In [2]:
```
#Import necessary libraries
#0.1 Adjusting Screen Width

from IPython.core.display import display, HTML
display(HTML("<style>.container { width:80% !important; }</style>"))
```

In [3]:
```
#0.2 Supressing Warnings
import warnings
warnings.filterwarnings('ignore')
```

In [8]:
```
#0.3 Import Necessary Python Libraries
# numpy & pandas
import numpy as np
import pandas as pd
from math import sqrt

#visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

#Machine learning Libraries
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import RFE
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
```

In [9]:
```
#Step 1: Reading & Understanding the data
# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all

import os
for dirname, _, filenames in os.walk('C:/Users/Admin/Desktop/Linear Regression Assig
    for filename in filenames:
        print(os.path.join(dirname, filename))

#From the Readme.txt file, it was understood that the field
#'dteday' is a date.Thus,parsing it as a date type while
#importing the bike data
```

In [10]:
```
#1.1 Importing the Data
bike = pd.read_csv("C:/Users/Admin/Desktop/Linear Regression Assignment/day.csv", pa
```

In [11]:
```
#1.2 Inspecting the Dataframe
# Checking the top 5 rows of the dataframe
bike.head()
```

Out[11]:

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	ate
0	1	2018-01-01	1	0	1	0	6	0	2	14.110847	18.18

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	ate
1	2	2018-02-01	1	0	1	0	0	0	2	14.902598	17.68
2	3	2018-03-01	1	0	1	0	1	1	1	8.050924	9.47
3	4	2018-04-01	1	0	1	0	2	1	1	8.200000	10.60
4	5	2018-05-01	1	0	1	0	3	1	1	9.305237	11.46

In [12]:
```
# Checking the last 5 rows of the dataframe
bike.tail()
```

Out[12]:

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	a
725	726	2019-12-27	1	1	12	0	4	1	2	10.420847	11.
726	727	2019-12-28	1	1	12	0	5	1	2	10.386653	12.
727	728	2019-12-29	1	1	12	0	6	0	2	10.386653	12.
728	729	2019-12-30	1	1	12	0	0	0	1	10.489153	11.
729	730	2019-12-31	1	1	12	0	1	1	2	8.849153	11.

In [13]:
```
#Checking the shape of the dataframe
bike.shape
```

Out[13]: (730, 16)

In [ ]:
```
#Note: The dataframe has 730 rows and 16 columns
```

In [14]:
```
# Checking the size of the dataframe
bike.size
```

Out[14]: 11680

In [16]:
```
# How many types of each data type column exists and total memory usage
bike.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    datetime64[ns]
 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: datetime64[ns](1), float64(4), int64(11)
memory usage: 91.4 KB
```

In [17]:
```
#Checking the numerical columns data distribution statistics
bike.describe()
```

Out[17]:

	instant	season	yr	mnth	holiday	weekday	workingday	weathe
count	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000
mean	365.500000	2.498630	0.500000	6.526027	0.028767	2.997260	0.683562	1.394
std	210.877136	1.110184	0.500343	3.450215	0.167266	2.006161	0.465405	0.544
min	1.000000	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000	1.000
25%	183.250000	2.000000	0.000000	4.000000	0.000000	1.000000	0.000000	1.000
50%	365.500000	3.000000	0.500000	7.000000	0.000000	3.000000	1.000000	1.000
75%	547.750000	3.000000	1.000000	10.000000	0.000000	5.000000	1.000000	2.000
max	730.000000	4.000000	1.000000	12.000000	1.000000	6.000000	1.000000	3.000

In [ ]:
```
'''Insight:
     Except one column which is date type, all other are either
float or integer type.
     There are some fields that are categorical in nature, but
are in integer/float type. Example : season, mnth,
weathersit etc.
     We will have to analyze and decide whether to convert them
to categorical or treat as integer. From Readme.txt file
more information of these categorical columns can be
inferred.'''
```

In [18]:
```
#1.3 Data quality check
# To check if there are any missing values in the dataset

#import pandas as pd
#import numpy as np

print(bike.isnull().sum())
```

```
instant       0
dteday        0
season        0
yr            0
mnth          0
holiday       0
weekday       0
workingday    0
weathersit    0
temp          0
atemp         0
hum           0
windspeed     0
casual        0
registered    0
```

```
cnt           0
dtype: int64
```

In [ ]:
```
#Insight: There are no missing values in any of the columns and rows.
```

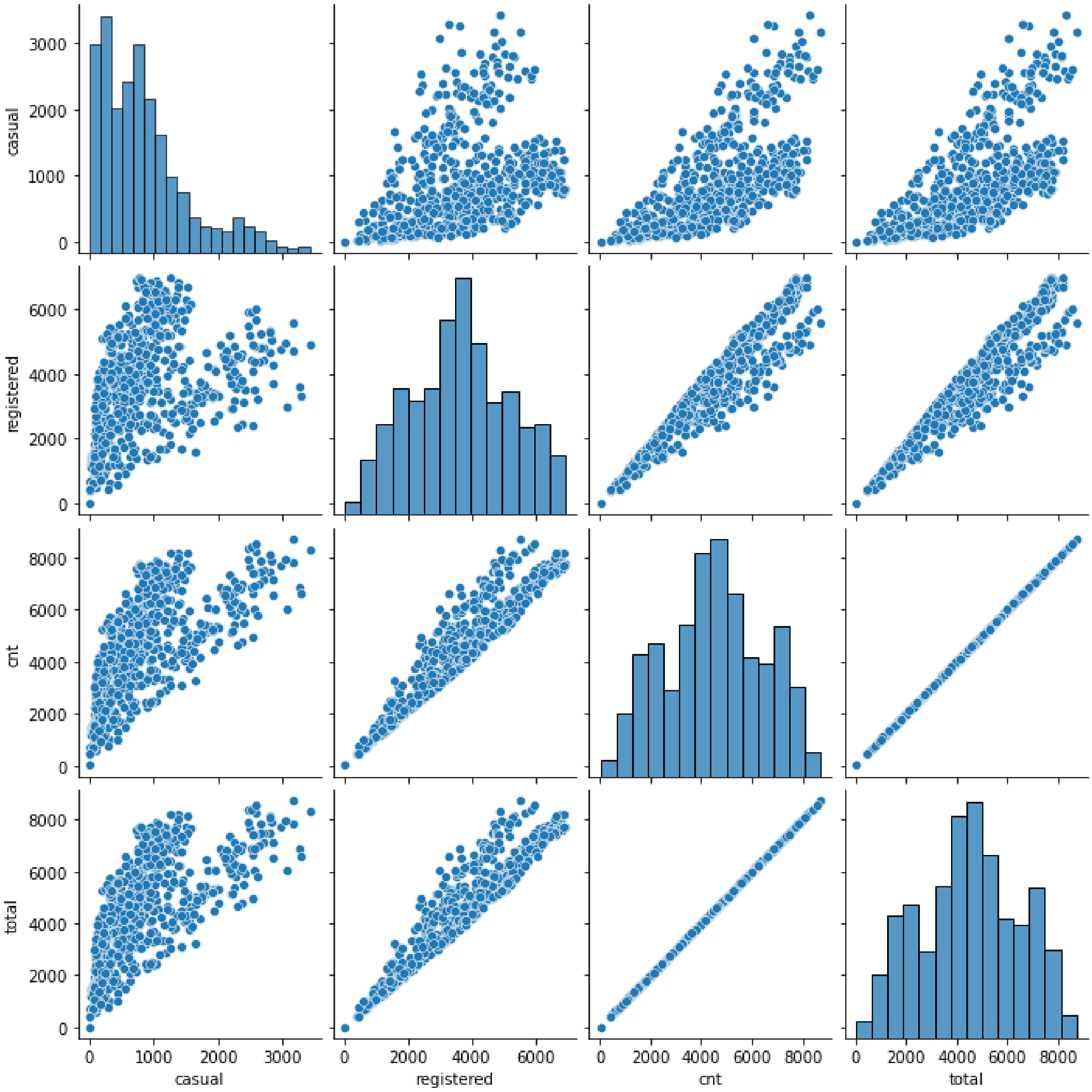
In [19]:
```
#1.4 Duplicate Checking
# Creating a copy of original dataframe for duplicate check
bike_dup = bike

# Checking for duplicates and dropping the entire duplicate row if any
bike_dup.drop_duplicates(subset=None, inplace=True)
bike_dup.shape
```

Out[19]:
```
(730, 16)
```

In [ ]:
```
#Insight: The shape after running the drop duplicate
#command is same as the original dataframe. Hence we can
#conclude that there were not any duplicate values in the
#dataset.
```

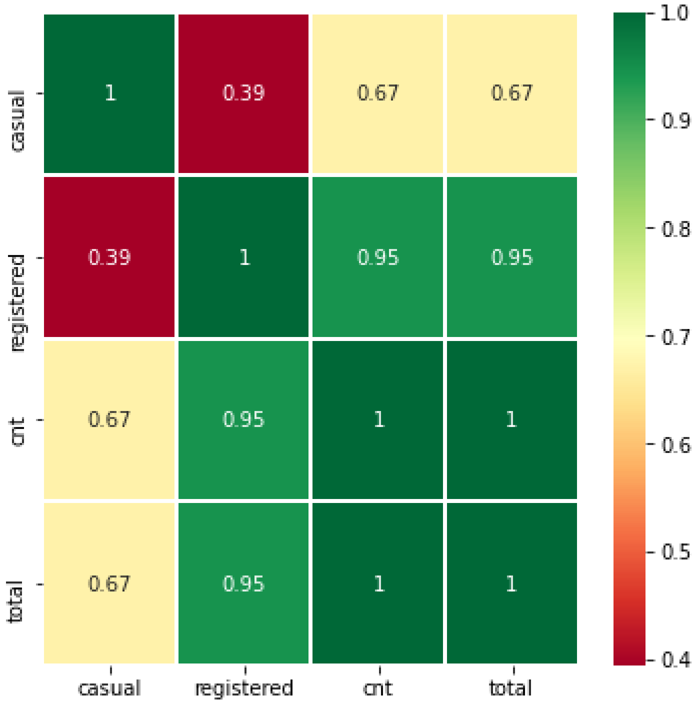
In [20]:
```
#1.5 Removing Redundant columns
# Checking the relationship between casual, registered and cnt column
bike_cnt = bike[['casual','registered','cnt']]
# Creating a column whch will show the value of casual + registered
bike_cnt['total'] = bike_cnt['casual'] + bike_cnt ['registered']
sns.pairplot(bike_cnt)
plt.show
```

Out[20]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [21]:

```
# also checking the correlation of the variables
plt.figure(figsize = (6,6))
ax= sns.heatmap(bike_cnt.corr(), annot = True, cmap="RdYlGn",linewidth =1)
plt.show()
```



In [ ]:

```
#Note:
'''Based on the high level analysis of the data and the data
dictionary, the following variables can be removed from
further analysis -'''

#instant: It is only an index value
#dteday:
    '''This has the date, Since we already have separate
columns for 'year' & 'month' we could live without this
column'''
#casual & registered:
    '''Both these columns contains the count of bike booked
    by different categories of customers. From the pairplot
    as well as the correlation heatmap, we can concur that
    total bike rental value 'cnt = 'casual' + 'registered'.
    Since our objective is to find the total count of bikes
    and not by specific category, we will ignore these two
    columns.'''
```

In [22]:

```
#dropping the unwanted columns
bike.drop(['instant','dteday','casual','registered'],axis=1,inplace=True)
bike.shape
```

Out[22]: (730, 12)

In [ ]:

```
#Step 2: Encoding & Visualizing the data
#2.1 Encoding Categorical columns
#Converting season, mnth,weathersit and weekday to
#categorical columns

'''season: converting season values as per criteria -
1:Spring, 2:Summer, 3:Fall, 4:Winter

mnth: converting mnth values as 1:Jan, 2:Feb, 3:Mar,
4:Apr, 5:May, 6:Jun, 7:Jul, 8:Aug, 9:Sep, 10:Oct, 11:Nov,
12:Dec

weathersit: converting weathersit values as 1:Clear,
2:Misty, 3:Light_RainSnow 4:Heavy_RainSnow
```

```
weekday: converting weekday values as 0:Sun, 1:Mon, 2:Tue,
3:Wed, 4:Thu, 5:Fri, 6:Sat'''
```

