Yulu_CaseStudy

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#**Business Case Study : Yulu**

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Yulu (About) :

Yulu is India's leading micro-mobility service provider, which offers unique vehicles for the daily commute. Starting off as a mission to eliminate traffic congestion in India, Yulu provides the safest commute solution through a user-friendly mobile app to enable shared, solo and sustainable commuting. Yulu zones are located at all the appropriate locations (including metro stations, bus stands, office spaces, residential areas, corporate offices, etc) to make those first and last miles smooth, affordable, and convenient! Yulu has recently suffered considerable dips in its revenues. They have contracted a consulting company to understand the factors on which the demand for these shared electric cycles depends. Specifically, they want to understand the factors affecting the demand for these shared electric cycles in the Indian market.

Problem Statement:

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:

- 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

Used Dataset Link : https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/original/bike_shar

0.1 Importing Libraries and Reading the Dataset

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

[ ]:
```
df = pd.read_csv('https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/
 ↪000/001/428/original/bike_sharing.csv?1642089089')
```

[ ]:
```
df
```

[ ]:
```
                  datetime  season  holiday  workingday  weather   temp  \
0      2011-01-01 00:00:00       1        0           0        1   9.84
1      2011-01-01 01:00:00       1        0           0        1   9.02
2      2011-01-01 02:00:00       1        0           0        1   9.02
3      2011-01-01 03:00:00       1        0           0        1   9.84
4      2011-01-01 04:00:00       1        0           0        1   9.84
…                      …     …       …          …      …    …
10881  2012-12-19 19:00:00       4        0           1        1  15.58
10882  2012-12-19 20:00:00       4        0           1        1  14.76
10883  2012-12-19 21:00:00       4        0           1        1  13.94
10884  2012-12-19 22:00:00       4        0           1        1  13.94
10885  2012-12-19 23:00:00       4        0           1        1  13.12

        atemp  humidity  windspeed  casual  registered  count
0      14.395        81     0.0000       3          13     16
1      13.635        80     0.0000       8          32     40
2      13.635        80     0.0000       5          27     32
3      14.395        75     0.0000       3          10     13
4      14.395        75     0.0000       0           1      1
…         …       …        …      …          …     …
10881  19.695        50    26.0027       7         329    336
10882  17.425        57    15.0013      10         231    241
10883  15.910        61    15.0013       4         164    168
10884  17.425        61     6.0032      12         117    129
```

```
10885  16.665         66     8.9981       4           84     88

[10886 rows x 12 columns]
```

0.2 Basic Analysis and Modifications

[ ]:
```python
df.shape
```

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

- The dataset has 10886 rows and 12 columns.

[ ]:
```python
df.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
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
```

[ ]:
```python
df.tail()
```

[ ]:
```
                 datetime  season  holiday  workingday  weather   temp  \
10881 2012-12-19 19:00:00       4        0           1        1  15.58
10882 2012-12-19 20:00:00       4        0           1        1  14.76
10883 2012-12-19 21:00:00       4        0           1        1  13.94
10884 2012-12-19 22:00:00       4        0           1        1  13.94
10885 2012-12-19 23:00:00       4        0           1        1  13.12

        atemp  humidity  windspeed  casual  registered  count
10881  19.695        50    26.0027       7         329    336
10882  17.425        57    15.0013      10         231    241
10883  15.910        61    15.0013       4         164    168
10884  17.425        61     6.0032      12         117    129
10885  16.665        66     8.9981       4          84     88
```

[ ]:
```python
df.columns
```

[ ]:
```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='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  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
```

- 'Season', 'holiday', 'workingday', 'weather', 'humidity', 'casual', 'registered', and 'count' are numerical columns.

[ ]:
```
np.any(df.duplicated())
```

[ ]: False

[ ]:
```
np.any(df.isna())
```

[ ]: False

- There are no duplicated values.
- There are no null values.

Converting DataTypes

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

categories = ['season', 'holiday', 'workingday', 'weather']
for col in categories:
```

```
    df[col] = df[col].astype('category')

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  category
 2   holiday     10886 non-null  category
 3   workingday  10886 non-null  category
 4   weather     10886 non-null  category
 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: category(4), datetime64[ns](1), float64(3), int64(4)
memory usage: 723.7 KB
```

- Converting categorical columns into category.

Mapping Data from Number to Variables

```
[ ]: df.season = df.season.replace({1: 'spring', 2: 'summer', 3: 'fall', 4:
      'winter'})

      df.weather = df.weather.replace({1: 'clear', 2: 'mist', 3: 'light_rain', 4:
      'heavy_rain'})

      df.holiday = df.holiday.replace({0: 'no', 1: 'yes'})

      df.workingday = df.workingday.replace({0: 'no', 1: 'yes'})
```

```
[ ]: df['month'] = df['datetime'].dt.month
     df.month = df.month.replace({1: 'January',2: 'February',3: 'March',4: 'April',5:
      'May',6: 'June',7: 'July',8: 'August',9: 'September',10: 'October',
                                  11: 'November',12: 'December'})
```

- Changing the data mapping for easy identification.

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

[ ]:
```
              count                           mean                  min  \
datetime      10886  2011-12-27 05:56:22.399411968  2011-01-01 00:00:00
temp        10886.0                       20.23086                 0.82
atemp       10886.0                      23.655084                 0.76
humidity    10886.0                       61.88646                  0.0
windspeed   10886.0                      12.799395                  0.0
casual      10886.0                      36.021955                  0.0
registered  10886.0                     155.552177                  0.0
count       10886.0                     191.574132                  1.0

                            25%                  50%                  75%  \
datetime    2011-07-02 07:15:00  2012-01-01 20:30:00  2012-07-01 12:45:00
temp                      13.94                 20.5                26.24
atemp                    16.665                24.24                31.06
humidity                   47.0                 62.0                 77.0
windspeed                7.0015               12.998              16.9979
casual                      4.0                 17.0                 49.0
registered                 36.0                118.0                222.0
count                      42.0                145.0                284.0

                            max         std
datetime    2012-12-19 23:00:00         NaN
temp                       41.0     7.79159
atemp                    45.455    8.474601
humidity                  100.0   19.245033
windspeed               56.9969    8.164537
casual                    367.0   49.960477
registered                886.0  151.039033
count                     977.0  181.144454
```

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

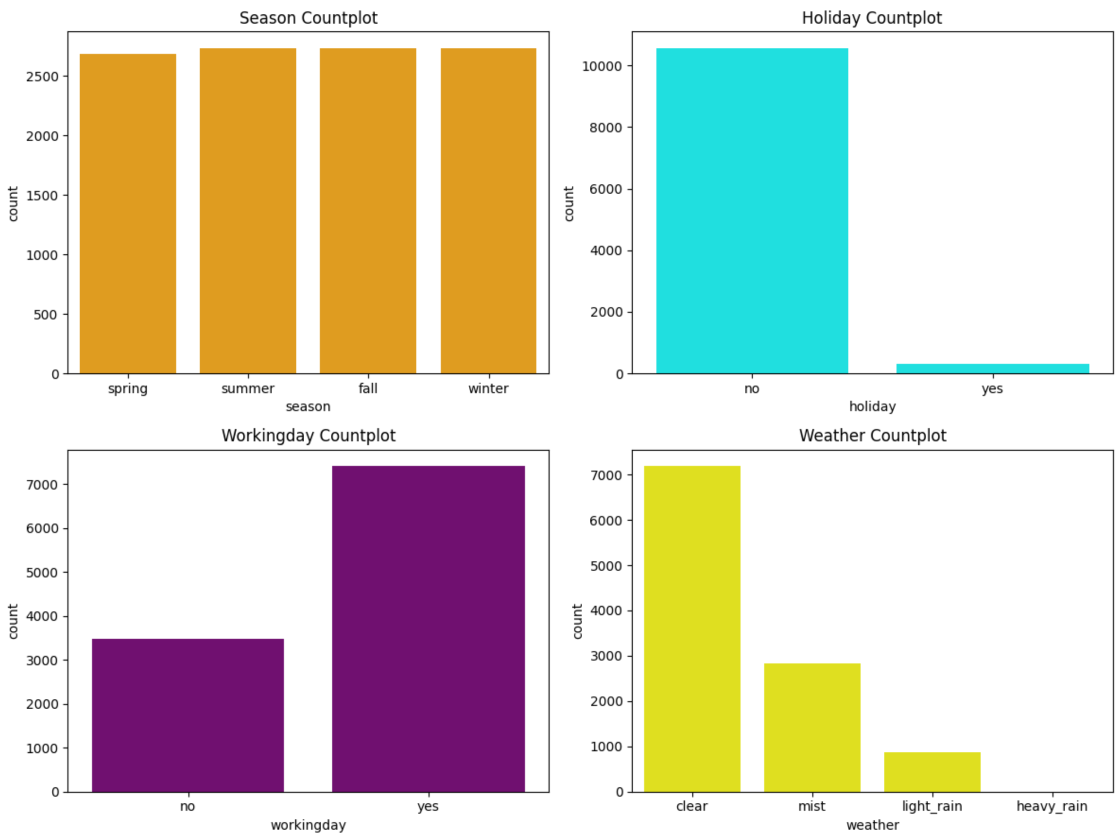
[ ]:
```
        season holiday workingday weather
count    10886   10886      10886   10886
unique       4       2          2       4
top     winter      no        yes   clear
freq      2734   10575       7412    7192
```

0.3 Univariate Analysis

Univariate for Categorical Data

[ ]:
```
fig, axes = plt.subplots(2, 2, figsize=(12, 9))

sns.countplot(x='season', data=df, ax=axes[0, 0],color='orange')
```

```
axes[0, 0].set_title('Season Countplot')

sns.countplot(x='holiday', data=df, ax=axes[0, 1],color='cyan')
axes[0, 1].set_title('Holiday Countplot')

sns.countplot(x='workingday', data=df, ax=axes[1, 0],color='purple')
axes[1, 0].set_title('Workingday Countplot')

sns.countplot(x='weather', data=df, ax=axes[1, 1],color='yellow')
axes[1, 1].set_title('Weather Countplot')
plt.tight_layout()

plt.show()
```



- Almost all the seasons have equal number of users.
- People hesitate to use the vehicle as the weather starts getting rainy.
- There are more number of electric cycles rented on non-holidays.

[ ]:
```
df['season'].value_counts()
```

[ ]:
```
season
winter    2734
summer    2733
fall      2733
spring    2686
Name: count, dtype: int64
```

[ ]:
```python
df['holiday'].value_counts()
```

[ ]:
```
holiday
no     10575
yes      311
Name: count, dtype: int64
```

[ ]:
```python
df['workingday'].value_counts()
```

[ ]:
```
workingday
yes    7412
no     3474
Name: count, dtype: int64
```

[ ]:
```python
df['weather'].value_counts()
```

[ ]:
```
weather
clear         7192
mist          2834
light_rain     859
heavy_rain       1
Name: count, dtype: int64
```

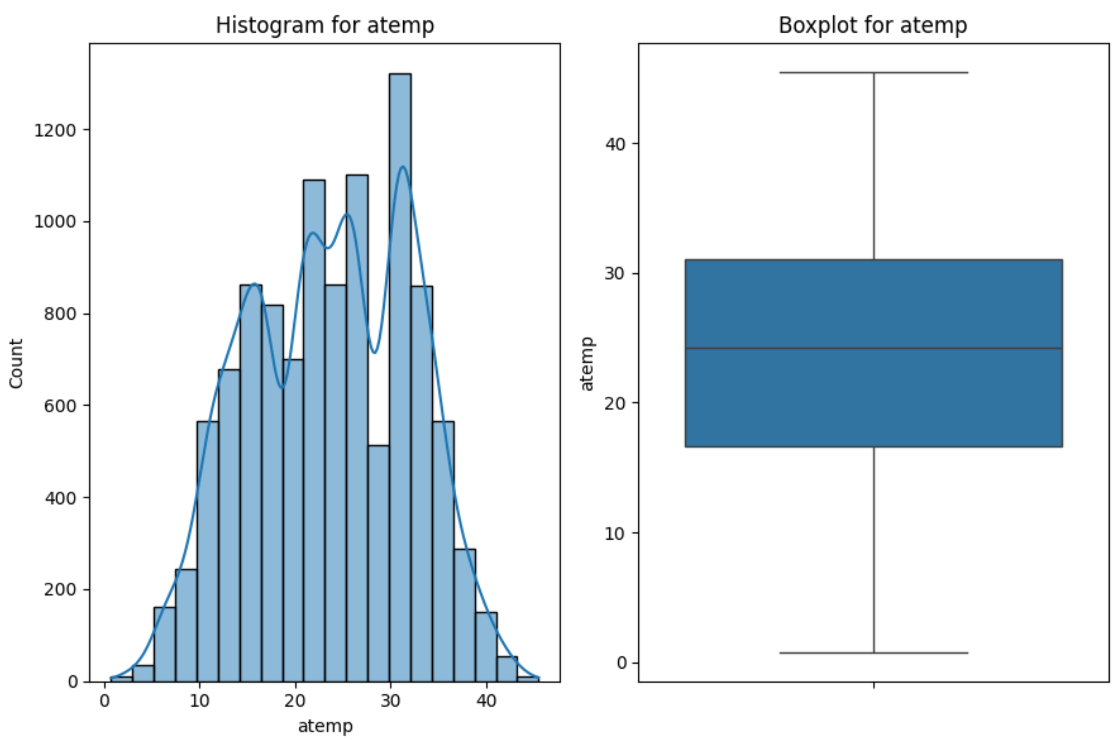
[ ]:
```python
df['month'].value_counts()
```

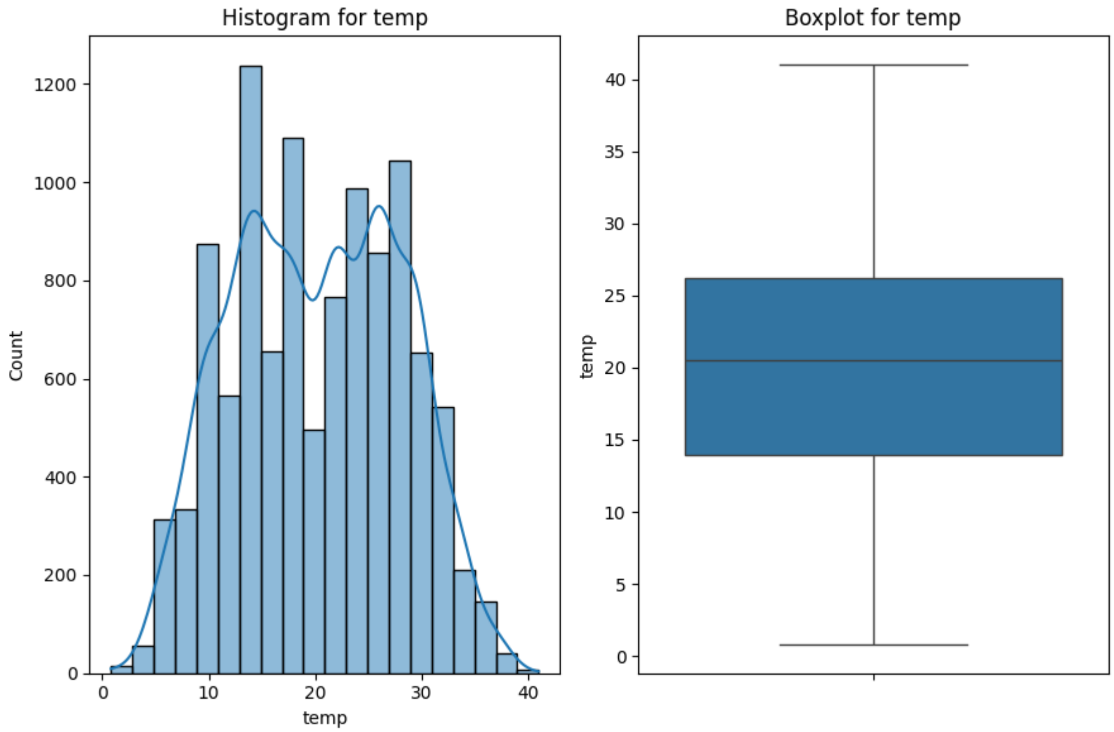
[ ]:
```
month
May          912
June         912
July         912
August       912
December     912
October      911
November     911
April        909
September    909
February     901
March        901
January      884
Name: count, dtype: int64
```

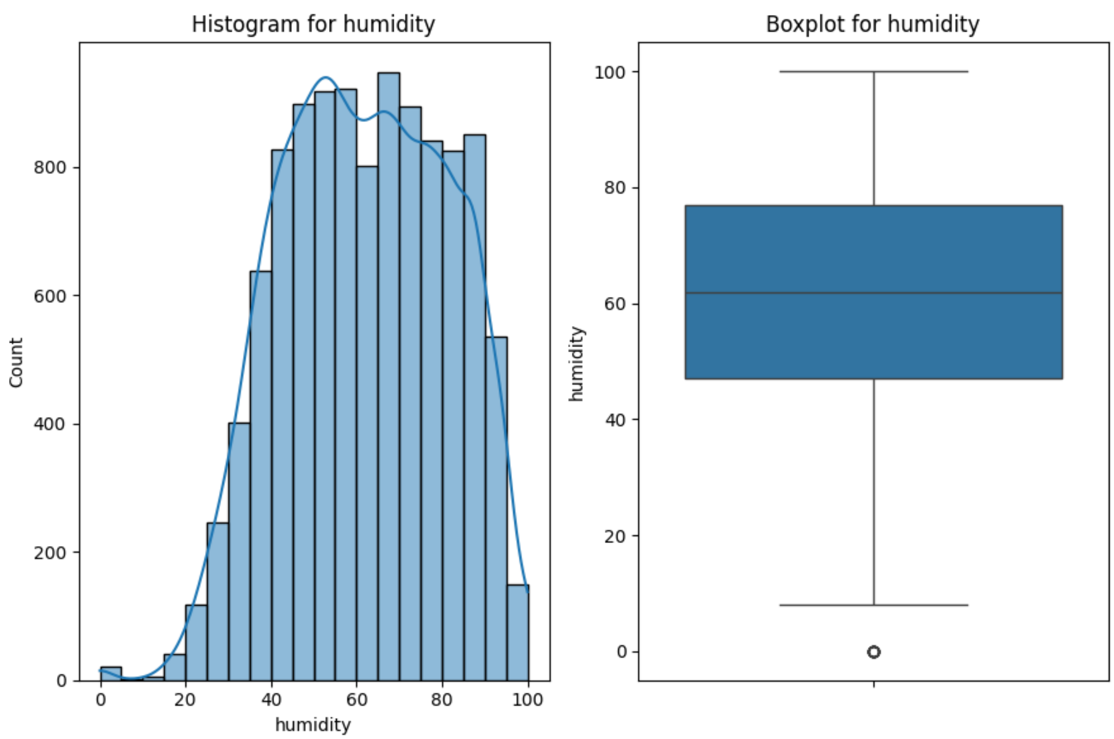
Univariate for Non-Categorical Data

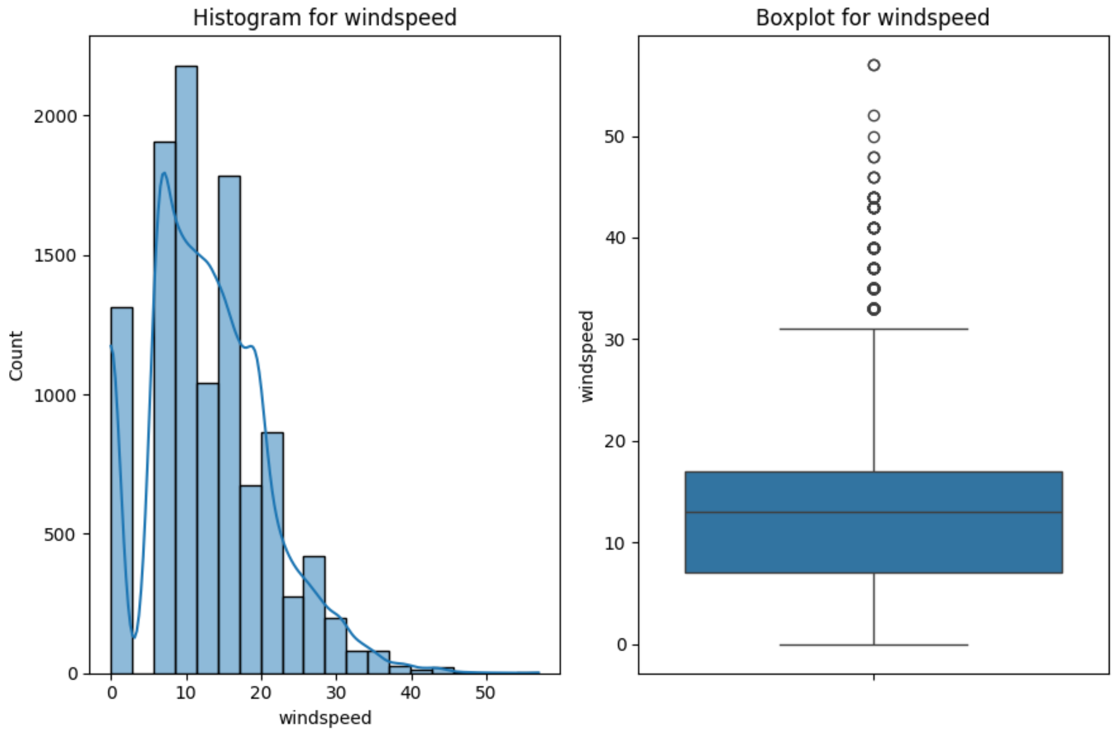
[ ]:
```
non_string_attributes =␣
↪['atemp','temp','humidity','windspeed','casual','registered','count']
```

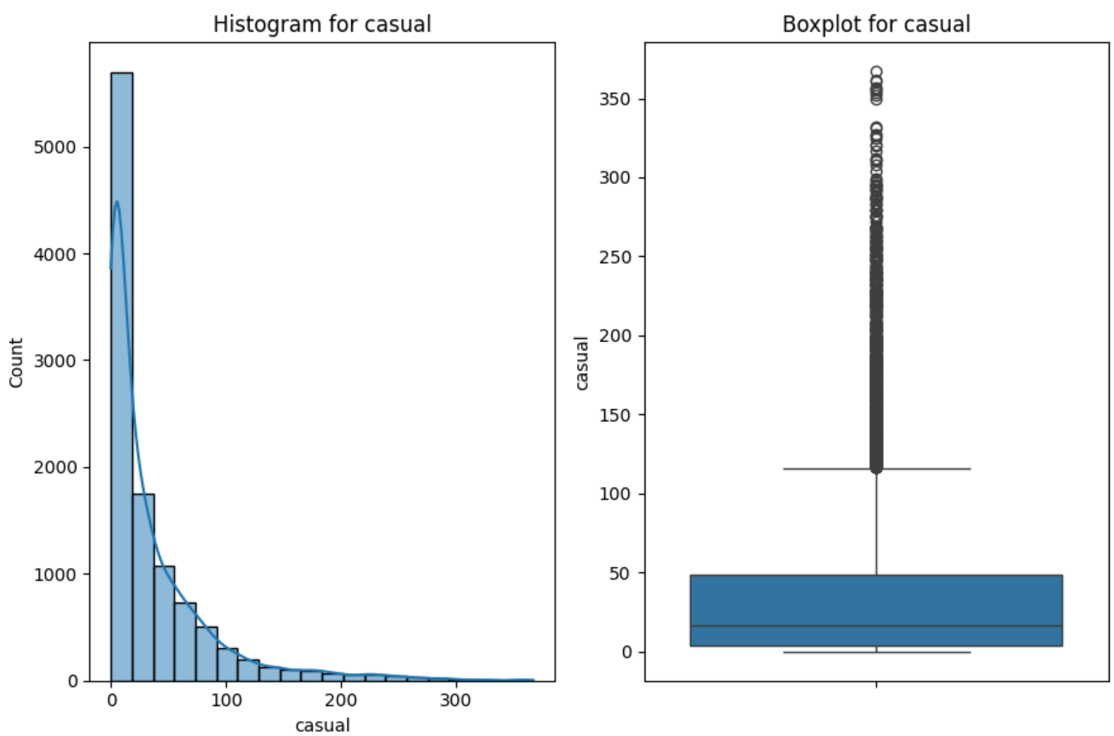
[ ]:
```
for col in non_string_attributes:
  fig,axes=plt.subplots(1,2,figsize=(9,6))

  plt.subplot(1,2,1)
  sns.histplot(df[col], bins=20, kde=True)
  plt.title(f'Histogram for {col}')

  plt.subplot(1,2,2)
  sns.boxplot(df[col])
  plt.title(f'Boxplot for {col}')

  plt.tight_layout()
  plt.show()
```

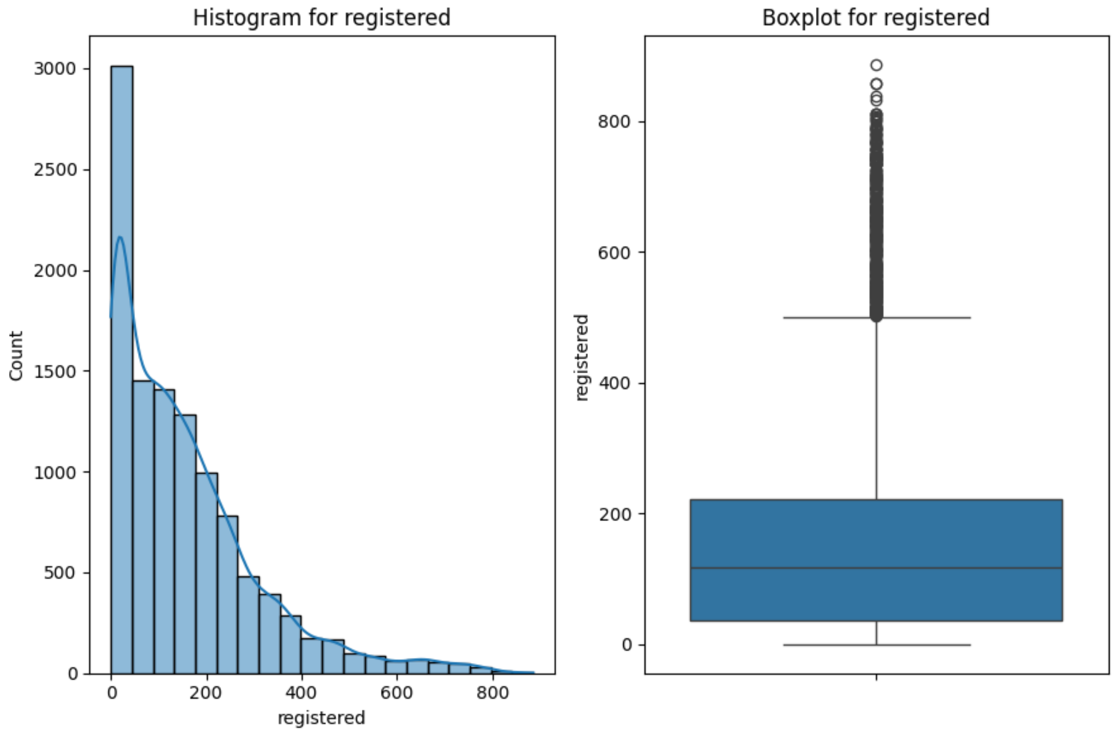


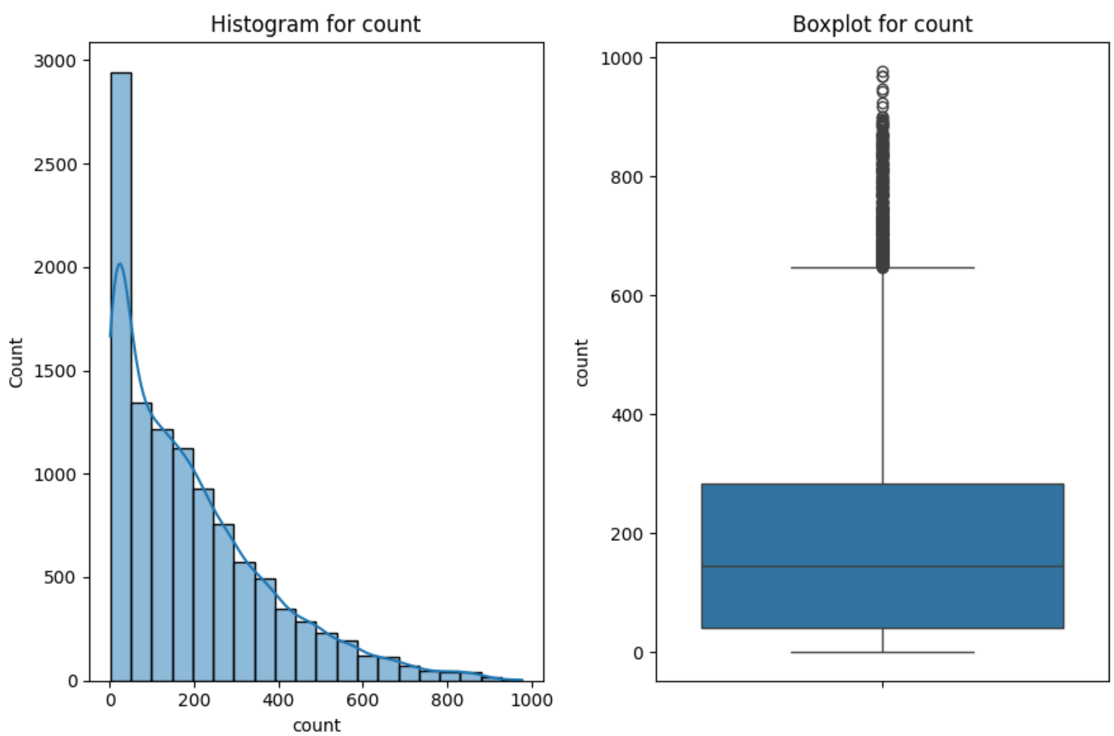

Histogram for temp
Count
temp
0
200
400
600
800
1000
1200
0
10
20
30
40
Boxplot for temp
temp
0
5
10
15
20
25
30
35
40


Histogram for humidity
Count
humidity
0
200
400
600
800
0
20
40
60
80
100
Boxplot for humidity
humidity
0
20
40
60
80
100


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


Histogram for casual
Count
5000
4000
3000
2000
1000
0
0
100
200
300
casual
Boxplot for casual
casual
350
300
250
200
150
100
50
0


Histogram for registered
Count
registered
Boxplot for registered
registered


Histogram for count
Count
count
Boxplot for count
count

Atemp:

- atemp has a range of apparent tempratures (0.76,45.455) and mean being 23.

Temp:

- temp also has a good range of tempratures from 0.82 to 41 degrees celsius and mean being 20 degrees celsius.

Humidity:

- humidity ranges from 0 to 100 and shows an average of 61.

WindSpeed:

- windspeed ranges from 0 to 57 with average being around 13. Windspeed also has many outliers.

Casual:

- casual shows range of casual electric cycle rental counts with values from 0 to 367. It contains too many outliers. It has mean around 36.

Registered:

- registered shows range of registered electric cycle rental counts with values from 0 to 886. Registered contains many outliers. It has a mean of around 155.

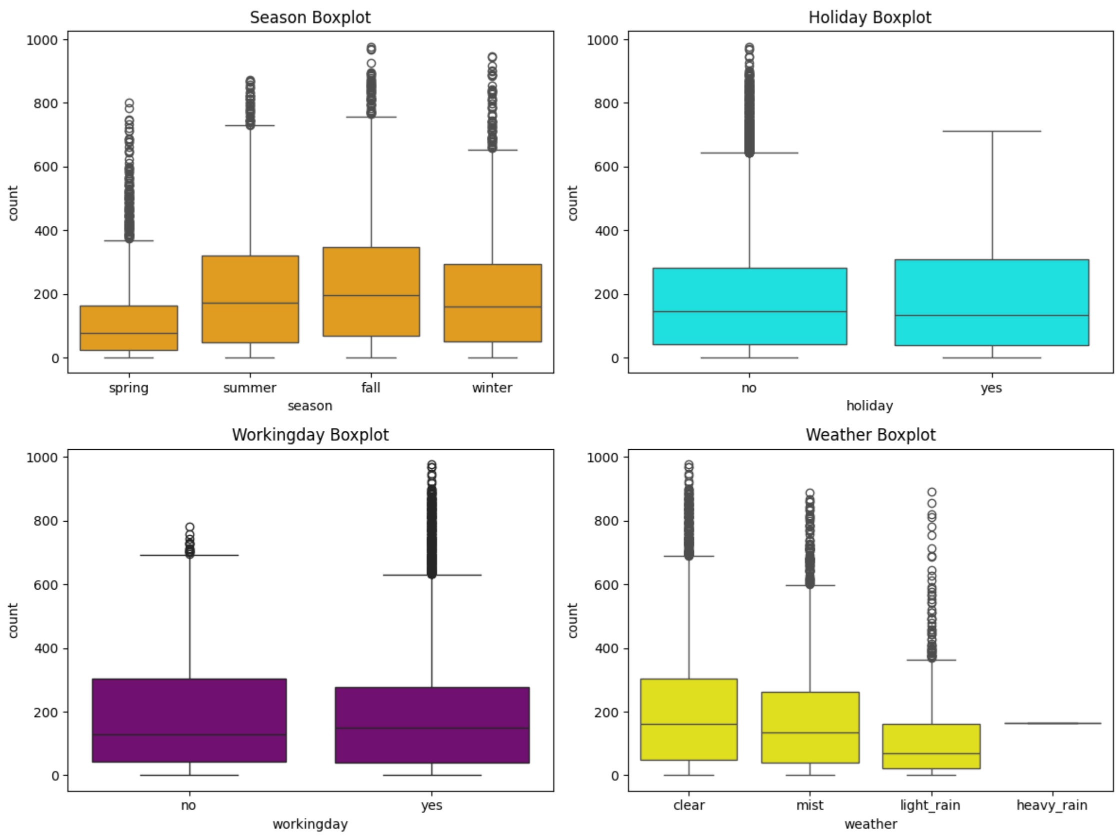
Count:

- count shows total electric cycle rental counts with values from 1 to 977. The mean is around 191.

0.4 Bivariate Analysis

Detecting Outliers

[ ]:
```python
fig, axes = plt.subplots(2, 2, figsize=(12, 9))

sns.boxplot(x='season', y='count', data=df, ax=axes[0, 0],color='orange')
axes[0, 0].set_title('Season Boxplot')

sns.boxplot(x='holiday', y='count', data=df, ax=axes[0, 1],color='cyan')
axes[0, 1].set_title('Holiday Boxplot')

sns.boxplot(x='workingday', y='count', data=df, ax=axes[1, 0],color='purple')
axes[1, 0].set_title('Workingday Boxplot')

sns.boxplot(x='weather', y='count', data=df, ax=axes[1, 1],color='yellow')
axes[1, 1].set_title('Weather Boxplot')
plt.tight_layout()

plt.show()
```



Season:

- Winter and Spring have more outliers compared to the other seasons.

Workingday and Holiday:

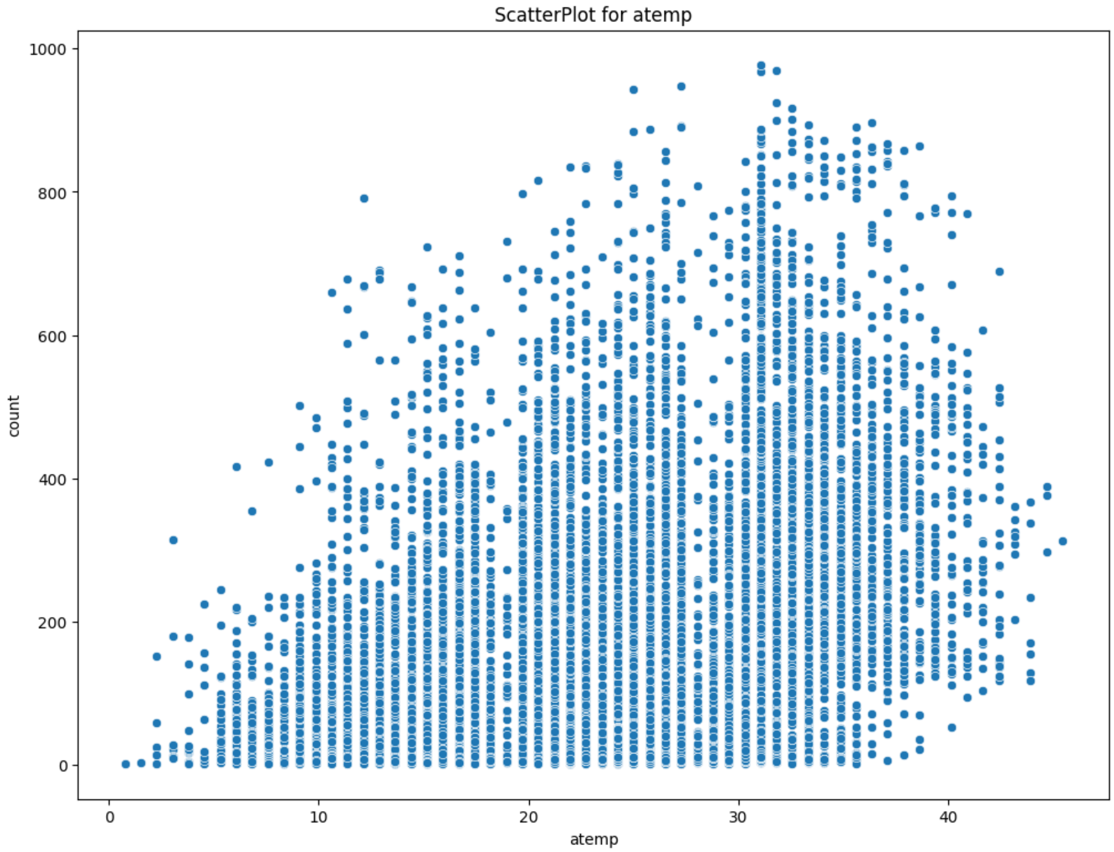
- On working day there are more outliers than holiday.

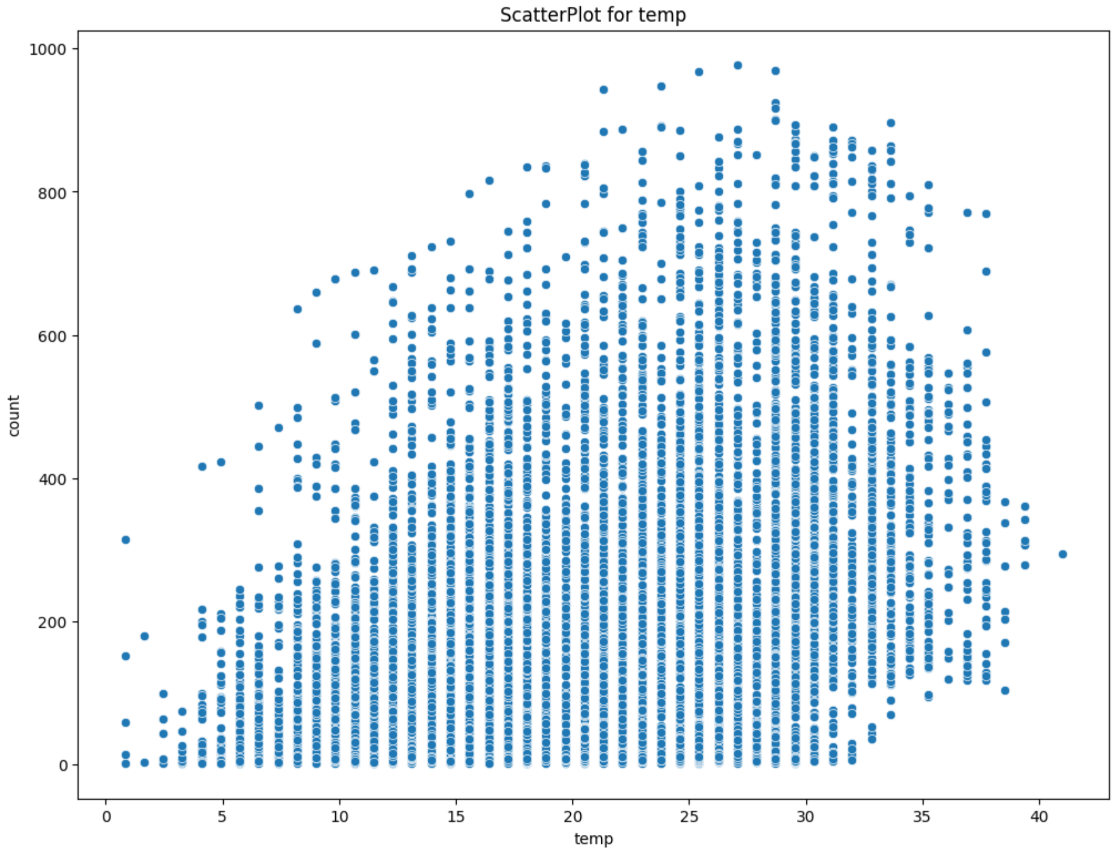
Weather:

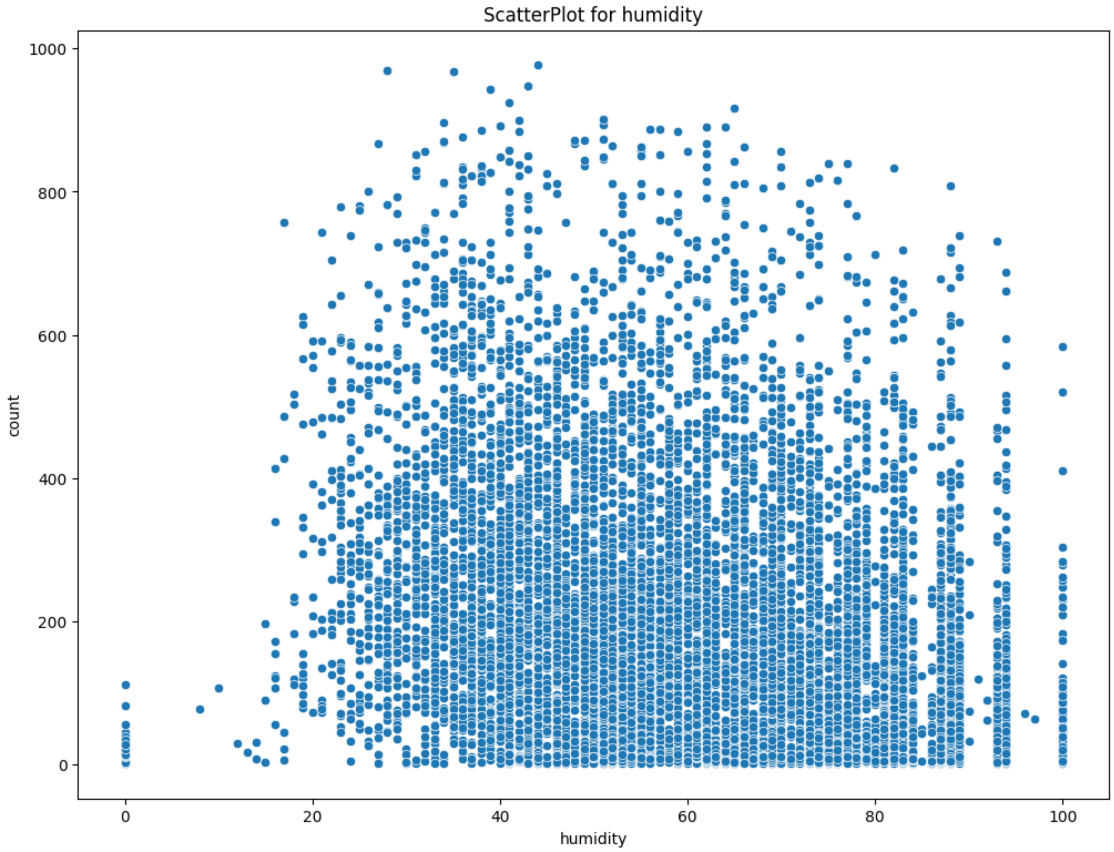
- During light rain there is a huge range of outliers.

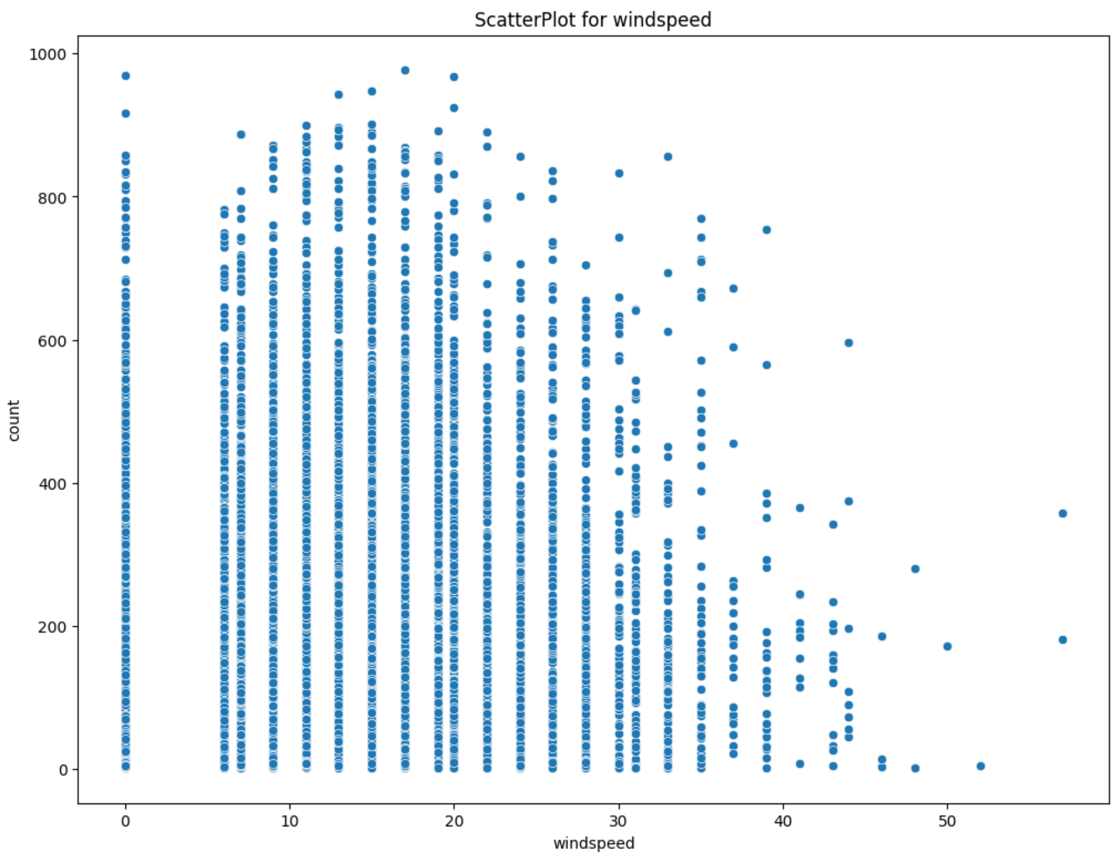
Plotting for Analysis

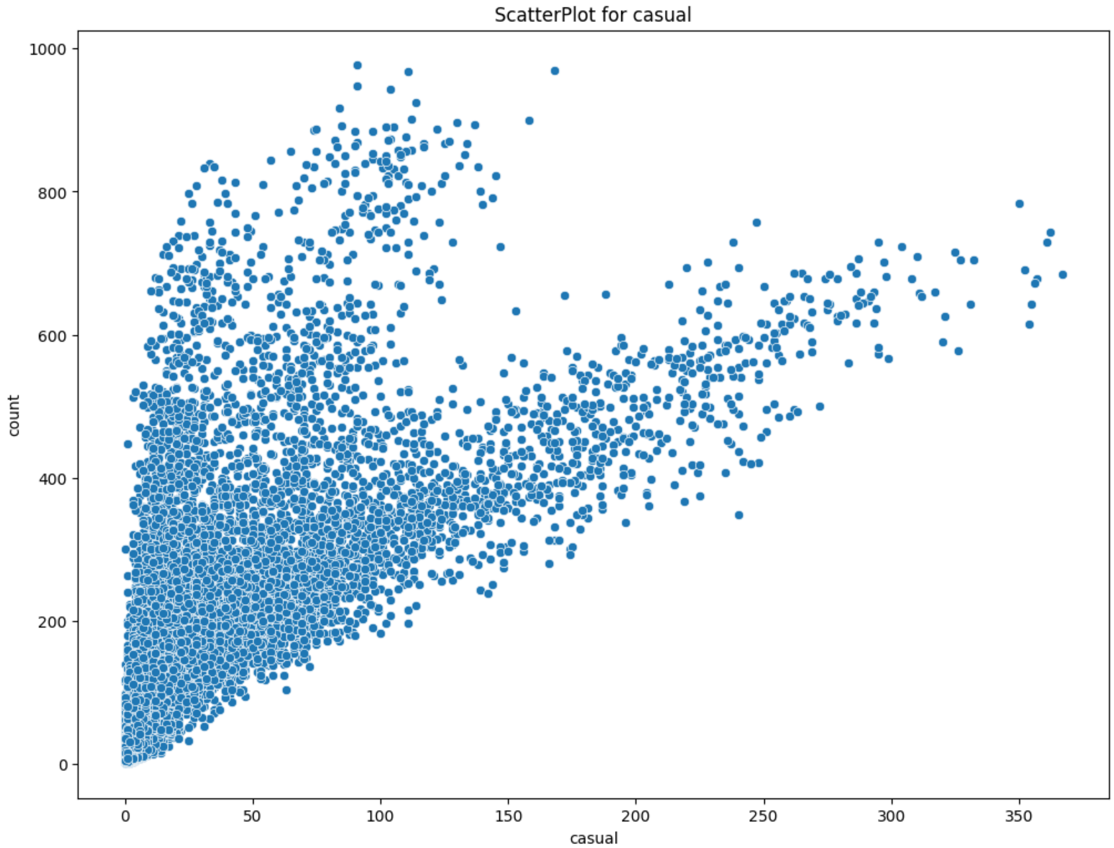
[ ]:
```
for col in non_string_attributes:
  plt.figure(figsize=(12,9))
  sns.scatterplot(data=df,x=col,y='count')
  plt.title(f'ScatterPlot for {col}')
  plt.show()
```

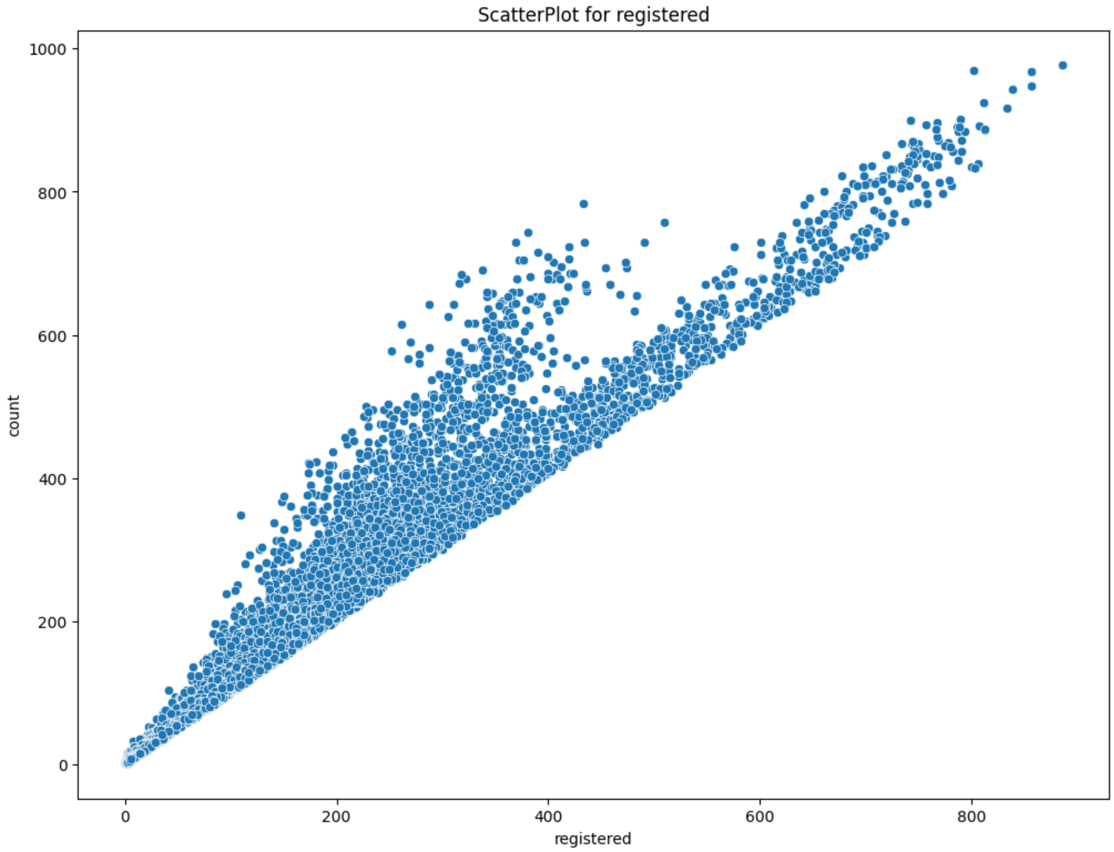

ScatterPlot for atemp
count
atemp
0
200
400
600
800
1000
0
10
20
30
40

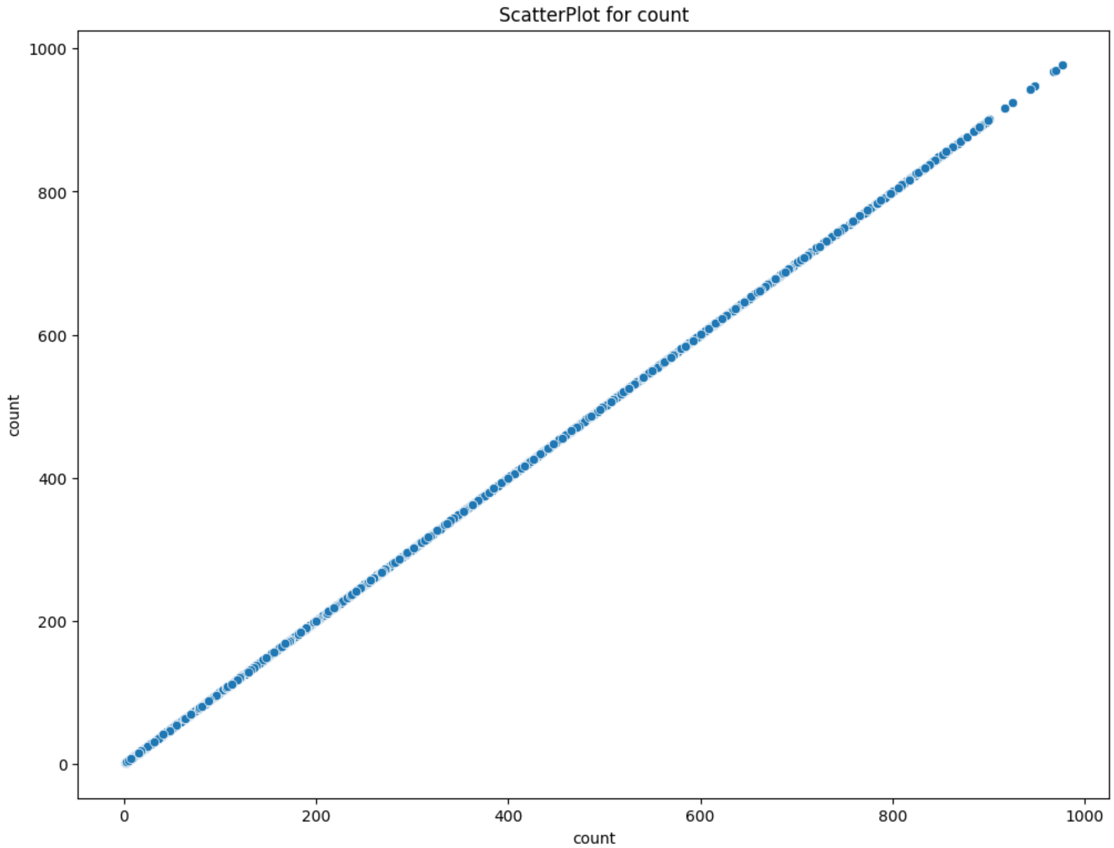

ScatterPlot for temp
count
temp
1000
800
600
400
200
0
0
5
10
15
20
25
30
35
40


ScatterPlot for humidity
1000
800
600
400
200
0
count
0
20
40
60
80
100
humidity


ScatterPlot for windspeed
count
1000
800
600
400
200
0
0
10
20
30
40
50
windspeed


ScatterPlot for casual
count
casual
0
200
400
600
800
1000
0
50
100
150
200
250
300
350


ScatterPlot for registered
count
registered
0
200
400
600
800
1000

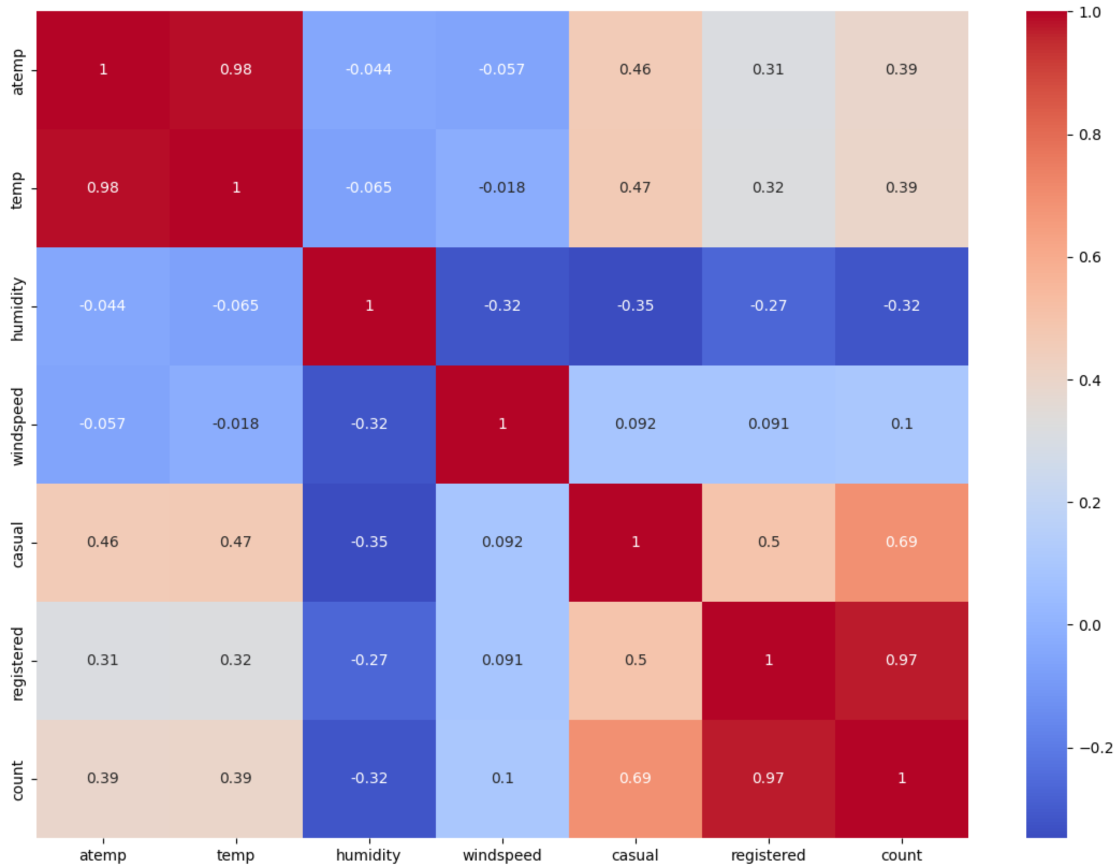


Observations:

- When the humidity is less than 20, number of electric cycles rented is very very low.
- When the temperature is less than 10, number of electric cycles rented is less.
- When the windspeed is greater than 35, number of electric cycles rented is less.

Analyzing Correlations

[ ]:
```
corr = df[non_string_attributes].corr()
plt.figure(figsize=(14,10))
sns.heatmap(corr,annot=True,cmap='coolwarm')
plt.show()
```



Correlation Analysis:

- Atemp & Temp:
  - Strong positive correlation with each other (0.98), indicating a close relationship.
  - Both have moderate positive correlation with registered (0.31) and casual (0.46).
  - Both show positive correlation with count (0.39), showing a relationship with overall electric cycle rentals.
- Humidity:
  - Moderate negative correlation with registered (-0.27), casual (-0.35), and count (-0.32).
  - Weak negative correlation with atemp (-0.044) and temp (-0.065).
  - Suggests a inclination for fewer electric cycle rentals during higher humidity.
- WindSpeed:
  - Weak negative correlation with atemp (-0.057) and temp (-0.018).
  - Weak positive correlation with casual (0.092), registered (0.091), and count (0.10).
  - Indicates a subtle influence on electric cycle rentals with increasing wind speed.
- Registered:
  - Negative correlation with humidity (-0.27) and positive correlation with windspeed (0.091).
  - Positive correlation with atemp (0.31) and temp (0.32).

  - Highly correlated with casual (0.50) and count (0.97), drawing a substantial impact on overall rentals.
- Casual:
  - Moderate negative correlation with humidity (-0.35) and positive correlation with windspeed (0.092).
  - Strong positive correlation with atemp (0.46) and temp (0.47).
  - Highly correlated with registered (0.50) and count (0.69), suggesting a huge impact on overall rentals.
- Count:
  - Negative correlation with humidity (-0.32).
  - Positive correlation with atemp (0.39), temp (0.39), and casual (0.69).
  - Highly correlated with registered (0.97), drawing the joint impact of casual and registered rentals on the overall count.

0.5 Hypothesis Testing

Effect of working day on number of electric cycles rented

Setting up the Hypotheses:

- Ho: Working Day has no effect on the number of electric cycles rented
- H1: Working Day has effect on the number of electric cycles rented
- Test Statistic: Two Sample T-test
- Significance Level( ): 0.05 or 5%

[ ]:
```
working_day_count =np.array(df[df['workingday']=='yes']['count'])
non_working_day_count =np.array(df[df['workingday']=='no']['count'])

stats.ttest_ind(working_day_count,non_working_day_count,equal_var=True)
```

[ ]:
```
TtestResult(statistic=1.2096277376026694, pvalue=0.22644804226361348,
df=10884.0)
```

- Since, pvalue is greater than significance level (0.22644804226361348 > 0.05) , we fail to reject the null hypothesis, working day has no effect on the number of electric cycles rented.
- At 95% confidence level, the mean of number of riders on non-working day is statistically not different from the mean number of riders on working day.

No. of cycles rented similar or different in different seasons

Setting up the Hypotheses: - Ho: Season has no effect on the number of electric cycles rented

- H1: Season has effect on the number of electric cycles rented
- Test Statistic: One Way ANOVA
- Significance Level( ): 0.05 or 5%

[ ]:
```
spring_cycles = np.array(df[df['season'] == 'spring']['count'])
summer_cycles = np.array(df[df['season'] == 'summer']['count'])
fall_cycles = np.array(df[df['season'] == 'fall']['count'])
winter_cycles = np.array(df[df['season'] == 'winter']['count'])

stats.f_oneway(spring_cycles,summer_cycles,fall_cycles,winter_cycles)
```

[ ]:
```
F_onewayResult(statistic=236.94671081032106, pvalue=6.164843386499654e-149)
```

- Since, pvalue is lesser than significance level (6.164843386499654e-149 < 0.05), we reject the null hypothesis, season has no effect on the number of electric cycles rented.
- At 95% confidence level, the mean of number of riders in different seasons is statistically different for atleast one season.

No. of cycles rented similar or different in different weather

Setting up the Hypotheses: - Ho: Weather has no effect on the number of electric cycles rented

- H1: Weather has effect on the number of electric cycles rented
- Test Statistic: One Way ANOVA
- Significance Level( ): 0.05 or 5%

[ ]:
```
clear_cycles = np.array(df[df['weather'] == 'clear']['count'])
mist_cycles = np.array(df[df['weather'] == 'mist']['count'])
light_rain_cycles = np.array(df[df['weather'] == 'light_rain']['count'])
heavy_rain_cycles = np.array(df[df['weather'] == 'heavy_rain']['count'])

stats.f_oneway(clear_cycles,mist_cycles,light_rain_cycles,heavy_rain_cycles)
```

[ ]:
```
F_onewayResult(statistic=65.53024112793271, pvalue=5.482069475935669e-42)
```

- Since, pvalue is lesser than significance level (5.482069475935669e-42 < 0.05), we reject the null hypothesis, weather has no effect on the number of electric cycles rented.
- At 95% confidence level, the mean of number of riders in different weather is statistically different for atleast one weather.

Weather is dependent on season

Setting up the Hypoptheses:

- Ho: Weather is independent of season
- H1: Weather is dependent on season
- Test Statistic: Chi-Square Test of Independence
- Significance Level( ): 0.05 or 5%

[ ]:
```
cont_table = pd.crosstab(df['season'],df['weather'])
cont_table
```

[ ]:

weather	clear	mist	light_rain	heavy_rain
season				
spring	1759	715	211	1
summer	1801	708	224	0
fall	1930	604	199	0
winter	1702	807	225	0

[ ]:
```
stats.chi2_contingency(cont_table)
```

[ ]:
```
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]]))
```

- Since, pvalue is lesser than significance level ($1.549925073686492e\text{-}07 < 0.05$), we reject the null hypothesis, weather is independent of season.
- At 95% confidence level, weather is dependent on seasons.

0.6 Inferences

Insights:

- During holidays more electric cycles are rented.
- When humidity is less than 20, number of eletric cycles rented is low.
- Fall and summer have the highest number of electric cycles rented.
- When the windspeed is greater than 35, number of electric cycles rented is less.
- Whenever the weather was getting misty and rainy there was a drop in rental.
- When temperature is less than 10, number of electric cycles rented is low.

Recommendations:

- Enhancing the User Experience by investing in technology and infrastructure, including app features, bike maintenance, and customer support, fostering loyalty and repeat business.
- Yulu should stock more electric cycles during fall and summer as these two seasons have higher demands for rentals. As seen by the ANOVA test number of riders is dependent on season.

- Yulu can make rentals available according to the weather to make sure customers can rent electric cycles when needed and the company can also save on costs. As seen by the ANOVA test number of riders is dependent on weather.
- Company should start making some models which are sustainable during mist and light rain weather to increase rental sales even more.
- Promotional offers should be given during different seasons and weather to engage more customers.
- Yulu should further investigate based on rider's age and gender, as it would help further in determining which category of customers prefer renting electric cycles.