In [3]:
```
# Importing the necessary libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from scipy.stats import ttest_ind,f_oneway, levene, kruskal, shapiro, chi2_conti
from statsmodels.graphics.gofplots import qqplot

import warnings
warnings.filterwarnings("ignore")
```

In [5]:
```
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving bike_sharing.csv to bike_sharing.csv
```

In [6]:
```
yulu = pd.read_csv('bike_sharing.csv')
```

In [9]:
```
df = yulu.copy()
```

In [10]:
```
df
```

Out[10]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	winc
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	
...	...	...	...	...	...	...	...	...	
10881	2012-12-19 19:00:00	4	0	1	1	15.58	19.695	50	2
10882	2012-12-19 20:00:00	4	0	1	1	14.76	17.425	57	1
10883	2012-12-19 21:00:00	4	0	1	1	13.94	15.910	61	1
10884	2012-12-19 22:00:00	4	0	1	1	13.94	17.425	61	
10885	2012-12-19 23:00:00	4	0	1	1	13.12	16.665	66	

10886 rows × 12 columns

In [11]:

```
df.shape
```

Out[11]: (10886, 12)

In [12]:

```
# Checking of null values

df.isna().sum()
```

Out[12]:

	0
datetime	0
season	0
holiday	0
workingday	0
weather	0
temp	0
atemp	0
humidity	0
windspeed	0
casual	0
registered	0
count	0

dtype: int64

There are totally 10886 rows and 12 columns in the data

The data does not contain any nulls, thus no need of handling the missing data.

In [13]:
```
# Duplicate values check

df.duplicated().sum()
```

Out[13]: 0

In [14]:
```
# skewness of each column

df.skew(numeric_only = True)
```

Out[14]:

	0
season	-0.007076
holiday	5.660517
workingday	-0.776163
weather	1.243484
temp	0.003691
atemp	-0.102560
humidity	-0.086335
windspeed	0.588767
casual	2.495748
registered	1.524805
count	1.242066

dtype: float64

Skewness Analysis of Variables

Symmetrical Majority:

The majority of the variables, including 'season' and 'temp', exhibit skewness values close to zero, suggesting relatively symmetrical distributions.

Positive Skewness Insights:

Variables such as 'holiday', 'weather', 'windspeed', 'casual', 'registered', and 'count' demonstrate positive skewness, pointing to a concentration of lower values and a rightward skew in their distributions.

Negative Skewness Observations:

In contrast, 'workingday', 'atemp', and 'humidity' exhibit negative skewness, implying a concentration of higher values and a leftward skew in their distributions.

In [15]:
```
# Uniques values of each columns

df.nunique()
```

Out[15]:

	0
datetime	10886
season	4
holiday	2
workingday	2
weather	4
temp	49
atemp	60
humidity	89
windspeed	28
casual	309
registered	731
count	822

dtype: int64

In [16]:
```
# data info

df.info()
```

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

In [17]:
```
(df['casual'] + df['registered'] == df['count']).value_counts()
```

Out[17]:

	count
True	10886

dtype: int64

In [19]:
```
# converting the categorical columns into category

cat_col = ['season', 'holiday', 'workingday', 'weather']

for _ in cat_col:
 df[_] = df[_].astype('category')

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  category
 2   holiday     10886 non-null  category
 3   workingday  10886 non-null  category
 4   weather     10886 non-null  category
 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: category(4), float64(3), int64(4), object(1)
memory usage: 723.7+ KB
```

In [21]:
```
# Converting datetime column into date time format

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

Out[21]:
```
dtype('<M8[ns]')
```

In [30]:
```
# Creating new columns from datetime and converting them to categories

df['year'] = df['datetime'].dt.year
df['month'] = df['datetime'].dt.month
df['day'] = df['datetime'].dt.day
df['hour'] = df['datetime'].dt.hour
```

In [31]:
```
df.head()
```

Out[31]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspee
0	2011-01-01 00:00:00	Spring	No	No	1	9.84	14.395	81	0
1	2011-01-01 01:00:00	Spring	No	No	1	9.02	13.635	80	0
2	2011-01-01 02:00:00	Spring	No	No	1	9.02	13.635	80	0
3	2011-01-01 03:00:00	Spring	No	No	1	9.84	14.395	75	0
4	2011-01-01 04:00:00	Spring	No	No	1	9.84	14.395	75	0

In [32]:

```
# replacing the number with category

# change of season
df['season'] = df['season'].replace({1:'Spring',2:'Summer',3:'Fall',4:'Winter'})

# change of holiday
df['holiday'] = df['holiday'].replace({0:'No',1:'Yes'})

# change of workingday
df['workingday'] = df['workingday'].replace({0:'No',1:'Yes'})

# change of month
df['month'] = df['month'].replace({1: 'January',
                                   2: 'February',
                                   3: 'March',
                                   4: 'April',
                                   5: 'May',
                                   6: 'June',
                                   7: 'July',
                                   8: 'August',
                                   9: 'September',
                                   10: 'October',
                                   11: 'November',
                                   12: 'December'})
```

In [34]:

```
df.describe(include = 'category').transpose()
```

Out[34]:

	count	unique	top	freq
season	10886	4	Winter	2734
holiday	10886	2	No	10575
workingday	10886	2	Yes	7412
weather	10886	4	1	7192

Overview and Feature Patterns

Temporal and Numerical Composition: The dataset encompasses both datetime information and various numerical features associated with bike rentals. The observations span from January 1, 2011, to December 19, 2012.

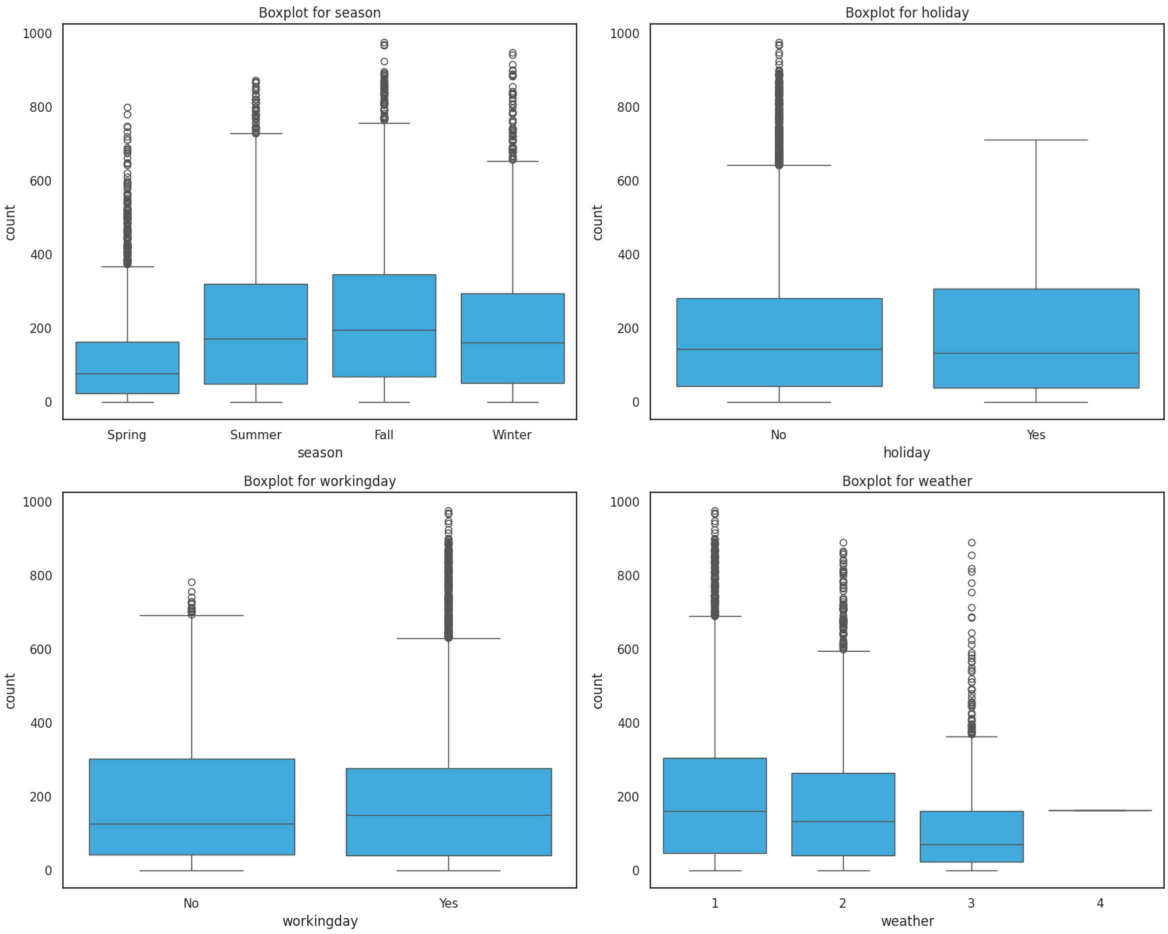
Diverse Numerical Feature Characteristics: Numerical features such as temperature, humidity, windspeed, and counts of casual and registered bike rentals show diverse ranges and distributions, highlighting the variability in rental patterns across different conditions.

Temporal Patterns and Concentrations: Observations on the year, day, and hour variables indicate temporal patterns, with a concentration in 2011 and 2012, a mean day value around 10, and an hourly distribution ranging from 0 to 23.

OUTLIER DETECTION

In [36]:

```
plt.figure(figsize=(15, 12))
sns.set(style="white")

for i, column in enumerate(cat_col,1):
    plt.subplot(2, 2, i)
    sns.boxplot(x=column, y='count', data=df, color="#29B6F6")
    plt.title(f'Boxplot for {column}')

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



Outlier Analysis

**Outliers in Different Seasons: **

In spring and winter, there are more unusual values in the data compared to other seasons.

Weather Outliers:

Category 3 weather has a lot of unusual values, while category 4 weather doesn't have any.

