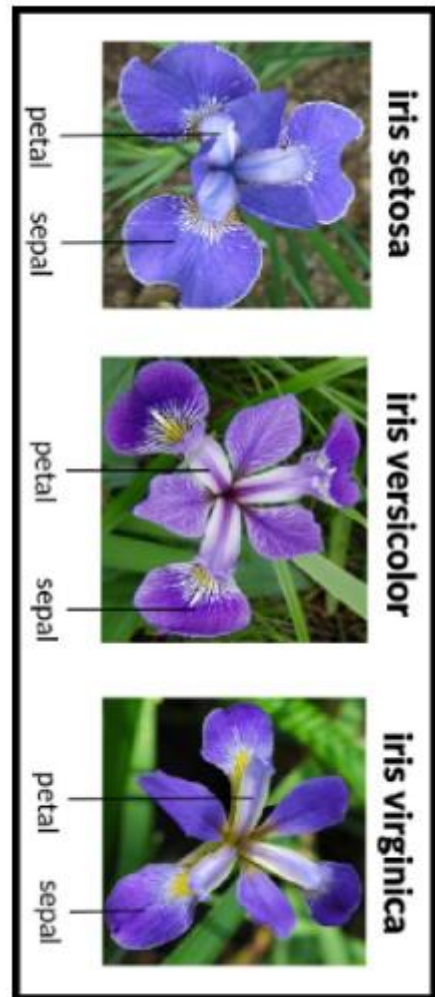


3 Different Types of Species each contain 50 Samples-



Practical no - 1

| Feature | | | |
|----------|---------------|---------------|--------------|
| Instance | x | y | z |
| 0 | 0.5351795402 | 0.9443102776 | 0.1682435145 |
| 1 | 0.2272136163 | 0.6406416746 | 0.2275491606 |
| 2 | 0.9115366348 | 0.3311024322 | 0.5615073269 |
| 3 | 0.6638070287 | 0.4183148036 | 0.1519004435 |
| 4 | 0.3729975195 | 0.3916657621 | 0.616341473 |
| 5 | 0.6783527289 | 0.938524515 | 0.5269012505 |
| 6 | 0.09568660734 | 0.04465749699 | 0.0133451798 |
| 7 | 0.2173318229 | 0.6170559076 | 0.3122273653 |
| 8 | 0.818890594 | 0.7459451367 | 0.9026713492 |
| 9 | 0.6064854042 | 0.5945985792 | 0.2168024961 |
| 10 | 0.1548966624 | 0.1579937453 | 0.1333579164 |

Train Dataset

Test Dataset

| Pandas dtype | Python type | NumPy type | Usage |
|---------------|--------------|--|--|
| object | str or mixed | string_, unicode_, mixed types | Text or mixed numeric and non-numeric values |
| int64 | int | int_, int8, int16, int32, int64, uint8, uint16, uint32, uint64 | Integer numbers |
| float64 | float | float_, float16, float32, float64 | Floating point numbers |
| bool | bool | bool_ | True/False values |
| datetime64 | NA | datetime64[ns] | Date and time values |
| timedelta[ns] | NA | NA | Differences between two datetimes |
| category | NA | NA | Finite list of text values |

| Samples (instances, observations) | | | | | |
|-----------------------------------|--------------|-------------|--------------|-------------|-------------|
| | Sepal length | Sepal width | Petal length | Petal width | Class label |
| 1 | 5.1 | 3.5 | 1.4 | 0.2 | Setosa |
| 2 | 4.9 | 3.0 | 1.4 | 0.2 | Setosa |
| ... | ... | ... | ... | ... | ... |
| 50 | 6.4 | 3.5 | 4.5 | 1.2 | Versicolor |
| ... | ... | ... | ... | ... | ... |
| 150 | 5.9 | 3.0 | 5.0 | 1.8 | Virginica |

Features (attributes, measurements, dimensions)

Class labels (targets)

Petal

Sepal

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|----|---------------|--------------|---------------|--------------|-------------|
| 0 | 1 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| 1 | 2 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| 2 | 3 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| 3 | 4 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| 4 | 5 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |

| Sr. No | Data Frame Function | Description |
|--------|--|---|
| 1 | <code>dataset.head(n=5)</code> | Return the first n rows. |
| 2 | <code>dataset.tail(n=5)</code> | Return the last n rows. |
| 3 | <code>dataset.index</code> | The index (row labels) of the Dataset. |
| 4 | <code>dataset.columns</code> | The column labels of the Dataset. |
| 5 | <code>dataset.shape</code> | Return a tuple representing the dimensionality of the Dataset. |
| 6 | <code>dataset.dtypes</code> | Return the dtypes in the Dataset. This returns a Series with the data type of each column. The result's index is the original Dataset's columns. Columns with mixed types are stored with the object dtype. |
| 7 | <code>dataset.columns.values</code> | Return the columns values in the Dataset in array format |
| 8 | <code>dataset.describe(include='all')</code> | Generate descriptive statistics. to view some basic statistical details like percentile, mean, std etc. of a data frame or a series of numeric values. Analyzes both numeric and object series, as well as Dataset column sets of mixed data types. |
| 9 | <code>dataset['Column name']</code> | Read the Data Column wise. |
| 10 | <code>dataset.sort_index(axis=1, ascending=False)</code> | Sort object by labels (along an axis). |

| Color |
|-------|
| Blue |
| Green |
| Red |



| d1 | d2 | d3 |
|----|----|----|
| 0 | 0 | 1 |
| 0 | 1 | 0 |
| 1 | 0 | 0 |

| Color |
|-------|
| Blue |
| Green |
| Red |



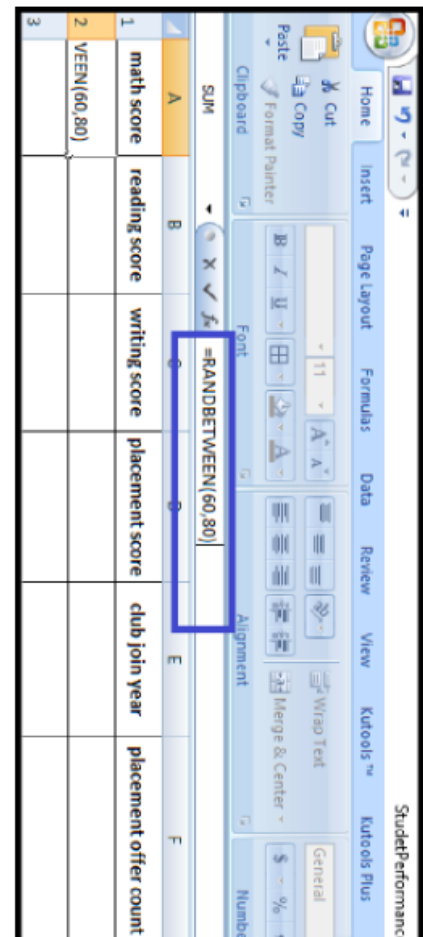
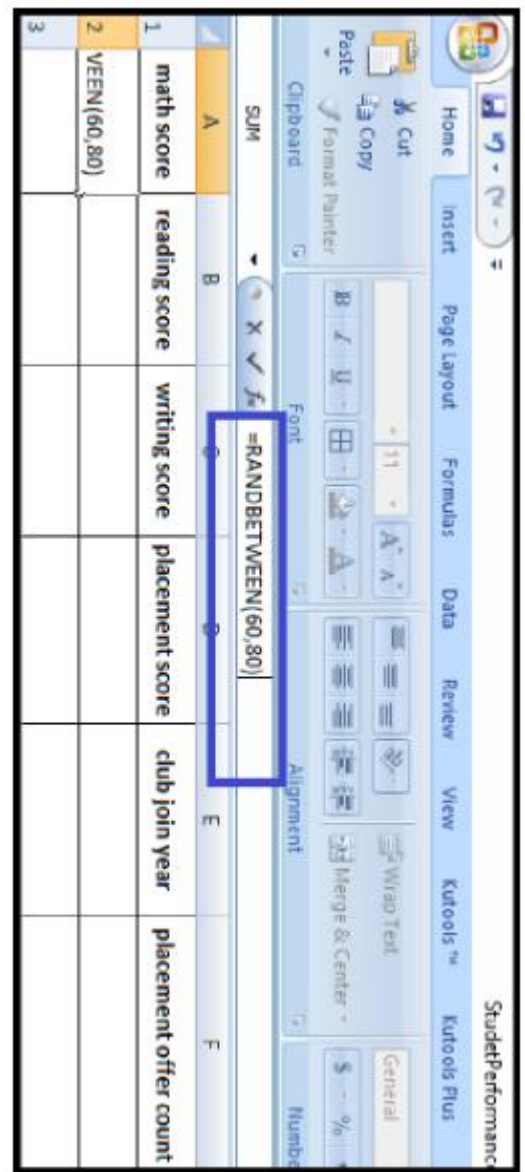
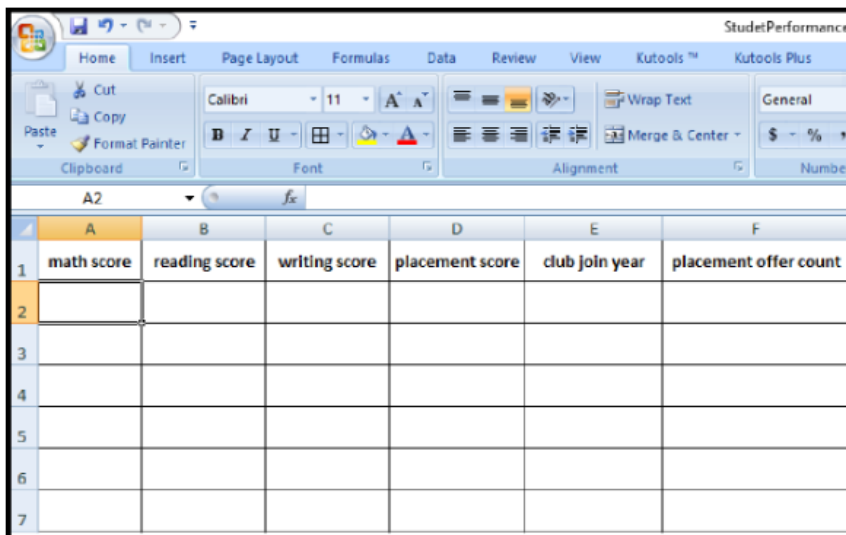
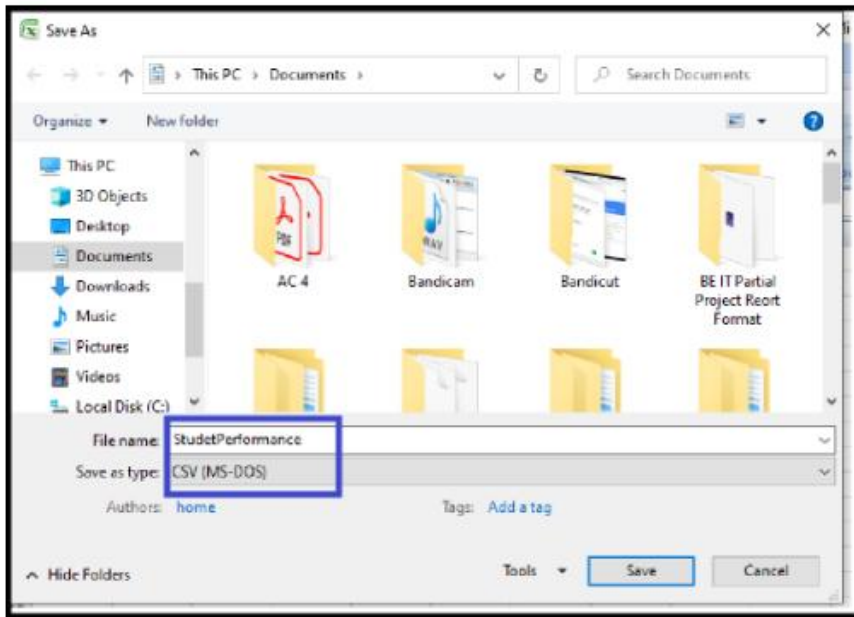
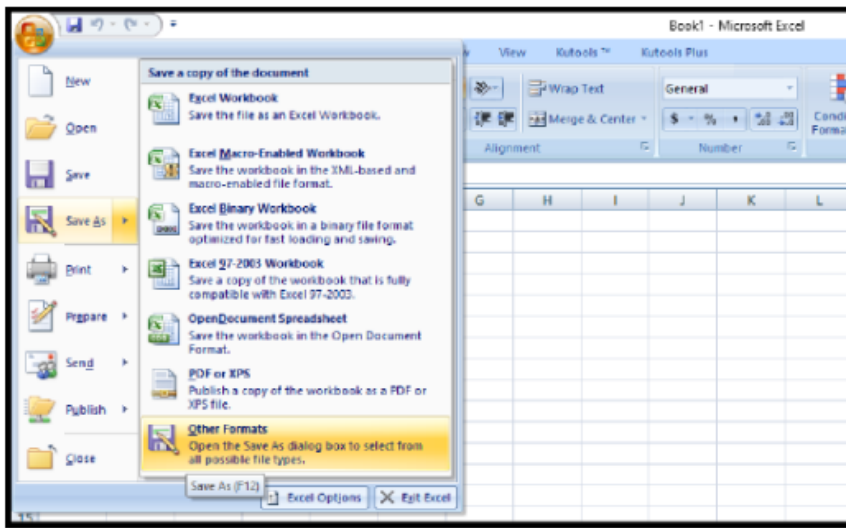
| d1 | d2 |
|----|----|
| 0 | 1 |
| 0 | 0 |
| 0 | 1 |

| Sr. No | Data Frame Function | Description | Output | | | | | | | | |
|--------|---------------------------------|--|---|----|---------------|---|-----|---|-----|---|-----|
| 1 | dataset.iloc[3:5, 0:2] | Slice the data | <table><tr><th>Id</th><th>SepalLengthCm</th></tr><tr><td>3</td><td>4.6</td></tr><tr><td>4</td><td>5.0</td></tr></table> | Id | SepalLengthCm | 3 | 4.6 | 4 | 5.0 | | |
| Id | SepalLengthCm | | | | | | | | | | |
| 3 | 4.6 | | | | | | | | | | |
| 4 | 5.0 | | | | | | | | | | |
| 2 | dataset.iloc[[1, 2, 4], [0, 2]] | By lists of integer position locations, similar to the NumPy/Python style: | <table><tr><th>Id</th><th>SepalWidthCm</th></tr><tr><td>1</td><td>3.0</td></tr><tr><td>2</td><td>3.2</td></tr><tr><td>4</td><td>3.6</td></tr></table> | Id | SepalWidthCm | 1 | 3.0 | 2 | 3.2 | 4 | 3.6 |
| Id | SepalWidthCm | | | | | | | | | | |
| 1 | 3.0 | | | | | | | | | | |
| 2 | 3.2 | | | | | | | | | | |
| 4 | 3.6 | | | | | | | | | | |

| | Sepal_Length | Sepal_Width | Petal_Length | Petal_Width | Species_1 | Species_2 |
|---|--------------|-------------|--------------|-------------|-----------|-----------|
| 0 | 5.1 | 3.5 | 1.4 | 0.2 | 0 | 0 |
| 1 | 4.9 | 3.0 | 1.4 | 0.2 | 0 | 0 |
| 2 | 4.7 | 3.2 | 1.3 | 0.2 | 0 | 0 |
| 3 | 4.6 | 3.1 | 1.5 | 0.2 | 0 | 0 |
| 4 | 5.0 | 3.6 | 1.4 | 0.2 | 0 | 0 |

| 3 | dataset.iloc[1:3, :] | For slicing rows explicitly: | <table><tr><th>id</th><th>SepalLengthCm</th><th>SepalWidthCm</th><th>PetalLengthCm</th><th>PetalWidthCm</th><th>Species</th></tr><tr><td>1</td><td>2</td><td>4.9</td><td>3.0</td><td>1.4</td><td>0.2 Iris-setosa</td></tr><tr><td>2</td><td>3</td><td>4.7</td><td>3.2</td><td>1.3</td><td>0.2 Iris-setosa</td></tr></table> | id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species | 1 | 2 | 4.9 | 3.0 | 1.4 | 0.2 Iris-setosa | 2 | 3 | 4.7 | 3.2 | 1.3 | 0.2 Iris-setosa |
|----|--|---|---|--------------|-----------------|---------------|---------------|--------------|---------|---|-----|-----|-----|-----|-----------------|---|-----|-----|-----|-----|-----------------|
| id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species | | | | | | | | | | | | | | | | |
| 1 | 2 | 4.9 | 3.0 | 1.4 | 0.2 Iris-setosa | | | | | | | | | | | | | | | | |
| 2 | 3 | 4.7 | 3.2 | 1.3 | 0.2 Iris-setosa | | | | | | | | | | | | | | | | |
| 4 | dataset.iloc[:, 1:3] | For slicing Column explicitly: | <table><tr><th></th><th>SepalLengthCm</th><th>SepalWidthCm</th></tr><tr><td>0</td><td>5.1</td><td>3.5</td></tr><tr><td>1</td><td>4.9</td><td>3.0</td></tr><tr><td>2</td><td>4.7</td><td>3.2</td></tr><tr><td>3</td><td>4.6</td><td>3.1</td></tr></table> | | SepalLengthCm | SepalWidthCm | 0 | 5.1 | 3.5 | 1 | 4.9 | 3.0 | 2 | 4.7 | 3.2 | 3 | 4.6 | 3.1 | | | |
| | SepalLengthCm | SepalWidthCm | | | | | | | | | | | | | | | | | | | |
| 0 | 5.1 | 3.5 | | | | | | | | | | | | | | | | | | | |
| 1 | 4.9 | 3.0 | | | | | | | | | | | | | | | | | | | |
| 2 | 4.7 | 3.2 | | | | | | | | | | | | | | | | | | | |
| 3 | 4.6 | 3.1 | | | | | | | | | | | | | | | | | | | |
| 5 | dataset.iloc[1, 1] | For getting a value explicitly: | 4.9 | | | | | | | | | | | | | | | | | | |
| 6 | dataset['SepalLengthCm'].iloc[5] | Accessing Column and Rows by position | 5.4 | | | | | | | | | | | | | | | | | | |
| 7 | cols_2_4=dataset.columns[2:4] dataset[cols_2_4] | Get Column Name then get data from column | <table><tr><th></th><th>SepalWidthCm</th><th>PetalLengthCm</th></tr><tr><td>0</td><td>3.5</td><td>1.4</td></tr><tr><td>1</td><td>3.0</td><td>1.4</td></tr><tr><td>2</td><td>3.2</td><td>1.3</td></tr><tr><td>3</td><td>3.1</td><td>1.5</td></tr></table> | | SepalWidthCm | PetalLengthCm | 0 | 3.5 | 1.4 | 1 | 3.0 | 1.4 | 2 | 3.2 | 1.3 | 3 | 3.1 | 1.5 | | | |
| | SepalWidthCm | PetalLengthCm | | | | | | | | | | | | | | | | | | | |
| 0 | 3.5 | 1.4 | | | | | | | | | | | | | | | | | | | |
| 1 | 3.0 | 1.4 | | | | | | | | | | | | | | | | | | | |
| 2 | 3.2 | 1.3 | | | | | | | | | | | | | | | | | | | |
| 3 | 3.1 | 1.5 | | | | | | | | | | | | | | | | | | | |
| 8 | dataset[dataset.columns[2:4]].iloc[5:10] | in one Expression answer for the above two commands | <table><tr><th></th><th>SepalWidthCm</th><th>PetalLengthCm</th></tr><tr><td>5</td><td>3.9</td><td>1.7</td></tr><tr><td>6</td><td>3.4</td><td>1.4</td></tr><tr><td>7</td><td>3.4</td><td>1.5</td></tr><tr><td>8</td><td>2.9</td><td>1.4</td></tr><tr><td>9</td><td>3.1</td><td>1.5</td></tr></table> | | SepalWidthCm | PetalLengthCm | 5 | 3.9 | 1.7 | 6 | 3.4 | 1.4 | 7 | 3.4 | 1.5 | 8 | 2.9 | 1.4 | 9 | 3.1 | 1.5 |
| | SepalWidthCm | PetalLengthCm | | | | | | | | | | | | | | | | | | | |
| 5 | 3.9 | 1.7 | | | | | | | | | | | | | | | | | | | |
| 6 | 3.4 | 1.4 | | | | | | | | | | | | | | | | | | | |
| 7 | 3.4 | 1.5 | | | | | | | | | | | | | | | | | | | |
| 8 | 2.9 | 1.4 | | | | | | | | | | | | | | | | | | | |
| 9 | 3.1 | 1.5 | | | | | | | | | | | | | | | | | | | |

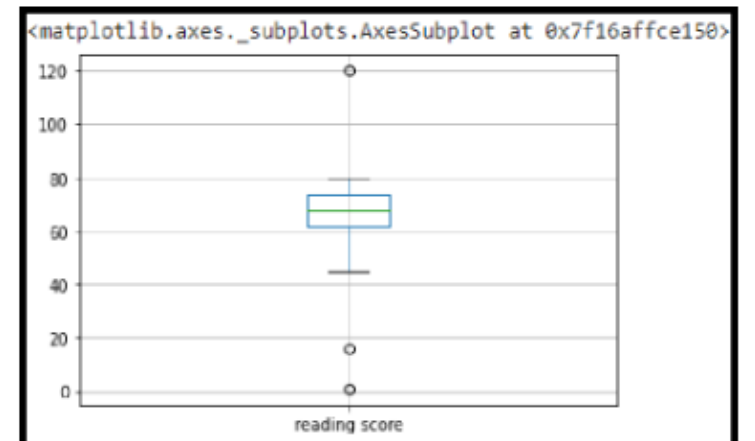
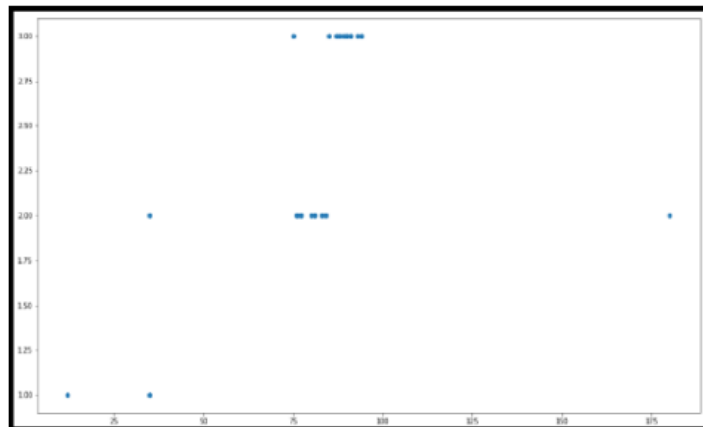
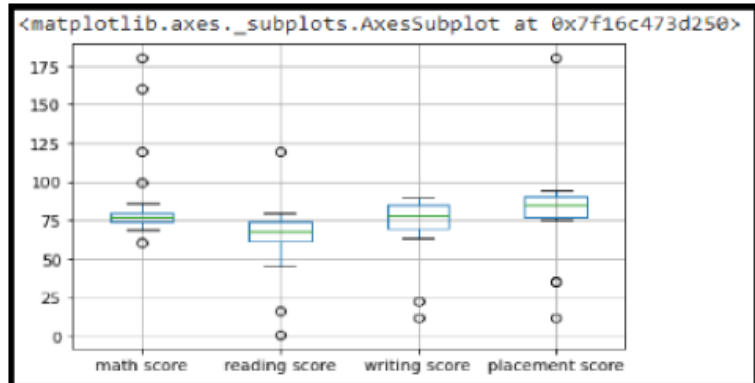
| Sr. No | Data Frame Function | Description | Output |
|--------|--|---|--|
| 1. | <code>df.dtypes</code> | To check the data type | <pre>df.dtypes sepal length (cm) float64 sepal width (cm) float64 petal length (cm) float64 petal width (cm) float64 dtype: object</pre> |
| 2. | <code>df['petal length (cm)'] = df['petal length (cm)'].astype("int")</code> | To change the data type (data type of 'petal length (cm)' changed to int) | <pre>df.dtypes sepal length (cm) float64 sepal width (cm) float64 petal length (cm) int64 petal width (cm) float64 dtype: object</pre> |



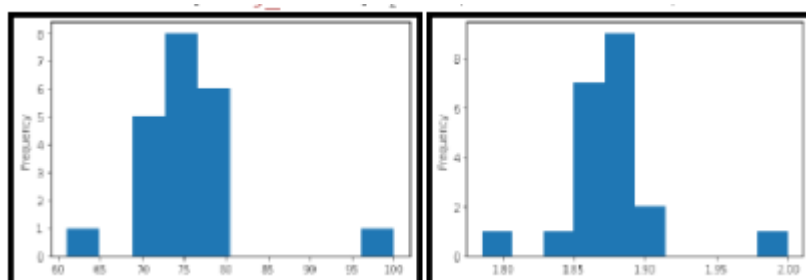
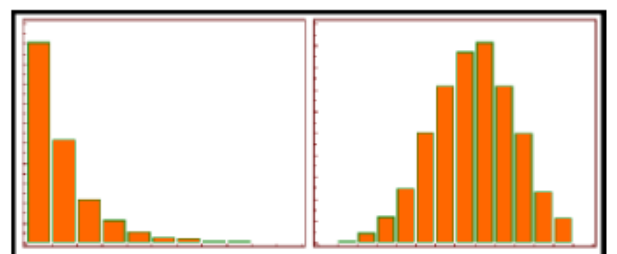
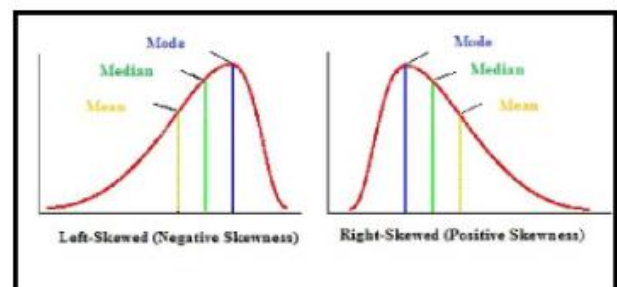
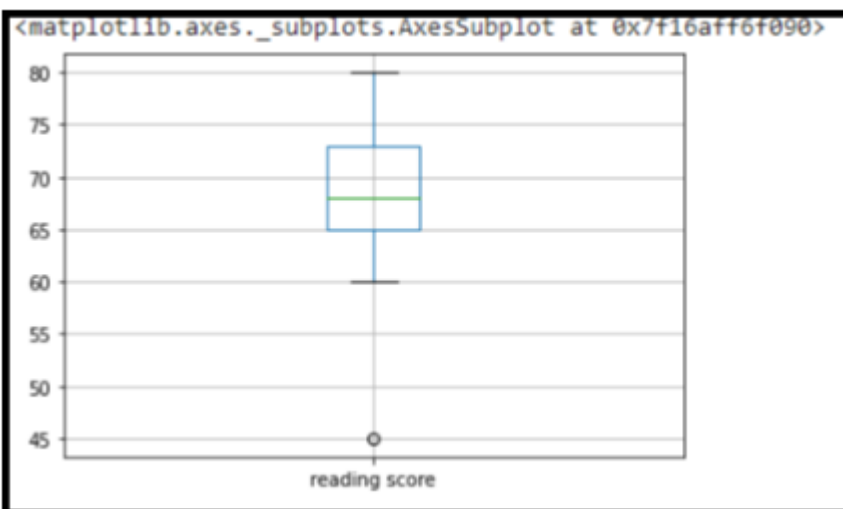
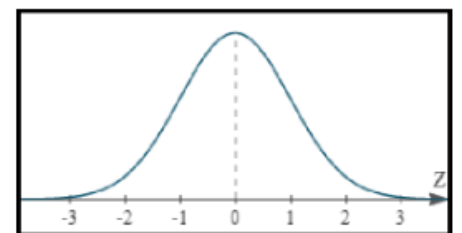
| with outlier | without outlier |
|------------------|-----------------|
| Mean: 20.08 | Mean: 12.72 |
| Median: 14.0 | Median: 13.0 |
| Mode: 15 | Mode: 15 |
| Variance: 614.74 | Variance: 21.28 |
| Std dev: 24.79 | Std dev: 4.61 |

