yulu-proj-sub2

September 26, 2023

[49]:
```python
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
from scipy.stats import ttest_ind
```

[2]:
```python
df=pd.read_csv('yulu_dataset.csv')
```

1 Basic Analysis of Dataset

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

[3]:
```
(10886, 12)
```

[4]:
```python
df.columns
```

[4]:
```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

[5]:
```python
df.head()
```

[5]:
```
              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
```

[6]:
```python
df.info()
```

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

No null value present in any column

[7]:
```python
df.describe()
```

[7]:
```
             season       holiday    workingday       weather         temp  \
count  10886.000000  10886.000000  10886.000000  10886.000000  10886.00000
mean       2.506614      0.028569      0.680875      1.418427     20.23086
std        1.116174      0.166599      0.466159      0.633839      7.79159
min        1.000000      0.000000      0.000000      1.000000      0.82000
25%        2.000000      0.000000      0.000000      1.000000     13.94000
50%        3.000000      0.000000      1.000000      1.000000     20.50000
75%        4.000000      0.000000      1.000000      2.000000     26.24000
max        4.000000      1.000000      1.000000      4.000000     41.00000

              atemp      humidity     windspeed        casual    registered  \
count  10886.000000  10886.000000  10886.000000  10886.000000  10886.000000
mean      23.655084     61.886460     12.799395     36.021955    155.552177
std        8.474601     19.245033      8.164537     49.960477    151.039033
min        0.760000      0.000000      0.000000      0.000000      0.000000
25%       16.665000     47.000000      7.001500      4.000000     36.000000
50%       24.240000     62.000000     12.998000     17.000000    118.000000
75%       31.060000     77.000000     16.997900     49.000000    222.000000
max       45.455000    100.000000     56.996900    367.000000    886.000000
```

```
              count
count  10886.000000
mean     191.574132
std      181.144454
min        1.000000
25%       42.000000
50%      145.000000
75%      284.000000
max      977.000000
```

[8]:
```
np.any(df.isna())
```

[8]:
```
False
```

[9]:
```
np.any(df.duplicated())
```

[9]:
```
False
```

No duplicate raws present in dataset

[10]:
```
df.dtypes
```

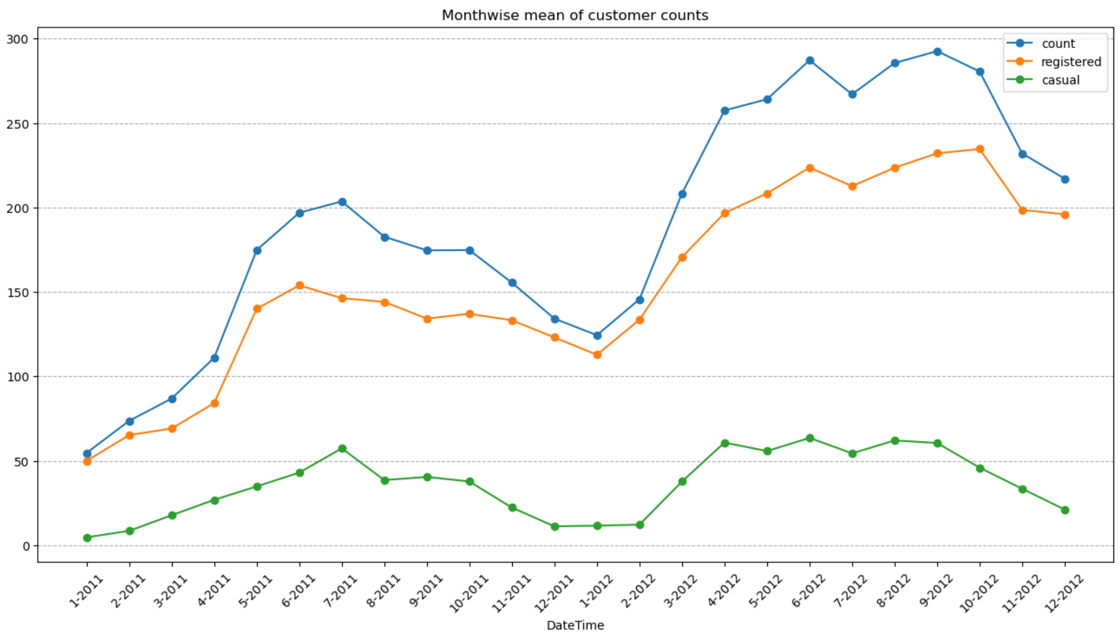
[10]:
```
datetime       object
season          int64
holiday         int64
workingday      int64
weather         int64
temp          float64
atemp         float64
humidity        int64
windspeed     float64
casual          int64
registered      int64
count           int64
dtype: object
```

Changing the type of datetime column

[12]:
```
df['datetime'] = pd.to_datetime(df['datetime'])
```

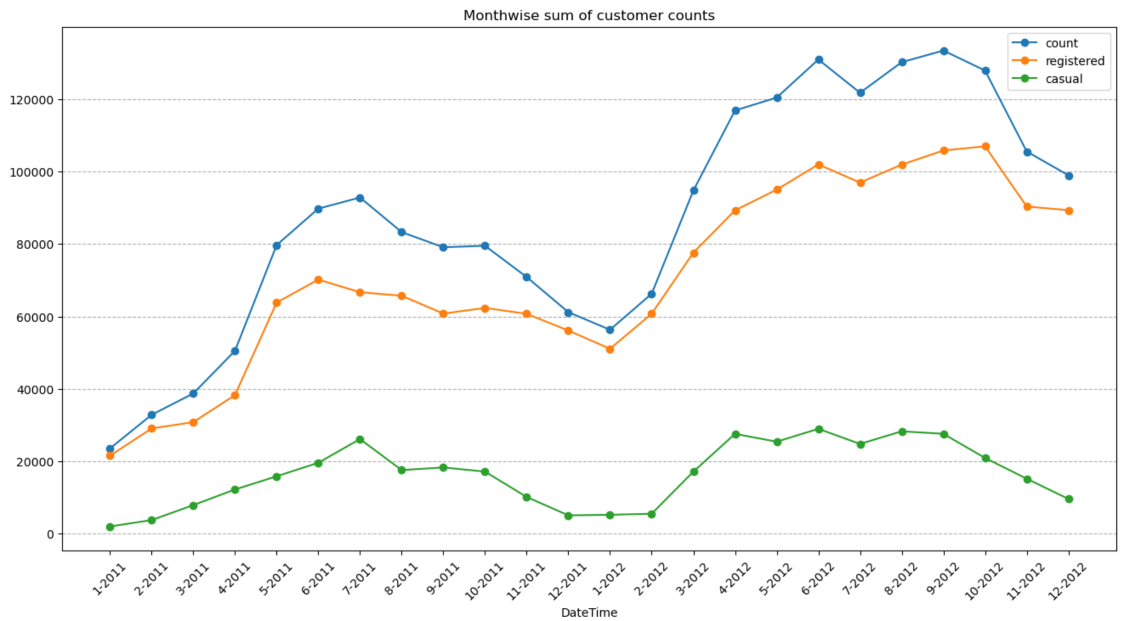
[19]:
```
df['month']=df['datetime'].dt.month

df['year']=df['datetime'].dt.year

result=df.groupby(['month','year'])[['casual','registered','count']].mean()
result

result=result.reset_index()
```

```
result=result.sort_values(['year','month'])

result['month-year']=result['month'].astype(str)+'-'+result['year'].astype(str)

plt.figure(figsize = (16, 8))
plt.plot(result['month-year'],result['count'],marker='o')
plt.plot(result['month-year'],result['registered'],marker='o')
plt.plot(result['month-year'],result['casual'],marker='o')
plt.grid(axis = 'y', linestyle = '--')
plt.legend(['count','registered','casual'])
plt.xticks(rotation=45)
plt.xlabel('DateTime')
plt.title("Monthwise mean of customer counts")
plt.show()
```



[20]:
```
result=df.groupby(['month','year'])[['casual','registered','count']].sum()
result=result.reset_index()
result=result.sort_values(['year','month'])
result['month-year']=result['month'].astype(str)+'-'+result['year'].astype(str)