Working Days vs. Holidays:

On regular working days, there are more unusual values in the data than on holidays. This suggests some unexpected patterns during typical workdays that might need a closer look.

UNIVARIATE ANALYSIS

In [38]:
```
# Time span of data
time_span = df['datetime'].max() - df['datetime'].min()
time_span
```

Out[38]:
```
Timedelta('718 days 23:00:00')
```

In [39]:
```python
# Season counts
df['season'].value_counts()
```

Out[39]:

season	count
Winter	2734
Summer	2733
Fall	2733
Spring	2686

dtype: int64

In [40]:
```python
# holiday counts
df['holiday'].value_counts()
```

Out[40]:

holiday	count
No	10575
Yes	311

dtype: int64

In [41]:
```python
# workingday counts
df['workingday'].value_counts()
```

Out[41]:

workingday	count
Yes	7412
No	3474

dtype: int64

In [42]:
```python
# weather counts
df['weather'].value_counts()
```

Out[42]:

weather	count
1	7192
2	2834
3	859
4	1

dtype: int64

In [43]:

```
# year counts
df['year'].value_counts()
```

Out[43]:

year	count
2012	5464
2011	5422

dtype: int64

In [44]:

```
# month counts
df['month'].value_counts()
```

Out[44]:

month	count
May	912
June	912
July	912
August	912
December	912
October	911
November	911
April	909
September	909
February	901
March	901
January	884

dtype: int64

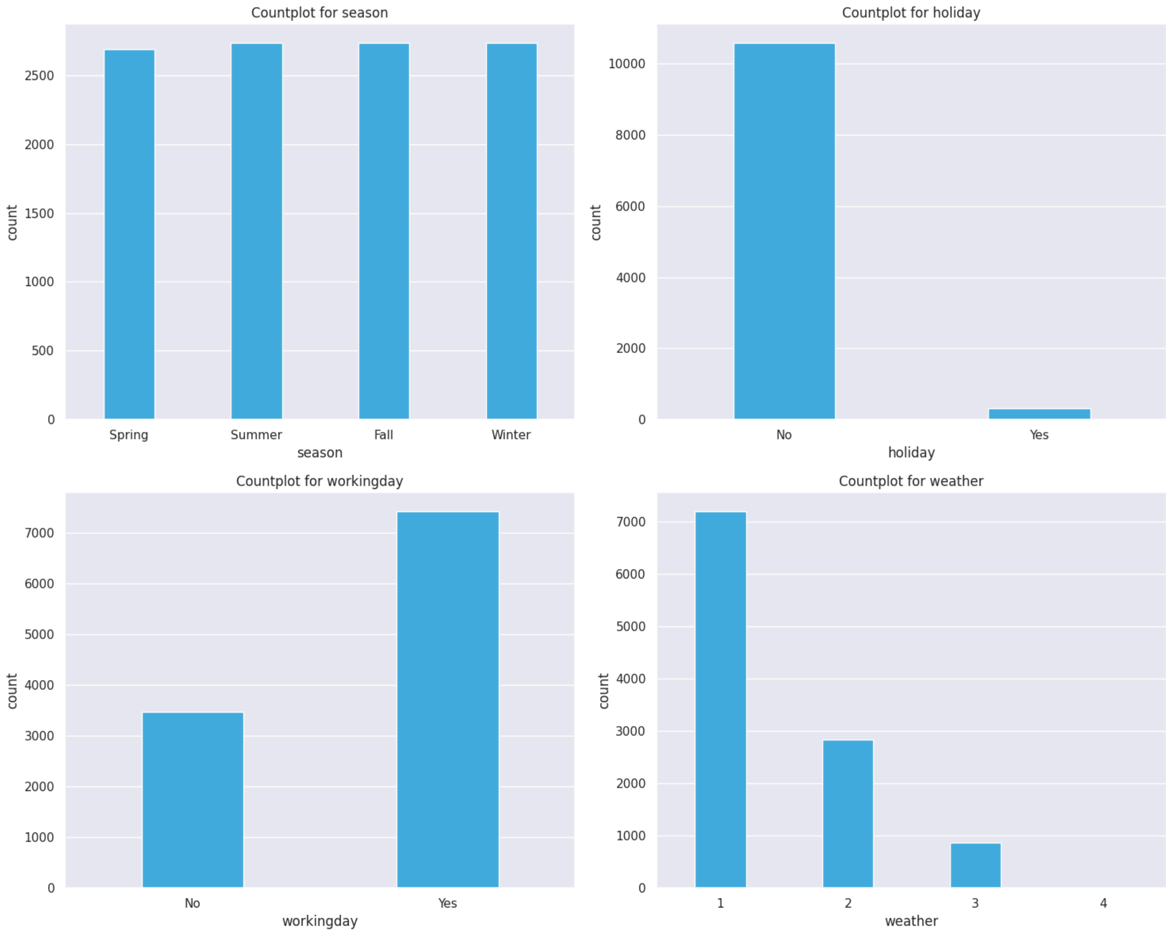
In [45]:
```
# day counts
df['day'].value_counts().sort_index()
```

Out[45]:

day	count
1	575
2	573
3	573
4	574
5	575
6	572
7	574
8	574
9	575
10	572
11	568
12	573
13	574
14	574
15	574
16	574
17	575
18	563
19	574

dtype: int64

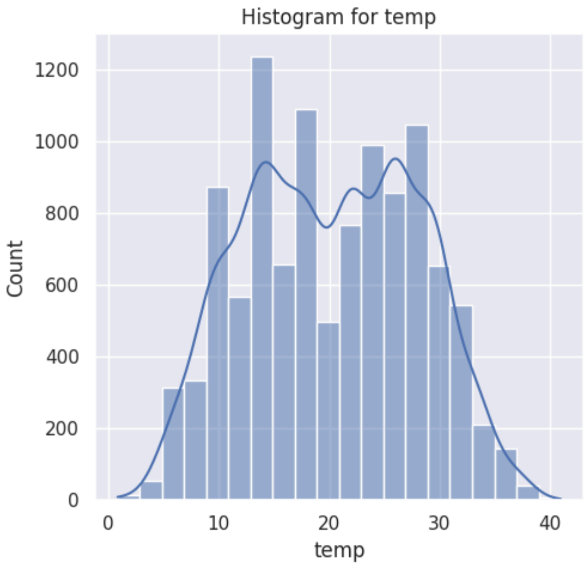
In [47]:
```
# countplot on categories

plt.figure(figsize=(15, 12))
sns.set(style="darkgrid")

for i, column in enumerate(cat_col, 1):
    plt.subplot(2, 2, i)
    sns.countplot(x=column, data=df, color="#29B6F6", width=0.4)
    plt.title(f'Countplot for {column}')

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

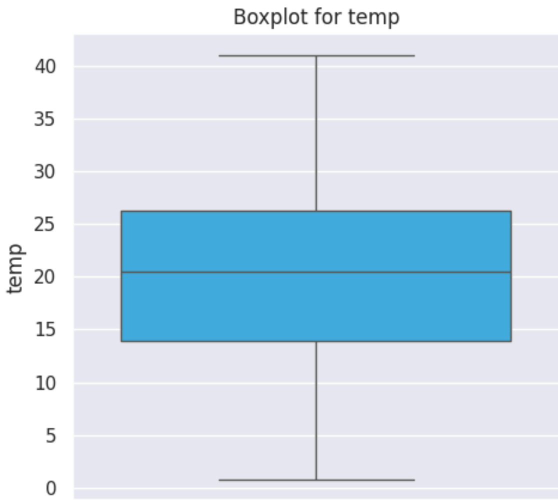


In [49]:
```
# Function for histogram & boxplot on numerical columns

def hist_box(column):
    f, axs = plt.subplots(1, 2, figsize=(10, 5))
    sns.set(style="darkgrid")

    # Histogram
    plt.subplot(1, 2, 1)
    sns.histplot(df[column], bins=20, kde=True)
    plt.title(f'Histogram for {column}')

    # Boxplot
    plt.subplot(1, 2, 2)
    sns.boxplot(df[column], color="#29B6F6")
    plt.title(f'Boxplot for {column}')

    tabular_data = df[column].describe().reset_index()
    tabular_data.columns = ['Statistic', 'Value']
    display(tabular_data)

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

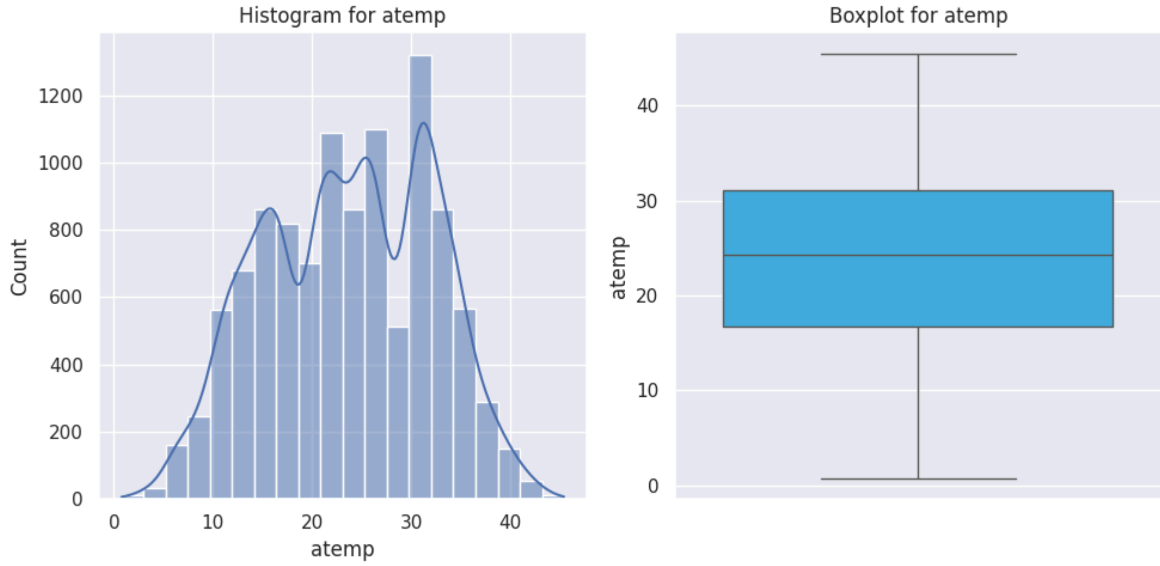
In [51]:
```
num_col = ['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'cc

for column in num_col:
    hist_box(column)
```

	Statistic	Value
0	count	10886.00000
1	mean	20.23086
2	std	7.79159
3	min	0.82000
4	25%	13.94000
5	50%	20.50000
6	75%	26.24000
7	max	41.00000

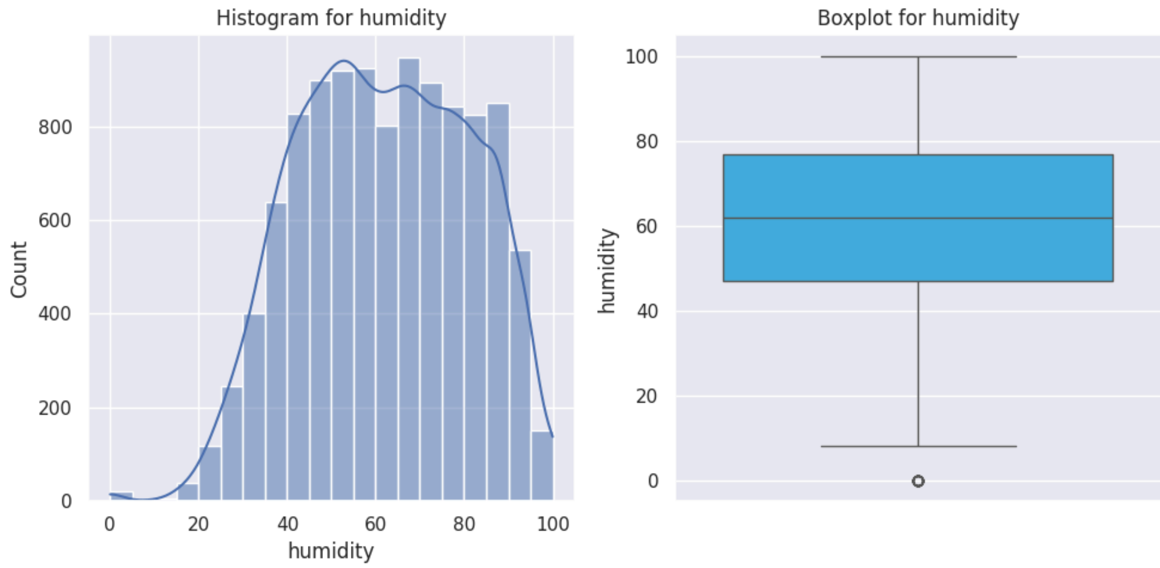




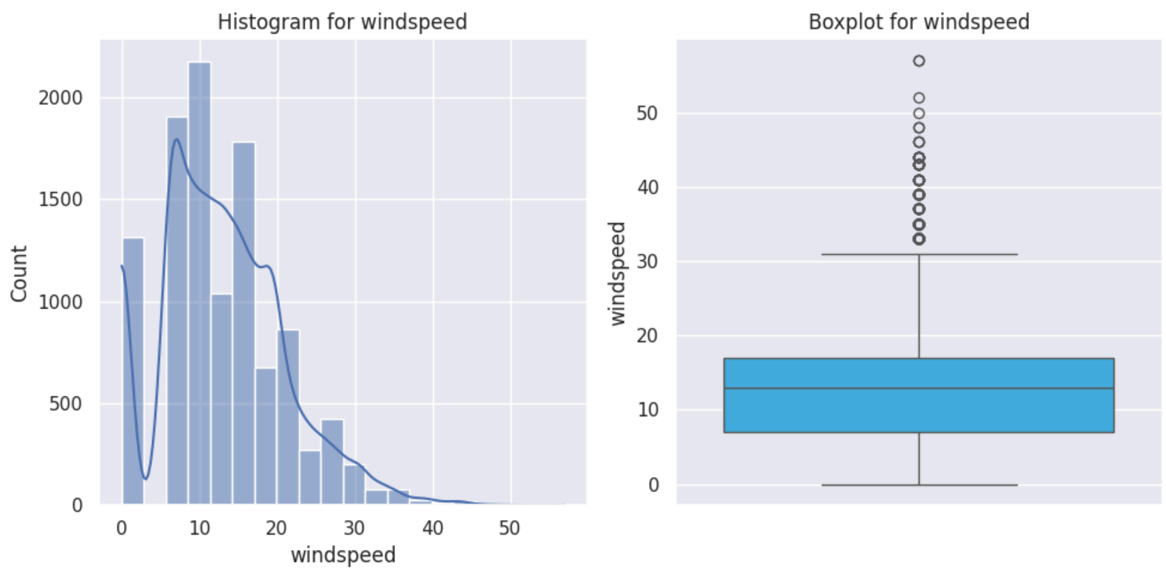
	Statistic	Value
0	count	10886.000000
1	mean	23.655084
2	std	8.474601
3	min	0.760000
4	25%	16.665000
5	50%	24.240000
6	75%	31.060000
7	max	45.455000



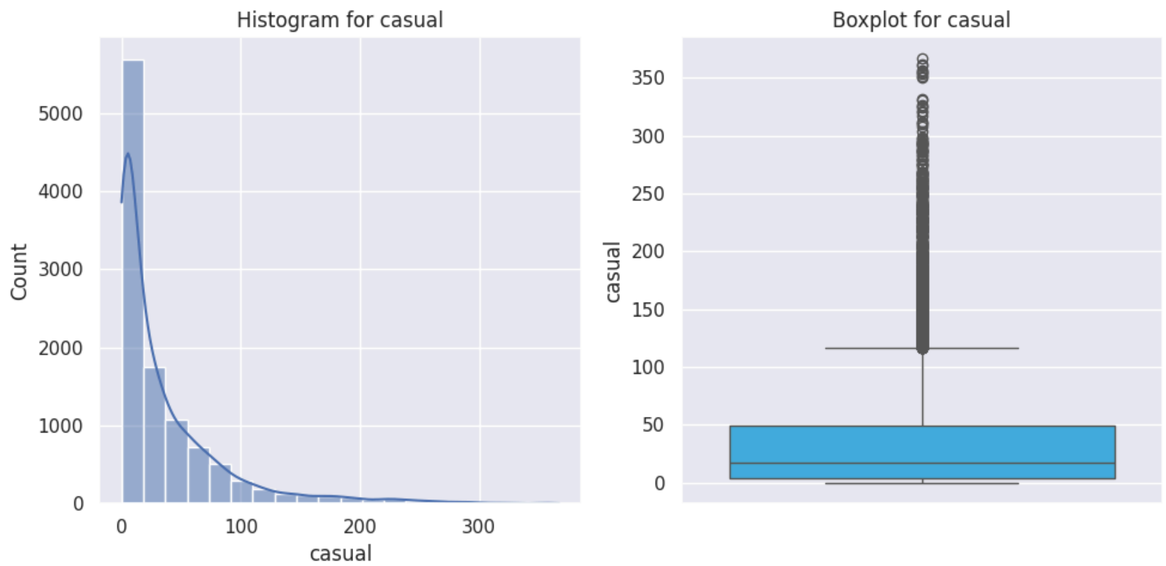
	Statistic	Value
0	count	10886.000000
1	mean	61.886460
2	std	19.245033
3	min	0.000000
4	25%	47.000000
5	50%	62.000000
6	75%	77.000000
7	max	100.000000



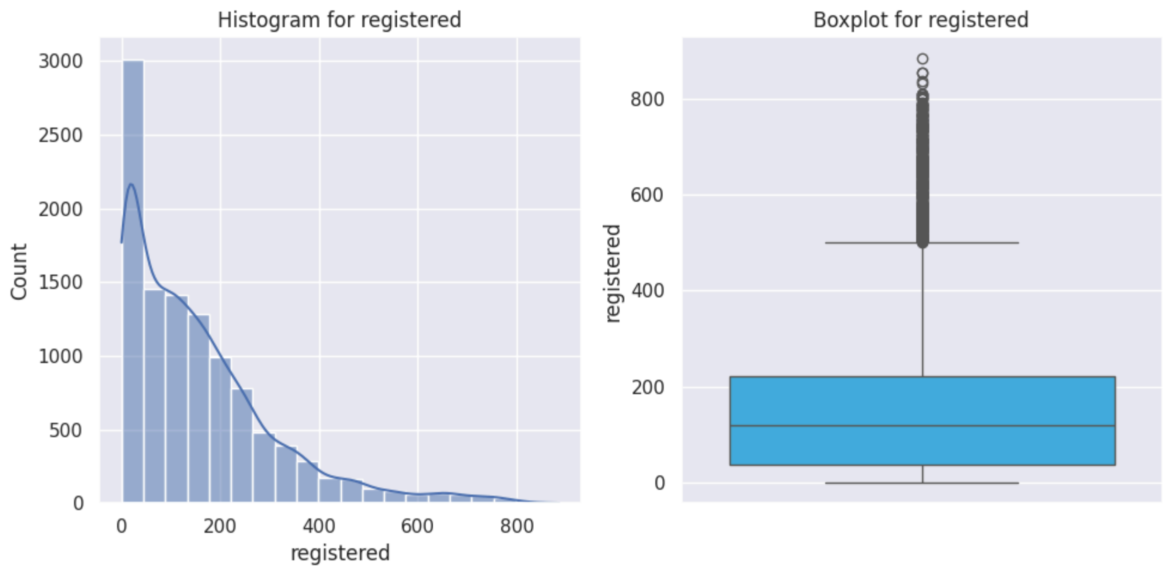
	Statistic	Value
0	count	10886.000000
1	mean	12.799395
2	std	8.164537
3	min	0.000000
4	25%	7.001500
5	50%	12.998000
6	75%	16.997900
7	max	56.996900



