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.

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.

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:

o 1: Clear, Few clouds, partly cloudy

o 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist

o 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds

o 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

##Define the Problem Statement, Import the required Libraries and perform Exploratory Data Analysis

###Problem Statement and EDA

1. Which variables are significant in predicting the demand for shared electric cycles in the Indian market?

2. How well those variables describe the electric cycle demands.

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as sc

data = pd.read_csv("yulu_dataset.csv")

data.head()

           datetime  season  holiday  workingday  weather  temp
atemp  \
0  01-01-2011 00:00       1        0           0        1  9.84
14.395
1  01-01-2011 01:00       1        0           0        1  9.02
13.635
2  01-01-2011 02:00       1        0           0        1  9.02
13.635
3  01-01-2011 03:00       1        0           0        1  9.84
14.395
4  01-01-2011 04:00       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

data.shape

(10886, 12)

data.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
```

```
data.isna().sum(axis = 0)
```

```
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
```

```
'''
Observations:
1. There are 10886 rows and 12 columns present in the dataset.
2. The data type for all the variables except datetime is int/float.
3. The data type has to be changed for the following variables:
    1. datetime to datetime
    2. season to categorical
    3. holiday to categorical
    4. workingday to categorical
    5. weather to categorical
4. There are no missing values in the dataset.
'''
```

{"type":"string"}

```
data.describe(include = 'all')
```

```
                datetime         season       holiday    workingday  \
count              10886  10886.000000  10886.000000  10886.000000
unique             10886           NaN           NaN           NaN
top     01-01-2011 00:00           NaN           NaN           NaN
freq                   1           NaN           NaN           NaN
mean                 NaN      2.506614      0.028569      0.680875
std                  NaN      1.116174      0.166599      0.466159
min                  NaN      1.000000      0.000000      0.000000
25%                  NaN      2.000000      0.000000      0.000000
50%                  NaN      3.000000      0.000000      1.000000
75%                  NaN      4.000000      0.000000      1.000000
max                  NaN      4.000000      1.000000      1.000000

             weather         temp         atemp      humidity
windspeed  \
count   10886.000000  10886.00000  10886.000000  10886.000000
10886.000000
unique           NaN          NaN           NaN           NaN
NaN
top              NaN          NaN           NaN           NaN
NaN
freq             NaN          NaN           NaN           NaN
NaN
mean        1.418427     20.23086     23.655084     61.886460
12.799395
std         0.633839      7.79159      8.474601     19.245033
8.164537
min         1.000000      0.82000      0.760000      0.000000
0.000000
25%         1.000000     13.94000     16.665000     47.000000
7.001500
50%         1.000000     20.50000     24.240000     62.000000
12.998000
75%         2.000000     26.24000     31.060000     77.000000
16.997900
max         4.000000     41.00000     45.455000    100.000000
56.996900

              casual    registered         count
count   10886.000000  10886.000000  10886.000000
unique           NaN           NaN           NaN
top              NaN           NaN           NaN
freq             NaN           NaN           NaN
mean       36.021955    155.552177    191.574132
std        49.960477    151.039033    181.144454
min         0.000000      0.000000      1.000000
25%         4.000000     36.000000     42.000000
50%        17.000000    118.000000    145.000000
```

```
75%        49.000000    222.000000    284.000000
max       367.000000    886.000000    977.000000
```

```
categorical_variables = ['season', 'holiday', 'workingday', 'weather']
for var in categorical_variables:
  data[var] = data[var].astype('object')

data.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  object
 2   holiday     10886 non-null  object
 3   workingday  10886 non-null  object
 4   weather     10886 non-null  object
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64
 10  registered  10886 non-null  int64
 11  count       10886 non-null  int64
dtypes: float64(3), int64(4), object(5)
memory usage: 1020.7+ KB
```

```
'''
Observations:
1. We have converted the below features from continuous to
categorical:
  1. season
  2. holiday
  3. workingday
  4. weather

2. Using the statistical analysis, we can see that the mean and median
are very far away for the variables 'casual' and 'registered'.
Also, the standard deviation is very high. This suggests that there
are outliers present in the data for these attributes.
'''
```


```
{"type":"string"}
```


```
#Creating a new column of data type datetime
data['datetime'] = pd.to_datetime(data['datetime'])

data.head()
```

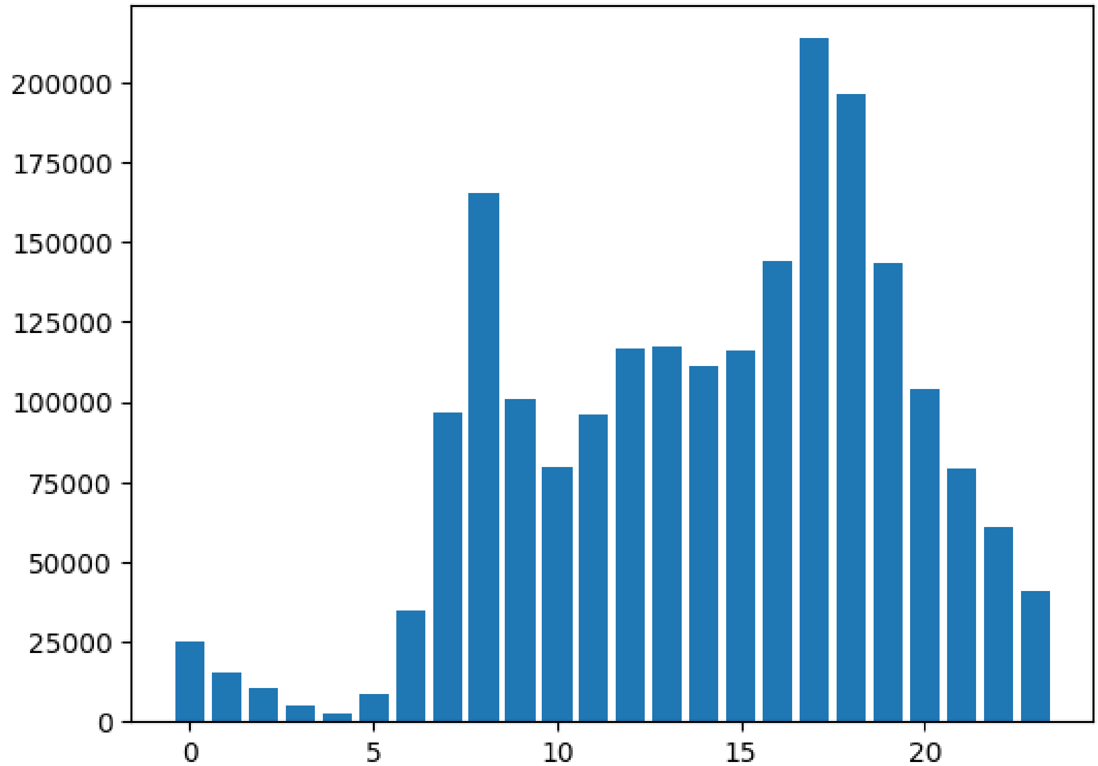
```
             datetime season holiday workingday weather  temp   atemp  \
0 2011-01-01 00:00:00      1       0          0       1  9.84  14.395   
1 2011-01-01 01:00:00      1       0          0       1  9.02  13.635   
2 2011-01-01 02:00:00      1       0          0       1  9.02  13.635   
3 2011-01-01 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  
```

```
data['hour'] = data['datetime'].dt.hour

data.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  hour  
0        81        0.0       3          13     16     0  
1        80        0.0       8          32     40     1  
2        80        0.0       5          27     32     2  
3        75        0.0       3          10     13     3  
4        75        0.0       0           1      1     4  
```

```
hour_wise_count = data.groupby('hour').agg({'count':'sum'})
plt.bar(data = hour_wise_count, x = hour_wise_count.index.values, 
height = 'count')
```

```
<BarContainer object of 24 artists>
```




```
'''
Observations:

1. Thus, we can see that the demand for rented bikes is more between
the timings 6 AM - 10 PM.
2. These are the peak hours when the demand is significantly higher
than the other hours.

'''
```

{"type":"string"}

```
data.duplicated().sum()
```

```
0
```

```
'''
There are no duplicated entries in the dataset.
'''
```

{"type":"string"}

###Univariate Analysis

```
min_datetime = data['datetime'].min()
max_datetime = data['datetime'].max()
```

```
print('Min datetime present: ', min_datetime)
print('Max datetime present: ', max_datetime)
```

```
Min datetime present:  2011-01-01 00:00:00
Max datetime present:  2012-12-19 23:00:00
```

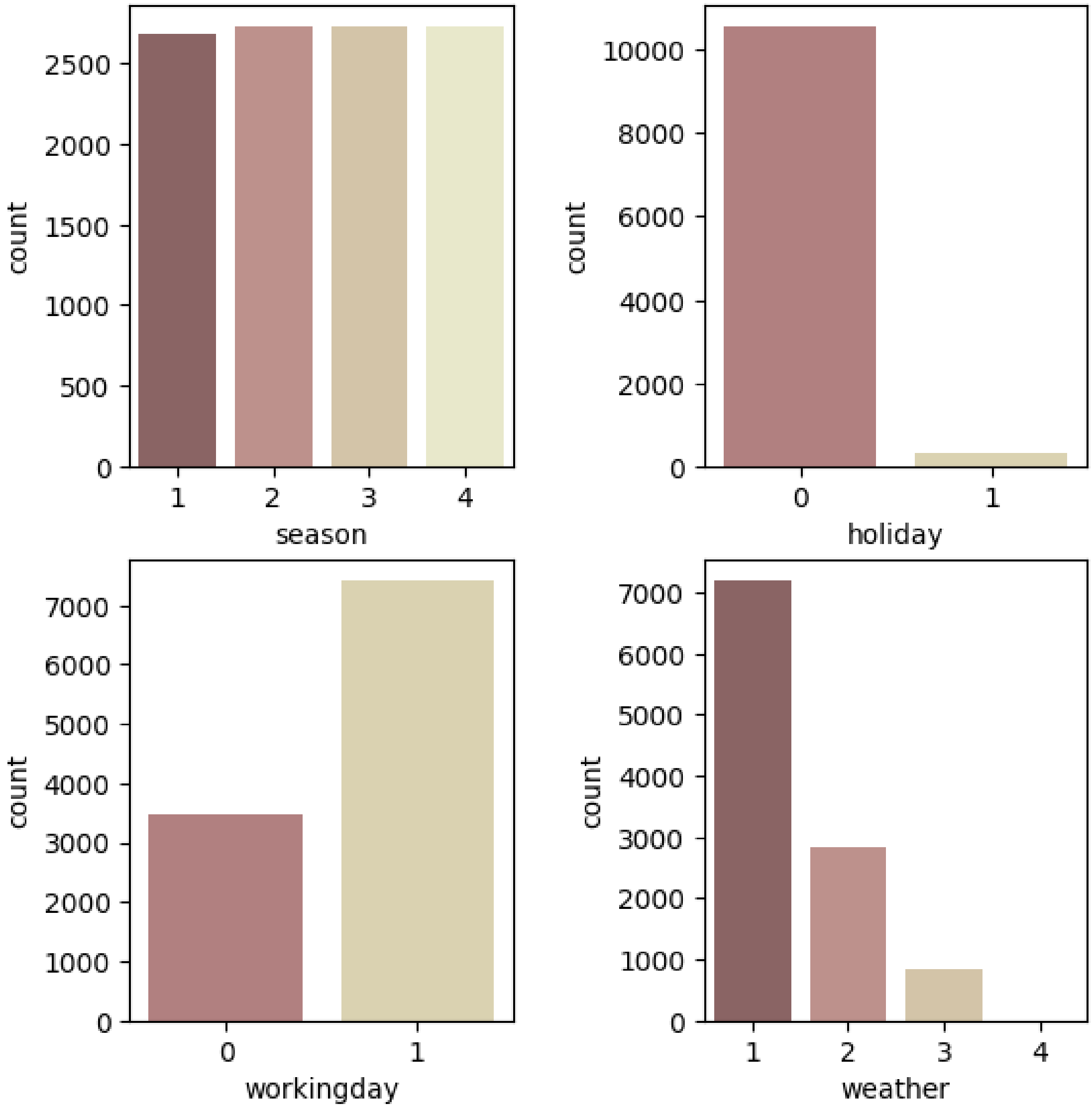
```
for column in data.columns.values:
  if data[column].dtype == 'object' and column != 'datetime':
    print('\n No of data-points for each of the unique values of :',
column)
    print(data[column].value_counts())
```

