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.

How you can help here?

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

Dataset:

Dataset Link: yulu_data.csv

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

Concept Used:

- Bi-Variate Analysis
- 2-sample t-test: testing for difference across populations
- ANNOVA
- Chi-square

```
yulu = pd.read_csv("yulu.txt")

yulu["datetime"] = pd.to_datetime(yulu.datetime)

yulu["date"] = yulu.datetime.dt.date


print(yulu.head())
```

```
             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

   humidity  windspeed  casual  registered  count        date
0        81        0.0       3          13     16  2011-01-01
1        80        0.0       8          32     40  2011-01-01
2        80        0.0       5          27     32  2011-01-01
3        75        0.0       3          10     13  2011-01-01
4        75        0.0       0           1      1  2011-01-01
```

```
print(yulu.info())
```

```
 #   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
 12  date        10886 non-null  object
```

```
yulu = yulu.astype({"season" : "object" , "holiday" : "object" ,
"workingday" : "object" , "weather" : "object"})
print(yulu.info())
```

```
 #   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
 12  date        10886 non-null  object
 13  month       10886 non-null  int64
```

```
print(yulu.isna().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
date          0
dtype: int64
```

```
print(yulu.describe())
```

```
              temp         atemp      humidity     windspeed        casual  \
count  10886.00000  10886.000000  10886.000000  10886.000000  10886.000000
mean      20.23086     23.655084     61.886460     12.799395     36.021955
std        7.79159      8.474601     19.245033      8.164537     49.960477
min        0.82000      0.760000      0.000000      0.000000      0.000000
25%       13.94000     16.665000     47.000000      7.001500      4.000000
50%       20.50000     24.240000     62.000000     12.998000     17.000000
75%       26.24000     31.060000     77.000000     16.997900     49.000000
max       41.00000     45.455000    100.000000     56.996900    367.000000

         registered         count         month
count  10886.000000  10886.000000  10886.000000
mean     155.552177    191.574132      6.521495
std      151.039033    181.144454      3.444373
min        0.000000      1.000000      1.000000
25%       36.000000     42.000000      4.000000
50%      118.000000    145.000000      7.000000
75%      222.000000    284.000000     10.000000
max      886.000000    977.000000     12.000000
```

```
shape = yulu.shape

print(f"Number of rows : {shape[0]} \nNumber of columns :
{shape[1]}")
```

```
Number of rows : 10886
Number of columns : 13
```

Observation :

1. Data has no missing values.

2. Data has 10886 rows and 13 columns.

3. There is a huge difference between mean and median of the data and also the standard deviation is large so we can infer that there might be outliers present.

```python
print(yulu.season.unique())
```

```
[1 2 3 4]
```

```python
print(yulu.holiday.unique())
```

```
[0 1]
```

```python
print(yulu.workingday.unique())
```

```
[0 1]
```

```python
print(yulu.weather.unique())
```

```
[1 2 3 4]
```

```python
print(yulu.season.value_counts())
```

```
4    2734
2    2733
3    2733
1    2686
Name: season, dtype: int64
```

```
print(yulu.holiday.value_counts())
```

```
0    10575
1      311
Name: holiday, dtype: int64
```

```
print(yulu.workingday.value_counts())
```

```
1    7412
0    3474
Name: workingday, dtype: int64
```

```
print(yulu.weather.value_counts())
```

```
1    7192
2    2834
3     859
4       1
Name: weather, dtype: int64
```

```
print(yulu.datetime.max())
```

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

```
print(yulu.datetime.min())
```

```
2011-01-01 00:00:00
```

```
print(yulu.datetime.max() - yulu.datetime.min())
```

```
718 days 23:00:00
```

```
print(np.any(yulu.duplicated()))
```

```
False
```

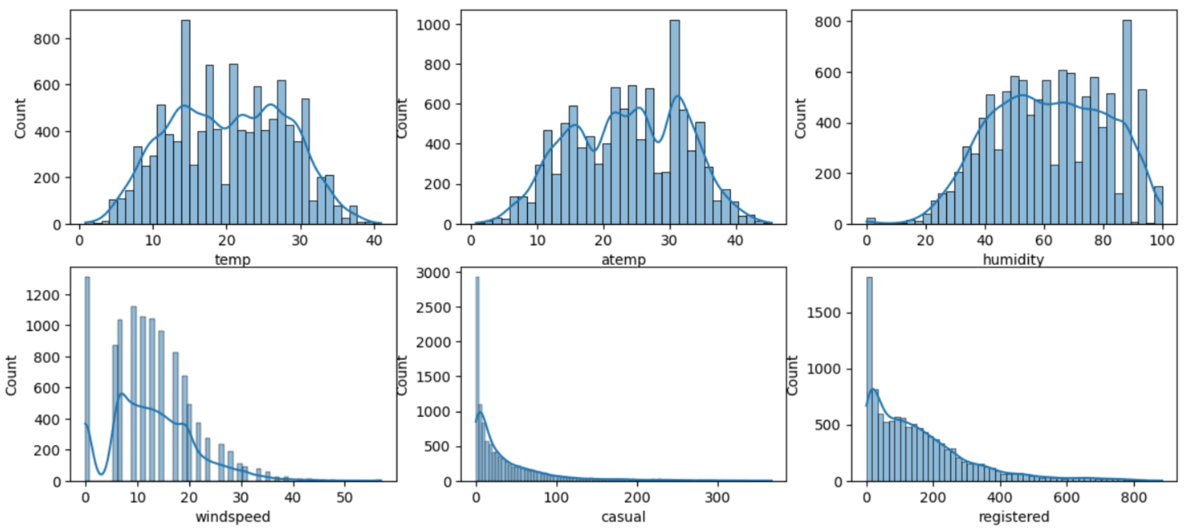
Observation:

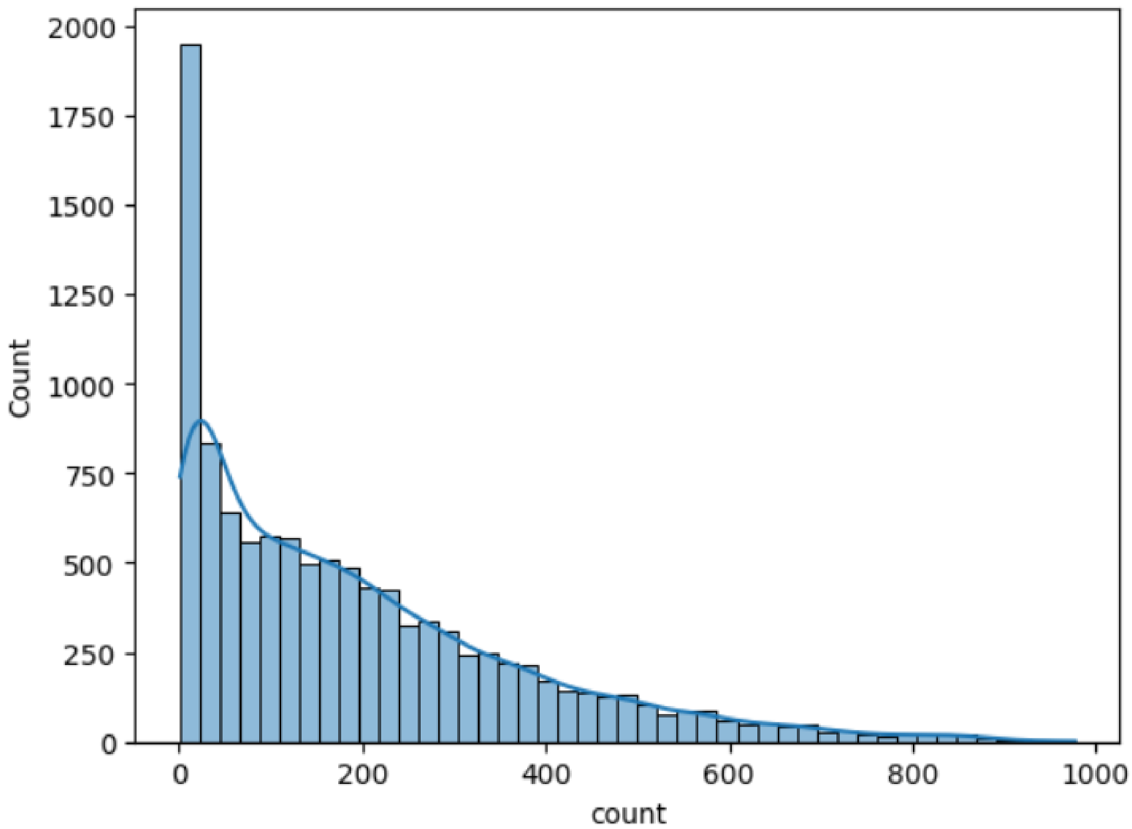
1. We have data between year 2011 to 2012.

2. There is no duplicate record in the data.

Uni-Variate Analysis :

```
num_cols = ["temp" , "atemp" , "humidity" , "windspeed" , "casual" ,
"registered" , "count"]

index = 0

fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(14, 6))


for i in range(2) :

  for j in range(3) :

    sns.histplot(x = num_cols[index] , data = yulu , ax = axis[i, j]
, kde = True )

    index = index + 1


plt.show()

sns.histplot(x = num_cols[-1] , data = yulu , kde = True)

plt.show()
```

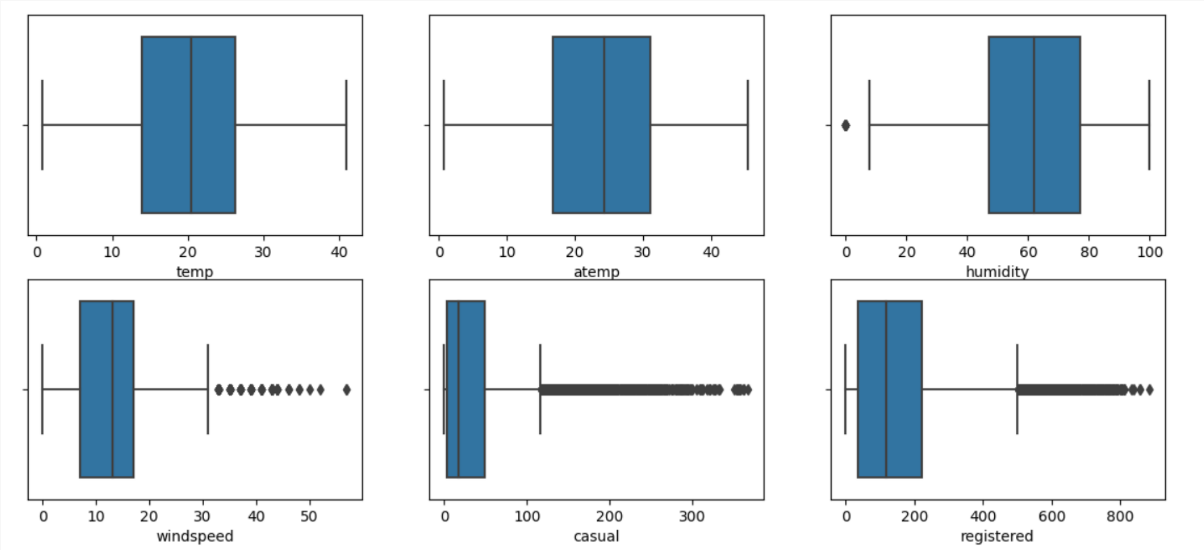


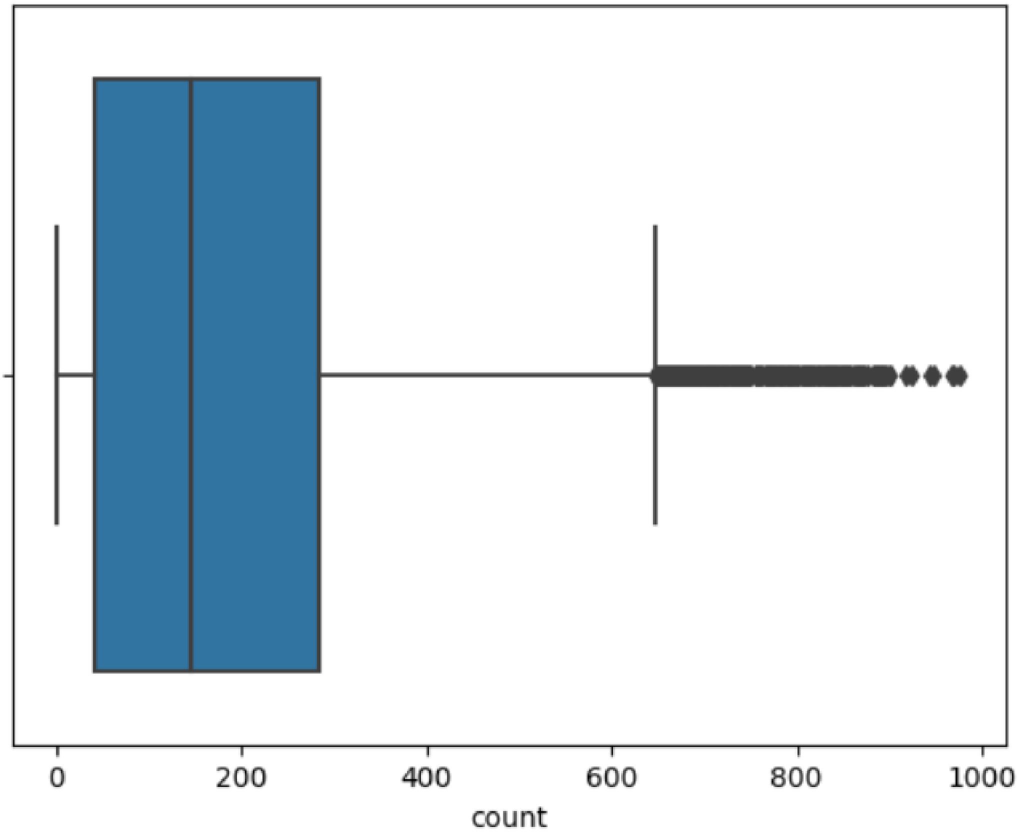


- **casual**, **registered** and **count** somewhat looks like **Log Normal Distribution.**
- **temp**, **atemp** and **humidity** looks like they follows the **Normal Distribution.**
- **windspeed** follows the **binomial distribution.**

<u>Outlier Check :</u>

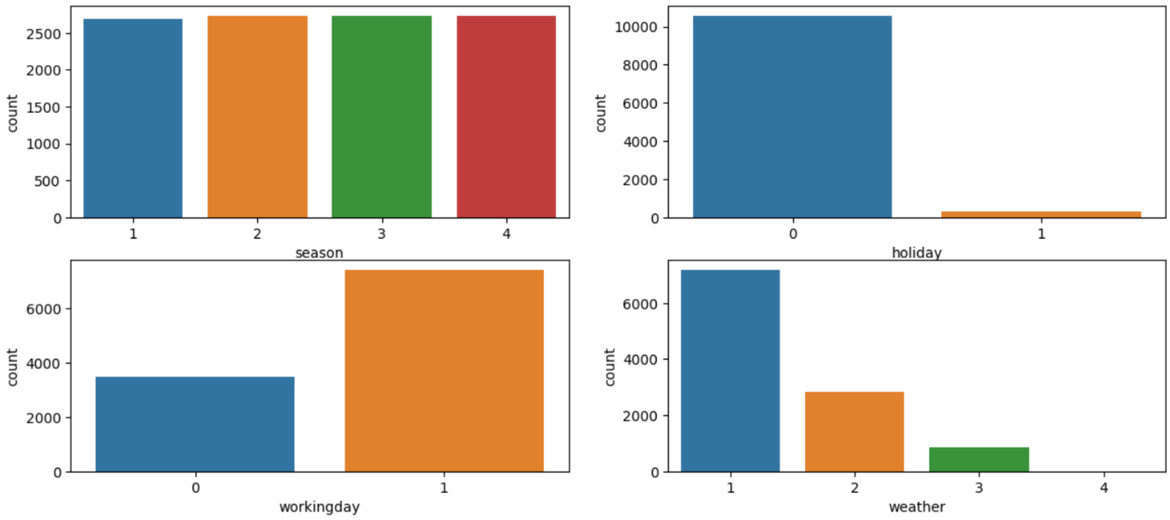
```
num_cols = ["temp" , "atemp" , "humidity" , "windspeed" , "casual" ,
"registered" , "count"]

index = 0

fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(14, 6))


for i in range(2) :

  for j in range(3) :

    sns.boxplot(x = num_cols[index] , data = yulu , ax = axis[i, j]
)

    index = index + 1


plt.show()

sns.boxplot(x = num_cols[-1] , data = yulu)

plt.show()
```





- **Windspeed**, **casual**, **registered** and **count** have outliers in the data.

```
cat_cols = ["season" , "holiday" , "workingday" , "weather"]
index = 0
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(14, 6))

for i in range(2) :
  for j in range(2) :
    sns.countplot(x = cat_cols[index] , data = yulu , ax = axis[i,
j] )
    index = index + 1

plt.show()
```

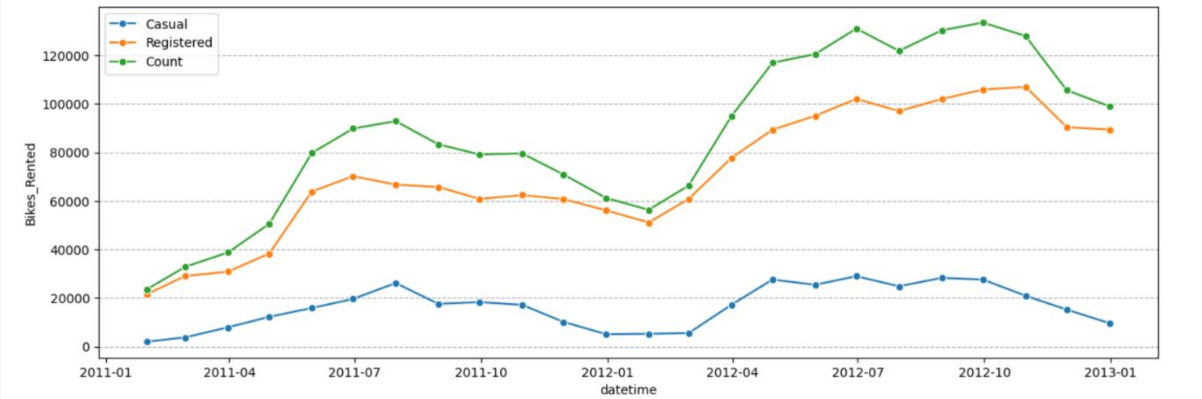


- Data looks common as it should be like equal number of days in each season, more working days and weather is mostly Clear, Few clouds, partly cloudy, partly cloudy.

-> Analysis based on Months, Hours and Years.

```
df = yulu.copy()

df.set_index("datetime" , inplace = True)


df_casual = df.resample("M")["casual"].sum()

df_registered = df.resample("M")["registered"].sum()

df_count = df.resample("M")["count"].sum()


plt.figure(figsize = (15, 5))

sns.lineplot(x = df_casual.index , y = df_casual , label = "Casual"
, marker = "o")

sns.lineplot(x = df_registered.index , y = df_registered , label =
"Registered" , marker = "o")

sns.lineplot(x = df_count.index , y = df_count, label = "Count" ,
marker = "o")
```

```
plt.grid(axis = "y" , linestyle = "--")

plt.ylabel("Bikes_Rented")

plt.legend()

plt.show()
```




```
df_month = yulu.groupby("month")["count"].sum().reset_index()

df_month["prev_count"] = df_month["count"].shift(1)

df_month["perc_increase"] = ((df_month["count"] -
df_month["prev_count"]) / df_month["prev_count"] ) * 100

print(df_month)
```

```
    month   count  prev_count  perc_increase
0       1   79884         NaN            NaN
1       2   99113     79884.0      24.071153
2       3  133501     99113.0      34.695751
3       4  167402    133501.0      25.393817
4       5  200147    167402.0      19.560698
5       6  220733    200147.0      10.285440
6       7  214617    220733.0      -2.770768
7       8  213516    214617.0      -0.513007
8       9  212529    213516.0      -0.462260
9      10  207434    212529.0      -2.397320
10     11  176440    207434.0     -14.941620
11     12  160160    176440.0      -9.226933
```

```
df_year =
yulu.groupby(yulu["datetime"].dt.year)["count"].sum().reset_index()
```

```
df_year["prev_count"] = df_year["count"].shift(1)

df_year["perc_increase"] = ((df_year["count"] -
df_year["prev_count"]) / df_year["prev_count"] ) * 100

print(df_year)
```

	datetime	count	prev_count	perc_increase
0	2011	781979	NaN	NaN
1	2012	1303497	781979.0	66.692072

Observation :

1. There is a good growth in number of cycles rented in the month Feb, March, April. after month May there is a negative

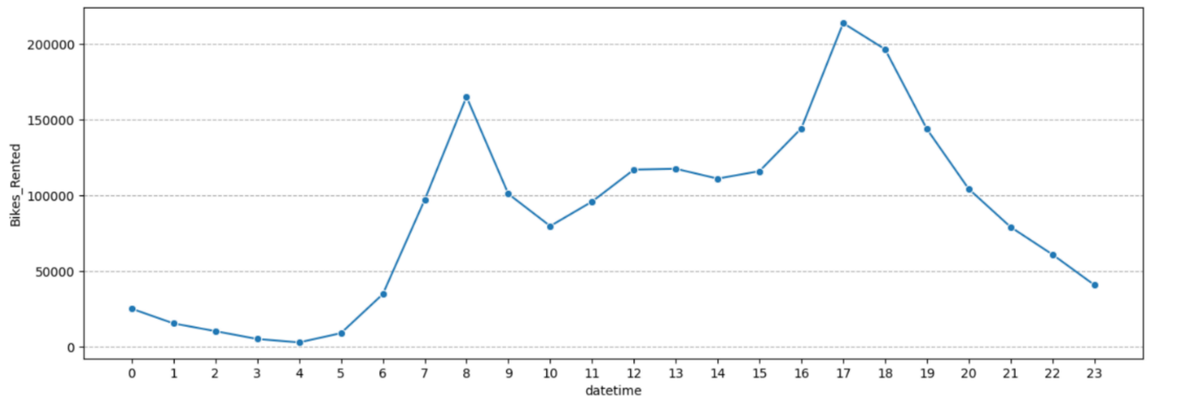
growth in cycles rented.

2. There is an increase of 66.7% in number of cycles rented in year 2012 than in 2011.

```
df_hour =
yulu.groupby(yulu["datetime"].dt.hour)["count"].sum().reset_index()

df_hour["prev_count"] = df_hour["count"].shift(1)

df_hour["perc_increase"] = ((df_hour["count"] -
df_hour["prev_count"]) / df_hour["prev_count"] ) * 100

print(df_hour)
```

	datetime	count	prev_count	perc_increase
0	0	25088	NaN	NaN
1	1	15372	25088.0	-38.727679
2	2	10259	15372.0	-33.261775
3	3	5091	10259.0	-50.375280
4	4	2832	5091.0	-44.372422
5	5	8935	2832.0	215.501412
6	6	34698	8935.0	288.337997
7	7	96968	34698.0	179.462793
8	8	165060	96968.0	70.221104
9	9	100910	165060.0	-38.864655
10	10	79667	100910.0	-21.051432
11	11	95857	79667.0	20.322091
12	12	116968	95857.0	22.023431
13	13	117551	116968.0	0.498427
14	14	111010	117551.0	-5.564393
15	15	115960	111010.0	4.459058
16	16	144266	115960.0	24.410141
17	17	213757	144266.0	48.168661
18	18	196472	213757.0	-8.086285
19	19	143767	196472.0	-26.825705
20	20	104204	143767.0	-27.518833
21	21	79057	104204.0	-24.132471
22	22	60911	79057.0	-22.953059
23	23	40816	60911.0	-32.990757

```
plt.figure(figsize = (15, 5))

sns.lineplot(x = df_hour["datetime"] , y = df_hour["count"] , marker
= "o")

plt.grid(axis = "y" , linestyle = "--")

plt.xticks(np.arange(0,24))

plt.ylabel("Bikes_Rented")

plt.show()
```



Observation:

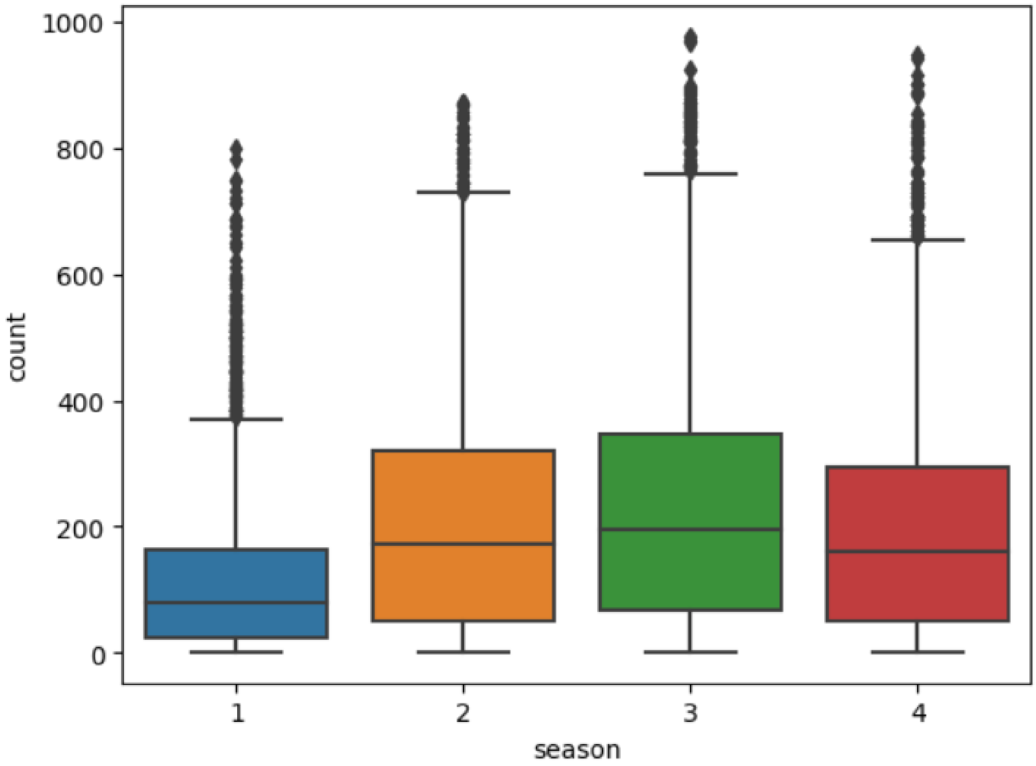
- During the early morning hours (hours 0 to 5), there is a significant decrease in the count, with negative growth percentages ranging from -38.59% to -48.66%.
- However, starting from hour 5, there is a sudden increase in count, with a sharp positive growth percentage of 208.52% observed from hour 4 to hour 5.
- The count continues to rise significantly until reaching its peak at hour 17, with a growth percentage of 48.17% compared to the previous hour.
- After hour 17, there is a gradual decrease in count, with negative growth percentages ranging from -8.08% to -32.99% during the late evening and nighttime hours.

Bi-Variate Analysis :

```
df_season = yulu.groupby("season")["count"].describe()
print(df_season)
```

```
         count        mean         std  min   25%    50%    75%    max
season
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
```

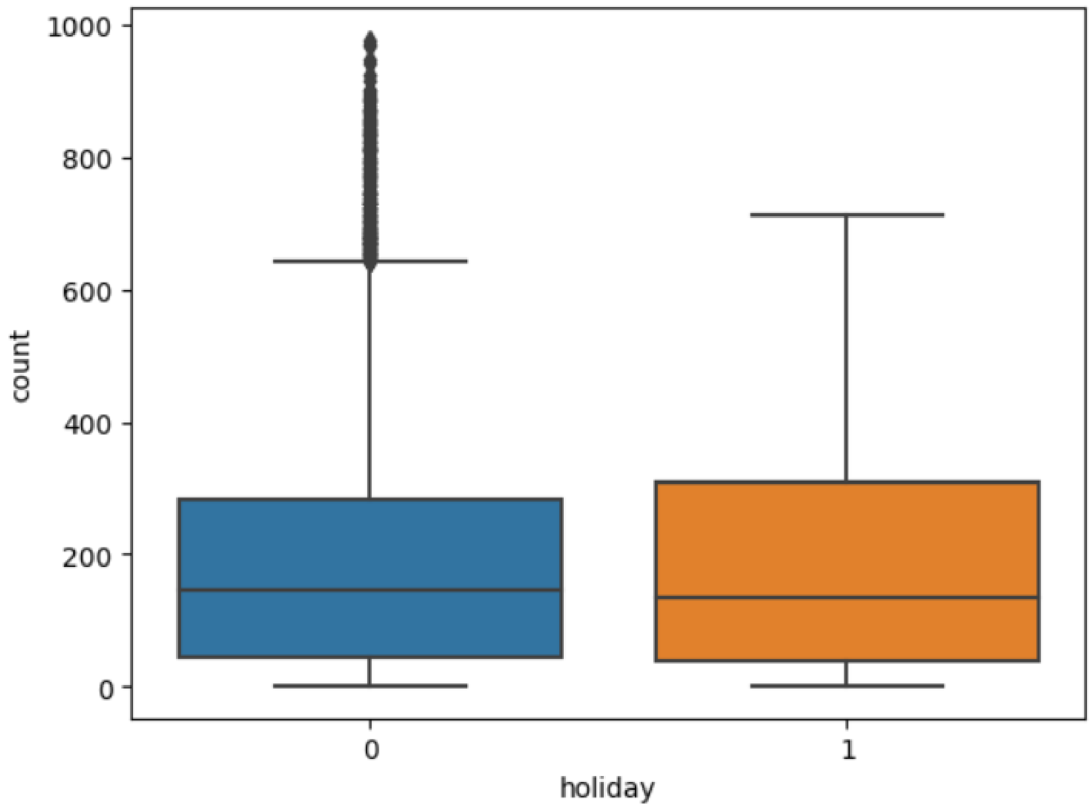
```
sns.boxplot(x = "season" , y = "count" , data = yulu)
plt.show()
```




```
holiday_describe = yulu.groupby("holiday")["count"].describe()
print(holiday_describe)
```

```
           count        mean         std  min   25%    50%    75%    max
holiday
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
```

