Capstone Project
Bike Sharing Demand Prediction

Team Members
Nivya T
Manjusree K C
Harsh Jain
Ammar Anjum

Bike Sharing System

A bicycle-sharing system, bike share program, public bicycle scheme, or public bike share (PBS) scheme, is a shared transport service in which bicycles are made available for shared use to individuals on a short term basis for a price or free.

Predicting bike sharing demand can help bike sharing companies to allocate bikes better and ensure a more sufficient circulation of bikes for customers.

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.

Objectives

1. Prediction of bike count required at each hour for the stable supply of rental bikes in bike sharing system.

2. Gathering information regarding the factors that affect this prediction the most.

Steps Involved

1. **Exploring the data**: Analyzing the features and target variable, checking for null values and duplicates, plotting the distribution of target variable etc.

2. **EDA:** Treating numerical and categorical features separately, VIF Analysis, Encoding, Outlier detection etc.

3. **Preprocessing of data**: Train test split, Transformation, Scaling etc.

4. **Creating models**: Create different models and evaluate them using different metrics.

Data Summary

The shape of the dataset is (8760,14)

Data

Features

Target Variable

Numeric:

1.Hour
2.Temperature
3.Humidity
4.Wind speed
5.Visibility
6.Dew point temperature
7.Solar radiation
8.Rainfall
9.Snowfall

Categorical:

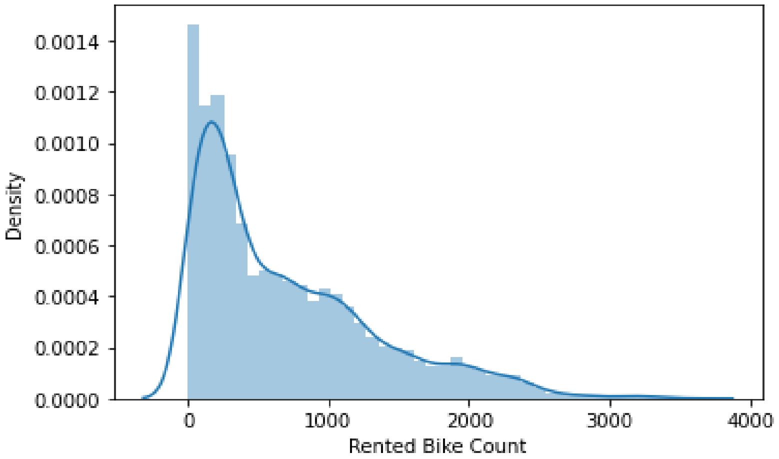
1.Season
2.Holiday
3.Functioning Day

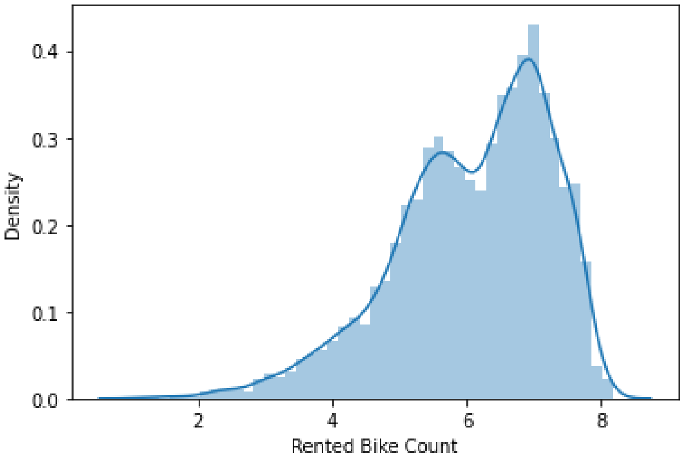
Rented bike count

Define Dependent Variable

In this project, the dependent variable is ‘Rented bike count’, the prediction of which gives us the exact number of bikes required per hour in order to reduce the waiting time.

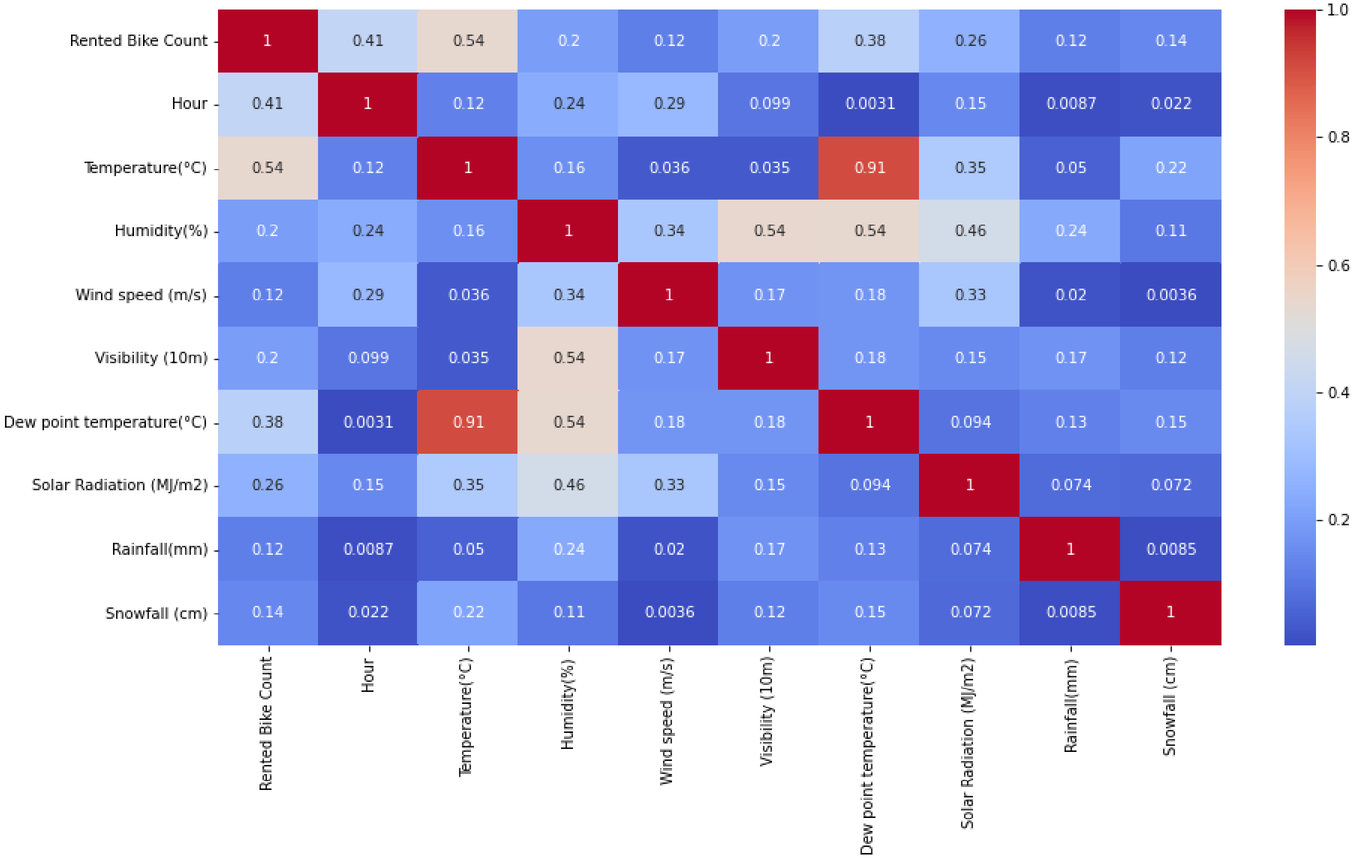
Plotting the distribution of dependent variable





The distribution of the dependent variable is skewed. Therefore we use log(1+x) transformation.

