q3

February 20, 2024

[47]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import scipy.stats as stats

def season_category(x):
    if x == 1:
        return 'season_1'
    elif x == 2:
        return 'season_2'
    elif x == 3:
        return 'season_3'
    else:
        return 'season_4'
```

Reading the dataset

[48]:
```
df = pd.read_csv('BRSM_Assignment_Datasets.csv')
data = df
print(df.head())
print()
print("Columns are given by:")
print(df.columns)
alpha = 0.05
```

```
              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

Columns are given by:
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

Shape of the dataset

[49]:
```python
df.shape
```

[49]:
```
(10886, 12)
```

Converting the datatype of datetime column from object to datetime

[50]:
```python
df['datetime'] = pd.to_datetime(df['datetime'])
```

[51]:
```python
df['season'] = df['season'].apply(season_category)
```

[52]:
```python
df['season'] = df['season'].astype('category')
df['holiday'] = df['holiday'].astype('category')
df['workingday'] = df['workingday'].astype('category')
df['weather'] = df['weather'].astype('category')
df['temp'] = df['temp'].astype('float32')
df['atemp'] = df['atemp'].astype('float32')
df['humidity'] = df['humidity'].astype('float32')
df['windspeed'] = df['windspeed'].astype('float32')
df['casual'] = df['casual'].astype('int32')
df['registered'] = df['registered'].astype('int32')
df['count'] = df['count'].astype('int32')
```

[53]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 12 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    10886 non-null  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  float32
 6   atemp       10886 non-null  float32
 7   humidity    10886 non-null  float32
 8   windspeed   10886 non-null  float32
 9   casual      10886 non-null  int32
```

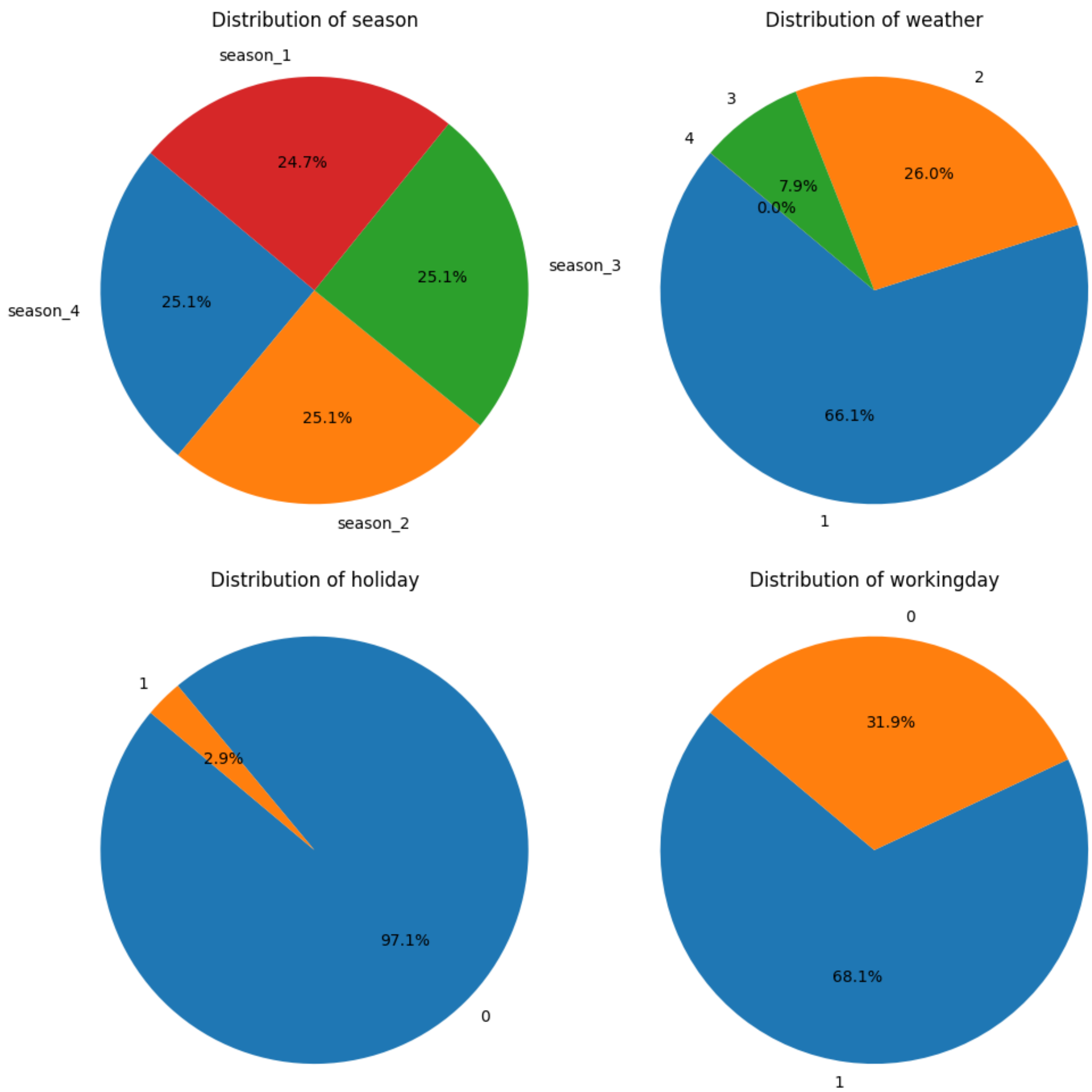
```
 10  registered  10886 non-null  int32
 11  count       10886 non-null  int32
dtypes: category(4), datetime64[ns](1), float32(4), int32(3)
memory usage: 426.0 KB
```

[54]:
```python
df.describe()
```

[54]:
```
                            datetime          temp         atemp  \
count                          10886  10886.000000  10886.000000
mean   2011-12-27 05:56:22.399411968     20.230862     23.655085
min              2011-01-01 00:00:00      0.820000      0.760000
25%              2011-07-02 07:15:00     13.940000     16.665001
50%              2012-01-01 20:30:00     20.500000     24.240000
75%              2012-07-01 12:45:00     26.240000     31.059999
max              2012-12-19 23:00:00     41.000000     45.455002
std                              NaN      7.791590      8.474601

           humidity     windspeed        casual    registered         count
count  10886.000000  10886.000000  10886.000000  10886.000000  10886.000000
mean      61.886459     12.799396     36.021955    155.552177    191.574132
min        0.000000      0.000000      0.000000      0.000000      1.000000
25%       47.000000      7.001500      4.000000     36.000000     42.000000
50%       62.000000     12.998000     17.000000    118.000000    145.000000
75%       77.000000     16.997900     49.000000    222.000000    284.000000
max      100.000000     56.996899    367.000000    886.000000    977.000000
std       19.245033      8.164537     49.960477    151.039033    181.144454
```

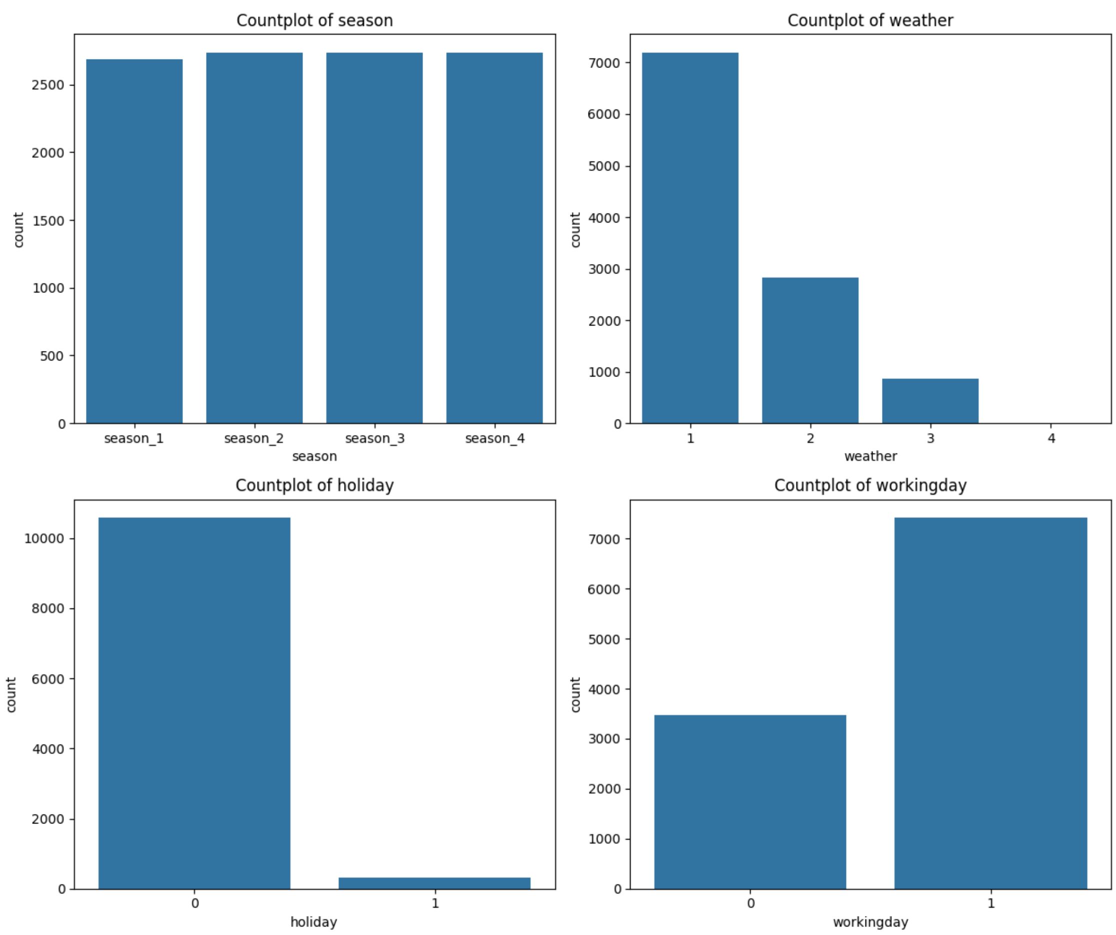
[55]:
```python
def plot_categorical_distribution(df, column, subplot_index):
    column_distribution = df[column].value_counts().reset_index()
    column_distribution.columns = [column, 'count']
    plt.subplot(subplot_index)
    plt.pie(column_distribution['count'], labels=column_distribution[column],␣
 ↪autopct='%1.1f%%', startangle=140)
    plt.title(f'Distribution of {column}')
    plt.axis('equal')

plt.figure(figsize=(10, 10))

plt.subplot(2, 2, 1)
plot_categorical_distribution(df, 'season', 221)

plt.subplot(2, 2, 2)
plot_categorical_distribution(df, 'weather', 222)

plt.subplot(2, 2, 3)
plot_categorical_distribution(df, 'holiday', 223)
```

```
plt.subplot(2, 2, 4)
plot_categorical_distribution(df, 'workingday', 224)

