yulucasestudy

April 2, 2024

1 Yulu-Hypothesis-Testing

1.1 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.

1.2 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

[53]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from scipy.stats import ttest_ind, chi2_contingency, f_oneway, shapiro,␣
 ↪kruskal, levene
from statsmodels.graphics.gofplots import qqplot
```

Column Profiling(Given) - datetime: datetime - season: season (1: spring, 2: summer, 3: fall, 4: winter) - holiday : whether day is a holiday or not - workingday : if day is neither weekend nor holiday is 1, otherwise is 0. - weather: - 1: Clear, Few clouds, 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 Pellets + 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

[2]:
```
df = pd.read_csv('./bike_sharing.csv')
df.head()
```

[2]:
```
              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
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
```

[4]:
```
df.shape
```

[4]:
```
(10886, 12)
```

[3]:
```
df.dtypes
```

[3]:
```
datetime       object
season          int64
holiday         int64
workingday      int64
weather         int64
temp          float64
atemp         float64
humidity        int64
windspeed     float64
casual          int64
registered      int64
count           int64
dtype: object
```

[4]:
```
df.describe()
```

[4]:
```
             season       holiday    workingday       weather         temp  \
count  10886.000000  10886.000000  10886.000000  10886.000000  10886.00000
mean       2.506614      0.028569      0.680875      1.418427     20.23086
std        1.116174      0.166599      0.466159      0.633839      7.79159
min        1.000000      0.000000      0.000000      1.000000      0.82000
25%        2.000000      0.000000      0.000000      1.000000     13.94000
50%        3.000000      0.000000      1.000000      1.000000     20.50000
75%        4.000000      0.000000      1.000000      2.000000     26.24000
```

```
max        4.000000      1.000000      1.000000      4.000000     41.00000

                atemp      humidity     windspeed        casual    registered  \
count  10886.000000  10886.000000  10886.000000  10886.000000  10886.000000
mean      23.655084     61.886460     12.799395     36.021955    155.552177
std        8.474601     19.245033      8.164537     49.960477    151.039033
min        0.760000      0.000000      0.000000      0.000000      0.000000
25%       16.665000     47.000000      7.001500      4.000000     36.000000
50%       24.240000     62.000000     12.998000     17.000000    118.000000
75%       31.060000     77.000000     16.997900     49.000000    222.000000
max       45.455000    100.000000     56.996900    367.000000    886.000000

                count
count  10886.000000
mean     191.574132
std      181.144454
min        1.000000
25%       42.000000
50%      145.000000
75%      284.000000
max      977.000000
```

[5]:
```
df.describe(include='object')
```

[5]:
```
                   datetime
count                 10886
unique                10886
top     2011-01-01 00:00:00
freq                      1
```

[6]:
```
df.isna().sum()
```

[6]:
```
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 is No missing values in the dataset.

[7]:
```python
df["humidity"].nunique()
```

[7]: 89

[8]:
```python
df["temp"].nunique()
```

[8]: 49

[9]:
```python
df["atemp"].nunique()
```

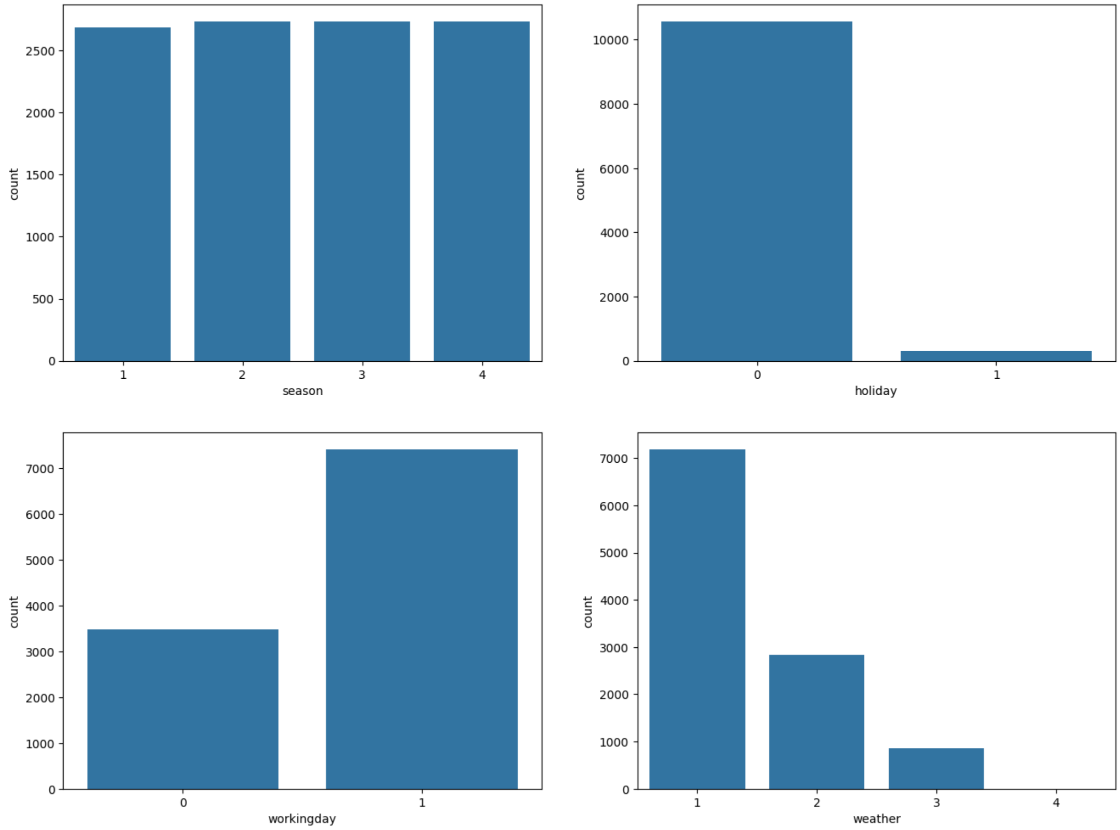
[9]: 60

[10]:
```python
df["windspeed"].nunique()
```

[10]: 28

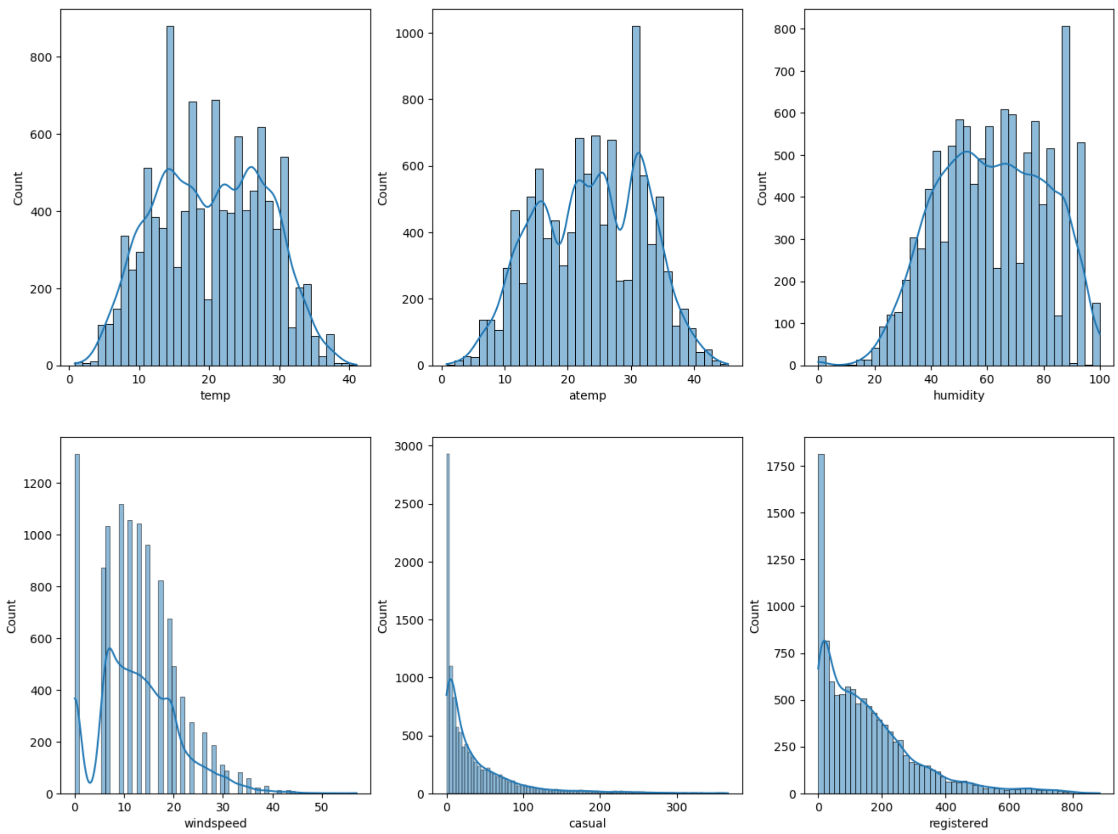
2 Univariate Analysis

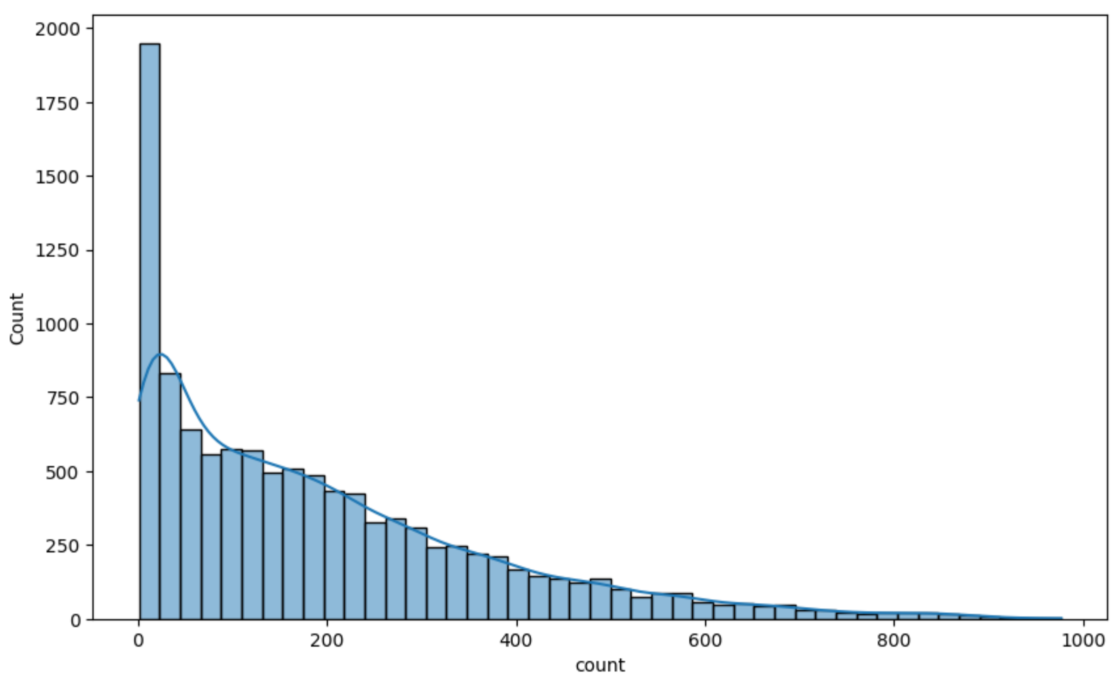
[11]:
```python
cat = ['season', 'holiday', 'workingday', 'weather']

fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))

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

plt.show()
```



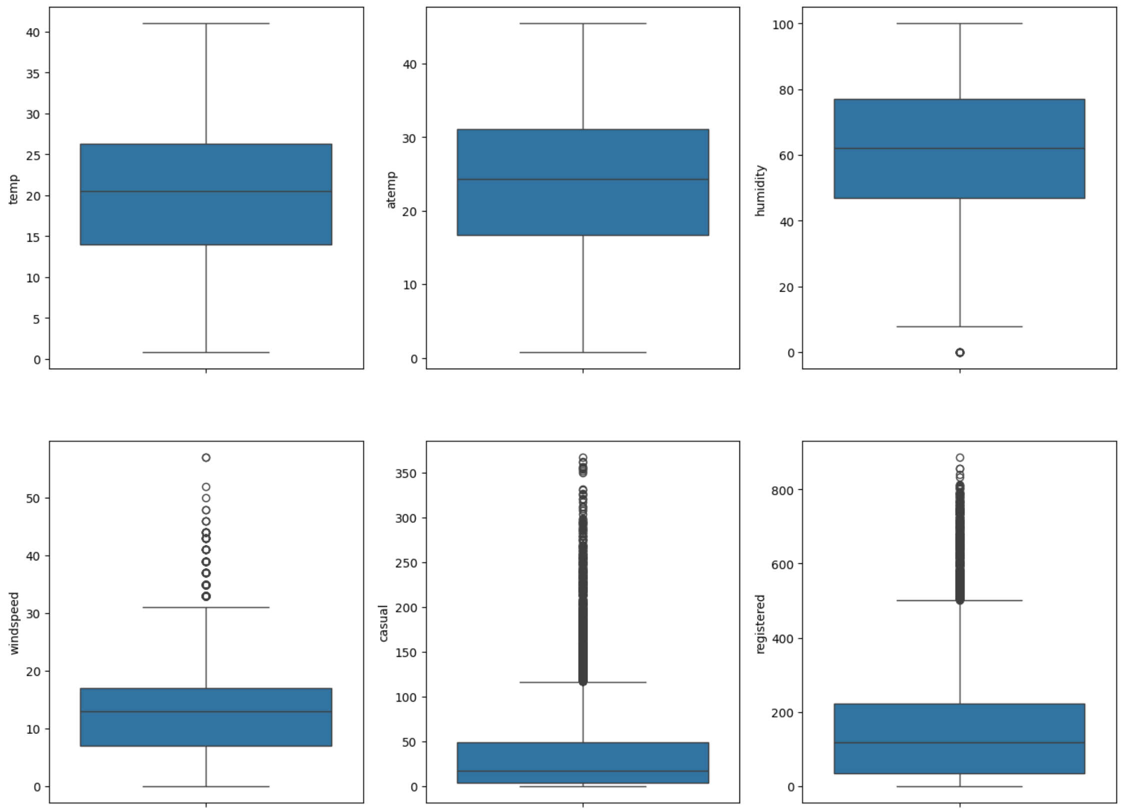
[12]:

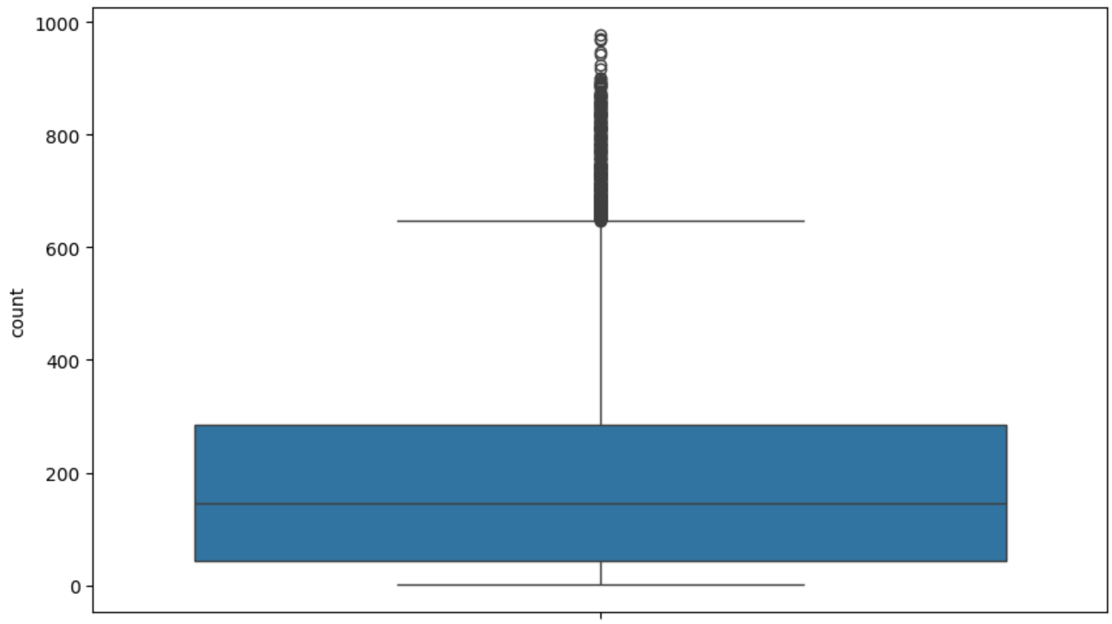
```
nums_cols = ['temp', 'atemp', 'humidity', 'windspeed','casual','registered','count']
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 12))

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

plt.show()
plt.figure(figsize=(10,6))
sns.histplot(df[nums_cols[-1]],kde=True)
plt.show()
```


Count
temp
atemp
humidity
windspeed
casual
registered


Count
count

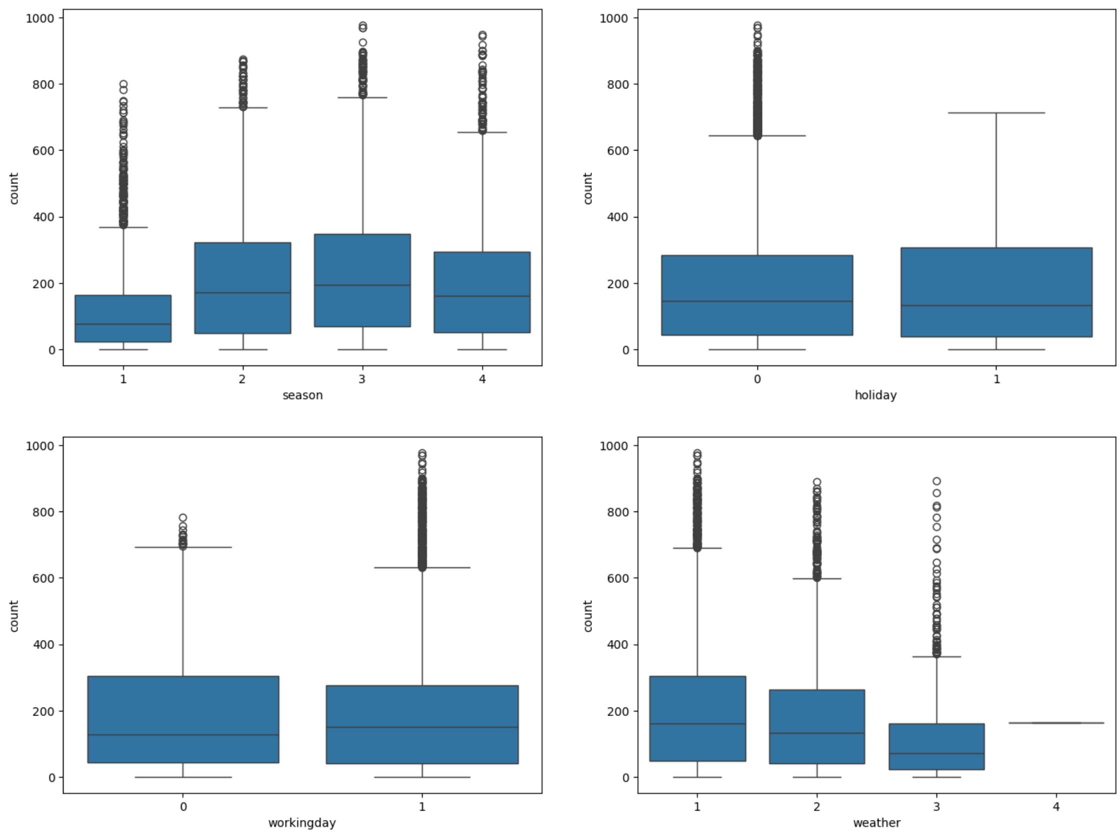
[13]:
```
nums_cols = ['temp', 'atemp', 'humidity',␣
↪'windspeed','casual','registered','count']
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 12))

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

plt.show()
plt.figure(figsize=(10,6))
sns.boxplot(df[nums_cols[-1]])
plt.show()
```



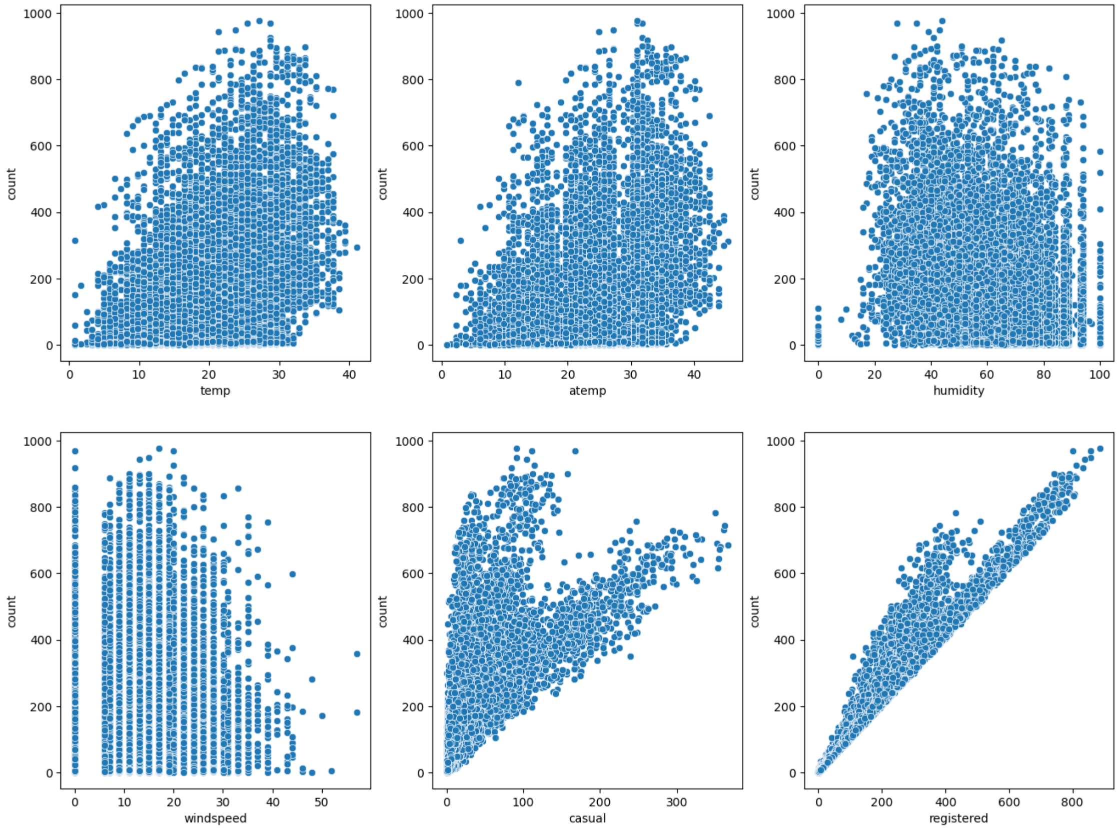


3 Bivariate Analysis

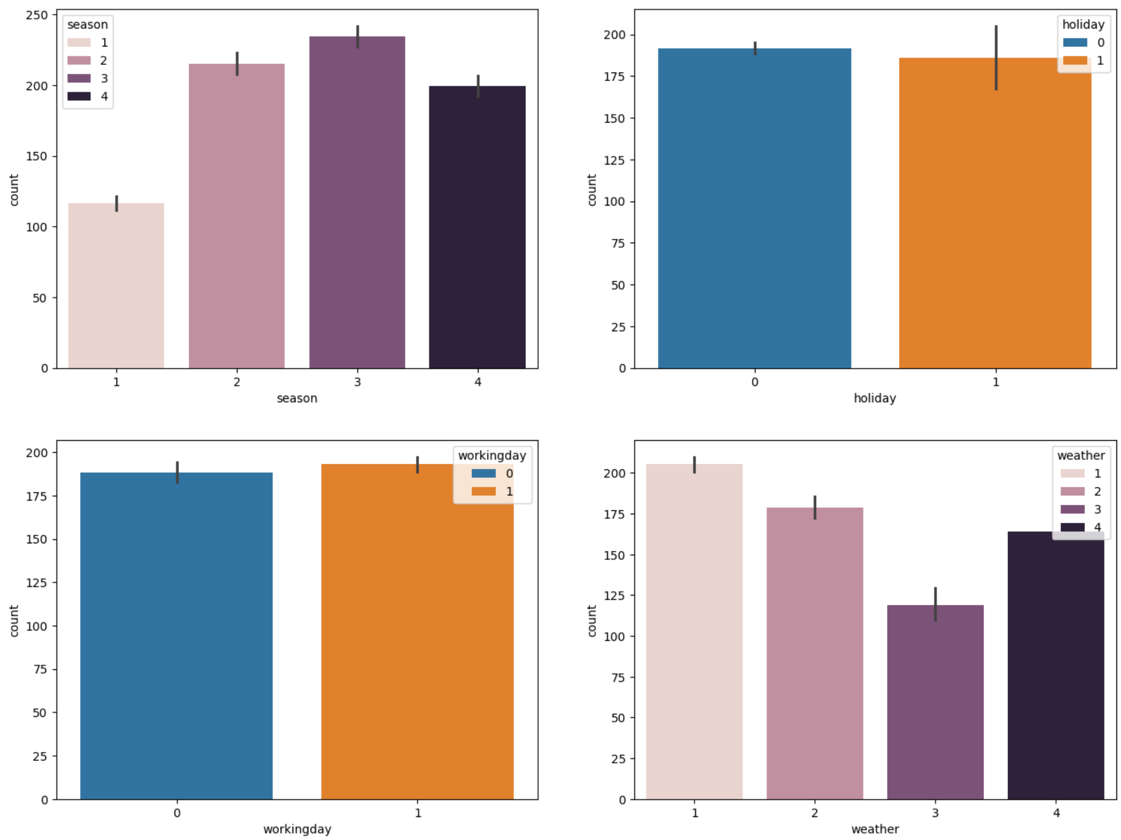
[14]:
```
cat = ['season', 'holiday', 'workingday', 'weather']
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))

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

plt.show()
```



[15]:
```
nums_cols = ['temp', 'atemp', 'humidity',␣
↪'windspeed','casual','registered','count']
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 12))

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

plt.show()
```



[98]:
```
# Count vs Categorical
cat = ['season', 'holiday', 'workingday', 'weather']
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))

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

plt.show()
```



Weather - Clear weather has most no of demand where as heavy rain has more demand than light rain(That is strange) - Cloudy weather also lowest no of demand for cycles.

Season - Fall has the highest demand for shared electric cycles - Summer and winter have almost the same demand - Spring Season has lowest no of demand

Holiday - Non-Holiday has the slightly more demand for shared electric cycles

Working Day - Working Day has slightly more demand for shared electric cycles than weekends

4 Multivariate Analysis

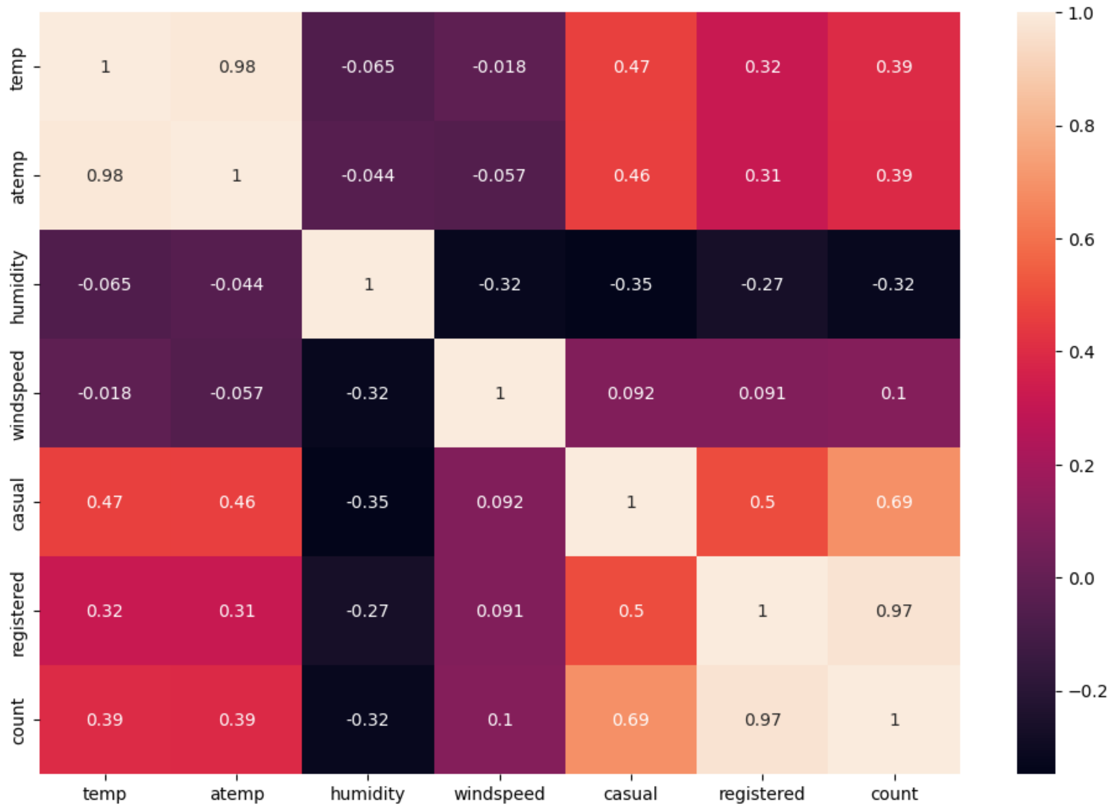
[24]:
```
df_num = df[nums_cols]
df_num.corr()
```

[24]:
```
                temp     atemp  humidity  windspeed    casual  registered  \
temp        1.000000  0.984948 -0.064949  -0.017852  0.467097    0.318571
atemp       0.984948  1.000000 -0.043536  -0.057473  0.462067    0.314635
humidity   -0.064949 -0.043536  1.000000  -0.318607 -0.348187   -0.265458
windspeed  -0.017852 -0.057473 -0.318607   1.000000  0.092276    0.091052
casual      0.467097  0.462067 -0.348187   0.092276  1.000000    0.497250
registered  0.318571  0.314635 -0.265458   0.091052  0.497250    1.000000
```

```
count        0.394454  0.389784 -0.317371   0.101369  0.690414    0.970948

                count
temp        0.394454
atemp       0.389784
humidity   -0.317371
windspeed   0.101369
casual      0.690414
registered  0.970948
count       1.000000
```

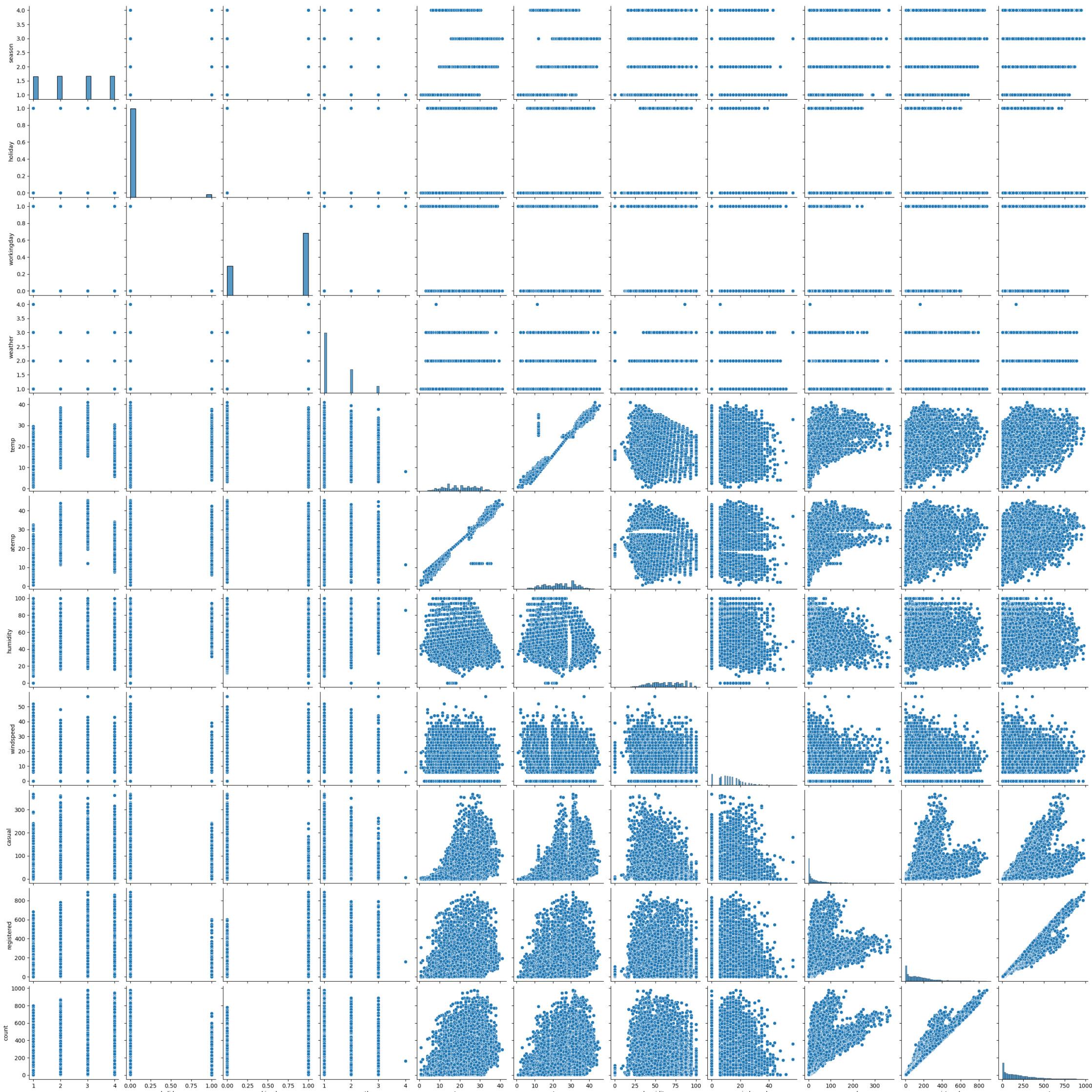
[25]:
```
plt.figure(figsize=(12,8))
sns.heatmap(df_num.corr(),annot=True)
```

[25]:
```
<Axes: >
```



[18]:
```
sns.pairplot(df)
```

[18]:
```
<seaborn.axisgrid.PairGrid at 0x222bbd628d0>
```



4.1 Hypothesis Testing

- We are taking significance level as 0.05 for all the hypothesis testing.

4.1.1 Chi-Square Test

Weather and season are dependent or Independent - Null Hypothesis(H0): Weather and season are independent. - Alternate Hypothesis(Ha): Weather and season are dependent.

[29]:
```
weather = df["weather"]
season = df["season"]
val = pd.crosstab(weather, season)
val
```

[29]:
```
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
```

[30]:
```python
# calculate chi2_contingency
chi2, p, dof, ex = chi2_contingency(val)
print(f"Chi2: {chi2}, p-value: {p}, dof: {dof}")

if p < 0.05:
    print("Reject H0: Weather and Season are dependent")
else:
    print("Fail to Reject H0: Weather and Season are independent")
```

```
Chi2: 49.15865559689363, p-value: 1.5499250736864862e-07, dof: 9
Reject H0: Weather and Season are dependent
```

4.1.2 T-Test

Working Day and Count are dependent or Independent - Null Hypothesis(H0): Working Day and Count are independent. - Alternate Hypothesis(Ha): Working Day and Count are dependent.

[34]:
```python
working_day = df[df["workingday"] ==1]['count']
nonWorking_day = df[df["workingday"] == 0]['count']
```

[35]:
```python
stats, p_value = ttest_ind(working_day, nonWorking_day)
print(f"p-value: {p_value}")
print(f"stats: {stats}")

if p_value < 0.05:
  print("Reject H0: Working Day and count are Dependent")
else:
  print("Reject Ha: Working Day and count are Independent")
```

```
p-value: 0.22644804226361348
stats: 1.2096277376026694
Reject Ha: Working Day and count are Independent
```

4.1.3 Anova Test

No. of cycles rented similar or different in different seasons - Null Hypothesis(H0): No. of cycles rented similar in different seasons. - Alternate Hypothesis(Ha): No. of cycles rented different in different seasons.

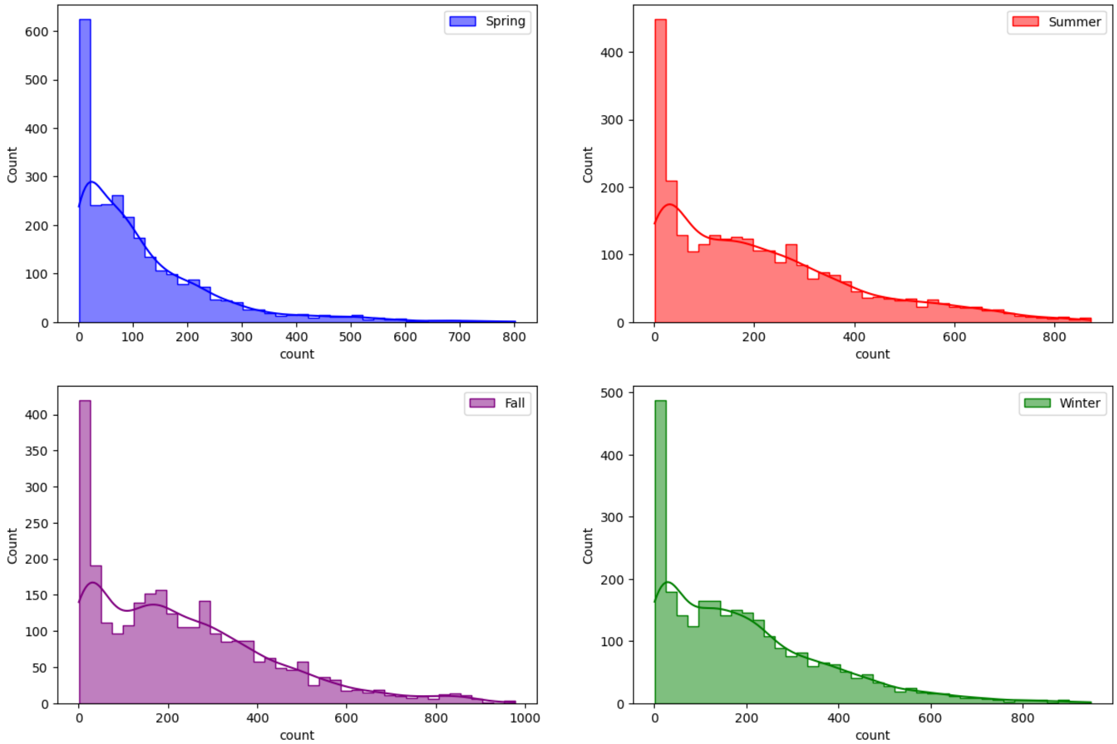
[41]:
```python
spring = df[df["season"] == 1]['count']
summer = df[df["season"] == 2]['count']
fall = df[df["season"] == 3]['count']
winter = df[df["season"] == 4]['count']

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

[41]:
```
season
1    116.343261
2    215.251372
3    234.417124
4    198.988296
Name: count, dtype: float64
```

To check the above hypothesis, we will perform the following steps: - Check normality of the data - Check variance of the data

Checking Normality

[80]:
```python
plt.figure(figsize=(15, 10))

plt.subplot(2, 2, 1)
sns.histplot(spring, bins=40, element='step', color='blue', kde=True,␣
 ↪label='Spring')
plt.legend()

plt.subplot(2, 2, 2)
sns.histplot(summer, bins=40, element='step', color='red', kde=True,␣
 ↪label='Summer')
plt.legend()

plt.subplot(2, 2, 3)
sns.histplot(fall, bins=40, element='step', color='purple', kde=True,␣
 ↪label='Fall')
plt.legend()

plt.subplot(2, 2, 4)
sns.histplot(winter, bins=40, element='step', color='green', kde=True,␣
 ↪label='Winter')
plt.legend()

plt.subplots_adjust(hspace=0.2, wspace=0.2)
plt.show()
```

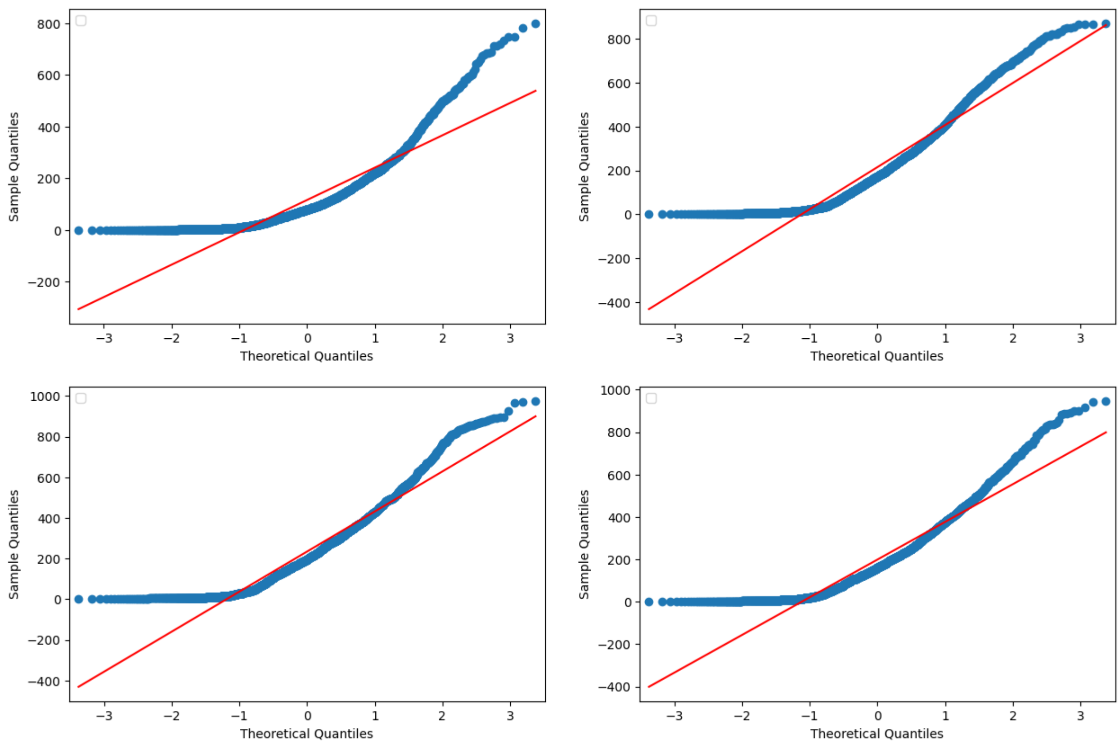


QQ plot to check normality

[52]:
```
plt.figure(figsize=(15, 10))

plt.subplot(2, 2, 1)
qqplot(spring, line='s', ax=plt.gca())
plt.legend()

plt.subplot(2, 2, 2)
qqplot(summer, line='s', ax=plt.gca())
plt.legend()

plt.subplot(2, 2, 3)
qqplot(fall, line='s', ax=plt.gca())
plt.legend()

plt.subplot(2, 2, 4)
qqplot(winter, line='s', ax=plt.gca())
plt.legend()

plt.subplots_adjust(hspace=0.2, wspace=0.2)
plt.show()
```

```
No artists with labels found to put in legend.  Note that artists whose label
```

```
start with an underscore are ignored when legend() is called with no argument.
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
No artists with labels found to put in legend.  Note that artists whose label
start with an underscore are ignored when legend() is called with no argument.
```



The Data is donot normally distributed.

Shapiro Test - Spairo wilk test is used to confirm the normality of the data.

4.1.4 H0: Data is Gaussian

4.1.5 Ha: Data is not Gaussian

[69]:
```python
def checkNormality(data,name):
  print("Normality Test for:", name, "->")
  test_stat, p_value = shapiro(data)
  print("Stats: ", test_stat)
  print("P-value: ", p_value)



  if p_value < 0.05:
```

```
    print("Reject H0")
    print("Data is not Gaussian")
  else:
    print("Fail to reject H0")
    print("Data is Gaussian")
```

[83]:
```
season = [spring, summer, fall, winter]
name = ['Spring', 'Summer', 'Fall', 'Winter']
for i in range(4):
  checkNormality(season[i].iloc[:100], name[i])
```

```
Normality Test for: Spring ->
Stats:  0.8698215484619141
P-value:  6.89496957306801e-08
Reject H0
Data is not Gaussian
Normality Test for: Summer ->
Stats:  0.8869026303291321
P-value:  3.598051705466787e-07
Reject H0
Data is not Gaussian
Normality Test for: Fall ->
Stats:  0.9146706461906433
P-value:  7.421303507726407e-06
Reject H0
Data is not Gaussian
Normality Test for: Winter ->
Stats:  0.8757838010787964
P-value:  1.2084964851055702e-07
Reject H0
Data is not Gaussian
```

Data is not normally distributed. So, we have to use Kruksal Wallis Test.

4.1.6 Kruskal Wallis Test

[87]:
```
stats, p_value = kruskal(spring, summer, fall, winter)
print("P-value: ", p_value)
print("Stats: ", stats)

if p_value < 0.05:
  print("Reject H0")
  print("No. of cycles rented different in different seasons.")
else:
  print("Fail to reject H0")
  print("No. of cycles rented similar in different seasons.")
```

```
P-value:  2.479008372608633e-151
```

```
Stats:  699.6668548181988
Reject H0
No. of cycles rented different in different seasons.
```

4.1.7 Hypothesis Testing-4 : No. of cycles rented similar or different in different weather

No. of cycles rented similar or different in different seasons - Null Hypothesis(H0): No. of cycles rented similar in different weather. - Alternate Hypothesis(Ha): No. of cycles rented different in different weather.

[63]:
```python
clear = df[df["season"] == 1]['count']
mist = df[df["season"] == 2]['count']
light_rain = df[df["season"] == 3]['count']
heavy_rain = df[df["season"] == 4]['count']

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

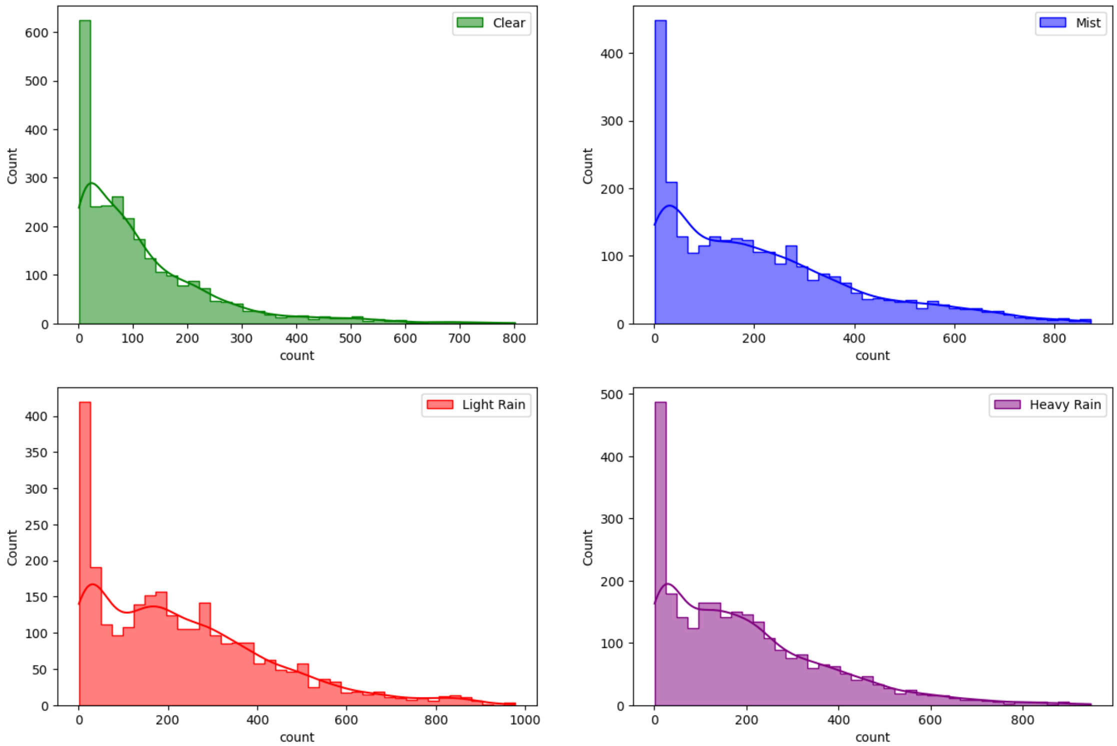
[63]:
```
weather
1    205.236791
2    178.955540
3    118.846333
4    164.000000
Name: count, dtype: float64
```

Check Normality

QQ plot

[82]:
```python
plt.figure(figsize=(15, 10))

plt.subplot(2, 2, 1)
sns.histplot(clear, bins=40, element='step', color='green', kde=True,␣
 ↪label='Clear')
plt.legend()

plt.subplot(2, 2, 2)
sns.histplot(mist, bins=40, element='step', color='blue', kde=True,␣
 ↪label='Mist')
plt.legend()

plt.subplot(2, 2, 3)
sns.histplot(light_rain, bins=40, element='step', color='red', kde=True,␣
 ↪label='Light Rain')
plt.legend()

plt.subplot(2, 2, 4)
sns.histplot(heavy_rain, bins=40, element='step', color='purple', kde=True,␣
 ↪label='Heavy Rain')
```

```
plt.legend()

plt.subplots_adjust(hspace=0.2, wspace=0.2)
plt.show()
```



Shapiro Test - Spairo wilk test is used to confirm the normality of the data.

4.1.8 H0: Data is Gaussian

4.1.9 Ha: Data is not Gaussian

[84]:
```
weathers = [clear, mist, light_rain, heavy_rain]
name = ['Clear', 'Mist', 'Light Rain', 'Heavy Rain']
for i in range(4):
  checkNormality(weathers[i].iloc[:100], name[i])
```

```
Normality Test for: Clear ->
Stats:  0.8698215484619141
P-value:  6.89496957306801e-08
Reject H0
Data is not Gaussian
Normality Test for: Mist ->
Stats:  0.8869026303291321
P-value:  3.598051705466787e-07
```

```
Reject H0
Data is not Gaussian
Normality Test for: Light Rain ->
Stats:  0.9146706461906433
P-value:  7.421303507726407e-06
Reject H0
Data is not Gaussian
Normality Test for: Heavy Rain ->
Stats:  0.8757838010787964
P-value:  1.2084964851055702e-07
Reject H0
Data is not Gaussian
```

Chekcing variance

[85]:
```python
# H0: Variance are equal
# Ha: Variance are not equal

levene_stat, p_value = levene(clear,mist,light_rain,heavy_rain)
print("Stats: ", levene_stat)
print("P-value: ", p_value)

if p_value < 0.05:
  print("Reject H0")
  print("Variance are not equal")
else:
  print("Fail to reject H0")
  print("Variance are equal")
```

```
Stats:  187.7706624026276
P-value:  1.0147116860043298e-118
Reject H0
Variance are not equal
```

We will use Kruskal Wallis Test as the data is not normally distributed.

[86]:
```python
stats, p_value = kruskal(clear, mist, light_rain, heavy_rain)
print("P-value: ", p_value)
print("Stats: ", stats)

if p_value < 0.05:
  print("Reject H0")
  print("No. of cycles rented different in different weathers.")
else:
  print("Fail to reject H0")
  print("No. of cycles rented similar in different weathers.")
```

```
P-value:  2.479008372608633e-151
Stats:  699.6668548181988
```

```
Reject H0
No. of cycles rented similar in different weathers.
```

5 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.

6 Recommendation

- 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 temprature 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.