Collinearity Between Variables

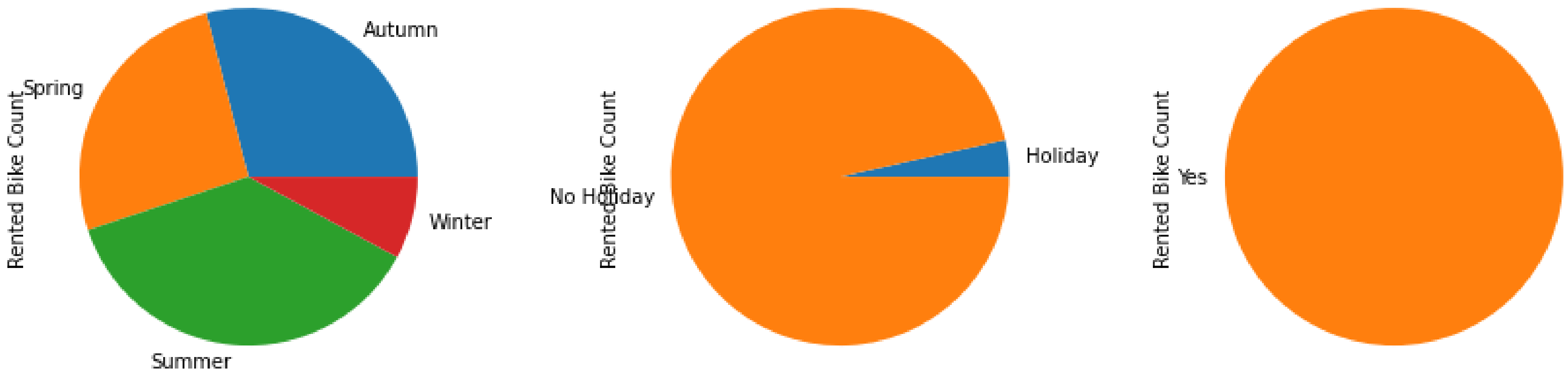


VIF Analysis

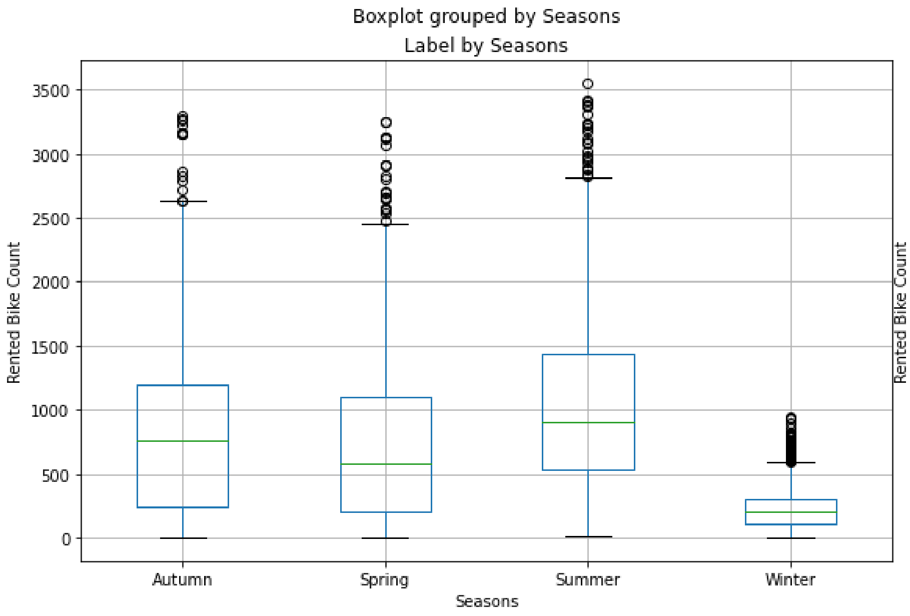
	variables	VIF
0	Hour	3.921832
1	Temperature(°C)	3.228318
2	Humidity(%)	4.868221
3	Wind speed (m/s)	4.608625
4	Visibility (10m)	4.710170
5	Solar Radiation (MJ/m2)	2.246791
6	Rainfall(mm)	1.079158
7	Snowfall (cm)	1.120579

