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October 26, 2024

1 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.

1.1 Import the Library

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import RFE
```

```python
from sklearn.linear_model import LinearRegression
import warnings
warnings.filterwarnings('ignore')
```

1.2 Reading & Understanding the data

[2]:
```python
bike_data = pd.read_csv("day.csv")
bike_data.head()
```

[2]:
```
   instant     dteday  season  yr  mnth  holiday  weekday  workingday  \
0        1  01-01-2018       1   0     1        0        6           0
1        2  02-01-2018       1   0     1        0        0           0
2        3  03-01-2018       1   0     1        0        1           1
3        4  04-01-2018       1   0     1        0        2           1
4        5  05-01-2018       1   0     1        0        3           1

   weathersit       temp     atemp      hum  windspeed  casual  registered  \
0           2  14.110847  18.18125  80.5833  10.749882     331         654
1           2  14.902598  17.68695  69.6087  16.652113     131         670
2           1   8.050924   9.47025  43.7273  16.636703     120        1229
3           1   8.200000  10.60610  59.0435  10.739832     108        1454
4           1   9.305237  11.46350  43.6957  12.522300      82        1518

    cnt
0   985
1   801
2  1349
3  1562
4  1600
```

[3]:
```python
bike_data.shape
```

[3]: (730, 16)

1.3 Checking for the presence of null values in any column.

[4]:
```python
bike_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   instant     730 non-null    int64
 1   dteday      730 non-null    object
 2   season      730 non-null    int64
 3   yr          730 non-null    int64
```

```
 4   mnth        730 non-null    int64
 5   holiday     730 non-null    int64
 6   weekday     730 non-null    int64
 7   workingday  730 non-null    int64
 8   weathersit  730 non-null    int64
 9   temp        730 non-null    float64
 10  atemp       730 non-null    float64
 11  hum         730 non-null    float64
 12  windspeed   730 non-null    float64
 13  casual      730 non-null    int64
 14  registered  730 non-null    int64
 15  cnt         730 non-null    int64
dtypes: float64(4), int64(11), object(1)
memory usage: 91.4+ KB
```

[5]:
```
bike_data.describe()
```

[5]:

	instant	season	yr	mnth	holiday	weekday
count	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000
mean	365.500000	2.498630	0.500000	6.526027	0.028767	2.997260
std	210.877136	1.110184	0.500343	3.450215	0.167266	2.006161
min	1.000000	1.000000	0.000000	1.000000	0.000000	0.000000
25%	183.250000	2.000000	0.000000	4.000000	0.000000	1.000000
50%	365.500000	3.000000	0.500000	7.000000	0.000000	3.000000
75%	547.750000	3.000000	1.000000	10.000000	0.000000	5.000000
max	730.000000	4.000000	1.000000	12.000000	1.000000	6.000000

	workingday	weathersit	temp	atemp	hum	windspeed
count	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000
mean	0.683562	1.394521	20.319259	23.726322	62.765175	12.763620
std	0.465405	0.544807	7.506729	8.150308	14.237589	5.195841
min	0.000000	1.000000	2.424346	3.953480	0.000000	1.500244
25%	0.000000	1.000000	13.811885	16.889713	52.000000	9.041650
50%	1.000000	1.000000	20.465826	24.368225	62.625000	12.125325
75%	1.000000	2.000000	26.880615	30.445775	72.989575	15.625589
max	1.000000	3.000000	35.328347	42.044800	97.250000	34.000021

	casual	registered	cnt
count	730.000000	730.000000	730.000000
mean	849.249315	3658.757534	4508.006849
std	686.479875	1559.758728	1936.011647
min	2.000000	20.000000	22.000000
25%	316.250000	2502.250000	3169.750000
50%	717.000000	3664.500000	4548.500000
75%	1096.500000	4783.250000	5966.000000
max	3410.000000	6946.000000	8714.000000

[6]:
```
bike_data.columns
```

[6]:
```
Index(['instant', 'dteday', 'season', 'yr', 'mnth', 'holiday', 'weekday',
       'workingday', 'weathersit', 'temp', 'atemp', 'hum', 'windspeed',
       'casual', 'registered', 'cnt'],
      dtype='object')
```

[7]:
```
bike_data.nunique()
```

[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
```

1.4 Remove columns that are not relevant for the analysis.

1) The instant column serves as an index, so we will drop it.
2) The dteday and yr_month columns contain similar information; therefore, we will drop dteday to avoid redundancy.
3) Since cnt (our target variable) is the sum of casual and registered, we will exclude casual and registered from the analysis.

[8]:
```
bike_data.drop(['instant','dteday','casual','registered'], axis = 1, inplace =␣
 ↪True)
bike_data.head()
```

[8]:
```
   season  yr  mnth  holiday  weekday  workingday  weathersit       temp  \
0       1   0     1        0        6           0           2  14.110847
1       1   0     1        0        0           0           2  14.902598
2       1   0     1        0        1           1           1   8.050924
3       1   0     1        0        2           1           1   8.200000
4       1   0     1        0        3           1           1   9.305237
```

```
     atemp      hum  windspeed   cnt
0  18.18125  80.5833  10.749882   985
1  17.68695  69.6087  16.652113   801
2   9.47025  43.7273  16.636703  1349
3  10.60610  59.0435  10.739832  1562
4  11.46350  43.6957  12.522300  1600
```

[9]:

```
bike_data.corr()
```

[9]:

```
                  season            yr          mnth   holiday   weekday  \
season      1.000000e+00 -3.279074e-16  8.310321e-01 -0.010868 -0.003081
yr         -3.279074e-16  1.000000e+00 -5.162656e-16  0.008195 -0.005466
mnth        8.310321e-01 -5.162656e-16  1.000000e+00  0.018905  0.009523
holiday    -1.086804e-02  8.195345e-03  1.890483e-02  1.000000 -0.101962
weekday    -3.081198e-03 -5.466369e-03  9.522969e-03 -0.101962  1.000000
workingday  1.376178e-02 -2.945396e-03 -4.687953e-03 -0.252948  0.035800
weathersit  2.130636e-02 -5.032247e-02  4.561335e-02 -0.034395  0.031112
temp        3.333607e-01  4.878919e-02  2.190833e-01 -0.028764 -0.000168
atemp       3.420139e-01  4.721519e-02  2.264302e-01 -0.032703 -0.007539
hum         2.082196e-01 -1.125471e-01  2.249368e-01 -0.015662 -0.052290
windspeed  -2.296069e-01 -1.162435e-02 -2.080131e-01  0.006257  0.014283
cnt         4.045838e-01  5.697285e-01  2.781909e-01 -0.068764  0.067534

            workingday  weathersit      temp     atemp       hum  windspeed  \
season        0.013762    0.021306  0.333361  0.342014  0.208220  -0.229607
yr           -0.002945   -0.050322  0.048789  0.047215 -0.112547  -0.011624
mnth         -0.004688    0.045613  0.219083  0.226430  0.224937  -0.208013
holiday      -0.252948   -0.034395 -0.028764 -0.032703 -0.015662   0.006257
weekday       0.035800    0.031112 -0.000168 -0.007539 -0.052290   0.014283
workingday    1.000000    0.060236  0.053470  0.052940  0.023202  -0.018666
weathersit    0.060236    1.000000 -0.119503 -0.120559  0.590277   0.039769
temp          0.053470   -0.119503  1.000000  0.991696  0.128565  -0.158186
atemp         0.052940   -0.120559  0.991696  1.000000  0.141512  -0.183876
hum           0.023202    0.590277  0.128565  0.141512  1.000000  -0.248506
windspeed    -0.018666    0.039769 -0.158186 -0.183876 -0.248506   1.000000
cnt           0.062542   -0.295929  0.627044  0.630685 -0.098543  -0.235132

                 cnt
season      0.404584
yr          0.569728
mnth        0.278191
holiday    -0.068764
weekday     0.067534
workingday  0.062542
weathersit -0.295929
temp        0.627044
atemp       0.630685
```

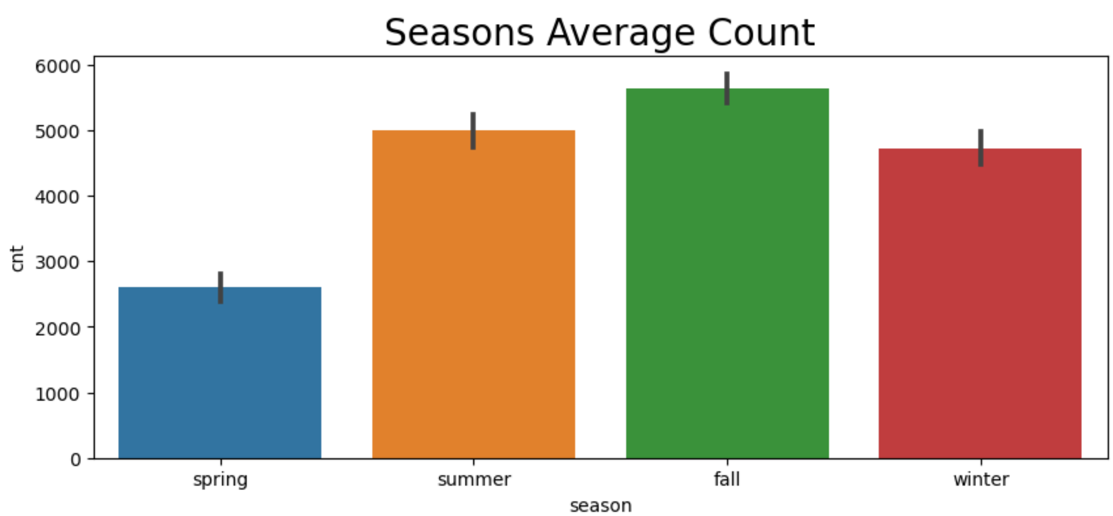
```
hum          -0.098543
windspeed    -0.235132
cnt           1.000000
```

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

1.5 Based on the data season, weathersit, weekday, holiday, mnth, workingday and yr are all categorical variables.

1.5.1 Map descriptive names for improved visibility: season (1: Spring, 2: Summer, 3: Fall, 4: Winter)

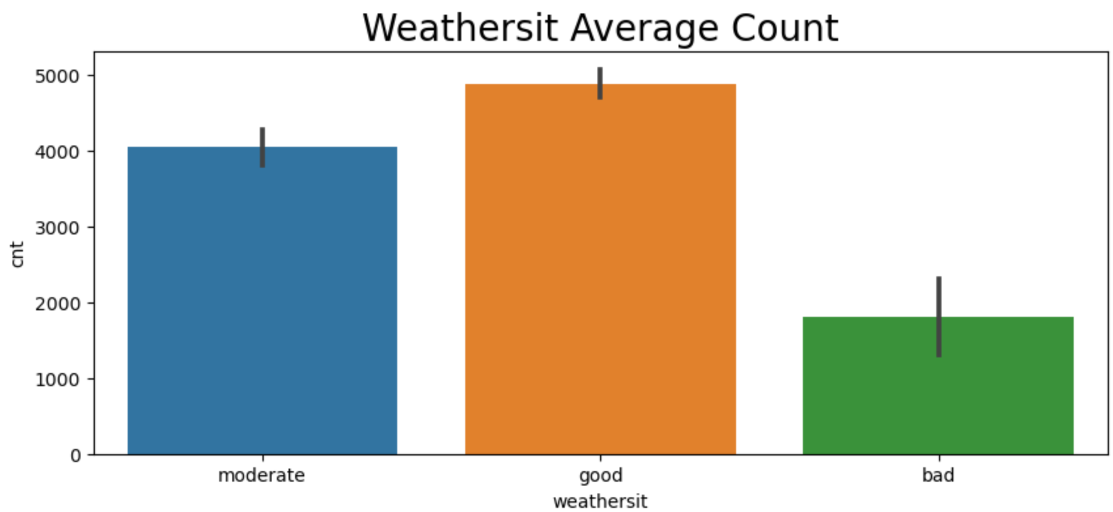
[10]:
```
bike_data['season'] = bike_data['season'].replace({1: "spring", 2: "summer", 3:␣
↪"fall", 4: "winter"})

plt.figure(figsize=[10, 4])
sns.barplot(x='season', y='cnt', data=bike_data)
plt.title('Seasons Average Count', fontsize=20)
plt.show()
```



In the fall, there appears to be the highest demand for rented bikes, followed by summer and winter.

