In [ ]:
```
import pandas as pd

url = "https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/original/bike_sharing.csv?1642089089"

# Read the data directly
df = pd.read_csv(url)

# Save it to a CSV file
df.to_csv("bike_sharing.csv", index=False)

print("✅ File saved as bike_sharing.csv")
```

```
✅ File saved as bike_sharing.csv
```

Problem Statement — Yulu Bike Sharing Case Study

About Yulu: Yulu is India's leading micro-mobility service provider that offers shared electric cycles for daily commuting. The company aims to reduce traffic congestion and pollution while promoting sustainable urban transportation.

Recently, Yulu has observed a decline in its revenues. To identify potential causes, the company wants to understand **which factors affect the demand for shared electric cycles** in the Indian market.

Objective / Goal

1. **Identify significant variables** that impact the demand (rental count) for Yulu bikes.
2. **Quantify how well** these variables explain variations in demand.
3. Use **statistical hypothesis testing** to validate relationships between variables.

Dataset Description

Column	Description
datetime	Date and time of observation
season	1: spring, 2: summer, 3: fall, 4: winter
holiday	Whether the day is a holiday or not
workingday	1 if it's a working day, 0 otherwise
weather	Weather condition (1–4 scale)
temp	Actual temperature (°C)
atemp	"Feeling" temperature (°C)
humidity	Percentage of humidity
windspeed	Wind speed
casual	Number of casual users
registered	Number of registered users
count	Total rental count (target variable)

Business Questions

1. Does the **working day** have an effect on the number of cycles rented?
   → (Use **Two-sample t-test**)

2. Are the **number of cycles rented** similar or different across **seasons**?
   → (Use **One-way ANOVA test**)

3. Are the **number of cycles rented** similar or different across **weather conditions**?
   → (Use **One-way ANOVA test**)

4. Is **weather dependent on season**?
   → (Use **Chi-square test of independence**)

Expected Outcomes

- Identify which factors significantly affect bike demand.
- Generate actionable insights for Yulu to improve utilization and revenue.
- Develop statistical reasoning and support data-driven decision-making.

Concepts Used

- Bi-variate Analysis
- 2-Sample t-Test
- ANOVA
- Chi-square Test

Data Import & EDA Setup

Step 2: Data Import & Exploratory Data Analysis (EDA)

In this section, we will:

- Import the dataset into Python using **pandas**
- Check the structure, shape, and data types of all variables
- Detect missing values, if any
- Get an overview of the data using `.info()` and `.describe()`
- Convert categorical variables (like season, weather, workingday) into category type (if required)

This is the first step to understand how the data looks before we perform hypothesis testing.

In [ ]:

```
# Import important libraries
import pandas as pd
```

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# To show plots inside notebook
%matplotlib inline

# Load the dataset from URL
url = "https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/428/original/bike_sharing.csv?1642089089"
df = pd.read_csv(url)

# Display first few rows
df.head()
```

Out[ ]:

	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

In [ ]:

```
# Shape of dataset
print("Shape of dataset:", df.shape)

# Column data types and non-null counts
print("\nDataset Information:")
df.info()

# Statistical summary for numerical columns
print("\nSummary Statistics:")
df.describe().T
```

```
Shape of dataset: (10886, 12)

Dataset Information:
<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

Summary Statistics:
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
season	10886.0	2.506614	1.116174	1.00	2.0000	3.000	4.0000	4.0000
holiday	10886.0	0.028569	0.166599	0.00	0.0000	0.000	0.0000	1.0000
workingday	10886.0	0.680875	0.466159	0.00	0.0000	1.000	1.0000	1.0000
weather	10886.0	1.418427	0.633839	1.00	1.0000	1.000	2.0000	4.0000
temp	10886.0	20.230860	7.791590	0.82	13.9400	20.500	26.2400	41.0000
atemp	10886.0	23.655084	8.474601	0.76	16.6650	24.240	31.0600	45.4550
humidity	10886.0	61.886460	19.245033	0.00	47.0000	62.000	77.0000	100.0000
windspeed	10886.0	12.799395	8.164537	0.00	7.0015	12.998	16.9979	56.9969
casual	10886.0	36.021955	49.960477	0.00	4.0000	17.000	49.0000	367.0000
registered	10886.0	155.552177	151.039033	0.00	36.0000	118.000	222.0000	886.0000
count	10886.0	191.574132	181.144454	1.00	42.0000	145.000	284.0000	977.0000

In [ ]:

```
# Check for missing values
print("\nMissing Values in Each Column:")
print(df.isnull().sum())
```

```
Missing Values in Each Column:
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
```

In [ ]:

```python
# Convert categorical columns to category dtype
categorical_cols = ['season', 'holiday', 'workingday', 'weather']
for col in categorical_cols:
    df[col] = df[col].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
```

Quick Summary of EDA Output

- The dataset has **10,886 rows and 12 columns**, containing both **categorical** and **numerical** variables.
- There are **no missing values**, and all columns are complete.
- Categorical variables include `season`, `holiday`, `workingday`, and `weather`.
- Numerical variables such as `temp`, `humidity`, and `count` show reasonable ranges and variation, indicating good data quality for analysis.

Step 3: Univariate Analysis (distribution of numerical & categorical variables)

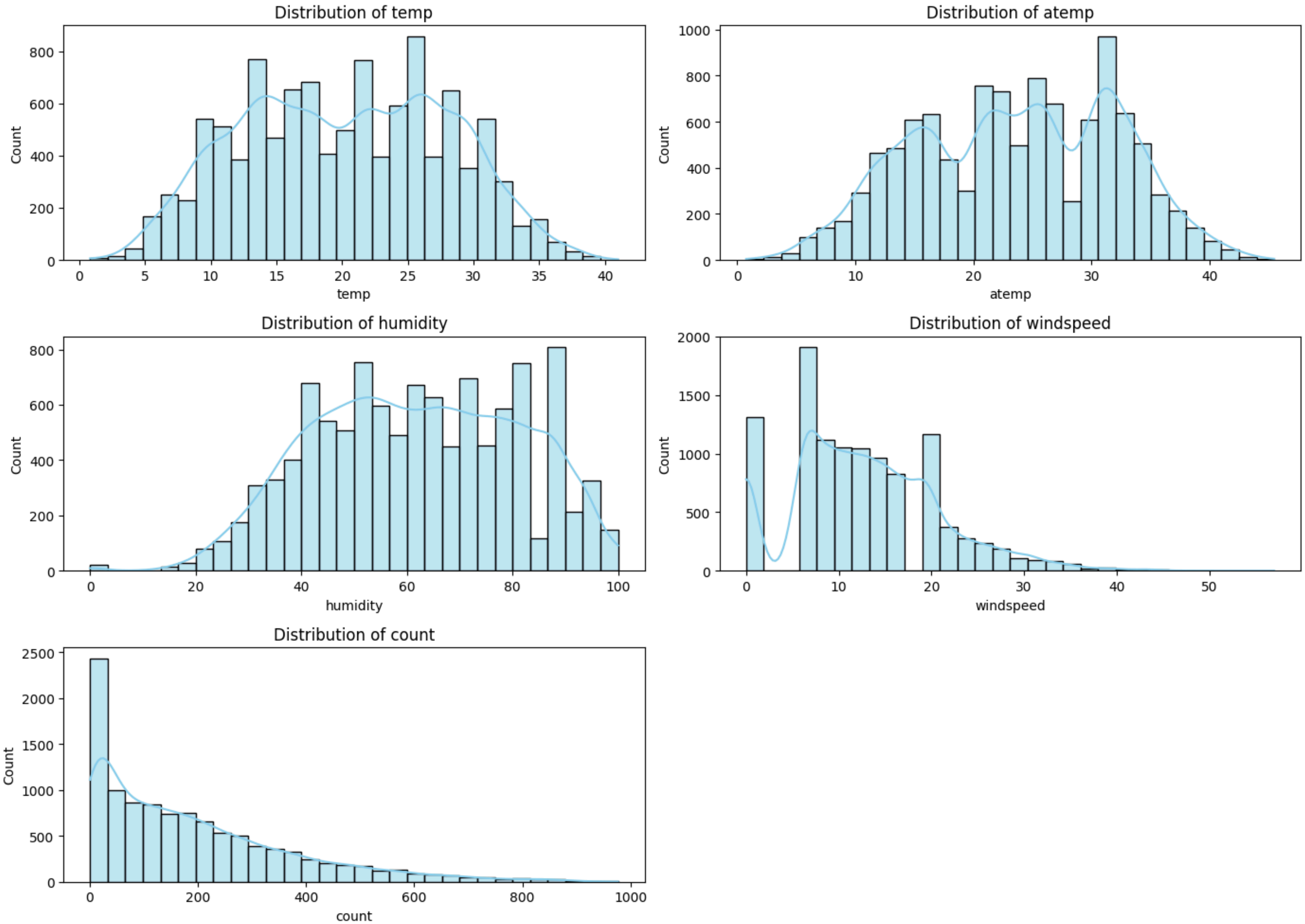
Step 3.1 — Univariate Analysis

Step 3.1: Univariate Analysis

In this step, we explore **each variable individually** to understand its distribution, range, and possible outliers.

- For **numerical variables**, we'll use histograms with density curves.
- For **categorical variables**, we'll use count plots (bar plots).
- We'll also interpret what each graph tells us about the data.

In [ ]:
```
# Continuous variables
num_cols = ['temp', 'atemp', 'humidity', 'windspeed', 'count']

plt.figure(figsize=(14, 10))
for i, col in enumerate(num_cols, 1):
    plt.subplot(3, 2, i)
    sns.histplot(df[col], kde=True, bins=30, color='skyblue')
    plt.title(f"Distribution of {col}")
plt.tight_layout()
plt.show()
```


Distribution of temp
Count
800
600
400
200
0
0 5 10 15 20 25 30 35 40
temp
Distribution of atemp
Count
1000
800
600
400
200
0
0 10 20 30 40
atemp
Distribution of humidity
Count
800
600
400
200
0
0 20 40 60 80 100
humidity
Distribution of windspeed
Count
2000
1500
1000
500
0
0 10 20 30 40 50
windspeed
Distribution of count
Count
2500
2000
1500
1000
500
0
0 200 400 600 800 1000
count

Observations — Continuous Variables

- **Temperature (temp)** and **Feeling Temperature (atemp)** both show roughly bell-shaped distributions (slightly right-skewed).
  → Most bike rides occur in pleasant weather between **15–30 °C**.

- **Humidity** is spread between **40–80 %**, showing moderate variation.
  → Extremely humid or very dry conditions are rare.

- **Windspeed** is highly right-skewed — most rides happen when the windspeed is low.
  → High windspeed days are uncommon and likely reduce bike usage.

- **Count (Total Rentals)** is strongly right-skewed — most hours have fewer rentals, with a few high-demand spikes.
  → Suggests that peak rentals occur only during specific times (like office rush hours).

