Capstone Project - 2

Bike Sharing Demand Prediction

Team Members

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Introduction

Bike sharing system is a shared transport service in which bicycles are made available for shared use to individuals on a short-term basis for a price.

This system is designed to resolve issues of traffic congestion, noise, and air pollution.

We have used Seoul's bike sharing system dataset which contains weather data and the number of bikes rented per hour.

Problem Statement

It is important to make the rental bike available and accessible to the public at the right time as it lessens the waiting time.

This project tackles the problem of predicting the number of bikes required at each hour for the stable supply of rental bikes.

The main objective is to build various regression models and analyze their performance with respect to each other so as to get the best performing model.

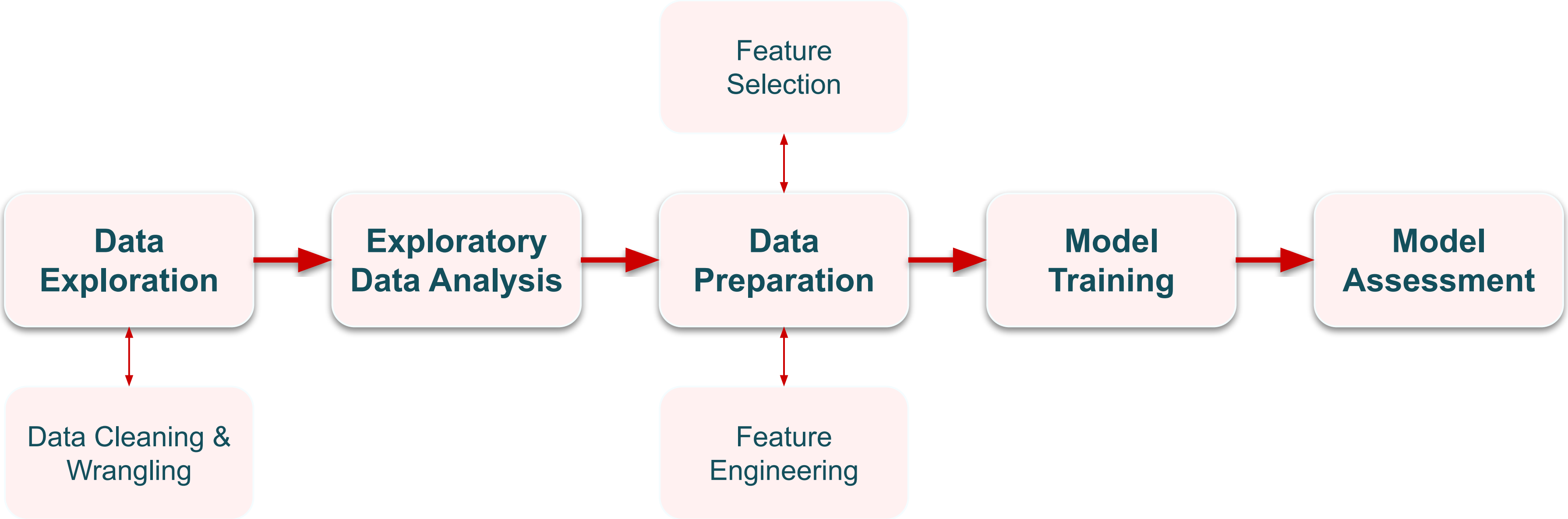
Data Overview

- ➢ We are provided with the Seoul Bike sharing demand dataset.
- ➢ The dataset contains weather information, the number of bikes rented per hour and date information.
- ➢ The time span of the dataset is 365 days from December 2017 to November 2018.

Attributes Information

- Date - year-month-day
- Rented Bike count - Count of bikes rented at each hour
- Hour - Hour of the 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 - No/Yes

Steps Involved



Data Exploration

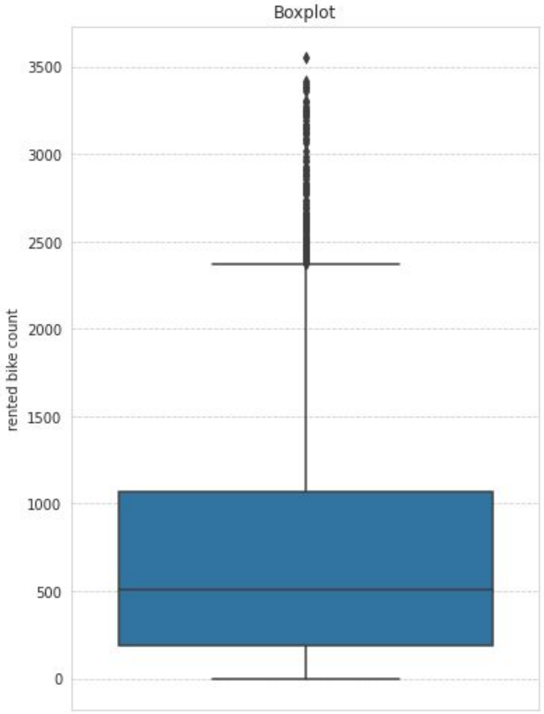
- The dataset consists of 8760 rows and 14 features(columns).
- Dependent Variable- Rented Bike Count
- Categorical variables - Seasons, Holiday and Functioning day
- Date variable was stored as string so converted it to Datetime format

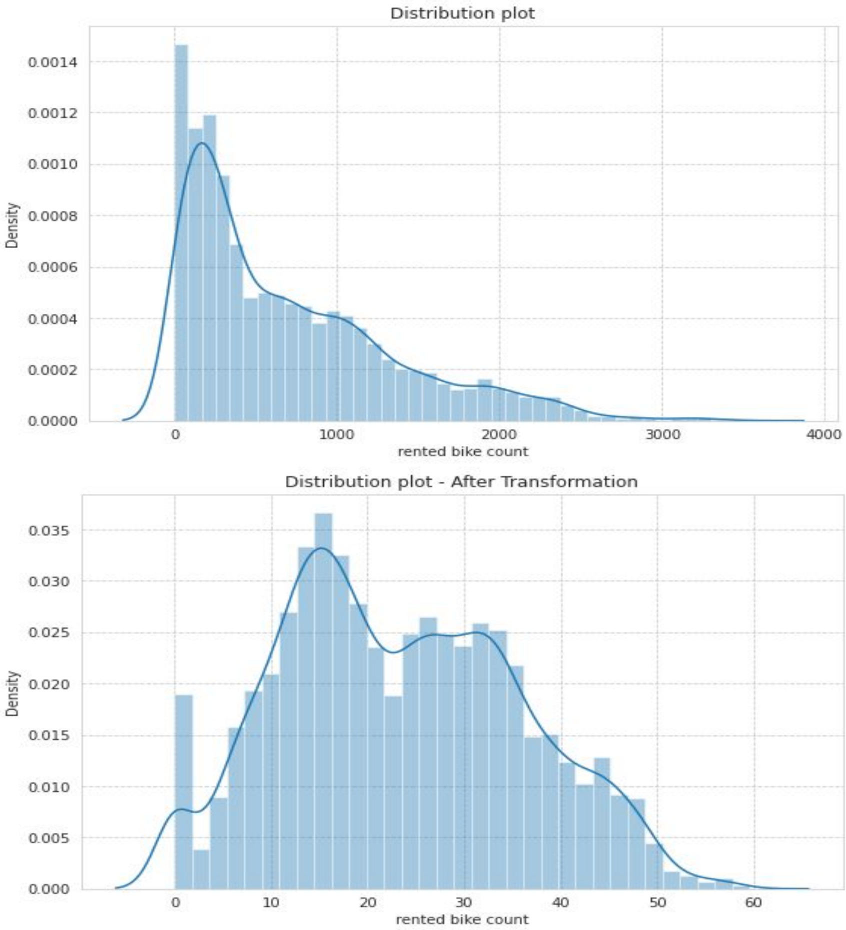
Data Cleaning & Wrangling

- Created some additional features from date.
- No duplicate values
- No missing values