plt.figure(figsize = (16, 8))
plt.plot(result['month-year'],result['count'],marker='o')
plt.plot(result['month-year'],result['registered'],marker='o')
plt.plot(result['month-year'],result['casual'],marker='o')
plt.grid(axis = 'y', linestyle = '--')
```

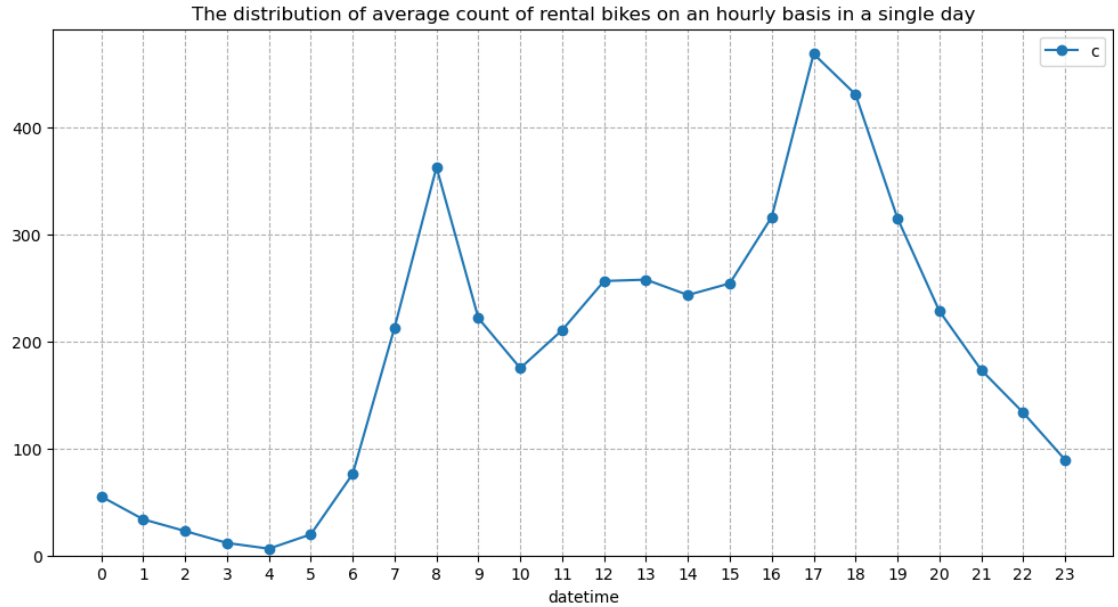
```
plt.legend(['count','registered','casual'])
plt.xticks(rotation=45)
plt.xlabel('DateTime')
plt.title("Monthwise sum of customer counts")
plt.show()
```



[23]:
```
df.drop(['month','year'],axis=1,inplace=True)
```

[25]:
```
plt.figure(figsize = (12, 6))
plt.title("The distribution of average count of rental bikes on an hourly basis␣
↪in a single day")
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()
```

[25]: []

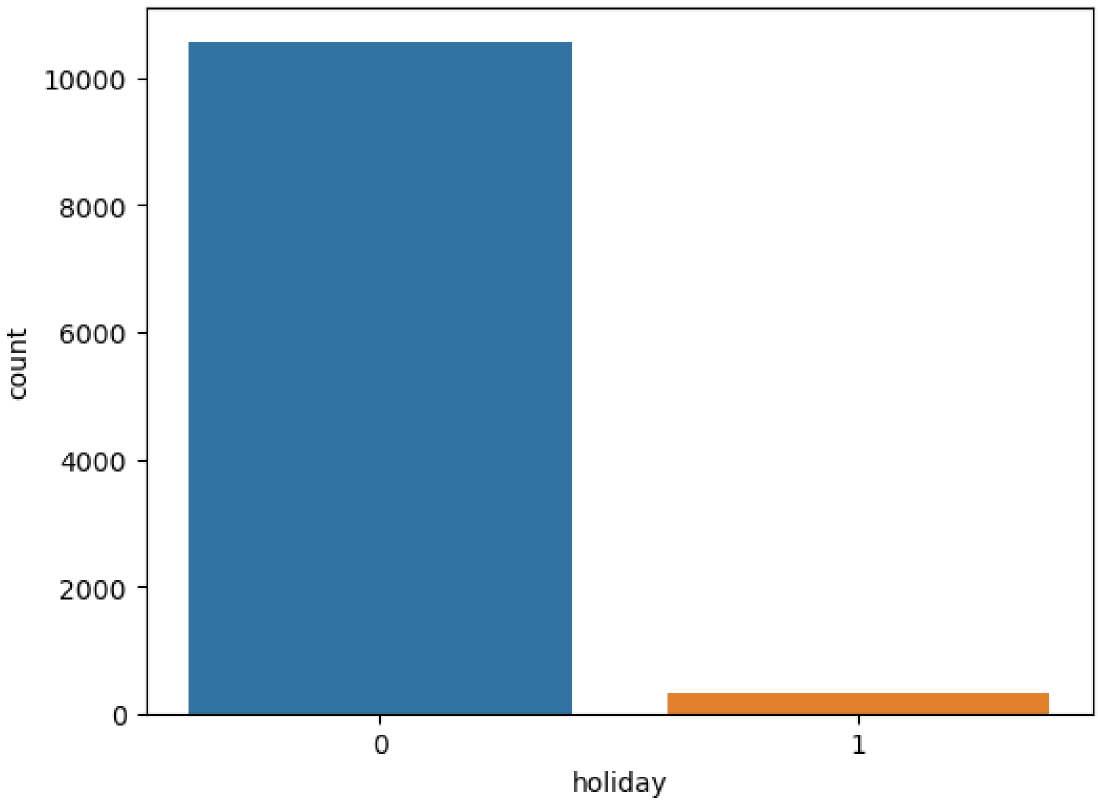


- The highest number of bikes are rented at 8 AM and 5PM
- Moorning (7-9) and evening(16-19) are pick hous for bike rent

2 Univariate Analysis

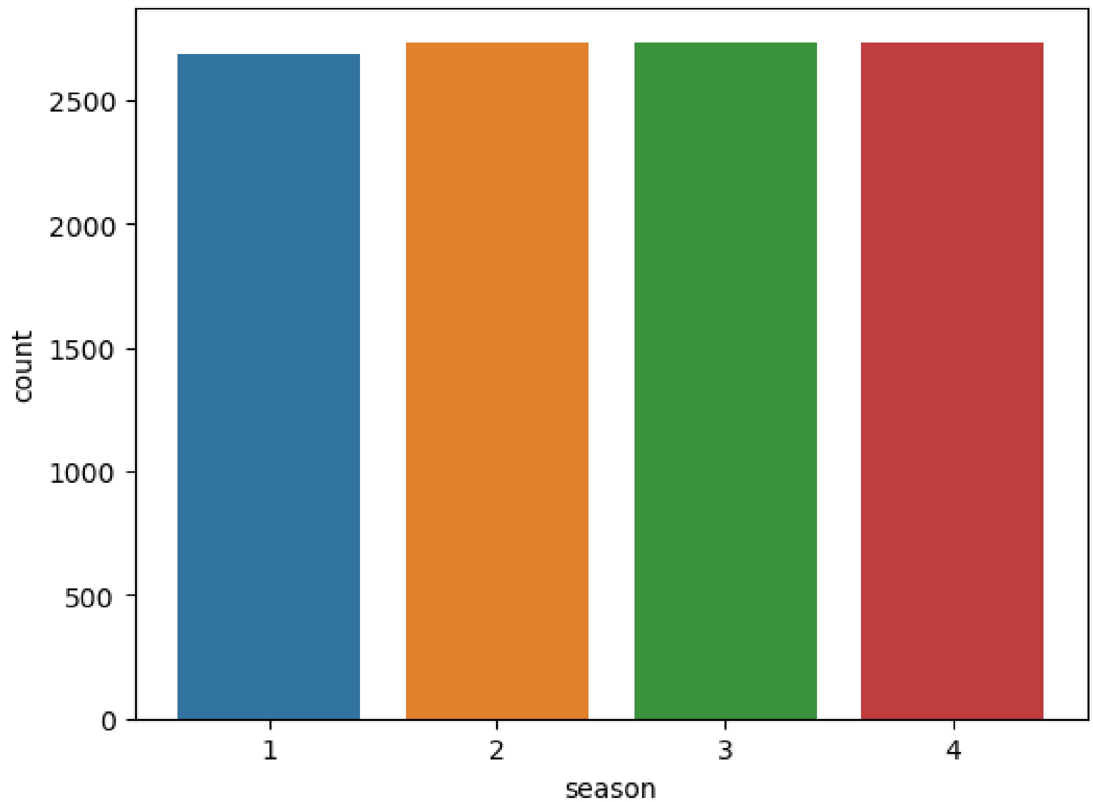
[28]:
```
#distribution of holidays in dataset
sns.countplot(data = df, x = 'holiday')
plt.plot()
```

[28]: []



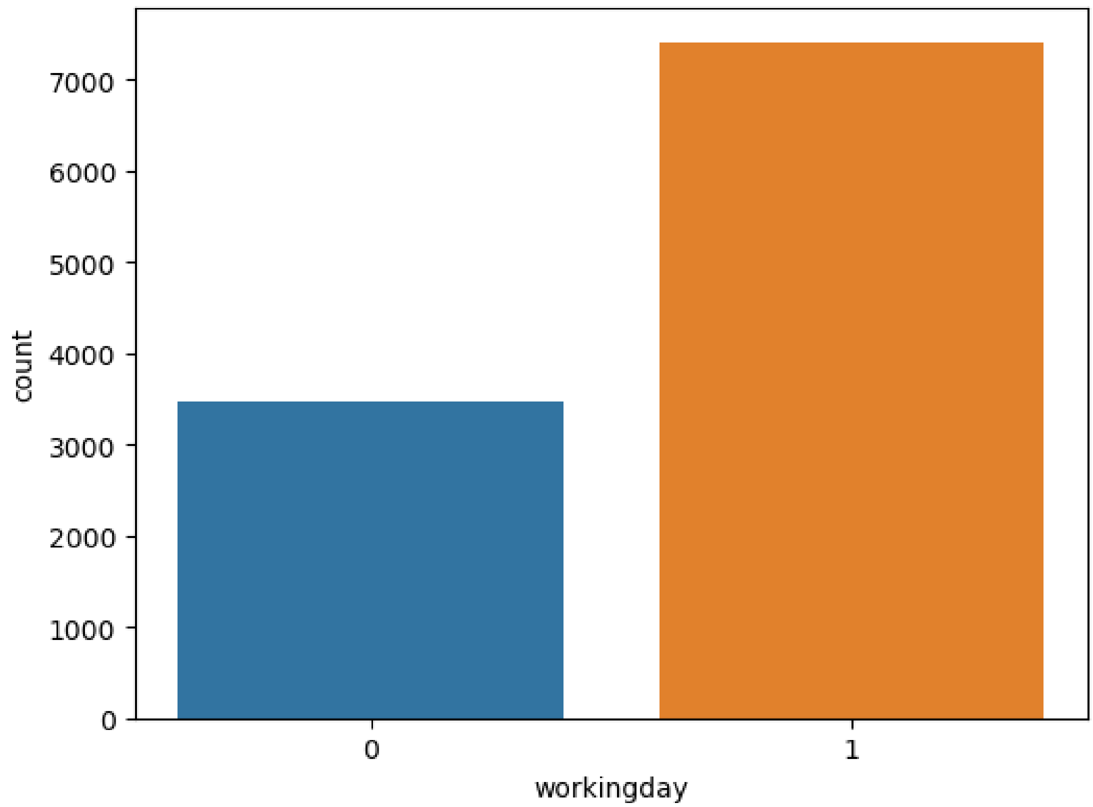
[29]:
```
#distribution of seasons in dataset
sns.countplot(data = df, x = 'season')
plt.plot()
```

[29]: []



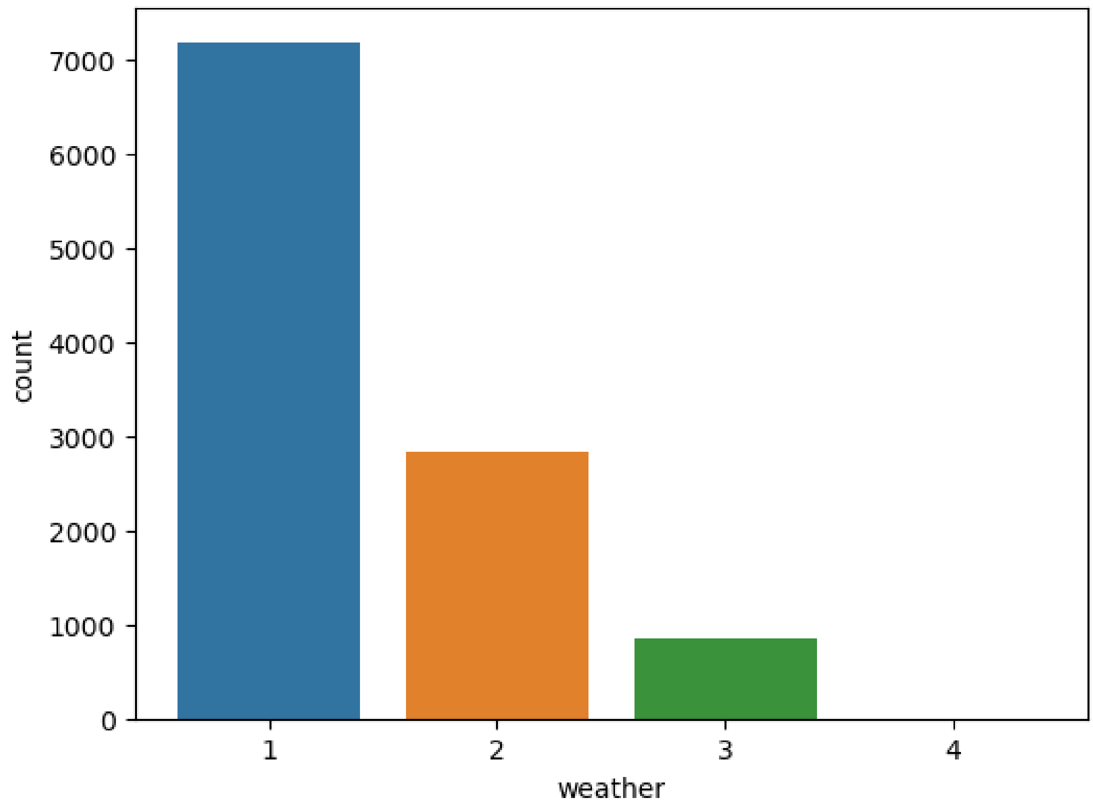
[31]:
```
#distribution of working days in dataset
sns.countplot(data = df, x = 'workingday')
plt.plot()
```

[31]: []



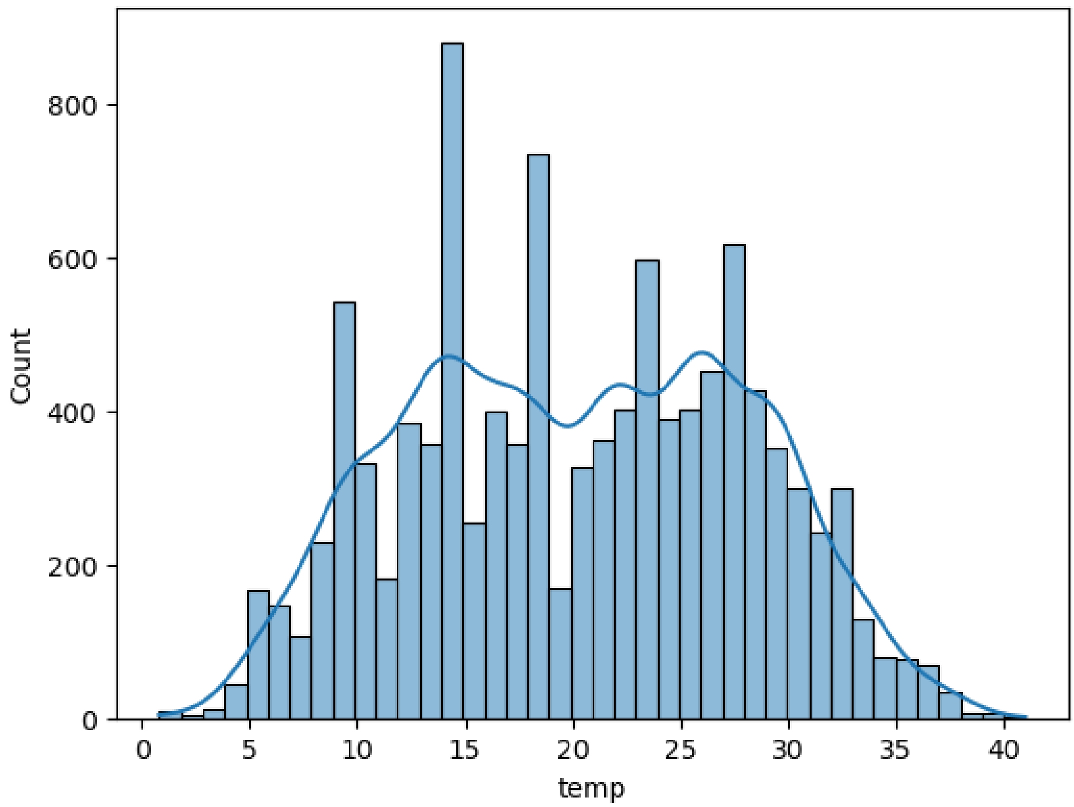
[32]:
```
sns.countplot(data = df, x = 'weather')
plt.plot()
```

[32]: []



[33]:
```
#distribution of temperature in dataset
sns.histplot(data = df, x = 'temp', kde = True, bins = 40)
plt.plot()
```

[33]: []



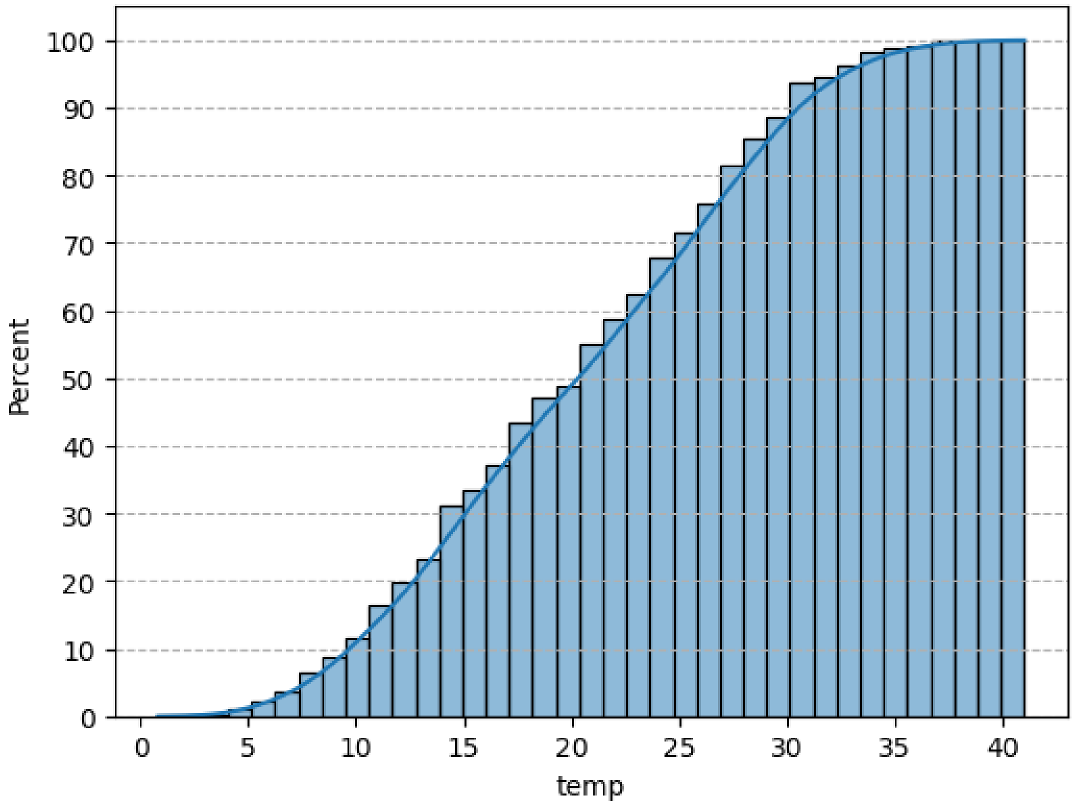
[34]:
```
temp_mean = np.round(df['temp'].mean(), 2)
temp_std = np.round(df['temp'].std(), 2)
temp_mean, temp_std
```

[34]: (20.23, 7.79)

[ ]:
```

```

[35]:
```
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()
```

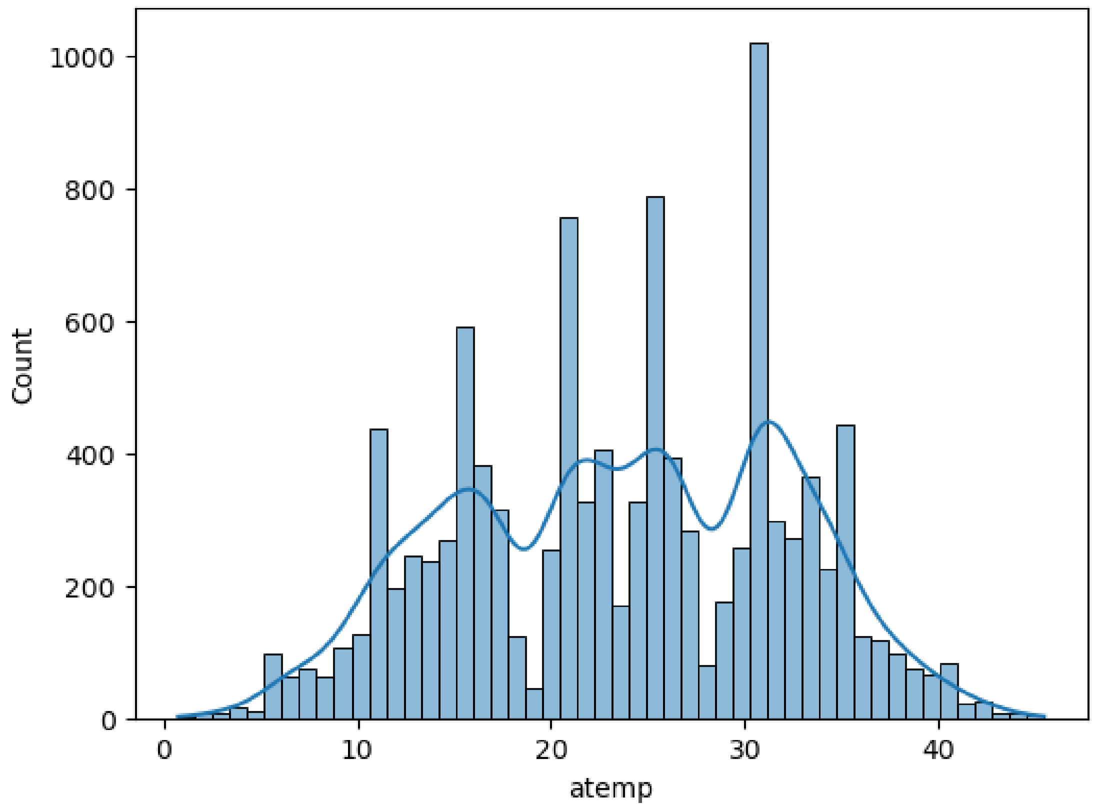
[35]: []



- More than 80 % of the time, the temperature is less than 28 degrees celcius.

[36]:
```
#distribution of atemp col in dataset
sns.histplot(data = df, x = 'atemp', kde = True, bins = 50)
plt.plot()          # displaying the chart

