Topic : Seoul Bike Sharing Demand Prediction

For capstone project using machine learning(regression)

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Abstract:

Our study encompasses the findings done on Seoul Bike (bike sharing demand prediction) csv data file.

In this we tackles the problem of predicting the number of bikes which will be rented at any given hour, henceforth referred to as the problem of ‘Bike Sharing Demand’. The date set consists of 8760 rows and 14 columns .

In this vein, we investigates the efficacy of standard machine learning techniques namely Regression, Random Forests, Boosting by implementing and analyzing their performance with respect to each other.

Problem statement:

Currently Rental bikes are introduced in many urban cities for the enhancement of mobility comfort. It is important to make the rental bike available and accessible to the public at the right time as it lessens the waiting time. Eventually, providing the city with a stable supply of rental bikes becomes a major concern. The crucial part is the prediction of bike count required at each hour for the stable supply of rental bikes.

Introduction to Seoul bike Data set.

There is 1 .csv file we have in our field of study namely 'seoul bike' data .csv we have delt with 14 columns namely Date, Rented bike count, Hour, Temperature, Humidity, Windspeed, Visibility, Due point temperature, Solar radiation, Rainfall, Snowfall, Seasons, Holiday, Functioning day .

The dataset contents weather information such as (temp, humidity, windspeed, visibility, dewpoint, solar radiation, snowfall, rainfall) the number of bikes rented per hour and date information

Attribute Information:

- **Date : year-month-day**
- **Rented Bike count - Count of bikes rented at each hour**
- **Hour - Hour of he day**
- **Temperature-Temperature in Celsius**
- **Humidity - %**
- **Windspeed - m/s**
- **Visibility - 10m**
- **Dew point temperature - Celsius**
- **Solar radiation - MJ/m2**
- **Rainfall - mm**
- **Snowfall - cm**
- **Seasons - Winter, Spring, Summer, Autumn**
- **Holiday - Holiday/No holiday**
- **Functional Day - NoFunc(Non Functional Hours), Fun(Functional hours)**

Below is the original actual info about the data set using df2.info() method

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8760 entries, 0 to 8759
Data columns (total 14 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Date                   8760 non-null   datetime64[ns]
 1   Rented_Bike_Count      8760 non-null   int64
 2   Hour                   8760 non-null   int64
 3   Temperature            8760 non-null   float64
 4   Humidity               8760 non-null   int64
 5   Wind_speed             8760 non-null   float64
 6   Visibility             8760 non-null   int64
 7   Dew_point_temperature  8760 non-null   float64
 8   Solar_Radiation        8760 non-null   float64
 9   Rainfall               8760 non-null   float64
 10  Snowfall               8760 non-null   float64
 11  Seasons                8760 non-null   object
 12  Holiday                8760 non-null   object
 13  Functioning_Day        8760 non-null   object
dtypes: datetime64[ns](1), float64(6), int64(4), object(3)
memory usage: 958.2+ KB
```

```
# Importing the libraries

import numpy as np
import pandas as pd
from numpy import math

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
import seaborn as sns
```

```
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
from sklearn.preprocessing import LabelEncoder,OneHotEncoder
warnings.filterwarnings('ignore')
```

```
#Mounting drive

from google.colab import drive
drive.mount('/content/drive')
```

```
#Reading the csv file and sorting in variable

df2 = pd.read_csv('/content/drive/MyDrive/Almabetter/ML project supervised Regression/SeoulBikeData.csv',encoding =('ISO-8859-1'),low_memory=False)
```

Processing of dataset :

- Changing date-time string to date time format
- Splitting timestamps into days, months, years and day of the week.
- Converting season, holiday, working day and weather into categoric variables or factors.
- Converting hours into a factor.

These transformations allowed us to extract certain key features of the dataset namely, the day of the week and the year, which proved to be pertinent in further analysis.

Such as null values, unique values, rename of columns for easier analysis

Exploratory Data Analysis

Objective

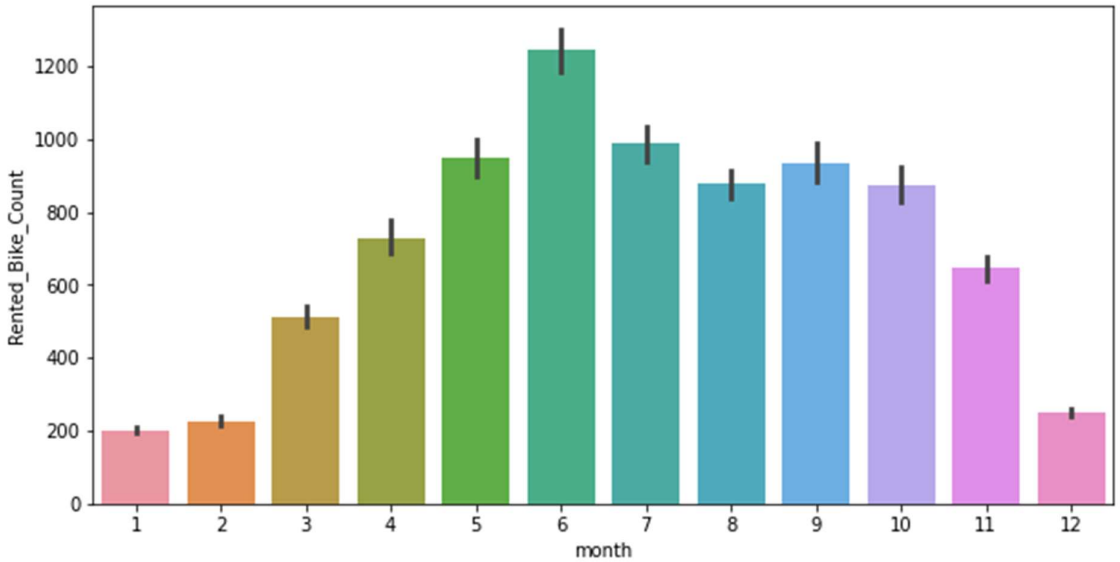
After cleaning of the data set ,we first wanted to do exploratory data analysis on the dataset to find out,

- The type of correlation of all independent variables vs dependant variables, to check whether they are positively correlated or negatively correlated.
- These analysis we have done for categorical variables and numerical variables separately.

Findings

On categorical variables

```
#Analysing on Month Basis
plt.figure(figsize=(10,5))
sns.barplot(data=df2,x='month',y='Rented_Bike_Count')
```

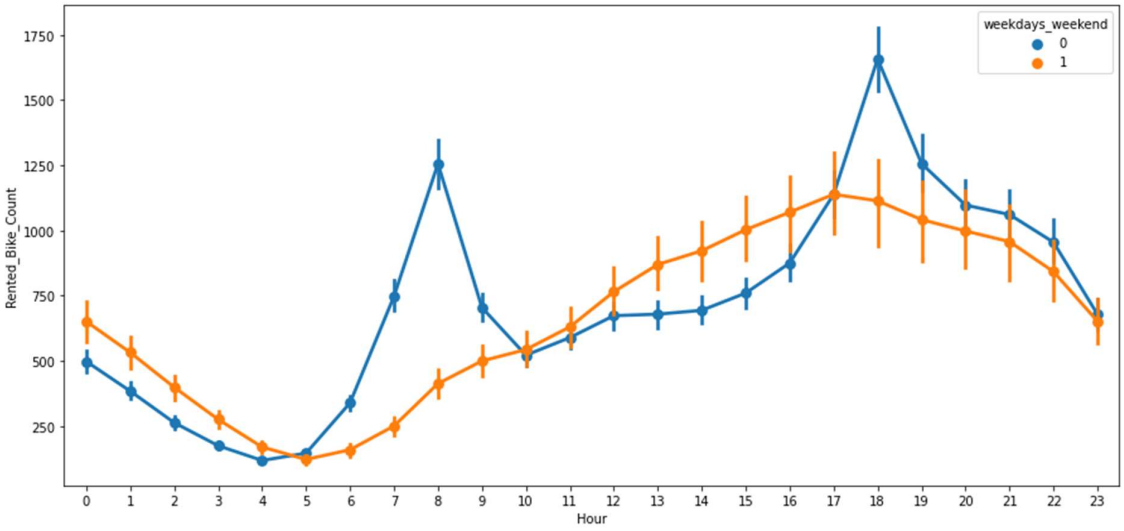


From above bar graph we can analyse that from April to October the Demand is high of Rented bike count being June as highest.

Findings & Recommendations

So it is our finding that as there is high no. of Rented bike count from May to October so during this period 1200 bikes should be made available to meet with the demand & supply requirement.

