Business Case: Yulu - Hypothesis Testing

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.

Why this case study?

- From Yulu's Perspective:
  - Strategic Expansion: Yulu's decision to enter the Indian market is a strategic move to expand its global footprint. Understanding the demand factors in this new market is essential to tailor their services and strategies accordingly.
  - Revenue Recovery: Yulu's recent revenue decline is a pressing concern. By analyzing the factors affecting demand for shared electric cycles in the Indian market, they can make informed adjustments to regain profitability.
- From Learners' Perspective:
  - Real-World Problem-Solving: It presents an opportunity to apply machine learning and data analysis techniques to address a real-world business problem.
  - Market Insights: Analyzing factors affecting demand in the Indian market equips learners with market research skills. This knowledge is transferable to various industries.
  - Consulting Skills: Learners can develop their ability to act as consultants, providing data-driven insights to organizations

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Business Problem:

- Which variables are significant in predicting the demand for shared electric cycles in the Indian market ?
- How well those variables describe the electric cycle demands.

Features of the dataset:

- Column Profiling:

Feature	Description
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.
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 - Total_riders	count of total rental bikes including both casual and registered

- weather

Category	Details
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

```
# 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")

# converting data into dataframe

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

```python
# making an copy of the dataset

df = yulu.copy()

# Top 5 rows of the dataframe

df.head()
```

```
              datetime  season  holiday  workingday  weather  temp  
atemp  \
0  2011-01-01 00:00:00       1        0           0        1  9.84  
14.395
1  2011-01-01 01:00:00       1        0           0        1  9.02  
13.635
2  2011-01-01 02:00:00       1        0           0        1  9.02  
13.635
3  2011-01-01 03:00:00       1        0           0        1  9.84  
14.395
4  2011-01-01 04:00:00       1        0           0        1  9.84  
14.395

   humidity  windspeed  casual  registered  count
0        81        0.0       3          13     16
1        80        0.0       8          32     40
2        80        0.0       5          27     32
3        75        0.0       3          10     13
4        75        0.0       0           1      1
```

```python
# No of rows and columns

df.shape
```

```
(10886, 12)
```

```python
# Checking of null values

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

```
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.

```
# Duplicate values check

df.duplicated().sum()

0

# skewness of each column

df.skew(numeric_only = True)

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.

```
# Uniques values of each columns

df.nunique()

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
```

```python
# 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
```

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

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

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

```python
# 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
```

```
# Converting datetime column into date time format

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

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

```
# 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

df.head(2)
```

```
             datetime season holiday workingday weather  temp   atemp
\
0 2011-01-01 00:00:00      1       0          0       1  9.84  14.395

1 2011-01-01 01:00:00      1       0          0       1  9.02  13.635


   humidity  windspeed  casual  registered  count  year  month  day
hour
0        81        0.0       3          13     16  2011      1    1
0
1        80        0.0       8          32     40  2011      1    1
1
```

```
# 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'})

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

```
              count                           mean
min  \
datetime      10886  2011-12-27 05:56:22.399411968  2011-01-01
00:00:00
temp        10886.0                       20.23086
0.82
atemp       10886.0                      23.655084
0.76
humidity    10886.0                       61.88646
0.0
windspeed   10886.0                      12.799395
0.0
casual      10886.0                      36.021955
0.0
registered  10886.0                     155.552177
0.0
count       10886.0                     191.574132
1.0
year        10886.0                    2011.501929
2011.0
day         10886.0                       9.992559
1.0
```

```
hour        10886.0                      11.541613
0.0

                             25%                    50%
75%  \
datetime    2011-07-02 07:15:00  2012-01-01 20:30:00  2012-07-01
12:45:00
temp                       13.94                  20.5
26.24
atemp                     16.665                 24.24
31.06
humidity                    47.0                  62.0
77.0
windspeed                 7.0015                12.998
16.9979
casual                       4.0                  17.0
49.0
registered                  36.0                 118.0
222.0
count                       42.0                 145.0
284.0
year                      2011.0                2012.0
2012.0
day                          5.0                  10.0
15.0
hour                         6.0                  12.0
18.0

                             max         std
datetime    2012-12-19 23:00:00         NaN
temp                        41.0     7.79159
atemp                     45.455    8.474601
humidity                   100.0   19.245033
windspeed                56.9969    8.164537
casual                     367.0   49.960477
registered                 886.0  151.039033
count                      977.0  181.144454
year                      2012.0    0.500019
day                         19.0    5.476608
hour                        23.0    6.915838
```

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

```
            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:

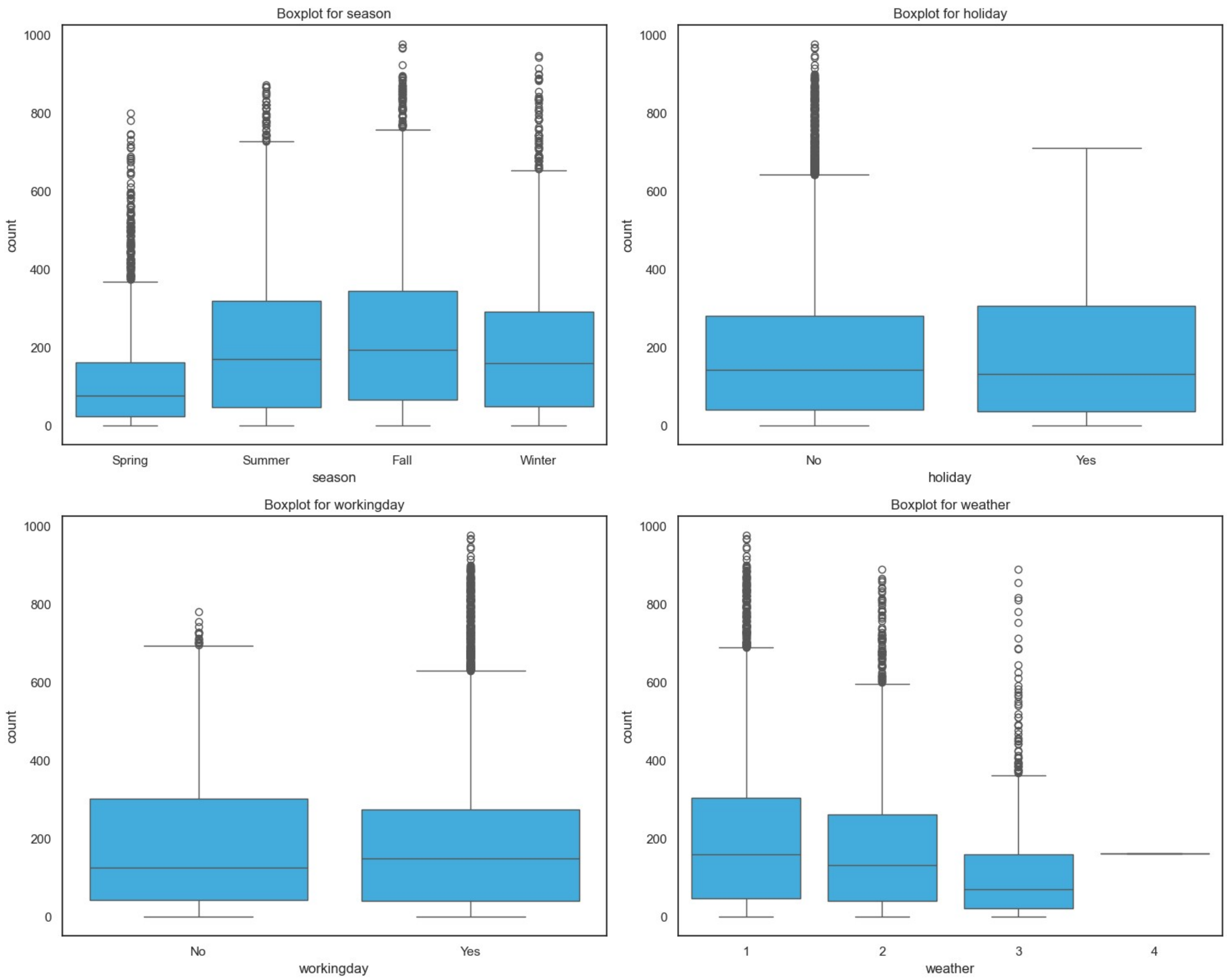
- Numerical features such as temperature, humidity, windspeed, and counts of casual and registered bike rentals show diverse ranges and distributions, highlighting the variability in rental patterns across different conditions.

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

```
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

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

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

```
df.columns
```

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

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

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

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

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

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

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

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

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

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

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

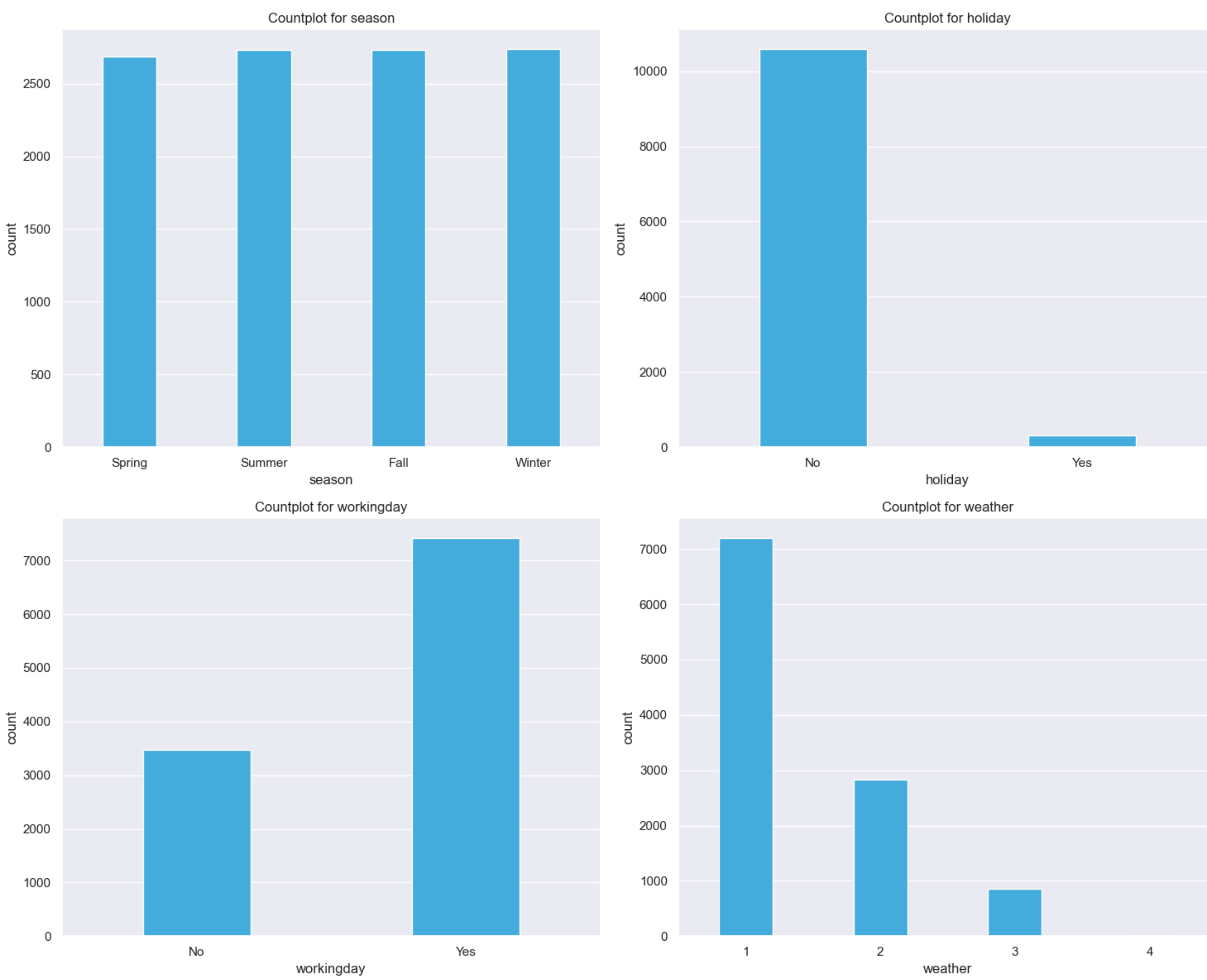
```
# month counts
df['month'].value_counts()
```

```
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
```

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

```
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
```

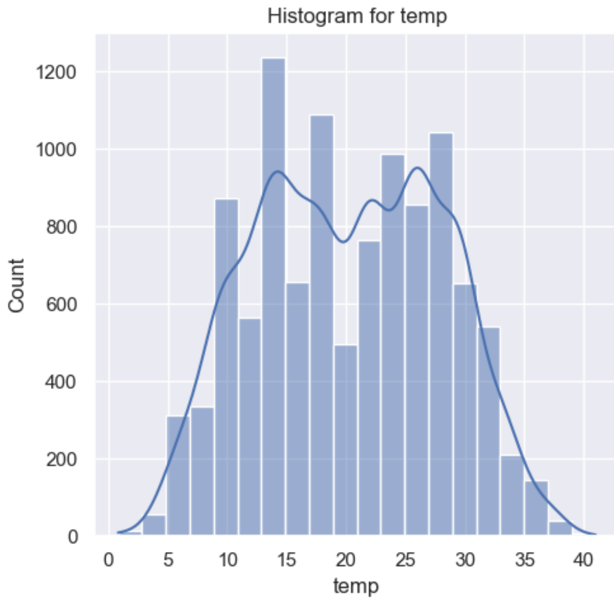
```
# countplot on categories

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()
```

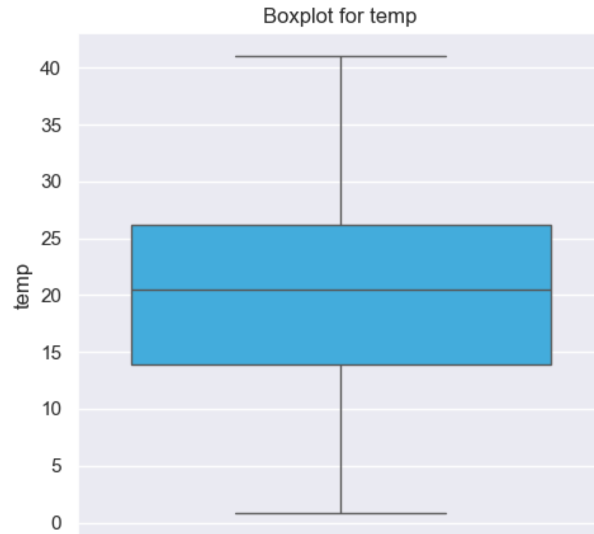



```
# Function for histogram & boxplot on numerical columns

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

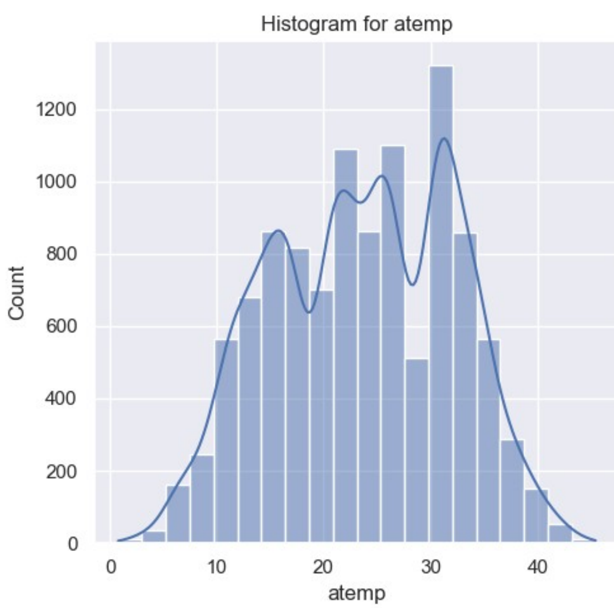
```python
    # Histogram
    plt.subplot(1, 2, 1)
    sns.histplot(df[column], bins=20, kde=True)
    plt.title(f'Histogram for {column}')

    # 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()

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

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

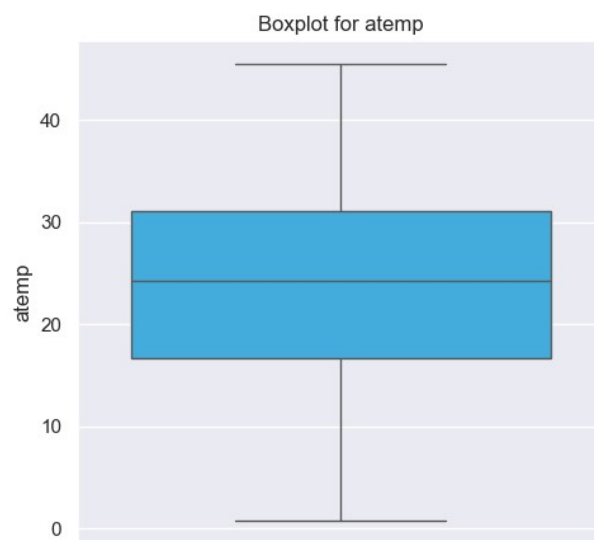
	Statistic	Value
0	count	10886.00000
1	mean	20.23086
2	std	7.79159
3	min	0.82000
4	25%	13.94000
5	50%	20.50000
6	75%	26.24000
7	max	41.00000



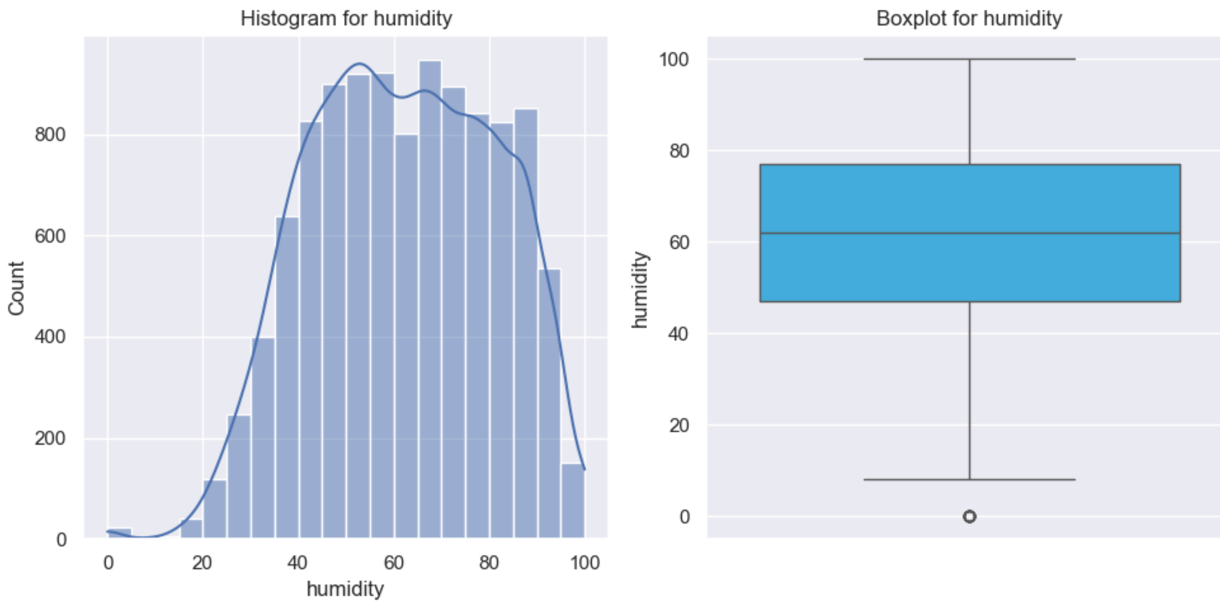


	Statistic	Value
0	count	10886.000000
1	mean	23.655084
2	std	8.474601
3	min	0.760000
4	25%	16.665000
5	50%	24.240000
6	75%	31.060000
7	max	45.455000

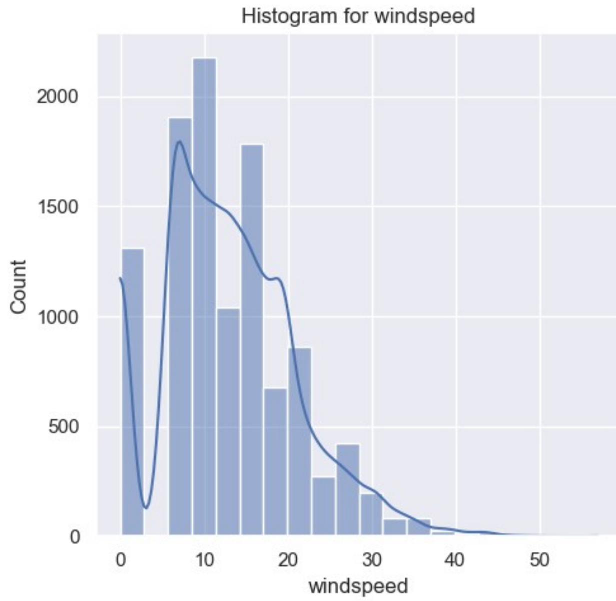


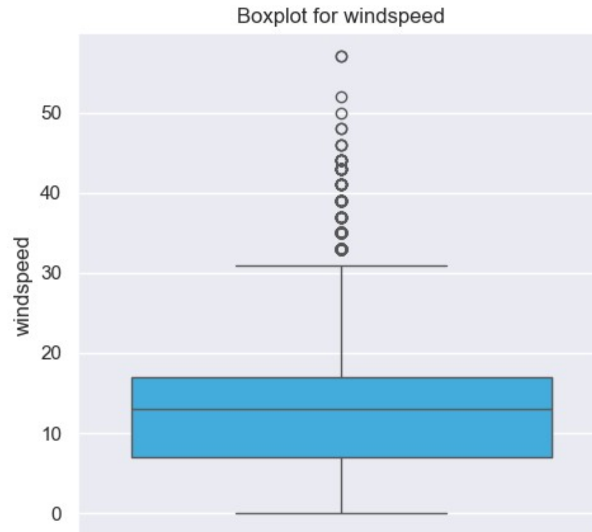


	Statistic	Value
0	count	10886.000000
1	mean	61.886460
2	std	19.245033
3	min	0.000000
4	25%	47.000000
5	50%	62.000000
6	75%	77.000000
7	max	100.000000

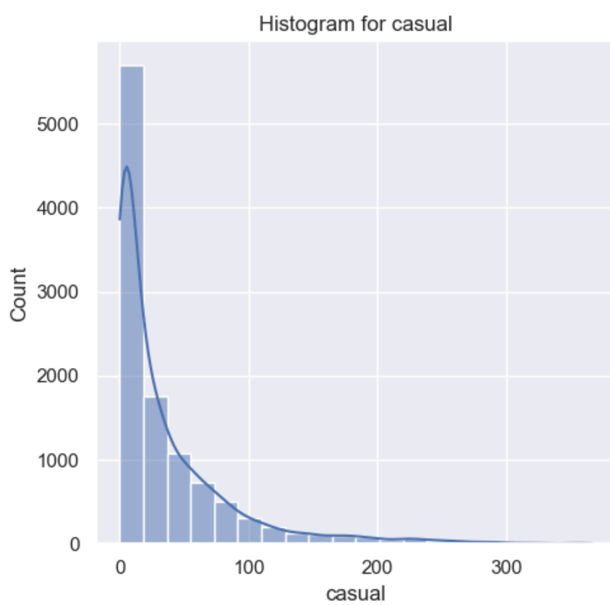


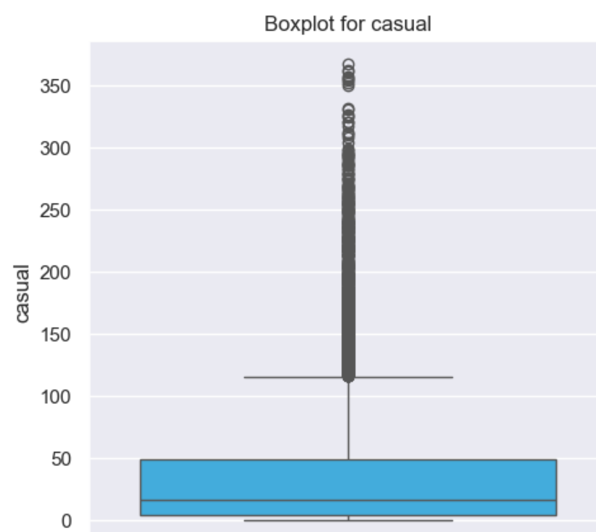
	Statistic	Value
0	count	10886.000000
1	mean	12.799395
2	std	8.164537
3	min	0.000000
4	25%	7.001500
5	50%	12.998000
6	75%	16.997900
7	max	56.996900



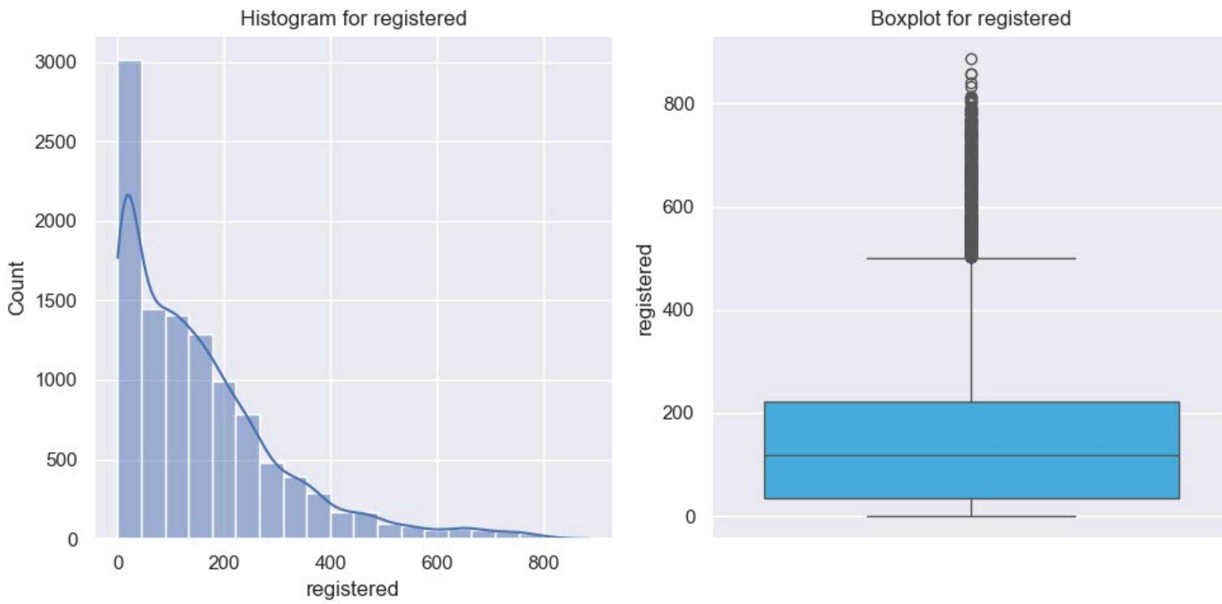


	Statistic	Value
0	count	10886.000000
1	mean	36.021955
2	std	49.960477
3	min	0.000000
4	25%	4.000000
5	50%	17.000000
6	75%	49.000000
7	max	367.000000

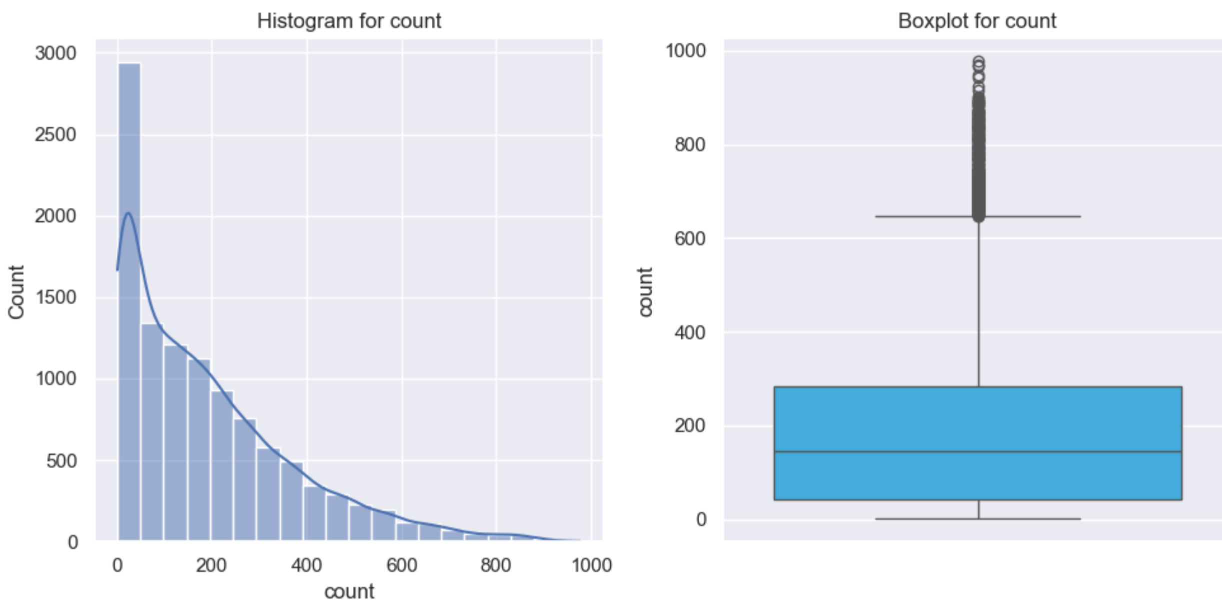




	Statistic	Value
0	count	10886.000000
1	mean	155.552177
2	std	151.039033
3	min	0.000000
4	25%	36.000000
5	50%	118.000000
6	75%	222.000000
7	max	886.000000



	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

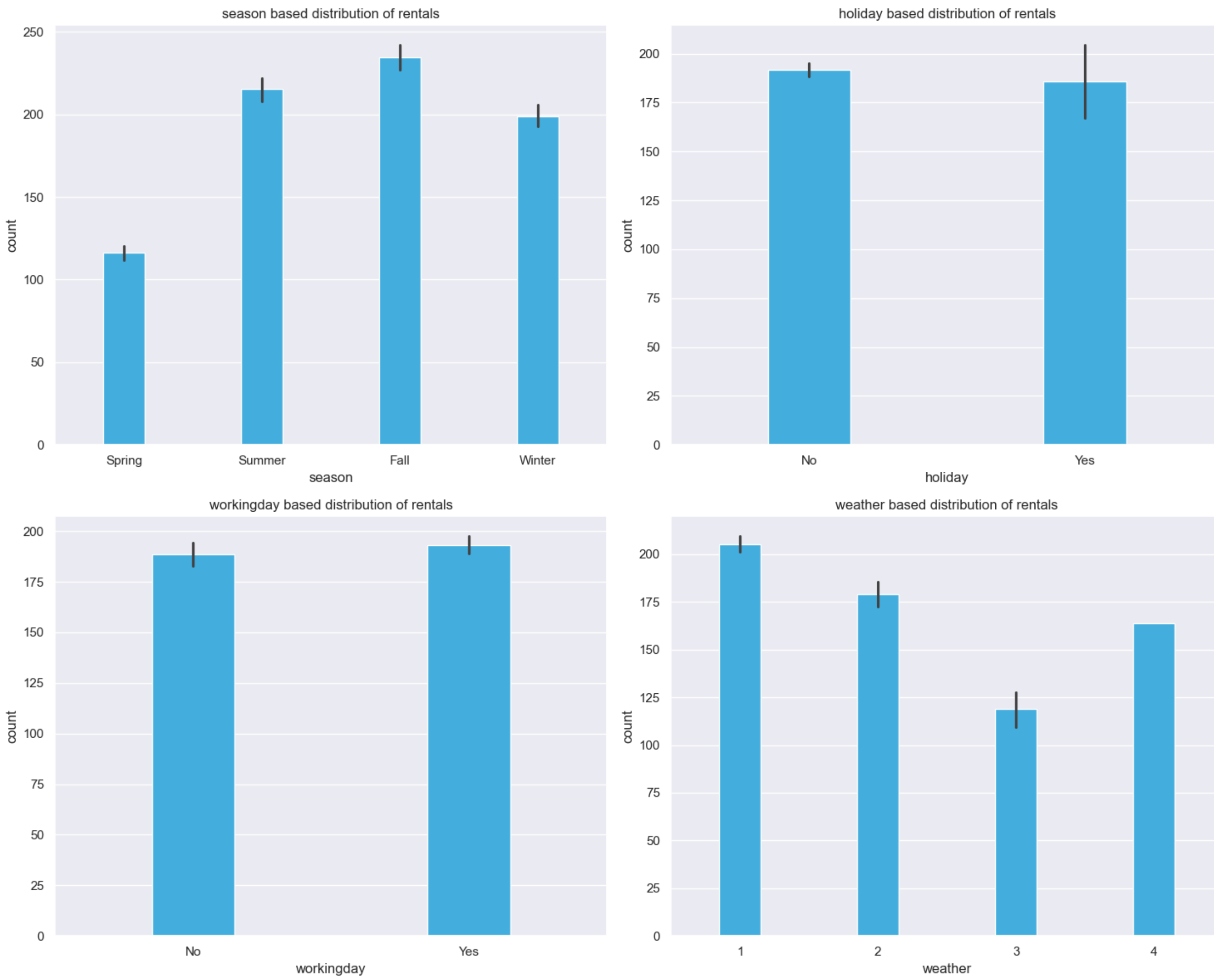
- The 'count' column reveals a wide range of total bike rental counts, varying from 1 to 977. The distribution is positively skewed, with a mean (191.57) greater than the median (145.0), indicating a concentration of lower values

