yulu-case-study-mohana-final

December 13, 2023

YULU CASE STUDY

1. Import the dataset and do usual exploratory data analysis steps like checking the structure & characteristics of the dataset

Import Libraries and load data

[63]:
```
import pandas as pd, numpy as np, matplotlib.pyplot as plt, seaborn as sns
from scipy.stats import␣
↪norm,binom,geom,t,ttest_1samp,ttest_ind,ttest_rel,chisquare,chi2_contingency,f_oneway,poiss
from statsmodels.graphics.gofplots import qqplot

from google.colab import drive
drive.mount('/content/drive')

data = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/yulu_data.csv')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

Initial Data analysis and Cleanup

[64]:
```
data.head(5)
```

[64]:

	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

[65]:
```
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
```

[66]:
```
print(f'Rows : {data.shape[0]}\nColumns : {data.shape[1]}')
```

```
Rows : 10886
Columns : 12
```

[67]:
```
#Converting columns to relevant datatypes
data['datetime'] = pd.to_datetime(data['datetime'])
convert_dict = {
                'season': object,
                'holiday': object,
                'workingday': object,
                'weather' : object
               }
data = data.astype(convert_dict)
```

[68]:
```
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  datetime64[ns]
 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: datetime64[ns](1), float64(3), int64(4), object(4)
memory usage: 1020.7+ KB
```

[69]:
```
#Checking missing values:
data.isnull().sum()/len(data)*100
```

[69]:
```
datetime      0.0
season        0.0
holiday       0.0
workingday    0.0
weather       0.0
temp          0.0
atemp         0.0
humidity      0.0
windspeed     0.0
casual        0.0
registered    0.0
count         0.0
dtype: float64
```

[70]:
```
#Checking if any duplicate values:
data.duplicated().sum()
```

[70]: 0

[71]:
```
data.describe(include="all")
```

```
<ipython-input-71-959e96f52f7b>:1: FutureWarning: Treating datetime data as
categorical rather than numeric in `.describe` is deprecated and will be removed
in a future version of pandas. Specify `datetime_is_numeric=True` to silence
this warning and adopt the future behavior now.
  data.describe(include="all")
```

[71]:
```
                   datetime   season  holiday  workingday  weather  \
count                 10886  10886.0  10886.0     10886.0  10886.0
unique                10886      4.0      2.0         2.0      4.0
top     2011-01-01 00:00:00      4.0      0.0         1.0      1.0
freq                      1   2734.0  10575.0      7412.0   7192.0
first   2011-01-01 00:00:00      NaN      NaN         NaN      NaN
last    2012-12-19 23:00:00      NaN      NaN         NaN      NaN
mean                    NaN      NaN      NaN         NaN      NaN
std                     NaN      NaN      NaN         NaN      NaN
```

```
min                      NaN       NaN       NaN         NaN       NaN
25%                      NaN       NaN       NaN         NaN       NaN
50%                      NaN       NaN       NaN         NaN       NaN
75%                      NaN       NaN       NaN         NaN       NaN
max                      NaN       NaN       NaN         NaN       NaN

               temp          atemp      humidity     windspeed        casual  \
count   10886.00000  10886.000000  10886.000000  10886.000000  10886.000000
unique          NaN           NaN           NaN           NaN           NaN
top             NaN           NaN           NaN           NaN           NaN
freq            NaN           NaN           NaN           NaN           NaN
first           NaN           NaN           NaN           NaN           NaN
last            NaN           NaN           NaN           NaN           NaN
mean       20.23086     23.655084     61.886460     12.799395     36.021955
std         7.79159      8.474601     19.245033      8.164537     49.960477
min         0.82000      0.760000      0.000000      0.000000      0.000000
25%        13.94000     16.665000     47.000000      7.001500      4.000000
50%        20.50000     24.240000     62.000000     12.998000     17.000000
75%        26.24000     31.060000     77.000000     16.997900     49.000000
max        41.00000     45.455000    100.000000     56.996900    367.000000

          registered         count
count   10886.000000  10886.000000
unique           NaN           NaN
top              NaN           NaN
freq             NaN           NaN
first            NaN           NaN
last             NaN           NaN
mean      155.552177    191.574132
std       151.039033    181.144454
min         0.000000      1.000000
25%        36.000000     42.000000
50%       118.000000    145.000000
75%       222.000000    284.000000
max       886.000000    977.000000
```

Initial data Insights :- * The data consists of total 10886 rows and 12 columns * There were no missing values or duplicates. * There are some columns in a irrelavent data type and so are converted to appropriate data type. * The mean of actual temperature, feeling temperature, humidity, wind speed, no.of bikes rented from the given data were 20.23, 23.65, 61.88, 12.79, 191.57 respectively.

[72]:
```
num_cols = [i for i in data.columns if data[i].dtype in ['float64', 'int64']]
cat_cols = [i for i in data.columns if data[i].dtype in ['object']]
```

[73]:
```
data[cat_cols].melt().groupby(['variable', 'value'])[['value']].count()
```

[73]:

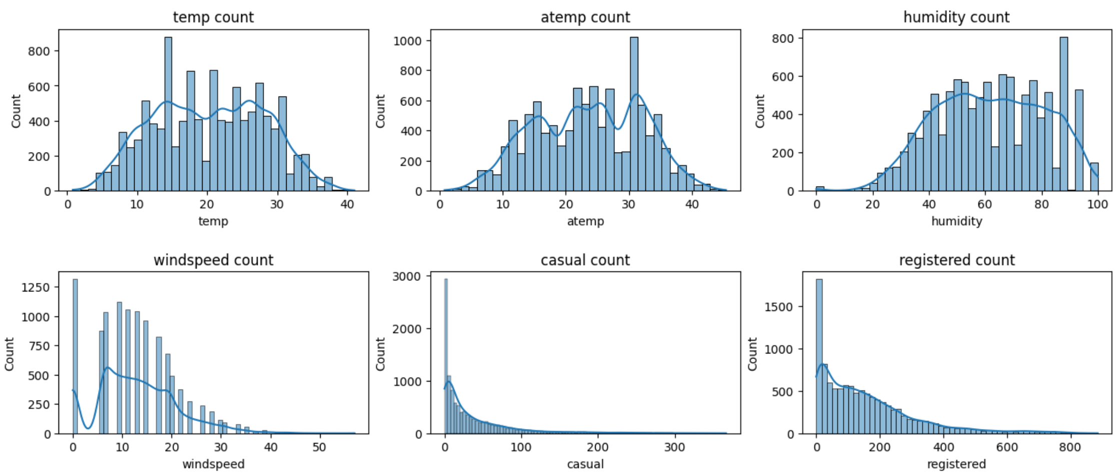
variable	value	value
holiday	0	10575
	1	311
season	1	2686
	2	2733
	3	2733
	4	2734
weather	1	7192
	2	2834
	3	859
	4	1
workingday	0	3474
	1	7412

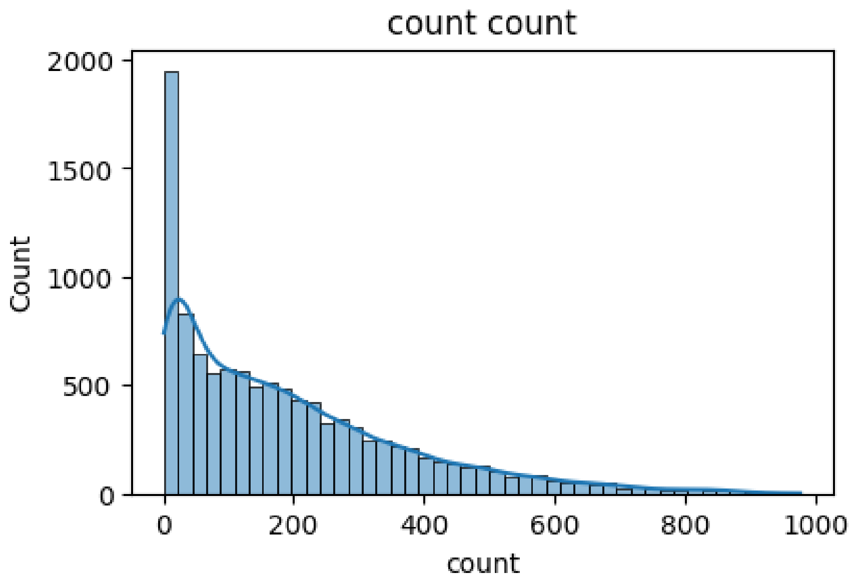
###**Distribution of Numerical variables**

[74]:
```
fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(16, 4))
fig.subplots_adjust(top=1.3, hspace=0.5)

count = 0
for row in range(2):
    for col in range(3):
        sns.histplot(data=data, x=num_cols[count], ax=axs[row, col], kde=True)
        axs[row, col].set_title(f'{num_cols[count]} count')
        count += 1

plt.figure(figsize=(4.7, 3))
sns.histplot(data=data,x=num_cols[count], kde=True)
plt.title(f'{num_cols[count]} count')
plt.show()
```

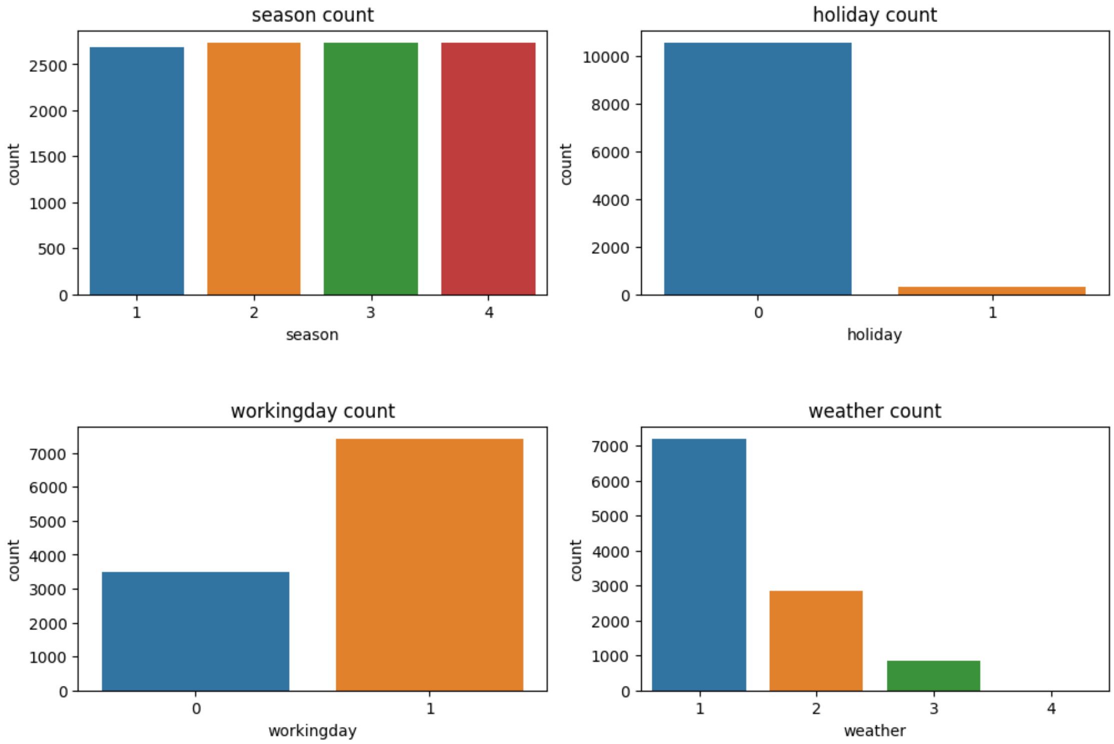




###**Distribution of Categorical variables**

[75]:
```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(12, 5))
fig.subplots_adjust(top=1.3, hspace=0.5)

count = 0
for row in range(2):
    for col in range(2):
        sns.countplot(data=data, x=cat_cols[count], ax=axs[row, col])
        axs[row, col].set_title(f'{cat_cols[count]} count')
        count += 1
```

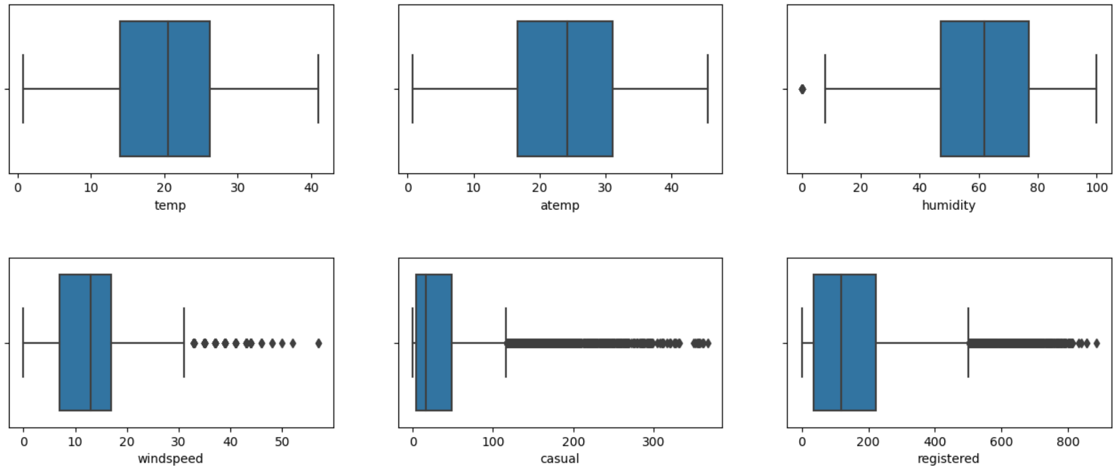


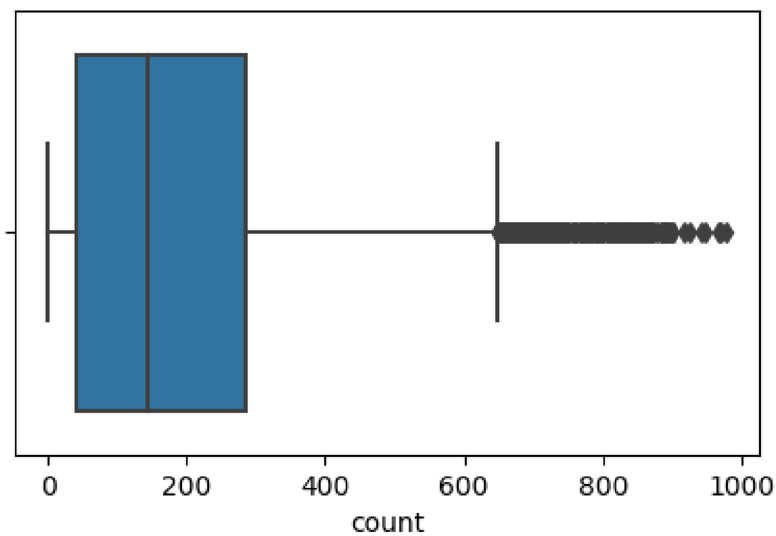
###Checking Outliers in Numerical Variables

[76]:
```
fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(16, 4))
fig.subplots_adjust(top=1.3, hspace=0.5)

count = 0
for row in range(2):
    for col in range(3):
        sns.boxplot(data=data, x=num_cols[count], ax=axs[row, col])
        count += 1

plt.figure(figsize=(5, 3))
sns.boxplot(data=data,x=num_cols[count])
plt.show()
```





###**Counting Outliers using IQR**

[77]:
```python
def outliers_count(col):
  Q1 = np.percentile(data[col], 25, method='midpoint')
  Q3 = np.percentile(data[col], 75, method='midpoint')
  IQR = Q3 - Q1
  upper_count = np.array(data[col] >= (Q3+1.5*IQR)).sum()
  lower_count = np.array(data[col] <= (Q1-1.5*IQR)).sum()
  print(f'Upper Outliers count for {col} column is {upper_count} and Lower Outliers count for {col} column is {lower_count}')
```

[78]:
```
outliers_count('windspeed')
outliers_count('casual')
outliers_count('registered')
outliers_count('count')
```

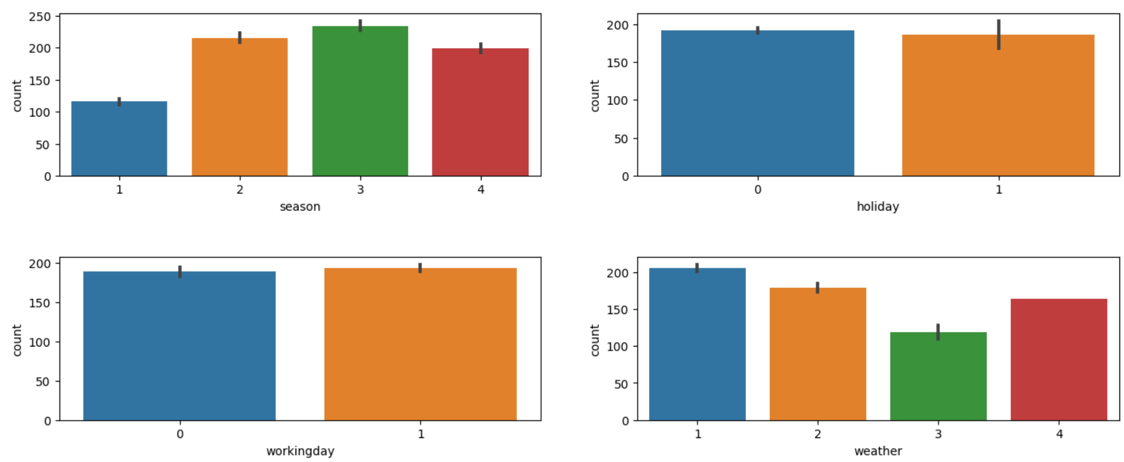
```
Upper Outliers count for windspeed column is 227 and Lower Outliers count for
windspeed column is 0
Upper Outliers count for casual column is 749 and Lower Outliers count for
casual column is 0
Upper Outliers count for registered column is 424 and Lower Outliers count for
registered column is 0
Upper Outliers count for count column is 303 and Lower Outliers count for count
column is 0
```

###**Categorical variables v/s count(no.of bikes rented)**

[79]:
```
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16,4))
fig.subplots_adjust(top=1.3, hspace=0.5)

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

plt.show()
```



Insights:

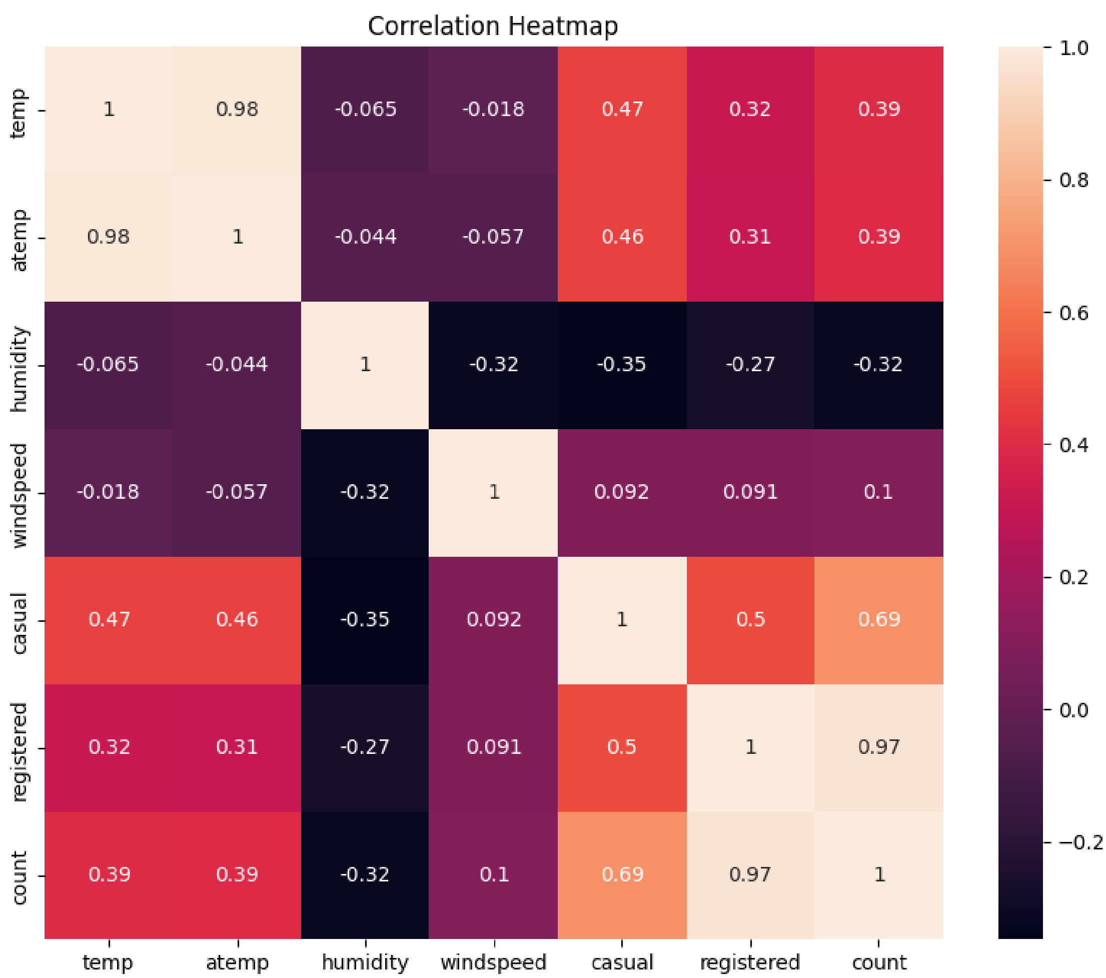
- From the given data temperature and humidity distributions look normally distributed whereas casual and registered users count distributions look right skewed.
- Count of outliers in windspeed, casual, registered, count were 227, 749, 424, 303 respectively.
- Holiday and working day categories has no affect on no.of cycles rented.

- More no.of cycles were rented in Season 3 (fall) and less no.of cycles were rented in season 1 (spring).
- More no.of cycles were rented during weather 1 (Clear, Few clouds, partly cloudy, partly cloudy) and less no.of cycles were rented during weather 3 (Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds).

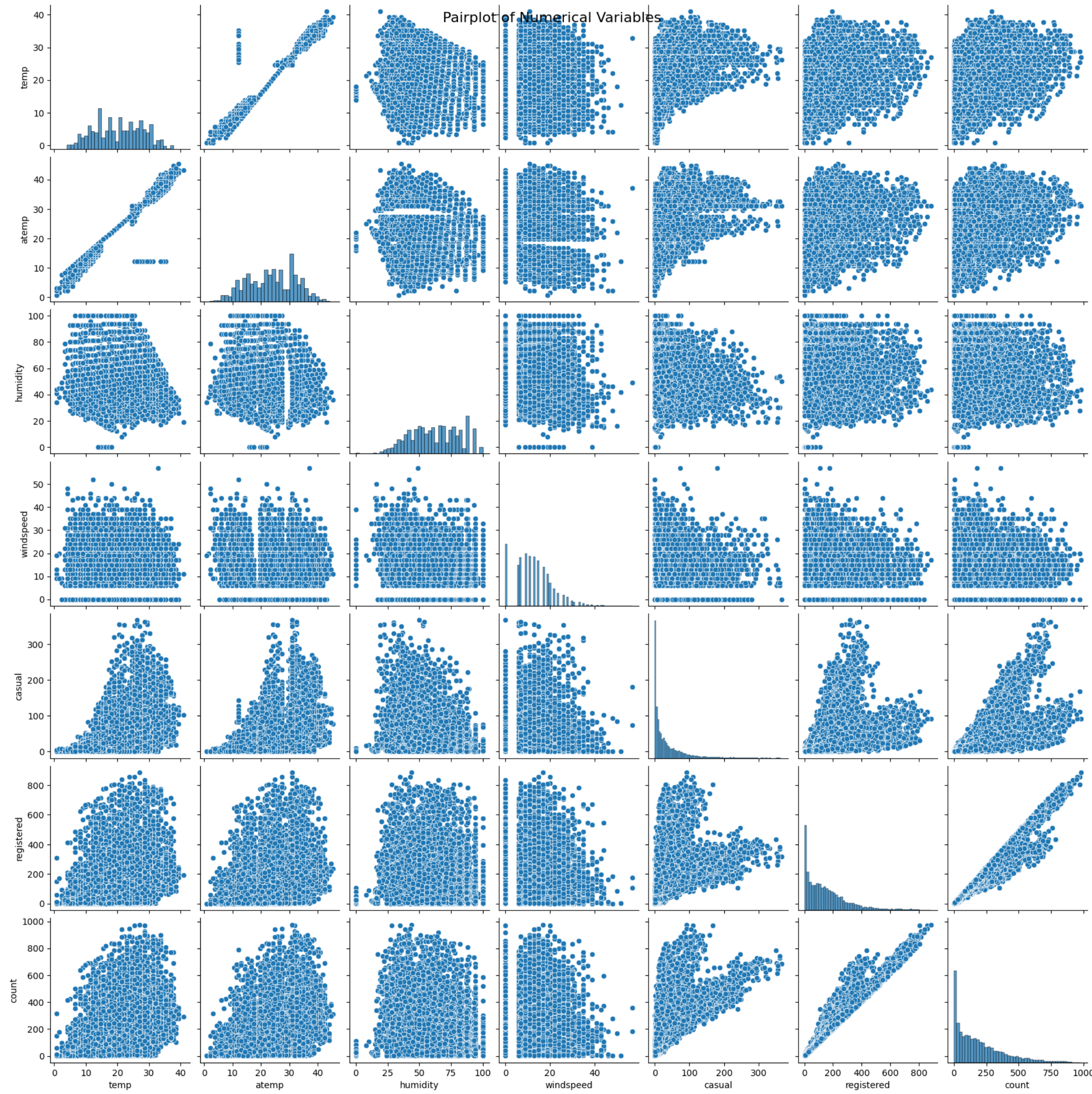
##**2. Try establishing a Relationship between the Dependent and Independent Variables.**

[80]:
```
plt.figure(figsize=(10, 8))
sns.heatmap(data.corr(), annot=True)
plt.title('Correlation Heatmap')
plt.show()
```

```
<ipython-input-80-3c5679f9b17a>:2: 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.
  sns.heatmap(data.corr(), annot=True)
```

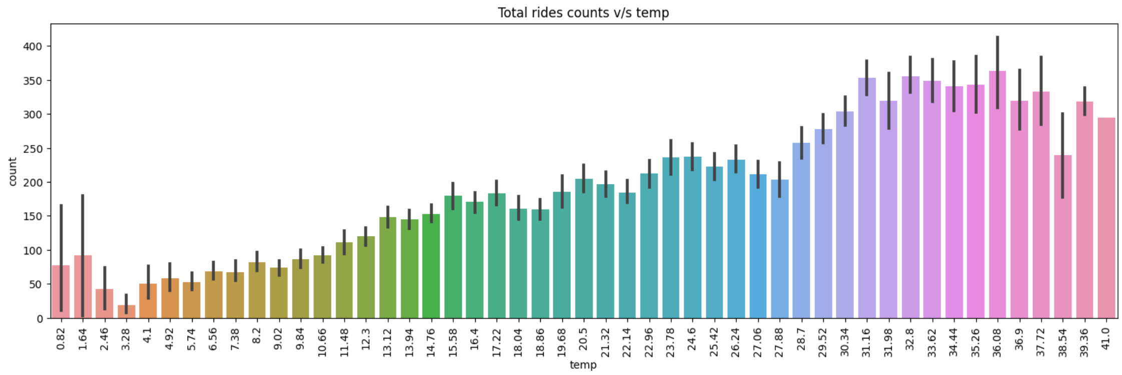


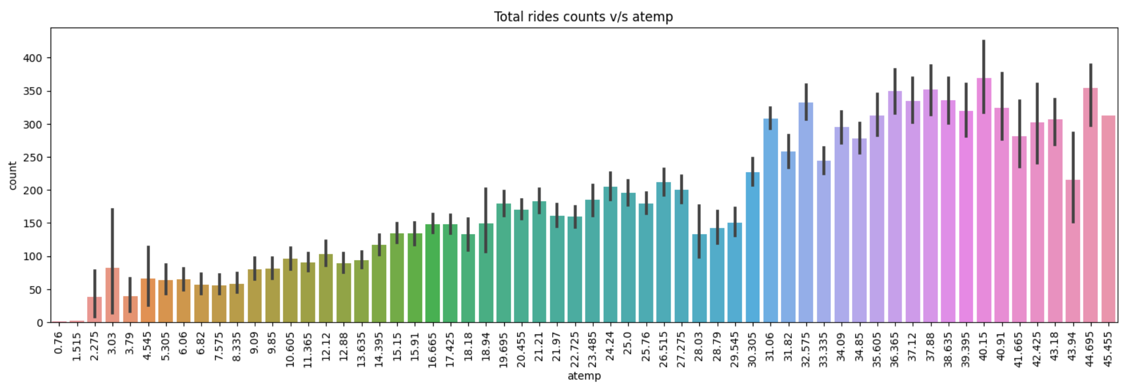
[81]:
```
# Plotting the pairplot
sns.pairplot(data[num_cols])
plt.suptitle('Pairplot of Numerical Variables', fontsize=16)
plt.show()
```

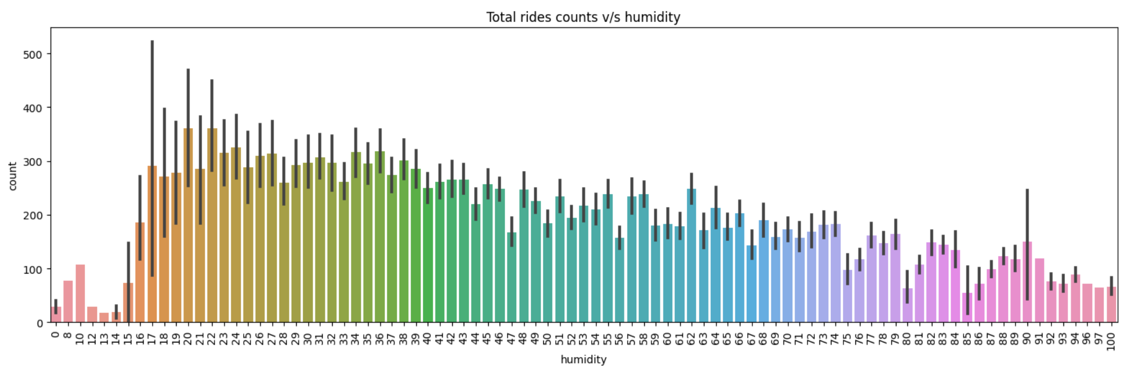


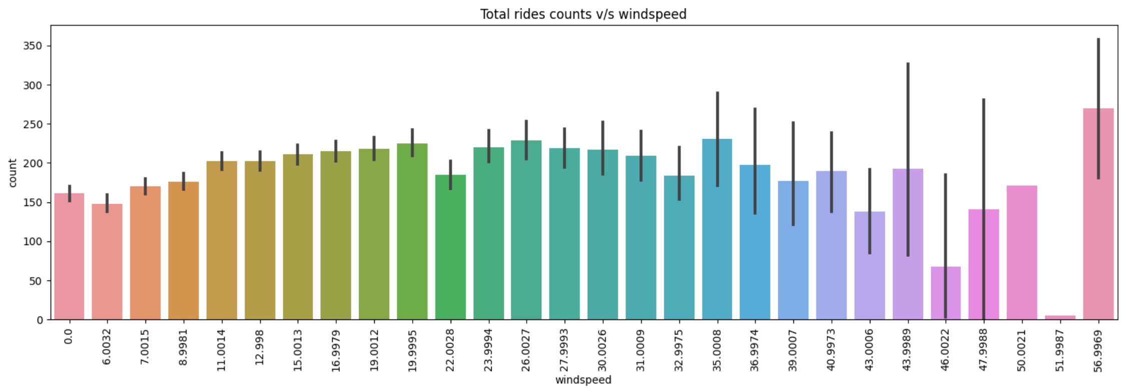
[82]:
```
catagories=['temp', 'atemp', 'humidity', 'windspeed']
for i in catagories:
  plt.figure(figsize=(18,5))
  sns.barplot(data=data,x=i,y='count')
  plt.xlabel(i)
  plt.ylabel('count')
```

```python
    plt.title(f'Total rides counts v/s {i}')
    plt.xticks(rotation=90)
    plt.show()
```









Insights:

- As the temperature decreases there is a decrease in no.of bikes rented.
- As the humidity increases there is a decrease in no.of bikes rented.
- Windspeed is not affecting the no.of bikes rented.

##3.1. Check whether working Day has effect on number of electric cycles rented

HO : Working Day has no effect on number of electric cycles rented

HA : Working Day has a significant effect on number of electric cycles rented

[83]:
```
alpha = 0.05
working_day_count = data.loc[data['workingday']==1]['count']
non_working_day_count = data.loc[data['workingday']==0]['count']
test_statistic,p_value =␣
↪ttest_ind(working_day_count,non_working_day_count,alternative="two-sided")
print(f'p-value is {p_value} \ntest-statistic is {test_statistic}' )
if p_value < alpha:
  print('Reject null hypothesis(HO)\nWorking Day has a significant effect on␣
↪number of electric cycles rented')
else:
  print('Failed to reject null hypothesis(HO)\nWorking Day has no effect on␣
↪number of electric cycles rented')
```

```
p-value is 0.22644804226361348
test-statistic is 1.2096277376026694
Failed to reject null hypothesis(HO)
Working Day has no effect on number of electric cycles rented
```

##3.2. Check whether No. of cycles rented similar or different in different seasons

HO : Seasons has no effect on number of electric cycles rented

HA : Seasons has a significant effect on number of electric cycles rented

[84]:

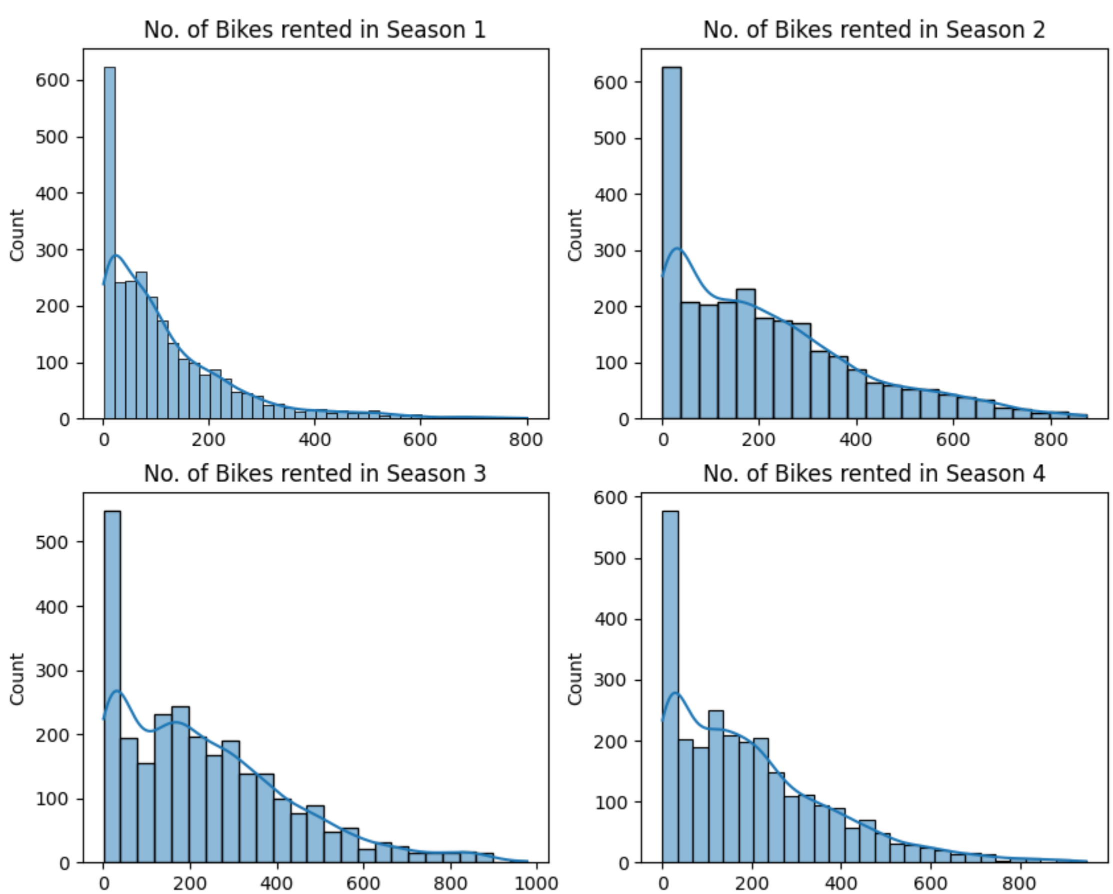
```
season_1_count = data.loc[data['season']==1]['count'].values
season_2_count = data.loc[data['season']==2]['count'].values
season_3_count = data.loc[data['season']==3]['count'].values
season_4_count = data.loc[data['season']==4]['count'].values
seasons=[season_1_count,season_2_count,season_3_count,season_4_count]
```

###Checking Assumptions

3.2.1 Normality check using Histplot

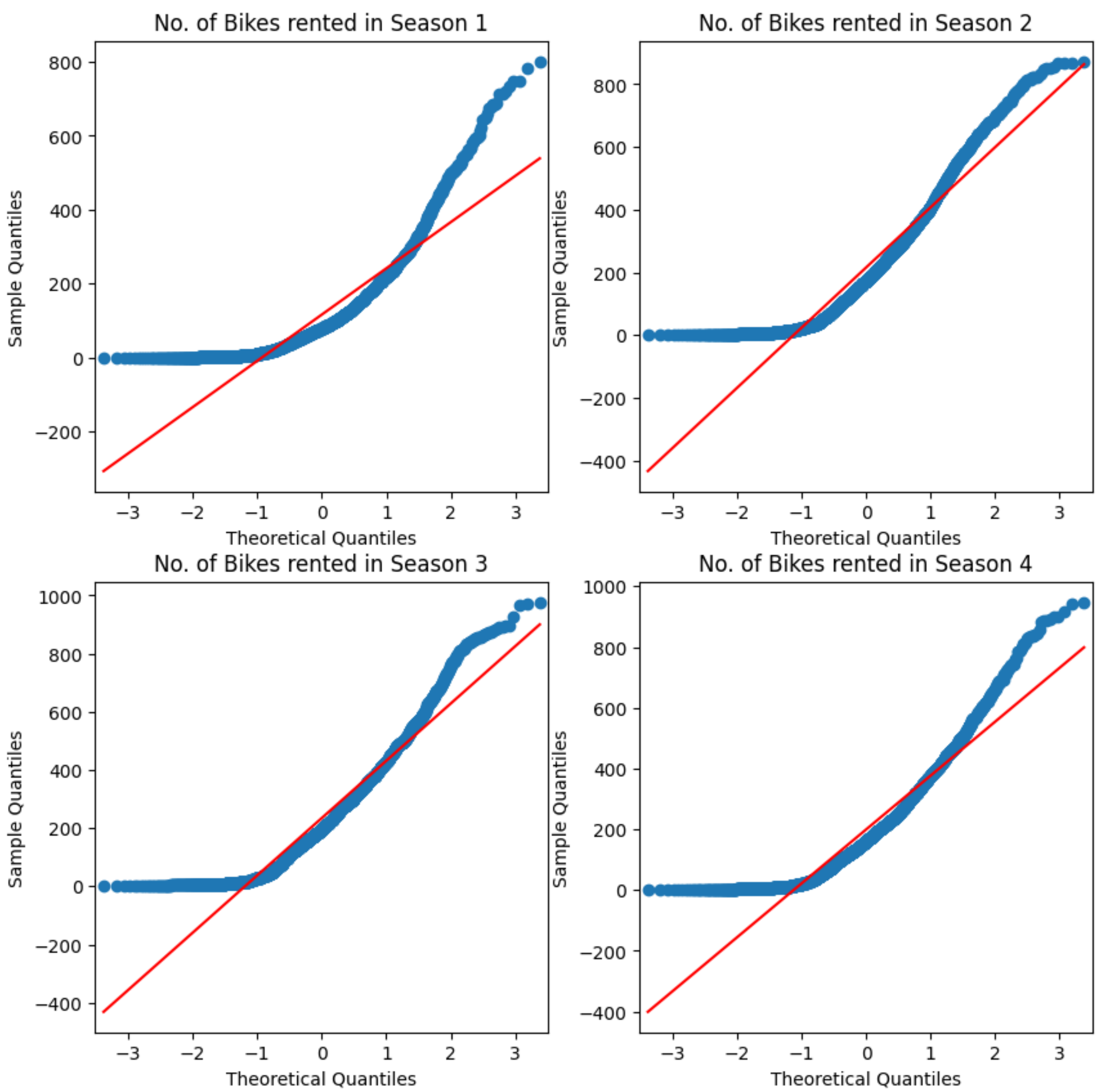
[85]:

```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(10,8))
count=0
for i in range(2):
  for j in range(2):
    sns.histplot(data=seasons[count],kde=True, ax=axs[i,j])
    axs[i,j].set_title(f'No. of Bikes rented in Season {count+1}')
    count+=1
plt.show()
```



3.2.2 Normality check using QQPlot

[86]:
```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(10,10))
count=0
for i in range(2):
  for j in range(2):
    qqplot(data=seasons[count],line="s", ax=axs[i,j])
    axs[i,j].set_title(f'No. of Bikes rented in Season {count+1}')
    count+=1
plt.show()
```



3.2.3 Normality check using Shapiro

[87]:
```
alpha=0.05
for i in range(len(seasons)):
```

```
    test_stat,p_value = shapiro(seasons[i])
    if p_value < alpha:
      print(f'Seasons {i+1} count Data is not normal')
    else:
      print(f'Seasons {i+1} count Data is normal')
```

```
Seasons 1 count Data is not normal
Seasons 2 count Data is not normal
Seasons 3 count Data is not normal
Seasons 4 count Data is not normal
```

3.2.4 Equality Variance check using Levene

[88]:
```
alpha=0.05
test_stat,p_value = levene(seasons[0],seasons[1],seasons[2],seasons[3])
if p_value < alpha:
  print(f'Seasons count data have unequal variance')
else:
  print(f'Seasons count data have equal variance')
```

```
Seasons count data have unequal variance
```

###Hypothesis test using ANOVA

[89]:
```
alpha = 0.05
test_statistic,p_value =␣
 ↪f_oneway(season_1_count,season_2_count,season_3_count,season_4_count)
print(f'p-value is {p_value} \ntest-statistic is {test_statistic}' )
if p_value < alpha:
  print('Reject null hypothesis(HO)\nSeason has a significant effect on the␣
 ↪number of electric cycles rented')
else:
  print('Failed to reject null hypothesis(HO)\nSeason has no effect on the␣
 ↪number of electric cycles rented')
```

```
p-value is 6.164843386499654e-149
test-statistic is 236.94671081032106
Reject null hypothesis(HO)
Season has a significant effect on the number of electric cycles rented
```

##3.3. Check whether No. of cycles rented similar or different in different weather

HO : Weather has no effect on number of electric cycles rented

HA : Weather has a significant effect on number of electric cycles rented

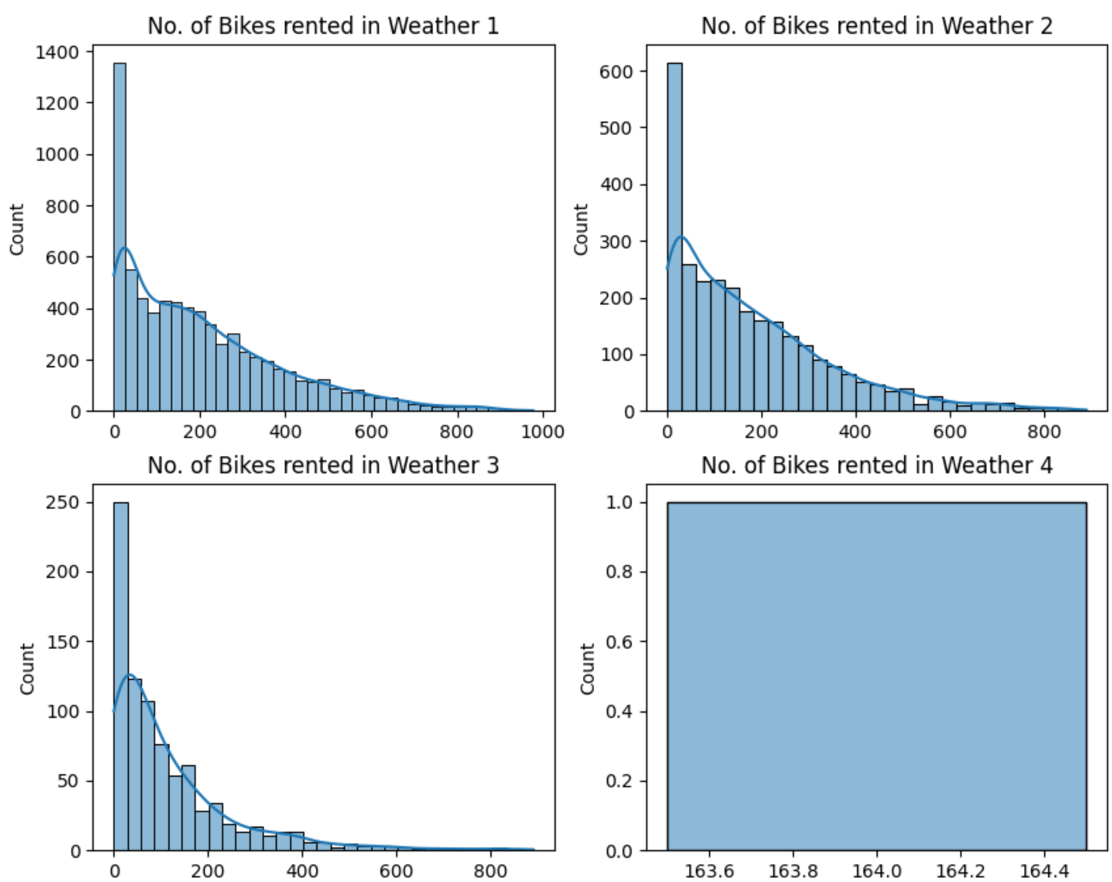
[90]:
```
weather_1_count = data.loc[data['weather']==1]['count'].values
weather_2_count = data.loc[data['weather']==2]['count'].values
weather_3_count = data.loc[data['weather']==3]['count'].values
weather_4_count = data.loc[data['weather']==4]['count'].values
```

```
weathers=[weather_1_count,weather_2_count,weather_3_count,weather_4_count]
```

###Checking Assumptions

3.3.1 Normality check using Histplot

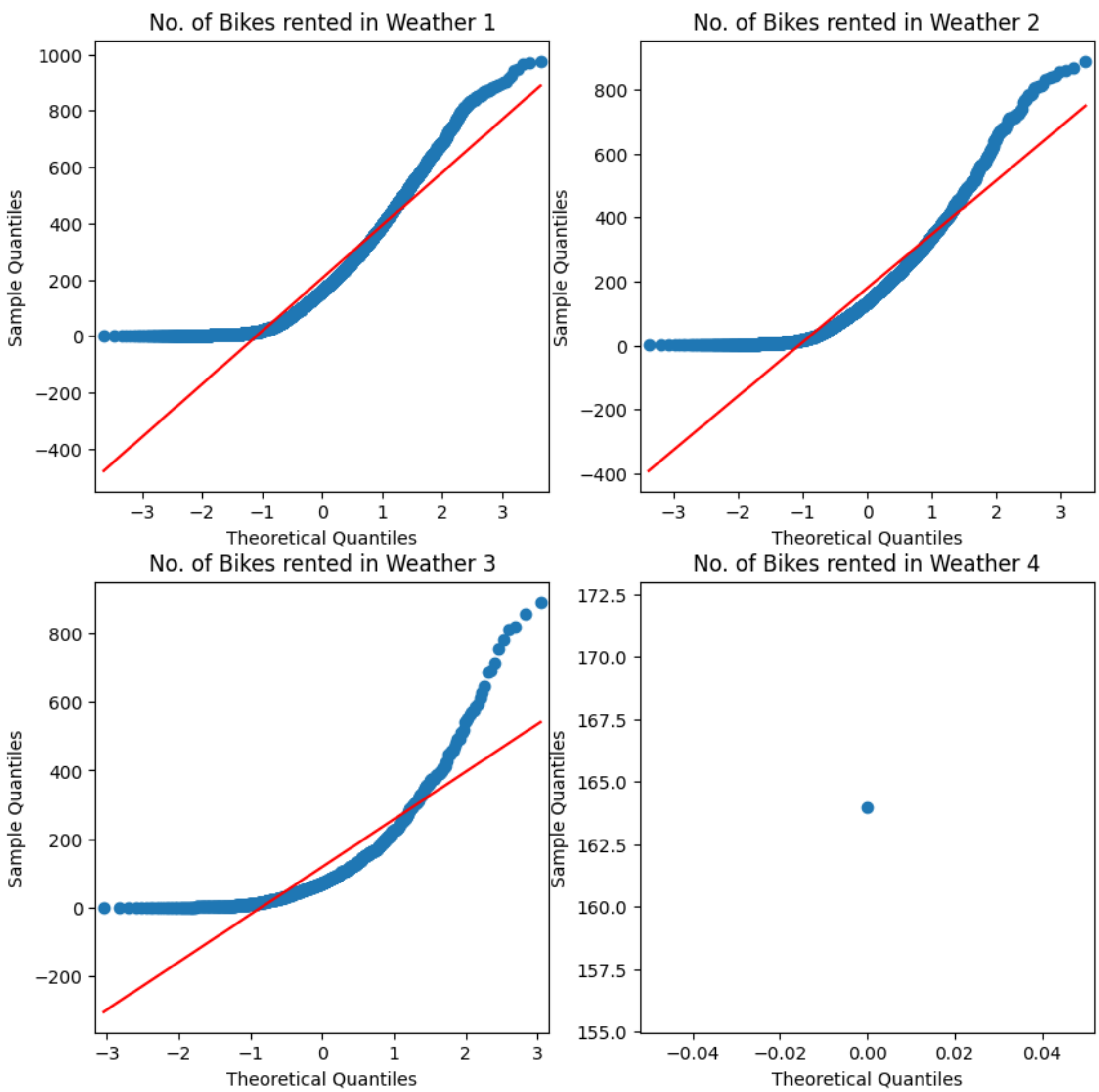
[91]:
```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(10,8))
count=0
for i in range(2):
  for j in range(2):
    sns.histplot(data=weathers[count],kde=True, ax=axs[i,j])
    axs[i,j].set_title(f'No. of Bikes rented in Weather {count+1}')
    count+=1
plt.show()
```



3.3.2 Normality check using QQPlot

[92]:
```
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(10,10))
count=0
for i in range(2):
```

```
  for j in range(2):
    qqplot(data=weathers[count],line="s", ax=axs[i,j])
    axs[i,j].set_title(f'No. of Bikes rented in Weather {count+1}')
    count+=1
plt.show()
```



3.3.3 Normality check using Shapiro

[93]:
```
alpha=0.05
for i in range(len(weathers)):
  if len(weathers[i])>=2:
    test_stat,p_value = shapiro(weathers[i])
    if p_value < alpha:
```

```
            print(f'Weather {i+1} count Data is not normal')
        else:
            print(f'Weather {i+1} count Data is normal')
    else:
        print(f'Weather {i+1} count Data is not normal')
```

```
Weather 1 count Data is not normal
Weather 2 count Data is not normal
Weather 3 count Data is not normal
Weather 4 count Data is not normal
```

```
/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.")
```

3.3.4 Equality Variance check using Levene

[94]:
```
alpha=0.05
test_stat,p_value = levene(weathers[0],weathers[1],weathers[2],weathers[3])
if p_value < alpha:
  print(f'Weathers count data have unequal variance')
else:
  print(f'Weathers count data have equal variance')
```

```
Weathers count data have unequal variance
```

###**Hypothesis test using ANOVA**

[95]:
```
alpha = 0.05
test_statistic,p_value =␣
 ↪f_oneway(weather_1_count,weather_2_count,weather_3_count,weather_4_count)
print(f'p-value is {p_value} \ntest-statistic is {test_statistic}' )
if p_value < alpha:
  print('Reject null hypothesis(HO)\nWeather has a significant effect on the␣
 ↪number of electric cycles rented')
else:
  print('Failed to reject null hypothesis(HO)\nWeather has no effect on the␣
 ↪number of electric cycles rented')
```

```
p-value is 5.482069475935669e-42
test-statistic is 65.53024112793271
Reject null hypothesis(HO)
Weather has a significant effect on the number of electric cycles rented
```

##**3.4. Check weather is dependent on season (check between 2 predictor variable)**

HO : Weather is independent on season

HA : Weather is dependent on season

###**Hypothesis test using chi2**

[96]:
```
#creating crosstab
weather_season_ct = pd.crosstab(data['season'],data['weather'])
weather_season_ct
```

[96]:
```
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
```

[97]:
```
alpha = 0.05
chi2_contingency(weather_season_ct)
print(f'p-value is {p_value} \ntest-statistic is {test_statistic}' )
if p_value < alpha:
  print('Reject null hypothesis(H0)\nWeather is dependent on season')
else:
  print('Failed to reject null hypothesis(H0)\nWeather is independent on␣
↪season')
```

```
p-value is 5.482069475935669e-42
test-statistic is 65.53024112793271
Reject null hypothesis(H0)
Weather is dependent on season
```

##**Insights and recommendations:**

Insights from the hypothesis testing with a significance level of 95%:

- Working Day has no effect on number of electric cycles rented
- Season has a significant effect on the number of electric cycles rented
- Weather has a significant effect on the number of electric cycles rented
- Weather is dependent on season

Recommendations:

- Adjust operations based on seasons; plan for peak times. During fall and summer season there was high demand. So maintain stock accordingly.
- During Spring season the demand is very less. So offer more discounts accordingly.
- Use weather info for smart strategies; offer discounts during bad weather (Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds).
- Maintain good stocks during clear weather conditions (Clear, Few clouds, partly cloudy, partly cloudy) as the number of rentals was more.
- Implement dynamic pricing models that adjust rental prices based on weather conditions, offering lower prices during colder temperatures and higher humidity.
- Keep an eye on unusual data points; make sure operations run smoothly.
- Engage users with loyalty programs and bonuses.
- Adjust pricing based on holidays and workdays.
- Work with weather services for real-time updates.
- Make sure enough bikes are available in popular locations during busy times.

- Teach users about the benefits of biking in different weather.
- Expand to areas where there's high demand during specific times.
- Keep checking how well strategies work and make improvements based on data.