Business Case Study Walmart

Note: I have addressed only questions mentioned in the pdf named Walmart Data Exploration Business Case solution Approach

https://colab.research.google.com/drive/19diU_81UWqS9xztcdOSZ3AvoTRJBmE8u?usp=sharing

Some plots might not get completely printed on the pdf hence providing google colab link.

Business Problem

● Yulu, India's pioneering micro-mobility service provider, has embarked on a mission to revolutionize daily commutes by offering unique, sustainable transportation solutions.

● However, recent revenue setbacks have prompted Yulu to seek the expertise of a consulting company to delve into the factors influencing the demand for their shared electric cycles, specifically in the Indian market.

The data includes the following variables:

1. **datetime:** datetime
2. **season:** season (1: spring, 2: summer, 3: fall, 4: winter)
3. **holiday :** whether day is a holiday or not
4. **workingday :** if day is neither weekend nor holiday is 1, otherwise is 0.
5. **weather:** o 1: Clear, Few clouds, partly cloudy o 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist o 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered clouds o 4: Heavy Rain + Ice Pellets + Thunderstorm + Mist, Snow + Fog
6. **temp:** temperature in Celsius
7. **atemp:** feeling temperature in Celsius
8. **humidity:** humidity
9. **windspeed:** wind speed
10. **casual:** count of casual users
11. **registered:** count of registered users
12. **count:** count of total rental bikes including both casual and registered

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1. Define the Problem Statement, Import the required Libraries and perform Exploratory Data Analysis.

a. Examine dataset structure, characteristics, and statistical summary.

b. Identify missing values and perform Imputation using an appropriate method.

c. Identify and remove duplicate records.

d. Analyze the distribution of Numerical & Categorical variables, separately

e. Check for Outliers and deal with them accordingly.

```
# Importing necessary libraries

import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
from scipy import stats
import warnings
warnings.filterwarnings('ignore')
```

```
# Loading the Yulu data

!gdown https://drive.google.com/file/d/1o94fXnmvrx6jRgI6S-SeZ3tfnKjCDY0i/view?usp=sharing
```

```
/usr/local/lib/python3.10/dist-packages/gdown/parse_url.py:48: UserWarning: You specified a Google Drive link that is not the correct link to download a file. You might want to try `--fuzzy` optic
  warnings.warn(
Downloading...
From: https://drive.google.com/file/d/1o94fXnmvrx6jRgI6S-SeZ3tfnKjCDY0i/view?usp=sharing
To: /content/view?usp=sharing
87.6kB [00:00, 43.7MB/s]
```

```
# Assuming 'data' is your DataFrame

df = pd.read_csv("bike_sharing.csv")

#Overview of head and tail combined of the yulu dataframe

df
```

	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	0.0000	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0000	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0000	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0000	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0000	0	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...
10881	2012-12-19 19:00:00	4	0	1	1	15.58	19.695	50	26.0027	7	329	336
10882	2012-12-19 20:00:00	4	0	1	1	14.76	17.425	57	15.0013	10	231	241

Next steps: Generate code with df View recommended plots

```
# Get a concise summary of the DataFrame

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  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
```

Insights

The Yulu dataset comprises 12 columns, with 1 column being categorical and 11 columns being numerical. While no columns showing null values.

```
#Check the null values

print('\nColumns with missing value:')
print(df.isnull().any())
```

```
Columns with missing value:
datetime      False
season        False
holiday       False
workingday    False
weather       False
temp          False
atemp         False
humidity      False
windspeed     False
casual        False
registered    False
count         False
dtype: bool
```

Insights

No columns showing null values.

```
# Display the first few rows of the DataFrame

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` View recommended plots

```
# Number of columns

df.columns
```

```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count'],
      dtype='object')
```

```
# Check the shape of the DataFrame

df.shape
```

```
(10886, 12)
```

```
#Check the dimensions of the DataFrame

df.ndim
```

```
2
```

**Insights*

The Yulu dataset is 2 dimensional with 10886 enteries and 12 descriptions.

Converting numerical datatype to categorical datatype, i.e changing the datatype of Occupation, Marital Status and Product Category.

```
#Changing datatype int64 to object
cols=['season', 'holiday', 'workingday', 'weather']
df[cols]=df[cols].astype("object")
df.dtypes

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

```
datetime      datetime64[ns]
season                object
holiday               object
workingday            object
weather               object
temp                 float64
atemp                float64
humidity               int64
windspeed            float64
casual                 int64
registered             int64
count                  int64
dtype: object
```

*This data seems to have no null values.

```
#Check duplicated rows
df.duplicated().sum()
```

```
0
```

```
# Summary statistics for numerical columns

df.describe(include='all')
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casu
count	10886	10886.0	10886.0	10886.0	10886.0	10886.00000	10886.000000	10886.000000	10886.000000	10886.0000
unique	NaN	4.0	2.0	2.0	4.0	NaN	NaN	NaN	NaN	Na
top	NaN	4.0	0.0	1.0	1.0	NaN	NaN	NaN	NaN	Na
freq	NaN	2734.0	10575.0	7412.0	7192.0	NaN	NaN	NaN	NaN	Na
mean	2011-12-27 05:56:22.399411968	NaN	NaN	NaN	NaN	20.23086	23.655084	61.886460	12.799395	36.0219
min	2011-01-01 00:00:00	NaN	NaN	NaN	NaN	0.82000	0.760000	0.000000	0.000000	0.0000
25%	2011-07-02 07:15:00	NaN	NaN	NaN	NaN	13.94000	16.665000	47.000000	7.001500	4.0000
50%	2012-01-01 20:30:00	NaN	NaN	NaN	NaN	20.50000	24.240000	62.000000	12.998000	17.0000
	2012-07-01									

*Insights

---

1)Minimum temperature in the sample data is 0.82 deg C where as Maximum temp is 41 deg C.

2) There are days when the number of casual users are 0 and number of registered users also O.

3)However, there is atleast 1 user in total count of users.

4) Maximum number of casual, registered and count are 367, 886 and 977 respectively.

Non graphical analysis

Value counts and unique attributes

```
# Uniques values of each columns

df.nunique()
```

```
datetime      10886
season            4
holiday           2
workingday        2
weather           4
temp             49
atemp            60
humidity         89
windspeed        28
casual          309
registered      731
count           822
dtype: int64
```

```
# Creating new columns from datetime and converting them to categories

df['year'] = df['datetime'].dt.year
df['month'] = df['datetime'].dt.month
df['day'] = df['datetime'].dt.day
df['hour'] = df['datetime'].dt.hour
```

```
df.head(2)
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	year	month	day
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13	16	2011	1	1

Next steps: Generate code with df View recommended plots

```
# replacing the number with category

# change of season
df['season'] = df['season'].replace({1:'Spring',2:'Summer',3:'Fall',4:'Winter'})

# change of holiday
df['holiday'] = df['holiday'].replace({0:'No',1:'Yes'})

# change of workingday
df['workingday'] = df['workingday'].replace({0:'No',1:'Yes'})

# change of month
df['month'] = df['month'].replace({1: 'January',
                                   2: 'February',
                                   3: 'March',
                                   4: 'April',
                                   5: 'May',
                                   6: 'June',
                                   7: 'July',
                                   8: 'August',
                                   9: 'September',
                                   10: 'October',
                                   11: 'November',
                                   12: 'December'})
```

```
df.describe().transpose()
```

	count	mean	min	25%	50%	75%	max	std
datetime	10886	2011-12-27 05:56:22.399411968	2011-01-01 00:00:00	2011-07-02 07:15:00	2012-01-01 20:30:00	2012-07-01 12:45:00	2012-12-19 23:00:00	NaN
temp	10886.0	20.23086	0.82	13.94	20.5	26.24	41.0	7.79159
atemp	10886.0	23.655084	0.76	16.665	24.24	31.06	45.455	8.474601
humidity	10886.0	61.88646	0.0	47.0	62.0	77.0	100.0	19.245033
windspeed	10886.0	12.799395	0.0	7.0015	12.998	16.9979	56.9969	8.164537
casual	10886.0	36.021955	0.0	4.0	17.0	49.0	367.0	49.960477
registered	10886.0	155.552177	0.0	36.0	118.0	222.0	886.0	151.039033
count	10886.0	191.574132	1.0	42.0	145.0	284.0	977.0	181.144454
year	10886.0	2011.501929	2011.0	2011.0	2012.0	2012.0	2012.0	0.500019
day	10886.0	9.992559	1.0	5.0	10.0	15.0	19.0	5.476608
hour	10886.0	11.541613	0.0	6.0	12.0	18.0	23.0	6.915838

```
# converting the categorical columns into category

cat_col = ['season', 'holiday', 'workingday', 'weather']

for _ in cat_col:
 df[_] = df[_].astype('category')


df.describe(include = 'category').transpose()
```

	count	unique	top	freq
season	10886	4	Winter	2734
holiday	10886	2	No	10575
workingday	10886	2	Yes	7412
weather	10886	4	1	7192

**Insights*

---

1)The dataset encompasses both datetime information and various numerical features associated with bike rentals. The observations span from January 1, 2011, to December 19, 2012.

2)Numerical features such as temperature, humidity, windspeed, and counts of casual and registered bike rentals show diverse ranges and distributions, highlighting the variability in rental patterns across different conditions.

