# Capstone Project

## Supervised ML - regression

# Bike sharing demand prediction

by

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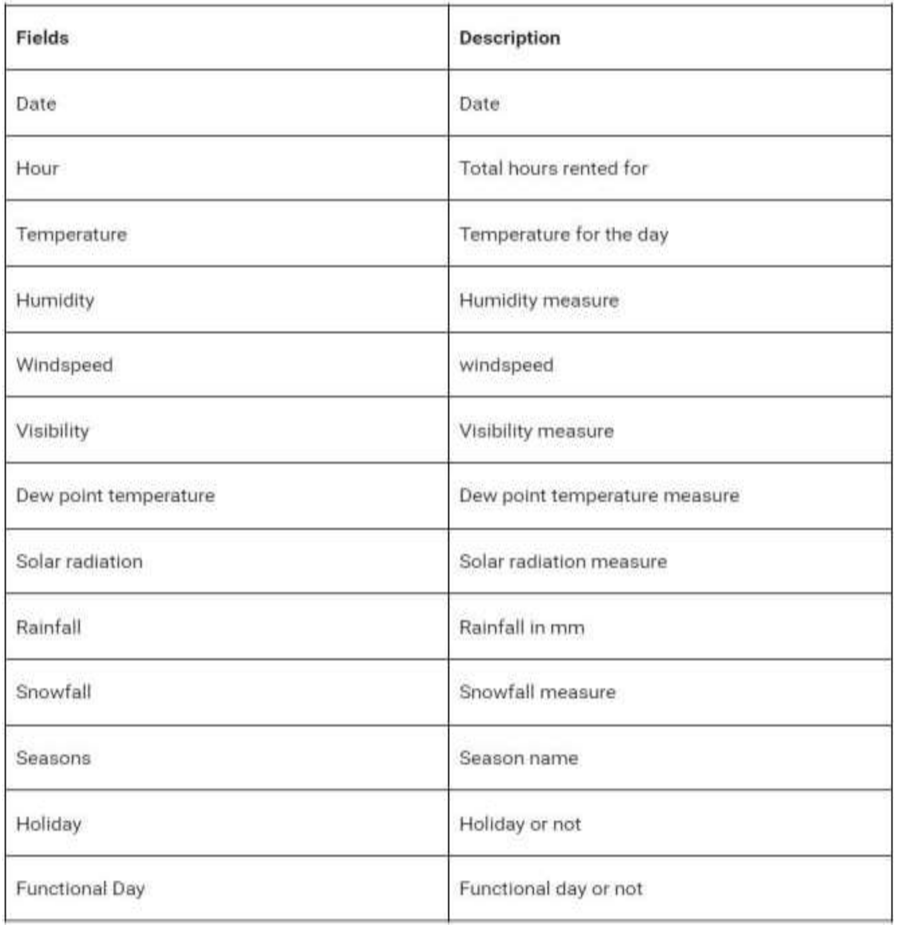
# Problem statement:

- 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.
- This prior knowledge of knowing the bike demand at the right time is crucial for bike rental companies in the city of Seoul.
- Our main aim here is to solve this problem and predict the bike demand across different hours and also various other inputs which are related to the weather conditions of the city.

# ❖ Understanding our data:

- To increase the efficiency of our analysis we will first have to understand the data and also check if there are some corruptions in the data and if any found we will try to treat it.
- The dataset that we are working with contains 8,760 observations and 14 columns.
- Each observation includes information about the bikes rented and the weather for a particular hour of a particular date.
- The 14 columns represent different fields. We will understand each column now.

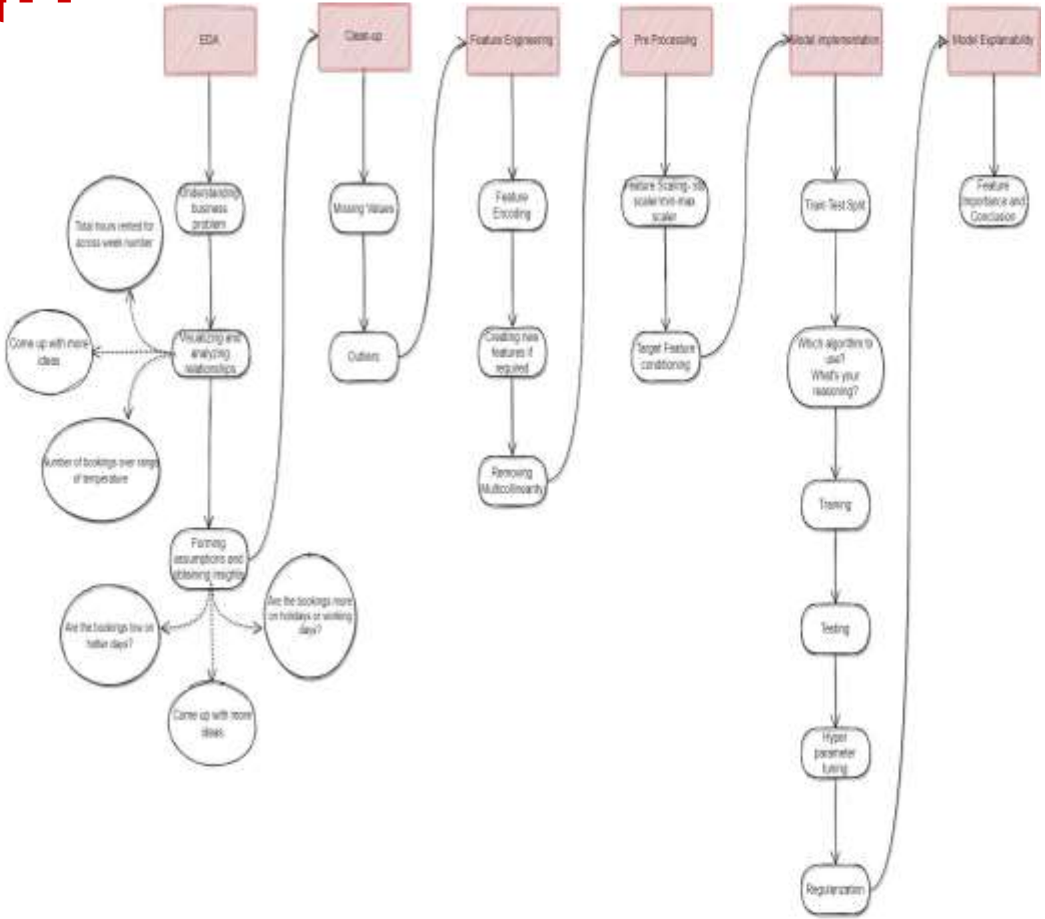
# ❖ The columns involved:



| Fields | Description |
|---|---|
| Date | Date |
| Hour | Total hours rented for |
| Temperature | Temperature for the day |
| Humidity | Humidity measure |
| Windspeed | windspeed |
| Visibility | Visibility measure |
| Dew point temperature | Dew point temperature measure |
| Solar radiation | Solar radiation measure |
| Rainfall | Rainfall in mm |
| Snowfall | Snowfall measure |
| Seasons | Season name |
| Holiday | Holiday or not |
| Functional Day | Functional day or not |

# ❖ Project Flowchart:

1. Initial preparations.
2. EDA.
3. Clean up.
4. Feature Engineering.
5. Pre processing the data.
6. Model implementation.
7. Model explainability.



EDA
Understanding business problem
Visualizing and analyzing relationships
Total hours rented for across week number
Come up with more ideas
Number of bookings over range of temperature
Forming assumptions and obtaining insights
Are the bookings low on hotter days?
Are the bookings more on holidays or working days?
Come up with more ideas
Clean-up
Missing Values
Outliers
Feature Engineering
Feature Encoding
Creating new features if required
Removing Multicollinearity
Pre Processing
Feature Scaling- std scaler/min-max scaler
Target Feature conditioning
Model Implementation
Train-Test Split
Which algorithm to use? What's your reasoning?
Training
Testing
Hyper parameter tuning
Regularization
Model Explainability
Feature Importance and Conclusion

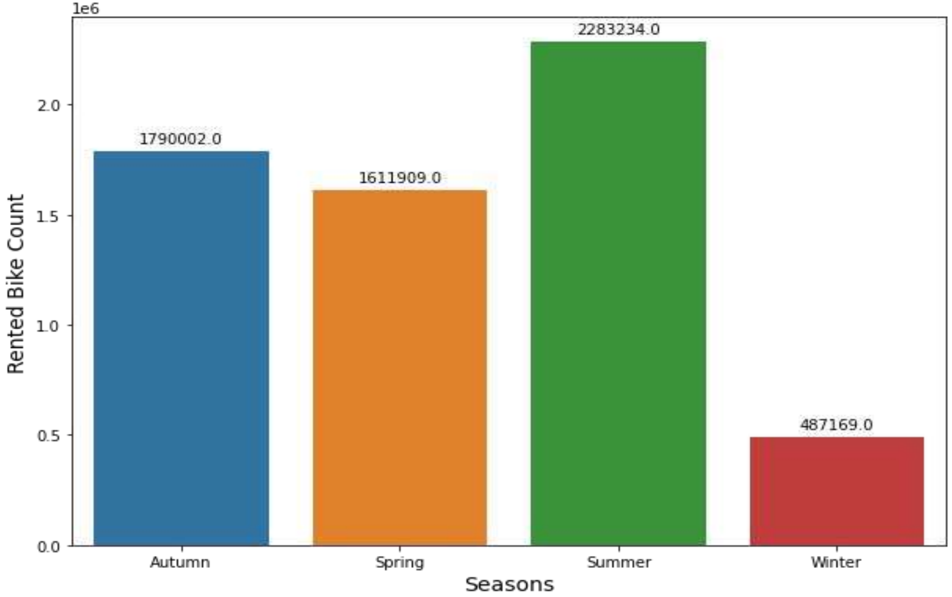
# 1. Initial preparation:

- In this section I’ve loaded in the dependencies, like pandas, seaborn, and many more from the scikit learn library.
- The next step was to mount the drive where the data was stored.
- After mounting the drive I used the pandas.read_csv() function to read the data given to us in csv format.

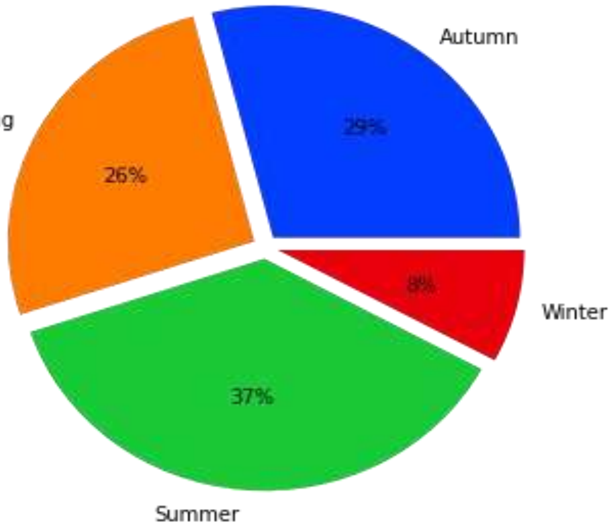
Note: The data for this project is given to us by the company, AlmaBetter.

