In [ ]:
```
import pandas
import seaborn
import matplotlib.pyplot as plt
import numpy
from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.metrics import r2_score,mean_squared_error
from decimal import *
import warnings
warnings.filterwarnings('ignore')
```

Data Read

Reading the Dataset

In [ ]:
```
bike_raw_dataframe=pandas.read_csv("/Users/karanprinja/Downloads/day.csv")
bike_raw_dataframe.shape
```

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

Printing the Columns

In [ ]:
```
bike_raw_dataframe.columns
```

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

Printing the dataframe to get overview

In [ ]:
```
bike_raw_dataframe.head().append(bike_raw_dataframe.tail())
```

Out[ ]:

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	ter
0	1	01-01-2018	1	0	1	0	6	0	2	14.1108
1	2	02-01-2018	1	0	1	0	0	0	2	14.9025
2	3	03-01-2018	1	0	1	0	1	1	1	8.0509
3	4	04-01-2018	1	0	1	0	2	1	1	8.2000
4	5	05-01-2018	1	0	1	0	3	1	1	9.3052
725	726	27-12-2019	1	1	12	0	4	1	2	10.4208
726	727	28-12-2019	1	1	12	0	5	1	2	10.3866
727	728	29-12-2019	1	1	12	0	6	0	2	10.3866
728	729	30-12-2019	1	1	12	0	0	0	1	10.4891
729	730	31-12-2019	1	1	12	0	1	1	2	8.8491

Data Cleaning

Checking for columnwise Null Values

In [ ]:
```
bike_raw_dataframe.isnull().sum()
```

Out[ ]:
```
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
```

Dropping all the rows having all Null Values

In [ ]:
```
bike_raw_dataframe.dropna(axis=0,thresh=16,inplace=True)
```

Printing Dataframe shape

In [ ]:
```
bike_raw_dataframe.shape
```

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

Finding columns having unique values

In [ ]:
```
bike_raw_dataframe.nunique()
```

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

Dropping columns 'instant','dteday','casual','registered' as per the information from the above execution as well as the information

shared in data dictionary

In [ ]:
```
bike_raw_dataframe.drop(['instant','dteday','casual','registered'],axis=1,in
```

Creating Labels of the columns as per Data Dictionary. We are only applying labels to non-binary columns.Columns such

as WorkingDay,Holiday,Year have been excluded

In [ ]:
```
season_labels = {
    1 : 'spring',
    2 : 'summer',
    3 : 'fall',
    4 : 'winter'
}

mnth_labels = {
    1 : 'january',
    2 : 'february',
    3 : 'march',
    4 : 'april',
    5 : 'may',
    6 : 'june',
    7 : 'july',
    8 : 'august',
    9 : 'september',
    10 : 'october',
    11 : 'november',
    12 : 'december'
}

weekday_labels = {
    0 : 'Sunday',
    1 : 'Monday',
```

```
    2 : 'Tuesday',
    3 : 'Wednesday',
    4 : 'Thursday',
    5 : 'Friday',
    6 : 'Saturday'
}

weathersit_labels = {
    1 : 'clear',
    2 : 'cloudy',
    3 : 'light snow_rain',
    4 : 'Heavy snow_rain'
}
```

Applying Labels to the Values present in Categorical Columns

In [ ]:

```
bike_raw_dataframe['season']=bike_raw_dataframe['season'].map(season_labels)
bike_raw_dataframe['mnth']=bike_raw_dataframe['mnth'].map(mnth_labels)
bike_raw_dataframe['weekday']=bike_raw_dataframe['weekday'].map(weekday_labe
bike_raw_dataframe['weathersit']=bike_raw_dataframe['weathersit'].map(weathe
```

In [ ]:

```
cat_vars = ['season','yr','mnth','holiday','weekday', 'workingday','weathers
numerical_vars=['temp','atemp','hum','windspeed','cnt']
```

Printing Values to confirm if labels have been applied

In [ ]:

```
bike_raw_dataframe.head(5)
```

Out[ ]:

	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp	
0	spring	0	january	0	Saturday	0	cloudy	14.110847	18.18125	8(
1	spring	0	january	0	Sunday	0	cloudy	14.902598	17.68695	6!
2	spring	0	january	0	Monday	1	clear	8.050924	9.47025	4
3	spring	0	january	0	Tuesday	1	clear	8.200000	10.60610	5!
4	spring	0	january	0	Wednesday	1	clear	9.305237	11.46350	4:

Exploratory Data Analysis

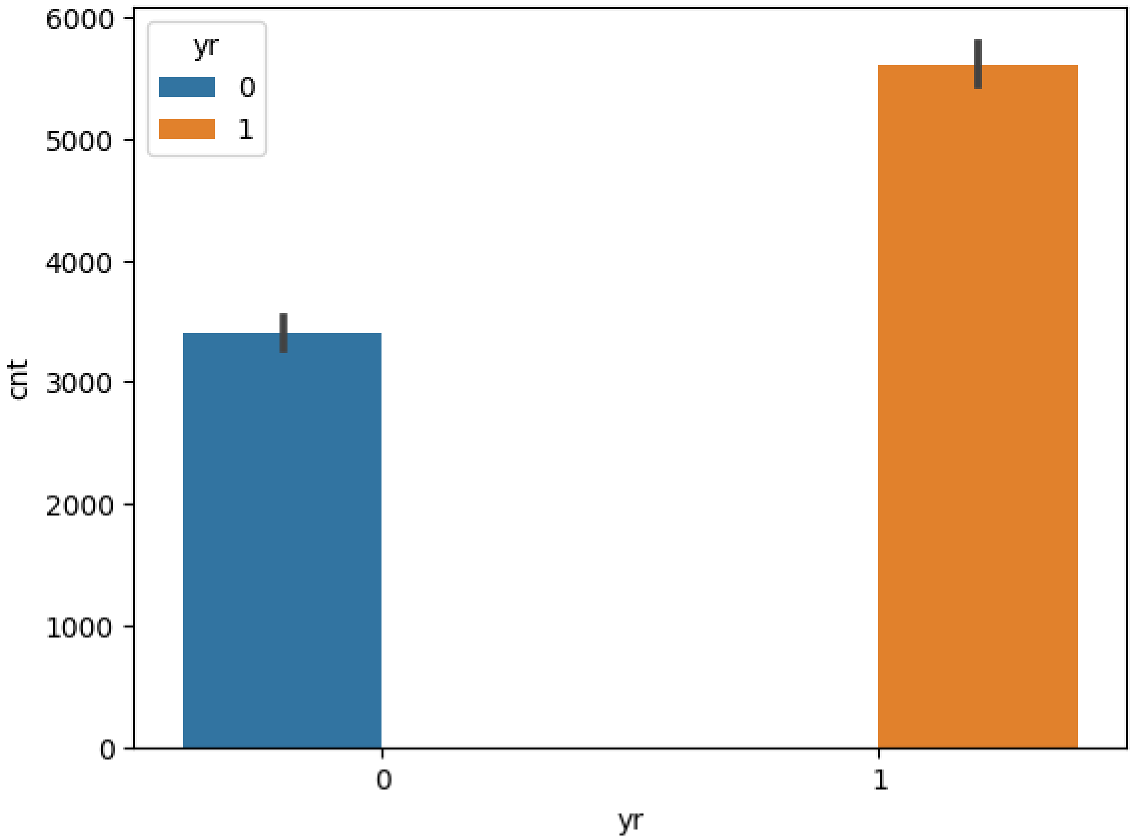
Plotting Graph between Season and Count.To observe relation between them

In [ ]:

```
seaborn.barplot(x='yr',y='cnt',data=bike_raw_dataframe,hue='yr')
```

Out[ ]:

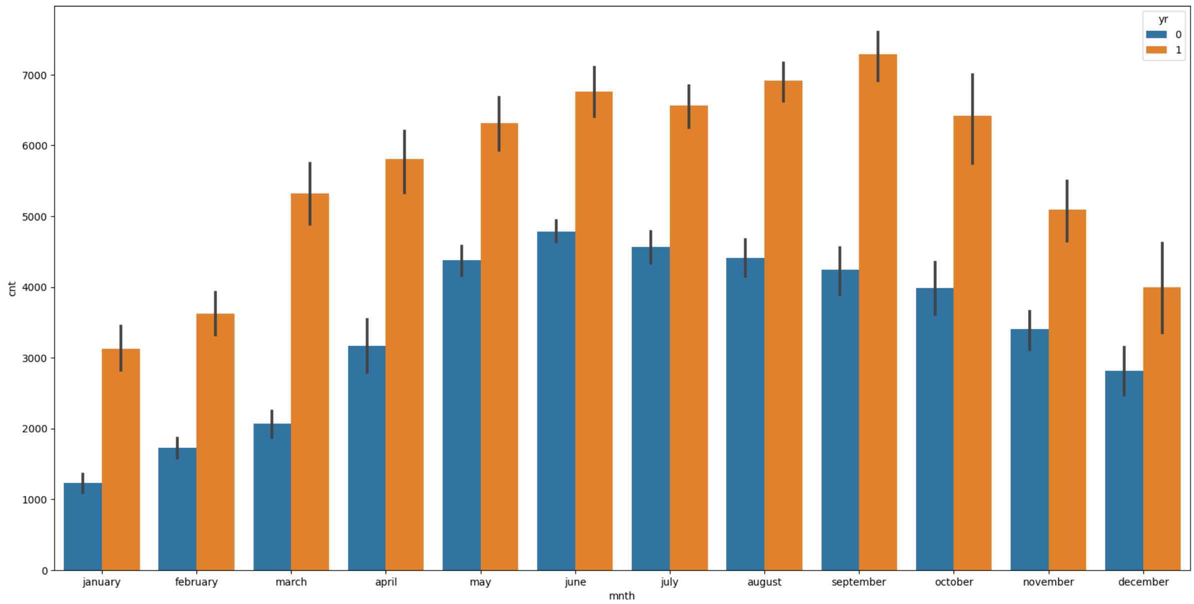
```
<Axes: xlabel='yr', ylabel='cnt'>
```



Plotting Graph between Month and Count.To observe relation between them

In [ ]:
```
plt.figure(figsize=(20,10))
seaborn.barplot(x='mnth',y='cnt',data=bike_raw_dataframe,hue='yr')
```

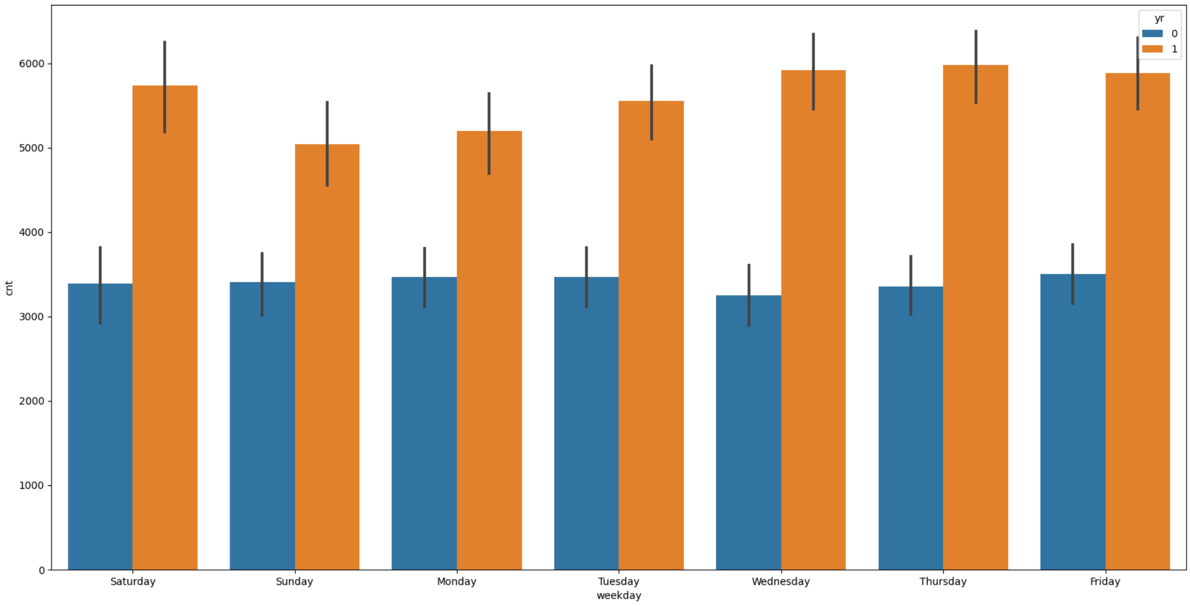
Out[ ]: `<Axes: xlabel='mnth', ylabel='cnt'>`



Plotting Graph between Weekday and Count.To observe relation between them

In [ ]:
```
plt.figure(figsize=(20,10))
seaborn.barplot(x='weekday',y='cnt',data=bike_raw_dataframe,hue='yr')
```

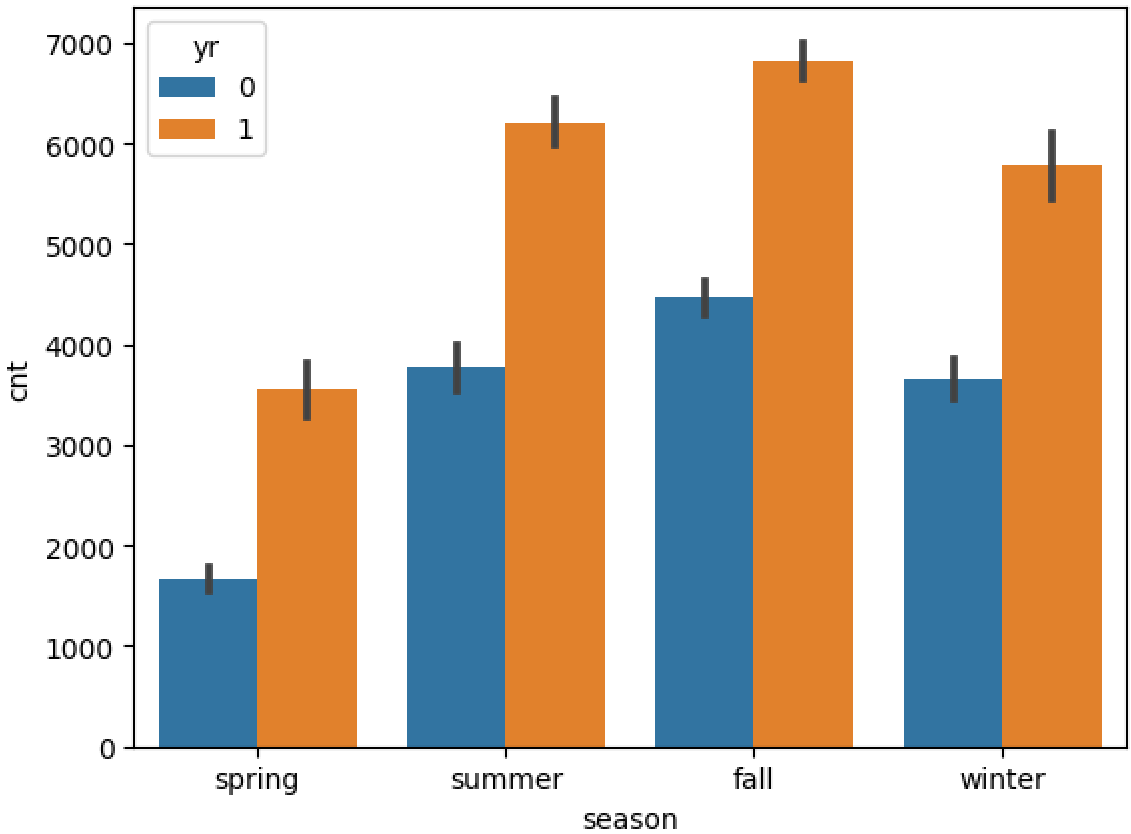
Out[ ]: `<Axes: xlabel='weekday', ylabel='cnt'>`



Plotting Graph between Season and Count.To observe relation between them

In [ ]:
```
seaborn.barplot(x='season',y='cnt',data=bike_raw_dataframe,hue='yr')
```

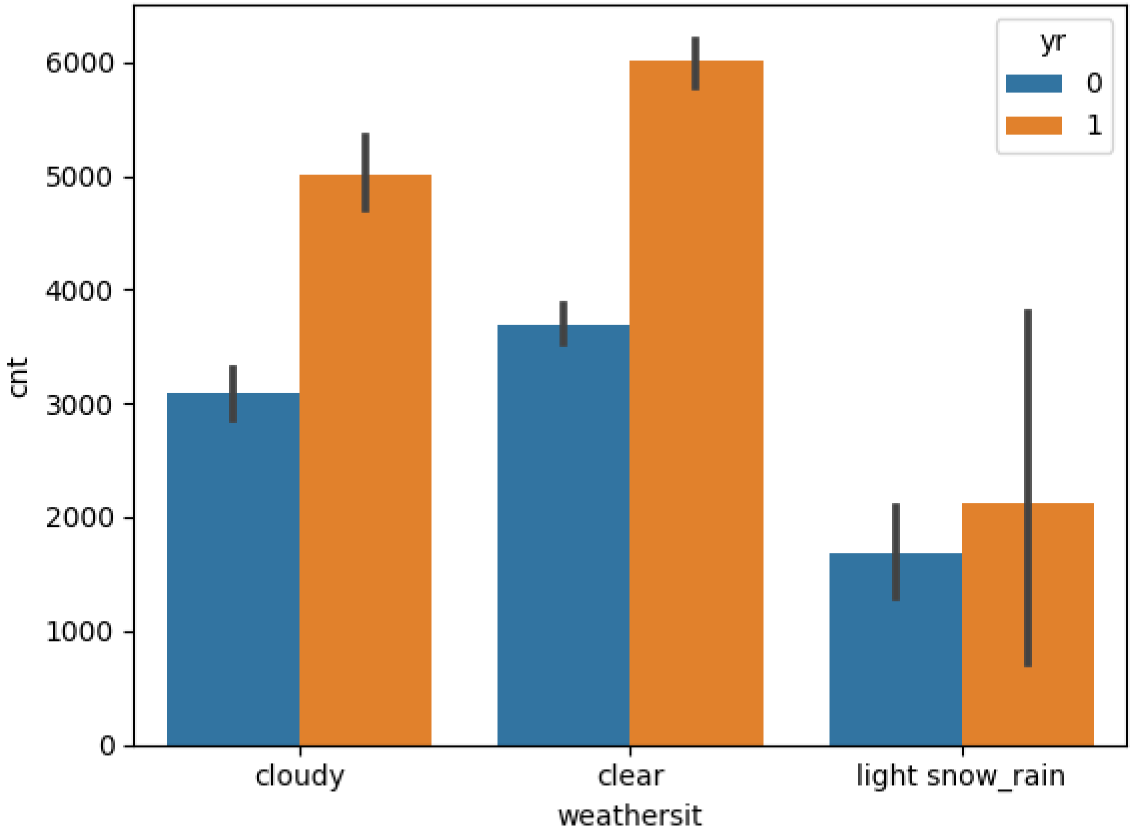
Out[ ]: <Axes: xlabel='season', ylabel='cnt'>



Plotting Graph to observe behvior between different weather and demand for bike

In [ ]:
```
seaborn.barplot(x='weathersit',y='cnt',data=bike_raw_dataframe,hue='yr')
```

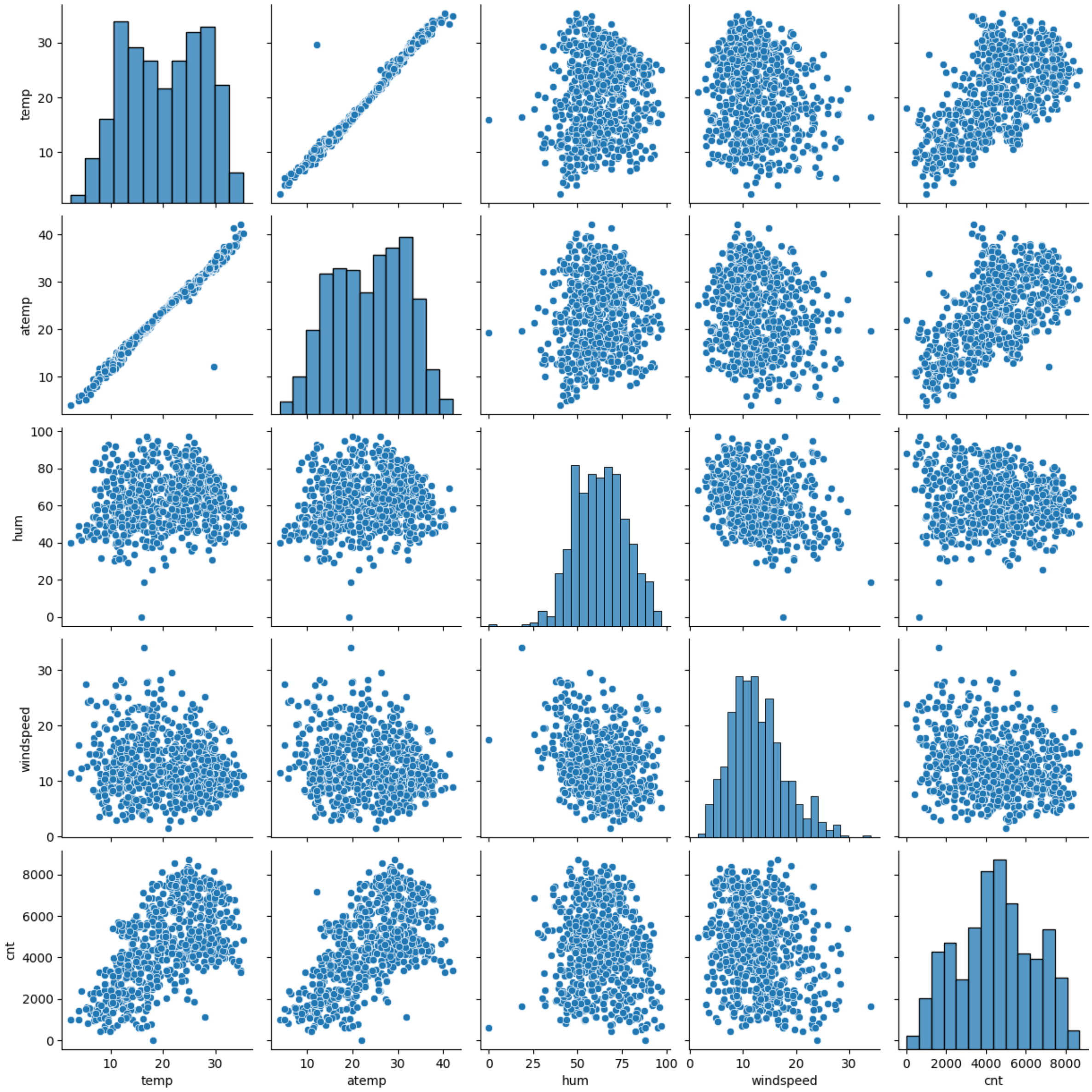
Out[ ]: <Axes: xlabel='weathersit', ylabel='cnt'>



Plotting Graph between Numerical Variables and Count.To observe relation between them

In [ ]:
```
seaborn.pairplot(data=bike_raw_dataframe,vars=numerical_vars)
```

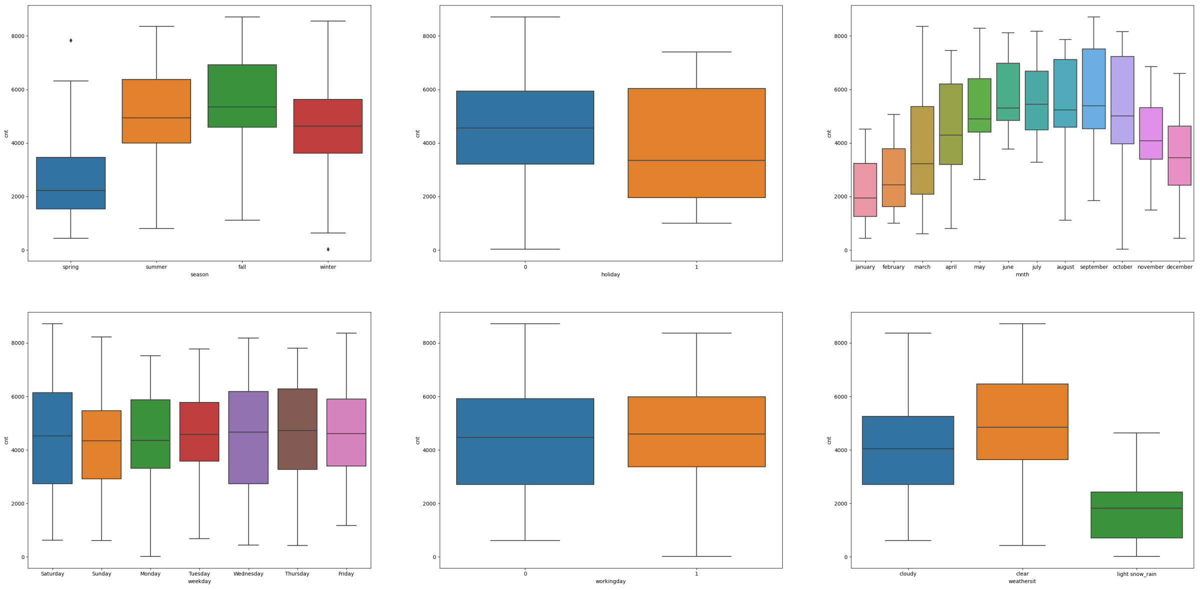
Out[ ]: <seaborn.axisgrid.PairGrid at 0x12c4ba370>



Plotting a Graph between Categorical Variables and Count.To remove outliers

In [ ]:
```
cat_vars = ['season','yr','mnth','holiday','weekday', 'workingday','weathers
fig=plt.figure(figsize=(40,30))
fig.add_subplot(3,3,1)
seaborn.boxplot(x='season',y='cnt',data=bike_raw_dataframe)
fig.add_subplot(3,3,2)
seaborn.boxplot(x='holiday',y='cnt',data=bike_raw_dataframe)
fig.add_subplot(3,3,3)
seaborn.boxplot(x='mnth',y='cnt',data=bike_raw_dataframe)
fig.add_subplot(3,3,4)
seaborn.boxplot(x='weekday',y='cnt',data=bike_raw_dataframe)
fig.add_subplot(3,3,5)
seaborn.boxplot(x='workingday',y='cnt',data=bike_raw_dataframe)
fig.add_subplot(3,3,6)
seaborn.boxplot(x='weathersit',y='cnt',data=bike_raw_dataframe)
```

Out[ ]:
```
<Axes: xlabel='weathersit', ylabel='cnt'>
```



Removing the outlier we observed in Graph for Season

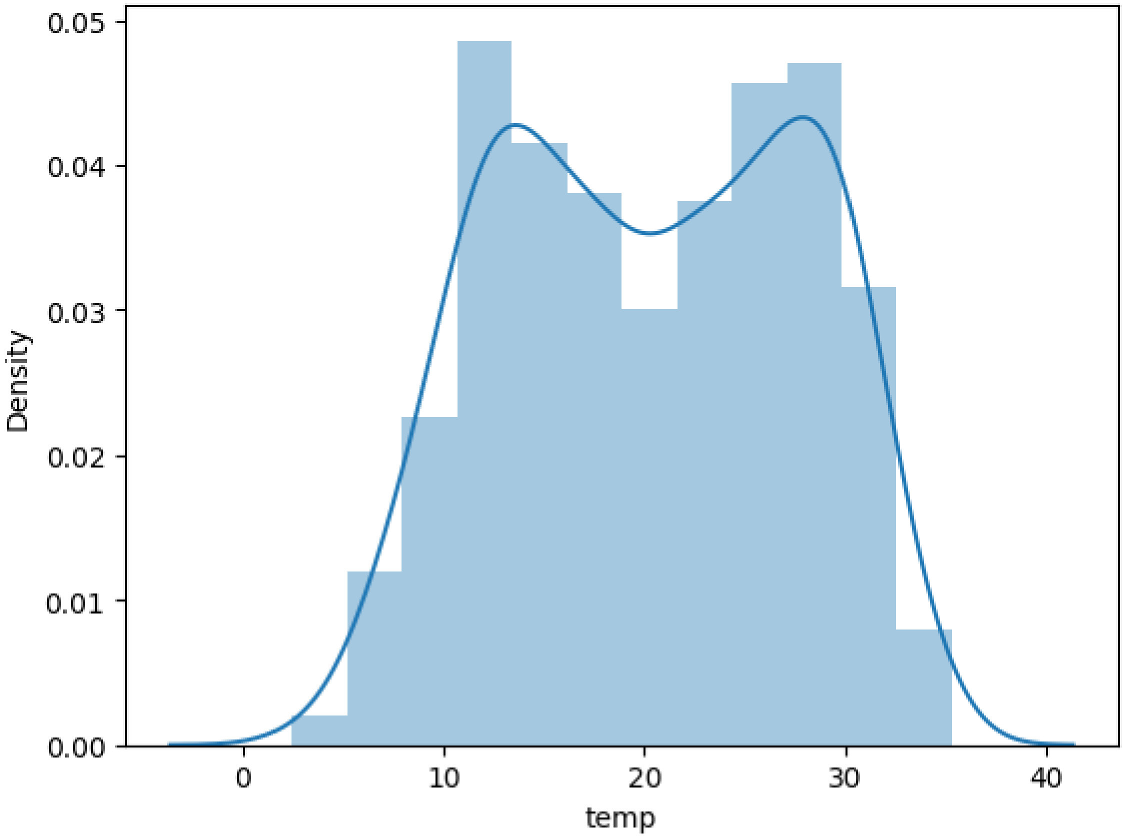
In [ ]:
```
bike_raw_dataframe.drop(bike_raw_dataframe[(bike_raw_dataframe['season']=='s
```

