## Business Problem

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.

Objective:

- To find which variables are significant in predicting the demand for shared electric cycles in the Indian market?
- To understand how well those variables describe the electric cycle demands

Concept Used:

- Bi-Variate Analysis
- 2-sample t-test: testing for difference across populations
- ANNOVA
- Chi-square

## import modules and load data

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

from scipy.stats import norm, chi2, f # distributions

from scipy.stats import ttest_ind, ttest_rel, f_oneway, kruskal # numerical vs categorical
from scipy.stats import chisquare, chi2_contingency # categorical features
from scipy.stats import pearsonr, spearmanr # numeric vs numeric

from scipy.stats import kstest # cdf

from statsmodels.distributions.empirical_distribution import ECDF
# Empirical CDF
```

```
df=pd.read_csv('/content/bike_sharing.txt')
```

```
df
```

| | datetime | season | holiday | workingday | weather | temp | atemp | humidity | windspeed | casual | registered | cc |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2011-01-01 00:00:00 | 1 | 0 | 0 | 1 | 9.84 | 14.395 | 81 | 0.0000 | 3 | 13 | |
| **1** | 2011-01-01 01:00:00 | 1 | 0 | 0 | 1 | 9.02 | 13.635 | 80 | 0.0000 | 8 | 32 | |
| **2** | 2011-01-01 02:00:00 | 1 | 0 | 0 | 1 | 9.02 | 13.635 | 80 | 0.0000 | 5 | 27 | |
| **3** | 2011-01-01 03:00:00 | 1 | 0 | 0 | 1 | 9.84 | 14.395 | 75 | 0.0000 | 3 | 10 | |
| **4** | 2011-01-01 04:00:00 | 1 | 0 | 0 | 1 | 9.84 | 14.395 | 75 | 0.0000 | 0 | 1 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| | 2012-12- | | | | | | | | | | | |

```
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
```

## Basic data exploration

```
df.shape
# 10886 rows, 12 columns
```

```
(10886, 12)
```

```
df.isna().sum()
# No missing value
```

```
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
```

```
df.dtypes
# checking datatype of columns
```

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

```
df.nunique()
# few int columns have very less unique values, we will convert them to object
```

```
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
```

```
# Drop unnecessary columns
df.drop('datetime',axis=1, inplace=True )
```

```
columns=['season','holiday','workingday','weather']
df[columns] = df[columns].astype('object')
```

```
df.dtypes
```

```
season         object
holiday        object
workingday     object
weather        object
temp          float64
atemp         float64
humidity        int64
```

```
windspeed     float64
casual          int64
registered      int64
count           int64
dtype: object
```

```
## separeate categorical and numeric features.
# catgeorical and numerical columns
cat_cols = df.dtypes =='object'
cat_cols = list(cat_cols[cat_cols].index)
cat_cols
```

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

```
num_cols = df.dtypes !='object'
num_cols = list(num_cols[num_cols].index)
num_cols
```

```
['temp', 'atemp', 'humidity', 'windspeed', 'casual', 'registered', 'count']
```

## Univariate Data Analysis

```
#Checking how the data is spread on basis of distinct users (customer analysis)
df2=df.copy()
cat_count = df2[cat_cols].melt().groupby(['variable', 'value'])[['value']].size().reset_index(name='counts')
s = df2[cat_cols].melt().variable.value_counts()
cat_count['Percent'] = cat_count['counts'].div(cat_count['variable'].map(s)).mul(100).round().astype('int')
cat_count.groupby(['variable', 'value']).first()

# only 1 electric cycles rented in extreame weather 4. (outlier)
# only 3% days are holidays.
```

| variable | value | counts | Percent |
|---|---|---|---|
| **holiday** | **0** | 10575 | 97 |
| | **1** | 311 | 3 |
| **season** | **1** | 2686 | 25 |
| | **2** | 2733 | 25 |
| | **3** | 2733 | 25 |
| | **4** | 2734 | 25 |
| **weather** | **1** | 7192 | 66 |
| | **2** | 2834 | 26 |
| | **3** | 859 | 8 |
| | **4** | 1 | 0 |
| **workingday** | **0** | 3474 | 32 |
| | **1** | 7412 | 68 |

```
df[df['weather']==4]

# Only one row where weather is 4, so will replace it's value with 3.
```

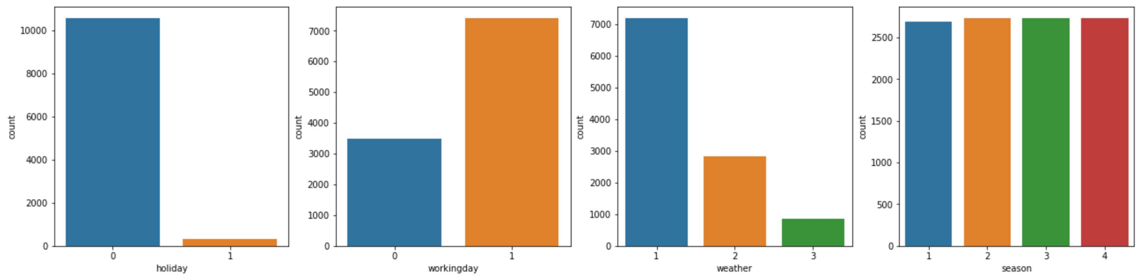
| | season | holiday | workingday | weather | temp | atemp | humidity | windspeed | casual | registered | count |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **5631** | 1 | 0 | 1 | 4 | 8.2 | 11.365 | 86 | 6.0032 | 6 | 158 | 164 |

```
df['weather'].replace(4,3,inplace=True)
df['weather'].value_counts()
```

```
1    7192
2    2834
3     860
Name: weather, dtype: int64
```

```
plt.figure(figsize = [22,5])
cat_cols = ['holiday','workingday','weather','season']
for i in range (len(cat_cols)):
  plt.subplot(1, 4, i+1)
  sns.countplot(data=df, x=cat_cols[i])
```

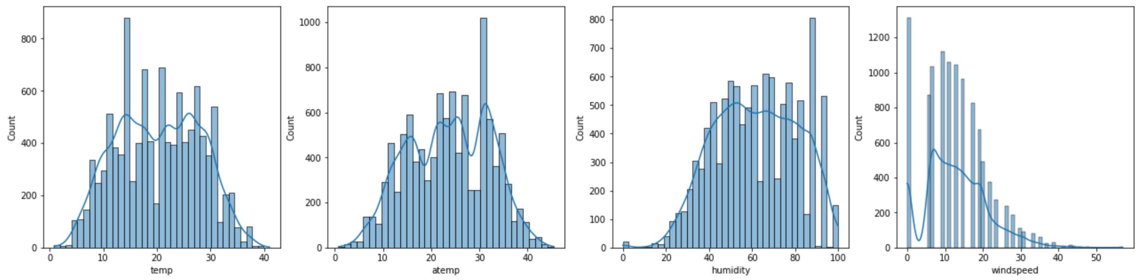
```

# Weather 1 is most liklihood weather.
```




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

| | season | holiday | workingday |
|---|---|---|---|
| **count** | 10886 | 10886 | 10886 |
| **unique** | 4 | 2 | 2 |
| **top** | 4 | 0 | 1 |
| **freq** | 2734 | 10575 | 7412 |

```
plt.figure(figsize = [22,5])
num_cols = ['temp', 'atemp', 'humidity', 'windspeed']
for i in range (len(num_cols)):
  plt.subplot(1, 4, i+1)
  sns.histplot(data=df, x=num_cols[i], kde=True)
```




```
for i in (num_cols):
  print(i, round(df[i].skew(),1))

# windspeed distributioni is right skewed, means it has some outliers in right.
```

```
temp 0.0
atemp -0.1
humidity -0.1
windspeed 0.6
```

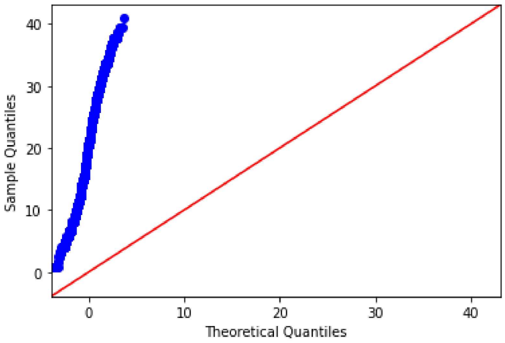
```
from scipy.stats import shapiro
num_cols = ['temp', 'atemp', 'humidity', 'windspeed']
for i in (num_cols):
  print(shapiro(df[i]).pvalue)

# Since the p-value is less than .05, we reject the null hypothesis.
# By shapiro test we can say that the sample data does not come from a normal distribution.
# We could normalize it but We will consider then normally distributed in further analysis.
# Because in visual plots we can see that variables are looking kind of normally distributed.
```

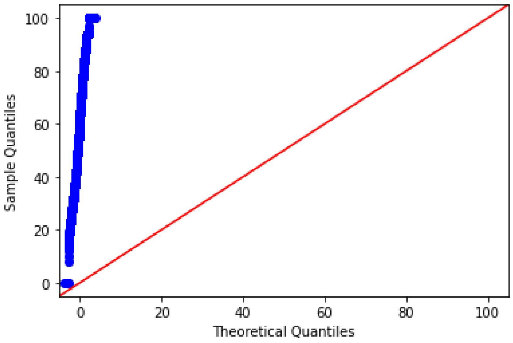
```
4.47221826500091e-36
3.4538982852050647e-35
1.245496990918048e-34
0.0
/usr/local/lib/python3.8/dist-packages/scipy/stats/morestats.py:1760: UserWarning: p-value may not be accurate for N > 5000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

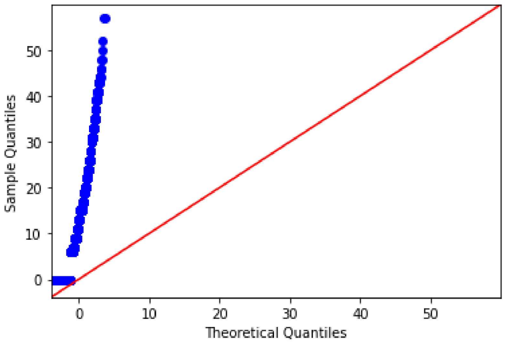
```
import statsmodels.api as sm
import matplotlib.pyplot as plt
plt.figure(figsize = [22,5])
num_cols = ['temp', 'humidity', 'windspeed']
for i in (num_cols):
```

```
  sm.qqplot(df[i], line ='45')

#The data values clearly do not follow the red 45-degree line,
# which is an indication that they do not follow a normal distribution.
```

```
<Figure size 1584x360 with 0 Axes>
```




```
from scipy.stats import levene
stat, p = levene(df['temp'],df['atemp'], center ='median')
p
```

```
1.3036286748857844e-16
```

```
from scipy.stats import levene
stat, p = levene(df['temp'],df['atemp'], center ='mean')
p
```

```
3.235293999853922e-17
```

```
alpha =0.05
# now we pass the groups and center value from the following
# ('trimmed mean', 'mean', 'median')
w_stats, p_value =levene(df['temp'],df['atemp'], center ='median')

if p_value > alpha :
  print("We do not reject the null hypothesis")
else:
  print("Reject the Null Hypothesis")

# This means we do have sufficient evidence to say that the variance between temp and atemp is significantly different.
```

```
Reject the Null Hypothesis
```

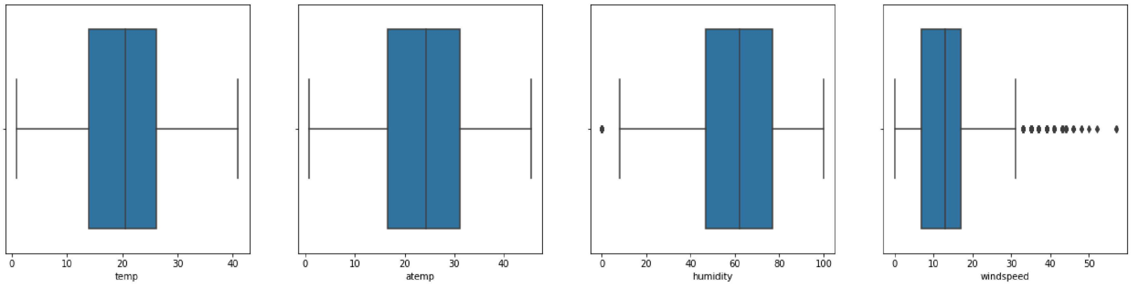
```
np.percentile(df['temp'],97.5)-np.percentile(df['temp'],2.5)
```

```
27.7775
```

```
np.percentile(df['atemp'],97.5)-np.percentile(df['atemp'],2.5)
```

31.06

```
plt.figure(figsize = [22,5])
num_cols = ['temp', 'atemp', 'humidity', 'windspeed']
for i in range (len(num_cols)):
  plt.subplot(1, 4, i+1)
  sns.boxplot(data=df, x=num_cols[i])
```




```
df[num_cols].describe()
```

| | temp | atemp | humidity | windspeed |
|---|---|---|---|---|
| **count** | 10886.00000 | 10886.000000 | 10886.000000 | 10886.000000 |
| **mean** | 20.23086 | 23.655084 | 61.886460 | 12.799395 |
| **std** | 7.79159 | 8.474601 | 19.245033 | 8.164537 |
| **min** | 0.82000 | 0.760000 | 0.000000 | 0.000000 |
| **25%** | 13.94000 | 16.665000 | 47.000000 | 7.001500 |
| **50%** | 20.50000 | 24.240000 | 62.000000 | 12.998000 |
| **75%** | 26.24000 | 31.060000 | 77.000000 | 16.997900 |
| **max** | 41.00000 | 45.455000 | 100.000000 | 56.996900 |

```
R_whisker = np.percentile(df['windspeed'],75)+(np.percentile(df['windspeed'],75)-np.percentile(df['windspeed'],25))*1.5
R_whisker
```

31.992500000000003

```
df[df['windspeed']>R_whisker].index.size
# 227 outliers showing in windspeed column (using 1.5*IQR method).
```

227

```
L_whisker = np.percentile(df['humidity'],25)-(np.percentile(df['humidity'],75)-np.percentile(df['humidity'],25))*1.5
L_whisker
```

2.0

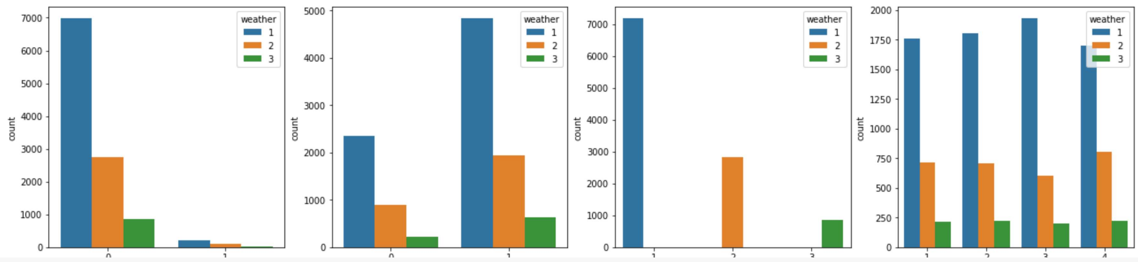
```
df[df['humidity']<L_whisker].index.size
# 22 outliers showing in humidity column (using 1.5*IQR method).
```

22

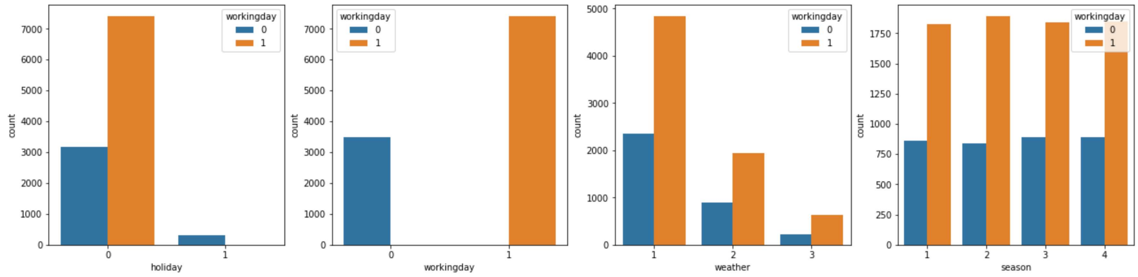
```
# We have found outliers and we could remove,
# Since we have limited data, we will keep outliers in further exploration and test.
# earlier we detected single outlier data point in weather column and we fixed it by imputation.
```

## Bivariate Data Analysis

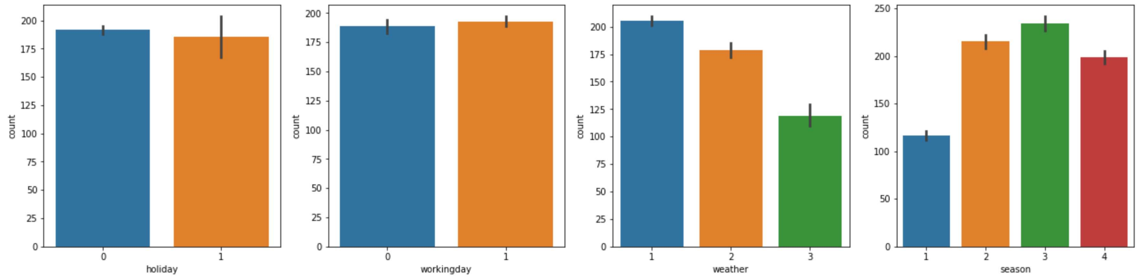
```
plt.figure(figsize = [22,5])
cat_cols = ['holiday','workingday','weather','season']
for i in range (len(cat_cols)):
  plt.subplot(1, 4, i+1)
  sns.countplot(data=df, x=cat_cols[i],hue=cat_cols[2])
```




```
plt.figure(figsize = [22,5])
cat_cols = ['holiday','workingday','weather','season']
for i in range (len(cat_cols)):
  plt.subplot(1, 4, i+1)
  sns.countplot(data=df, x=cat_cols[i],hue=cat_cols[1])
```




```
plt.figure(figsize = [22,5])
cat_cols = ['holiday','workingday','weather','season']
for i in range (len(cat_cols)):
  plt.subplot(1, 4, i+1)
  sns.barplot(data=df, x=cat_cols[i], y='count')
```




## 2 Sample T-Test

```
# Checking: Does number of electric cycles rented on weekday greater than weekend?

null_hypothesis = 'number of electric cycles rented are similer on weekday and weekend'
alternative_hypothesis = 'number of electric cycles rented higher on weekday than weekend'

sample1 = df[df['workingday']==0]['count']
sample2 = df[df['workingday']==1]['count']
t_stat, p_value = ttest_ind(sample1, sample2, equal_var=False, alternative='greater')
print(t_stat, p_value)

if(p_value < 0.05):
  print('Since, p-value < 0.05, the null hypothesis is rejected')
  print(alternative_hypothesis)
else:
  print('Since p-value > 0.05, we fail to reject null hypothesis')
  print(null_hypothesis)

# conclusion: number of electric cycles rented are similer on weekday and weekend.
```

```
-1.2362580418223226 0.8917984385965245
Since p-value > 0.05, we fail to reject null hypothesis
number of electric cycles rented are similer on weekday and weekend
```

```
# Checking: Does the Working Day has an effect on number of electric cycles rented?

null_hypothesis = 'Working Day has no effect on number of electric cycles rented'
```

```
alternative_hypothesis = 'Working Day has effect on number of electric cycles rented'

sample1 = df[df['workingday']==0]['count']
sample2 = df[df['workingday']==1]['count']
t_stat, p_value = ttest_ind(sample1, sample2)
print(t_stat, p_value)

if(p_value < 0.05):
  print('Since, p-value < 0.05, the null hypothesis is rejected')
  print(alternative_hypothesis)
else:
  print('Since p-value > 0.05, we fail to reject null hypothesis')
  print(null_hypothesis)

# conclusion: workingday has no effect on number of electric cycles rented.
```

```
-1.2096277376026694 0.22644804226361348
Since p-value > 0.05, we fail to reject null hypothesis
Working Day has no effect on number of electric cycles rented
```

```
print(np.std(sample1),np.std(sample2))
# There is not huge difference in standerd deviation, so no need to equalize size of samples.
```

```
173.69901006897658 184.501211667422
```

```
df['workingday'].value_counts()
# We could make sample size equal for both variable (by considering lesser variable size).
# But we are not doing it because it is giving difference p_value and different result when doing same test multiple times.
# So we are considering unequal sample size to get fixed p_value (it might increase type 1 error, but it will give sure result).
```

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

## ANNOVA test

```
# Checking : Are the number of cycles rented similar or different in the different seasons?

null_hypothesis = 'There is no significant difference in the No. of cycles rented in the different seasons'
alternative_hypothesis = 'There is significant difference in No. of cycles rented in the different seasons'

sample1 = df[df['season']==1]['count']
sample2 = df[df['season']==2]['count']
sample3 = df[df['season']==3]['count']
sample4 = df[df['season']==4]['count']
t_stat, p_value = f_oneway(sample1,sample2,sample3,sample4)
print(t_stat, p_value)

if(p_value < 0.05):
  print('Since, p-value < 0.05, the null hypothesis is rejected')
  print(alternative_hypothesis)
else:
  print('Since p-value > 0.05, we fail to reject null hypothesis')
  print(null_hypothesis)

# conclusion: Number of cycles rented are similar in different seasons.
```

```
236.94671081032106 6.164843386499654e-149
Since, p-value < 0.05, the null hypothesis is rejected
There is significant difference in No. of cycles rented in the different seasons
```

```
# Checking : Are the number of cycles rented similar or different in the different weather?

null_hypothesis = 'There is no significant difference in the No. of cycles rented in the different weather'
alternative_hypothesis = 'There is significant difference in No. of cycles rented in the different weather'

sample1 = df[df['weather']==1]['count']
sample2 = df[df['weather']==2]['count']
sample3 = df[df['weather']==3]['count']
t_stat, p_value = f_oneway(sample1,sample2,sample3)
print(t_stat, p_value)

if(p_value < 0.05):
  print('Since, p-value < 0.05, the null hypothesis is rejected')
  print(alternative_hypothesis)
else:
  print('Since p-value > 0.05, we fail to reject null hypothesis')
  print(null_hypothesis)
```

```
# conclusion: Number of cycles rented are similar in different weather.
```

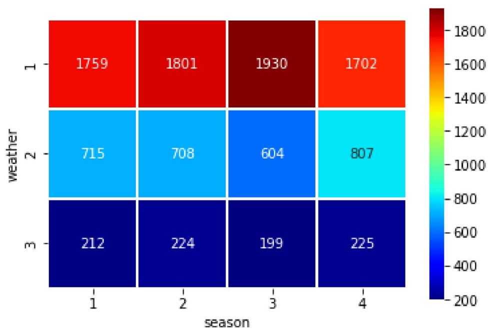
```
98.27223794468608 5.031744319425167e-43
Since, p-value < 0.05, the null hypothesis is rejected
There is significant difference in No. of cycles rented in the different weather
```

## Chi-square test

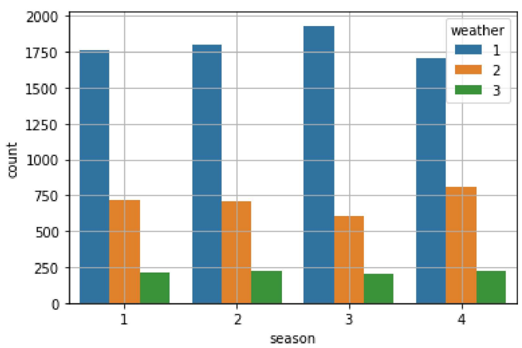
```
# Checking : Is Weather is dependent on season?

null_hypothesis = 'There is no relationship between Weather and Season'
alternative_hypothesis = 'There is relationship between Weather and Season'

contingency = pd.crosstab(df['weather'], df['season'])
print(contingency)

# p-value calculation
p_value = chi2_contingency(contingency)[1]
print('p-value:',round(p_value,4))

if(p_value < 0.05):
  print('Since, p-value < 0.05, the null hypothesis is rejected')
  print(alternative_hypothesis)
else:
  print('Since p-value > 0.05, we fail to reject null hypothesis')
  print(null_hypothesis)

# conclusion: Weather and Season are dependent.
```

```
season      1     2     3     4
weather
1        1759  1801  1930  1702
2         715   708   604   807
3         212   224   199   225
p-value: 0.0
Since, p-value < 0.05, the null hypothesis is rejected
There is relationship between Weather and Season
```

```
sns.heatmap(pd.crosstab(df['weather'], df['season']), cmap= "jet", annot = True, fmt = 'd', square=1, linewidth=1.)
plt.show()

# Proportion of season differ across different weather.
```




```
sns.countplot(data=df, x='season',hue='weather')
plt.grid()
plt.show()

# In season 3 most of the days have weather 1 and less days have with weather 3, Compared to other season.
# likelihood of weather 1 is different in different seasons.
```



All appropriate insights are mentioned with relevent code as comments. All the results are printed for relevent test.