```
import pandas as pd
import seaborn as sbn
```

```
df=pd.read_csv('C:/Users/ASUS/Downloads/bike_sharing.csv')
```

```
df.head()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	winds
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	
2	2011-01-01	1	0	0	1	9.02	13.635	80	

```
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
```

```
df.season.value_counts()
```

```
4    2734
2    2733
3    2733
1    2686
Name: season, dtype: int64
```

```
df.weather.value_counts()
```

```
1    7192
2    2834
```

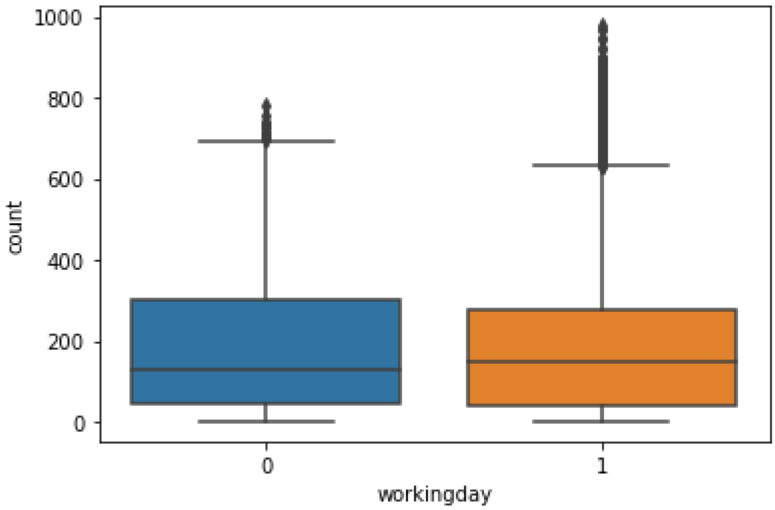
```
3      859
4        1
Name: weather, dtype: int64
```

```
df.workingday.value_counts()
```

```
1    7412
0    3474
Name: workingday, dtype: int64
```

```
sbn.boxplot(x='workingday', y='count', data =df)
```

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




```
q1=df['count'].quantile(0.25)
q3=df['count'].quantile(0.75)
iqr=q3-q1
```

```
df=df[(df['count']>(q1-1.5*iqr) ) & (df['count']<(q3+1.5*iqr))]
```

```
df.shape
```

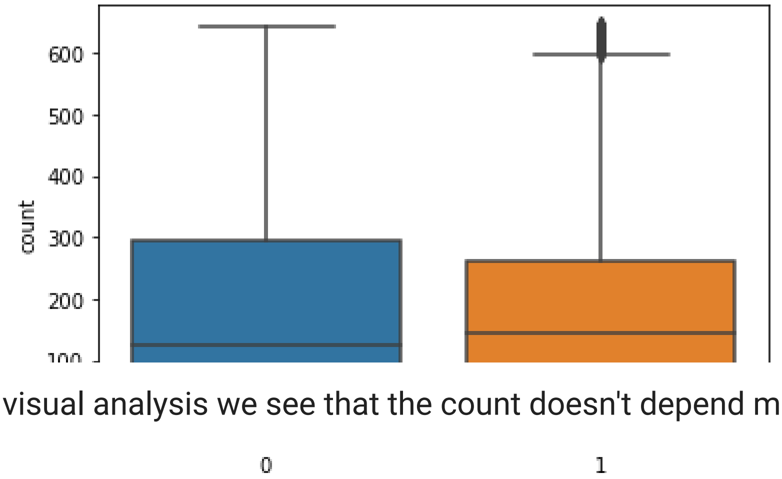
```
(10583, 12)
```

```
df.workingday.value_counts()
```

```
1    7161
0    3422
Name: workingday, dtype: int64
```

```
sbn.boxplot(x='workingday', y='count', data =df)
```

<AxesSubplot:xlabel='workingday', ylabel='count'>



With visual analysis we see that the count doesn't depend much on the working day

Need to check using statistical methods

The t test as compared with z test is its advantage for small sample comparison. As n increases, t approaches to z. The advantage of t test disappears, and t distribution simply becomes z distribution. In other words, with large n. t test is just close to z test. and one don't loose anything to continue to use t test. In the past, for convenience, we use z table when n > 30. We don't have to do it anymore. In fact, all statistical packages use t test even n is large. This is easy, convenience with computer programming, and is correct. All statistical packages are good references.

Population std is unknown

Step 1: Define the null and alternate hypotheses

$H_0:$ The count on weekday is equal to the count on weekend.

$H_a:$ The count on weekday is greater than count on weekend.

Let μ_1 and μ_2 be the mean time spent by the users on the new and old page respectively.

Mathematically, the above formulated hypotheses can be written as:

$H_0: \mu_1 = \mu_2$

$H_a: \mu_1 > \mu_2$

Step 2: Select Appropriate test

This is a one-tailed test concerning two population means from two independent populations. As the population standard deviations are unknown, the two sample independent t-test will be the appropriate test for this problem.

Step 3: Decide the significance level

As given in the problem statement, we select α = 0.05.

Step 4: Collect and prepare data

```
weekday = df[df['workingday'] == 1]['count'].sample(3422)
weekend = df[df['workingday'] == 0]['count'].sample(3422)
```

```
print('The sample standard deviation of the count on weekday is:', round(weekday.st
print('The sample standard deviation of the count on weekend is:', round(weekend.st
```

```
The sample standard deviation of the count on weekday is: 152.24
The sample standard deviation of the count on weekend is: 163.78
```

As the sample standard deviations are different, the population standard deviations may be assumed to be different.

Step 5: Calculate the p-value

```
# import the required function
from scipy.stats import ttest_ind
# find the p-value
test_stat, p_value = ttest_ind(weekday, weekend, equal_var = False, alternative = '
print('The p-value is', p_value)
```

```
The p-value is 0.9962219969001282
```

```
# print the conclusion based on p-value
if p_value < 0.05:
    print(f'As the p-value {p_value} is less than the level of significance, we rej
else:
    print(f'As the p-value {p_value} is greater than the level of significance, we
```

```
As the p-value 0.9962219969001282 is greater than the level of significance, w
```

Is the demand of electric cycles same for different weather?

```
df.weather.value_counts()
```

```
1    6962
2    2770
3     850
```

```
4        1
Name: weather, dtype: int64
```

```
df=df[~(df['weather']==4)]
```

```
w1 = df[df['weather'] == 1]['count'].sample(850)
w2= df[df['weather'] == 2]['count'].sample(850)
w3 = df[df['weather'] == 3]['count'].sample(850)
```

```
df.groupby(['weather'])['count'].describe()
```

weather	count	mean	std	min	25%	50%	75%	max
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

Step 1: Define the null and alternate hypotheses

$H_0:$$H_0:$ The mean count in different weather are equal.

$H_a:$$H_a:$ The mean count in different weather are different.

Step 2: Select Appropriate test

This is a problem, concerning three population means. One-way ANOVA could be the appropriate test here provided normality and equality of variance assumptions are verified.

- For testing of normality, Shapiro-Wilk’s test is applied to the response variable.
- For equality of variance, Levene test is applied to the response variable.

Shapiro-Wilk’s test

We will test the null hypothesis

> $H_0:$$H_0:$ Count follows normal distribution

against the alternative hypothesis

> $H_a:$$H_a:$ Count doesn't follow normal distribution

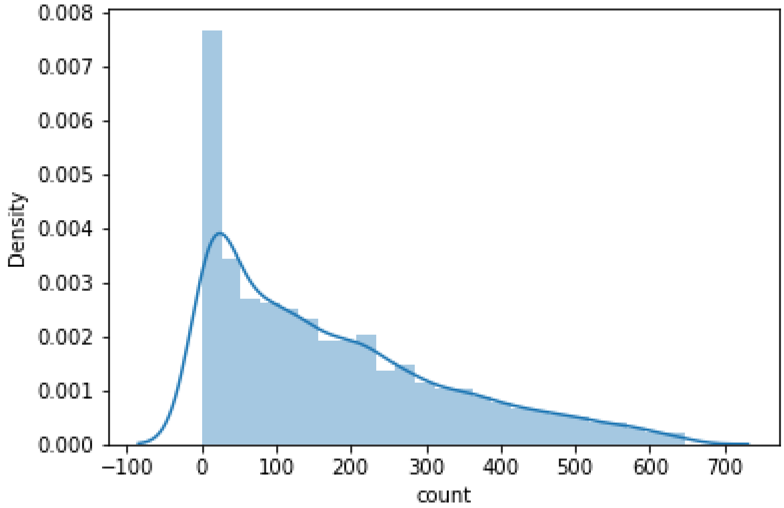
```
# Assumption 1: Normality
# import the required function
from scipy.stats import shapiro

# find the p-value
```

```
w, p_value = shapiro(df['count'].sample(4999))
print('The p-value is', p_value)
```

```
The p-value is 0.0
```

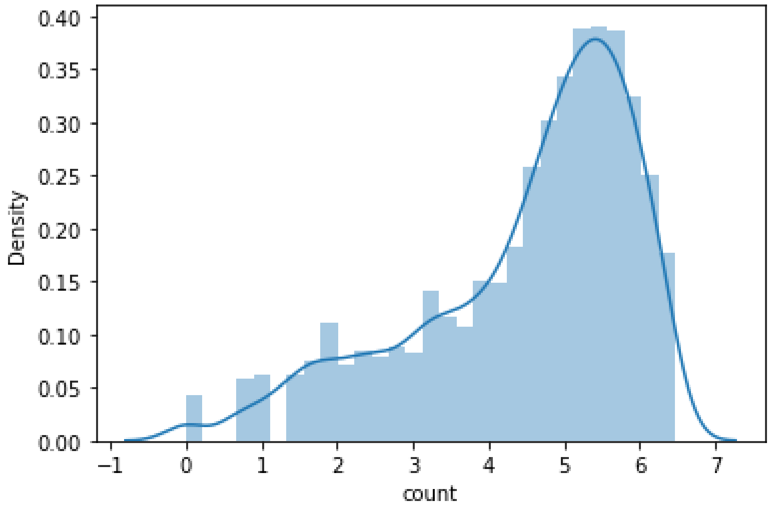
```
sbn.distplot(df['count'].sample(4999))
```

```
C:\Users\ASUS\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Futur
  warnings.warn(msg, FutureWarning)
<AxesSubplot:xlabel='count', ylabel='Density'>
```




```
import numpy as np
sbn.distplot(np.log(df['count'].sample(4999)))
```

```
C:\Users\ASUS\anaconda3\lib\site-packages\seaborn\distributions.py:2619: Futur
  warnings.warn(msg, FutureWarning)
<AxesSubplot:xlabel='count', ylabel='Density'>
```



Please continue doing the analysis even If some assumptions fail (levene's test or Shapiro-wilk test) but double check using visual analysis and report wherever necessary

Levene's test

We will test the null hypothesis

> $H_0$$H_0$: All the count variances are equal

against the alternative hypothesis

> $H_a$$H_a$: At least one variance is different from the rest

```
#Assumption 2: Homogeneity of Variance
#import the required function
from scipy.stats import levene
statistic, p_value = levene( w1,
                             w2,
                             w3)
# find the p-value
print('The p-value is', p_value)
```

```
The p-value is 5.4137990743466145e-20
```

```
p_value>0.05
```

```
False
```

```
print(w1.var(), w2.var(), w3.var())
```

```
26472.897670615952 20337.245844938676 14697.534623432408
```

ANOVA

```
# import the required function
from scipy.stats import f_oneway
# find the p-value
test_stat, p_value = f_oneway(w1,w2,w3)
# print the p-value
print('The p-value is', p_value)
```

```
The p-value is 1.457244731807399e-25
```

```
# print the conclusion based on p-value
if p_value < 0.05:
    print(f'As the p-value {p_value} is less than the level of significance, we rej
else:
    print(f'As the p-value {p_value} is greater than the level of significance, we
```

```
As the p-value 1.457244731807399e-25 is less than the level of significance, w
```

Since the p-value is greater than the 5% significance level, we fail to reject the null hypothesis. Hence, we have enough statistical evidence to say that the mean count of rented bicycles are not equal.