```
#Count of Rented Bike on Hour Basis
plt.figure(figsize = (15,7))
sns.pointplot(data=df2,x='Hour', y='Rented_Bike_Count',hue='weekdays_weekend')
```



From the above point plot it can be analysed that the usage of rented bikes are more during weekdays than weekends.

Also that during weekdays from 5 am to 10 am and evening from 4 pm to 8 pm the renting is highest .

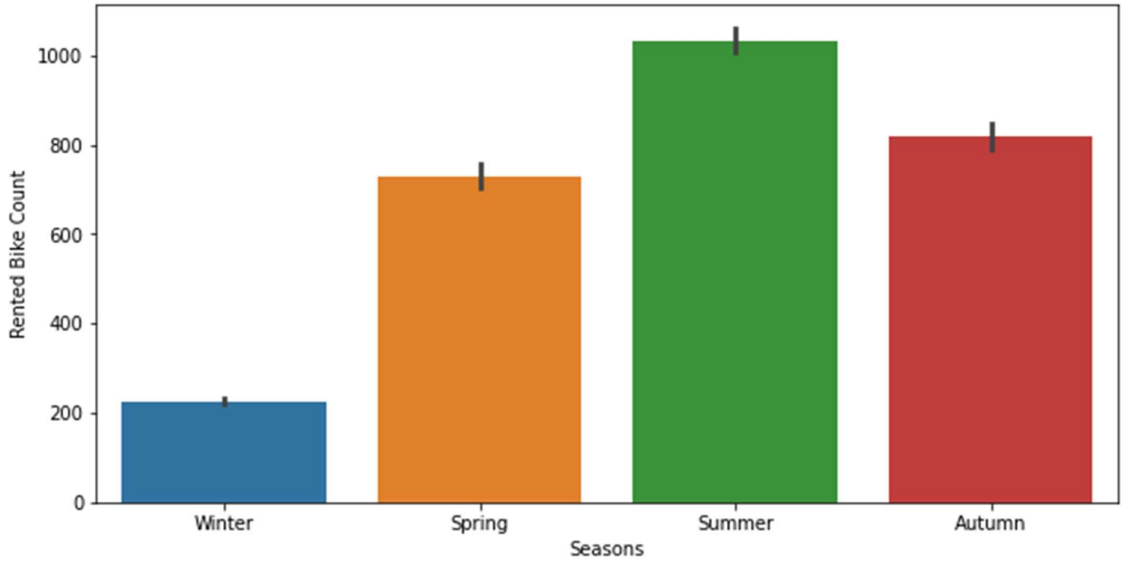
looking at orange line it can be said that during weekends the renting is very low during morning hours but as the evening comes closer gradually the rented

numbers increases being maximum around 5 pm .It can be inferred that may be these must be getting used by people for leisure or family /personal use , as it's a non-official day ,being weekend.

Findings & Recommendations

Our Findings are that concentration of more available bikes should be made in and around commercial office sectors during weekdays and can be shifted to residential areas during weekends.

```
# Analysing Bike rented with regards to Seasons
plt.figure(figsize=(10,5))
sns.barplot(data=df, x='Seasons', y='Rented Bike Count')
```



From Above barplot it can be seen easily that that Winters are the down season for renting , the number of rented bikes increases in Spring and Autumn and are nearly equal .

Also it can be seen that during summers the rented bike count is highest , concluded earlier also the average

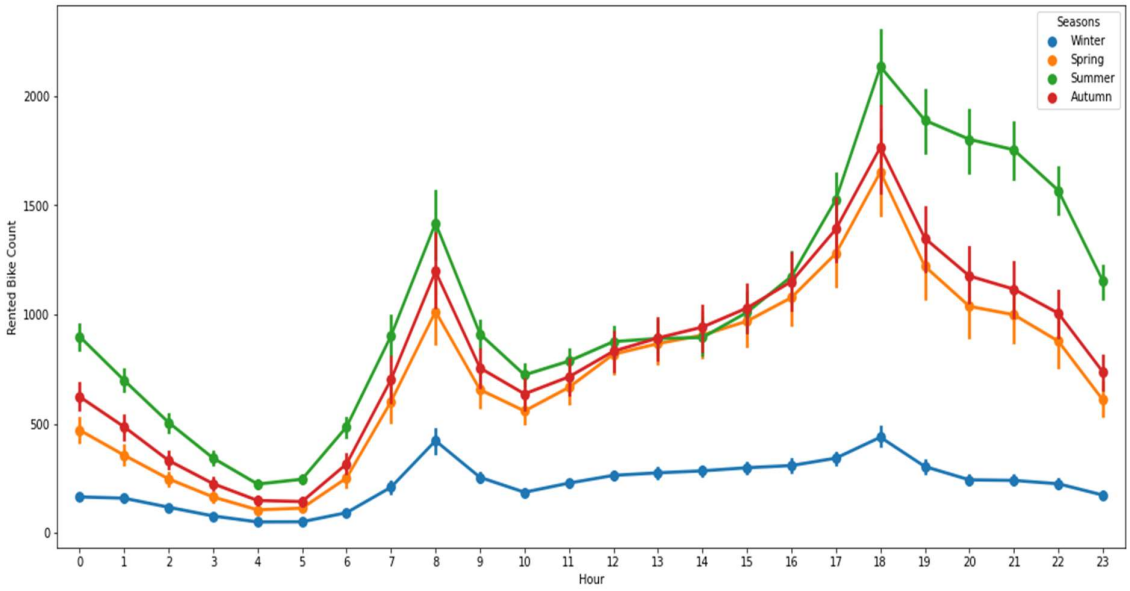
demand during summers is 1000 no. and peak requirement reaches during June which is around 1200 no.

Also the renting of Bikes during Summers is approximately 30% higher than Spring and Autumn .

Findings & Recommendations

The infrastructure required of the rented bike company and the no. of available rented bikes should be at its best during summers , to cater to approximate 1000 - 1200 numbers per day.

```
# Analysing the bike rented according to seasons and hour
plt.figure(figsize=(18,8))
sns.pointplot(data=df, x="Hour", y='Rented Bike Count', hue='Seasons')
```



Above point plot shows that the trend of booking is similar for Summer , Autumn and Spring , which shows peak renting from 6 am to 9 am & from 4 Pm to 10 Pm.

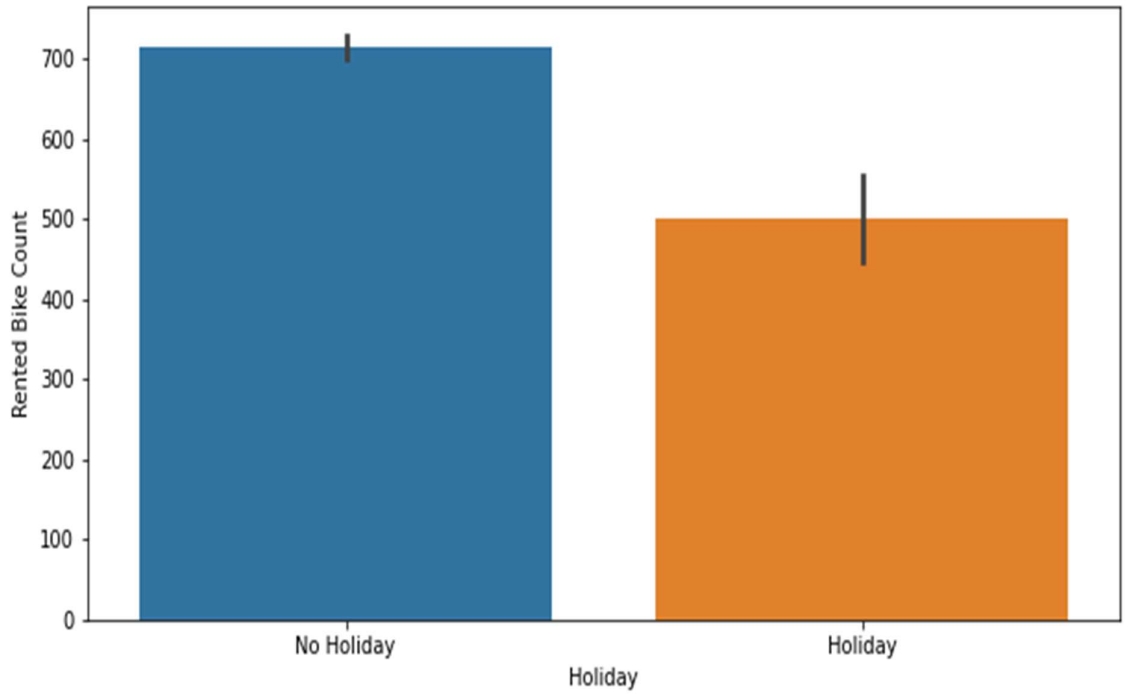
Also it can be observed that at seoul , people prefer to use rented bikes more during evening hours than morning hours.

The renting is lowest in Winter season.

Findings & Recommendations

Evenings of summers are most crucial part as the demand is highest reaching 1900 no. of bike requirement. The arrangement should be accordingly to cater to the demand.

```
#Analysing according to Holiday
plt.figure(figsize = (10,5))
sns.barplot(data=df, x='Holiday', y='Rented Bike Count')
```



It can be easily seen from above that the higher number of Renting is done on weekdays and lower on holidays

Findings & Recommendations

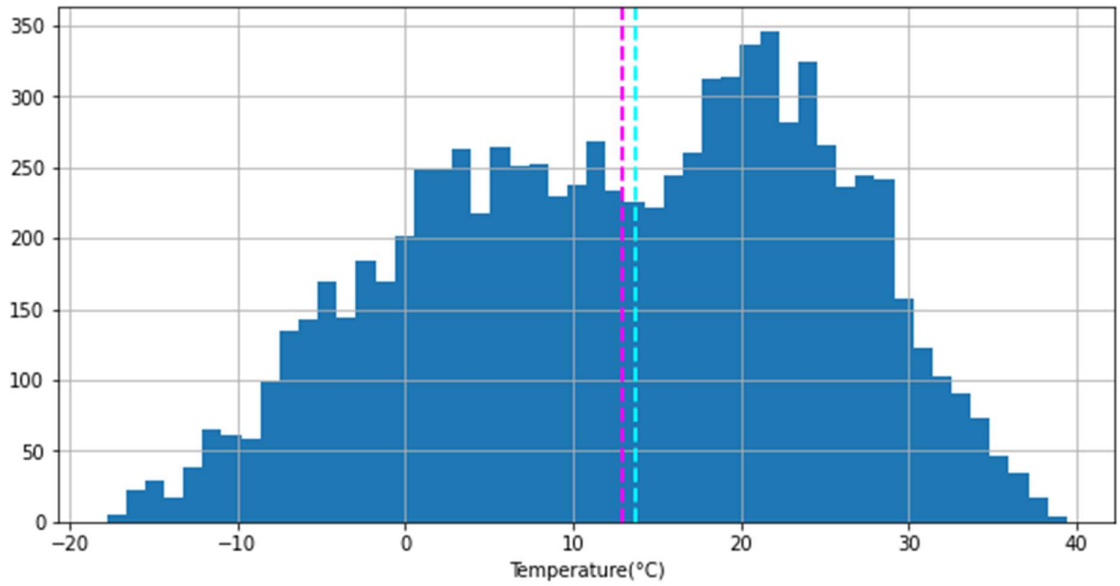
The demand during Holidays is 40% lesser than working days , so if the Bike numbers are enough for working days , Holidays demand numbers can be managed easily .

Findings done on numerical variables

Filtering all numerical columns

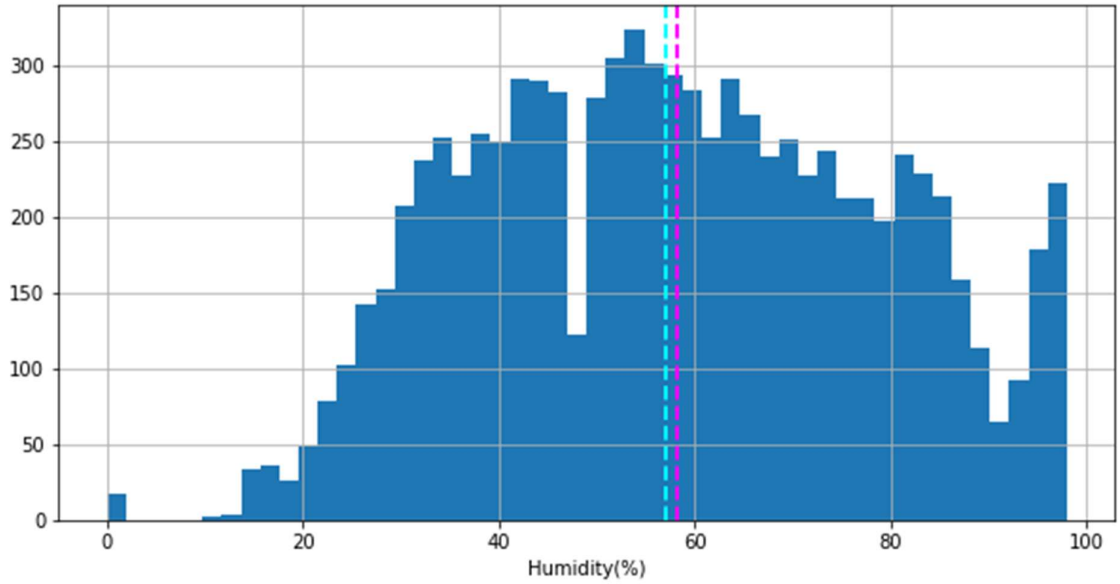
```
numerical_variables = list(df.select_dtypes(['int64','float64']).columns)
```

```
Used for loop for plotting histograms to show distribution of all
independent variables .
#displaying displots to analyze the distribution of all numerical featu
res
for col in numerical_variables:
  fig = plt.figure(figsize = (10,5))
  ax = fig.gca()
  feature = df[col]
  feature.hist(bins=50, ax=ax)
  ax.axvline(feature.mean(), color='magenta', linestyle='dashed', linew
idth=2)
  ax.axvline(feature.median(), color='cyan', linestyle='dashed', linewi
dth=2)
  plt.xlabel(col)
  plt.show()
```



Here we have used histogram to find the distribution of data for ‘Temperature’ variable , also to check its mean and mode ,
By looking at it we can say that the distribution resembles Normal distribution .

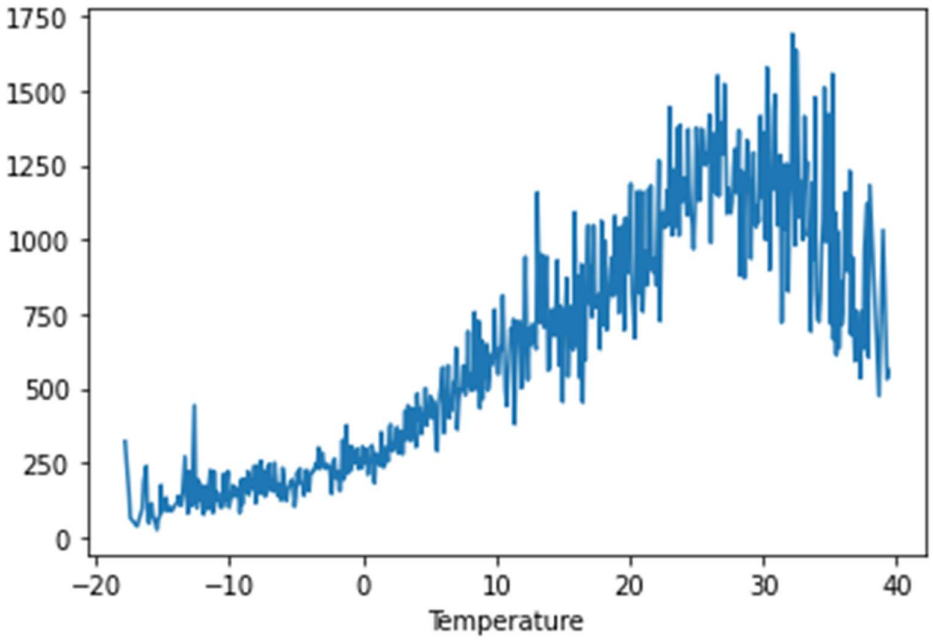
We checked such distributions for all independent variables .



‘Humidity’ variable also shows close to normal distribution.

Analysing Rented Bike Count (Dependent Variable) Vs ('Temperature' , 'Snowfall' ,'Rainfall' using their mean value)

```
df2.groupby('Temperature').mean()['Rented_Bike_Count'].plot()
```

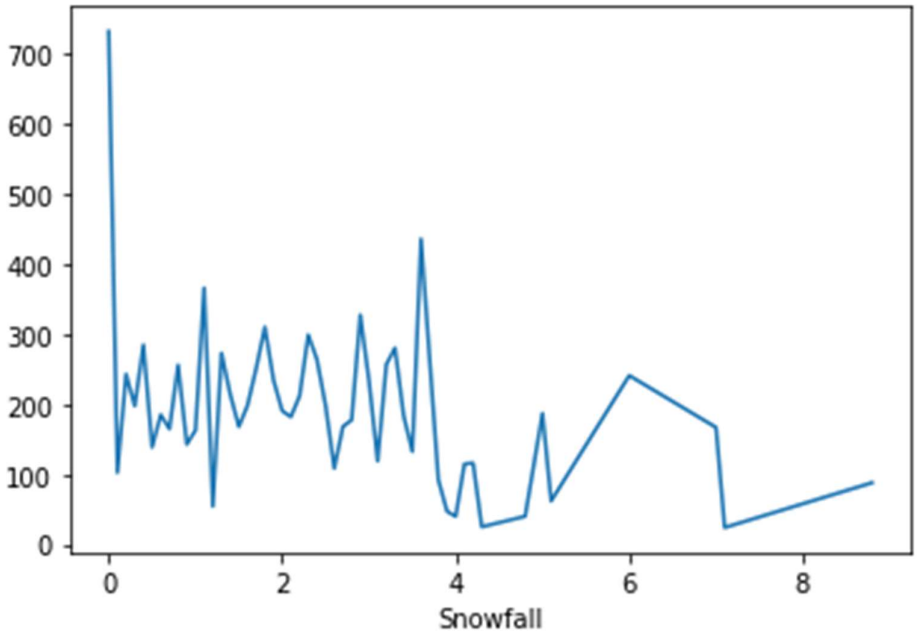


From Above it can be inferred that People prefer to rent a bike most , when the temperature is around 25-33 degree Centigrade.

Findings & Recommendations

Using the weather forecast the estimate of normal to high renting of bikes can be made as if the days temperature is between 25-33 degrees the demand can be higher than normal and to be prepared accordingly.

