Business Case: Yulu - Hypothesis Testing

In [1]:

```
# 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_contingency
from statsmodels.graphics.gofplots import qqplot

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

In [2]:

```
# converting data into dataframe

yulu = pd.read_csv('bike_sharing.csv')
```

In [3]:

```
# making an copy of the dataset

df = yulu.copy()
```

In [4]:

```
# Top 5 rows of the dataframe

df.head()
```

Out[4]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0	0	1	1

In [5]:

```
# No of rows and columns

df.shape
```

Out[5]:

```
(10886, 12)
```

In [6]:

```
# Checking of null values
```

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

Out[6]:

```
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 [7]:

```
# Duplicate values check

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

Out[7]:

```
0
```

In [8]:

```
# skewness of each column

df.skew(numeric_only = True)
```

Out[8]:

```
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 [9]:

```
# Uniques values of each columns

df.nunique()
```

Out[9]:

```
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 [10]:

```
# 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 [11]:

```
# count column is sum of casual and the registered users

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

Out[11]:

```
True    10886
Name: count, dtype: int64
```

In [12]:

```
# 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 [13]:

```python
# Converting datetime column into date time format

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

Out[13]:

```
dtype('<M8[ns]')
```

In [14]:

```python
# 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 [15]:

```python
df.head(2)
```

Out[15]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	year	mon
0	**2011-01-01 00:00:00**	1	0	0	1	9.84	14.395	81	0.0	3	13	16	2011	
1	**2011-01-01 01:00:00**	1	0	0	1	9.02	13.635	80	0.0	8	32	40	2011	

In [16]:

```python
# 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 [17]:

```
df.describe().transpose()
```

Out[17]:

	count	mean	min	25%	50%	75%	max	std
datetime	10886	2011-12-27 05:56:22.399411968	2011-01-01 00:00:00	2011-07-02 07:15:00	2012-01-01 20:30:00	2012-07-01 12:45:00	2012-12-19 23:00:00	NaN
temp	10886.0	20.23086	0.82	13.94	20.5	26.24	41.0	7.79159
atemp	10886.0	23.655084	0.76	16.665	24.24	31.06	45.455	8.474601
humidity	10886.0	61.88646	0.0	47.0	62.0	77.0	100.0	19.245033
windspeed	10886.0	12.799395	0.0	7.0015	12.998	16.9979	56.9969	8.164537
casual	10886.0	36.021955	0.0	4.0	17.0	49.0	367.0	49.960477
registered	10886.0	155.552177	0.0	36.0	118.0	222.0	886.0	151.039033
count	10886.0	191.574132	1.0	42.0	145.0	284.0	977.0	181.144454
year	10886.0	2011.501929	2011.0	2011.0	2012.0	2012.0	2012.0	0.500019
day	10886.0	9.992559	1.0	5.0	10.0	15.0	19.0	5.476608
hour	10886.0	11.541613	0.0	6.0	12.0	18.0	23.0	6.915838

In [18]:

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

Out[18]:

	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.

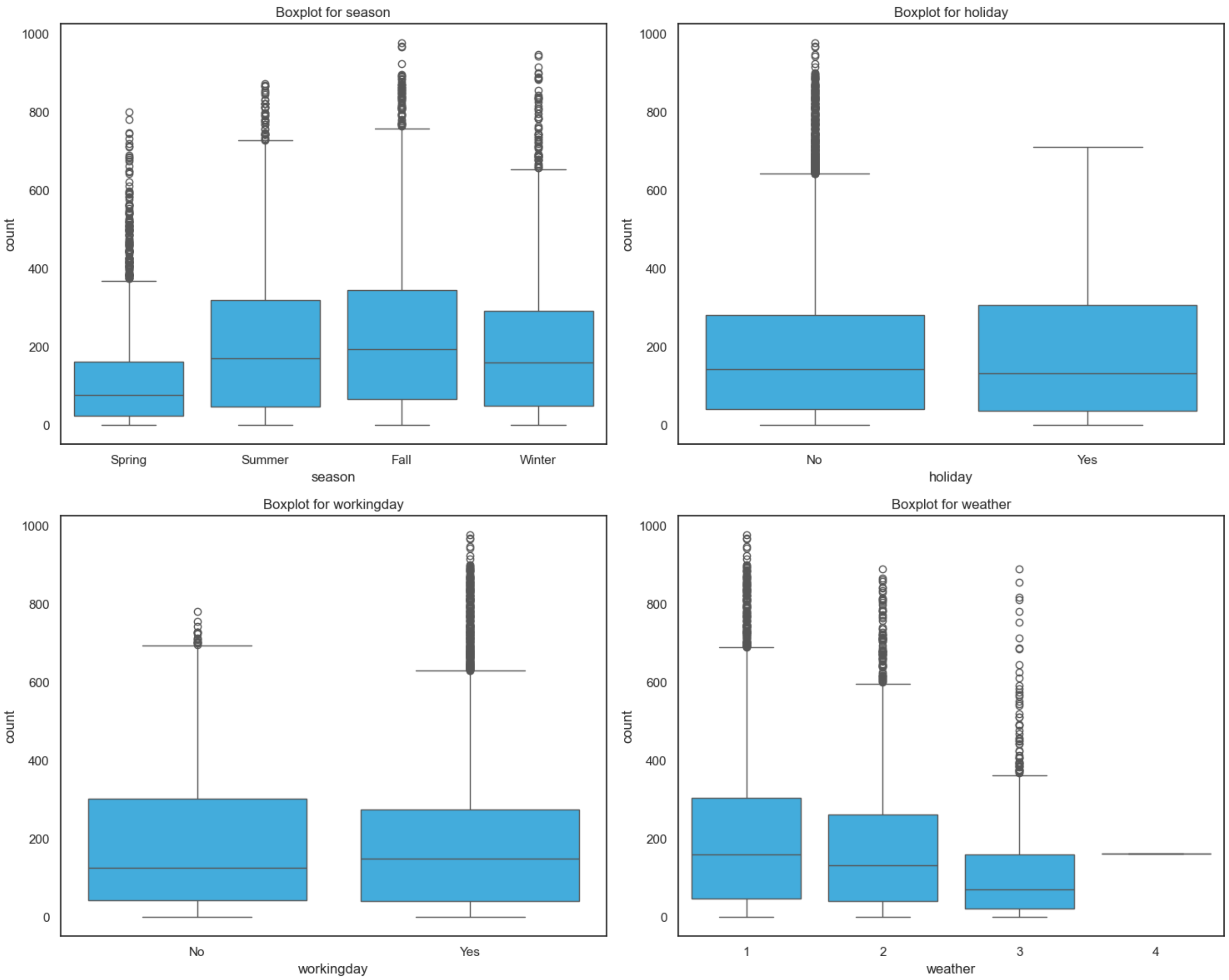
Temporal Patterns and Concentrations:

- 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 [19]:

```
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 [20]:

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

Out[20]:

```
Timedelta('718 days 23:00:00')
```

In [21]:

```
df.columns
```

Out[21]:

```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count',
       'year', 'month', 'day', 'hour'],
      dtype='object')
```

In [22]:

```
# Season counts
df['season'].value_counts()
```

Out[22]:

```
season
Winter    2734
Summer    2733
Fall      2733
Spring    2686
Name: count, dtype: int64
```

In [23]:

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

Out[23]:

```
holiday
No     10575
Yes      311
Name: count, dtype: int64
```

In [24]:

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

Out[24]:

```
workingday
Yes    7412
No     3474
Name: count, dtype: int64
```

In [25]:

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

Out[25]:

```
weather
1    7192
2    2834
3     859
4       1
Name: count, dtype: int64
```

```
Name: count, dtype: int64
```

In [26]:

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

Out[26]:

```
year
2012    5464
2011    5422
Name: count, dtype: int64
```

In [27]:

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

Out[27]:

```
month
May          912
June         912
July         912
August       912
December     912
October      911
November     911
April        909
September    909
February     901
March        901
January      884
Name: count, dtype: int64
```

In [28]:

```python
# day counts
df['day'].value_counts().sort_index()
```

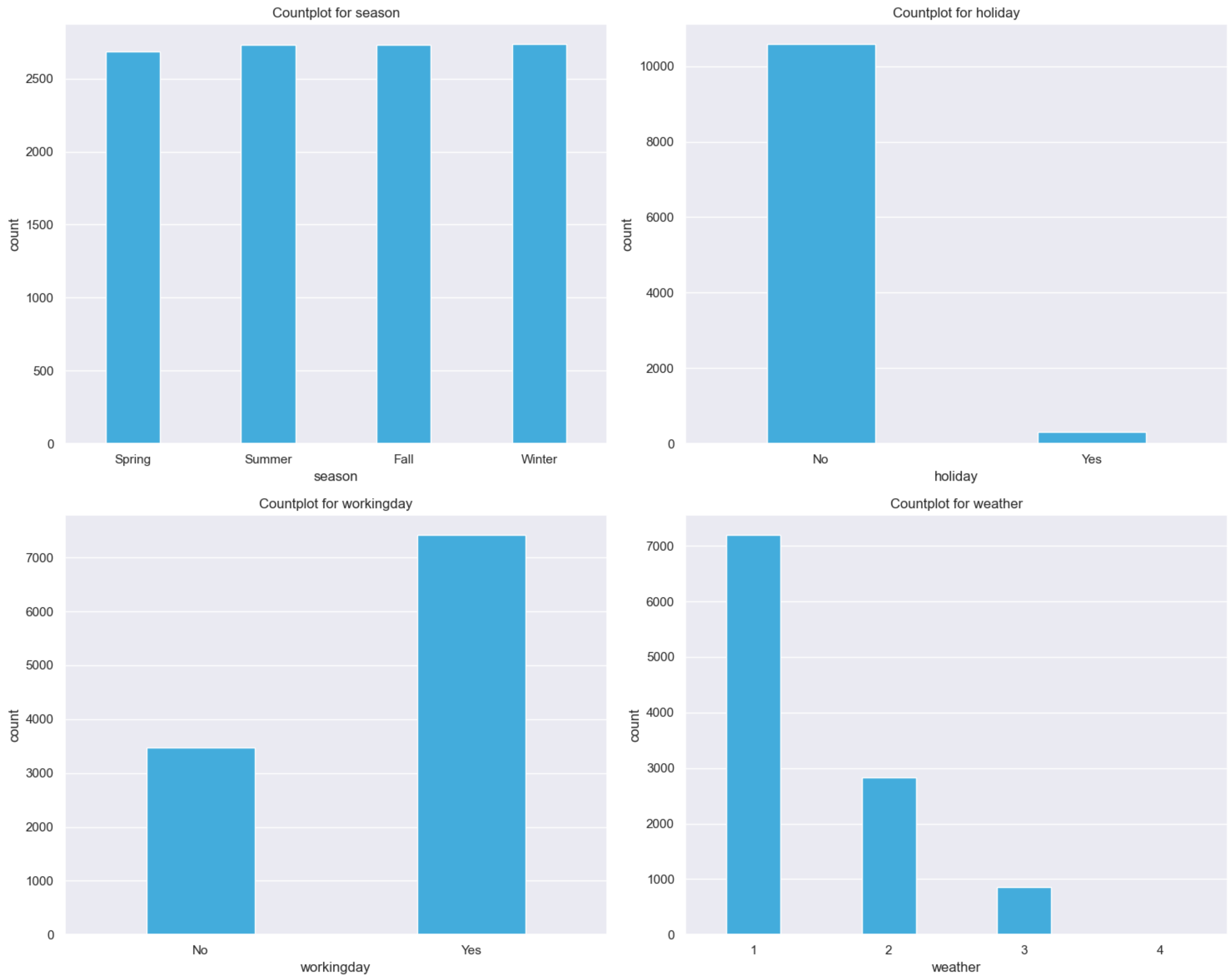
Out[28]:

```
day
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
Name: count, dtype: int64
```

In [29]:

```python
# 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()
```



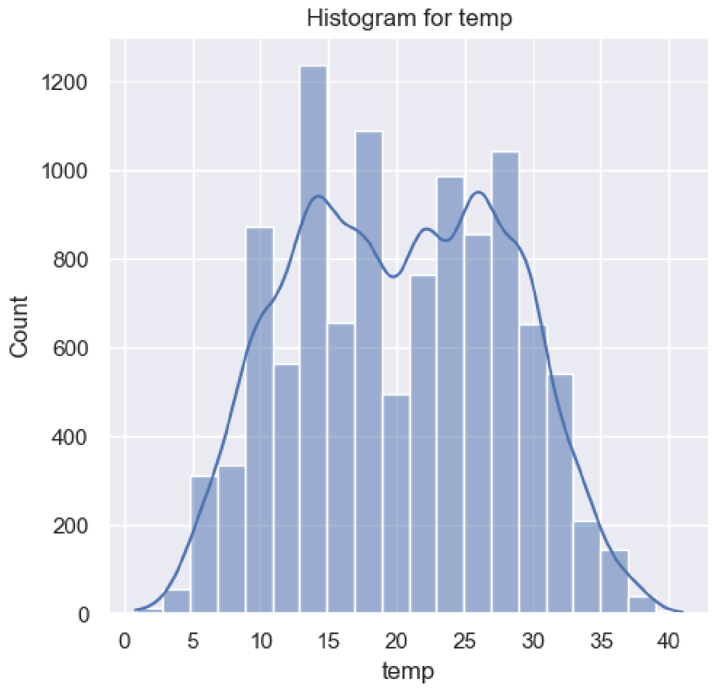
In [30]:

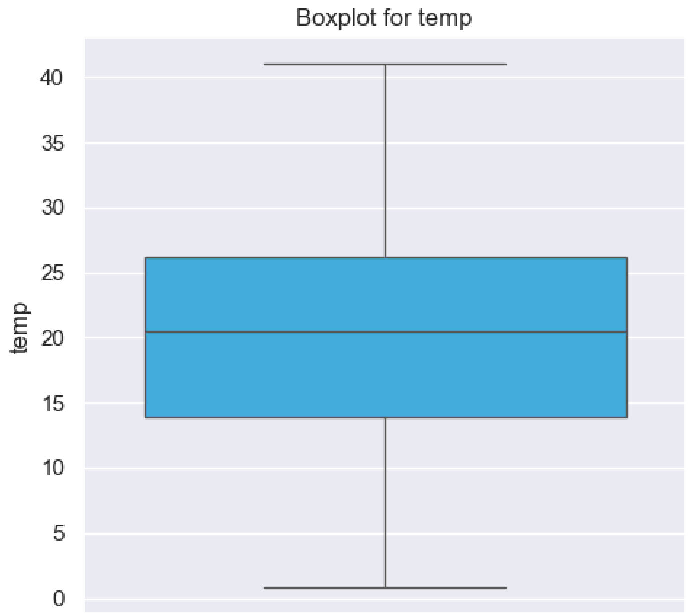
```
# Function for histogram & boxplot on numerical columns

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 [31]:

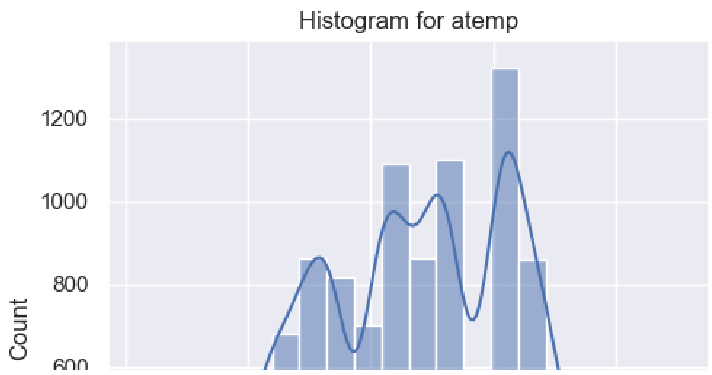
```
num_col = ['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count']

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

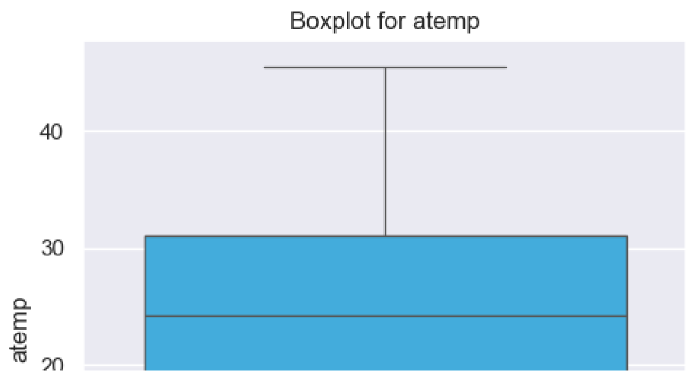
	Statistic	Value
0	count	10886.00000
1	mean	20.23086
2	std	7.79159
3	min	0.82000
4	25%	13.94000
5	50%	20.50000
6	75%	26.24000
7	max	41.00000

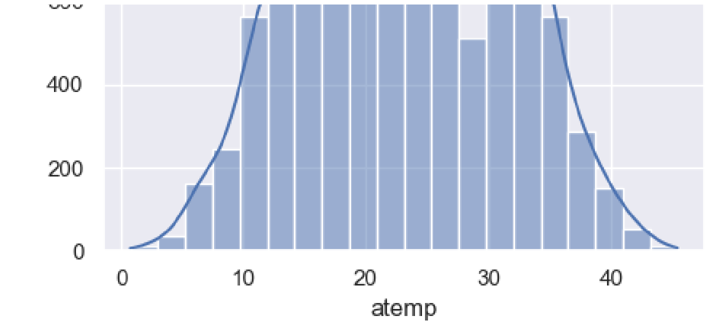


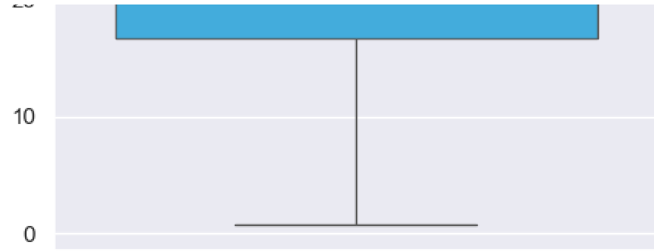


	Statistic	Value
0	count	10886.000000
1	mean	23.655084
2	std	8.474601
3	min	0.760000
4	25%	16.665000
5	50%	24.240000
6	75%	31.060000
7	max	45.455000



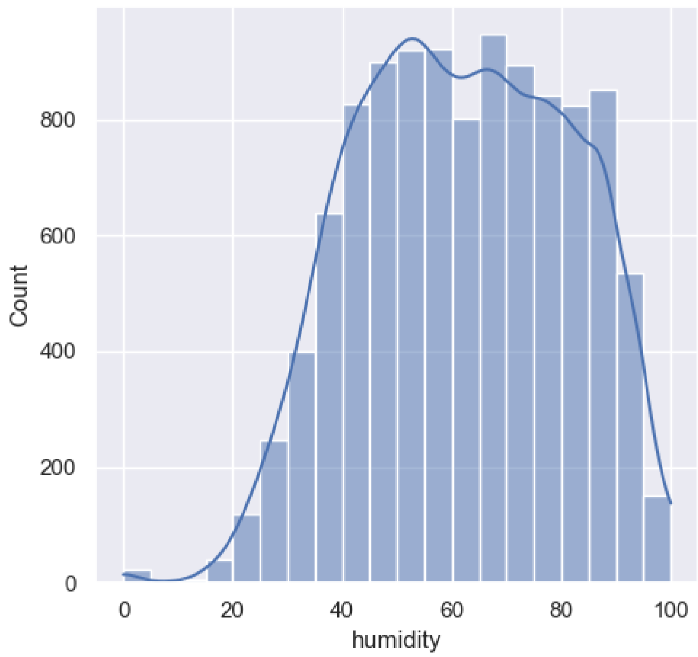




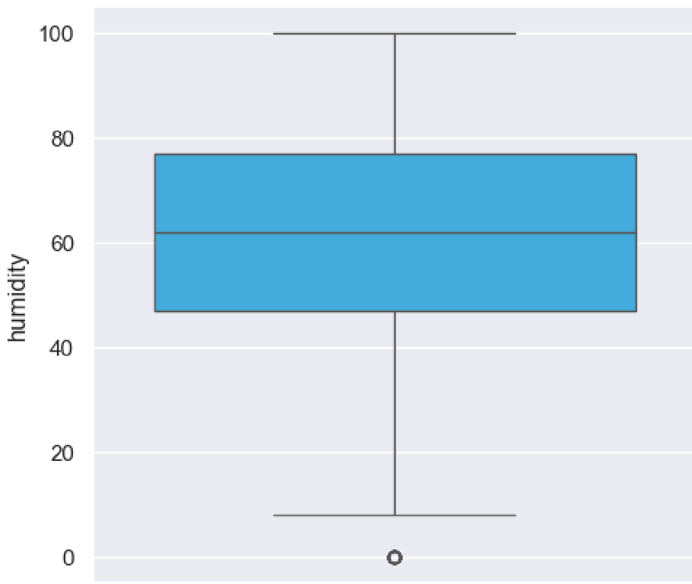


	Statistic	Value
0	count	10886.000000
1	mean	61.886460
2	std	19.245033
3	min	0.000000
4	25%	47.000000
5	50%	62.000000
6	75%	77.000000
7	max	100.000000

Histogram for humidity



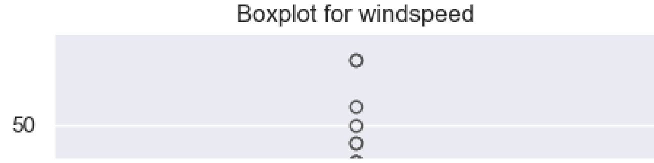
Boxplot for humidity

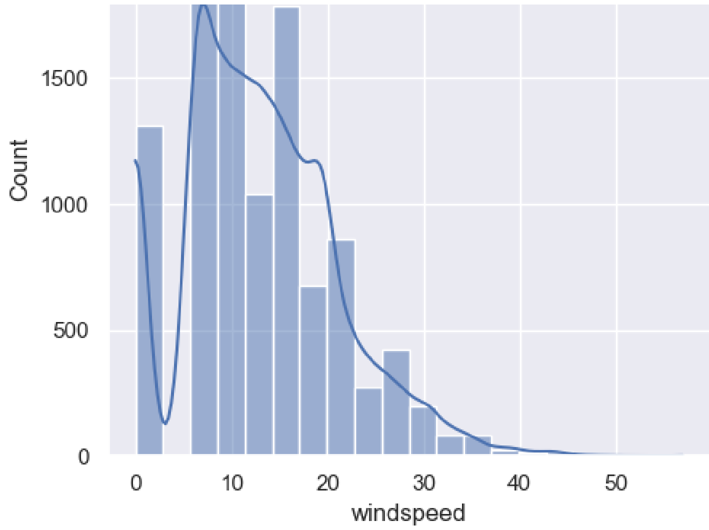


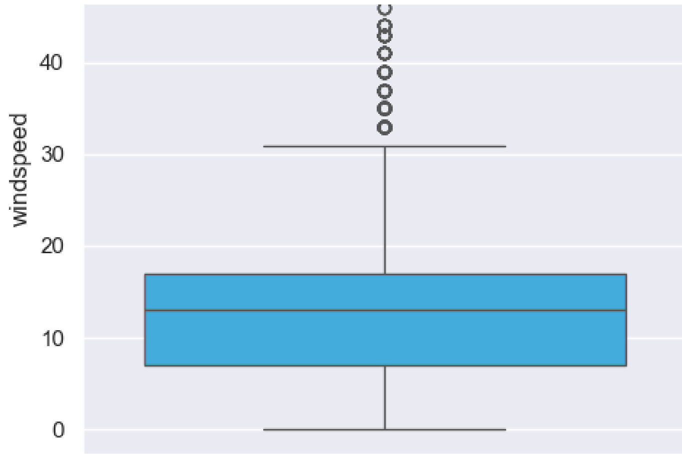
	Statistic	Value
0	count	10886.000000
1	mean	12.799395
2	std	8.164537
3	min	0.000000
4	25%	7.001500
5	50%	12.998000
6	75%	16.997900
7	max	56.996900

Histogram for windspeed

Boxplot for windspeed

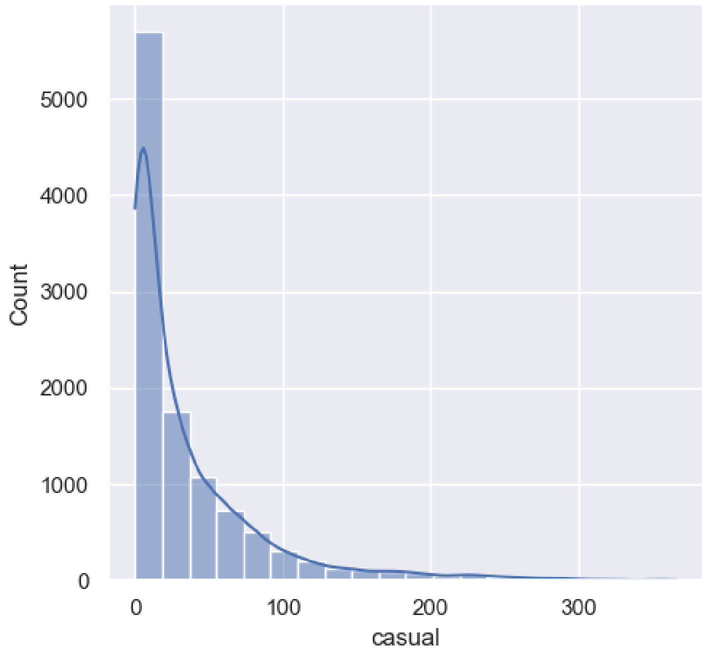




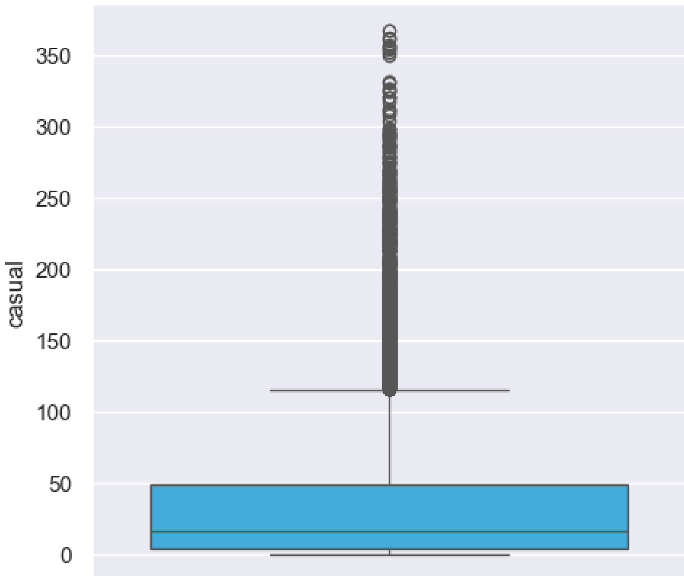


	Statistic	Value
0	count	10886.000000
1	mean	36.021955
2	std	49.960477
3	min	0.000000
4	25%	4.000000
5	50%	17.000000
6	75%	49.000000
7	max	367.000000

Histogram for casual

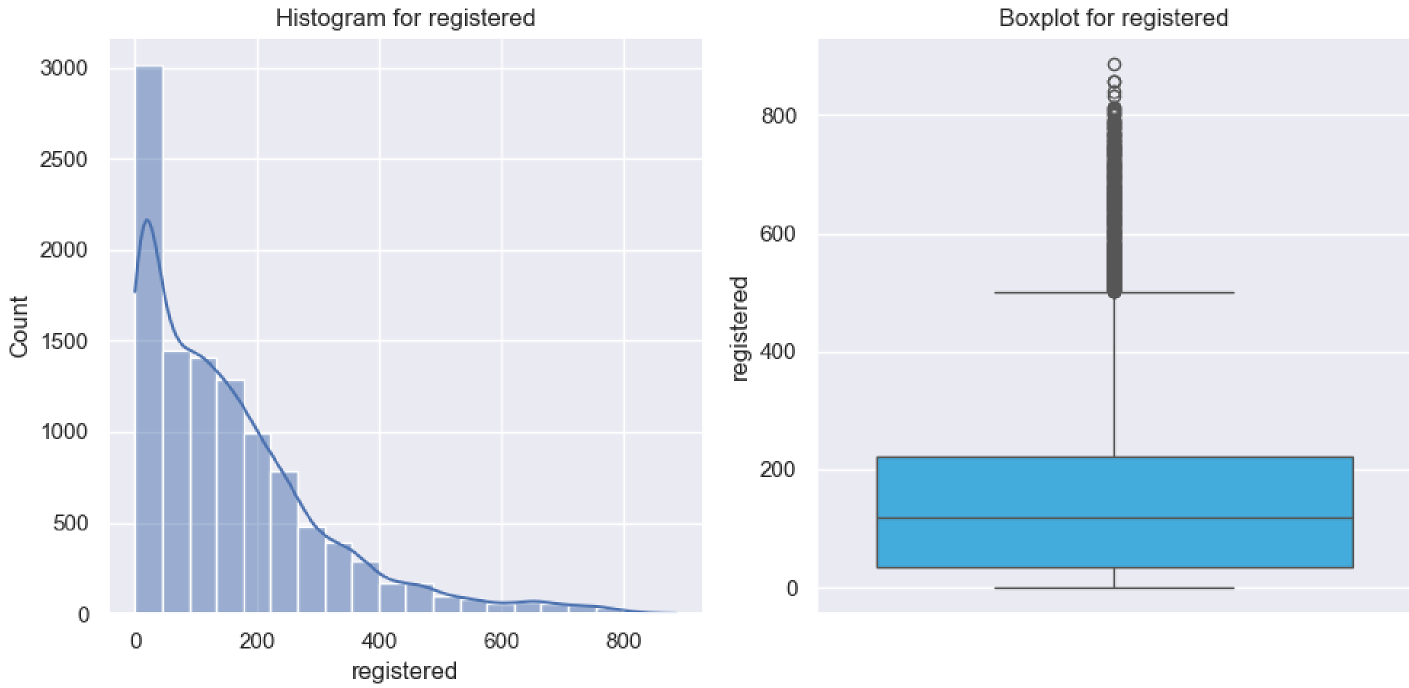


Boxplot for casual

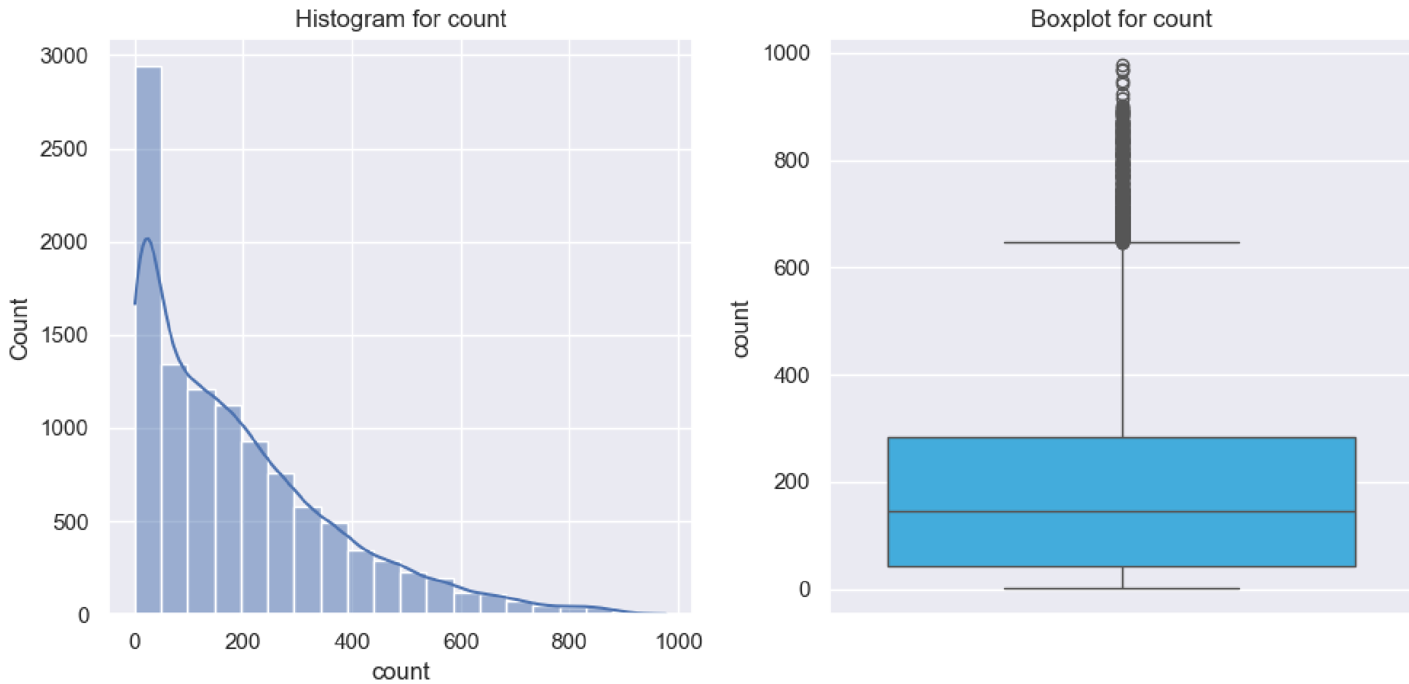


	Statistic	Value
0	count	10886.000000
1	mean	155.552177
2	std	151.039033
3	min	0.000000
4	25%	36.000000
5	50%	118.000000
6	75%	222.000000
7	max	886.000000

Statistic	Value



	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 [32]:

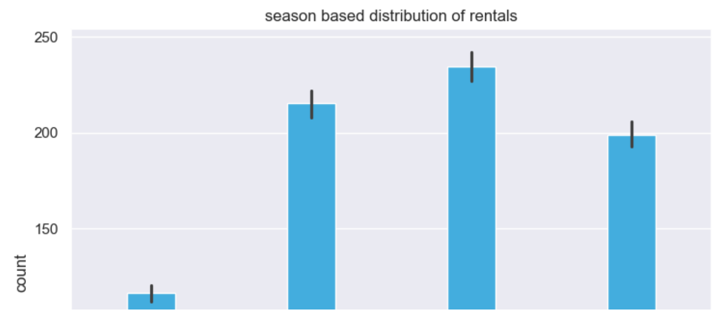
```
cat_col
```

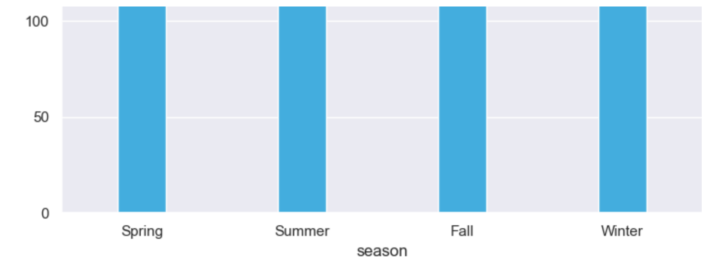
Out[32]:

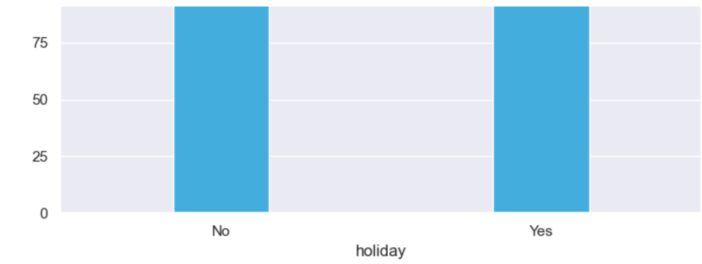
```
['season', 'holiday', 'workingday', 'weather']
```

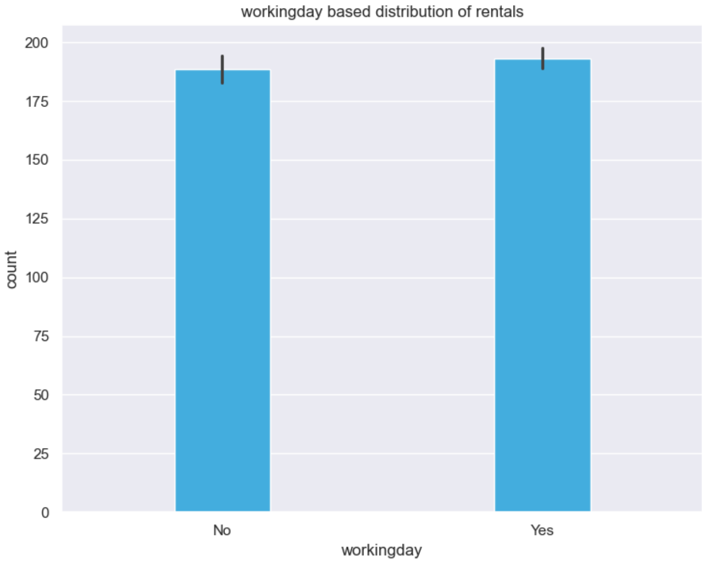
In [33]:

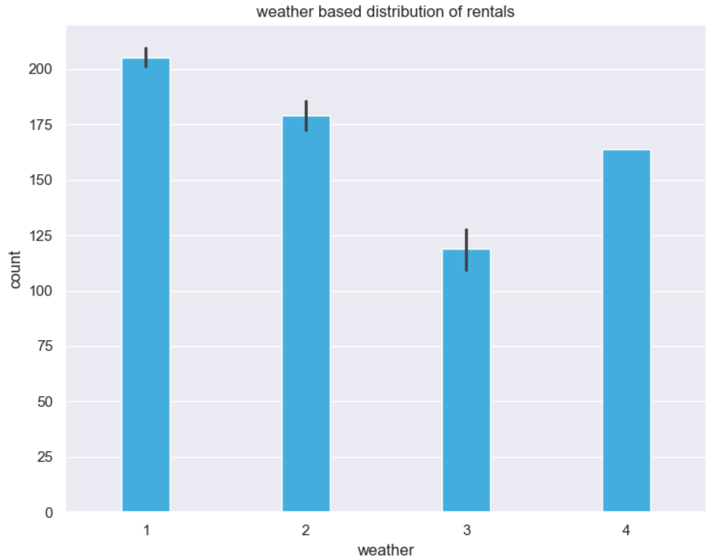
```
# barplot of categories

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 [34]:

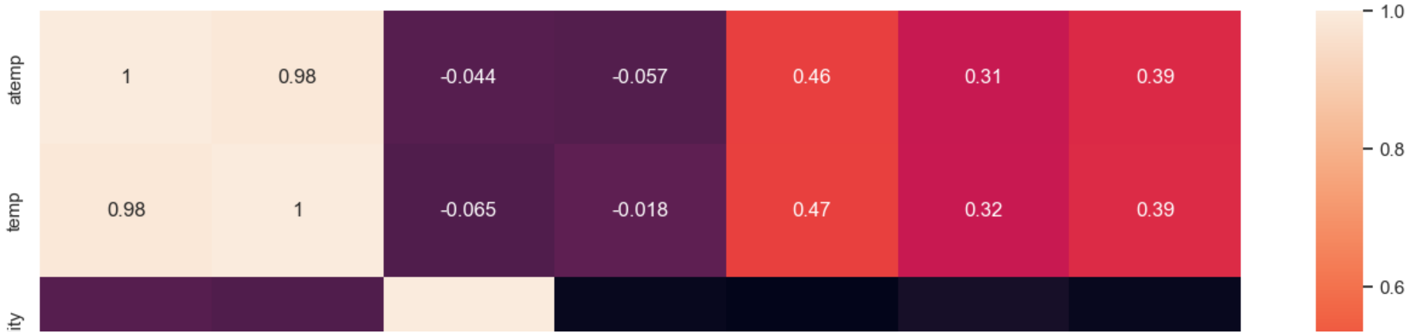
```
# corrrelation analysis

correlation_matrix = df[["atemp", "temp", "humidity", "windspeed", "casual", "registered
", "count"]].corr()
correlation_df = pd.DataFrame(correlation_matrix)
correlation_df
```

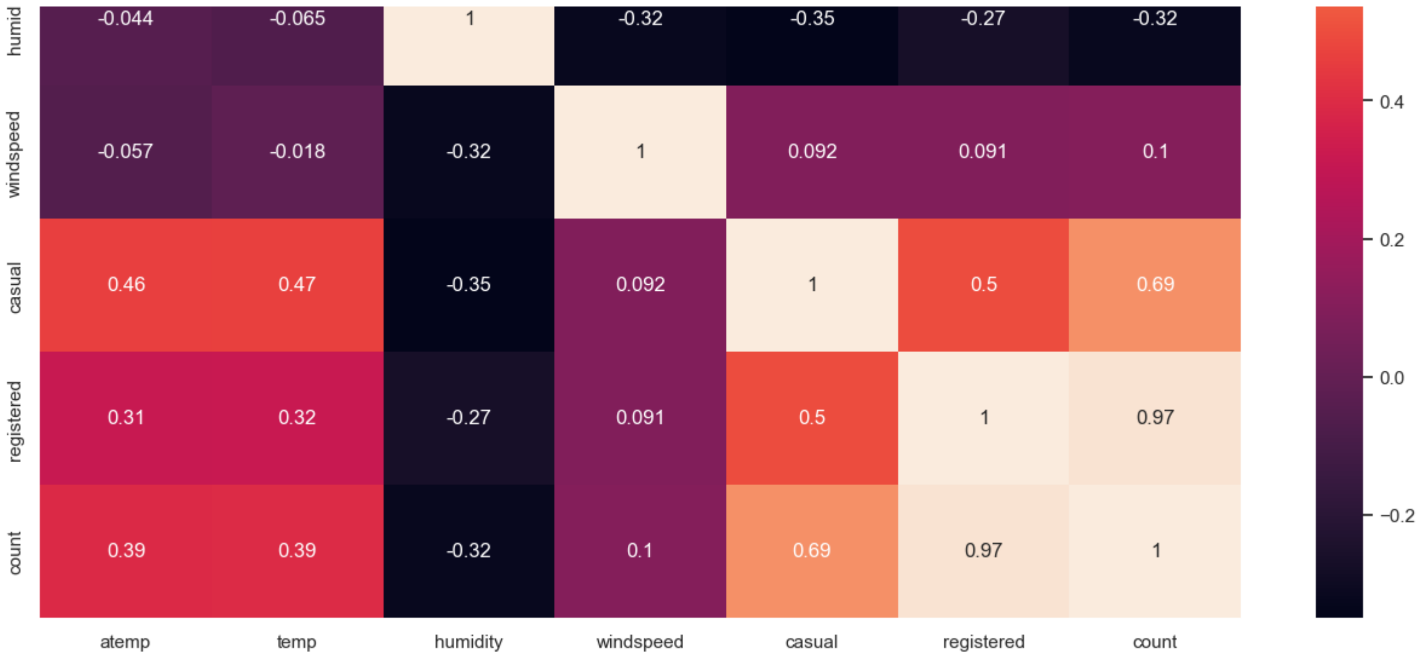
Out[34]:

	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 [35]:

```
# 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 [36]:

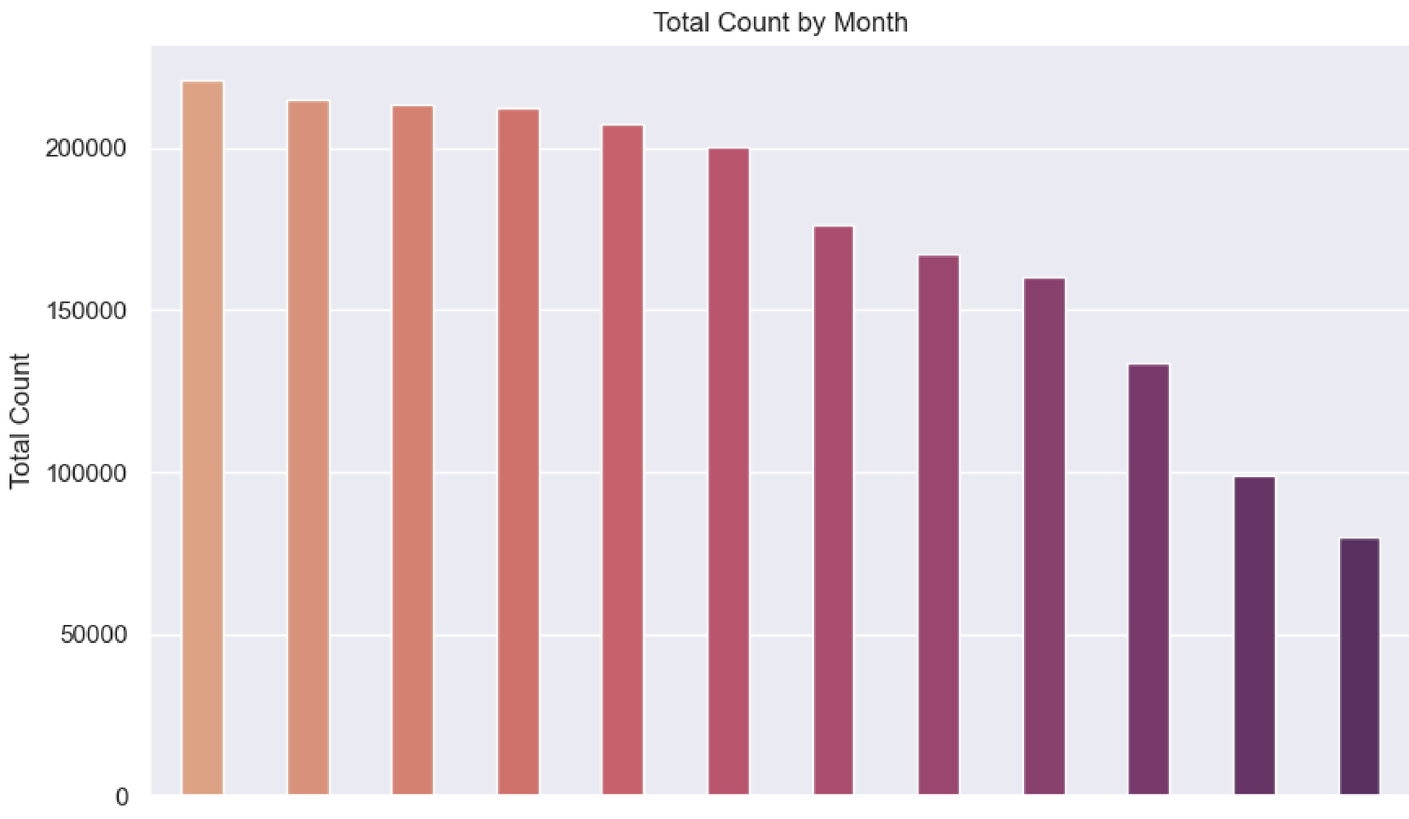
```
# counts based on months

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

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

monthly_count
```

Out[36]:

	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 [37]:

```
# rentals on monthly counts

plt.figure(figsize=(10, 6))
sns.barplot(x='month', y='count', data=monthly_count, palette='flare', width = 0.4)

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



June July August September October May November April December March February January
Month

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 [38]:

```
np.random.seed(41)

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

test_stat, p_val = shapiro(df_subset)

p_val
```

Out[38]:

```
2.6341072612012795e-07
```

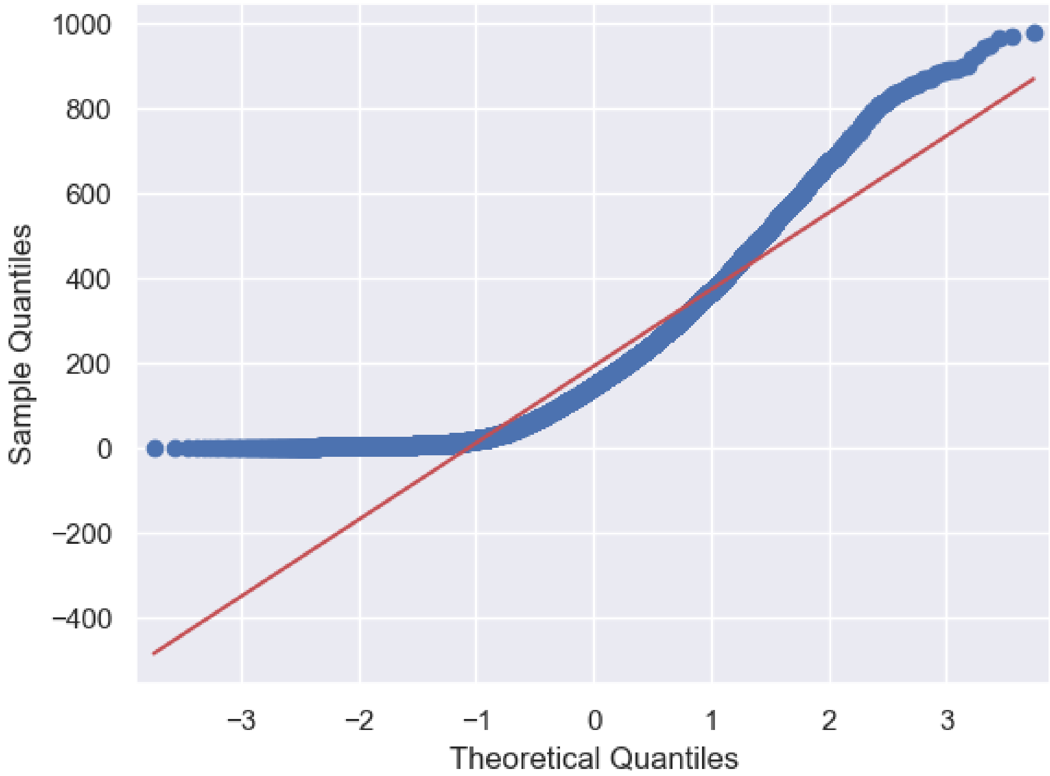
Hence the p_values is lesser than the significance level, Null hypothesis can be rejected.

Therefore, the Data is not normally distributed.

QQ Plot analysis

In [39]:

```
# QQ plot

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 [40]:

```
working_day = df[df['workingday'] == 'Yes']['count']

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

levene_stat, p_val = levene(working_day, holiday)

p_val
```

Out[40]:

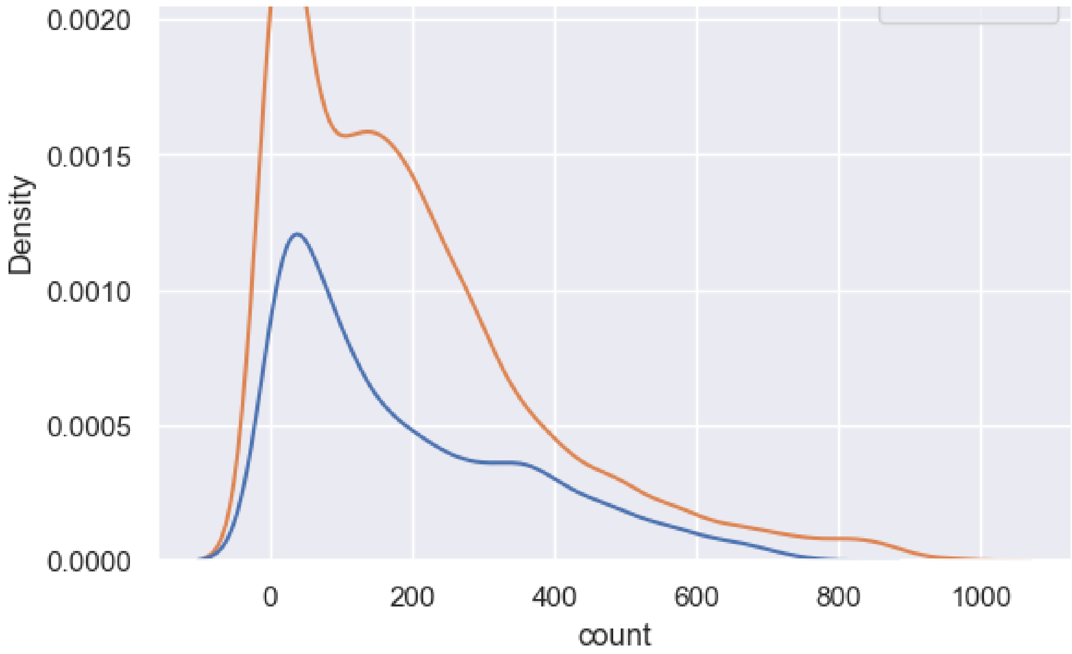
```
0.9437823280916695
```

In [41]:

```
sns.kdeplot(data = df, x = 'count', hue = 'workingday')
```

Out[41]:

```
<Axes: xlabel='count', ylabel='Density'>
```

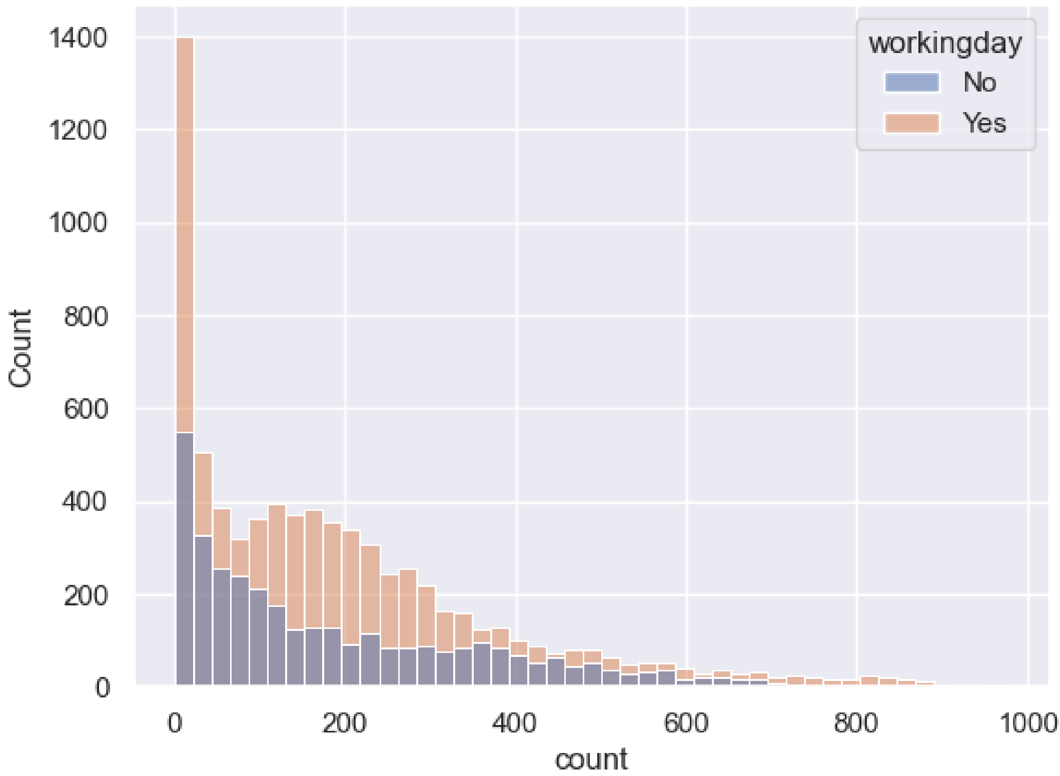


In [61]:

```
sns.histplot(data = df, x = 'count', hue = 'workingday')
```

Out[61]:

```
<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 [43]:

```
ttest_stat, p_val = ttest_ind(working_day, holiday)

p_val
```

Out[43]:

```
0.22644804226361348
```

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.

In [44]:

```
kruskal_stat, p_val = kruskal(working_day, holiday)

p_val
```

Out[44]:

```
0.9679113872727798
```

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

Since we have more than two categories now, so will use ANOVA here.

Assumptions for ANOVA are:

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

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

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

In [45]:

```
# skewness of weather

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

Out[45]:

```
weather
1    1.139857
2    1.294444
3    2.187137
4         NaN
Name: count, dtype: float64
```

In [46]:

```
# kurtosis test of weather

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

Out[46]:

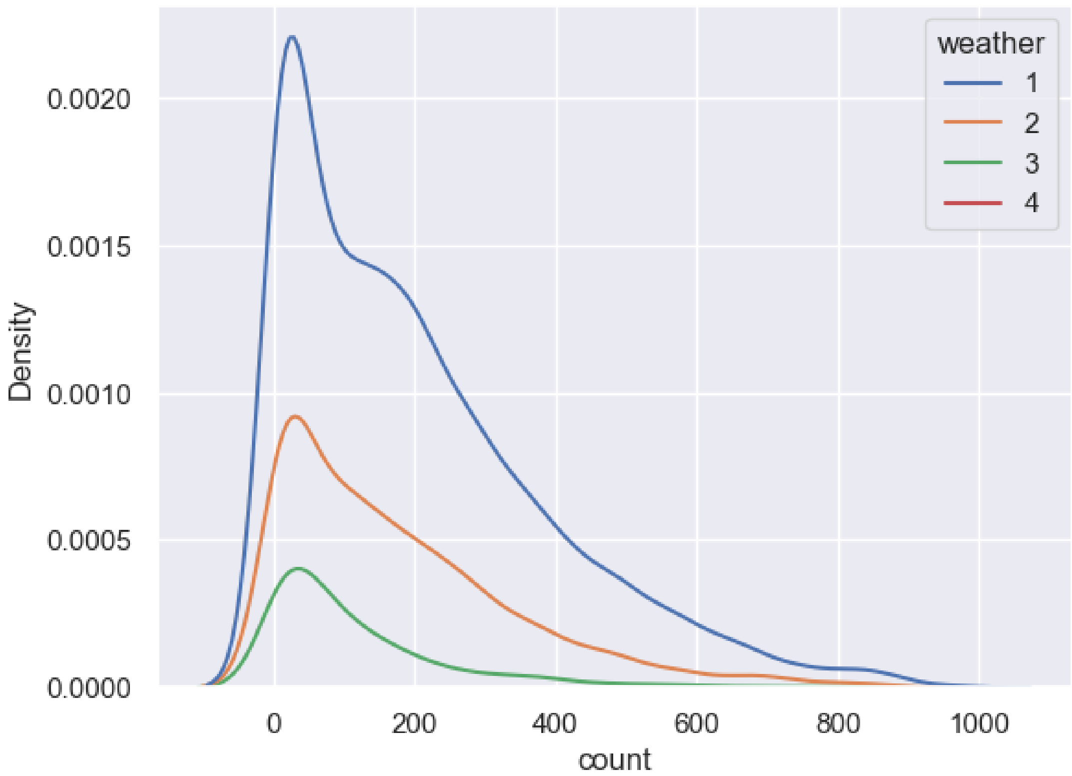
```
weather
1    0.964720
2    1.588430
3    6.003054
4         NaN
Name: count, dtype: float64
```

In [47]:

```
sns.kdeplot(data = df, x = 'count', hue = 'weather')
```

Out[47]:

```
<Axes: xlabel='count', ylabel='Density'>
```

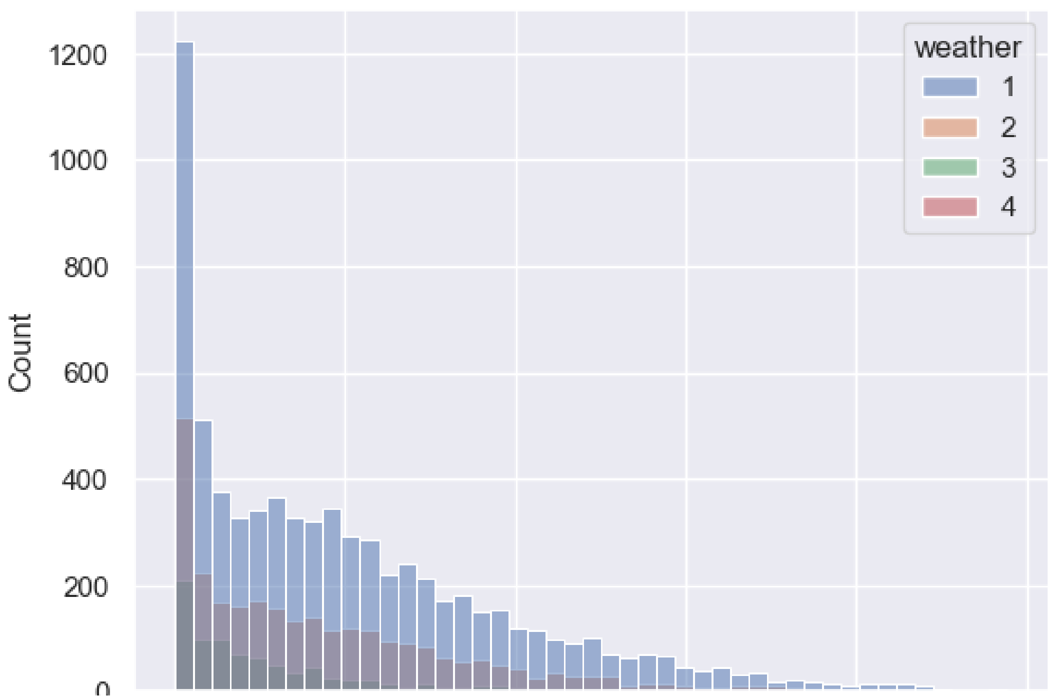


In [48]:

```
sns.histplot(data = df, x = 'count', hue = 'weather')
```

Out[48]:

```
<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 [49]:

```
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[49]:

```
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 [50]:

```
anova_stat, p_val = f_oneway(weather1, weather2, weather3,weather4)

p_val
```

Out[50]:

```
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.

Kruskal Test on weather

In [51]:

```
kruskal_stat, p_val = kruskal(weather1, weather2, weather3,weather4)

p_val
```

Out[51]:

```
3.501611300708679e-44
```

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

Therefore, we can conclude that there is a significant difference between demand of bicycles for different Weather conditions.

Demand of bicycles on rent is the same for different Seasons

Here also we have more than two categories now, so will use ANOVA here.

Assumptions for ANOVA are:

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

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

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

In [52]:

```python
# skewness of seasons

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

Out[52]:

```
season
Spring    1.888056
Summer    1.003264
Fall      0.991495
Winter    1.172117
Name: count, dtype: float64
```

In [53]:

```python
# kurtosis test of seasons

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

Out[53]:

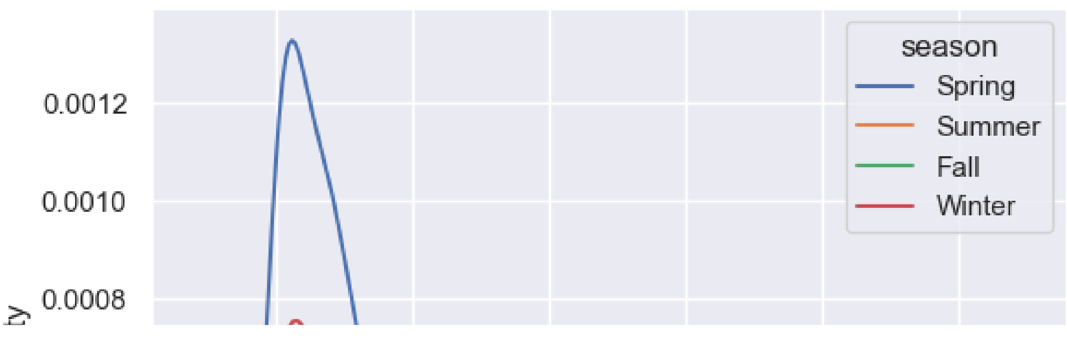
```
weather
1    0.964720
2    1.588430
3    6.003054
4         NaN
Name: count, dtype: float64
```

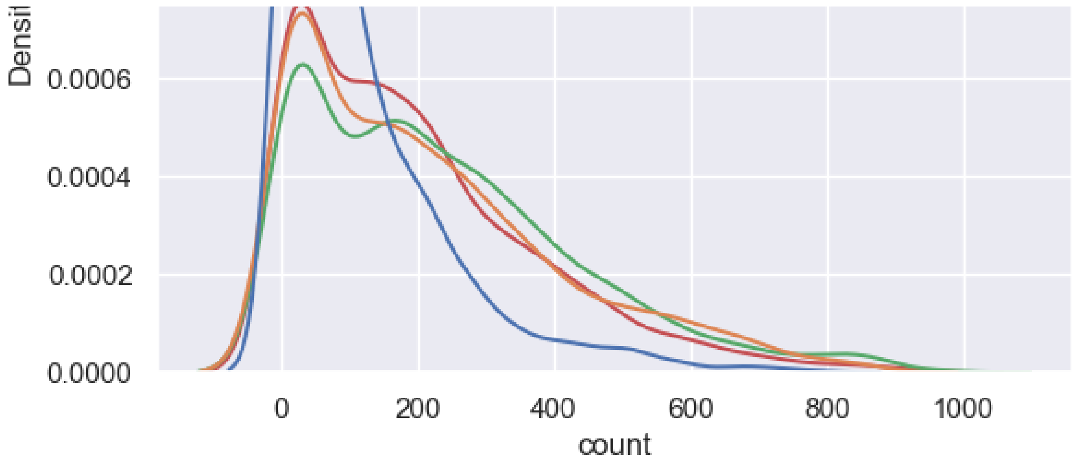
In [54]:

```python
sns.kdeplot(data = df, x = 'count', hue = 'season')
```

Out[54]:

```
<Axes: xlabel='count', ylabel='Density'>
```



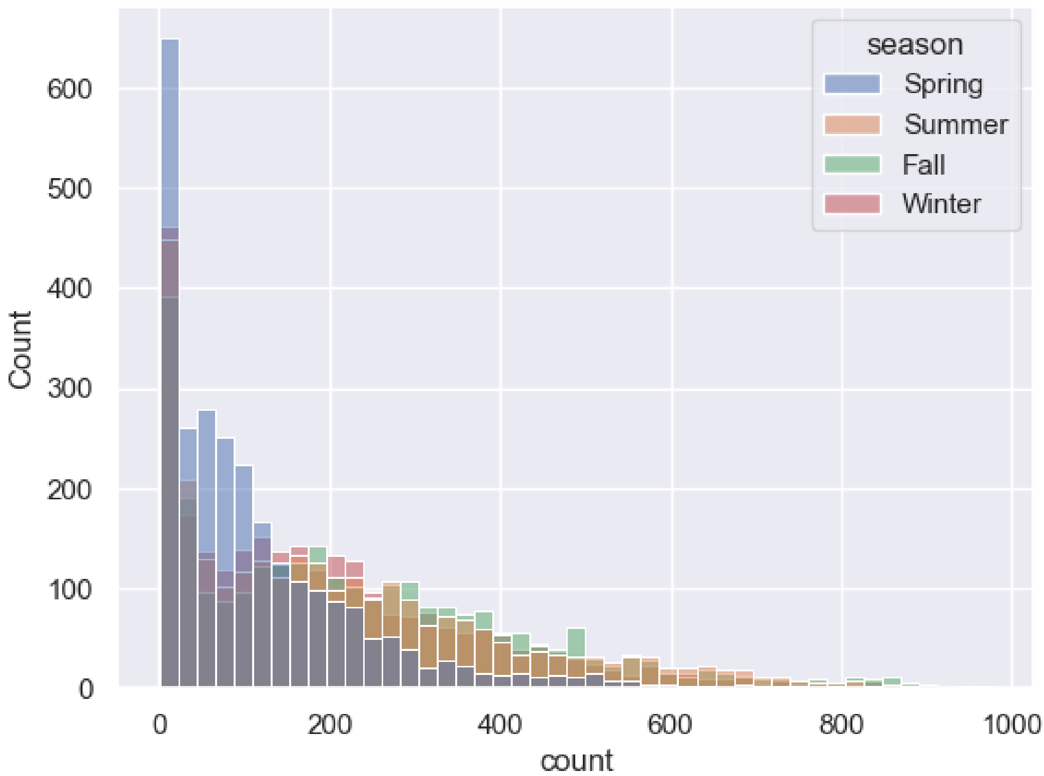


In [55]:

```
sns.histplot(data = df, x = 'count', hue = 'season')
```

Out[55]:

```
<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 [56]:

```
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[56]:

```
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 [57]:

```
anova_stat, p_val = f_oneway(spring ,summer, fall, winter)

p_val
```

Out[57]:

```
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.

Kruskal Test on season

In [58]:

```
kruskal_stat, p_val = kruskal(spring ,summer, fall, winter)

p_val
```

Out[58]:

```
2.479008372608633e-151
```

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

Therefore, we can conclude that 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 [59]:

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

contingency_table
```

Out[59]:

season	Spring	Summer	Fall	Winter
weather				

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 [60]:

```
chi2_contingency(contingency_table)
```

Out[60]:

```
Chi2ContingencyResult(statistic=49.15865559689363, pvalue=1.5499250736864862e-07, 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.**