**LA Metro Bike Share Project**

**Introduction :**

The following project is focused on a analyzing the Los Angles Metro Bike Share data. Los Angles Metro Bike Share operation provides rental bicycles 365 days a year since the 2d quarter of 2016. The main objective of the project is to focus on predicting the number of bicycles needed at each station, evaluating the pricing system currently used to make recommendations for possible pricing changes and expanding the network. Forecasting the number of bicycles needed at each station is done using time series analysis and linear regression. An in-depth evaluation of pricing system was carried out and the linear as well as quadratic optimization algorithms have been used based on the number of riders and the price of each ride to find the optimal solution for maximizing revenue. Pricing model of the competitors have also been considered while evaluating and optimizing the total revenue. Based on the forecasting models, exploratory data analysis and the evaluation of pricing system, recommendations for expanding the network has been made.

**Data Collection :**

The data is collected from the official website of Los Angeles Metro Bike Share. Dataset consist of information about the bike rides and the bike stations in Los Angeles areas. The data represents 4 regions of Los Angeles- Downtown LA, Pasedena, Port of LA, Venice

The bike rides data consist of information about:

* Trip\_id: the unique value of individual trip (no repetition in dataset)
* Bike\_id: the unique value of individual bike used for the trip (total 1505 different bikes were used for the trip)
* Start\_station: the unique value of individual station from where trip start (total 141 station were used actively for trip)
* End\_station: the unique value of individual station on which trip ends (total 143 station were used actively for trip)
* Trip\_route\_category: the two type of trip used-round trip or one-way trip
* Start\_time: Time at which the trip begins
* End\_time: Time at which the trip ends
* Start\_lat: Latitude geographical value from where trip start
* Start\_lon: Longitude geographical value from where trip start
* End\_lat: Latitude geographical value on which trip end
* End\_lon: Longitude geographical value on which trip end
* Passholder\_type: 4 type of passes available for the trip. Every pass has individual cost structure. Annual pass for 365 days, Monthly pass for 30 days, Flex pass for 1 day and walk up is not for any particular time
* Plan\_duration: The number of days pass is entitled

The station data consist of information about:

* Station\_id: the unique value of individual station from where trip start (total 143 station)
* Station\_name: Name of location of station in Los Angeles as per unique station\_id
* Region: The region where these individual stations is located in LA
* Go\_live\_data: Date from which the station got activated
* Status: Tells whether station is active or inactive

**Data Preprocessing:**

The bike ride data consist of total 639786 rows and 13 columns. Missing values in the dataset is shown below:

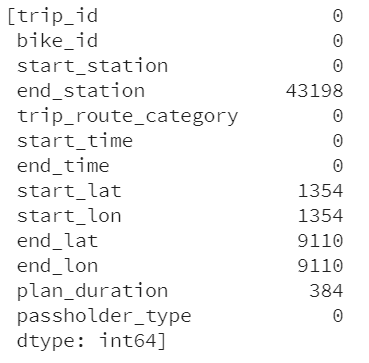


Fig: Null values sum in individual column

New variables were created for predicting the number of bikes in each station. The distance variable was created using longitude and longitude column to get the distance for individual trip and similarly the time duration variable was introduced using tart time and end time column to get individual trip duration.

All the null values in latitude and longitude column were removed. Total 9946 rows were found to be null and were removed.

After removing the missing values, the data set was divided into four cluster based on region to do further prediction or recommend network expansion. This cluster was made in Tableau using world map. After visualizing data, it was found that some data points have latitudes and longitudes in china and on the equator. It indicates some error in data collection so the corresponding rows which were having 0 in latitude and longitude were eliminated. The point which were located in china were simply because of the sign issue in the longitude so the sign was reversed for those points. Finally, the points were visualized as shown below:

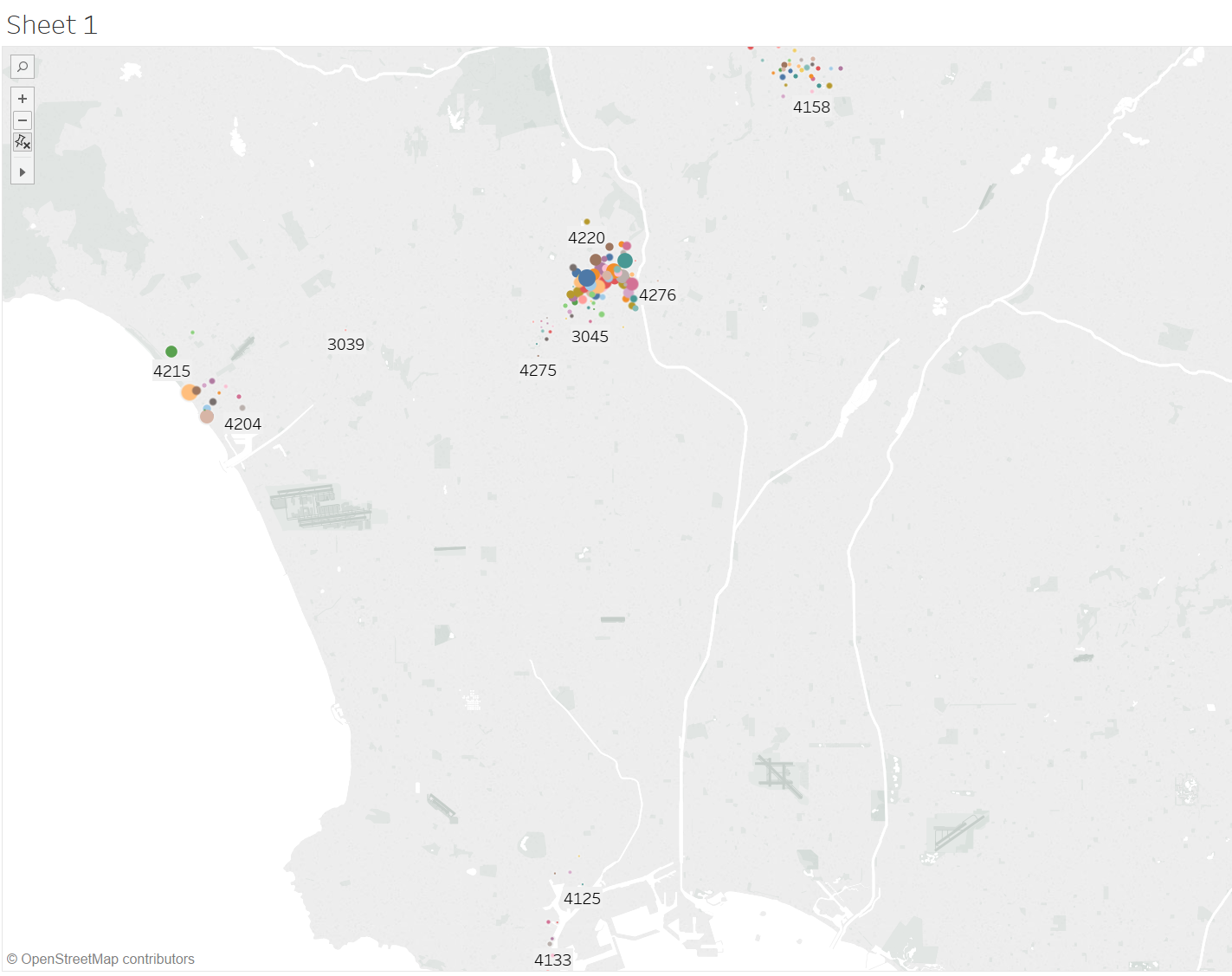


Fig: Cluster of data based on four regions

Outliers and missing values total were removed leaving behind 577223 rows. The distance and time duration for individual trip was then calculated.

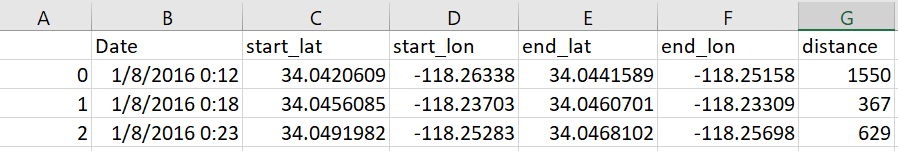
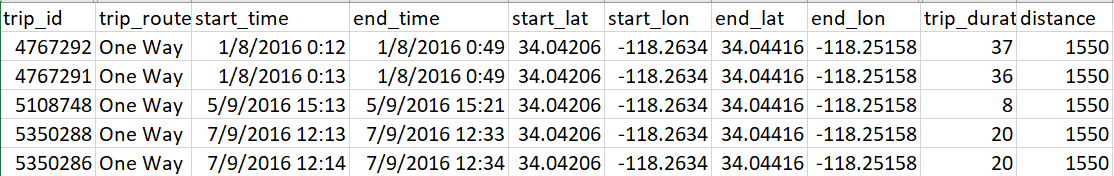
 Distance was calculated using Distance Matrix API available in google maps by setting the mode of transport to bike ride.

Table: Distance column added to each trip

Table: Trip duration added to each trip

Some of the trip duration calculation resulted in negative values. Upon further inspection it was found that end time format in some rows were opposite to start time format. So, all the negative trip durations were deleted. Some values of trip duration were extremely large. So, the durations were normalized separately based on one-way trip and round trip. Upper limit was set at 90 percentile value and the lower limit was 0 minutes. The result is shown below:

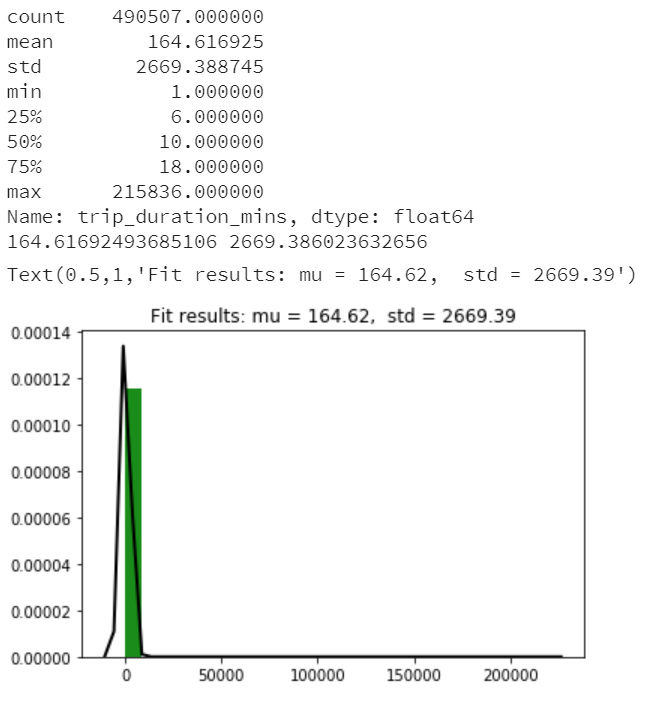


Fig: One way trip normalization

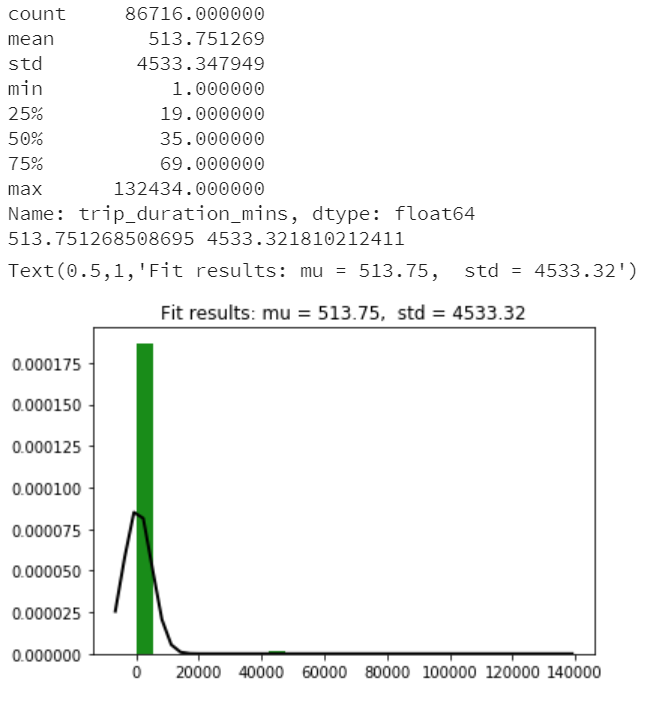


Fig: Round trip normalization

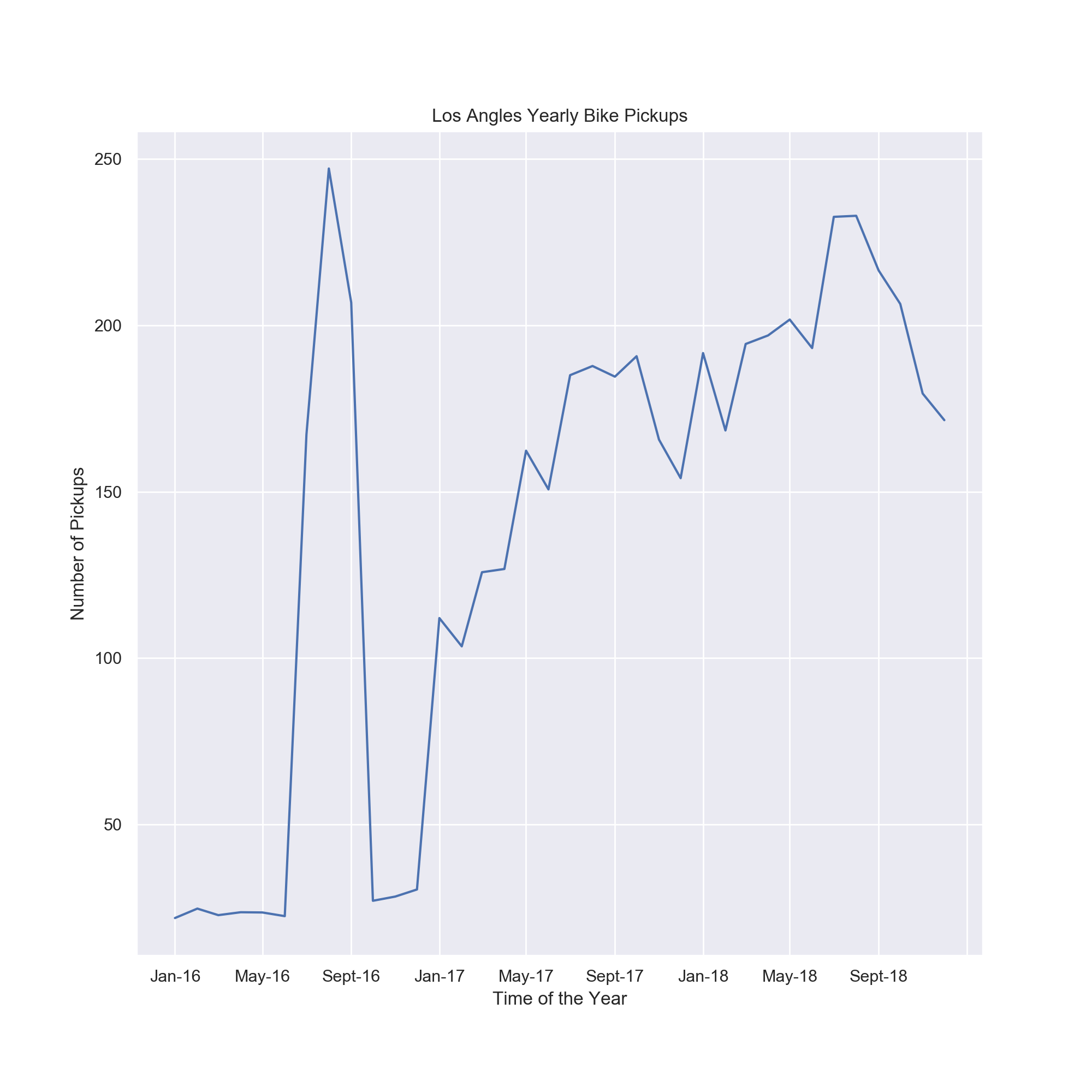
After removing all such upper limit values, the preprocessed dataset had 521140 rows with new variable distance and trip duration for individual trip.

It was also found that from January 2016 to June 2016, data for 2 days were present in each month. So, in order to maintain consistency for time series analysis rows corresponding to July 2016 and earlier were removed. Finally, the preprocessed dataset was having 513685 rows. The cleaned and preprocessed data was used for data visualization and analysis.

**Exploratory Data Analysis**

To better understand this huge dataset and the features it contains, exploratory data analysis was performed. The objective was to realize how the prediction variable behaves with various features and leverage the insights from the data to achieve better results.

**Analyzing the general trend in the usage of number of bikes:**

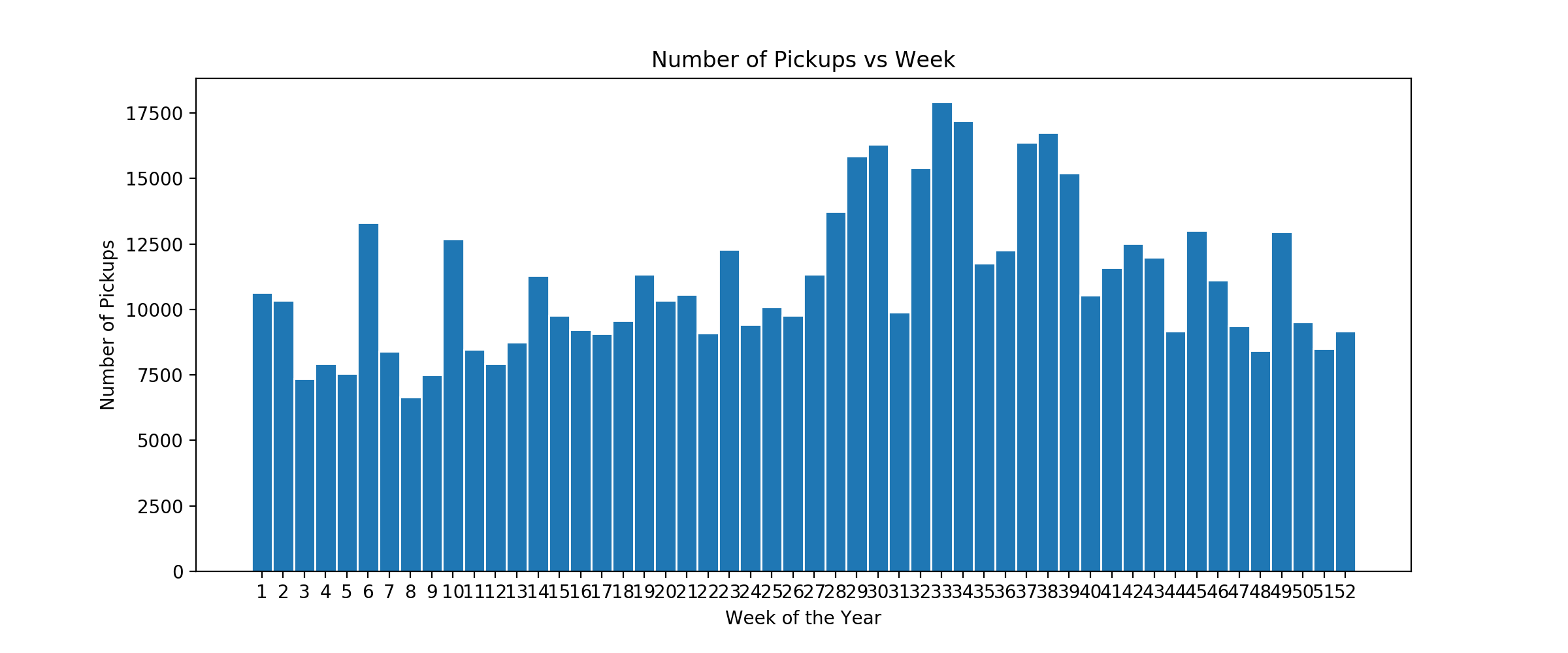
Figure

From Figure 1, the rise in the number of bike pickups can be observed between July 2016 and September 2016 reaching up-to 250 pickups around August 2016.

To understand the pattern of pickup density in greater detail, analysis by different components of the year like by week, day of week, month and hours. while but it again picked up during the end of the year. Since January 2017 the number of pickups has been consistently increasing over 150 pickups without any major drop in the usage. The general

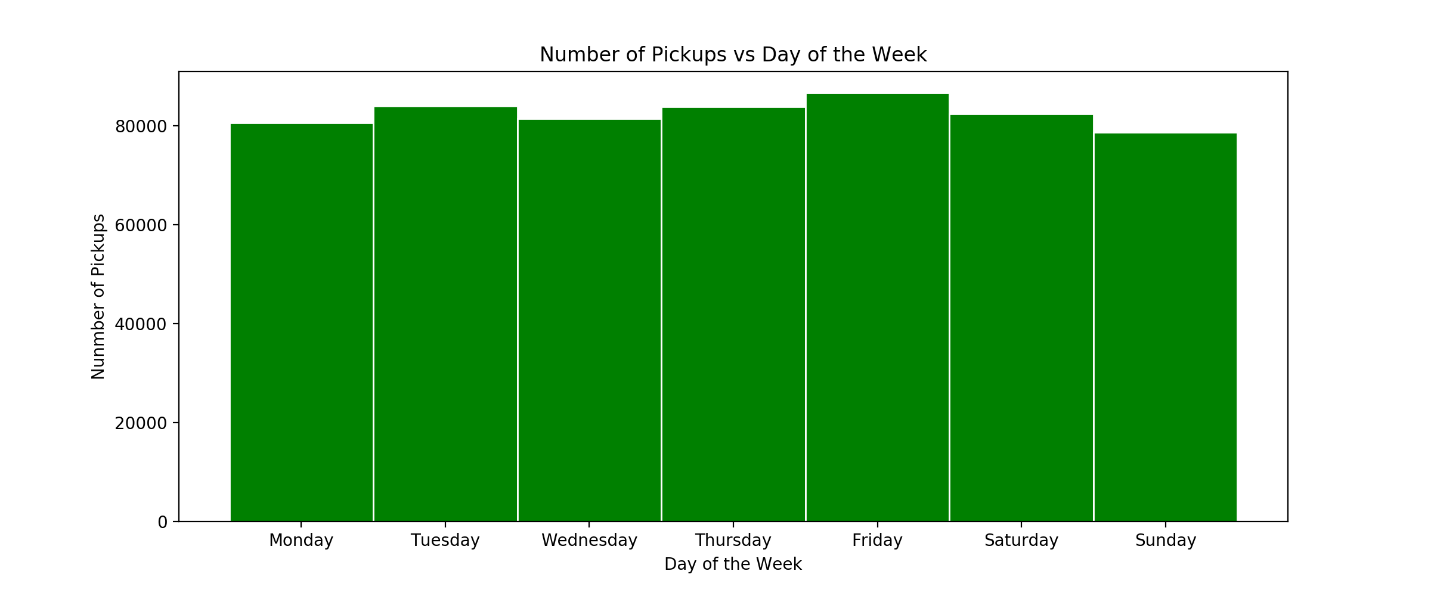
increasing trend clearly suggest that the LA metro bikes company is performing very well in the revenue share of the market and is a quite popular mode of transport.

**Exploring the number of trips at each timestamp:**



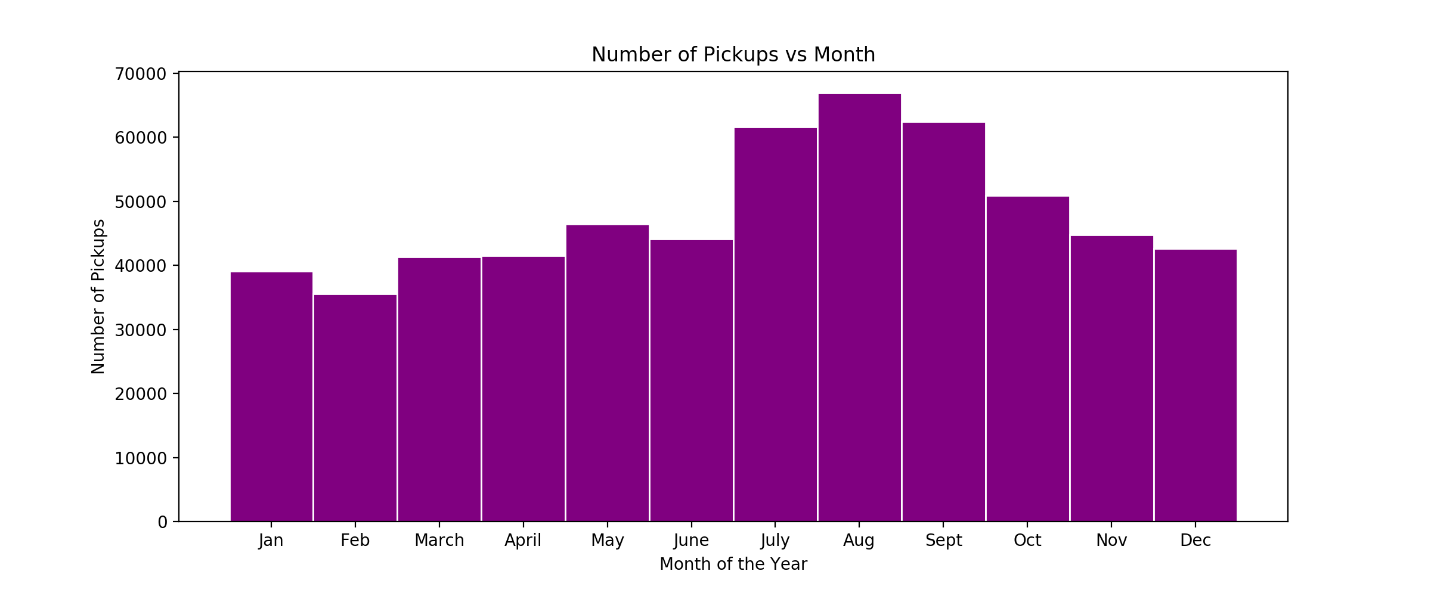
**Figure 2** shows the variation in the demand of the bikes by week.

It can be seen that mostly the demand remains consistent around 1000 bikes per week except some weeks like 29, 30, 33and 34 experienced very high demand. This is an indication of increase in the demand of bikes during July-August.



**Figure 3** shows the variation in the demand of the bikes by day of week.

The trend was uniform for most of the days while Friday and Tuesday had the maximum number of rides.



**Figure 4** shows the demand of the bikes by month of the year.

As it was observed in the figure that the maximum demand is during the months of July, August and September. This is also the fall season in los Angeles and thus people like to bike around the city for enjoying the weather.

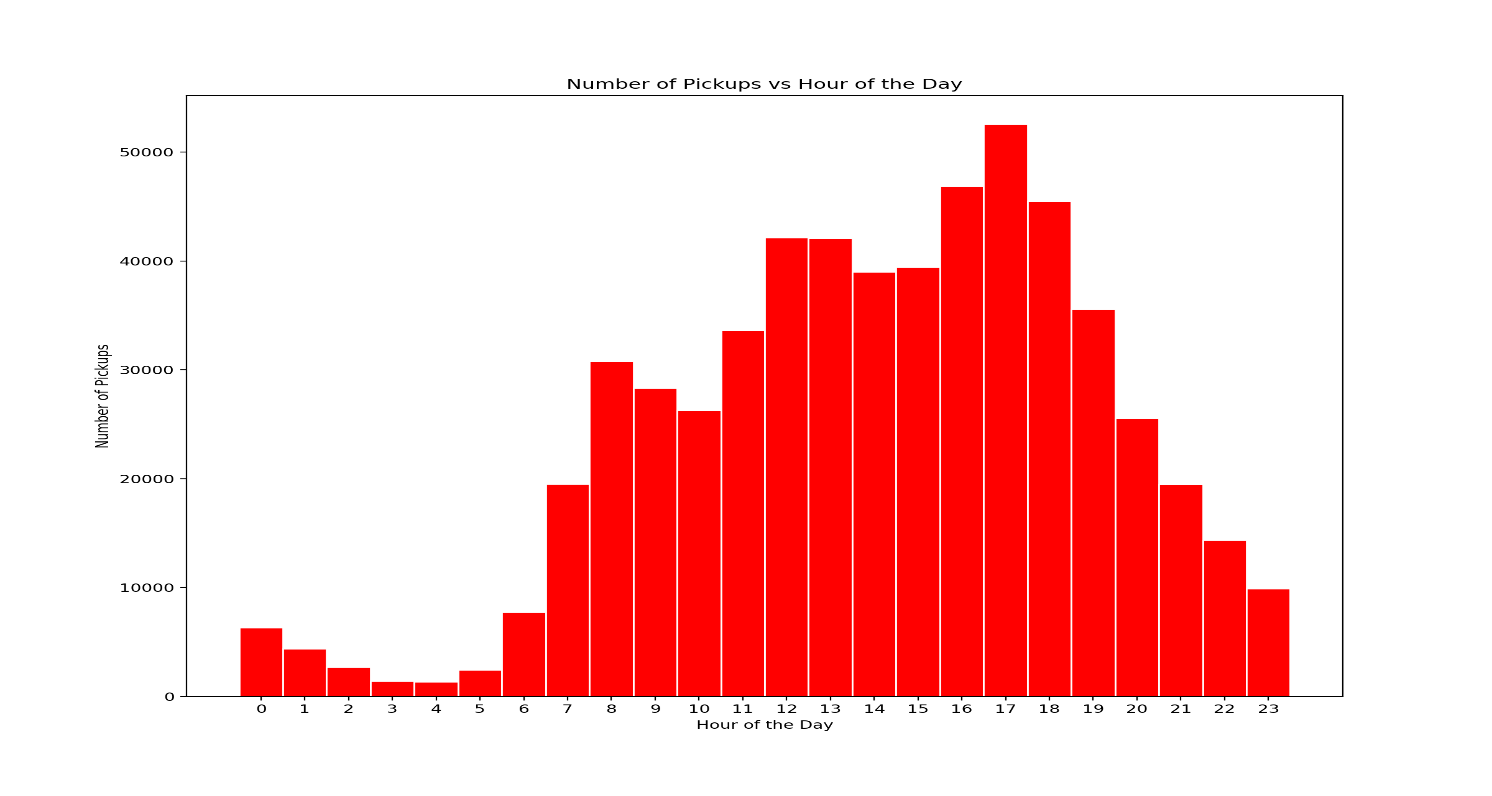
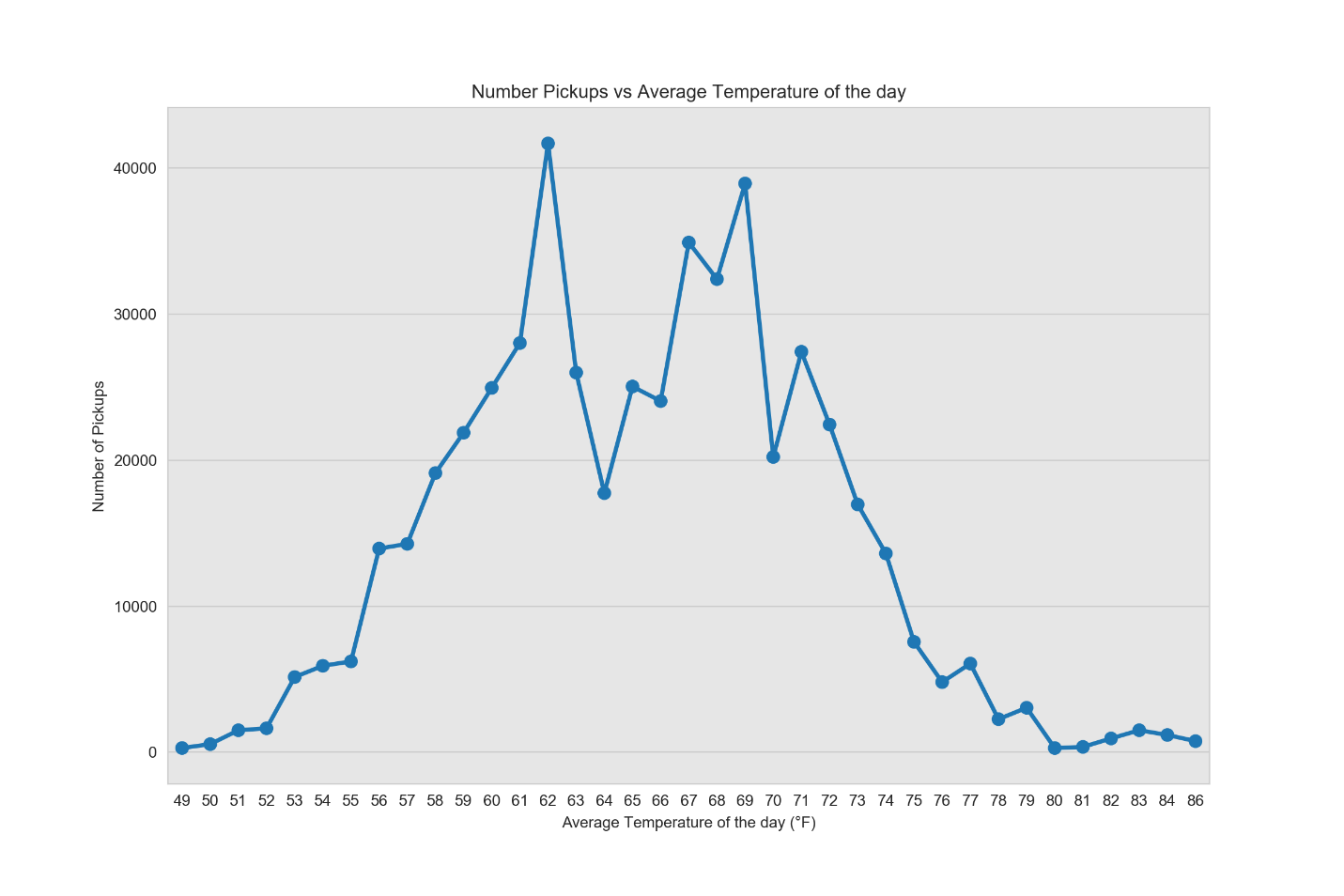


Figure 5

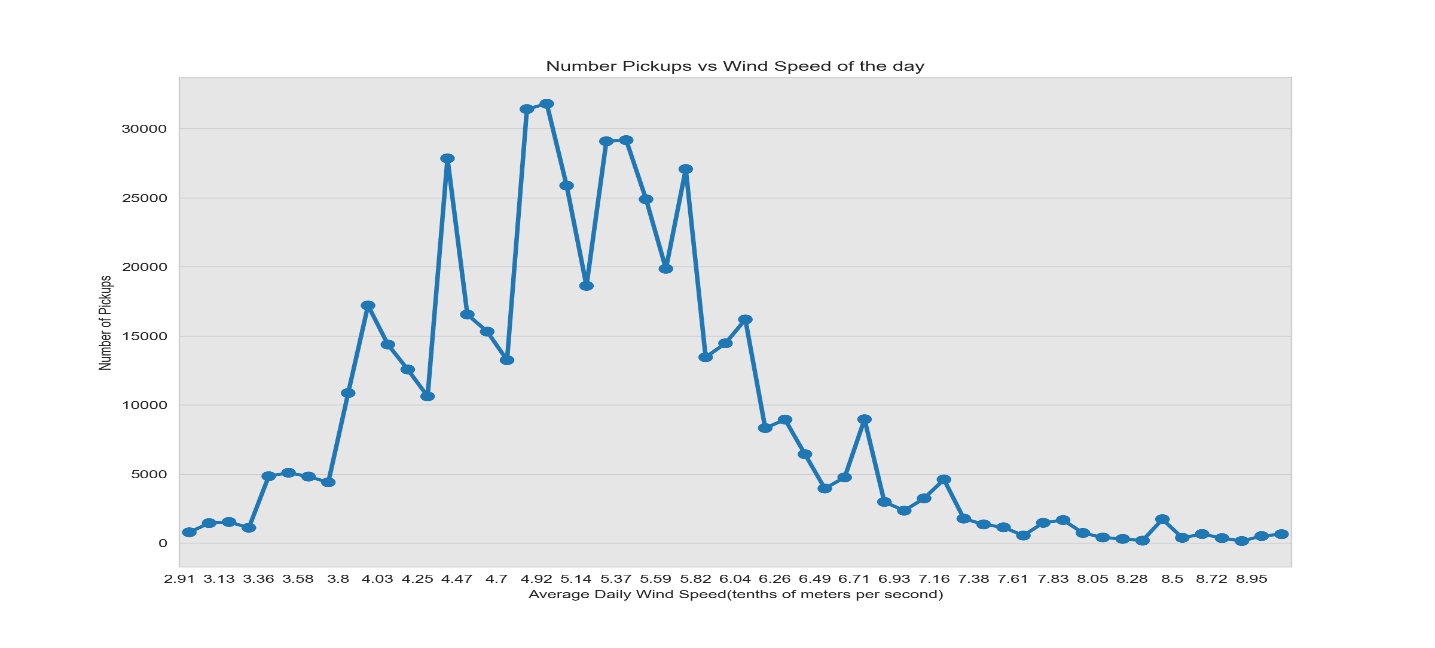
The Figure 5 depicts the variation in the demand by hour of the day. It clearly shows the bikes are in maximum demand between 4pm and 7pm with the maximum number pickups (more than 50k) at around 5pm in the evening.

**Analyzing the effect of temperature and wind-speed on the number of rides:**

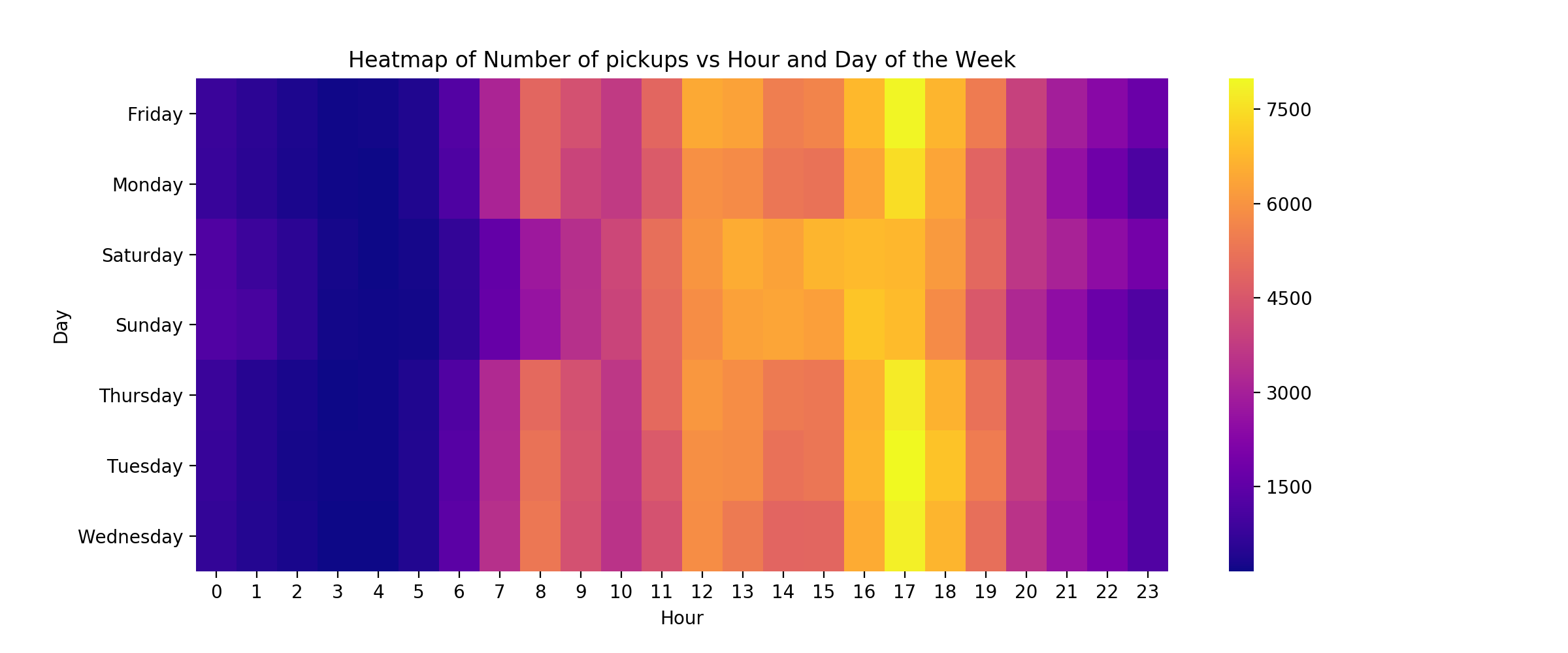


**Figure 6**

As expected the number of bike pickups decreases as the average temperature of the day increases. The highest number of bike trips is recorded around 62 °F

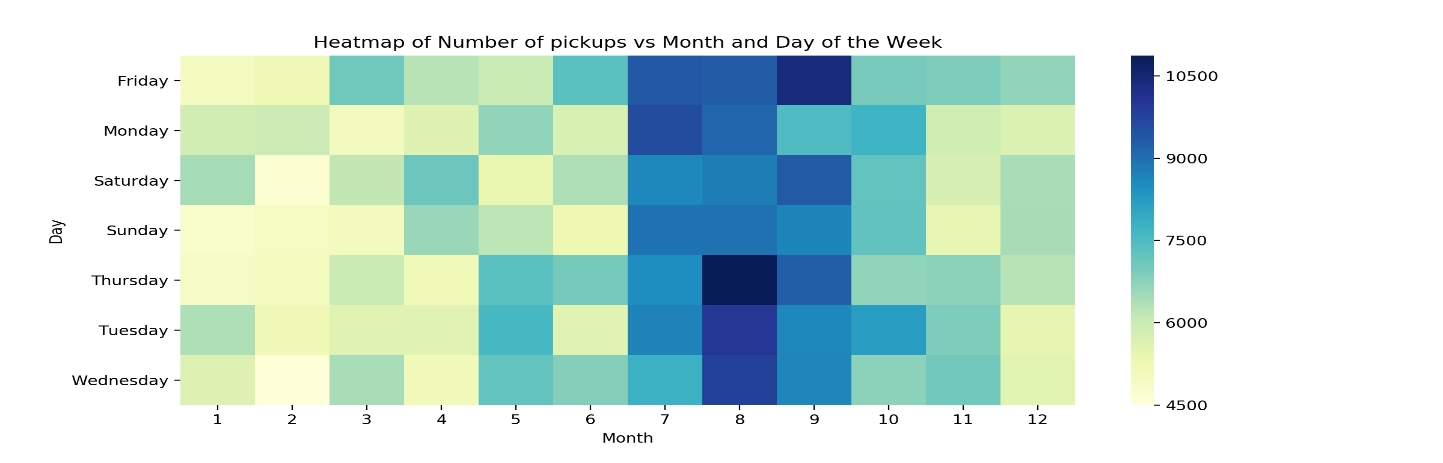


The number of bike pickups is maximum when there is a breeze at 0.4 to 0.6 meters/second and the value decreased with increase in the wind speed. `



**Figure 7**

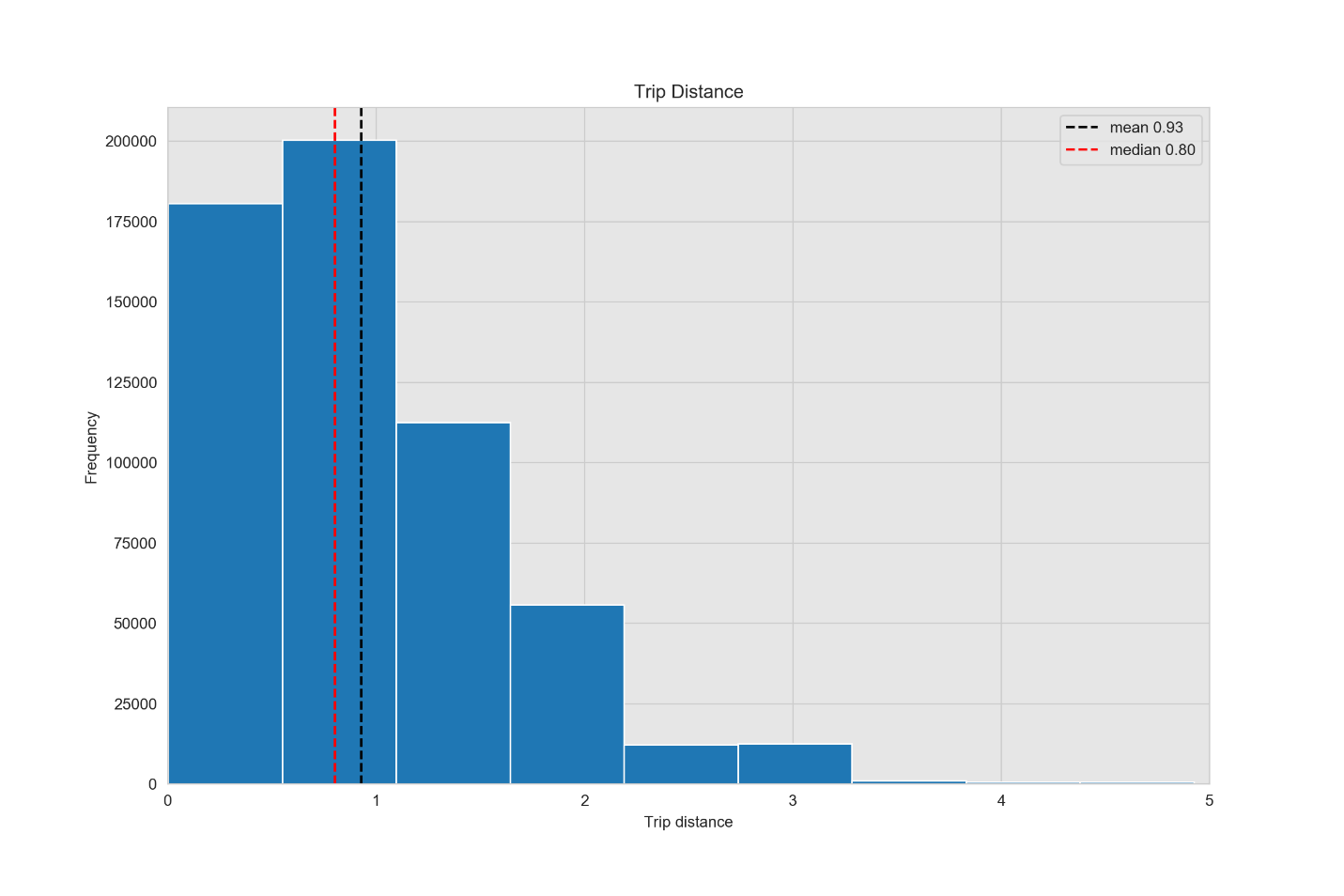
For more granular details regarding the usage of the LA metro bikes a heatmap was plotted. This (Figure 7) gives a clear picture about dependence of both the parameters on number of rides. From 0-6 on Monday through Friday there are a fewer number of rides, hence a smaller number of bikes required to balance the demand. Angelenos generally like using the bike for moving around city during evening which gives rise to a greater number of rides. Also, talking about allocation of resources LA metro bike should have large number of bikes from 16 hour to 19 hour and large number of bikes from 11am 2 pm on all the days. Another important insight can be drawn from this that except Sunday and Saturday there is high usage of the bikes in the morning around 8am as well.



**Figure 8**

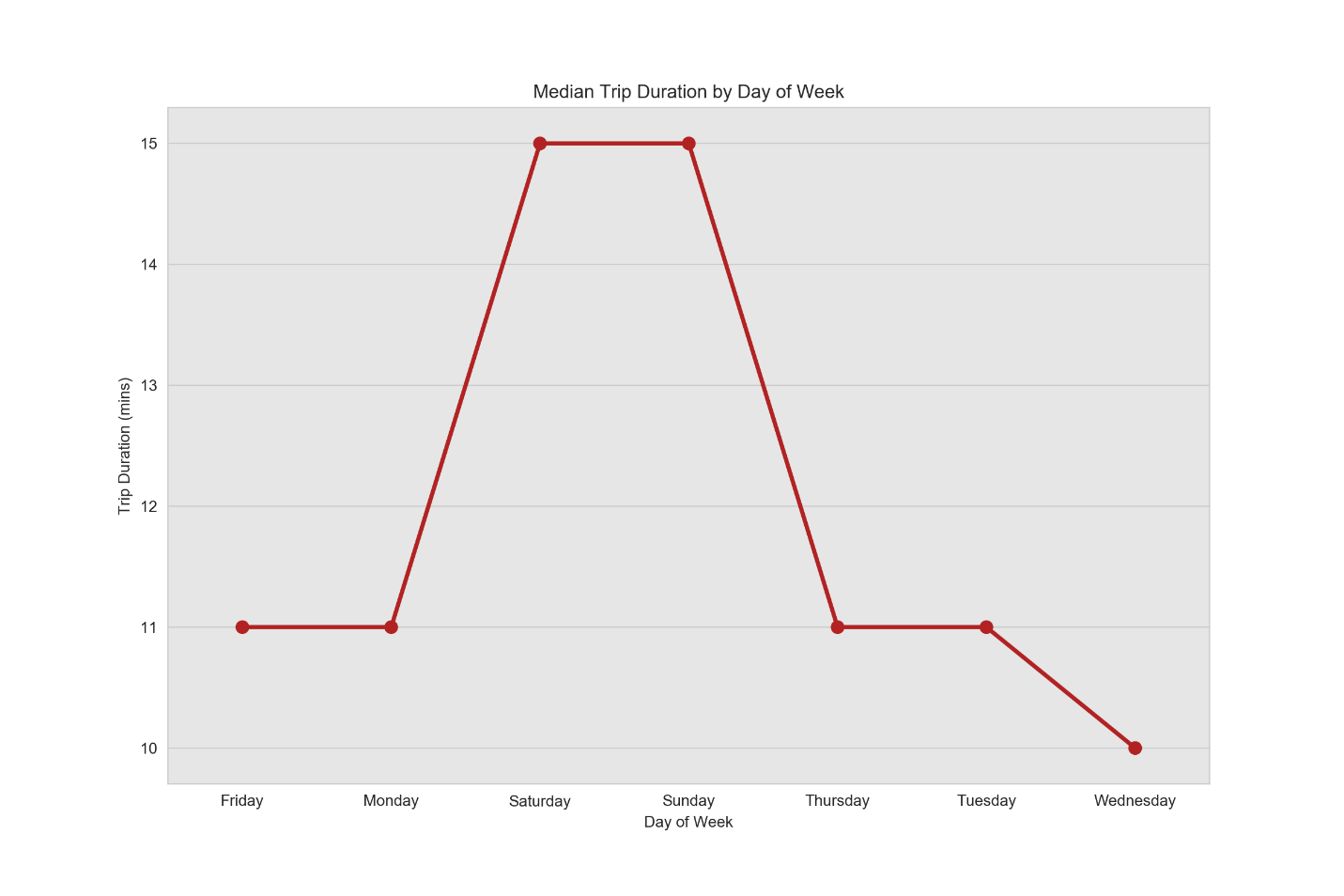
The above heatmap also confirms the findings from the Figure 4 that generally the usage of the bikes on all the days has been between July and September. This shows that people like to use bike for moving around LA during the Fall season enjoying the weather. The maximum number of trips is recorded on Thursday, August over all the years.

Trip Duration and Distance Analysis

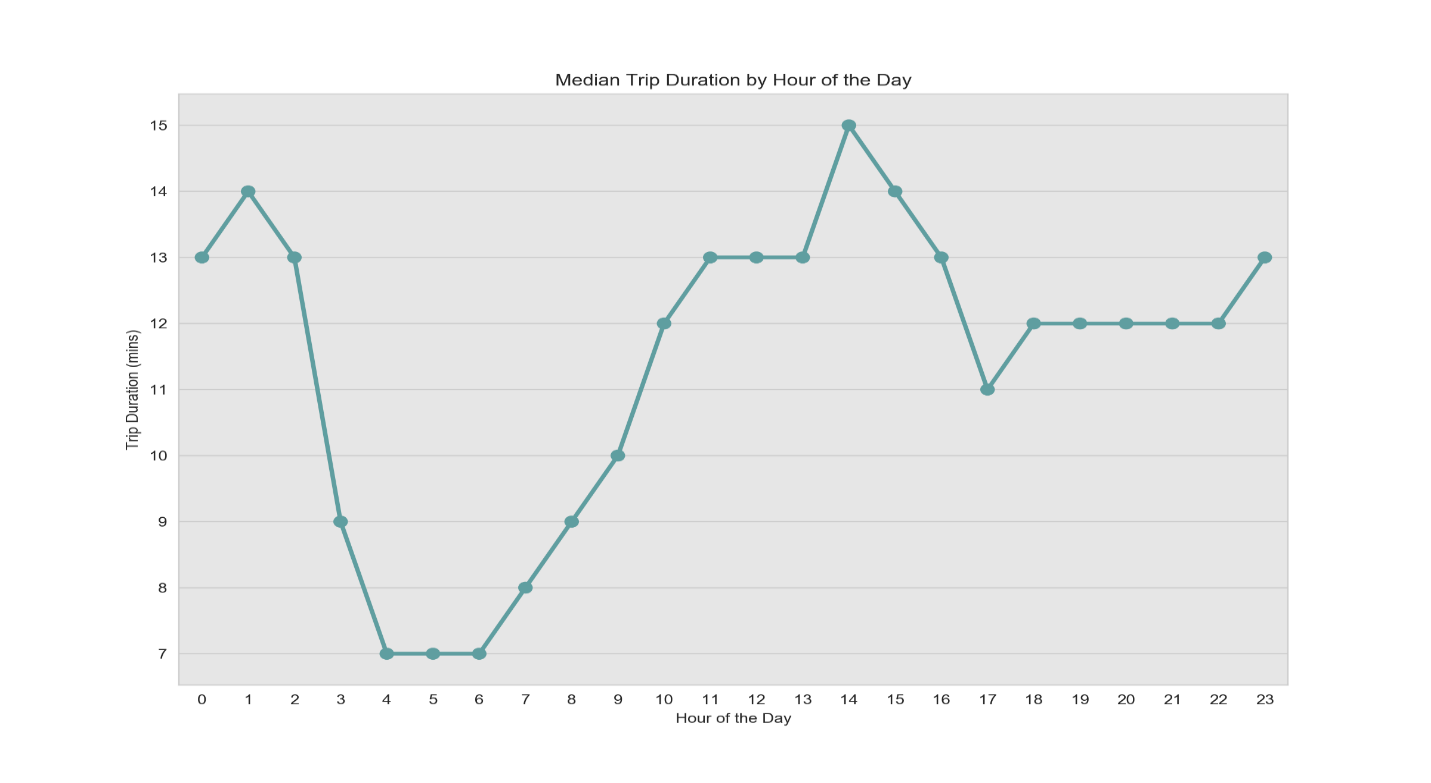


**Figure 9**

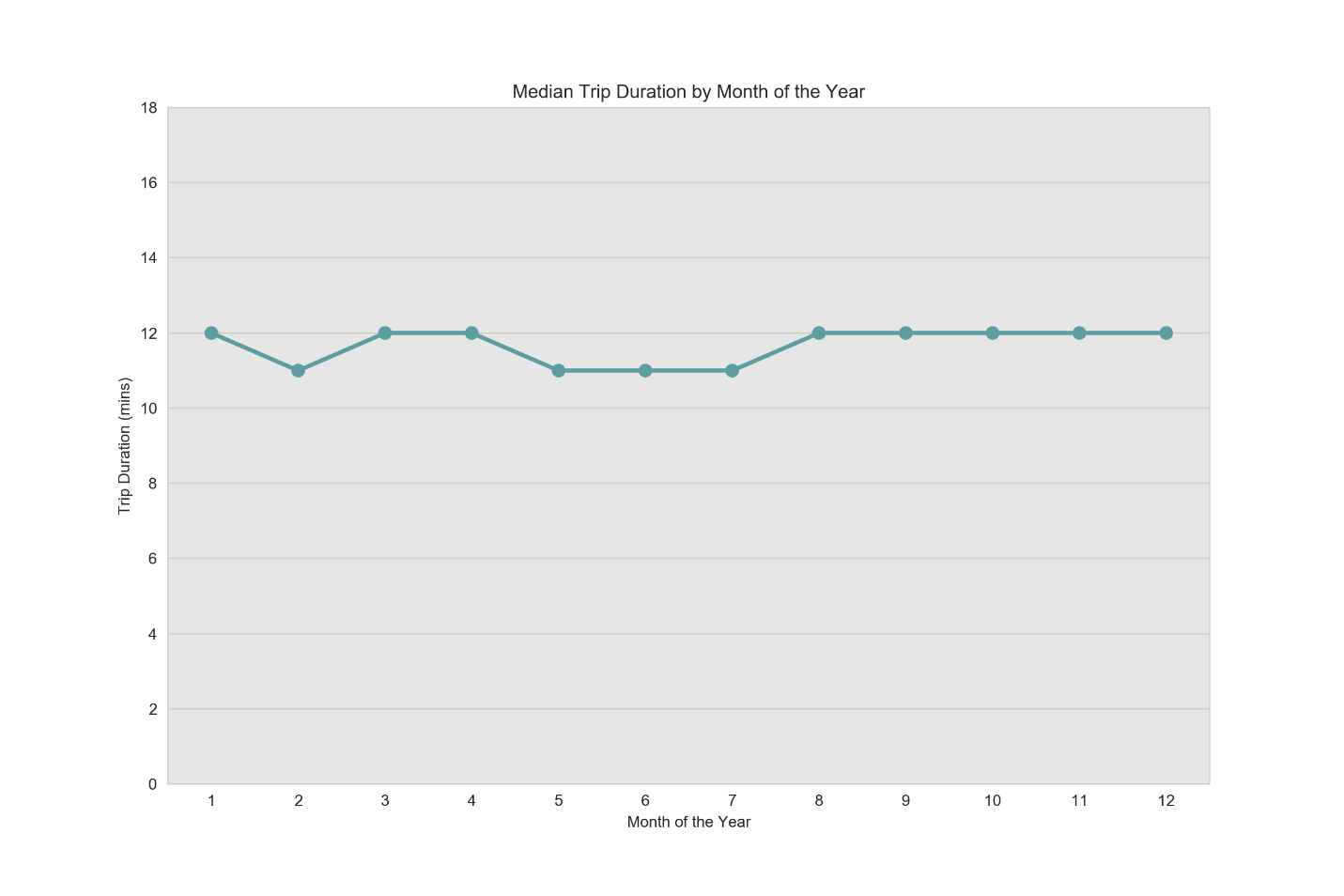
The Figure 9 shows the distance travelled by Angelenos (People of los Angeles). The maximum number of rides were found to be around 200k has been between 0.5 miles and 1mile with the median and average value to be 0.80 miles and 0.93 miles respectively. It is a very critical insight and an important feature for data preparation with respect to dealing with the outliers and the future forecasting of number of bikes. This leads to the conclusion that mostly the bikes are used for short trips only within the city.

In order to visualize the trip duration behavior, it would be important to aggregate the trip duration at each of the timestamp feature levels. Since there could be outliers in the trip duration variable (and outlier detection has not yet been performed for this variable) median would be a more representative measure, rather than the mean.

**Figure 10**



**Figure 11**



**Figure 12**

* Observation at a week-level:

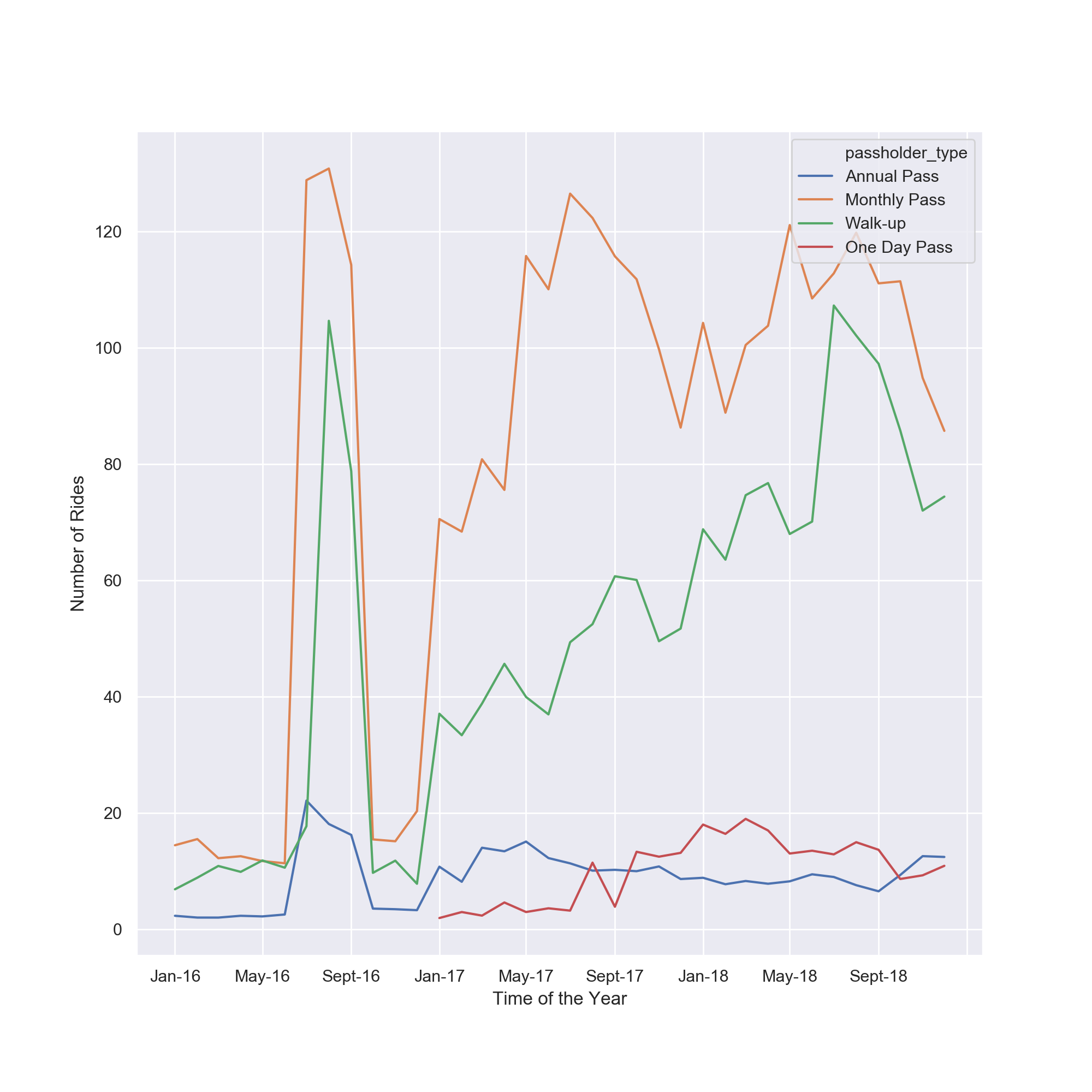
Trip durations are the most on Saturday and Sunday (15 mins) except on Wednesday’s the median trip duration is 11 minutes during the other days.

* Observation at an hour-level:

Trip durations are consistently around the 12 mins throughout the day after 10 am and experiences drop post-midnight.

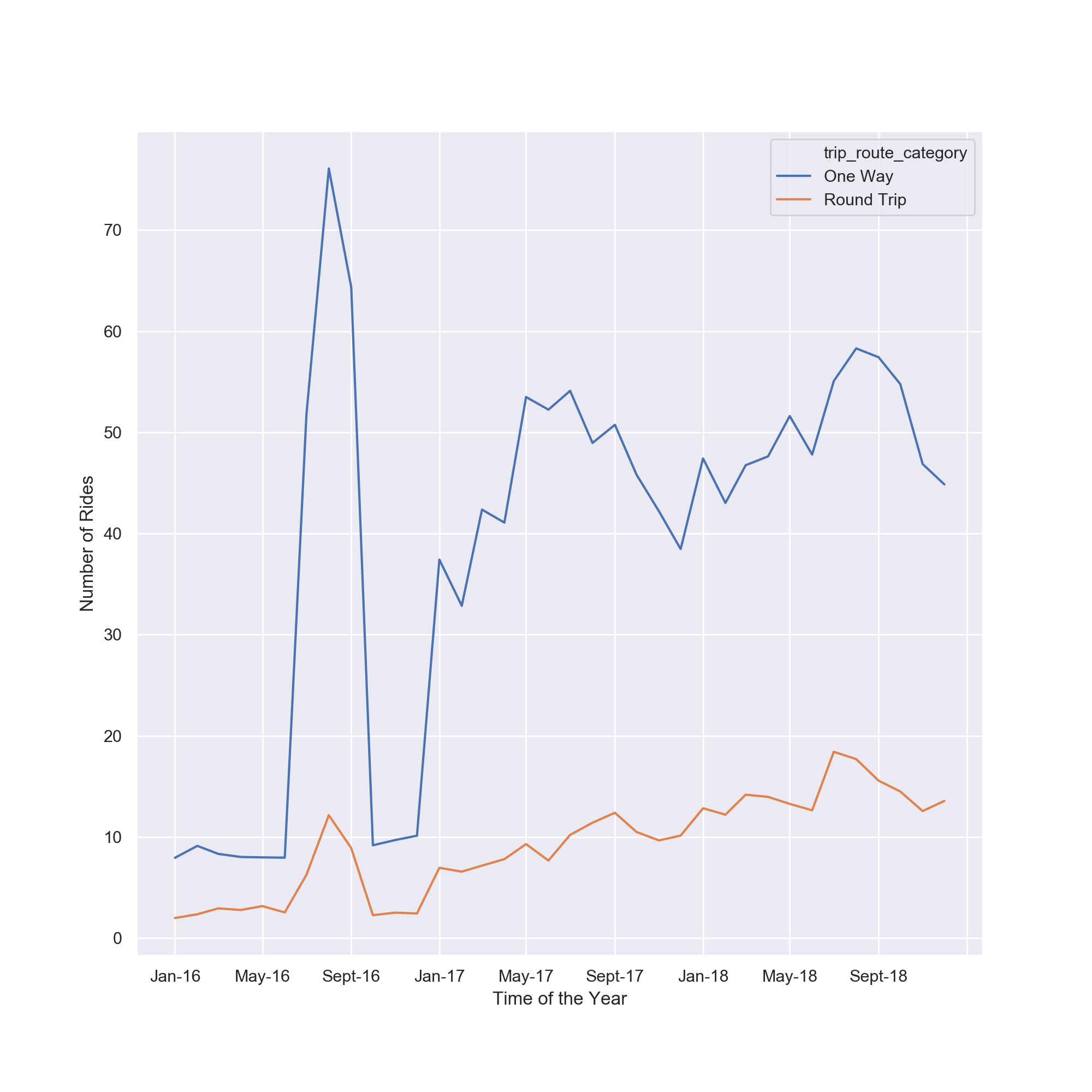
* *Obs*ervation at a month-level:

There seems to be a linear increase in the median trip duration from the month of July to the month of August, although the increase is fairly minimal and then it remains constant afterwards.



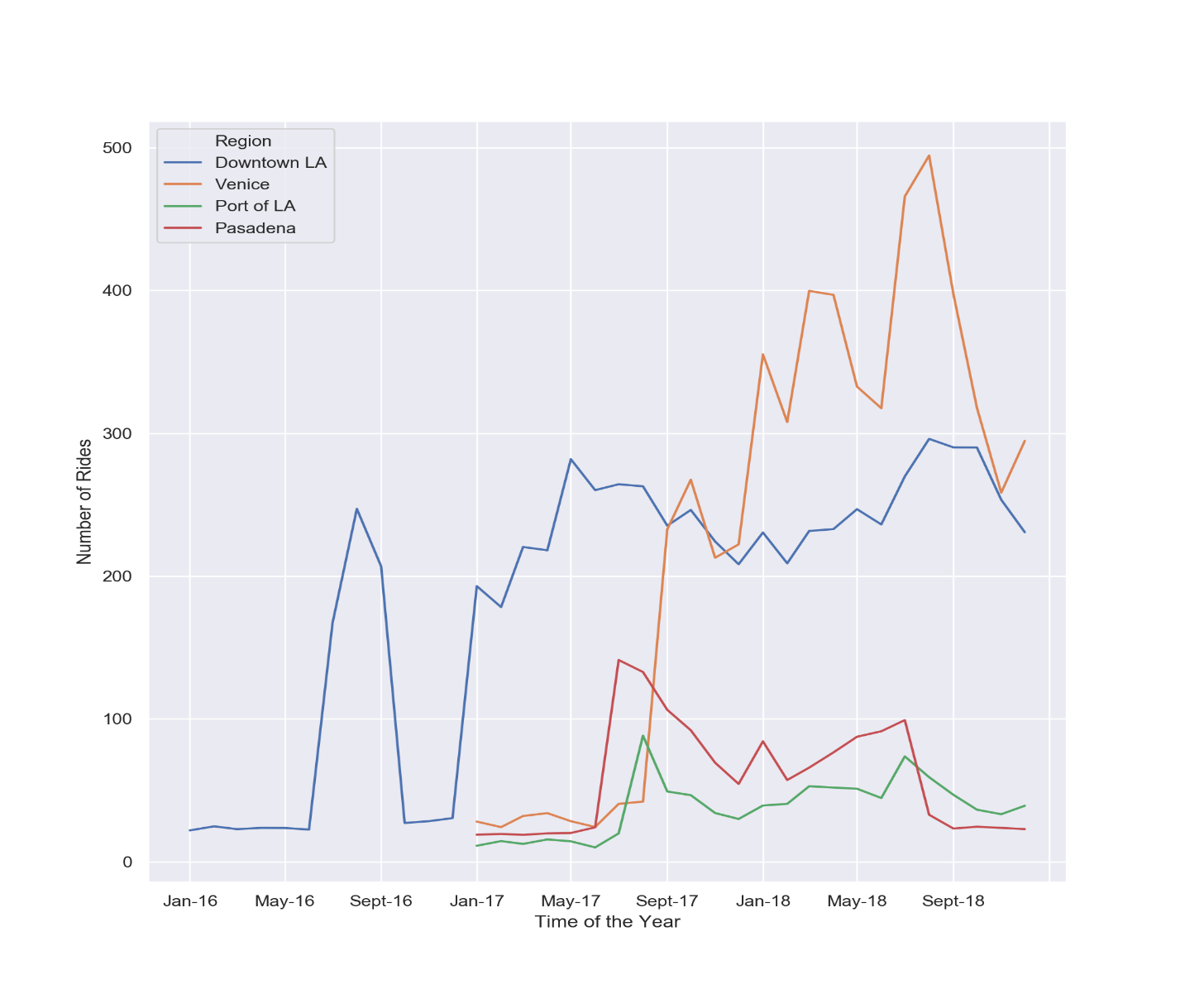
**Figure 13**

Figure 13 shows variation in the number of rides taken by different types of pass holders and without pass holders. The monthly pass is found to be very popular followed by walk-up (without pass) rides. Another interesting scenario can be observed regarding the consistent increase in the popularity of walkup rides post January 2017 and during the end of year it almost reaches the number of the month passes rides as well. As per the trend, it could be possible that walk-up rides would become more popular than the monthly pass rides in the future and this is a very important insight for the bike company regarding the pricing of the passes and walk-up rides.



**Figure 14**

Figure 14 shows the difference in the type of ride taken along different times of the year. The usage of bikes for one-way ride is more than the round-trip rides throughout. This is also an important feature for estimating the number bikes to be placed at the docks in various regions.



**Figure 15**

Figure 15 shows variation in the number of rides taken across all the four regions of Los Angeles given in the data. One of the parameters that is most important for any bike company to track is what are some of the most influential pick up areas in a city. Generally, these are the areas which have a great revenue potential and by focusing on these areas one can maximize the overall profit. It can be observed that during 2016 the available data was only from the Downtown LA stations and since January 2017 people started using LA metro bikes in Venice, Port of LA and Pasadena. The number of pickups in downtown LA was always on the higher side and this might be because of the reason that students of University of Southern California are using bikes more frequently. The number of pickups at the stations in Venice area is on the increasing trend since its inception and even outnumbered the usage at the Downtown LA stations after September 2017. Venice is a buzzing beach town with upscale commercial and residential pockets. Venice Boardwalk is the site of funky shops, street performers and thus a great choice for moving around the area on bike

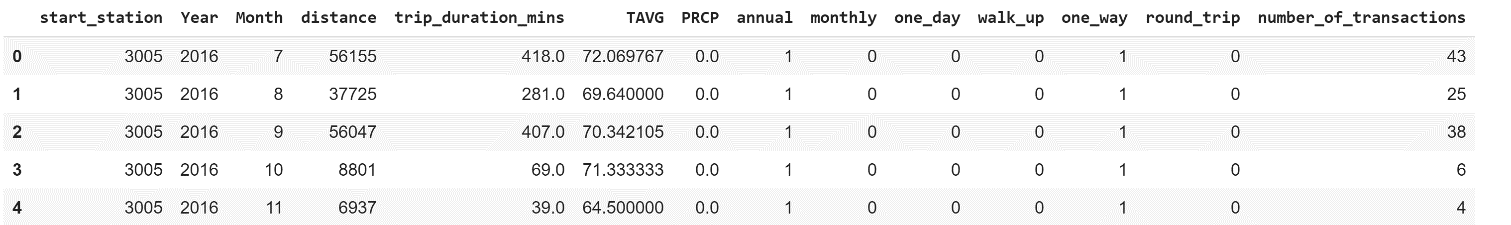
**Forecasting Bicycle Demand:**

To forecast bicycle, demand every station must be taken separately. Location of a station is one of the prime factors when it comes to bicycle demand. So, take every station and forecast for it. Assuming one station is independent from the other.

To evaluate how different variables are related to number of transactions at a station. Start with a simple linear regression model and then move to non-linear machine learning techniques depending on the results. In this case linear regression then, random forest and then time-series analysis is used. All models are compared by their performance on test-data.

After doing the data pre-processing dummy variables for pass-type (walkup, one day, monthly and annually) and trip-type (round trip & one-way trip) are added. Then total number of combinations are 8 for every pass-type and trip-type.

Further data for every station is separated. Then monthly group the transactions to do the final analysis. For e.g. if data is of 3 years i.e. from 2016 to 2018 (36 months) then for every station there are 36\*8 rows (eight rows corresponding to every month). Below is the figure which shows the final dataset which will be used for forecasting. ‘Number of transactions’ will be response variable and all other variable will be predictors.

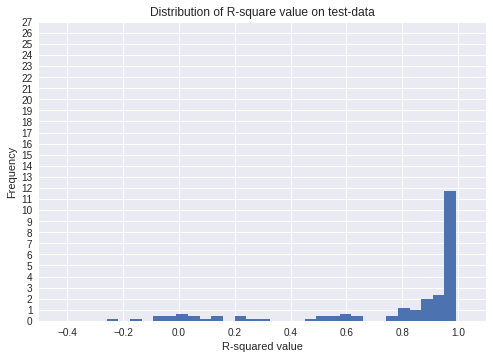
Figure 2:- Format of final data set

**Linear Regression**

Starting with the simple linear regression model with only one predictor i.e. ‘distance’. Performance is evaluated based on r-square value on test-data.

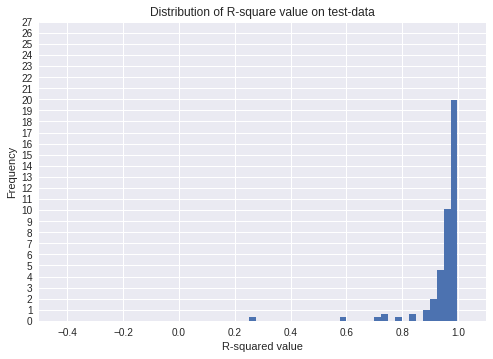
R-square value is not a good measure especially when comparing two models with different number of predictors. But here performance is evaluated looking at the r-square value of test data not on trained data.

Data corresponding to every station is divided into 80%(training) and 20%(testing). To have enough rows in test-data only those stations which have more than 6 months of data are considered (125 stations).

* **Model 1**: - y= Trip id, X=Distance (Distribution of R-square values corresponding to all stations is shown below in the figure)

As observed from the histogram that r-square values are spread all over the number line.

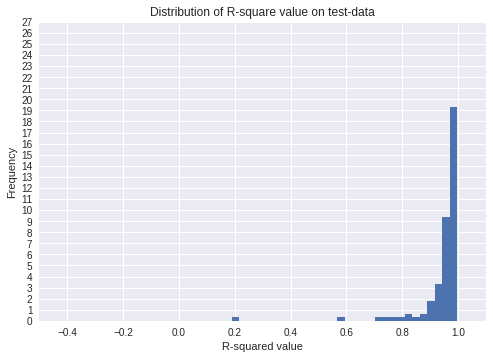
Further add another variable and then compare the performance.

* **Model 2: -** y= Trip id, X=Distance, Duration.

As observed from the histogram that only one station (station 3013) has r-square value less than 0.5.

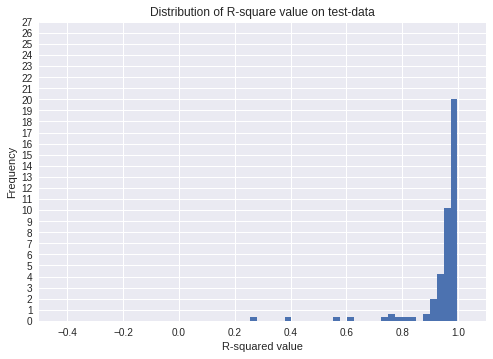
After observing station 3013 it is clear that there are outliers in the distance column due to which it has low r-square value.

Hence, Model 2 is much better than Model 1.

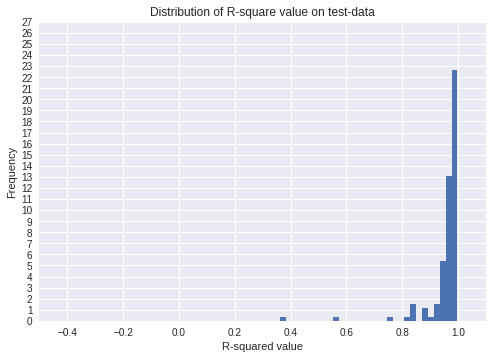


* **Model 3: -** y =Trip id, X = Distance, duration, average temperature

R-square value on test-data after adding average temperature didn’t improve. Instead it came down for some stations. So, we will not consider average temperature in further models

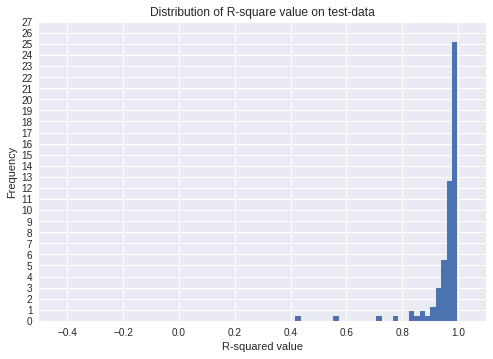
* **Model 4: -** y= Trip id, X = = Distance, duration, precipitation

R-square value on test-data after adding precipitation didn’t improve. Instead it came down for some stations. So, we will not consider precipitation in further models



* **Model 5: -** y =Trip id, X = Distance, duration, pass-type

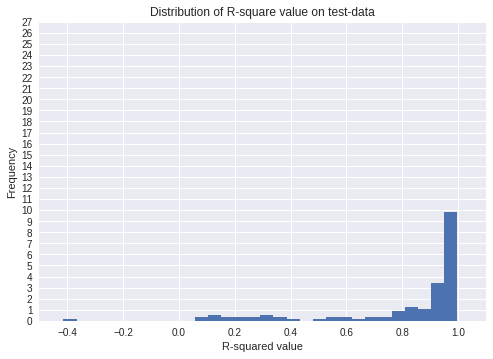
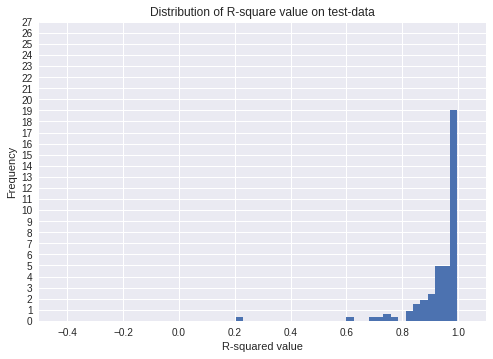
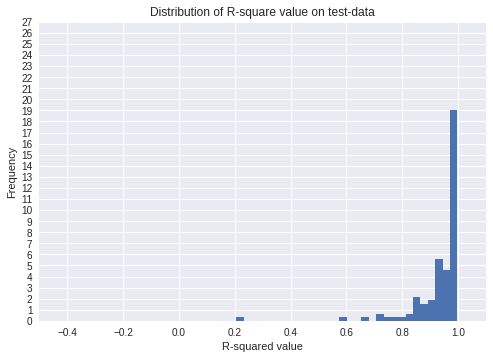
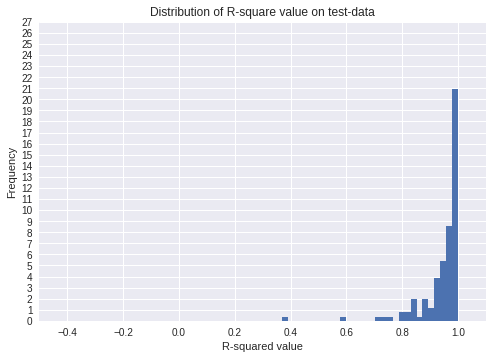
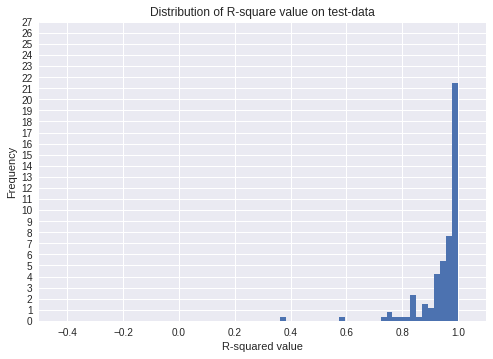
After adding pass-type to the regression r-square value of station 3013 improved further and same can be seen for other stations also. As all the r-square values are on the test data so it proves that model 5 is performing better than model 2

* **Model 4: -** y= Trip id, X = = Distance, duration, pass-type, trip-type

After adding trip-type to the regression r-square value of station 3013 improved further and same can be seen for other stations also. As all the r-square values are on the test data so it proves that model 6 is performing better than model 5.

**Random Forest**

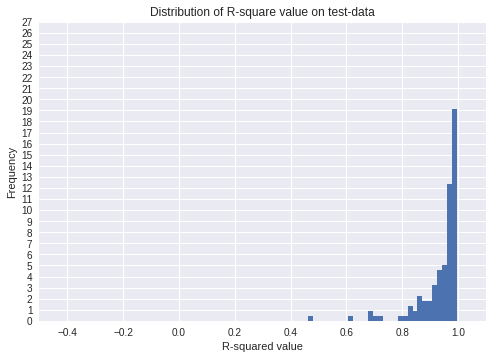
Random-forest will take in account non-linearities which are there in the data much better than linear regression. Building the same 6 models for random forest which were built for linear regression and comparing the performance on test data using r-square value.



R-square values for Model 3 with random forest

R-square values for Model 2 with random forest

R-square values for Model 1 with random forest

R-square values for Model 4 with random forest

R-square values for Model 6 with random forest

R-square values for Model 5 with random forest

It can be observed from the histograms above that none of the model using random forest is performing better than Model 6 with Linear regression.

**Time Series Analysis**

Time series analysis is a technique of analyzing a series of data collected at different points in time highly correlated to the adjacent points. This restricts the applicability of the many traditional statistical methods which are dependent on the assumption that adjacent data points are independent and identically distributed. Operating under this assumption, a linear regression model trained on time series data may fail to perform.

In this section, an attempt is made to analyse our dataset from the perspective of the Time Series Analysis and compare the results with the forecasting obtained by the regression method. On the onset, an appropriate time series was prepared using the 'trip\_id' and 'start\_time' variables. We have considered 'trip\_id' as a random variable 'X' and 'start\_time' as the timestamp of the event ‘X’. As the first step of all the time series investigation, we have plotted observed data over time.

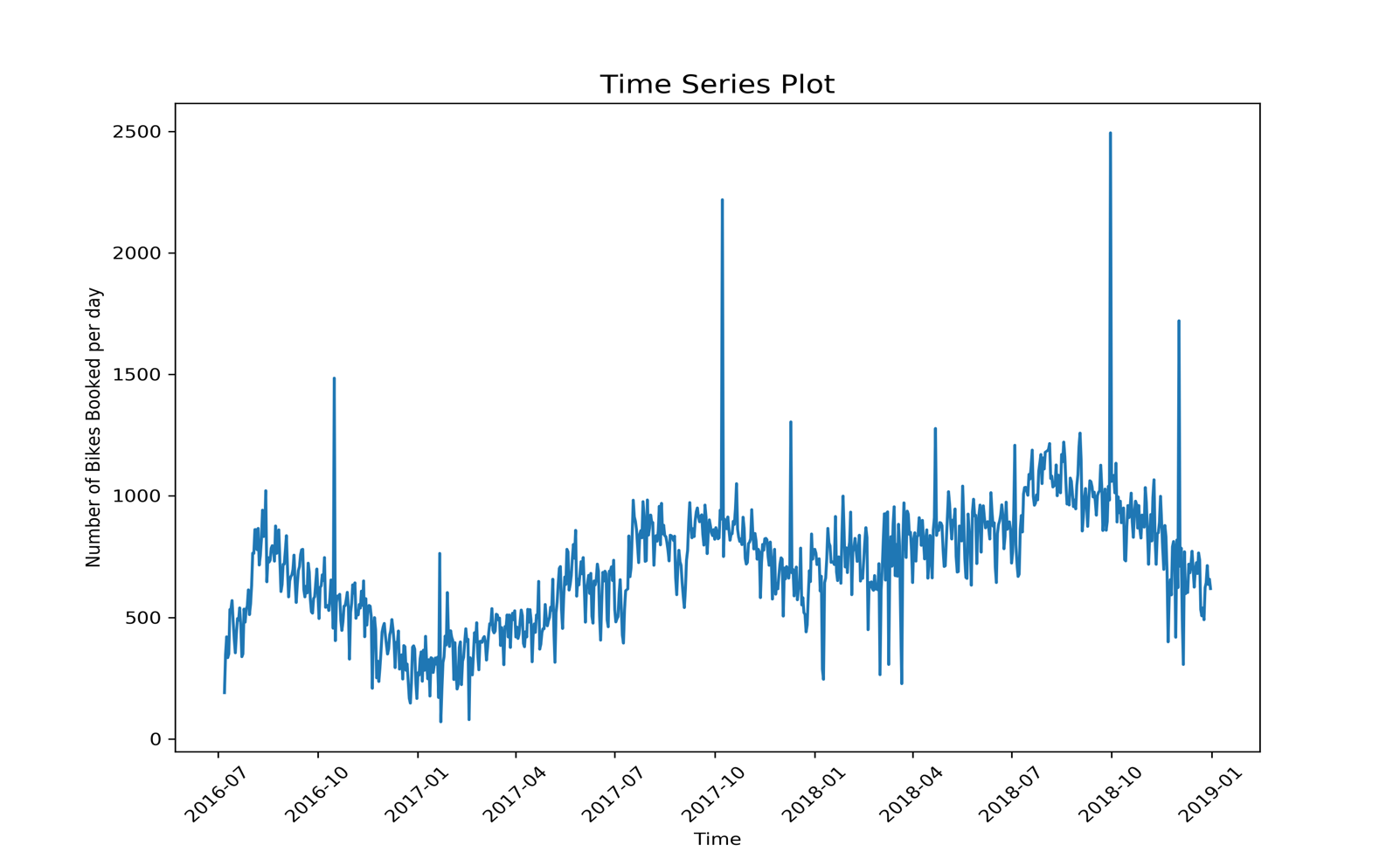


Figure shows total numbers of bikes booked per day. We can see a gradually increasing underlying trend and a regular variation superimposed on the trend that seems to repeat yearly.

Looking at the plot, it is clear that the time series is a non-stationary as the mean of the series is changing with the time (the trend in the plot), the variance of the series is changing with the time (heteroscedasticity in the series), and there is change in covariance with time. These are an evident proof that the data is time series which is not a stationary series.

Another way to check the stationarity of the series is the Dickey-Fuller Test. The null hypothesis is that the series is non-stationary. The test results include Test statistic and some critical values for different confidence level. If the 'Test Statistic' is less than the 'Critical Value,' we can reject the null hypothesis and can say that the series is stationary.

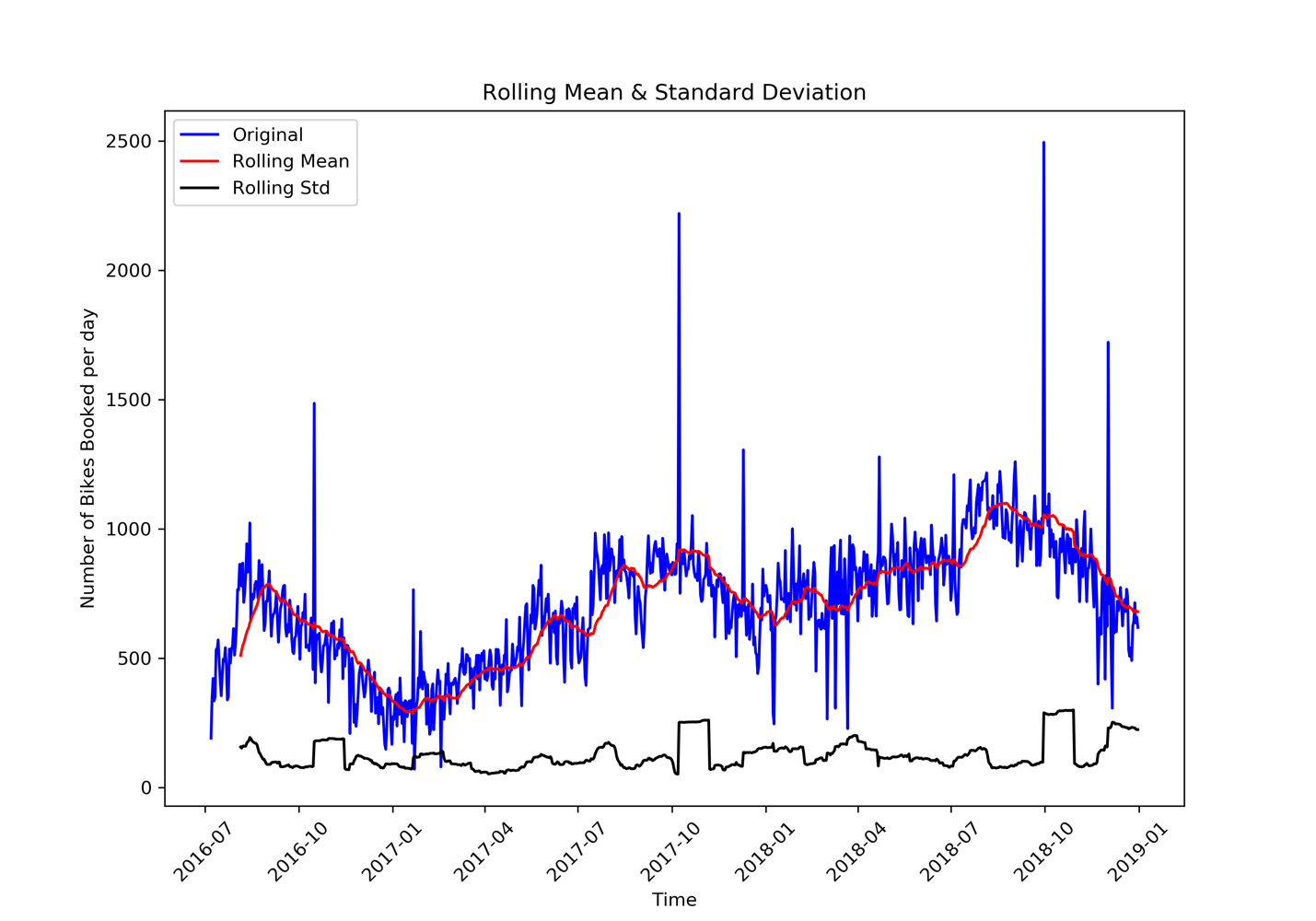


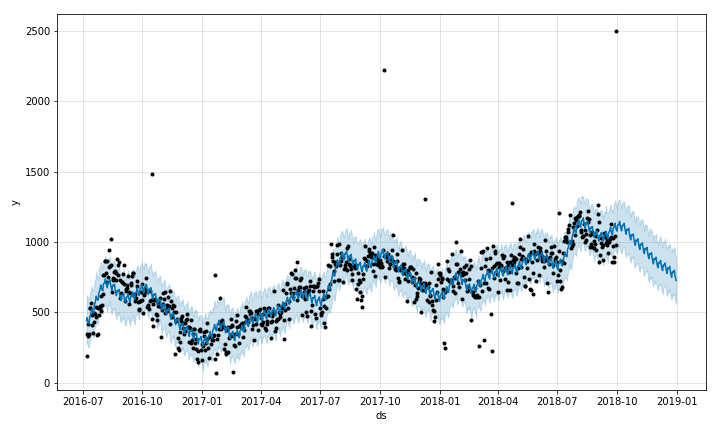
Figure Dicky Fuller Test performed on Time series of demand of bikes per day.

|  |  |
| --- | --- |
| **Parameters** | **Values** |
| Test Statistics | -2.08776 |
| p-value | 0.24946 |
| Number of Lags Used | 13.00000 |
| Number of Observations Used | 894.00000 |
| Critical value (1%) | -3.43768 |
| Critical value (5%) | -2.86478 |
| Critical value (10%) | -2.56849 |

Figure Results of Dickey-Fuller Test

From the Dickey Fuller test, we got the p value for the null hypothesis as 0.24946 which is higher than 0.05 but not sufficiently large to support the argument that the data is stationary. On the other hand, we are less than approx. 75% confident that the data is stationary. The most basic assumption of the time series models is that the series is stationary. In this case time series is not stationary, hence various methods should be used to stationarize the series. Some of the methods used are elimination method (removal of trend and seasonality), Decomposition (decomposing series in trend, season and residual). Once the series is stationary, ARIMA models can be used to obtain the forecasting of the given timeseries data. We have implemented various transformation methods and applied ARIMA model. However, results obtained from ARIMA models were not significant and it failed to converge at high backlogs.

Apart from the traditional time series models, we have also used a python package named Prophet. It is developed by Facebook for forecasting time series data based on an additive model where non-linear trends are fit with different seasonality. It is robust to missing data, outliers and change in trend. This model is used to forecast the future demands. To check the performance of the model, Data is divided into training and testing data. Q4 of 2018 is kept for testing and Q3 2016 to Q3 2018 was used for training the model. Below is the graph for the fitted model along with the original dataset.



Prediction Trend

Figure Prophet prediction graph

The graph below is to compare the predicted values to the original values. It can be seen that the prediction values are very close to the actual values indicating the better performance of the model.

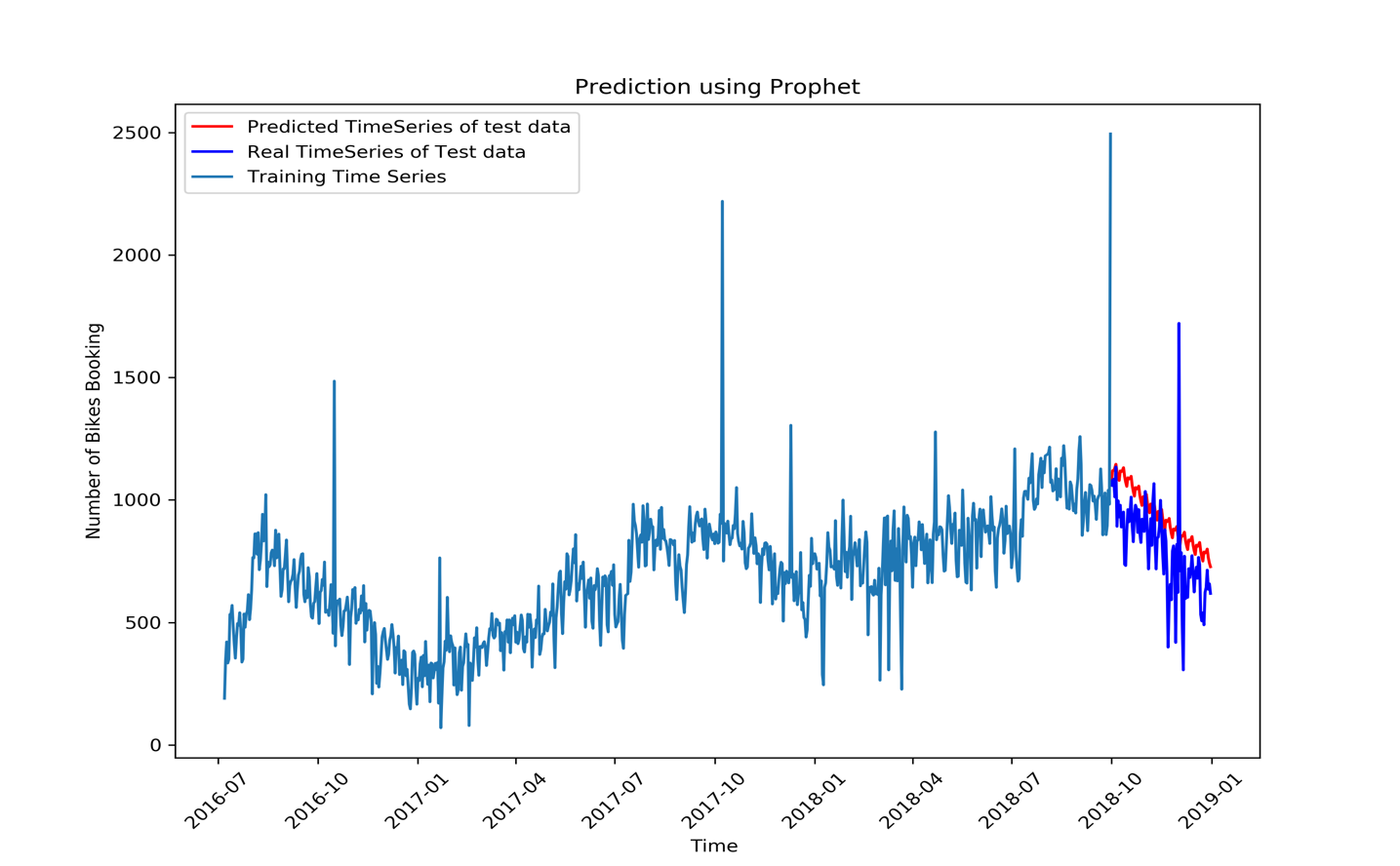


Figure Predicted TimeSeries Against the Actual TimeSeries

The following is the forecast components of the model. The graphs are the trend, weekly seasonality and yearly seasonality in the order plotted

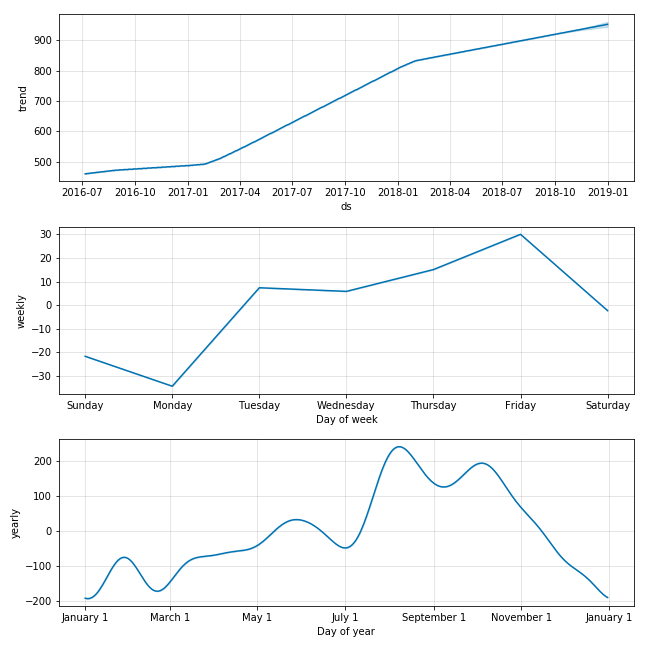


Figure Forecast Components

To find the performance of the model, cross validation is performed on the dataset. The following are the results of the cross validation.

|  |  |
| --- | --- |
| **Parameters** | **Values** |
| RSME (Root Mean Square) | 193.5309 |
| MAE (Mean Absolute Error) | 156.9437 |
| MAPE (Mean Absolute Percentage Error) | 0.1949 |
|  |  |

**Recommendations for possible pricing modifications**

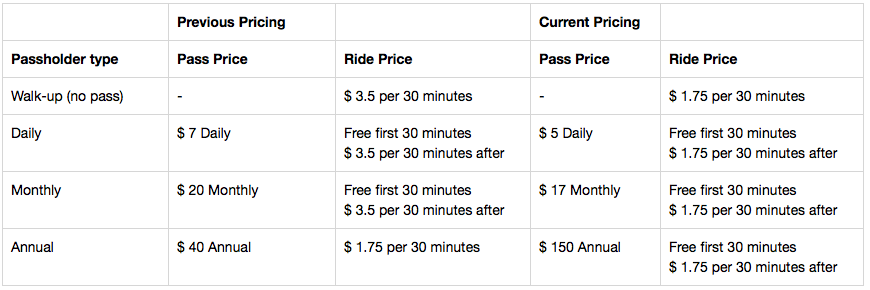
Recommendations for possible pricing modification can be made only after understanding the current pricing model. The pricing model then needs to be optimized to maximize total revenue.

The total revenue can be split into two main components viz Total fare of all rides and Total sales of passes (Daily, Monthly, Annual).

A demand model also needs to be estimated to derive the appropriate price to demand relationship. For this purpose, number of passes sold for each pass type is estimated as shown below:

Since the pricing system is based on 30 minutes blocks spent by a user on the bike, a column is coded to calculate the number of 30 minutes block spent by each rider on a trip. The pass holders would be charged for one less time block than the walk-up riders so the passholders get the first 30 minutes of their ride free. Therefore, two columns are added namely “time\_block\_count” and “time\_block\_count\_post\_free” for getting the 30 minutes block that the walk-up users have to pay for and the second column for 30 minutes blocks for passholders that excludes first 30 minutes block.

Moreover, the pricing model of Metro bike company was changed on July 12, 2018 so in order to analyze and optimize the pricing model correctly, the dataset was divided into two parts with one having data before the data July 12, 2018 and the second dataset having data after that date.



The total number of trips in each segment of the monthly pass, daily pass, annual pass and walk-up are calculated along with the total duration of the rides.

There is no unique identifier for passholders so the number of passes sold can’t be inferred from data itself. Total number of passes sold since January 2016 is 67,013 in 3-year period so it would be safe to expect roughly 20,000 passes sold during the year-long period for first two years and the remaining during the last year. The sales of each pass type would be estimated from a breakeven perspective i.e the average number of trips needed to cover the price of a pass.

**Breakeven analysis for estimating number of passes sold:**

The breakeven analysis is conducted for trips under 30 minutes since the median trip duration is 12 minutes. Number of rides to break even is calculated by dividing the pass price by the difference in the price to ride without pass and the price to ride with pass. Then, the number of passes sold is estimated by dividing the total number of rides by the number of rides to break even.

This calculation provided the number of rides per day required for daily pass: 2.0 Rides per month required for monthly pass: 5.714285714285714 Rides per year required for annual pass: 22.857142857142858 under the old pricing model. These numbers seem to be on the low side looking at the number of rides required to breakeven and assessing the numbers since Daily pass holders are likely to perform more than a round trip if they were purchasing a day pass and Monthly pass holders are likely to be the occasional commuters and even at a conservative 2 rides/week to work would tally 8 rides a month. Annual pass holders are the hardest to gauge due to the low $40 price point of the flex point from the previous pricing plan. They'll be scaled to the same factor as day and monthly pass numbers by a common factor of 40%. Under the old pricing model, the number of rides required per day for daily pass was scaled up to 3. Similarly, the number of rides required per month for monthly pass was scaled up to 8 and the number of rides required per year for annual pass was scaled up to 32. The total number of trips under different pass types were divided by the scaled-up value of the number of rides required for that particular passholder calculated above.

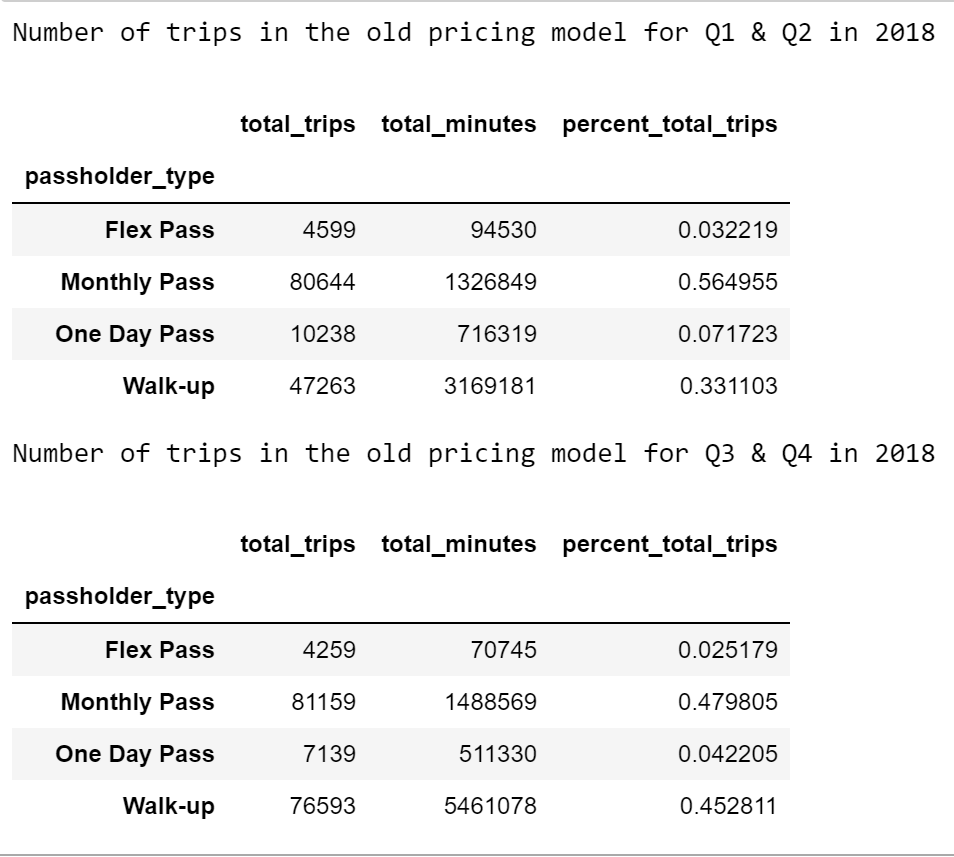
The estimated number of passes sold for daily pass, monthly pass and annual pass were 5299, 35507 and 711 respectively.

The total revenue was calculated by adding the revenue from 30 minutes blocks used by different types of riders, revenue from post 30 minutes usage and the revenue from selling passes. The total revenue calculation under the old pricing model came out to be $1479654.25 from July 2016 to July 2018.

**Linear Optimization:**

An objective function was formulated for this optimization model to maximize the total revenue from pass sales and rides. Binary variables for each plan are created and a basic optimization is run over the previous price plans. Given that riders have already been complaining about the $3.50 per half hour block rate, any dropping of passes in the past pricing scheme would have led to a precipitous drop in ridership. Furthermore, given the fierce competition in the area of bike and scooter sharing, the dropping of certain passes could simply lead to riders moving to other competitors. A baseline attrition of 30% for each category is assumed and the parameters adjusted as the model is run. The optimal solution returned the following numbers: $1614687.75 for the old pricing model which is higher than the total revenue estimated. The optimization results for the old pricing model favored the monthly pass and the annual pass but the daily pass was not fruitful according to the results.

**Comparison of the number of rides in each category between the old and new pricing model**

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A comparison is carried out between the old and new pricing model by considering the data of the same time frame for both old and new pricing model. The estimated number of passes sold for daily pass, monthly pass and annual pass was 10238, 80644 and 4599 respectively under the old pricing model for quarter 1 and quarter 2 of 2018 whereas the estimated number of passes sold for daily pass, monthly pass and annual pass was 7139, 81159 and 4259 respectively. This steep fall in the number of daily passes sold indicate that the customers are not willing to invest in the daily pass under the new pricing model as the price of the walk-up has been reduced from $3.5 for 30 minutes to $1.75 for 30 minutes. Furthermore, it can be observed that the number of walk-up has also increased from 47623 to 76593. The increase in number of walk-up and the decrease in the number of passes sold suggests us that the bike riders prefer to use the walk-up option under the new pricing model.

**Optimization Using additional Information**

There are multiple ways in which the pricing scheme can be structured such as:

1) Variable rate by minute

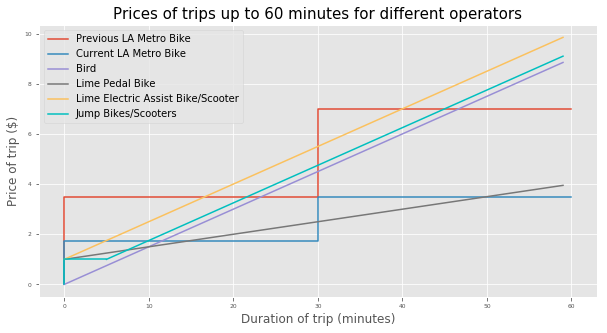
2) Variable rate by time intervals (30 minutes for LA Metro currently)

3) Fixed fee for any ride

4) Fixed fee for a time interval before implementing a variable rate

5) Weekly, monthly passes that cover all rides up to a particular duration. Variable rate thereafter

The current model by LA metro is examined and compared with other competitors in the market.



It can be observed from the above plot that the current pricing model enacted by LA Metro is one of cheapest being $3.5 for an hour-long bike ride. For rides shorter than 15 minutes and between 30 to 50 minutes, Lime pedal bike is the cheapest. These values are used to set up upper bound on prices to be used in the optimization model.

1. The variable rate per minute without a pass is set under the average of the two most common prices of 0.05 and 0.15:

Variable rate per minute without pass <= $0.10

1. The variable rate per minute with a plan is set under the average of the LA Metro’s current $0.06 and Jump’s $0.07:

Variable rate per minute with pass <= $0.065

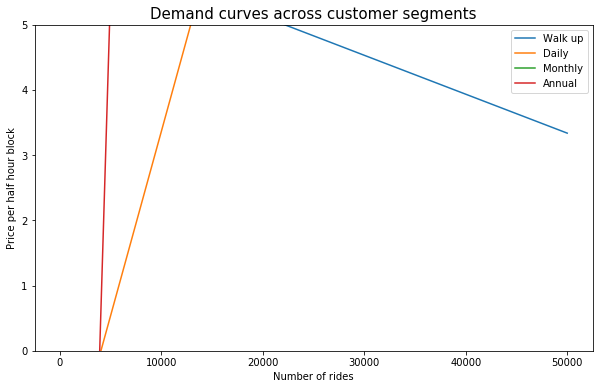
1. The variable rate per 30 minutes is set under the nearest competitor (Lime pedal):

Variable rate per 30 minutes <= $2.5

**Quadratic Optimization:**

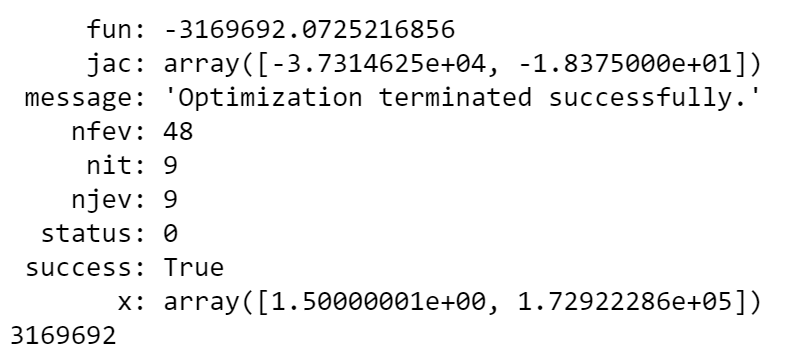
The total revenue would be optimized for two main factors: price and number of rides. If a simple linear optimization with an upper bound for price was run, it would intuitively move towards the upper bound for optimization so a demand curve that would vary total rides taken along with the prices charged for each hour block is taken into consideration.

For Demand curve estimation, 2018 Q1 and Q2 would be considered for data before the price change and Q3 and Q4 would be considered for data after the price change since 2018 Q2 was the last datapoint before the price change and 2018 Q3 was the first after. The slope for the demand curve was calculated by dividing the difference in price change with the difference in the number of bike rides.



It can be noted from the above figure that the typical demand curve with a negative slope is observed only for the walk-up riders. This is because of the drastic rate cut in rates from $3.5 to $1.75 which motivated customers to start using walk-up option instead of purchasing the passes and the prices for passes did not fall proportionately for half hourly rates so it became more economical to forgo the passes.

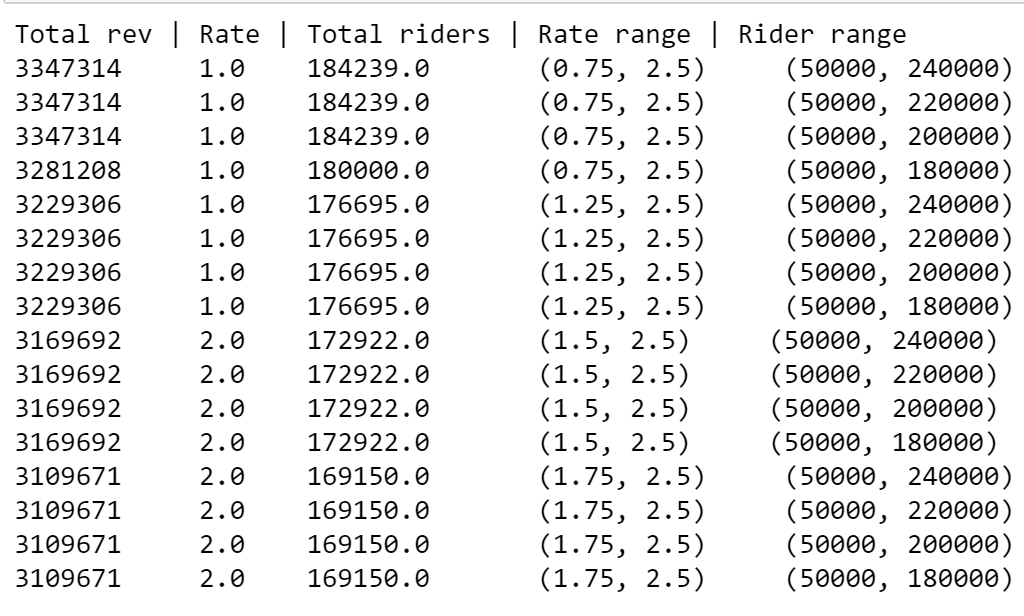
An objective function of total revenue based on the price and the number of rides was defined.



From the optimization results, it can be observed that the revenue is optimized when the price is set at $1.5 for every half hour. This would increase the total number of rides to 172,922 and the maximized revenue would be $3,169,692 which is much higher than what was observed in the previous pricing model.

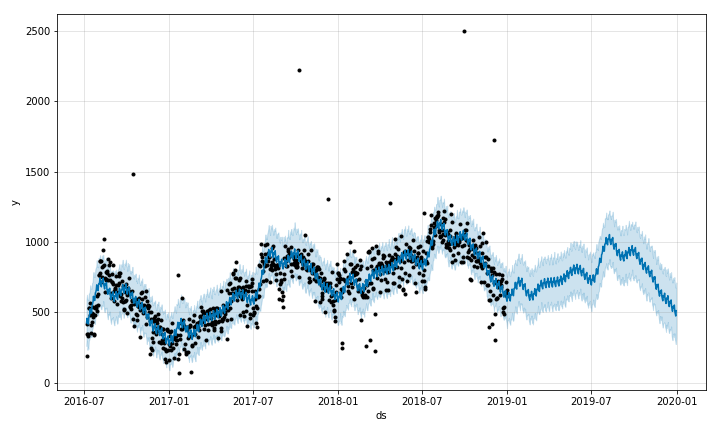
**Sensitivity analysis :**

A further sensitivity analysis is carried out on both the factors viz price and the number of rides to observe the effect on the objective function the total revenue.



It can be observed that adopting the lowest possible price of Dollar 1 results in a maximum of 184,239 rides. It also results in the highest possible revenue of Dollar 3,347,77314. Across the board, it seems that as long as LA Metro is able to attract more than 180,000 rides, the strategy should be to reduce prices. Given the results seen here, perhaps the drastic drop of 50% from the previous pricing scheme is justified.

**Summary :**

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Time series forecasting results in an average demand of the bike equal to 762 with a lower limit of 584 and the upper limit of 938. The demand is expected to increase in the second quarter of the year till the end of the year and thus opening more stations in Venice and Downtown LA would be very lucrative since the usage of bikes in those regions were following an increasing trend based on the last quarter data of 2018.

Prediction from regression provided the average, minimum and maximum demands for each station. Some of the results are shown below:

|  |  |
| --- | --- |
| Station\_number | Average Demand |
| 3074 | 395.6132878 |
| 3075 | 363.7571829 |
| 3076 | 253.9277905 |
| 3077 | 119.4493144 |
| 3078 | 92.13950702 |
| 3079 | 11.71469557 |
| 3081 | 89.43570656 |

Based on the prediction of demands, the number of bicycles required can be observed for each and every station and it can be used as a recommendation for staging bicycles in 2019 and for expanding the network. Detailed result for predicted demand of all the stations can be found on [GitHub Repository for the project](https://github.com/biharicoder/LABike_DataScienceCompetition) under the file name predicted\_demand\_stationwise.

**Final Recommendation for optimizing revenue:**

The price should be dropped to $1.5 for every half hour for maximizing the total number of rides to 172,922 and the total revenue to $3,169,692. An additional surge pricing can be added during the peak hours which is 4 pm to 7 pm since this time period has the highest number of bike rides as seen from the data visualization part. The surge pricing should be for walk-up which will encourage the riders to buy a greater number of passes thus maximizing revenue by the sale of the passes as well as by the increase in the walk-up price during the peak hours. Another point to be considered while adding surge pricing is that it can lead to the downfall in the number of riders as they might tend to choose other competitors if available at that time. This experimentation can be carried out for a trial period of a month or so and the difference in total revenue calculations can justify whether or not to include the surge pricing during peak hours.