filter(DEST == airport) %>%
  filter(CARRIER_DELAY > 0) %>%
  group_by(as.numeric(format(FL_DATE, "%m"))) %>%
  summarize(total_delayed=sum(CARRIER_DELAY)) %>%
  mutate(year=2014)

weather_delay_by_airport_2015.gorupby <-
  flight.data.y2015 %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY)) %>%
  filter(DEST == airport) %>%
  filter(CARRIER_DELAY > 0) %>%
  group_by(as.numeric(format(FL_DATE, "%m"))) %>%
  summarize(total_delayed=sum(CARRIER_DELAY)) %>%
  mutate(year=2015)

weather_delay_by_airport_2016.gorupby <-
  flight.data.y2016 %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY)) %>%
  filter(DEST == airport) %>%
  filter(CARRIER_DELAY > 0) %>%
  group_by(as.numeric(format(FL_DATE, "%m"))) %>%
  summarize(total_delayed=sum(CARRIER_DELAY)) %>%
  mutate(year=2016)
```

```
weather_delay_by_airport_2017.gorupby <-
  flight.data.y2017 %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY)) %>%
  filter(DEST == airport) %>%
  filter(CARRIER_DELAY > 0) %>%
  group_by(as.numeric(format(FL_DATE, "%m"))) %>%
  summarize(total_delayed=sum(CARRIER_DELAY)) %>%
  mutate(year=2017)

weather_delay_by_airport_2018.gorupby <-
  flight.data.y2018 %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY)) %>%
  filter(DEST == airport) %>%
  filter(CARRIER_DELAY > 0) %>%
  group_by(as.numeric(format(FL_DATE, "%m"))) %>%
  summarize(total_delayed=sum(CARRIER_DELAY)) %>%
  mutate(year=2018)

month_Delay<-rbind(weather_delay_by_airport_2014.gorupby,
                   weather_delay_by_airport_2015.gorupby,
                   weather_delay_by_airport_2016.gorupby,
                   weather_delay_by_airport_2017.gorupby,
                   weather_delay_by_airport_2018.gorupby)

ggplot(month_Delay,
       aes(x = `as.numeric(format(FL_DATE, "%m"))`,
           y = total_delayed,
           color = factor(year), group = factor(year))) +
geom_line(linetype = 1) +
  labs(title="Total Flights Delayed across Months",
       y = 'Number of Delays',x = 'Months', fill='YEAR')
```



There was a spike in graph for year 2016, Aug due to ground stop issued for all Delta flight during that timeframe.

```
flight.data.y2018
```

```
## # A tibble: 949,283 x 6
##    FL_DATE    DEST  CARRIER_DELAY WEATHER_DELAY AIR_TIME CRS_ARR_TIME
```

```
##    <date>     <chr>         <dbl>         <dbl>    <dbl>        <dbl>
##  1 2018-01-01 TPA              NA            NA      158         2325
##  2 2018-01-01 JFK              NA            NA      218         1756
##  3 2018-01-01 SLC              NA            NA       83         1605
##  4 2018-01-01 LAX              NA            NA       85          750
##  5 2018-01-01 MCI              NA            NA       60         2138
##  6 2018-01-01 ATL               0             0       68         1523
##  7 2018-01-01 TPA              NA            NA       65         2015
##  8 2018-01-01 DTW              NA            NA      141         1453
##  9 2018-01-01 MCO              27             0       66         2131
## 10 2018-01-01 ATL              NA            NA       64         1004
## # ... with 949,273 more rows
```

```
carrier_delay_by_airport_2018.totalFlights <-
  flight.data.y2018 %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY)) %>%
  group_by(FL_DATE) %>% count() %>% mutate(year=2018)

carrier_delay_by_airport_2018.carrierDelay <-
  flight.data.y2018 %>%
  select(c(FL_DATE, DEST, CARRIER_DELAY)) %>%
  filter(CARRIER_DELAY >= 0) %>%
  group_by(FL_DATE) %>%
  summarize(total_delayed=sum(CARRIER_DELAY > 0)) %>%
  mutate(year=2018)

dataset <- bind_cols(carrier_delay_by_airport_2018.totalFlights,
                     carrier_delay_by_airport_2018.carrierDelay)
```

