Yulu Business Case - Hypothesis Testing

About Yulu :

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.

Problem Statement :

The company wants to know:

- 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

Column Profiling :

- datetime: datetime
- season: season (1: spring, 2: summer, 3: fall, 4: winter)
- holiday: whether day is a holiday or not (extracted from http://dchr.dc.gov/page/holiday-schedule)
- workingday: if day is neither weekend nor holiday is 1, otherwise is 0.
- 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
- temp: temperature in Celsius
- atemp: feeling temperature in Celsius
- humidity: humidity
- windspeed: wind speed
- casual: count of casual users
- registered: count of registered users
- count: count of total rental bikes including both casual and registered

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/original/bike_sharing.csv?1642089089')
```

```
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

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	temp	atemp	humidity	windspeed
count	10886	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000	10886.000000	10886.000000	10886.000000
mean	2011-12-27 05:56:22.399411968	2.506614	0.028569	0.680875	1.418427	20.23086	23.655084	61.886460	12.799395
min	2011-01-01 00:00:00	1.000000	0.000000	0.000000	1.000000	0.82000	0.760000	0.000000	0.000000
25%	2011-07-02 07:15:00	2.000000	0.000000	0.000000	1.000000	13.94000	16.665000	47.000000	7.001500
50%	2012-01-01 20:30:00	3.000000	0.000000	1.000000	1.000000	20.50000	24.240000	62.000000	12.998000
75%	2012-07-01 12:45:00	4.000000	0.000000	1.000000	2.000000	26.24000	31.060000	77.000000	16.997900
max	2012-12-19 23:00:00	4.000000	1.000000	1.000000	4.000000	41.00000	45.455000	100.000000	56.996900

```
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

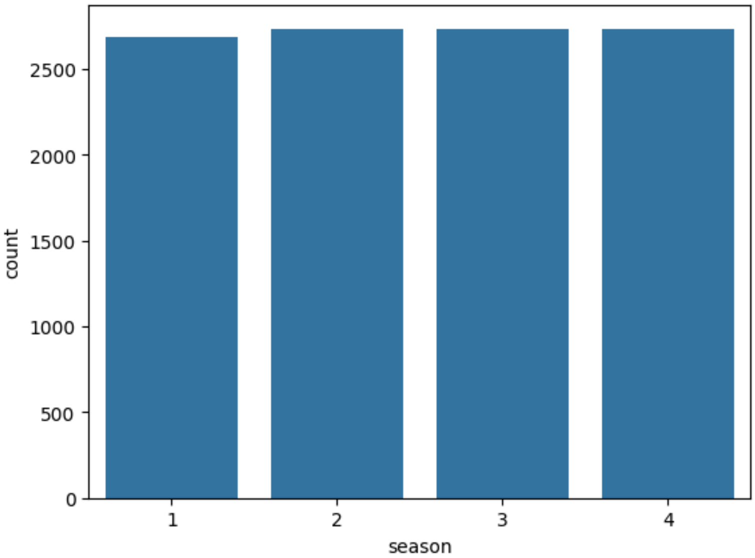
```
data['registered'].sum()
```

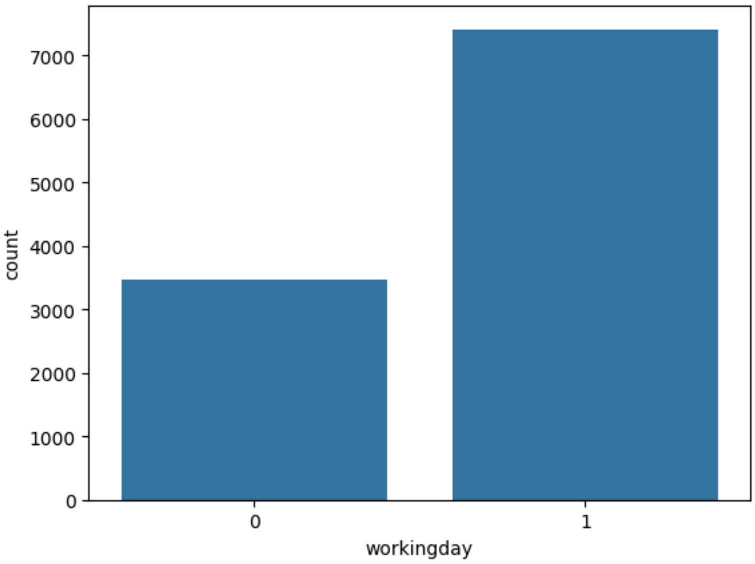
```
1693341
```

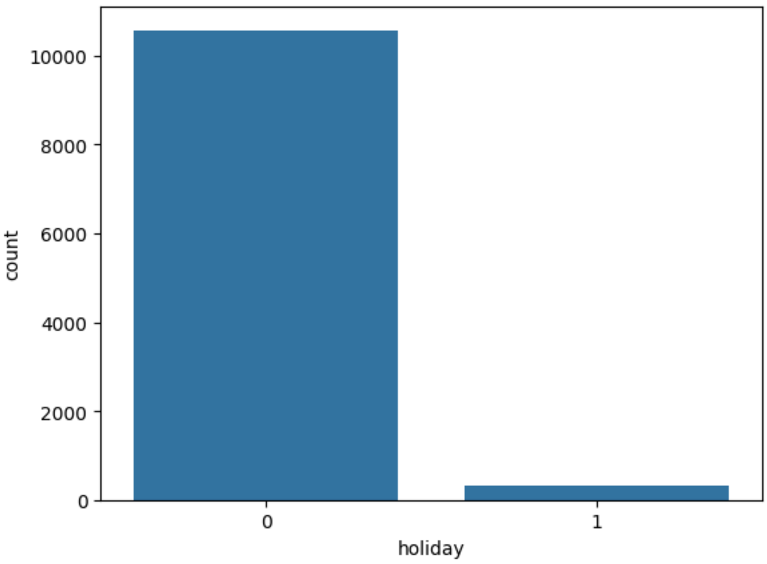
Univariate Analysis

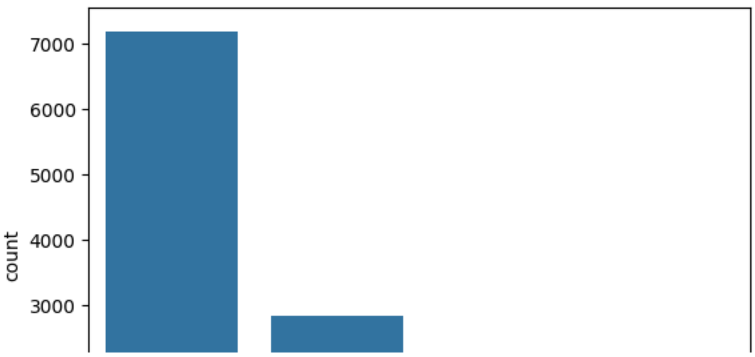
```
cat_cols=['season','workingday','holiday','weather']
```

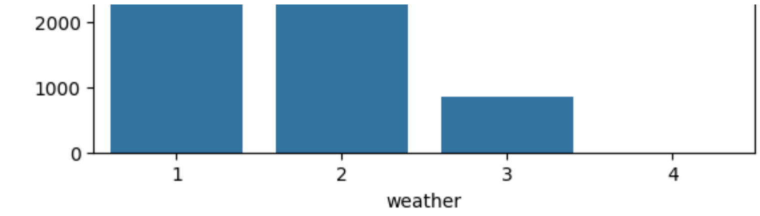
```
for i in cat_cols:
    sns.countplot(x=i,data=data)
    plt.show()
```


count
2500
2000
1500
1000
500
0
1
2
3
4
season


count
7000
6000
5000
4000
3000
2000
1000
0
0
1
workingday


count
10000
8000
6000
4000
2000
0
0
1
holiday


count
7000
6000
5000
4000
3000

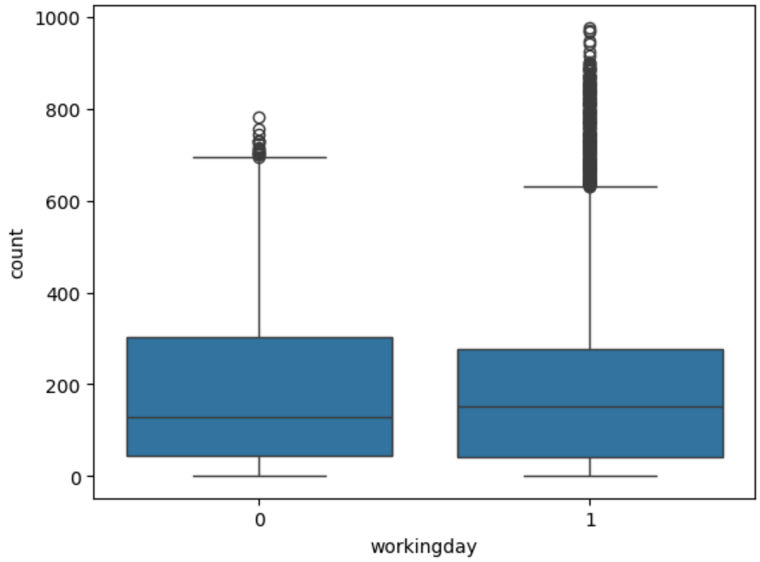


Insights from Univariate Analysis

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

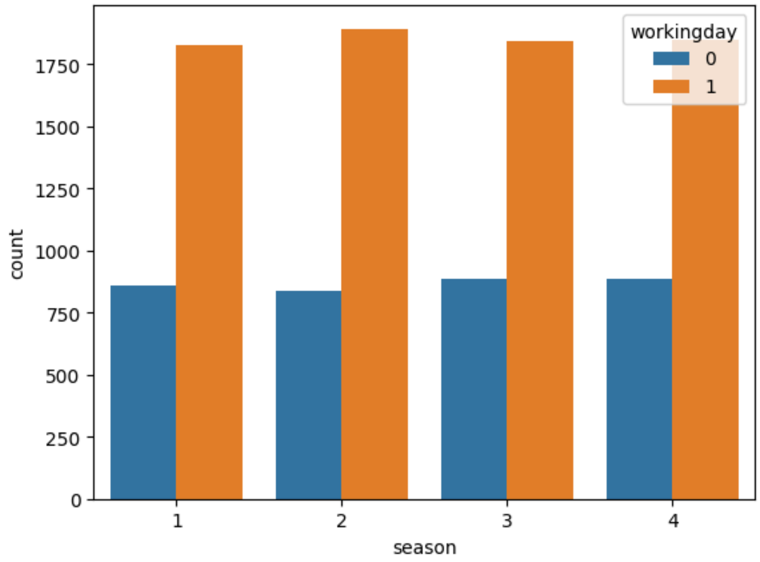
Removing outliers from the sample removes extreme conditions of the population. Removing outliers from the sensitive data may cause a problem. Hence while do hypothesis it is better to have outliers

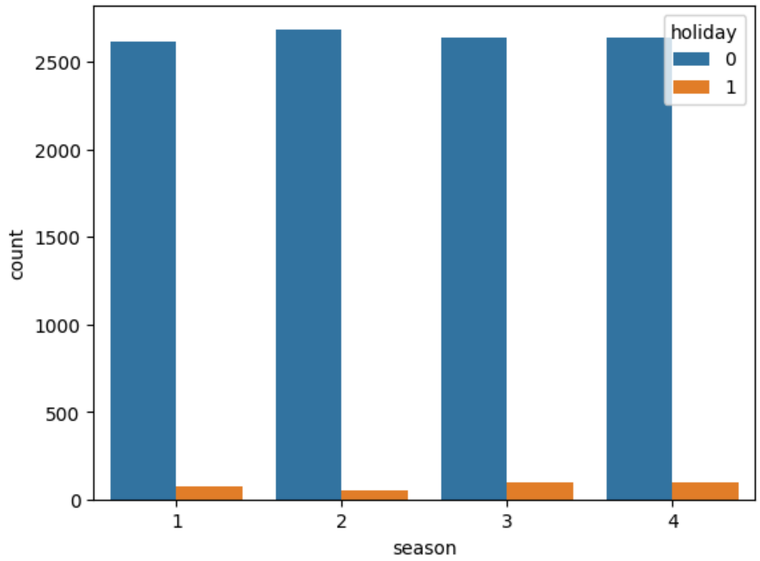
Bivariate Analysis

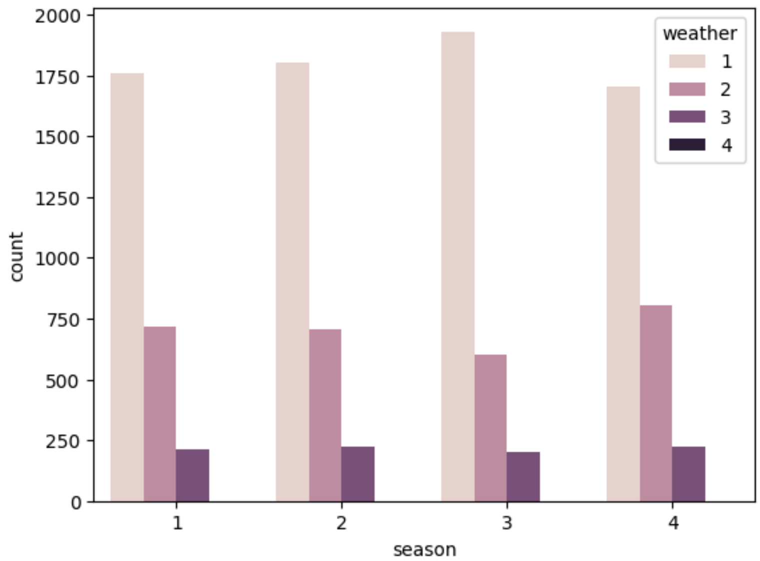
```
data.head()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	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

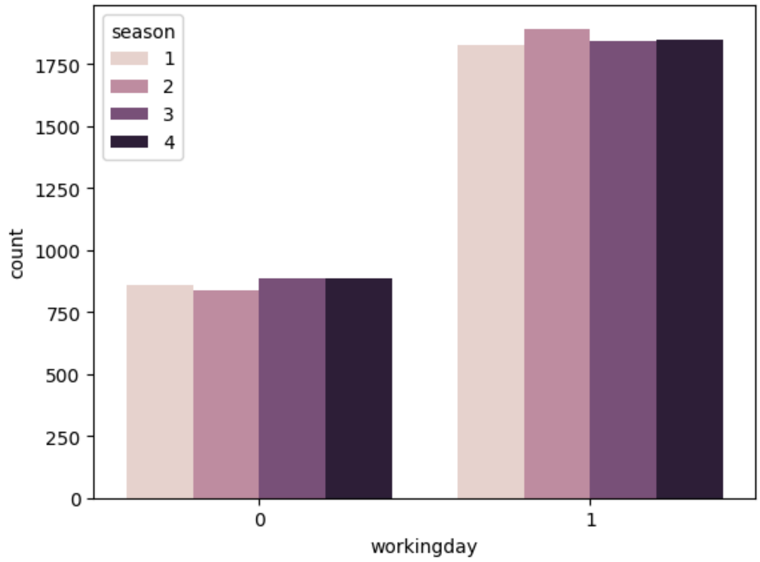
```
cols=['workingday','holiday','weather']
for i in cols:
  sns.countplot(x='season',hue=i,data=data)
  plt.show()
```

