In [ ]:

```
import pandas as pd
import seaborn as sns
```

Problem Statement:

Yulu has recently suffered considerable dips in its revenues. They have contracted a consulting company to understand the factors on which the demand for these shared electric cycles depends. Specifically, they want to understand the factors affecting the demand for these shared electric cycles in the Indian market.

We have to look into the factors that are dependent on sales and then share it with the team to take appropriate actions.

EDA

In [ ]:

```
yulu = pd.read_csv("yulu.csv")
yulu.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 [ ]:

```
yulu.shape
```

Out[ ]:

```
(10886, 12)
```

In [ ]:

```
yulu.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
```

In [ ]:

```
# datetime: datetime
# object: season, holiday, workingday, weather,
# int: "temp", "atemp", "humidity", "windspeed", "casual", "casual", "registered", "count"

yulu[["season", "holiday", "workingday", "weather"]] = yulu[["season", "holiday", "workingday", "weather"]].astype(str)

# List of column names you want to convert to integer type
columns_to_convert = ["temp", "atemp", "humidity", "windspeed", "casual", "casual", "registered", "count"]

# Loop through each column and convert its values to integer type
for column in columns_to_convert:
    yulu[column] = yulu[column].astype(int)

yulu["datetime"] = pd.to_datetime(yulu['datetime'], errors='coerce', format='%Y-%m-%d %H:%M:%S')
```

In [ ]:

```
yulu.describe(include="all")
```

Out[ ]:

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count
count	10886	10886	10886	10886	10886	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000	10886.000000
unique	NaN	4	2	2	4	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	NaN	4	0	1	1	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	NaN	2734	10575	7412	7192	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	2011-12-27 05:56:22.399411968	NaN	NaN	NaN	NaN	19.740492	23.185468	61.886460	12.425684	36.021955	155.552177	191.574132
min	2011-01-01 00:00:00	NaN	NaN	NaN	NaN	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000
25%	2011-07-02 07:15:00	NaN	NaN	NaN	NaN	13.000000	16.000000	47.000000	7.000000	4.000000	36.000000	42.000000
50%	2012-01-01 20:30:00	NaN	NaN	NaN	NaN	20.000000	24.000000	62.000000	12.000000	17.000000	118.000000	145.000000
75%	2012-07-01 12:45:00	NaN	NaN	NaN	NaN	26.000000	31.000000	77.000000	16.000000	49.000000	222.000000	284.000000
max	2012-12-19 23:00:00	NaN	NaN	NaN	NaN	41.000000	45.000000	100.000000	56.000000	367.000000	886.000000	977.000000
std	NaN	NaN	NaN	NaN	NaN	7.792108	8.500893	19.245033	8.045583	49.960477	151.039033	181.144454

In [ ]:

```
yulu.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  object        
 2   holiday     10886 non-null  object        
 3   workingday  10886 non-null  object        
 4   weather     10886 non-null  object        
 5   temp        10886 non-null  int64         
 6   atemp       10886 non-null  int64         
 7   humidity    10886 non-null  int64         
 8   windspeed   10886 non-null  int64         
 9   casual      10886 non-null  int64         
 10  registered  10886 non-null  int64         
 11  count       10886 non-null  int64         
dtypes: datetime64[ns](1), int64(7), object(4)
memory usage: 1020.7+ KB
```

In [ ]:

```
yulu.head(5)
```

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	14	81	0	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9	13	80	0	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9	13	80	0	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9	14	75	0	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9	14	75	0	0	1	1

In [ ]:
```
yulu.workingday.value_counts()
```

Out[ ]:
```
workingday
1    7412
0    3474
Name: count, dtype: int64
```

In [ ]:
```
yulu.weather.value_counts()
```

Out[ ]:
```
weather
1    7192
2    2834
3     859
4       1
Name: count, dtype: int64
```

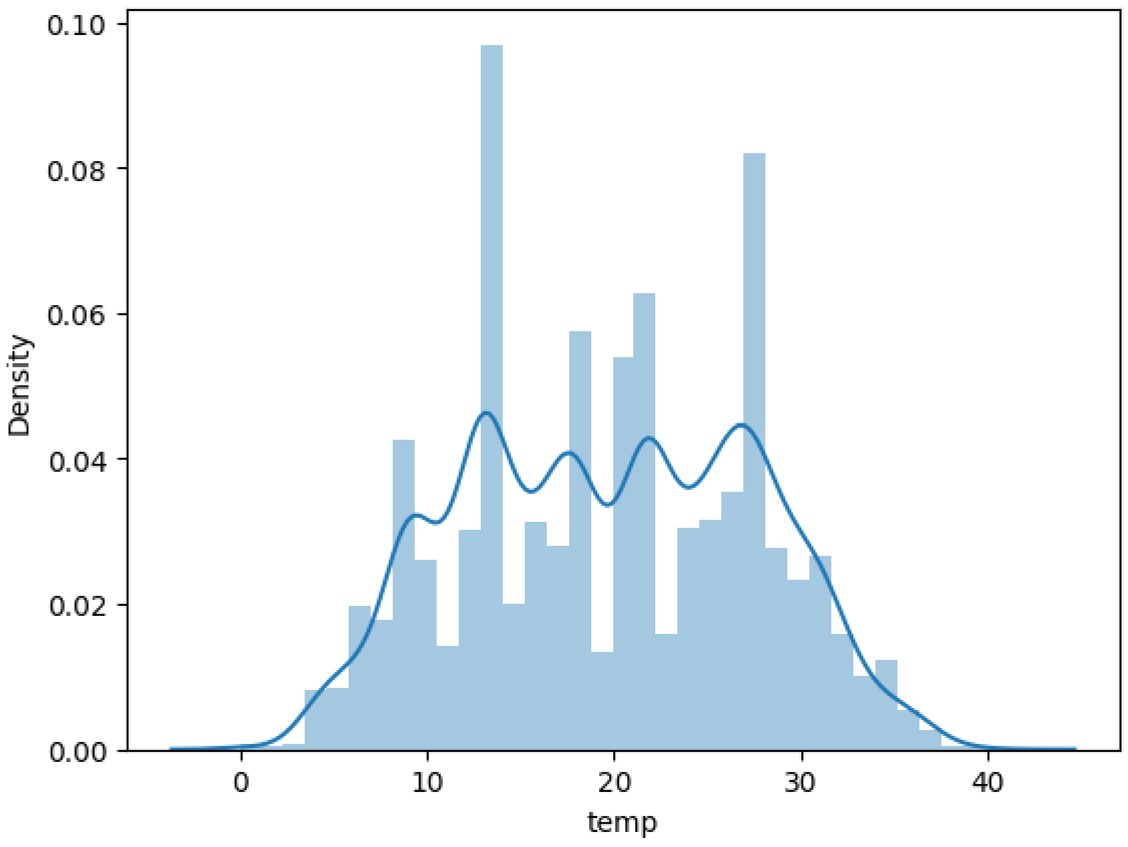
In [ ]:
```
yulu.season.value_counts()
```

Out[ ]:
```
season
4    2734
2    2733
3    2733
1    2686
Name: count, dtype: int64
```

In [ ]:
```
# Plot the distribution
sns.distplot(yulu["temp"])
```

```
/tmp/ipykernel_17497/105219704.py:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(yulu["temp"])
```

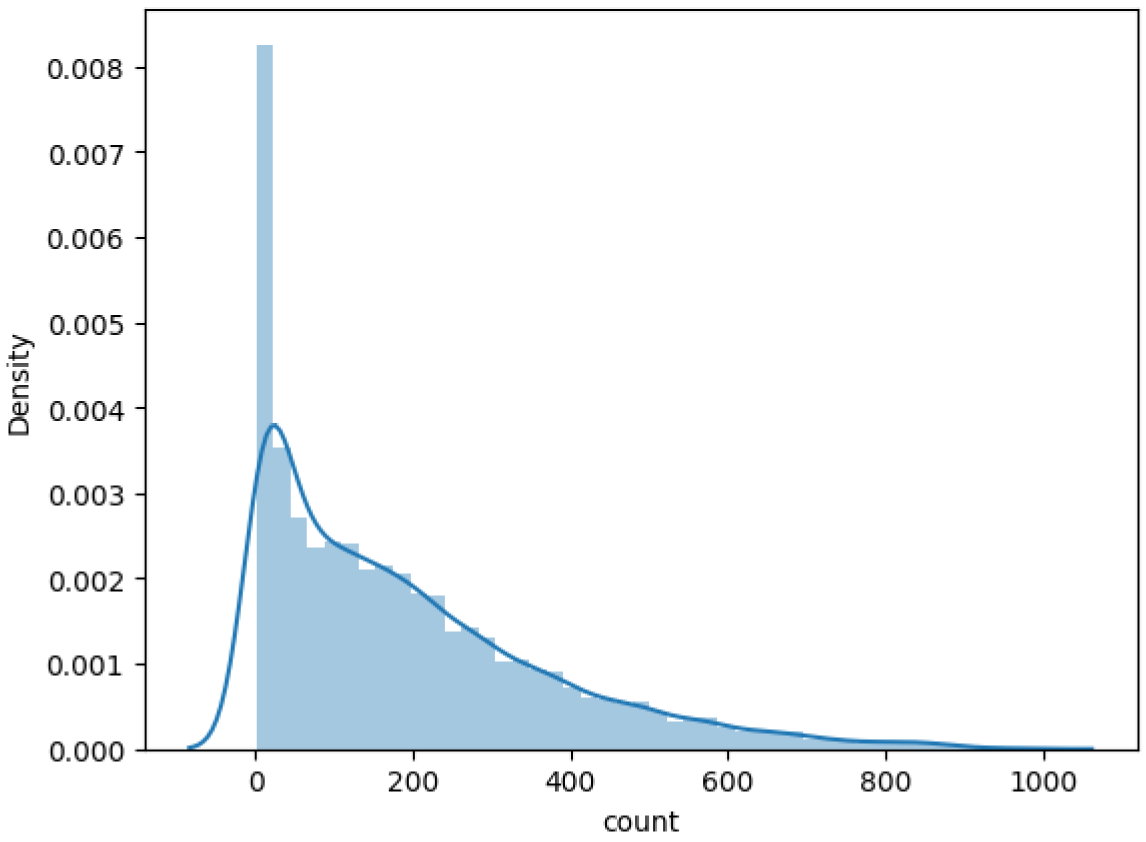
Out[ ]:
```
<Axes: xlabel='temp', ylabel='Density'>
```



In [ ]:
```
# Plot the distribution
sns.distplot(yulu["count"])
```

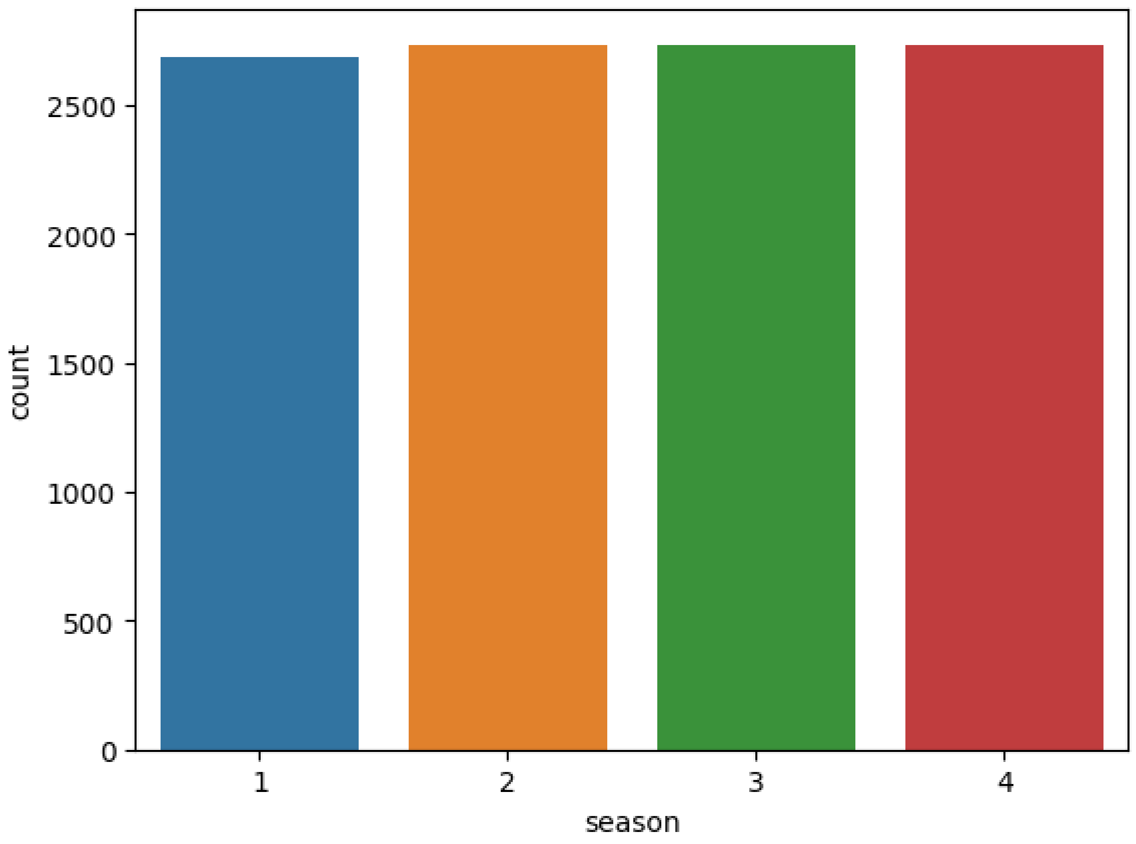
```
/tmp/ipykernel_17497/3034417654.py:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(yulu["count"])
```

Out[ ]:
```
<Axes: xlabel='count', ylabel='Density'>
```



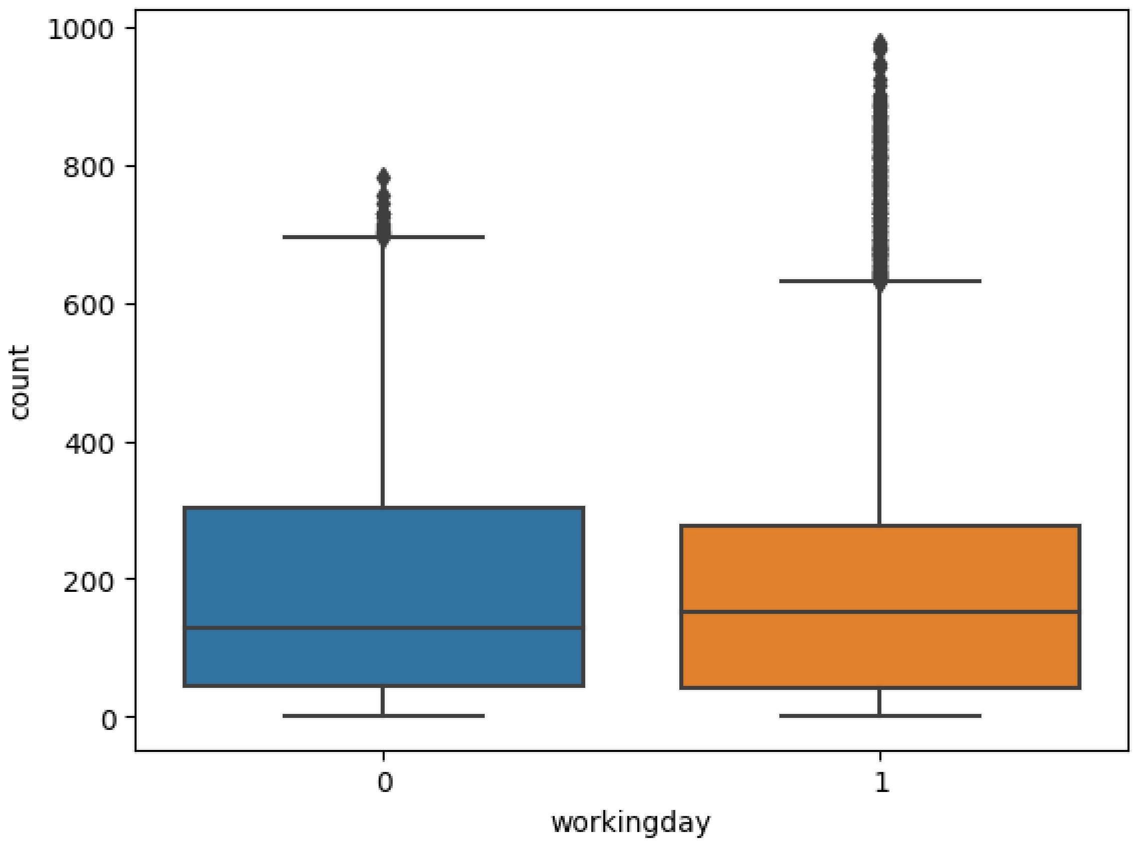
In [ ]:
```
sns.countplot(x="season", data=yulu)
```

Out[ ]:
```
<Axes: xlabel='season', ylabel='count'>
```



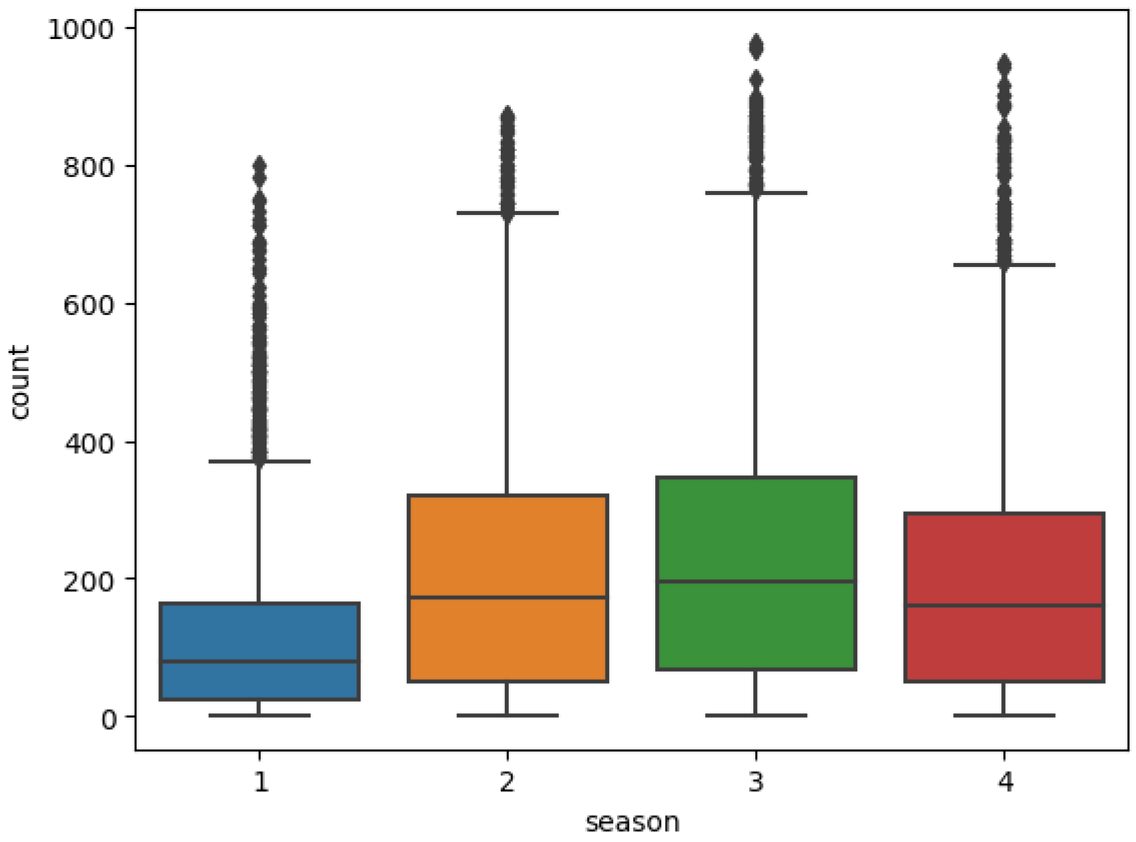
```
In [ ]: sns.boxplot(x="workingday", y="count", data=yulu)
```

```
Out[ ]: <Axes: xlabel='workingday', ylabel='count'>
```



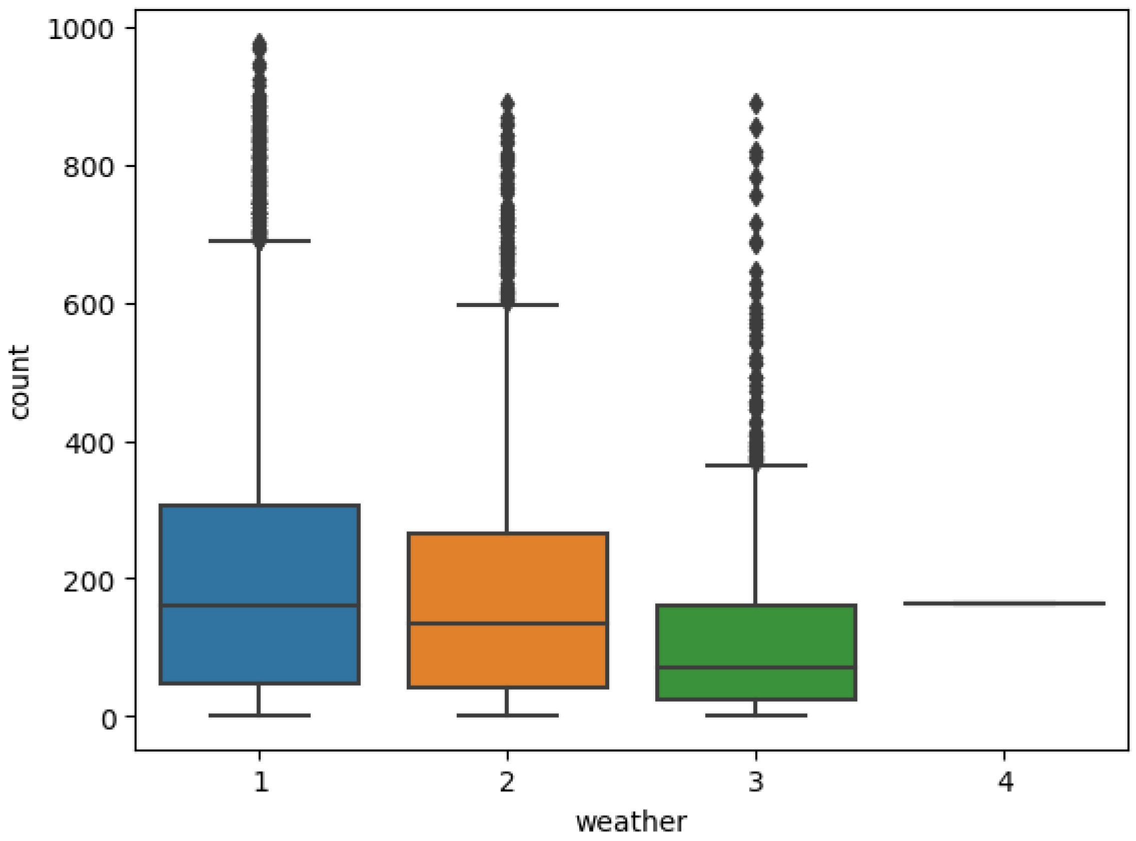
```
In [ ]: sns.boxplot(x="season", y="count", data=yulu)
```

```
Out[ ]: <Axes: xlabel='season', ylabel='count'>
```



```
In [ ]: sns.boxplot(x="weather", y="count", data=yulu)
```

```
Out[ ]: <Axes: xlabel='weather', ylabel='count'>
```



```
In [ ]: ## Since we can see that count is not normalized, let's try to handle by removing outliers
        #optional
        q1=yulu['count'].quantile(0.25)
        q3=yulu['count'].quantile(0.75)
        iqr=q3-q1
        iqr
```

```
Out[ ]: 242.0
```

In [ ]:

```
yulu = yulu[(yulu["count"]>(q1-1.5*iqr)) & (yulu["count"]<(q3+1.5*iqr))]
yulu.shape
```

Out[ ]:

```
(10583, 12)
```

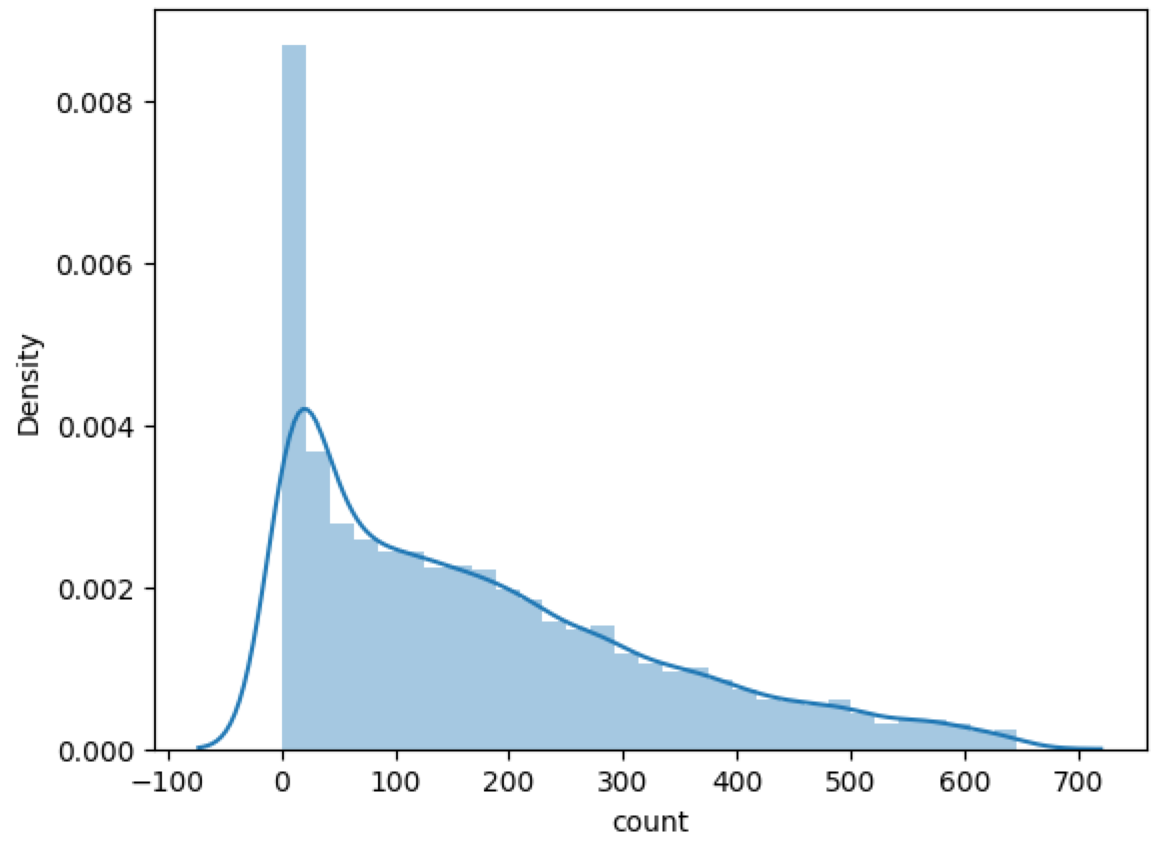
In [ ]:

```
# Plot the distribution
sns.distplot(yulu["count"])
```

```
/tmp/ipykernel_17497/3034417654.py:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(yulu["count"])
```

Out[ ]:

```
<Axes: xlabel='count', ylabel='Density'>
```

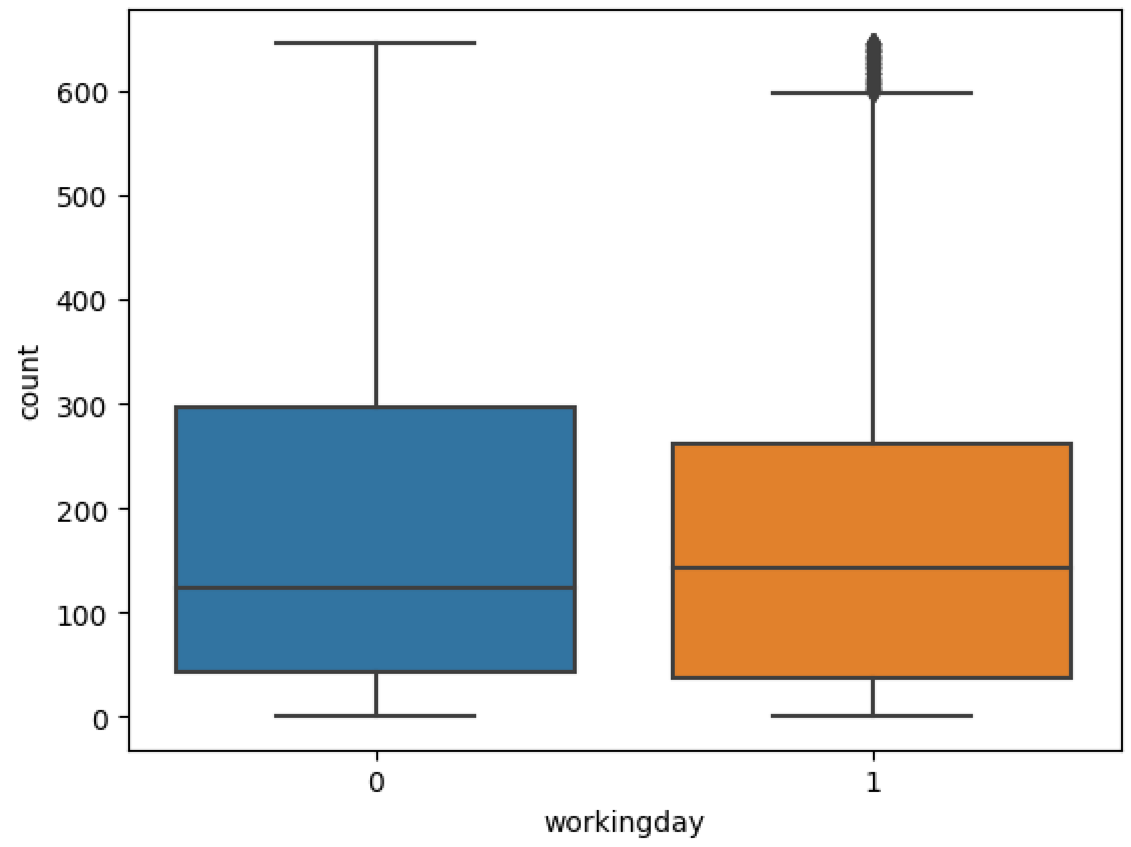


In [ ]:

```
sns.boxplot(x="workingday", y="count", data=yulu)
```

Out[ ]:

```
<Axes: xlabel='workingday', ylabel='count'>
```



In [ ]:

```
yulu
```

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	14	81	0	3	13	16
1	2011-01-01 01:00:00	1	0	0	1	9	13	80	0	8	32	40
2	2011-01-01 02:00:00	1	0	0	1	9	13	80	0	5	27	32
3	2011-01-01 03:00:00	1	0	0	1	9	14	75	0	3	10	13
4	2011-01-01 04:00:00	1	0	0	1	9	14	75	0	0	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...
10881	2012-12-19 19:00:00	4	0	1	1	15	19	50	26	7	329	336
10882	2012-12-19 20:00:00	4	0	1	1	14	17	57	15	10	231	241
10883	2012-12-19 21:00:00	4	0	1	1	13	15	61	15	4	164	168
10884	2012-12-19 22:00:00	4	0	1	1	13	17	61	6	12	117	129
10885	2012-12-19 23:00:00	4	0	1	1	13	16	66	8	4	84	88

10583 rows × 12 columns

EDA Analysis:

1. The data shape after removing the outliers based on rides taken is 10583 values, 12 features with labels.
2. Data doesn't look liek Normal Distribution after doing visualization.
3. There is no significant difference in the quartile ranges for working days with respect to bike hired.
4. In Season Vs Rides taken, season 1 i.e. spring season shows least values, while Season 3 i.e. Fall show maximum rides taken.
5. In weather Vs Rides taken, weather 3 i.e. Light Snow shows least rider takes while weather 1 i.e. Clear shows maximum rides taken.

In [ ]:

```
## We'll be considering 5% significance value throughout the usecase
alpha = 0.05
```

Working Day has effect on number of electric cycles rented

In [ ]:

```
"""
H0 : The count of weekday is LESS THAN or equal to the count on weekend
H1 : The count on weekday is GREATER THAN count on weekend

We'll be using T-Test sinse our sample size is large enough
"""
```

```
weekday = yulu.loc[yulu["workingday"]=="1"]["count"].sample(3300)
weekend = yulu.loc[yulu["workingday"]=="0"]["count"].sample(3300)
```

In [ ]:

```
## Standard deviation for both the samples
weekday.std(), weekend.std()
```

Out[ ]:

```
(152.3914891210599, 163.75505394941317)
```

In [ ]:

```
## Compute the p-value
from scipy.stats import ttest_ind

test_stat, p_value = ttest_ind(weekday, weekend, equal_var=False, alternative="greater")
test_stat, p_value
```

Out[ ]:

```
(-1.7028493882895281, 0.9556782003426753)
```

In [ ]:

```
if p_value < alpha:
    print("We reject the null Hypothesis")
else:
    print("Fail to reject the null Hypothesis")
```

```
Fail to reject the null Hypothesis
```

Based on the evaluation, we conclude that :

1. We fail to reject our NULL Hypothesis i.e. Rides count on weekday is LESS THAN or equal to the count on weekend

In [ ]:

No. of cycles rented similar or different in different seasons

In [ ]:

```
yulu["season"].value_counts()
```

Out[ ]:

```
season
1    2670
4    2664
2    2633
3    2616
Name: count, dtype: int64
```

In [ ]:

```
yulu.groupby(["season"])["count"].describe()
```

Out[ ]:

season	count	mean	std	min	25%	50%	75%	max
1	2670.0	112.795131	116.884929	1.0	24.00	78.0	161.00	644.0
2	2633.0	195.653627	166.170802	1.0	45.00	165.0	299.00	646.0
3	2616.0	210.484327	164.055532	1.0	59.75	185.0	323.25	646.0
4	2664.0	184.404655	154.563069	1.0	48.75	154.0	276.25	646.0

In [ ]:

```
"""
H0 : The mean COUNT is same in all SEASON
H1 : The mean COUNT is different in all SEASON

We'll be using ANNOVA after testing the case conditions using Shapiro and Levene Test
"""

s1 = yulu.loc[yulu["season"]=="1"]["count"].sample(2500)
s2 = yulu.loc[yulu["season"]=="2"]["count"].sample(2500)
s3 = yulu.loc[yulu["season"]=="3"]["count"].sample(2500)
s4 = yulu.loc[yulu["season"]=="4"]["count"].sample(2500)
```

In [ ]:

```
## Shapiro Test
from scipy.stats import shapiro

e, p_value = shapiro(yulu["count"].sample(7000))

if p_value < alpha:
    print("REJECT our NULL Hypothesis that our data follows Gaussian Distribution")
else:
    print("FAIL REJECT our NULL Hypothesis that our data follows Gaussian Distribution")
```

```
REJECT our NULL Hypothesis that our data follows Gaussian Distribution
```

```
/home/varun/Documents/workspace/neoversity/6 Data Analytics and Visualisation - Fundamentals/.venv/lib/python3.10/site-packages/scipy/stats/_morestats.py:1882: UserWarning: p-
value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

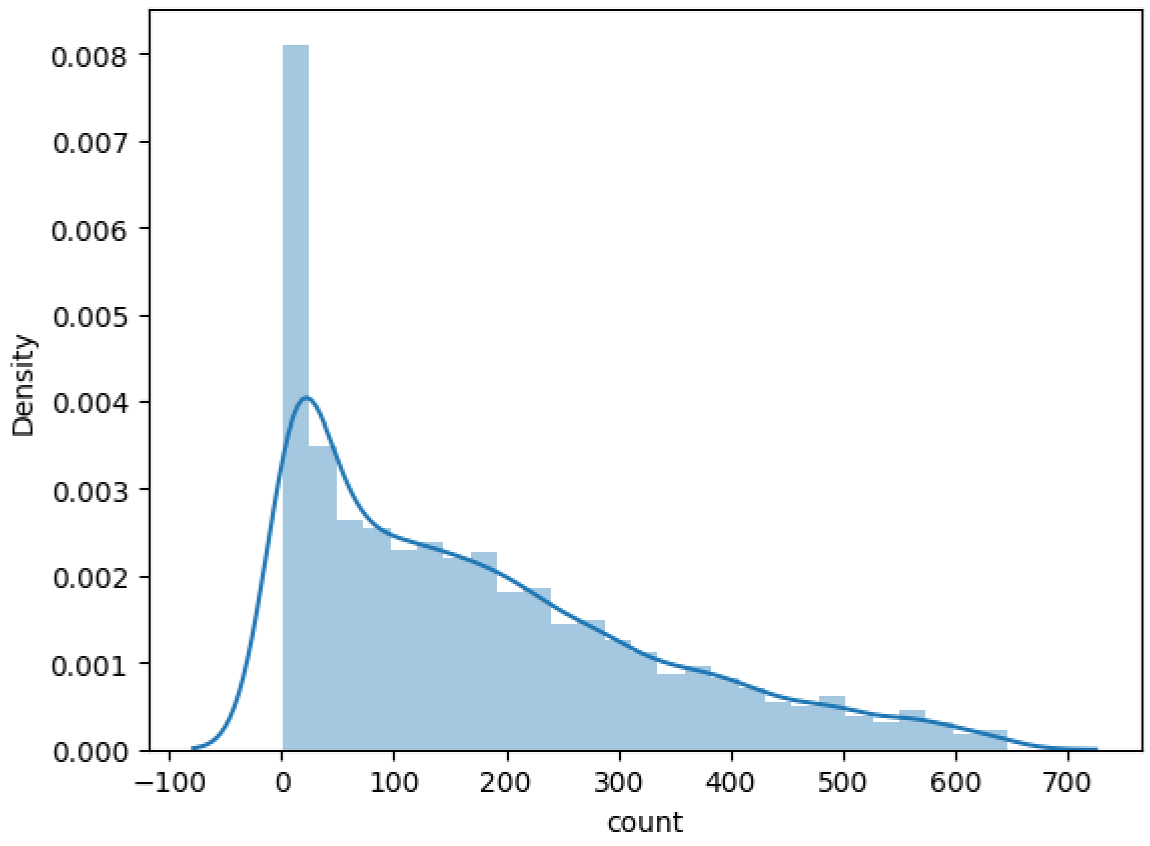
In [ ]:

```
sns.distplot(yulu["count"].sample(7000))
```

```
/tmp/ipykernel_17497/258741346.py:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(yulu["count"].sample(7000))
```

Out[ ]:

```
<Axes: xlabel='count', ylabel='Density'>
```



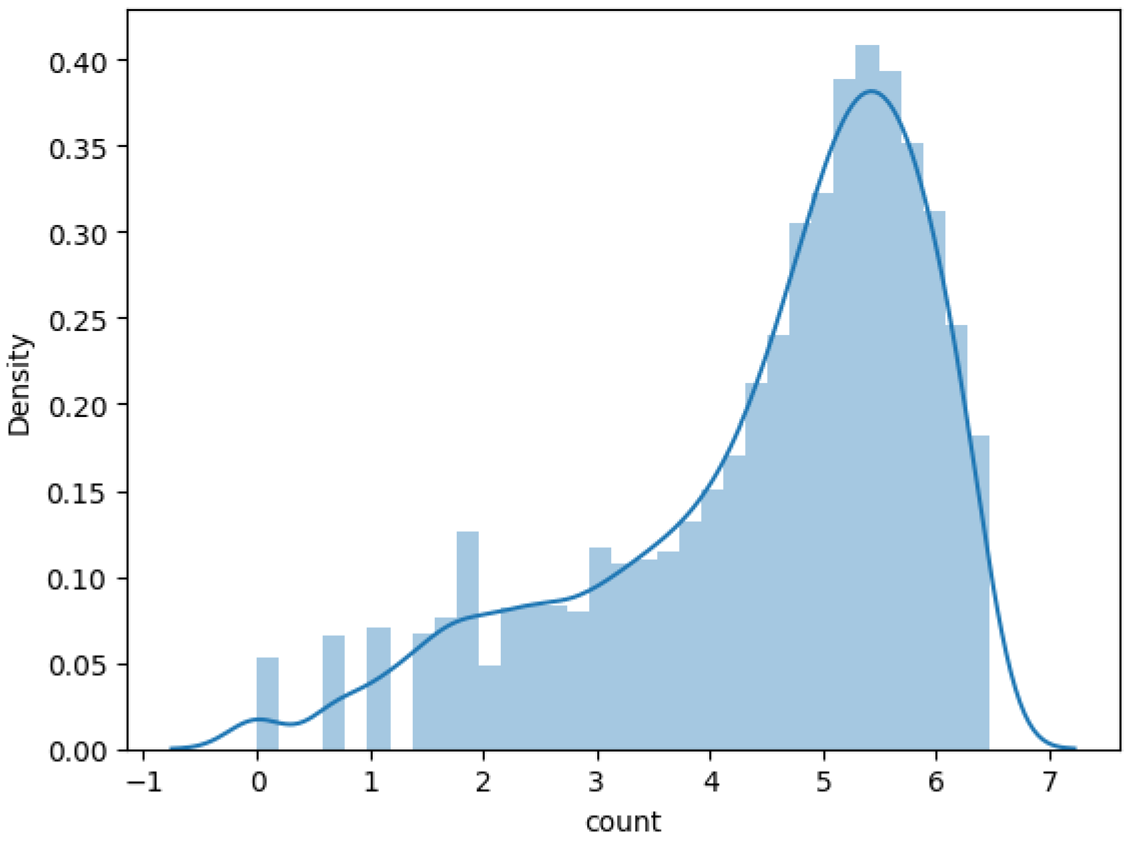
In [ ]:

```
import numpy as np
sns.distplot(np.log(yulu["count"].sample(7000)))
```

```
/tmp/ipykernel_17497/3643855242.py:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(np.log(yulu["count"].sample(7000)))
```

Out[ ]:

```
<Axes: xlabel='count', ylabel='Density'>
```



In [ ]:

```
## Levene's Test
from scipy.stats import levene

statistics, p_value = levene(s1,s2,s3,s4)

if p_value < alpha:
    print("Reject the NULL Hypothesis that sets have Equal Variances")
else:
    print("FAIL to Reject the NULL Hypothesis that Equal Variances")
```

```
Reject the NULL Hypothesis that sets have Equal Variances
```

In [ ]:

```
## By looking at the analysis it states that out criterio doesn't matches, but still we will be following ANOVA since it is more generalized and detailed and results right ou
from scipy.stats import f_oneway
test_stats, p_value = f_oneway(s1,s2,s3,s4)
print(test_stats, p_value,"\n")

if p_value < alpha:
    print("Reject the NULL hypothesis that mean COUNT is same in all SEASON")
else:
    print("FAIL TO Reject the NULL hypothesis that mean COUNT is same in all SEASON")
```

```
202.3759638409876 1.967778746443962e-127

Reject the NULL hypothesis that mean COUNT is same in all SEASON
```

Based on the evaluation, we conclude that :

1. We reject our NULL Hypothesis i.e. that mean COUNT of rides is same in all SEASON.

In [ ]:

No. of cycles rented similar or different in different weather

In [ ]:

```
yulu["weather"].value_counts()
```

Out[ ]:

```
weather
1    6962
2    2770
3     850
4       1
Name: count, dtype: int64
```

In [ ]:

```
## Remove the weather type 4 from the categorization since it has only 1 value in count.
yulu = yulu.loc[~(yulu["weather"]=="4")]
yulu["weather"].value_counts()
```

Out[ ]:

```
weather
1    6962
2    2770
3     850
Name: count, dtype: int64
```

In [ ]:

```
"""
H0 : The mean COUNT is same in all WEATHER, weather has no impact on Rides
H1 : The mean COUNT is different in all WEATHER, weather has impact on Rides

We'll be using ANNOVA after testing the case conditions using Shapiro and Levene Test
"""

w1 = yulu.loc[yulu["weather"]=="1"]["count"].sample(800)
w2 = yulu.loc[yulu["weather"]=="2"]["count"].sample(800)
w3 = yulu.loc[yulu["weather"]=="3"]["count"].sample(800)
```

In [ ]:

```
yulu.groupby(["weather"])["count"].describe()
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
weather								
1	6962.0	187.131140	161.333785	1.0	45.0	153.0	286.0	646.0
2	2770.0	166.117690	146.992422	1.0	39.0	130.0	254.0	646.0
3	850.0	111.862353	121.233389	1.0	23.0	70.5	157.0	646.0

In [ ]:

```
## Normality we already checked in out previous test case, now let's check Levene's test
## Levene's Test
from scipy.stats import levene

statistics, p_value = levene(w1,w2,w3)

if p_value < alpha:
    print("Reject the NULL Hypothesis that sets have Equal Variances")
else:
    print("FAIL to Reject the NULL Hypothesis that Equal Variances")
```

```
Reject the NULL Hypothesis that sets have Equal Variances
```

In [ ]:

```python
## By looking at the analysis it states that out criterio doesn't matches.
## But still we will be following ANOVA since it is more generalized and detailed and results right output.
from scipy.stats import f_oneway
test_stats, p_value = f_oneway(w1,w2,w3)
print(test_stats, p_value,"\n")
if p_value < alpha:
    print("REJECT the NULL Hypothesis, that < mean COUNT is same in all WEATHER and that weather has no impact on Rides >")
else:
    print("FAIL to reject the NULL Hypothesis")
```

```
57.11857817188354 5.843810077596215e-25

REJECT the NULL Hypothesis, that < mean COUNT is same in all WEATHER and that weather has no impact on Rides >
```

Based on the evaluation, we conclude that :

1. We reject our NULL Hypothesis i.e. mean COUNT OF rides is same in all WEATHER and that weather has no impact on Rides

In [ ]:

Weather is dependent on season (check between 2 predictor variable)

In [ ]:

```python
yulu["weather"].value_counts()
```

Out[ ]:

```
weather
1    6962
2    2770
3     850
Name: count, dtype: int64
```

In [ ]:

```python
yulu["season"].value_counts()
```

Out[ ]:

```
season
1    2669
4    2664
2    2633
3    2616
Name: count, dtype: int64
```

In [ ]:

```python
"""
# H0: Weather and Season are independent
# Ha: Weather and Season are dependent

We'll be using CHISQUARE, since both are categorical types
"""

weather_season = pd.crosstab(index=yulu['weather'],columns=yulu['season'])
weather_season
```

Out[ ]:

season	1	2	3	4
weather				
1	1744	1720	1842	1656
2	714	690	579	787
3	211	223	195	221

In [ ]:

```python
from scipy.stats import chi2_contingency

chi_stat, p_value, df, exp_value = chi2_contingency(weather_season)
print(chi_stat, p_value, df, exp_value,"\n")

if p_value < 0.05:
    print("Reject NULL HYPOTHESIS i.e. Weather and Season are independent")
else:
    print("Wheather and Season are DEPENDENT")
```

```
44.19795559650439 6.75312212866461e-08 6 [[1755.96087696 1732.27612928 1721.09166509 1752.67132867]
 [ 698.65148365  689.22793423  684.77792478  697.34265734]
 [ 214.38763939  211.4959365   210.13041013  213.98601399]]

Reject NULL HYPOTHESIS i.e. Weather and Season are independent
```

Based on the evaluation, we conclude that :

1. We reject our NULL Hypothesis i.e. WHETHER AND SEASON are INDEPENDENT.

In [ ]:

Recommendations :

1. We have sufficient evidence to say that Weekdays rides are less than Weekend rides. Hence we should plan the bussiness and create the pipeline accordingly.
2. For SEASON and WEATHER we reject that their is no impact on rides taken, they have their impact and we should do proper analysis to check all scenaios where our revenue is not improving.
3. We saw that whether and season not INDEPENDENT hence we should focus on such structural planning that can have an impacts on both.

In [ ]: