Business Case: Yulu - Hypothesis Testing

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https://colab.research.google.com/drive/1JNDt-05x6ruFLWXh7CngPZE8xn4BAEWs?usp=sharing

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About Yulu

Yulu is India's leading micro-mobility service provider, which offers unique vehicles for the daily commute. Starting off as a mission to eliminate traffic congestion in India, Yulu provides the safest commute solution through a user-friendly mobile app to enable shared, solo and sustainable commuting.

Yulu zones are located at all the appropriate locations (including metro stations, bus stands, office spaces, residential areas, corporate offices, etc) to make those first and last miles smooth, affordable, and convenient!

Yulu has recently suffered considerable dips in its revenues. They have contracted a consulting company to understand the factors on which the demand for these shared electric cycles depends. Specifically, they want to understand the factors affecting the demand for these shared electric cycles in the Indian market.

Column Profiling:

datetime: datetime season: season (1: spring, 2: summer, 3: fall, 4: winter)

holiday: whether day is a holiday or not (extracted from http://dchr.dc.gov/page/holiday-schedule)

workingday: if day is neither weekend nor holiday is 1, otherwise is 0. weather:

1. Clear, Few clouds, partly cloudy, partly cloudy

2. Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
3. Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds
4. Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog

temp: temperature in Celsius

atemp: feeling temperature in Celsius

humidity: humidity

windspeed: wind speed

casual: count of casual users

registered: count of registered users

count: count of total rental bikes including both casual and registered

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In [72]:
```
# 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_cor
from statsmodels.graphics.gofplots import qqplot
import warnings
warnings.filterwarnings("ignore")
```

In [5]:
```
# converting data into dataframe
yulu = pd.read_csv('bike_sharing.csv')
```

In [6]:
```
# making an copy of the dataset
df = yulu.copy()
```

In [74]:
```
# Top 5 rows of the dataframe
df.head()
```

Out[74]:

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

In [8]:

```
# No of rows and columns
df.shape
```

Out[8]: (10886, 12)

In [9]:

```
# Checking of null values
df.isna().sum()
```

Out[9]:

	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 [10]:
```python
# Duplicate values check
df.duplicated().sum()
```

Out[10]:
```
np.int64(0)
```

In [11]:
```python
# skewness of each column
df.skew(numeric_only = True)
```

Out[11]:

	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 [13]:
```
# Uniques values of each columns
df.nunique()
```

Out[13]:

	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 [14]:
```
# 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 [15]:

```
# count column is sum of casual and the registered users
(df['casual'] + df['registered'] == df['count']).value_counts()
```

Out[15]:

	count
True	10886

dtype: int64

In [17]:

```
# 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 [18]:

```
# Converting datetime column into date time format
df['datetime'] = pd.to_datetime(df['datetime'])
df['datetime'].dtype
```

Out[18]:

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

In [19]:

```
# 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 [20]:

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

Out[20]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	w
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	

In [21]:

```
# 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 [22]:
```
df.describe().transpose()
```

Out[22]:

	count	mean	min	25%	50%	
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 12
temp	10886.0	20.23086	0.82	13.94	20.5	
atemp	10886.0	23.655084	0.76	16.665	24.24	
humidity	10886.0	61.88646	0.0	47.0	62.0	
windspeed	10886.0	12.799395	0.0	7.0015	12.998	1(
casual	10886.0	36.021955	0.0	4.0	17.0	
registered	10886.0	155.552177	0.0	36.0	118.0	
count	10886.0	191.574132	1.0	42.0	145.0	
year	10886.0	2011.501929	2011.0	2011.0	2012.0	:
day	10886.0	9.992559	1.0	5.0	10.0	
hour	10886.0	11.541613	0.0	6.0	12.0	

In [23]:
```
df.describe(include = 'category').transpose()
```

Out[23]:

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

Dataset Overview and Feature Patterns:

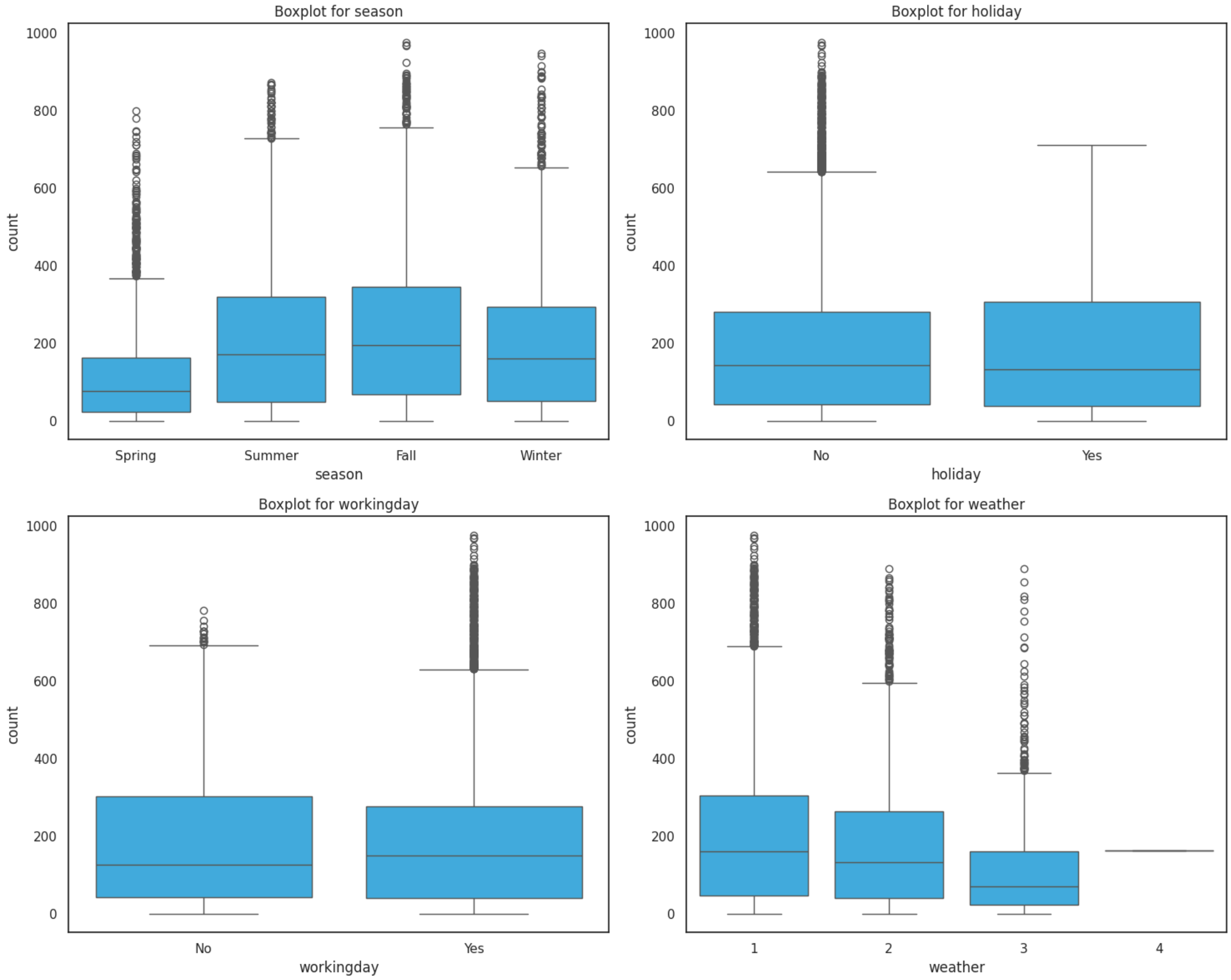
This dataset contains information about bike rentals, including timestamps and various numerical features. It covers a period from January 1, 2011, to December 19, 2012.

Key Feature Characteristics:

Numerical Data: Features like temperature, humidity, windspeed, and the counts of casual and registered users show a wide range of values and distributions, indicating how different conditions affect rental numbers. Temporal Trends: The data reveals patterns based on time, with observations concentrated in 2011 and 2012. There's an average "day" value around 10, and the hourly distribution covers all 24 hours.

Outlier Detection

In [24]:
```
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

Seasonal Outliers:

The data shows more outliers during spring and winter than in other seasons.

Weather Outliers:

Weather categorized as Category 3 displays numerous outliers, whereas Category 4 weather shows none.

Working Days vs. Holidays:

There are more outliers on regular working days compared to holidays. This indicates unexpected patterns on typical workdays that may warrant further investigation.

Univariate Analysis

In [25]:
```
# Time span of data
time_span = df['datetime'].max() - df['datetime'].min()
time_span
```

Out[25]:
```
Timedelta('718 days 23:00:00')
```

In [26]:
```
df.columns
```

Out[26]:
```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count',
       'year', 'month', 'day', 'hour'],
      dtype='object')
```

In [27]:
```
# Season counts
df['season'].value_counts()
```

Out[27]:

season	count
Winter	2734
Summer	2733
Fall	2733
Spring	2686

dtype: int64

In [28]:
```
# holiday counts
df['holiday'].value_counts()
```

Out[28]:

	count
holiday	
No	10575
Yes	311

dtype: int64

In [29]:

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

Out[29]:

	count
workingday	
Yes	7412
No	3474

dtype: int64

In [30]:

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

Out[30]:

	count
weather	
1	7192
2	2834
3	859
4	1

dtype: int64

In [31]:

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

Out[31]:

	count
year	
2012	5464
2011	5422

dtype: int64

In [32]:
```
# month counts
df['month'].value_counts()
```

Out[32]:

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

dtype: int64

In [33]:
```
# day counts
df['day'].value_counts().sort_index()
```

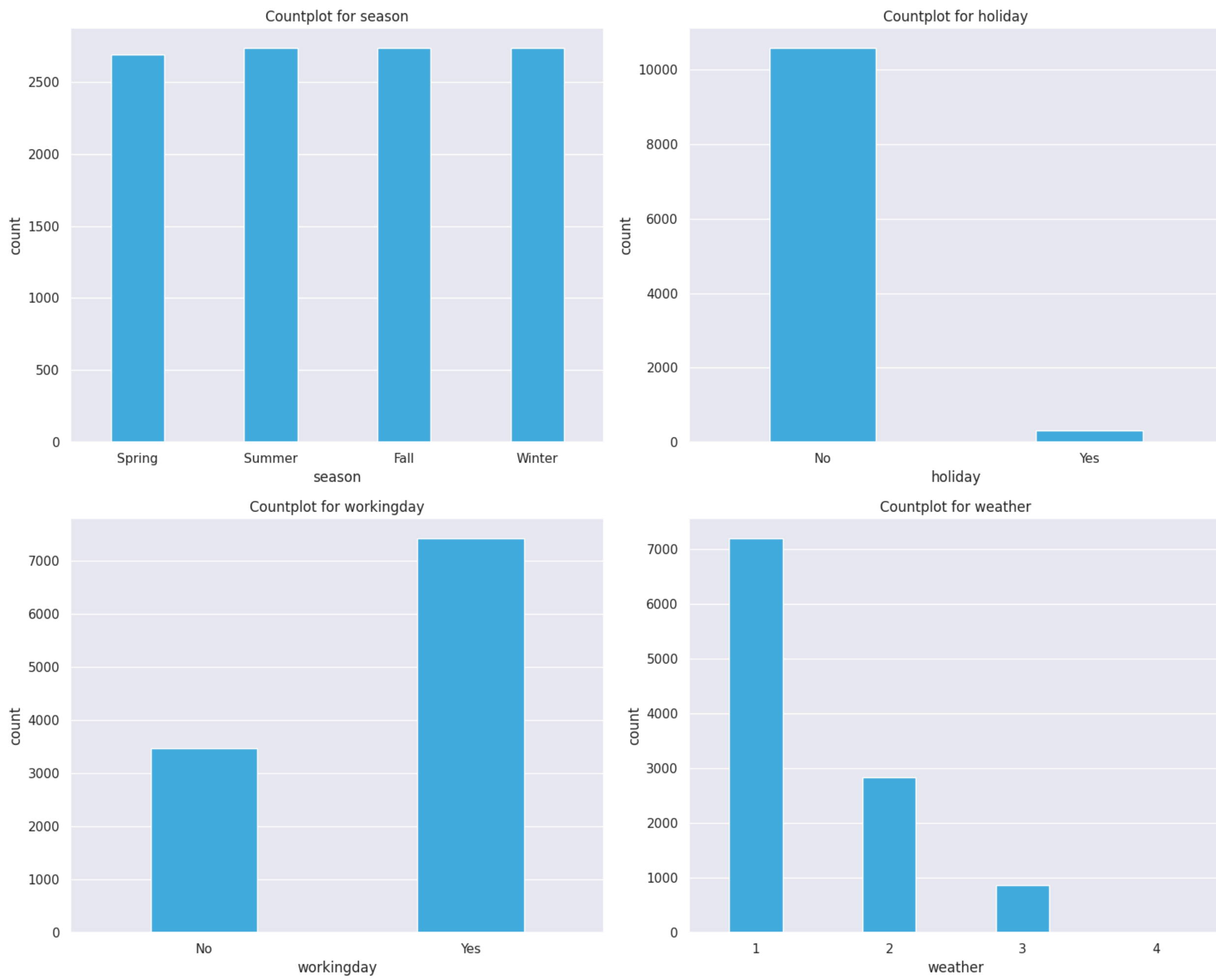
Out[33]:

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 [34]:

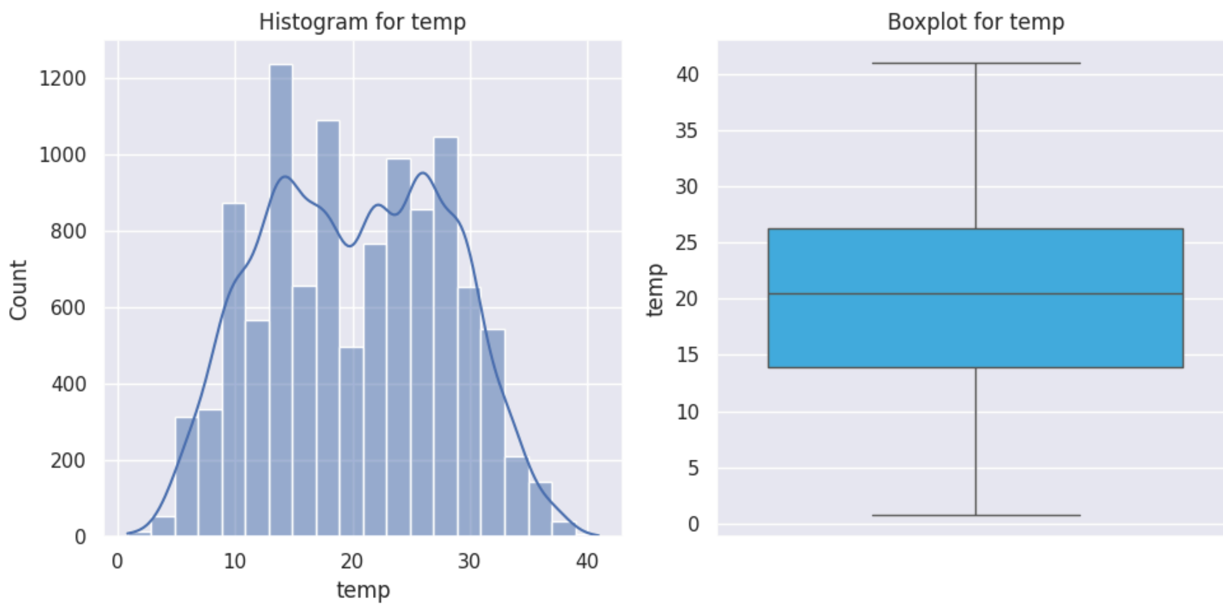
```
# countplot on categories
plt.figure(figsize=(15, 12))
sns.set(style="darkgrid")
for i, column in enumerate(cat_col, 1):
 plt.subplot(2, 2, i)
 sns.countplot(x=column, data=df, color="#29B6F6", width=0.4)
 plt.title(f'Countplot for {column}')

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



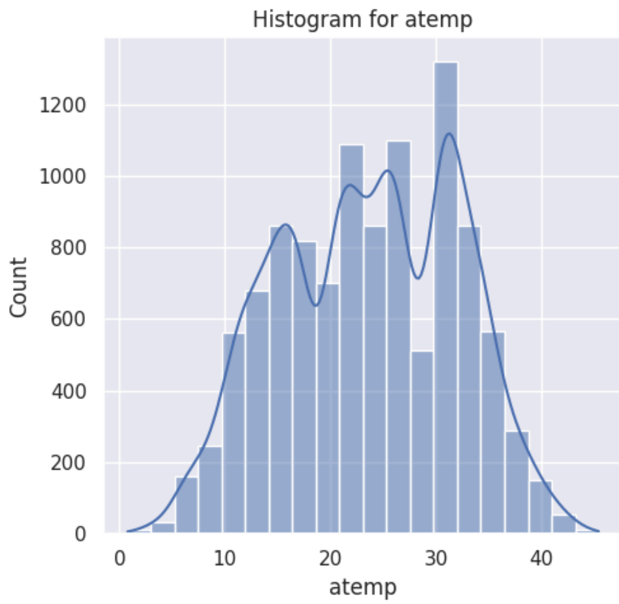
In [35]:
```
# Function for histogram & boxplot on numerical columns
def hist_box(column):
 f, axs = plt.subplots(1, 2, figsize=(10, 5))
 sns.set(style="darkgrid")

 # 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()
```

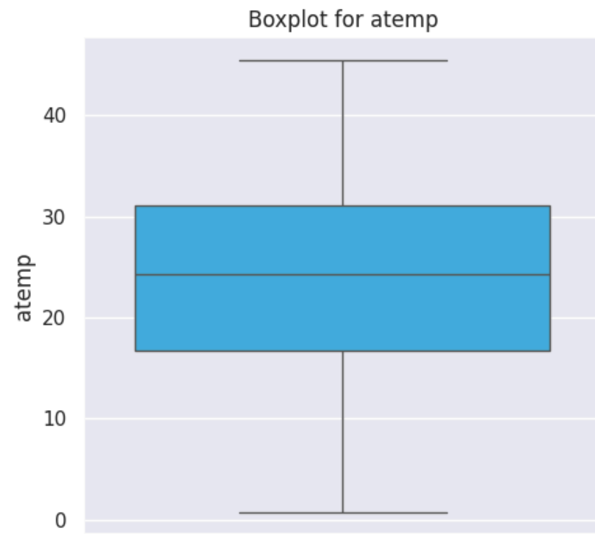
In [38]:
```
num_col = ['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered','c
for column in num_col:
 hist_box(column)
```