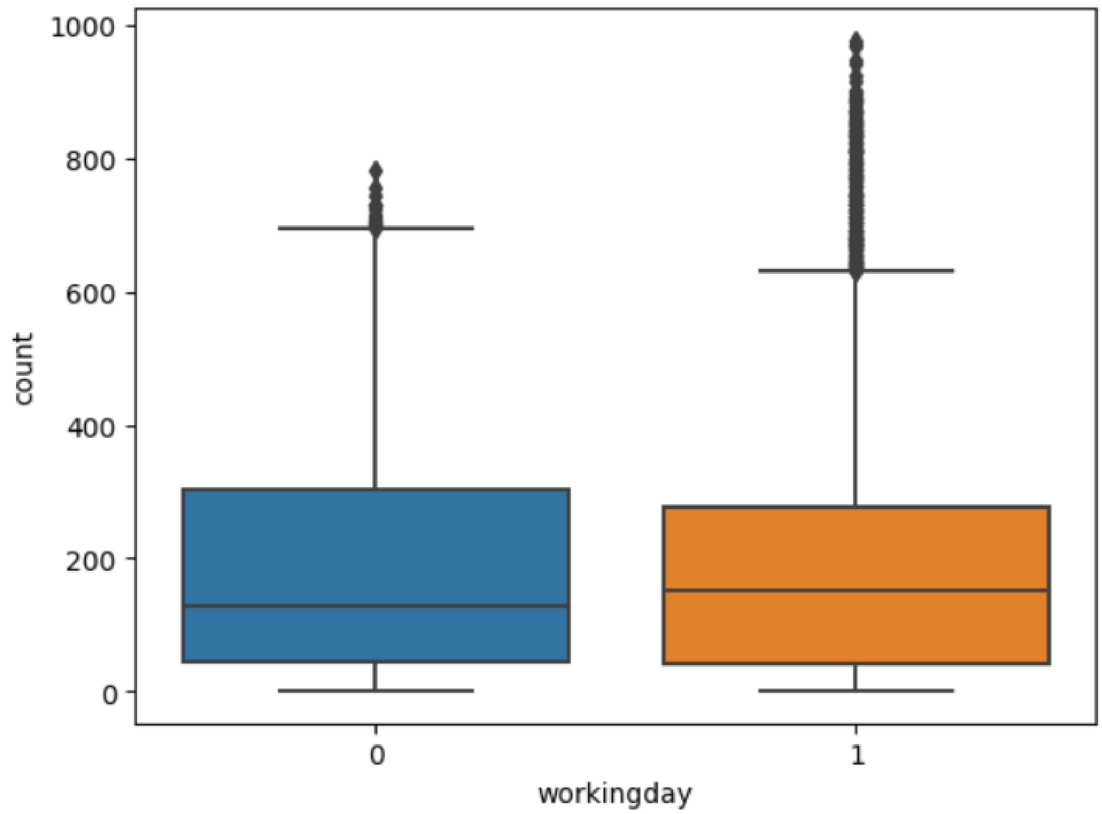
```
sns.boxplot(x = "holiday" , y = "count" , data = yulu)
plt.show()
```




```
workingday_describe = yulu.groupby("workingday")["count"].describe()
print(workingday_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
```

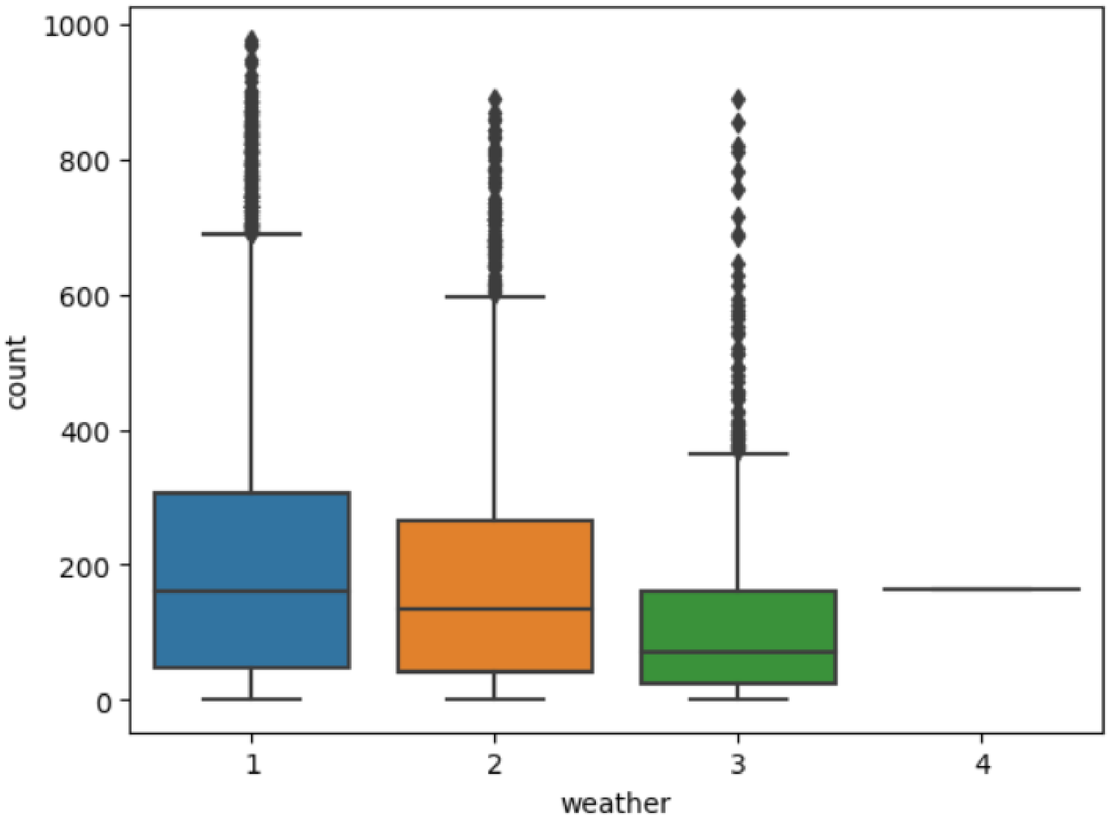
```
sns.boxplot(x = "workingday" , y = "count" , data = yulu)
plt.show()
```




```
weather_describe = yulu.groupby("weather")["count"].describe()

print(weather_describe)
```

```
          count        mean         std    min    25%    50%    75%    max
weather
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
```

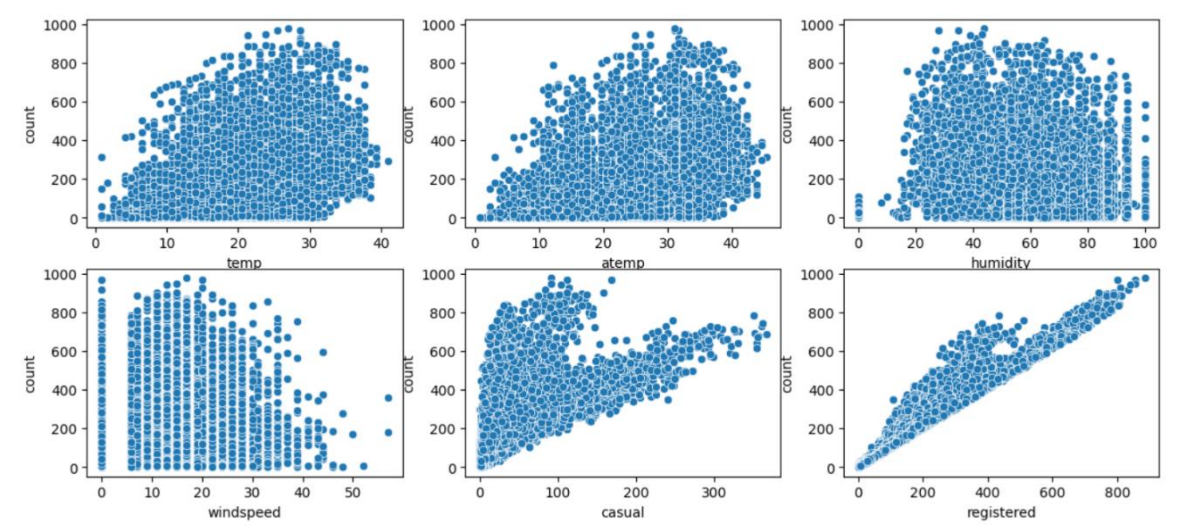
```
sns.boxplot(x = "weather" , y = "count" , data = yulu)

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.

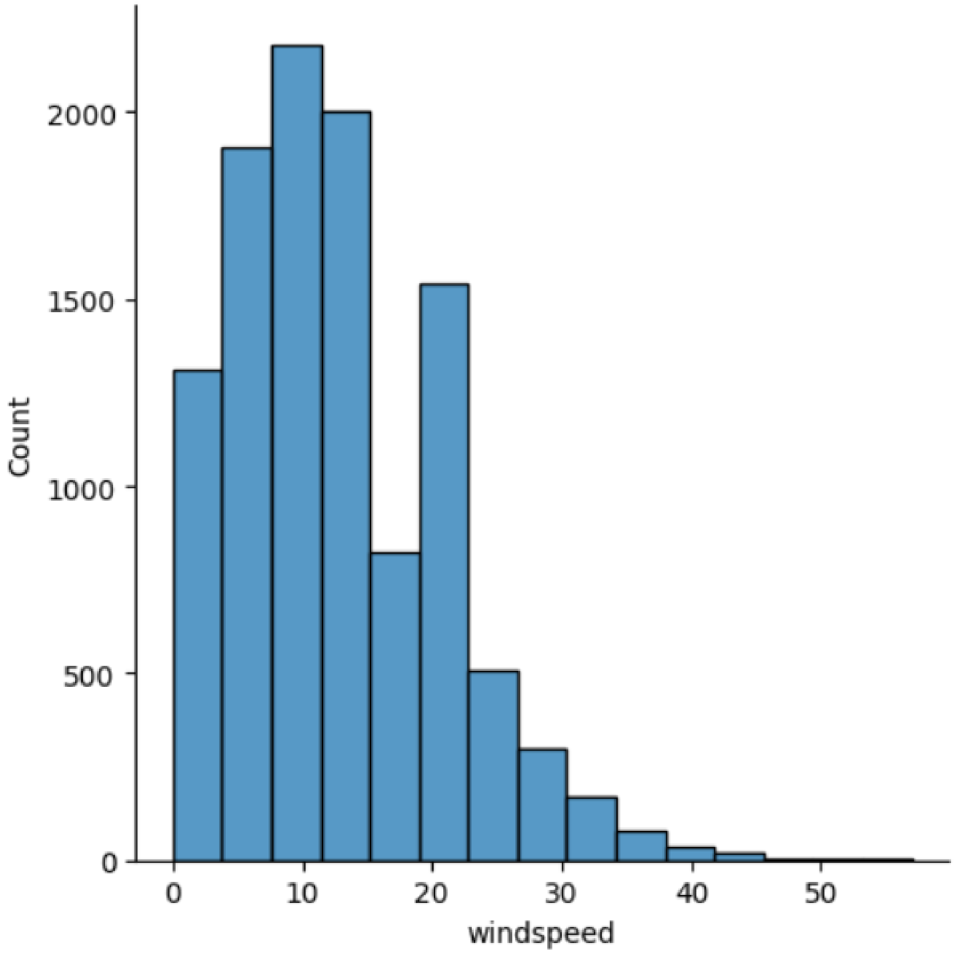
```
num_cols = ["temp" , "atemp" , "humidity" , "windspeed" , "casual" ,
"registered" , "count"]

index = 0

fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(14, 6))


for i in range(2) :
```

```
    for j in range(3) :

        sns.scatterplot(x = num_cols[index] , y = "count" , data = yulu
, ax = axis[i, j] )

        index = 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.

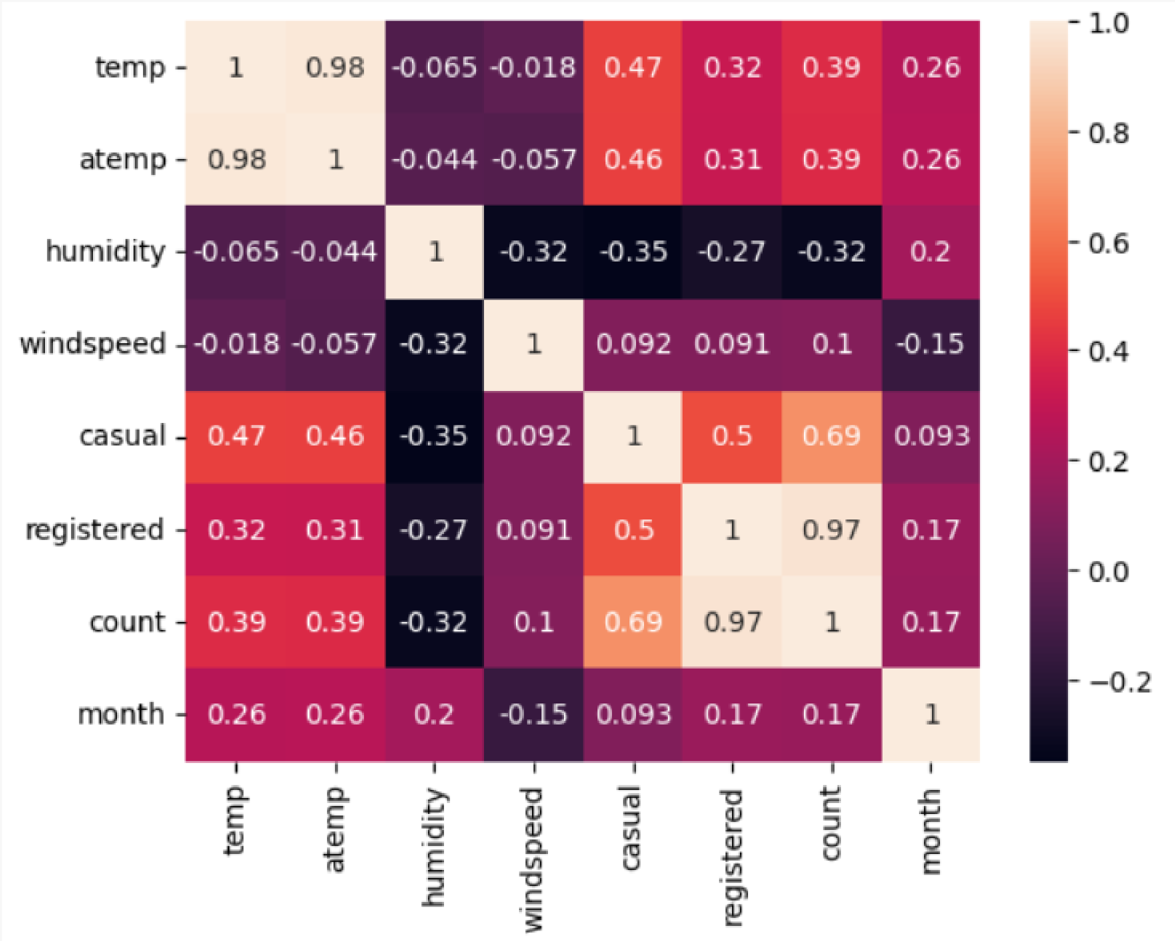
```
plt.figure(figsize = (15, 6))

sns.displot(x = "windspeed" , data = yulu , bins = 15)

plt.show()
```



2000
1500
1000
500
0
Count
0
10
20
30
40
50
windspeed

Multi-Variate Analysis :

```
sns.heatmap(data = yulu.corr() , annot = True )
plt.show()
```



- Temperature and number of cycles rented are positively correlated.
- Humidity and number of cycles rented are negatively correlated.
- There is a very high correlation between columns [temp , atemp] and [count , registered].

Hypothesis Testing on Working Day and Electric cycles rented :

Null Hypothesis (H0) : Working Day has no effect on number of electric cycles rented.

Alternative Hypothesis (H1) : Working Day has an effect on number of electric cycles rented.

Significance Value (alpha) : 0.05

We will use T-test for this case as Working Day has 2 categories

```
t_stat , p_value = ttest_ind(yulu.loc[yulu.workingday == 1 ,
"count"] , yulu.loc[yulu.workingday == 0 , "count"])


print(np.round(t_stat , 2))
```

```
1.21
```

```
print(p_value)
```

```
0.23
```

Since p_value is greater than significance values we can not reject null hypothesis. Hence we don't have enough evidence to conclude that working day has an effect on number of electric cycles rented.

Hypothesis Testing on Holiday and Electric cycles rented :

Null Hypothesis (H0) : Holiday has no effect on number of electric cycles rented.

Alternative Hypothesis (H1) : Holiday has an effect on number of electric cycles rented.

Significance Value (alpha) : 0.05

We will use T-test for this case as Holiday has 2 categories

```
t_stat , p_value = ttest_ind(yulu.loc[yulu.holiday == 1 , "count"]
, yulu.loc[yulu.holiday == 0 , "count"])


print(np.round(t_stat , 2))
```

```
-0.56
```

```
print(p_value)
```

```
0.57
```

Since p_value is greater than significance values we can not reject null hypothesis. Hence we don't have enough evidence to conclude that holiday has an effect on number of electric cycles rented.

Hypothesis Testing on Season and Electric cycles rented :

```
print(yulu.season.unique())
```

```
[1 2 3 4]
```

We can use ANOVA for this case as Season has more than 2 categories.

Checking conditions of ANOVA :

1. Normal Distribution.

2. Categories should be independent of each other.

3. There should be equal variance between the categories.

If any of the above conditions fails we will not proceed with ANOVA for Hypothesis testing we will use KRUSKAL test.

Checking Normal Distribution for count column:

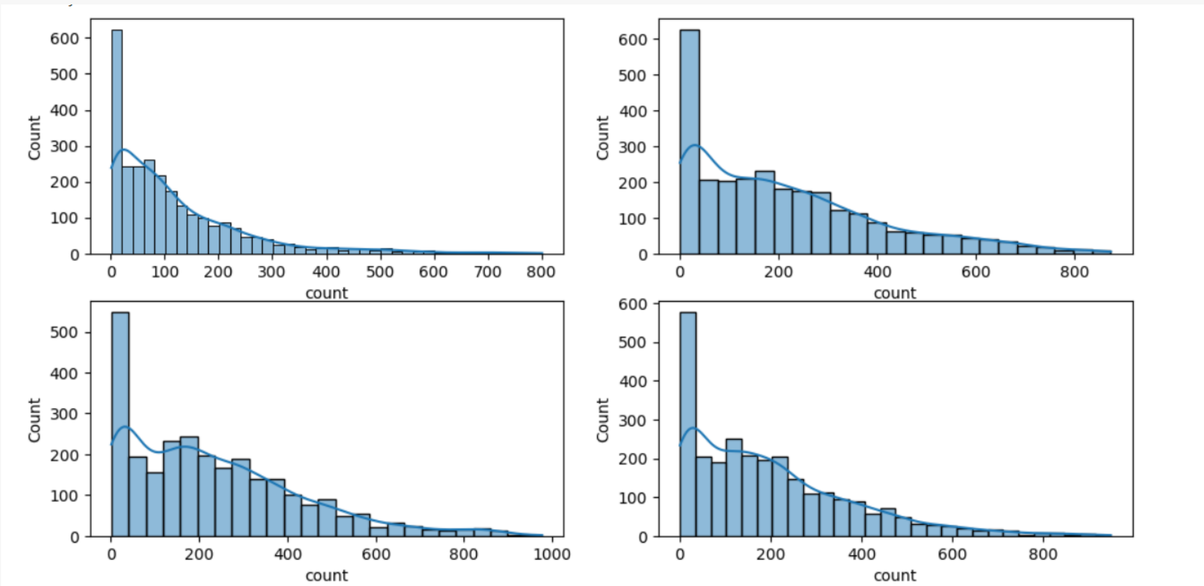
<u>SHAPIRO TEST -></u>

Null Hypothesis : Data follow Normal Distribution.

Alternative Hypothesis : Data doesn't follow Normal Distribution.

Significance value = 0.05

```
plt.figure(figsize = (12, 6))
for i in range(1, 5) :
  df_season = yulu[yulu.season == i]["count"]
  plt.subplot(2, 2, i)
  sns.histplot(x = df_season, kde = True )
plt.show()
```



From histplot we can say that it does not follows normal distribution.

Taking sample size as 100

```
count_subset = yulu["count"].sample(100)

shapiro_stat , p_value2 = shapiro(count_subset)


print(np.round(shapiro_stat , 2))
```

```
0.9
```

```
print(p_value2)
```

```
2.114466290947803e-08
```

Since p_value is less than significance value we reject null hypothesis. Hence we don't have enough evidence to conclude that column count follows normal distribution.

Checking equal variance for the categories:

<u>LEVENE TEST -></u>

Null Hypothesis : Variance is same for different categories.

Alternative Hypothesis : Variance is not same for different categories.

Significance value = 0.05

```
levene_stat , p_value = levene(yulu.loc[yulu.season == 1 , "count"]
, yulu.loc[yulu.season == 2 , "count"], yulu.loc[yulu.season == 3 ,
"count"], yulu.loc[yulu.season == 4 , "count"])
```

```
print(np.round(levene_stat , 2))
```

```
187.77
```

```
print(p_value)
```

```
1.0147116860043298e-118
```

Since p_value is less than significance value we reject null hypothesis. Hence we don't have enough evidence to conclude that column season categories have equal variance.

-> As conditions of ANOVA is not satisfied we will proceed with KRUSKAL.

<u>KRUSKAL TEST -></u>

Null Hypothesis : Weather has no effect on number of electric cycles rented.

Alternative Hypothesis : Weather has an effect on number of electric cycles rented.

Significance value = 0.05

```
kruskal_stat , p_value = kruskal(yulu.loc[yulu.season == 1 ,
"count"] , yulu.loc[yulu.season == 2 , "count"],
yulu.loc[yulu.season == 3 , "count"], yulu.loc[yulu.season == 4 ,
"count"])
```

```python
print(np.round(kruskal_stat , 2))
```

```
699.67
```

```python
print(p_value)
```

```
2.479008372608633e-151
```

Since p_value is less than significance value we can reject null hypothesis. Hence we have enough evidence to conclude that season has an effect on number of electric cycles rented.

If we use ANOVA :

<u>ANOVA TEST -></u>

Null Hypothesis : Weather has no effect on number of electric cycles rented.

Alternative Hypothesis : Weather has an effect on number of electric cycles rented.

Significance value = 0.05

```python
anova_stat , p_value = f_oneway(yulu.loc[yulu.season == 1 ,
"count"] , yulu.loc[yulu.season == 2 , "count"],
yulu.loc[yulu.season == 3 , "count"], yulu.loc[yulu.season == 4 ,
"count"])
```

```python
print(np.round(anova_stat , 2))
```

```
236.95
```

```python
print(p_value)
```

```
6.164843386499654e-149
```

Since p_value is less than significance value we can reject null hypothesis. Hence we do have enough evidence to conclude that season has an effect on number of electric cycles rented.

Hypothesis Testing on Weather and Electric cycles rented :

```
print(yulu.weather.unique())
```

```
[1 2 3 4]
```

We can use ANOVA for this case as Weather has more than 2 categories.

Checking conditions of ANOVA :

1. Normal Distribution.

2. Categories should be independent of each other.

3. There should be equal variance between the categories.

If any of the above conditions fails we will not proceed with ANOVA for Hypothesis testing we will use KRUSKAL.

Checking Normal Distribution for count column:

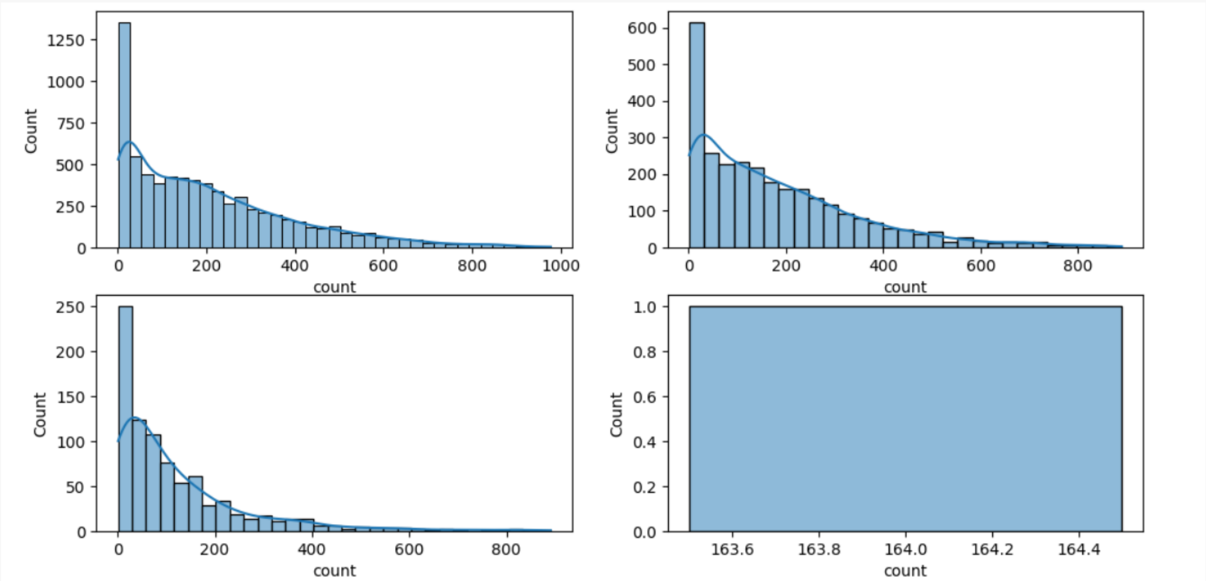
SHAPIRO TEST ->

Null Hypothesis : Data follow Normal Distribution.

Alternative Hypothesis : Data doesn't follow Normal Distribution.

Significance value = 0.05

```
plt.figure(figsize = (12, 6))
for i in range(1, 5) :
  df_season = yulu[yulu.weather == i]["count"]
  plt.subplot(2, 2, i)
  sns.histplot(x = df_season, kde = True )
plt.show()
```



From histplot we can say that it does not follows normal distribution.

Taking sample size as 100

```
count_subset = yulu["count"].sample(100)

shapiro_stat , p_value2 = shapiro(count_subset)


print(np.round(shapiro_stat , 2))
```

```
0.83
```

```
print(p_value2)
```

```
7.298385895637693e-08
```

Since p_value is less than significance value we reject null hypothesis. Hence we don't have enough evidence to conclude that column count follows normal distribution.

Checking equal variance for the categories:

<u>LEVENE TEST -></u>

Null Hypothesis : Variance is same for different categories.

Alternative Hypothesis : Variance is not same for different categories.

Significance value = 0.05

```
levene_stat , p_value = levene(yulu.loc[yulu.weather == 1 ,
"count"] , yulu.loc[yulu.weather == 2 , "count"],
yulu.loc[yulu.weather == 3 , "count"], yulu.loc[yulu.weather == 4 ,
"count"])


print(np.round(levene_stat , 2))
```

```
54.85
```

```python
print(p_value)
```

```
3.504937946833238e-35
```

Since p_value is less than significance value we reject null hypothesis. Hence we don't have enough evidence to conclude that column weather categories have equal variance.

-> As conditions of ANOVA is not satisfied we will proceed with KRUSKAL.

KRUSKAL TEST ->

Null Hypothesis : Weather has no effect on number of electric cycles rented.

Alternative Hypothesis : Weather has an effect on number of electric cycles rented.

Significance value = 0.05

```python
kruskal_stat , p_value = kruskal(yulu.loc[yulu.weather == 1 ,
"count"] , yulu.loc[yulu.weather == 2 , "count"],
yulu.loc[yulu.weather == 3 , "count"], yulu.loc[yulu.weather == 4 ,
"count"])
```

```python
print(np.round(kruskal_stat , 2))
```

```
205.0
```

```python
print(p_value)
```

```
3.501611300708679e-44
```

Since p_value is less than significance value we can reject null hypothesis. Hence we have enough evidence to conclude that weather has an effect on number of electric cycles rented.

If we use ANOVA :

<u>ANOVA TEST -></u>

Null Hypothesis : Weather has no effect on number of electric cycles rented.

Alternative Hypothesis : Weather has an effect on number of electric cycles rented.

Significance value = 0.05

```
anova_stat , p_value = f_oneway(yulu.loc[yulu.weather == 1 ,
"count"] , yulu.loc[yulu.weather == 2 , "count"],
yulu.loc[yulu.weather == 3 , "count"], yulu.loc[yulu.weather == 4 ,
"count"])



print(np.round(anova_stat , 2))
```

```
65.53
```

```
print(p_value)
```

```
5.482069475935669e-42
```

Since p_value is less than significance value we can reject null hypothesis. Hence we have enough evidence to conclude that weather has an effect on number of electric cycles rented.

Hypothesis Testing on Weather and Season:

Null Hypothesis (H0) : Weather and Season are independent on each other.

Alternative Hypothesis (H1) : Weather and Season are dependent on each other.

Significance Value (alpha) : 0.05

We will use Chi-Square test for this case as we are dealing with two individual categorical fields.

```
crosstab = pd.crosstab(yulu.weather , yulu.season)
print(crosstab)
```

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

```
chi2_stat , p_value, df, exp_value = chi2_contingency(crosstab)

print(np.round(chi2_stat , 2))
```

```
49.16
```

```
print(p_value)
```

```
1.5499250736864862e-07
```

Since p_value is less than significance values we reject null hypothesis. Hence the column season and weather are dependent on each other.

Insights:

- In **summer** and **fall** seasons more bikes are rented as compared to other seasons.
- The average hourly count of rental bikes is the lowest in the month of January followed by February and March.
- Whenever it's a **holiday** more bikes are rented.
- It is also clear from the working day also that whenever day is holiday or weekend, slightly more bikes were rented.
- There is statistically significant dependency of weather and season based on the total number of bikes 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.
- With a significance level of 0.05, working day and holiday has no effect on the number of bikes being rented.
- With a significance level of 0.05, Season and Weather has an effect on the number of bikes being rented.

Recommendations:

- **Seasonal Marketing**: Since there is a clear seasonal pattern in the count of rental bikes, Yulu can adjust its marketing strategies accordingly. Focus on promoting bike rentals during the spring and summer months when there is higher demand. Offer seasonal discounts or special packages to attract more customers during these periods.

- **Time-based Pricing**: Take advantage of the hourly fluctuation in bike rental counts throughout the day. Consider implementing time-based pricing where rental rates are lower during off-peak hours and higher during peak hours. This can encourage customers to rent bikes during less busy times, balancing out the demand and optimizing the resources.

- **Weather-based Promotions**: Recognize the impact of weather on bike rentals. Create weather-based promotions that target customers during clear and cloudy weather, as these conditions show the highest rental counts. Yulu can offer weather-specific discounts to attract more customers during these favorable weather conditions.

- **User Segmentation**: Given that around 81% of users are registered, and the remaining 19% are casual, Yulu can tailor its marketing and communication strategies accordingly. Provide loyalty programs, exclusive offers, or personalized recommendations for registered users to encourage repeat business. For casual users, focus on providing a seamless rental experience and promoting the benefits of bike rentals for occasional use.

- **Optimize Inventory**: Analyze the demand patterns during different months and adjust the inventory accordingly. During months with lower rental counts such as January, February, and March, Yulu can optimize its inventory levels to avoid excess bikes. On the other hand, during peak months, ensure having sufficient bikes available to meet the higher demand.

- **Improve Weather Data Collection**: Given the lack of records for extreme weather conditions, consider improving the data collection process for such scenarios. Having more data on extreme weather conditions can help to understand customer behavior and adjust the operations accordingly, such as offering specialized bike models for different weather conditions or implementing safety measures during extreme weather.

- **Customer Comfort**: Since humidity levels are generally high and temperature is often below 28 degrees Celsius, consider providing amenities like umbrellas, rain jackets, or water bottles to enhance the comfort and convenience of the customers. These small touches can contribute to a positive customer experience and encourage repeat business.

- **Collaborations with Weather Services**: Consider collaborating with weather services to provide real-time weather updates and forecasts to potential customers. Incorporate weather information into your marketing campaigns or rental app to showcase the ideal biking conditions and attract users who prefer certain weather conditions.

- **Seasonal Bike Maintenance**: Allocate resources for seasonal bike maintenance. Before the peak seasons, conduct thorough maintenance checks on the bike fleet to ensure they are in top condition. Regularly inspect and service bikes throughout the year to prevent breakdowns and maximize customer satisfaction.
- **Customer Feedback and Reviews**: Encourage customers to provide feedback and reviews on their biking experience. Collecting feedback can help identify areas for improvement, understand customer preferences, and tailor the services to better meet customer expectations.
- **Social Media Marketing**: Leverage social media platforms to promote the electric bike rental services. Share captivating visuals of biking experiences in different weather conditions, highlight customer testimonials, and engage with potential customers through interactive posts and contests. Utilize targeted advertising campaigns to reach specific customer segments and drive more bookings.
- **Special Occasion Discounts**: Since Yulu focusses on providing a sustainable solution for vehicular pollution, it should give special discounts on the occasions like Zero Emissions Day (21st September), Earth Day (22nd April), World Environment Day (5th June) etc in order to attract new users.