Skewness Check and Skewness Removal in Numerical Columns

Checking Skewness in the Numerical Columns Temprature

In [ ]:
```
numerical_vars=['temp','atemp','hum','windspeed','cnt']
seaborn.distplot(bike_raw_dataframe['temp'],kde=True)
bike_raw_dataframe['temp'].skew()
```

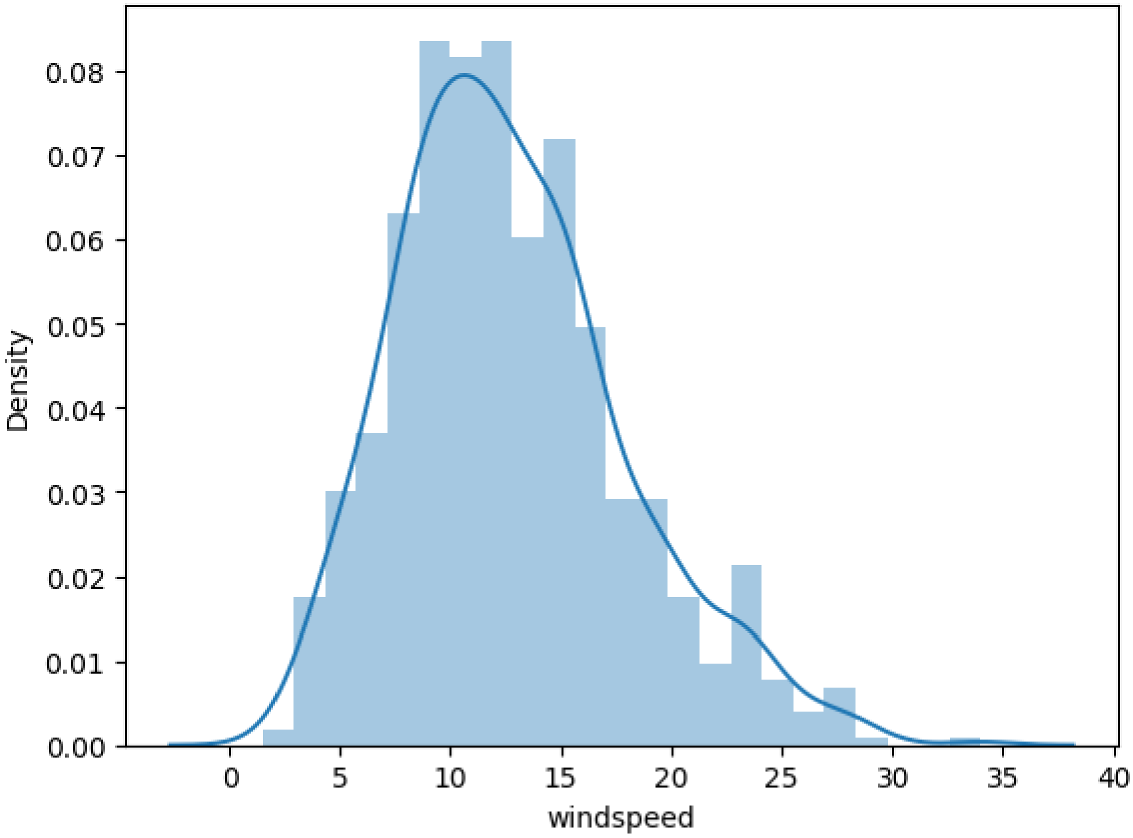
Out[ ]:
```
-0.055082380076152626
```



Checking Skewness in the Numerical Columns Windspeed

In [ ]:
```
seaborn.distplot(bike_raw_dataframe['windspeed'],kde=True)
bike_raw_dataframe['windspeed'].skew()
```

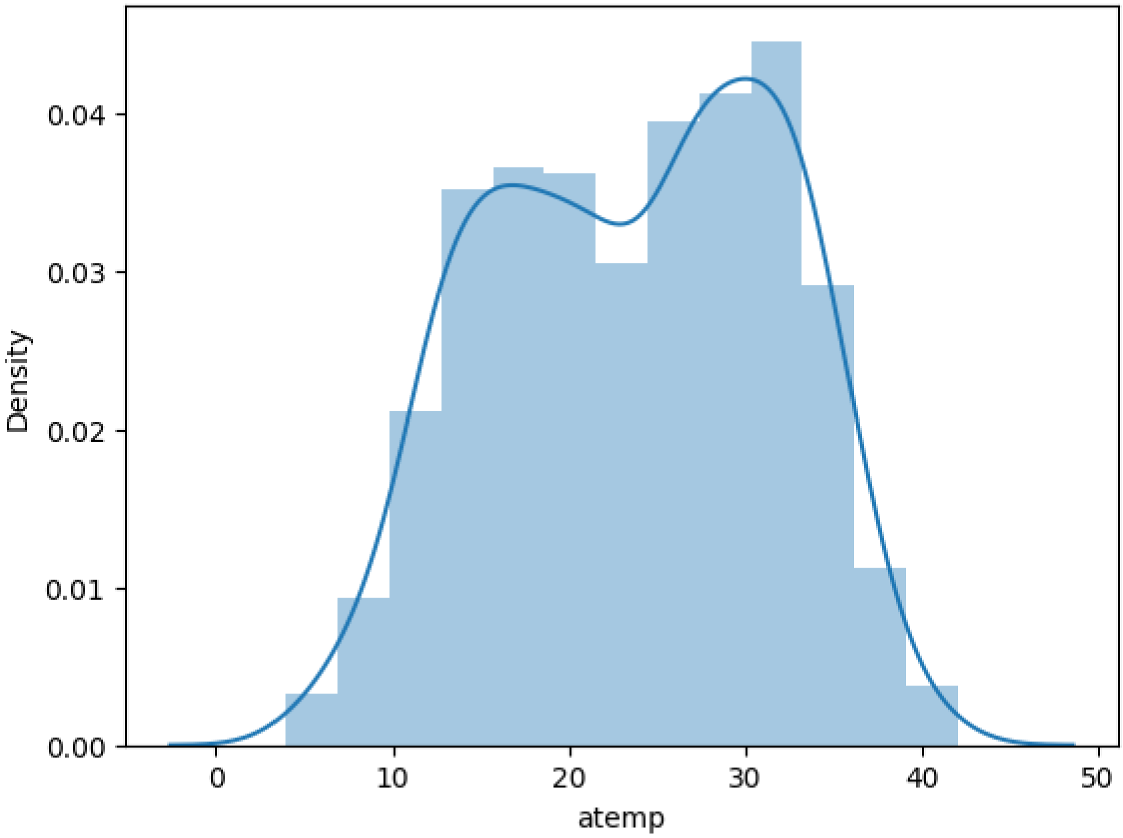
Out[ ]: 0.6726952901705223



Checking Skewness in the Numerical Columns ATemp

In [ ]:
```
seaborn.distplot(bike_raw_dataframe['atemp'],kde=True)
bike_raw_dataframe['atemp'].skew()
```

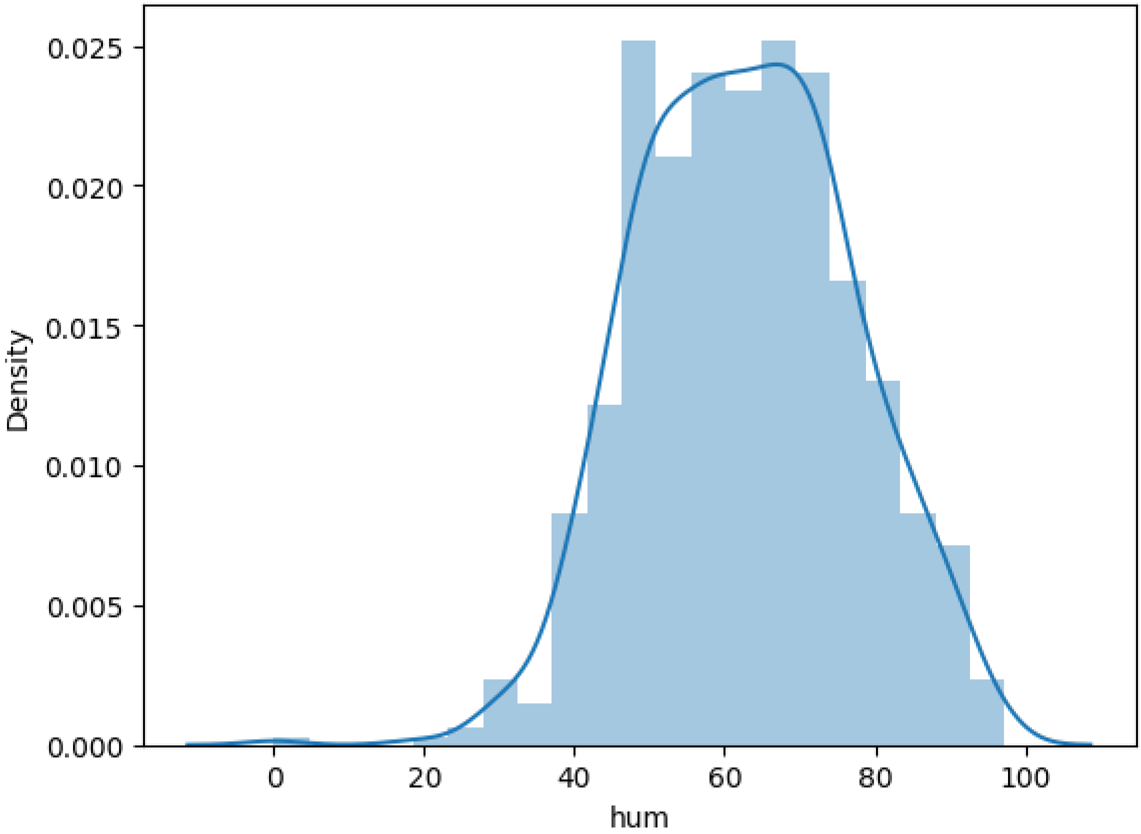
Out[ ]: `-0.1310820446584857`



Checking Skewness in the Numerical Columns Humidity

In [ ]:
```
seaborn.distplot(bike_raw_dataframe['hum'],kde=True)
bike_raw_dataframe['hum'].skew()
```

