seoul-bike-pranali

May 20, 2024

1 Project Name Machine Learning Project on Bike Rent Demand

Project Type - Regression Pranali Yadav

2 Project Summary -

Bike Seoul is a bike sharing service in the city of Seoul. It is part of the city's efforts to promote sustainable transportation and reduce traffic congestion. The service allows residents and visitors to rent bicycles at various stations across the city and return them to any other station, providing a convenient and eco-friendly mode of transportation. In recent years, the demand for bike rentals in Seoul has increased, leading to the need for a more efficient and effective way to manage the bike sharing operations. Accurately predicting bike demand is crucial for optimizing fleet management, ensuring the availability of bikes at high-demand locations, and reducing waste and costs.

The main objective of this project is to develop a machine learning model that can accurately predict the demand for bike rentals in Seoul, South Korea, based on historical data and various relevant factors such as weather conditions, time of day, and public holidays. In this project we have used regression analysis techniques to model the bike demand data. The model trained on a large dataset of past bike rental information, along with relevant weather and time data. The model then be tested and evaluated using metrics such as mean squared error and r-squared values. The actual data is from the Seoul city government's open data portal, and this dataset is also available on Kaggle.

So, our main goal was to achieve an accuracy of at least 85% in the bike demand predictions, which would help the city's bike sharing service providers plan their fleet operations more effectively and respond to demand changes in real-time. We have performed lots of regression algorithms like linear regression, random forest, decision tree, gradient boosting , Xtreme gradient boosting, also we tried to do hyperparameter tuning and cross validation to improve the accuracy of the model. And finally we have decided to select Xtreme gradient boosting algorithm because it gave us high accuracy around 93% and 90% on train and test data respectively.

This project not only provided valuable insights into bike demand patterns in Seoul but also demonstrated the practical applications of machine learning in addressing real-world problems. The findings could potentially be extended to other cities with similar bike sharing systems, leading to improved services for bike users and more sustainable transportation systems.

3 Problem Statement

Currently Rental bikes are introduced in many urban cities. The business problem is to ensure a stable supply of rental bikes in urban cities by predicting the demand for bikes at each hour. By providing a stable supply of rental bikes, the system can enhance mobility comfort for the public and reduce waiting time, leading to greater customer satisfaction.

To address this problem, i need to develop a predictive model that takes into account various factors that may influence demand, such as time of day, seasonality, weather conditions, and holidays. By accurately predicting demand, the bike sharing system operators can ensure that there is an adequate supply of bikes available at all times, which can improve the user experience and increase usage of the bike sharing system. This can have a positive impact on the sustainability of urban transportation, as it can reduce congestion, air pollution, and greenhouse gas emissions.

[5]:
```python
# Import Libraries
import numpy as np
import pandas as pd
```

[6]:
```python
from numpy import math

from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
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
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
#from xgboost import XGBRFRegressor

import warnings
warnings.filterwarnings('ignore')
```

```
C:\Users\ADMIN\AppData\Local\Temp\ipykernel_10804\2533403659.py:1:
DeprecationWarning: `np.math` is a deprecated alias for the standard library
`math` module (Deprecated Numpy 1.25). Replace usages of `np.math` with `math`
  from numpy import math
```

3.0.1 Dataset Loading

[7]:
```python
df = pd.read_csv('c:\\Users\\ADMIN\\Downloads\\SeoulBikeData.csv',header=0,␣
 ↪encoding= 'unicode_escape')
```

3.0.2 Dataset Information

[8]:
```python
df.info()
```

```
<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   object
 1   Rented Bike Count          8760 non-null   int64
 2   Hour                       8760 non-null   int64
 3   Temperature(°C)            8760 non-null   float64
 4   Humidity(%)                8760 non-null   int64
 5   Wind speed (m/s)           8760 non-null   float64
 6   Visibility (10m)           8760 non-null   int64
 7   Dew point temperature(°C)  8760 non-null   float64
 8   Solar Radiation (MJ/m2)    8760 non-null   float64
 9   Rainfall(mm)               8760 non-null   float64
 10  Snowfall (cm)              8760 non-null   float64
 11  Seasons                    8760 non-null   object
 12  Holiday                    8760 non-null   object
 13  Functioning Day            8760 non-null   object
dtypes: float64(6), int64(4), object(4)
memory usage: 958.3+ KB
```

[9]:
```
# Dataset Describe (all columns included)
df.describe()
```

[9]:
```
       Rented Bike Count         Hour  Temperature(°C)  Humidity(%)  \
count        8760.000000  8760.000000      8760.000000  8760.000000
mean          704.602055    11.500000        12.882922    58.226256
std           644.997468     6.922582        11.944825    20.362413
min             0.000000     0.000000       -17.800000     0.000000
25%           191.000000     5.750000         3.500000    42.000000
50%           504.500000    11.500000        13.700000    57.000000
75%          1065.250000    17.250000        22.500000    74.000000
max          3556.000000    23.000000        39.400000    98.000000

       Wind speed (m/s)  Visibility (10m)  Dew point temperature(°C)  \
count       8760.000000       8760.000000                8760.000000
mean           1.724909       1436.825799                   4.073813
std            1.036300        608.298712                  13.060369
min            0.000000         27.000000                 -30.600000
25%            0.900000        940.000000                  -4.700000
50%            1.500000       1698.000000                   5.100000
75%            2.300000       2000.000000                  14.800000
max            7.400000       2000.000000                  27.200000

       Solar Radiation (MJ/m2)  Rainfall(mm)  Snowfall (cm)
count              8760.000000   8760.000000    8760.000000
mean                  0.569111      0.148687       0.075068
```

```
std                   0.868746      1.128193       0.436746
min                   0.000000      0.000000       0.000000
25%                   0.000000      0.000000       0.000000
50%                   0.010000      0.000000       0.000000
75%                   0.930000      0.000000       0.000000
max                   3.520000     35.000000       8.800000
```

3.0.3 Dataset First View

[10]:
```
df.head()
```

[10]:
```
         Date  Rented Bike Count  Hour  Temperature(°C)  Humidity(%)  \
0  01/12/2017                254     0             -5.2           37
1  01/12/2017                204     1             -5.5           38
2  01/12/2017                173     2             -6.0           39
3  01/12/2017                107     3             -6.2           40
4  01/12/2017                 78     4             -6.0           36

   Wind speed (m/s)  Visibility (10m)  Dew point temperature(°C)  \
0               2.2              2000                      -17.6
1               0.8              2000                      -17.6
2               1.0              2000                      -17.7
3               0.9              2000                      -17.6
4               2.3              2000                      -18.6

   Solar Radiation (MJ/m2)  Rainfall(mm)  Snowfall (cm) Seasons     Holiday  \
0                      0.0           0.0            0.0  Winter  No Holiday
1                      0.0           0.0            0.0  Winter  No Holiday
2                      0.0           0.0            0.0  Winter  No Holiday
3                      0.0           0.0            0.0  Winter  No Holiday
4                      0.0           0.0            0.0  Winter  No Holiday

  Functioning Day
0             Yes
1             Yes
2             Yes
3             Yes
4             Yes
```

3.0.4 Dataset Rows & Columns count

[11]:
```
# Dataset Rows & Columns count
# Checking number of rows and columns of the dataset using shape
print("Number of rows are: ",df.shape[0])
print("Number of columns are: ",df.shape[1])
```

```
Number of rows are:  8760
```

```
Number of columns are:  14
```

Missing Values/Null Values

[12]:
```python
# Checking Missing Values/Null Values Count
df.isnull().sum()
```

[12]:
```
Date                         0
Rented Bike Count            0
Hour                         0
Temperature(°C)              0
Humidity(%)                  0
Wind speed (m/s)             0
Visibility (10m)             0
Dew point temperature(°C)    0
Solar Radiation (MJ/m2)      0
Rainfall(mm)                 0
Snowfall (cm)                0
Seasons                      0
Holiday                      0
Functioning Day              0
dtype: int64
```

[13]:
```python
df.value_counts(normalize=True, sort=True, dropna=True, ascending=False)
```

[13]:
```
Date        Rented Bike Count  Hour  Temperature(°C)  Humidity(%)  Wind speed
(m/s)  Visibility (10m)  Dew point temperature(°C)  Solar Radiation (MJ/m2)
Rainfall(mm)  Snowfall (cm)  Seasons  Holiday     Functioning Day
01/01/2018  61                 5     -4.4             54           0.8
1786          -12.3                      0.00                     0.0
0.0            Winter   Holiday     Yes               0.000114
21/04/2018  707                0      16.3            59           0.2
756           8.2                        0.00                     0.0
0.0            Spring   No Holiday  Yes               0.000114
            324                7      12.5            68           1.1
457           6.7                        0.22                     0.0
0.0            Spring   No Holiday  Yes               0.000114
            436                2      14.7            63           1.8
611           7.7                        0.00                     0.0
0.0            Spring   No Holiday  Yes               0.000114
            600                8      14.6            54           0.9
431           5.3                        0.89                     0.0
0.0            Spring   No Holiday  Yes               0.000114
                                                                   …
11/02/2018  112                0     -6.9             36           2.1
2000          -19.5                      0.00                     0.0
0.0            Winter   No Holiday  Yes               0.000114
            103                22    -5.8             57           3.2
```

```
1980               -12.9                     0.00                      0.0
0.0           Winter    No Holiday  Yes              0.000114
             95                 1     -7.0              38           2.6
2000               -18.9                     0.00                      0.0
0.0           Winter    No Holiday  Yes              0.000114
             93                 2     -7.0              42           1.6
2000               -17.7                     0.00                      0.0
0.0           Winter    No Holiday  Yes              0.000114
31/12/2017  300                15      3.1              25           3.9
2000               -15.0                     0.90                      0.0
0.0           Winter    Holiday     Yes              0.000114
Name: proportion, Length: 8760, dtype: float64
```

[15]:
```python
df["Date"] = pd.to_datetime(df["Date"],dayfirst=True)
df.Date.head()
```

[15]:
```
0   2017-12-01
1   2017-12-01
2   2017-12-01
3   2017-12-01
4   2017-12-01
Name: Date, dtype: datetime64[ns]
```

#Data Visualization

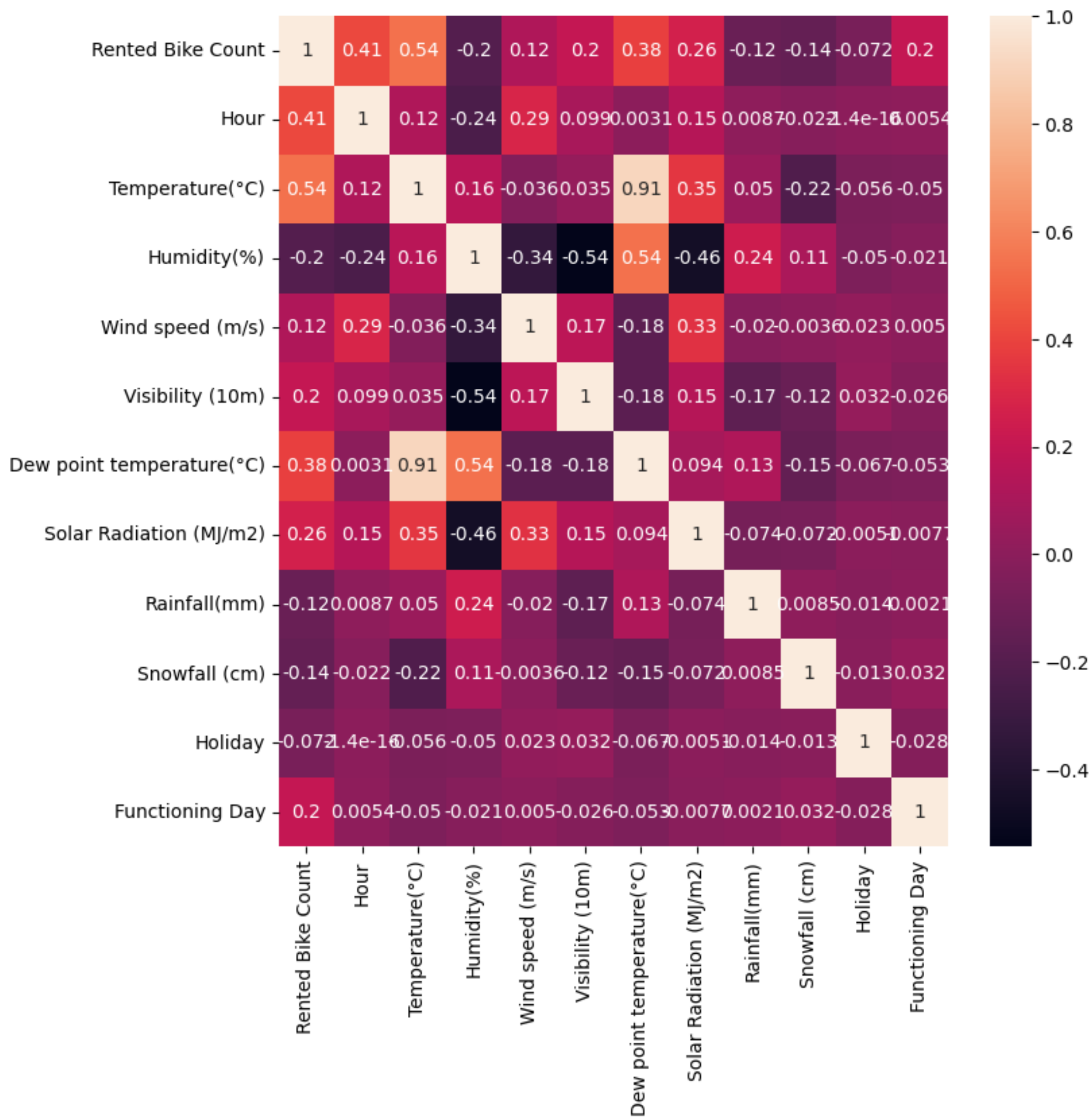
[22]:
```python
df.corr(numeric_only=True)
```

[22]:
```
                           Rented Bike Count      Hour  Temperature(°C)  \
Rented Bike Count                   1.000000  0.410257         0.538558
Hour                                0.410257  1.000000         0.124114
Temperature(°C)                     0.538558  0.124114         1.000000
Humidity(%)                        -0.199780 -0.241644         0.159371
Wind speed (m/s)                    0.121108  0.285197        -0.036252
Visibility (10m)                    0.199280  0.098753         0.034794
Dew point temperature(°C)           0.379788  0.003054         0.912798
Solar Radiation (MJ/m2)             0.261837  0.145131         0.353505
Rainfall(mm)                       -0.123074  0.008715         0.050282
Snowfall (cm)                      -0.141804 -0.021516        -0.218405

                           Humidity(%)  Wind speed (m/s)  Visibility (10m)  \
Rented Bike Count            -0.199780          0.121108          0.199280
Hour                         -0.241644          0.285197          0.098753
Temperature(°C)               0.159371         -0.036252          0.034794
Humidity(%)                   1.000000         -0.336683         -0.543090
Wind speed (m/s)             -0.336683          1.000000          0.171507
Visibility (10m)             -0.543090          0.171507          1.000000
Dew point temperature(°C)     0.536894         -0.176486         -0.176630
```

```
Solar Radiation (MJ/m2)     -0.461919        0.332274        0.149738
Rainfall(mm)                 0.236397       -0.019674       -0.167629
Snowfall (cm)                0.108183       -0.003554       -0.121695

                           Dew point temperature(°C)  Solar Radiation (MJ/m2)  \
Rented Bike Count                           0.379788                 0.261837
Hour                                        0.003054                 0.145131
Temperature(°C)                             0.912798                 0.353505
Humidity(%)                                 0.536894                -0.461919
Wind speed (m/s)                           -0.176486                 0.332274
Visibility (10m)                           -0.176630                 0.149738
Dew point temperature(°C)                   1.000000                 0.094381
Solar Radiation (MJ/m2)                     0.094381                 1.000000
Rainfall(mm)                                0.125597                -0.074290
Snowfall (cm)                              -0.150887                -0.072301

                           Rainfall(mm)  Snowfall (cm)
Rented Bike Count             -0.123074      -0.141804
Hour                           0.008715      -0.021516
Temperature(°C)                0.050282      -0.218405
Humidity(%)                    0.236397       0.108183
Wind speed (m/s)              -0.019674      -0.003554
Visibility (10m)              -0.167629      -0.121695
Dew point temperature(°C)      0.125597      -0.150887
Solar Radiation (MJ/m2)       -0.074290      -0.072301
Rainfall(mm)                   1.000000       0.008500
Snowfall (cm)                  0.008500       1.000000
```

[78]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 8))
sns.heatmap(df.corr(numeric_only=True), annot=True)
```

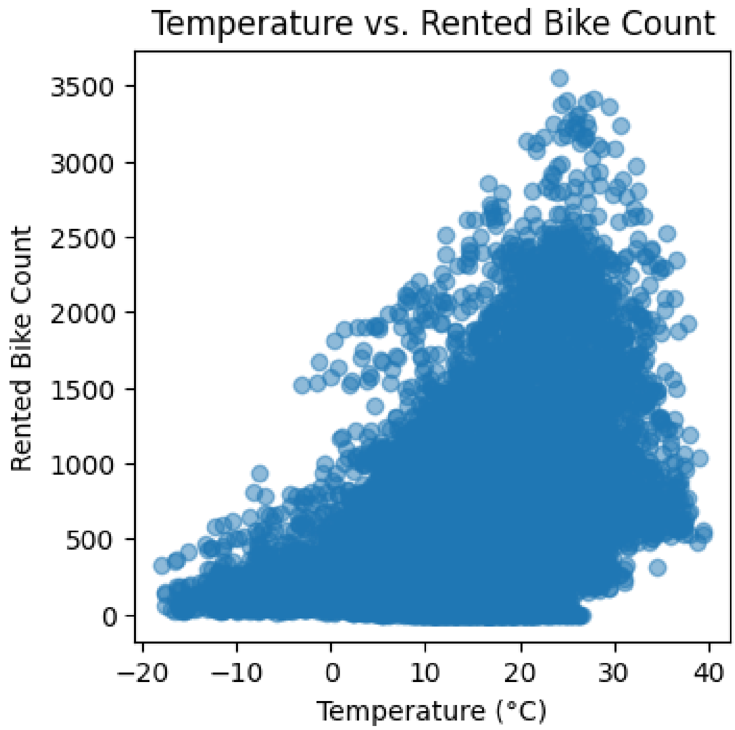
[78]: <Axes: >



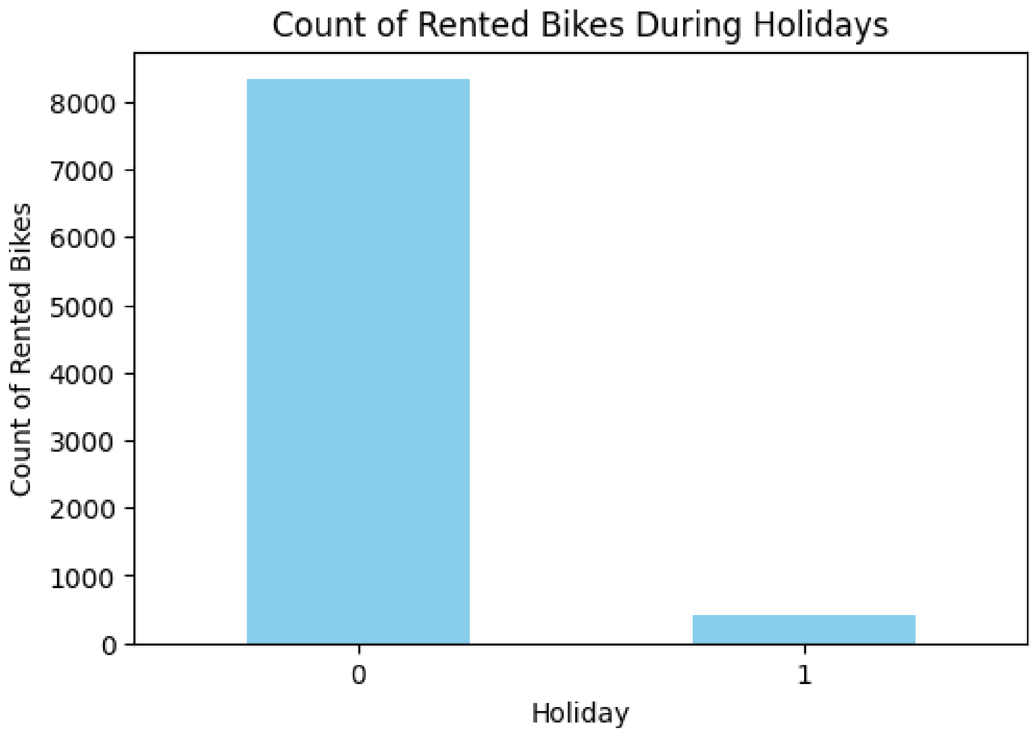
Only Temperature and Hour has considerable correlation wit our arget variable 'Rented Bike Count' There is correlation between Temperature and Dew point Temperature(°C)

[85]:
```
temperature = df['Temperature(°C)']
rented_bike_count = df['Rented Bike Count']

# Plot the scatter plot
plt.figure(figsize=(4, 4))
plt.scatter(temperature, rented_bike_count, alpha=0.5)
plt.title('Temperature vs. Rented Bike Count')
plt.xlabel('Temperature (°C)')
plt.ylabel('Rented Bike Count')
```

```
plt.show()
```

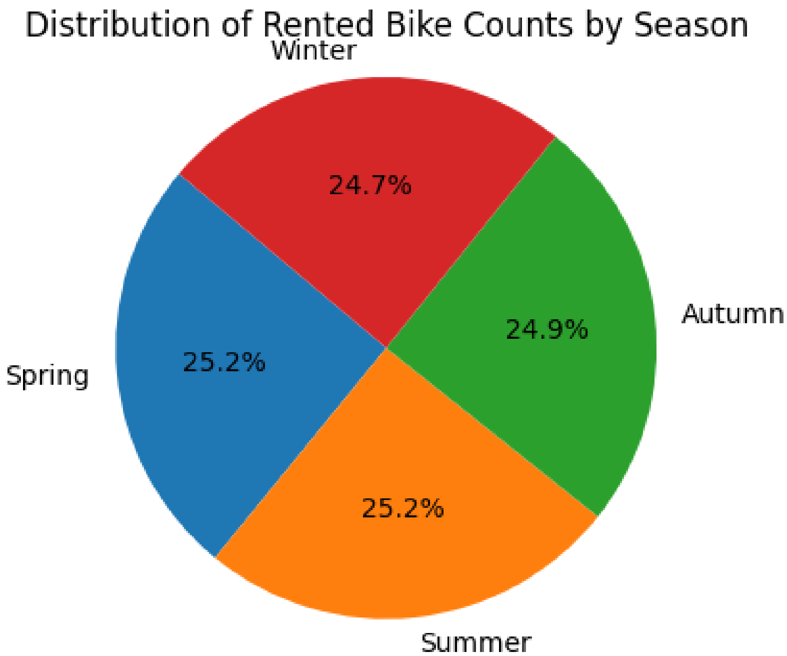


[82]:
```
holiday_counts = df['Holiday'].value_counts()

# Plot the bar graph
plt.figure(figsize=(6, 4))
holiday_counts.plot(kind='bar', color='skyblue')
plt.title('Count of Rented Bikes During Holidays')
plt.xlabel('Holiday')
plt.ylabel('Count of Rented Bikes')
plt.xticks(rotation=0)
plt.show()
```

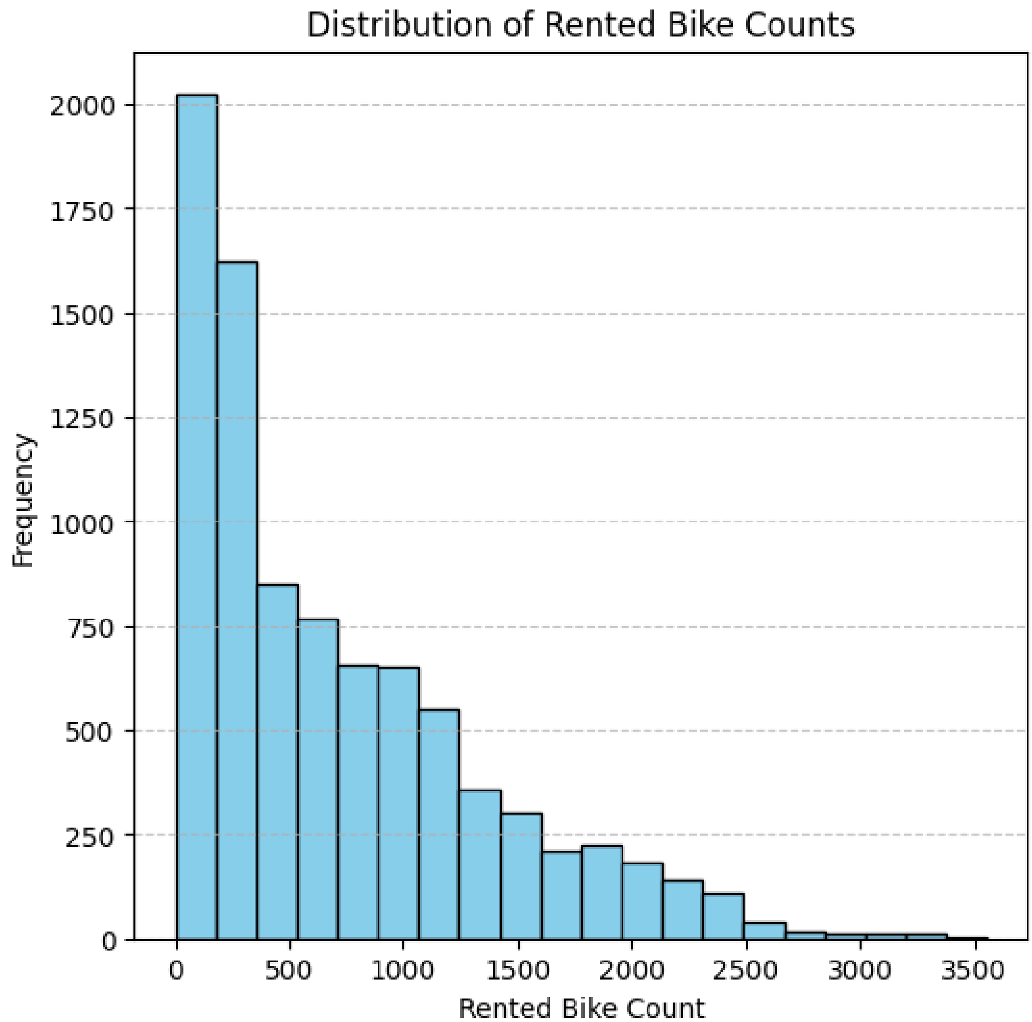


[84]:

```
season_counts = df['Seasons'].value_counts()

# Plot the pie chart
plt.figure(figsize=(4, 4))
plt.pie(season_counts, labels=season_counts.index, autopct='%1.1f%%',␣
 ↪startangle=140)
plt.title('Distribution of Rented Bike Counts by Season')
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle
plt.show()
```



[89]:
```
rented_bike_counts = df['Rented Bike Count']

# Plot the histogram
plt.figure(figsize=(6, 6))
plt.hist(rented_bike_counts, bins=20, color='skyblue', edgecolor='black')
plt.title('Distribution of Rented Bike Counts')
plt.xlabel('Rented Bike Count')
plt.ylabel('Frequency')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



Converting categorical data into machine redable data

[16]:
```
new_df = df.copy()
```

[17]:
```
new_df.head()
```

[17]:
```
         Date  Rented Bike Count  Hour  Temperature(°C)  Humidity(%)  \
0  2017-12-01                254     0             -5.2           37
1  2017-12-01                204     1             -5.5           38
2  2017-12-01                173     2             -6.0           39
3  2017-12-01                107     3             -6.2           40
4  2017-12-01                 78     4             -6.0           36

   Wind speed (m/s)  Visibility (10m)  Dew point temperature(°C)  \
0               2.2              2000                      -17.6
```

```
1              0.8           2000                    -17.6
2              1.0           2000                    -17.7
3              0.9           2000                    -17.6
4              2.3           2000                    -18.6

   Solar Radiation (MJ/m2)  Rainfall(mm)  Snowfall (cm) Seasons     Holiday  \
0                      0.0           0.0            0.0  Winter  No Holiday
1                      0.0           0.0            0.0  Winter  No Holiday
2                      0.0           0.0            0.0  Winter  No Holiday
3                      0.0           0.0            0.0  Winter  No Holiday
4                      0.0           0.0            0.0  Winter  No Holiday

  Functioning Day
0             Yes
1             Yes
2             Yes
3             Yes
4             Yes
```

We have dichotomous in Holiday and Functioning Day we can convert them into 0 nad 1

[18]:
```
df['Holiday'] = df['Holiday'].replace('No Holiday',0)
df['Holiday'] = df['Holiday'].replace('Holiday',1)
```

[19]:
```
df['Functioning Day'] = df['Functioning Day'].replace('No',0)
df['Functioning Day'] = df['Functioning Day'].replace('Yes',1)
```

For Seasons we can use one hot key encoding as we have nominal data in this feature

