About Yulu:

Yulu is India's leading micro-mobility service provider, which offers unique vehicles for the daily commute. Starting off as a mission to eliminate traffic congestion in India, Yulu provides the safest commute solution through a user-friendly mobile app to enable shared, solo and sustainable commuting.

Yulu zones are located at all the appropriate locations (including metro stations, bus stands, office spaces, residential areas, corporate offices, etc) to make those first and last miles smooth, affordable, and convenient!

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.

The company wants to know:

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

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

```
df =pd.read_csv("Yulu_dataset.csv",delimiter=",")
```

```
df.head()
```

	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered
0	2011-01-01 00:00:00	1	0	0	1	9.84	14.395	81	0.0	3	13
1	2011-01-01 01:00:00	1	0	0	1	9.02	13.635	80	0.0	8	32
2	2011-01-01	1	0	0	1	9.02	13.635	80	0.0	5	27

```
df.tail()
```

datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	regis

```
# no of rows amd columns in dataset
print(f"# rows: {df.shape[0]} \n# columns: {df.shape[1]}")
```

```
# rows: 10886
# columns: 12
```

20:00:00

```
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.describe()
```

	season	holiday	workingday	weather	temp	atemp	humidity	
count	10886.000000	10886.000000	10886.000000	10886.000000	10886.00000	10886.000000	10886.000000	1(
mean	2.506614	0.028569	0.680875	1.418427	20.23086	23.655084	61.886460	
std	1.116174	0.166599	0.466159	0.633839	7.79159	8.474601	19.245033	
min	1.000000	0.000000	0.000000	1.000000	0.82000	0.760000	0.000000	
25%	2.000000	0.000000	0.000000	1.000000	13.94000	16.665000	47.000000	
50%	3.000000	0.000000	1.000000	1.000000	20.50000	24.240000	62.000000	
75%	4.000000	0.000000	1.000000	2.000000	26.24000	31.060000	77.000000	
max	4.000000	1.000000	1.000000	4.000000	41.00000	45.455000	100.000000	

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

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

```
df['datetime']
```

```
0       2011-01-01 00:00:00
1       2011-01-01 01:00:00
2       2011-01-01 02:00:00
3       2011-01-01 03:00:00
4       2011-01-01 04:00:00
                ...
10881   2012-12-19 19:00:00
10882   2012-12-19 20:00:00
10883   2012-12-19 21:00:00
10884   2012-12-19 22:00:00
10885   2012-12-19 23:00:00
Name: datetime, Length: 10886, dtype: datetime64[ns]
```

```
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	

1. There are no missing values in the dataset.
2. Casual and registered attributes might have outliers because their mean and median are very far away to one another and the value of standard deviation is also high which tells us that there is high variance in the data of these attributes.

```
# detecting missing values in the dataset
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
```

There are no missing values present in the dataset.

```
# minimum datetime and maximum datetime
df['datetime'].min(), df['datetime'].max()
```

```
(Timestamp('2011-01-01 00:00:00'), Timestamp('2012-12-19 23:00:00'))
```

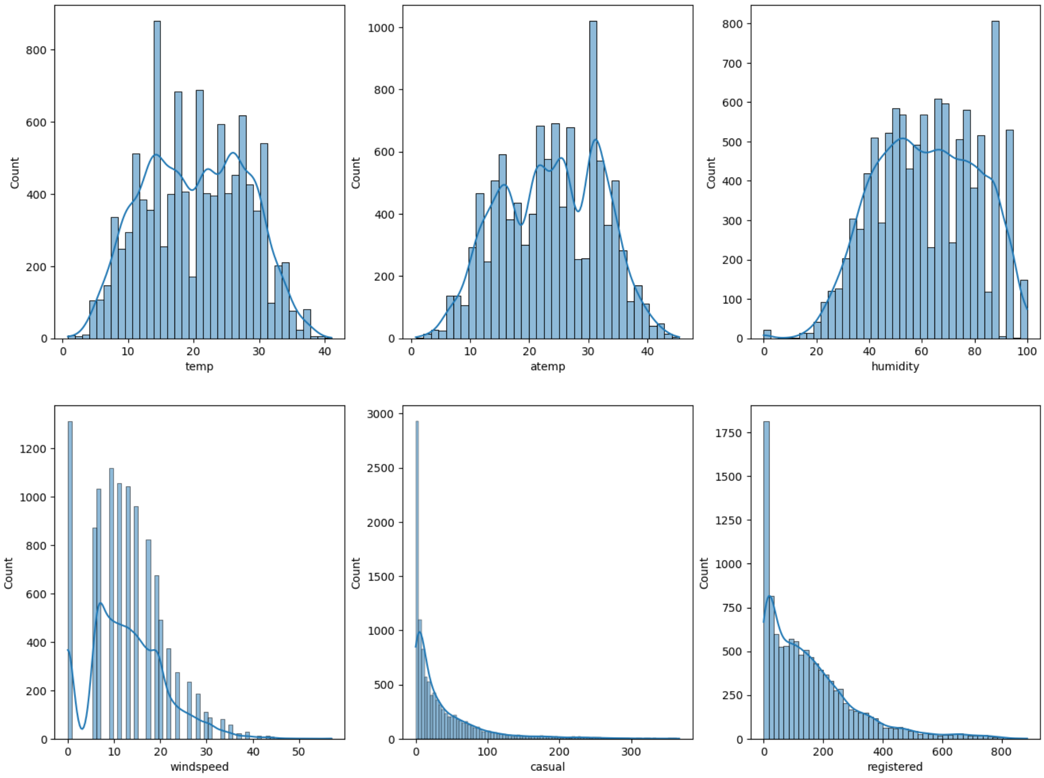
```
# number of unique values in each categorical columns
df[cat_cols].melt().groupby(['variable', 'value'])[['value']].count()
```

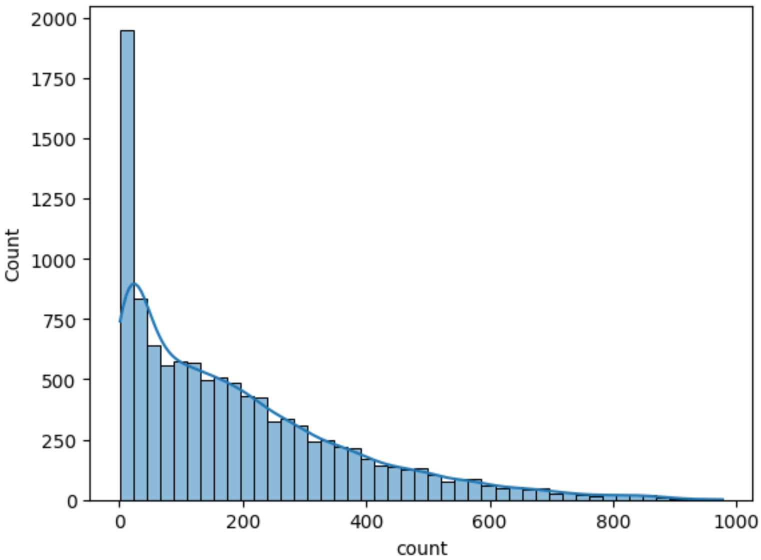
variable	value	value
holiday	**0**	10575
	1	311
season	**1**	2686
	2	2733
	3	2733
	4	2734
weather	**1**	7192
	2	2834
	3	859
	4	1
workingday	**0**	3474
	1	7412

Univariate Analysis

```
# understanding the distribution for numerical variables
num_cols = ['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered','count']

fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 12))

index = 0
for row in range(2):
    for col in range(3):
```

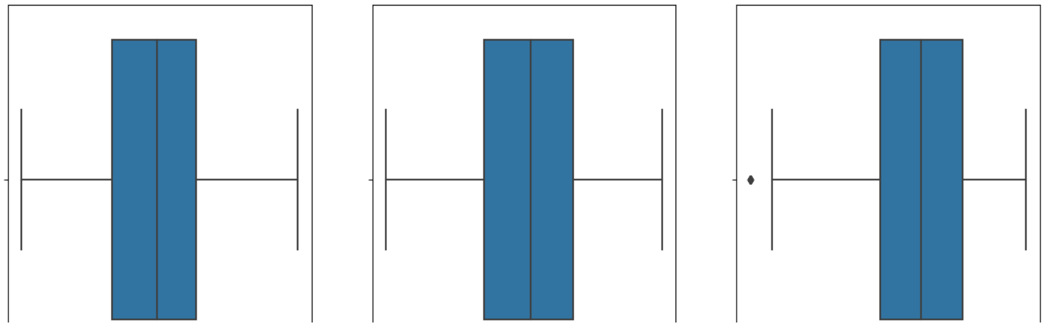
```
        sns.histplot(df[num_cols[index]], ax=axis[row, col], kde=True)
        index += 1

plt.show()
sns.histplot(df[num_cols[-1]], kde=True)
plt.show()
```





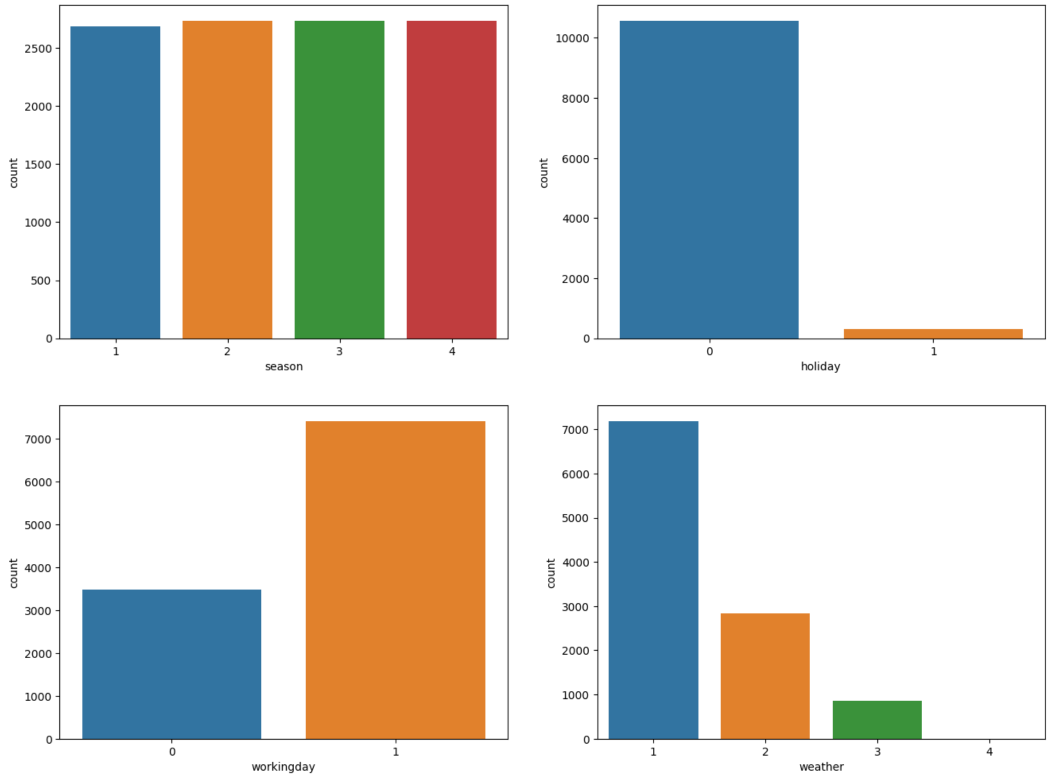
1. casual, registered and count somewhat looks like Log Normal Distribution
2. temp, atemp and humidity looks like they follows the Normal Distribution
3. windspeed follows the binomial distribution

```
# plotting box plots to detect outliers in the data
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 12))

index = 0
for row in range(2):
    for col in range(3):
        sns.boxplot(x=df[num_cols[index]], ax=axis[row, col])
        index += 1

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



Looks like humidity, casual, registered and count have outliers in the data.

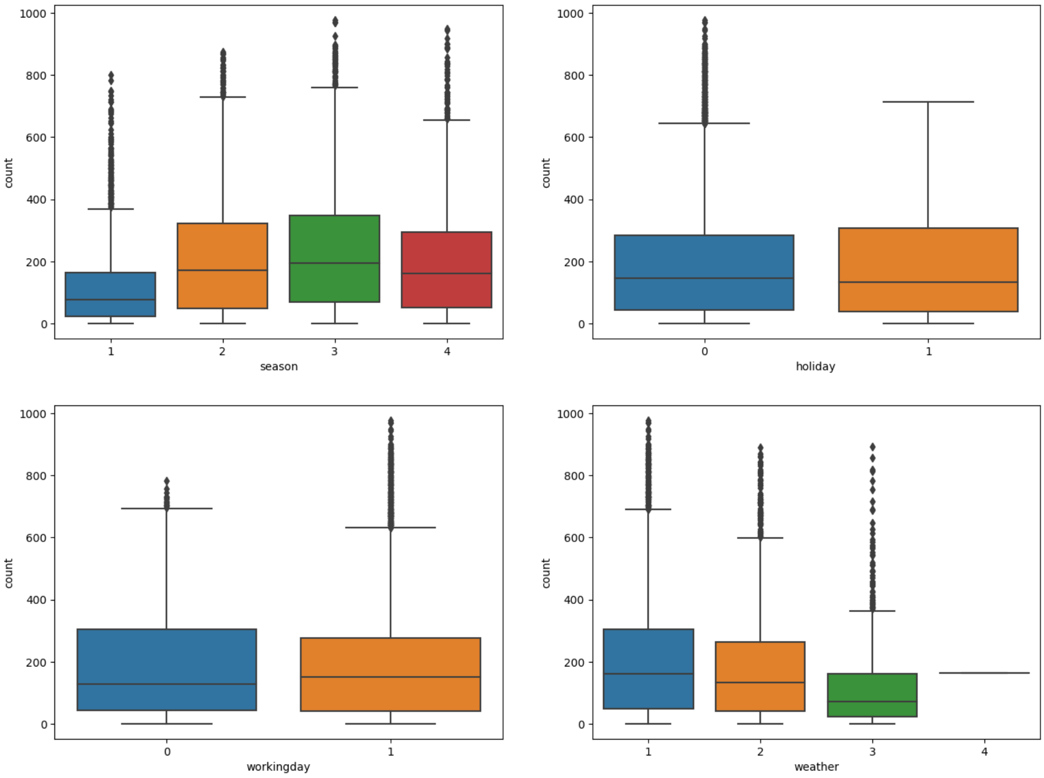
```
# countplot of each categorical column
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))

index = 0
for row in range(2):
    for col in range(2):
        sns.countplot(data=df, x=cat_cols[index], ax=axis[row, col])
        index += 1

plt.show()
```



Data looks common as it should be like equal number of days in each season, more working days and weather is mostly Clear, Few clouds, partly cloudy, partly cloudy.

Bi-variate Analysis

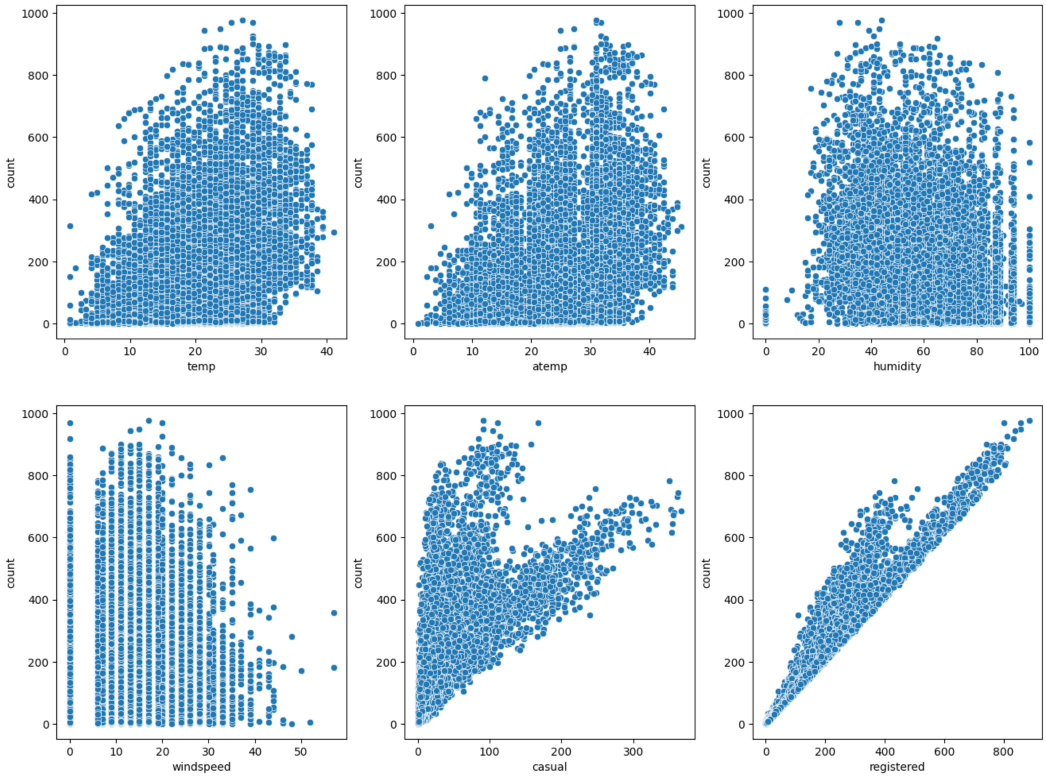
```
# plotting categorical variables againt count using boxplots
fig, axis = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))

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 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.

```
# plotting numerical variables againt count using scatterplot
fig, axis = plt.subplots(nrows=2, ncols=3, figsize=(16, 12))
```

```
index = 0
for row in range(2):
    for col in range(3):
        sns.scatterplot(data=df, x=num_cols[index], y='count', ax=axis[row, col])
        index += 1

plt.show()
```



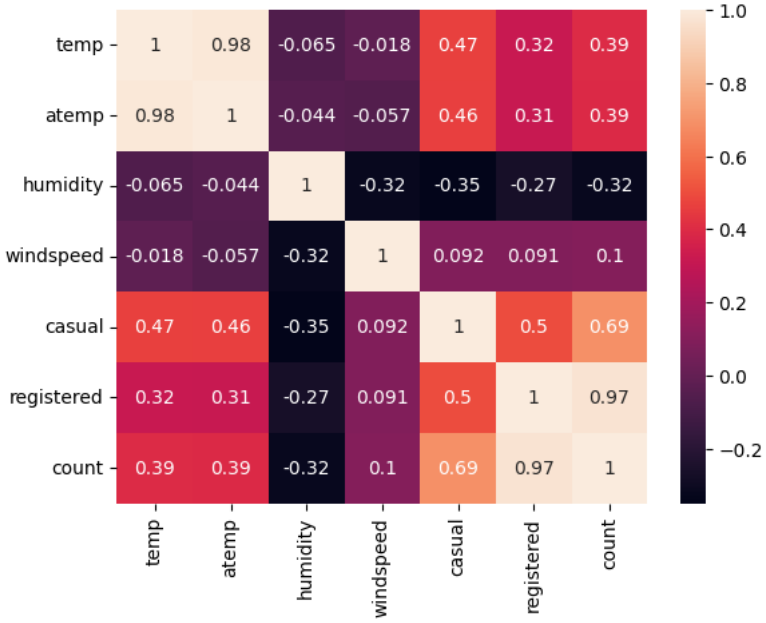
1. Whenever the humidity is less than 20, number of bikes rented is very very low.
2. Whenever the temperature is less than 10, number of bikes rented is less.
3. Whenever the windspeed is greater than 35, number of bikes rented is less.

```
# understanding the correlation between count and numerical variables
df.corr()['count']
```

```
<ipython-input-24-85b774de02c3>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future ve
  df.corr()['count']
temp          0.394454
atemp         0.389784
humidity     -0.317371
windspeed     0.101369
casual        0.690414
registered    0.970948
count         1.000000
Name: count, dtype: float64
```

```
sns.heatmap(df.corr(), annot=True)
plt.show()
```

```
<ipython-input-25-6522c2b4e5f9>:1: FutureWarning: The default value of numeric_only in DataFrame.corr i
  sns.heatmap(df.corr(), annot=True)
```



Hypothesis Testing - 1

Null Hypothesis (H0): Weather is independent of the season

Alternate Hypothesis (H1): Weather is not independent of the season

Significance level (alpha): 0.05

We will use chi-square test to test hypyothesis defined above.

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

Observed values:

weather	1	2	3	4
season				
1	1759	715	211	1
2	1801	708	224	0
3	1930	604	199	0
4	1702	807	225	0

```
val = stats.chi2_contingency(data_table)
expected_values = val[3]
expected_values
```

```
array([[1.77454639e+03, 6.99258130e+02, 2.11948742e+02, 2.46738931e-01],
       [1.80559765e+03, 7.11493845e+02, 2.15657450e+02, 2.51056403e-01],
       [1.80559765e+03, 7.11493845e+02, 2.15657450e+02, 2.51056403e-01],
       [1.80625831e+03, 7.11754180e+02, 2.15736359e+02, 2.51148264e-01]])
```

```
nrows, ncols = 4, 4
dof = (nrows-1)*(ncols-1)
print("degrees of freedom: ", dof)
alpha = 0.05
```

```
chi_sqr = sum([(o-e)**2/e for o, e in zip(data_table.values, expected_values)])
chi_sqr_statistic = chi_sqr[0] + chi_sqr[1]
print("chi-square test statistic: ", chi_sqr_statistic)
```

```
critical_val = stats.chi2.ppf(q=1-alpha, df=dof)
print(f"critical value: {critical_val}")

p_val = 1-stats.chi2.cdf(x=chi_sqr_statistic, df=dof)
print(f"p-value: {p_val}")

if p_val <= alpha:
    print("\nSince p-value is less than the alpha 0.05, We reject the Null Hypothesis. Meaning that weather is dependent on the season.")
else:
    print("Since p-value is greater than the alpha 0.05, We do not reject the Null Hypothesis")
```

```
degrees of freedom:  9
chi-square test statistic:  44.09441248632364
critical value: 16.918977604620448
p-value: 1.3560001579371317e-06

Since p-value is less than the alpha 0.05, We reject the Null Hypothesis. Meaning that weather is dependent on the season.
```

Hypothesis Testing - 2

Null Hypothesis: Working day has no effect on the number of cycles being rented.

Alternate Hypothesis: Working day has effect on the number of cycles being rented.

Significance level (alpha): 0.05

We will use the 2-Sample T-Test to test the hypothess defined above

```
data_group1 = df[df['workingday']==0]['count'].values
data_group2 = df[df['workingday']==1]['count'].values

np.var(data_group1), np.var(data_group2)
```

```
(30171.346098942427, 34040.69710674686)
```

Before conducting the two-sample T-Test we need to find if the given data groups have the same variance. If the ratio of the larger data groups to the small data group is less than 4:1 then we can consider that the given data groups have equal variance.

Here, the ratio is 34040.70 / 30171.35 which is less than 4:1

```
stats.ttest_ind(a=data_group1, b=data_group2, equal_var=True)
```

```
Ttest_indResult(statistic=-1.2096277376026694, pvalue=0.22644804226361348)
```

Since pvalue is greater than 0.05 so we can not 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.

Hypothesis Testing - 3

Null Hypothesis: Number of cycles rented is similar in different weather and season.

Alternate Hypothesis: Number of cycles rented is not similar in different weather and season.

Significance level (alpha): 0.05

Here, we will use the ANOVA to test the hypothess defined above

```
# defining the data groups for the ANOVA

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

gp5 = df[df['season']==1]['count'].values
gp6 = df[df['season']==2]['count'].values
gp7 = df[df['season']==3]['count'].values
gp8 = df[df['season']==4]['count'].values

# conduct the one-way anova
stats.f_oneway(gp1, gp2, gp3, gp4, gp5, gp6, gp7, gp8)
```

```
F_onewayResult(statistic=127.96661249562491, pvalue=2.8074771742434642e-185)
```

Since p-value is less than 0.05, we reject the null hypothesis. This implies that Number of cycles rented is not similar in different weather and season conditions

Insights//

In summer and fall seasons more bikes are rented as compared to other seasons. Whenever its a holiday more bikes are rented. It is also clear from the workingday also that whenever day is holiday or weekend, slightly more bikes were rented. 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. Whenever the temperature is less than 10, number of bikes rented is less. Whenever the windspeed is greater than 35, number of bikes rented is less.

Recommendations //

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. With a significance level of 0.05, workingday has no effect on the number of bikes being rented. In very low humid days, company should have less bikes in the stock to be rented. Whenever temprature is less than 10 or in very cold days, company should have less bikes. Whenever the windspeed is greater than 35 or in thunderstorms, company should have less bikes in stock to be rented.

✓ 1s completed at 13:35