```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as st
```

Problem Statement:

Analyzing different factors affecting the demand of shared electric cylecs in the Indian market.

```
data=pd.read_csv("/content/bike_sharing.txt")
data.head()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0	1	1

```
data.shape
```

```
(10886, 12)
```

```
data.dtypes
```

```
datetime      object
season         int64
```

```
holiday         int64
workingday      int64
weather         int64
temp          float64
atemp         float64
humidity        int64
windspeed     float64
casual          int64
registered      int64
count           int64
dtype: object
```

Description of the data:Summary Statistics

```
data['count'].describe()
```

```
count    10886.000000
mean       191.574132
std        181.144454
min          1.000000
25%         42.000000
50%        145.000000
75%        284.000000
max        977.000000
Name: count, dtype: float64
```

There is a significant difference between mean(**191.574**) and median(**145**) of the **count** column which indicates it contains outliers.

```
data['casual'].describe()
```

```
count    10886.000000
mean        36.021955
std         49.960477
min          0.000000
25%          4.000000
```

```
50%          17.000000
75%          49.000000
max         367.000000
Name: casual, dtype: float64
```

```
data['registered'].describe()
```

```
count    10886.000000
mean       155.552177
std        151.039033
min          0.000000
25%         36.000000
50%        118.000000
75%        222.000000
max        886.000000
Name: registered, dtype: float64
```

Also there are outliers in the columns **casual** and **registered** as there is a siginificant difference betwee mean and median

Minimum **casual** users is 0 and maximum is **367**

Minimum **registered** users is 0 and maximum is **886**

```
data['humidity'].describe()
```

```
count    10886.000000
mean        61.886460
std         19.245033
min          0.000000
25%         47.000000
50%         62.000000
75%         77.000000
max        100.000000
Name: humidity, dtype: float64
```

```
data['windspeed'].describe()
```

```
count    10886.000000
mean        12.799395
std          8.164537
min          0.000000
25%          7.001500
50%         12.998000
75%         16.997900
max         56.996900
Name: windspeed, dtype: float64
```

```
data['temp'].describe()
```

```
count    10886.00000
mean        20.23086
std          7.79159
min          0.82000
25%         13.94000
50%         20.50000
75%         26.24000
max         41.00000
Name: temp, dtype: float64
```

The columns **temp** ,**atemp**,**humidity**,and **windspeed** seems to be free from outliers as there is not much significant difference between means and medians

Missing values

```
data.isna().sum()
```

```
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
```

No missing value in the data

Frequency distribution of the values of some columns

```
# replace season with descriptive name
data['season']=data['season'].map({1: 'spring', 2: 'summer', 3: 'fall', 4: 'winter'})
```

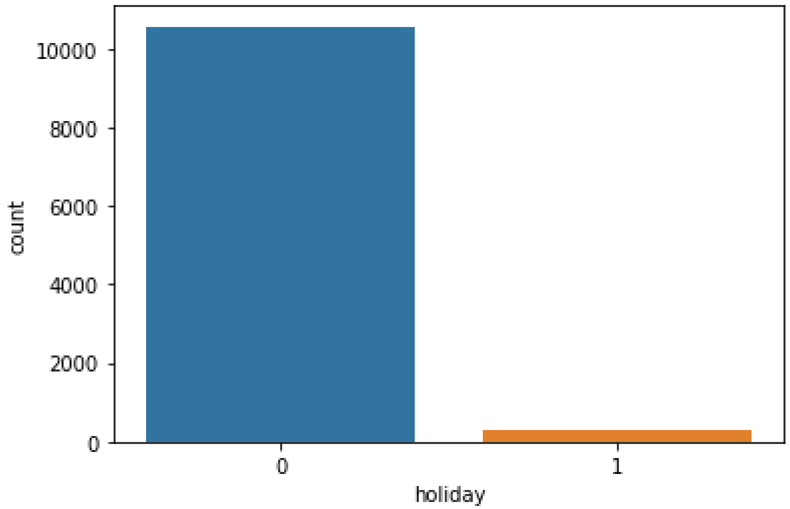
```
data['season'].value_counts().sort_values(ascending=False)
sns.countplot(x='season',data=data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd1bed3b590>
```

The data distribution for different seasons is almost same

```
data['holiday'].value_counts().sort_values(ascending=False)
sns.countplot(x='holiday',data=data)
```

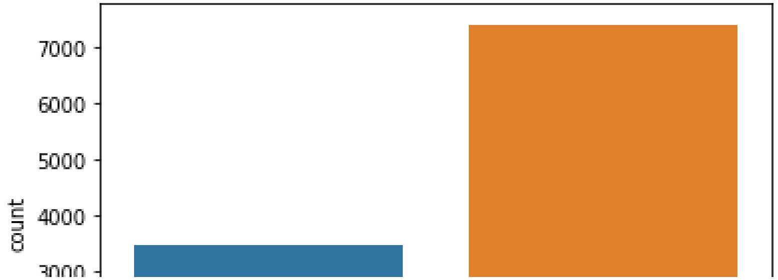
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd1bebe6d50>
```



It makes sense of the distribution of data as there are not many holidays in a year

```
data['workingday'].value_counts().sort_values(ascending=False)
sns.countplot(x='workingday',data=data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd1beb423d0>
```



Excluding holidays and weekend it makes sense of the distribution of the data

```
# convert datetime column into datetime object
data['datetime']=pd.to_datetime(data['datetime'])
```

```
data['datetime'].dt.year.unique()
```

```
array([2011, 2012])
```

data collected for the years **2011 and 2012**

```
data['weather'].value_counts().sort_values(ascending=False)
sns.countplot(x='weather',data=data)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd1bed1ef90>
```

It makes sense that during thunderstorm or heavy rain(**weather=4**) the people would not go outside for bicyle ride.Still we have some users who dared to went outside for a bicyle ride


```
data['casual'].value_counts().sort_values(ascending=False)
```

```
0      986
1      667
2      487
3      438
4      354
      ...
310      1
245      1
297      1
299      1
304      1
Name: casual, Length: 309, dtype: int64
```

There are heavy of number of non casual users (**986**)

```
data[data['casual']==367] # max casual users
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
6729	2012-03-17 16:00:00	spring	0	0	1	26.24	31.06	50	0.0	367	318	685

During weekend in the spring season in the year 2012 at 4 PM company witnessed maximum number of casual users.Also it was a clear weather.

```
data['registered'].value_counts().sort_values(ascending=False)
```

```
3      195
4      190
5      177
6      155
2      150
      ...
694      1
650      1
559      1
666      1
636      1
Name: registered, Length: 731, dtype: int64
```

On the other hand 195 times of the years **2011** and **2012** there are three users registered for bike rentals

```
data[data['registered']==886] # maximum registered
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
9345	2012-09-12 18:00:00	fall	0	1	1	27.06	31.06	44	16.9979	91	886	977

In the year 2012 september, during fall with clear sky at 6 PM company registed 886 number of users.

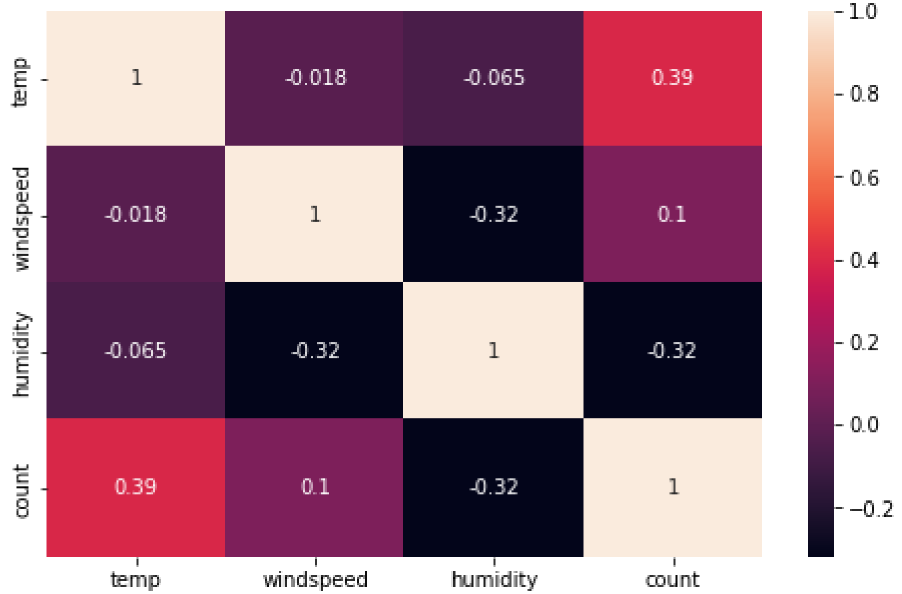
Reason: Workingday,clear sky,low humidity and temperature was also good.

Relationship between windpseed,temp,humidity,and count

```
fig,ax=plt.subplots(figsize=(8,5))
correlation=data[['temp','windspeed','humidity','count']].corr(method='pearson') # pearson correlation
```

```
sns.heatmap(correlation,annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd1b8b09e90>
```

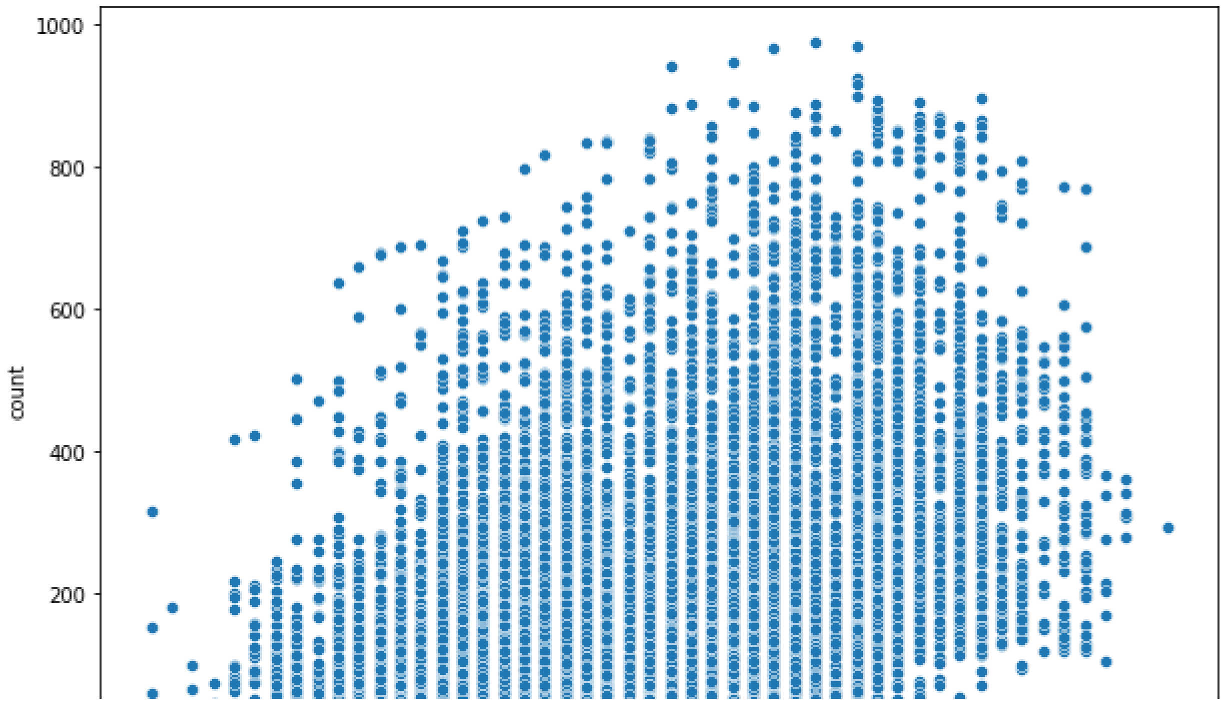


The pearson correlation between count and temp is **0.39** which is also heighest among all correlation values.

Second heighest is -0.32 but in negative quantity between count and humidity

Scatter plot between temp and count

```
fig,ax=plt.subplots(figsize=(10,7))
sns.scatterplot(x='temp',y='count',data=data)
plt.show()
```



From scatter plot as well as from correlation values temperature plays an important role in rental counts.

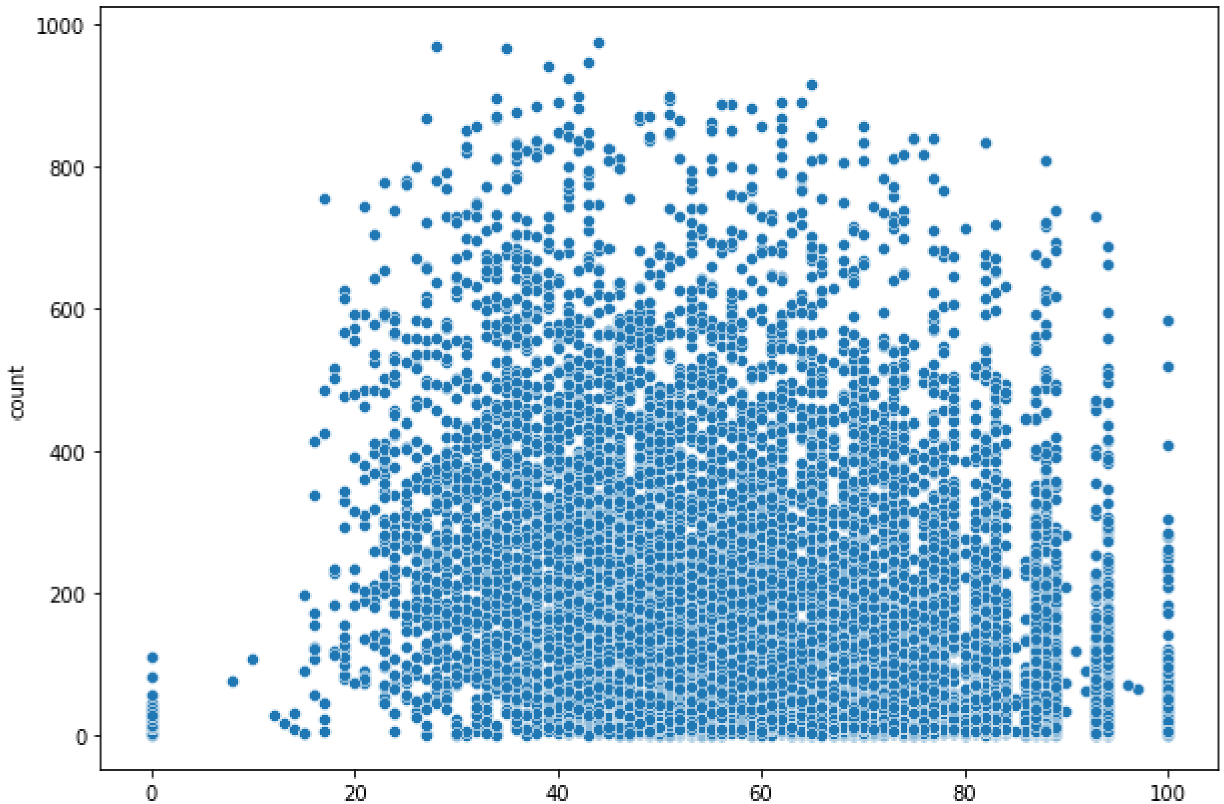
With temperature (20 to 30) rental counts is good but as soon as temperature reaches more than 35 degree, there is not much rentals.

On the other hand when temperature is below 10 degree there is also number of rentals

These makes sense as obviously in low temperature people don't bother to ride cycle and similarly in high temperature.

Scatter plot between count and humidity

```
fig,ax=plt.subplots(figsize=(10,7))
sns.scatterplot(x='humidity',y='count',data=data)
plt.show()
```



Though there are some outliers but most of the rentals falls 600. On the other hand the as humidity there are less people going for bicyle ride.

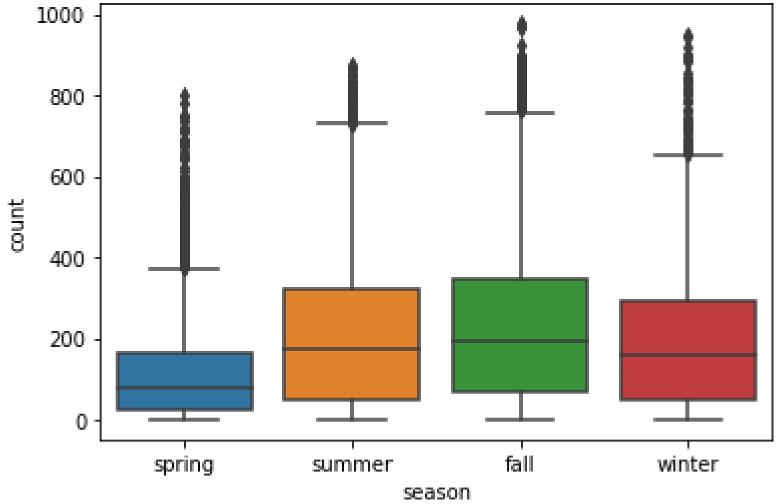
Visual Representation of data as well as hypothesis testing

According to summary statistics only **count** column has outliers

So we will check for outliers for count with respect to workingday,seasons,weather and holidays

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

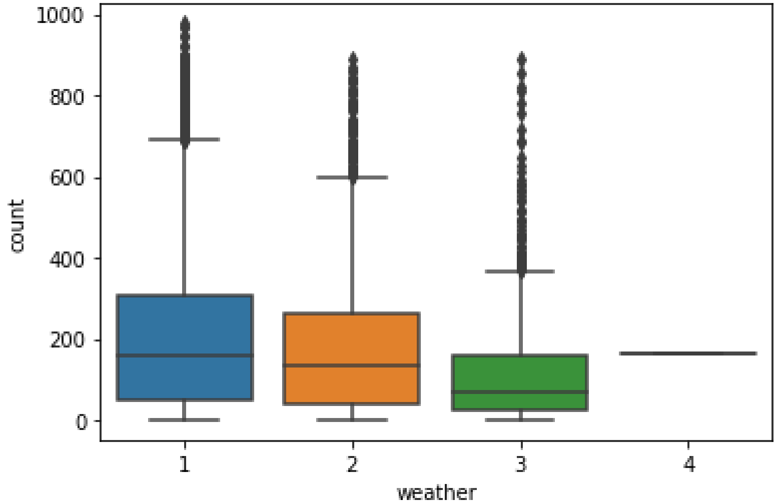
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd1beac7b90>
```



According to boxplot there are heavy number of outliers for all the season.

```
sns.boxplot(data=data,x='weather',y='count') # box plot for count vs weather
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd1be9c8650>
```



Again the count has outliers with respect to each weather category

ANOVA for number of rentals with respect to different seasons

Assumptions:

1. Each group's(season) sample is gaussian
2. Each gp's variance is roughly the same
3. Each observation is independent i.e number of bike rentals in 2011 at 6PM is independent of number of bike rentals at 7 PM.

We will consider that the data already follows third assumption.For the rest two assumptions we need some bit of work.

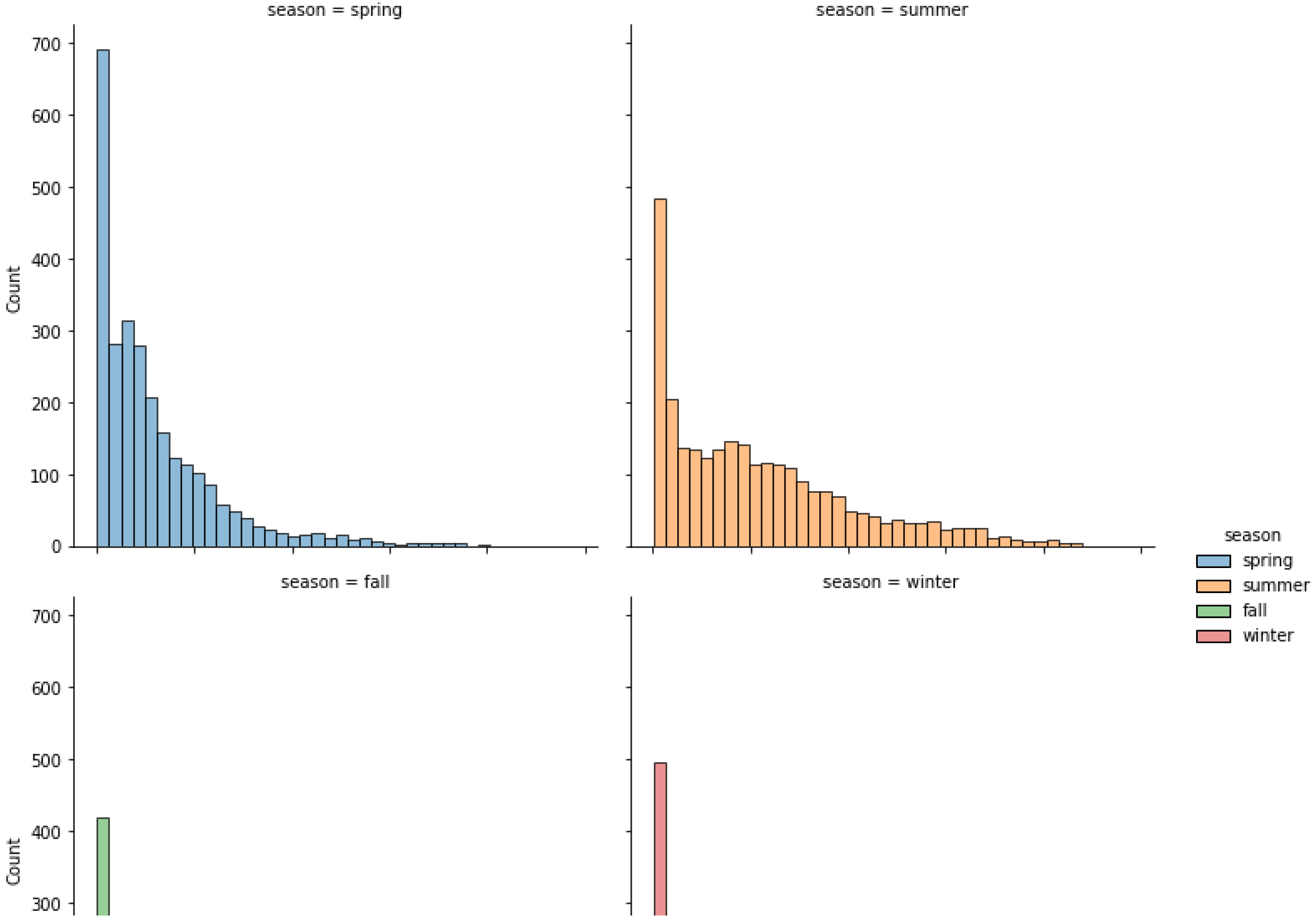
H0:Each group's means are same i.e average number of bike rentals is similar in different season

H1:otherwise

Check for **Gaussianity** of each season's bike rentals

```
# histogram plot
sns.displot(data=data,x='count',col='season',col_wrap=2,hue='season',kind='hist',bins=40)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fd1be90e890>
```



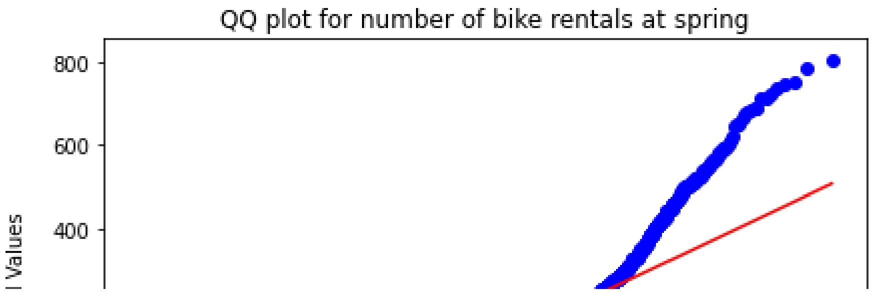
It is clearly visible from the plot that the data for each seasons are right skewed ,so clearly they are not normally distributed.

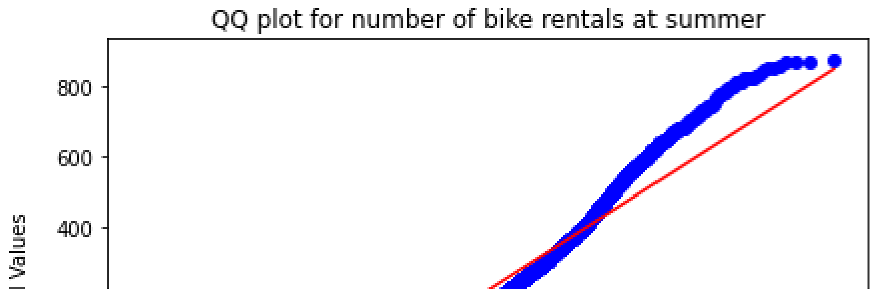
Nevertheless the distribution is almost identical for each season

QQ plot

```
# QQ -plot
fig,ax=plt.subplots(nrows=2,ncols=2,figsize=(15,10))
ax=ax.flatten() # flatten the axes as ax was a 2D array ,flattening makes it a 1D array
seasons=data['season'].unique()

for i in range(4):
  season_data=data[data['season']==seasons[i]]['count']
  st.probplot(season_data, dist="norm", plot=ax[i]) # quantile plot with respect to theoretical normal data
  ax[i].set_title(f"QQ plot for number of bike rentals at {seasons[i]}")
plt.show()
```





Clearly the data are not normaly distributed

Shapior-WIlk test for normality

H0: a sample x1, ..., xn came from a normally distributed population.

H1: Otherwise

```
seasons=data['season'].unique()
for s in seasons:
  print(f"Testing for normality of bike rentals in {s}:")
  test=st.shapiro(data[data['season']==s]['count'].to_numpy())
  print(test)
  print("****************************************************")
  print()
```

```
Testing for normality of bike rentals in spring:
ShapiroResult(statistic=0.8087379336357117, pvalue=0.0)
****************************************************

Testing for normality of bike rentals in summer:
ShapiroResult(statistic=0.9004813432693481, pvalue=6.038565025570219e-39)
****************************************************

Testing for normality of bike rentals in fall:
ShapiroResult(statistic=0.9148167371749878, pvalue=1.0437356147871525e-36)
****************************************************
```

```
Testing for normality of bike rentals in winter:
ShapiroResult(statistic=0.8954642415046692, pvalue=1.130082751748606e-39)
****************************************************
```

For all the data the p-values are very less.Even with 0.1% level of significance, the null hypothesis can not be saved i.e the data are not normaly distributed

Anderson Darling test for normality

H0: Samples drawn from normal distribution

H1:They are not

```
seasons=data['season'].unique()
for s in seasons:
  print(f"Testing for normality of bike rentals in {s}:")
  test=st.anderson(data[data['season']==s]['count'].to_numpy(),dist='norm')
  print(test)
  print("****************************************************")
  print()
```

```
Testing for normality of bike rentals in spring:
AndersonResult(statistic=134.99126589743582, critical_values=array([0.575, 0.655, 0.786, 0.917, 1.09 ]), significanc
****************************************************

Testing for normality of bike rentals in summer:
AndersonResult(statistic=73.98826756049948, critical_values=array([0.575, 0.655, 0.786, 0.917, 1.09 ]), significance
****************************************************

Testing for normality of bike rentals in fall:
AndersonResult(statistic=54.3859876350034, critical_values=array([0.575, 0.655, 0.786, 0.917, 1.09 ]), significance_
****************************************************
```

```
Testing for normality of bike rentals in winter:
AndersonResult(statistic=70.89794313022367, critical_values=array([0.575, 0.655, 0.786, 0.917, 1.09 ]), significance
****************************************************
```

If the returned statistic is larger than the returned critical values then for the corresponding significance level, the null hypothesis that the data come from the chosen distribution can be rejected.

Test statistic for every samples is way larger than the all the crictical values which indicates null hypothesis must be rejected i.e the samples are not drawn from normal distribution

Second Assumption: Test for equal variance

F-test: For equal variance.For sample 1 and sample 2

Note: F-test is estremely sensitive to non-normality of samples 1 and samples2

H0:The variance of two samples are equal H1:otherwise

Test statistic in F-test follows F-distribution under null hypothesis

```
# F-test : This is just for demonstration purposes
s1='fall' # fall season
s2='spring' # season spring
variance_fall=np.var(data[data['season']==s1]['count'],ddof=1)
variance_spring=np.var(data[data['season']==s2]['count'],ddof=1)
df1=len(data[data['season']==s1]['count'])-1 # degree of freedom for sample 1
df2=len(data[data['season']==s2]['count'])-1 # degree of freedom for sample 1

test_stat=variance_fall/variance_spring # test statistic
print("Test statistic: ",test_stat)
p_value=st.f.cdf(test_stat,df1,df2)
print("P-value: ",p_value)
```

```
Test statistic:  2.476716301276862
P-value:  0.9999999999999999
```

This is clearly saying the variance for bike rentals in **fall** is same as the variance in **spring**

As F-test is extremely sensitive to non-normality.Therefor we can't rely on it as the data are not normaly distrbuted

Levene's test for equal variance: Leven's test is more robust to non-normality data compared to F-test,bartlette test .

H0: The variances of sample1,sample2,sample3,... are equal i.e all input samples are from populations with equal variances.

H1: Otherwise

```
fall=data[data['season']=='fall']['count']
spring=data[data['season']=='spring']['count']
summer=data[data['season']=='summer']['count']
winter=data[data['season']=='winter']['count']

# center will be used in the test, since the data has
# outliers therefore use median which is very much robust to outliers
# proportiontocut is the fraction to cut off of both tails of the distribution.
# this parameter is very usefull if the data has outliers
# from both side 0.01= 1% data will be ignored
test=st.levene(fall,spring,summer,winter,center='median', proportiontocut=0.01)
print(test)
```

```
LeveneResult(statistic=187.7706624026276, pvalue=1.0147116860043298e-118)
```

The p-value is very very less almost zero ,which indicates the variances are not equal i.e null hypothesis is not true

Bartlette test for equal variance:

This test is very sensitive to non-normality of data

H0: Samples variances are equal

H1: Otherwise

```
# this is just for demonstration purposes

st.bartlett(fall,winter,spring,summer) # this function has no parameters other than samples
```

```
    BartlettResult(statistic=621.1563038449796, pvalue=2.611321958807742e-134)
```

Bartlette also says the variances are not equal as p-value is way less than 5% level of significance

Since the data has very much outliers and also they are not normal.Hence we will perform some transformation(**Box-Cox**) to convert the data into normality(approximation)

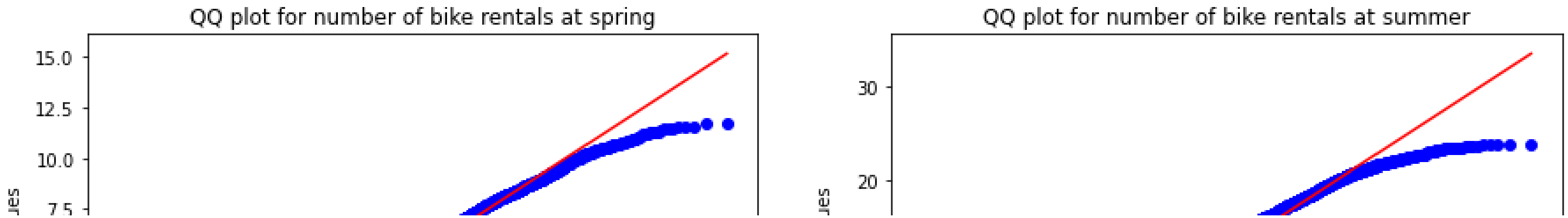
If the transformed data are not approximately normal still we will carry out one-way anova for equality of means on the original data.

```
#fall=data[data['season']=='fall']['count']
#fall=np.log(fall+1) # add 1 to the data ,as data could have zero values
                    # this will not affect hypothesis tesing
#spring=data[data['season']=='spring']['count']
#spring=np.log(spring+1)
#summer=data[data['season']=='summer']['count']
#summer=np.log(summer+1)
#winter=data[data['season']=='winter']['count']
#winter=np.log(winter+1)

# Now plot QQ-plot to check for normality
```

```
fig,ax=plt.subplots(nrows=2,ncols=2,figsize=(15,10))
ax=ax.flatten() # flatten the axes as ax was a 2D array ,flattening makes it a 1D array
seasons=data['season'].unique()

for i in range(4):
  season_data=np.log(data[data['season']==seasons[i]]['count']+1)
  season_data,_=st.boxcox(season_data)
  qq=st.probplot(season_data, dist="norm", plot=ax[i]) # quantile plot with respect to theoretical normal data
  ax[i].set_title(f"QQ plot for number of bike rentals at {seasons[i]}")
plt.show()
```



Even after transformation the transformed are not normal.Alos the the transformed data has outliers.

One-way anova: Since the data has very much outliers,checking for means equality would be misleading,what we can do we can remove the outliers. Then do the necessary testing

```
# removing outliers
fall=data[data['season']=='fall']['count']
Q1=np.quantile(fall,0.25) # first quantile is the 25th percentile
Q3=np.quantile(fall,0.75) # third quantile
IQR=Q3-Q1 # inter-quantile range
# remove those points which are less than Q1-1.5*IQR or more than Q3+1.5*IQR
fall=fall.loc[(fall<=(Q3+1.5*IQR)) & (fall>=(Q1-1.5*IQR))]

spring=data[data['season']=='spring']['count']
Q1=np.quantile(spring,0.25) # first quantile is the 25th percentile
Q3=np.quantile(spring,0.75) # third quantile
IQR=Q3-Q1 # inter-quantile range
# remove those points which are less than Q1-1.5*IQR or more than Q3+1.5*IQR
spring=spring.loc[(spring<=(Q3+1.5*IQR)) & (spring>=(Q1-1.5*IQR))]

summer=data[data['season']=='summer']['count']
Q1=np.quantile(summer,0.25) # first quantile is the 25th percentile
Q3=np.quantile(summer,0.75) # third quantile
IQR=Q3-Q1 # inter-quantile range
# remove those points which are less than Q1-1.5*IQR or more than Q3+1.5*IQR
summer=summer.loc[(summer<=(Q3+1.5*IQR)) & (summer>=(Q1-1.5*IQR))]
```

```
winter=data[data['season']=='winter']['count']
Q1=np.quantile(winter,0.25) # first quantile is the 25th percentile
Q3=np.quantile(winter,0.75) # third quantile
IQR=Q3-Q1 # inter-quantile range
# remove those points which are less than Q1-1.5*IQR or more than Q3+1.5*IQR
winter=winter.loc[(winter<=(Q3+1.5*IQR)) & (winter>=(Q1-1.5*IQR))]

# Now do the oneway anova
st.f_oneway(fall,spring,summer,winter)
```

```
F_onewayResult(statistic=340.40707265879576, pvalue=4.955446274536036e-211)
```

P-value is very less which indicates that the means(average number of bike rentals for each season) are not same.

Hence,no. of cycles rented is different in different seasons

We will carry out kruskals-Wallis test: This test is non-parameteric(that is no underlying assumption for the data unlike ANOVA) and also it is robust to outliers.

Ho:Number of bike rentals is similar in different seasons

H1:Number of bike rentals is different in different seasons

```
fall=data[data['season']=='fall']['count']
spring=data[data['season']=='spring']['count']
summer=data[data['season']=='summer']['count']
winter=data[data['season']=='winter']['count']
st.kruskal(fall,spring,summer,winter)
```

```
KruskalResult(statistic=699.6668548181988, pvalue=2.479008372608633e-151)
```

Since p-values is very less therefore the number of bike rentals is different in different seasons.

KS-test: Check whether the distribution of no. of bike rentals is same both in summer and winter

H0: Distribution of no. of bike rentals is same in both summer and winter

H1: They are not

```
st.ks_2samp(data[data['season']=='winter']['count'],data[data['season']=='summer']['count'])
```

```
KstestResult(statistic=0.05133590345424572, pvalue=0.0014473767980579533)
```

P-value is not that much less than 5% level of significance.Since it is less than 5% level of significance we need to reject null hypothesis i.e distribution of no. of bike rentals is different in both summer and winter.

ANOVA for number of rentals with respect to different weathers

Assumptions:

1. Each group's(weather) sample is gaussian
2. Each gp's variance is roughly the same
3. Each observation is independent i.e number of bike rentals in 2011 at 6PM is independent of number of bike rentals at 7 PM.

We will consider that the data already follows third assumption.For the rest two assumptions we need some bit of work.

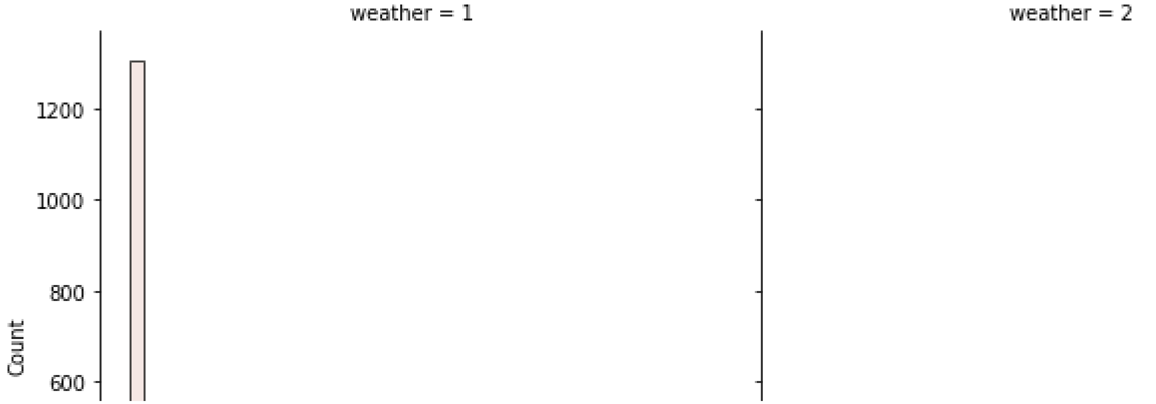
H0:Each group's means are same i.e average number of bike rentals is similar in different weather

H1:otherwise

Check for **Gaussianity** of each weather's bike rentals

```
# histogram plot
sns.displot(data=data,x='count',col='weather',col_wrap=2,hue='weather',kind='hist',bins=40)
```

<seaborn.axisgrid.FacetGrid at 0x7fd1be9658d0>



Weather **4** has almost no data.Also weather **3** has little data compared to weather **1** and **2**

The distribution are not normal ,they are rightly skewed

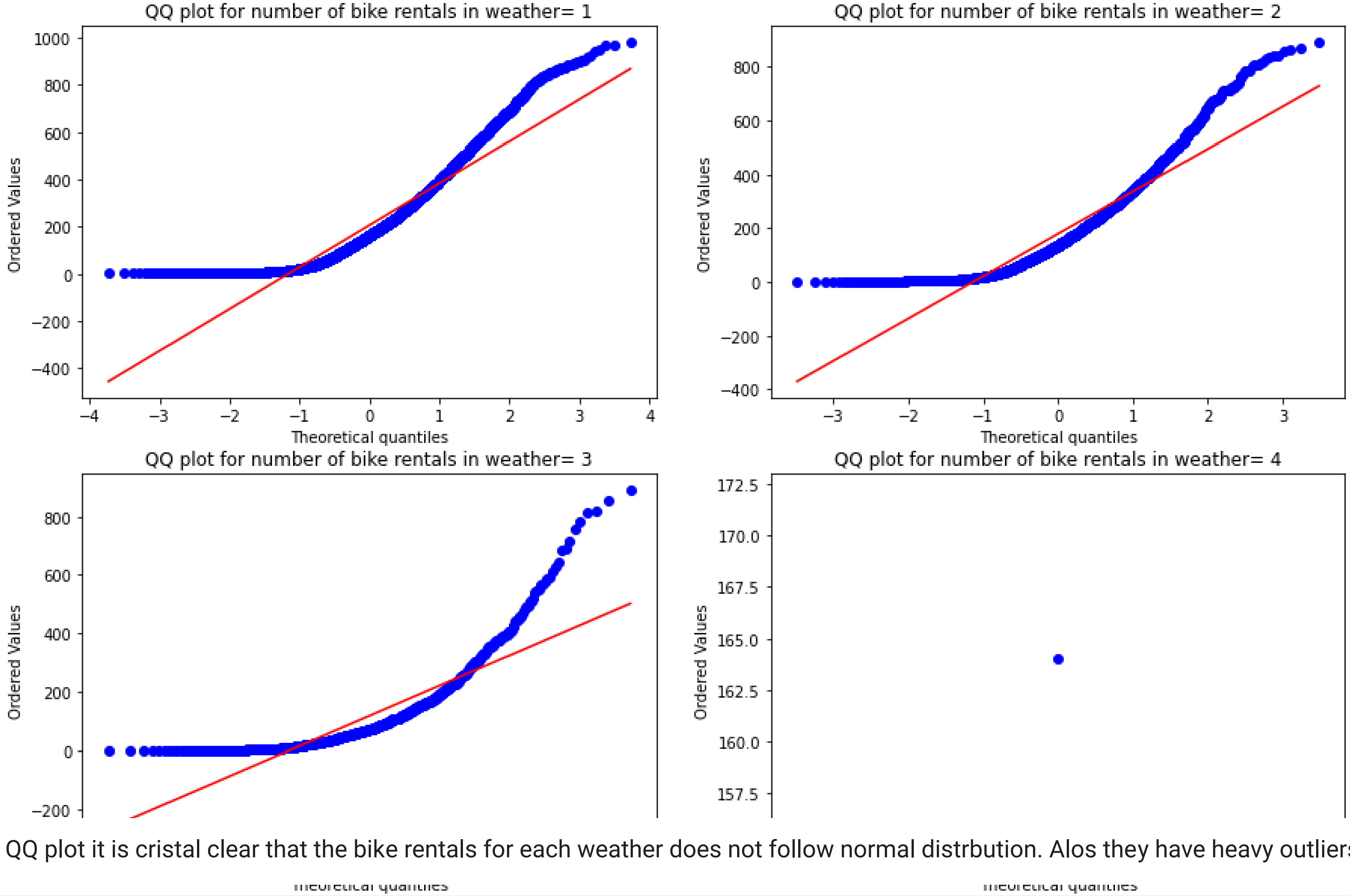
We will skip weather **4** from doing any hypothesis test as it has almost no data

QQ plot