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

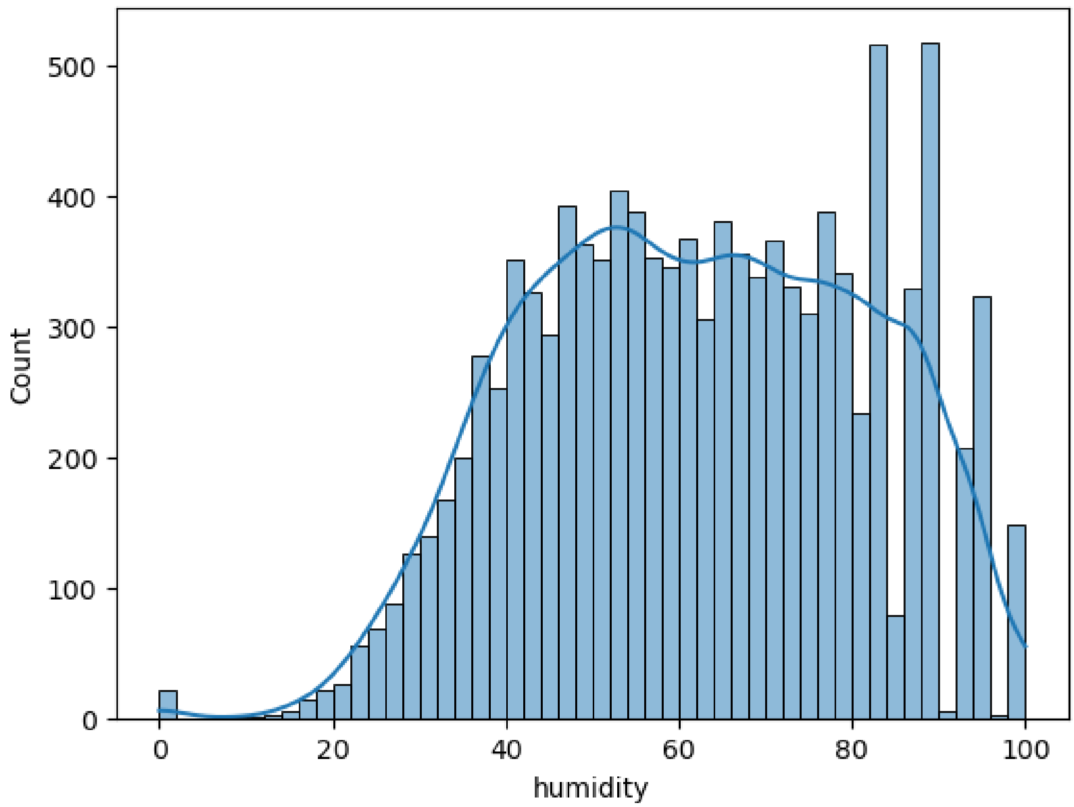
[36]: (23.66, 8.47)