	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

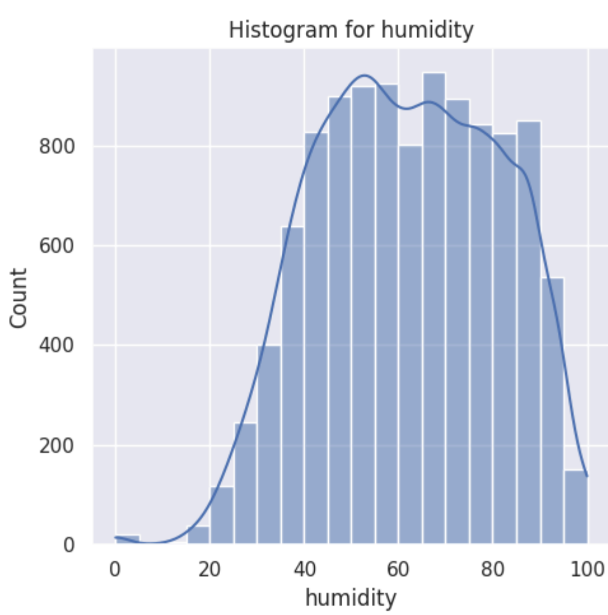


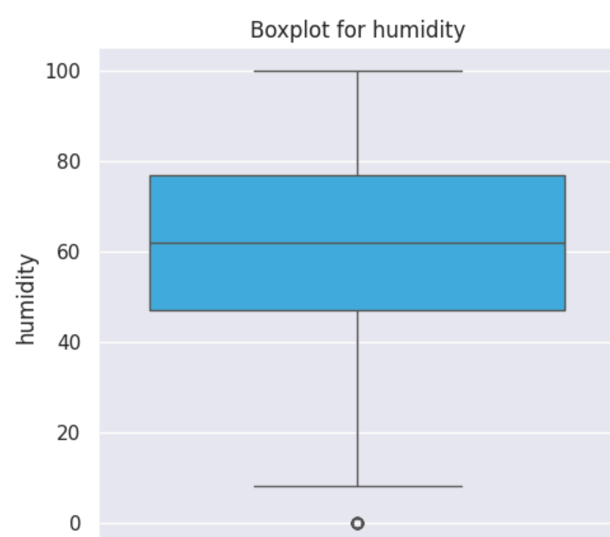
	Statistic	Value
0	count	10886.000000
1	mean	23.655084
2	std	8.474601
3	min	0.760000
4	25%	16.665000
5	50%	24.240000
6	75%	31.060000
7	max	45.455000



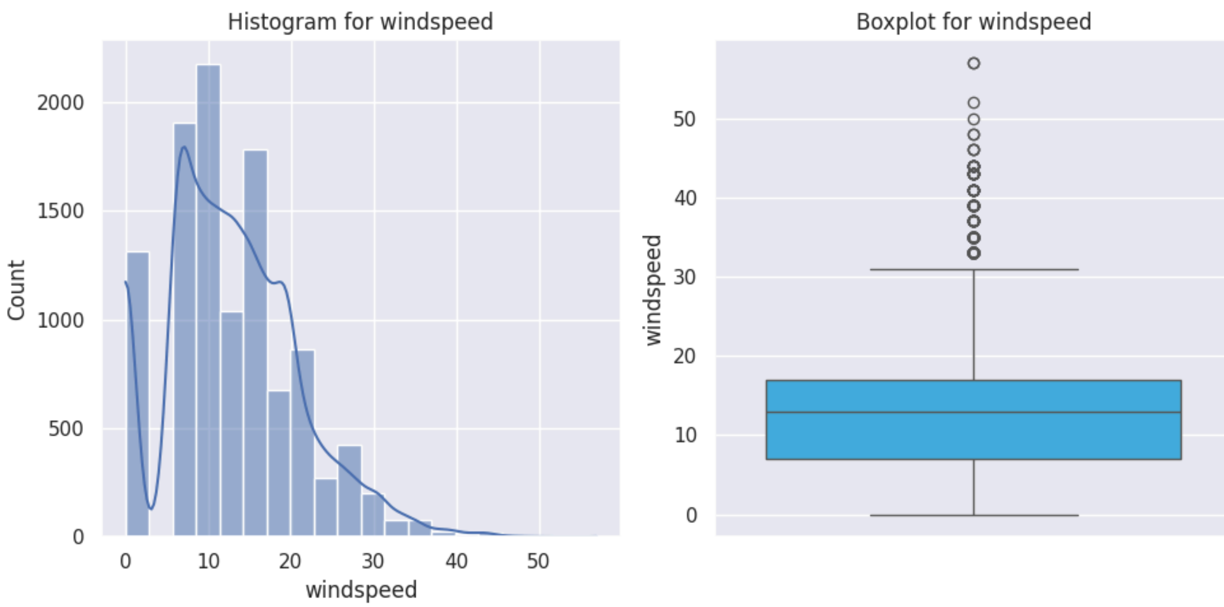


	Statistic	Value
0	count	10886.000000
1	mean	61.886460
2	std	19.245033
3	min	0.000000
4	25%	47.000000
5	50%	62.000000
6	75%	77.000000
7	max	100.000000

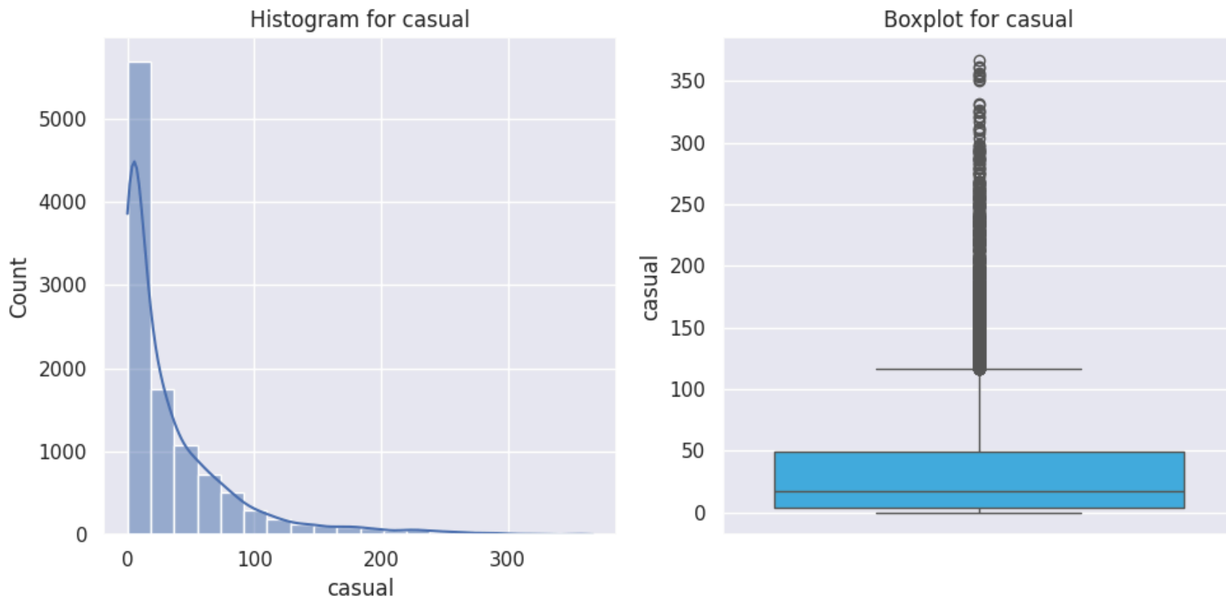




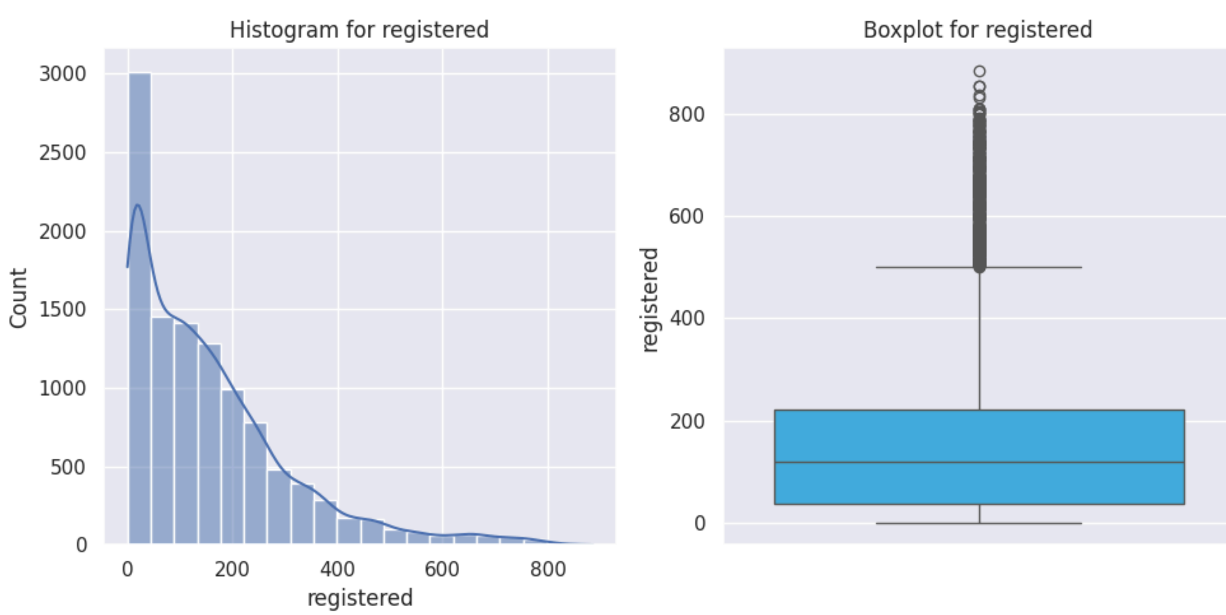
	Statistic	Value
0	count	10886.000000
1	mean	12.799395
2	std	8.164537
3	min	0.000000
4	25%	7.001500
5	50%	12.998000
6	75%	16.997900
7	max	56.996900



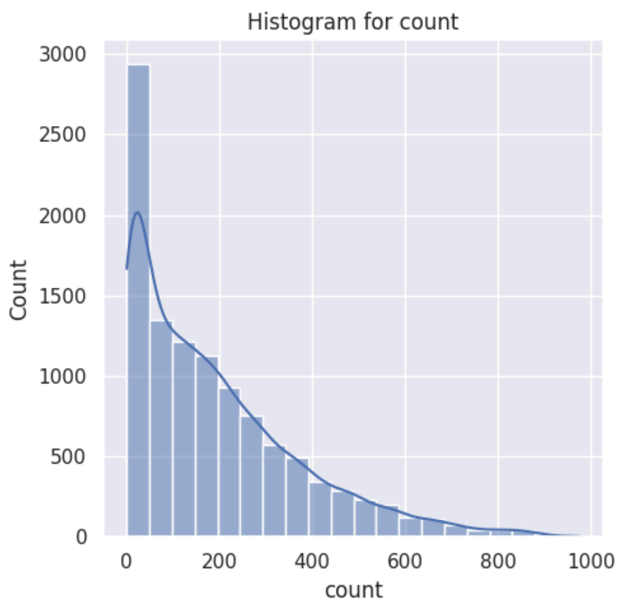
	Statistic	Value
0	count	10886.000000
1	mean	36.021955
2	std	49.960477
3	min	0.000000
4	25%	4.000000
5	50%	17.000000
6	75%	49.000000
7	max	367.000000

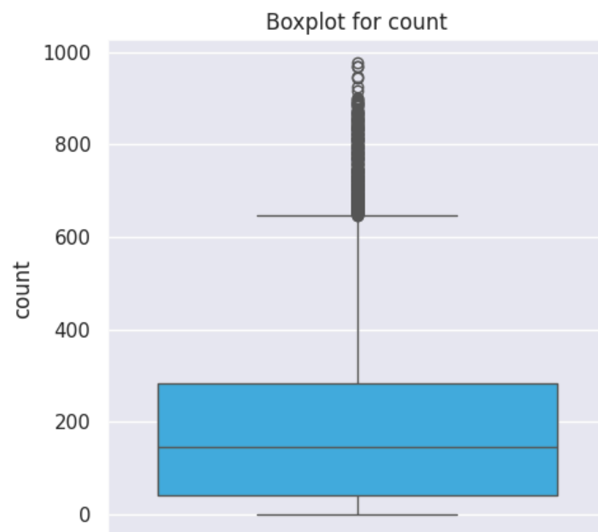


	Statistic	Value
0	count	10886.000000
1	mean	155.552177
2	std	151.039033
3	min	0.000000
4	25%	36.000000
5	50%	118.000000
6	75%	222.000000
7	max	886.000000



	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





Temperature (Temp):

The temp column records a wide temperature range, from 0.82°C to 41.0°C, with a median of 20.5°C and a mean of about 20.23°C, indicating moderate variation around the average.

Apparent Temperature (Atemp):

The atemp column shows a broad range of apparent temperatures, from 0.76°C to 45.455°C, with a mean of around 23.66°C and moderate variation around the median of 24.24°C.

Humidity:

Humidity values range from 0% to 100%, with an average of about 61.89%. The distribution shows moderate spread, with the 25th percentile at 47% and the 75th percentile at 77%, reflecting diverse humidity conditions in the dataset.

Wind Speed:

The windspeed column captures wind speeds ranging from 0 to 56.9979, with an average of roughly 12.80, indicating varied wind conditions.

Casual Users:

The casual column represents the number of casual bike rentals, ranging from 0 to 367. The distribution is right-skewed, with a mean of 36.02 and a median of 17.0, suggesting more instances of lower rental counts.

Registered Users:

The registered column highlights the count of registered bike rentals, which varies from 0 to 886. The distribution is positively skewed, with a mean of 155.55 and a median of 118.0, indicating a tendency toward lower counts with occasional higher values.

Total Count:

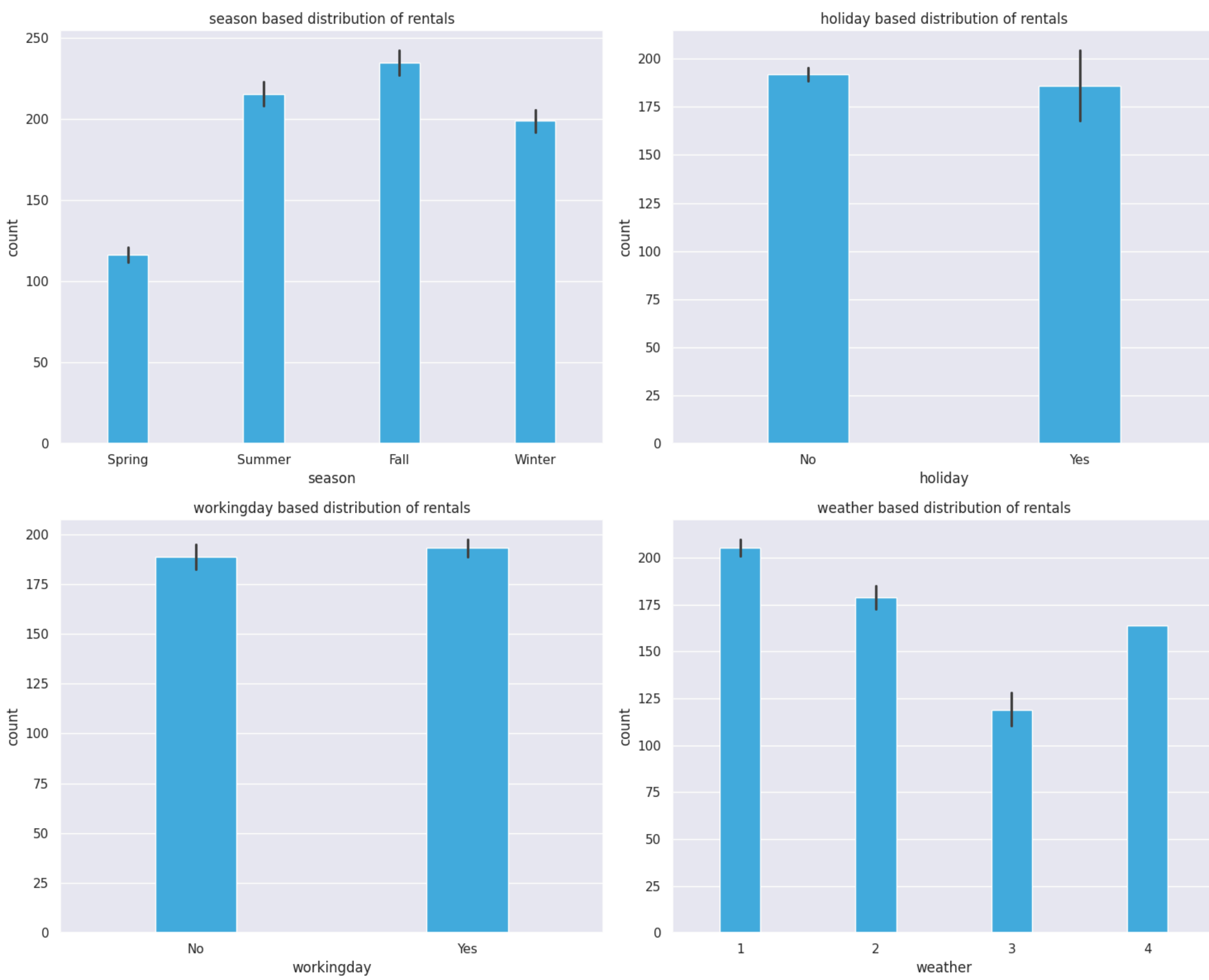
The count column shows total bike rentals, ranging from 1 to 977. The distribution is also right-skewed, with a mean of 191.57 and a median of 145.0, pointing to a higher frequency of lower rental counts.

Bivariate Analysis

In [39]:
```
cat_col
```

Out[39]: ['season', 'holiday', 'workingday', 'weather']

In [40]:
```
# 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()
```



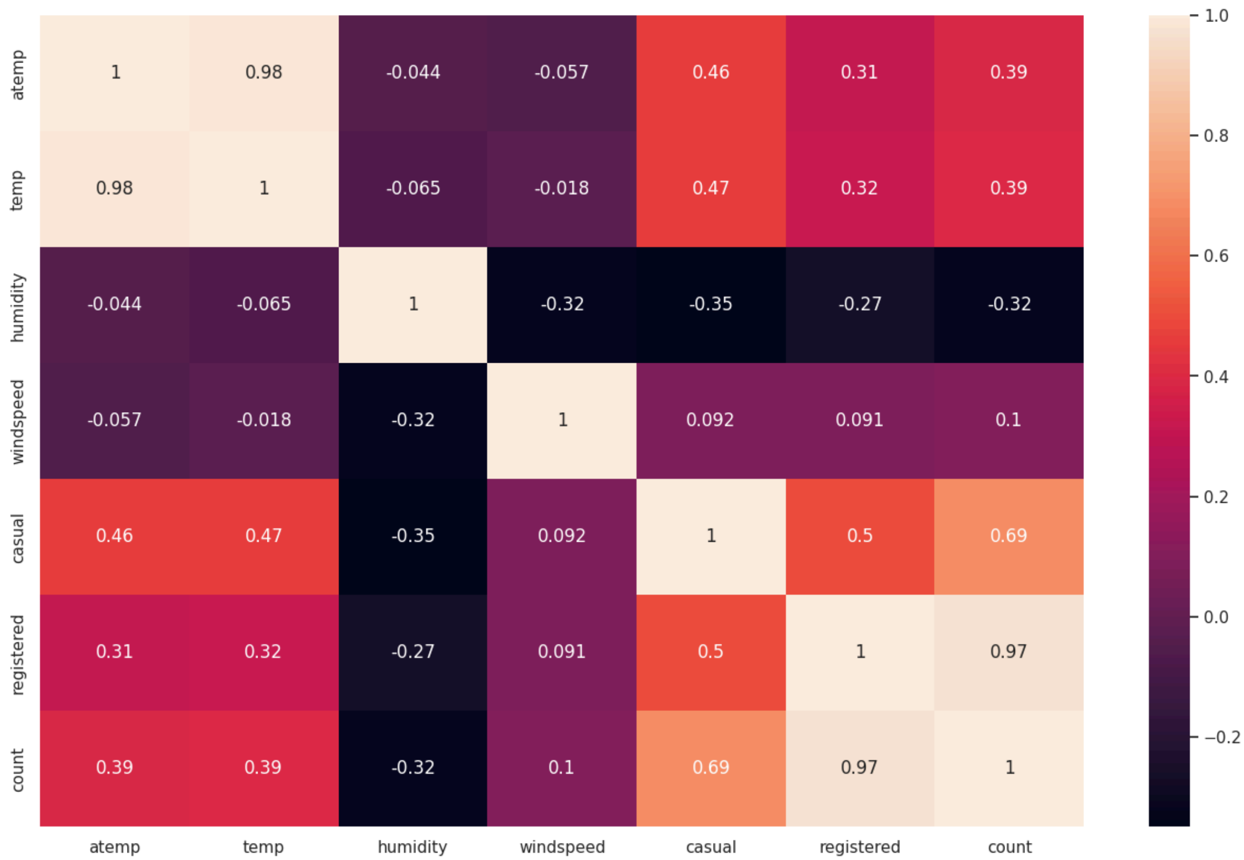
In [44]:
```
# corrrelation analysis
correlation_cols = ['atemp', 'temp', 'humidity', 'windspeed', 'casual', 'regis
correlation_matrix = correlation_df[correlation_cols].corr()
correlation_matrix
```

Out[44]:

	atemp	temp	humidity	windspeed	casual	registered	
atemp	1.000000	0.984948	-0.043536	-0.057473	0.462067	0.314635	0.
temp	0.984948	1.000000	-0.064949	-0.017852	0.467097	0.318571	0.
humidity	-0.043536	-0.064949	1.000000	-0.318607	-0.348187	-0.265458	-0.
windspeed	-0.057473	-0.017852	-0.318607	1.000000	0.092276	0.091052	0.
casual	0.462067	0.467097	-0.348187	0.092276	1.000000	0.497250	0.
registered	0.314635	0.318571	-0.265458	0.091052	0.497250	1.000000	0.
count	0.389784	0.394454	-0.317371	0.101369	0.690414	0.970948	1.

In [45]:

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



Correlation Analysis

Apparent Temperature (Atemp)

- Strong positive correlation with **Temp** *(0.98)* → indicates a very close relationship.
- Moderately positive correlation with **Casual** *(0.46)* and **Registered** *(0.31)* rentals.
- Positive correlation with **Count** *(0.39)* → suggests a link with total bike rentals.

Temperature (Temp)

- Highly correlated with **Atemp** *(0.98)* → strong connection.
- Moderately positive correlation with **Casual** *(0.47)* and **Registered** *(0.32)* rentals.
- Positive correlation with **Count** *(0.39)* → shows a relationship with overall 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 fewer bike rentals during periods of high 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 wind speed has a slight influence on rentals.

Casual Rentals

- Strong positive correlation with **Atemp** *(0.46)* and **Temp** *(0.47)*.
- Moderate negative correlation with **Humidity** *(-0.35)*.
- Slight positive correlation with **Windspeed** *(0.09)*.
- Strongly correlated with **Registered** *(0.50)* and **Count** *(0.69)* → significant impact on total rentals.

Registered Rentals

- Positive correlation with **Atemp** *(0.31)* and **Temp** *(0.32)*.
- Negative correlation with **Humidity** *(-0.27)*.
- Slight positive correlation with **Windspeed** *(0.09)*.
- Strongly correlated with **Casual** *(0.50)* and **Count** *(0.97)* → major contributor to total rentals.

Total Count

- Positive correlation with **Atemp** *(0.39)*, **Temp** *(0.39)*, and **Casual** *(0.69)*.
- Negative correlation with **Humidity** *(-0.32)*.
- Very strong correlation with **Registered** *(0.97)* → highlights the combined effect of casual and registered rentals on total counts.

Insight: Higher temperatures and apparent temperatures tend to increase bike rentals, while higher humidity reduces them. Wind speed has only a minor effect.

In [46]:

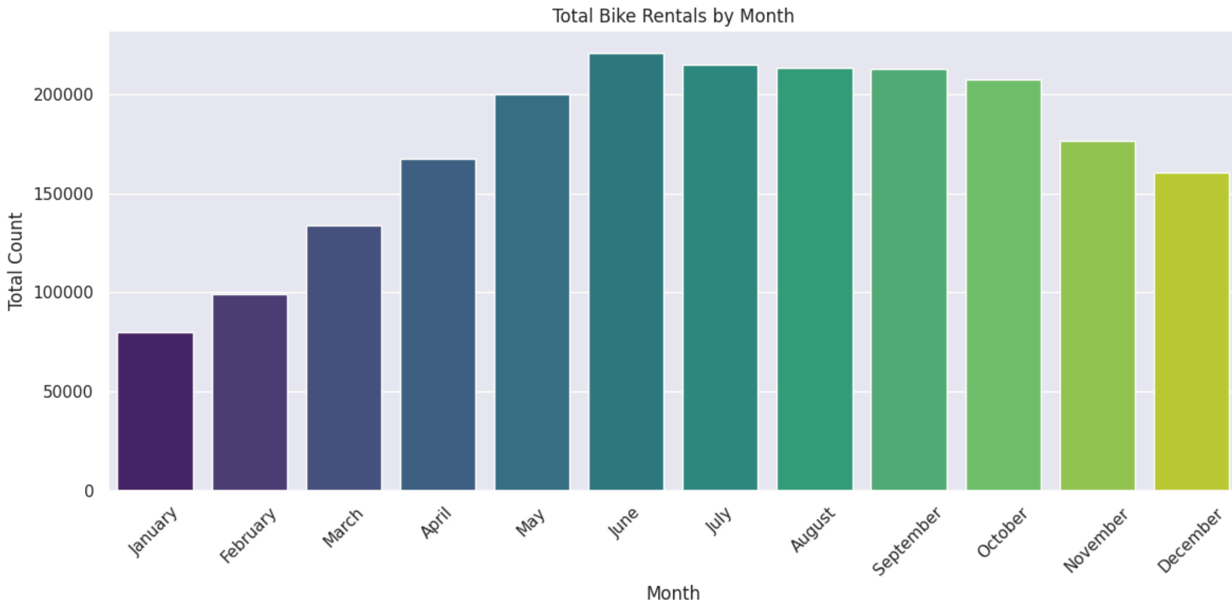
```
# counts based on months
monthly_count = df.groupby('month')['count'].sum().reset_index()
monthly_count = monthly_count.sort_values(by='count', ascending=False)
monthly_count
```

Out[46]:

	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 [48]:

```
# prompt: Total Count by month by Total Count

monthly_count = df.groupby('month')['count'].sum().reset_index()
# Sort the months in chronological order for better visualization
month_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July',
monthly_count['month'] = pd.Categorical(monthly_count['month'], categories=mor
monthly_count = monthly_count.sort_values(by='month')

plt.figure(figsize=(12, 6))
sns.barplot(x='month', y='count', data=monthly_count, palette='viridis')
plt.title('Total Bike Rentals by Month')
plt.xlabel('Month')
plt.ylabel('Total Count')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

print("Total Count by Month:")
monthly_count
```




```
Total Count by Month:
```

Out[48]:

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

Monthly Analysis on Bike Rentals

Peak Rental Months:

June records the highest number of bike rentals at 220,733, with July and August also showing high rental volumes.

Seasonal Trend:

The summer months (June, July, and August) consistently see increased bike rentals, likely due to favorable weather conditions.

Off-Peak Months:

Rental counts drop significantly in January, February, and March, suggesting off-peak periods influenced by colder weather and reduced outdoor activities.

Hypothesis Testing

Hypothesis:

The demand for bicycle rentals is the same on weekdays and weekends.

Test Selection:

Since we have two independent samples (weekdays vs. weekends), we will use a Two-Sample Independent T-Test.

Assumptions for the Two-Sample Independent T-Test:

1. The data should be normally distributed.
2. The variances of the two groups should be equal.

We will use a 95% confidence interval, so the significance level (α) is 0.05.

Checking Normality:

To check if the data is normally distributed, we will use the Shapiro-Wilk Test.

1. Null Hypothesis (H_0): The data is normally distributed.
2. Alternative Hypothesis (H_1): The data is not normally distributed.

In [49]:
```
np.random.seed(41)
df_subset = df.sample(100)["count"]
test_stat, p_val = shapiro(df_subset)
p_val
```

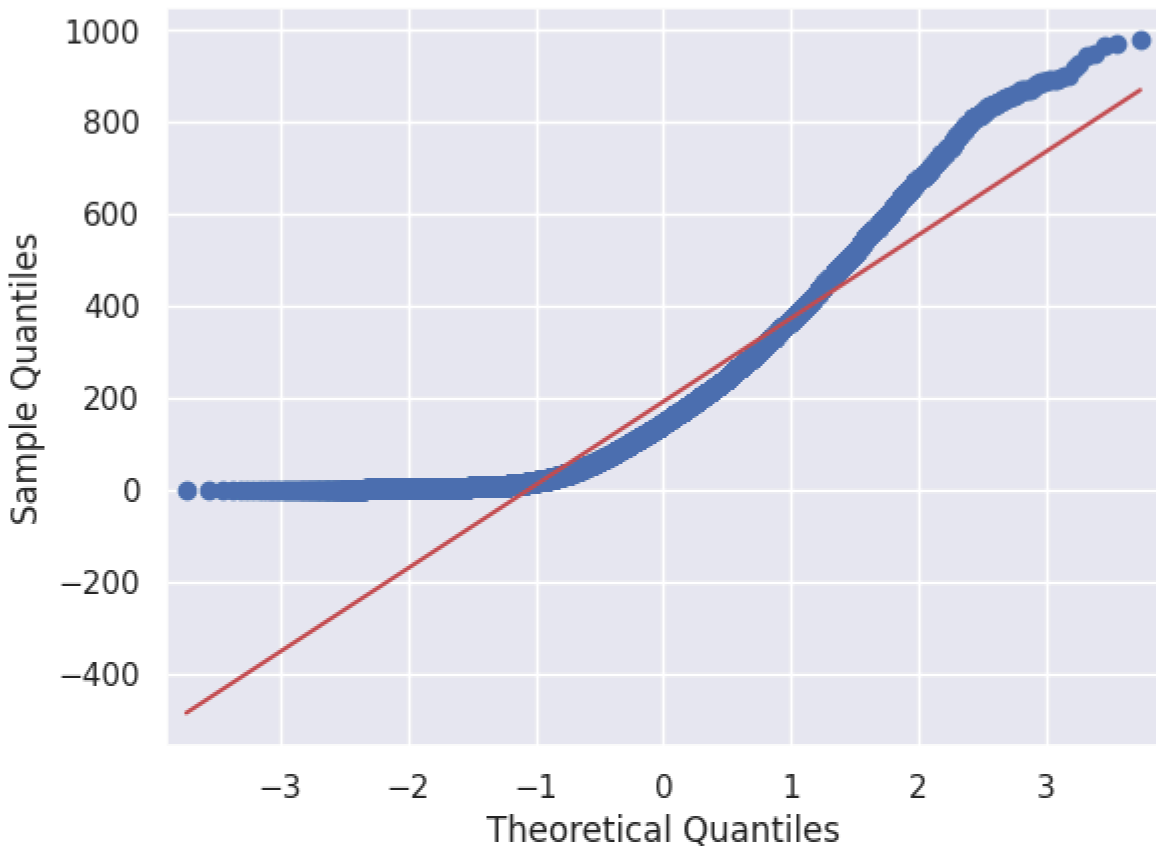
Out[49]:
```
np.float64(2.6341210395843134e-07)
```

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 [50]:
```
# QQ plot
qqplot(df['count'], line = 's')
plt.show()
```



Checking Equality of Variances:

To test whether the variances of the two groups are equal, we will use Levene's Test.

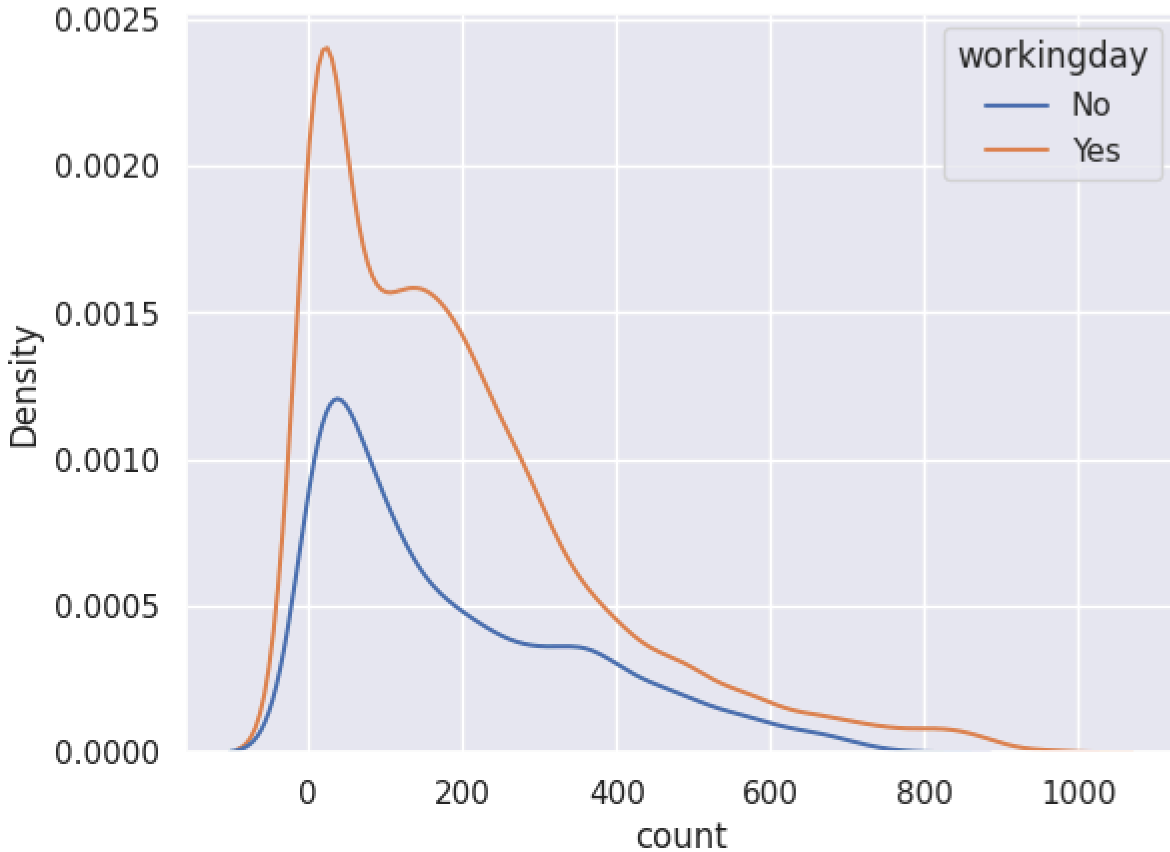
1. Null Hypothesis (H_0): The variances of the two groups are equal.
2. Alternative Hypothesis (H_1): The variances of the two groups are not equal.

In [51]:
```
working_day = df[df['workingday'] == 'Yes']['count']
holiday = df[df['workingday'] == 'No']['count']
levene_stat, p_val = levene(working_day, holiday)
p_val
```

Out[51]:
```
np.float64(0.9437823280916695)
```

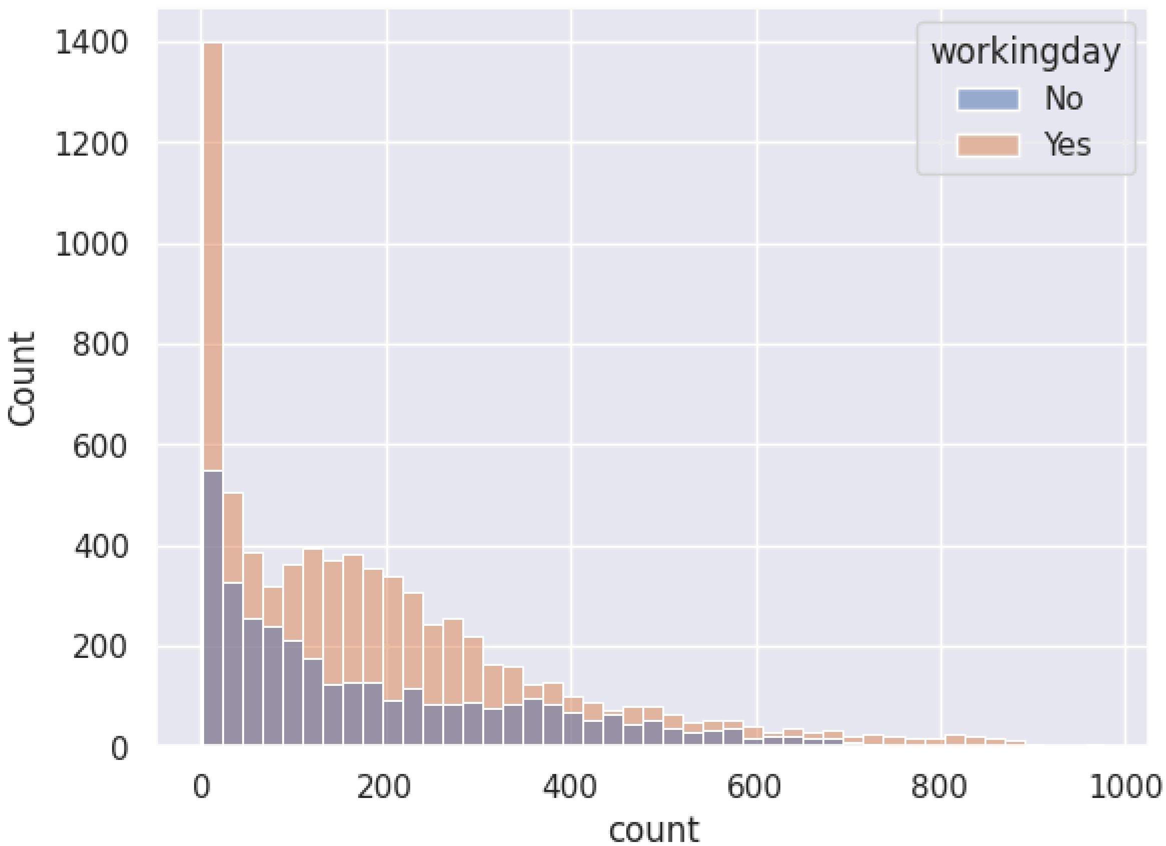
In [52]:
```
sns.kdeplot(data = df, x = 'count', hue = 'workingday')
```

Out[52]:
```
<Axes: xlabel='count', ylabel='Density'>
```



In [53]:
```
sns.histplot(data = df, x = 'count', hue = 'workingday')
```

Out[53]:
```
<Axes: xlabel='count', ylabel='Count'>
```



Conclusion on Variance and Normality:

Since the p-value is greater than the significance level ($\alpha = 0.05$), we fail to reject the null hypothesis for Levene's Test. Therefore, the variances of the two groups are approximately equal.

However, the data is not normally distributed, as indicated by both the Shapiro-Wilk Test and the QQ plot. Despite this, it's important to note that the equality of variances holds.

Proceeding with the Two-Sample Independent T-Test:

Given that the variances are equal, we can proceed with the Two-Sample Independent T-Test.

1. Null Hypothesis (H_0): There is no significant difference in bike rental demand between working days and non-working days.

2. Alternative Hypothesis (H_1): There is a significant difference in bike rental demand between working days and non-working days.

In [54]:
```
ttest_stat, p_val = ttest_ind(working_day, holiday)
p_val
```

Out[54]: np.float64(0.22644804226361348)

Conclusion:

Since the p-value is greater than the significance level ($\alpha = 0.05$), we fail to reject the null hypothesis.

- Therefore, there is no significant difference in bike rental demand between working days and non-working days.

In [55]:
```
kruskal_stat, p_val = kruskal(working_day, holiday)
p_val
```

Out[55]: np.float64(0.9679113872727798)

Conclusion:

Since the p-value is greater than the significance level, we fail to reject the null hypothesis.

- Therefore, there is no significant difference in bike rentals between working days and non-working days.

Hypothesis Testing for Weather Conditions

Hypothesis:

The demand for bicycle rentals is the same across different weather conditions.

Test Selection:

Since there are more than two categories, we will use ANOVA (Analysis of Variance) to test this hypothesis.

Assumptions for ANOVA:

1. Normality: The data should be normally distributed — however, this condition is not met, as confirmed by the Shapiro-Wilk Test and QQ plot.
2. Independence: The data points must be independent — this condition is satisfied.
3. Equal Variance: The variances within the groups should be approximately equal — this will be tested using Levene’s Test.