```

 No of data-points for each of the unique values of : season
4    2734
2    2733
3    2733
1    2686
Name: season, dtype: int64

 No of data-points for each of the unique values of : holiday
0    10575
1      311
Name: holiday, dtype: int64

 No of data-points for each of the unique values of : workingday
1    7412
0    3474
Name: workingday, dtype: int64

 No of data-points for each of the unique values of : weather
1    7192
2    2834
3     859
4       1
Name: weather, dtype: int64
```

```
i = 1
for column in data.columns.values:
  if data[column].dtype == 'object' and column != 'datetime':
    #plt.subplot.title('\n Boxplot for analysis of :', column)
    plt.subplot(5, 2, i)
    sns.countplot(data = data, x = column, palette = 'pink')
    i += 1

plt.subplots_adjust(top = 3.0, wspace = 0.5)
plt.show()
```

```
<ipython-input-431-49357aacbff5>:6: FutureWarning:
```

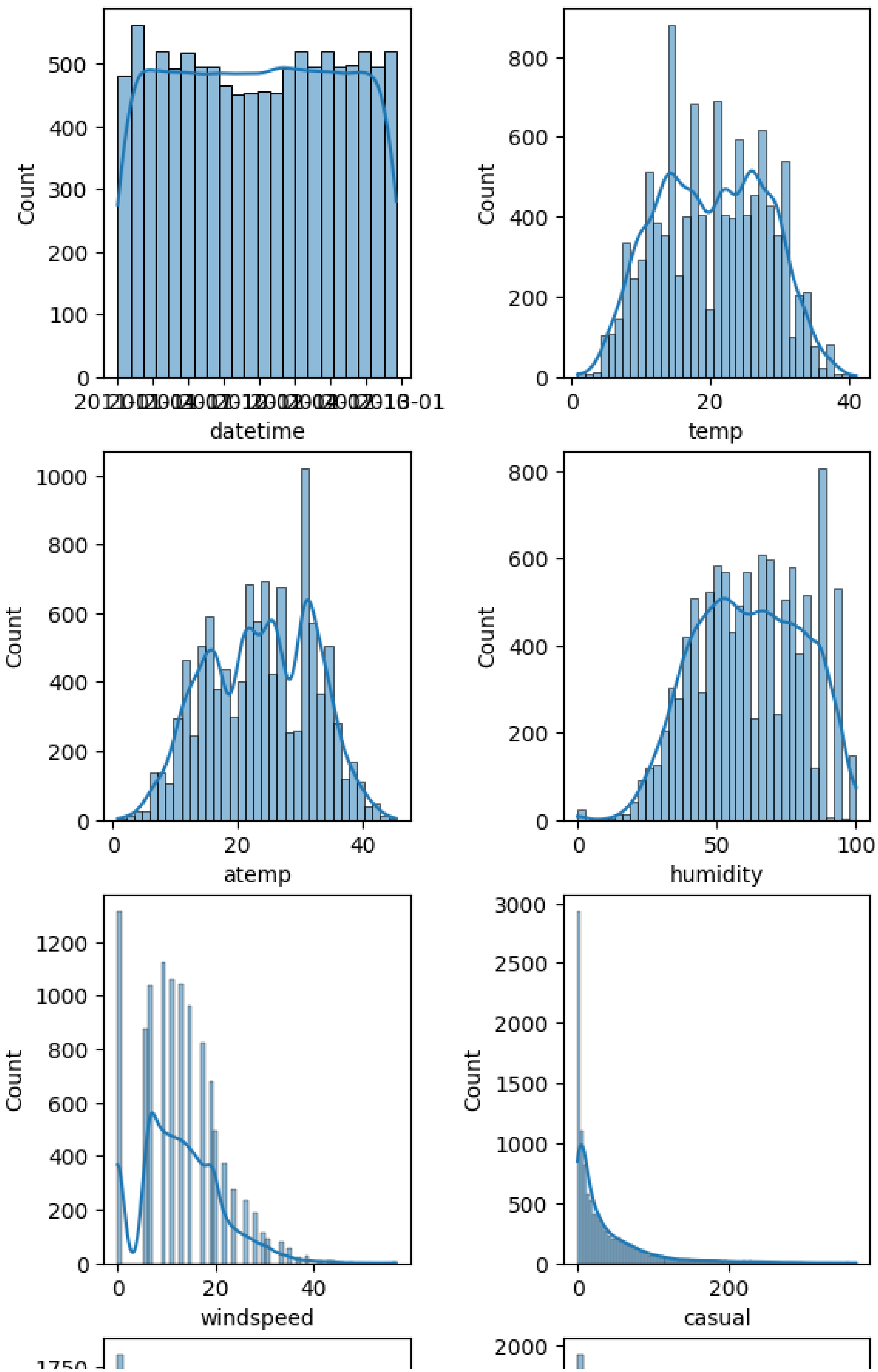
```
Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data = data, x = column, palette = 'pink')
<ipython-input-431-49357aacbff5>:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data = data, x = column, palette = 'pink')
<ipython-input-431-49357aacbff5>:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data = data, x = column, palette = 'pink')
<ipython-input-431-49357aacbff5>:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data = data, x = column, palette = 'pink')
```




```
'''
Observations:
1. Almost equal data-points are present for each of the values of
season.
2. We have majority data-points for holiday = 0 which means people
mostly use yulu on non-holiday days.
3. We have more data-points for workingday = 1
4. Maximum data-points are having weather = 1 which is Clear, Few
clouds, partly cloudy and literally no row for weather = 4
which means nobody prefers to take yulu when there's Heavy Rain + Ice
Pellets + Thunderstorm + Mist, Snow + Fog.
'''
```

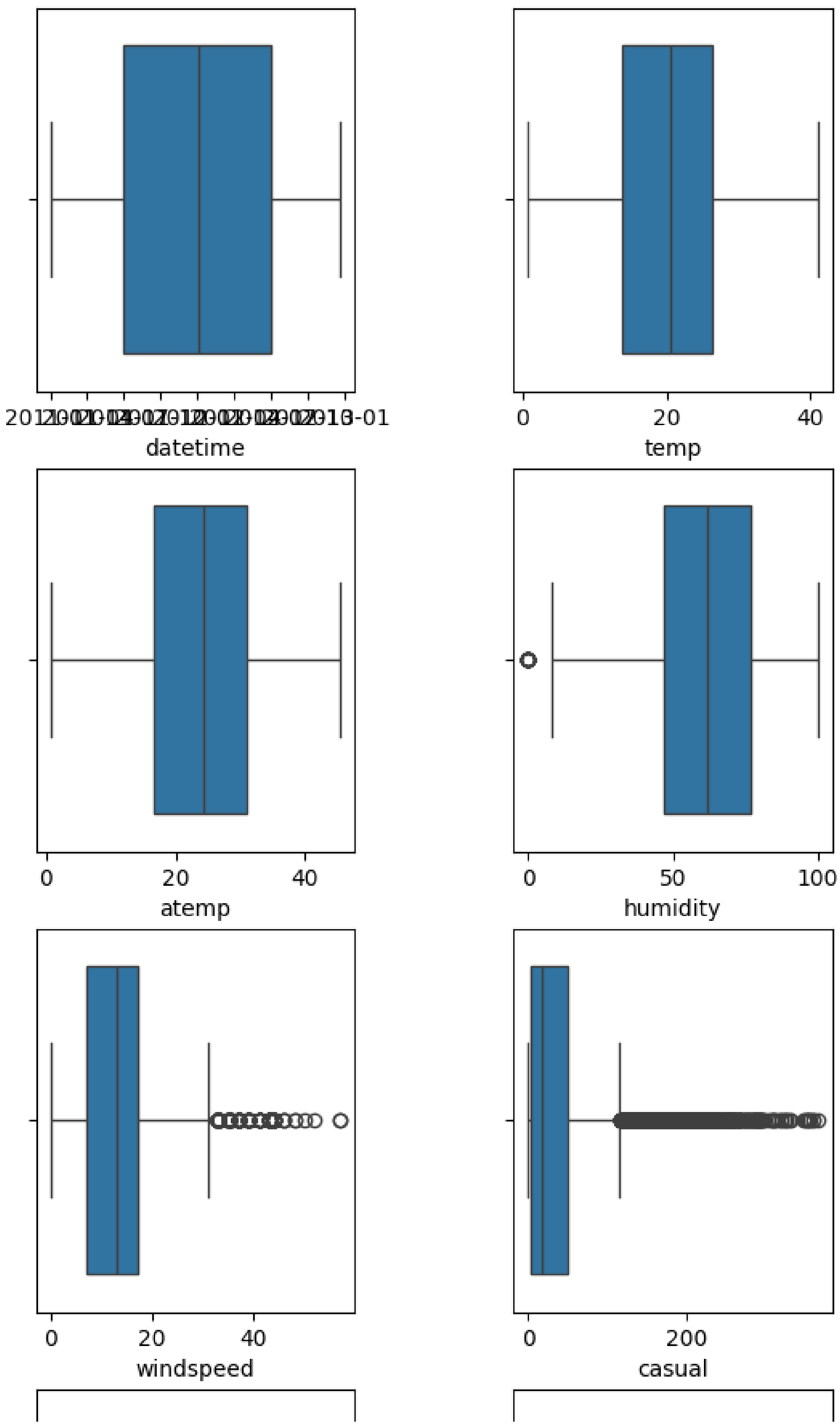
{"type":"string"}

```python
i = 1
for column in data.columns.values:
  if data[column].dtype != 'object':
    #print('\n Boxplot for analysis of :', column)
    plt.subplot(5, 2, i)
    sns.histplot(data = data, x = column, kde = True)
    i += 1

plt.subplots_adjust(top = 3.0, wspace = 0.5)
plt.show()
```



Count
datetime
temp
atemp
humidity
windspeed
casual

```python
i = 1
for column in data.columns.values:
  if data[column].dtype != 'object':
    #print('\n Boxplot for analysis of :', column)
    plt.subplot(5, 2, i)
    sns.boxplot(data = data, x = column, orient = 'h')
    i += 1

plt.subplots_adjust(top = 3.0, wspace = 0.5)
plt.show()
```



datetime
0
20
40
temp
0
20
40
atemp
0
50
100
humidity
0
20
40
windspeed
0
200
casual

