Start coding or generate with AI.

```
# Importing necessary Libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import scipy.stats as stats
import statsmodels.api as sm
import statsmodels.formula.api as smf
import seaborn as sns
from sklearn.impute import SimpleImputer
```

```
# Loading Dataset

df = pd.read_csv('/kaggle/input/yulu-data/yulu_data.csv')
df.head()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	cas
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	
	2011-01-									

Defining Problem Statement

To find the variables with significance in predicting the demand for shared electric cycles in the Indian market.

```
# Convert 'season', 'holiday', 'workingday', and 'weather' to categorical data type
categorical_columns = ['season', 'holiday', 'workingday', 'weather']
for col in categorical_columns:
    df[col] = df[col].astype('category')

df['datetime'] = pd.to_datetime(df['datetime'])
df['year'] = df['datetime'].dt.year
df['month'] = df['datetime'].dt.month
```

```
# Display the structure of the dataset

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10886 entries, 0 to 10885
Data columns (total 14 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
 12  year        10886 non-null  int32
 13  month       10886 non-null  int32
dtypes: category(4), datetime64[ns](1), float64(3), int32(2), int64(4)
memory usage: 808.7 KB
```

```
# Display the summary of the dataset

df.describe()
```

	datetime	temp	atemp	humidity	windspeed	cas
count	10886	10886.00000	10886.000000	10886.000000	10886.000000	10886.000
mean	2011-12-27 05:56:22.399411968	20.23086	23.655084	61.886460	12.799395	36.021
min	2011-01-01 00:00:00	0.82000	0.760000	0.000000	0.000000	0.000
25%	2011-07-02 07:15:00	13.94000	16.665000	47.000000	7.001500	4.000
50%	2012-01-01 20:30:00	20.50000	24.240000	62.000000	12.998000	17.000
	2012-07-01					

```
# Check for missing values
df.isnull().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
year          0
month         0
dtype: int64
```

Univariate Analysis

```
# Distribution plots for continuous variables
continuous_vars = ['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count']
plt.figure(figsize=(15, 15))
i = 1
for var in continuous_vars:
    plt.subplot(3, 3, i)
    sns.histplot(df[var], kde=True)
    plt.title(f'Distribution of {var}')
    i = i+1
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf
  with pd.option_context('mode.use_inf_as_na', True):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf
  with pd.option_context('mode.use_inf_as_na', True):
/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf
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/opt/conda/lib/python3.10/site-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf
  with pd.option_context('mode.use_inf_as_na', True):
```
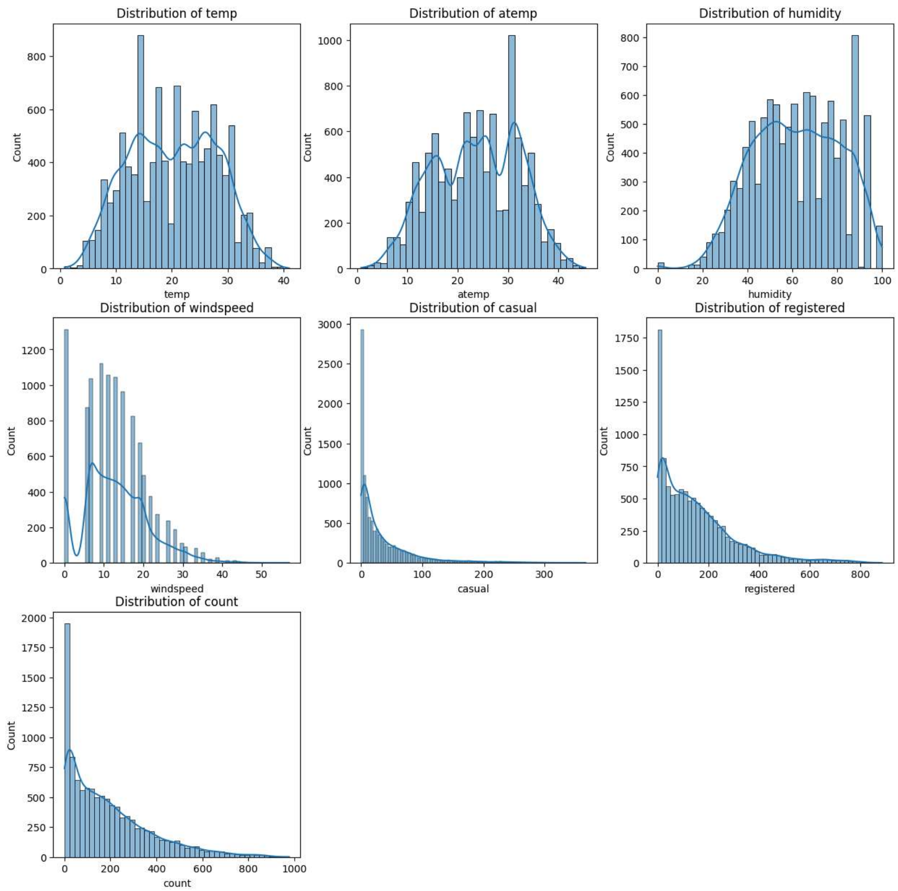
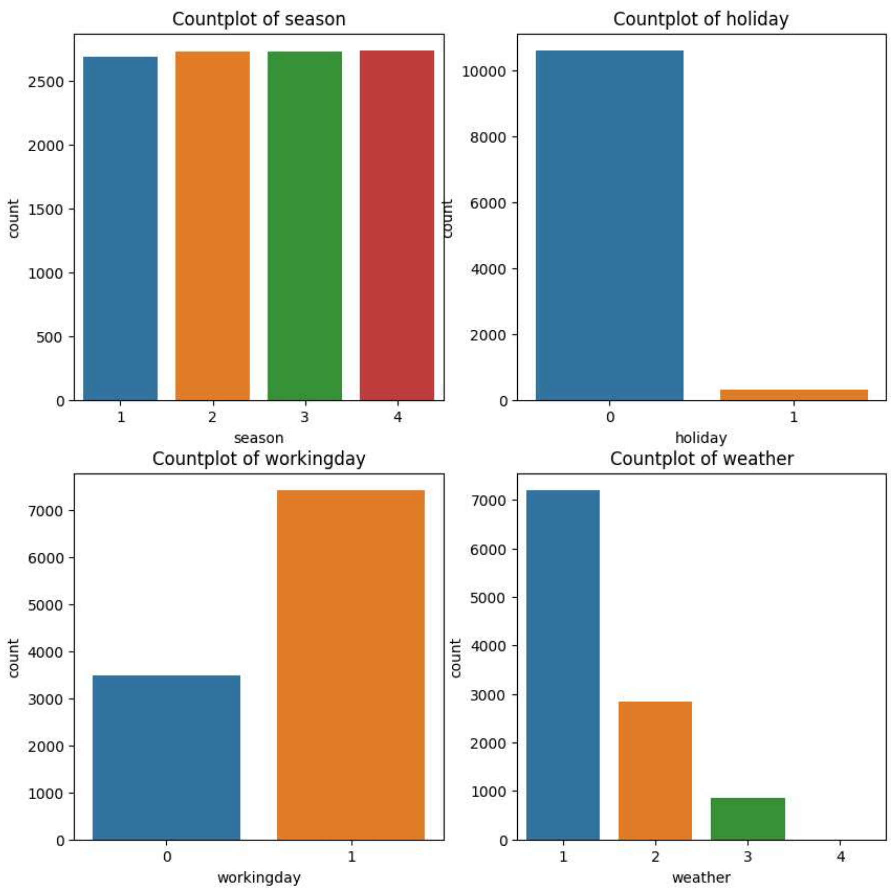



Data in columns 'casual', 'windspeed and 'registered' are all right-skewed while 'temp', 'atemp' and 'humidity' are more close to normal distribution.

```
# Countplots for categorical variables
categorical_vars = ['season', 'holiday', 'workingday', 'weather']
i = 1
plt.figure(figsize=(10, 10))
for var in categorical_vars:
    plt.subplot(2, 2, i)
    sns.countplot(x=df[var])
    plt.title(f'Countplot of {var}')
    i += 1
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The c
  grouped_vals = vals.groupby(grouper)
```



While seasons has equal distributions among its groups, categories 'workingday', 'holiday', 'weather' has clear disparity among their groups.

Bivariate Analysis

```
# Relationship between categorical variables and count
i = 1
plt.figure(figsize=(10, 10))
for var in categorical_vars:
    plt.subplot(2, 2, i)
    sns.boxplot(x=var, y='count', data=df)
    i += 1
    plt.title(f'Boxplot of Count by {var}')
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The c
  grouped_vals = vals.groupby(grouper)
/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The c
  grouped_vals = vals.groupby(grouper)
/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The c
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/opt/conda/lib/python3.10/site-packages/seaborn/categorical.py:641: FutureWarning: The c
  grouped_vals = vals.groupby(grouper)
```
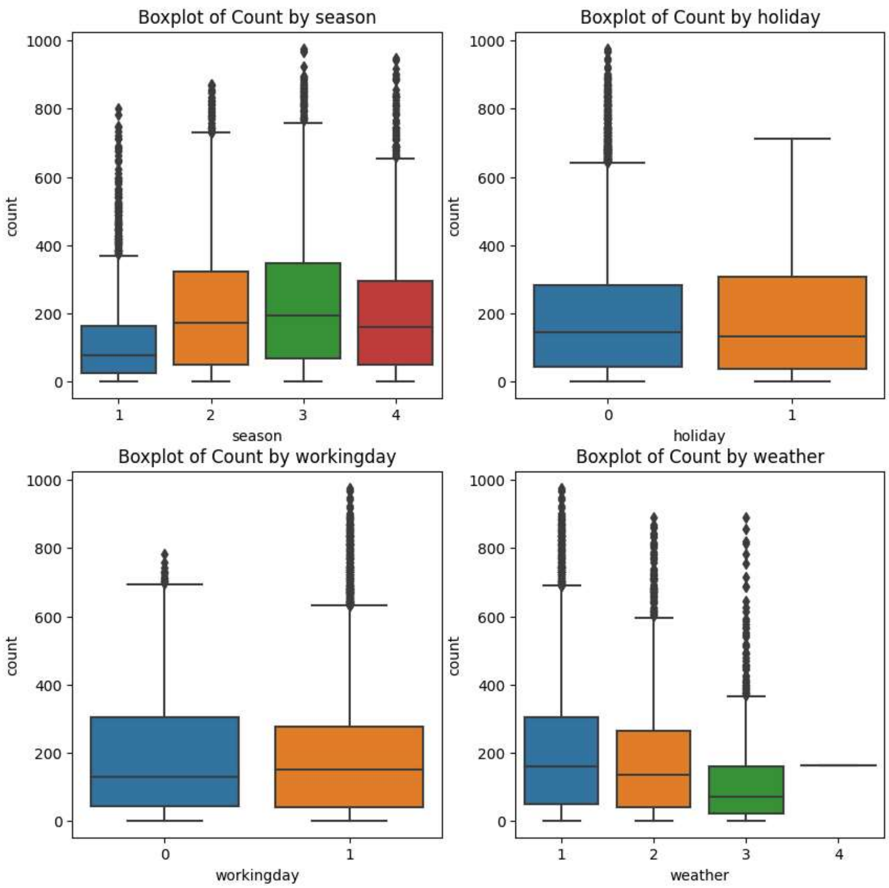
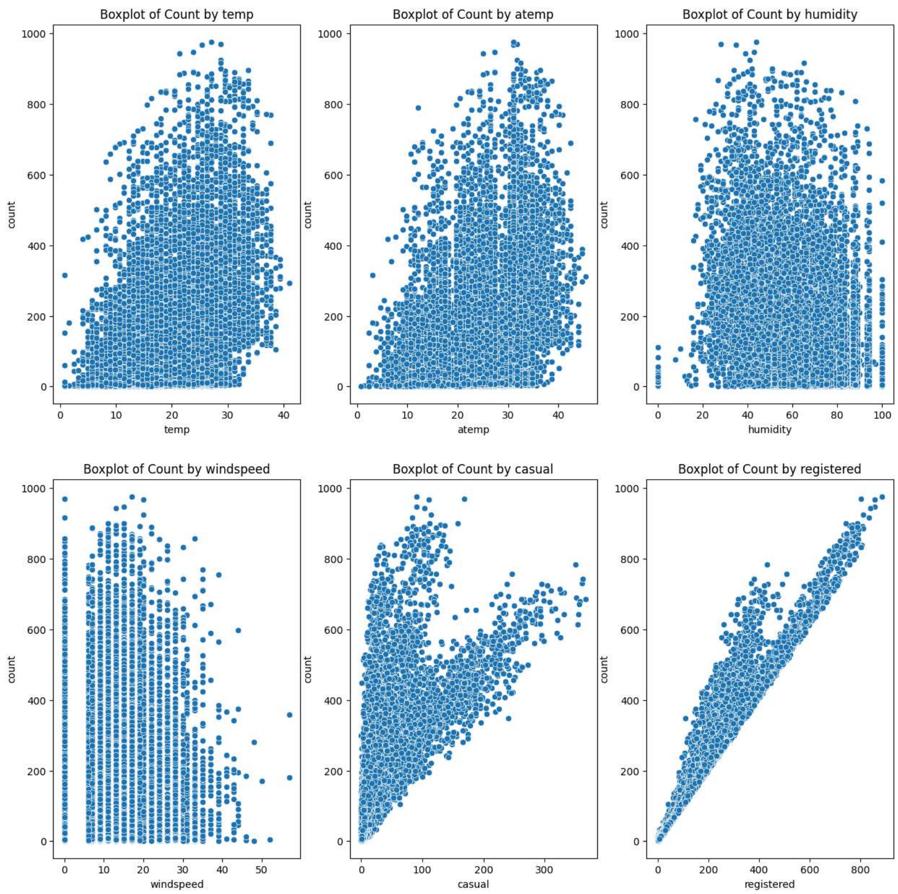



Majority of the category data has outliers in with 'count' values

```
# Relation between Continuous variables and count

i = 1
plt.figure(figsize=(15, 15))
for var in continuous_vars[:-1]:
    plt.subplot(2, 3, i)
    sns.scatterplot(x=var, y='count', data=df)
    i += 1
    plt.title(f'Boxplot of Count by {var}')
plt.show()
```

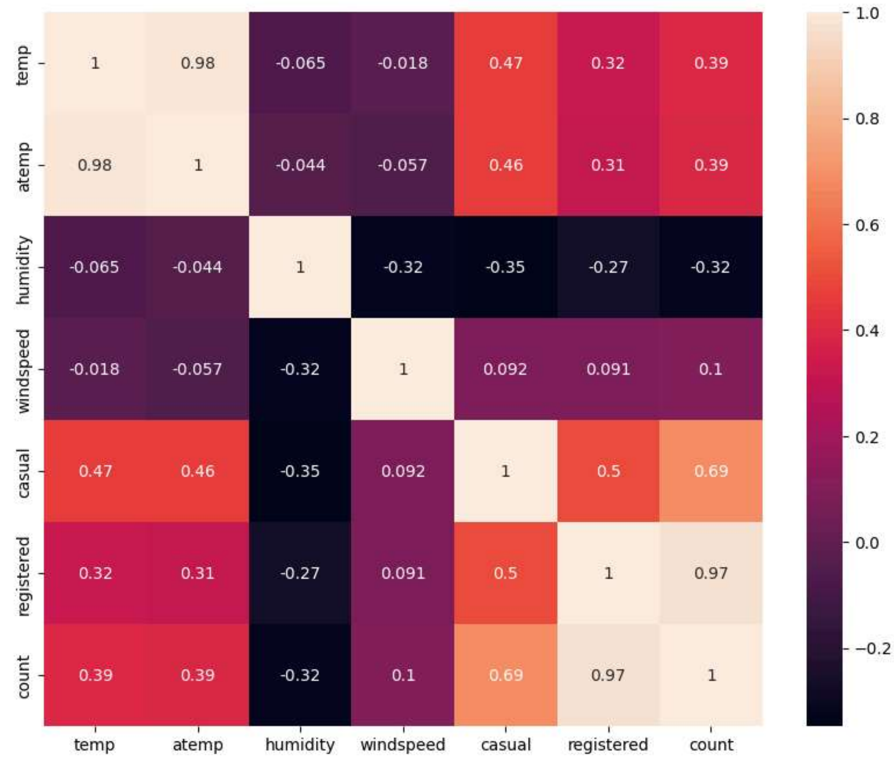


Only 'Casual' and 'Registered' columns are somewhat poisitvely correlated with 'count' data.

Correlation Analysis

```
correlation_matrix = df[continuous_vars].corr()
plt.figure(figsize=(10,8))
sns.heatmap(correlation_matrix, annot=True)
```

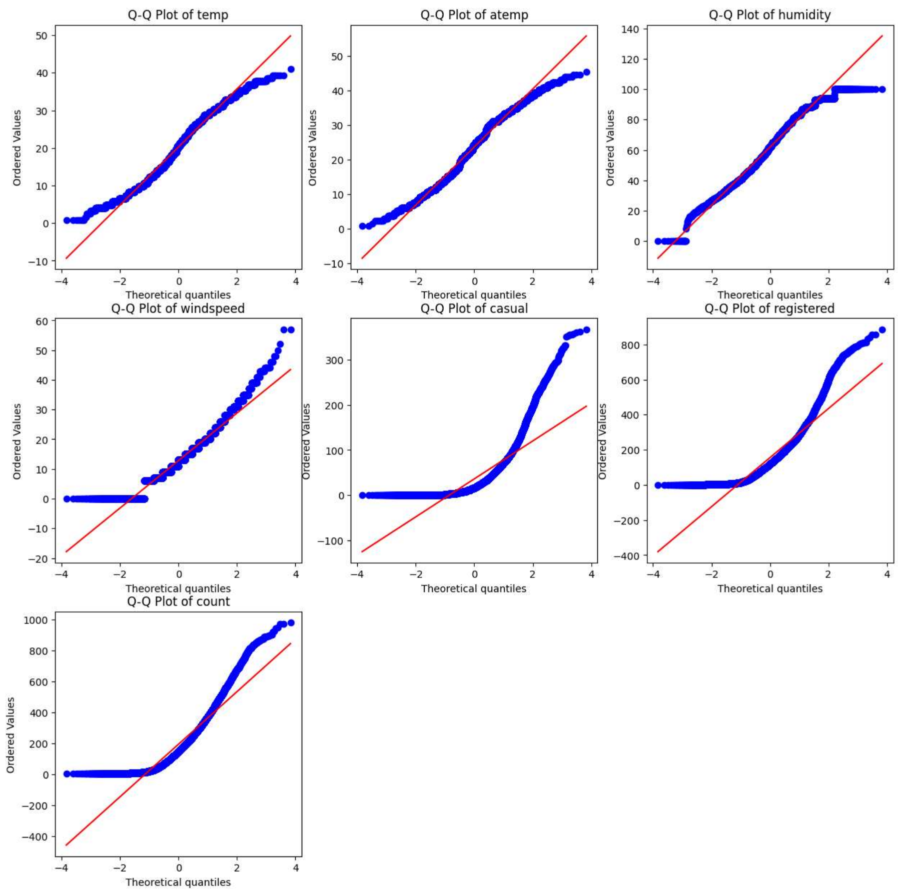
```
<Axes: >
```



Assumptions

```
def alpha_test(p_value, alpha=0.05):
    if p_value < alpha:
        return "Ha"
    else:
        return "H0"
```

```
# Q-Q Plot for 'count'
plt.figure(figsize=(15, 15))
i = 1
for var in continuous_vars:
    plt.subplot(3, 3, i)
    stats.probplot(df[var], dist="norm", plot=plt)
    plt.title(f'Q-Q Plot of {var}')
    i = i+1
plt.show()
```



From the Q-Q plot we can say that columns 'temp', 'atemp' and 'humidity' are close to normal while 'windspeed', 'causal' and 'registered' aren't.

```
# Separate data into working day and non-working day
working_day_data = df[df['workingday'] == 1]['count']
non_working_day_data = df[df['workingday'] == 0]['count']

# Levene's test for equal variance between working day and non working day data
levene_test = stats.levene(working_day_data, non_working_day_data)
print(f'Levene Test: {levene_test}')

# Levene's test for equal variance among season groups
season_groups = [df[df['season'] == i]['count'] for i in range(1, 5)]
levene_stat_season, levene_p_season = stats.levene(*season_groups)

print(f"Levene's Test for Seasons - Statistics: {levene_stat_season}, P-value: {levene_p_season}")

# Levene's test for equal variance among weather groups
weather_groups = [df[df['weather'] == i]['count'] for i in range(1, 5)]
levene_stat_weather, levene_p_weather = stats.levene(*weather_groups)

print(f"Levene's Test for Weather - Statistics: {levene_stat_weather}, P-value: {levene_p_weather}")

if alpha_test(levene_test[1]) == "Ha":
    print("We can conclude variance between Working day and non-working day data are not equal")
else:
    print("We can conclude variance between Working day and non-working day data are equal")

if alpha_test(levene_p_season) == "Ha":
    print("We can conclude variance of Season groups are not equal")
else:
    print("We can conclude variance of Season groups are equal")
if alpha_test(levene_p_weather) == "Ha":
    print("We can conclude variance of Weather groups are not equal")
else:
    print("We can conclude variance of Weather groups are equal")
```

```
Levene Test: LeveneResult(statistic=0.004972848886504472, pvalue=0.9437823280916695)
Levene's Test for Seasons - Statistics: 187.7706624026276, P-value: 1.0147116860043298e-118
Levene's Test for Weather - Statistics: 54.85106195954556, P-value: 3.504937946833238e-35
We can conclude variance between Working day and non-working day data are equal
We can conclude variance of Season groups are not equal
We can conclude variance of Weather groups are not equal
```

- **We can conclude variance between Working day and non-working day data are equal**
- **We can conclude variance of Season groups are not equal**
- **We can conclude variance of Weather groups are not equal**

Hypothesis Testing

1. Working Day Effect on Demand (2-Sample T-Test)

```
from scipy.stats import ttest_ind

# Null Hypothesis (H0): No difference in number of cycles rented on working day vs non-working day
# Alternate Hypothesis (H1): Difference in number of cycles rented on working day vs non-working day

# Separate data into working day and non-working day
working_day_data = df[df['workingday'] == 1]['count']
non_working_day_data = df[df['workingday'] == 0]['count']

# Perform the t-test
t_stat, p_value = ttest_ind(working_day_data, non_working_day_data)

print(f'T-Test Statistics: {t_stat}, P-value: {p_value}')
if alpha_test(levene_p_weather) == "Ha":
    print("We can conclude that working day has an effect on the number of cycles rented.")
else:
    print("We can conclude that working day has no effect on the number of cycles rented.")
```

```
T-Test Statistics: 1.2096277376026694, P-value: 0.22644804226361348
We can conclude that working day has an effect on the number of cycles rented.
```

We can conclude that working day has an effect on the number of cycles rented.

2. Cycle Demand Across Seasons and Weather (ANOVA)

```
from scipy.stats import f_oneway

# ANOVA for seasons
season_groups = [df[df['season'] == i]['count'] for i in range(1, 5)]
f_stat_season, p_value_season = f_oneway(*season_groups)

print(f'ANOVA for Seasons - F-statistics: {f_stat_season}, P-value: {p_value_season}')

# ANOVA for weather
weather_groups = [df[df['weather'] == i]['count'] for i in range(1, 5)]
f_stat_weather, p_value_weather = f_oneway(*weather_groups)

print(f'ANOVA for Weather - F-statistics: {f_stat_weather}, P-value: {p_value_weather}')

if alpha_test(p_value_season) == "Ha":
    print("We can conclude that the number of cycles rented differs across seasons.")
else:
    print("We can conclude that the number of cycles rented doesn't differs across seasons.")

if alpha_test(p_value_weather) == "Ha":
    print("We can conclude that the number of cycles rented differs across weather conditions.")
else:
    print("We can conclude that the number of cycles rented doesn't differs across weather conditions.")
```

```
ANOVA for Seasons - F-statistics: 236.94671081032106, P-value: 6.164843386499654e-149
ANOVA for Weather - F-statistics: 65.53024112793271, P-value: 5.482069475935669e-42
We can conclude that the number of cycles rented differs across seasons.
We can conclude that the number of cycles rented differs across weather conditions.
```

We can conclude that the number of cycles rented differs across seasons.

We can conclude that the number of cycles rented differs across weather conditions.

3. Dependency Between Weather and Season (Chi-Square Test)

```
from scipy.stats import chi2_contingency

# Contingency table for weather and season
contingency_table = pd.crosstab(df['weather'], df['season'])

# Perform Chi-Square Test
chi2, p, dof, expected = chi2_contingency(contingency_table)

print(f'Chi-Square Statistics: {chi2}, P-value: {p}')

if alpha_test(p) == "Ha":
    print("We can conclude that weather is dependent on the season.")
else:
    print("We can conclude that weather is independent on the season.")
```

```
Chi-Square Statistics: 49.15865559689363, P-value: 1.5499250736864862e-07
We can conclude that weather is dependent on the season.
```

We can conclude that weather is dependent on the season.

Actionable Insights

1. Optimize Operations Based on Day of the Week

Insight: Working days have a significant effect on the number of cycles rented. **Action:** Increase the availability of cycles on working days to meet higher demand. Adjust maintenance schedules to weekends or non-working days when demand is lower.

2. Seasonal Demand Planning

Insight: The number of cycles rented differs significantly across seasons, and the variance among season groups is not equal. **Action:** Plan for seasonal fluctuations by increasing the fleet size during high-demand seasons (e.g., spring and fall) and reducing it during low-demand seasons (e.g., summer and winter). Offer seasonal promotions or discounts to encourage usage during off-peak seasons.

3. Weather-Based Adjustments

Insight: The number of cycles rented varies significantly with different weather conditions, and the variance among weather groups is not equal. **Action:** Implement dynamic pricing based on weather forecasts, offering discounts during unfavorable weather conditions (e.g., heavy rain) to encourage usage. Ensure that the fleet is well-maintained and equipped to handle adverse weather conditions.

4. Targeted Marketing Strategies

Insight: 'Casual' and 'Registered' users are positively correlated with the total count, indicating different user behaviors. **Action:** Develop targeted marketing campaigns for both casual and registered users. For casual users, promote short-term offers and easy sign-up processes. For registered users, offer loyalty programs and subscription plans to encourage frequent usage.

5. Addressing Outliers and Improving User Experience