```
# QQ -plot
fig,ax=plt.subplots(nrows=2,ncols=2,figsize=(15,10))
ax=ax.flatten() # flatten the axes as ax was a 2D array ,flattening makes it a 1D array
weathers=data['weather'].unique()

for i in range(4):
  weather_data=data[data['weather']==weathers[i]]['count']
  st.probplot(weather_data, dist="norm", plot=ax[i]) # quantile plot with respect to theoretical normal data
  ax[i].set_title(f"QQ plot for number of bike rentals in weather= {weathers[i]}")
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/scipy/stats/_stats_mstats_common.py:170: RuntimeWarning: invalid value encoun
  slope = ssxym / ssxm
/usr/local/lib/python3.7/dist-packages/scipy/stats/_stats_mstats_common.py:184: RuntimeWarning: invalid value encoun
  t = r * np.sqrt(df / ((1.0 - r + TINY)*(1.0 + r + TINY)))
/usr/local/lib/python3.7/dist-packages/scipy/stats/_stats_mstats_common.py:187: RuntimeWarning: invalid value encoun
  slope_stderr = np.sqrt((1 - r**2) * ssym / ssxm / df)
```



From QQ plot it is cristal clear that the bike rentals for each weather does not follow normal distrbution. Alos they have heavy outliers

Shapior-WIlk test for normality

H0: a sample x1, ..., xn came from a normally distributed population.

H1: Otherwise

```
weather=data['weather'].unique()
for s in weather:
  if s!=4: # exclude weather 4
     print(f"Testing for normality of bike rentals in weather={s}:")
     test=st.shapiro(data[data['weather']==s]['count'].to_numpy())
     print(test)
     print("****************************************************")
     print()
```

```
Testing for normality of bike rentals in weather=1:
ShapiroResult(statistic=0.8909225463867188, pvalue=0.0)
****************************************************

Testing for normality of bike rentals in weather=2:
ShapiroResult(statistic=0.8767690658569336, pvalue=9.781063280987223e-43)
****************************************************

Testing for normality of bike rentals in weather=3:
ShapiroResult(statistic=0.7674333453178406, pvalue=3.876134581802921e-33)
****************************************************

/usr/local/lib/python3.7/dist-packages/scipy/stats/morestats.py:1760: UserWarning: p-value may not be accurate for N
  warnings.warn("p-value may not be accurate for N > 5000.")
```

For every weather ,the number of bike rentals not following normal distribution as p-values are way less than 5% level of significance

Second Assumption:Test for equal variance

Levene's test for equal variance: Leven's test is more robust to non-normality data compared to F-test,bartlette test .

H0: The variances of sample1,sample2,sample3,... are equal i.e all input samples are from populations with equal variances.

H1: Otherwise

```
w1=data[data['weather']==1]['count']
w2=data[data['weather']==2]['count']
w3=data[data['weather']==3]['count']

# center=median will be used in the test, since the data has
# outliers therefore use median which is very much robust to outliers
# proportiontocut is the fraction to cut off of both tails of the distribution.
# this parameter is very usefull if the data has outliers
# from both side 0.01= 1% data will be ignored
test=st.levene(w1,w2,w3,center='median', proportiontocut=0.01)
print(test)
```

```
LeveneResult(statistic=81.67574924435011, pvalue=6.198278710731511e-36)
```

According to **Lvene's** test the variances of number of bike rentals is different in different weather as P-value is way less than 5% level of significance

One-way anova: Since the data has very much outliers,checking for means equality would be misleading,what we can do we can remove the outliers. Then do the necessary testing

```
# removing outliers:Using simple method
w1=data[data['weather']==1]['count']
```

```
Q1=np.quantile(w1,0.25) # first quantile is the 25th percentile
Q3=np.quantile(w1,0.75) # third quantile
IQR=Q3-Q1 # inter-quantile range
# remove those points which are less than Q1-1.5*IQR or more than Q3+1.5*IQR
w1=w1.loc[(w1<=(Q3+1.5*IQR)) & (w1>=(Q1-1.5*IQR))]

w2=data[data['weather']==2]['count']
Q1=np.quantile(w2,0.25) # first quantile is the 25th percentile
Q3=np.quantile(w2,0.75) # third quantile
IQR=Q3-Q1 # inter-quantile range
# remove those points which are less than Q1-1.5*IQR or more than Q3+1.5*IQR
w2=w2.loc[(w2<=(Q3+1.5*IQR)) & (w2>=(Q1-1.5*IQR))]

w3=data[data['weather']==3]['count']
Q1=np.quantile(w3,0.25) # first quantile is the 25th percentile
Q3=np.quantile(w3,0.75) # third quantile
IQR=Q3-Q1 # inter-quantile range
# remove those points which are less than Q1-1.5*IQR or more than Q3+1.5*IQR
w3=w3.loc[(w3<=(Q3+1.5*IQR)) & (w3>=(Q1-1.5*IQR))]

# Now do the oneway anova
st.f_oneway(w1,w2,w3)
```

```
F_onewayResult(statistic=162.9056065738177, pvalue=2.0801584856212998e-70)
```

p-value is way less than 5% level of significance.Therefore the null hypothesis must go.That is the number of bike rentals is different in different weather

We will carry out kruskals-Wallis test: This test is non-parameteric(no underlying assumption for the data unlike ANOVA) and also it is robust to outliers.

Ho:Number of bike rentals is similar in different weathers

H1:Number of bike rentals is different in different weathers

```
w1=data[data['weather']==1]['count']
w2=data[data['weather']==2]['count']
w3=data[data['weather']==3]['count']
st.kruskal(w1,w2,w3)
```

```
KruskalResult(statistic=204.95566833068537, pvalue=3.122066178659941e-45)
```

Kruska-Wallis test also fails to establish connection between no. of bike rentals in different weather.In other words no. of bike rentals is different in different weather

Working Day has effect on number of electric cycles rented:2- Sample independent T-Test

Comparing average number of bike rentals in working and non-working day.

Assumptions:

1. Distribution of no.of bike rentals in working day is independent of no.bike of rentals in non-working day.
2. Population mean and standard devition are finite .

Standard deviation can be known,or unknown or equal variance.

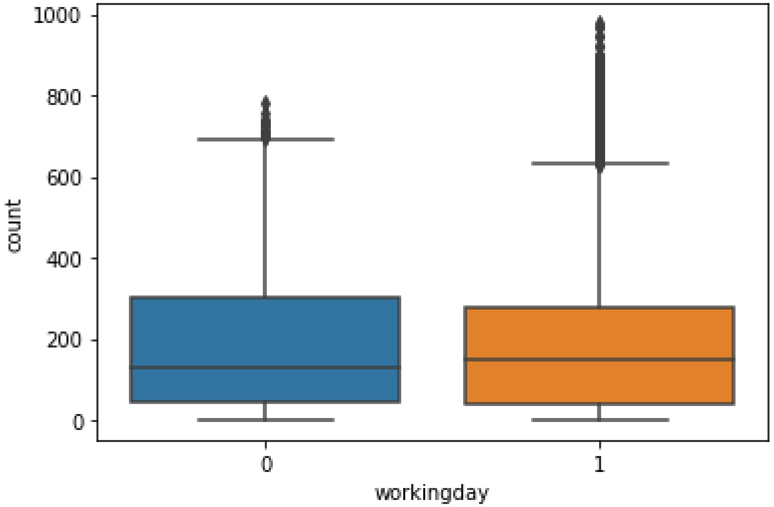
Note: **T-test** for large of number of samples behaves almost similar to z-test

H0: Average no. of bike rentals in working day is same as average number of bike rentals in non-working day.

H1: They are not

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd1be8ee550>
```



Number of bike renatals for both working and non-working day has heavy number of outliers as per box plot

```
sns.displot(data=data,x='count',col='workingday',kind='hist',bins=40)
```

```
<seaborn.axisgrid.FacetGrid at 0x7fd1bb8ed810>
```

The data distribution for working and non-working days are right skewed.They are not not normal

Since the data has outliers testing for means would be misleading .What we can do we can remove outliers and then perform t-test

```
# removing outliers using IQR
working=data[data['workingday']==1]['count']
Q1=np.quantile(working,0.25) # first quantile is the 25th percentile
Q3=np.quantile(working,0.75) # third quantile
IQR=Q3-Q1 # inter-quantile range
# remove those points which are less than Q1-1.5*IQR or more than Q3+1.5*IQR
working=working.loc[(working<=(Q3+1.5*IQR)) & (working>=(Q1-1.5*IQR))]

# removing outliers using IQR
nonworking=data[data['workingday']==0]['count']
Q1=np.quantile(nonworking,0.25) # first quantile is the 25th percentile
Q3=np.quantile(nonworking,0.75) # third quantile
IQR=Q3-Q1 # inter-quantile range
# remove those points which are less than Q1-1.5*IQR or more than Q3+1.5*IQR
nonworking=nonworking.loc[(nonworking<=(Q3+1.5*IQR)) & (nonworking>=(Q1-1.5*IQR))]


# Now perform 2 sample t-test

st.ttest_ind(working,nonworking,equal_var=False,random_state=0) # with unequal variance
```

```
Ttest_indResult(statistic=-4.3557584779909035, pvalue=1.3477043623680231e-05)
```

With 5% level of significance , working day has effect on the number of cycles rented.In other words number of rentals is different in working and non working day

Ch-square-test:

H0:Weather dependent on season

H1: Weather does not depend on season

Note: Dependency will be measure best on total number of rentals for each weather and seasons

```
observed_count_table=pd.crosstab(index=data['season'],columns=data['weather'],values=data['count'],aggfunc='sum',
                                 margins=False)
observed_count_table=observed_count_table.iloc[:,0:3] # drop weather 4 as weather 4 corresponds to single row only
```

```
observed_count_table
```

weather	1	2	3
season			
fall	470116.0	139386.0	31160.0
spring	223009.0	76406.0	12919.0
summer	426350.0	134177.0	27755.0
winter	356588.0	157191.0	30255.0

```
# to calculate expected_freq table
# you need to assume that weather does not depend on season
# pandas has a function called expected_freq but for clarity
# I implemented it
```

```
def expected_freq(observed):
  observed=np.asarray(observed,dtype=np.float64)
  # calculate the sum of each column of the observed frequency
  col_sum=np.sum(observed,axis=0)
  total_sum=observed.sum() # total sum
  prob_col=col_sum/total_sum

  # now calculate expected frequency for each cell in the observed data
  results=[]
  m,n=observed.shape
  for i in range(m):
    row_i=[]
    row_i_sum=sum(observed[i])
    for j in range(n):
      row_i.append(prob_col[j]*row_i_sum)
    results.append(row_i)
  return np.asarray(results,dtype=np.float64)
```

```
expected_freq_count=expected_freq(observed_count_table.to_numpy())
```

```
expected_freq_count
```

```
array([[453484.88557396, 155812.72247031,  31364.39195574],
       [221081.86259035,  75961.44434981,  15290.69305984],
       [416408.3330293 , 143073.60199337,  28800.06497733],
       [385087.91880639, 132312.23118651,  26633.8500071 ]])
```

```
expected_freq=st.contingency.expected_freq(observed_count_table.to_numpy()) # expected frequency ,pandas bultin
```

```
expected_freq
```

```
array([[453484.88557396, 155812.72247031,  31364.39195574],
       [221081.86259035,  75961.44434981,  15290.69305984],
       [416408.3330293 , 143073.60199337,  28800.06497733],
       [385087.91880639, 132312.23118651,  26633.8500071 ]])
```

```
# now do the chi-square test
st.chisquare(observed_count_table.to_numpy().ravel(),expected_freq_count.ravel())
```

```
Power_divergenceResult(statistic=10838.372332480209, pvalue=0.0)
```

Since the p-value is 0.0 which is less than 5% level of significance therefore we need to reject null hypothesis .In other words weather does not depend on season

Summary Insights:

1. Every season plays an important role for the demand of cycles.The demand is different for different season
2. Similarly weather also plays an important role.The demand is different for different weather.
3. Weathers does not depend on seasons
4. Working and non-working day also effects the number of rentals.The number is different.
5. Temperature and humidity are good factors for the demand of cycles.In high temperature people don't bother to go for a ride.

Recommendations:

1. Supply of cyles can be increased in fall and spring
2. Increase stock of cycles during good weather like with clear sky,little cloudy.
3. Do not treat working and non-working day with same importance.
4. Increase stock of cycles when the temperature is in the range of 20 to 30 degrees.