Bivariate Analysis

```
cat_col
```

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

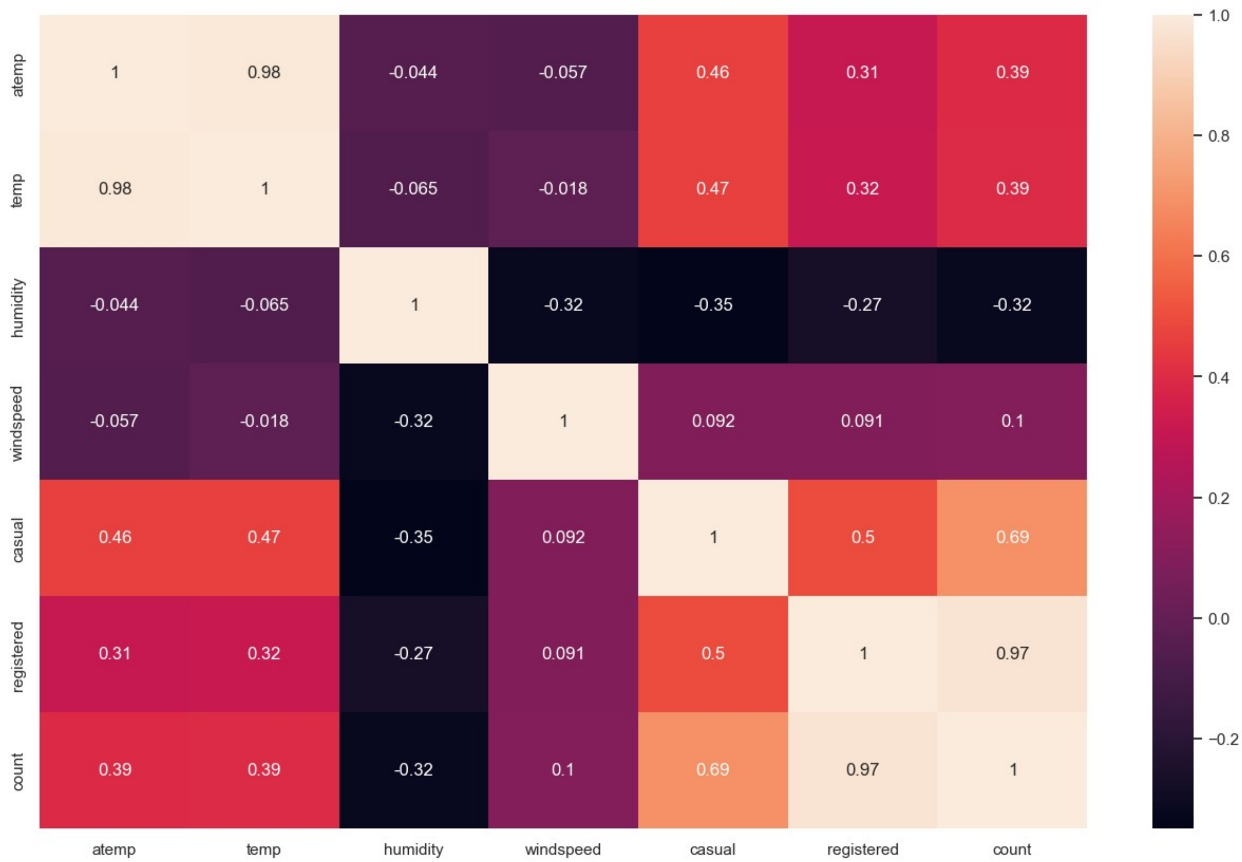
```
# barplot of categories

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()
```




```python
# corrrelation analysis

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

```
               atemp      temp  humidity  windspeed    casual
registered  \
atemp       1.000000  0.984948 -0.043536  -0.057473  0.462067
0.314635
temp        0.984948  1.000000 -0.064949  -0.017852  0.467097
0.318571
humidity   -0.043536 -0.064949  1.000000  -0.318607 -0.348187   -
0.265458
windspeed  -0.057473 -0.017852 -0.318607   1.000000  0.092276
0.091052
casual      0.462067  0.467097 -0.348187   0.092276  1.000000
0.497250
registered  0.314635  0.318571 -0.265458   0.091052  0.497250
```

```
1.000000
count        0.389784  0.394454 -0.317371   0.101369  0.690414
0.970948

               count
atemp       0.389784
temp        0.394454
humidity   -0.317371
windspeed   0.101369
casual      0.690414
registered  0.970948
count       1.000000

# 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):

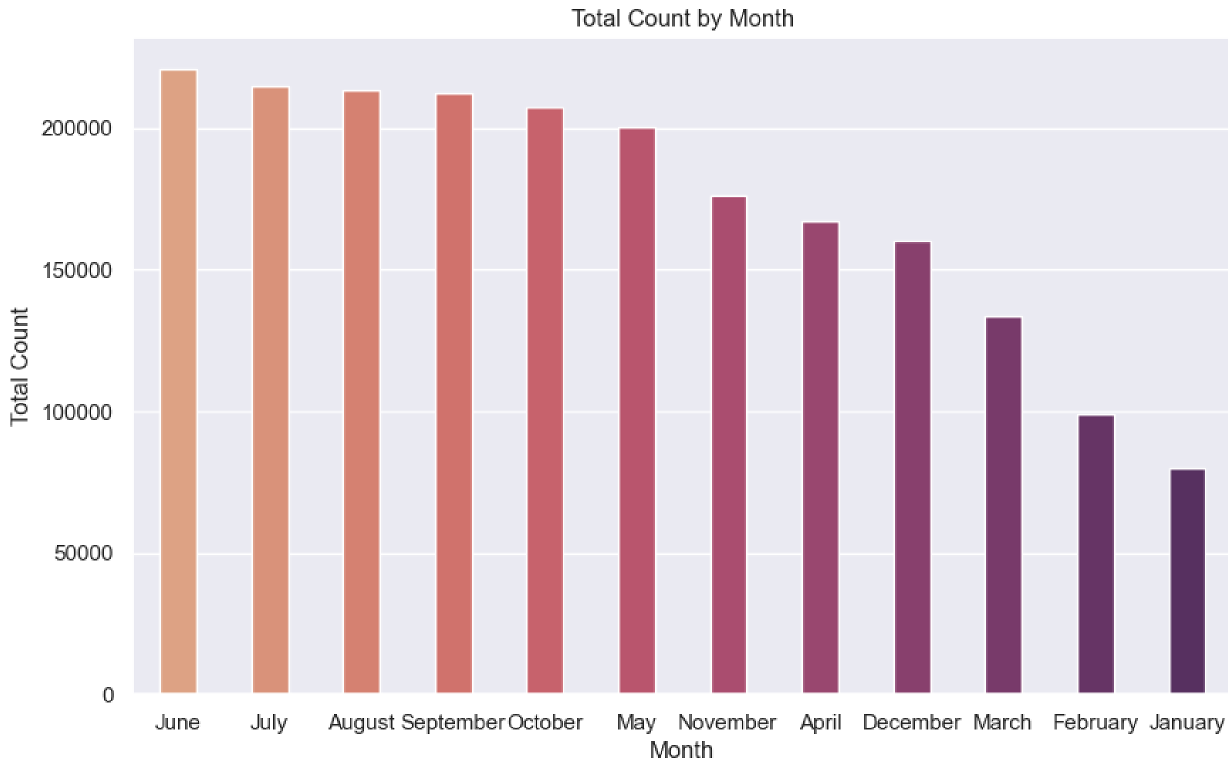
- Positive correlation with 'atemp' (0.39), 'temp' (0.39), and 'casual' (0.69).
- Negative correlation with 'humidity' (-0.32).
- Highly correlated with 'registered' (0.97), emphasizing the joint impact of casual and registered rentals on the overall count.

```
# 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
```

	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

```
# 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()
```



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.**

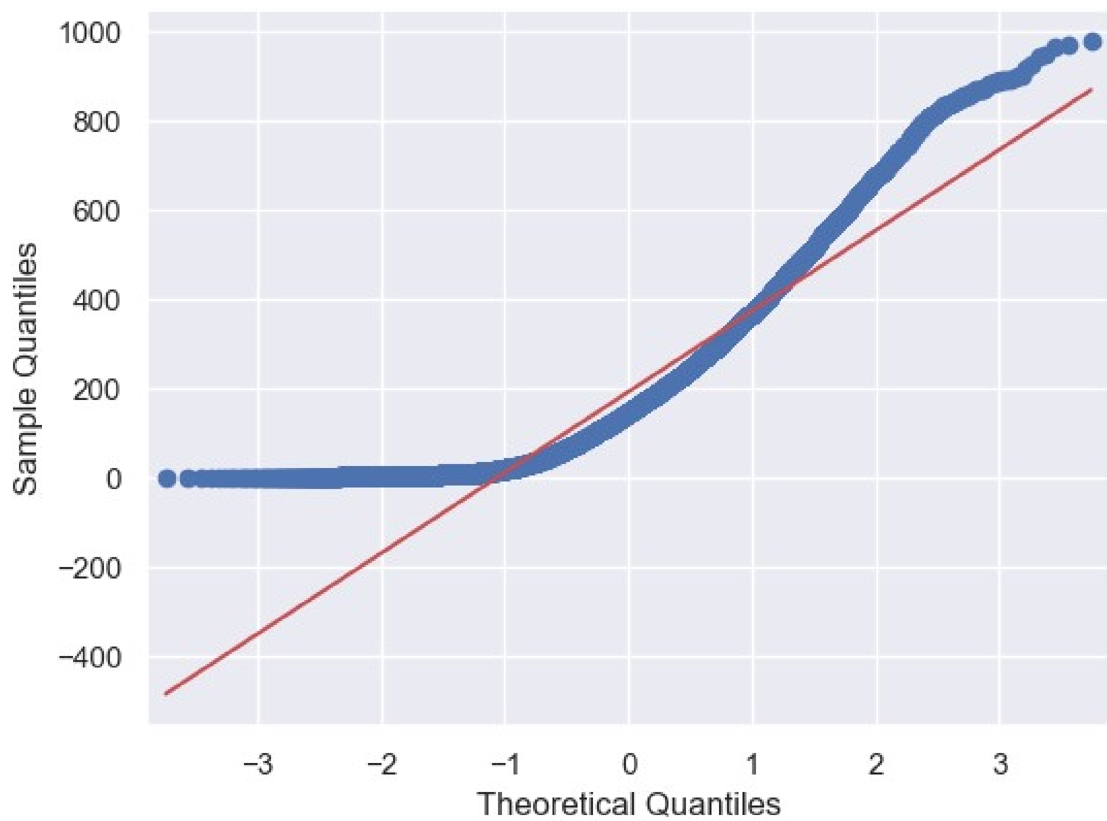
```
np.random.seed(41)

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

test_stat, p_val = shapiro(df_subset)

p_val

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

```
# QQ plot

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

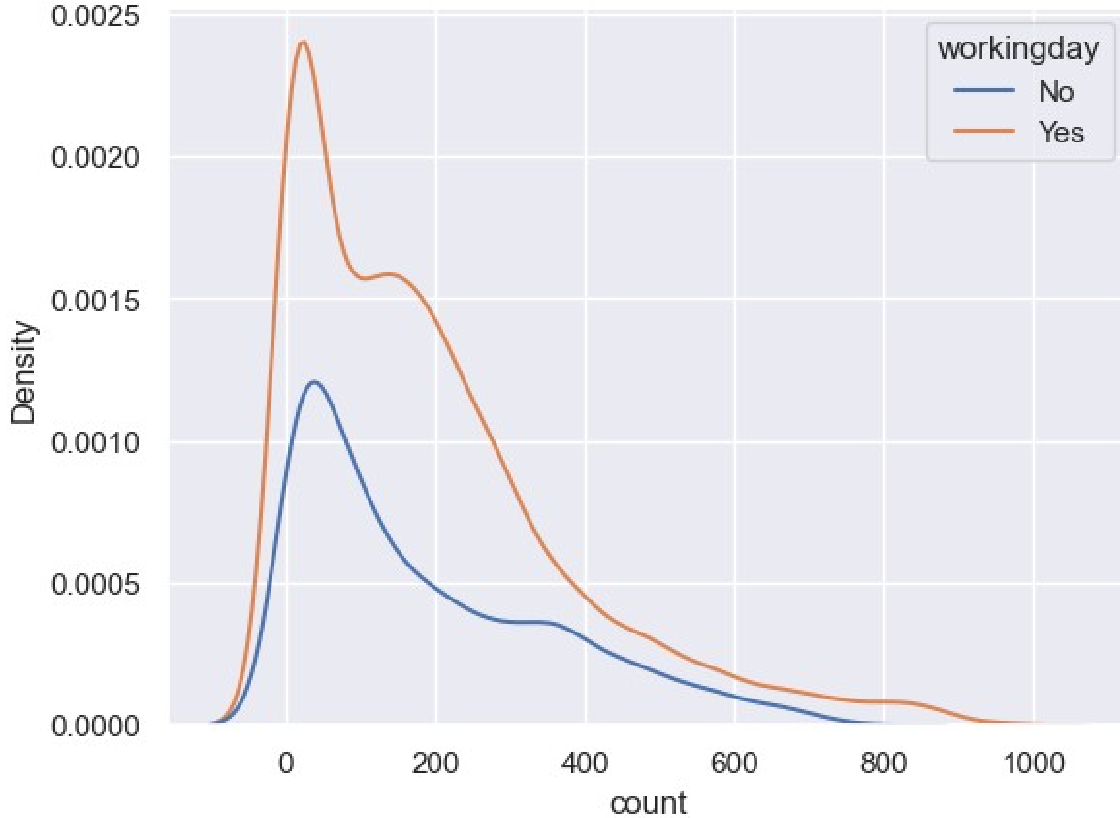


To check if the variances of two groups are equal. We will perform Levene's test

The Test hypotheses for Levene's test are:

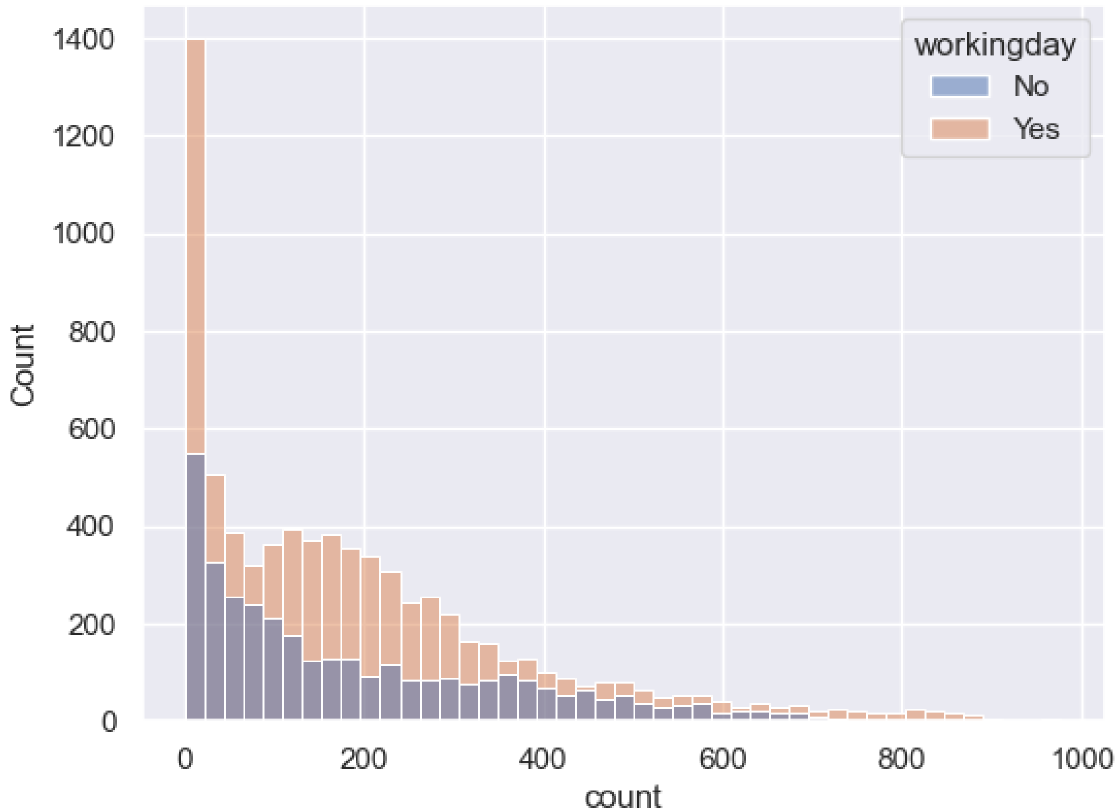
- **Ho: The variances are equal.**
- **Ha: The variances are not equal.**

