Business Case

YULU - HYPOTHESIS TESTING

PROBLEM STATEMENT:

1. Analysing, which of the 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.

EXPLORATORY DATA ANALYSIS:

In [1]:

```
# Importing the relevant packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb
import math
import scipy.stats as st
```

In [7]:

```
# Loading the Yulu File
yulu = pd.read_csv('yulu.txt')
yulu.head(5)
```

Out[7]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	ca
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	

In [8]:
```python
# Analysing the Meta data
yulu.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
```

In [9]:
```python
# shape of dataframe
yulu.shape
```

Out[9]:
```
(10886, 12)
```

In [114]:
```python
# Missing value detection
yulu.isna().sum().sum()
```

Out[114]:
```
0
```

Observations:
1. Yulu is a company about rental electriv bikes.
2. Yulu dataset contains data about different features, ranging from count of users split between casual and registered, to features like wheather, working day, temperature, humidity etc.
3. The Dataset has 10886 entries, of which none of the features have any missing values.
4. There are in total 12 features, of which few are numerical and others are categorical, but most of the categorical features have also been converted to integers for ease of calculations, also one of the feature is a datatimestamp.
5. The Shape of the dataset is (10886,12).

In [12]:

```
# Analysing each feature
# Converting each feature to appropriate datatype for better an
yulu.describe(include='all')
```

Out[12]:

	datetime	season	holiday	workingday	weather	temp
count	10886	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000
unique	10886	NaN	NaN	NaN	NaN	NaN
top	2012-03-13 06:00:00	NaN	NaN	NaN	NaN	NaN
freq	1	NaN	NaN	NaN	NaN	NaN
mean	NaN	2.506614	0.028569	0.680875	1.418427	20.23086
std	NaN	1.116174	0.166599	0.466159	0.633839	7.79159
min	NaN	1.000000	0.000000	0.000000	1.000000	0.82000
25%	NaN	2.000000	0.000000	0.000000	1.000000	13.94000
50%	NaN	3.000000	0.000000	1.000000	1.000000	20.50000
75%	NaN	4.000000	0.000000	1.000000	2.000000	26.24000
max	NaN	4.000000	1.000000	1.000000	4.000000	41.00000

In [18]:

```
# Converting Datetime to type Datetime
yulu['datetime'] = pd.to_datetime(yulu['datetime'])
```

In [33]:

```
# Converting appropriate columns to Category type
columns=['season','holiday','workingday','weather']
yulu[columns]=yulu[columns].astype('category')
yulu.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
```

In [35]:

```
# let's see the Dataframe's proper statistical summary
yulu.describe(include='all',datetime_is_numeric=True)
```

Out[35]:

	datetime	season	holiday	workingday	weather	temp	ate
count	10886	10886.0	10886.0	10886.0	10886.0	10886.00000	10886.000
unique	NaN	4.0	2.0	2.0	4.0	NaN	N
top	NaN	4.0	0.0	1.0	1.0	NaN	N
freq	NaN	2734.0	10575.0	7412.0	7192.0	NaN	N
mean	2011-12-27 05:56:22.399411968	NaN	NaN	NaN	NaN	20.23086	23.655
min	2011-01-01 00:00:00	NaN	NaN	NaN	NaN	0.82000	0.760
25%	2011-07-02 07:15:00	NaN	NaN	NaN	NaN	13.94000	16.665
50%	2012-01-01 20:30:00	NaN	NaN	NaN	NaN	20.50000	24.240
75%	2012-07-01 12:45:00	NaN	NaN	NaN	NaN	26.24000	31.060
max	2012-12-19 23:00:00	NaN	NaN	NaN	NaN	41.00000	45.455
std	NaN	NaN	NaN	NaN	NaN	7.79159	8.474

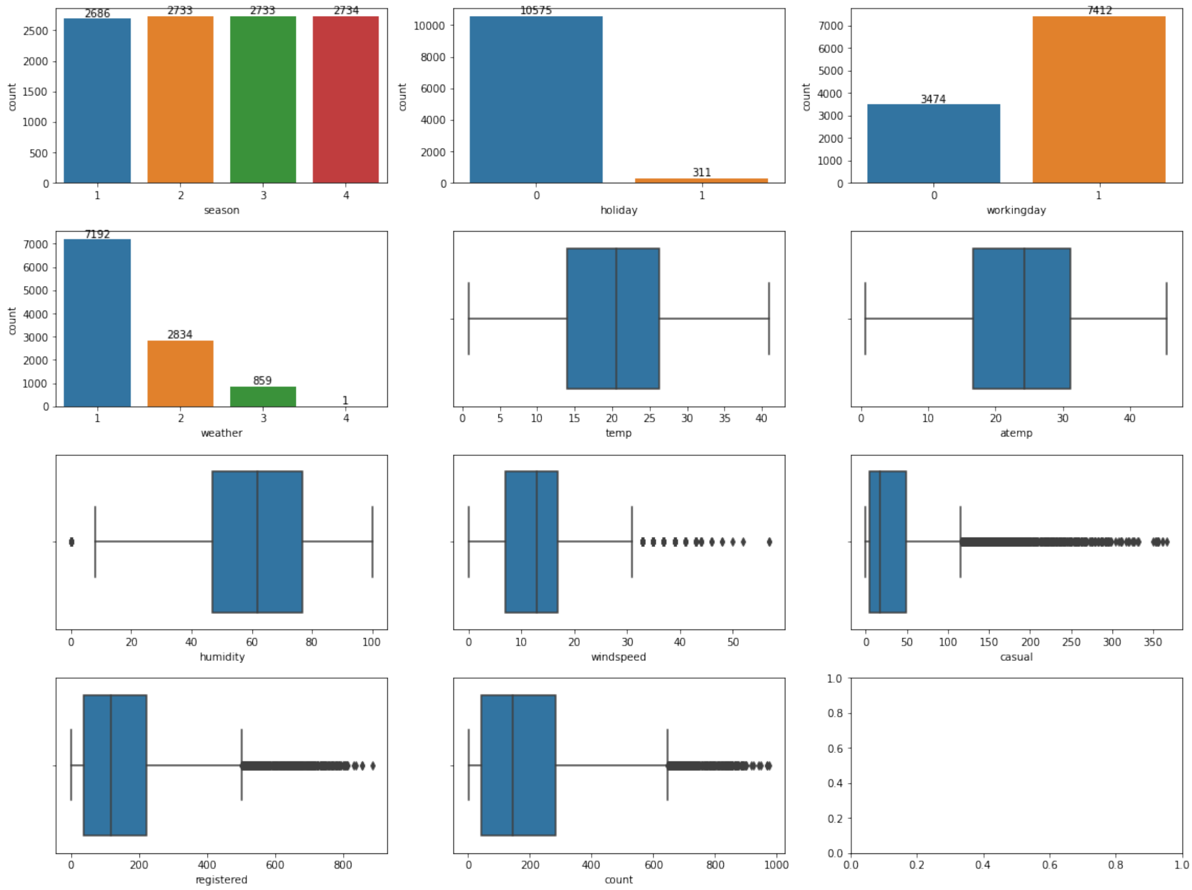
Observations:

1. For the feature Season, Season 4 is the most frequent, and there are in total 4 unique seasons.
2. For the feature Holiday, there are 10575 days with no holidays from a total of 10886.
3. For the feature Workingday, there are 7412 working days, rest are either weekend or holidays.
4. For the feature Weather, weather type 1 is the most frequent with 4 unique weather types.
5. For the numerical feature Temp, mean is 20.23, median is 20.50, signifying robustness of the data, with a standard deviation of 7.8, in celcius, with minimum temperature as 0.82 and maximum as 41.
6. For the numerical feature aTemp, mean is 23.65, median is 24.24, signifying robustness of the data, with a standard deviation of 8.4, in celcius, with minimum temperature as 0.76 and maximum as 45.45.
7. For the numerical feature Humidity, mean is 61.88, median is 62, signifying robustness of the data, with a standard deviation of 19.24, with minimum value as 0 and maximum as 100.
8. For the numerical feature Windspeed, mean is 12.9, median is 13, signifying robustness of the data, with a standard deviation of 8.2, with minimum windspeed as 0 and maximum as 56.99.
9. For the numerical feature Casual, mean is 36, median is 17, signifying weakness of the data, with a standard deviation of 49, with minimum count as 0 and maximum as 367.
10. For the numerical feature Registered, mean is 155, median is 118, signifying weakness of the data, with a standard deviation of 151, with minimum count as 0 and maximum as 886.
11. For the numerical feature Count, mean is 191, median is 141, signifying weakness of the data, with a standard deviation of 181, with minimum count as 0 and maximum as 977.
12. For the Datetime feature, the starting date is 2011-01-01 00:00:00 and it goes till 2012-12-19 23:00:00, spanning almost 2 years.

UNIVARIATE ANALYSIS

In [112]:

```python
# Plotting the corresponding univariate graph for each feature
plt.subplots(4,3,figsize=(16,12))
pos = 0
for feat in yulu.columns:
    if feat=='datetime':
        continue
    pos += 1
    if yulu[feat].dtype == 'int' or yulu[feat].dtype == 'float'
        plt.subplot(4,3,pos)
        ax = sb.boxplot(data=yulu,x=feat)

    else:
        plt.subplot(4,3,pos)
        ax = sb.countplot(data=yulu,x=feat)
        plt.bar_label(ax.containers[0], label_type='edge')
plt.tight_layout()
plt.show()
```

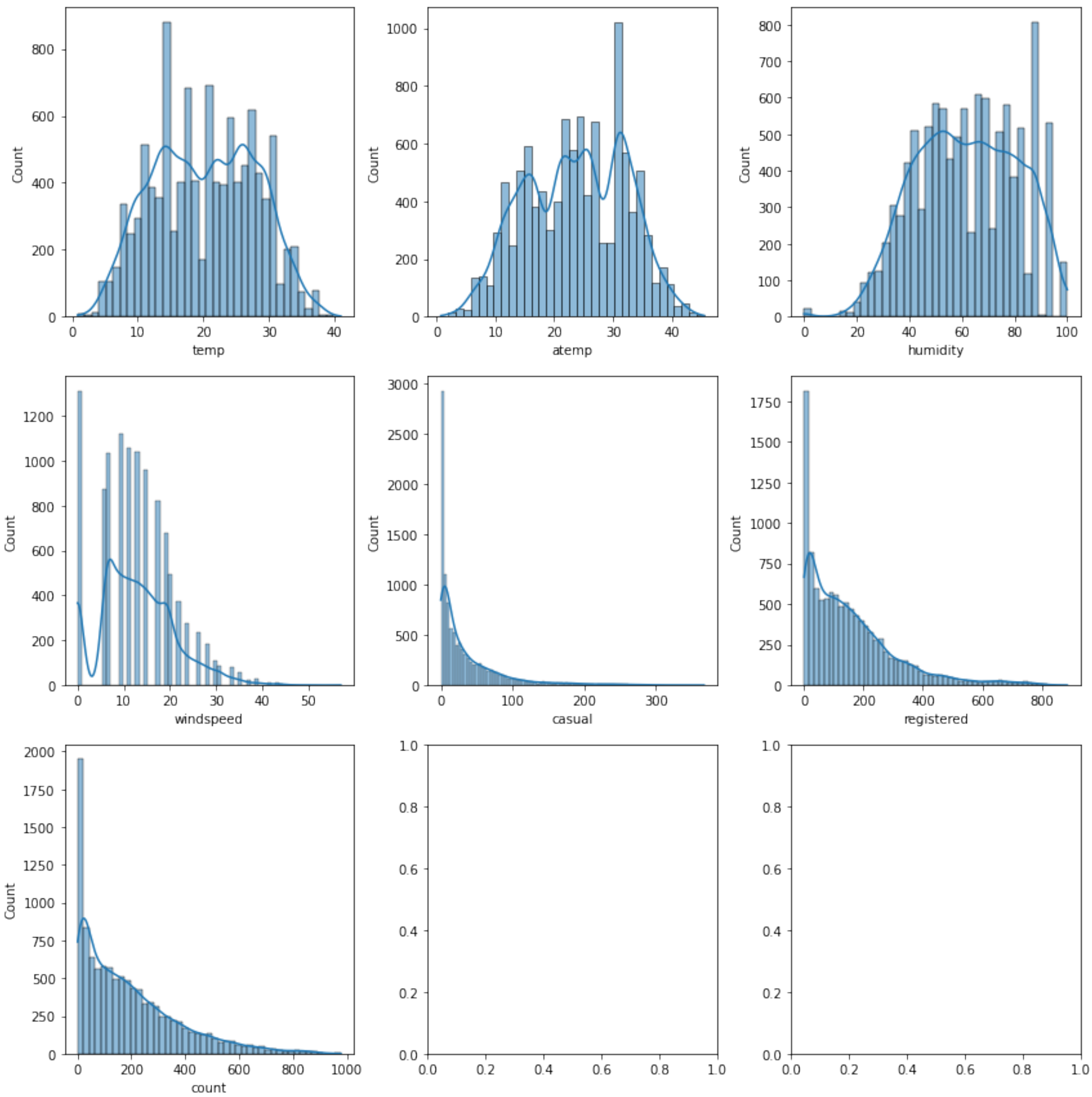


Observations: Apart from the earlier stated observations, some new things which have come to light are:

1. The Four season types are almost equal in number.
2. Weather type 4 is only 1 in number
3. Humidity, windspeed, casual counts, registered counts, and over all counts have legitimate outliers.

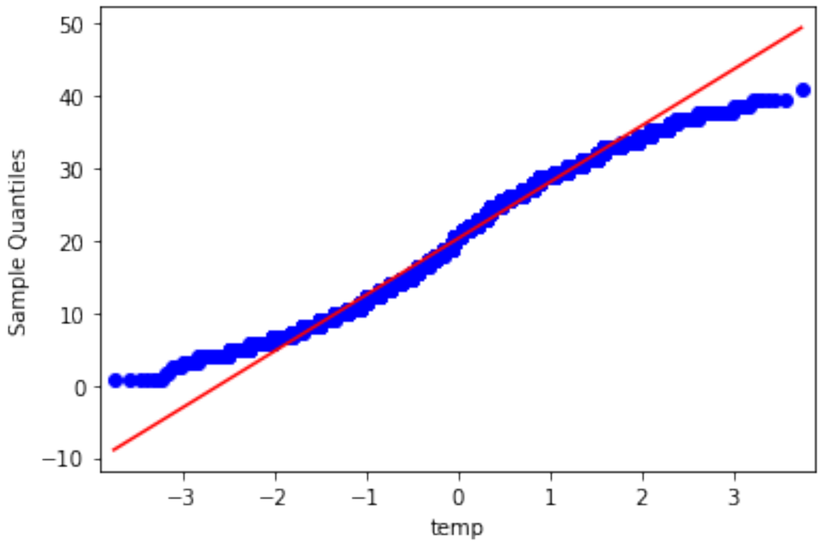
In [135]:

```python
# Plotting the corresponding univariate graph for each feature
plt.subplots(3,3,figsize=(12,12))
pos = 0
for feat in yulu.columns:
    if yulu[feat].dtype == 'int' or yulu[feat].dtype == 'float':
        pos += 1
        plt.subplot(3,3,pos)
        ax = sb.histplot(data=yulu,x=feat,kde=True)

#     else:
#         plt.subplot(4,3,pos)
#         ax = sb.countplot(data=yulu,x=feat)
#         plt.bar_label(ax.containers[0], label_type='edge')
plt.tight_layout()
plt.show()
```

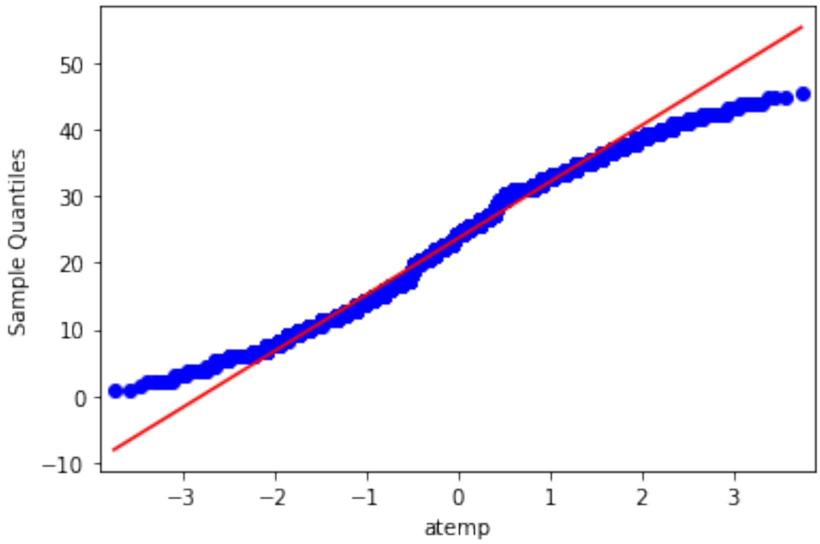


In [200]:

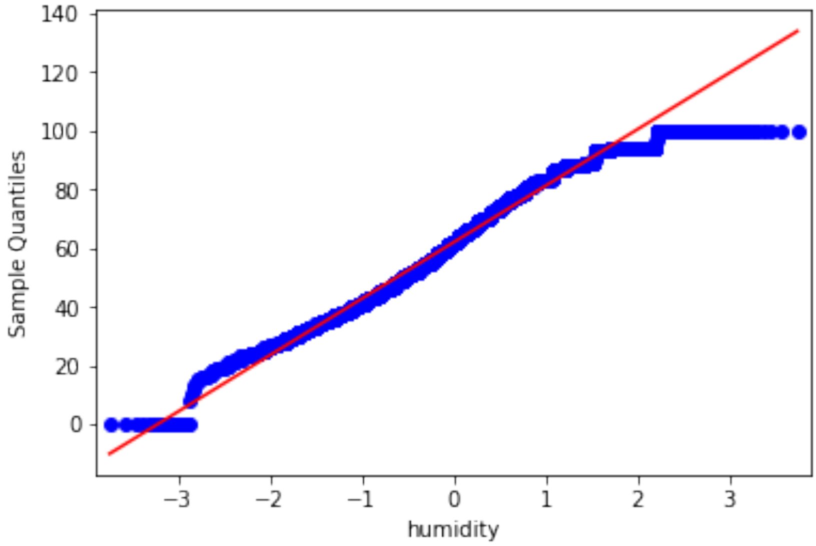
```python
# Plotting the corresponding QQ Plots for each feature
import statsmodels.api as sm
for feat in num_cols:
    sm.qqplot(yulu[feat],line='s')
    plt.xlabel(feat)

```



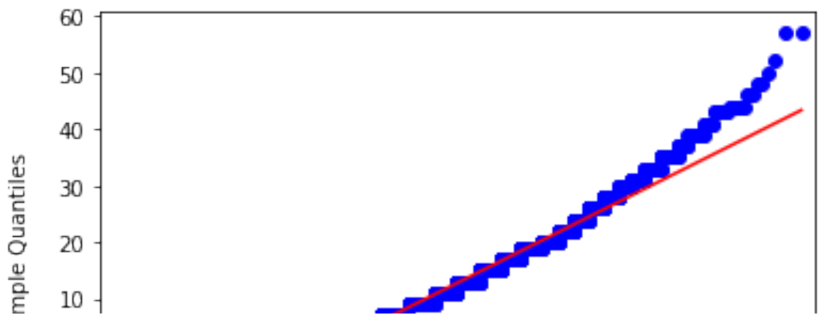
Sample Quantiles
temp



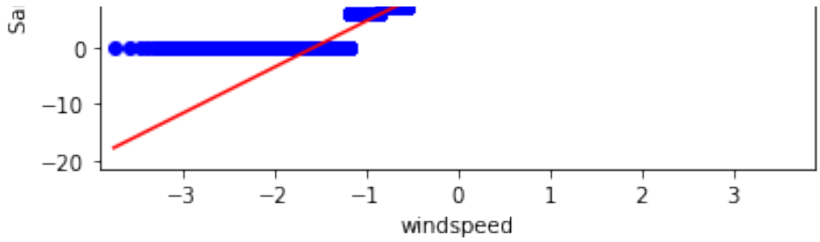
Sample Quantiles
atemp

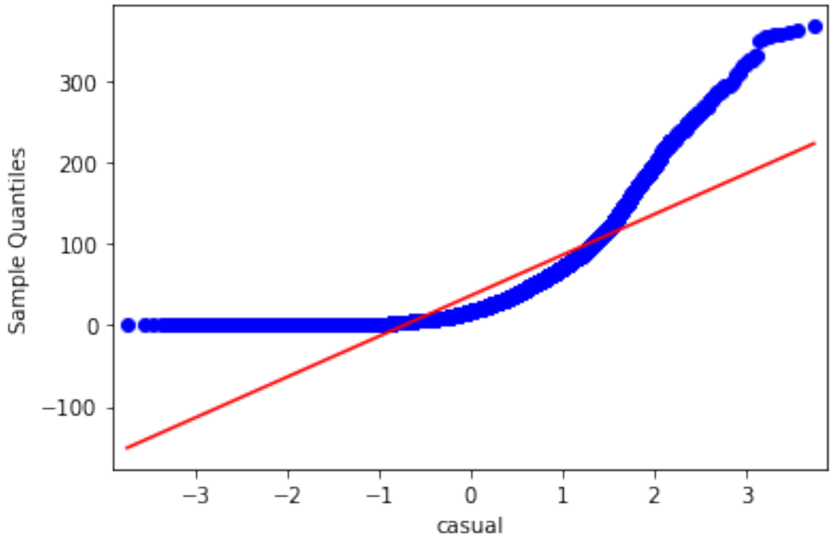


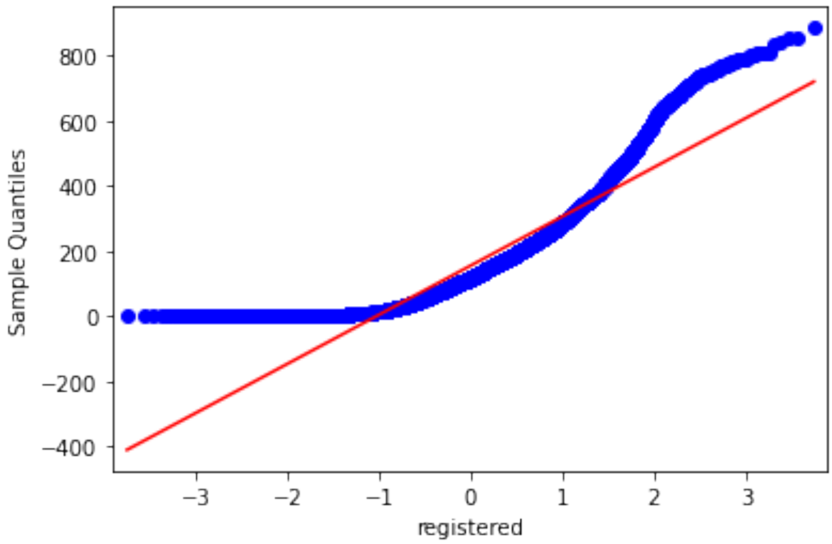
Sample Quantiles
humidity

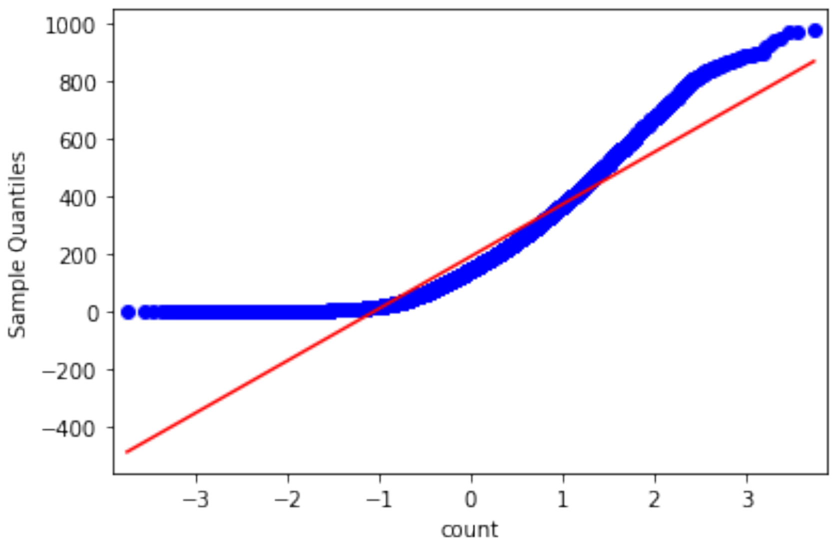


mple Quantiles


Sa
windspeed


Sample Quantiles
casual


Sample Quantiles
registered


Sample Quantiles
count

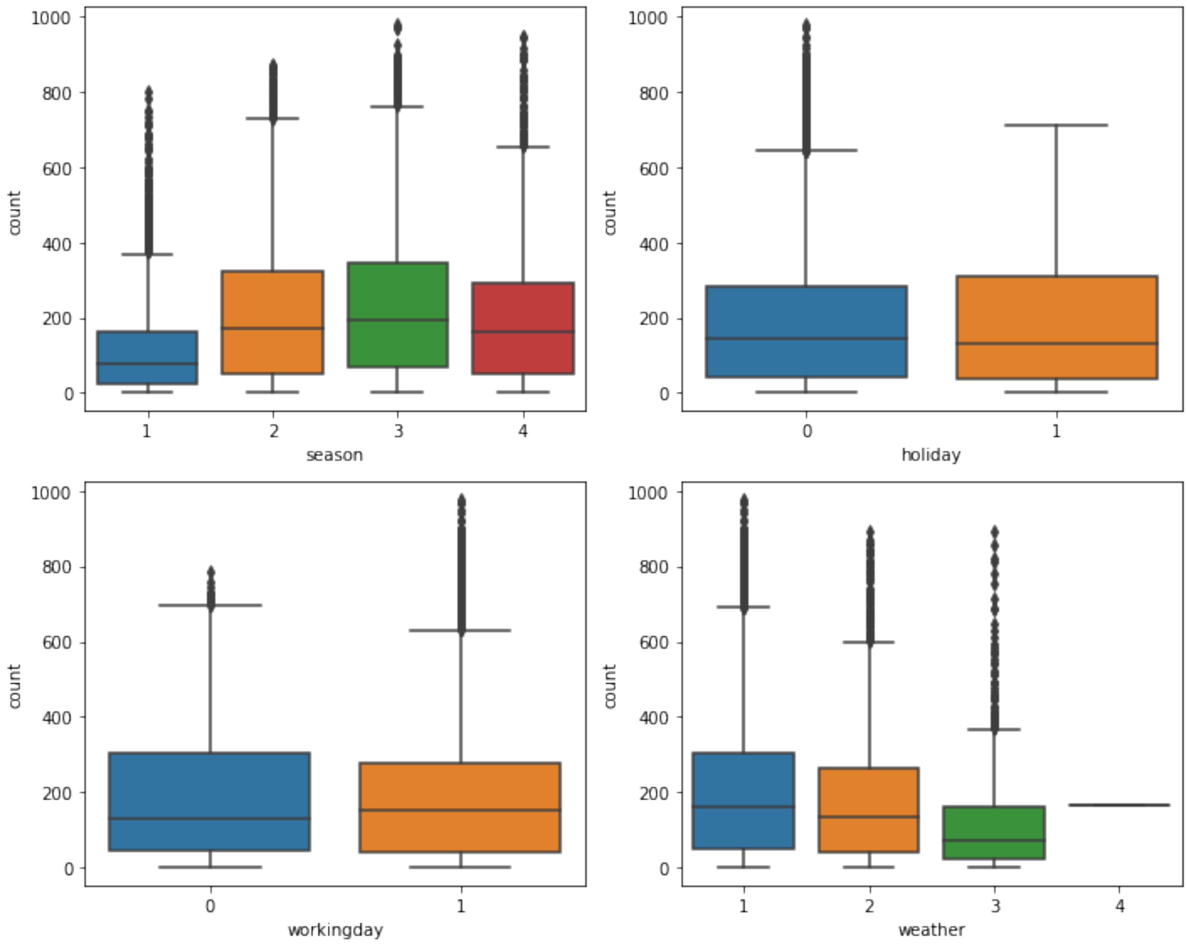
Observations:

1. Casual, Registered and Count features somewhat look like Log Normal Distribution, but not at all a normal distribution.
2. Temp, atemp and humidity look somewhat like they follow the Normal Distribution.
3. Windspeed follows the binomial distribution.

BIVARIATE ANALYSIS

In [178]:

```
# plotting categorical variables againt count using boxplots
cat_cols= yulu.select_dtypes('category').columns
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(10, 8))
index = 0
for row in range(2):
    for col in range(2):
        sb.boxplot(data=yulu, x=cat_cols[index], y='count', ax=
        index += 1
plt.tight_layout()
plt.show()
```



In [173]:

```
for i in cat_cols:
    print(f'{i.capitalize()} vs Count:')
    print(yulu.groupby(i)['count'].describe())
    print('\n\n')
```

Season vs Count:

season	count	mean	std	min	25%	50%	75%	max
1	2686.0	116.343261	125.273974	1.0	24.0	78.0	164.0	801.0
2	2733.0	215.251372	192.007843	1.0	49.0	172.0	321.0	873.0
3	2733.0	234.417124	197.151001	1.0	68.0	195.0	347.0	977.0
4	2734.0	198.988296	177.622409	1.0	51.0	161.0	294.0	948.0

Holiday vs Count:

holiday	count	mean	std	min	25%	50%	75%	max
0	10575.0	191.741655	181.513131	1.0	43.0	145.0	283.0	977.0
1	311.0	185.877814	168.300531	1.0	38.5	133.0	308.0	712.0

Workingday vs Count:

workingday	count	mean	std	min	25%	50%	75%	max
0	3474.0	188.506621	173.724015	1.0	44.0	128.0	304.0	783.0
1	7412.0	193.011873	184.513659	1.0	41.0	151.0	277.0	977.0

Weather vs Count:

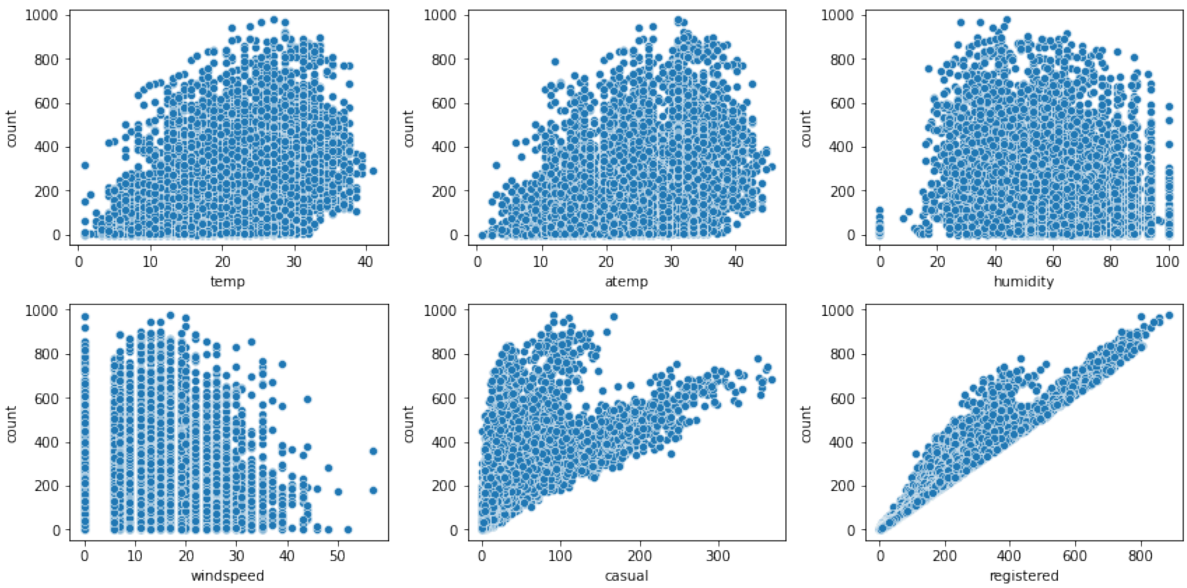
weather	count	mean	std	min	25%	50%	75%	max
1	7192.0	205.236791	187.959566	1.0	48.0	161.0	305.0	977.0
2	2834.0	178.955540	168.366413	1.0	41.0	134.0	264.0	890.0
3	859.0	118.846333	138.581297	1.0	23.0	71.0	161.0	891.0
4	1.0	164.000000	NaN	164.0	164.0	164.0	164.0	164.0

Observations:

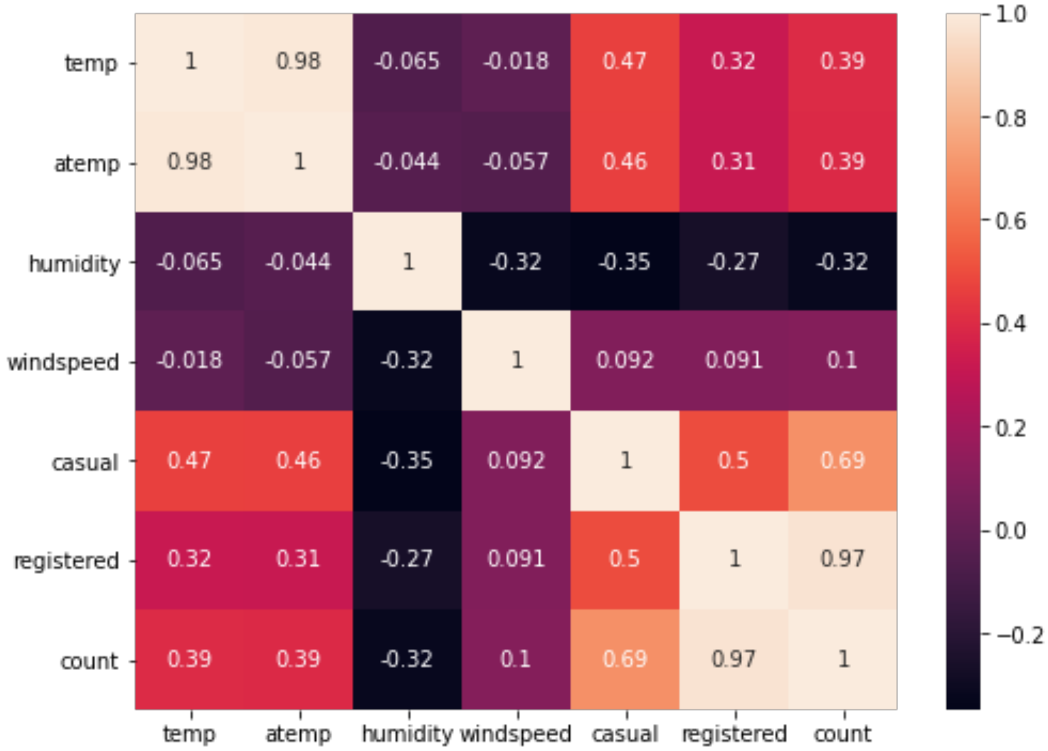
1. In summer(2) and fall(3) seasons, more bikes are rented as compared to other seasons.
2. It seems, whenever its not a holiday more bikes are rented.
3. It also seems, from the workingday, that whenever day is not holiday or weekend, slightly more bikes were rented, hence complimenting our previous analysis.
4. Whenever there is rain, thunderstorm, snow or fog, ie, weather type 4, there were almost no bikes rented, and on the contrary, on Clear, Few clouds, partly cloudy, partly cloudy days, ie, weather type 1, maximum number of bikes were rented.

In [177]:

```
# plotting numerical variables againt count using scatterplot
num_cols = yulu.select_dtypes(['int','float']).columns
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(12, 6))
index = 0
for row in range(2):
    for col in range(3):
        sb.scatterplot(data=yulu, x=num_cols[index], y='count',
        index += 1
plt.tight_layout()
plt.show()
```



In [188]:
```python
plt.figure(figsize=(8,6))
sb.heatmap(yulu.corr(),annot=True)
plt.show()
```



Observations: From the above Correlation heatmap and scatter plots, it can be observed that:

1. Registered Counts and Counts are highly correlated.
2. Casual counts and over all counts also have comparatively high correlation.
3. Humidity and Count are negatively correlated.
4. Rest of the numerical features are corelated to count positively, ranging from 0.1 to 0.97, windspeed being most weakly correlated.

HYPOTHESIS TESTING

1. 2-Sample T-Test to check if Working Day has an effect on the number of electric cycles rented

In [ ]:
```python
# Null Hypothesis: Working day has no effect on the number of c
# Alternate Hypothesis: Working day has effect on the number of
# Significance level (alpha): 0.05
# We will use the 2-Sample T-Test to test the hypothess defined
group1 = yulu[yulu['workingday']==0]['count'].values
group2 = yulu[yulu['workingday']==1]['count'].values
```

In [205]:

```
# performing the levene's test to confirm equal variance
# Null hypothesis (H₀): there is no significant difference in t
# of the populations from which the samples were drawn.
# Alternative hypothesis (H₁): there is a statistically signifi
# difference in the variances between the populations.
from scipy.stats import levene
stat,pval = levene(group1,group2)
if pval < 0.05:
    print(f'with pvalue as {pval}, it can be concluded that, th
else:
    print(f'with pvalue as {pval}, it can be concluded that, th
```

```
with pvalue as 0.9437823280916695, it can be concluded that, the t
wo groups have statistically similar variances
```

In [208]:

```
from scipy.stats import ttest_ind
stat,pval=ttest_ind(a=group1, b=group2, equal_var=True)
if pval < 0.05:
    print(f'with pvalue as {pval}, it can be concluded that, th
else:
    print(f'with pvalue as {pval}, it can be concluded that, th
```

```
with pvalue as 0.22644804226361348, it can be concluded that, the
working day has no impact on counts of rented bikes
```

2. ANNOVA to check if No. of cycles rented is similar or different in different 1. weather 2. season

In [223]:

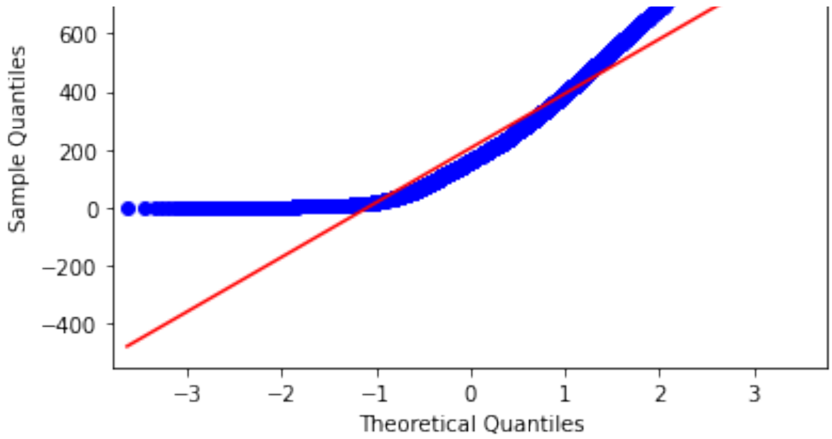
```
# Null Hypothesis: Number of cycles rented is similar in differe
# season.
# Alternate Hypothesis: Number of cycles rented is not similar i
# weather and season.
# Significance level (alpha): 0.05
# Creating respective groups
groups = []
for i in yulu['weather'].unique():
    groups.append(yulu[yulu['weather']==i]['count'].values)
for i in yulu['season'].unique():
    groups.append(yulu[yulu['season']==i]['count'].values)
```

Confirming the Assumptions necessary for performing an Annova test

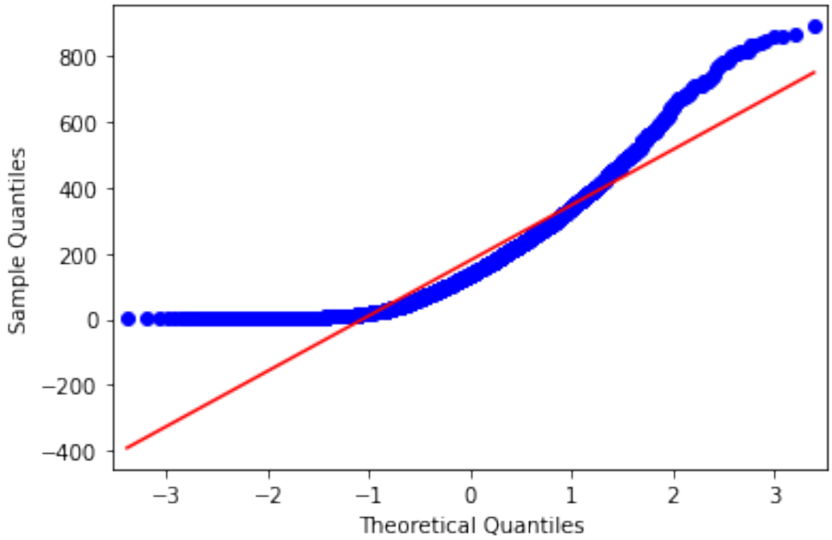
First Assumption: Gaussian

In [232]:

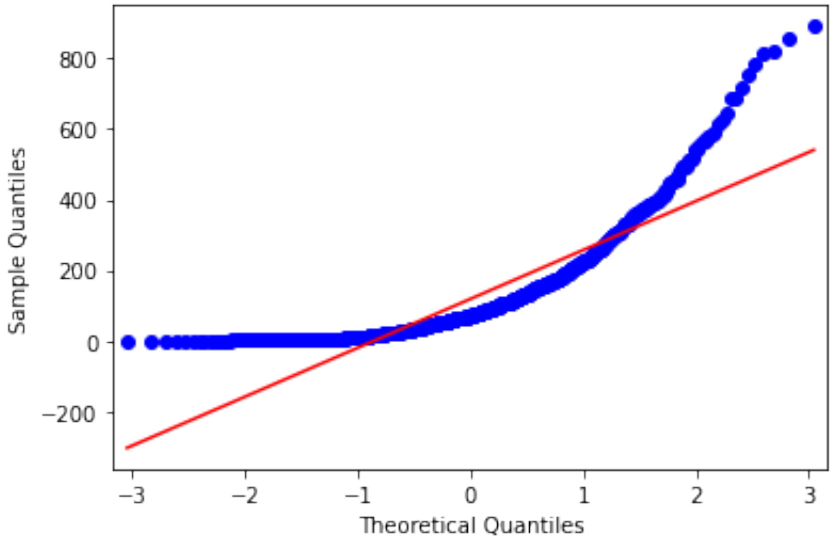
```
for feat in range(len(groups)):
    sm.qqplot(groups[feat],line='s')
```



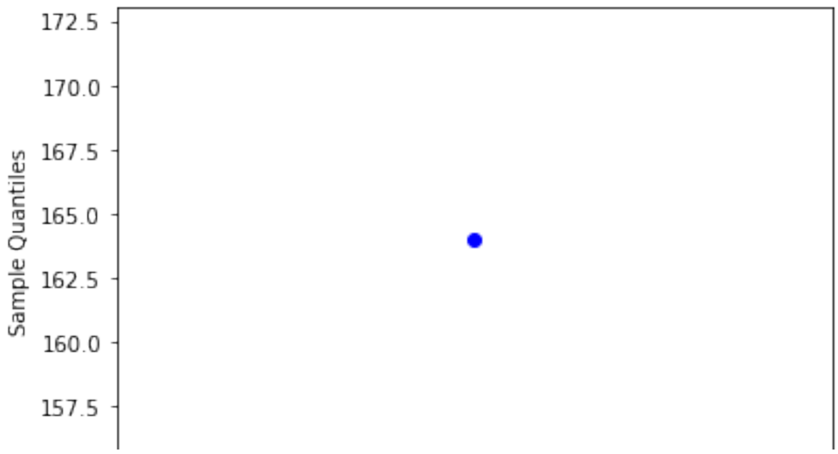
Sample Quantiles
Theoretical Quantiles



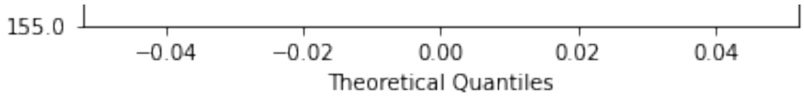
Sample Quantiles
Theoretical Quantiles

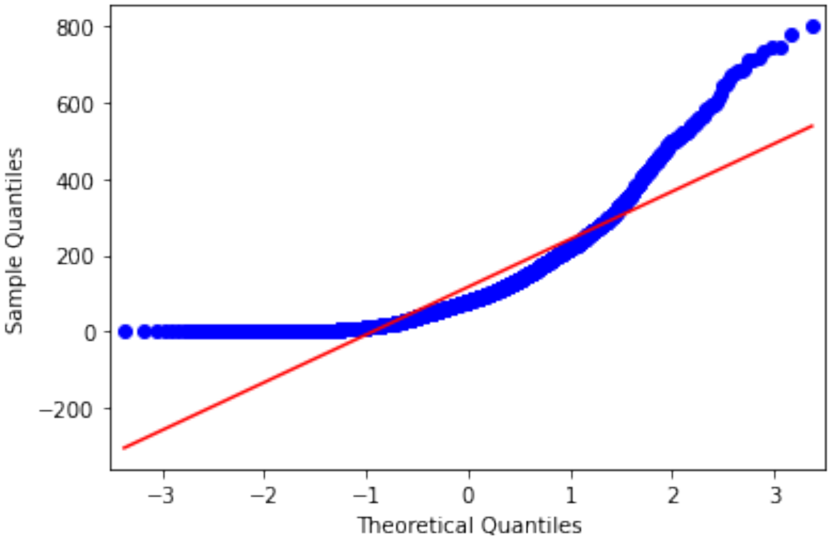


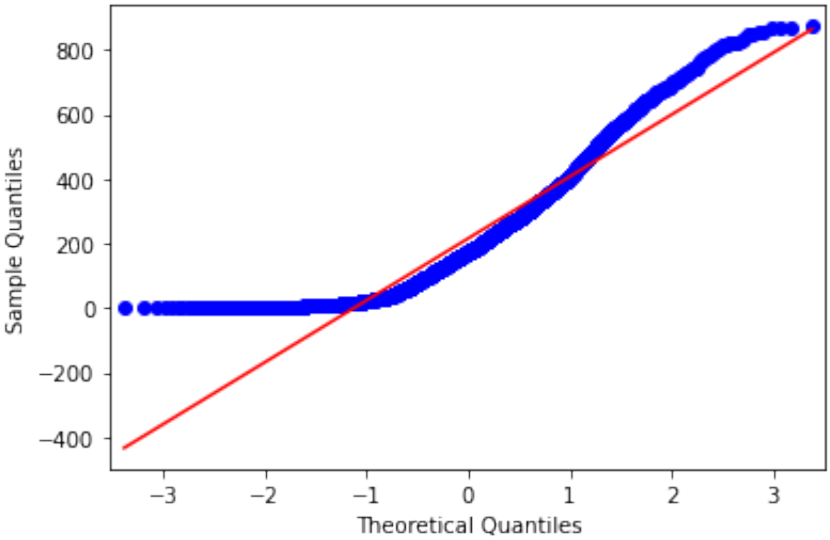
Sample Quantiles
Theoretical Quantiles

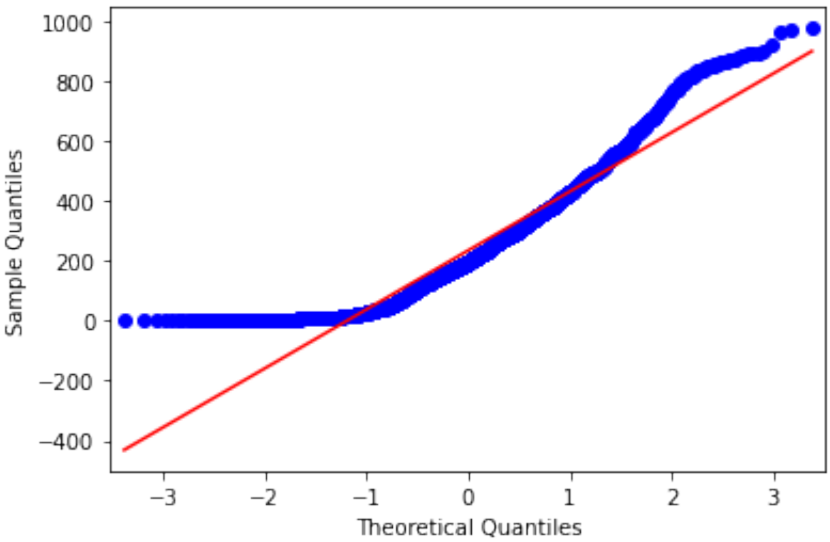


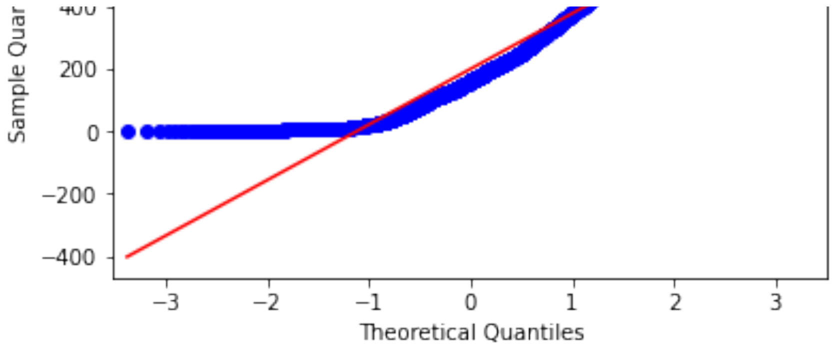
Sample Quantiles


155.0
−0.04
−0.02
0.00
0.02
0.04
Theoretical Quantiles


Sample Quantiles
Theoretical Quantiles


Sample Quantiles
Theoretical Quantiles


Sample Quantiles
Theoretical Quantiles



It can be observed from above that, none of the groups are following a normal distribution.

Second Assumption: Data is independent

Third Assumption: Equal Variance

In [237]:
```
# Performing Levene's test to check for equal variances

#Null Hypothesis: Variances are similar in different weather an
#Alternate Hypothesis: Variances are not similar in different we
#Significance level (alpha): 0.05
levene_stat, p_value = levene(groups[0],groups[1],groups[2],gro
print(p_value)
if p_value < 0.05:
    print("Reject the Null hypothesis.Variances are not equal")
else:
    print("Fail to Reject the Null hypothesis.Variances are equ
```

```
3.463531888897594e-148
Reject the Null hypothesis.Variances are not equal
```

As we can see from above,the variances are not equal, hence the third assumption is also not fulfilled.

As None of assumptions for an Annova test have been fulfilled, we shall perform a Kruskal Test.

In [238]:
```
from scipy.stats import kruskal
kruskal_stat, p_value = kruskal(groups[0],groups[1],groups[2],g
if p_value<0.05:
    print("Since p-value is less than 0.05, we reject the null
else:
    print("Since p-value is greater than 0.05, we fail to rejec

```

```
Since p-value is less than 0.05, we reject the null hypothesis, An
d hence conclude that the Seasons and Weather dont have similar im
pact on count
```

3. Chi-square test to check if Weather is dependent on the season

In [239]:
```
# Null Hypothesis (H0): Weather is independent of the season
# Alternate Hypothesis (H1): Weather is not independent of the
# Significance level (alpha): 0.05
table = pd.crosstab(yulu['season'], yulu['weather'])
print("Observed values:")
table
```

```
Observed values:
```

Out[239]:

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

In [245]:
```
from scipy.stats import chi2_contingency
stat,pval,dof,tab = chi2_contingency(table)

if pval <= 0.05:
    print(f"Since p-value, ie, {pval} is less than the alpha 0.
else:
    print(f"Since p-value, ie, {pval} is greater than the alpha

```

```
Since p-value, ie, 1.549925073686492e-07 is less than the alpha 0.
05, We reject the Null Hypothesis.
Hence Weather is dependent on the season.
```

Insights

1. In summer and fall seasons more bikes are rented as compared to other seasons.
2. Whenever its not holiday more bikes are rented.
3. It is also clear from the workingday also that whenever day is not holiday or weekend, slightly more bikes are rented.
4. Whenever there is rain, thunderstorm, snow or fog, there were less bikes rented.
5. Anova test assumption fails in the case study. As neither variance are equal and disb of variables are normal. Variance equality test was done using Levene's test, which helps reject assumption for one way annova.
6. Normal distribution check was done by using QQ plot test.
7. Practical data almost never follows normal disb hence mention of non parametric test like Krushkal Welch test.
8. Detection of outlier data using IQR principles, visualized using boxplots.

Recommendations

1. In summer and fall seasons the company should have more bikes in stock.
2. With a significance level of 0.05, workingday has no effect on the number of bikes being rented.
3. Yulu should try to attract more customers on working days and try to make it as an alternate to work travel mode. Special peak timing offers and high availabilty of yulu bikes will contribute to the increase in bookings.
4. Using anova test, taking alpha as 5%, we still see pvalue<0.05 hence we reject the HO and accept ha that is yes the weather has affect on the number of cycles rented out. Yulu needs to pay attention on the weather conditions to increase it's bike active users. Weather and customer profiling will help to come up with new product features on yulu.
5. Using anova, taking alpha as 5%, we still see pvalue<0.05 hence we reject the HO and accept ha that is yes the season has affect on the number of cycles rented out. Yulu needs to focus more on the seasonal offerings of the bikes to make more active users retention. Student discounts in summer and school hours will also attract new customer base.
6. Using chi square test, the p value is very less than alpha at 5%, we reject the h0 and accept h1. Season has some influence on the weather, We say it with high confidence. Use of meterological features will help in boosting the bookings.

In [ ]:

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