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LR-Bike-Sharing / Nov 28 Linear Regression Bike Sharing.ipynb

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1 contributor

2.46 MB

Problem Statement

A bike-sharing system is a service in which bikes are made available for shared use to individuals on a short term basis for a price or free. Many bike share systems allow people to borrow a bike from a "dock" which is usually computer-controlled wherein the user enters the payment information, and the system unlocks it. This bike can then be returned to another dock belonging to the same system.

A US bike-sharing provider BoomBikes has recently suffered considerable dips in their revenues due to the ongoing Corona pandemic. The company is finding it very difficult to sustain in the current market scenario. So, it has decided to come up with a mindful business plan to be able to accelerate its revenue as soon as the ongoing lockdown comes to an end, and the economy restores to a healthy state.

In such an attempt, BoomBikes aspires to understand the demand for shared bikes among the people after this ongoing quarantine situation ends across the nation due to Covid-19. They have planned this to prepare themselves to cater to the people's needs once the situation gets better all around and stand out from other service providers and make huge profits.

They have contracted a consulting company to understand the factors on which the demand for these shared bikes depends. Specifically, they want to understand the factors affecting the demand for these shared bikes in the American market. The company wants to know:

Which variables are significant in predicting the demand for shared bikes. How well those variables describe the bike demands Based on various meteorological surveys and people's styles, the service provider firm has gathered a large dataset on daily bike demands across the American market based on some factors.

Business Goal: You are required to model the demand for shared bikes with the available independent variables. It will be used by the management to understand how exactly the demands vary with different features. They can accordingly manipulate the business strategy to meet the demand levels and meet the customer's expectations. Further, the model will be a good way for management to understand the demand dynamics of a new market.

Data Preparation:

You can observe in the dataset that some of the variables like 'weathersit' and 'season' have values as 1, 2, 3, 4 which have specific labels associated with them (as can be seen in the data dictionary). These numeric values associated with the labels may indicate that there is some order to them - which is actually not the case (Check the data dictionary and think why). So, it is advisable to convert such feature values into categorical string values before proceeding with model building. Please refer the data dictionary to get a better understanding of all the independent variables.

You might notice the column 'yr' with two values 0 and 1 indicating the years 2018 and 2019 respectively. At the first instinct, you might think it is a good idea to drop this column as it only has two values so it might not be a value-add to the model. But in reality, since these bike-sharing systems are slowly gaining popularity, the demand for these bikes is increasing every year proving that the column 'yr' might be a good variable for prediction. So think twice before dropping it.

Model Building

In the dataset provided, you will notice that there are three columns named 'casual', 'registered', and 'cnt'. The variable 'casual' indicates the number casual users who have made a rental. The variable 'registered' on the other hand shows the total number of registered users who have made a booking on a given day. Finally, the 'cnt' variable indicates the total number of bike rentals, including both casual and registered. The model should be built taking this 'cnt' as the target variable.

Step 1: Reading and Understanding the Data

Let us first import NumPy and Pandas and read the housing dataset

In [2]:
```
#supress warnings
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [4]:
```
df=pd.read_csv("day.csv")
```

In [5]:
```
df.isna().sum()
```

Out[5]:
```
instant       0
dteday        0
season        0
yr            0
mnth          0
holiday       0
weekday       0
workingday    0
weathersit    0
temp          0
atemp         0
hum           0
windspeed     0
casual        0
registered    0
cnt           0
dtype: int64
```

In [6]:

```
(df.isna().sum()).sum()
```

Out[6]: 0

In [7]:

```
#No of unique values
df.nunique()
```

Out[7]:

```
instant       730
dteday        730
season          4
yr              2
mnth           12
holiday         2
weekday         7
workingday      2
weathersit      3
temp          498
atemp         689
hum           594
windspeed     649
casual        605
registered    678
cnt           695
dtype: int64
```

In [8]:

```
df.head()
```

Out[8]:

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	
0	1	01-01-2018	1	0	1	0	1	1	2	14.1
1	2	02-01-2018	1	0	1	0	2	1	2	14.9(
2	3	03-01-2018	1	0	1	0	3	1	1	8.0!
3	4	04-01-2018	1	0	1	0	4	1	1	8.2(
4	5	05-01-2018	1	0	1	0	5	1	1	9.3(

In [9]:

```
df=df.drop(columns=['instant', 'dteday'])
df.drop(['casual','registered'],axis=1,inplace=True)
#since Instant is jst index, dteday is redundant as details are given in
#here i have used both ways to delete, for personal practice
df.head()
```

Out[9]:

	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp
0	1	0	1	0	1	1	2	14.110847	18.18125
1	1	0	1	0	2	1	2	14.902598	17.68695
2	1	0	1	0	3	1	1	8.050924	9.47025
3	1	0	1	0	4	1	1	8.200000	10.60610

4	1	0	1	0	5	1	1	9.305237	11.46350

In [10]:

```
df.shape
```

Out[10]: (730, 12)

In [11]:

```
df[['season']]=df[['season']].apply(lambda x: x.map ({1:"spring",2:"summe
# or df['season'].replace({1:"spring",2:"summer",3:"fall",4:"winter"},inp
```

In [12]:

```
# Other way
df['weathersit'].replace({1:"Clear_Few Clouds",2:"Mist_cloudy",3:"Light r
```

In [13]:

```
# by Defining the map function
def binary_map(x):
    return x.map({0:"Sunday",1:"Monday",2:"Tuesday",3:"Wednesday",4:"Thur

# Applying the function to the housing list
df[['weekday']] = df[['weekday']].apply(binary_map)
```

In [14]:

```
df.head()
```

Out[14]:

	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp
0	spring	0	1	0	Monday	1	Mist_cloudy	14.110847	18.18125
1	spring	0	1	0	Tuesday	1	Mist_cloudy	14.902598	17.68695
2	spring	0	1	0	Wednesday	1	Clear_Few Clouds	8.050924	9.47025
3	spring	0	1	0	Thursday	1	Clear_Few Clouds	8.200000	10.6061(
4	spring	0	1	0	Friday	1	Clear_Few Clouds	9.305237	11.4635(

In [15]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   season      730 non-null    object
 1   yr          730 non-null    int64
 2   mnth        730 non-null    int64
 3   holiday     730 non-null    int64
 4   weekday     730 non-null    object
 5   workingday  730 non-null    int64
 6   weathersit  730 non-null    object
 7   temp        730 non-null    float64
 8   atemp       730 non-null    float64
 9   hum         730 non-null    float64
 10  windspeed   730 non-null    float64
```

```
 11  cnt         730 non-null    int64
dtypes: float64(4), int64(5), object(3)
memory usage: 68.6+ KB
```

In [16]:

```
#changing datatypes of numerical columns to appropriate types

df[['temp','atemp','hum','windspeed','cnt']]=df[['temp','atemp','hum','wi
#This function will try to change non-numeric objects (such as strings) i
df.head()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   season      730 non-null    object
 1   yr          730 non-null    int64
 2   mnth        730 non-null    int64
 3   holiday     730 non-null    int64
 4   weekday     730 non-null    object
 5   workingday  730 non-null    int64
 6   weathersit  730 non-null    object
 7   temp        730 non-null    float64
 8   atemp       730 non-null    float64
 9   hum         730 non-null    float64
 10  windspeed   730 non-null    float64
 11  cnt         730 non-null    int64
dtypes: float64(4), int64(5), object(3)
memory usage: 68.6+ KB
```

In [17]:

```
df.describe()
```

Out[17]:

	yr	mnth	holiday	workingday	temp	atemp	h
count	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.00(
mean	0.500000	6.526027	0.028767	0.690411	20.319259	23.726322	62.765
std	0.500343	3.450215	0.167266	0.462641	7.506729	8.150308	14.237
min	0.000000	1.000000	0.000000	0.000000	2.424346	3.953480	0.00(
25%	0.000000	4.000000	0.000000	0.000000	13.811885	16.889713	52.00(
50%	0.500000	7.000000	0.000000	1.000000	20.465826	24.368225	62.625
75%	1.000000	10.000000	0.000000	1.000000	26.880615	30.445775	72.98
max	1.000000	12.000000	1.000000	1.000000	35.328347	42.044800	97.25(

In [18]:

```
df.columns
```

Out[18]:

```
Index(['season', 'yr', 'mnth', 'holiday', 'weekday', 'workingday',
       'weathersit', 'temp', 'atemp', 'hum', 'windspeed', 'cnt'],
      dtype='object')
```