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



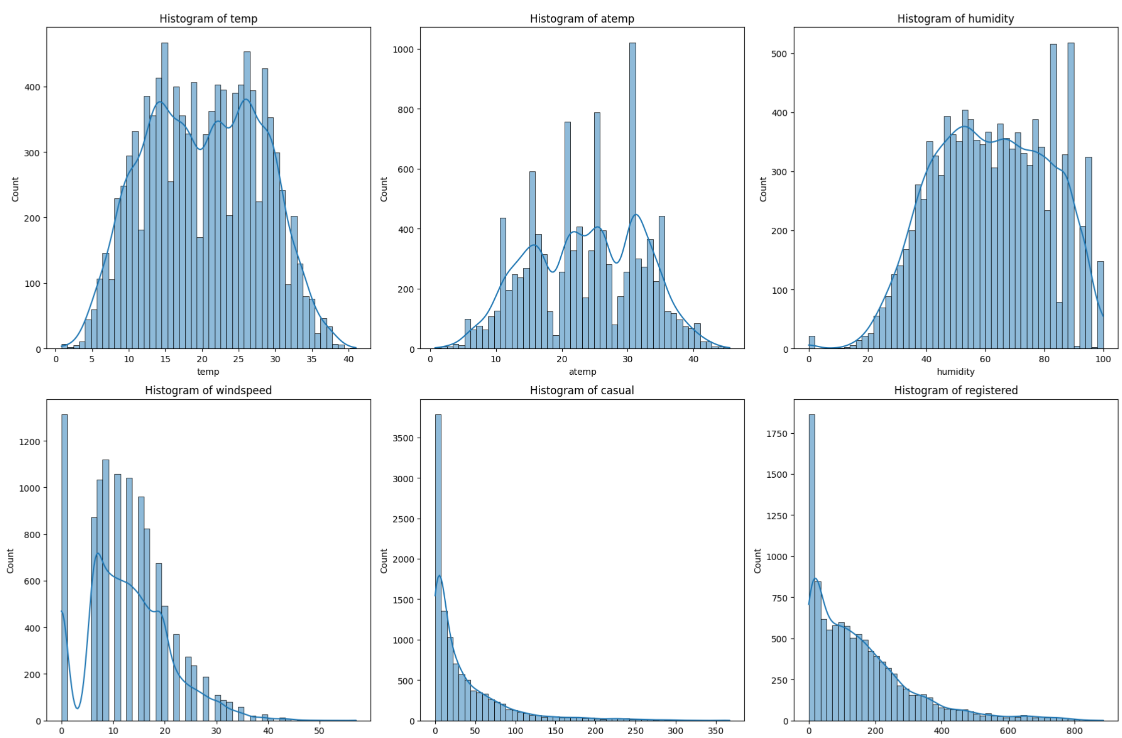
[56]:
```
def plot_countplot(df, column, subplot_index):
    plt.subplot(subplot_index)
    sns.countplot(data=df, x=column)
    plt.title(f'Countplot of {column}')

plt.figure(figsize=(12, 10))
```

```
plt.subplot(2, 2, 1)
plot_countplot(df, 'season', 221)

plt.subplot(2, 2, 2)
plot_countplot(df, 'weather', 222)

plt.subplot(2, 2, 3)
plot_countplot(df, 'holiday', 223)

plt.subplot(2, 2, 4)
plot_countplot(df, 'workingday', 224)

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



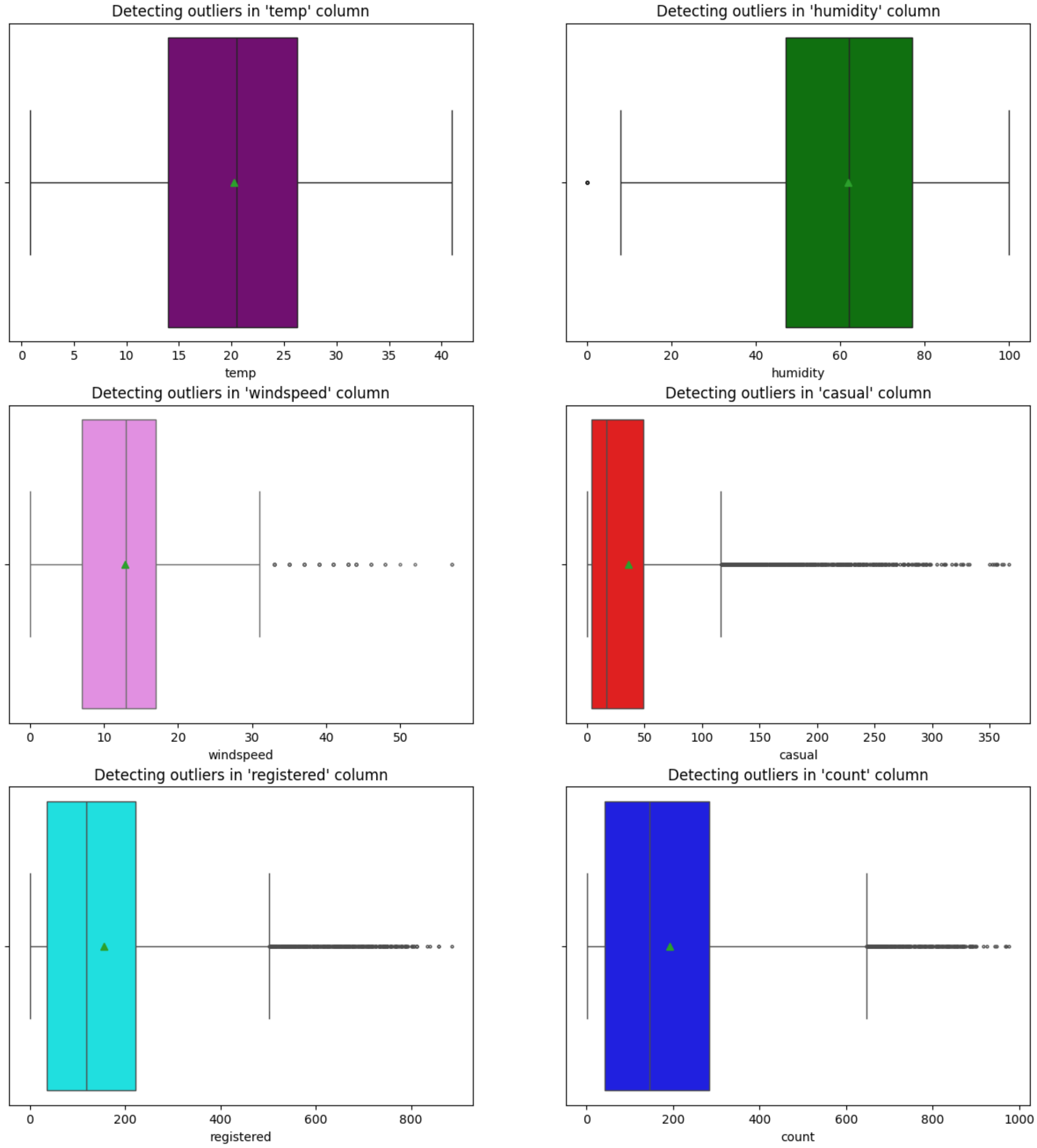
[57]:
```
def plot_histplot(df, column, subplot_index):
    plt.subplot(subplot_index)
    sns.histplot(data=df, x=column, kde=True, bins=50)
```

```
    plt.title(f'Histogram of {column}')

plt.figure(figsize=(18, 12))

plt.subplot(2, 3, 1)
plot_histplot(df, 'temp', 231)

plt.subplot(2, 3, 2)
plot_histplot(df, 'atemp', 232)

plt.subplot(2, 3, 3)
plot_histplot(df, 'humidity', 233)

plt.subplot(2, 3, 4)
plot_histplot(df, 'windspeed', 234)

plt.subplot(2, 3, 5)
plot_histplot(df, 'casual', 235)

plt.subplot(2, 3, 6)
plot_histplot(df, 'registered', 236)

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



0.0.1 Detecting Outliers in the dataset

[58]:
```
def plot_outliers(df, columns):
    colors = np.random.permutation(['green', 'blue', 'red', 'purple', 'cyan',␣
 ↪'violet'])
    count = 1
    plt.figure(figsize=(15, 16))
    for i in columns:
        plt.subplot(3, 2, count)
        plt.title(f"Detecting outliers in '{i}' column")
        sns.boxplot(data=df, x=df[i], color=colors[count - 1], showmeans=True,␣
 ↪fliersize=2)
        plt.plot()
        count += 1

columns = ['temp', 'humidity', 'windspeed', 'casual', 'registered', 'count']
plot_outliers(df, columns)
```



1 Exploratory Analysis

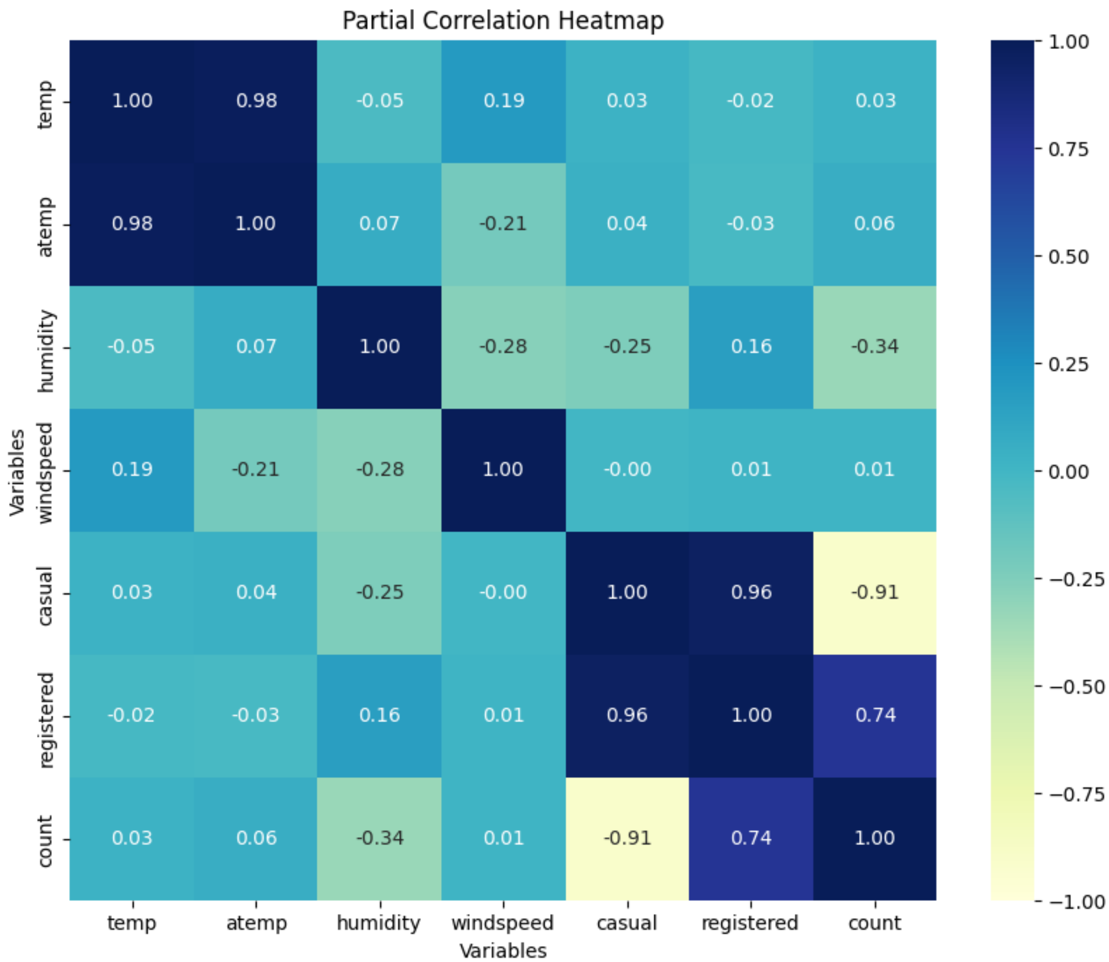
- The lowest average hourly count of rental bikes is observed in January, followed by February and March.
- Out of every 100 users, approximately 19 are casual users, and 81 are registered users.
- Over 85% of the recorded windspeed data has a value of less than 20.
- The mean total hourly count of rental bikes is 144 for the year 2011 and 239 for the year 2012, indicating an annual growth rate of 65.41%.
- The dataset spans from January 1, 2011, to December 19, 2012, totaling 718 days and 23

hours.
- More than 80% of the time, the temperature remains below 28 degrees Celsius.
- Similarly, more than 80% of the time, the humidity value exceeds 40, indicating varying levels from optimum to too moist.
- Throughout the day, there is a notable fluctuation in counts, with lower counts during early morning hours, a morning peak, a peak count in the afternoon, and a gradual decline in the evening and nighttime.
- The count of rental bikes exhibits a seasonal pattern, with higher demand during the season_1 and season_2 months, a slight decline in the season_3, and further decrease in season_4.

2 Correlation between the Variables

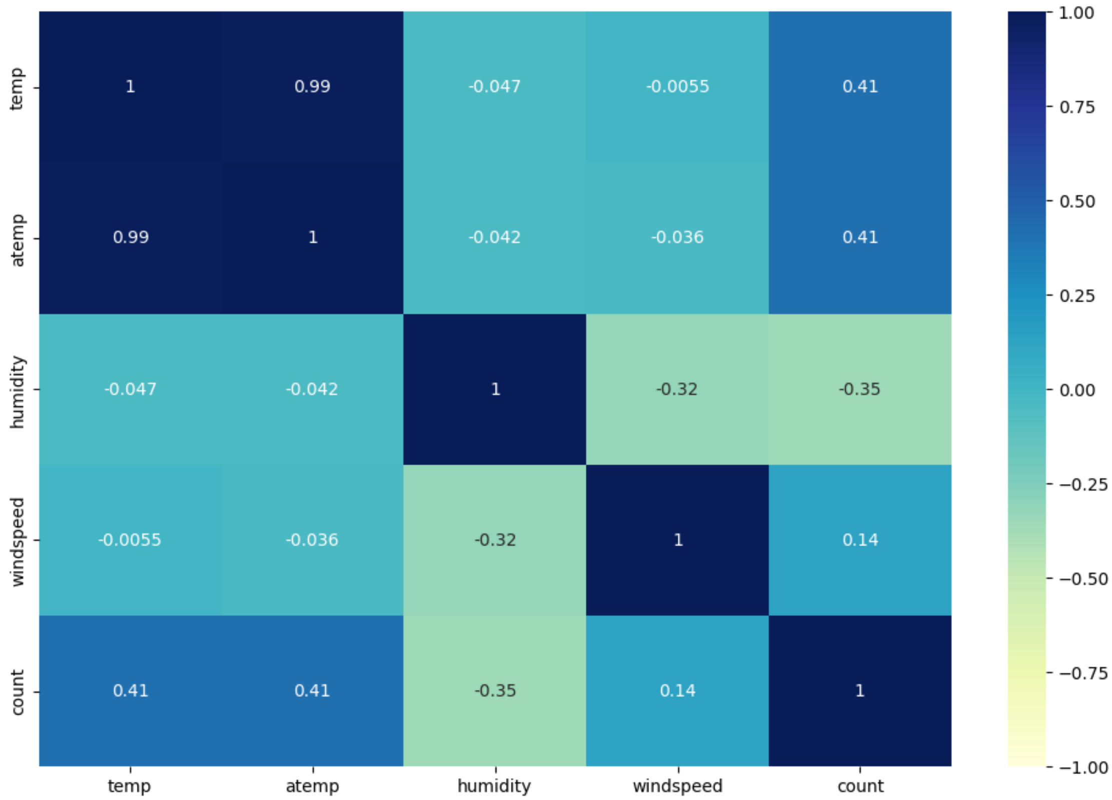
Partial Correlations between Variables

[59]:
```
import pingouin as pg
def plot_partial_corr_heatmap(df):
    df_subset = df
    partial_corr = df_subset.pcorr()
    plt.figure(figsize=(10, 8))
    sns.heatmap(data=partial_corr, cmap='YlGnBu', annot=True, fmt=".2f",␣
 ↪vmin=-1, vmax=1)
    plt.title('Partial Correlation Heatmap')
    plt.xlabel('Variables')
    plt.ylabel('Variables')
    plt.show()

plot_partial_corr_heatmap(data)
```

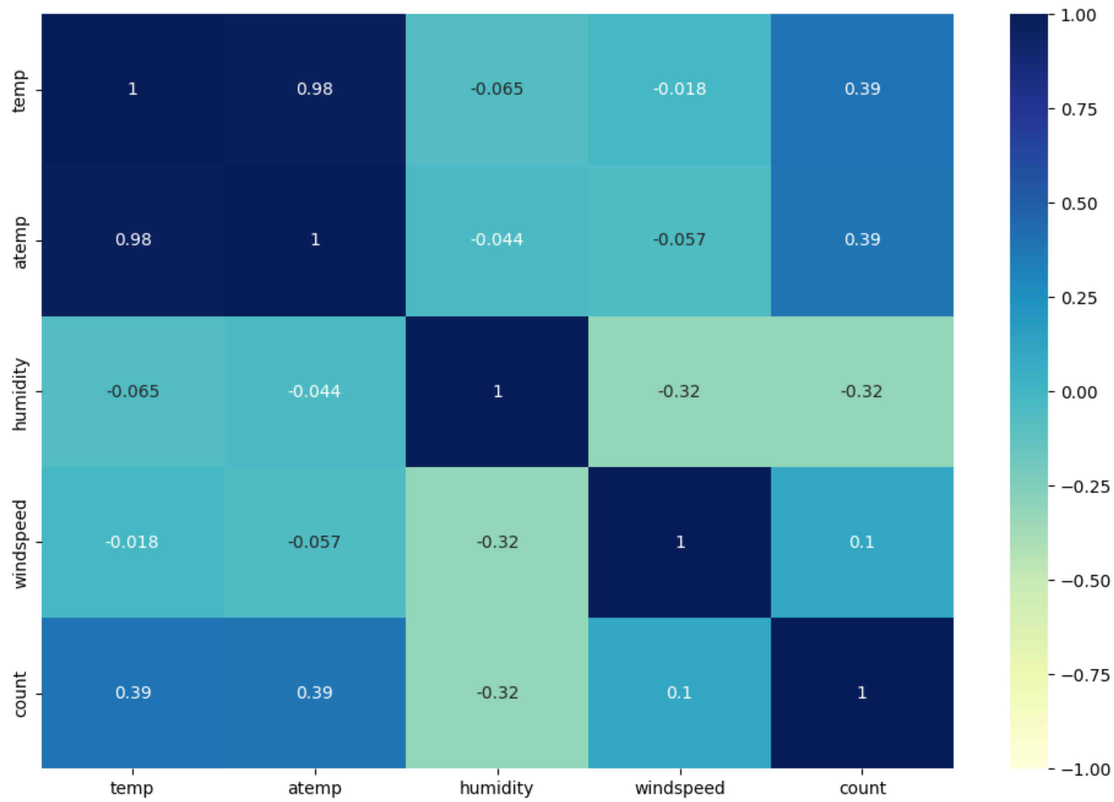


Semi-Partial Correlations between Variables

[60]:
```
def plot_semi_partial_corr_heatmap(df):
    new_df = df[['temp', 'atemp', 'humidity', 'windspeed', 'count']]
    corr_data = new_df.corr(method='spearman')
    plt.figure(figsize=(12, 8))
    sns.heatmap(data=corr_data, cmap='YlGnBu', annot=True, vmin=-1, vmax=1)
    plt.show()

plot_semi_partial_corr_heatmap(df)
```



[61]:
```python
def plot_correlation_heatmap(df):
    new_df = df[['temp', 'atemp', 'humidity', 'windspeed', 'count']]
    corr_data = new_df.corr()
    plt.figure(figsize=(12, 8))
    sns.heatmap(data=corr_data, cmap='YlGnBu', annot=True, vmin=-1, vmax=1)
    plt.show()

plot_correlation_heatmap(data)
```



2.0.1 Inferences on Correlations

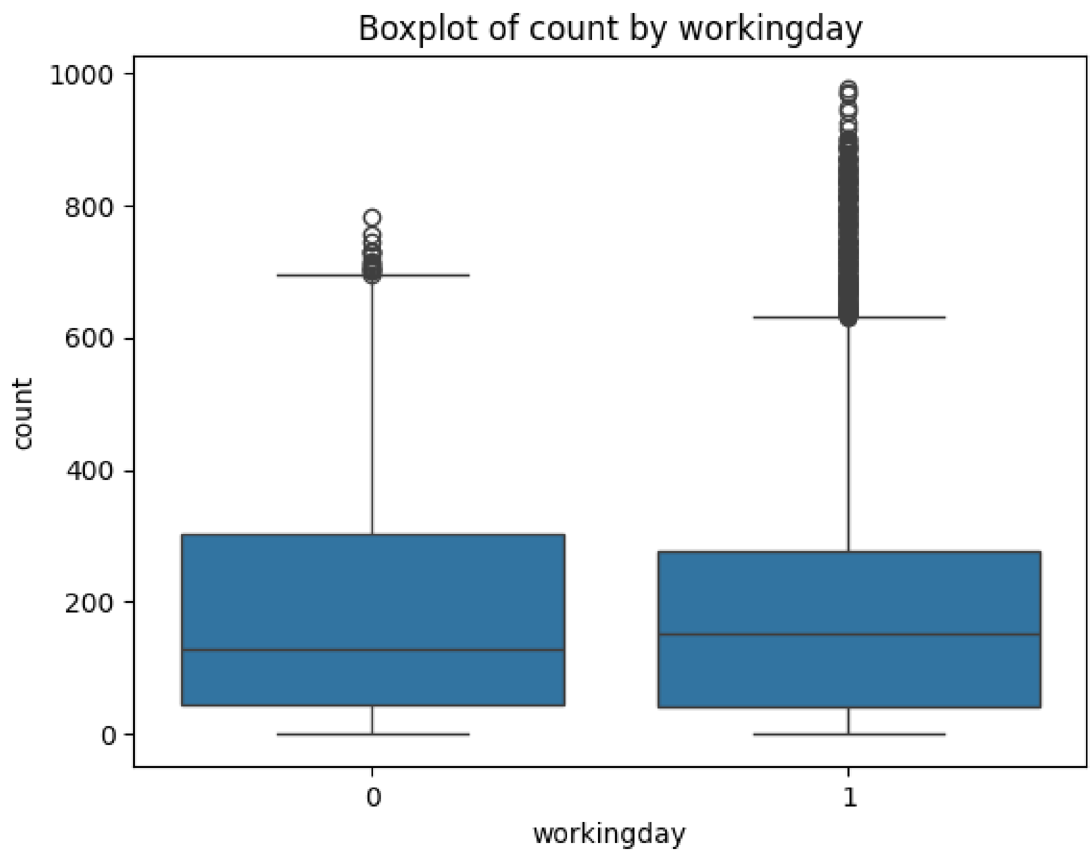
- No high positive or negative correlations (0.7 - 0.9) are found between any columns.
- Low positive correlations (0.3 - 0.5) exist between the columns [count, temp], [count, atemp], and [casual, atemp].
- Moderate positive correlations (0.5 - 0.7) are observed between the columns [casual, count] and [casual, registered].
- A very high correlation (> 0.9) is observed between the columns [atemp, temp] and [count, registered].
- Negligible correlation is noted between all other combinations of columns

2.1 Does the presence of a working day influence the quantity of electric cycles rented ?

STEPS : Set up Null Hypothesis

[62]:
```
def plot_boxplot(df, x_column, y_column):
    sns.boxplot(data=df, x=x_column, y=y_column)
    plt.title(f'Boxplot of {y_column} by {x_column}')
    plt.show()
```

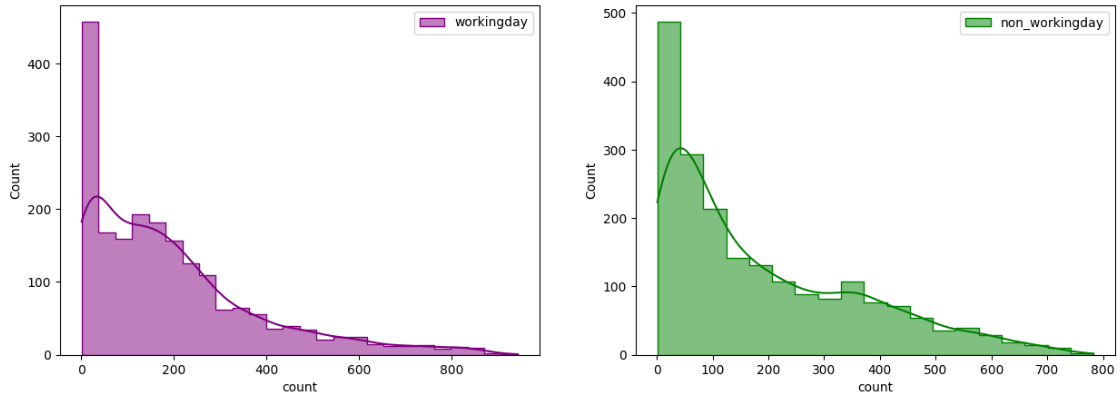
```
plot_boxplot(df, 'workingday', 'count')
```



Visual examinations to ascertain whether the samples adhere to a normal distribution

[63]:
```
def plot_workingday_comparison_hist(df, column, sample_size=2000):
    plt.figure(figsize=(15, 5))

    plt.subplot(1, 2, 1)
    sns.histplot(df.loc[df['workingday'] == 1, column].sample(sample_size),
                 element='step', color='purple', kde=True, label='workingday')
    plt.legend()

    plt.subplot(1, 2, 2)
    sns.histplot(df.loc[df['workingday'] == 0, column].sample(sample_size),
                 element='step', color='green', kde=True,␣
↪label='non_workingday')
    plt.legend()

    plt.show()
```

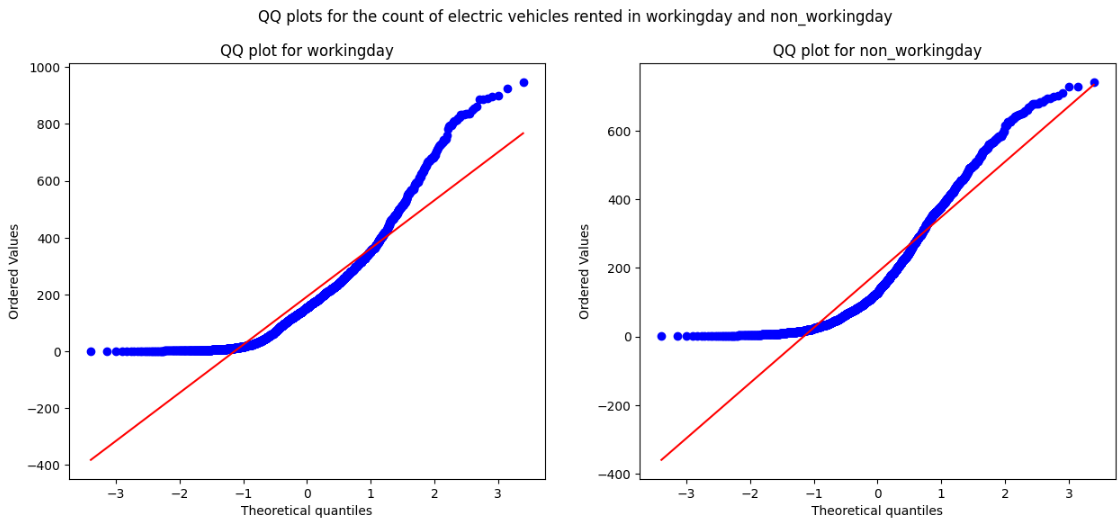
```
plot_workingday_comparison_hist(df, 'count')
```



Based on the plot above, it can be deduced that the distributions deviate from the normal dist

Assessing distribution via QQ Plot

[64]:
```
def qq_plot_workingday_comparison(df, column, sample_size=2000):
    plt.figure(figsize=(15, 6))
    plt.suptitle('QQ plots for the count of electric vehicles rented in␣
 ↪workingday and non_workingday')

    plt.subplot(1, 2, 1)
    stats.probplot(df.loc[df['workingday'] == 1, column].sample(sample_size),␣
 ↪plot=plt, dist='norm')
    plt.title('QQ plot for workingday')

    plt.subplot(1, 2, 2)
    stats.probplot(df.loc[df['workingday'] == 0, column].sample(sample_size),␣
 ↪plot=plt, dist='norm')
    plt.title('QQ plot for non_workingday')

    plt.show()

qq_plot_workingday_comparison(df, 'count')
```




```
In a QQ plot, if data points closely align with the diagonal line, the distribution is likely n
```

Conducting the Shapiro-Wilk test to assess normality. H_0: The sample conforms to a normal distribution.
H_1: The sample deviates from a normal distribution.

Significance Level $(\alpha) = 0.05$

Test Statistics: Shapiro-Wilk test for normality

[65]:
```
def shapiro_test_normality(data, column, condition_column, condition_value,␣
↪sample_size=2000, alpha=0.05):
    sample = data.loc[data[condition_column] == condition_value, column].
↪sample(sample_size)
    test_stat, p_value = stats.shapiro(sample)
    print('p-value:', p_value)
    if p_value < alpha:
        print('The sample does not follow a normal distribution')
    else:
        print('The sample follows a normal distribution')

print("Workingday")
shapiro_test_normality(df, 'count', 'workingday', 1)
print()
print("Non-Workingday")
shapiro_test_normality(df, 'count', 'workingday', 0)
```

```
Workingday
p-value: 2.914531643120015e-38
The sample does not follow a normal distribution
```

```
Non-Workingday
p-value: 9.117709753918228e-36
The sample does not follow a normal distribution
```

Applying the Box-Cox transformation to the data and assessing whether the transformed data adheres to a normal distribution.

[66]:
```python
def boxcox_shapiro_test_normality(data, column, condition_column, condition_value, alpha=0.05):
    transformed_data = stats.boxcox(data.loc[data[condition_column] == condition_value, column])[0]
    test_stat, p_value = stats.shapiro(transformed_data)
    print('p-value:', p_value)
    if p_value < alpha:
        print('The sample does not follow a normal distribution')
    else:
        print('The sample follows a normal distribution')

print("Workingday")
boxcox_shapiro_test_normality(df, 'count', 'workingday', 1)
print()
print("Non-Workingday")
boxcox_shapiro_test_normality(df, 'count', 'workingday', 0)
```

```
Workingday
p-value: 1.606449722752868e-33
The sample does not follow a normal distribution

Non-Workingday
p-value: 8.140929444965395e-24
The sample does not follow a normal distribution
```

```
/var/folders/kk/7w6727t942z6xwr_96jpcwtc0000gn/T/ipykernel_989/1579685415.py:3:
UserWarning: scipy.stats.shapiro: For N > 5000, computed p-value may not be
accurate. Current N is 7412.
  test_stat, p_value = stats.shapiro(transformed_data)
```

Workingday: ***The sample does not follow a normal distribution ($p < 0.05$)***

Non-Workingday: ***Similarly, the sample does not follow a normal distribution ($p < 0.05$)***

Both samples fail the test for normality.

Despite applying the Box-Cox transformation to both the "workingday" and "non_workingday" datasets, neither conforms to a normal distribution.

```
As the samples do not exhibit a normal distribution, the application of the T-Test is inapprop
```

Ho : Mean number of electric cycles rented is the same for working and non-working days

Ha : Mean number of electric cycles rented is not the same for working and non-working days

Assuming a significance level of 0.05

Test statistics: Mann-Whitney U rank test for two independent samples

[67]:
```
import scipy.stats as stats

def mann_whitney_test(df, column, condition_column, condition_value, alpha=0.
↪05):
    test_stat, p_value = stats.mannwhitneyu(df.loc[df[condition_column] ==␣
↪condition_value, column],
                                            df.loc[df[condition_column] !=␣
↪condition_value, column])
    print('P-value:', p_value)
    if p_value < alpha:
        print('Mean number of electric cycles rented is not the same for␣
↪working and non-working days')
    else:
        print('Mean number of electric cycles rented is the same for working␣
↪and non-working days')


mann_whitney_test(df, 'count', 'workingday', 1)
```

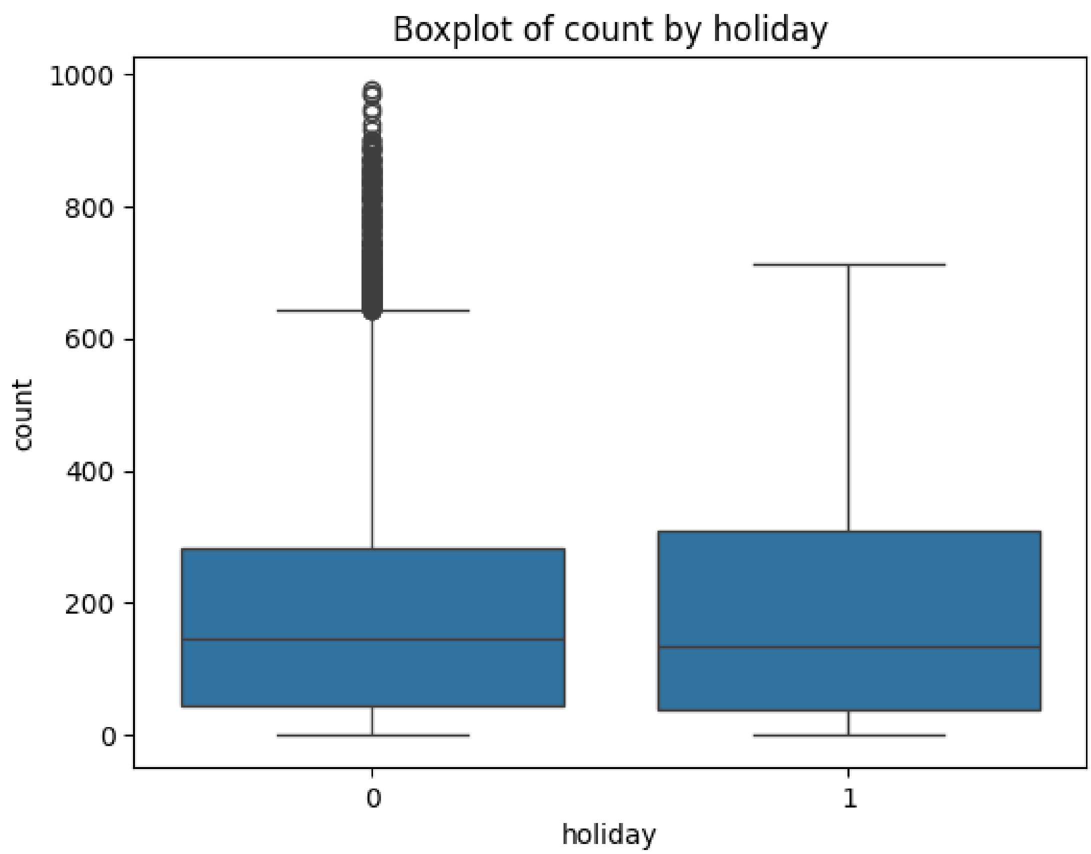
```
P-value: 0.9679139953914079
Mean number of electric cycles rented is the same for working and non-working
days
```

Hence, there is no statistically significant difference in the mean hourly count of total rental bikes between working and non-working days.

2.2 Does the presence of holidays affect the number of electric cycles rented?

STEPS : Set up Null Hypothesis

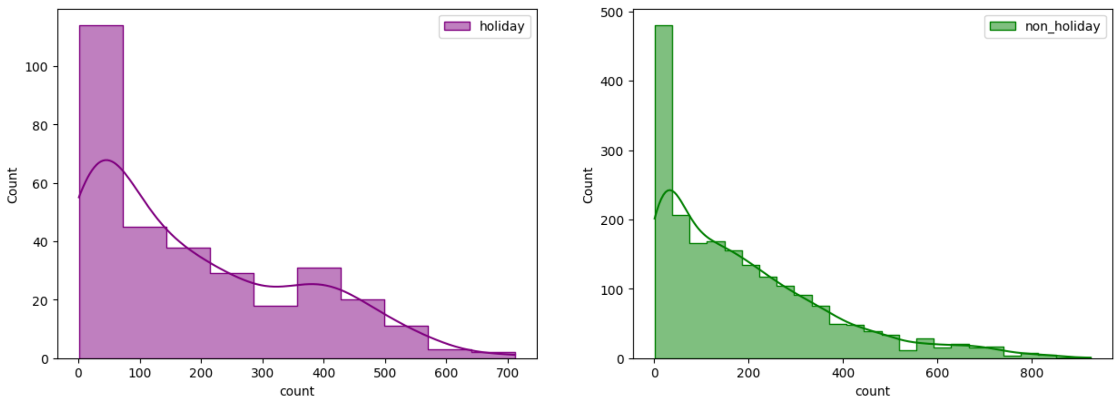
[68]:
```
def plot_boxplot(df, x_column, y_column):
    sns.boxplot(data=df, x=x_column, y=y_column)
    plt.title(f'Boxplot of {y_column} by {x_column}')
    plt.show()


plot_boxplot(df, 'holiday', 'count')
```



Visual examinations to ascertain whether the samples adhere to a normal distribution

[69]:
```
def plot_holiday_comparison_hist(df, column, sample_size=2000):
    holiday_sample = df.loc[df['holiday'] == 1, column]
    non_holiday_sample = df.loc[df['holiday'] == 0, column]

    if sample_size > len(holiday_sample):
        holiday_sample_size = len(holiday_sample)
    else:
        holiday_sample_size = sample_size

    if sample_size > len(non_holiday_sample):
        non_holiday_sample_size = len(non_holiday_sample)
    else:
        non_holiday_sample_size = sample_size

    plt.figure(figsize=(15, 5))
    plt.subplot(1, 2, 1)
    sns.histplot(holiday_sample.sample(holiday_sample_size, replace=False),
                 element='step', color='purple', kde=True, label='holiday')
```

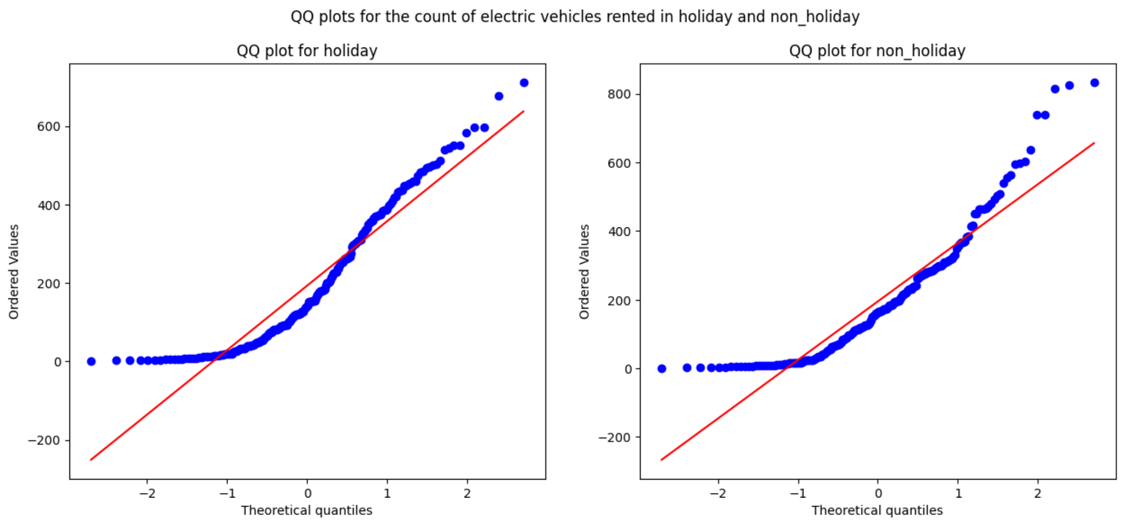
```
    plt.legend()
    plt.subplot(1, 2, 2)
    sns.histplot(non_holiday_sample.sample(non_holiday_sample_size,␣
↪replace=False),
                 element='step', color='green', kde=True, label='non_holiday')
    plt.legend()
    plt.show()

plot_holiday_comparison_hist(df, 'count')
```



Based on the plot above, it can be deduced that the distributions deviate from the normal dist

Assessing distribution via QQ Plot

[70]:
```
def plot_qq_holiday_comparison(df, column, sample_size=200):
    plt.figure(figsize=(15, 6))
    plt.suptitle('QQ plots for the count of electric vehicles rented in holiday␣
↪and non_holiday')

    plt.subplot(1, 2, 1)
    stats.probplot(df.loc[df['holiday'] == 1, column].sample(sample_size),␣
↪plot=plt, dist='norm')
    plt.title('QQ plot for holiday')

    plt.subplot(1, 2, 2)
    stats.probplot(df.loc[df['holiday'] == 0, column].sample(sample_size),␣
↪plot=plt, dist='norm')
    plt.title('QQ plot for non_holiday')

    plt.show()

plot_qq_holiday_comparison(df, 'count')
```



In a QQ plot, if data points closely align with the diagonal line, the distribution is likely r

Conducting the Shapiro-Wilk test to assess normality. H_0: The sample conforms to a normal distribution.
H_1: The sample deviates from a normal distribution.

Significance Level $(\alpha) = 0.05$

Test Statistics: Shapiro-Wilk test for normality

[71]:
```
def shapiro_test_holiday(df, column, holiday_value, alpha=0.05,␣
↪sample_size=200):
    sample = df.loc[df['holiday'] == holiday_value, column].sample(sample_size)
    test_stat, p_value = stats.shapiro(sample)
    print('p-value:', p_value)
    if p_value < alpha:
        print('The sample does not follow normal distribution')
    else:
        print('The sample follows normal distribution')

print('Holiday')
shapiro_test_holiday(df, 'count', 1)
print()
print('Non-Holiday')
shapiro_test_holiday(df, 'count', 0)
```

```
Holiday
p-value: 7.312238915724563e-11
The sample does not follow normal distribution

Non-Holiday
```

```
p-value: 1.721475698571981e-12
The sample does not follow normal distribution
```

Applying the Box-Cox transformation to the data and assessing whether the transformed data adheres to a normal distribution.

[72]:
```python
def boxcox_shapiro_test_holiday(df, column, holiday_value, alpha=0.05):
    transformed_data = stats.boxcox(df.loc[df['holiday'] == holiday_value,␣
 ↪column])[0]
    test_stat, p_value = stats.shapiro(transformed_data)
    print('p-value:', p_value)
    if p_value < alpha:
        print('The sample does not follow normal distribution')
    else:
        print('The sample follows normal distribution')

print('Holiday')
boxcox_shapiro_test_holiday(df, 'count', 1)
print()
print('Non-Holiday')
boxcox_shapiro_test_holiday(df, 'count', 0)
```

```
Holiday
p-value: 2.134933458313291e-07
The sample does not follow normal distribution

Non-Holiday
p-value: 1.411562913878583e-36
The sample does not follow normal distribution
```

```
/var/folders/kk/7w6727t942z6xwr_96jpcwtc0000gn/T/ipykernel_989/764229625.py:3:
UserWarning: scipy.stats.shapiro: For N > 5000, computed p-value may not be
accurate. Current N is 10575.
  test_stat, p_value = stats.shapiro(transformed_data)
```

Holiday: ***The sample does not follow a normal distribution ($p < 0.05$)***

Non-Holiday: ***Similarly, the sample does not follow a normal distribution ($p < 0.05$)***

Both samples fail the test for normality.

Despite employing the Box-Cox transformation on both the "holiday" and "non-holiday" datasets, the samples do not conform to a normal distribution.***

```
As the samples do not exhibit a normal distribution, the application of the T-Test is not appr
```

Ho : Number of electric cycles rented is similar for holidays and non-holidays

Ha : Number of electric cycles rented is not similar for holidays and non-holidays days

Assuming significance level to be 0.05

Test statistics : Mann-Whitney U rank test for two independent samples

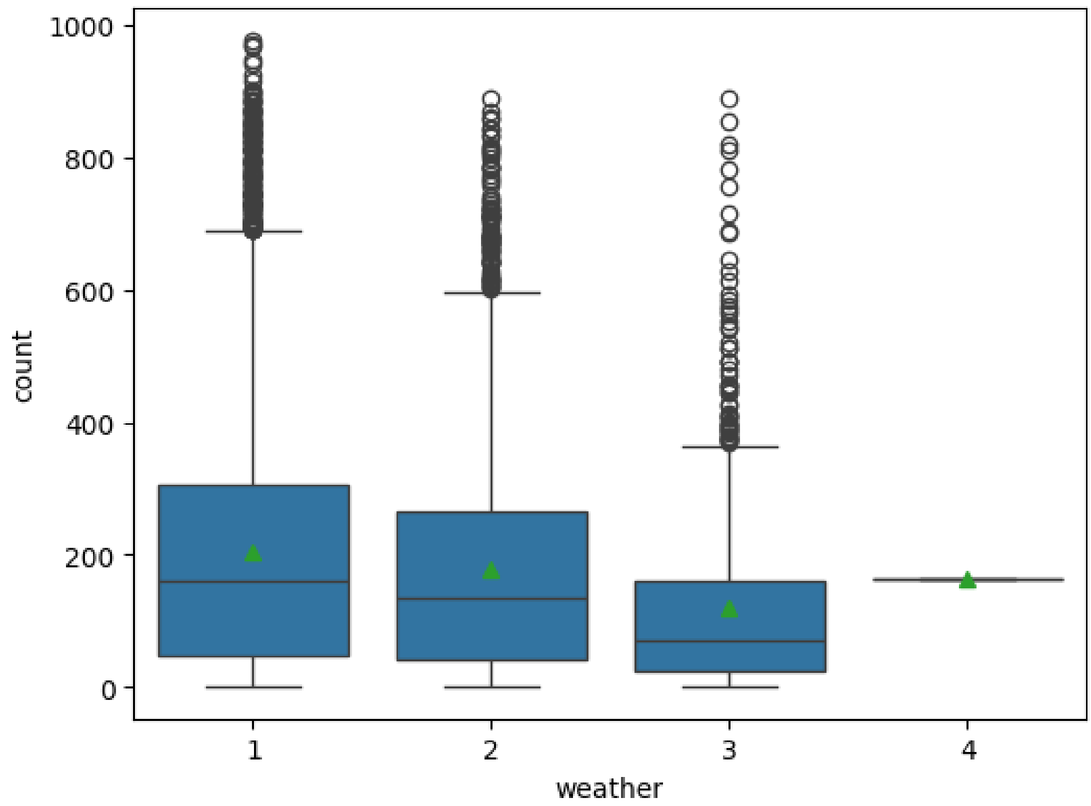
[73]:
```
def mann_whitney_holiday_test(df, column, alpha=0.05, sample_size=200):
    test_stat, p_value = stats.mannwhitneyu(df.loc[df['holiday'] == 0, column].
 ↪sample(sample_size),
                                             df.loc[df['holiday'] == 1, column].
 ↪sample(sample_size))
    print('P-value:', p_value)
    if p_value < alpha:
        print('Number of electric cycles rented is not similar for holidays and␣
 ↪non-holidays days')
    else:
        print('Number of electric cycles rented is similar for holidays and␣
 ↪non-holidays')


mann_whitney_holiday_test(df, 'count')
```

```
P-value: 0.8355488880092926
Number of electric cycles rented is similar for holidays and non-holidays
```

Thus, the quantity of electric cycles rented shows statistical similarity between holidays and non-holidays.

2.3 Does the number of rented cycles remain consistent or vary across different weather conditions?

[74]:
```
def plot_boxplot_weather(df):
    sns.boxplot(data=df, x='weather', y='count', showmeans=True)
    plt.show()

plot_boxplot_weather(df)
df_weather1 = df.loc[df['weather'] == 1]
print("len(df_weather1) = ", len(df_weather1))
df_weather2 = df.loc[df['weather'] == 2]
print("len(df_weather2) = ", len(df_weather2))
df_weather3 = df.loc[df['weather'] == 3]
print("len(df_weather3) = ", len(df_weather3))
df_weather4 = df.loc[df['weather'] == 4]
print("len(df_weather4) = ", len(df_weather4))
```



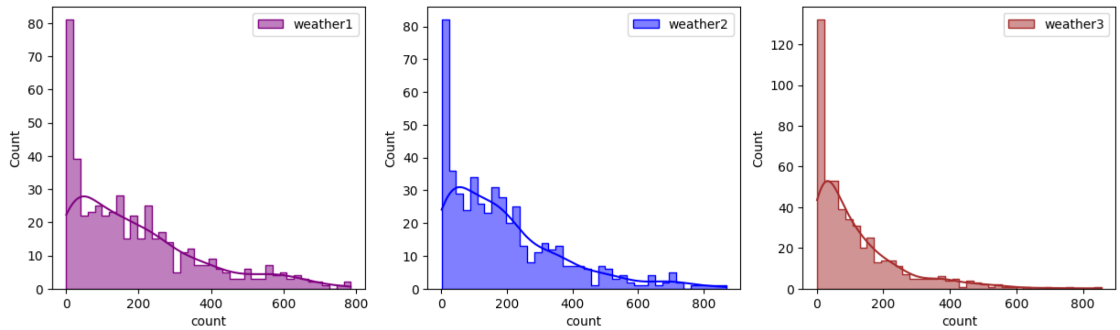

```
len(df_weather1) =  7192
len(df_weather2) =  2834
len(df_weather3) =  859
len(df_weather4) =  1
```

STEPS : Set up Null Hypothesis

Visual examinations to ascertain whether the samples adhere to a normal distribution

[75]:
```
import seaborn as sns
import matplotlib.pyplot as plt

def plot_histplot_weather(df_weather1, df_weather2, df_weather3,␣
↪sample_size=500):
    plt.figure(figsize=(15, 4))
    plt.subplot(1, 3, 1)
    sns.histplot(df_weather1.loc[:, 'count'].sample(sample_size), bins=40,
                 element='step', color='purple', kde=True, label='weather1')
    plt.legend()
    plt.subplot(1, 3, 2)
    sns.histplot(df_weather2.loc[:, 'count'].sample(sample_size), bins=40,
                 element='step', color='blue', kde=True, label='weather2')
```

```
    plt.legend()
    plt.subplot(1, 3, 3)
    sns.histplot(df_weather3.loc[:, 'count'].sample(sample_size), bins=40,
                 element='step', color='brown', kde=True, label='weather3')
    plt.legend()
    plt.show()

plot_histplot_weather(df_weather1, df_weather2, df_weather3)
```

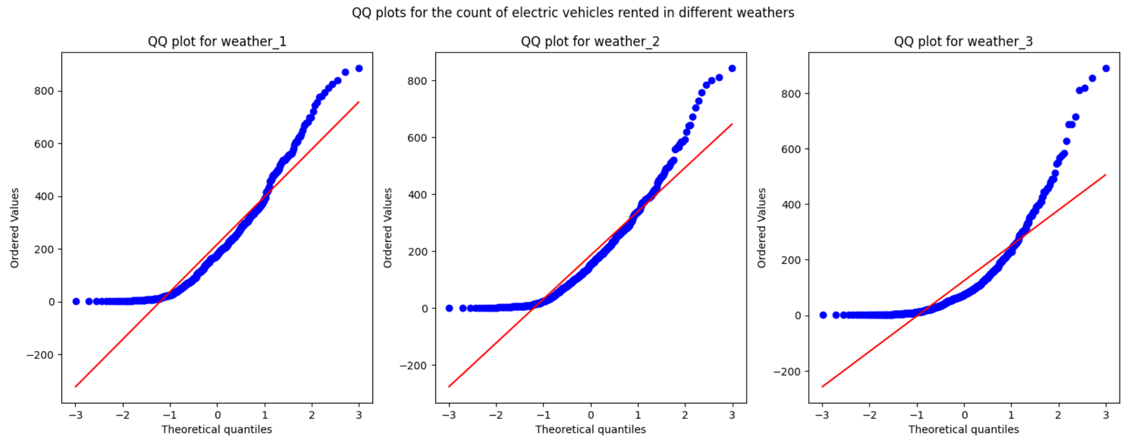


Based on the plot above, it can be deduced that the distributions deviate from the normal dist

Assessing distribution via QQ Plot

[76]:
```
def plot_qq_weather(df_weather1, df_weather2, df_weather3, sample_size=500):
    plt.figure(figsize=(18, 6))
    plt.suptitle('QQ plots for the count of electric vehicles rented in␣
↪different weathers')

    plt.subplot(1, 3, 1)
    stats.probplot(df_weather1.loc[:, 'count'].sample(sample_size), plot=plt,␣
↪dist='norm')
    plt.title('QQ plot for weather_1')

    plt.subplot(1, 3, 2)
    stats.probplot(df_weather2.loc[:, 'count'].sample(sample_size), plot=plt,␣
↪dist='norm')
    plt.title('QQ plot for weather_2')

    plt.subplot(1, 3, 3)
    stats.probplot(df_weather3.loc[:, 'count'].sample(sample_size), plot=plt,␣
↪dist='norm')
    plt.title('QQ plot for weather_3')

    plt.show()
```

```
plot_qq_weather(df_weather1, df_weather2, df_weather3)
```




```
In a QQ plot, if data points closely align with the diagonal line, the distribution is likely n
```

Conducting the Shapiro-Wilk test to assess normality. H_0: The sample conforms to a normal distribution.
H_1: The sample deviates from a normal distribution.

Significance Level $(\alpha) = 0.05$

Test Statistics: Shapiro-Wilk test for normality

[77]:
```
def shapiro_test_weather(df_weather, sample_size=500):
    for i, df in enumerate(df_weather, start=1):
        test_stat, p_value = stats.shapiro(df.loc[:, 'count'].
 ↪sample(sample_size))
        print(f'Weather {i}:')
        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')
        print()

shapiro_test_weather([df_weather1, df_weather2, df_weather3])
```

```
Weather 1:
P-value: 8.614116830276308e-19
The sample does not follow normal distribution

Weather 2:
P-value: 2.967472244980559e-20
The sample does not follow normal distribution
```

```
Weather 3:
P-value: 1.6592084087139088e-25
The sample does not follow normal distribution
```

Applying the Box-Cox transformation to the data and assessing whether the transformed data adheres to a normal distribution

[78]:
```python
def boxcox_shapiro_test_weather(df_weather, sample_size=500):
    for i, df in enumerate(df_weather, start=1):
        df_size = len(df.loc[:, 'count'])
        if sample_size > df_size:
            sample_size = df_size
            print(f"Sample size reduced to {sample_size} due to population size␣
↪limitation.")

        transformed_data = stats.boxcox(df.loc[:, 'count'].sample(sample_size,␣
↪replace=True))[0]
        test_stat, p_value = stats.shapiro(transformed_data)
        print(f'Weather {i}:')
        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')
        print()

boxcox_shapiro_test_weather([df_weather1, df_weather2, df_weather3])
```

```
Weather 1:
P-value: 4.7547315711167956e-08
The sample does not follow normal distribution

Weather 2:
P-value: 8.312635723806701e-07
The sample does not follow normal distribution

Weather 3:
P-value: 6.832002469702163e-05
The sample does not follow normal distribution
```

Weather 1: ***The sample does not follow a normal distribution ($p < 0.05$)***

Weather 2: ***Similarly, the sample does not follow a normal distribution ($p < 0.05$)***

Weather 3: ***Likewise, the sample does not follow a normal distribution ($p < 0.05$)***

All weather samples fail the test for normality.