1.5.2 Map descriptive names for enhanced clarity: weathersit (1: 'Good', 2: 'Moderate', 3: 'Bad', 4: 'Severe')

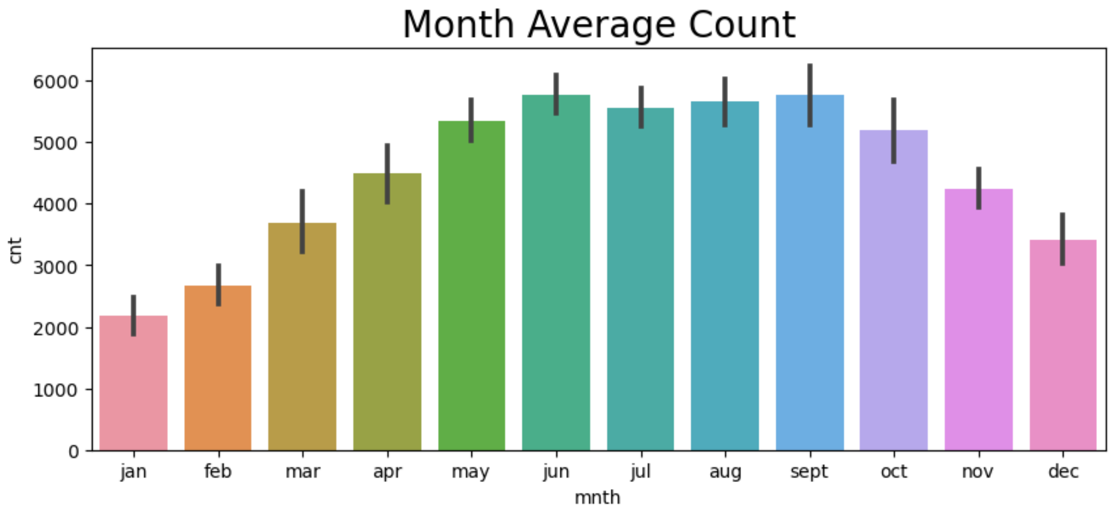
[11]:
```
bike_data['weathersit']=bike_data['weathersit'].replace({1:'good',2:
↪'moderate',3:'bad',4:'severe'})
plt.figure(figsize=[10, 4])
sns.barplot(x='weathersit', y='cnt', data=bike_data)
plt.title('Weathersit Average Count', fontsize=20)
plt.show()
```



It clearly shows that if the weather is clear, the demand is more

1.5.3 Map descriptive names for enhanced clarity: Month (1: 'jan',2: 'feb',3: 'mar',4: 'apr',5: 'may',6: 'jun', 7: 'jul',8: 'aug',9: 'sept',10: 'oct',11: 'nov',12: 'dec')

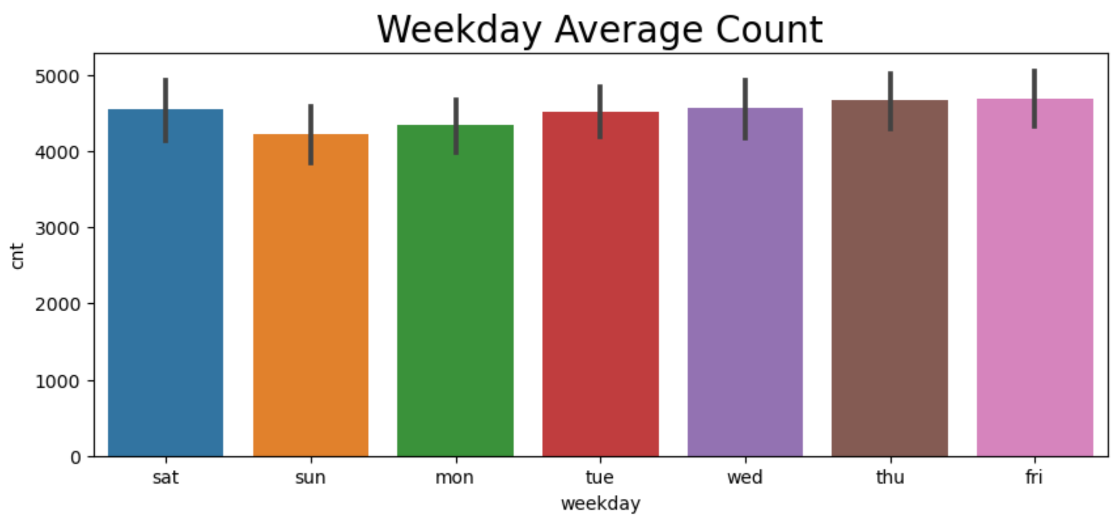
[12]:
```
bike_data['mnth'] = bike_data['mnth'].replace({1: 'jan',2: 'feb',3: 'mar',4:␣
↪'apr',5: 'may',6: 'jun',
                  7: 'jul',8: 'aug',9: 'sept',10: 'oct',11: 'nov',12: 'dec'})

plt.figure(figsize=[10, 4])
sns.barplot(x='mnth', y='cnt', data=bike_data)
plt.title('Month Average Count', fontsize=20)
plt.show()
```



- There is a consistently high average count of rented bikes in August, June, September, and July, followed closely by May and October. The company should ensure high availability during these peak months.
- Conversely, December, January, and February show the lowest demand, likely due to the winter season.

1.5.4 Map descriptive names for enhanced clarity: Weekday (0: 'sun',1: 'mon',2: 'tue',3: 'wed',4: 'thu',5: 'fri',6: 'sat')

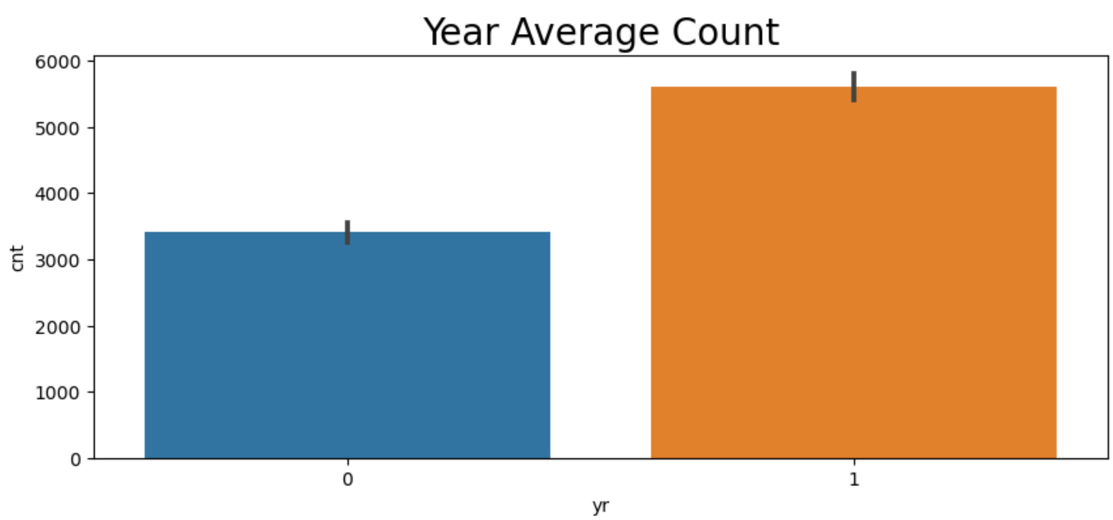
[13]:
```
bike_data['weekday'] = bike_data['weekday'].replace({0: 'sun',1: 'mon',2:␣
↪'tue',3: 'wed',4: 'thu',5: 'fri',6: 'sat'})
plt.figure(figsize=[10, 4])
sns.barplot(x='weekday', y='cnt', data=bike_data)
plt.title('Weekday Average Count', fontsize=20)
plt.show()
```



- It appears that the demand for rented bikes is generally consistent across all days. However, demand is notably higher on Sunday, Monday, Saturday, and Friday compared to other days.
- Conversely, people tend to prefer renting bikes less on Thursday, Wednesday, and Tuesday.

1.5.5 Map descriptive names for enhanced clarity: Year (0: 2018 , 1: 2019)

[14]:
```
bike_data['yr'].replace({0: '2018', 1: '2019'})
plt.figure(figsize=[10, 4])
sns.barplot(x='yr', y='cnt', data=bike_data)
plt.title('Year Average Count', fontsize=20)
plt.show()
```



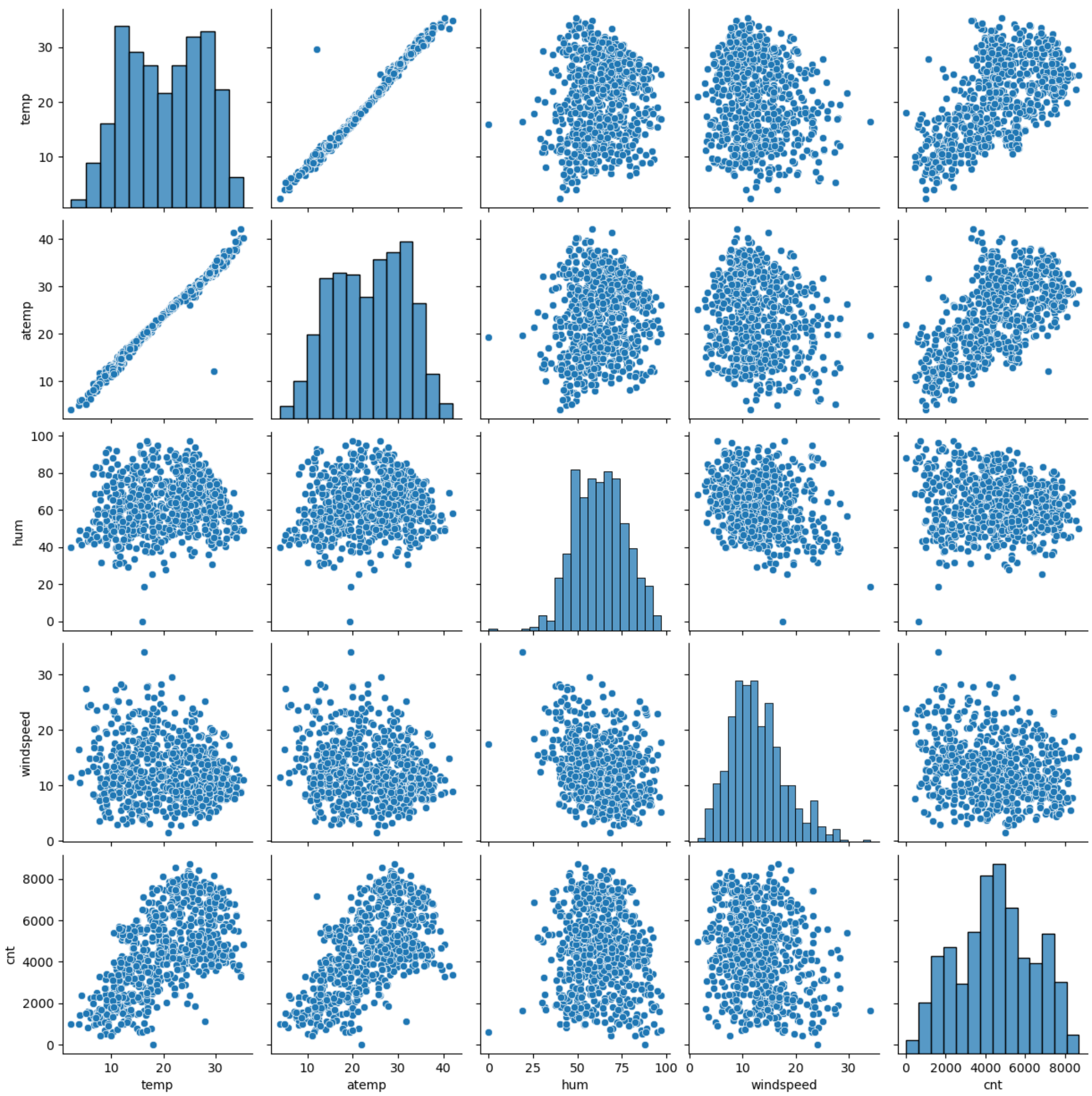
- We can observe a significant trend: the average number of rented bikes nearly doubled in 2019 compared to 2018.

1.6 Prepare the data for Model

[15]:
```python
bike_data['season'] = bike_data.season.replace({1: "spring", 2: "summer", 3:␣
↪"fall", 4: "winter"})
bike_data['weathersit']=bike_data.weathersit.replace({1:'good',2:'moderate',3:
↪'bad',4:'severe'})
bike_data['mnth'] = bike_data.mnth.replace({1: 'jan',2: 'feb',3: 'mar',4:␣
↪'apr',5: 'may',6: 'jun', 7: 'jul',8: 'aug',9: 'sept',10: 'oct',11: 'nov',12:␣
↪'dec'})
bike_data['weekday']= bike_data.weekday.replace({0: 'sun',1: 'mon',2: 'tue',3:␣
↪'wed',4: 'thu',5: 'fri',6: 'sat'})

bike_data.head()
```

[15]:
```
   season  yr mnth  holiday weekday  workingday weathersit       temp  \
0  spring   0  jan        0     sat           0   moderate  14.110847
1  spring   0  jan        0     sun           0   moderate  14.902598
2  spring   0  jan        0     mon           1       good   8.050924
3  spring   0  jan        0     tue           1       good   8.200000
4  spring   0  jan        0     wed           1       good   9.305237

      atemp      hum  windspeed   cnt
0  18.18125  80.5833  10.749882   985
1  17.68695  69.6087  16.652113   801
2   9.47025  43.7273  16.636703  1349
3  10.60610  59.0435  10.739832  1562
4  11.46350  43.6957  12.522300  1600
```

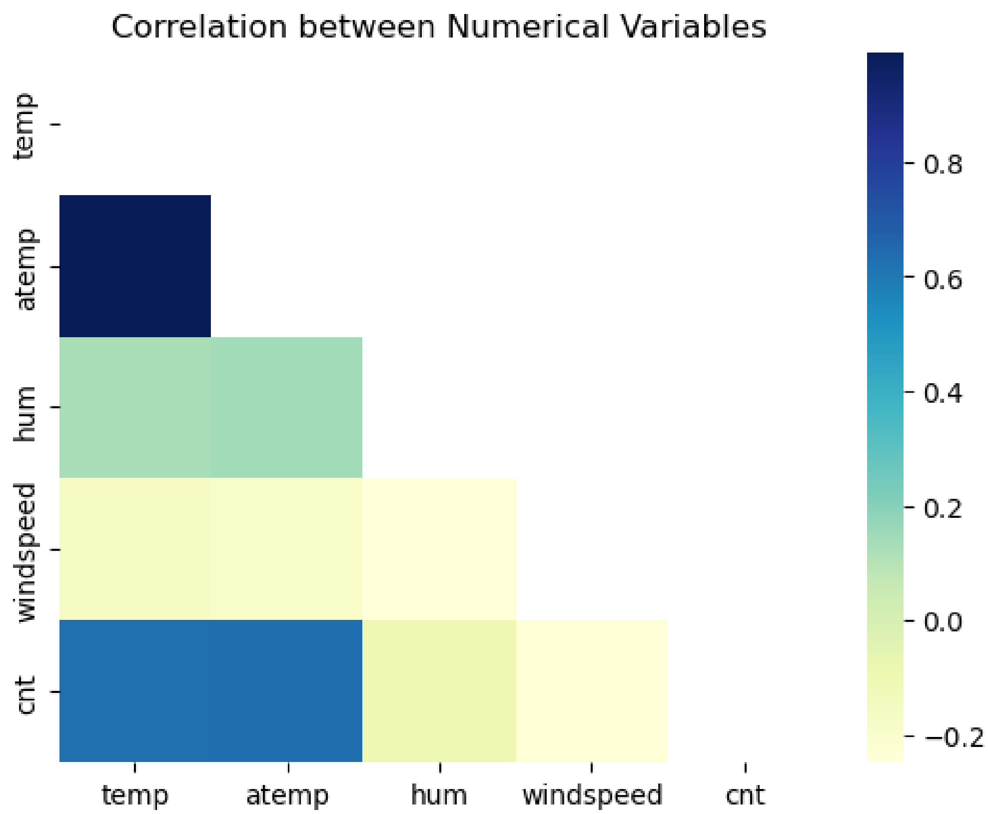
[16]:
```python
sns.pairplot(bike_data, vars=['temp','atemp','hum','windspeed',"cnt"])
plt.show()
```



1.7 Based on the data, temp, atemp, humidity, windspeed, and count are numeric variables.

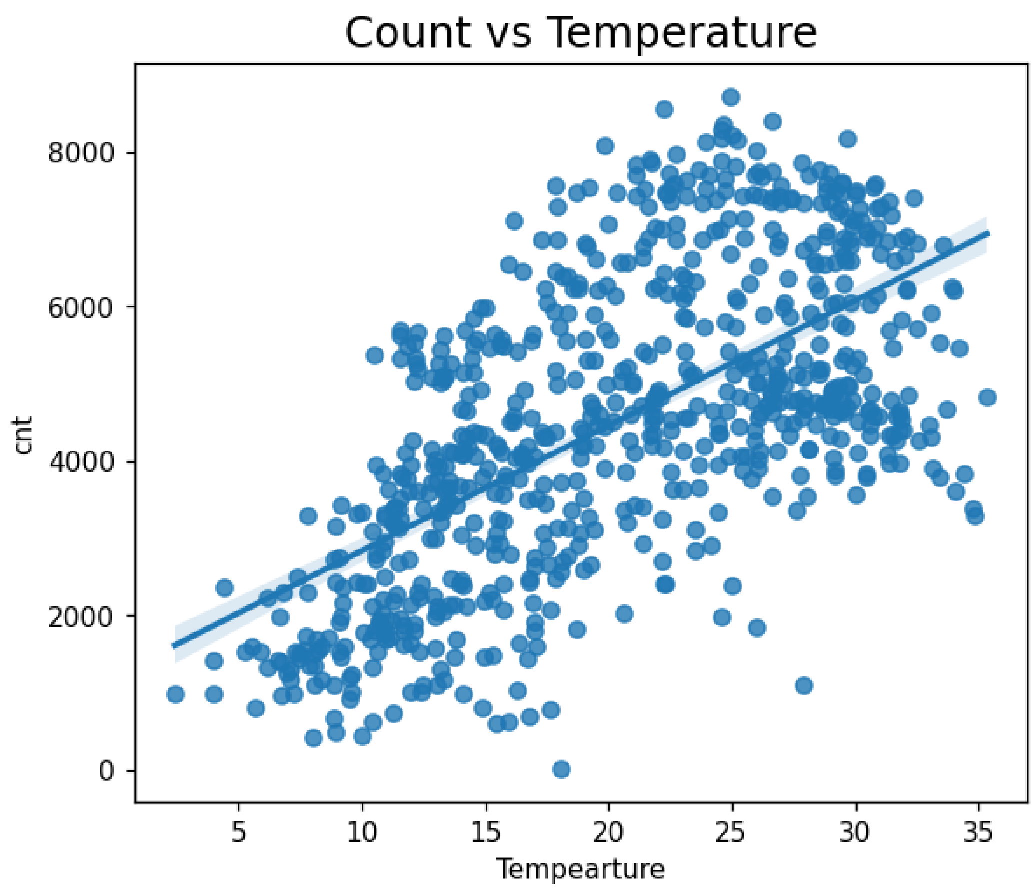
1.7.1 Correlation Graph for Numnerical variable

[17]:
```
matrix = np.triu(bike_data[['temp','atemp','hum','windspeed','cnt']].corr())
sns.heatmap(bike_data[['temp','atemp','hum','windspeed','cnt']].corr(),cmap␣
↪='YlGnBu',annot = True,  mask=matrix)
plt.title("Correlation between Numerical Variables")
plt.show()
```

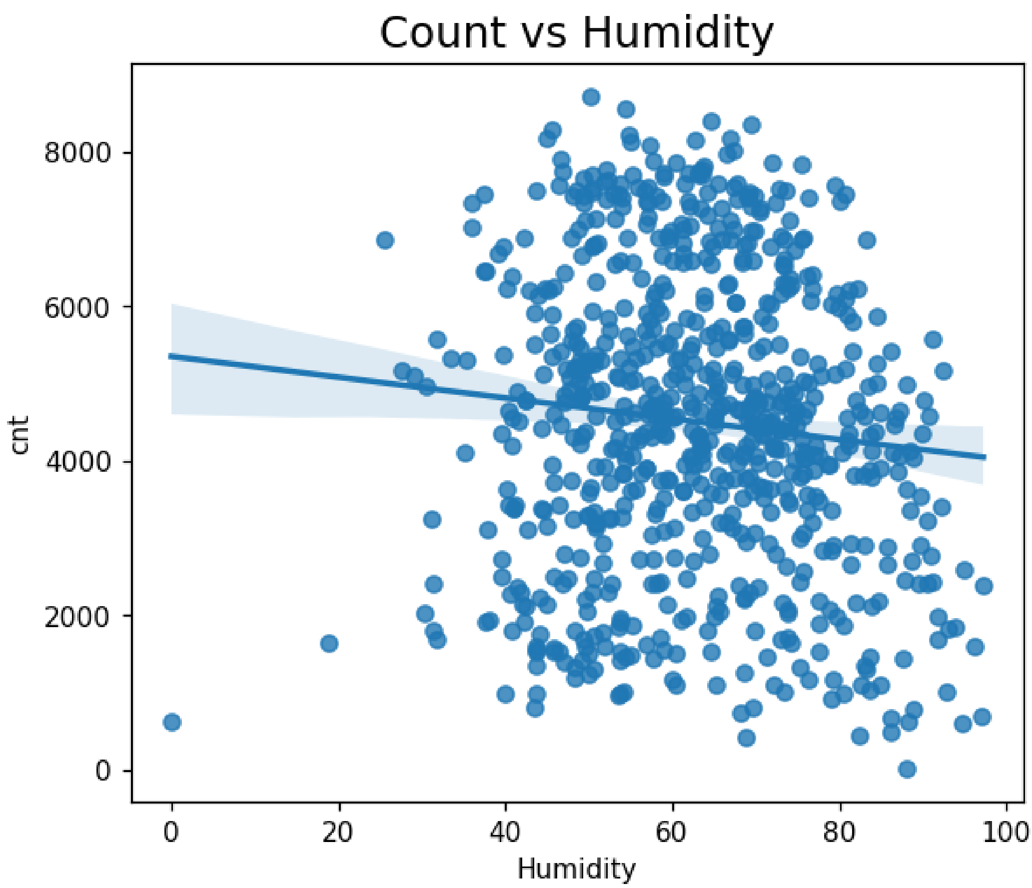


1.8 Regression of data

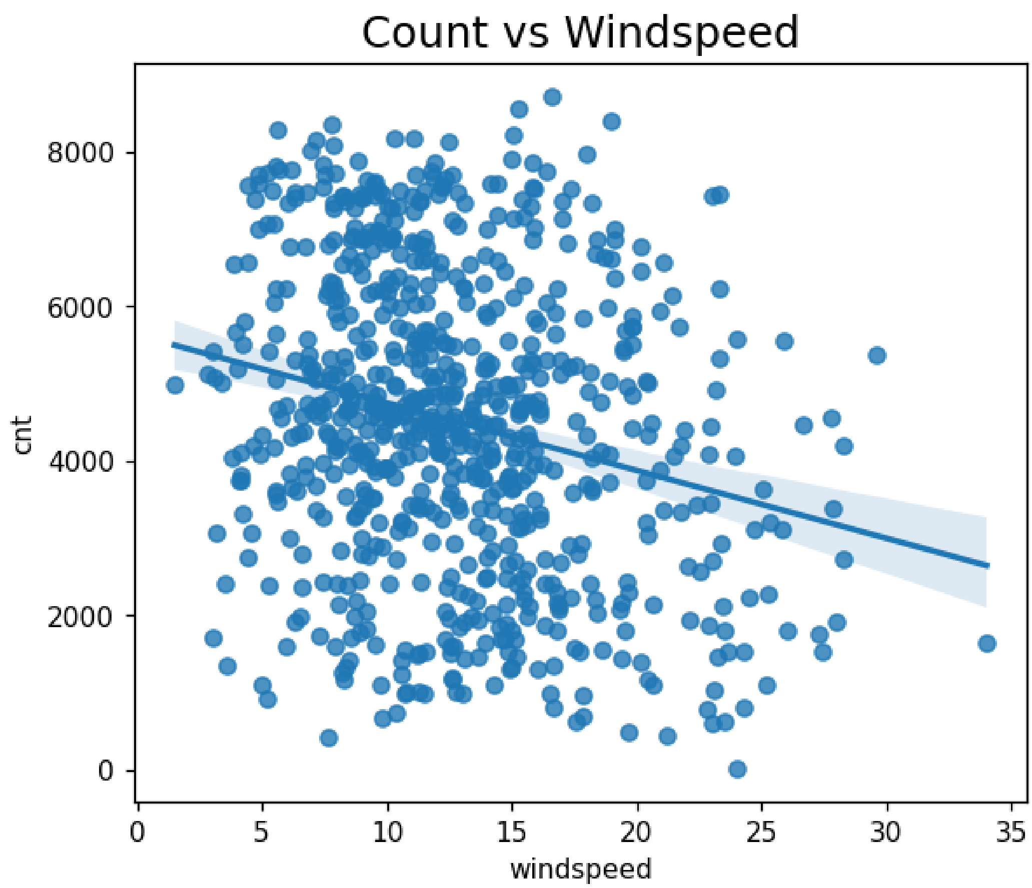
[18]:
```
plt.figure(figsize=(6,5),dpi=110)
plt.title('Count vs Temperature',fontsize = 16)
sns.regplot(data = bike_data,y = 'cnt', x='temp')
plt.xlabel('Tempearture')
plt.show()
```



[19]:
```
plt.figure(figsize = (6,5),dpi = 110)
plt.title('Count vs Humidity',fontsize = 16)
sns.regplot(data = bike_data, y = 'cnt', x ='hum')
plt.xlabel('Humidity')
plt.show()
```



[20]:
```
plt.figure(figsize =(6,5),dpi = 110)
plt.title('Count vs Windspeed',fontsize = 16)
sns.regplot(data = bike_data, y ='cnt', x = 'windspeed')
plt.show()
```



1.8.1 Creating Dummy Variable For Categorical Data

[21]:
```
# List of categorical columns to create dummies
cat = ['season', 'mnth', 'weekday', 'weathersit']

# Create dummy variables
dummy = pd.get_dummies(bike_data[cat], drop_first=True).astype(int)
bike_data = pd.concat([bike_data, dummy], axis=1)
bike_data.drop(columns=cat, inplace=True)



bike_data.head()
```

[21]:

	yr	holiday	workingday	temp	atemp	hum	windspeed	cnt	\
0	0	0	0	14.110847	18.18125	80.5833	10.749882	985	
1	0	0	0	14.902598	17.68695	69.6087	16.652113	801	
2	0	0	1	8.050924	9.47025	43.7273	16.636703	1349	
3	0	0	1	8.200000	10.60610	59.0435	10.739832	1562	

```
4   0        0           1   9.305237  11.46350  43.6957  12.522300  1600

   season_spring  season_summer  …  mnth_oct  mnth_sept  weekday_mon  \
0              1              0  …         0          0            0
1              1              0  …         0          0            0
2              1              0  …         0          0            1
3              1              0  …         0          0            0
4              1              0  …         0          0            0

   weekday_sat  weekday_sun  weekday_thu  weekday_tue  weekday_wed  \
0            1            0            0            0            0
1            0            1            0            0            0
2            0            0            0            0            0
3            0            0            0            1            0
4            0            0            0            0            1

   weathersit_good  weathersit_moderate
0                0                    1
1                0                    1
2                1                    0
3                1                    0
4                1                    0

[5 rows x 30 columns]
```

1.8.2 Verifying the info of the dataset after generating dummy variables.

[22]:
```python
bike_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 30 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   yr                   730 non-null    int64
 1   holiday              730 non-null    int64
 2   workingday           730 non-null    int64
 3   temp                 730 non-null    float64
 4   atemp                730 non-null    float64
 5   hum                  730 non-null    float64
 6   windspeed            730 non-null    float64
 7   cnt                  730 non-null    int64
 8   season_spring        730 non-null    int32
 9   season_summer        730 non-null    int32
 10  season_winter        730 non-null    int32
 11  mnth_aug             730 non-null    int32
 12  mnth_dec             730 non-null    int32
```

```
 13  mnth_feb            730 non-null    int32
 14  mnth_jan            730 non-null    int32
 15  mnth_jul            730 non-null    int32
 16  mnth_jun            730 non-null    int32
 17  mnth_mar            730 non-null    int32
 18  mnth_may            730 non-null    int32
 19  mnth_nov            730 non-null    int32
 20  mnth_oct            730 non-null    int32
 21  mnth_sept           730 non-null    int32
 22  weekday_mon         730 non-null    int32
 23  weekday_sat         730 non-null    int32
 24  weekday_sun         730 non-null    int32
 25  weekday_thu         730 non-null    int32
 26  weekday_tue         730 non-null    int32
 27  weekday_wed         730 non-null    int32
 28  weathersit_good     730 non-null    int32
 29  weathersit_moderate 730 non-null    int32
dtypes: float64(4), int32(22), int64(4)
memory usage: 108.5 KB
```

1.8.3 Verifying the shapes of the dataset after generating dummy variables.

[23]:
```
bike_data.shape
```

[23]:
```
(730, 30)
```

1.8.4 Verifying the columns of the dataset after generating dummy variables.

[24]:
```
bike_data.columns
```

[24]:
```
Index(['yr', 'holiday', 'workingday', 'temp', 'atemp', 'hum', 'windspeed',
       'cnt', 'season_spring', 'season_summer', 'season_winter', 'mnth_aug',
       'mnth_dec', 'mnth_feb', 'mnth_jan', 'mnth_jul', 'mnth_jun', 'mnth_mar',
       'mnth_may', 'mnth_nov', 'mnth_oct', 'mnth_sept', 'weekday_mon',
       'weekday_sat', 'weekday_sun', 'weekday_thu', 'weekday_tue',
       'weekday_wed', 'weathersit_good', 'weathersit_moderate'],
      dtype='object')
```

1.8.5 Splitting the dataset into training and testing sets.

[25]:
```
from sklearn.model_selection import train_test_split

# Assuming bike_data is your DataFrame and 'cnt' is the target variable
X = bike_data.drop('cnt', axis=1)
y = bike_data['cnt']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=100)

# Display the shapes of the resulting datasets
print("Training data shape:", X_train.shape)
print("Testing data shape:", X_test.shape)
```

```
Training data shape: (511, 29)
Testing data shape: (219, 29)
```

1.9 Rescaling

[26]:
```
# Instant the object
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
```

[27]:
```
# create the list of Numeric value
num_vars = ['temp','atemp','hum','windspeed']

#Fit on the data
X_train[num_vars] = scaler.fit_transform(X_train[num_vars])
X_train.head()
```

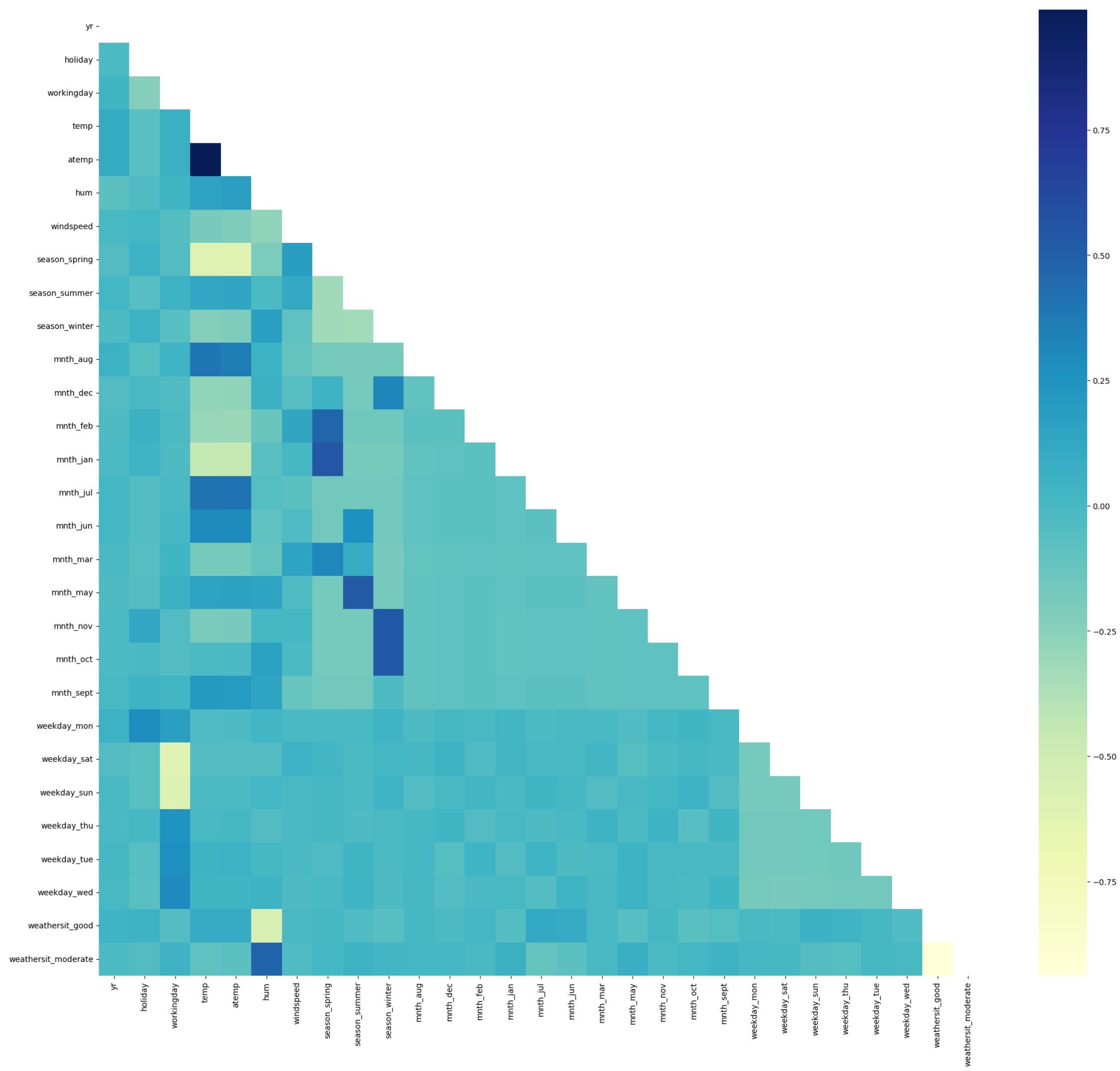
[27]:
```
     yr  holiday  workingday      temp     atemp       hum  windspeed  \
653   1        0           1  0.509887  0.501133  0.575354   0.300794
576   1        0           1  0.815169  0.766351  0.725633   0.264686
426   1        0           0  0.442393  0.438975  0.640189   0.255342
728   1        0           0  0.245101  0.200348  0.498067   0.663106
482   1        0           0  0.395666  0.391735  0.504508   0.188475

     season_spring  season_summer  season_winter  …  mnth_oct  mnth_sept  \
653              0              0              1  …         1          0
576              0              0              0  …         0          0
426              1              0              0  …         0          0
728              1              0              0  …         0          0
482              0              1              0  …         0          0

     weekday_mon  weekday_sat  weekday_sun  weekday_thu  weekday_tue  \
653            0            0            0            0            1
576            0            0            0            0            1
426            0            1            0            0            0
728            0            0            1            0            0
482            0            1            0            0            0

     weekday_wed  weathersit_good  weathersit_moderate
653            0                1                    0
576            0                1                    0
```

```
426            0                  0                     1
728            0                  1                     0
482            0                  0                     1

[5 rows x 29 columns]
```

1.10 Training the Model

[28]:
```python
plt.figure(figsize =(25,22))
matrix = np.triu(X_train.corr())
sns.heatmap(X_train.corr(), annot=True, cmap="YlGnBu", mask=matrix)
```

[28]:
```
<Axes: >
```



- The heatmap effectively highlights the multicollinearity among the variables, pinpointing those that exhibit high collinearity with the target variable.
- We will refer to this map during the development of our linear model to evaluate various correlated values, alongside the Variance Inflation Factor (VIF) and p-values. This will assist in selecting or eliminating appropriate variables from the model.

1.11 RFE for variable Selection

[29]:
```
from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import RFE

# Create and fit the linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Initialize RFE with the linear model and specify the number of features to
 ↪select
rfe = RFE(estimator=model, n_features_to_select=15)

# Fit RFE to the training data
rfe.fit(X_train, y_train)

# Get the selected features
selected_features = X_train.columns[rfe.support_]


# Display the selected features
print("Selected Features:", selected_features)
```

```
Selected Features: Index(['yr', 'holiday', 'workingday', 'temp', 'hum',
'windspeed',
       'season_spring', 'season_summer', 'season_winter', 'mnth_jan',
       'mnth_jul', 'mnth_sept', 'weekday_sat', 'weathersit_good',
       'weathersit_moderate'],
      dtype='object')
```

[30]:
```
list(zip(X_train.columns,rfe.support_,rfe.ranking_))
```

[30]:
```
[('yr', True, 1),
 ('holiday', True, 1),
 ('workingday', True, 1),
 ('temp', True, 1),
 ('atemp', False, 5),
 ('hum', True, 1),
 ('windspeed', True, 1),
 ('season_spring', True, 1),
 ('season_summer', True, 1),
 ('season_winter', True, 1),
```

```
('mnth_aug', False, 7),
('mnth_dec', False, 3),
('mnth_feb', False, 4),
('mnth_jan', True, 1),
('mnth_jul', True, 1),
('mnth_jun', False, 14),
('mnth_mar', False, 15),
('mnth_may', False, 6),
('mnth_nov', False, 2),
('mnth_oct', False, 11),
('mnth_sept', True, 1),
('weekday_mon', False, 9),
('weekday_sat', True, 1),
('weekday_sun', False, 8),
('weekday_thu', False, 12),
('weekday_tue', False, 10),
('weekday_wed', False, 13),
('weathersit_good', True, 1),
('weathersit_moderate', True, 1)]
```

1.11.1 Creating a new training DataFrame using features selected by RFE.

[31]:
```python
X_train_rfe = X_train[selected_features]
X_train_rfe.head()
```

[31]:
```
     yr  holiday  workingday      temp       hum  windspeed  season_spring  \
653   1        0           1  0.509887  0.575354   0.300794              0
576   1        0           1  0.815169  0.725633   0.264686              0
426   1        0           0  0.442393  0.640189   0.255342              1
728   1        0           0  0.245101  0.498067   0.663106              1
482   1        0           0  0.395666  0.504508   0.188475              0

     season_summer  season_winter  mnth_jan  mnth_jul  mnth_sept  weekday_sat  \
653              0              1         0         0          0            0
576              0              0         0         1          0            0
426              0              0         0         0          0            1
728              0              0         0         0          0            0
482              1              0         0         0          0            1

     weathersit_good  weathersit_moderate
653                1                    0
576                1                    0
426                0                    1
728                1                    0
482                0                    1
```

[32]:
```python
X_train_rfe.columns
```

[32]:
```
Index(['yr', 'holiday', 'workingday', 'temp', 'hum', 'windspeed',
       'season_spring', 'season_summer', 'season_winter', 'mnth_jan',
       'mnth_jul', 'mnth_sept', 'weekday_sat', 'weathersit_good',
       'weathersit_moderate'],
      dtype='object')
```

[33]:
```python
X_train_rfe.shape
```

[33]:
```
(511, 15)
```

1.12 Adding constant and intercept

1.12.1 Creating the Function for lm summary and VIF

[34]:
```python
def model(column):
    X_train_sm = sm.add_constant(X_train[column])
    lm = sm.OLS(y_train, X_train_sm).fit()
    print(lm.summary())
    return lm
```

[35]:
```python
#Function to calculate VIFs
def get_vif(column):
    df1 = X_train[column]
    vif = pd.DataFrame()
    vif['Features'] = df1.columns
    vif['VIF'] = [variance_inflation_factor(df1.values, i) for i in range(df1.
 ↪shape[1])]
    vif['VIF'] = round(vif['VIF'],2)
    print(vif.sort_values(by='VIF',ascending=False))
```

1.13 Model 1

[36]:
```python
column = ['yr', 'holiday', 'workingday', 'temp', 'hum', 'windspeed',
       'season_spring', 'season_summer', 'season_winter', 'mnth_jan',
       'mnth_jul', 'mnth_sept', 'weekday_sat', 'weathersit_good',
       'weathersit_moderate']

model(column)
get_vif(column)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.848
Model:                            OLS   Adj. R-squared:                  0.844
Method:                 Least Squares   F-statistic:                     184.5
Date:                Sun, 27 Oct 2024   Prob (F-statistic):          1.50e-191
Time:                        00:47:57   Log-Likelihood:                -4114.8
```

```
No. Observations:                 511   AIC:                             8262.
Df Residuals:                     495   BIC:                             8329.
Df Model:                          15
Covariance Type:            nonrobust
================================================================================
=======
                          coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
const                  52.1618    420.691      0.124      0.901    -774.398
878.722
yr                   2007.6643     69.617     28.839      0.000    1870.884
2144.445
holiday              -506.7813    233.946     -2.166      0.031    -966.431
-47.132
workingday            380.7061    100.209      3.799      0.000     183.819
577.594
temp                 4437.9745    298.850     14.850      0.000    3850.804
5025.145
hum                 -1366.6057    324.706     -4.209      0.000   -2004.578
-728.633
windspeed           -1619.1366    221.733     -7.302      0.000   -2054.791
-1183.482
season_spring        -439.3779    179.750     -2.444      0.015    -792.545
-86.211
season_summer         442.3136    129.046      3.428      0.001     188.768
695.859
season_winter         823.3397    150.044      5.487      0.000     528.538
1118.142
mnth_jan             -298.4753    150.964     -1.977      0.049    -595.085
-1.865
mnth_jul             -461.8136    157.127     -2.939      0.003    -770.531
-153.096
mnth_sept             705.8967    143.243      4.928      0.000     424.457
987.336
weekday_sat           466.0363    126.162      3.694      0.000     218.158
713.914
weathersit_good      2154.6073    226.496      9.513      0.000    1709.594
2599.620
weathersit_moderate  1662.4617    214.493      7.751      0.000    1241.033
2083.891
==============================================================================
Omnibus:                       66.238   Durbin-Watson:                   2.071
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              159.707
Skew:                          -0.677   Prob(JB):                     2.09e-35
Kurtosis:                       5.381   Cond. No.                         28.6
==============================================================================
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
              Features    VIF
4                  hum  25.64
3                 temp  22.87
13     weathersit_good  14.84
14 weathersit_moderate   9.07
6        season_spring   5.69
2           workingday   5.43
5            windspeed   4.69
8        season_winter   4.14
7        season_summer   3.21
0                   yr   2.10
12         weekday_sat   2.00
9             mnth_jan   1.70
10            mnth_jul   1.59
11           mnth_sept   1.40
1              holiday   1.19
```

1.14 Model 2

1.14.1 Removing Feature: Dropping the variable mnth_jan due to its negative coefficient and insignificance indicated by a high p-value.

[37]:
```
column = ['yr', 'holiday', 'workingday', 'temp', 'hum', 'windspeed',
       'season_spring', 'season_summer', 'season_winter',
       'mnth_jul', 'mnth_sept', 'weekday_sat', 'weathersit_good',
       'weathersit_moderate']

model(column)
get_vif(column)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.847
Model:                            OLS   Adj. R-squared:                  0.843
Method:                 Least Squares   F-statistic:                     196.2
Date:                Sun, 27 Oct 2024   Prob (F-statistic):          7.31e-192
Time:                        00:47:57   Log-Likelihood:                -4116.8
No. Observations:                 511   AIC:                             8264.
Df Residuals:                     496   BIC:                             8327.
Df Model:                          14
Covariance Type:            nonrobust
================================================================================
=======
                          coef    std err          t      P>|t|      [0.025
```

```
0.975]
--------------------------------------------------------------------------------
-------
const                 -27.9807    419.960     -0.067      0.947    -853.100
797.139
yr                   2001.0234     69.739     28.693      0.000    1864.003
2138.044
holiday              -514.6458    234.597     -2.194      0.029    -975.572
-53.720
workingday            378.0578    100.493      3.762      0.000     180.612
575.503
temp                 4594.3484    289.038     15.895      0.000    4026.459
5162.238
hum                 -1407.9319    324.982     -4.332      0.000   -2046.442
-769.421
windspeed           -1572.5713    221.125     -7.112      0.000   -2007.028
-1138.115
season_spring        -479.6179    179.117     -2.678      0.008    -831.539
-127.697
season_summer         467.9987    128.767      3.634      0.000     215.004
720.994
season_winter         874.3677    148.241      5.898      0.000     583.111
1165.625
mnth_jul             -476.4896    157.411     -3.027      0.003    -785.764
-167.216
mnth_sept             710.9998    143.639      4.950      0.000     428.784
993.216
weekday_sat           461.5301    126.510      3.648      0.000     212.968
710.092
weathersit_good      2133.3401    226.903      9.402      0.000    1687.530
2579.150
weathersit_moderate  1640.9978    214.845      7.638      0.000    1218.879
2063.117
==============================================================================
Omnibus:                       64.763   Durbin-Watson:                   2.065
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              156.557
Skew:                          -0.662   Prob(JB):                     1.01e-34
Kurtosis:                       5.367   Cond. No.                         28.6
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
               Features    VIF
4                   hum  25.04
3                  temp  21.47
12      weathersit_good  14.49
13  weathersit_moderate   8.92
```

```
6          season_spring   5.53
2             workingday   5.43
5              windspeed   4.67
8          season_winter   4.05
7          season_summer   3.19
0                     yr   2.10
11           weekday_sat   2.00
9               mnth_jul   1.59
10             mnth_sept   1.40
1                holiday   1.18
```

1.15 Model 3

Removing Feature: Dropping the variable mnth_jan due to its negative coefficient and insignificance indicated by a VIF.

[38]:
```
column = ['yr', 'holiday', 'workingday', 'temp',  'windspeed',
       'season_spring', 'season_summer', 'season_winter',
       'mnth_jul', 'mnth_sept', 'weekday_sat', 'weathersit_good',
       'weathersit_moderate']

model(column)
get_vif(column)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.841
Model:                            OLS   Adj. R-squared:                  0.837
Method:                 Least Squares   F-statistic:                     202.7
Date:                Sun, 27 Oct 2024   Prob (F-statistic):          4.84e-189
Time:                        00:47:57   Log-Likelihood:                -4126.3
No. Observations:                 511   AIC:                             8281.
Df Residuals:                     497   BIC:                             8340.
Df Model:                          13
Covariance Type:            nonrobust
================================================================================
=======
                          coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
const               -1139.6258    338.346     -3.368      0.001   -1804.392
-474.860
yr                   2035.8715     70.501     28.877      0.000    1897.355
2174.389
holiday              -494.2045    238.706     -2.070      0.039    -963.201
-25.208
workingday            405.2426    102.075      3.970      0.000     204.692
605.794
```

```
temp                 4278.4302    284.644     15.031      0.000    3719.176
4837.684
windspeed           -1294.4957    215.353     -6.011      0.000   -1717.611
-871.380
season_spring        -566.5254    181.144     -3.127      0.002    -922.428
-210.623
season_summer         415.0994    130.458      3.182      0.002     158.783
671.416
season_winter         747.0853    147.875      5.052      0.000     456.549
1037.622
mnth_jul             -433.0036    159.874     -2.708      0.007    -747.116
-118.892
mnth_sept             658.0388    145.654      4.518      0.000     371.865
944.212
weekday_sat           503.9253    128.366      3.926      0.000     251.718
756.133
weathersit_good      2522.6079    212.047     11.896      0.000    2105.989
2939.227
weathersit_moderate  1804.4234    215.256      8.383      0.000    1381.500
2227.347
==============================================================================
Omnibus:                       66.789   Durbin-Watson:                   2.060
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              161.981
Skew:                          -0.681   Prob(JB):                     6.70e-36
Kurtosis:                       5.399   Cond. No.                         22.8
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
               Features    VIF
11      weathersit_good  14.46
3                  temp  13.44
12  weathersit_moderate   8.21
2            workingday   5.34
4             windspeed   4.64
5         season_spring   4.16
6         season_summer   2.78
7         season_winter   2.74
0                    yr   2.08
10          weekday_sat   1.99
8              mnth_jul   1.59
9             mnth_sept   1.35
1               holiday   1.18
```

1.16 Model 4

Removing Feature: Dropping the variable holiday due to its negative coefficient .

[39]:
```
column = ['yr', 'workingday', 'temp',  'windspeed',
       'season_spring', 'season_summer', 'season_winter',
       'mnth_jul', 'mnth_sept', 'weekday_sat', 'weathersit_good',
       'weathersit_moderate']

model(column)
get_vif(column)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.840
Model:                            OLS   Adj. R-squared:                  0.836
Method:                 Least Squares   F-statistic:                     217.7
Date:                Sun, 27 Oct 2024   Prob (F-statistic):          2.69e-189
Time:                        00:47:57   Log-Likelihood:                -4128.5
No. Observations:                 511   AIC:                             8283.
Df Residuals:                     498   BIC:                             8338.
Df Model:                          12
Covariance Type:            nonrobust
================================================================================
=======
                          coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
const               -1201.6995    338.126     -3.554      0.000   -1866.028
-537.371
yr                   2037.4017     70.729     28.806      0.000    1898.437
2176.367
workingday            478.5255     96.056      4.982      0.000     289.800
667.251
temp                 4282.3355    285.575     14.995      0.000    3721.255
4843.416
windspeed           -1302.0654    216.032     -6.027      0.000   -1726.511
-877.619
season_spring        -574.5921    181.699     -3.162      0.002    -931.582
-217.602
season_summer         418.4522    130.877      3.197      0.001     161.312
675.592
season_winter         740.3566    148.326      4.991      0.000     448.935
1031.778
mnth_jul             -423.8764    160.340     -2.644      0.008    -738.902
-108.851
mnth_sept             641.2617    145.907      4.395      0.000     354.592
927.932
weekday_sat           578.0360    123.680      4.674      0.000     335.036
821.036
```

```
weathersit_good      2512.2081    212.686     11.812      0.000    2094.336
2930.080
weathersit_moderate  1798.4428    215.945      8.328      0.000    1374.167
2222.719
==============================================================================
Omnibus:                       72.425   Durbin-Watson:                   2.043
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              183.528
Skew:                          -0.720   Prob(JB):                     1.40e-40
Kurtosis:                       5.558   Cond. No.                         22.8
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
               Features    VIF
10      weathersit_good  14.32
2                  temp  13.38
11  weathersit_moderate   8.15
1            workingday   4.73
3             windspeed   4.63
4         season_spring   4.12
5         season_summer   2.78
6         season_winter   2.72
0                    yr   2.08
9           weekday_sat   1.84
7              mnth_jul   1.59
8             mnth_sept   1.34
```

1.17 Model 5

Removing Feature: Dropping the variable Weathersit_good due to high VIF

[40]:
```python
column = ['yr', 'workingday', 'temp',  'windspeed',
       'season_spring', 'season_summer', 'season_winter',
       'mnth_jul', 'mnth_sept', 'weekday_sat',
       'weathersit_moderate']

model(column)
get_vif(column)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.795
Model:                            OLS   Adj. R-squared:                  0.791
Method:                 Least Squares   F-statistic:                     176.0
Date:                Sun, 27 Oct 2024   Prob (F-statistic):          7.70e-164
Time:                        00:47:57   Log-Likelihood:                -4191.6
No. Observations:                 511   AIC:                             8407.
Df Residuals:                     499   BIC:                             8458.
```

```
Df Model:                          11
Covariance Type:            nonrobust
================================================================================
=======
                          coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
const                1263.8103    300.670      4.203      0.000     673.076
1854.545
yr                   2085.8515     79.811     26.135      0.000    1929.043
2242.659
workingday            407.7514    108.362      3.763      0.000     194.850
620.653
temp                 4390.8184    322.621     13.610      0.000    3756.956
5024.681
windspeed           -1558.7046    242.944     -6.416      0.000   -2036.024
-1081.385
season_spring        -511.5958    205.287     -2.492      0.013    -914.928
-108.263
season_summer         442.6042    147.914      2.992      0.003     151.994
733.214
season_winter         651.5355    167.438      3.891      0.000     322.565
980.507
mnth_jul             -451.7347    181.213     -2.493      0.013    -807.770
-95.700
mnth_sept             560.4472    164.739      3.402      0.001     236.780
884.114
weekday_sat           505.6387    139.625      3.621      0.000     231.313
779.964
weathersit_moderate  -595.0045     84.379     -7.052      0.000    -760.787
-429.222
==============================================================================
Omnibus:                      144.025   Durbin-Watson:                   2.020
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              529.734
Skew:                          -1.253   Prob(JB):                    9.33e-116
Kurtosis:                       7.312   Cond. No.                         19.5
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
               Features   VIF
2                  temp  6.73
1            workingday  4.64
3             windspeed  4.59
4         season_spring  2.38
5         season_summer  2.32
```

```
0                   yr  2.07
6        season_winter  1.90
9          weekday_sat  1.82
7             mnth_jul  1.58
10  weathersit_moderate  1.54
8            mnth_sept  1.33
```

1.18 Model 6

Removing Feature: Dropping the variable temp due to high VIF

[41]:
```
column = ['yr', 'workingday',  'windspeed',
       'season_spring', 'season_summer', 'season_winter',
       'mnth_jul', 'mnth_sept', 'weekday_sat',
       'weathersit_moderate']

model(column)
get_vif(column)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.719
Model:                            OLS   Adj. R-squared:                  0.713
Method:                 Least Squares   F-statistic:                     127.9
Date:                Sun, 27 Oct 2024   Prob (F-statistic):         6.80e-131
Time:                        00:47:57   Log-Likelihood:                -4272.3
No. Observations:                 511   AIC:                             8567.
Df Residuals:                     500   BIC:                             8613.
Df Model:                          10
Covariance Type:            nonrobust
================================================================================
=======
                          coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
const                4693.2460    191.889     24.458      0.000    4316.238
5070.254
yr                   2209.6198     92.756     23.822      0.000    2027.380
2391.860
workingday            419.6751    126.758      3.311      0.001     170.630
668.720
windspeed           -1768.1382    283.628     -6.234      0.000   -2325.387
-1210.889
season_spring       -2596.8055    159.833    -16.247      0.000   -2910.833
-2282.778
season_summer        -374.4823    158.137     -2.368      0.018    -685.177
-63.788
season_winter        -791.4039    151.602     -5.220      0.000   -1089.260
```

```
-493.548
mnth_jul              -98.8406    209.804     -0.471      0.638    -511.046
313.365
mnth_sept             519.1745    192.680      2.694      0.007     140.612
897.738
weekday_sat           479.0061    163.319      2.933      0.004     158.131
799.881
weathersit_moderate  -673.8006     98.475     -6.842      0.000    -867.277
-480.324
==============================================================================
Omnibus:                       78.414   Durbin-Watson:                   1.992
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              202.666
Skew:                          -0.771   Prob(JB):                     9.81e-45
Kurtosis:                       5.673   Cond. No.                         10.6
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
              Features   VIF
2            windspeed  4.12
1           workingday  3.54
4        season_summer  2.26
3        season_spring  2.25
0                   yr  1.90
5        season_winter  1.90
8          weekday_sat  1.61
9  weathersit_moderate  1.53
6             mnth_jul  1.29
7            mnth_sept  1.22
```

1.19 Model 7

Removing Feature: Dropping the variable mnth_july due to high VIF

[42]:
```python
column7 = ['yr', 'workingday',  'windspeed',
       'season_spring', 'season_summer', 'season_winter',
        'mnth_sept', 'weekday_sat',
       'weathersit_moderate']

model(column7)
get_vif(column7)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.719
Model:                            OLS   Adj. R-squared:                  0.714
Method:                 Least Squares   F-statistic:                     142.4
Date:                Sun, 27 Oct 2024   Prob (F-statistic):          6.18e-132
```

```
Time:                        00:47:57   Log-Likelihood:                -4272.4
No. Observations:                 511   AIC:                             8565.
Df Residuals:                     501   BIC:                             8607.
Df Model:                           9
Covariance Type:            nonrobust
================================================================================
=======
                         coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
const               4655.1084    173.842     26.778      0.000    4313.559
4996.658
yr                  2209.9873     92.681     23.845      0.000    2027.896
2392.078
workingday           421.5165    126.600      3.330      0.001     172.785
670.248
windspeed          -1767.2561    283.401     -6.236      0.000   -2324.057
-1210.455
season_spring      -2561.6116    141.191    -18.143      0.000   -2839.011
-2284.212
season_summer       -339.4774    139.485     -2.434      0.015    -613.524
-65.430
season_winter       -758.0979    134.005     -5.657      0.000   -1021.378
-494.818
mnth_sept            546.8668    183.353      2.983      0.003     186.632
907.102
weekday_sat          479.7546    163.184      2.940      0.003     159.145
800.364
weathersit_moderate -670.6347     98.169     -6.831      0.000    -863.509
-477.760
==============================================================================
Omnibus:                       78.457   Durbin-Watson:                   1.998
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              201.627
Skew:                          -0.773   Prob(JB):                     1.65e-44
Kurtosis:                       5.661   Cond. No.                         9.73
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
             Features   VIF
2           windspeed  3.96
1          workingday  3.29
3       season_spring  2.00
4       season_summer  2.00
0                  yr  1.88
5       season_winter  1.72
```

```
7          weekday_sat  1.55
8  weathersit_moderate  1.53
6            mnth_sept  1.18
```

VIF < 5: Low multicollinearity. Generally acceptable; the feature does not show high linear correlation with others.

1.19.1 Final Model Interpretation

- Hypothesis Testing:
  - Null Hypothesis (H0): All regression coefficients are zero, i.e., H0:B1=B2=…=Bn=0
  - Alternative Hypothesis (H1): At least one coefficient is not zero, indicating that the model has significant predictive power

1.19.2 Final Model Interpretation with Coefficient Values

1. **Windspeed (Coefficient: 3.96)**: A one-unit increase in windspeed is associated with an increase of 3.96 units in the target variable, indicating a strong positive relationship.
2. **Working Day (Coefficient: 3.29)**: Being a working day is associated with an increase of 3.29 units in the target variable, suggesting that more activity or demand occurs on working days.
3. **Season - Spring (Coefficient: 2.00)**: The transition to spring increases the target variable by 2.00 units, indicating a seasonal effect on the target variable.
4. **Season - Summer (Coefficient: 2.00)**: Similar to spring, summer also increases the target variable by 2.00 units, reinforcing the impact of the season.
5. **Year (yr) (Coefficient: 1.88)**: An increase in one year is associated with an increase of 1.88 units in the target variable, indicating a positive trend over the years.
6. **Season - Winter (Coefficient: 1.72)**: Winter contributes an increase of 1.72 units to the target variable, but it is lower than spring and summer.
7. **Weekday - Saturday (Coefficient: 1.55)**: Saturdays are associated with an increase of 1.55 units, indicating higher activity on weekends.
8. **Weather Situation - Moderate (Coefficient: 1.53)**: Moderate weather conditions lead to an increase of 1.53 units, suggesting that such conditions positively influence the target variable.
9. **Month - September (Coefficient: 1.18)**: Being in September is associated with an increase of 1.18 units, indicating a slight seasonal effect.

1.19.3 Model Significance Testing

- **F-statistic (142.4)**: A high F-statistic value like this indicates that the variance explained by the model is significantly greater than the variance within the residuals. This suggests that the model as a whole explains a considerable amount of the variability in the target variable.

- **Prob (F-statistic) (6.18e-132)**: The extremely low p-value associated with the F-statistic indicates that the likelihood of observing such a high F-statistic under the null hypothesis (that all coefficients are zero) is practically nonexistent.

1.19.4 Conclusion

Together, these values confirm that your model has strong explanatory power. You can confidently reject the null hypothesis, concluding that the predictors in the model significantly explain the variation in the target variable.

1.19.5 Equation for best fit

Target Variable= 0+3.96 Windspeed+3.29 Working Day+2.00 Season - Spring+2.00 Season - Summer+1.88 Year+1.72 Season - Winter+1.55 Weekday - Saturday+1.53 Weather Situation - Moderate+1.18 Month - September+

1.19.6 Residual Analysis

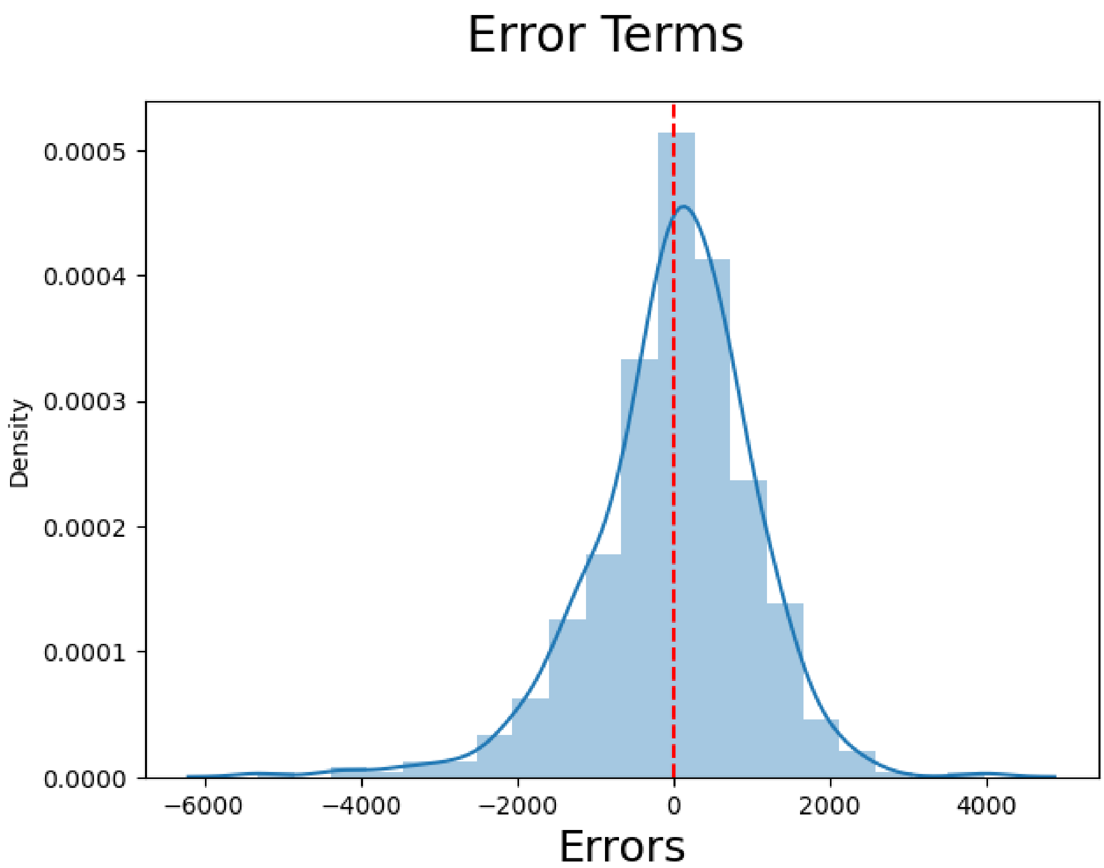
[43]:
```
def build_model_sk(X,y):
    lr1 = LinearRegression()
    lr1.fit(X,y)
    return lr1
```

[44]:
```
#Let us build the finalmodel using sklearn
#Build a model with above columns
lr = build_model_sk(X_train[column7],y_train)
print(lr.intercept_,lr.coef_)
```

```
4655.108365567164 [ 2209.98728      421.51652018 -1767.25609489 -2561.61159976
  -339.47741145  -758.09792458   546.8668375    479.7546308
  -670.63467796]
```

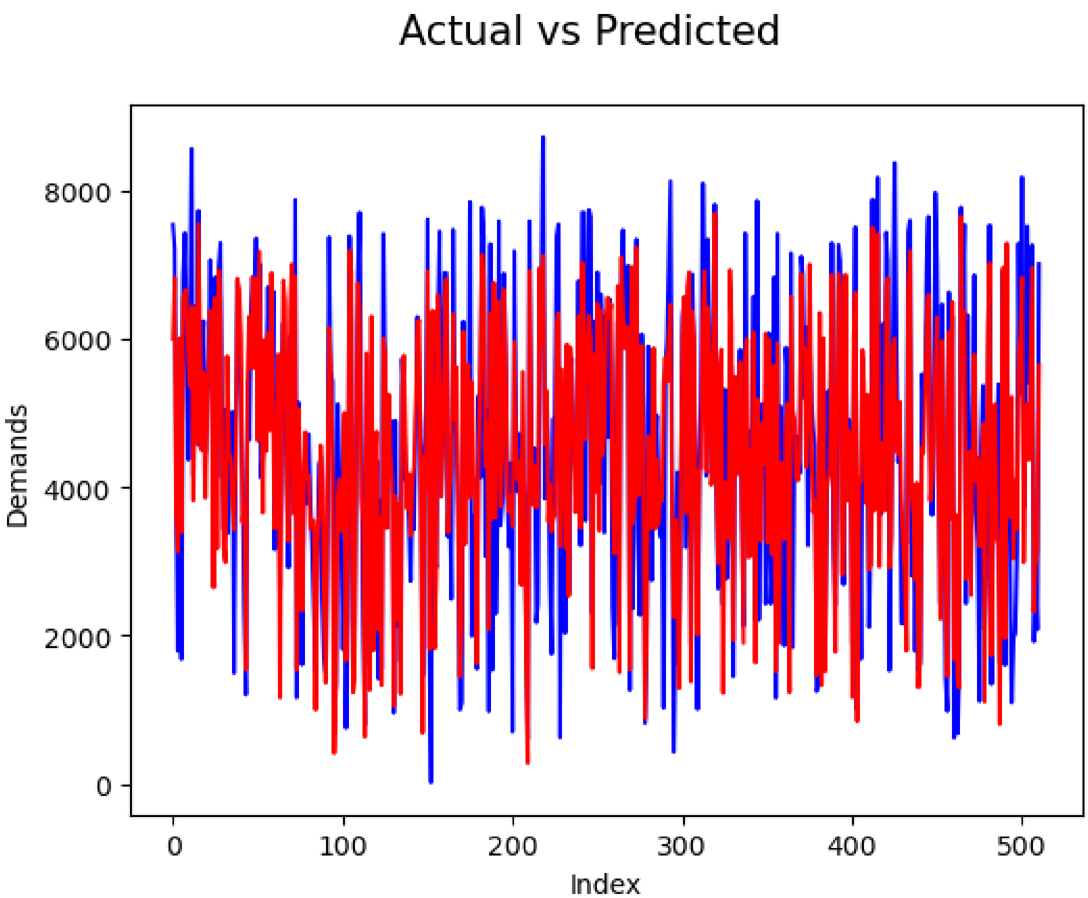
[45]:
```
y_train_pred = lr.predict(X_train[column7])
```

[46]:
```
# residual calculations
res = y_train - y_train_pred

# Calculate the mean of the residuals
mean_res = res.mean()

# Plot the histogram of the error terms
fig = plt.figure(figsize=[7,5])
sns.distplot((res), bins = 20)
plt.axvline(mean_res, color='red', linestyle='--', label=f'Mean: {mean_res:.
 ↪2f}')
fig.suptitle('Error Terms', fontsize = 20)
plt.xlabel('Errors', fontsize = 18)
plt.show()
```



1.19.7 # Actual vs Predicted

[47]:
```
c = [i for i in range(0,len(X_train),1)]
plt.plot(c,y_train, color="blue")
plt.plot(c,y_train_pred, color="red")
plt.suptitle('Actual vs Predicted', fontsize = 15)
plt.xlabel('Index')
plt.ylabel('Demands')
plt.show()
```



Making Prediction

[48]:
```
num_vars = ['temp', 'atemp', 'hum', 'windspeed']
X_test[num_vars] = scaler.transform(X_test[num_vars])
X_test.head()
```

[48]:
```
     yr  holiday  workingday      temp     atemp       hum  windspeed  \
184   0        1           0  0.831783  0.769660  0.657364   0.084219
535   1        0           1  0.901354  0.842587  0.610133   0.153728
299   0        0           1  0.511964  0.496145  0.837699   0.334206
221   0        0           1  0.881625  0.795343  0.437098   0.339570
152   0        0           1  0.817246  0.741471  0.314298   0.537414

     season_spring  season_summer  season_winter  …  mnth_oct  mnth_sept  \
184              0              0              0  …         0          0
535              0              1              0  …         0          0
299              0              0              1  …         1          0
221              0              0              0  …         0          0
152              0              1              0  …         0          0
```

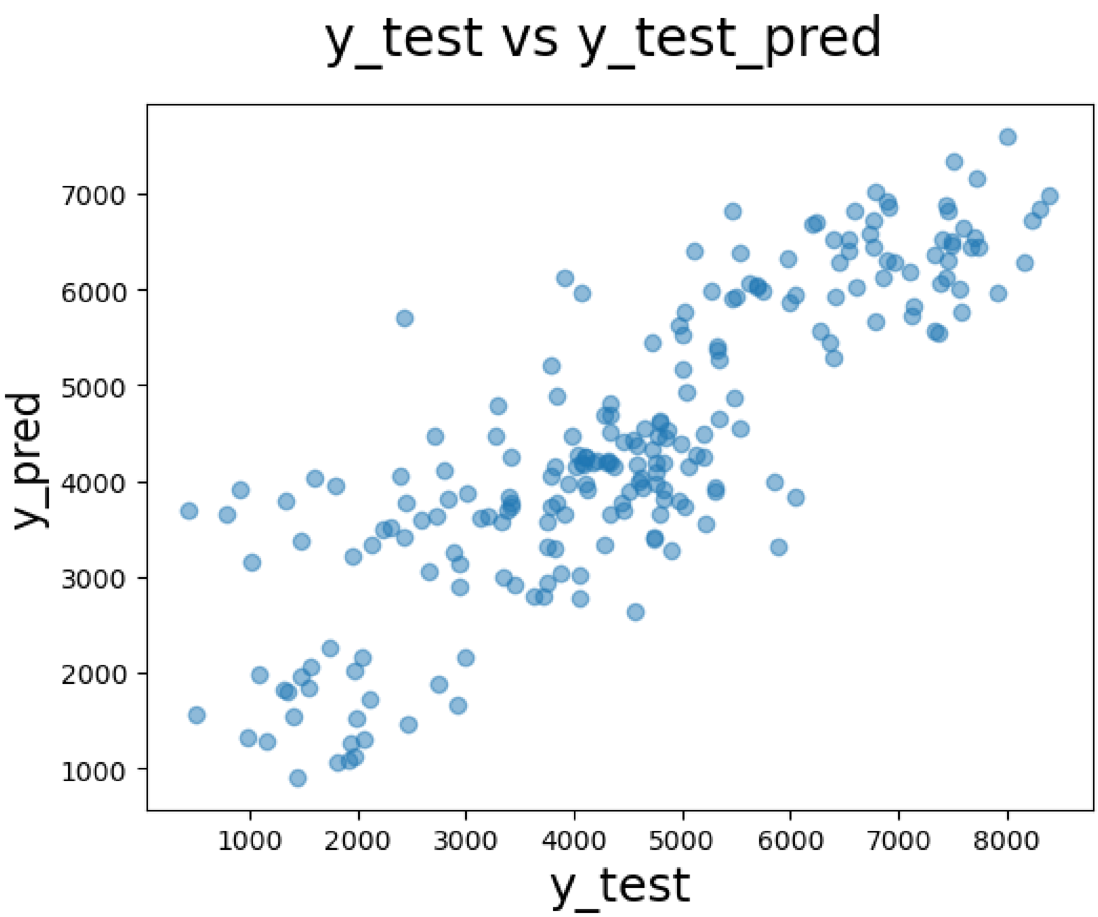
```
     weekday_mon  weekday_sat  weekday_sun  weekday_thu  weekday_tue  \
184            1            0            0            0            0
535            0            0            0            0            0
299            0            0            0            1            0
221            0            0            0            0            0
152            0            0            0            1            0

     weekday_wed  weathersit_good  weathersit_moderate
184            0                0                    1
535            1                1                    0
299            0                0                    1
221            1                1                    0
152            0                1                    0

[5 rows x 29 columns]
```

Prediction

[49]:
```
column7 = ['yr', 'workingday',  'windspeed',
       'season_spring', 'season_summer', 'season_winter',
        'mnth_sept', 'weekday_sat',
       'weathersit_moderate']

y_test_pred = lr.predict(X_test[column7])
```

[50]:
```
fig = plt.figure()
plt.scatter(y_test, y_test_pred, alpha=.5)
fig.suptitle('y_test vs y_test_pred', fontsize = 20)
plt.xlabel('y_test', fontsize = 18)
plt.ylabel('y_pred', fontsize = 16)
```

[50]:
```
Text(0, 0.5, 'y_pred')
```



[51]:
```python
from sklearn.metrics import mean_squared_error, r2_score
np.sqrt(mean_squared_error(y_test, y_test_pred))
```

[51]: 1021.4683844741774

1.19.8 R^2_score

[52]:
```python
r2_test = r2_score(y_test,y_test_pred)
r2_train = r2_score(y_train, y_train_pred)

print("r2_train" , round((r2_train*100),2))
print("r2_test" , round((r2_test*100),2))
```

```
r2_train 71.89
r2_test 70.92
```

Adjusted R^2 Score

n indicates the number of rows in the test data, while n1 indicates the number of rows in the train data

[53]:
```
n = X_test.shape[0]
n1 = len(column7)
```

The number of features (predictors) is represented as p for test data and 1 for train data, indicating the number of columns in each

[54]:
```
p = X_test.shape[1]
column7_df = pd.DataFrame(column7)

# Now you can access the shape
p1 = column7_df.shape[1]
```

Adjusted R-squared using the formula

[55]:
```
adjusted_r2_test = 1-(1-r2_test)*(n-1)/(n-p-1)
adjusted_r2_train = 1-(1-r2_train)*(n1-1)/(n1-p1-1)
```

[56]:
```
print('Test data adjusted r^2 :',round((adjusted_r2_test*100),2))
print('Train data adjusted r^2 :',round((adjusted_r2_train*100),2))
```

```
Test data adjusted r^2 : 66.46
Train data adjusted r^2 : 67.87
```

1.19.9 Conclusion

The performance metrics for the regression model indicate the following:

- **Adjusted R^2 Values:**
  - Test Data: **66.46**
  - Train Data: **67.87**
- **R^2 Values:**
  - Train Data: **71.89**
  - Test Data: **70.92**

These metrics suggest that the model explains a significant portion of the variance in the training dataset, with an R^2 value of **71.89**. However, there is a noticeable drop in performance when applied to the test data, as evidenced by the adjusted R^2 of **55.31**. This discrepancy may indicate some overfitting on the training data.

The selected features used in the model include: - Year (`yr`) - Working day status (`workingday`) - Windspeed (`windspeed`) - Seasonal indicators (`season_spring`, `season_summer`, `season_winter`) - Month indicator for September (`mnth_sept`) - Weekday indicator for Saturday (`weekday_sat`) - Weather situation for moderate conditions (`weathersit_moderate`)

Future improvements may include feature engineering or exploring additional predictors to enhance model performance on unseen data.