```
#print the plot to analyze the relationship between "Rented_Bike_Count"
 and "Snowfall"
df2.groupby('Snowfall').mean()['Rented_Bike_Count'].plot()
```

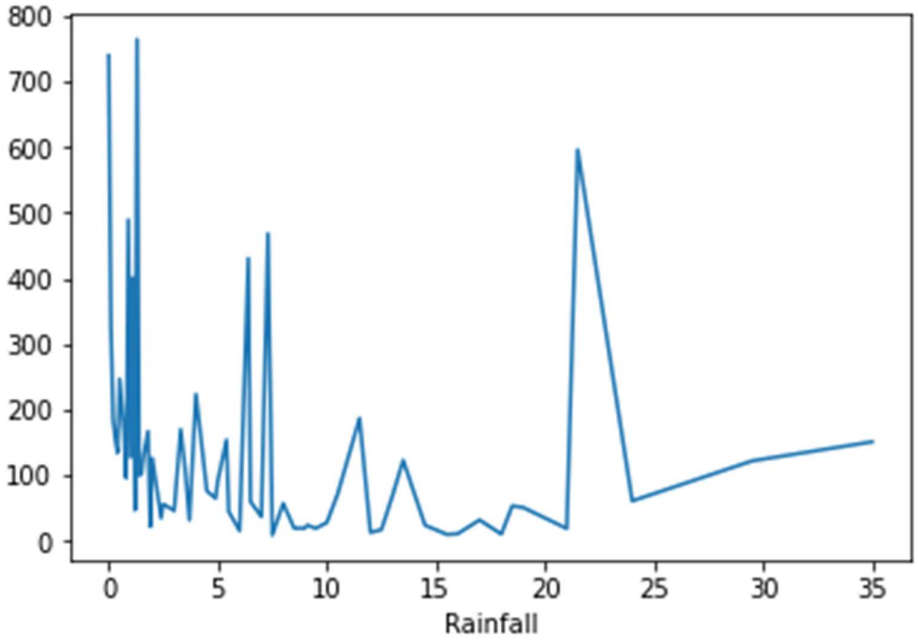


It can be analysed that renting of the bikes are maximum when there is no Snow but it decreases as snowfall starts and drastically slows down after 4 cm of snowfall.

Findings & Recommendations

During winters and areas where snowfall is likely to take place can expect downfall in demand by around 40-45%.

```
#print the plot to analyze the relationship between "Rented_Bike_Count"
 and "Rainfall"
df2.groupby('Rainfall').mean()['Rented_Bike_Count'].plot()
```



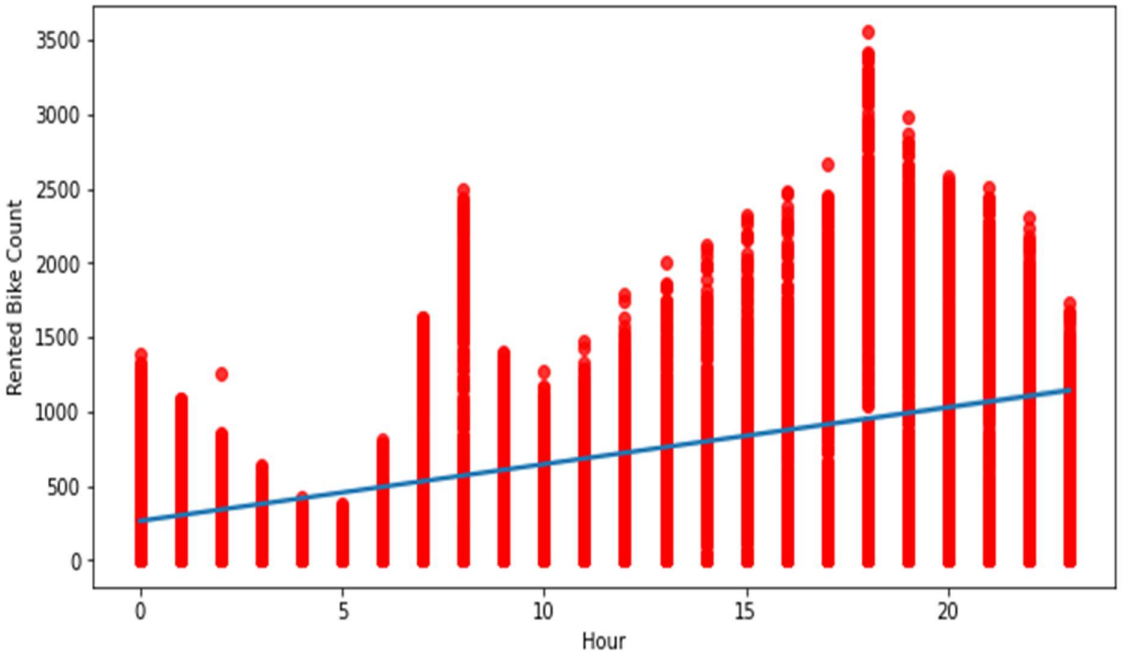
It can be seen that opposite of the expectation, there is little decrease in the renting of the bikes even if its raining, intermittently there are surges in the renting numbers.

Findings & Recommendations

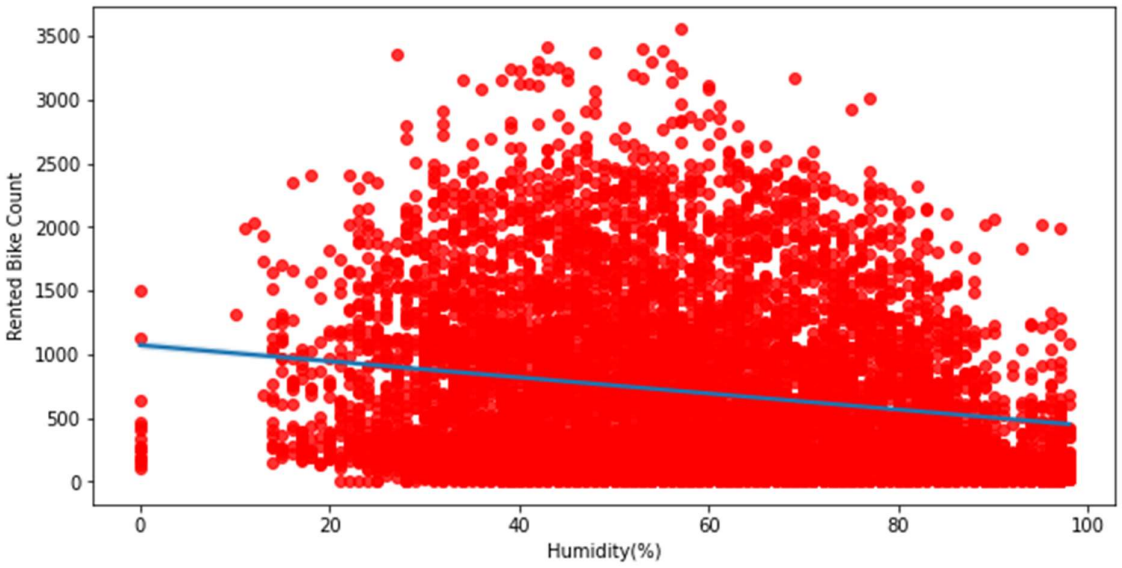
The Rain does not slows down the Renting rate as much as Snowfall does.

We plotted regression Plot to show their Linear Relationship with Target Variables.(+tive or –tive)

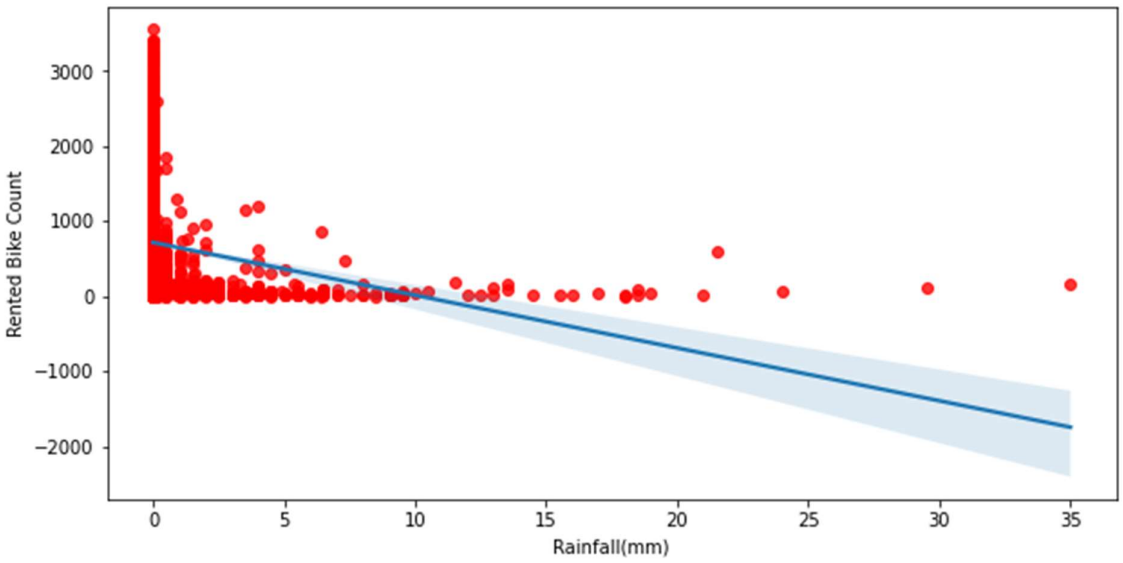
```
# the regression plot for all the numerical features
for col in numerical_variables:
  plt.figure(figsize=(10,5))
  sns.regplot(x=df[col], y='Rented Bike Count',data=df, scatter_kws ={'
color':'red'})
```



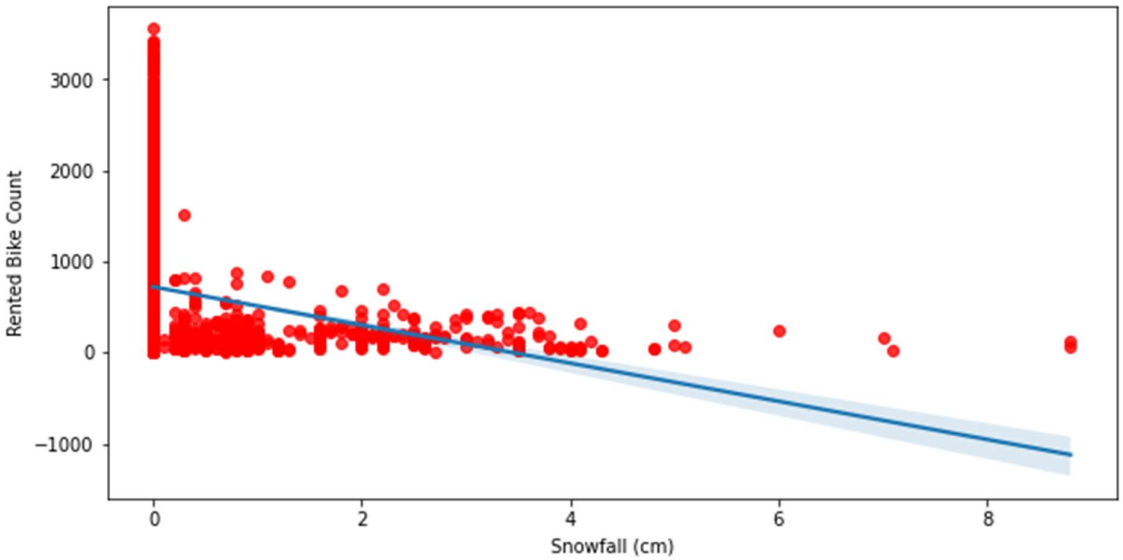
By applying regression plot and by looking at the best fit line we can clearly say that ‘Hour’ variable is Positively correlated with rented bike count variable.



‘Humidity’ variable is Negatively correlated with Rented Bike Count dependant variable ..,



‘ Rainfall ‘ is negatively correlated variable to Rented bike count.



From the above regression plot of all numerical features

we see that the columns 'Temperature', 'Wind_speed', 'Visibility', 'Dew_point_temperature', 'Solar_Radiation' are positively relation to the target variable which means the rented bike count increases with increase of these features.

Rainfall' ,'Snowfall' ,'Humidity' these features are negatively related with the target variable which means the rented bike count decreases when intensity of these features increase.

Firstly we want to convert data columns to data format conversion

```
# Date columns to Date format conversion
df2['Date'] = df2['Date'].apply(lambda x:dt.datetime.strptime(x, "%d/%m
/%Y"))
```

```
# extracting day,month, day of week and weekdays/weekend from date colu
mn

df2['day'] = df2['Date'].dt.day_name()
df2['month'] = df2['Date'].dt.month
df2['year'] = df2['Date'].dt.year
df2.drop(columns = 'Date', axis=1, inplace=True)
```

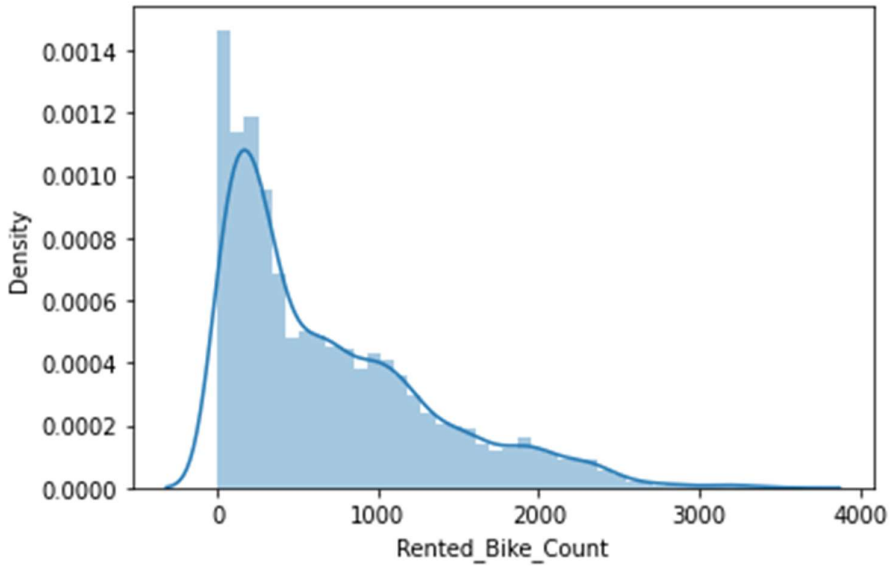
```
df2['weekdays_weekend'] = df2['day'].apply(lambda x: 1 if x=='Saturday'
 or x=='Sunday' else 0)
df2.drop(columns={'day','year'},axis=1,inplace=True)
```

#Visualising distribution

The first visualization I usually make for distributions is a histogram. You can see here that this is a terrible and

uninformative way to look at the data. The differences in the sample sizes between the different groups makes them incomparable using this method.

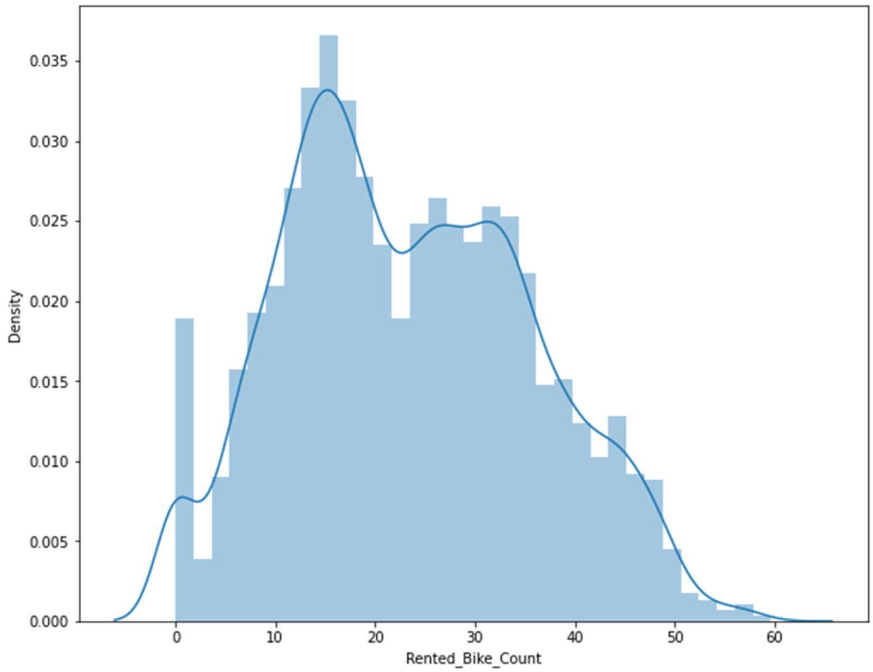
```
#visualising distribution
sns.distplot(df2['Rented_Bike_Count'])
```



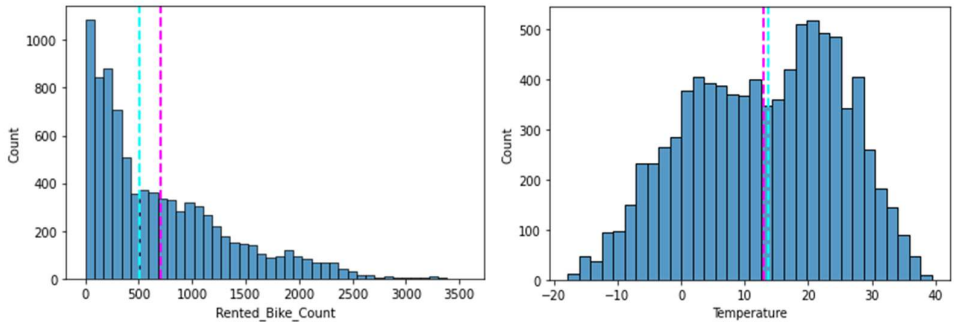
Square Root Transformation

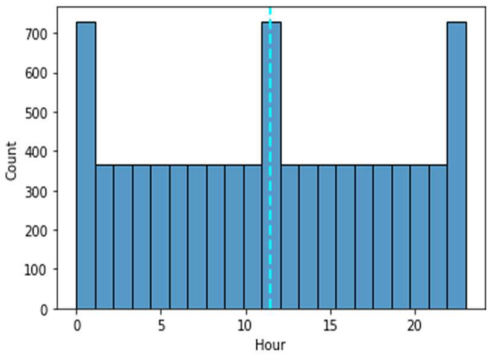
When you apply a square root transformation to a variable, high values get compressed and low values become more spread out. Log transformation does the same thing but more aggressively.

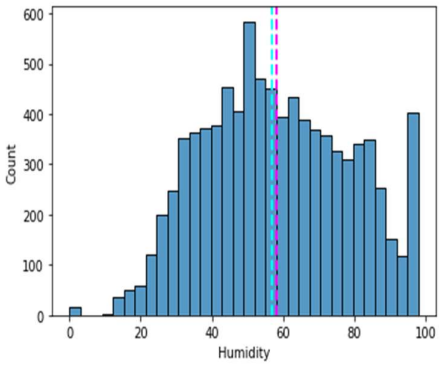
```
# square_root transformation

plt.figure(figsize=(10,8))
sns.distplot(np.sqrt(df2['Rented_Bike_Count']))
```

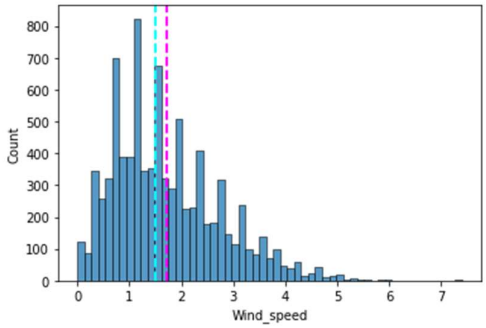


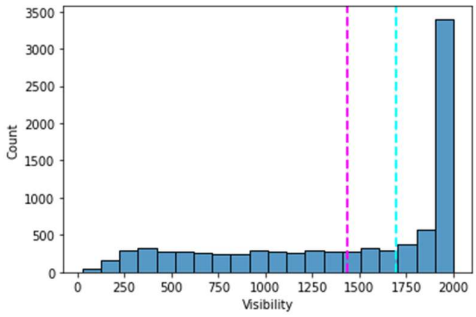

```
#plotting histogram

for col in numeric_features[:]:
  sns.histplot(df2[col])
  plt.axvline(df2[col].mean(), color='magenta', linestyle='dashed', lin
ewidth=2)
  plt.axvline(df2[col].median(), color='cyan', linestyle='dashed', line
width=2)
  plt.show()
```

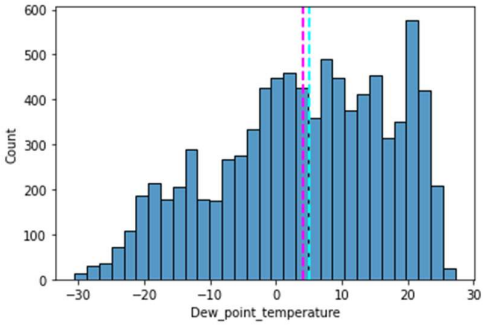


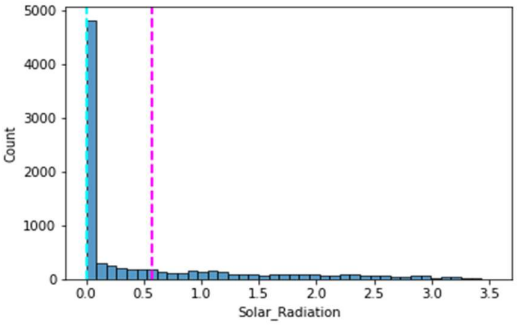

Count
Hour

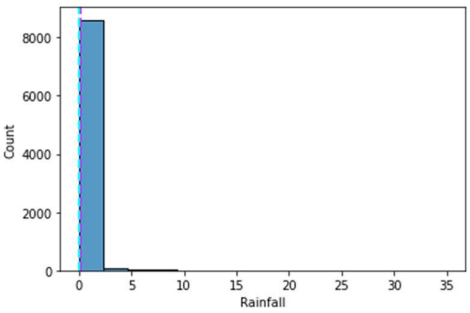

Count
Humidity

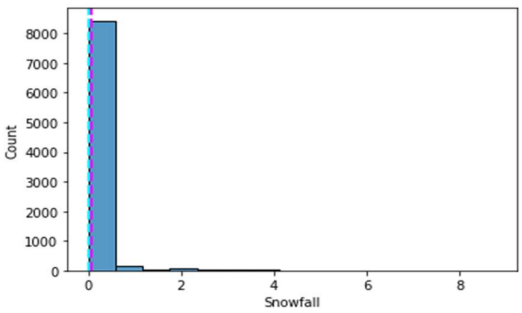

Count
Wind_speed

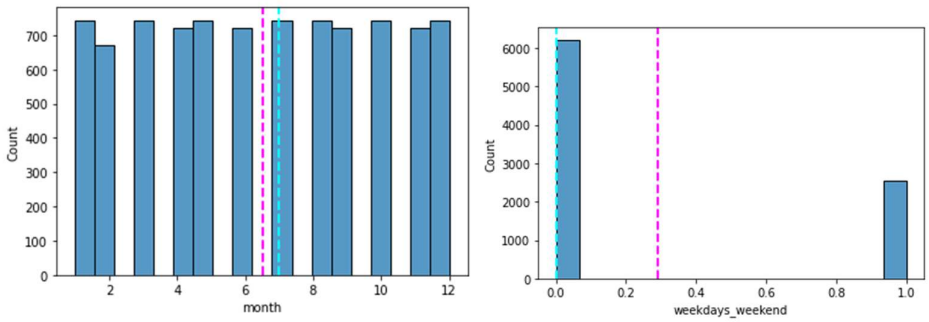

Count
Visibility


Count
Dew_point_temperature

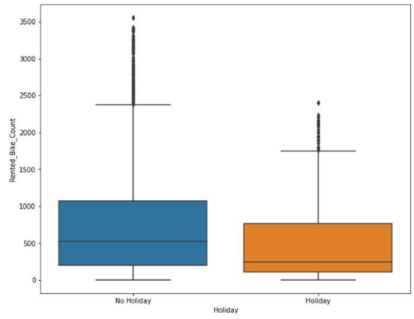

Count
Solar_Radiation

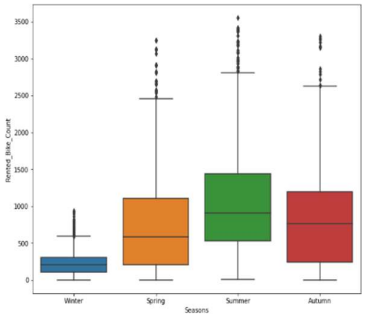

Count
Rainfall

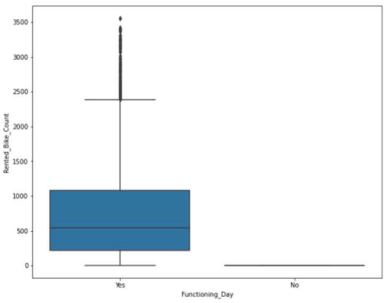

Count
Snowfall




```
#ploting Box plot to visualize and trying to get info
rmation from plot

for col in categorical_features:
  plt.figure(figsize=(10,8))
  sns.boxplot(x=df2[col],y=df2["Rented_Bike_Count"])
  plt.show()
```







Conclusion

Less demand on winter seasons

Sligthly Higher demand during Non holidays

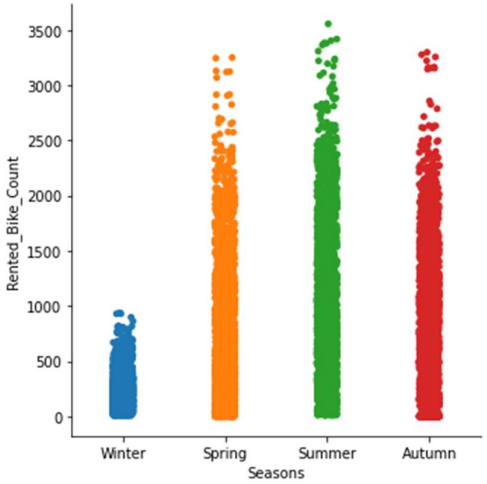
Almost no demnad on non functioning day

```
#checking counts of functioning day
df2['Functioning_Day'].value_counts()
```

```
#ploting cat plot for more info
```

here we describe the seasons on x-axis and rented bike count on y-axis

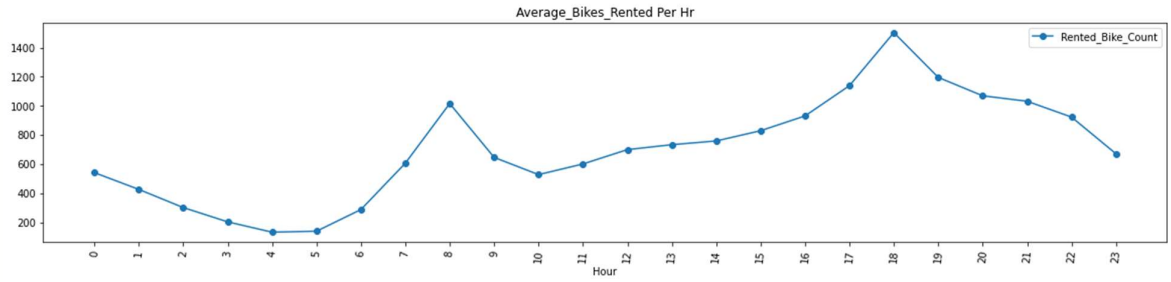
```
sns.catplot(x='Seasons',y='Rented_Bike_Count',data=df2)
```



Conclusion

we can clearly see that there less demand of rented bik e during winter season.

```
#ploting line graph
# group by Hrs and get average Bikes rented, and precent change
avg_rent_hrs = df2.groupby('Hour')['Rented_Bike_Count'].mean()

# plot average rent over time(hrs)
plt.figure(figsize=(20,4))
a=avg_rent_hrs.plot(legend=True,marker='o',title="Average_Bikes_Rented
Per Hr")
a.set_xticks(range(len(avg_rent_hrs)));
a.set_xticklabels(avg_rent_hrs.index.tolist(), rotation=85);
```



Conclusion

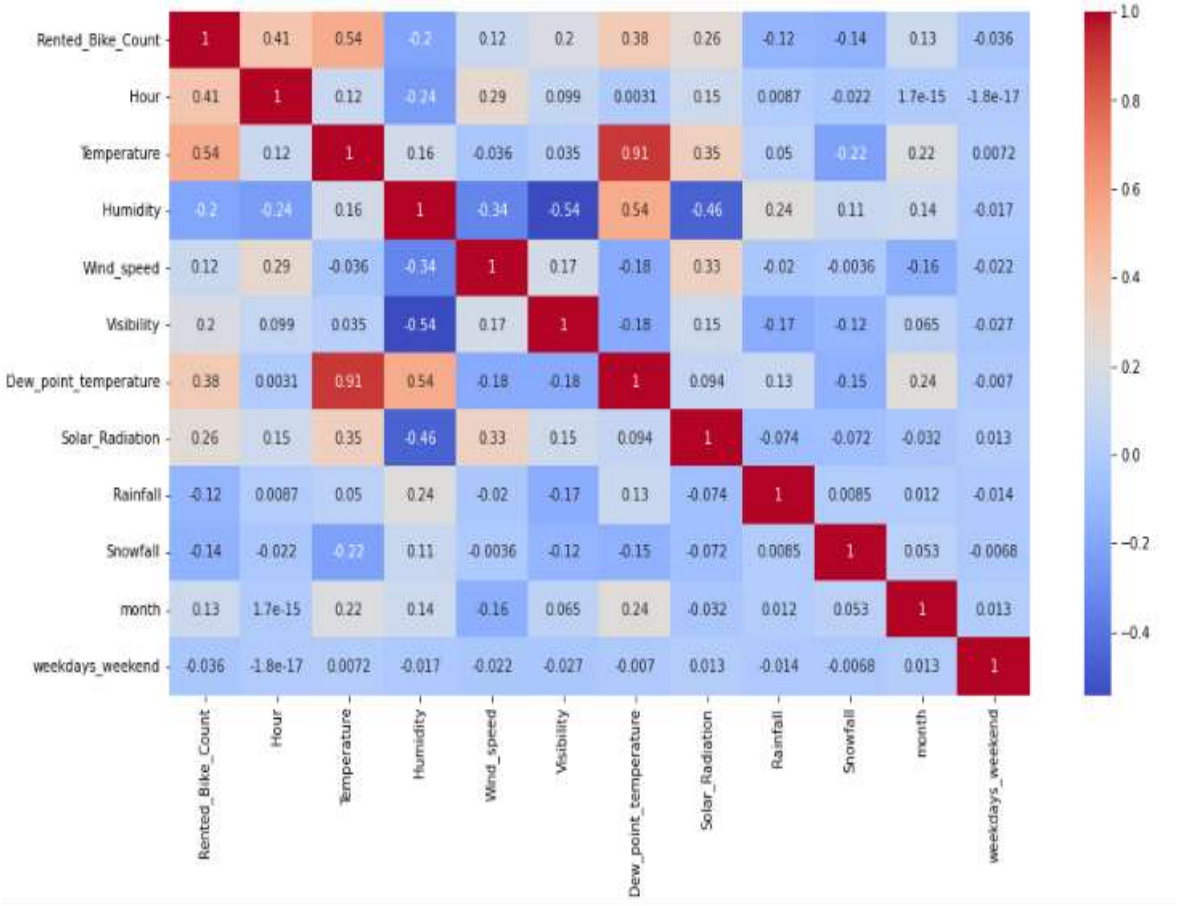
High rise of Rented Bikes from 8:00 a.m to 9:00 p.m means people prefer rented bike during rush hour. we can clearly see that demand rises most at 8 a.m and 6:00 p.m so we can say that that during office opening and closing time there is much high demand

Heatmap

Heatmap is a two dimensional representation of information with the help of colors. Heatmap can help the user to visualize simple or complex information. Heat maps are used in many area such as defence, marketing and understanding consumer behavior. Basically Heatmap is used to check the correlation between the dependent variables and independent variables.

From the Heatmap we can say that the relation between temperature and dew_point_temperature is very high i.e, 0.91.

So we can remove the dew_point_temperature columns from the dataset and it don't affect the outcome of our analysis.



Categorical Encoding:

Encoding categorical data is a process of converting categorical data into integer format so that the data with converted categorical values can be provided to the models to give and improve the predictions.

There are two types of Categorical Encoding

1. One-Hot Encoding
2. Label Encoding

1. One-Hot Encoding:

One hot encoding is the most widespread approach, and it works very well unless your categorical variable takes on a large number of values (i.e. you generally won't it for variables taking more than 15 different values. It'd be a poor choice in some cases with fewer values, though that varies.)

One hot encoding creates new (binary) columns, indicating the presence of each possible value from the original data. Let's work through an example.

In our dataset, we had converted datatypes of categorical variables like seasons, Hours, etc to int datatypes. So now we can push that variables to our machine learning model and get our analysis.

Model Training:
In model training our first step is to do a train test split of our data.

The train-test split procedure is used to estimate the performance of machine learning algorithms when they are used to make predictions on data not used to train the model.
It is a fast and easy procedure to perform, the results of which allow you to compare the performance of machine learning algorithms for your predictive modeling problem. Although simple to use and interpret, there are times when the procedure should not be used, such as when you have a small dataset and situations where additional configuration is required, such as when it is used for classification and the dataset is not balanced.

The Machine Learning algorithm we used in this project are as follows:

1. Linear Regression
2. Decision Tree
3. Random Forest
4. Elastic Net Regression

1.**Linear Regression:**
Linear Regression is a machine learning algorithm based on supervised learning. It performs a regression task. Regression models a target prediction value based on

independent variables. It is mostly used for finding out the relationship between variables and forecasting.

We use Linear Regression model and evaluate our machine score which are as follows:
We calculate Mean Squared Error(MSE), Root Mean Squared Error(RMSE),
Mean Absolute Error(MAE) and R2_Score of the Linear Regression.

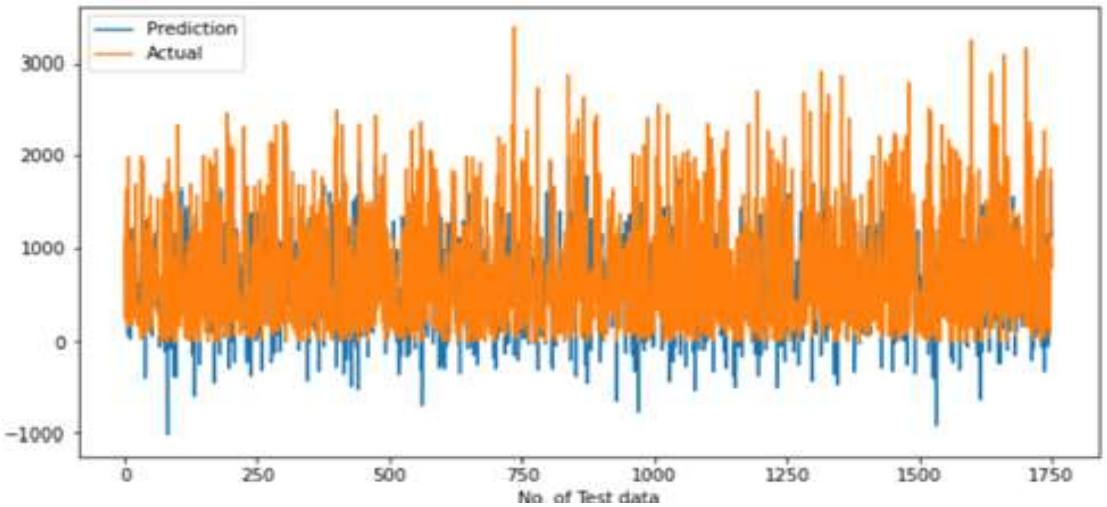
Train Data

```
MSE: 140206.61624939015
RMSE: 374.44173945941196
MAE : 282.480522260274
R2_Score: 0.6638417466299076
```

Test Data

```
MSE: 136823.99994832542
RMSE: 369.8972829696447
MAE : 278.93567479799873
R2_score: 0.6673417356182685
```

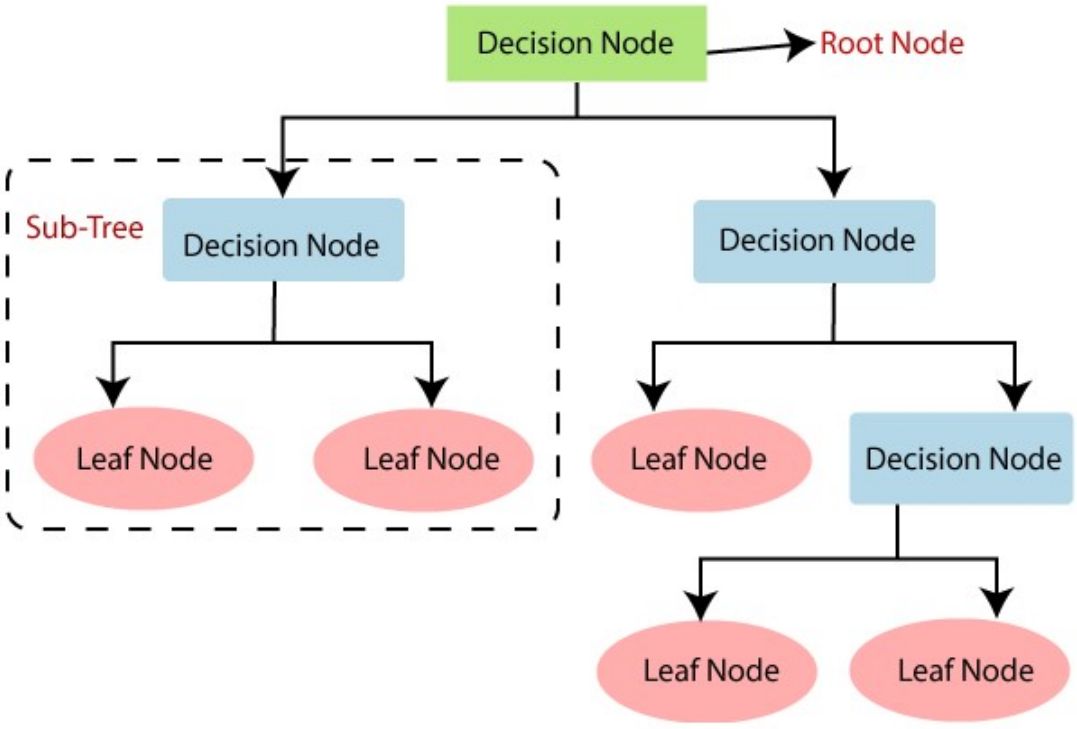
Analysis based on predicted value and actual value



2. Decision Tree:

Decision Tree is a Supervised learning technique that can be used for both classification and Regression problems, but mostly it is preferred for solving Classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome.

In a Decision tree, there are two nodes, which are the Decision Node and Leaf Node. Decision nodes are used to make any decision and have multiple branches, whereas Leaf nodes are the output of those decisions and do not contain any further branches.



We use Elastic Net Regression model and evaluate our machine score which are as follows:

We calculate Mean Squared Error(MSE), Root Mean Squared Error(RMSE),
Mean Absolute Error(MAE) and R2_Score of the Elastic Net Regression.

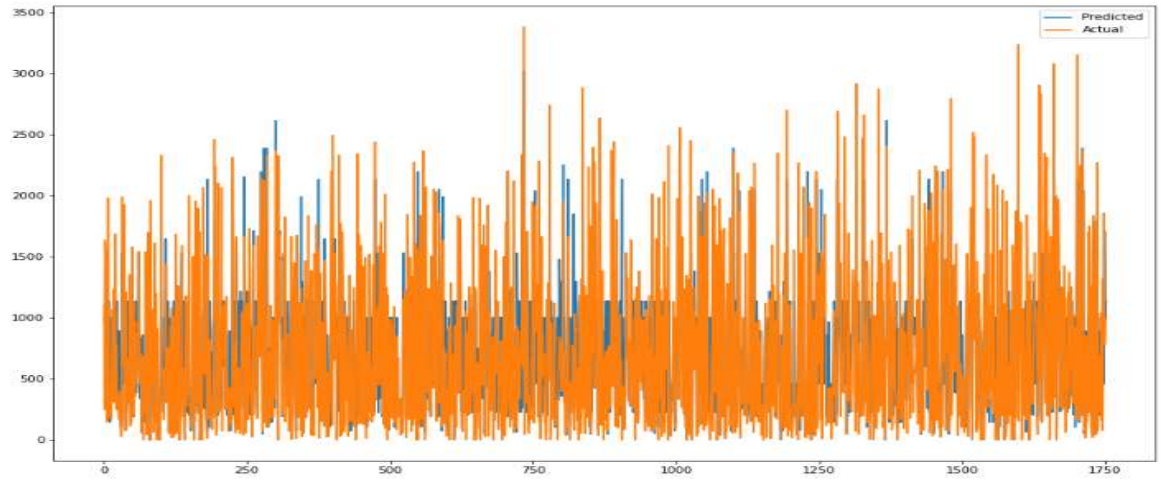
Train Data

```
Model score: 0.5757435377609246
MSE: 176951.07109861638
RMSE: 420.6555254583213
MAE : 288.42324530629
R2_score: 0.5757435377609246
```

Test Data

```
MSE : 192208.7355797449
RMSE : 438.41616710580473
MAE : 304.7141588337355
R2 : 0.53268560777997
```

Analysis based on predicted value and actual value

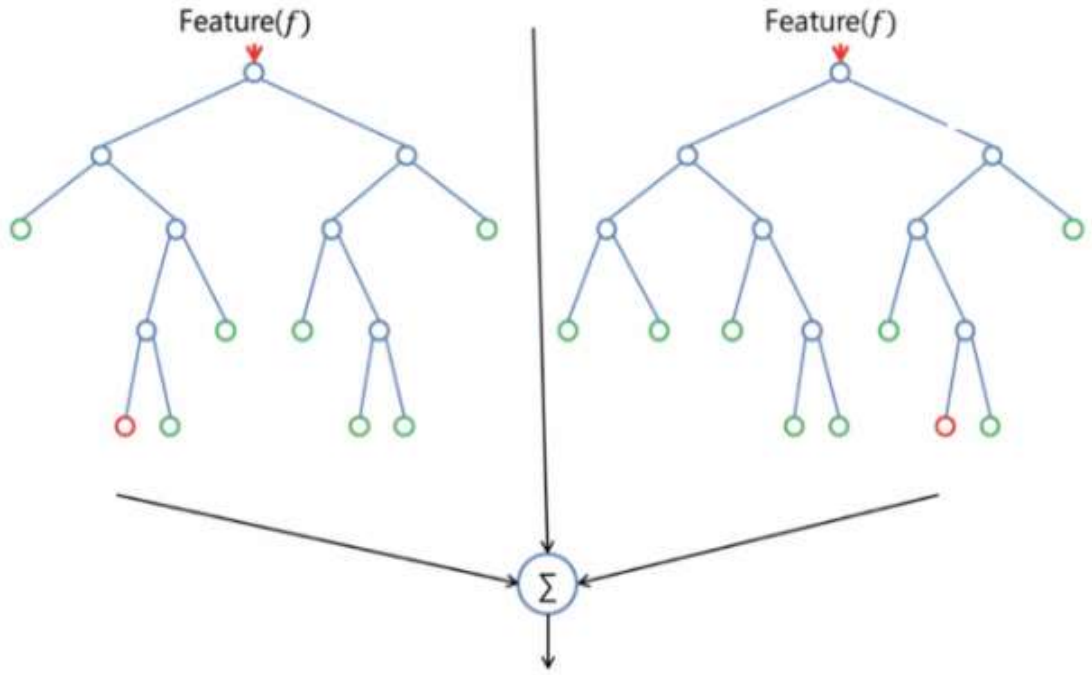


3. Random Forest:

Random forest is a Supervised Machine Learning Algorithm that is used widely in Classification and Regression problems. It builds decision trees on different samples and takes their majority vote for classification and average in case of regression

Random forest builds multiple decision trees and merges them together to get a more accurate and stable prediction.

Random forest has nearly the same hyperparameters as a decision tree or a bagging classifier. Fortunately, there’s no need to combine a decision tree with a bagging classifier because you can easily use the classifier-class of random forest. With random forest, you can also deal with regression tasks by using the algorithm’s regressor.



We use Random Forest model and evaluate our machine score which are as follows:
We calculate Mean Squared Error(MSE), Root Mean Squared Error(RMSE),
Mean Absolute Error(MAE) and R2_Score of the Random Forest.

Train Data

```
Model Score: 0.9873599030046023
MSE: 5271.99677836758
RMSE: 72.60851725774036
MAE : 41.69463470319635
R2_score: 0.9873599030046023
```

Test Data

```
MSE : 32425.597170890414
RMSE : 180.07108921448332
MAE : 111.38534246575342
R2_Score : 0.9211641022007586
```

4. Elastic Net Regression:

In statitics and, in particular, in the fitting of linear or logistics regression models, the elastic net is a regularized regression method that linearly combines the L_1 and L_2 penalties of the lasso and ridge methods.

Elastic Net first emerged as a result of critique on lasso, whose variable selection can be too dependent on data and thus unstable. The solution is to combine the penalties of ridge regression and lasso to get the best of both worlds. Elastic Net aims at minimizing the following loss function:

$$L_{enet}(\hat{\beta}) = \frac{\sum_{i-1}^{n}(y_i - x_i'\hat{\beta})^2}{2n} + \lambda\left(\frac{1-\alpha}{2}\sum_{j-1}^{m}\hat{\beta}_j^2 + \alpha\sum_{j-1}^{m}|\hat{\beta}_j|\right),$$

where α is the mixing parameter between ridge ($\alpha = 0$) and lasso ($\alpha = 1$).

Train Data	Test Data
MSE : 177834.94694853635	MSE : 175442.3949535531
RMSE : 421.704810203223	RMSE : 418.8584426194046
MAE : 309.0419441515174	MAE : 309.43682474292893
R2 : 0.5736243641452045	R2 : 0.5734493756485335

Conclusion:

During the time of our analysis, we initially did EDA on all the features of our datset. We first analysed our dependent variable, 'Rented Bike Count' and also transformed it. Next we analysed categorical variable and dropped the variable who had majority of one class, we also analysed numerical variable, found out the correlation, distribution and their relationship with the dependent variable. We also removed some numerical features who had mostly 0 values and hot encoded the categorical variables.

We implemented 4 Machine Learning algorithms Linear Regression, Decision Tree, Random Forest and Elastic Net Regression.

Random Forest Regressor gives highest R2 Score of 98 % for training set and 92% for testing set Decision Tree gives the lowest R2 Score of 57% for training set and 53 % for testing set