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



from scipy.stats import chi2
from scipy.stats import chisquare
from scipy.stats import chi2_contingency
from scipy.stats import ttest_rel,ttest_1samp,ttest_ind
from scipy.stats import binom,t,norm
from scipy.stats import f,f_oneway,kruskal,ttest_ind,levene,shapiro


#downloading the csv file
!gdown 1EQ-4PSjLmeb-N-pxIvFMM_1u-bFfCNrm
```

```
Downloading...
From: https://drive.google.com/uc?id=1EQ-4PSjLmeb-N-pxIvFMM_1u-bFfCNrm
To: /content/Business Case Yulu - Hypothesis Testing.csv
100% 648k/648k [00:00<00:00, 91.0MB/s]
```

```
df=pd.read_csv("Business Case Yulu - Hypothesis Testing.csv")
df
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	regis
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0000	3	
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0000	8	
2	2011-01-01 02:00:00	1	0	0	1	9.02	13.635	80	0.0000	5	
3	2011-01-01 03:00:00	1	0	0	1	9.84	14.395	75	0.0000	3	
4	2011-01-01 04:00:00	1	0	0	1	9.84	14.395	75	0.0000	0	
...	...	...	...	...	...	...	...	...	...	...	
	2012-12-										

```
# Summary of columns and data types
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
```

```
"""
Datatype of following attributes needs to change to proper data type
-datetime - to datetime
-season - to categorical
- holiday - to categorical
-workingday - to categorical
- weather - to categorical

"""

df['datetime'] = pd.to_datetime(df['datetime'])
df["season"] = df['season'].astype('object')
df["holiday"] = df['holiday'].astype('object')
df["workingday"] = df['workingday'].astype('object')
df["weather"] = df['weather'].astype('object')
```

```
# Checking the Null Value

df.isnull().sum()
```

```
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
```

```
# Describing All the Columns

df.iloc[:,1:].describe(include='all')
```

	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	
count	10886.0	10886.0	10886.0	10886.0	10886.00000	10886.000000	10886.000000	10886.000000	108
unique	4.0	2.0	2.0	4.0	NaN	NaN	NaN	NaN	
top	4.0	0.0	1.0	1.0	NaN	NaN	NaN	NaN	
freq	2734.0	10575.0	7412.0	7192.0	NaN	NaN	NaN	NaN	
mean	NaN	NaN	NaN	NaN	20.23086	23.655084	61.886460	12.799395	
std	NaN	NaN	NaN	NaN	7.79159	8.474601	19.245033	8.164537	
min	NaN	NaN	NaN	NaN	0.82000	0.760000	0.000000	0.000000	
25%	NaN	NaN	NaN	NaN	13.94000	16.665000	47.000000	7.001500	
50%	NaN	NaN	NaN	NaN	20.50000	24.240000	62.000000	12.998000	
75%	NaN	NaN	NaN	NaN	26.24000	31.060000	77.000000	16.997900	
max	NaN	NaN	NaN	NaN	41.00000	45.455000	100.000000	56.996900	3

```
# Getting the date range for the data set

print(f"Data Set is from : {df['datetime'].min()} -{df['datetime'].max()}")
```

```
Data Set is from : 2011-01-01 00:00:00 -2012-12-19 23:00:00
```

```
# Let's Check the Count of Bicycles Season wise
# season: season (1: spring, 2: summer, 3: fall, 4: winter)
seasonal_count = df.groupby('season')[['count']].count()
seasonal_count
```

season	count

```
#workingday: if day is neither weekend nor holiday is 1, otherwise is 0.
workink_day_count = df.groupby('workingday')[['count']].count()
workink_day_count
```

workingday	count
0	3474
1	7412

```
"""
weather:
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
"""

weather_count = df.groupby('weather')[['count']].count()
weather_count
```

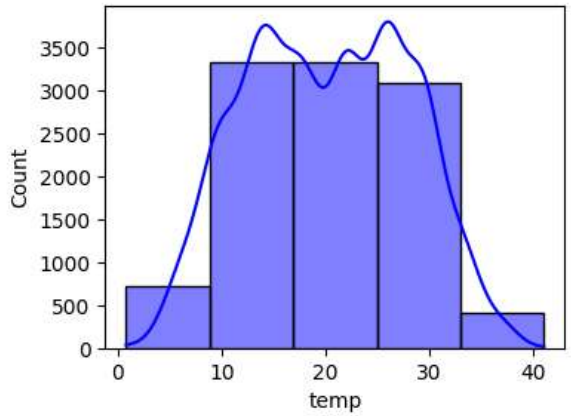
weather	count
1	7192
2	2834
3	859
4	1

```
holiday_versus_nonholiday_count = df.groupby('holiday')[['count']].count()
holiday_versus_nonholiday_count
```

holiday	count
0	10575
1	311

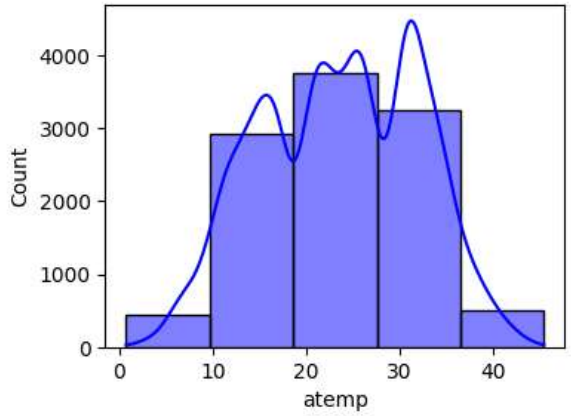
```
# Univariate Analysis:

#Let's see the distribution of Measure Values like temp,atemp,etc

plt.figure(figsize=(4, 3))
sns.histplot(df['temp'], bins=5, kde=True, color='blue')
```

```
<Axes: xlabel='temp', ylabel='Count'>
```



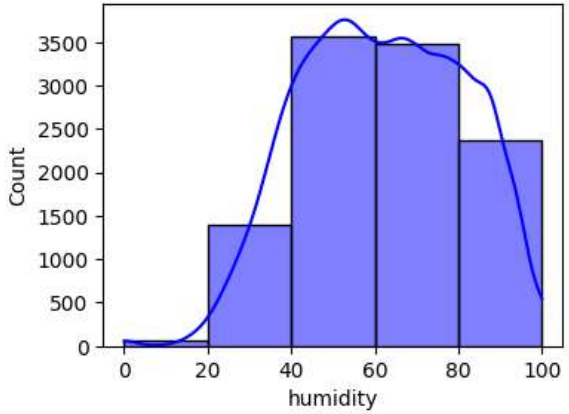

```
plt.figure(figsize=(4, 3))
sns.histplot(df['atemp'], bins=5, kde=True, color='blue')
```

```
<Axes: xlabel='atemp', ylabel='Count'>
```



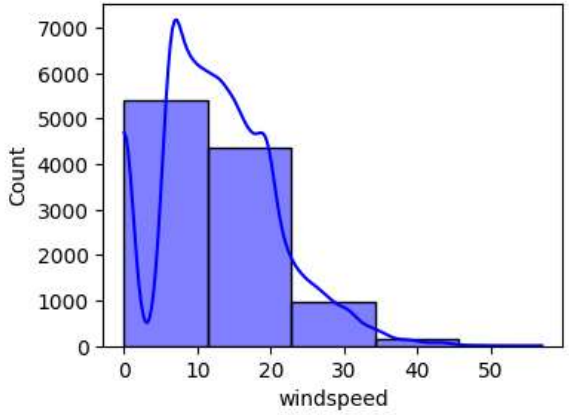
```
plt.figure(figsize=(4, 3))
sns.histplot(df['humidity'], bins=5, kde=True, color='blue')
```

```
<Axes: xlabel='humidity', ylabel='Count'>
```



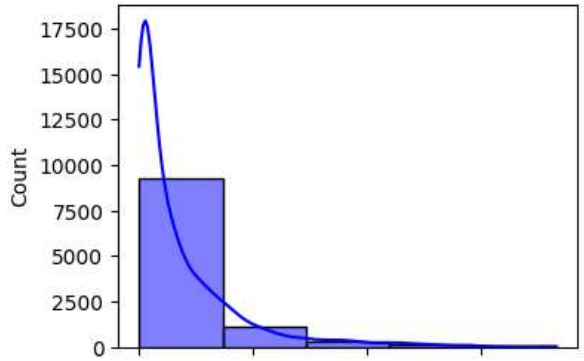

```
plt.figure(figsize=(4, 3))
sns.histplot(df['windspeed'], bins=5, kde=True, color='blue')
```

```
<Axes: xlabel='windspeed', ylabel='Count'>
```



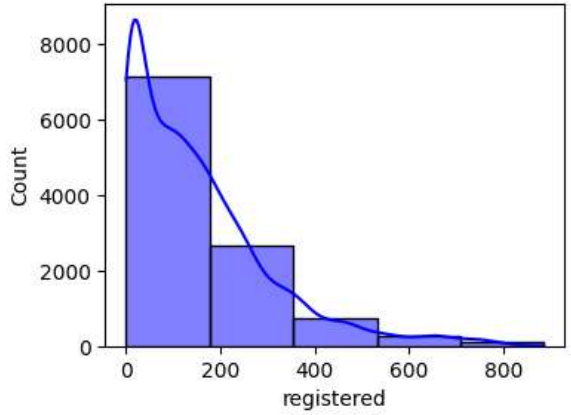

```
plt.figure(figsize=(4, 3))
sns.histplot(df['casual'], bins=5, kde=True, color='blue')
```

```
<Axes: xlabel='casual', ylabel='Count'>
```



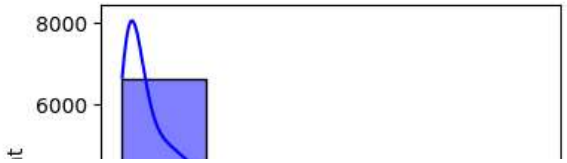

```
plt.figure(figsize=(4, 3))
sns.histplot(df['registered'], bins=5, kde=True, color='blue')
```

```
<Axes: xlabel='registered', ylabel='Count'>
```

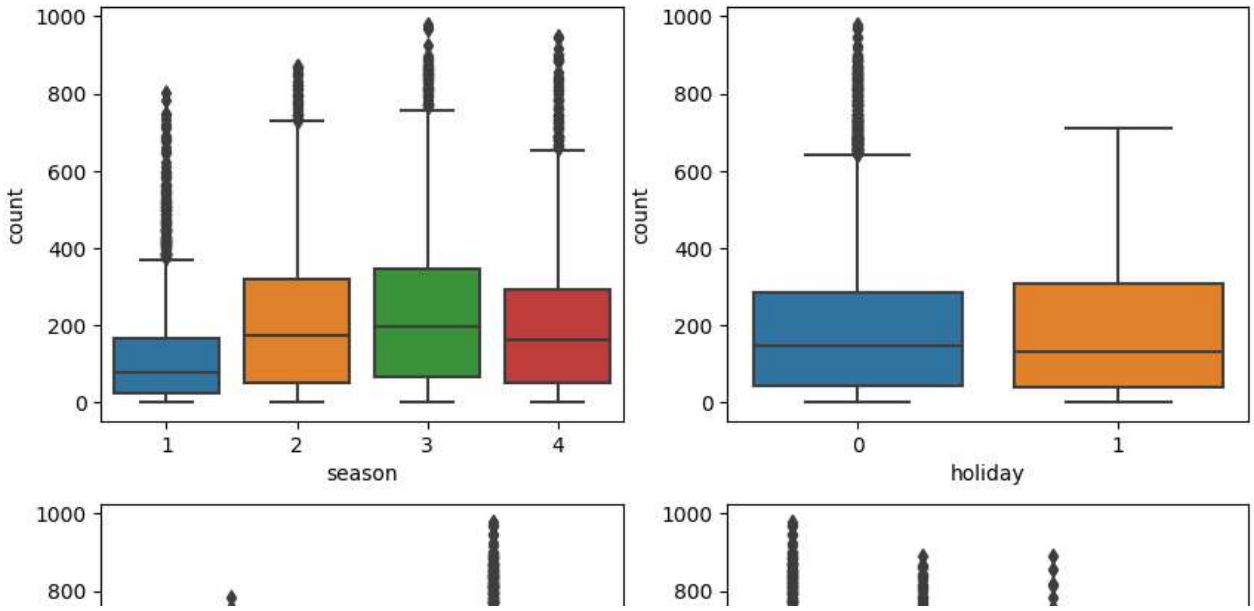



```
plt.figure(figsize=(4, 3))
sns.histplot(df['count'], bins=5, kde=True, color='blue')
```

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




```
"""
Concept Used:

1. Bi-Variate Analysis
2.Hypothesis testing
t-test
ANNOVA
Chi-square

"""


#1. Bi-Variate Analysis


cat_cols= ['season', 'holiday', 'workingday', 'weather']
for col in cat_cols:
  df[col] = df[col].astype('object')

# plotting categorical variables againt count using boxplots
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(10, 8))
index = 0
for row in range(2):
  for col in range(2):
    sns.boxplot(data=df, x=cat_cols[index], y='count', ax=axis[row,col])
    index += 1
plt.show()
```



1. In summer(season 2) and fall(season 3) seasons more bikes are rented as compared to other seasons.

2. Whenever its a holiday more bikes are rented.

3. More bike rented on non working(0) day

#2: Hypothesis Testing:

"""
 Chi-square test to check if Weather is dependent on the season

Null Hypothesis (H0): Weather is independent of the season
Alternate Hypothesis (H1): Weather is not independent of the season
Significance level (alpha): 0.05
"""

```
data_table=pd.crosstab(df['season'],df["weather"])
data_table
```

weather	1	2	3	4
season				

```
observed_value=[[1759,715,211],[1801,708,224],[1930,604,199],[1702,807,225]]
```

```
chi_stat,p_value,dof,expected_frequency=chi2_contingency(observed_value)
print("chi_stat :",chi_stat)
print("p_value :",p_value)
print("dof :",dof)
print("expected_frequency :",expected_frequency)
```

```
chi_stat : 46.10145731073249
p_value : 2.8260014509929343e-08
dof : 6
expected_frequency : [[1774.04869086  699.06201194  211.8892972 ]
 [1805.76352779  711.55920992  215.67726229]
 [1805.76352779  711.55920992  215.67726229]
 [1806.42425356  711.81956821  215.75617823]]
```

```
alpha=0.05
if p_value<alpha:
  print("Reject Ho")
  print("Interpretation : Weather and season are associated")
else:
  print("failed to reject Ho")
```

```
Reject Ho
Interpretation : Weather and season are associated
```

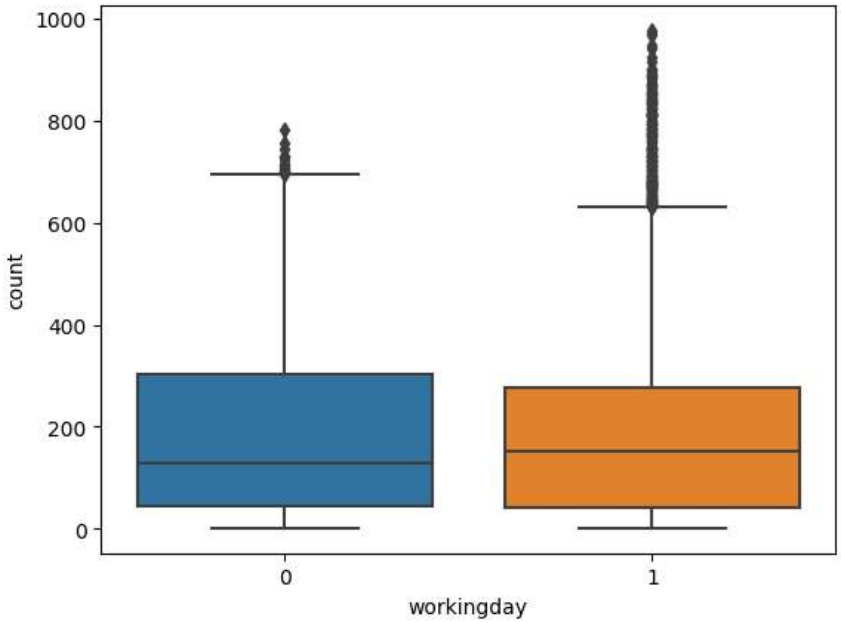
```
"""

2- Sample T-Test to check if Working Day has an effect on the number of electric
cycles rented :
mu1--> mean of non - working day
mu2--> mean of working day
Null Hypothesis: Working day has no effect on the number of cycles being rented.--> mu2<=mu1
Alternate Hypothesis: Working day has effect on the number of cycles being-->mu2>mu1
rented.
Significance level (alpha): 0.05
We will use the 1-Sample T-Test to test the hypothess defined above
"""
workink_day_count
```

count

workingday

```
# visualizing the data first after that we will do hypothesis testing to prove statistically significant
sns.boxplot(x='workingday',y="count",data=df)
```

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




```
non_working_day = df[df['workingday']==0]['count'].sample(3474)
```

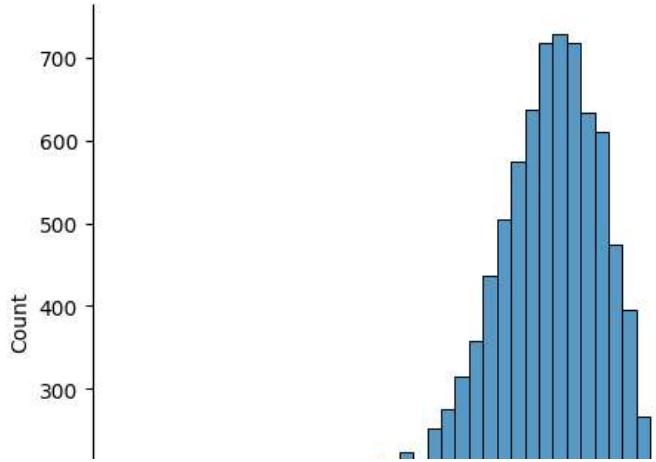
```
working_day= df[df['workingday']==1]['count'].sample(3474)
```

```
t_stat,p_value=ttest_ind(working_day,non_working_day,equal_var=False,alternative="greater")
print("t_stat : ",t_stat)
print("p_value : ",p_value)
alpha= 0.05
if p_value < alpha :
 print("Reject Ho")
else :
 print("Fail to Reject Ho")
 print("Interpretation : Since pvalue is greater than 0.05 so we failed to  reject the Null hypothesis. We don't \nhave the sufficient evidence to say that working day \n has effect
```

```
t_stat :  0.4721110011972705
p_value :  0.3184312192961206
Fail to Reject Ho
Interpretation : Since pvalue is greater than 0.05 so we failed to  reject the Null hypothesis. We don't
have the sufficient evidence to say that working day
 has effect on the number of cycles being rented
```

```
"""
3: -ANNOVA to check if No. of cycles rented is similar or different in
different 1. weather 2. Season


"""


# Weather Check
"""
Null Hypothesis: Number of cycles rented is similar in different weather --> mean of all the weather are same
Alternate Hypothesis: Number of cycles rented is  different in weather --> mean of all the weather are diifferent
Significance level (alpha): 0.05


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

# we will not consider weather 4 as it is outlier


# ANOVA Test

# we wiil check the assumptiom

#1 Normality

sns.displot(np.log(df['count']))
```

```
<seaborn.axisgrid.FacetGrid at 0x7c68738ae620>
```




```
# Now we will check if w1,w2,w3 has equal variance or not

# we can do groupby and describe
# or we can do levenes test

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

weather	count	mean	std	min	25%	50%	75%	max
1	7192.0	205.236791	187.959566	1.0	48.0	161.0	305.0	977.0
2	2834.0	178.955540	168.366413	1.0	41.0	134.0	264.0	890.0
3	859.0	118.846333	138.581297	1.0	23.0	71.0	161.0	891.0
4	1.0	164.000000	NaN	164.0	164.0	164.0	164.0	164.0

```
# 2 variance check
print(w1.var(),w2.var(),w3.var())
```

```
34874.49498233215 28713.657120487773 19305.95310884778
```

```
#Levene's Test

#Ho:all the count variane are equal
#Ha:atleast one variance is different

stat,p_value=levene(w1,w2,w3)
```

```
if p_value<0.05:
  print("Reject Ho")
  print("atleast one variance is different")
else:
  print("Failed to reject Ho")
  print("all the count variane are equal")
```

```
Reject Ho
atleast one variance is different
```

```
#now we will do kruskal test
stat,p_value=kruskal(w1,w2,w3)
print("p_value:",p_value)
if p_value<0.05:
  print("Reject Ho")
  print("Weather has effect on rented cycle")
else:
  print("Failed to reject Ho")
  print("Weather has not effect")
```

```
p_value: 9.136763731489565e-24
Reject Ho
Weather has effect on rented cycle
```

```
# Season Check
"""
Null Hypothesis: Number of cycles rented is similar in different weather --> mean of all the weather are same
Alternate Hypothesis: Number of cycles rented is  different in weather --> mean of all the weather are diifferent
Significance level (alpha): 0.05

"""
```

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

season	count	mean	std	min	25%	50%	75%	max
1	2686.0	116.343261	125.273974	1.0	24.0	78.0	164.0	801.0
2	2733.0	215.251372	192.007843	1.0	49.0	172.0	321.0	873.0
3	2733.0	234.417124	197.151001	1.0	68.0	195.0	347.0	977.0
4	2734.0	198.988296	177.622409	1.0	51.0	161.0	294.0	948.0

```
# We will do kruskal test as count is not normally distibuted
s1=df[df['season']==1]['count'].sample(850)
s2=df[df['season']==2]['count'].sample(850)
s3=df[df['season']==3]['count'].sample(850)
```

```
s4=df[df['season']==4]['count'].sample(850)

stat,p_value=kruskal(s1,s2,s3,s4)
print("p_value:" ,p_value)
if p_value<0.05:
  print("Reject Ho")
  print("season has effect on rented cycle")
else:
  print("Failed to reject Ho")
  print("season has not effect")
```

```
p_value: 1.5440589696519812e-47
Reject Ho
season has effect on rented cycle
```

Insights 1.In summer and fall seasons more bikes are rented as compared to other seasons. 2.Whenever its a holiday more bikes are rented.

3. It is also clear from the workingday also that whenever day is holiday or weekend, slightly more bikes were rented.
4. Whenever there is rain, thunderstorm, snow or fog, there were less bikes were rented. Whenever the humidity is less than 20, number of bikes rented is very very low.
5. Whenever the temperature is less than 10, number of bikes rented is less.
6. Whenever the windspeed is greater than 35, number of bikes rented is less.

Recommendations

1. In summer and fall seasons the company should have more bikes in stock to be rented. Because the demand in these seasons is higher as compared to other seasons.
2. With a significance level of 0.05, workingday has no effect on the number of bikes being rented.Q
3. In very low humid days, company should have less bikes in the stock to be rented.
4. Whenever temperature is less than 10 or in very cold days, company should have less bikes.
5. Whenever the windspeed is greater than 35 or in thunderstorms, company should have less bikes in stock to be rented.

✓ 1s completed at 12:50 AM