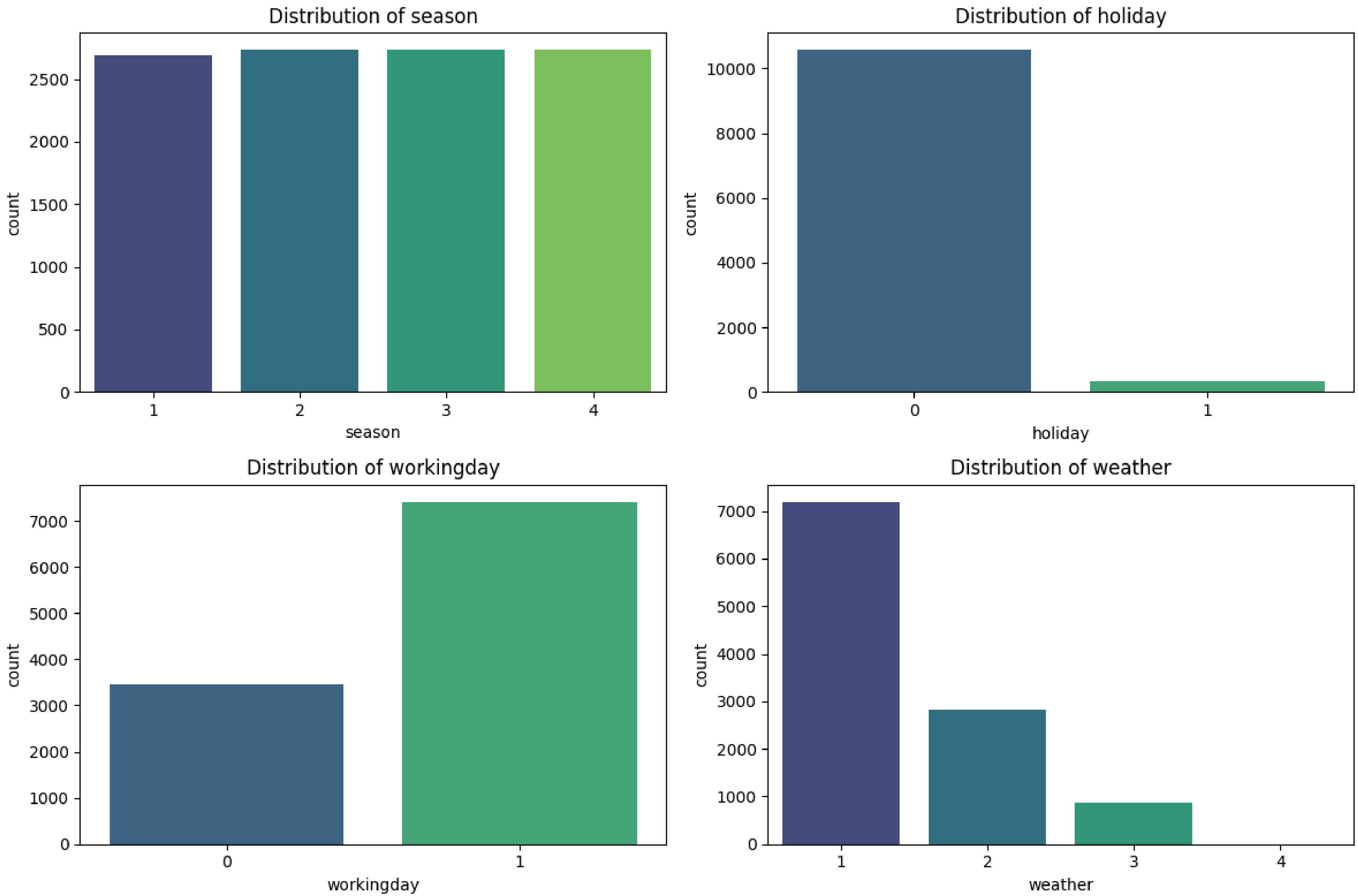
Overall, the continuous variables show reasonable variation and no extreme outliers.
Next, we'll visualize **categorical variables** such as season, weather, and workingday.

Step 3.2 — Categorical Variables

In [ ]:

```
# Categorical variables
cat_cols = ['season', 'holiday', 'workingday', 'weather']

plt.figure(figsize=(12, 8))
for i, col in enumerate(cat_cols, 1):
    plt.subplot(2, 2, i)
    sns.countplot(x=col, data=df, palette='viridis')
    plt.title(f"Distribution of {col}")
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-2380889129.py:7: FutureWarning: 

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se
t `legend=False` for the same effect.

  sns.countplot(x=col, data=df, palette='viridis')
/tmp/ipython-input-2380889129.py:7: FutureWarning: 

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se
t `legend=False` for the same effect.

  sns.countplot(x=col, data=df, palette='viridis')
/tmp/ipython-input-2380889129.py:7: FutureWarning: 

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se
t `legend=False` for the same effect.

  sns.countplot(x=col, data=df, palette='viridis')
/tmp/ipython-input-2380889129.py:7: FutureWarning: 

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se
t `legend=False` for the same effect.

  sns.countplot(x=col, data=df, palette='viridis')
```



Observations — Categorical Variables

- **Season:**
  Data is evenly distributed across all four seasons (Spring, Summer, Fall, Winter).
  → This means the dataset represents all seasons fairly well, ensuring balanced analysis.

- **Holiday:**
  Very few holidays are recorded — most days are **non-holidays**.
  → This indicates most rentals happen on regular working days.

- **Workingday:**
  Around **68% of days are working days (1)** and 32% are weekends or holidays (0).
  → Suggests Yulu bike demand is likely higher during weekdays (commuting pattern).

- **Weather:**
  Most rides occur when the weather is **clear or partly cloudy (weather = 1)**.
  → Very few rides in bad weather (rain, snow, or mist).
  → This shows that people avoid riding in poor weather conditions.

No category imbalance — all categorical features are properly represented,
and the data seems realistic and ready for deeper relationship analysis.

Step 4: Bivariate Analysis

Step 4: Bivariate Analysis

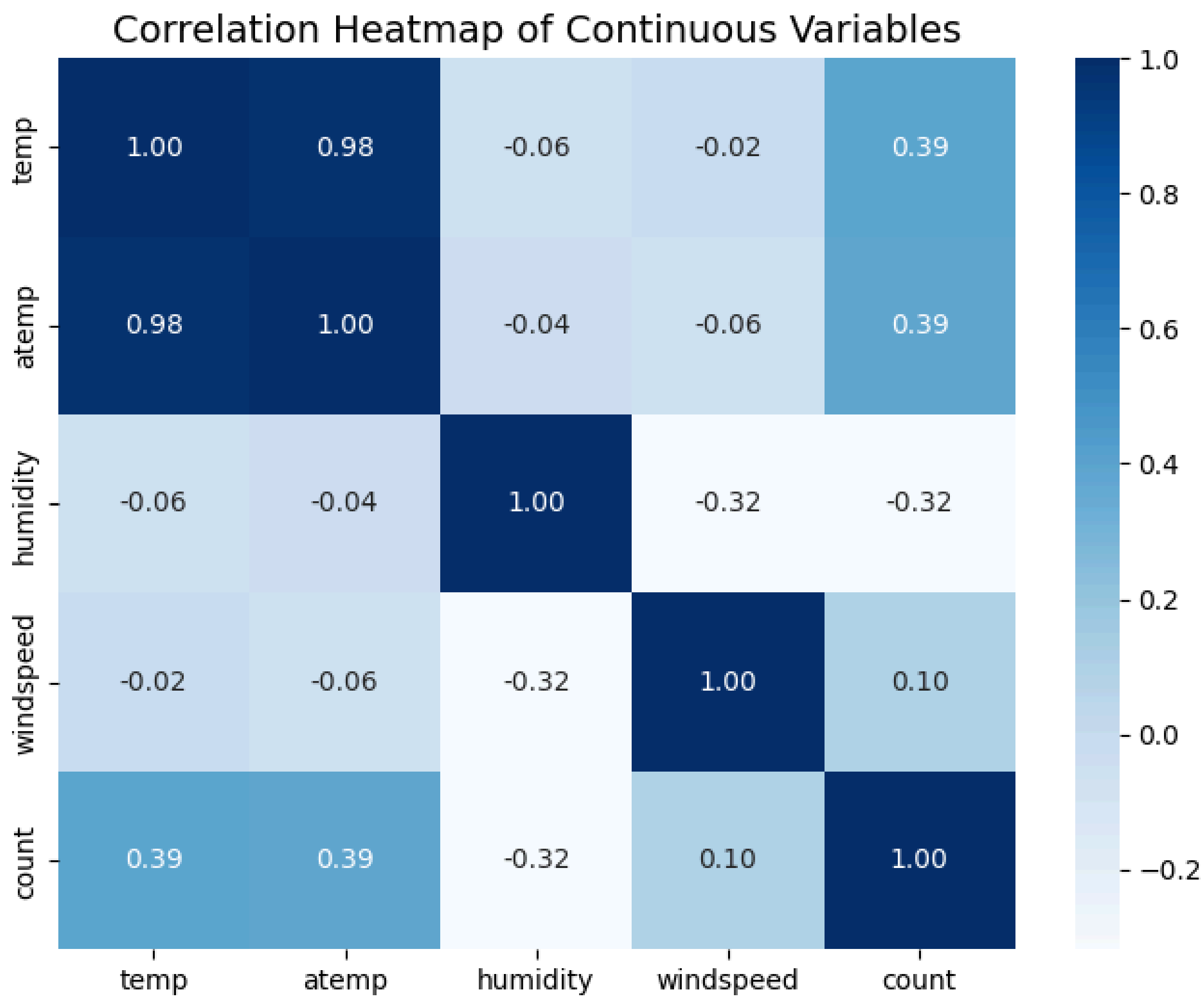
In this step, we study the **relationship between two variables** —
especially how different factors (like workingday, weather, season) affect the demand (`count`) of Yulu bikes.

We'll use:

- **Boxplots** → to compare distributions across groups
- **Correlation heatmaps** → to see linear relationships between numerical variables

Step 4.1 — Relationship Between Continuous Variables

In [ ]:
```
# Continuous variables vs target
num_cols = ['temp', 'atemp', 'humidity', 'windspeed', 'count']

# Correlation heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(df[num_cols].corr(), annot=True, cmap="Blues", fmt=".2f")
plt.title("Correlation Heatmap of Continuous Variables", fontsize=14)
plt.show()
```



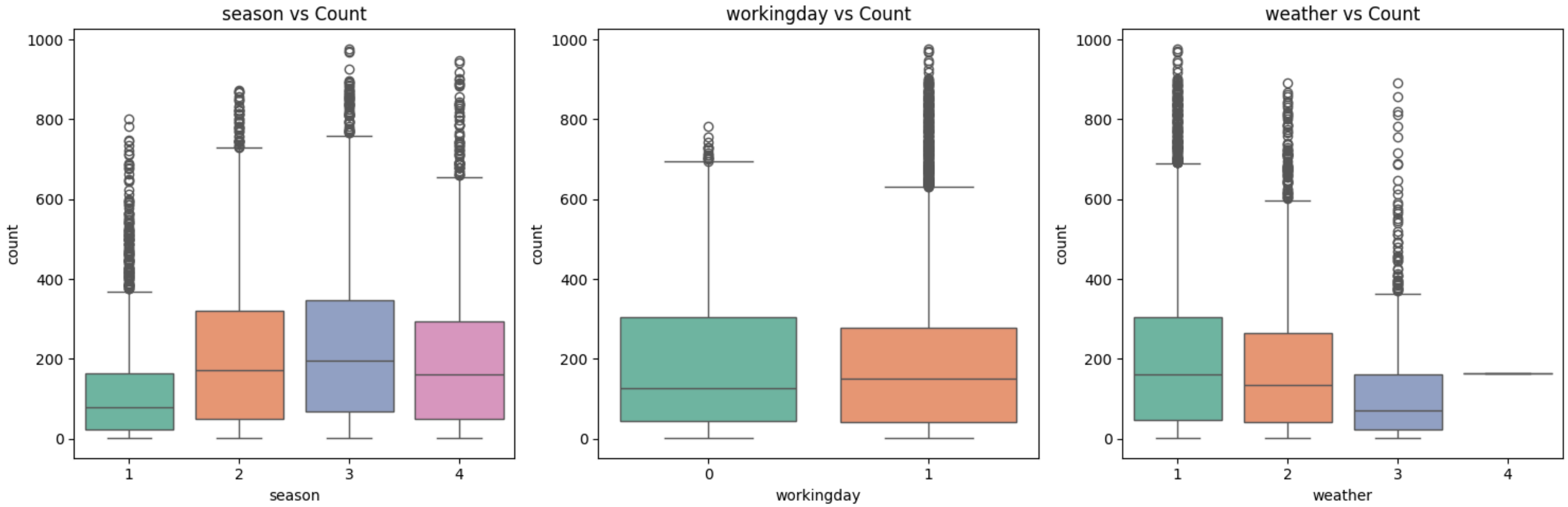
Observation

Temperature (`temp` and `atemp`) shows a **strong positive correlation (0.39)** with bike demand (`count`), while **humidity (-0.32)** has a weak negative effect and **windspeed (0.10)** has almost no impact on rentals.

Step 4.2 — Relationship Between Categorical Variables and Target

In [ ]:
```python
# List of categorical columns
cat_cols = ['season', 'workingday', 'weather']

plt.figure(figsize=(15, 5))
for i, col in enumerate(cat_cols, 1):
    plt.subplot(1, 3, i)
    sns.boxplot(x=col, y='count', data=df, palette='Set2')
    plt.title(f"{col} vs Count")
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-2112721803.py:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se
t `legend=False` for the same effect.

  sns.boxplot(x=col, y='count', data=df, palette='Set2')
/tmp/ipython-input-2112721803.py:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se
t `legend=False` for the same effect.

  sns.boxplot(x=col, y='count', data=df, palette='Set2')
/tmp/ipython-input-2112721803.py:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and se
t `legend=False` for the same effect.

  sns.boxplot(x=col, y='count', data=df, palette='Set2')
```



Observation

- **Season:** Rentals are highest in **summer (2)** and **fall (3)**, showing that warm weather increases bike demand.
- **Workingday:** Slightly more bikes are rented on **working days (1)** than on weekends (0).
- **Weather:** Clear weather (1) shows the **highest rentals**, while rainy/snowy weather (3, 4) drastically reduces usage.

Step 4.3 — Summary of Bivariate Analysis

- The number of bikes rented (`count`) increases with **temperature** and decreases slightly with **humidity**.
- **Windspeed** has very little impact on bike demand.
- **Season:** Summer and Fall show the highest demand, while Winter is relatively low.
- **Workingday:** More rentals are seen on working days, indicating office commute influence.
- **Weather:** Clear weather encourages the most rides; poor weather significantly reduces demand.

Overall Insight: Yulu bike demand is strongly affected by **weather conditions** and **working schedules** — people rent more on clear, pleasant working days.

Step 5: Hypothesis Testing

Step 5.1 — Two-Sample T-Test

Q1: “Does the number of electric cycles rented differ on working days vs non-working days?”

Null Hypothesis (H_0) There is no difference in mean rentals between working and non-working days.

Alternate Hypothesis (H_1) There is a difference in mean rentals between working and non-working days.

In [ ]:
```
from scipy.stats import ttest_ind

# Split data
workingday_count = df[df['workingday'] == 1]['count']
nonworkingday_count = df[df['workingday'] == 0]['count']

# Perform independent 2-sample t-test
t_stat, p_val = ttest_ind(workingday_count, nonworkingday_count, equal_var=False)

print("T-statistic:", t_stat)
print("P-value:", p_val)
```

```
T-statistic: 1.2362580418223226
P-value: 0.21640312280695098
```

T-Test Result Interpretation

- T-statistic = 1.236, P-value = 0.216 (> 0.05)
- We **fail to reject the null hypothesis (H_0)**.
- This means there is **no significant difference** in the number of bikes rented between working and non-working days.
- In other words, **people rent bikes equally on both types of days**.

Step 5.2 — ANOVA test

We'll check if the average number of bikes rented (count) is significantly different across different seasons or weather conditions.

Q: "Does the number of bikes rented differ across different seasons?"

H_0 (Null) Mean bike rentals are same across all seasons

H_1 (Alternate) Mean bike rentals are different for at least one season

In [ ]:
```
from scipy.stats import f_oneway

# Divide rentals by seasons
season1 = df[df['season'] == 1]['count']
season2 = df[df['season'] == 2]['count']
season3 = df[df['season'] == 3]['count']
season4 = df[df['season'] == 4]['count']

# Perform ANOVA test
F_stat, p_val = f_oneway(season1, season2, season3, season4)

print("F-statistic:", F_stat)
print("P-value:", p_val)
```

```
F-statistic: 236.94671081032098
P-value: 6.164843386499654e-149
```

ANOVA Test – Season vs Count

- F-statistic = 236.94
- P-value = 6.16e-149 (< 0.05)

Decision: Reject Null Hypothesis (H_0)
→ There is a **significant difference** in bike rentals across different seasons.

Conclusion:
Season has a strong influence on demand —
people rent more Yulu bikes in **summer and fall**, and less in **winter**.

Q: “Does the number of bikes rented differ across different weather conditions?”

In [ ]:
```
# Divide rentals by weather conditions
w1 = df[df['weather'] == 1]['count']
w2 = df[df['weather'] == 2]['count']
w3 = df[df['weather'] == 3]['count']

# Perform ANOVA test
F_stat_weather, p_val_weather = f_oneway(w1, w2, w3)

print("F-statistic (Weather):", F_stat_weather)
print("P-value (Weather):", p_val_weather)
```

```
F-statistic (Weather): 98.28356881946705
P-value (Weather): 4.976448509904196e-43
```

ANOVA Test – Weather vs Count

- F-statistic = 98.28
- P-value = 4.97e-43 (< 0.05)

Decision: Reject Null Hypothesis (H_0)
→ There is a **significant difference** in bike rentals across different weather conditions.

Conclusion:
Weather strongly impacts Yulu bike demand —
rentals are **highest on clear days** and **drop significantly** during rainy or cloudy weather.

Step 5.3 — Chi-Square Test of Independence

Q: “Is weather dependent on season?”

We use Chi-square when both variables are categorical, like:

Weather types (1 = Clear, 2 = Mist, 3 = Rainy)

Seasons (1 = Spring, 2 = Summer, 3 = Fall, 4 = Winter)

H_0 (Null Hypothesis) Weather and season are independent (no relationship).

H_1 (Alternate Hypothesis) Weather and season are dependent (related).

In [ ]:
```
from scipy.stats import chi2_contingency

# Create a cross-tabulation table
contingency_table = pd.crosstab(df['season'], df['weather'])
print("Contingency Table:\n", contingency_table)

# Perform chi-square test
chi2, p, dof, expected = chi2_contingency(contingency_table)

print("\nChi-square value:", chi2)
print("Degrees of Freedom:", dof)
print("P-value:", p)
```

```
Contingency Table:
 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

Chi-square value: 49.158655596893624
Degrees of Freedom: 9
P-value: 1.549925073686492e-07
```

Chi-Square Test – Weather vs Season

- Chi-square value = 49.16
- Degrees of Freedom = 9
- P-value = 1.55e-07 (< 0.05)

Decision: Reject Null Hypothesis (H_0)
→ There is a **significant relationship** between weather and season.

Conclusion:
Weather patterns depend on seasons — for example, clear weather occurs more often in summer,
while mist or rain occurs more in other seasons.
Hence, **seasonal changes influence weather conditions**.

Step 6 — Final Conclusions & Recommendations

Objective Recap

The goal of this analysis was to understand **which factors affect the demand** for Yulu shared electric cycles and how well they explain the variation in usage (`count`).

We explored the dataset through EDA and performed statistical hypothesis testing (T-test, ANOVA, Chi-square) to validate our insights.

Summary of Statistical Tests

Test	Variables Compared	p-value	Decision	Insight
Two-Sample T-test	Workingday vs Count	0.216 (>0.05)	Fail to Reject H_0	Rentals are statistically similar on working and non-working days.
ANOVA (1)	Season vs Count	6.16e-149 (<0.05)	Reject H_0	Bike demand differs significantly across seasons.
ANOVA (2)	Weather vs Count	4.97e-43 (<0.05)	Reject H_0	Weather conditions significantly impact rentals.
Chi-Square	Weather vs Season	1.55e-07 (<0.05)	Reject H_0	Weather is dependent on season.

Key Insights from the Analysis

1. **Seasonal Impact:**
   Bike demand changes with season — highest during **Summer and Fall**, lowest in **Winter**.

2. **Weather Influence:**
   Rentals peak on **clear weather days** and drop sharply on **rainy or misty days**.

3. **Working Days:**
   Although not statistically significant, working days show **slightly higher rentals**, likely due to office commute.

4. **Temperature:**
   Pleasant temperatures (15–30°C) are linked with higher rentals.

5. **Humidity & Windspeed:**
   High humidity or strong wind discourages rentals — moderate values are optimal.

Business Recommendations for Yulu

1. **Seasonal Pricing Strategy:**
   Offer discounts or promotions in low-demand seasons (e.g., Winter) to balance usage.

2. **Weather-based Demand Forecasting:**
   Integrate weather prediction models to anticipate dips in rentals during bad weather.

3. **Optimize Fleet Placement:**
   During Summer/Fall, allocate more bikes to high-demand zones (office areas, metro stations).

4. **Awareness Campaigns:**
   Promote Yulu bikes as a convenient commuting option on working days and weekends.

5. **Predictive Modeling (Future Work):**
   Use regression or ML models to predict demand and plan dynamic pricing.

Final Conclusion

- **Season and weather** are the most significant factors affecting Yulu's bike demand.
- Rentals are **highest on clear, warm days** and **lowest during poor weather or cold seasons**.
- These insights can help Yulu optimize pricing, marketing, and fleet deployment to **maximize utilization and revenue**.

In summary:

> "Yulu's bike demand is weather- and season-driven. Understanding these patterns enables data-driven decisions for smarter operations."