Business Case: Yulu - 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.

A) Import the dataset and do usual exploratory data analysis steps like checking the structure & characteristics of the dataset.

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
csv_path = "yulu dataset.txt"
df = pd.read_csv(csv_path, delimiter=",")
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

```
# no of rows amd columns in dataset
print(f"# rows: {df.shape[0]} \n# columns: {df.shape[1]}")
```

rows: 10886
columns: 12

```
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
```

Datatype of following attributes needs to change to proper data type

- **datetime** - to datetime
- **season** - to categorical
- **holiday** - to categorical
- **workingday** - to categorical
- **weather** - to categorical

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

cat_cols= ['season', 'holiday', 'workingday', 'weather']
for col in cat_cols:
    df[col] = df[col].astype('object')
```

```
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  datetime64[ns]
 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: datetime64[ns](1), float64(3), int64(4), object(4)
memory usage: 1020.7+ KB
```

```
df.iloc[:, 1:].describe(include='all')
```

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
count	10886.0	10886.0	10886.0	10886.0	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000
unique	4.0	2.0	2.0	4.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	4.0	0.0	1.0	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	2734.0	10575.0	7412.0	7192.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	NaN	NaN	NaN	20.23086	23.655084	61.886460	12.799395	36.021955	155.552177	191.574132
std	NaN	NaN	NaN	NaN	7.79159	8.474601	19.245033	8.164537	49.960477	151.039033	181.144454
min	NaN	NaN	NaN	NaN	0.82000	0.760000	0.000000	0.000000	0.000000	0.000000	1.000000
25%	NaN	NaN	NaN	NaN	13.94000	16.665000	47.000000	7.001500	4.000000	36.000000	42.000000
50%	NaN	NaN	NaN	NaN	20.50000	24.240000	62.000000	12.998000	17.000000	118.000000	145.000000
75%	NaN	NaN	NaN	NaN	26.24000	31.060000	77.000000	16.997900	49.000000	222.000000	284.000000
max	NaN	NaN	NaN	NaN	41.00000	45.455000	100.000000	56.996900	367.000000	886.000000	977.000000

- There are no missing values in the dataset.
- **casual** and **registered** attributes might have outliers because their mean and median are very far away to one another and the value of standard deviation is also high which tells us that there is high variance in the data of these attributes.

```
# detecting missing values in the dataset
df.isnull().sum()
```

```
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
```

There are no missing values present in the dataset.

```
# minimum datetime and maximum datetime
print(df['datetime'].min(), df['datetime'].max())
# number of unique values in each categorical columns
df[cat_cols].melt().groupby(['variable', 'value'])[['value']].count()
```

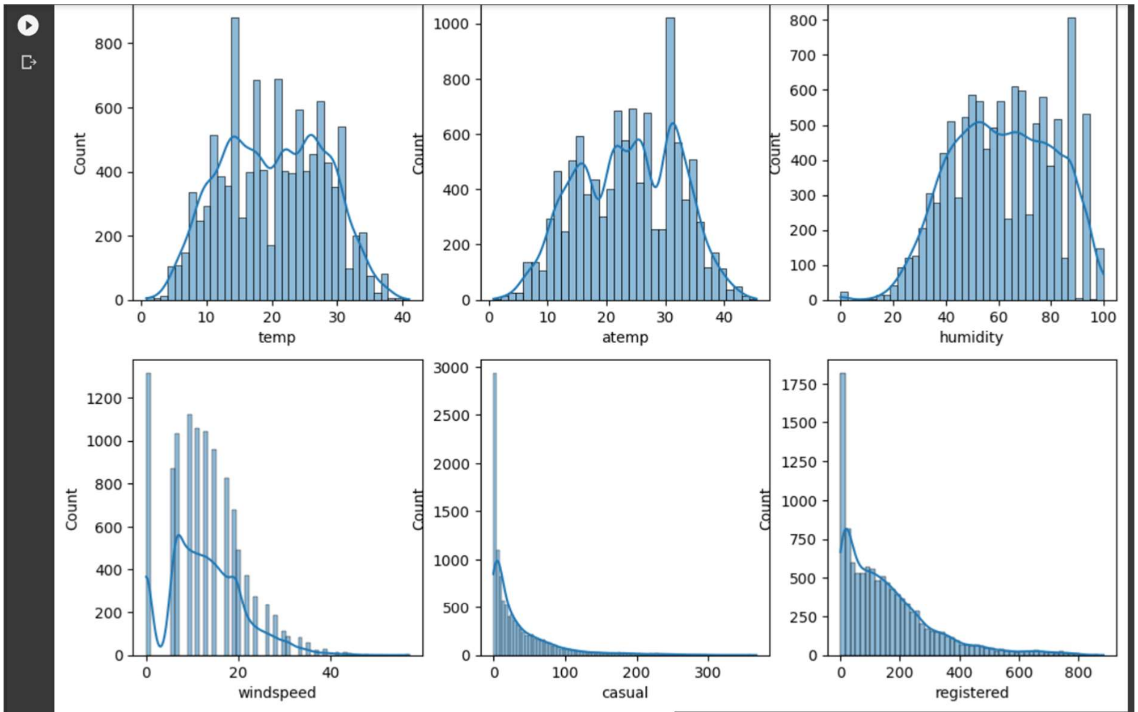
```
2011-01-01 00:00:00 2012-12-19 23:00:00
```

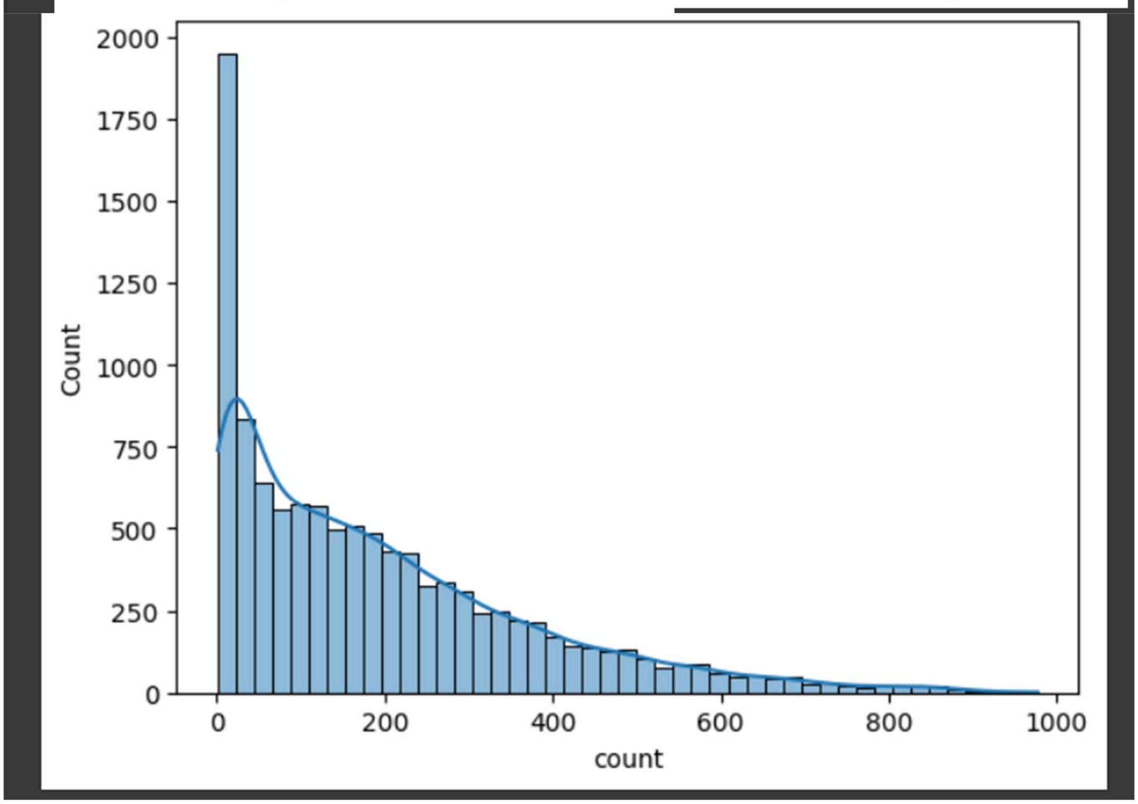
variable	value	value
holiday	0	10575
	1	311
season	1	2686
	2	2733
	3	2733
	4	2734
weather	1	7192
	2	2834
	3	859
	4	1
workingday	0	3474
	1	7412

Try establishing a relation between the dependent and independent variable (Dependent "Count" & Independent: Workingday, Weather, Season etc)

Univariate Analysis:

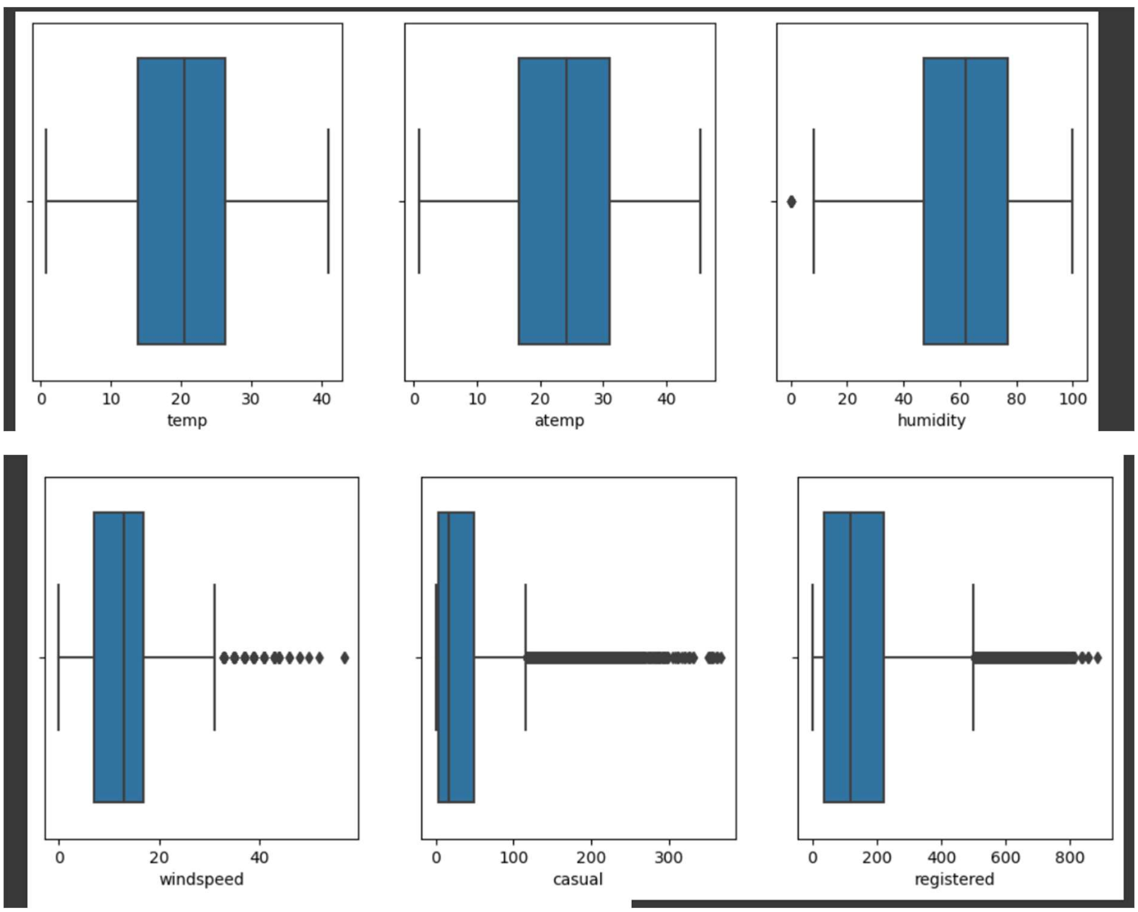
```
# understanding the distribution for numerical variables
num_cols = ['temp', 'atemp', 'humidity', 'windspeed', 'casual',
'registered','count']

fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(12, 8))

index = 0
for row in range(2):
    for col in range(3):
        sns.histplot(df[num_cols[index]], ax=axis[row, col], kde=True)
        index += 1

plt.show()
sns.histplot(df[num_cols[-1]], kde=True)
plt.show()
```

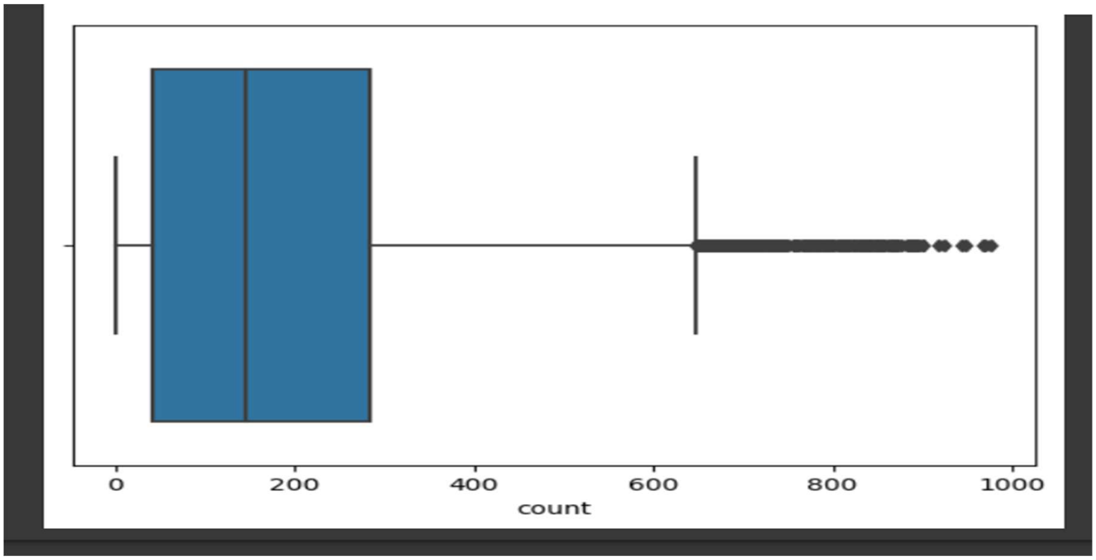




- **casual**, **registered** and **count** somewhat looks like **Log Normal Distribution**
- **temp**, **atemp** and **humidity** looks like they follows the **Normal Distribution**
- **windspeed** follows the **binomial distribution**

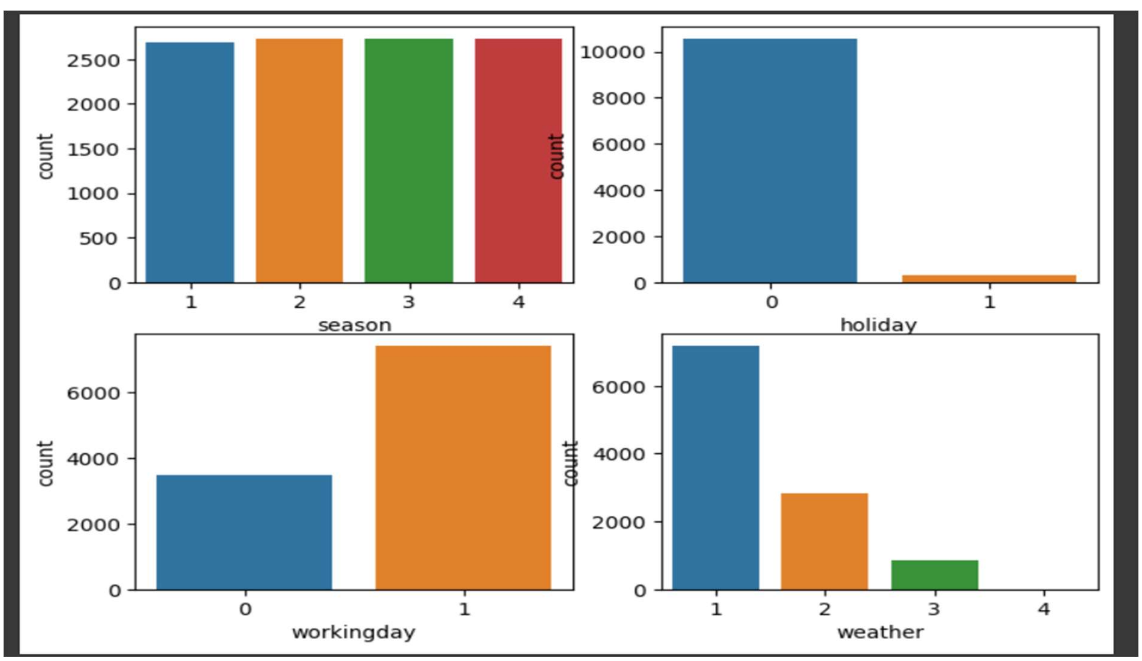
```
# plotting box plots to detect outliers in the data
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 12))

index = 0
for row in range(2):
    for col in range(3):
        sns.boxplot(x=df[num_cols[index]], ax=axis[row, col])
        index += 1

plt.show()
sns.boxplot(x=df[num_cols[-1]])
plt.show()
```





Looks like **humidity**, **casual**, **registered** and **count** have outliers in the data.

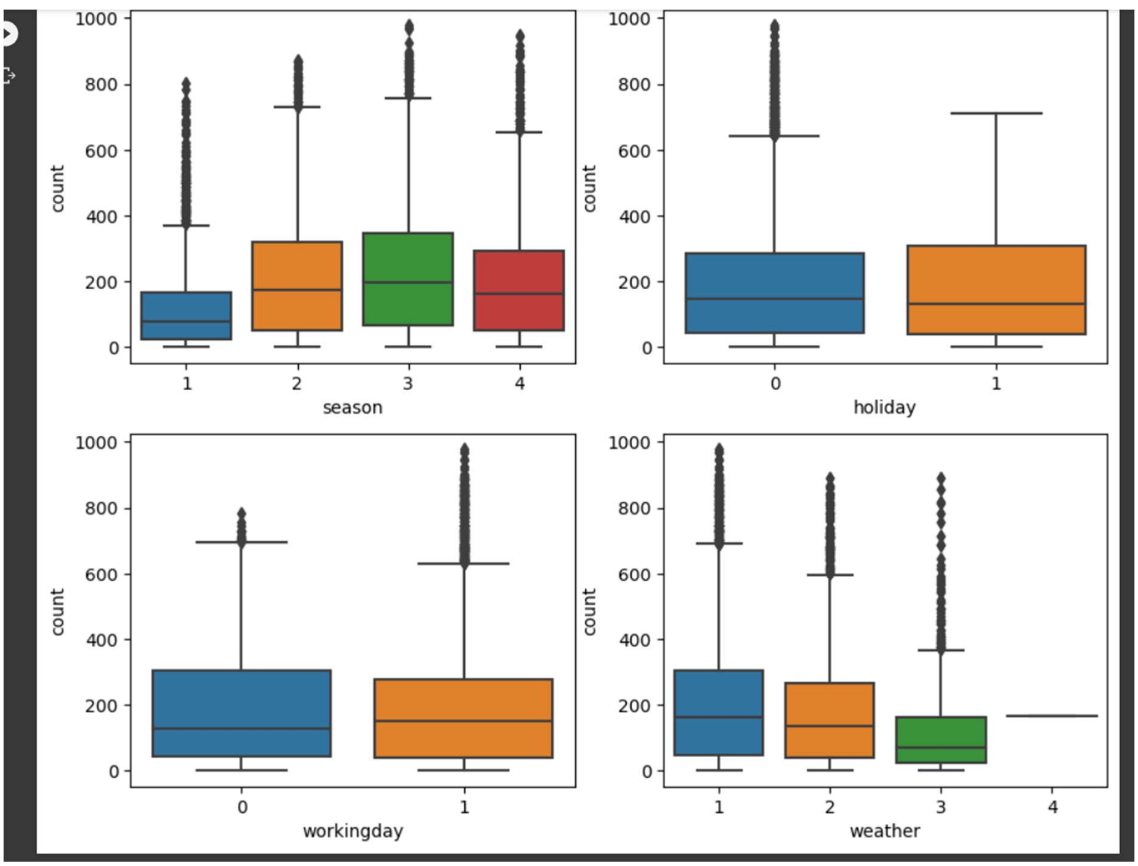
```
# countplot of each categorical column
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(8, 6))

index = 0
for row in range(2):
    for col in range(2):
        sns.countplot(data=df, x=cat_cols[index], ax=axis[row, col])
        index += 1

plt.show()
```



Data looks common as it should be like equal number of days in each season, more working days and weather is mostly `Clear, Few clouds, partly cloudy, partly cloudy`.

Bi-variate Analysis

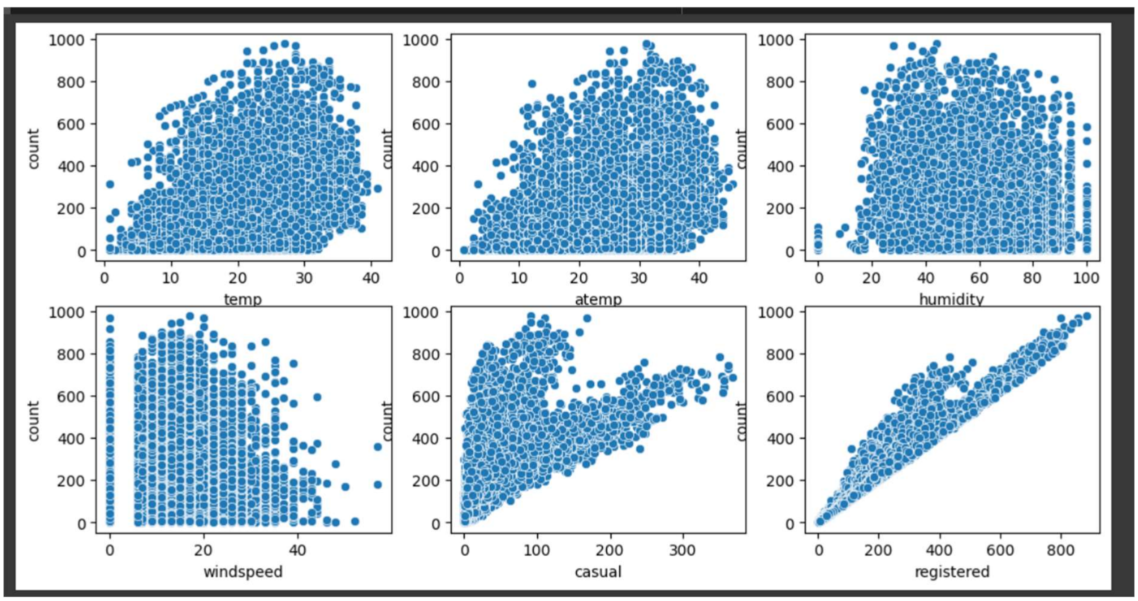
```
# plotting categorical variables againt count using boxplots
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(10, 8))

index = 0
for row in range(2):
    for col in range(2):
        sns.boxplot(data=df, x=cat_cols[index], y='count', ax=axis[row,
col])
        index += 1

plt.show()
```



- In **summer** and **fall** seasons more bikes are rented as compared to other seasons.
- Whenever its a **holiday** more bikes are rented.
- It is also clear from the workingday also that whenever day is holiday or weekend, slightly more bikes were rented.

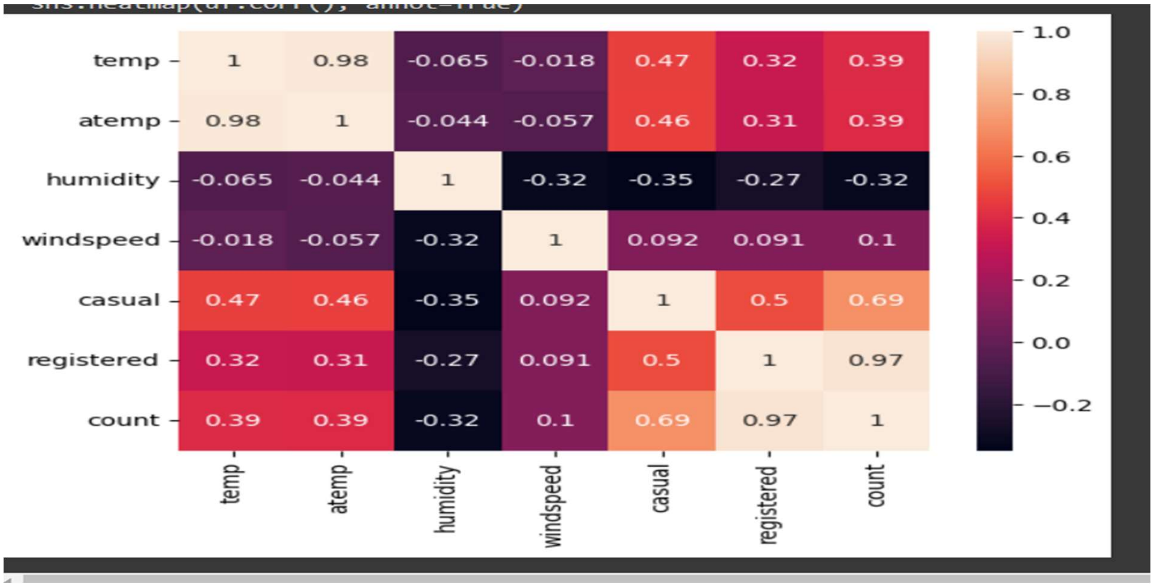
- Whenever there is **rain, thunderstorm, snow or fog**, there were less bikes were rented.

```
# plotting numerical variables againt count using scatterplot
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(12, 6))

index = 0
for row in range(2):
    for col in range(3):
        sns.scatterplot(data=df, x=num_cols[index], y='count',
ax=axis[row, col])
        index += 1

plt.show()
```



- Whenever the humidity is less than 20, number of bikes rented is very very low.
- Whenever the temperature is less than 10, number of bikes rented is less.
- Whenever the windspeed is greater than 35, number of bikes rented is less.

```
# understanding the correlation between count and numerical variables
df.corr()['count']
sns.heatmap(df.corr(), annot=True)
plt.show()
```



2: Hypothesis Testing:

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

Null Hypothesis (H0): Weather is independent of the season

Alternate Hypothesis (H1): Weather is not independent of the season

Significance level (alpha): 0.05

```
data_table = pd.crosstab(df['season'], df['weather'])
print("Observed values:")
data_table
```

Observed values:

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

```
val = stats.chi2_contingency(data_table)
print(val)
```

```
expected_values = val[3]
print(expected_values)
nrows, ncols = 4, 4
dof = (nrows-1)*(ncols-1)
print("degrees of freedom: ", dof)
alpha = 0.05


chi_sqr = sum([(o-e)**2/e for o, e in zip(data_table.values,
expected_values)])
chi_sqr_statistic = chi_sqr[0] + chi_sqr[1]
print("chi-square test statistic: ", chi_sqr_statistic)

critical_val = stats.chi2.ppf(q=1-alpha, df=dof)
print(f"critical value: {critical_val}")

p_val = 1-stats.chi2.cdf(x=chi_sqr_statistic, df=dof)
print(f"p-value: {p_val}")

if p_val <= alpha:
    print("\nSince p-value is less than the alpha 0.05, We reject the
Null Hypothesis. Meaning that\
    Weather is dependent on the season.")
else:
    print("Since p-value is greater than the alpha 0.05, We do not
reject the Null Hypothesis")
```

```
Chi2ContingencyResult(statistic=49.158655596893624,
pvalue=1.549925073686492e-07, dof=9, expected_freq=array([[1.77454639e+03,
6.99258130e+02, 2.11948742e+02, 2.46738931e-01],
       [1.80559765e+03, 7.11493845e+02, 2.15657450e+02, 2.51056403e-01],
       [1.80559765e+03, 7.11493845e+02, 2.15657450e+02, 2.51056403e-01],
       [1.80625831e+03, 7.11754180e+02, 2.15736359e+02, 2.51148264e-01]]))

[[1.77454639e+03 6.99258130e+02 2.11948742e+02 2.46738931e-01]
 [1.80559765e+03 7.11493845e+02 2.15657450e+02 2.51056403e-01]
 [1.80559765e+03 7.11493845e+02 2.15657450e+02 2.51056403e-01]
 [1.80625831e+03 7.11754180e+02 2.15736359e+02 2.51148264e-01]]

degrees of freedom:  9
chi-square test statistic:  44.09441248632364
critical value: 16.918977604620448
p-value: 1.3560001579371317e-06

Since p-value is less than the alpha 0.05, We reject the Null Hypothesis. Meaning
that    Weather is dependent on the season.
```

2- Sample T-Test to check if Working Day has an effect on the number of electric cycles rented :

Null Hypothesis: Working day has no effect on the number of cycles being rented.
Alternate Hypothesis: Working day has effect on the number of cycles being rented.
Significance level (alpha): 0.05
We will use the **2-Sample T-Test** to test the hypothess defined above

```
data_group1 = df[df['workingday']==0]['count'].values
data_group2 = df[df['workingday']==1]['count'].values

print(np.var(data_group1), np.var(data_group2))
np.var(data_group2)// np.var(data_group1)
```

Before conducting the two-sample T-Test we need to find if the given data groups have the same variance. If the ratio of the larger data groups to the small data group is less than 4:1 then we can consider that the given data groups have equal variance.

```
30171.346098942427 34040.69710674686
1.0
```

Here, the ratio is 34040.70 / 30171.35 which is less than 4:1

```
stats.ttest_ind(a=data_group1, b=data_group2, equal_var=True)
```

```
Ttest_indResult(statistic=-1.2096277376026694,
pvalue=0.22644804226361348)
```

Since pvalue is greater than 0.05 so we cannot reject the Null hypothesis. We don't have the sufficient evidence to say that working day has effect on the number of cycles being rented.

3: -ANNOVA to check if No. of cycles rented is similar or different in different 1. weather 2. Season

Null Hypothesis: Number of cycles rented is similar in different weather and season.
Alternate Hypothesis: Number of cycles rented is not similar in different weather and season.
Significance level (alpha): 0.05

```
index = 0
for row in range(4):
    for col in range(2):
        qqplot(groups[index], line="s")
        index += 1

plt.show()
```

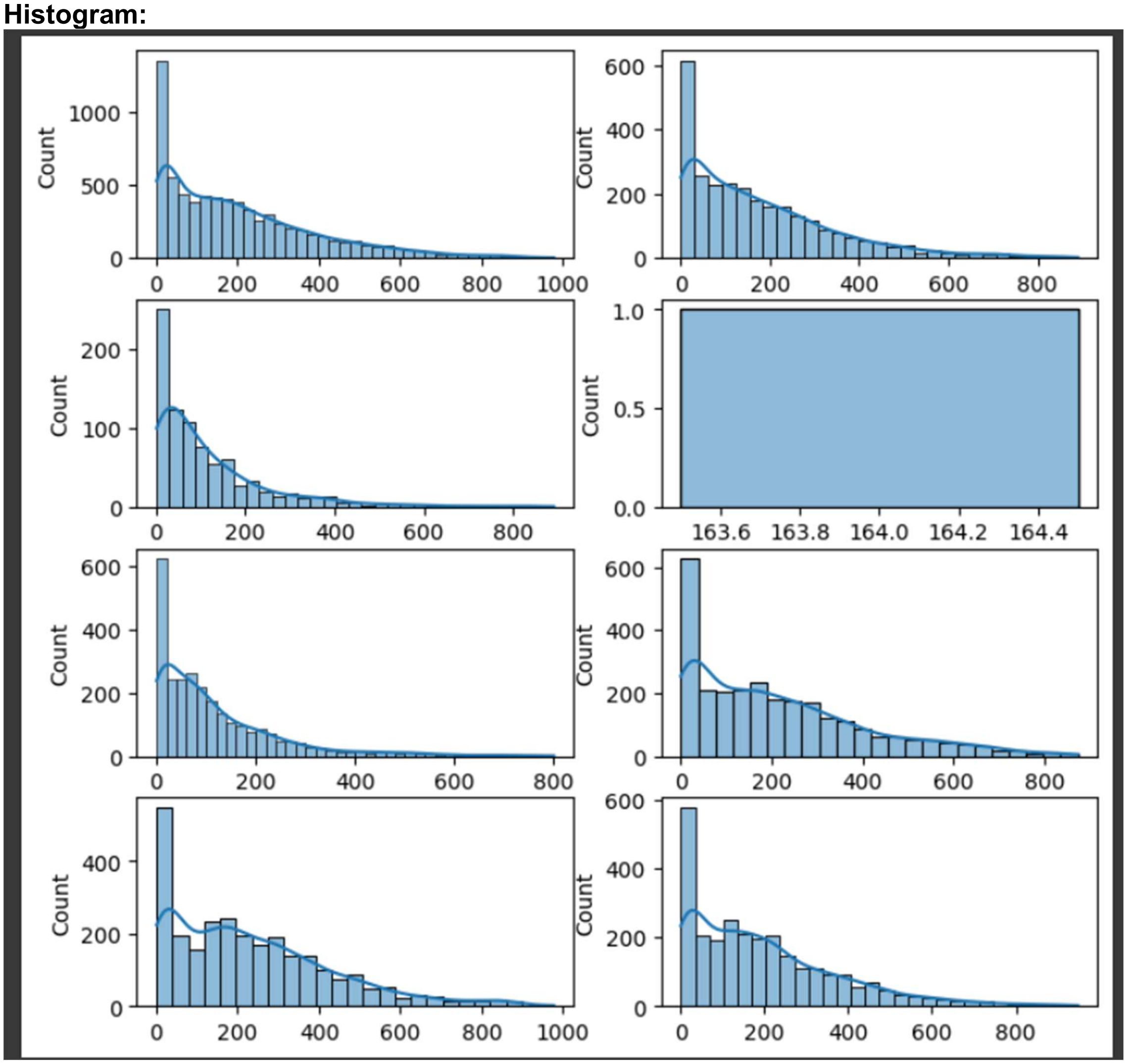
```
fig, axis = plt.subplots(nrows=4, ncols=2, figsize=(8, 8))
```

```
index = 0
for row in range(4):
    for col in range(2):
        sns.histplot(groups[index], ax=axis[row, col], kde=True)
        index += 1

plt.show()
```

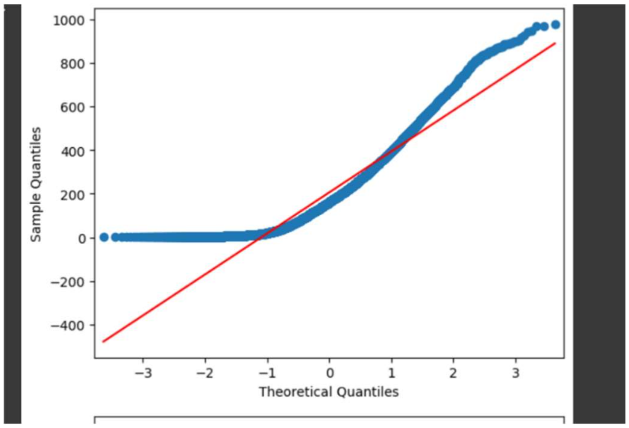
Assumptions of ANOVA

1. **Gaussian**

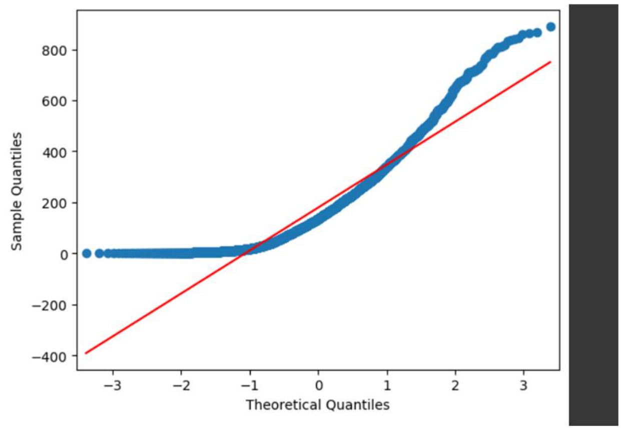
Histogram:



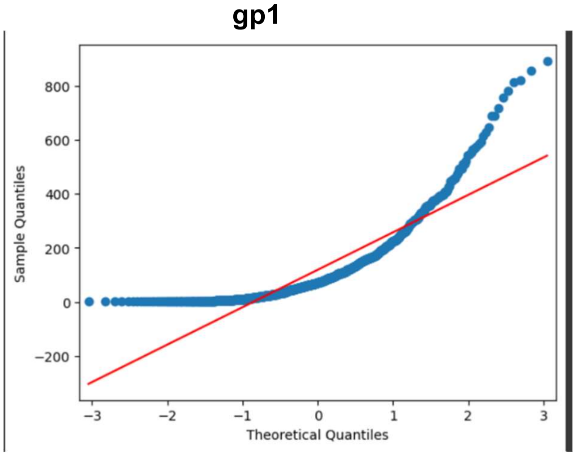
QQ plot



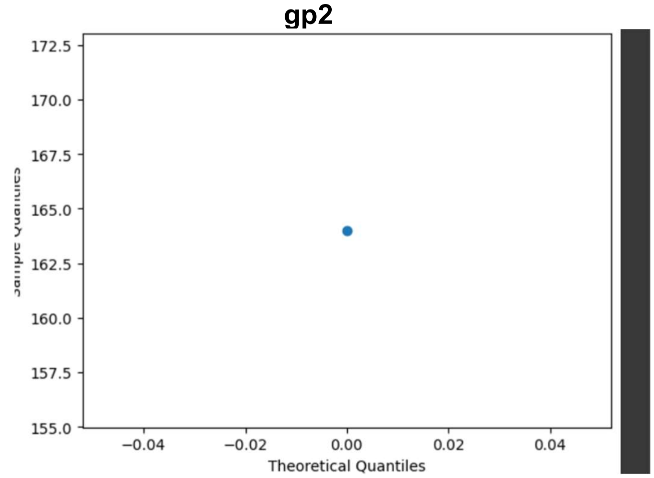
gp1



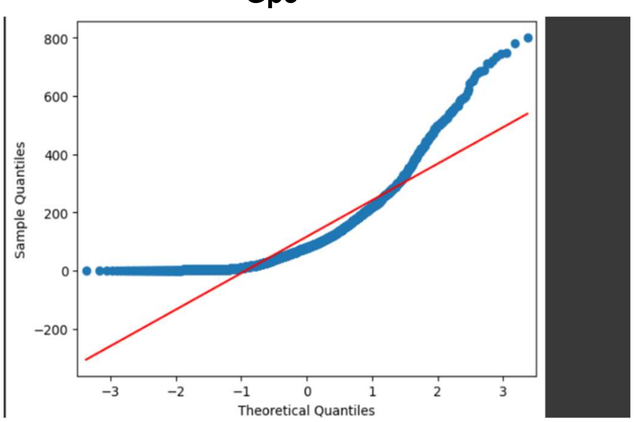
gp2



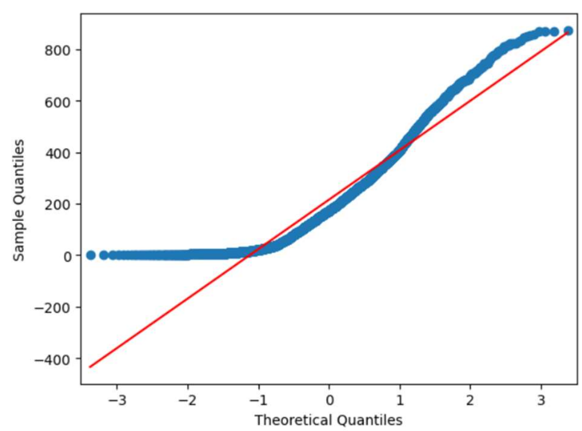
Gp3



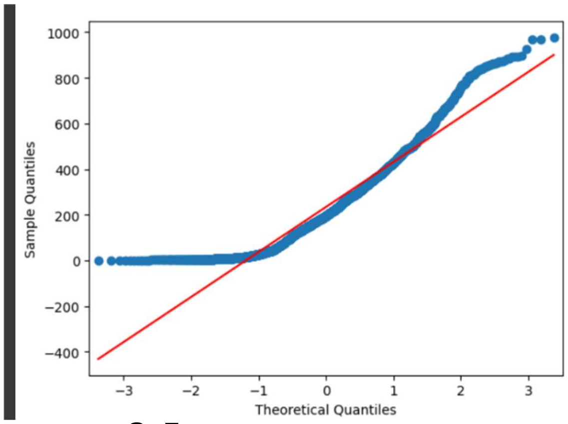
gp4



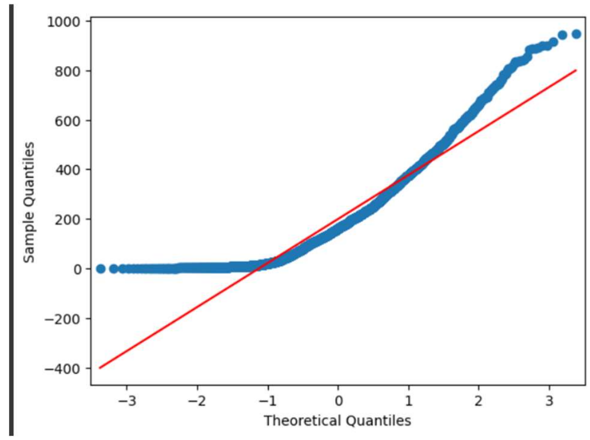
Gp5



Gp6



Gp7



Gp8

As per above graphs, all groups are not following Gaussian distribution

2: **Data is Independent**

3: Equal variance: Levene's Test

