## Hindi Vidya Prachar Samiti's

# RAMNIRANJAN JHUNJHUNWALA COLLEGE OF ARTS, SCIENCE & COMMERCE (AUTONOMOUS)

## statistics for Data Science

**Name:** Vikas Rajendra Yadav
**Roll No**: 714
**Class:** MSc Data Science and Artificial Intelligence Part I

# Hindi vidya prachar samiti’s Ramniranjan Jhunjhunwala College of Arts, Science and Commerce

## Department of Data Science and Artificial Intelligence

# CERTIFICATE

This is to certify **Vikas R. Yadav** of Msc. Data Science and Artificial Intelligence Roll No **714** has successfully completed the practical **Statistics for data science** during the Academic Year 2023-2024.

Date :

**(Prof.Rahul Yadav)**

**Prof-In-Charge** **External Examiner**

# INDEX

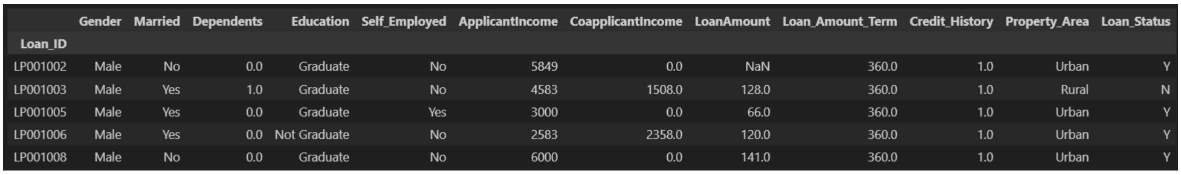
# Practical 1

# Data collection,

# cleaning, modeling and compilation

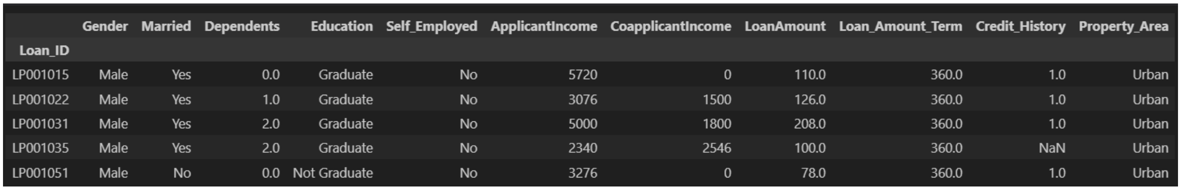
## Input and output

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

data=pd.read_csv(r"C:\Users\ocmodels03dev\Desktop\SAMEER\risk_analytics_train - risk_analytics_train - risk_analytics_train - risk_analytics_train.csv",index_col=0,header=0)
data.head()
```



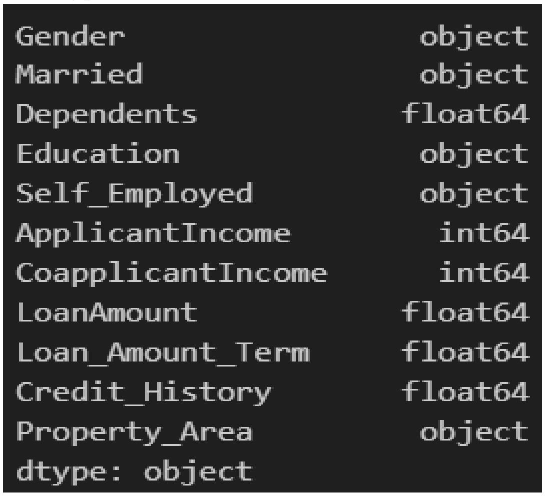
| | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History | Property_Area | Loan_Status |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Loan_ID | | | | | | | | | | | | |
| LP001002 | Male | No | 0.0 | Graduate | No | 5849 | 0.0 | NaN | 360.0 | 1.0 | Urban | Y |
| LP001003 | Male | Yes | 1.0 | Graduate | No | 4583 | 1508.0 | 128.0 | 360.0 | 1.0 | Rural | N |
| LP001005 | Male | Yes | 0.0 | Graduate | Yes | 3000 | 0.0 | 66.0 | 360.0 | 1.0 | Urban | Y |
| LP001006 | Male | Yes | 0.0 | Not Graduate | No | 2583 | 2358.0 | 120.0 | 360.0 | 1.0 | Urban | Y |
| LP001008 | Male | No | 0.0 | Graduate | No | 6000 | 0.0 | 141.0 | 360.0 | 1.0 | Urban | Y |

```
data=pd.read_csv(r"C:\Users\ocmodels03dev\Desktop\SAMEER\risk_analytics_test - risk_analytics_test.csv",index_col=0,header=0)
data.head()
```



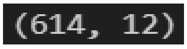
| | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History | Property_Area |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Loan_ID | | | | | | | | | | | |
| LP001015 | Male | Yes | 0.0 | Graduate | No | 5720 | 0 | 110.0 | 360.0 | 1.0 | Urban |
| LP001022 | Male | Yes | 1.0 | Graduate | No | 3076 | 1500 | 126.0 | 360.0 | 1.0 | Urban |
| LP001031 | Male | Yes | 2.0 | Graduate | No | 5000 | 1800 | 208.0 | 360.0 | 1.0 | Urban |
| LP001035 | Male | Yes | 2.0 | Graduate | No | 2340 | 2546 | 100.0 | 360.0 | NaN | Urban |
| LP001051 | Male | No | 0.0 | Not Graduate | No | 3276 | 0 | 78.0 | 360.0 | 1.0 | Urban |

```
data.dtypes
```



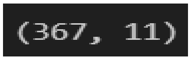
```
Gender                object
Married               object
Dependents           float64
Education             object
Self_Employed         object
ApplicantIncome        int64
CoapplicantIncome      int64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
dtype: object
```

data.shape # for train



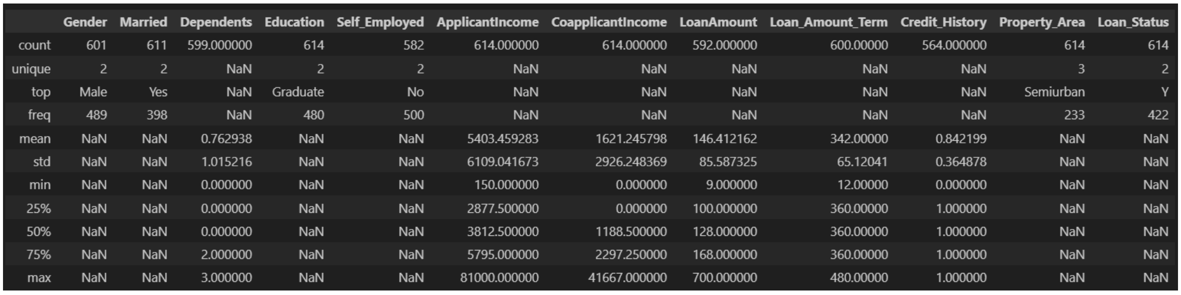
```
(614, 12)
```

data.shape # for test



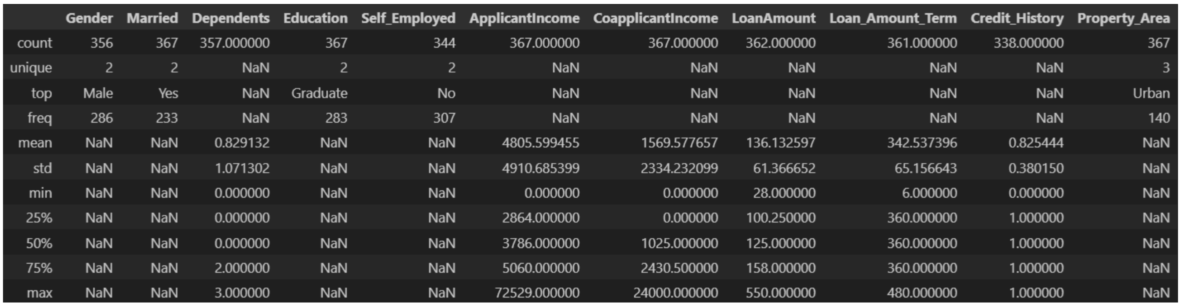
```
(367, 11)
```

data.describe(include='all') # for train



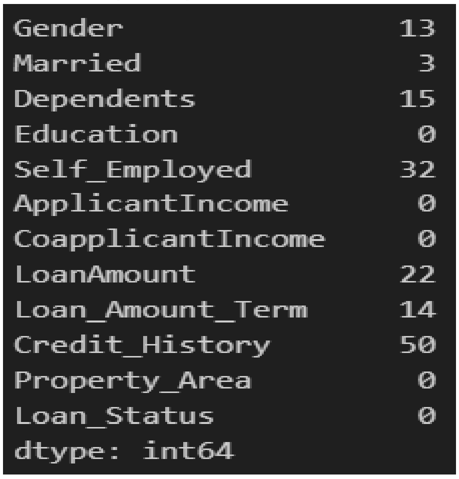
| | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History | Property_Area | Loan_Status |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| count | 601 | 611 | 599.000000 | 614 | 582 | 614.000000 | 614.000000 | 592.000000 | 600.00000 | 564.000000 | 614 | 614 |
| unique | 2 | 2 | NaN | 2 | 2 | NaN | NaN | NaN | NaN | NaN | 3 | 2 |
| top | Male | Yes | NaN | Graduate | No | NaN | NaN | NaN | NaN | NaN | Semiurban | Y |
| freq | 489 | 398 | NaN | 480 | 500 | NaN | NaN | NaN | NaN | NaN | 233 | 422 |
| mean | NaN | NaN | 0.762938 | NaN | NaN | 5403.459283 | 1621.245798 | 146.412162 | 342.00000 | 0.842199 | NaN | NaN |
| std | NaN | NaN | 1.015216 | NaN | NaN | 6109.041673 | 2926.248369 | 85.587325 | 65.12041 | 0.364878 | NaN | NaN |
| min | NaN | NaN | 0.000000 | NaN | NaN | 150.000000 | 0.000000 | 9.000000 | 12.00000 | 0.000000 | NaN | NaN |
| 25% | NaN | NaN | 0.000000 | NaN | NaN | 2877.500000 | 0.000000 | 100.000000 | 360.00000 | 1.000000 | NaN | NaN |
| 50% | NaN | NaN | 0.000000 | NaN | NaN | 3812.500000 | 1188.500000 | 128.000000 | 360.00000 | 1.000000 | NaN | NaN |
| 75% | NaN | NaN | 2.000000 | NaN | NaN | 5795.000000 | 2297.250000 | 168.000000 | 360.00000 | 1.000000 | NaN | NaN |
| max | NaN | NaN | 3.000000 | NaN | NaN | 81000.000000 | 41667.000000 | 700.000000 | 480.00000 | 1.000000 | NaN | NaN |

data.describe(include='all') # for test



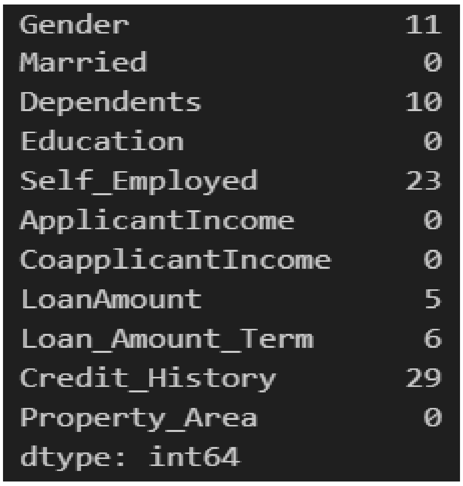
| | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History | Property_Area |
|---|---|---|---|---|---|---|---|---|---|---|---|
| count | 356 | 367 | 357.000000 | 367 | 344 | 367.000000 | 367.000000 | 362.000000 | 361.000000 | 338.000000 | 367 |
| unique | 2 | 2 | NaN | 2 | 2 | NaN | NaN | NaN | NaN | NaN | 3 |
| top | Male | Yes | NaN | Graduate | No | NaN | NaN | NaN | NaN | NaN | Urban |
| freq | 286 | 233 | NaN | 283 | 307 | NaN | NaN | NaN | NaN | NaN | 140 |
| mean | NaN | NaN | 0.829132 | NaN | NaN | 4805.599455 | 1569.577657 | 136.132597 | 342.537396 | 0.825444 | NaN |
| std | NaN | NaN | 1.071302 | NaN | NaN | 4910.685399 | 2334.232099 | 61.366652 | 65.156643 | 0.380150 | NaN |
| min | NaN | NaN | 0.000000 | NaN | NaN | 0.000000 | 0.000000 | 28.000000 | 6.000000 | 0.000000 | NaN |
| 25% | NaN | NaN | 0.000000 | NaN | NaN | 2864.000000 | 0.000000 | 100.250000 | 360.000000 | 1.000000 | NaN |
| 50% | NaN | NaN | 0.000000 | NaN | NaN | 3786.000000 | 1025.000000 | 125.000000 | 360.000000 | 1.000000 | NaN |
| 75% | NaN | NaN | 2.000000 | NaN | NaN | 5060.000000 | 2430.500000 | 158.000000 | 360.000000 | 1.000000 | NaN |
| max | NaN | NaN | 3.000000 | NaN | NaN | 72529.000000 | 24000.000000 | 550.000000 | 480.000000 | 1.000000 | NaN |

data.isnull().sum() # for train



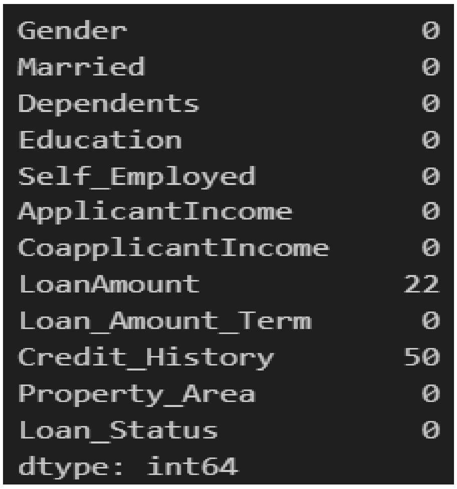
```
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

data.isnull().sum() # for test



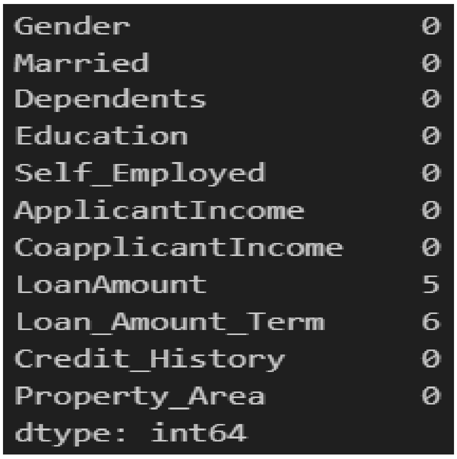
```
Gender               11
Married               0
Dependents           10
Education             0
Self_Employed        23
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            5
Loan_Amount_Term      6
Credit_History       29
Property_Area         0
dtype: int64
```

```
for value in ['Gender','Married','Dependents','Self_Employed','Loan_Amount_Term']:
   data[value].fillna(data[value].mode()[0],inplace=True)
data.isnull().sum()                          # for train
```



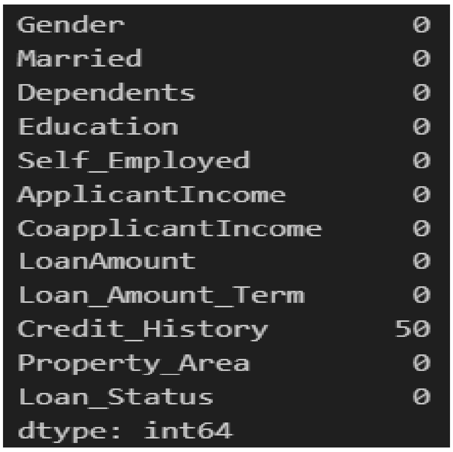
```
Gender                0
Married               0
Dependents            0
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term      0
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

```
categorical_data=['Gender','Dependents','Self_Employed','Credit_History']
for i in categorical_data:
   data[i].fillna(data[i].mode()[0],inplace=True)
data.isnull().sum()                          # for test
```



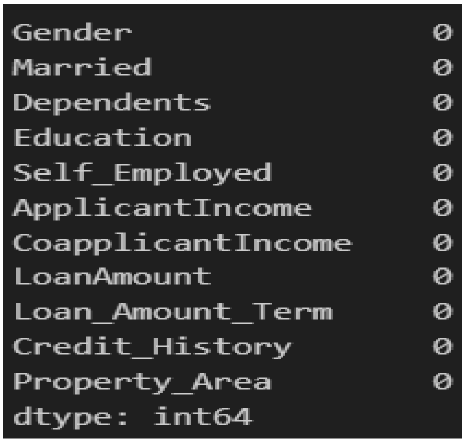
```
Gender                0
Married               0
Dependents            0
Education             0
Self_Employed         0
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            5
Loan_Amount_Term      6
Credit_History        0
Property_Area         0
dtype: int64
```

```
data['LoanAmount'].fillna(round(data['LoanAmount'].mean(),0),inplace=True)
data.isnull().sum()                          # for train
```



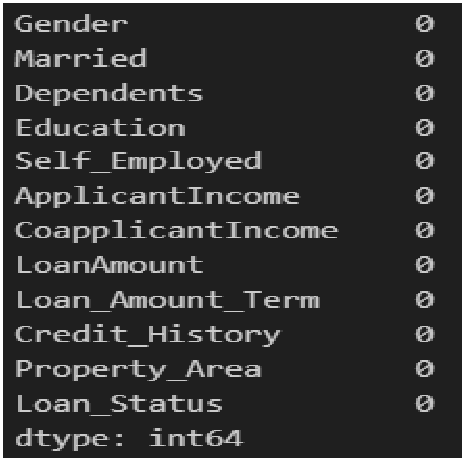
```
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History      50
Property_Area        0
Loan_Status          0
dtype: int64
```

```
numerical_data=['LoanAmount','Loan_Amount_Term']
for i in numerical_data:
   data[i].fillna(data[i].mean(),inplace=True)
data.isnull().sum()                          # for test
```



```
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
dtype: int64
```

```
data['Credit_History'].fillna(value=0,inplace=True)
print(data.isnull().sum())                   # for train
```



```
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

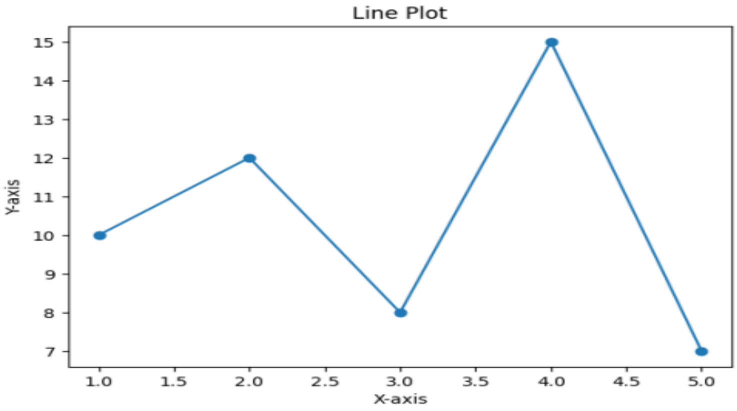
**Signature : ____________**

# Practical 2
# Explore Data Visualization Techniques

## input and output:

1  Line Plot:

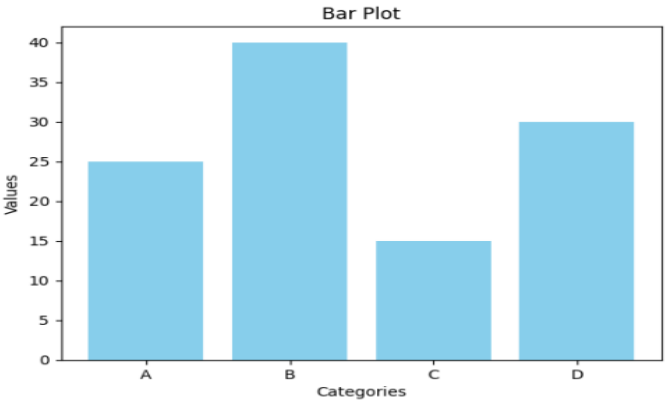
```
import matplotlib.pyplot as plt
x = [1, 2, 3, 4, 5]
y = [10, 12, 8, 15, 7]
plt.plot(x, y, marker='o')
plt.title("Line Plot")
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.show()
```



1

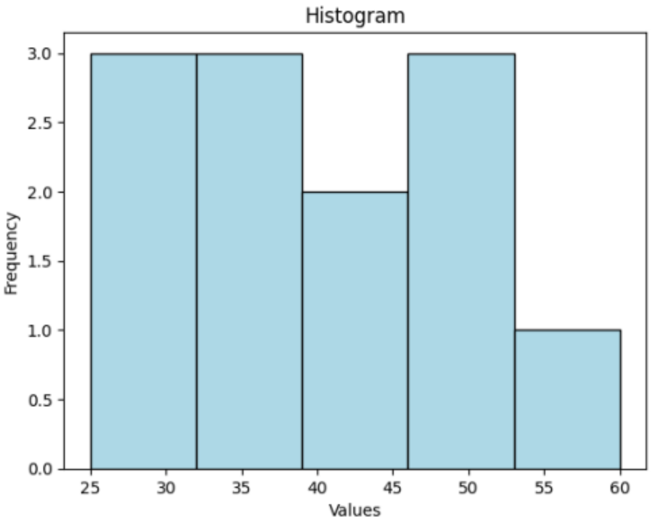
2 Bar Plot:

```
categories = ['A', 'B', 'C', 'D']
values = [25, 40, 15, 30]
plt.bar(categories, values, color='skyblue')
plt.title("Bar Plot")
plt.xlabel("Categories")
plt.ylabel("Values")
plt.show()
```



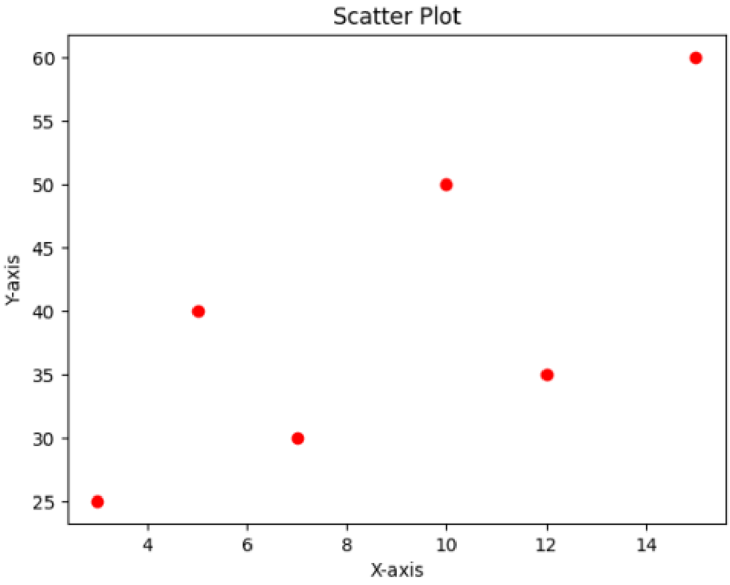
3 Histogram:

```
data = [32, 45, 50, 28, 36, 42, 38, 25, 29, 52, 48, 60] plt.hist(data, bins=5, color='lightblue',
edgecolor='black')
plt.title("Histogram")
plt.xlabel("Values")
plt.ylabel("Frequency")
```



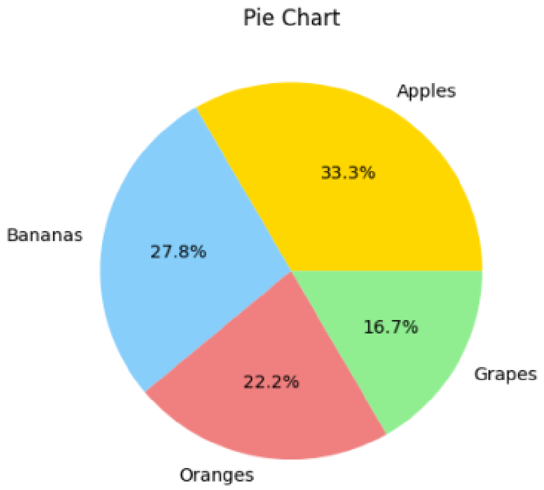
4 Scatter Plot:

```
x = [3, 5, 7, 10, 12, 15]
y = [25, 40, 30, 50, 35, 60]
plt.scatter(x, y, color='red', marker='o')
plt.title("Scatter Plot")
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.show()
```



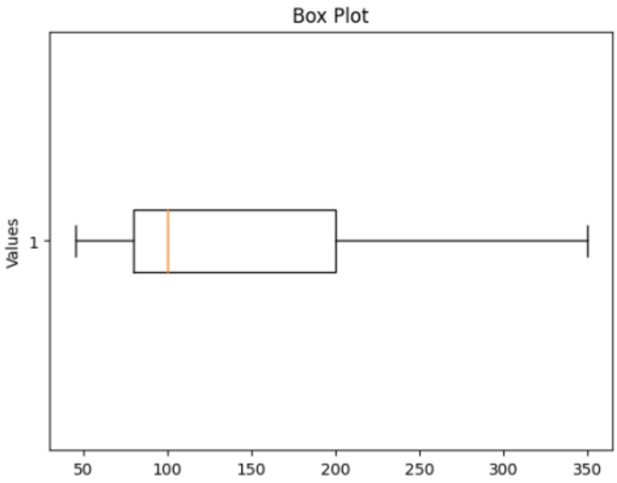
5 Pie Chart:

```
 labels = ['Apples', 'Bananas', 'Oranges', 'Grapes']
sizes = [30, 25, 20, 15]
plt.pie(sizes, labels=labels, autopct='%1.1f%%', colors=['gold', ␣
↪'lightskyblue', 'lightcoral', 'lightgreen'])
plt.title("Pie Chart")
plt.show()
```



6 Box Plot:

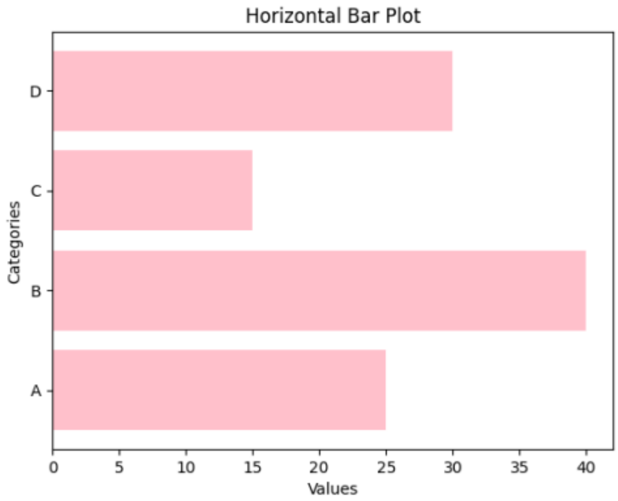
```
 data = [45, 60, 75,300, 80,350, 90, 95, 100, 110, 120,250,200]
plt.boxplot(data,vert=False,)
plt.title("Box Plot")
plt.ylabel("Values")
plt.show()
```



7 Barh Plot:

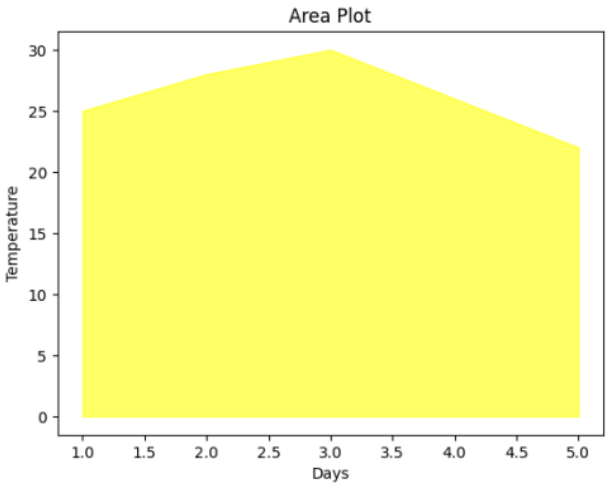
```
categories = ['A', 'B', 'C', 'D']
```

```
values = [25, 40, 15, 30]
plt.barh(categories, values, color='pink')
plt.title("Horizontal Bar Plot")
plt.xlabel("Values")
plt.ylabel("Categories")
plt.show(
```



8 Area Plot:

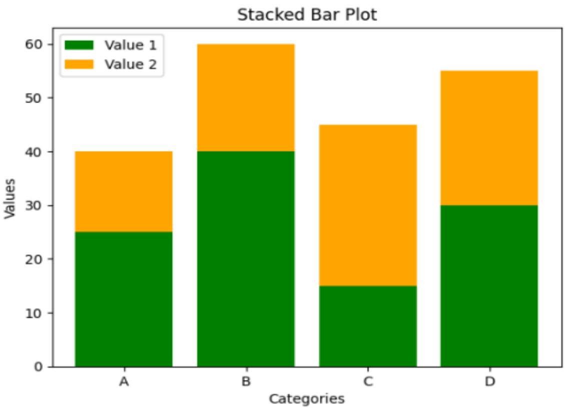
```
days = [1, 2, 3, 4, 5]
temperature = [25, 28, 30, 26, 22]
plt.fill_between(days, temperature, color='yellow', alpha=0.6)
plt.title("Area Plot")
plt.xlabel("Days")
plt.ylabel("Temperature")
plt.show()
```



9 Stacked Bar Plot:

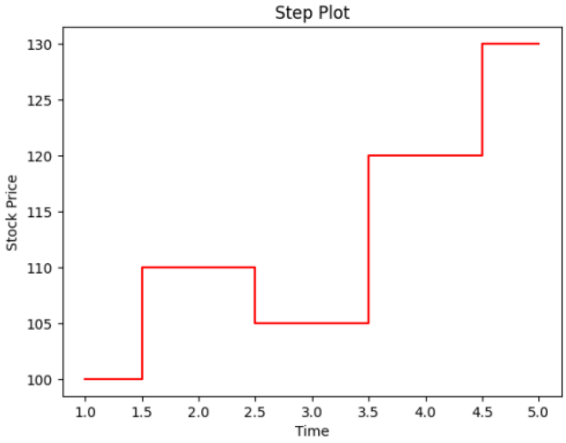
```
categories = ['A', 'B', 'C', 'D']
values1 = [25, 40, 15, 30]
values2 = [15, 20, 30, 25]
```

```
plt.bar(categories, values1, color='green', label='Value 1')
plt.bar(categories, values2, bottom=values1, color='orange', label='Value 2')
plt.title("Stacked Bar Plot")
plt.xlabel("Categories")
plt.ylabel("Values")
plt.legend()
plt.show()
```



10 Step Plot:

```
time = [1, 2, 3, 4, 5]
stock_price = [100, 110, 105, 120, 130]
plt.step(time, stock_price, color='red', where='mid')
plt.title("Step Plot")
plt.xlabel("Time")
plt.ylabel("Stock Price")
plt.show()
```



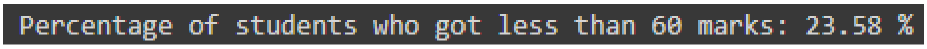
**Signature** ____________________

# Practical 3 Implement statistics distribution

## a) Normal distribution

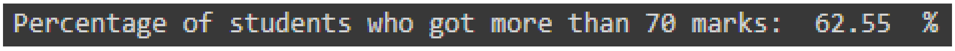
## Input and output

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
from scipy import stats

# Given information
mean = 78
std_dev = 25
total_students = 100
score = 60

# Calculate z-score for 60
z_score = (score - mean) / std_dev

# Calculate the probability of getting a score less than 60
prob = norm.cdf(z_score)

# Calculate the percentage of students who got less than 60 marks
percent = prob * 100

# Print the result
print("Percentage of students who got less than 60 marks:", round(percent, 2), "%")
```



```
Percentage of students who got less than 60 marks: 23.58 %
```

```
# Given information
mean = 78
std_dev = 25
total_students = 100
score = 70

# Calculate z-score for 70
z_score = (score - mean) / std_dev

# Calculate the probability of getting a more than 70
prob = norm.cdf(z_score)

# Calculate the percentage of students who got more than 70 marks
percent = (1-prob) * 100

# Print the result
print("Percentage of students who got more than 70 marks: ", round(percent, 2), " %")
```

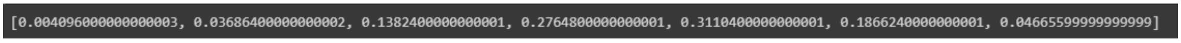


```
Percentage of students who got more than 70 marks:  62.55  %
```

## b) Binomial distribution

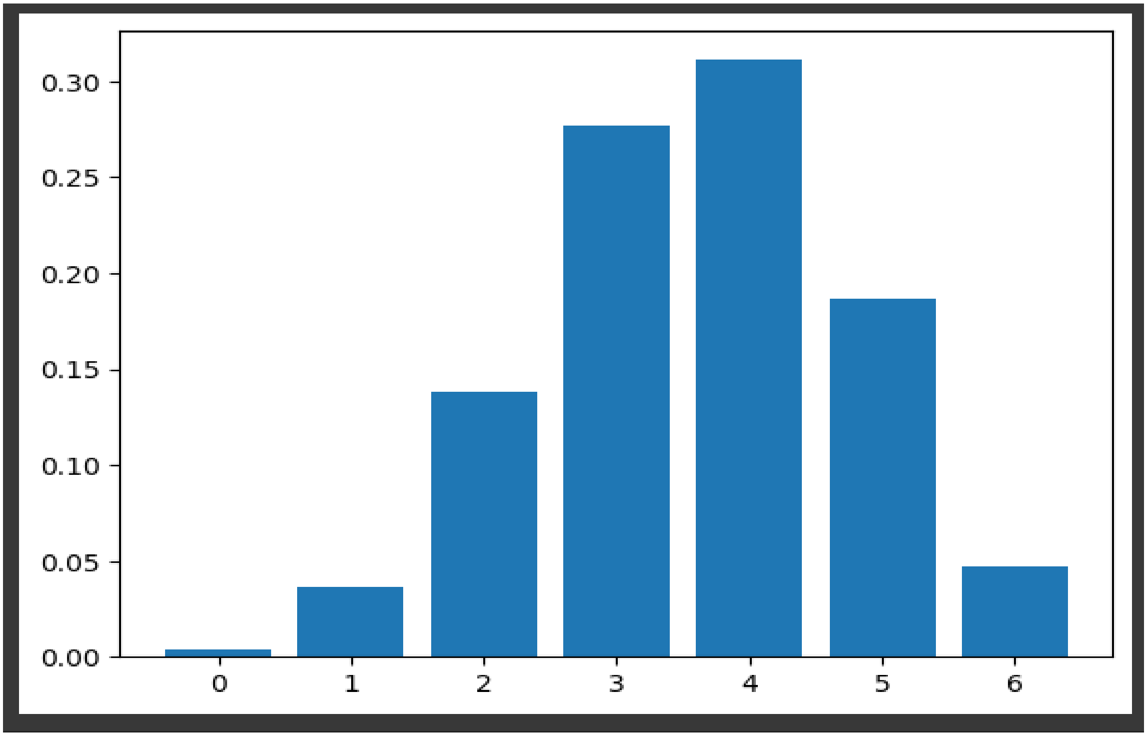
## Input and output

```
from scipy.stats import binom

# setting the values
# of n and p
n = 6
p = 0.6

# defining list of r values
r_values = list(range(n + 1))
# list of pmf values
dist = [binom.pmf(r, n, p) for r in r_values ]
print(dist)
```



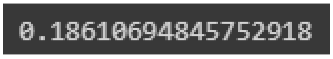
```
[0.004096000000000003, 0.03686400000000002, 0.1382400000000001, 0.2764800000000001, 0.3110400000000001, 0.1866240000000001, 0.04665599999999999]
```

```
# plotting the graph
plt.bar(r_values, dist)
plt.show()
```



When success and failure are equally likely, the binomial distribution is a normal distribution.

```
#Expected number of successful trials = 5
#total number of trails =30
#The probability of success = 0.15
stats.binom.pmf(5, 30, 0.15)
```



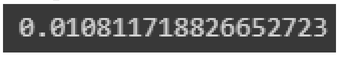
```
0.18610694845752918
```

the corresponding probability is 0.1861, that is the probability that exactly 5 customers will return items is approximately 18.61%

## c) Poisson distribution

## Input and output

```
#Question : The number of calls arriving at a call center follows a Poisson distribution at 20 calls per hour.
#Calculate the probability that the number of calls will be maximum 10.

stats.poisson.cdf(10,20)
```



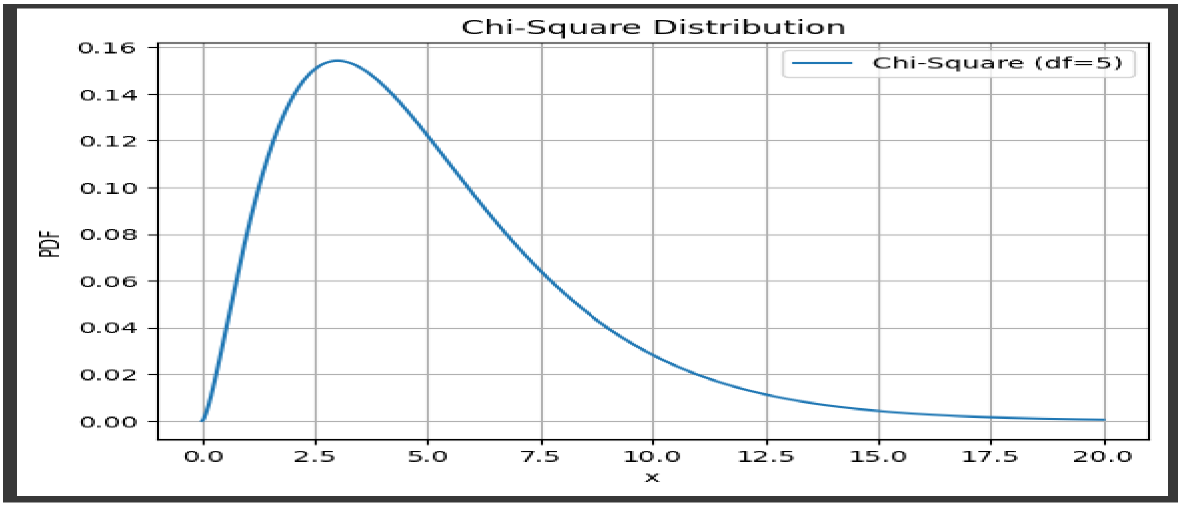
```
0.010811718826652723
```

the corresponding probability is 0.0108

## d) Chi-square distribution

## Input and output

```
from scipy.stats import chi2
# Parameters for the Chi-Square distribution
degrees_of_freedom = 5  # Degrees of freedom
# Generate a range of x values
x = np.linspace(0, 20, 1000)
# Calculate the probability density function (PDF) for the Chi-Square distribution
pdf = chi2.pdf(x, degrees_of_freedom)
# Plot the PDF
plt.plot(x, pdf, label=f'Chi-Square (df={degrees_of_freedom})')
plt.xlabel('x')
plt.ylabel('PDF')
plt.legend()
plt.title('Chi-Square Distribution')
plt.grid()
plt.show()
```



**Signature : ____________**

# Practical 4 Perform hypothesis testing

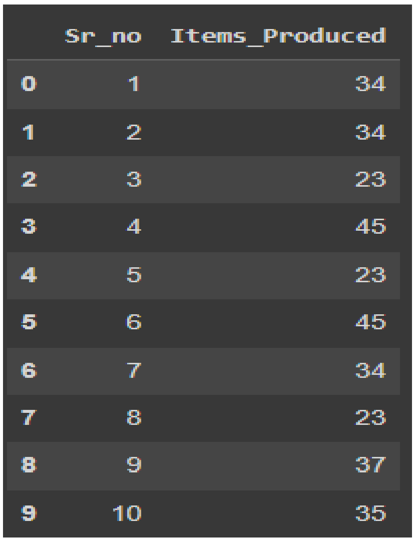
## a) One sample t test for small samples

### i) Two-sided

## Input and output

Q) The Violet industries produces furniture for home and office use. The production engineer claims that the average number of furniture items produced is 30. Test his claim.

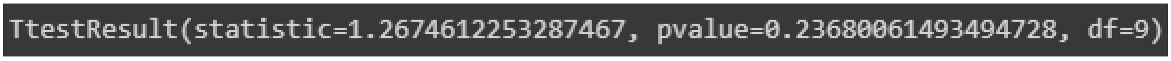
```
import pandas as pd
df=pd.DataFrame({
   'Sr_no':[1,2,3,4,5,6,7,8,9,10],
   'Items_Produced':[34,34,23,45,23,45,34,23,37,35]
})
df
```



|   | Sr_no | Items_Produced |
|---|---|---|
| 0 | 1 | 34 |
| 1 | 2 | 34 |
| 2 | 3 | 23 |
| 3 | 4 | 45 |
| 4 | 5 | 23 |
| 5 | 6 | 45 |
| 6 | 7 | 34 |
| 7 | 8 | 23 |
| 8 | 9 | 37 |
| 9 | 10 | 35 |

Let
X : The number of furniture items produced by machine A.
Thus μ : The average number of furniture items produced by machine A.
The Hypothesis is
H0 : The mean number of items produced by machine A is equal to 30 i.e μ = 30 Against
H1 : The mean number of items produced by machine A is not equal toi 30 i.e μ ≠ 30

```
#import library
from scipy.stats import ttest_1samp
#conduct the test
ttest_1samp(df['Items_Produced'],30)
```



```
TtestResult(statistic=1.2674612253287467, pvalue=0.23680061493494728, df=9)
```

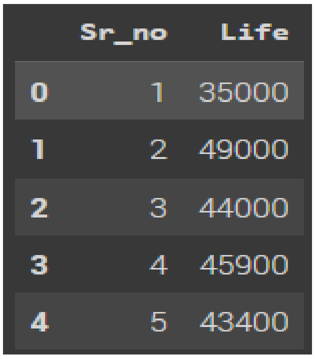
We see that the p-value(0.2368) > 0.05(l.o.s) , Hence we do not reject H0
We may conclude that the average number of items produced by machine A = 30.

### ii) one-sided

## Input and output

The blaze industries pvt.ltd claims that their manufactured electric bulbs have LIFE OF 45000 hrs.Test their claims at 5% level of significance.

```
data=pd.DataFrame({
    'Sr_no':[1,2,3,4,5,6,7,8,9,10,11,12,13,14,15],
'Life':[35000,49000,44000,45900,43400,50000,47200,32700,33200,43000,46300,47800,32100,33200,33900]
})
data.head()
```

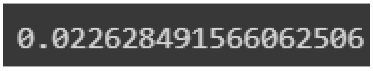


|  | Sr_no | Life |
|---|---|---|
| 0 | 1 | 35000 |
| 1 | 2 | 49000 |
| 2 | 3 | 44000 |
| 3 | 4 | 45900 |
| 4 | 5 | 43400 |

Let
X : The life of bulb in hours
Thus µA : The average life of bulb in hours

The hypothesis is
H0: The mean life of bulb in hours is equal to 45000 , i.e. µA = 45000
AGAINST
H1 : The mean life of bulb in hours is less than equal to 45000, i.e. µA ≤ 45000\

```
#conduct the test
#this is the test is two tailed
t_test_less=ttest_1samp(data['Life'],45000)

#to get the p-value for one-tailed test
#divide the p-value by 2
p_value_less=t_test_less.pvalue/2

#print p-value
p_value_less
```



```
0.022628491566062506
```

we see that p-value(0.02) is less than 0.05(l.o.s), hence we reject H0.
We may conclude that the avg life of a bulb in an hour is less than or equal to 45000. And the manufacturer's claim is wrong.

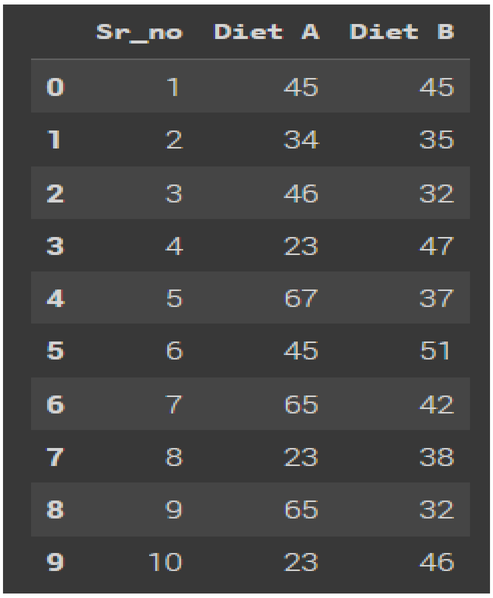
**Signature : ____________**

## b) Two sample t test for small samples

## Input and output

In a pig farm, to increase the weight of the pig, two different diets were given. The data for gain in weight is as given. Test whether the two diets differ significantly regarding their effect on increase in weight.

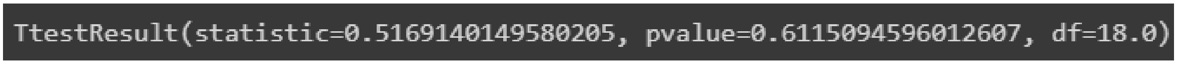
```
f1=pd.DataFrame({
  'Sr_no':[1,2,3,4,5,6,7,8,9,10],
  'Diet A':[45,34,46,23,67,45,65,23,65,23],
  'Diet B':[45,35,32,47,37,51,42,38,32,46]
})
df1
```



| | Sr_no | Diet A | Diet B |
|---|---|---|---|
| 0 | 1 | 45 | 45 |
| 1 | 2 | 34 | 35 |
| 2 | 3 | 46 | 32 |
| 3 | 4 | 23 | 47 |
| 4 | 5 | 67 | 37 |
| 5 | 6 | 45 | 51 |
| 6 | 7 | 65 | 42 |
| 7 | 8 | 23 | 38 |
| 8 | 9 | 65 | 32 |
| 9 | 10 | 23 | 46 |

Let
X : The gain in weight due to diet A
Y : The gain in weight due to diet B
Thus
µa : The average gain in weight due to diet A
AGAINST
µb : The average gain in weight due to diet B
The Hypothesis is
H0 : The average gain in weight due to diet A is equal to The average gain in weight due to diet B i.e µa = µb
H1 : The average gain in weight due to diet A is not equal to The average gain in weight due to diet B i.e µa ≠µb

```
#t-test for testing equality of means
from scipy.stats import ttest_ind
#conduct the test
ttest_ind(df1['Diet A'],df1['Diet B'])
```



```
TtestResult(statistic=0.5169140149580205, pvalue=0.6115094596012607, df=18.0)
```

since the p-value (0.611) > 0.05(level of significance) hence we fail to reject H0
we may conclude that the average gain in weight due to diet A is not equal to the average gain in weight due to diet B

**Signature : ____________**

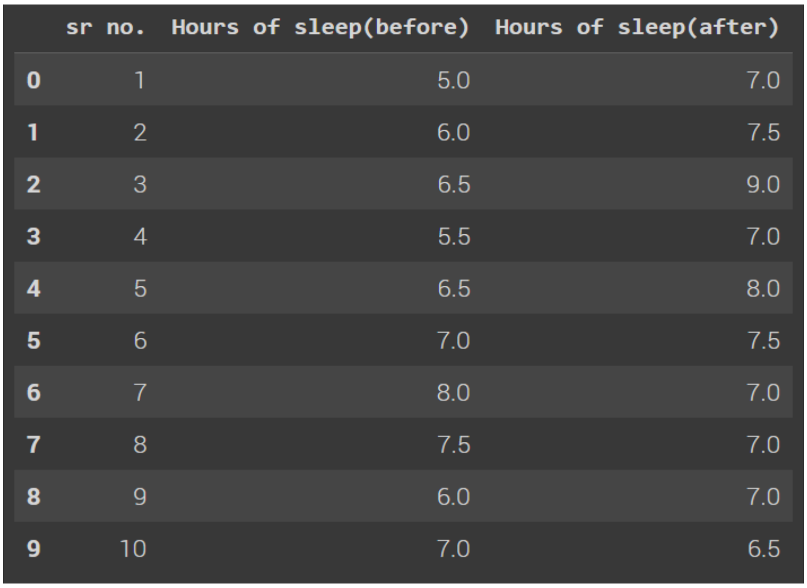
## c) Paired t test

## Input and output

A Pharma company claims to have produced a new drug which improves sleep of 18 year old teenagers . The hours of sleep for 10 teenagers before and after giving the new drug is recorded. Test whether there is a significant difference in the average hours of sleep.

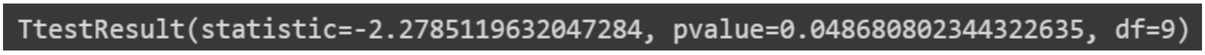
Let
X : Hours of sleep before medication
Y : Hours of sleep after medication
Thus,
The Hypothesis is
H0 : The average hours of sleep before medication is equal to the average of sleep after medication.
i.e.µA=µB
H1 : The average hours of sleep before medication is not equal to the average of sleep after medication.
i.e.µA≠µB

```
data=pd.DataFrame({
   'sr no.':[1,2,3,4,5,6,7,8,9,10],
   'Hours of sleep(before)':[5.0,6.0,6.5,5.5,6.5,7,8,7.5,6,7],
   'Hours of sleep(after)':[7,7.5,9,7,8,7.5,7,7,7,6.5]
})
data
```



| | sr no. | Hours of sleep(before) | Hours of sleep(after) |
|---|---|---|---|
| 0 | 1 | 5.0 | 7.0 |
| 1 | 2 | 6.0 | 7.5 |
| 2 | 3 | 6.5 | 9.0 |
| 3 | 4 | 5.5 | 7.0 |
| 4 | 5 | 6.5 | 8.0 |
| 5 | 6 | 7.0 | 7.5 |
| 6 | 7 | 8.0 | 7.0 |
| 7 | 8 | 7.5 | 7.0 |
| 8 | 9 | 6.0 | 7.0 |
| 9 | 10 | 7.0 | 6.5 |

```
from scipy.stats import ttest_rel
ttest_rel(data['Hours of sleep(before)'],data['Hours of sleep(after)'])
```



```
TtestResult(statistic=-2.2785119632047284, pvalue=0.048680802344322635, df=9)
```

Since the p-value(0.048) is less than 0.05 (level of significance),hence we reject H0.
We may conclude that the average hours of sleep before medication is not equal to the average of sleep after medication.
i.e µa ≠ µb

**Signature : _____________**

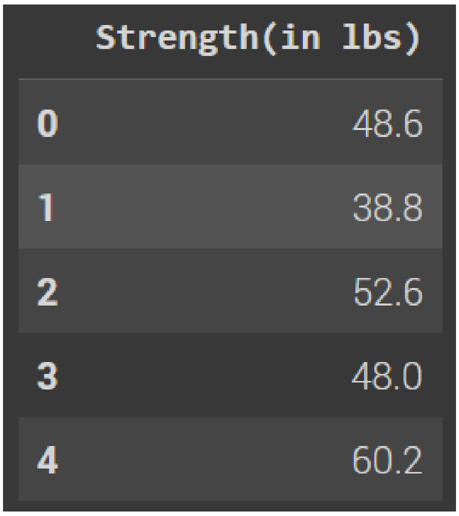
## d) One sample z test for large samples

## Input and output

A random sample of 40 glass rod is taken from a lot manufactured under a new process. they are tested for their strength. Can we claim that the breaking strength is equal to 55 lbs?

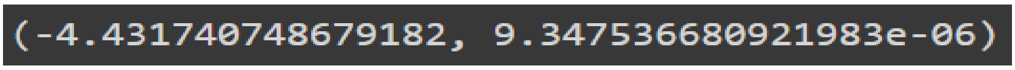
The hypothesis is,
H0 : The mean of the breaking strength of glass rod is equal to 55 i.e. μ = 55
H1 : The mean of the breaking strength of glass rod is not equal to 55 i.e. μ ≠ 55

```
data1=pd.DataFrame({
    'Strength(in lbs)':[48.6,38.8,52.6,48,60.2,54.6,42.7,42.1,49.8,57.8,57.9,46.4,52.5,55.5,53.5,54.9,58.8,
41.8,58.6,48.7,55,50.2,57,51.2,39.5,58.2,46.8,38,56.6,41,54.8,55.6,58.4,45,42.8,54.8,45.7,44.3,38.4,54.3]})
data1.head
```



|   | Strength(in lbs) |
|---|---|
| 0 | 48.6 |
| 1 | 38.8 |
| 2 | 52.6 |
| 3 | 48.0 |
| 4 | 60.2 |

```
#import the library
from statsmodels.stats import weightstats as stests

# conduct the test
stests.ztest(data1['Strength(in lbs)'],value=55)
```



```
(-4.431740748679182, 9.347536680921983e-06)
```

Since, the p-value(0.00) is less than 0.05 (LO.S), hence we reject Ho.
We may conclude that the average  breaking strength of the glass rod is not equal to 55 lbs.

**Signature : ____________**

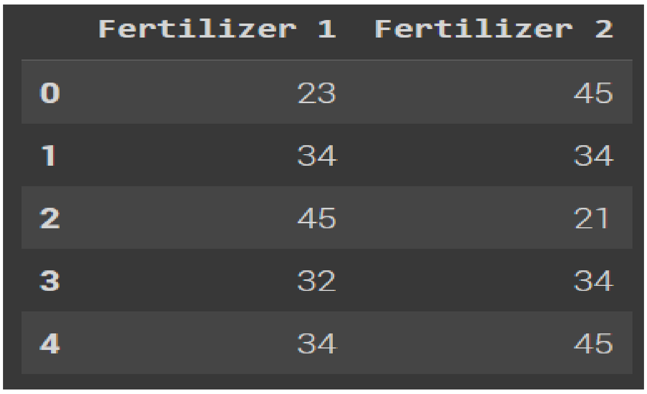
## e) Two sample z test for large samples

## Input and output

Two types of fertilisers are tested on farm lands of the same size. The yields in quintals are given below. Can we conclude that the two fertilisers have the same yield?

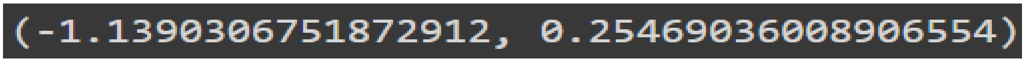
Let,
x:yield due to fertiliser 1
y:yield due to fertiliser 2
Thus,
µA=The average yield due to fertiliser 1
µB=The average yield due to fertiliser 2
The Hypothesis is,
i.e. µA=µB
Ho:The average yield due to fertiliser 1 is equal to the average yield due to fertiliser 2
Ha:The average yield due to fertiliser 1 is not equal to the average yield due to fertiliser 2
i.e. µA≠µB

```
df_fertilizer=pd.DataFrame({
    'Fertilizer 1':[23,34,45,32,34,51,39,34,28,30,46,41,35,43,24,36,25,33,36,43,26,45,32,47,42,31,35,46,34,32,46,36,25,46,34],
    'Fertilizer 2':[45,34,21,34,45,32,46,53,24,23,54,53,34,45,43,45,32,47,36,37,37,29,30,31,38,42,48,29,37,35,47,43,31,43,43]
})
df_fertilizer.head()
```



| | Fertilizer 1 | Fertilizer 2 |
|---|---|---|
| 0 | 23 | 45 |
| 1 | 34 | 34 |
| 2 | 45 | 21 |
| 3 | 32 | 34 |
| 4 | 34 | 45 |

```
#import the library
from statsmodels.stats import weightstats as stests
#conduct the test
stests.ztest(df_fertilizer['Fertilizer 1'],df_fertilizer['Fertilizer 2'])
```



```
(-1.1390306751872912, 0.25469036008906554)
```

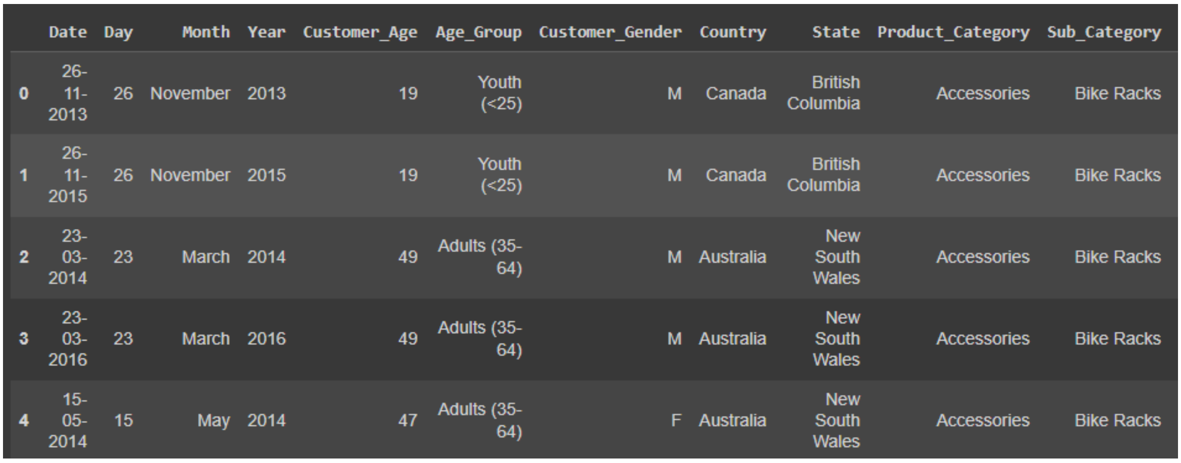
Since the p-value (0.255) is more than 0.05 (level of significance).
hence,we accept Ho.
We may conclude that the average yeild due to fertilizer 1 is equal to the average yeild due to fertilizer 2.

**Signature : ____________**

# Practical 5 Exploring categorical and binary data

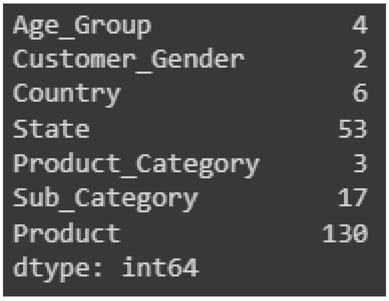
## Input and output

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

# Load your dataset
df = pd.read_csv(r"C:\Users\rahul\Downloads\sales_data.csv")
df.head()
```



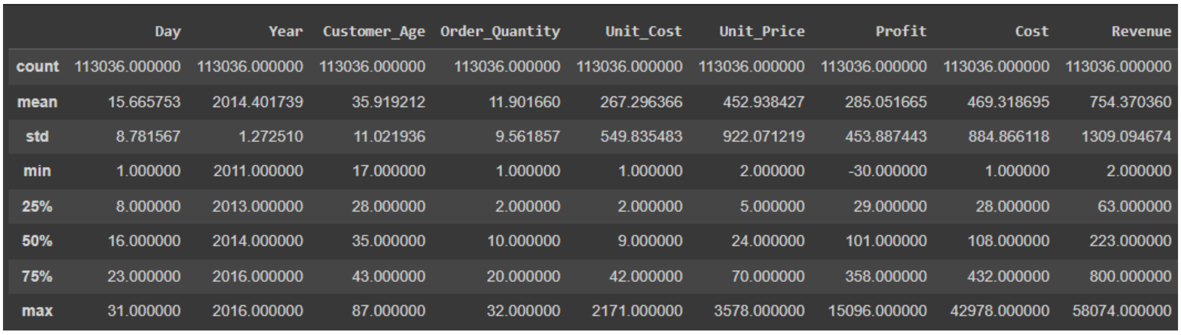
| | Date | Day | Month | Year | Customer_Age | Age_Group | Customer_Gender | Country | State | Product_Category | Sub_Category |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 26-11-2013 | 26 | November | 2013 | 19 | Youth (<25) | M | Canada | British Columbia | Accessories | Bike Racks |
| 1 | 26-11-2015 | 26 | November | 2015 | 19 | Youth (<25) | M | Canada | British Columbia | Accessories | Bike Racks |
| 2 | 23-03-2014 | 23 | March | 2014 | 49 | Adults (35-64) | M | Australia | New South Wales | Accessories | Bike Racks |
| 3 | 23-03-2016 | 23 | March | 2016 | 49 | Adults (35-64) | M | Australia | New South Wales | Accessories | Bike Racks |
| 4 | 15-05-2014 | 15 | May | 2014 | 47 | Adults (35-64) | F | Australia | New South Wales | Accessories | Bike Racks |

```
#df.info()
df.iloc[:,5:12].nunique()
#df[['Age_Group ','Customer_Gender','Country','State','Product_Category','Sub_Category','Product']]
```



```
Age_Group             4
Customer_Gender       2
Country               6
State                53
Product_Category      3
Sub_Category         17
Product             130
dtype: int64
```

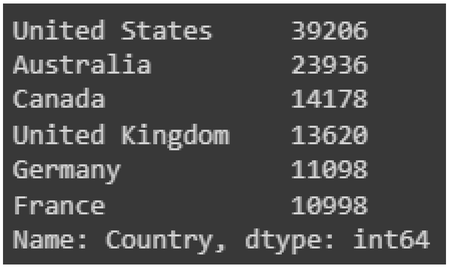
```
df.describe()
```



| | Day | Year | Customer_Age | Order_Quantity | Unit_Cost | Unit_Price | Profit | Cost | Revenue |
|---|---|---|---|---|---|---|---|---|---|
| count | 113036.000000 | 113036.000000 | 113036.000000 | 113036.000000 | 113036.000000 | 113036.000000 | 113036.000000 | 113036.000000 | 113036.000000 |
| mean | 15.665753 | 2014.401739 | 35.919212 | 11.901660 | 267.296366 | 452.938427 | 285.051665 | 469.318695 | 754.370360 |
| std | 8.781567 | 1.272510 | 11.021936 | 9.561857 | 549.835483 | 922.071219 | 453.887443 | 884.866118 | 1309.094674 |
| min | 1.000000 | 2011.000000 | 17.000000 | 1.000000 | 1.000000 | 2.000000 | -30.000000 | 1.000000 | 2.000000 |
| 25% | 8.000000 | 2013.000000 | 28.000000 | 2.000000 | 2.000000 | 5.000000 | 29.000000 | 28.000000 | 63.000000 |
| 50% | 16.000000 | 2014.000000 | 35.000000 | 10.000000 | 9.000000 | 24.000000 | 101.000000 | 108.000000 | 223.000000 |
| 75% | 23.000000 | 2016.000000 | 43.000000 | 20.000000 | 42.000000 | 70.000000 | 358.000000 | 432.000000 | 800.000000 |
| max | 31.000000 | 2016.000000 | 87.000000 | 32.000000 | 2171.000000 | 3578.000000 | 15096.000000 | 42978.000000 | 58074.000000 |

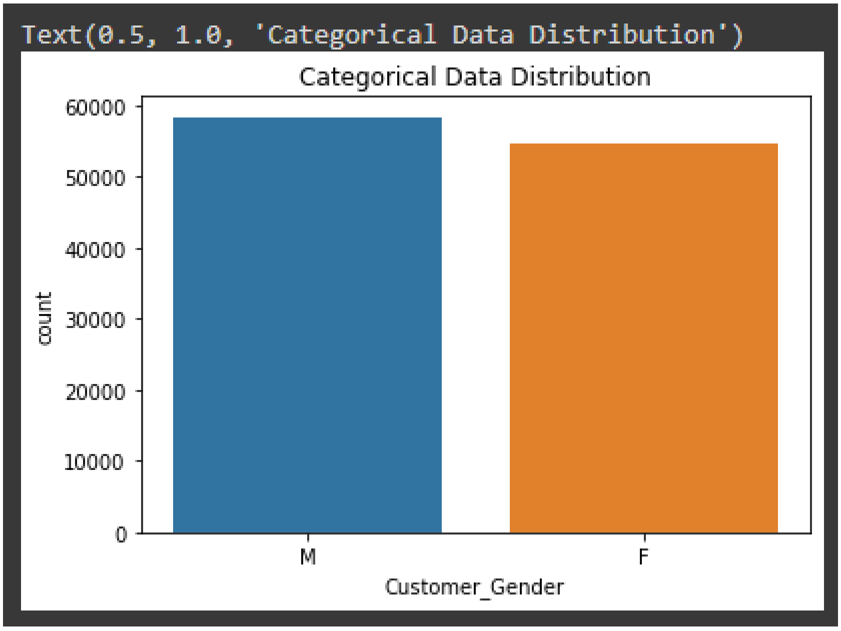
```
category_counts = df['Country'].value_counts()
```

print(category_counts)



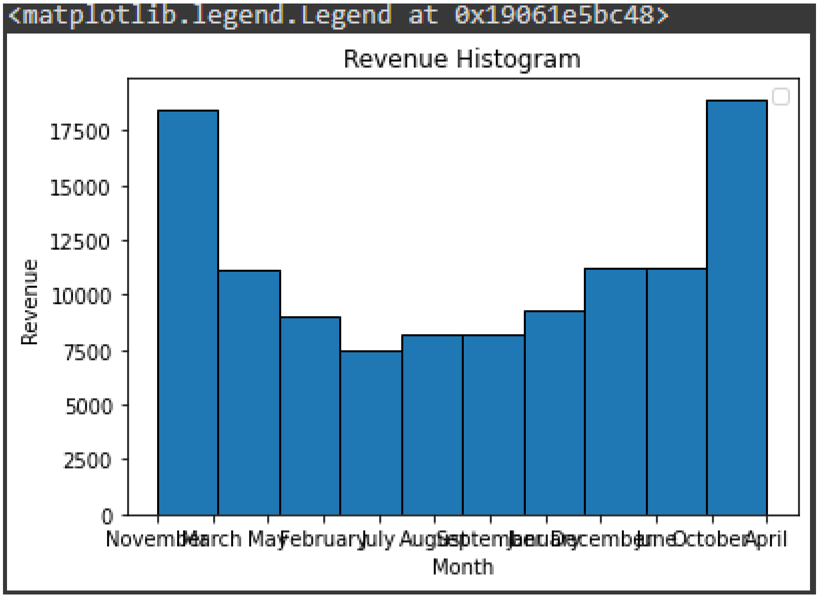
```
United States     39206
Australia         23936
Canada            14178
United Kingdom    13620
Germany           11098
France            10998
Name: Country, dtype: int64
```

```
sns.countplot(data=df, x='Customer_Gender')
plt.title("Categorical Data Distribution")
```



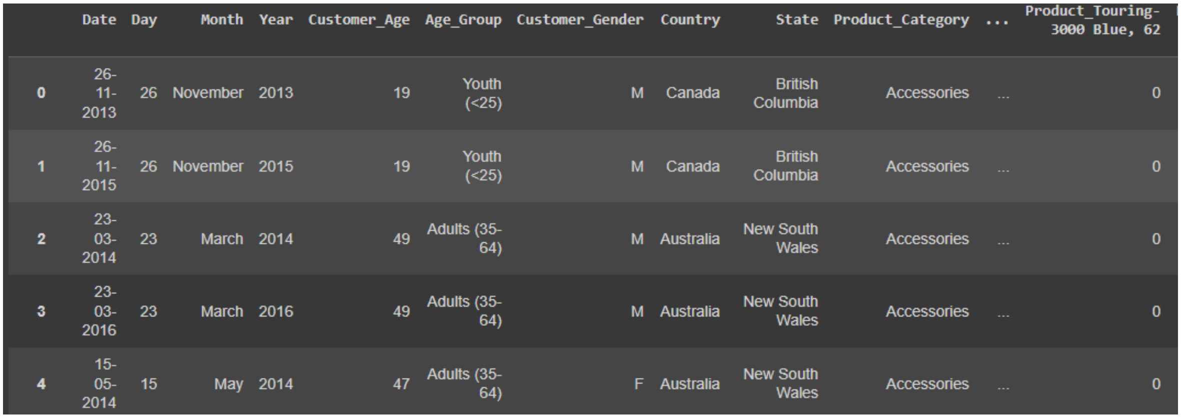
```
Text(0.5, 1.0, 'Categorical Data Distribution')
```

```
plt.hist(df['Month'], bins=10, edgecolor='black')
plt.title('Revenue Histogram')
plt.xlabel('Month')
plt.ylabel('Revenue')
plt.legend()
```



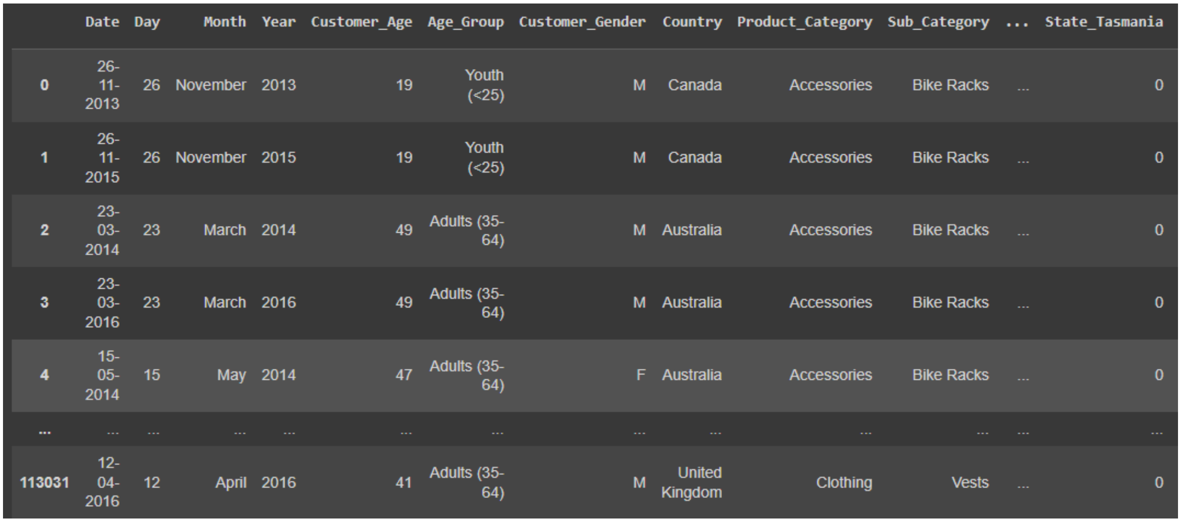
```
<matplotlib.legend.Legend at 0x19061e5bc48>
```

```
one_hot_encoded_data = pd.get_dummies(df, columns = ['Product'])
one_hot_encoded_data
```



| | Date | Day | Month | Year | Customer_Age | Age_Group | Customer_Gender | Country | State | Product_Category | ... | Product_Touring-3000 Blue, 62 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 26-11-2013 | 26 | November | 2013 | 19 | Youth (<25) | M | Canada | British Columbia | Accessories | ... | 0 |
| 1 | 26-11-2015 | 26 | November | 2015 | 19 | Youth (<25) | M | Canada | British Columbia | Accessories | ... | 0 |
| 2 | 23-03-2014 | 23 | March | 2014 | 49 | Adults (35-64) | M | Australia | New South Wales | Accessories | ... | 0 |
| 3 | 23-03-2016 | 23 | March | 2016 | 49 | Adults (35-64) | M | Australia | New South Wales | Accessories | ... | 0 |
| 4 | 15-05-2014 | 15 | May | 2014 | 47 | Adults (35-64) | F | Australia | New South Wales | Accessories | ... | 0 |

```
one_hot_encoded_data = pd.get_dummies(df, columns = ['State'])
one_hot_encoded_data
```



| | Date | Day | Month | Year | Customer_Age | Age_Group | Customer_Gender | Country | Product_Category | Sub_Category | ... | State_Tasmania |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 26-11-2013 | 26 | November | 2013 | 19 | Youth (<25) | M | Canada | Accessories | Bike Racks | ... | 0 |
| 1 | 26-11-2015 | 26 | November | 2015 | 19 | Youth (<25) | M | Canada | Accessories | Bike Racks | ... | 0 |
| 2 | 23-03-2014 | 23 | March | 2014 | 49 | Adults (35-64) | M | Australia | Accessories | Bike Racks | ... | 0 |
| 3 | 23-03-2016 | 23 | March | 2016 | 49 | Adults (35-64) | M | Australia | Accessories | Bike Racks | ... | 0 |
| 4 | 15-05-2014 | 15 | May | 2014 | 47 | Adults (35-64) | F | Australia | Accessories | Bike Racks | ... | 0 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 113031 | 12-04-2016 | 12 | April | 2016 | 41 | Adults (35-64) | M | United Kingdom | Clothing | Vests | ... | 0 |

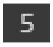
**Signature : ____________**

# Practical 6 Implementation of non parametric test

## a) Sign test

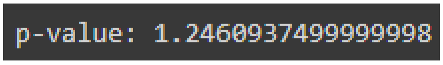
## Input and output

```
import numpy as np
from scipy.stats import binom

data = [
    (4, 3),
    (5, 6),
    (7, 6),
    (4, 5),
    (3, 2),
    (6, 6),

    (8, 7),
    (5, 4),
    (6, 6),
    (4, 4),
]

differences = [x - y for x, y in data]
positive_diff = sum(1 for diff in differences if diff > 0)
negative_diff = sum(1 for diff in differences if diff < 0)
n = len(data)
k = positive_diff
print(k)
```



```
5
```

```
p_value = binom.cdf(k, n, 0.5) + binom.sf(k - 1, n, 0.5)

print("p-value:", p_value)
```



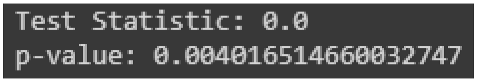
```
p-value: 1.2460937499999998
```

## b) Wilcoxon matched pair test (or sign rank test)

## Input and output

```
import numpy as np
from scipy.stats import wilcoxon

before = [35, 42, 38, 46, 33, 29, 42, 37, 40, 32]
after = [30, 40, 36, 44, 28, 24, 41, 35, 38, 30]

differences = [after[i] - before[i] for i in range(len(before))]
```

```
statistic, p_value = wilcoxon(differences)

print("Test Statistic:", statistic)
print("p-value:", p_value)
```

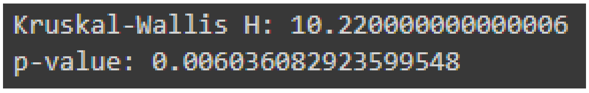


```
Test Statistic: 0.0
p-value: 0.004016514660032747
```

## c) Kruskal wallis test

# Input and output

```
import scipy.stats as stats

group_A = [23, 27, 21, 19, 25]
group_B = [18, 16, 20, 24, 22]
group_C = [10, 13, 15, 11, 12]

H, p_value = stats.kruskal(group_A, group_B, group_C)

print("Kruskal-Wallis H:", H)
print("p-value:", p_value)
```



```
Kruskal-Wallis H: 10.220000000000006
p-value: 0.006036082923599548
```

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# Practical 7 Perform ANOVA testing

## a) One way ANOVA

## Input and output

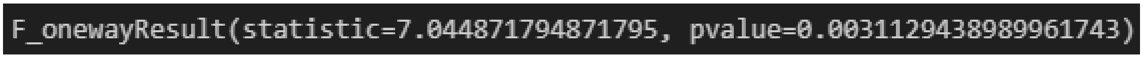
Q. A firm wishes to compare 4 programmes for training workers to perform a certain task. 20 new employees are randomly assigned to these programmes with 5 in each. At the end of the training, a test is conducted to see how quickly the trainees perform that task. The number of times the task is performed per hour is recorded for each trainee. Perform ANOVA to check the effectiveness of the programme. (Assume the level of significance = 0.05) Programme_1= [9, 12, 14, 11, 13] programme_2=[10, 6, 9, 9, 10] Programme_3= [12, 14, 11, 13, 11] Programme_4= [9, 8, 11, 7,8]

Null Hypothesis: The average number of times the task is performed are equal
Alternative Hypothesis: At least one pair of averages is not equal

```
from scipy.stats import f_oneway

programme_1=[9,12,14,11,13]
programme_2=[10,6,9,9,10]
programme_3=[12,14,11,13,11]
programme_4=[9,8,11,7,8]

f_oneway(programme_1,programme_2,programme_3,programme_4)
```



```
F_onewayResult(statistic=7.044871794871795, pvalue=0.0031129438989961743)
```

Conclusion:- we see that p-value(0.003) is less than 0.05(level of significance)
hence,we reject null null hypothesis
we may conclude that at least one of the training programme has different effect

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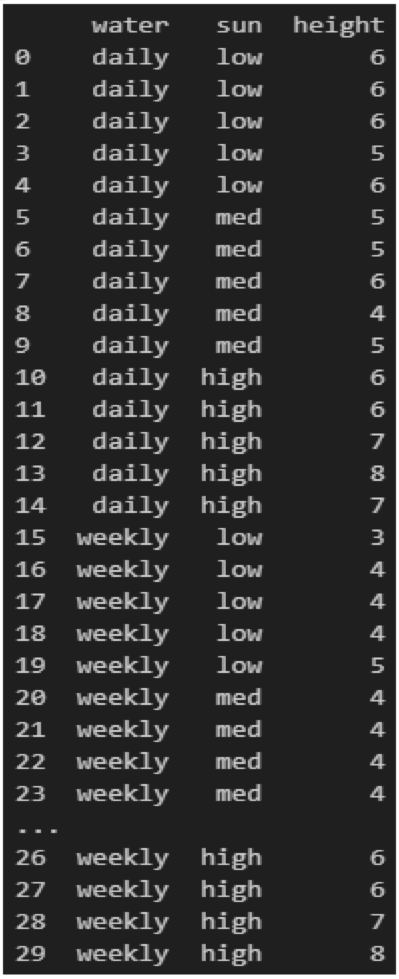
## b) Two way ANOVA

# Input and output

A botanist wants to know whether or not plant growth is influenced by sunlight exposure and watering frequency. She plants 30 seeds and lets them grow for two months under different conditions for sunlight exposure and watering frequency. After two months, she records the height of each plant, in inches. Use the following steps to perform a two-way ANOVA to determine if watering frequency and sunlight exposure ave a significant effect on plant growth, and to determine if there is any interaction effect between watering frequency and sunlight exposure.

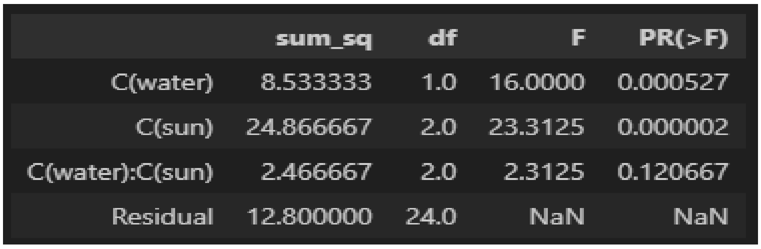
```
import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.formula.api import ols

df=pd.DataFrame({
    'water':np.repeat(['daily','weekly'],15),
    'sun':np.tile(np.repeat(['low','med','high'],5),2),
    'height':[6,6,6,5,6,5,5,6,4,5,6,6,7,8,7,3,4,4,4,5,4,4,4,4,4,5,6,6,7,8,]
})
print(df)
```



```
      water   sun  height
0    daily   low       6
1    daily   low       6
2    daily   low       6
3    daily   low       5
4    daily   low       6
5    daily   med       5
6    daily   med       5
7    daily   med       6
8    daily   med       4
9    daily   med       5
10   daily  high       6
11   daily  high       6
12   daily  high       7
13   daily  high       8
14   daily  high       7
15  weekly   low       3
16  weekly   low       4
17  weekly   low       4
18  weekly   low       4
19  weekly   low       5
20  weekly   med       4
21  weekly   med       4
22  weekly   med       4
23  weekly   med       4
...
26  weekly  high       6
27  weekly  high       6
28  weekly  high       7
29  weekly  high       8
```

```
model=ols('height ~ C(water) + C(sun) + C(water):C(sun)', data=df).fit()
sm.stats.anova_lm(model,typ=2)
```



```
                     sum_sq    df        F    PR(>F)
C(water)           8.533333   1.0  16.0000  0.000527
C(sun)            24.866667   2.0  23.3125  0.000002
C(water):C(sun)    2.466667   2.0   2.3125  0.120667
Residual          12.800000  24.0      NaN       NaN
```

```
# water: p-value = 0.000527
# sun: p-value = 0.000002
# water*sun: p-value = 0.120667
```

Since the values for water and sun lite both less than 05 this means that both factors have a statistically significant effect on plant height. And since the p-value for the interaction effect (120667) is not less than 05, this tells us that there is no significant interaction effect between sunlight exposure and watering frequency

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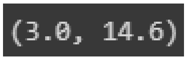
# Practical 8  Implement regression analysis and fit a straight line

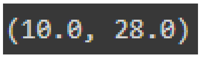
## Input and output

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression

x=np.array([1,2,3,4,5])
y=np.array([7,14,15,18,19])
n=np.size(x)

x_mean=np.mean(x)
y_mean=np.mean(y)
x_mean,y_mean
```



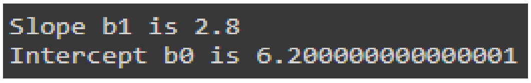
```
(3.0, 14.6)
```

```
Sxx=np.sum(x*x)-n*x_mean*x_mean
Sxy=np.sum(x*y)-n*x_mean*y_mean
Sxx,Sxy
```



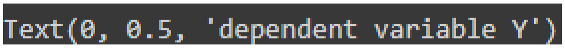
```
(10.0, 28.0)
```

```
b1=Sxy/Sxx
b0=y_mean - b1*x_mean
print('Slope b1 is' ,b1)
print('Intercept b0 is' ,b0)
```

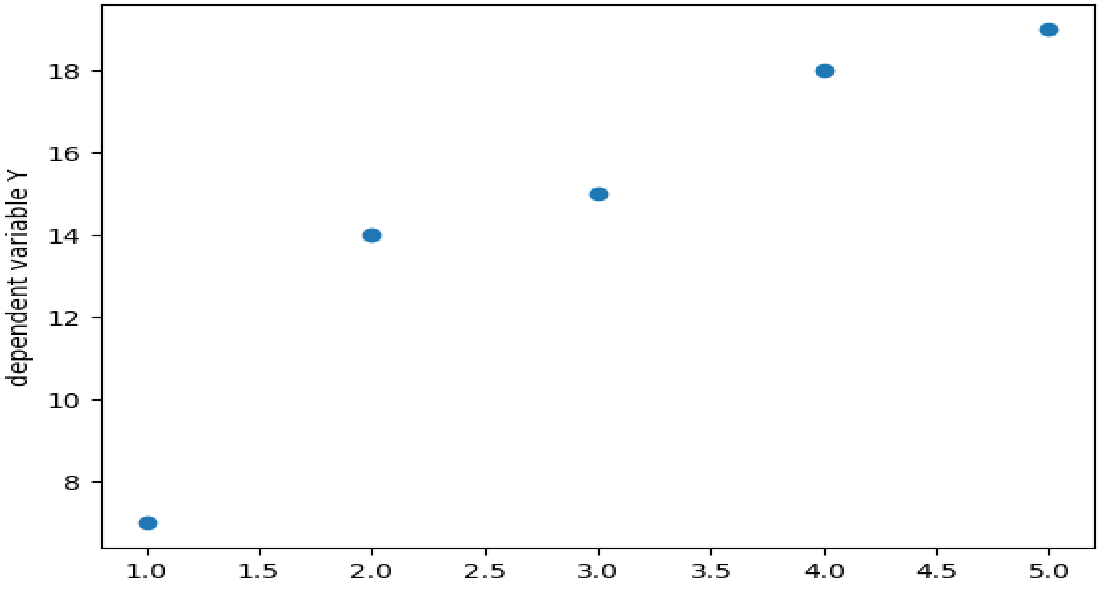


```
Slope b1 is 2.8
Intercept b0 is 6.200000000000001
```

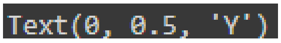
```
plt.scatter(x,y)
plt.xlabel('Independent variable X')
plt.ylabel('dependent variable Y')
```



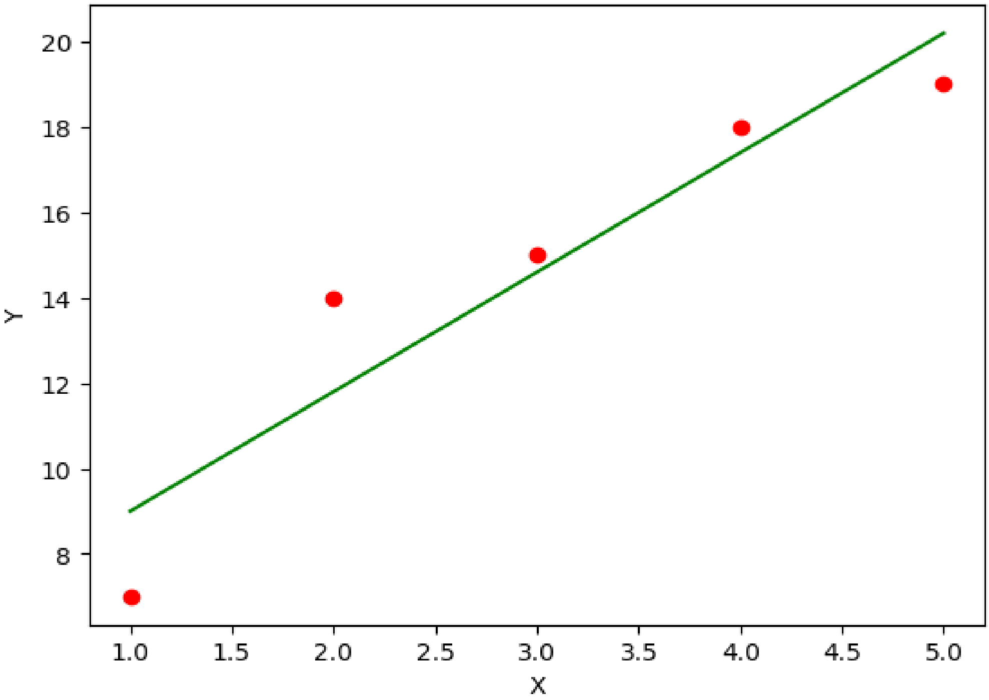
```
Text(0, 0.5, 'dependent variable Y')
```



```
y_pred=b1*x+b0
plt.scatter(x,y,color='red')
plt.plot(x,y_pred,color='green')
plt.xlabel('X')
plt.ylabel('Y')
```



```
Text(0, 0.5, 'Y')
```



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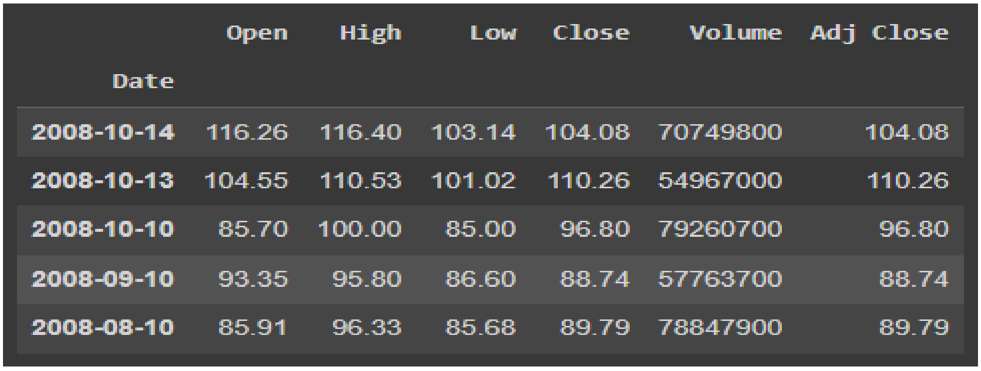
# Practical 9 Perform time series analysis

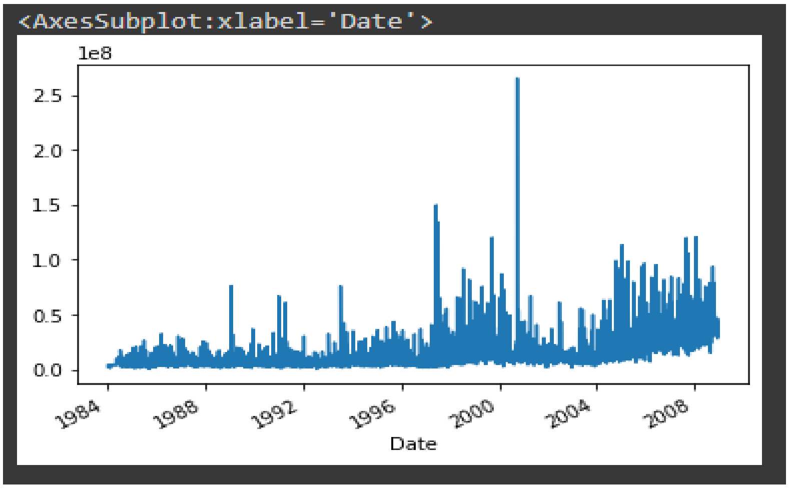
## Input and output

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

df = pd.read_csv(r"C:\Users\rahul\Desktop\RJ COLLEGE\aapl.csv", parse_dates=True,index_col="Date")
df.head()
```



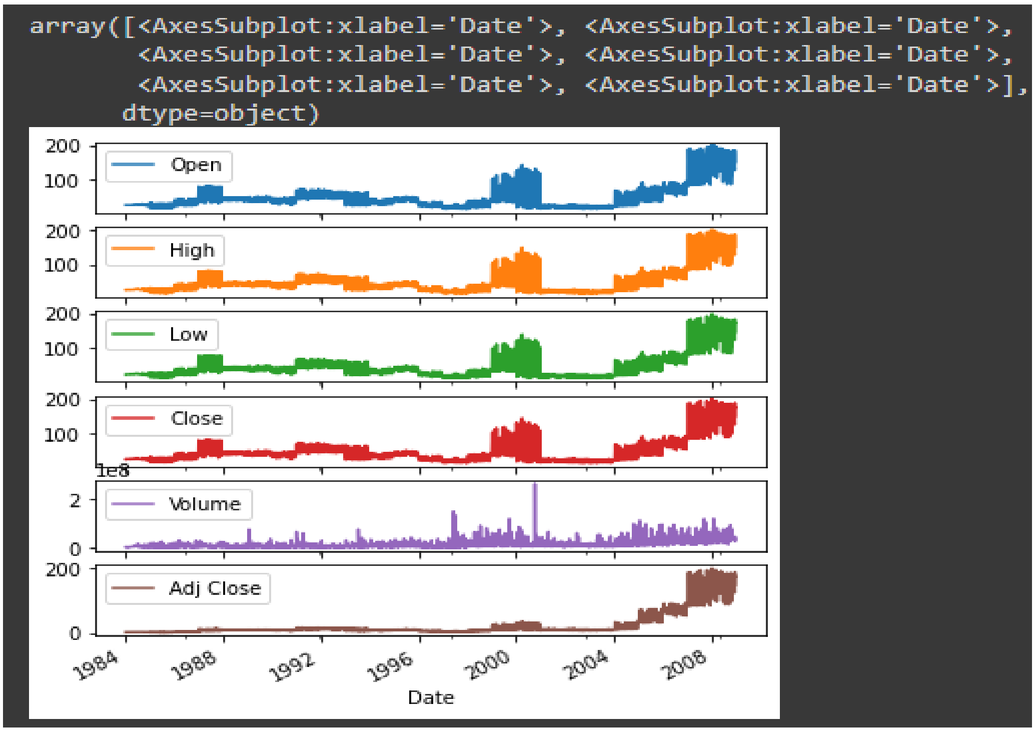
| | Open | High | Low | Close | Volume | Adj Close |
|---|---|---|---|---|---|---|
| Date | | | | | | |
| 2008-10-14 | 116.26 | 116.40 | 103.14 | 104.08 | 70749800 | 104.08 |
| 2008-10-13 | 104.55 | 110.53 | 101.02 | 110.26 | 54967000 | 110.26 |
| 2008-10-10 | 85.70 | 100.00 | 85.00 | 96.80 | 79260700 | 96.80 |
| 2008-09-10 | 93.35 | 95.80 | 86.60 | 88.74 | 57763700 | 88.74 |
| 2008-08-10 | 85.91 | 96.33 | 85.68 | 89.79 | 78847900 | 89.79 |

```
print(df)
```



```
<AxesSubplot:xlabel='Date'>
```

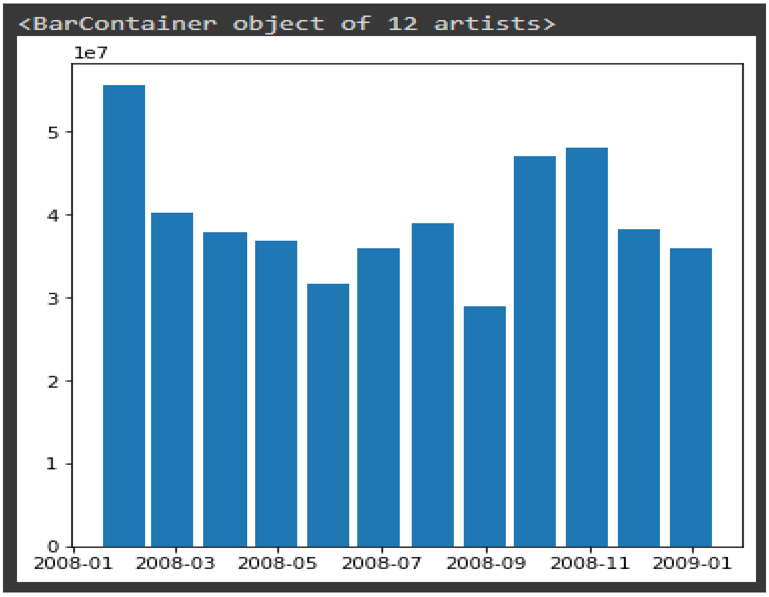
```
df.plot(subplots=True, figsize=(6, 6))
```



```
array([<AxesSubplot:xlabel='Date'>, <AxesSubplot:xlabel='Date'>,
       <AxesSubplot:xlabel='Date'>, <AxesSubplot:xlabel='Date'>,
       <AxesSubplot:xlabel='Date'>, <AxesSubplot:xlabel='Date'>],
      dtype=object)
```

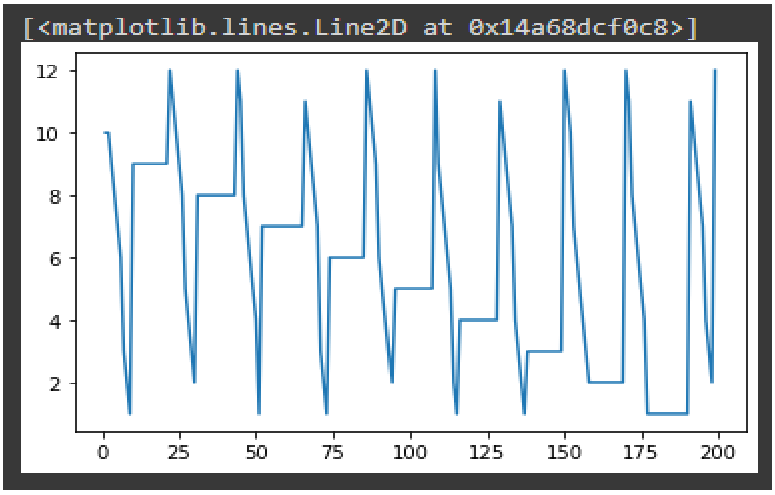
Resampling: Resampling is a methodology of economically using a data sample to improve the accuracy and quantify the uncertainty of a population parameter. Resampling for months or weeks and making bar plots is another very simple and widely used method of finding seasonality.

```
# Resampling the time series data based on monthly 'M' frequency
df_month = df.resample("M").mean()

# using subplot
fig, ax = plt.subplots(figsize=(6, 6))

# plotting bar graph
ax.bar(df_month['2008':].index,
      df_month.loc['2008':, "Volume"],
      width=25, align='center')
```



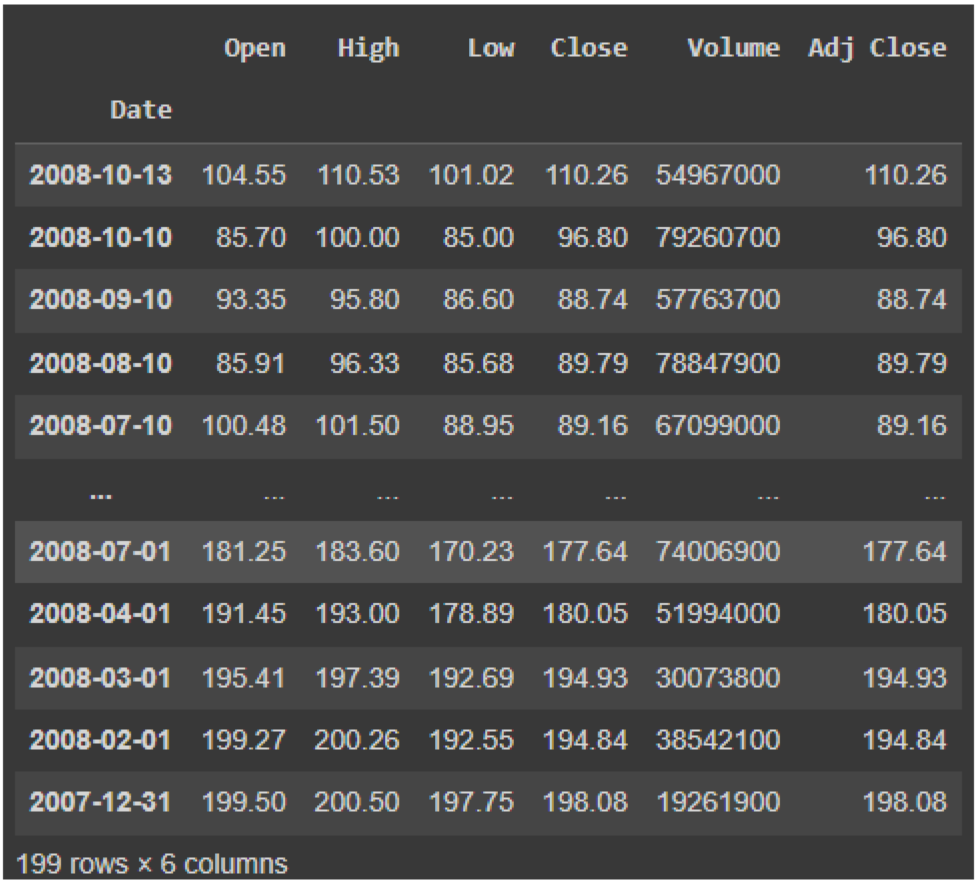
```
<BarContainer object of 12 artists>
```

```
df = pd.read_csv(r"C:\Users\rahul\Desktop\RJ COLLEGE\aapl.csv")
import datetime as dt
df['Date']= pd.to_datetime(df['Date'])
plt.plot(df['Date'][1:200].dt.month)
```



```
[<matplotlib.lines.Line2D at 0x14a68dcf0c8>]
```

```
df.iloc[1:200,:]
```



| | Open | High | Low | Close | Volume | Adj Close |
|---|---|---|---|---|---|---|
| **Date** | | | | | | |
| **2008-10-13** | 104.55 | 110.53 | 101.02 | 110.26 | 54967000 | 110.26 |
| **2008-10-10** | 85.70 | 100.00 | 85.00 | 96.80 | 79260700 | 96.80 |
| **2008-09-10** | 93.35 | 95.80 | 86.60 | 88.74 | 57763700 | 88.74 |
| **2008-08-10** | 85.91 | 96.33 | 85.68 | 89.79 | 78847900 | 89.79 |
| **2008-07-10** | 100.48 | 101.50 | 88.95 | 89.16 | 67099000 | 89.16 |
| **...** | ... | ... | ... | ... | ... | ... |
| **2008-07-01** | 181.25 | 183.60 | 170.23 | 177.64 | 74006900 | 177.64 |
| **2008-04-01** | 191.45 | 193.00 | 178.89 | 180.05 | 51994000 | 180.05 |
| **2008-03-01** | 195.41 | 197.39 | 192.69 | 194.93 | 30073800 | 194.93 |
| **2008-02-01** | 199.27 | 200.26 | 192.55 | 194.84 | 38542100 | 194.84 |
| **2007-12-31** | 199.50 | 200.50 | 197.75 | 198.08 | 19261900 | 198.08 |

199 rows × 6 columns

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