yulu

March 27, 2025

1 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.

1.1 Business Problem

The company wants to know: * 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

1.2 Customer Profiling

Column Name	Description
datetime	Datetime of the cycles rental
season	Season (1: spring, 2: summer, 3: fall, 4: winter)
holiday	Whether the day is a holiday or not (extracted from DCHR Holiday Schedule)
workingday	If the day is neither a weekend nor holiday, it is 1, otherwise 0
weather	1: Clear, Few clouds, Partly cloudy2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog
temp	Temperature in Celsius
atemp	Feeling temperature in Celsius
humidity	Humidity percentage
windspeed	Wind speed in km/h
casual	Count of casual users
registered	Count of registered users

Column Name	Description
count	Total rental cycles including both casual and registered users

2 1. Defining Problem Statement and Analysing basic metrics:

Observations on shape of data, data types of all the attributes, conversion of categorical attributes to 'category' (If required), statistical summary

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import␣
↪ttest_ind,ttest_rel,ttest_1samp,chi2_contingency,chi2,f_oneway,levene,shapiro,kruskal,zscor
from statsmodels.stats.proportion import proportions_ztest
from statsmodels.graphics.gofplots import qqplot
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
data = pd.read_csv('yulu.csv')
```

3 Basic data exploration:

[3]:
```
data.head()
```

[3]:
```
              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
```

[4]:
```
data.tail()
```

[4]:
```
                  datetime  season  holiday  workingday  weather   temp  \
10881  2012-12-19 19:00:00       4        0           1        1  15.58
10882  2012-12-19 20:00:00       4        0           1        1  14.76
```

```
10883  2012-12-19 21:00:00       4        0           1         1  13.94
10884  2012-12-19 22:00:00       4        0           1         1  13.94
10885  2012-12-19 23:00:00       4        0           1         1  13.12

        atemp  humidity  windspeed  casual  registered  count
10881  19.695        50    26.0027       7         329    336
10882  17.425        57    15.0013      10         231    241
10883  15.910        61    15.0013       4         164    168
10884  17.425        61     6.0032      12         117    129
10885  16.665        66     8.9981       4          84     88
```

[5]:

```python
print(f"Shape:\n {data.shape}")
print("-------------------------------------------------------------------------------")
print(f"Columns of this data set are:\n {data.columns}")
print("-------------------------------------------------------------------------------")
print(f"Data types: \n{data.dtypes}")
print("-------------------------------------------------------------------------------")
```

```
Shape:
 (10886, 12)
-------------------------------------------------------------------------------
Columns of this data set are:
 Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
-------------------------------------------------------------------------------
Data types:
datetime       object
season          int64
holiday         int64
workingday      int64
weather         int64
temp          float64
atemp         float64
humidity        int64
windspeed     float64
casual          int64
registered      int64
count           int64
dtype: object
-------------------------------------------------------------------------------
```

[6]:

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

# Converting categorical columns into category
cat_cols = ['season','holiday','workingday','weather']
```

```python
for _ in cat_cols:
    data[_] = data[_].astype('category')
data.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  datetime64[ns]
 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), datetime64[ns](1), float64(3), int64(4)
memory usage: 723.7 KB
```

Observation:

1. The Dataset consists of 10886 rows and 12 columns

Column Name	Description	Data Type
datetime	Datetime of the cycles rental	object
season	Season (1: spring, 2: summer, 3: fall, 4: winter)	int64
holiday	Whether day is a holiday or not	int64
workingday	If the day is neither weekend nor holiday, it is 1, otherwise 0	int64
weather	1: Clear, Few clouds, Partly cloudy2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog	int64

Column Name	Description	Data Type
temp	Temperature in Celsius	float64
atemp	Feeling temperature in Celsius	float64
humidity	Humidity percentage	int64
windspeed	Wind speed in km/h	float64
casual	Count of casual users	int64
registered	Count of registered users	int64
count	Total rental cycles including both casual and registered users	int64

2.

---

4 Statistical summary:

[7]:
```
data.describe().T
```

[7]:
```
              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

                            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

                            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
```

[8]:
```
data.describe(include = 'category').T
```

[8]:

	count	unique	top	freq
season	10886	4	4	2734
holiday	10886	2	0	10575
workingday	10886	2	1	7412
weather	10886	4	1	7192

[9]:
```
for col in data.select_dtypes(np.number):
  mean = np.round(data[col].mean(),2)
  sd = np.round(data[col].std(),2)
  median = np.round(data[col].median(),2)
  minimum = data[col].min()
  maximum = data[col].max()
  q3 = np.percentile(data[col],75)
  q1 = np.percentile(data[col], 25)
  IQR = q3 - q1
  Upper = q3 + 1.5 * IQR
  Lower = q1 - 1.5 * IQR
  print(f"-----DESCRIPTIVE STATISTICS OF {col} COLUMN--------")
  print(f"Mean:{mean}")
  print(f"Standard deviation:{sd}")
  print(f"Median:{median}")
  print(f"Minimum:{minimum}")
  print(f"Maximum:{maximum}")
  print(f"25 Percentile:{q1}")
  print(f"75 Percentile:{q3}")
  print(f"Inter Quartile Range:{IQR}")
  print(f"Upper bound:{Upper}")
  print(f"Lower bound:{Lower}")
  print()
```

```
-----DESCRIPTIVE STATISTICS OF temp COLUMN--------
Mean:20.23
Standard deviation:7.79
Median:20.5
Minimum:0.82
Maximum:41.0
25 Percentile:13.94
75 Percentile:26.24
Inter Quartile Range:12.299999999999999
Upper bound:44.69
Lower bound:-4.51
```

```
-----DESCRIPTIVE STATISTICS OF atemp COLUMN--------
Mean:23.66
Standard deviation:8.47
Median:24.24
Minimum:0.76
Maximum:45.455
25 Percentile:16.665
75 Percentile:31.06
Inter Quartile Range:14.395
Upper bound:52.6525
Lower bound:-4.927500000000002

-----DESCRIPTIVE STATISTICS OF humidity COLUMN--------
Mean:61.89
Standard deviation:19.25
Median:62.0
Minimum:0
Maximum:100
25 Percentile:47.0
75 Percentile:77.0
Inter Quartile Range:30.0
Upper bound:122.0
Lower bound:2.0

-----DESCRIPTIVE STATISTICS OF windspeed COLUMN--------
Mean:12.8
Standard deviation:8.16
Median:13.0
Minimum:0.0
Maximum:56.9969
25 Percentile:7.0015
75 Percentile:16.9979
Inter Quartile Range:9.996400000000001
Upper bound:31.992500000000003
Lower bound:-7.993100000000002

-----DESCRIPTIVE STATISTICS OF casual COLUMN--------
Mean:36.02
Standard deviation:49.96
Median:17.0
Minimum:0
Maximum:367
25 Percentile:4.0
75 Percentile:49.0
Inter Quartile Range:45.0
Upper bound:116.5
Lower bound:-63.5
```

```
-----DESCRIPTIVE STATISTICS OF registered COLUMN--------
Mean:155.55
Standard deviation:151.04
Median:118.0
Minimum:0
Maximum:886
25 Percentile:36.0
75 Percentile:222.0
Inter Quartile Range:186.0
Upper bound:501.0
Lower bound:-243.0

-----DESCRIPTIVE STATISTICS OF count COLUMN--------
Mean:191.57
Standard deviation:181.14
Median:145.0
Minimum:1
Maximum:977
25 Percentile:42.0
75 Percentile:284.0
Inter Quartile Range:242.0
Upper bound:647.0
Lower bound:-321.0
```

font color = 'blue'>**Observation:** 1. Numerical features such as temperature,humidity,windspeed,counts of casual and registered cycles rentals shows the rental patterns in different conditions 2. The observations for datetime information span from January 1, 2011 to December 19,2012

5 Missing Values and Outlier Detection

[10]:
```
np.any(data.isnull())
```

[10]: np.False_

[11]:
```
np.any(data.duplicated().isnull())
```

[11]: np.False_

[12]:
```
# Handling Outliers using Z-score
z_scores = np.abs(zscore(data[['temp', 'humidity', 'windspeed', 'count',
 'atemp', 'casual', 'registered']]))
df_clean = data[(z_scores < 3).all(axis=1)]  # Removing outliers beyond 3
 standard deviations
```

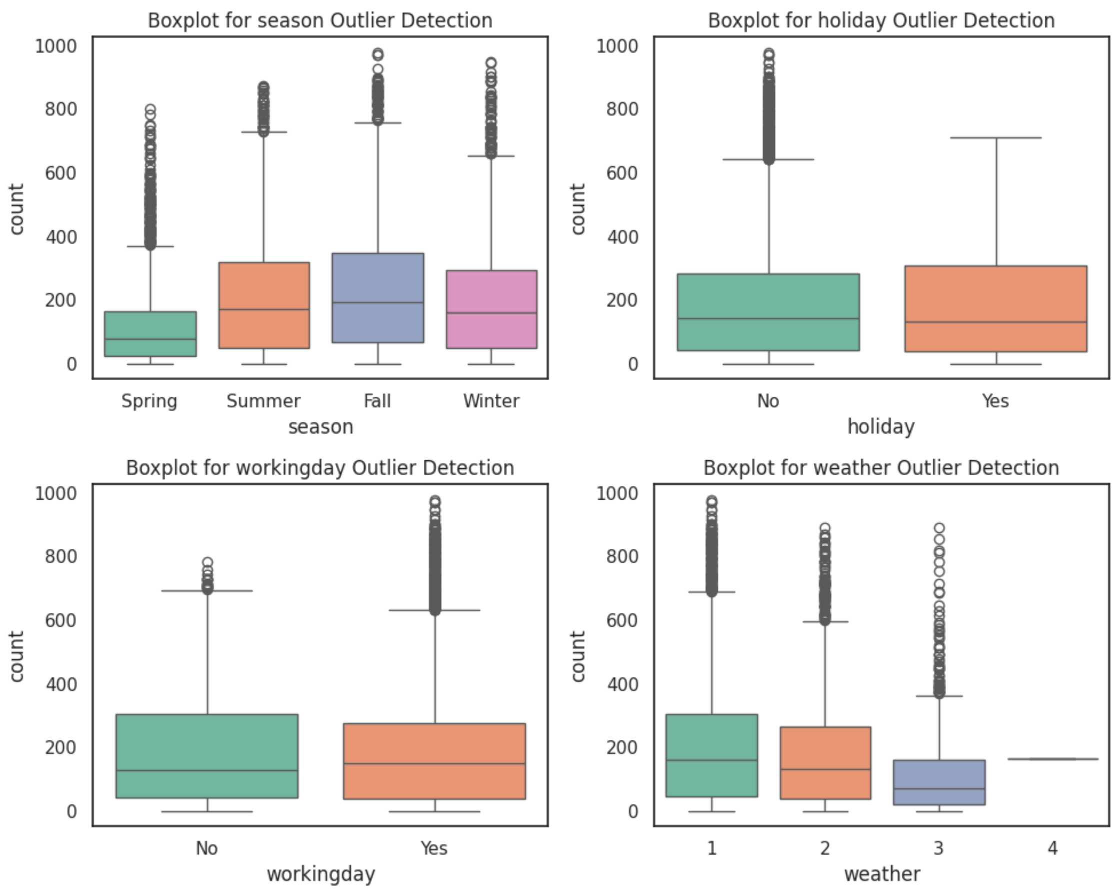
[13]:
```
data['season'] = data['season'].replace({1:'Spring',
                                         2:'Summer',
                                         3:'Fall',
                                         4:'Winter'})
data['holiday'] = data['holiday'].replace({0:'No',
                                           1:'Yes'})
data['workingday'] = data['workingday'].replace({0:'No',
                                                 1:'Yes'})
```

[14]:
```
# Function to find outliers using IQR for a specific column
def find_outliers_IQR(column):
    q1 = column.quantile(0.25)
    q3 = column.quantile(0.75)
    IQR = q3 - q1
    outliers = column[((column < (q1 - 1.5 * IQR)) | (column > (q3 + 1.5 *␣
 ↪IQR)))]
    return outliers

# List of numeric columns to find outliers for (replace with the actual column␣
 ↪names)
numeric_columns = ["count", "casual", "registered", "temp", "atemp",␣
 ↪"humidity", "windspeed"]

# Loop through each numeric column and detect outliers
for col in numeric_columns:
    outliers = find_outliers_IQR(data[col])

    # Print the number of outliers and their details
    print(f"Outliers for column: {col}")
    print(f"Number of outliers: {len(outliers)}")
    print(f"Max outlier value: {outliers.max()}")
    print(f"Min outlier value: {outliers.min()}")
    print('---------------------------')
```

```
Outliers for column: count
Number of outliers: 300
Max outlier value: 977
Min outlier value: 648
---------------------------
Outliers for column: casual
Number of outliers: 749
Max outlier value: 367
Min outlier value: 117
---------------------------
Outliers for column: registered
Number of outliers: 423
Max outlier value: 886
```

```
Min outlier value: 502
---------------------------
Outliers for column: temp
Number of outliers: 0
Max outlier value: nan
Min outlier value: nan
---------------------------
Outliers for column: atemp
Number of outliers: 0
Max outlier value: nan
Min outlier value: nan
---------------------------
Outliers for column: humidity
Number of outliers: 22
Max outlier value: 0
Min outlier value: 0
---------------------------
Outliers for column: windspeed
Number of outliers: 227
Max outlier value: 56.9969
Min outlier value: 32.9975
---------------------------
```

[15]:
```python
# Outlier Detection using Boxplots
plt.figure(figsize=(10, 8))
sns.set(style = 'white')
for i , col in enumerate(cat_cols,1):
    plt.subplot(2,2,i)
    sns.boxplot(data=data,x = col,y = 'count',palette = 'Set2')
    plt.title(f'Boxplot for {col} Outlier Detection')
plt.tight_layout()
plt.show()
```



Observation: 1. In spring and winter there are more outliers present compared to other seasons 2. Weather 3 category has more outliers whereas, category 4 doesn't have any 3. working days vs Holidays : Regular working days has more unusual data than on holidays.

6 2 Non-Graphical Analysis: Value counts and unique attributes:

[16]:
```
for column in cat_cols:
    print(f"Value counts for column '{column}':\n{data[column].value_counts()}")
    print("\n")

    print(f"Unique Count of {column} : {data[column].nunique()}")
    print("\n")
```

```
Value counts for column 'season':
season
Winter    2734
Summer    2733
Fall      2733
Spring    2686
```

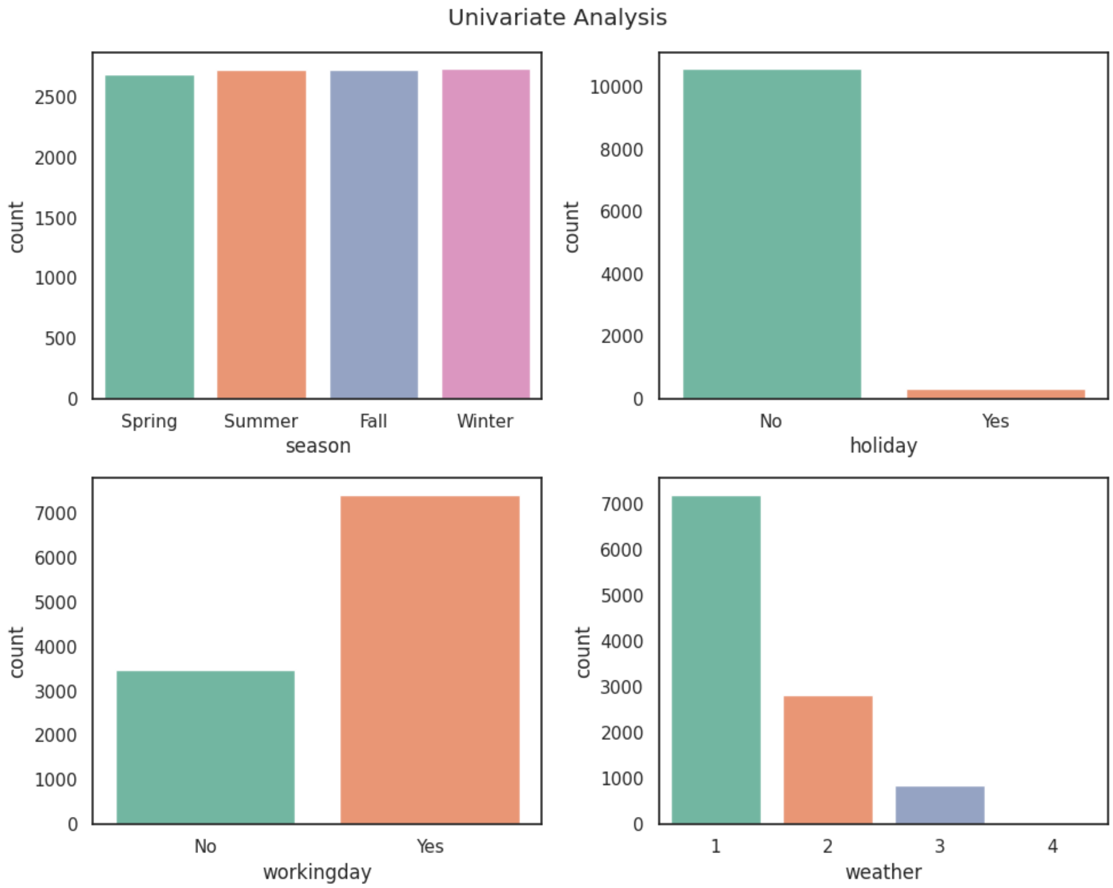
```
Name: count, dtype: int64


Unique Count of season : 4


Value counts for column 'holiday':
holiday
No     10575
Yes      311
Name: count, dtype: int64


Unique Count of holiday : 2


Value counts for column 'workingday':
workingday
Yes    7412
No     3474
Name: count, dtype: int64


Unique Count of workingday : 2


Value counts for column 'weather':
weather
1    7192
2    2834
3     859
4       1
Name: count, dtype: int64


Unique Count of weather : 4
```

7 3.Visual Analysis - Univariate,Bivariate

7.1 Univariate

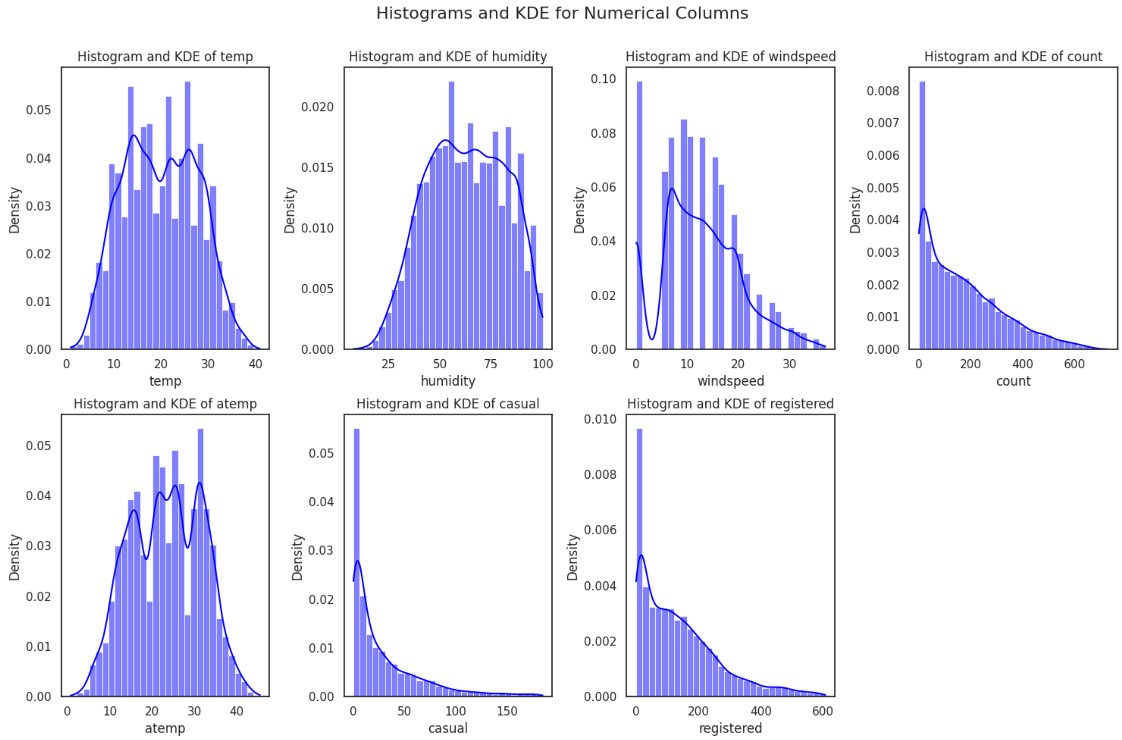
[17]:
```
plt.figure(figsize=(10, 8))
sns.set(style = 'white')
for i , col in enumerate(cat_cols,1):
    plt.subplot(2,2,i)
```

```
    sns.countplot(data=data,x = col,palette = 'Set2')
    plt.suptitle('Univariate Analysis')
plt.tight_layout()
plt.show()
```



[18]:
```
num_cols = ['temp', 'humidity', 'windspeed', 'count', 'atemp', 'casual',␣
 ↪'registered']

# 1. Histograms and KDE (overlaid)
plt.figure(figsize=(15, 10))
for i, col in enumerate(num_cols):
    plt.subplot(2, 4, i+1)  # Create subplots in a 2x4 grid
    sns.histplot(df_clean[col], bins=30, kde=True, color='blue', stat='density')
    plt.title(f'Histogram and KDE of {col}')
    plt.xlabel(col)
    plt.ylabel('Density')
plt.tight_layout()
plt.suptitle('Histograms and KDE for Numerical Columns', fontsize=16)
plt.subplots_adjust(top=0.9)  # Adjust the title to fit within the figure
```

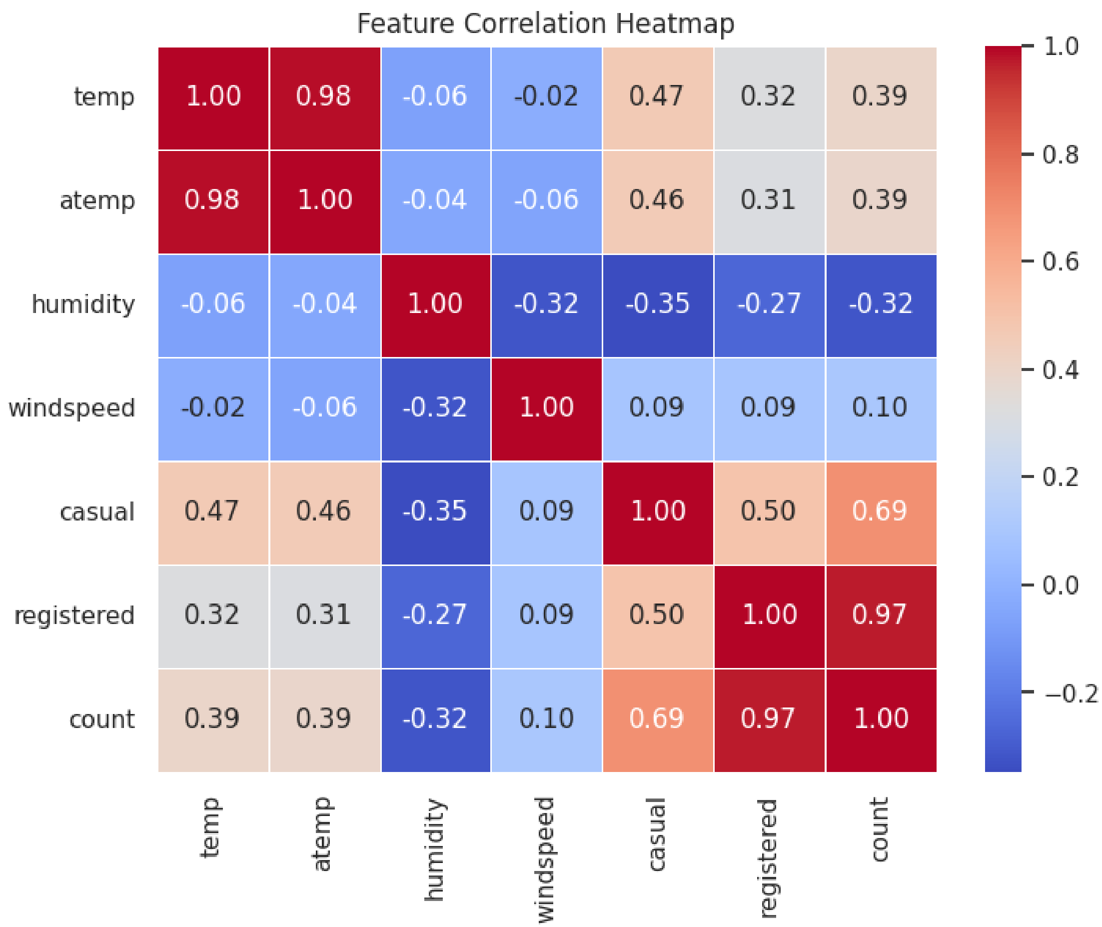
```python
plt.show()
```



Observation: 1. **"count"** ,**Casual** and **Registered** columns has a right-skewed distribution, this could suggest that the majority of cycles rentals are lower, with fewer days having very high rental counts. 2. **temp** and **atemp** might show a more uniform distribution depending on the climate patterns, as temperatures in a given area typically dont vary drastically in short periods. 3. **humidity** histogram, a peak might show that certain humidity levels are more frequent.

7.2 Bivariate

[19]:
```python
plt.figure(figsize=(8, 6))
numerical_data = data.select_dtypes(include=np.number)
sns.heatmap(numerical_data.corr(), annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Feature Correlation Heatmap')
plt.show()
```



Observation:

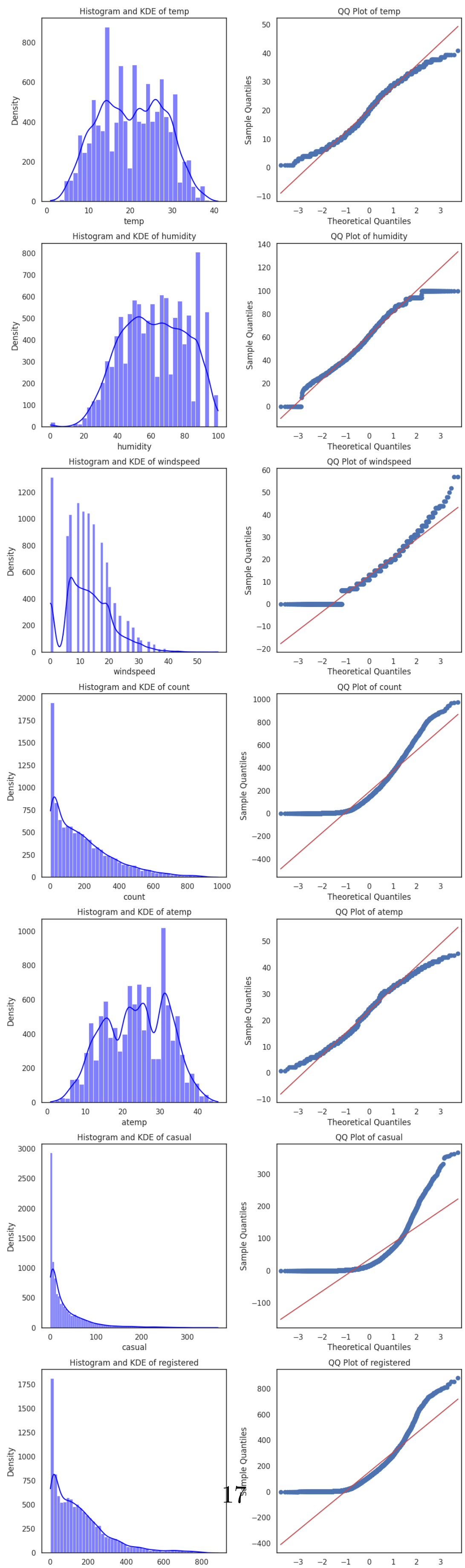
1. A high positive correlation between temp and count,would suggest that cycles rentals increase as the temperature rises.
2. A negative correlation might indicate that cycles rentals decrease with higher wind speeds or humidity.
3. If the winter season shows lower cycles rentals with less variability, it suggests that colder months are less favorable for biking.
4. If spring has more non-holiday rentals, it could indicate that people prefer biking during the spring season when the weather is milder and fewer people are on holiday.

8 Hypothesis Testing

[33]:
```
fig, axes = plt.subplots(len(num_cols), 2, figsize=(10, 5 * len(num_cols))

for i, col in enumerate(num_cols):
    # Histogram with KDE
    sns.histplot(data[col], kde=True, ax=axes[i, 0], color='blue')
```

```
    axes[i, 0].set_title(f'Histogram and KDE of {col}')
    axes[i, 0].set_xlabel(col)
    axes[i, 0].set_ylabel('Density')

    # QQ Plot
    qqplot(data[col], line='s', ax=axes[i, 1])
    axes[i, 1].set_title(f'QQ Plot of {col}')

# Adjust layout
plt.tight_layout()
plt.suptitle('Testing Normality of Numerical Columns', fontsize=16)
plt.subplots_adjust(top=0.95)  # Adjust the title to fit within the figure
plt.show()
```

Testing Normality of Numerical Columns



8.1 Q1 Check if Working Day has an effect on the number of electric cycles rented?

Set up null hypothesis(H0)& Alternative hypothesis (Ha):

Hypothesis Setup

Null Hypothesis (H0)

The average number of cycles rentals on working days is the same as on non-working days.

Alternative Hypothesis (Ha)

The average number of cycles rentals on working days is greater than on non-working days.

Ttest_ind: 1. The **ttest_ind** function in SciPy is used to perform an independent two-sample t-test. 2. This test compares the means of two independent groups to determine if there is a significant difference between them. 3. It is commonly used when you want to compare the means of two distinct groups (e.g., working days vs. non-working days) to see if they differ significantly.

Steps to perform Ttest 1. First, you need to split the data into two groups 2. To compare the means of cycles rentals on working and non-working days. 3. p-value is less than a significance level (usually 0.05), you can reject the null hypothesis (i.e., conclude that the means are significantly different). 4. If the p-value is greater than 0.05, you fail to reject the null hypothesis (i.e., there is no significant difference between the means).

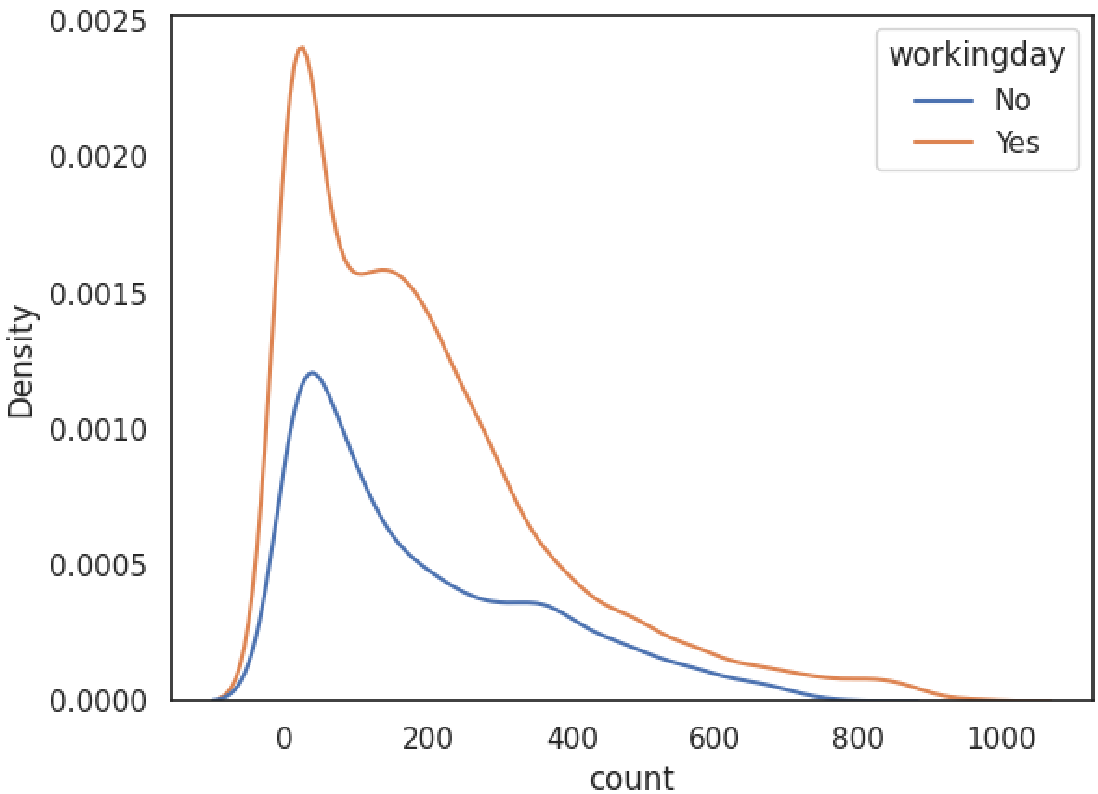
[21]:
```python
working_day = data[data['workingday']=='Yes']['count']
non_working_day = data[data['workingday']=='No']['count']
```

[22]:
```python
ttest,p_value = ttest_ind(working_day,non_working_day)
print(f"p_value:{p_value} \nttest:'{ttest}")
alpha = 0.05
if p_value >= alpha:
    print("Fail to reject H0:\nThe average number of cycles rentals is the same␣
 ↪on working and non-working days.")
else:
    print("Reject H0: There is a significant difference in cycles rentals␣
 ↪between working and non-working days.")
```

```
p_value:0.22644804226361348
ttest:'1.2096277376026694
Fail to reject H0:
The average number of cycles rentals is the same on working and non-working
days.
```

[23]:
```python
sns.kdeplot(data, x= 'count',hue = 'workingday')
```

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



T-Test Results

Test Statistic (t)

1.2096277376026694

P-value

0.22644804226361348

Conclusion

Fail to reject H0:The average number of cycles rentals is the same on working and non-working days.

8.2 Q2. Check if No. of cycles rented is similar or different in different 1. weather 2. season ?

Lets check for demand of cycles is same for different weather conditions:

one way Anova:

To compare means of 4 independent groups(spring,summer,fall,winter)

Assumptions:

1. Independence of Observations

   - The samples must be independent of each other.
   - This means that the cycles rentals for one season should not influence the rentals for another season.
   - This condition is already satisfied since all seasons are independent of each other

2. Normality (Each Group is Normally Distributed)

   - The distribution of cycles rentals within each season should be approximately normal.

3. Homogeneity of Variance (Equal Variances in Groups)

   - The variance of cycles rentals should be similar across all seasons.
   - Check if all groups have same variance using Levene test Here is the text version of the content:

8.2.1 What to Do If ANOVA Assumptions Are Violated

Violation	Solution
Non-normal data	Use log/sqrt transformation or Kruskal-Wallis test
Unequal variances	Use Welch's ANOVA instead
Dependent variable not continuous	Convert count to numeric

Levene's Test:

To perform Levene's test for equality of variances based on the weather variable, we need to first group the data by the weather categories (e.g., different weather conditions) and then perform the test to see if the variances of the count variable (number of cycles rentals) differ across the different weather conditions.

Set up null hypothesis(H0)& Alternative hypothesis (Ha):

- Null Hypothesis (H): The variances are equal
- Alternative Hypothesis (H): The variances are not equal

[24]:

```
weather_1 = data[data['weather'] == 1]['count']
weather_2 = data[data['weather'] == 2]['count']
weather_3 = data[data['weather'] == 3]['count']
weather_4 = data[data['weather'] == 4]['count']
```

[25]:

```
# Perform Levene's test for homogeneity of variances
stat, p_value = levene(weather_1,weather_2,weather_3,weather_4)

# Print results
print(f"Levene's Test Results:\nStatistic: {stat}, p-value: {p_value}")

# Define significance level
```

```
alpha = 0.05

# Hypothesis testing
if p_value < alpha:
    print("Reject H0:\nVariances are not equal")
else:
    print("Fail to reject H0:\nVariances are equal")
```

```
Levene's Test Results:
Statistic: 54.85106195954556, p-value: 3.504937946833238e-35
Reject H0:
Variances are not equal
```

Levene's Test Results for Weather

Levene Test Statistic:54.85106195954556

P-value:3.504937946833238e-35

ConclusionReject H0: Variances are not equal.

Two of three conditions of **anova** are not met,still perform anova

Set up null hypothesis(H0)& Alternative hypothesis (Ha):

Hypothesis Setup

Null Hypothesis (H0):No significant demand of bicycles for different weather conditions

Alternative Hypothesis (Ha):significant demand of bicycles for different weather conditions

[26]:
```
an_stat,p_value = f_oneway(weather_1,weather_2,weather_3,weather_4)
print(f"Anova Test Results:\nStatistic: {an_stat}, p-value: {p_value}")
alpha = 0.05
if p_value < alpha:
    print("Reject H0:\nsignificant demand of bicycles for different weather␣
 ↪conditions.")
else:
    print("Fail to reject H0:\n No significant demand of bicycles for different␣
 ↪weather conditions.")
```

```
Anova Test Results:
Statistic: 65.53024112793271, p-value: 5.482069475935669e-42
Reject H0:
significant demand of bicycles for different weather conditions.
```

Anova test Results

Anova statistic: 65.53024112793271

P-value: 5.482069475935669e-42

ConclusionReject H0: There is significant demand of bicycles for different weather conditions.

Kruskal-Wallis Test

The **Kruskal-Wallis** Test is a non-parametric method used to compare three or more independent groups to determine if there is a statistically significant difference in the medians of the groups. This test is the non-parametric equivalent to one-way ANOVA and does not assume a normal distribution of the data.

[27]:
```
stat, p_value = kruskal(weather_1, weather_2, weather_3, weather_4)
print(f"Kruskal-Wallis Test Results:\nStatistic: {stat}, p-value: {p_value}")
if p_value < alpha:
    print("Reject H0: \nAverage number of cycless rented is diferent for␣
↪different weather conditions.")
else:
    print("Fail to reject H0:\n Average number of cycless rented is same for␣
↪different conditions")
```

```
Kruskal-Wallis Test Results:
Statistic: 205.00216514479087, p-value: 3.501611300708679e-44
Reject H0:
Average number of cycless rented is diferent for different weather conditions.
```

Hence pvalue is smaller than the significance level,Reject H0.

Therefore, significant demand of bicycles on different weather conditions

Lets check for demand of cycles is same for different weather conditions:

Set up null hypothesis(H0)& Alternative hypothesis (Ha):

Hypothesis Setup

Null Hypothesis (H0)

Average number of cycless rented is same for all seasons

Alternative Hypothesis (Ha)

Average number of cycless rented differ for atleast one season.

Set up null hypothesis(H0)& Alternative hypothesis (Ha):

Hypothesis Setup for levene test

Null Hypothesis (H0)

The variances are equal

Alternative Hypothesis (Ha)

The variances are not equal

[28]:
```
spring = data[data['season'] == 'Spring']['count']
summer = data[data['season'] == 'Summer']['count']
fall = data[data['season'] == 'Fall']['count']
winter = data[data['season'] == 'Winter']['count']
stat, p_value = levene(spring, summer, fall, winter)
print(f"Levene's Test Results:\nStatistic: {stat}, p-value: {p_value}")
```

```
alpha = 0.05
if p_value < alpha:
    print("Reject H0:\nVariances are not equal across seasons.")
else:
    print("Fail to reject H0:\nVariances are equal across seasons.")
```

```
Levene's Test Results:
Statistic: 187.7706624026276, p-value: 1.0147116860043298e-118
Reject H0:
Variances are not equal across seasons.
```

Levene test Results

Levene Test

187.7706624026276

P-value

1.0147116860043298e-118

Conclusion

Fail to reject H0:Variances are not equal across seasons..

Set up null hypothesis(H0)& Alternative hypothesis (Ha):

Hypothesis Setup

Null Hypothesis (H0)

No significant demand of bicycles for different seasons

Alternative Hypothesis (Ha)

significant demand of bicycles for different seasons

[29]:
```
an_stat,p_value = f_oneway(spring, summer, fall, winter)
print(f"Anova Test Results:\nStatistic: {an_stat}, p-value: {p_value}")
alpha = 0.05
if p_value < alpha:
    print("Reject H0:\nsignificant demand of bicycles for different weather␣
 ↪conditions.")
else:
    print("Fail to reject H0:\n No significant demand of bicycles for different␣
 ↪weather conditions.")
```

```
Anova Test Results:
Statistic: 236.94671081032106, p-value: 6.164843386499654e-149
Reject H0:
significant demand of bicycles for different weather conditions.
```

Anova test Results

Anova statistic

236.94671081032106

P-value

6.164843386499654e-149

Conclusion

Reject H0: There is significant demand of bicycles for different weather conditions.

Kruskal-Wallis Test

The **Kruskal-Wallis** Test is a non-parametric method used to compare three or more independent groups to determine if there is a statistically significant difference in the medians of the groups. This test is the non-parametric equivalent to one-way ANOVA and does not assume a normal distribution of the data.

[30]:
```
stat, p_value = kruskal(spring, summer, fall, winter)
print(f"Kruskal-Wallis Test Results:\nStatistic: {stat}, p-value: {p_value}")
if p_value < alpha:
    print("Reject H0: \nAverage number of cycless rented is diferent for␣
 ↪different seasons.")
else:
    print("Fail to reject H0:\n Average number of cycless rented is same for␣
 ↪different seasons")
```

```
Kruskal-Wallis Test Results:
Statistic: 699.6668548181988, p-value: 2.479008372608633e-151
Reject H0:
Average number of cycless rented is diferent for different seasons.
```

Here pvalue is smaller than significance level,Reject H0

Therefore, conclude that there is a significant difference between demand of cycles for different seasons

8.3 Q3. Check if Weather is dependent on the season

Chisquare Test:

The chisquare function in Python (from scipy.stats) is used to perform the Chi-Square test. The Chi-Square test is often used for hypothesis testing in categorical data, to determine whether there is a significant difference between the expected and observed frequencies.

There are two common types of Chi-Square tests:

1. Chi-Square Goodness of Fit Test: Tests whether the observed data follows a specified distribution.
2. Chi-Square Test of Independence: Tests whether two categorical variables are independent or associated.

Set up null hypothesis(H0)& Alternative hypothesis (Ha):

Hypothesis Setup

Null Hypothesis (H0)

Weather and Season are independent.There is no stastically significant difference on average number of rentals between working and non working days.

Alternative Hypothesis (Ha)

Weather is dependent.There is no stastically significant difference on average number of rentals between working and non working days.

Chisquare test of independence: relationship between 2 categorical variable

[31]:
```
weather_season = pd.crosstab(data['weather'],data['season'],)
print("Observed Values are as follows:\n")
weather_season
```

```
Observed Values are as follows:
```

[31]:
```
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
```

[32]:
```
stat, p, dof, expected= chi2_contingency(weather_season)
print(f"Chi-Square Test Results:\nChi square Test Statistic: {stat},\np-value:␣
 ↪{p},\nDegrees of Freedom: {dof}")
print("\nExpected Values are as follows:")
print(expected)
alpha = 0.05
print(f"\nCritical value:{chi2.ppf(1 - alpha,df = dof)}")

if p < alpha:
    print("\nReject H0:\nWeather and Season are dependent.")
else:
    print("\nFail to reject H0:\nWeather and Season are independent.")
```

```
Chi-Square Test Results:
Chi square Test Statistic: 49.15865559689363,
p-value: 1.5499250736864862e-07,
Degrees of Freedom: 9

Expected Values are as follows:
[[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]]
```

```
Critical value:16.918977604620448

Reject H0:
Weather and Season are dependent.
```

8.3.1 Chi-Square Test Results

Chi-Square Test Statistic	P-Value	Degrees of Freedom	Critical Value
49.16	1.55e-07	9	16.92

8.3.2 Expected Values

1774.55	1805.60	1805.60	1806.26
699.26	711.49	711.49	711.75
211.95	215.66	215.66	215.74
0.25	0.25	0.25	0.25

8.3.3 Conclusion

Reject H : Weather and Season are dependent.

Insights 1. cycles rentals are higher in warmer months, especially during the summer and fall. The demand tends to decrease significantly in the colder winter months. 2. cycles rentals tend to increase on holidays. 3. Similarly, cycles rentals are slightly higher on weekends or holidays, as indicated by the "working day" variable. 4. Rainy days, thunderstorms, snow, and fog lead to a notable drop in cycles rentals. Bad weather conditions reduce the willingness of people to rent cycless due to comfort and safety concerns. 5. When humidity levels drop below 20%, the number of cycless rented is significantly lower. 6. On days when the temperature is below 10°C, cycles rentals are also lower. 7. If wind speeds exceed 35 km/h, cycles rentals decrease. 8. Rentals are higher during public holidays and weekends. People are more likely to rent cycless for recreational purposes or short trips when they have more free time.

Recommendations 1. During the summer and fall seasons, the company should increase its cycles stock to meet the higher demands. 2. Based on a significance level of 0.05, the "working day" variable does not significantly impact the number of cycles rented. 3. On days with very low humidity, the company should reduce the number of cycles available for rent. 4. On days with temperatures below 10°C or in very cold weather, the company should decrease its cycle stock. 5. During periods of high winds (greater than 35 km/h) or adverse weather conditions such as thunderstorms, the company should have fewer cycless available for rent. 6. On rainy, snowy, or foggy days, the company should either reduce the number of cycless available or implement a flexible booking policy where users can cancel or reschedule without penalties. 7. Incorporate weather forecasts into fleet management practices, so cycless can be redistributed based on predicted weather conditions, ensuring a balance between availability and demand. 8. Use weather and seasonality data to design targeted marketing campaigns that promote cycles rentals in favorable conditions (e.g., sunny days) and offer special promotions during slower periods (e.g., rainy days).