In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
import scipy.stats as spy
```

Reading the Dataset

In [2]:
```
df = pd.read_csv("C:\\Users\\Dell\\Downloads\\bike_sharing.csv")
df.head()
```

Out[2]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	27
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	10
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0	1

In [3]:
```
df.shape
```

Out[3]: (10886, 12)

In [4]:
```
# Finding any null values in the dataset
np.any(df.isna())
```

Out[4]: False

In [5]:
```
# Finding any duplicated value in the dataset
np.any(df.duplicated())
```

Out[5]: False

In [6]:
```
# Data ype of the columns
df.dtypes
```

Out[6]:
```
datetime       object
season          int64
holiday         int64
workingday      int64
weather         int64
temp          float64
atemp         float64
humidity        int64
windspeed     float64
casual          int64
registered      int64
count           int64
dtype: object
```

Converting the datatype of datetime column from object to datetime

In [7]:
```
df['datetime'] = pd.to_datetime(df['datetime'])
```

In [8]:
```
df['datetime'].min()
```

Out[8]:
```
Timestamp('2011-01-01 00:00:00')
```

In [9]:
```
df['datetime'].max()
```

Out[9]:
```
Timestamp('2012-12-19 23:00:00')
```

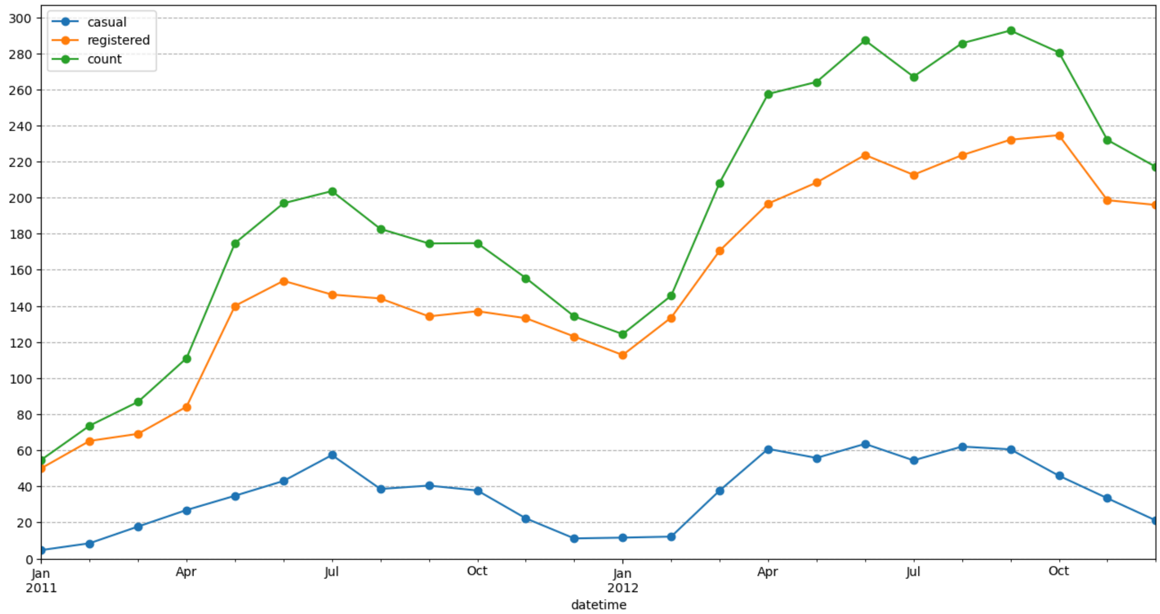
In [10]:
```
df['datetime'].max() - df['datetime'].min()
```

Out[10]:
```
Timedelta('718 days 23:00:00')
```

In [11]:
```
df['day'] = df['datetime'].dt.day_name()
```

In [12]:
```
# setting the 'datetime' column as the index of the DataFrame 'df'
df.set_index('datetime', inplace = True)

# By setting the 'datetime' column as the index, it allows for easier and more efficien
    # filtering, and manipulation of the data based on the datetime values.
# It enables operations such as resampling, slicing by specific time periods, and
    # applying time-based calculations.
```

In [13]:
```
# The below code visualizes the trend of the monthly average values for the 'casual', 'r
    # and 'count' variables, allowing for easy comparison and analysis of their pattern

plt.figure(figsize = (16, 8))

# plotting a lineplot by resampling the data on a monthly basis, and calculating the mea
    # of 'casual', 'registered' and 'count' users for each month
df.resample('M')['casual'].mean().plot(kind = 'line', legend = 'casual', marker = 'o')
df.resample('M')['registered'].mean().plot(kind = 'line', legend = 'registered', marker
df.resample('M')['count'].mean().plot(kind = 'line', legend = 'count', marker = 'o')

plt.grid(axis = 'y', linestyle = '--')    # adding gridlines only along the y-axis
plt.yticks(np.arange(0, 301, 20))
plt.ylim(0,)    # setting the lower y-axis limit to 0
plt.show()      # displaying the plot
```



If there is an increase in the average hourly count of rental bikes from the year 2011 to 2012

In [14]:
```
# resampling the DataFrame by the year
df1 = df.resample('Y')['count'].mean().to_frame().reset_index()

# Create a new column 'prev_count' by shifting the 'count' column one position up
    # to compare the previous year's count with the current year's count
df1['prev_count'] = df1['count'].shift(1)

# Calculating the growth percentage of 'count' with respect to the 'count' of previous y
df1['growth_percent'] = (df1['count'] - df1['prev_count']) * 100 / df1['prev_count']
df1
```

Out[14]:

	datetime	count	prev_count	growth_percent
0	2011-12-31	144.223349	NaN	NaN
1	2012-12-31	238.560944	144.223349	65.410764

- This data suggests that there was substantial growth in the count of the variable over the course of one year.
- 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.

It indicates positive growth and potentially a successful outcome or increasing demand for the variable being measured.

In [15]:
```
df.reset_index(inplace = True)
```

How does the average hourly count of rental bikes varies for different month

In [16]:
```
# Grouping the DataFrame by the month
df1 = df.groupby(by = df['datetime'].dt.month)['count'].mean().reset_index()
df1.rename(columns = {'datetime' : 'month'}, inplace = True)

# Create a new column 'prev_count' by shifting the 'count' column one position up
    # to compare the previous month's count with the current month's count
df1['prev_count'] = df1['count'].shift(1)

# Calculating the growth percentage of 'count' with respect to the 'count' of previous r
df1['growth_percent'] = (df1['count'] - df1['prev_count']) * 100 / df1['prev_count']
df1.set_index('month', inplace = True)
df1
```

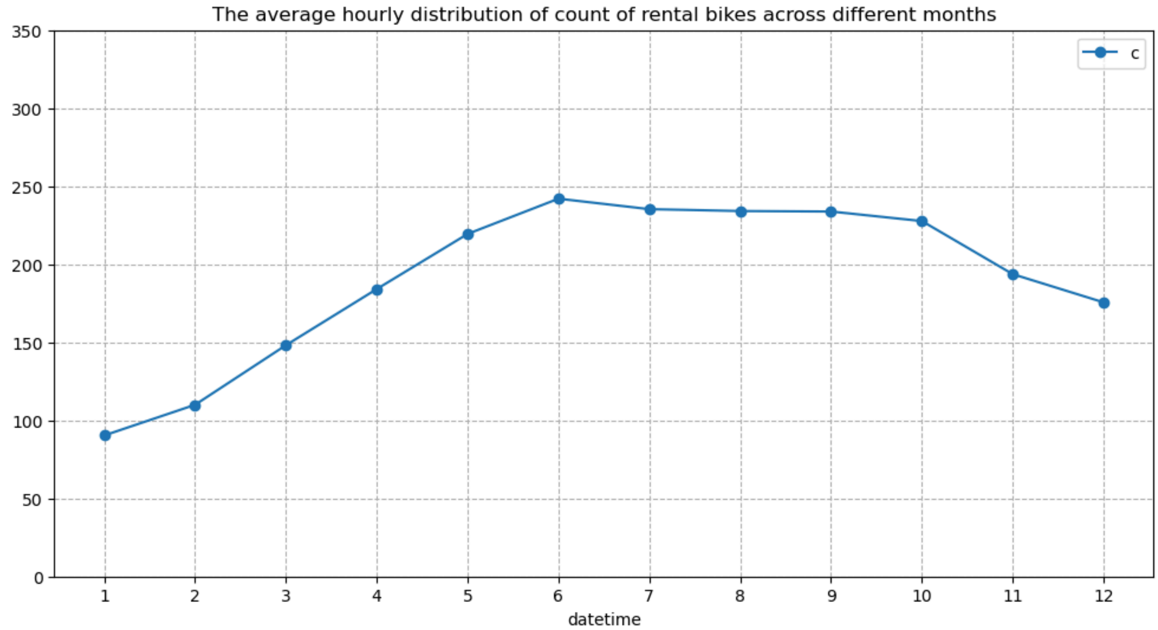
Out[16]:

month	count	prev_count	growth_percent
1	90.366516	NaN	NaN
2	110.003330	90.366516	21.730188
3	148.169811	110.003330	34.695751
4	184.160616	148.169811	24.290241
5	219.459430	184.160616	19.167406
6	242.031798	219.459430	10.285440
7	235.325658	242.031798	-2.770768
8	234.118421	235.325658	-0.513007
9	233.805281	234.118421	-0.133753
10	227.699232	233.805281	-2.611596
11	193.677278	227.699232	-14.941620
12	175.614035	193.677278	-9.326465

- The count of rental bikes shows an increasing trend from January to March, with a significant growth rate of 34.70% between February and March.
- The growth rate starts to stabilize from April to June, with a relatively smaller growth rate.
- From July to September, there is a slight decrease in the count of rental bikes, with negative growth rates.
- The count further declines from October to December, with the largest drop observed between October and November (-14.94%).

In [17]:
```
# The resulting plot visualizes the average hourly distribution of the count of rental l
    # month, allowing for comparison and identification of any patterns or trends throu

# Setting the figure size for the plot
plt.figure(figsize = (12, 6))

# Setting the title for the plot
plt.title("The average hourly distribution of count of rental bikes across different mo

# Grouping the DataFrame by the month and calculating the mean of the 'count' column fo
    # Ploting the line graph using markers ('o') to represent the average count per mon
df.groupby(by = df['datetime'].dt.month)['count'].mean().plot(kind = 'line', marker = '

plt.ylim(0,)    # Setting the y-axis limits to start from zero
plt.xticks(np.arange(1, 13))   # Setting the x-ticks to represent the months from 1 to 
plt.legend('count')    # Adding a legend to the plot for the 'count' line.
plt.yticks(np.arange(0, 400, 50))
# Adding gridlines to both the x and y axes with a dashed line style
plt.grid(axis = 'both', linestyle = '--')
plt.plot()
```

Out[17]: []



- The average hourly count of rental bikes is the highest in the month of June followed by July and August.
- The average hourly count of rental bikes is the lowest in the month of January followed by February and March.

Overall, these trends suggest 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. It could be useful for the rental bike company to consider these patterns for resource allocation, marketing strategies, and operational planning throughout the year.

What is the distribution of average count of rental bikes on an hourly basis in a single day ?

In [18]:

```
# Grouping the DataFrame by the hour
df1 = df.groupby(by = df['datetime'].dt.hour)['count'].mean().reset_index()
df1.rename(columns = {'datetime' : 'hour'}, inplace = True)

# Create a new column 'prev_count' by shifting the 'count' column one position up
    # to compare the previous hour's count with the current hour's count
df1['prev_count'] = df1['count'].shift(1)

# Calculating the growth percentage of 'count' with respect to the 'count' of previous h
df1['growth_percent'] = (df1['count'] - df1['prev_count']) * 100 / df1['prev_count']
df1.set_index('hour', inplace = True)
df1
```

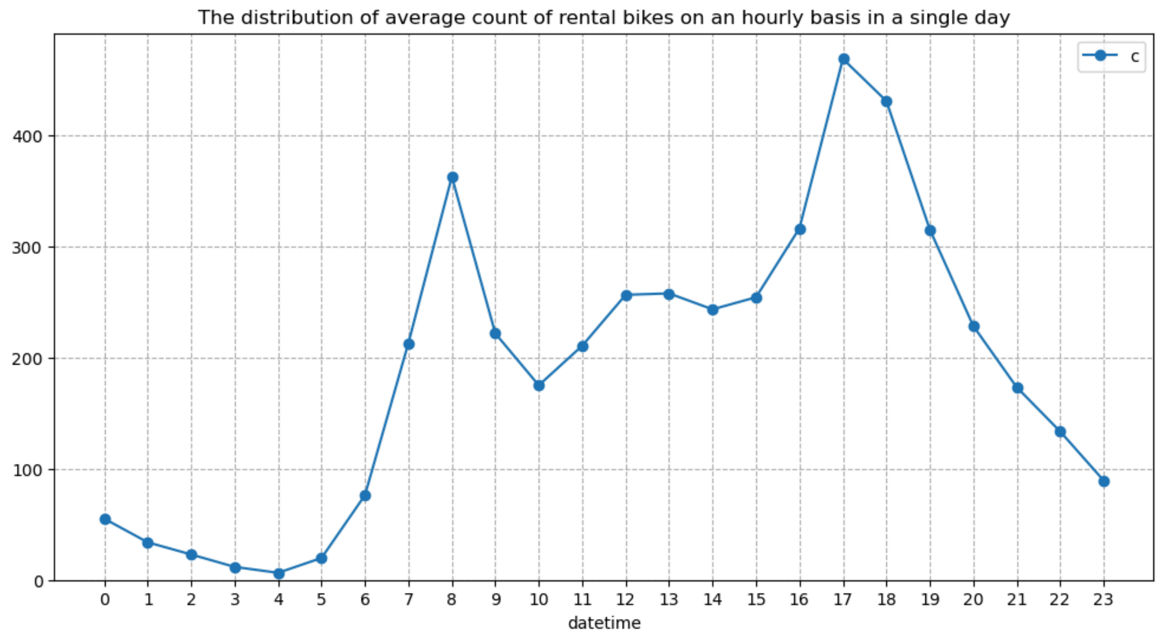
Out[18]:

hour	count	prev_count	growth_percent
0	55.138462	NaN	NaN
1	33.859031	55.138462	-38.592718
2	22.899554	33.859031	-32.367959
3	11.757506	22.899554	-48.656179
4	6.407240	11.757506	-45.505110
5	19.767699	6.407240	208.521293
6	76.259341	19.767699	285.777526
7	213.116484	76.259341	179.462793
8	362.769231	213.116484	70.221104
9	221.780220	362.769231	-38.864655
10	175.092308	221.780220	-21.051432
11	210.674725	175.092308	20.322091
12	256.508772	210.674725	21.755835
13	257.787281	256.508772	0.498427
14	243.442982	257.787281	-5.564393
15	254.298246	243.442982	4.459058
16	316.372807	254.298246	24.410141
17	468.765351	316.372807	48.168661
18	430.859649	468.765351	-8.086285
19	315.278509	430.859649	-26.825705
20	228.517544	315.278509	-27.518833
21	173.370614	228.517544	-24.132471
22	133.576754	173.370614	-22.953059
23	89.508772	133.576754	-32.990757

- During the early morning hours (hours 0 to 5), there is a significant decrease in the count, with negative growth percentages ranging from -38.59% to -48.66%.
- However, starting from hour 5, there is a sudden increase in count, with a sharp positive growth percentage of 208.52% observed from hour 4 to hour 5.
- The count continues to rise significantly until reaching its peak at hour 17, with a growth percentage of 48.17% compared to the previous hour.
- After hour 17, there is a gradual decrease in count, with negative growth percentages ranging from -8.08% to -32.99% during the late evening and nighttime hours.

In [19]:
```
plt.figure(figsize = (12, 6))
plt.title("The distribution of average count of rental bikes on an hourly basis in a si
df.groupby(by = df['datetime'].dt.hour)['count'].mean().plot(kind = 'line', marker = 'o
plt.ylim(0,)
plt.xticks(np.arange(0, 24))
plt.legend('count')
plt.grid(axis = 'both', linestyle = '--')
plt.plot()
```

Out[19]: []



- The average count of rental bikes is the highest at 5 PM followed by 6 PM and 8 AM of the day.
- The average count of rental bikes is the lowest at 4 AM followed by 3 AM and 5 AM of the day.

These patterns indicate that 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.

In [20]:
```
# Basic info about the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 13 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   datetime    10886 non-null  datetime64[ns]
 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
 12  day         10886 non-null  object
dtypes: datetime64[ns](1), float64(3), int64(8), object(1)
memory usage: 1.1+ MB
```

In [21]:

```
# 1: spring, 2: summer, 3: fall, 4: winter
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)
```

Optimizing Memory Usage of the Dataframe

Updating dtype of season column

In [22]:

```
print('Memory usage of season column : ', df['season'].memory_usage())
# Since the dtype of season column is object, we can convert the dtype to category to s
df['season'] = df['season'].astype('category')
print('Updated Memory usage of season column : ', df['season'].memory_usage())
```

```
Memory usage of season column :  87220
Updated Memory usage of season column :  11222
```

Updating dtype of holiday column

In [23]:

```
print('Max value entry in holiday column : ', df['holiday'].max())
print('Memory usage of holiday column : ', df['holiday'].memory_usage())
# Since the maximum entry in holiday column is 1 and the dtype is int64, we can convert
df['holiday'] = df['holiday'].astype('category')
print('Updated Memory usage of holiday column : ', df['holiday'].memory_usage())
```

```
Max value entry in holiday column :  1
Memory usage of holiday column :  87220
Updated Memory usage of holiday column :  11142
```

Updating dtype of workingday column

In [24]:

```
print('Max value entry in workingday column : ', df['workingday'].max())
print('Memory usage of workingday column : ', df['workingday'].memory_usage())
# Since the maximum entry in workingday column is 1 and the dtype is int64, we can conve
df['workingday'] = df['workingday'].astype('category')
print('Updated Memory usage of workingday column : ', df['workingday'].memory_usage())
```

```
Max value entry in workingday column :  1
Memory usage of workingday column :  87220
Updated Memory usage of workingday column :  11142
```

Updating dtype of weather column

In [25]:

```
print('Max value entry in weather column : ', df['weather'].max())
print('Memory usage of weather column : ', df['weather'].memory_usage())
# Since the maximum entry in weather column is 4 and the dtype is int64, we can convert
df['weather'] = df['weather'].astype('category')
print('Updated Memory usage of weather column : ', df['weather'].memory_usage())
```

```
Max value entry in weather column :  4
Memory usage of weather column :  87220
Updated Memory usage of weather column :  11222
```

Updating dtype of temp column

In [26]:
```
print('Max value entry in temp column : ', df['temp'].max())
print('Memory usage of temp column : ', df['temp'].memory_usage())
# Since the maximum entry in temp column is 41.0 and the dtype is float64, we can conve
df['temp'] = df['temp'].astype('float32')
print('Updated Memory usage of temp column : ', df['temp'].memory_usage())
```

```
Max value entry in temp column :  41.0
Memory usage of temp column :  87220
Updated Memory usage of temp column :  43676
```

Updating dtype of atemp column

In [27]:
```
print('Max value entry in atemp column : ', df['atemp'].max())
print('Memory usage of atemp column : ', df['atemp'].memory_usage())
# Since the maximum entry in atemp column is 45.455 and the dtype is float64, we can co
df['atemp'] = df['atemp'].astype('float32')
print('Updated Memory usage of atemp column : ', df['atemp'].memory_usage())
```

```
Max value entry in atemp column :  45.455
Memory usage of atemp column :  87220
Updated Memory usage of atemp column :  43676
```

Updating dtype of humidity column

In [28]:
```
print('Max value entry in humidity column : ', df['humidity'].max())
print('Memory usage of humidity column : ', df['temp'].memory_usage())
# Since the maximum entry in humidity column is 100 and the dtype is int64, we can conve
df['humidity'] = df['humidity'].astype('int8')
print('Updated Memory usage of humidity column : ', df['humidity'].memory_usage())
```

```
Max value entry in humidity column :  100
Memory usage of humidity column :  43676
Updated Memory usage of humidity column :  11018
```

Updating dtype of windspeed column

In [29]:
```
print('Max value entry in windspeed column : ', df['windspeed'].max())
print('Memory usage of windspeed column : ', df['windspeed'].memory_usage())
# Since the maximum entry in windspeed column is 56.9969 and the dtype is float64, we c
df['windspeed'] = df['windspeed'].astype('float32')
print('Updated Memory usage of windspeed column : ', df['windspeed'].memory_usage())
```

```
Max value entry in windspeed column :  56.9969
Memory usage of windspeed column :  87220
Updated Memory usage of windspeed column :  43676
```

Updating dtype of casual column

In [30]:
```
print('Max value entry in casual column : ', df['casual'].max())
print('Memory usage of casual column : ', df['casual'].memory_usage())
# Since the maximum entry in casual column is 367 and the dtype is int64, we can conver
df['casual'] = df['casual'].astype('int16')
print('Updated Memory usage of casual column : ', df['casual'].memory_usage())
```

```
Max value entry in casual column :  367
Memory usage of casual column :  87220
Updated Memory usage of casual column :  21904
```

Updating dtype of registered column

In [31]:
```
print('Max value entry in registered column : ', df['registered'].max())
print('Memory usage of registered column : ', df['registered'].memory_usage())
# Since the maximum entry in registered column is 886 and the dtype is int64, we can co
df['registered'] = df['registered'].astype('int16')
print('Updated Memory usage of registered column : ', df['registered'].memory_usage())
```

```
Max value entry in registered column :  886
Memory usage of registered column :  87220
Updated Memory usage of registered column :  21904
```

Updating dtype of count column

In [32]:
```
print('Max value entry in count column : ', df['count'].max())
print('Memory usage of count column : ', df['count'].memory_usage())
# Since the maximum entry in count column is 977 and the dtype is int64, we can convert
df['count'] = df['count'].astype('int16')
print('Updated Memory usage of count column : ', df['count'].memory_usage())
```

```
Max value entry in count column :  977
Memory usage of count column :  87220
Updated Memory usage of count column :  21904
```

In [33]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 13 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  int8
 8   windspeed   10886 non-null  float32
 9   casual      10886 non-null  int16
 10  registered  10886 non-null  int16
 11  count       10886 non-null  int16
 12  day         10886 non-null  object
dtypes: category(4), datetime64[ns](1), float32(3), int16(3), int8(1), object(1)
memory usage: 415.4+ KB
```

Earlier the dataset was using 1.1+ MB of memory but now it has been reduced to 415.2+ KB. Around 63.17 % reduction in the memory usage.

In [34]:
```
# Basic Description of the Dataset
df.describe()
```

Out[34]:

	datetime	temp	atemp	humidity	windspeed	casual	registe
count	10886	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000
mean	2011-12-27 05:56:22.399411968	20.230862	23.655085	61.886460	12.799396	36.021955	155.552
min	2011-01-01 00:00:00	0.820000	0.760000	0.000000	0.000000	0.000000	0.000
25%	2011-07-02 07:15:00	13.940000	16.665001	47.000000	7.001500	4.000000	36.000
50%	2012-01-01 20:30:00	20.500000	24.240000	62.000000	12.998000	17.000000	118.000
75%	2012-07-01 12:45:00	26.240000	31.059999	77.000000	16.997900	49.000000	222.000
max	2012-12-19 23:00:00	41.000000	45.455002	100.000000	56.996899	367.000000	886.000
std	NaN	7.791600	8.474654	19.245033	8.164592	49.960477	151.039

- These statistics provide insights into the central tendency, spread, and range of the numerical features in the dataset.

In [35]:
```
np.round(df['season'].value_counts(normalize = True) * 100, 2)
```

Out[35]:
```
season
winter    25.11
fall      25.11
summer    25.11
spring    24.67
Name: proportion, dtype: float64
```

In [36]:
```
np.round(df['holiday'].value_counts(normalize = True) * 100, 2)
```

Out[36]:
```
holiday
0    97.14
1     2.86
Name: proportion, dtype: float64
```

In [37]:
```
np.round(df['workingday'].value_counts(normalize = True) * 100, 2)
```

Out[37]:
```
workingday
1    68.09
0    31.91
Name: proportion, dtype: float64
```

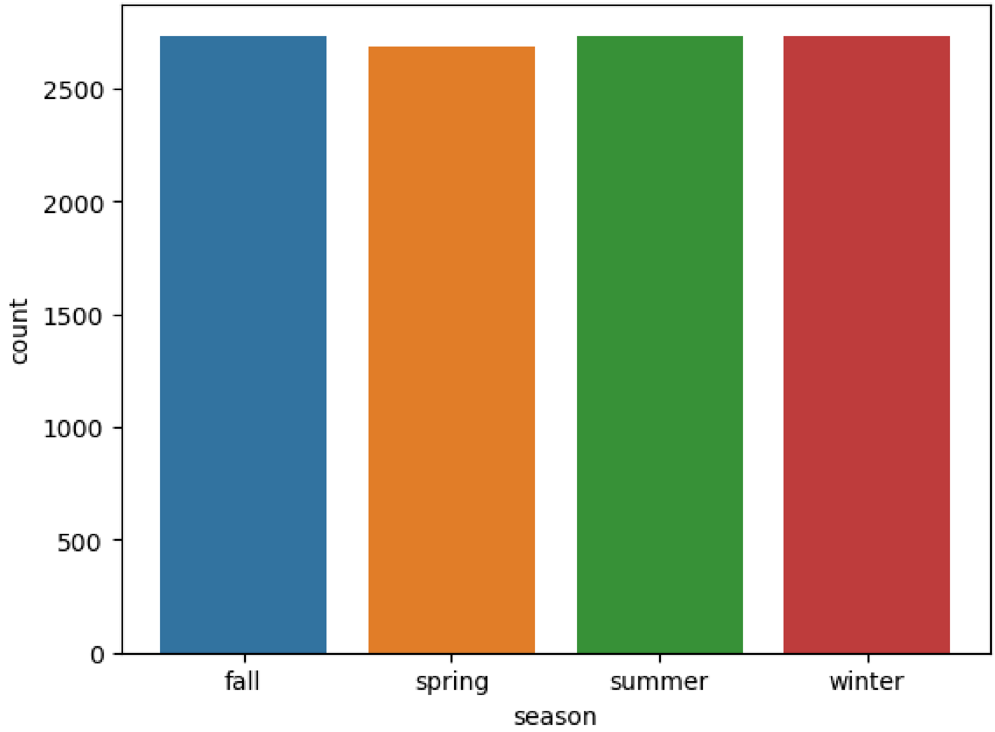
In [38]:
```
np.round(df['weather'].value_counts(normalize = True) * 100, 2)
```

Out[38]:
```
weather
1    66.07
2    26.03
3     7.89
4     0.01
Name: proportion, dtype: float64
```

Univariate Analysis

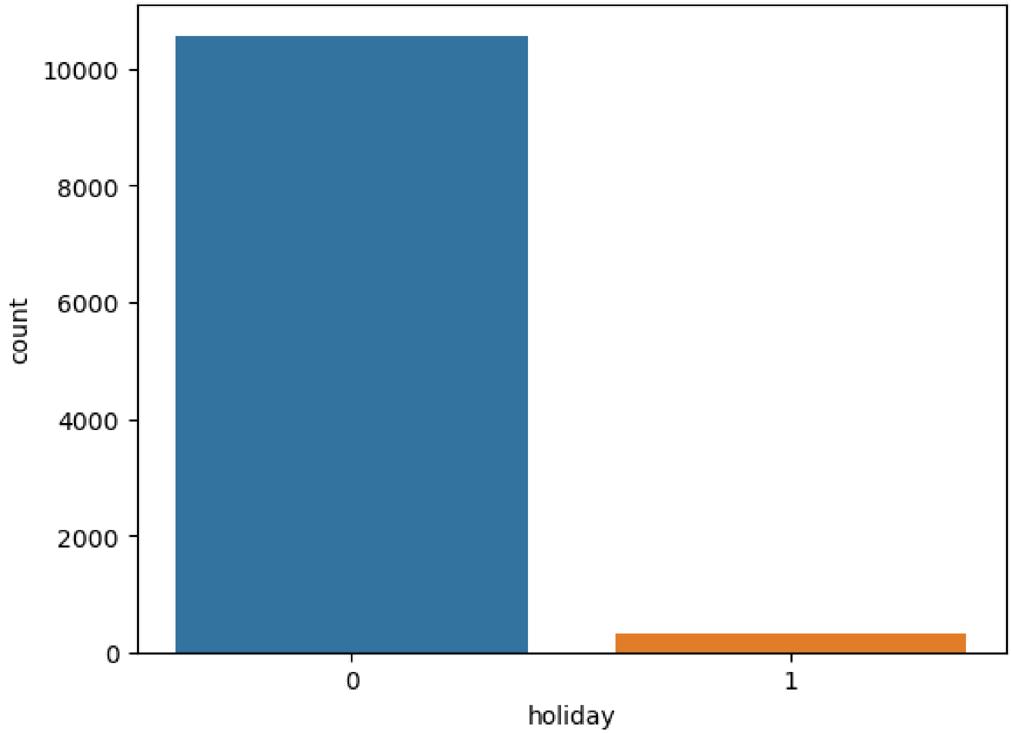
In [39]:
```
sns.countplot(data = df, x = 'season')
plt.plot()
```

Out[39]: []



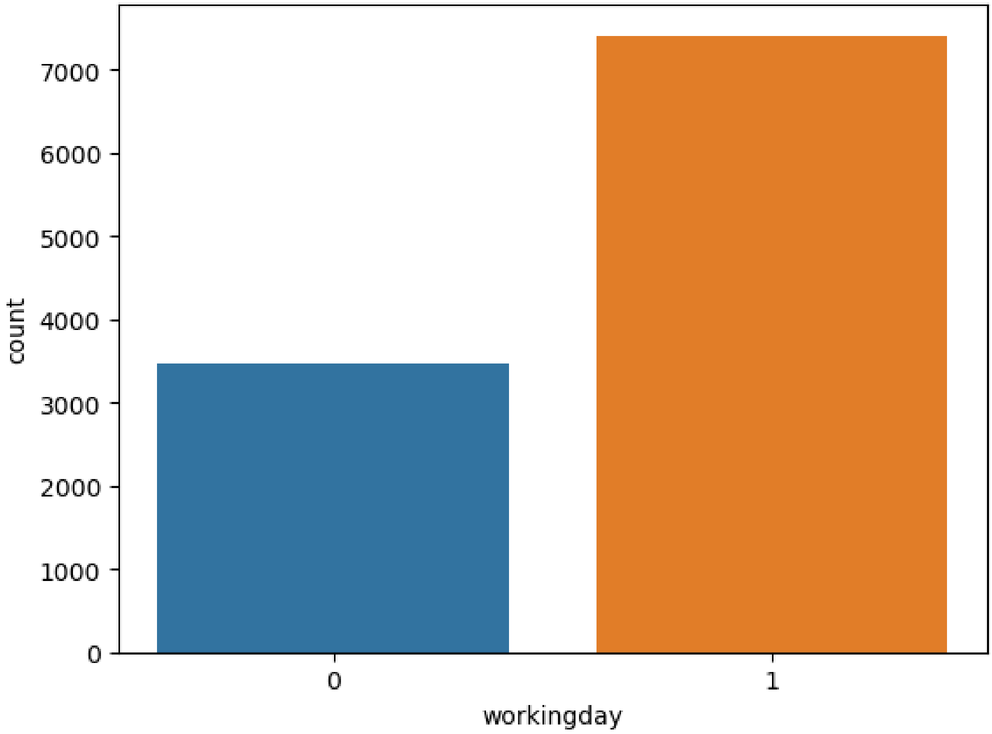
In [40]:
```
sns.countplot(data = df, x = 'holiday')
plt.plot()
```

Out[40]: []



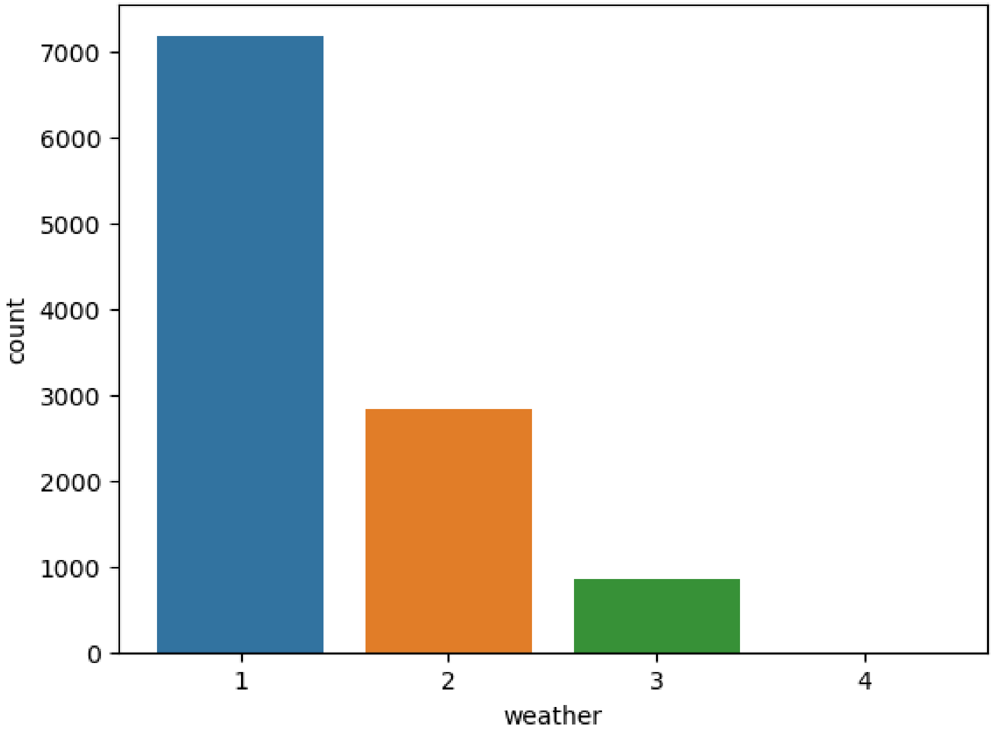
In [41]:
```
sns.countplot(data = df, x = 'workingday')
plt.plot()
```

Out[41]: []



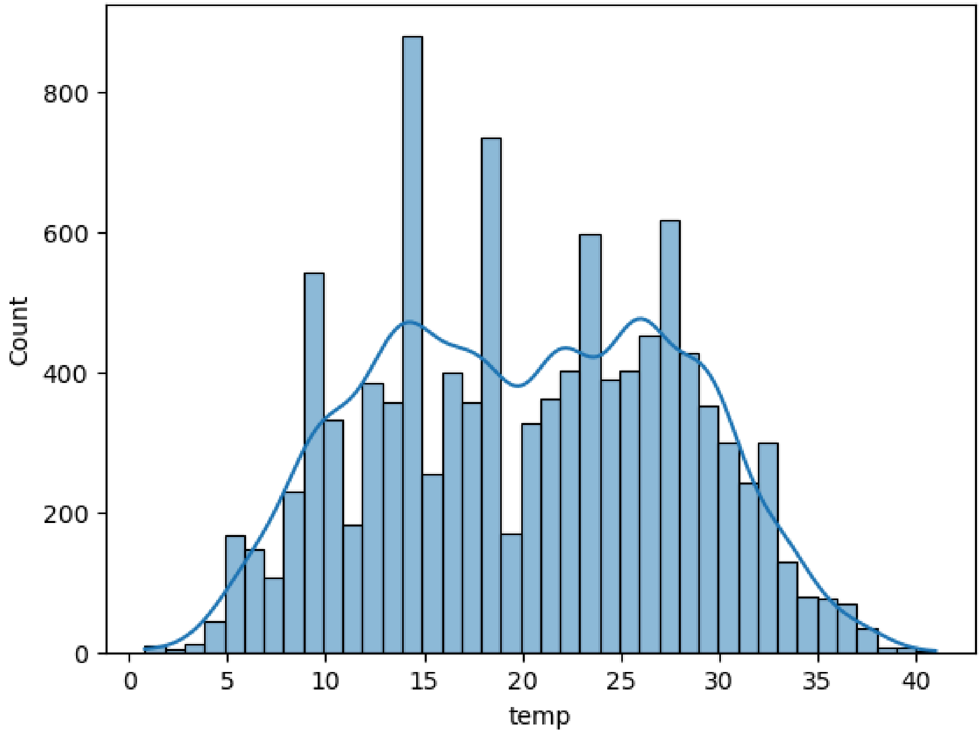
In [42]:
```
sns.countplot(data = df, x = 'weather')
plt.plot()
```

Out[42]: []



In [43]:
```
# The below code generates a histogram plot for the 'temp' feature, showing the distribu
    # temperature values in the dataset.
# The addition of the kernel density estimation plot provides
    # a visual representation of the underlying distribution shape, making it easier to
    # data distribution.

sns.histplot(data = df, x = 'temp', kde = True, bins = 40)
plt.plot()
```

Out[43]: []



In [44]:
```
temp_mean = np.round(df['temp'].mean(), 2)
temp_std = np.round(df['temp'].std(), 2)
temp_mean, temp_std
```

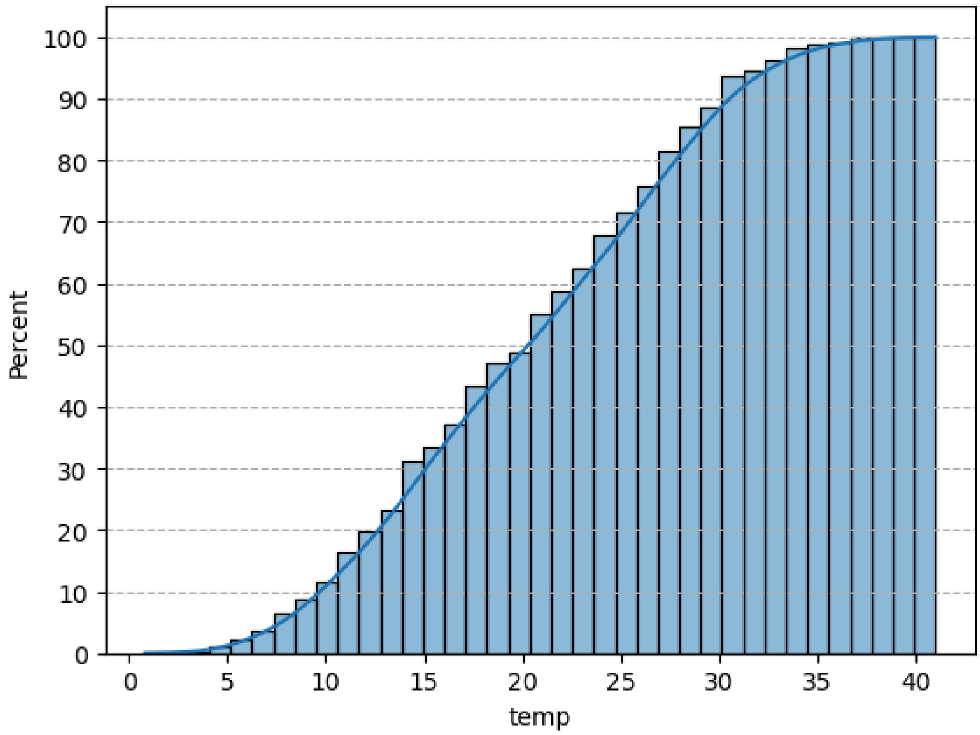
Out[44]: (20.23, 7.79)

- The mean and the standard deviation of the temp column is 20.23 and 7.79 degree celcius respectively.

In [45]:

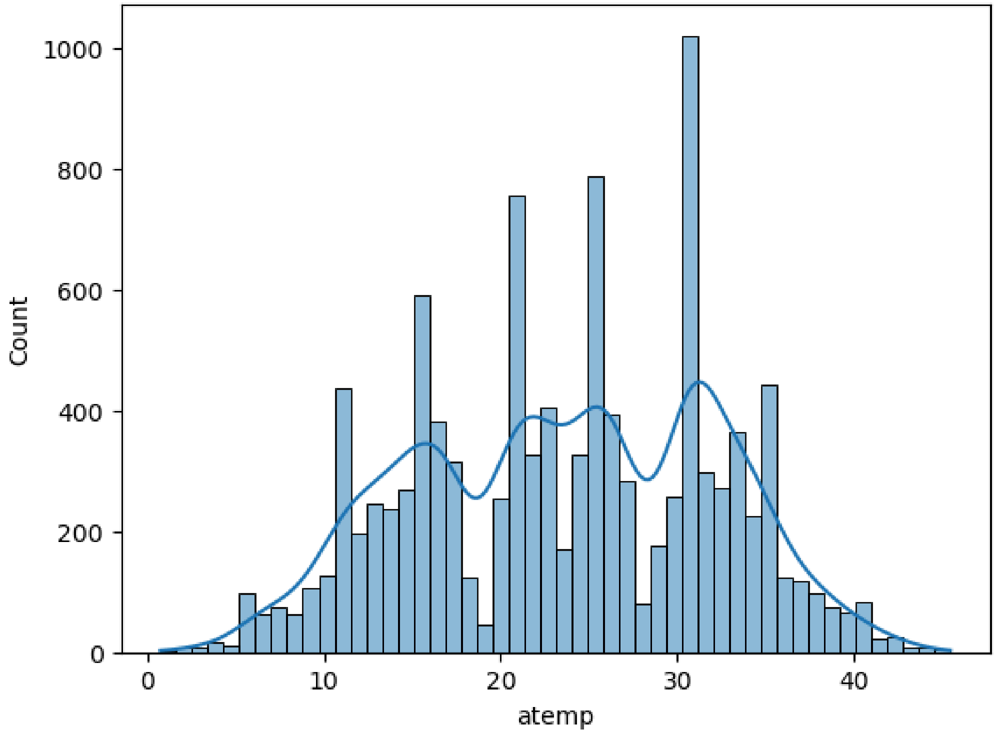
```
# The below code generates a histogram plot for the 'temp' feature, showing the cumulat
    # distribution of temperature values in the dataset.
# The addition of the kernel density estimation plot provides
    # a visual representation of the underlying distribution shape, making it easier to
    # data distribution.

sns.histplot(data = df, x = 'temp', kde = True, cumulative = True, stat = 'percent')
plt.grid(axis = 'y', linestyle = '--')
plt.yticks(np.arange(0, 101, 10))
plt.plot()
```

Out[45]: []



In [46]:
```
# The below code generates a histogram plot for the 'atemp' feature, showing the distril
    # feeling temperature values in the dataset.
# The addition of the kernel density estimation plot provides
    # a visual representation of the underlying distribution shape, making it easier to
    # data distribution.

sns.histplot(data = df, x = 'atemp', kde = True, bins = 50)
plt.plot()
```

Out[46]: []



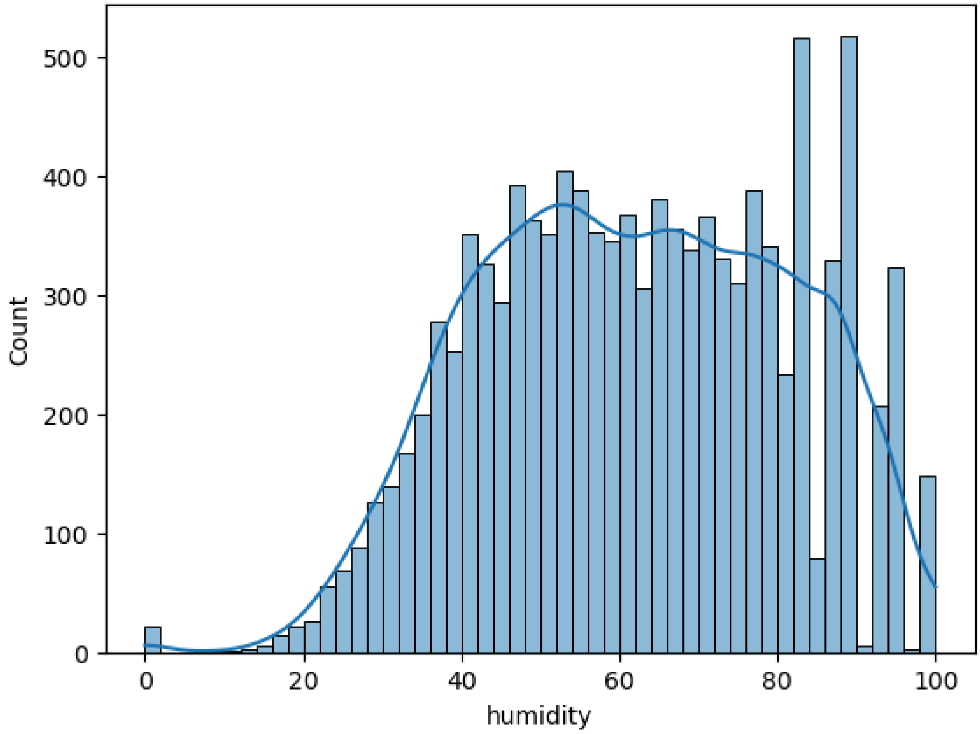
In [47]:
```
temp_mean = np.round(df['atemp'].mean(), 2)
temp_std = np.round(df['atemp'].std(), 2)
temp_mean, temp_std
```

Out[47]: (23.66, 8.47)

- The mean and the standard deviation of the atemp column is 23.66 and 8.47 degree celcius respectively.

In [48]:
```
# The below code generates a histogram plot for the 'humidity' feature, showing the dis
    # humidity values in the dataset.
# The addition of the kernel density estimation plot provides
    # a visual representation of the underlying distribution shape, making it easier to
    # data distribution.

sns.histplot(data = df, x = 'humidity', kde = True, bins = 50)
plt.plot()
```

Out[48]: []



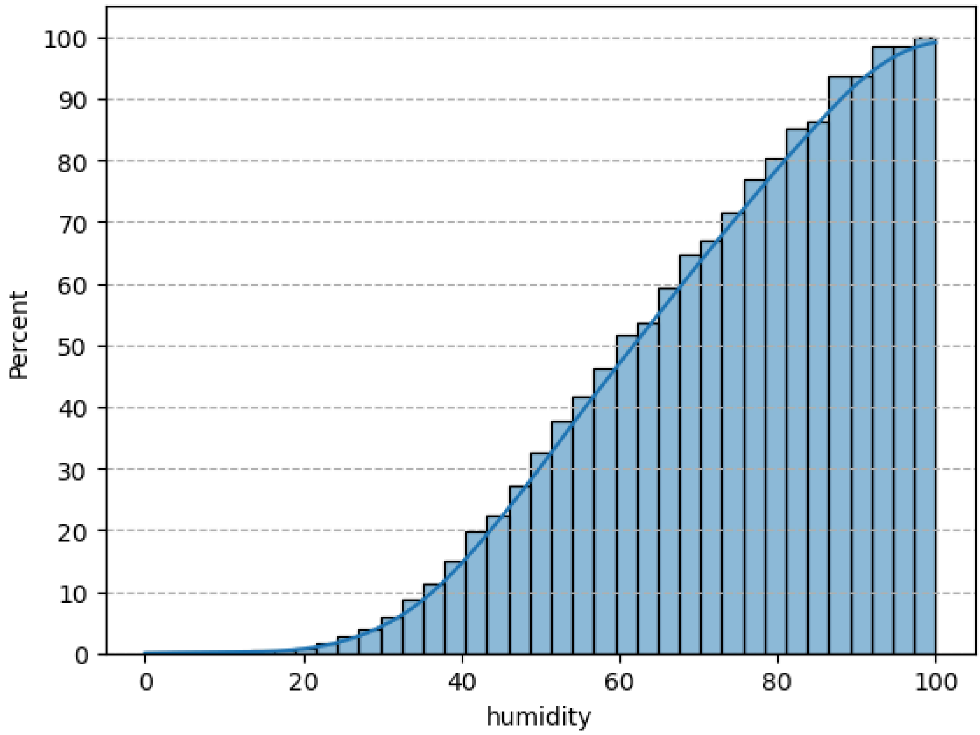
In [49]:
```
humidity_mean = np.round(df['humidity'].mean(), 2)
humidity_std = np.round(df['humidity'].std(), 2)
humidity_mean, humidity_std
```

Out[49]: (61.89, 19.25)

- The mean and the standard deviation of the humidity column is 61.89 and 19.25 respectively.

In [50]:
```
# The below code generates a histogram plot for the 'humidity' feature, showing the cumu
    # distribution of humidity values in the dataset.
# The addition of the kernel density estimation plot provides
    # a visual representation of the underlying distribution shape, making it easier to
    # data distribution.

sns.histplot(data = df, x = 'humidity', kde = True, cumulative = True, stat = 'percent'
plt.grid(axis = 'y', linestyle = '--')    # setting the gridlines along y axis
plt.yticks(np.arange(0, 101, 10))
plt.plot()
```

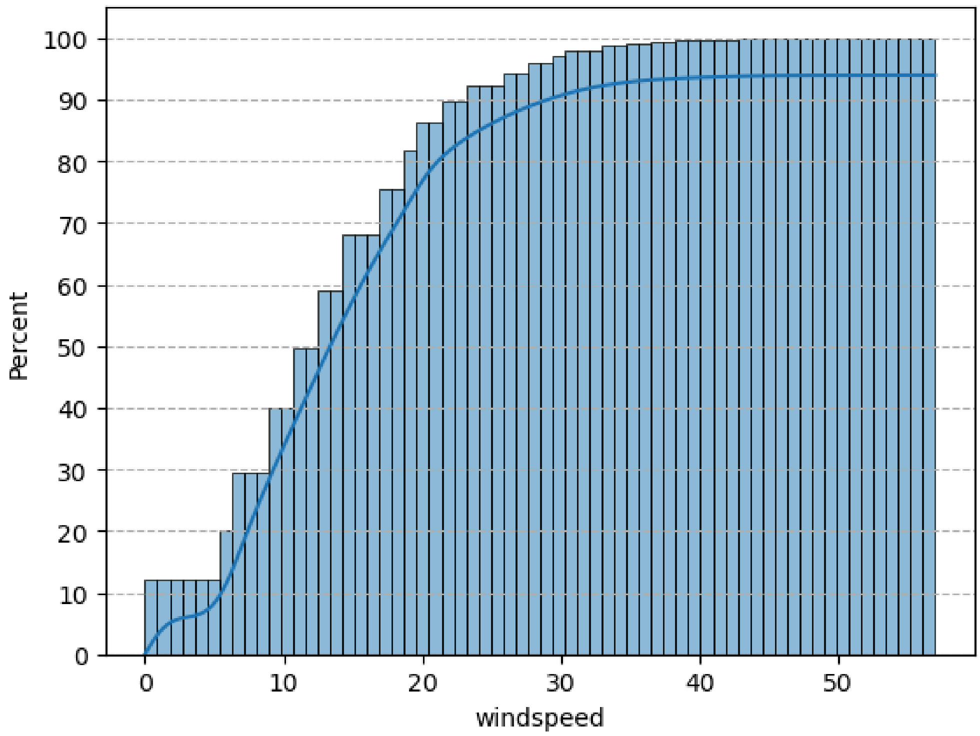
Out[50]: []



- 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.

In [51]:
```
sns.histplot(data = df, x = 'windspeed', kde = True, cumulative = True, stat = 'percent
plt.grid(axis = 'y', linestyle = '--')
plt.yticks(np.arange(0, 101, 10))
plt.plot()
```

Out[51]: []



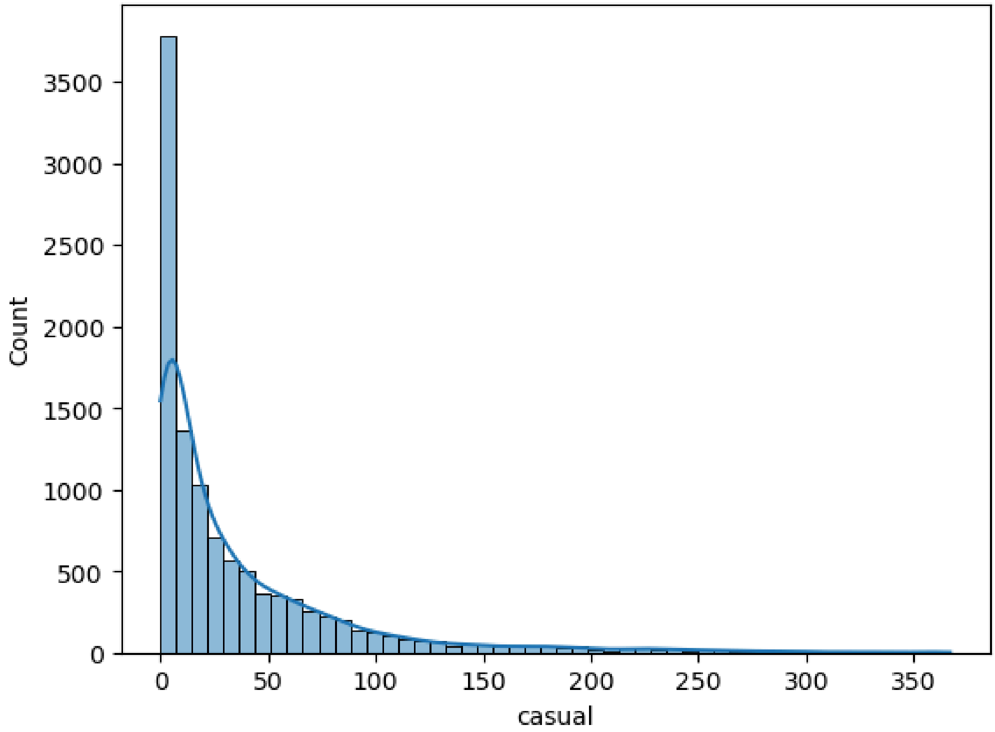
- More than 85 % of the total windspeed data has a value of less than 20.

In [52]:
```
len(df[df['windspeed'] < 20]) / len(df)
```

Out[52]: 0.8626676465184641

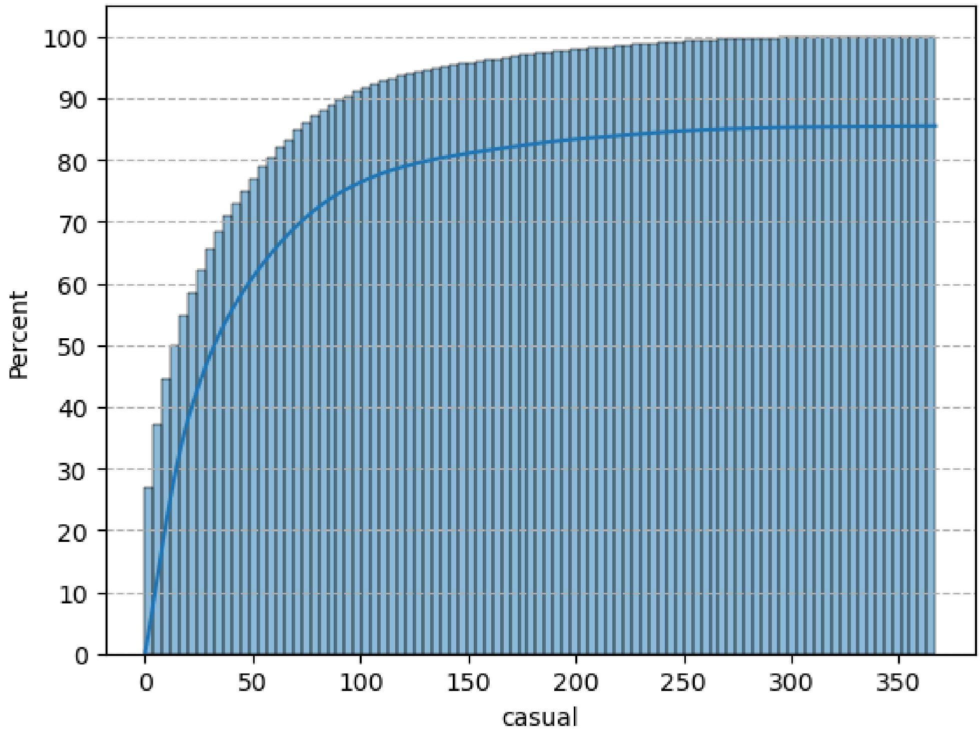
In [53]:
```
# The below code generates a histogram plot for the 'casual' feature, showing the distr
    # casual users' values in the dataset.
# The addition of the kernel density estimation plot provides
    # a visual representation of the underlying distribution shape, making it easier to
    # data distribution.

sns.histplot(data = df, x = 'casual', kde = True, bins = 50)
plt.plot()
```

Out[53]: []



In [54]:
```
sns.histplot(data = df, x = 'casual', kde = True, cumulative = True, stat = 'percent')
plt.grid(axis = 'y', linestyle = '--')
plt.yticks(np.arange(0, 101, 10))
plt.plot()
```

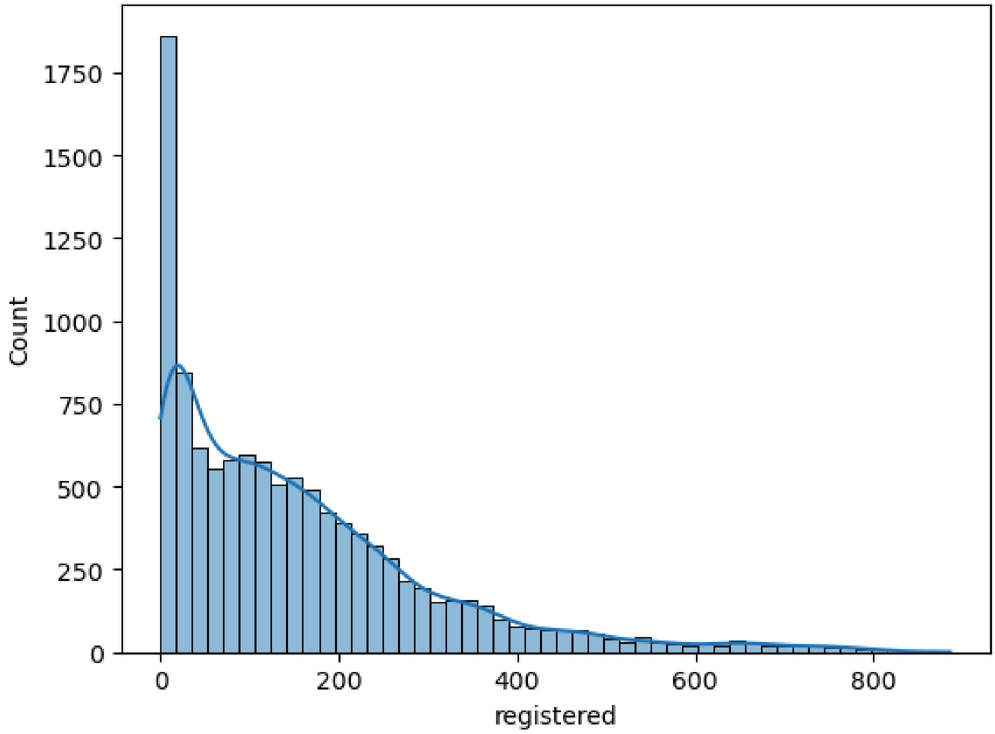
Out[54]: []



- More than 80 % of the time, the count of casual users is less than 60.

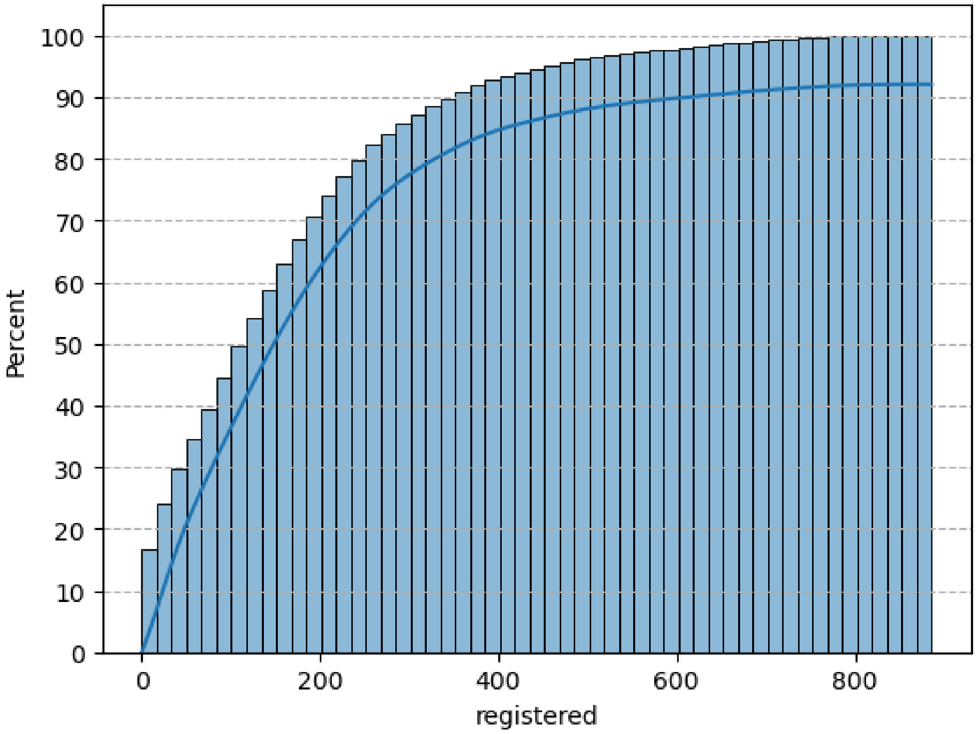
In [55]:
```
# The below code generates a histogram plot for the 'registered' feature, showing the d
    # registered users' values in the dataset.
# The addition of the kernel density estimation plot provides
    # a visual representation of the underlying distribution shape, making it easier to
    # data distribution.

sns.histplot(data = df, x = 'registered', kde = True, bins = 50)
plt.plot()
```

Out[55]: []



In [56]:
```
sns.histplot(data = df, x = 'registered', kde = True, cumulative = True, stat = 'percen
plt.grid(axis = 'y', linestyle = '--')
plt.yticks(np.arange(0, 101, 10))
plt.plot()
```

Out[56]: []

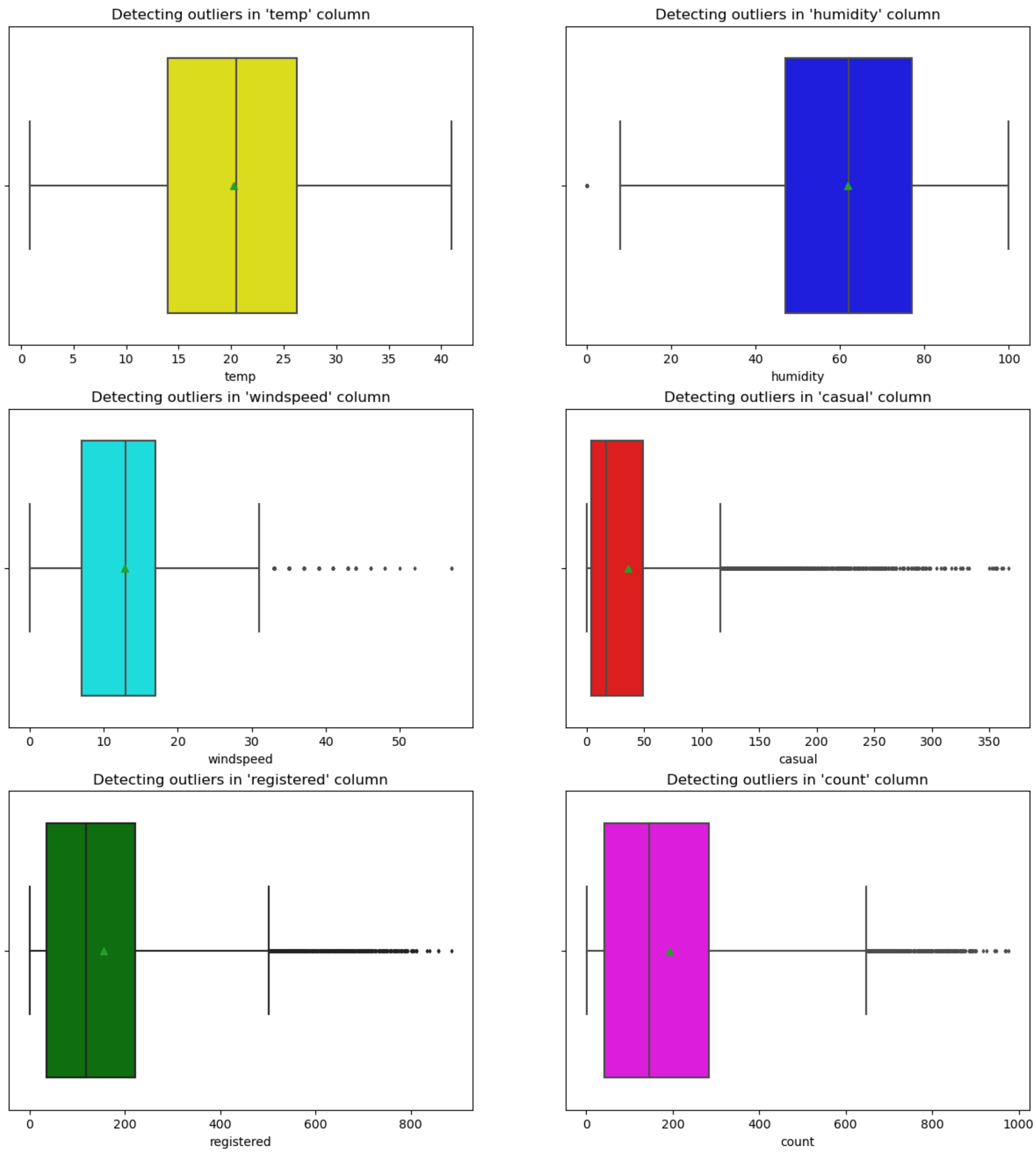


- More than 85 % of the time, the count of registered users is less than 300.

Detection of Outliers

In [57]:

```
columns = ['temp', 'humidity', 'windspeed', 'casual', 'registered', 'count']
colors = np.random.permutation(['red', 'blue', 'green', 'magenta', 'cyan', 'yellow'])
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, flie
    plt.plot()
    count += 1
```

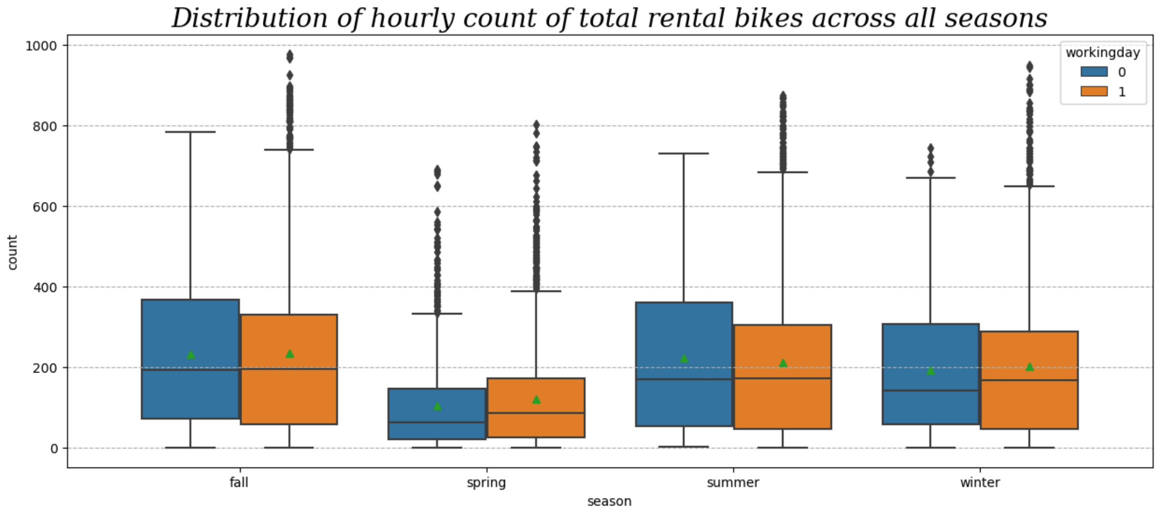


- There is no outlier in the temp column.
- There are few outliers present in humidity column.
- There are many outliers present in each of the columns : windspeed, casual, registered, count.

Bivariate Analysis

In [58]:
```
plt.figure(figsize = (15, 6))
plt.title('Distribution of hourly count of total rental bikes across all seasons',
         fontdict = {'size' : 20,
                     'style' : 'oblique',
                     'family' : 'serif'})
sns.boxplot(data = df, x = 'season', y = 'count', hue = 'workingday', showmeans = True)
plt.grid(axis = 'y', linestyle = '--')
plt.plot()
```

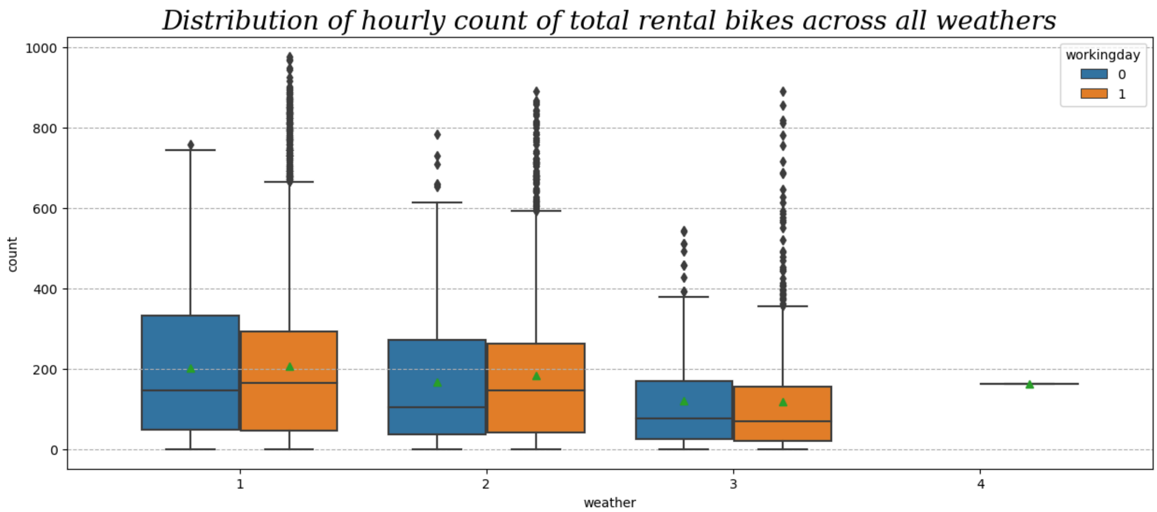
Out[58]: []



The hourly count of total rental bikes is higher in the fall season, followed by the summer and winter seasons. It is generally low in the spring season.

In [59]:
```
plt.figure(figsize = (15, 6))
plt.title('Distribution of hourly count of total rental bikes across all weathers',
         fontdict = {'size' : 20,
                     'style' : 'oblique',
                     'family' : 'serif'})
sns.boxplot(data = df, x = 'weather', y = 'count', hue = 'workingday', showmeans = True
plt.grid(axis = 'y', linestyle = '--')
plt.plot()
```

Out[59]: []



- The hourly count of total rental bikes is higher in the clear and cloudy weather, followed by the misty weather and rainy weather. There are very few records for extreme weather conditions.

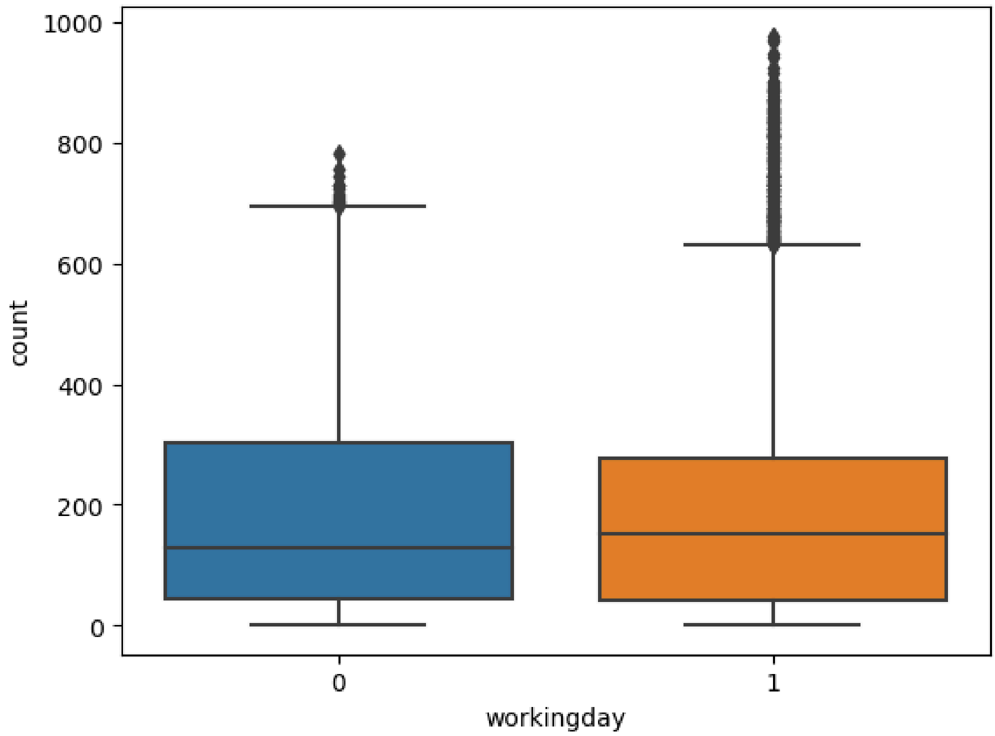
In [60]:
```
# Is there any effect of Working Day on the number of electric cycles rented ?
df.groupby(by = 'workingday')['count'].describe()
```

Out[60]:

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 [61]:
```
sns.boxplot(data = df, x = 'workingday', y = 'count')
plt.plot()
```

Out[61]: []



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

- Distribution check using QQ Plot
- Homogeneity of Variances using Levene's test

STEP-3: Define Test statistics; Distribution of T under H0.

- 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.

- We set our alpha to be 0.05

STEP-5: Compare p-value and alpha.

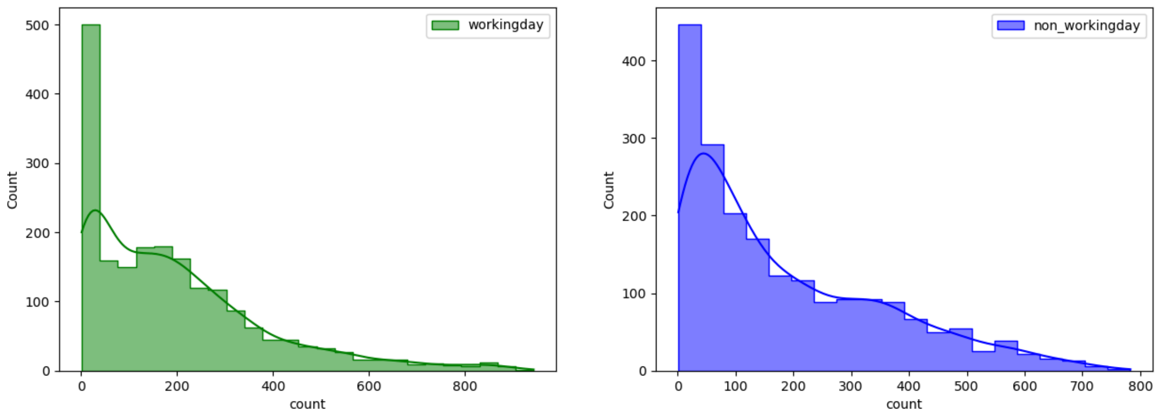
- Based on p-value, we will accept or reject H0.

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

Visual Tests to know if the samples follow normal distribution

In [62]:
```
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()
```

Out[62]: []

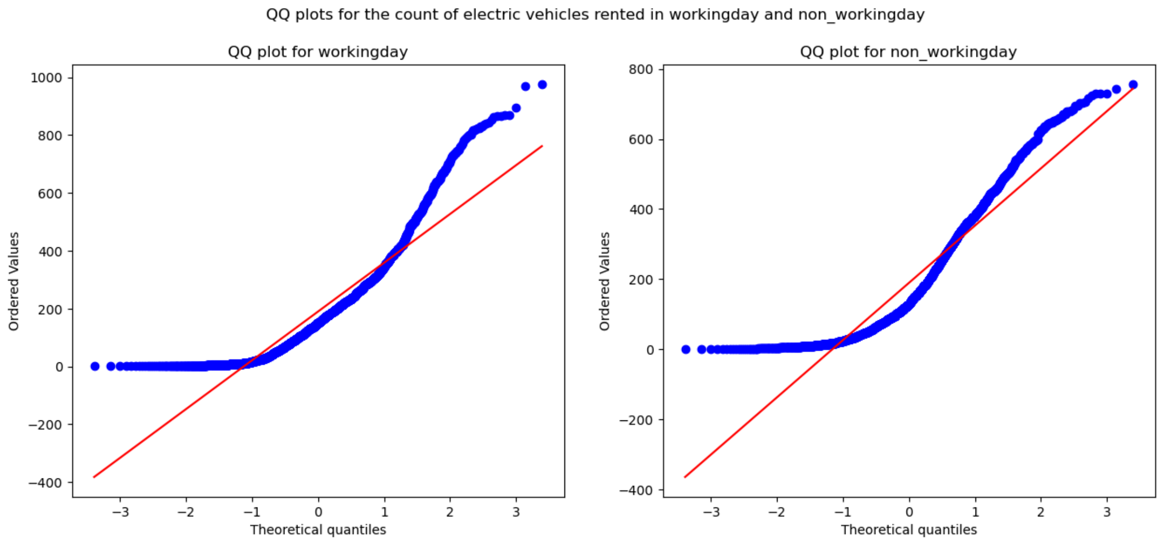


- It can be inferred from the above plot that the distributions do not follow normal distribution.

Distribution check using QQ Plot

In [63]:
```
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_w
spy.probplot(df.loc[df['workingday'] == 1, 'count'].sample(2000), plot = plt, dist = 'no
plt.title('QQ plot for workingday')
plt.subplot(1, 2, 2)
spy.probplot(df.loc[df['workingday'] == 0, 'count'].sample(2000), plot = plt, dist = 'no
plt.title('QQ plot for non_workingday')
plt.plot()
```

Out[63]: []



- 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{o}: The sample follows normal distribution

H{a}: The sample does not follow normal distribution

alpha = 0.05

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

In [64]:
```
test_stat, p_value = spy.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 2.5155672826438247e-37
The sample does not follow normal distribution
```

In [65]:
```
test_stat, p_value = spy.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 7.535852210493531e-36
The sample does not follow normal distribution
```

Transforming the data using boxcox transformation and checking if the transformed data follows

In [66]:

```
transformed_workingday = spy.boxcox(df.loc[df['workingday'] == 1, 'count'])[0]
test_stat, p_value = spy.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 1.6136246052607705e-33
The sample does not follow normal distribution

C:\Users\Dell\Downloads\ANA\Lib\site-packages\scipy\stats\_morestats.py:1882: UserWarn
ing: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

In [67]:

```
transformed_non_workingday = spy.boxcox(df.loc[df['workingday'] == 1, 'count'])[0]
test_stat, p_value = spy.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 1.6136246052607705e-33
The sample does not follow normal distribution
```

- 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***

In [68]:

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

# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.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 0.6127238333828101
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.

In [69]:

```
# 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 = spy.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 day
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

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

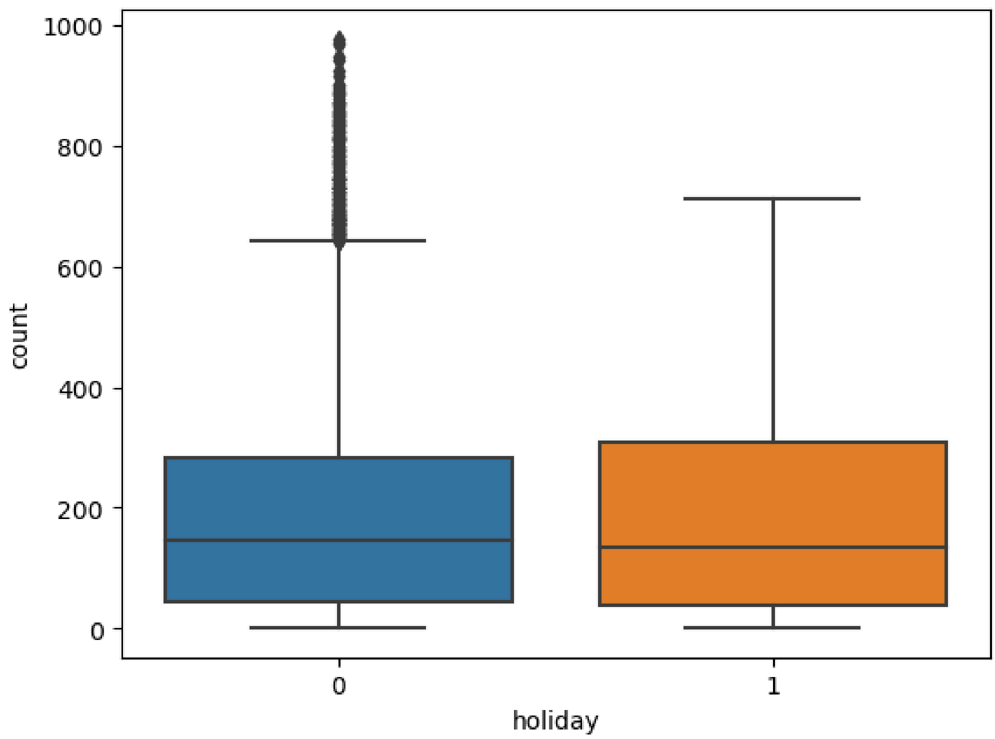
In [70]:
```
df.groupby(by = 'holiday')['count'].describe()
```

Out[70]:

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

In [71]:
```
sns.boxplot(data = df, x = 'holiday', y = 'count')
plt.plot()
```

Out[71]: []



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

- Distribution check using QQ Plot
- Homogeneity of Variances using Levene's test

STEP-3: Define Test statistics; Distribution of T under H0.

- 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.

- We set our alpha to be 0.05

STEP-5: Compare p-value and alpha.

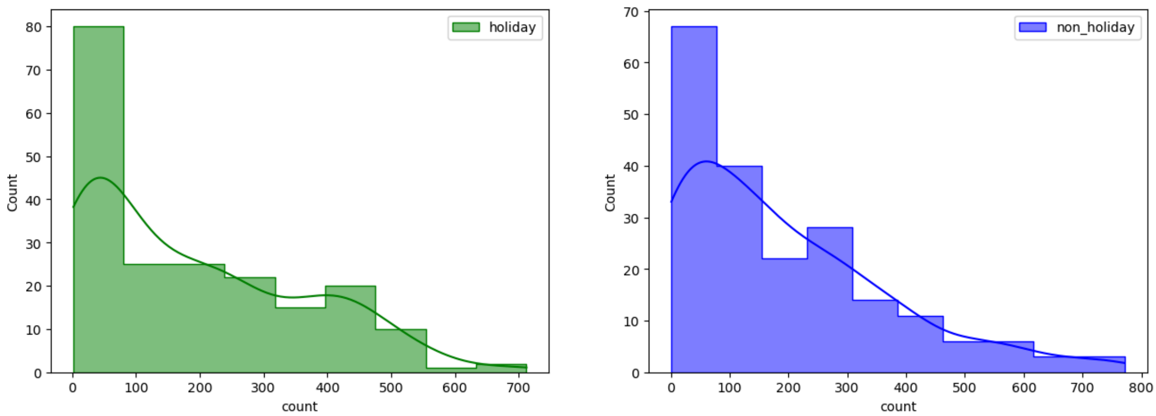
- Based on p-value, we will accept or reject H0.

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

Visual Tests to know if the samples follow normal distribution

In [72]:
```
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()
```

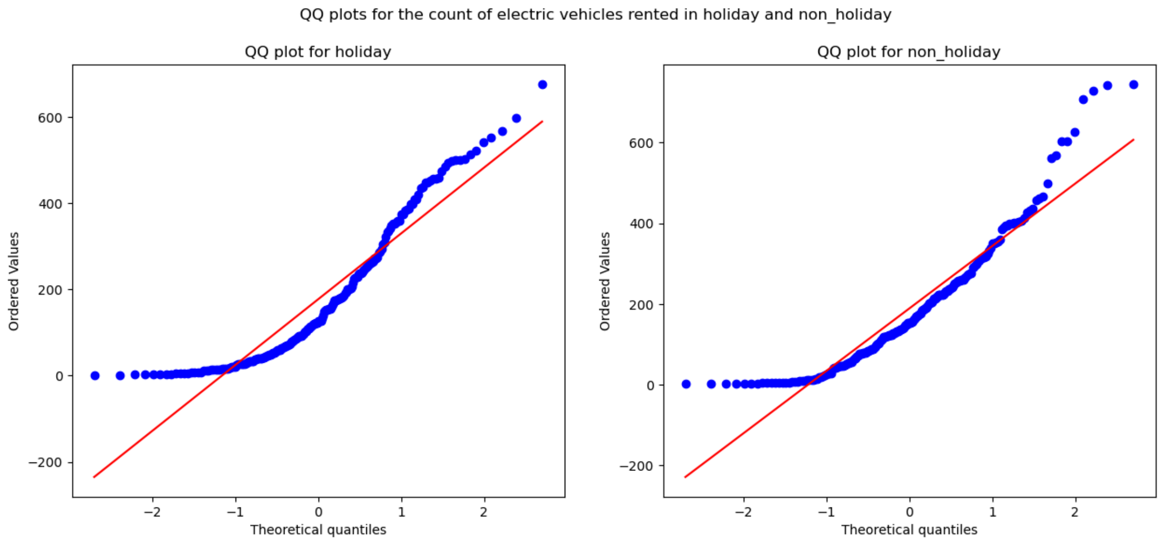
Out[72]: []



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

In [73]:
```
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_hol:
spy.probplot(df.loc[df['holiday'] == 1, 'count'].sample(200), plot = plt, dist = 'norm'
plt.title('QQ plot for holiday')
plt.subplot(1, 2, 2)
spy.probplot(df.loc[df['holiday'] == 0, 'count'].sample(200), plot = plt, dist = 'norm'
plt.title('QQ plot for non_holiday')
plt.plot()
```

Out[73]: []



- 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{o}: The sample follows normal distribution

H{a}: The sample does not follow normal distribution

alpha = 0.05

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

In [74]:
```
test_stat, p_value = spy.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 1.615053646375486e-10
The sample does not follow normal distribution
```

In [75]:
```
test_stat, p_value = spy.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 4.443317675600911e-12
The sample does not follow normal distribution
```

Transforming the data using boxcox transformation and checking if the transformed data follows

In [76]:
```
transformed_holiday = spy.boxcox(df.loc[df['holiday'] == 1, 'count'])[0]
test_stat, p_value = spy.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 2.1349180201468698e-07
The sample does not follow normal distribution
```

In [77]:
```
transformed_non_holiday = spy.boxcox(df.loc[df['holiday'] == 0, 'count'].sample(5000))[
test_stat, p_value = spy.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 5.671610387914124e-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

In [78]:
```
# Null Hypothesis(H0) - Homogenous Variance

# Alternate Hypothesis(HA) - Non Homogenous Variance

test_stat, p_value = spy.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 0.21924612661913362
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.

In [79]:
```
# 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 = spy.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 da
else:
    print('No.of electric cycles rented is similar for holidays and non-holidays')
```

```
P-value : 0.4481106271582377
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.

Is weather dependent on the season ?

In [80]:
```
df[['weather', 'season']].describe()
```

Out[80]:

	weather	season
count	10886	10886
unique	4	4
top	1	winter
freq	7192	2734

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

STEP-1 : Set up Null Hypothesis

- ***Null Hypothesis (H0)*** - weather is independent of season
- ***Alternate Hypothesis (HA)*** - weather is dependent of seasons.

STEP-2: Define Test statistics

- 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)

---

1. The data in the cells should be frequencies, or counts of cases.
2. The levels (or categories) of the variables are mutually exclusive. That is, a particular subject fits into one and only one level of each of the variables.
3. There are 2 variables, and both are measured as categories.
4. The value of the cell expecteds should be 5 or more in at least 80% of the cells, and no cell should have an expected of less than one (3).

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

---

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

In [81]:
```
# First, finding the contingency table such that each value is the total number of tota
  # 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
```

Out[81]:

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.

In [82]:
```
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
```

Out[82]:
```
array([[470116, 139386,  31160],
       [223009,  76406,  12919],
       [426350, 134177,  27755],
       [356588, 157191,  30255]], dtype=int64)
```

In [83]:
```
chi_test_stat, p_value, dof, expected = spy.chi2_contingency(observed = cross_table)
print('Test Statistic =', chi_test_stat)
print('p value =', p_value)
print('-' * 65)
print("Expected : '\n'", expected)
alpha = 0.05
```

```
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

In [84]:
```
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.

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

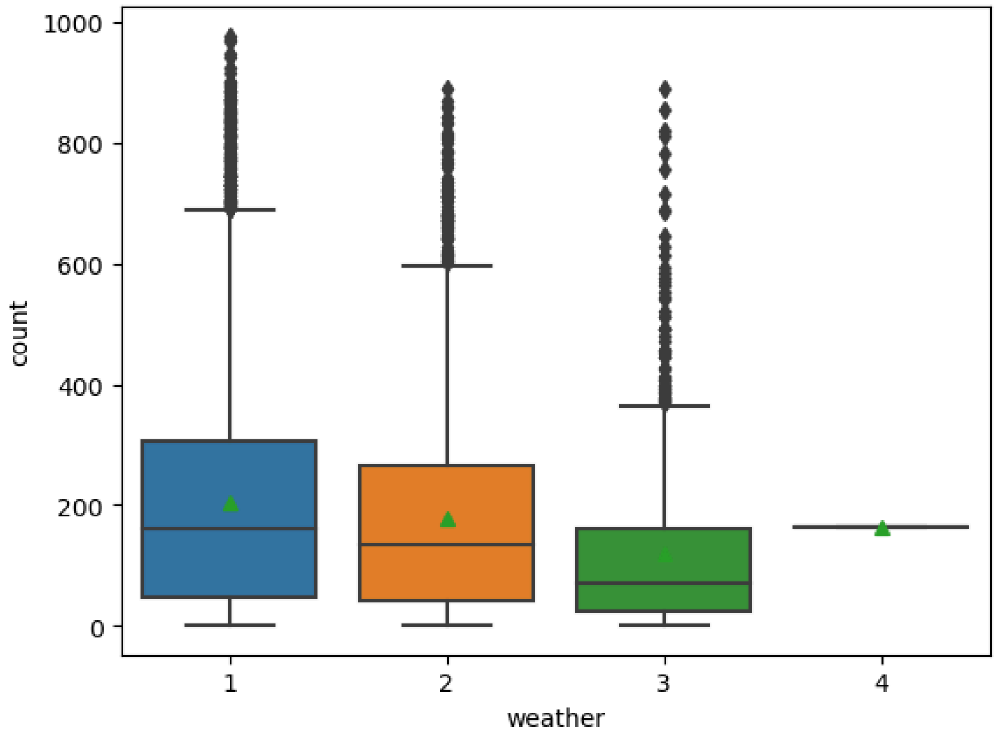
In [85]:
```
df.groupby(by = 'weather')['count'].describe()
```

Out[85]:

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

In [86]:
```
sns.boxplot(data = df, x = 'weather', y = 'count', showmeans = True)
plt.plot()
```

Out[86]: []



In [87]:
```
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)
```

Out[87]: (7192, 2834, 859, 1)

STEP-1 : Set up Null Hypothesis

- ***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.

STEP-2 : Checking for basic assumpitons for the 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

- The test statistic for a One-Way ANOVA is denoted as F. For an independent variable with k groups, the F statistic evaluates whether the group means are significantly different.

F=MSB / MSW

Under H0, the test statistic should follow F-Distribution.

STEP-4: Decide the kind of test.

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.

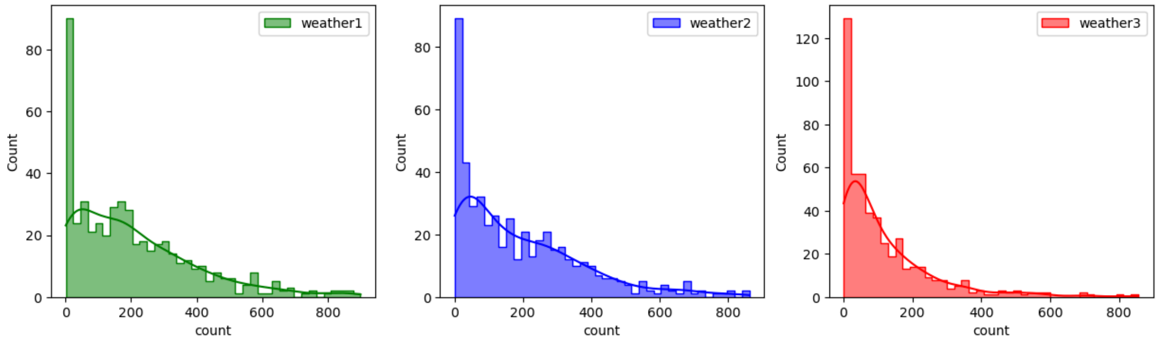
Based on p-value, we will accept or reject H0.

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

Visual Tests to know if the samples follow normal distribution

In [88]:
```
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()
```

Out[88]: []

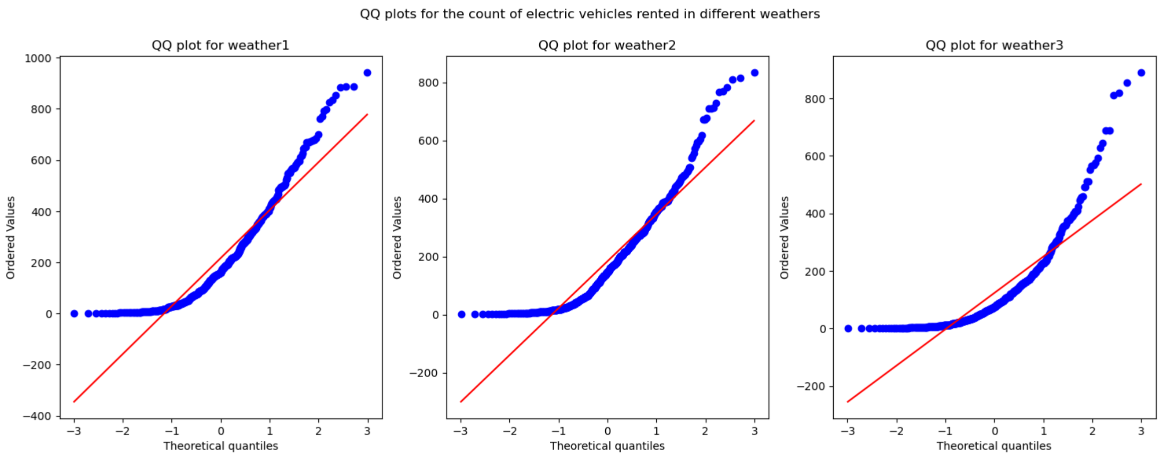


It can be inferred from the above plot that the distributions do not follow normal distribution.

Distribution check using QQ Plot

In [89]:
```
plt.figure(figsize = (18, 6))
plt.subplot(1, 3, 1)
plt.suptitle('QQ plots for the count of electric vehicles rented in different weathers'
spy.probplot(df_weather1.loc[:, 'count'].sample(500), plot = plt, dist = 'norm')
plt.title('QQ plot for weather1')
plt.subplot(1, 3, 2)
spy.probplot(df_weather2.loc[:, 'count'].sample(500), plot = plt, dist = 'norm')
plt.title('QQ plot for weather2')
plt.subplot(1, 3, 3)
spy.probplot(df_weather3.loc[:, 'count'].sample(500), plot = plt, dist = 'norm')
plt.title('QQ plot for weather3')
plt.plot()
```

Out[89]: []



- 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{o}: The sample follows normal distribution H{a}: The sample does not follow normal distribution

alpha = 0.05

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

In [90]:
```
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 2.0368669886916214e-19
The sample does not follow normal distribution
```

In [91]:
```
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 4.700569119130454e-19
The sample does not follow normal distribution
```

In [92]:
```
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 4.5729854526653955e-27
The sample does not follow normal distribution
```

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

In [93]:
```
transformed_weather1 = spy.boxcox(df_weather1.loc[:, 'count'].sample(5000))[0]
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 2.1352450663093447e-28
The sample does not follow normal distribution
```

In [94]:
```
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 1.9219748327822736e-19
The sample does not follow normal distribution
```

In [95]:
```
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 1.4137293646854232e-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 [96]:
```
# 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 1.3862827717464844e-08
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 [97]:
```
# 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 = [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
 7.08445555e+01]
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
 4.13333147e-16]
```

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

In [98]:
```
df.groupby(by = 'season')['count'].describe()
```

Out[98]:

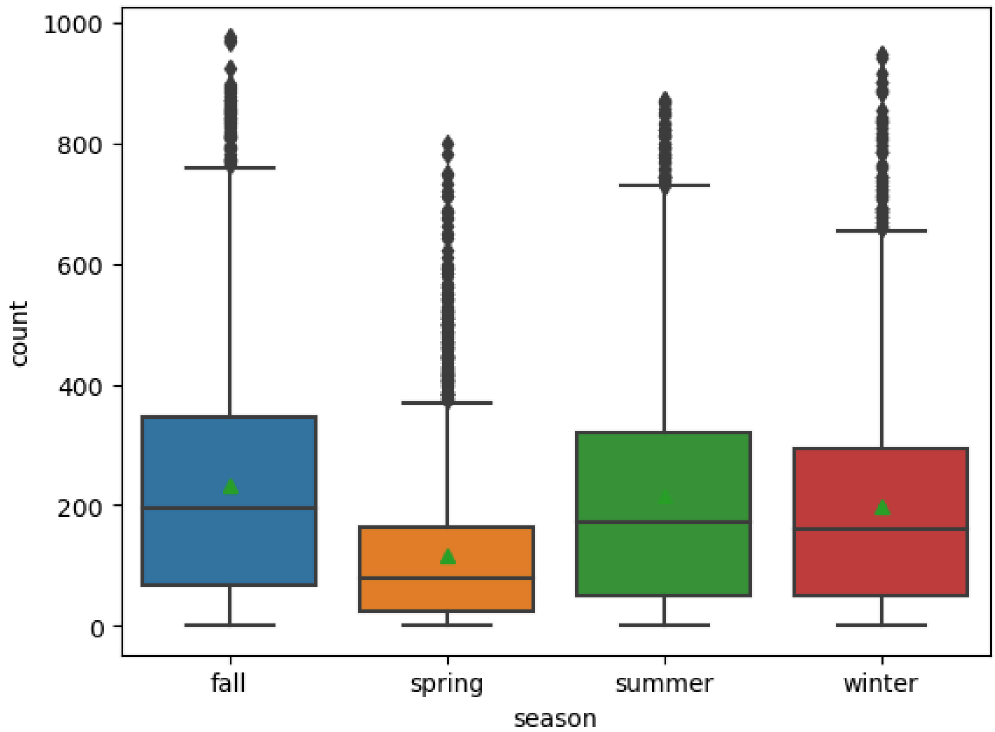
season	count	mean	std	min	25%	50%	75%	max
fall	2733.0	234.417124	197.151001	1.0	68.0	195.0	347.0	977.0
spring	2686.0	116.343261	125.273974	1.0	24.0	78.0	164.0	801.0
summer	2733.0	215.251372	192.007843	1.0	49.0	172.0	321.0	873.0
winter	2734.0	198.988296	177.622409	1.0	51.0	161.0	294.0	948.0

In [99]:
```
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(df_season_winter
```

Out[99]: (2686, 2733, 2733, 2734)

In [100]:
```
sns.boxplot(data = df, x = 'season', y = 'count', showmeans = True)
plt.plot()
```

Out[100]: []



STEP-1 : Set up Null Hypothesis

- ***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.

STEP-2 : Checking for basic assumpitons for the 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

- The test statistic for a One-Way ANOVA is denoted as F. For an independent variable with k groups, the F statistic evaluates whether the group means are significantly different.
- **F=MSB/MSW**
- Under H0, the test statistic should follow F-Distribution.

STEP-4: Decide the kind of test.

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.

1. p-val > alpha : Accept H0
2. 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):

μ1 = μ2 = μ3 = ... = μk

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

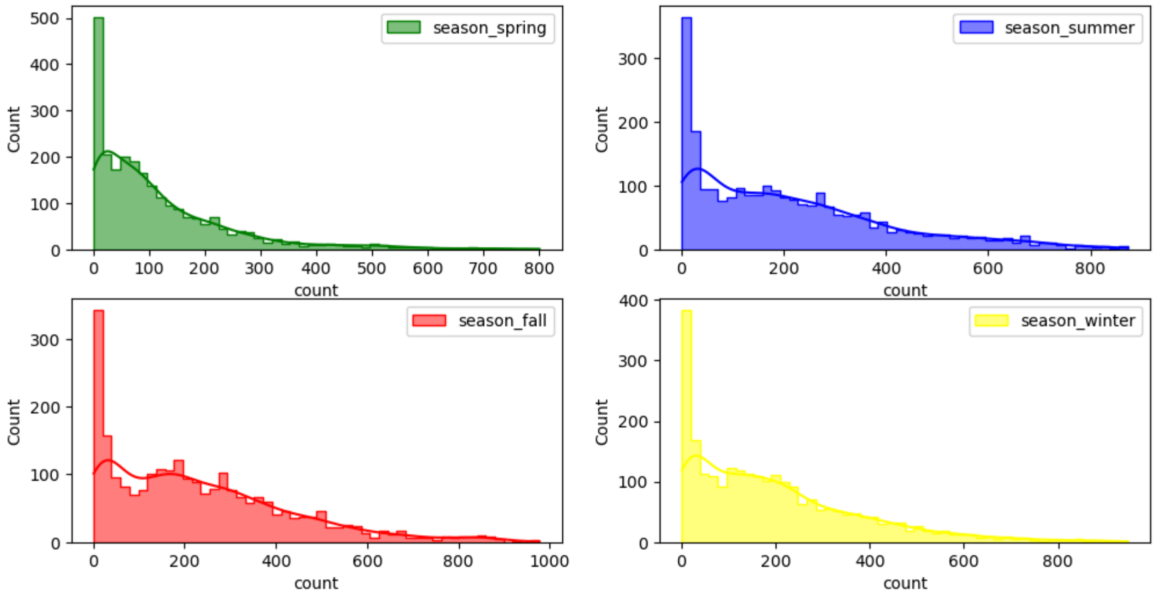
If, however, the one-way ANOVA returns a statistically significant result, we accept the alternative hypothesis (HA), which is that there are at least two group means that are statistically significantly different from each other

Visual Tests to know if the samples follow normal distribution

In [101]:

```
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 = 'season_spring')
plt.legend()
plt.subplot(2, 2, 2)
sns.histplot(df_season_summer.sample(2500), bins = 50,
             element = 'step', color = 'blue', kde = True, label = 'season_summer')
plt.legend()
plt.subplot(2, 2, 3)
sns.histplot(df_season_fall.sample(2500), bins = 50,
             element = 'step', color = 'red', kde = True, label = 'season_fall')
plt.legend()
plt.subplot(2, 2, 4)
sns.histplot(df_season_winter.sample(2500), bins = 50,
             element = 'step', color = 'yellow', kde = True, label = 'season_winter')
plt.legend()
plt.plot()
```

Out[101]: []



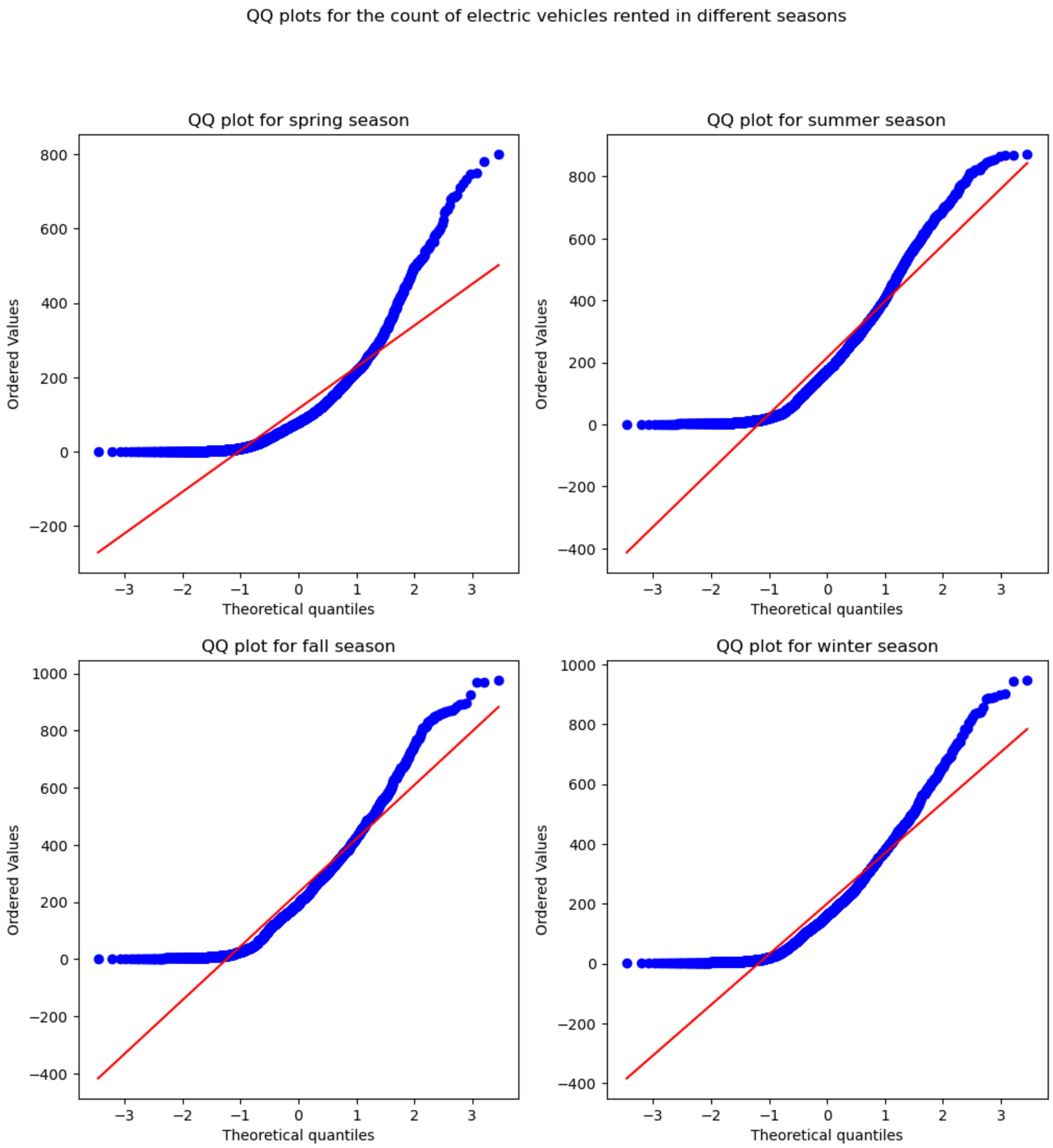
It can be inferred from the above plot that the distributions do not follow normal distribution.

Distribution check using QQ Plot

In [102]:

```
plt.figure(figsize = (12, 12))
plt.subplot(2, 2, 1)
plt.suptitle('QQ plots for the count of electric vehicles rented in different seasons')
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[102]: []



- 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{o}: The sample follows normal distribution

H{a}: The sample does not follow normal distribution

alpha = 0.05

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

In [103]:

```
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 [104]:

```
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 1.2847559462671136e-37
The sample does not follow normal distribution
```

In [105]:

```
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 2.112328623130666e-35
The sample does not follow normal distribution
```

In [106]:

```
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 2.370046921278778e-38
The sample does not follow normal distribution
```

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

In [107]:

```
transformed_df_season_spring = spy.boxcox(df_season_spring.sample(2500))[0]
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 2.752154570625847e-16
The sample does not follow normal distribution
```

In [108]:
```
transformed_df_season_summer = spy.boxcox(df_season_summer.sample(2500))[0]
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 4.614046172460025e-21
The sample does not follow normal distribution
```

In [109]:
```
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 4.872023126000225e-21
The sample does not follow normal distribution
```

In [110]:
```
transformed_df_season_winter = spy.boxcox(df_season_winter.sample(2500))[0]
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 3.3154584792081626e-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 [111]:
```
# 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 1.932115371043261e-110
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 [112]:

```
# 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_season_fall,df_
print('Test Statistic =', test_stat)
print('p value =', p_value)
```

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

In [113]:

```
# Comparing p value with significance level
if p_value < alpha:
    print('Reject Null Hypothesis')
else:
    print('Failed to reject Null Hypothesis')
```

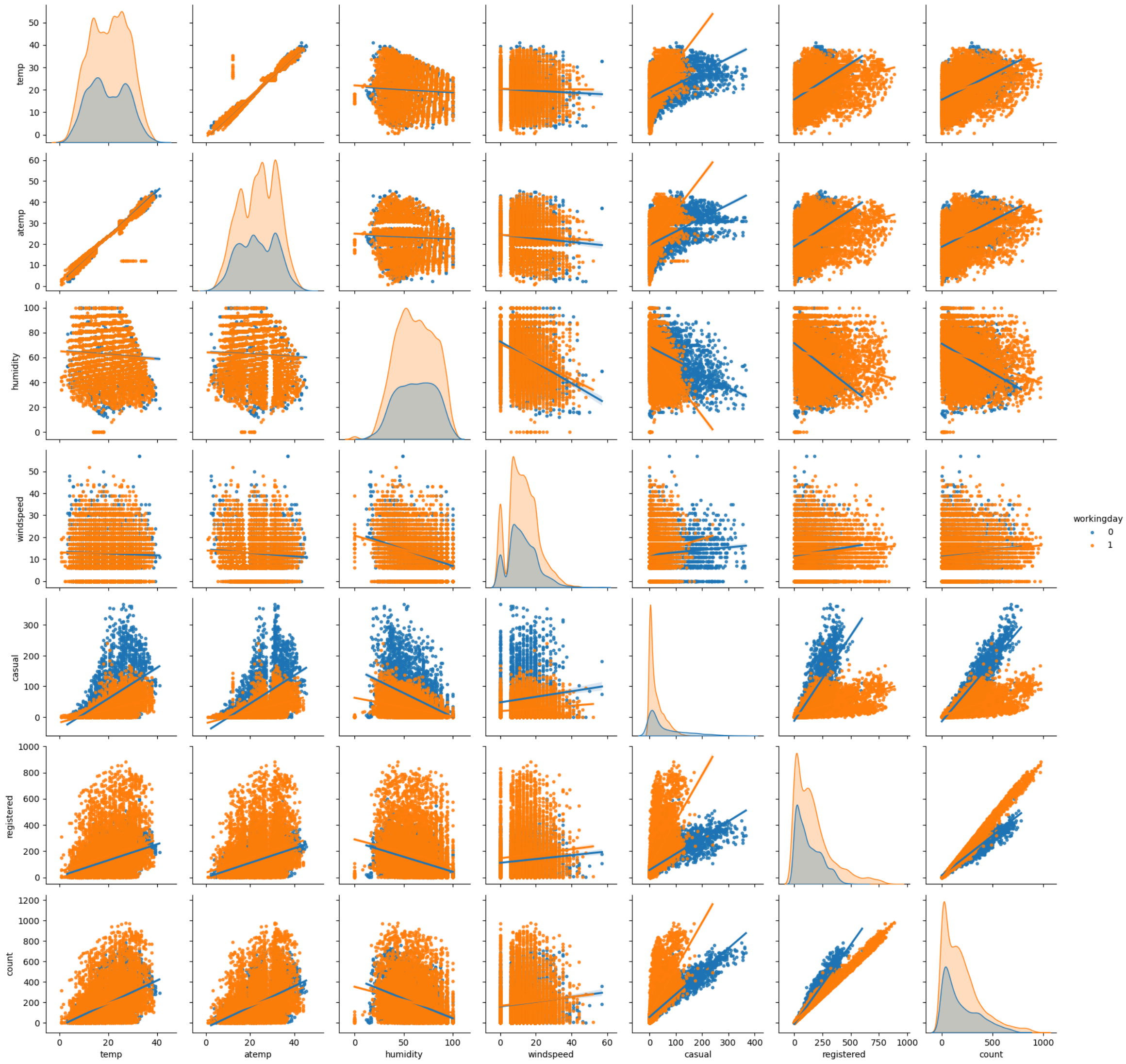
```
Reject Null Hypothesis
```

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

In [114]:
```
sns.pairplot(data = df,
             kind = 'reg',
             hue = 'workingday',
             markers = '.')
plt.plot()
```

```
C:\Users\Dell\Downloads\ANA\Lib\site-packages\seaborn\axisgrid.py:118: UserWarning: Th
e figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

Out[114]: []



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.

Recommendation

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.

In [ ]:

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