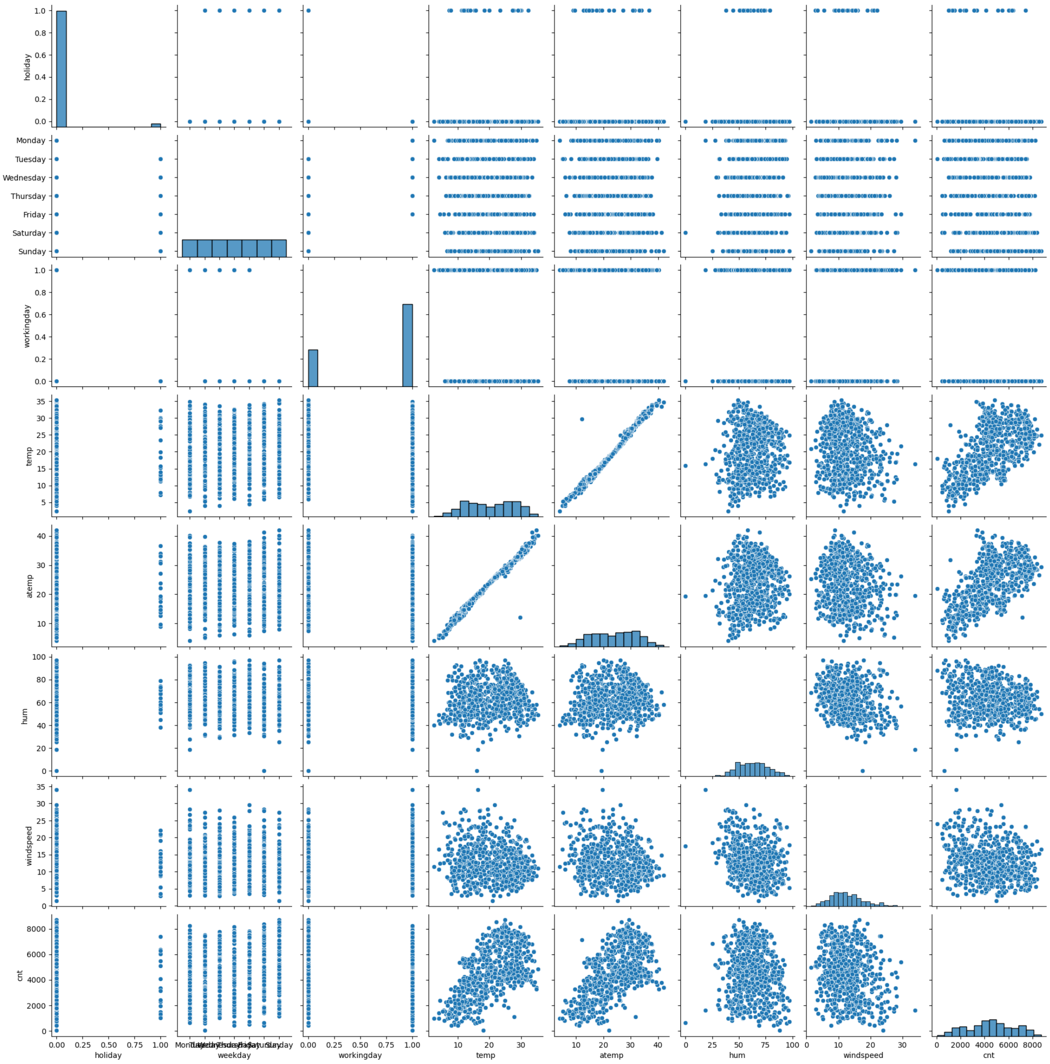
Step 2: Visualising the Data

In [19]:

```
plt.figure(figsize = (16, 10))
```

```
sns.pairplot(df,vars=['holiday', 'weekday', 'workingday','temp', 'atemp',
plt.show()
```

<Figure size 1600x1000 with 0 Axes>



In [20]:

```
df.corr()
```

Out[20]:

	yr	mnth	holiday	workingday	temp	atemp
yr	1.000000e+00	-5.162656e-16	0.008195	-0.011852	0.048789	0.047215
mnth	-5.162656e-16	1.000000e+00	0.018905	-0.010414	0.219083	0.226430
holiday	8.195345e-03	1.890483e-02	1.000000	-0.257009	-0.028764	-0.032703
workingday	-1.185197e-02	-1.041372e-02	-0.257009	1.000000	0.002044	0.010657
temp	4.878919e-02	2.190833e-01	-0.028764	0.002044	1.000000	0.991696
atemp	4.721519e-02	2.264302e-01	-0.032703	0.010657	0.991696	1.000000
hum	-1.125471e-01	2.249368e-01	-0.015662	0.053770	0.128565	0.141512
windspeed	-1.162435e-02	-2.080131e-01	0.006257	-0.002453	-0.158186	-0.183876
cnt	5.697285e-01	2.781909e-01	-0.068764	-0.027640	0.627044	0.630685

In [21]:
```
plt.figure(figsize = (16, 10))
sns.heatmap(df.corr(),annot=True)
plt.show()
```

from above chart it is visible that corilation between temp i.e temperature in Celsius and atemp: feeling temperature in Celsius is 0.99 which is very high that means they are inter-dependant variables. Hence we will drop any one of them.

In [22]:
```
df.drop(["temp"],axis=1,inplace=True)
df.head(3)
```

Out[22]:

	season	yr	mnth	holiday	weekday	workingday	weathersit	atemp	hum
0	spring	0	1	0	Monday	1	Mist_cloudy	18.18125	80.5833
1	spring	0	1	0	Tuesday	1	Mist_cloudy	17.68695	69.6087
2	spring	0	1	0	Wednesday	1	Clear_Few Clouds	9.47025	43.7273

Visualising Categorical Variables

As you might have noticed, there are a few categorical variables as well. Let's make a boxplot for some of these variables.

In [23]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype
```

```
 ---  ------      --------------  -----
 0    season      730 non-null    object
 1    yr          730 non-null    int64
 2    mnth        730 non-null    int64
 3    holiday     730 non-null    int64
 4    weekday     730 non-null    object
 5    workingday  730 non-null    int64
 6    weathersit  730 non-null    object
 7    atemp       730 non-null    float64
 8    hum         730 non-null    float64
 9    windspeed   730 non-null    float64
 10   cnt         730 non-null    int64
dtypes: float64(3), int64(5), object(3)
memory usage: 62.9+ KB
```

In [24]:

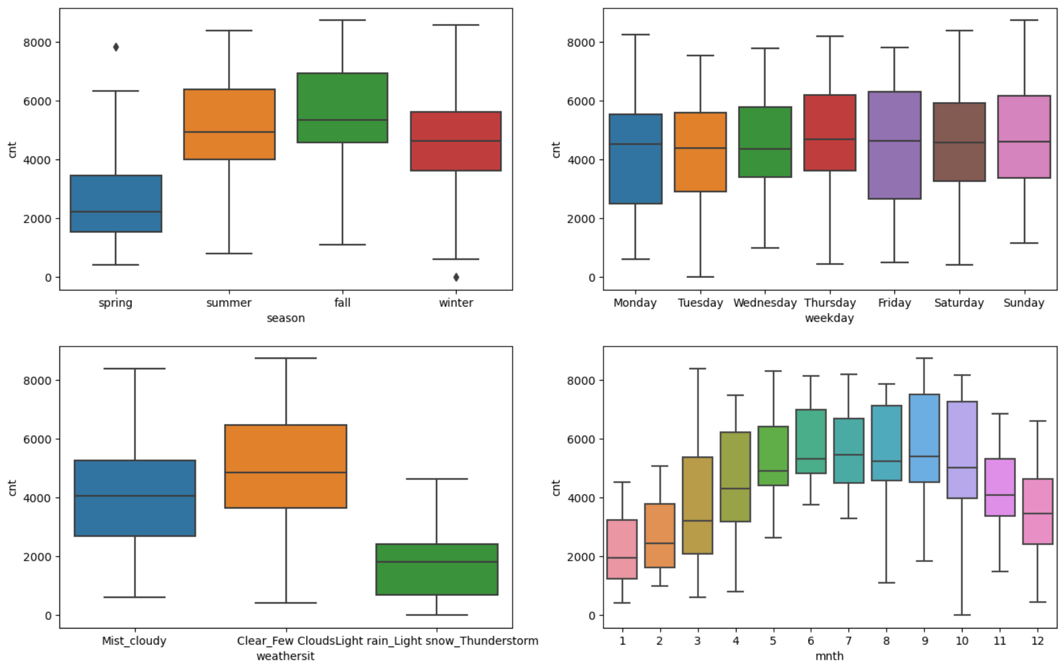
```
df.columns
```

Out[24]:

