+ Code + Text

[2]

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind,chi2_contingency,levene,kruskal,f_oneway
from statsmodels.graphics.gofplots import qqplot
```

```
df=pd.read_csv('yulu.csv')
df.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

Next steps: Generate code with df | View recommended plots | New interactive sheet

```
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
```

```
#conversion of categorical attributes to 'category'
df[['season','holiday','workingday','weather']]=df[['season','holiday','workingday','weather']].astype('str')
```

[7]

```
#season category
df['season'] = df['season'].str.strip()
df['season'] = df['season'].apply(lambda x: 'spring' if x == '1'
                                  else ('summer' if x == '2' else ('fall' if x == '3' else 'winter')))
print(df['season'].unique())
```

```
['spring' 'summer' 'fall' 'winter']
```

[8]

```
#weather category
df['weather'] = df['weather'].str.strip()
df['weather']=df['weather'].apply(lambda x: 'Clear, Few clouds, partly cloudy' if x=='1'
else('Mist + Cloudy, Mist + Broken clouds,Mist + Few clouds,Mist'
if x=='2' else('Light Snow,Light Rain + Thunderstorm + Scattered clouds,Light Rain + Scattered clouds'
if x=='3' else 'Heavy Rain + Ice Pallets + Thunderstorm + Mist,Snow + Fog')))
print(df['weather'].unique())
```

```
['Clear, Few clouds, partly cloudy'
 'Mist + Cloudy, Mist + Broken clouds,Mist + Few clouds,Mist'
 'Light Snow,Light Rain + Thunderstorm + Scattered clouds,Light Rain + Scattered clouds'
 'Heavy Rain + Ice Pallets + Thunderstorm + Mist,Snow + Fog']
```

```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  object
 2   holiday     10886 non-null  object
 3   workingday  10886 non-null  object
 4   weather     10886 non-null  object
 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(4), object(5)
memory usage: 1020.7+ KB
```

```python
#summary
df.describe()
```

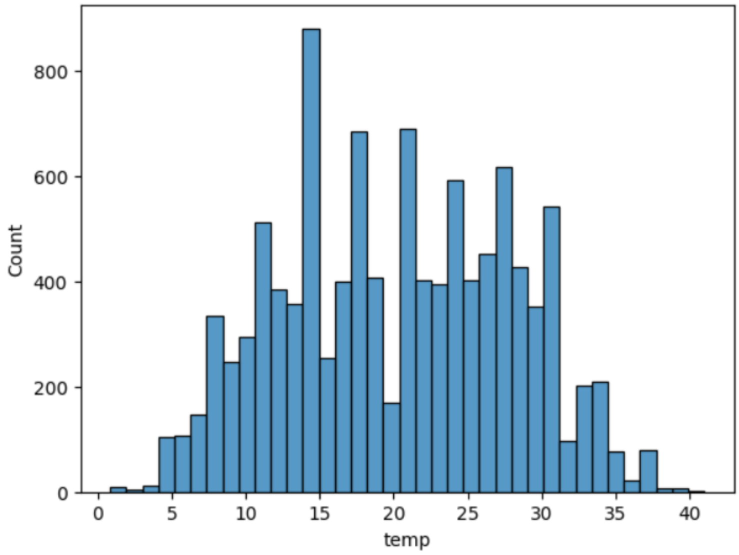
	temp	atemp	humidity	windspeed	casual	registered	count
count	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000
mean	20.23086	23.655084	61.886460	12.799395	36.021955	155.552177	191.574132
std	7.79159	8.474601	19.245033	8.164537	49.960477	151.039033	181.144454
min	0.82000	0.760000	0.000000	0.000000	0.000000	0.000000	1.000000
25%	13.94000	16.665000	47.000000	7.001500	4.000000	36.000000	42.000000
50%	20.50000	24.240000	62.000000	12.998000	17.000000	118.000000	145.000000
75%	26.24000	31.060000	77.000000	16.997900	49.000000	222.000000	284.000000
max	41.00000	45.455000	100.000000	56.996900	367.000000	886.000000	977.000000

[11]
```python
df.describe(include=object)
```

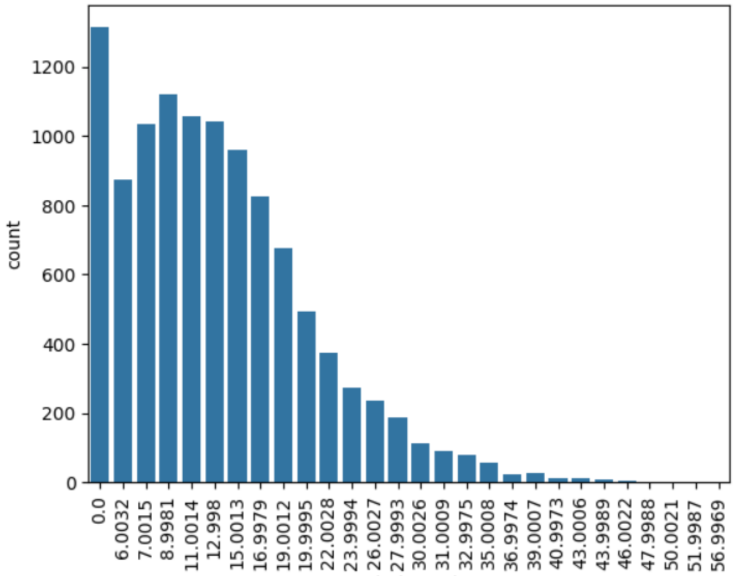
	datetime	season	holiday	workingday	weather
count	10886	10886	10886	10886	10886
unique	10886	4	2	2	4
top	2011-01-01 00:00:00	winter	0	1	Clear, Few clouds, partly cloudy
freq	1	2734	10575	7412	7192

```python
sns.histplot(x='temp',data=df)
```

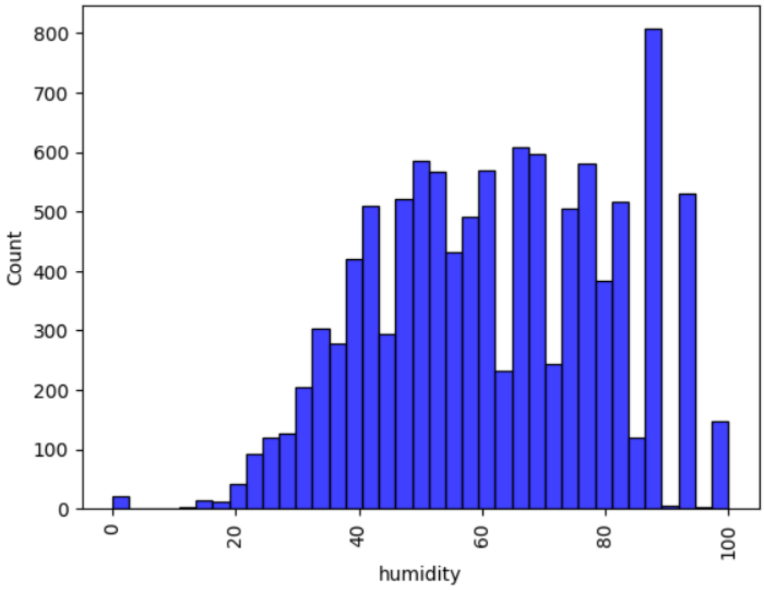
```
<Axes: xlabel='temp', ylabel='Count'>
```




```python
sns.countplot(x='windspeed',data=df)
plt.xticks(rotation=90)
plt.show()
```



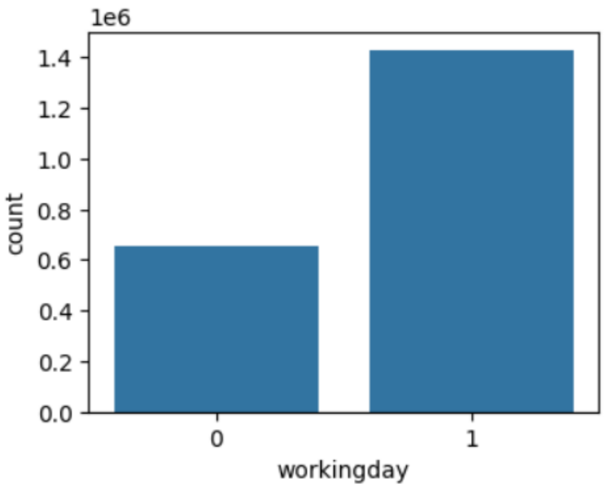

```python
sns.histplot(x='humidity',data=df,color='b')
plt.xticks(rotation=90)
plt.show()
```




```
[15] #Relation between working day and count
workday=df.groupby('workingday')['count'].sum().reset_index()
workday
```

	workingday	count
0	0	654872
1	1	1430604

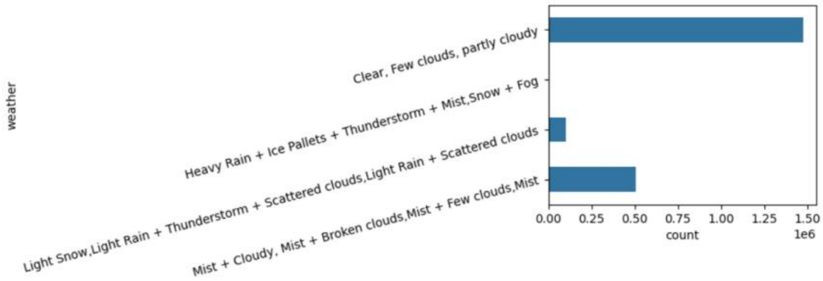
```
fig=plt.figure(figsize=(4,3))
sns.barplot(x='workingday',y='count',data=workday,width=0.8)
plt.show()
```




```
#Relation between weather and count
df_weather=df.groupby('weather')['count'].sum().reset_index()
df_weather
```

	weather	count
0	Clear, Few clouds, partly cloudy	1476063
1	Heavy Rain + Ice Pallets + Thunderstorm + Mist...	164
2	Light Snow,Light Rain + Thunderstorm + Scatter...	102089
3	Mist + Cloudy, Mist + Broken clouds,Mist + Few...	507160

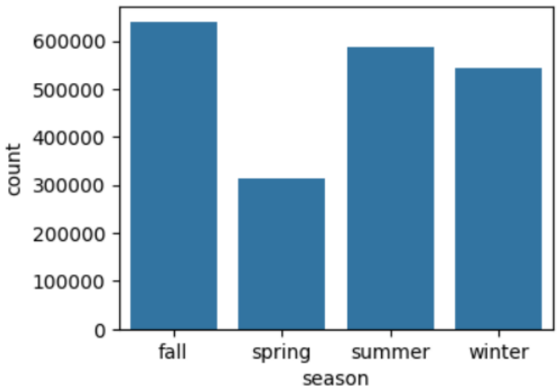
```
fig=plt.figure(figsize=(4,3))
sns.barplot(y='weather',x='count',data=df_weather,width=0.5)
plt.yticks(rotation=15)
plt.show()
```




```
[19] #Relation between season and count
df_season=df.groupby('season')['count'].sum().reset_index()
df_season
```

	season	count
0	fall	640662
1	spring	312498
2	summer	588282
3	winter	544034

```
fig=plt.figure(figsize=(4,3))
sns.barplot(x='season',y='count',data=df_season,width=0.8)
plt.show()
```



1)Checking wheather Working Day has an effect on the number of electric cycles rented

```
#h0:There is no significance difference between working and number of electric cycles rented
#ha:There is a significance difference between working and number of electric cycles rented
holiday=df[df['workingday']=='0']['count']
workday=df[df['workingday']=='1']['count']
t_statistic,p_val=ttest_ind(workday,holiday)
print('statistic:',t_statistic,'p_value:',p_val)
if p_val>0.05:
  print('Accept H0,There is no significance difference between working and number of electric cycles rented')
else:
   print('Reject H0,There is a significance difference between working and number of electric cycles rented')
```

```
statistic: 1.2096277376026694 p_value: 0.22644804226361348
Accept H0,There is no significance difference between working and number of electric cycles rented
```

2)Check if no. of cycles rented is similar or different in different seasons

```
df.head()
```

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

Next steps: Generate code with df View recommended plots New interactive sheet

Anova test

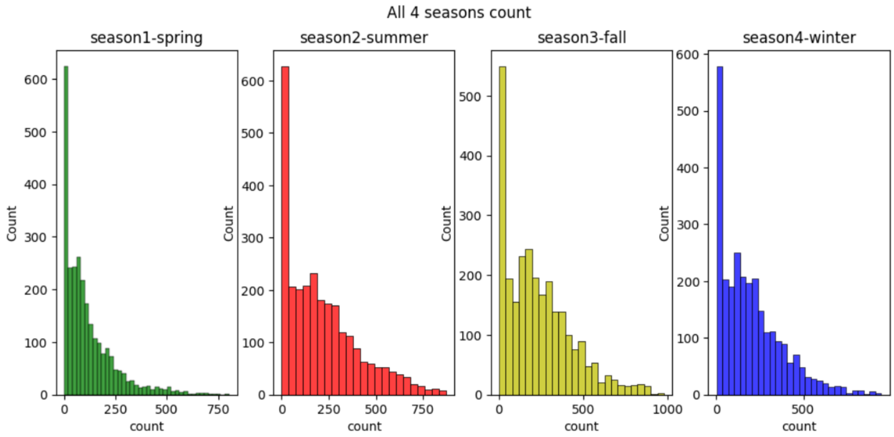
```
df.groupby('season')['count'].sum()
```

season	count
fall	640662
spring	312498
summer	588282
winter	544034

dtype: int64

#Test whether data is guassian or not

```python
season_1 = df[df['season'] == 'spring']['count']
season_2 = df[df['season'] == 'summer']['count']
season_3 = df[df['season'] == 'fall']['count']
season_4 = df[df['season'] == 'winter']['count']
fig=plt.figure(figsize=(12,5))
plt.subplot(1,4,1)
sns.histplot(season_1,color='g')
plt.title('season1-spring')
plt.subplot(1,4,2)
sns.histplot(season_2,color='r')
plt.title('season2-summer')
plt.subplot(1,4,3)
sns.histplot(season_3,color='y')
plt.title('season3-fall')
plt.subplot(1,4,4)
sns.histplot(season_4,color='b')
plt.title('season4-winter')
plt.suptitle('All 4 seasons count')
plt.show()
```



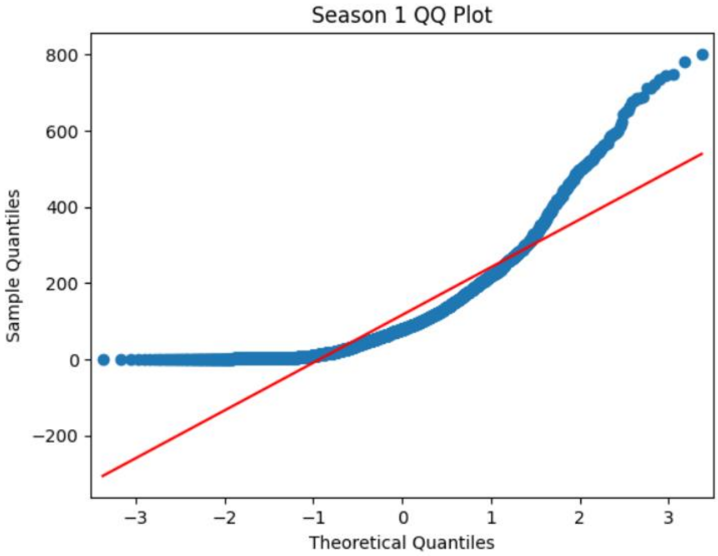
****From above plots we can see that the data points are leftly skewed and they are not normally distributed/guassian distribution

#qqplot

```python
[25] qqplot(season_1, line='s')
     plt.title('Season 1 QQ Plot')
```

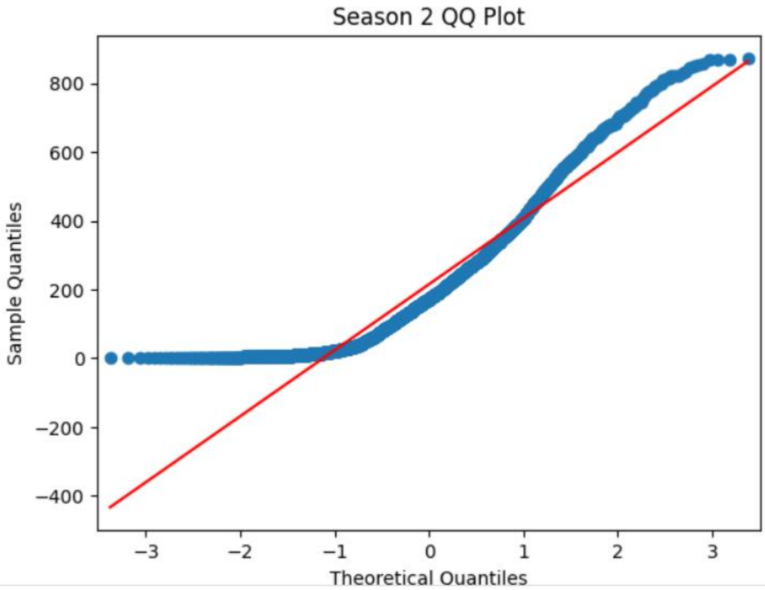
```
Text(0.5, 1.0, 'Season 1 QQ Plot')
```

```
Text(0.5, 1.0, 'Season 1 QQ Plot')
```



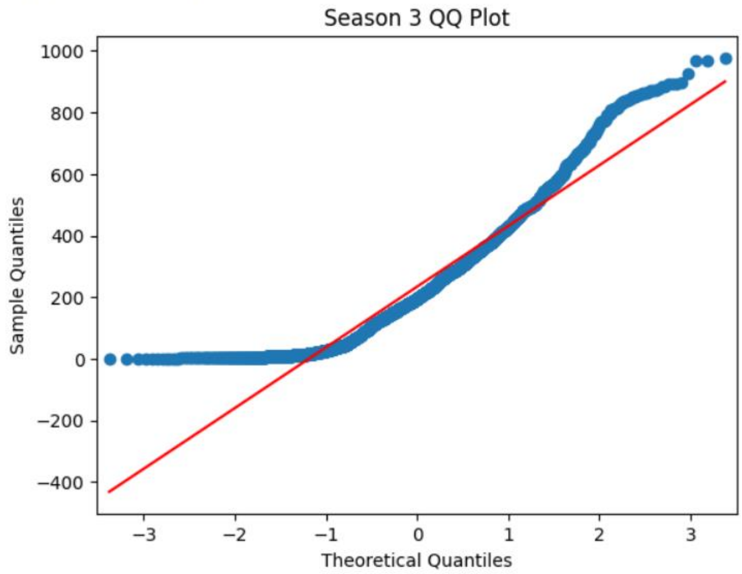

```
fig=plt.figure(figsize=(4,3))
qqplot(season_2, line='s')
plt.title('Season 2 QQ Plot')
plt.show()
```

```
<Figure size 400x300 with 0 Axes>
```



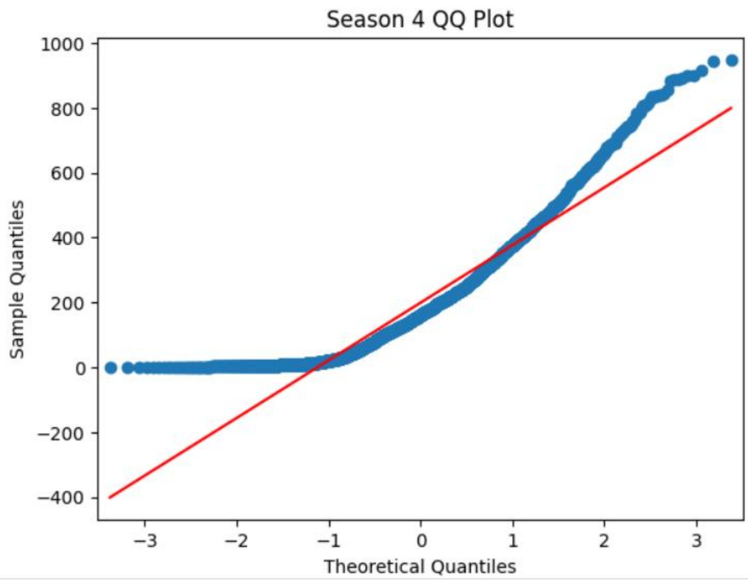
```
fig=plt.figure(figsize=(4,3))
qqplot(season_3, line='s')
plt.title('Season 3 QQ Plot')
plt.show()
```

```
<Figure size 400x300 with 0 Axes>
```




```
fig=plt.figure(figsize=(4,3))
qqplot(season_4, line='s')
plt.title('Season 4 QQ Plot')
plt.show()
```

```
<Figure size 400x300 with 0 Axes>
```



****From above we can say that the data is not guassian

Shapiro test

---It only works for 50 to 200 samples

Shapiro test

---It only works for 50 to 200 samples

```
[ ] #H0: the sample has a Gaussian distribution.
    #Ha: the sample does not have a Gaussian distribution.
    from scipy.stats import shapiro
    season1_samp=season_1.sample(200)
    season2_samp=season_2.sample(200)
    season3_samp=season_3.sample(200)
    season4_samp=season_4.sample(200)
    stat,p=shapiro(season1_samp)
    print('stat=%.3f, p=%.3f' % (stat, p))
    if p >0.05:
        print('Accept H0,Probably  Gaussian')
    else:
        print('Reject H0,Probably not Gaussian')
```

```
stat=0.810, p=0.000
Reject H0,Probably not Gaussian
```

```
#season2
stat,p=shapiro(season2_samp)
print('stat=%.3f, p=%.3f' % (stat, p))
if p <0.05:
    print('Probably not Gaussian')
else:
    print('Probably Gaussian')
```

```
stat=0.896, p=0.000
Probably not Gaussian
```

```
[31] #season3
stat,p=shapiro(season3_samp)
print('stat=%.3f, p=%.3f' % (stat, p))
if p <0.05:
    print('Probably not Gaussian')
else:
    print('Probably Gaussian')
```

```
stat=0.944, p=0.000
Probably not Gaussian
```

```
#season4
stat,p=shapiro(season4_samp)
print('stat=%.3f, p=%.3f' % (stat, p))
if p <0.05:
    print('Probably not Gaussian')
else:
    print('Probably Gaussian')
```

```
stat=0.886, p=0.000
Probably not Gaussian
```

Levene's test

---To check equality of variance between two different samples

Levene's test

---To check equality of variance between two different samples


```
#H0: All the samples variances are equal
#H1: At least one variance is different from the rest
stat, p = levene(season_1,season_2,season_3,season_4)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Probably the same variances')
else:
    print('Probably at least one variance is different from the rest')
```

```
stat=187.771, p=0.000
Probably at least one variance is different from the rest
```

***Thus from levene test we can conclude that there is a significance difference between there variances

***since the assumptions of Anova test does not followed,so we use kruskal test

```
[34] #H0:There is no significance difference between the number of cycles rented in different seasons
     #Ha:There is a significance difference between the number of cycles rented in different seasons
     stat,p=kruskal(season_1,season_2,season_3,season_4)
     print('stat=%.3f, p=%.3f' % (stat, p))
     if p > 0.05:
         print('Accept H0,There is no significance difference between the number of cycles rented in different seasons')
     else:
         print('Reject H0,There is a significance difference between the number of cycles rented in different seasons')
```

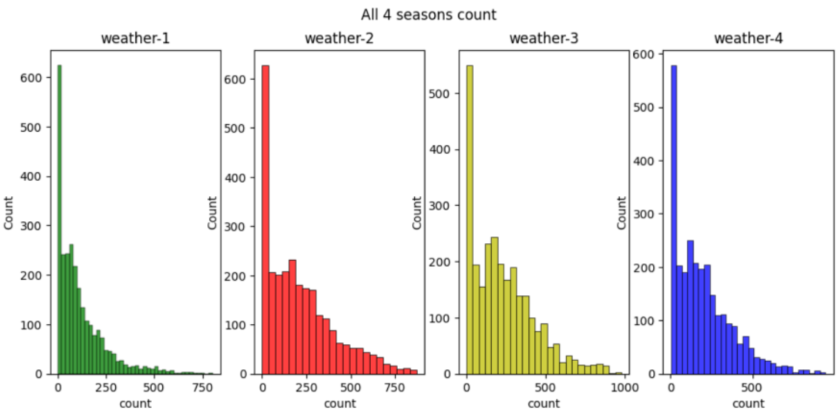
```
stat=699.667, p=0.000
Reject H0,There is a significance difference between the number of cycles rented in different seasons
```

3)Check if no. of cycles rented is similar or different in different weathers

Anova

#Test whether data is guassian or not

```
weather_1 = df[df['weather'].str.strip() == 'Clear, Few clouds, partly cloudy']['count']
weather_2 = df[df['weather'].str.strip() == 'Mist + Cloudy, Mist + Broken clouds,Mist + Few clouds,Mist']['count']
weather_3 = df[df['weather'].str.strip() == 'Light Snow,Light Rain + Thunderstorm + Scattered clouds,Light Rain + Scattered clouds']['count']
weather_4 = df[df['weather'].str.strip() == 'Heavy Rain + Ice Pallets + Thunderstorm + Mist,Snow + Fog']['count']
fig=plt.figure(figsize=(12,5))
plt.subplot(1,4,1)
sns.histplot(season_1,color='g')
plt.title('weather-1')
plt.subplot(1,4,2)
sns.histplot(season_2,color='r')
plt.title('weather-2')
plt.subplot(1,4,3)
sns.histplot(season_3,color='y')
plt.title('weather-3')
plt.subplot(1,4,4)
sns.histplot(season_4,color='b')
plt.title('weather-4')
plt.suptitle('All 4 seasons count')
plt.show()
```



***so from above,the data is not guassian

Levene's test

---To check equality of variance between two different samples

Levene's test

---To check equality of variance between two different samples

```
#H0: All the samples variances are equal
#Ha: At least one variance is different from the rest
stat, p = levene(weather_1,weather_2,weather_3,weather_4)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Probably the same variances')
else:
    print('Probably at least one variance is different from the rest')
```

```
stat=54.851, p=0.000
Probably at least one variance is different from the rest
```

***so from above we can conclude that, there is sightly differnece in number of cycles rented in different weathers...

***since the assumptions of Anova test does not followed,so we use kruskal test

```
#H0:There is no significance difference between the number of cycles rented in different weathers
#Ha:There is a significance difference between the number of cycles rented in different weathers
stat,p=kruskal(weather_1,weather_2,weather_3,weather_4)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Accept H0,There is no significance difference between the number of cycles rented in different weathers')
else:
    print('Reject H0,There is a significance difference between the number of cycles rented in different weathers')
```

```
stat=205.002, p=0.000
Reject H0,There is a significance difference between the number of cycles rented in different weathers
```

4)To Check whether,Weather is dependent on season

Chi-Square

```
table=pd.crosstab(df['weather'],df['season'])
table
```

season	fall	spring	summer	winter
weather				
Clear, Few clouds, partly cloudy	1930	1759	1801	1702
Heavy Rain + Ice Pallets + Thunderstorm + Mist,Snow + Fog	0	1	0	0
Light Snow,Light Rain + Thunderstorm + Scattered clouds,Light Rain + Scattered clouds	199	211	224	225
Mist + Cloudy, Mist + Broken clouds,Mist + Few clouds,Mist	604	715	708	807

Next steps: Generate code with table | View recommended plots | New interactive sheet

```
#H0:Weather is independent on season
#ha:Weather is dependent on season
stat, p, dof, expected = chi2_contingency(table)
print('stat=%.3f, p=%.3f' % (stat, p))
if p >0.05:
    print('Accept H0 ,weather is independent on season')
else:
    print('Reject H0,weather is dependent on season')
```

```
stat=49.159, p=0.000
Reject H0,weather is dependent on season
```

***so from above we can conclude that,weather and season are dependent

1)**Working Day Influence:** The analysis suggests that the day of the week (working day or non-working day) does not significantly impact the number of electric cycles rented.

2)**Seasonal Variations:** There is a statistically significant difference in the number of cycles rented across different seasons.

3)**Weather Variations:** There is a statistically significant difference in the number of cycles rented across different weathers.

4)**Weather and Season Dependency:** The analysis indicates a dependency between weather conditions and seasonal variations in the demand for shared electric cycles.

Recommendations

- 1)**Seasonal Marketing:** Tailor marketing campaigns to highlight benefits during specific seasons.

2)**Dynamic Pricing:** Adjust pricing for peak and off-peak seasons.

3)**Accessories:** Offer weather-appropriate accessories.

4)**Maintenance Planning:** Prioritize cycle maintenance by season.

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