Practical No - 2

| | math score | reading score | writing score | placement score | placement offer count |
|----|------------|---------------|---------------|-----------------|-----------------------|
| 0 | 80 | 68 | 70 | 89 | 3 |
| 1 | 71 | 61 | 85 | 91 | 3 |
| 2 | 79 | 16 | 87 | 77 | 2 |
| 3 | 61 | 77 | 74 | 76 | 2 |
| 4 | 78 | 71 | 67 | 90 | 3 |
| 5 | 73 | 68 | 90 | 80 | 2 |
| 6 | 77 | 62 | 70 | 35 | 2 |
| 7 | 74 | 45 | 80 | 12 | 1 |
| 8 | 76 | 60 | 79 | 77 | 2 |
| 9 | 75 | 65 | 85 | 87 | 3 |
| 10 | 160 | 67 | 12 | 83 | 2 |
| 11 | 79 | 72 | 88 | 180 | 2 |
| 12 | 80 | 80 | 78 | 94 | 3 |



```
[0.17564553 0.5282877 0.21482799 0.92011234 0.25401045 0.44992277
0.29319292 0.41074031 0.33237538 0.37155785 2.95895157 0.21482799
0.17564553 0.25401045 0.37155785 0.25401045 0.05944926 0.17564553
0.37155785 0.0972806 0.60665263 0.60800375 0.48910524 0.41074031
0.37155785 3.74260085 0.48910524 0.5282877 1.39165302]
```




```
1 (600, 10)
2
3 <class 'pandas.core.frame.DataFrame'>
4 RangeIndex: 600 entries, 0 to 599
5 Data columns (total 10 columns):
6 Marital_status    600 non-null object
7 Dependents        600 non-null int64
8 Is_graduate       600 non-null object
9 Income            600 non-null int64
10 Loan_amount       600 non-null int64
11 Term_months       600 non-null int64
12 Credit_score      600 non-null object
13 approval_status   600 non-null object
14 Age               600 non-null int64
15 Sex               600 non-null object
16 dtypes: int64(5), object(5)
17 memory usage: 47.0+ KB
18 None
```

```
1 51.0
2 508350.0
3
4 0    102.0
5 1    192.0
6 2    192.0
7 3    192.0
8 4    192.0
9 dtype: float64
```

Practical No - 3

```
1 0    70096.0
2 1    161274.0
3 2    125113.4
4 3    119853.8
5 4    120653.8
6 dtype: float64
```

```
1 Dependents    0.748333
2 Income        705541.333333
3 Loan_amount   323793.666667
4 Term_months   183.350000
5 Age           49.450000
6 dtype: float64
```

| | Marital_status | Dependents | Is_graduate | Income | Loan_amount |
|--------|----------------|------------|-------------|--------------|--------------|
| count | 600 | 600.000000 | 600 | 6.000000e+02 | 6.000000e+02 |
| unique | 2 | NaN | 2 | NaN | NaN |
| top | Yes | NaN | Yes | NaN | NaN |
| freq | 391 | NaN | 470 | NaN | NaN |
| mean | NaN | 0.748333 | NaN | 7.055413e+05 | NaN |
| std | NaN | 1.026362 | NaN | 7.114218e+05 | 7.242935e+05 |
| min | NaN | 0.000000 | NaN | 3.000000e+04 | 1.090000e+04 |
| 25% | NaN | 0.000000 | NaN | 3.849750e+05 | NaN |
| 50% | NaN | 0.000000 | NaN | 5.083500e+05 | NaN |
| 75% | NaN | 1.000000 | NaN | 7.661000e+05 | NaN |
| max | NaN | 6.000000 | NaN | 8.444900e+06 | NaN |

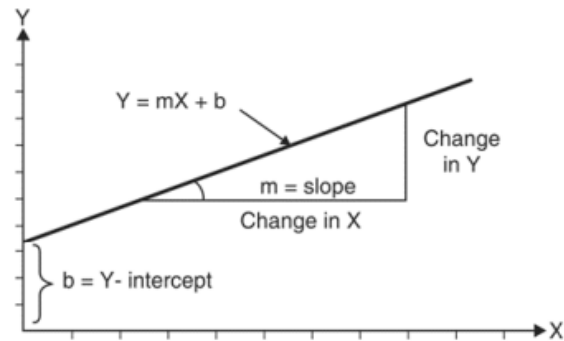
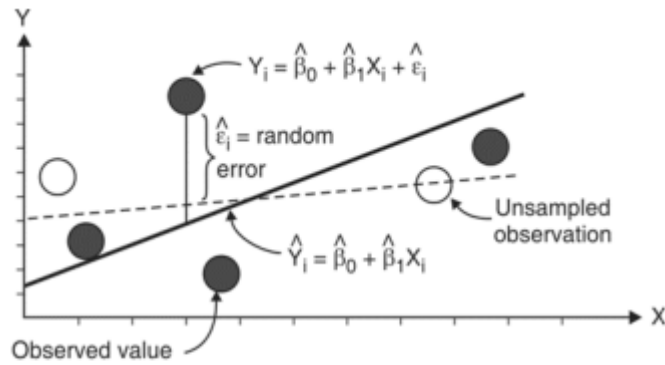
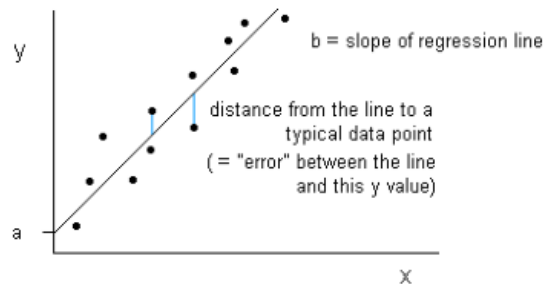
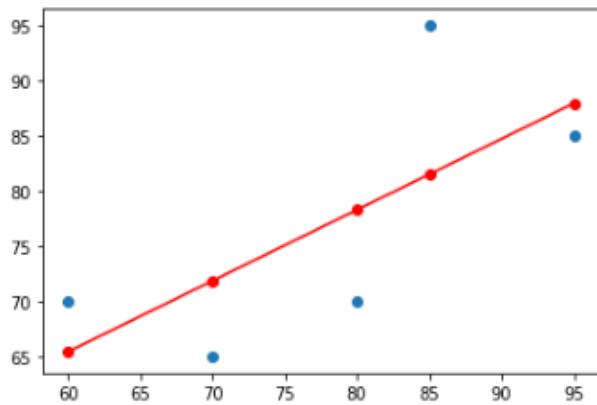
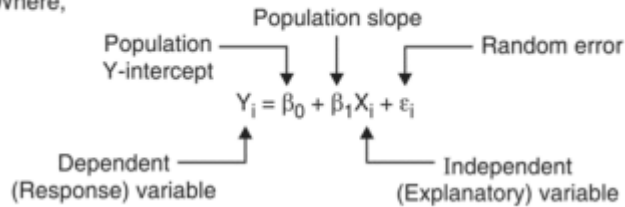


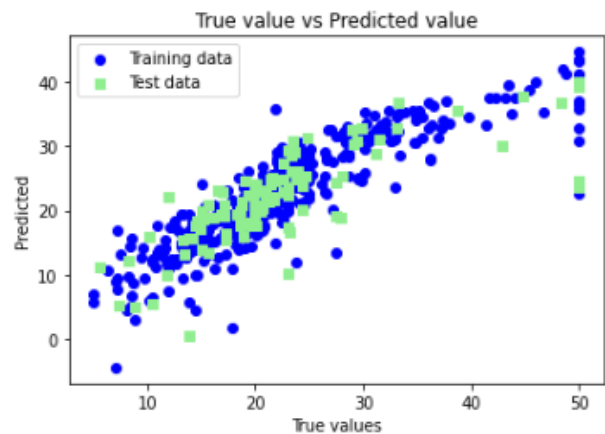
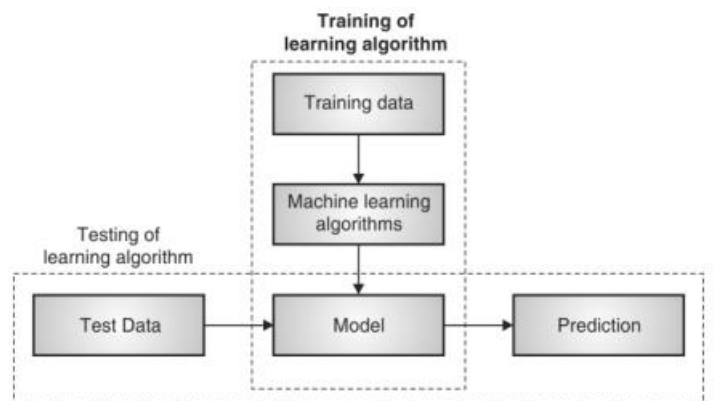
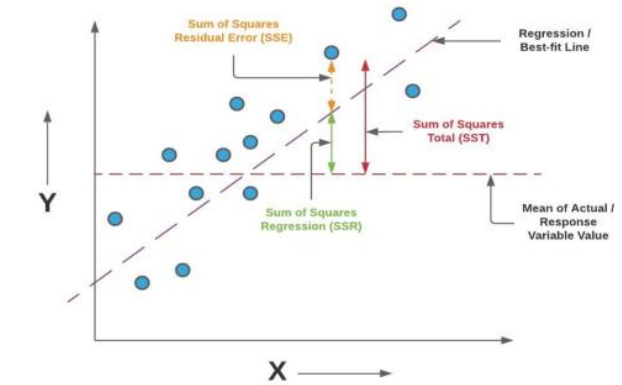
Fig. 1: geometry of linear regression



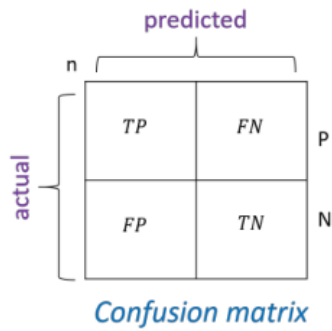
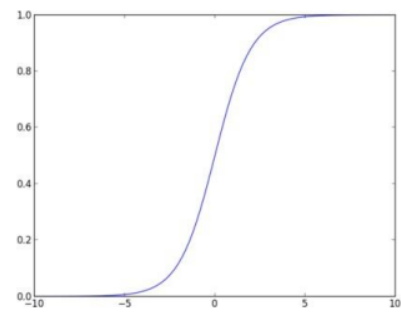
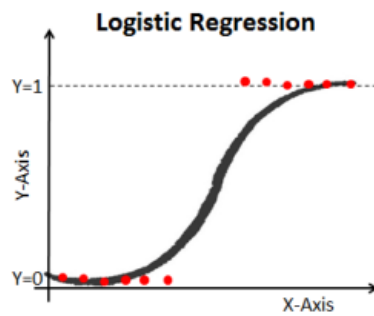
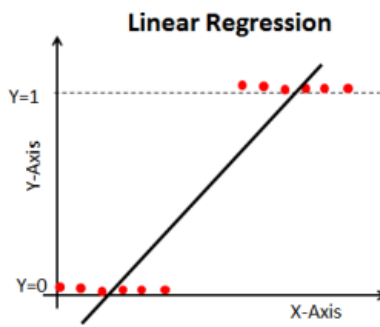
Where,



Practical No. - 4



| x | y | $x - \bar{x}$ | $y - \bar{y}$ | $(x - \bar{x})^2$ | $(x - \bar{x})(y - \bar{y})$ |
|----------------|----------------|---------------|---------------|--------------------------------|---|
| 95 | 85 | 17 | 8 | 289 | 136 |
| 85 | 95 | 7 | 18 | 49 | 126 |
| 80 | 70 | 2 | -7 | 4 | -14 |
| 70 | 65 | -8 | -12 | 64 | 96 |
| 60 | 70 | -18 | -7 | 324 | 126 |
| $\bar{x} = 78$ | $\bar{y} = 77$ | | | $\Sigma (x - \bar{x})^2 = 730$ | $\Sigma (x - \bar{x})(y - \bar{y}) = 470$ |



Practical No . – 5

Practical No - 6

| Outlook | Temp | Humidity | Windy | Play |
|----------|------|----------|-------|------|
| sunny | hot | high | FALSE | no |
| sunny | hot | high | TRUE | no |
| overcast | hot | high | FALSE | yes |
| rainy | mild | high | FALSE | yes |
| rainy | cool | normal | FALSE | yes |
| rainy | cool | normal | TRUE | no |
| overcast | cool | normal | TRUE | yes |
| sunny | mild | high | FALSE | no |
| sunny | cool | normal | FALSE | yes |
| rainy | mild | normal | FALSE | yes |
| sunny | mild | normal | TRUE | yes |
| overcast | mild | high | TRUE | yes |
| overcast | hot | normal | FALSE | yes |
| rainy | mild | high | TRUE | no |

$$X = [\text{Outlook}, \text{Temp}, \text{Humidity}, \text{Windy}]$$

$$\begin{matrix} \underbrace{\hspace{1cm}} & \underbrace{\hspace{1cm}} & \underbrace{\hspace{1cm}} & \underbrace{\hspace{1cm}} \\ x_1 & x_2 & x_3 & x_4 \end{matrix}$$

$$C_k = [\text{Yes}, \text{No}]$$

$$\begin{matrix} \underbrace{\hspace{1cm}} & \underbrace{\hspace{1cm}} \\ C_1 & C_2 \end{matrix}$$

| Example No. | Color | Type | Origin | Stolen? |
|-------------|--------|--------|----------|---------|
| 1 | Red | Sports | Domestic | Yes |
| 2 | Red | Sports | Domestic | No |
| 3 | Red | Sports | Domestic | Yes |
| 4 | Yellow | Sports | Domestic | No |
| 5 | Yellow | Sports | Imported | Yes |
| 6 | Yellow | SUV | Imported | No |
| 7 | Yellow | SUV | Imported | Yes |
| 8 | Yellow | SUV | Domestic | No |
| 9 | Red | SUV | Imported | No |
| 10 | Red | Sports | Imported | Yes |

| Outlook | Temp | Humidity | Windy | Play |
|---------|------|----------|-------|------|
| Rainy | Cool | High | True | ? |

$$P(\text{Yes} | X) = P(\text{Rainy} | \text{Yes}) \times P(\text{Cool} | \text{Yes}) \times P(\text{High} | \text{Yes}) \times P(\text{True} | \text{Yes}) \times P(\text{Yes})$$

$$P(\text{Yes} | X) = 2/9 \times 3/9 \times 3/9 \times 3/9 \times 9/14 = 0.00529 \rightarrow 0.2 = \frac{0.00529}{0.02057 + 0.00529}$$

$$P(\text{No} | X) = P(\text{Rainy} | \text{No}) \times P(\text{Cool} | \text{No}) \times P(\text{High} | \text{No}) \times P(\text{True} | \text{No}) \times P(\text{No})$$

$$P(\text{No} | X) = 3/5 \times 1/5 \times 4/5 \times 3/5 \times 5/14 = 0.02057 \rightarrow 0.8 = \frac{0.02057}{0.02057 + 0.00529}$$

$$P(C_1 | x_1 \cap x_2 \cap x_3 \cap x_4) = \frac{P(x_1 | C_1) * P(x_2 | C_1) * P(x_3 | C_1) * P(x_4 | C_1) * P(C_1)}{P(x_1) * P(x_2) * P(x_3) * P(x_4)}$$

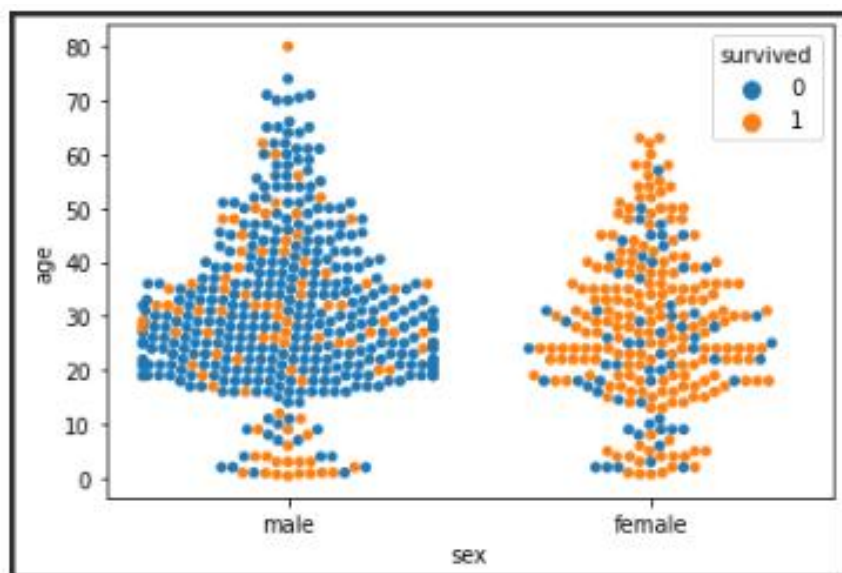
practical No - 7

| Documents | Text | Total number of words in a document |
|-----------|--|-------------------------------------|
| A | Jupiter is the largest planet | 5 |
| B | Mars is the fourth planet from the sun | 8 |

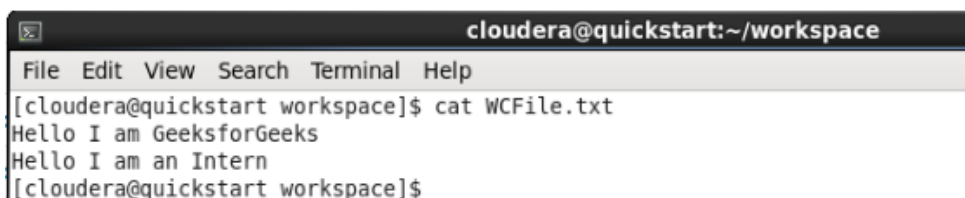
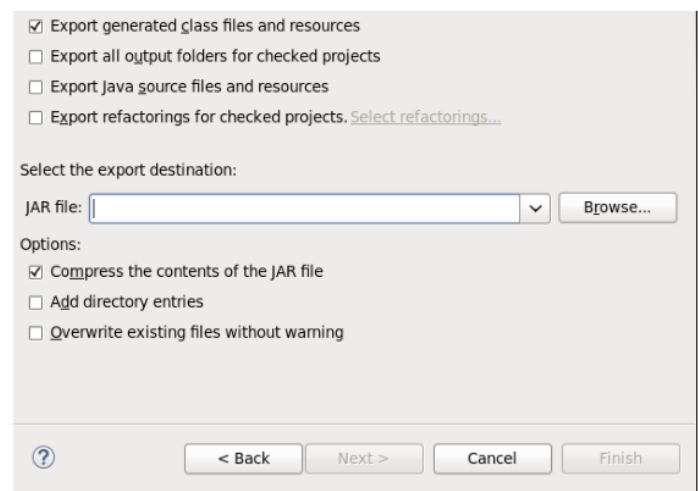
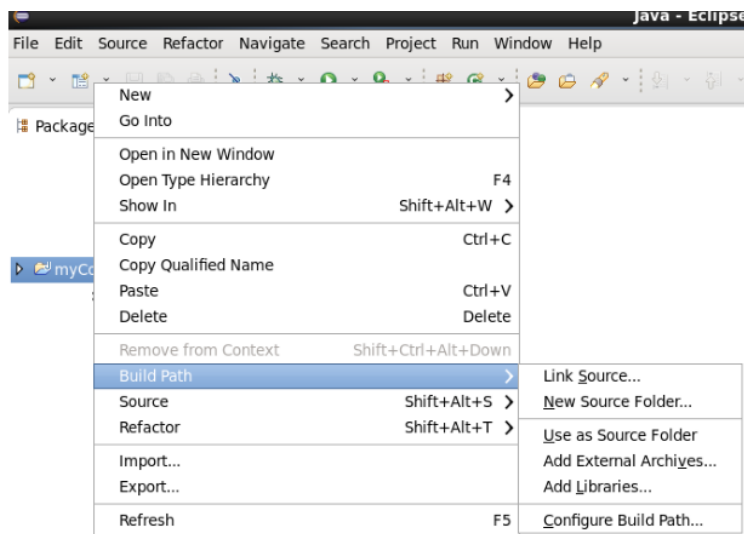
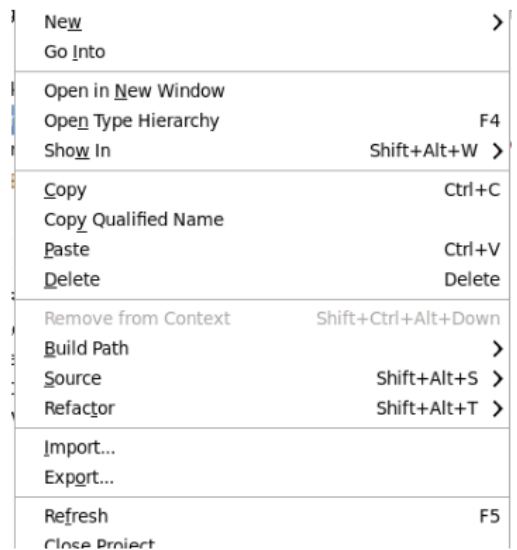
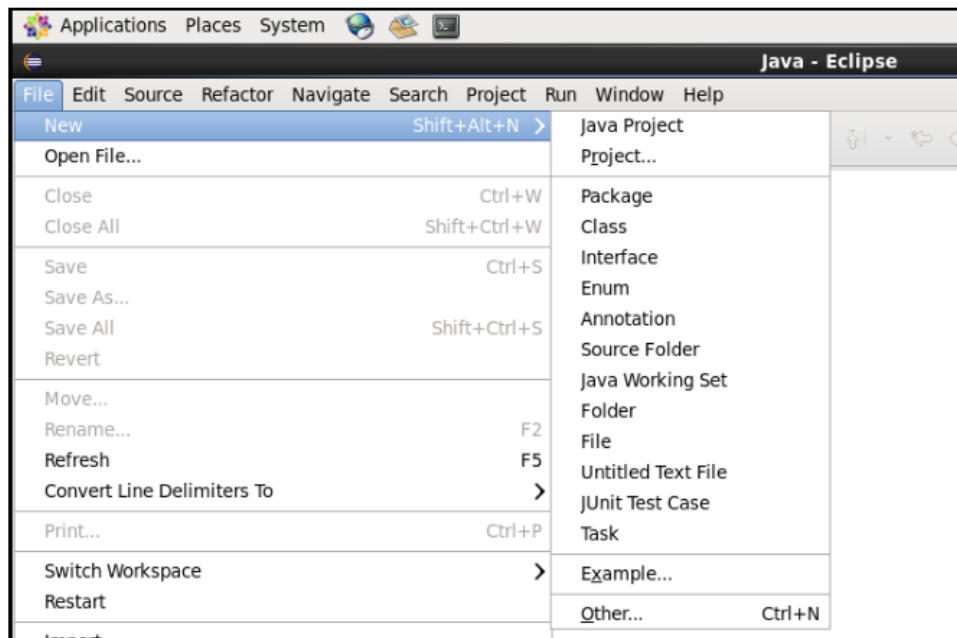
| Words | TF (for A) | TF (for B) | IDF |
|---------|------------|------------|-------------------|
| Jupiter | 1/5 | 0 | $\ln(2/1) = 0.69$ |
| Is | 1/5 | 1/8 | $\ln(2/2) = 0$ |
| The | 1/5 | 2/8 | $\ln(2/2) = 0$ |
| largest | 1/5 | 0 | $\ln(2/1) = 0.69$ |
| Planet | 1/5 | 1/8 | $\ln(2/2) = 0$ |
| Mars | 0 | 1/8 | $\ln(2/1) = 0.69$ |
| Fourth | 0 | 1/8 | $\ln(2/1) = 0.69$ |
| From | 0 | 1/8 | $\ln(2/1) = 0.69$ |
| Sun | 0 | 1/8 | $\ln(2/1) = 0.69$ |

| Words | TF (for A) | TF (for B) | IDF | TFIDF (A) | TFIDF (B) |
|---------|------------|------------|-------------------|-----------|-----------|
| Jupiter | 1/5 | 0 | $\ln(2/1) = 0.69$ | 0.138 | 0 |
| Is | 1/5 | 1/8 | $\ln(2/2) = 0$ | 0 | 0 |
| The | 1/5 | 2/8 | $\ln(2/2) = 0$ | 0 | 0 |
| largest | 1/5 | 0 | $\ln(2/1) = 0.69$ | 0.138 | 0 |
| Planet | 1/5 | 1/8 | $\ln(2/2) = 0$ | 0.138 | 0 |
| Mars | 0 | 1/8 | $\ln(2/1) = 0.69$ | 0 | 0.086 |
| Fourth | 0 | 1/8 | $\ln(2/1) = 0.69$ | 0 | 0.086 |
| From | 0 | 1/8 | $\ln(2/1) = 0.69$ | 0 | 0.086 |
| Sun | 0 | 1/8 | $\ln(2/1) = 0.69$ | 0 | 0.086 |

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No Practical 9 & 10;



Practical No . - 11