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

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

levene_stat, p_val = levene(working_day, holiday)

p_val

0.9437823280916695

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

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




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

```
<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.**

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

p_val

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.

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

p_val

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.

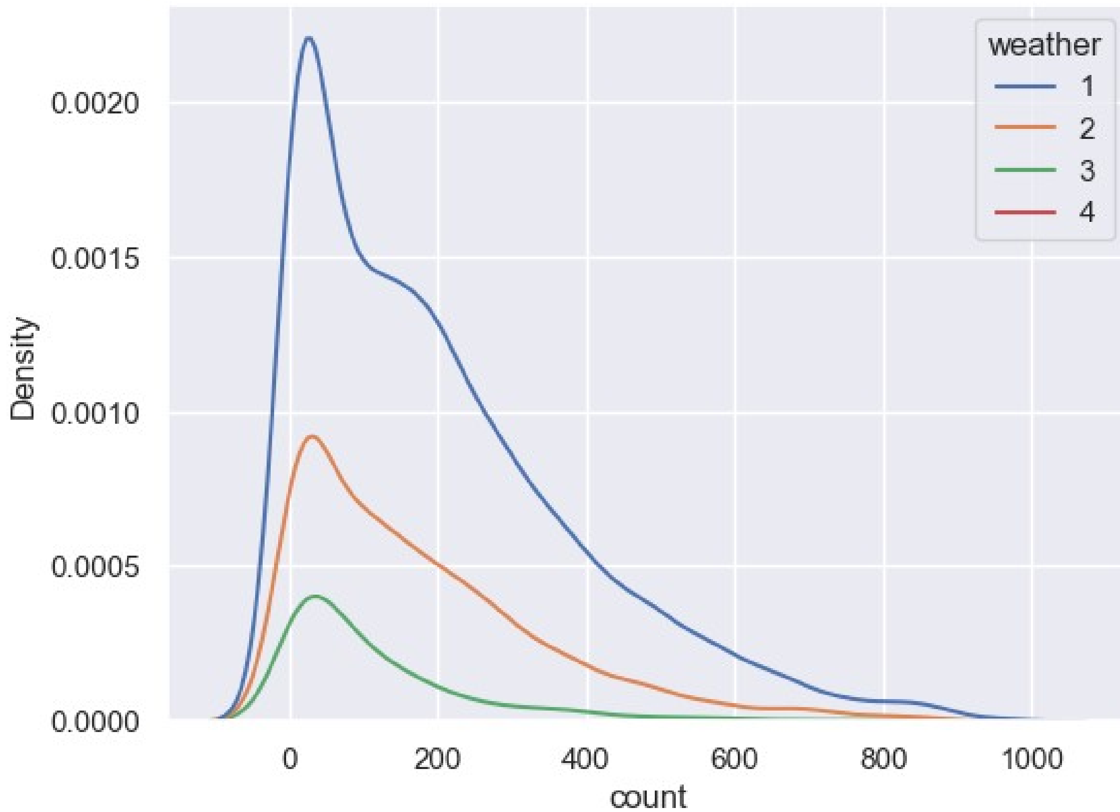
Demand of bicycles on rent is the same for different Weather conditions

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

Assumptions for ANOVA are:

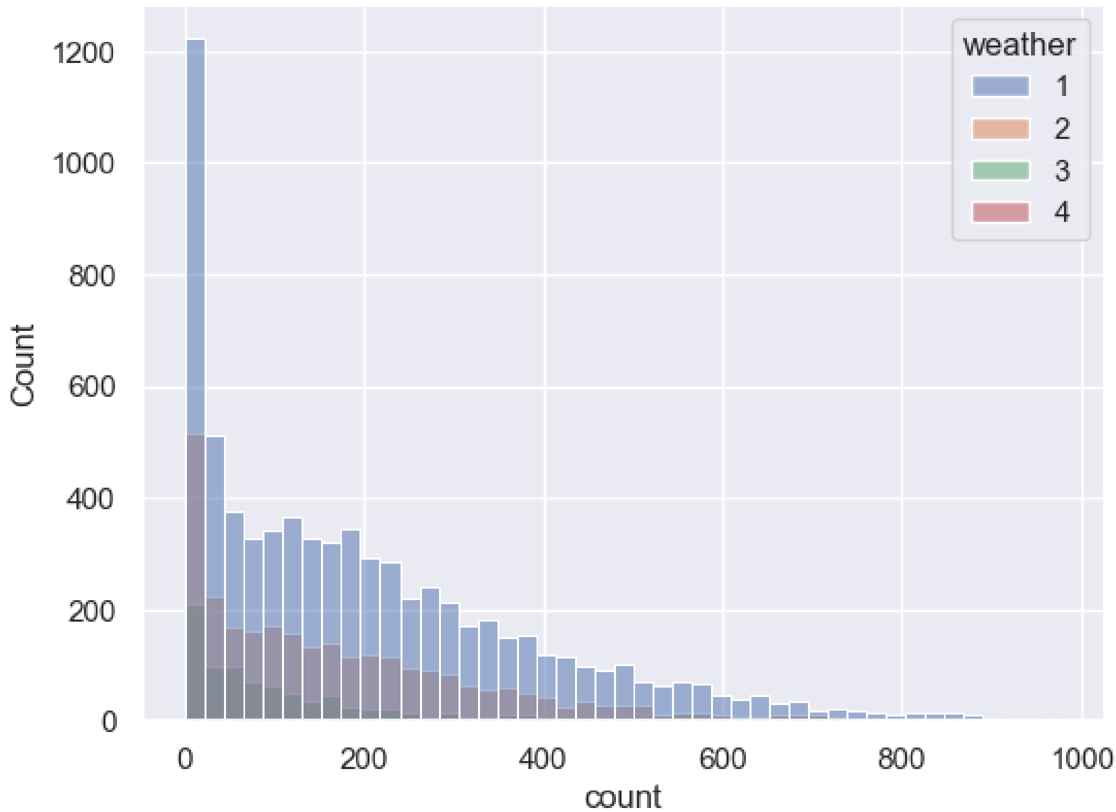
1. The population data should be normally distributed- The data is not normal as verified by **Wilkin-Shapiro test and the qqplot.**
2. The data points must be independent- This condition is satisfied.
3. Approximately equal variance within groups- This will be verified using **Levene's test.**

```
# skewness of weather

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

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

# kurtosis test of weather

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

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

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

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




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

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



The Test hypothesis for Levene's test are:

- **Ho: The variances are equal.**
- **Ha: The variances are not equal.**

```
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

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.**

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

p_val

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

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

p_val

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.**

