New York City Bike Trip Analysis

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Contents

Initialization, Import Required Libraries

```r
library(bigrquery)
library(tidyverse)
```

Now, the next step of the analysis would be the writing the SQL query to retrieve the data from the Google Cloud Platform. The data set could be found from: LINK TO DATA SET

SQL for Query

Firs, in order to have the overview on the data-set, we import all the columns and but in order to avoid the massive data-set, we limit the rows to 1000.

```r
# Project ID
project_id <- "xenon-muse-261616" # put your project ID here

# query
sql_string <- "SELECT *
FROM
  [bigquery-public-data.new_york.citibike_trips]
LIMIT
  1000"

# Execute the query and store the result
NY_sample <- query_exec(sql_string, project = project_id,
                        useLegacySql = FALSE)
```

```
## Using an auto-discovered, cached token.
## To suppress this message, modify your code or options to clearly consent to the use of a cached toke
## See gargle's "Non-interactive auth" vignette for more details:
## https://gargle.r-lib.org/articles/non-interactive-auth.html
## The bigrquery package is using a cached token for kor.peyman@gmail.com.
```

```
## 0 bytes processed
```

Now, have a look on the head of the data:

DATA Overview

First, let's have the first look on the head of the data to get to know the data.

```r
head(NY_sample)
```

```
##   tripduration           starttime            stoptime start_station_id
## 1          766 2016-03-22 17:24:23 2016-03-22 17:37:09             3230
## 2        96235 2015-10-23 19:36:55 2015-10-24 22:20:51              493
## 3        36395 2016-03-15 21:36:55 2016-03-16 07:43:31              375
## 4       659210 2015-11-04 07:20:10 2015-11-11 22:27:00              519
## 5          139 2015-11-02 16:56:06 2015-11-02 16:58:25              311
## 6          178 2016-01-15 07:09:38 2016-01-15 07:12:36              311
##        start_station_name start_station_latitude start_station_longitude
## 1      Penn Station Valet               40.75128               -73.99692
## 2         W 45 St & 6 Ave               40.75680               -73.98291
## 3 Mercer St & Bleecker St               40.72679               -73.99695
## 4   Pershing Square North               40.75187               -73.97771
## 5  Norfolk St & Broome St               40.71723               -73.98802
## 6  Norfolk St & Broome St               40.71723               -73.98802
##   end_station_id      end_station_name end_station_latitude
## 1           3240 NYCBS Depot BAL - DYR              0.00000
## 2           3019     NYCBS Depot - DEL             40.71663
## 3           3019     NYCBS Depot - DEL             40.71663
## 4           3019     NYCBS Depot - DEL             40.71663
## 5           3019     NYCBS Depot - DEL             40.71663
## 6           3019     NYCBS Depot - DEL             40.71663
##   end_station_longitude bikeid   usertype birth_year gender
## 1               0.00000  22812 Subscriber       1975   male
## 2             -73.98193  18137 Subscriber       1957   male
## 3             -73.98193  19910 Subscriber       1979   male
## 4             -73.98193  20894 Subscriber       1965   male
## 5             -73.98193  15608 Subscriber       1993 female
## 6             -73.98193  19800 Subscriber       1988 female
```

Another important will be to look whether the data contain any NA values, so that we could be cautious about our analysis in the next steps. Now, the following code will provide the NA values in each columns:

```r
colSums(is.na(NY_sample))
```

```
##             tripduration                starttime                 stoptime
##                        0                        0                        0
##         start_station_id       start_station_name   start_station_latitude
##                        0                        0                        0
## start_station_longitude           end_station_id         end_station_name
##                        0                        0                        0
##     end_station_latitude    end_station_longitude                   bikeid
##                        0                        0                        0
##                 usertype               birth_year                   gender
##                        0                      139                        0
```

Mostly GOOD!. However, we notice that the *birth_year* column contains NA values. Another point is the *Column Type* we want to look that the imported data has the right format as we believe based on our understanding of the data, let's have look:

```r
sapply(NY_sample, class)
```

```
## $tripduration
## [1] "integer"
##
## $starttime
## [1] "POSIXct" "POSIXt"
```

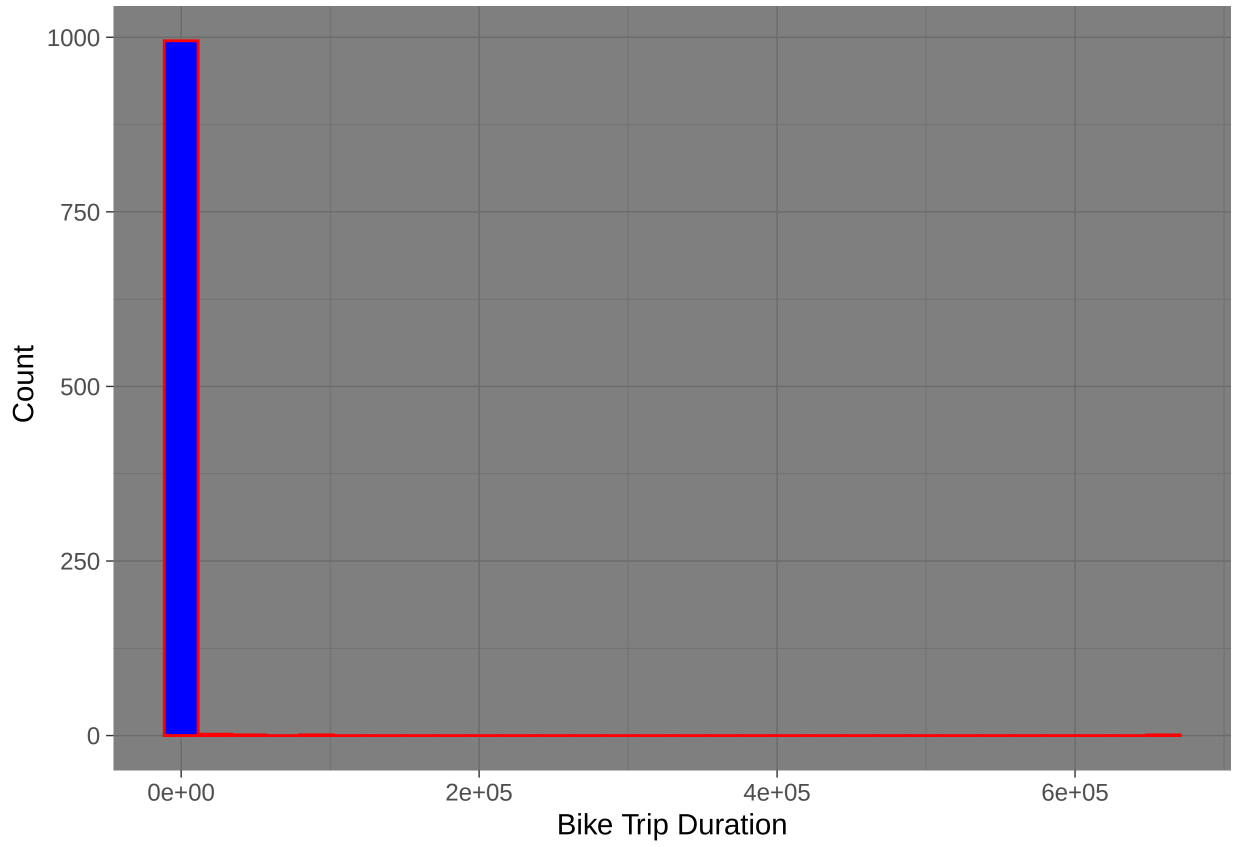
```
##
## $stoptime
## [1] "POSIXct" "POSIXt"
##
## $start_station_id
## [1] "integer"
##
## $start_station_name
## [1] "character"
##
## $start_station_latitude
## [1] "numeric"
##
## $start_station_longitude
## [1] "numeric"
##
## $end_station_id
## [1] "integer"
##
## $end_station_name
## [1] "character"
##
## $end_station_latitude
## [1] "numeric"
##
## $end_station_longitude
## [1] "numeric"
##
## $bikeid
## [1] "integer"
##
## $usertype
## [1] "character"
##
## $birth_year
## [1] "integer"
##
## $gender
## [1] "character"
```

Seems the column format is appropriate and no further change is needed at least in this stage.

Question: What is the trip duration distribution of Citibike trips?

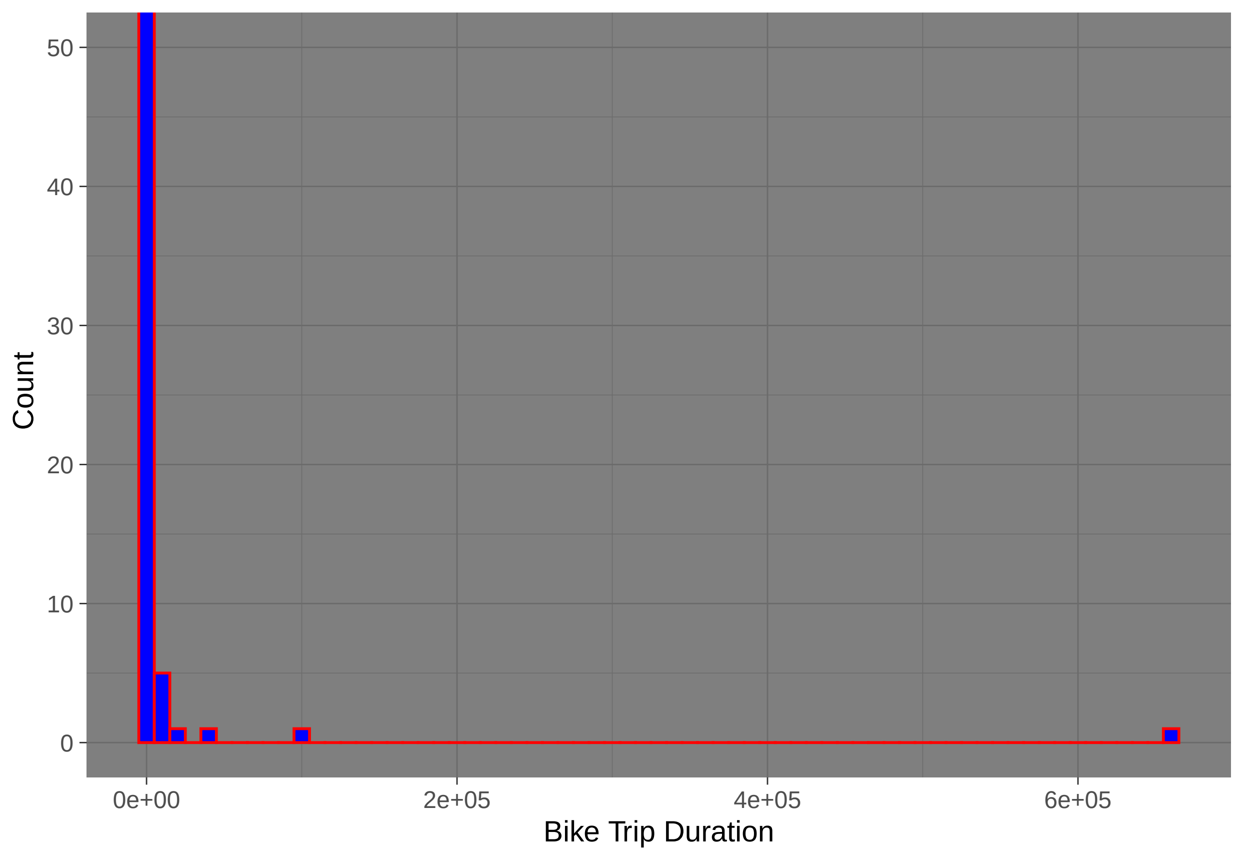
So, if we want to have look on the trip distribution, first we have look on the data-set we imported (1000) as the sample from the whole population. In the next steps, we further increase the size of the data to see is there any significant change from the analysis of the initial sample size.

```r
ggplot(NY_sample, aes(tripduration)) +
  geom_histogram(fill = 'blue',color='red') +
  xlab("Bike Trip Duration") +
  ylab(" Count") +
  theme_dark()
```



Closer look on the *tripduration* we could figure out that the data has some outlier or possible some very off value. To have better understanding of this issue, we reduce the y axis limit to see where the outlier are:

```
ggplot(NY_sample, aes(tripduration)) +
  geom_histogram(binwidth = 10000, fill = 'blue',color='red') +
  coord_cartesian(ylim = c(0,50)) +
  xlab("Bike Trip Duration") +
  ylab(" Count") +
  theme_dark()
```



Seems, there are some very long bike trip, let's have look on them; let's say the all bike trips more than 30000 sec:

```
NY_sample %>%
  filter(tripduration > 30000) %>%
  arrange(tripduration)
```

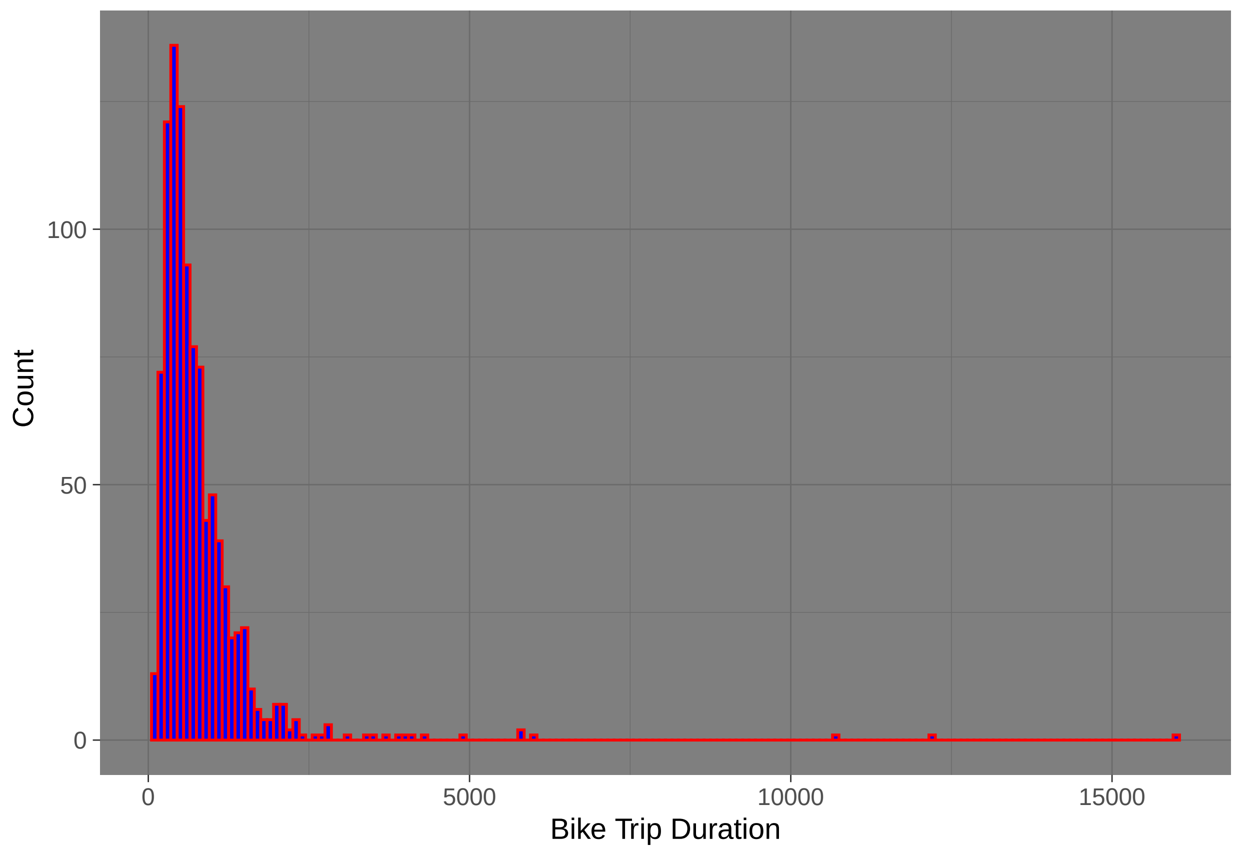
```
##   tripduration           starttime            stoptime start_station_id
## 1        36395 2016-03-15 21:36:55 2016-03-16 07:43:31              375
## 2        96235 2015-10-23 19:36:55 2015-10-24 22:20:51              493
## 3       659210 2015-11-04 07:20:10 2015-11-11 22:27:00              519
##        start_station_name start_station_latitude start_station_longitude
## 1 Mercer St & Bleecker St               40.72679               -73.99695
## 2         W 45 St & 6 Ave               40.75680               -73.98291
## 3   Pershing Square North               40.75187               -73.97771
##   end_station_id  end_station_name end_station_latitude
## 1           3019 NYCBS Depot - DEL             40.71663
## 2           3019 NYCBS Depot - DEL             40.71663
## 3           3019 NYCBS Depot - DEL             40.71663
##   end_station_longitude bikeid   usertype birth_year gender
## 1             -73.98193  19910 Subscriber       1979   male
## 2             -73.98193  18137 Subscriber       1957   male
## 3             -73.98193  20894 Subscriber       1965   male
```

What we can say these three trips are about more than 10 hours of biking!, seems something unusual and probably are not the correct data due to error in registering the time or other issues, now we in this case considering theses cases, we do not include these three rows in the further analysis.

```r
NY_sample_fil <- NY_sample %>%
  filter(tripduration < 30000)
```

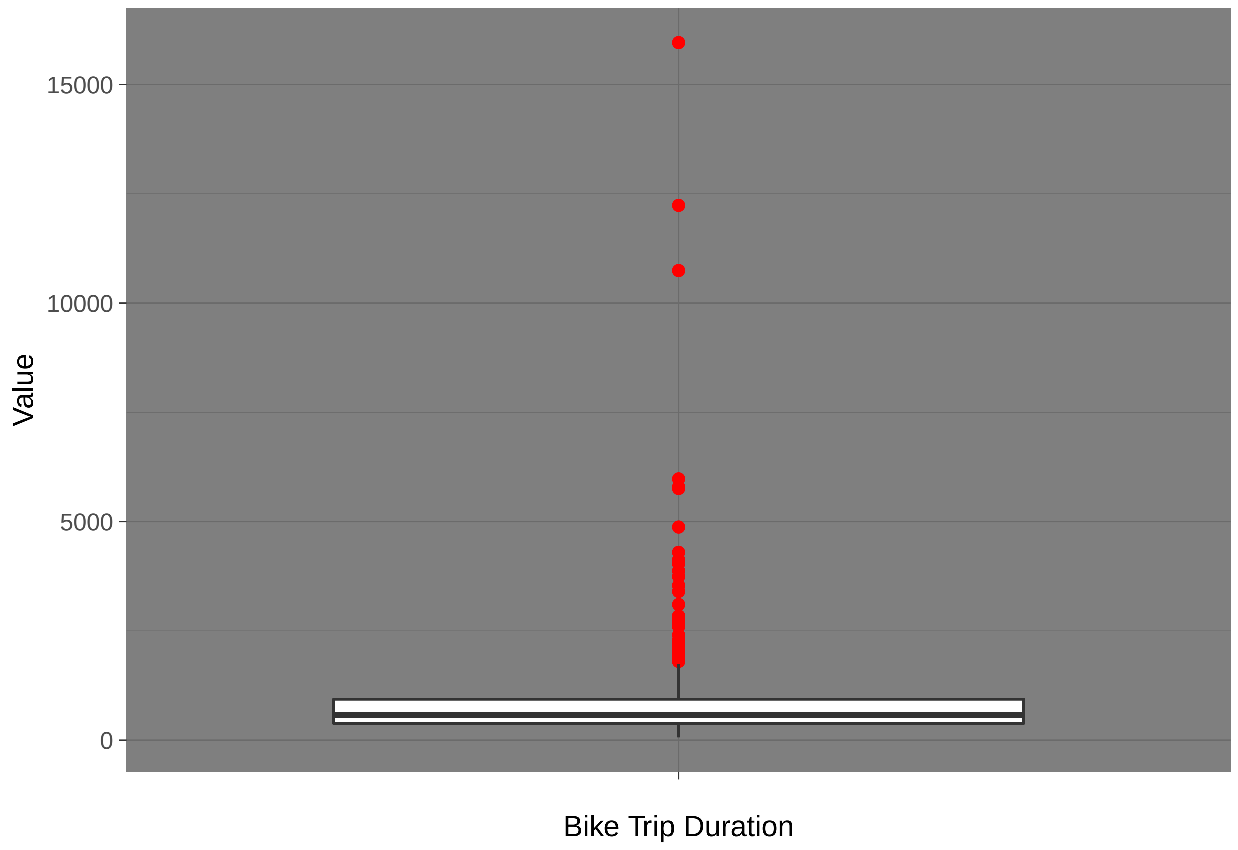
Now, let's plot the filtered data set and see the distribution of the *tripduration*:

```r
ggplot(NY_sample_fil, aes(tripduration)) +
  geom_histogram(binwidth = 100, fill='blue', color='red') +
  xlab("Bike Trip Duration") +
  ylab(" Count") +
  theme_dark()
```



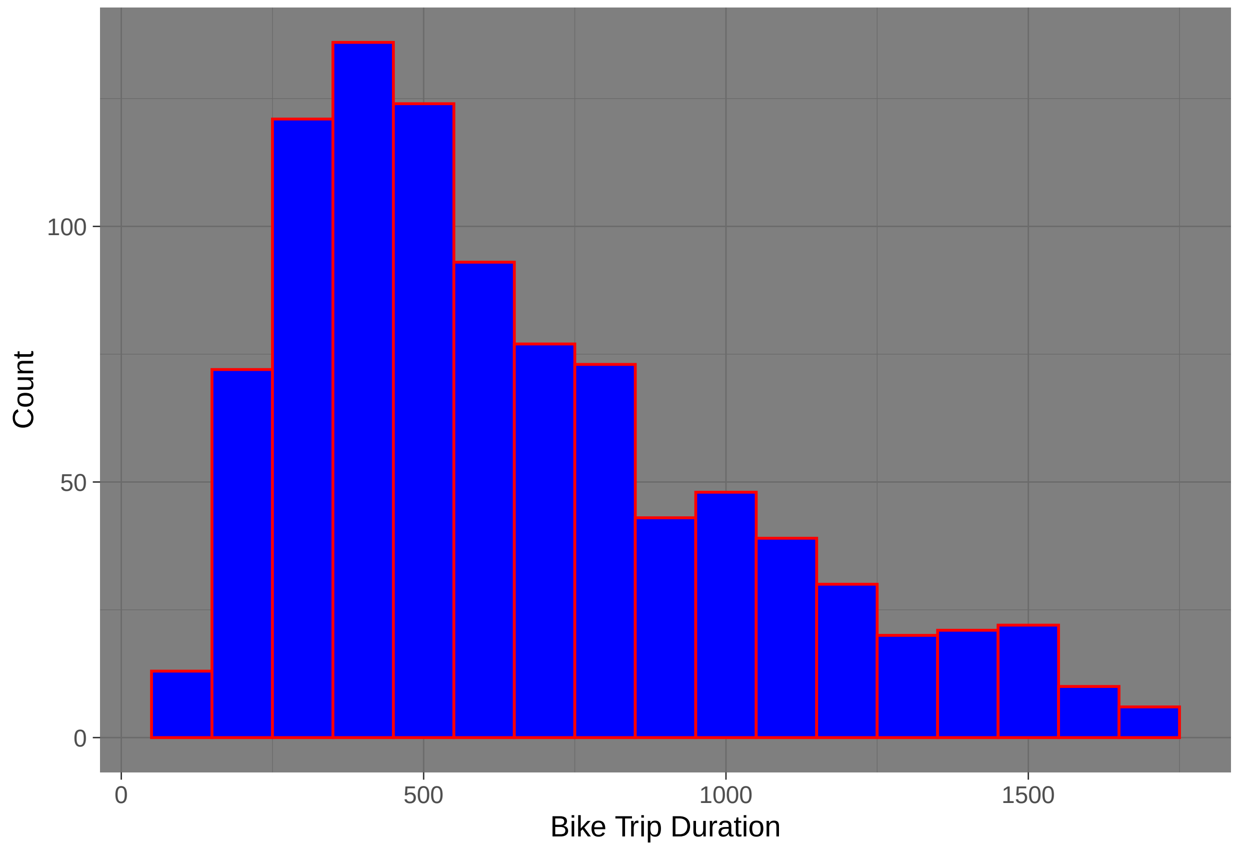
Ok, now we could see that the data has the outlier. To further check this issue, we draw the BOX plot of the data to look:

```r
ggplot(NY_sample_fil, aes(x = "", y=tripduration)) +
  geom_boxplot(outlier.colour="red",
               outlier.shape=16,
               outlier.size=2, notch=FALSE) +
  xlab("Bike Trip Duration") +
  ylab("Value") +
  theme_dark()
```



Now, to be more clear about the real distribution of trip time, we again plot the distribution, yet this time we do not include the outlier in the dataset. By definition, here the outlier means the data *outside* of the 1.5 IQR from the 75% and 25 % quantile of the data. Have look on the distribution without the outliers:

```
quantile_query <- quantile(NY_sample_fil$tripduration,c(0.25,0.75))
lower_range <- quantile_query[1]-1.5*IQR(NY_sample_fil$tripduration)
upper_range <- quantile_query[2]+1.5*IQR(NY_sample_fil$tripduration)

NY_sample_fil %>%
  filter(tripduration > lower_range & tripduration < upper_range) %>%
  ggplot(aes(tripduration)) +
  geom_histogram(binwidth = 100, fill='blue', color='red') +
  xlab("Bike Trip Duration") +
  ylab("Count") +
  theme_dark()
```



However, the above data analysis were for the small sample (10000 rows), how about the large data-set. Here, we include the 1,000,000 rows to be included in the analysis to provide the better understanding the distribution.

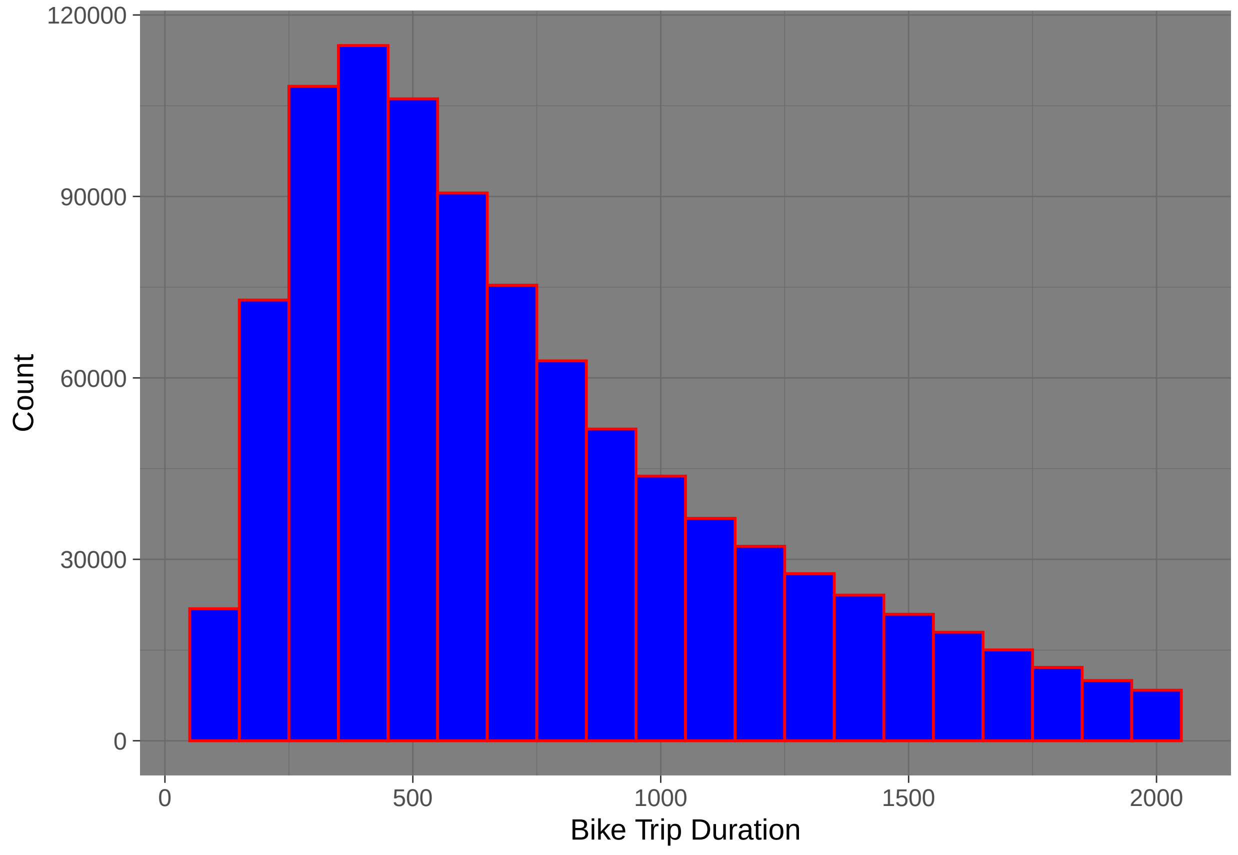
```
# Project ID
project_id <- "xenon-muse-261616" # put your project ID here

# query
sql_string_tot <- "SELECT
  tripduration
FROM
  [bigquery-public-data.new_york.citibike_trips]
LIMIT
1000000"
# Execute the query and store the result
NY_Lsample <- query_exec(sql_string_tot, project = project_id,
                         useLegacySql = FALSE, max_pages = 100)
```

```
## 0 bytes processed
```