Due to the samples' lack of normal distribution and unequal variance, the f_oneway test cannot

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

[79]:
```
import numpy as np
import scipy.stats as stats

def kruskal_wallis_test_weather(df_weather1, df_weather2, df_weather3, alpha=0.
↪05):
    test_stat, p_value = stats.kruskal(df_weather1, df_weather2, df_weather3)
    print('Test Statistic =', test_stat)
    print('p value =', p_value)
    p_value = np.mean(p_value)
    if p_value < alpha:
        print('Reject Null Hypothesis')
    else:
        print('Failed to reject Null Hypothesis')

kruskal_wallis_test_weather(df_weather1, df_weather2, df_weather3)
```

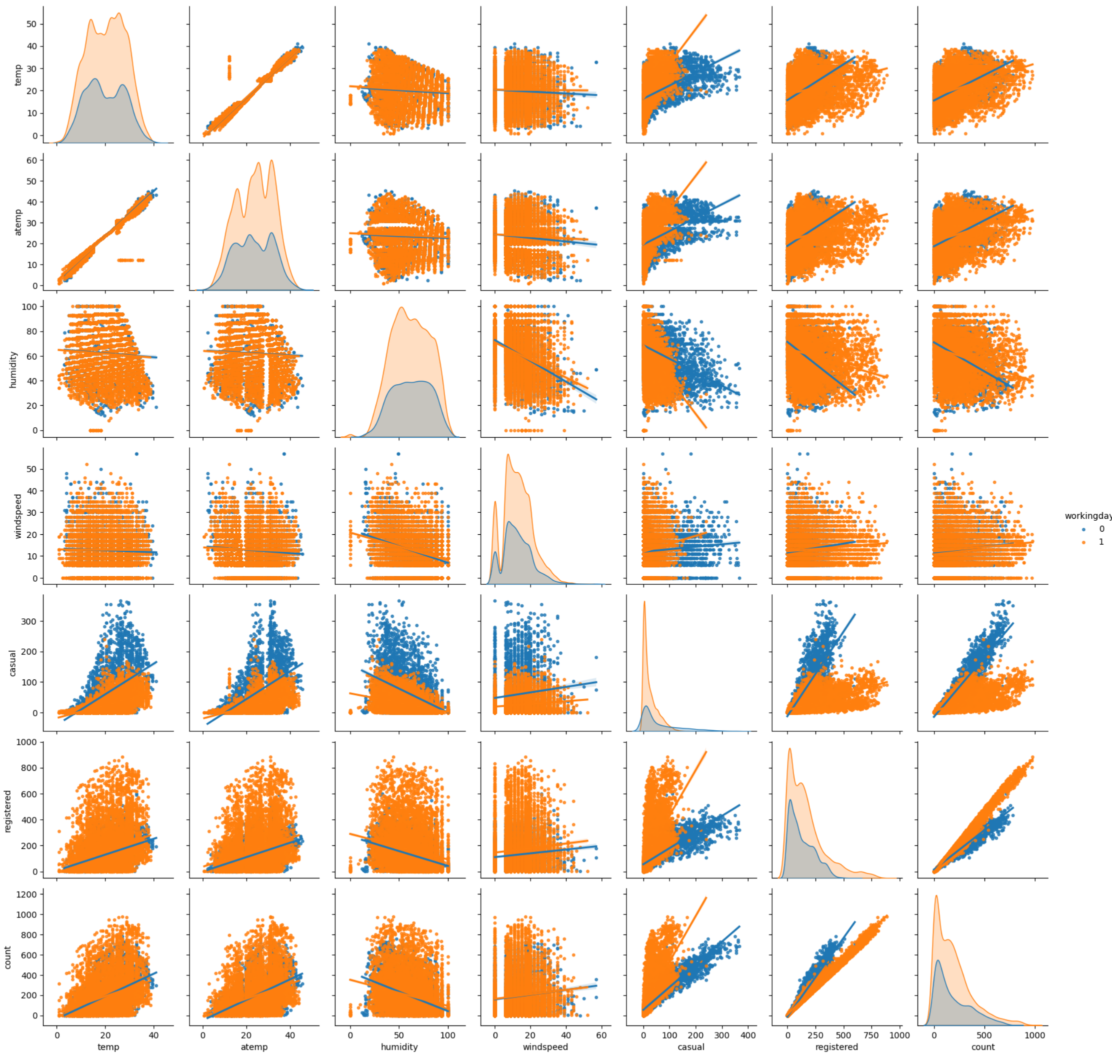
```
Test Statistic = [1.36471292e+01 1.83091584e+00 5.37649760e+00 1.56915686e+01
 1.08840000e+04 3.70017441e+01 4.14298489e+01 1.83168690e+03
 2.80380482e+01 2.84639685e+02 1.73745440e+02 2.04955668e+02]
p value = [1.08783632e-03 4.00333264e-01 6.79999165e-02 3.91398508e-04
 0.00000000e+00 9.22939752e-09 1.00837627e-09 0.00000000e+00
 8.15859150e-07 1.55338046e-62 1.86920588e-38 3.12206618e-45]
Reject Null Hypothesis
```

Hence, there is a statistically significant difference in the average number of rental bikes across varying weather conditions.

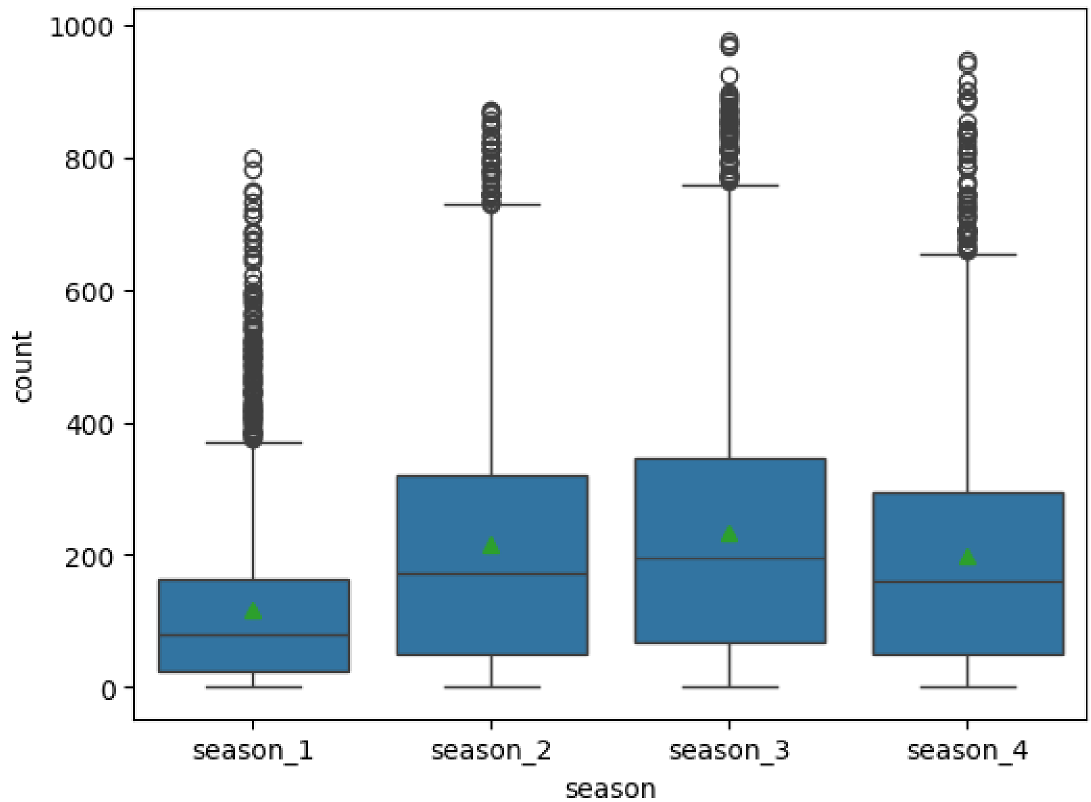
2.4 Does the number of rented cycles vary across different seasons ?

STEPS : Set up Null Hypothesis

[80]:
```
def plot_pairplot_with_regression(df, hue_column='workingday'):
    sns.pairplot(data=df, kind='reg', hue=hue_column, markers='.')
    plt.show()

plot_pairplot_with_regression(df)
```



[81]:
```
def boxplot_season_count(df):
    sns.boxplot(data=df, x='season', y='count', showmeans=True)
    plt.show()

boxplot_season_count(df)
df_season_1 = df.loc[df['season'] == 'season_1', 'count']
print("len(df_season_1) = ", len(df_season_1))
df_season_2 = df.loc[df['season'] == 'season_2', 'count']
print("len(df_season_2) = ", len(df_season_2))
df_season_3 = df.loc[df['season'] == 'season_3', 'count']
print("len(df_season_3) = ", len(df_season_3))
df_season_4 = df.loc[df['season'] == 'season_4', 'count']
print("len(df_season_4) = ", len(df_season_4))
```

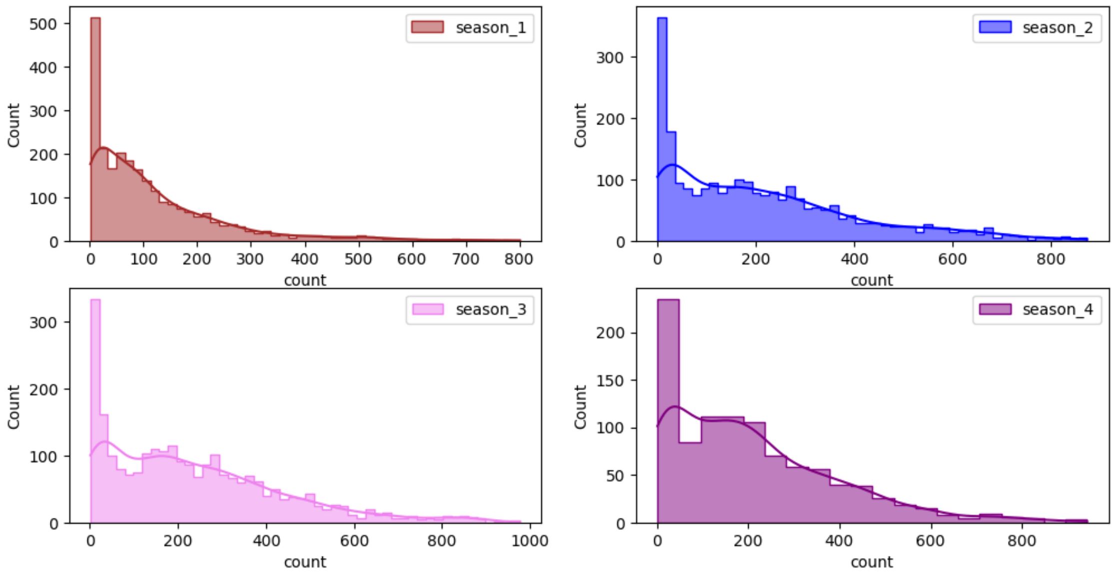



```
len(df_season_1) =  2686
len(df_season_2) =  2733
len(df_season_3) =  2733
len(df_season_4) =  2734
```

Visual examinations to ascertain whether the samples adhere to a normal distribution

[82]:
```
def plot_season_histograms(df_season_1, df_season_2, df_season_3, df_season_4):
    plt.figure(figsize=(12, 6))
    plt.subplot(2, 2, 1)
    sns.histplot(df_season_1.sample(2500), bins=50, element='step',␣
 ↪color='brown', kde=True, label='season_1')
    plt.legend()
    plt.subplot(2, 2, 2)
    sns.histplot(df_season_2.sample(2500), bins=50, element='step',␣
 ↪color='blue', kde=True, label='season_2')
    plt.legend()
    plt.subplot(2, 2, 3)
    sns.histplot(df_season_3.sample(2500), bins=50, element='step',␣
 ↪color='violet', kde=True, label='season_3')
    plt.legend()
    plt.subplot(2, 2, 4)
```

```
    sns.histplot(df_season_4.sample(1000), bins=20, element='step',␣
↪color='purple', kde=True, label='season_4')
    plt.legend()
    plt.show()

plot_season_histograms(df_season_1, df_season_2, df_season_3, df_season_4)
```

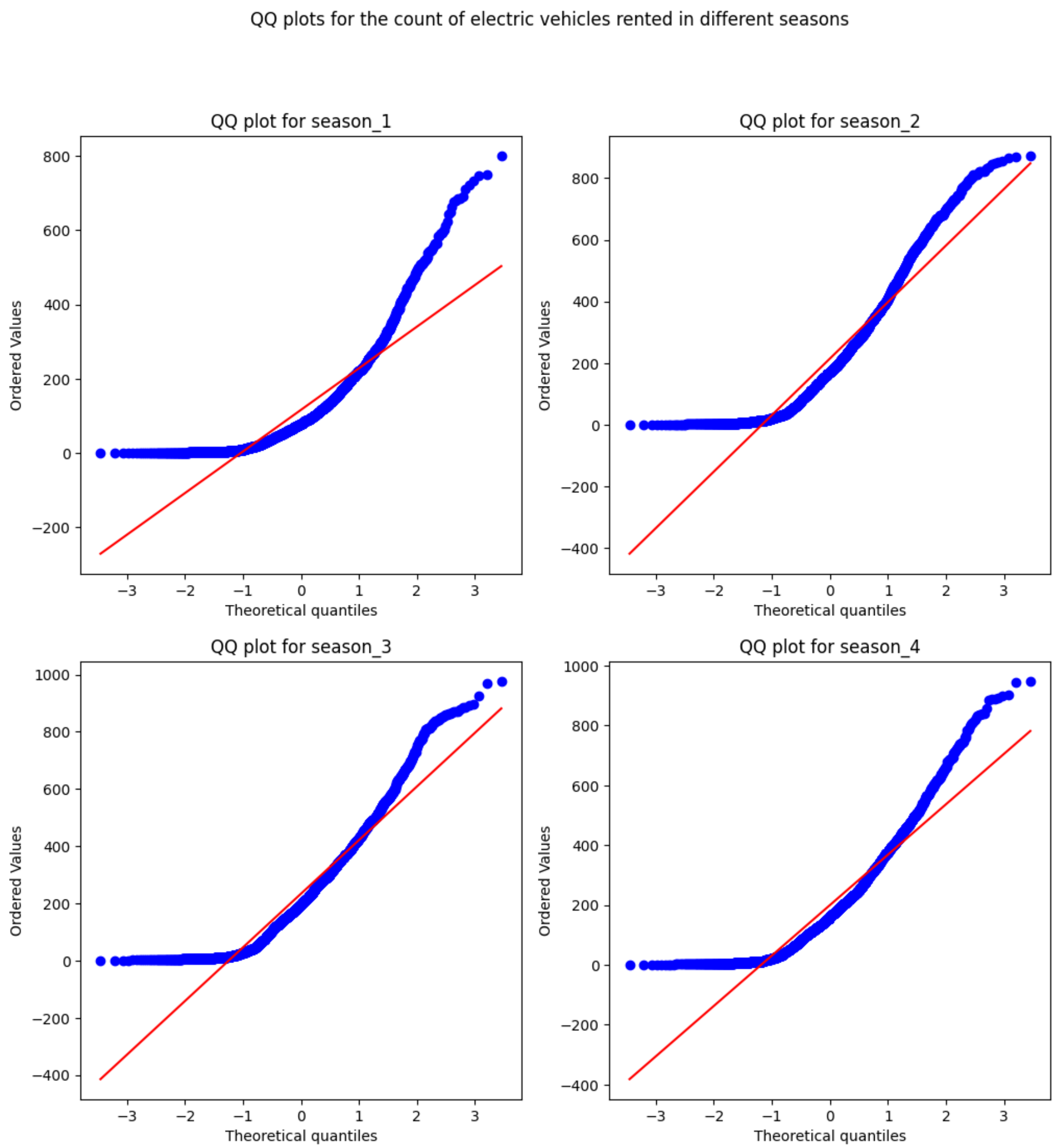


Based on the plot above, it can be deduced that the distributions deviate from the normal dist

Assessing distribution via QQ Plot

[83]:
```
import matplotlib.pyplot as plt
import scipy.stats as stats

def plot_qq_plots_seasons(df_season_1, df_season_2, df_season_3, df_season_4):
    plt.figure(figsize=(12, 12))
    plt.suptitle('QQ plots for the count of electric vehicles rented in␣
↪different seasons')
    sample_size = min(2500, len(df_season_1))
    plt.subplot(2, 2, 1)
    stats.probplot(df_season_1.sample(sample_size), plot=plt, dist='norm')
    plt.title('QQ plot for season_1')
    sample_size = min(2500, len(df_season_2))
    plt.subplot(2, 2, 2)
    stats.probplot(df_season_2.sample(sample_size), plot=plt, dist='norm')
    plt.title('QQ plot for season_2')
    sample_size = min(2500, len(df_season_3))
    plt.subplot(2, 2, 3)
```

```
    stats.probplot(df_season_3.sample(sample_size), plot=plt, dist='norm')
    plt.title('QQ plot for season_3')
    sample_size = min(2500, len(df_season_4))
    plt.subplot(2, 2, 4)
    stats.probplot(df_season_4.sample(sample_size), plot=plt, dist='norm')
    plt.title('QQ plot for season_4')

    plt.show()


plot_qq_plots_seasons(df_season_1, df_season_2, df_season_3, df_season_4)
```



In a QQ plot, if data points closely align with the diagonal line, the distribution is likely r

Conducting the Shapiro-Wilk test to assess normality.

H_0: The sample conforms to a normal distribution.
H_1: The sample deviates from a normal distribution.

Significance Level $(\alpha) = 0.05$

Test Statistics: Shapiro-Wilk test for normality

[84]:
```python
def shapiro_test_seasons(df_season_1, df_season_2, df_season_3, df_season_4):
    test_stat, p_value = stats.shapiro(df_season_1.sample(2500))
    print('Season_1:')
    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')

    test_stat, p_value = stats.shapiro(df_season_2.sample(2500))
    print('\nSeason_2:')
    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')

    test_stat, p_value = stats.shapiro(df_season_3.sample(2500))
    print('\nSeason_3:')
    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')

    test_stat, p_value = stats.shapiro(df_season_4.sample(2500))
    print('\nSeason_4:')
    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')

shapiro_test_seasons(df_season_1, df_season_2, df_season_3, df_season_4)
```

```
Season_1:
p-value: 2.3486954673453084e-47
```

```
The sample does not follow normal distribution

Season_2:
p-value: 3.650035838253269e-37
The sample does not follow normal distribution

Season_3:
p-value: 2.9123312767678484e-35
The sample does not follow normal distribution

Season_4:
p-value: 5.72429242739374e-38
The sample does not follow normal distribution
```

Applying the Box-Cox transformation to the data and assessing whether the transformed data adheres to a normal distribution

[85]:
```python
def boxcox_shapiro_test_seasons(df_season_1, df_season_2, df_season_3,␣
↪df_season_4):
    transformed_df_season_1 = stats.boxcox(df_season_1.sample(2500))[0]
    test_stat, p_value = stats.shapiro(transformed_df_season_1)
    print('Season_1:')
    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')

    transformed_df_season_2 = stats.boxcox(df_season_2.sample(2500))[0]
    test_stat, p_value = stats.shapiro(transformed_df_season_2)
    print('\nSeason_2:')
    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')

    transformed_df_season_3 = stats.boxcox(df_season_3.sample(2500))[0]
    test_stat, p_value = stats.shapiro(transformed_df_season_3)
    print('\nSeason_3:')
    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')

    transformed_df_season_4 = stats.boxcox(df_season_4.sample(2500))[0]
    test_stat, p_value = stats.shapiro(transformed_df_season_4)
```

```
    print('\nSeason_4:')
    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')


boxcox_shapiro_test_seasons(df_season_1, df_season_2, df_season_3, df_season_4)
```

```
Season_1:
p-value: 1.2712345021107283e-16
The sample does not follow normal distribution

Season_2:
p-value: 2.811170815583834e-21
The sample does not follow normal distribution

Season_3:
p-value: 7.10322875709124e-21
The sample does not follow normal distribution

Season_4:
p-value: 6.495794591680147e-20
The sample does not follow normal distribution
```

Season 1: ***The sample does not follow a normal distribution (p < 0.05)***

Season 2: ***Similarly, the sample does not follow a normal distribution (p < 0.05)***

Season 3: ***Likewise, the sample does not follow a normal distribution (p < 0.05)***

Season 4: ***Similarly, the sample does not follow a normal distribution (p < 0.05)***

All samples fail the test for normality.

`Due to the lack of normal distribution and unequal variance among the samples, the f_oneway tes`

Ho : Mean no. of cycles rented is same for different seasons

Ha : Mean no. of cycles rented is different for different seasons

Assuming significance Level to be 0.05

[86]:
```
def kruskal_test(df1, df2, df3, df4):
    alpha = 0.05
    test_stat, p_value = stats.kruskal(df1, df2, df3, df4)
    print('Test Statistic =', test_stat)
    print('p value =', p_value)

    if p_value < alpha:
```

```
        print('Reject Null Hypothesis')
    else:
        print('Failed to reject Null Hypothesis')

kruskal_test(df_season_1, df_season_2, df_season_3, df_season_4)
```

```
Test Statistic = 699.6668548181988
p value = 2.479008372608633e-151
Reject Null Hypothesis
```

Hence, there is a statistically significant difference in the average number of rental bikes across different seasons.

2.4.1 Inferences from Analysis

- The average hourly count of rental bikes shows no significant difference between working and non-working days.
- There is no statistically significant relationship between weather types 1, 2, and 3 and seasons concerning the average hourly total number of bikes rented.
- The hourly total number of rental bikes significantly varies across different seasons.
- The hourly total number of rental bikes varies significantly across different weather conditions.