YULU BUSINESS CASE STUDY

PROBLEM STATEMENT

Yulu is **India's leading micro-mobility platform** that provides electric cycles and scooters for short-distance urban travel. **The company aims to optimize fleet utilization by understanding the factors that affect rental demand**.

This analysis focuses on exploring Yulu's rental data to identify patterns and relationships influencing the number of electric cycles rented. Specifically, it seeks to determine whether:

1. The number of electric cycles rented differs between working and non-working days.
2. The rental counts vary significantly across different weather conditions and seasons.
3. Weather conditions are dependent on the season.

To address these questions, **exploratory data analysis** and **hypothesis testing** (**2-sample t-test, ANOVA, and chi-square test**) are performed on the given dataset containing variables such as datetime, season, workingday, weather, temperature, humidity, windspeed, and rental counts.

MODULES' IMPORT

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
```

DATA IMPORT

```
!wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/original/bike_sharing.csv?1642089089
```

```
--2025-10-19 09:24:02--  https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/original/bike_sharing.csv?1642089089
Resolving d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)... 108.157.172.183, 108.157.172.176, 108.157.172.173, ...
Connecting to d2beiqkhq929f0.cloudfront.net (d2beiqkhq929f0.cloudfront.net)|108.157.172.183|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 648353 (633K) [text/plain]
Saving to: ‘bike_sharing.csv?1642089089.1’

bike_sharing.csv?16 100%[===================>] 633.16K  --.-KB/s    in 0.05s

2025-10-19 09:24:02 (12.1 MB/s) - ‘bike_sharing.csv?1642089089.1’ saved [648353/648353]
```

```
df = pd.read_csv('bike_sharing.csv?1642089089')
df.head()
```

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

Next steps: Generate code with df New interactive sheet

```
# season :: 1: spring, 2: summer, 3: fall, 4: winter
# weather:: 1: clear, 2: mist, 3: light rain/snow, 4: heavy rain/snow
```

BASIC METRICS

```
df.dtypes # checking the structure & characteristics of the dataset
```

	0
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

```
df.isna().sum() # 0 => No NULL values => clean data
```

	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

DATA PREPARATION

1. Parse datetime column correctly

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

The datetime column was converted into a proper datetime object to facilitate efficient extraction of temporal components such as day, month, and hour.

2. Convert categorical fields to category data type

```
cat_cols = ['season','holiday','workingday','weather']
for col in cat_cols:
  df[col] = df[col].astype('category')
```

Casting these columns to the category type improves memory efficiency and explicitly indicates to the statistical models that they represent nominal or ordinal attributes.

EXPLORATORY DATA ANALYSIS (EDA)

1. Numeric Summary

```
df.describe()
```

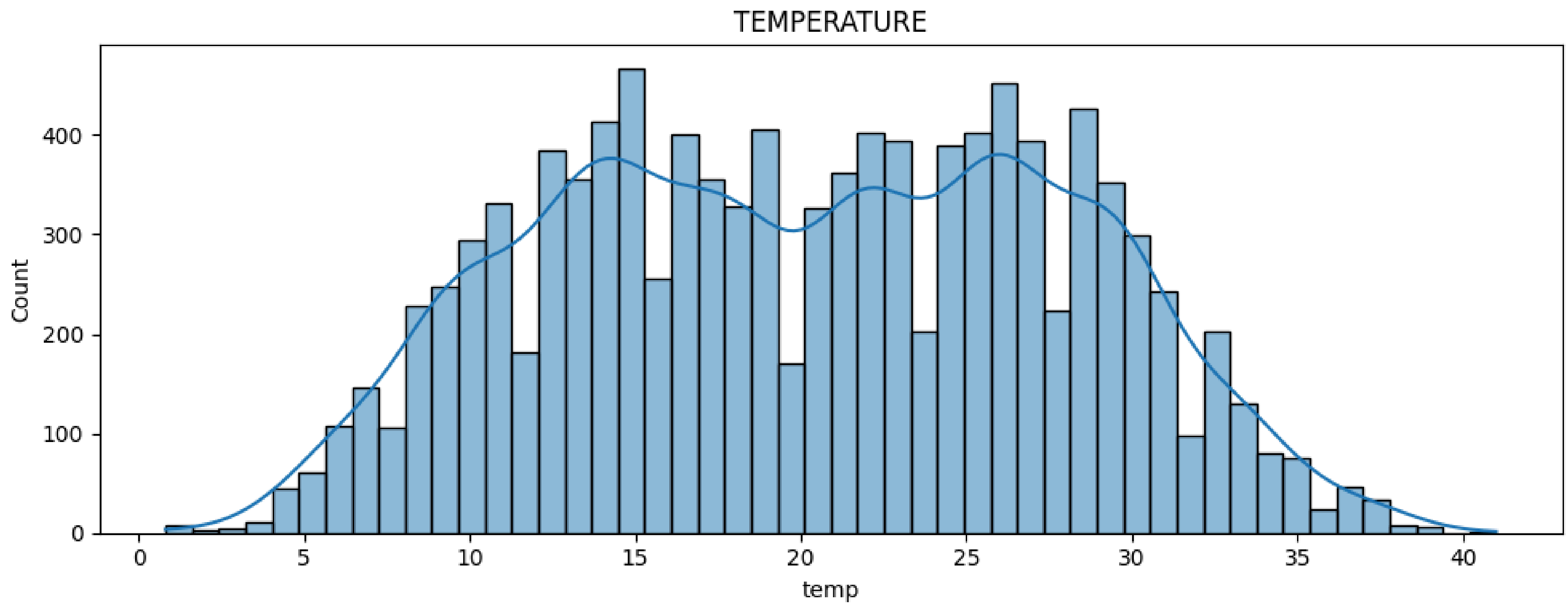
	datetime	temp	atemp	humidity	windspeed	casual	registered	count
count	10886	10886.00000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000
mean	2011-12-27 05:56:22.399411968	20.23086	23.655084	61.886460	12.799395	36.021955	155.552177	191.574132
min	2011-01-01 00:00:00	0.82000	0.760000	0.000000	0.000000	0.000000	0.000000	1.000000
25%	2011-07-02 07:15:00	13.94000	16.665000	47.000000	7.001500	4.000000	36.000000	42.000000
50%	2012-01-01 20:30:00	20.50000	24.240000	62.000000	12.998000	17.000000	118.000000	145.000000
75%	2012-07-01 12:45:00	26.24000	31.060000	77.000000	16.997900	49.000000	222.000000	284.000000
max	2012-12-19 23:00:00	41.00000	45.455000	100.000000	56.996900	367.000000	886.000000	977.000000
std	NaN	7.79159	8.474601	19.245033	8.164537	49.960477	151.039033	181.144454

2. Univariate Analysis — Continuous Variables

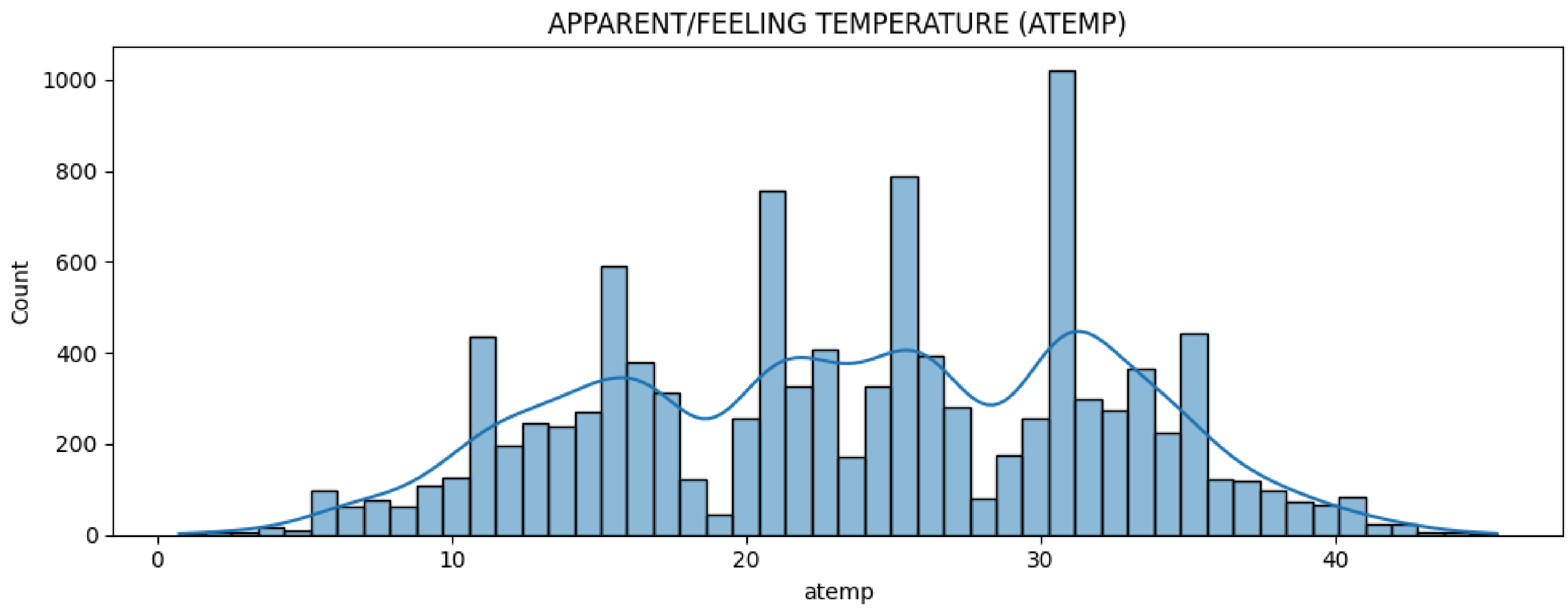
Histograms display the distribution of **continuous variables** — whether they are symmetric, skewed, or contain outliers.

The **kde=True option** overlays a **smooth density curve** to visualize the **shape of the distribution**.

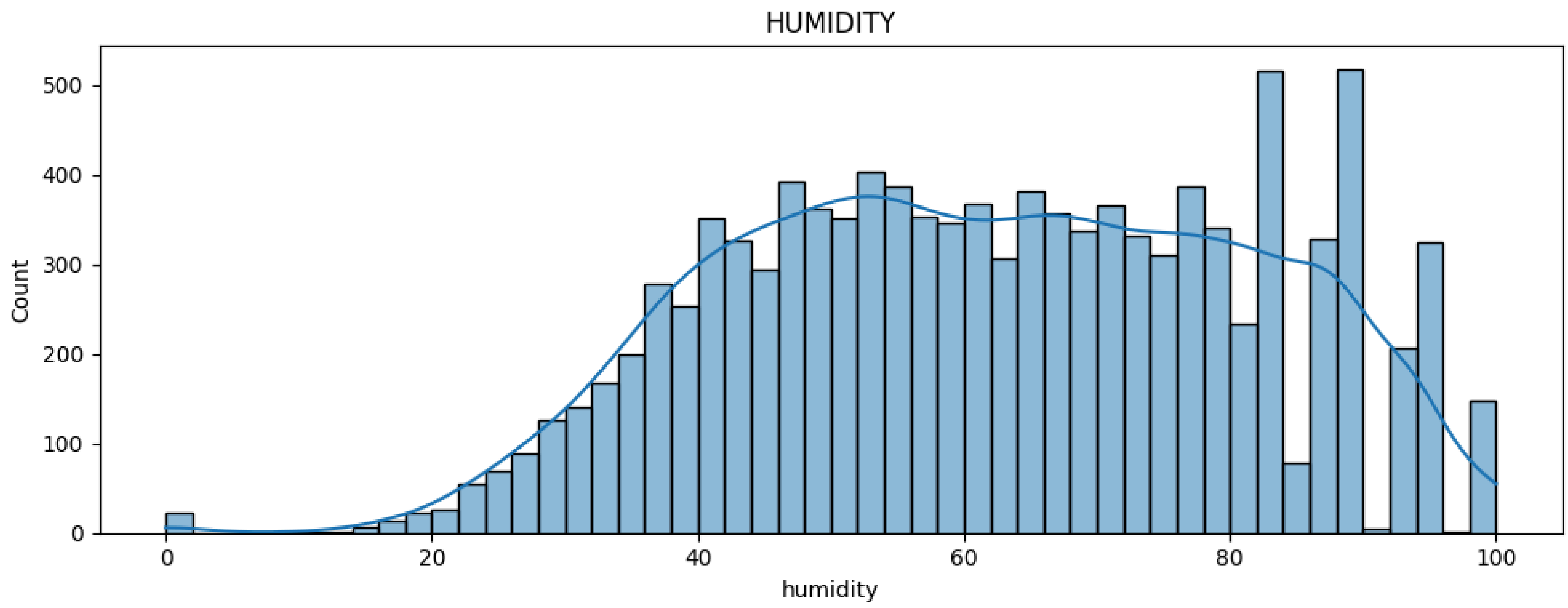
```
fig,axis = plt.subplots(1,1,figsize=(10,4))
sns.histplot(data=df,x='temp',ax=axis,bins=50,kde=True)
axis.set_title('TEMPERATURE')
plt.tight_layout()
plt.show()
```



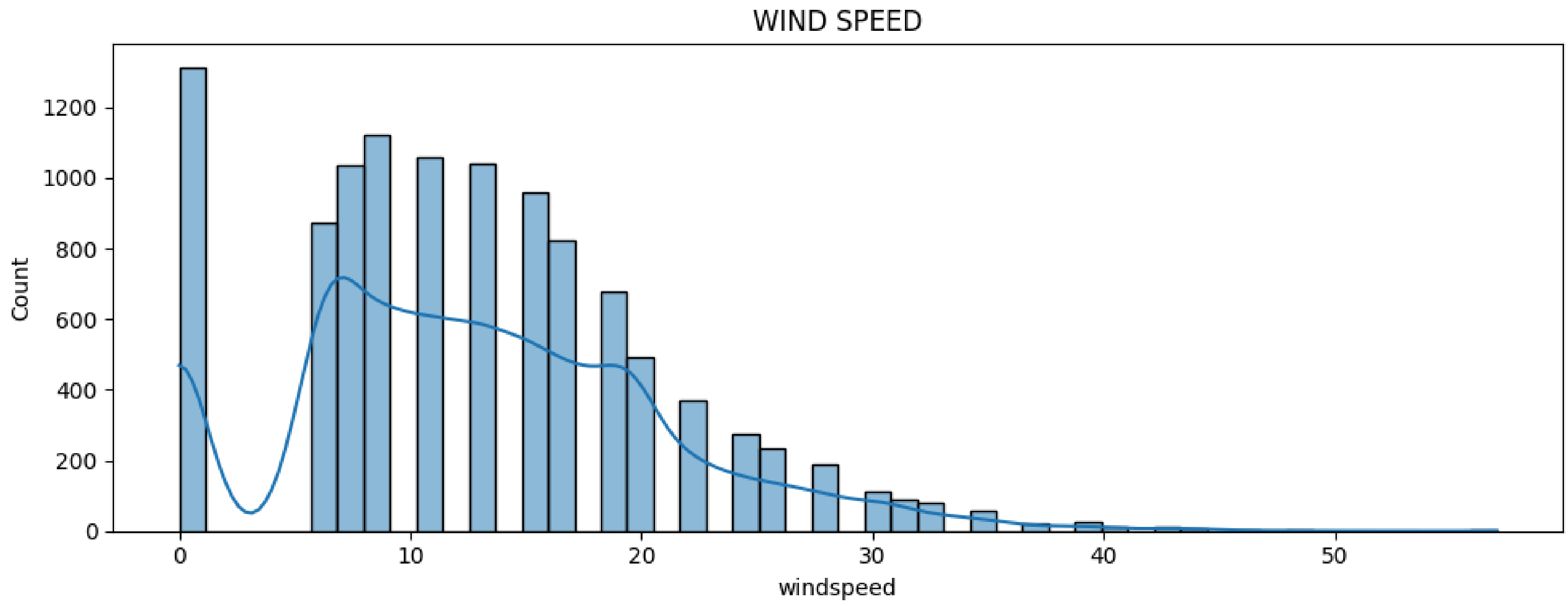

```
fig,axis = plt.subplots(1,1,figsize=(10,4))
sns.histplot(data=df,x='atemp',ax=axis,bins=50,kde=True)
#In the Yulu dataset, atemp stands for "feeling temperature" or "apparent temperature"
axis.set_title('APPARENT/FEELING TEMPERATURE (ATEMP)')
plt.tight_layout()
plt.show()
```



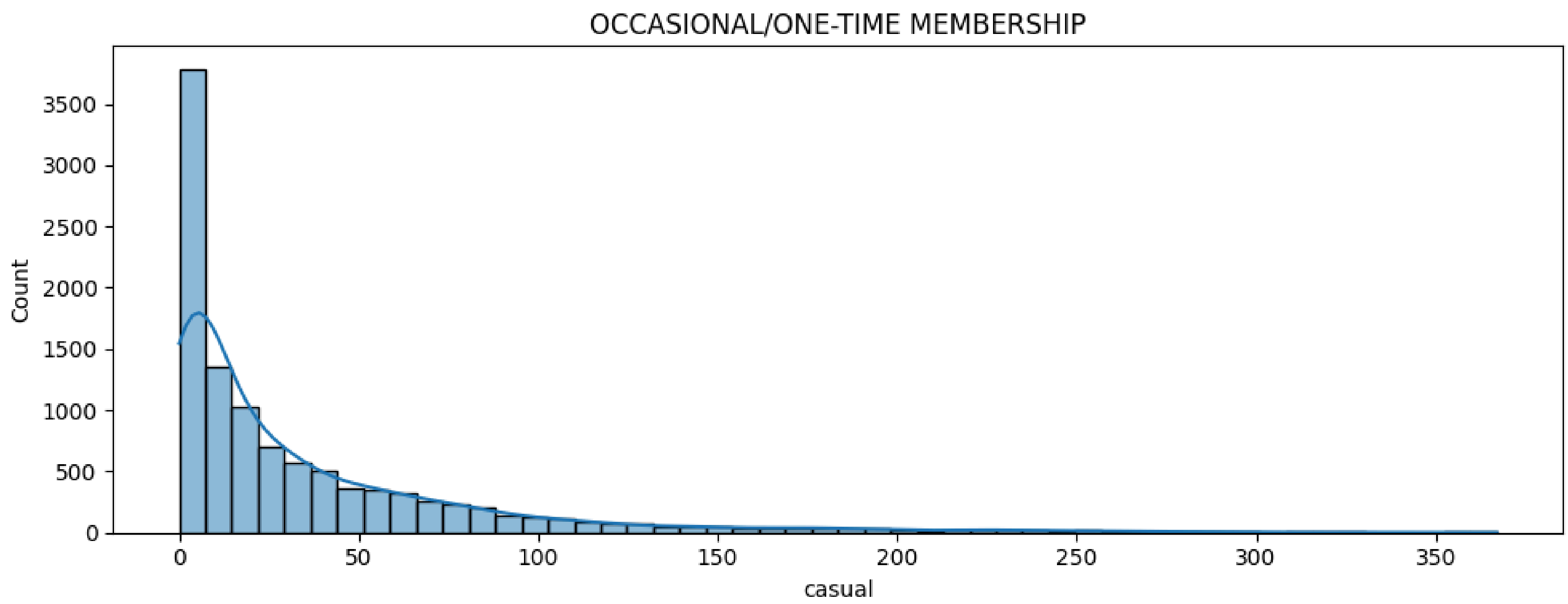

```
fig,axis = plt.subplots(1,1,figsize=(10,4))
sns.histplot(data=df,x='humidity',ax=axis,bins=50,kde=True)
axis.set_title('HUMIDITY')
plt.tight_layout()
plt.show()
```



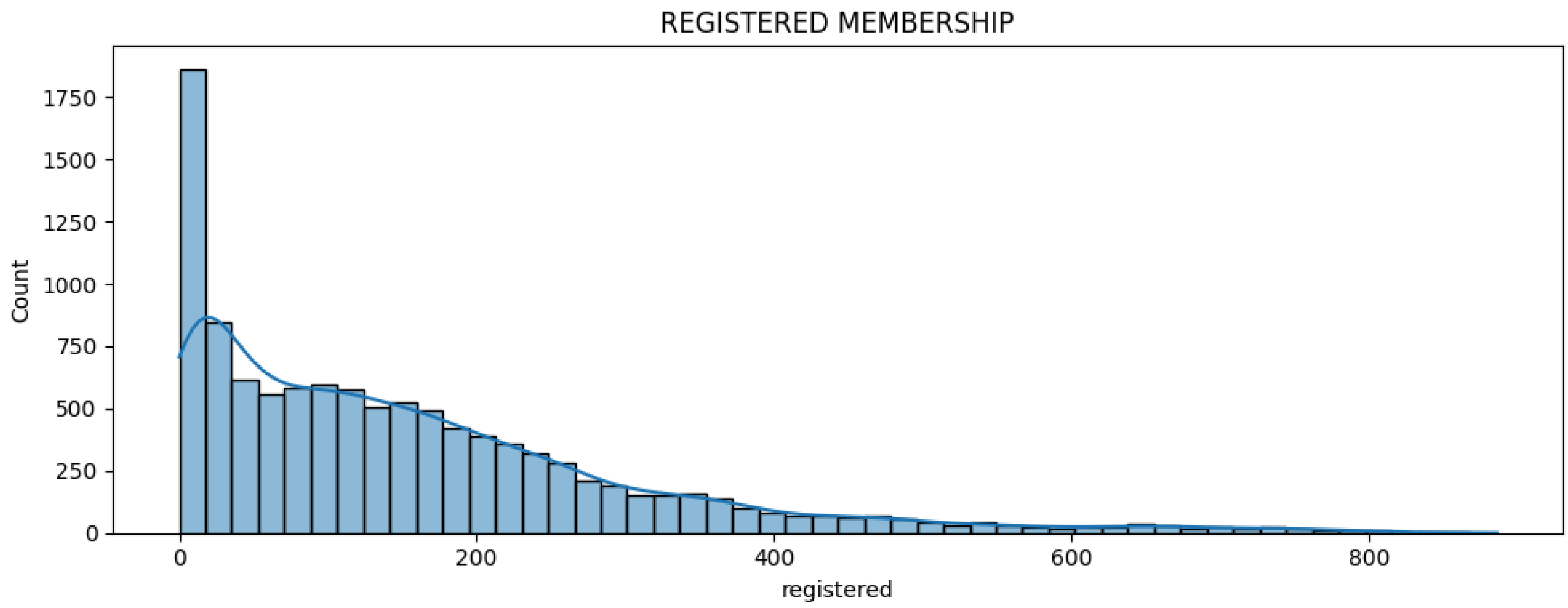

```
fig,axis = plt.subplots(1,1,figsize=(10,4))
sns.histplot(data=df,x='windspeed',ax=axis,bins=50,kde=True)
axis.set_title('WIND SPEED')
plt.tight_layout()
plt.show()
```



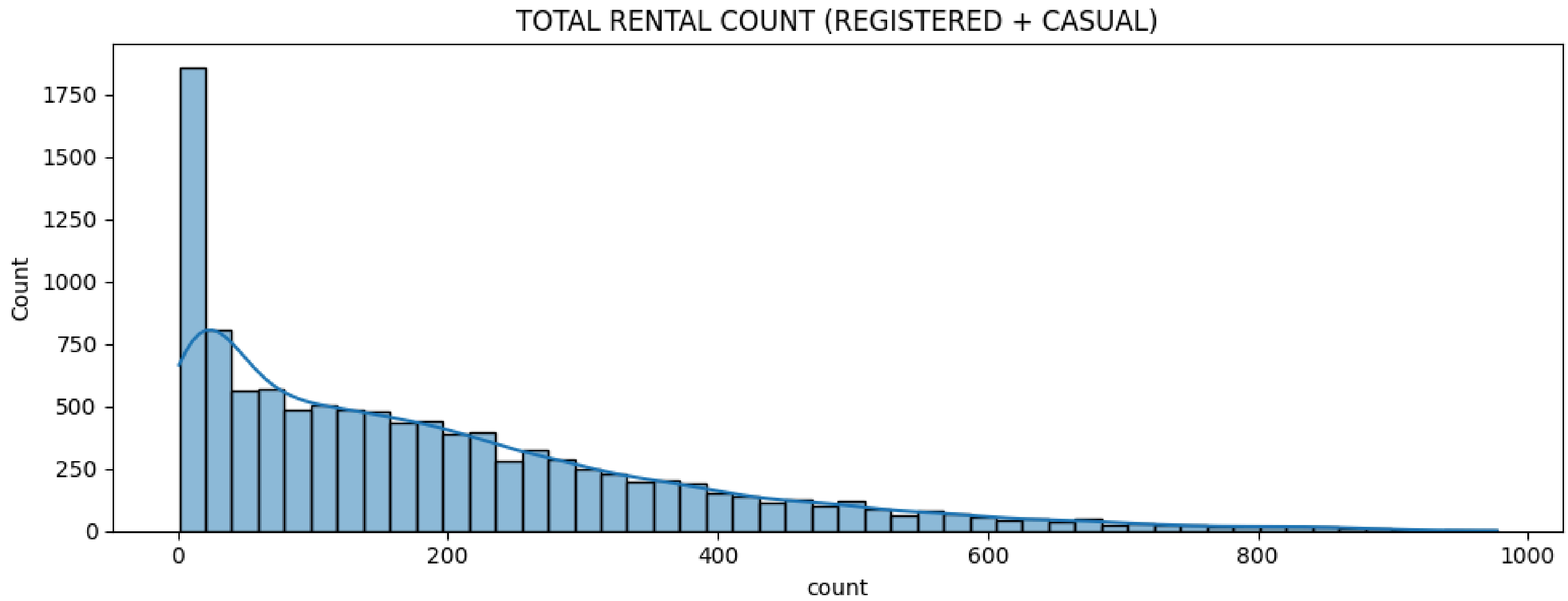

```
fig,axis = plt.subplots(1,1,figsize=(10,4))
sns.histplot(data=df,x='casual',ax=axis,bins=50,kde=True)
# In the Yulu dataset, casual refers to the count of users who rented bikes without a registered membership.
axis.set_title('OCCASIONAL/ONE-TIME MEMBERSHIP')
plt.tight_layout()
plt.show()
```




```
fig,axis = plt.subplots(1,1,figsize=(10,4))
sns.histplot(data=df,x='registered',ax=axis,bins=50,kde=True)
# In the Yulu dataset, registered refers to the count of users who rented bikes with a registered membership.
axis.set_title('REGISTERED MEMBERSHIP')
plt.tight_layout()
plt.show()
```



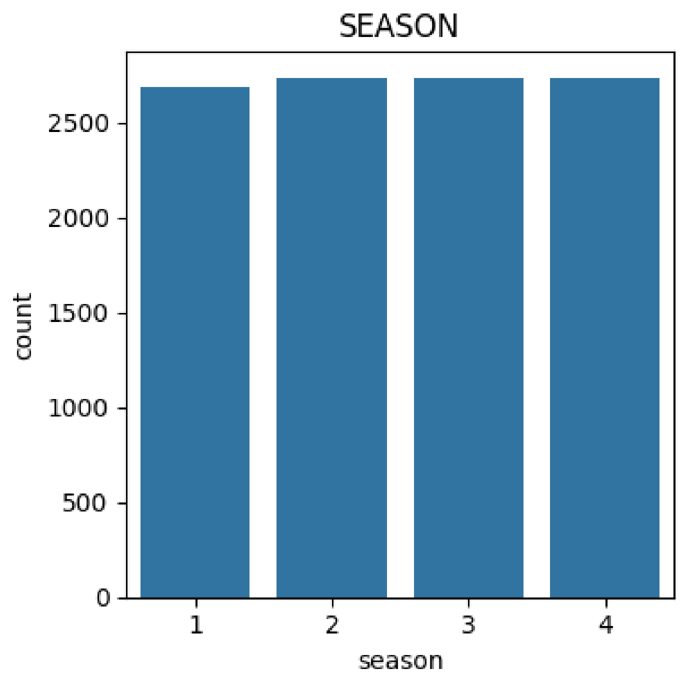

```
fig,axis = plt.subplots(1,1,figsize=(10,4))
sns.histplot(data=df,x='count',ax=axis,bins=50,kde=True)
axis.set_title('TOTAL RENTAL COUNT (REGISTERED + CASUAL)')
plt.tight_layout()
plt.show()
```



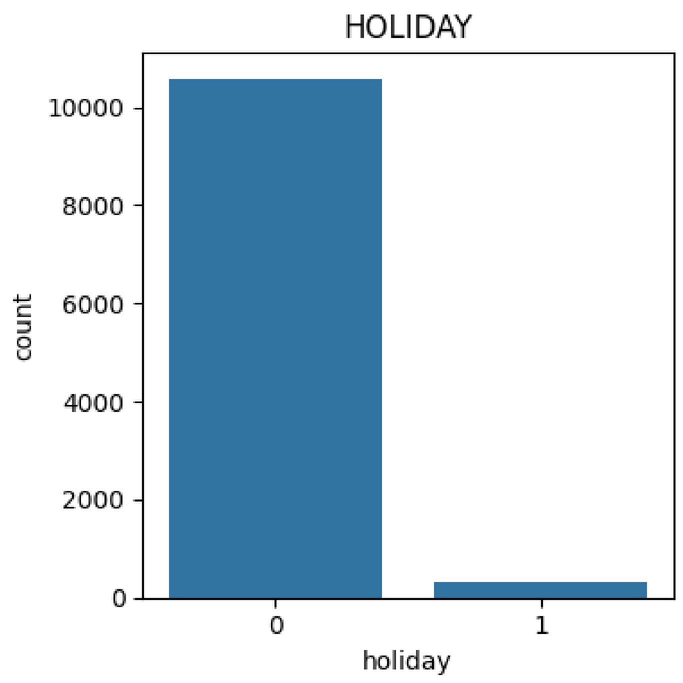
3. Univariate Analysis — Categorical Variables

Countplots show the **frequency** of each category — helping us understand which season or weather type occurs most frequently.

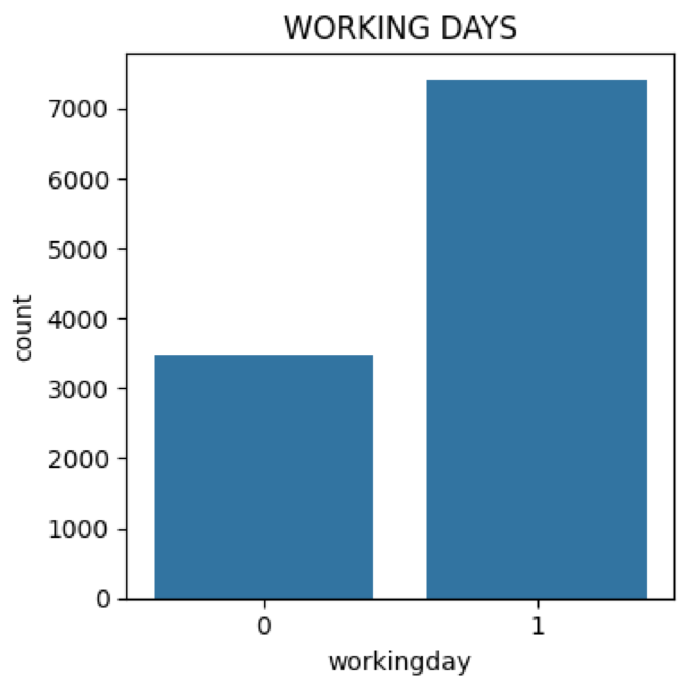
```
fig,axis = plt.subplots(1,1,figsize=(4,4))
sns.countplot(data=df,x='season',ax=axis)
axis.set_title('SEASON')
plt.tight_layout()
plt.show()
```



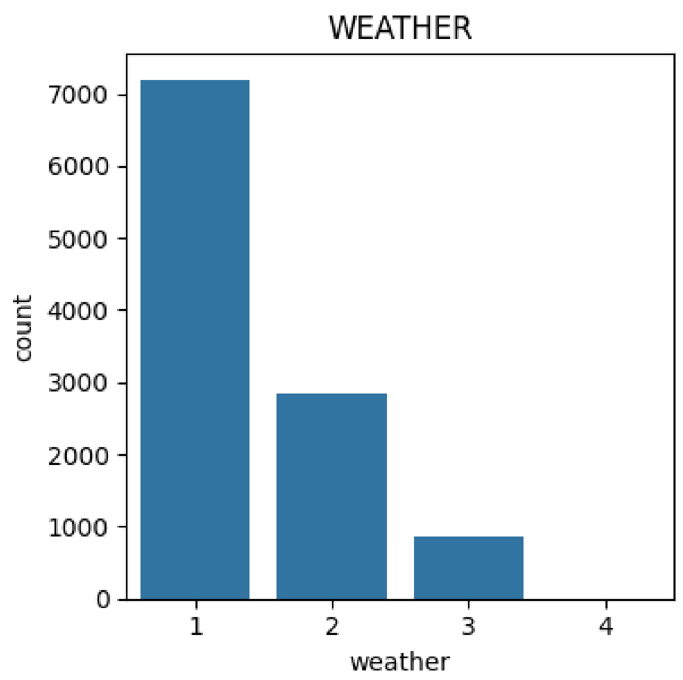
```
fig,axis = plt.subplots(1,1,figsize=(4,4))
sns.countplot(data=df,x='holiday',ax=axis)
axis.set_title('HOLIDAY')
plt.tight_layout()
plt.show()
```




```
fig,axis = plt.subplots(1,1,figsize=(4,4))
sns.countplot(data=df,x='workingday',ax=axis)
axis.set_title('WORKING DAYS')
plt.tight_layout()
plt.show()
```




```
fig,axis = plt.subplots(1,1,figsize=(4,4))
sns.countplot(data=df,x='weather',ax=axis)
axis.set_title('WEATHER')
plt.tight_layout()
plt.show()
```

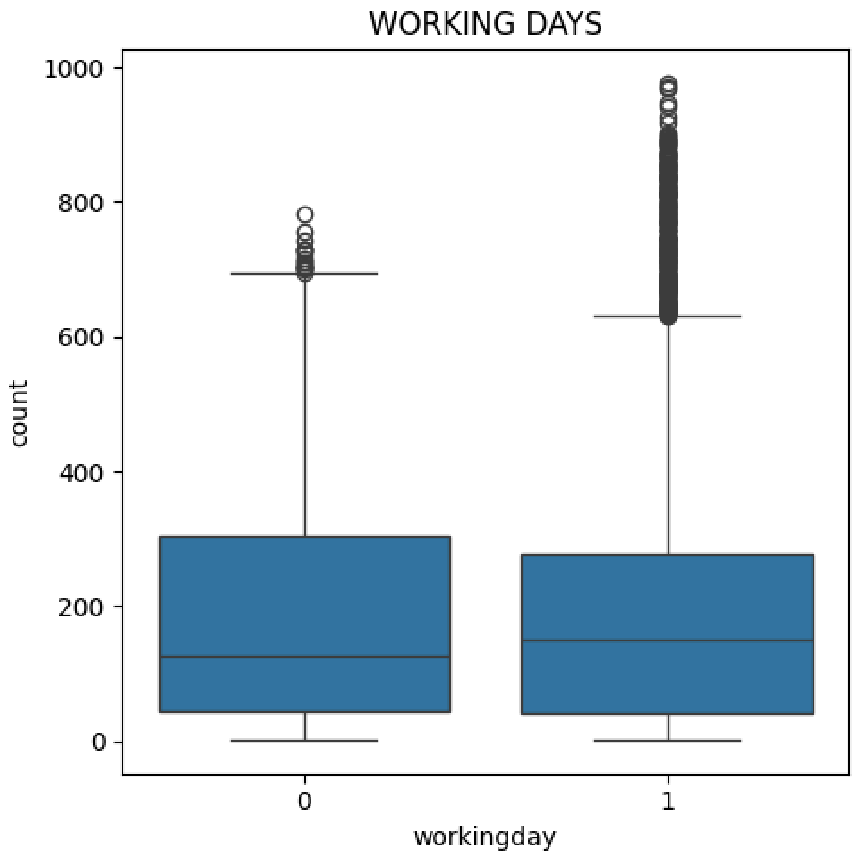


4. Bivariate Analysis — Boxplots

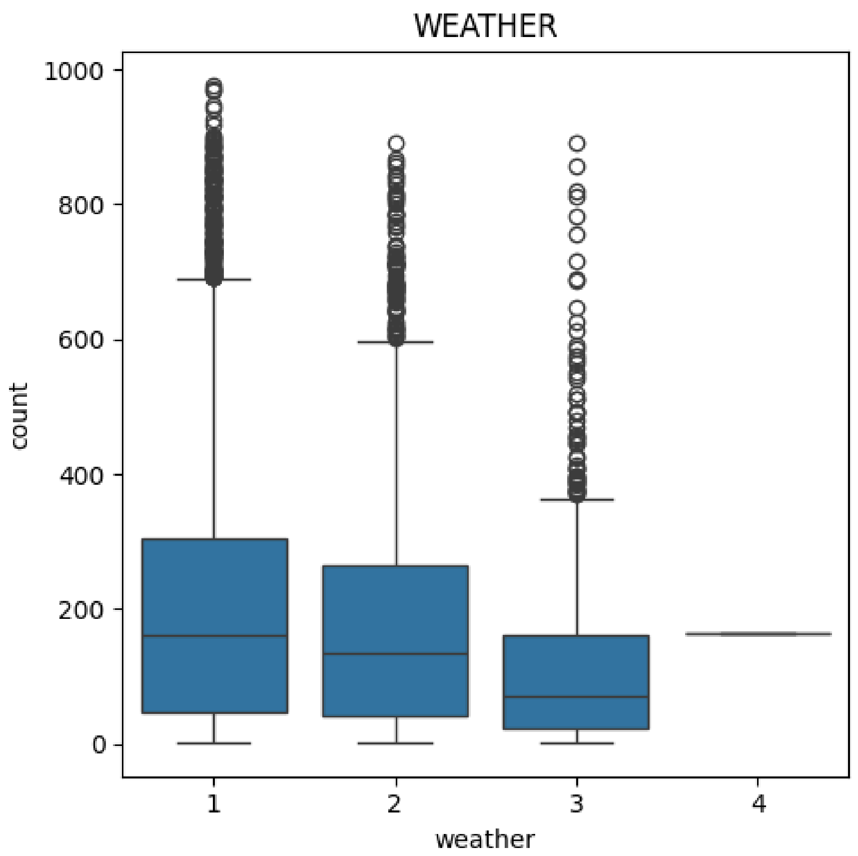
Boxplots visualize how the distribution of count (dependent variable) changes across different categories such as workingday, season, and weather. They reveal **median differences, spread, and potential outliers** — essential for deciding which factors might influence rental counts

```
# Establishing a relation between the dependent and independent variable
# Dependent : "count"
# Independent: "workingday", "weather", "season"
```

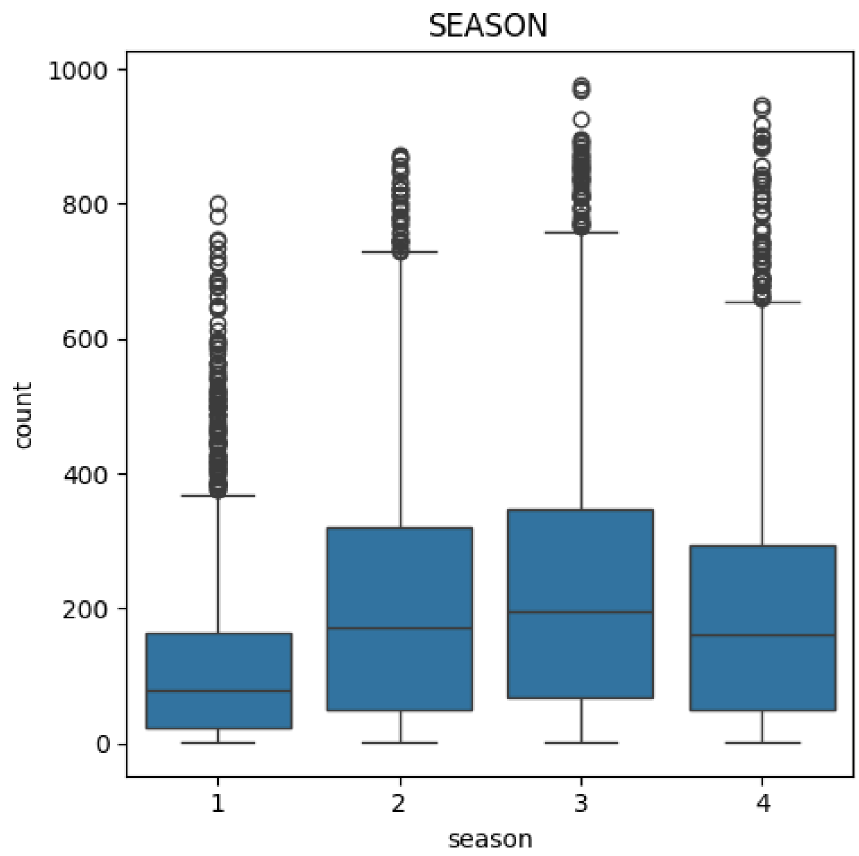
```
fig,axis = plt.subplots(1,1,figsize=(5,5))
sns.boxplot(data=df,x='workingday',y='count',ax=axis)
axis.set_title('WORKING DAYS')
plt.tight_layout()
plt.show()
```




```
fig,axis = plt.subplots(1,1,figsize=(5,5))
sns.boxplot(data=df,x='weather',y='count',ax=axis)
axis.set_title('WEATHER')
plt.tight_layout()
plt.show()
```



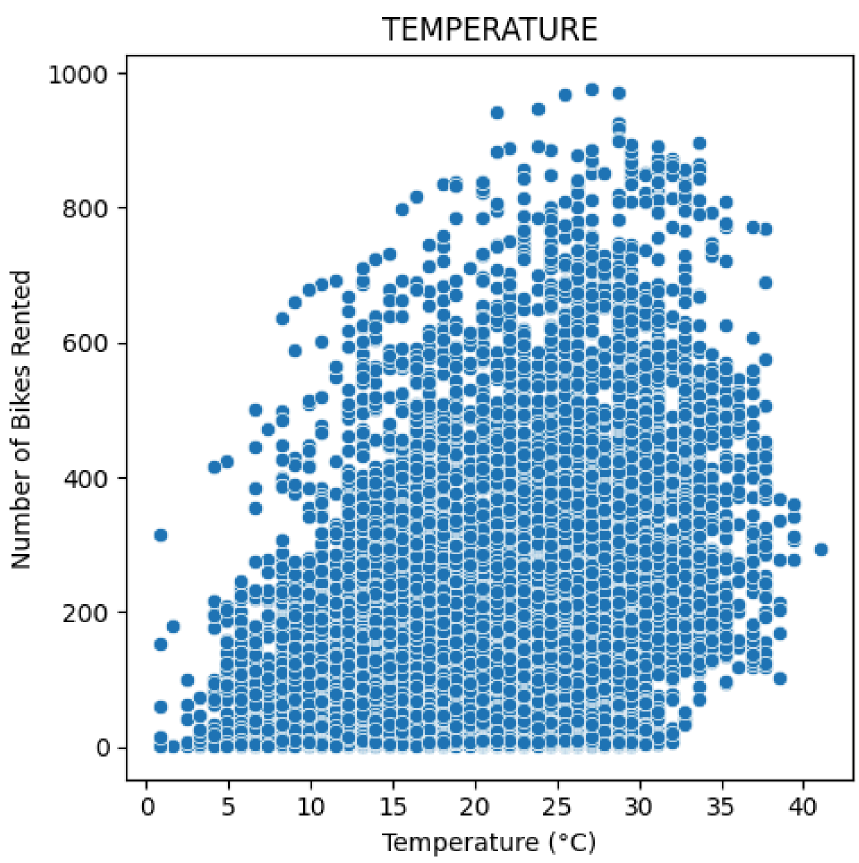

```
fig,axis = plt.subplots(1,1,figsize=(5,5))
sns.boxplot(data=df,x='season',y='count',ax=axis)
axis.set_title('SEASON')
plt.tight_layout()
plt.show()
```



5. Bivariate Analysis — Scatter Plot

The **scatterplot** helps detect the **correlation between continuous variables**. For instance, as temperature increases, the rental count might also rise — indicating weather comfort influences user behavior.

```
fig,axis = plt.subplots(1,1,figsize=(5,5))
sns.scatterplot(data=df,x='temp',y='count',ax=axis)
axis.set_title('TEMPERATURE')
plt.xlabel('Temperature (°C)')
plt.ylabel('Number of Bikes Rented')
plt.tight_layout()
plt.show()
```



HYPOTHESIS TESTING

```
# Set a significance level (alpha) at 95% confidence level
alpha = 0.05
```

1. Effect of Working Day on Rental Count: 2-SAMPLE T-TEST

Defining Hypotheses

H_0: Mean number of bikes rented is the same on working and non-working days.

H_1: Mean number of bikes rented differs between working and non-working days.

Test Assumptions

- Normality of Data
- Homogeneity of Variances (Equal Variance Assumption)
- Independence of Observations

Hypothesis Testing

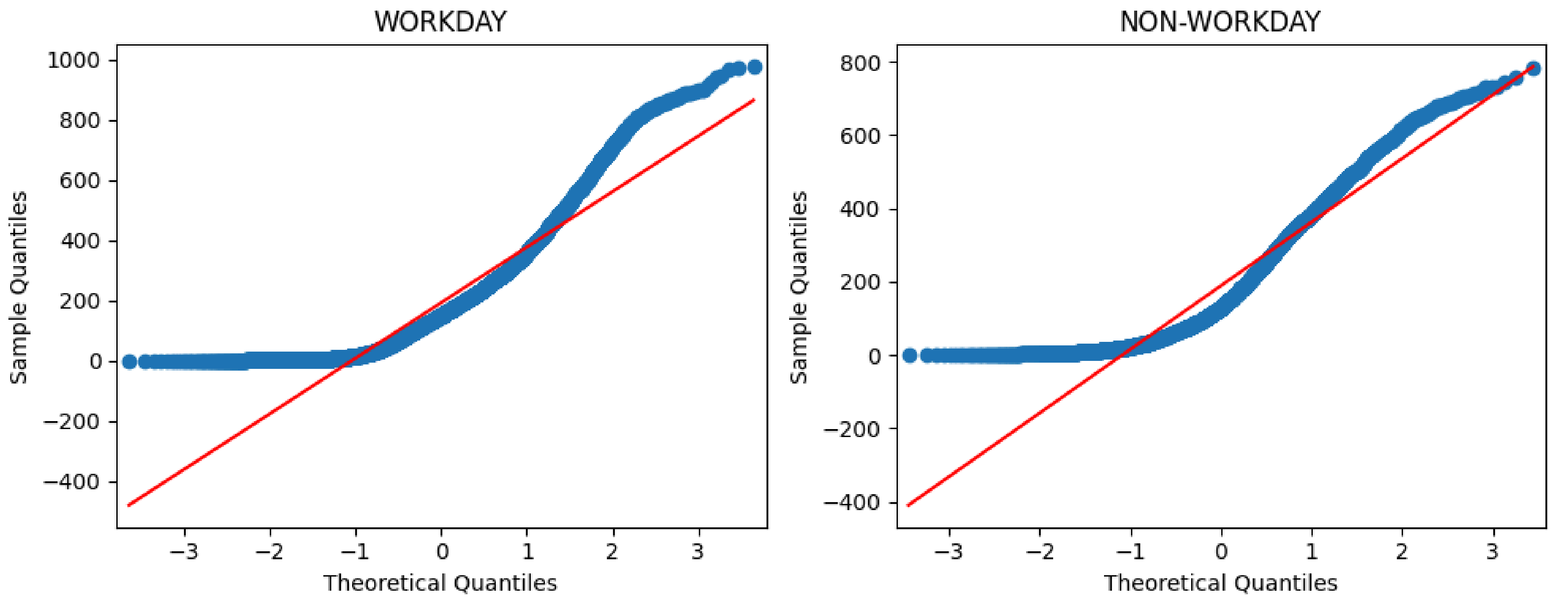
```
# Split data into two groups
workday = df[df['workingday'] == 1]['count']
non_workday = df[df['workingday'] == 0]['count']
print(workday.shape,non_workday.shape)
```

```
(7412,) (3474,)
```

```
# Check normality (Shapiro-Wilk test)
shapiro_workday = stats.shapiro(workday.sample(500))
shapiro_nonwork = stats.shapiro(non_workday.sample(500))
print("Shapiro-Wilk test p-value for workday:",shapiro_workday.pvalue)
print("Shapiro-Wilk test p-value for non-workday:",shapiro_nonwork.pvalue)
```

```
Shapiro-Wilk test p-value for workday: 2.845518369489204e-19
Shapiro-Wilk test p-value for non-workday: 4.814484088177835e-19
```

```
# QQ Plot
from statsmodels.graphics.gofplots import qqplot
fig,axis = plt.subplots(1,2,figsize=(10,4))
qqplot(workday,line='s',ax=axis[0])
qqplot(non_workday,line='s',ax=axis[1])
axis[0].set_title('WORKDAY')
axis[1].set_title('NON-WORKDAY')
plt.tight_layout()
plt.show()
```




```
# Check equality of variances
levene_test = stats.levene(workday, non_workday)
print("Levene’s test p-value:",levene_test.pvalue)
```

```
Levene’s test p-value: 0.9437823280916695
```

```
# Perform independent 2-sample t-test (assuming equal variances)
t_stat, p_val = stats.ttest_ind(workday, non_workday, equal_var=True)
print("T-stat:", t_stat)
print("P-value:", p_val)
```

```
T-stat: 1.2096277376026694
P-value: 0.22644804226361348
```

```
# Non-parametric alternative (Mann-Whitney U)
u_stat, p_val_mw = stats.mannwhitneyu(workday, non_workday)
print("U-stat:", u_stat)
print("P-value:", p_val_mw)
```

```
U-stat: 12868495.5
P-value: 0.9679139953914079
```

Interpretation of Test Results

- Normality tests (**Shapiro–Wilk**) indicates that the rental counts are **not perfectly normally distributed ($p < 0.05$)**. However, given the large sample size, the **CENTRAL LIMIT THEOREM ensures approximate normality** of the sampling distribution of the mean

- Variance-equality test (**Levene's test**) indicates **approximately equal variances** across workday and non_workday (p > 0.05)
- Since the normality assumption was violated, a Mann–Whitney U test was also conducted to verify the robustness of the result.
- In our data, both t-test and Mann–Whitney had p > 0.05, indicating that (non-)working days do not affect rentals.

2. Difference in Rentals Across Weather Types — ANOVA

Defining Hypotheses

H_0: Mean rental counts are equal across all weather categories.

H_1: At least one weather category has a different mean count.

Test Assumptions

- Normality of Data
- Homogeneity of Variances (Equal Variance Assumption)
- Independence of Observations
- No Significant Outliers

Hypothesis Testing

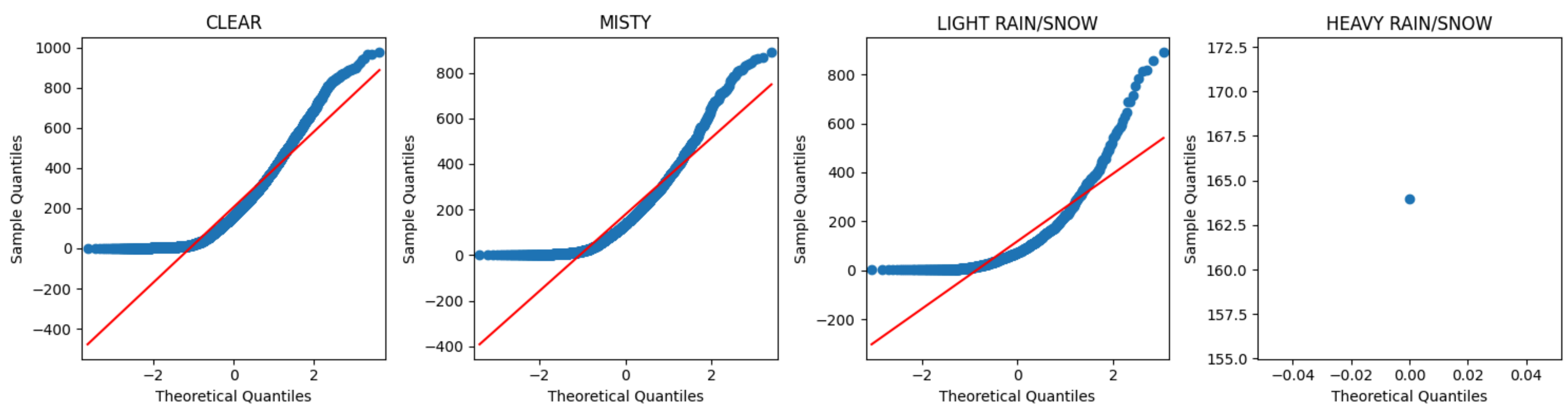
```
# Extract groups for each weather
groups_weather = [group['count'].values for name, group in df.groupby('weather')]
```

```
/tmp/ipython-input-2648311280.py:2: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future version o
  groups_weather = [group['count'].values for name, group in df.groupby('weather')]
```

```
# Check normality (Shapiro-Wilk test)
for i, group in enumerate(groups_weather):
    if len(group) >= 50:
        shapiro_weather = stats.shapiro(group)
        print(f"Shapiro-Wilk test p-value for weather group {i+1}: {shapiro_weather.pvalue}")
    else:
        print(f"Skipping Shapiro-Wilk test for weather group {i+1} due to small sample size ({len(group)}).")
```

```
Shapiro-Wilk test p-value for weather group 1: 1.5964921477006555e-57
Shapiro-Wilk test p-value for weather group 2: 9.777839106111785e-43
Shapiro-Wilk test p-value for weather group 3: 3.875893017396149e-33
Skipping Shapiro-Wilk test for weather group 4 due to small sample size (1).
/usr/local/lib/python3.12/dist-packages/scipy/stats/_axis_nan_policy.py:579: UserWarning: scipy.stats.shapiro: For N > 5000, computed p-value ma
  res = hypotest_fun_out(*samples, **kwds)
```

```
# QQ Plot
from statsmodels.graphics.gofplots import qqplot
fig,axis = plt.subplots(1,4,figsize=(15,4))
for i, group in enumerate(groups_weather):
    qqplot(group,line='s',ax=axis[i])
axis[0].set_title('CLEAR')
axis[1].set_title('MISTY')
axis[2].set_title('LIGHT RAIN/SNOW')
axis[3].set_title('HEAVY RAIN/SNOW')
plt.tight_layout()
plt.show()
```




```
# Check equal variances
levene_weather = stats.levene(*groups_weather)
print("Levene_statistic:",levene_weather[0])
print("Levene_pvalue:",levene_weather[1])
```

```
Levene_statistic: 54.85106195954556
Levene_pvalue: 3.504937946833238e-35
```

```
# Perform One-Way ANOVA
f_stat, p_val_anova = stats.f_oneway(*groups_weather)
```

```
print("f_statistic:", f_stat)
print("p_value:", p_val_anova)
```

```
f_statistic: 65.53024112793265
p_value: 5.482069475935669e-42
```

```
# Non-parametric alternative (Kruskal-Wallis)
h_stat, p_val_kw = stats.kruskal(*groups_weather)
print("h_statistic:", h_stat)
print("p_value:", p_val_kw)
```

```
h_statistic: 205.00216514479087
p_value: 3.501611300708679e-44
```

Interpretation of Test Results

- The p-value in **Levene's test** is extremely small (<< 0.05), so we reject the null hypothesis of equal variances across weather groups. This means the **variances** among the different weather groups are **significantly different**.
- The **ANOVA** shows a highly significant result, indicating that at least one weather group has a different mean count compared to others. This tells us **weather categories significantly affect bike rental counts**.
- Because Levene's test indicated unequal variances, the standard ANOVA test (which is based on equal variances' assumption) was interpreted in conjunction with the **Kruskal–Wallis Test (Non-parametric Alternative)** which provides a robust non-parametric alternative **that does not assume equal variances or normality**; it further confirms that the groups differ significantly in their distributions.

3. Difference in Rentals Across Seasons — ANOVA

Defining Hypotheses

H_0: Mean rental counts are the same across seasons.

H_1: At least one season differs.

Test Assumptions

- Normality of Data
- Homogeneity of Variances (Equal Variance Assumption)
- Independence of Observations
- No Significant Outliers

Hypothesis Testing

```
# Extract group for each season
groups_season = [group['count'].values for name, group in df.groupby('season')]
```

```
/tmp/ipython-input-3210807788.py:2: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future version o
  groups_season = [group['count'].values for name, group in df.groupby('season')]
```

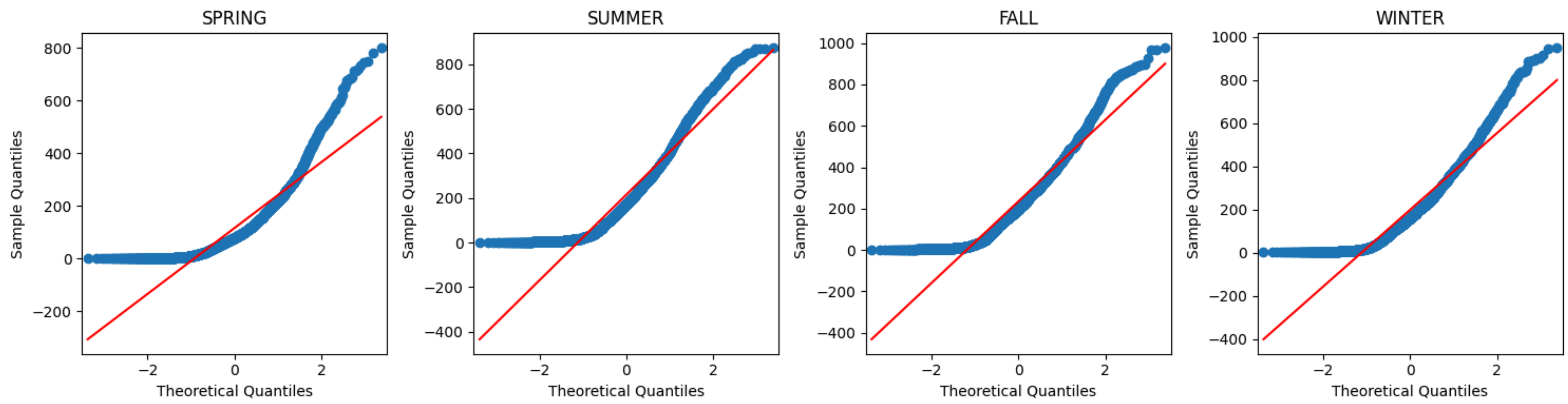
```
# Check normality (Shapiro-Wilk test)
for i, group in enumerate(groups_season):
    if len(group) >= 50:
        shapiro_season = stats.shapiro(group)
        print(f"Shapiro-Wilk test p-value for season group {i+1}: {shapiro_season.pvalue}")
```

```
Shapiro-Wilk test p-value for season group 1: 8.749584618867662e-49
Shapiro-Wilk test p-value for season group 2: 6.039374406270491e-39
Shapiro-Wilk test p-value for season group 3: 1.043680518918597e-36
Shapiro-Wilk test p-value for season group 4: 1.1299244409282836e-39
```

```
# Levene’s test for equal variances
levene_season = stats.levene(*groups_season)
print("Levene_statistic:",levene_season[0])
print("Levene_pvalue:",levene_season[1])
```

```
Levene_statistic: 187.7706624026276
Levene_pvalue: 1.0147116860043298e-118
```

```
# QQ Plot
from statsmodels.graphics.gofplots import qqplot
fig,axis = plt.subplots(1,4,figsize=(15,4))
for i, group in enumerate(groups_season):
    qqplot(group,line='s',ax=axis[i])
axis[0].set_title('SPRING')
axis[1].set_title('SUMMER')
axis[2].set_title('FALL')
axis[3].set_title('WINTER')
plt.tight_layout()
plt.show()
```




```
# ANOVA
f_stat_season, p_val_season = stats.f_oneway(*groups_season)
print("f_statistic:", f_stat_season)
print("p_value:", p_val_season)
```

```
f_statistic: 236.94671081032098
p_value: 6.164843386499654e-149
```

```
# Kruskal-Wallis
h_stat_season, p_val_kw_season = stats.kruskal(*groups_season)
print("h_statistic:", h_stat_season)
print("p_value:", p_val_kw_season)
```

```
h_statistic: 699.6668548181988
p_value: 2.479008372608633e-151
```

Interpretation of Test Results

- Both **ANOVA and Kruskal–Wallis** yielded $p \ll 0.05$, confirming **rental counts differ significantly across seasons**.
- Since variances were unequal [using **Levene's test**], we rely more on the Kruskal–Wallis test for robust inference.

4. Dependence Between Weather and Season — CHI-SQUARE TEST

Defining Hypotheses

H_0: Weather and season are independent.

H_1: Weather and season are dependent.

Test Assumptions

- Variables Should Be Categorical and Discrete
- Categories Must Be Mutually Exclusive
- Adequate Sample Size (>5)
- Observations Must Be Independent

Hypothesis Testing

```
# Create contingency table
contingency = pd.crosstab(df['season'], df['weather'])
print(contingency)
```

```
weather     1    2    3  4
season
1        1759  715  211  1
2        1801  708  224  0
3        1930  604  199  0
4        1702  807  225  0
```

```
# Perform Chi-square test of independence
chi2_stat, p_val_chi, dof, expected = stats.chi2_contingency(contingency)
```

```
Chi2_statistic: 49.158655596893624
p_value: 1.549925073686492e-07
```

Interpretation of Test Results

- Since $p < 0.05$, we reject H_0, thereby concluding that **weather and season are dependent**.

COMPREHENSIVE STATISTICAL CONCLUSIONS

1. There is **no statistically significant difference** in the number of cycles rented between **working and non-working days**. This implies that Yulu's **rental activity remains consistent** across weekdays and weekends, possibly due to **balanced demand** from both commuters and leisure users.
2. Rental activity **varies significantly with weather conditions**. Yulu rentals are likely **higher on clear or partly cloudy days** and **drop during adverse weather** such as rain or mist.
3. There is a highly **significant seasonal effect** on Yulu rentals. Rental demand is **highest during moderate or pleasant seasons** (e.g., spring or autumn) and **lower during extreme weather seasons** such as winter or heavy monsoon.
4. There is a **significant association between season and weather**, meaning weather patterns vary systematically with seasons (e.g., higher chances of rain in monsoon or clearer skies in summer).

BUSINESS TAKEAWAY & ACTIONABLE INSIGHTS

1. **Stable Demand Across Workdays and Weekends**: Since rental activity does not significantly differ between working and non-working days, Yulu can maintain a fairly consistent fleet distribution throughout the week.

- **Action**: Avoid drastic reallocation of cycles solely based on weekday/weekend differentiation. Instead, focus operational efforts on other demand drivers like weather and seasonality.

2. **Weather-Adaptive Fleet Management**: Rental counts fluctuate significantly with weather, with drops during adverse conditions like rain or mist. This suggests the need for dynamic, **weather-responsive resource planning**.

- **Action**: Develop **predictive models integrating weather forecasts** to preemptively adjust fleet size and distribution, ensuring bikes are concentrated in favorable weather locations and **minimizing operational costs during inclement weather**.

3. **Seasonal Demand Optimization**: The strong seasonal effect — higher rentals during pleasant seasons — indicates demand cycles throughout the year.

- **Action**: Plan marketing promotions, **seasonal discounts**, and maintenance schedules aligned with peak seasons (spring, autumn) to maximize utilization, and consider **cost control strategies during low-demand winter or monsoon periods**.

4. **Integrated Weather-Season Strategy**: The significant association between weather and season underscores the importance of combining these variables in demand forecasting. Certain weather patterns systematically align with seasons, influencing usage patterns.

- **Action**: Implement an integrated demand forecasting system incorporating both weather and seasonal trends to optimize fleet allocation, ensure availability where demand surges, and **reduce oversupply during off-peak weather-season combinations**.