In [24]:

```
#Converting season
bike.season.replace((1,2,3,4), ('W1_Spring','W2_Summer','W3_Fall','W4_Winter'), inpl
bike.season.value_counts(normalize=True)
```

Out[24]:

```
W3_Fall      0.257534
W2_Summer    0.252055
W1_Spring    0.246575
W4_Winter    0.243836
Name: season, dtype: float64
```

In [26]:

```
#Converting mnth
bike.mnth.replace((1,2,3,4,5,6,7,8,9,10,11,12),('Jan','Feb','Mar','Apr','May','Jun',
bike.mnth.value_counts(normalize=True)
```

Out[26]:

```
Jan    0.084932
Dec    0.084932
Oct    0.084932
Jul    0.084932
Aug    0.084932
Mar    0.084932
May    0.084932
Sep    0.082192
Jun    0.082192
Nov    0.082192
Apr    0.082192
Feb    0.076712
Name: mnth, dtype: float64
```

In [28]:

```
#Converting weathersit
bike.weathersit.replace((1,2,3,4), ('Clear','Misty','Light_rainsnow','Heavy_rainsnow
bike.weathersit.value_counts(normalize=True)
```

Out[28]:

```
Clear             0.634247
Misty             0.336986
Light_rainsnow    0.028767
Name: weathersit, dtype: float64
```

In [29]:

```
#Converting weathersit
bike.weekday.replace((0,1,2,3,4,5,6), ('Sunday','Monday','Tuesday','Wednesday','Thur
bike.weekday.value_counts(normalize=True)
```

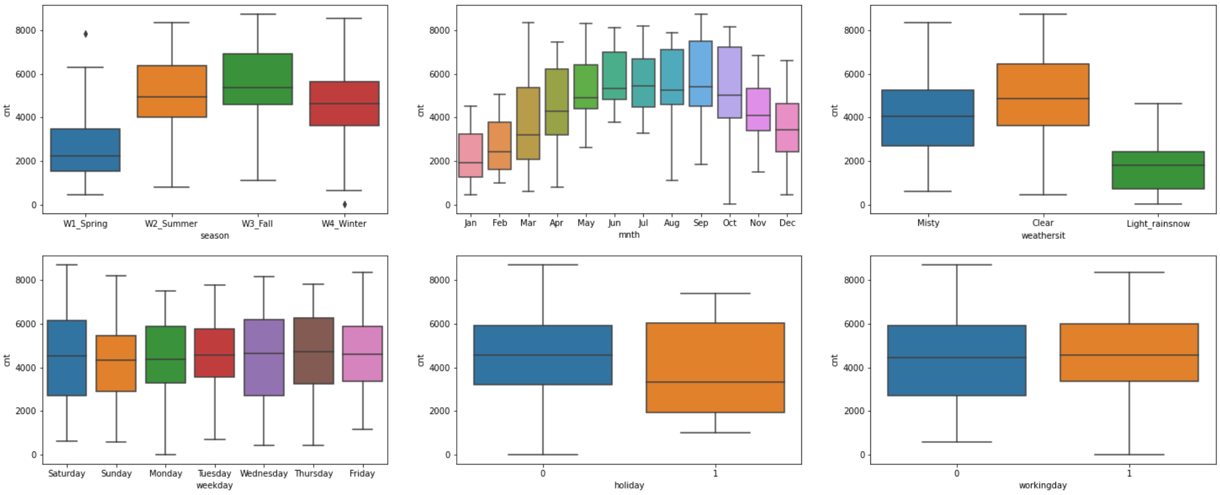
Out[29]:

```
Monday       0.143836
Sunday       0.143836
Saturday     0.143836
Tuesday      0.142466
Friday       0.142466
Thursday     0.142466
Wednesday    0.141096
Name: weekday, dtype: float64
```

In [30]:

```
#2.2 Categorical Variable Analysis
# Build boxplot of all categorical variables (before creating dummies) againt the ta
# to see how each of the predictor variable stackup against the target variable.

plt.figure(figsize=(25, 10))
plt.subplot(2,3,1)
sns.boxplot(x = 'season', y = 'cnt', data = bike)
plt.subplot(2,3,2)
sns.boxplot(x = 'mnth', y = 'cnt', data = bike)
plt.subplot(2,3,3)
sns.boxplot(x = 'weathersit', y = 'cnt', data = bike)
plt.subplot(2,3,4)
sns.boxplot(x = 'weekday', y = 'cnt', data = bike)
```

```
plt.subplot(2,3,5)
sns.boxplot(x = 'holiday', y = 'cnt', data = bike)
plt.subplot(2,3,6)
sns.boxplot(x = 'workingday', y = 'cnt', data = bike)
plt.show()
```



In [31]:

```
# function to generate statistics related to Categorical Variables
def categorical_stats(col):
    cat_df = bike.groupby(col)['cnt'].agg(['sum', 'mean','count']).sort_values('sum'
    cat_df['sum_perc']=cat_df['sum']/bike.cnt.sum()*100
    cat_df['count_perc']=cat_df['count']/bike.cnt.count()*100
    return round(cat_df,2)
```

In [32]:

```
# function to generate plots related to Categorical Variables
def categorical_plot(col,x,y):
    plt.figure(figsize = (x,y))
    plt.subplot(1,2,1)
    sns.barplot(col,'cnt',data=bike)
    plt.subplot(1,2,2)
    sns.barplot(col,'cnt',data=bike, hue='yr',palette='Paired')
    plt.legend(labels=['2018', '2019'])
    return
```

In [34]:

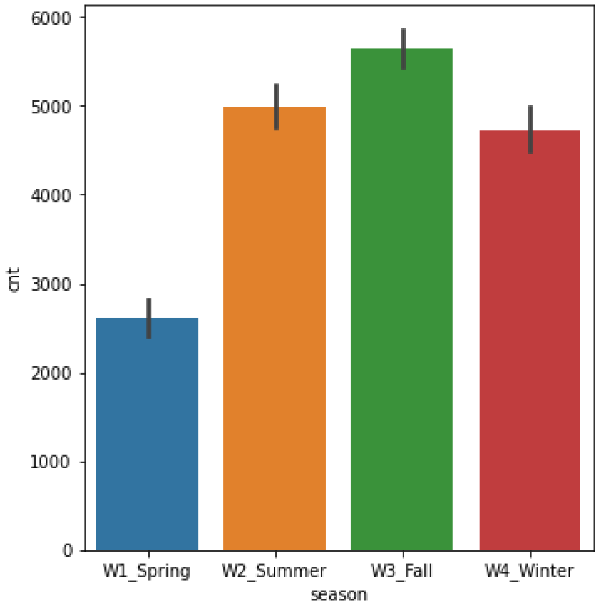
```
#2.2.1 Season :
categorical_stats('season')
```

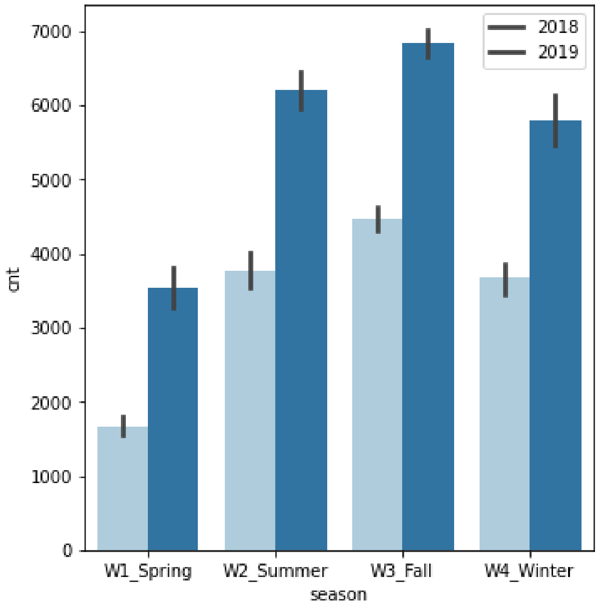
Out[34]:

	sum	mean	count	sum_perc	count_perc
season					
W3_Fall	1061129	5644.30	188	32.24	25.75
W2_Summer	918589	4992.33	184	27.91	25.21
W4_Winter	841613	4728.16	178	25.57	24.38
W1_Spring	469514	2608.41	180	14.27	24.66

In [35]:

```
categorical_plot('season',12,6)
```





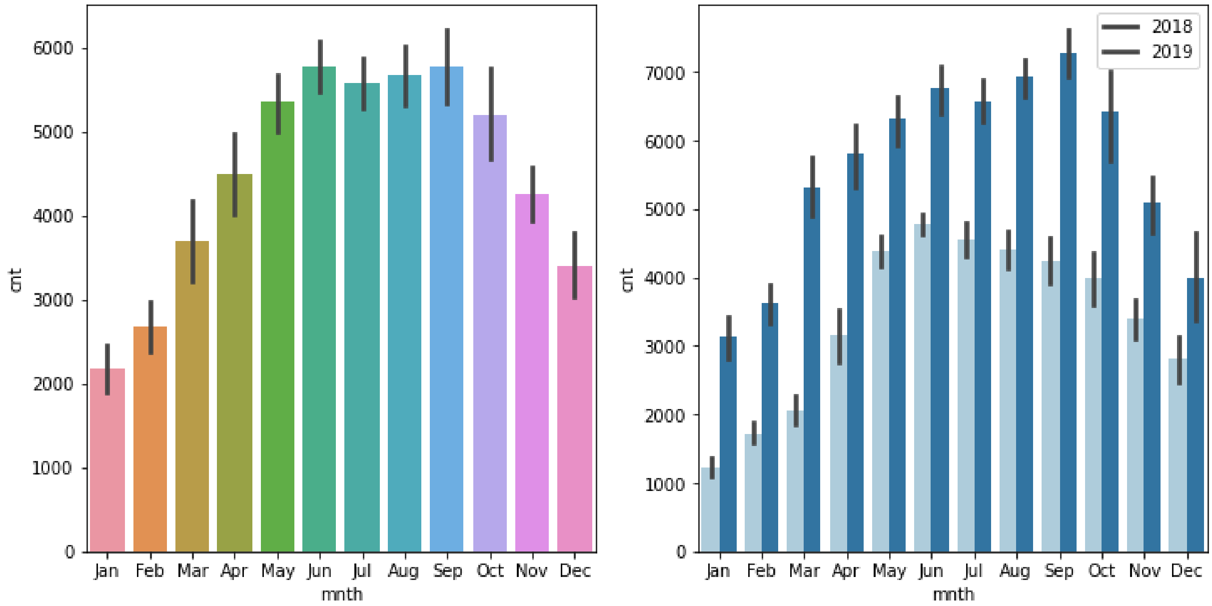
In [ ]:
```
#Insight:
'''Almost 32% of the bike booking were happening in Fall
with a median of over 5000 bookings (for two years). It is
followed by Summer & Winter with 27% & 25% of total booking
. It indicates that the season can be a good predictor of
the dependent variable.'''
```

In [36]:
```
#2.2.2 Month :
categorical_stats('mnth')
```

Out[36]:

mnth	sum	mean	count	sum_perc	count_perc
Aug	351194	5664.42	62	10.67	8.49
Jun	346342	5772.37	60	10.52	8.22
Sep	345991	5766.52	60	10.51	8.22
Jul	344948	5563.68	62	10.48	8.49
May	331686	5349.77	62	10.08	8.49
Oct	322352	5199.23	62	9.80	8.49
Apr	269094	4484.90	60	8.18	8.22
Nov	254831	4247.18	60	7.74	8.22
Mar	228920	3692.26	62	6.96	8.49
Dec	211036	3403.81	62	6.41	8.49
Feb	149518	2669.96	56	4.54	7.67
Jan	134933	2176.34	62	4.10	8.49

In [37]:
```
categorical_plot('mnth',12,6)
```



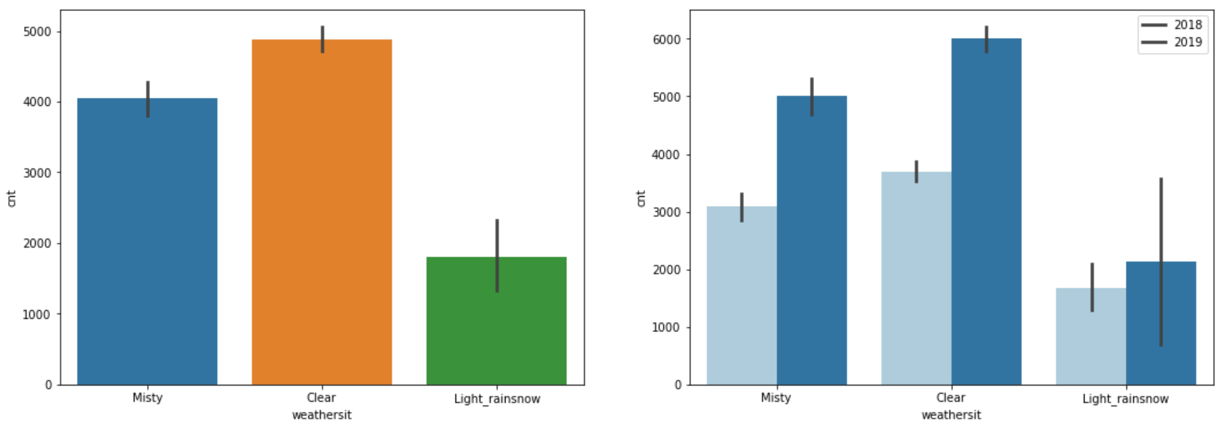
In [ ]:
```
#Insight:
'''Almost 10% of the bike booking was happening in the
months' May to Sep with a median of over 4000 bookings per
month. It indicates that the mnth has some trend for
bookings and can be a good predictor for the dependent
variable.'''
```

In [39]:
```
#2.2.3 Weather:
categorical_stats('weathersit')
```

Out[39]:

weathersit	sum	mean	count	sum_perc	count_perc
Clear	2257952	4876.79	463	68.61	63.42
Misty	995024	4044.81	246	30.24	33.70
Light_rainsnow	37869	1803.29	21	1.15	2.88

In [40]:
```
categorical_plot('weathersit',18,6)
```



In [ ]:
```
#Insight:
'''Almost 68.6% of the bike booking was happening during
Clear weather with a median of close to 5000 bookings (for
two years). This was followed by Misty with 30% of the
total booking. It indicates that the weathersit does show
some trend towards the bike bookings, and it can be a good
predictor for the dependent variable. The current data
```

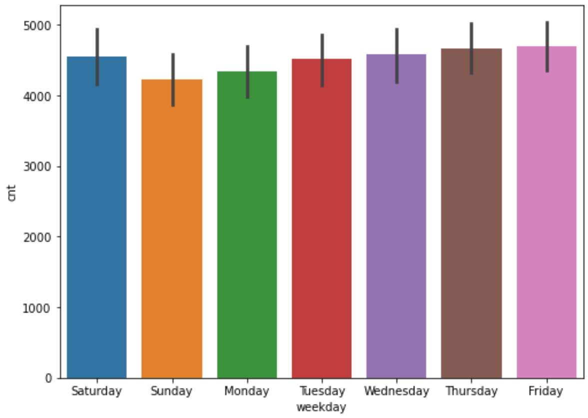
```
frame does not have any data where the weather is
Heavy_RainSnow'''
```

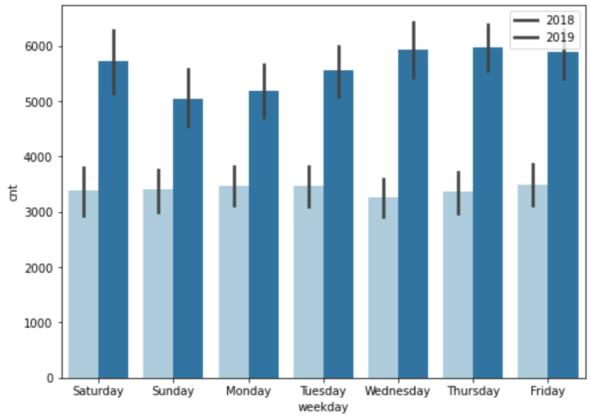
In [41]:
```
#2.2.4 Weekday :
categorical_stats('weekday')
```

Out[41]:

weekday	sum	mean	count	sum_perc	count_perc
Friday	487790	4690.29	104	14.82	14.25
Thursday	485395	4667.26	104	14.75	14.25
Saturday	477807	4550.54	105	14.52	14.38
Wednesday	471214	4574.89	103	14.32	14.11
Tuesday	469109	4510.66	104	14.25	14.25
Monday	455503	4338.12	105	13.84	14.38
Sunday	444027	4228.83	105	13.49	14.38

In [42]:
```
categorical_plot('weekday',18,6)
```





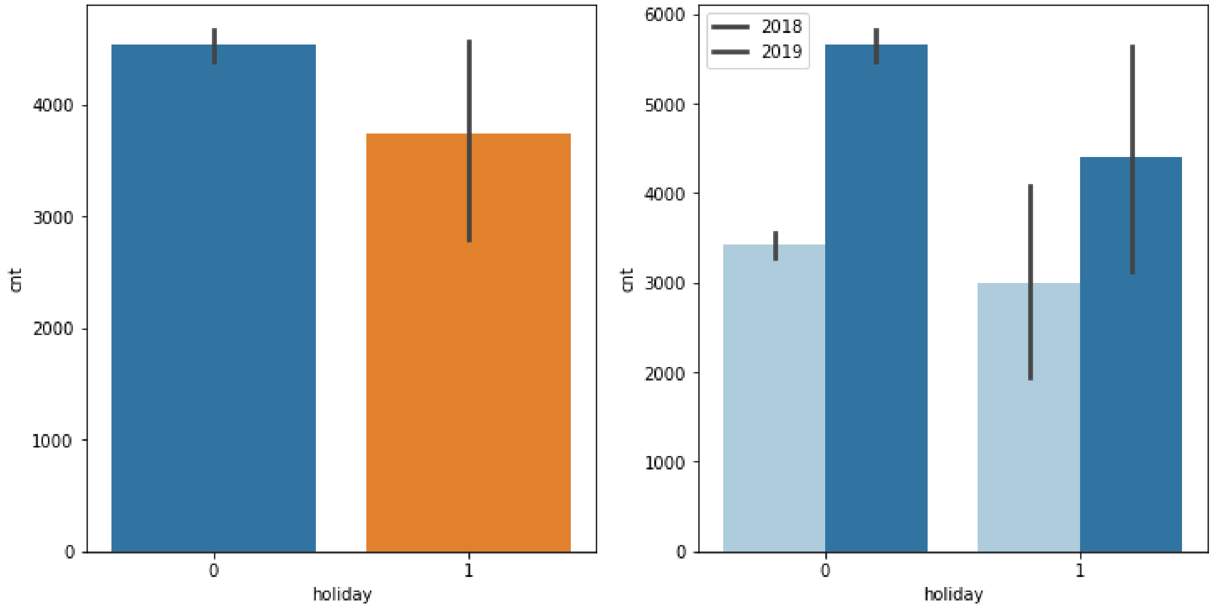
In [ ]:
```
#Insight:
'''weekday variable shows the very close trend
(between 13.5%-14.8% of total booking on all days of the
week) having their independent medians between 4000 to
5000 bookings. This variable can have some or no influence
on the predictor. Further analysis would be needed to
determine whether this attribute needs to be included in
the model parameter selection'''
```

In [44]:
```
#2.2.5 Holiday :
categorical_stats('holiday')
```

Out[44]:

holiday	sum	mean	count	sum_perc	count_perc
0	3212410	4530.9	709	97.62	97.12
1	78435	3735.0	21	2.38	2.88

In [45]:
```
categorical_plot('holiday',12,6)
```



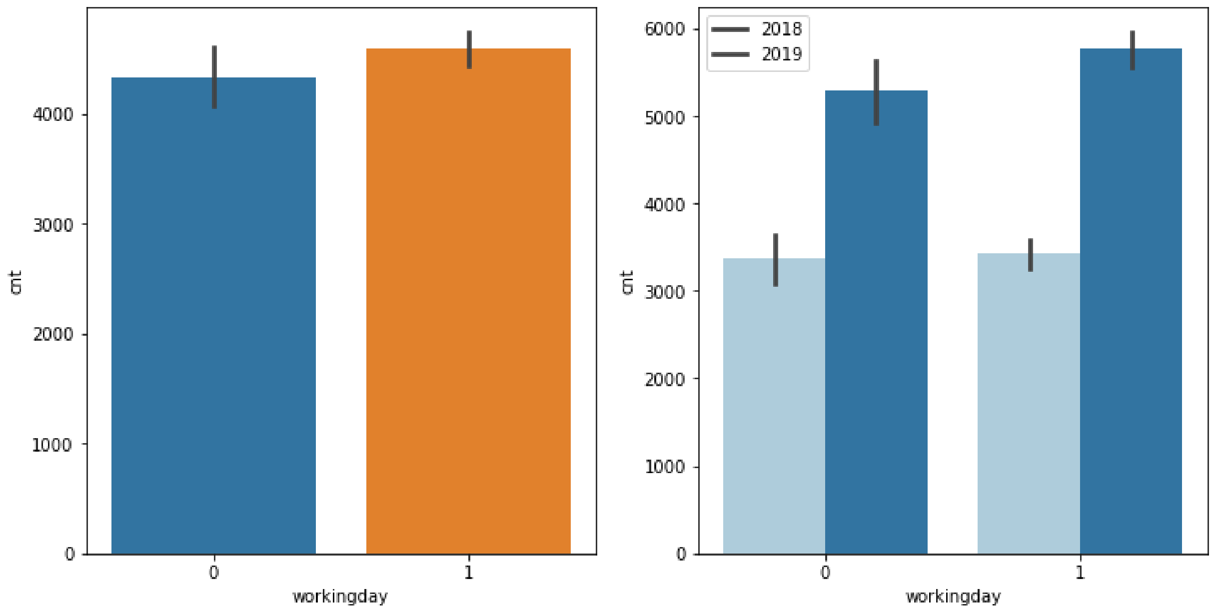
In [ ]:
```
#Insight:
'''Almost 97% of bike rentals are happening during non-holiday
time.'''
```

In [47]:
```
#2.2.6 Working Day :
categorical_stats('workingday')
```

Out[47]:

workingday	sum	mean	count	sum_perc	count_perc
1	2290576	4590.33	499	69.6	68.36
0	1000269	4330.17	231	30.4	31.64

In [48]:
```
categorical_plot('workingday',12,6)
```



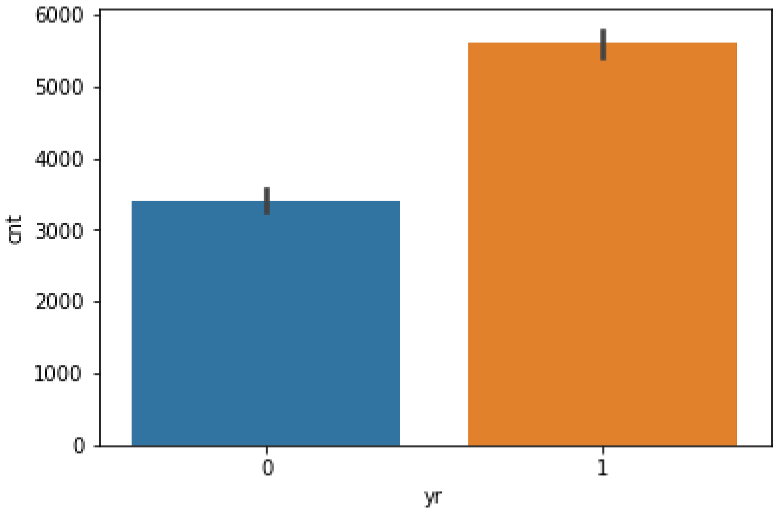
In [ ]:
```
#Insight:
'''Almost 69% of the bike booking were happening in
'workingday' with a median of close to 5000 bookings (for
two years). It indicates that the workingday can be a good
predictor of the dependent variable'''
```

In [50]:
```
#2.2.7 Year :
categorical_stats('yr')
```

Out[50]:

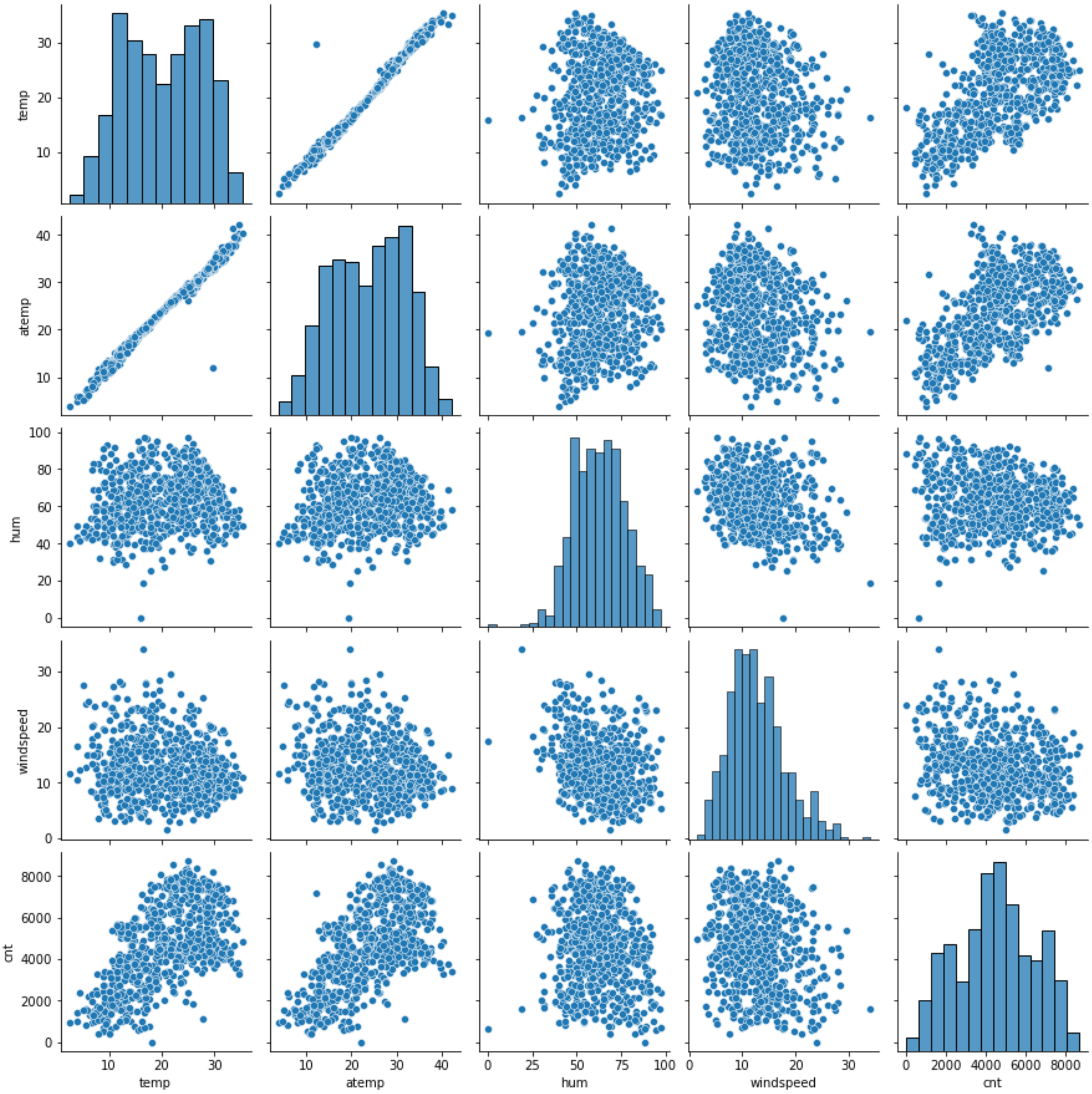
yr	sum	mean	count	sum_perc	count_perc
1	2047742	5610.25	365	62.23	50.0
0	1243103	3405.76	365	37.77	50.0

In [51]:
```
sns.barplot('yr','cnt',data=bike)
plt.show()
```



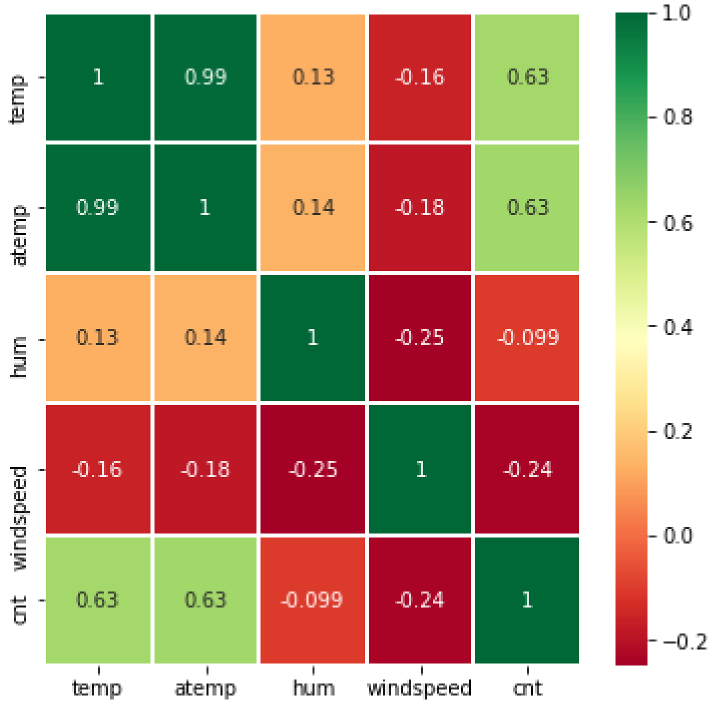
In [ ]:
```
'''Insight:
Bike rental demand has gone up from 2018 to 2019'''
```

In [52]:
```
#2.3 Numerical Variable Analysis
#Generating pairplot to check the relationships between numeric variables variables
bike_num = bike[['temp','atemp','hum','windspeed','cnt']]
sns.pairplot(bike_num)
plt.show()
```



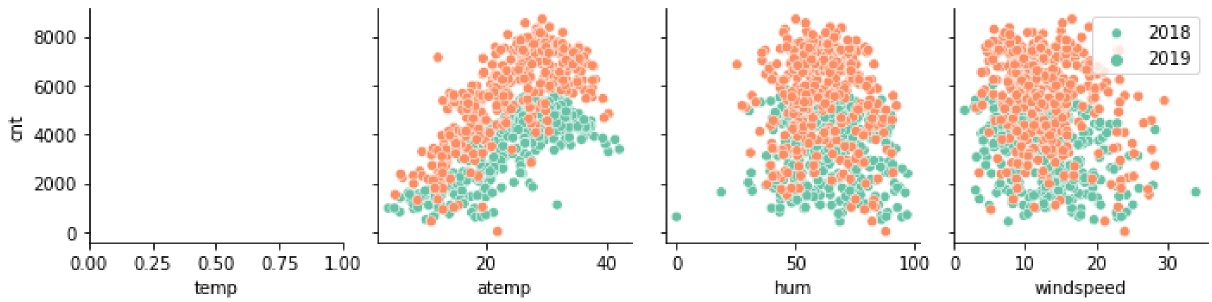
In [54]:

```
# Checking correlation of the parameters by mapping a correlation heatmap

plt.figure(figsize = (6,6))
ax= sns.heatmap(bike_num.corr(), annot = True, cmap="RdYlGn",linewidth =1)
```



In [ ]:
```
'''Insight: There is linear relationship between temp and
atemp. Both of the parameters cannot be used in the model
due to multicolinearity. We will decide which parameters
to keep based on VIF and p-value w.r.t other variables
'''
```

In [55]:
```
# Checking the impact of year against the numerical
#variable :
ax = sns.pairplot(x_vars=['temp', 'atemp', 'hum', 'windspeed'], y_vars=['cnt'] , dat
ax._legend.remove()
plt.legend(labels=['2018', '2019'])
plt.show()
```



In [ ]:
```
'''Insight: All the parameters have increased values in
2019 compared to 2019. Thus, year may become a key
paratemeter in the model
'''
```

In [56]:
```
#Step 3: Data Preparation

#3.1 Dummy Variable Creation

#Season

season = pd.get_dummies(bike['season'], drop_first = True)
season.head(3)
```

Out[56]:

W2_Summer	W3_Fall	W4_Winter

	W2_Summer	W3_Fall	W4_Winter
0	0	0	0
1	0	0	0
2	0	0	0

In [57]:
```
#Weather

weather = pd.get_dummies(bike['weathersit'], drop_first = True)
weather.head(3)
```

Out[57]:

	Light_rainsnow	Misty
0	0	1
1	0	1
2	0	0

In [58]:
```
#Month

month = pd.get_dummies(bike['mnth'], drop_first = True)
month.head(3)
```

Out[58]:

	Aug	Dec	Feb	Jan	Jul	Jun	Mar	May	Nov	Oct	Sep
0	0	0	0	1	0	0	0	0	0	0	0
1	0	0	0	1	0	0	0	0	0	0	0
2	0	0	0	1	0	0	0	0	0	0	0

In [59]:
```
#Weekday

weekday = pd.get_dummies(bike['weekday'], drop_first = True)
weekday.head(3)
```

Out[59]:

	Monday	Saturday	Sunday	Thursday	Tuesday	Wednesday
0	0	1	0	0	0	0
1	0	0	1	0	0	0
2	1	0	0	0	0	0

In [60]:
```
#3.2 Merging the Dataframes
# Creating a new dataframe called bike_new where season, month, weather and weekday

bike_new = pd.concat([bike,season,month,weather,weekday], axis = 1)
bike_new.head(3)
```

Out[60]:

	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum
0	W1_Spring	0	Jan	0	Saturday	0	Misty	14.110847	18.18125	80.5833
1	W1_Spring	0	Jan	0	Sunday	0	Misty	14.902598	17.68695	69.6087
2	W1_Spring	0	Jan	0	Monday	1	Clear	8.050924	9.47025	43.7273

3 rows × 34 columns

In [61]:
```
bike_new.shape
```

Out[61]:
```
(730, 34)
```

In [62]:
```
bike_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 730 entries, 0 to 729
Data columns (total 34 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   season          730 non-null    object 
 1   yr              730 non-null    int64  
 2   mnth            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   atemp           730 non-null    float64
 9   hum             730 non-null    float64
 10  windspeed       730 non-null    float64
 11  cnt             730 non-null    int64  
 12  W2_Summer       730 non-null    uint8  
 13  W3_Fall         730 non-null    uint8  
 14  W4_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  Light_rainsnow  730 non-null    uint8  
 27  Misty           730 non-null    uint8  
 28  Monday          730 non-null    uint8  
 29  Saturday        730 non-null    uint8  
 30  Sunday          730 non-null    uint8  
 31  Thursday        730 non-null    uint8  
 32  Tuesday         730 non-null    uint8  
 33  Wednesday       730 non-null    uint8  
dtypes: float64(4), int64(4), object(4), uint8(22)
memory usage: 109.8+ KB
```

In [63]:
```
#3.3 Removing unnecessary columns

#deleting the unnecessry column season, mnth, weathersit
#and weekday as the respective values are already populated
#as binary columns data

bike_new.drop(['season','mnth','weathersit','weekday'],axis=1,inplace=True)
bike_new.shape
```

Out[63]:
```
(730, 30)
```

In [64]:
```
bike_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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   W2_Summer       730 non-null    uint8
 9   W3_Fall         730 non-null    uint8
 10  W4_Winter       730 non-null    uint8
 11  Aug             730 non-null    uint8
 12  Dec             730 non-null    uint8
 13  Feb             730 non-null    uint8
 14  Jan             730 non-null    uint8
 15  Jul             730 non-null    uint8
 16  Jun             730 non-null    uint8
 17  Mar             730 non-null    uint8
 18  May             730 non-null    uint8
 19  Nov             730 non-null    uint8
 20  Oct             730 non-null    uint8
 21  Sep             730 non-null    uint8
 22  Light_rainsnow  730 non-null    uint8
 23  Misty           730 non-null    uint8
 24  Monday          730 non-null    uint8
 25  Saturday        730 non-null    uint8
 26  Sunday          730 non-null    uint8
 27  Thursday        730 non-null    uint8
 28  Tuesday         730 non-null    uint8
 29  Wednesday       730 non-null    uint8
dtypes: float64(4), int64(4), uint8(22)
memory usage: 87.0 KB
```

In [ ]:

```
'''Insight: All the 30 columns are now as numeric value.
The dataframe is ready now for splitting into Train & Test
dataframes
'''
```

In [65]:

```
#Step 4: Splitting the data into Train & Test Dataset

#4.1. Train & Test Split

# We specify this so that the train and test data set
#always have the same rows, respectively

np.random.seed(0)
bike_train, bike_test = train_test_split(bike_new, train_size = 0.7, random_state =
```