Exploratory Data Analysis

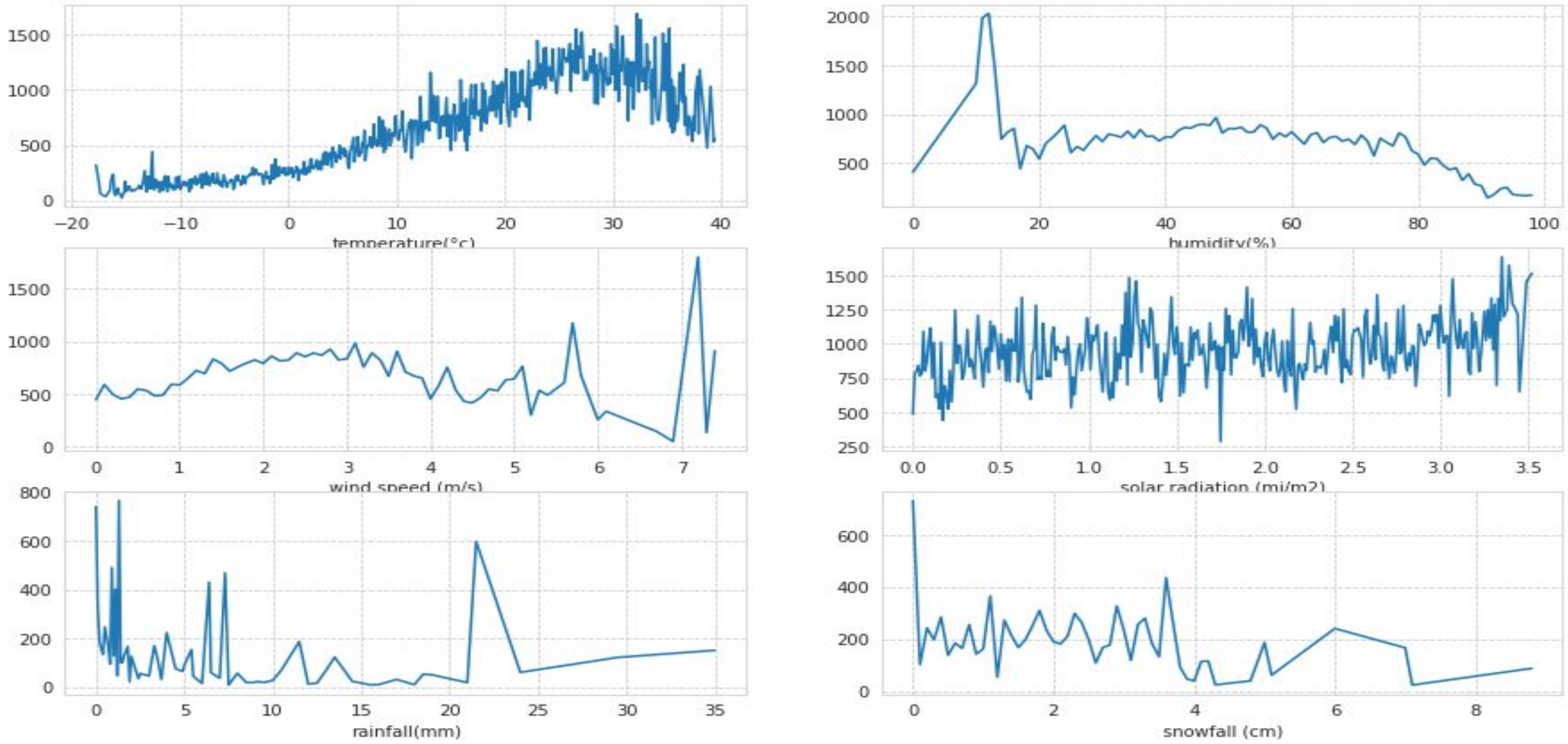
Dependent Variable - Rented Bike Count



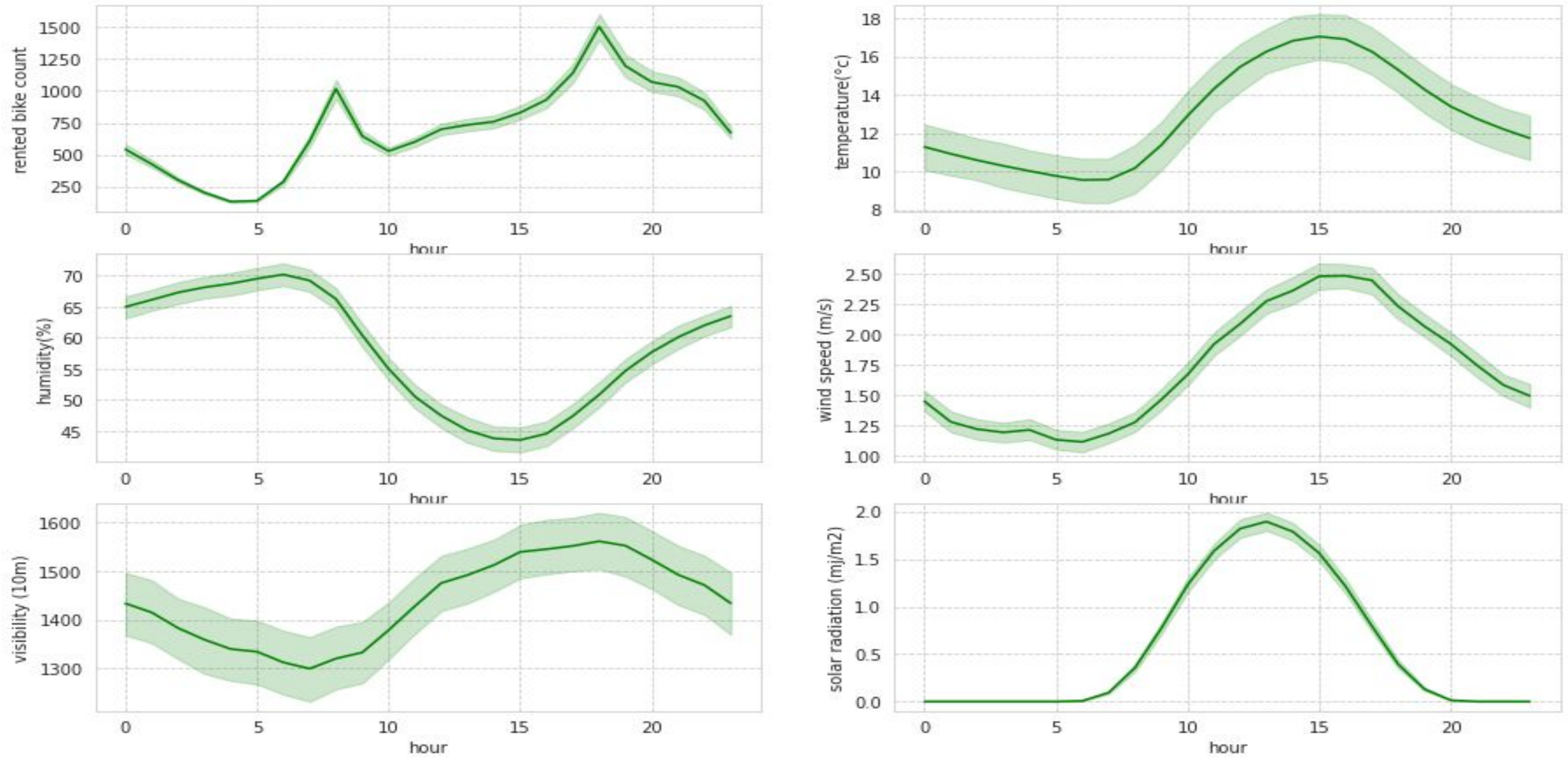


Bivariate Analysis - Numerical Variables

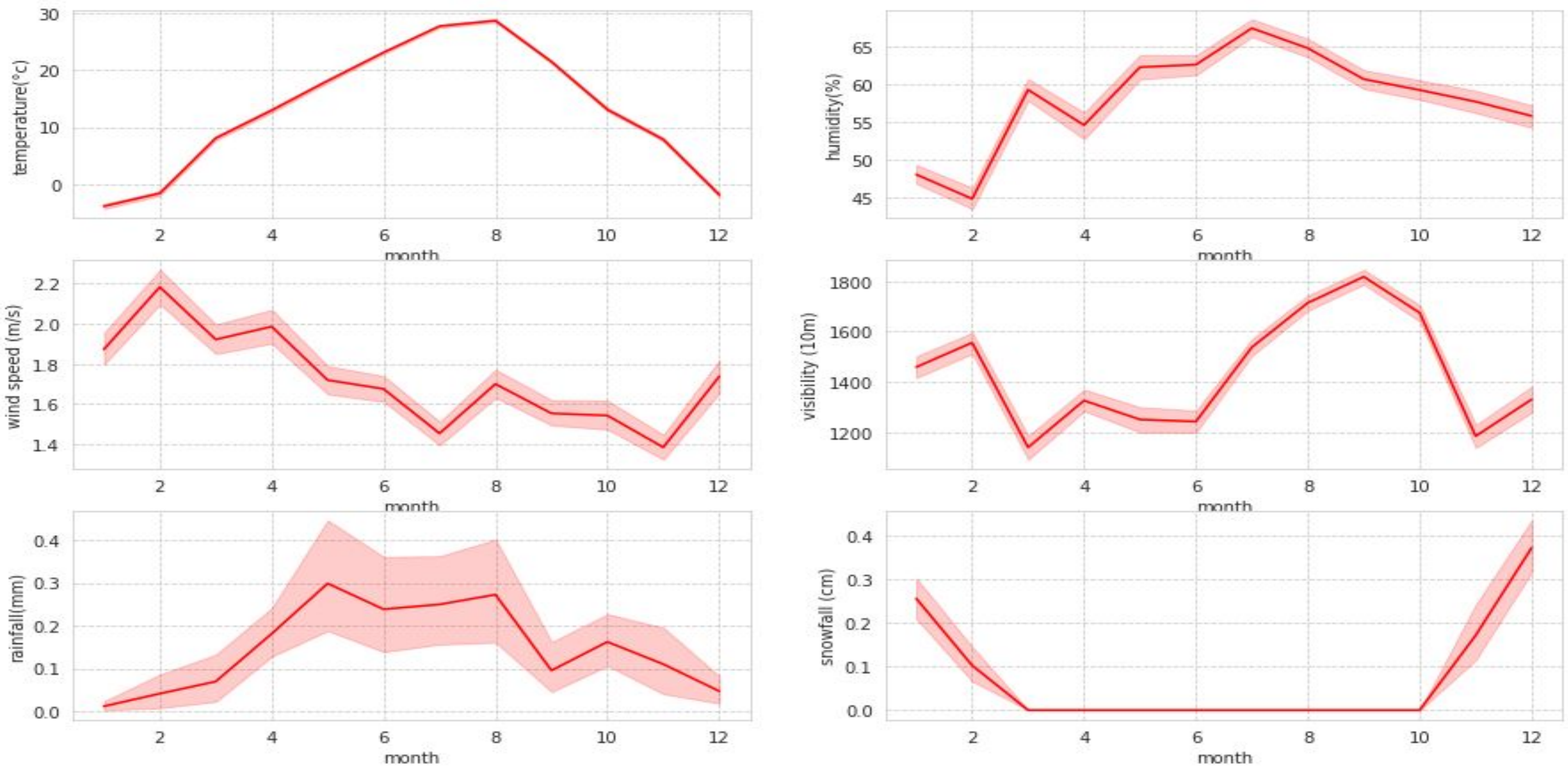