```
# skewness of seasons

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

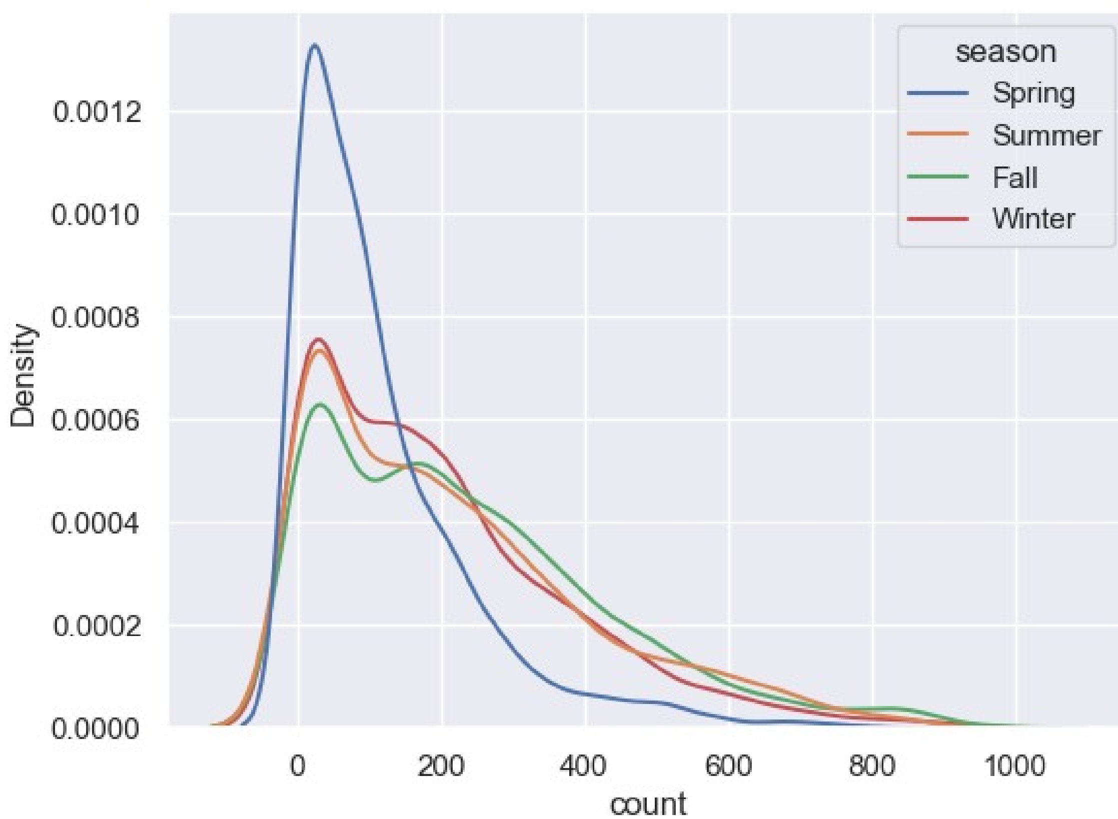
```
season
Spring    1.888056
Summer    1.003264
Fall      0.991495
Winter    1.172117
Name: count, dtype: float64
```

```
# kurtosis test of seasons

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

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

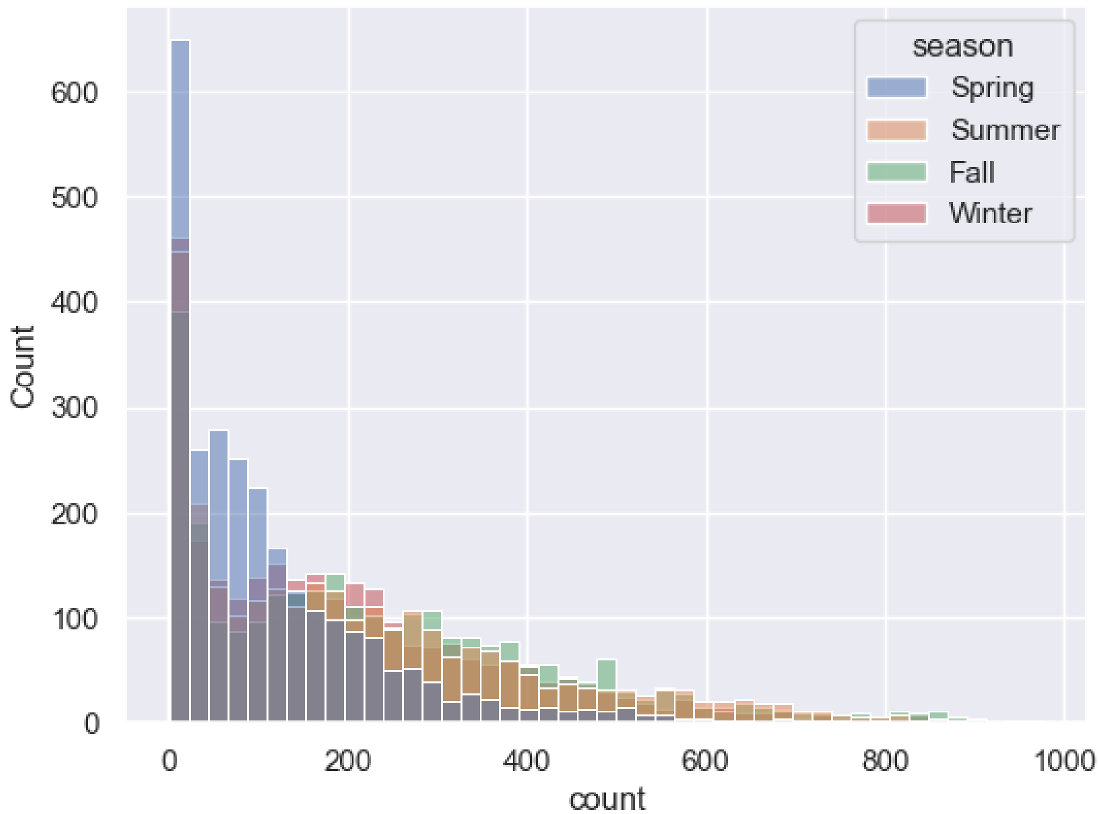
```
sns.kdeplot(data = df, x = 'count', hue = 'season')
```

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



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

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



The Test hypothesis for Levene's test are:

- **Ho: The variances are equal.**
- **Ha: The variances are not equal.**

```
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
```

```
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.**

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

p_val

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

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

p_val

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.

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

contingency_table

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
```

```
chi2_contingency(contingency_table)
```

```
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.

Buisness Insights

Seasonal Patterns

- Maximum bike rentals occur during summer, while the minimum is observed in winter.

Conditions Impact

- Clear weather is associated with the highest bike rental counts, whereas rentals sharply decrease in rain, thunderstorm, snow, or fog.
- Humidity, windspeed, temperature and weather are correlated with season and impacts the count of cycles rented.

Temperature Influence

- Lower temperatures correspond to lower bike rentals, and demand rises with increasing temperatures.

Time-of-Day Trends

- Bike rentals peak during the day, decline through the night, indicating a pattern fluctuation.

Holiday and Working Day Dynamics

- Less rentals on holidays and weekends, with a demand increase on non-working days. However, the overall count on working and non-holiday days are similar.

User Type Behavior

- Casual riders dominate on weekends, while registered users are more active on working days.

Yearly Growth and User Composition

- The hourly rental count shows impressive annual growth from 2011 to 2012.

- Approximately 19% of users are casual, and 81% are registered.

Monthly and Daily Usage Patterns

- Notable seasonal patterns, with peak demand in spring and summer, and a decline in fall and winter.
- January to March sees the lowest rental counts, and a distinctive daily trend shows peak usage during the afternoon.

Weather Impact on Usage

- Clear and partly_cloudy weather correlates with higher rental counts, while extreme weather conditions have limited data representation.

Statistical Significance

- ANOVA tests confirm statistically significant impacts of seasons and weather on bike rentals.
- Working days vs. holidays have limited impact according to a 2-sample t-test.
- ChiSquare confirms that the Weather is dependent on the Seasons.

Business Recommendations

Strategic Seasonal Marketing

- Leverage seasonal patterns by implementing targeted marketing during peak seasons (spring and summer).
- Introduce seasonal incentives and exclusive packages to drive higher demand.

Dynamic Time-based Pricing

- Optimize resource utilization by implementing dynamic time-based pricing.
- Adjust rental rates to encourage bike usage during off-peak hours, enhancing accessibility.

Weather-sensitive Promotions

- Launch weather-specific promotional campaigns focusing on clear and partly cloudy conditions.
- Introduce weather-based discounts to attract more users during favorable weather.

User-Centric Segmentation

- Tailor marketing strategies for registered and casual users.
- Offer loyalty programs and personalized incentives for registered users, highlighting occasional use benefits for casual users.

Optimized Inventory Management

- Fine-tune inventory levels based on monthly demand patterns.
- Avoid overstocking during low-demand months and ensure sufficient bikes during peak periods.

Customer Comfort and Convenience

- Provide amenities like umbrellas or rain jackets to enhance customer comfort.

- Elevate the overall biking experience, contributing to positive customer feedback.

Collaboration with Weather Services

- Partner with weather services for real-time updates in marketing campaigns.
- Showcase ideal biking conditions through app integration, appealing to weather-specific preferences.

Strategic Social Media Marketings

- Utilize social media platforms for strategic promotions and engagement.
- Share diverse biking experiences, customer testimonials, and run targeted advertising campaigns.