```
#Null Hypothesis: Variances is similar in different weather and season.

#Alternate Hypothesis: Variances is not similar in different weather
and season.

#Significance level (alpha): 0.05
levene_stat, p_value = stats.levene(gp1,gp2,gp3,gp4,gp5,gp6,gp7,gp8)
print(p_value)
if p_value < 0.05:
    print("Reject the Null hypothesis.Variances are not equal")
else:
  print("Fail to Reject the Null hypothesis.Variances are  equal")
```

p_value: 3.4635318888897594e-148
Reject the Null hypothesis. Variances are not equal

As per QQ plot and Levene's Test, We cannot ANOVA Test.

Assumptions of ANOVA fail, use Kruskal

```
#assumptions of ANOVA don't hold, we need Kruskal Wallis
kruskal_stat, p_value = stats.kruskal(gp1,gp2,gp3,gp4,gp5,gp6,gp7,gp8)
```

```
print("p_value===",p_value)
if p_value<0.05:
  print("Since p-value is less than 0.05, we reject the null
hypothesis")
```

p_value=== 4.614440933900297e-191
Since p-value is less than 0.05, we reject the null hypothesis

Since p-value is less than 0.05, we reject the null hypothesis. This implies that Number of cycles rented is not similar in different weather and season conditions

Insights

- In summer and fall seasons more bikes are rented as compared to other seasons.
- Whenever its a holiday more bikes are rented.
- It is also clear from the workingday also that whenever day is holiday or weekend, slightly more bikes were rented.
- Whenever there is rain, thunderstorm, snow or fog, there were less bikes were rented.
- Whenever the humidity is less than 20, number of bikes rented is very very low.
- Whenever the temperature is less than 10, number of bikes rented is less.
- Whenever the windspeed is greater than 35, number of bikes rented is less.

Recommendations

- In summer and fall seasons the company should have more bikes in stock to be rented. Because the demand in these seasons is higher as compared to other seasons.
- With a significance level of 0.05, workingday has no effect on the number of bikes being rented.
- In very low humid days, company should have less bikes in the stock to be rented.
- Whenever temperature is less than 10 or in very cold days, company should have less bikes.
- Whenever the windspeed is greater than 35 or in thunderstorms, company should have less bikes in stock to be rented.