```
## New names:
## * `FL_DATE` -> `FL_DATE...1`
## * `year` -> `year...3`
## * `FL_DATE` -> `FL_DATE...4`
## * `year` -> `year...6`
```

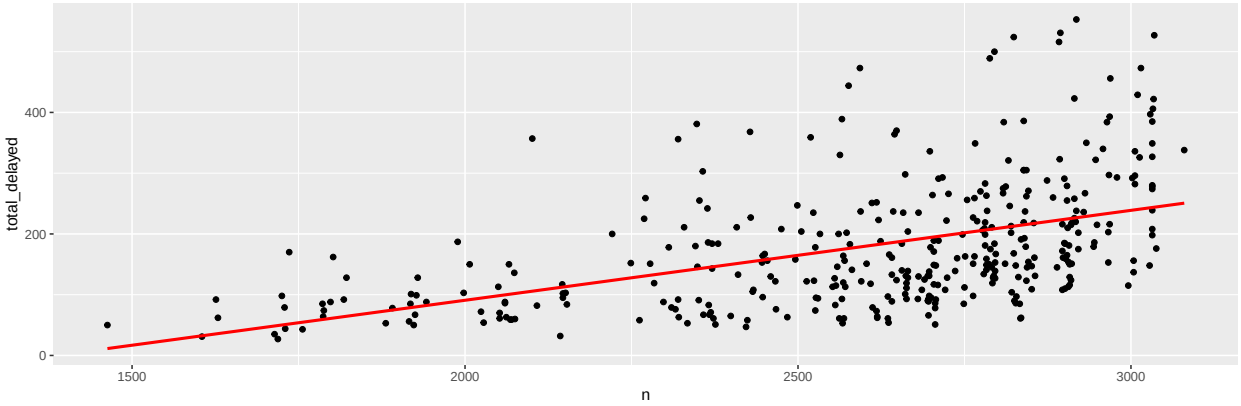
```
linear_model <- lm(total_delayed ~ n,
                   data=dataset)
summary(linear_model)
```

```
##
## Call:
## lm(formula = total_delayed ~ n, data = dataset)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -153.25  -65.22  -16.27   46.79  326.31
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -205.18138   37.26136  -5.507 6.94e-08 ***
## n              0.14800    0.01421  10.418  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 92.41 on 363 degrees of freedom
## Multiple R-squared:  0.2302, Adjusted R-squared:  0.2281
## F-statistic: 108.5 on 1 and 363 DF,  p-value: < 2.2e-16
```

```
ggplot(dataset, aes(x=n,
                    y=total_delayed)) +
  geom_point() +
  geom_smooth(method='lm', se=FALSE, col="red", size=1)
```

```
## `geom_smooth()` using formula 'y ~ x'
```



There appears to be have a linear relation between carrier delay and total flights. Since there is a linear relation between number of flights arrived and carrier delay, it could be due to airline operations issue(like crew/pilot scheduling issue or some other operational issues when there is an increase in number of flights operated by the airline.)

Topics From Class

Topic 1:

R Markdown - I will be presenting the project in R Markdown and knit the file to a pdf document. Will be using R chunks to demonstrate and build the project components.

Topic 2:

GitHub - Will host the project in github repository for others to view my project components.

Topic 3:

Sampling strategies for an Observational study - Will be using sampling strategies - Simple random sampling, Stratified sampling, Cluster sampling and multistage sampling to group the data together by using different variables from the dataset and then use one of the sampling result to build topic#4 and 5.

Topic 4:

Detailing Summary statistics (Min. , 1st Qu., Median, Mean, 3rd Qu., Max.) of a variable and plotting graphs using ggplot2

Topic 5:

Regression (if an increase in number of schedules has any impact/variace on carrier delays).

Conclusion

I designed this project as a way to review some of the topics we learned in the class/homework/assignments to reinforce some topics learned and also as an opportunity to refer back some of the materials. Hence I thought of picking a variety of topics like sampling strategies, summary statistics, ANOVA and regressions will be the best approach and most I can get from this project. If I have more time, I would have included some more topics (like binom, dbinom, geom. . . etc distributions) and see if my dataset have variables that can fit these distributions. Given only a academic background in statistics almost almost 20 years ago, I think this subject has given me much learning experience in statistics and I appreciate how these topics are applicable to find solutions in reality.

References:

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