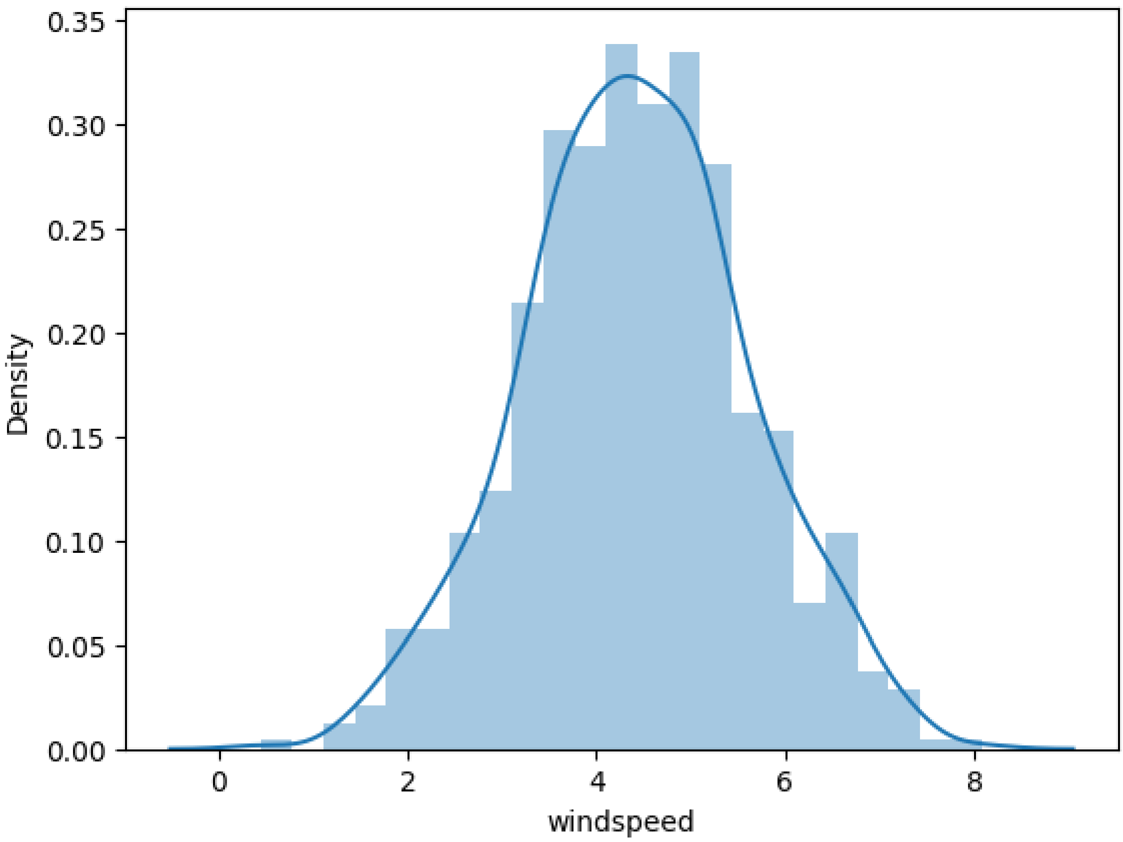
Out[ ]: `-0.06754397155614854`



Since we observed skewness in the Windspeed Column.We will apply BoxCox Transformation to make it normally distributed

In [ ]:
```
bike_raw_dataframe['windspeed']=stats.boxcox(bike_raw_dataframe['windspeed']
bike_raw_dataframe['windspeed'].skew()
seaborn.distplot(bike_raw_dataframe['windspeed'],kde=True)
```

Out[ ]: <Axes: xlabel='windspeed', ylabel='Density'>

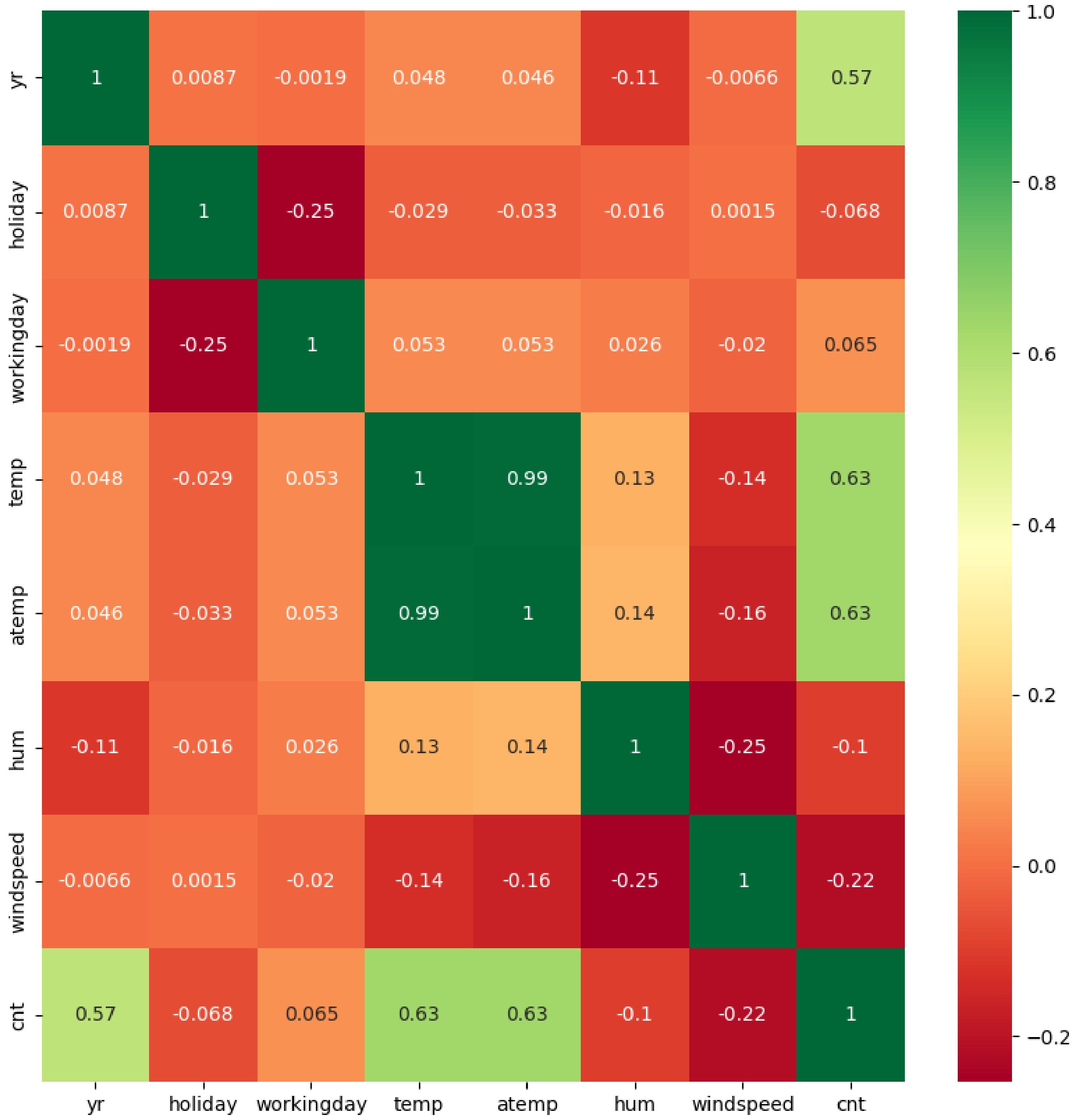


Correlation Graph between Variable

Plotting a heatmap between the variable to observed correlation

In [ ]:
```
plt.figure(figsize=(10,10))
seaborn.heatmap(bike_raw_dataframe.corr(),cmap='RdYlGn', annot = True)
```

Out[ ]: <Axes: >



Dummy Variable Creation

Creating Dummy Variables for the Categorical Variables

In [ ]:
```
seasons = pandas.get_dummies(bike_raw_dataframe['season'],drop_first=True)

weather= pandas.get_dummies(bike_raw_dataframe['weathersit'],drop_first=True

month= pandas.get_dummies(bike_raw_dataframe['mnth'],drop_first=True)

week_day= pandas.get_dummies(bike_raw_dataframe['weekday'],drop_first=True)
```

In [ ]:
```
bike_dataframe=pandas.concat([bike_raw_dataframe,seasons,weather,month,week_
```

We will drop the Categorical Columns since we have the dummy variables present

In [ ]:
```
bike_dataframe.drop(['season','weathersit','mnth','weekday','atemp'],axis=1,
```

In [ ]:
```
bike_dataframe.shape
```

Out[ ]:
```
(728, 29)
```

Model Creation and Feature Selection

Parameters and Assumption

Multicollinearity < 5 and P-value <.05

Error values should be normally distributed

Mean of Error should be zero

Getting the Target Column in variable Y

In [ ]:
```
Y=bike_dataframe.pop('cnt')
```

Splitting the Data in Test and Train

In [ ]:
```
X_train,X_test,Y_train,Y_test=train_test_split(bike_dataframe,Y,test_size=0.
```

Applying Min-Max scaling on the variables

In [ ]:
```
minmaxscaler=MinMaxScaler()
X_train['temp']=minmaxscaler.fit_transform(X_train['temp'].values.reshape(-1
X_train['hum']=minmaxscaler.fit_transform(X_train['hum'].values.reshape(-1,1
X_train['windspeed']=minmaxscaler.fit_transform(X_train['windspeed'].values.
```

In [ ]:
```
X_train.head(10)
X_train.columns
```

Out[ ]:
```
Index(['yr', 'holiday', 'workingday', 'temp', 'hum', 'windspeed', 'spring',
       'summer', 'winter', 'cloudy', 'light snow_rain', 'august', 'decembe
r',
       'february', 'january', 'july', 'june', 'march', 'may', 'november',
       'october', 'september', 'Monday', 'Saturday', 'Sunday', 'Thursday',
       'Tuesday', 'Wednesday'],
      dtype='object')
```

Applying RFE on the Training Dataset

In [ ]:
```
lm = LinearRegression()
rfe = RFE(lm, n_features_to_select=15)
rfe = rfe.fit(X_train, Y_train)
```

Below are the Columns which RFE support

In [ ]:
```
col_support=X_train.columns[rfe.support_]
col_support
```

Out[ ]:
```
Index(['yr', 'holiday', 'temp', 'hum', 'windspeed', 'spring', 'summer',
       'cloudy', 'light snow_rain', 'august', 'december', 'july', 'novembe
r',
       'october', 'september'],
      dtype='object')
```

Columns which RE does not support

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

Out[ ]:
```
Index(['workingday', 'winter', 'february', 'january', 'june', 'march', 'ma
y',
       'Monday', 'Saturday', 'Sunday', 'Thursday', 'Tuesday', 'Wednesday'],
      dtype='object')
```

Creating Dataset from the RFE selected Columns

In [ ]:
```
X_Train_RFE=X_train[col_support]
```

In [ ]:
```
def get_sm_model(dependent_var,independent_var):
    X_Train_RFE=sm.add_constant(independent_var)
    predict_model=sm.OLS(dependent_var,X_Train_RFE).fit()
    return predict_model
```

Creating a Model from the features that were selected and printing out the summary

In [ ]:
```
model_1=get_sm_model(dependent_var=Y_train,independent_var=X_Train_RFE)
model_1.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	cnt	**R-squared:**	0.866
Model:	OLS	**Adj. R-squared:**	0.856
Method:	Least Squares	**F-statistic:**	87.31
Date:	Mon, 12 Jun 2023	**Prob (F-statistic):**	1.50e-79
Time:	20:35:35	**Log-Likelihood:**	-1735.5
No. Observations:	218	**AIC:**	3503.
Df Residuals:	202	**BIC:**	3557.
Df Model:	15		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4775.6491	512.376	9.321	0.000	3765.357	5785.941
yr	2111.5691	101.743	20.754	0.000	1910.954	2312.184
holiday	-728.9450	310.577	-2.347	0.020	-1341.334	-116.556
temp	3493.8739	427.231	8.178	0.000	2651.470	4336.278
hum	-731.6111	360.423	-2.030	0.044	-1442.285	-20.937
windspeed	-1275.0245	315.248	-4.045	0.000	-1896.624	-653.425
spring	-2910.6179	384.441	-7.571	0.000	-3668.650	-2152.586
summer	-1687.8063	388.908	-4.340	0.000	-2454.646	-920.967
cloudy	-558.9580	132.298	-4.225	0.000	-819.821	-298.095
light snow_rain	-2009.9359	328.895	-6.111	0.000	-2658.444	-1361.428
august	-1693.6275	426.828	-3.968	0.000	-2535.238	-852.017
december	-1336.6564	356.820	-3.746	0.000	-2040.226	-633.087
july	-2012.7142	425.978	-4.725	0.000	-2852.648	-1172.780
november	-1399.0601	422.949	-3.308	0.001	-2233.021	-565.100
october	-798.1561	414.833	-1.924	0.056	-1616.114	19.802
september	-944.4353	426.524	-2.214	0.028	-1785.446	-103.424

Omnibus:	24.200	**Durbin-Watson:**	2.224
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	33.229
Skew:	-0.706	**Prob(JB):**	6.09e-08
Kurtosis:	4.290	**Cond. No.**	37.5

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

Determining Multicollinerity in the columns

In [ ]:

```
VIF_dataframe=pandas.DataFrame()
X_VIF=sm.add_constant(X_Train_RFE)
```

```
VIF_dataframe['features']=X_VIF.columns
VIF_dataframe['VIF'] = [variance_inflation_factor(X_VIF.values, i) for i in
print(VIF_dataframe)
```

```
            features         VIF
0              const  110.181615
1                 yr    1.076985
2            holiday    1.083539
3               temp    4.063570
4                hum    2.162444
5          windspeed    1.230500
6             spring   10.650445
7             summer   12.662510
8             cloudy    1.774625
9   light snow_rain    1.410956
10            august    6.083185
11          december    3.634025
12              july    7.461142
13          november    5.398066
14           october    6.018103
15         september    5.489726
```

Dropping Summer Column because of High P Value and High Collinearity

In [ ]:
```
X_Train_RFE_2=X_Train_RFE.drop(['summer'],axis=1)
model_2=get_sm_model(dependent_var=Y_train,independent_var=X_Train_RFE_2)
model_2.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	cnt	**R-squared:**	0.854
Model:	OLS	**Adj. R-squared:**	0.844
Method:	Least Squares	**F-statistic:**	84.75
Date:	Mon, 12 Jun 2023	**Prob (F-statistic):**	1.18e-76
Time:	20:35:35	**Log-Likelihood:**	-1745.2
No. Observations:	218	**AIC:**	3520.
Df Residuals:	203	**BIC:**	3571.
Df Model:	14		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3285.2920	396.613	8.283	0.000	2503.283	4067.301
yr	2117.0803	106.110	19.952	0.000	1907.861	2326.299
holiday	-903.4235	321.207	-2.813	0.005	-1536.754	-270.093
temp	3370.6990	444.618	7.581	0.000	2494.037	4247.361
hum	-817.6447	375.353	-2.178	0.031	-1557.736	-77.554
windspeed	-1229.2596	328.621	-3.741	0.000	-1877.207	-581.312
spring	-1451.6957	194.531	-7.463	0.000	-1835.256	-1068.136
cloudy	-582.9032	137.867	-4.228	0.000	-854.739	-311.067
light snow_rain	-1967.9679	342.890	-5.739	0.000	-2644.051	-1291.885
august	-75.5706	216.723	-0.349	0.728	-502.887	351.746
december	-119.2805	230.016	-0.519	0.605	-572.807	334.246
july	-391.2732	213.417	-1.833	0.068	-812.071	29.525
november	170.8723	228.569	0.748	0.456	-279.801	621.546
october	800.4983	198.974	4.023	0.000	408.177	1192.819
september	678.1486	214.101	3.167	0.002	256.001	1100.296

Omnibus:	28.045	**Durbin-Watson:**	2.220
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	38.792
Skew:	-0.800	**Prob(JB):**	3.77e-09
Kurtosis:	4.308	**Cond. No.**	18.9

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

Dropping August Column because of High P Value

In [ ]:

```
X_Train_RFE_3=X_Train_RFE_2.drop(['august'],axis=1)
model_3=get_sm_model(dependent_var=Y_train,independent_var=X_Train_RFE_3)
model_3.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	cnt	**R-squared:**	0.854
Model:	OLS	**Adj. R-squared:**	0.845
Method:	Least Squares	**F-statistic:**	91.66
Date:	Mon, 12 Jun 2023	**Prob (F-statistic):**	1.28e-77
Time:	20:35:36	**Log-Likelihood:**	-1745.3
No. Observations:	218	**AIC:**	3519.
Df Residuals:	204	**BIC:**	3566.
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3299.3459	393.709	8.380	0.000	2523.085	4075.607
yr	2120.2891	105.482	20.101	0.000	1912.314	2328.265
holiday	-897.5365	320.072	-2.804	0.006	-1528.610	-266.463
temp	3306.8844	404.334	8.179	0.000	2509.675	4104.094
hum	-803.9438	372.486	-2.158	0.032	-1538.361	-69.527
windspeed	-1224.6518	327.647	-3.738	0.000	-1870.661	-578.643
spring	-1457.4743	193.406	-7.536	0.000	-1838.805	-1076.144
cloudy	-587.3265	136.987	-4.287	0.000	-857.418	-317.235
light snow_rain	-1972.5821	341.896	-5.770	0.000	-2646.686	-1298.479
december	-120.9535	229.470	-0.527	0.599	-573.391	331.484
july	-360.7445	194.213	-1.857	0.065	-743.666	22.177
november	170.8990	228.076	0.749	0.455	-278.790	620.588
october	811.0830	196.221	4.134	0.000	424.202	1197.965
september	699.3206	204.869	3.414	0.001	295.389	1103.252

Omnibus:	27.424	**Durbin-Watson:**	2.216
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	37.657
Skew:	-0.788	**Prob(JB):**	6.65e-09
Kurtosis:	4.289	**Cond. No.**	18.3

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

Dropping November Column because of High P Value

In [ ]:

```
X_Train_RFE_4=X_Train_RFE_3.drop(['november'],axis=1)
model_4=get_sm_model(dependent_var=Y_train,independent_var=X_Train_RFE_4)
model_4.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	cnt	**R-squared:**	0.853
Model:	OLS	**Adj. R-squared:**	0.845
Method:	Least Squares	**F-statistic:**	99.46
Date:	Mon, 12 Jun 2023	**Prob (F-statistic):**	1.66e-78
Time:	20:35:36	**Log-Likelihood:**	-1745.6
No. Observations:	218	**AIC:**	3517.
Df Residuals:	205	**BIC:**	3561.
Df Model:	12		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3402.0218	368.699	9.227	0.000	2675.093	4128.950
yr	2129.4581	104.658	20.347	0.000	1923.114	2335.802
holiday	-870.6646	317.716	-2.740	0.007	-1497.075	-244.254
temp	3164.5019	356.520	8.876	0.000	2461.586	3867.418
hum	-767.4999	368.902	-2.080	0.039	-1494.829	-40.171
windspeed	-1236.9938	326.883	-3.784	0.000	-1881.477	-592.511
spring	-1528.0336	168.753	-9.055	0.000	-1860.747	-1195.320
cloudy	-597.7581	136.132	-4.391	0.000	-866.156	-329.360
light snow_rain	-1986.6595	341.014	-5.826	0.000	-2659.005	-1314.314
december	-175.6057	217.337	-0.808	0.420	-604.109	252.897
july	-355.7933	193.892	-1.835	0.068	-738.072	26.486
october	770.4909	188.393	4.090	0.000	399.055	1141.927
september	682.8554	203.469	3.356	0.001	281.695	1084.016

Omnibus:	25.682	**Durbin-Watson:**	2.230
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	33.708
Skew:	-0.770	**Prob(JB):**	4.79e-08
Kurtosis:	4.156	**Cond. No.**	17.1

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

Dropping December Column because of High P Value

In [ ]:

```
X_Train_RFE_5=X_Train_RFE_4.drop(['december'],axis=1)
model_5=get_sm_model(dependent_var=Y_train,independent_var=X_Train_RFE_5)
model_5.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	cnt	**R-squared:**	0.853
Model:	OLS	**Adj. R-squared:**	0.845
Method:	Least Squares	**F-statistic:**	108.6
Date:	Mon, 12 Jun 2023	**Prob (F-statistic):**	2.14e-79
Time:	20:35:36	**Log-Likelihood:**	-1745.9
No. Observations:	218	**AIC:**	3516.
Df Residuals:	206	**BIC:**	3556.
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3315.9214	352.667	9.402	0.000	2620.623	4011.220
yr	2126.2619	104.495	20.348	0.000	1920.245	2332.279
holiday	-888.5086	316.681	-2.806	0.006	-1512.859	-264.158
temp	3264.9023	333.883	9.779	0.000	2606.637	3923.168
hum	-808.7193	365.050	-2.215	0.028	-1528.432	-89.007
windspeed	-1187.3129	320.777	-3.701	0.000	-1819.740	-554.886
spring	-1494.9144	163.561	-9.140	0.000	-1817.382	-1172.446
cloudy	-592.1041	135.837	-4.359	0.000	-859.913	-324.295
light snow_rain	-1979.5740	340.614	-5.812	0.000	-2651.111	-1308.037
july	-360.2882	193.649	-1.861	0.064	-742.077	21.500
october	798.8776	184.932	4.320	0.000	434.275	1163.480
september	695.9577	202.651	3.434	0.001	296.422	1095.493

Omnibus:	27.068	**Durbin-Watson:**	2.232
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	35.923
Skew:	-0.800	**Prob(JB):**	1.58e-08
Kurtosis:	4.181	**Cond. No.**	16.9

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

Dropping July Column because of High P Value

In [ ]:

```
X_Train_RFE_6=X_Train_RFE_5.drop(['july'],axis=1)
model_6=get_sm_model(dependent_var=Y_train,independent_var=X_Train_RFE_6)
model_6.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	cnt	**R-squared:**	0.850
Model:	OLS	**Adj. R-squared:**	0.843
Method:	Least Squares	**F-statistic:**	117.7
Date:	Mon, 12 Jun 2023	**Prob (F-statistic):**	1.06e-79
Time:	20:35:36	**Log-Likelihood:**	-1747.8
No. Observations:	218	**AIC:**	3518.
Df Residuals:	207	**BIC:**	3555.
Df Model:	10		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3381.3714	352.988	9.579	0.000	2685.459	4077.284
yr	2125.3490	105.113	20.220	0.000	1918.119	2332.579
holiday	-856.1107	318.076	-2.692	0.008	-1483.194	-229.027
temp	2974.8916	297.013	10.016	0.000	2389.332	3560.451
hum	-773.5959	366.723	-2.109	0.036	-1496.586	-50.606
windspeed	-1129.1992	321.145	-3.516	0.001	-1762.334	-496.064
spring	-1533.7395	163.186	-9.399	0.000	-1855.459	-1212.020
cloudy	-589.1455	136.633	-4.312	0.000	-858.516	-319.775
light snow_rain	-2025.8591	341.718	-5.928	0.000	-2699.553	-1352.165
october	844.0274	184.420	4.577	0.000	480.445	1207.609
september	782.4000	198.422	3.943	0.000	391.213	1173.587

Omnibus:	27.484	**Durbin-Watson:**	2.194
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	36.450
Skew:	-0.812	**Prob(JB):**	1.22e-08
Kurtosis:	4.173	**Cond. No.**	16.8

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

Checking Collinearity among remaining Columns

In [ ]:

```
VIF_dataframe=pandas.DataFrame()
X_VIF=sm.add_constant(X_Train_RFE_6)
VIF_dataframe['features']=X_VIF.columns
VIF_dataframe['VIF'] = [variance_inflation_factor(X_VIF.values, i) for i in
print(VIF_dataframe)
```

```
            features        VIF
0              const  47.894160
1                 yr   1.052807
2            holiday   1.040876
3               temp   1.798736
4                hum   2.050344
5          windspeed   1.169530
6             spring   1.757541
7             cloudy   1.733568
8    light snow_rain   1.394977
9            october   1.089332
10         september   1.088116
```

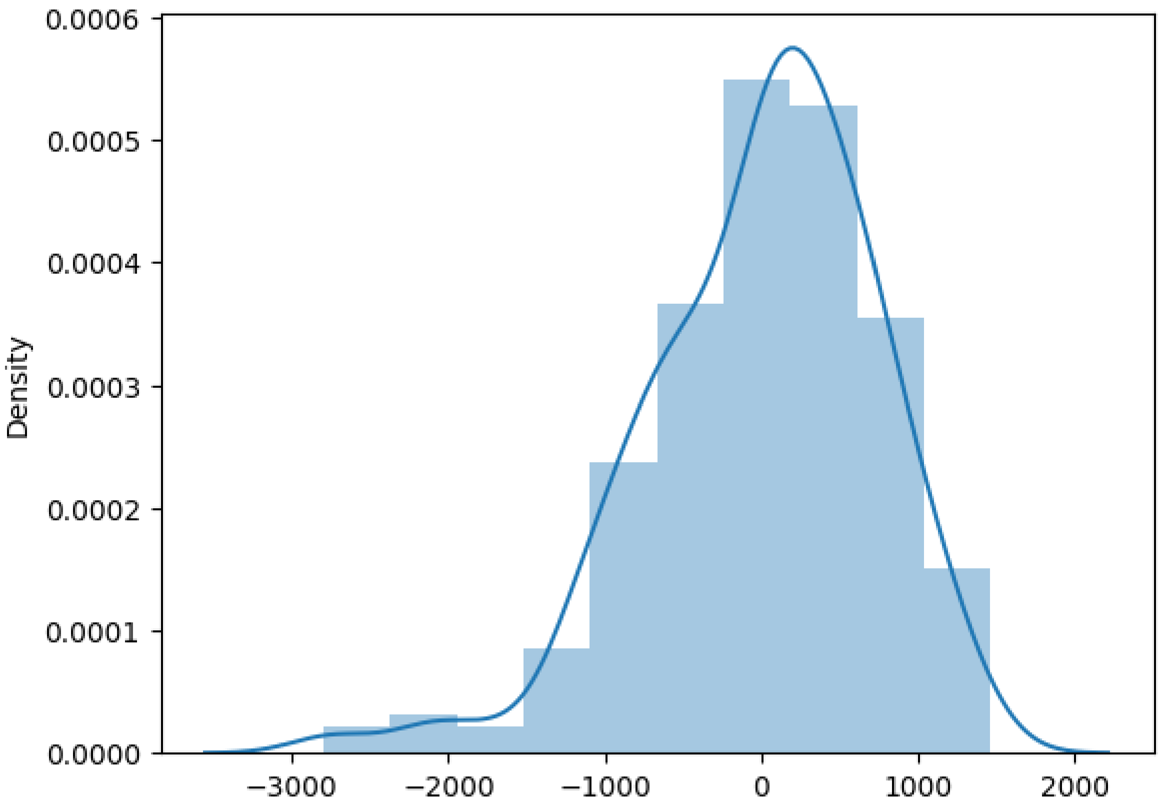
Getting the predicted Values for the Training Dataset and performing Residual Analysis

In [ ]:
```
X_Train_RFE_const=sm.add_constant(X_Train_RFE_6)
```

Plotting Graph between Errors and we observe that they are normally distributed along 0

In [ ]:
```
Y_train_predict=model_6.predict(X_Train_RFE_const)
seaborn.distplot(Y_train-Y_train_predict,kde=True,bins=10)
```

Out[ ]: <Axes: ylabel='Density'>



Mean of the error is also zero

In [ ]:
```
int((Y_train-Y_train_predict).mean())
```

Out[ ]: 0

Applying Model on Test Dataset

Scaling the Test Data based on min-max scaling

In [ ]:
```
X_test['temp']=minmaxscaler.fit_transform(X_test['temp'].values.reshape(-1,1
X_test['hum']=minmaxscaler.fit_transform(X_test['hum'].values.reshape(-1,1))
X_test['windspeed']=minmaxscaler.fit_transform(X_test['windspeed'].values.re
```

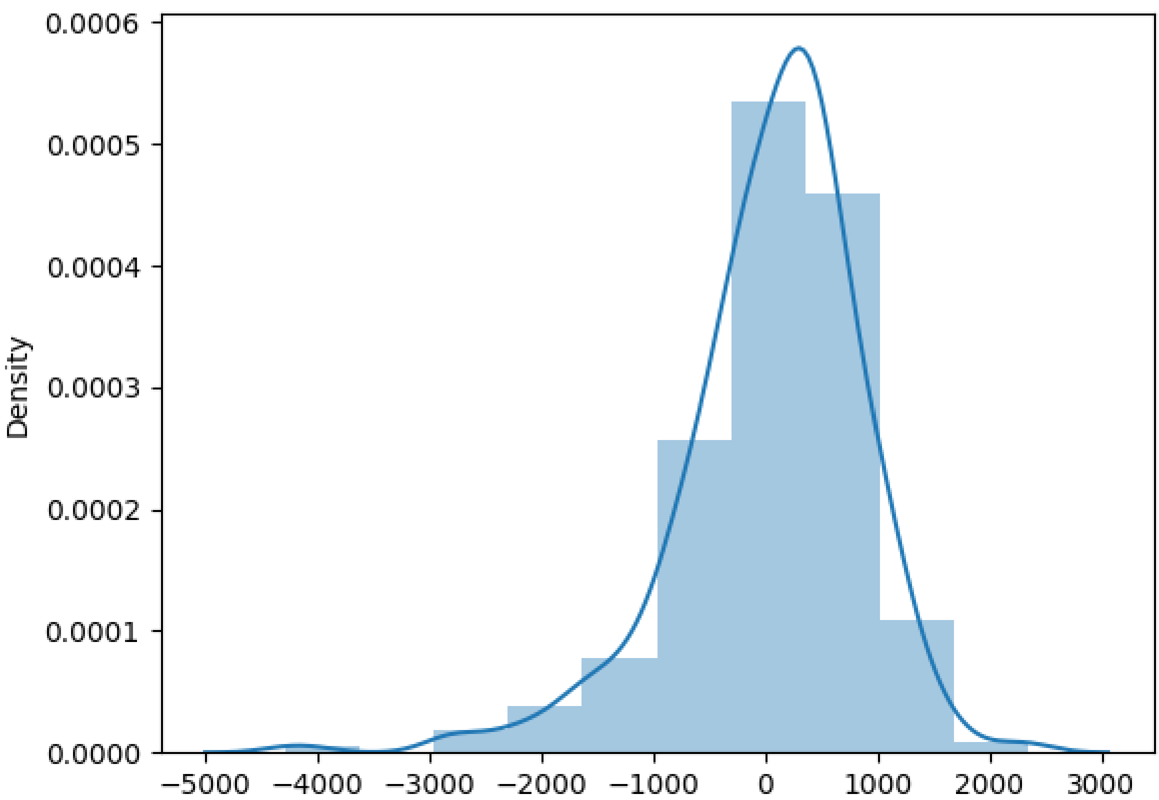
Predicting values for the test dataset

In [ ]:
```
X_test_RFE=X_test[X_Train_RFE_6.columns]
X_test_const=sm.add_constant(X_test_RFE)
Y_predict=model_6.predict(X_test_const)
```

Performing Residual Analysis on the Test values

In [ ]:
```
seaborn.distplot(Y_test-Y_predict,kde=True,bins=10)
```

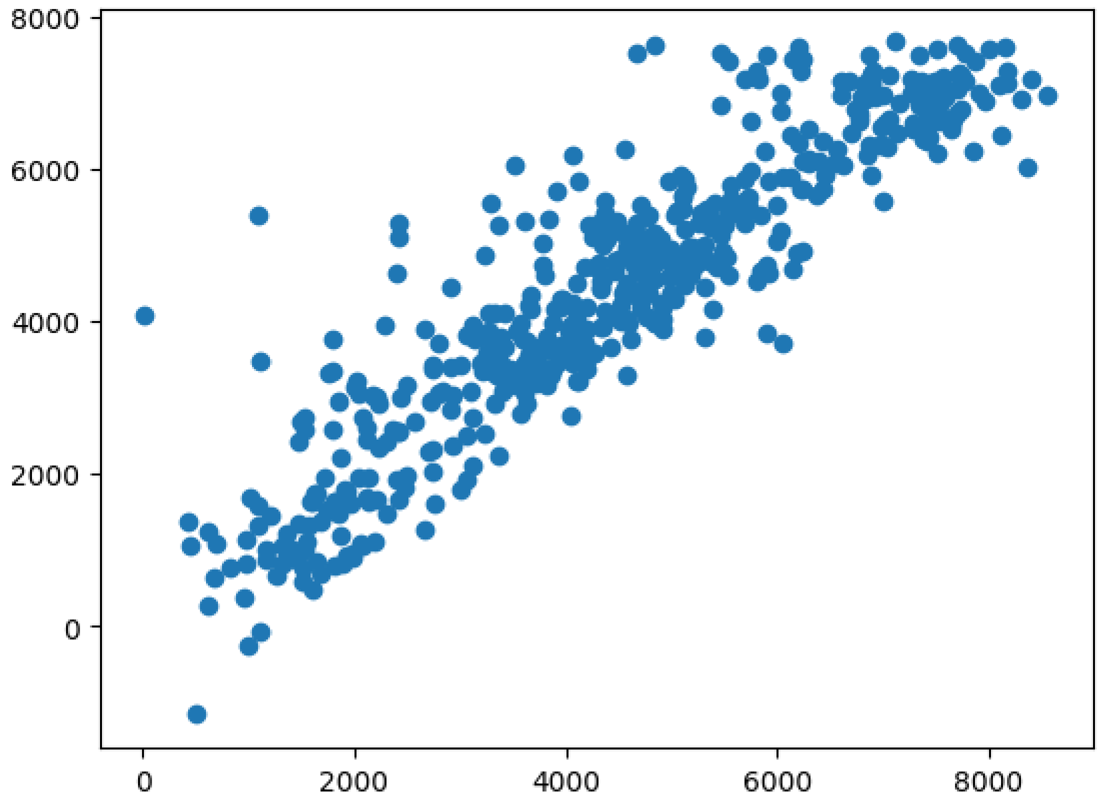
Out[ ]: <Axes: ylabel='Density'>



In [ ]:

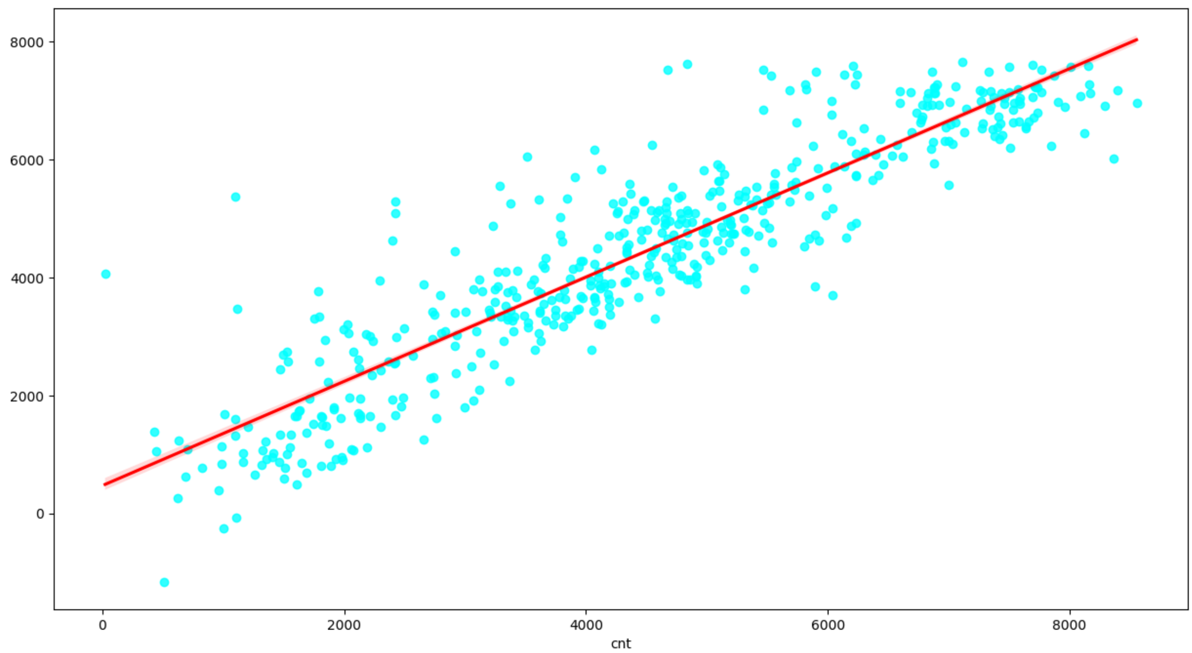
In [ ]:
```
plt.scatter(Y_test,Y_predict)
```

Out[ ]: <matplotlib.collections.PathCollection at 0x12d55b190>



In [ ]:
```
plt.figure(figsize=(15,8))
seaborn.regplot(x=Y_test, y=Y_predict, ci=68, fit_reg=True,scatter_kws={"col
```

Out[ ]: <Axes: xlabel='cnt'>



Feature Coffecients

In [ ]:
```
model_1.params
```

Out[ ]:
```
const               4775.649051
yr                  2111.569089
holiday             -728.945049
temp                3493.873913
hum                 -731.611131
windspeed          -1275.024515
spring             -2910.617891
summer             -1687.806323
cloudy              -558.958026
light snow_rain    -2009.935903
august             -1693.627482
december           -1336.656385
july               -2012.714243
november           -1399.060094
october             -798.156137
september           -944.435306
dtype: float64
```

Model Evaluation Parameters

In [ ]:
```
r2_score(Y_test,Y_predict)
mean_squared_error(Y_test,Y_predict)
rmse=numpy.sqrt(mean_squared_error(Y_test,Y_predict))
print("R2 Score of the model on the Train Dataset {}".format(r2_score(Y_trai
print("R2 Score of the model on the Test Dataset {}".format(r2_score(Y_test,
```

```
R2 Score of the model on the Train Dataset 0.8504799608453713
R2 Score of the model on the Test Dataset 0.819033897236972
```