Line Plots - Numerical variables v/s Rented Bike Count



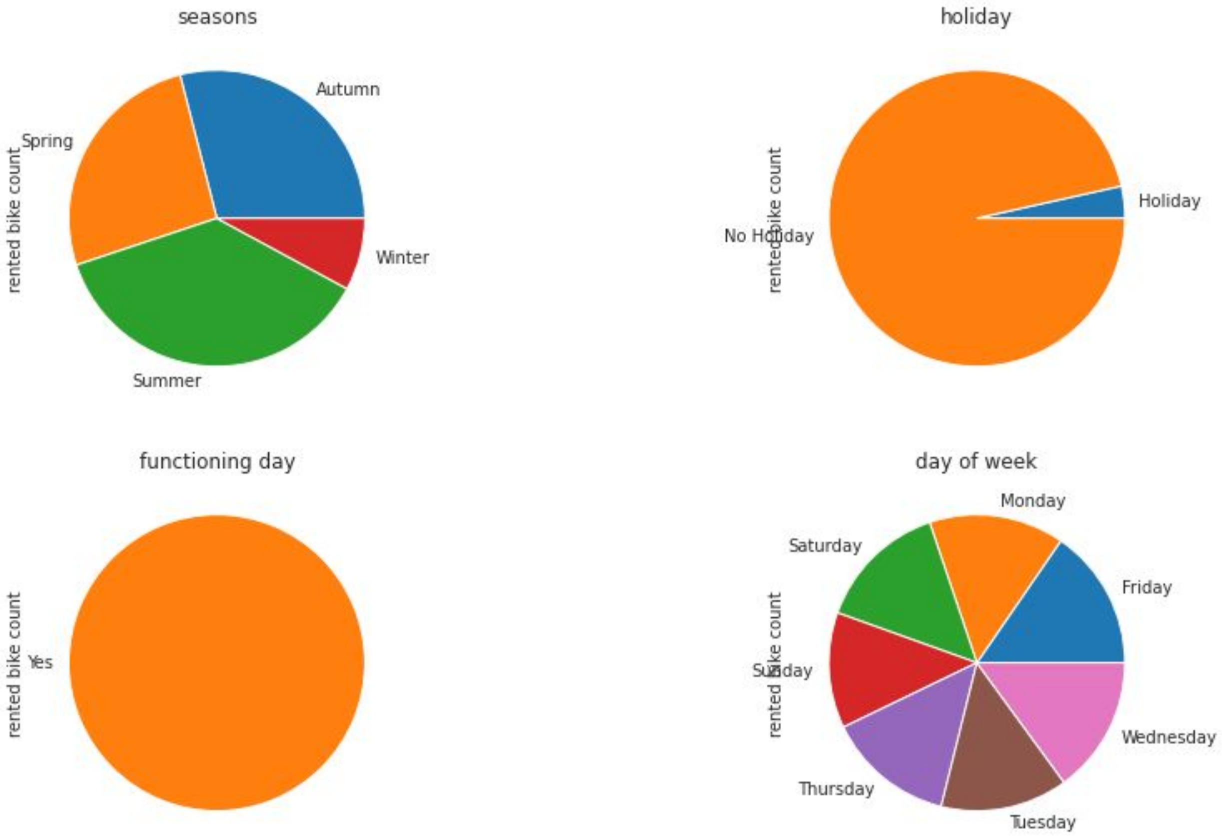
Spread of Numerical variables across hours



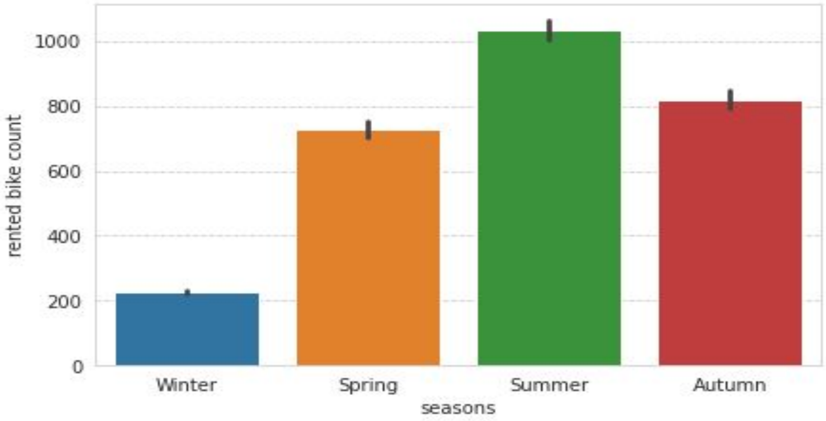
Spread of Numerical variables across months

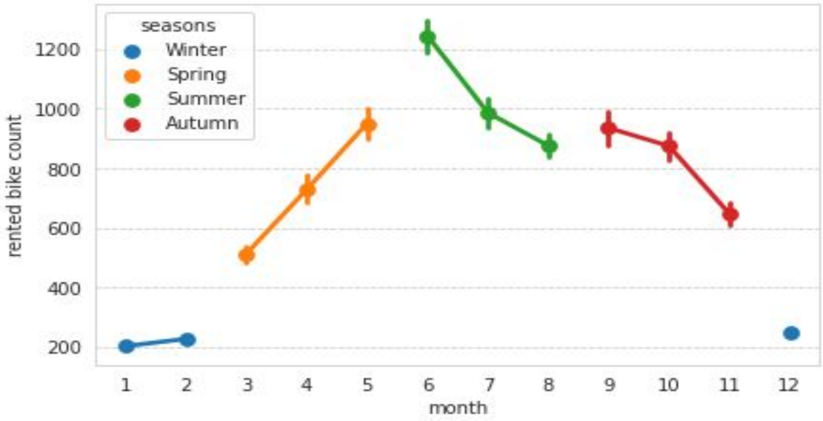


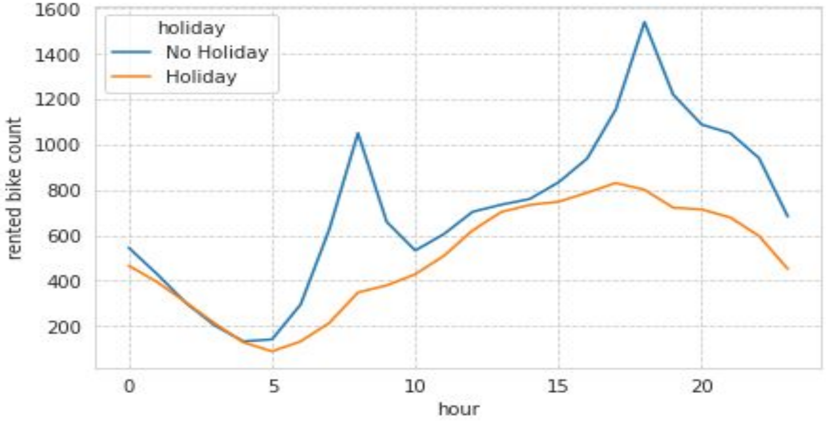
Bivariate Analysis - Categorical Variables

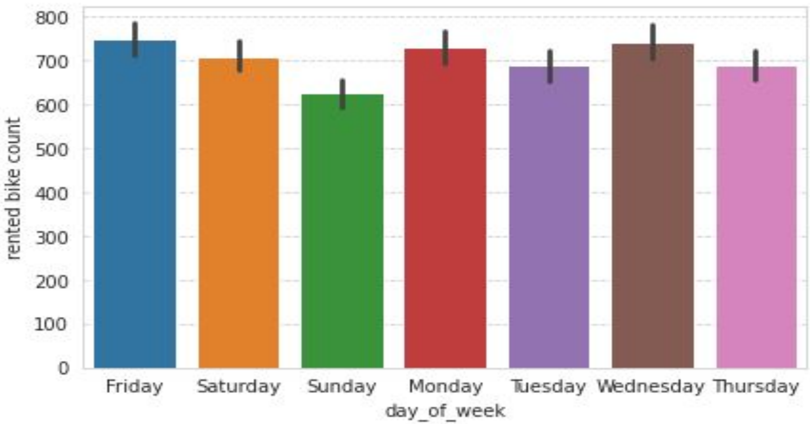


Spread of Rented Bike Count across categorical variables









Data Preparation

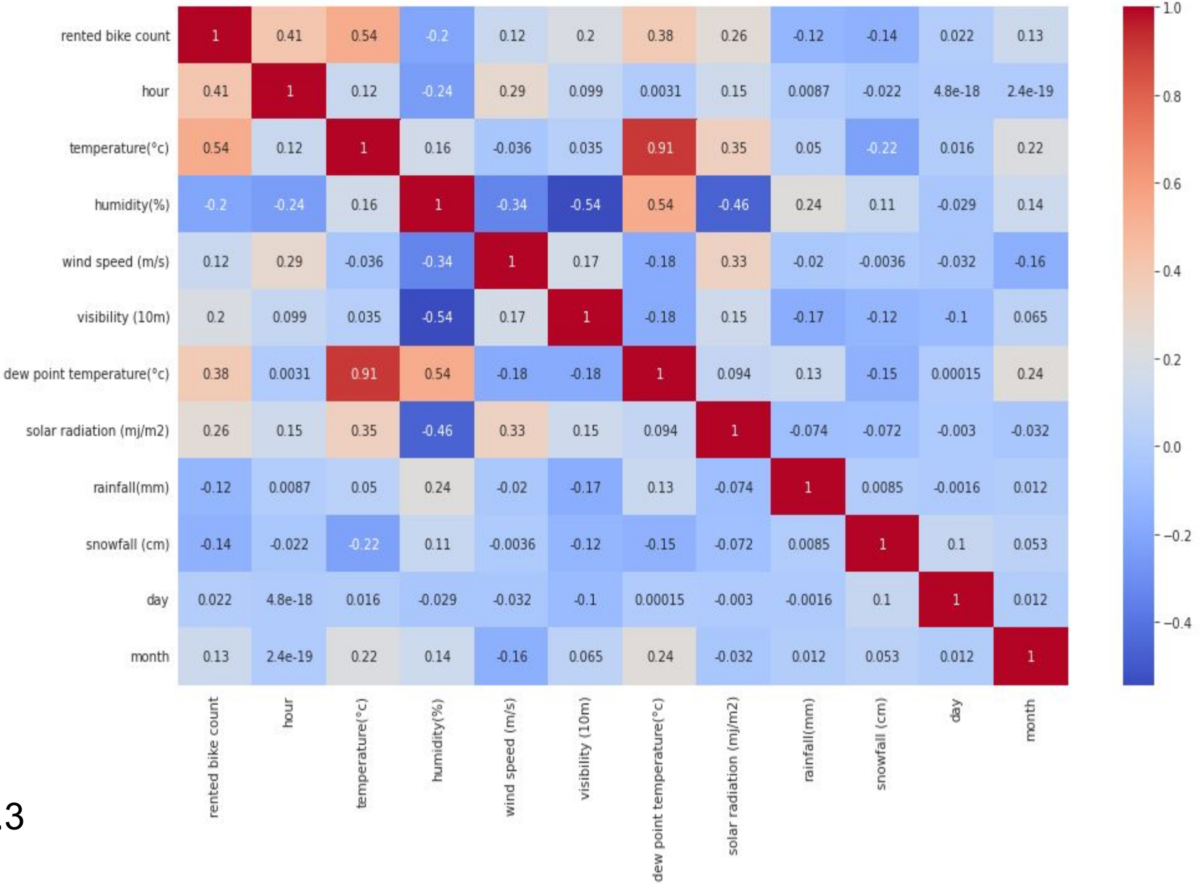
Feature Selection

- Feature Selection with Pearson Correlation Heatmap
- Detecting multicollinearity using Variance Inflation Factor(VIF)
- Dropping highly correlated features

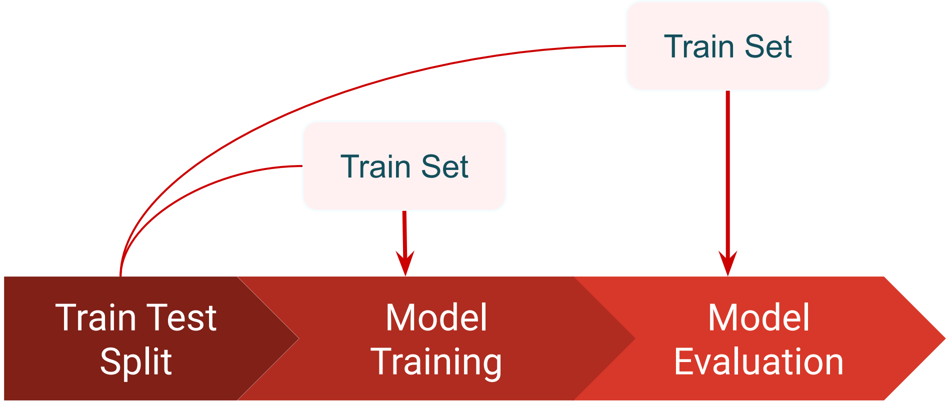
Feature Engineering

- Created additional column of weekend
- Label Encoding of categorical variables
- Train Test Split having test size = 0.3

Correlation Heatmap



Predictive Modeling



Regression Models used -

1)Linear Regression	2)Lasso Regression
3)Ridge Regression	4)Elastic Net
5)Decision Tree	6)Random Forest
7)Gradient Boosting	8)XGBoost Regression

Predictive modeling includes -

- Building and training the models
- Tuning the hyperparameters to get better performance
- Model Evaluation and Selection

Linear Regression

Train set Metrics

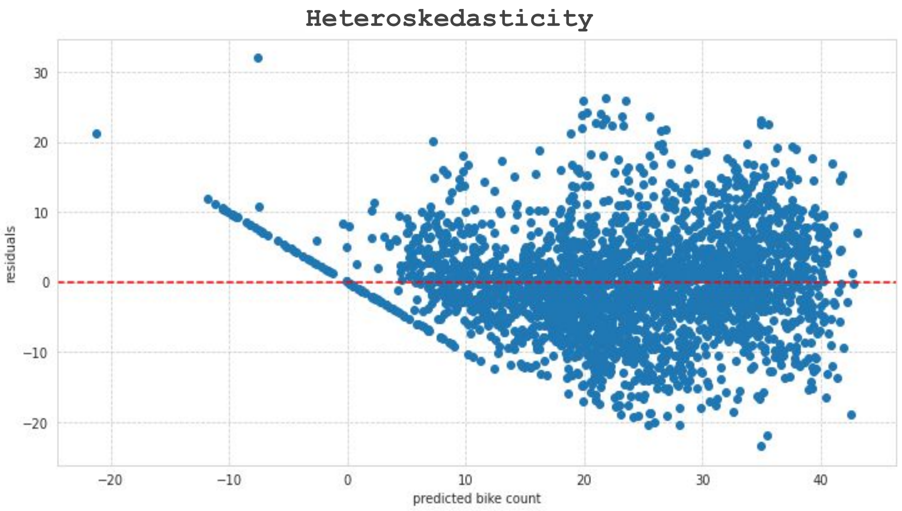
MSE : 53.80611459663623
RMSE : 7.335265134719823
MAE : 5.63805172995284

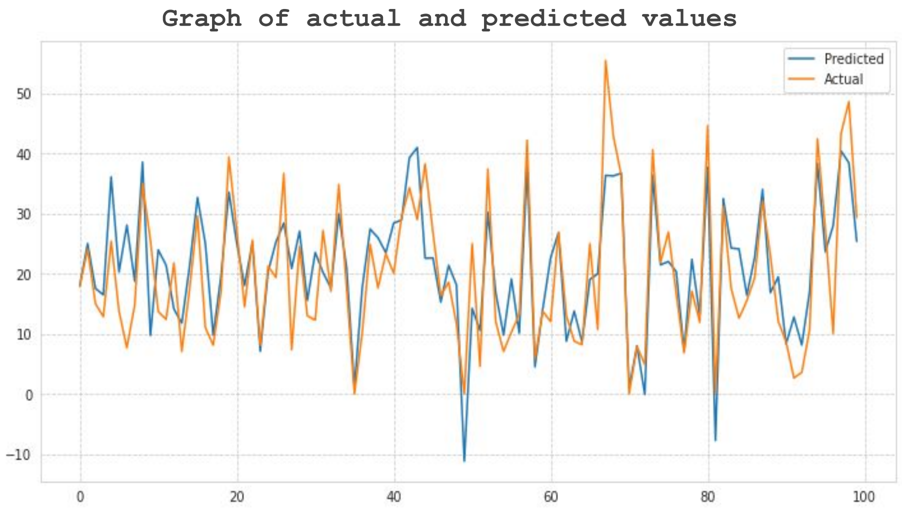
R2 : 0.6540967727241054
Adjusted R2 : 0.65250945389913

Test set Metrics

MSE : 53.740491144516426
RMSE : 7.330790622062291
MAE : 5.661287586240897

R2 : 0.6501226505752834
Adjusted R2 : 0.6485170948609061





Lasso Regression

```
Parameters = {'alpha': [1e-15,1e-10,1e-8,1e-5,1e-4,1e-3,1e-2,1e-1,1,5,10,20,30,40,45,50,55,60,100]}

The best fit alpha value is found out to be : {'alpha': 0.0001}
```

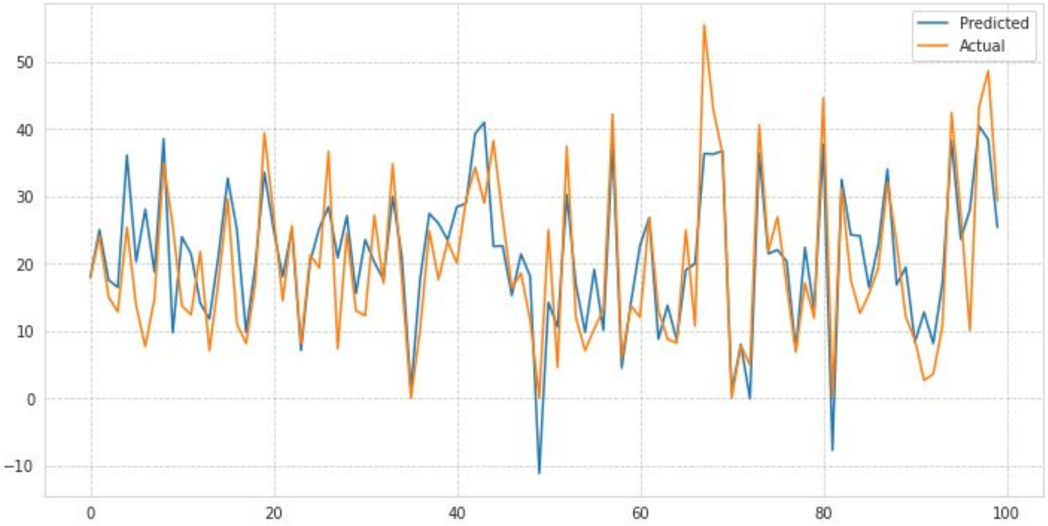
Train set Metrics

```
MSE : 53.80611534623119
RMSE : 7.3352651858151106
MAE : 5.63804777968967

R2 : 0.6540967679051862
Adjusted R2 :  0.6525094490580972
```

Test set Metrics

```
MSE : 53.74016699398597
RMSE : 7.330768513190549
MAE : 5.661284867852185

R2 : 0.6501247609565992
Adjusted R2 :  0.6485192149265722
```

Graph of actual and predicted values



Ridge Regression

```
Parameters = {'alpha': [1e-10,1e-5,1e-4,1e-3,1e-2,0.5,1,1.5,5,10,20,30,35,40,45,50,55,60,100]}

The best fit alpha value is found out to be : {'alpha': 1e-10}
```

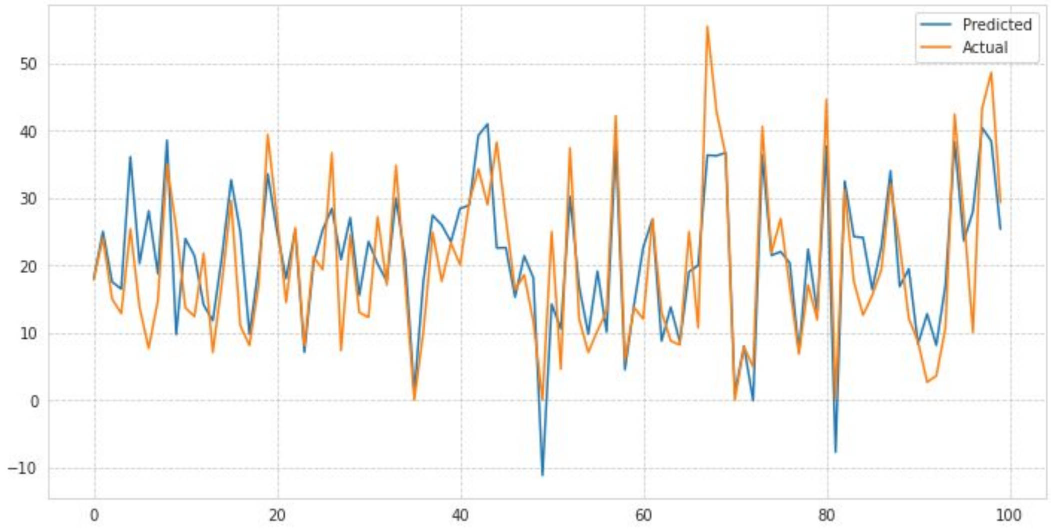
Train set Metrics

```
MSE : 53.80611459663623
RMSE : 7.335265134719823
MAE : 5.638051729952847

R2 : 0.6540967727241054
Adjusted R2 :  0.65250945389913
```

Test set Metrics

```
MSE : 53.74049114451563
RMSE : 7.330790622062237
MAE : 5.661287586240932

R2 : 0.6501226505752886
Adjusted R2 :  0.6485170948609114
```

Graph of actual and predicted values



Elastic Net Regression

```
Parameters = {'alpha': [1e-15,1e-10,1e-5,1e-3,1e-2,1e-1,1,5,10,20,30,40,50,100],
              'l1_ratio':[0.1,0.2,0.3,0.4,0.5]}
The best parameters found out : {'alpha': 1e-15, 'l1_ratio': 0.2}
```

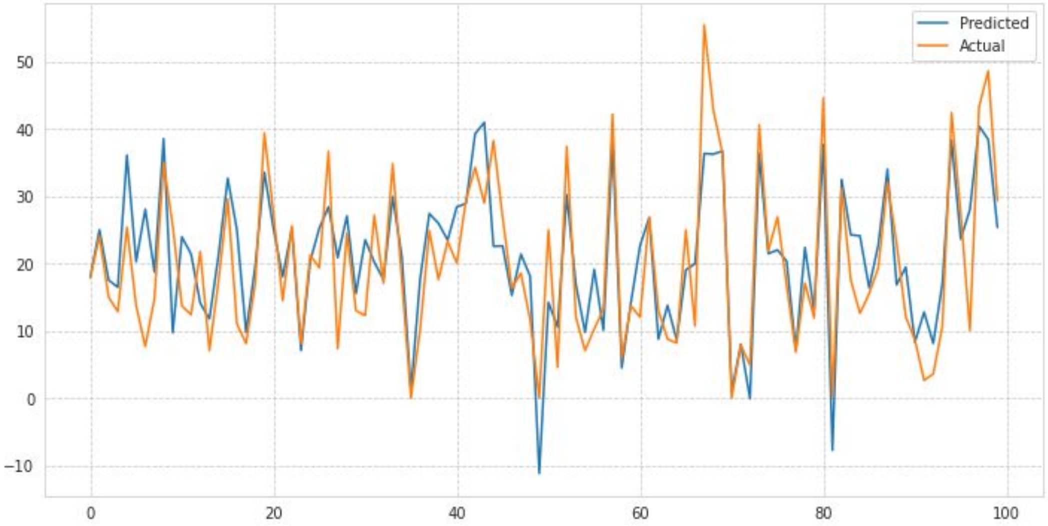
Train set Metrics

```
MSE : 53.80611459663623
RMSE : 7.335265134719823
MAE : 5.638051729952843

R2 : 0.6540967727241054
Adjusted R2 :  0.65250945389913
```

Test set Metrics

```
MSE : 53.740491144516405
RMSE : 7.330790622062289
MAE : 5.661287586240901

R2 : 0.6501226505752835
Adjusted R2 :  0.6485170948609063
```

Graph of actual and predicted values



Decision Tree Regression

```
Grid = {"criterion": ["mse", "mae"],
        "max_depth": [5, 6, 7, 8],
        "min_samples_split": [10, 20, 40],
        "min_samples_leaf": [20, 40, 100]}
```

```
Best Parameters = {'criterion': 'mse',
                   'max_depth': 8,
                   'min_samples_split': 10,
                   'min_samples_leaf': 20}
```

Train set Metrics

MSE : 21.56339216605
RMSE : 4.643639969468994
MAE : 3.218932170884279

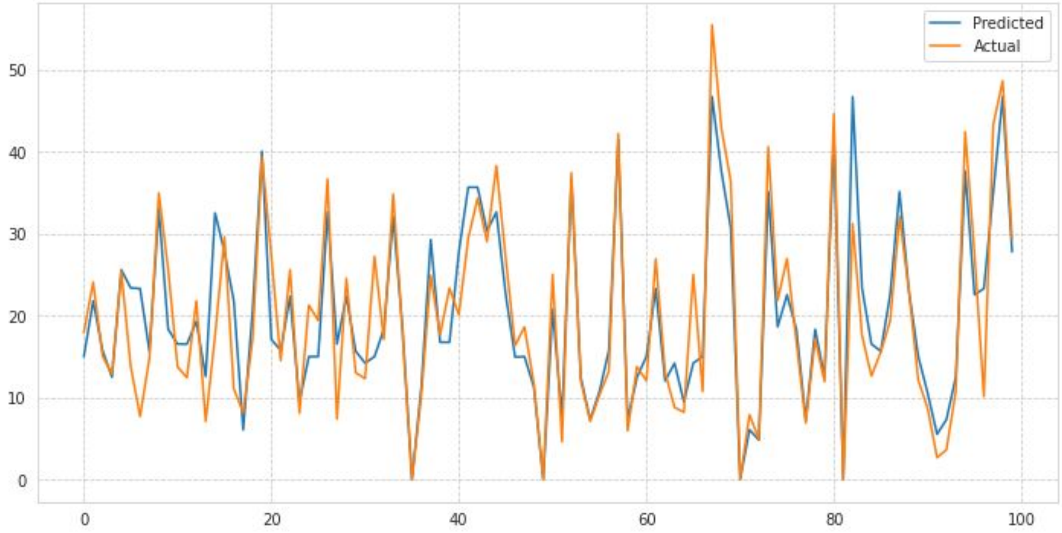
R2 : 0.8613754775424959
Adjusted R2 : 0.8607393420665914

Test set Metrics

MSE : 24.623417452837717
RMSE : 4.962198852609367
MAE : 3.4556336932227647

R2 : 0.8396892948185077
Adjusted R2 : 0.8389536433989369

Graph of actual and predicted values



Random Forest Regression

```
Grid = {'n_estimators': [50, 100, 150],
        'max_depth': [5, 6, 7, 8],
        'min_samples_split': [50, 100, 150],
       'min_samples_leaf': [40, 50]}
```

```
Best Parameters = {'n_estimators': 150,
                   'max_depth': 8,
                   'min_samples_split': 100,
                   'min_samples_leaf': 40}
```

Train set Metrics

MSE : 21.09551559724364
RMSE : 4.592985477578134
MAE : 3.3044192561703136

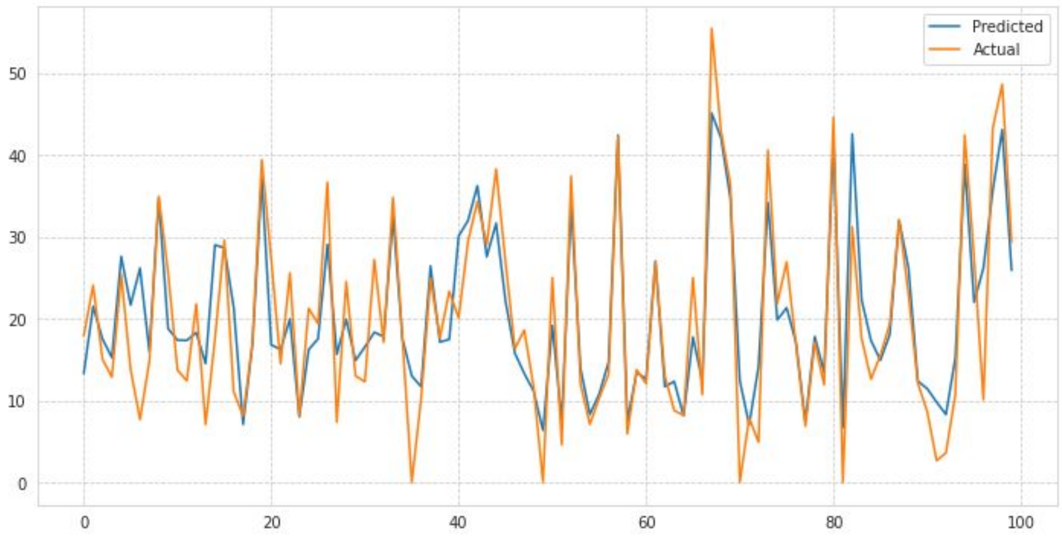
R2 : 0.8643833144088102
Adjusted R2 : 0.8637609816259826

Test set Metrics

MSE : 24.422199390470553
RMSE : 4.941882170840433
MAE : 3.5404879225490267

R2 : 0.8409993245710845
Adjusted R2 : 0.8402696847603208

Graph of actual and predicted values



Gradient Boosting Regression

```
Grid = {'n_estimators': [50, 100, 150],
        'max_depth': [5, 6, 7, 8],
        'min_samples_split': [50, 80],
        'min_samples_leaf': [40, 50]}
```

```
Best Parameters = {'max_depth': 8,
                   'min_samples_leaf': 40,
                   'min_samples_split': 50,
                   'n_estimators': 150}
```

Train set Metrics

MSE : 4.917277342679263
RMSE : 2.217493481992509
MAE : 1.4896685104851668

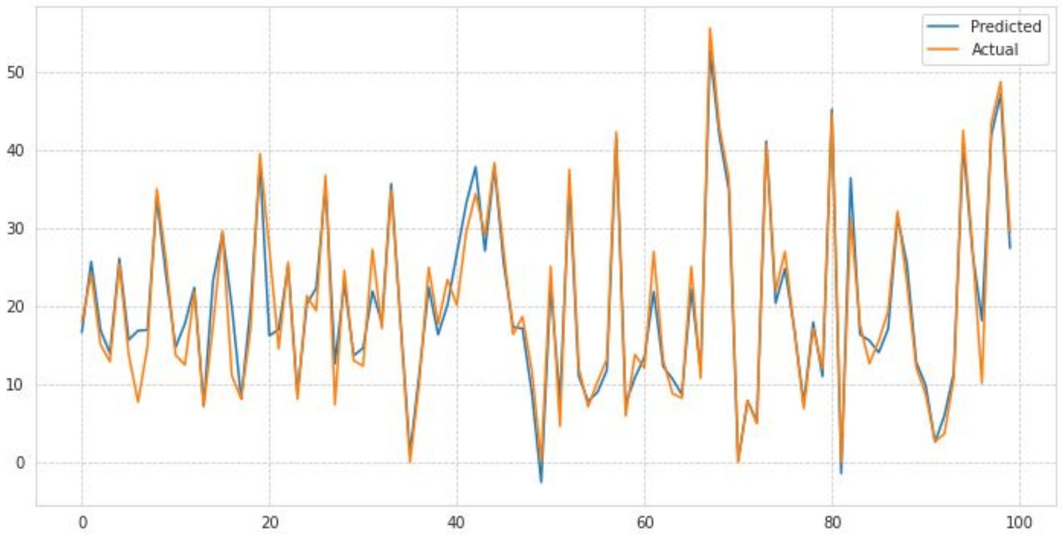
R2 : 0.9683883120906536
Adjusted R2 : 0.9682432488956585

Test set Metrics

MSE : 10.055935052912352
RMSE : 3.1711094356569203
MAE : 2.080602955504996

R2 : 0.9345308569503262
Adjusted R2 : 0.9342304249363316

Graph of actual and predicted values



XGBoost Regression

```
Grid = {'max_depth': [5,6,7,8],
        'learning_rate': [0.05, 0.1, 0.3],
        'n_estimators': [80,100,150],
        'colsample_bytree': [0.5,0.7]}
```

```
Best Parameters = {'colsample_bytree': 0.7,
                   'learning_rate': 0.1,
                   'max_depth': 7,
                   'n_estimators': 150}
```

Train set Metrics

MSE : 2.9450939077909637
RMSE : 1.7161275907667715
MAE : 1.1572887392163702

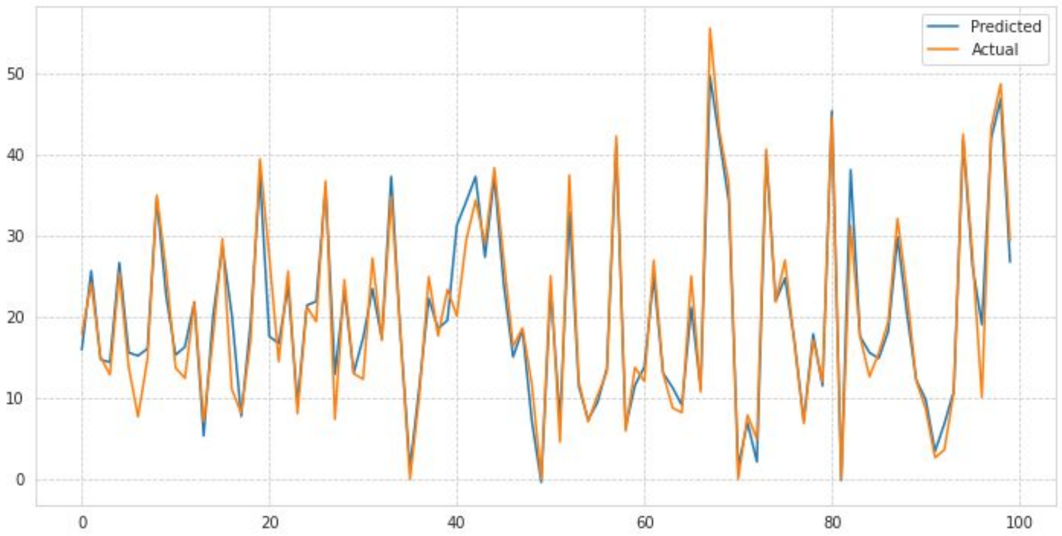
R2 : 0.9810668825472272
Adjusted R2 : 0.9809800001726829

Test set Metrics

MSE : 9.46132555407195
RMSE : 3.0759267796994045
MAE : 2.0349535013806364

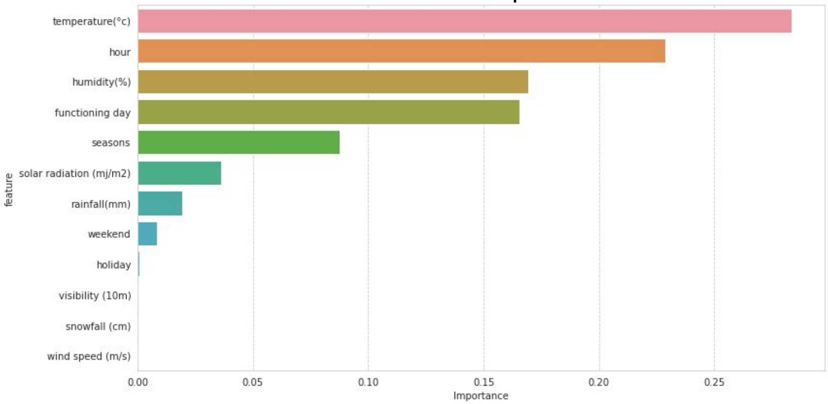
R2 : 0.9384020607850212
Adjusted R2 : 0.9381193933775337