```
'''
Observations:
1. Using the box-plot, we can infer that there are outliers present in the variables: windspeed, casual, registered and count.
2. Using the histplots, we can see that the data distributions for variables: casual, registered and count look somewhat like log-normal distribution.
Whereas for temp, atemp and humidity, looks like normal distribution.
'''
```

{"type":"string"}

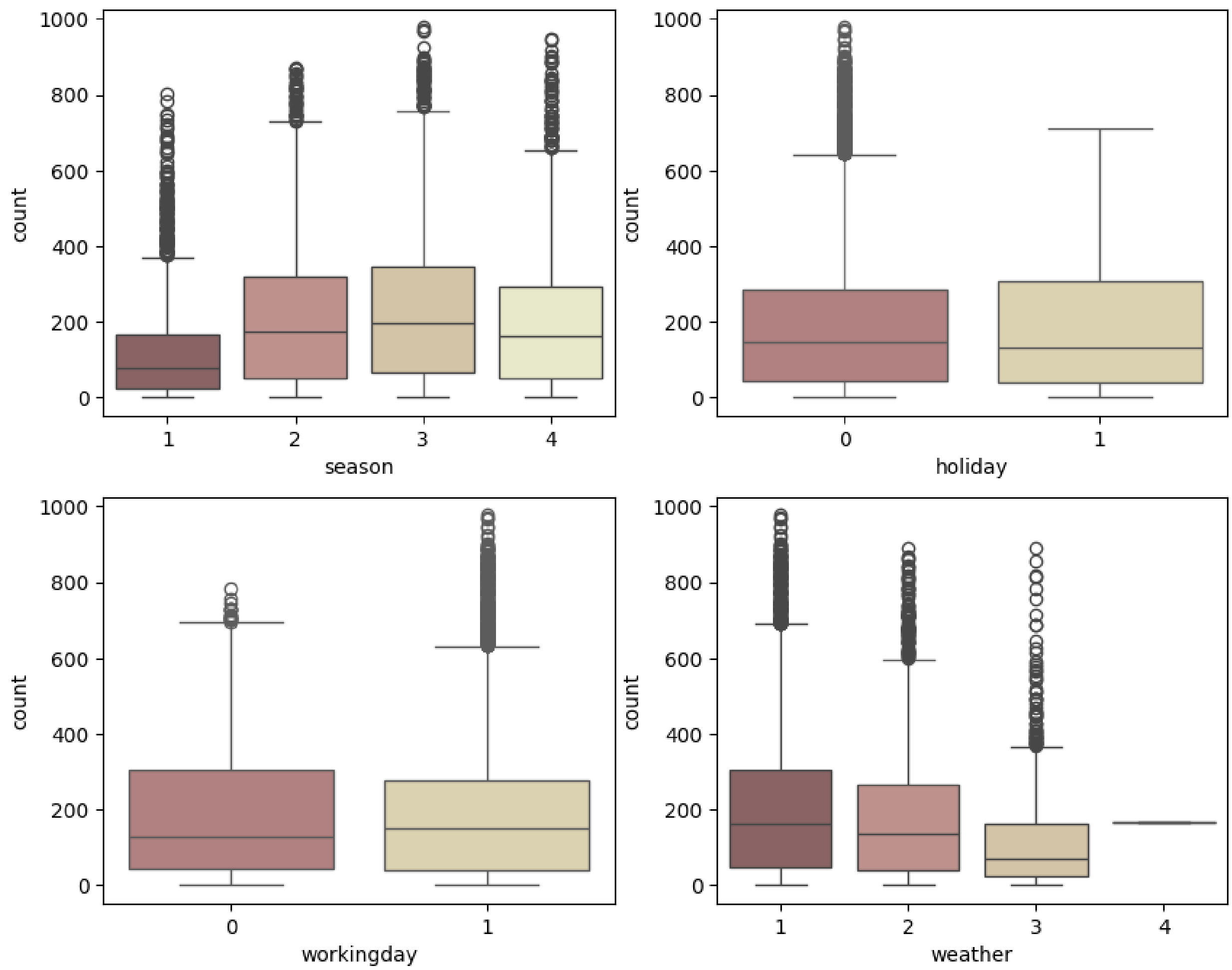
##Relationship between the Dependent and Independent Variables

###Bivariate Analysis

```
# plotting categorical variables againt count using boxplots

cat_cols= ['season', 'holiday', 'workingday', 'weather']
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(10, 8))

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

plt.show()
```

```
<ipython-input-436-b8f46b61398f>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.boxplot(data=data, x=cat_cols[index], y='count', ax=axis[row,
col], palette='pink')
<ipython-input-436-b8f46b61398f>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.boxplot(data=data, x=cat_cols[index], y='count', ax=axis[row,
col], palette='pink')
<ipython-input-436-b8f46b61398f>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
```

```
`legend=False` for the same effect.

  sns.boxplot(data=data, x=cat_cols[index], y='count', ax=axis[row,
col], palette='pink')
<ipython-input-436-b8f46b61398f>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.boxplot(data=data, x=cat_cols[index], y='count', ax=axis[row,
col], palette='pink')
```

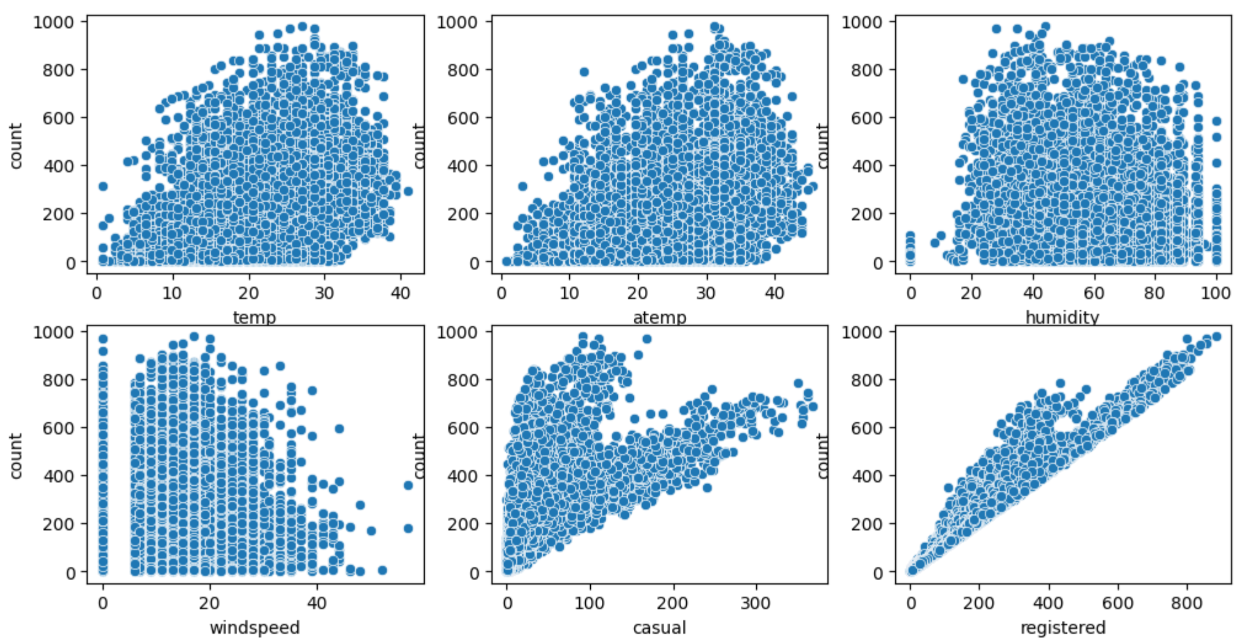



```
'''
Observations:
Using the above box-plots we can infer that:
1. The number of bikes rented is higher for summer and fall seasons.
2. The number of bikes rented is higher for non-holiday days.
3. The number of bikes rented is higher for working days.
```

```
4. The number of bikes rented is higher when weather conditions are:
Clear, Few clouds, partly cloudy.
The number of bikes rented is very less when there's Heavy Rain + Ice
Pellets + Thunderstorm + Mist, Snow + Fog.
'''
```

{"type":"string"}

```
# plotting numerical variables againt count using scatterplot

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

fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(12, 6))

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

plt.show()
```



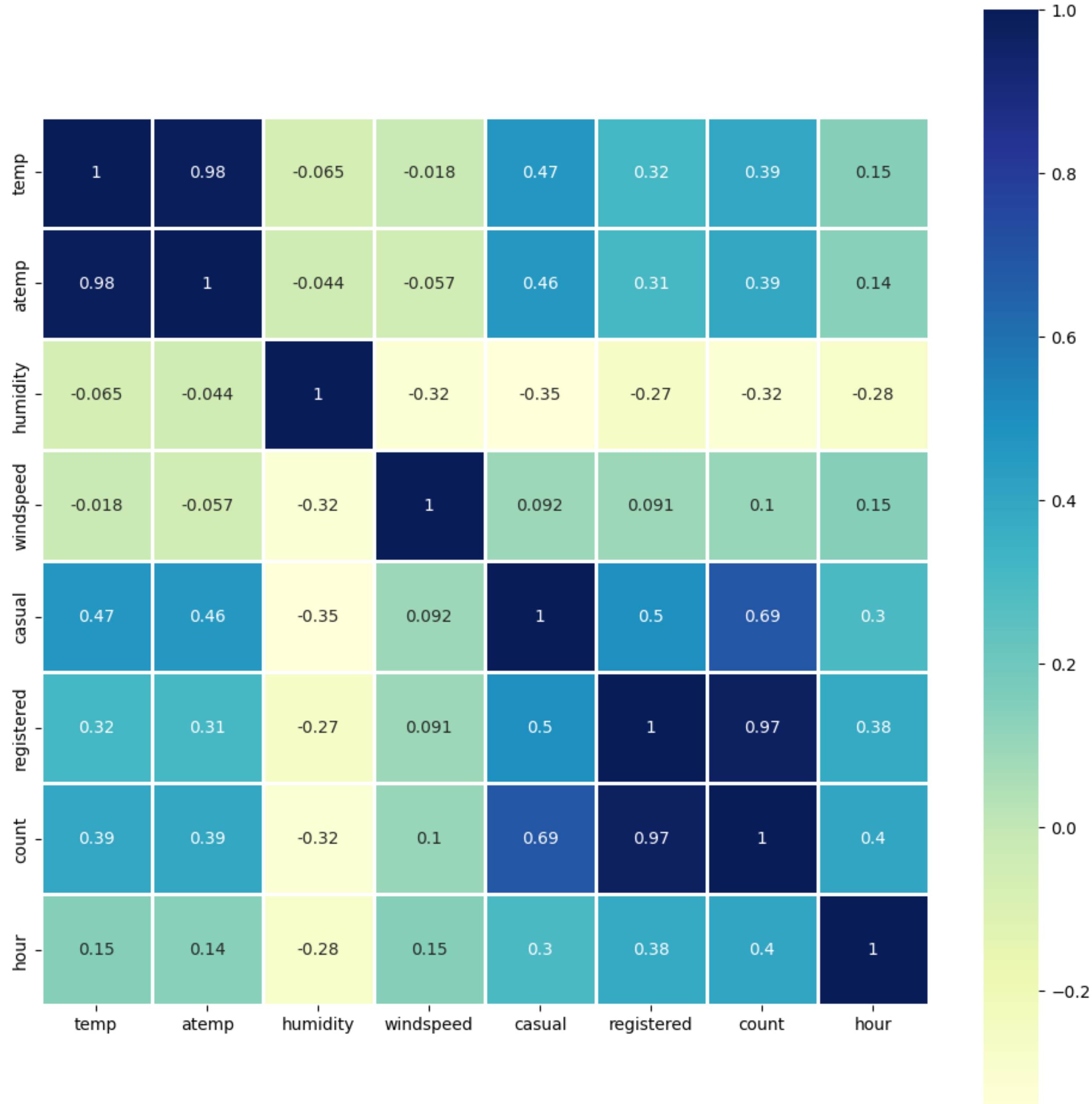

```
'''
Observations:
Using the above scatter-plots, we can infer that:
1. Whenever the humidity is less than 20, number of bikes rented is
very very low.
2. Whenever the temperature is less than 10, number of bikes rented is
```

```
less.
3. Whenever the windspeed is greater than 40, number of bikes rented
is very less.
'''
```

{"type":"string"}

```
# understanding the correlation between count and numerical variables

plt.figure(figsize = (12, 12))
#data_new = data.drop(['dayofweek', 'is_weekend'], axis = 1)
correlation_table = data.corr()
sns.heatmap(correlation_table, annot = True, linewidths = 2, square =
True, cmap = 'YlGnBu')
plt.show()
```

```
<ipython-input-440-1e1bdccfb7e9>:5: FutureWarning: The default value
of numeric_only in DataFrame.corr is deprecated. In a future version,
it will default to False. Select only valid columns or specify the
value of numeric_only to silence this warning.
  correlation_table = data.corr()
```




```
'''
Observations:
1. We can see that there's a high positive correlation between count
and registered variables which means that registered users account
more towards the count than the casual users.
2. We can see that there's a significant negative correlation between
count of users and humidity
which suggests that as the humidity increases the count of users
taking the yulu decreases and vice-a-versa.
3. There's a high positive correlation between temp and atemp
variables which means that as the actual temperature
```

```
increases/decreases, the feeling temperature also increase/decreases.
'''
```

```
{"type":"string"}
```

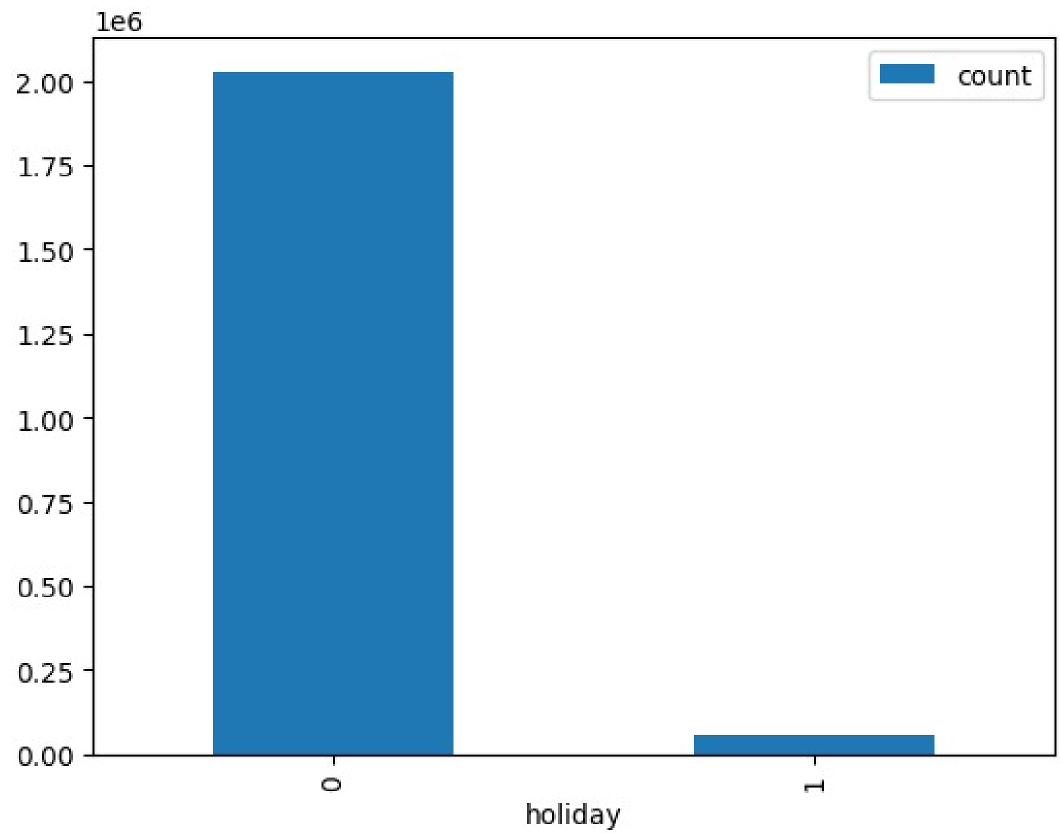
####Categorical Variables vs Number of Total users

```
#holiday vs sum(count)
grouped_data = data.groupby(['holiday']).agg({'count': 'sum'})
grouped_data
```

	count
holiday	
0	2027668
1	57808

```
#analysing using bar plot
grouped_data.plot(kind = 'bar')
```

```
<Axes: xlabel='holiday'>
```




```
#analysing using pie plot

bikes = []
```

```python
for val in grouped_data.values:
  #print(int(val))
  bikes.append(int(val))

bikes
```

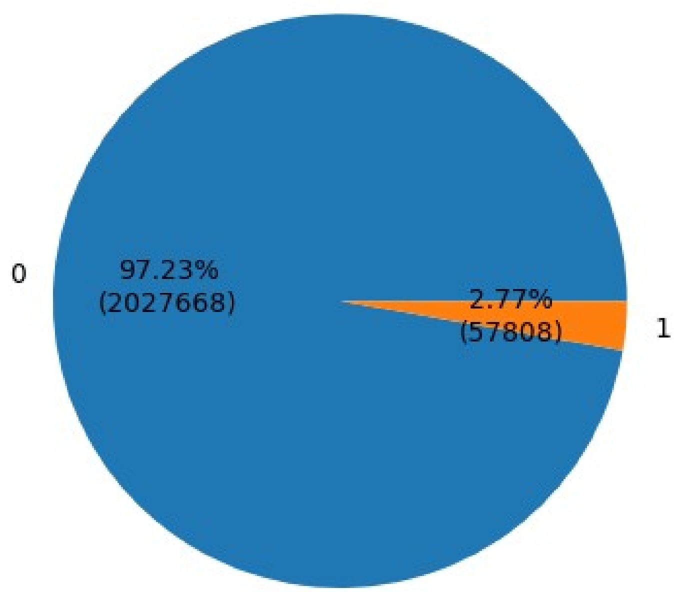
```
[2027668, 57808]
```

```python
holiday_values = list(grouped_data.index.values)
holiday_values
```

```
[0, 1]
```

```python
def my_fmt(x):
    print(x)
    return '{:.2f}%\n({:.0f})'.format(x, total*x/100)

total = np.sum(bikes)
plt.pie(bikes, labels = holiday_values, autopct = my_fmt)
plt.show()
```

```
97.22806811332703
2.771933190524578
```




```python
data[(data['holiday'] == 1)]['count'].sum()
```

```
57808
```

```python
#season vs sum(count)
data.groupby('season')['count'].sum()
```

```
season
1    312498
2    588282
3    640662
4    544034
Name: count, dtype: int64
```

```python
#weather vs sum(count)
data.groupby('weather')['count'].sum()
```

```
weather
1    1476063
2     507160
3     102089
4        164
Name: count, dtype: int64
```

```python
#workingday vs sum(count)
data.groupby('workingday')['count'].sum()
```

```
workingday
0     654872
1    1430604
Name: count, dtype: int64
```

```python
#percentage of casual and registered users

total_count = data['count'].sum()
casual_count = data['casual'].sum()
registered_count = data['registered'].sum()


print('Percentage of casual users: ', casual_count*100/total_count)
print('Percentage of registered users: ',
registered_count*100/total_count)
```

```
Percentage of casual users:  18.8031413451893
Percentage of registered users:  81.1968586548107
```

```python
'''
Observations:
1. The number of total rental bikes is greater for fall season
followed by summer, winter and spring.
2. The number of total rental bikes is greater on working days than
non-working days.
3. The number of total rental bikes is greater for the weather -
Clear, Few clouds, partly cloudy as compared to other weather
conditions.
```

```
4. The percentage of casual users is way lesser than the percentage of
registered users.
'''

{"type":"string"}
```

##Outlier Detection and Treatment

###Outlier Detection

```
#Calculating few more statistical measures such as 'Range', 'IQR',
'Lower Whisker' and 'Upper Whisker'
descriptive_stats = data.describe()
descriptive_stats =
descriptive_stats.reindex(descriptive_stats.index.values.tolist()+
['Range', 'IQR', 'Lower Whisker', 'Upper Whisker'])

for col in descriptive_stats.columns:
  if data[col].dtype != 'object':
    descriptive_stats.loc['Range'][col] = descriptive_stats.loc['max']
[col] - descriptive_stats.loc['min'][col]
    descriptive_stats.loc['IQR'][col] = descriptive_stats.loc['75%']
[col] - descriptive_stats.loc['25%'][col]
    descriptive_stats.loc['Lower Whisker'][col] =
descriptive_stats.loc['25%'][col] - (1.5 *
descriptive_stats.loc['IQR'][col])
    descriptive_stats.loc['Upper Whisker'][col] =
descriptive_stats.loc['75%'][col] + (1.5 *
descriptive_stats.loc['IQR'][col])

descriptive_stats
```

	temp	atemp	humidity	windspeed \
count	10886.00000	10886.000000	10886.000000	10886.000000
mean	20.23086	23.655084	61.886460	12.799395
std	7.79159	8.474601	19.245033	8.164537
min	0.82000	0.760000	0.000000	0.000000
25%	13.94000	16.665000	47.000000	7.001500
50%	20.50000	24.240000	62.000000	12.998000
75%	26.24000	31.060000	77.000000	16.997900
max	41.00000	45.455000	100.000000	56.996900
Range	40.18000	44.695000	100.000000	56.996900

IQR	12.30000	14.395000	30.000000	9.996400
Lower Whisker	-4.51000	-4.927500	2.000000	-7.993100
Upper Whisker	44.69000	52.652500	122.000000	31.992500

	casual	registered	count	hour
count	10886.000000	10886.000000	10886.000000	10886.000000
mean	36.021955	155.552177	191.574132	11.541613
std	49.960477	151.039033	181.144454	6.915838
min	0.000000	0.000000	1.000000	0.000000
25%	4.000000	36.000000	42.000000	6.000000
50%	17.000000	118.000000	145.000000	12.000000
75%	49.000000	222.000000	284.000000	18.000000
max	367.000000	886.000000	977.000000	23.000000
Range	367.000000	886.000000	976.000000	23.000000
IQR	45.000000	186.000000	242.000000	12.000000
Lower Whisker	-63.500000	-243.000000	-321.000000	-12.000000
Upper Whisker	116.500000	501.000000	647.000000	36.000000

```
#counting the number of outliers present in each variable using IQR method
for col in descriptive_stats.columns:
  print(col, ':', data[(data[col] < descriptive_stats.loc['Lower Whisker'][col]) | (data[col] > descriptive_stats.loc['Upper Whisker'][col])][col].count())
```

```
temp : 0
atemp : 0
humidity : 22
windspeed : 227
casual : 749
registered : 423
count : 300
hour : 0
```

```python
#calculating the percentage of outliers present in each variable
for col in descriptive_stats.columns:
  print(col, ':', data[(data[col] < descriptive_stats.loc['Lower Whisker'][col]) | (data[col] > descriptive_stats.loc['Upper Whisker'][col])][col].count()*100/len(data))
```

```
temp : 0.0
atemp : 0.0
humidity : 0.20209443321697593
windspeed : 2.085247106375161
casual : 6.880396839977953
registered : 3.885724784126401
count : 2.75583318023149
hour : 0.0
```

```python
'''
Observations:

1. There are significant number of outliers present in windspeed, casual, registered and count variables.
2. Also, humidity has a few outliers.
'''
```

{"type":"string"}

###Outlier Treatment

```python
#Clip the outliers using minimum and maximum i.e. if value < minimum then update value to minimum and similarly is value > maximum then update value to maximum.

for col in descriptive_stats.columns:
  data.loc[data[col] < descriptive_stats.loc['Lower Whisker'][col], col] = descriptive_stats.loc['Lower Whisker'][col]
  data.loc[data[col] > descriptive_stats.loc['Upper Whisker'][col], col] = descriptive_stats.loc['Upper Whisker'][col]

for col in descriptive_stats.columns:
  print(col, ':', data[(data[col] < descriptive_stats.loc['Lower Whisker'][col]) | (data[col] > descriptive_stats.loc['Upper Whisker'][col])][col].count())
```

```
temp : 0
atemp : 0
humidity : 0
windspeed : 0
casual : 0
registered : 0
count : 0
hour : 0
```

##Hypothesis Testing

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

```
#Adding a new column 'dayofweek' which will be having value [0-6] for
[Mon-Sun]
from datetime import datetime
data['dayofweek'] = data['datetime'].dt.dayofweek

data.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  hour  dayofweek
0        81        0.0     3.0          13     16     0          5
1        80        0.0     8.0          32     40     1          5
2        80        0.0     5.0          27     32     2          5
3        75        0.0     3.0          10     13     3          5
4        75        0.0     0.0           1      1     4          5
```

```
#Adding a new column to identify if the day was on weekday or on
weekend
data['is_weekend'] = (data['dayofweek'] > 4)

data.groupby(['is_weekend'])['count'].sum()
```

```
is_weekend
False    1451356
True      602885
Name: count, dtype: int64
```

```
data.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  hour  dayofweek
is_weekend
0        81        0.0     3.0          13     16     0          5
True
1        80        0.0     8.0          32     40     1          5
True
2        80        0.0     5.0          27     32     2          5
True
3        75        0.0     3.0          10     13     3          5
True
4        75        0.0     0.0           1      1     4          5
True
```

```
#Two Sample Independent T-Test
#Since we have to compare the demand for two samples --> weekdays and
weekends so we will perform T-Test

from scipy.stats import ttest_ind

#H0 [Null Hypothesis]: demand for bikes is same on weekdays and
weekends
#Ha [Alternate Hypothesis]: demand for bikes is different on weekdays
and weekends

alpha = 0.05

weekdays = data[data['is_weekend'] == False]['count']
weekends = data[data['is_weekend'] == True]['count']

'''
Before conducting the two-sample T-Test we need to find if the given
data groups have
the same variance. If the ratio of the larger data groups to the small
data group is less
than 4:1 then we can consider that the given data groups have equal
variance.
'''
```

{"type":"string"}

```
print(np.var(weekdays), np.var(weekends))
print(np.var(weekdays) // np.var(weekends))
```

```
29297.3452549416 30763.766315011857
0.0
```

```
t_stat, p_val = ttest_ind(weekdays, weekends)
t_stat, p_val
```

```
(-0.8983490774297157, 0.36901934792790525)
```

```
if p_val < alpha:
  print('Since the p-value {:.2f} is less than or equal to the predetermined level of significance (alpha = 0.05), we have evidence to reject the null hypothesis. Meaning that there is a significant difference between the no. of bike rides on Weekdays and Weekends'.format(p_val))
else:
  print('Since the p-value {:.2f} is greater than the predetermined level of significance (alpha = 0.05), we do not have sufficient evidence to reject the null hypothesis. Meaning that there is no significant difference between the no. of bike rides on Weekdays and Weekends'.format(p_val))
```

```
Since the p-value 0.37 is greater than the predetermined level of
significance (alpha = 0.05), we do not have sufficient evidence to
reject the null hypothesis. Meaning that there is no significant
difference between the no. of bike rides on Weekdays and Weekends
```

```
'''
Conclusion:
Since p_val > 0.05 so, we fail to reject H0. So, demand is same on weekdays and weekends.
'''
```

{"type":"string"}

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

```
'''
1. Since, we are supposed to compare 4 different groups so we can use one-way ANOVA

2. But first we will check if the assumptions of one-way ANOVA hold true
If yes, then we will perform one-way ANOVA else we will peform Kruskal Wallis Test.

3. One-way ANOVA compares the means of three or more different groups whereas Kruskal Wallis compares the medians of three or more different groups when data is normally distributed

4. One-Way ANOVA is a parametric test whereas Kruskal Wallis is non-parametric test.
'''
```

{"type":"string"}

```
data.groupby('weather')['count'].sum()
```

```
weather
1    1451617
2     501554
3     100906
4        164
Name: count, dtype: int64
```

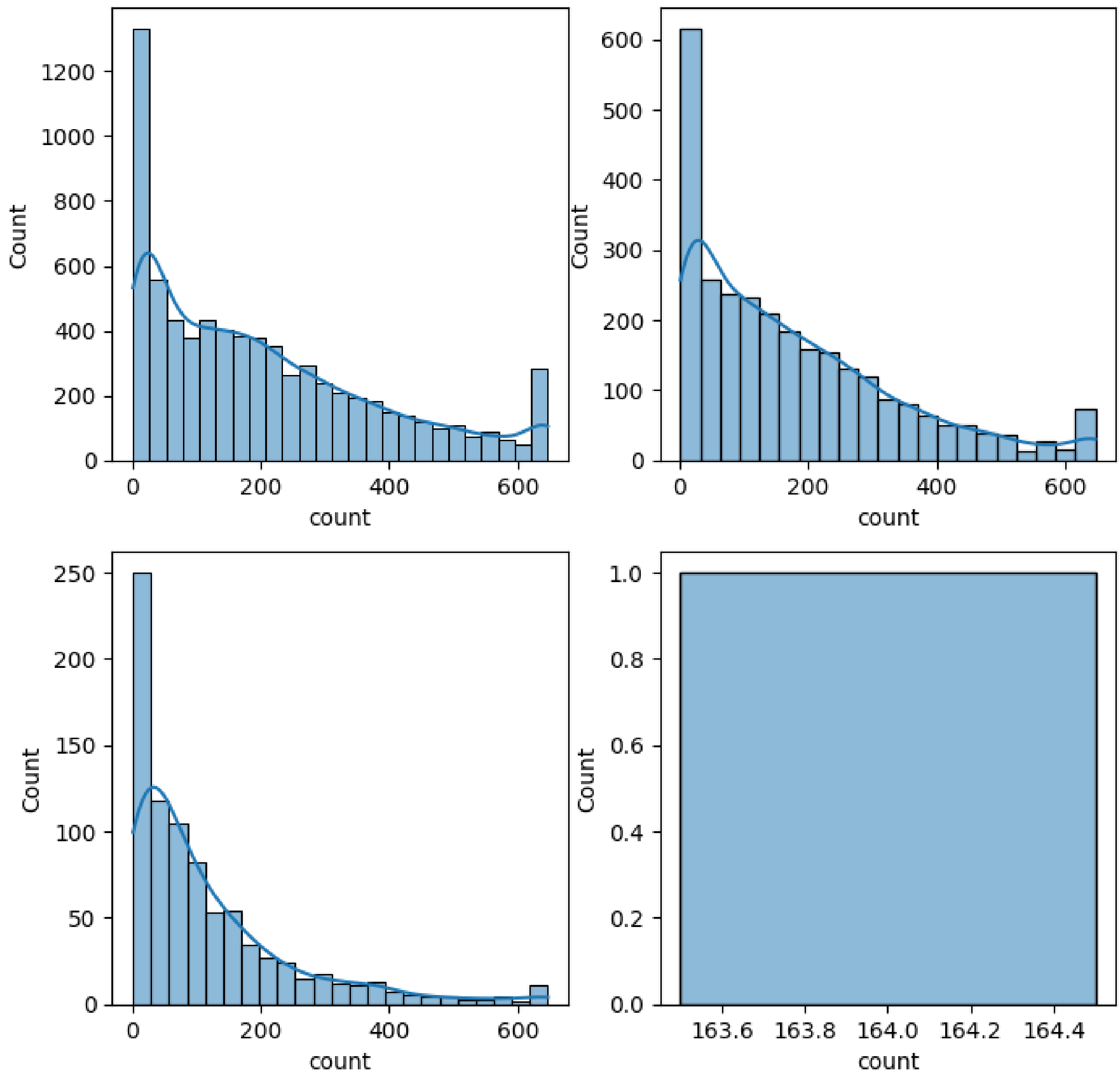
```
from statsmodels.graphics.gofplots import qqplot

#H0: The demand for the bicycles on rent is same for all 4 weather
conditions
#Ha: The demand for the bicycles on rent is different for at least one
of the 4 weather conditions

#significance level = alpha

alpha = 0.05

weather_1 = data[data['weather'] == 1]['count']
weather_2 = data[data['weather'] == 2]['count']
weather_3 = data[data['weather'] == 3]['count']
weather_4 = data[data['weather'] == 4]['count']

weather_groups = [weather_1, weather_2, weather_3, weather_4]

'''
Checking the assumptions for ANOVA
1. Normality Test for normal distribution of data of each group
2. Variability Test for equal variances within groups
3. Data is independent
'''
```

{"type":"string"}

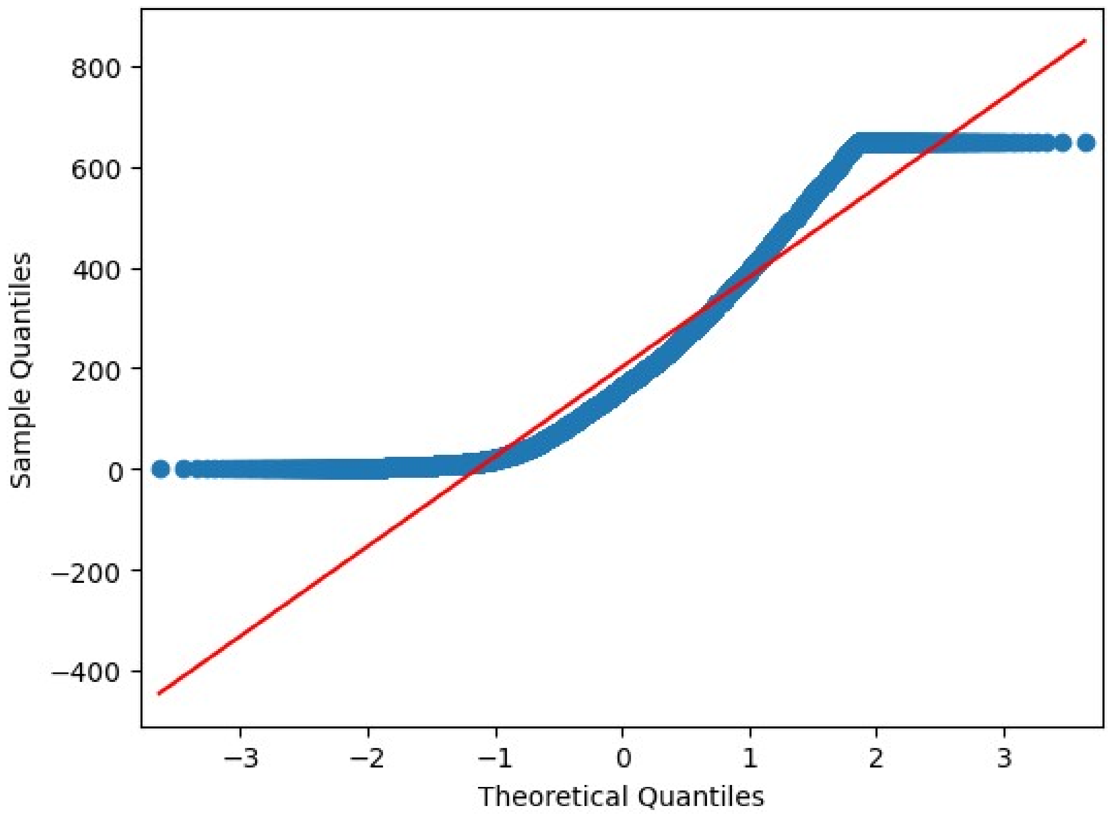
```
#Normality Test: Shapiro Wilk Test
from scipy.stats import shapiro

#H0: Data is gaussian
#Ha: Data is not gaussian

test_stat, p_val = shapiro(weather_1)
test_stat, p_val
```

```
/usr/local/lib/python3.10/dist-packages/scipy/stats/
_morestats.py:1882: UserWarning: p-value may not be accurate for N >
5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

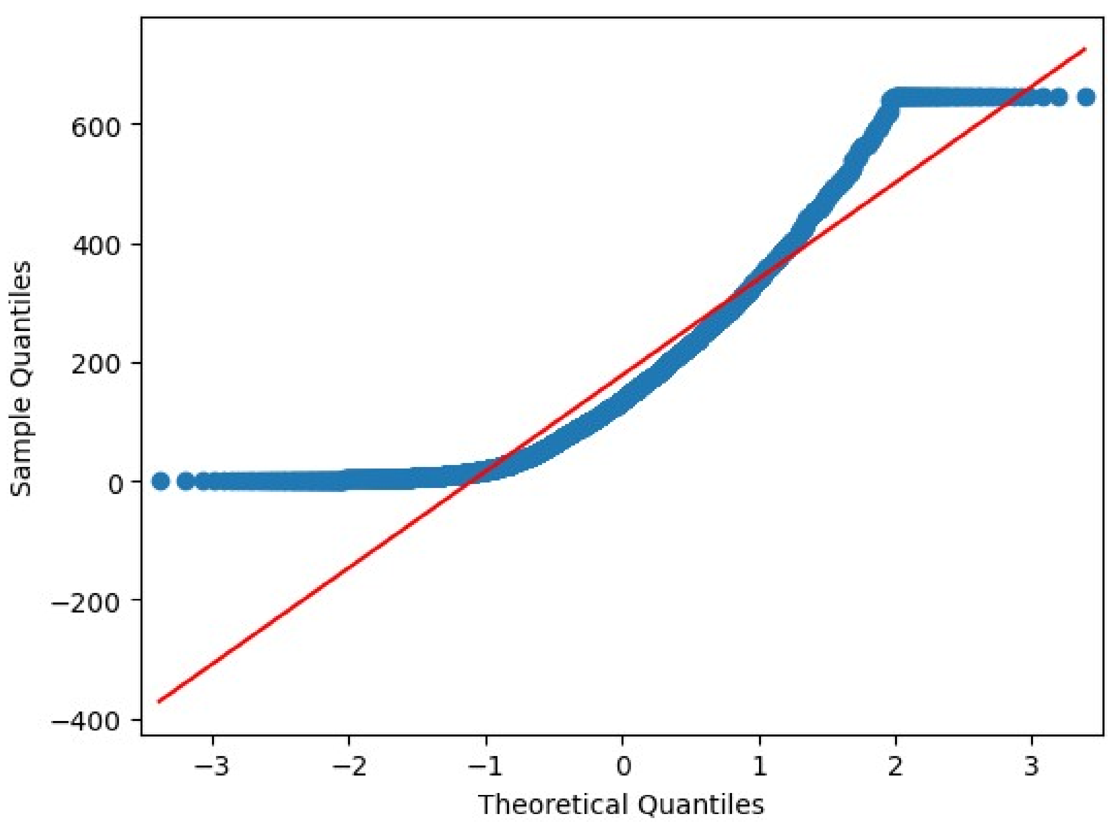
```
(0.8987792730331421, 0.0)

test_stat, p_val = shapiro(weather_2)
test_stat, p_val

(0.8865376710891724, 1.7712412589065688e-41)

test_stat, p_val = shapiro(weather_3)
test_stat, p_val

(0.788669764995575, 6.402264154069943e-32)

weather_4

5631    164
Name: count, dtype: int64

#Plot Histogram for analysing the data distribution for each weather
group
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(8, 8))

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

plt.show()
```



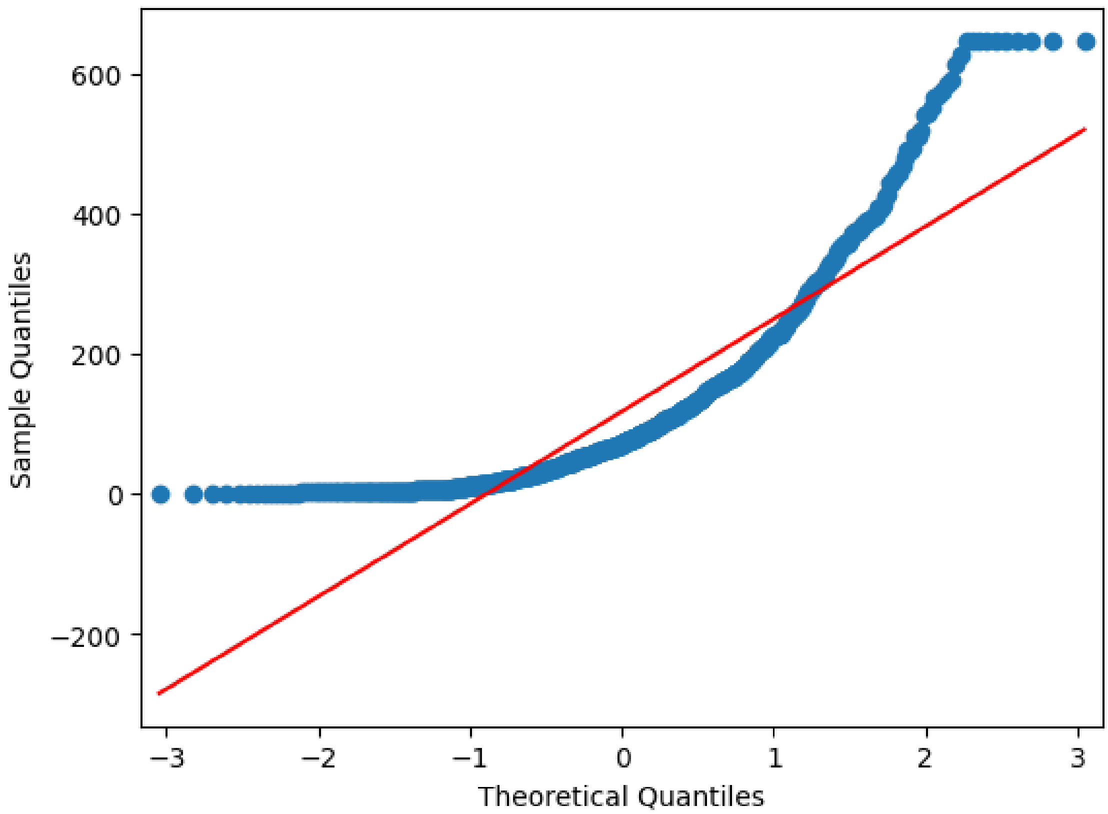

```
##Plot Q-Q Plot [Quantile Quantile Plot] for analysing the data
distribution for each weather group
index = 0
for row in range(2):
    for col in range(2):
        qqplot(weather_groups[index], line="s")
        index += 1

plt.show()
```



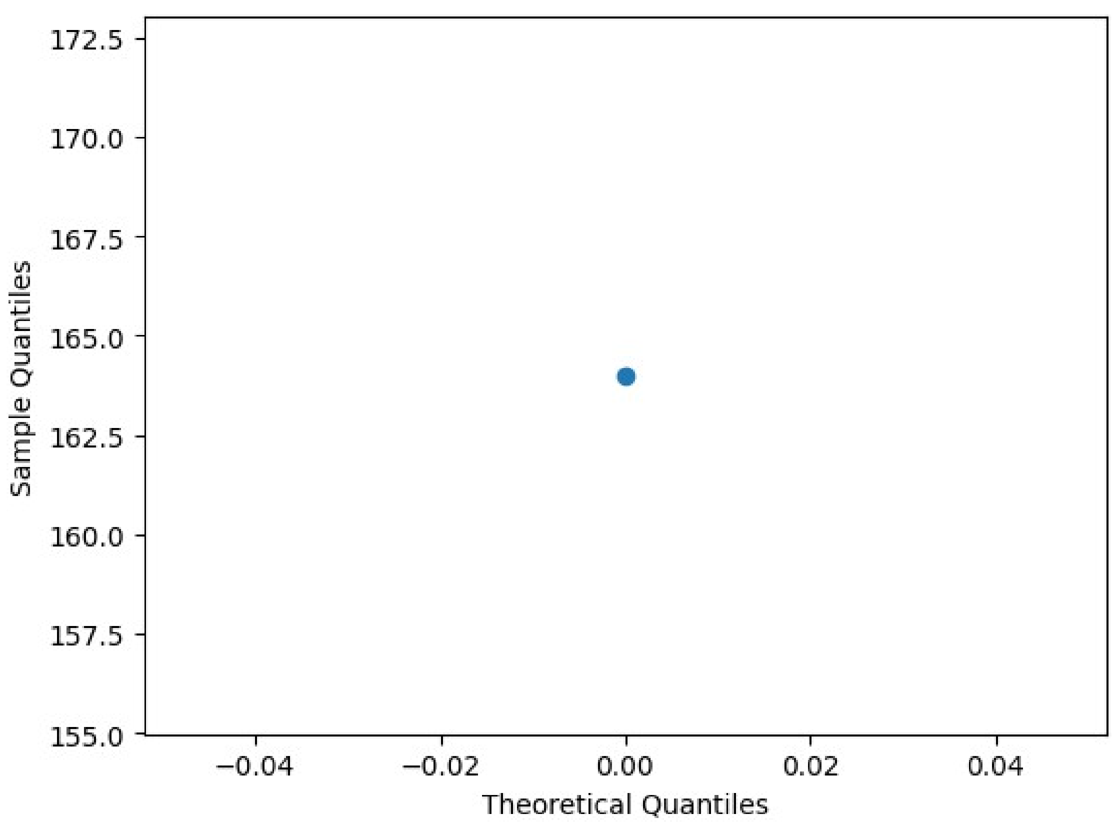
800
600
400
200
0
−200
−400
Sample Quantiles
−3
−2
−1
0
1
2
3
Theoretical Quantiles



600
400
200
0
−200
−400
Sample Quantiles
−3
−2
−1
0
1
2
3
Theoretical Quantiles



600
400
200
0
−200
Sample Quantiles
−3
−2
−1
0
1
2
3
Theoretical Quantiles



172.5
170.0
167.5
165.0
162.5
160.0
157.5
155.0
Sample Quantiles
−0.04
−0.02
0.00
0.02
0.04
Theoretical Quantiles

```
'''
Observations:
1. Using the Shpairo Wilk Test, we can see that the p_val < 0.05 so,
the 4 weather groups' data distributions don't follow gaussian
(normal) disribution.
2. So, Shapiro's Test for normality has been failed.
3. The results of Shapiro test have been verified using the Q-Q Plot
as well.
'''
```

{"type":"string"}

```
#Skewness
skew_1 = weather_1.skew()
skew_2 = weather_2.skew()
skew_3 = weather_3.skew()
skew_4 = weather_4.skew()

skew_1, skew_2, skew_3, skew_4
```

```
(0.889718073393374, 1.0865993527456523, 1.866516508736173, nan)
```

```
#Kurtosis
kurt_1 = weather_1.kurt()
kurt_2 = weather_2.kurt()
kurt_3 = weather_3.kurt()
kurt_4 = weather_4.kurt()

kurt_1, kurt_2, kurt_3, kurt_4
```

```
(-0.07675757291483398, 0.5909595721045058, 3.637210263162605, nan)
```

```
#Thus, we can see that the data is positively skewed i.e. right tailed
skewness is present.
```

```
#Variability Test : Levene's Test
from scipy.stats import levene

#H0: Varinaces are equal within the groups
#Ha: Varinaces are not equal within the groups

test_stat, p_val = levene(weather_1, weather_2, weather_3, weather_4)
test_stat, p_val
```

```
(59.78620431801216, 2.499984328437755e-38)
```

```
'''
Observations:
1. Since, p_val < 0.05 so we reject null hypothesis which means the
variances are not equal within the groups.
2. Thus, Levene's test for equal variances within groups has been
```

```
failed.
'''
```

{"type":"string"}

```
'''
Conclusion:
Thus, we cant't perform one-way ANOVA as the assumptions for ANOVA don't hold true.
So, we will perform Kruskal Wallis Test which compares medians of different groups.
'''
```

{"type":"string"}

```
#Kruskal Wallis Test

#H0: The medians of groups are same
#Ha: The medians of groups are not the same

from scipy.stats import kruskal
test_stat, p_val = kruskal(weather_1, weather_2, weather_3, weather_4)
test_stat, p_val
```

```
(205.04853208154285, 3.421748763291878e-44)
```

```
if p_val < alpha:
  print('Since the p-value {:.2f} is less than or equal to the predetermined level of significance (alpha = 0.05), we have evidence to reject the null hypothesis. Meaning that the demand for bicycles is not the same for different weather conditions.'.format(p_val))
else:
  print('Since the p-value {:.2f} is greater than the predetermined level of significance (alpha = 0.05), we do not have sufficient evidence to reject the null hypothesis. Meaning that the demand for bicycles is the same for different weather conditions.'.format(p_val))
```

```
Since the p-value 0.00 is less than or equal to the predetermined level of significance (alpha = 0.05), we have evidence to reject the null hypothesis. Meaning that the demand for bicycles is not the same for different weather conditions.
```

```
'''
Observations:
Since, p_val < alpha (0.05) so we can reject the null hypothesis
So, the demand is not the same for all weather conditions
'''
```

{"type":"string"}

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

```
'''
1. Since, we are supposed to compare 4 different groups so we can use
one-way ANOVA

2. But first we will check if the assumptions of one-way ANOVA hold
true
If yes, then we will perform one-way ANOVA else we will peform Kruskal
Wallis Test.

3. One-way ANOVA compares the means of three or more different groups
whereas Kruskal Wallis compares the medians of three or more different
groups when data is normally distributed

4. One-Way ANOVA is a parametric test whereas Kruskal Wallis is non-
parametric test.
'''
```

{"type":"string"}

```
data.groupby('season')['count'].sum()
```

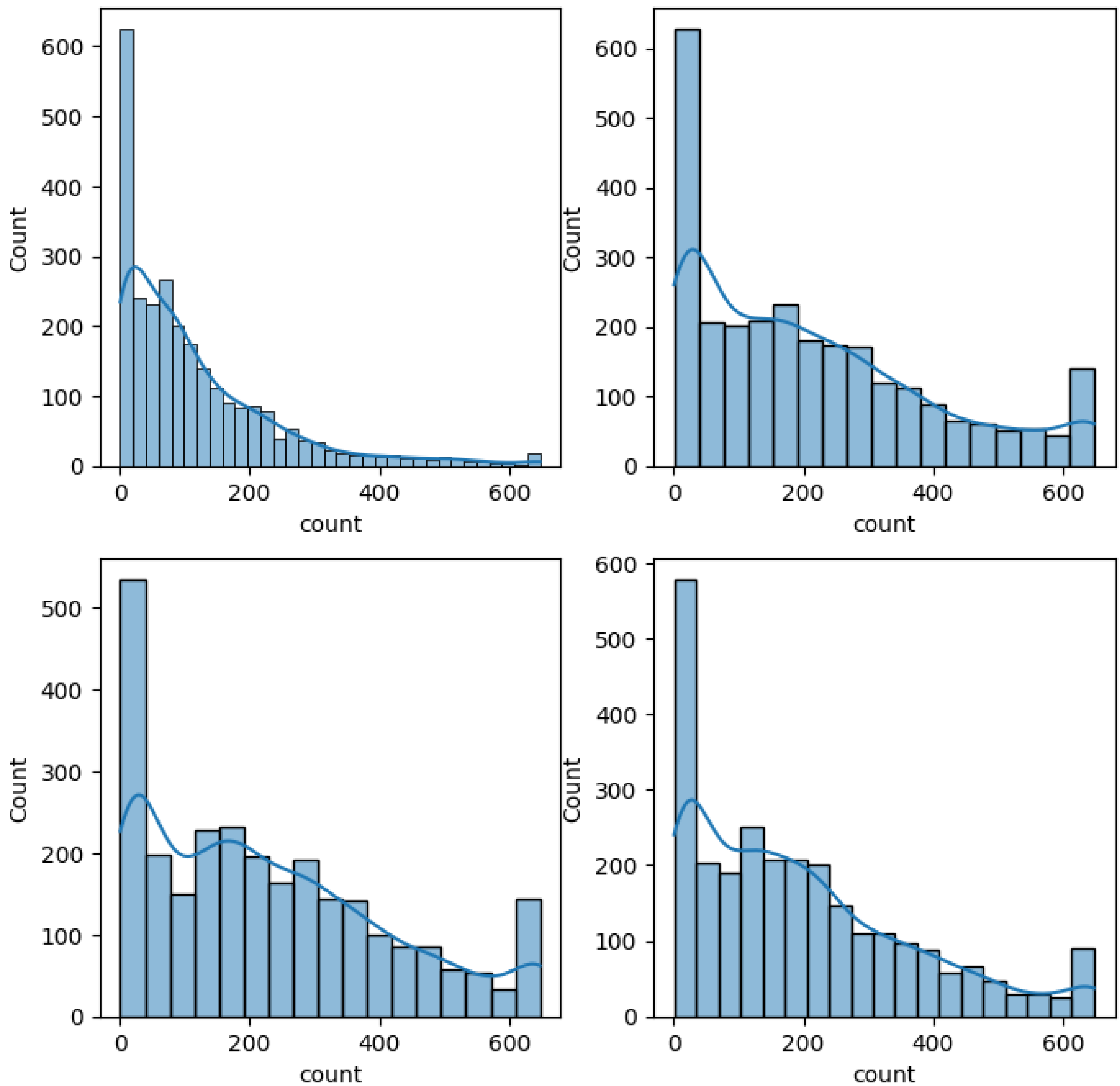
```
season
1    311515
2    579856
3    626326
4    536544
Name: count, dtype: int64
```

```
'''
Checking the assumptions for ANOVA
1. Normality Test for normal distribution of data of each group
2. Variability Test for equal variances within groups
'''
```

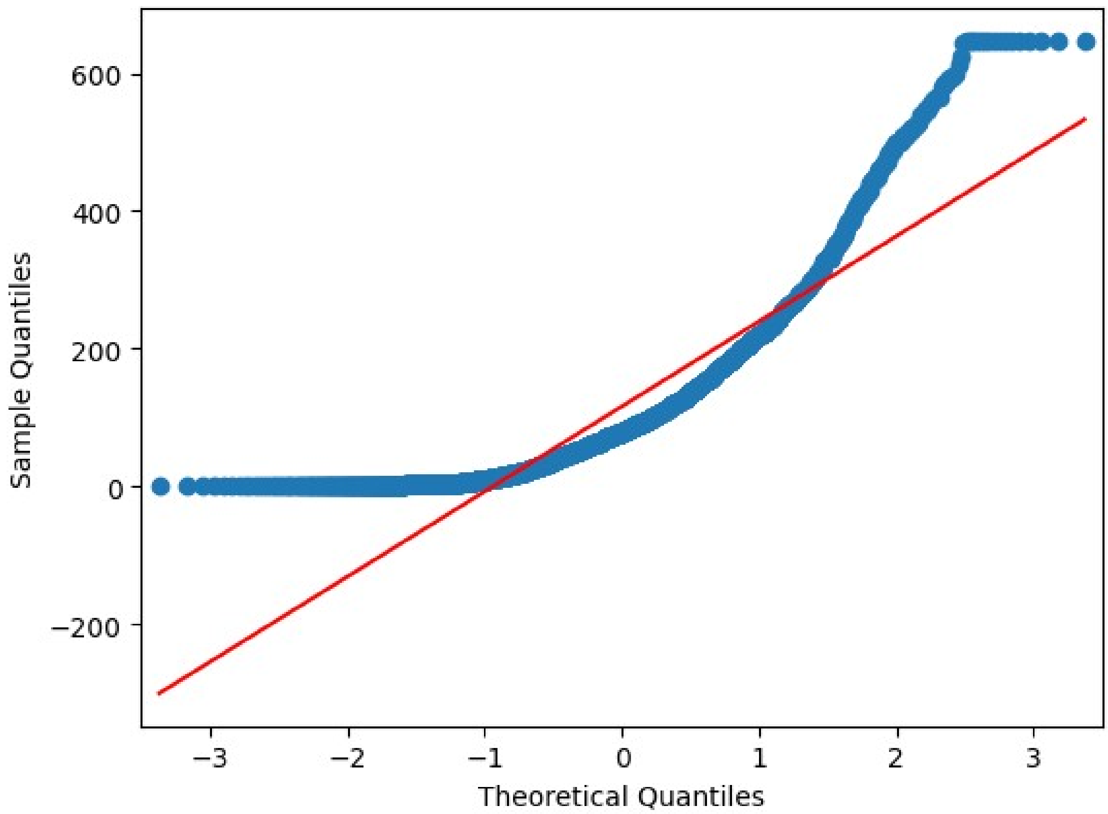
{"type":"string"}

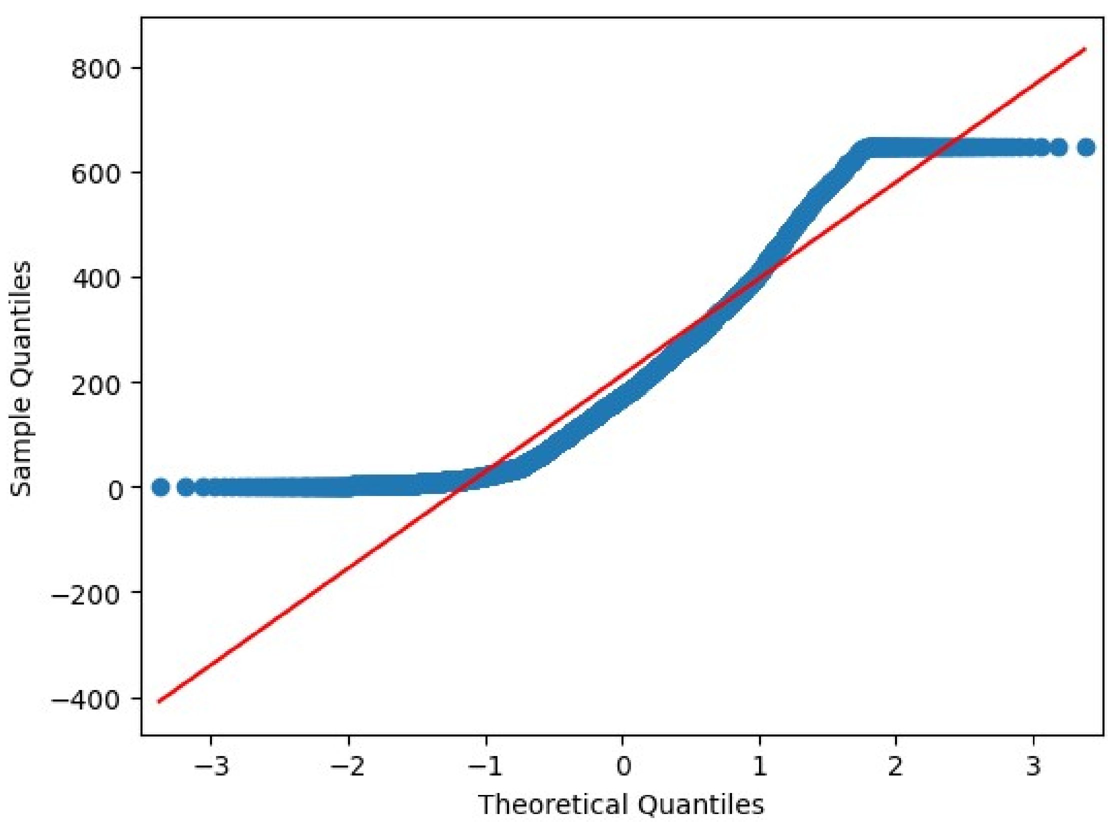
```
#Normality Test: Shapiro Wilk Test
from scipy.stats import shapiro

#H0: Data is gaussian
#Ha: Data is not gaussian

season_1 = data[data['season'] == 1]['count']
season_2 = data[data['season'] == 2]['count']
season_3 = data[data['season'] == 3]['count']
season_4 = data[data['season'] == 4]['count']

season_groups = [season_1, season_2, season_3, season_4]
```

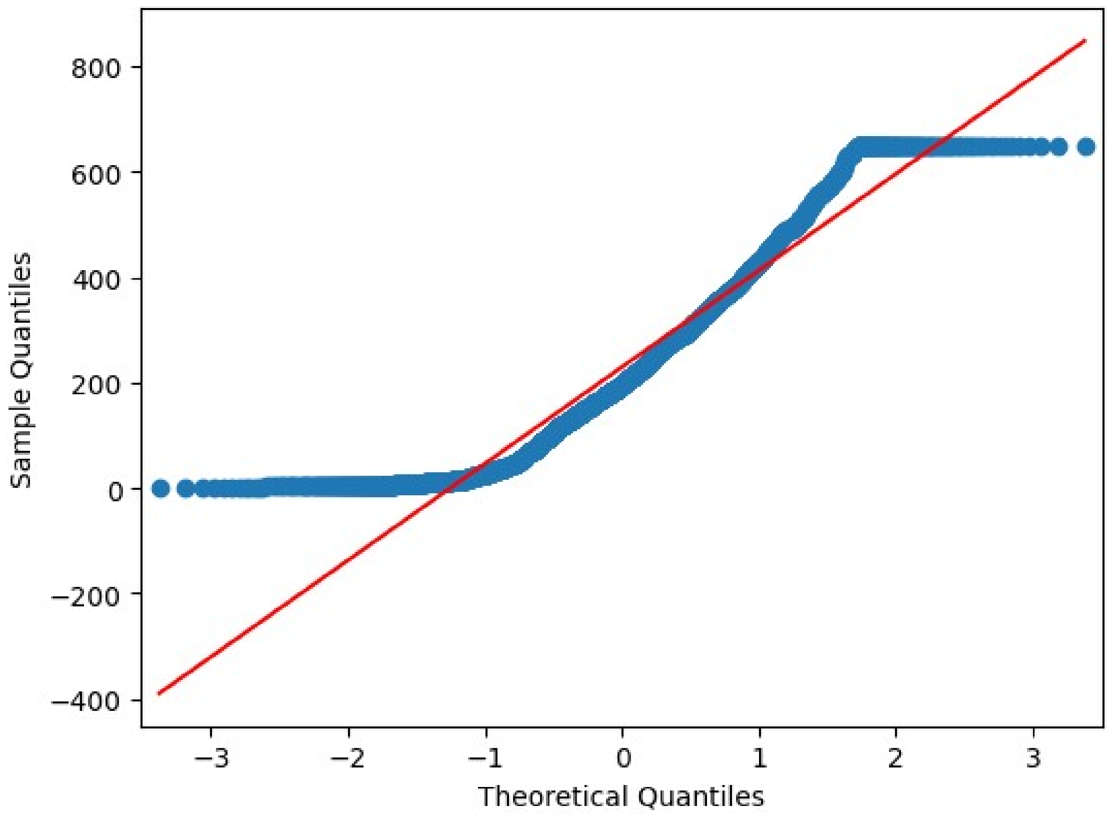
```
alpha = 0.05

test_stat, p_val = shapiro(season_1)
test_stat, p_val

(0.8147448301315308, 0.0)

test_stat, p_val = shapiro(season_2)
test_stat, p_val

(0.9027974009513855, 1.3308493050696584e-38)

test_stat, p_val = shapiro(season_3)
test_stat, p_val

(0.9245859384536743, 5.281442164890545e-35)

test_stat, p_val = shapiro(season_4)
test_stat, p_val

(0.9057514071464539, 3.6797419444712963e-38)

'''
Since, p_val < 0.05 for each season group so, we can reject null
hypothesis which means that the data distribution is not gaussian
normal for each group.
Thus, the normality test for data to have normal distribution has been
failed.
'''

{"type":"string"}

#Plot Histogram for analysing the data distribution for each weather
group

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

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

plt.show()
```

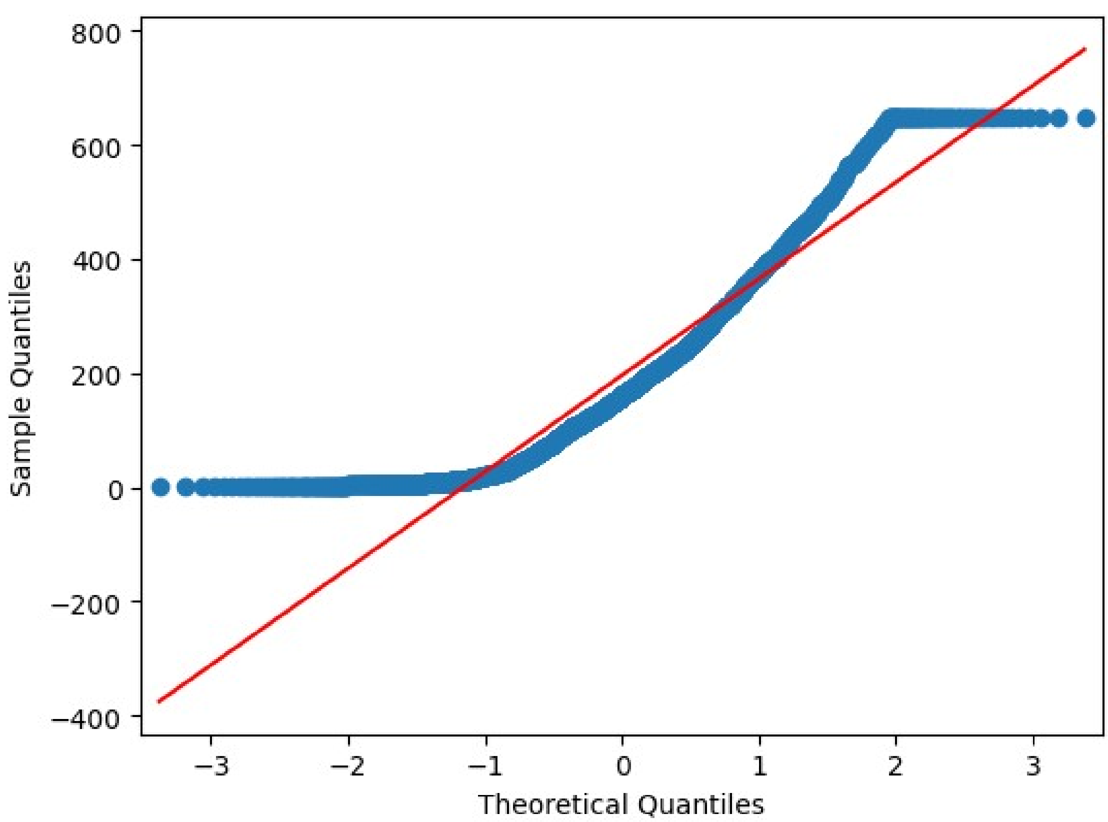



```
#Plot Q-Q Plot for analysing the data distribution for each weather
group

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

plt.show()
```


600
400
200
0
−200
Sample Quantiles
−3
−2
−1
0
1
2
3
Theoretical Quantiles


800
600
400
200
0
−200
−400
Sample Quantiles
−3
−2
−1
0
1
2
3
Theoretical Quantiles


800
600
400
200
0
−200
−400
Sample Quantiles
−3
−2
−1
0
1
2
3
Theoretical Quantiles


800
600
400
200
0
−200
−400
Sample Quantiles
−3
−2
−1
0
1
2
3
Theoretical Quantiles

```python
'''
The results of Shapiro Wilk test have been verified using the QQ Plot.
We can see that the data distribution for each group doesn't follow
normal distribution.
'''
```

{"type":"string"}

```python
#Levene's Test for checking equal variances within the groups

test_stat, p_val = levene(season_1, season_2, season_3, season_4)
test_stat, p_val
```

```
(199.5119672794296, 5.7233179707619984e-126)
```

```python
'''
Observations:
Since p_val < 0.05 so we can reject the null hypothesis which means
that the variances are not equal within the groups.
Thus, variability test has been failed.
'''
```

{"type":"string"}

```python
'''
Conclusion:
1. Since the assumptions of ANOVA don't hold true so we proceed with
Kruskal Wallis Test which compares medians of groups.
'''
```

{"type":"string"}

```python
#Kruskal Wallis Test

#H0: The medians of groups are same
#Ha: The medians of groups are not the same

test_stat, p_val = kruskal(season_1, season_2, season_3, season_4)
test_stat, p_val
```

```
(699.2817665514561, 3.0045514163996123e-151)
```

```python
if p_val < alpha:
  print('Since the p-value {:.2f} is less than or equal to the predetermined level of significance (alpha = 0.05), we have evidence to reject the null hypothesis. Meaning that the demand for bicycles is not the same across different seasons.'.format(p_val))
else:
  print('Since the p-value {:.2f} is greater than the predetermined level of significance (alpha = 0.05), we do not have sufficient evidence to reject the null hypothesis. Meaning that the demand for bicycles is the same across different seasons.'.format(p_val))
```

```
Since the p-value 0.00 is less than or equal to the predetermined
level of significance (alpha = 0.05), we have evidence to reject the
null hypothesis. Meaning that the demand for bicycles is not the same
across different seasons.

#since, p_val < alpha so, demand is not the same across seasons
```

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

```
#Chi-squared Contingency Test
# Since, we are checking the association between two categorical
variables so will go for Chi squared contingency test

#H0: No association between season and weather
#Ha: There's an association between season and weather

contingency_table = pd.crosstab(data['season'], data['weather'])

contingency_table

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

from scipy.stats import chi2_contingency

chi_stat, p_val, dof, expected_values =
chi2_contingency(contingency_table)
chi_stat, p_val, dof, expected_values

(49.158655596893624,
 1.549925073686492e-07,
 9,
 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]]))

if p_val < alpha:
  print('Since the p-value {:.2f} is less than or equal to the
predetermined level of significance (alpha = 0.05), we have evidence
to reject the null hypothesis. Meaning that there is an impact of
season on weather conditions.'.format(p_val))
```

```
else:
  print('Since the p-value {:.2f} is greater than the predetermined level of significance (alpha = 0.05), we do not have sufficient evidence to reject the null hypothesis. Meaning that there is no impact of season on weather conditions.'.format(p_val))
```

```
Since the p-value 0.00 is less than or equal to the predetermined level of significance (alpha = 0.05), we have evidence to reject the null hypothesis. Meaning that there is an impact of season on weather conditions.
```

```
#Since p_val < alpha so, we reject H0. So, there's an association between season and weather
#Thus, season has an impact on weather
```

#Insights

1. A Two-sample Independent T-test on weekdays and weekends with respect to count,implies that the mean population count of both categories are the same. Thus, the demand for the rented bikes is the same on weekdays and weekends.

2. A One-Way ANOVA test on different seasons with respect to count,implies that population count means under different seasons are not the same, meaning there is a difference in the usage of Yulu bikes across different seasons.

3. By performing a One-Way ANOVA test on different weather conditions except 4 with respect to count, we can infer that population count means under different weather conditions are not the same, meaning there is a difference in the usage of Yulu bikes across different weather conditions.

4. By performing a Chi-squared contingency test on season and weather (categorical variables), we can infer that there is an impact on weather dependent on season.

5. The maximum number of holidays can be seen during the fall and winter seasons.

6. There is a positive corelation between count and temperature.

7. There is a negative corelation between count and humidity.

8. More number of rented bikes when weather is clear with less clouds, proved by annova hypothesis test.

9. The usage of Yulu bikes is lesser during extreme weather conditions like Heavy Rain + Ice Pellets + Thunderstorm + Mist, Snow + Fog.

10. The usage of Yulu bikes is more on working days.

11. The usage of Yulu bikes is lesser when the temp is less than 10 or humidity is less than 20.

12. The usage of Yulu bikes is lesser when windspeed is greater than 40.

#Recommendations

1. As the usage of Yulu is more during summer and fall seasons, so Yulu should make sure that the number of bikes available should be more than usual at the Yulu stations.

2. As the demand for the Yulu bikes is the same for weekdays and weekends, so company should keep special peak timing offers and high availability of yulu bikes which will boost the customer bookings.

3. Since the demand for rented bikes is different across different weather conditions so Yulu should perform the customer profiling as per weather conditions which will help the company to come up with new product features.

4. Since the demand for the rented bikes is different across different seasons so Yulu should come up with special seasonal offerings which will help to retain the active customers. Also, can keep special student discounts during summers and during school hours to attract student customer base.

5. As casual users are very less Yulu should focus on marketing startegy to bring more customers. for eg. first time user discounts, friends and family discounts, referral bonuses, budget friendly plans, etc.

6. On non working days as count is very low Yulu can think on the promotional activities like city exploration activities, some health campaigns etc. to spread the awareness about the Yulu bikes.

7. In heavy rains as rented bike count is very low Yulu can introduce a different vehicle such as car or having shade or have protection from the rain for Yulu.

8. The registered users count is very high as compared to casual ones so Yulu should offer good renewal plans to these customers.