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

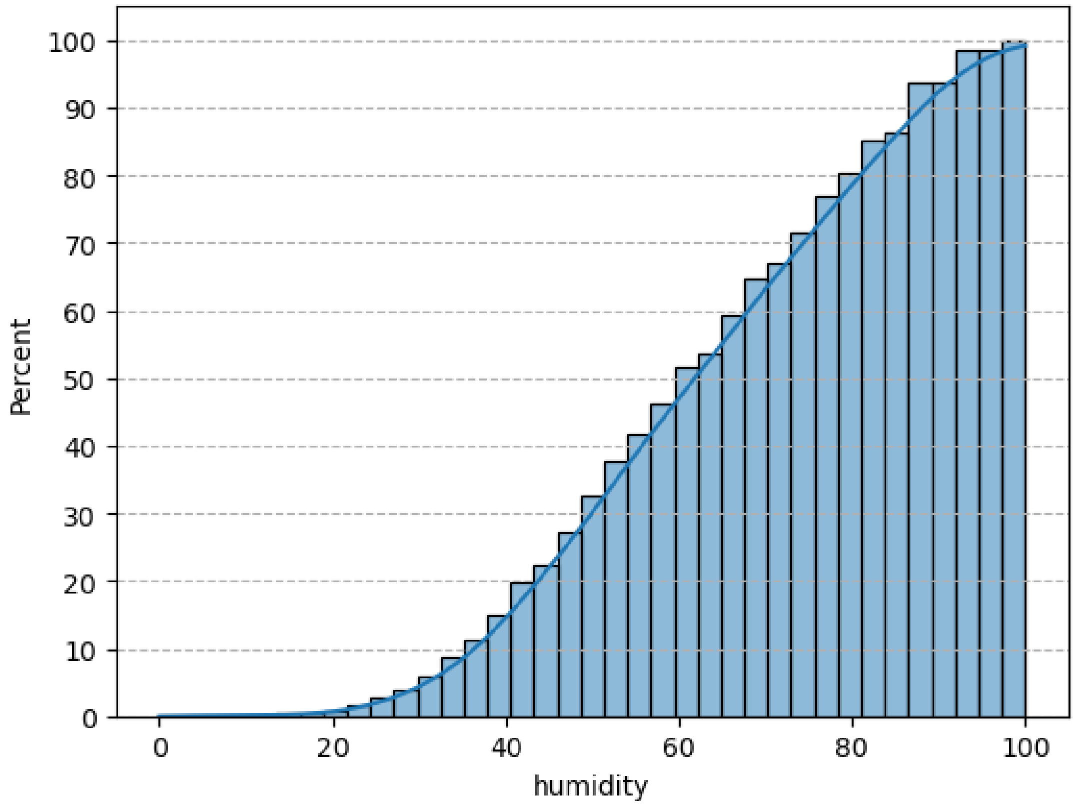
[39]:
```
#distribution of humidity in dataset
sns.histplot(data = df, x = 'humidity', kde = True, bins = 50)
plt.plot()        # displaying the chart

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

[39]:
```
(61.89, 19.25)
```



[40]:
```
sns.histplot(data = df, x = 'humidity', kde = True, cumulative = True, stat =␣
↪'percent')
plt.grid(axis = 'y', linestyle = '--')
plt.yticks(np.arange(0, 101, 10))
plt.plot()        # displaying the chart
```

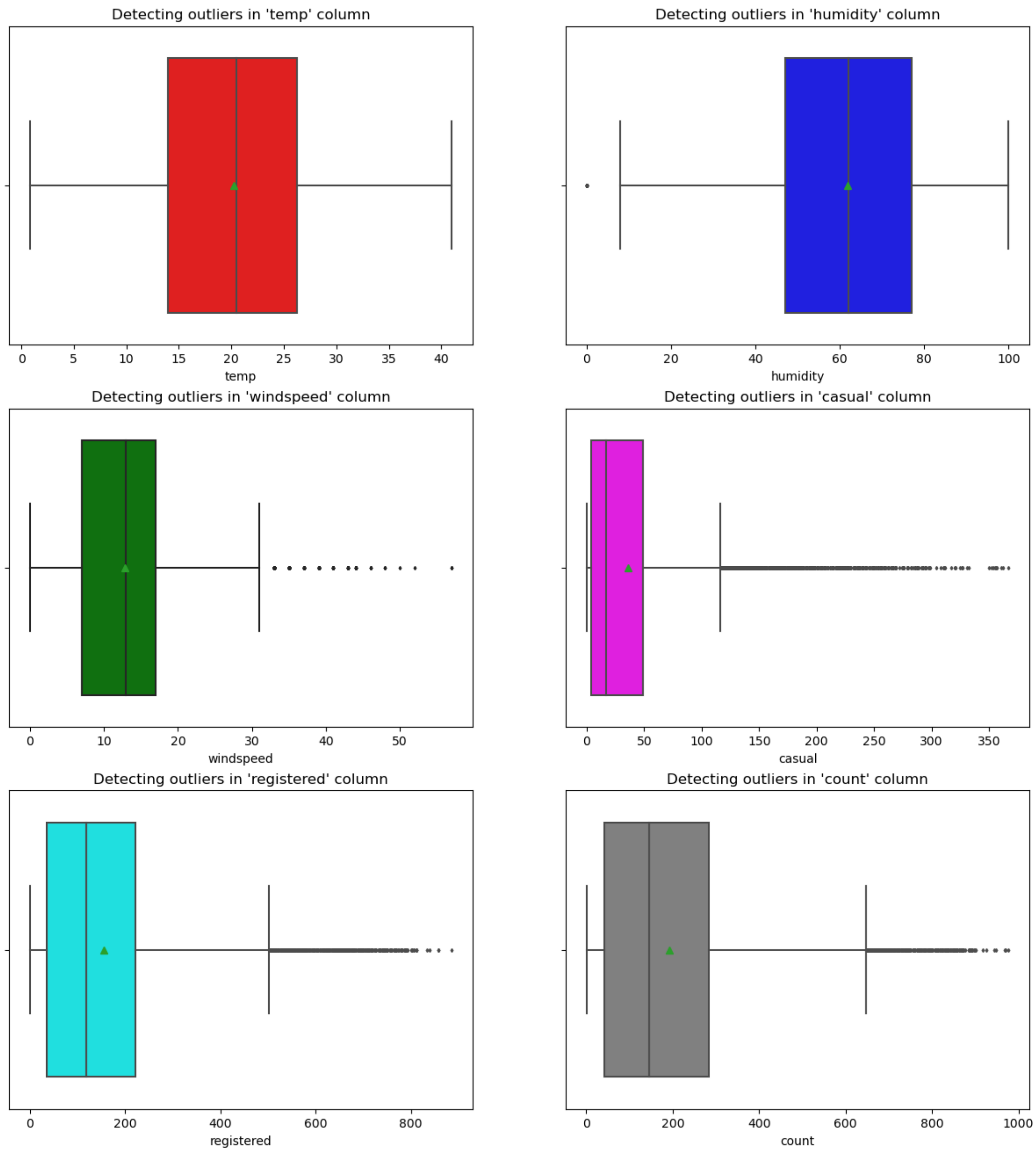
[40]: []



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

3 Outlier detection

[41]:
```
columns = ['temp', 'humidity', 'windspeed', 'casual', 'registered', 'count']
colors = ['red', 'blue', 'green', 'magenta', 'cyan', 'gray']
count = 1
plt.figure(figsize = (15, 16))
for i in columns:
    plt.subplot(3, 2, count)
    plt.title(f"Detecting outliers in '{i}' column")
    sns.boxplot(data = df, x = df[i], color = colors[count-1], showmeans =␣
 ↪True, fliersize = 2)
    plt.plot()
    count += 1
```

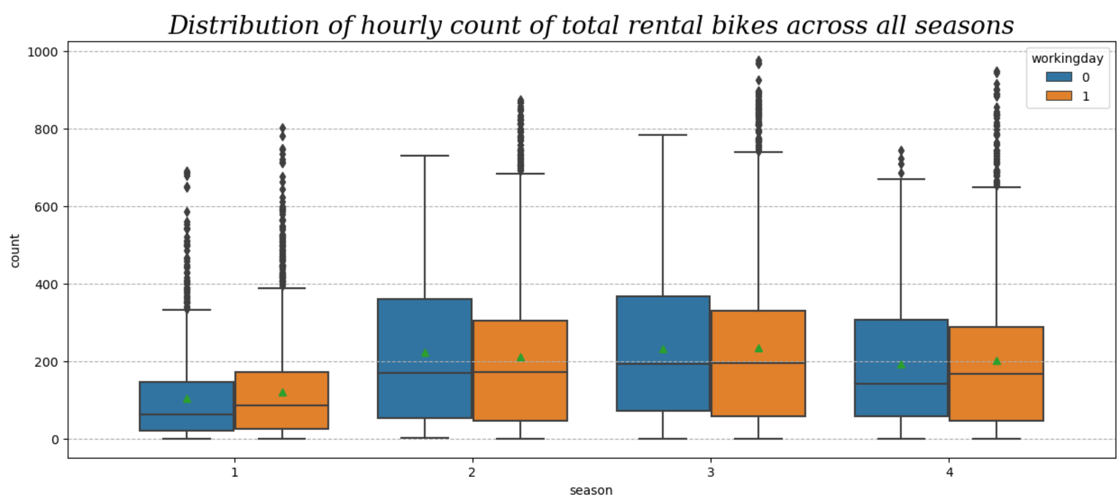


- temp column contains no outliers.
- humidity column contains few outliers.
- windspeed, casual, registered, count column contains many outlieras

4 Bivariate analysis

[42]:
```
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()
```

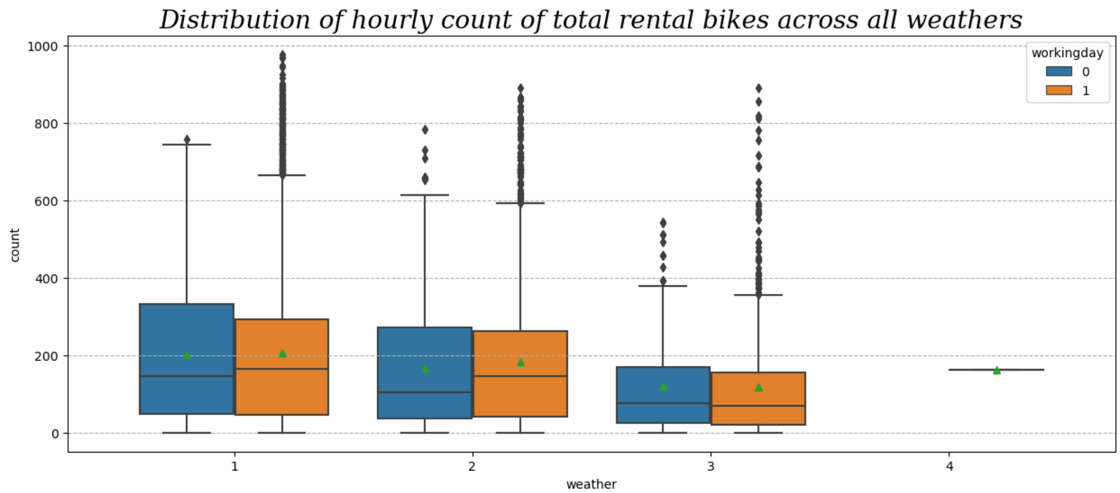
[42]: []



- 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.

[43]:
```
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()
```

[43]: []



- 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.

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

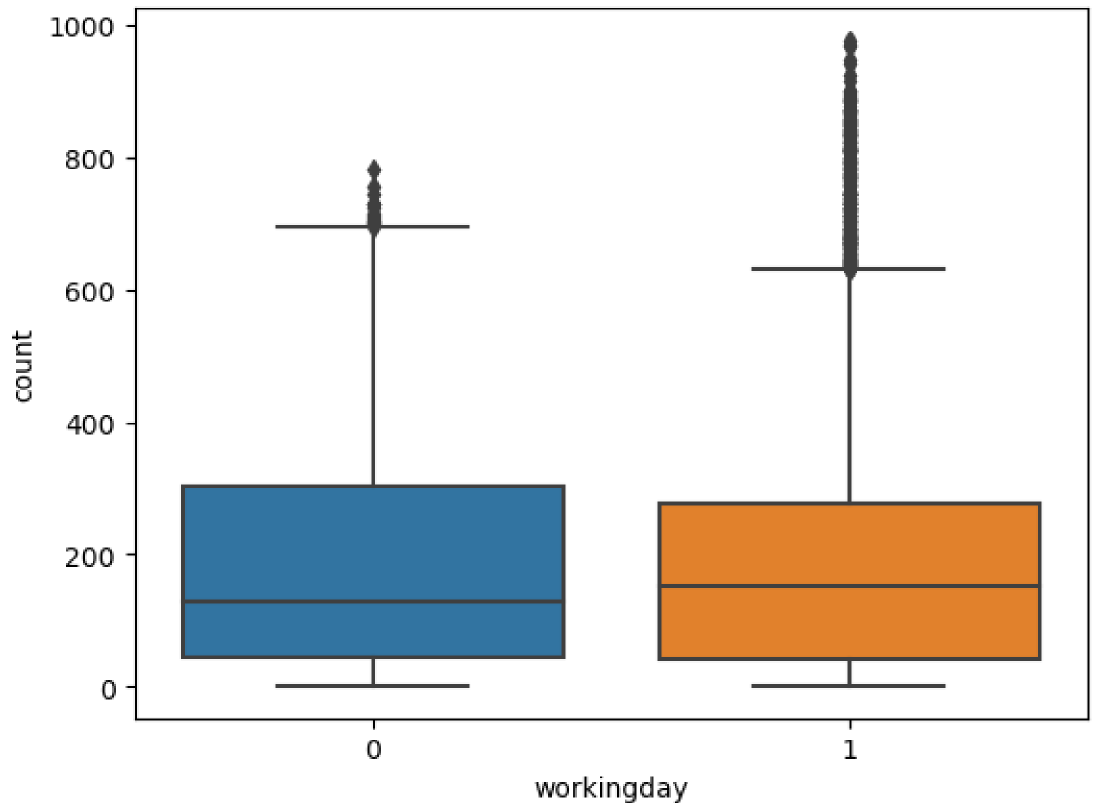
[45]:
```
df.groupby(by = 'workingday')['count'].describe()
```

[45]:

	count	mean	std	min	25%	50%	75%	max
workingday								
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

[46]:
```
sns.boxplot(data = df, x = 'workingday', y = 'count')
plt.plot()
```

[46]: []



STEP-1 : Set up Null Hypothesis

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

STEP-2: 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

[53]:
```
wd_0=df[df['workingday']==0]['count']
wd_1=df[df['workingday']==1]['count']
ttest_ind(wd_0,wd_1)
```

[53]:
```
Ttest_indResult(statistic=-1.2096277376026694, pvalue=0.22644804226361348)
```

Here P-value> alpha so we fail to reject the null hypothesis

So We can conclude that Working day have no effect on the number of electric vehicles rented

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

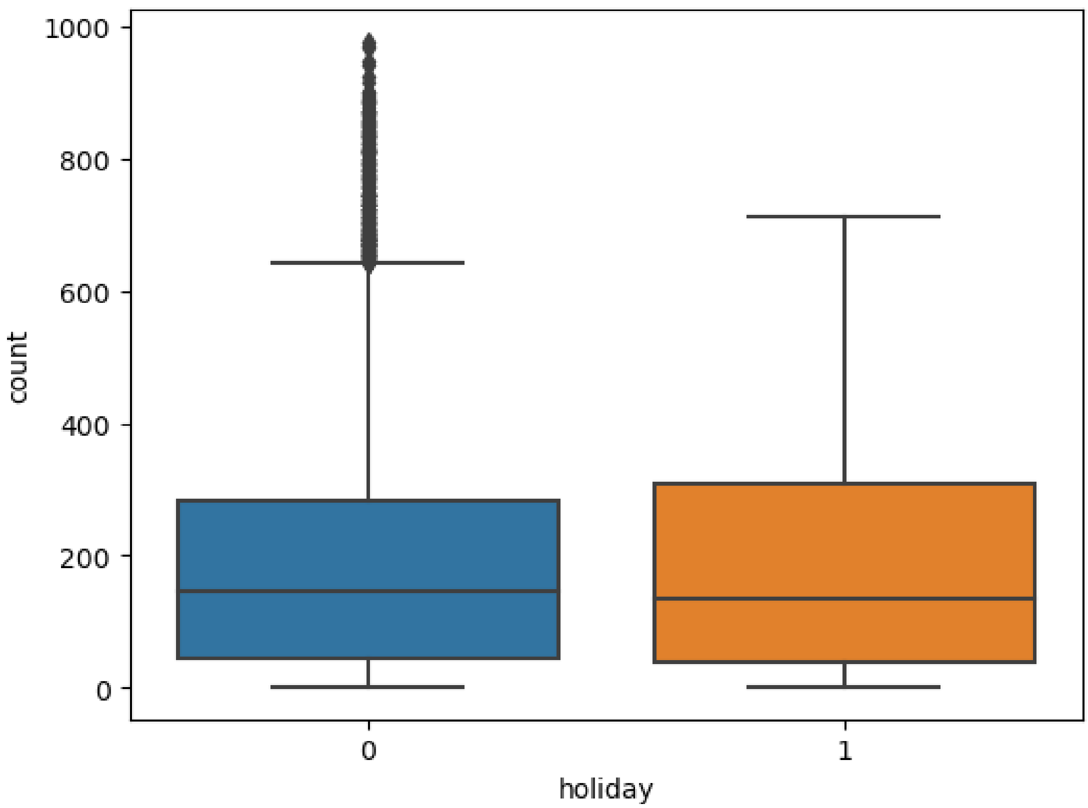
[54]:
```
df.groupby(by = 'holiday')['count'].describe()
```

[54]:

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

[55]:
```
sns.boxplot(data = df, x = 'holiday', y = 'count')
plt.plot()
```

[55]: []



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: 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

[56]:
```
holiday_0=df[df['holiday']==0]['count']
holiday_1=df[df['holiday']==1]['count']
```

[57]:
```
ttest_ind(holiday_0,holiday_1)
```

[57]:
```
Ttest_indResult(statistic=0.5626388963477119, pvalue=0.5736923883271103)
```

Here P-value> alpha so we fail to reject the null hypothesis

So We can conclude that Holiday have no effect on the number of electric vehicles rented

4.1 Is weather dependent on the season ?

[58]:
```
df[['weather', 'season']].describe()
```

[58]:

	weather	season
count	10886.000000	10886.000000
mean	1.418427	2.506614
std	0.633839	1.116174
min	1.000000	1.000000
25%	1.000000	2.000000
50%	1.000000	3.000000
75%	2.000000	4.000000
max	4.000000	4.000000

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

[59]:
```
# 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
```

[59]:
```
weather         1         2        3      4
season
1        223009.0   76406.0  12919.0  164.0
2        426350.0  134177.0  27755.0    0.0
3        470116.0  139386.0  31160.0    0.0
4        356588.0  157191.0  30255.0    0.0
```

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.

[60]:
```
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
```

[60]:
```
array([[223009,  76406,  12919],
       [426350, 134177,  27755],
       [470116, 139386,  31160],
       [356588, 157191,  30255]], dtype=int64)
```

[61]:
```
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)
```

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

[63]:
```
if p_value < 0.05:
    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.

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

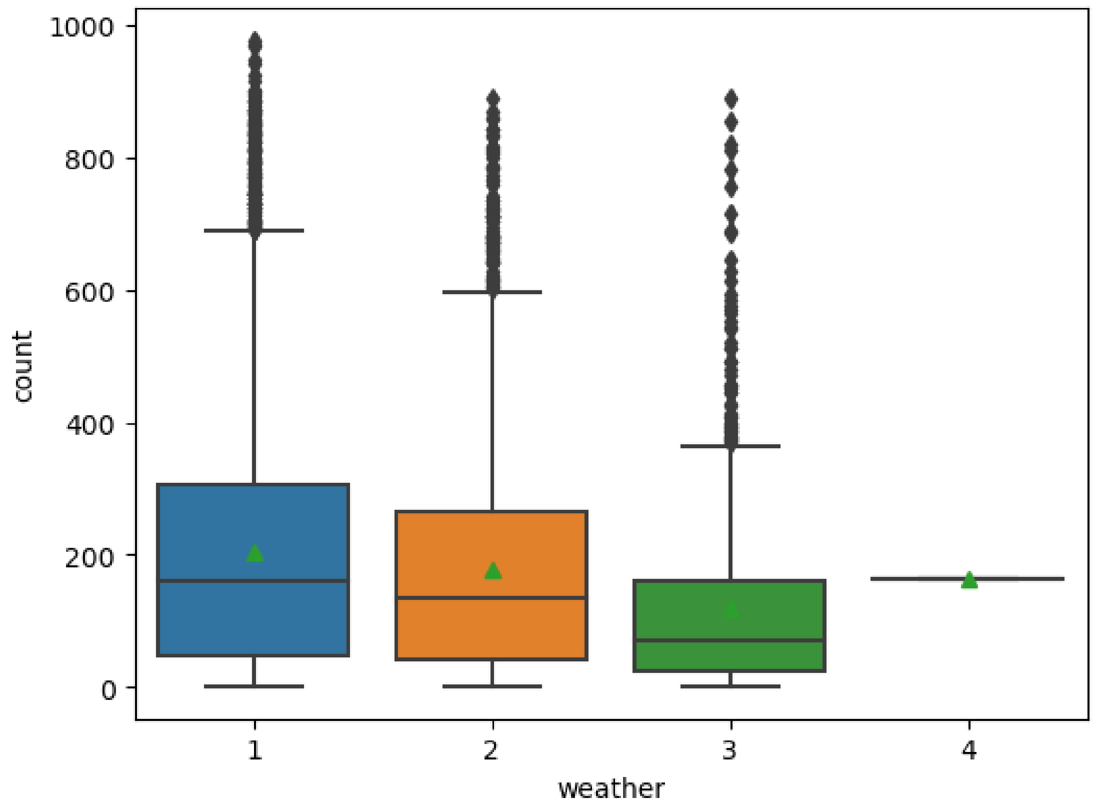
[64]:
```
df.groupby(by = 'weather')['count'].describe()
```

[64]:

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

[65]:
```
sns.boxplot(data = df, x = 'weather', y = 'count', showmeans = True)
plt.plot()
```

[65]: []




```
[66]: 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)
```

```
[66]: (7192, 2834, 859, 1)
```

STEP-1 : Set up Null Hypothesis

Normality check using **QQ Plot**.

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

Each observations are **independent**.

STEP-3: Define **Test statistics**

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

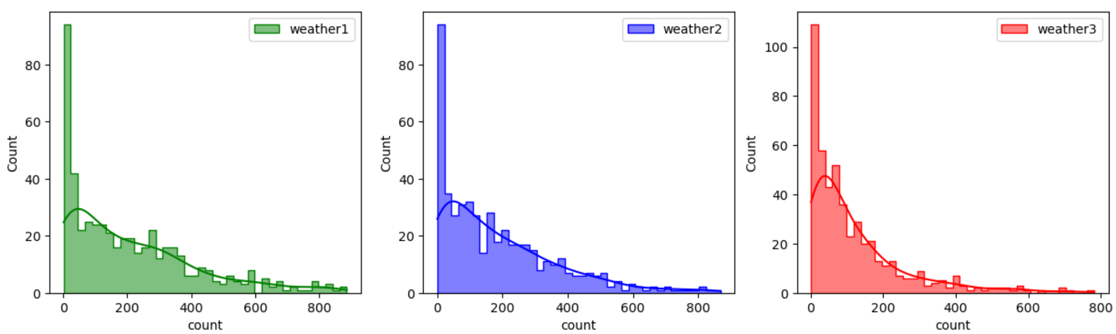
STEP-5: Compute the **p-value** and fix value of alpha.

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

[68]:
```
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()
```

[68]: []

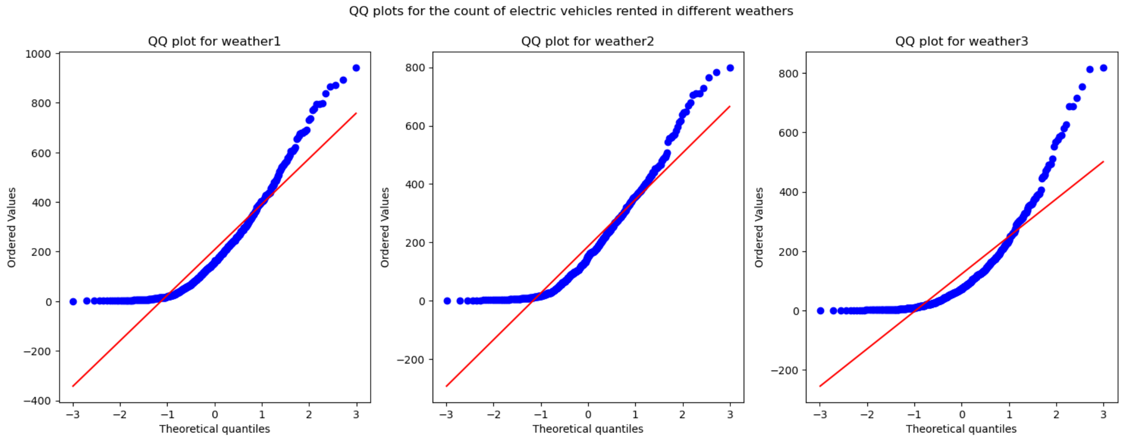


- It can be inferred from the above plot that the distributions do not follow normal distribution.

Distribution check using QQ Plot

[69]:
```
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()
```

[69]: []



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

Homogeneity of Variances using Levene's test

[71]:
```
# 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 4.184637996898б4e-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.

[76]:
```
alpha = 0.05
test_stat, p_value = spy.kruskal(df_weather1['count'], df_weather2['count'],␣
  ↪df_weather3['count'])
print('Test Statistic =', test_stat)
print('p value =', p_value)
```

```
Test Statistic = 204.95566833068537
p value = 3.122066178659941e-45
```

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

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

[77]:
```
df.groupby(by = 'season')['count'].describe()
```

[77]:

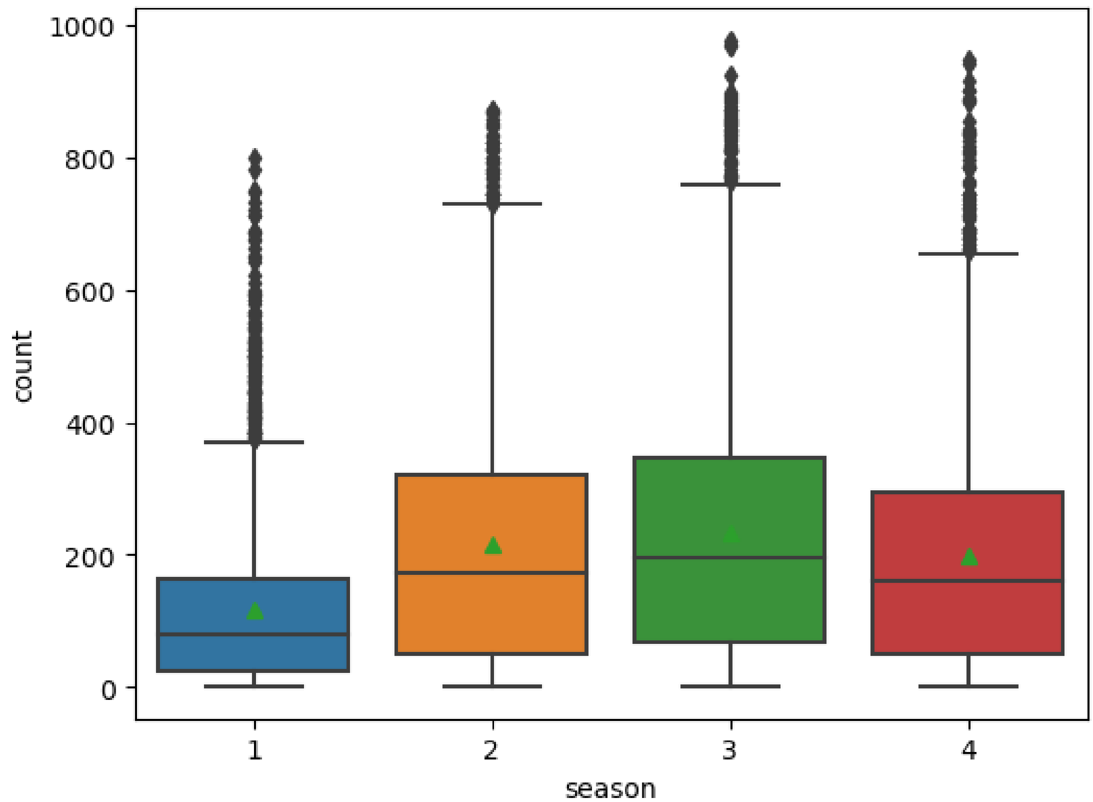
season	count	mean	std	min	25%	50%	75%	max
1	2686.0	116.343261	125.273974	1.0	24.0	78.0	164.0	801.0
2	2733.0	215.251372	192.007843	1.0	49.0	172.0	321.0	873.0
3	2733.0	234.417124	197.151001	1.0	68.0	195.0	347.0	977.0
4	2734.0	198.988296	177.622409	1.0	51.0	161.0	294.0	948.0

[79]:
```
df_season_spring = df.loc[df['season'] == 1, 'count']
df_season_summer = df.loc[df['season'] == 2, 'count']
df_season_fall = df.loc[df['season'] == 3, 'count']
df_season_winter = df.loc[df['season'] == 4, 'count']
len(df_season_spring), len(df_season_summer), len(df_season_fall),
 ↪len(df_season_winter)
```

[79]: (2686, 2733, 2733, 2734)

[80]:
```
sns.boxplot(data = df, x = 'season', y = 'count', showmeans = True)
plt.plot()
```

[80]: []



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.

---

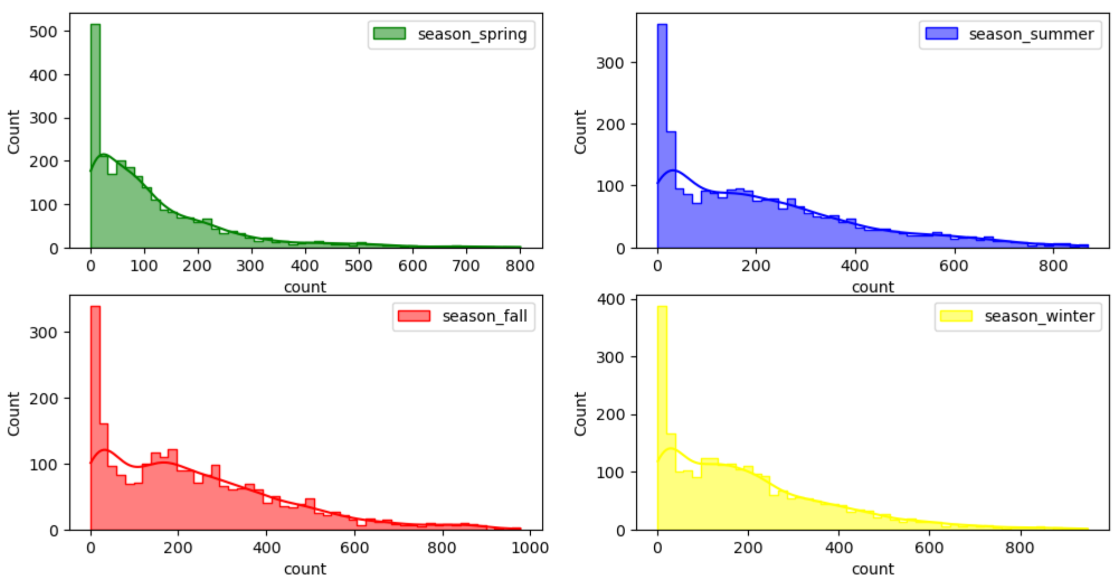
we will be computing the anova-test p-value using the **f_oneway** function using scipy.stats. We set our alpha to be **0.05**

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

[81]:
```
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()
```

[81]: []



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

[82]:
```
# 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 1.640141547262728e-106
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.

[84]:
```
# 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_season_winter)
print('Test Statistic =', test_stat)
print('p value =', p_value)
```

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

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

4.2.2 Insights

- 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.

[ ]:

```

```