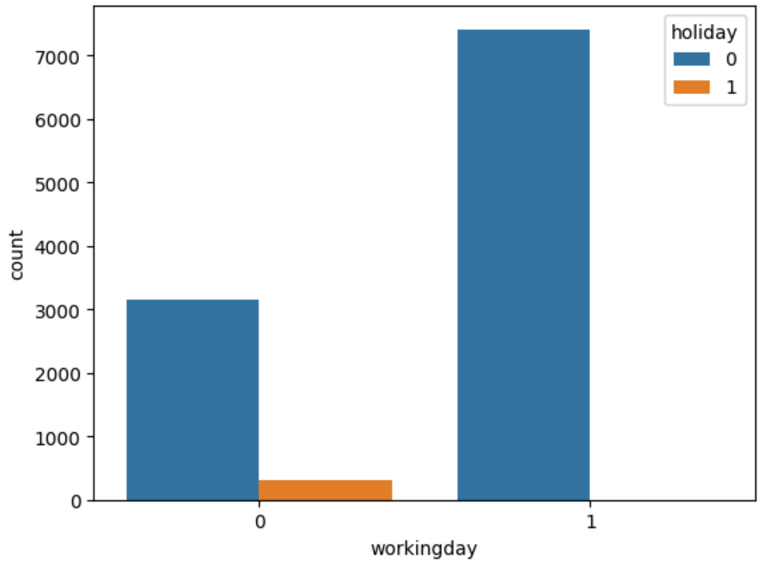


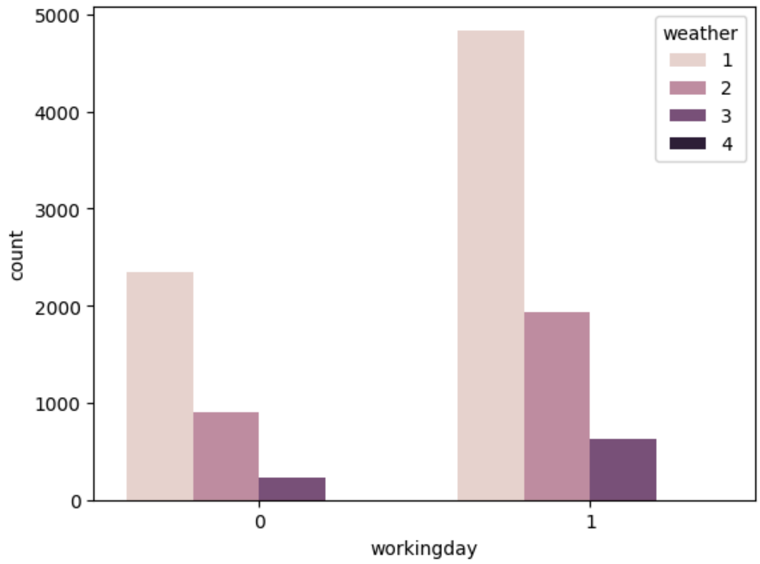




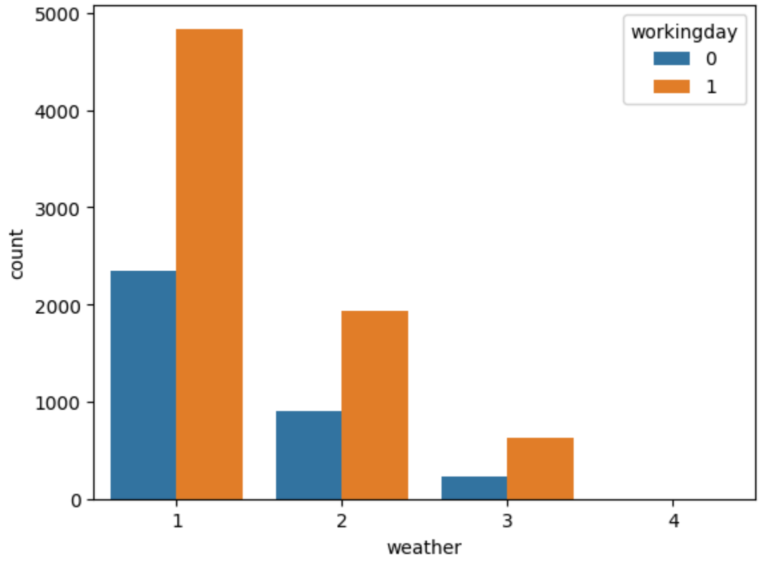

```
cols=['season','holiday','weather']
for i in cols:
  sns.countplot(x='workingday',hue=i,data=data)
  plt.show()
```

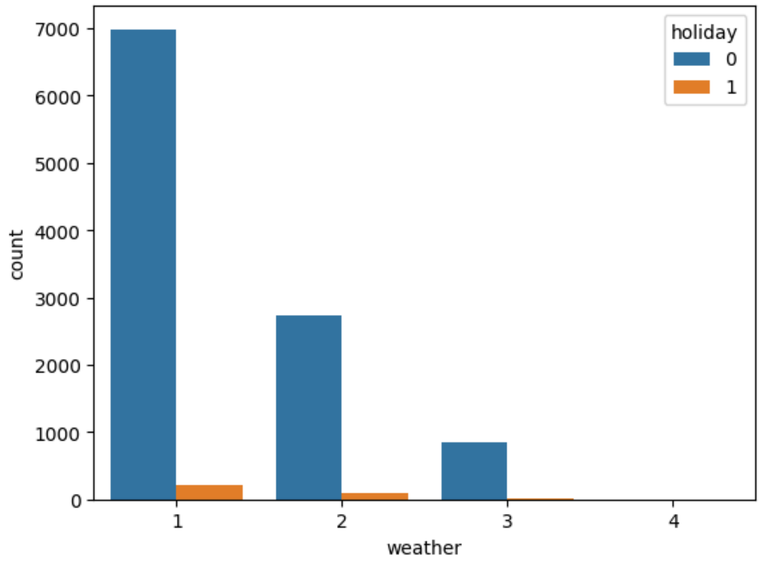


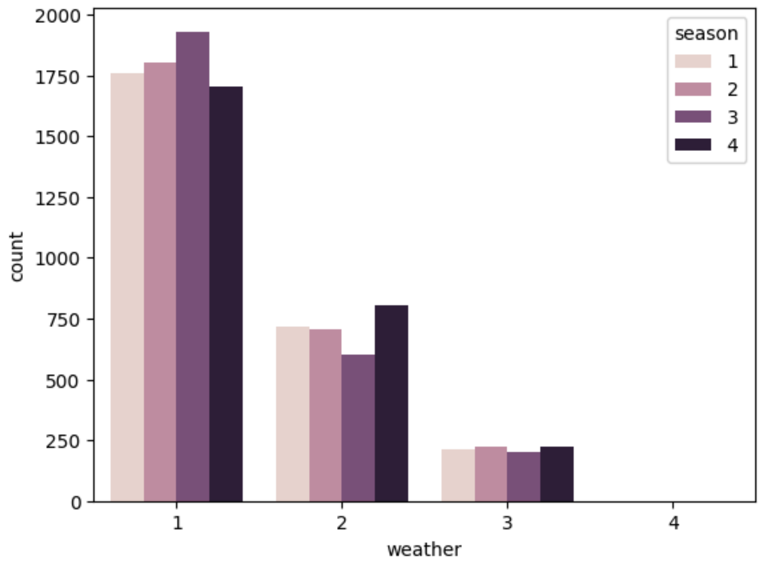




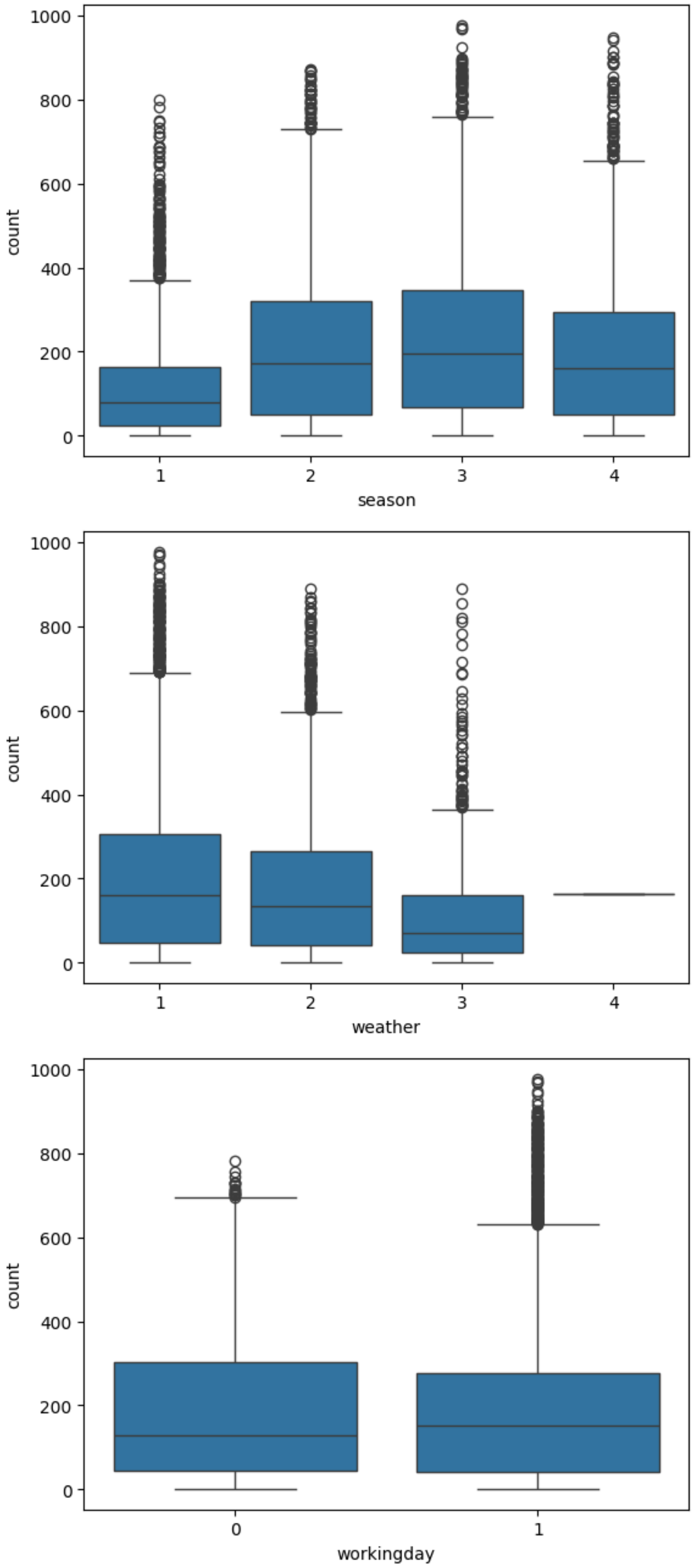

```
cols=['workingday','holiday','season']
for i in cols:
  sns.countplot(x='weather',hue=i,data=data)
  plt.show()
```








```
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
```

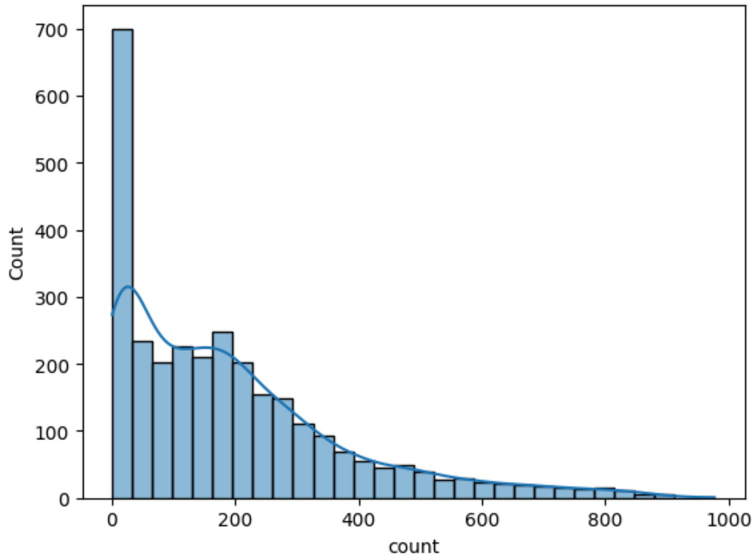
```
if pvalue1>0.05:
    print('Data is normally distributed')
else:
    print('Data is not normally distributed')
```

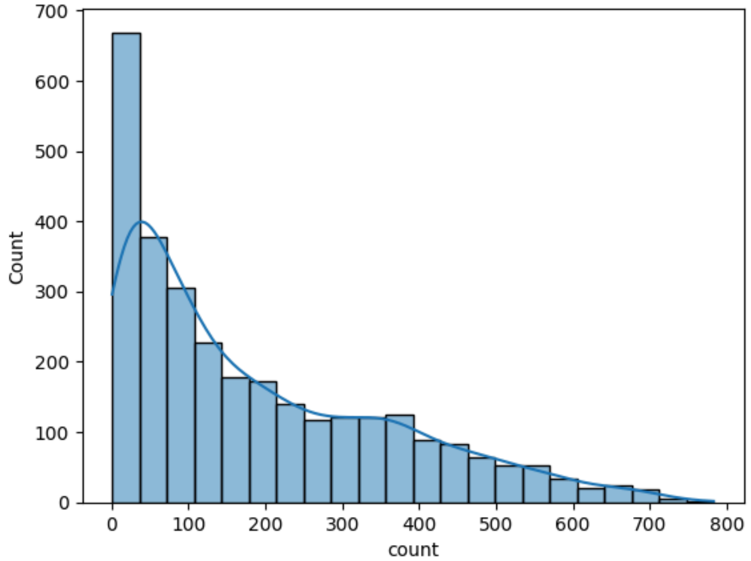
```
Data is not normally distributed
```

```
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.

```
##########################################################################################3
```

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

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

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

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

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

weather	count
1	7192
2	2834
3	859

dtype: int64

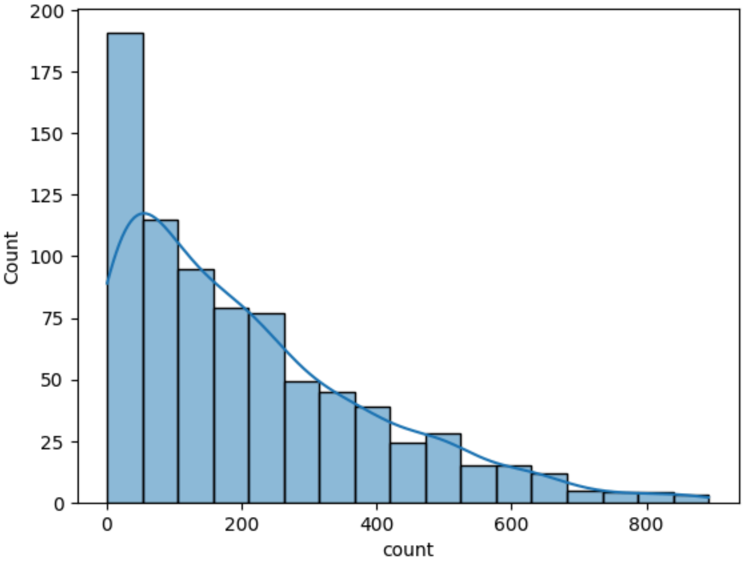
```
weather1=data[data['weather']==1]['count'].sample(800)
weather2=data[data['weather']==2]['count'].sample(800)
weather3=data[data['weather']==3]['count'].sample(800)
```

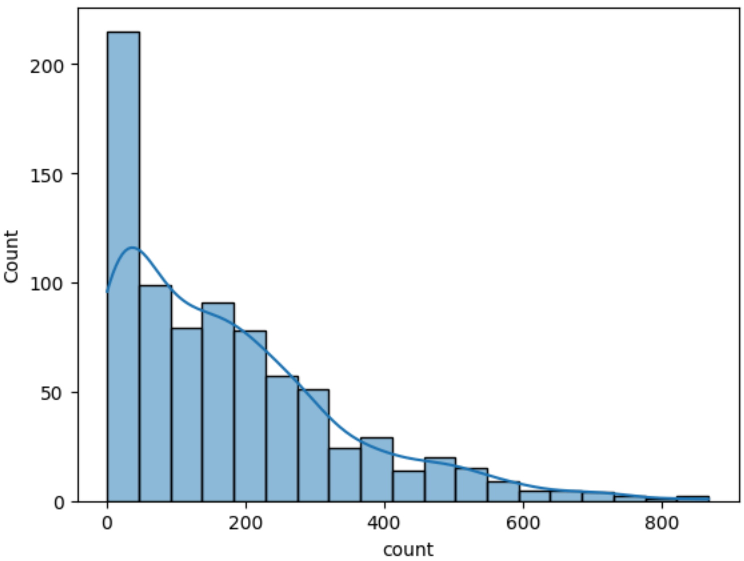
```
tstat,pvalue=shapiro(weather1)
print(pvalue)
tstat,pvalue=shapiro(weather1)
print(pvalue)
tstat,pvalue=shapiro(weather1)
print(pvalue)
```

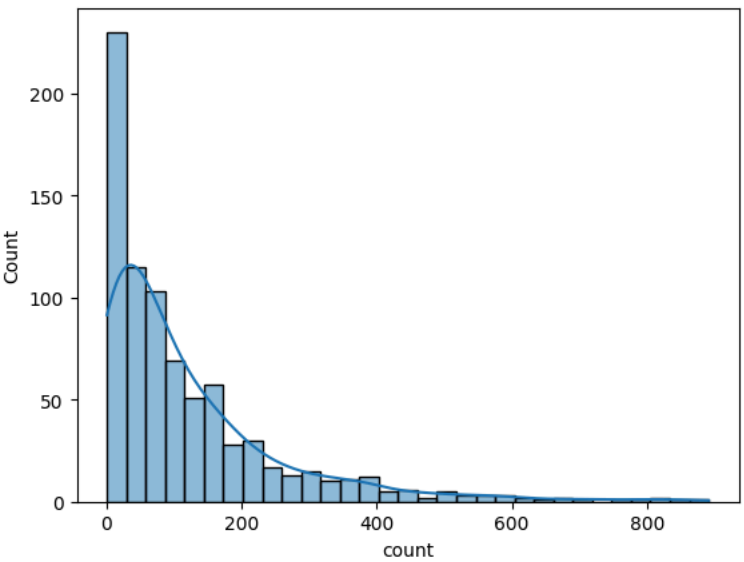
```
4.34050797204664e-23
4.34050797204664e-23
4.34050797204664e-23
```

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
```