We again plot the data-set this time without the outlier when the larger rows were included in the data-set.

```
quantile_queryL <- quantile(NY_Lsample$tripduration,c(0.25,0.75))
lower_rangeL <- quantile_queryL[1]-1.5*IQR(NY_Lsample$tripduration)
upper_rangeL <- quantile_queryL[2]+1.5*IQR(NY_Lsample$tripduration)
```

```r
NY_Lsample %>%
  filter(tripduration > lower_rangeL & tripduration < upper_rangeL) %>%
ggplot(aes(tripduration)) +
  geom_histogram(binwidth = 100, fill='blue', color='red') +
  xlab("Bike Trip Duration") +
  ylab("Count") +
  theme_dark()
```



Question: What is the most popular Citibike trip?

So, from the previous question we got to know the data and how is look like. For this question we only import the two rows we needed in the question, *start_station_id* and *end_station_id*, also we get the about 1,000,000 rows this time:

```r
# Project ID
project_id <- "xenon-muse-261616" # put your project ID here

# query
sql_string_tot_trip <- "SELECT
  start_station_id,
  end_station_id
FROM
  [bigquery-public-data.new_york.citibike_trips]
```

```
LIMIT
1000000"
# Execute the query and store the result
NYL_trip <- query_exec(sql_string_tot_trip, project = project_id, useLegacySql = FALSE, max_pages = 100
```

```
## 0 bytes processed
```

have the brief look on the data:

```
head(NYL_trip)
```

```
##   start_station_id end_station_id
## 1              512            512
## 2              512            512
## 3              512            512
## 4              512            512
## 5              512            512
## 6              512            512
```

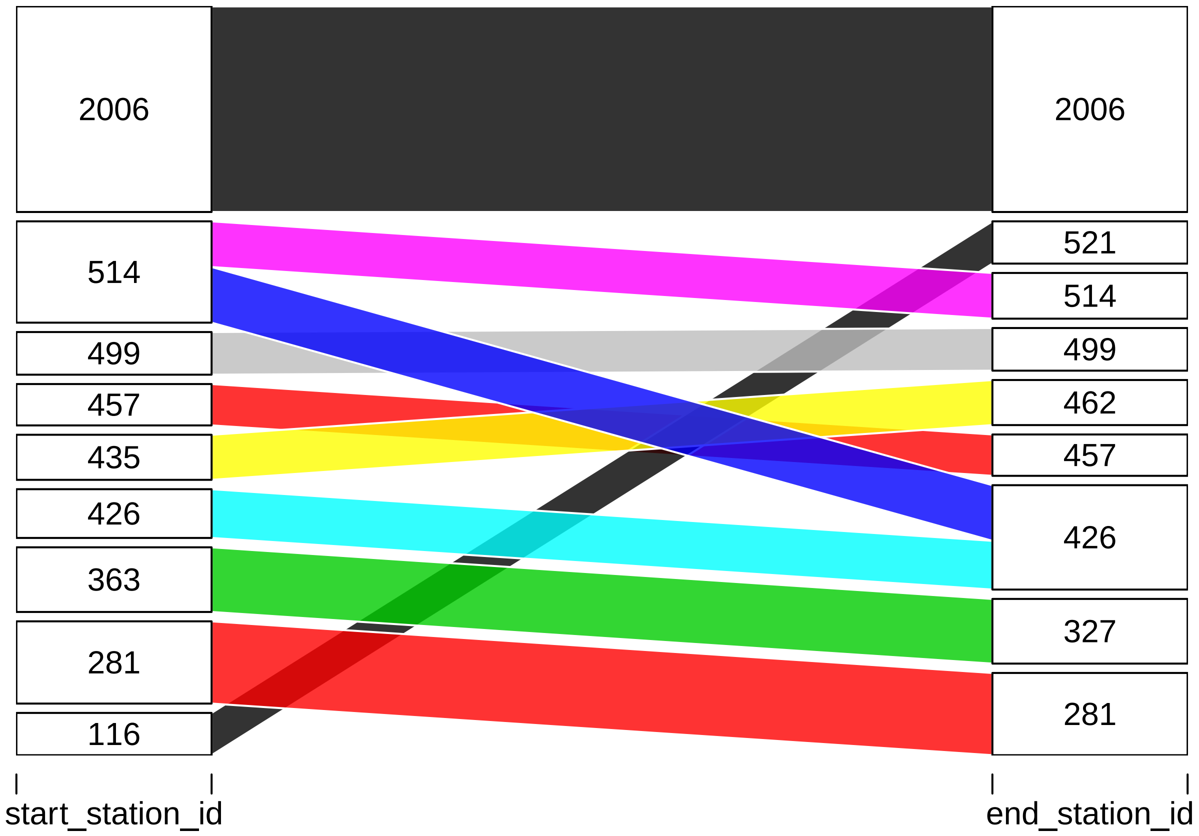
Here, we group the data based on the *start_station_id* and as well *end_station_id* and then we count the number of trip between any two starting and end station:

```
NYL_trip_group <- NYL_trip %>%
  count(start_station_id,end_station_id) %>%
  filter(n > 300) %>%
  arrange(desc(n))
NYL_trip_group
```

```
## # A tibble: 10 x 3
##    start_station_id end_station_id     n
##               <int>          <int> <int>
##  1             2006           2006  1615
##  2              281            281   646
##  3              363            327   508
##  4              514            426   437
##  5              426            426   383
##  6              514            514   359
##  7              435            462   354
##  8              499            499   335
##  9              116            521   332
## 10              457            457   325
```

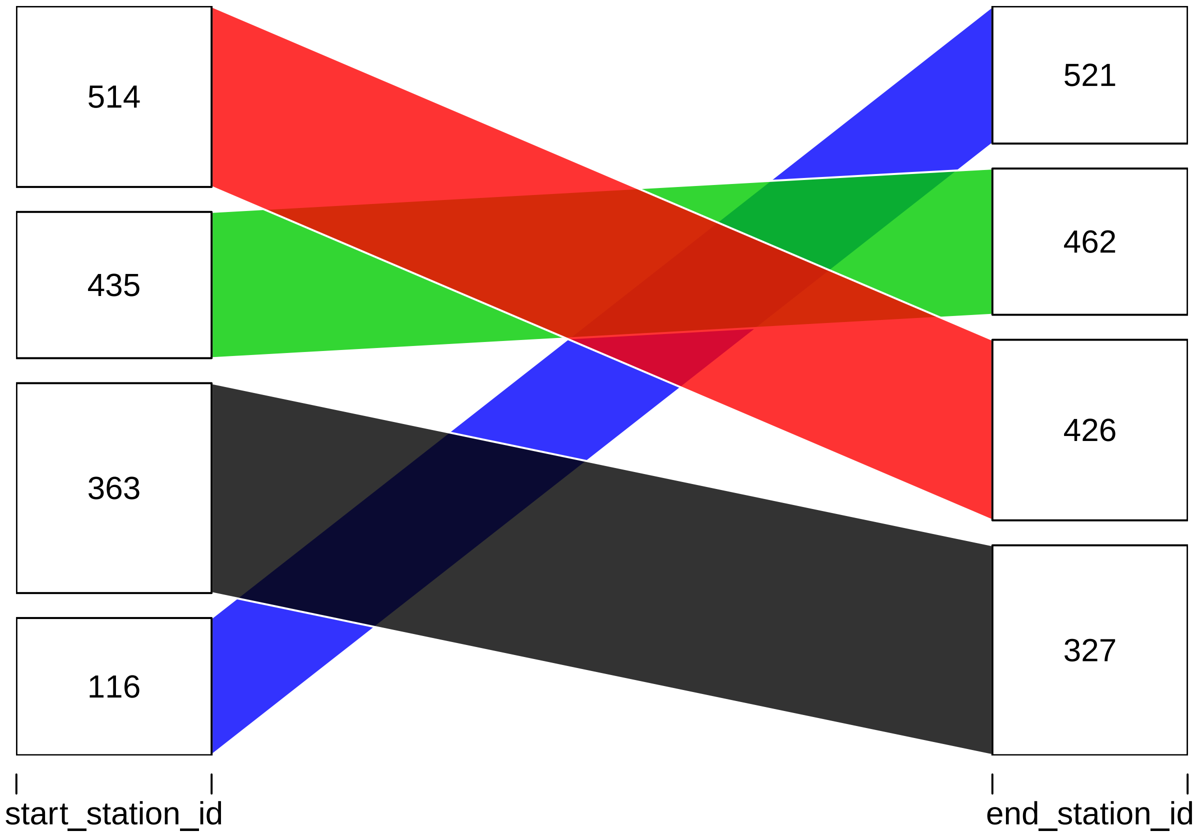
Now, we can plot the result in one river plot which thickness of the each river show the *count* of the trip between two two stations:

```
library(alluvial)
alluvial(NYL_trip_group[,1:2], freq=NYL_trip_group$n, xw=0.0, alpha=0.8,
         gap.width=0.1, col= 1:10, border="white")
```



However, maybe the the trip between the same *station_id* may not be informative, therefore in the new plot we removed the same start and end stations and includes the only trips where have different start and end point:

```
library(alluvial)
NYL_trip_group_nonsim <- NYL_trip %>%
  filter(start_station_id != end_station_id) %>%
  count(start_station_id,end_station_id) %>%
  filter(n > 300) %>%
  arrange(desc(n))


alluvial(NYL_trip_group_nonsim[,1:2], freq=NYL_trip_group_nonsim$n, xw=0.0, alpha=0.8,
          gap.width=0.1, col= 1:4, border="white")
```



Question: Were there new bike stations introduced or removed at any point in time? What makes you think it were or weren't?

So, to answer this question we first need to import the two columns , *starttime* and *start_station_id*. Here we assume if new station was introduced in the start station so that the new trips could be done using this station.

```
# Project ID
project_id <- "xenon-muse-261616" # put your project ID here

# query
sql_string_newsta <- "SELECT
  starttime,
  start_station_id
FROM
  [bigquery-public-data.new_york.citibike_trips]
LIMIT
1000000"
# Execute the query and store the result
NYL_newsta <- query_exec(sql_string_newsta, project = project_id,
                         useLegacySql = FALSE, max_pages = 100)
```

```
## 0 bytes processed
```

Now, the code below shows the distinct start station id per month. So, this could be helpful when in the next stage when we want to know which station was added or removed.

```
NYL_newsta_group <- NYL_newsta %>%
  mutate(month = as.numeric(format(starttime, "%m")), year = as.numeric(format(starttime, "%Y")),
         day=as.numeric(format(starttime, "%d"))) %>%
  select(year, month, start_station_id) %>%
  distinct(year, month, start_station_id, .keep_all = TRUE) %>%
  group_by(year, month, start_station_id) %>%
  arrange(year, month)
```

For example, we could ask what station was added to the trips on month 8 of 2013. To do that, we compare the whole recorded trip until the month 7 of 2013 and compare it with the month 8 of 2013.

```
old <- NYL_newsta_group %>%
  filter(year<=2013 & month <= 10) %>%
  pull(start_station_id)

old <- unique(old)

new <- NYL_newsta_group %>%
  filter(year==2014 & month == 10) %>%
  pull(start_station_id)
```

The new stations added to the biking trips on the month 8 of 2013 are includes:

```
new[!(new %in% old)]
```

```
## [1] 519 530 320 491
```

Now, we can see that the station number 502 was added to the traveling route on month 8th of 2013.