Graph of actual and predicted values

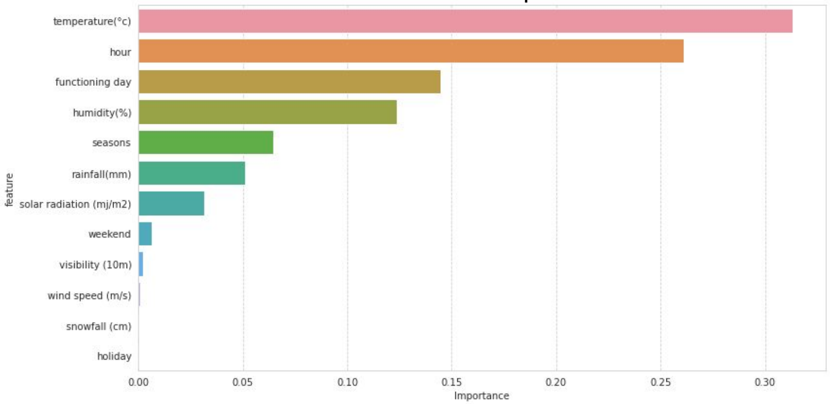


Feature Importance

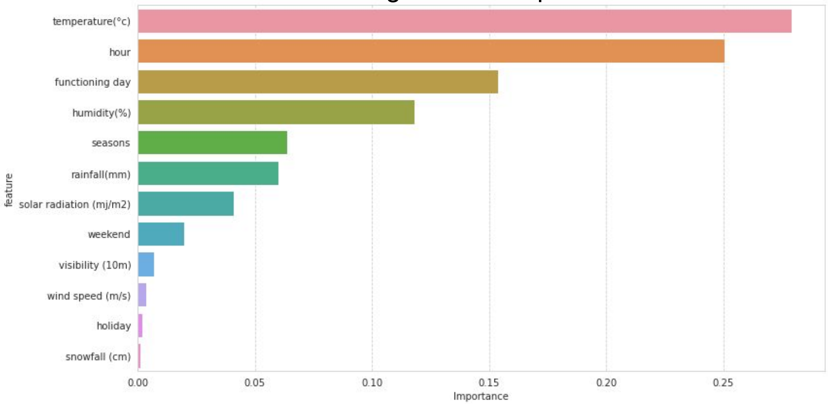
Decision Tree Feature Importance



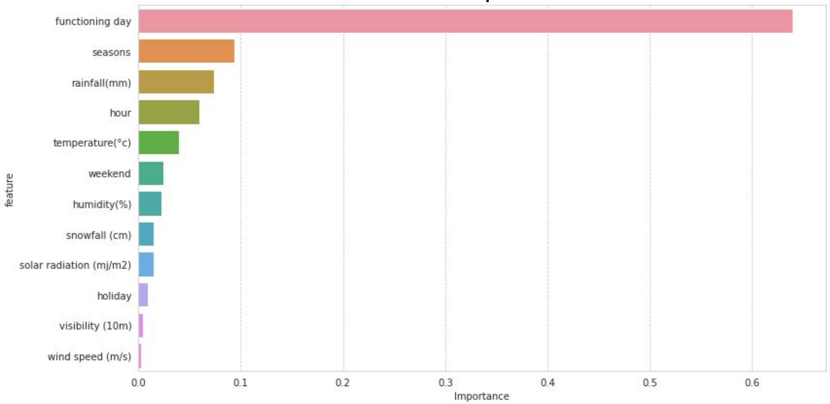
Random Forest Feature Importance



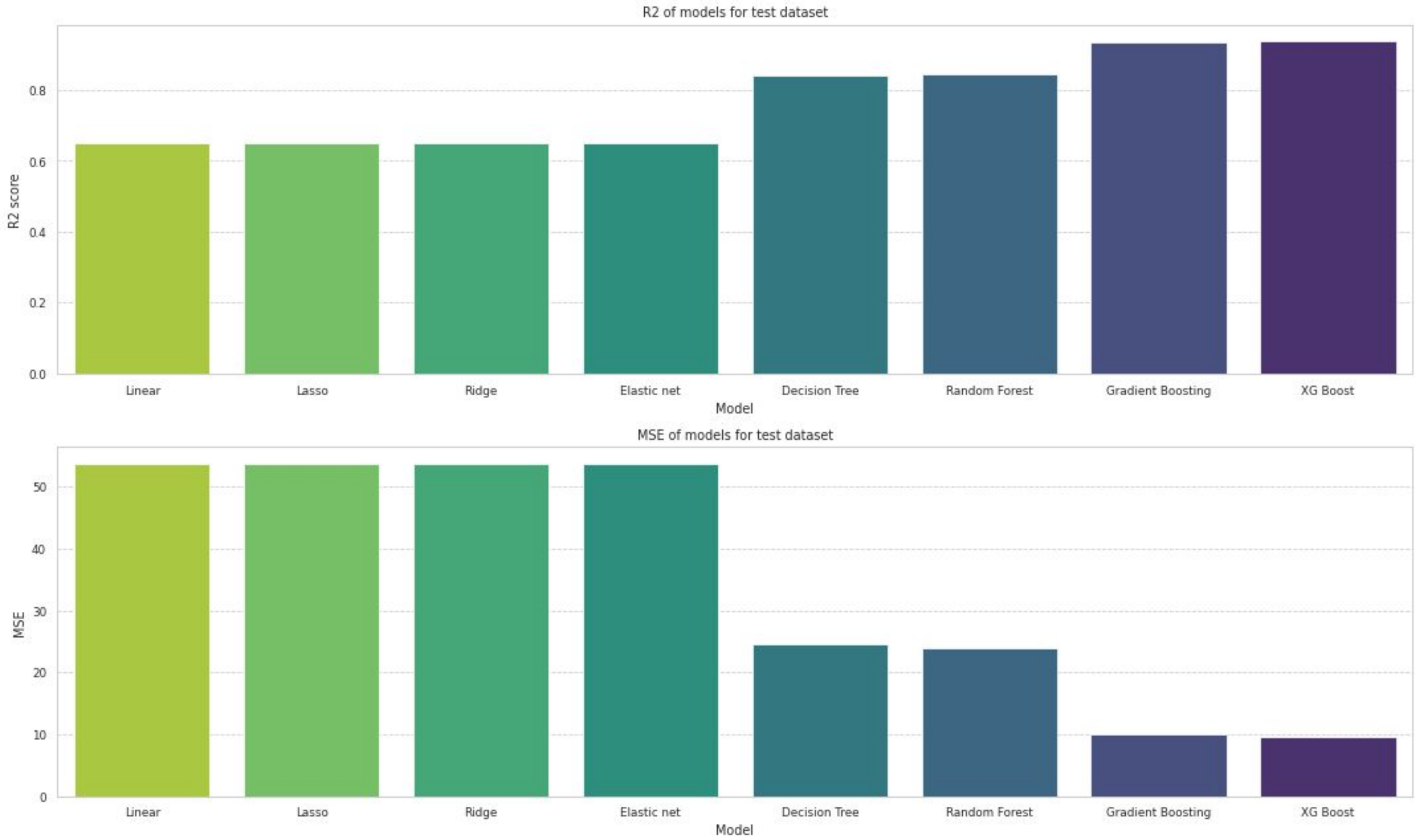
Gradient Boosting Feature Importance



XGBoost Feature Importance



Result


R2 of models for test dataset
R2 score
0.0
0.2
0.4
0.6
0.8
Linear
Lasso
Ridge
Elastic net
Decision Tree
Random Forest
Gradient Boosting
XG Boost
Model
MSE of models for test dataset
MSE
0
10
20
30
40
50
Linear
Lasso
Ridge
Elastic net
Decision Tree
Random Forest
Gradient Boosting
XG Boost
Model

Challenges

- It was time series type data so little difficult to handle.
- Dependent variable had outliers so removing them or not was good point of discussion
- Plotting lots of charts and graphs were needed for data analysis
- Feature selection was important
- Randomly selecting hyperparameters and tuning them was also difficult task.

Conclusion

- ➢ There is a huge demand for bike rents in the summer season while the least bike rents occur in winter.
- ➢ The demand for rental bikes is at peak at 8am and 6pm so we can say that demand is more during office opening and closing time.
- ➢ Temperature and hour are the most influential features to predict the rental bike count.
- ➢ Gradient Boosting and XGBoost models are found to be the best models.
- ➢ Therefore, either Gradient Boosting or XGBoost model can be used to predict the number of bikes required at each hour.

Q & A