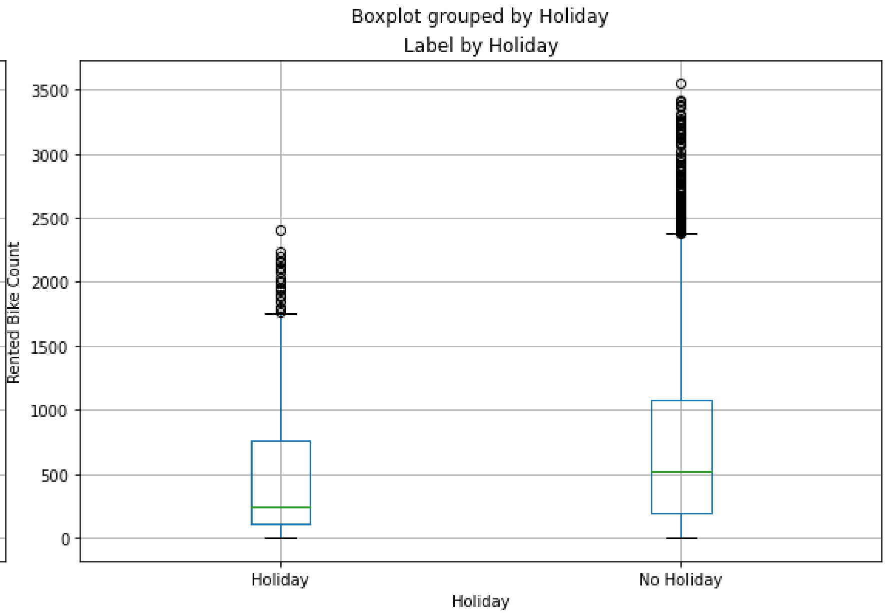
VIF is under 5 for all the variables. Therefore we can neglect the chances of multicollinearity.

Bike Demand Based on Seasons, Holiday and Functioning Day



Outlier Detection: Box Plot





Preparing Dataset for Modelling

Hour	Temperature(°C)	Humidity(%)	Wind speed (m/s)	Visibility (10m)	Dew point temperature(°C)	Solar Radiation (MJ/m2)	Rain
0	-5.2	37	2.2	2000	-17.6	0.0	
1	-5.5	38	0.8	2000	-17.6	0.0	
2	-6.0	39	1.0	2000	-17.7	0.0	
3	-6.2	40	0.9	2000	-17.6	0.0	
4	-6.0	36	2.3	2000	-18.6	0.0	

Task :Regression
Train Set :(7008, 11)
Test Set: : (1752,11)

Linear Regression

The scores obtained while performing Linear Regression is:

	Metric	Train Score	Test Score
0	MAE	287.44	279.07
1	MSE	202203.58	195114.04
2	RMSE	449.67	441.72
3	r2	0.51	0.53
4	adj_r2	0.51	0.53

Lasso Regression

	Metric	Train Score	Test Score
0	MAE	287.46	279.09
1	MSE	202234.96	195153.97
2	RMSE	449.71	441.76
3	r2	0.51	0.53
4	adj_r2	0.51	0.53

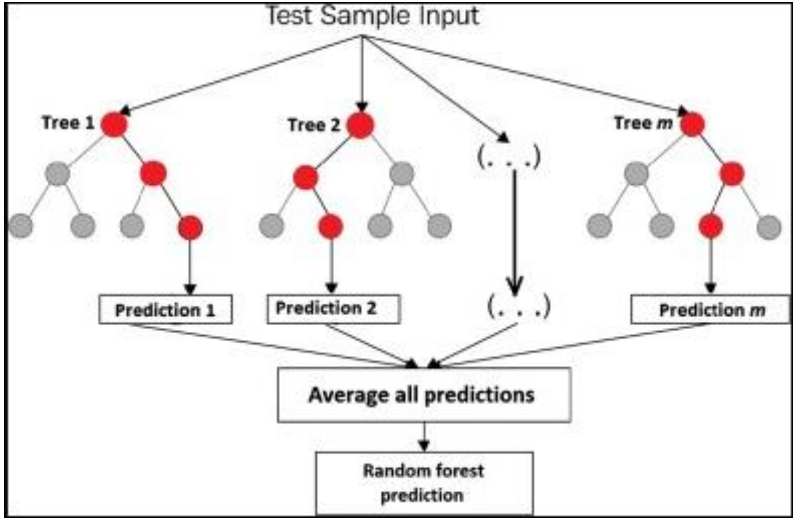
Ridge Regression

	Metric	Train Score	Test Score
0	MAE	287.45	279.08
1	MSE	202213.50	195127.98
2	RMSE	449.68	441.73
3	r2	0.51	0.53
4	adj_r2	0.51	0.53