In [66]:

```
#Verifying the train - test split and new dataframe details

bike_train.shape
```

Out[66]: (510, 30)

In [67]:

```
bike_train.describe()
```

Out[67]:

	yr	holiday	workingday	temp	atemp	hum	windspeed	
count	510.000000	510.000000	510.000000	510.000000	510.000000	510.000000	510.000000	510.00
mean	0.501961	0.023529	0.684314	20.218078	23.590696	62.340743	12.771365	4494.10
std	0.500487	0.151726	0.465245	7.500110	8.138271	14.418728	5.205888	1948.31
min	0.000000	0.000000	0.000000	2.424346	3.953480	0.000000	1.500244	22.00

	yr	holiday	workingday	temp	atemp	hum	windspeed	
25%	0.000000	0.000000	0.000000	13.717924	16.744800	51.604150	9.011098	3146.50
50%	1.000000	0.000000	1.000000	20.209597	23.973425	62.233700	12.125057	4508.00
75%	1.000000	0.000000	1.000000	26.786653	30.327087	72.958300	15.624869	5962.75
max	1.000000	1.000000	1.000000	35.328347	42.044800	96.250000	34.000021	8714.00

8 rows × 30 columns

In [68]:
```
bike_test.shape
```

Out[68]:
```
(220, 30)
```

In [69]:
```
bike_test.describe()
```

Out[69]:

	yr	holiday	workingday	temp	atemp	hum	windspeed	
count	220.000000	220.000000	220.000000	220.000000	220.000000	220.000000	220.000000	220.00
mean	0.495455	0.040909	0.681818	20.553817	24.040727	63.749086	12.745665	4540.23
std	0.501120	0.198531	0.466833	7.533926	8.188064	13.790510	5.184271	1911.19
min	0.000000	0.000000	0.000000	3.957390	4.941955	29.000000	3.875669	506.00
25%	0.000000	0.000000	0.000000	14.189577	17.366525	53.260450	9.041851	3193.00
50%	0.000000	0.000000	1.000000	20.756250	24.762725	63.687500	12.146128	4593.50
75%	1.000000	0.000000	1.000000	27.119778	30.903325	73.333350	15.643227	5959.75
max	1.000000	1.000000	1.000000	34.815847	41.318550	97.250000	28.292425	8395.00

8 rows × 30 columns

In [ ]:
```
'''Insight: Based on the 70% - 30% split between train and
test dataset we have 510 rows in train dataset and 220 in
test dataset
'''
```

In [70]:
```
#4.2 Rescalling bike_train dataframe

# Rescaling using MinMaxCcaler
scaler = MinMaxScaler()

#Dataframe before scaling
bike_train.head(3)
```

Out[70]:

	yr	holiday	workingday	temp	atemp	hum	windspeed	cnt	W2_Summer	W3_Fall
650	1	0	0	16.126653	19.5698	49.4583	9.791514	7109	0	0
212	0	0	1	31.638347	35.1646	55.0833	10.500039	4266	0	1
714	1	0	0	14.862500	18.4969	83.8750	6.749714	3786	0	0

3 rows × 30 columns

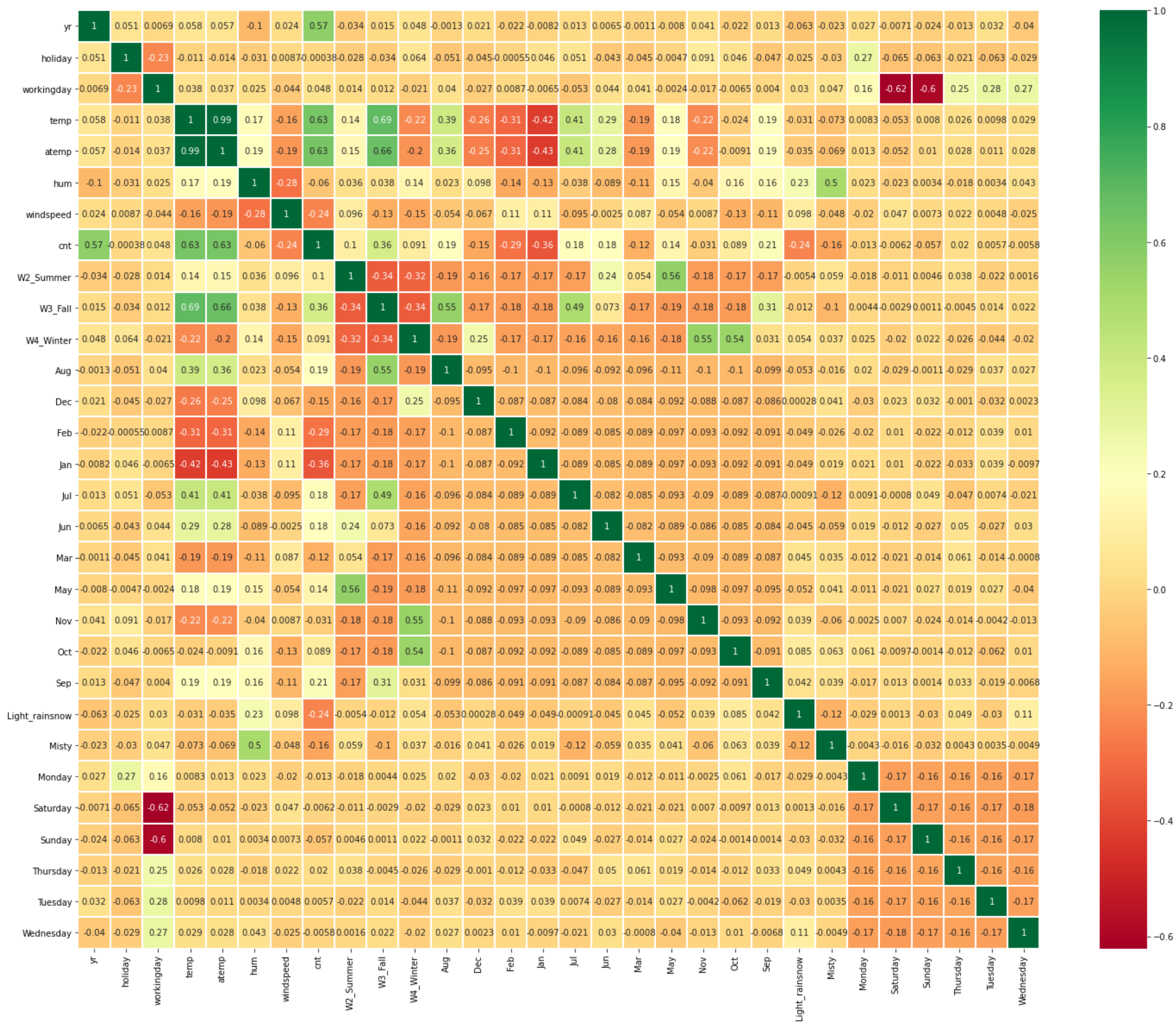
In [71]:
```
# Apply scaler() to all the columns except the 'yes-no' and 'dummy' variables
num_vars = ['temp','atemp','hum','windspeed','cnt']
bike_train[num_vars] = scaler.fit_transform(bike_train[num_vars])

#Checking after rescalling
bike_train.head(3)
```

Out[71]:

	yr	holiday	workingday	temp	atemp	hum	windspeed	cnt	W2_Summer	W3
650	1	0	0	0.416433	0.409971	0.513852	0.255118	0.815347	0	
212	0	0	1	0.887856	0.819376	0.572294	0.276919	0.488265	0	
714	1	0	0	0.378013	0.381804	0.871429	0.161523	0.433042	0	

3 rows × 30 columns

In [72]:
```
#4.3 Checking Correlation Coefficient
plt.figure(figsize = (25,20))
ax= sns.heatmap(bike_train.corr(), annot = True, cmap="RdYlGn",linewidth =1)
plt.show()
```



In [ ]:
```
'''Insight:
There is multi-colinearity between the variables. We need
to consider the factors when developing the model.

temp and atemp has very high correlation value of 0.99.
This suggest, we can use only one of these two variables
```

```
workingday variable has high negative correlation with Sat
& Sun (where workingday =0)

Spring is negatively correlated with cnt

emp, atemp and yr has strong correlation with cnt

misty weather and humidity has correlation

various months and corresponding weather has correlation'''
```

In [73]:
```
#Step 5: Building the Linear Model

#5.1 Dividing into X_train and y_train
y_train = bike_train.pop('cnt')
X_train = bike_train
```

In [74]:
```
#5.2 RFE

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

# Running RFE with the output number of the variable equal to 15
lm = LinearRegression()
lm.fit(X_train, y_train)

rfe = RFE(lm, 15)             # running RFE
rfe = rfe.fit(X_train, y_train)

# Checking which parameters have been selected in that list
#of 15
list(zip(X_train.columns,rfe.support_,rfe.ranking_))
```

Out[74]:
```
[('yr', True, 1),
 ('holiday', False, 11),
 ('workingday', True, 1),
 ('temp', True, 1),
 ('atemp', True, 1),
 ('hum', True, 1),
 ('windspeed', True, 1),
 ('W2_Summer', True, 1),
 ('W3_Fall', True, 1),
 ('W4_Winter', True, 1),
 ('Aug', False, 13),
 ('Dec', False, 2),
 ('Feb', False, 7),
 ('Jan', False, 6),
 ('Jul', False, 3),
 ('Jun', False, 12),
 ('Mar', True, 1),
 ('May', False, 4),
 ('Nov', True, 1),
 ('Oct', False, 10),
 ('Sep', True, 1),
 ('Light_rainsnow', True, 1),
 ('Misty', True, 1),
 ('Monday', False, 5),
 ('Saturday', True, 1),
 ('Sunday', False, 8),
 ('Thursday', False, 14),
 ('Tuesday', False, 9),
 ('Wednesday', False, 15)]
```

In [75]:
```
# storing the selected 15 variables in col list
```

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

Out[75]:
```
Index(['yr', 'workingday', 'temp', 'atemp', 'hum', 'windspeed', 'W2_Summer',
       'W3_Fall', 'W4_Winter', 'Mar', 'Nov', 'Sep', 'Light_rainsnow', 'Misty',
       'Saturday'],
      dtype='object')
```

In [76]:
```
# checking which columns have been eleminated
X_train.columns[~rfe.support_]
```

Out[76]:
```
Index(['holiday', 'Aug', 'Dec', 'Feb', 'Jan', 'Jul', 'Jun', 'May', 'Oct',
       'Monday', 'Sunday', 'Thursday', 'Tuesday', 'Wednesday'],
      dtype='object')
```

In [77]:
```
# Creating X_train dataframe with RFE selected variables
X_train_rfe = X_train[col]
```

In [78]:
```
#5.3 Manual Model Development using statsmodel

# Function for VIF Calculation

def calculateVIF(df):
    vif = pd.DataFrame()
    vif['Features'] = df.columns
    vif['VIF'] = [variance_inflation_factor(df.values, i) for i in range(df.shape[1]
    vif['VIF'] = round(vif['VIF'], 2)
    vif = vif.sort_values(by = "VIF", ascending = False)
    return vif
```

In [79]:
```
#5.3.1 Model 1

# Create a dataframe that will contain the names of all
#the feature variables and their respective VIFs
calculateVIF(X_train_rfe)
```

Out[79]:

	Features	VIF
2	temp	384.25
3	atemp	362.64
4	hum	17.60
7	W3_Fall	7.21
5	windspeed	4.75
1	workingday	4.66
8	W4_Winter	3.57
6	W2_Summer	3.51
13	Misty	2.16
0	yr	2.02
14	Saturday	1.81
10	Nov	1.70
11	Sep	1.28
9	Mar	1.20
12	Light_rainsnow	1.16

In [80]:
```
# Add a constant
X_train_lm1 = sm.add_constant(X_train_rfe)

# Create a first fitted model
lr1 = sm.OLS(y_train, X_train_lm1).fit()

# Print a summary of the linear regression model obtained
print(lr1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.840
Model:                            OLS   Adj. R-squared:                  0.835
Method:                 Least Squares   F-statistic:                     173.3
Date:                Tue, 03 Aug 2021   Prob (F-statistic):          1.13e-185
Time:                        21:27:25   Log-Likelihood:                 507.29
No. Observations:                 510   AIC:                            -982.6
Df Residuals:                     494   BIC:                            -914.8
Df Model:                          15
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const              0.1926      0.030      6.447      0.000       0.134       0.251
yr                 0.2272      0.008     27.760      0.000       0.211       0.243
workingday         0.0421      0.011      3.795      0.000       0.020       0.064
temp               0.4386      0.135      3.260      0.001       0.174       0.703
atemp              0.0601      0.138      0.436      0.663      -0.211       0.331
hum               -0.1796      0.037     -4.792      0.000      -0.253      -0.106
windspeed         -0.1832      0.028     -6.508      0.000      -0.238      -0.128
W2_Summer          0.1280      0.015      8.393      0.000       0.098       0.158
W3_Fall            0.0796      0.021      3.770      0.000       0.038       0.121
W4_Winter          0.1871      0.016     12.059      0.000       0.157       0.218
Mar                0.0471      0.016      2.948      0.003       0.016       0.079
Nov               -0.0392      0.018     -2.191      0.029      -0.074      -0.004
Sep                0.0883      0.016      5.551      0.000       0.057       0.120
Light_rainsnow    -0.2641      0.028     -9.289      0.000      -0.320      -0.208
Misty             -0.0468      0.011     -4.379      0.000      -0.068      -0.026
Saturday           0.0568      0.014      3.941      0.000       0.028       0.085
==============================================================================
Omnibus:                       78.666   Durbin-Watson:                   2.033
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              170.766
Skew:                          -0.835   Prob(JB):                     8.29e-38
Kurtosis:                       5.291   Cond. No.                         85.8
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
```

In [ ]:
```
#5.3.2 Model 2
#Insight:
         '''Both temp and atemp has high VIF but atemp has
high p-value additionally. We will go ahead with dropping
atemp from the equation'''
```

In [93]:
```
X_train_new = X_train_rfe.drop(['atemp'], axis = 1)
# Run the function to calculate VIF for the new model
calculateVIF(X_train_new)
```

Out[93]:

	Features	VIF
2	temp	23.28
3	hum	17.31
6	W3_Fall	7.12

	Features	VIF
1	workingday	4.65
4	windspeed	4.59
7	W4_Winter	3.57
5	W2_Summer	3.51
12	Misty	2.15
0	yr	2.02
13	Saturday	1.80
9	Nov	1.70
10	Sep	1.28
8	Mar	1.20
11	Light_rainsnow	1.16

In [94]:

```
# Add a constant
X_train_lm1 = sm.add_constant(X_train_rfe)

# Create a first fitted model
lr1 = sm.OLS(y_train, X_train_lm1).fit()

# Print a summary of the linear regression model obtained
print(lr1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.840
Model:                            OLS   Adj. R-squared:                  0.835
Method:                 Least Squares   F-statistic:                     173.3
Date:                Tue, 03 Aug 2021   Prob (F-statistic):          1.13e-185
Time:                        21:41:43   Log-Likelihood:                 507.29
No. Observations:                 510   AIC:                            -982.6
Df Residuals:                     494   BIC:                            -914.8
Df Model:                          15
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const              0.1926      0.030      6.447      0.000       0.134       0.251
yr                 0.2272      0.008     27.760      0.000       0.211       0.243
workingday         0.0421      0.011      3.795      0.000       0.020       0.064
temp               0.4386      0.135      3.260      0.001       0.174       0.703
atemp              0.0601      0.138      0.436      0.663      -0.211       0.331
hum               -0.1796      0.037     -4.792      0.000      -0.253      -0.106
windspeed         -0.1832      0.028     -6.508      0.000      -0.238      -0.128
W2_Summer          0.1280      0.015      8.393      0.000       0.098       0.158
W3_Fall            0.0796      0.021      3.770      0.000       0.038       0.121
W4_Winter          0.1871      0.016     12.059      0.000       0.157       0.218
Mar                0.0471      0.016      2.948      0.003       0.016       0.079
Nov               -0.0392      0.018     -2.191      0.029      -0.074      -0.004
Sep                0.0883      0.016      5.551      0.000       0.057       0.120
Light_rainsnow    -0.2641      0.028     -9.289      0.000      -0.320      -0.208
Misty             -0.0468      0.011     -4.379      0.000      -0.068      -0.026
Saturday           0.0568      0.014      3.941      0.000       0.028       0.085
==============================================================================
Omnibus:                       78.666   Durbin-Watson:                   2.033
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              170.766
Skew:                          -0.835   Prob(JB):                     8.29e-38
Kurtosis:                       5.291   Cond. No.                         85.8
==============================================================================
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
```

In [ ]:

```
'''5.3.3 Model 3
Insight: As hum has the highest VIF value, we will remove
the variable next
'''
```

In [95]:

```
X_train_new = X_train_new.drop(['hum'], axis = 1)
# Run the function to calculate VIF for the new model
calculateVIF(X_train_new)
```

Out[95]:

	Features	VIF
2	temp	16.95
5	W3_Fall	6.86
3	windspeed	4.31
1	workingday	4.14
4	W2_Summer	3.49
6	W4_Winter	3.49
0	yr	2.02
8	Nov	1.70
12	Saturday	1.66
11	Misty	1.55
9	Sep	1.27
7	Mar	1.20
10	Light_rainsnow	1.07

In [96]:

```
# Add a constant
X_train_lm3 = sm.add_constant(X_train_new)

# Create a first fitted model
lr3 = sm.OLS(y_train, X_train_lm3).fit()

# Print a summary of the linear regression model obtained
print(lr3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.833
Model:                            OLS   Adj. R-squared:                  0.828
Method:                 Least Squares   F-statistic:                     190.1
Date:                Tue, 03 Aug 2021   Prob (F-statistic):          4.33e-183
Time:                        21:42:01   Log-Likelihood:                 495.68
No. Observations:                 510   AIC:                            -963.4
Df Residuals:                     496   BIC:                            -904.1
Df Model:                          13
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const              0.0881      0.020      4.303      0.000       0.048       0.128
yr                 0.2316      0.008     27.891      0.000       0.215       0.248
workingday         0.0437      0.011      3.860      0.000       0.021       0.066
```

```
temp                0.4631      0.034     13.718      0.000       0.397       0.529
windspeed          -0.1472      0.027     -5.449      0.000      -0.200      -0.094
W2_Summer           0.1297      0.016      8.329      0.000       0.099       0.160
W3_Fall             0.0877      0.021      4.108      0.000       0.046       0.130
W4_Winter           0.1825      0.016     11.556      0.000       0.151       0.214
Mar                 0.0554      0.016      3.415      0.001       0.024       0.087
Nov                -0.0367      0.018     -2.007      0.045      -0.073      -0.001
Sep                 0.0801      0.016      4.959      0.000       0.048       0.112
Light_rainsnow     -0.3176      0.027    -11.898      0.000      -0.370      -0.265
Misty              -0.0767      0.009     -8.644      0.000      -0.094      -0.059
Saturday            0.0575      0.015      3.914      0.000       0.029       0.086
==============================================================================
Omnibus:                       73.931   Durbin-Watson:                   2.006
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              156.694
Skew:                          -0.797   Prob(JB):                     9.43e-35
Kurtosis:                       5.198   Cond. No.                         16.5
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
```

In [ ]:

```
'''5.3.4 Model 4
Insight: Next we will remove W3_Fall as it has high VIF
'''
```

In [97]:

```
X_train_new = X_train_new.drop(['W3_Fall'], axis = 1)
# Run the function to calculate VIF for the new model
calculateVIF(X_train_new)
```

Out[97]:

	Features	VIF
2	temp	4.85
3	windspeed	4.17
1	workingday	4.10
0	yr	2.01
5	W4_Winter	1.99
11	Saturday	1.66
7	Nov	1.63
4	W2_Summer	1.56
10	Misty	1.55
8	Sep	1.21
6	Mar	1.15
9	Light_rainsnow	1.07

In [98]:

```
# Add a constant
X_train_lm4 = sm.add_constant(X_train_new)

# Create a first fitted model
lr4 = sm.OLS(y_train, X_train_lm4).fit()

# Print a summary of the linear regression model obtained
print(lr4.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.827
```

```
Model:                            OLS   Adj. R-squared:                  0.823
Method:                 Least Squares   F-statistic:                     198.2
Date:                Tue, 03 Aug 2021   Prob (F-statistic):         1.16e-180
Time:                        21:43:01   Log-Likelihood:                 487.14
No. Observations:                 510   AIC:                            -948.3
Df Residuals:                     497   BIC:                            -893.2
Df Model:                          12
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const              0.0733      0.020      3.580      0.000       0.033       0.113
yr                 0.2298      0.008     27.281      0.000       0.213       0.246
workingday         0.0434      0.012      3.768      0.000       0.021       0.066
temp               0.5743      0.020     28.046      0.000       0.534       0.615
windspeed         -0.1527      0.027     -5.572      0.000      -0.207      -0.099
W2_Summer          0.0820      0.011      7.776      0.000       0.061       0.103
W4_Winter          0.1427      0.013     11.266      0.000       0.118       0.168
Mar                0.0447      0.016      2.750      0.006       0.013       0.077
Nov               -0.0210      0.018     -1.156      0.248      -0.057       0.015
Sep                0.0947      0.016      5.917      0.000       0.063       0.126
Light_rainsnow    -0.3115      0.027    -11.504      0.000      -0.365      -0.258
Misty             -0.0768      0.009     -8.515      0.000      -0.094      -0.059
Saturday           0.0588      0.015      3.936      0.000       0.029       0.088
==============================================================================
Omnibus:                       61.495   Durbin-Watson:                   2.038
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              113.734
Skew:                          -0.722   Prob(JB):                     2.01e-25
Kurtosis:                       4.807   Cond. No.                         12.5
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
```

In [ ]:

```python
#5.3.5 Model 5

#Insight: Next we will remove Nov due to high p-value
```

In [99]:

```python
X_train_new = X_train_new.drop(['Nov'], axis = 1)
# Run the function to calculate VIF for the new model
calculateVIF(X_train_new)
```

Out[99]:

	Features	VIF
2	temp	4.80
3	windspeed	4.12
1	workingday	4.10
0	yr	2.01
10	Saturday	1.66
4	W2_Summer	1.56
9	Misty	1.53
5	W4_Winter	1.41
7	Sep	1.20
6	Mar	1.15
8	Light_rainsnow	1.07

In [100…

```python
# Add a constant
```

```
X_train_lm5 = sm.add_constant(X_train_new)

# Create a first fitted model
lr5 = sm.OLS(y_train, X_train_lm5).fit()

# Print a summary of the linear regression model obtained
print(lr5.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.827
Model:                            OLS   Adj. R-squared:                  0.823
Method:                 Least Squares   F-statistic:                     216.0
Date:                Tue, 03 Aug 2021   Prob (F-statistic):          1.51e-181
Time:                        21:44:20   Log-Likelihood:                 486.46
No. Observations:                 510   AIC:                            -948.9
Df Residuals:                     498   BIC:                            -898.1
Df Model:                          11
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const              0.0726      0.020      3.547      0.000       0.032       0.113
yr                 0.2296      0.008     27.253      0.000       0.213       0.246
workingday         0.0431      0.012      3.746      0.000       0.021       0.066
temp               0.5766      0.020     28.280      0.000       0.537       0.617
windspeed         -0.1551      0.027     -5.674      0.000      -0.209      -0.101
W2_Summer          0.0821      0.011      7.780      0.000       0.061       0.103
W4_Winter          0.1353      0.011     12.356      0.000       0.114       0.157
Mar                0.0454      0.016      2.789      0.005       0.013       0.077
Sep                0.0965      0.016      6.060      0.000       0.065       0.128
Light_rainsnow    -0.3114      0.027    -11.496      0.000      -0.365      -0.258
Misty             -0.0758      0.009     -8.440      0.000      -0.093      -0.058
Saturday           0.0584      0.015      3.912      0.000       0.029       0.088
==============================================================================
Omnibus:                       61.344   Durbin-Watson:                   2.030
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              113.251
Skew:                          -0.721   Prob(JB):                     2.56e-25
Kurtosis:                       4.802   Cond. No.                         12.4
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
```

In [ ]:

```
#5.3.6 Model 6
#Insight: Next we will remove Mar due to high p-value
```

In [101…

```
X_train_new = X_train_new.drop(['Mar'], axis = 1)
# Run the function to calculate VIF for the new model
calculateVIF(X_train_new)
```

Out[101…

	Features	VIF
2	temp	4.71
1	workingday	4.03
3	windspeed	4.03
0	yr	2.00
9	Saturday	1.65
4	W2_Summer	1.55
8	Misty	1.53
5	W4_Winter	1.38

	Features	VIF
6	Sep	1.20
7	Light_rainsnow	1.07

In [102…

```
# Add a constant
X_train_lm6 = sm.add_constant(X_train_new)

# Create a first fitted model
lr6 = sm.OLS(y_train, X_train_lm6).fit()

# Print a summary of the linear regression model obtained
print(lr6.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.824
Model:                            OLS   Adj. R-squared:                  0.820
Method:                 Least Squares   F-statistic:                     233.6
Date:                Tue, 03 Aug 2021   Prob (F-statistic):          4.48e-181
Time:                        21:45:32   Log-Likelihood:                 482.51
No. Observations:                 510   AIC:                            -943.0
Df Residuals:                     499   BIC:                            -896.4
Df Model:                          10
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
const              0.0828      0.020      4.083      0.000       0.043       0.123
yr                 0.2303      0.008     27.157      0.000       0.214       0.247
workingday         0.0440      0.012      3.794      0.000       0.021       0.067
temp               0.5644      0.020     28.148      0.000       0.525       0.604
windspeed         -0.1542      0.028     -5.606      0.000      -0.208      -0.100
W2_Summer          0.0823      0.011      7.750      0.000       0.061       0.103
W4_Winter          0.1292      0.011     11.960      0.000       0.108       0.150
Sep                0.0948      0.016      5.918      0.000       0.063       0.126
Light_rainsnow    -0.3071      0.027    -11.280      0.000      -0.361      -0.254
Misty             -0.0749      0.009     -8.294      0.000      -0.093      -0.057
Saturday           0.0578      0.015      3.848      0.000       0.028       0.087
==============================================================================
Omnibus:                       62.180   Durbin-Watson:                   2.030
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              122.524
Skew:                          -0.707   Prob(JB):                     2.48e-27
Kurtosis:                       4.941   Cond. No.                         12.3
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spe
cified.
```

In [103…

```
# Checking the parameters obtained
lr6.params
```

Out[103…

```
const             0.082768
yr                0.230252
workingday        0.043963
temp              0.564438
windspeed        -0.154241
W2_Summer         0.082300
W4_Winter         0.129186
Sep               0.094832
Light_rainsnow   -0.307082
Misty            -0.074921
Saturday          0.057838
dtype: float64
```

In [ ]:
```
'''Insight: This model looks good, as there seems to be
VERY LOW Multicollinearity between the predictors and the
p-values for all the predictors seems to be significant.
For now, we will consider this as our final model (unless
the Test data metrics are not significantly close to this
number)
'''
```

In [ ]:
```
'''Step 6: Final Model Interpretation

Hypothesis Testing :
Hypothesis Testing States that

H0:B1=B2=...=Bn=0
H1: at least one Bi!=0
'''
```

In [ ]:
```
'''Insight: From the lr6 model summary, it is evident that
all our coefficients are not equal to zero, which means we
REJECT the NULL HYPOTHESIS

'''
```

In [ ]:
```
'''F-Staitsics :
F-Statistics is used for testing the overall significance
of the Model. The higher the F-Statistics, the more
significant the Model is.

F-Statistics : 233.6
Prob (F-statistic): 4.48e-181
Insight: The F-Statistics value of 233 (which is greater
than 1) and the p-value of '~0.0000' states that the
overall model is significant

The equation of best fitted surface based on model lr6:
cnt=0.082768 + (0.230252 x yr) + (0.043963 x workingday) +
(0.564438 x temp) – (0.154241 x windspeed) + (0.082300 x
W2_Summer) + (0.129186 x W4_Winter) + (0.094832 x Sep) +
(0.057838 x Saturday) – (0.074921 x Misty) – (0.307082 x
Light_rainsnow)


'''
```

In [ ]:
```
'''Interpretation of coefficients :
const : The Constant value of ‘0.082768’ indicated that,
in the absence of all other predictor variables (i.e. when
x1,x2...xn =0), The bike rental can still increase by
0.084143 units

yr : A coefficient value of ‘0.230252’ indicated that a
unit increase in yr variable, increases the bike hire
numbers by 0.230252 units

workingday : A coefficient value of ‘0.043963’ indicated
that, a unit increase in workingday variable increases the
bike hire numbers by 0.043963 units

temp : A coefficient value of ‘0.564438’ indicated that a
unit increase in temp variable, increases the bike hire
numbers by 0.564438 units

windspeed : A coefficient value of ‘-0.154241’ indicated
```

```
that, a unit increase in windspeed variable decreases the
bike hire numbers by 0.154241 units

W2_Summer : A coefficient value of ‘0.082300’ indicated
that a unit increase in W2_Summer variable decreases the
bike hire numbers by 0.082300 units

W4_Winter : A coefficient value of ‘0.129186’ indicated
that a unit increase in W4_Winter variable increases the
bike hire numbers by 0.129186 units

Sep : A coefficient value of ‘0.094832’ indicated that a
unit increase in Sep variable increases the bike hire
numbers by 0.094832 units

Light_rainsnow : A coefficient value of ‘-0.307082’
indicated that, a unit increase in Weathersit3 variable,
decreases the bike hire numbers by -0.307082 units

Misty : A coefficient value of ‘-0.074921’ indicated that
a unit increase in Misty weather variable, decreases the
bike hire numbers by 0.074921 units

Saturday : A coefficient value of ‘0.057838’ indicated
that a unit increase in Saturday variable increases the
bike hire numbers by 0.057838 units
'''
```

In [ ]:

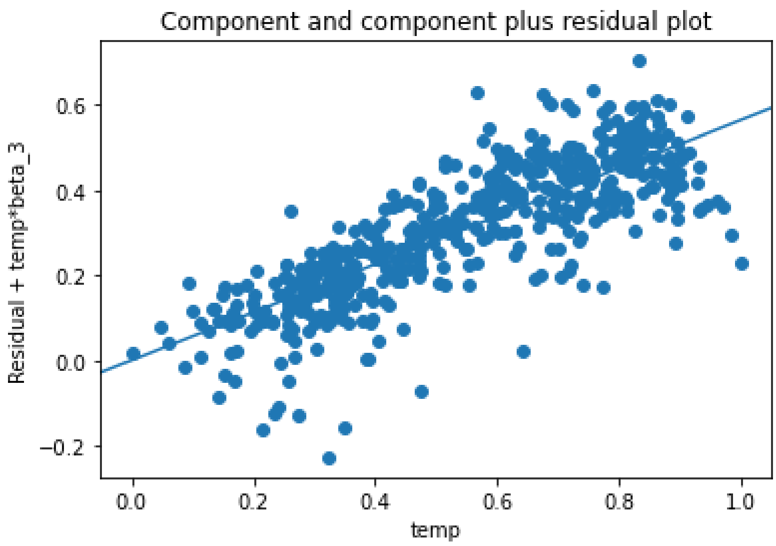
```
'''Step 7: Model Validation
Validating the assumption of Linear Regression Model :

Linear Relationship
Homoscedasticity
Absence of Multicollinearity
Independence of residuals
Normality of Errors
'''
```

In [104…

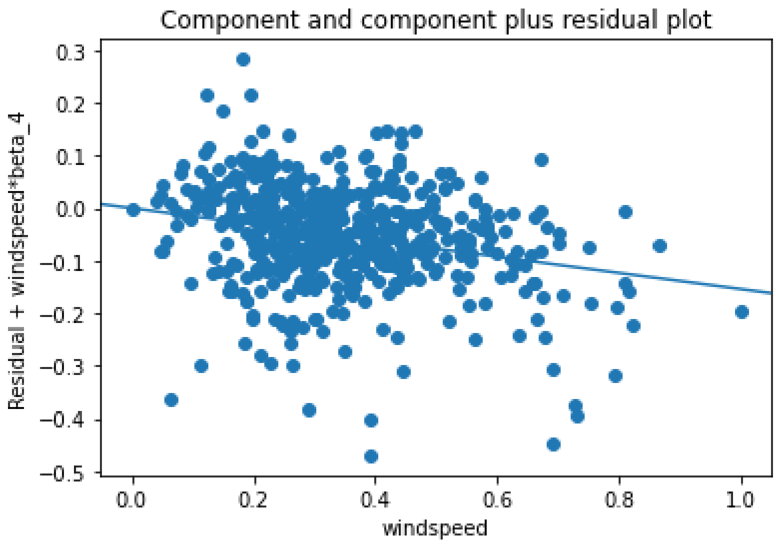
```
#7.1 Linear Relationship

sm.graphics.plot_ccpr(lr6, 'temp')
plt.show()
```



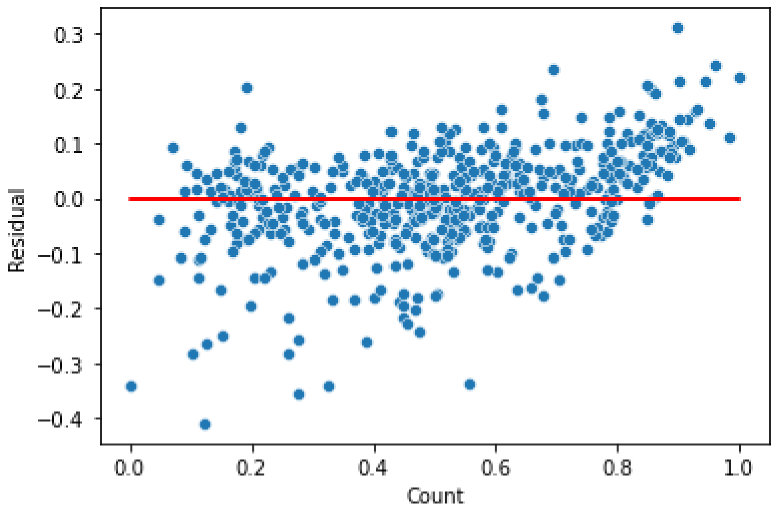
In [105…

```
sm.graphics.plot_ccpr(lr6, 'windspeed')
plt.show()
```



In [ ]:
```
'''Insight: The above plots represents the relationship
between the model and the predictor variables. As we can
see, linearity is well preserved
'''
```

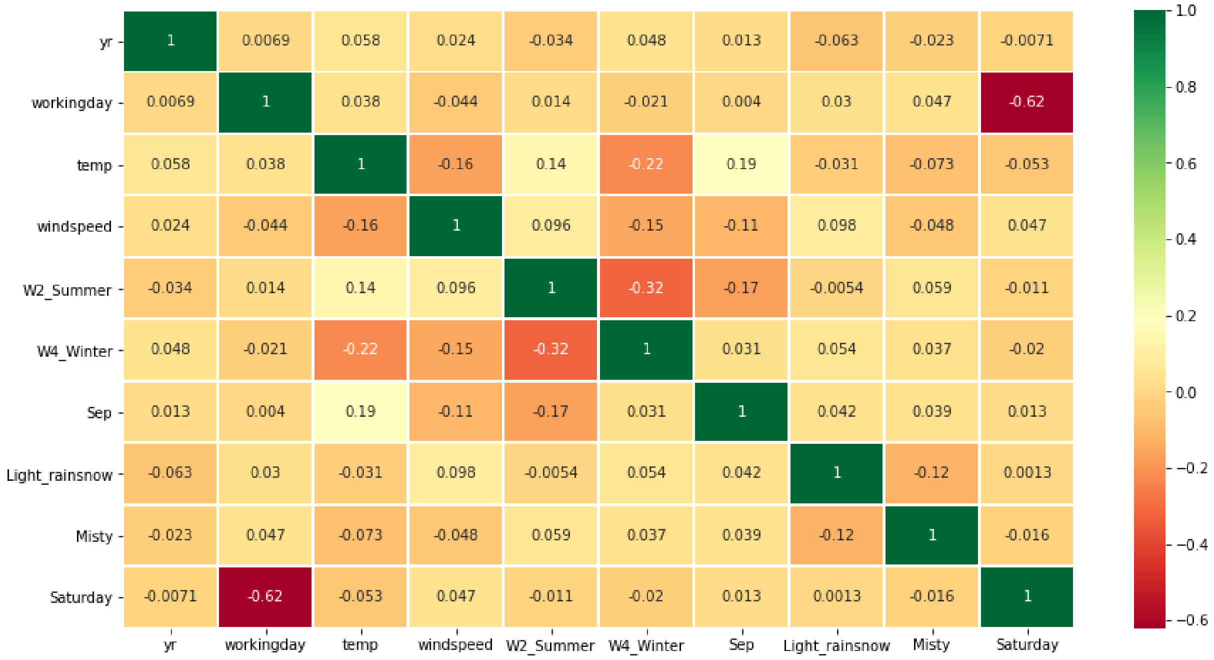
In [106…
```
#7.2 Homoscedasticity
y_train_pred = lr6.predict(X_train_lm6)
residual = y_train - y_train_pred
sns.scatterplot(y_train,residual)
plt.plot(y_train,(y_train - y_train), '-r')
plt.xlabel('Count')
plt.ylabel('Residual')
plt.show()
```



In [ ]:
```
'''Insight: There is no visible pattern in residual values,
thus homoscedacity is well preserved
'''
```

In [107…
```
#7.3 Absence of Multicolinearity
# Validating Multi Colinearity

plt.figure(figsize=(15,8))
sns.heatmap(X_train_new.corr(),annot = True, cmap="RdYlGn",linewidth =1)
plt.show()
```



In [108…:
```
# Run the function to calculate VIF for the final model
calculateVIF(X_train_new)
```

Out[108…:

	Features	VIF
2	temp	4.71
1	workingday	4.03
3	windspeed	4.03
0	yr	2.00
9	Saturday	1.65
4	W2_Summer	1.55
8	Misty	1.53
5	W4_Winter	1.38
6	Sep	1.20
7	Light_rainsnow	1.07

In [ ]:
```
'''Insight: All the predictor variables have VIF value less
than 5. So we can consider that there is insignificant
multicolinearity among the predictor variables.
'''
```

In [ ]:
```
'''7.4 Independence of residuals
Autocorrelation refers to the fact that observations’
errors are correlated. To verify that the observations are
not auto-correlated, we can use the Durbin-Watson test.
The test will output values between 0 and 4. The closer it
is to 2, the less auto-correlation there is between the
various variables.

0 – 2: positive auto-correlation
2 – 4: negative auto-correlation)
'''
```

In [109…:
```
print('The Durbin-Watson value for Final Model lr 6 is',round(sm.stats.stattools.dur
```

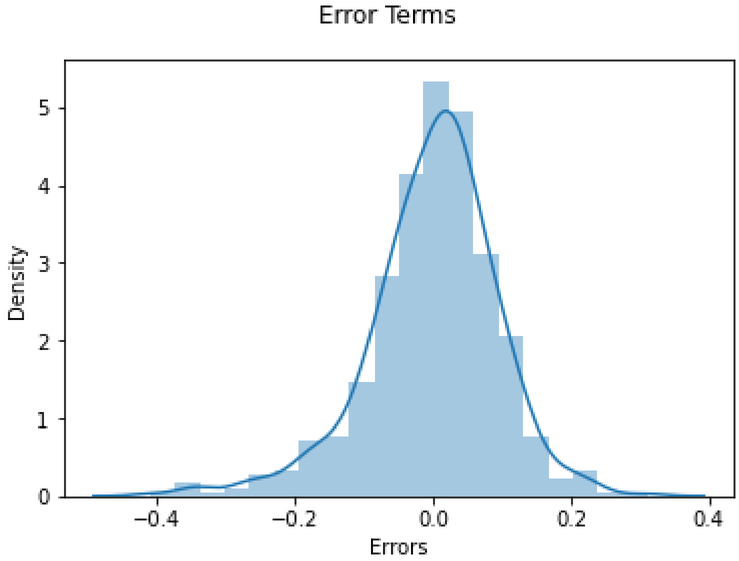
```
The Durbin-Watson value for Final Model lr 6 is 2.0296
```

In [ ]:
```
'Insight: There is almost no autocorrelation.'
```

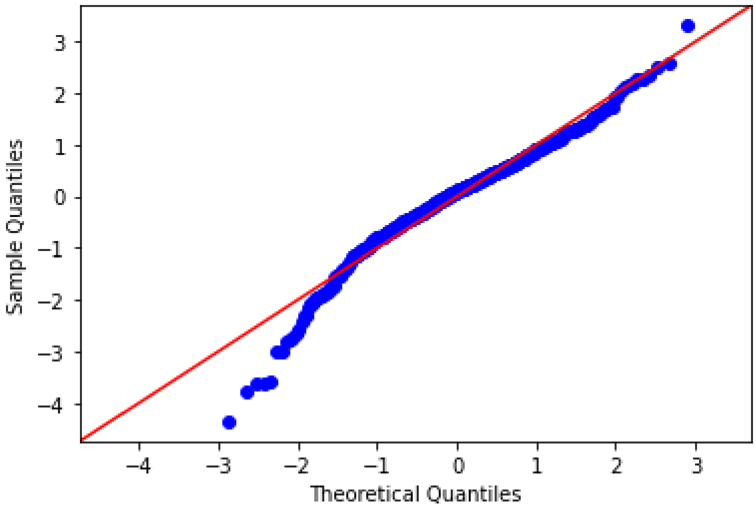
In [110…
```
#7.5 Normality of error

res = y_train-y_train_pred

# Plot the histogram of the error terms
fig = plt.figure()
sns.distplot((res), bins = 20)
fig.suptitle('Error Terms')
plt.xlabel('Errors')
plt.show()
```



In [111…
```
sm.qqplot((y_train - y_train_pred), fit=True, line='45')
plt.show()
```



In [ ]:
```
'''Insight: Based on the histogram, we can conclude that
error terms are following a normal distribution
'''
```

In [ ]:
```
'''Step 8: Making Predictions using final model
8.1 Scaling bike_test dataframe
Apply scaler() to all numeric variables in test dataset.
Note: we will only use scaler.transform, as we want to use
the metrics that the model learned from the training data
to be applied on the test data.In other words, we want to
```

```
prevent the information leak from train to test dataset.
'''
```

In [112…

```
num_vars = ['temp', 'atemp', 'hum', 'windspeed','cnt']
bike_test[num_vars] = scaler.transform(bike_test[num_vars])
bike_test.head()
```

Out[112…

	yr	holiday	workingday	temp	atemp	hum	windspeed	cnt	W2_Summer	W3
22	0	0	0	0.046591	0.025950	0.453529	0.462217	0.110907	0	
468	1	0	0	0.543115	0.536771	0.522511	0.347424	0.855729	1	
553	1	0	0	0.951196	0.933712	0.596104	0.212829	0.534975	0	
504	1	0	0	0.699909	0.662746	0.551083	0.478229	0.817648	1	
353	0	0	1	0.407087	0.416610	0.618615	0.080770	0.428900	0	

5 rows × 30 columns

In [113…

```
bike_test.describe()
```

Out[113…

	yr	holiday	workingday	temp	atemp	hum	windspeed	
count	220.000000	220.000000	220.000000	220.000000	220.000000	220.000000	220.000000	220.000
mean	0.495455	0.040909	0.681818	0.550981	0.527344	0.662328	0.346015	0.519
std	0.501120	0.198531	0.466833	0.228967	0.214959	0.143278	0.159517	0.219
min	0.000000	0.000000	0.000000	0.046591	0.025950	0.301299	0.073090	0.055
25%	0.000000	0.000000	0.000000	0.357562	0.352129	0.553355	0.232051	0.364
50%	0.000000	0.000000	1.000000	0.557133	0.546299	0.661688	0.327568	0.525
75%	1.000000	0.000000	1.000000	0.750530	0.707506	0.761905	0.435172	0.683
max	1.000000	1.000000	1.000000	0.984424	0.980934	1.010390	0.824380	0.963

8 rows × 30 columns

In [114…

```
#8.2 Dividing X_test and y_test

y_test = bike_test.pop('cnt')
X_test = bike_test
#Selecting the variables that were part of final model.
col1=X_train_new.columns

X_test=X_test[col1]

# Adding constant variable to test dataframe
X_test_lm6 = sm.add_constant(X_test)

X_test_lm6.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 220 entries, 22 to 483
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   const           220 non-null    float64
```

```
 1   yr              220 non-null    int64
 2   workingday      220 non-null    int64
 3   temp            220 non-null    float64
 4   windspeed       220 non-null    float64
 5   W2_Summer       220 non-null    uint8
 6   W4_Winter       220 non-null    uint8
 7   Sep             220 non-null    uint8
 8   Light_rainsnow  220 non-null    uint8
 9   Misty           220 non-null    uint8
 10  Saturday        220 non-null    uint8
dtypes: float64(3), int64(2), uint8(6)
memory usage: 11.6 KB
```

In [115…

```
# Making predictions using the final model (lr6)

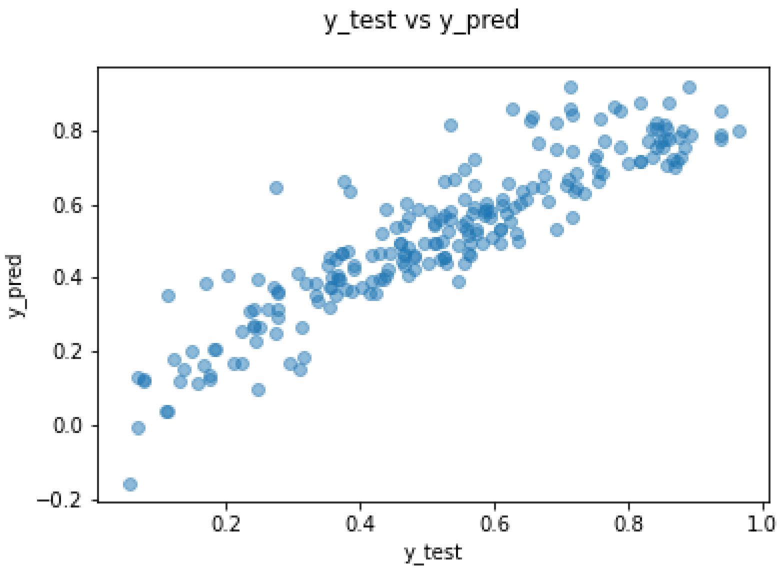
y_pred = lr6.predict(X_test_lm6)
```

In [116…

```
#Step 9: Model Evaluation
# plotting y_test and y_pred to understand the spread
fig = plt.figure()
plt.scatter(y_test, y_pred,alpha = 0.5)
fig.suptitle('y_test vs y_pred')
plt.xlabel('y_test')
plt.ylabel('y_pred')
```

Out[116…

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



In [117…

```
#R2 Value Calculation for bike_test dataframe

r2 = round(r2_score(y_test, y_pred),4)
r2
```

Out[117…

```
0.8206
```

In [118…

```
#Adjusted R2 Value Calculation for bike_test dataframe

# n is number of rows in test dataset
n = X_test.shape[0]

# Number of features (predictors, p) is the shape along axis 1
p = X_test.shape[1]

# We find the Adjusted R-squared using the formula
adjusted_r2 = round(1-(1-r2)*(n-1)/(n-p-1),4)
adjusted_r2
```

Out[118… 0.812

In [119…
```
#Calculating RMSE for the selected Model

RMSE = round(sqrt(mean_squared_error(y_test, y_pred)),4)
RMSE
```

Out[119… 0.0929

In [120…
```
#Calculating Mean Absolute Error for the selected Model

MAE = round(mean_absolute_error(y_test, y_pred),4)
MAE
```

Out[120… 0.0714

In [ ]:
```
'''Insight: The Root Mean Squared Error value for the test
dataset based on final model is 0.093 and Mean Absolute
Error is 0.0714, which indicates that the model is really
good.
'''
```

In [ ]:
```
#Model Outcome Summary

'''As per the final model, the top 5 predictor variables
that influences bike booking are:

Temperature (Temp)
A coefficient value of ‘0.564438’ indicated that a
temperature has significant impact on bike rentals

Light Rain & Snow (weathersit =3)
A coefficient value of ‘-0.307082’ indicated that the
light snow and rain deters people from renting out bikes

Year (yr)
A coefficient value of ‘0.230252’ indicated that a year
wise the rental numbers are increasing

It is recommended to give utmost importance to these three
variables while planning to achieve maximum bike rental
booking.

As high temperature and good weather positively impacts
bike rentals, it is recommended that bike availability and
promotions to be increased during summer months to further
increase bike rentals.

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