```
Index(['season', 'yr', 'mnth', 'holiday', 'weekday', 'workingday',
       'weathersit', 'atemp', 'hum', 'windspeed', 'cnt'],
      dtype='object')
```

In [25]:

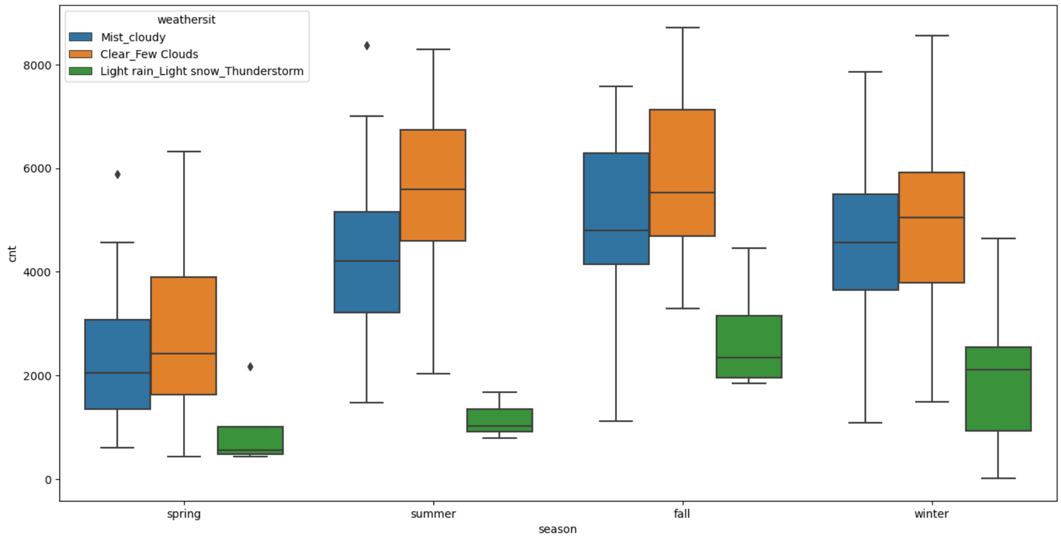
```
plt.figure(figsize=(16, 10))
plt.subplot(2,2,1)
sns.boxplot(x='season',y='cnt',data=df)
plt.subplot(2,2,2)
sns.boxplot(x='weekday',y='cnt',data=df)
plt.subplot(2,2,3)
sns.boxplot(x='weathersit',y='cnt',data=df)
plt.subplot(2,2,4)
sns.boxplot(x='mnth',y='cnt',data=df)
plt.show()
```



We can also visualise some of these categorical features parallely by using the hue argument. Below is the plot for furnishingstatus with airconditioning as the hue.

In [26]:

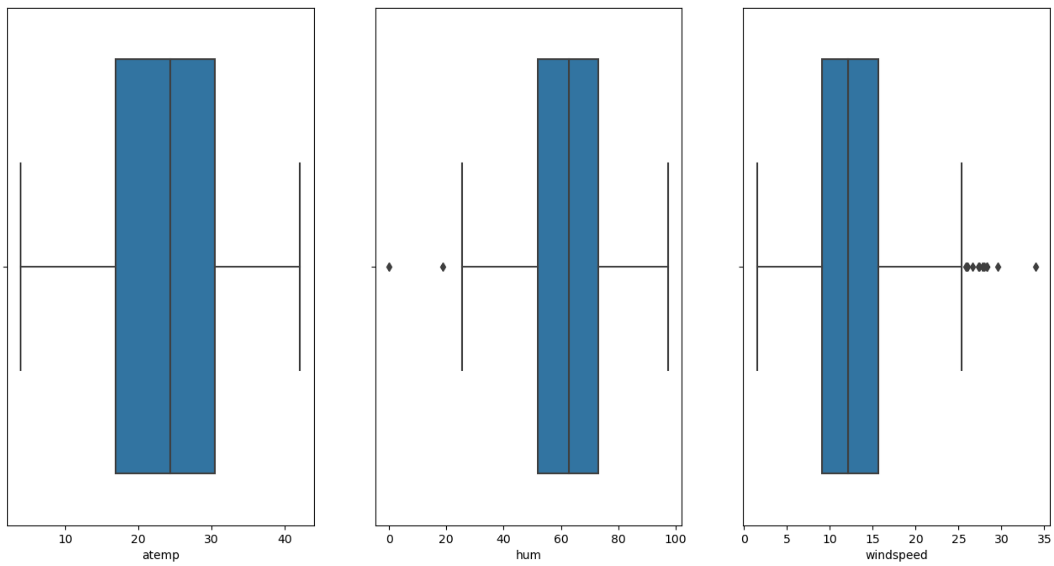
```
plt.figure(figsize = (16, 8))
sns.boxplot(x = 'season', y = 'cnt', hue = 'weathersit', data = df)
plt.show()
```



Dealing with Outliers

In [27]:

```
plt.figure(figsize = (16, 8))
plt.subplot(1,3,1)
sns.boxplot(df['atemp'])
plt.subplot(1,3,2)
sns.boxplot(df['hum'])
plt.subplot(1,3,3)
sns.boxplot(df['windspeed'])
plt.show()
```



In [28]:

```
df = df.drop(index = df[(df['windspeed'] > 30)].index)
df = df.drop(index = df[(df['hum'] < 20)].index)
```

In [29]:

```
df.shape
```

Out[29]: (728, 11)

Data Preparation

In [30]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 728 entries, 0 to 729
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   season      728 non-null    object 
 1   yr          728 non-null    int64  
 2   mnth        728 non-null    int64  
 3   holiday     728 non-null    int64  
 4   weekday     728 non-null    object 
 5   workingday  728 non-null    int64  
 6   weathersit  728 non-null    object 
 7   atemp       728 non-null    float64
 8   hum         728 non-null    float64
 9   windspeed   728 non-null    float64
 10  cnt         728 non-null    int64  
dtypes: float64(3), int64(5), object(3)
memory usage: 68.2+ KB
```

In [31]:

```
#Converting variables to object type
df['mnth']=df['mnth'].astype(object)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 728 entries, 0 to 729
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   season      728 non-null    object 
 1   yr          728 non-null    int64  
 2   mnth        728 non-null    object 
 3   holiday     728 non-null    int64  
 4   weekday     728 non-null    object 
 5   workingday  728 non-null    int64  
 6   weathersit  728 non-null    object 
 7   atemp       728 non-null    float64
 8   hum         728 non-null    float64
 9   windspeed   728 non-null    float64
 10  cnt         728 non-null    int64  
dtypes: float64(3), int64(4), object(4)
memory usage: 68.2+ KB
```

Dummy variables

In [32]:

```
d1 = pd.get_dummies(df['season'], drop_first = True)
d2 = pd.get_dummies(df['mnth'], drop_first = True)
d3=pd.get_dummies(df["weekday"], drop_first=True)
d4=pd.get_dummies(df["weathersit"],drop_first=True)
```

In [33]:

```
df=pd.concat([df,d1,d3,d4,d2],axis=1)
```

In [34]:

```
df=df.drop(columns=['season','weekday','weathersit','mnth'])
df.head()
```

Out[34]:

	yr	holiday	workingday	atemp	hum	windspeed	cnt	spring	summer	wint
0	0	0	1	18.18125	80.5833	10.749882	985	1	0	
1	0	0	1	17.68695	69.6087	16.652113	801	1	0	

2	0	0	1	9.47025	43.7273	16.636703	1349	1	0
3	0	0	1	10.60610	59.0435	10.739832	1562	1	0
4	0	0	1	11.46350	43.6957	12.522300	1600	1	0

5 rows × 29 columns

Splitting the Data into Training and Testing Sets

In [35]:
```
from sklearn.model_selection import train_test_split
```

In [36]:
```
df_train, df_test = train_test_split(df,train_size=0.8,random_state=20)
```

In [37]:
```
df_train.shape
```

Out[37]:
```
(582, 29)
```

In [38]:
```
df_train.columns
```

Out[38]:
```
Index([                                 'yr',
                                   'holiday',
                                'workingday',
                                     'atemp',
                                       'hum',
                                 'windspeed',
                                       'cnt',
                                    'spring',
                                    'summer',
                                    'winter',
                                    'Monday',
                                  'Saturday',
                                    'Sunday',
                                  'Thursday',
                                   'Tuesday',
                                 'Wednesday',
       'Light rain_Light snow_Thunderstorm',
                                'Mist_cloudy',
                                           2,
                                           3,
                                           4,
                                           5,
                                           6,
                                           7,
                                           8,
                                           9,
                                          10,
                                          11,
                                          12],
      dtype='object')
```

Rescaling the Features

We will use MinMax scaling.

In [39]:
```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
```

In [40]:
```
num_vars=['atemp','hum','windspeed','cnt']
df_train[num_vars]=scaler.fit_transform(df_train[num_vars])
df_train.head()
```

Out[40]:

	yr	holiday	workingday	atemp	hum	windspeed	cnt	spring	summe
591	1	0	1	0.754722	0.508700	0.351597	0.834963	0	
294	0	0	1	0.454726	0.522042	0.167652	0.468067	0	
207	0	0	1	0.802804	0.207077	0.384261	0.510081	0	
253	0	0	1	0.695906	0.639791	0.221061	0.557165	0	
405	1	0	0	0.281545	0.397912	0.225534	0.410479	1	

5 rows × 29 columns

In [41]:
```
df_train.describe()
```

Out[41]:

	yr	holiday	workingday	atemp	hum	windspeed	
count	582.000000	582.000000	582.000000	582.000000	582.000000	582.000000	582.00
mean	0.498282	0.027491	0.689003	0.522913	0.524668	0.396548	0.491
std	0.500427	0.163651	0.463300	0.214666	0.198397	0.181852	0.231
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
25%	0.000000	0.000000	0.000000	0.340567	0.373840	0.267066	0.33
50%	0.000000	0.000000	1.000000	0.543405	0.515081	0.373142	0.49
75%	1.000000	0.000000	1.000000	0.698389	0.667343	0.497535	0.66
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.00

8 rows × 29 columns

Dividing into X and Y sets for the model building

In [42]:
```
y_train=df_train.pop("cnt")
X_train=df_train
```

In [43]:
```
X_train.head()
```

Out[43]:

	yr	holiday	workingday	atemp	hum	windspeed	spring	summer	winter
591	1	0	1	0.754722	0.508700	0.351597	0	0	0
294	0	0	1	0.454726	0.522042	0.167652	0	0	1

207	0	0	1	0.802804	0.207077	0.384261	0	0	0
253	0	0	1	0.695906	0.639791	0.221061	0	0	0
405	1	0	0	0.281545	0.397912	0.225534	1	0	0

5 rows × 28 columns

In [44]:

```
y_train.head()
```

Out[44]:

```
591    0.834963
294    0.468067
207    0.510081
253    0.557165
405    0.410479
Name: cnt, dtype: float64
```

Building our model

We will be using the LinearRegression function from SciKit Learn for its compatibility with RFE (Recursive feature elimination)

In [45]:

```
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
```

In [46]:

```
lm=LinearRegression()
lm.fit(X_train,y_train)

rfe=RFE(lm,n_features_to_select=15, step=1, verbose=0, importance_getter=
#or rfe=RFE(lm)
rfe=rfe.fit(X_train,y_train)
```

In [47]:

```
list(zip(X_train.columns,rfe.support_,rfe.ranking_))
```

Out[47]:

```
[('yr', True, 1),
 ('holiday', True, 1),
 ('workingday', False, 3),
 ('atemp', True, 1),
 ('hum', True, 1),
 ('windspeed', True, 1),
 ('spring', True, 1),
 ('summer', False, 14),
 ('winter', True, 1),
 ('Monday', False, 8),
 ('Saturday', False, 4),
 ('Sunday', False, 5),
 ('Thursday', False, 13),
 ('Tuesday', False, 9),
 ('Wednesday', False, 10),
 ('Light rain_Light snow_Thunderstorm', True, 1),
 ('Mist_cloudy', False, 2),
 (2, False, 6),
 (3, True, 1),
 (4, True, 1),
 (5, True, 1),
 (6, True, 1)
```

```
 (6, True, 1),
 (7, False, 7),
 (8, True, 1),
 (9, True, 1),
 (10, True, 1),
 (11, False, 12),
 (12, False, 11)]
```

In [48]:

```python
# RFE Feature Ranking
rfe_ranking = pd.DataFrame({'features' : X_train.columns,'rank' : rfe.ran
rfe_ranking
```

Out[48]:

	features	rank	support
0	yr	1	True
19	4	1	True
18	3	1	True
15	Light rain_Light snow_Thunderstorm	1	True
23	8	1	True
24	9	1	True
20	5	1	True
8	winter	1	True
21	6	1	True
6	spring	1	True
5	windspeed	1	True
4	hum	1	True
3	atemp	1	True
1	holiday	1	True
25	10	1	True
16	Mist_cloudy	2	False
2	workingday	3	False
10	Saturday	4	False
11	Sunday	5	False
17	2	6	False
22	7	7	False
9	Monday	8	False
13	Tuesday	9	False
14	Wednesday	10	False
27	12	11	False
26	11	12	False
12	Thursday	13	False
7	summer	14	False

In [49]:

In [49]:
```
col=X_train.columns[rfe.support_]
col

#"""OR Coll = rfe_ranking.loc[rfe_ranking['rank'] == 1 & 2,'features'].va
```

Out[49]:
```
Index([                              'yr',
                                'holiday',
                                  'atemp',
                                    'hum',
                              'windspeed',
                                 'spring',
                                 'winter',
       'Light rain_Light snow_Thunderstorm',
                                        3,
                                        4,
                                        5,
                                        6,
                                        8,
                                        9,
                                       10],
      dtype='object')
```

In [50]:
```
X_train.columns[~rfe.support_]
```

Out[50]:
```
Index([ 'workingday',      'summer',      'Monday',    'Saturday',
           'Sunday',    'Thursday',     'Tuesday',   'Wednesday',
       'Mist_cloudy',             2,             7,            11,
                  12],
      dtype='object')
```

Building model using statsmodel, for the detailed statistics

In [51]:
```
# Creating X_train dataframe with RFE selected variables
X_train_rfe = X_train[col]
```

In [52]:
```
#adding constant variable
import statsmodels.api as sm
X_train_rfe1=sm.add_constant(X_train_rfe)
```

In [53]:
```
# Running the linear model
lm=sm.OLS(y_train,X_train_rfe1).fit()
```

In [54]:
```
#summary of our linear model
print(lm.summary())
```

```
                            OLS Regression Results
==========================================================================
=====
Dep. Variable:                    cnt   R-squared:
0.835
Model:                            OLS   Adj. R-squared:
0.831
Method:                 Least Squares   F-statistic:
191.1
Date:                Tue, 29 Nov 2022   Prob (F-statistic):           4.72
e-210
```

```
Time:                        22:23:22   Log-Likelihood:                    5
50.84
No. Observations:                 582   AIC:                               -
1070.
Df Residuals:                     566   BIC:                               -
999.8
Df Model:                          15
Covariance Type:            nonrobust
==========================================================================
=============================
                                          coef    std err          t
P>|t|      [0.025      0.975]
--------------------------------------------------------------------------
-----------------------------
const                                   0.2759      0.029      9.362
0.000       0.218       0.334
yr                                      0.2381      0.008     29.644
0.000       0.222       0.254
holiday                                -0.0625      0.024     -2.566
0.011      -0.110      -0.015
atemp                                   0.4931      0.033     14.897
0.000       0.428       0.558
hum                                    -0.2591      0.024    -11.023
0.000      -0.305      -0.213
windspeed                              -0.1533      0.024     -6.363
0.000      -0.201      -0.106
spring                                 -0.0923      0.019     -4.911
0.000      -0.129      -0.055
winter                                  0.0848      0.017      4.850
0.000       0.050       0.119
Light rain_Light snow_Thunderstorm    -0.1313      0.025     -5.326
0.000      -0.180      -0.083
3                                       0.0591      0.015      3.887
0.000       0.029       0.089
4                                       0.0565      0.019      2.937
0.003       0.019       0.094
5                                       0.1047      0.018      5.808
0.000       0.069       0.140
6                                       0.0554      0.018      3.099
0.002       0.020       0.091
8                                       0.0494      0.018      2.758
0.006       0.014       0.085
9                                       0.1232      0.017      7.335
0.000       0.090       0.156
10                                      0.0720      0.018      4.042
0.000       0.037       0.107
==========================================================================
=====
Omnibus:                       83.236   Durbin-Watson:
1.824
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                 15
5.046
Skew:                          -0.845   Prob(JB):                        2.1
5e-34
Kurtosis:                       4.880   Cond. No.
17.6
==========================================================================
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is co
rrectly specified.
```

In [55]:

```python
# Calculate the VIFs
```

```
from statsmodels.stats.outliers_influence import variance_inflation_facto

vif = pd.DataFrame()
X = X_train_rfe
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.sha
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[55]:

	Features	VIF
2	atemp	10.47
3	hum	9.55
4	windspeed	5.81
6	winter	2.98
5	spring	2.94
0	yr	2.03
12	8	1.75
10	5	1.72
9	4	1.68
11	6	1.67
14	10	1.60
13	9	1.48
8	3	1.33
7	Light rain_Light snow_Thunderstorm	1.26
1	holiday	1.05

In [56]:

```
X_train_rfe.columns
```

Out[56]:

```
Index([                               'yr',
                                 'holiday',
                                   'atemp',
                                     'hum',
                               'windspeed',
                                  'spring',
                                  'winter',
       'Light rain_Light snow_Thunderstorm',
                                         3,
                                         4,
                                         5,
                                         6,
                                         8,
                                         9,
                                        10],
      dtype='object')
```

In [57]:

```
# VIF for 'hum' is too high so we delete it 1st and then check rest
X_train_rfe=X_train_rfe.drop(['hum'],axis=1)
```

In [58]:

```
X_train_rfe2=sm.add_constant(X_train_rfe)
lm=sm.OLS(y_train,X_train_rfe2).fit()
print(lm.summary())
```

```
                            OLS Regression Results
==========================================================================
=====
Dep. Variable:                    cnt   R-squared:
0.800
Model:                            OLS   Adj. R-squared:
0.795
Method:                 Least Squares   F-statistic:
161.7
Date:                Tue, 29 Nov 2022   Prob (F-statistic):          2.19
e-187
Time:                        22:23:22   Log-Likelihood:                 4
94.25
No. Observations:                 582   AIC:                            -
958.5
Df Residuals:                     567   BIC:                            -
893.0
Df Model:                          14
Covariance Type:            nonrobust
==========================================================================
=============================
                                      coef    std err          t
P>|t|      [0.025      0.975]
--------------------------------------------------------------------------
-----------------------------
const                               0.1527      0.030      5.086
0.000       0.094       0.212
yr                                  0.2502      0.009     28.568
0.000       0.233       0.267
holiday                            -0.0636      0.027     -2.370
0.018      -0.116      -0.011
atemp                               0.4501      0.036     12.435
0.000       0.379       0.521
windspeed                          -0.0840      0.026     -3.280
0.001      -0.134      -0.034
spring                             -0.1102      0.021     -5.344
0.000      -0.151      -0.070
winter                              0.0563      0.019      2.956
0.003       0.019       0.094
Light rain_Light snow_Thunderstorm  -0.2334      0.025     -9.282
0.000      -0.283      -0.184
3                                   0.0523      0.017      3.127
0.002       0.019       0.085
4                                   0.0371      0.021      1.758
0.079      -0.004       0.079
5                                   0.0662      0.019      3.397
0.001       0.028       0.104
6                                   0.0595      0.020      3.019
0.003       0.021       0.098
8                                   0.0341      0.020      1.732
0.084      -0.005       0.073
9                                   0.0945      0.018      5.171
0.000       0.059       0.130
10                                  0.0666      0.020      3.398
0.001       0.028       0.105
==========================================================================
=====
Omnibus:                       95.812   Durbin-Watson:
1.878
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              18
```

```
6.510
Skew:                          -0.939   Prob(JB):                   3.1
6e-41
Kurtosis:                       5.040   Cond. No.
16.4
==========================================================================
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is co
rrectly specified.
```

We can observe that not much difference is seen in the R-squared & Adj. R-squared after deleting the column "Hum"

In [59]:

```python
vif = pd.DataFrame()
X = X_train_rfe
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.sha
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[59]:

	Features	VIF
2	atemp	6.38
3	windspeed	5.73
5	winter	2.22
4	spring	2.17
0	yr	2.01
11	8	1.72
10	6	1.66
13	10	1.60
8	4	1.56
9	5	1.55
12	9	1.42
7	3	1.31
6	Light rain_Light snow_Thunderstorm	1.09
1	holiday	1.05

In [60]:

```python
# VIF for 'atemp' is  high so we delete it and then check
df1=X_train_rfe
X_train_rfe3=df1.drop(['atemp'],axis=1)
X_train_rfe3.head()
```

Out[60]:

	yr	holiday	windspeed	spring	winter	Light rain_Light snow_Thunderstorm	3	4	5	6	8	9	1
591	1	0	0.351597	0	0	0	0	0	0	0	1	0	
294	0	0	0.167652	0	1	0	0	0	0	0	0	0	
207	0	0	0.384261	0	0	0	0	0	0	0	0	0	

253	0	0	0.221061	0	0		0	0	0	0	0	0	1
405	1	0	0.225534	1	0		0	0	0	0	0	0	0

In [61]:

```
X_train_rfe3=sm.add_constant(X_train_rfe3)
lm=sm.OLS(y_train,X_train_rfe3).fit()
print(lm.summary())
```

```
                            OLS Regression Results
==========================================================================
=====
Dep. Variable:                    cnt   R-squared:
0.745
Model:                            OLS   Adj. R-squared:
0.739
Method:                 Least Squares   F-statistic:
127.7
Date:                Tue, 29 Nov 2022   Prob (F-statistic):          6.12
e-159
Time:                        22:23:22   Log-Likelihood:                 4
24.07
No. Observations:                 582   AIC:                            -
820.1
Df Residuals:                     568   BIC:                            -
759.0
Df Model:                          13
Covariance Type:            nonrobust
==========================================================================
=============================
                                          coef    std err          t
P>|t|      [0.025      0.975]
--------------------------------------------------------------------------
-----------------------------
const                                   0.4678      0.018     25.766
0.000       0.432       0.503
yr                                      0.2583      0.010     26.231
0.000       0.239       0.278
holiday                                -0.0585      0.030     -1.937
0.053      -0.118       0.001
windspeed                              -0.1090      0.029     -3.789
0.000      -0.166      -0.053
spring                                 -0.2864      0.017    -16.952
0.000      -0.320      -0.253
winter                                 -0.0736      0.018     -4.103
0.000      -0.109      -0.038
Light rain_Light snow_Thunderstorm     -0.2564      0.028     -9.070
0.000      -0.312      -0.201
3                                       0.0382      0.019      2.028
0.043       0.001       0.075
4                                      -0.0426      0.023     -1.882
0.060      -0.087       0.002
5                                       0.0420      0.022      1.924
0.055      -0.001       0.085
6                                       0.0802      0.022      3.628
0.000       0.037       0.124
8                                       0.0661      0.022      3.004
0.003       0.023       0.109
9                                       0.1106      0.021      5.382
0.000       0.070       0.151
10                                      0.1230      0.021      5.725
0.000       0.081       0.165
```

```
0.000        0.081        0.165
==============================================================================
=====
Omnibus:                       90.793   Durbin-Watson:                  
1.868
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             17
7.549
Skew:                          -0.893   Prob(JB):                     2.7
9e-39
Kurtosis:                       5.033   Cond. No.                       
10.8
==============================================================================
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is co
rrectly specified.
```

We can observe that much difference is seen in the R-squared & Adj. R-squared after deleting the column "atemp", hence it is not advisable

Let us check the VIF and R-squared & Adj. R-squared after deleting "windspeed"

In [62]:

```
df3=X_train_rfe
X_train_rfe5=df1.drop(['windspeed'],axis=1)
X_train_rfe5.head()
```

Out[62]:

	yr	holiday	atemp	spring	winter	Light rain_Light snow_Thunderstorm	3	4	5	6	8	9	10
591	1	0	0.754722	0	0	0	0	0	0	0	1	0	0
294	0	0	0.454726	0	1	0	0	0	0	0	0	0	1
207	0	0	0.802804	0	0	0	0	0	0	0	0	0	0
253	0	0	0.695906	0	0	0	0	0	0	0	0	1	0
405	1	0	0.281545	1	0	0	0	0	0	0	0	0	0

In [63]:

```
X_train_rfe5=sm.add_constant(X_train_rfe5)
lm=sm.OLS(y_train,X_train_rfe5).fit()
print(lm.summary())
```

```
                            OLS Regression Results
==============================================================================
=====
Dep. Variable:                    cnt   R-squared:                      
0.796
Model:                            OLS   Adj. R-squared:                 
0.791
Method:                 Least Squares   F-statistic:                    
170.4
Date:                Tue, 29 Nov 2022   Prob (F-statistic):          3.29
e-186
Time:                        22:23:23   Log-Likelihood:                 4
88.78
No. Observations:                 582   AIC:                            -
949.6
Df Residuals:                     568   BIC:                            -
888.4
Df Model:                          13
Covariance Type:            nonrobust
==============================================================================
```

```
-----------------------------------------------------------------------------
============================
                                                  coef    std err          t
P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------
----------------------------
const                                           0.1168      0.028      4.143
0.000       0.061       0.172
yr                                              0.2499      0.009     28.295
0.000       0.233       0.267
holiday                                        -0.0672      0.027     -2.487
0.013      -0.120      -0.014
atemp                                           0.4594      0.036     12.624
0.000       0.388       0.531
spring                                         -0.1132      0.021     -5.448
0.000      -0.154      -0.072
winter                                          0.0595      0.019      3.102
0.002       0.022       0.097
Light rain_Light snow_Thunderstorm             -0.2444      0.025     -9.722
0.000      -0.294      -0.195
3                                               0.0470      0.017      2.797
0.005       0.014       0.080
4                                               0.0251      0.021      1.197
0.232      -0.016       0.066
5                                               0.0649      0.020      3.303
0.001       0.026       0.103
6                                               0.0576      0.020      2.901
0.004       0.019       0.097
8                                               0.0318      0.020      1.603
0.109      -0.007       0.071
9                                               0.0958      0.018      5.200
0.000       0.060       0.132
10                                              0.0677      0.020      3.428
0.001       0.029       0.107
=============================================================================
=====
Omnibus:                       99.170   Durbin-Watson:
1.903
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                  20
2.043
Skew:                          -0.950   Prob(JB):                         1.3
4e-44
Kurtosis:                       5.173   Cond. No.
15.6
=============================================================================
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is co
rrectly specified.
```

In [64]:

```
X_train_rfe=X_train_rfe.drop(['windspeed'],axis=1)
X_train_rfe.head()
```

Out[64]:

	yr	holiday	atemp	spring	winter	Light rain_Light snow_Thunderstorm	3	4	5	6	8	9	10
591	1	0	0.754722	0	0	0	0	0	0	0	1	0	0
294	0	0	0.454726	0	1	0	0	0	0	0	0	0	1
207	0	0	0.802804	0	0	0	0	0	0	0	0	0	0
253	0	0	0.695906	0	0	0	0	0	0	0	0	1	0

405	1	0	0.281545	1	0		0	0	0	0	0	0	0	0

In [65]:

```
vif = pd.DataFrame()
X = X_train_rfe
vif['Features'] = X.columns
vif['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.sha
vif['VIF'] = round(vif['VIF'], 2)
vif = vif.sort_values(by = "VIF", ascending = False)
vif
```

Out[65]:

	Features	VIF
2	atemp	5.04
0	yr	2.01
4	winter	2.00
10	8	1.70
9	6	1.64
12	10	1.59
8	5	1.51
3	spring	1.49
11	9	1.41
7	4	1.30
6	3	1.28
5	Light rain_Light snow_Thunderstorm	1.06
1	holiday	1.04

In [66]:

```
X_train_rfe.head()
```

Out[66]:

	yr	holiday	atemp	spring	winter	Light rain_Light snow_Thunderstorm	3	4	5	6	8	9	10
591	1	0	0.754722	0	0	0	0	0	0	0	1	0	0
294	0	0	0.454726	0	1	0	0	0	0	0	0	0	1
207	0	0	0.802804	0	0	0	0	0	0	0	0	0	0
253	0	0	0.695906	0	0	0	0	0	0	0	0	1	0
405	1	0	0.281545	1	0	0	0	0	0	0	0	0	0

As we can see that by removing "windspeed" the VIF for "atemp" goes down and the value of R-squared & Adj. R-squared after deleting the column is also not much affected. Hence we will keep with "atemp" while removing "windspeed"

