Problem Statement

Yulu, India's leading micro-mobility service provider, is facing a significant decline in revenues. To understand the factors influencing the demand for shared electric cycles in the Indian market, Yulu has engaged a consulting company. The primary objectives are to identify significant variables predicting the demand, assess the descriptive power of these variables, and gain insights into the factors affecting the demand. The analysis involves exploring a dataset (yulu_data.csv) and performing various statistical tests such as 2-sample T-Test, ANOVA, and Chi-square. Key questions to address include the impact of working days on cycle rentals, variations in rental numbers across different seasons and weather conditions, and the dependency between weather and season. The analysis aims to provide actionable insights for Yulu to optimize its micro-mobility services.

In [30]:
```
# Importing Python libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
import scipy.stats as spy
```

In [2]:
```
#Reading dataset in pandas dataframe
df = pd.read_csv('bike_sharing.txt')
```

In [3]:
```
df.head()
```

Out[3]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed
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 [4]:
```
df.shape # Rows- 10886, Columns- 12
```

Out[4]: (10886, 12)

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   datetime    10886 non-null  object 
 1   season      10886 non-null  int64  
 2   holiday     10886 non-null  int64  
 3   workingday  10886 non-null  int64  
 4   weather     10886 non-null  int64  
 5   temp        10886 non-null  float64
 6   atemp       10886 non-null  float64
 7   humidity    10886 non-null  int64  
 8   windspeed   10886 non-null  float64
 9   casual      10886 non-null  int64  
 10  registered  10886 non-null  int64  
 11  count       10886 non-null  int64  
dtypes: float64(3), int64(8), object(1)
memory usage: 1020.7+ KB
```

In [6]:
```
df['datetime'] = pd.to_datetime(df['datetime']) #Conversion of "datetim
```

In [7]:
```
df.describe() #Statistical summary of the continuous columns
```

Out[7]:

	datetime	season	holiday	workingday	weather	
count	10886	10886.000000	10886.000000	10886.000000	10886.000000	108
mean	2011-12-27 05:56:22.399411968	2.506614	0.028569	0.680875	1.418427	
min	2011-01-01 00:00:00	1.000000	0.000000	0.000000	1.000000	
25%	2011-07-02 07:15:00	2.000000	0.000000	0.000000	1.000000	
50%	2012-01-01 20:30:00	3.000000	0.000000	1.000000	1.000000	
75%	2012-07-01 12:45:00	4.000000	0.000000	1.000000	2.000000	
max	2012-12-19 23:00:00	4.000000	1.000000	1.000000	4.000000	
std	NaN	1.116174	0.166599	0.466159	0.633839	

In [8]:
```
df.isnull().sum() #Null values check for each column
```

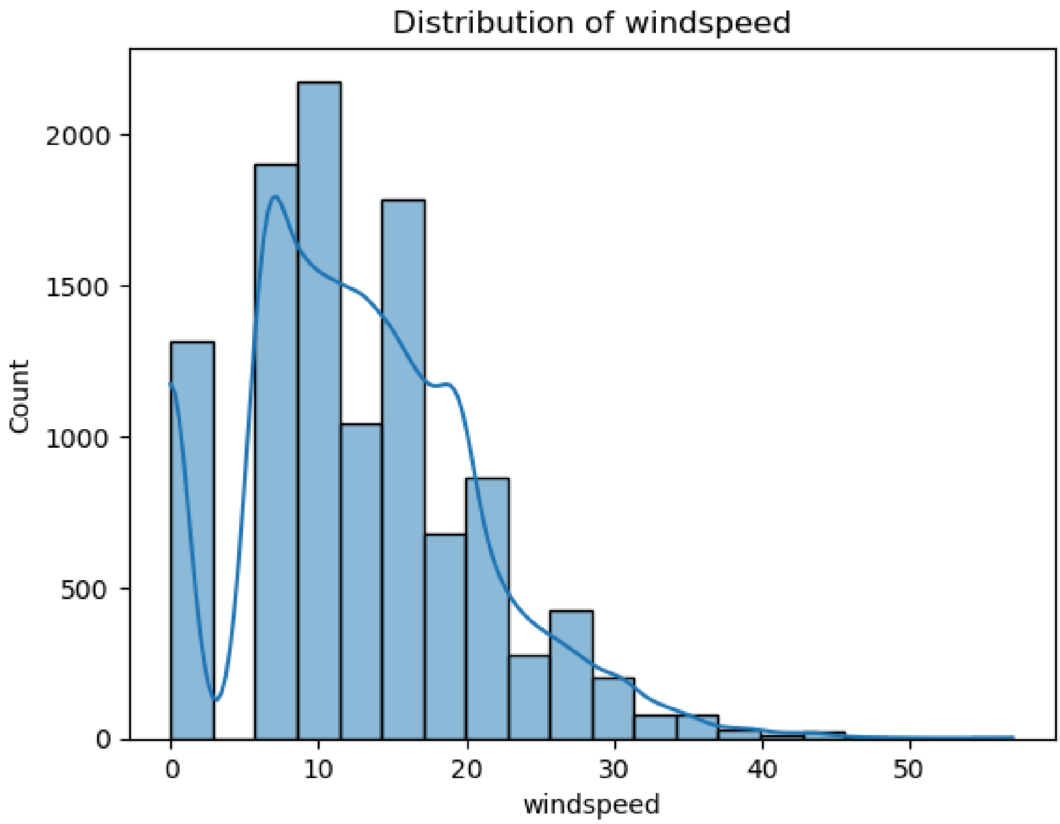
Out[8]:
```
datetime      0
season        0
holiday       0
workingday    0
weather       0
temp          0
atemp         0
humidity      0
windspeed     0
casual        0
registered    0
count         0
dtype: int64
```

In [9]:
```
df.duplicated().sum() # Checking duplicate values in the dataset
```

Out[9]:
```
0
```

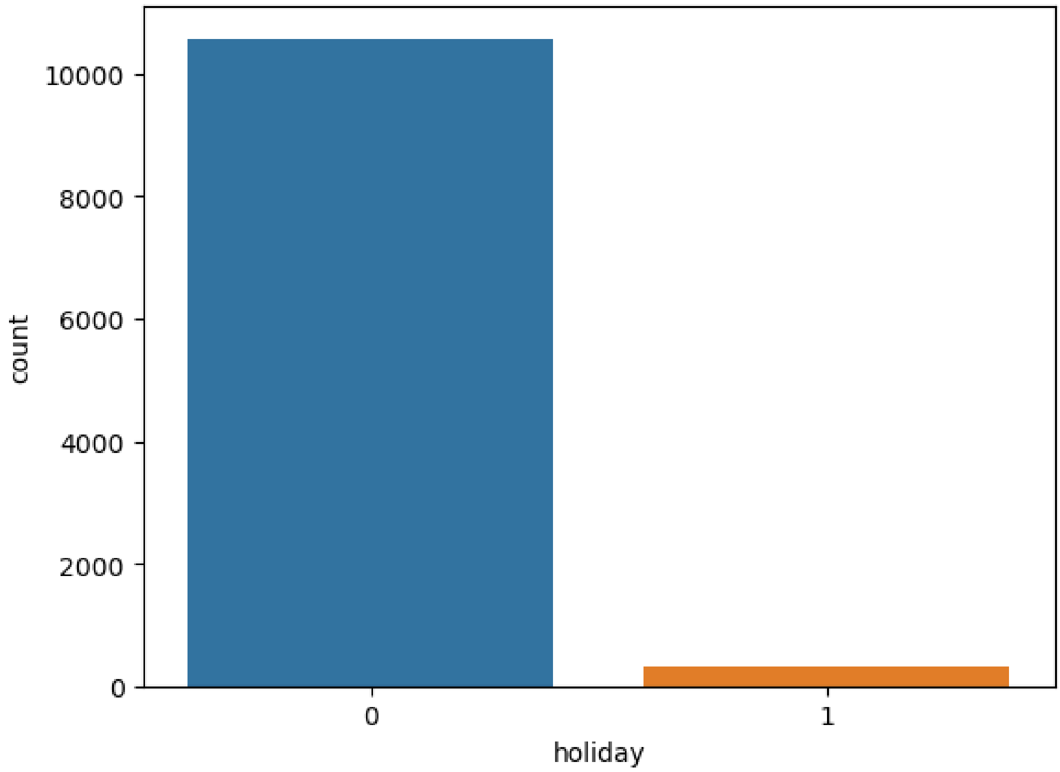
Graphical Analysis

In [10]:
```
sns.histplot(df['windspeed'], kde=True, bins =20)
plt.title("Distribution of windspeed")
plt.show()
```



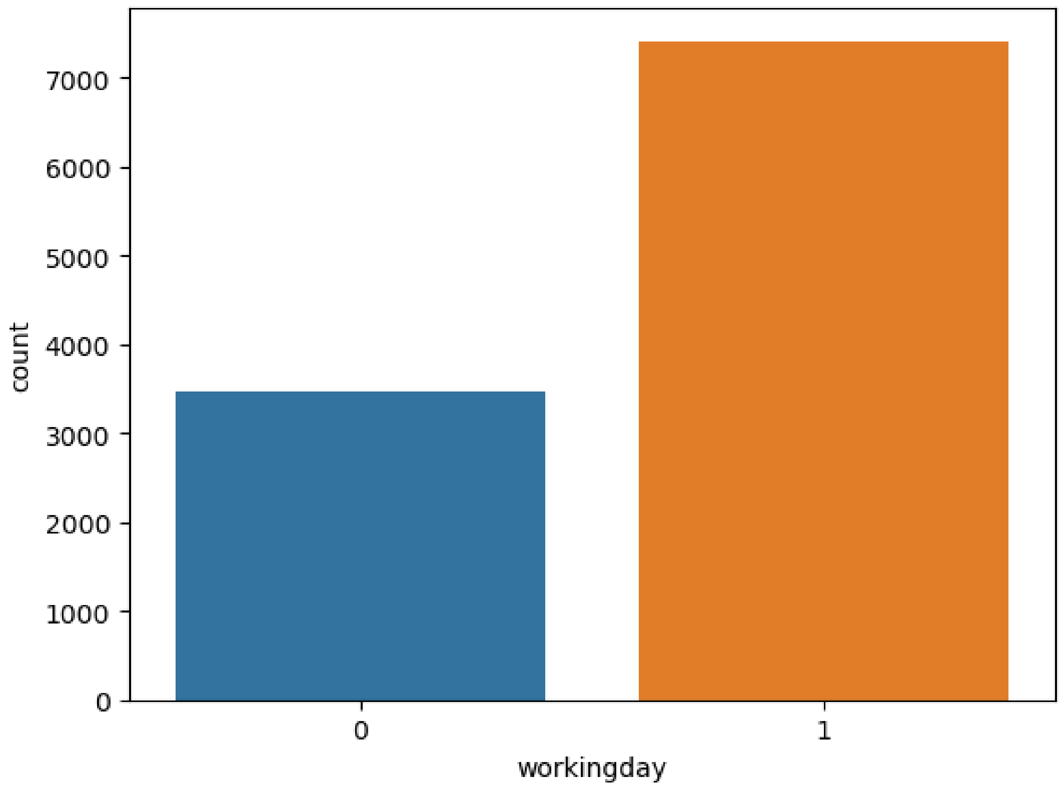
In [11]:
```
sns.countplot(data=df, x='holiday')
```

Out[11]: <Axes: xlabel='holiday', ylabel='count'>

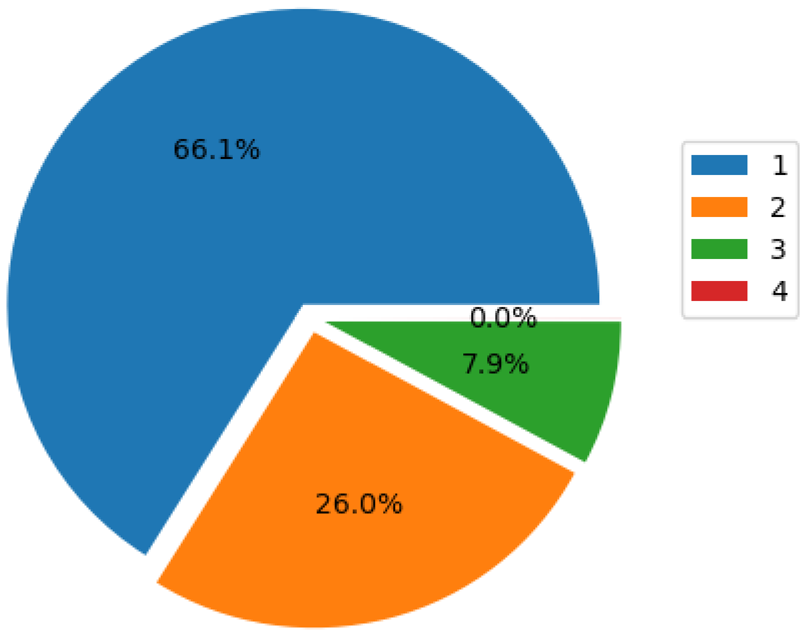


In [12]:
```
sns.countplot(data=df, x='workingday')
```

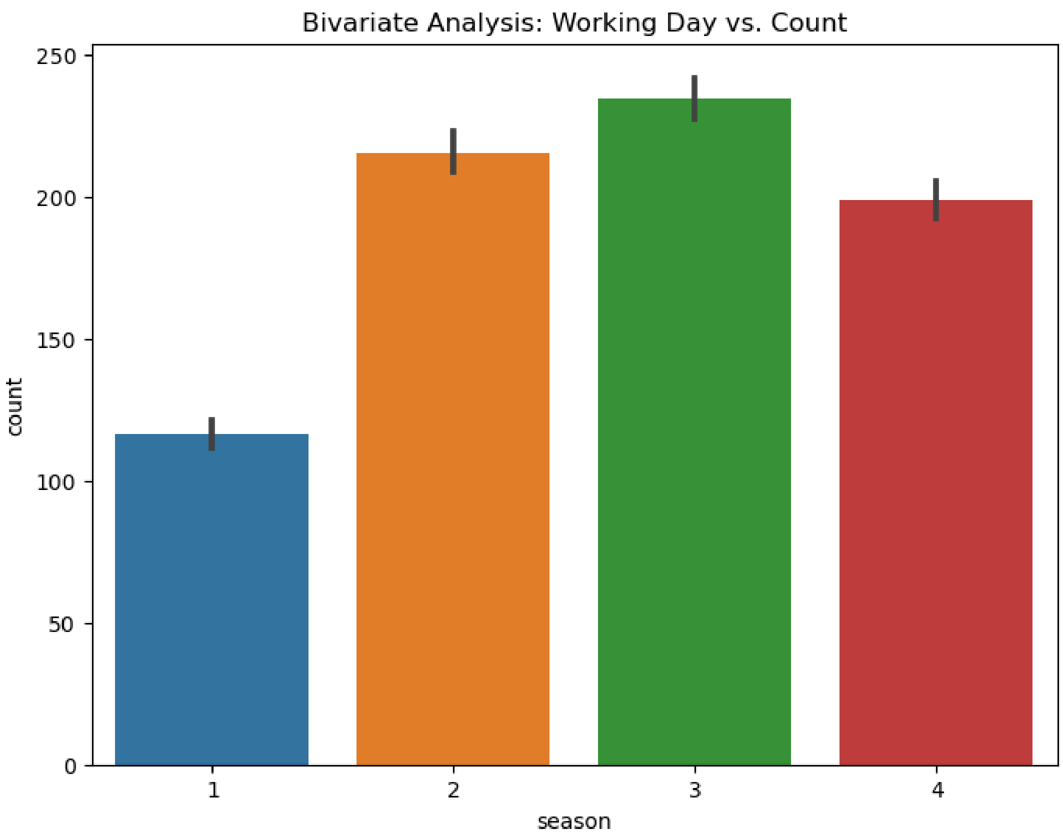
Out[12]: <Axes: xlabel='workingday', ylabel='count'>



In [13]:
```
plt.pie(df['weather'].value_counts(), autopct='%2.1f%%', explode=[0.05,
plt.legend(df['weather'].value_counts().index, loc=[1,0.5])
plt.show()
```



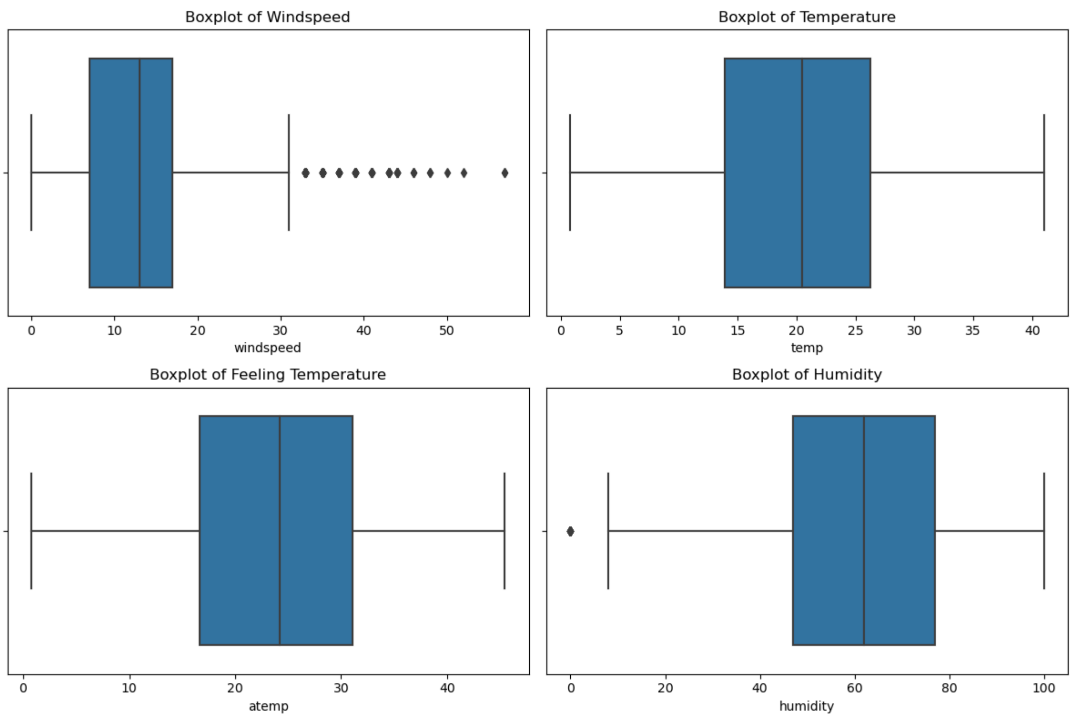
In [20]:
```
plt.figure(figsize=(8, 6))
sns.barplot(x='season', y='count', data=df)
plt.title('Bivariate Analysis: Working Day vs. Count')
plt.show()
```



Outliers Detection and Treatment

In [14]:

```
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12, 8))


sns.boxplot(data=df, x='windspeed', ax=axes[0, 0])
axes[0, 0].set_title('Boxplot of Windspeed')


sns.boxplot(data=df, x='temp', ax=axes[0, 1])
axes[0, 1].set_title('Boxplot of Temperature')


sns.boxplot(data=df, x='atemp', ax=axes[1, 0])
axes[1, 0].set_title('Boxplot of Feeling Temperature')


sns.boxplot(data=df, x='humidity', ax=axes[1, 1])
axes[1, 1].set_title('Boxplot of Humidity')


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



In [15]:

```
# Calculating 5th and 95th percentile for 'Windspeed', 'Humidity'

windspeed_5 = np.percentile(df['windspeed'], 5)
windspeed_95 = np.percentile(df['windspeed'], 95)

df['windspeed'] = np.clip(df['windspeed'], windspeed_5, windspeed_95)
```

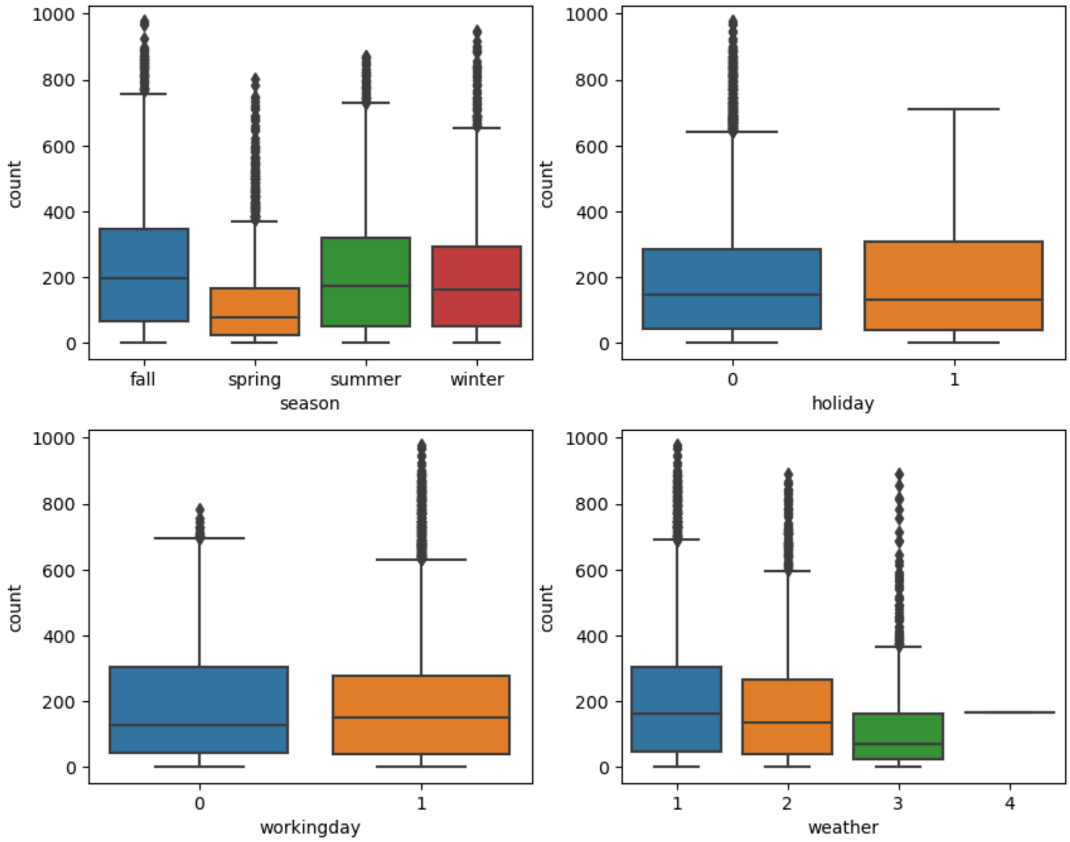
In [16]:

```
humidity_5 = np.percentile(df['humidity'], 5)
humidity_95  = np.percentile(df['humidity'], 95)

df['humidity'] = np.clip(df['humidity'], humidity_5, humidity_95)
```

Bi-Variate Analysis

In [70]:

```
# 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=df, x=cat_cols[index], y='count', ax=axis[row,
        index += 1
plt.show()
```



- In summer and fall seasons more bikes are rented as compared to other seasons.
- Whenever its a holiday more bikes are rented.
- It is also clear from the workingday also that whenever day is holiday or weekend, slightly more bikes were rented.
- Whenever there is rain, thunderstorm, snow or fog, there were less bikes were rented.

Correlation

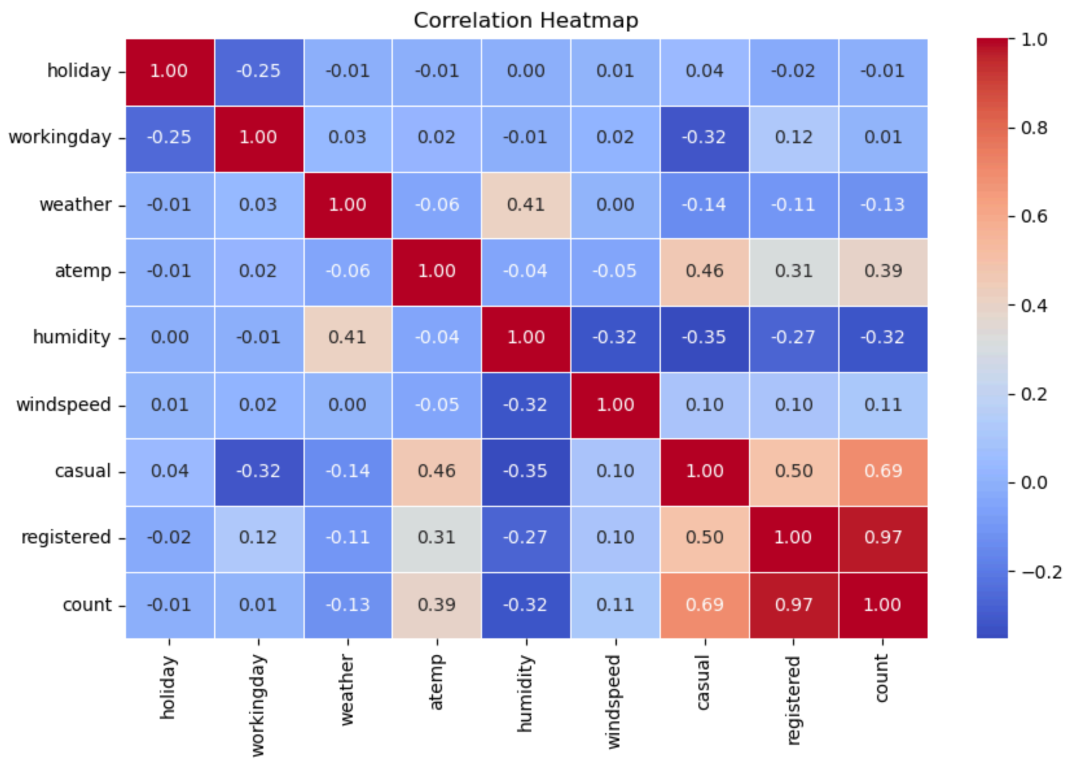
In [17]:
```
correlation_matrix = df[['holiday','workingday','weather', 'atemp', 'hu
```

In [18]:
```
correlation_matrix
```

Out[18]:

	holiday	workingday	weather	atemp	humidity	windspeed	casua
holiday	1.000000	-0.250491	-0.007074	-0.005215	0.000110	0.009155	0.04379
workingday	-0.250491	1.000000	0.033772	0.024660	-0.009697	0.015318	-0.31911
weather	-0.007074	0.033772	1.000000	-0.055376	0.414295	0.003731	-0.13591
atemp	-0.005215	0.024660	-0.055376	1.000000	-0.042611	-0.051960	0.46206
humidity	0.000110	-0.009697	0.414295	-0.042611	1.000000	-0.320708	-0.35238
windspeed	0.009155	0.015318	0.003731	-0.051960	-0.320708	1.000000	0.09833
casual	0.043799	-0.319111	-0.135918	0.462067	-0.352384	0.098339	1.00000
registered	-0.020956	0.119460	-0.109340	0.314635	-0.271640	0.098031	0.49725
count	-0.005393	0.011594	-0.128655	0.389784	-0.323683	0.108861	0.69041

In [19]:
```
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f",
plt.title('Correlation Heatmap')
plt.show()
```



Hypothesis Testing - 1

- Problem Statement: Check if there any significant difference between the no. of bike rides on Weekdays and Weekends?
- Null Hypothesis: Working day has no effect on the number of cycles being rented.
- Alternate Hypothesis: Working day has effect on the number of cycles being rented.
- Significance level (alpha): 0.05

In [22]:
```
df.groupby(by = 'workingday')['count'].describe()
```

Out[22]:

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

In [23]:
```
data_group1 = df[df['workingday']==0]['count'].values
data_group2 = df[df['workingday']==1]['count'].values
print(np.var(data_group1), np.var(data_group2))
np.var(data_group2)// np.var(data_group1)
```

```
30171.346098942427 34040.69710674686
```

Out[23]: 1.0

In [24]:
```
stats.ttest_ind(a=data_group1, b=data_group2, equal_var=True)
```

Out[24]:
```
TtestResult(statistic=-1.2096277376026694, pvalue=0.22644804226361348,
df=10884.0)
```

- Conclusion: Since pvalue is greater than 0.05 so we cannot reject the Null hypothesis. We don't have the sufficient evidence to say that working day has effect on the number of cycles being rented.

Hypothesis Testing - 2

- Problem Statement: Check if the demand of bicycles on rent is the same for different Weather conditions?
- Null Hypothesis (H0) - Mean of cycle rented per hour is same for weather 1, 2 and 3. (We wont be considering weather 4 as there in only 1 data point for weather 4 and we cannot perform a ANOVA test with a single data point for a group)
- Alternate Hypothesis (HA) -Mean of cycle rented per hour is not same for season 1,2,3 and 4 are different.
- Significance level (alpha): 0.05

In [26]:
```
df.groupby(by = 'weather')['count'].describe()
```

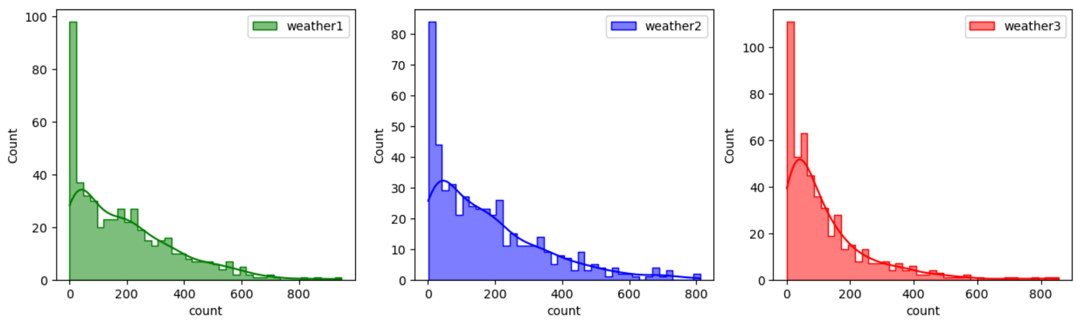
Out[26]:

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

- Visual Tests to know if the samples follow normal distribution

In [28]:
```
df_weather1 = df.loc[df['weather'] == 1]
df_weather2 = df.loc[df['weather'] == 2]
df_weather3 = df.loc[df['weather'] == 3]
df_weather4 = df.loc[df['weather'] == 4]
len(df_weather1), len(df_weather2), len(df_weather3), len(df_weather4)

plt.figure(figsize = (15, 4))
plt.subplot(1, 3, 1)
sns.histplot(df_weather1.loc[:, 'count'].sample(500), bins = 40,
             element = 'step', color = 'green', kde = True, label = 'we
plt.legend()
plt.subplot(1, 3, 2)
sns.histplot(df_weather2.loc[:, 'count'].sample(500), bins = 40,
             element = 'step', color = 'blue', kde = True, label = 'wea
plt.legend()
plt.subplot(1, 3, 3)
sns.histplot(df_weather3.loc[:, 'count'].sample(500), bins = 40,
             element = 'step', color = 'red', kde = True, label = 'weat
plt.legend()
plt.plot()
```

Out[28]: []

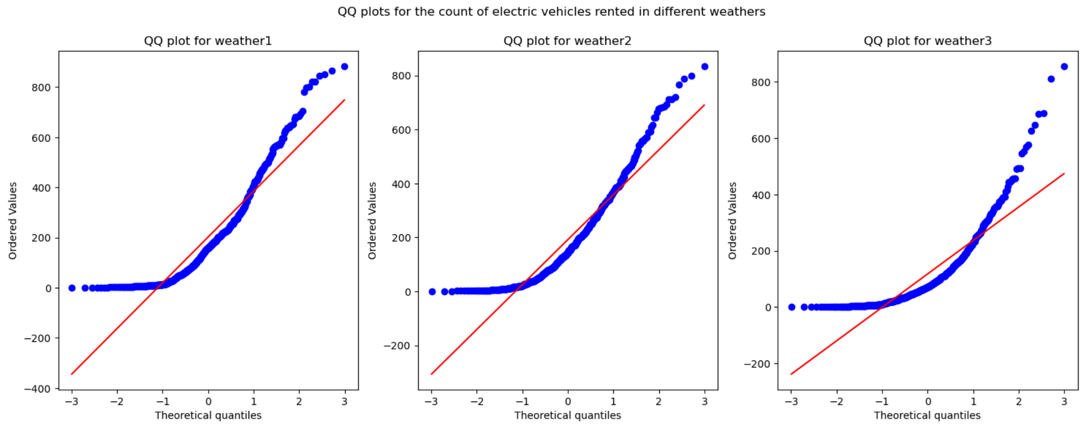


It can be inferred from the above plot that the distributions do not follow normal distribution.

Distribution check using QQ Plot

In [31]:
```
plt.figure(figsize = (18, 6))
plt.subplot(1, 3, 1)
plt.suptitle('QQ plots for the count of electric vehicles rented in dif
spy.probplot(df_weather1.loc[:, 'count'].sample(500), plot = plt, dist
plt.title('QQ plot for weather1')
plt.subplot(1, 3, 2)
spy.probplot(df_weather2.loc[:, 'count'].sample(500), plot = plt, dist
plt.title('QQ plot for weather2')
plt.subplot(1, 3, 3)
spy.probplot(df_weather3.loc[:, 'count'].sample(500), plot = plt, dist
plt.title('QQ plot for weather3')
plt.plot()
```

Out[31]: []



- It can be inferred from the above plot that the distributions do not follow normal distribution.
- Applying Shapiro-Wilk test for normality : The sample follows normal distribution : The sample does not follow normal distribution
- alpha = 0.05
- Test Statistics : Shapiro-Wilk test for normality

In [32]:
```
test_stat, p_value = spy.shapiro(df_weather1.loc[:, 'count'].sample(500
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 3.577414300741489e-20
The sample does not follow normal distribution
```

In [33]:
```
test_stat, p_value = spy.shapiro(df_weather2.loc[:, 'count'].sample(500
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 8.358062322608804e-20
The sample does not follow normal distribution
```

In [34]:
```
test_stat, p_value = spy.shapiro(df_weather3.loc[:, 'count'].sample(500
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 3.584672700176115e-25
The sample does not follow normal distribution
```

Transforming the data using boxcox transformation and checking if the transformed data follows normal distribution.

In [35]:
```
transformed_weather1 = spy.boxcox(df_weather1.loc[:, 'count'].sample(50
test_stat, p_value = spy.shapiro(transformed_weather1)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 2.626948944103503e-28
The sample does not follow normal distribution
```

In [36]:
```
transformed_weather2 = spy.boxcox(df_weather2.loc[:, 'count'])[0]
test_stat, p_value = spy.shapiro(transformed_weather2)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 1.9216098393369846e-19
The sample does not follow normal distribution
```

In [37]:
```
transformed_weather3 = spy.boxcox(df_weather3.loc[:, 'count'])[0]
test_stat, p_value = spy.shapiro(transformed_weather3)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 1.4133181593933841e-06
The sample does not follow normal distribution
```

Even after applying the boxcox transformation on each of the weather data, the samples do not follow normal distribution.

Homogeneity of Variances using Levene's test

In [38]:

```
# Null Hypothesis(H0) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.levene(df_weather1.loc[:, 'count'].sample(500)
                                df_weather2.loc[:, 'count'].sample(500)
                                df_weather3.loc[:, 'count'].sample(500)
print('p-value', p_value)
if p_value < 0.05:
    print('The samples do not have  Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 1.9207844914637 85e-15
The samples do not have  Homogenous Variance
```

-- Since the samples are not normally distributed and do not have the same variance, f_oneway test cannot be performed here, we can perform its non parametric equivalent test i.e., Kruskal-Wallis H-test for independent samples.

In [ ]:

```
# Ho : Mean no. of cycles rented is same for different weather
# Ha : Mean no. of cycles rented is different for different weather
# Assuming significance Level to be 0.05
alpha = 0.05
test_stat, p_value = spy.kruskal(df_weather1, df_weather2, df_weather3)
print('Test Statistic =', test_stat)
print('p value =', p_value)
```

Test Statistic = 204.95566833068537 p value = 3.122066178659941e-45

In [ ]:

```
if p_value < alpha:
    print('Reject Null Hypothesis')
else:
    print('Failed to reject Null Hypothesis')
```

Reject Null Hypothesis

Therefore, the average number of rental bikes is statistically different for different weathers.

Hypothesis Testing- 3

- Problem: Check if the demand of bicycles on rent is the same for different Seasons?
- Null Hypothesis (H0) - Mean of cycle rented per hour is same for season 1,2,3 and 4.
- Alternate Hypothesis (HA) -Mean of cycle rented per hour is different for season 1,2,3 and 4.

In [43]:
```
df.groupby(by = 'season')['count'].describe()
```

Out[43]:

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

In [50]:
```
def season_category(x):
    if x == 1:
        return 'spring'
    elif x == 2:
        return 'summer'
    elif x == 3:
        return 'fall'
    else:
        return 'winter'
df['season'] = df['season'].apply(season_category)
```

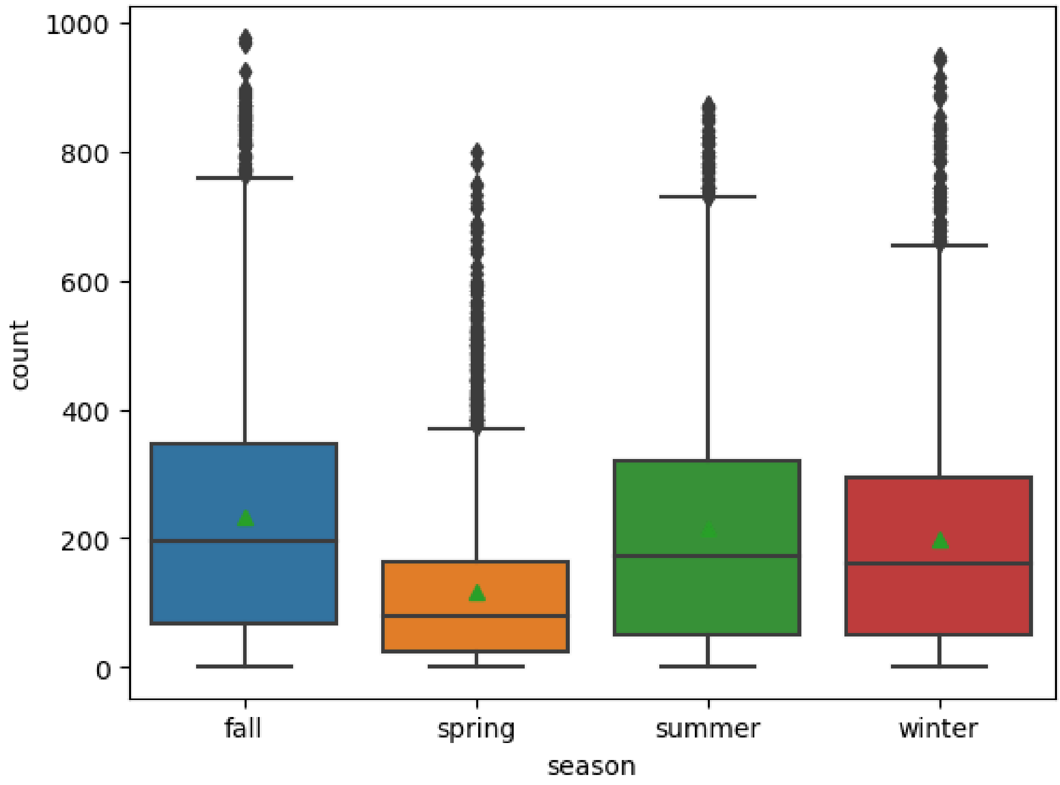
In [51]:
```
df['season'] = df['season'].astype('category')
```

In [52]:
```
df_season_spring = df.loc[df['season'] == 'spring', 'count']
df_season_summer = df.loc[df['season'] == 'summer', 'count']
df_season_fall = df.loc[df['season'] == 'fall', 'count']
df_season_winter = df.loc[df['season'] == 'winter', 'count']
len(df_season_spring), len(df_season_summer), len(df_season_fall), len(
```

Out[52]: (2686, 2733, 2733, 2734)

In [53]:
```
sns.boxplot(data = df, x = 'season', y = 'count', showmeans = True)
plt.plot()
```

Out[53]: []

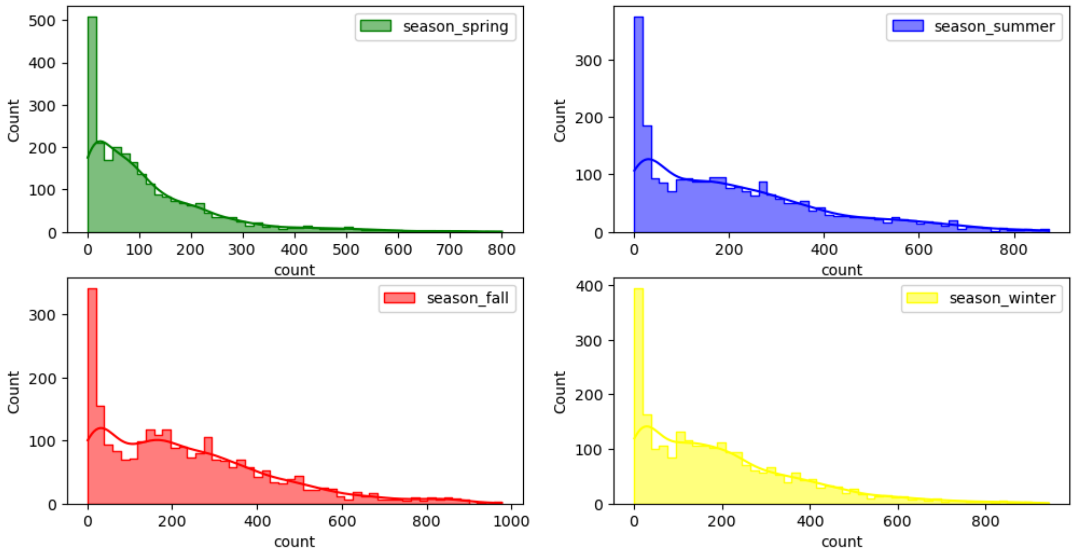


Visual Tests to know if the samples follow normal distribution

In [54]:

```
plt.figure(figsize = (12, 6))
plt.subplot(2, 2, 1)
sns.histplot(df_season_spring.sample(2500), bins = 50,
             element = 'step', color = 'green', kde = True, label = 'se
plt.legend()
plt.subplot(2, 2, 2)
sns.histplot(df_season_summer.sample(2500), bins = 50,
             element = 'step', color = 'blue', kde = True, label = 'sea
plt.legend()
plt.subplot(2, 2, 3)
sns.histplot(df_season_fall.sample(2500), bins = 50,
             element = 'step', color = 'red', kde = True, label = 'seas
plt.legend()
plt.subplot(2, 2, 4)
sns.histplot(df_season_winter.sample(2500), bins = 50,
             element = 'step', color = 'yellow', kde = True, label = 's
plt.legend()
plt.plot()
```

Out[54]: []

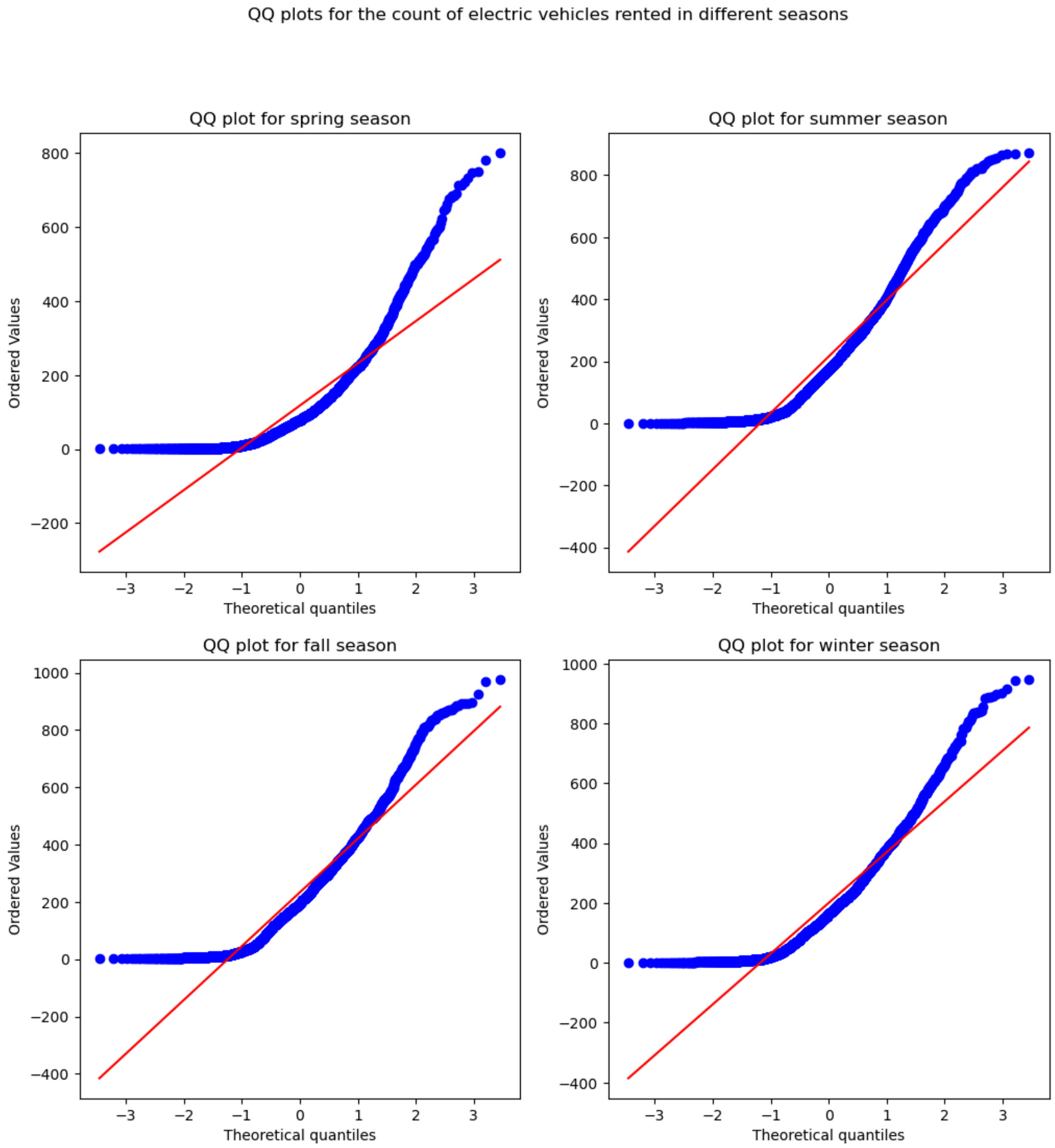


It can be inferred from the above plot that the distributions do not follow normal distribution.

Distribution check using QQ Plot

In [55]:
```
plt.figure(figsize = (12, 12))
plt.subplot(2, 2, 1)
plt.suptitle('QQ plots for the count of electric vehicles rented in dif
spy.probplot(df_season_spring.sample(2500), plot = plt, dist = 'norm')
plt.title('QQ plot for spring season')

plt.subplot(2, 2, 2)
spy.probplot(df_season_summer.sample(2500), plot = plt, dist = 'norm')
plt.title('QQ plot for summer season')

plt.subplot(2, 2, 3)
spy.probplot(df_season_fall.sample(2500), plot = plt, dist = 'norm')
plt.title('QQ plot for fall season')

plt.subplot(2, 2, 4)
spy.probplot(df_season_winter.sample(2500), plot = plt, dist = 'norm')
plt.title('QQ plot for winter season')
plt.plot()
```

Out[55]: []



- It can be inferred from the above plots that the distributions do not follow normal distribution.

- It can be seen from the above plots that the samples do not come from normal distribution.
- Applying Shapiro-Wilk test for normality : The sample follows normal distribution : The sample does not follow normal distribution
- alpha = 0.05
- Test Statistics : Shapiro-Wilk test for normality

In [56]:

```
test_stat, p_value = spy.shapiro(df_season_spring.sample(2500))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.0
The sample does not follow normal distribution
```

In [57]:

```
test_stat, p_value = spy.shapiro(df_season_summer.sample(2500))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 1.4892451890884912e-37
The sample does not follow normal distribution
```

In [58]:

```
test_stat, p_value = spy.shapiro(df_season_fall.sample(2500))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 7.157952731127466e-36
The sample does not follow normal distribution
```

In [59]:

```

test_stat, p_value = spy.shapiro(df_season_winter.sample(2500))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 3.2174364852492744e-38
The sample does not follow normal distribution
```

Transforming the data using boxcox transformation and checking if the transformed data follows normal distribution.

In [60]:

```
transformed_df_season_spring = spy.boxcox(df_season_spring.sample(2500)
test_stat, p_value = spy.shapiro(transformed_df_season_spring)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 7.553432189007984e-17
The sample does not follow normal distribution
```

In [61]:

```
transformed_df_season_summer = spy.boxcox(df_season_summer.sample(2500)
test_stat, p_value = spy.shapiro(transformed_df_season_summer)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 4.210886904513714e-21
The sample does not follow normal distribution
```

In [62]:

```
transformed_df_season_fall = spy.boxcox(df_season_fall.sample(2500))[0]
test_stat, p_value = spy.shapiro(transformed_df_season_fall)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 4.792420724532634e-21
The sample does not follow normal distribution
```

In [63]:

```

transformed_df_season_winter = spy.boxcox(df_season_winter.sample(2500)
test_stat, p_value = spy.shapiro(transformed_df_season_winter)
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 5.15185501527329e-20
The sample does not follow normal distribution
```

- Even after applying the boxcox transformation on each of the season data, the samples do not follow normal distribution.

Homogeneity of Variances using Levene's test

In [65]:
```
# Null Hypothesis(H0) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.levene(df_season_spring.sample(2500),
                                df_season_summer.sample(2500),
                                df_season_fall.sample(2500),
                                df_season_winter.sample(2500))
print('p-value', p_value)
if p_value < 0.05:
    print('The samples do not have  Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 1.5022520137817830e-109
The samples do not have  Homogenous Variance
```

Since the samples are not normally distributed and do not have the same variance, f_oneway test cannot be performed here, we can perform its non parametric equivalent test i.e., Kruskal-Wallis H-test for independent samples.

In [66]:
```
# Ho : Mean no. of cycles rented is same for different weather
# Ha : Mean no. of cycles rented is different for different weather
# Assuming significance Level to be 0.05
alpha = 0.05
test_stat, p_value = spy.kruskal(df_season_spring, df_season_summer, df
print('Test Statistic =', test_stat)
print('p value =', p_value)
```

```
Test Statistic = 699.6668548181988
p value = 2.479008372608633e-151
```

In [67]:
```
if p_value < alpha:
    print('Reject Null Hypothesis')
else:
    print('Failed to reject Null Hypothesis')
```

```
Reject Null Hypothesis
```

Therefore, the average number of rental bikes is statistically different for different seasons.

Hypothesis Testing- 4:

- Problem: Chi-square test to check if Weather is dependent on the season
- Null Hypothesis (H0): Weather is independent of the season
- Alternate Hypothesis (H1): Weather is not independent of the season
- Significance level (alpha): 0.05

In [71]:

```
data_table = pd.crosstab(df['season'], df['weather'])
print("Observed values:")
data_table
```

```
Observed values:
```

Out[71]:

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

In [77]:

```
val = stats.chi2_contingency(data_table)
expected_values = val[3]
print(expected_values)
nrows, ncols = 4, 4
dof = (nrows-1)*(ncols-1)
print("degrees of freedom: ", dof)
alpha = 0.05

chi_sqr = sum([(o-e)**2/e for o, e in zip(data_table.values, expected_v
chi_sqr_statistic = chi_sqr[0] + chi_sqr[1]
print("chi-square test statistic: ", chi_sqr_statistic)
critical_val = stats.chi2.ppf(q=1-alpha, df=dof)
print(f"critical value: {critical_val}")
p_val = 1-stats.chi2.cdf(x=chi_sqr_statistic, df=dof)
print(f"p-value: {p_val}")
if p_val <= alpha:
    print("\nSince p-value is less than the alpha 0.05, We reject the N
else:
    print("Since p-value is greater than the alpha 0.05, We do not reje
```

```
[[1.80559765e+03 7.11493845e+02 2.15657450e+02 2.51056403e-01]
 [1.77454639e+03 6.99258130e+02 2.11948742e+02 2.46738931e-01]
 [1.80559765e+03 7.11493845e+02 2.15657450e+02 2.51056403e-01]
 [1.80625831e+03 7.11754180e+02 2.15736359e+02 2.51148264e-01]]
degrees of freedom:  9
chi-square test statistic:  44.09441248632364
critical value: 16.918977604620448
p-value: 1.3560001579371317e-06

Since p-value is less than the alpha 0.05, We reject the Null Hypothes
is. Meaning that Weather is dependent on the season.
```

Data Overview

1. Data Timeframe: Dataset spans from January 1st, 2011 to December 19th, 2012 (718 days).
2. User Types: Approximately 19% casual users, 81% registered users.

Bike Rental Trends

1. Annual Growth: Mean hourly bike rentals increased by 65.41% from 2011 (144 bikes/hour) to 2012 (239 bikes/hour).
2. Seasonal Demand: Highest demand in spring/summer, declining through fall/winter.
3. Daily Fluctuations: Demand peaks in the afternoon, with lower usage in the early morning and late at night.
4. Lowest Usage Months: January, February, and March see the least average hourly rentals.

Enviornmental factrors

1. Temperature: Over 80% of data points have temperatures below 28 degrees Celsius.
2. Humidity: Over 80% of the time, humidity exceeds 40%, indicating often humid conditions.
3. Windspeed: Over 85% of data points show wind speeds below 20 (units needed - kmh, mph, etc.).
4. Weather Impact: Highest bike rentals occur during clear or cloudy weather, fewer during mist or rain. Extreme weather conditions are infrequent in the data.

Statistical Insights

1. Working vs. Non-Working Days: No statistically significant difference in mean hourly bike rentals.
2. Weather/Season Dependency: Hourly bike rentals show statistical dependency on weather and season.
3. Weather-Based Differences: Hourly bike rentals vary significantly across different weather types.
4. Weather 1,2,3 vs. Season: No statistically significant dependency between these specific weather types (1, 2, 3) and season in terms of bike rentals.

In [ ]:

```

```