Linear Regression Assignment (Bike Share)

Reading and Understanding the Data

In [1]:

```
# Import all the required libraries

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [2]:

```
# Import the data

bike_data = pd.read_csv('day.csv')
bike_data.head()
```

Out[2]:

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp
0	1	01-01-2018	1	0	1	0	6	0	2	14.110847
1	2	02-01-2018	1	0	1	0	0	0	2	14.902598
2	3	03-01-2018	1	0	1	0	1	1	1	8.050924
3	4	04-01-2018	1	0	1	0	2	1	1	8.200000
4	5	05-01-2018	1	0	1	0	3	1	1	9.305237

In [3]:

```
# Check the shape

bike_data.shape
```

Out[3]:

```
(730, 16)
```

In [4]:

```
# Check data-info and other info regarding the null data
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
```

Observation

- We see that the there are *no null datapoint* available in any columns.
- Total *16 features* are availble to study the data.

In [5]:

```
# Describe the numeric columns of the dataset

bike_data.describe()
```

Out[5]:

	instant	season	yr	mnth	holiday	weekday	workingday
count	730.000000	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	0.683562
std	210.877136	1.110184	0.500343	3.450215	0.167266	2.006161	0.465405
min	1.000000	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000
25%	183.250000	2.000000	0.000000	4.000000	0.000000	1.000000	0.000000
50%	365.500000	3.000000	0.500000	7.000000	0.000000	3.000000	1.000000
75%	547.750000	3.000000	1.000000	10.000000	0.000000	5.000000	1.000000
max	730.000000	4.000000	1.000000	12.000000	1.000000	6.000000	1.000000

In [6]:

```
# Rename few columns name for better understanding and interpretation

bike_data.rename(columns={"yr":"year",
                          "mnth":"month",
                          "atemp":"abs-temp",
                          "hum":"humidity"}, inplace=True)
bike_data.head()
```

Out[6]:

	instant	dteday	season	year	month	holiday	weekday	workingday	weathersit	ten
0	1	01-01-2018	1	0	1	0	6	0	2	14.1108
1	2	02-01-2018	1	0	1	0	0	0	2	14.9025
2	3	03-01-2018	1	0	1	0	1	1	1	8.0509
3	4	04-01-2018	1	0	1	0	2	1	1	8.2000
4	5	05-01-2018	1	0	1	0	3	1	1	9.3052

Drop the following columns

- `instant` : record index
- `dteday` : date
- `casual` and `registered` : Due to a feature column `cnt` , which is a sum of these two columns.

In [7]:

```
# Drop some columns

bike_data.drop(['instant', 'dteday', 'casual', 'registered'], axis=1, inplace=True)
```

In [8]:

```
# We, see that after dropping some columns, the remaining features are 12.

bike_data.shape
```

Out[8]:

```
(730, 12)
```

Visualising the Data

Let's now spend some time doing what is arguably the most important step - **understanding the data**.

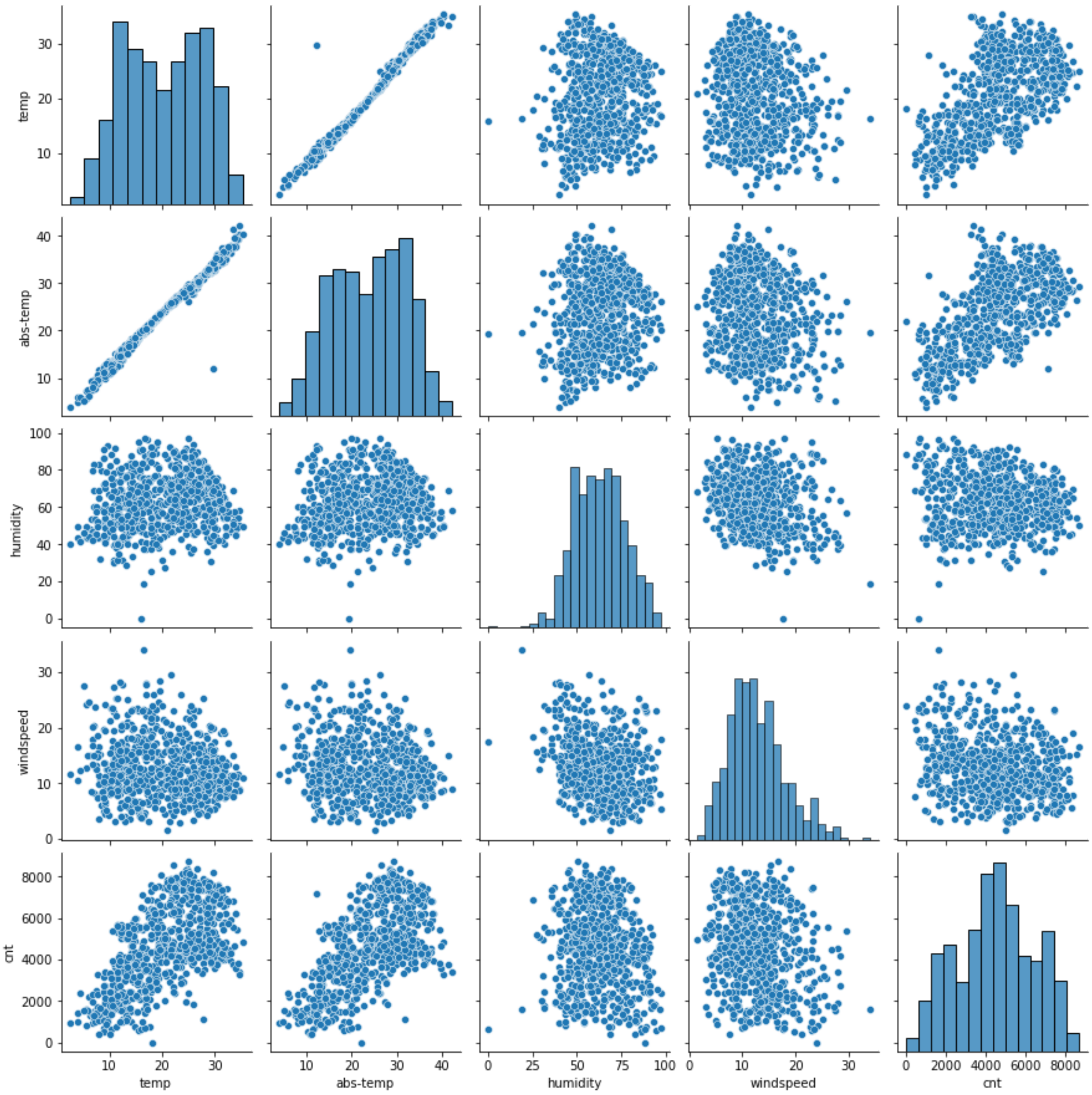
- If there is some obvious multicollinearity going on, this is the first place to catch it

- Here's where you'll also identify if some predictors directly have a strong association with the outcome variable

We'll visualise our data using `matplotlib` and `seaborn` .

In [9]:

```
# Lets see pair plot to understand the behaviour of one feature w.r.t to other feature

sns.pairplot(data=bike_data,vars=['temp','abs-temp','humidity','windspeed','cnt'])
plt.show()
```



Observation

- We see some very strong linear relation between `temp` , `abs-temp` and `cnt` .
- We see `temp` and `abs-temp` are very strongly correlated with each other.

In [10]:

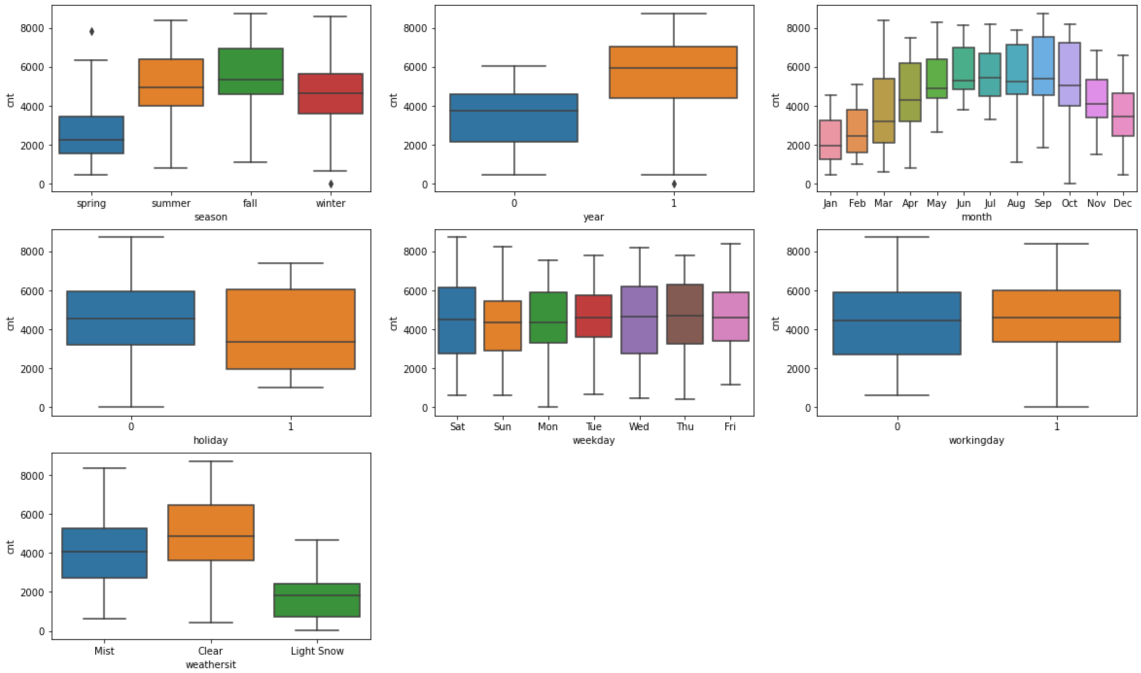
```
# Lets map the data based on the data dictionaty in ordet to create dummy columns

bike_data['season'] = bike_data['season'].map({1:"spring", 2:"summer", 3:"fall", 4:"wint

bike_data['month'] = bike_data['month'].map({1:"Jan", 2:"Feb", 3:"Mar", 4:"Apr", 5:"May"
                                              6:"Jun", 7:"Jul", 8:"Aug", 9:"Sep", 10:"Oct
                                              11:"Nov", 12:"Dec"})

bike_data['weekday'] = bike_data['weekday'].map({0:"Sun", 1:"Mon", 2:"Tue", 3:"Wed",
                                                  4:"Thu", 5:"Fri", 6:"Sat"})

bike_data['weathersit'] = bike_data['weathersit'].map({1:"Clear", 2:"Mist",
                                                        3:"Light Snow", 4:"Heavy Rain"})

bike_data.head()
```

Out[10]:

	season	year	month	holiday	weekday	workingday	weathersit	temp	abs-temp	hu
0	spring	0	Jan	0	Sat	0	Mist	14.110847	18.18125	80
1	spring	0	Jan	0	Sun	0	Mist	14.902598	17.68695	69
2	spring	0	Jan	0	Mon	1	Clear	8.050924	9.47025	43
3	spring	0	Jan	0	Tue	1	Clear	8.200000	10.60610	59
4	spring	0	Jan	0	Wed	1	Clear	9.305237	11.46350	43

In [11]:

```
# Lets understand the behaviour of some categorical data

plt.figure(figsize=(20, 12))
plt.subplot(3,3,1)
sns.boxplot(x = 'season', y = 'cnt', data = bike_data)
plt.subplot(3,3,2)
sns.boxplot(x = 'year', y = 'cnt', data = bike_data)
plt.subplot(3,3,3)
sns.boxplot(x = 'month', y = 'cnt', data = bike_data)
plt.subplot(3,3,4)
sns.boxplot(x = 'holiday', y = 'cnt', data = bike_data)
plt.subplot(3,3,5)
sns.boxplot(x = 'weekday', y = 'cnt', data = bike_data)
plt.subplot(3,3,6)
sns.boxplot(x = 'workingday', y = 'cnt', data = bike_data)
plt.subplot(3,3,7)
sns.boxplot(x = 'weathersit', y = 'cnt', data = bike_data)
plt.show()
```

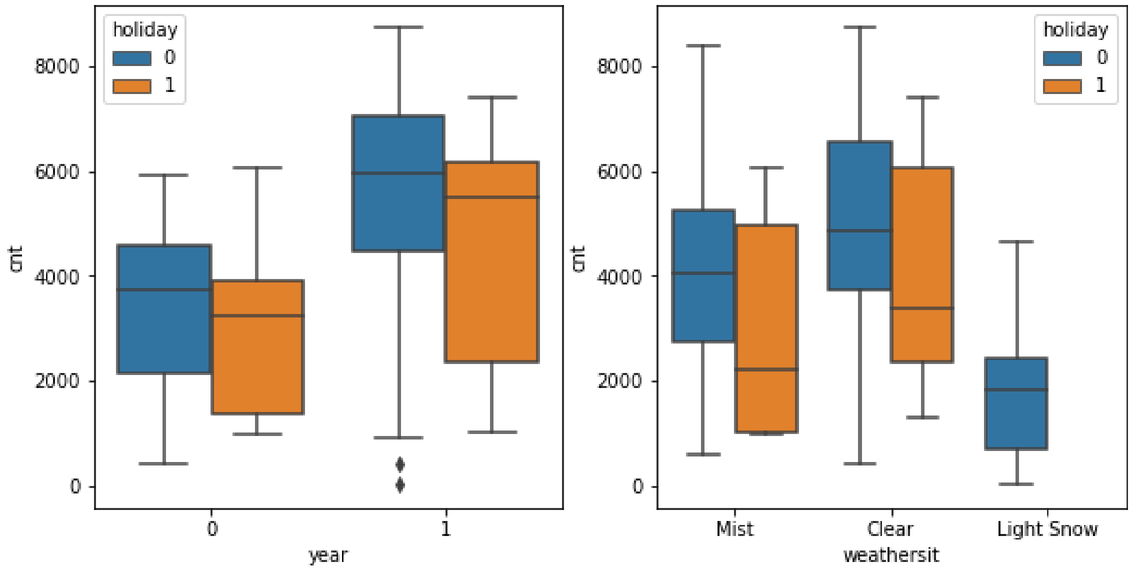


Observation

- Fall `season` has the most bike share count, where as the Spring has minimum count.
- Number of count in `2019` are significantly (33.33%) more than that of 2018.
- Number of count in the `month` of Jun, July, Aug and Sep are the most.
- Count is more when the weather is clear.

In [12]:

```
# Bivariate analysis

plt.figure(figsize = (10, 5))
plt.subplot(1,2,1)
sns.boxplot(x = 'year', y = 'cnt', hue = 'holiday', data = bike_data)
plt.subplot(1,2,2)
sns.boxplot(x = 'weathersit', y = 'cnt', hue = 'holiday', data = bike_data)
plt.show()
```



Observation

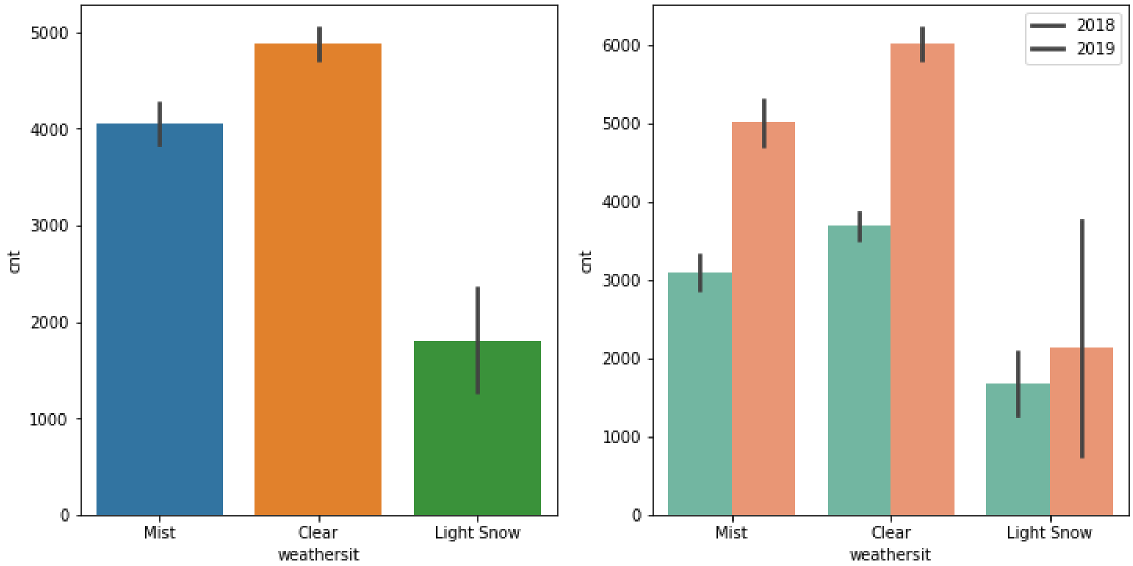
- More people use the bike during the non-holiday time and clear weather.

In [13]:

```
# Define a function to get the bar plots

def get_bar_plot(column):
    plt.figure(figsize = (12,6))
    plt.subplot(1,2,1)
    sns.barplot(column,'cnt',data=bike_data)
    plt.subplot(1,2,2)
    sns.barplot(column,'cnt',data=bike_data, hue='year',palette='Set2')
    plt.legend(labels=['2018', '2019'])
    plt.show()
```

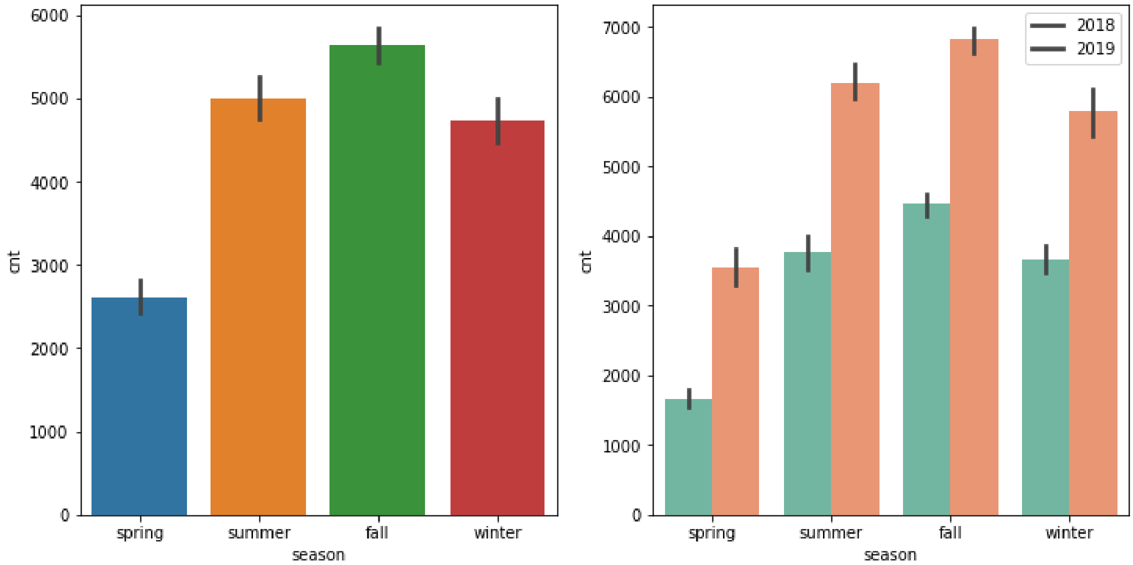
In [14]:

```
get_bar_plot('weathersit')
```



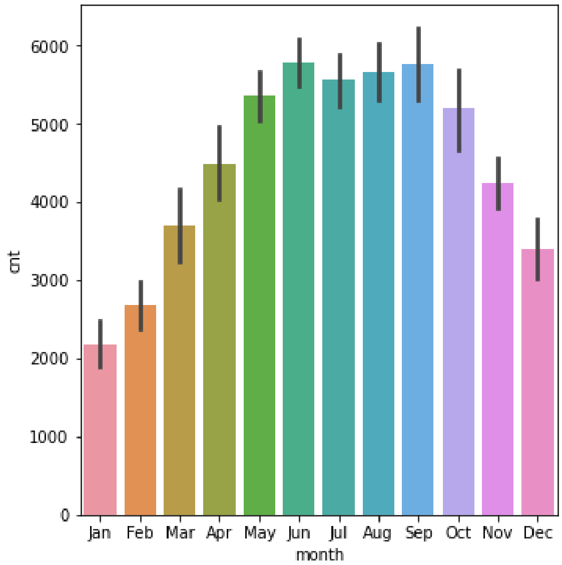
In [15]:

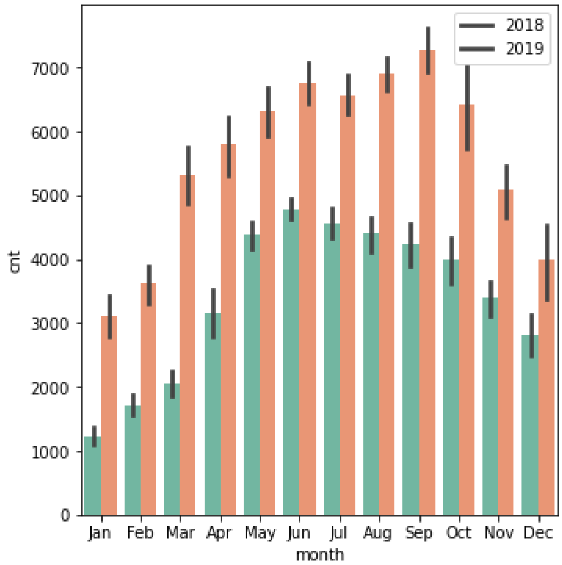
```
get_bar_plot('season')
```



In [16]:

```
get_bar_plot('month')
```





Observation

- More people use the bike during the non-holiday time and clear weather.
- Fall `season` has the most bike share count, where as the Spring has minimum count.
- Number of count in `2019` are significantly (33.33%) more than that of 2018.
- Number of count in the `month` of Jun, July, Aug and Sep are the most.
- Count is more when the weather is clear.

Create dummy variable

In [17]:

```
# Create a function to get the dummy variable dataframe

def get_dummy_dataframe(column_name: list[str]):
    output = pd.DataFrame()
    for column in column_name:
        status = pd.get_dummies(bike_data[column], drop_first=True)
        output = pd.concat([output, status], axis=1)  # Concatenate the status DataFrame
    return output
```

In [18]:

```
# Dummy dataframe from the below categorical columns

dummy_df = get_dummy_dataframe(column_name=['season', 'month', 'weekday', 'weathersit'])
```

In [19]:

```
# Dummy variable column name

dummy_df.columns
```

Out[19]:

```
Index(['spring', 'summer', 'winter', 'Aug', 'Dec', 'Feb', 'Jan', 'Jul', 'J
un',
       'Mar', 'May', 'Nov', 'Oct', 'Sep', 'Mon', 'Sat', 'Sun', 'Thu', 'Tu
e',
       'Wed', 'Light Snow', 'Mist'],
      dtype='object')
```

In [20]:

```
# Dummy variable dataframe

dummy_df
```

Out[20]:

	spring	summer	winter	Aug	Dec	Feb	Jan	Jul	Jun	Mar	...	Oct	Sep	Mon	Sat
0	1	0	0	0	0	0	1	0	0	0	...	0	0	0	1
1	1	0	0	0	0	0	1	0	0	0	...	0	0	0	0
2	1	0	0	0	0	0	1	0	0	0	...	0	0	1	0
3	1	0	0	0	0	0	1	0	0	0	...	0	0	0	0
4	1	0	0	0	0	0	1	0	0	0	...	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
725	1	0	0	0	1	0	0	0	0	0	...	0	0	0	0
726	1	0	0	0	1	0	0	0	0	0	...	0	0	0	0
727	1	0	0	0	1	0	0	0	0	0	...	0	0	0	1
728	1	0	0	0	1	0	0	0	0	0	...	0	0	0	0
729	1	0	0	0	1	0	0	0	0	0	...	0	0	1	0

730 rows × 22 columns

In [21]:

```
# Concatenate dummy dataframe with the original dataframe

bike_data = pd.concat([bike_data, dummy_df], axis=1)
```

In [22]:

```
# Concatinated dataframe

bike_data
```

Out[22]:

	season	year	month	holiday	weekday	workingday	weathersit	temp	abs-temp
0	spring	0	Jan	0	Sat	0	Mist	14.110847	18.18125
1	spring	0	Jan	0	Sun	0	Mist	14.902598	17.68695
2	spring	0	Jan	0	Mon	1	Clear	8.050924	9.47025
3	spring	0	Jan	0	Tue	1	Clear	8.200000	10.60610
4	spring	0	Jan	0	Wed	1	Clear	9.305237	11.46350
...	...	...	...	...	...	...	...	...	...
725	spring	1	Dec	0	Thu	1	Mist	10.420847	11.33210
726	spring	1	Dec	0	Fri	1	Mist	10.386653	12.75230
727	spring	1	Dec	0	Sat	0	Mist	10.386653	12.12000
728	spring	1	Dec	0	Sun	0	Clear	10.489153	11.58500
729	spring	1	Dec	0	Mon	1	Mist	8.849153	11.17435

730 rows × 34 columns

In [23]:

```
# Data info

bike_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 34 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   season      730 non-null    object 
 1   year        730 non-null    int64  
 2   month       730 non-null    object 
 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   abs-temp    730 non-null    float64
 9   humidity    730 non-null    float64
 10  windspeed   730 non-null    float64
 11  cnt         730 non-null    int64  
 12  spring      730 non-null    uint8  
 13  summer      730 non-null    uint8  
 14  winter      730 non-null    uint8  
 15  Aug         730 non-null    uint8  
 16  Dec         730 non-null    uint8  
 17  Feb         730 non-null    uint8  
 18  Jan         730 non-null    uint8  
 19  Jul         730 non-null    uint8  
 20  Jun         730 non-null    uint8  
 21  Mar         730 non-null    uint8  
 22  May         730 non-null    uint8  
 23  Nov         730 non-null    uint8  
 24  Oct         730 non-null    uint8  
 25  Sep         730 non-null    uint8  
 26  Mon         730 non-null    uint8  
 27  Sat         730 non-null    uint8  
 28  Sun         730 non-null    uint8  
 29  Thu         730 non-null    uint8  
 30  Tue         730 non-null    uint8  
 31  Wed         730 non-null    uint8  
 32  Light Snow  730 non-null    uint8  
 33  Mist        730 non-null    uint8  
dtypes: float64(4), int64(4), object(4), uint8(22)
memory usage: 84.2+ KB
```

In [24]:

```
# Drop columns for which dummy df created

bike_data.drop(['season', 'month', 'weekday', 'weathersit'],
               axis=1, inplace=True)

bike_data.head()
```

Out[24]:

	year	holiday	workingday	temp	abs-temp	humidity	windspeed	cnt	spring	sumr
0	0	0	0	14.110847	18.18125	80.5833	10.749882	985	1	
1	0	0	0	14.902598	17.68695	69.6087	16.652113	801	1	
2	0	0	1	8.050924	9.47025	43.7273	16.636703	1349	1	
3	0	0	1	8.200000	10.60610	59.0435	10.739832	1562	1	
4	0	0	1	9.305237	11.46350	43.6957	12.522300	1600	1	

5 rows × 30 columns

In [25]:

```
# Final dataframe

bike_data.columns
```

Out[25]:

```
Index(['year', 'holiday', 'workingday', 'temp', 'abs-temp', 'humidity',
       'windspeed', 'cnt', 'spring', 'summer', 'winter', 'Aug', 'Dec', 'Fe
b',
       'Jan', 'Jul', 'Jun', 'Mar', 'May', 'Nov', 'Oct', 'Sep', 'Mon', 'Sa
t',
       'Sun', 'Thu', 'Tue', 'Wed', 'Light Snow', 'Mist'],
      dtype='object')
```

In [26]:

```
# We specify this so that the train and test data set always have the same rows, respect
# Create a train test split

np.random.seed(0)
df_train, df_test = train_test_split(bike_data, train_size = 0.7, test_size = 0.3, rando
```

In [27]:

```
# Test data

df_test
```

Out[27]:

	year	holiday	workingday	temp	abs-temp	humidity	windspeed	cnt	spring	su
184	0	1	0	29.793347	33.27085	63.7917	5.459106	6043	0	
535	1	0	1	32.082500	36.04875	59.2083	7.625404	6211	0	
299	0	0	1	19.270000	22.85230	81.2917	13.250121	2659	0	
221	0	0	1	31.433347	34.24915	42.4167	13.417286	4780	0	
152	0	0	1	29.315000	32.19710	30.5000	19.583229	4968	0	
...	...	...	...	...	...	...	...	...	...	
400	1	0	0	10.899153	13.22605	68.7917	11.791732	2947	1	
702	1	0	1	19.509153	23.45270	73.3750	11.666643	6606	0	
127	0	0	0	21.661653	25.94665	63.1667	5.000712	4333	0	
640	1	0	1	26.957500	29.95665	79.3750	4.458569	7572	0	
72	0	0	1	13.333897	16.60000	49.6957	9.174042	2046	1	

219 rows × 30 columns

In [28]:

```
# Train data

df_train
```

Out[28]:

	year	holiday	workingday	temp	abs-temp	humidity	windspeed	cnt	spring	su
653	1	0	1	19.201653	23.04230	55.8333	12.208807	7534	0	
576	1	0	1	29.246653	33.14480	70.4167	11.083475	7216	0	
426	1	0	0	16.980847	20.67460	62.1250	10.792293	4066	1	
728	1	0	0	10.489153	11.58500	48.3333	23.500518	1796	1	
482	1	0	0	15.443347	18.87520	48.9583	8.708325	4220	0	
...	...	...	...	...	...	...	...	...	...	
526	1	0	1	29.554153	32.98605	58.7917	13.916771	6664	0	
578	1	0	1	30.852500	35.35440	65.9583	8.666718	7261	0	
53	0	0	1	9.091299	12.28585	42.3043	6.305571	1917	1	
350	0	0	0	10.591653	12.46855	56.0833	16.292189	2739	0	
79	0	0	1	17.647835	20.48675	73.7391	19.348461	2077	0	

510 rows × 30 columns

In [29]:

```
# Use scalling for some numeric feature

scaler = MinMaxScaler()
num_var  = ['temp', 'abs-temp', 'humidity', 'windspeed', 'cnt']
df_train[num_var]  = scaler.fit_transform(df_train[num_var])
df_train
```

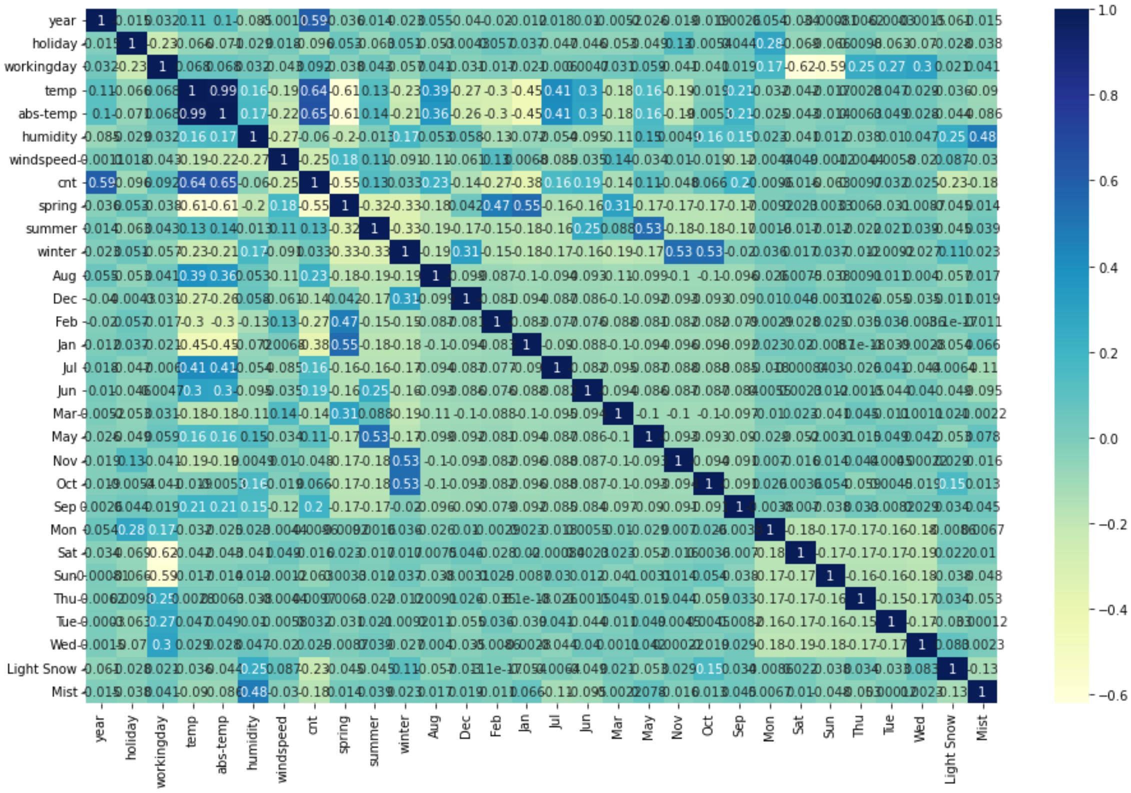
Out[29]:

	year	holiday	workingday	temp	abs-temp	humidity	windspeed	cnt	spring
653	1	0	1	0.509887	0.501133	0.575354	0.300794	0.864243	0
576	1	0	1	0.815169	0.766351	0.725633	0.264686	0.827658	0
426	1	0	0	0.442393	0.438975	0.640189	0.255342	0.465255	1
728	1	0	0	0.245101	0.200348	0.498067	0.663106	0.204096	1
482	1	0	0	0.395666	0.391735	0.504508	0.188475	0.482973	0
...	...	...	...	...	...	...	...	...	...
526	1	0	1	0.824514	0.762183	0.605840	0.355596	0.764151	0
578	1	0	1	0.863973	0.824359	0.679690	0.187140	0.832835	0
53	0	0	1	0.202618	0.218747	0.435939	0.111379	0.218017	1
350	0	0	0	0.248216	0.223544	0.577930	0.431816	0.312586	0
79	0	0	1	0.462664	0.434043	0.759870	0.529881	0.236424	0

510 rows × 30 columns

In [30]:

```
# Correlation plot for train dataset

plt.figure(figsize = (16, 10))
sns.heatmap(df_train.corr(), annot = True, cmap="YlGnBu")
plt.show()
```

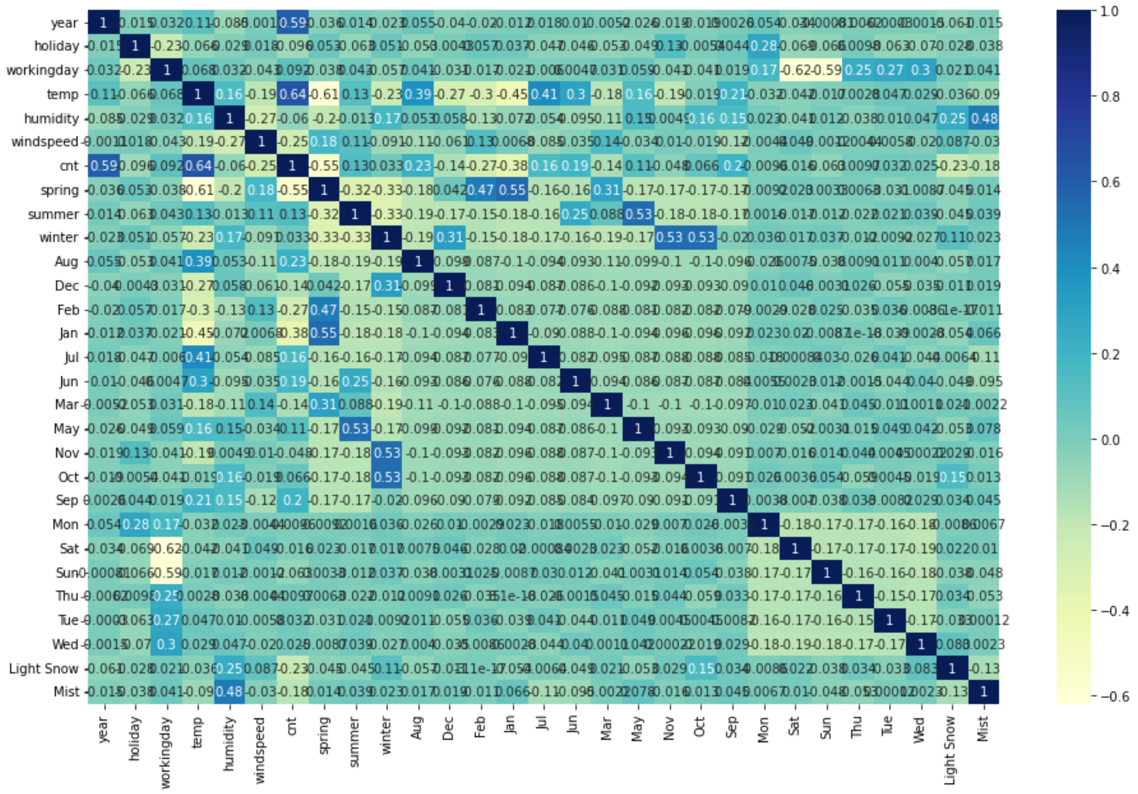


Observation

- We see that temp and abs_temp are highly correlated, therefore we will remove one of these feature.

In [31]:

```
# Drop 'abs-temp' columns

df_train.drop(['abs-temp'], axis=1, inplace=True)
plt.figure(figsize = (16, 10))
sns.heatmap(df_train.corr(), annot = True, cmap="YlGnBu")
plt.show()
```



Observation

- Now, the strong correlation effect has been removed.

Fit the model and predict using best model

In [32]:

```
# Select target feature and apply model
# Use RFE to select the best features

y_train = df_train.pop('cnt')
X_train = df_train

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

rfe  =RFE(lm, 20)
rfe = rfe.fit(X_train, y_train)
```

In [33]:

```
# List of features with their names and ranking

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

Out[33]:

```
[('year', True, 1),
 ('holiday', True, 1),
 ('workingday', True, 1),
 ('temp', True, 1),
 ('humidity', True, 1),
 ('windspeed', True, 1),
 ('spring', True, 1),
 ('summer', True, 1),
 ('winter', True, 1),
 ('Aug', False, 2),
 ('Dec', True, 1),
 ('Feb', True, 1),
 ('Jan', True, 1),
 ('Jul', True, 1),
 ('Jun', False, 8),
 ('Mar', False, 9),
 ('May', True, 1),
 ('Nov', True, 1),
 ('Oct', False, 5),
 ('Sep', True, 1),
 ('Mon', False, 3),
 ('Sat', True, 1),
 ('Sun', True, 1),
 ('Thu', False, 6),
 ('Tue', False, 4),
 ('Wed', False, 7),
 ('Light Snow', True, 1),
 ('Mist', True, 1)]
```

In [34]:

```
# Colums which supports the model

col = X_train.columns[rfe.support_]
col
```

Out[34]:

```
Index(['year', 'holiday', 'workingday', 'temp', 'humidity', 'windspeed',
       'spring', 'summer', 'winter', 'Dec', 'Feb', 'Jan', 'Jul', 'May', 'N
ov',
       'Sep', 'Sat', 'Sun', 'Light Snow', 'Mist'],
      dtype='object')
```

In [35]:

```
# Column which does not support the model

X_train.columns[~rfe.support_]
```

Out[35]:

```
Index(['Aug', 'Jun', 'Mar', 'Oct', 'Mon', 'Thu', 'Tue', 'Wed'], dtype='obj
ect')
```

In [36]:

```
# Build a model WITH required feature which supports the model

X_train_rfe_1 = X_train[col]
```

In [37]:

```
# Add constant to the model

import statsmodels.api as sm
X_train_lm_1 = sm.add_constant(X_train_rfe_1)
```

In [38]:

```
# Fit the model

lm_1 = sm.OLS(y_train, X_train_lm_1).fit()
```

In [39]:

```
# Print the model summary

print(lm_1.summary())
```

```
                            OLS Regression Results                            
=======================================================================
=======
Dep. Variable:                    cnt   R-squared:                       
0.852
Model:                            OLS   Adj. R-squared:                  
0.847
Method:                 Least Squares   F-statistic:                     
148.8
Date:                Wed, 16 Aug 2023   Prob (F-statistic):          1.
59e-189
Time:                        18:10:28   Log-Likelihood:                  
526.24
No. Observations:                 510   AIC:                             
-1012.
Df Residuals:                     490   BIC:                             
-927.8
Df Model:                          19                                         
Covariance Type:            nonrobust                                         
```

In [40]:

```
# Write a function to create a VIF dataframe

def get_vif_dataframe(dataframe: pd.DataFrame):
    vif = pd.DataFrame()
    vif['Features'] = dataframe.columns
    vif['VIF'] = [variance_inflation_factor(dataframe.values, i) for i in range(datafram
    vif['VIF'] = round(vif['VIF'], 2)
    vif = vif.sort_values(by = "VIF", ascending = False)
    return vif
```

In [41]:

```
# Get VIF for 1st set if data

get_vif_dataframe(X_train_rfe_1)
```

Out[41]:

	Features	VIF
2	workingday	60.93
16	Sat	14.59
17	Sun	13.91
6	spring	5.79
3	temp	4.88
8	winter	3.88
7	summer	3.49
1	holiday	3.43
11	Jan	2.38
4	humidity	1.97
10	Feb	1.87
14	Nov	1.81
9	Dec	1.65
19	Mist	1.58
13	May	1.52
12	Jul	1.49
15	Sep	1.34
18	Light Snow	1.28
5	windspeed	1.22
0	year	1.04

In [42]:

```
# Perform the second iteration (As the feature 'holiday' is not significant), so will rei

X_train_rfe_2 = X_train_rfe_1.drop(['holiday'], axis=1)
```

In [43]:

```
# Fit the model based on feature selecte in 2nd iteration

X_train_lm_2 = sm.add_constant(X_train_rfe_2)
lm_2 = sm.OLS(y_train, X_train_lm_2).fit()
print(lm_2.summary())
```

```
                            OLS Regression Results                            
==============================================================================
====
Dep. Variable:                    cnt   R-squared:                       
0.852
Model:                            OLS   Adj. R-squared:                  
0.847
Method:                 Least Squares   F-statistic:                     1
48.8
Date:                Wed, 16 Aug 2023   Prob (F-statistic):          1.59e
-189
Time:                        18:10:28   Log-Likelihood:                  52
6.24
No. Observations:                 510   AIC:                             -1
012.
Df Residuals:                     490   BIC:                             -9
27.8
Df Model:                          19                                         
Covariance Type:            nonrobust                                         
==============================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
------------------------------------------------------------------------------
----
const          0.2494      0.045      5.516      0.000       0.161       
0.338
year           0.2317      0.008     29.150      0.000       0.216       
0.247
workingday     0.0933      0.025      3.685      0.000       0.044       
0.143
temp           0.4500      0.038     11.796      0.000       0.375       
0.525
humidity      -0.1521      0.038     -4.055      0.000      -0.226      -
0.078
windspeed     -0.1868      0.025     -7.365      0.000      -0.237      -
0.137
spring        -0.0560      0.022     -2.563      0.011      -0.099      -
0.013
summer         0.0269      0.017      1.593      0.112      -0.006       
0.060
winter         0.1012      0.018      5.705      0.000       0.066       
0.136
Dec           -0.0506      0.018     -2.807      0.005      -0.086      -
0.015
Feb           -0.0355      0.021     -1.661      0.097      -0.077       
0.006
Jan           -0.0658      0.021     -3.110      0.002      -0.107      -
0.024
Jul           -0.0512      0.018     -2.858      0.004      -0.086      -
0.016
May            0.0250      0.017      1.449      0.148      -0.009       
0.059
Nov           -0.0483      0.019     -2.592      0.010      -0.085      -
0.012
Sep            0.0718      0.017      4.324      0.000       0.039       
0.104
Sat            0.1038      0.027      3.876      0.000       0.051       
0.156
Sun            0.0491      0.027      1.827      0.068      -0.004       
0.102
```

```
Light Snow    -0.2564      0.026     -9.847      0.000     -0.308      -
0.205
Mist          -0.0599      0.010     -5.807      0.000     -0.080      -
0.040
==========================================================================
====
Omnibus:                     84.215   Durbin-Watson:                   
2.035
Prob(Omnibus):                0.000   Jarque-Bera (JB):              24
1.321
Skew:                        -0.792   Prob(JB):                    3.96
e-53
Kurtosis:                     5.974   Cond. No.                        
27.5
==========================================================================
====

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

In [44]:

```
# VIF for 2nd set of data

get_vif_dataframe(X_train_rfe_2)
```

Out[44]:

	Features	VIF
3	humidity	34.79
2	temp	22.48
1	workingday	19.10
5	spring	6.06
15	Sat	5.11
4	windspeed	5.06
16	Sun	4.89
7	winter	4.40
6	summer	3.71
10	Jan	2.42
18	Mist	2.35
0	year	2.11
9	Feb	1.92
13	Nov	1.83
8	Dec	1.70
11	Jul	1.61
12	May	1.60
14	Sep	1.41
17	Light Snow	1.29

In [45]:

```
# 3rd iteration
# As the feature 'May' is not significant), so will remove that

X_train_rfe_3 = X_train_rfe_2.drop(['May'], axis=1)
X_train_lm_3 = sm.add_constant(X_train_rfe_3)
lm_3 = sm.OLS(y_train, X_train_lm_3).fit()
print(lm_3.summary())
```

```
                            OLS Regression Results
==============================================================================
====
Dep. Variable:                    cnt   R-squared:
0.852
Model:                            OLS   Adj. R-squared:
0.846
Method:                 Least Squares   F-statistic:                     1
56.6
Date:                Wed, 16 Aug 2023   Prob (F-statistic):          3.55e
-190
Time:                        18:10:28   Log-Likelihood:                 52
5.15
No. Observations:                 510   AIC:                            -1
012.
Df Residuals:                     491   BIC:                            -9
31.8
Df Model:                          18
Covariance Type:            nonrobust
==============================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
------------------------------------------------------------------------------
----
const          0.2374      0.044      5.335      0.000       0.150
0.325
year           0.2311      0.008     29.082      0.000       0.215
0.247
workingday     0.0943      0.025      3.722      0.000       0.045
0.144
temp           0.4598      0.038     12.233      0.000       0.386
0.534
humidity      -0.1456      0.037     -3.904      0.000      -0.219       -
0.072
windspeed     -0.1887      0.025     -7.440      0.000      -0.239       -
0.139
spring        -0.0518      0.022     -2.390      0.017      -0.094       -
0.009
summer         0.0377      0.015      2.483      0.013       0.008
0.068
winter         0.1035      0.018      5.852      0.000       0.069
0.138
Dec           -0.0491      0.018     -2.727      0.007      -0.085       -
0.014
Feb           -0.0339      0.021     -1.591      0.112      -0.076
0.008
Jan           -0.0640      0.021     -3.025      0.003      -0.106       -
0.022
Jul           -0.0517      0.018     -2.883      0.004      -0.087       -
0.016
Nov           -0.0465      0.019     -2.499      0.013      -0.083       -
0.010
Sep            0.0718      0.017      4.319      0.000       0.039
0.104
Sat            0.1042      0.027      3.886      0.000       0.051
0.157
Sun            0.0499      0.027      1.857      0.064      -0.003
0.103
Light Snow    -0.2583      0.026     -9.924      0.000      -0.309       -
0.207
```

```
Mist            -0.0600      0.010     -5.813      0.000      -0.080       -
0.040
==========================================================================
====
Omnibus:                       81.478   Durbin-Watson:                   
2.041
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              21
9.245
Skew:                          -0.787   Prob(JB):                    2.46
e-48
Kurtosis:                       5.800   Cond. No.                        
27.0
==========================================================================
====

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

In [46]:

```
# VIF dataframe

get_vif_dataframe(X_train_rfe_3)
```

Out[46]:

	Features	VIF
3	humidity	34.69
2	temp	22.29
1	workingday	18.92
5	spring	6.05
14	Sat	5.04
4	windspeed	4.99
15	Sun	4.85
7	winter	4.40
6	summer	3.09
10	Jan	2.42
17	Mist	2.35
0	year	2.10
9	Feb	1.92
12	Nov	1.83
8	Dec	1.70
11	Jul	1.61
13	Sep	1.41
16	Light Snow	1.29

In [47]:

```
# 4th iteration for the model fitting
# As the feature 'Feb' is not significant), so will remove that
X_train_rfe_4 = X_train_rfe_3.drop(['Feb'], axis=1)
X_train_lm_4 = sm.add_constant(X_train_rfe_4)
lm_4 = sm.OLS(y_train, X_train_lm_4).fit()
print(lm_4.summary())
```

```
                            OLS Regression Results
==========================================================================
====
Dep. Variable:                    cnt   R-squared:
0.851
Model:                            OLS   Adj. R-squared:
0.846
Method:                 Least Squares   F-statistic:                     1
65.2
Date:                Wed, 16 Aug 2023   Prob (F-statistic):          9.55e
-191
Time:                        18:10:28   Log-Likelihood:                 52
3.84
No. Observations:                 510   AIC:                            -1
012.
Df Residuals:                     492   BIC:                            -9
35.5
Df Model:                          17
Covariance Type:            nonrobust
==========================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
--------------------------------------------------------------------------
----
const          0.2239      0.044      5.118      0.000       0.138
0.310
year           0.2308      0.008     29.005      0.000       0.215
0.246
workingday     0.0966      0.025      3.812      0.000       0.047
0.146
temp           0.4750      0.036     13.038      0.000       0.403
0.547
humidity      -0.1474      0.037     -3.949      0.000      -0.221      -
0.074
windspeed     -0.1876      0.025     -7.388      0.000      -0.237      -
0.138
spring        -0.0611      0.021     -2.925      0.004      -0.102      -
0.020
summer         0.0409      0.015      2.708      0.007       0.011
0.071
winter         0.1052      0.018      5.949      0.000       0.070
0.140
Dec           -0.0405      0.017     -2.351      0.019      -0.074      -
0.007
Jan           -0.0458      0.018     -2.570      0.010      -0.081      -
0.011
Jul           -0.0526      0.018     -2.932      0.004      -0.088      -
0.017
Nov           -0.0420      0.018     -2.277      0.023      -0.078      -
0.006
Sep            0.0732      0.017      4.404      0.000       0.041
0.106
Sat            0.1070      0.027      3.997      0.000       0.054
0.160
Sun            0.0520      0.027      1.933      0.054      -0.001
0.105
Light Snow    -0.2571      0.026     -9.865      0.000      -0.308      -
0.206
Mist          -0.0598      0.010     -5.781      0.000      -0.080      -
0.039
```

```
==============================================================================
====
Omnibus:                       76.965   Durbin-Watson:                   
2.041
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               20
5.539
Skew:                          -0.747   Prob(JB):                       2.33
e-45
Kurtosis:                       5.727   Cond. No.                        
26.4
==============================================================================
====

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

In [ ]:

```

```

In [48]:

```python
# VIF dataframe for 4th iteration

get_vif_dataframe(X_train_rfe_4)
```

Out[48]:

	Features	VIF
3	humidity	34.24
2	temp	21.56
1	workingday	18.83
5	spring	5.06
13	Sat	5.03
4	windspeed	4.98
14	Sun	4.83
7	winter	4.40
6	summer	3.08
16	Mist	2.34
0	year	2.10
11	Nov	1.81
9	Jan	1.77
10	Jul	1.61
8	Dec	1.58
12	Sep	1.41
15	Light Snow	1.29

In [49]:

```
# 5th iteration for the model fitting
# As the feature 'Nov' is not significant), so will remove that

X_train_rfe_5 = X_train_rfe_4.drop(['Nov'], axis=1)
X_train_lm_5 = sm.add_constant(X_train_rfe_5)
lm_5 = sm.OLS(y_train, X_train_lm_5).fit()
print(lm_5.summary())
```

```
                            OLS Regression Results
==========================================================================
====
Dep. Variable:                    cnt   R-squared:
0.849
Model:                            OLS   Adj. R-squared:
0.844
Method:                 Least Squares   F-statistic:                     1
73.7
Date:                Wed, 16 Aug 2023   Prob (F-statistic):          9.27e
-191
Time:                        18:10:28   Log-Likelihood:                 52
1.17
No. Observations:                 510   AIC:                            -1
008.
Df Residuals:                     493   BIC:                            -9
36.3
Df Model:                          16
Covariance Type:            nonrobust
==========================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
--------------------------------------------------------------------------
----
const          0.1997      0.043      4.686      0.000       0.116
0.283
year           0.2306      0.008     28.866      0.000       0.215
0.246
workingday     0.1033      0.025      4.088      0.000       0.054
0.153
temp           0.4959      0.035     14.010      0.000       0.426
0.565
humidity      -0.1484      0.037     -3.959      0.000      -0.222      -
0.075
windspeed     -0.1888      0.025     -7.405      0.000      -0.239      -
0.139
spring        -0.0525      0.021     -2.543      0.011      -0.093      -
0.012
summer         0.0467      0.015      3.130      0.002       0.017
0.076
winter         0.0954      0.017      5.538      0.000       0.062
0.129
Dec           -0.0251      0.016     -1.579      0.115      -0.056
0.006
Jan           -0.0406      0.018     -2.287      0.023      -0.076      -
0.006
Jul           -0.0526      0.018     -2.916      0.004      -0.088      -
0.017
Sep            0.0790      0.016      4.791      0.000       0.047
0.111
Sat            0.1142      0.027      4.274      0.000       0.062
0.167
Sun            0.0593      0.027      2.208      0.028       0.007
0.112
Light Snow    -0.2527      0.026     -9.682      0.000      -0.304      -
0.201
Mist          -0.0589      0.010     -5.671      0.000      -0.079      -
0.038
==========================================================================
====
```

```
Omnibus:                       70.775   Durbin-Watson:                   
2.062
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               17
7.450
Skew:                          -0.709   Prob(JB):                     2.93
e-39
Kurtosis:                       5.518   Cond. No.                         
25.5
==========================================================================
====

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

In [ ]:

```

```

In [50]:

```
# VIF dataframe for 5th iteration

get_vif_dataframe(X_train_rfe_5)
```

Out[50]:

	Features	VIF
3	humidity	33.73
2	temp	21.06
1	workingday	18.81
5	spring	5.04
12	Sat	5.03
4	windspeed	4.93
13	Sun	4.83
7	winter	3.79
6	summer	3.06
15	Mist	2.33
0	year	2.10
9	Jan	1.76
10	Jul	1.61
11	Sep	1.39
8	Dec	1.37
14	Light Snow	1.27

In [51]:

```
# 6th iteration for model fitting
# As the feature 'Dec' is not significant), so will remove that

X_train_rfe_6 = X_train_rfe_5.drop(['Dec'], axis=1)
X_train_lm_6 = sm.add_constant(X_train_rfe_6)
lm_6 = sm.OLS(y_train, X_train_lm_6).fit()
print(lm_6.summary())
```

```
                            OLS Regression Results                            
==============================================================================
====
Dep. Variable:                    cnt   R-squared:                       
0.849
Model:                            OLS   Adj. R-squared:                  
0.844
Method:                 Least Squares   F-statistic:                     1
84.6
Date:                Wed, 16 Aug 2023   Prob (F-statistic):          2.31e
-191
Time:                        18:10:28   Log-Likelihood:                  51
9.88
No. Observations:                 510   AIC:                             -1
008.
Df Residuals:                     494   BIC:                             -9
40.0
Df Model:                          15                                         
Covariance Type:            nonrobust                                         
==============================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
------------------------------------------------------------------------------
----
const          0.1925      0.042      4.537      0.000       0.109       
0.276
year           0.2305      0.008     28.807      0.000       0.215       
0.246
workingday     0.1021      0.025      4.035      0.000       0.052       
0.152
temp           0.5098      0.034     14.851      0.000       0.442       
0.577
humidity      -0.1547      0.037     -4.145      0.000      -0.228      -
0.081
windspeed     -0.1860      0.025     -7.301      0.000      -0.236      -
0.136
spring        -0.0508      0.021     -2.461      0.014      -0.091      -
0.010
summer         0.0497      0.015      3.346      0.001       0.020       
0.079
winter         0.0944      0.017      5.479      0.000       0.061       
0.128
Jan           -0.0343      0.017     -1.980      0.048      -0.068      -
0.000
Jul           -0.0532      0.018     -2.947      0.003      -0.089      -
0.018
Sep            0.0812      0.016      4.934      0.000       0.049       
0.114
Sat            0.1123      0.027      4.200      0.000       0.060       
0.165
Sun            0.0585      0.027      2.178      0.030       0.006       
0.111
Light Snow    -0.2488      0.026     -9.560      0.000      -0.300      -
0.198
Mist          -0.0578      0.010     -5.574      0.000      -0.078      -
0.037
==============================================================================
====
Omnibus:                       66.344   Durbin-Watson:                   
2.071
```

```
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              16
1.565
Skew:                          -0.676   Prob(JB):                    8.25
e-36
Kurtosis:                       5.403   Cond. No.
25.4
==========================================================================
====

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

In [52]:

```
# VIF for 6th iteration

get_vif_dataframe(X_train_rfe_6)
```

Out[52]:

	Features	VIF
3	humidity	32.81
2	temp	19.97
1	workingday	18.57
5	spring	5.04
11	Sat	4.95
4	windspeed	4.92
12	Sun	4.79
7	winter	3.76
6	summer	3.03
14	Mist	2.31
0	year	2.10
8	Jan	1.68
9	Jul	1.60
10	Sep	1.38
13	Light Snow	1.25

In [53]:

```
# 7th iteration for the model fitting
# As the feature 'May' is not significant due to high VIF), so will remove that

X_train_rfe_7 = X_train_rfe_6.drop(['humidity'], axis=1)
X_train_lm_7 = sm.add_constant(X_train_rfe_7)
lm_7 = sm.OLS(y_train, X_train_lm_7).fit()
print(lm_7.summary())
```

```
                            OLS Regression Results                            
==============================================================================
====
Dep. Variable:                    cnt   R-squared:                       
0.843
Model:                            OLS   Adj. R-squared:                  
0.839
Method:                 Least Squares   F-statistic:                     1
90.3
Date:                Wed, 16 Aug 2023   Prob (F-statistic):          7.33e
-189
Time:                        18:10:28   Log-Likelihood:                 51
1.16
No. Observations:                 510   AIC:                            -9
92.3
Df Residuals:                     495   BIC:                            -9
28.8
Df Model:                          14                                         
Covariance Type:            nonrobust                                         
==============================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
------------------------------------------------------------------------------
----
const          0.1175      0.039      3.012      0.003       0.041       
0.194
year           0.2344      0.008     29.019      0.000       0.218       
0.250
workingday     0.1027      0.026      3.996      0.000       0.052       
0.153
temp           0.4728      0.034     14.037      0.000       0.407       
0.539
windspeed     -0.1563      0.025     -6.292      0.000      -0.205      -
0.107
spring        -0.0597      0.021     -2.861      0.004      -0.101      -
0.019
summer         0.0434      0.015      2.890      0.004       0.014       
0.073
winter         0.0797      0.017      4.650      0.000       0.046       
0.113
Jan           -0.0389      0.018     -2.215      0.027      -0.073      -
0.004
Jul           -0.0482      0.018     -2.635      0.009      -0.084      -
0.012
Sep            0.0753      0.017      4.522      0.000       0.043       
0.108
Sat            0.1146      0.027      4.222      0.000       0.061       
0.168
Sun            0.0562      0.027      2.058      0.040       0.003       
0.110
Light Snow    -0.2917      0.024    -12.027      0.000      -0.339      -
0.244
Mist          -0.0826      0.009     -9.592      0.000      -0.100      -
0.066
==============================================================================
====
Omnibus:                       67.959   Durbin-Watson:                   
2.066
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              16
6.078
```

```
Skew:                          -0.690   Prob(JB):                        8.64
e-37
Kurtosis:                       5.431   Cond. No.
23.0
==========================================================================
====

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

In [54]:

```
# VIF dataframe for 7th iteration

get_vif_dataframe(X_train_rfe_7)
```

Out[54]:

	Features	VIF
1	workingday	16.57
2	temp	13.12
3	windspeed	4.79
10	Sat	4.54
11	Sun	4.28
4	spring	4.22
6	winter	2.80
5	summer	2.75
0	year	2.08
7	Jan	1.65
8	Jul	1.60
13	Mist	1.59
9	Sep	1.35
12	Light Snow	1.09

In [55]:

```
# 8th iteration for the model fitting
# As the feature 'workingday' is not significant), so will remove that

X_train_rfe_8 = X_train_rfe_7.drop(['workingday'], axis=1)
X_train_lm_8 = sm.add_constant(X_train_rfe_8)
lm_8 = sm.OLS(y_train, X_train_lm_8).fit()
print(lm_8.summary())
```

```
                            OLS Regression Results
==============================================================================
====
Dep. Variable:                    cnt   R-squared:
0.838
Model:                            OLS   Adj. R-squared:
0.834
Method:                 Least Squares   F-statistic:                     1
97.7
Date:                Wed, 16 Aug 2023   Prob (F-statistic):          1.27e
-186
Time:                        18:10:28   Log-Likelihood:                 50
3.07
No. Observations:                 510   AIC:                            -9
78.1
Df Residuals:                     496   BIC:                            -9
18.9
Df Model:                          13
Covariance Type:            nonrobust
==============================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
------------------------------------------------------------------------------
----
const          0.2172      0.030      7.138      0.000       0.157
0.277
year           0.2349      0.008     28.657      0.000       0.219
0.251
temp           0.4737      0.034     13.856      0.000       0.407
0.541
windspeed     -0.1586      0.025     -6.293      0.000      -0.208      -
0.109
spring        -0.0622      0.021     -2.936      0.003      -0.104      -
0.021
summer         0.0437      0.015      2.868      0.004       0.014
0.074
winter         0.0767      0.017      4.411      0.000       0.043
0.111
Jan           -0.0398      0.018     -2.231      0.026      -0.075      -
0.005
Jul           -0.0474      0.019     -2.551      0.011      -0.084      -
0.011
Sep            0.0717      0.017      4.247      0.000       0.039
0.105
Sat            0.0159      0.011      1.391      0.165      -0.007
0.038
Sun           -0.0425      0.012     -3.600      0.000      -0.066      -
0.019
Light Snow    -0.2871      0.025    -11.675      0.000      -0.335      -
0.239
Mist          -0.0807      0.009     -9.247      0.000      -0.098      -
0.064
==============================================================================
====
Omnibus:                       82.611   Durbin-Watson:
2.013
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              21
7.073
Skew:                          -0.806   Prob(JB):                     7.30
e-48
```

```
Kurtosis:                        5.760   Cond. No.
17.9
==========================================================================
====

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

In [56]:

```
# VIF dataframe for 8th iteration

get_vif_dataframe(X_train_rfe_8)
```

Out[56]:

	Features	VIF
1	temp	5.22
2	windspeed	4.64
3	spring	2.78
4	summer	2.24
0	year	2.07
5	winter	1.83
6	Jan	1.61
7	Jul	1.59
12	Mist	1.56
8	Sep	1.33
9	Sat	1.22
10	Sun	1.21
11	Light Snow	1.08

In [57]:

```
# Model fitting for the 9th iteration
# As the feature 'temp' is not significant), so will remove that

X_train_rfe_9 = X_train_rfe_8.drop(['temp'], axis=1)
X_train_lm_9 = sm.add_constant(X_train_rfe_9)
lm_9 = sm.OLS(y_train, X_train_lm_9).fit()
print(lm_9.summary())
```

```
                            OLS Regression Results
==========================================================================
====
Dep. Variable:                    cnt   R-squared:
0.776
Model:                            OLS   Adj. R-squared:
0.770
Method:                 Least Squares   F-statistic:                     1
43.2
Date:                Wed, 16 Aug 2023   Prob (F-statistic):          1.19e
-152
Time:                        18:10:28   Log-Likelihood:                 41
9.63
No. Observations:                 510   AIC:                            -8
13.3
Df Residuals:                     497   BIC:                            -7
58.2
Df Model:                          12
Covariance Type:            nonrobust
==========================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
--------------------------------------------------------------------------
----
const          0.5905      0.017     35.515      0.000       0.558
0.623
year           0.2483      0.010     25.933      0.000       0.230
0.267
windspeed     -0.1903      0.030     -6.444      0.000      -0.248      -
0.132
spring        -0.2632      0.018    -14.507      0.000      -0.299      -
0.228
summer        -0.0439      0.016     -2.690      0.007      -0.076      -
0.012
winter        -0.0783      0.016     -5.004      0.000      -0.109      -
0.048
Jan           -0.1035      0.020     -5.099      0.000      -0.143      -
0.064
Jul           -0.0089      0.022     -0.412      0.680      -0.051
0.034
Sep            0.0671      0.020      3.380      0.001       0.028
0.106
Sat            0.0124      0.013      0.923      0.356      -0.014
0.039
Sun           -0.0439      0.014     -3.162      0.002      -0.071      -
0.017
Light Snow    -0.2997      0.029    -10.367      0.000      -0.357      -
0.243
Mist          -0.0877      0.010     -8.552      0.000      -0.108      -
0.068
==========================================================================
====
Omnibus:                       46.366   Durbin-Watson:
1.987
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                9
9.978
Skew:                          -0.514   Prob(JB):                     1.95
e-22
Kurtosis:                       4.910   Cond. No.
9.29
```

```
==============================================================================
====

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

In [58]:

```
# VIF dataframe for 9th iteration

get_vif_dataframe(X_train_rfe_9)
```

Out[58]:

	Features	VIF
1	windspeed	3.91
2	spring	2.78
3	summer	2.04
0	year	1.84
4	winter	1.79
5	Jan	1.60
11	Mist	1.52
6	Jul	1.22
8	Sat	1.21
9	Sun	1.20
7	Sep	1.16
10	Light Snow	1.08

In [59]:

```
# Model fitting for 10th iteration
# As the feature 'JUL' is not significant), so will remove that

X_train_rfe_10 = X_train_rfe_9.drop(['Jul'], axis=1)
X_train_lm_10 = sm.add_constant(X_train_rfe_10)
lm_10 = sm.OLS(y_train, X_train_lm_10).fit()
print(lm_10.summary())
```

```
                            OLS Regression Results
==========================================================================
====
Dep. Variable:                    cnt   R-squared:
0.776
Model:                            OLS   Adj. R-squared:
0.771
Method:                 Least Squares   F-statistic:                     1
56.5
Date:                Wed, 16 Aug 2023   Prob (F-statistic):          1.01e
-153
Time:                        18:10:28   Log-Likelihood:                 41
9.54
No. Observations:                 510   AIC:                            -8
15.1
Df Residuals:                     498   BIC:                            -7
64.3
Df Model:                          11
Covariance Type:            nonrobust
==========================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
--------------------------------------------------------------------------
----
const          0.5872      0.015     40.182      0.000       0.559
0.616
year           0.2483      0.010     25.959      0.000       0.230
0.267
windspeed     -0.1902      0.030     -6.447      0.000      -0.248      -
0.132
spring        -0.2600      0.016    -15.849      0.000      -0.292      -
0.228
summer        -0.0407      0.014     -2.830      0.005      -0.069      -
0.012
winter        -0.0753      0.014     -5.442      0.000      -0.102      -
0.048
Jan           -0.1035      0.020     -5.106      0.000      -0.143      -
0.064
Sep            0.0696      0.019      3.683      0.000       0.032
0.107
Sat            0.0123      0.013      0.916      0.360      -0.014
0.039
Sun           -0.0442      0.014     -3.184      0.002      -0.071      -
0.017
Light Snow    -0.2999      0.029    -10.380      0.000      -0.357      -
0.243
Mist          -0.0874      0.010     -8.551      0.000      -0.107      -
0.067
==========================================================================
====
Omnibus:                       46.458   Durbin-Watson:
1.991
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                9
9.734
Skew:                          -0.516   Prob(JB):                     2.20
e-22
Kurtosis:                       4.905   Cond. No.
8.92
==========================================================================
====
```

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

In [60]:

```
# VIF for the 10th iteration

get_vif_dataframe(X_train_rfe_10)
```

Out[60]:

	Features	VIF
1	windspeed	3.60
2	spring	2.58
3	summer	1.87
0	year	1.78
4	winter	1.66
5	Jan	1.60
10	Mist	1.51
7	Sat	1.20
8	Sun	1.18
6	Sep	1.14
9	Light Snow	1.08

In [61]:

```
# Model fitting for 11th iteration
# As the feature 'Sat' is not significant), so will remove that

X_train_rfe_11 = X_train_rfe_10.drop(['Sat'], axis=1)
X_train_lm_11 = sm.add_constant(X_train_rfe_11)
lm_11 = sm.OLS(y_train, X_train_lm_11).fit()
print(lm_11.summary())
```

```
                            OLS Regression Results                            
==============================================================================
====
Dep. Variable:                    cnt   R-squared:                       
0.775
Model:                            OLS   Adj. R-squared:                  
0.771
Method:                 Least Squares   F-statistic:                     1
72.1
Date:                Wed, 16 Aug 2023   Prob (F-statistic):          1.14e
-154
Time:                        18:10:28   Log-Likelihood:                 41
9.11
No. Observations:                 510   AIC:                            -8
16.2
Df Residuals:                     499   BIC:                            -7
69.6
Df Model:                          10                                         
Covariance Type:            nonrobust                                         
==============================================================================
====
                 coef    std err          t      P>|t|      [0.025      0.
975]
------------------------------------------------------------------------------
----
const          0.5891      0.014     40.705      0.000       0.561       
0.617
year           0.2481      0.010     25.947      0.000       0.229       
0.267
windspeed     -0.1889      0.029     -6.411      0.000      -0.247      -
0.131
spring        -0.2599      0.016    -15.845      0.000      -0.292      -
0.228
summer        -0.0408      0.014     -2.837      0.005      -0.069      -
0.013
winter        -0.0750      0.014     -5.423      0.000      -0.102      -
0.048
Jan           -0.1033      0.020     -5.095      0.000      -0.143      -
0.063
Sep            0.0695      0.019      3.678      0.000       0.032       
0.107
Sun           -0.0464      0.014     -3.399      0.001      -0.073      -
0.020
Light Snow    -0.2997      0.029    -10.376      0.000      -0.356      -
0.243
Mist          -0.0874      0.010     -8.550      0.000      -0.107      -
0.067
==============================================================================
====
Omnibus:                       44.678   Durbin-Watson:                   
1.989
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              10
0.042
Skew:                          -0.483   Prob(JB):                     1.89
e-22
Kurtosis:                       4.943   Cond. No.                        
8.86
==============================================================================
====

Notes:
```

```
[1] Standard Errors assume that the covariance matrix of the errors is cor
rectly specified.
```

In [62]:

```
# VIF for 11th iteration

get_vif_dataframe(X_train_rfe_11)
```

Out[62]:

	Features	VIF
1	windspeed	3.52
2	spring	2.58
3	summer	1.86
0	year	1.78
4	winter	1.64
5	Jan	1.59
9	Mist	1.51
7	Sun	1.15
6	Sep	1.13
8	Light Snow	1.08

Observation

- We see, model lm_11, is having all the significant feature and having VIF <5. So, we will proceed with this model.
- R square and the adjusted R square values are: 0.775 and 0.771, which are pretty goood to show the variation.

In [63]:

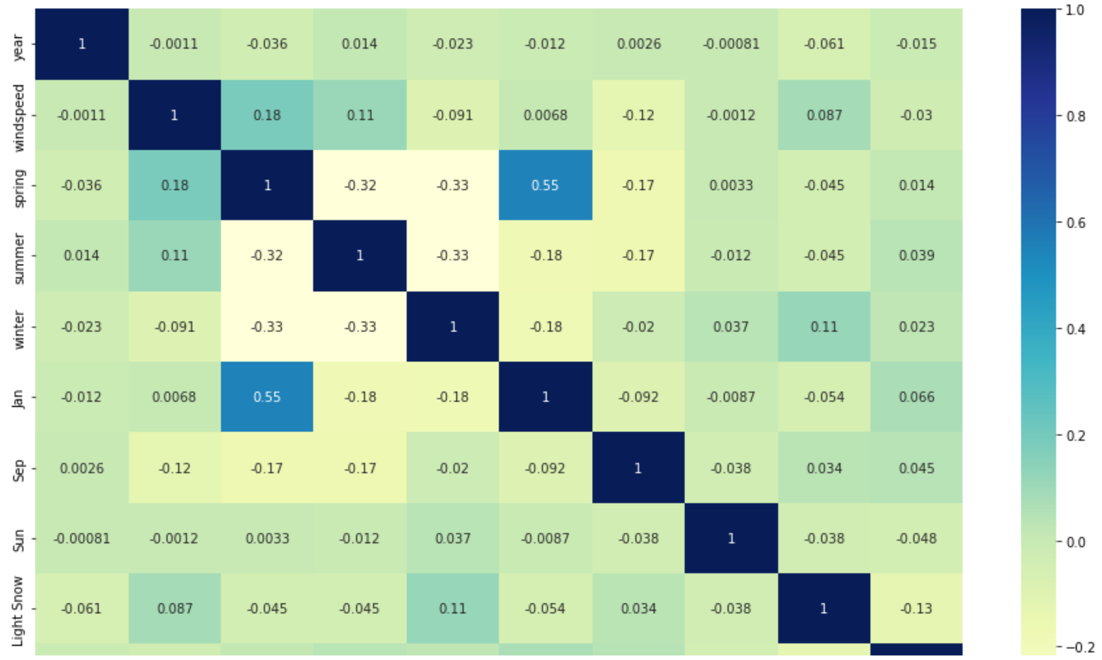
```
# Get the prediction on X_train_lm_11

y_train_cnt = lm_11.predict(X_train_lm_11)
y_train_cnt
```

Out[63]:

```
653    0.705298
576    0.787127
426    0.441624
728    0.405578
482    0.673354
         ...
526    0.641783
578    0.801776
53     0.308135
350    0.345105
79     0.360795
Length: 510, dtype: float64
```

In [64]:

```
# Plot heatmap for final train data after feature removal

plt.figure(figsize = (16, 10))
sns.heatmap(X_train_rfe_11.corr(), annot = True, cmap="YlGnBu")
plt.show()
```



Observation

- We see all the feature, which are relavent are having no multi-collinearity.

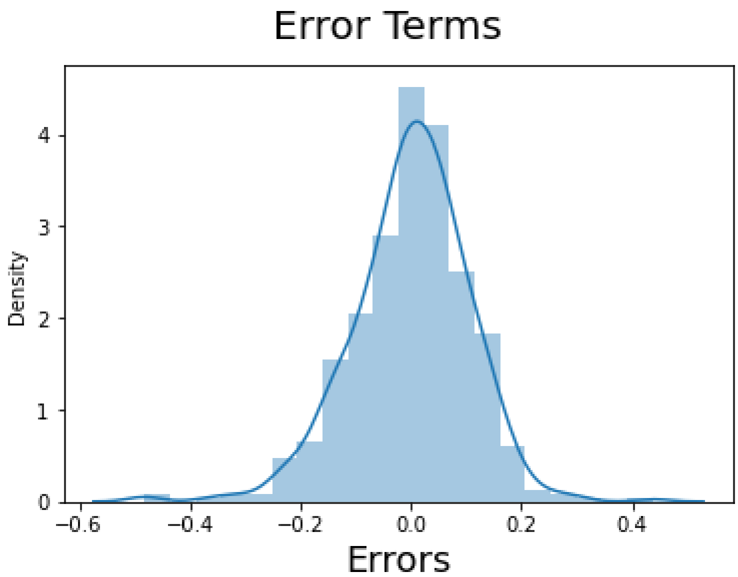
Plot histogram for Error terms

In [65]:

```
# Plot the histogram of the error terms
# We see, mean is almost zero and this shoud be the case.

fig = plt.figure()
sns.distplot((y_train - y_train_cnt), bins = 20)
fig.suptitle('Error Terms', fontsize = 20)                  # Plot heading
plt.xlabel('Errors', fontsize = 18)
```

Out[65]:

```
Text(0.5, 0, 'Errors')
```



Prepare the test set based on the train set

In [66]:

```
# Select the colums to be transformed in the test set

num_var  = ['temp', 'abs-temp', 'humidity', 'windspeed', 'cnt']

df_test[num_var] = scaler.transform(df_test[num_var])
```

In [67]:

```
# Drop target and abs-temp from the test set

X_test = df_test.drop(['cnt', 'abs-temp'], axis=1)
y_test = df_test[['cnt']]
```

In [68]:

```
# Add a constant for test dataset

X_test_lm_11 = sm.add_constant(X_test)
```

In [69]:

```
# Select required columns for X_test_lm_11 WHICH are available in X_train_lm_11

X_test_lm_11 = X_test_lm_11[X_train_lm_11.columns]
X_test_lm_11
```

Out[69]:

	const	year	windspeed	spring	summer	winter	Jan	Sep	Sun	Light Snow	Mist
184	1.0	0	0.084219	0	0	0	0	0	0	0	1
535	1.0	1	0.153728	0	1	0	0	0	0	0	0
299	1.0	0	0.334206	0	0	1	0	0	0	0	1
221	1.0	0	0.339570	0	0	0	0	0	0	0	0
152	1.0	0	0.537414	0	1	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...
400	1.0	1	0.287411	1	0	0	0	0	1	0	1
702	1.0	1	0.283397	0	0	1	0	0	0	0	0
127	1.0	0	0.069510	0	1	0	0	0	1	0	0
640	1.0	1	0.052115	0	0	1	0	0	0	0	1
72	1.0	0	0.203418	1	0	0	0	0	0	0	0

219 rows × 11 columns

Get the prediction for test set

In [70]:

```
# we will use lm_11 model as this was the best model.
# Get the prediction

y_pred = lm_11.predict(X_test_lm_11)
```

In [71]:

```
# Predicted dataframe

y_pred
```

Out[71]:

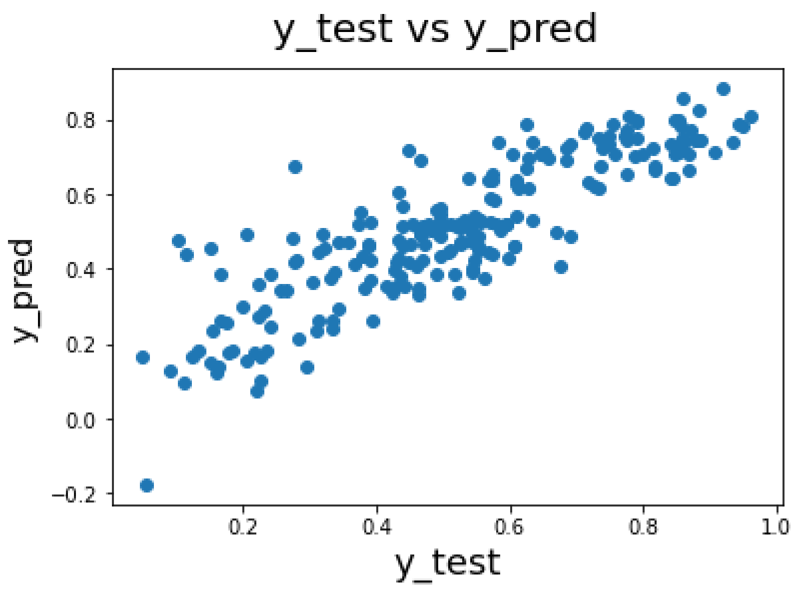
```
184    0.485778
535    0.767296
299    0.363545
221    0.524917
152    0.446750
         ...
400    0.389174
702    0.708584
127    0.488750
640    0.664898
72     0.290748
Length: 219, dtype: float64
```

In [72]:

```
# Plot test and pred datapoints

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)
```

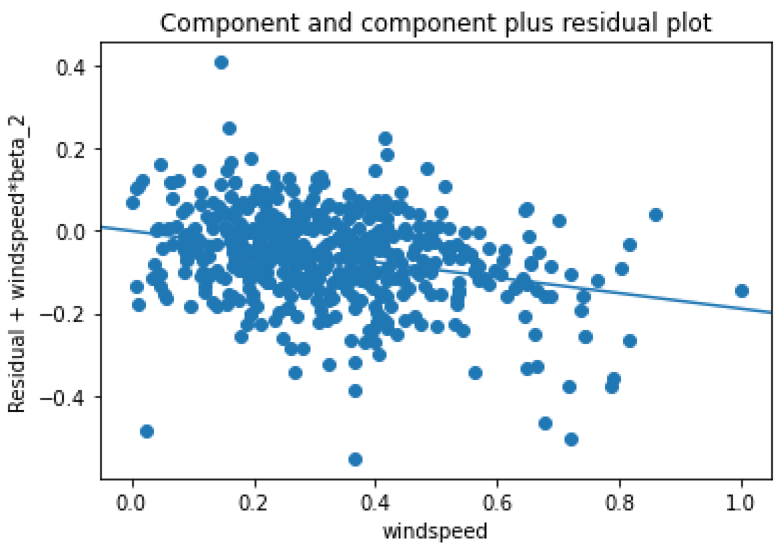
Out[72]:

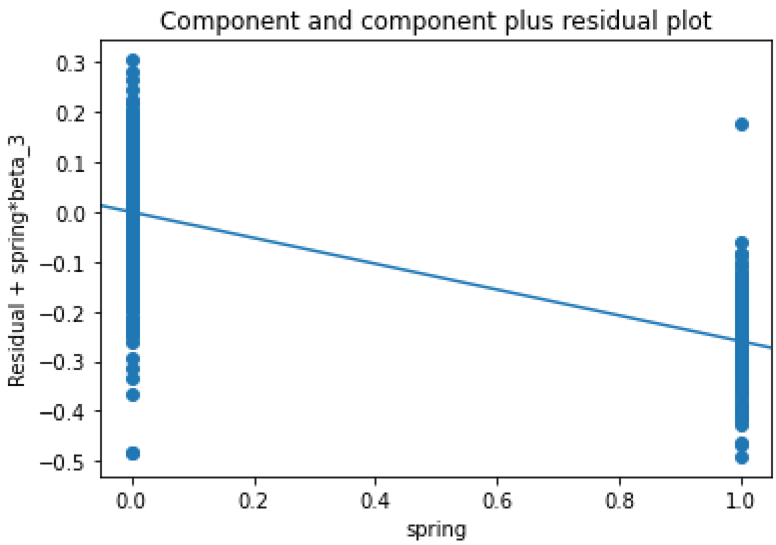
```
Text(0, 0.5, 'y_pred')
```

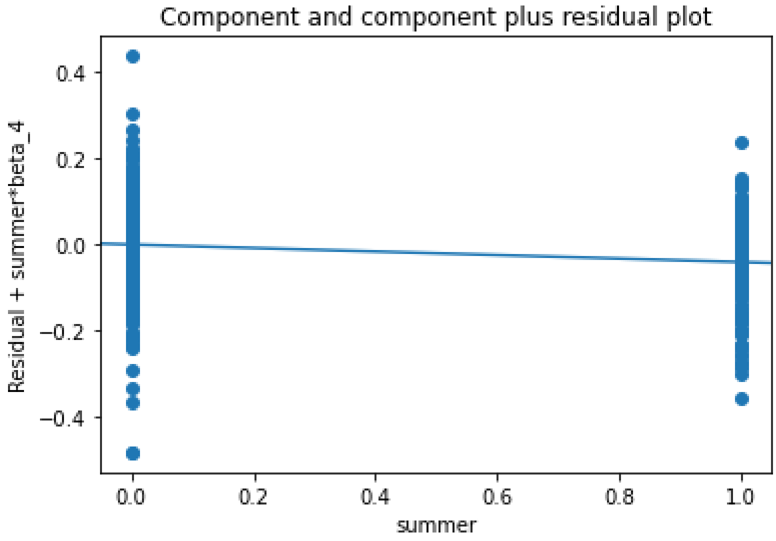


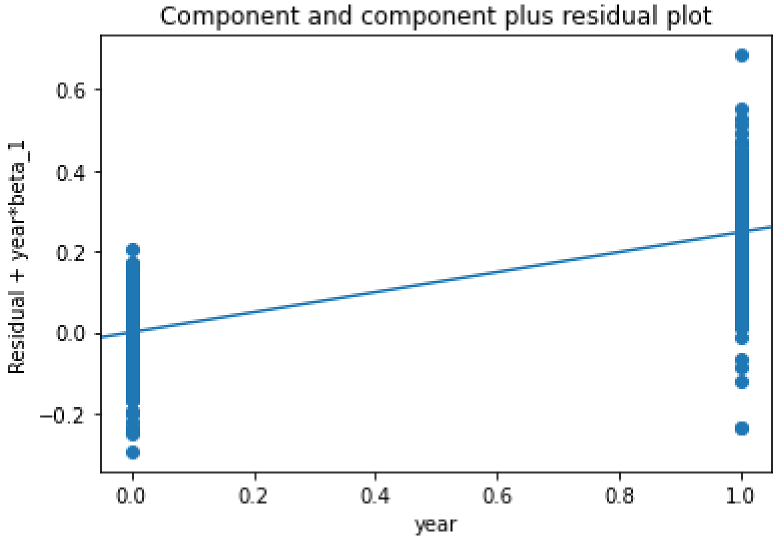
In [73]:

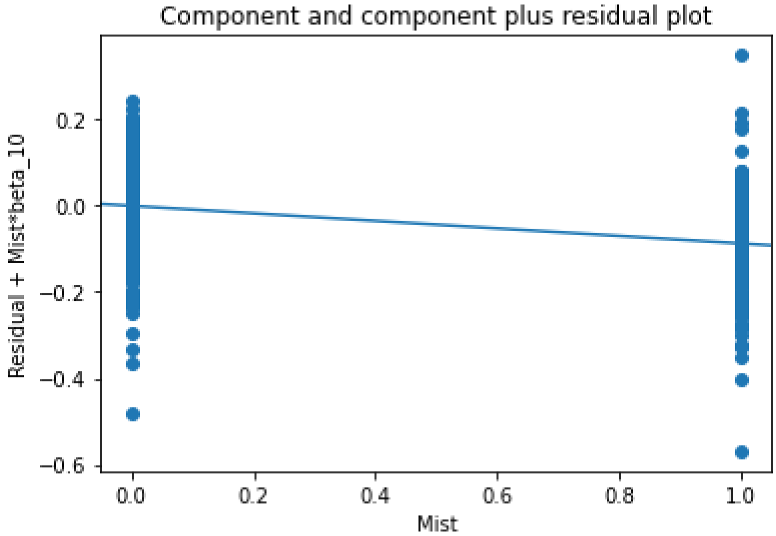
```
# Get the ccpr plots for some feature

sm.graphics.plot_ccpr(lm_11, 'windspeed')
plt.show()


sm.graphics.plot_ccpr(lm_11, 'spring')
plt.show()

sm.graphics.plot_ccpr(lm_11, 'summer')
plt.show()

sm.graphics.plot_ccpr(lm_11, 'year')
plt.show()

sm.graphics.plot_ccpr(lm_11, 'Mist')
plt.show()

sm.graphics.plot_ccpr(lm_11, 'Light Snow')
plt.show()
```

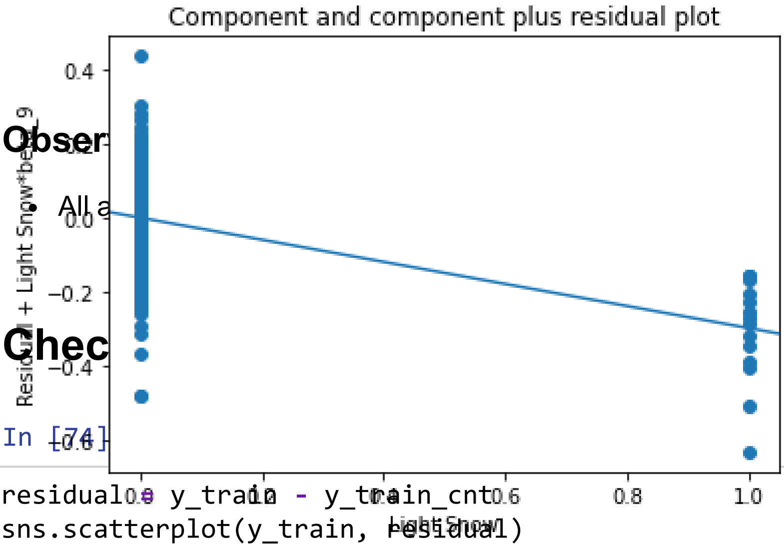





Component and component plus residual plot
Residual + summer*beta_4
summer
0.4
0.2
0.0
−0.2
−0.4
0.0
0.2
0.4
0.6
0.8
1.0


Component and component plus residual plot
Residual + year*beta_1
year
0.6
0.4
0.2
0.0
−0.2
0.0
0.2
0.4
0.6
0.8
1.0


Component and component plus residual plot
Residual + Mist*beta_10
Mist
0.2
0.0
−0.2
−0.4
−0.6
0.0
0.2
0.4
0.6
0.8
1.0



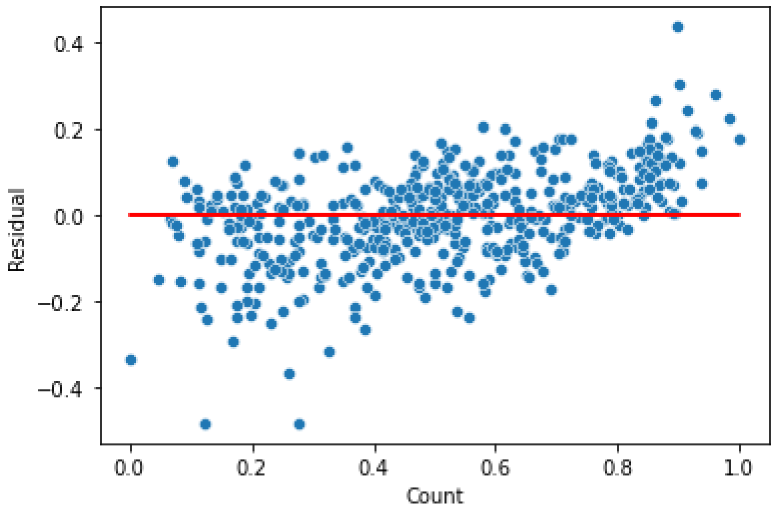
Obser

- All a

Chec

In [74]:

```
residual = y_train - y_train_cnt
sns.scatterplot(y_train, residual)
plt.plot(y_train,(y_train - y_train), '-r')
plt.xlabel('Count')
plt.ylabel('Residual')
plt.show()
```



Observation

- We see that residul is almost zero and constant.

In [75]:

```
## Get some derived metrics for test and train dataset
# Get r2 score for test
from sklearn.metrics import r2_score
r2_test = r2_score(y_test, y_pred)
print(r2_test)
```

```
0.7395825489781629
```

In [76]:

```
# Get r2 score for test
from sklearn.metrics import r2_score
r2_train = r2_score(y_train, y_train_cnt)
print(r2_train)
```

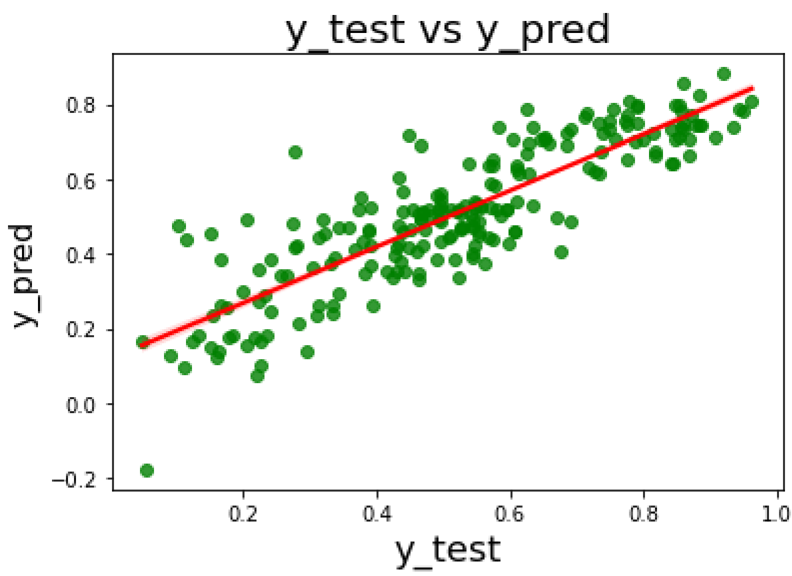
```
0.7752016324072822
```

Observation

- We see that the varivation is test and train dataset is almost uniform w.r.t prediction.

In [77]:

```
# Plot y_test vs y_pred with the best fit line

plt.figure()
sns.regplot(x=y_test, y=y_pred, ci=68, fit_reg=True,
            scatter_kws={"color": "green"}, line_kws={"color": "red"})
plt.title('y_test vs y_pred', fontsize=20)
plt.xlabel('y_test', fontsize=18)
plt.ylabel('y_pred', fontsize=16)
plt.show()
```



In [78]:

```
# Final model coefficients

print(lm_11.params)
```

```
const         0.589066
year          0.248063
windspeed    -0.188912
spring       -0.259890
summer       -0.040792
winter       -0.075008
Jan          -0.103274
Sep           0.069520
Sun          -0.046392
Light Snow   -0.299689
Mist         -0.087378
dtype: float64
```

Observation

- We, see the important feature are: year, windspeed, spring, summer, winter, Jan, Sep, Sun, LightSnow and Mist

Final Model Eqaution

The equation of our model is:

$$cnt = 0.5891 + 0.2481 \times year - 0.1889 \times windspeed - 0.2599 \times spring - 0.0408 \times summer - 0.07$$
$$\times Sep - 0.0464 \times Sun - 0.2997 \times LightSnow - 0.0874 \times Mist$$