yulu-project-pns

May 9, 2024

1 YULU BUSINESS CASE STUDY

Yulu is India's leading ***micro-mobility service provider***, which ***offers unique vehicles for the daily commute***. Starting off as a ***mission to eliminate traffic congestion in India***, Yulu provides the safest commute solution through a ***user-friendly mobile app to enable shared, solo and sustainable commuting.***

Yulu zones are located at all the appropriate locations (including ***metro stations, bus stands, office spaces, residential areas, corporate offices, etc***) to make those first and last miles smooth, affordable, and convenient!

Yulu has recently suffered considerable dips in its revenues. They have contracted a consulting company to understand the factors on which the demand for these shared electric cycles depends. Specifically, they want ***to understand the factors affecting the demand for these shared electric cycles in the Indian market***.

2 Problem Statement

Company wants to know about : - **Which variables are significant in predicting the demand for shared electric cycles in the Indian market?**

- **How well those variables describe the electric cycle demands**

3 Analysis

[1]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats
```

[2]:
```
!gdown https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/
↪original/bike_sharing.csv?1642089089 -O yulu.csv
```

```
Downloading…
From: https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/ori
ginal/bike_sharing.csv?1642089089
To: /content/yulu.csv
100% 648k/648k [00:00<00:00, 21.9MB/s]
```

[3]:
```python
data = pd.read_csv("yulu.csv")
```

[4]:
```python
data
```

[4]:
```
                  datetime  season  holiday  workingday  weather   temp  \
0      2011-01-01 00:00:00       1        0           0        1   9.84
1      2011-01-01 01:00:00       1        0           0        1   9.02
2      2011-01-01 02:00:00       1        0           0        1   9.02
3      2011-01-01 03:00:00       1        0           0        1   9.84
4      2011-01-01 04:00:00       1        0           0        1   9.84
…                      …     …       …          …       …     …
10881  2012-12-19 19:00:00       4        0           1        1  15.58
10882  2012-12-19 20:00:00       4        0           1        1  14.76
10883  2012-12-19 21:00:00       4        0           1        1  13.94
10884  2012-12-19 22:00:00       4        0           1        1  13.94
10885  2012-12-19 23:00:00       4        0           1        1  13.12

        atemp  humidity  windspeed  casual  registered  count
0      14.395        81     0.0000       3          13     16
1      13.635        80     0.0000       8          32     40
2      13.635        80     0.0000       5          27     32
3      14.395        75     0.0000       3          10     13
4      14.395        75     0.0000       0           1      1
…         …         …         …       …           …     …
10881  19.695        50    26.0027       7         329    336
10882  17.425        57    15.0013      10         231    241
10883  15.910        61    15.0013       4         164    168
10884  17.425        61     6.0032      12         117    129
10885  16.665        66     8.9981       4          84     88

[10886 rows x 12 columns]
```

[5]:
```python
data.shape
```

[5]:
```
(10886, 12)
```

##Data Characteristics

Data attributes are :

- *Datetime* : datetime
- *Season* : season (1: spring, 2: summer, 3: fall, 4: winter)
- *Holiday* : whether day is a holiday or not.
- *Workingday* : if day is either holiday or weekend then 0 otherwise 1 .
- *Weather* :
  1. Clear, Few clouds, partly cloudy, partly cloudy

2. Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
3. Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
4. Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog

Data includes 12 attributes with a total of 10886 records.

[6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    10886 non-null  object
 1   season      10886 non-null  int64
 2   holiday     10886 non-null  int64
 3   workingday  10886 non-null  int64
 4   weather     10886 non-null  int64
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64
 10  registered  10886 non-null  int64
 11  count       10886 non-null  int64
dtypes: float64(3), int64(8), object(1)
memory usage: 1020.7+ KB
```

[7]:
```
data['datetime'] = pd.to_datetime(data['datetime'])
```

[8]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    10886 non-null  datetime64[ns]
 1   season      10886 non-null  int64
 2   holiday     10886 non-null  int64
 3   workingday  10886 non-null  int64
 4   weather     10886 non-null  int64
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64
```

```
 10  registered  10886 non-null  int64
 11  count       10886 non-null  int64
dtypes: datetime64[ns](1), float64(3), int64(8)
memory usage: 1020.7 KB
```

[9]:
```
data.isnull().sum()
```

[9]:
```
datetime      0
season        0
holiday       0
workingday    0
weather       0
temp          0
atemp         0
humidity      0
windspeed     0
casual        0
registered    0
count         0
dtype: int64
```

Data type of each attribute are :

- *DateTime* : Datetime
- *Float* : Temp , ATemp , Windspeed
- *Integer* : Season , Holiday , Workingday , Weather , Humidity ,Casual , Registered , Count

NOTE : ___All the attributes are non-null ,so we don't need to make any changes in the dataset__

`Categorical Data` are **Datetime** , **Season** , **Holiday** ,**Workingday** and **Weather**.

`Quantitative Data` are **Temp** , **ATemp** , **Windspeed**, **Humidity**, **Casual** , **Registered** , **Count**

##Descriptive Analaysis

[10]:
```
data.describe()
```

[10]:
```
                            datetime        season       holiday  \
count                          10886  10886.000000  10886.000000
mean   2011-12-27 05:56:22.399411968      2.506614      0.028569
min              2011-01-01 00:00:00      1.000000      0.000000
25%              2011-07-02 07:15:00      2.000000      0.000000
50%              2012-01-01 20:30:00      3.000000      0.000000
75%              2012-07-01 12:45:00      4.000000      0.000000
max              2012-12-19 23:00:00      4.000000      1.000000
std                              NaN      1.116174      0.166599

         workingday       weather         temp         atemp      humidity  \
count  10886.000000  10886.000000  10886.00000  10886.000000  10886.000000
```

```
mean        0.680875    1.418427    20.23086    23.655084    61.886460
min         0.000000    1.000000     0.82000     0.760000     0.000000
25%         0.000000    1.000000    13.94000    16.665000    47.000000
50%         1.000000    1.000000    20.50000    24.240000    62.000000
75%         1.000000    2.000000    26.24000    31.060000    77.000000
max         1.000000    4.000000    41.00000    45.455000   100.000000
std         0.466159    0.633839     7.79159     8.474601    19.245033

          windspeed        casual    registered         count
count  10886.000000  10886.000000  10886.000000  10886.000000
mean      12.799395     36.021955    155.552177    191.574132
min        0.000000      0.000000      0.000000      1.000000
25%        7.001500      4.000000     36.000000     42.000000
50%       12.998000     17.000000    118.000000    145.000000
75%       16.997900     49.000000    222.000000    284.000000
max       56.996900    367.000000    886.000000    977.000000
std        8.164537     49.960477    151.039033    181.144454
```

Observation	Range	Minimum	Maximum	Mean/Average
DateTime	01-01-2011 : 19-12-2012	01-01-2011	19-12-2012	NA
Season	1-4	1	4	2.506
Holiday	0-1	0	1	0.028
Workingday	0-1	0	1	0.681
Weather	1-4	1	4	1.418
Temp	0.82 - 41	0.82	41	20.23
ATemp	0.76-45.55	0.76	45.55	23.65
Humidity	0-100	0	100	61.88
Windspeed	0-57	0	57	12.79
Casual	0-367	0	367	36.02
Registered	0-886	0	886	155.55
Count	1-977	1	977	191.57

[11]:
```
data['datetime'].max()-data['datetime'].min()
```

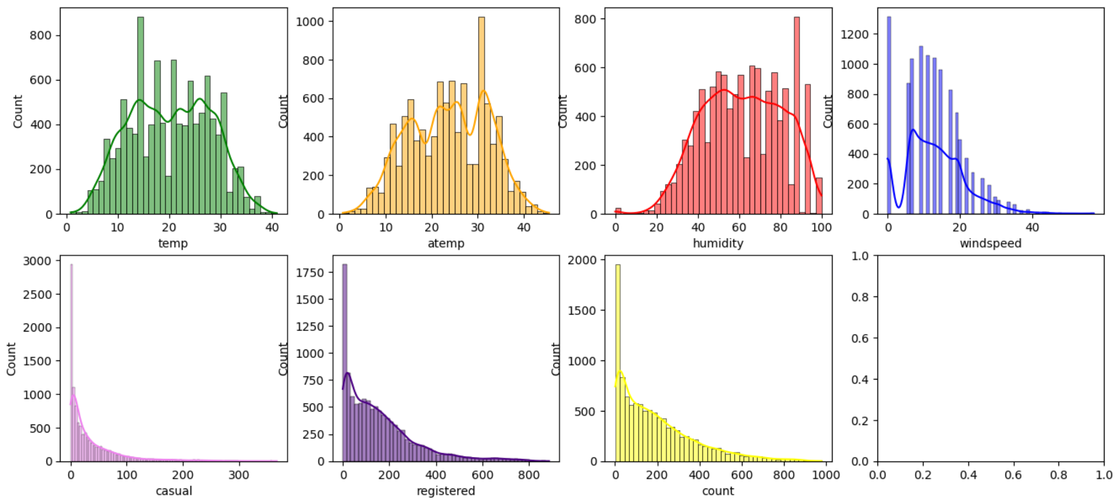
[11]:
```
Timedelta('718 days 23:00:00')
```

This data is of 718 days

3.1 Univariate Analysis

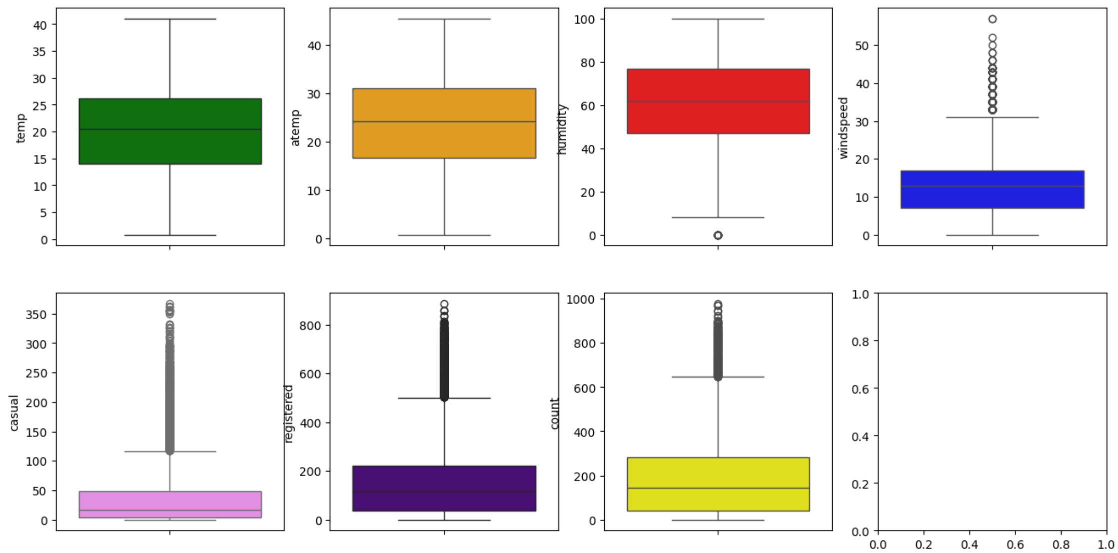
[57]:
```
fig, axis = plt.subplots(nrows=2,ncols=4,figsize=(16,7))
sns.histplot(data['temp'],ax=axis[0,0],color='green',kde='true')
sns.histplot(data['atemp'],ax=axis[0,1],color='orange',kde='true')
sns.histplot(data['humidity'],ax=axis[0,2],color='red',kde='true')
sns.histplot(data['windspeed'],ax=axis[0,3],color='blue',kde='true')
sns.histplot(data['casual'],ax=axis[1,0],color='violet',kde='true')
```

```
sns.histplot(data['registered'],ax=axis[1,1],color='indigo',kde='true')
sns.histplot(data['count'],ax=axis[1,2],color='yellow',kde='true')
plt.show()
```



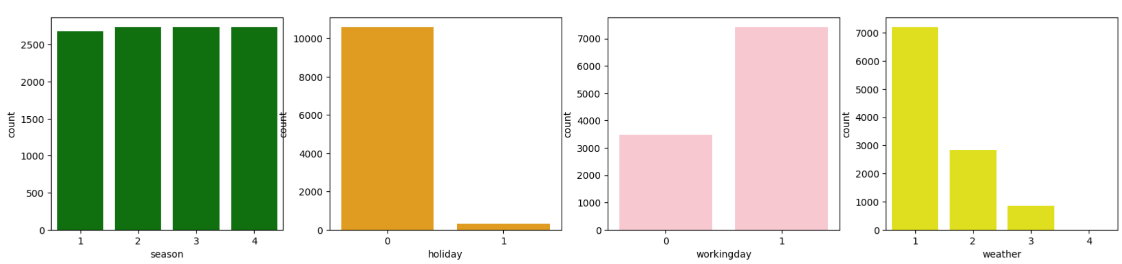
Observation : * When the temperature is between 10 and 30…the nos of customer increases. * As the windspeed increases , there is a downfall in the number of customers. * Casual , Registered and Count decreases in a logrithmic function.

[13]:
```
fig, axis = plt.subplots(nrows=2,ncols=4,figsize=(16,8))
sns.boxplot(data['temp'],ax=axis[0,0],color='green')
sns.boxplot(data['atemp'],ax=axis[0,1],color='orange')
sns.boxplot(data['humidity'],ax=axis[0,2],color='red')
sns.boxplot(data['windspeed'],ax=axis[0,3],color='blue')
sns.boxplot(data['casual'],ax=axis[1,0],color='violet')
sns.boxplot(data['registered'],ax=axis[1,1],color='indigo')
sns.boxplot(data['count'],ax=axis[1,2],color='yellow')
plt.show()
```



Observation : * There are a lot of outliers of casual , registered and count

[14]:
```
fig, axis = plt.subplots(nrows=1,ncols=4,figsize=(20,4))
sns.countplot(data=data,x='season',ax=axis[0],color='green')
sns.countplot(data=data,x='holiday',ax=axis[1],color='orange')
sns.countplot(data=data,x='workingday',ax=axis[2],color='pink')
sns.countplot(data=data,x='weather',ax=axis[3],color='yellow')
plt.show()
```

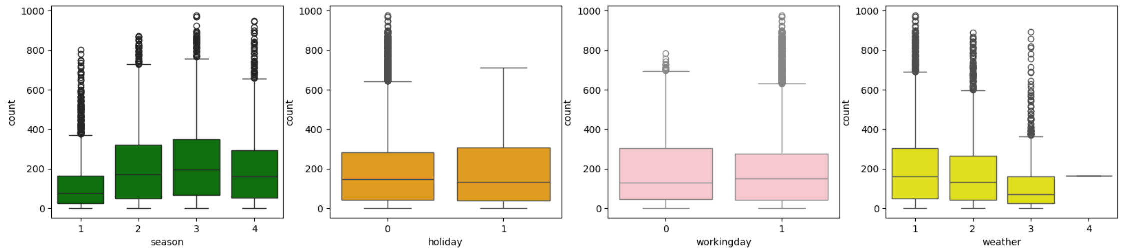


Observation: * Season has no impact on bikes usage. * On holidays ,people are not at all using yulu. * More than 60% of people seem to use it on a working day . * As the weather goes from clear to cloudy , people decrease the use of yulu.

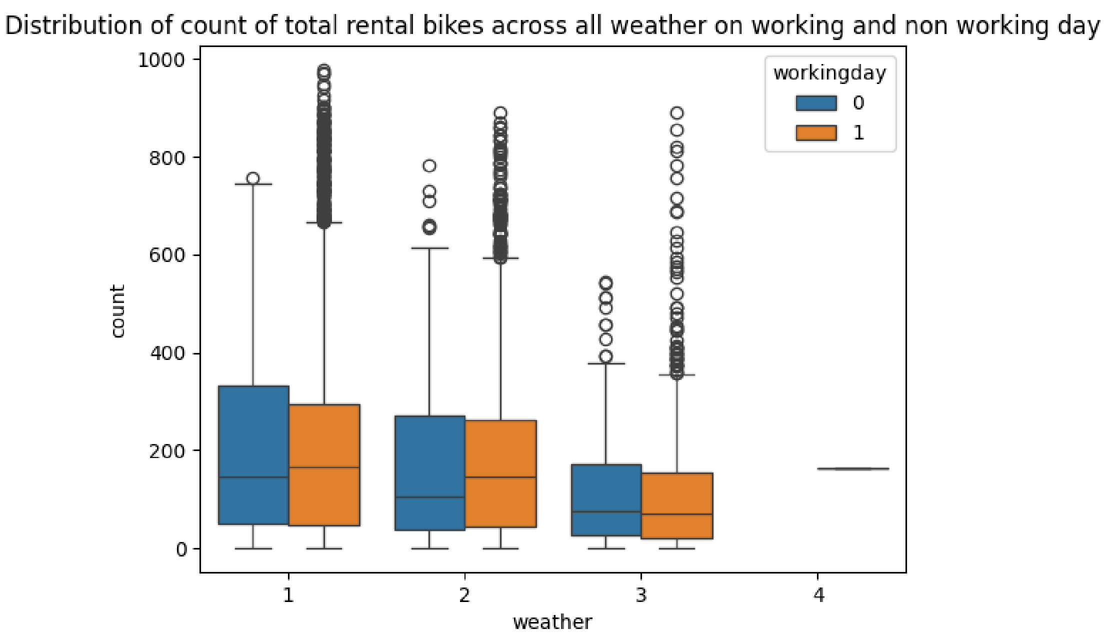
3.2 Bi-Variate Analysis

[15]:
```
fig, axis = plt.subplots(nrows=1,ncols=4,figsize=(20,4))
sns.boxplot(data=data,x='season',y='count',ax=axis[0],color='green')
sns.boxplot(data=data,x='holiday',y='count',ax=axis[1],color='orange')
sns.boxplot(data=data,x='workingday',y='count',ax=axis[2],color='pink')
```

```
sns.boxplot(data=data,x='weather',y='count',ax=axis[3],color='yellow')
plt.show()
```



[58]:
```
plt.title('Distribution of count of total rental bikes across all weather on␣
↪working and non working day')
sns.boxplot(data = data, x = 'weather', y = 'count', hue = 'workingday')
plt.show()
```

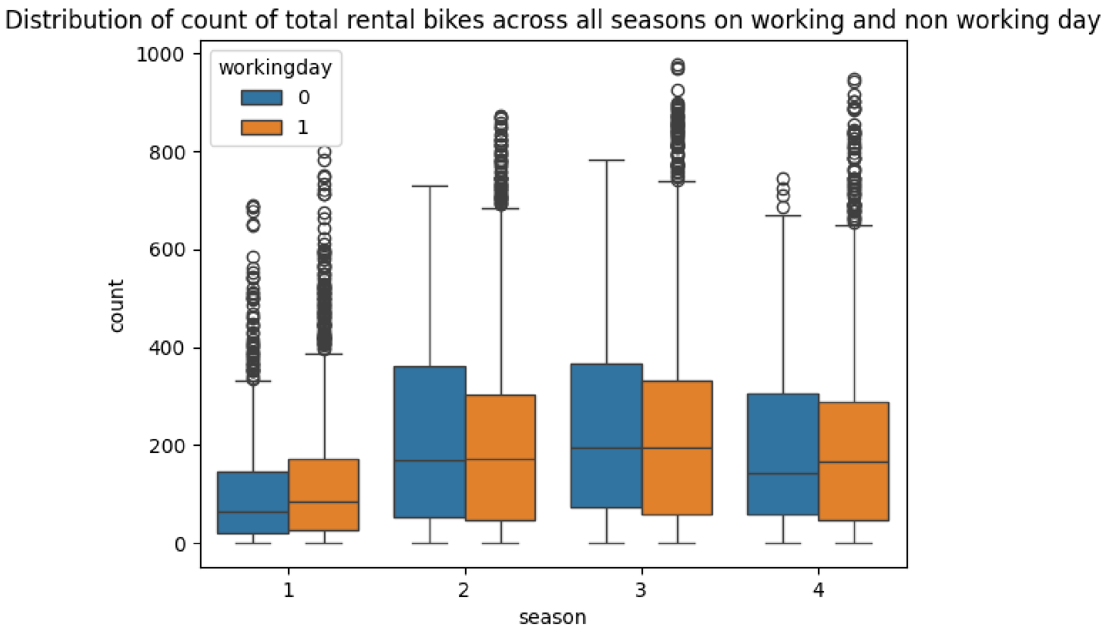


Observation:

The count of total rental bikes is maximmum in the clear and cloudy weather…then it is in the misty weather and then in the rainy weather.

In extreme weather conditions ……very less people rented the rental bikes as it would be difficult to drive in extreme weather conditions.

```
[17]: plt.title('Distribution of count of total rental bikes across all seasons on␣
        ↪working and non working day')
      sns.boxplot(data = data, x = 'season', y = 'count', hue = 'workingday')
      plt.show()
```



Observation:

The count of total rental bikes is higher in the season 2 and 3 ,i.e in summer and fall season followed by winter and spring.Spring has the lowest count of rental bikes.

No significant difference can be seen in working and non working day here.

3.3 Hypothesis Testing :

3.3.1 Is there any effect of working Day on number of bikes rented ?

```
[18]: data.groupby('workingday')['count'].describe() #Count of rental bikes of workin␣
        ↪and non working day
```

[18]:

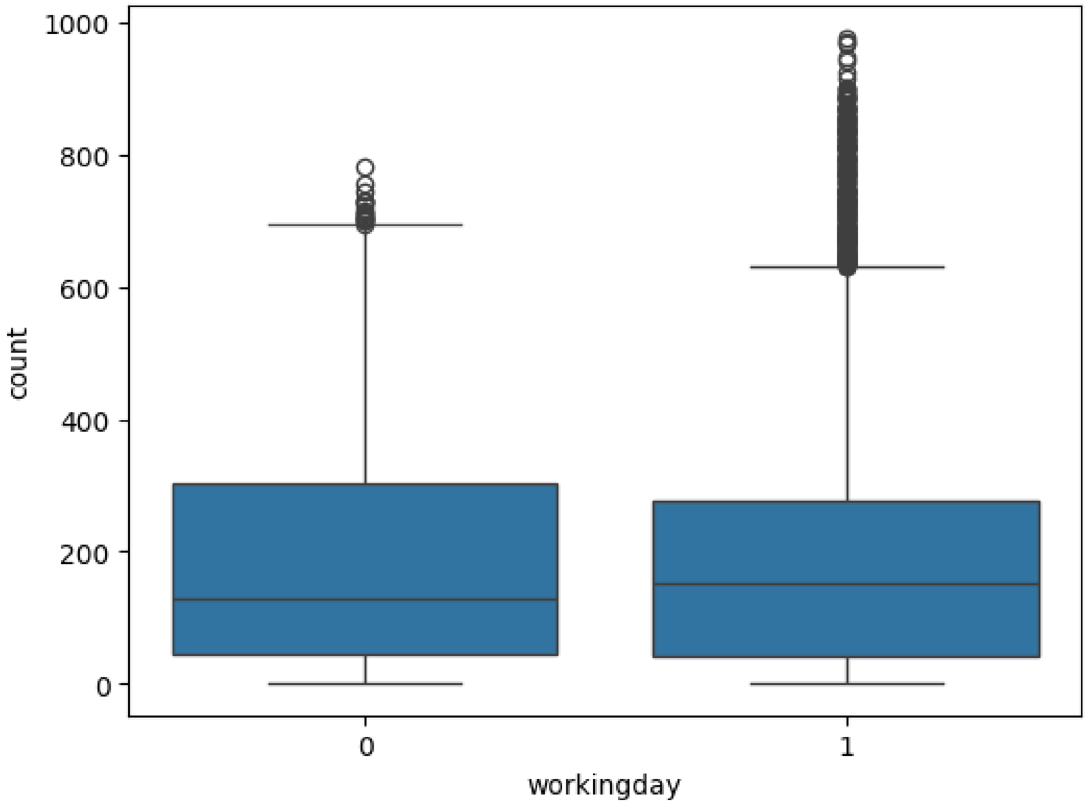
workingday	count	mean	std	min	25%	50%	75%	max
0	3474.0	188.506621	173.724015	1.0	44.0	128.0	304.0	783.0
1	7412.0	193.011873	184.513659	1.0	41.0	151.0	277.0	977.0

Observation: * The nos of bikes rented on working day is double than the bikes rented on non-working day.

- Standard deviation is also more for working day.

[19]:
```
sns.boxplot(data = data, x = 'workingday', y = 'count')
plt.plot()
```

[19]: []



STEP-1 : Set up Null Hypothesis (H0)

- **Null Hypothesis (H0)** - Working Day does not have any effect on the number of bikes rented.
- **Alternate Hypothesis (H1)** - Working Day has some effect on the number of bikes rented

STEP-2 : Checking for basic assumpitons for the hypothesis

- We set our ***alpha to be 0.05***

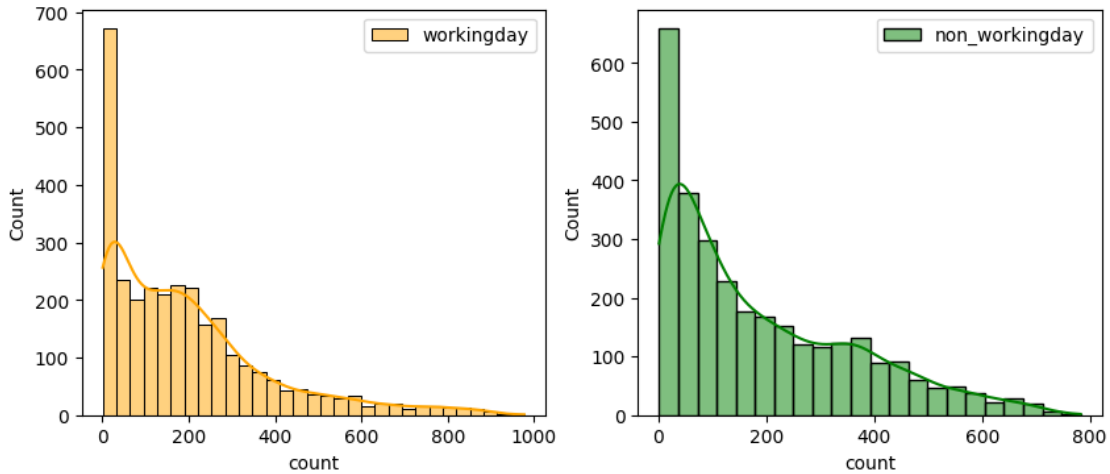
STEP-4: Compare p-value and alpha.

- Based on p-value, we will accept or reject H0.
  1. **p-val > alpha** : Can't reject H0
  2. **p-val < alpha** : Reject H0

Visual Test for normal Distribution

[20]:
```
plt.figure(figsize = (10, 4))
plt.subplot(1, 2, 1)
sns.histplot(data.loc[data['workingday'] == 1, 'count'].sample(3000), color =␣
↪'orange', kde = True, label = 'workingday')
plt.legend()
plt.subplot(1, 2, 2)
sns.histplot(data.loc[data['workingday'] == 0, 'count'].sample(3000), color =␣
↪'green', kde = True, label = 'non_workingday')
plt.legend()
plt.plot()
```

[20]: []



Observation: * The graph doesn't follow normal distribution.

Shapiro test for normal distribution H0 : **follows normal distribution**

H1 : **does not follow normal distribution**

alpha = 0.05

[21]:
```
from scipy.stats import shapiro
test_stat, p_value = shapiro(data.loc[data['workingday'] == 0, 'count'].
↪sample(3000))
if p_value < 0.05:
  print("Reject the null hypothesis , graph does not follows normal␣
↪distribution")
else :
  print("Can't reject the null hypothesis , graph follows normal distribution")
```

```
Reject the null hypothesis , graph does not follows normal distribution
```

[22]:
```
from scipy.stats import shapiro
test_stat, p_value = shapiro(data.loc[data['workingday'] == 1, 'count'].
 ↪sample(3000))
if p_value < 0.05:
  print("Reject the null hypothesis , graph does not follows normal␣
 ↪distribution")
else :
  print("Can't reject the null hypothesis , graph follows normal distribution")
```

```
Reject the null hypothesis , graph does not follows normal distribution
```

QQ Plot test for normal

[59]:
```
from statsmodels.graphics.gofplots import qqplot
```

[24]:
```
qqplot(data.loc[data['workingday'] == 1, 'count'].sample(3000),line='s')
plt.title('QQ plot for workingday')

qqplot(data.loc[data['workingday'] == 0, 'count'].sample(3000),line='s')
plt.title('QQ plot for non_workingday')
plt.show()
```

Observation: * The conclusion is that it is not a normal distribution.

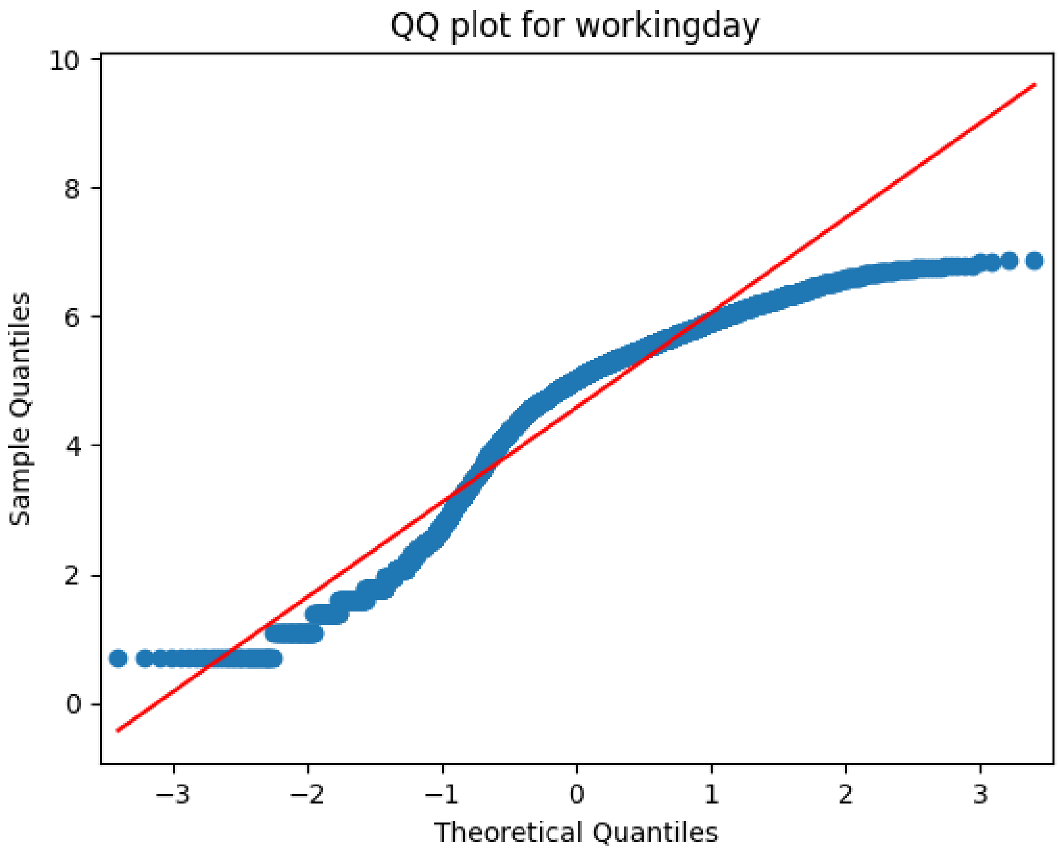
Conclusion-Distribution Assumptions of ANNOVA has failed , it's not a normal distribution

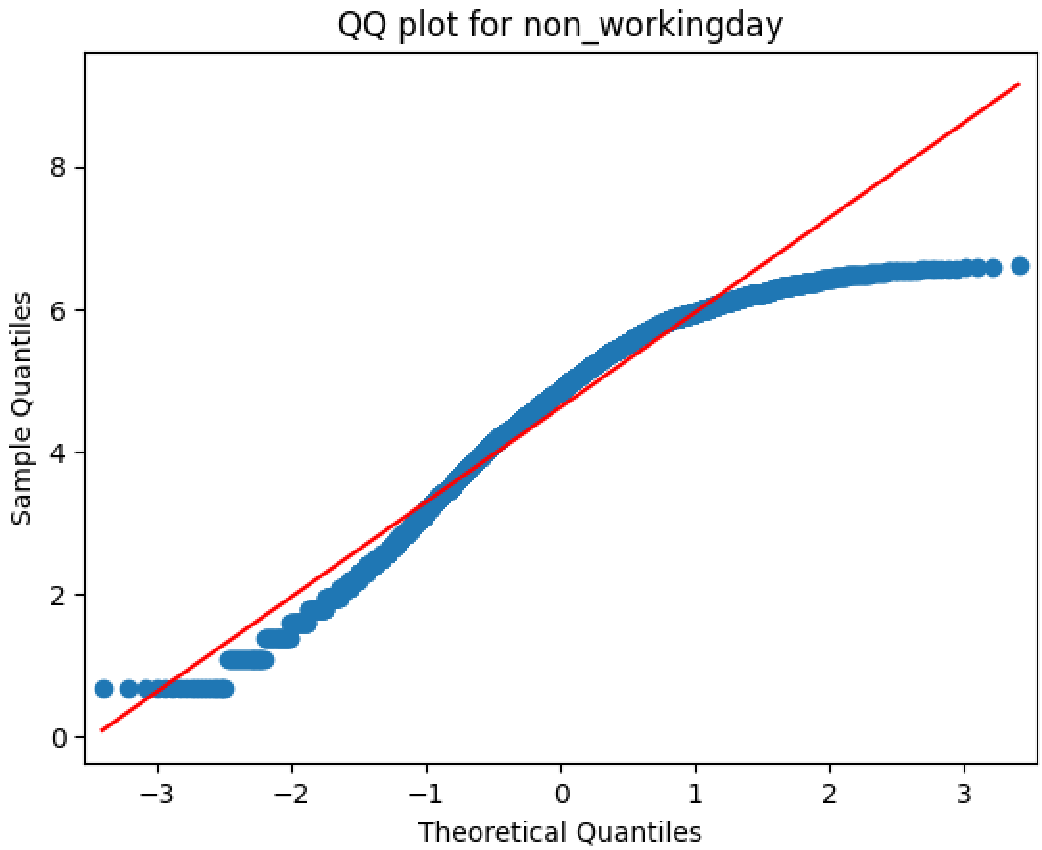
We will perform log transformation to make it normal

Log Transformation

[25]:
```
sample_data_1 = data.loc[data['workingday'] == 1, 'count'].sample(3000)
log_transformed_data_1 = np.log1p(sample_data_1)
sample_data_0 = data.loc[data['workingday'] == 0, 'count'].sample(3000)
log_transformed_data_0 = np.log1p(sample_data_0)


qqplot(log_transformed_data_1,line='s')
plt.title('QQ plot for workingday')

qqplot(log_transformed_data_0,line='s')
plt.title('QQ plot for non_workingday')
```

```
plt.show()
```


QQ plot for workingday
Sample Quantiles
Theoretical Quantiles
10
8
6
4
2
0
−3
−2
−1
0
1
2
3

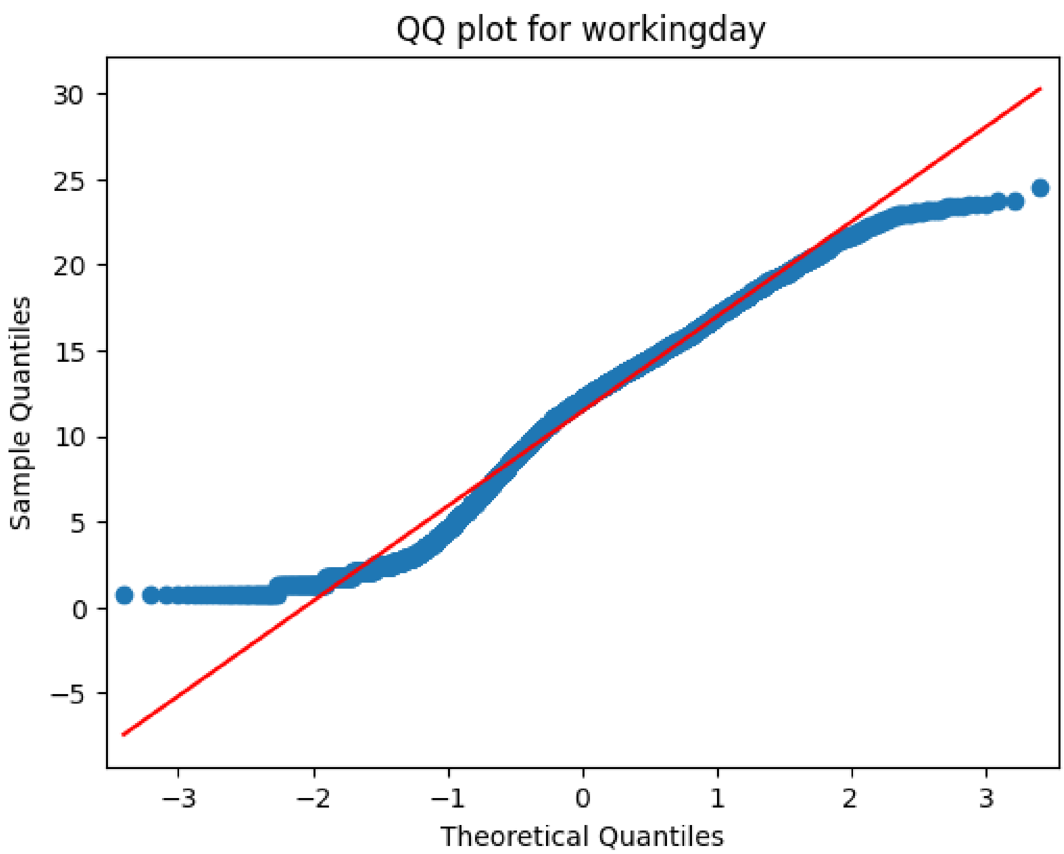


Observation * It is also not able to make data normal * So we will apply yeo johnson transformation

Yeo-Johnson Transformation

[60]:
```python
from scipy.stats import yeojohnson
yeo_transformed_0,lambda_0=yeojohnson(data.loc[data['workingday']==0,'count'].
  ↪sample(3000))
yeo_transformed_1,lambda_1=yeojohnson(data.loc[data['workingday']==1,'count'].
  ↪sample(3000))

qqplot(yeo_transformed_0,line='s')
plt.title('QQ plot for non-workingday')

qqplot(yeo_transformed_1,line='s')
plt.title('QQ plot for workingday')
plt.show()
```


QQ plot for non-workingday
Sample Quantiles
Theoretical Quantiles
25
20
15
10
5
0
−5
−3
−2
−1
0
1
2
3



Krushkal Wallis Test

[61]:
```
from scipy.stats import kruskal
```

[28]:
```
stat, p_value = kruskal(data.loc[data['workingday'] == 1, 'count'].
 ↪sample(3000),data.loc[data['workingday'] == 0, 'count'].sample(3000))
if p_value < 0.05 :
  print ("Reject the null hypothesis . So, working Day has some effect on the␣
 ↪number of bikes rented ")
else :
  print ("Accept the null hypothesis. So , working Day has no effect on the␣
 ↪number of bikes rented ")
```

```
Accept the null hypothesis. So , working Day has no effect on the number of
bikes rented
```

Sample T-Test on transformed data

> Add blockquote

[29]:
```
from scipy.stats import ttest_ind
```

[30]:
```python
test_stat,p_value = ttest_ind(yeo_transformed_0,yeo_transformed_0)
if(p_value<0.05):
  print("Reject the null hypothesis .So, working Day has some effect on the␣
↪number of bikes rented")
else:
  print("Accept the null hypothesis .So, working Day has some effect on the␣
↪number of bikes rented")
```

```
Accept the null hypothesis .So, working Day has some effect on the number of
bikes rented
```

Conclusion Since we had to transform the data a lot to apply t-test so we can't confirm about the accuracy of this.

So we will consider the krushkal wallis test , and hence There's no effect on the number of bikes rented

[31]:
```python
data.groupby('holiday')['count'].describe()
```

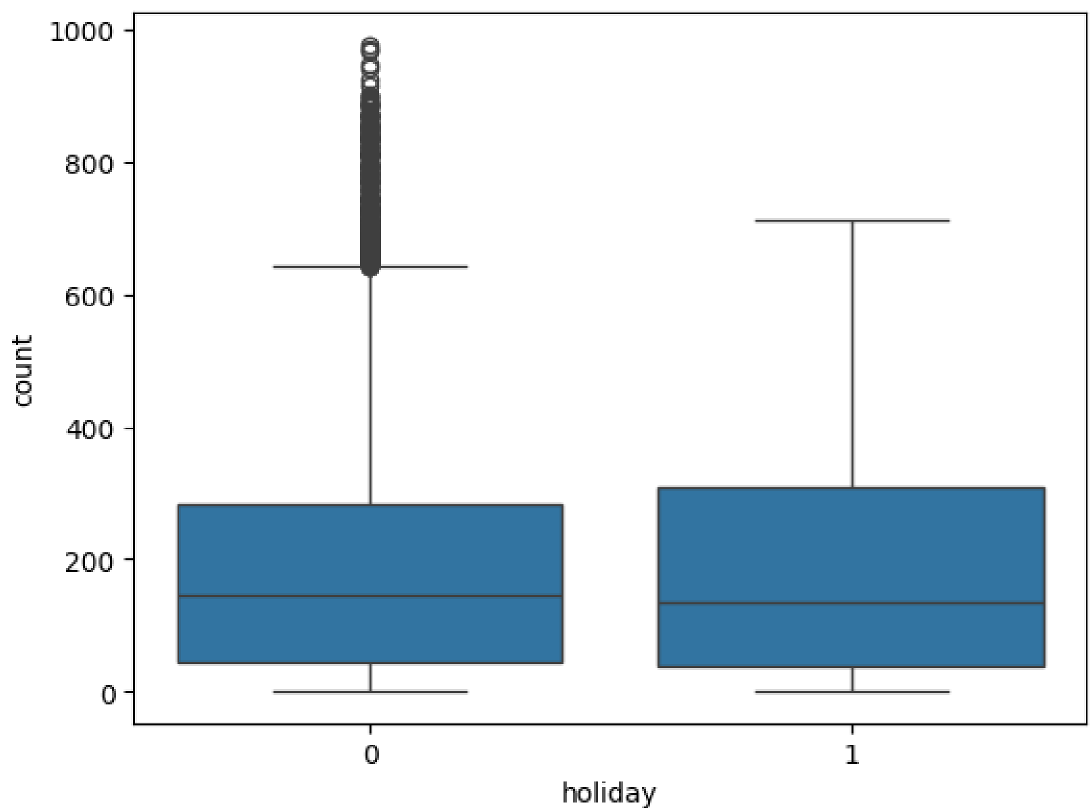
[31]:

holiday	count	mean	std	min	25%	50%	75%	max
0	10575.0	191.741655	181.513131	1.0	43.0	145.0	283.0	977.0
1	311.0	185.877814	168.300531	1.0	38.5	133.0	308.0	712.0

Observation: * There's a significant difference in the number of bikes rented on holiday and non-holiday

[32]:
```python
sns.boxplot(data = data, x = 'holiday', y = 'count')
plt.plot()
```

[32]: []



STEP-1 : Set up Null Hypothesis (H0)

- **Null Hypothesis (H0)** - Holiday does not have any effect on the number of bikes rented.
- **Alternate Hypothesis (H1)** - Holiday has some effect on the number of bikes rented

STEP-2 : Checking for basic assumpitons for the hypothesis

- We set our ***alpha to be 0.05***

STEP-4: Compare p-value and alpha.

- Based on p-value, we will accept or reject H0.

  1. **p-val > alpha** : Can't reject H0
  2. **p-val < alpha** : Reject H0

3.3.2 Is the number of bikes rented is similar or different in different season ?

[33]:
```
data.groupby(by = 'season')['count'].describe()
```

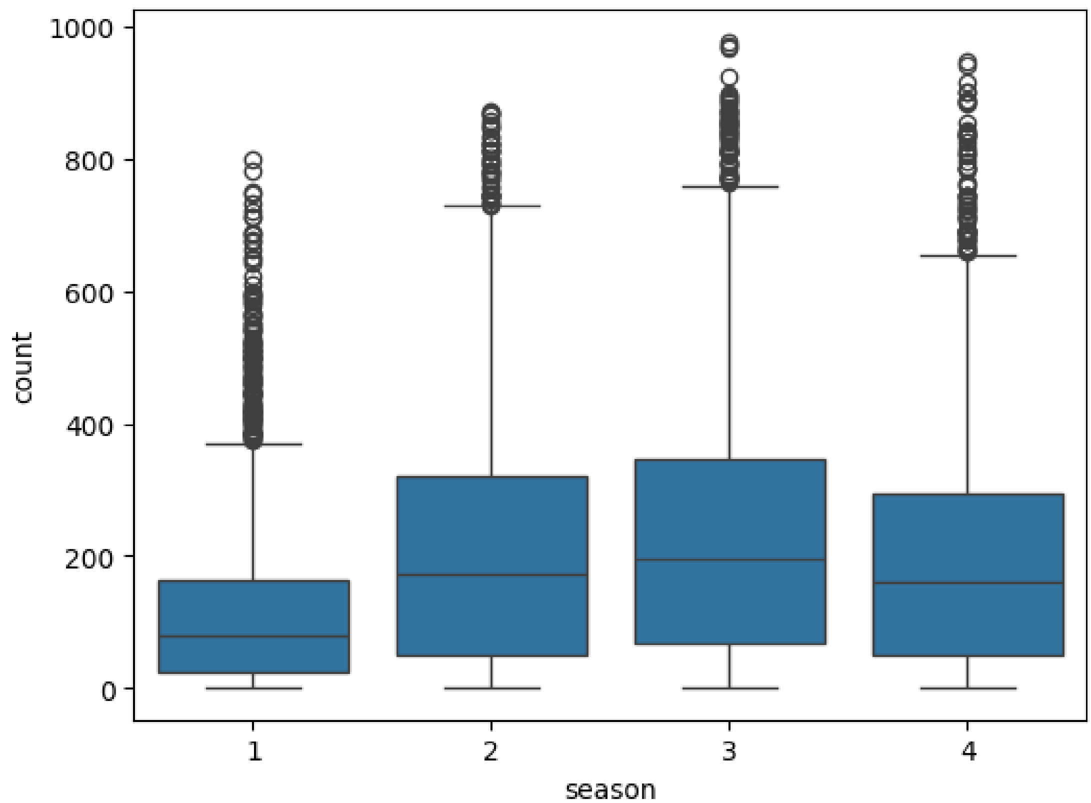
[33]:

season	count	mean	std	min	25%	50%	75%	max
1	2686.0	116.343261	125.273974	1.0	24.0	78.0	164.0	801.0
2	2733.0	215.251372	192.007843	1.0	49.0	172.0	321.0	873.0
3	2733.0	234.417124	197.151001	1.0	68.0	195.0	347.0	977.0
4	2734.0	198.988296	177.622409	1.0	51.0	161.0	294.0	948.0

[34]:

```
sns.boxplot(data=data,x='season',y='count')
```

[34]: <Axes: xlabel='season', ylabel='count'>



STEP-1 : Set up Null Hypothesis (H0)

- Distribution check using **QQ Plot**
- Visual test for normal distribution.
- Shapiro test for normal distribution

STEP-3 : Compute the p-value and fix value of alpha.

We will be computing the multiple sample anova-test p-value using the **f_oneway** function using scipy.stats. We set our alpha to be **0.05**

STEP-4 : Compare p-value and alpha.

Based on p-value, we will accept or reject H0.

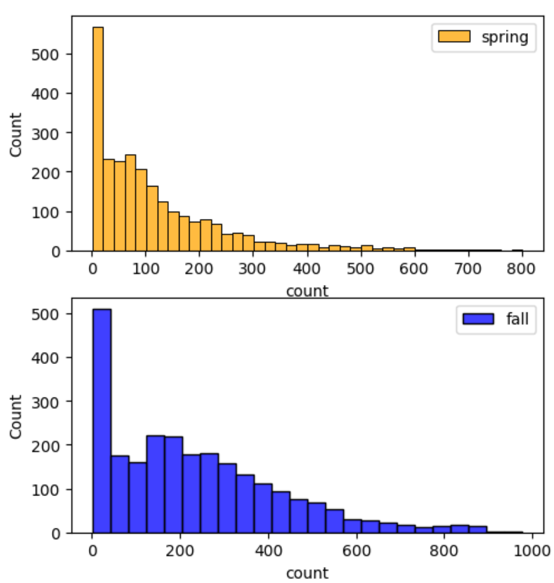
p-val > alpha : Accept H0

p-val < alpha : Reject H0

Visual Test for normal Distribution

[35]:
```python
plt.figure(figsize = (12, 6))
plt.subplot(2, 2, 1)
sns.histplot(data.loc[data['season'] == 1, 'count'].sample(2500), color =␣
 ↪'orange', label = 'spring')
plt.legend()
plt.subplot(2, 2, 2)
sns.histplot(data.loc[data['season'] == 2, 'count'].sample(2500),color =␣
 ↪'green',  label = 'summer')
plt.legend()
plt.subplot(2, 2, 3)
sns.histplot(data.loc[data['season'] == 3, 'count'].sample(2500),color =␣
 ↪'blue',  label = 'fall')
plt.legend()
plt.subplot(2, 2, 4)
sns.histplot(data.loc[data['season'] == 4, 'count'].sample(2500),color = 'red',␣
 ↪ label = 'winter')
plt.legend()
plt.plot()
```

[35]: []



Observation: * The graph is also not normal

Shapiro test for normal distribution H0 : **follows normal distribution**

H1 : **does not follow normal distribution**

alpha = 0.05

[36]:
```
from scipy.stats import shapiro
test_stat, p_value = shapiro(data.loc[data['season'] == 1, 'count'].
 ↪sample(2000))
if p_value < 0.05:
  print("Reject the null hypothesis , graph does not follows normal␣
 ↪distribution")
else :
  print("Can't reject the null hypothesis , graph follows normal distribution")
```

```
Reject the null hypothesis , graph does not follows normal distribution
```

[37]:
```
from scipy.stats import shapiro
test_stat, p_value = shapiro(data.loc[data['season'] == 2, 'count'].
 ↪sample(2000))
if p_value < 0.05:
  print("Reject the null hypothesis , graph does not follows normal␣
 ↪distribution")
else :
  print("Can't reject the null hypothesis , graph follows normal distribution")
```

```
Reject the null hypothesis , graph does not follows normal distribution
```

[38]:
```
from scipy.stats import shapiro
test_stat, p_value = shapiro(data.loc[data['season'] == 3, 'count'].
 ↪sample(2000))
if p_value < 0.05:
  print("Reject the null hypothesis , graph does not follows normal␣
 ↪distribution")
else :
  print("Can't reject the null hypothesis , graph follows normal distribution")
```

```
Reject the null hypothesis , graph does not follows normal distribution
```

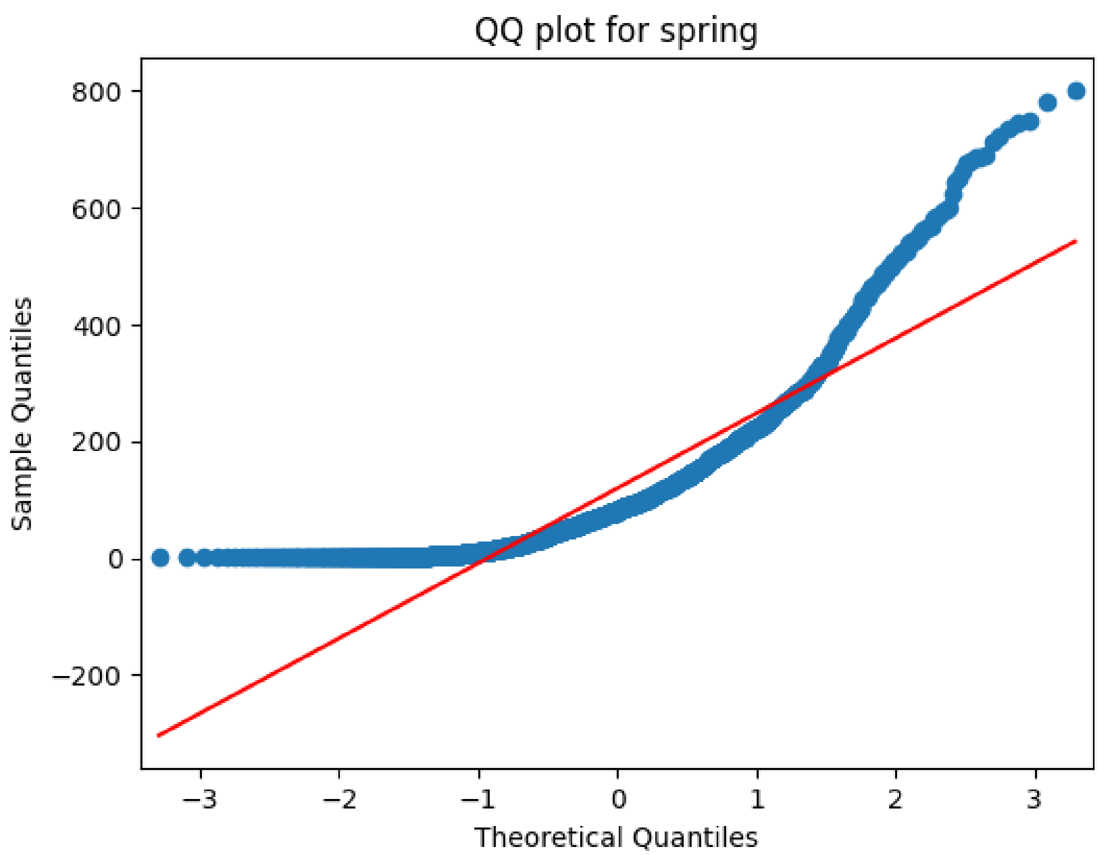
[39]:
```
from scipy.stats import shapiro
test_stat, p_value = shapiro(data.loc[data['season'] == 4, 'count'].
 ↪sample(2000))
if p_value < 0.05:
```

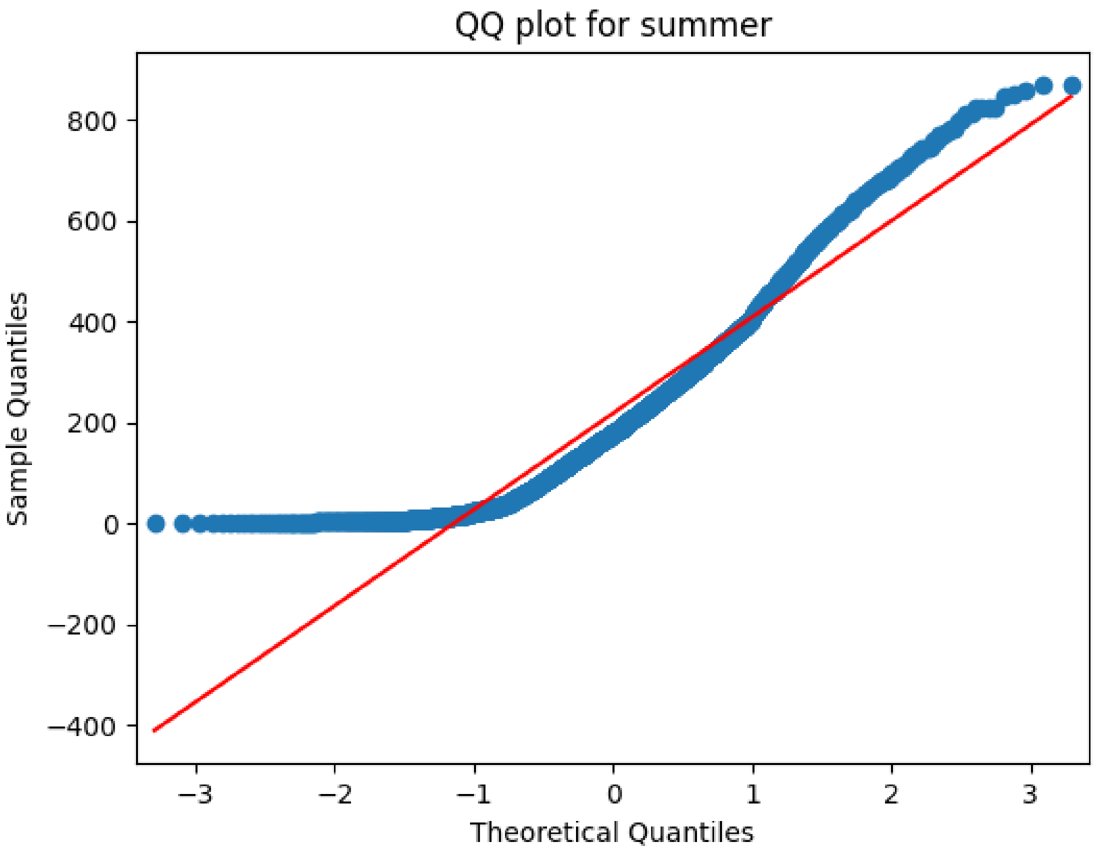
```
  print("Reject the null hypothesis , graph does not follows normal␣
 ↪distribution")
else :
  print("Can't reject the null hypothesis , graph follows normal distribution")
```

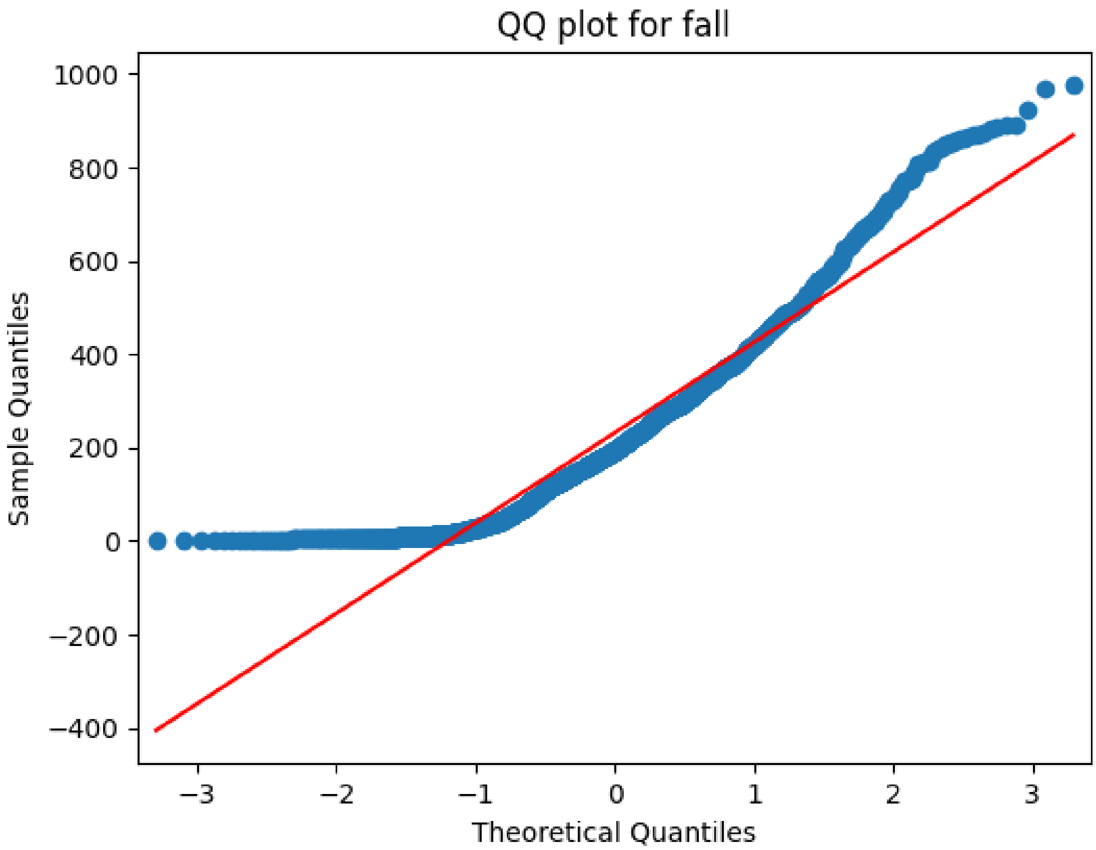
```
Reject the null hypothesis , graph does not follows normal distribution
```

QQ Plot test for normal distribution

[62]:
```
qqplot(data.loc[data['season'] == 1, 'count'].sample(2000),line='s')
plt.title('QQ plot for spring')
qqplot(data.loc[data['season'] == 2, 'count'].sample(2000),line='s')
plt.title('QQ plot for summer')
qqplot(data.loc[data['season'] == 3, 'count'].sample(2000),line='s')
plt.title('QQ plot for fall')
qqplot(data.loc[data['season'] == 4, 'count'].sample(2000),line='s')
plt.title('QQ plot for winter')
plt.show()
```




QQ plot for summer
Sample Quantiles
Theoretical Quantiles
800
600
400
200
0
−200
−400
−3
−2
−1
0
1
2
3


QQ plot for fall
Sample Quantiles
Theoretical Quantiles
1000
800
600
400
200
0
−200
−400
−3
−2
−1
0
1
2
3

Conclusion on Distribution

- This is also not a normal distribution so we will first perform krushkal wallis test .

Krushkal Wallis Test

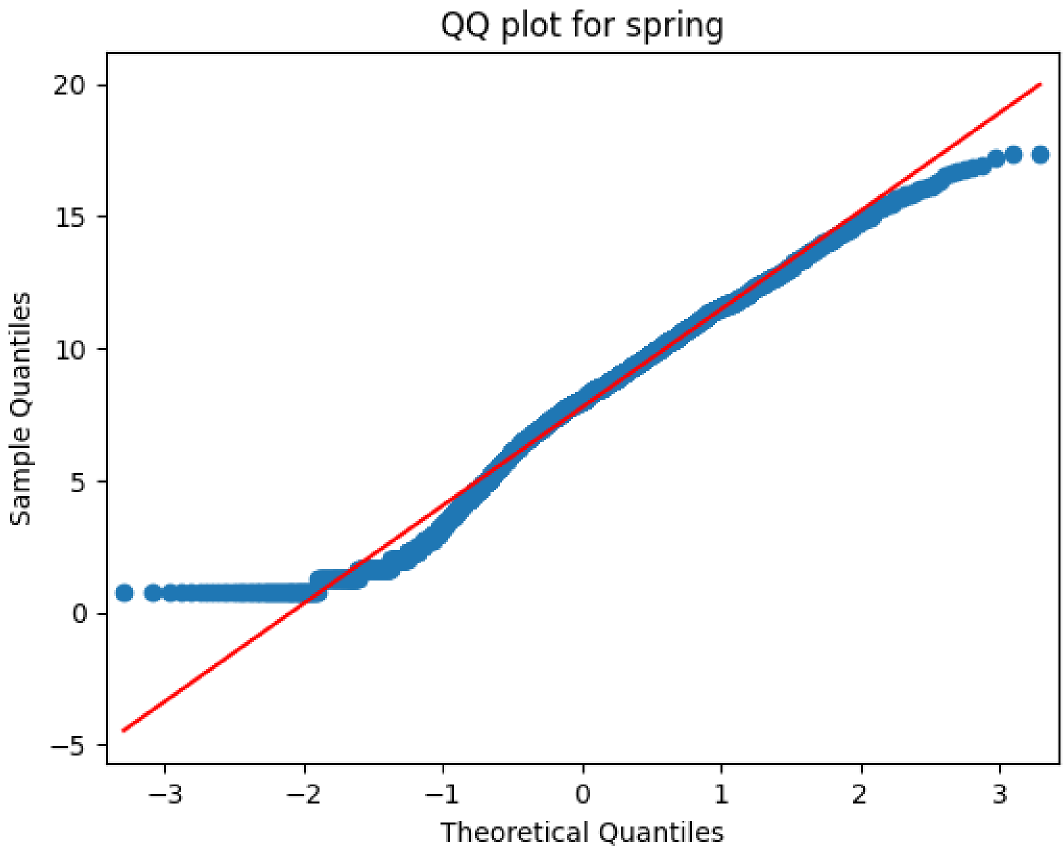
[41]:
```
spring =data.loc[data['season'] == 1, 'count'].sample(2000)
summer = data.loc[data['season'] == 2, 'count'].sample(2000)
fall =  data.loc[data['season'] == 3, 'count'].sample(2000)
winter =  data.loc[data['season'] == 4, 'count'].sample(2000)

stat, p_value = kruskal(spring,summer,fall,winter)
if p_value < 0.05 :
  print ("Reject the null hypothesis . So, working Day has some effect on the␣
↪number of bikes rented ")
else :
  print ("Accept the null hypothesis. So , working Day has no effect on the␣
↪number of bikes rented ")
```

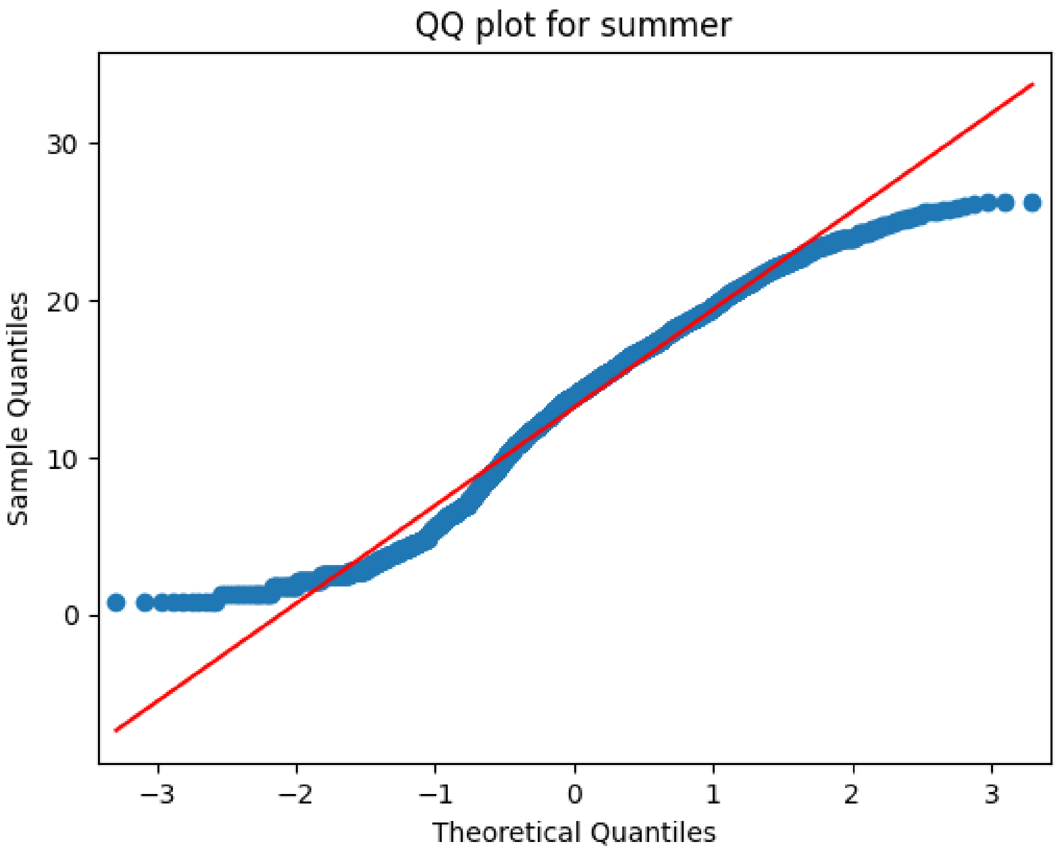
```
Reject the null hypothesis . So, working Day has some effect on the number of
bikes rented
```

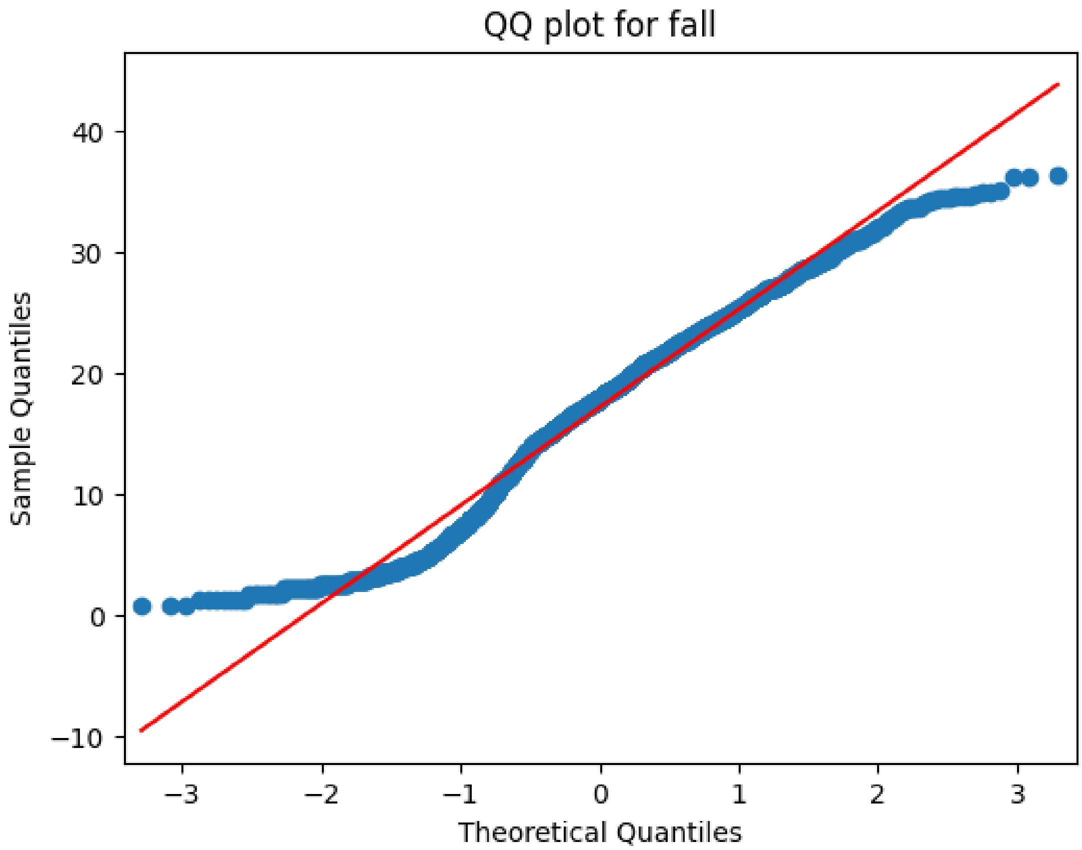
Yeo-Johnson Transformation Lets apply yeo johnson transformation to make it normal.

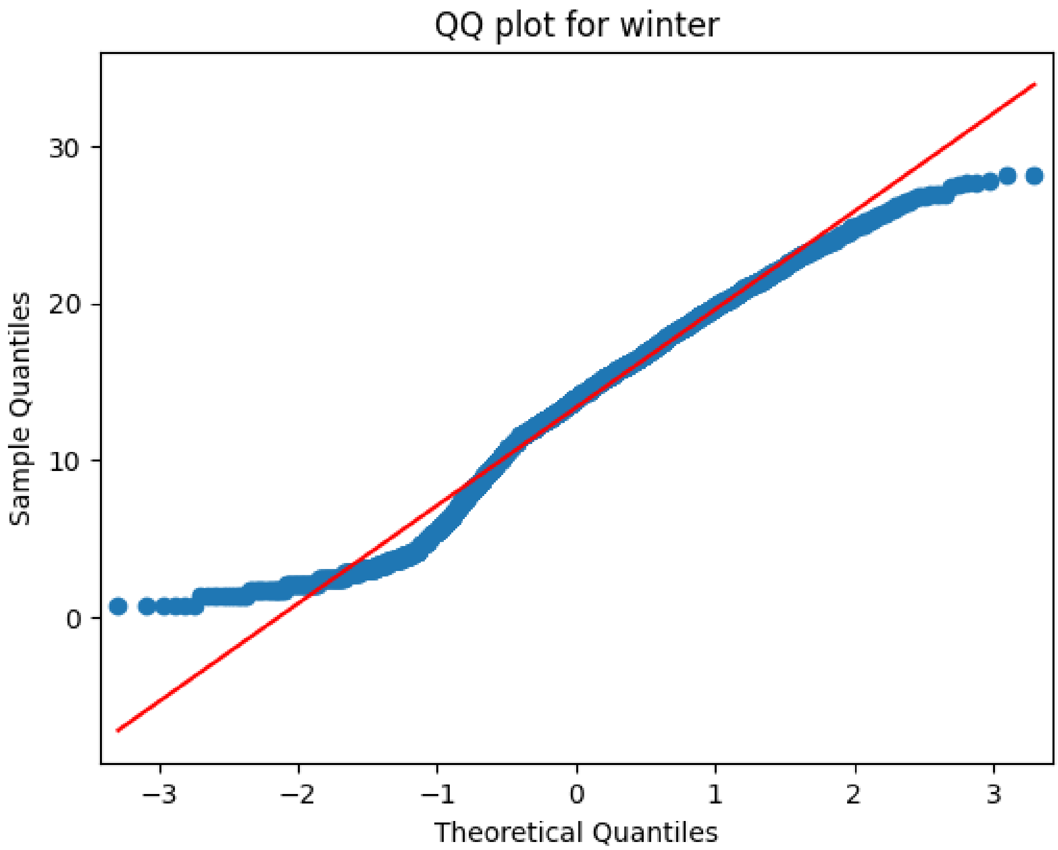
[42]:
```
from scipy.stats import yeojohnson
season_transformed_1,lambda_1=yeojohnson(data.loc[data['season']==1,'count'].
  ↪sample(2000))
season_transformed_2,lambda_2=yeojohnson(data.loc[data['season']==2,'count'].
  ↪sample(2000))
season_transformed_3,lambda_3=yeojohnson(data.loc[data['season']==3,'count'].
  ↪sample(2000))
season_transformed_4,lambda_4=yeojohnson(data.loc[data['season']==4,'count'].
  ↪sample(2000))

qqplot(season_transformed_1,line='s')
plt.title('QQ plot for spring')

qqplot(season_transformed_2,line='s')
plt.title('QQ plot for summer')

qqplot(season_transformed_3,line='s')
plt.title('QQ plot for fall')

qqplot(season_transformed_4,line='s')
plt.title('QQ plot for winter')
```

[42]:
```
Text(0.5, 1.0, 'QQ plot for winter')
```


QQ plot for spring
Sample Quantiles
Theoretical Quantiles
20
15
10
5
0
−5
−3
−2
−1
0
1
2
3


QQ plot for summer
Sample Quantiles
Theoretical Quantiles
30
20
10
0
−3
−2
−1
0
1
2
3


QQ plot for fall
Sample Quantiles
Theoretical Quantiles
40
30
20
10
0
−10
−3
−2
−1
0
1
2
3



ANNOVA Test

[43]:
```
from scipy.stats import f_oneway
```

[44]:
```
f_stats, p_value =␣
↪f_oneway(season_transformed_1,season_transformed_2,season_transformed_3,season_transformed_
if(p_value<0.05):
  print("Reject the null hypothesis .So, season has some effect on the number␣
↪of bikes rented")
else:
  print("Accept the null hypothesis .So, season has no effect on the number of␣
↪bikes rented")
```

```
Reject the null hypothesis .So, season has some effect on the number of bikes
rented
```

Conclusion

- In both the test we can see that we get to reject the null hypothesis . So we can conclude that there's a significantly different in different seasons.

3.3.3 Is the number of bikes rented is similar or different in different weather ?

[45]:
```
data.groupby(by = 'weather')['count'].describe()
```

[45]:

weather	count	mean	std	min	25%	50%	75%	max
1	7192.0	205.236791	187.959566	1.0	48.0	161.0	305.0	977.0
2	2834.0	178.955540	168.366413	1.0	41.0	134.0	264.0	890.0
3	859.0	118.846333	138.581297	1.0	23.0	71.0	161.0	891.0
4	1.0	164.000000	NaN	164.0	164.0	164.0	164.0	164.0

Since we only have 1 count for bad weather , so we will not consider that for our analaysis

STEP-1 : Set up Null Hypothesis (H0)

- Distribution check using **QQ Plot**
- Visual test for normal distribution.
- Shapiro test for normal distribution

STEP-3 : Compute the p-value and fix value of alpha.

We will be computing the multiple sample anova-test p-value using the **f_oneway** function using scipy.stats. We set our alpha to be **0.05**

STEP-4 : Compare p-value and alpha.

Based on p-value, we will accept or reject H0.

p-val > alpha : Accept H0

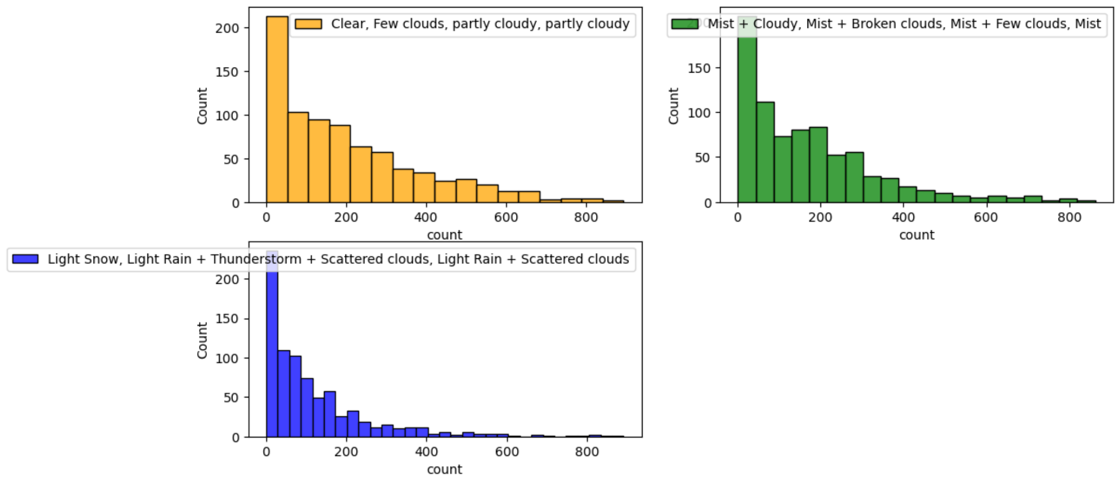
p-val < alpha : Reject H0

Visual test for normal distribution

[46]:
```
plt.figure(figsize = (12, 6))
plt.subplot(2, 2, 1)
sns.histplot(data.loc[data['weather'] == 1, 'count'].sample(800), color =␣
↪'orange', label = 'Clear, Few clouds, partly cloudy, partly cloudy')
plt.legend()
plt.subplot(2, 2, 2)
sns.histplot(data.loc[data['weather'] == 2, 'count'].sample(800),color =␣
↪'green',  label = 'Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds,␣
↪Mist')
plt.legend()
plt.subplot(2, 2, 3)
sns.histplot(data.loc[data['weather'] == 3, 'count'].sample(800),color =␣
↪'blue',  label = 'Light Snow, Light Rain + Thunderstorm + Scattered clouds,␣
↪Light Rain + Scattered clouds')
```

```
plt.legend()

plt.plot()
```

[46]: []



Observation: * The graph doesn't seem to be a normal graph...so we have to conduct shapiro test.

Shapiro test for normal distribution H0 : **follows normal distribution**

H1 : **does not follow normal distribution**

alpha = 0.05

[47]:
```
from scipy.stats import shapiro
test_stat, p_value = shapiro(data.loc[data['weather'] == 1, 'count'].
 ↪sample(800))
if p_value < 0.05:
  print("Reject the null hypothesis , graph does not follows normal␣
 ↪distribution")
else :
  print("Can't reject the null hypothesis , graph follows normal distribution")
```

```
Reject the null hypothesis , graph does not follows normal distribution
```

[48]:
```
from scipy.stats import shapiro
test_stat, p_value = shapiro(data.loc[data['season'] == 2, 'count'].sample(800))
if p_value < 0.05:
  print("Reject the null hypothesis , graph does not follows normal␣
 ↪distribution")
else :
```

```
    print("Can't reject the null hypothesis , graph follows normal distribution")
```

```
Reject the null hypothesis , graph does not follows normal distribution
```

[49]:
```
from scipy.stats import shapiro
test_stat, p_value = shapiro(data.loc[data['season'] == 3, 'count'].sample(800))
if p_value < 0.05:
  print("Reject the null hypothesis , graph does not follows normal␣
 ↪distribution")
else :
  print("Can't reject the null hypothesis , graph follows normal distribution")
```

```
Reject the null hypothesis , graph does not follows normal distribution
```

Conclusion on Distribution We can conclude that distribution is not normal

so lets first perform krushkal wallis test and then make the graph normal and then perform ANNOVA test

Krushkal Wallis Test

[50]:
```
good_weather =data.loc[data['weather'] == 1, 'count'].sample(800)
not_good_weather = data.loc[data['weather'] == 2, 'count'].sample(800)
bad_weather =  data.loc[data['weather'] == 3, 'count'].sample(800)


stat, p_value = kruskal(good_weather,not_good_weather,bad_weather)
if p_value < 0.05 :
  print ("Reject the null hypothesis . So, working Day has some effect on the␣
 ↪number of bikes rented ")
else :
  print ("Accept the null hypothesis. So , working Day has no effect on the␣
 ↪number of bikes rented ")
```

```
Reject the null hypothesis . So, working Day has some effect on the number of
bikes rented
```

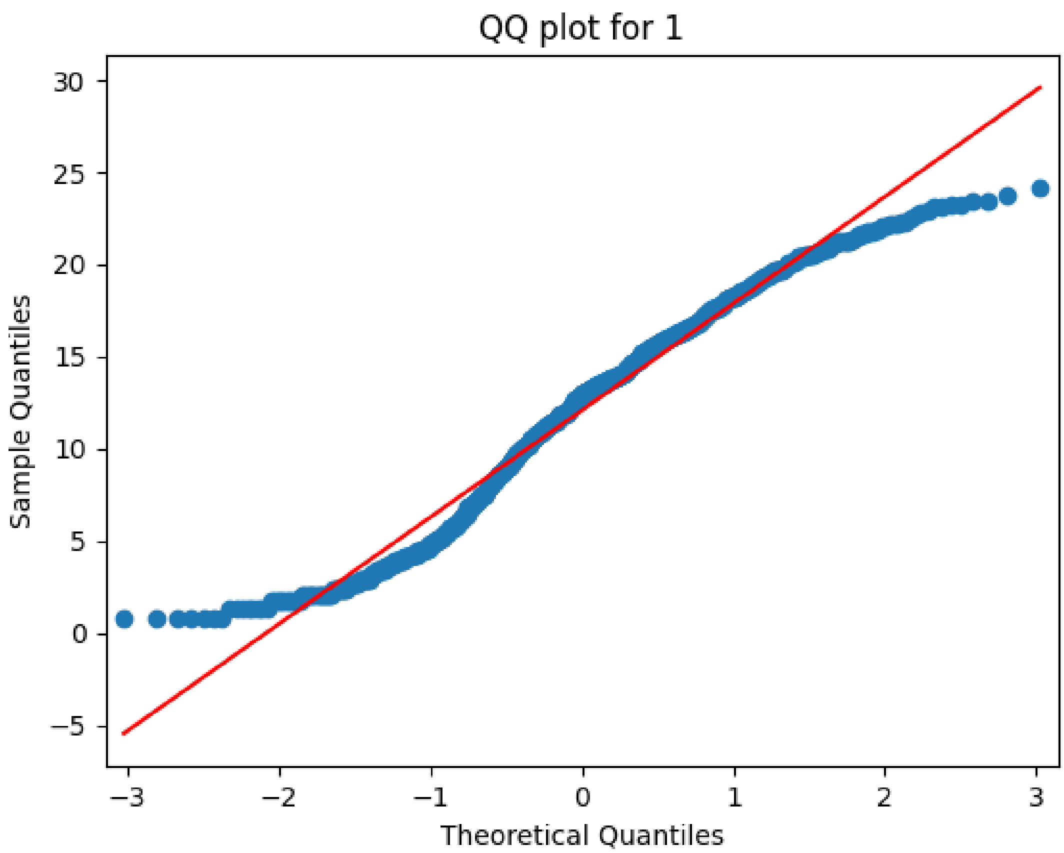
Observation * Krushkal Wallis test has given that there is an effect of weather . Lets now tranform the distribution and then try with annova

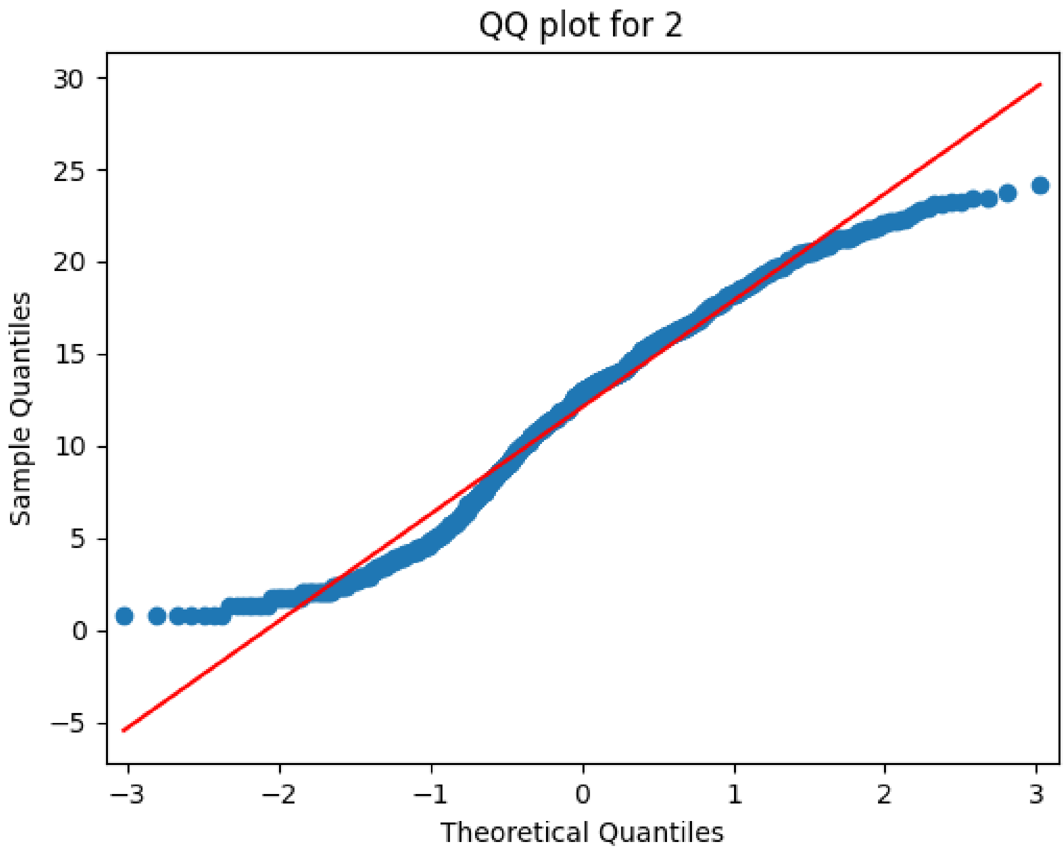
Yeo-Johnson Transformation

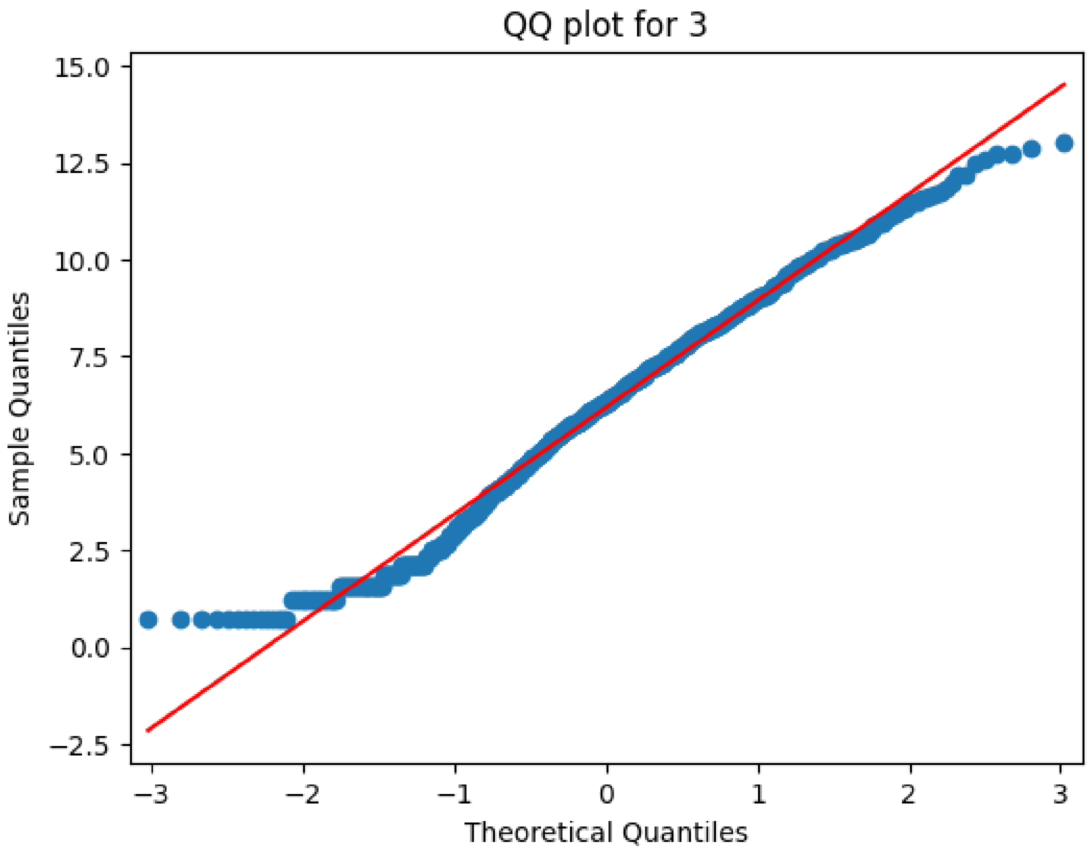
[51]:
```
from scipy.stats import yeojohnson
weather_transformed_1,lambda_1=yeojohnson(data.loc[data['weather']==1,'count'].
 ↪sample(800))
weather_transformed_2,lambda_2=yeojohnson(data.loc[data['weather']==2,'count'].
 ↪sample(800))
weather_transformed_3,lambda_3=yeojohnson(data.loc[data['weather']==3,'count'].
 ↪sample(800))
```

```
qqplot(weather_transformed_1,line='s')
plt.title('QQ plot for 1')

qqplot(weather_transformed_1,line='s')
plt.title('QQ plot for 2')

qqplot(weather_transformed_3,line='s')
plt.title('QQ plot for 3')
```

[51]: Text(0.5, 1.0, 'QQ plot for 3')




QQ plot for 2
Sample Quantiles
Theoretical Quantiles
30
25
20
15
10
5
0
−5
−3
−2
−1
0
1
2
3



ANNOVA Test

[52]:
```
from scipy.stats import f_oneway
f_stats, p_value =␣
↪f_oneway(weather_transformed_1,weather_transformed_2,weather_transformed_3)
if(p_value<0.05):
  print("Reject the null hypothesis .So, weather has some effect on the number␣
↪of bikes rented")
else:
  print("Accept the null hypothesis .So, weather has no effect on the number of␣
↪bikes rented")
```

```
Reject the null hypothesis .So, weather has some effect on the number of bikes
rented
```

Conclusion

- In both the test we can see that we get to reject the null hypothesis .So we can conclude that in different weather people rent bikes in different numbers.

3.3.4 Is weather dependent on the season ?

[53]:
```
data[['weather', 'season']].describe()
```

[53]:

	weather	season
count	10886.000000	10886.000000
mean	1.418427	2.506614
std	0.633839	1.116174
min	1.000000	1.000000
25%	1.000000	2.000000
50%	1.000000	3.000000
75%	2.000000	4.000000
max	4.000000	4.000000

STEP-1 : Set up Null Hypothesis (H0)

- Since both are categorical data, so we will perform *Chi-Square test*

STEP-3 : Compute the p-value and fix value of alpha.

We will be using the chi2_contigency function using scipy.stats. We set our alpha to be **0.05**

STEP-4 : Compare p-value and alpha.

Based on p-value, we will accept or reject H0.

p-val > alpha : Accept H0

p-val < alpha : Reject H0

- We dont need to perfrom any test for distribution as chi-square test is non parametric ;i.e. distribution free.

Crosstab

[54]:
```
# Creating the cross tab
cross_table = pd.crosstab(index = data['season'],
                          columns = data['weather'],
                          values = data['count'],
                          aggfunc = np.sum)
cross_table
```

[54]:

weather	1	2	3	4
season				
1	223009.0	76406.0	12919.0	164.0
2	426350.0	134177.0	27755.0	NaN
3	470116.0	139386.0	31160.0	NaN
4	356588.0	157191.0	30255.0	NaN

- Since we dont have any data in 4th column so we can remove that from our data.

[55]:
```
cross_table = pd.crosstab(index = data['season'],
                          columns = data.loc[data['weather'] != 4, 'weather'],
                          values = data['count'],
                          aggfunc = np.sum)
cross_table
```

[55]:

weather	1	2	3
season			
1	223009	76406	12919
2	426350	134177	27755
3	470116	139386	31160
4	356588	157191	30255

Chi-Square Test

[56]:
```
from scipy.stats import chi2_contingency
chi_test_stat, pvalue, dof, expected = chi2_contingency(cross_table)
if(pvalue<0.05):
  print("Reject the null hypothesis , there is a dependency of weather on␣
 ↪season")
else:
  print("Accept the null hypothesis , there is no dependency of weather on␣
 ↪season")
```

```
Reject the null hypothesis , there is a dependency of weather on season
```

Conclusion We can conclude that weather is dependent on the season as per the bike rental data

4 Conclusions

- Maximum bikes are rented during clear and cloudy weather…then in misty condition….and then in rainy condition.Data for extreme weather is limited.
- Average bike counts are similar on both working and non-working days.
- Weather and season have a significant impact on bike rental counts.
- Bike rental count vary significantly across different weather conditions because it is very likely that people will not rent bike in rainy or extreme weather conditions,so weather has a huge impact on bikes rental.
- Weather types 1, 2, and 3 show no significant seasonal dependency in average rental counts.
- Rental bike numbers differ significantly across seasons.

5 Recommendation

- **Improve Collection of Weather Data**: Improve data collection for extreme weather conditions so as to plan the operations accordingly in extreme weather conditions.

- **Time-based Pricing**: Set lower rates during off-peak hours and higher rates during peak hours to balance demand.
- **Seasonal Marketing**: The marketing should be adjusted for high-demand spring and summer months.Discounts should be there during these times.
- **Weather-based Promotions**: Offer discounts during favorable weather conditions to boost rentals but when there is peak hour increase the rates so as to cater the needs.
- **User Experience**: Give perks to the users so that they have great user experience.
- **Customer Feedback and Reviews**: Encourage feedback to improve services and meet customer expectations.
- **Social Media Marketing**: Utilize social media for marketing,running ads,collaborate with famous social media influencers to promote services and engage with customers.
- **Special Occasion Discounts**: Offer discounts on environmental awareness days to attract users.