# 2. EDA:

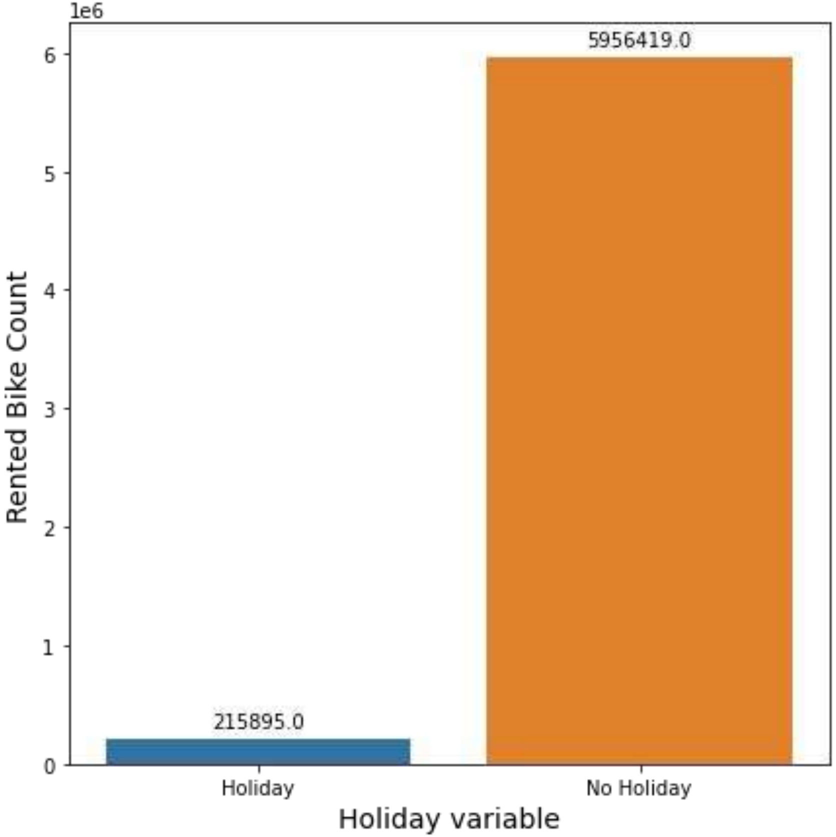
**In this step I’ve performed exploratory data analysis on the dataset to retrieve important information from the data we have received. I’ve produced visualizations by plotting all the columns individually against the target column (i.e. Rented Bike Count)**

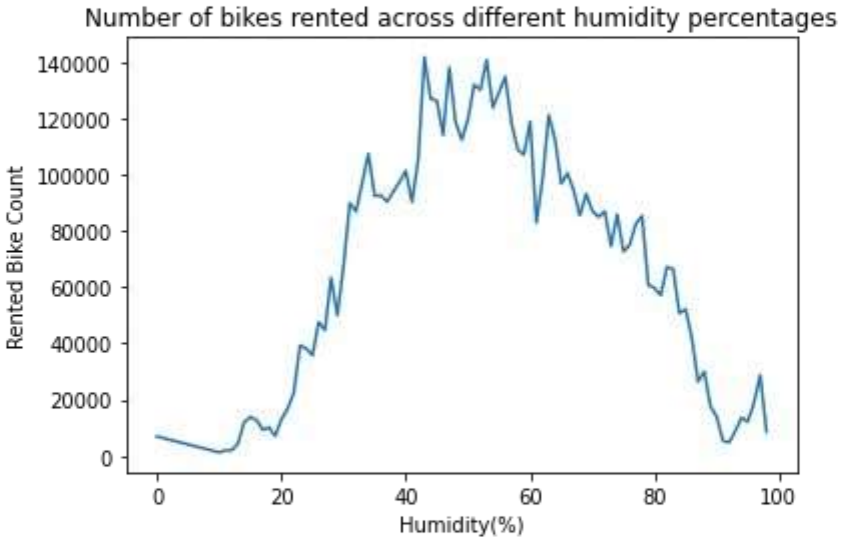


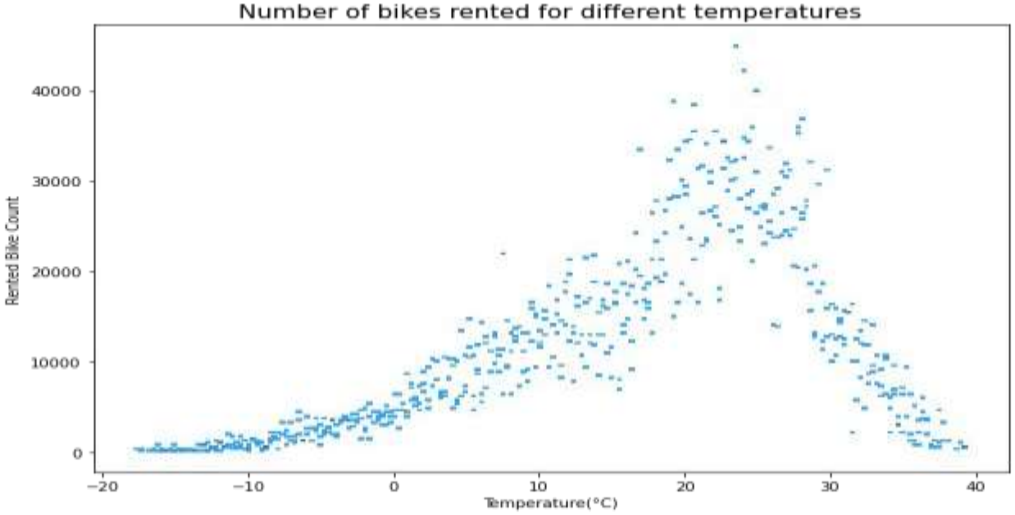
Percentage of total number of bikes rented for each season



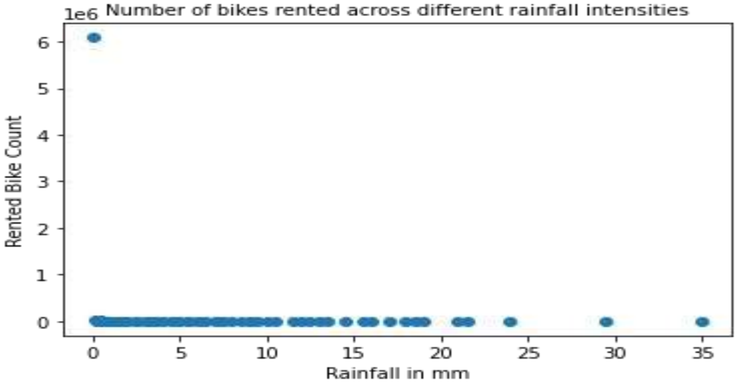
# 2. EDA(Contd):

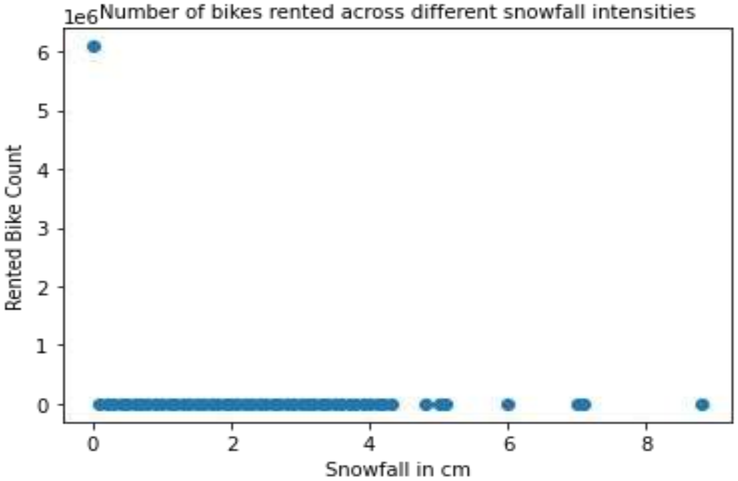

1e6
6
5
4
3
2
1
0
Rented Bike Count
5956419.0
215895.0
Holiday
No Holiday
Holiday variable

