Importing Libraries

In [1]:
```python
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
from scipy import stats
from statsmodels.graphics.gofplots import qqplot_2samples
import warnings
warnings.filterwarnings('ignore')
```

Loading the data

In [2]:
```python
df = pd.read_csv('C:/Users/akash/Desktop/Scaler/Case_Study/Yulu/yulu.csv')
df.head()
```

Out[2]:

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

No missing values

In [3]:
```python
df.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
```

In [4]:
```python
print("season - %s"  %df['season'].unique())
print("holiday - %s"  %df['holiday'].unique())
print("workingday - %s"  %df['workingday'].unique())
print("Weather - %s"  %df['weather'].unique())
```

```
season - [1 2 3 4]
holiday - [0 1]
workingday - [0 1]
Weather - [1 2 3 4]
```

Converting Categorical values to object

In [5]:
```python
df['season'] = df['season'].astype('object')
df['holiday'] = df['holiday'].astype('object')
df['workingday'] = df['workingday'].astype('object')
df['Weather'] = df['season'].astype('object')
```

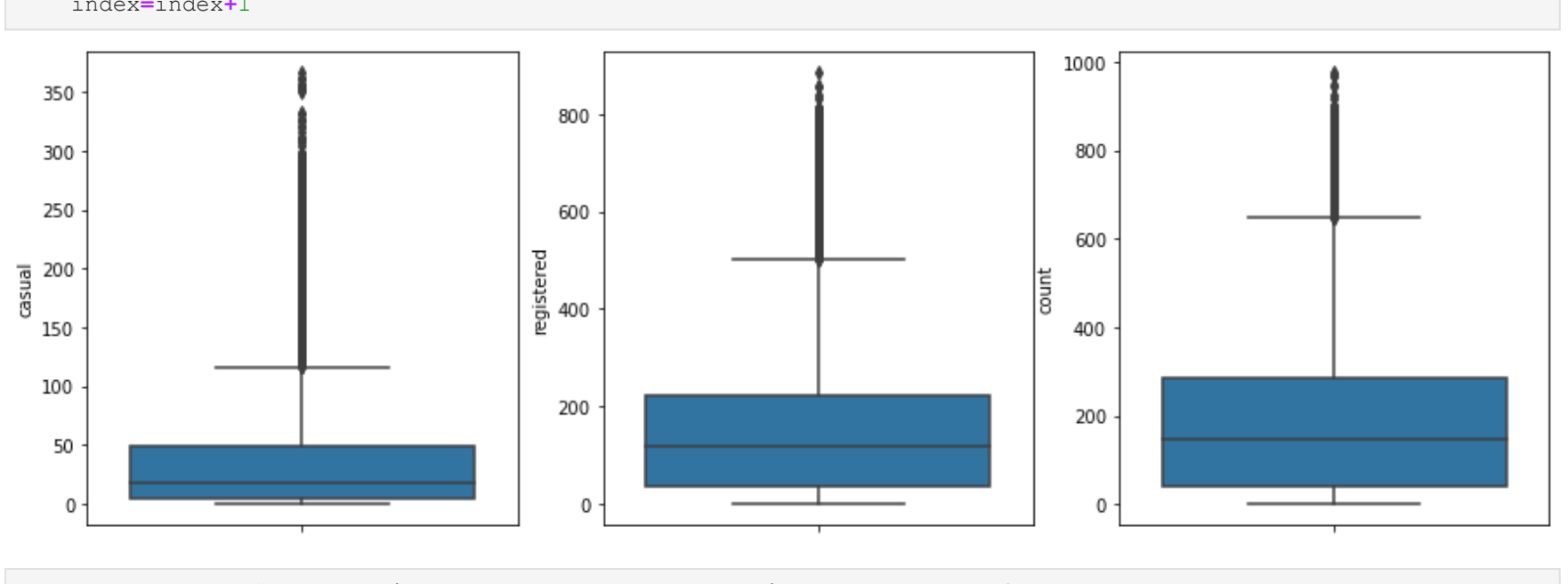
In [6]:
```python
df.describe(include = ['int64' , 'float64', 'object'])
```

Out[6]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registe
count	10886	10886.0	10886.0	10886.0	10886.000000	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000
unique	10886	4.0	2.0	2.0	NaN	NaN	NaN	NaN	NaN	NaN	N
top	10-01-2012 09:00	4.0	0.0	1.0	NaN	NaN	NaN	NaN	NaN	NaN	N
freq	1	2734.0	10575.0	7412.0	NaN	NaN	NaN	NaN	NaN	NaN	N
mean	NaN	NaN	NaN	NaN	1.418427	20.23086	23.655084	61.886460	12.799395	36.021955	155.552
std	NaN	NaN	NaN	NaN	0.633839	7.79159	8.474601	19.245033	8.164537	49.960477	151.039
min	NaN	NaN	NaN	NaN	1.000000	0.82000	0.760000	0.000000	0.000000	0.000000	0.000
25%	NaN	NaN	NaN	NaN	1.000000	13.94000	16.665000	47.000000	7.001500	4.000000	36.000
50%	NaN	NaN	NaN	NaN	1.000000	20.50000	24.240000	62.000000	12.998000	17.000000	118.000
75%	NaN	NaN	NaN	NaN	2.000000	26.24000	31.060000	77.000000	16.997900	49.000000	222.000
max	NaN	NaN	NaN	NaN	4.000000	41.00000	45.455000	100.000000	56.996900	367.000000	886.000

Checking for outliers in casual and registered as their meian and mean have significant difference.

In [7]:
```python
l = ['casual','registered','count']
fig,axs = plt.subplots(ncols = 3, nrows = 1,figsize=(15,5))
index=0
for i in l:
    sns.boxplot(y = i , data = df , ax = axs[index])
    index=index+1
```



In [8]:
```python
Upper_bound_C = (1.5*stats.iqr(df['casual']))+np.quantile(df['casual'],0.75)
Upper_bound_R = (1.5*stats.iqr(df['registered']))+np.quantile(df['registered'],0.75)
Upper_bound_Co = (1.5*stats.iqr(df['count']))+np.quantile(df['count'],0.75)
print('No of Outliers for casual - %s' %len(df.loc[df['casual']>Upper_bound_C]))
print('No of Outliers for registered - %s' %len(df.loc[df['registered']>Upper_bound_R]))
print('No of Outliers for count - %s' %len(df.loc[df['count']>Upper_bound_Co]))
```

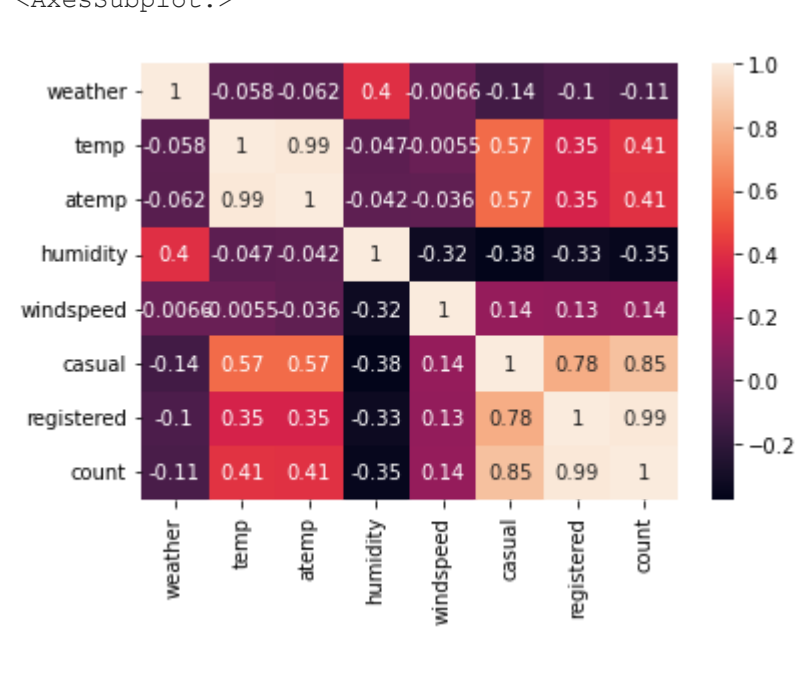
```
No of Outliers for casual - 749
No of Outliers for registered - 423
No of Outliers for count - 300
```

Temp have positive correlation with count

humidity have negative correlation with count

In [9]:
```python
sns.heatmap(df.corr(method="spearman"),annot=True)
```

Out[9]: <AxesSubplot:>



We cant remove all of these as it is 10 percent of our data.

In [10]:
```python
(len(df[(df['casual']>Upper_bound_C) | (df['registered']>Upper_bound_R) | (df['count']>Upper_bound_Co)])/len(df
```

Out[10]: 10.490538306081206

Lets check for common rows which have outlier in all 3 columns -- As it is only .275 percent ,this we can remove it from dataframe

In [11]:
```python
(len(df[(df['casual']>Upper_bound_C) & (df['registered']>Upper_bound_R) & (df['count']>Upper_bound_Co)])/len(df
```

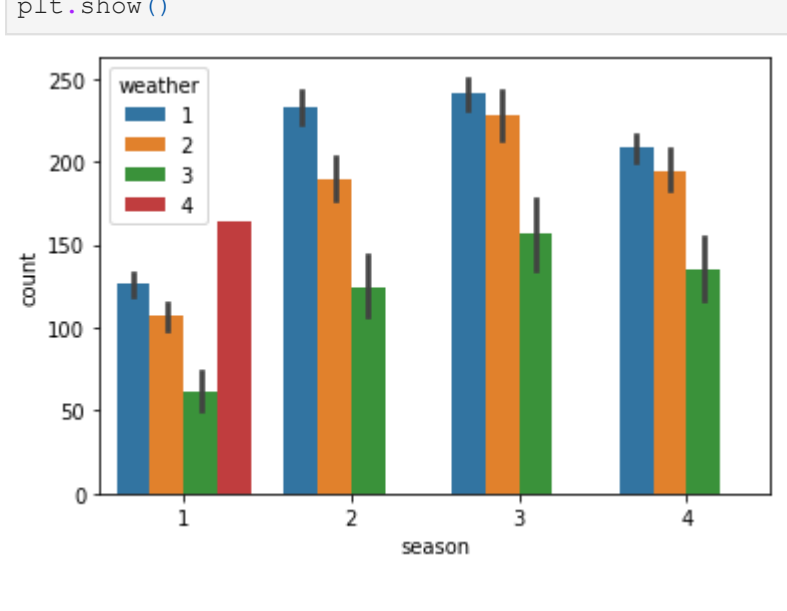
Out[11]: 0.275583318023149

In [12]:
```python
drop = df[(df['casual']>Upper_bound_C) & (df['registered']>Upper_bound_R) & (df['count']>Upper_bound_Co)].index
df.drop(drop,inplace=True)
```

As we see here count is mostly high in weather 1 and weather 2

As per season count is mostly high in season 2 and season 3

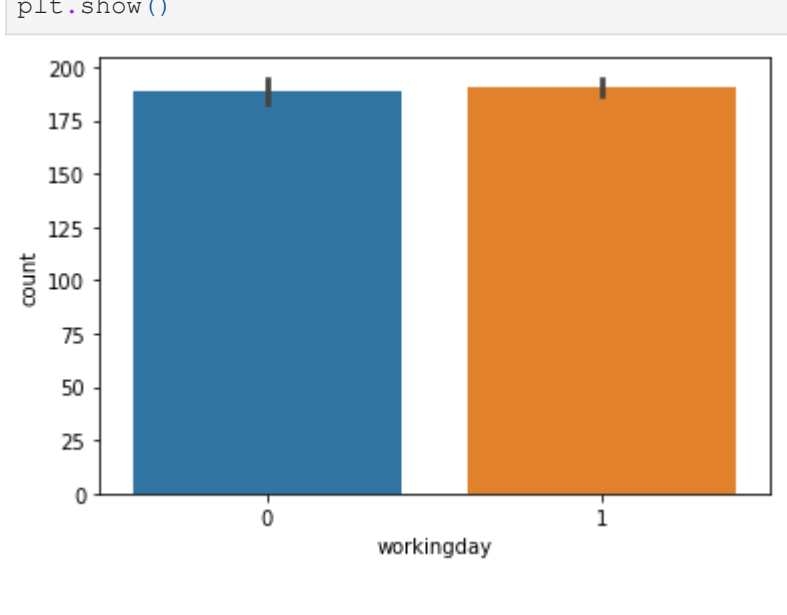
In [13]:
```python
sns.barplot(x='season',y='count',hue='weather',data=df)
plt.show()
```



Working Day has effect on number of electric cycles rented

The mean looks more are less same as per the graph lets do Hypothesis test to find out

In [14]:
```python
sns.barplot(y='count',x='workingday',data=df)
plt.show()
```



T- Test - two sided

Assuming counts of cycle for different datetime is independent events

Null Hypothessis is both population mean of number of cycles/bikes rented are same for Working and non working.

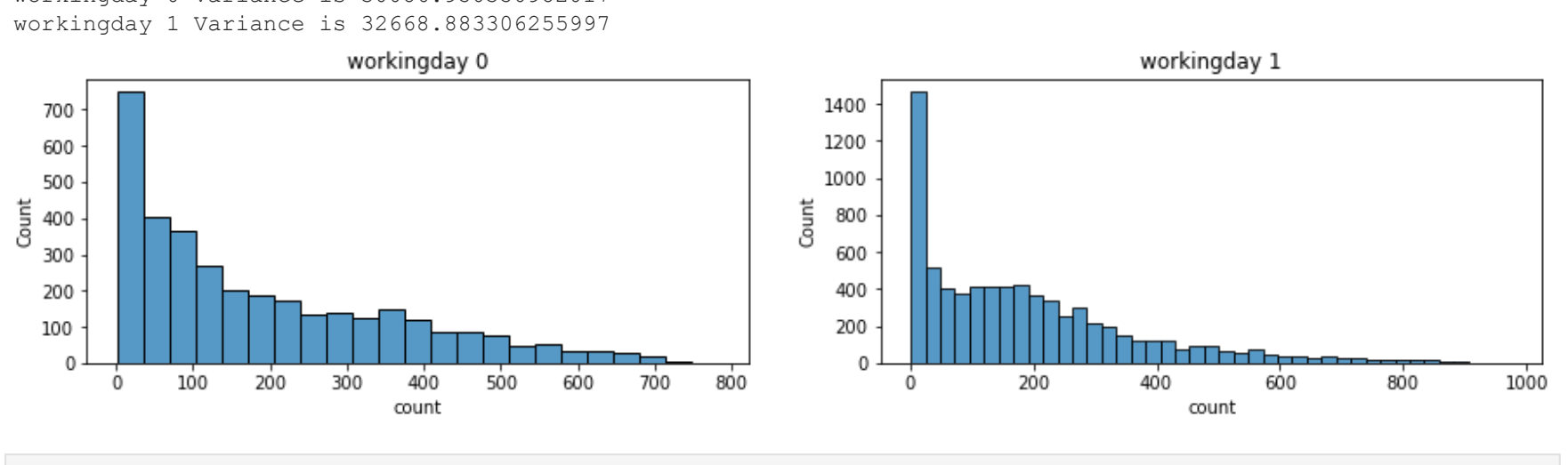
Alternative Hypothesis is both population mean of number of cycles/bikes rented are not equal for Working and non working.

Significance = 5%

In [15]:
```python
df_working = df[df['workingday'] == 1]
df_nonworking = df[df['workingday'] == 0]
```

In [16]:
```python
fig,axs = plt.subplots(nrows = 1,ncols = 2,figsize=(15,3))
index = 0
axs = axs.flatten()
for i in range(0,2):
    sns.histplot(x = 'count',data= df[df['workingday']==i],ax = axs[index]).set(title = "workingday {}".format(
    print("workingday {} Variance is {}".format(i,np.var(df[df['workingday']==i]['count'])))
    index=index+1
plt.show()
```

```
workingday 0 Variance is 30086.950350982017
workingday 1 Variance is 32668.883306255997
```



In [17]:
```python
stats.ttest_ind(df_working['count'],df_nonworking['count'])
```

Out[17]: Ttest_indResult(statistic=0.6161762184303081, pvalue=0.5377911440927007)

pvalue is significantly greater than .05 , so we can conclude with it that both population mean are same.

Anova

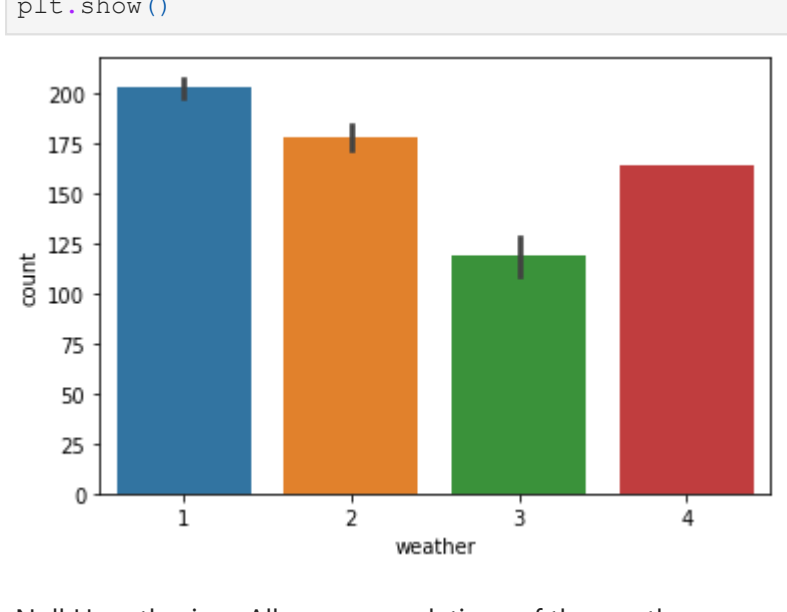
Weather -- No. of cycles rented is similar or different in different weathers

In [18]:
```python
df['weather'].unique()
```

Out[18]: array([1, 2, 3, 4], dtype=int64)

We see noticeable differnce in sample mean

In [19]:
```python
sns.barplot(y='count',x='weather',data=df)
plt.show()
```



Null Hypothesis -- All mean populations of the weather are same

Alternative Hypothesis -- Not all are equal

Significance level = 5% percent

In [20]:
```python
df_1=df[df['weather']==1]
df_2=df[df['weather']==2]
df_3=df[df['weather']==3]
df_4=df[df['weather']==4]
```

In [21]:
```python
df_4
```

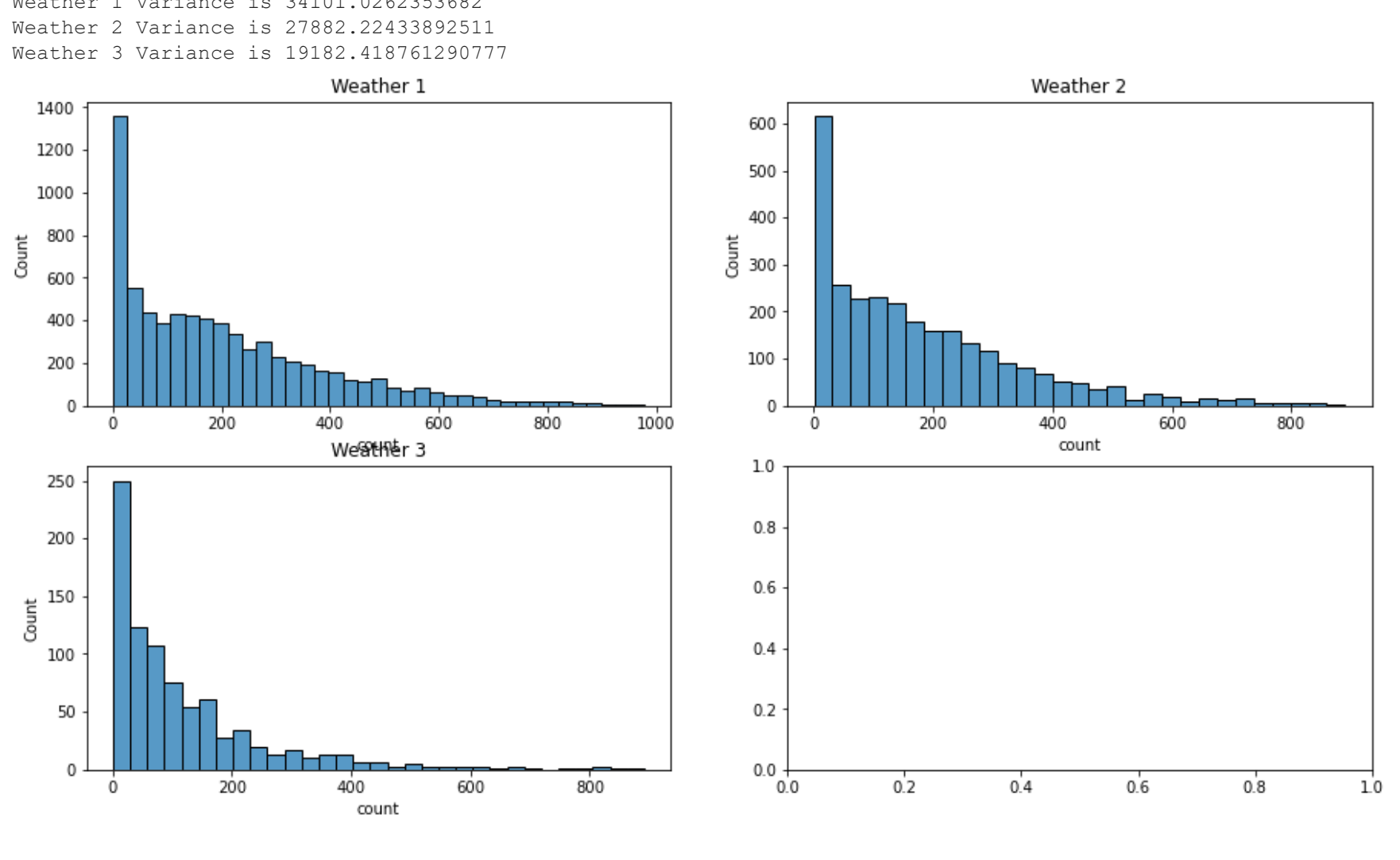
Out[21]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	Weather
5631	09-01-2012 18:00	1	0	1	4	8.2	11.365	86	6.0032	6	158	164	1

As we have only one observation under weather 4 will check for other weathers

In [22]:
```python
fig,axs = plt.subplots(nrows = 2,ncols = 2,figsize=(15,8))
index = 0
axs = axs.flatten()
for i in range(1,4):
    sns.histplot(x = 'count',data= df[df['weather']==i],ax = axs[index]).set(title = "Weather {}".format(i))
    print("Weather {} Variance is {}".format(i,np.var(df[df['weather']==i]['count'])))
    index=index+1
plt.show()
```

```
Weather 1 Variance is 34101.0262353682
Weather 2 Variance is 27882.22433892511
Weather 3 Variance is 19182.418761290777
```

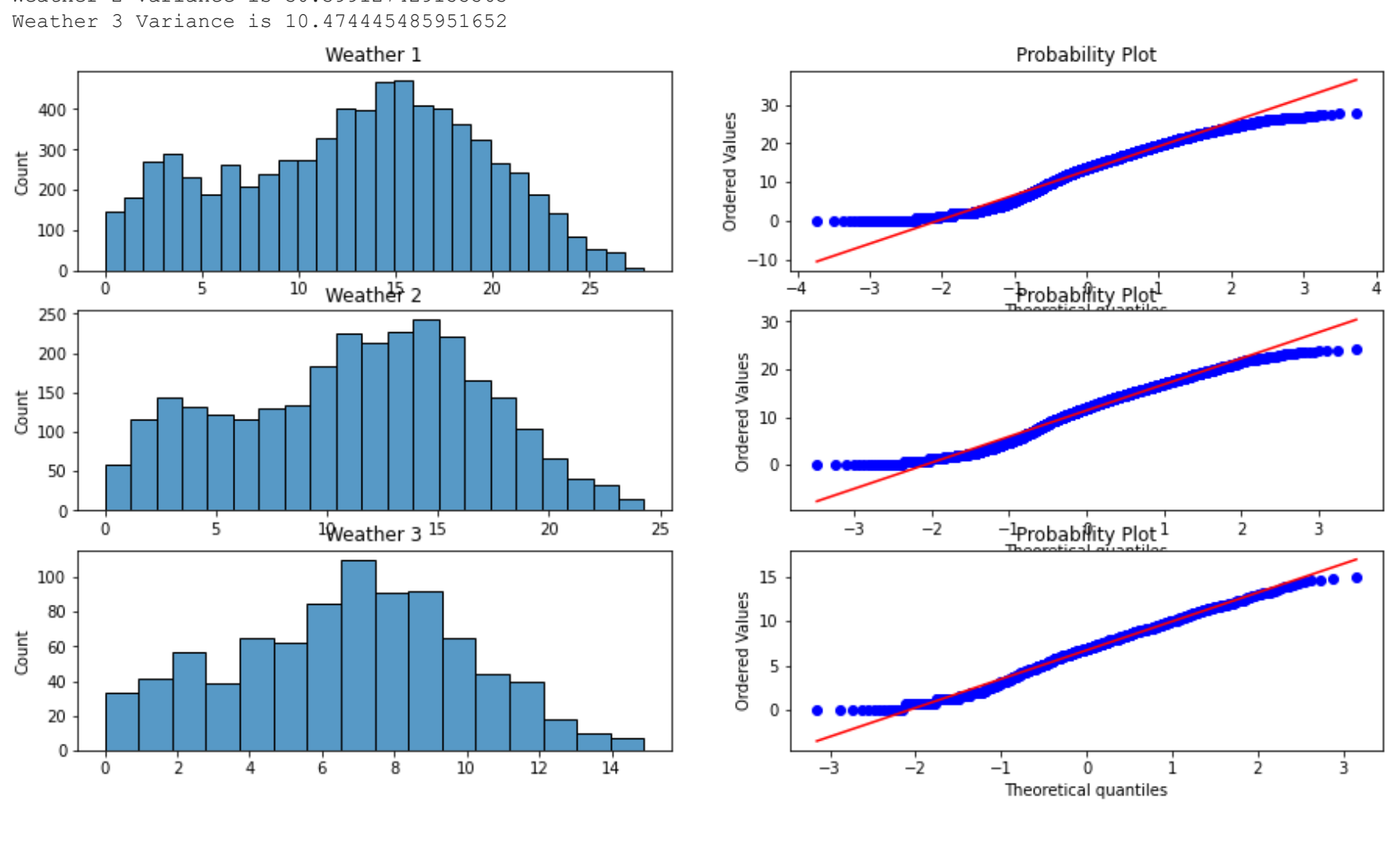


Lets do boxcox and try to make it as Approximately Normal dist then will perform Anova

we have variations but approximately we can go with this data.

In [23]:
```python
fig,axs = plt.subplots(nrows = 3,ncols = 2,figsize=(15,8))
index = 0
axs = axs.flatten()
boxcox =[]
for i in range(1,4):
    f,h = stats.boxcox(df[df['weather']==i]['count'])
    boxcox.append(f)
    sns.histplot(x = f ,ax = axs[index]).set(title = "Weather {}".format(i))
    print("Weather {} Variance is {}".format(i,np.var(f)))
    index=index+1
    stats.probplot(f, dist="norm", plot =axs[index])
    index+=1
plt.show()
```

```
Weather 1 Variance is 40.66658225318325
Weather 2 Variance is 30.399127429155563
Weather 3 Variance is 10.474445485951652
```



As P-Value is lesser than 0.05 we reject Null Hypothesis , Population means are not same.

In [24]:
```python
stats.f_oneway(boxcox[0],boxcox[1],boxcox[2])
```

Out[24]: F_onewayResult(statistic=440.1904898946861, pvalue=1.537464542423308e-184)

As we know population mean for all weathers are not equal and from above we discovered approximated weather 1 and weather 2 have high mean lets do Hypothesis testing on these 2 weathers

T-Test -- One Sided

Null Hypothesis -- weather1 and weather2 population mean are same for number of bikes.

Alternative Hypothesis -- weather1 population mean for number of bikes is greater than weather2 population mean for number of bikes.

Significance value = 5%

In [25]:
```python
stats.ttest_ind(df_1['count'],df_2['count'],alternative='greater')
```

Out[25]: Ttest_indResult(statistic=6.202267793294654, pvalue=2.8929219970924407e-10)

As pvalue is lesser than 0.05 we reject NULL Hypothesis and confirm that weather1 population mean is greater than weather2 population

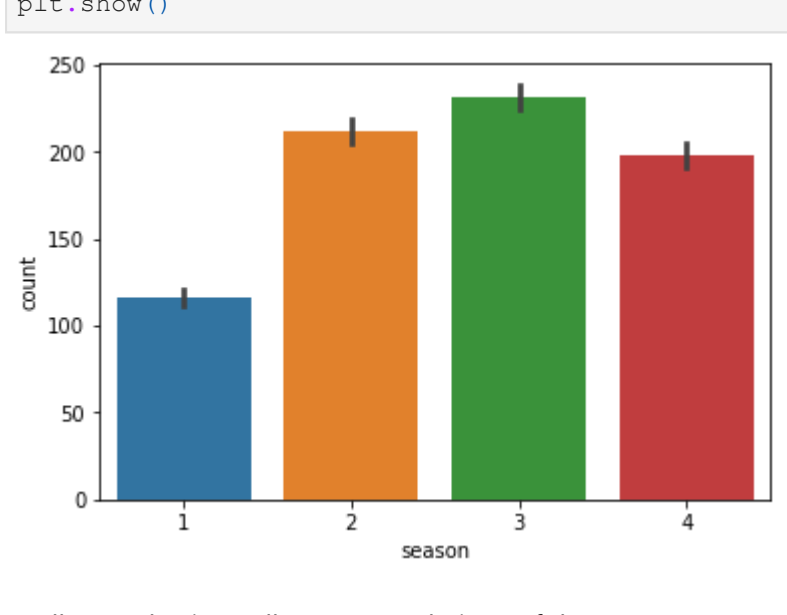
Season -- No. of cycles rented is similar or different in different seasons

In [26]:
```python
df['season'].value_counts()
```

Out[26]:
```
4    2731
3    2721
2    2720
1    2684
Name: season, dtype: int64
```

We see noticeable differnce in sample mean

In [27]:
```python
sns.barplot(y='count',x='season',data=df)
plt.show()
```



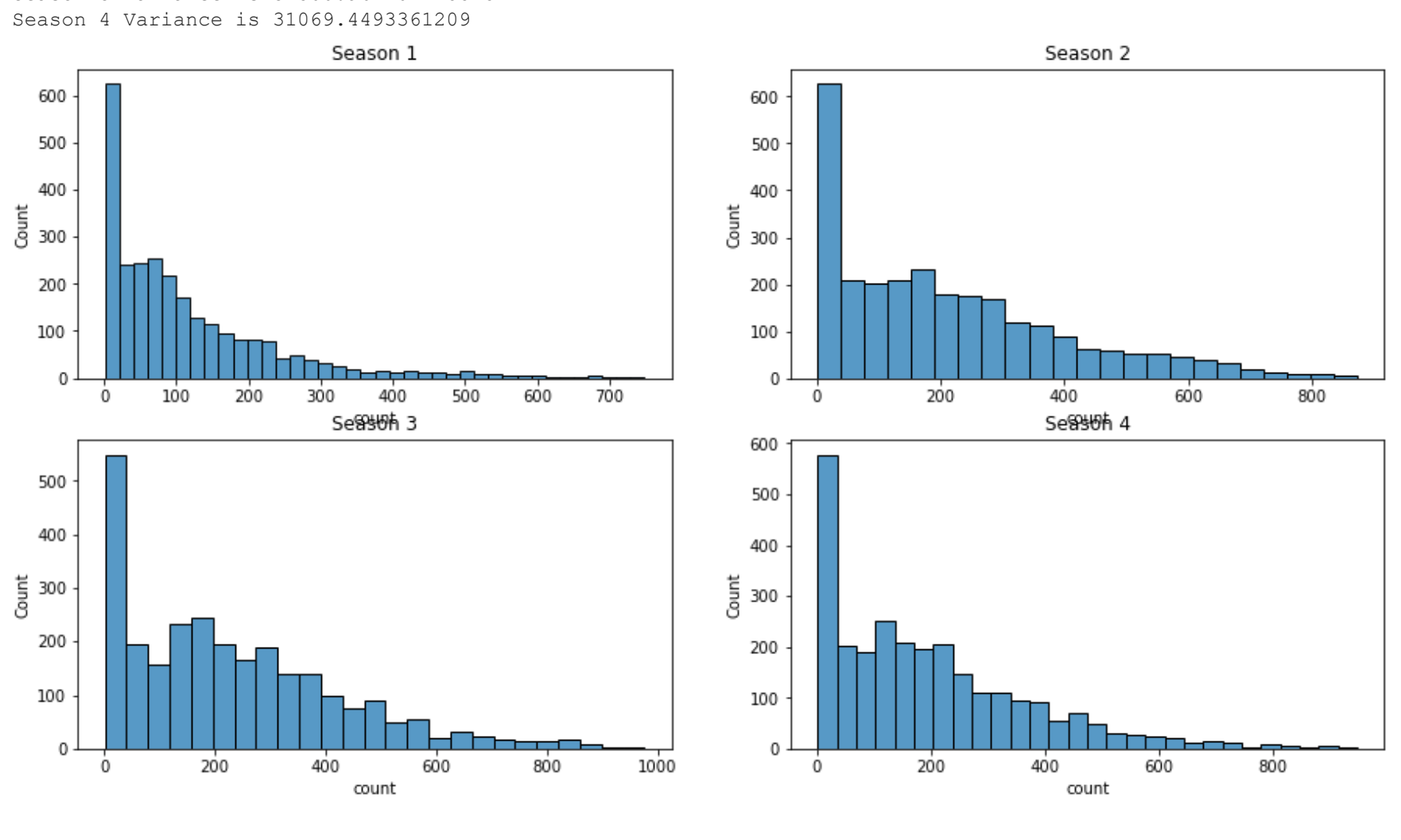
Null Hypothesis -- All mean populations of the season are same

Alternative Hypothesis -- Not all are equal

Significance level = 5% percent

In [28]:
```python
fig,axs = plt.subplots(nrows = 2,ncols = 2,figsize=(15,8))
index = 0
axs = axs.flatten()
for i in range(1,5):
    sns.histplot(x = 'count',data= df[df['season']==i],ax = axs[index]).set(title = "Season {}".format(i))
    print("Season {} Variance is {}".format(i,np.var(df[df['season']==i]['count'])))
    index=index+1
plt.show()
```

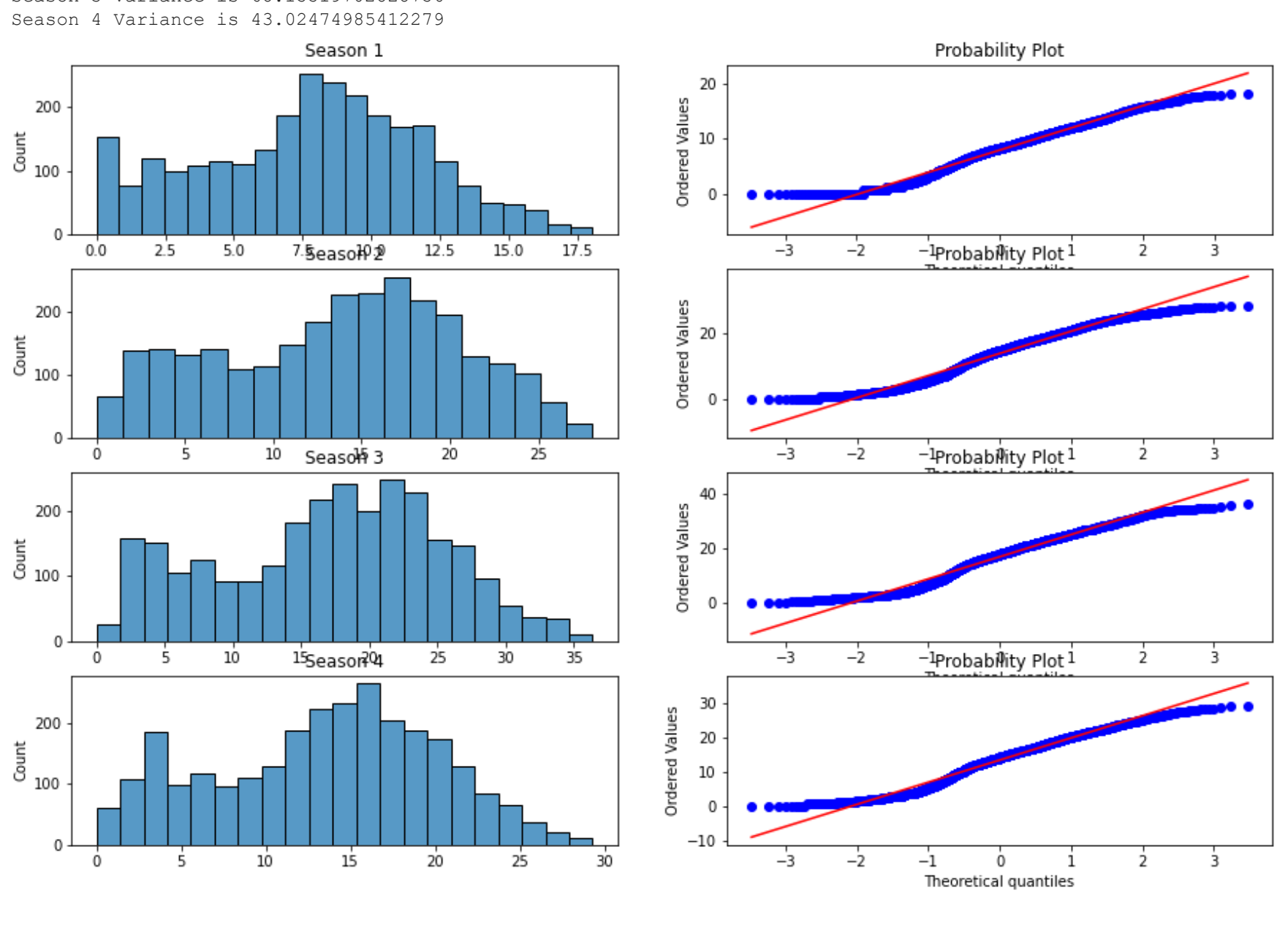
```
Season 1 Variance is 15359.425644682515
Season 2 Variance is 35472.23384934581
Season 3 Variance is 37500.967107748525
Season 4 Variance is 31069.4493361209
```



Lets do boxcox and try to make it as Approximately Normal dist then will perform Anova

In [29]:
```python
fig,axs = plt.subplots(nrows = 4,ncols = 2,figsize=(15,10))
index = 0
axs = axs.flatten()
boxcox =[]
for i in range(1,5):
    f,h = stats.boxcox(df[df['season']==i]['count'])
    boxcox.append(f)
    sns.histplot(x = f ,ax = axs[index]).set(title = "Season {}".format(i))
    print("Season {} Variance is {}".format(i,np.var(f)))
    index=index+1
    stats.probplot(f, dist="norm", plot =axs[index])
    index+=1
plt.show()
```

```
Season 1 Variance is 16.433125091465634
Season 2 Variance is 45.6556456476883
Season 3 Variance is 68.15519702828756
Season 4 Variance is 43.02474985412279
```



As P-Value is lesser than 0.05 we reject Null Hypothesis , Population means are not same.

In [30]:
```python
stats.f_oneway(boxcox[0],boxcox[1],boxcox[2],boxcox[3])
```

Out[30]: F_onewayResult(statistic=901.2720662453708, pvalue=0.0)

As we know population mean for all seasons are not equal and from above we discovered approximated season 2 and season 3 have high mean lets do Hypothesis testing on these 2 seasons

T-Test -- One Sided

Null Hypothesis -- season2 and season3 population mean for number of bikes are same.

Alternative Hypothesis -- season3 population mean for number of bikes is greater than season2 population mean for number of bikes.

Significance value = 5%

In [31]:
```python
stats.ttest_ind(df[df['season'] == 3]['count'],df[df['season'] == 2]['count'],alternative='greater')
```

Out[31]: Ttest_indResult(statistic=3.729353817838736, pvalue=9.696243142925167e-05)

As pvalue is lesser than 0.05 we reject NULL Hypothesis and confirm that season3 population mean is greater than season2 population

CHI - Square Test

Checking if Weather is dependent on the season

Null Hypothesis -- season and weather are independent

Alternative Hypothesis -- season and weather are dependent

Significance = 5%

In [32]:
```python
ct = pd.crosstab(df['season'],df['weather'])
ct
```

Out[32]:

weather season	1	2	3	4
1	1757	715	211	1
2	1788	708	224	0
3	1921	601	199	0
4	1699	807	225	0

As P-Value is lesser than 0.05 we reject Null Hypothesis , season and weather are dependent

In [33]:
```python
t_stat,pvalue,dof,expected = stats.chi2_contingency(ct)
print("P-Value is {}".format(pvalue))
print("Chi-square_statistics is {}".format(t_stat))
print()
print("----------Expected Values-----------")
pd.DataFrame(expected)
```

```
P-Value is 1.40722395162225833e-07
Chi-square_statistics is 49.38223405442044

----------Expected Values-----------
```

Out[33]:

	0	1	2	3
0	1771.449889	699.926676	212.376197	0.247237
1	1795.210022	709.314665	215.224761	0.250553
2	1795.870026	709.575442	215.303887	0.250645
3	1802.470063	712.183217	216.095155	0.251566

Whether Number of cycles rented in waether is dependent on Number of rented in season

In [34]:
```python
df1 = df[~(df['weather'] == 4)]
ct = pd.pivot_table(data = df1, index = 'season', columns = 'weather',aggfunc=np.sum)['count']
ct
```

Out[34]:

weather season	1	2	3
1	221426	76406	12919
2	416195	134177	27755
3	462924	136821	31160
4	353963	157191	30255

Chi-square_statistics is very high and P value is zero so there is very strong conclusion that these 2 are related.

In [35]:
```python
t_stat,pvalue,dof,expected = stats.chi2_contingency(ct)
print("P-Value is {}".format(pvalue))
print("Chi-square_statistics is {}".format(t_stat))
print()
print("----------Expected Values-----------")
pd.DataFrame(expected)
```

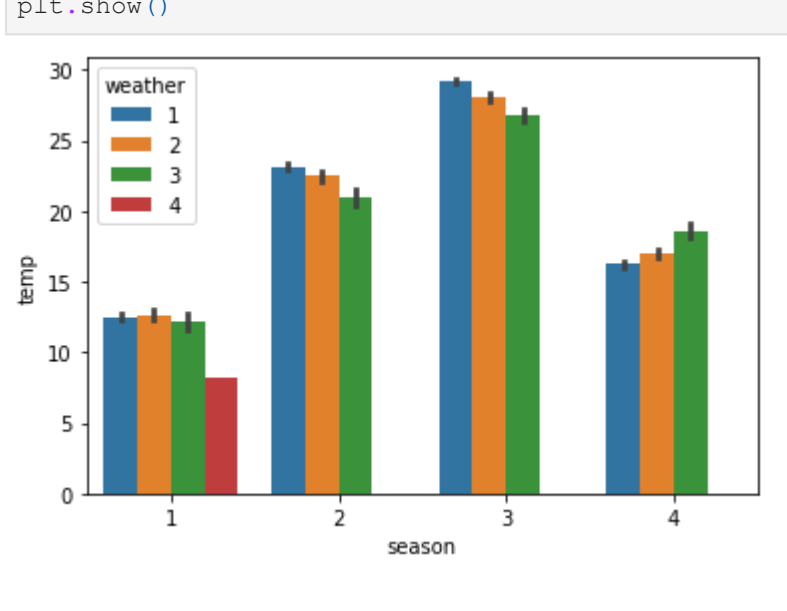
```
P-Value is 0.0
Chi-square_statistics is 10802.911433682099

----------Expected Values-----------
```

Out[35]:

	0	1	2
0	219285.644185	76074.136153	15391.219663
1	407963.133234	141529.752476	28634.114291
2	445206.642438	154450.196039	31248.161523
3	382052.580144	132540.915332	26815.504524

temp vs weather and season

In [36]:
```python
sns.barplot(x='season',y='temp',hue='weather',data=df)
plt.show()
```



Lets check population mean of temp between weather1 and weather2 , season2 and season3

One sided T-Test

Null Hypothesis -- season2 and season3 population mean for temp are same.

Alternative Hypothesis -- season3 population mean of temp is greater than season2 population mean of temp.

Significance value = 5%

In [37]:
```python
stats.ttest_ind(df[df['season'] == 3]['temp'],df[df['season'] == 2]['temp'],alternative='greater')
```

Out[37]: Ttest_indResult(statistic=48.17366279423885, pvalue=0.0)

Season 3 have mean temp greater than season 2, As pvalue is lesser than 0.05

With same set up but instead of season 2 lets check with season 1 and season 4

In [38]:
```python
stats.ttest_ind(df[df['season'] == 3]['temp'],df[df['season'] == 1]['temp'],alternative='greater')
```

Out[38]: Ttest_indResult(statistic=130.59859318642657, pvalue=0.0)

In [39]:
```python
stats.ttest_ind(df[df['season'] == 3]['temp'],df[df['season'] == 4]['temp'],alternative='greater')
```

Out[39]: Ttest_indResult(statistic=103.24270640527541, pvalue=0.0)

Season 3 have mean temp greater than season 1 and season 4 , As pvalue is lesser than 0.05

One sided T-Test

Null Hypothesis -- weather1 and weather2 population mean for temp are same.

Alternative Hypothesis -- weather1 population mean of temp is greater than weather2 population mean of temp.

Significance value = 5%

In [40]:
```python
stats.ttest_ind(df[df['weather'] == 1]['temp'],df[df['weather'] == 2]['temp'],alternative='greater')
```

Out[40]: Ttest_indResult(statistic=5.317100387752267, pvalue=5.3854527146646476e-08)

Weather 1 have mean temp greater than weather 2 as pvalue is lesser than 0.05

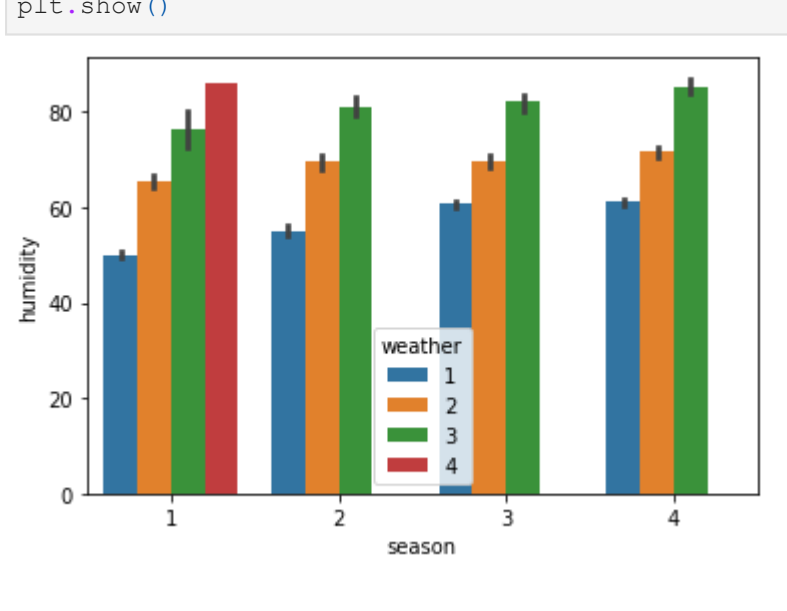
With same set up but instead of weather 2 lets check with weather 3

In [41]:
```python
stats.ttest_ind(df[df['weather'] == 1]['temp'],df[df['weather'] == 3]['temp'],alternative='greater')
```

Out[41]: Ttest_indResult(statistic=3.417921895115183, pvalue=0.0003170743930708656)

Weather 1 have mean temp greater than weather 3 as pvalue is lesser than 0.05

In [42]:
```python
sns.barplot(x='season',y='humidity',hue='weather',data=df)
plt.show()
```



One sided T-Test

Null Hypothesis -- weather1 and weather2 population mean for humidity are same.

Alternative Hypothesis -- weather1 population mean of humidity is lesser than weather2 population mean of humidity.

Significance value = 5%

In [43]:
```python
stats.ttest_ind(df[df['weather'] == 1]['humidity'],df[df['weather'] == 2]['humidity'],alternative='less')
```

Out[43]: Ttest_indResult(statistic=-31.68480268442733, pvalue=2.4419351964198334e-210)

weather 1 mean population for humidity is lesser than weather 2 as pvalue is lesser than 0.05

With same set up but instead of weather 2 lets check with weather 3

In [44]:
```python
stats.ttest_ind(df[df['weather'] == 1]['humidity'],df[df['weather'] == 3]['humidity'],alternative='less')
```

Out[44]: Ttest_indResult(statistic=-38.46973136343918, pvalue=1.3444440531767446e-297)

weather 1 mean population for humidity is lesser than weather 3 as pvalue is lesser than 0.05

One sided T-Test

Null Hypothesis -- season2 and season3 population mean for humidity are same.

Alternative Hypothesis -- season3 population mean of humidity is lesser than season2 population mean of humidity.

Significance value = 5%

In [45]:
```python
stats.ttest_ind(df[df['season'] == 3]['humidity'],df[df['season'] == 2]['humidity'],alternative='less')
```

Out[45]: Ttest_indResult(statistic=6.3254244099668515, pvalue=0.9999999998636447)

Season 3 and season 2 population mean are same as pvalue is much hihger than 0.05

With same set up but instead of season 2 lets check with season 1 and season 4

In [46]:
```python
stats.ttest_ind(df[df['season'] == 3]['humidity'],df[df['season'] == 1]['humidity'],alternative='less')
```

Out[46]: Ttest_indResult(statistic=15.501248179964632, pvalue=1.0)

In [47]:
```python
stats.ttest_ind(df[df['season'] == 3]['humidity'],df[df['season'] == 4]['humidity'],alternative='less')
```

Out[47]: Ttest_indResult(statistic=-4.202109168200038, pvalue=1.343331995600396e-05)

As per season it doesnt seems to follow the trend as no of bikes increases in one seaon and humidity decreases