q3

February 19, 2024

[37]:
```
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

[38]:
```
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

[39]:
```
df.shape
```

[39]:
```
(10886, 12)
```

Converting the datatype of datetime column from object to datetime

[40]:
```
df['datetime'] = pd.to_datetime(df['datetime'])
```

[41]:
```
df['season'] = df['season'].apply(season_category)
```

[42]:
```
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')
```

[43]:
```
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
```

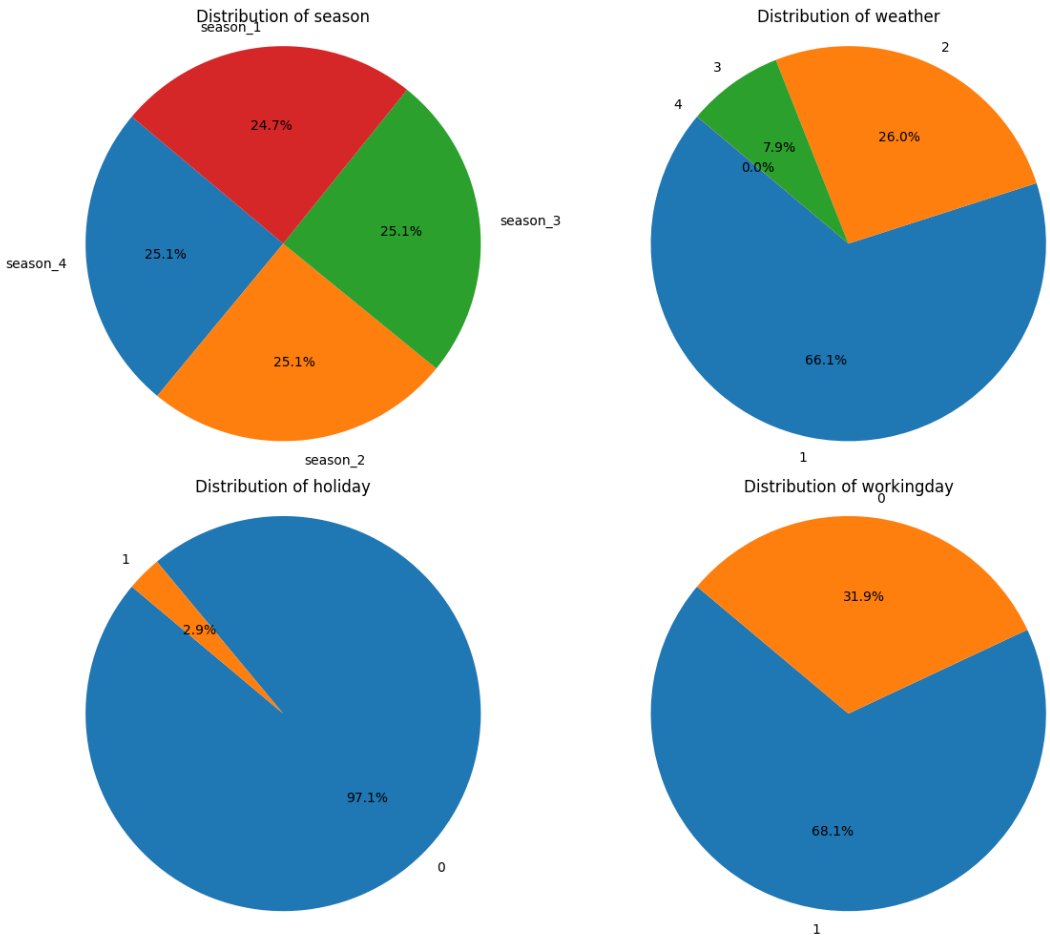
```
 10  registered  10886 non-null  int32
 11  count       10886 non-null  int32
dtypes: category(4), datetime64[ns](1), float32(4), int32(3)
memory usage: 426.0 KB
```

[44]:
```
df.describe()
```

[44]:
```
                            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
```

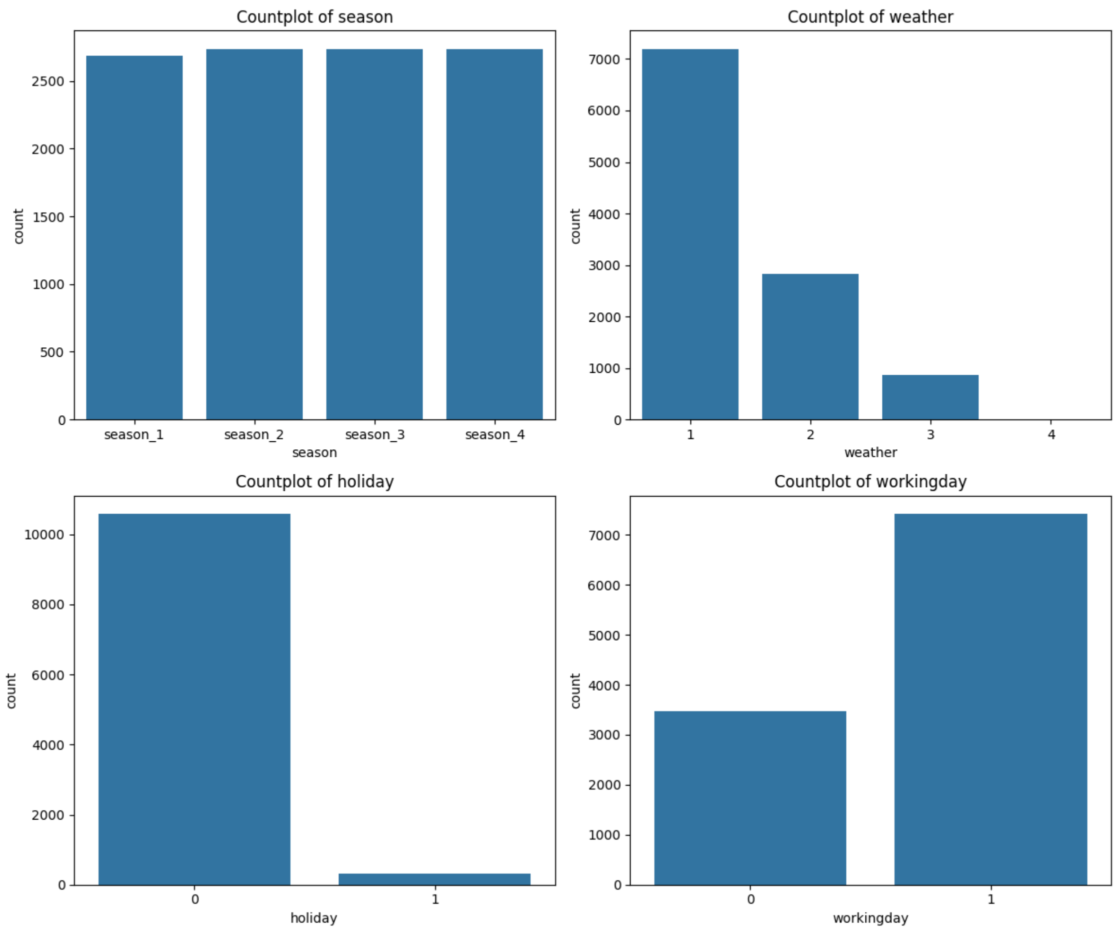
[46]:
```
def plot_categorical_distribution(df, column, subplot_index):
    column_distribution = df[column].value_counts().reset_index()
    column_distribution.columns = [column, 'count']
    plt.subplot(subplot_index)
    plt.pie(column_distribution['count'], labels=column_distribution[column],␣
 ↪autopct='%1.1f%%', startangle=140)
    plt.title(f'Distribution of {column}')
    plt.axis('equal')

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



[47]:
```
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)
```

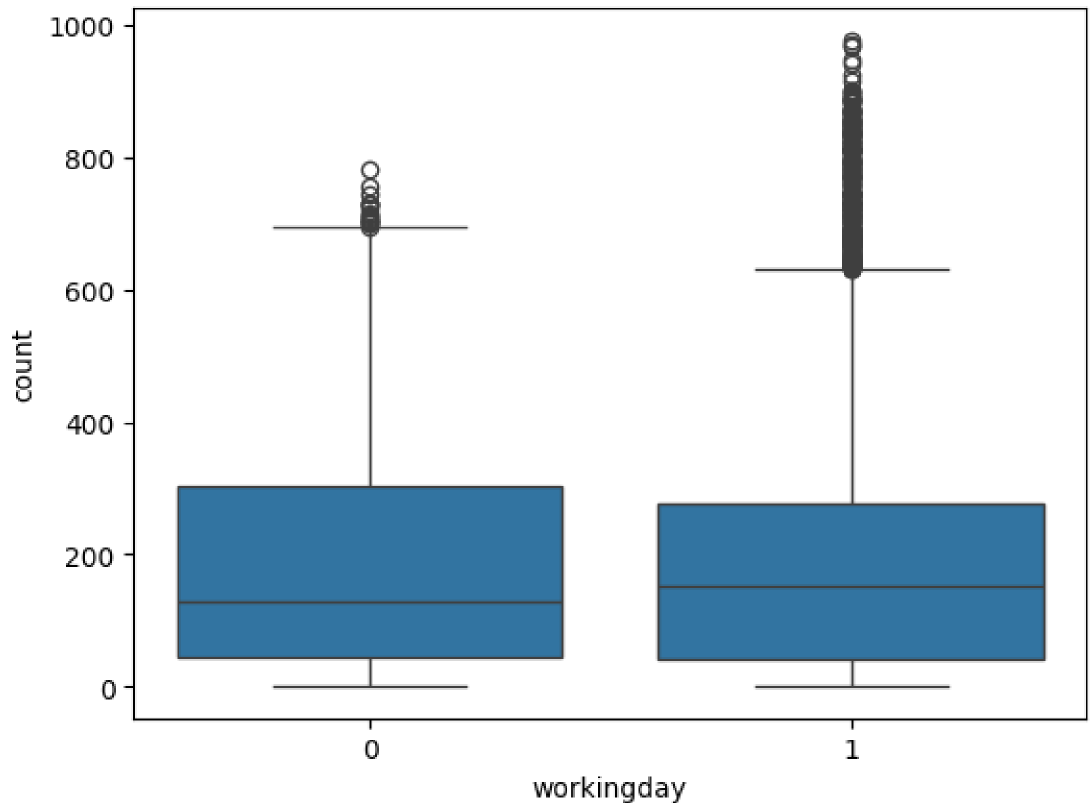
```
plt.subplot(2, 2, 3)
plot_countplot(df, 'holiday', 223)

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

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



0.0.1 Is there any effect of Working Day on the number of electric cycles rented ?

[179]:
```
sns.boxplot(data = df, x = 'workingday', y = 'count')
plt.plot()
```

[179]: []



STEP-1 : Set up Null Hypothesis

- **Null Hypothesis (H0)** - Working Day does not have any effect on the number of electric cycles rented.
- **Alternate Hypothesis (HA)** - Working Day has some effect on the number of electric cycles rented

STEP-2 : Checking for basic assumpitons for the hypothesis

- If the assumptions of T Test are met then we can proceed performing T Test for independent samples else we will perform the non parametric test equivalent to T Test for independent sample i.e., Mann-Whitney U rank test for two independent samples.

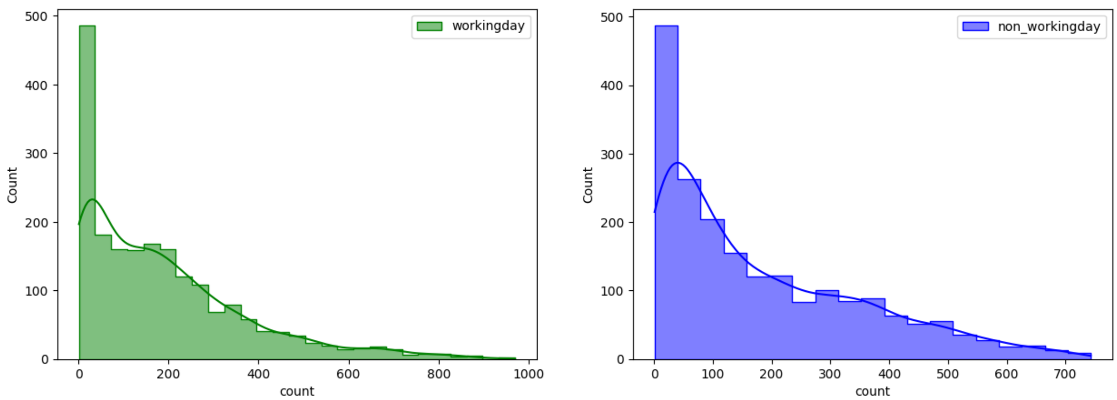
STEP-4: Compute the p-value and fix value of alpha.

- Based on p-value, we will accept or reject H0.
   1. **p-val > alpha** : Accept H0
   2. **p-val < alpha** : Reject H0

Visual Tests to know if the samples follow normal distribution

[180]:
```
plt.figure(figsize = (15, 5))
plt.subplot(1, 2, 1)
sns.histplot(df.loc[df['workingday'] == 1, 'count'].sample(2000),
             element = 'step', color = 'green', kde = True, label =␣
 ↪'workingday')
plt.legend()
plt.subplot(1, 2, 2)
sns.histplot(df.loc[df['workingday'] == 0, 'count'].sample(2000),
             element = 'step', color = 'blue', kde = True, label =␣
 ↪'non_workingday')
plt.legend()
plt.plot()
```

[180]: []

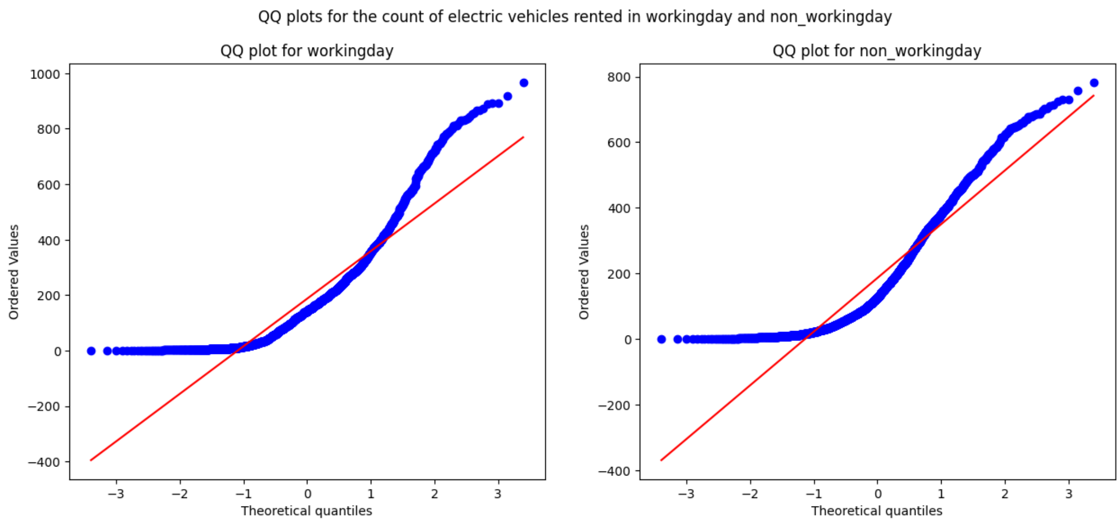


- It can be inferred from the above plot that the distributions do not follow normal distribution.

Distribution check using QQ Plot

[181]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for the count of electric vehicles rented in workingday␣
 ↪and non_workingday')
stats.probplot(df.loc[df['workingday'] == 1, 'count'].sample(2000), plot = plt,␣
 ↪dist = 'norm')
plt.title('QQ plot for workingday')
plt.subplot(1, 2, 2)
stats.probplot(df.loc[df['workingday'] == 0, 'count'].sample(2000), plot = plt,␣
 ↪dist = 'norm')
plt.title('QQ plot for non_workingday')
plt.plot()
```

[181]: []



- It can be inferred from the above plot 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

H_0 : The sample **follows normal distribution** H_1 : The sample **does not follow normal distribution**

alpha = 0.05

Test Statistics : **Shapiro-Wilk test for normality**

[182]:
```
test_stat, p_value = stats.shapiro(df.loc[df['workingday'] == 1, 'count'].
  ↪sample(2000))
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 3.080388130885043 5e-37
The sample does not follow normal distribution
```

[183]:
```
test_stat, p_value = stats.shapiro(df.loc[df['workingday'] == 0, 'count'].
  ↪sample(2000))
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 3.747149247129874e-36
The sample does not follow normal distribution
```

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

[184]:
```python
transformed_workingday = stats.boxcox(df.loc[df['workingday'] == 1, 'count'])[0]
test_stat, p_value = stats.shapiro(transformed_workingday)
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 1.606449722752868e-33
The sample does not follow normal distribution

/var/folders/kk/7w6727t942z6xwr_96jpcwtc0000gn/T/ipykernel_2852/1999844435.py:2:
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_workingday)
```

[185]:
```python
transformed_non_workingday = stats.boxcox(df.loc[df['workingday'] == 1,␣
↪'count'])[0]
test_stat, p_value = stats.shapiro(transformed_non_workingday)
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 1.606449722752868e-33
The sample does not follow normal distribution

/var/folders/kk/7w6727t942z6xwr_96jpcwtc0000gn/T/ipykernel_2852/3440035996.py:2:
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_non_workingday)
```

- Even after applying the boxcox transformation on each of the “workingday” and “non_workingday” data, the samples do not follow normal distribution.
- Homogeneity of Variances using **Lavene’s test**

[186]:
```python
# Null Hypothesis(H0) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = stats.levene(df.loc[df['workingday'] == 1, 'count'].
↪sample(2000),
```

```
                                        df.loc[df['workingday'] == 0, 'count'].
 ↪sample(2000))
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 0.1508588318316367
The samples have Homogenous Variance
```

Since the samples are not normally distributed, T-Test cannot be applied here, we can perform its non parametric equivalent test i.e., Mann-Whitney U rank test for two independent samples.

[187]:
```
# Ho : Mean no.of electric cycles rented is same for working and non-working␣
 ↪days
# Ha : Mean no.of electric cycles rented is not same for working and␣
 ↪non-working days
# Assuming significance Level to be 0.05
# Test statistics : Mann-Whitney U rank test for two independent samples

test_stat, p_value = stats.mannwhitneyu(df.loc[df['workingday'] == 1, 'count'],
                                      df.loc[df['workingday'] == 0, 'count'])
print('P-value :',p_value)
if p_value < 0.05:
    print('Mean no.of electric cycles rented is not same for working and␣
 ↪non-working days')
else:
    print('Mean no.of electric cycles rented is same for working and␣
 ↪non-working days')
```

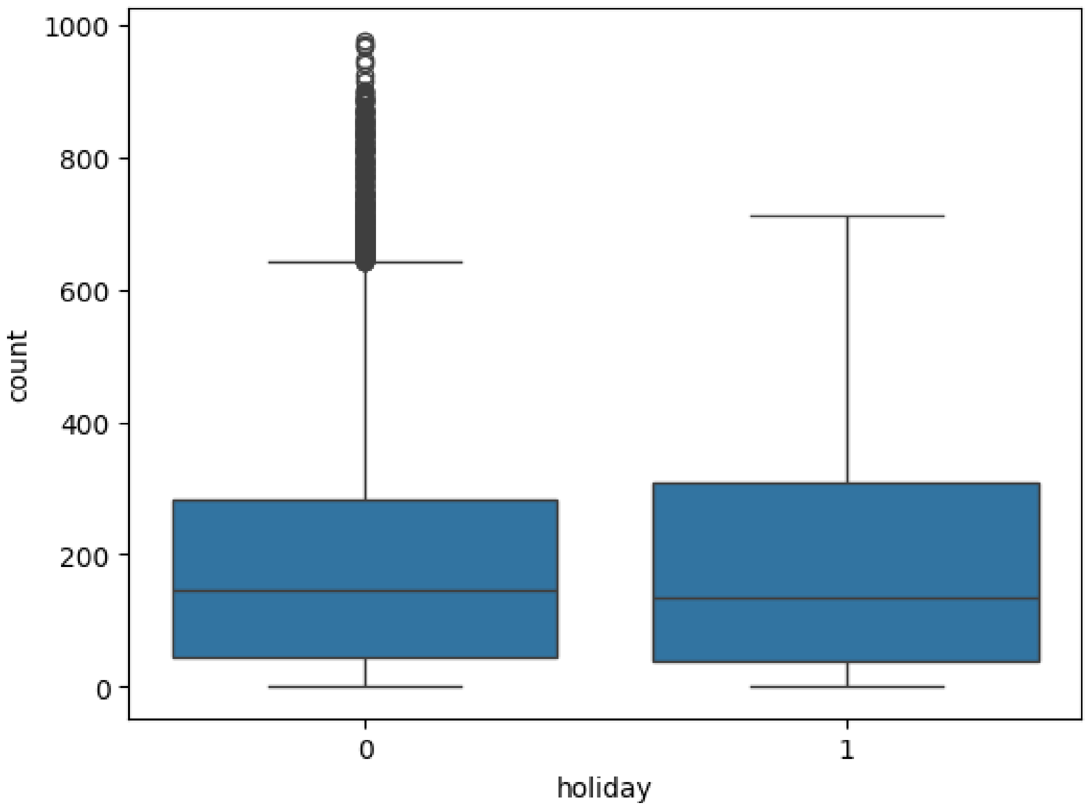
```
P-value : 0.9679139953914079
Mean no.of electric cycles rented is same for working and non-working days
```

Therefore, the mean hourly count of the total rental bikes is statistically same for both working and non- working days .

0.0.2 Is there any effect of holidays on the number of electric cycles rented ?

[189]:
```
sns.boxplot(data = df, x = 'holiday', y = 'count')
plt.plot()
```

[189]: []



STEP-1 : Set up Null Hypothesis

- **Null Hypothesis (H0)** - Holidays have no effect on the number of electric vehicles rented
- **Alternate Hypothesis (HA)** - Holidays has some effect on the number of electric vehicles rented

STEP-2 : Checking for basic assumpitons for the hypothesis

- If the assumptions of T Test are met then we can proceed performing T Test for independent samples else we will perform the non parametric test equivalent to T Test for independent sample i.e., Mann-Whitney U rank test for two independent samples.

STEP-4: Compute the p-value and fix value of alpha.

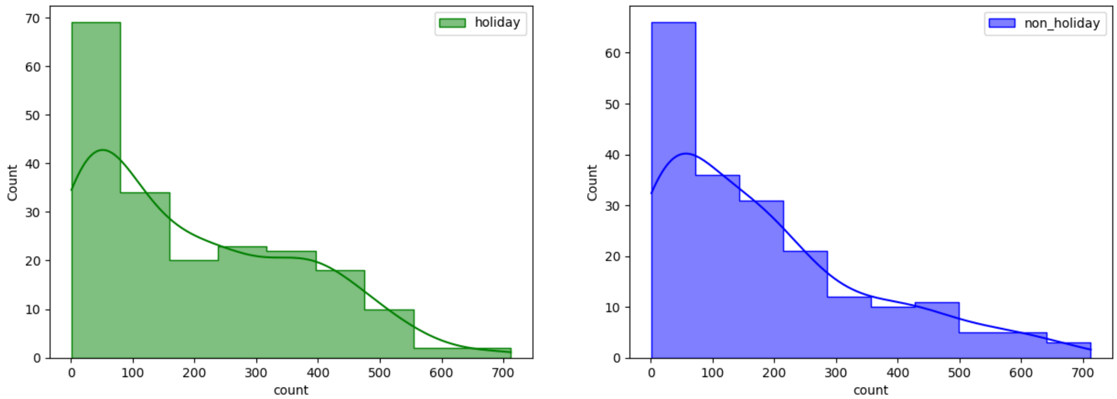
- Based on p-value, we will accept or reject H0.
    1. **p-val > alpha** : Accept H0
    2. **p-val < alpha** : Reject H0

Visual Tests to know if the samples follow normal distribution

[190]:
```
plt.figure(figsize = (15, 5))
plt.subplot(1, 2, 1)
```

```
sns.histplot(df.loc[df['holiday'] == 1, 'count'].sample(200),
             element = 'step', color = 'green', kde = True, label = 'holiday')
plt.legend()
plt.subplot(1, 2, 2)
sns.histplot(df.loc[df['holiday'] == 0, 'count'].sample(200),
             element = 'step', color = 'blue', kde = True, label =␣
 ↪'non_holiday')
plt.legend()
plt.plot()
```

[190]: []

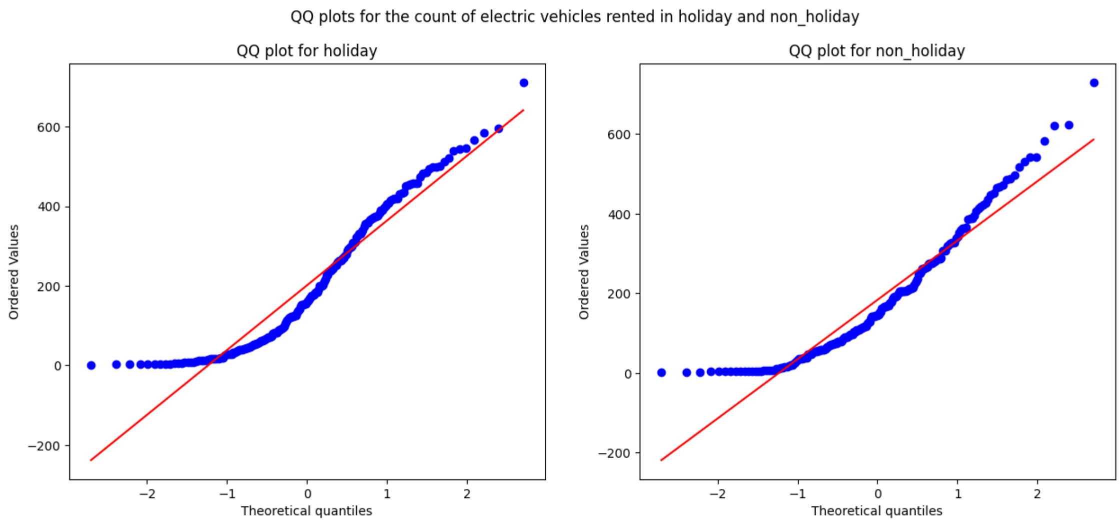


- It can be inferred from the above plot that the distributions do not follow normal distribution.

Distribution check using QQ Plot

[191]:
```
plt.figure(figsize = (15, 6))
plt.subplot(1, 2, 1)
plt.suptitle('QQ plots for the count of electric vehicles rented in holiday and␣
 ↪non_holiday')
stats.probplot(df.loc[df['holiday'] == 1, 'count'].sample(200), plot = plt,␣
 ↪dist = 'norm')
plt.title('QQ plot for holiday')
plt.subplot(1, 2, 2)
stats.probplot(df.loc[df['holiday'] == 0, 'count'].sample(200), plot = plt,␣
 ↪dist = 'norm')
plt.title('QQ plot for non_holiday')
plt.plot()
```

[191]: []



- It can be inferred from the above plot 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

H_0 : The sample **follows normal distribution** H_1 : The sample **does not follow normal distribution**

alpha = 0.05

Test Statistics : **Shapiro-Wilk test for normality**

[192]:
```
test_stat, p_value = stats.shapiro(df.loc[df['holiday'] == 1, 'count'].
  ↪sample(200))
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 3.3808217549719775e-10
The sample does not follow normal distribution
```

[193]:
```
test_stat, p_value = stats.shapiro(df.loc[df['holiday'] == 0, 'count'].
  ↪sample(200))
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 2.472583582364814e-10
The sample does not follow normal distribution
```

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

[194]:
```python
transformed_holiday = stats.boxcox(df.loc[df['holiday'] == 1, 'count'])[0]
test_stat, p_value = stats.shapiro(transformed_holiday)
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 2.134933458313291e-07
The sample does not follow normal distribution
```

[195]:
```python
transformed_non_holiday = stats.boxcox(df.loc[df['holiday'] == 0, 'count'].
 ↪sample(5000))[0]
test_stat, p_value = stats.shapiro(transformed_non_holiday)
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 1.7201936785463507e-26
The sample does not follow normal distribution
```

- Even after applying the boxcox transformation on each of the “holiday” and “non_holiday” data, the samples do not follow normal distribution.

Homogeneity of Variances using Levene’s test

[196]:
```python
# Null Hypothesis(H0) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = stats.levene(df.loc[df['holiday'] == 0, 'count'].
 ↪sample(200),
                                df.loc[df['holiday'] == 1, 'count'].sample(200))
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 0.97995944627749
The samples have Homogenous Variance
```

Since the samples are not normally distributed, T-Test cannot be applied here, we can perform its non parametric equivalent test i.e., Mann-Whitney U rank test for two independent samples.

[197]:
```
# Ho : No.of electric cycles rented is similar for holidays and non-holidays
# Ha : No.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

test_stat, p_value = stats.mannwhitneyu(df.loc[df['holiday'] == 0, 'count'].
↪sample(200),
                                        df.loc[df['holiday'] == 1, 'count'].
↪sample(200))
print('P-value :',p_value)
if p_value < 0.05:
    print('No.of electric cycles rented is not similar for holidays and␣
↪non-holidays days')
else:
    print('No.of electric cycles rented is similar for holidays and␣
↪non-holidays')
```

```
P-value : 0.3858752041666006
No.of electric cycles rented is similar for holidays and non-holidays
```

Therefore, the number of electric cycles rented is statistically similar for both holidays and non - holidays.

0.0.3 Is weather dependent on the season ?

- It is clear from the above statistical description that both 'weather' and 'season' features are categorical in nature.

STEP-1 : Set up Null Hypothesis

Since we have two categorical features, the Chi- square test is applicable here. Under H0, the test statistic should follow **Chi-Square Distribution**.

STEP-3: Checking for basic assumptons for the hypothesis (Non-Parametric Test)

we will be computing the chi square-test p-value using the chi2_contingency function using scipy.stats. We set our **alpha to be 0.05**

STEP-5: Compare p-value and alpha.

Based on p-value, we will accept or reject H0.

1. **p-val > alpha** : Accept H0
2. **p-val < alpha** : Reject H0

The **Chi-square statistic is a non-parametric** (distribution free) tool designed to analyze group differences when the dependent variable is measured at a nominal level. Like all non-parametric statistics, the Chi-square is robust with respect to the distribution of the data. Specifically, it does not require equality of variances among the study groups or homoscedasticity in the data.

[199]:
```
# First, finding the contingency table such that each value is the total number␣
↪of total bikes rented
 # for a particular season and weather
cross_table = pd.crosstab(index = df['season'],
                          columns = df['weather'],
                          values = df['count'],
                          aggfunc = np.sum).replace(np.nan, 0)
cross_table
```

```
/var/folders/kk/7w6727t942z6xwr_96jpcwtc0000gn/T/ipykernel_2852/1300981298.py:3:
FutureWarning: The provided callable <function sum at 0x114a71a80> is currently
using DataFrameGroupBy.sum. In a future version of pandas, the provided callable
will be used directly. To keep current behavior pass the string "sum" instead.
  cross_table = pd.crosstab(index = df['season'],
```

[199]:

weather	1	2	3	4
season				
fall	470116	139386	31160	0
spring	223009	76406	12919	164
summer	426350	134177	27755	0
winter	356588	157191	30255	0

Since the above contingency table has one column in which the count of the rented electric vehicle is less than 5 in most of the cells, we can remove the weather 4 and then proceed further.

[200]:
```
cross_table = pd.crosstab(index = df['season'],
                          columns = df.loc[df['weather'] != 4, 'weather'],
                          values = df['count'],
                          aggfunc = np.sum).to_numpy()[:, :3]
cross_table
```

```
/var/folders/kk/7w6727t942z6xwr_96jpcwtc0000gn/T/ipykernel_2852/110451809.py:1:
FutureWarning: The provided callable <function sum at 0x114a71a80> is currently
using DataFrameGroupBy.sum. In a future version of pandas, the provided callable
will be used directly. To keep current behavior pass the string "sum" instead.
  cross_table = pd.crosstab(index = df['season'],
```

[200]:
```
array([[470116, 139386,  31160],
       [223009,  76406,  12919],
       [426350, 134177,  27755],
       [356588, 157191,  30255]], dtype=int32)
```

[201]:
```
chi_test_stat, p_value, dof, expected = stats.chi2_contingency(observed =␣
 ↪cross_table)
print('Test Statistic =', chi_test_stat)
print('p value =', p_value)
print('-' * 65)
print("Expected : '\n'", expected)
```

```
Test Statistic = 10838.372332480214
p value = 0.0
-----------------------------------------------------------------
Expected : '
' [[453484.88557396 155812.72247031  31364.39195574]
 [221081.86259035  75961.44434981  15290.69305984]
 [416408.3330293  143073.60199337  28800.06497733]
 [385087.91880639 132312.23118651  26633.8500071 ]]
```

Comparing p value with significance level

[202]:
```
if p_value < alpha:
    print('Reject Null Hypothesis')
else:
    print('Failed to reject Null Hypothesis')
```

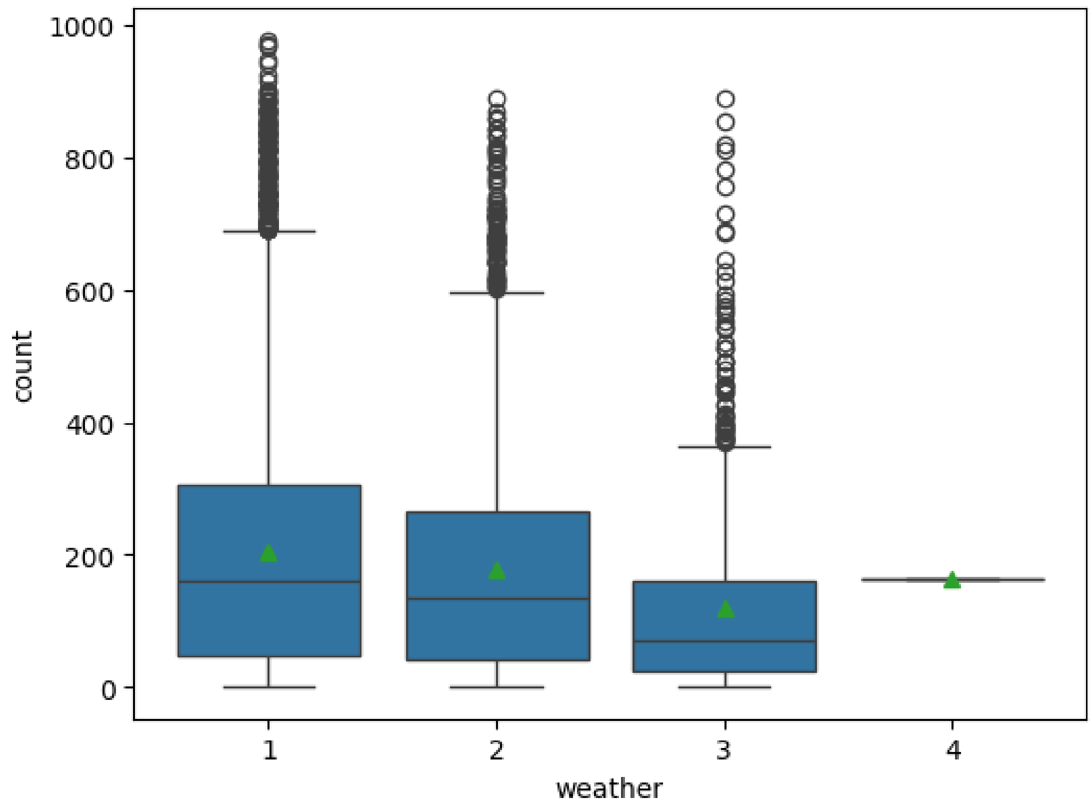
```
Reject Null Hypothesis
```

Therefore, there is statistically significant dependency of weather and season based on the number of number of bikes rented.

0.0.4 Is the number of cycles rented is similar or different in different weather ?

[204]:
```
sns.boxplot(data = df, x = 'weather', y = 'count', showmeans = True)
plt.plot()
```

[204]: []



[205]:
```
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)
```

[205]:
```
(7192, 2834, 859, 1)
```

STEP-1 : Set up Null Hypothesis

Normality check using **QQ Plot**. If the distribution is not normal, use **BOX-COX transform** to transform it to normal distribution.

Homogeneity of Variances using **Levene's test**

Each observations are **independent**.

STEP-3: Define **Test statistics**

We will be performing **right tailed f-test**

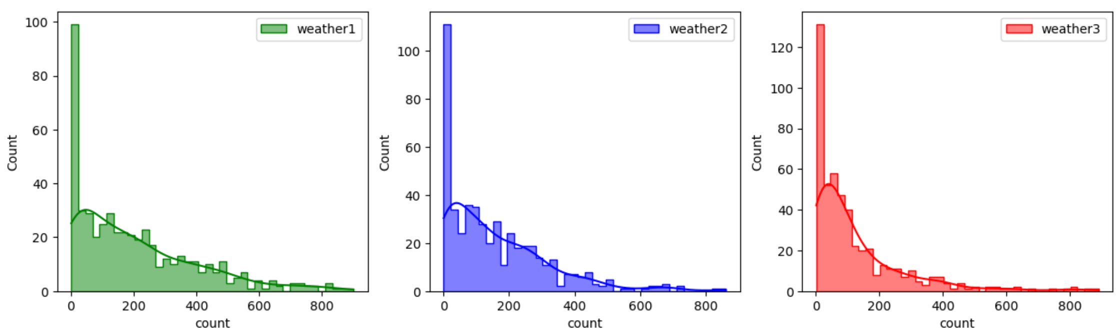
STEP-5: Compute the **p-value** and fix value of alpha.

Based on p-value, we will accept or reject H0. * **p-val > alpha** : Accept H0 * **p-val < alpha** : Reject H0

Visual Tests to know if the samples follow normal distribution

[206]:
```
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 = 'weather1')
plt.legend()
plt.subplot(1, 3, 2)
sns.histplot(df_weather2.loc[:, 'count'].sample(500), bins = 40,
             element = 'step', color = 'blue', kde = True, label = 'weather2')
plt.legend()
plt.subplot(1, 3, 3)
sns.histplot(df_weather3.loc[:, 'count'].sample(500), bins = 40,
             element = 'step', color = 'red', kde = True, label = 'weather3')
plt.legend()
plt.plot()
```

[206]: []



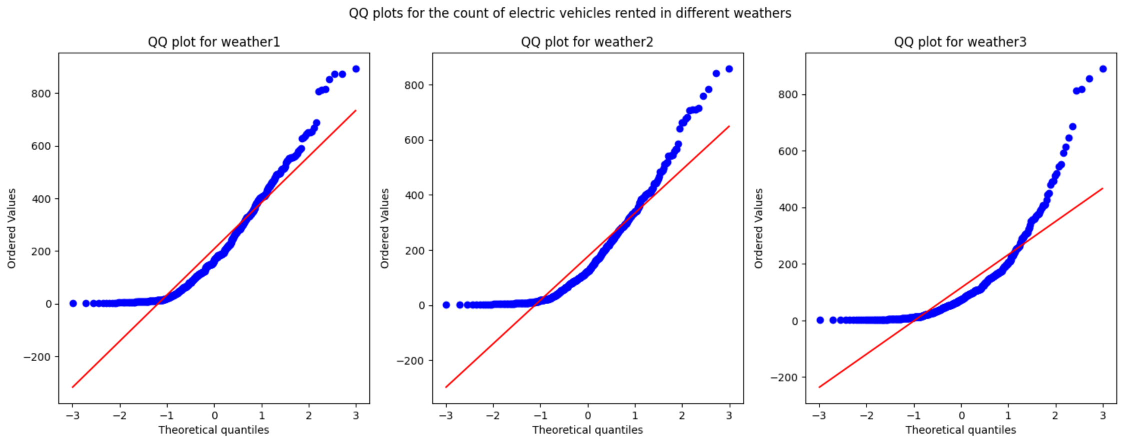
- It can be inferred from the above plot that the distributions do not follow normal distribution.

Distribution check using QQ Plot

[207]:
```
plt.figure(figsize = (18, 6))
plt.subplot(1, 3, 1)
plt.suptitle('QQ plots for the count of electric vehicles rented in different␣
 ↪weathers')
stats.probplot(df_weather1.loc[:, 'count'].sample(500), plot = plt, dist =␣
 ↪'norm')
plt.title('QQ plot for weather1')
plt.subplot(1, 3, 2)
stats.probplot(df_weather2.loc[:, 'count'].sample(500), plot = plt, dist =␣
 ↪'norm')
plt.title('QQ plot for weather2')
plt.subplot(1, 3, 3)
```

```
stats.probplot(df_weather3.loc[:, 'count'].sample(500), plot = plt, dist =␣
↪'norm')
plt.title('QQ plot for weather3')
plt.plot()
```

[207]: []



- It can be inferred from the above plot 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

H_0 : The sample **follows normal distribution** H_1 : The sample **does not follow normal distribution**

alpha = 0.05

Test Statistics : **Shapiro-Wilk test for normality**

[208]:
```
test_stat, p_value = stats.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 2.8256202778718335e-18
The sample does not follow normal distribution
```

[209]:
```
test_stat, p_value = stats.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 6.116655019332107e-19
The sample does not follow normal distribution
```

[210]:
```
test_stat, p_value = stats.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 2.4998291292995494e-26
The sample does not follow normal distribution
```

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

[211]:
```
transformed_weather1 = stats.boxcox(df_weather1.loc[:, 'count'].sample(5000))[0]
test_stat, p_value = stats.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 4.0000413689403576e-28
The sample does not follow normal distribution
```

[212]:
```
transformed_weather2 = stats.boxcox(df_weather2.loc[:, 'count'])[0]
test_stat, p_value = stats.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 1.924543439675978e-19
The sample does not follow normal distribution
```

[213]:
```
transformed_weather3 = stats.boxcox(df_weather3.loc[:, 'count'])[0]
test_stat, p_value = stats.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 1.4117561575225677e-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

[214]:
```
# Null Hypothesis(HO) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = stats.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 1.6774547265912305e-12
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.

[215]:
```
# 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 = stats.kruskal(df_weather1, df_weather2, df_weather3)
print('Test Statistic =', test_stat)
print('p value =', p_value)
```

```
Test Statistic = [1.36471292e+01 3.87838808e+01 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 3.78605818e-09 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]
```

Comparing p value with significance level

[216]:
```
# 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]
# calculate mean of p value
p_value = np.mean(p_value)
```

```
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.

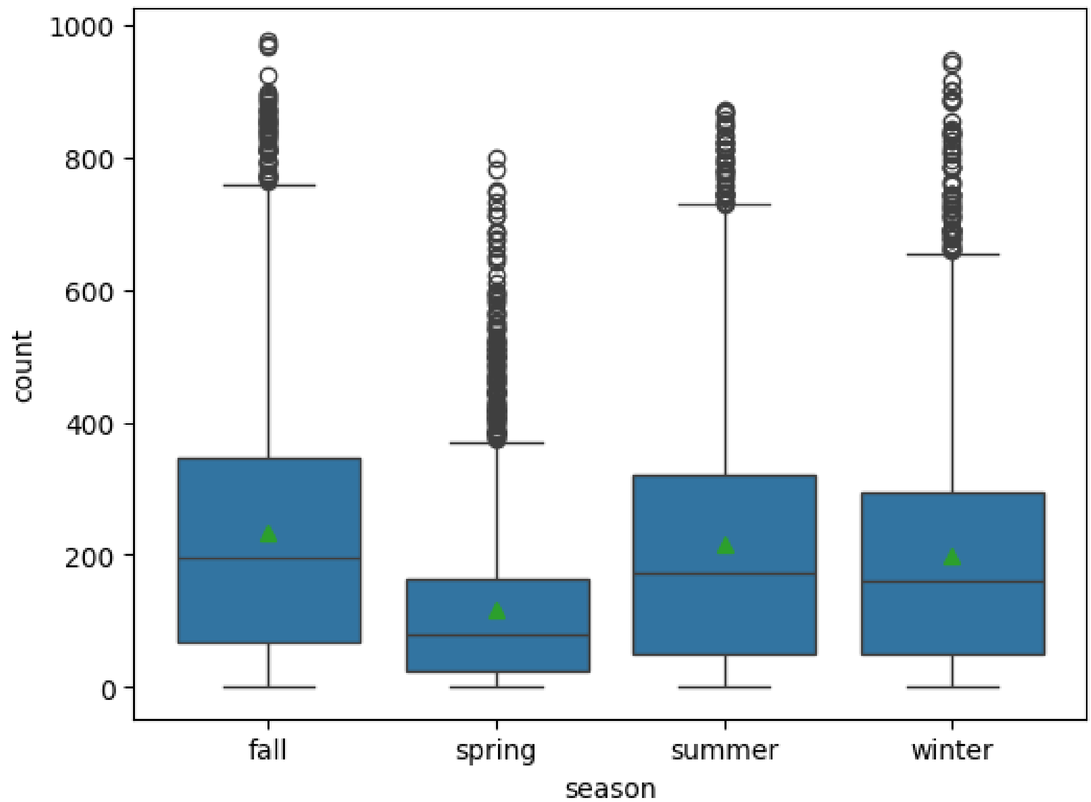
0.0.5 Is the number of cycles rented is similar or different in different season ?

[218]:
```
df_season_1 = df.loc[df['season'] == 1, 'count']
df_season_2 = df.loc[df['season'] == 2, 'count']
df_season_3 = df.loc[df['season'] == 3, 'count']
df_season_4 = df.loc[df['season'] == 4, 'count']
len(df_season_1), len(df_season_2), len(df_season_3), len(df_season_4)
```

[218]:
```
(2686, 2733, 2733, 2734)
```

[219]:
```
sns.boxplot(data = df, x = 'season', y = 'count', showmeans = True)
plt.plot()
```

[219]:
```
[]
```



STEP-1 : Set up Null Hypothesis

1. **Normality check** using QQ Plot. If the distribution is not normal, use **BOX-COX transform** to transform it to normal distribution.
2. Homogeneity of Variances using **Levene's test**
3. Each observations are **independent**.

STEP-3: Define Test statistics

We will be performing **right tailed f-test**

STEP-5: Compute the p-value and fix value of alpha.

---

we will be computing the anova-test p-value using the **f_oneway** function using scipy.stats. We set our alpha to be **0.05**

STEP-6: Compare p-value and alpha.

Based on p-value, we will accept or reject H0. p-val > alpha : Accept H0 p-val < alpha : Reject H0

The one-way ANOVA compares the means between the groups you are interested in and determines whether any of those means are statistically significantly different from each other.

Specifically, it tests the null hypothesis (H0):

$$\mu 1 = \mu 2 = \mu 3 = ... = \mu k$$

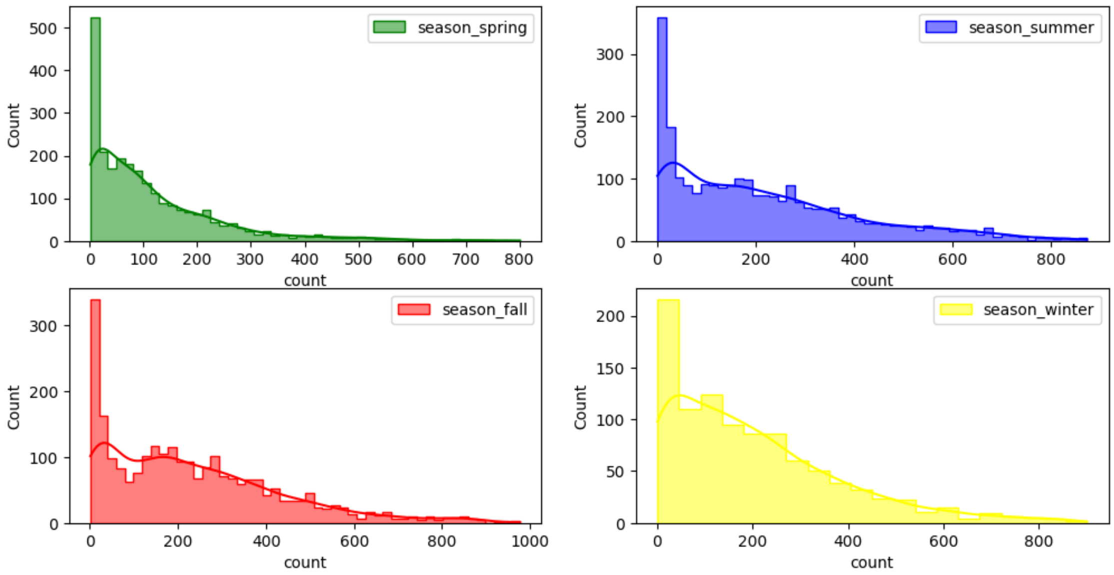
where, μ = group mean and k = number of groups.

If, however, the one-way ANOVA returns a statistically significant result, we accept the alternative hypothesis (HA), which is that there are at least two group means that are statistically significantly different from each other.

Visual Tests to know if the samples follow normal distribution

[220]:
```
plt.figure(figsize = (12, 6))
plt.subplot(2, 2, 1)
sns.histplot(df_season_1.sample(2500), bins = 50,
             element = 'step', color = 'green', 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 = 'red', kde = True, label = 'season_3')
plt.legend()
plt.subplot(2, 2, 4)
sns.histplot(df_season_4.sample(1000), bins = 20,
             element = 'step', color = 'yellow', kde = True, label = 'season_4')
plt.legend()
plt.plot()
```

[220]: []



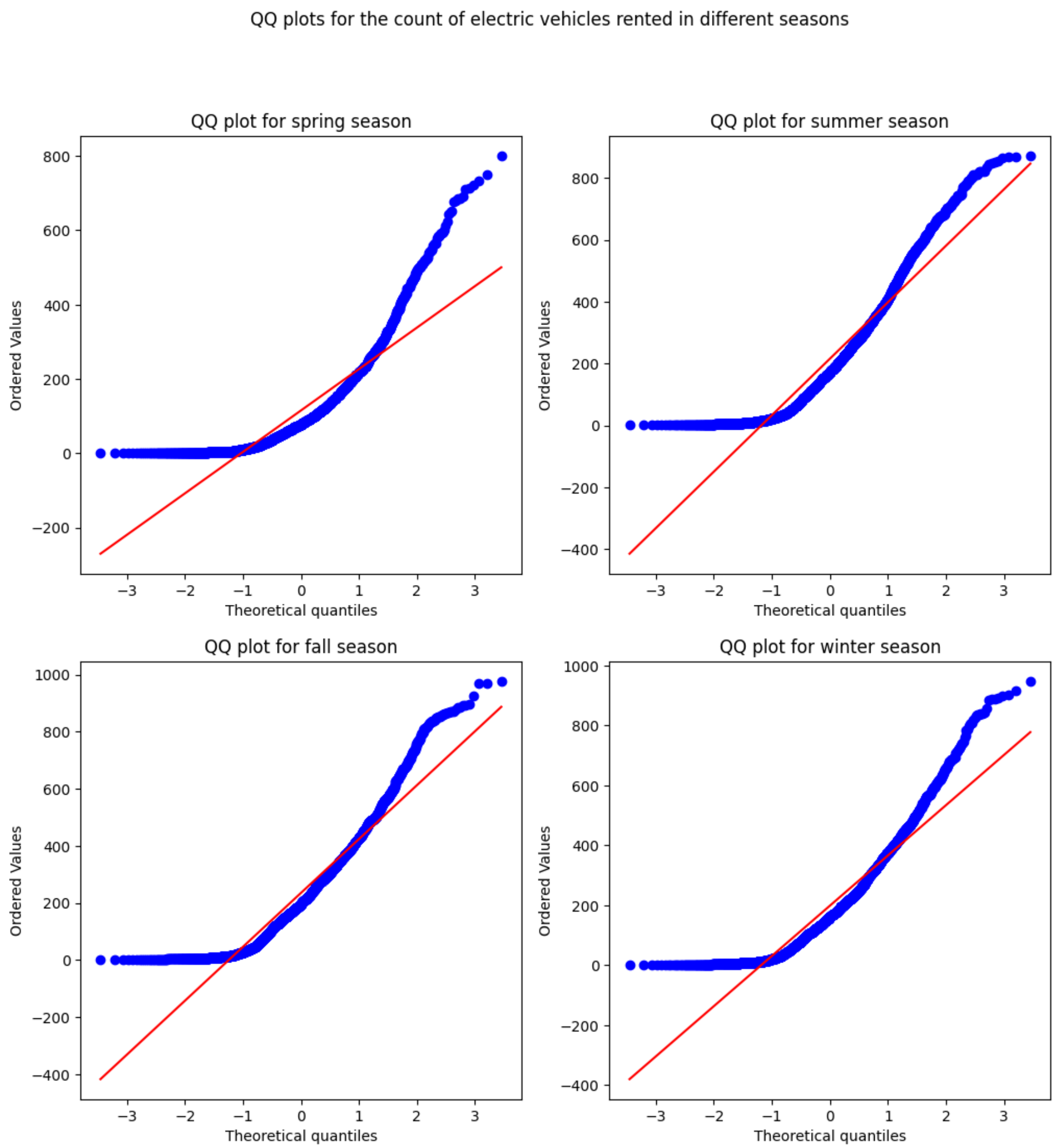
- It can be inferred from the above plot that the distributions do not follow normal distribution.

Distribution check using QQ Plot

[221]:
```
import matplotlib.pyplot as plt
import scipy.stats as stats

# Assuming df_season_spring, df_season_summer, df_season_fall, and␣
↪df_season_winter are already defined
plt.figure(figsize=(12, 12))
plt.suptitle('QQ plots for the count of electric vehicles rented in different␣
↪seasons')

# Sample size should not exceed the length of the DataFrame
print('Sample size for spring season:', len(df_season_1))
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 spring season')

# Similarly, sample sizes for other seasons
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 summer season')

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 fall season')

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 winter season')

plt.show()
```

```
Sample size for spring season: 2686
```



- 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

H_0 : The sample **follows normal distribution** H_1 : The sample **does not follow normal distribution**

alpha = 0.05

Test Statistics : **Shapiro-Wilk test for normality**

[222]:
```
test_stat, p_value = stats.shapiro(df_season_1.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 5.797246274861404e-48
The sample does not follow normal distribution
```

[223]:
```
test_stat, p_value = stats.shapiro(df_season_2.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 1.5179007125046372e-37
The sample does not follow normal distribution
```

[224]:
```
test_stat, p_value = stats.shapiro(df_season_3.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 1.4190528593344954e-35
The sample does not follow normal distribution
```

[225]:
```
test_stat, p_value = stats.shapiro(df_season_4.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 4.492385395963885e-38
The sample does not follow normal distribution
```

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

[226]:
```
transformed_df_season_spring = stats.boxcox(df_season_1.sample(2500))[0]
test_stat, p_value = stats.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 5.867618289946908e-17
The sample does not follow normal distribution
```

[227]:
```
transformed_df_season_summer = stats.boxcox(df_season_2.sample(2500))[0]
test_stat, p_value = stats.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 3.010313848274155e-21
The sample does not follow normal distribution
```

[228]:
```
transformed_df_season_fall = stats.boxcox(df_season_3.sample(2500))[0]
test_stat, p_value = stats.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 1.4249843059425422e-21
The sample does not follow normal distribution
```

[229]:
```
transformed_df_season_winter = stats.boxcox(df_season_4.sample(2500))[0]
test_stat, p_value = stats.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 2.7037822415314507e-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

[230]:
```python
# Null Hypothesis(HO) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = stats.levene(df_season_1.sample(2500),
                                df_season_2.sample(2500),
                                df_season_3.sample(2500),
                                df_season_4.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 5.158782305864923e-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.

[231]:
```python
# 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 = stats.kruskal(df_season_1, df_season_2,␣
 ↪df_season_3,df_season_4)
print('Test Statistic =', test_stat)
print('p value =', p_value)
```

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

Comparing p value with significance level

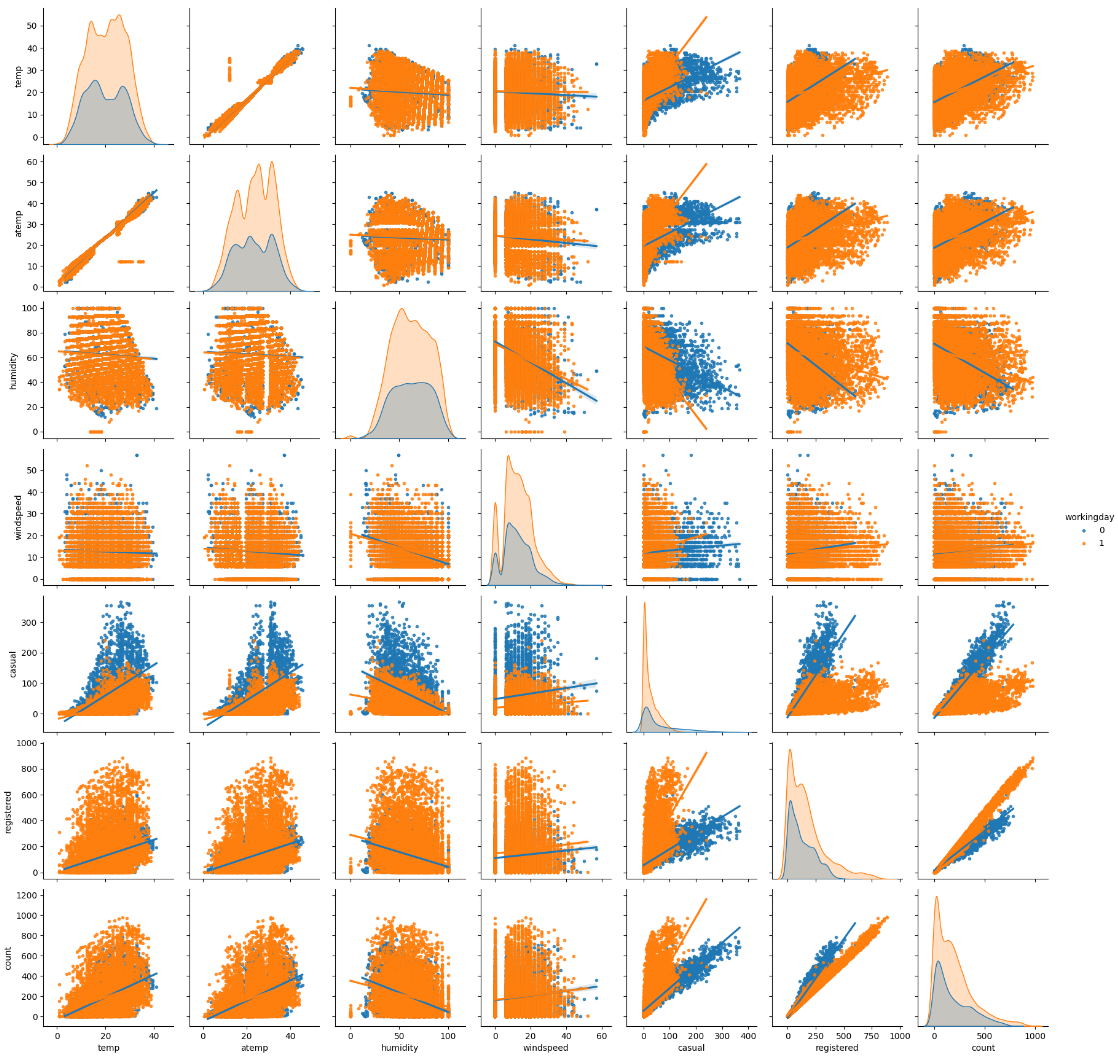
[232]:
```python
if p_value < alpha:
    print('Reject Null Hypothesis')
else:
    print('Failed to reject Null Hypothesis')
```

```
Reject Null Hypothesis
```

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

[233]:
```
sns.pairplot(data = df,
             kind = 'reg',
             hue = 'workingday',
             markers = '.')
plt.plot()
```

[233]: []



[238]:
```
new_df = df[['temp', 'atemp', 'humidity', 'windspeed', 'count']]
corr_data = new_df.corr()
corr_data
```

[238]:

```
                temp     atemp  humidity  windspeed     count
temp        1.000000  0.984948 -0.064949  -0.017852  0.394454
atemp       0.984948  1.000000 -0.043536  -0.057473  0.389784
humidity   -0.064949 -0.043536  1.000000  -0.318607 -0.317371
windspeed  -0.017852 -0.057473 -0.318607   1.000000  0.101369
count       0.394454  0.389784 -0.317371   0.101369  1.000000
```

[239]:

```python
plt.figure(figsize = (12, 8))
sns.heatmap(data = corr_data, cmap = 'Greens', annot = True, vmin = -1, vmax =
 ↪1)
plt.plot()
```

[239]: []

- Very High Correlation (> 0.9) exists between columns [atemp, temp] and [count, registered]
- High positively / negatively correlation (0.7 - 0.9) does not exist between any columns.
- Moderate positive correlation (0.5 - 0.7) exists between columns [casual, count], [casual, registered].
- Low Positive correlation (0.3 - 0.5) exists between columns [count, temp], [count, atemp], [casual, atemp]
- Negligible correlation exists between all other combinations of columns.

0.0.6 Insights

- The data is given from Timestamp('2011-01-01 00:00:00') to Timestamp('2012-12-19 23:00:00'). The total time period for which the data is given is '718 days 23:00:00'.
- Out of every 100 users, around 19 are casual users and 81 are registered users.
- The mean total hourly count of rental bikes is 144 for the year 2011 and 239 for the year 2012. An annual growth rate of 65.41 % can be seen in the demand of electric vehicles on an hourly basis.
- There is a seasonal pattern in the count of rental bikes, with higher demand during the spring and summer months, a slight decline in the fall, and a further decrease in the winter months.
- The average hourly count of rental bikes is the lowest in the month of January followed by February and March.
- There is a distinct fluctuation in count throughout the day, with low counts during early morning hours, a sudden increase in the morning, a peak count in the afternoon, and a gradual decline in the evening and nighttime.
- More than 80 % of the time, the temperature is less than 28 degrees celcius.
- More than 80 % of the time, the humidity value is greater than 40. Thus for most of the time, humidity level varies from optimum to too moist.
- More than 85 % of the total, windspeed data has a value of less than 20.
- The hourly count of total rental bikes is the highest in the clear and cloudy weather, followed by the misty weather and rainy weather. There are very few records for extreme weather conditions.
- The mean hourly count of the total rental bikes is statistically similar for both working and non- working days.
- There is statistically significant dependency of weather and season based on the hourly total number of bikes rented.
- The hourly total number of rental bikes is statistically different for different weathers.
- There is no statistically significant dependency of weather 1, 2, 3 on season based on the average hourly total number of bikes rented.
- The hourly total number of rental bikes is statistically different for different seasons.

0.0.7 Recommendations

- **Seasonal Marketing**: Since there is a clear seasonal pattern in the count of rental bikes, Yulu can adjust its marketing strategies accordingly. Focus on promoting bike rentals during the spring and summer months when there is higher demand. Offer seasonal discounts or special packages to attract more customers during these periods.

- **Time-based Pricing**: Take advantage of the hourly fluctuation in bike rental counts throughout the day. Consider implementing time-based pricing where rental rates are lower during off-peak hours and higher during peak hours. This can encourage customers to rent bikes during less busy times, balancing out the demand and optimizing the resources.

- **Weather-based Promotions**: Recognize the impact of weather on bike rentals. Create weather-based promotions that target customers during clear and cloudy weather, as these conditions show the highest rental counts. Yulu can offer weather-specific discounts to attract more customers during these favorable weather conditions.

- **User Segmentation**: Given that around 81% of users are registered, and the remaining 19% are casual, Yulu can tailor its marketing and communication strategies accordingly. Provide loyalty programs, exclusive offers, or personalized recommendations for registered users to encourage repeat business. For casual users, focus on providing a seamless rental experience and promoting the benefits of bike rentals for occasional use.

- **Optimize Inventory**: Analyze the demand patterns during different months and adjust the inventory accordingly. During months with lower rental counts such as January, February, and March, Yulu can optimize its inventory levels to avoid excess bikes. On the other hand, during peak months, ensure having sufficient bikes available to meet the higher demand.
- **Improve Weather Data Collection**: Given the lack of records for extreme weather conditions, consider improving the data collection process for such scenarios. Having more data on extreme weather conditions can help to understand customer behavior and adjust the operations accordingly, such as offering specialized bike models for different weather conditions or implementing safety measures during extreme weather.
- **Customer Comfort**: Since humidity levels are generally high and temperature is often below 28 degrees Celsius, consider providing amenities like umbrellas, rain jackets, or water bottles to enhance the comfort and convenience of the customers. These small touches can contribute to a positive customer experience and encourage repeat business.
- **Collaborations with Weather Services**: Consider collaborating with weather services to provide real-time weather updates and forecasts to potential customers. Incorporate weather information into your marketing campaigns or rental app to showcase the ideal biking conditions and attract users who prefer certain weather conditions.
- **Seasonal Bike Maintenance**: Allocate resources for seasonal bike maintenance. Before the peak seasons, conduct thorough maintenance checks on the bike fleet to ensure they are in top condition. Regularly inspect and service bikes throughout the year to prevent breakdowns and maximize customer satisfaction.
- **Customer Feedback and Reviews**: Encourage customers to provide feedback and reviews on their biking experience. Collecting feedback can help identify areas for improvement, understand customer preferences, and tailor the services to better meet customer expectations.
- **Social Media Marketing**: Leverage social media platforms to promote the electric bike rental services. Share captivating visuals of biking experiences in different weather conditions, highlight customer testimonials, and engage with potential customers through interactive posts and contests. Utilize targeted advertising campaigns to reach specific customer segments and drive more bookings.
- **Special Occasion Discounts**: Since Yulu focusses on providing a sustainable solution for vehicular pollution, it should give special discounts on the occassions like Zero Emissions Day (21st September), Earth day (22nd April), World Environment Day (5th June) etc in order to attract new users.