Project Report

On

Cab fare Prediction

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Chapter 1

Introduction

1.1 Problem Statement

You are a cab rental start-up company. You have successfully run the pilot project and now want to launch your cab service across the country. You have collected the historical data from your pilot project and now have a requirement to apply analytics for fare prediction. You need to design a system that predicts the fare amount for a cab ride in the city.

1.2 Data

Understanding of data is the very first and important step in the process of finding solution of any business problem. Here in our case our company has provided a data set with following features, we need to go through each and every variable of it to understand and for better functioning.

Size of Dataset Provided: - 16067 rows, 7 Columns (including dependent variable).

Missing Values: Yes

Outliers Presented: Yes

Below mentioned is a list of all the variable names with their meanings:

Variables	Description
fare_amount	Fare amount
pickup_datetime	Cab pickup date with time
pickup_longitude	Pickup location longitude
pickup_latitude	Pickup location latitude
dropoff_longitude	Drop location longitude
dropoff_latitude	Drop location latitude
passenger_count	Number of passengers sitting in the cab

Chapter 2

Methodology

➢ Pre-Processing

When we required to build a predictive model, we require to look and manipulate the data before we start modelling which includes multiple preprocessing steps such as exploring the data, cleaning the data as well as visualizing the data through graph and plots, all these steps is combined under one shed which is **Exploratory Data Analysis**, which includes following steps:

- Data exploration and Cleaning
- Missing values treatment
- Outlier Analysis
- Feature Selection
- Features Scaling
- Visualization

➢ Modelling

Once all the Pre-Processing steps has been done on our data set, we will now further move to our next step which is modelling. Modelling plays an important role to find out the good inferences from the data. Choice of models depends upon the problem statement and data set. As per our problem statement and dataset, we will try some models on our preprocessed data and post comparing the output results we will select the best suitable model for our problem. As per our data set following models need to be tested:

- Linear regression
- Decision Tree
- Random forest
- Gradient Boosting

➢ Model Selection

The final step of our methodology will be the selection of the model based on the different output and results shown by different models. We have multiple parameters which we will study further in our report to test whether the model is suitable for our problem statement or not.

Chapter 3

Pre-Processing

3.1 Data exploration and Cleaning (Missing Values and Outliers)

The very first step which comes with any data science project is data exploration and cleaning which includes following points as per this project:

a. Separate the combined variables.
b. As we know we have some negative values in fare amount so we have to remove those values.
c. Passenger count would be max 6 if it is a SUV vehicle not more than that. We have to remove the rows having passengers counts more than 6 and less than 1.
d. There are some outlier figures in the fare (like top 3 values) so we need to remove those.
e. Latitudes range from -90 to 90. Longitudes range from -180 to 180. We need to remove the rows if any latitude and longitude lies beyond the ranges.

3.2 Creating some new variables from the given variables.

Here in our data set our variable name pickup_datetime contains date and time for pickup. So, we tried to extract some important variables:

- Year
- Month
- Date
- Day of Week
- Hour
- Minute

Also, we tried to find out the distance using the haversine formula which says:

The **haversine formula** determines the great-circle distance between two points on a sphere given their longitudes and latitudes. Important in navigation, it is a special case of a more general formula in spherical trigonometry, the law of haversines, that relates the sides and angles of spherical triangles.

So, our new extracted variables are:

- fare_amount
- pickup_datetime
- pickup_longitude
- pickup_latitude
- dropoff_longitude
- dropoff_latitude
- passenger_count
- year
- Month
- Date
- Day of Week
- Hour
- Minute
- Distance

3.3 Selection of variables

Now as we know that all above variables are of now use so we will drop the redundant variables:

- pickup_datetime
- pickup_longitude
- pickup_latitude
- dropoff_longitude
- dropoff_latitude
- Minute

<u>Now only following variables we will use for further steps:</u>

	fare_amount	passenger_count	year	Month	Date	Day of Week	Hour	distance
0	4.5	1.0	2009.0	6.0	15.0	0.0	17.0	1.030764
1	16.9	1.0	2010.0	1.0	5.0	1.0	16.0	8.450134
2	5.7	2.0	2011.0	8.0	18.0	3.0	0.0	1.389525
3	7.7	1.0	2012.0	4.0	21.0	5.0	4.0	2.799270
4	5.3	1.0	2010.0	3.0	9.0	1.0	7.0	1.999157
5	12.1	1.0	2011.0	1.0	6.0	3.0	9.0	3.787239
6	7.5	1.0	2012.0	11.0	20.0	1.0	20.0	1.555807
8	8.9	2.0	2009.0	9.0	2.0	2.0	1.0	2.849627
9	5.3	1.0	2012.0	4.0	8.0	6.0	7.0	1.374577
10	5.5	3.0	2012.0	12.0	24.0	0.0	11.0	0.000000

3.4 Some more data exploration

In this report we are trying to predict the fare prices of a cab rental company. So here we have a data set of 16067 observations with 8 variables including one dependent variable.

3.4.1 Below are the names of Independent variables:

passenger_count, year, Month, Date, Day of Week, Hour, distance

Our Dependent variable is: **fare_amount**

3.4.2 Uniqueness in Variable

We need to look at the unique number in the variables which help us to decide whether the variable is categorical or numeric. So, by using python script 'nunique' we tried to find out the unique values in each variable. We have also added the table below:

Variable Name	Unique Counts
fare_amount	450
passenger_count	7
Year	7
Month	12
Date	31
Day of Week	7
Hour	24
Distance	15424

3.4.3 Dividing the variables into two categories basis their data types:

Continuous variables - 'fare_amount', 'distance'.

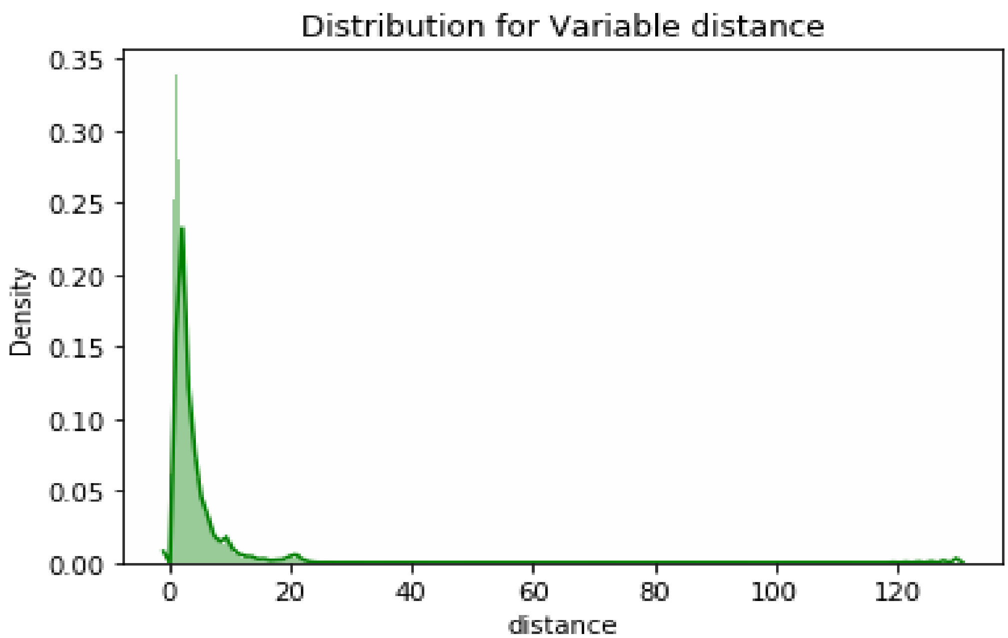
Categorical Variables - 'year', 'Month', 'Date', 'Day of Week', 'Hour', 'passenger_count'

3.5 Feature Scaling

Skewness is asymmetry in a statistical distribution, in which the curve appears distorted or skewed either to the left or to the right. Skewness can be quantified to define the extent to which a distribution differs from a normal distribution.

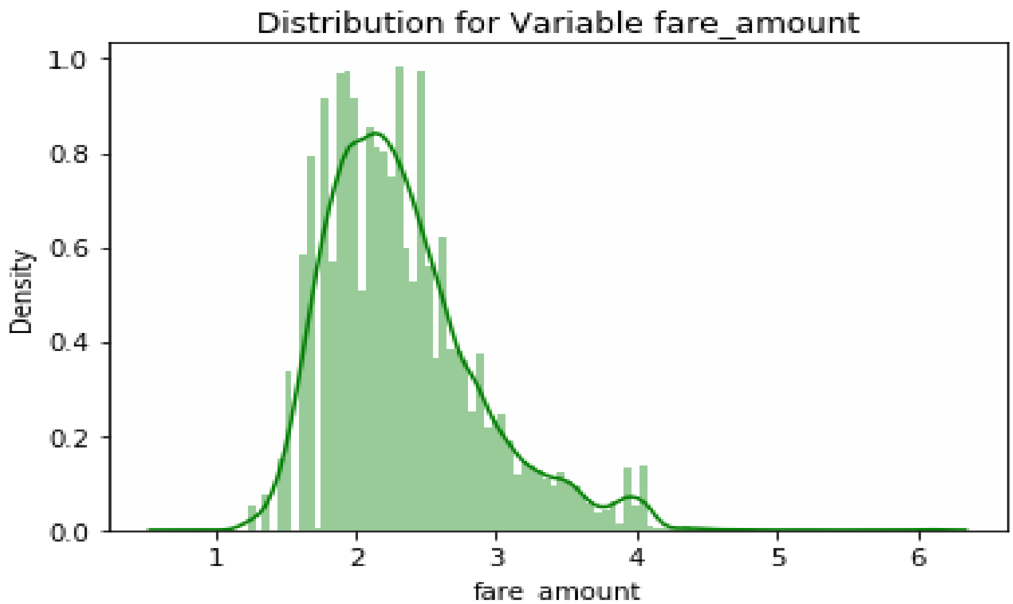
Below mentioned graphs shows the probability distribution plot to check distribution

<u>Before Scaling:</u>



Below mentioned graphs shows the probability distribution plot to check distribution
after scaling

As our continuous variables appears to be normally distributed so we don't need to use feature scaling techniques like normalization and standardization for the same.



Chapter 4

Modelling

After a thorough preprocessing, we will use some regression models on our processed data to predict the target variable. Following are the models which we have built –

1. Linear Regression
2. Decision Tree
3. Random Forest
4. Gradient Boosting

Before running any model, we will split our data into two parts which is train and test data. Here in our case we have taken 80% of the data as our train data.

4.1 Linear Regression

Multiple linear regression is the most common form of linear regression analysis. Multiple regression is an extension of simple linear regression. It is used as a predictive analysis, when we want to predict the value of a variable based on the value of two or more other variables. The variable we want to predict is called the dependent variable (or sometimes, the outcome, target or criterion variable).

4.2 Decision Tree

A tree has many analogies in real life, and turns out that it has influenced a wide area of machine learning, covering both classification and regression. In decision analysis, a decision tree can be used to visually and explicitly represent decisions and decision making. As the name goes, it uses a tree-like model of decisions.

4.3 Random Forest

Random forests or random decision forests are an ensemble learning method for classification, regression and other task, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random decision forests correct for decision trees' habit of overfitting to their training set.

To say it in simple words: Random forest builds multiple decision trees and merges them together to get a more accurate and stable prediction.

4.4 Gradient Boosting

Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function.

Chapter 5

Conclusion

5.1 Model Evaluation

The main concept of looking at what is called residuals or difference between our predictions f(x[I,]) and actual outcomes y[i].

In general, most data scientists use two methods to evaluate the performance of the model:

I. **RMSE** (Root Mean Square Error): is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{mo\,del,i})^2}{n}}$$

II. **R Squared(R^2):** is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, or the coefficient of multiple determination for multiple regression. In other words, we can say it explains as to how much of the variance of the target variable is explained.

III. We have shown both train and test data results, the main reason behind showing both the results is to check whether our data is overfitted or not.

Below table shows the model results:

Model Name	RMSE		R Squared	
	Train	Test	Train	Test
`Linear Regression	8.70	6.85	0.37	0.42
Decision Tree	7.53	4.88	0.53	0.70
Random Forest	2.83	6.05	0.93	0.55
Gradient Boosting	5.66	4.54	0.74	0.73

5.2 Model Selection

On the basis RMSE and R Squared results a good model should have least RMSE and max R Squared value. So, from above tables we can see:

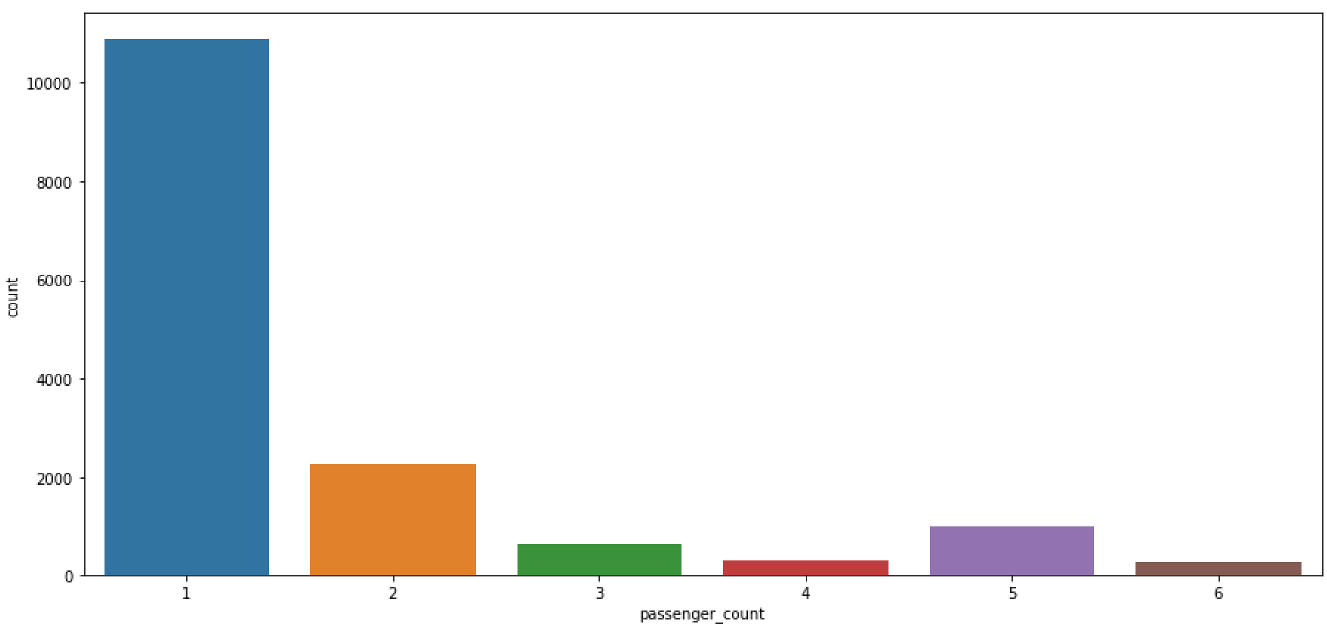
- From the observation of all RMSE Value and R-Squared Value we have concluded that, both the models- Gradient Boosting Default and Random Forest perform comparatively well while comparing their RMSE and R-Squared value.
- So finally, we can say that Gradient Boosting model is the best method to make predictions for this project with highest explained variance of the target variables

Finally, I used this method to predict the target variable for the test data file shared in the problem statement. Results that I found are attached with my submissions.

5.3 Some more visualization facts:

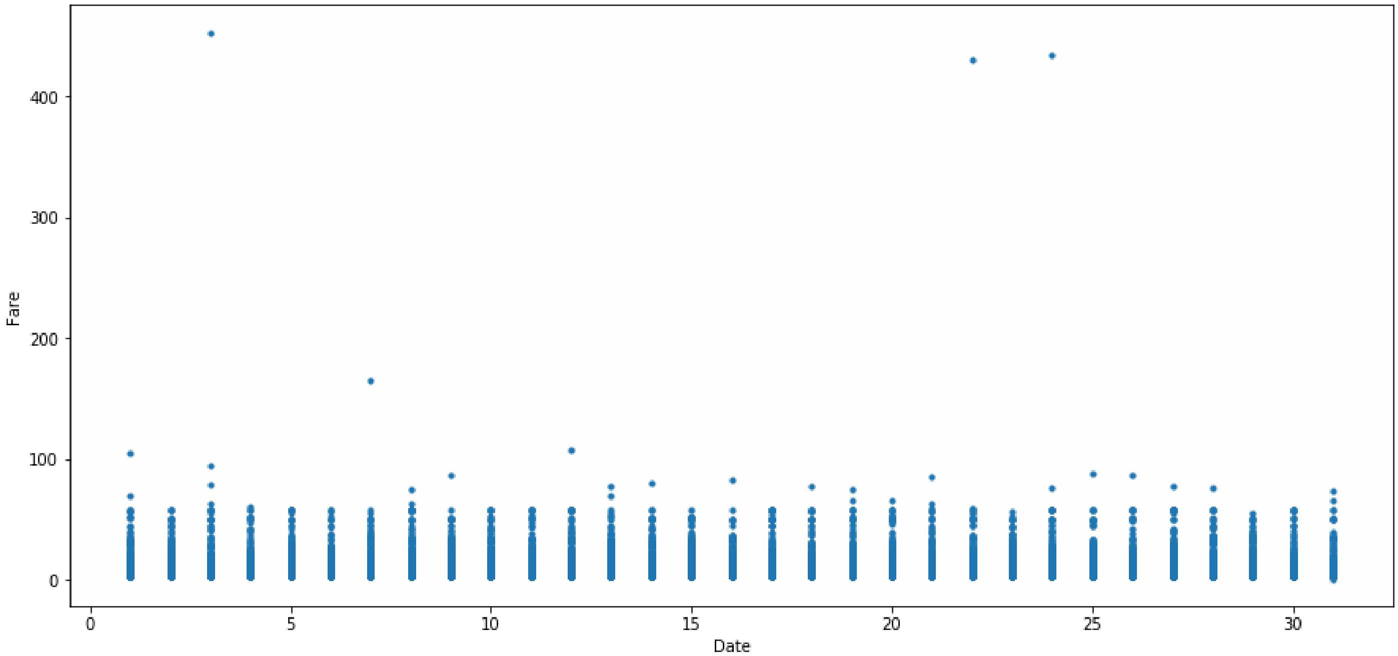
1. <u>Number of passengers and fare</u>

We can see in below graph that single passengers are the most frequent travelers, and the highest fare also seems to come from cabs which carry just 1 passenger.



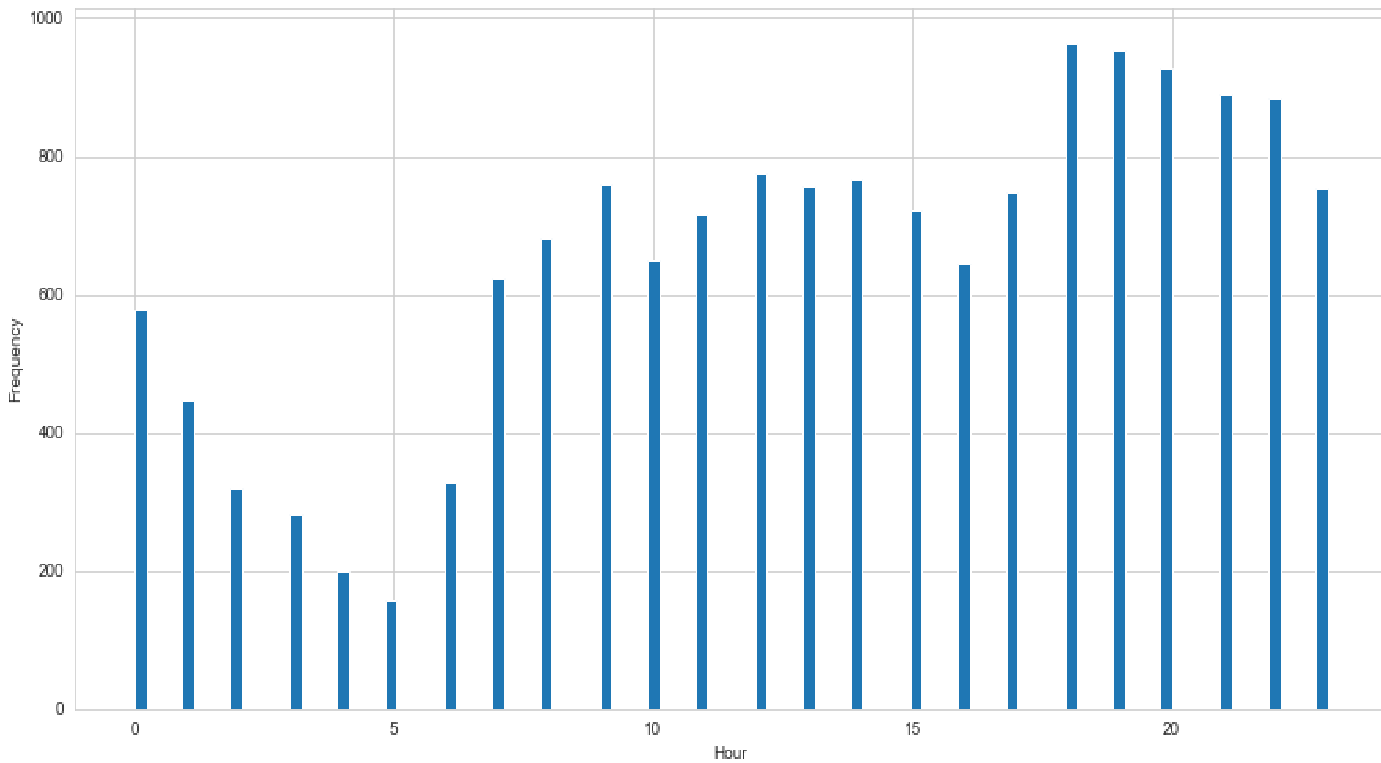
2. Date of month and fares

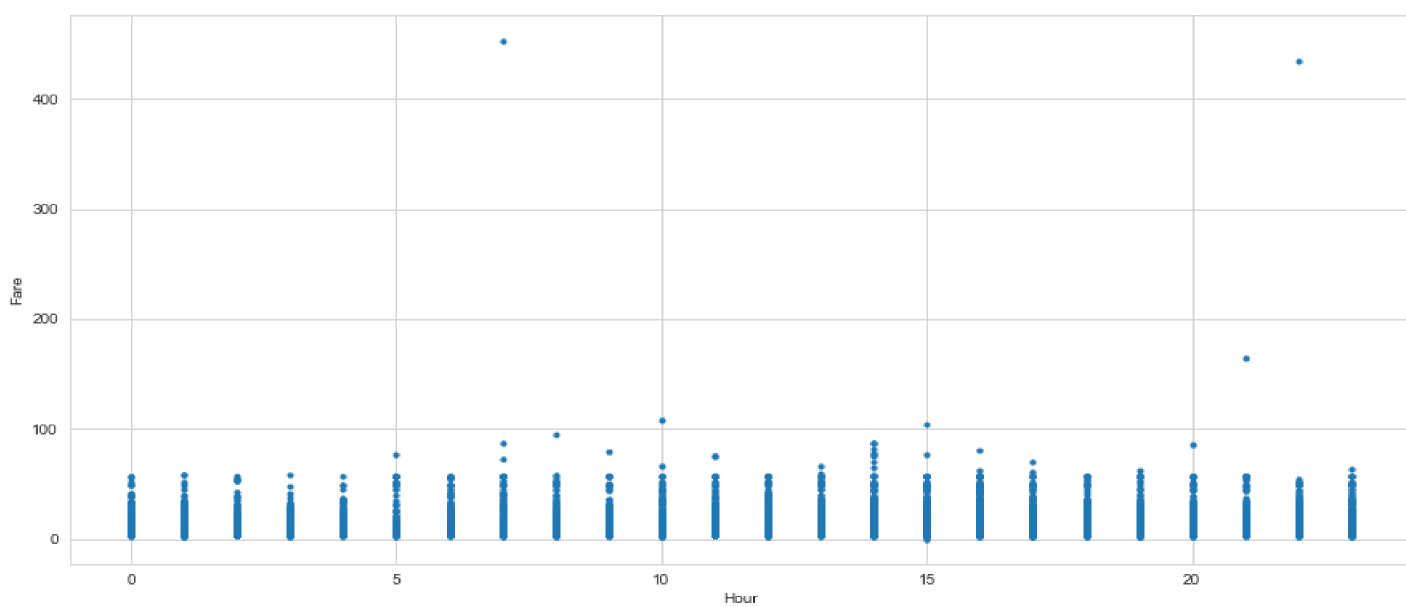
The fares throughout the month mostly seem uniform.



3. <u>Hours and Fares</u>

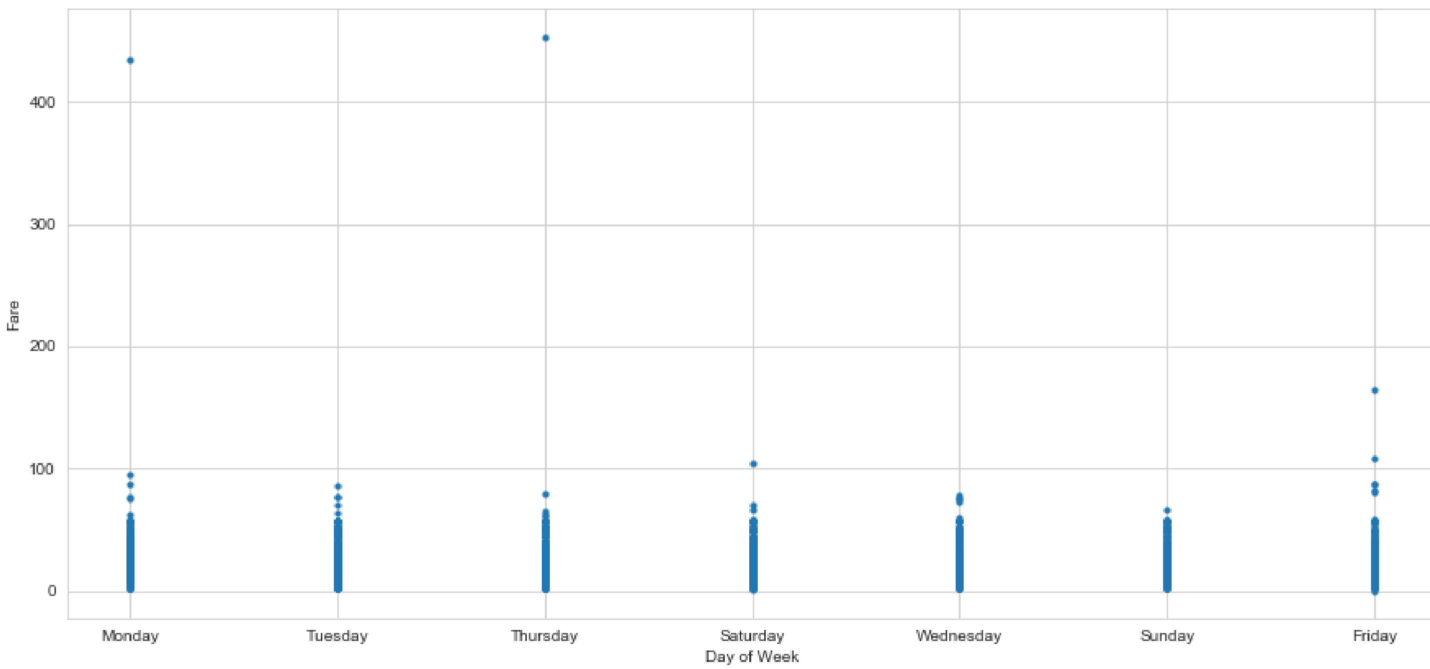
- During hours 6 PM to 11PM the frequency of cab boarding is very due to peak hours
- Fare prices during 2PM to 8PM is bit high compared to all other time might be due to high demands.



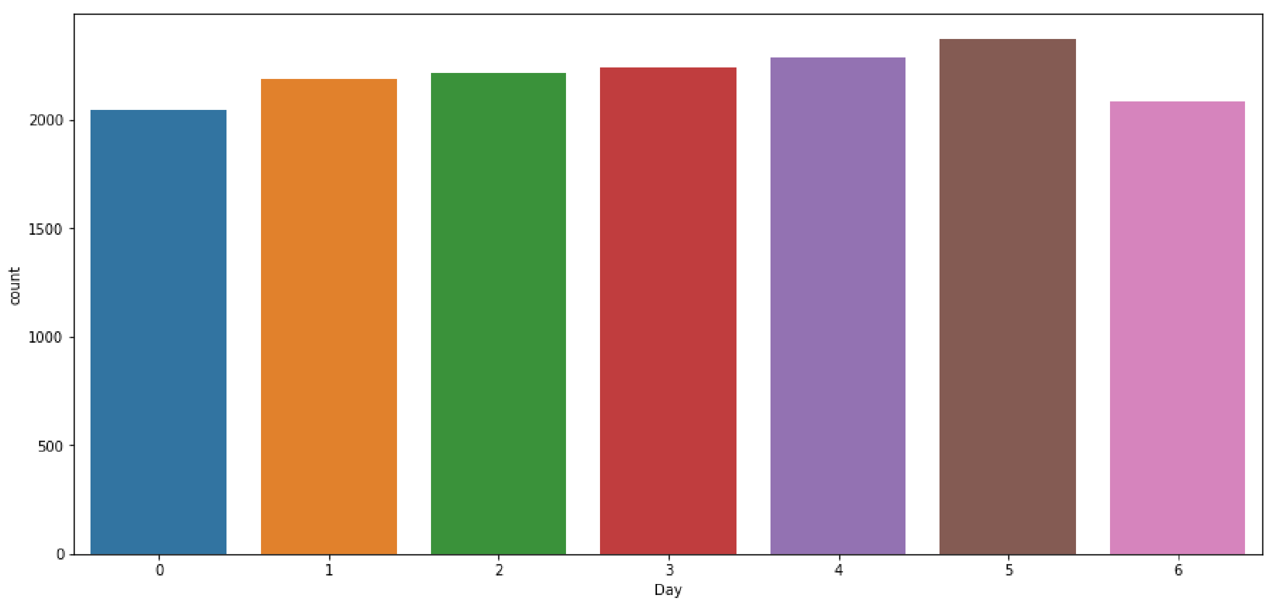


4. <u>Week Day and fare</u>

- Cab fare is high on Friday, Saturday and Monday, may be during weekend and first day of the working day they charge high fares because of high demands of cabs.



5. <u>Impact of Day on the Number of Cab rides :</u>



Observation : The day of the week does not seem to have much influence on the number of cabs ride

References

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3. For Visualization –
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