[20]:
```
categorical_columns2 = new_df.select_dtypes(['object'])
```

[21]:
```
encoded = pd.get_dummies(categorical_columns2, dtype='int64')
```

[30]:
```
encoded.head()
```

[30]:
```
   Seasons_Autumn  Seasons_Spring  Seasons_Summer  Seasons_Winter  \
0               0               0               0               1
1               0               0               0               1
2               0               0               0               1
3               0               0               0               1
4               0               0               0               1

   Holiday_Holiday  Holiday_No Holiday  Functioning Day_No  \
0                0                   1                   0
1                0                   1                   0
2                0                   1                   0
3                0                   1                   0
4                0                   1                   0
```

```
   Functioning Day_Yes
0                    1
1                    1
2                    1
3                    1
4                    1
```

Dropping unnecessary coulumns • dropping categorical data which has been converted into numerical data • dropping date • Dew point temperature(°C) because its correlated with Temperature(°C) we can keep only one

[22]:
```
new_df.drop(categorical_columns2,axis=1,inplace=True)
```

Let's concatenate our encoded dataframe with datframe that has only numerical columns

[23]:
```
new_df = pd.concat([new_df,encoded],axis = 1)
```

[24]:
```
new_df.drop('Date', axis=1, inplace=True)
```

[25]:
```
new_df.drop('Dew point temperature(°C)', axis=1, inplace=True)
```

Data Splitting Now our dataset is ready for modelling.

[26]:
```
X = new_df.drop(columns='Rented Bike Count')
y = new_df['Rented Bike Count']
```

[27]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=0)
```

[37]:
```
print(f'The shapes of train and test set for independent variables are:␣
 ↪X_train={X_train.shape}, X_test={X_test.shape}')
print(f'The shapes of train and test set for dependent variables are:␣
 ↪y_train={y_train.shape}, y_test={y_test.shape}')
```

```
The shapes of train and test set for independent variables are: X_train=(7008,
16), X_test=(1752, 16)
The shapes of train and test set for dependent variables are: y_train=(7008,),
y_test=(1752,)
```

[28]:
```
X_train.values
```

[28]:
```
array([[15. ,  8.2, 62. , …,  1. ,  0. ,  1. ],
       [18. , 28.4, 57. , …,  1. ,  0. ,  1. ],
       [11. , 29.9, 57. , …,  1. ,  0. ,  1. ],
       …,
       [11. , 25.5, 57. , …,  1. ,  0. ,  1. ],
       [ 0. ,  8.3, 59. , …,  1. ,  0. ,  1. ],
```

```
         [20. ,   7.1, 83. , …,   1. ,   0. ,   1. ]])
```

[29]:
```
from sklearn.preprocessing import StandardScaler
```

[30]:
```
from sklearn.model_selection import train_test_split, GridSearchCV,␣
 ↪RandomizedSearchCV
from sklearn.metrics import␣
 ↪mean_absolute_error,mean_squared_error,root_mean_squared_error,r2_score,accuracy_score
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
#from xgboost import XGBRFRegressor

import warnings
warnings.filterwarnings('ignore')
```

Data Scaling

[31]:
```
scaler=StandardScaler()
X_train=scaler.fit_transform(X_train)
X_test=scaler.transform(X_test)
```

[32]:
```
#after transformation
X_train
```

[32]:
```
array([[ 0.50774916, -0.38874606,  0.18996015, …,  0.23202281,
        -0.18254726,  0.18254726],
       [ 0.9408263 ,  1.29850393, -0.05608294, …,  0.23202281,
        -0.18254726,  0.18254726],
       [-0.06968702,  1.42379477, -0.05608294, …,  0.23202281,
        -0.18254726,  0.18254726],
       …,
       [-0.06968702,  1.05627497, -0.05608294, …,  0.23202281,
        -0.18254726,  0.18254726],
       [-1.65763652, -0.38039334,  0.0423343 , …,  0.23202281,
        -0.18254726,  0.18254726],
       [ 1.22954439, -0.48062601,  1.22334111, …,  0.23202281,
        -0.18254726,  0.18254726]])
```

ML Model Implementation

#Decision tree regressor

[33]:
```
dt_model = DecisionTreeRegressor()
dt_model.fit(X_train, y_train)
```

[33]:
```
DecisionTreeRegressor()
```

[34]:
```
reg = DecisionTreeRegressor(criterion='squared_error', max_leaf_nodes=25,␣
↪random_state=0)
reg.fit(X_train, y_train)
```

[34]:
```
DecisionTreeRegressor(max_leaf_nodes=25, random_state=0)
```

[35]:
```
y_predicted = reg.predict(X_test)
y_train_prediction = reg.predict(X_train)
```

[36]:
```
# test results
print(mean_squared_error(y_test, y_predicted))
print(r2_score(y_test, y_predicted))
print(mean_absolute_error(y_test, y_predicted))
print(root_mean_squared_error(y_test, y_predicted))
```

```
106123.70920344388
0.7464325412031669
219.78681996507268
325.7663414219521
```

[37]:
```
# test results
print(mean_squared_error(y_train, y_train_prediction))
print(r2_score(y_train, y_train_prediction))
print(mean_absolute_error(y_train, y_train_prediction))
print(root_mean_squared_error(y_train, y_train_prediction))
```

```
96596.14855320382
0.7673744199148671
211.18037322540002
310.7992093831704
```

Let's store metric values of train and test set for later comparisons.

CROSS VALIDATION

[38]:
```
param_dict = {"criterion":['squared_error', 'absolute_error'],
              "max_depth":
↪[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,21,22,23,24]}
```

[39]:
```
grid = GridSearchCV(reg,param_grid=param_dict,cv=10,n_jobs=-1)
```

[40]:
```
grid.fit(X_train,y_train)
```

[40]:
```
GridSearchCV(cv=10,
             estimator=DecisionTreeRegressor(max_leaf_nodes=25, random_state=0),
             n_jobs=-1,
             param_grid={'criterion': ['squared_error', 'absolute_error'],
                         'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,
                                       13, 14, 15, 16, 17, 18, 19, 21, 22, 23,
```

