yulu-case-study-1

May 31, 2024

1 PROBLEM STATEMENT

Understand the factors affecting the demand for these shared electric cycles in the Indian market.

The company wants to know:

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

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
```

[2]:
```
csv_path = "yulu_data.csv"
df = pd.read_csv(csv_path, delimiter=",")
df.head()
```

[2]:
```
              datetime  season  holiday  workingday  weather  temp   atemp  \
0  2011-01-01 00:00:00       1        0           0        1  9.84  14.395
1  2011-01-01 01:00:00       1        0           0        1  9.02  13.635
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
```

[3]:
```
df.shape
```

[3]: (10886, 12)

[4]:
```
# Convert columns to appropriate data types for EDA

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

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

[5]:
```
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  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
```

[6]:
```
df.drop(columns=df.columns[0]).describe(include='all')
```

[6]:
```
         season   holiday  workingday  weather         temp         atemp  \
count   10886.0   10886.0     10886.0  10886.0  10886.00000  10886.000000
unique      4.0       2.0         2.0      4.0          NaN           NaN
top         4.0       0.0         1.0      1.0          NaN           NaN
freq     2734.0   10575.0      7412.0   7192.0          NaN           NaN
mean        NaN       NaN         NaN      NaN     20.23086     23.655084
std         NaN       NaN         NaN      NaN      7.79159      8.474601
min         NaN       NaN         NaN      NaN      0.82000      0.760000
25%         NaN       NaN         NaN      NaN     13.94000     16.665000
50%         NaN       NaN         NaN      NaN     20.50000     24.240000
75%         NaN       NaN         NaN      NaN     26.24000     31.060000
max         NaN       NaN         NaN      NaN     41.00000     45.455000

            humidity     windspeed        casual    registered         count
count   10886.000000  10886.000000  10886.000000  10886.000000  10886.000000
```

```
unique           NaN          NaN          NaN          NaN          NaN
top              NaN          NaN          NaN          NaN          NaN
freq             NaN          NaN          NaN          NaN          NaN
mean       61.886460    12.799395    36.021955   155.552177   191.574132
std        19.245033     8.164537    49.960477   151.039033   181.144454
min         0.000000     0.000000     0.000000     0.000000     1.000000
25%        47.000000     7.001500     4.000000    36.000000    42.000000
50%        62.000000    12.998000    17.000000   118.000000   145.000000
75%        77.000000    16.997900    49.000000   222.000000   284.000000
max       100.000000    56.996900   367.000000   886.000000   977.000000
```

[7]:
```python
# detecting missing values in the dataset
df.isnull().sum()
```

[7]:
```
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
```

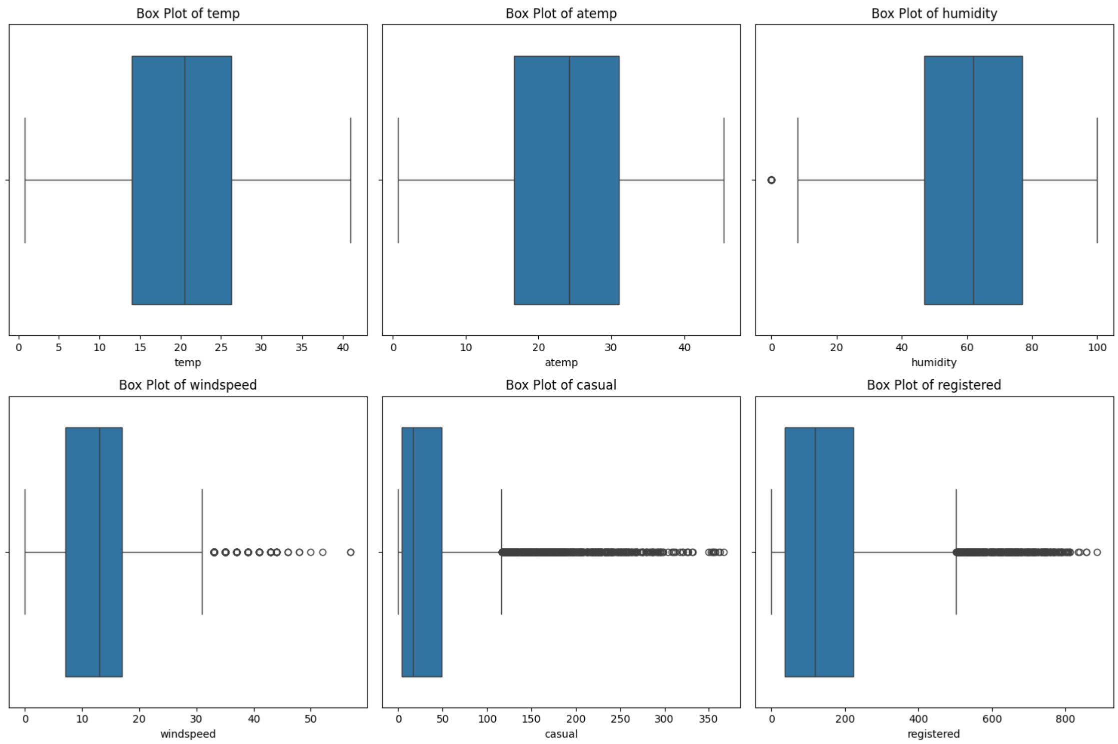
[8]:
```python
min_datetime = df['datetime'].min()
max_datetime = df['datetime'].max()
print("Minimum datetime:", min_datetime)
print("Maximum datetime:", max_datetime)

# Number of unique values in each categorical column
categorical_columns = ['season', 'holiday', 'workingday', 'weather']
for col in categorical_columns:
    print(f"\nColumn: {col}")
    print(df[col].value_counts())
```

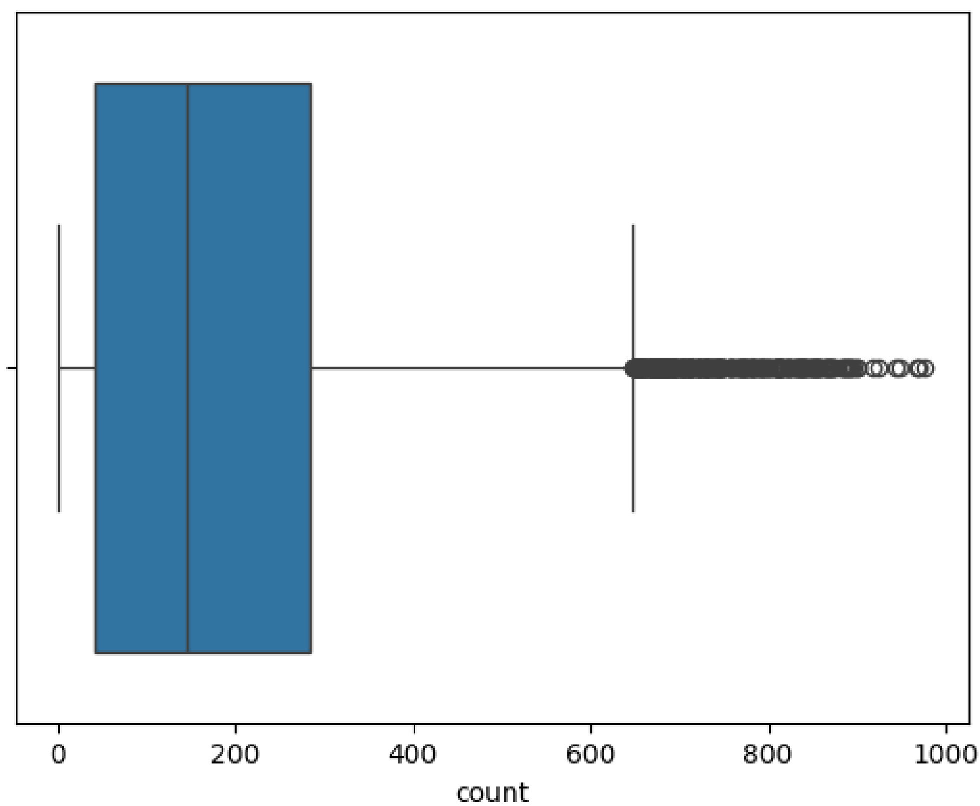
```
Minimum datetime: 2011-01-01 00:00:00
Maximum datetime: 2012-12-19 23:00:00

Column: season
season
4    2734
2    2733
3    2733
```

```
1    2686
Name: count, dtype: int64

Column: holiday
holiday
0    10575
1      311
Name: count, dtype: int64

Column: workingday
workingday
1    7412
0    3474
Name: count, dtype: int64

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

[9]:

```
# Define numerical columns
numerical_columns = ['temp', 'atemp', 'humidity', 'windspeed', 'casual',␣
 ↪'registered', 'count']

# Create a 3x3 grid for box plots
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(15, 10))

# Flatten axes for easy iteration
axes = axes.flatten()

# Plot box plots for each numerical column
for ax, col in zip(axes, numerical_columns[:-1]):
    sns.boxplot(x=df[col], ax=ax)
    ax.set_title(f'Box Plot of {col}')

# Show the figure
plt.tight_layout()
plt.show()

sns.boxplot(x=df[numerical_columns[-1]])
plt.show()
```

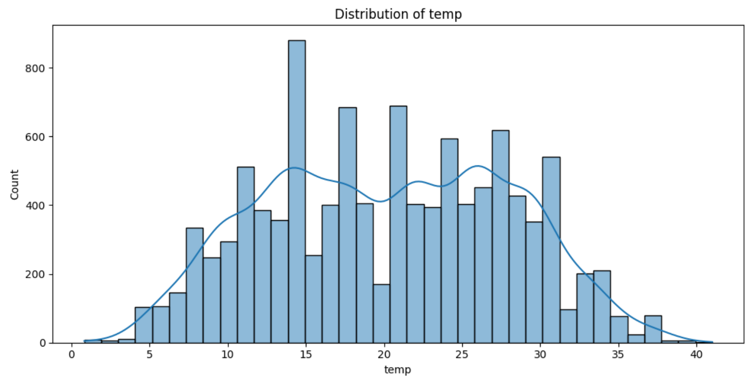

Box Plot of temp
temp
Box Plot of atemp
atemp
Box Plot of humidity
humidity
Box Plot of windspeed
windspeed
Box Plot of casual
casual
Box Plot of registered
registered

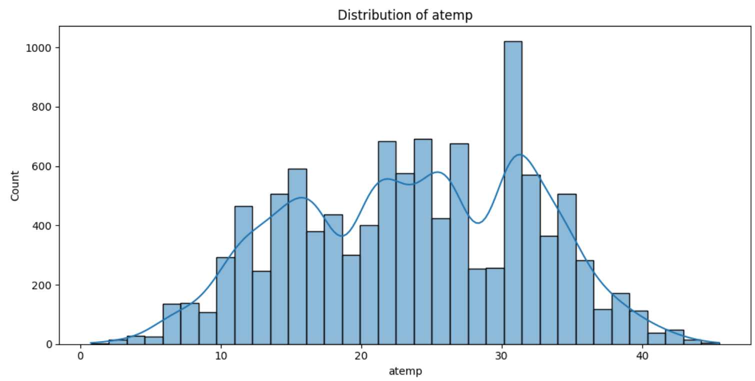

count

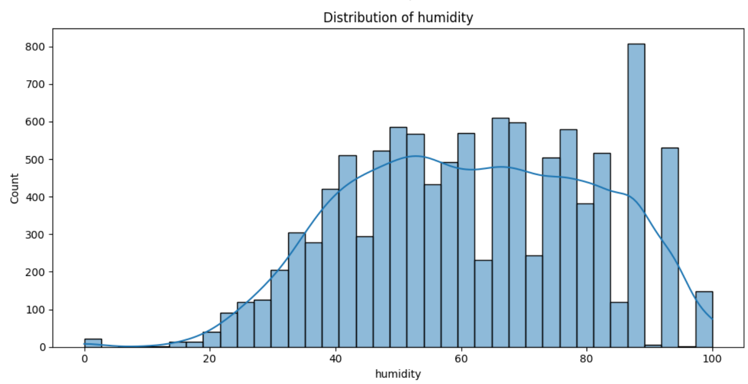
[10]:
```python
# Define a function to calculate outliers using IQR
def detect_outliers_iqr(df, col):
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = df[(df[col] < lower_bound) | (df[col] > upper_bound)]
    return outliers

# Identify outliers in 'casual' and 'registered' columns
casual_outliers = detect_outliers_iqr(df, 'casual')
registered_outliers = detect_outliers_iqr(df, 'registered')
count_outliers = detect_outliers_iqr(df, 'count')

print(f"Number of outliers in 'casual': {len(casual_outliers)}")
print(f"Number of outliers in 'registered': {len(registered_outliers)}")
print(f"Number of outliers in 'count': {len(count_outliers)}")
```

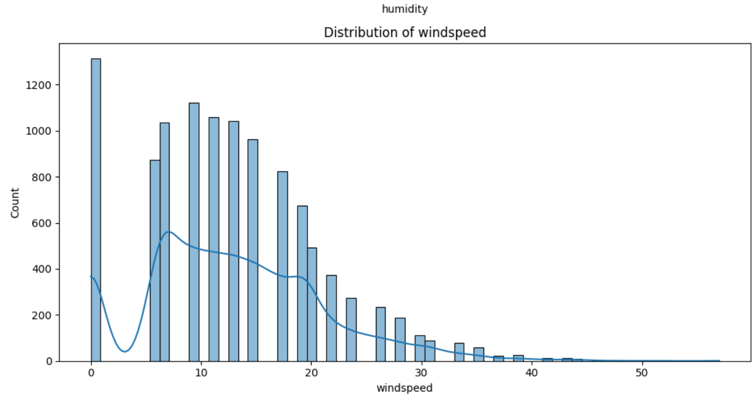
```
Number of outliers in 'casual': 749
Number of outliers in 'registered': 423
Number of outliers in 'count': 300
```

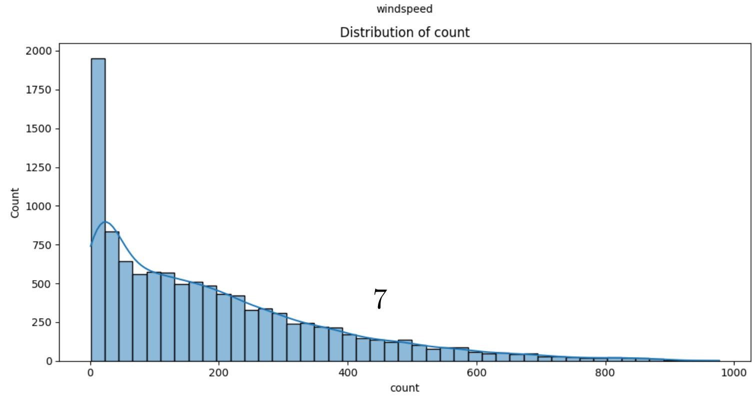
[11]:
```python
continuous_vars = ['temp', 'atemp', 'humidity', 'windspeed', 'count']

fig, axes = plt.subplots(len(continuous_vars), 1, figsize=(10, 25))
for i, var in enumerate(continuous_vars):
    sns.histplot(df[var], kde=True, ax=axes[i])
    axes[i].set_title(f'Distribution of {var}')
plt.tight_layout()
plt.show()
```


Distribution of temp
Count
temp


Distribution of atemp
Count
atemp


Distribution of humidity
Count
humidity


Distribution of windspeed
Count
windspeed


Distribution of count
Count
count

[12]:
```
for var in continuous_vars:
    skewness = df[var].skew()
    mean = df[var].mean()
    median = df[var].median()
    print(f'{var}: Skewness={skewness}, Mean={mean}, Median={median}')
```

```
temp: Skewness=0.003690844422472008, Mean=20.23085981995223, Median=20.5
atemp: Skewness=-0.10255951346908665, Mean=23.655084052912, Median=24.24
humidity: Skewness=-0.08633518364548581, Mean=61.88645967297446, Median=62.0
windspeed: Skewness=0.5887665265853944, Mean=12.7993954069447, Median=12.998
count: Skewness=1.2420662117180776, Mean=191.57413191254824, Median=145.0
```

TEMP

- The skewness is very close to 0, indicating an almost perfectly symmetric distribution. The mean and median are also very close, further confirming a near-normal distribution.

ATEMP

- The skewness is slightly negative, close to 0, indicating a nearly symmetric distribution. The mean and median are also very close, indicating an almost normal distribution with a slight left skew.

COMMENT

- The distributions are fairly uniform, indicating a wide range of recorded temperatures. Both variables show a fairly normal distribution with slight skewness.

HUMIDITY

- The skewness is slightly negative, close to 0, indicating a nearly symmetric distribution. The mean and median are also very close, indicating an almost normal distribution with a slight left skew.

COMMENT

- The distribution shows a peak around 50-70%, which is expected in many climates. There are few instances of very low humidity and very high humidity.

WINDSPEED

- The windspeed data shows a noticeable right skew, with more values concentrated on the lower end and a few higher values extending the tail to the right. This is supported by the positive skewness value.

COMMENT

- High wind speeds are less frequent.

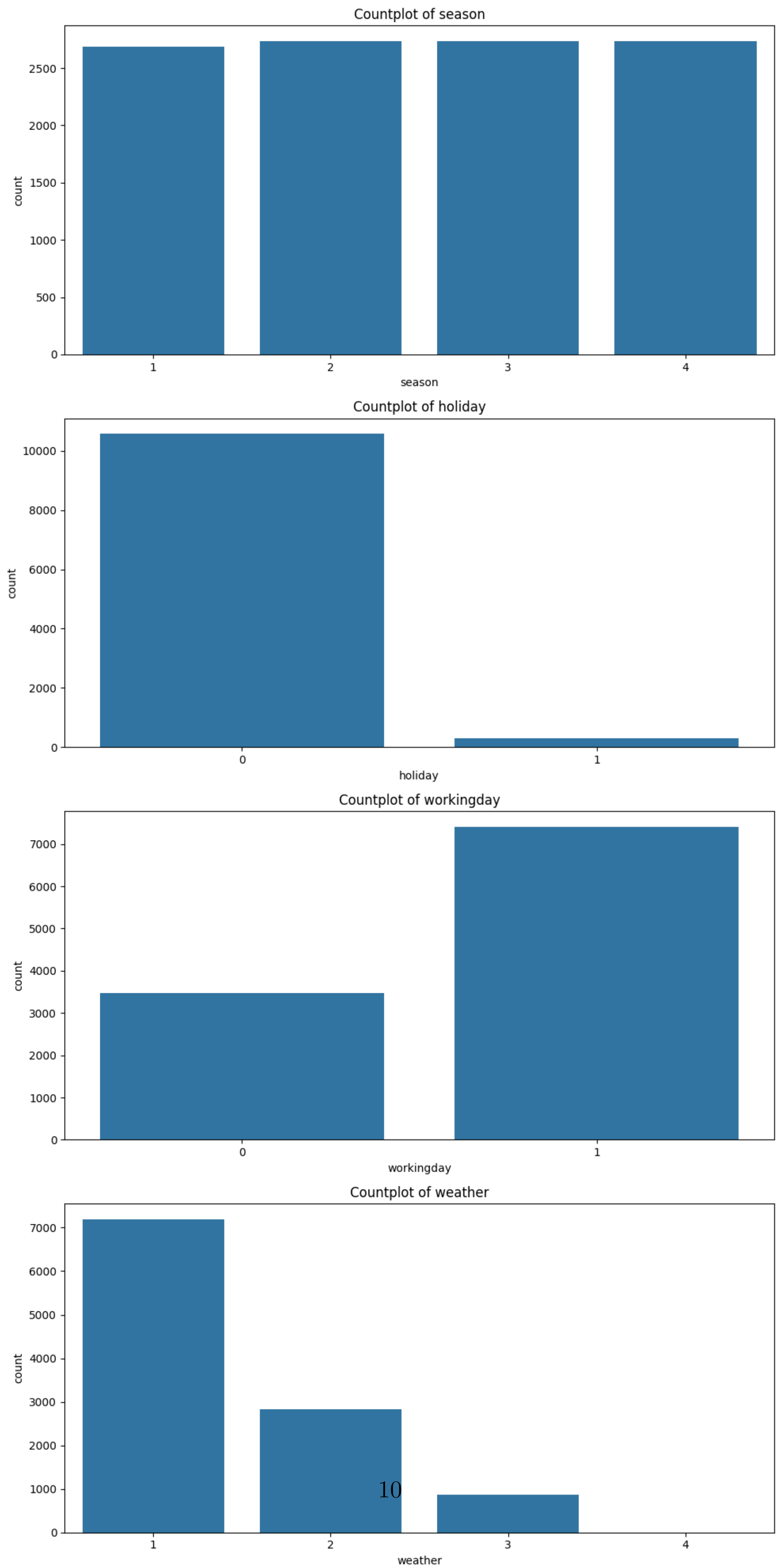
COUNT

- The count distribution is right-skewed, indicating that most rental counts are lower, with fewer instances of very high rentals.

COMMENT

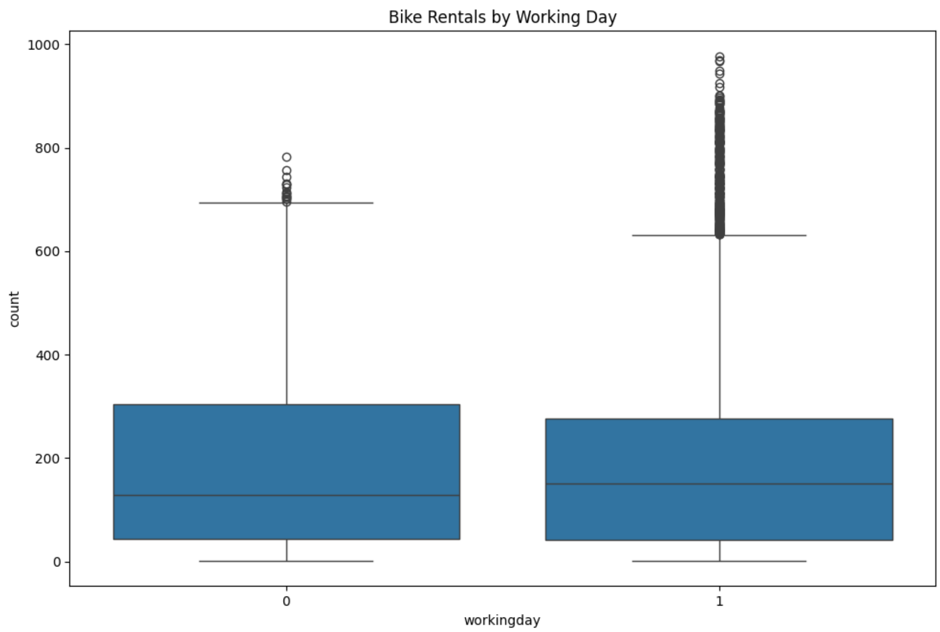
- There are some days with very high rental counts. This distribution suggests variability in rental counts, possibly due to varying factors like weather, season, and working days.

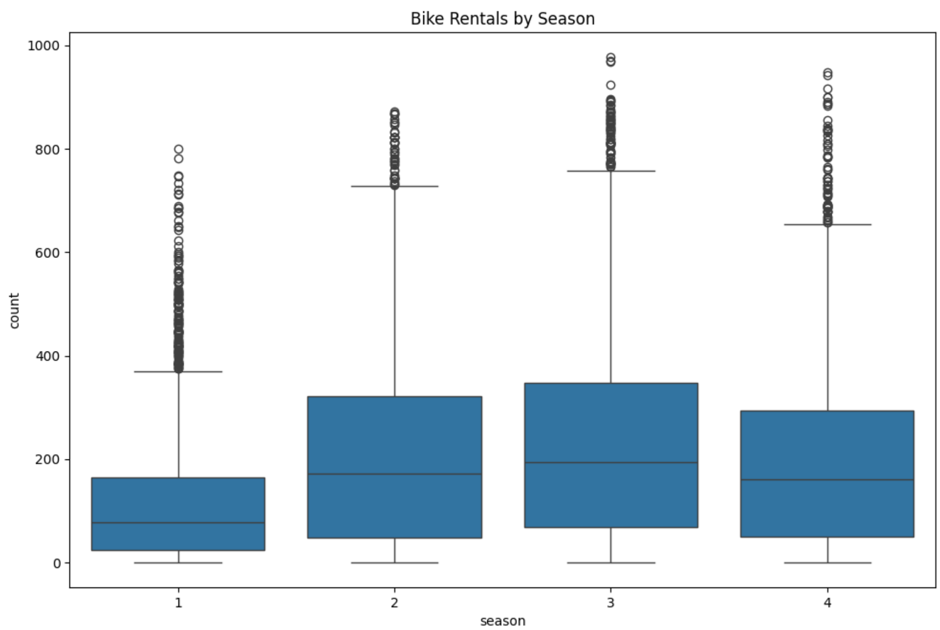
[13]:
```
categorical_vars = ['season', 'holiday', 'workingday', 'weather']

fig, axes = plt.subplots(len(categorical_vars), 1, figsize=(10, 20))
for i, var in enumerate(categorical_vars):
    sns.countplot(x=df[var], ax=axes[i])
    axes[i].set_title(f'Countplot of {var}')
plt.tight_layout()
plt.show()
```

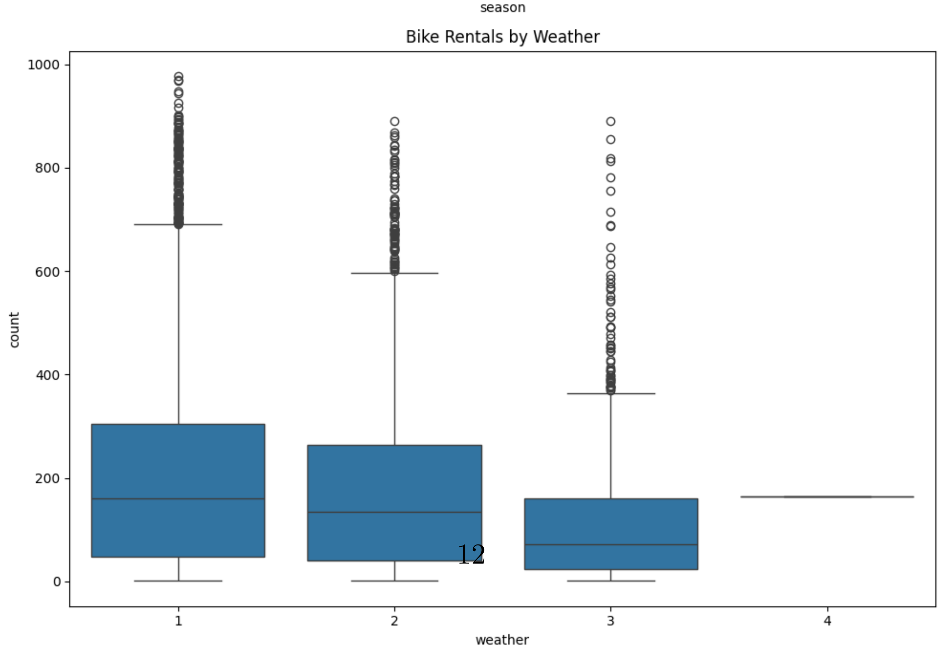

Countplot of season
count
0
500
1000
1500
2000
2500
1
2
3
4
season
Countplot of holiday
count
0
2000
4000
6000
8000
10000
0
1
holiday
Countplot of workingday
count
0
1000
2000
3000
4000
5000
6000
7000
0
1
workingday
Countplot of weather
count
0
1000
2000
3000
4000
5000
6000
7000
1
2
3
4
weather

BIVARIATE ANALYSIS

[14]:
```
fig, axes = plt.subplots(3, 1, figsize=(10, 20))

sns.boxplot(x='workingday', y='count', data=df, ax=axes[0])
axes[0].set_title('Bike Rentals by Working Day')

sns.boxplot(x='season', y='count', data=df, ax=axes[1])
axes[1].set_title('Bike Rentals by Season')

sns.boxplot(x='weather', y='count', data=df, ax=axes[2])
axes[2].set_title('Bike Rentals by Weather')

plt.tight_layout()
plt.show()
```


Bike Rentals by Working Day
count
0
200
400
600
800
1000
0
1
workingday


Bike Rentals by Season
count
0
200
400
600
800
1000
1
2
3
4
season


Bike Rentals by Weather
count
0
200
400
600
800
1000
1
2
3
4
weather

Bike Rentals by Working Day:

- The median count of bike rentals is higher on working days compared to non-working days. The noticeable difference in bike rental behavior based on whether it is a working day or not suggests that people might be using it for commute to work.

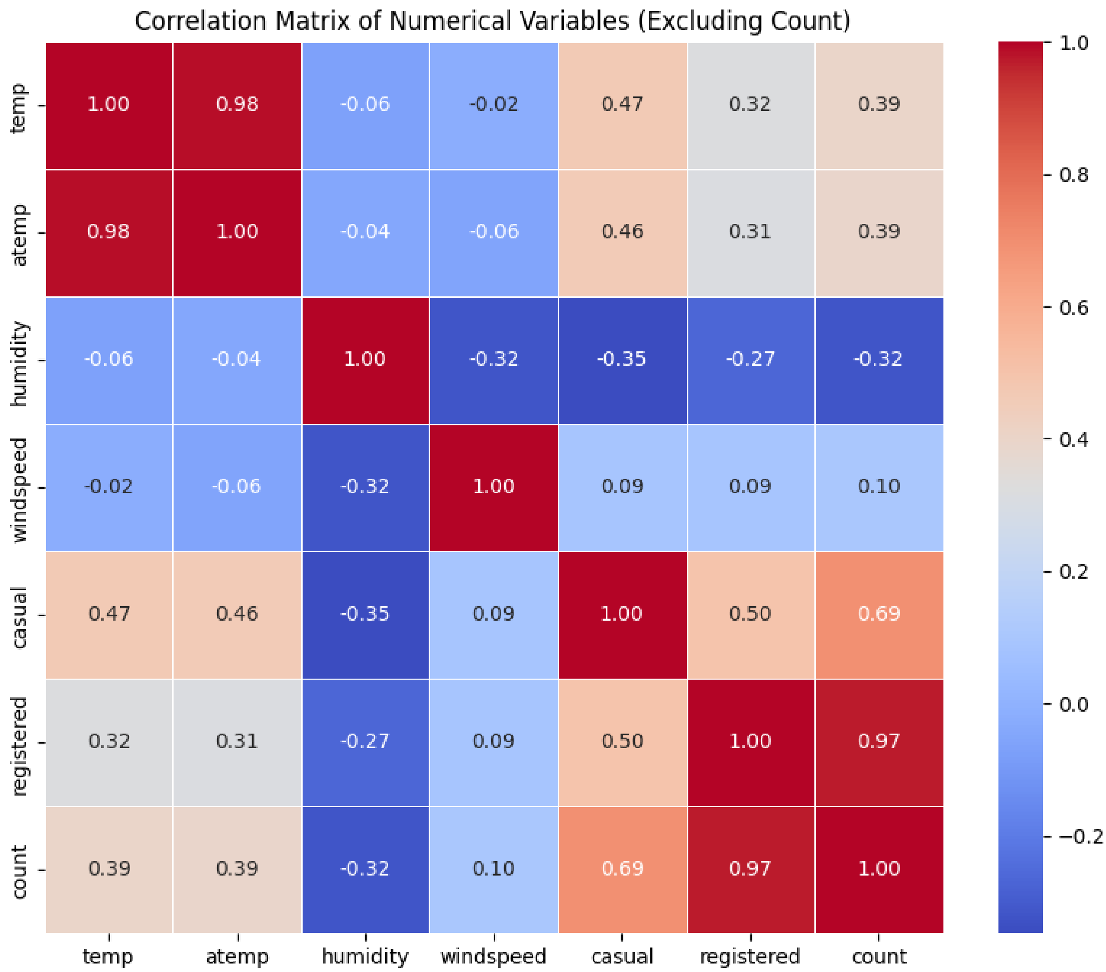
Bike Rentals by Season:

- The highest median rentals occur in season 3 (fall), while season 1 (spring) has the lowest median rentals. Seasonality affects bike rental counts significantly.

Bike Rentals by Weather:

- Bike rentals are highest in clear weather conditions with few clouds. Mist + Cloudy weather still retains much of the demand. Poor weather conditions (e.g., heavy rain, snow) lead to collapse in demand.

[15]:
```
# Select only numerical columns
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns

# Compute correlation matrix for numerical columns
numerical_corr_matrix = df[numerical_cols].corr()

plt.figure(figsize=(10, 8))
sns.heatmap(numerical_corr_matrix, annot=True, cmap='coolwarm', fmt=".2f",␣
 ↪linewidths=0.5)
plt.title('Correlation Matrix of Numerical Variables (Excluding Count)')
plt.show()
```



Interpretation of the correlation coefficients between the count variable and other numerical variables:

temp and atemp: Both temp and atemp have a positive correlation with count, with correlation coefficients of approximately 0.39. This suggests that as the temperature or apparent temperature increases, the number of electric cycles rented (count) tends to increase as well, although the correlation is moderate.

humidity: Humidity has a negative correlation with count, with a correlation coefficient of approximately -0.32. This suggests that as humidity increases, the number of electric cycles rented (count) tends to decrease. However, the correlation is not very strong.

windspeed: Windspeed has a weak positive correlation with count, with a correlation coefficient of approximately 0.10. This suggests that there is a slight tendency for the number of electric cycles rented (count) to increase with higher windspeed, but the correlation is quite weak.

casual: The variable casual has a strong positive correlation with count, with a correlation coefficient of approximately 0.69. This suggests that there is a strong positive relationship between the number of casual rentals and the total number of rentals (count).

registered: The variable registered has a very strong positive correlation with count, with a correlation coefficient of approximately 0.97. This indicates that there is an extremely strong positive relationship between the number of registered rentals and the total number of rentals (count).

2 1) Test for the Effect of Working Day on Number of Electric Cycles Rented

Significance Level (alpha): Typically set at 0.05.

1. List item
2. List item

2-Sample T-Test

The 2-sample T-test is used to determine if there is a significant difference between the means of two independent groups. Here, we will compare the mean number of electric cycles rented on working days versus non-working days.

Null Hypothesis (0): The mean number of cycles rented on working days is equal to the mean number on non-working days.

Alternative Hypothesis (1): The mean number of cycles rented on working days is different from the mean number on non-working days.

[16]:
```
# Separate the data into two groups
working_day_rentals = df[df['workingday'] == 1]['count']
non_working_day_rentals = df[df['workingday'] == 0]['count']

# Perform the 2-sample T-test
t_stat, p_value = stats.ttest_ind(working_day_rentals, non_working_day_rentals)

print(f'T-statistic: {t_stat}, P-value: {p_value}')
```

```
T-statistic: 1.2096277376026694, P-value: 0.22644804226361348
```

INSIGHT

With a p-value of 0.226, which is greater than the significance level (typically 0.05), we fail to reject the null hypothesis. Therefore, we do not have enough evidence to conclude that there is a significant difference in the number of electric cycles rented between working days and non-working days at a 5% significance level.

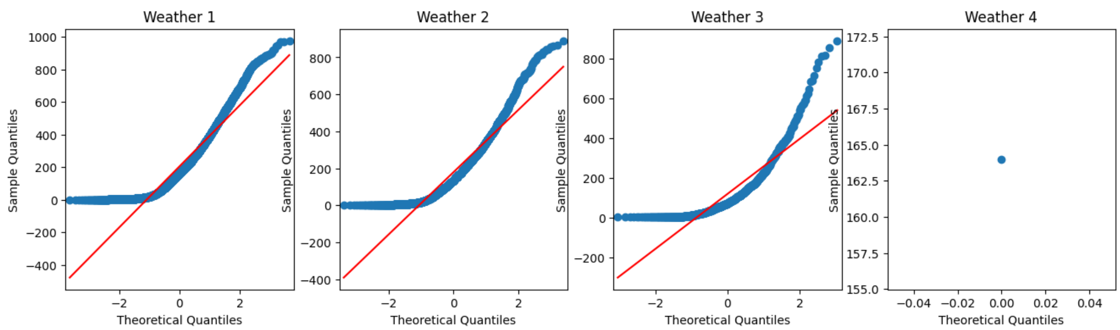
3 2) Test for Differences in Number of Cycles Rented Across Weather conditions.

ANOVA (Analysis of Variance) is used to compare the means of three or more groups. We will check if the number of cycles rented differs significantly across different weather conditions.

Null Hypothesis (0): The mean number of cycles rented is the same across different weather conditions.

Alternative Hypothesis (1): The mean number of cycles rented is different across different weather conditions.

[38]:
```
# Check Normality using Q-Q plots

groups_weather = [gp1, gp2, gp3, gp4]

fig, axes = plt.subplots(1, 4, figsize=(16, 4))
for i, group in enumerate(groups_weather):
    sm.qqplot(group, line='s', ax=axes[i])
    axes[i].set_title(f'Weather {i+1}')
```



[39]:
```
from scipy.stats import kruskal

# Groups for Weather
gp1 = df[df['weather'] == 1]['count'].values
gp2 = df[df['weather'] == 2]['count'].values
gp3 = df[df['weather'] == 3]['count'].values
gp4 = df[df['weather'] == 4]['count'].values

# Kruskal-Wallis Test for Weather
kruskal_weather_stat, kruskal_weather_p_value = kruskal(gp1, gp2, gp3, gp4)
print(f"Kruskal-Wallis Test for Weather: stat={kruskal_weather_stat:.3f},␣
↪p={kruskal_weather_p_value:.3e}")

# Interpretation
if kruskal_weather_p_value < 0.05:
    print("Reject the null hypothesis: There is a significant difference in the␣
↪number of cycles rented across different weather conditions.")
else:
    print("Fail to reject the null hypothesis: There is no significant␣
↪difference in the number of cycles rented across different weather␣
↪conditions.")
```

```
Kruskal-Wallis Test for Weather: stat=205.002, p=3.502e-44
Reject the null hypothesis: There is a significant difference in the number of
```

```
cycles rented across different weather conditions.
```

[44]:
```python
#Check Homogeneity of Variances:

from scipy.stats import levene

# Levene's test
stat, p = levene(df['count'][df['weather'] == 1],
                 df['count'][df['weather'] == 2],
                 df['count'][df['weather'] == 3],
                 df['count'][df['weather'] == 4])
print('Levene’s Test: Statistics=%.3f, p=%.3f' % (stat, p))
```

```
Levene’s Test: Statistics=54.851, p=0.000
```

Null Hypothesis (H0): The variances are equal across different weather.

Alternative Hypothesis (H1): The variances are not equal across different weather.

Given the p-value is 0.000, which is less than the significance level of 0.05, we reject the null hypothesis. This indicates that the variances are not equal across different weather.

Since the assumption of equal variances is violated, using ANOVA would not be appropriate as it assumes equal variances. Instead, we should use a non-parametric test like the Kruskal-Wallis test, which does not assume equal variances or normality.

INSIGHT

For the Kruskal-Wallis test concerning number of cycles rented across different weather conditions :

The p-value is very close to zero. Since the p-value is much smaller than the significance level of 0.05, we reject the null hypothesis.

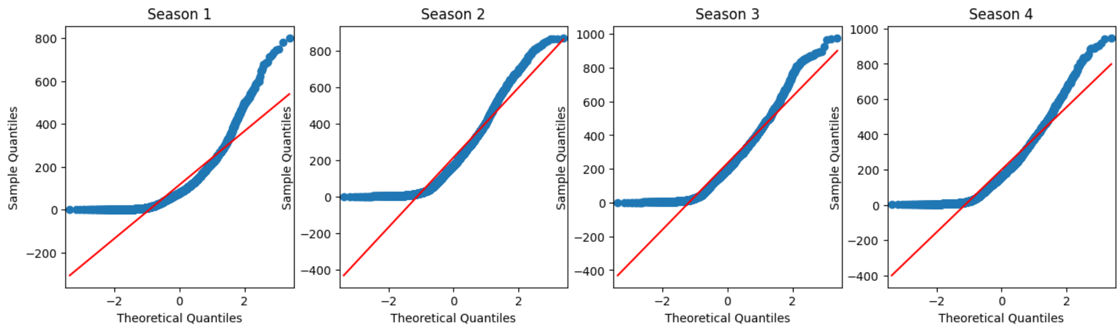
Therefore, we conclude that there is a statistically significant difference in the number of electric cycles rented across different weather conditions.

In other words, the weather condition significantly affects the number of electric cycles rented, according to the ANOVA test.

3.1 3) Test for Differences in Number of Cycles Rented Across Seasons

[41]:
```python
from statsmodels.graphics.gofplots import qqplot

# Define the data groups for the ANOVA
grp1 = df[df['season'] == 1]['count'].values
grp2 = df[df['season'] == 2]['count'].values
grp3 = df[df['season'] == 3]['count'].values
grp4 = df[df['season'] == 4]['count'].values

# Check Normality using Q-Q plots
groups = [grp1, grp2, grp3, grp4]
```

```
fig, axes = plt.subplots(1, 4, figsize=(16, 4))
for i, group in enumerate(groups_season):
    sm.qqplot(group, line='s', ax=axes[i])
    axes[i].set_title(f'Season {i+1}')
```



[42]:
```
from scipy.stats import shapiro

group_names = ['Season 1', 'Season 2', 'Season 3', 'Season 4']

# Perform Shapiro-Wilk test for each group
for i, group in enumerate(groups):
    if len(group) >= 3:
        stat, p = shapiro(group)
        print(f'{group_names[i]}: Shapiro-Wilk Test: stat={stat:.3f}, p={p:.
 ↪3f}')
        if p > 0.05:
            print(f'{group_names[i]}: Sample looks Gaussian (fail to reject␣
 ↪H0)')
        else:
            print(f'{group_names[i]}: Sample does not look Gaussian (reject␣
 ↪H0)')
    else:
        print(f'{group_names[i]}: Not enough data to perform Shapiro-Wilk Test␣
 ↪(less than 3 samples)')
```

```
Season 1: Shapiro-Wilk Test: stat=0.809, p=0.000
Season 1: Sample does not look Gaussian (reject H0)
Season 2: Shapiro-Wilk Test: stat=0.900, p=0.000
Season 2: Sample does not look Gaussian (reject H0)
Season 3: Shapiro-Wilk Test: stat=0.915, p=0.000
Season 3: Sample does not look Gaussian (reject H0)
Season 4: Shapiro-Wilk Test: stat=0.895, p=0.000
Season 4: Sample does not look Gaussian (reject H0)
```

[43]:
```python
#Check Homogeneity of Variances:

from scipy.stats import levene

# Levene's test
stat, p = levene(df['count'][df['season'] == 1],
                 df['count'][df['season'] == 2],
                 df['count'][df['season'] == 3],
                 df['count'][df['season'] == 4])
print('Levene’s Test: Statistics=%.3f, p=%.3f' % (stat, p))
```

```
Levene’s Test: Statistics=187.771, p=0.000
```

Null Hypothesis (H0): The variances are equal across different seasons.

Alternative Hypothesis (H1): The variances are not equal across different seasons.

Given the p-value is 0.000, which is less than the significance level of 0.05, we reject the null hypothesis. This indicates that the variances are not equal across different seasons.

Since the assumption of equal variances is violated, using ANOVA would not be appropriate as it assumes equal variances. Instead, we should use a non-parametric test like the Kruskal-Wallis test, which does not assume equal variances or normality.

#4) Test for Dependency of Weather on Season Chi-Square Test

The Chi-Square Test is used to determine if there is a significant association between two categorical variables. We will check if weather is dependent on the season.

Null Hypothesis (0): Weather is independent of the season.

Alternative Hypothesis (1): Weather is dependent on the season.

[21]:
```python
# Create a contingency table
contingency_table = pd.crosstab(df['weather'], df['season'])

# Perform the Chi-Square test
chi2, p, dof, expected = stats.chi2_contingency(contingency_table)

print(f'Chi-Square statistic: {chi2}, P-value: {p}, Degrees of freedom: {dof}')
```

```
Chi-Square statistic: 49.15865559689363, P-value: 1.5499250736864862e-07,
Degrees of freedom: 9
```

INSIGHT

Since the p-value is much smaller than the significance level of 0.05, we reject the null hypothesis. Therefore, we conclude that there is a statistically significant association between weather and season.

In other words, weather is dependent on the season, according to the Chi-Square test.