Importing libraries and Dataset

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
data=pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/
```

```
data.head()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0

Observations from the dataset

```
data.shape
```

```
(10886, 12)
```

```
data.ndim
```

```
2
```

```
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
```

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

```
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
```

```
data.isnull().sum()
```

	0
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.nunique()
```

	0
datetime	10886
season	4
holiday	2
workingday	2
weather	4
temp	49
atemp	60
humidity	89
windspeed	28
casual	309
registered	731
count	822

dtype: int64

```
data.describe()
```

	datetime	season	holiday	workingday	weather	
count	10886	10886.000000	10886.000000	10886.000000	10886.000000	1088
mean	2011-12-27 05:56:22.399411968	2.506614	0.028569	0.680875	1.418427	2
min	2011-01-01 00:00:00	1.000000	0.000000	0.000000	1.000000	(
25%	2011-07-02 07:15:00	2.000000	0.000000	0.000000	1.000000	1
50%	2012-01-01 20:30:00	3.000000	0.000000	1.000000	1.000000	2
75%	2012-07-01 12:45:00	4.000000	0.000000	1.000000	2.000000	2
max	2012-12-19 23:00:00	4.000000	1.000000	1.000000	4.000000	4

```
data['season'].value_counts()
```

season	count
4	2734
2	2733
3	2733
1	2686

dtype: int64

```
data['holiday'].value_counts()
```

holiday	count
0	10575
1	311

dtype: int64

```
data['weather'].value_counts()
```

weather	count
1	7192
2	2834
3	859
4	1

dtype: int64

```
data['workingday'].value_counts()
```

workingday	count
1	7412
0	3474

dtype: int64

Working day there is more demand

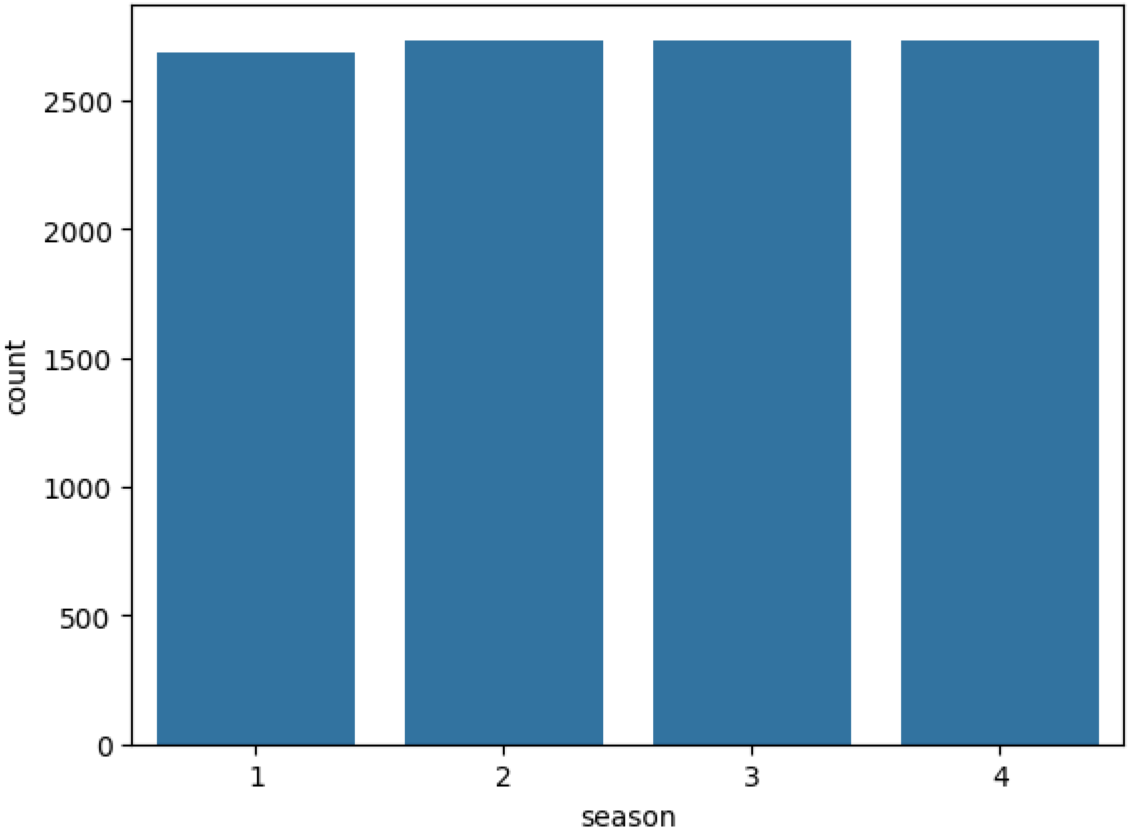
```
data['registered'].sum()
```

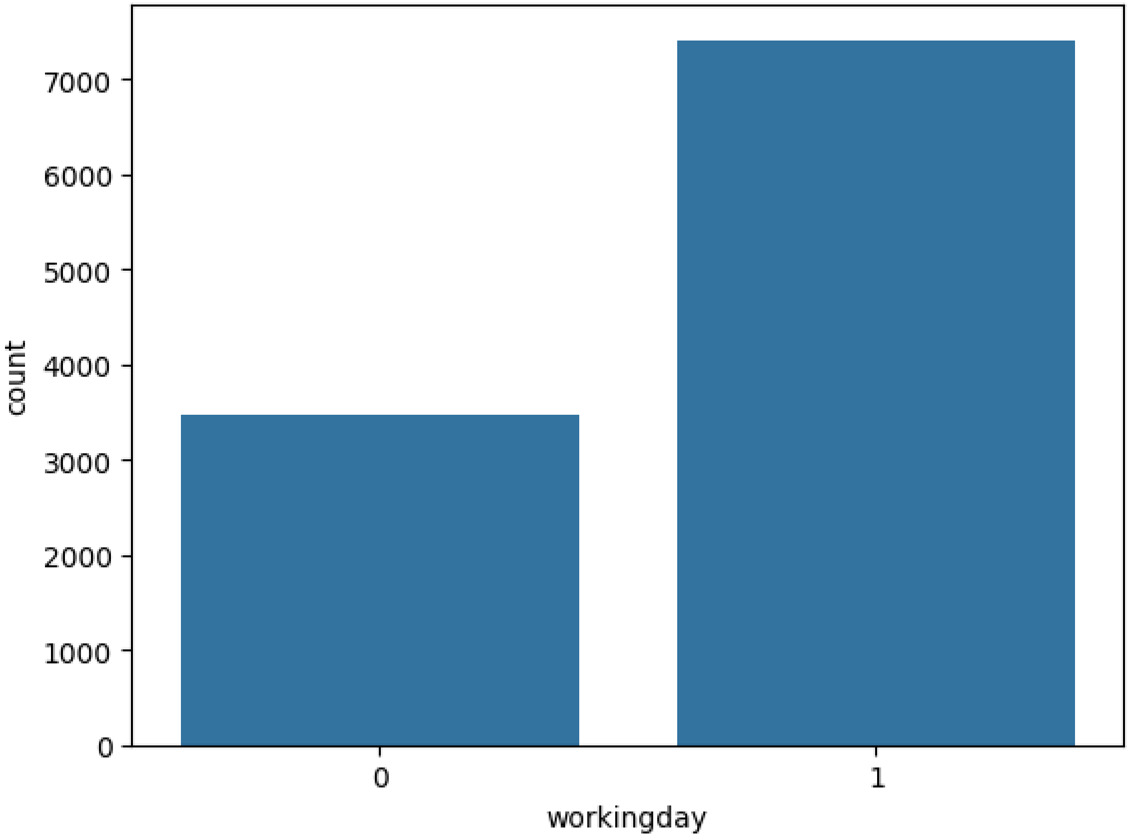
```
1693341
```

Univariate Analysis

```
cat_cols=['season','workingday','holiday','weather']
```

```
for i in cat_cols:
    sns.countplot(x=i,data=data)
    plt.show()
```



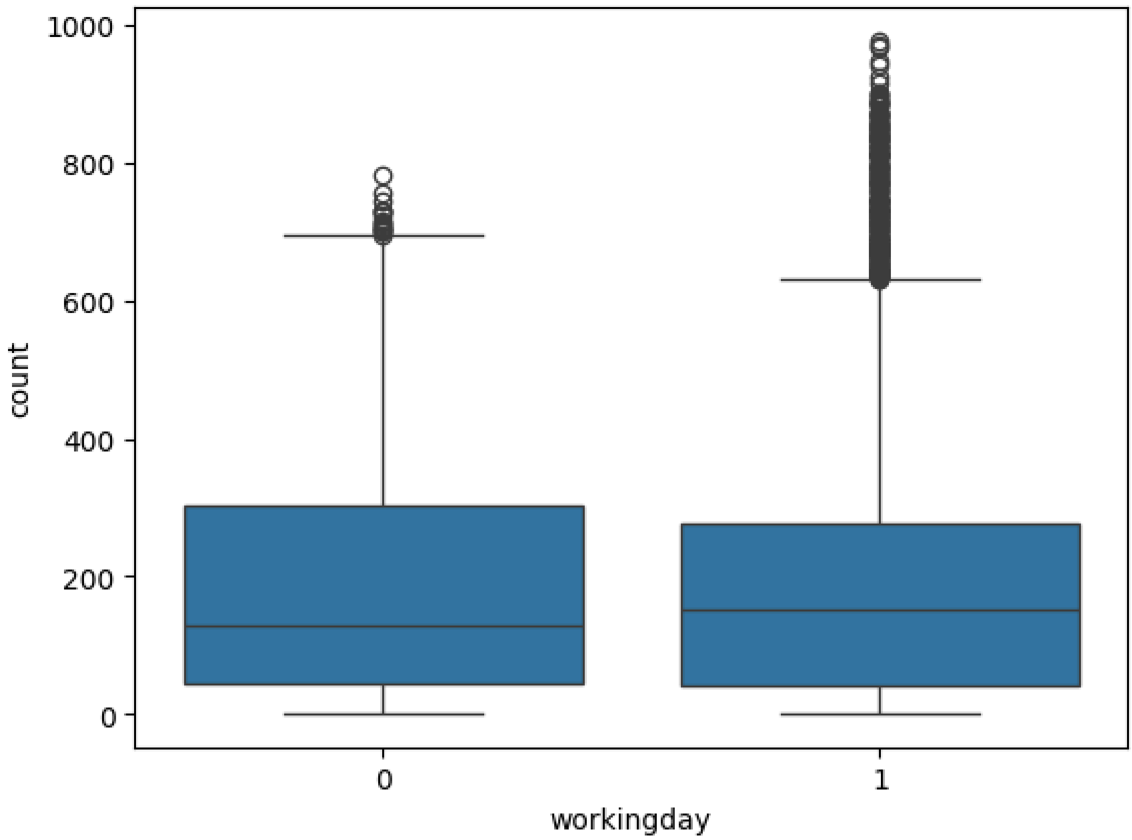


Insights from Univariate Analysis

1. The data contains more no of working days when compared to Non Working Days
2. Weather from Category 1 were the most found in the data followed by Category 2 & 3.

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

```
<Axes: xlabel='workingday', ylabel='count'>
```



Outliers

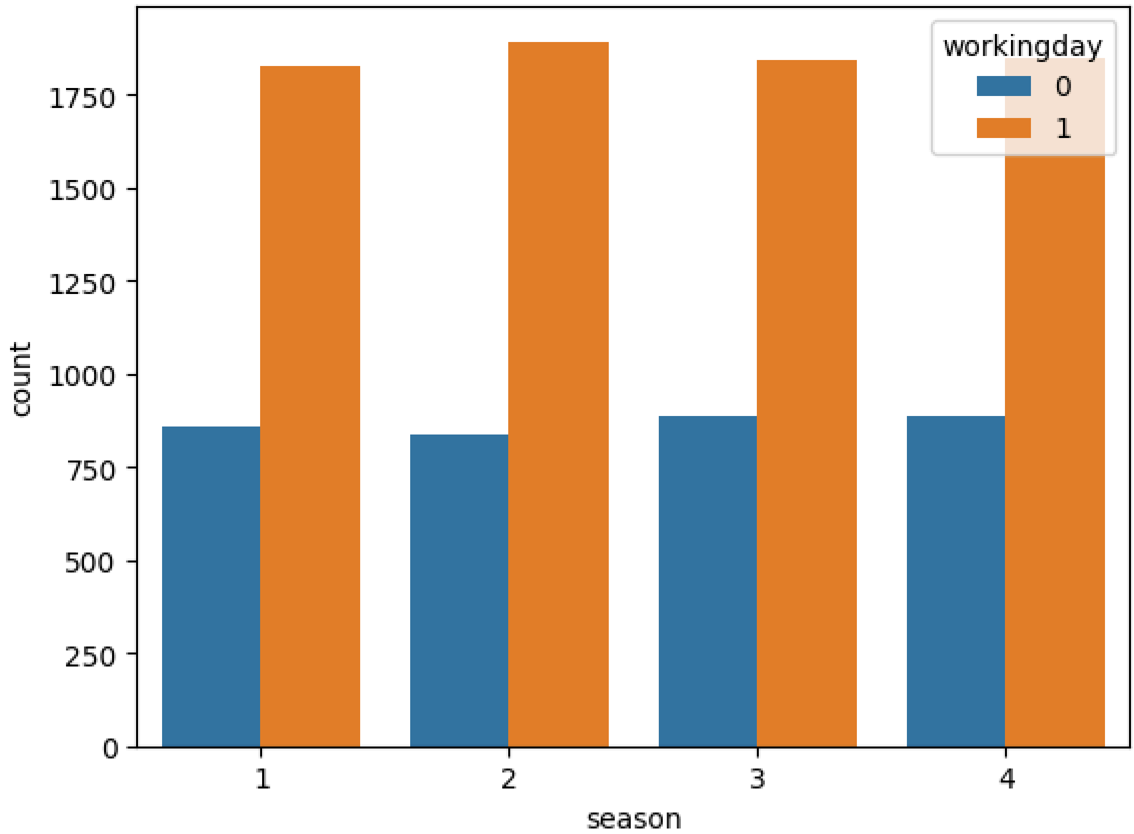
Removing outliers from the sample removes extreme conditions of the population. Removing outliers from the sensitive data may cause a problem. Hence while do hypothesis it is better to have outliers

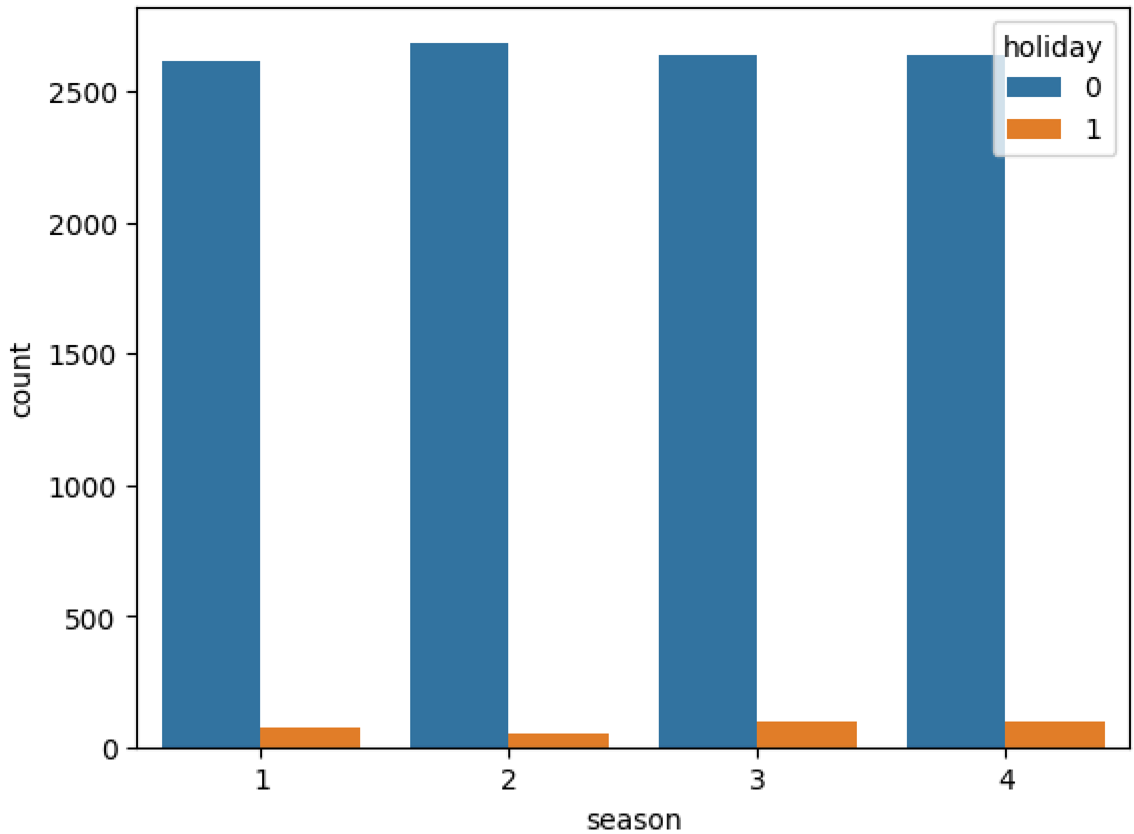
Bivariate Analysis

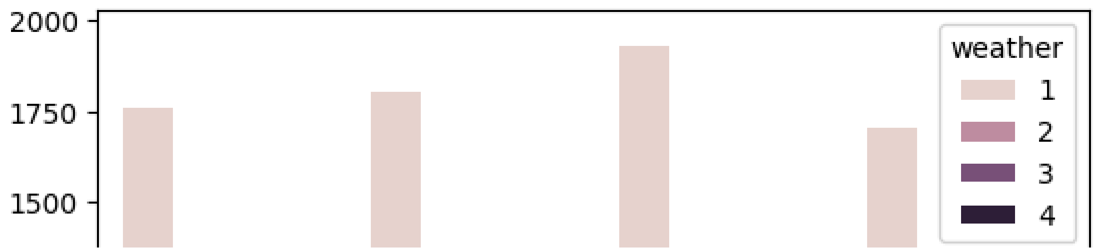
```
data.head()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0

```
cols=['workingday','holiday','weather']
for i in cols:
  sns.countplot(x='season',hue=i,data=data)
  plt.show()
```

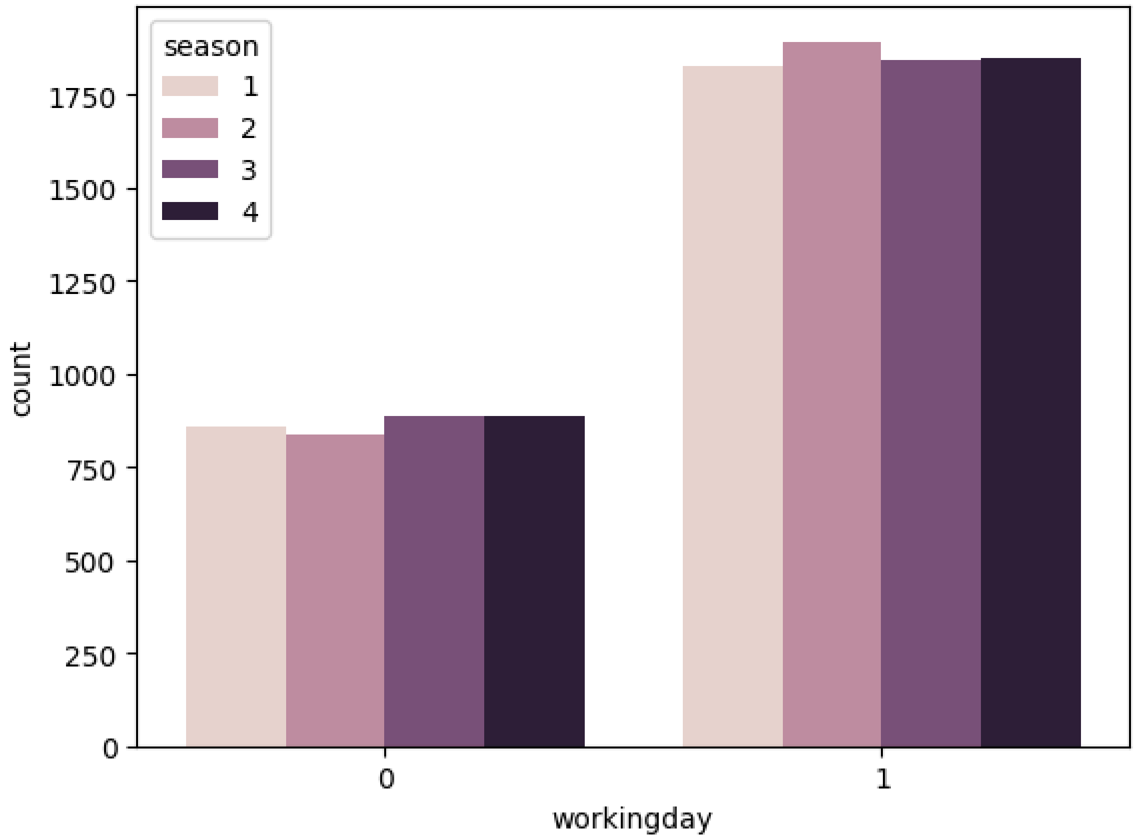


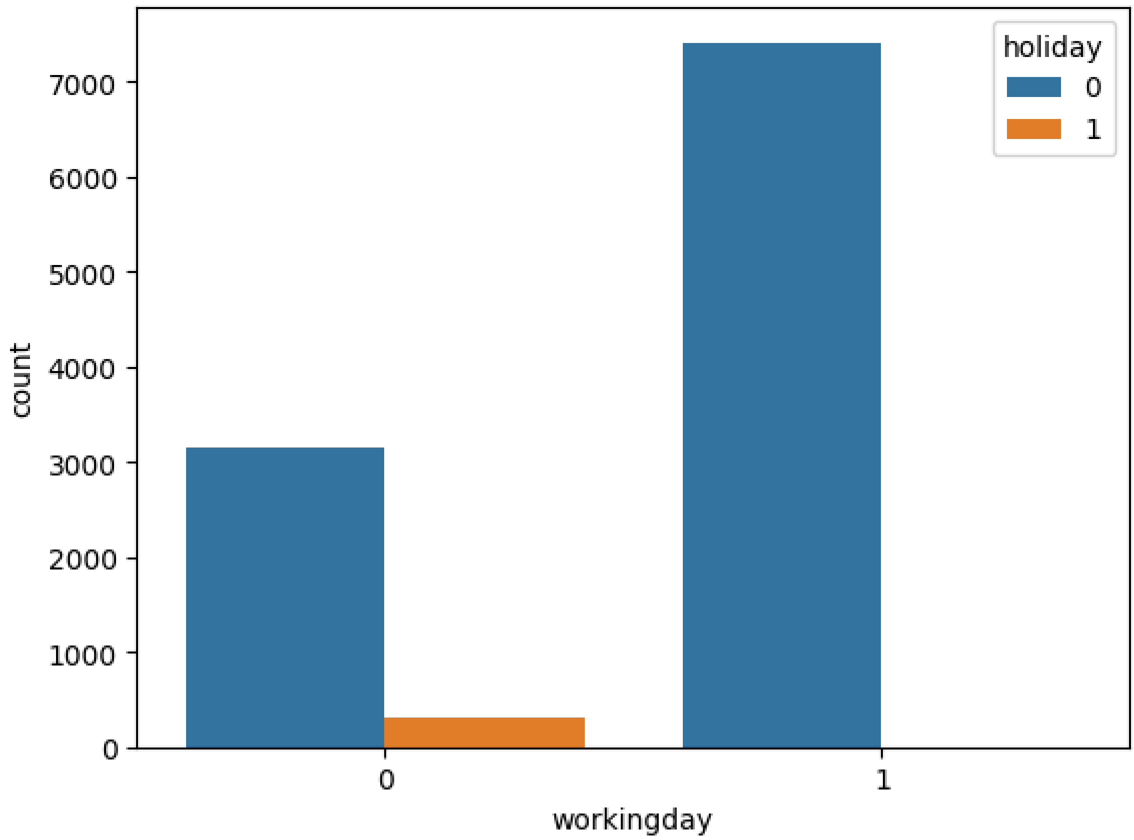


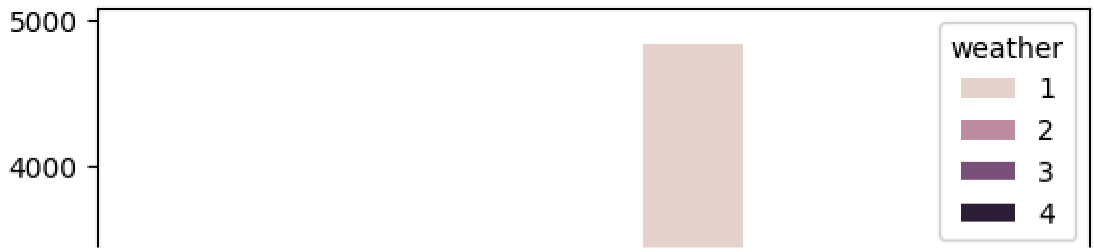



```
cols=['season','holiday','weather']
for i in cols:
```

```
sns.countplot(x='workingday',hue=i,data=data)
plt.show()
```

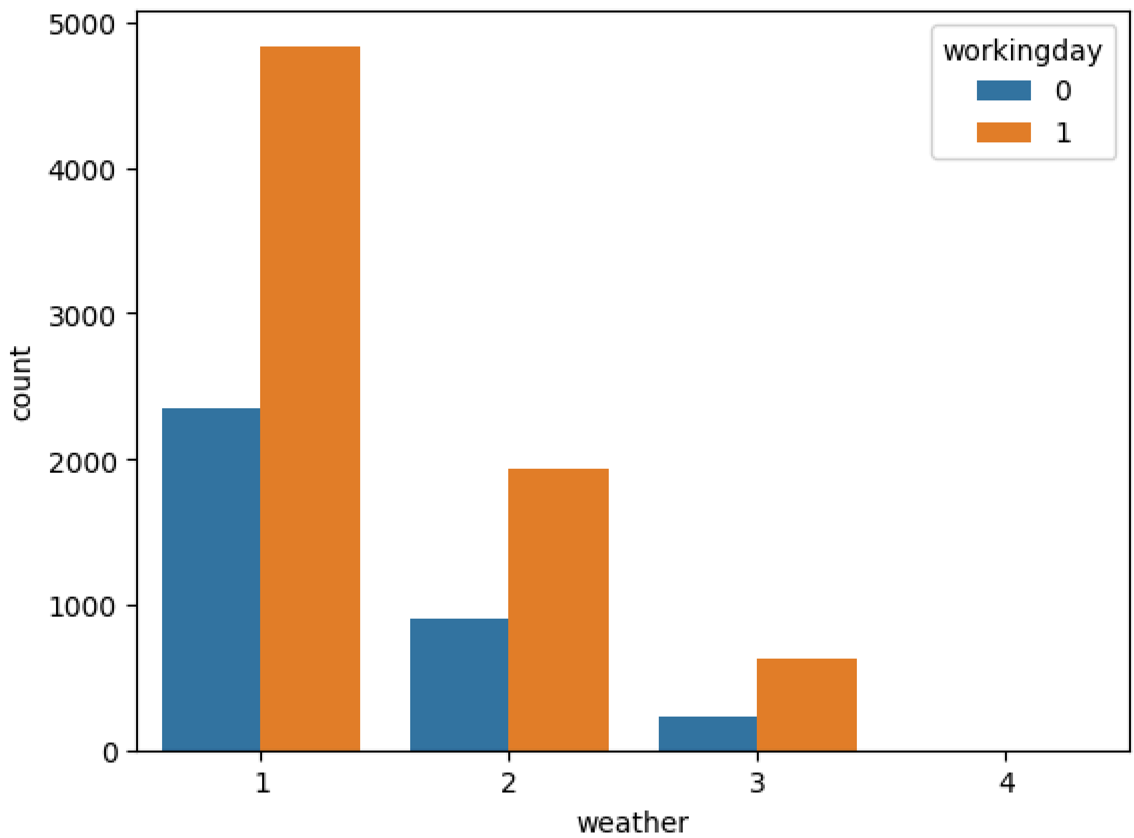


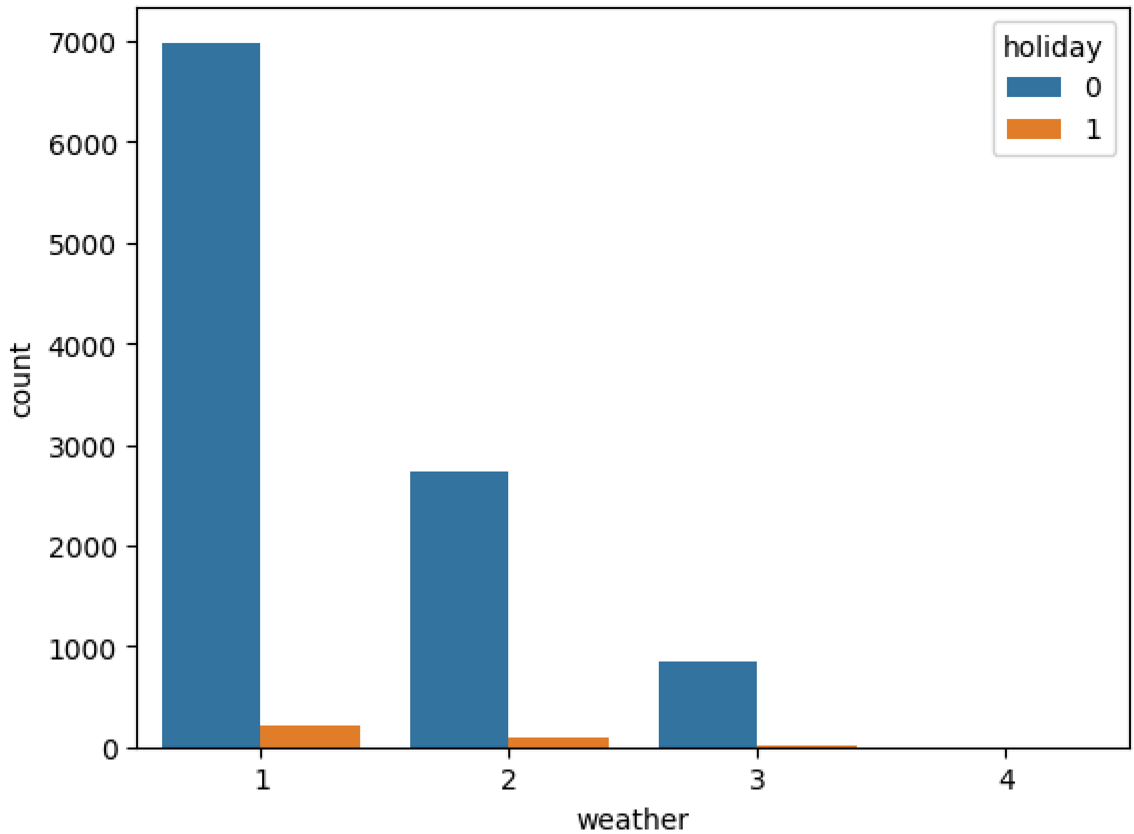


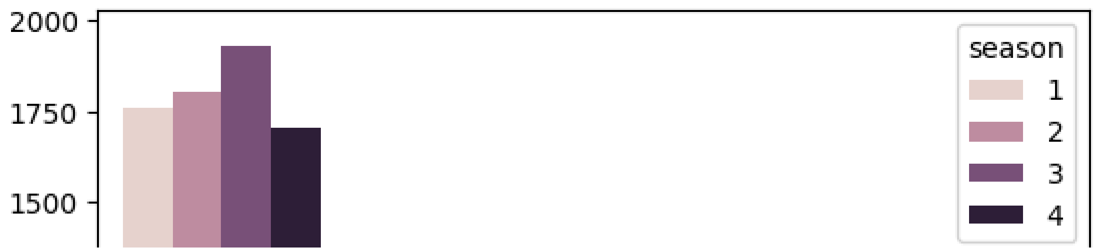



```
cols=['workingday','holiday','season']
for i in cols:
```

```
sns.countplot(x='weather',hue=i,data=data)
plt.show()
```

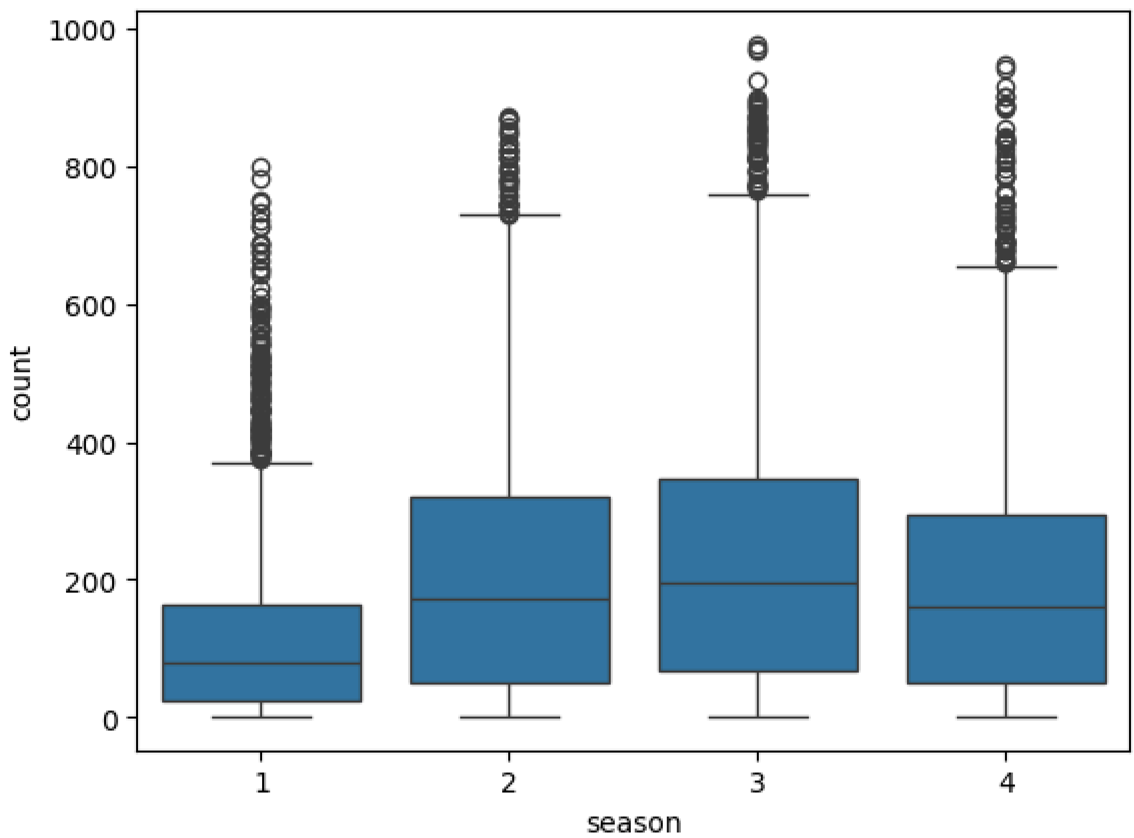


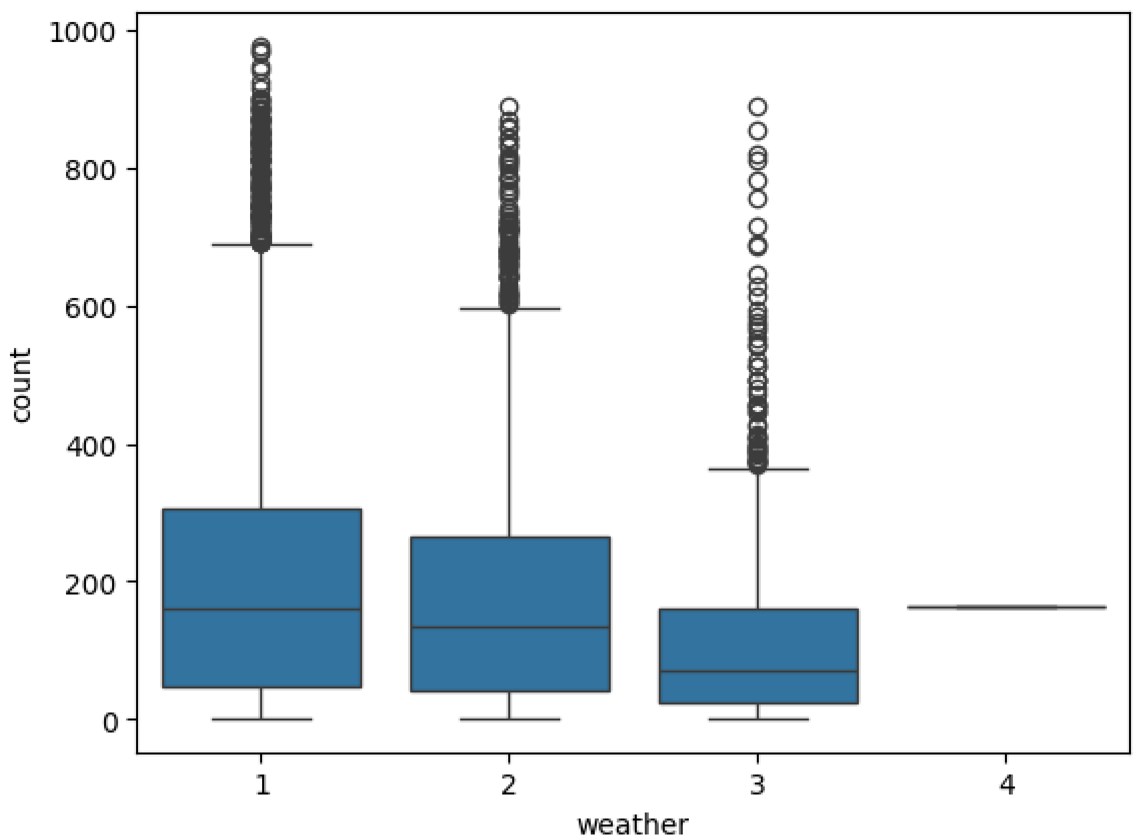


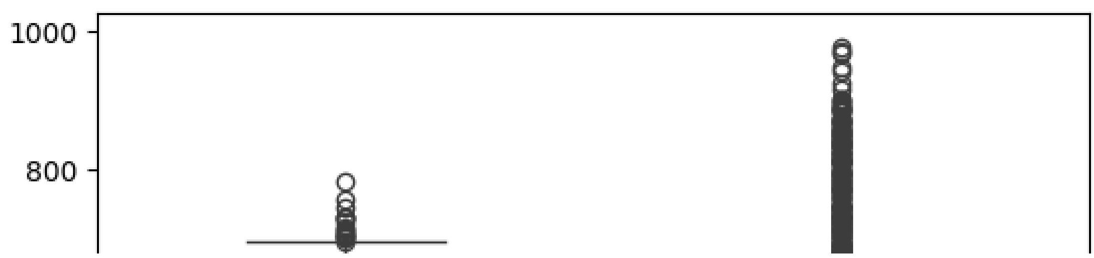



```
sns.boxplot(x='season',y='count',data=data)
plt.show()
```

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







Insights from Bivariate Analysis between Count & Season

The season 1 contains more outliers and the medians between the season 2,3 and 4 were siimilar.

The medians os weather 1 & 2 were almost equal.

The medians of Working Day and Non Working Day were equal.

Hypothesis Test between Working Day (independent) and Count (dependent)

```
Workingday=data[data['workingday']==1]['count'].sample(3000)
Non_Workingday=data[data['workingday']==0]['count'].sample(3000)
```

```
print(Workingday.std())
print(Non_Workingday.std())
```

```
184.95826682446796
172.86010269107027
```

```
from scipy.stats import shapiro
```

```
test_stat,pvalue1= shapiro(Workingday)
print(pvalue1)
```

```
1.2733833206297761e-44
```

```
if pvalue1>0.05:
    print('Data is normally distributed')
else:
    print('Data is not normally distributed')
```

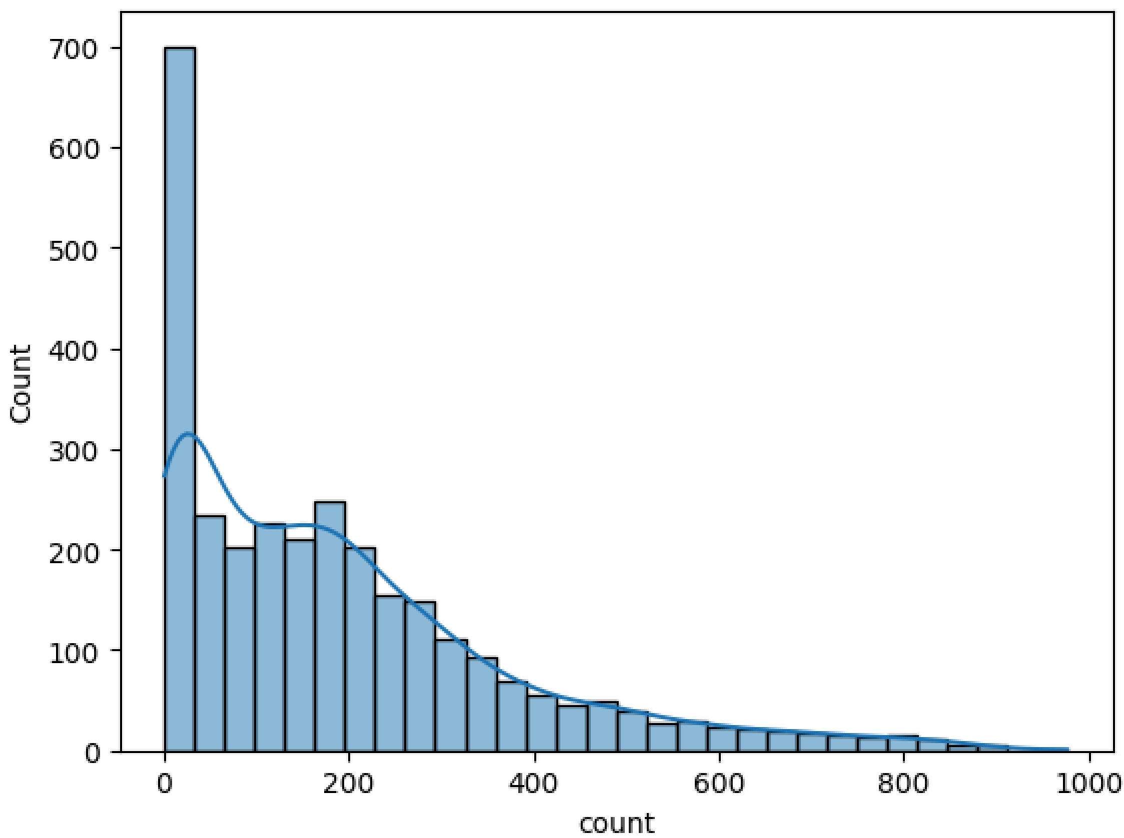
```
Data is not normally distributed
```

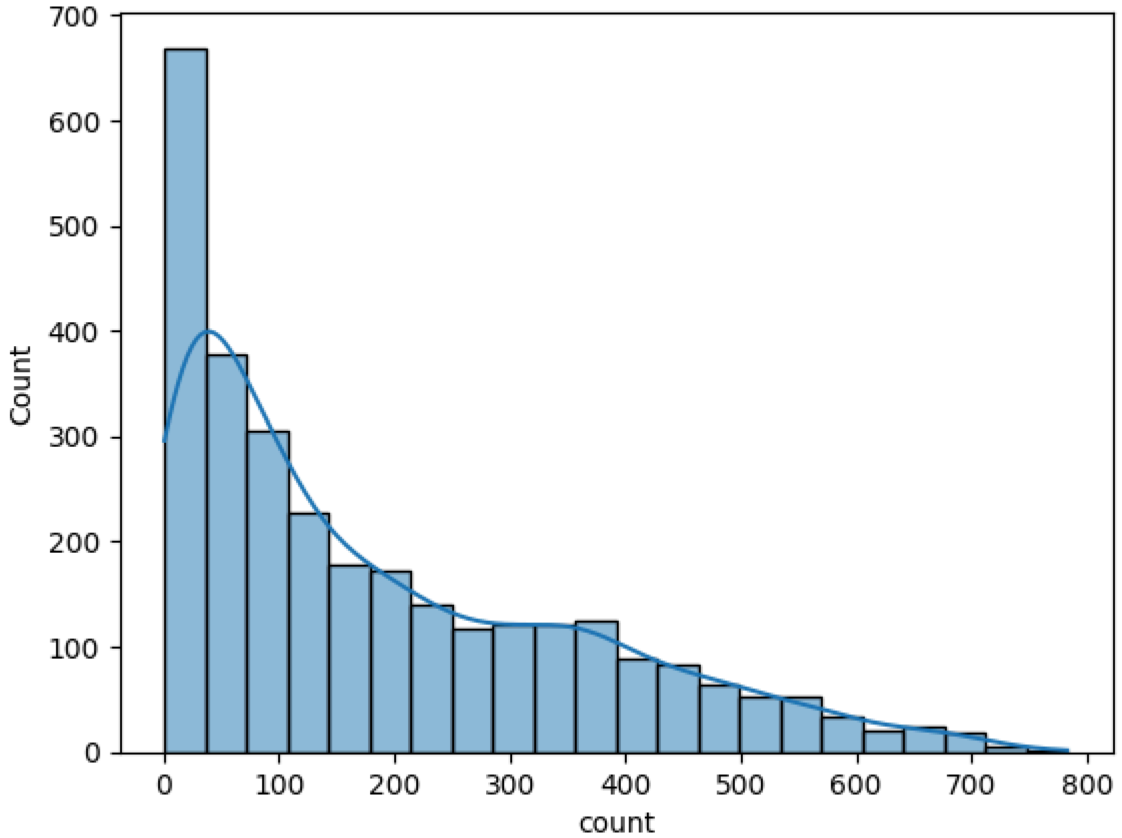
```
test_stat,pvalue2= shapiro(Non_Workingday)
print(pvalue2)
if pvalue1>0.05:
    print('Data is normally distributed')
else:
    print('Data is not normally distributed')
```

```
1.3192108255182832e-42
Data is not normally distributed
```

```
cols=[Workingday,Non_Workingday]
for i in cols:
```

```
sns.histplot(i,kde=True)
plt.show()
```





Step1: Defining Alternate and Null Hypothesis

Null Hypothesis (Ho) : The mean count on the Workingday is equal to the mean count of Non_Working day.

Alternate Hypothesis (Ha) : The mean count on the Workingday is not equal to the mean count of Non_Workingday.

Step-2: Choosing Appropriate test

Here we are using Two Sample T-Test

Step-3: Choosing Significance level

Here we are aiming for 95% confidence, hence alpha=0.05

Step-4: Perform the test and determine the pvalue

```
from scipy.stats import ttest_ind
tstat,pvalue=ttest_ind(Workingday,Non_Workingday,alternative='two-sided')
print(pvalue)
```

```
0.30614752691239205
```

Step-5: Compare the pvalue with alpha

```
if pvalue>0.05:
    print(f'pvalue {pvalue} is greater than alpha, we accept the null hypothesis')
else:
    print(f'pvalue {pvalue} is lesser than alpha, we reject the null hypothesis')
```

```
pvalue 0.30614752691239205 is greater than alpha, we accept the null hypothesis
```

Insights from the Testing

As a conclusion the mean count between the Working Day and Non Working Day were equal.

```
##########################################################################################
```

Hypothesis Test between Weather (independent) and Count (dependent)

```
data[data['weather']==4]
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspee
	2012-01-								

```
data.drop([5631],axis=0,inplace=True)
```

```
data['weather'].value_counts()
```

	count
weather	
1	7192
2	2834
3	859

dtype: int64

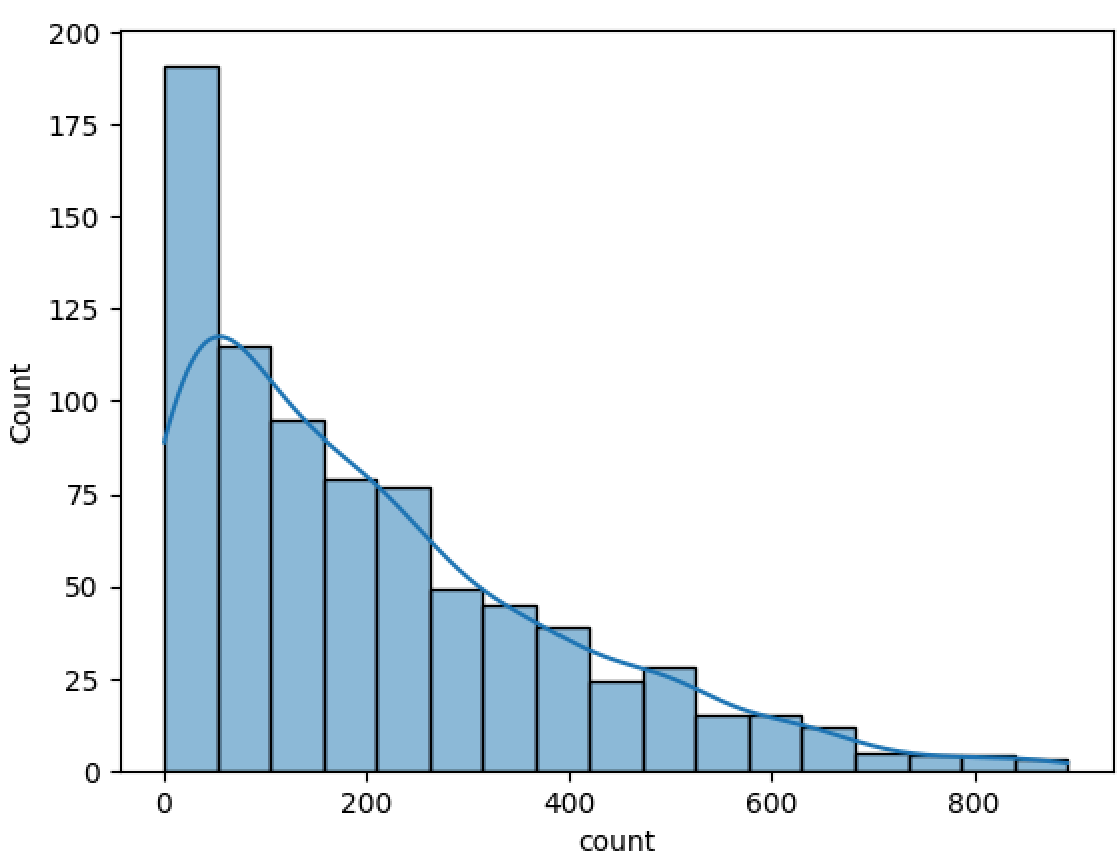
```
weather1=data[data['weather']==1]['count'].sample(800)
weather2=data[data['weather']==2]['count'].sample(800)
weather3=data[data['weather']==3]['count'].sample(800)
```

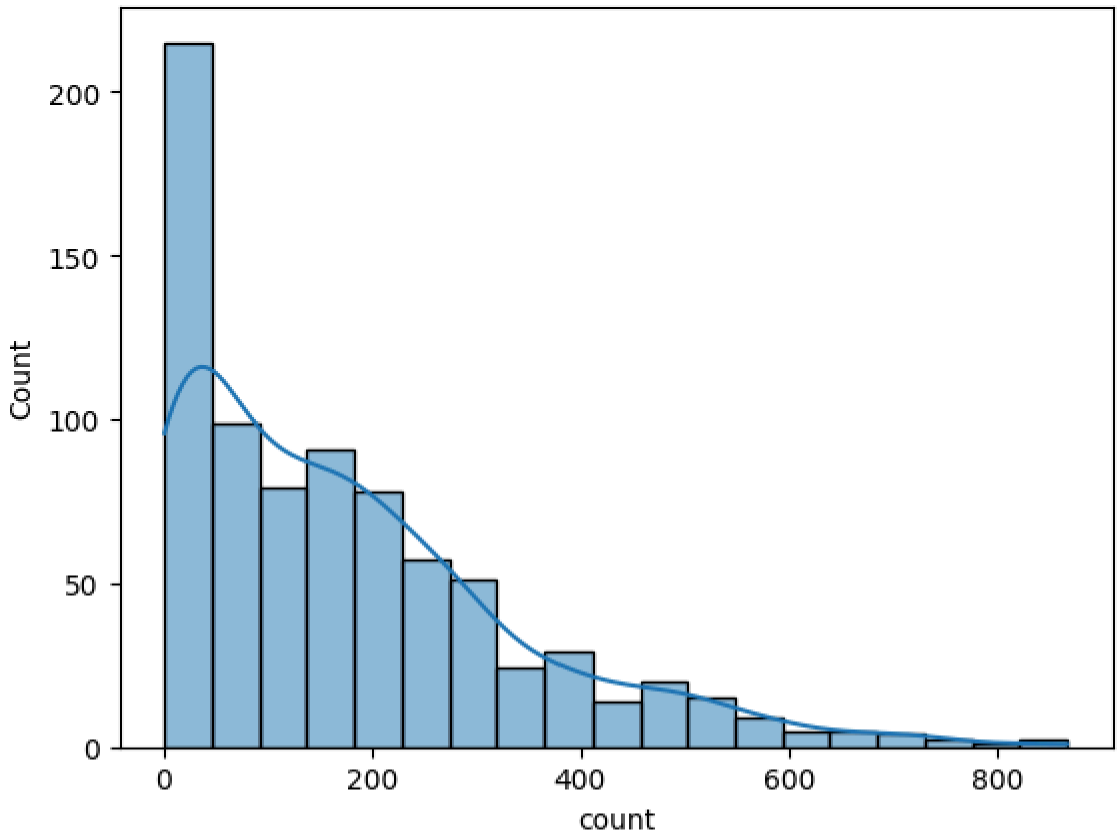
```
tstat,pvalue=shapiro(weather1)
print(pvalue)
tstat,pvalue=shapiro(weather1)
print(pvalue)
tstat,pvalue=shapiro(weather1)
print(pvalue)
```

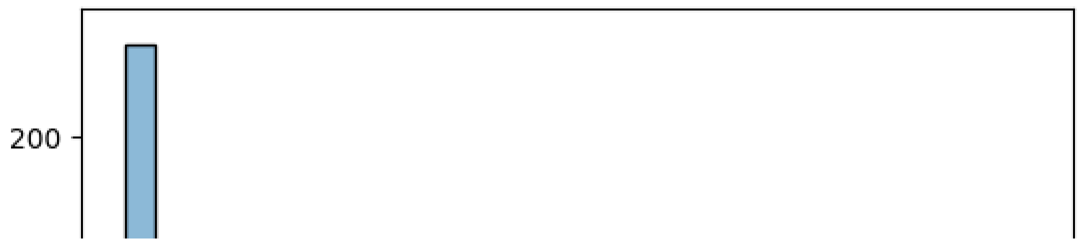
```
4.34050797204664e-23
4.34050797204664e-23
4.34050797204664e-23
```

As the pvalue is less than alpha(0.05), the distribution is not normal.

```
cols=[weather1,weather2,weather3]
for i in cols:
  sns.histplot(i,kde=True)
  plt.show()
```







Checking for variance

```
from scipy.stats import levene
stat,pvalue=levene(weather1,weather2,weather3)
print(pvalue)
```

```
1.417646661847725e-17
```

As the pvalue is less than alpha, it states that variance is significantly different among groups.

Step1: Defining Alternate and Null Hypothesis

Null Hypothesis (Ho) : The median counts of all the weather are equal.

Alternate Hypothesis (Ha) : Atleast one of the weather's median count is different

Step-2: Choosing Appropriate test

As it is failing for the assumptions we cannot use One-way Anova. So we are using Kruskal-Wallis test.

Step-3: Choosing Significance level

Here we are aiming for 95% confidence, hence alpha=0.05

Step-4: Perform the test and determine the pvalue

```
from scipy.stats import kruskal
stat,pvalue=kruskal(weather1,weather2,weather3)
print(pvalue)
```

```
2.8739227393795696e-27
```

Step-5: Compare the pvalue with alpha

```
if pvalue>0.05:
    print(f'pvalue {pvalue} is greater than alpha, we accept the null hypothesis')
else:
    print(f'pvalue {pvalue} is lesser than alpha, we reject the null hypothesis')
```

```
pvalue 2.8739227393795696e-27 is lesser than alpha, we reject the null hypothesis
```

Insights from the Testing

As a conclusion the median count between different Weather Categories were different.

```
####################################################################################333
```

Hypothesis Test between Seasons (independent) and Count (dependent)

```
data['season'].value_counts()
```

season	count
4	2734
2	2733
3	2733
1	2685

dtype: int64

```
Season1=data[data['season']==1]['count'].sample(2500)
Season2=data[data['season']==2]['count'].sample(2500)
Season3=data[data['season']==3]['count'].sample(2500)
Season4=data[data['season']==4]['count'].sample(2500)
```

```
tstat,pvalue=shapiro(Season1)
print(pvalue)
tstat,pvalue=shapiro(Season2)
print(pvalue)
tstat,pvalue=shapiro(Season3)
print(pvalue)
tstat,pvalue=shapiro(Season4)
print(pvalue)
```

```
2.5127894407619837e-47
2.2167613911197442e-37
2.451460577249318e-35
2.0045225695297553e-38
```

The data's are not normally distributed.

```
cols=[Season1,Season2,Season3,Season4]
for i in cols:
  sns.histplot(i,kde=True)
  plt.show()
```