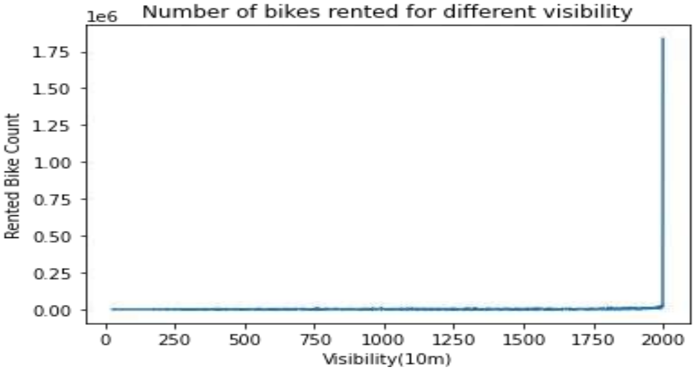

Number of bikes rented across different humidity percentages
140000
120000
100000
80000
60000
40000
20000
0
Rented Bike Count
0
20
40
60
80
100
Humidity(%)

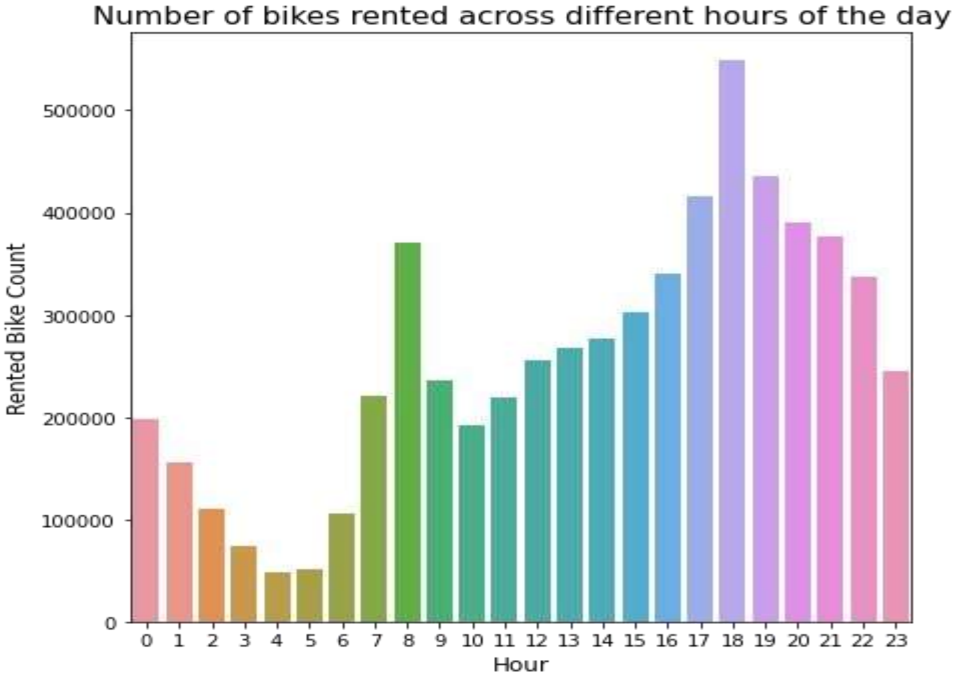

Number of bikes rented for different temperatures
40000
30000
20000
10000
0
Rented Bike Count
−20
−10
0
10
20
30
40
Temperature(°C)

# 2. EDA(Contd):


Number of bikes rented across different rainfall intensities
1e6
Rented Bike Count
0
1
2
3
4
5
6
0
5
10
15
20
25
30
35
Rainfall in mm


Number of bikes rented across different snowfall intensities
1e6
Rented Bike Count
0
1
2
3
4
5
6
0
2
4
6
8
Snowfall in cm


Number of bikes rented for different visibility
1e6
Rented Bike Count
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
0
250
500
750
1000
1250
1500
1750
2000
Visibility(10m)


Number of bikes rented across different hours of the day
Rented Bike Count
0
100000
200000
300000
400000
500000
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
Hour

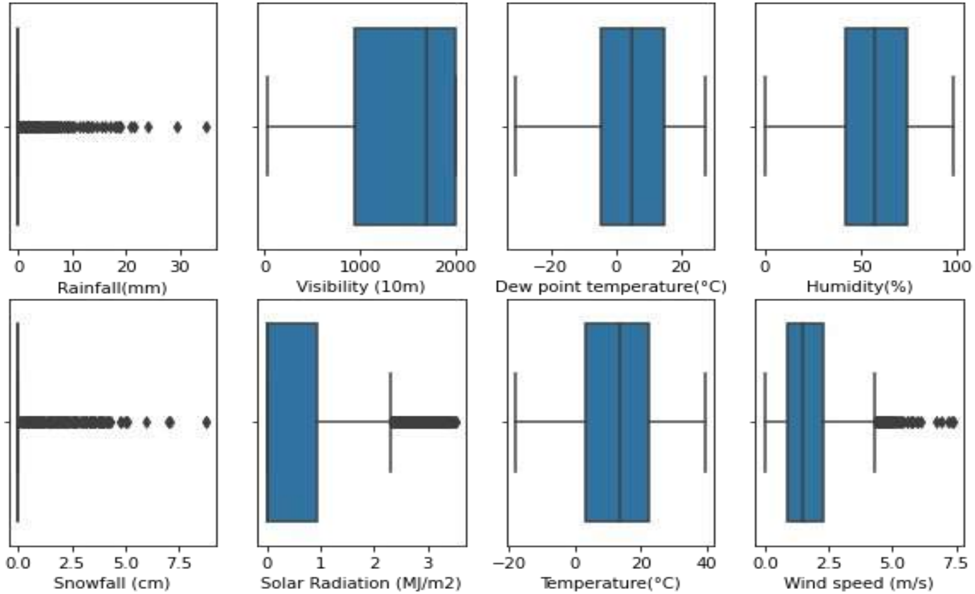
# 3. Clean up:

- ❖ Handling Null values: In this project the first step in Data cleaning is Handling the null values. Null values can affect the accuracy and quality of our ML models, therefore it is a good practice to handle null values. In our case, fortunately there are no null values in our dataset, so we are good to go.
- ❖ Handling duplicate values: Duplicate values can have adverse effects on our ML models, therefore we have to try and remove it. Luckily we don’t have any duplicate values either so we can move on to the next step in data cleaning.

# 3. Clean up(Contd):

- **Removing Outliers: First of all we find the variables that may contain outliers, to detect this I’ve used the box plot offered by seaborn library.**

**As we can see here that out of the possible columns the columns that contain outliers are Rainfall, Snowfall, Solar Radiation and Wind speed. Now we will operate on these columns and try to remove the outliers from them using the IQR method.**



# 3. Clean up(Contd):

- By using the IQR (Interquartile range) method we have found out the upper fence and lower fence and removed all the elements that have values greater or lesser than them respectively.
- Once we remove all the outliers, another problem arises. Many null values are created in place of these outliers.
- To fix this I have imputed them with the median value of that particular column or field.
- Usually mean is used to impute null values, but since mean is highly affected by outliers and median is not really affected, therefore I have chosen the median to impute these null values created by outlier removal.

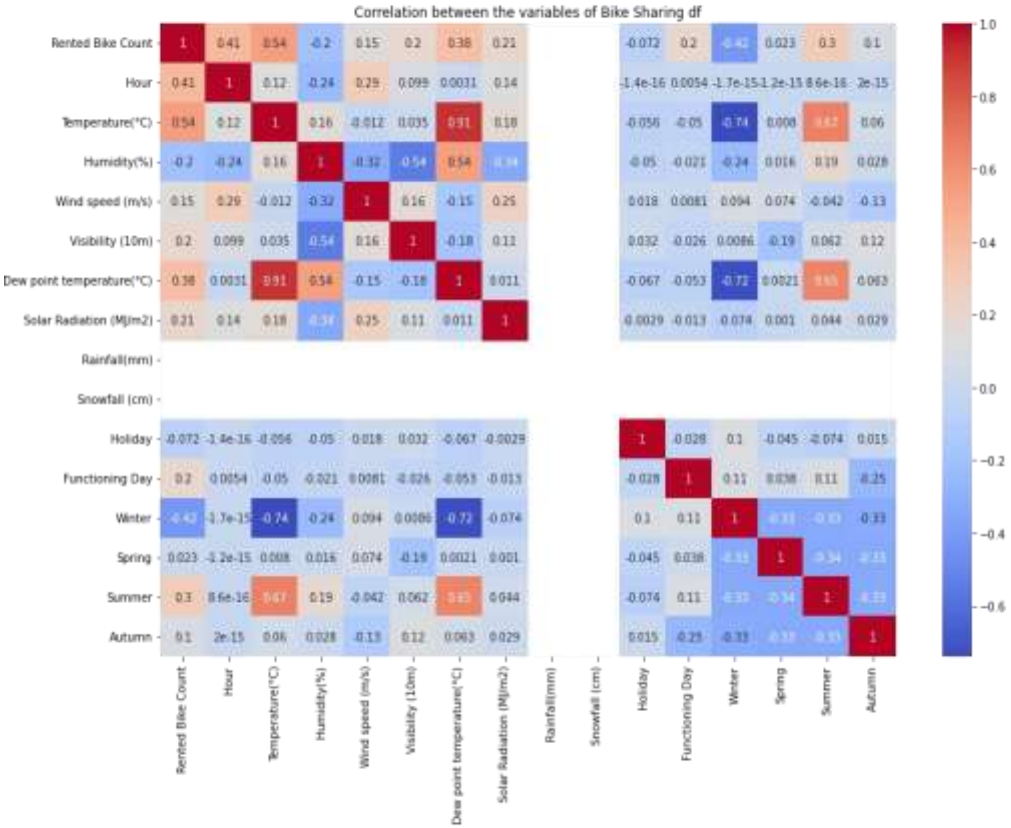
# 4. Feature Engineering:

- Feature encoding: Machine learning models can only work with numerical values and therefore we have to turn the categorical columns to numerical columns, and this is achieved by feature encoding.
- In our dataset, we have three columns that have to be converted into numerical columns and they are Season, Holiday, Functioning day.
- Holiday and Functioning day is directly converted by one hot encoding. For Seasons column, I have created 4 different new columns for each season and used one hot encoding on them and deleted the original seasons column.

# 4. Feature Engineering(Contd):

## ❖ Checking correlation for feature removal:

Here we can see that the column Dew point temperature has high correlation with the Temperature column. I also don’t think that the dew point temperature would add any value to the ML model, therefore keeping these things in mind, I’ve dropped the Dew point temperature column.



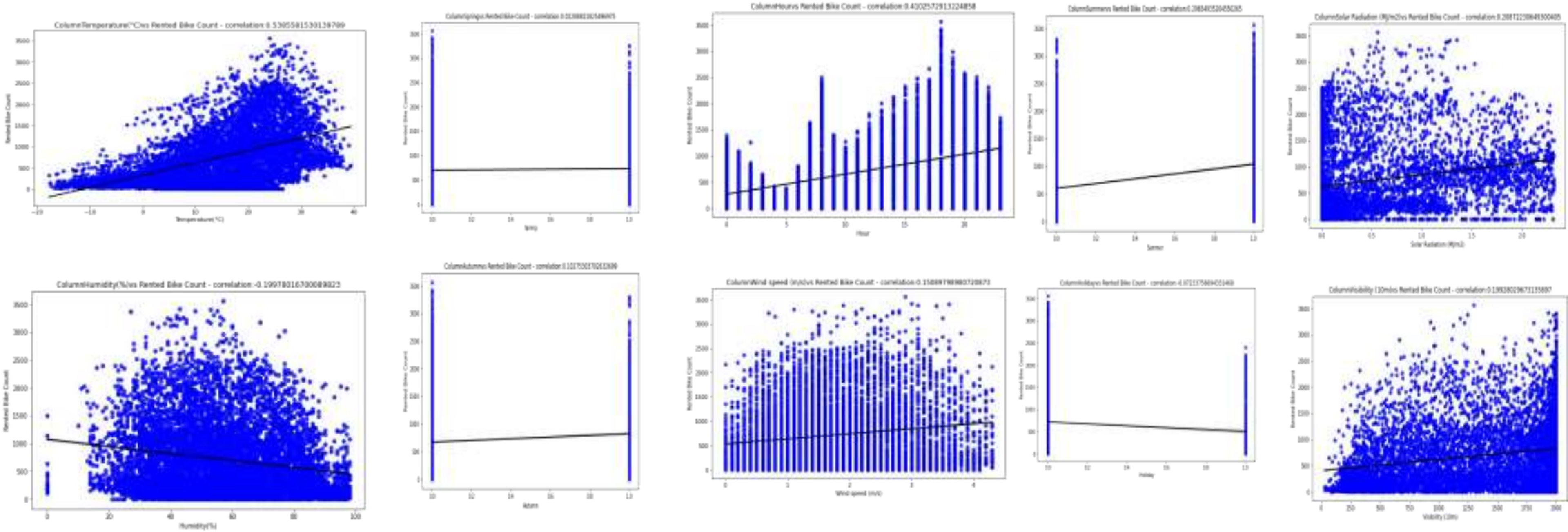
# 4. Feature Engineering(Contd):

- Removing multicollinearity: Multicollinearity is when two independent variables are highly correlated to each other
- I’ve checked for multicollinearity by using the variance inflation factor. For this project I’ve kept the accepted range for VIF below 10.
- All the seasons columns had high VIF so I removed the winter column and also Functioning day had to be removed so that all the columns have a VIF less than 10.

| | |
|---|---|
| Hour | 4.025 |
| Spring | 3.927 |
| Visibility(10m) | 5.216 |
| Summer | 9.167 |
| Holiday | 1.070 |
| Autumn | 4.437 |
| Humidity(%) | 5.401 |
| Solar Radiation(Mj/m2) | 1.598 |
| Temperature(°C) | 9.481 |
| Wind speed(m/s) | 4.707 |

# 4. Feature Engineering(Contd):

- ❖ **Obtaining correlation between independent and dependent variables: Linear regression considers an important assumption, which is that there should exist a linear relationship between the independent and dependent variable. To check this assumption these plots are done.**

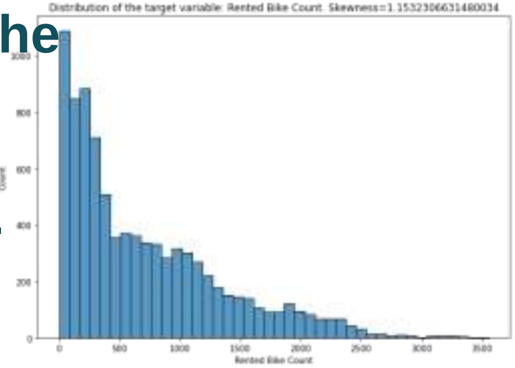


# 5. Pre processing of data:

## This consists of 3 parts:

- Target variable conditioning - Normalising the target variable.
- Dividing the dataset into train and test dataset with a ratio of 7:3
- Scaling the independent variables.

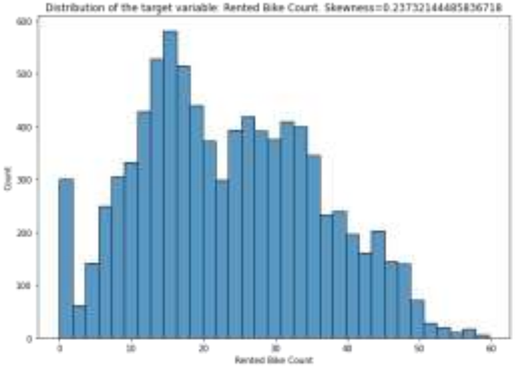
Distribution of the target variable(before normalisation) - positively skewed.



Distribution of the target variable: Rented Bike Count. Skewness=1.1532306631480034

After normalisation

Log transformation



Distribution of the target variable: Rented Bike Count. Skewness=0.23732144485836718

# 6&7. Model implementation and explainability:

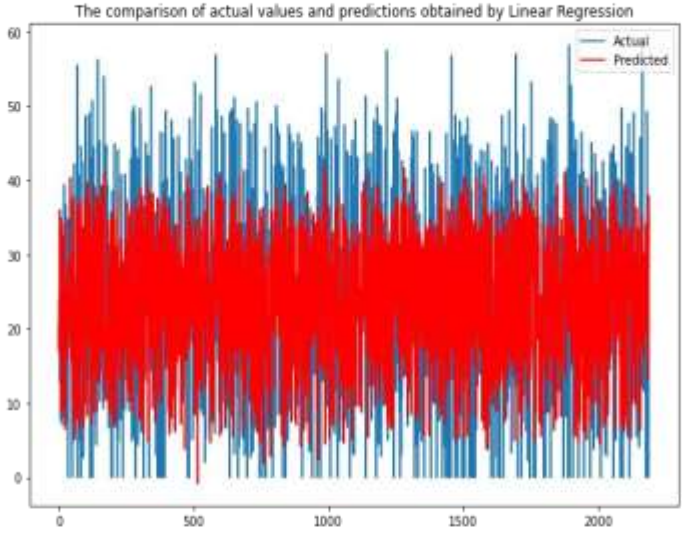
These are two different processes in the flowchart, but for explaining purposes I’m clubbing the two into a single process.

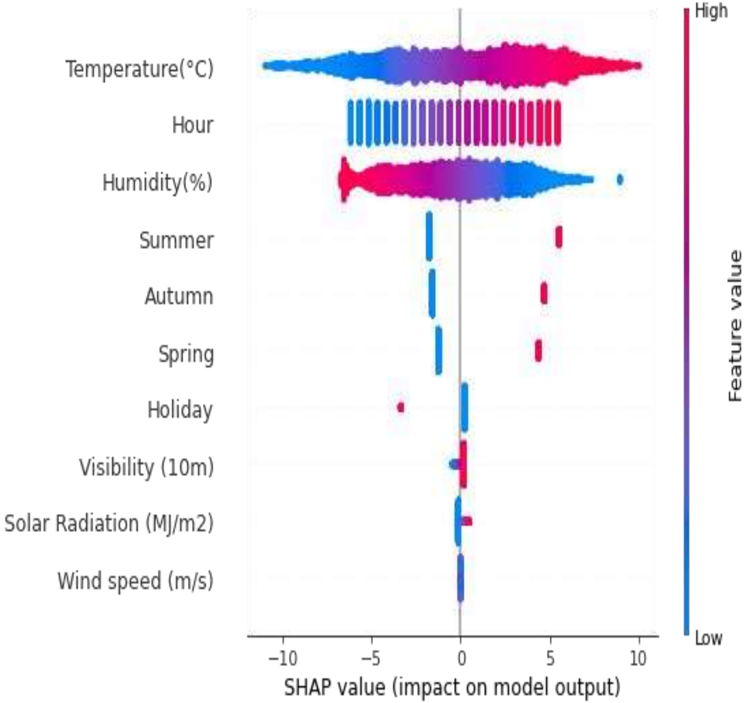
## ❖LINEAR REGRESSION:

## SHAP Summary plot

## Evaluation Metrics:

| |
|---|
| MSE - 86.3959 |
| RMSE - 9.2949 |
| R2 - 0.4530 |
| Adj R2 - 0.4505 |



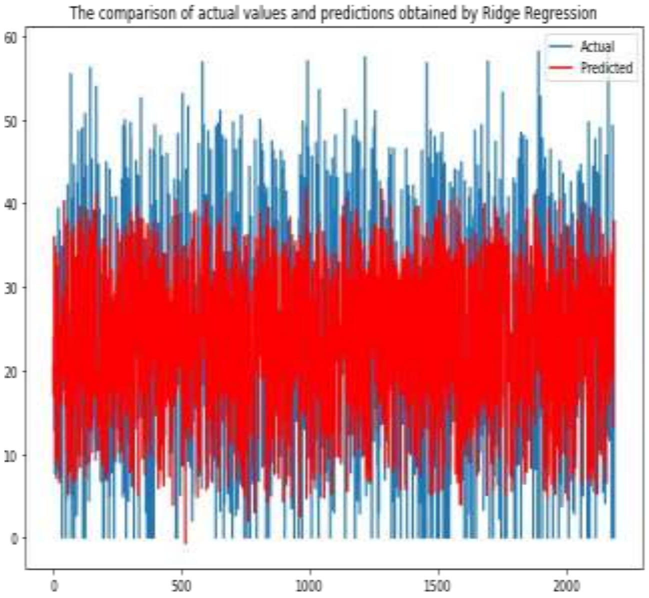


# 6&7. Model implementation and explainability:

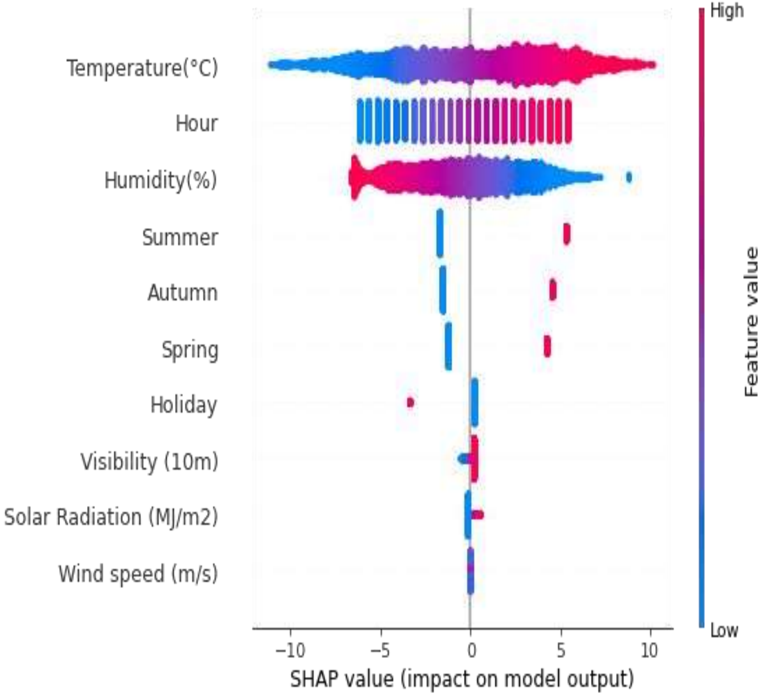
## ❖ RIDGE REGRESSION:

### Evaluation Metrics:

|  |
|---|
| MSE - 86.3913 |
| RMSE - 9.2946 |
| R2 - 0.4531 |
| Adj R2 - 0.4506 |



### SHAP Summary plot

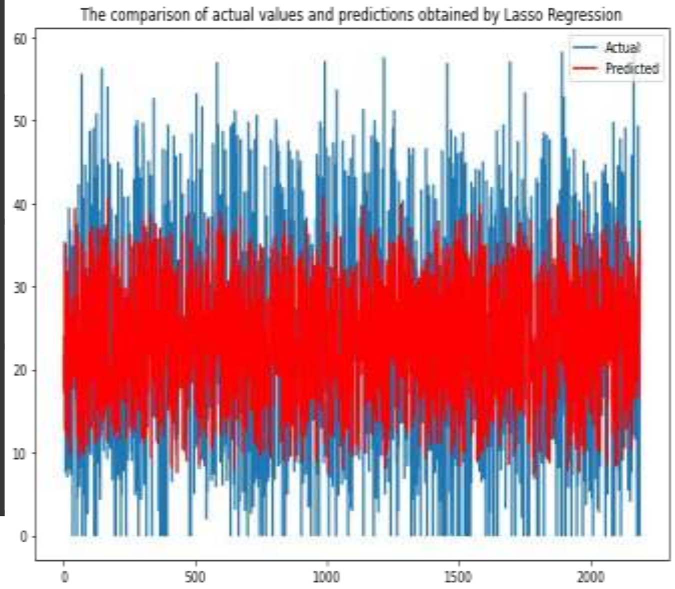


# 6&7. Model implementation and explainability:

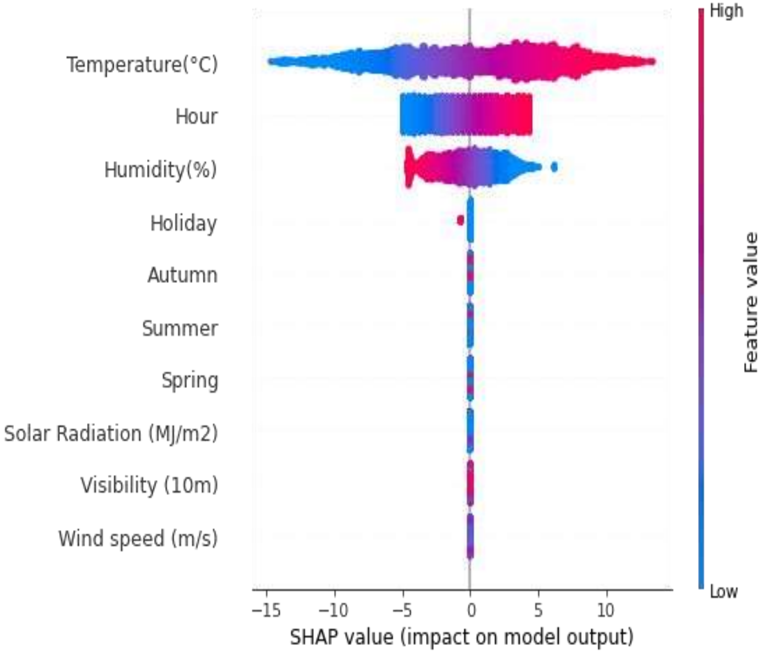
## ❖ LASSO REGRESSION:

### Evaluation Metrics:

| |
|---|
| MSE - 90.60 |
| RMSE - 9.51 |
| R2 - 0.4264 |
| Adj R2 - 0.4237 |



### SHAP Summary plot



# 6&7. Model implementation and explainability:

## ❖ RANDOM FOREST REGRESSION:

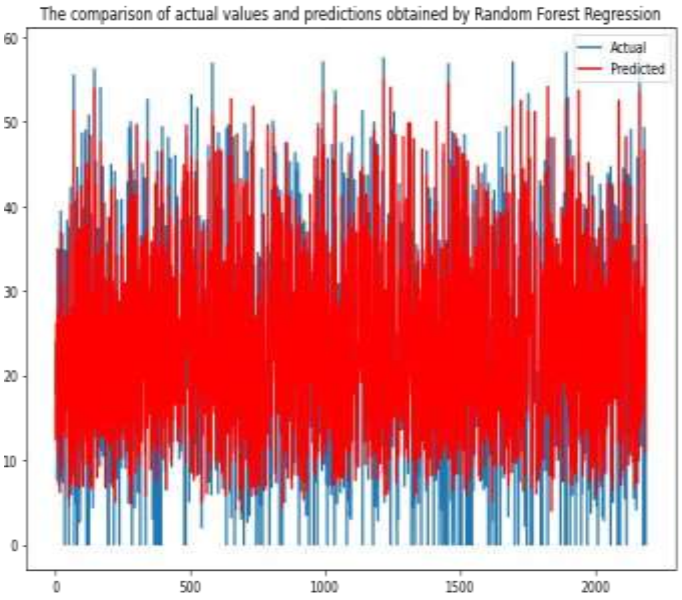
### Evaluation Metrics:

**MSE - 51.84**

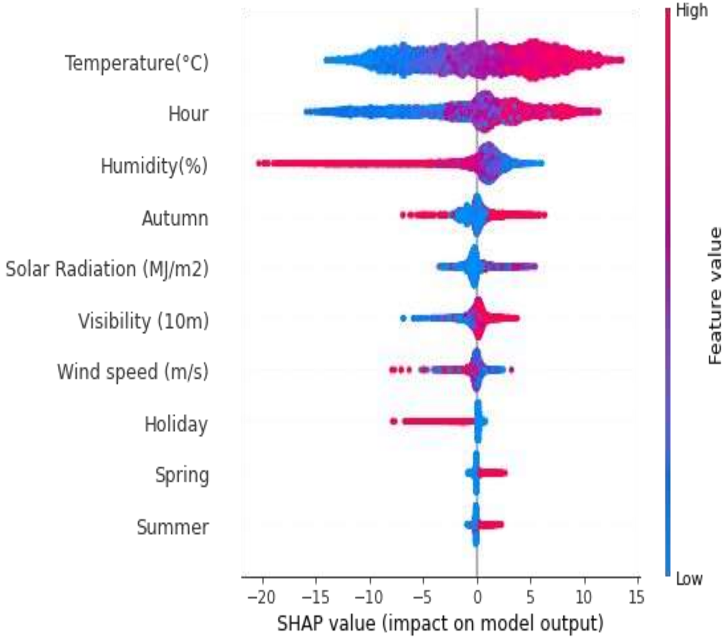
**RMSE - 7.20**

**R2 - 0.6718**

**Adj R2 - 0.6703**



### SHAP Summary plot



# ❖ Conclusion:

## EDA insights:

❖ Most number of bikes are rented in the Summer season and the lowest in the winter season.

❖ Over 96% of the bikes are rented on days that are considered as No Holiday.

❖ Most number of bikes are rented in the temperature range of 15 degrees to 30 degrees.

❖ Most number of bikes are rented when there is no snowfall or rainfall.

❖ Majority of the bikes are rented for a humidity percentage range of 30 to 70.

❖ The highest number of bike rentals have been done in the 18th hour, i.e 6pm, and lowest in the 4th hour, i.e 4am.

❖ Most of the bike rentals have been made when there is high visibility

# ❖ Conclusion(Contd):

## Results from ML models:

- Random Forest Regression is the best performing model with an r2 score of 0.6718.
- Lasso Regression(L1 regularization) is the worst performing model with an r2 score of 0.4264.
- Actual vs Prediction visualisation is done for all the 4 models.
- All 4 models have been explained with the help of SHAP library.
- Temperature and Hour are the two most important factors according to all the models.

## Challenges faced:

- Removing Outliers.
- Encoding the categorical columns.
- Removing Multicollinearity from the dataset.
- Choosing Model explainability technique.

# THANKYOU!!