In [56]:
```
# skewness of weather
df.groupby('weather')['count'].skew()
```

Out[56]:

weather	count
1	1.139857
2	1.294444
3	2.187137
4	NaN

dtype: float64

In [57]:
```
# kurtosis test of weather
df.groupby('weather')['count'].apply(lambda x: x.kurtosis())
```

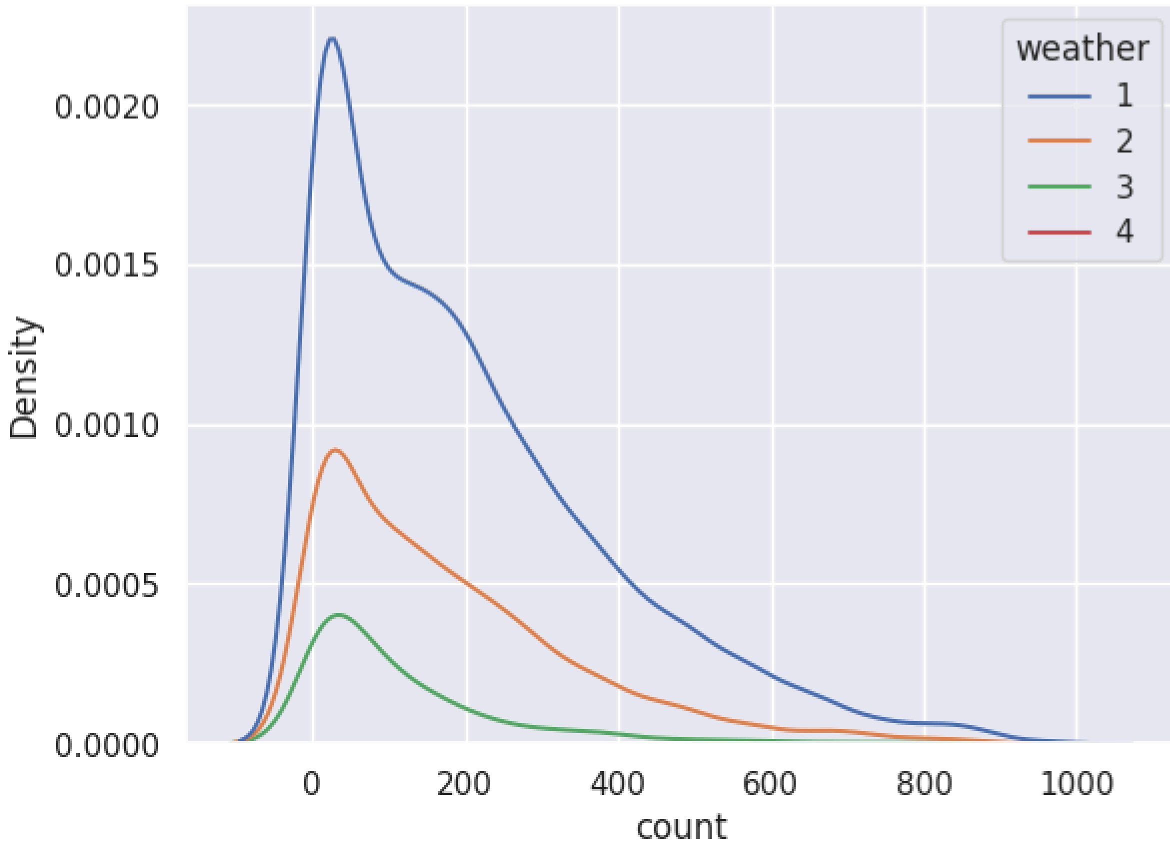
Out[57]:

weather	count
1	0.964720
2	1.588430
3	6.003054
4	NaN

dtype: float64

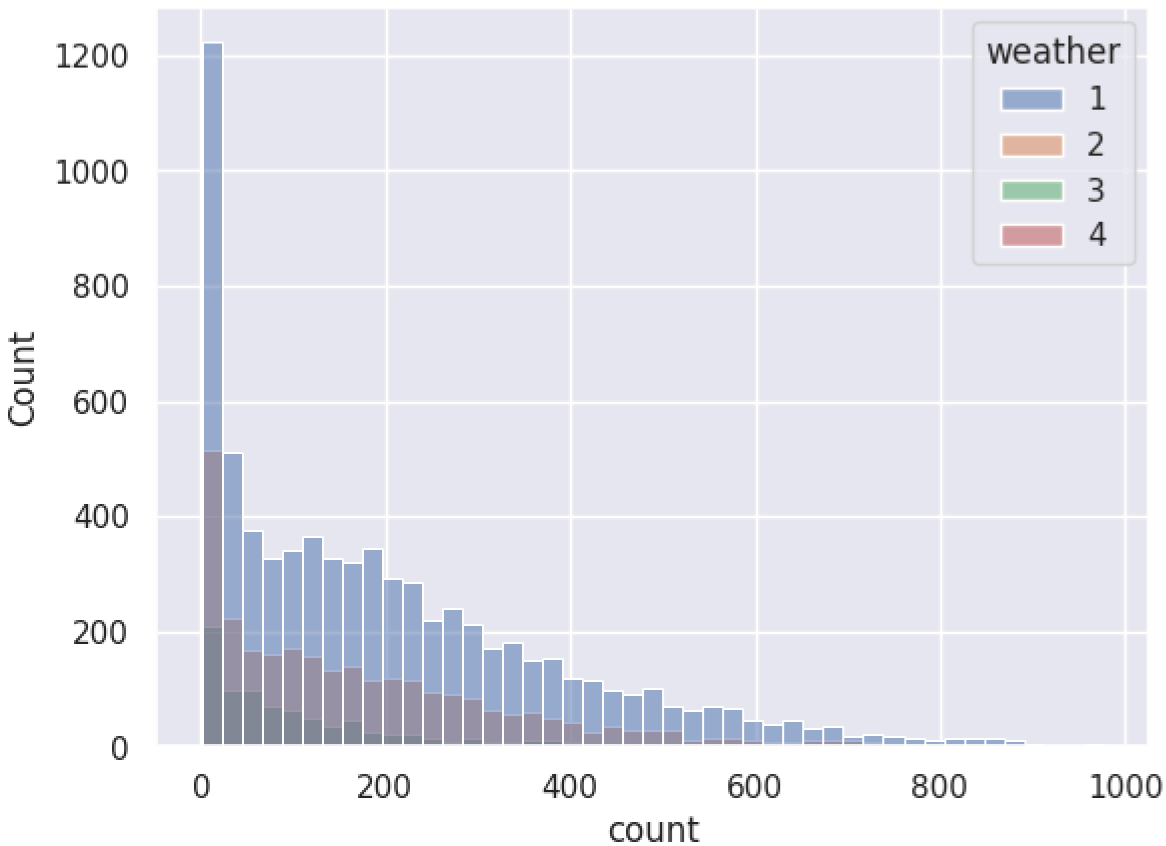
In [58]:
```
sns.kdeplot(data = df, x = 'count', hue = 'weather')
```

Out[58]: <Axes: xlabel='count', ylabel='Density'>



In [59]:
```
sns.histplot(data = df, x = 'count', hue = 'weather')
```

Out[59]: <Axes: xlabel='count', ylabel='Count'>



The Test hypothesis for Levene's test are:

1. Ho: The variances are equal.
2. Ha: The variances are not equal.

In [60]:
```
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[60]:
```
np.float64(3.504937946833238e-35)
```

Variance Test Conclusion:

Since the p-value is smaller than the significance level (α = 0.05), we reject the null hypothesis for Levene’s Test. Therefore, the variances are not equal across weather conditions.

ANOVA Assumptions:

Two out of the three ANOVA assumptions (normality and equal variance) are not met. Despite this, we will still perform ANOVA to compare results.

Additionally, we will perform the Kruskal-Wallis Test, which is a non-parametric alternative that does not assume normality or equal variances.

If there is any discrepancy between the ANOVA and Kruskal-Wallis results, the Kruskal-Wallis Test outcome will be considered more reliable for this dataset.

Hypotheses for ANOVA:

1. Null Hypothesis (H_0): There is no significant difference in bicycle rental demand across different weather conditions.
2. Alternative Hypothesis (H_1): There is a significant difference in bicycle rental demand across different weather conditions.

In [61]:
```
anova_stat, p_val = f_oneway(weather1, weather2, weather3,weather4)
p_val
```

Out[61]: np.float64(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 [62]:
```
kruskal_stat, p_val = kruskal(weather1, weather2, weather3,weather4)
p_val
```

Out[62]: np.float64(3.501611300708679e-44)

ANOVA Result for Weather Conditions:

Since the p-value is smaller than the significance level (α = 0.05), we reject the null hypothesis. Therefore, we conclude that there is a significant difference in bicycle rental demand across different weather conditions.

Hypothesis Testing for Seasons

Hypothesis:

The demand for bicycle rentals is the same across different seasons.

Test Selection:

As there are more than two categories, we will use ANOVA to test this hypothesis as well.

Assumptions for ANOVA:

Normality: The data should be normally distributed — however, this condition is not met, as confirmed by the Shapiro-Wilk Test and QQ plot.

Independence: The data points must be independent — this condition is satisfied.

In [63]:

```
# skewness of seasons
df.groupby('season')['count'].skew()
```

Out[63]:

season	count
Spring	1.888056
Summer	1.003264
Fall	0.991495
Winter	1.172117

dtype: float64

In [64]:

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

Out[64]:

weather	count
1	0.964720
2	1.588430
3	6.003054
4	NaN

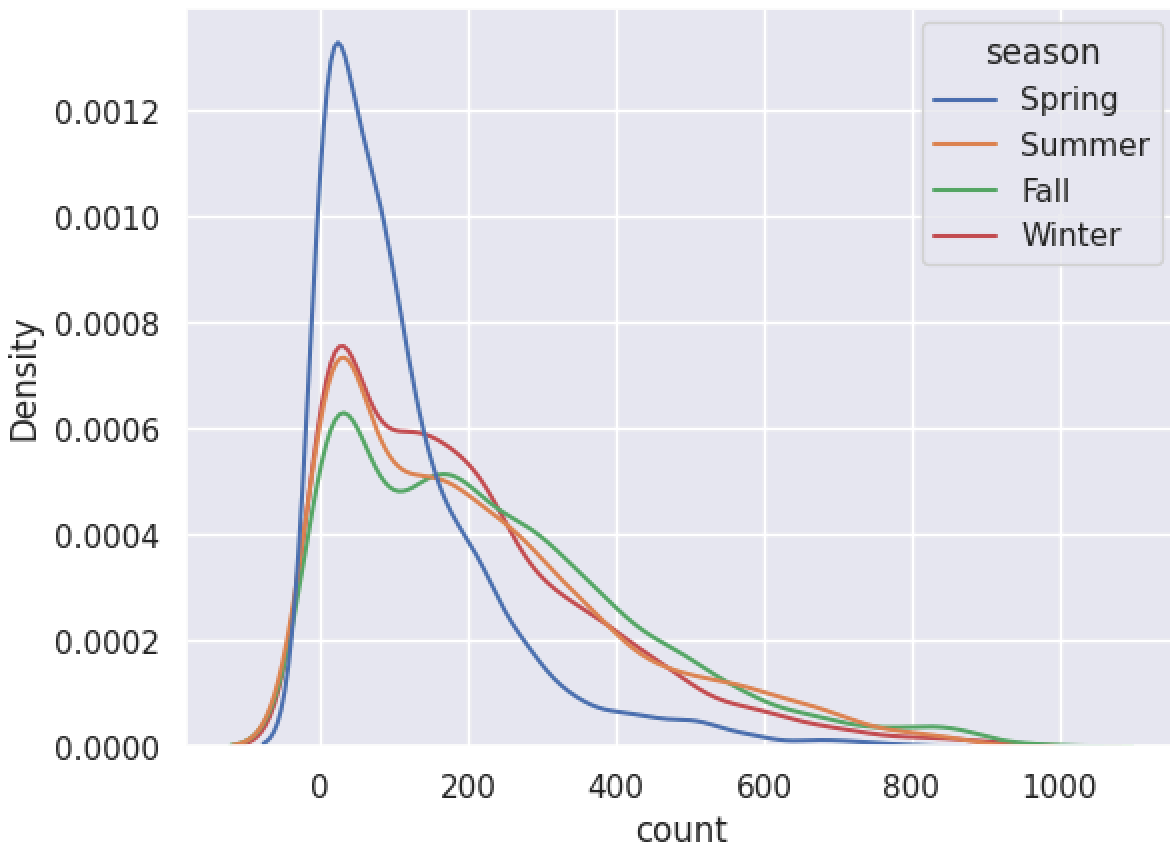
dtype: float64

In [65]:

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

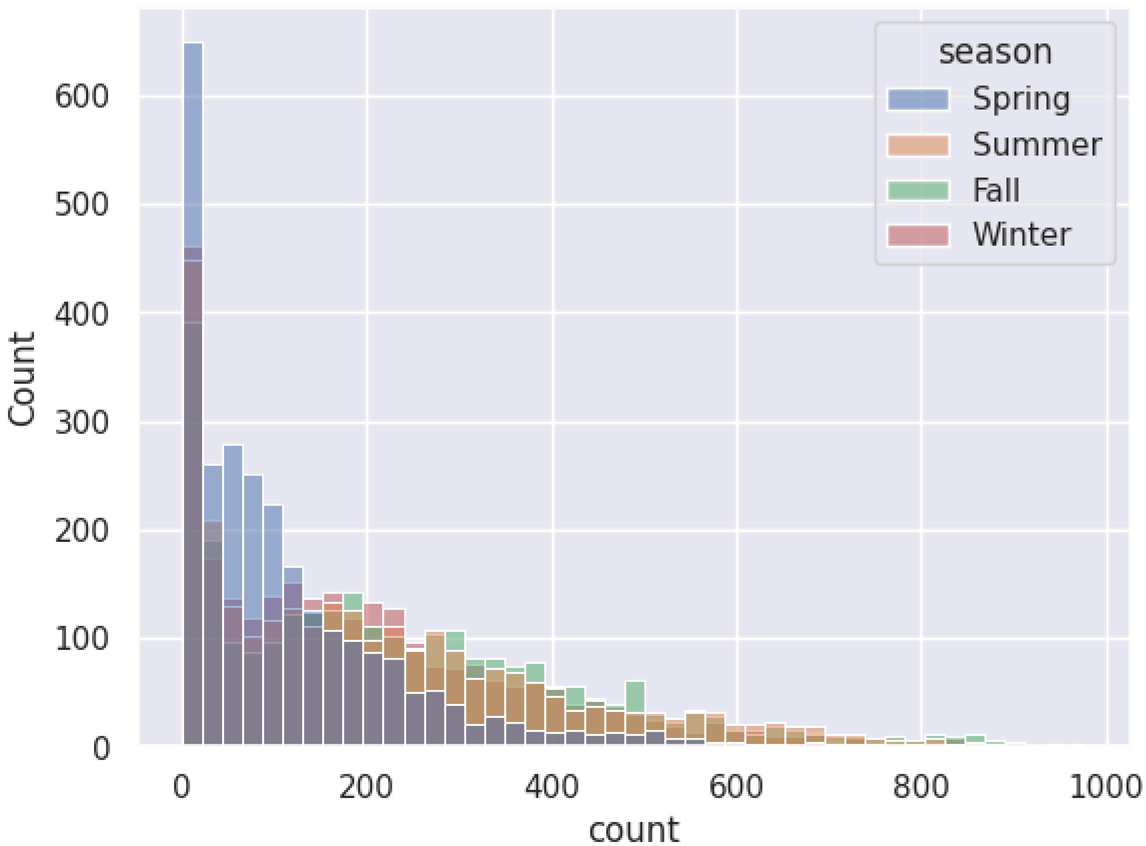
Out[65]:

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



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

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



The Test hypothesis for Levene's test are:

1. Ho: The variances are equal.
2. Ha: The variances are not equal.

In [67]:
```
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[67]:
```
np.float64(1.0147116860043298e-118)
```

Variance Test Conclusion for Seasons:

Since the p-value is smaller than the significance level (α = 0.05), we reject the null hypothesis for Levene’s Test. Therefore, the variances are not equal across different seasons.

ANOVA Assumptions:

As before, because normality and equal variances assumptions are not met, we will still perform ANOVA but also run the Kruskal-Wallis Test as a robust non-parametric alternative.

If there is any difference in the results, we will rely on the Kruskal-Wallis Test, since the data does not fully meet ANOVA's assumptions.

Hypotheses for ANOVA (Seasons):

Null Hypothesis (H_0): There is no significant difference in bicycle rental demand across different seasons.

Alternative Hypothesis (H_1): There is a significant difference in bicycle rental demand across different seasons.

In [68]:
```
anova_stat, p_val = f_oneway(spring ,summer, fall, winter)
p_val
```

Out[68]: `np.float64(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 [69]:
```
kruskal_stat, p_val = kruskal(spring ,summer, fall, winter)
p_val
```

Out[69]: `np.float64(2.479008372608633e-151)`

ANOVA/Kruskal-Wallis Result for Seasons:

Since the p-value is smaller than the significance level ($\alpha = 0.05$), we reject the null hypothesis. Therefore, we conclude that there is a significant difference in bicycle rental demand across different seasons.

Analysis of Weather Conditions Across Seasons — Chi-Square Test

---

Hypotheses for the Chi-Square Test:

Null Hypothesis (H_0): Season and Weather Condition are independent of each other.

Alternative Hypothesis (H_1): Season and Weather Condition are dependent on each other.

In [70]:
```
contingency_table = pd.crosstab(df['weather'], df['season'])
contingency_table
```

Out[70]:

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

In [73]:
```
chi2_contingency(contingency_table)
```

Out[73]:
```
Chi2ContingencyResult(statistic=np.float64(49.15865559689363), pvalue=np.floa
t64(1.5499250736864862e-07), dof=9, expected_freq=array([[1.77454639e+03, 1.8
0559765e+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]]))
```

Chi-Square Test Conclusion: Since the p-value (1.55×10^{-7}) is smaller than the significance level ($\alpha = 0.05$), we reject the null hypothesis.

- Therefore, we conclude that season and weather conditions are dependent on each other.

Strategic Recommendations for Yulu's Profitable Growth

Optimize Bike Distribution in Peak Months

Deploy more bikes during peak demand months — especially June, July, and August — to meet higher usage and maximize revenue during favorable weather.

Seasonal Marketing Campaigns

Strengthen marketing efforts in the summer months by promoting special offers or campaigns to attract more riders when demand is naturally higher.

Boost Engagement in Off-Peak Months

Run targeted promotions or discounts during off-peak periods (January–March) to maintain steady rental activity and revenue flow during slower months.

Weather-Responsive Pricing

Adopt dynamic pricing that adjusts rental rates based on weather conditions — for example, offering discounts during rainy or extreme weather days to encourage usage.

Diversify Revenue Streams

Expand revenue opportunities through partnerships, sponsorships, or premium memberships with added perks, helping reduce dependency on rentals alone.

Enhance User Experience

Invest in app improvements, regular bike maintenance, and excellent customer support to build user loyalty and encourage repeat rentals.

Optimize Deployment for Working Days

Since rental demand is similar on working and non-working days, adjust bike deployment for balanced availability throughout the entire week.

Adapt Promotions to Weather Changes

Offer weather-based deals — for example, special discounts on rainy days — to keep demand stable regardless of weather fluctuations.

Season-Specific Campaigns

Customize advertising to highlight what appeals most in each season — such as promoting outdoor summer rides and eco-friendly travel during peak months.

Integrate Seasonal & Weather Plans

Align bike availability with both seasonal trends and daily weather forecasts — for instance, ensure more bikes are ready on clear, warm days to meet higher demand.