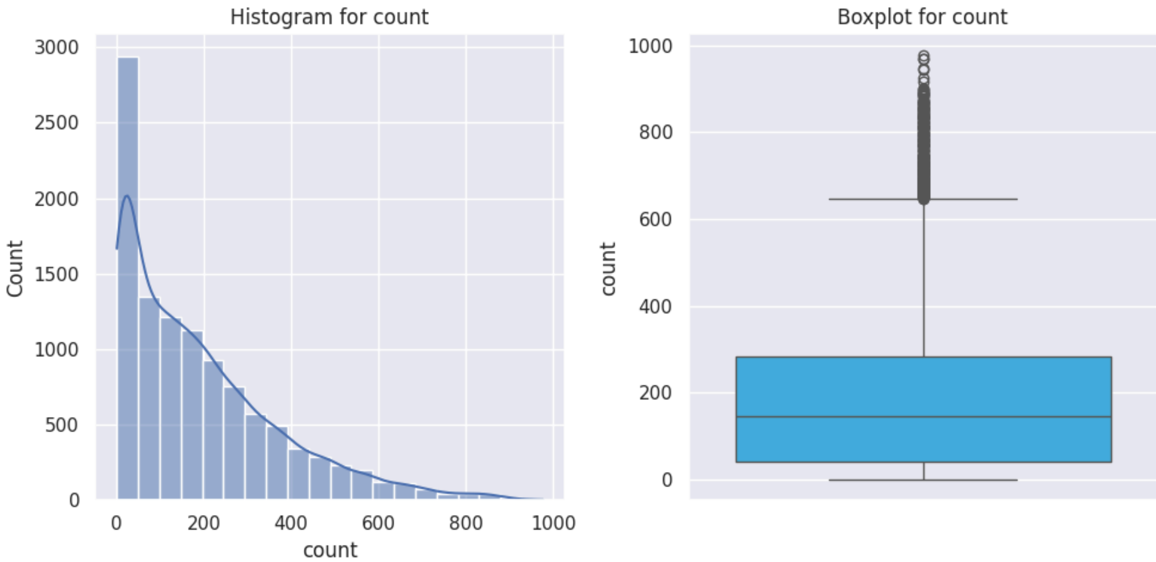
	Statistic	Value
0	count	10886.000000
1	mean	36.021955
2	std	49.960477
3	min	0.000000
4	25%	4.000000
5	50%	17.000000
6	75%	49.000000
7	max	367.000000



	Statistic	Value
0	count	10886.000000
1	mean	155.552177
2	std	151.039033
3	min	0.000000
4	25%	36.000000
5	50%	118.000000
6	75%	222.000000
7	max	886.000000



	Statistic	Value
0	count	10886.000000
1	mean	191.574132
2	std	181.144454
3	min	1.000000
4	25%	42.000000
5	50%	145.000000
6	75%	284.000000
7	max	977.000000



Numerical column analysis

Temp:

The 'temp' column shows a diverse temperature range (0.82 to 41.0), with a median of 20.5 and moderate variability around the mean of approximately 20.23 degrees Celsius.

Atemp

The 'atemp' column displays a wide range of apparent temperatures (0.76 to 45.455), with a mean of approximately 23.66 and moderate variability around the median of 24.24.

Humidity

The 'humidity' column depicts a range of humidity values (0 to 100), with an average around 61.89. The distribution shows moderate variability, from 47 at the 25th percentile to 77 at the 75th percentile, indicating diverse humidity levels in the dataset.

WindSpeed

The 'windspeed' column displays a range of wind speeds from 0 to 56.9979, with a mean of approximately 12.80.

Casual

The 'casual' column demonstrates a broad range of casual bike rental counts, with values spanning from 0 to 367. The distribution is positively skewed, as indicated by the mean (36.02) being less than the median (17.0).

Registered

The 'registered' column showcases a diverse range of registered bike rental counts, ranging from 0 to 886. The distribution is positively skewed, evidenced by the mean (155.55) being less than the median (118.0).

Count

The 'count' column reveals a wide range of total bike rental counts, varying from 1 to 977. The distribution is positively skewed, with a mean (191.57) greater than the median (145.0), indicating a concentration of lower values

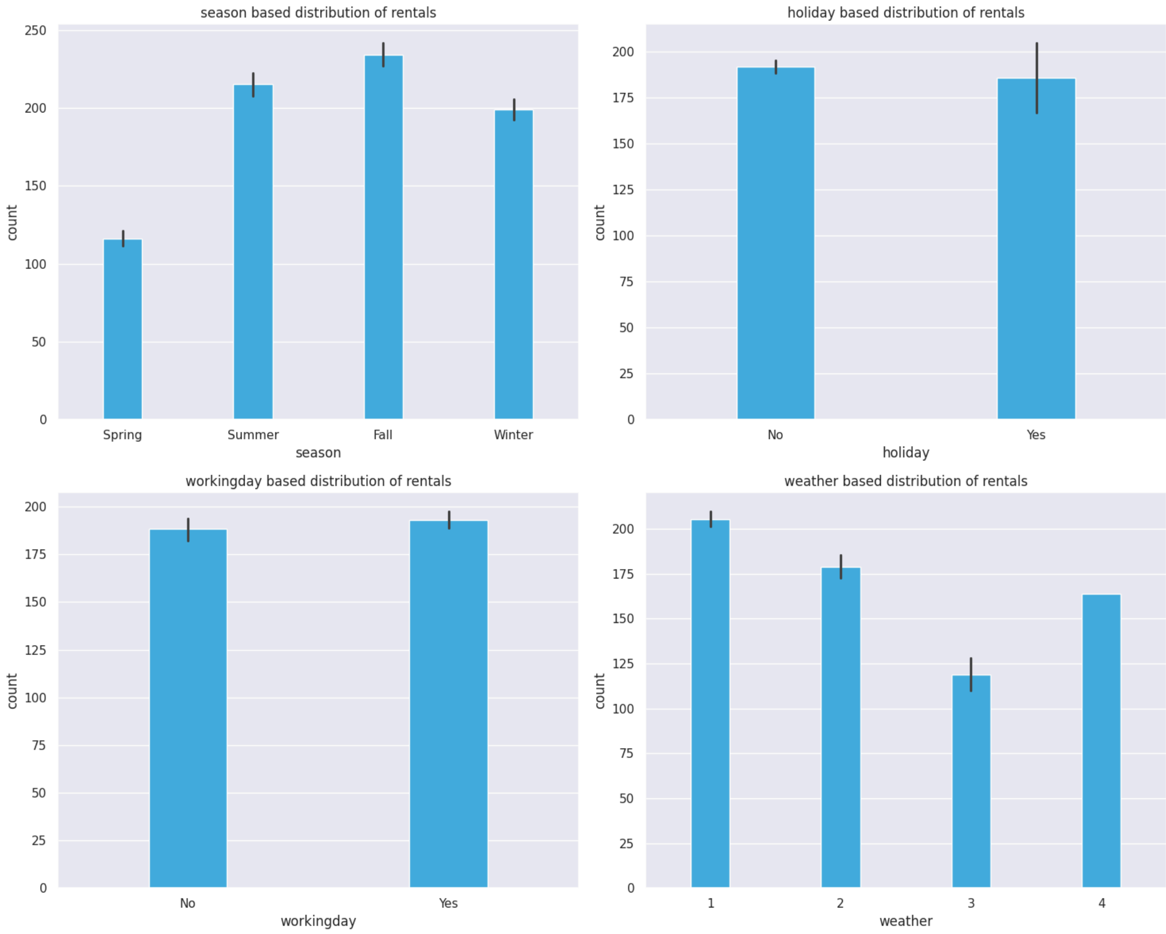
---

BIVARIATE ANALYSIS

In [52]:
```
cat_col
```

Out[52]:
```
['season', 'holiday', 'workingday', 'weather']
```

In [53]:
```
# barplot of categories

plt.figure(figsize=(15, 12))
sns.set(style="darkgrid")

for i, column in enumerate(cat_col,1):
    plt.subplot(2, 2, i)
    sns.barplot(x=column, y='count', data=df, color="#29B6F8", width = 0.3)
    plt.title(f'{column} based distribution of rentals')

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

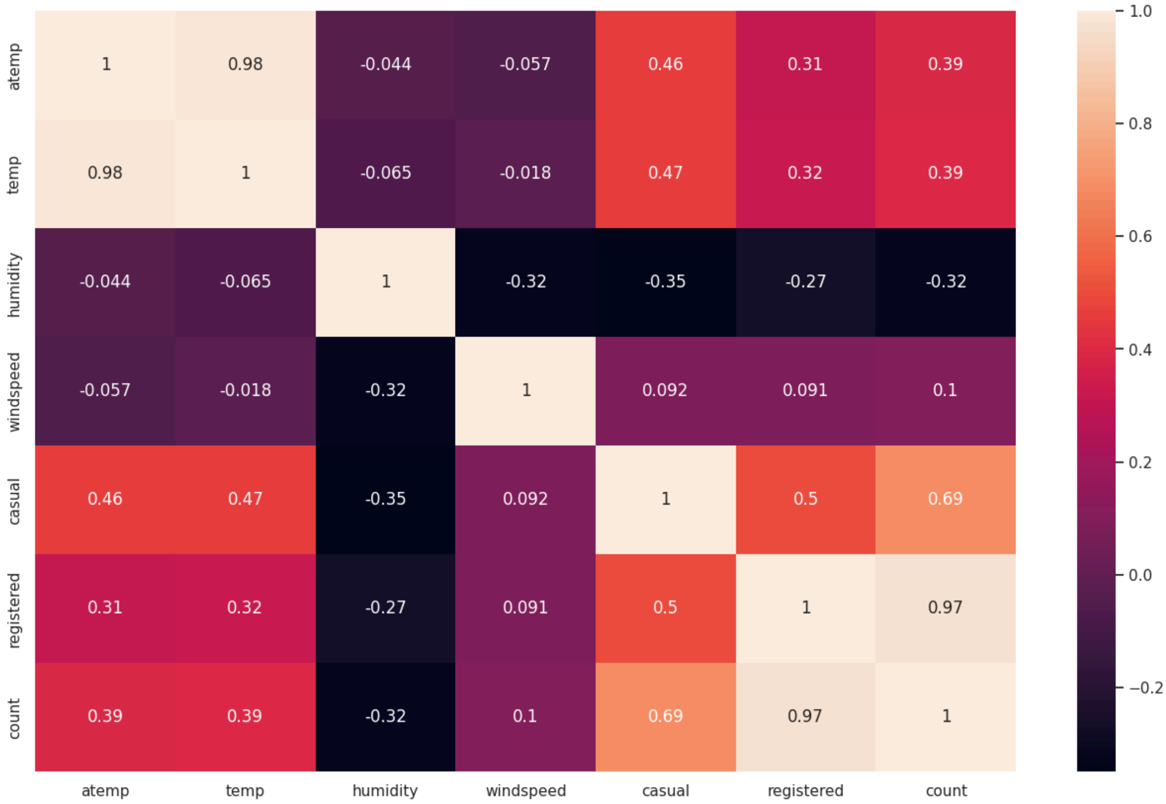


In [55]:
```
# corrrelation analysis

correlation_matrix = df[["atemp", "temp", "humidity", "windspeed", "casual", "re
correlation_df = pd.DataFrame(correlation_matrix)
correlation_df
```

Out[55]:

	atemp	temp	humidity	windspeed	casual	registered	count
atemp	1.000000	0.984948	-0.043536	-0.057473	0.462067	0.314635	0.389784
temp	0.984948	1.000000	-0.064949	-0.017852	0.467097	0.318571	0.394454
humidity	-0.043536	-0.064949	1.000000	-0.318607	-0.348187	-0.265458	-0.317371
windspeed	-0.057473	-0.017852	-0.318607	1.000000	0.092276	0.091052	0.101369
casual	0.462067	0.467097	-0.348187	0.092276	1.000000	0.497250	0.690414
registered	0.314635	0.318571	-0.265458	0.091052	0.497250	1.000000	0.970948
count	0.389784	0.394454	-0.317371	0.101369	0.690414	0.970948	1.000000

In [56]:
```
# correlation chart

plt.figure(figsize = (16, 10))
sns.heatmap(correlation_matrix, annot = True)
plt.show()
```



Correlation Analysis

Atemp:

Strong positive correlation with 'temp' (0.98), indicating a close relationship. Moderate positive correlation with 'casual' (0.46) and 'registered' (0.31). Positive correlation with 'count' (0.39), suggesting a relationship with overall bike rentals.

Temp (Temperature):

Highly correlated with 'atemp' (0.98), indicating a strong connection. Moderate positive correlation with 'casual' (0.47) and 'registered' (0.32). Positive correlation with 'count' (0.39), showing a relationship with overall bike rentals.

Humidity:

Weak negative correlation with 'atemp' (-0.04) and 'temp' (-0.06). Moderate negative correlation with 'casual' (-0.35), 'registered' (-0.27), and 'count' (-0.32). Indicates a tendency for fewer bike rentals during higher humidity.

Windspeed:

Weak negative correlation with 'atemp' (-0.06) and 'temp' (-0.02). Weak positive correlation with 'casual' (0.09), 'registered' (0.09), and 'count' (0.10). Suggests a subtle influence on bike rentals with increasing wind speed.

Casual (Casual Bike Rentals):

Strong positive correlation with 'atemp' (0.46) and 'temp' (0.47). Moderate negative correlation with 'humidity' (-0.35) and positive correlation with 'windspeed' (0.09). Highly correlated with 'registered' (0.50) and 'count' (0.69), indicating a significant impact on overall rentals.

Registered (Registered Bike Rentals):

Positive correlation with 'atemp' (0.31) and 'temp' (0.32). Negative correlation with 'humidity' (-0.27) and positive correlation with 'windspeed' (0.09). Highly correlated with 'casual' (0.50) and 'count' (0.97), emphasizing a substantial impact on overall rentals.

Count (Total Bike Rentals):

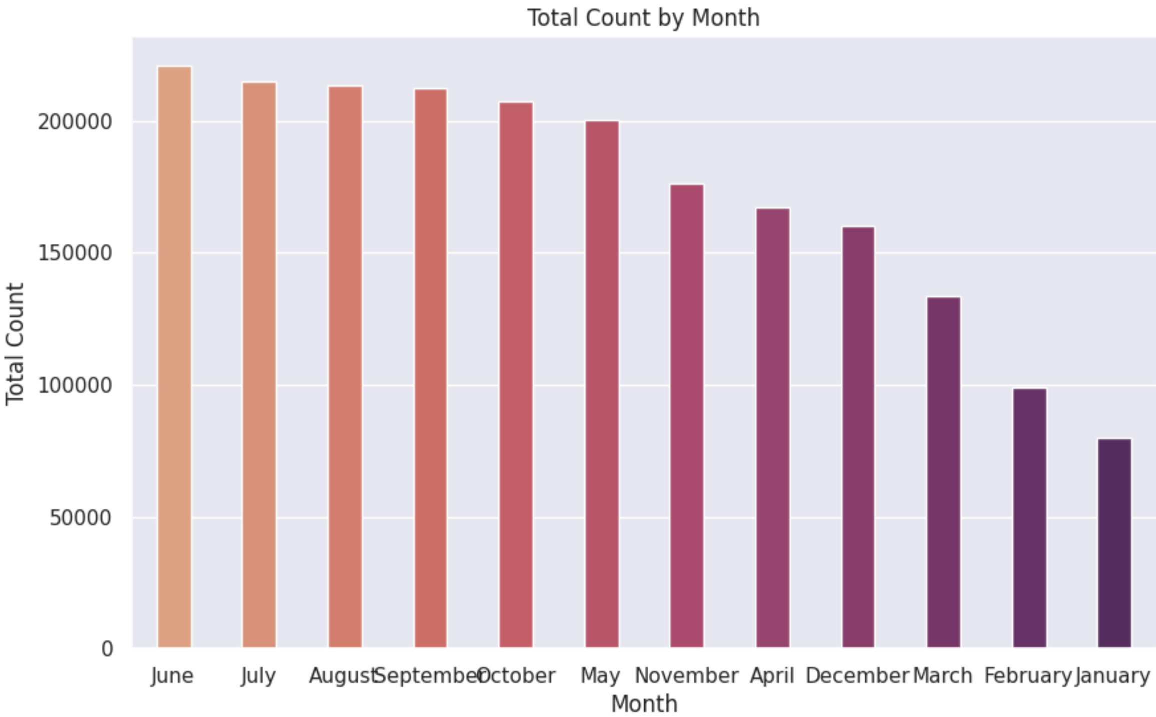
Positive correlation with 'atemp' (0.39), 'temp' (0.39), and 'casual' (0.69). Negative correlation with 'humidity' (-0.32). Highly correlated with 'registered' (0.97), emphasizing the joint impact of casual and registered rentals on the overall count.

In [58]:
```
# counts based on months

monthly_count = df.groupby('month')['count'].sum().reset_index()

monthly_count = monthly_count.sort_values(by='count', ascending=False)

monthly_count
```

Out[58]:

	month	count
6	June	220733
5	July	214617
1	August	213516
11	September	212529
10	October	207434
8	May	200147
9	November	176440
0	April	167402
2	December	160160
7	March	133501
3	February	99113
4	January	79884

In [60]:
```
# rentals on monthly counts

plt.figure(figsize=(10, 6))
sns.barplot(x='month', y='count', data=monthly_count, palette='flare', width = 0

plt.title('Total Count by Month')
plt.xlabel('Month')
plt.ylabel('Total Count')
plt.show()
```



Monthly analysis on rentals

Peak Rental Months:

June stands out as the peak month for bike rentals, with the highest count of 220,733, followed closely by July and August.

Seasonal Trend:

Summer months (June, July, August) show higher bike rental counts, consistent with favorable weather conditions.

Off-Peak Rental Months:

January, February, and March have notably lower bike rental counts, indicating potential off-peak periods, possibly influenced by colder weather or fewer outdoor activities.

Hypothesis Testing

Demand of bicycles on rent is the same on Weekdays & Weekends

Since we have two independent saples, we can go with Two Sample Independent T-Test.

Assumptions of Two Sample Independent T-Test :

The data should be normall distributed

variances of the two groups are equal

Let the Confidence interval be 95%, so siginificance (alpha) is 0.05

To check if the data is normal, we will go with Wilkin-ShapiroTest.

The test hypothesis for the Wilkin-Shapiro test are:

Ho: Data is normally distributed

Ha: Data is not normally distributed.

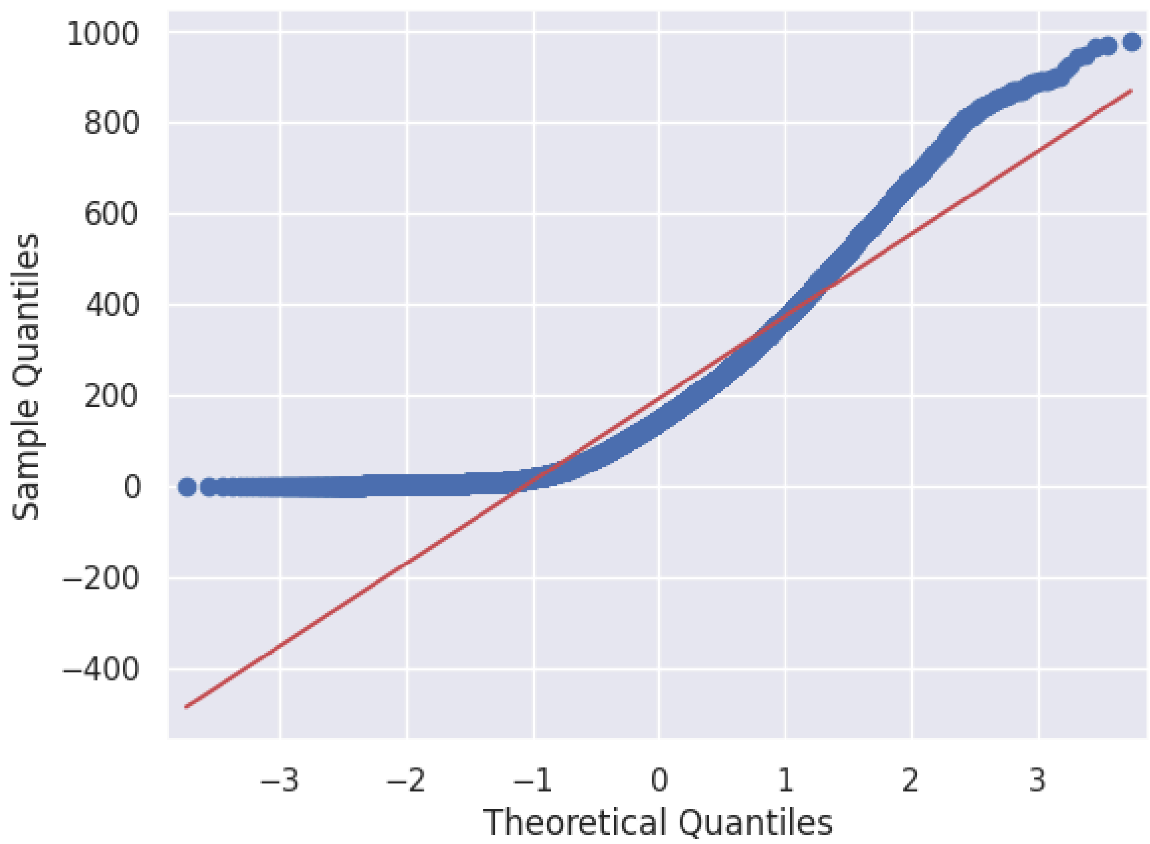
In [62]:
```
np.random.seed(41)

df_subset = df.sample(100)["count"]

test_stat, p_val = shapiro(df_subset)

p_val
```

Out[62]: 2.6341210395843134e-07

p_value is less than the significance value .

Null Hypothesis will be rejected.

In [63]:
```
# QQ Plot analysis


qqplot(df['count'], line = 's')
plt.show()
```



To check if the variances of two groups are equal. We will perform Levene's test

The Test hypotheses for Levene's test are:

Ho: The variances are equal.

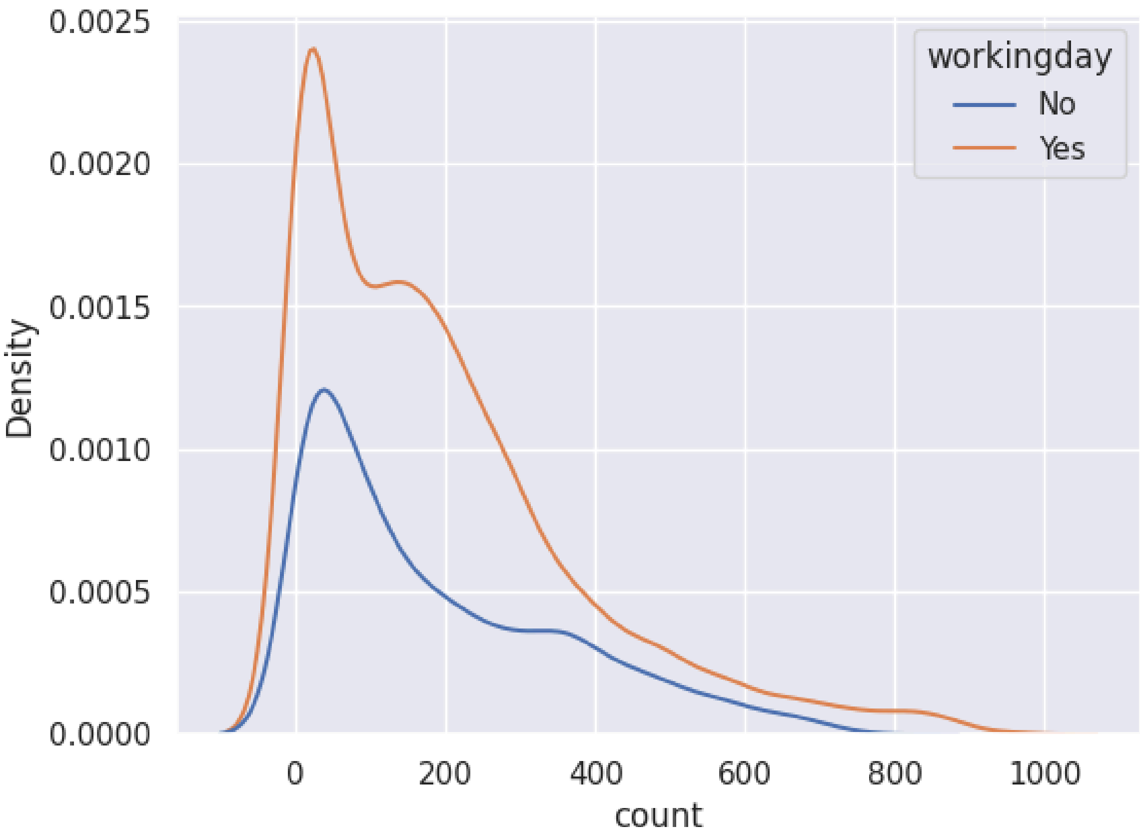
Ha: The variances are not equal.

In [65]:
```
working_day = df[df['workingday'] == 'Yes']['count']

holiday = df[df['workingday'] == 'No']['count']

levene_stat, p_val = levene(working_day, holiday)

p_val
```

Out[65]: 0.9437823280916695

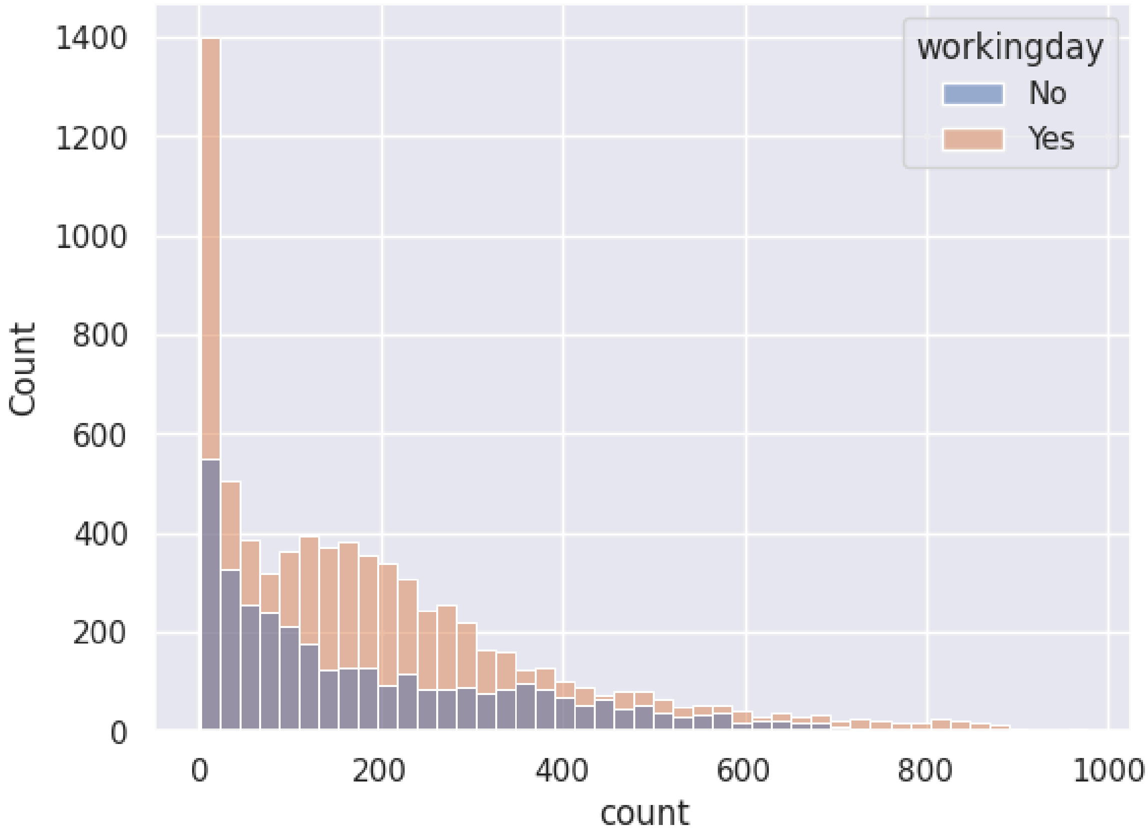
In [66]:
```
sns.kdeplot(data = df, x = 'count', hue = 'workingday')
```

Out[66]: <Axes: xlabel='count', ylabel='Density'>



In [67]:
```
sns.histplot(data = df, x = 'count', hue = 'workingday')
```

Out[67]: <Axes: xlabel='count', ylabel='Count'>



Hence the p_values is greater than the significance level, Null hypothesis can be accepted.

Therefore, the variances are approximately equal.

Despite the data is not normally distributed according to both the Wilkin-ShapiroTest and qq-plot

It is important to highlight that the variances between the two groups are equal

So we can proceed with the Two Sample Independent T-Test.

The hypothesis for the t-test are:

Ho: There is no significant difference between working and non-working days.

Ha: There is a significant difference between working and non-working days.

In [68]:
```
ttest_stat, p_val = ttest_ind(working_day, holiday)

p_val
```

Out[68]: 0.9437823280916695

Hence the p_values is greater than the significance level, Null hypothesis can be accepted.

Therefore, There is no significant difference on bike rentals between working and non-working days.

Demand of bicycles on rent is the same for different Weather conditions

Assumptions for ANOVA are:

The population data should be normally distributed- The data is not normal as verified by Wilkin-Shapiro test and the qqplot.

The data points must be independent- This condition is satisfied.

Approximately equal variance within groups- This will be verified using Levene's test.

In [69]:
```
# skewness of weather

df.groupby('weather')['count'].skew()
```

Out[69]:

weather	count
1	1.139857
2	1.294444
3	2.187137
4	NaN

dtype: float64

In [70]:
```
# kurtosis test of weather

df.groupby('weather')['count'].apply(lambda x: x.kurtosis())
```

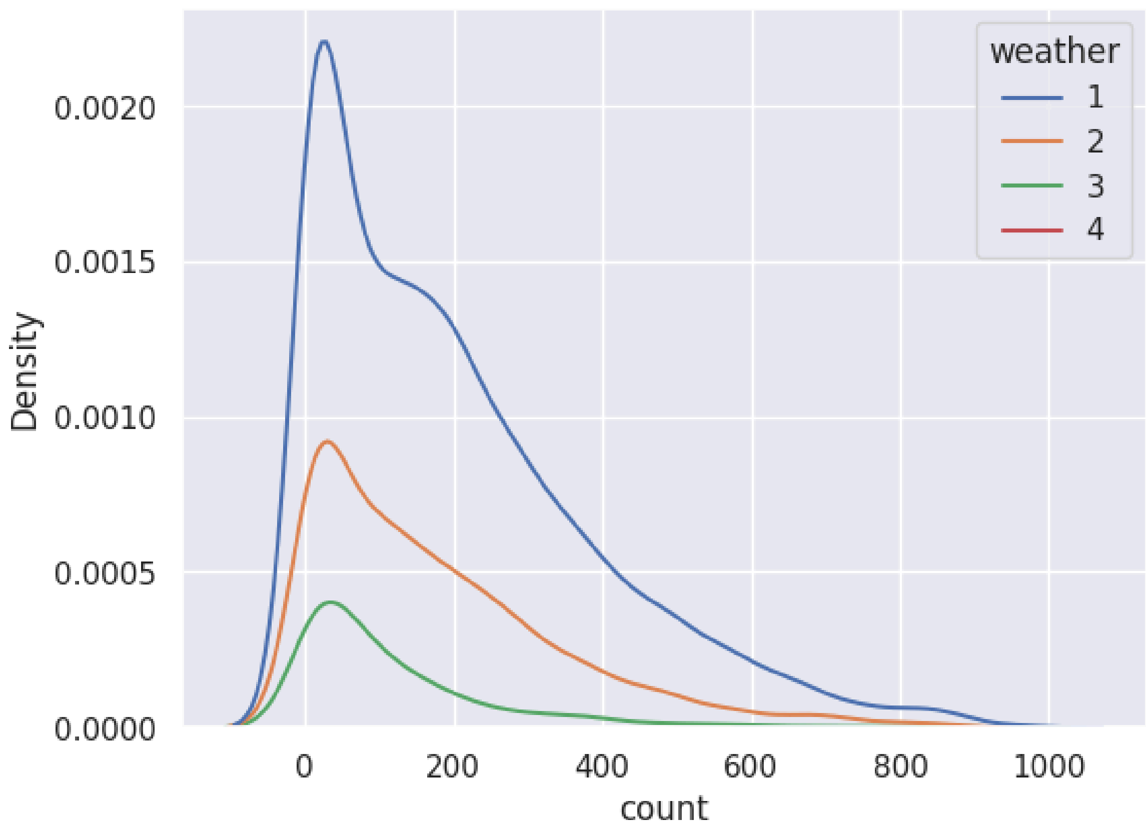
Out[70]:

weather	count
1	0.964720
2	1.588430
3	6.003054
4	NaN

dtype: float64

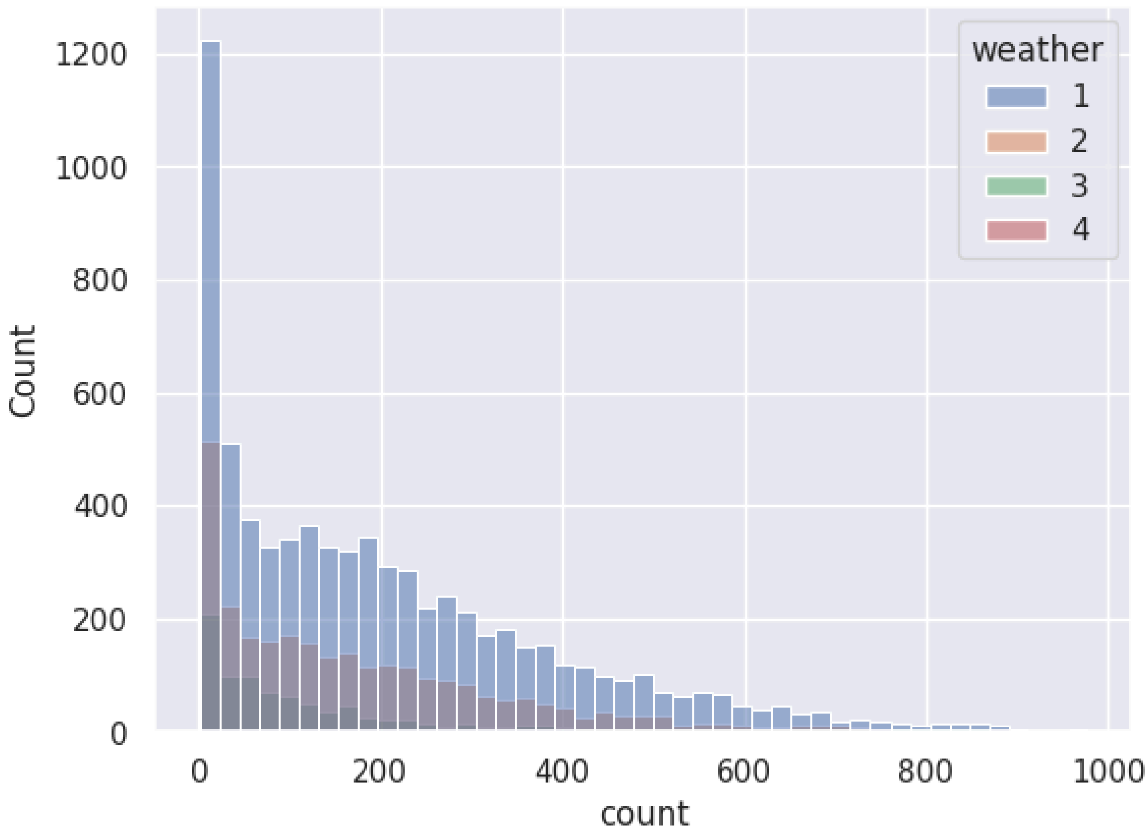
In [71]:
```
sns.kdeplot(data = df, x = 'count', hue = 'weather')
```

Out[71]: `<Axes: xlabel='count', ylabel='Density'>`



In [72]:
```
sns.histplot(data = df, x = 'count', hue = 'weather')
```

Out[72]: <Axes: xlabel='count', ylabel='Count'>



The Test hypothesis for Levene's test are:

Ho: The variances are equal.

Ha: The variances are not equal.

In [74]:
```
weather1 = df[df['weather'] == 1]['count']
weather2 = df[df['weather'] == 2]['count']
weather3 = df[df['weather'] == 3]['count']
weather4 = df[df['weather'] == 4]['count']

levene_stat, p_val = levene(weather1, weather2, weather3,weather4)

p_val
```

Out[74]: 3.504937946833238e-35

Hence the p_values is smaller than the significance level, Null hypothesis can be rejected.

Therefore, the variances are not equal.

Two of the three conditions of ANOVA are not met, **We will still perform ANOVA.**

Then We will also perform Kruskal's test and compare the results.

In case of any discrepancies, Kruskal's test results will be considered, since data does not met conditions of ANOVA.

The hypothesis for ANOVA are:

Ho: There is no significant difference between demand of bicycles for different Weather conditions.

Ha: There is a significant difference between demand of bicycles for different Weather conditions.

In [76]:
```
anova_stat, p_val = f_oneway(weather1, weather2, weather3,weather4)

p_val
```

Out[76]: 5.482069475935669e-42

Hence the p_values is smaller than the significance level, Null hypothesis can be rejected.

Therefore, There is a significant difference between demand of bicycles for different Weather conditions.

Demand of bicycles on rent is the same for different Seasons

Assumptions for ANOVA are:

The population data should be normally distributed- The data is not normal as verified by Wilkin-Shapiro test and the qqplot.

The data points must be independent- This condition is satisfied.

Approximately equal variance within groups- This will be verified using Levene's test.

In [77]:
```
# skewness of seasons

df.groupby('season')['count'].skew()
```

Out[77]:

season	count
Spring	1.888056
Summer	1.003264
Fall	0.991495
Winter	1.172117

dtype: float64

In [78]:
```
# kurtosis test of seasons

df.groupby('weather')['count'].apply(lambda x: x.kurtosis())
```

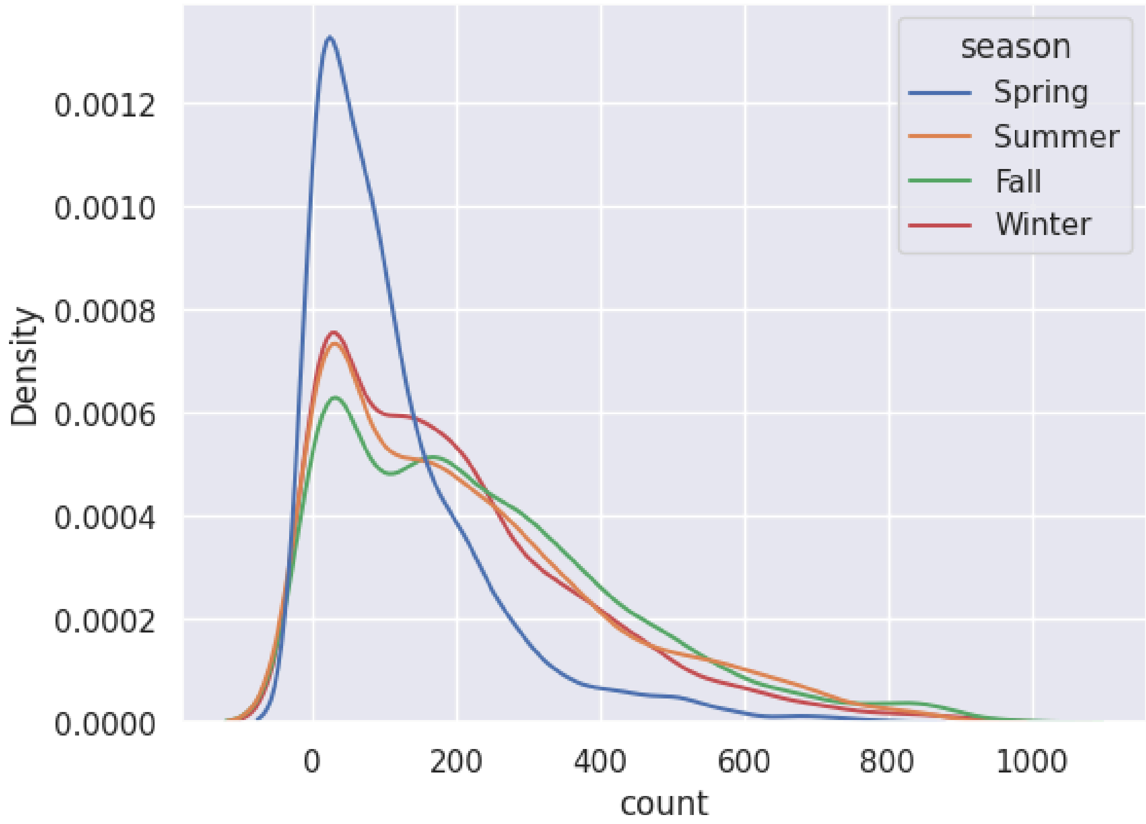
Out[78]:

weather	count
1	0.964720
2	1.588430
3	6.003054
4	NaN

dtype: float64

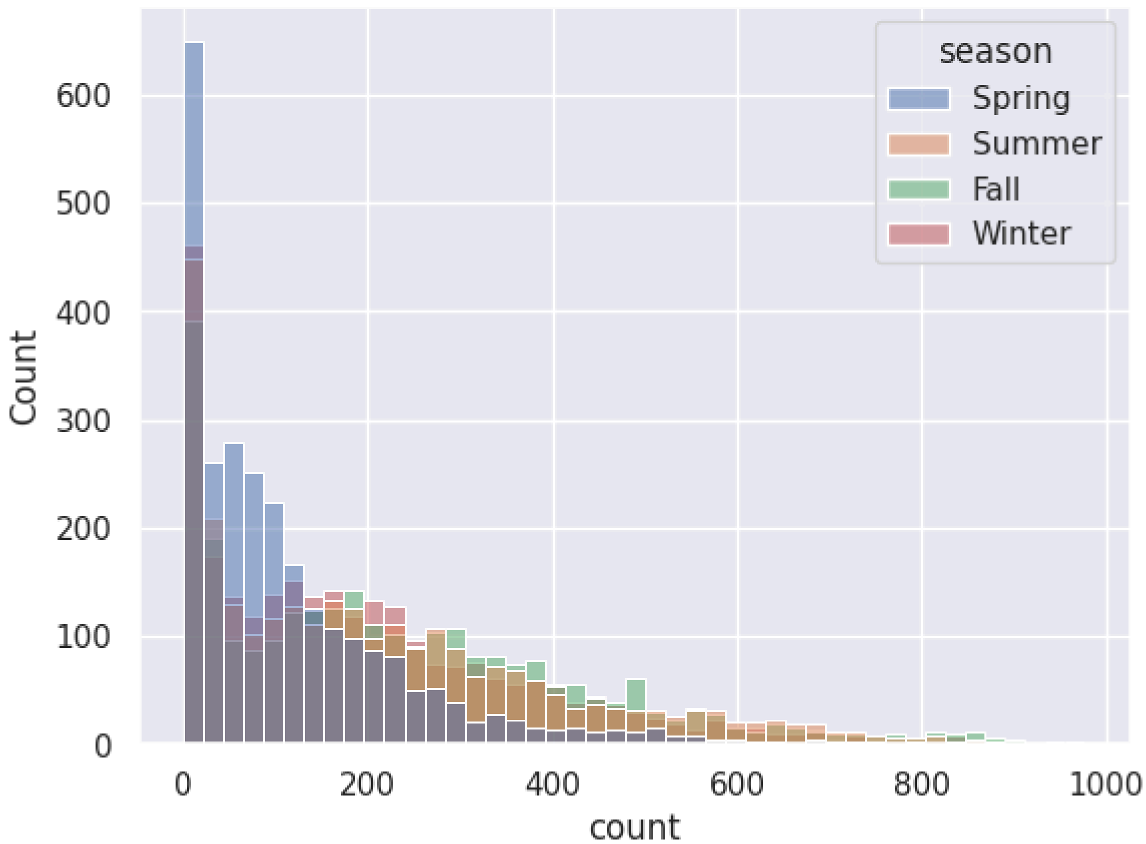
In [79]:
```
sns.kdeplot(data = df, x = 'count', hue = 'season')
```

Out[79]:
```
<Axes: xlabel='count', ylabel='Density'>
```



In [80]:
```python
sns.histplot(data = df, x = 'count', hue = 'season')
```

Out[80]: <Axes: xlabel='count', ylabel='Count'>



In [82]:
```python
spring = df[df['season'] == 'Spring']['count']
summer = df[df['season'] == 'Summer']['count']
fall = df[df['season'] == 'Fall']['count']
```

```
winter = df[df['season'] == 'Winter']['count']

levene_stat, p_val = levene(spring,summer,fall,winter)

p_val
```

Out[82]: 1.0147116860043298e-118

Hence the p_values is smaller than the significance level, Null hypothesis can be rejected.

Therefore, the variances are not equal.

As like before, we still use both ANOVA and Kruskal's test, comparing the results.

If discrepancies arise, we'll rely on Kruskal's test, Since data does not met the conditions for ANOVA.

The hypothesis for ANOVA are:

Ho: There is no significant difference between demand of bicycles for different Seasons.

Ha: There is a significant difference between demand of bicycles for different Seasons.

In [84]:
```
anova_stat, p_val = f_oneway(spring ,summer, fall, winter)

p_val
```

Out[84]: 6.164843386499654e-149

Hence the p_values is smaller than the significance level, Null hypothesis can be rejected.

Therefore, There is a significant difference between demand of bicycles for different Seasons.

Analysis of Weather Conditions Across Seasons using Chi-square Test

The hypothesis for the chi-square test are:

Ho: Season and Weather are independent of each other.

Ha: Season and Weather are dependent on each other.

In [86]:
```
contingency_table = pd.crosstab(df['weather'], df['season'])

contingency_table
```

Out[86]:

season weather	Spring	Summer	Fall	Winter
1	1759	1801	1930	1702
2	715	708	604	807
3	211	224	199	225
4	1	0	0	0

In [88]:

```
chi2_contingency(contingency_table)
```

Out[88]:

```
Chi2ContingencyResult(statistic=49.15865559689363, pvalue=1.5499250736864862e-0
7, dof=9, expected_freq=array([[1.77454639e+03, 1.80559765e+03, 1.80559765e+03,
1.80625831e+03],
       [6.99258130e+02, 7.11493845e+02, 7.11493845e+02, 7.11754180e+02],
       [2.11948742e+02, 2.15657450e+02, 2.15657450e+02, 2.15736359e+02],
       [2.46738931e-01, 2.51056403e-01, 2.51056403e-01, 2.51148264e-01]]))
```

Hence the p_values(1.5499250736864862e-07) is smaller than the significance level, Null hypothesis can be rejected.

Therefore, we can conclude that Season and Weather are dependent on each other.

Strategic Recommendations for Yulu's Profitable Growth

Optimize Bike Distribution in Peak Months:

Concentrate bike deployment efforts during peak months, especially in June, July, and August, to meet increased demand and capitalize on favorable weather conditions.

Seasonal Marketing Strategies:

Tailor marketing efforts to leverage the seasonal trend, promoting Yulu's services more aggressively during summer months to attract a larger user base.

Enhance User Engagement in Off-Peak Months:

Implement targeted promotional campaigns or discounts during off-peak months (e.g., January to March) to encourage increased bike rentals and maintain consistent revenue flow.

Weather-Responsive Pricing:

Consider implementing dynamic pricing strategies that respond to weather conditions. For example, adjusting rental rates during extreme weather days to optimize revenue.

Diversify Revenue Streams:

Explore additional revenue streams, such as partnerships, sponsorships, or offering premium membership services with added benefits, to diversify income sources and boost overall profitability.

Enhance User Experience:

Invest in technology and infrastructure to improve the overall user experience, including app features, bike maintenance, and customer support, fostering loyalty and repeat business.

Optimize Bike Deployment on Working Days:

Given the lack of significant differences in bike rentals between working and non-working days, consider adjusting bike deployment strategies to ensure optimal resource allocation throughout the week.

Adapt to Different Weather Conditions:

Change promotions or discounts based on the weather. If it's rainy, for example, offer special deals to encourage more people to use the bikes.

Promote Bikes Differently in Each Season:

Advertise the bikes differently in each season. For example, highlight summer promotions in June, July, and August when more people want to ride bikes.

Combine Season and Weather Plans:

Plan bike availability based on both the season and the weather to make sure people have the bikes they need when they want them. For example, have more bikes available on sunny days in the summer.

In [ ]: