Notebook

March 19, 2024

1 Problem Statement

A bike-sharing system is a service in which bikes are made available for shared use to individuals on a short term basis for a price or free. Many bike share systems allow people to borrow a bike from a "dock" which is usually computer-controlled wherein the user enters the payment information, and the system unlocks it. This bike can then be returned to another dock belonging to the same system.

A US bike-sharing provider BoomBikes has recently suffered considerable dips in their revenues due to the ongoing Corona pandemic. The company is finding it very difficult to sustain in the current market scenario. So, it has decided to come up with a mindful business plan to be able to accelerate its revenue as soon as the ongoing lockdown comes to an end, and the economy restores to a healthy state.

In such an attempt, BoomBikes aspires to understand the demand for shared bikes among the people after this ongoing quarantine situation ends across the nation due to Covid-19. They have planned this to prepare themselves to cater to the people's needs once the situation gets better all around and stand out from other service providers and make huge profits.

They have contracted a consulting company to understand the factors on which the demand for these shared bikes depends. Specifically, they want to understand the factors affecting the demand for these shared bikes in the American market. The company wants to know:

Which variables are significant in predicting the demand for shared bikes. How well those variables describe the bike demands Based on various meteorological surveys and people's styles, the service provider firm has gathered a large dataset on daily bike demands across the American market based on some factors.

2 Business Goal

You 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.

[45]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
import seaborn as sns
import statsmodels
import statsmodels.api as sm
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import MinMaxScaler
from statsmodels.stats.outliers_influence import variance_inflation_factor

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

[46]:
```
bike_sharing_data = pd.read_csv('day.csv')      ## ../15 Upgrad/05 Machine␣
  ↪Learning 01/Assignment-Bike-Sharing/
bike_sharing_data.head()
```

[46]:
```
   instant      dteday  season  yr  mnth  holiday  weekday  workingday  \
0        1  01-01-2018       1   0     1        0        6           0
1        2  02-01-2018       1   0     1        0        0           0
2        3  03-01-2018       1   0     1        0        1           1
3        4  04-01-2018       1   0     1        0        2           1
4        5  05-01-2018       1   0     1        0        3           1

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

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

[47]:
```
bike_sharing_data.shape         # data has 730 records and 16 columns (or␣
  ↪features)
```

[47]: (730, 16)

3 Finding the datatypes of the columns in the dataset

[48]:
```
bike_sharing_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   instant     730 non-null    int64
 1   dteday      730 non-null    object
 2   season      730 non-null    int64
 3   yr          730 non-null    int64
 4   mnth        730 non-null    int64
 5   holiday     730 non-null    int64
 6   weekday     730 non-null    int64
 7   workingday  730 non-null    int64
 8   weathersit  730 non-null    int64
 9   temp        730 non-null    float64
 10  atemp       730 non-null    float64
 11  hum         730 non-null    float64
 12  windspeed   730 non-null    float64
 13  casual      730 non-null    int64
 14  registered  730 non-null    int64
 15  cnt         730 non-null    int64
dtypes: float64(4), int64(11), object(1)
memory usage: 91.4+ KB
```

4 No Null/blank values obseved in the dataset

[49]:
```
bike_sharing_data.isnull().sum()
```

[49]:
```
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
```

5 checking for duplicate records and no duplicates are seen

[50]:
```
duplicateRows = bike_sharing_data[bike_sharing_data.duplicated()]
duplicateRows.count()
```

[50]:
```
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
```

6 Removing unwanted columns, viewing left over columns

[51]:
```
bike_sharing_data = bike_sharing_data.drop(['instant', 'dteday'], axis=1)
bike_sharing_data.columns
```

[51]:
```
Index(['season', 'yr', 'mnth', 'holiday', 'weekday', 'workingday',
       'weathersit', 'temp', 'atemp', 'hum', 'windspeed', 'casual',
       'registered', 'cnt'],
      dtype='object')
```

7 'casual' + 'registered' = 'cnt'. Target var is 'cnt', so removing columns 'casual' and 'registered'

[52]:
```
bike_sharing_data = bike_sharing_data.drop(['casual', 'registered'], axis=1)
bike_sharing_data.columns
```

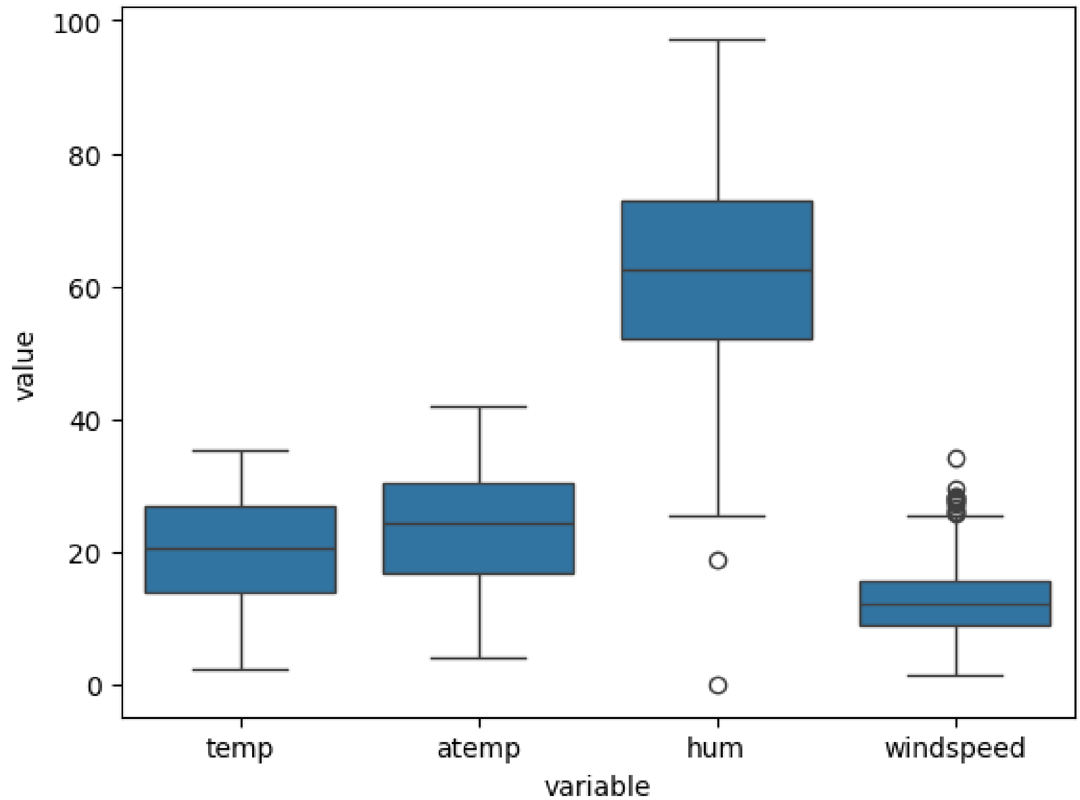
[52]:
```
Index(['season', 'yr', 'mnth', 'holiday', 'weekday', 'workingday',
       'weathersit', 'temp', 'atemp', 'hum', 'windspeed', 'cnt'],
      dtype='object')
```

8 converting 'yr' to int64 from categorical

[53]:
```
bike_sharing_data['yr'] = bike_sharing_data.yr.astype('int64')
```

9 Boxplot for 4 important numeric columns

[54]:
```
df = pd.DataFrame(data = bike_sharing_data, columns =
 ↪['temp','atemp','hum','windspeed'])
sns.boxplot(x="variable", y="value", data=pd.melt(df))
plt.show()
```



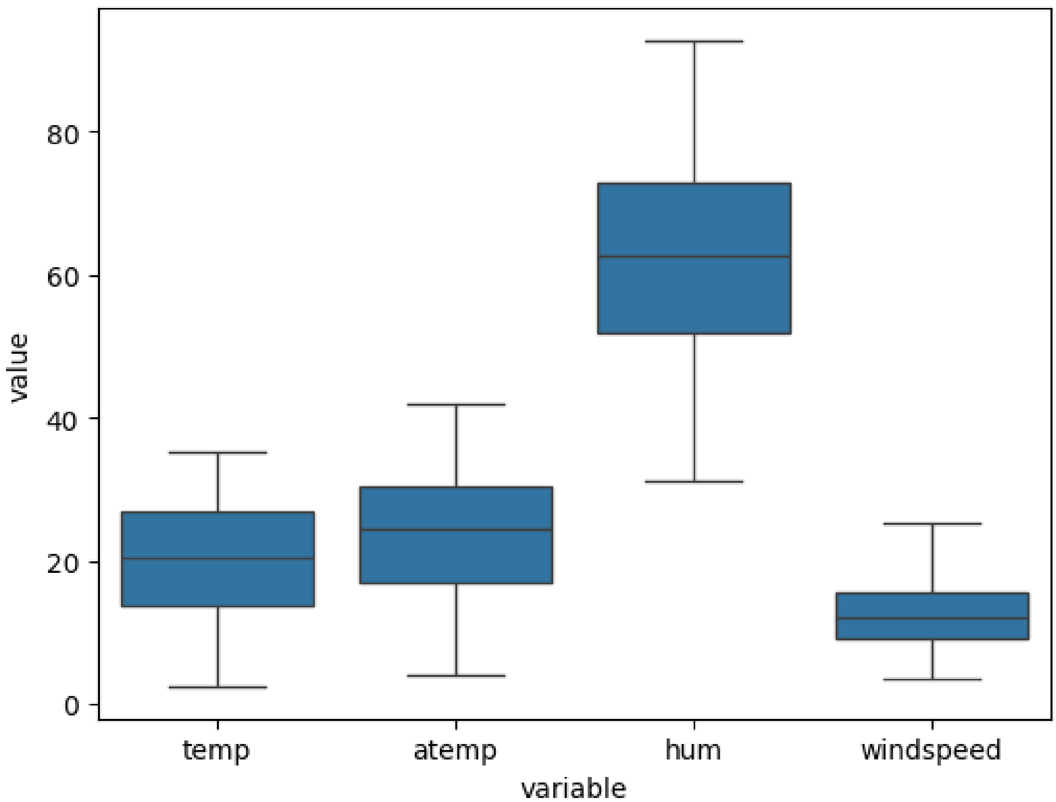
10 Treating outlier for columns 'hum' and 'windspeed'

[55]:
```
upper_limit = bike_sharing_data['hum'].quantile(0.99)
lower_limit = bike_sharing_data['hum'].quantile(0.01)
bike_sharing_data['hum'] = np.where(bike_sharing_data['hum'] >= upper_limit,
 ↪upper_limit, np.where(bike_sharing_data['hum'] <= lower_limit, lower_limit,
 ↪bike_sharing_data['hum']))
```

[56]:
```
upper_limit = bike_sharing_data['windspeed'].quantile(0.98)
lower_limit = bike_sharing_data['windspeed'].quantile(0.01)
bike_sharing_data['windspeed'] = np.where(bike_sharing_data['windspeed'] >=
 ↪upper_limit, upper_limit, np.where(bike_sharing_data['windspeed'] <=
 ↪lower_limit, lower_limit, bike_sharing_data['windspeed']))
```

11 Checking the data distribution through boxplots again, after treating the outliers

[57]:
```
df = pd.DataFrame(data = bike_sharing_data, columns =
 ↪['temp','atemp','hum','windspeed'])
sns.boxplot(x="variable", y="value", data=pd.melt(df))
plt.show()
```



12 changing numeric columns to categorical

[58]:
```
bike_sharing_data['season'] = bike_sharing_data.season.astype('category')
bike_sharing_data['weathersit'] = bike_sharing_data.weathersit.
    ↪astype('category')
bike_sharing_data['mnth'] = bike_sharing_data.mnth.astype('category')
bike_sharing_data['weekday'] = bike_sharing_data.weekday.astype('category')
```

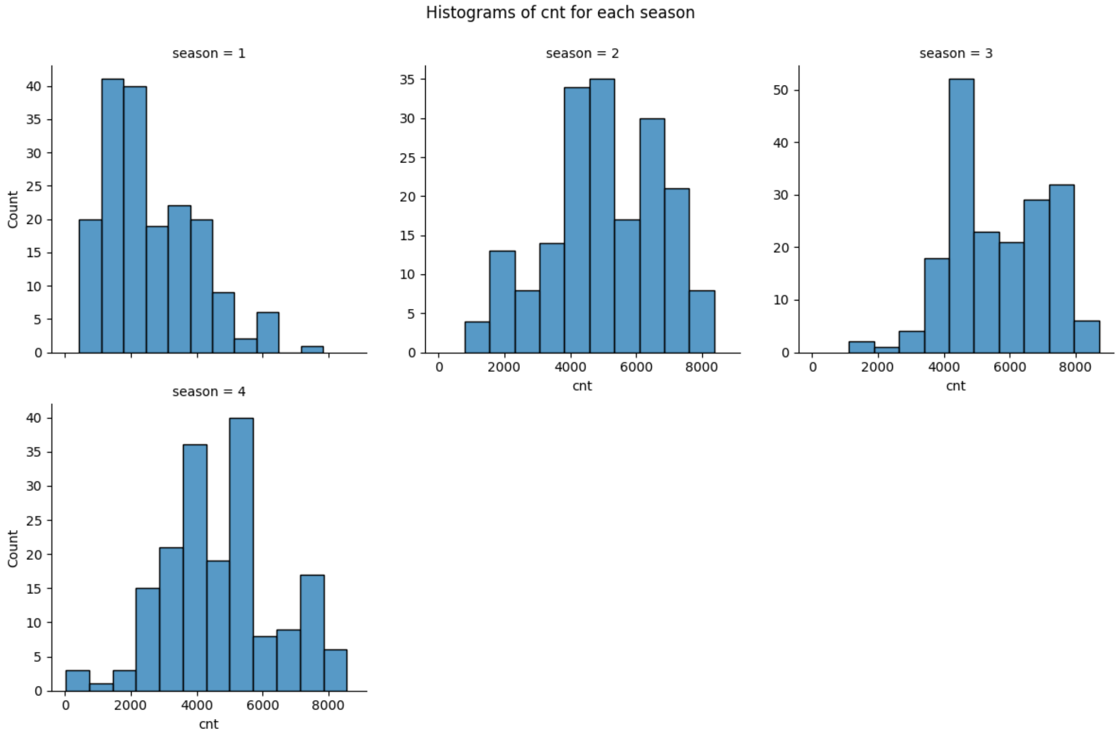
[59]:
```
bike_sharing_data.info()
```

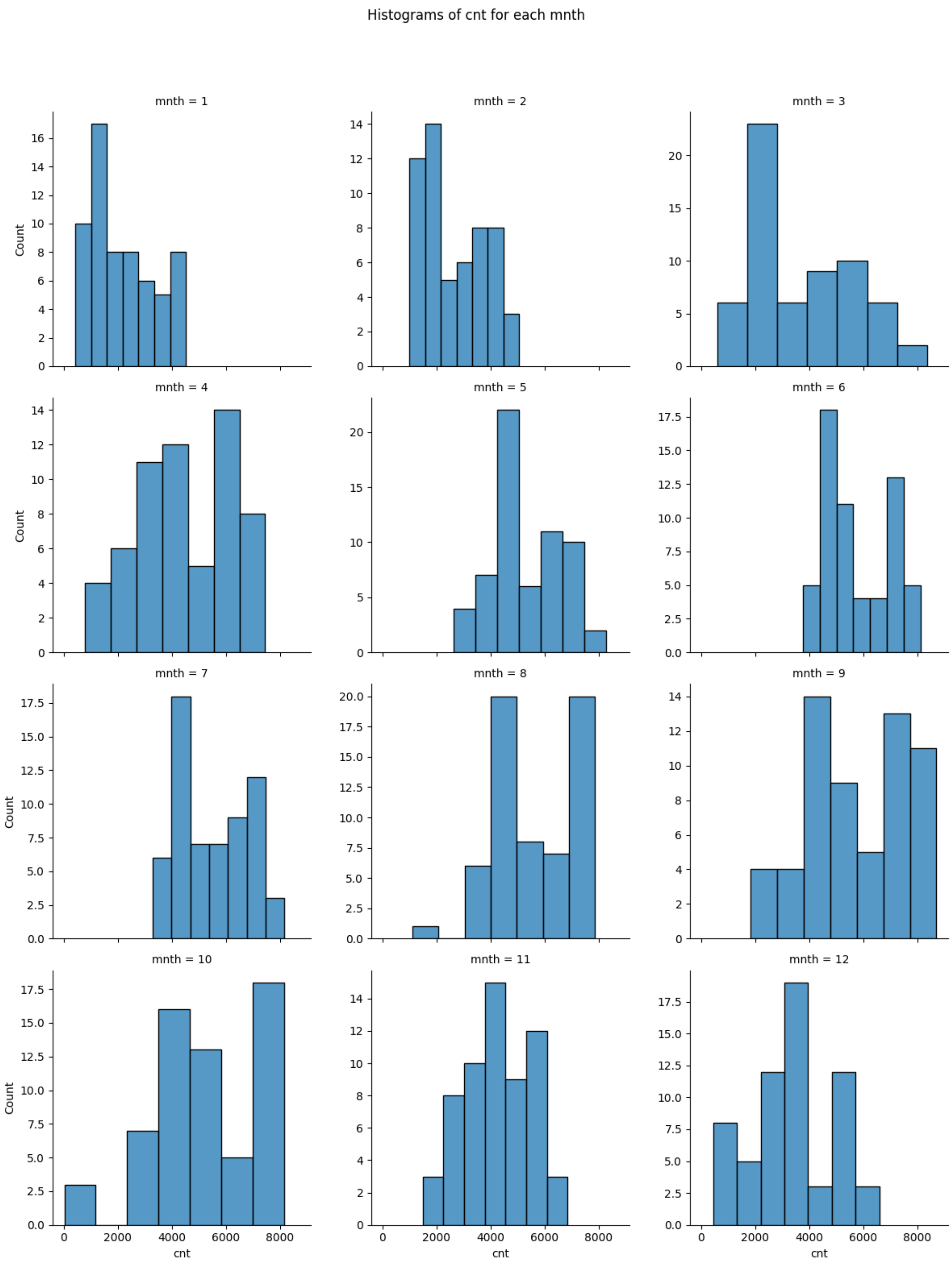
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   season      730 non-null    category
 1   yr          730 non-null    int64
 2   mnth        730 non-null    category
 3   holiday     730 non-null    int64
 4   weekday     730 non-null    category
 5   workingday  730 non-null    int64
 6   weathersit  730 non-null    category
 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
dtypes: category(4), float64(4), int64(4)
memory usage: 49.7 KB
```

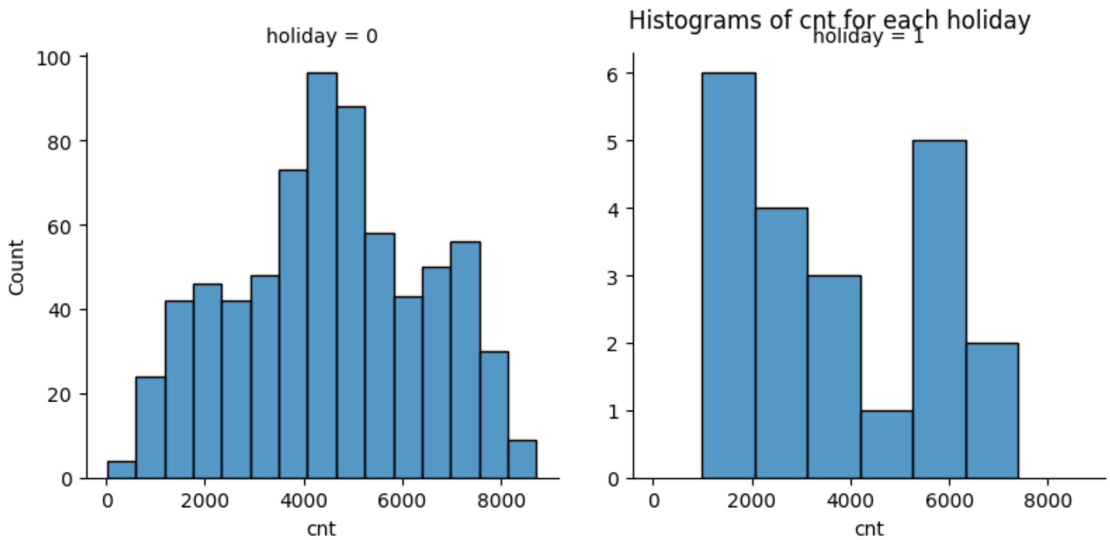
13 Viewing histogrms for categorical data

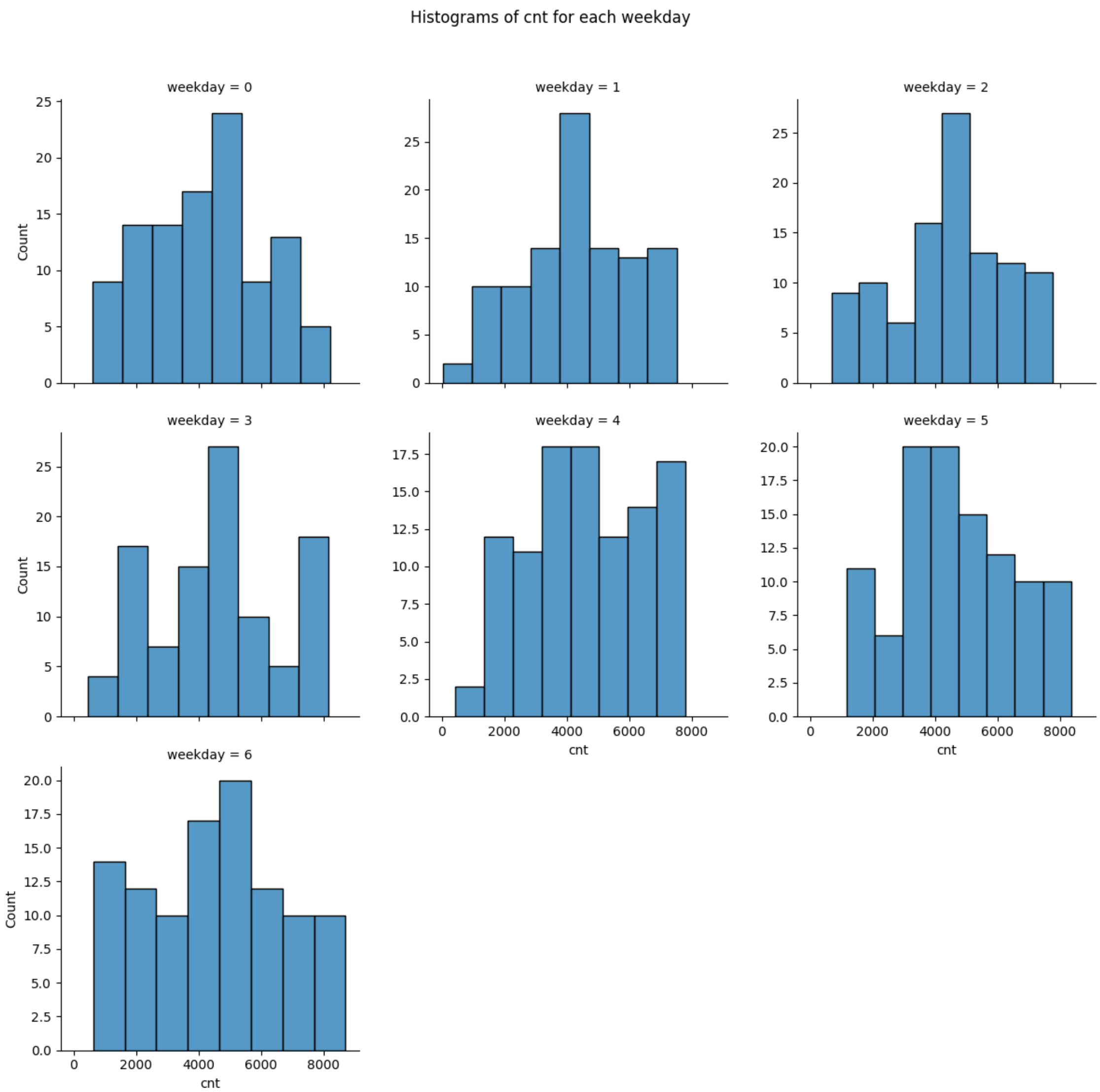
[60]:
```
plt.figure(figsize = (20,10))
categorical_columns = ['season', 'mnth',␣
    ↪'holiday','weekday','workingday','weathersit']
target_column = 'cnt'
for cat_column in categorical_columns:
    g = sns.FacetGrid(bike_sharing_data, col=cat_column, col_wrap=3, height=4,␣
    ↪sharey=False)
    g.map(sns.histplot, target_column)
    g.set_axis_labels(target_column, "Count")
    g.fig.subplots_adjust(top=0.9)
    g.fig.suptitle(f'Histograms of {target_column} for each {cat_column}')

    plt.show()
```

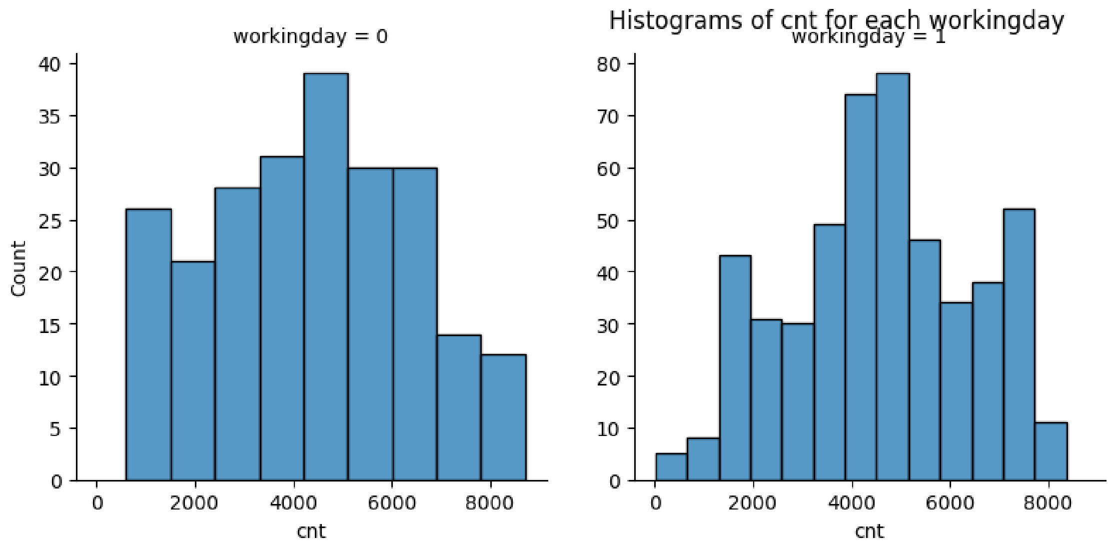
```
<Figure size 2000x1000 with 0 Axes>
```

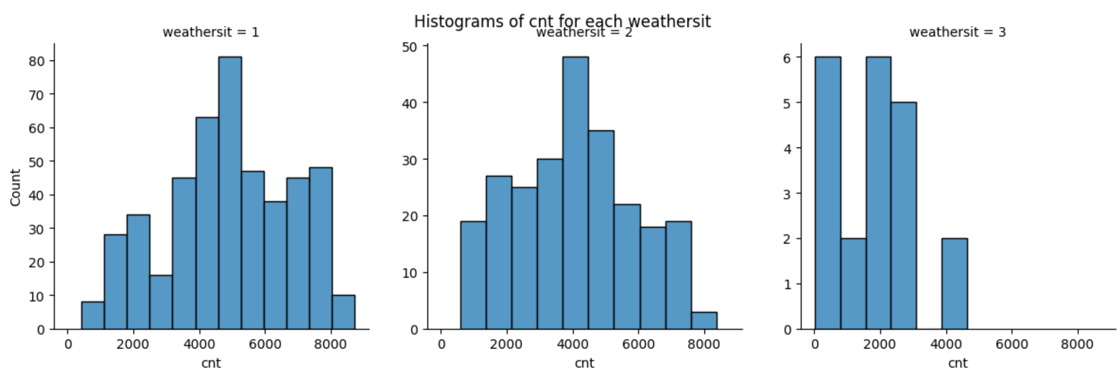

Histograms of cnt for each season
season = 1
season = 2
season = 3
season = 4
Count
cnt
0
2000
4000
6000
8000


Histograms of cnt for each mnth
mnth = 1
mnth = 2
mnth = 3
mnth = 4
mnth = 5
mnth = 6
mnth = 7
mnth = 8
mnth = 9
mnth = 10
mnth = 11
mnth = 12
Count
cnt
0
2000
4000
6000
8000


Histograms of cnt for each holiday
holiday = 0
holiday = 1
Count
cnt
cnt
0
20
40
60
80
100
0
1
2
3
4
5
6
0
2000
4000
6000
8000
0
2000
4000
6000
8000


Histograms of cnt for each weekday
weekday = 0
weekday = 1
weekday = 2
weekday = 3
weekday = 4
weekday = 5
weekday = 6
Count
cnt
0
2000
4000
6000
8000

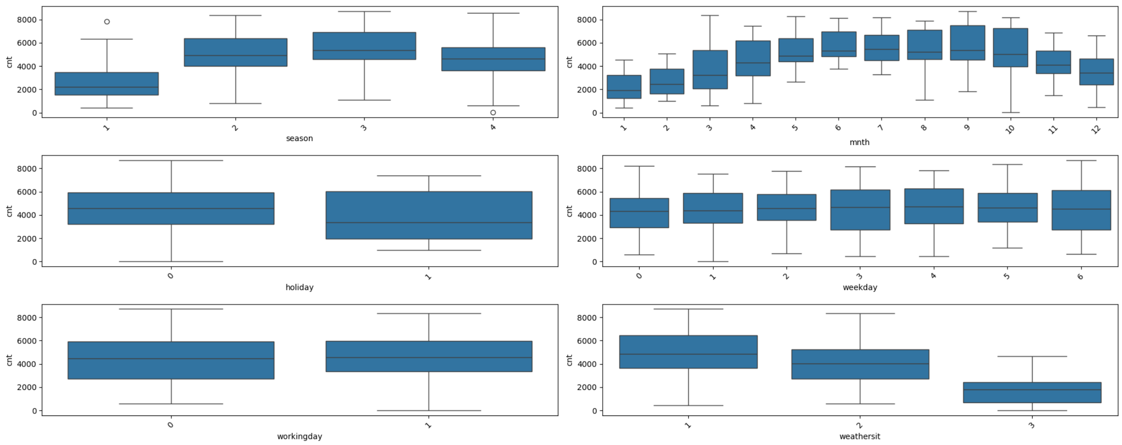




14 Understanding the distribution, using boxplots

[61]:
```
plt.figure(figsize=(20, 8))
categorical_columns = ['season','mnth',␣
↪'holiday','weekday','workingday','weathersit']
target_column = bike_sharing_data['cnt']

for i, col in enumerate(categorical_columns):
    plt.subplot(3, 2, i + 1)
    sns.boxplot(x=bike_sharing_data[col], y=target_column)
    plt.xlabel(col)
    plt.xticks(rotation=45)

plt.tight_layout()
```

```
plt.show()
```



15 Understanding the boxplots

season: median close to 55000, season 3 takes more booking, followed by season 2 and season 4. Out of all season 1, we have very less demand.

mnth: more booking in the months of 6, 7, 8, 9, 10 with almost the same median value. Of all considerable booking from April to November, higher demand

holiday: 3000 to 6000 bikes booked. Mean shows little above to 4000 bikes. And even on holidays, there is more booking. But median stands less than 4000.

weekday: the median lies between 4000 to 4500 and more booking on wednesdays. Very close trend each day as compared all the days in the week.

workingday: the median stands same for working day and NOT a working a day. But working day spread more even & perfect. Seems to be a good variable

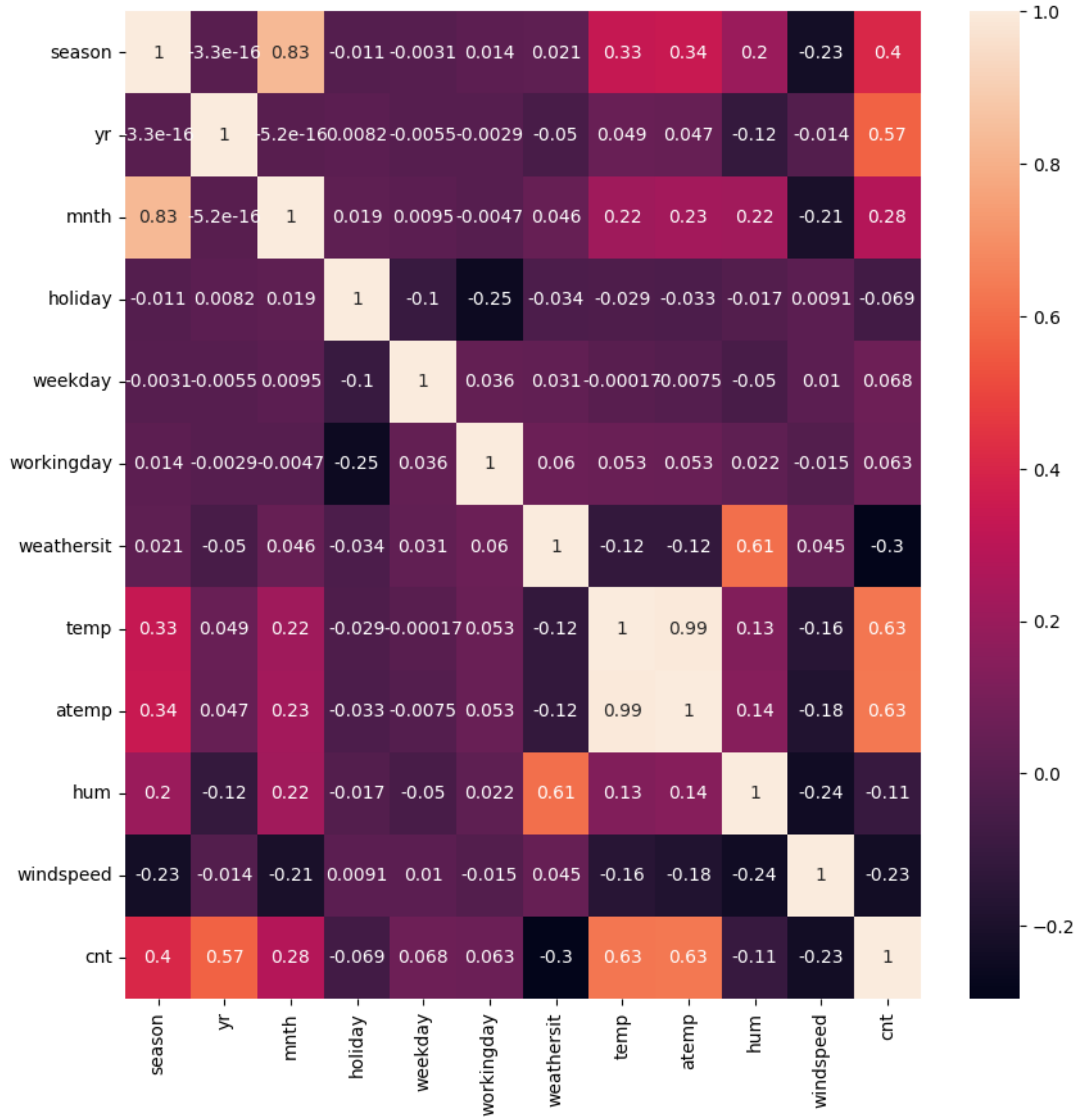
weathersit: very look demand in weathersit-3. More demand in weathersit-1 then comes weather-2. Varying median in all the weathersit 1,2,3

16 viewing the correlation

16.0.1 atemp vs temp are the only two features having high correlation, indicates that they are highly linearly dependent.

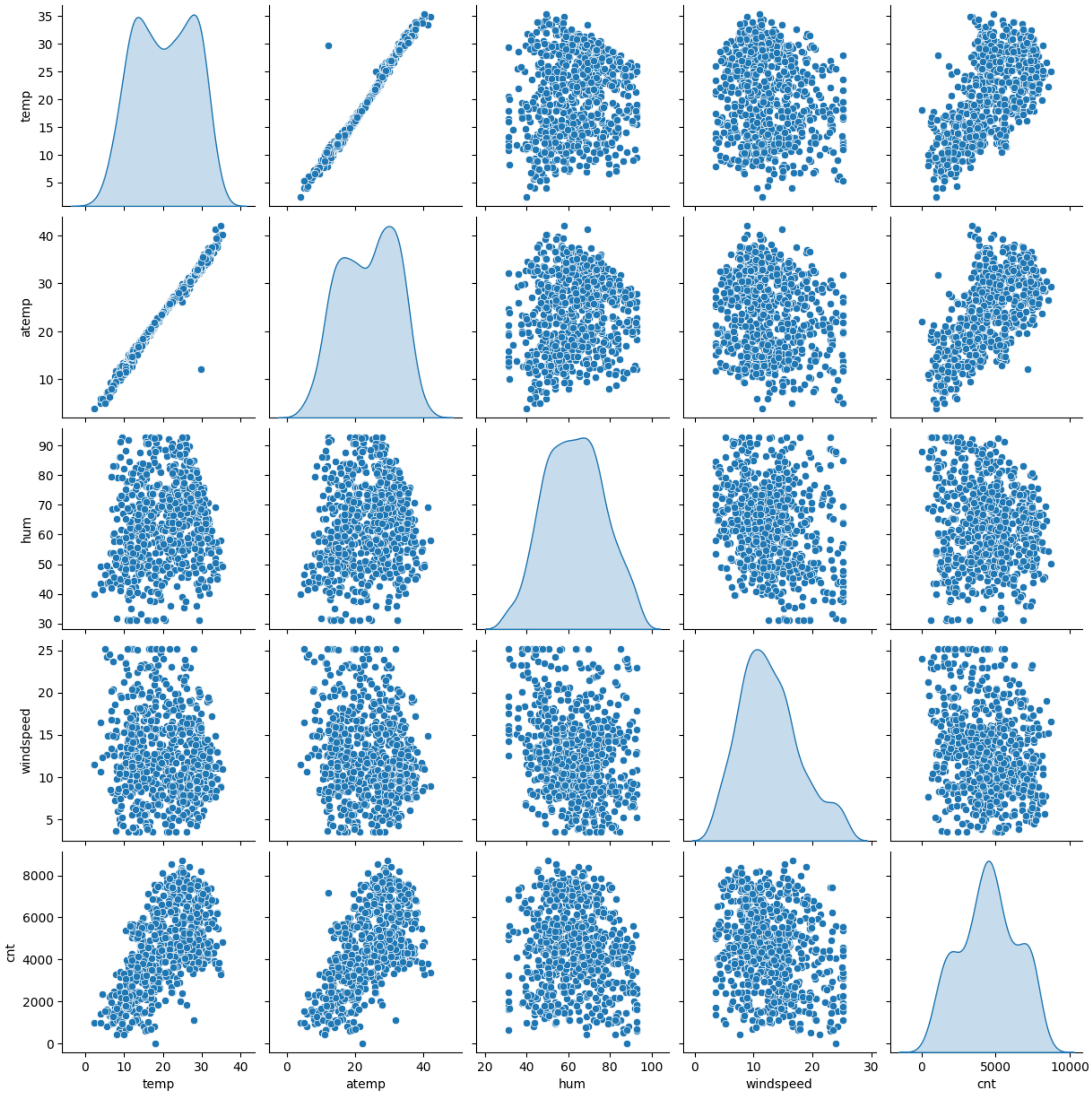
16.0.2 also, all these variables are correlated with the target variable cnt.

[62]:
```
plt.figure(figsize = (10,10))
sns.heatmap(bike_sharing_data.corr(), annot = True)
plt.show()
```



17 Viewing pair-plot for numeric columns

[63]:
```
num_cols = bike_sharing_data[[ 'temp', 'atemp', 'hum', 'windspeed','cnt']]
sns.pairplot(num_cols, diag_kind='kde')
plt.show()
```



18 Encoding of categorical columns

[64]:
```
bike_sharing_data_encoded = pd.get_dummies(bike_sharing_data, drop_first=True)
bike_sharing_data_encoded.columns
```

[64]:
```
Index(['yr', 'holiday', 'workingday', 'temp', 'atemp', 'hum', 'windspeed',
       'cnt', 'season_2', 'season_3', 'season_4', 'mnth_2', 'mnth_3', 'mnth_4',
       'mnth_5', 'mnth_6', 'mnth_7', 'mnth_8', 'mnth_9', 'mnth_10', 'mnth_11',
       'mnth_12', 'weekday_1', 'weekday_2', 'weekday_3', 'weekday_4',
       'weekday_5', 'weekday_6', 'weathersit_2', 'weathersit_3'],
      dtype='object')
```

19 Final list of columns, after removing unwanted ones and categorical encoding

[65]:
```
bike_sharing_data_encoded.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 30 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   yr            730 non-null    int64  
 1   holiday       730 non-null    int64  
 2   workingday    730 non-null    int64  
 3   temp          730 non-null    float64
 4   atemp         730 non-null    float64
 5   hum           730 non-null    float64
 6   windspeed     730 non-null    float64
 7   cnt           730 non-null    int64  
 8   season_2      730 non-null    bool   
 9   season_3      730 non-null    bool   
 10  season_4      730 non-null    bool   
 11  mnth_2        730 non-null    bool   
 12  mnth_3        730 non-null    bool   
 13  mnth_4        730 non-null    bool   
 14  mnth_5        730 non-null    bool   
 15  mnth_6        730 non-null    bool   
 16  mnth_7        730 non-null    bool   
 17  mnth_8        730 non-null    bool   
 18  mnth_9        730 non-null    bool   
 19  mnth_10       730 non-null    bool   
 20  mnth_11       730 non-null    bool   
 21  mnth_12       730 non-null    bool   
 22  weekday_1     730 non-null    bool   
 23  weekday_2     730 non-null    bool   
 24  weekday_3     730 non-null    bool   
 25  weekday_4     730 non-null    bool   
 26  weekday_5     730 non-null    bool   
 27  weekday_6     730 non-null    bool   
 28  weathersit_2  730 non-null    bool   
 29  weathersit_3  730 non-null    bool   
```

```
dtypes: bool(22), float64(4), int64(4)
memory usage: 61.4 KB
```

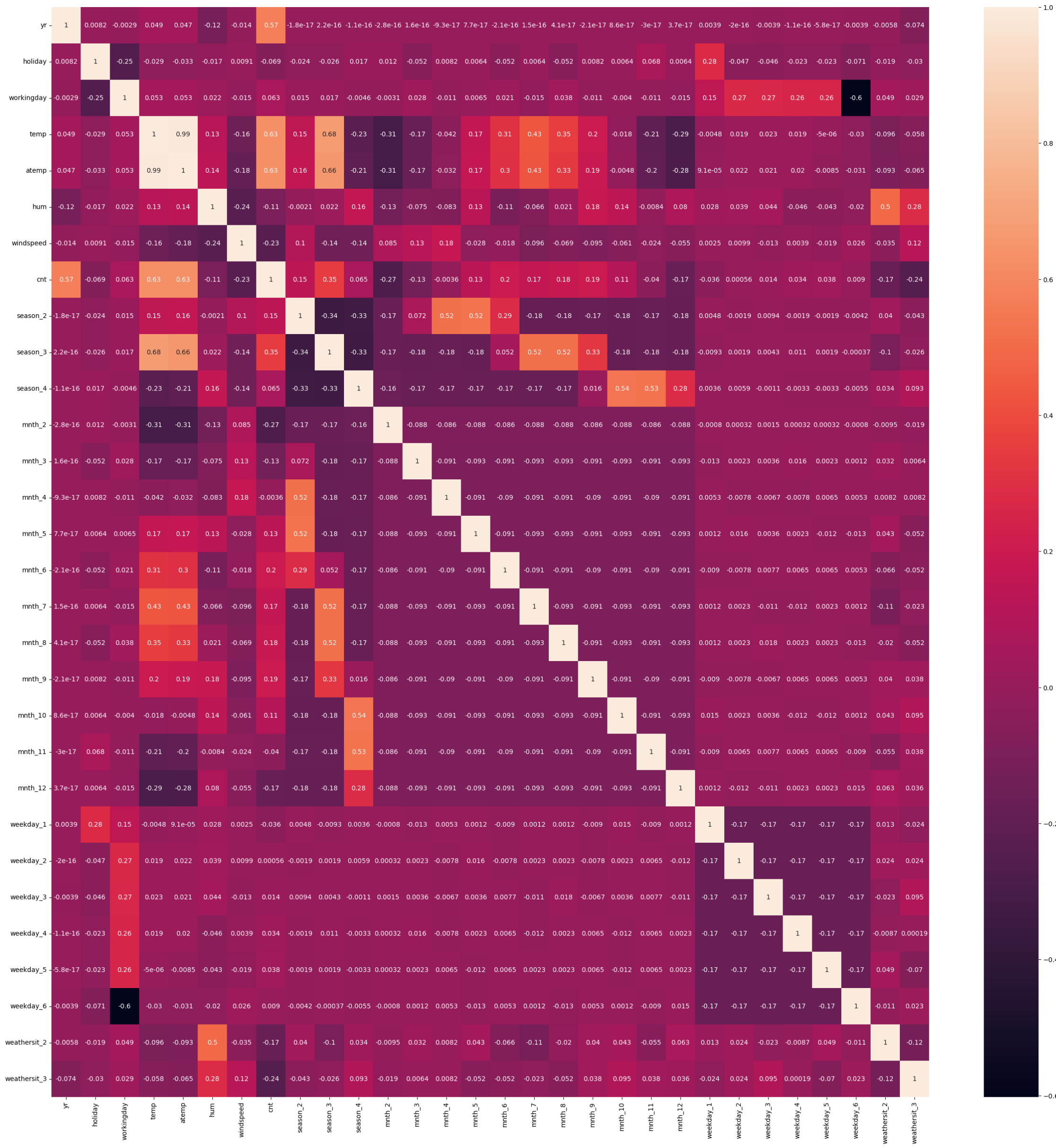
[66]:
```
bike_sharing_data.shape
```

[66]:
```
(730, 12)
```

20 Re-visiting the heatmap for correlation, after encoding

20.0.1 the correlation of different variables with the target variable seems good. not dropping any column for now

[67]:
```
plt.figure(figsize = (30,30))
sns.heatmap(bike_sharing_data_encoded.corr(), annot = True)
plt.show()
```



21 Framing x and y datasets

[68]:
```
x = bike_sharing_data_encoded.drop(['cnt'], axis=1)
y = bike_sharing_data_encoded['cnt']

x.head()
```

[68]:
```
   yr  holiday  workingday       temp     atemp      hum  windspeed  season_2  \
0   0        0           0  14.110847  18.18125  80.5833  10.749882     False
```

```
1   0          0             0  14.902598  17.68695  69.6087  16.652113     False
2   0          0             1   8.050924   9.47025  43.7273  16.636703     False
3   0          0             1   8.200000  10.60610  59.0435  10.739832     False
4   0          0             1   9.305237  11.46350  43.6957  12.522300     False

   season_3  season_4  …  mnth_11  mnth_12  weekday_1  weekday_2  weekday_3  \
0     False     False  …    False    False      False      False      False
1     False     False  …    False    False      False      False      False
2     False     False  …    False    False       True      False      False
3     False     False  …    False    False      False       True      False
4     False     False  …    False    False      False      False       True

   weekday_4  weekday_5  weekday_6  weathersit_2  weathersit_3
0      False      False       True          True         False
1      False      False      False          True         False
2      False      False      False         False         False
3      False      False      False         False         False
4      False      False      False         False         False

[5 rows x 29 columns]
```

[69]:
```python
y.head()
```

[69]:
```
0     985
1     801
2    1349
3    1562
4    1600
Name: cnt, dtype: int64
```

22 spitting the data into train and test

[70]:
```python
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.25,␣
 ↪random_state=101)
print('X_train:', X_train.shape, 'X_test:', X_test.shape, 'y_train:', y_train.
 ↪shape, 'y_test:', y_test.shape)
```

```
X_train: (547, 29) X_test: (183, 29) y_train: (547,) y_test: (183,)
```

[71]:
```python
X_train.head()
```

[71]:
```
     yr  holiday  workingday       temp     atemp      hum  windspeed  \
182   0        0           0  30.271653  33.36540  44.4583   7.709154
261   0        0           1  22.515847  26.48375  69.0000  10.166714
431   1        0           1  21.627500  26.23020  56.7500  25.201627
62    0        0           1  10.728347  12.78395  61.0417  13.624182
473   1        0           1  20.431653  24.65230  61.2500   4.417256
```

```
     season_2  season_3  season_4  …  mnth_11  mnth_12  weekday_1  \
182     False      True     False  …    False    False      False
261     False      True     False  …    False    False       True
431     False     False     False  …    False    False      False
62      False     False     False  …    False    False      False
473      True     False     False  …    False    False      False

     weekday_2  weekday_3  weekday_4  weekday_5  weekday_6  weathersit_2  \
182      False      False      False      False       True         False
261      False      False      False      False      False          True
431      False      False       True      False      False         False
62       False      False      False       True      False          True
473      False      False       True      False      False         False

     weathersit_3
182         False
261         False
431         False
62          False
473         False

[5 rows x 29 columns]
```

[72]:

```
y_train.head()
```

[72]:

```
182    5119
261    4539
431    5382
62     1944
473    6565
Name: cnt, dtype: int64
```

23 Scalling X_train

[73]:

```
scaler = MinMaxScaler()
X_train[['temp', 'atemp', 'hum', 'windspeed']] = scaler.
 ↪fit_transform(X_train[['temp', 'atemp', 'hum', 'windspeed']])
X_train.head()
```

[73]:

```
     yr  holiday  workingday      temp     atemp       hum  windspeed  \
182   0        0           0  0.846320  0.772142  0.215124   0.192132
261   0        0           1  0.610610  0.591480  0.613617   0.305631
431   1        0           1  0.583612  0.584824  0.414709   1.000000
62    0        0           1  0.252371  0.231824  0.484395   0.465310
473   1        0           1  0.547268  0.543400  0.487778   0.040100
```

```
     season_2  season_3  season_4  …  mnth_11  mnth_12  weekday_1  \
182     False      True     False  …    False    False      False
261     False      True     False  …    False    False       True
431     False     False     False  …    False    False      False
62      False     False     False  …    False    False      False
473      True     False     False  …    False    False      False

     weekday_2  weekday_3  weekday_4  weekday_5  weekday_6  weathersit_2  \
182      False      False      False      False       True         False
261      False      False      False      False      False          True
431      False      False       True      False      False         False
62       False      False      False       True      False          True
473      False      False       True      False      False         False

     weathersit_3
182         False
261         False
431         False
62          False
473         False

[5 rows x 29 columns]
```

24 unfortunately y__train happens to be a series object, so, a bit lengthly code.

[74]:
```
y_train_cnt = y_train.values.reshape(-1, 1)
y_train_cnt_scaled = scaler.fit_transform(y_train_cnt)
y_train_scaled = pd.Series(y_train_cnt_scaled.flatten(), name=y_train.name,␣
 ↪index=y_train.index)


y_train_scaled.head()
```

[74]:
```
182    0.597328
261    0.529357
431    0.628150
62     0.225243
473    0.766788
Name: cnt, dtype: float64
```

25 Model 1 - Linear Regression model using statstatsmodels

[75]:
```
X_train['season_2'] = X_train['season_2'].map({True: 1, False: 0})
X_train['season_3'] = X_train['season_2'].map({True: 1, False: 0})
X_train['mnth_2'] = X_train['mnth_2'].map({True: 1, False: 0})
X_train['mnth_3'] = X_train['mnth_3'].map({True: 1, False: 0})
X_train['mnth_4'] = X_train['mnth_4'].map({True: 1, False: 0})
X_train['mnth_5'] = X_train['mnth_5'].map({True: 1, False: 0})
X_train['mnth_6'] = X_train['mnth_6'].map({True: 1, False: 0})
X_train['mnth_7'] = X_train['mnth_7'].map({True: 1, False: 0})
X_train['mnth_8'] = X_train['mnth_8'].map({True: 1, False: 0})
X_train['mnth_9'] = X_train['mnth_9'].map({True: 1, False: 0})
X_train['mnth_10'] = X_train['mnth_10'].map({True: 1, False: 0})
X_train['mnth_11'] = X_train['mnth_11'].map({True: 1, False: 0})
X_train['mnth_12'] = X_train['mnth_12'].map({True: 1, False: 0})
X_train['weekday_1'] = X_train['weekday_1'].map({True: 1, False: 0})
X_train['weekday_2'] = X_train['weekday_2'].map({True: 1, False: 0})
X_train['weekday_3'] = X_train['weekday_3'].map({True: 1, False: 0})
```

[76]:
```
print(X_train.select_dtypes(include = 'bool'))
```

```
     season_4  weekday_4  weekday_5  weekday_6  weathersit_2  weathersit_3
182     False      False      False       True         False         False
261     False      False      False      False          True         False
431     False       True      False      False         False         False
62      False      False       True      False          True         False
473     False       True      False      False         False         False
..        …          …          …          …            …             …
75      False       True      False      False         False         False
599     False       True      False      False         False         False
575     False      False      False      False         False         False
337      True      False      False      False         False         False
523     False      False       True      False         False         False

[547 rows x 6 columns]
```

[77]:
```
print(y_train_scaled.dtypes)
```

```
float64
```

[78]:
```
X_train_sm = sm.add_constant(X_train)
lr_1 = sm.OLS(np.asarray(y_train_scaled), X_train_sm)
lr_1_model = lr_1.fit()

lr_1_model.params
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
```

```
Cell In[78], line 2
      1 X_train_sm = sm.add_constant(X_train)
----> 2 lr_1 = sm.OLS(np.asarray(y_train_scaled), X_train_sm)
      3 lr_1_model = lr_1.fit()
      5 lr_1_model.params

File c:
 ↪\Users\sndur\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\regress
 ↪py:923, in OLS.__init__(self, endog, exog, missing, hasconst, **kwargs)
    920     msg = ("Weights are not supported in OLS and will be ignored"
    921            "An exception will be raised in the next version.")
    922     warnings.warn(msg, ValueWarning)
--> 923 super(OLS, self).__init__(endog, exog, missing=missing,
    924                           hasconst=hasconst, **kwargs)
    925 if "weights" in self._init_keys:
    926     self._init_keys.remove("weights")

File c:
 ↪\Users\sndur\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\regress
 ↪py:748, in WLS.__init__(self, endog, exog, weights, missing, hasconst,␣
 ↪**kwargs)
    746 else:
    747     weights = weights.squeeze()
--> 748 super(WLS, self).__init__(endog, exog, missing=missing,
    749                           weights=weights, hasconst=hasconst, **kwargs)
    750 nobs = self.exog.shape[0]
    751 weights = self.weights

File c:
 ↪\Users\sndur\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\regress
 ↪py:202, in RegressionModel.__init__(self, endog, exog, **kwargs)
    201 def __init__(self, endog, exog, **kwargs):
--> 202     super(RegressionModel, self).__init__(endog, exog, **kwargs)
    203     self.pinv_wexog: Float64Array | None = None
    204     self._data_attr.extend(['pinv_wexog', 'wendog', 'wexog', 'weights']

File c:
 ↪\Users\sndur\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\base\mod
 ↪py:270, in LikelihoodModel.__init__(self, endog, exog, **kwargs)
    269 def __init__(self, endog, exog=None, **kwargs):
--> 270     super().__init__(endog, exog, **kwargs)
    271     self.initialize()

File c:
 ↪\Users\sndur\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\base\mod
 ↪py:95, in Model.__init__(self, endog, exog, **kwargs)
     93 missing = kwargs.pop('missing', 'none')
     94 hasconst = kwargs.pop('hasconst', None)
---> 95 self.data = self._handle_data(endog, exog, missing, hasconst,
```

```
     96                                **kwargs)
     97 self.k_constant = self.data.k_constant
     98 self.exog = self.data.exog

File c:
 ↪\Users\sndur\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\base\mod
 ↪py:135, in Model._handle_data(self, endog, exog, missing, hasconst, **kwargs)
    134 def _handle_data(self, endog, exog, missing, hasconst, **kwargs):
--> 135     data = handle_data(endog, exog, missing, hasconst, **kwargs)
    136     # kwargs arrays could have changed, easier to just attach here
    137     for key in kwargs:

File c:
 ↪\Users\sndur\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\base\dat
 ↪py:675, in handle_data(endog, exog, missing, hasconst, **kwargs)
    672     exog = np.asarray(exog)
    674 klass = handle_data_class_factory(endog, exog)
--> 675 return klass(endog, exog=exog, missing=missing, hasconst=hasconst,
    676              **kwargs)

File c:
 ↪\Users\sndur\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\base\dat
 ↪py:84, in ModelData.__init__(self, endog, exog, missing, hasconst, **kwargs)
     82     self.orig_endog = endog
     83     self.orig_exog = exog
---> 84     self.endog, self.exog = self._convert_endog_exog(endog, exog)
     86 self.const_idx = None
     87 self.k_constant = 0

File c:
 ↪\Users\sndur\AppData\Local\Programs\Python\Python311\Lib\site-packages\statsmodels\base\dat
 ↪py:509, in PandasData._convert_endog_exog(self, endog, exog)
    507 exog = exog if exog is None else np.asarray(exog)
    508 if endog.dtype == object or exog is not None and exog.dtype == object:
--> 509     raise ValueError("Pandas data cast to numpy dtype of object. "
    510                      "Check input data with np.asarray(data).")
    511 return super(PandasData, self)._convert_endog_exog(endog, exog)

ValueError: Pandas data cast to numpy dtype of object. Check input data with np
 ↪asarray(data).
```

26 In the below summary table:

26.0.1 R-squared: 0.846, means that approximately 84.6% of the variability in the dependent variable is explained by the independent variables in your model. This is a relatively high R-squared value, indicating that the model is quite effective in explaining and predicting the variation in the dependent variable

26.0.2 F-statistic (101.3) suggests that the model, as a whole, is more likely to be statistically significant

26.0.3 Prob (F-statistic): 4.33e-190" suggests that the overall model is statistically significant. More specifically

[ ]:
```
lr_1_model.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.846
Model:                            OLS   Adj. R-squared:                  0.837
Method:                 Least Squares   F-statistic:                     101.3
Date:                Wed, 13 Dec 2023   Prob (F-statistic):         4.33e-190
Time:                        11:42:30   Log-Likelihood:                 546.48
No. Observations:                 547   AIC:                            -1035.
Df Residuals:                     518   BIC:                            -910.1
Df Model:                          28
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.1416      0.023      6.072      0.000       0.096       0.187
yr               0.2368      0.008     29.140      0.000       0.221       0.253
holiday         -0.0579      0.024     -2.442      0.015      -0.104      -0.011
workingday       0.0373      0.009      3.997      0.000       0.019       0.056
temp             0.0392      0.258      0.152      0.879      -0.468       0.546
atemp            0.4125      0.265      1.556      0.120      -0.108       0.933
hum             -0.1196      0.027     -4.508      0.000      -0.172      -0.067
windspeed       -0.1143      0.020     -5.808      0.000      -0.153      -0.076
season_2         0.0902      0.025      3.657      0.000       0.042       0.139
season_3         0.0740      0.030      2.505      0.013       0.016       0.132
season_4         0.1863      0.026      7.110      0.000       0.135       0.238
mnth_2           0.0180      0.020      0.917      0.360      -0.021       0.056
mnth_3           0.0731      0.022      3.317      0.001       0.030       0.116
mnth_4           0.0596      0.034      1.760      0.079      -0.007       0.126
mnth_5           0.0967      0.037      2.645      0.008       0.025       0.169
mnth_6           0.0651      0.039      1.662      0.097      -0.012       0.142
mnth_7           0.0168      0.043      0.386      0.700      -0.069       0.102
mnth_8           0.0683      0.042      1.626      0.105      -0.014       0.151
```

```
mnth_9          0.1277      0.037      3.434      0.001       0.055       0.201
mnth_10         0.0489      0.034      1.421      0.156      -0.019       0.117
mnth_11        -0.0254      0.033     -0.770      0.441      -0.090       0.039
mnth_12        -0.0174      0.027     -0.647      0.518      -0.070       0.035
weekday_1      -0.0194      0.010     -1.979      0.048      -0.039      -0.000
weekday_2      -0.0086      0.011     -0.776      0.438      -0.031       0.013
weekday_3      -0.0020      0.011     -0.176      0.860      -0.024       0.020
weekday_4       0.0049      0.010      0.471      0.638      -0.015       0.025
weekday_5       0.0046      0.011      0.424      0.672      -0.017       0.026
weekday_6       0.0503      0.015      3.459      0.001       0.022       0.079
weathersit_2   -0.0529      0.011     -4.789      0.000      -0.075      -0.031
weathersit_3   -0.2325      0.029     -7.977      0.000      -0.290      -0.175
==============================================================================
Omnibus:                       97.916   Durbin-Watson:                   1.886
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              251.917
Skew:                          -0.901   Prob(JB):                     1.98e-55
Kurtosis:                       5.794   Cond. No.                     2.25e+15
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 3.59e-28. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
"""
```

27 Model 1 -> find VIF (i) = 1 / (1 - rsquare)

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

[ ]:

	Features	VIF
24	weekday_4	inf
2	workingday	inf
23	weekday_3	inf
22	weekday_2	inf
21	weekday_1	inf
25	weekday_5	inf
1	holiday	inf
3	temp	1506.52
4	atemp	1434.59

8	season_3	14.67
5	hum	11.81
15	mnth_7	10.59
9	season_4	10.57
7	season_2	10.02
16	mnth_8	9.26
14	mnth_6	8.79
13	mnth_5	7.34
17	mnth_9	7.25
18	mnth_10	6.20
12	mnth_4	6.12
19	mnth_11	5.31
6	windspeed	4.40
20	mnth_12	3.69
11	mnth_3	2.78
27	weathersit_2	2.60
0	yr	2.13
26	weekday_6	1.89
10	mnth_2	1.81
28	weathersit_3	1.46

28 Proceding with the below interpretation

28.1 Features with High p-value and High VIF:

28.1.1 Interpretation: These features are both statistically insignificant and contribute to multicollinearity.

28.1.2 Action: Consider removing these features from the model. They don't provide significant explanatory power, and their presence may lead to multicollinearity issues.

28.2 Features with High p-value and Low VIF:

28.2.1 Interpretation: These features are statistically insignificant but don't contribute significantly to multicollinearity.

28.2.2 Action: Evaluate the importance of these features in the context of your problem. If they are not essential, consider removing them. If they are important, you may want to explore other transformations or interactions.

28.3 Features with Low p-value and High VIF:

28.3.1 Interpretation: These features are statistically significant, but their presence may contribute to multicollinearity.

28.3.2 Action: Assess the importance of these features. If they are crucial for your analysis, you might consider keeping them but explore options to address multicollinearity, such as feature engineering, regularization, or removing one of the correlated variables.

28.4 Features with Low p-value and Low VIF:

28.4.1 Interpretation: These features are statistically significant and do not exhibit high multicollinearity.

28.4.2 Action: These are generally desirable features to include in your model. They contribute meaningfully to the prediction without introducing multicollinearity concerns.

29 Model 1 - Removing the features

'weekday_4','weekday_3.'weekday_2','weekday_1','weekday_5','weekday_6','holiday','temp'

really sure why these weekday_n columns are showing infinite 'inf' as VIF. They should have some value. Followed all basics in the coding and these are just categorical encoded colums. Anyway deleting them.

[ ]:
```
X_train_sm.
↪drop(['weekday_4','weekday_3','weekday_2','weekday_1','weekday_5','weekday_6','holiday','at
↪axis=1, inplace=True)
X_train_sm.columns
```

[ ]:
```
Index(['const', 'yr', 'workingday', 'temp', 'hum', 'windspeed', 'season_2',
       'season_3', 'season_4', 'mnth_2', 'mnth_3', 'mnth_4', 'mnth_5',
```

```
       'mnth_6', 'mnth_7', 'mnth_8', 'mnth_9', 'mnth_10', 'mnth_11', 'mnth_12',
       'weathersit_2', 'weathersit_3'],
      dtype='object')
```

30 Model 2

[ ]:
```
#X_train_sm = sm.add_constant(X_train)
lr_2 = sm.OLS(y_train_scaled, X_train_sm)
lr_2_model = lr_2.fit()

lr_2_model.params
```

[ ]:
```
const           0.161548
yr              0.236744
workingday      0.015476
temp            0.427190
hum            -0.119108
windspeed      -0.124409
season_2        0.089848
season_3        0.073186
season_4        0.189928
mnth_2          0.019817
mnth_3          0.080483
mnth_4          0.067760
mnth_5          0.100508
mnth_6          0.070580
mnth_7          0.022345
mnth_8          0.072521
mnth_9          0.129320
mnth_10         0.055612
mnth_11        -0.024016
mnth_12        -0.010312
weathersit_2   -0.051371
weathersit_3   -0.229131
dtype: float64
```

[ ]:
```
lr_2_model.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.836
Model:                            OLS   Adj. R-squared:                  0.829
Method:                 Least Squares   F-statistic:                     127.1
Date:                Wed, 13 Dec 2023   Prob (F-statistic):          2.63e-190
Time:                        11:42:30   Log-Likelihood:                 529.36
```

```
No. Observations:                 547   AIC:                            -1015.
Df Residuals:                     525   BIC:                            -920.0
Df Model:                          21
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.1615      0.023      7.177      0.000       0.117       0.206
yr               0.2367      0.008     28.497      0.000       0.220       0.253
workingday       0.0155      0.009      1.780      0.076      -0.002       0.033
temp             0.4272      0.047      9.149      0.000       0.335       0.519
hum             -0.1191      0.027     -4.454      0.000      -0.172      -0.067
windspeed       -0.1244      0.019     -6.508      0.000      -0.162      -0.087
season_2         0.0898      0.025      3.556      0.000       0.040       0.139
season_3         0.0732      0.030      2.421      0.016       0.014       0.133
season_4         0.1899      0.027      7.108      0.000       0.137       0.242
mnth_2           0.0198      0.020      0.989      0.323      -0.020       0.059
mnth_3           0.0805      0.022      3.587      0.000       0.036       0.125
mnth_4           0.0678      0.035      1.958      0.051      -0.000       0.136
mnth_5           0.1005      0.037      2.691      0.007       0.027       0.174
mnth_6           0.0706      0.040      1.781      0.076      -0.007       0.148
mnth_7           0.0223      0.044      0.507      0.612      -0.064       0.109
mnth_8           0.0725      0.043      1.703      0.089      -0.011       0.156
mnth_9           0.1293      0.038      3.427      0.001       0.055       0.203
mnth_10          0.0556      0.035      1.583      0.114      -0.013       0.125
mnth_11         -0.0240      0.034     -0.713      0.476      -0.090       0.042
mnth_12         -0.0103      0.027     -0.377      0.707      -0.064       0.043
weathersit_2    -0.0514      0.011     -4.603      0.000      -0.073      -0.029
weathersit_3    -0.2291      0.029     -7.859      0.000      -0.286      -0.172
==============================================================================
Omnibus:                       85.499   Durbin-Watson:                   1.904
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              226.252
Skew:                          -0.782   Prob(JB):                     7.41e-50
Kurtosis:                       5.735   Cond. No.                         43.6
==============================================================================

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

31 VIF after Model 2

```
[ ]: vif = pd.DataFrame()
     vif['Features'] = X_train_sm.columns
```

```python
vif['VIF'] = [variance_inflation_factor(X_train_sm.values,i) for i in range(X_train_sm.shape[1])]
vif['VIF'] = round(vif['VIF'],2)
vif = vif.sort_values(by = 'VIF', ascending=False)
vif
```

[ ]:

	Features	VIF
0	const	31.47
7	season_3	10.86
14	mnth_7	9.48
15	mnth_8	8.33
8	season_4	7.99
13	mnth_6	7.81
6	season_2	7.48
3	temp	7.13
12	mnth_5	6.67
16	mnth_9	6.54
17	mnth_10	5.67
11	mnth_4	5.62
18	mnth_11	5.00
19	mnth_12	3.51
10	mnth_3	2.60
4	hum	2.29
9	mnth_2	1.85
20	weathersit_2	1.71
21	weathersit_3	1.41
5	windspeed	1.26
1	yr	1.07
2	workingday	1.02

32 Model 2 -Removing features based on the explained criteria of p-value and vif

[ ]:
```python
X_train_sm.drop(['mnth_6', 'mnth_4', 'mnth_6', 'mnth_3', 'mnth_8', 'mnth_9', 'mnth_10', 'mnth_12'], axis=1, inplace=True)
X_train_sm.columns
```

[ ]:
```
Index(['const', 'yr', 'workingday', 'temp', 'hum', 'windspeed', 'season_2',
       'season_3', 'season_4', 'mnth_2', 'mnth_5', 'mnth_7', 'mnth_11',
       'weathersit_2', 'weathersit_3'],
      dtype='object')
```

33 Model 3

[ ]:
```
#X_train_sm = sm.add_constant(X_train)
lr_3 = sm.OLS(y_train_scaled, X_train_sm)
lr_3_model = lr_3.fit()

lr_3_model.params
```

[ ]:
```
const           0.159836
yr              0.234738
workingday      0.016842
temp            0.501077
hum            -0.113947
windspeed      -0.115592
season_2        0.112901
season_3        0.102954
season_4        0.190347
mnth_2         -0.007744
mnth_5          0.022623
mnth_7         -0.075229
mnth_11        -0.057754
weathersit_2   -0.049597
weathersit_3   -0.229116
dtype: float64
```

[ ]:
```
lr_3_model.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.823
Model:                            OLS   Adj. R-squared:                  0.818
Method:                 Least Squares   F-statistic:                     176.7
Date:                Wed, 13 Dec 2023   Prob (F-statistic):          1.49e-189
Time:                        11:42:30   Log-Likelihood:                 509.12
No. Observations:                 547   AIC:                            -988.2
Df Residuals:                     532   BIC:                            -923.7
Df Model:                          14
Covariance Type:            nonrobust
================================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const          0.1598      0.022      7.407      0.000       0.117       0.202
yr             0.2347      0.008     27.784      0.000       0.218       0.251
workingday     0.0168      0.009      1.884      0.060      -0.001       0.034
temp           0.5011      0.035     14.415      0.000       0.433       0.569
```

```
hum             -0.1139      0.027     -4.286      0.000      -0.166      -0.062
windspeed       -0.1156      0.019     -5.958      0.000      -0.154      -0.077
season_2         0.1129      0.017      6.614      0.000       0.079       0.146
season_3         0.1030      0.022      4.782      0.000       0.061       0.145
season_4         0.1903      0.016     12.073      0.000       0.159       0.221
mnth_2          -0.0077      0.018     -0.437      0.662      -0.043       0.027
mnth_5           0.0226      0.018      1.257      0.209      -0.013       0.058
mnth_7          -0.0752      0.018     -4.246      0.000      -0.110      -0.040
mnth_11         -0.0578      0.019     -3.119      0.002      -0.094      -0.021
weathersit_2    -0.0496      0.011     -4.343      0.000      -0.072      -0.027
weathersit_3    -0.2291      0.030     -7.663      0.000      -0.288      -0.170
==============================================================================
Omnibus:                       65.758   Durbin-Watson:                   1.894
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              160.137
Skew:                          -0.632   Prob(JB):                     1.69e-35
Kurtosis:                       5.330   Cond. No.                         17.6
==============================================================================

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

34 VIF after Model 3

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

[ ]:

	Features	VIF
0	const	27.22
7	season_3	5.18
3	temp	3.72
6	season_2	3.21
8	season_4	2.62
4	hum	2.13
13	weathersit_2	1.69
10	mnth_5	1.46
11	mnth_7	1.44
12	mnth_11	1.42
14	weathersit_3	1.39
9	mnth_2	1.36

```
5      windspeed   1.23
1             yr   1.04
2     workingday   1.02
```

———————- RFE ————————————

35 Model 3 - Removing features based on the explained criteria of p-value and vif

35.0.1 'hum', 'season_3'

[ ]:
```
X_train_sm.drop(['hum', 'season_3'], axis=1, inplace=True)
X_train_sm.columns
```

[ ]:
```
Index(['const', 'yr', 'workingday', 'temp', 'windspeed', 'season_2',
       'season_4', 'mnth_2', 'mnth_5', 'mnth_7', 'mnth_11', 'weathersit_2',
       'weathersit_3'],
      dtype='object')
```

36 Model 4

[ ]:
```
#X_train_sm = sm.add_constant(X_train)
lr_4 = sm.OLS(y_train_scaled, X_train_sm)
lr_4_model = lr_4.fit()

lr_4_model.params
```

[ ]:
```
const           0.099902
yr              0.236613
workingday      0.017476
temp            0.600506
windspeed      -0.094492
season_2        0.063354
season_4        0.138822
mnth_2         -0.025982
mnth_5          0.000188
mnth_7         -0.054405
mnth_11        -0.044890
weathersit_2   -0.076087
weathersit_3   -0.284441
dtype: float64
```

[ ]:
```
lr_4_model.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
```

```
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.809
Model:                            OLS   Adj. R-squared:                  0.804
Method:                 Least Squares   F-statistic:                     188.0
Date:                Wed, 13 Dec 2023   Prob (F-statistic):          7.64e-183
Time:                        11:42:30   Log-Likelihood:                 487.74
No. Observations:                 547   AIC:                            -949.5
Df Residuals:                     534   BIC:                            -893.5
Df Model:                          12
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.0999      0.019      5.239      0.000       0.062       0.137
yr               0.2366      0.009     27.404      0.000       0.220       0.254
workingday       0.0175      0.009      1.886      0.060      -0.001       0.036
temp             0.6005      0.023     25.609      0.000       0.554       0.647
windspeed       -0.0945      0.019     -4.909      0.000      -0.132      -0.057
season_2         0.0634      0.013      4.905      0.000       0.038       0.089
season_4         0.1388      0.013     10.499      0.000       0.113       0.165
mnth_2          -0.0260      0.018     -1.465      0.143      -0.061       0.009
mnth_5           0.0002      0.018      0.010      0.992      -0.036       0.036
mnth_7          -0.0544      0.018     -3.007      0.003      -0.090      -0.019
mnth_11         -0.0449      0.019     -2.355      0.019      -0.082      -0.007
weathersit_2    -0.0761      0.009     -8.077      0.000      -0.095      -0.058
weathersit_3    -0.2844      0.027    -10.557      0.000      -0.337      -0.232
==============================================================================
Omnibus:                       53.239   Durbin-Watson:                   1.913
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              107.001
Skew:                          -0.576   Prob(JB):                     5.82e-24
Kurtosis:                       4.835   Cond. No.                         11.4
==============================================================================

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

37 VIF after Model 4

[ ]:
```
vif = pd.DataFrame()
vif['Features'] = X_train_sm.columns
vif['VIF'] = [variance_inflation_factor(X_train_sm.values,i) for i in ␣
 ↪range(X_train_sm.shape[1])]
vif['VIF'] = round(vif['VIF'],2)
vif = vif.sort_values(by = 'VIF', ascending=False)
```

```
vif
```

```
[ ]:        Features    VIF
0           const  19.73
5        season_2   1.71
6        season_4   1.71
3            temp   1.57
8          mnth_5   1.40
10        mnth_11   1.40
9          mnth_7   1.39
7          mnth_2   1.26
4       windspeed   1.12
11   weathersit_2   1.07
12   weathersit_3   1.05
1              yr   1.01
2      workingday   1.01
```

38 Parameters after Model 4, we can remove mnth_2 and mnth_5, as the p-value is more and VIF is low, these two become insignificant

```
[ ]: X_train_sm.drop(['mnth_2','mnth_5'], axis=1, inplace=True)
X_train_sm.columns
```

```
[ ]: Index(['const', 'yr', 'workingday', 'temp', 'windspeed', 'season_2',
       'season_4', 'mnth_7', 'mnth_11', 'weathersit_2', 'weathersit_3'],
      dtype='object')
```

39 Model 5

```
[ ]: #X_train_sm = sm.add_constant(X_train)
lr_5 = sm.OLS(y_train_scaled, X_train_sm)
lr_5_model = lr_5.fit()

lr_5_model.params
```

```
[ ]: const           0.091109
yr              0.236081
workingday      0.016914
temp            0.610654
windspeed      -0.096030
season_2        0.067240
season_4        0.143748
mnth_7         -0.053292
mnth_11        -0.043904
```

```
weathersit_2   -0.075563
weathersit_3   -0.283563
dtype: float64
```

[ ]:
```
lr_5_model.summary()
```

[ ]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:                    cnt   R-squared:                       0.808
Model:                            OLS   Adj. R-squared:                  0.804
Method:                 Least Squares   F-statistic:                     225.4
Date:                Wed, 13 Dec 2023   Prob (F-statistic):          9.85e-185
Time:                        11:42:31   Log-Likelihood:                 486.64
No. Observations:                 547   AIC:                            -951.3
Df Residuals:                     536   BIC:                            -903.9
Df Model:                          10
Covariance Type:            nonrobust
================================================================================
                   coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------
const            0.0911      0.018      5.038      0.000       0.056       0.127
yr               0.2361      0.009     27.363      0.000       0.219       0.253
workingday       0.0169      0.009      1.827      0.068      -0.001       0.035
temp             0.6107      0.022     27.408      0.000       0.567       0.654
windspeed       -0.0960      0.019     -5.009      0.000      -0.134      -0.058
season_2         0.0672      0.011      6.034      0.000       0.045       0.089
season_4         0.1437      0.013     11.238      0.000       0.119       0.169
mnth_7          -0.0533      0.018     -2.951      0.003      -0.089      -0.018
mnth_11         -0.0439      0.019     -2.304      0.022      -0.081      -0.006
weathersit_2    -0.0756      0.009     -8.033      0.000      -0.094      -0.057
weathersit_3    -0.2836      0.027    -10.527      0.000      -0.336      -0.231
==============================================================================
Omnibus:                       50.158   Durbin-Watson:                   1.905
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              100.181
Skew:                          -0.548   Prob(JB):                     1.76e-22
Kurtosis:                       4.787   Cond. No.                         10.8
==============================================================================

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

40 VIF after Model 5

[ ]:
```
vif = pd.DataFrame()
vif['Features'] = X_train_sm.columns
vif['VIF'] = [variance_inflation_factor(X_train_sm.values,i) for i in ␣
 ↪range(X_train_sm.shape[1])]
vif['VIF'] = round(vif['VIF'],2)
vif = vif.sort_values(by = 'VIF', ascending=False)
vif
```

[ ]:

	Features	VIF
0	const	17.74
6	season_4	1.60
3	temp	1.42
8	mnth_11	1.40
7	mnth_7	1.39
5	season_2	1.27
4	windspeed	1.11
9	weathersit_2	1.06
10	weathersit_3	1.05
1	yr	1.01
2	workingday	1.01

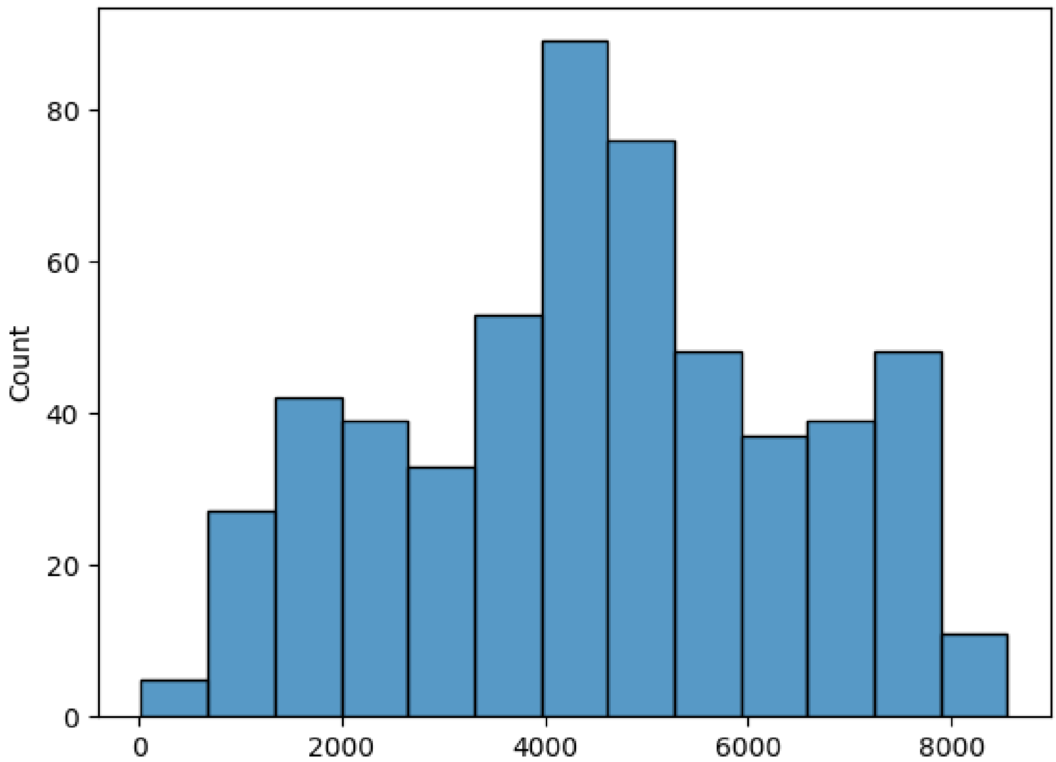
41 Residual Analysis

[ ]:
```
y_train_pred = lr_5_model.predict(X_train_sm)
y_train_pred
```

[ ]:
```
182    0.536175
261    0.375980
431    0.604458
62     0.141887
473    0.741684
         …
75     0.332270
599    0.819176
575    0.772007
337    0.432388
523    0.823930
Length: 547, dtype: float64
```

42 Visualizing the residuals - not a 100% normally distributed one :-(

[ ]:
```
res = y_train - y_train_pred
x = sns.histplot(res)
plt.show()
```



43 Predicting the Model on test data

[ ]:
```
scaler = MinMaxScaler()
X_test[['temp', 'atemp', 'hum', 'windspeed']] = scaler.
 ↪fit_transform(X_test[['temp', 'atemp', 'hum', 'windspeed']])
X_test.head()
```

[ ]:

	yr	holiday	workingday	temp	atemp	hum	windspeed	\
299	0	0	1	0.502885	0.478679	0.813203	0.447619	
723	1	1	0	0.261711	0.249188	0.686333	0.357702	
647	1	0	1	0.562495	0.543746	0.517546	0.416832	
520	1	0	1	0.598484	0.575859	0.489130	0.484197	
114	0	0	1	0.687336	0.644471	0.754342	0.409128	

```
     season_2  season_3  season_4  …  mnth_11  mnth_12  weekday_1  \
299         0         0         1  …        0        0          0
723         0         0         0  …        0        1          0
647         0         0         1  …        0        0          0
520         1         0         0  …        0        0          0
114         1         0         0  …        0        0          1

     weekday_2  weekday_3  weekday_4  weekday_5  weekday_6  weathersit_2  \
299          0          0          1          0          0             1
723          1          0          0          0          0             1
647          0          1          0          0          0             0
520          1          0          0          0          0             1
114          0          0          0          0          0             0

     weathersit_3
299             0
723             0
647             0
520             0
114             0

[5 rows x 29 columns]
```

[ ]:
```
y_test_cnt = y_test.values.reshape(-1, 1)
y_test_cnt_scaled = scaler.fit_transform(y_test_cnt)
y_test_scaled = pd.Series(y_test_cnt_scaled.flatten(), name=y_test.name,␣
 ↪index=y_test.index)
```

[ ]:
```
X_test.drop(['holiday','hum','season_3','atemp',␣
 ↪'weekday_4','weekday_3','weekday_2','weekday_1','weekday_5','weekday_6',
             'mnth_6', 'mnth_4', 'mnth_3', 'mnth_2','mnth_5', 'mnth_8',␣
 ↪'mnth_9', 'mnth_10', 'mnth_12'], axis=1, inplace=True)
X_test.columns
```

[ ]:
```
Index(['yr', 'workingday', 'temp', 'windspeed', 'season_2', 'season_4',
       'mnth_7', 'mnth_11', 'weathersit_2', 'weathersit_3'],
      dtype='object')
```

[ ]:
```
X_test_sm = sm.add_constant(X_test)
y_test_pred = lr_5_model.predict(X_test_sm)
y_test_pred
```

[ ]:
```
299    0.440311
723    0.377091
647    0.791312
520    0.654749
114    0.555698
```

```
        …
227     0.550901
424     0.612566
80      0.407693
98      0.261043
467     0.665359
Length: 183, dtype: float64
```

44 Evaluating the Model after test run, using r2_score

45 r2score on test = 0.808 is a good score

46 And variable 'temp' has the highest co-efficient of 0.6017

[ ]:
```
print(r2_score(y_true=y_test_scaled, y_pred=y_test_pred))
```

```
0.808456818436182
```

47 Using RFE of sklearn

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

[ ]:
```
print(X_train.shape, y_train.shape)
```

```
(547, 29) (547,)
```

[ ]:
```
lm = LinearRegression()
lm.fit(X_train, y_train)
rfe = RFE(lm, step=15)             # top ten features
rfe = rfe.fit(X_train, y_train)
```

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

[ ]:
```
[('yr', True, 1),
 ('holiday', True, 1),
 ('workingday', True, 1),
 ('temp', False, 2),
 ('atemp', True, 1),
 ('hum', True, 1),
 ('windspeed', True, 1),
 ('season_2', False, 2),
 ('season_3', False, 2),
 ('season_4', True, 1),
 ('mnth_2', False, 2),
 ('mnth_3', False, 2),
```

```
('mnth_4', False, 2),
('mnth_5', False, 2),
('mnth_6', False, 2),
('mnth_7', False, 2),
('mnth_8', False, 2),
('mnth_9', True, 1),
('mnth_10', False, 2),
('mnth_11', False, 2),
('mnth_12', False, 2),
('weekday_1', True, 1),
('weekday_2', True, 1),
('weekday_3', True, 1),
('weekday_4', True, 1),
('weekday_5', True, 1),
('weekday_6', False, 2),
('weathersit_2', False, 2),
('weathersit_3', True, 1)]
```

48 Support cols

[ ]:
```
X_train_support_cols = X_train.columns[rfe.support_]
X_train_support_cols
```

[ ]:
```
Index(['yr', 'holiday', 'workingday', 'atemp', 'hum', 'windspeed', 'season_4',
       'mnth_9', 'weekday_1', 'weekday_2', 'weekday_3', 'weekday_4',
       'weekday_5', 'weathersit_3'],
      dtype='object')
```

49 Not supported cols

[ ]:
```
X_train_support_cols = X_train.columns[~rfe.support_]
X_train_support_cols
```

[ ]:
```
Index(['temp', 'season_2', 'season_3', 'mnth_2', 'mnth_3', 'mnth_4', 'mnth_5',
       'mnth_6', 'mnth_7', 'mnth_8', 'mnth_10', 'mnth_11', 'mnth_12',
       'weekday_6', 'weathersit_2'],
      dtype='object')
```

50 We see the best supported features (from sklearn) are well included in the final features Model_5 (using statsmodel).

51 Further if we run the Model and performs the same analysis using VIF and p-value, it is expected to the last 11 features