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1 Yulu : Hypothesis Testing

2 Introduction:

Yulu, India's pioneering micro-mobility service provider, has embarked on a mission to revolutionize daily commutes by offering unique, sustainable transportation solutions. However, recent revenue setbacks have prompted Yulu to seek the expertise of a consulting company to delve into the factors influencing the demand for their shared electric cycles, specifically in the Indian market. # - Why this case study? ### From Yulu's Perspective:

Strategic Expansion: Yulu's decision to enter the Indian market is a strategic move to expand its global footprint. Understanding the demand factors in this new market is essential to tailor their services and strategies accordingly.

Revenue Recovery: Yulu's recent revenue decline is a pressing concern. By analyzing the factors affecting demand for shared electric cycles in the Indian market, they can make informed adjustments to regain profitability.

3 Column Profiling:

- 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

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```python
!wget "https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/
↪original/bike_sharing.csv?1642089089"
```

```
--2024-06-15 13:35:46--  https://d2beiqkhq929f0.cloudfront.net/public_assets/ass
ets/000/001/428/original/bike_sharing.csv?1642089089
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)…
52.85.39.92, 52.85.39.121, 52.85.39.27, …
Connecting to d2beiqkhq929f0.cloudfront.net
(d2beiqkhq929f0.cloudfront.net)|52.85.39.92|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: 648353 (633K) [text/plain]
Saving to: ‘bike_sharing.csv?1642089089’

bike_sharing.csv?16 100%[===================>] 633.16K  --.-KB/s    in 0.05s

2024-06-15 13:35:46 (12.1 MB/s) - ‘bike_sharing.csv?1642089089’ saved
[648353/648353]
```

[21]:
```python
df = pd.read_csv("/content/bike_sharing.csv?1642089089")
df
```

[21]:
```
                  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]
```

4 a. Examine dataset structure, characteristics, and statistical summary

[4]:
```python
# checkin no of rows and column
df.shape
```

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

[5]:
```python
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
```

5 Identify missing values and perform Imputation using an appropriate method.

[6]:
```
# checking null values
df.isnull().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
```

insights: - Dataset doesn't have null values. ——

[7]:
```
df.describe()
```

[7]:
```
             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
```

6 c. Identify and remove duplicate records.

[8]:
```python
# checking duplicate values
df.duplicated().sum()
```

[8]:
```
0
```

insights:

- Dataset doesn't have null values.

[ ]:
```python
df['season'].unique()
```

[ ]:
```
array([1, 2, 3, 4])
```

season (1: spring,

2: summer,

3: fall,

4: winter)

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

[ ]:
```
array([0, 1])
```

whether day is a holiday or not

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

[ ]:
```
array([0, 1])
```

if day is neither weekend nor holiday is 1, otherwise is 0.

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

[ ]:
```
array([1, 2, 3, 4])
```

- 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

[25]:
```python
df['datetime']=pd.to_datetime(df['datetime'])
```

[26]:
```python
df['year']=df['datetime'].dt.year
df.head()
```

[26]:
```
             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  year
0        81        0.0       3          13     16  2011
1        80        0.0       8          32     40  2011
2        80        0.0       5          27     32  2011
3        75        0.0       3          10     13  2011
4        75        0.0       0           1      1  2011
```

[11]:
```python
col = ['season','holiday','workingday','weather'] # converting all col into␣
↪categorical datatype
for i in col:
  df[i]=df[i].astype('category')
```

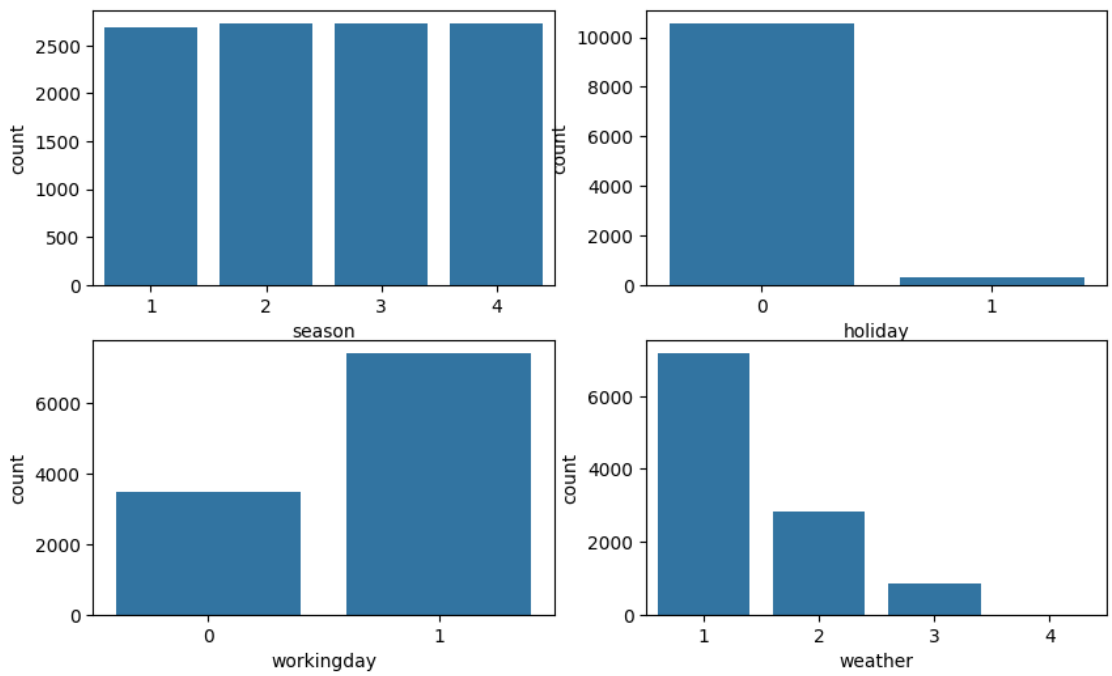
[12]:
```python
df.dtypes
```

[12]:
```
datetime      datetime64[ns]
season              category
holiday             category
workingday          category
weather             category
temp                 float64
atemp                float64
humidity               int64
windspeed            float64
casual                 int64
registered             int64
count                  int64
year                   int32
dtype: object
```

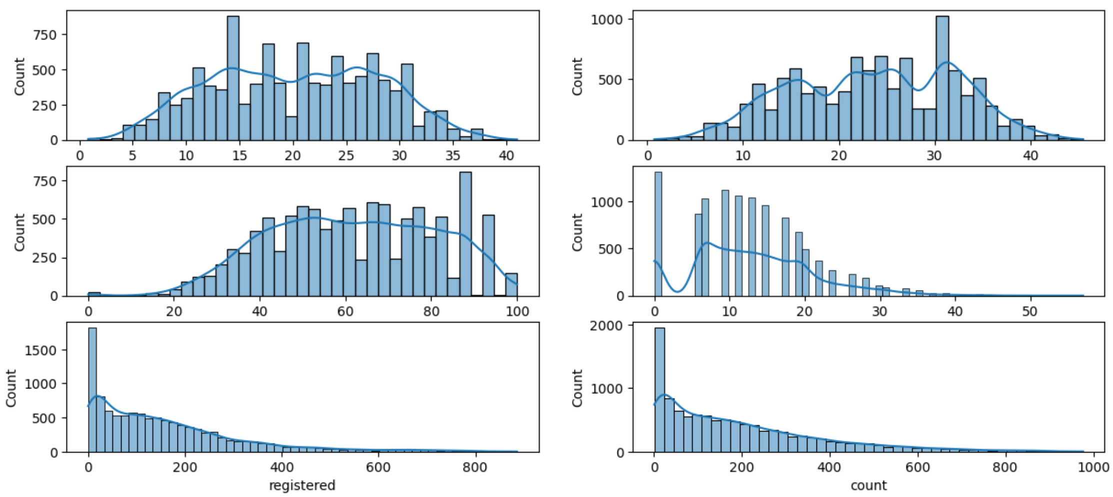
7 d. Analyze the distribution of Numerical & Categorical variables, separately

8 Univariate Analysis

[ ]:
```
fig,ax=plt.subplots(2,2,figsize=(10,6))
sns.countplot(x='season',data=df,ax=ax[0,0])
sns.countplot(x='holiday',data=df,ax=ax[0,1])
sns.countplot(x='workingday',data=df,ax=ax[1,0])
sns.countplot(x='weather',data=df,ax=ax[1,1])
plt.show()
```

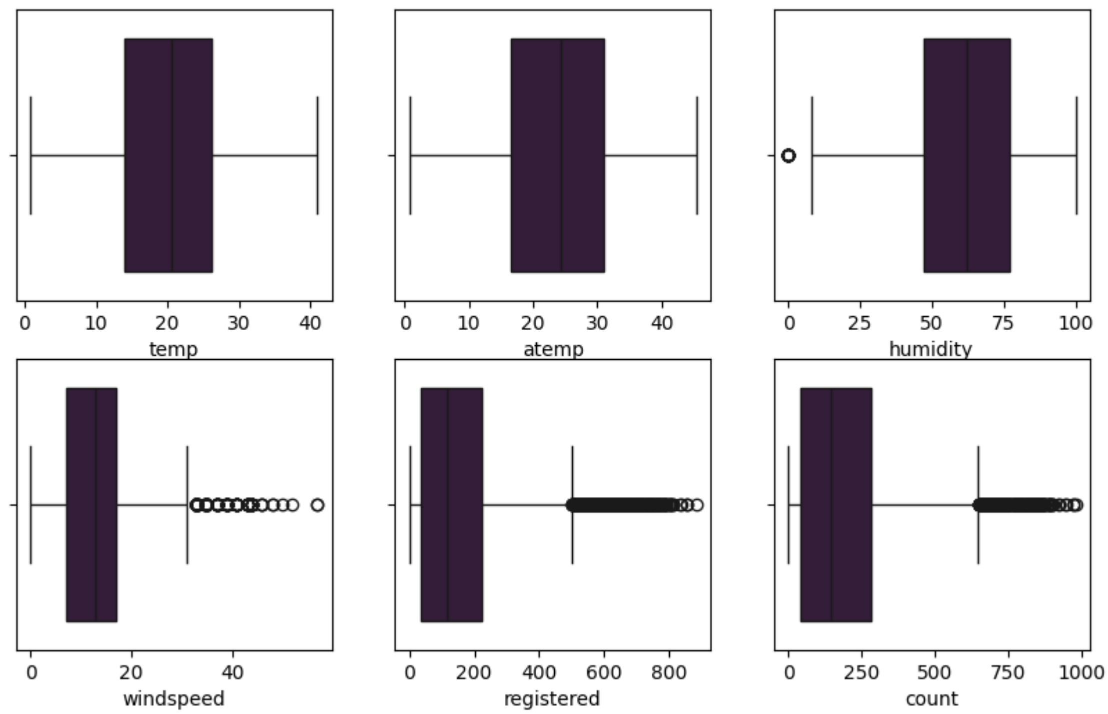


[ ]:
```
fig,ax=plt.subplots(3,2,figsize=(14,6))
sns.histplot(x='temp',data=df,ax=ax[0,0],kde=True)
sns.histplot(x='atemp',data=df,ax=ax[0,1],kde=True)
sns.histplot(x='humidity',data=df,ax=ax[1,0],kde=True)
sns.histplot(x='windspeed',data=df,ax=ax[1,1],kde=True)
sns.histplot(x='registered',data=df,ax=ax[2,0],kde=True)
sns.histplot(x='count',data=df,ax=ax[2,1],kde=True)
plt.show()
```



9 Check for Outliers and deal with them accordingly.

[58]:
```
fig,ax = plt.subplots(2,3, figsize=(10,6))
sns.boxplot(x='temp',data=df,ax=ax[0,0])
sns.boxplot(x='atemp',data=df,ax=ax[0,1])
sns.boxplot(x='humidity',data=df,ax=ax[0,2])
sns.boxplot(x='windspeed',data=df,ax=ax[1,0])
sns.boxplot(x='registered',data=df,ax=ax[1,1])
sns.boxplot(x='count',data=df,ax=ax[1,2])
plt.show()
```

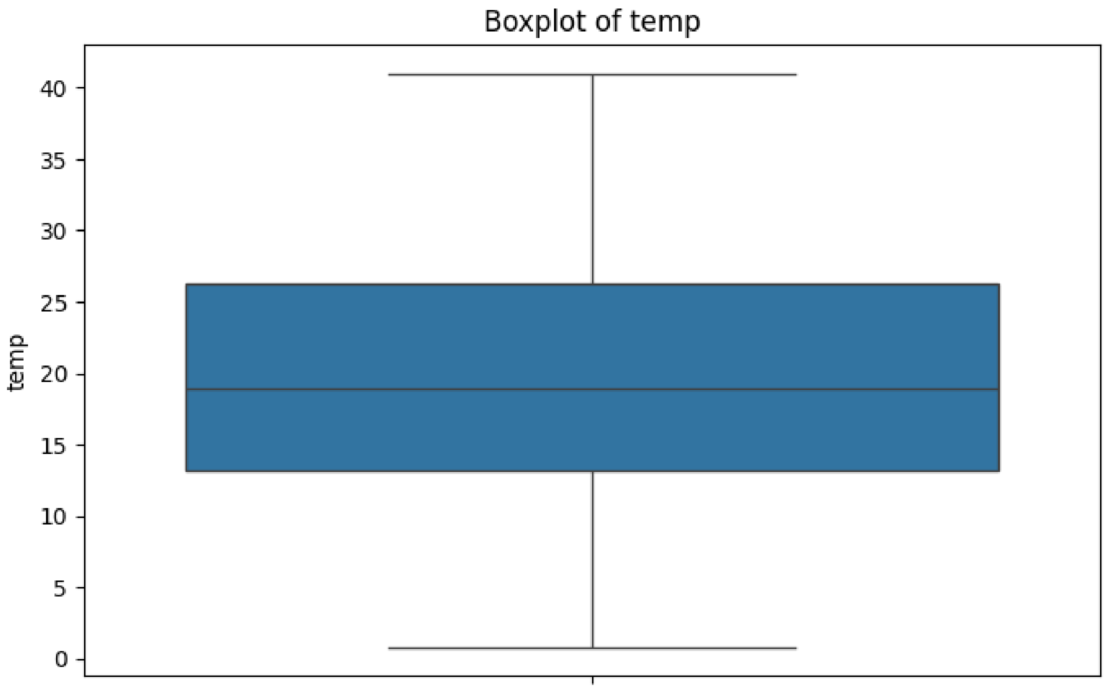


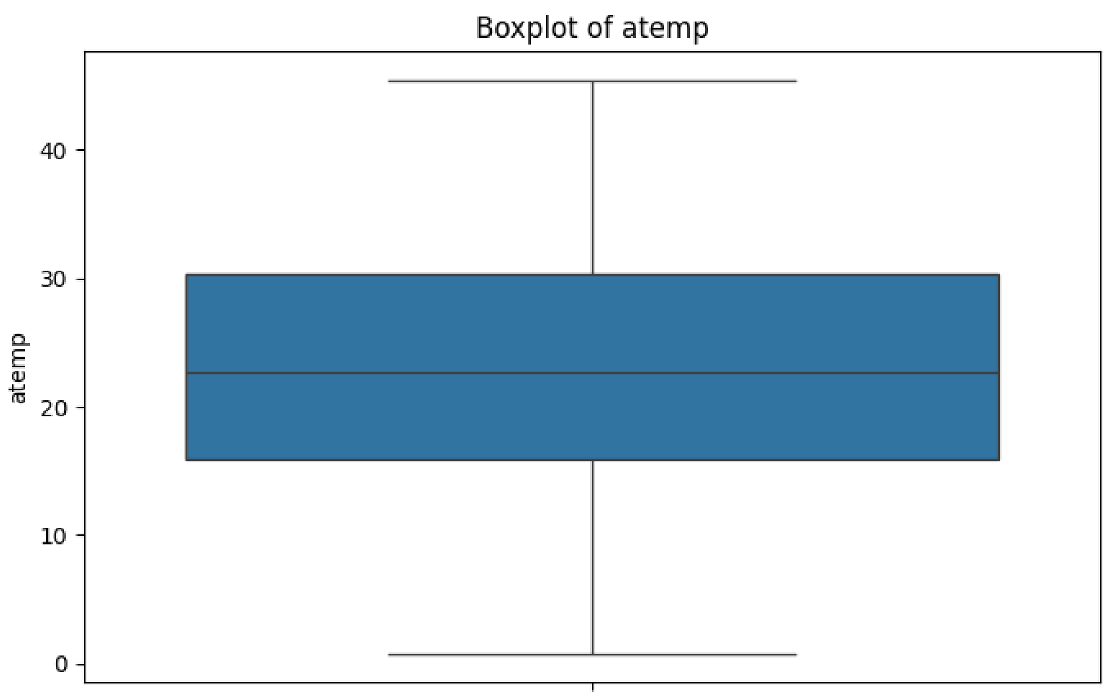
10 Remove/Clip existing outliers as necessary.

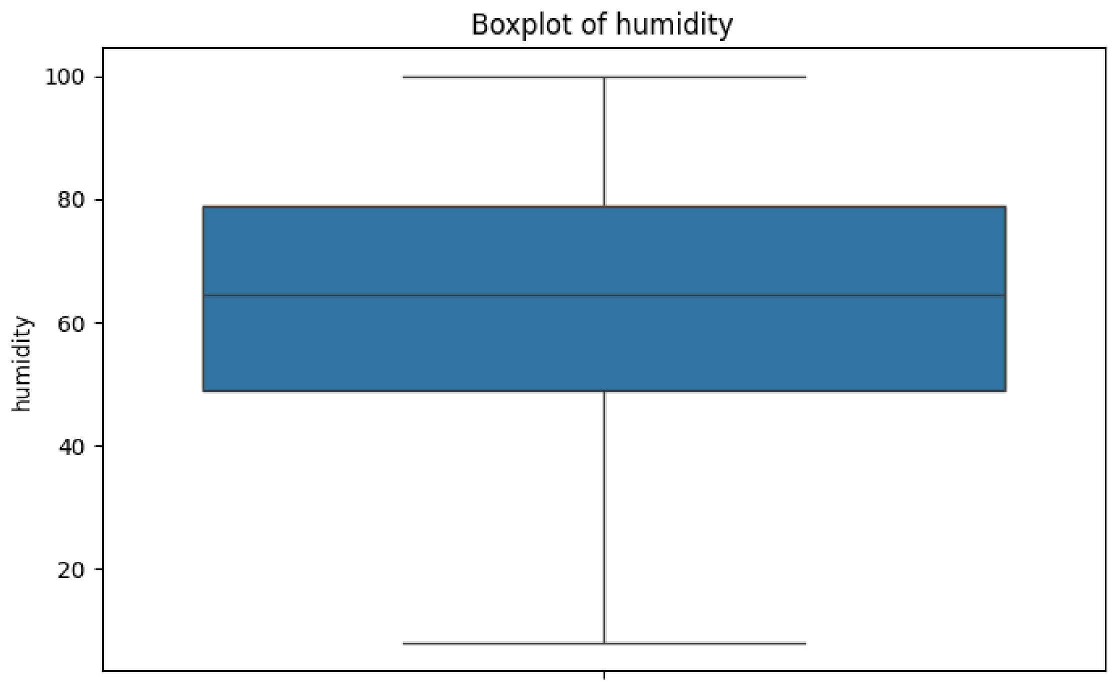
[15]:
```
#Removing Outliers using IQR Method
numerical_cols=['temp', 'atemp', 'humidity', 'windspeed', 'casual',␣
↪'registered', 'count']
data_num=df[numerical_cols]
Q1=data_num.quantile(0.25)
Q3=data_num.quantile(0.75)
IQR=Q3-Q1
print(IQR)
data=df[~((data_num<(Q1-1.5*IQR)) | (data_num>(Q3+1.5*IQR))).any(axis=1)]
print('Shape of data after removing outliers:',data.shape)
#Box plot after removing outliers
for col in numerical_cols:
  plt.figure(figsize=(8,5))
  sns.boxplot(data[col])
  plt.title(f"Boxplot of {col}")
```

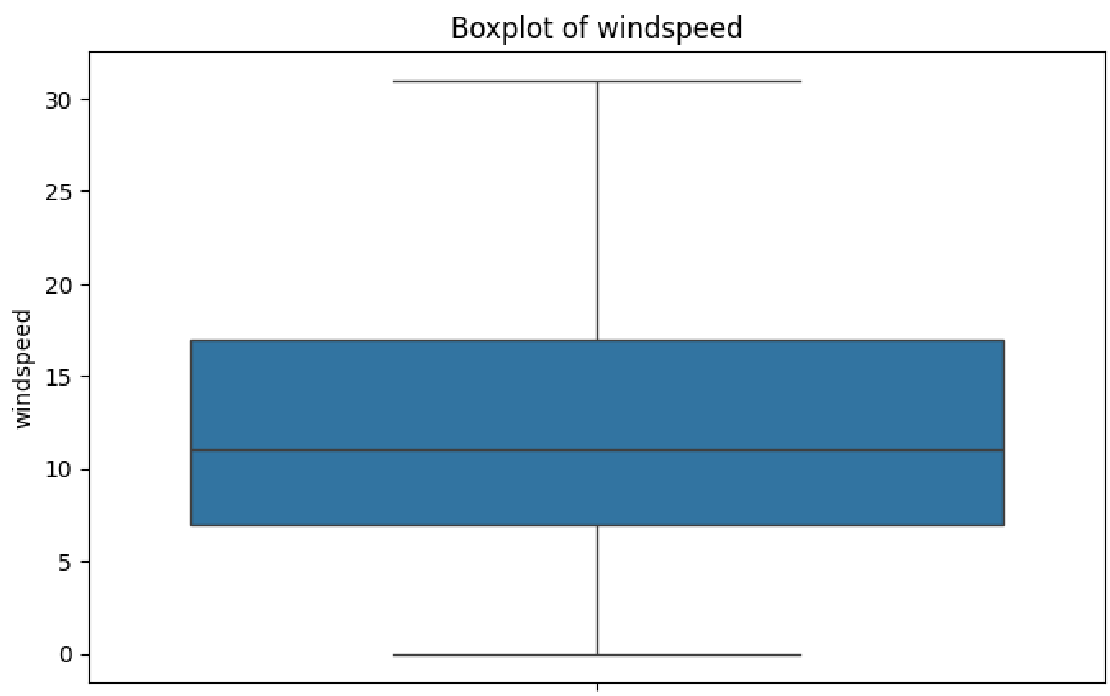
```
temp          12.3000
atemp         14.3950
humidity      30.0000
windspeed      9.9964
casual        45.0000
```

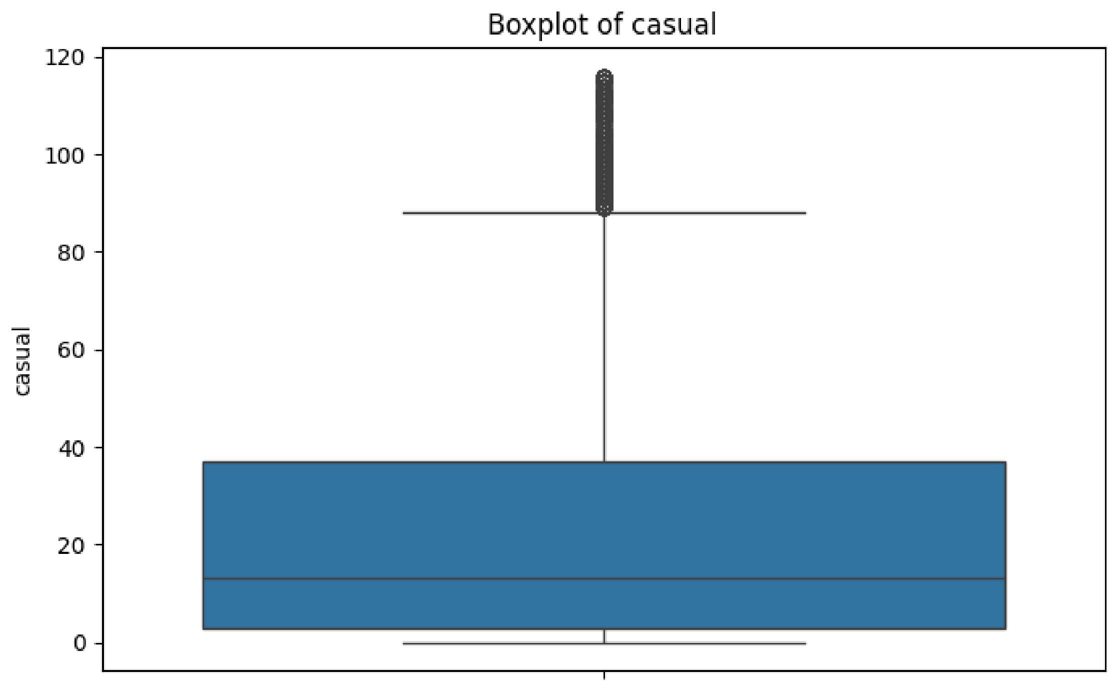
```
registered    186.0000
count         242.0000
dtype: float64
Shape of data after removing outliers: (9518, 13)
```

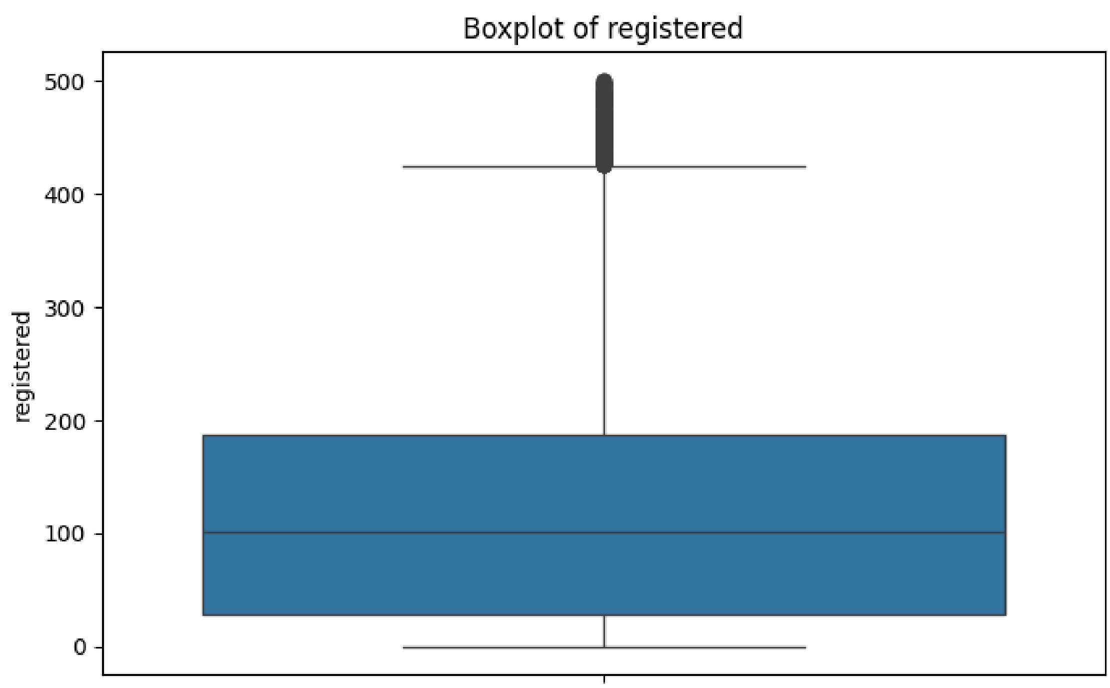


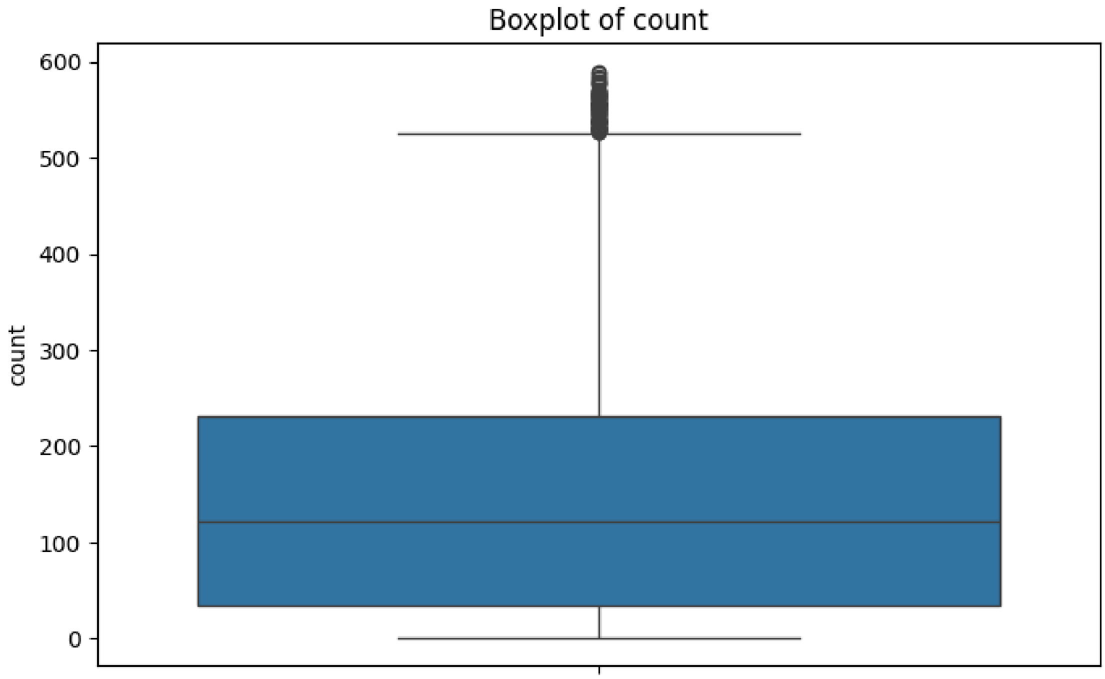



Boxplot of humidity
100
80
60
40
20
humidity


Boxplot of windspeed
30
25
20
15
10
5
0
windspeed

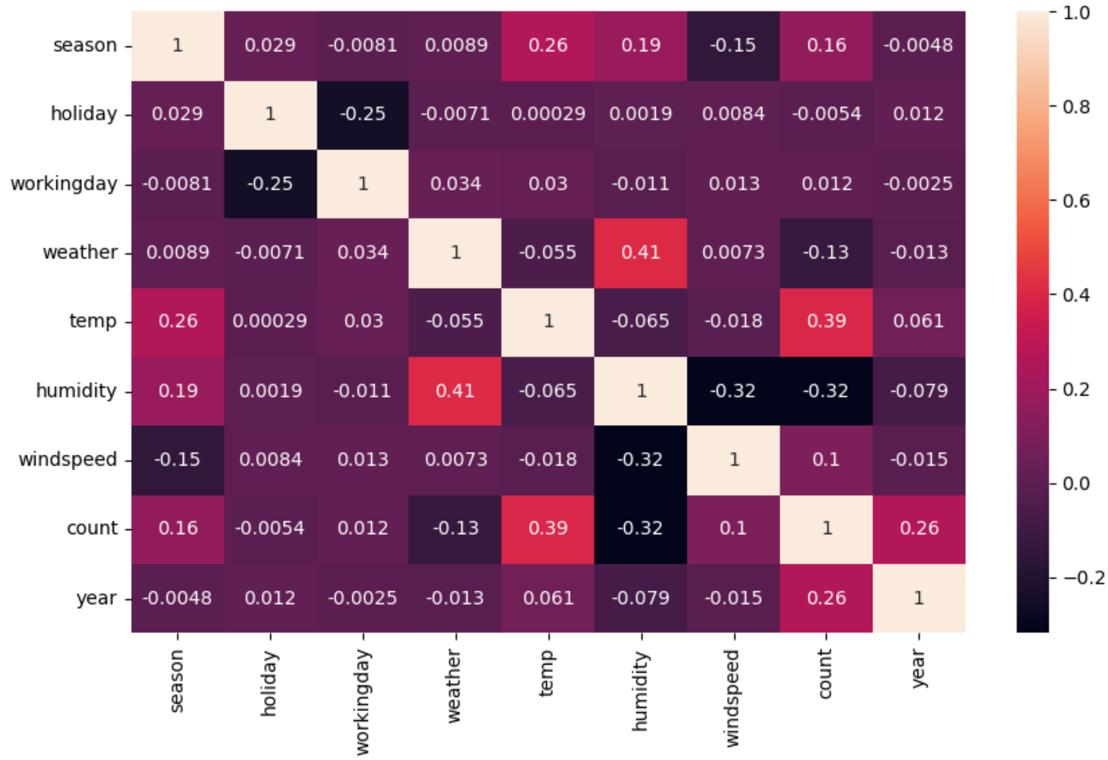

Boxplot of casual
casual
0
20
40
60
80
100
120


Boxplot of registered
registered
0
100
200
300
400
500



11 Try establishing a Relationship between the Dependent and Independent Variables.

[55]:
```
plt.figure(figsize=(10,6))
sns.heatmap(data.corr(numeric_only=True), annot=True)
plt.show()
```



Here, count column seems to have positive correlation with atemp and and negative with humidity. Although they around only 30-40%. But we can see people go out with bike more when the temp is high and humidity is low. Seems expected.

12 Remove the highly correlated variables, if any.

[27]:
```
data = df.drop(columns=['casual', 'registered', 'atemp'])
```

13 Hypothesis Testing:

14 Check if there any significant difference between the no. of bike rides on Weekdays and Weekends?

[57]:
```
from scipy.stats import ttest_1samp, ttest_ind, ttest_rel, f_oneway, chisquare,␣
↪chi2_contingency
from scipy.stats import shapiro # Shapiro-Wilk’s test for Normality
from scipy.stats import levene # Levene's test for Equality of Variance
from scipy.stats import kruskal
from statsmodels.api import qqplot
warnings.filterwarnings("ignore")
```

15 HO:There is no significant difference between no. of bike rides on weekdays and no. of bike rides on weekend.

16 H1:There is a significant difference between no. of bike rides on weekdays and no. of bike rides on weekend.

17 b. Select an appropriate test -

A t-test looks at two sets of data that are different from each other, with no standard deviation or variance. And in the Problem,we are talking about two independent groups.So we will apply the 2- Sample Independent T-test

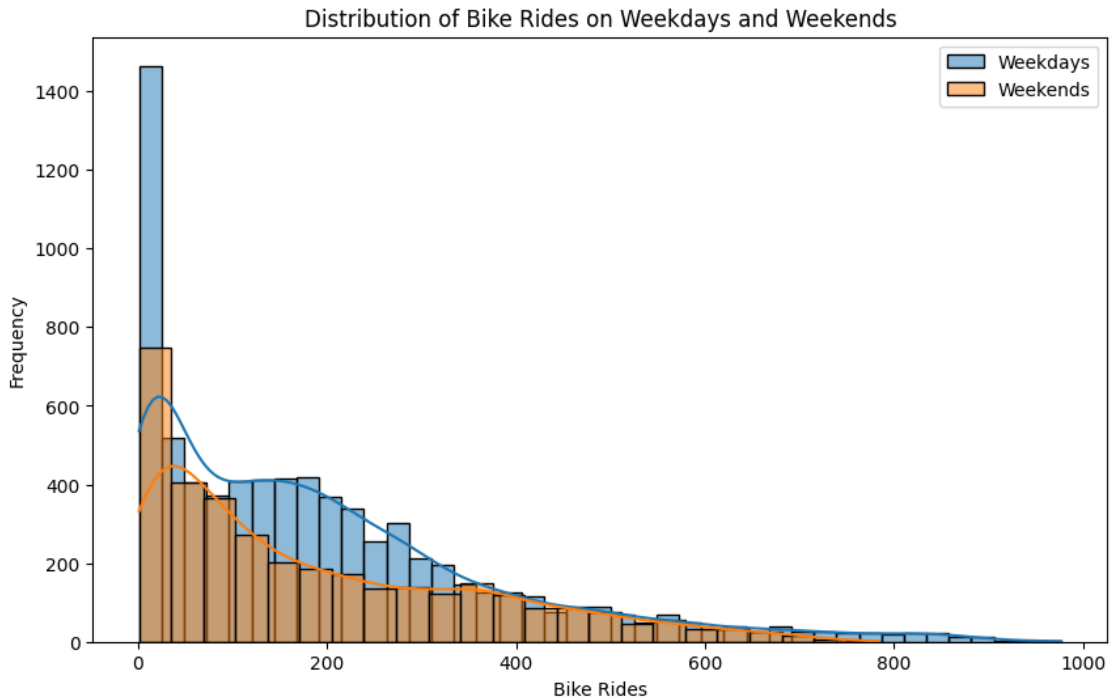
[28]:
```
# c. Set a significance level**
alpha = 0.05

Weekdays=data[data['workingday']==1]['count']
Weekends=data[data['workingday']==0]['count']

tstats,p_value=ttest_ind(Weekdays,Weekends)
print('t_Statistics:',tstats)
print('p_value:',p_value)
if p_value<alpha:
  print('Reject Null Hypothesis')
  print('There is a significant difference between no. of bike rides on␣
 ↪weekdays and no. of bike rides on weekend.')
else:
  print('Fail to reject Null Hypothesis')
  print('There is no significant difference between no. of bike rides on␣
 ↪weekdays and no. of bike rides on weekend.')
```

```
t_Statistics: 1.2096277376026694
p_value: 0.22644804226361348
Fail to reject Null Hypothesis
There is no significant difference between no. of bike rides on weekdays and no.
of bike rides on weekend.
```

[29]:
```
plt.figure(figsize=(10, 6))
sns.histplot(Weekdays, label='Weekdays', kde=True)
sns.histplot(Weekends, label='Weekends', kde=True)
plt.title('Distribution of Bike Rides on Weekdays and Weekends')
plt.xlabel('Bike Rides')
plt.ylabel('Frequency')
plt.legend()
plt.show()
```



18 Check if the demand of bicycles on rent is the same for different Weather conditions?

[37]:
```
# H0: Weathers has No effect on number of electric cycles rented
# H1: Weathers has effect on number of electric cycles rented
gp1 = data[data['weather']==1]['count']
gp2 = data[data['weather']==2]['count']
gp3 = data[data['weather']==3]['count']
gp4 = data[data['weather']==4]['count']

gp5 = data[data['season']==1]['count']
gp6 = data[data['season']==2]['count']
gp7 = data[data['season']==3]['count']
gp8 = data[data['season']==4]['count']
```

19 Here we will use ANOVA test

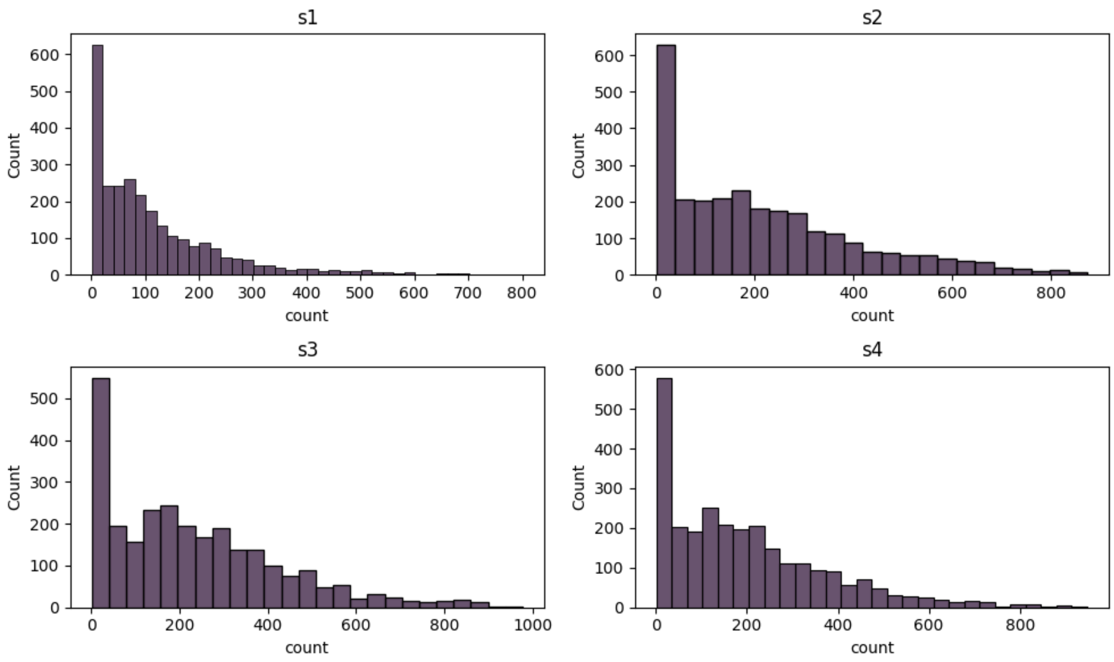
[38]:
```
from scipy import stats
stats.f_oneway(gp1,gp2,gp3,gp4,gp5,gp6,gp7,gp8)
```

[38]:
```
F_onewayResult(statistic=127.96661249562491, pvalue=2.8074771742434642e-185)
```

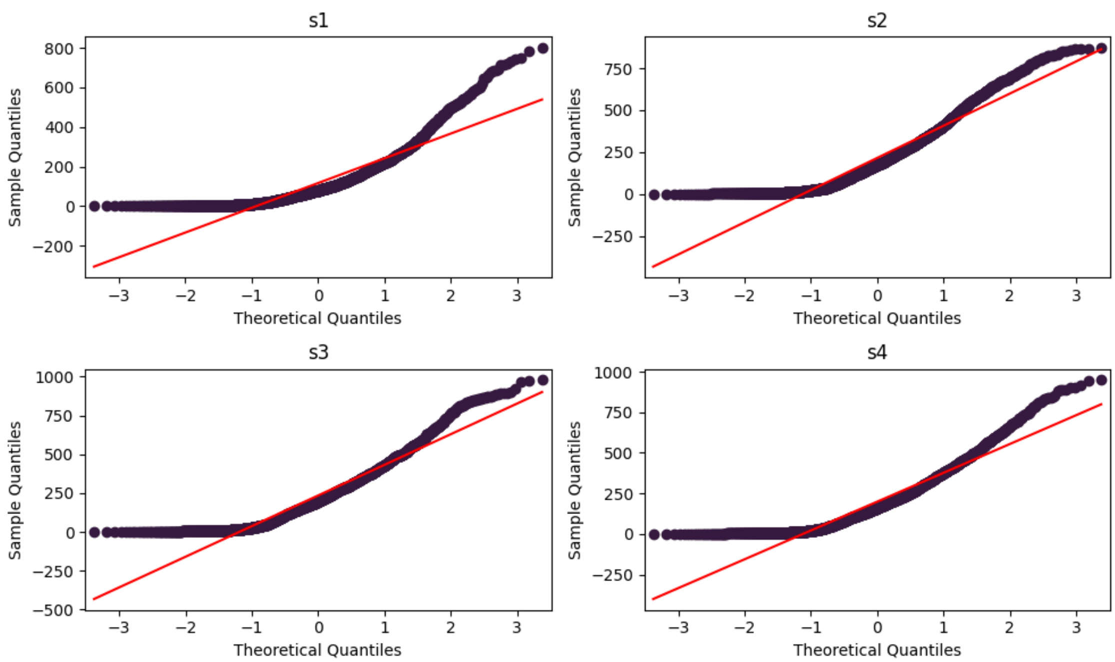
Since p-value is less than 0.05, **we reject the null hypothesis**. This implies that Number of cycles rented is not similar in different weather and season conditions

20 5. Check if the demand of bicycles on rent is the same for different Seasons?

[54]:
```
# H0 = There is no significant difference in the demand for bicycles on rent␣
↪across different seasons.
# H1 = There is a significant difference in the demand for bicycles on rent␣
↪across different seasons.
s1=data[data['season']==1]['count']
s2=data[data['season']==2]['count']
s3=data[data['season']==3]['count']
s4=data[data['season']==4]['count']
plt.figure(figsize=(10, 6))
seasons = [s1, s2, s3, s4]
for i, season in enumerate(seasons):
    plt.subplot(2, 2, i+1)
    sns.histplot(season)
    plt.title(f's{i+1}')
plt.tight_layout()
plt.show()
```



[53]:
```python
# QQ-Plot
plt.figure(figsize=(10, 6))
for i, season in enumerate(seasons):
    plt.subplot(2, 2, i+1)
    qqplot(season,line='s',ax=plt.gca())
    plt.title(f's{i+1}')
plt.tight_layout()
plt.show()
```



[51]:
```python
#Levene's test for equality of variance
stats,p_value=levene(s1,s2,s3,s4)
print('Test statistic:',stats)
print('p-value:',p_value)
if p_value<0.05:
  print('Reject Null Hypothesis')
  print('Variance of the groups are not equal')
else:
  print('Fail to reject Null Hypothesis')
  print('Variance of the groups are equal')
```

```
Test statistic: 187.7706624026276
p-value: 1.0147116860043298e-118
Reject Null Hypothesis
Variance of the groups are not equal
```

[52]:
```
#Perform Kruskal-Walis Test
stats,p_value=kruskal(s1,s2,s3,s4)
print('Test statistic:',stats)
print('p-value:',p_value)
#e. Decide whether to accept or reject the Null Hypothesis.
if p_value<alpha:
  print('Reject Null Hypothesis')
  print('There is a significant difference in the demand for bicycles on rent␣
 ↪across different seasons.')
else:
  print('Fail to reject Null Hypothesis')
  print('There is no significant difference in the demand for bicycles on rent␣
 ↪across different seasons.')
```

```
Test statistic: 699.6668548181988
p-value: 2.479008372608633e-151
Reject Null Hypothesis
There is a significant difference in the demand for bicycles on rent across
different seasons.
```

The results from the Kruskal-Wallis H-test show a significant difference in demand for bicycles across different seasons.

The visualizations support the findings, providing a comprehensive understanding of how seasons affect bicycle demand.

Insights - In summer and fall seasons more bikes are rented as compared to other seasons. - Whenever its a holiday more hikes are renteri - 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.

21 . Check if the Weather conditions are significantly different during different Seasons?

Null Hypothesis (H0): The weather conditions are not dependent on different seasons.

Alternative Hypothesis (H1): The weather conditions are dependent on different seasons.

[43]:
```
weather_category = {1: 'sunny-pleasant',
                    2: 'cloudy-delightful',
                    3: 'rainy-drenching'}
data['weather_encoded'] = data['weather'].map(weather_category)

season_category = {1: 'spring',
                   2: 'summer',
                   3: 'fall',
                   4: 'winter'}
```

```
data['season_encoded'] = data['season'].map(season_category)

# chisquare test is appropriate for Analysis
```

[45]:
```
alpha=0.05
contigency_table = pd.crosstab(data['weather_encoded'], data['season_encoded'])
contigency_table
```

[45]:

season_encoded	fall	spring	summer	winter
weather_encoded				
cloudy-delightful	604	715	708	807
rainy-drenching	199	211	224	225
sunny-pleasant	1930	1759	1801	1702

[46]:
```
# chisquare test is appropriate for Analysis
stats,p_value,dof,expected=chi2_contingency(contigency_table)
print('Test statistic:',stats)
print('p-value:',p_value)

#e. Decide whether to accept or reject the Null Hypothesis.

if p_value<alpha:
  print('Reject Null Hypothesis')
  print('The weather conditions are dependent on different seasons.')
else:
  print('Fail to reject Null Hypothesis')
  print('The weather conditions are not dependent on different seasons.')
```

```
Test statistic: 46.10145731073249
p-value: 2.8260014509929343e-08
Reject Null Hypothesis
The weather conditions are dependent on different seasons.
```

insights

p-value is less than the 5% significance level, we reject the null hypothesis. Hence, we have enough statistical evidence to say that the weather conditions are dependent on the ongoing season.

22 Recommendations

- Advertise the bikes differently in each season. For example, highlight summer promotions in June, July, and August when more people want to ride bikes.
- Change promotions or discounts based on the weather. If it's rainy, for example, offer special deals to encourage more people to use the bikes.
- Invest in technology and infrastructure to improve the overall user experience, including app features, bike maintenance, and customer support, fostering loyalty and repeat business.
- Concentrate bike deployment efforts during peak months, especially in June, July, and August, to meet increased demand and capitalize on favorable weather conditions.

- 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.
- 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.
- 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.