Now, let's look what station was removed during the time. Let's say what station were removed at October of 2014 when compared to October of the 2013.

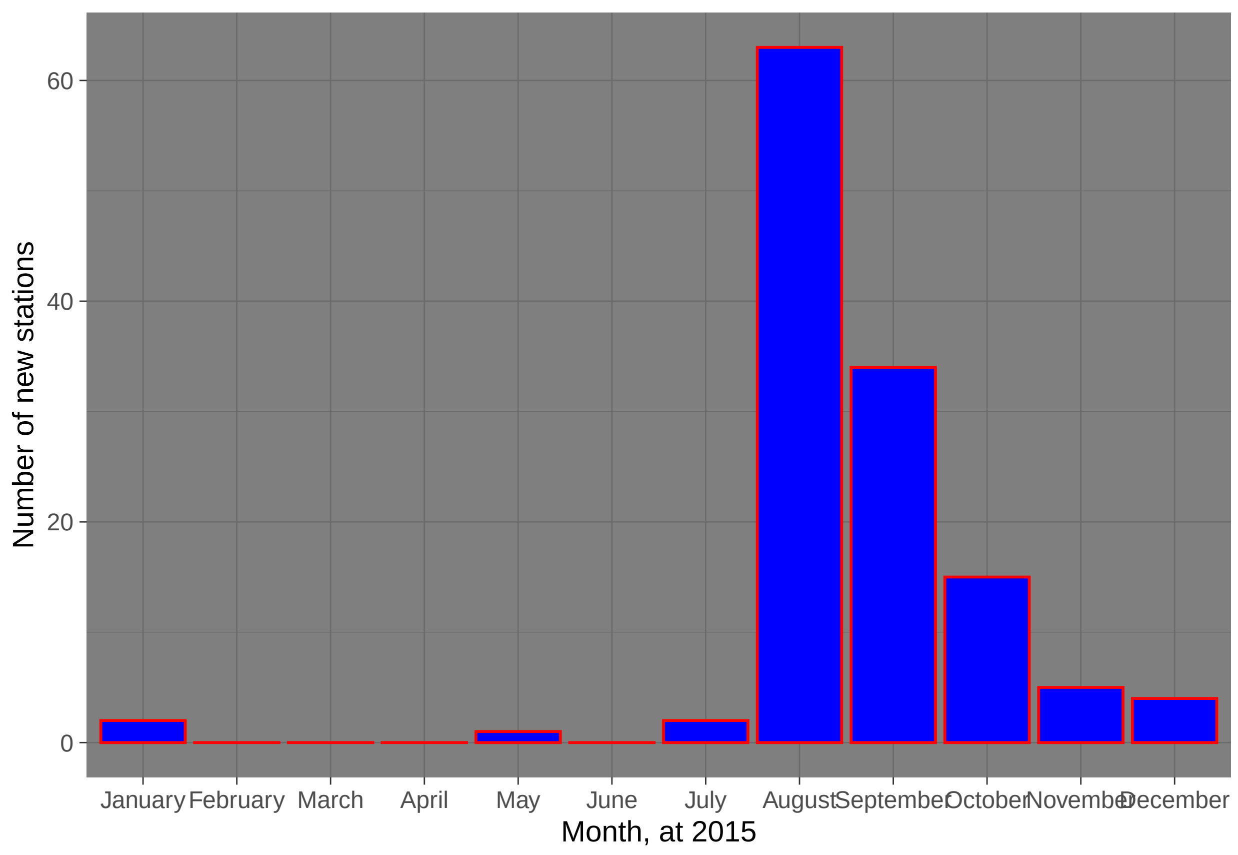
```
old <- NYL_newsta_group %>%
  filter(year<=2013 & month <= 10) %>%
  pull(start_station_id)

old <- unique(old)

new <- NYL_newsta_group %>%
  filter(year==2014 & month == 10) %>%
  pull(start_station_id)

old[!(old %in% new)]
```

```
## [1] 517 243
```

The stations named 517 and 243 were available on October of 2013 but, were not available on the October of 2014.

For the number of stations added to the route, we here calculate the number of stations were added at 2015, per month.

```r
new_station <- numeric(12)
for (mnt in 1:12) {
  if (mnt==1) {
    yr = 2014
    mnth = 12
    mnt = 1
} else {
yr = 2015
mnth = mnt-1
}

old <- NYL_newsta_group %>%
  filter(year<=yr & month <= mnth) %>%
  pull(start_station_id)

old <- unique(old)

new <- NYL_newsta_group %>%
  filter(year==2015 & month == (mnt)) %>%
  pull(start_station_id)

new_station[mnt] <- length(new[!(new %in% old)])
}

months <- c("January", "February", "March", "April","May","June", "July",
            "August", "September", "October", "November", "December" )

df_newstat <- data.frame(month=months,
                         New_Stations = new_station)


ggplot(data=df_newstat, aes(x=factor(month,levels=month.name), y=New_Stations)) +
  geom_bar(stat="identity", fill='blue', color='red') +
  xlab("Month, at 2015") +
  ylab("Number of new stations") +
  theme_dark()
```


Number of new stations
60
40
20
0
January
February
March
April
May
June
July
August
September
October
November
December
Month, at 2015