Residual Analysis of the train data

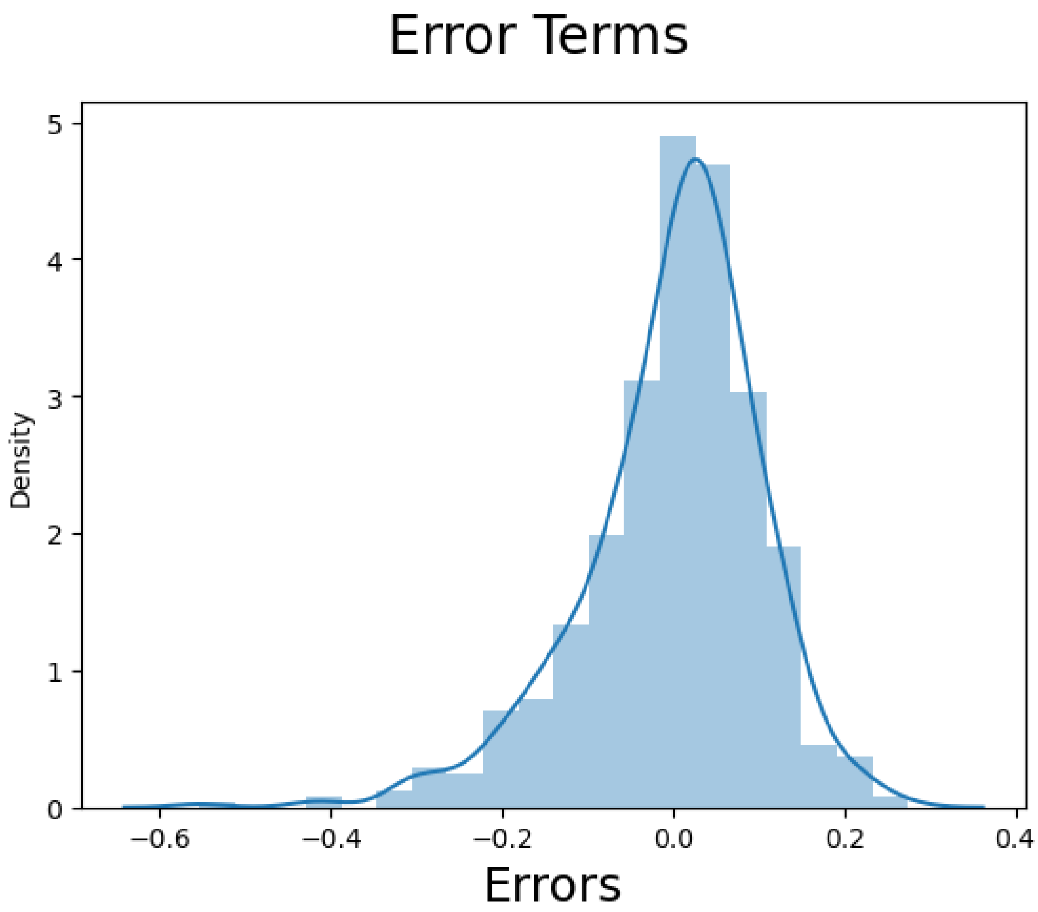
Checking if the error terms are also normally distributed.

In [67]:
```
y_train_cnt=lm.predict(X_train_rfe5)
```

In [68]:
```
# Importing the required libraries for plots.
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

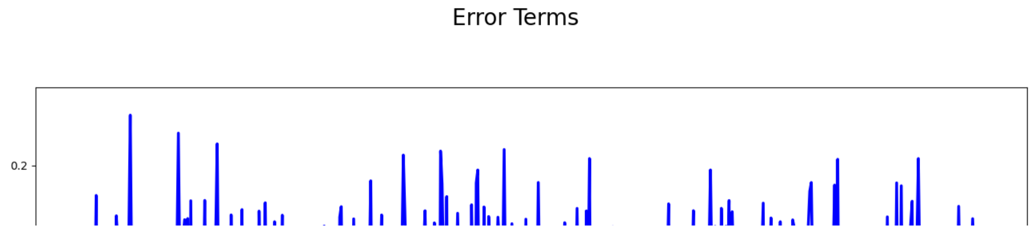
In [69]:
```
fig=plt.figure()
sns.distplot((y_train-y_train_cnt),bins=20)
fig.suptitle('Error Terms', fontsize = 20)                  # Plot headin
plt.xlabel('Errors', fontsize = 18)                         # X-label
```

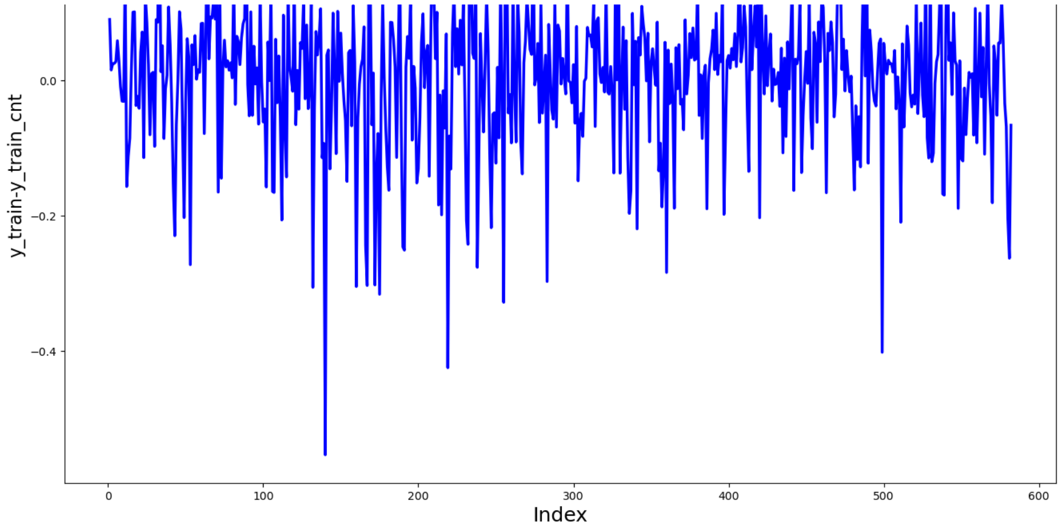
Out[69]: Text(0.5, 0, 'Errors')



In [70]:
```
# Error terms
c = [i for i in range(1,len(X_train)+1,1)]
fig = plt.figure(figsize = (16, 10))
plt.plot(c,y_train-y_train_cnt, color="blue", linewidth=2.5, linestyle="-
fig.suptitle('Error Terms', fontsize=20)              # Plot heading
plt.xlabel('Index', fontsize=18)                      # X-label
plt.ylabel('y_train-y_train_cnt', fontsize=16)                # Y-label
```

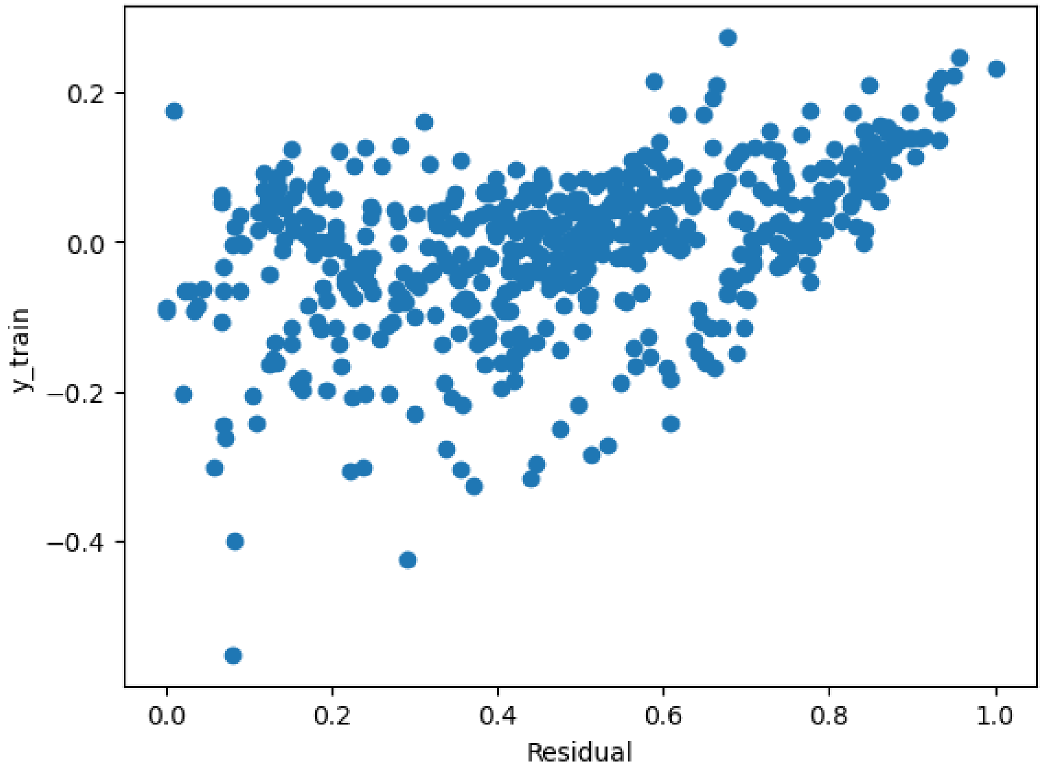
Out[70]: Text(0, 0.5, 'y_train-y_train_cnt')





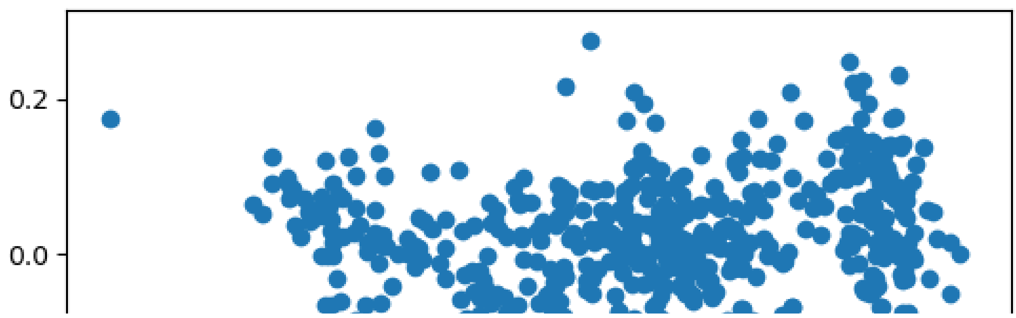
In [71]:

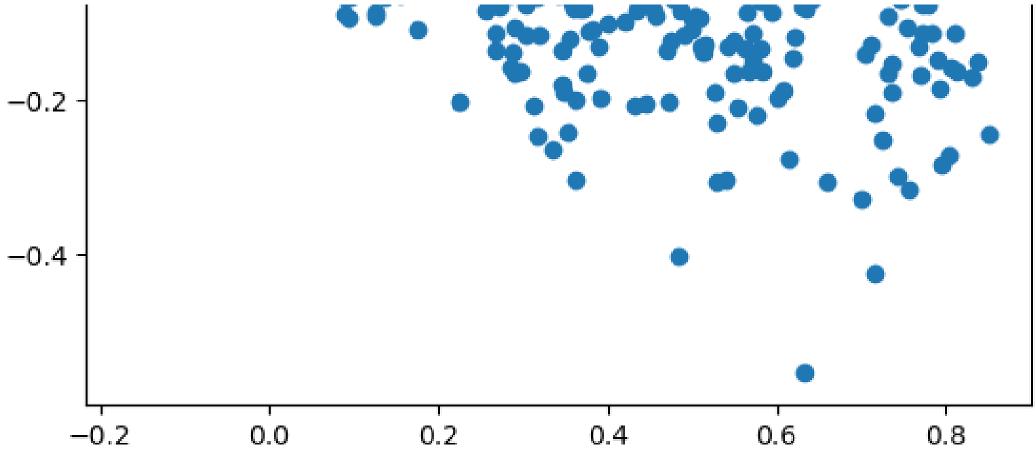
```
res=(y_train-y_train_cnt)
plt.scatter(y_train,res)
plt.ylabel("y_train")
plt.xlabel("Residual")
plt.show()
```



In [72]:

```
res=(y_train-y_train_cnt)
plt.scatter(y_train_cnt,res)
plt.show()
```

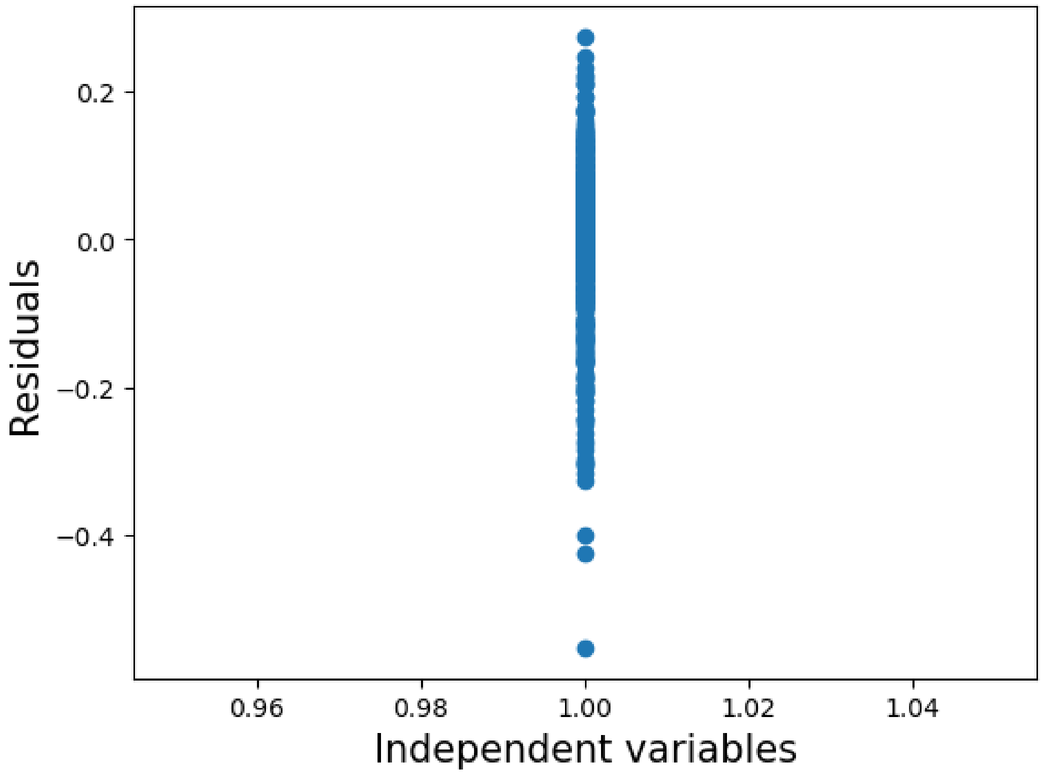




In [73]:
```
X_t=X_train_rfe5.iloc[:,0].values
X_t.shape
```

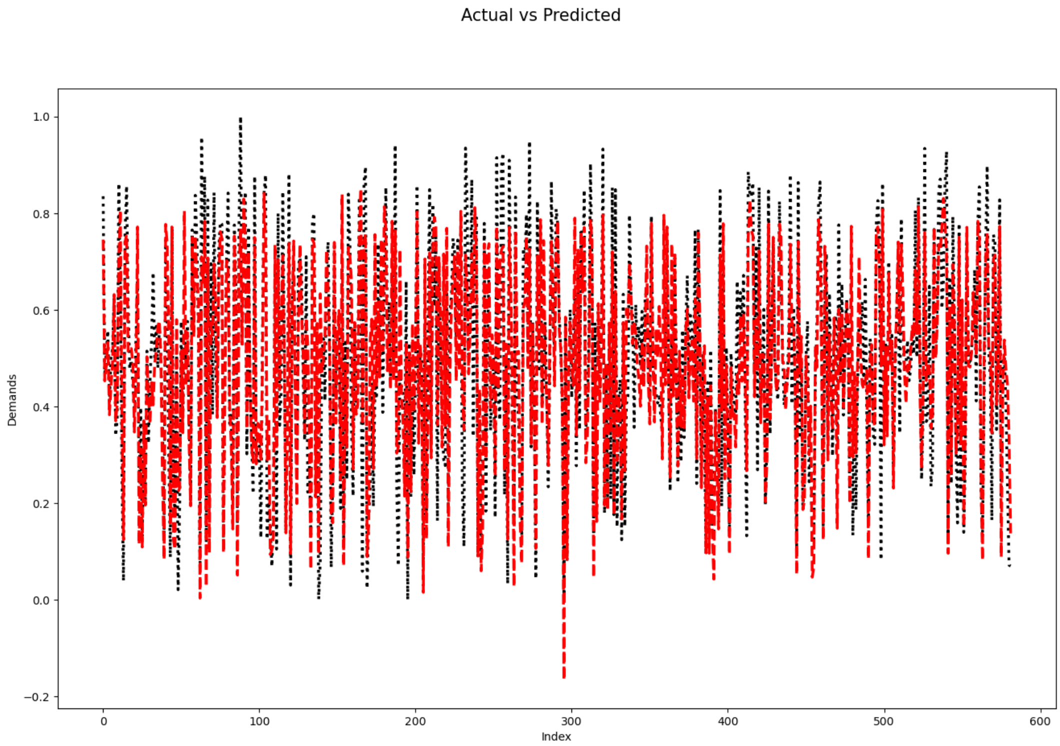
Out[73]: (582,)

In [74]:
```
"""TEST"""
#PLotting the residuals to check for pattern existance
#Checking the assumption of autocorrelation and homoscedasticity
plt.figure()
plt.scatter(X_t,res)
fig.suptitle('Independent vars vs res', fontsize=15)
plt.xlabel('Independent variables', fontsize=15)
plt.ylabel('Residuals', fontsize=15)
plt.show()
```



In [75]:
```
c = [i for i in range(0,len(y_train),1)]
plt.figure(figsize = (16, 10))
plt.plot(c,y_train, color="black", linewidth=2.5, linestyle='dotted')
plt.plot(c,y_train_cnt, color="red",  linewidth=2.5, linestyle='dashed')
plt.suptitle('Actual vs Predicted', fontsize = 15)
plt.xlabel('Index')
```

```
plt.xlabel('Index')
plt.ylabel('Demands')
plt.show()
```



Making Predictions

Applying the scaling on the test sets

In [76]:

```
num_vars=['atemp','hum','windspeed','cnt']
df_test[num_vars]=scaler.transform(df_test[num_vars])
#Dividing into X_test and y_test
y_test = df_test.pop('cnt')
X_test = df_test
```

In [77]:

```
# Now using our model to make predictions.

# Creating X_test_new dataframe by dropping variables from X_test
X_test_new = X_test[X_train_rfe.columns]

# Adding a constant variable
X_test_new = sm.add_constant(X_test_new)
```

In [78]:

```
# Making predictions
y_pred = lm.predict(X_test_new)
```

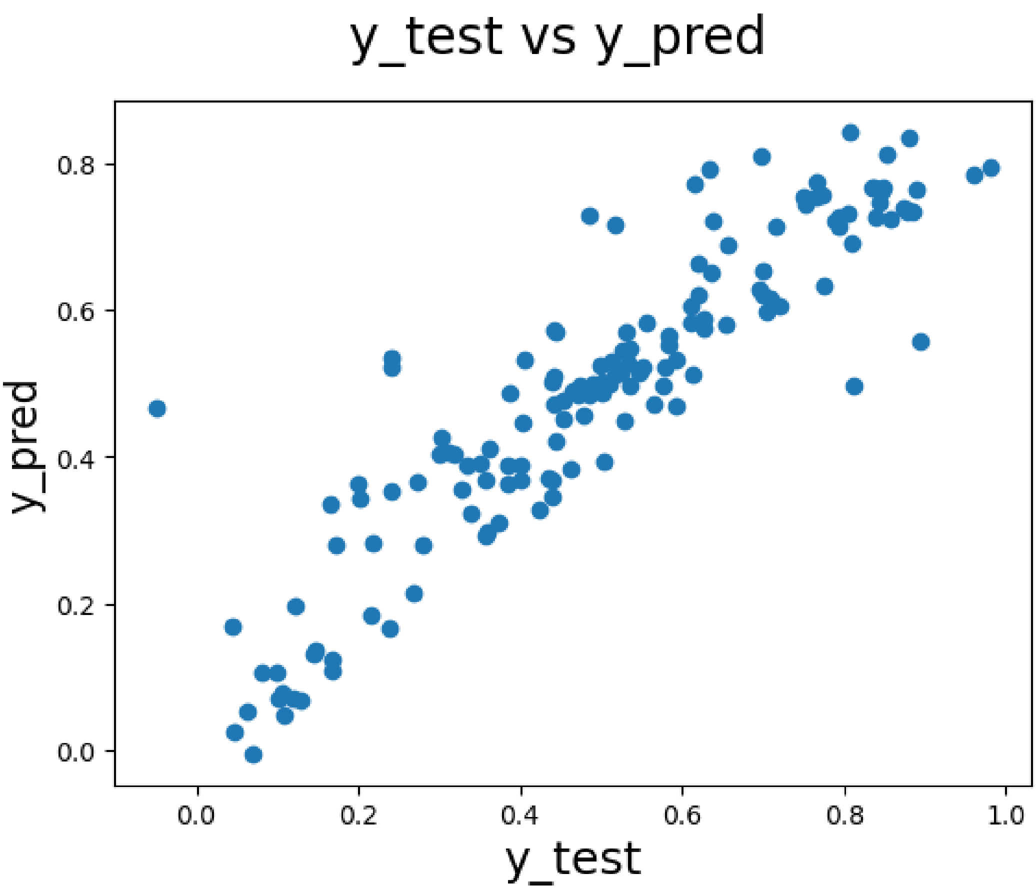
Model Evaluation

In [79]:

```
# Plotting y_test and y_pred to understand the spread.
fig = plt.figure()
plt.scatter(y_test,y_pred)
fig.suptitle('y_test vs y_pred', fontsize=20)              # Plot heading
plt.xlabel('y_test', fontsize=18)                          # X-label
plt.ylabel('y_pred', fontsize=16)
```

```
plt.ylabel('y_pred', fontsize=16)
```

Out[79]: Text(0, 0.5, 'y_pred')



In [80]:

```
from sklearn.metrics import mean_squared_error
mean_squared_error(y_test, y_pred)
```

Out[80]: 0.010767731569945415

In [81]:

```
np.sqrt(mean_squared_error(y_test, y_pred))
```

Out[81]: 0.10376768075824676

r2_score

In [82]:

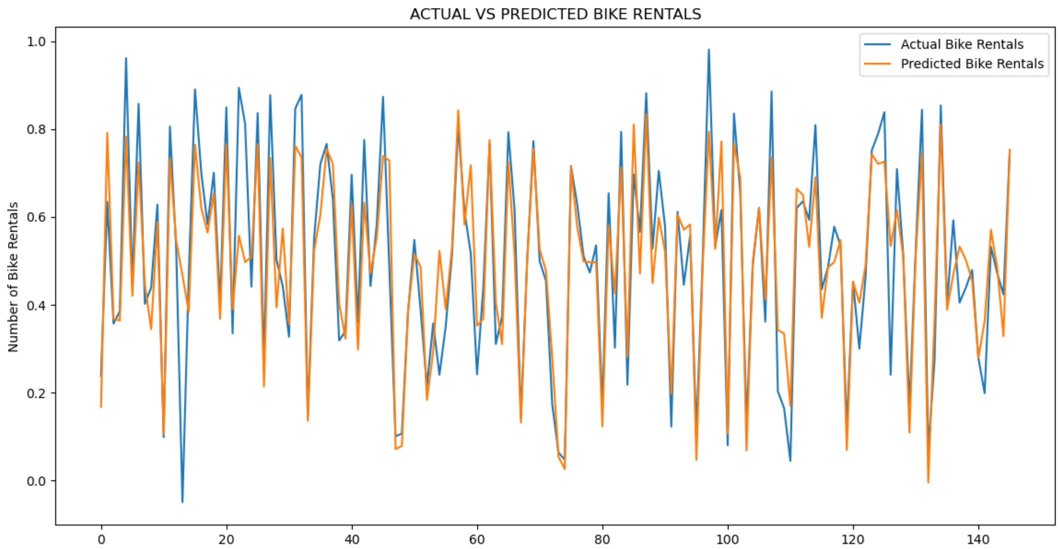
```
from sklearn.metrics import r2_score
r2_score(y_true=y_test,y_pred=y_pred)
```

Out[82]: 0.8116226094187877

In [83]:

```
# Plotting Actual vs Predicted No of rentals
fig,ax = plt.subplots()
fig.set_figheight(7)
fig.set_figwidth(14)
l1,=ax.plot(range(len(y_test)),y_test)
l2, = ax.plot(range(len(y_pred)),y_pred)
plt.legend([l1,l2],['Actual Bike Rentals','Predicted Bike Rentals'])
plt.title('ACTUAL VS PREDICTED BIKE RENTALS');
plt.ylabel('Number of Bike Rentals')
#plt.xticks([])
```

```
plt.show()
```



In [84]:

```
print(lm.summary())
```

```
                            OLS Regression Results
==========================================================================
=====
Dep. Variable:                    cnt   R-squared:
0.796
Model:                            OLS   Adj. R-squared:
0.791
Method:                 Least Squares   F-statistic:
170.4
Date:                Tue, 29 Nov 2022   Prob (F-statistic):          3.29
e-186
Time:                        22:23:24   Log-Likelihood:                 4
88.78
No. Observations:                 582   AIC:                            -
949.6
Df Residuals:                     568   BIC:                            -
888.4
Df Model:                          13
Covariance Type:            nonrobust
==========================================================================
=============================
                                          coef    std err          t
P>|t|      [0.025      0.975]
--------------------------------------------------------------------------
-----------------------------
const                                   0.1168      0.028      4.143
0.000       0.061       0.172
yr                                      0.2499      0.009     28.295
0.000       0.233       0.267
holiday                                -0.0672      0.027     -2.487
0.013      -0.120      -0.014
atemp                                   0.4594      0.036     12.624
0.000       0.388       0.531
spring                                 -0.1132      0.021     -5.448
0.000      -0.154      -0.072
winter                                  0.0595      0.019      3.102
0.002       0.022       0.097
Light rain_Light snow_Thunderstorm     -0.2444      0.025     -9.722
0.000      -0.294      -0.195
3                                       0.0470      0.017      2.797
0.005       0.014       0.080
```

```
4                                           0.0251      0.021      1.197
0.232      -0.016       0.066
5                                           0.0649      0.020      3.303
0.001       0.026       0.103
6                                           0.0576      0.020      2.901
0.004       0.019       0.097
8                                           0.0318      0.020      1.603
0.109      -0.007       0.071
9                                           0.0958      0.018      5.200
0.000       0.060       0.132
10                                          0.0677      0.020      3.428
0.001       0.029       0.107
==========================================================================
=====
Omnibus:                       99.170   Durbin-Watson:
1.903
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               20
2.043
Skew:                          -0.950   Prob(JB):                      1.3
4e-44
Kurtosis:                       5.173   Cond. No.
15.6
==========================================================================
=====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is co
rrectly specified.
```

We can see that the equation of our best fitted line is:

cnt = 0.1168 + 0.2499*yr - 0.0672*holiday + 0.4594*atemp - 0.1132*spring + 0.0595*winter - 0.2444*(Light rain_Light snow_Thunderstorm) +0.0470*March + 0.0251*April + 0.0649*May + 0.0576*June + 0.0318*August+0.0958*September +0.0677*October

Accuracy i.e R2_Score comes out to be 81.16%

Root mean square error comes out to be 0.10

R-squared: 0.796,

Adj. R-squared: 0.791,

F-statistic: 170.4

Doing the same using sklearn.linear_model

In [85]:
```
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(X_train_rfe5,y_train)
re=lr.predict(X_test_new)
```

In [86]:
```
re.shape
```

Out[86]: (146,)

In [87]:
```
lr.score(X_test_new,y_test)  #model.score is another way of checking r_2
```

Out[87]: 0.8116226094187877

In [88]:
```
r2_score(y_true=y_test,y_pred=re)
```

Out[88]: 0.8116226094187877

In [89]:
```
print(lr.intercept_)
print(lr.coef_)
```

```
0.11684365664749408
[ 0.          0.24994937 -0.06721987  0.45943455 -0.11319517  0.05949854
 -0.24439452  0.04695559  0.02508593  0.06485776  0.0575881   0.0317963
  0.09580722  0.06774628]
```

the intercept and coefficient above comes out to be same as in statsmodel.api

In [90]:
```
#cross_val_score in module sklearn.model_selection._validation
from sklearn.model_selection import cross_val_score
cvr = cross_val_score(lr,X_train_rfe5,y_train, cv=20, n_jobs=1, verbose=5
cvr
```

```
[CV] END .............................. score: (test=0.858) total time=
0.0s
[CV] END .............................. score: (test=0.698) total time=
```