3)Observations on the year, day, and hour variables indicate temporal patterns, with a concentration in 2011 and 2012, a mean day value around 10, and an hourly distribution ranging from 0 to 23.

```
#names of columns
df.columns
```

```
Index(['datetime', 'season', 'holiday', 'workingday', 'weather', 'temp',
       'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count',
       'year', 'month', 'day', 'hour'],
      dtype='object')
```

```
# Checking the uniques values of the column and its unique counts

for i in df.columns:
  print("*The unique values in",i, "column are :")
  print(df[i].unique())
  print(f"*Count of unique values : \n {df[i].nunique()}")
  print("-"*70)
```

```
 397 492 427 461 422 305 375 376 414 447 408 418 457 545 496 368 245 596
 563 443 562 229 316 402 287 372 514 472 511 488 419 595 578 400 348 587
 497 433 475 406 430 324 262 323 412 530 543 413 435 555 523 441 529 532
 585 399 584 559 307 582 571 426 516 465 329 483 600 570 628 531 455 389
 505 359 431 460 590 429 599 338 566 482 568 540 495 345 591 593 446 485
 393 500 473 352 320 479 444 462 405 620 499 625 395 528 319 519 445 512
 471 508 526 509 484 448 515 549 501 612 597 464 644 712 676 734 662 782
 749 623 713 746 651 686 690 679 685 648 560 503 521 554 541 721 801 561
 573 589 729 618 494 757 800 684 744 759 822 698 490 536 655 643 626 615
 567 617 632 646 692 704 624 656 610 738 671 678 660 658 635 681 616 522
 673 781 775 576 677 748 776 557 743 666 813 504 627 706 641 575 639 769
 680 546 717 710 458 622 705 630 732 770 439 779 659 602 478 733 650 873
 846 474 634 852 868 745 812 669 642 730 672 645 694 493 668 647 702 665
 834 850 790 415 724 869 700 793 723 534 831 613 653 857 719 867 823 403
```

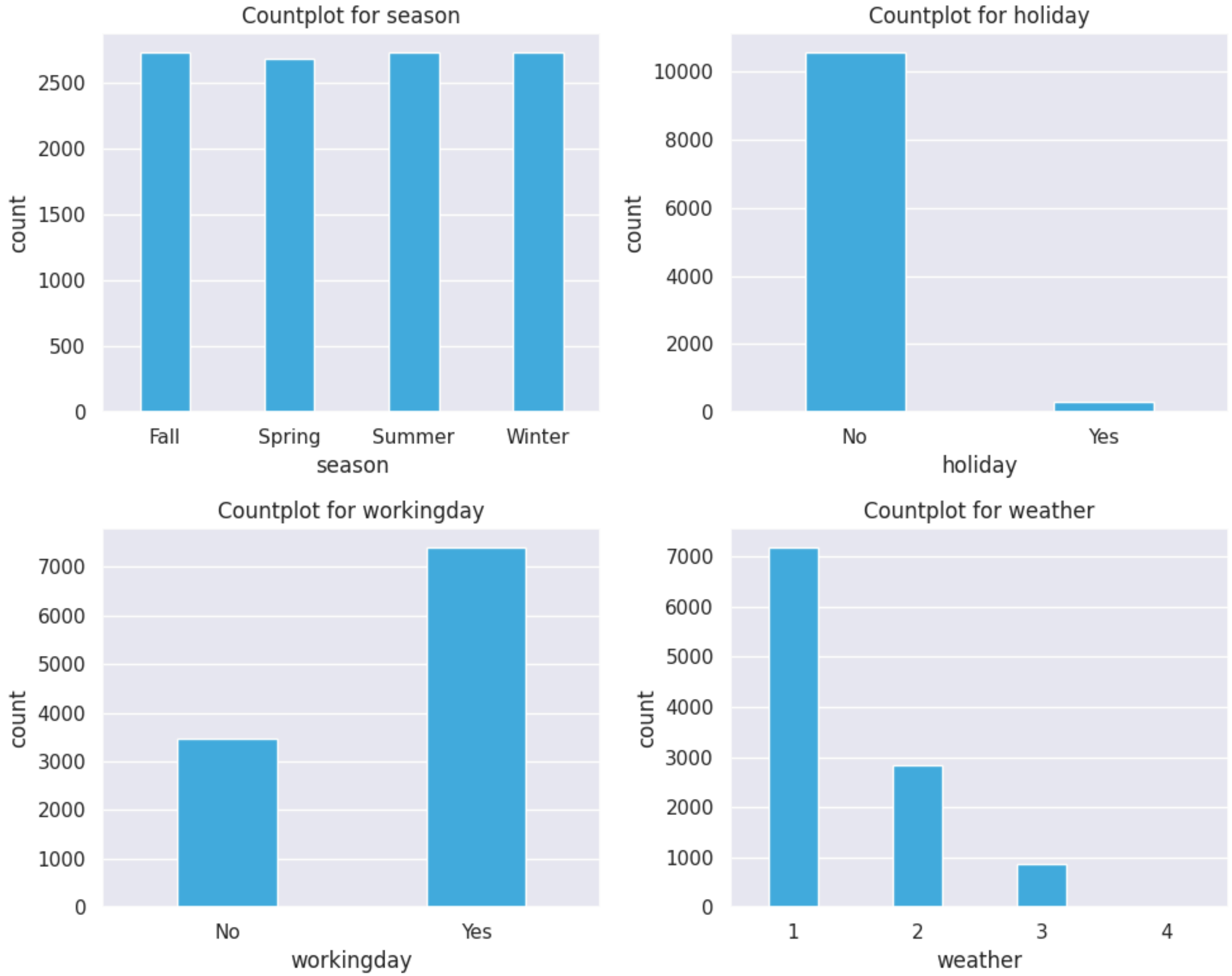
```
# Checking the value counts of the column.

for i in df.columns:
  print("*The value counts in",i, "column are :")
  print(df[i].value_counts())
  print("-"*70)
```

```
*The value counts in datetime column are :
datetime
2011-01-01 00:00:00    1
2012-05-01 21:00:00    1
2012-05-01 13:00:00    1
2012-05-01 14:00:00    1
2012-05-01 15:00:00    1
                      ..
2011-09-02 04:00:00    1
2011-09-02 05:00:00    1
2011-09-02 06:00:00    1
2011-09-02 07:00:00    1
2012-12-19 23:00:00    1
Name: count, Length: 10886, dtype: int64
----------------------------------------------------------------------
*The value counts in season column are :
season
Winter    2734
Fall      2733
Summer    2733
Spring    2686
Name: count, dtype: int64
----------------------------------------------------------------------
*The value counts in holiday column are :
holiday
No     10575
Yes      311
Name: count, dtype: int64
----------------------------------------------------------------------
*The value counts in workingday column are :
workingday
Yes    7412
No     3474
Name: count, dtype: int64
----------------------------------------------------------------------
*The value counts in weather column are :
weather
1    7192
2    2834
```

```
3     859
4       1
Name: count, dtype: int64
----------------------------------------------------------------------
*The value counts in temp column are :
temp
14.76    467
26.24    453
28.70    427
13.94    413
18.86    406
22.14    403
25.42    403
16.40    400
22.96    395
27.06    394
24.60    390
12.30    385
21.32    362
```

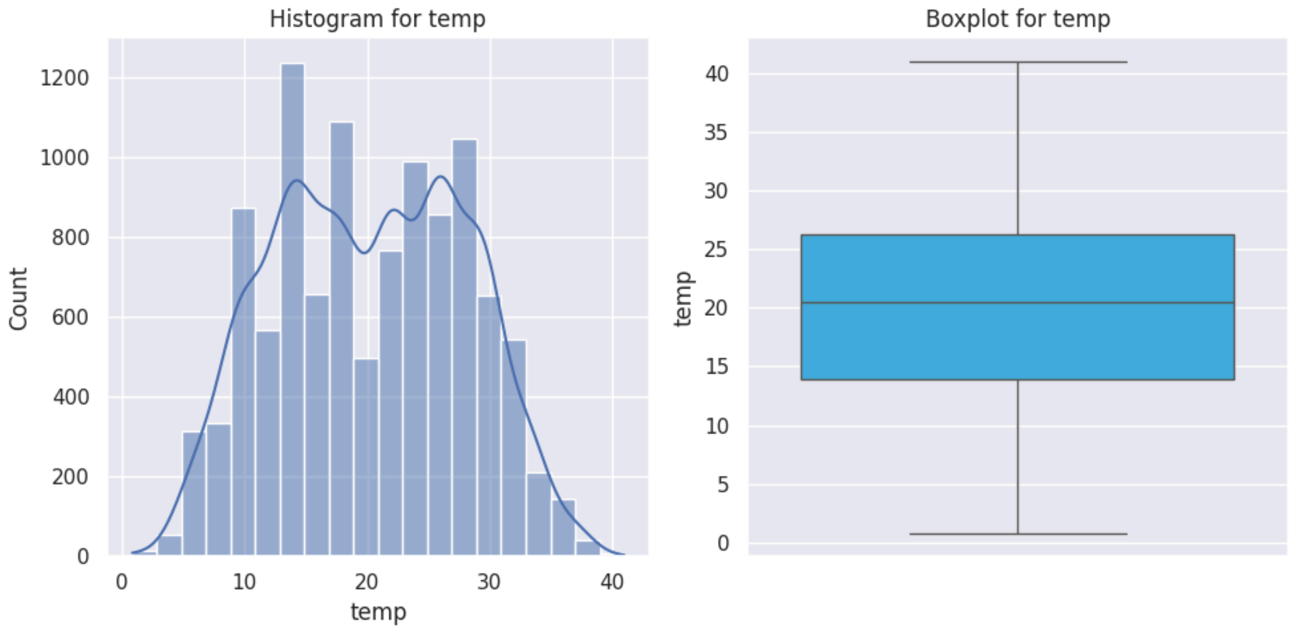
Graphical analysis

```
# countplot on categories

plt.figure(figsize=(10, 8))
sns.set(style="darkgrid")

for i, column in enumerate(cat_col, 1):
    plt.subplot(2, 2, i)
    sns.countplot(x=column, data=df, color="#29B6F6", width=0.4)
    plt.title(f'Countplot for {column}')

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


Countplot for season
count
2500
2000
1500
1000
500
0
Fall
Spring
Summer
Winter
season
Countplot for holiday
count
10000
8000
6000
4000
2000
0
No
Yes
holiday
Countplot for workingday
count
7000
6000
5000
4000
3000
2000
1000
0
No
Yes
workingday
Countplot for weather
count
7000
6000
5000
4000
3000
2000
1000
0
1
2
3
4
weather

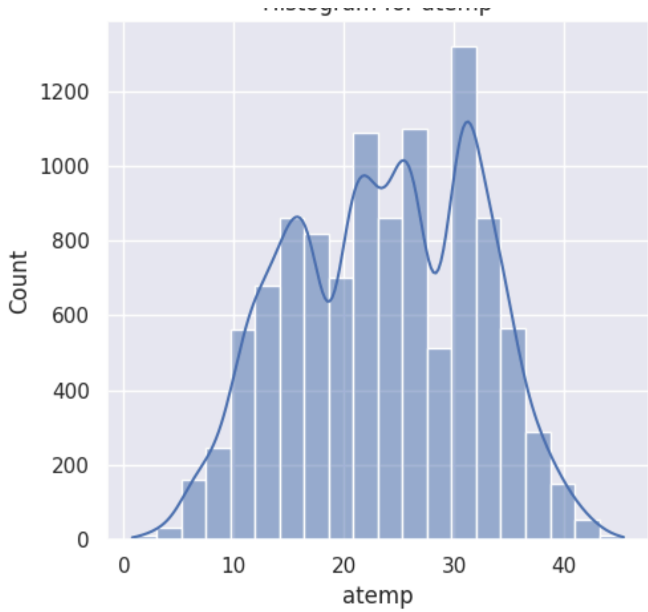
```
# Function for histogram & boxplot on numerical columns

def hist_box(column):
    f, axs = plt.subplots(1, 2, figsize=(10, 5))
    sns.set(style="darkgrid")

    # Histogram
    plt.subplot(1, 2, 1)
    sns.histplot(df[column], bins=20, kde=True)
    plt.title(f'Histogram for {column}')

    # Boxplot
    plt.subplot(1, 2, 2)
    sns.boxplot(df[column], color="#29B6F6")
    plt.title(f'Boxplot for {column}')

    tabular_data = df[column].describe().reset_index()
    tabular_data.columns = ['Statistic', 'Value']
    display(tabular_data)

    plt.tight_layout()
    plt.show()


num_col = ['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count']

for column in num_col:
    hist_box(column)
```

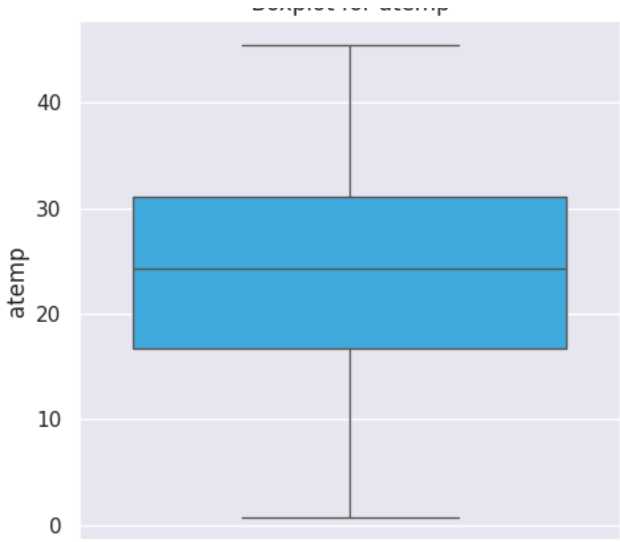
	Statistic	Value
0	count	10886.00000
1	mean	20.23086
2	std	7.79159
3	min	0.82000
4	25%	13.94000
5	50%	20.50000
6	75%	26.24000
7	max	41.00000



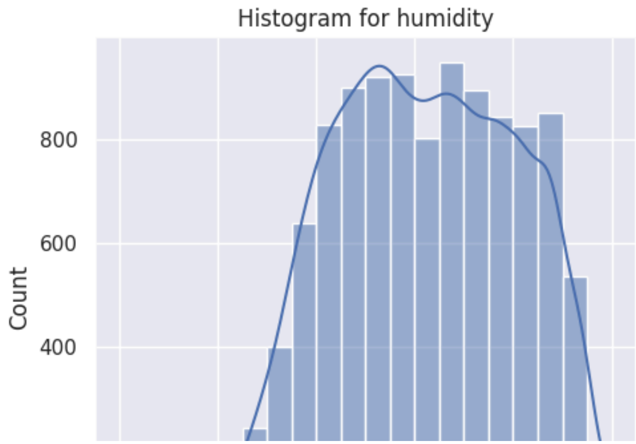
	Statistic	Value
0	count	10886.000000
1	mean	23.655084
2	std	8.474601
3	min	0.760000
4	25%	16.665000
5	50%	24.240000
6	75%	31.060000
7	max	45.455000

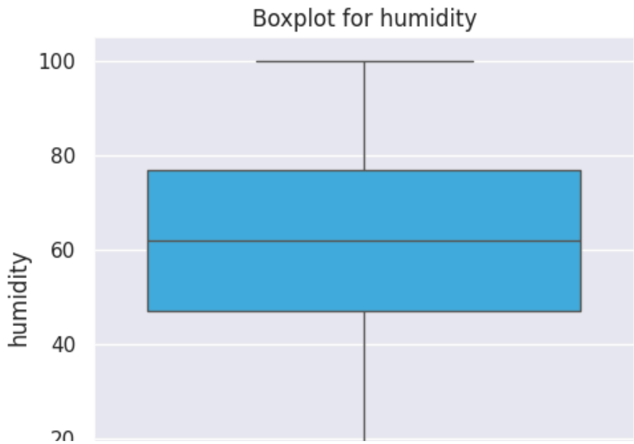
Histogram for atemp Boxplot for atemp

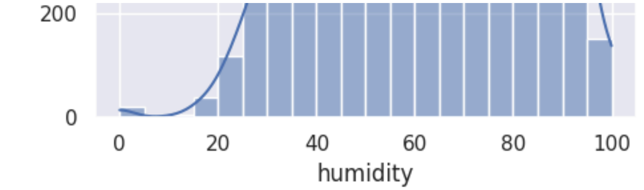


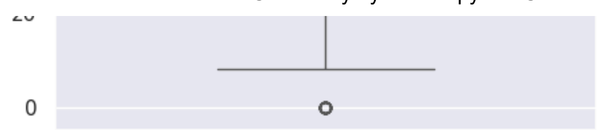


	Statistic	Value
0	count	10886.000000
1	mean	61.886460
2	std	19.245033
3	min	0.000000
4	25%	47.000000
5	50%	62.000000
6	75%	77.000000
7	max	100.000000

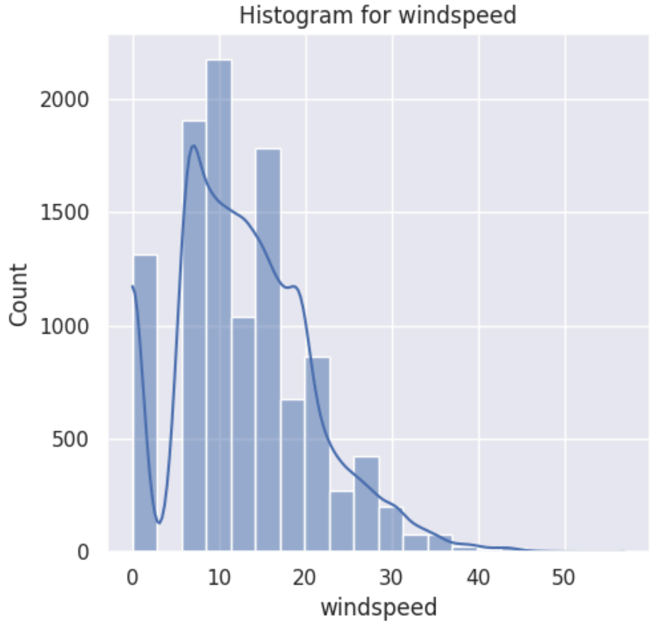


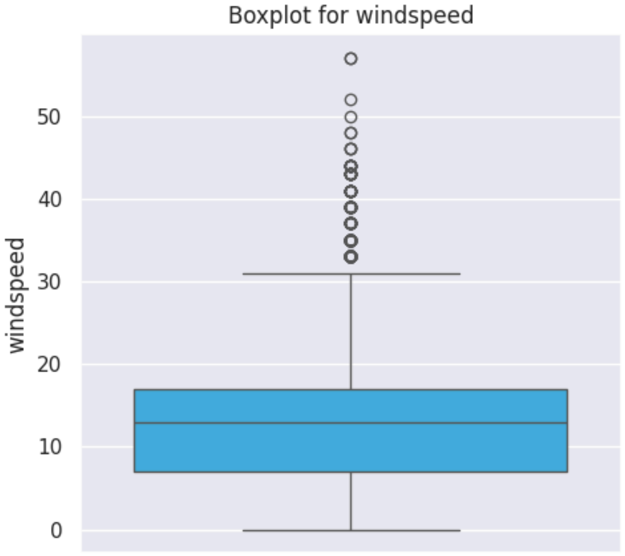






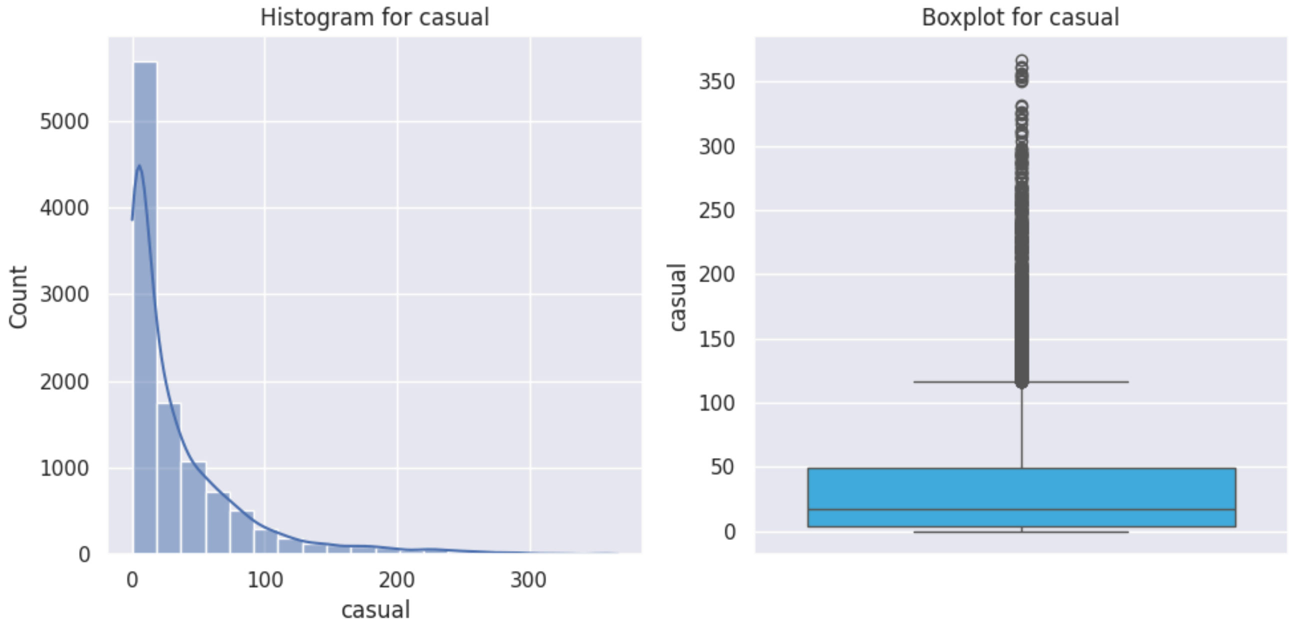
	Statistic	Value
0	count	10886.000000
1	mean	12.799395
2	std	8.164537
3	min	0.000000
4	25%	7.001500
5	50%	12.998000
6	75%	16.997900
7	max	56.996900



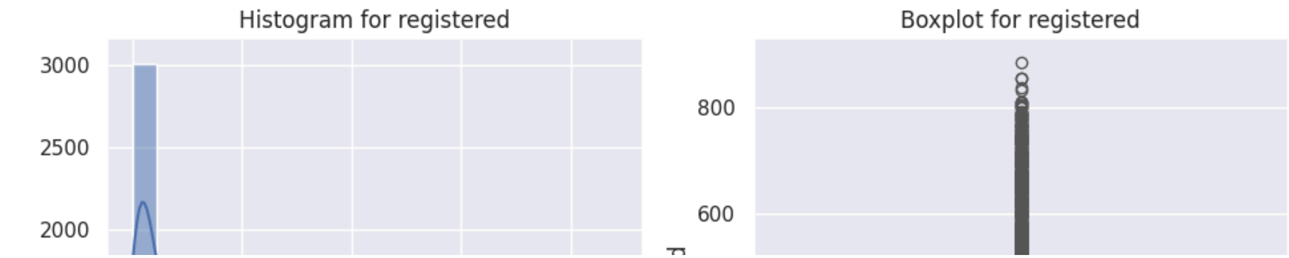


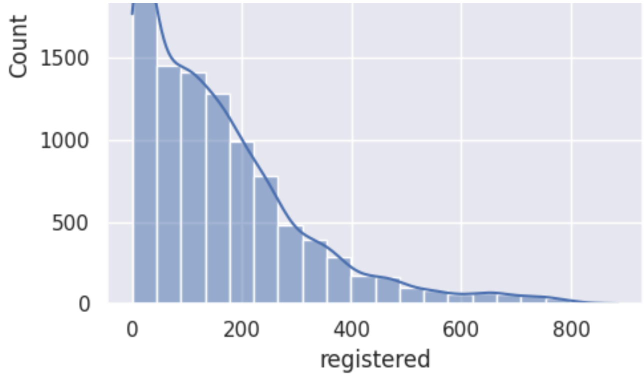
	Statistic	Value
0	count	10886.000000
1	mean	36.021955
2	std	49.960477
3	min	0.000000

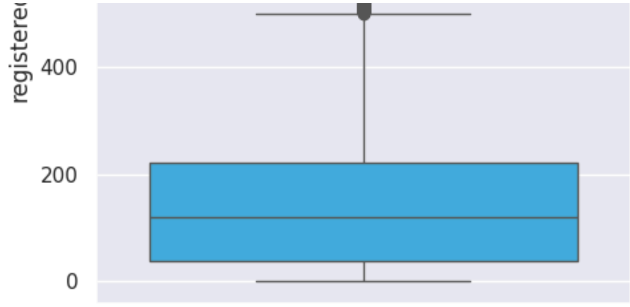
4	25%	4.000000
5	50%	17.000000
6	75%	49.000000
7	max	367.000000



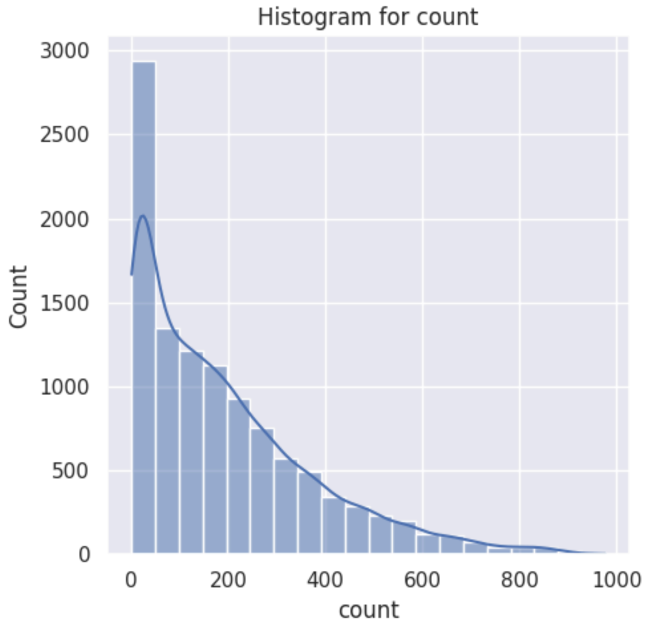
	Statistic	Value
0	count	10886.000000
1	mean	155.552177
2	std	151.039033
3	min	0.000000
4	25%	36.000000
5	50%	118.000000
6	75%	222.000000
7	max	886.000000

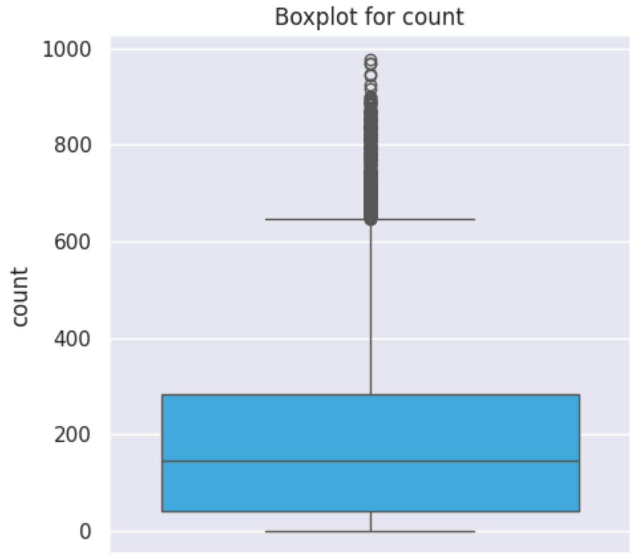






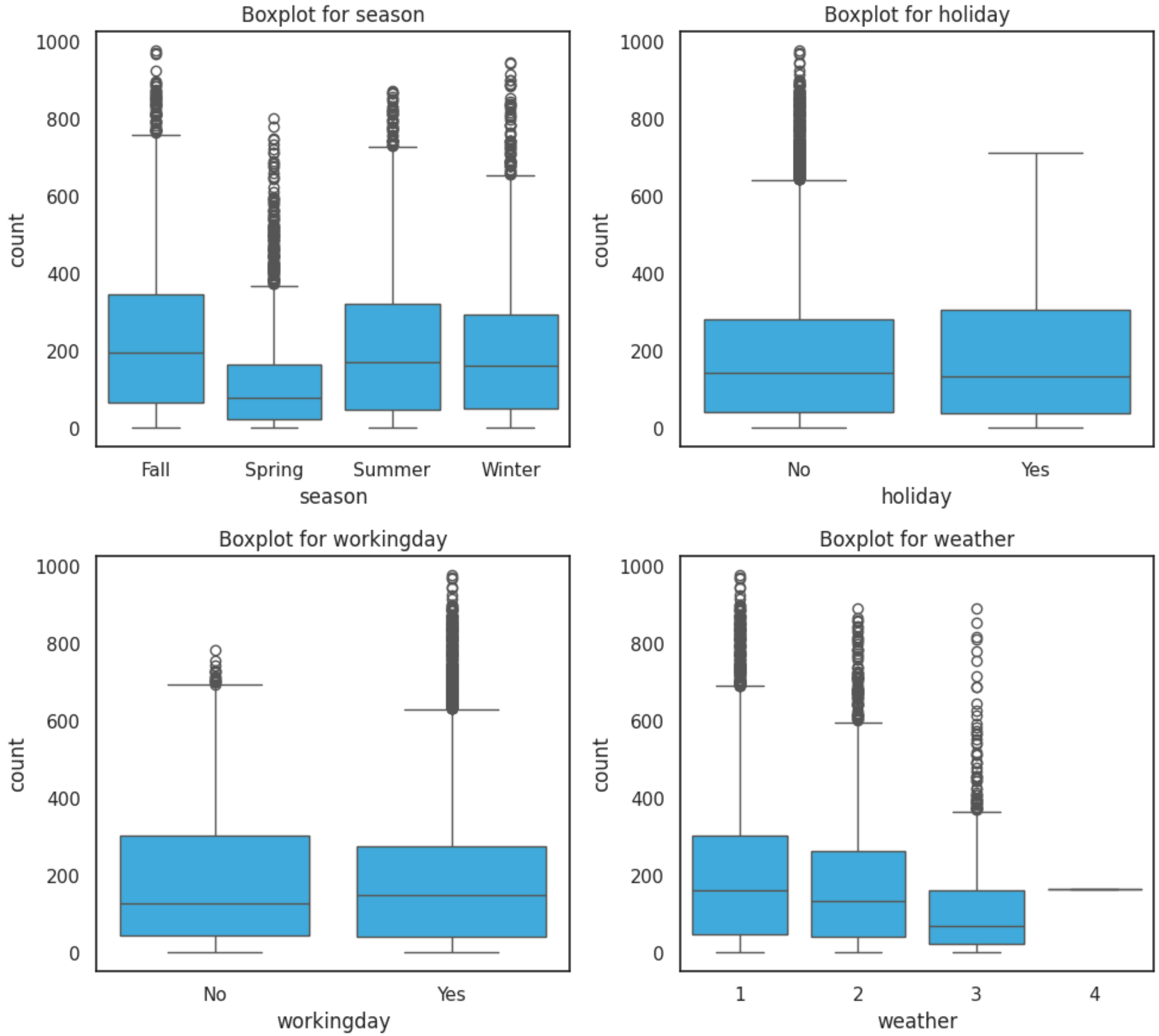
	Statistic	Value
0	count	10886.000000
1	mean	191.574132
2	std	181.144454
3	min	1.000000
4	25%	42.000000
5	50%	145.000000
6	75%	284.000000
7	max	977.000000





Outlier Detection

```
plt.figure(figsize=(10, 9))
sns.set(style="white")

for i, column in enumerate(cat_col,1):
    plt.subplot(2, 2, i)
    sns.boxplot(x=column, y='count', data=df, color="#29B6F6")
    plt.title(f'Boxplot for {column}')

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



*Insights

1)Outliers in Different Seasons: In spring and winter, there are more unusual values in the data compared to other seasons.

2)Weather Outliers: Category 3 weather has a lot of unusual values, while category 4 weather doesn't have any.

3)Working Days vs. Holidays: On regular working days, there are more unusual values in the data than on holidays. This suggests some unexpected patterns during typical workdays that might need a closer look.

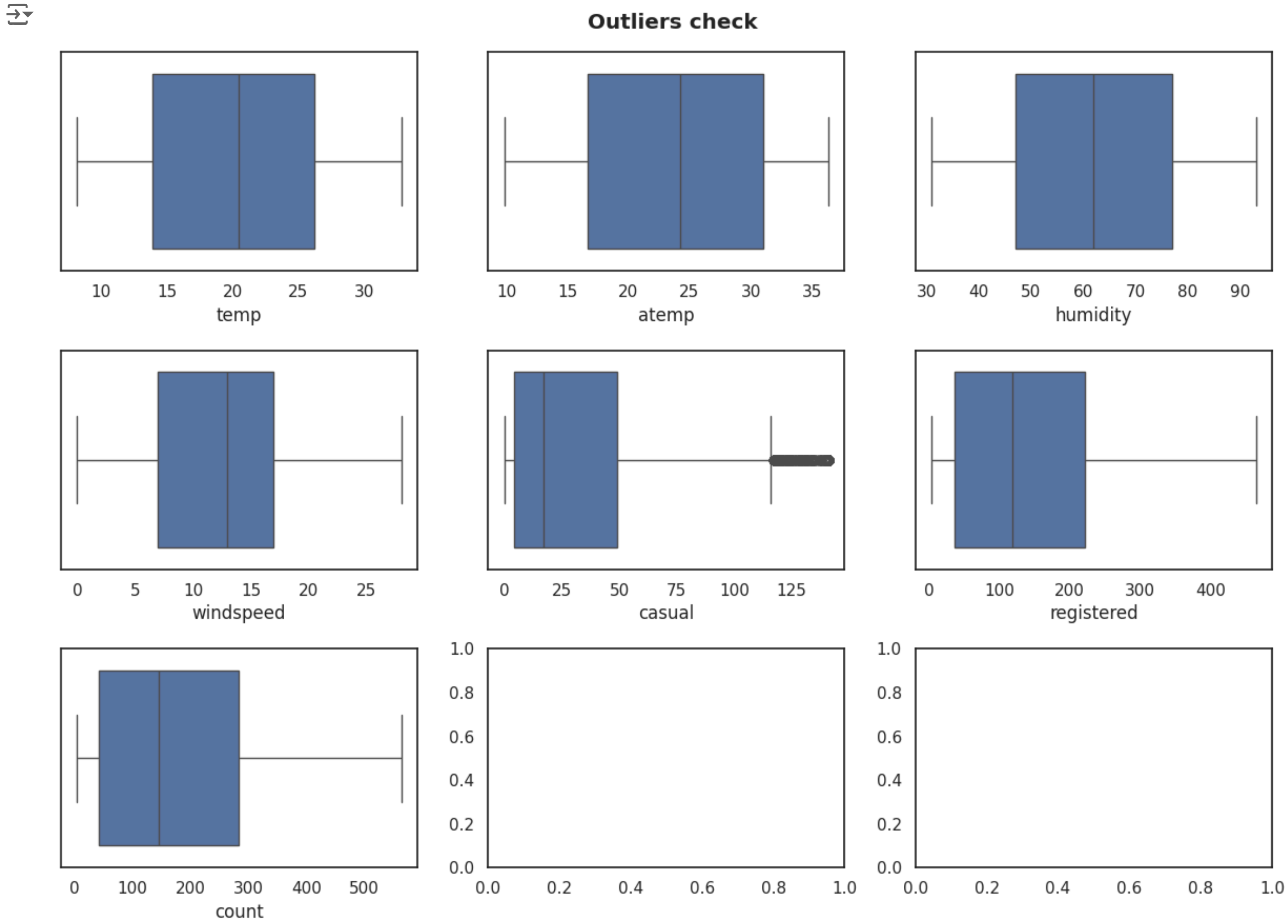
```
import pandas as pd
import numpy as np

# Assuming 'df' is your DataFrame
num_col = ['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count']

# Calculate percentiles for numerical columns only
percentiles = df[num_col].quantile([0.05, 0.95])

# Clip numerical columns to remove outliers
for col in num_col:
    lower_bound = percentiles.loc[0.05, col]
    upper_bound = percentiles.loc[0.95, col]
    df[col] = np.clip(df[col], lower_bound, upper_bound)
```

```
num_col
percentiles
```

	temp	atemp	humidity	windspeed	casual	registered	count
0.05	8.2	9.850	31.0	0.0000	0.0	4.0	5.00
0.95	32.8	36.365	93.0	27.9993	141.0	464.0	563.75

Next steps: Generate code with `percentiles` View recommended plots

```
fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(12, 9))  # Adjust figsize for better visibility
fig.suptitle("Outliers check", weight='bold')

# Iterate over numerical columns and create boxplots
for i, col in enumerate(num_col):
    row = i // 3
    col_num = i % 3
    sns.boxplot(data=df, x=col, orient='h', ax=axes[row, col_num])

plt.tight_layout()  # Adjust spacing between subplots
plt.show()
```



**Insights*

---

1) Casual column has outliers still left.

2)Temp: The 'temp' column shows a diverse temperature range (0.82 to 41.0), with a median of 20.5 and moderate variability around the mean of approximately 20.23 degrees Celsius.

3)Atemp The 'atemp' column displays a wide range of apparent temperatures (0.76 to 45.455), with a mean of approximately 23.66 and moderate variability around the median of 24.24.

4)Humidity The 'humidity' column depicts a range of humidity values (0 to 100), with an average around 61.89. The distribution shows moderate variability, from 47 at the 25th percentile to 77 at the 75th percentile, indicating diverse humidity levels in the dataset.

5)WindSpeed The 'windspeed' column displays a range of wind speeds from 0 to 56.9979, with a mean of approximately 12.80.

6)Casual The 'casual' column demonstrates a broad range of casual bike rental counts, with values spanning from 0 to 367. The distribution is positively skewed, as indicated by the mean (36.02) being less than the median (17.0).

7)Registered The 'registered' column showcases a diverse range of registered bike rental counts, ranging from 0 to 886. The distribution is positively skewed, evidenced by the mean (155.55) being less than the median (118.0).

8)Count The 'count' column reveals a wide range of total bike rental counts, varying from 1 to 977. The distribution is positively skewed, with a mean (191.57) greater than the median (145.0), indicating a concentration of lower values

2. Try establishing a Relationship between the Dependent and Independent Variables.

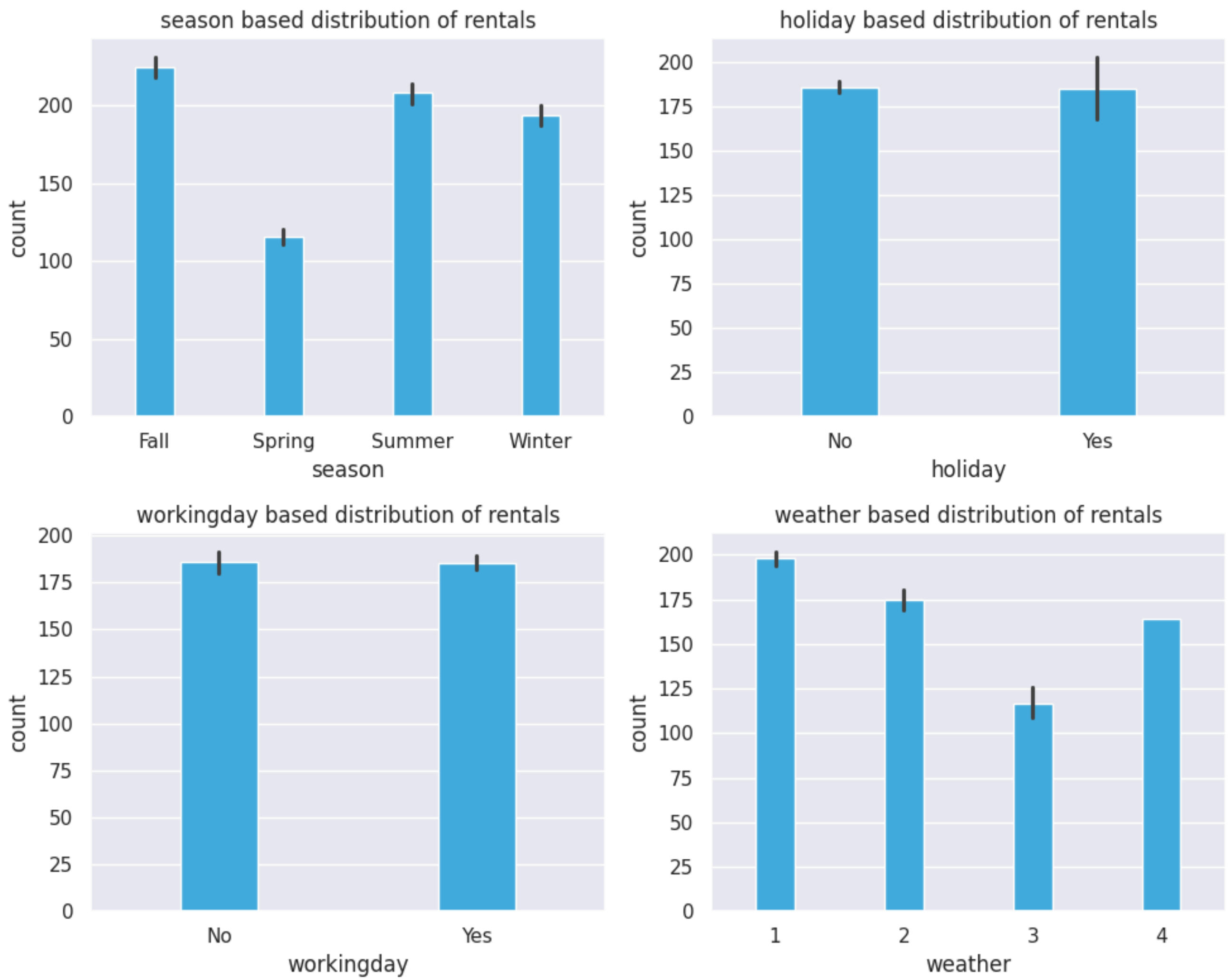
i. Plot a Correlation Heatmap and draw insights.

ii. Remove the highly correlated variables, if any.

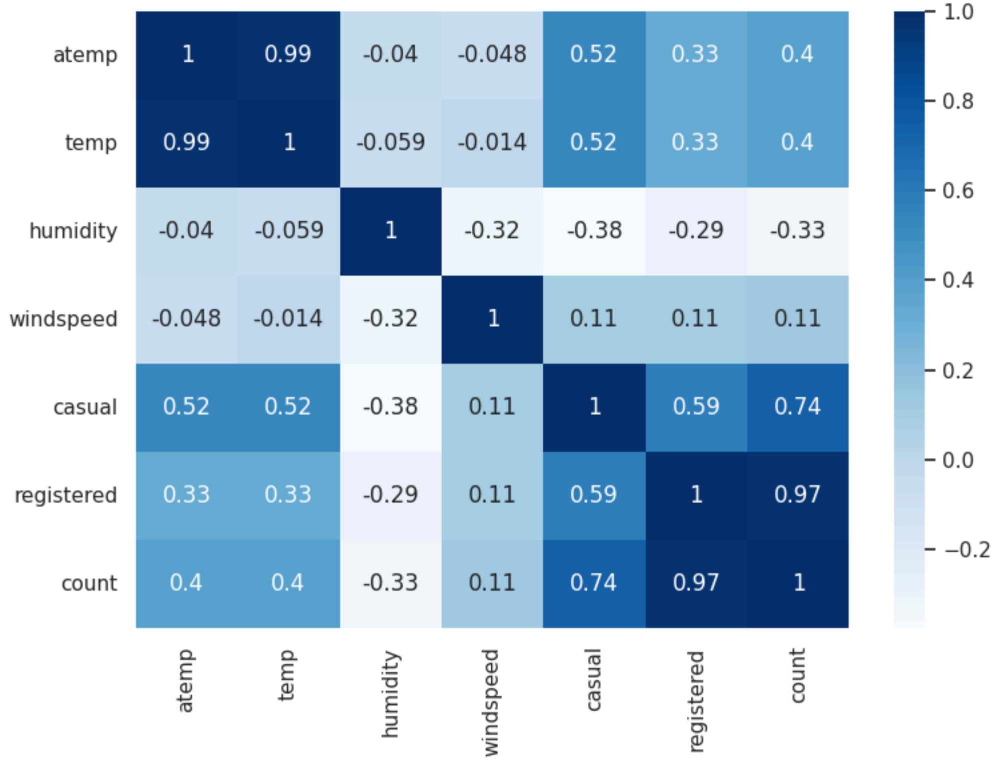
```
cat_col
```

```
['season', 'holiday', 'workingday', 'weather']
```

```
# barplot of categories

plt.figure(figsize=(10, 8))
sns.set(style="darkgrid")

for i, column in enumerate(cat_col,1):
    plt.subplot(2, 2, i)
    sns.barplot(x=column, y='count', data=df, color="#29B6F8", width = 0.3)
    plt.title(f'{column} based distribution of rentals')

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




```
# corrrelation chart

correlation_matrix = df[["atemp", "temp", "humidity", "windspeed", "casual", "registered", "count"]].corr()
plt.figure(figsize = (8, 6))
sns.heatmap(correlation_matrix, annot = True, cmap="Blues")
plt.tight_layout()
plt.show()
```



*Insights

The correlation matrix shows the Pearson correlation coefficients between pairs of variables. These coefficients range from -1 to 1, where:

1 indicates a perfect positive correlation.

-1 indicates a perfect negative correlation.

0 indicates no correlation.

Detailed Interpretation

Temperature (Atemp and Temp):

Strong positive correlation with bike rentals.

Higher temperatures increase both casual and registered rentals.

Humidity:

Moderate negative correlation with bike rentals.

Higher humidity decreases both casual and registered rentals.

Windspeed:

Very weak positive correlation with bike rentals.

Slight increase in bike rentals with higher windspeed.

Casual Rentals:

Strong positive correlation with total bike rentals.

Significantly impacted by temperature (positive) and humidity (negative).

Registered Rentals:

Very strong positive correlation with total bike rentals.

Also influenced by temperature (positive) and humidity (negative).

Total Bike Rentals (Count):

Driven significantly by both casual and registered rentals.

Positively correlated with temperature and negatively with humidity.

3. Check if there any significant difference between the no. of bike rides on Weekdays and Weekends?

a. Formulate Null Hypothesis (H0) and Alternate Hypothesis (H1)

b. Select an appropriate test

c. Set a significance level

d. Calculate test Statistics / p-value

e. Decide whether to accept or reject the Null Hypothesis.

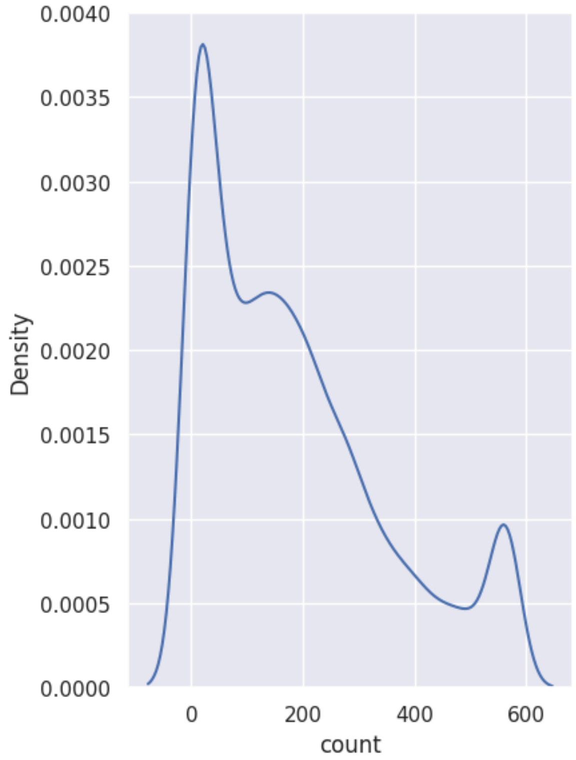
f. Draw inferences & conclusions from the analysis and provide recommendations.

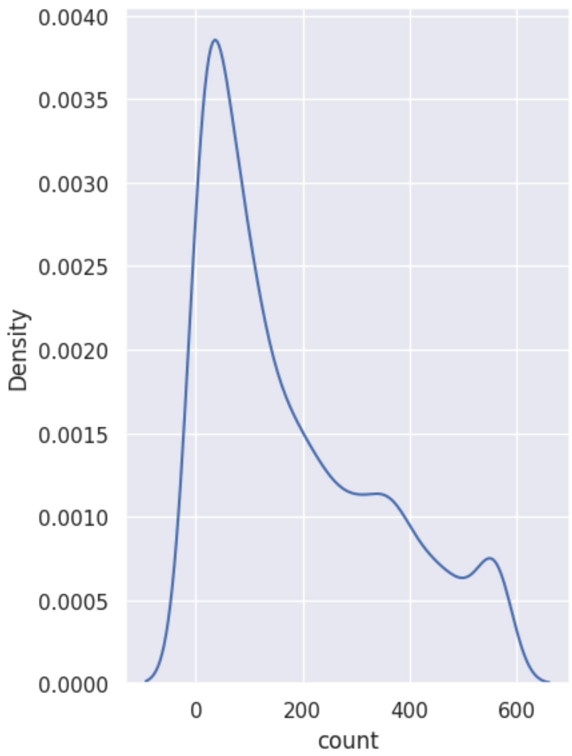
Let,

H0: Working day has No effect on number of electric cycles rented

H1: Working day has effect on number of electric cycles rented

```
working_day = df.loc[df['workingday']=="Yes", 'count']
non_working_day = df.loc[df['workingday']=="No", 'count']

fig, ax = plt.subplots(1,2,figsize=(9,6))
working_day_plot = sns.kdeplot(working_day,ax=ax[0])
non_working_day_plot = sns.kdeplot(non_working_day,ax=ax[1])
plt.tight_layout()
plt.show()
```





It's a two-sided test with one categorical and one numirical column where the distribution is not normal. We can use a non parametric method Wilcoxon-Mann-Whitney test here.

```
!pip install pingouin
import pingouin
```

Show hidden output

```
pingouin.mwu(working_day,non_working_day).round(3)
```

	U-val	alternative	p-val	RBC	CLES
MWU	12857582.0	two-sided	0.911	0.001	0.499

Here p-value is 0.911 which is greater than alpha =0.05.

So we fail to reject the hypothesis. That means, working day or non-working day has no effects on number of users

4. Check if the demand of bicycles on rent is the same for different Weather conditions?

a. Formulate Null Hypothesis (H0) and Alternate Hypothesis (H1)

b. Select an appropriate test -

c. Check assumptions of the test

i. Normality

ii. Equality Variance

iii. Please continue doing the analysis even if some assumptions f(Levene's test or Shapiro-wilk test) but double check using visanalysis and report wherever necessary.

d. Set a significance level and Calculate the test Statistics / p-value.

e. Decide whether to accept or reject the Null Hypothesis.

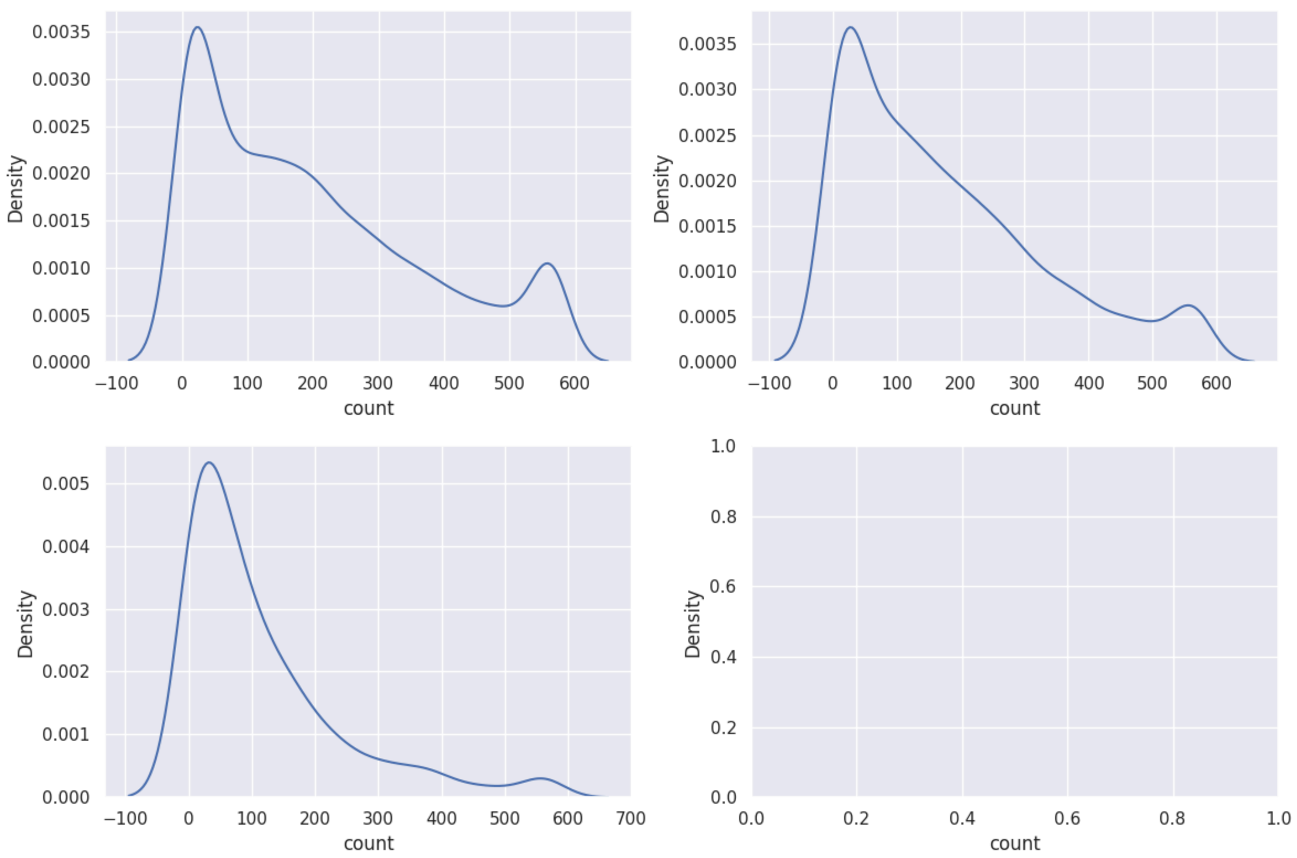
f. Draw inferences & conclusions from the analysis and provide recommendations.

***Let,**

H0: Weathers has No effect on number of electric cycles rented

H1: Weathers has effect on number of electric cycles rented

```
# 1: Clear, Few clouds, partly cloudy, partly cloudy
# 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
# 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds, Light Rain + Scattered  clouds
# 4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog
clear = df.loc[df['weather']==1,'count']
mist = df.loc[df['weather']==2,'count']
light_rain = df.loc[df['weather']==3,'count']
heavy_rain = df.loc[df['weather']==4,'count']
fig, ax = plt.subplots(2,2,figsize=(12,8))
sns.kdeplot(clear,ax=ax[0,0])
sns.kdeplot(mist,ax=ax[0,1])
sns.kdeplot(light_rain,ax=ax[1,0])
sns.kdeplot(heavy_rain,ax=ax[1,1])
plt.tight_layout()
plt.show()
```



*It's a four-sided test with one categorical and one numerical column where the distribution is not normal. We can use a non parametric method kruskals test here.

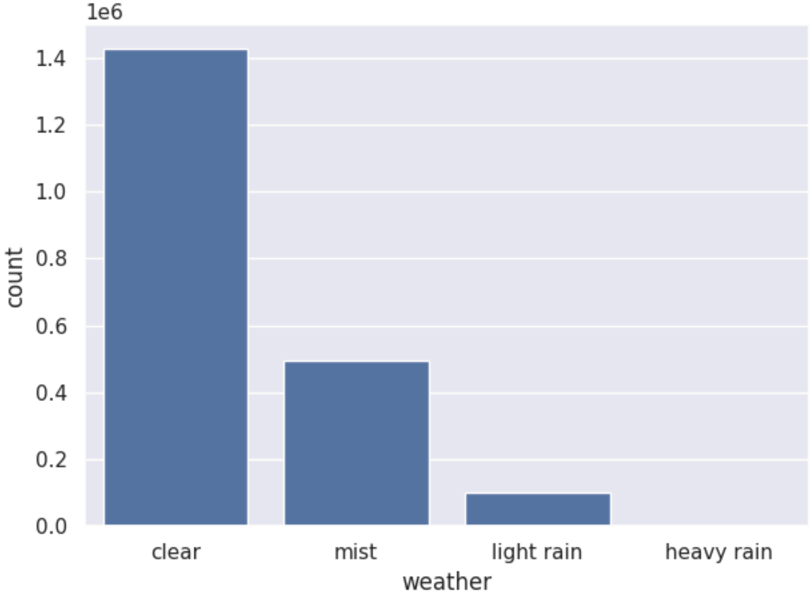
```
pingouin.kruskal(data=df[['weather','count']],dv='count',between='weather')
```

	Source	ddof1	H	p-unc
Kruskal	weather	3	204.785397	3.900417e-44

Here, P-value is 3.900417e-44 which is way too smaller than alpha=0.05.

We can reject the null hypothesis and say that,Weather effects the number of riders.

```
weather_grouped = pd.DataFrame(df.groupby('weather')['count'].sum())
sns.barplot(data=weather_grouped,x=weather_grouped.index,y='count')
plt.xticks(range(4),['clear','mist','light rain','heavy rain'])
plt.tight_layout()
plt.show()
```



*We have no count for heavy rain section hence all the plots have been empty.

5. Check if the demand of bicycles on rent is the same for different Seasons?

a. Formulate Null Hypothesis (H0) and Alternate Hypothesis (H1)

b. Select an appropriate test -

c. Check assumptions of the test

i. Normality

ii. Equality Variance

iii. Please continue doing the analysis even if some assumptions f(Levene's test or Shapiro-wilk test) but double check using visanalysis and report wherever necessary.

d. Set a significance level and Calculate the test Statistics / p-value.

e. Decide whether to accept or reject the Null Hypothesis.

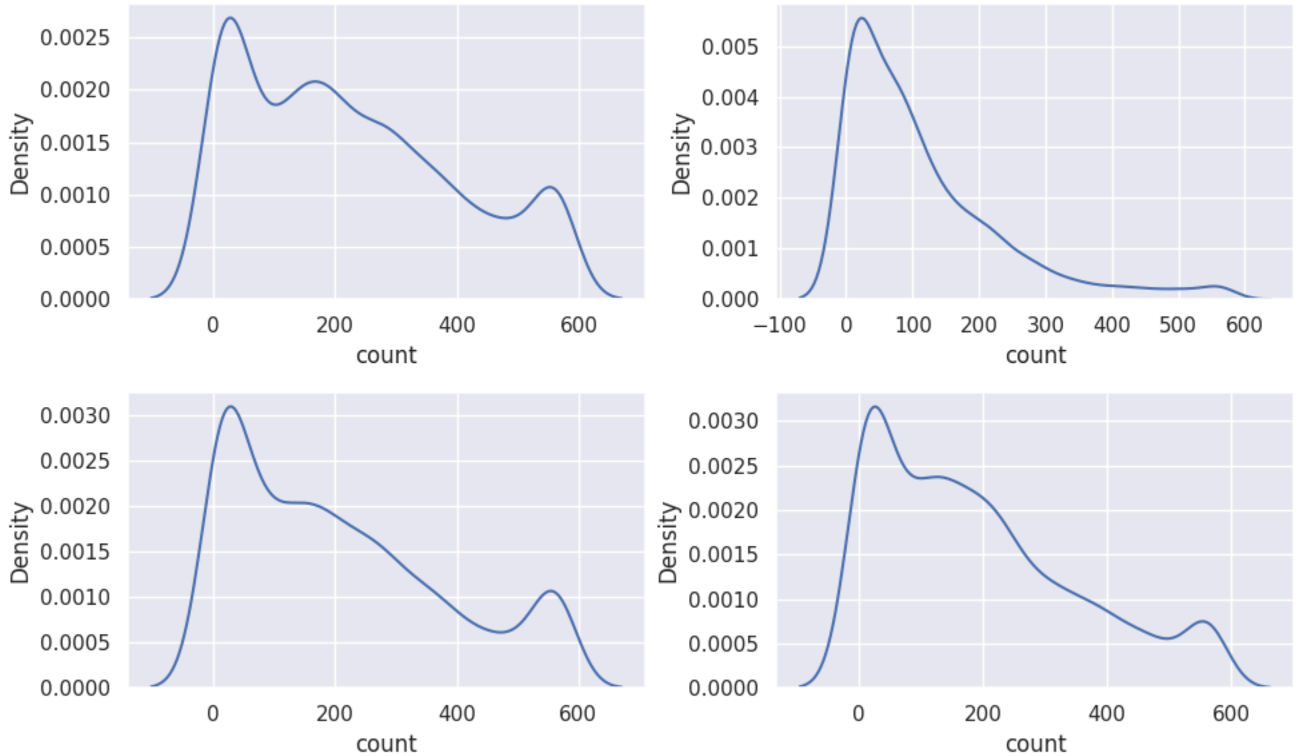
f. Draw inferences & conclusions from the analysis and provide recommendations.

***Let,**

H0: Seasons has No effect on number of electric cycles rented

H1: Seasons has effect on number of electric cycles rented

```
# 1: spring, 2: summer, 3: fall, 4: winter
spring = df.loc[df['season']=="Fall",'count']
summer = df.loc[df['season']=="Spring",'count']
fall = df.loc[df['season']=="Summer",'count']
winter = df.loc[df['season']=="Winter",'count']
fig, ax = plt.subplots(2,2,figsize=(10,6))
sns.kdeplot(spring,ax=ax[0,0])
sns.kdeplot(summer,ax=ax[0,1])
sns.kdeplot(fall,ax=ax[1,0])
sns.kdeplot(winter,ax=ax[1,1])
plt.tight_layout()
plt.show()
```



It's a four-sided test with one categorical and one numirical column where the distribution is not normal. We can use a non parametric method kruskals test here.

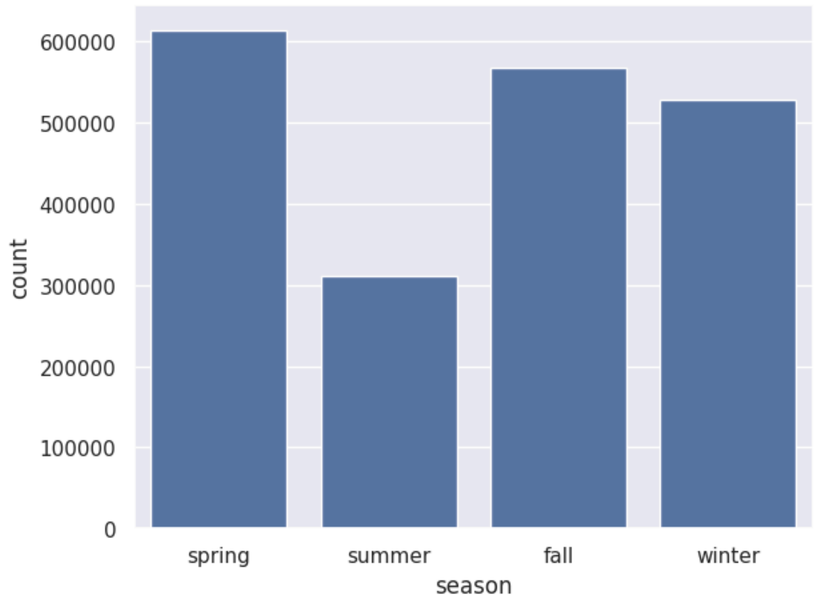
```
pingouin.kruskal(data=df,dv='count',between='season')
```

	Source	ddof1	H	p-unc
Kruskal	season	3	690.451523	2.468829e-149

Here, P-value is 2.468829e-149 which is way too smaller than alpha=0.05.

We can reject the null hypothesis and say that, Season effects the number of riders.

```
season_grouped = pd.DataFrame(df.groupby('season')['count'].sum())
sns.barplot(data=season_grouped,x=season_grouped.index,y='count')
plt.xticks(range(4),['spring','summer','fall','winter'])
plt.tight_layout()
plt.show()
```



6. Check if the Weather conditions are significantly different during different Seasons?

a. Formulate Null Hypothesis (H0) and Alternate Hypothesis (H1)

b. Select an appropriate test -

c. Check assumptions of the test

i. Normality

ii. Equality Variance

iii. Please continue doing the analysis even if some assumptions f(Levene's test or Shapiro-wilk test) but double check using visanalysis and report wherever necessary.

d. Set a significance level and Calculate the test Statistics / p-value.

e. Decide whether to accept or reject the Null Hypothesis.

f. Draw inferences & conclusions from the analysis and provide recommendations.

Let,

H0: Weather and Season are two independent columns

H1: Weather and Season are two indifferent columns

Here both the columns are categorical. So we can do a chi-square independence test.

```
expected, observed, stats=pingouin.chi2_independence(df[['season', 'weather','count']], 'season', 'weather')
stats.loc[stats['test']=='pearson']
```

	test	lambda	chi2	dof	pval	cramer	power
0	pearson	1.0	49.158656	9.0	1.549925e-07	0.038798	0.821837

Here the P-value is 1.549925e-07 which is much smaller than alpha =0.05.

So we can reject the null hypothesis and estabish that the weather and season column depends on each other.

Insights

1)Working day or non-working day has no effects on number of users.

2)Weather effects the number of riders.

3)Season effects the number of riders.

4)Weather and season column depends on each other

Recommendations

1) Optimize Bike Distribution in Peak Months: Concentrate bike deployment efforts during peak months, especially in June, July, and August, to meet increased demand and capitalize on favorable weather conditions.

2)Seasonal Marketing Strategies: Tailor marketing efforts to leverage the seasonal trend, promoting Yulu's services more aggressively during summer months to attract a larger user base.

3)Enhance User Engagement in Off-Peak Months: Implement targeted promotional campaigns or discounts during off-peak months (e.g., January to March) to encourage increased bike rentals and maintain consistent revenue flow.

4)Weather-Responsive Pricing: Consider implementing dynamic pricing strategies that respond to weather conditions. For example, adjusting rental rates during extreme weather days to optimize revenue.

5)Diversify Revenue Streams: Explore additional revenue streams, such as partnerships, sponsorships, or offering premium membership services with added benefits, to diversify income sources and boost overall profitability.

6)Enhance User Experience: Invest in technology and infrastructure to improve the overall user experience, including app features, bike maintenance, and customer support, fostering loyalty and repeat business.

7)Optimize Bike Deployment on Working Days: Given the lack of significant differences in bike rentals between working and non-working days, consider adjusting bike deployment strategies to ensure optimal resource allocation throughout the week.

8)Adapt to Different Weather Conditions: Change promotions or discounts based on the weather. If it's rainy, for example, offer special deals to encourage more people to use the bikes.

9)Promote Bikes Differently in Each Season: Advertise the bikes differently in each season. For example, highlight summer promotions in June, July, and August when more people want to ride bikes.

10)Combine Season and Weather Plans: Plan bike availability based on both the season and the weather to make sure people have the bikes they need when they want them. For example, have more bikes available on sunny days in the summer.

Double-click (or enter) to edit

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