Bike Sharing with Multiple Linear Regression

Business Goal:

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

So interpretation is important!

The Steps we will follow in this assignment as follow:

1. Reading, understanding and visualising the data
2. Preparing the data for modelling(train-test split,rescaling etc)
3. Training the model
4. Residual analysis
5. Predictions and evaluation

Step 1: Reading, understanding the data

Let us first import Numpy and pandas and read the housing dataset

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import sklearn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import r2_score,mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import RFE

import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor

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

In [2]:
```
# Reading the data
bikedata  = pd.read_csv("day.csv")
bikedata.head()
```

Out[2]:

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	a
0	1	01-01-2018	1	0	1	0	6	0	2	14.110847	18.
1	2	02-01-2018	1	0	1	0	0	0	2	14.902598	17.
2	3	03-01-2018	1	0	1	0	1	1	1	8.050924	9.
3	4	04-01-2018	1	0	1	0	2	1	1	8.200000	10.
4	5	05-01-2018	1	0	1	0	3	1	1	9.305237	11.

In [3]:

```
bikedata.shape
```

Out[3]:

```
(730, 16)
```

In [4]:

```
bikedata.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
```

Dataframe consists of 730 rows and 16 columns

In [5]:

```
bikedata.describe()
```

Out[5]:

	instant	season	yr	mnth	holiday	weekday	workingday	weat
count	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.000000	730.0
mean	365.500000	2.498630	0.500000	6.526027	0.028767	2.997260	0.683562	1.3
std	210.877136	1.110184	0.500343	3.450215	0.167266	2.006161	0.465405	0.5
min	1.000000	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000	1.0
25%	183.250000	2.000000	0.000000	4.000000	0.000000	1.000000	0.000000	1.0
50%	365.500000	3.000000	0.500000	7.000000	0.000000	3.000000	1.000000	1.0
75%	547.750000	3.000000	1.000000	10.000000	0.000000	5.000000	1.000000	2.0
max	730.000000	4.000000	1.000000	12.000000	1.000000	6.000000	1.000000	3.0

Data Cleaning

Drop columns that are not useful for data analysis

- `instant` :as it is the record index
- `dteday` : as the features of date are alreeady there like yr as year, mnth as month and weekday
- `casual` and `registered` : as the are in cnt, because cnt is sum of both the values

In [6]:
```
# Dropping instant column as it is merely a index column which has no significance
bikedata.drop(['instant'],axis=1,inplace=True)

# dteday is not useful as month,year and weekday are covering it
bikedata.drop(['dteday'],axis=1,inplace=True)

#Removing casual and registered as cnt is sum of these
bikedata.drop(['casual','registered'],axis=1,inplace=True)
#bikedata.drop(['registered'],axis=1,inplace=True)
```

Checking any `null data` in provided dataset

In [7]:
```
bikedata.columns
```

Out[7]:
```
Index(['season', 'yr', 'mnth', 'holiday', 'weekday', 'workingday',
       'weathersit', 'temp', 'atemp', 'hum', 'windspeed', 'cnt'],
      dtype='object')
```

In [8]:
```
bikedata.isnull().sum()
```

Out[8]:
```
season        0
yr            0
mnth          0
holiday       0
weekday       0
workingday    0
weathersit    0
temp          0
atemp         0
hum           0
windspeed     0
cnt           0
dtype: int64
```

data file does not have any null records.

Step 2: Visualising the Data for better understand the data and variables

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]:
```
bikedata.corr()
```

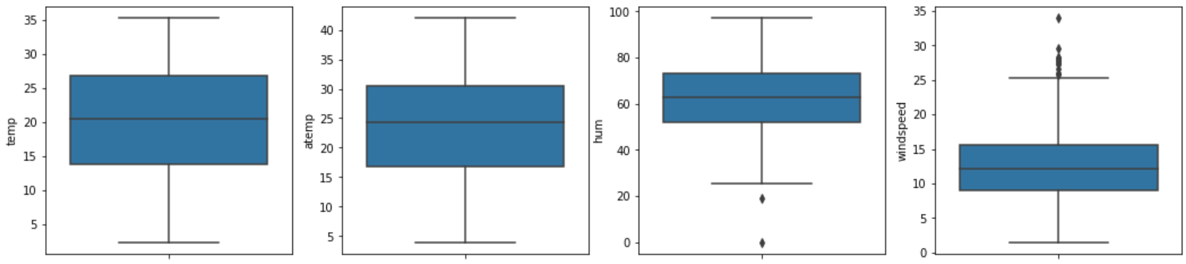
Out[9]:

	season	yr	mnth	holiday	weekday	workingday	weath
season	1.000000e+00	-3.279074e-16	8.310321e-01	-0.010868	-0.003081	0.013762	0.02
yr	-3.279074e-16	1.000000e+00	-5.162656e-16	0.008195	-0.005466	-0.002945	-0.05
mnth	8.310321e-01	-5.162656e-16	1.000000e+00	0.018905	0.009523	-0.004688	0.04
holiday	-1.086804e-02	8.195345e-03	1.890483e-02	1.000000	-0.101962	-0.252948	-0.03
weekday	-3.081198e-03	-5.466369e-03	9.522969e-03	-0.101962	1.000000	0.035800	0.03
workingday	1.376178e-02	-2.945396e-03	-4.687953e-03	-0.252948	0.035800	1.000000	0.06
weathersit	2.130636e-02	-5.032247e-02	4.561335e-02	-0.034395	0.031112	0.060236	1.00
temp	3.333607e-01	4.878919e-02	2.190833e-01	-0.028764	-0.000168	0.053470	-0.11
atemp	3.420139e-01	4.721519e-02	2.264302e-01	-0.032703	-0.007539	0.052940	-0.12
hum	2.082196e-01	-1.125471e-01	2.249368e-01	-0.015662	-0.052290	0.023202	0.59
windspeed	-2.296069e-01	-1.162435e-02	-2.080131e-01	0.006257	0.014283	-0.018666	0.03
cnt	4.045838e-01	5.697285e-01	2.781909e-01	-0.068764	0.067534	0.062542	-0.29

Visualising data to find correlation from numerical variables

Let's make pair-plot charts among the numerical variables

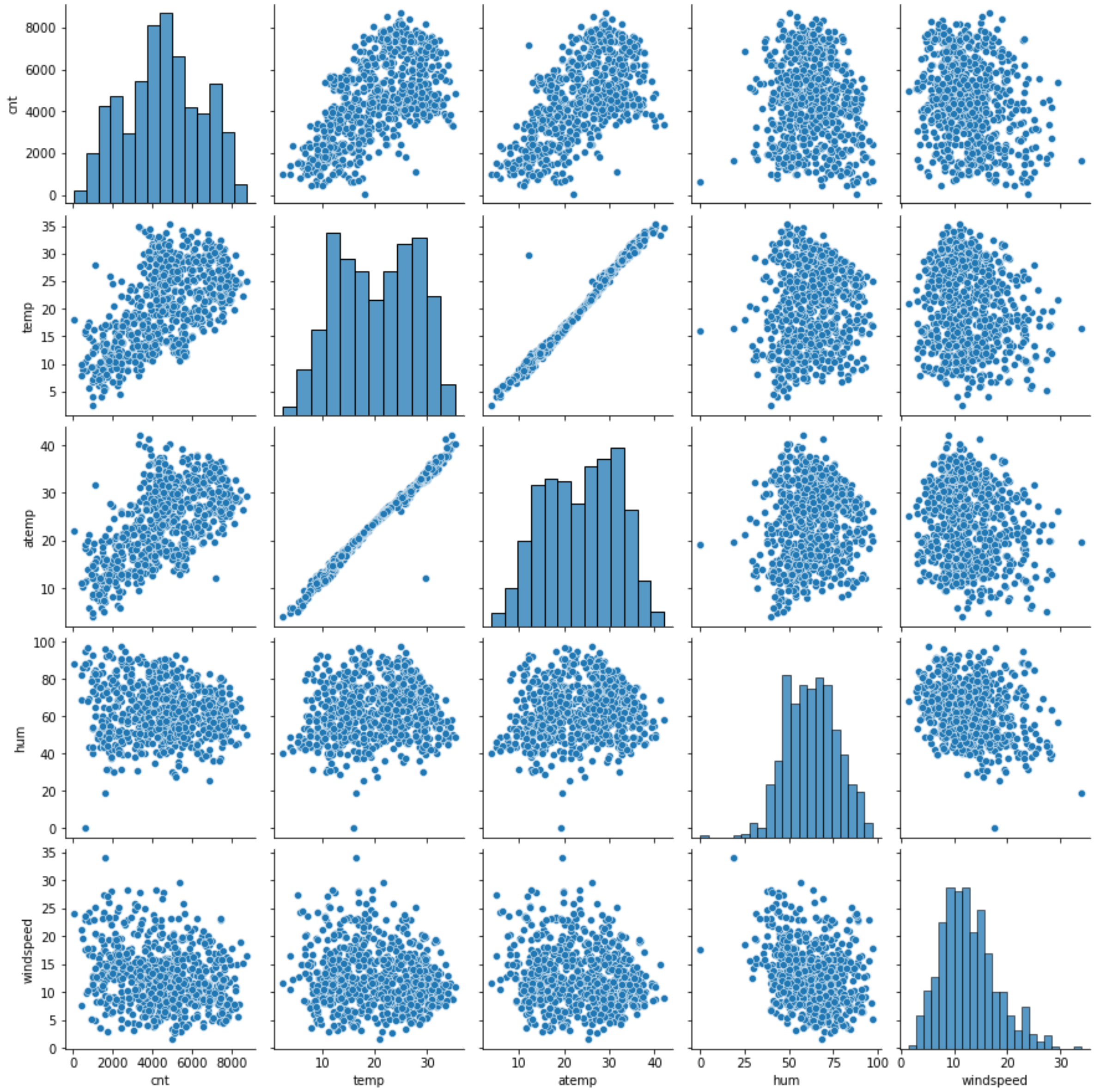
In [10]:
```
#Visualizing the numerical variables
cols = ['temp', 'atemp', 'hum', 'windspeed']
plt.figure(figsize=(18,4))

i = 1
for col in cols:
    plt.subplot(1,4,i)
    sns.boxplot(y=col, data=bikedata)
    i+=1
```



Checking `Correlation` with help of pairplots

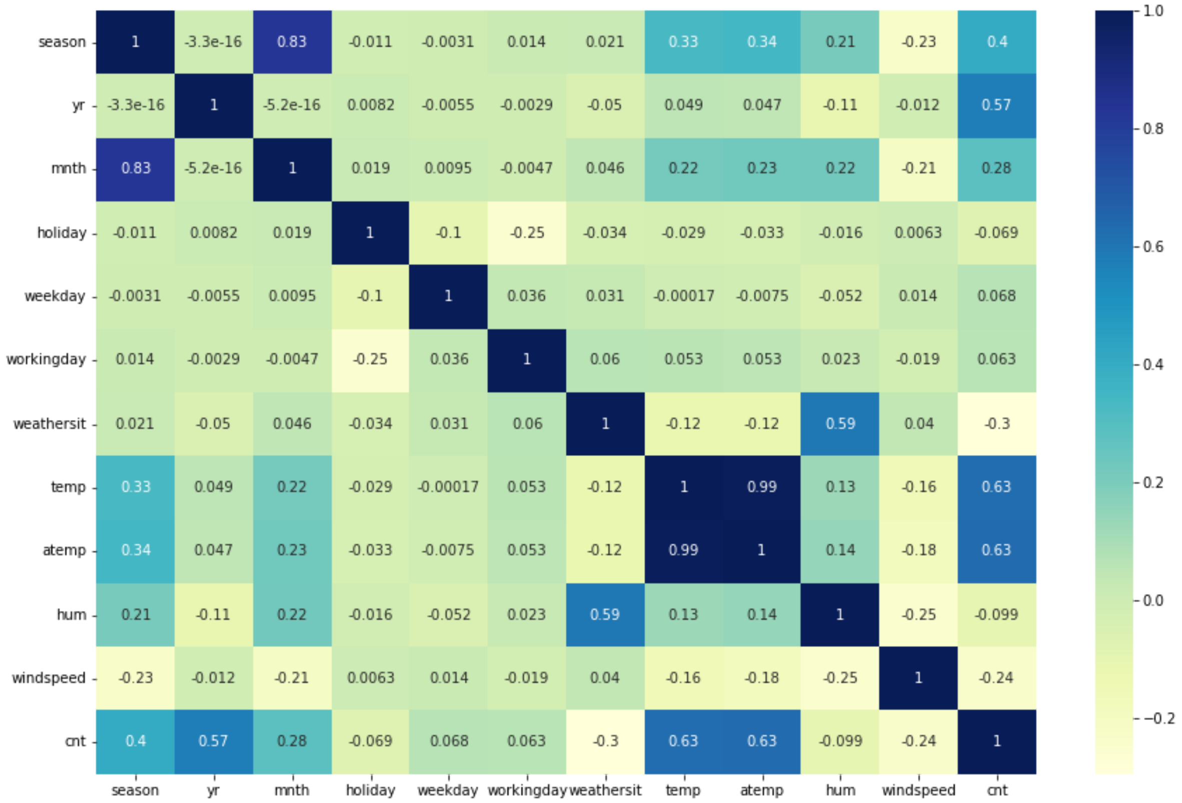
In [11]:
```
plt.figure(figsize = (15,30))
sns.pairplot(data=bikedata,vars=['cnt', 'temp', 'atemp', 'hum','windspeed'])
plt.show()
```

```
<Figure size 1080x2160 with 0 Axes>
```

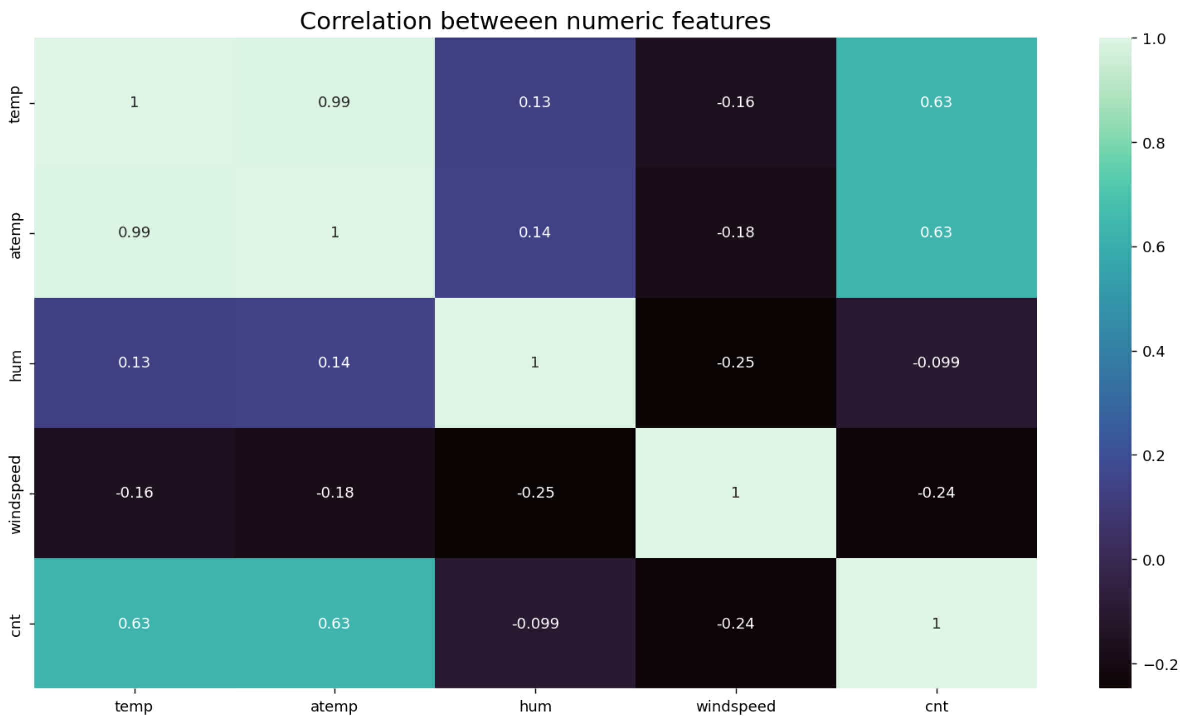


In [12]:
```
### Checking the `Correlation` for Numerical variables with help of Heatmaps
```

In [13]:
```
plt.figure(figsize=(15,10))
sns.heatmap(bikedata.corr(),cmap="YlGnBu",annot=True)
plt.show()
```



In [14]:
```
num_features = ["temp","atemp","hum","windspeed","cnt"]
plt.figure(figsize=(15,8),dpi=130)
plt.title("Correlation betweeen numeric features",fontsize=16)
sns.heatmap(bikedata[num_features].corr(),annot= True,cmap="mako")
plt.show()
```

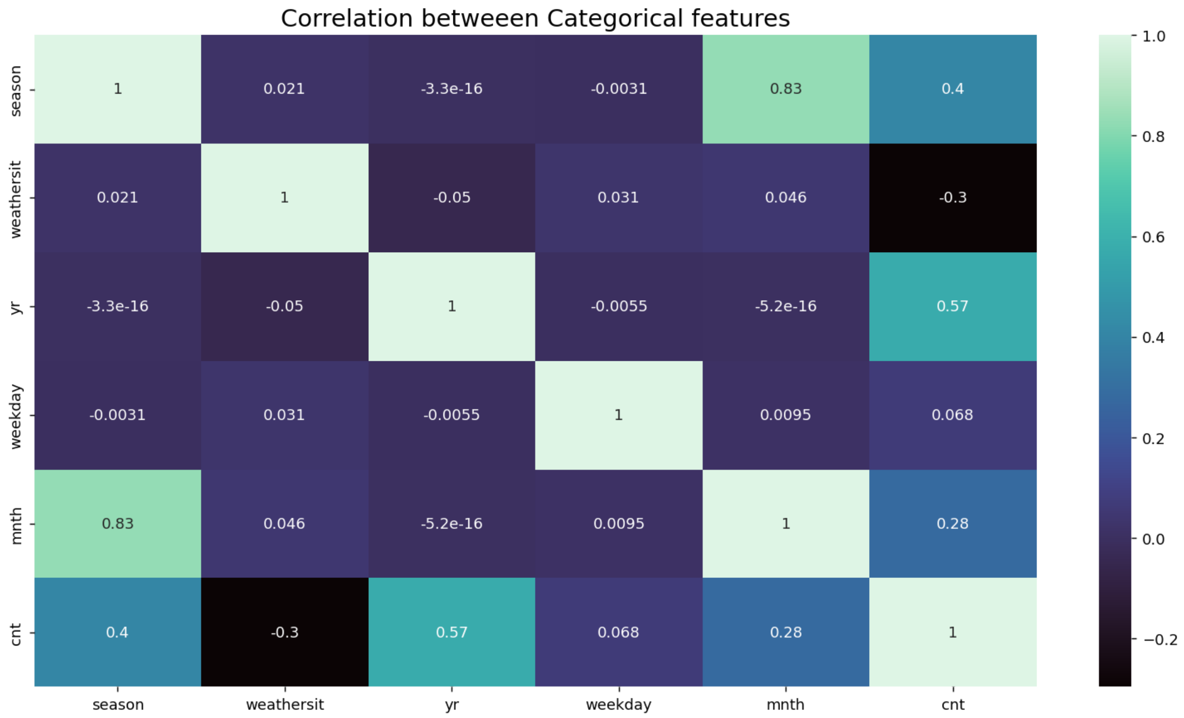


Visualising Categorical Variables

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

In [15]:
```
cat_features = ["season","weathersit","yr","weekday","mnth","cnt"]
plt.figure(figsize=(15,8),dpi=130)
```

```
plt.title("Correlation betweeen Categorical features",fontsize=16)
sns.heatmap(bikedata[cat_features].corr(),annot= True,cmap="mako")
plt.show()
```



In [16]:

```
bikedata.season.replace({1:"Spring", 2:"Summer", 3:"Fall", 4:"Winter"},inplace = T
bikedata.weathersit.replace({1:'Good',2:'Moderate',3:'Bad',4:'Severe'},inplace = T
bikedata.yr.replace({0:'2018',1:'2019'},inplace = True)
bikedata.weekday.replace({0: 'Tue',1: 'Wed',2: 'Thu',3: 'Fri',4: 'Sat',5: 'Sun',6:
bikedata.mnth = bikedata.mnth.replace({1: 'Jan',2: 'Feb',3: 'Mar',4: 'Apr',5: 'May
                    7: 'Jul',8: 'Aug',9: 'Sept',10: 'Oct',11: 'Nov',12: 'Dec'})
bikedata.head()
```

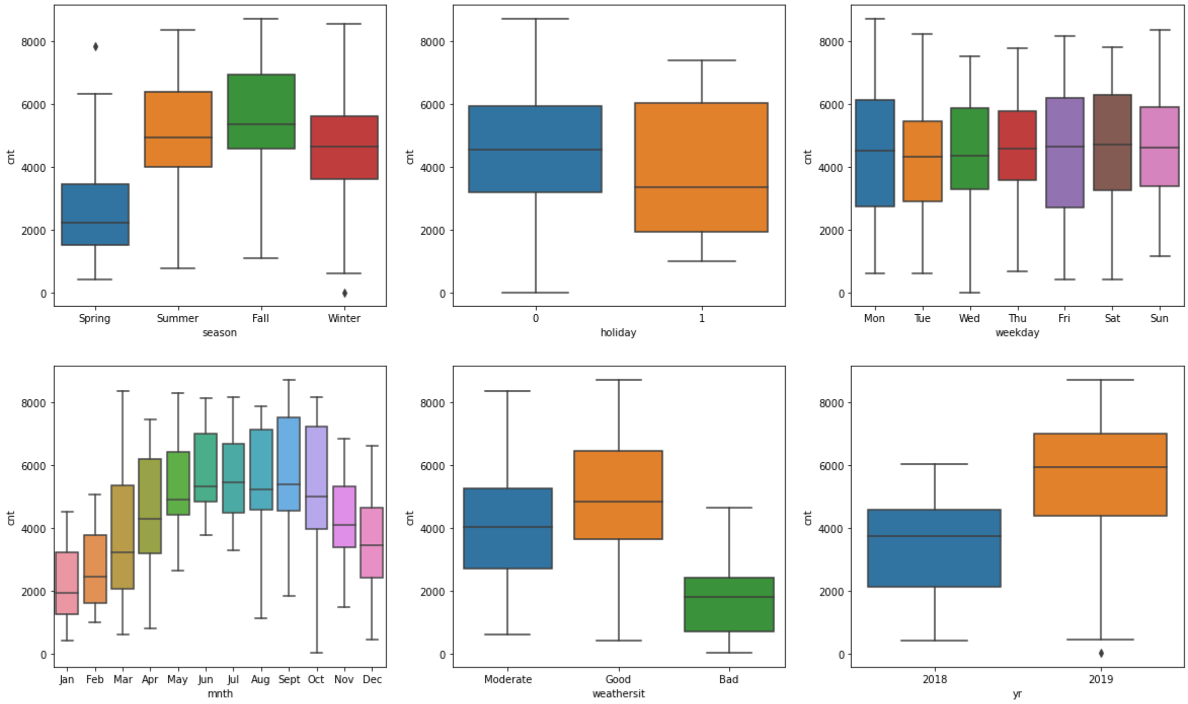
Out[16]:

	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	hum
0	Spring	2018	Jan	0	Mon	0	Moderate	14.110847	18.18125	80.5833
1	Spring	2018	Jan	0	Tue	0	Moderate	14.902598	17.68695	69.6087
2	Spring	2018	Jan	0	Wed	1	Good	8.050924	9.47025	43.7273
3	Spring	2018	Jan	0	Thu	1	Good	8.200000	10.60610	59.0435
4	Spring	2018	Jan	0	Fri	1	Good	9.305237	11.46350	43.6957

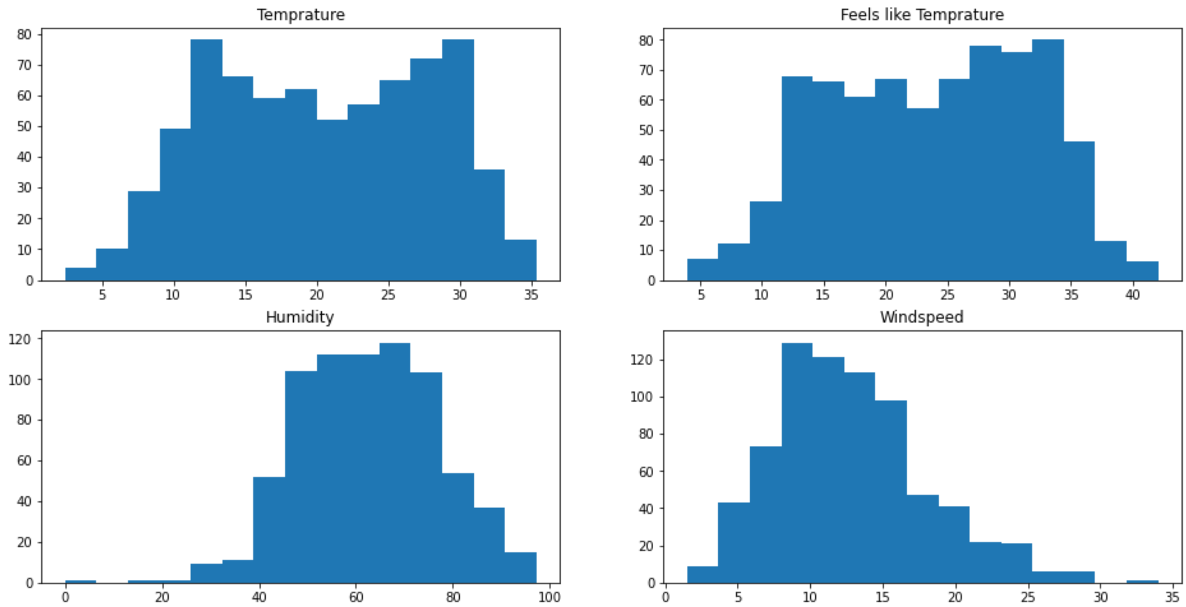
In [17]:

```
# Visualizing the categorical variables
#control the size of figure
plt.figure(figsize=(20,12))
plt.subplot(2,3,1)
sns.boxplot(x='season',y='cnt',data=bikedata)

plt.subplot(2,3,2)
sns.boxplot(x='holiday',y='cnt',data=bikedata)

plt.subplot(2,3,3)
sns.boxplot(x='weekday',y='cnt',data=bikedata)

plt.subplot(2,3,4)
sns.boxplot(x='mnth',y='cnt',data=bikedata)
```

```
plt.subplot(2,3,5)
sns.boxplot(x='weathersit',y='cnt',data=bikedata)

plt.subplot(2,3,6)
sns.boxplot(x='yr',y='cnt',data=bikedata)

plt.show()
```

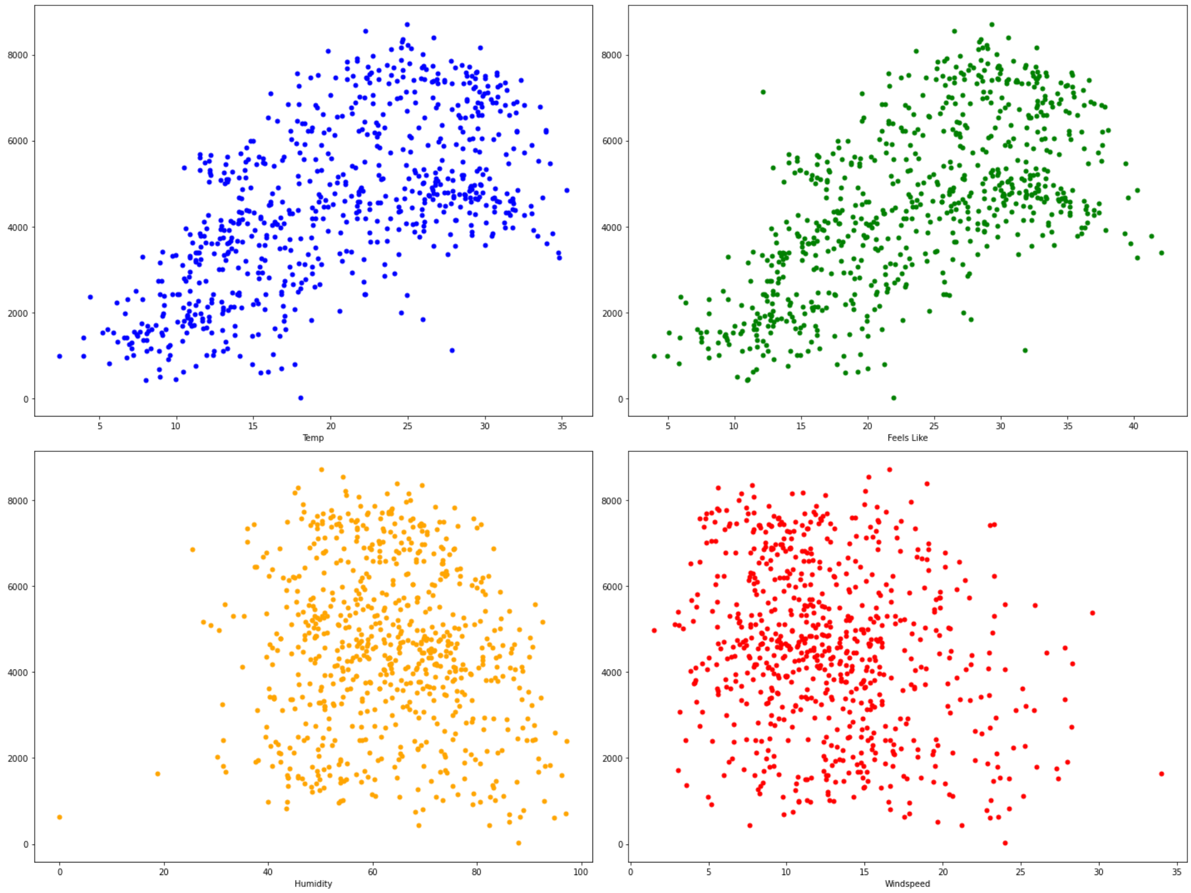


In [18]:
```
# Histogram Data Visualization
fig, axs = plt.subplots(nrows = 2, ncols =2, figsize = (16,8))
axs[0, 0].hist(bikedata["temp"], bins = 15)
axs[0, 0].set_title("Temprature")
axs[0, 1].hist(bikedata ["atemp"],  bins = 15)
axs[0, 1].set_title("Feels like Temprature")
axs[1, 0].hist(bikedata["hum"],  bins = 15)
axs[1, 0].set_title("Humidity")
axs[1, 1].hist(bikedata["windspeed"],  bins = 15)
axs[1, 1].set_title("Windspeed");
```



In [19]:
```
# Scatter visualization
fig = plt.figure(figsize = (20, 15))
```

```
fig.add_subplot(221, xlabel ="Temp").scatter(bikedata["temp"], bikedata["cnt"],c="|
fig.add_subplot(222, xlabel ="Feels Like").scatter(bikedata["atemp"], bikedata["cn
fig.add_subplot(223, xlabel ="Humidity").scatter(bikedata["hum"], bikedata["cnt"],
fig.add_subplot(224, xlabel ="Windspeed").scatter(bikedata["windspeed"], bikedata[
plt.tight_layout();
```



As per above charts observation

- Highest bike demand during Temprature between (10 to 33) degree
- Highest bike demand during Humidity from (40 to 90)%
- Highest bike demand during Windspeed from (0 to 20) knots

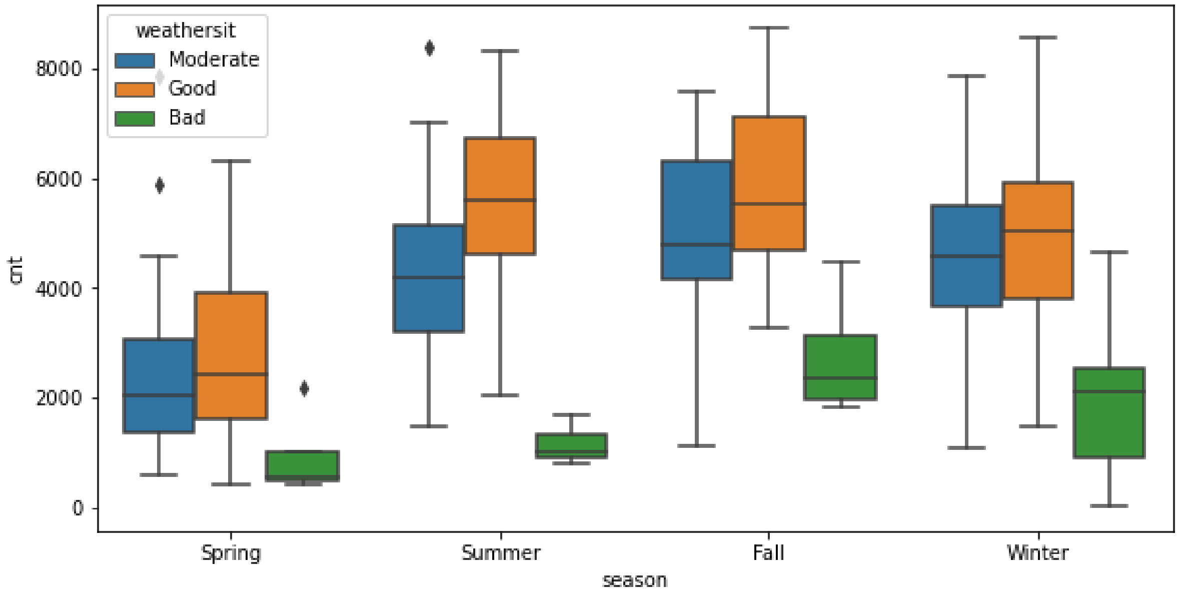
In [20]:
```
bikedata.groupby('weekday').describe()['cnt'].transpose()
```

Out[20]:

weekday	Fri	Mon	Sat	Sun	Thu	Tue	W
count	103.000000	105.000000	104.000000	104.000000	104.000000	105.000000	105.000
mean	4574.893204	4550.542857	4667.259615	4690.288462	4510.663462	4228.828571	4338.123
std	2030.176095	2196.693009	1939.433317	1874.624870	1826.911642	1872.496629	1793.074
min	441.000000	627.000000	431.000000	1167.000000	683.000000	605.000000	22.000
25%	2731.000000	2732.000000	3270.750000	3390.750000	3579.250000	2918.000000	3310.000
50%	4656.000000	4521.000000	4721.000000	4601.500000	4576.500000	4334.000000	4359.000
75%	6182.500000	6140.000000	6286.000000	5900.500000	5769.000000	5464.000000	5875.000
max	8173.000000	8714.000000	7804.000000	8362.000000	7767.000000	8227.000000	7525.000

In [21]:
```
plt.figure(figsize = (10, 5))
sns.boxplot(x = 'season', y = 'cnt', hue = 'weathersit', data = bikedata)
```

```
plt.show()
```



Step 2: Preparing the Data for Modeling

Encoding:

- Checking unique values from each variables
- creating categorical variables convert to dummy variables
- Splitting data into train and test
- Rescaling of variables

In [22]:
```
bikedata.columns
```

Out[22]:
```
Index(['season', 'yr', 'mnth', 'holiday', 'weekday', 'workingday',
       'weathersit', 'temp', 'atemp', 'hum', 'windspeed', 'cnt'],
      dtype='object')
```

In [23]:
```
bikedata.nunique() #gives info about unique values present in data
```

Out[23]:
```
season          4
yr              2
mnth           12
holiday         2
weekday         7
workingday      2
weathersit      3
temp          498
atemp         689
hum           594
windspeed     649
cnt           695
dtype: int64
```

In [ ]:

In [ ]:

Dropping redudndent variables `holiday` with `workingday` and `temp` with `atemp`; Hence, dropping the `holiday` and `atemp`

In [24]:
```
#bikedata.drop(['holiday','atemp','yr'],axis=1,inplace=True) #dropping the redundai
bikedata.drop(['holiday','atemp'],axis=1,inplace=True) #dropping the redundant var
```

In [25]:
```
bikedata.head()
```

Out[25]:

	season	yr	mnth	weekday	workingday	weathersit	temp	hum	windspeed	cnt
0	Spring	2018	Jan	Mon	0	Moderate	14.110847	80.5833	10.749882	985
1	Spring	2018	Jan	Tue	0	Moderate	14.902598	69.6087	16.652113	801
2	Spring	2018	Jan	Wed	1	Good	8.050924	43.7273	16.636703	1349
3	Spring	2018	Jan	Thu	1	Good	8.200000	59.0435	10.739832	1562
4	Spring	2018	Jan	Fri	1	Good	9.305237	43.6957	12.522300	1600

In [26]:
```
bikedata = bikedata.rename(columns={'mnth': 'month','yr':'year'}) # renaming varial
```

In [27]:
```
bikedata.year.replace({'2018':0,'2019':1},inplace = True)
bikedata.head()
```

Out[27]:

	season	year	month	weekday	workingday	weathersit	temp	hum	windspeed	cnt
0	Spring	0	Jan	Mon	0	Moderate	14.110847	80.5833	10.749882	985
1	Spring	0	Jan	Tue	0	Moderate	14.902598	69.6087	16.652113	801
2	Spring	0	Jan	Wed	1	Good	8.050924	43.7273	16.636703	1349
3	Spring	0	Jan	Thu	1	Good	8.200000	59.0435	10.739832	1562
4	Spring	0	Jan	Fri	1	Good	9.305237	43.6957	12.522300	1600

Dummy Variables

The Categorical variable `season`, `month`, `weekday`, `year` and `weathersit` are converted to dummies variables.

In [28]:
```
# creating dummy variables for season
season =  pd.get_dummies(bikedata['season'])
season.head()
```

Out[28]:

	Fall	Spring	Summer	Winter
0	0	1	0	0
1	0	1	0	0
2	0	1	0	0
3	0	1	0	0
4	0	1	0	0

Now, we don't need four columns. You can drop the `Fall` column, as the type of `season` can be identified with just the last three columns where -

```
- `100` will correspond to `Spring`
- `010` will correspond to `Summer`
- `001` will correspond to `Winter`
```

- `drop_first=True` as it helps in reducing the extra column created during dummy variable creation. Hence it reduces the correlations created among dummy variables.
- Similar way others variables `month`, `weekday`, `year` and `weathersit`

In [29]:
```
# creating dummy variables for season,month,weekday,year and weathersit variables i
#bikedata =  pd.get_dummies(data=bikedata, columns=['season','month','weekday','yea
bikedata =  pd.get_dummies(data=bikedata, columns=['season','month','weekday','wea
bikedata.head()
```

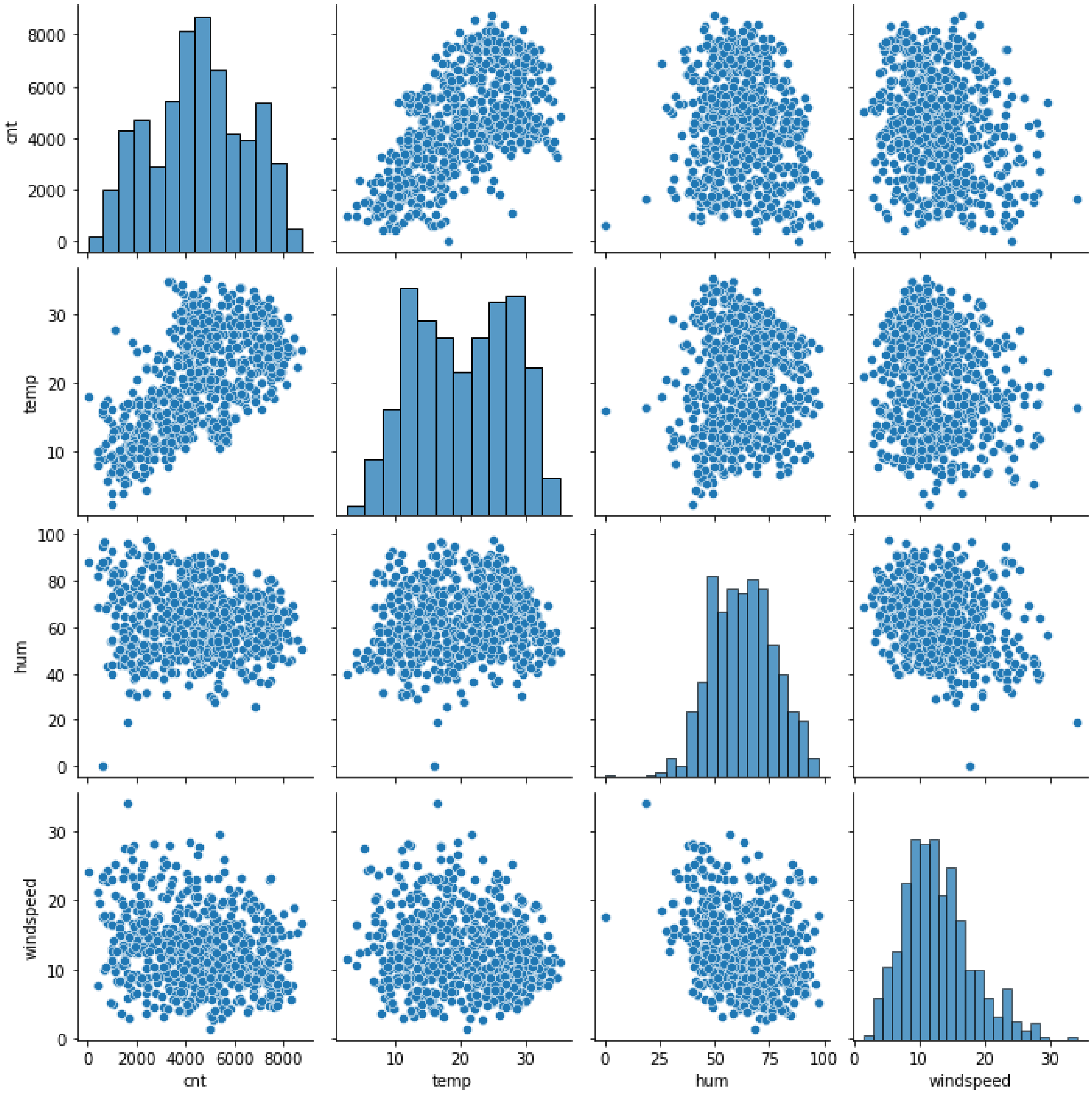
Out[29]:

	year	workingday	temp	hum	windspeed	cnt	season_Spring	season_Summer	seas
0	0	0	14.110847	80.5833	10.749882	985	1	0	
1	0	0	14.902598	69.6087	16.652113	801	1	0	
2	0	1	8.050924	43.7273	16.636703	1349	1	0	
3	0	1	8.200000	59.0435	10.739832	1562	1	0	
4	0	1	9.305237	43.6957	12.522300	1600	1	0	

5 rows × 28 columns

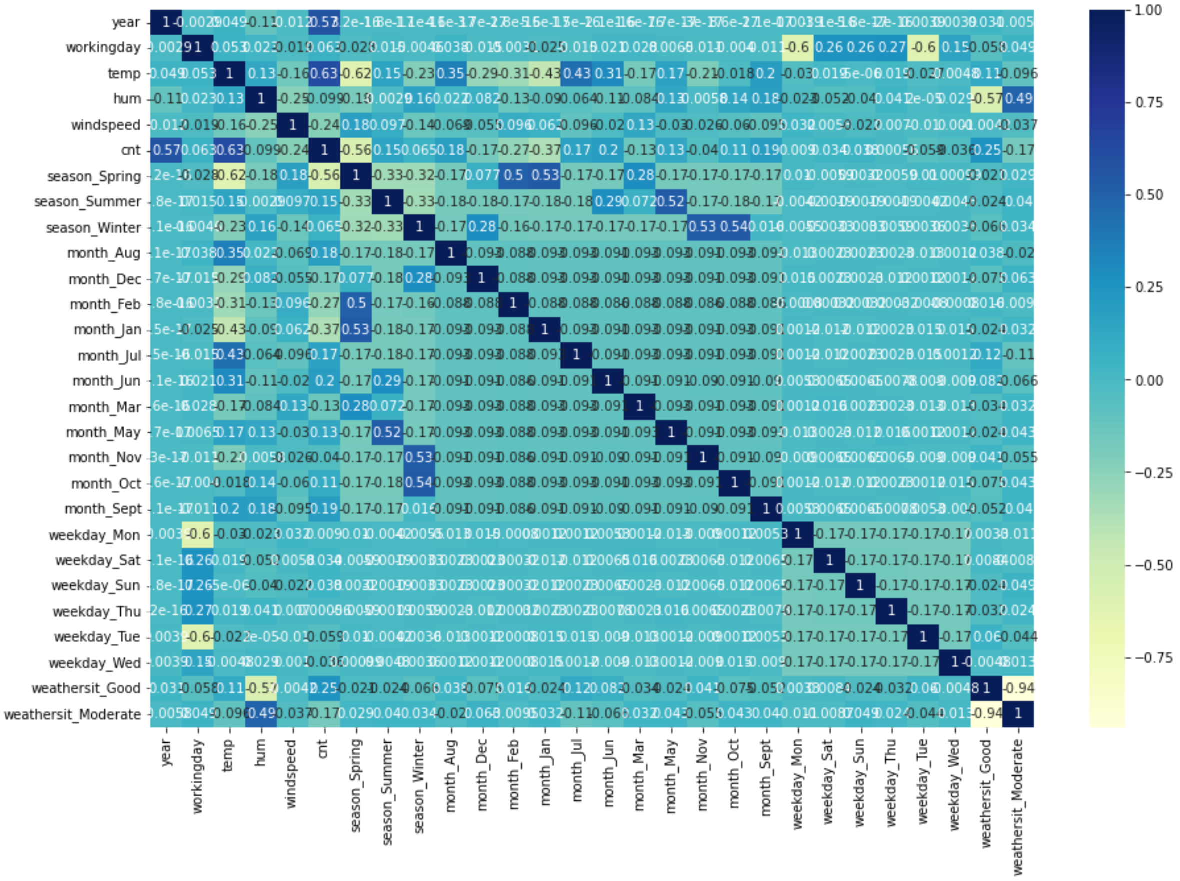
In [30]:
```
plt.figure(figsize = (15,30))
sns.pairplot(data=bikedata,vars=['cnt', 'temp','hum','windspeed'])
plt.show()
```

```
<Figure size 1080x2160 with 0 Axes>
```



In [31]:
```
#plt.figure(figsize=(20,15))
#sns.pairplot(bikedata)
#plt.show()
```

In [32]:
```
plt.figure(figsize=(15,10))
sns.heatmap(bikedata.corr(),cmap="YlGnBu",annot=True)
plt.show()
```



Splitting into train and test

In [33]:
```
bikedata.columns
```

Out[33]:
```
Index(['year', 'workingday', 'temp', 'hum', 'windspeed', 'cnt',
       'season_Spring', 'season_Summer', 'season_Winter', 'month_Aug',
       'month_Dec', 'month_Feb', 'month_Jan', 'month_Jul', 'month_Jun',
       'month_Mar', 'month_May', 'month_Nov', 'month_Oct', 'month_Sept',
       'weekday_Mon', 'weekday_Sat', 'weekday_Sun', 'weekday_Thu',
       'weekday_Tue', 'weekday_Wed', 'weathersit_Good', 'weathersit_Moderate'],
      dtype='object')
```

In [34]:
```
# creating train and test
df_train,df_test = train_test_split(bikedata,train_size=0.7, random_state=100)
print(df_train.shape)
print(df_test.shape)
```

```
(510, 28)
(220, 28)
```

Rescaling the Features

Here we have more than one variables. it's extremely import to rescale the variables so that they have a comparable scale. If we don't have comparable scales, then some of the cofficients as obtained by fitting the regression model might be very large or very small as compared to the other coffients. This might become very annoying at the time of model evaluation. So it's advised to use standardization or normalization so that the units of the coefficients obtained are all on the same scale. As you know, there are two common ways of rescaling:

- Min-Max scaling (normalisation) => convert data into between 0 and 1

- Standardization(mean-0,sigma-1)

Here, we will use MinMax scaling.

In [35]:
```
# X is vector
#normalisation  ==> (x- xmin)/(xmax-xmin)
#standardization ==> (x- mean)/sigma
```

In [36]:
```
bikedata.head()
```

Out[36]:

	year	workingday	temp	hum	windspeed	cnt	season_Spring	season_Summer	seas
0	0	0	14.110847	80.5833	10.749882	985	1	0	
1	0	0	14.902598	69.6087	16.652113	801	1	0	
2	0	1	8.050924	43.7273	16.636703	1349	1	0	
3	0	1	8.200000	59.0435	10.739832	1562	1	0	
4	0	1	9.305237	43.6957	12.522300	1600	1	0	

5 rows × 28 columns

In [37]:
```
# 1. Instantiate MinMaxScaler object
scaler = MinMaxScaler()
num_vars = ['temp', 'hum','windspeed','cnt']
df_train[num_vars] = scaler.fit_transform(df_train[num_vars])
df_train[num_vars].head()
```

Out[37]:

	temp	hum	windspeed	cnt
576	0.815169	0.725633	0.264686	0.827658
426	0.442393	0.640189	0.255342	0.465255
728	0.245101	0.498067	0.663106	0.204096
482	0.395666	0.504508	0.188475	0.482973
111	0.345824	0.751824	0.380981	0.191095

In [38]:
```
df_train[num_vars].describe()
```

Out[38]:

	temp	hum	windspeed	cnt
count	510.000000	510.000000	510.000000	510.000000
mean	0.537440	0.650480	0.320883	0.513499
std	0.225858	0.145846	0.169803	0.224421
min	0.000000	0.000000	0.000000	0.000000
25%	0.339853	0.538643	0.199179	0.356420
50%	0.542596	0.653714	0.296763	0.518638
75%	0.735215	0.754830	0.414447	0.684710
max	1.000000	1.000000	1.000000	1.000000

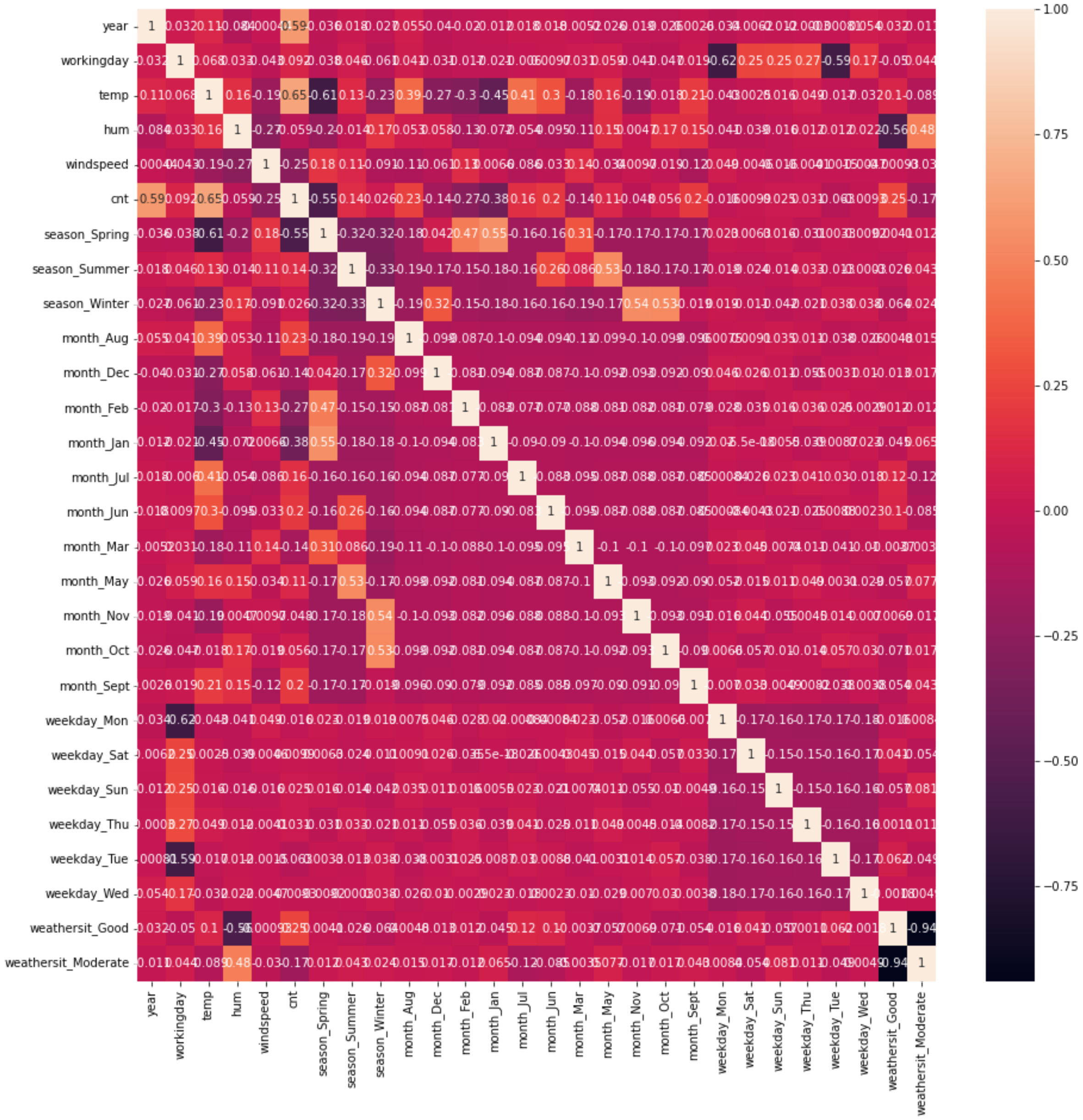
In [39]:
```
df_train.describe()
```

Out[39]:

	year	workingday	temp	hum	windspeed	cnt	season_Spring	s
count	510.000000	510.000000	510.000000	510.000000	510.000000	510.000000	510.000000	
mean	0.507843	0.676471	0.537440	0.650480	0.320883	0.513499	0.243137	
std	0.500429	0.468282	0.225858	0.145846	0.169803	0.224421	0.429398	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.339853	0.538643	0.199179	0.356420	0.000000	
50%	1.000000	1.000000	0.542596	0.653714	0.296763	0.518638	0.000000	
75%	1.000000	1.000000	0.735215	0.754830	0.414447	0.684710	0.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 28 columns

In [40]:
```
plt.figure(figsize = (15, 15))  #Checking if the variables are highly correlated
sns.heatmap(df_train.corr(), annot = True)
plt.show()
```



Build model using RFE

Dividing into X and Y sets for the model building

In [41]:
```
y_train = df_train.pop("cnt")
X_train = df_train
lr = LinearRegression()
lr.fit(X_train,y_train)
```

Out[41]:
```
LinearRegression()
```

In [42]:
```
# Cut down number of features to 10 using automated approach
rfe = RFE(lr,step=10)
rfe.fit(X_train,y_train)
```

Out[42]:
```
RFE(estimator=LinearRegression(), step=10)
```

In [43]:
```
#Columns selected by RFE and their weights
list(zip(X_train.columns,rfe.support_,rfe.ranking_))
```

Out[43]:
```
[('year', True, 1),
 ('workingday', True, 1),
 ('temp', True, 1),
 ('hum', True, 1),
 ('windspeed', True, 1),
 ('season_Spring', True, 1),
 ('season_Summer', False, 2),
 ('season_Winter', True, 1),
 ('month_Aug', False, 3),
 ('month_Dec', False, 2),
 ('month_Feb', False, 3),
 ('month_Jan', False, 2),
 ('month_Jul', True, 1),
 ('month_Jun', False, 3),
 ('month_Mar', False, 3),
 ('month_May', False, 3),
 ('month_Nov', False, 2),
 ('month_Oct', False, 3),
 ('month_Sept', True, 1),
 ('weekday_Mon', True, 1),
 ('weekday_Sat', False, 3),
 ('weekday_Sun', False, 3),
 ('weekday_Thu', False, 3),
 ('weekday_Tue', True, 1),
 ('weekday_Wed', False, 3),
 ('weathersit_Good', True, 1),
 ('weathersit_Moderate', True, 1)]
```

In [44]:
```
col = X_train.columns[rfe.support_]
col
```

Out[44]:
```
Index(['year', 'workingday', 'temp', 'hum', 'windspeed', 'season_Spring',
       'season_Winter', 'month_Jul', 'month_Sept', 'weekday_Mon',
       'weekday_Tue', 'weathersit_Good', 'weathersit_Moderate'],
      dtype='object')
```

In [45]:
```
X_train.columns[~rfe.support_]
```

Out[45]:
```
Index(['season_Summer', 'month_Aug', 'month_Dec', 'month_Feb', 'month_Jan',
       'month_Jun', 'month_Mar', 'month_May', 'month_Nov', 'month_Oct',
       'weekday_Sat', 'weekday_Sun', 'weekday_Thu', 'weekday_Wed'],
      dtype='object')
```

Building model using statsmodel for the detailed statistics

In [46]:
```
# Generic function to calculate VIF of variables
def calculateVIF(df):
    vif = pd.DataFrame()
    vif['Features'] = df.columns
    vif['VIF'] = [variance_inflation_factor(df.values, i) for i in range(df.shape[
    vif['VIF'] = round(vif['VIF'], 2)
    vif = vif.sort_values(by = "VIF", ascending = False)
    return vif
```

In [47]:
```
# Generic function to create a model with help of stats api
def buildModelWithStats(df):
    #import statsmodels.api as sm
    X_train_lm = sm.add_constant(df)
    lm = sm.OLS(y_train,X_train_lm).fit()   # Running the linear model
    #Let's see the summary of our linear model
```

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

In [48]:
```
# Creating x_test dataframe with RFE selected variables
X_train_rfe = X_train[col]
```

In [49]:
```
calculateVIF(X_train_rfe)
```

Out[49]:

	Features	VIF
3	hum	25.82
1	workingday	20.91
2	temp	18.99
11	weathersit_Good	15.21
12	weathersit_Moderate	9.23
9	weekday_Mon	5.48
10	weekday_Tue	5.35
4	windspeed	4.50
5	season_Spring	3.08
6	season_Winter	2.23
0	year	2.09
7	month_Jul	1.40
8	month_Sept	1.20

In [50]:
```
# build a model with all variables
buildModelWithStats(X_train_rfe)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.843
Model:                            OLS   Adj. R-squared:                  0.839
Method:                 Least Squares   F-statistic:                     204.7
Date:                Wed, 12 Oct 2022   Prob (F-statistic):          9.38e-190
Time:                        23:19:50   Log-Likelihood:                 510.91
No. Observations:                 510   AIC:                            -993.8
Df Residuals:                     496   BIC:                            -934.5
Df Model:                          13
Covariance Type:            nonrobust
==================================================================================
=====
                          coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------------------
-----
const                  -0.0144      0.052     -0.276      0.783      -0.117
0.088
year                    0.2308      0.008     28.455      0.000       0.215
0.247
workingday              0.1028      0.026      4.001      0.000       0.052
0.153
temp                    0.4776      0.031     15.613      0.000       0.418
0.538
hum                    -0.1482      0.038     -3.938      0.000      -0.222      -
0.074
windspeed              -0.1687      0.025     -6.616      0.000      -0.219      -
0.119
season_Spring          -0.1080      0.015     -7.280      0.000      -0.137      -
0.079
season_Winter           0.0558      0.012      4.528      0.000       0.032
0.080
month_Jul              -0.0782      0.017     -4.571      0.000      -0.112      -
0.045
month_Sept              0.0591      0.015      3.829      0.000       0.029
0.089
weekday_Mon             0.1125      0.027      4.146      0.000       0.059
0.166
weekday_Tue             0.0601      0.027      2.203      0.028       0.006
0.114
weathersit_Good         0.2499      0.026      9.482      0.000       0.198
0.302
weathersit_Moderate     0.1921      0.025      7.694      0.000       0.143
0.241
==============================================================================
Omnibus:                       60.956   Durbin-Watson:                   2.033
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              156.410
Skew:                          -0.606   Prob(JB):                     1.09e-34
Kurtosis:                       5.427   Cond. No.                         30.3
==============================================================================

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

Out[50]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x2897e754130>
```

Removing the `hum` variable is insignificant in presence of other variables; can be dropped

In [51]:
```
X_train_new = X_train_rfe.drop(["hum"], axis = 1)
```

In [52]:
```
calculateVIF(X_train_new)
```

Out[52]:

	Features	VIF
1	workingday	17.27
10	weathersit_Good	15.21
2	temp	14.88
11	weathersit_Moderate	8.71
8	weekday_Mon	4.71
9	weekday_Tue	4.51
3	windspeed	4.48
4	season_Spring	2.79
0	year	2.07
5	season_Winter	1.85
6	month_Jul	1.38
7	month_Sept	1.20

Rebuilding the model without month_November

In [53]:
```
# building model with Stats model
buildModelWithStats(X_train_new)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.838
Model:                            OLS   Adj. R-squared:                  0.834
Method:                 Least Squares   F-statistic:                     214.3
Date:                Wed, 12 Oct 2022   Prob (F-statistic):          1.26e-187
Time:                        23:19:50   Log-Likelihood:                 503.06
No. Observations:                 510   AIC:                            -980.1
Df Residuals:                     497   BIC:                            -925.1
Df Model:                          12
Covariance Type:            nonrobust
==================================================================================
=====
                          coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------------------
-----
const                  -0.1354      0.043     -3.167      0.002      -0.219      -
0.051
year                    0.2344      0.008     28.661      0.000       0.218
0.250
workingday              0.1034      0.026      3.967      0.000       0.052
0.155
temp                    0.4493      0.030     14.895      0.000       0.390
0.509
windspeed              -0.1404      0.025     -5.657      0.000      -0.189      -
0.092
season_Spring          -0.1118      0.015     -7.441      0.000      -0.141      -
0.082
season_Winter           0.0468      0.012      3.808      0.000       0.023
0.071
month_Jul              -0.0711      0.017     -4.120      0.000      -0.105      -
0.037
month_Sept              0.0559      0.016      3.573      0.000       0.025
0.087
weekday_Mon             0.1148      0.028      4.171      0.000       0.061
0.169
weekday_Tue             0.0578      0.028      2.089      0.037       0.003
0.112
weathersit_Good         0.2907      0.025     11.824      0.000       0.242
0.339
weathersit_Moderate     0.2091      0.025      8.381      0.000       0.160
0.258
==============================================================================
Omnibus:                       64.352   Durbin-Watson:                   2.027
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              162.995
Skew:                          -0.644   Prob(JB):                     4.04e-36
Kurtosis:                       5.452   Cond. No.                         24.6
==============================================================================

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

Out[53]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x2897e36f5b0>
```

Removing the `workingday` variable is insignificant in presence of other variables due to high VIF value; can be dropped

In [54]:
```python
X_train_new = X_train_new.drop(["workingday"], axis = 1)
```

In [55]:
```python
calculateVIF(X_train_new)
```

Out[55]:

	Features	VIF
1	temp	12.25
9	weathersit_Good	11.51
10	weathersit_Moderate	6.38
2	windspeed	4.25
3	season_Spring	2.56
0	year	2.07
4	season_Winter	1.70
5	month_Jul	1.38
7	weekday_Mon	1.22
8	weekday_Tue	1.21
6	month_Sept	1.20

Rebuilding the model without `month_January`

In [56]:

```
#building mode with stats model
buildModelWithStats(X_train_new)
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.833
Model:                            OLS   Adj. R-squared:                  0.829
Method:                 Least Squares   F-statistic:                     225.6
Date:                Wed, 12 Oct 2022   Prob (F-statistic):          1.84e-185
Time:                        23:19:50   Log-Likelihood:                 495.11
No. Observations:                 510   AIC:                            -966.2
Df Residuals:                     498   BIC:                            -915.4
Df Model:                          11                                         
Covariance Type:            nonrobust                                         
==================================================================================
=====
                          coef    std err          t      P>|t|      [0.025      
0.975]
----------------------------------------------------------------------------------
-----
const                  -0.0303      0.034     -0.889      0.375      -0.097      
0.037
year                    0.2349      0.008     28.308      0.000       0.219      
0.251
temp                    0.4502      0.031     14.711      0.000       0.390      
0.510
windspeed              -0.1425      0.025     -5.661      0.000      -0.192      -
0.093
season_Spring          -0.1148      0.015     -7.539      0.000      -0.145      -
0.085
season_Winter           0.0435      0.012      3.497      0.001       0.019      
0.068
month_Jul              -0.0704      0.017     -4.024      0.000      -0.105      -
0.036
month_Sept              0.0521      0.016      3.289      0.001       0.021      
0.083
weekday_Mon             0.0154      0.012      1.332      0.184      -0.007      
0.038
weekday_Tue            -0.0415      0.012     -3.468      0.001      -0.065      -
0.018
weathersit_Good         0.2860      0.025     11.478      0.000       0.237      
0.335
weathersit_Moderate     0.2064      0.025      8.153      0.000       0.157      
0.256
==============================================================================
Omnibus:                       77.949   Durbin-Watson:                   1.986
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              209.347
Skew:                          -0.755   Prob(JB):                     3.47e-46
Kurtosis:                       5.752   Cond. No.                         18.2
==============================================================================

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

Out[56]:

```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x2897edcbc40>
```

Removing the `weekday_Mon` variable is insignificant due to high `p-value`; can be dropped

In [57]:

```
X_train_new = X_train_new.drop(["weekday_Mon"], axis = 1)
```

In [58]:

```
calculateVIF(X_train_new)
```

Out[58]:

	Features	VIF
1	temp	12.24
8	weathersit_Good	11.47
9	weathersit_Moderate	6.35
2	windspeed	4.23
3	season_Spring	2.56
0	year	2.07
4	season_Winter	1.70
5	month_Jul	1.38
6	month_Sept	1.20
7	weekday_Tue	1.18

In [59]:

```
# building model with stats model
buildModelWithStats(X_train_new)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.832
Model:                            OLS   Adj. R-squared:                  0.829
Method:                 Least Squares   F-statistic:                     247.6
Date:                Wed, 12 Oct 2022   Prob (F-statistic):          2.75e-186
Time:                        23:19:51   Log-Likelihood:                 494.20
No. Observations:                 510   AIC:                            -966.4
Df Residuals:                     499   BIC:                            -919.8
Df Model:                          10
Covariance Type:            nonrobust
==================================================================================
=====
                          coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------------------
-----
const                  -0.0273      0.034     -0.802      0.423      -0.094
0.040
year                    0.2346      0.008     28.259      0.000       0.218
0.251
temp                    0.4493      0.031     14.674      0.000       0.389
0.509
windspeed              -0.1410      0.025     -5.603      0.000      -0.191      -
0.092
season_Spring          -0.1147      0.015     -7.528      0.000      -0.145      -
0.085
season_Winter           0.0438      0.012      3.522      0.000       0.019
0.068
month_Jul              -0.0698      0.018     -3.986      0.000      -0.104      -
0.035
month_Sept              0.0522      0.016      3.291      0.001       0.021
0.083
weekday_Tue            -0.0443      0.012     -3.760      0.000      -0.067      -
0.021
weathersit_Good         0.2859      0.025     11.462      0.000       0.237
0.335
weathersit_Moderate     0.2062      0.025      8.140      0.000       0.156
0.256
==============================================================================
Omnibus:                       73.106   Durbin-Watson:                   1.985
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              205.558
Skew:                          -0.694   Prob(JB):                     2.31e-45
Kurtosis:                       5.784   Cond. No.                         18.1
==============================================================================

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

Out[59]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x2897f2a3a00>
```

Removing the `weathersit_Good` variable is insignificant due to high `VIF` compare with other variables; can be dropped

In [60]:
```
X_train_new = X_train_new.drop(["weathersit_Good"], axis = 1)
```

In [61]:
```
calculateVIF(X_train_new)
```

Out[61]:

	Features	VIF
1	temp	4.67
2	windspeed	3.94
0	year	2.05
3	season_Spring	1.64
8	weathersit_Moderate	1.49
4	season_Winter	1.37
5	month_Jul	1.35
6	month_Sept	1.19
7	weekday_Tue	1.17

In [62]:

```
# building model with stats model
buildModelWithStats(X_train_new)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.788
Model:                            OLS   Adj. R-squared:                  0.784
Method:                 Least Squares   F-statistic:                     206.7
Date:                Wed, 12 Oct 2022   Prob (F-statistic):          3.15e-162
Time:                        23:19:51   Log-Likelihood:                 434.60
No. Observations:                 510   AIC:                            -849.2
Df Residuals:                     500   BIC:                            -806.9
Df Model:                           9
Covariance Type:            nonrobust
==================================================================================
=====
                         coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------------------
-----
const                  0.2488      0.027      9.233      0.000       0.196
0.302
year                   0.2400      0.009     25.795      0.000       0.222
0.258
temp                   0.4591      0.034     13.357      0.000       0.392
0.527
windspeed             -0.1697      0.028     -6.033      0.000      -0.225      -
0.114
season_Spring         -0.1100      0.017     -6.431      0.000      -0.144      -
0.076
season_Winter          0.0316      0.014      2.272      0.024       0.004
0.059
month_Jul             -0.0742      0.020     -3.774      0.000      -0.113      -
0.036
month_Sept             0.0421      0.018      2.369      0.018       0.007
0.077
weekday_Tue           -0.0377      0.013     -2.854      0.004      -0.064      -
0.012
weathersit_Moderate   -0.0662      0.010     -6.737      0.000      -0.086      -
0.047
==============================================================================
Omnibus:                      137.442   Durbin-Watson:                   1.979
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              510.174
Skew:                          -1.191   Prob(JB):                    1.65e-111
Kurtosis:                       7.281   Cond. No.                         14.1
==============================================================================

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

Out[62]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x2897f29afa0>
```

Removing the `season_Winter` variable is insignificant due to high `p-value` compare with other variables; can be dropped

In [63]:
```python
X_train_new = X_train_new.drop(["season_Winter"], axis = 1)
```

In [64]:
```python
calculateVIF(X_train_new)
```

Out[64]:

	Features	VIF
1	temp	4.67
2	windspeed	3.73
0	year	2.03
3	season_Spring	1.52
7	weathersit_Moderate	1.47
4	month_Jul	1.33
5	month_Sept	1.19
6	weekday_Tue	1.15

In [65]:

```
# building model with stats model
buildModelWithStats(X_train_new)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.786
Model:                            OLS   Adj. R-squared:                  0.783
Method:                 Least Squares   F-statistic:                     229.9
Date:                Wed, 12 Oct 2022   Prob (F-statistic):          2.60e-162
Time:                        23:19:51   Log-Likelihood:                 431.98
No. Observations:                 510   AIC:                            -846.0
Df Residuals:                     501   BIC:                            -807.9
Df Model:                           8
Covariance Type:            nonrobust
==================================================================================
=====
                         coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------------------
-----
const                  0.2871      0.021     13.594      0.000       0.246
0.329
year                   0.2406      0.009     25.760      0.000       0.222
0.259
temp                   0.4172      0.029     14.324      0.000       0.360
0.474
windspeed             -0.1771      0.028     -6.311      0.000      -0.232      -
0.122
season_Spring         -0.1332      0.014     -9.676      0.000      -0.160      -
0.106
month_Jul             -0.0747      0.020     -3.786      0.000      -0.113      -
0.036
month_Sept             0.0418      0.018      2.338      0.020       0.007
0.077
weekday_Tue           -0.0367      0.013     -2.764      0.006      -0.063      -
0.011
weathersit_Moderate   -0.0671      0.010     -6.806      0.000      -0.087      -
0.048
==============================================================================
Omnibus:                      124.410   Durbin-Watson:                   2.000
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              428.005
Skew:                          -1.099   Prob(JB):                     1.15e-93
Kurtosis:                       6.913   Cond. No.                         11.1
==============================================================================

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

Out[65]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x2897f2927f0>
```

Removing the `month_Sept` variable is insignificant due to high `p-value` compare with other variables; can be dropped

In [66]:
```
X_train_new = X_train_new.drop(["month_Sept"], axis = 1)
```

In [67]:
```
calculateVIF(X_train_new)
```

Out[67]:

	Features	VIF
1	temp	4.25
2	windspeed	3.68
0	year	2.03
3	season_Spring	1.51
6	weathersit_Moderate	1.47
4	month_Jul	1.28
5	weekday_Tue	1.15

In [68]:

```
# building model with stats model
buildModelWithStats(X_train_new)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.784
Model:                            OLS   Adj. R-squared:                  0.781
Method:                 Least Squares   F-statistic:                     259.7
Date:                Wed, 12 Oct 2022   Prob (F-statistic):          2.33e-162
Time:                        23:19:51   Log-Likelihood:                 429.22
No. Observations:                 510   AIC:                            -842.4
Df Residuals:                     502   BIC:                            -808.6
Df Model:                           7
Covariance Type:            nonrobust
==================================================================================
=====
                          coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------------------
-----
const                   0.2860      0.021     13.485      0.000       0.244
0.328
year                    0.2401      0.009     25.597      0.000       0.222
0.259
temp                    0.4305      0.029     15.002      0.000       0.374
0.487
windspeed              -0.1827      0.028     -6.506      0.000      -0.238      -
0.127
season_Spring          -0.1339      0.014     -9.686      0.000      -0.161      -
0.107
month_Jul              -0.0832      0.019     -4.274      0.000      -0.122      -
0.045
weekday_Tue            -0.0375      0.013     -2.816      0.005      -0.064      -
0.011
weathersit_Moderate    -0.0662      0.010     -6.686      0.000      -0.086      -
0.047
==============================================================================
Omnibus:                      116.176   Durbin-Watson:                   1.979
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              388.330
Skew:                          -1.034   Prob(JB):                     4.73e-85
Kurtosis:                       6.742   Cond. No.                         11.0
==============================================================================

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

Out[68]:

```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x2897e32cd30>
```

Removing the `weekday_Tue` variable is insignificant due to high `p-value` compare with other variables; can be dropped

In [69]:
```
X_train_new = X_train_new.drop(["weekday_Tue"], axis = 1)
```

In [70]:
```
calculateVIF(X_train_new)
```

Out[70]:

	Features	VIF
1	temp	4.19
2	windspeed	3.67
0	year	2.03
3	season_Spring	1.51
5	weathersit_Moderate	1.47
4	month_Jul	1.28

In [71]:
```
# building model with stats model
X_train_lm = sm.add_constant(X_train_new)
lm = sm.OLS(y_train,X_train_lm).fit()    # Running the linear model
#Let's see the summary of our linear model
print(lm.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.780
Model:                            OLS   Adj. R-squared:                  0.778
Method:                 Least Squares   F-statistic:                     297.6
Date:                Wed, 12 Oct 2022   Prob (F-statistic):          6.56e-162
Time:                        23:19:51   Log-Likelihood:                 425.22
No. Observations:                 510   AIC:                            -836.4
Df Residuals:                     503   BIC:                            -806.8
Df Model:                           6
Covariance Type:            nonrobust
==================================================================================
=====
                          coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------------------
-----
const                   0.2784      0.021     13.145      0.000       0.237
0.320
year                    0.2400      0.009     25.415      0.000       0.221
0.259
temp                    0.4335      0.029     15.017      0.000       0.377
0.490
windspeed              -0.1822      0.028     -6.446      0.000      -0.238      -
0.127
season_Spring          -0.1333      0.014     -9.577      0.000      -0.161      -
0.106
month_Jul              -0.0853      0.020     -4.355      0.000      -0.124      -
0.047
weathersit_Moderate    -0.0648      0.010     -6.512      0.000      -0.084      -
0.045
==============================================================================
Omnibus:                      113.218   Durbin-Watson:                   1.968
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              368.211
Skew:                          -1.016   Prob(JB):                     1.11e-80
Kurtosis:                       6.633   Cond. No.                         10.9
==============================================================================

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

In [72]:

```
X_train_new.columns
```

Out[72]:

```
Index(['year', 'temp', 'windspeed', 'season_Spring', 'month_Jul',
       'weathersit_Moderate'],
      dtype='object')
```

Residual Analysis of the train data

So, now to check if the error terms are also normally distributed (which is infact, one of the major assumptions of linear regression), let us plot the histogram of the error terms and see what it looks like.

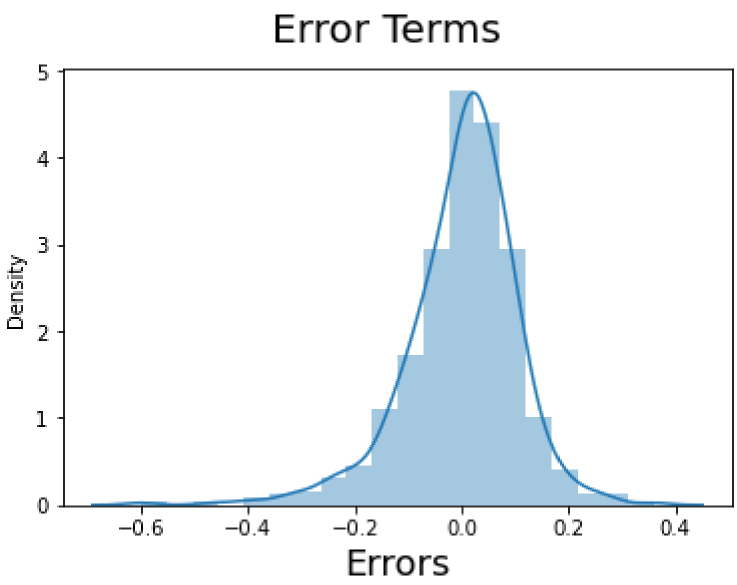
In [73]:

```
y_train_cnt = lm.predict(X_train_lm)
```

In [74]:

```
# Plot the histogram of the error terms
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)                         # X-label
```

Out[74]: Text(0.5, 0, 'Errors')



Making Predictions

Applying the scaling on the test sets

In [75]:
```
num_vars = ['temp', 'hum','windspeed','cnt']
df_test[num_vars] = scaler.transform(df_test[num_vars])
```

Dividing into X_test and y_test

In [76]:
```
y_test = df_test.pop('cnt')
X_test = df_test
```

In [77]:
```
# Now let's use our model to make predictions.
# Creating X_test_new dataframe by dropping variables from X_test
X_test_new = X_test[X_train_new.columns]

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

In [78]:
```
# Making predictions
y_pred = lm.predict(X_test_new)
```

R-Squared value for train predictions

In [79]:
```
#Print R-squared Value
r2_score(y_train,y_train_cnt)
```

Out[79]: 0.7801873103743808

Prediction of values on test dataset

In [80]:
```
#Print R-squared Value
r2_score(y_test,y_pred)
```

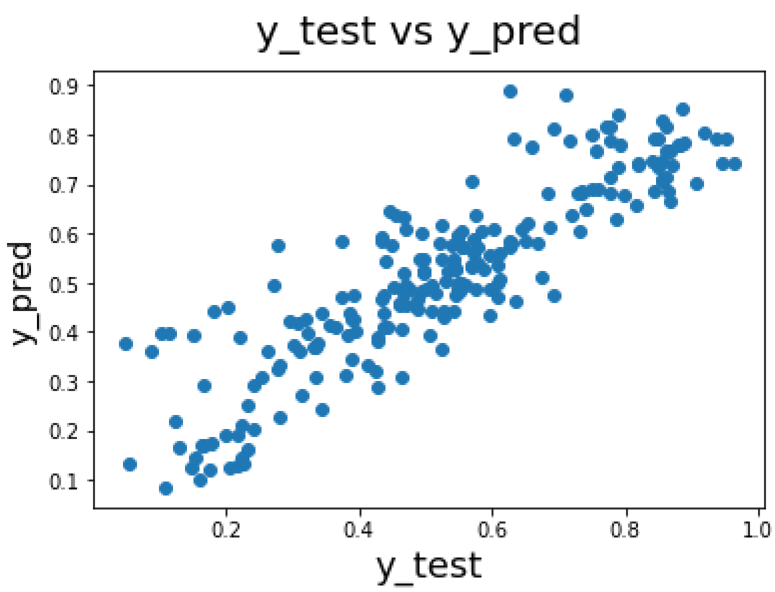
Out[80]: 0.7722148714221881

Model Evaluation

In [ ]:

In [81]:
```
# Plotting y_test and y_pred to understand the spread.
fig = plt.figure()
plt.scatter(y_test,y_pred)
fig.suptitle('y_test vs y_pred', fontsize=20)              # Plot heading
plt.xlabel('y_test', fontsize=18)                          # X-label
plt.ylabel('y_pred', fontsize=16)                          # Y-label
```

Out[81]: `Text(0, 0.5, 'y_pred')`



In [82]:
```
round(lm.params,4)
```

Out[82]:
```
const                   0.2784
year                    0.2400
temp                    0.4335
windspeed              -0.1822
season_Spring          -0.1333
month_Jul              -0.0853
weathersit_Moderate    -0.0648
dtype: float64
```

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

cnt = 0.2784 + 0.2400 x year + 0.4335 x temp - 0.1822 x windspeed - 0.1333 x season_Spring - 0.0853 x month_Jul - 0.0648 x weathersit_Moderate

Demand of bikes depend on year, temp, windspeed, season spring,July month, weathersit moderate

Conclusion: Year, Temp and windspeed more dominating features for contributing significatly towards the Bike share

In [ ]: