Uber Data Analysis

Data Import and sanity checks

```
>install.packages("tidyverse")
```

```
>library(tidyverse)
```

Read data into R

```
uber = read.csv("uber.csv")
```

Check the dimension of data set

```
dim(uber)
29101    13
#Uber dataset is of 29101 uber rides (for 6 six months) for 13 different vari
ables
```

View top and bottom rows to make sure no formatting issues are there or header and footer is i ncluded in data set

```
head(uber)
            pickup_dt       borough pickups spd vsb temp dewp    slp pcp01 pc
p06 pcp24 sd
1 2015-01-01 01:00:00         Bronx     152   5  10   30    7 1023.5     0
0     0  0
2 2015-01-01 01:00:00      Brooklyn    1519   5  10   30    7 1023.5     0
0     0  0
3 2015-01-01 01:00:00           EWR       0   5  10   30    7 1023.5     0
0     0  0
4 2015-01-01 01:00:00     Manhattan    5258   5  10   30    7 1023.5     0
0     0  0
5 2015-01-01 01:00:00        Queens     405   5  10   30    7 1023.5     0
0     0  0
6 2015-01-01 01:00:00 Staten Island       6   5  10   30    7 1023.5     0
0     0  0
  hday
1    Y
2    Y
3    Y
4    Y
5    Y
6    Y
```

```
tail(uber)
                pickup_dt       borough pickups spd vsb temp dewp    slp pcp0
1 pcp06 pcp24 sd
29096 2015-06-30 23:00:00      Brooklyn     990   7  10   75   65 1011.8
0     0     0  0
29097 2015-06-30 23:00:00           EWR       0   7  10   75   65 1011.8
0     0     0  0
```

```
29098 2015-06-30 23:00:00     Manhattan    3828    7  10    75    65 1011.8
0      0      0  0
29099 2015-06-30 23:00:00        Queens     580    7  10    75    65 1011.8
0      0      0  0
29100 2015-06-30 23:00:00 Staten Island       0    7  10    75    65 1011.8
0      0      0  0
29101 2015-06-30 23:00:00          <NA>       3    7  10    75    65 1011.8
0      0      0  0
      hday
29096    N
29097    N
29098    N
29099    N
29100    N
29101    N
0      0      0  0     N
```

This looks fine, let us now check for data types and structure

```
str(uber)
'data.frame':	29101 obs. of  13 variables:
 $ pickup_dt: Factor w/ 4343 levels "2015-01-01 01:00:00",..: 1 1 1 1 1 1 1 2
2 2 ...
 $ borough  : Factor w/ 6 levels "Bronx","Brooklyn",..: 1 2 3 4 5 6 NA 1 2 3
...
 $ pickups  : int  152 1519 0 5258 405 6 4 120 1229 0 ...
 $ spd      : num  5 5 5 5 5 5 5 3 3 3 ...
 $ vsb      : num  10 10 10 10 10 10 10 10 10 10 ...
 $ temp     : num  30 30 30 30 30 30 30 30 30 30 ...
 $ dewp     : num  7 7 7 7 7 7 7 6 6 6 ...
 $ slp      : num  1024 1024 1024 1024 1024 ...
 $ pcp01    : num  0 0 0 0 0 0 0 0 0 0 ...
 $ pcp06    : num  0 0 0 0 0 0 0 0 0 0 ...
 $ pcp24    : num  0 0 0 0 0 0 0 0 0 0 ...
 $ sd       : num  0 0 0 0 0 0 0 0 0 0 ...
 $ hday     : Factor w/ 2 levels "N","Y": 2 2 2 2 2 2 2 2 2 2 ...
```

- Pickup date is date & time stamp and taken as factor
- Borough and hday are factors, rest all are numeric variables

Check summary statistics

```
summary(uber)
               pickup_dt                 borough         pickups             spd
 2015-01-01 01:00:00:    7    Bronx        :4343   Min.   :    0.0   Min.   : 0
.000
 2015-01-01 02:00:00:    7    Brooklyn     :4343   1st Qu.:    1.0   1st Qu.: 3
.000
 2015-01-01 03:00:00:    7    EWR          :4343   Median :   54.0   Median : 6
.000
 2015-01-01 04:00:00:    7    Manhattan    :4343   Mean   : 490.2   Mean   : 5
.985
 2015-01-01 05:00:00:    7    Queens       :4343   3rd Qu.: 449.0   3rd Qu.: 8
.000
```

```
 2015-01-01 10:00:00:    7   Staten Island:4343   Max.   :7883.0   Max.   :21
.000
 (Other)            :29059   NA's         :3043
      vsb              temp            dewp             slp             pcp01
 Min.   : 0.000   Min.   : 2.00   Min.   :-16.00   Min.   : 991.4   Min.   :0
.00000
 1st Qu.: 9.100   1st Qu.:32.00   1st Qu.: 14.00   1st Qu.:1012.5   1st Qu.:0
.00000
 Median :10.000   Median :46.00   Median : 30.00   Median :1018.2   Median :0
.00000
 Mean   : 8.818   Mean   :47.67   Mean   : 30.82   Mean   :1017.8   Mean   :0
.00383
 3rd Qu.:10.000   3rd Qu.:64.50   3rd Qu.: 50.00   3rd Qu.:1022.9   3rd Qu.:0
.00000
 Max.   :10.000   Max.   :89.00   Max.   : 73.00   Max.   :1043.4   Max.   :0
.28000

     pcp06             pcp24               sd          hday
 Min.   :0.00000   Min.   :0.00000   Min.   : 0.000   N:27980
 1st Qu.:0.00000   1st Qu.:0.00000   1st Qu.: 0.000   Y: 1121
 Median :0.00000   Median :0.00000   Median : 0.000
 Mean   :0.02613   Mean   :0.09046   Mean   : 2.529
 3rd Qu.:0.00000   3rd Qu.:0.05000   3rd Qu.: 2.958
 Max.   :1.24000   Max.   :2.10000   Max.   :19.000
```

Almost all borough has identical distribution, few NA's are observed
pickup shows possibility of outliers
visibility of 0 shows extreme conditions, but cannot be ruled out
temperatures are in Fahrenheit so given range of 2 to 89 translates roughly -16 to 31 Celsius
#NYC's borough - for six areas (Bronx, Brooklyn, EWR, Manhattan , Queens & Staten Island)
#pickups: Number of pickups - from 0 to 7883
#Wind speed in miles/hour - from 0 to 21
Snow depth in inches - from 0 to 19
hday: showing 1121 rides on holidays as compared to 27980 rides on working days
#Dew point in Fahrenheit - from -16 to 73
Sea level pressure - from 991.4 to 1043.4
Snow depth in inches - from 0 to 19
liquid precipitation from 0 to 2.1
Different scales and different variations in weather and local conditions effecting uber rides.

Check for any missing Values : To find NAs in the dataset

```
anyNA(uber)
[1] TRUE

sum(is.na(uber))
[1] 3043
```

- This corresponds to missing value of borough as seen in summary output

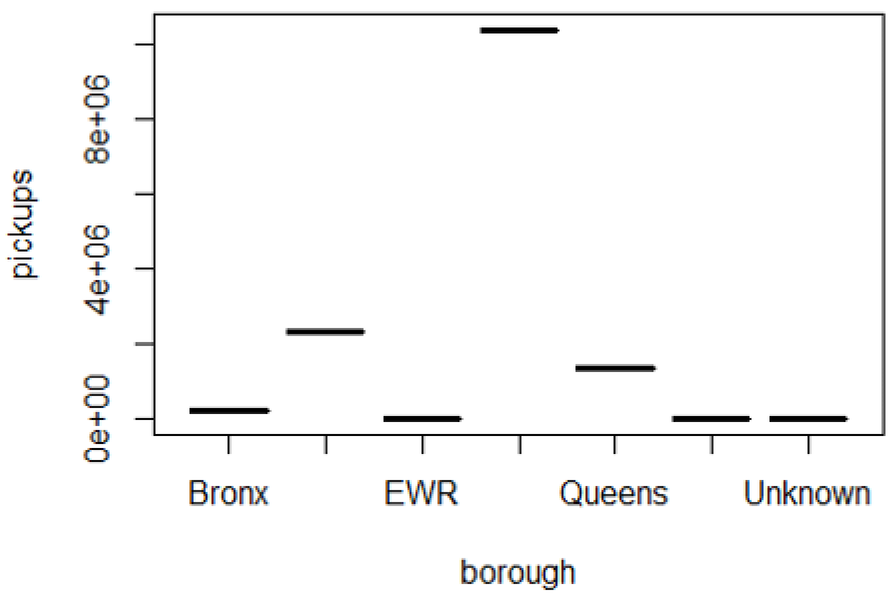
```
sapply(uber, function(x) sum(is.na(x)))
```

```
pickup_dt    borough    pickups        spd        vsb        temp        dewp         s
lp       pcp01
        0       3043          0          0          0          0          0
0          0
    pcp06      pcp24          sd       hday
        0          0          0          0
```

Sapply() iterates over all columns and checks for NA values in given command
This confirm only one column (borough) has NA

Also, borough contains high number of NA values, imputing with any technique might introduce bias. We would instead create a new category called “Unknown” for missing values here.

```
> uber$borough = as.factor(replace(as.character(uber$borough), is.na(uber$borough),"Unknown"))
> plot(aggregate(pickups~borough,data=uber, sum), type="b")
```




```
> table(uber$borough)

        Bronx       Brooklyn            EWR      Manhattan         Queens
         4343           4343           4343           4343           4343
Staten Island        Unknown
         4343           3043
```

```
# To inspect the proportions of different areas
```
- ➢ notice all areas have equally represented excluding Unknowns
- ➢ Plot shows Manhattan highest number of rides and almost equally distributed rides to Bronx, EWR, Queens and unknowns borough

Generate features from date variable:

Given date variable is in factor form which might not provide meaningful insights.
Let is try to breaking pickup_dt them into features like month, day , hour etc

convert date into date form first
##study strptime function..advance functions for treating time stamp variable

```
> ?strptime
```

strptime {base} R Documentation

Date-time Conversion Functions to and from Character

Description

Functions to convert between character representations and objects of classes "`POSIXlt`" and"`POSIXct`" representing calendar dates and times.

```
> uber$start_date = strptime(uber$pickup_dt,'%Y-%m-%d %H:%M')

> library(lubridate) #Lubridate is an R package that makes it easier to work
with dates and times
> uber$start_month = month(uber$start_date)
> uber$start_day = day(uber$start_date)
> uber$start_hour = hour(uber$start_date)
> uber$wday = weekdays(uber$start_date)
> uber = uber[,-14]
```

- We have added new features for month of ride, day of month and hour of ride. Also wday represent which day of week it is.

Check for number of holidays each month

```
> # try to get no. of holidays in each month
> #unique function used to keep only unique/distinct rows from a data frame
> unique(uber[which(uber$hday=="Y"),c("start_day","start_month")])
      start_day start_month
1             1           1
2848         19           1
6649         12           2
7293         16           2
20608        10           5
23055        25           5
24526         3           6
```

- We can see that we have two holidays in Jan (1st & 19th), 2 in Feb (12th & 16th), 2 in May(10th & 25th) and 1 in June(3rd). No holidays in March and April

```
>table(uber$hday,uber$start_month)

       1    2    3    4    5    6
  N 4588 4169 4957 4798 4730 4738
  Y  309  323    0    0  328  161
```

- No trips in 3rd and 4th month…Looks like no holidays in these month

This shows number of trips in holidays vs non-holidays in month
We will come again to check the effect on trips on holidays vs non-holidays
Before that let us do some univariate analysis

```
> library(data.table) #widely used for fast aggregation of large datasets
> ?uniqueN
```

duplicated {data.table}

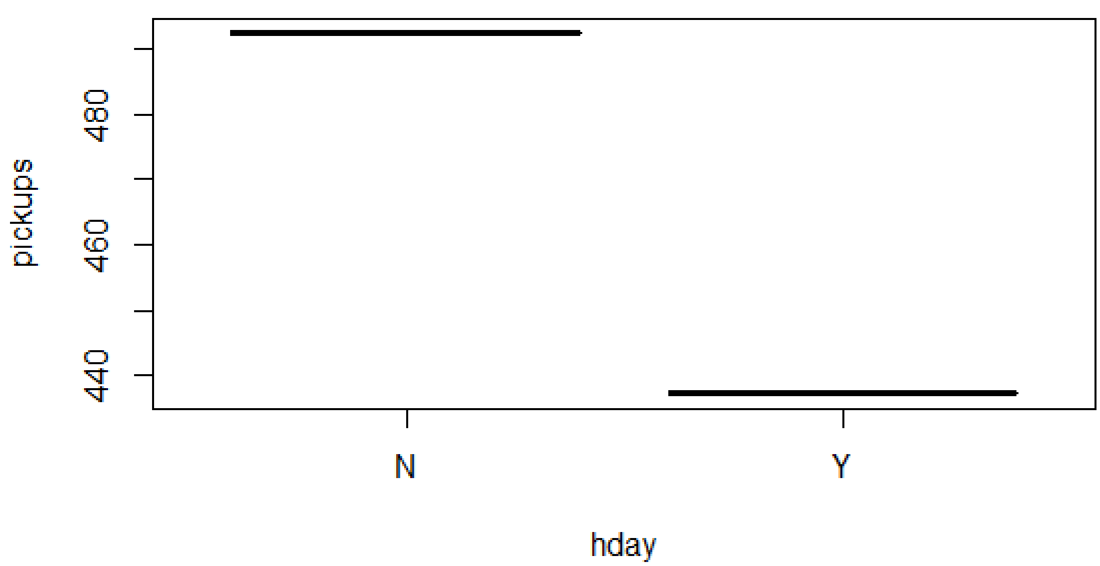
Determine Duplicate Rows

`uniqueN` is equivalent to `length(unique(x))` when x is an `atomic vector`, and `nrow(unique(x))` when x is a `data.frame` or `data.table`. The number of unique rows are computed directly without materialising the intermediate unique data.table and is therefore faster and memory efficient.

```
> uniqueN(uber, by=c('start_month', 'start_day'))
[1] 181
```

- In total, our days is for 181 days in Jan 2015 to June 2015

```
> plot(aggregate(pickups~hday,data=uber, mean), type="b")
```

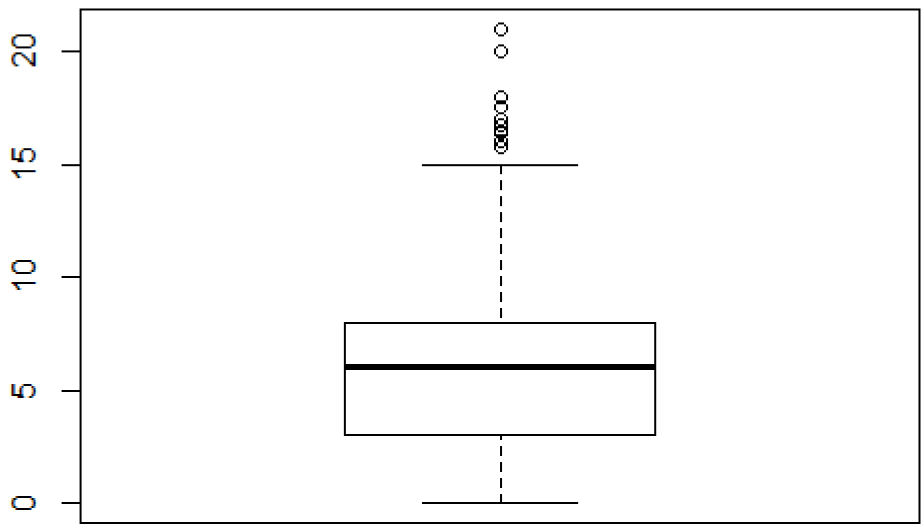


- Rides on working days is higher than on holidays

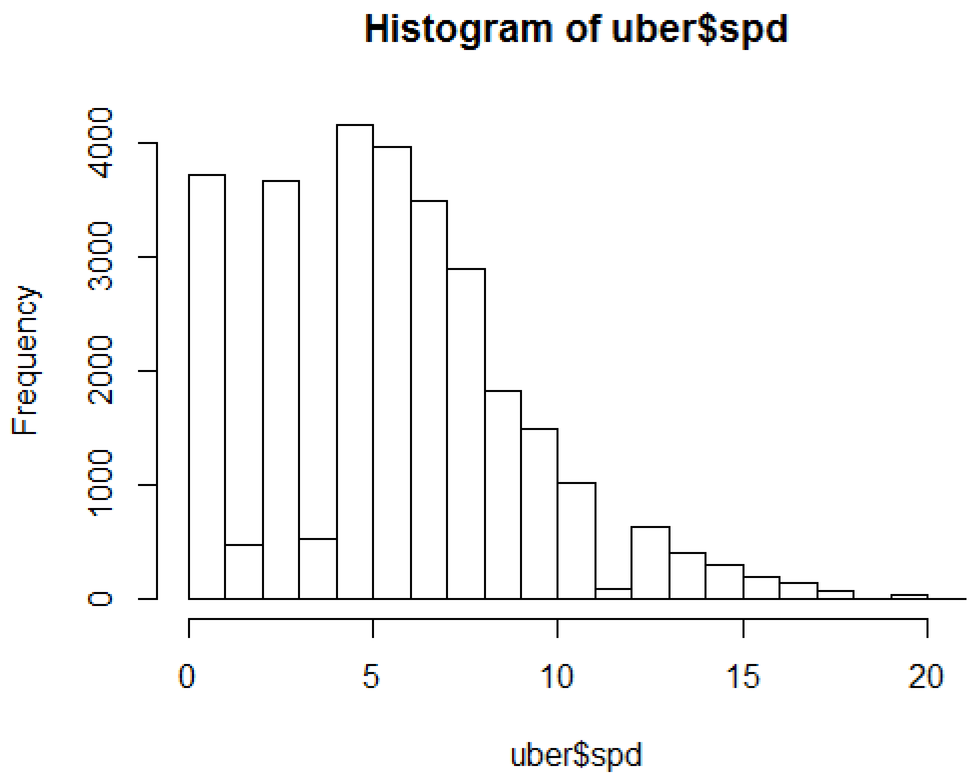
Uni-Variate Analysis

Speed:

```
>boxplot(uber$spd) # outlier present
```




```
> hist(uber$spd)# skewed histogram
```

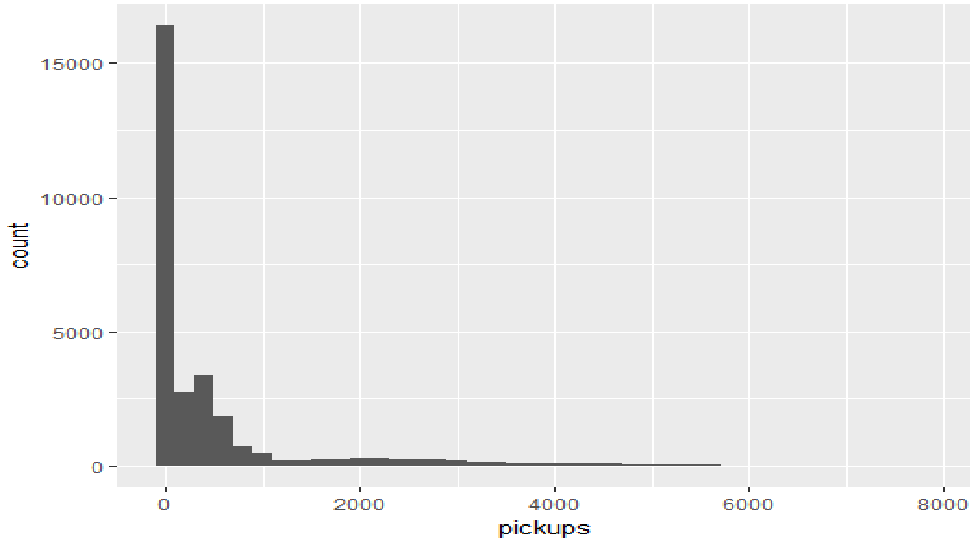


- Boxplot shows there are outliers in data set.
- Histogram also shows the right skew in distribution
- On an average speed is 5 miles/hour

Check the distribution for pickups

```
> library(ggplot2) #a system for declaratively creating graphics
> #for pick up counts
> ggplot(uber, aes(pickups)) +
+   geom_histogram(binwidth = 200)
```

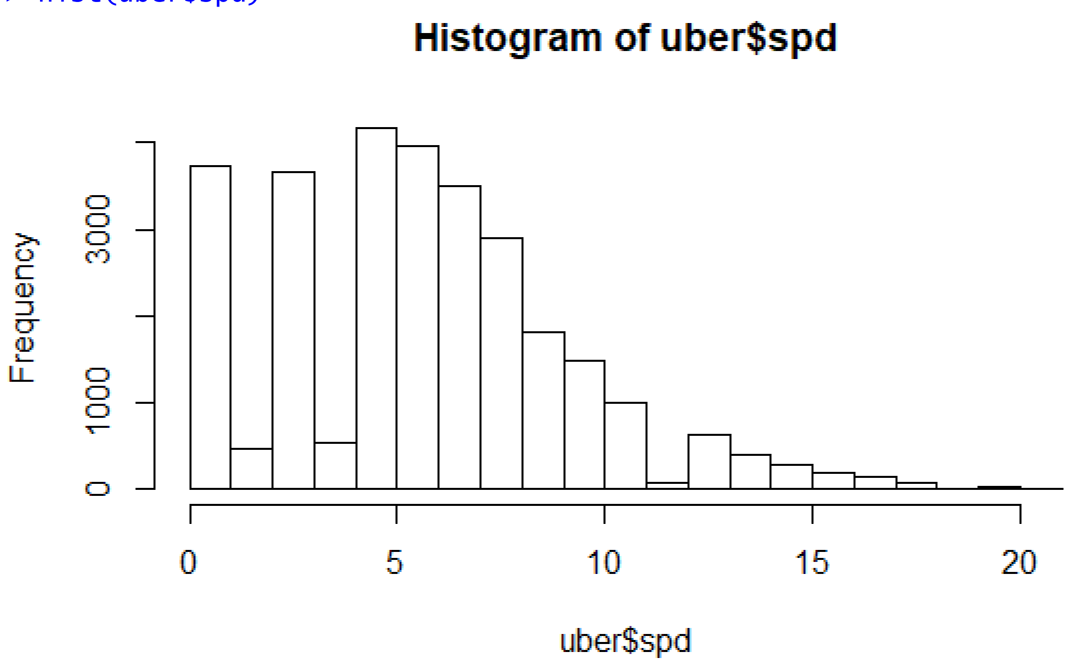
 # Histogram is heavily skewed



- Many have 0 rides or close to it.
- But skew is clearly visible
- **check for outliers in other variable as well**

For wind speed:

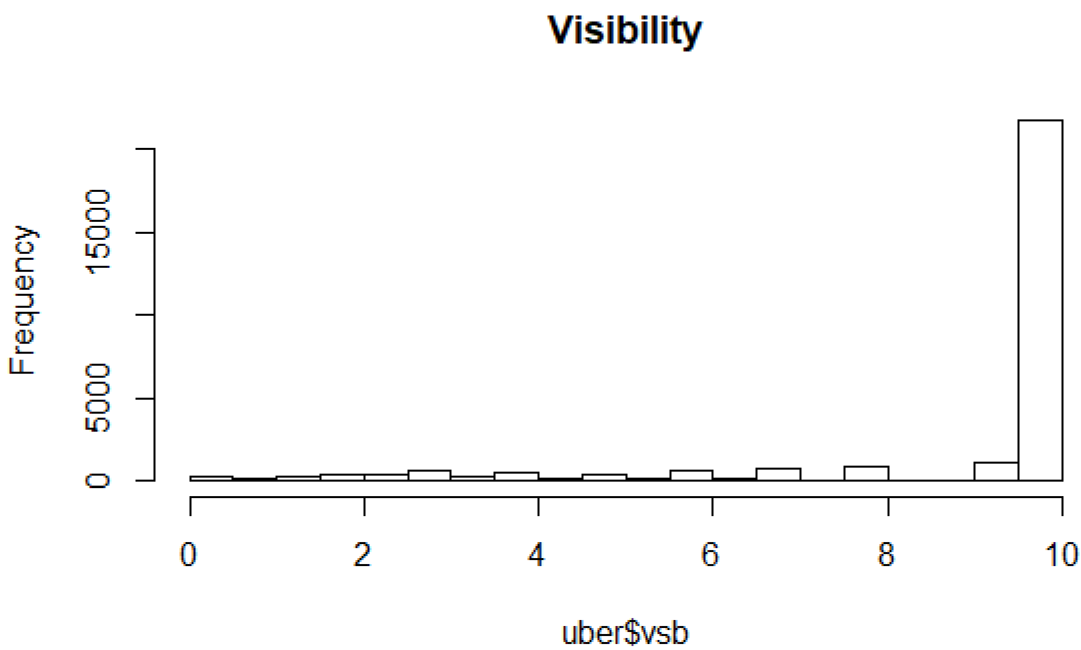
```
> hist(uber$spd)
```



- Low speed for duration, except few outliers, avg is around 5

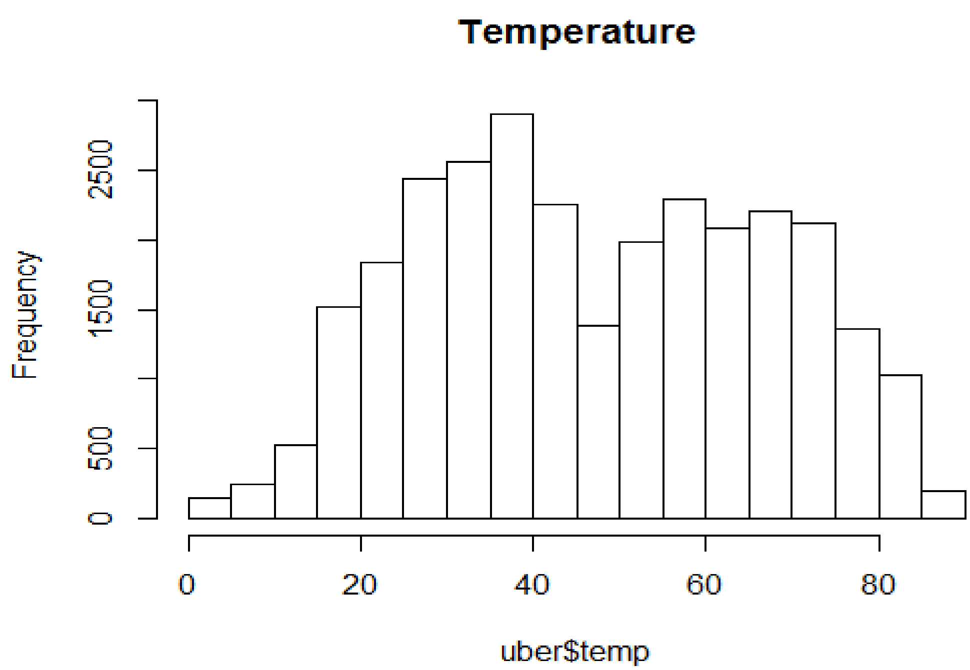
Visibility

```
> hist(uber$vsb, main= "Visibility")
```



- Almost clear weather

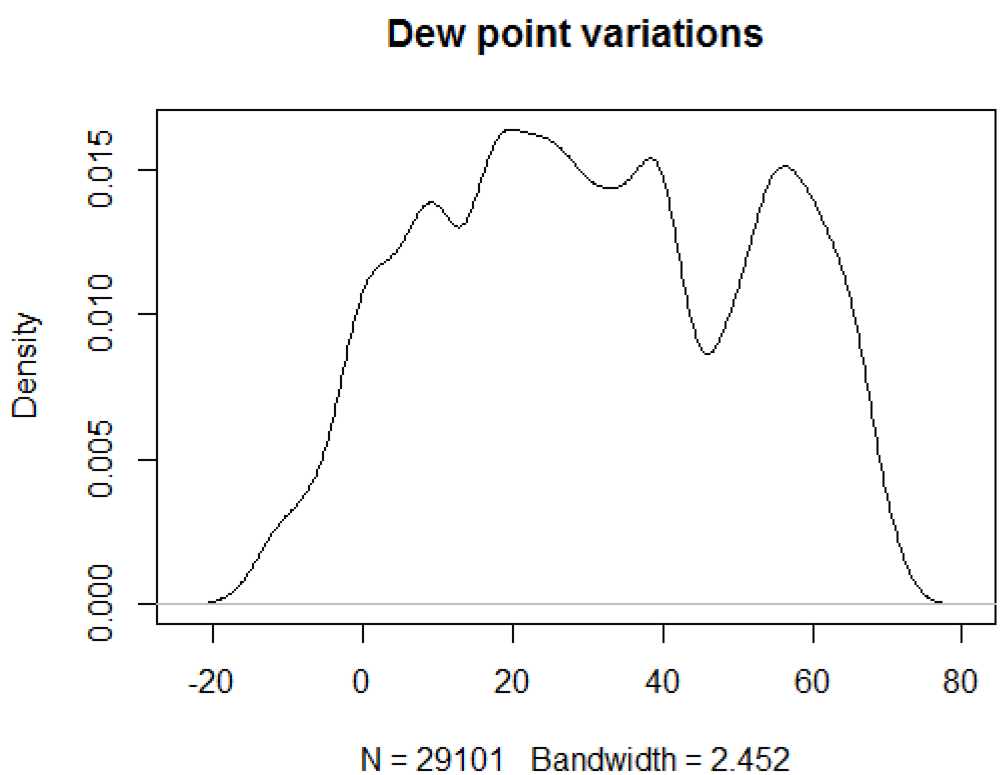
Temperature



- Two peaks can be seen, one at around 35F and other one at around 60F (bi-modal)
- It peaks at 35 (~1.5 C) suggest cold weather conditions, summers are not so intense

Dew Point

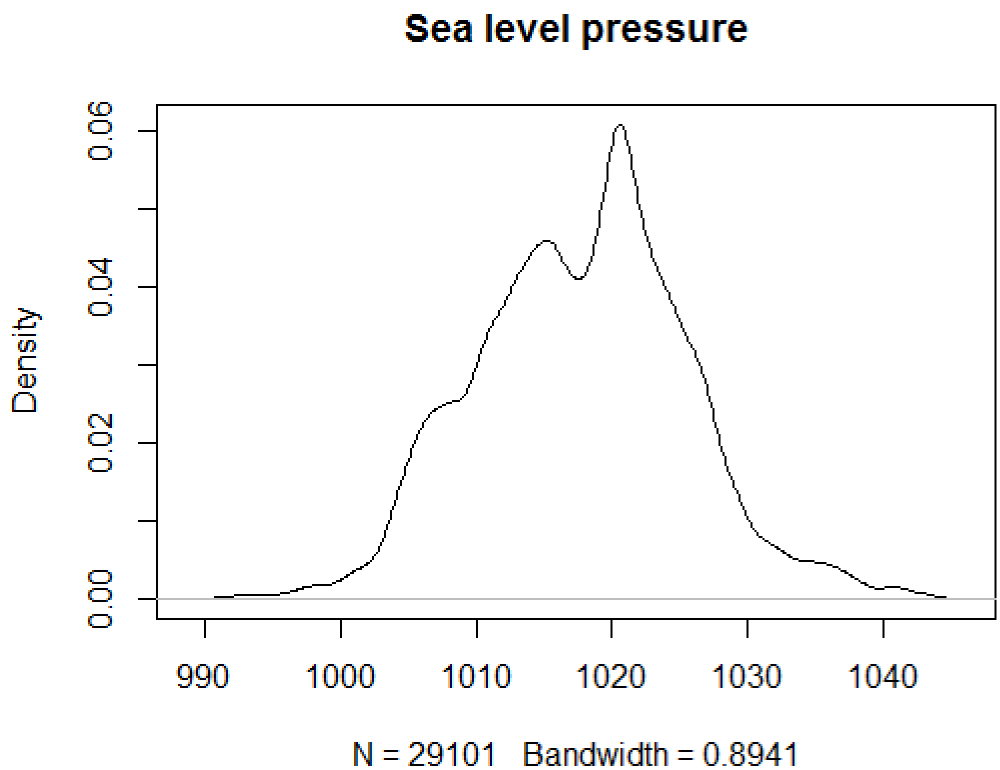
```
> plot(density(uber$dewp), main="Dew point variations")
```



