Problem Statement:

Yulu's revenue has recently experienced signi cant declines. In order to comprehend the variables that affect the demand for these shared electric cycles, they have hired a consultancy rm. They are particularly interested in comprehending what in uences demand for these shared electric cycles in the Indian market.

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

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
df = pd.read_csv("/content/drive/MyDrive/CSV datasets/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.shape
```

```
(10886, 12)
```

```
# Check for null values in the DataFrame
null_counts = df.isnull().sum() # or df.isna()
print(null_counts)
```

```
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 types of all the attributes
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
```

```
columns = ['season','holiday','workingday','weather','temp','atemp','humidity','windspeed','casual','registered']
df[columns] = df[columns].astype(object)
#conversion of categorical attributes to 'category' (If required)
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  object
 6   atemp       10886 non-null  object
 7   humidity    10886 non-null  object
 8   windspeed   10886 non-null  object
 9   casual      10886 non-null  object
 10  registered  10886 non-null  object
 11  count       10886 non-null  int64
dtypes: int64(1), object(11)
memory usage: 1020.7+ KB
```

```
#Checking the characteristics of the data:
df.describe(include = 'all')
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
count	10886	10886.0	10886.0	10886.0	10886.0	10886.00	10886.00	10886.0	10886.0	10886.0	10886.0	10886.000000
unique	10886	4.0	2.0	2.0	4.0	49.00	60.00	89.0	28.0	309.0	731.0	NaN
top	2011-01-01 00:00:00	4.0	0.0	1.0	1.0	14.76	31.06	88.0	0.0	0.0	3.0	NaN
freq	1	2734.0	10575.0	7412.0	7192.0	467.00	671.00	368.0	1313.0	986.0	195.0	NaN
mean	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	191.574132
std	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	181.144454
min	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.000000
25%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	42.000000
50%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	145.000000
75%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	284.000000

Observations:

1.Among 4seasons ,season-4 winter has the more count of rental bikes.

2.on weekends/holidays ,more count of rental bikes.

3.Among 4 weather conditions,weather cond-1(Clear, Few clouds, partly cloudy, partly cloudy)has highest count of rental bikes.

4.Highest temp -49C among that highest count of rental bikes took around 14.76C.

5.Highest atemp -60C among that highest count of rental bikes took around 31C.

6.count of registered users are 731 among them 3 users are using bikes.

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

season	count	mean	std	min	25%	50%	75%	max
1	2686.0	116.343261	125.273974	1.0	24.0	78.0	164.0	801.0
2	2733.0	215.251372	192.007843	1.0	49.0	172.0	321.0	873.0
3	2733.0	234.417124	197.151001	1.0	68.0	195.0	347.0	977.0
4	2734.0	198.988296	177.622409	1.0	51.0	161.0	294.0	948.0

season-4 having more count of rental bikes

```
df.groupby('holiday')['count'].describe()
```

holiday	count	mean	std	min	25%	50%	75%	max
0	10575.0	191.741655	181.513131	1.0	43.0	145.0	283.0	977.0
1	311.0	185.877814	168.300531	1.0	38.5	133.0	308.0	712.0

```
df.groupby('weather')['count'].describe()
```

weather	count	mean	std	min	25%	50%	75%	max
1	7192.0	205.236791	187.959566	1.0	48.0	161.0	305.0	977.0
2	2834.0	178.955540	168.366413	1.0	41.0	134.0	264.0	890.0
3	859.0	118.846333	138.581297	1.0	23.0	71.0	161.0	891.0
4	1.0	164.000000	NaN	164.0	164.0	164.0	164.0	164.0

weather cond-1 having more count of rental bikes with mean 205.24

```
df.groupby('workingday')['count'].describe()
```

workingday	count	mean	std	min	25%	50%	75%	max
0	3474.0	188.506621	173.724015	1.0	44.0	128.0	304.0	783.0
1	7412.0	193.011873	184.513659	1.0	41.0	151.0	277.0	977.0

on weekends/holidays peak in count of rental bikes

```
df.groupby('temp')['count'].count().nlargest(5)
```

temp	count
14.76	467
26.24	453
28.70	427
13.94	413
18.86	406

dtype: int64

when temp-14.76 count of bikes is high

```
pd.crosstab(index = df['season'],columns = df['workingday'])
```

season \ workingday	0	1
1	858	1828
2	840	1893
3	888	1845
4	888	1846

In summer on weekend/holidays -more count of rental bikes i.e.1893 bikes

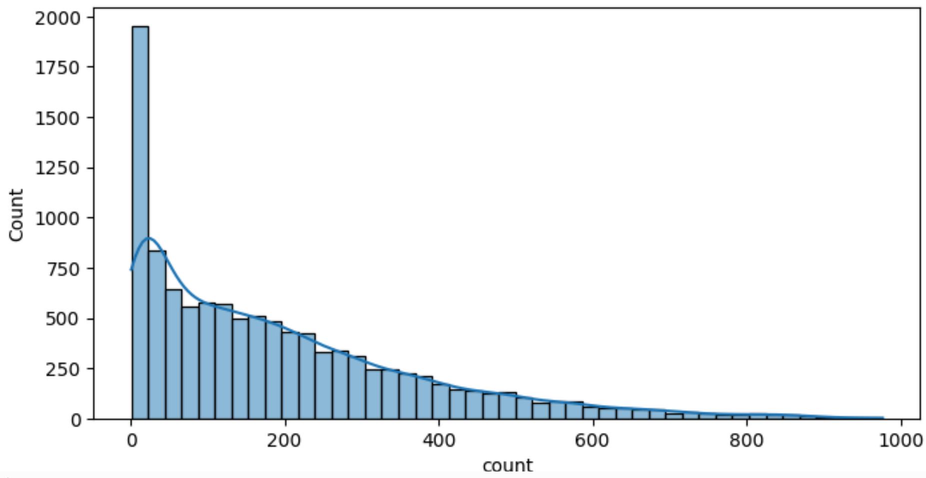
```
pd.crosstab(index = df['season'],columns = df['weather'])
```

weather	1	2	3	4
season				
1	1759	715	211	1
2	1801	708	224	0
3	1930	604	199	0
4	1702	807	225	0

In fall season under weather cond- Clear/Few clouds-more count of rental bikes i.e.1930 bikes

Univariate analysis

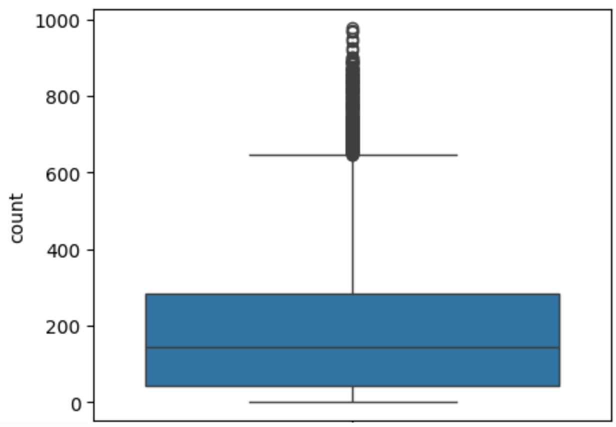
```
plt.figure(figsize=(8,4))
sns.histplot(data=df, x="count", kde=True)
plt.show()
```



1.we can observe that less than 400 bikes are using by around 250 customers.

2.From the initial observation we have already seen the mean and median is 191 and 145 respectively. Also, we can see there are outliers in the data.

```
plt.figure(figsize=(5, 4))
sns.boxplot(data=df, y='count')
plt.show()
```



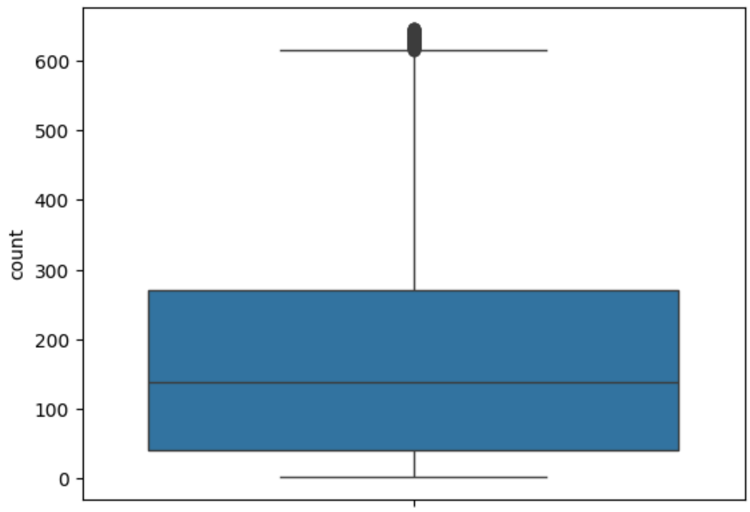

```
# Outlier detection by IQR method
q1= df['count'].quantile(0.25)
q3= df['count'].quantile(0.75)
iqr = q3-q1 # iqr- inter quatile range
print('q1','q3','iqr:',q1,q3,iqr)
lower_limit = q1 - (1.5*iqr)
upper_limit = q3 + (1.5*iqr)
print('lower_limit' ',' 'upper_limit:', lower_limit, upper_limit)
#trimming - delete outlier data
new_df = df.loc[(df['count'] < upper_limit) & (df['count'] > lower_limit)]
```

```
print('before removing outliers:', len(df))
print('after removing outliers:', len(new_df))
print('num of outliers:',len(df)-len(new_df))
#capping - upper,lower limit
new_df.loc[(new_df['count'] > upper_limit), 'count'] = upper_limit
new_df.loc[(new_df['count'] < lower_limit), 'count'] = lower_limit
print(new_df)
sns.boxplot(new_df['count'])
```

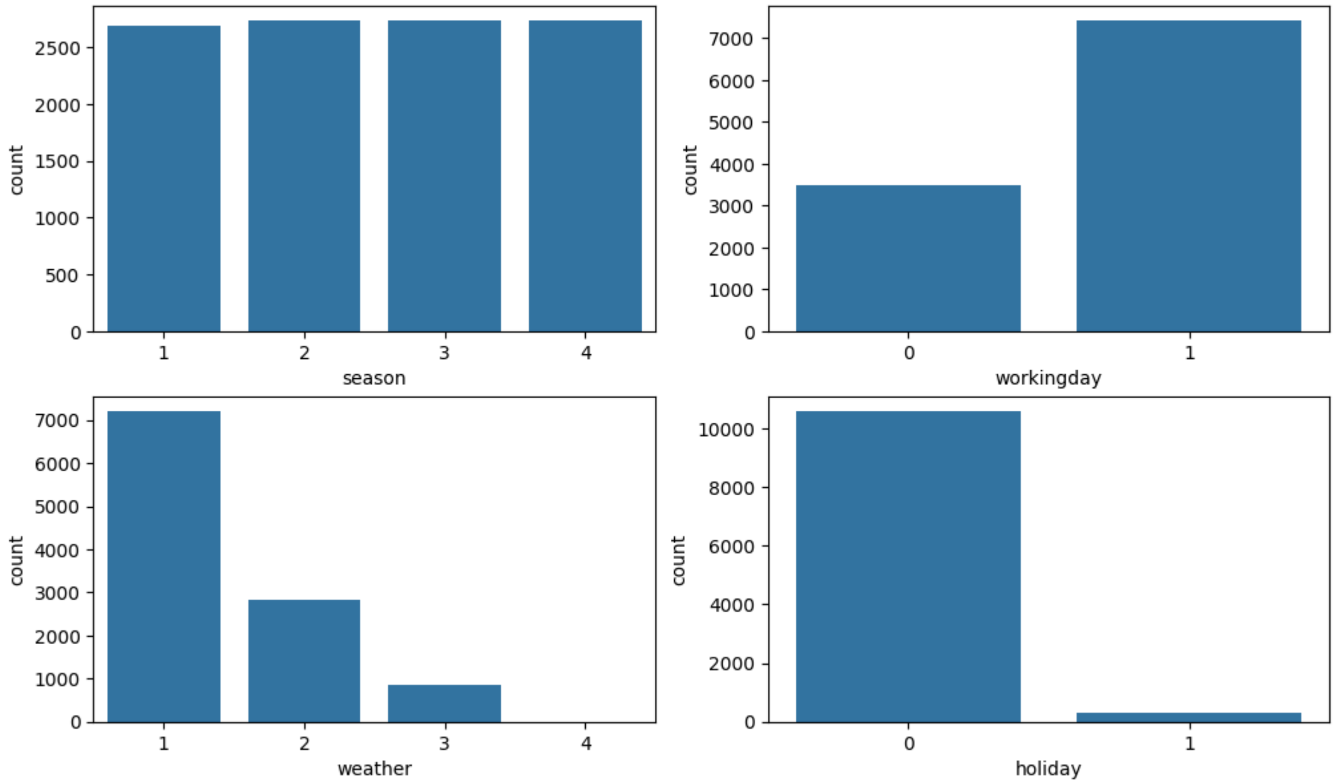
```
q1 q3 iqr: 42.0 284.0 242.0
lower_limit,upper_limit: -321.0 647.0
before removing outliers: 10886
after removing outliers: 10583
num of outliers: 303
                  datetime season holiday workingday weather   temp   atemp  \
0      2011-01-01 00:00:00      1       0          0       1   9.84  14.395
1      2011-01-01 01:00:00      1       0          0       1   9.02  13.635
2      2011-01-01 02:00:00      1       0          0       1   9.02  13.635
3      2011-01-01 03:00:00      1       0          0       1   9.84  14.395
4      2011-01-01 04:00:00      1       0          0       1   9.84  14.395
...                    ...    ...     ...        ...     ...    ...     ...
10881  2012-12-19 19:00:00      4       0          1       1  15.58  19.695
10882  2012-12-19 20:00:00      4       0          1       1  14.76  17.425
10883  2012-12-19 21:00:00      4       0          1       1  13.94   15.91
10884  2012-12-19 22:00:00      4       0          1       1  13.94  17.425
10885  2012-12-19 23:00:00      4       0          1       1  13.12  16.665

      humidity windspeed casual registered  count
0           81       0.0      3         13     16
1           80       0.0      8         32     40
2           80       0.0      5         27     32
3           75       0.0      3         10     13
4           75       0.0      0          1      1
...        ...       ...    ...        ...    ...
10881       50   26.0027      7        329    336
10882       57   15.0013     10        231    241
10883       61   15.0013      4        164    168
10884       61    6.0032     12        117    129
10885       66    8.9981      4         84     88

[10583 rows x 12 columns]
<Axes: ylabel='count'>
```




```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(12, 7))
sns.countplot(data=df, x='season', ax=axs[0,0])
sns.countplot(data=df, x='workingday', ax=axs[0,1])
sns.countplot(data=df, x='weather', ax=axs[1,0])
sns.countplot(data=df, x='holiday', ax=axs[1,1])
plt.show()
```



observations from above graphs by univariate analysis:

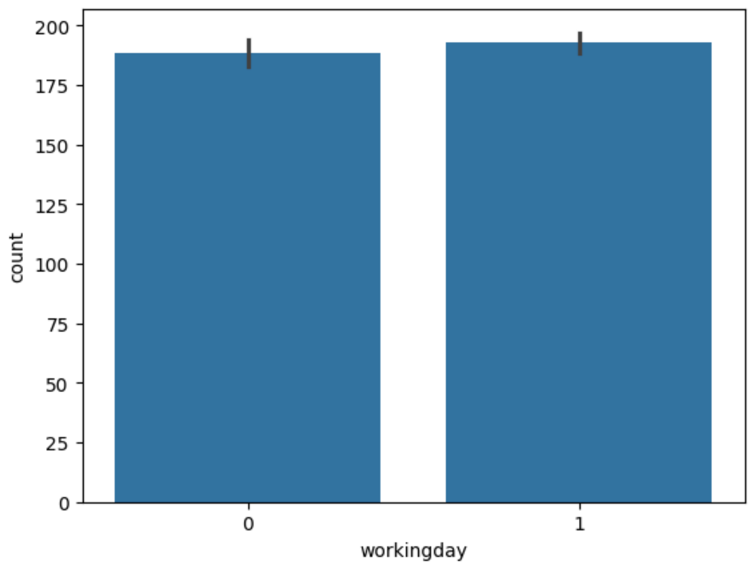
1.Almost all seasons had uniform good count of bikes.

2.weekned/holiday had more count.

3.weather-1 Clear, Few clouds, partly cloudy, partly cloudy had more count followed by 2 ,3

Bivariate analysis

```
# Relationship between workday and count
sns.barplot(data=df, x='workingday', y='count')
plt.show()
```

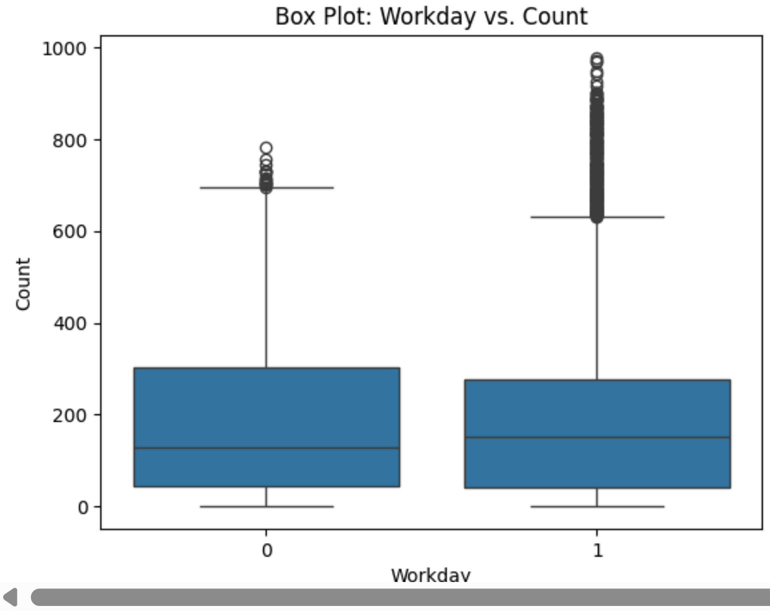


Bar plot gives- mean value count

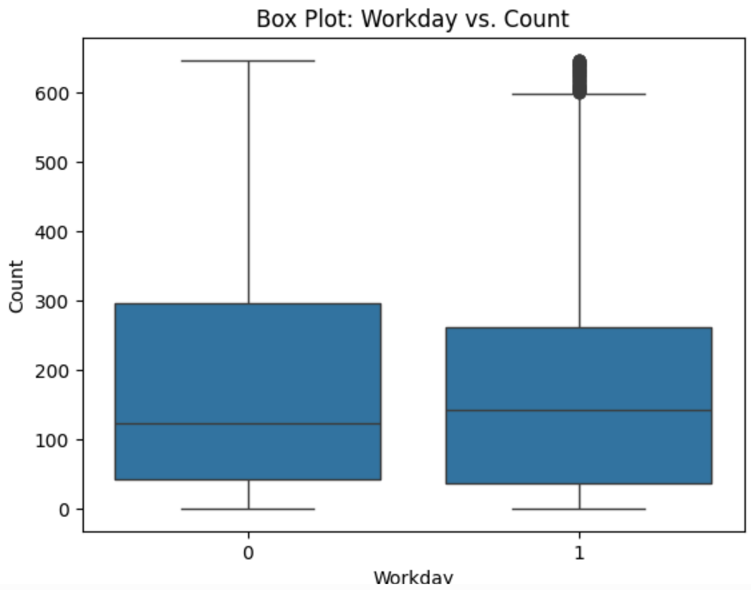
On workingdays the mean value count is less than weekend/holidays coun

```
#Box plot with outliers -bivariate analysis
sns.boxplot(data=df, x='workingday', y='count')
plt.title('Box Plot: Workday vs. Count')
plt.xlabel('Workday')
plt.ylabel('Count')
```

```
plt.show()
```




```
#Box plot after removing outliers -bivariate analysis
#box plot can use to visualize relationship between categorical vs numeric variables.
sns.boxplot(data=new_df, x='workingday', y='count')
plt.title('Box Plot: Workday vs. Count')
plt.xlabel('Workday')
plt.ylabel('Count')
plt.show()
```

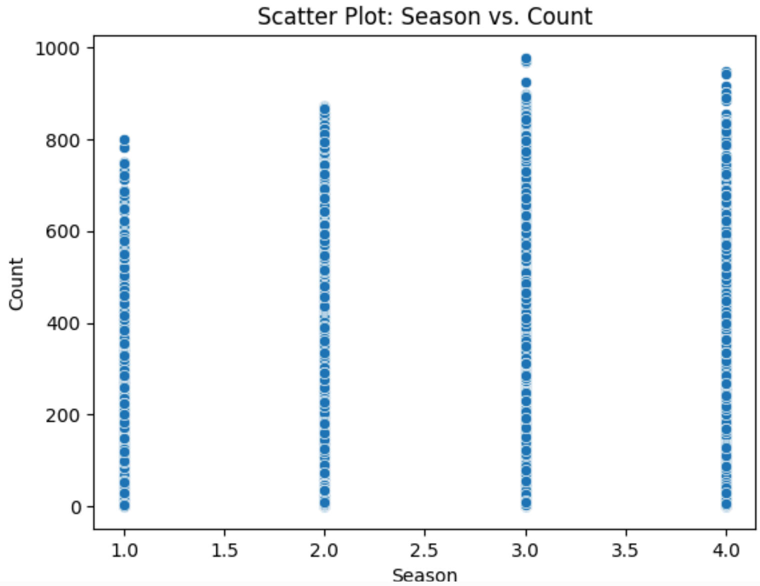


From box plot

Among workingday and weekend/holiday we can observe the count of bikes is between 45 t0 300

Relationship between season and count

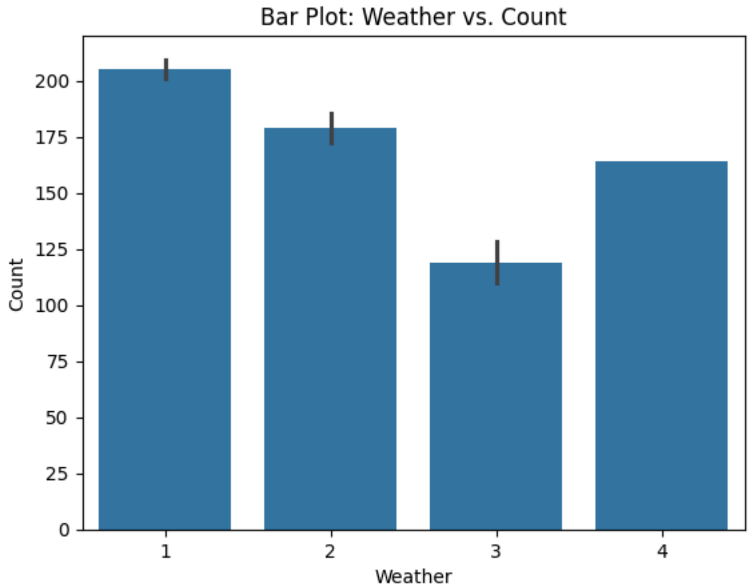
```
#we can use a scatter plot to visualize the relationship between two numeric variables.
sns.scatterplot(data=df, x='season', y='count')
plt.title('Scatter Plot: Season vs. Count')
plt.xlabel('Season')
plt.ylabel('Count')
plt.show()
```



Among 4 seasons ,season-3 had more count of rental bikes with count near to 950,followed by season-4,2,1

Relationship between weather and count

```
sns.barplot(data=df, x='weather', y='count')
plt.title('Bar Plot: Weather vs. Count')
plt.xlabel('Weather')
plt.ylabel('Count')
plt.show()
```



Among 4 weather conditions,weather condition-1 had more average count (>200)followed by weather conditions-2,4,3

Hypothesis Testing

```
df.groupby('workingday')['count'].describe()
```

	count	mean	std	min	25%	50%	75%	max
workingday								
0	3474.0	188.506621	173.724015	1.0	44.0	128.0	304.0	783.0
1	7412.0	193.011873	184.513659	1.0	41.0	151.0	277.0	977.0

2 sample ttest:

```
#Null Hypothesis (H0): There is no significant difference in the number of bikes rented between working days and non-working days.
#Alternative Hypothesis (H1): There is a significant difference in the number of bikes rented between working days and non-working days.
a = df[df['workingday'] == 0]['count']
b = df[df['workingday'] == 1]['count']
from scipy.stats import ttest_ind
t_stat, p_value = ttest_ind(a,b)
print(p_value)
if p_value < 0.05:
    print("Reject H0")
else:
    print("Fail to reject H0")
```

```
0.22644804226361348
Fail to reject H0
```

observations:

1.As (p-value=0.22) > 0.05 we should accept HO statistically at at 5% signi cance.

2.By two sample ttest we can say statistically that there is a no difference in mean count of rental bikes on weekends/holidays to working days at 5% significance.

ANNOVA test -- To check if No. of cycles rented is similar or different in different

1.season 2.weather

season vs count

```
s1 = df[df['season'] == 1]['count']
s2 = df[df['season'] == 2]['count']
s3 = df[df['season'] == 3]['count']
s4 = df[df['season'] == 4]['count']
```

```
#checking anova test assumptions:by levene method
from scipy.stats import levene
import numpy as np
#levene test
levene_p_value = levene(s1,s2,s3,s4, center='median')[1]
print("levene test p-value", round(levene_p_value,2))
print("Variance of s1:",round(np.var(s1),2))
print("Variance of s2:",round(np.var(s2),2))
print("Variance of s3:",round(np.var(s3),2))
print("Variance of s4:",round(np.var(s4),2))
```

```
levene test p-value 0.0
Variance of s1: 15687.73
Variance of s2: 36853.52
Variance of s3: 38854.3
Variance of s4: 31538.18
```

observations:

1.Statistically we can conclude that variances are not equal by performing levene test for 4 seasons.

2.variances of season -2,3,4 are similar but season-1 had quite large difference

```
from scipy.stats import f_oneway
#H0 : season wrt count are equal
#Ha : Not  equal
test_statistic, p_value = f_oneway(s1,s2,s3,s4)
print(p_value)
if p_value < 0.05:
 print("Reject H0")
else:
 print("Fail to reject H0")
```

```
6.164843386499654e-149
Reject H0
```

observations:

1.As p-value < 0.05 we should reject HO statistically at at 5% signi cance.

2.From one anova test we can conclude , seasons has a impact on yulu bikes count at 5% sig

3.Accept Ha:signi cant difference in count in different seasons weather vs count

```
w1 = df[df['weather'] == 1]['count']
w2 = df[df['weather'] == 2]['count']
w3 = df[df['weather'] == 3]['count']
w4 = df[df['weather'] == 4]['count']
from scipy.stats import f_oneway
#H0 : weather wrt count are equal
#Ha : Not  equal
test_statistic, p_value = f_oneway(w1,w2,w3,w4)
print(p_value)
if p_value < 0.05:
 print("Reject H0")
else:
 print("Fail to reject H0")
```

```
5.482069475935669e-42
Reject H0
```

observations:

1.As p-value < 0.05 we should reject HO statistically at at 5% signi cance.

2.From one anova test we can conclude , weather has a impact on yulu bikes count at 5% signi cance.

3.Accept Ha:signi cant difference in count in different weathers

```
from scipy.stats import levene
#levene test
levene_p_value = levene(w1,w2,w3,w4, center='median')[1]
print("levene test p-value", round(levene_p_value,2))
print("Variance of w1:",round(np.var(w1),2))
print("Variance of w2:",round(np.var(w2),2))
print("Variance of w3:",round(np.var(w3),2))
print("Variance of w4:",round(np.var(w4),2))
```

```
levene test p-value 0.0
Variance of w1: 35323.89
Variance of w2: 28337.25
Variance of w3: 19182.42
Variance of w4: 0.0
```

observations:

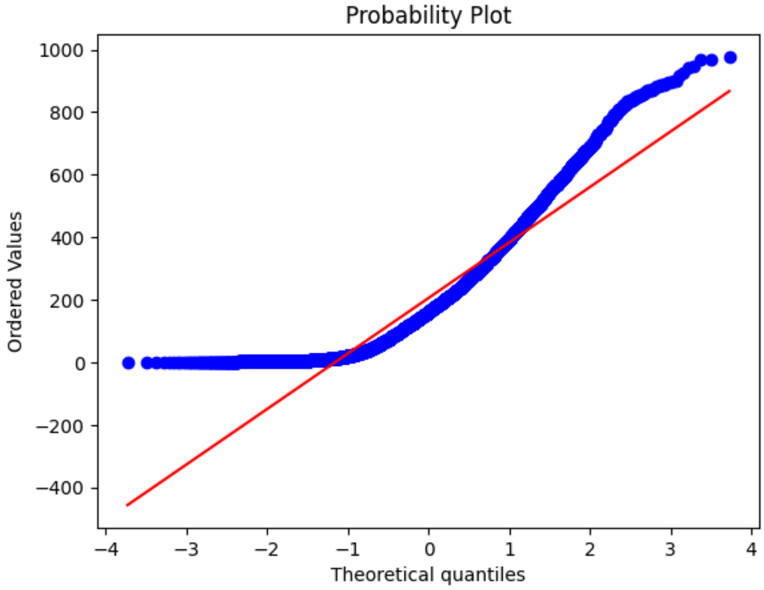
1.Statistically we can conclude that variances are not equal by performing levene test for 4 weather conditions.

2.variances of weather conditions -1,2 are near and weather-3 had quite large difference followed by weather-4 had zero variance(bcz no count of rental bikes on that weather condition).

Normality test:

```
 #Normality test for weather-1
from scipy import stats
stats.probplot(w1,plot=plt)
plt.figure()
```

```
<Figure size 640x480 with 0 Axes>
```




```
<Figure size 640x480 with 0 Axes>
```

From above plot we can conclude that data points are away from linear line implies that data is not normally distributed for weather condition-1

Shapiro test:

```
#Shapiro test for weather-1
#H0 : data is normally distributed
#Ha : data not  normally distributed
test_statistic, p_value = stats.shapiro(w1)
print(p_value)
if p_value < 0.05:
 print("Reject H0")
else:
 print("Fail to reject H0")
```

```
1.5964921477006555e-57
Reject H0
/usr/local/lib/python3.11/dist-packages/scipy/stats/_axis_nan_policy.py:573: UserWarning: scipy.stats.shapiro: For N > 5000, compute
  res = hypotest_fun_out(*samples, **kwds)
```

As p-value< 0.05 we conclude that data is not normally distributed

Chi-square test to check if Weather is dependent on the season

```
#Null Hypothesis (H0): weather and season are independent
#Alternative Hypothesis (Ha):weather and season are dependent
from scipy.stats import chi2_contingency
contingency = pd.crosstab(index = df['season'],columns = df['weather'])
contingency
test_statistic, p_value, dof, expected_values = chi2_contingency(contingency)
print("Test statistic:", test_statistic)
print("p-value:", p_value)
alpha = 0.05
if(p_value < alpha):
 print("Reject H0 ")
else:
 print("Fail to Reject H0 ")
```

```
Test statistic: 49.158655596893624
p-value: 1.549925073686492e-07
Reject H0
```

observations:

1.After performing chisquare test, we can conclude that there is a signi cant impact on season

2.Aceept Ha: weather and season are dependent

Insights:

1.Two sample ttest suggests that we should accept HO statistically at at 5% signi cance (As (p-value=0.22) > 0.05.)