Random Forest

The scores obtained while performing Random Forest Regression is:

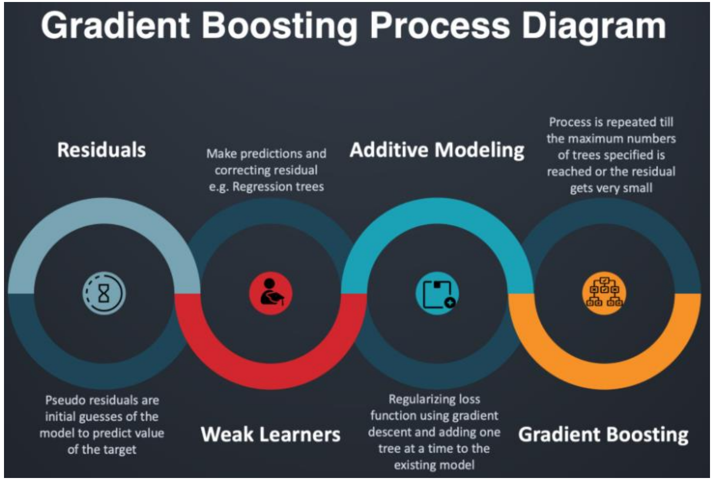
	Metric	Train Score	Test Score
0	MAE	53.83	140.68
1	MSE	9083.60	55662.80
2	RMSE	95.31	235.93
3	r2	0.98	0.87
4	adj_r2	0.98	0.87



Gradient Boosting Machine

The scores obtained while performing Gradient Boosting Machine is:

	Metric	Train Score	Test Score
0	MAE	196.04	196.02
1	MSE	104082.42	108884.17
2	RMSE	322.62	329.98
3	r2	0.75	0.74
4	adj_r2	0.75	0.74



XGBoost

The scores obtained while performing XGBoost is:

	Metric	Train Score	Test Score
0	MAE	120.88	146.87
1	MSE	39415.53	59618.05
2	RMSE	198.53	244.17
3	r2	0.91	0.86
4	adj_r2	0.90	0.86

How XGBoost optimizes standard GBM algorithm

Scores After Cross Validation and Hyperparameter Tuning

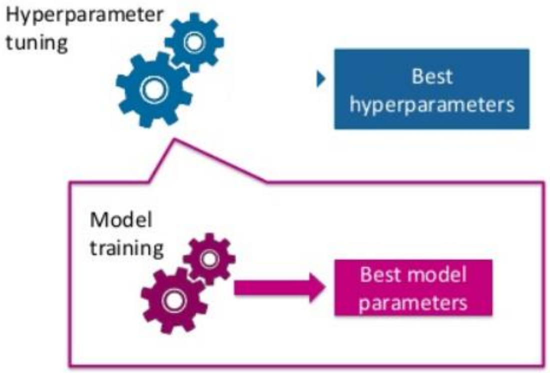
	Model	Train MAE	Test MAE	Train MSE	Test MSE	Train RMSE	Test RMSE	Train r2	Test r2	Train adj r2	Test adj r2
0	Linear	287.44	279.07	202203.58	195114.04	449.67	441.72	0.51	0.53	0.51	0.53
1	Lasso	287.44	279.07	202203.58	195114.04	449.67	441.72	0.51	0.53	0.51	0.53
2	Ridge	287.45	279.08	202213.50	195127.98	449.68	441.73	0.51	0.53	0.51	0.53
3	Random Forest CV	176.08	179.53	84522.73	89452.62	290.73	299.09	0.80	0.79	0.80	0.78
4	GBMCV	125.96	142.83	42643.99	56999.00	206.50	238.74	0.90	0.86	0.90	0.86
5	XGboost CV	75.20	139.62	16533.00	54594.92	128.58	233.66	0.96	0.87	0.96	0.87

Observations

- Comparing the R2 score of all the models, one can see that XGBoost performs better.
- R2 score in Linear Regression is 0.51 for the train data and 0.53 for the test data. Clearly, Linear Regression model fails in this case.
- Gradient Boosting Machine has a test accuracy of 86% making it the second-best model.
- Random Forest is also found to perform well on the data.

Best Parameters:

- **Random Forest:**
- max_depth’: 8
- 'min_samples_leaf': 40
- 'min_samples_split': 50
- 'n_estimators': 100



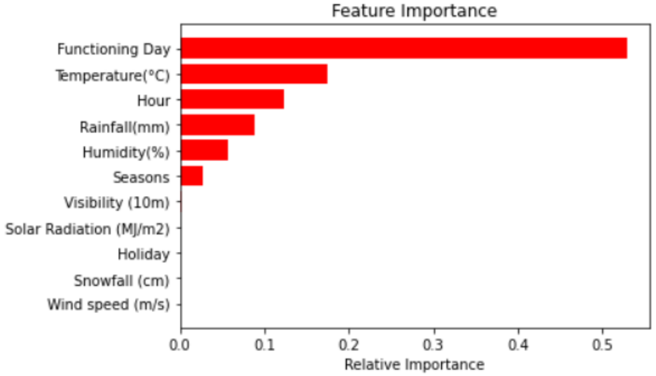
- **GBM:**
- max_depth=8
- min_samples_leaf=40
- min_samples_split=50
- n_estimators=80

XGBoost:

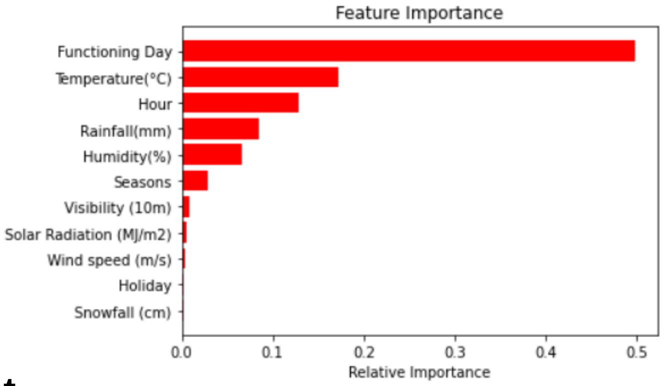
- 'eval_metric': 'rmse’,
- 'max_depth': 6,
- 'n_estimators': 500,
- 'objective': 'reg:squarederror'

Feature Importance

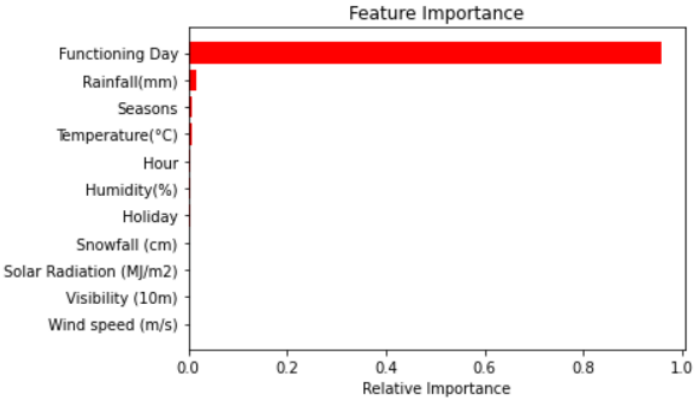
Random Forest



GBM



XGBoost



Observations

- The feature ‘Functioning Day’ has the highest impact on the dependent variable ‘Rented Bike Count’.
- In Random Forest and GBM, ‘Temperature’ is making an impact while ‘Rainfall’ is the second most important factor in XGBoost.
- Random Forest and GBM give importance to 6-7 features while XGBoost considers only the top 3-4 features and almost neglects the rest.

Conclusion

This project focus on predicting the bike-sharing demand using Seoul Dataset.

The results show that XGBoost, Random Forest and GBM algorithms perform well on the dataset whereas Linear Regression fails in this case. Among these three models, XGBoost is found to have better performance.
Therefore XGBoost algorithm can be used as an effective tool for Bike Sharing Demand Prediction.

We did a variable analysis to identify the hidden relationship between the variables. For all the models, functioning day, temperature, and rainfall were ranked as the most influential variables to predict the rental bike demand at each hour.
This project identifies the curious relationship among the variables which can directly impact the dependent variable, 'Rented Bike Count'.

This project will be helpful for the company to predict the hourly bike demand and enrich the user experience.

Thank You