- Distribution is quite like that of temperature(bi-modal)

Sea level pressure

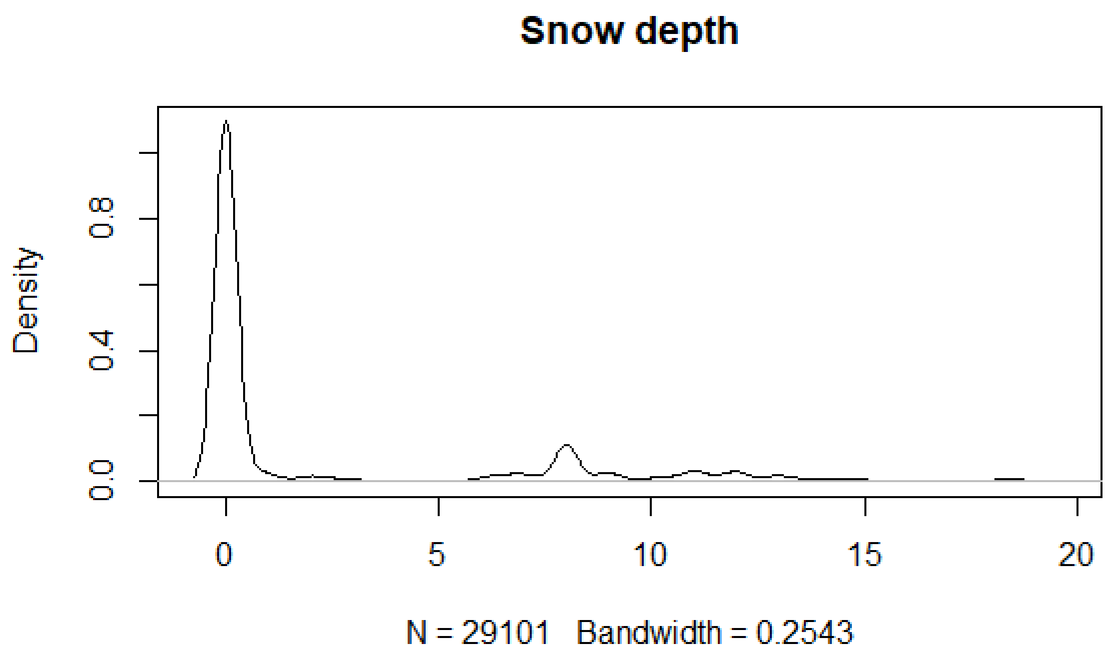
```
> plot(density(uber$slp), main="Sea level pressure")
```



- This resembles normal distribution
- We would expect pressure, temperature and dew points to show some correlation, hen ce we can expect similar distribution for them.

Snow depth

```
> plot(density(uber$sd), main="Snow depth")
```

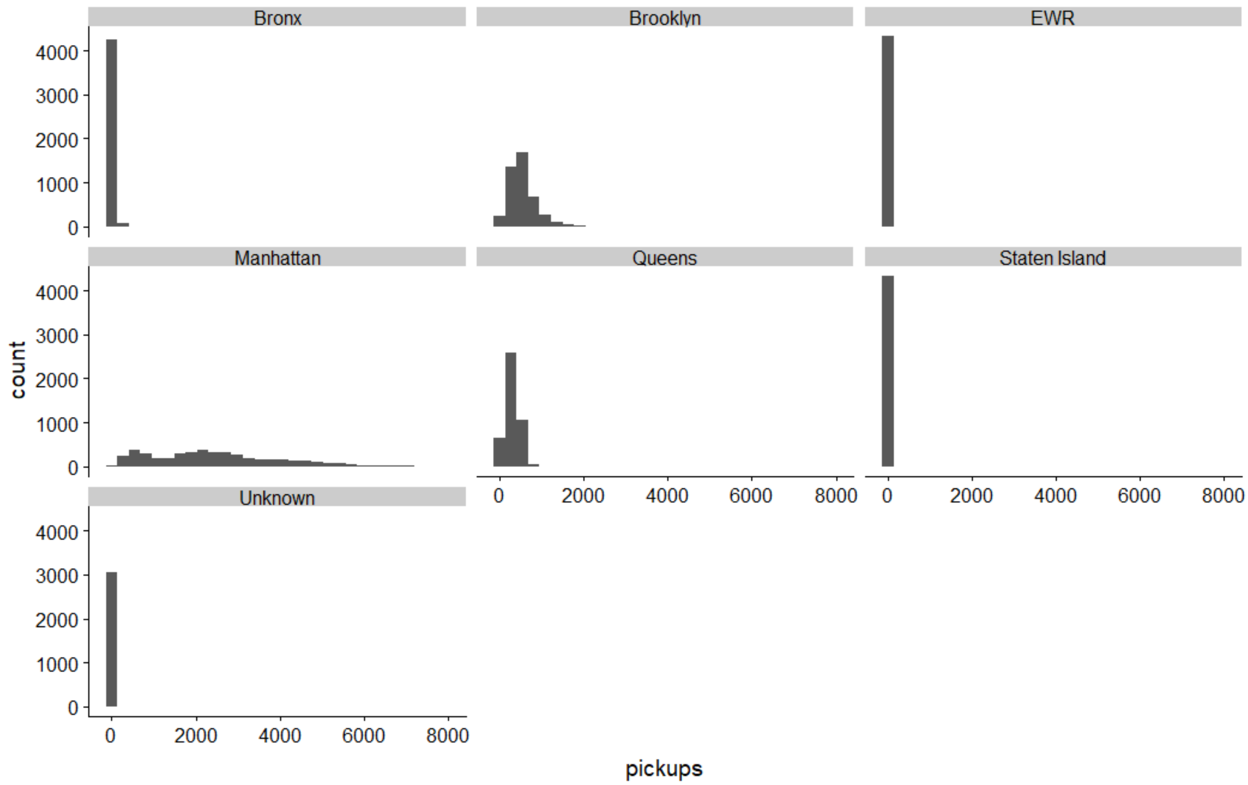


- No snow for majority of times

Bi-variate Analysis

```
> #Borough wise pickup
> ggplot(uber, aes(pickups)) +
+       geom_histogram() +
+       facet_wrap(~ borough, ncol = 3)
```

```
Pickups broken by boroughs
```

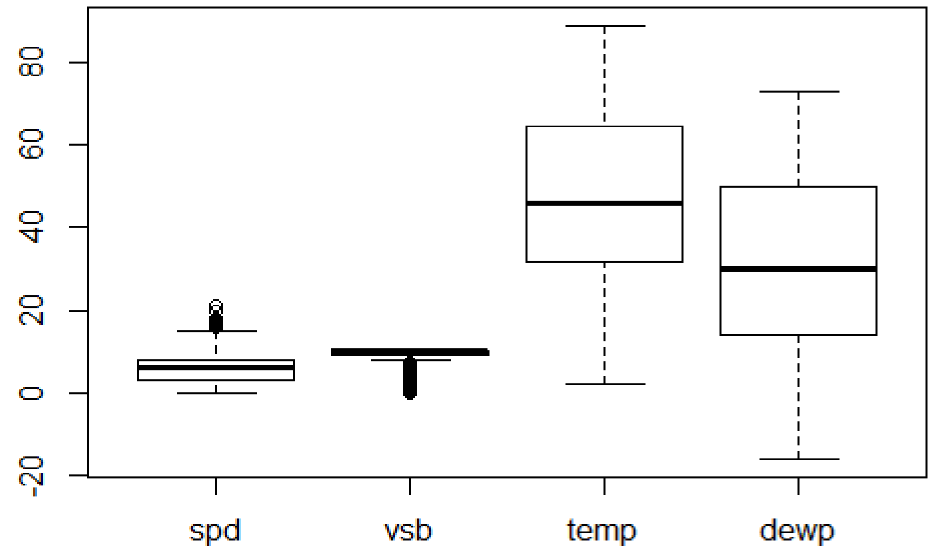



```
> uber %>% group_by(borough) %>%
+   summarise(`Total Pickups` = sum(pickups)) %>%
+   arrange(desc(`Total Pickups`))
# A tibble: 7 x 2
  borough       `Total Pickups`
  <fct>                   <int>
1 Manhattan            10367841
2 Brooklyn              2321035
3 Queens                1343528
4 Bronx                  220047
5 Staten Island            6957
6 Unknown                  6260
7 EWR                       105
```

- Majority of 0 rides are in unknown, Staten Island, EWR and Bronx
- Manhattan seems to have highest demand and then Brooklyn

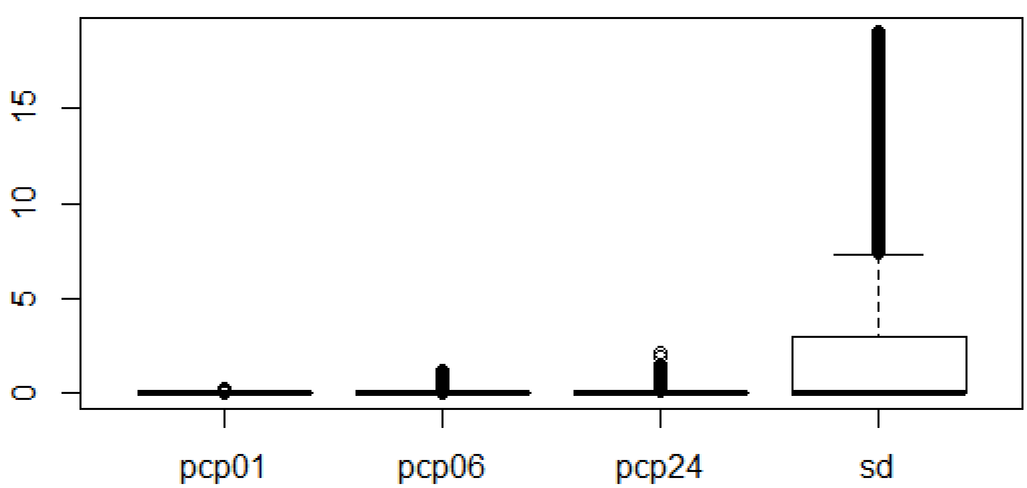
Multivariate Analysis:

```
> boxplot(uber[,c(4:7)])
```



➢ Temperature and dew points doesn’t show any outliers

```
> boxplot(uber[,c(9:12)])
```



➢ Pcp01 has less of outliers, sd shows plenty
➢ Check variable distributions

Inference:

We did univariate, bivariate and multivariate analysis to examine each variable and with other variable contributing toward uber rides.

Our analysis is for six boroughs in NYC for 181 total days and also looked at number of holiday every month.

In terms of borough, Manhattan contributes to largest share in bookings done

Holiday was another variable which show number of bookings on non-holidays compared to holidays. Point to note is that holidays and non-holidays does not include week day off. It just compares 6 holidays against the regular days. We can stretch this by considering all Sundays as holiday and replotting the difference

We used different libraries to plot and examine these variables like tidyverse, ggplot2, data.table and lubridata(for date variable).