```
24]})
```

[41]:
```
grid.best_estimator_
```

[41]:
```
DecisionTreeRegressor(criterion='absolute_error', max_depth=11,
                      max_leaf_nodes=25, random_state=0)
```

[42]:
```
grid.best_params_
```

[42]:
```
{'criterion': 'absolute_error', 'max_depth': 11}
```

[43]:
```
grid.best_score_
```

[43]:
```
0.7502315477044867
```

[44]:
```
dt_model_tunned = grid.best_estimator_
```

[45]:
```
y_train_prediction2 =dt_model_tunned.predict(X_train)
y_predicted2 =dt_model_tunned.predict(X_test)
```

[46]:
```
# train results
print(mean_squared_error(y_train, y_train_prediction2))
print(r2_score(y_train, y_train_prediction2))
print( mean_absolute_error(y_train, y_train_prediction2))
print( root_mean_squared_error(y_train, y_train_prediction2))
```

```
103383.40218321918
0.7510291635406172
205.53852739726028
321.5328944030753
```

[47]:
```
# test results

print(mean_squared_error(y_test, y_predicted2))
print(r2_score(y_test, y_predicted2))
print(mean_absolute_error(y_test, y_predicted2))
print( root_mean_squared_error(y_test, y_predicted2))
```

```
108667.37428652968
0.7403548164799213
207.33533105022832
329.6473483687222
```

#RANDOM REGRESSOR

[48]:
```
reg = RandomForestRegressor(criterion='squared_error', max_leaf_nodes=25,␣
 ↪random_state=0)
reg.fit(X_train, y_train)
```

[48]: RandomForestRegressor(max_leaf_nodes=25, random_state=0)

[49]:
```
y_predicted1 = reg.predict(X_test)
y_train_prediction1 = reg.predict(X_train)
```

[50]:
```
#TEST RESULT
print(mean_squared_error(y_test, y_predicted1))
print(r2_score(y_test, y_predicted1))
print(mean_absolute_error(y_test, y_predicted1))
print(root_mean_squared_error(y_test, y_predicted1))
```

```
85796.80872060338
0.795000769164075
199.7319376231824
292.9109228427704
```

[51]:
```
#TRAIN RESULT
print(mean_squared_error(y_train, y_train_prediction1))
print(r2_score(y_train, y_train_prediction1))
print(mean_absolute_error(y_train, y_train_prediction1))
print(root_mean_squared_error(y_train, y_train_prediction1))
```

```
77600.7997196457
0.8131195568329513
191.77284840191143
278.56920095309476
```

- From evaluation metrics result we can conclude our model is overfitting • We need to do hyperparameter tunning to prevent overfitting Cross-validation using GridSearch

[52]:
```
# Setting the parameters to tune

# Number of trees
n_estimators = list(np.arange(80,200,20,dtype='int64'))

# Maximum depth of trees
max_depth = list(np.arange(12,30,2,dtype='int64'))

# HYperparameter Grid
param_dict1 = {'n_estimators' : n_estimators,
              'max_depth' : max_depth}
```

[ ]:
```

```

[53]:
```
rf_random = GridSearchCV(estimator=reg,param_grid= param_dict1,cv = 5,n_jobs=-1)
rf_random.fit(X_train,y_train)
```

[53]: GridSearchCV(cv=5,
             estimator=RandomForestRegressor(max_leaf_nodes=25, random_state=0),
             n_jobs=-1,
             param_grid={'max_depth': [12, 14, 16, 18, 20, 22, 24, 26, 28],
                         'n_estimators': [80, 100, 120, 140, 160, 180]})

[54]:
```
rf_random.best_score_
```

[54]: 0.7991689153496643

[55]:
```
rf_model_tunned = rf_random.best_estimator_
```

[56]:
```
y_train_prediction2 = rf_model_tunned.predict(X_train)
y_predicted2 = rf_model_tunned.predict(X_test)
```

[57]:
```
# train results

print( mean_squared_error(y_train, y_train_prediction2))
print(r2_score(y_train, y_train_prediction2))
print( mean_absolute_error(y_train, y_train_prediction2))
print(root_mean_squared_error(y_train, y_train_prediction2))
```

```
77109.84039903947
0.8143018989704468
191.29197361101134
277.686586638677
```

[58]:
```
# test results
print( mean_squared_error(y_test, y_predicted2))
print(r2_score(y_test, y_predicted2))
print( mean_absolute_error(y_test, y_predicted2))
print( root_mean_squared_error(y_test, y_predicted2))
```

```
85144.54841046767
0.7965592520945772
199.32218974995013
291.79538791843106
```

#***XGBOOST REGRESSOR**

[59]:
```
pip install xgboost
```

```
Requirement already satisfied: xgboost in c:\users\admin\appdata\local\packages\
pythonsoftwarefoundation.python.3.11_qbz5n2kfra8p0\localcache\local-
packages\python311\site-packages (2.0.3)
Requirement already satisfied: numpy in c:\users\admin\appdata\local\packages\py
thonsoftwarefoundation.python.3.11_qbz5n2kfra8p0\localcache\local-
packages\python311\site-packages (from xgboost) (1.26.4)
```

```
Requirement already satisfied: scipy in c:\users\admin\appdata\local\packages\py
thonsoftwarefoundation.python.3.11_qbz5n2kfra8p0\localcache\local-
packages\python311\site-packages (from xgboost) (1.13.0)
Note: you may need to restart the kernel to use updated packages.
```

[60]:
```
from xgboost import XGBRFRegressor
```

[61]:
```
xgb_model=XGBRFRegressor(random_state=0,n_jobs=-1)
xgb_model.fit(X_train,y_train)
```

[61]:
```
XGBRFRegressor(base_score=None, booster=None, callbacks=None,
               colsample_bylevel=None, colsample_bytree=None, device=None,
               early_stopping_rounds=None, enable_categorical=False,
               eval_metric=None, feature_types=None, gamma=None,
               grow_policy=None, importance_type=None,
               interaction_constraints=None, max_bin=None,
               max_cat_threshold=None, max_cat_to_onehot=None,
               max_delta_step=None, max_depth=None, max_leaves=None,
               min_child_weight=None, missing=nan, monotone_constraints=None,
               multi_strategy=None, n_estimators=None, n_jobs=-1,
               num_parallel_tree=None, objective='reg:squarederror',
               random_state=0, reg_alpha=None, …)
```

[62]:
```
y_predicted2 = reg.predict(X_test)
y_train_prediction2 = reg.predict(X_train)
```

[63]:
```
print(mean_squared_error(y_test, y_predicted2))
print(r2_score(y_test, y_predicted2))
print(mean_absolute_error(y_test, y_predicted2))
print(root_mean_squared_error(y_test, y_predicted2))
```

```
85796.80872060338
0.795000769164075
199.7319376231824
292.9109228427704
```

[64]:
```
print(mean_squared_error(y_train, y_train_prediction2))
print(r2_score(y_train, y_train_prediction2))
print(mean_absolute_error(y_train, y_train_prediction2))
print(root_mean_squared_error(y_train, y_train_prediction2))
```

```
77600.7997196457
0.8131195568329513
191.77284840191143
278.56920095309476
```

From evaluation metrics result we can conclude our model is underfitting • We need to do hyper-parameter tunning to prevent underfitting Cross-validation using GridSearch

[65]:
```
# Number of trees
n_estimators = list(np.arange(5,15,2,dtype='int64'))

# Maximum depth of trees
max_depth = list(np.arange(10,20,1,dtype='int64'))

# learning rate
learning_rate=list(np.arange(0.05,0.15,0.01))

# gamma
gamma=list(np.linspace(10,20,num=20))

# subsamples
subsample=[0.3,0.5,0.6]

# HYperparameter Grid
param_dict1 = {'n_estimators' : n_estimators,
              'max_depth' : max_depth,
               'gamma':gamma,
               'subsample':subsample,
               'learning_rate':learning_rate}
```

[66]:
```
xgb_random = RandomizedSearchCV(estimator=xgb_model,param_distributions =␣
 ↪param_dict1,cv = 5,n_jobs=-1,random_state=12)
xgb_random.fit(X_train,y_train)
```

[66]:
```
RandomizedSearchCV(cv=5,
                   estimator=XGBRFRegressor(base_score=None, booster=None,
                                            callbacks=None,
                                            colsample_bylevel=None,
                                            colsample_bytree=None, device=None,
                                            early_stopping_rounds=None,
                                            enable_categorical=False,
                                            eval_metric=None,
                                            feature_types=None, gamma=None,
                                            grow_policy=None,
                                            importance_type=None,
                                            interaction_constraints=None,
                                            max_bin=None,
                                            max_cat_threshold=Non…
                                                  17.36842105263158,
                                                  17.894736842105264,
                                                  18.421052631578945,
                                                  18.94736842105263,
                                                  19.473684210526315, 20.0],
                                        'learning_rate': [0.05,
                                                          0.060000000000000005,
```

```
                                                    0.07,
                                                    0.08000000000000002,
                                                    0.09000000000000001,
                                                    0.1,
                                                    0.11000000000000001,
                                                    0.12000000000000001,
                                                    0.13, 0.14],
                                  'max_depth': [10, 11, 12, 13, 14, 15,
                                                16, 17, 18, 19],
                                  'n_estimators': [5, 7, 9, 11, 13],
                                  'subsample': [0.3, 0.5, 0.6]},
                   random_state=12)
```

[67]:
```
xgb_random.best_estimator_
```

[67]:
```
XGBRFRegressor(base_score=None, booster=None, callbacks=None,
               colsample_bylevel=None, colsample_bytree=None, device=None,
               early_stopping_rounds=None, enable_categorical=False,
               eval_metric=None, feature_types=None, gamma=12.105263157894736,
               grow_policy=None, importance_type=None,
               interaction_constraints=None, learning_rate=0.14, max_bin=None,
               max_cat_threshold=None, max_cat_to_onehot=None,
               max_delta_step=None, max_depth=13, max_leaves=None,
               min_child_weight=None, missing=nan, monotone_constraints=None,
               multi_strategy=None, n_estimators=13, n_jobs=-1,
               num_parallel_tree=None, objective='reg:squarederror',
               random_state=0, …)
```

[68]:
```
xgb_random.best_score_
```

[68]:
```
0.22151846133825778
```

[69]:
```
xgb_model_tunned = xgb_random.best_estimator_
```

[72]:
```
y_train_prediction2 = xgb_model_tunned.predict(X_train)
y_predicted2 = xgb_model_tunned.predict(X_test)
```

[75]:
```
# train results

print( mean_squared_error(y_train, y_train_prediction2))
print(r2_score(y_train, y_train_prediction2))
print( mean_absolute_error(y_train, y_train_prediction2))
print( root_mean_squared_error(y_train, y_train_prediction2))
```

```
315844.0674950709
0.23937537347029325
451.8844554500493
```

```
562.0000600489923
```

[76]:
```python
# test results

print( mean_squared_error(y_test, y_predicted2))
print(r2_score(y_test, y_predicted2))
print( mean_absolute_error(y_test, y_predicted2))
print(root_mean_squared_error(y_test, y_predicted2))
```

```
324480.7585626313
0.22469953232161322
458.67157449243274
569.6321256413048
```

Conclusion

After having experimented two machine learning algorithms namely; Decision Tree, Random forest and Xgboost, we can say that the best performance is given by Random Fprest model with r2_score of 0.81 and 0.79 for training and test set respectively using RandomSearch. The best hyperparameter values are:

We have come to an end of our long exercise. Throughout the analysis we went through various steps to determine our predictions for bike rent demand. We started with simple EDA where we analysed our dependent variable as well as other independent variables. We found out the correlation, count, relationships with the dependent variable. We looked for missing values and outliers and did some feature modifications.

Finally we implemented 3 machine learning algorithms namely; DecisionTree, RandomForest and XGBoost. We tried hyperparameter tuning to reduce overfitting and increase model performance. The best performance was given by our RandomForest model.

The r2_score of our best model was 0.81 and 0.79 for training and test set respectively. Performance can be improved even further by applying fine tunings and gathering more amount of observations so that the models can identify more patterns and become less prone to overfitting. With evolution of new technology, these numbers can change in future hence there will always be a need to check on the model from time to time. I hope this exercise will help you to take a step forward!