

USN: 1BM20CS147

Date: 1-04-2023

Lab 1: Exploring Datasets

IRIS DATASET:

- Features in the Iris dataset:
 1. sepal length in cm
 2. sepal width in cm
 3. petal length in cm
 4. petal width in cm
- Target classes to predict:
 1. Iris Setosa
 2. Iris Versicolour
 3. Iris Virginica

```
In [9]: print(iris)
```

```
{'data': array([[5.1, 3.5, 1.4, 0.2],
 [4.9, 3. , 1.4, 0.2],
 [4.7, 3.2, 1.3, 0.2],
 [4.6, 3.1, 1.5, 0.2],
 [5. , 3.6, 1.4, 0.2],
 [5.4, 3.9, 1.7, 0.4],
 [4.6, 3.4, 1.4, 0.3],
 [5. , 3.4, 1.5, 0.2],
 [4.4, 2.9, 1.4, 0.2],
 [4.9, 3.1, 1.5, 0.1],
 [5.4, 3.7, 1.5, 0.2],
 [4.8, 3.4, 1.6, 0.2],
 [4.8, 3. , 1.4, 0.1],
 [4.3, 3. , 1.1, 0.1],
 [5.8, 4. , 1.2, 0.2],
 [5.7, 4.4, 1.5, 0.4],
 [5.4, 3.9, 1.3, 0.4],
 [5.1, 3.5, 1.4, 0.3],
 [5.7, 3.8, 1.7, 0.3],
```

Out[5]: function

```
Out[12]: dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names', 'filename', 'data_module'])
```

```
In [13]: iris
```

[4.7, 3.2, 1.6, 0.2],
[4.8, 3.1, 1.6, 0.2],
[5.4, 3.4, 1.5, 0.4],
[5.2, 4.1, 1.5, 0.1],
[5.5, 4.2, 1.4, 0.2],
[4.9, 3.1, 1.5, 0.2],
[5, 3.2, 1.2, 0.2],
[5.5, 3.5, 1.3, 0.2],
[4.9, 3.6, 1.4, 0.1],
[4.4, 3, 1.3, 0.2],
[5.1, 3.4, 1.5, 0.2],
[5, 3.5, 1.3, 0.3],
[4.5, 2.3, 1.3, 0.3],
[4.4, 3.2, 1.3, 0.2],
[5, 3.5, 1.6, 0.6],
[5.1, 3.8, 1.9, 0.4],
[4.8, 3, 1.4, 0.3],
[5.1, 3.8, 1.6, 0.2],

```
In [17]: print(iris['target_names'])

['setosa' 'versicolor' 'virginica']
```

```
In [20]: n_samples,n_features=iris.data.shape
print("no.of samples:",n_samples)
print("no.of features:",n_features)

no.of samples: 150
no.of features: 4
```

```
In [28]: iris.data[[12,26,89,114]]
```

```
Out[28]: array([[4.8, 3. , 1.4, 0.1],
               [5. , 3.4, 1.6, 0.4],
               [5.5, 2.5, 4. , 1.3],
               [5.8, 2.8, 5.1, 2.4]])
```

```
In [29]: print(iris.data.shape)

(150, 4)
```

```
In [31]: print(iris.target.shape)

(150,)
```

```
In [32]: import numpy as np
np.bincount(iris.target)
```

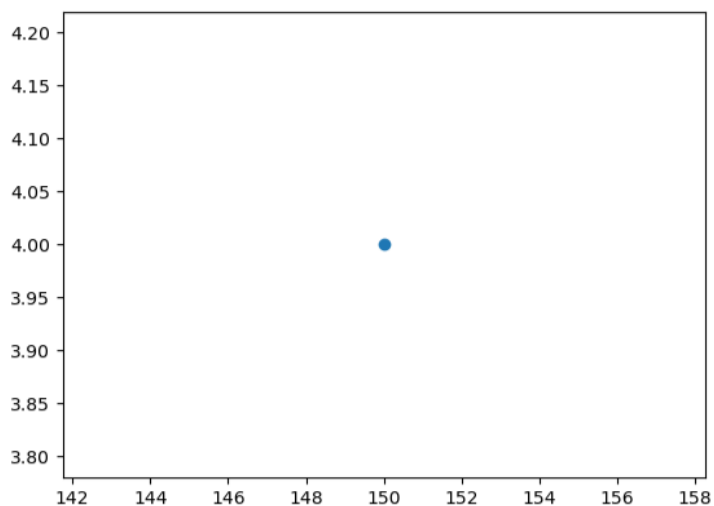
Scattered graph for samples vs features.

```
In [32]: import numpy as np
np.bincount(iris.target)
```

```
Out[32]: array([50, 50, 50], dtype=int64)
```

```
In [42]: import matplotlib.pyplot as plt
plt.scatter(n_samples,n_features)
```

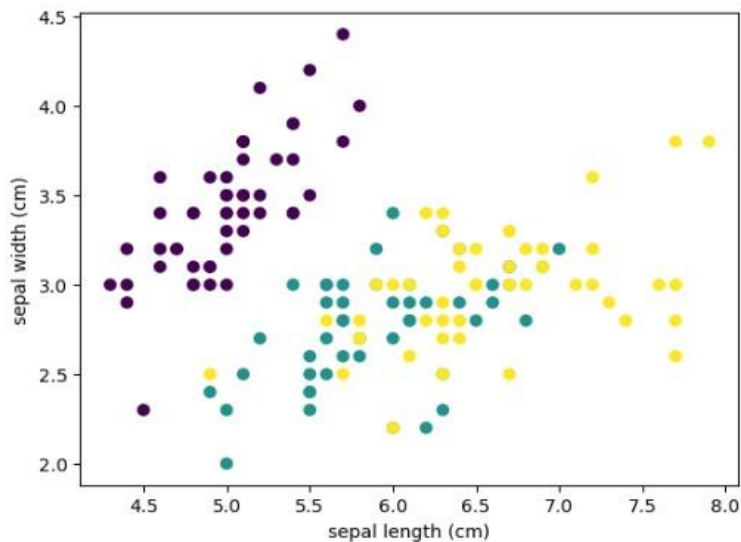
```
Out[42]: <matplotlib.collections.PathCollection at 0x1d1c8c45550>
```



Scattered graph: with first two features(sepal width vs sepal length)
The three colors represents three different classes respectively.

In [47]:

```
features = iris.data.T
plt.scatter(features[0], features[1],
            c=iris.target)
plt.xlabel(iris.feature_names[0])
plt.ylabel(iris.feature_names[1]);
```



In [49]: iris.data[[1,2,3,4,5]]

```
Out[49]: array([[4.9, 3. , 1.4, 0.2],
                [4.7, 3.2, 1.3, 0.2],
                [4.6, 3.1, 1.5, 0.2],
                [5. , 3.6, 1.4, 0.2],
                [5.4, 3.9, 1.7, 0.4]])
```

WINE DATASET:

```
In [51]: from sklearn.datasets import load_wine
wine=load_wine()
```

```
In [52]: print(wine)
```

```
{'data': array([[1.423e+01, 1.710e+00, 2.430e+00, ..., 1.040e+00, 3.920e+00,
                1.065e+03],
                [1.320e+01, 1.780e+00, 2.140e+00, ..., 1.050e+00, 3.400e+00,
                1.050e+03],
                [1.316e+01, 2.360e+00, 2.670e+00, ..., 1.030e+00, 3.170e+00,
```

```
In [57]: wine.data
```

```
Out[57]: array([[1.423e+01, 1.710e+00, 2.430e+00, ..., 1.040e+00, 3.920e+00,
                1.065e+03],
                [1.320e+01, 1.780e+00, 2.140e+00, ..., 1.050e+00, 3.400e+00,
                1.050e+03],
                [1.316e+01, 2.360e+00, 2.670e+00, ..., 1.030e+00, 3.170e+00,
                1.185e+03],
                ...,
                [1.327e+01, 4.280e+00, 2.260e+00, ..., 5.900e-01, 1.560e+00,
                8.350e+02],
                [1.317e+01, 2.590e+00, 2.370e+00, ..., 6.000e-01, 1.620e+00,
                8.400e+02],
                [1.413e+01, 4.100e+00, 2.740e+00, ..., 6.100e-01, 1.600e+00,
                5.600e+02]])
```

```
In [58]: wine.keys()
```

```
Out[58]: dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names'])
```

```
In [60]: print(wine['target_names'])
```

```
['class_0' 'class_1' 'class_2']
```

```
In [9]: print(wine['feature_names'])
```

```
['alcohol', 'malic_acid', 'ash', 'alcalinity_of_ash', 'magnesium', 'total_phenols', 'flavanoids', 'nonflavanoid_phenols', 'proanthocyanins', 'color_intensity', 'hue', 'od280/od315_of_diluted_wines', 'proline']
```

```
In [11]: import numpy as np  
np.bincount(wine.target)
```

```
Out[11]: array([59, 71, 48], dtype=int64)
```

Date: 15/04/2023

Lab 2: FIND-S ALGORITHM FOR ENJOY SPORT:

Program 2 – Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples. Read the training data from a .CSV file Data set:Enjoysport

a. Enjoysport

Example	Sky	AirTemp	Humidity	Wind	Water	Forecast	EnjoySport
1	Sunny	Warm	Normal	Strong	Warm	Same	Yes
2	Sunny	Warm	High	Strong	Warm	Same	Yes
3	Rainy	Cold	High	Strong	Warm	Change	No
4	Sunny	Warm	High	Strong	Cool	Change	Yes

Algorithm:

initialize h to the most specific hypothesis in H $h = (\emptyset, \emptyset, \emptyset, \emptyset, \emptyset, \emptyset)$

1. First training example $X_1 = \langle \text{Sunny, Warm, Normal, Strong Warm Same} \rangle$. EnjoySport=+ve Observing. The first training example, it is clear that hypothesis h is too specific. None of the " \emptyset " constraints in h are satisfied by this example, so each is replaced by the next more general constraint that fits the example $h_1 = \langle \text{Sunny, Warm, Normal, Strong Warm, Same} \rangle$.

2. Consider the second training example $x_2 = \langle \text{Sunny, Warm, High, Strong, Warm, Same} \rangle$. EnjoySport+ve. The second training example forces the algorithm to further generalize h, this time substituting a "?" in place of any attribute value in h that is not satisfied by the new example. Now $h_2 = \langle \text{Sunny, Warm, ?, Strong, Warm, Same} \rangle$

3. Consider the third training example $x_3 = \langle \text{Rainy, Cold, High, Strong, Warm, Change} \rangle$ EnjoySport ve. The FIND-S algorithm simply ignores every negative example. So the hypothesis remain as before, so $h_3 = \langle \text{Sunny, Warm, ?, Strong, Warm, Same} \rangle$

4. Consider the fourth training example $x_4 = \langle \text{Sunny, Warm, High, Strong, Cool, Change} \rangle$ EnjoySport +ve. The fourth example leads to a further generalization of h as $h_4 = \langle \text{Sunny, Warm, ?, Strong, ?, ?} \rangle$

5. So the final hypothesis is $\langle \text{Sunny, Warm, ?, Strong, ?, ?} \rangle$

05/07/2023

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Find S Algorithm.

- 1) Initialize the h to the most specific hypo in H
- 2) For each positive training instance x
 For each attribute constraint a_i in h
 if the constraint a_i is satisfied by x
 then do nothing
 else replace a_i in h by the next more general constraint that is replaced by x
- 3) Return hypothesis h

Hypothesis

H

Specific

Dataset

Sky - Sunny/rainy

AirTemp - Warm/Cold

Humidity - Normal/high

Wind - Strong

Water - Warm/Cool

Forecast - Same

Input

Enjoys sports? - YES or NO (Output)

eg: Sunny, warm, high, strong, cool, change, YES

O/P:

Hypothesis: ['sunny', 'warm', '?', 'strong', '?', '?']

5/4/23

10/10

O/P

Heur

eg

CREATING CSV FILE:

enjoysport.csv

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A1 Sky

	A	B	C	D	E	F	G
1	Sky	AirTemp	Humidity	Wind	Water	Forecast	EnjoySport
2	Sunny	Warm	Normal	Strong	Warm	Same	Yes
3	Sunny	Warm	High	Strong	Warm	Same	Yes
4	Rainy	Cold	High	Strong	Warm	Change	No
5	Sunny	Warm	High	Strong	Cool	Change	Yes
6							
7							

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```
[ ] import numpy as np
import pandas as pd

from google.colab import drive
drive.mount("/content/drive")

path = "/content/enjoysport.csv.csv"

Double-click (or enter) to edit

[ ] data = pd.read_csv(path)

[ ] print(data, "\n")
```

```
[ ]
```

	Sky	AirTemp	Humidity	Wind	Water	Forecast	EnjoySport
0	Sunny	Warm	Normal	Strong	Warm	Same	Yes
1	Sunny	Warm	High	Strong	Warm	Same	Yes
2	Rainy	Cold	High	Strong	Warm	Change	No
3	Sunny	Warm	High	Strong	Cool	Change	Yes

```
[ ] d = np.array(data)[:,-1]
print("\n The attributes are: ",d)

The attributes are: [['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
['Sunny' 'Warm' 'High' 'Strong' 'Warm' 'Same']
['Rainy' 'Cold' 'High' 'Strong' 'Warm' 'Change']
['Sunny' 'Warm' 'High' 'Strong' 'Cool' 'Change']]
```

```
[ ] target = np.array(data)[:,-1]
print("\n The target is: ",target)

The target is: ['Yes' 'Yes' 'No' 'Yes']
```



```
[ ] def findS(c,t):
    for i, val in enumerate(t):
        if val == "Yes":
            specific_hypothesis = c[i].copy()
            break

    for i, val in enumerate(c):
        if t[i] == "Yes":
            for x in range(len(specific_hypothesis)):
                if val[x] != specific_hypothesis[x]:
                    specific_hypothesis[x] = '?'
            else:
                pass

    return specific_hypothesis


print("\n The final hypothesis is:",findS(d,target))
```

The final hypothesis is: ['Sunny' 'Warm' '?' 'Strong' '?' '?']

SECOND DATASET: FIND-S ALGORITHM

example	citations	size	inLibrary	price	editions	buy
1	some	small	no	affordable	many	no
2	many	big	no	expensive	one	yes
3	some	big	always	expensive	few	no
4	many	medium	no	expensive	many	yes
5	many	small	no	affordable	many	yes

CREATING CSV FILE


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A1 ▾ | *fx* citation

	A	B	C	D	E	F
1	citation	size	inLibrary	price	editions	buy
2	some	small	no	affordable	many	no
3	many	big	no	expensive	one	yes
4	some	big	always	expensive	few	no
5	many	medium	no	expensive	many	yes
6	many	small	noo	affordable	many	yes
7						
8						


```
import numpy as np
import pandas as pd
```

```
[ ] from google.colab import drive
drive.mount("/content/drive")
```

Mounted at /content/drive

```
[ ] path = "/content/finde_1BM20CS066 - Sheet1.csv"
```

```
[ ] data = pd.read_csv(path)
```

```
[ ] print(data,"\n")
```

	citation	size	inLibrary	price	editions	buy
0	some	small	no	affordable	many	no
1	many	big	no	expensive	one	yes
2	some	big	always	expensive	few	no
3	many	medium	no	expensive	many	yes
4	many	small	noo	affordable	many	yes

```
[ ] d = np.array(data)[:,-1]
print("\n The attributes are: ",d)
```

```
The attributes are: [['some' 'small' 'no' 'affordable' 'many']
['many' 'big' 'no' 'expensive' 'one']
['some' 'big' 'always' 'expensive' 'few']
['many' 'medium' 'no' 'expensive' 'many']
['many' 'small' 'noo' 'affordable' 'many']]
```

```
target = np.array(data)[:,-1]
print("\n The target is: ",target)
```

The target is: ['no' 'yes' 'no' 'yes' 'yes']

+ Code

+ Text

```
[ ] def find_s(d,target):
    for i,val in enumerate(target):
        if val=='yes':
            hypothesis=d[i].copy()
            break

    for i,var in enumerate(d):
        if target[i]=="yes":
            for x in range(len(hypothesis)):
                if var[x]!=hypothesis[x]:
                    hypothesis[x]='?'
            else:
                pass

    return hypothesis

print("The Hypothesis is",find_s(d,target))
```

The Hypothesis is ['many' '?' '?' '?' '?']

DATE: 15/04/2023

LAB 3: CANDIDATE- ELIMINATION- ENJOY SPORT

Program 3:For a given set of training data examples stored in a .CSV file, implement and demonstrate the Candidate-Elimination algorithm to output a description of the set of all hypotheses consistent with the training examples.Data set:Enjoysport

Example	Sky	AirTemp	Humidity	Wind	Water	Forecast	EnjoySport
1	Sunny	Warm	Normal	Strong	Warm	Same	Yes
2	Sunny	Warm	High	Strong	Warm	Same	Yes
3	Rainy	Cold	High	Strong	Warm	Change	No
4	Sunny	Warm	High	Strong	Cool	Change	Yes

ALGORITHM:

Step1: Load Data set

Step2: Initialize General Hypothesis and Specific Hypothesis.

Step3: For each training example

Step4: If example is positive example

 if attribute_value == hypothesis_value:

 Do nothing

 else:

 replace attribute value with '?' (Basically generalizing it)

Step5: If example is Negative example

 Make generalize hypothesis more specific.

Candidate Elimination Learning Algorithm

Initialize G to the set of maximally general hypothesis in H

Initialize S to the set of maximally specific hypothesis in H

- For each training example d , do
 - If d is a positive example
 - Remove from G any hypothesis inconsistent with d
 - For each hypothesis s in S that is not consistent with d
 - Remove s from S
 - Add to S all minimal generalizations h of s such that
 - h is consistent with d and some member of G is more general than h
 - Remove from S any hypothesis that is more general than another hypothesis in S
 - If d is a negative example
 - Remove from S any hypothesis inconsistent with d
 - For each hypothesis g in G that is not consistent with d
 - Remove g from G
 - Add to G all minimal specializations h of g such that
 - h is consistent with d , and some member of S is more specific than h

	Citations	Size	In library	Price	Editions	Buy
1	Some	Small	No	Affordable	One	No (-ve)
2	Many	big	No	Expensive	Many	Yes (+ve)
3	Many	Medium	No	Expensive	Few	Yes
4	Many	Small	No	Affordable	Many	Yes

* Initialization

$Q_0 = \langle ?, ?, ?, ?, ? \rangle$

$S_0 = \langle \phi, \phi, \phi, \phi, \phi \rangle$

$\langle e_1 \rangle = \langle \text{Some, Small, No, Affordable, One} \rangle$

output is -ve

$S_1 = S_0$ (since o/p is -ve)

$Q_1 = \langle \text{Many, ?, ?, ?, ?} \rangle, \langle ?, \text{Big, ?, ?, ?} \rangle, \langle ?, \text{Medium, ?}, ?, ? \rangle, \langle \text{No attribute exists} \rangle, \langle ?, ?, ?, \text{Expensive}, ? \rangle, \langle ?, ?, ?, \text{Few} \rangle, \langle ?, ?, ?, \text{Many} \rangle$

$\langle e_2 \rangle = \langle \text{Many big No Expensive Many} \rangle$

output is +ve

10/10 $Q_2 = Q_1$ Since output is +ve

$S_2 = \langle \text{Many, big, No, Expensive, Many} \rangle$

$\langle e_3 \rangle = \langle \text{Many, Medium No expensive Few} \rangle$

o/p is +ve

6/14 $Q_3 = Q_2$
 $S_3 = \langle \text{Many, ?, No, Expensive, ?} \rangle$

$\langle e_4 \rangle = \langle \text{Many, Small, No, Affordable, Many} \rangle$

output is +ve

$S_4 = \langle \text{Many, ?, No, ?, ?} \rangle$

CREATING CSV FILE:

enjoysport.csv

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	A	B	C	D	E	F	G
1	Sky	AirTemp	Humidity	Wind	Water	Forecast	EnjoySport
2	Sunny	Warm	Normal	Strong	Warm	Same	Yes
3	Sunny	Warm	High	Strong	Warm	Same	Yes
4	Rainy	Cold	High	Strong	Warm	Change	No
5	Sunny	Warm	High	Strong	Cool	Change	Yes
6							
7							

```
[ ] import numpy as np
import pandas as pd
```

```
[ ]
from google.colab import drive
drive.mount('/content/drive')
```

```
[ ]
data = pd.DataFrame(data=pd.read_csv('/content/enjoysport.csv.csv'))
```

```
[ ] print(data, "\n")
```

	Sky	AirTemp	Humidity	Wind	Water	Forecast	EnjoySport
0	Sunny	Warm	Normal	Strong	Warm	Same	Yes
1	Sunny	Warm	High	Strong	Warm	Same	Yes
2	Rainy	Cold	High	Strong	Warm	Change	No
3	Sunny	Warm	High	Strong	Cool	Change	Yes

```
[ ] concepts = np.array(data.iloc[:,0:-1])
```

```
[ ] print(concepts)
```

```
[['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
['Sunny' 'Warm' 'High' 'Strong' 'Warm' 'Same']
['Rainy' 'Cold' 'High' 'Strong' 'Warm' 'Change']
['Sunny' 'Warm' 'High' 'Strong' 'Cool' 'Change']]
```

```
[ ] target = np.array(data.iloc[:, -1])
print(target)
```

```
['Yes' 'Yes' 'No' 'Yes']
```

```
[ ] import csv
```



```

with open("/content/enjoysport.csv") as f:
    csv_file = csv.reader(f)
    data = list(csv_file)

    specific = data[1][:-1]
    general = [['?' for i in range(len(specific))] for j in range(len(specific))]

    for i in data:
        if i[-1] == "Yes":
            for j in range(len(specific)):
                if i[j] != specific[j]:
                    specific[j] = "?"
                    general[j][j] = "?"

            elif i[-1] == "No":
                for j in range(len(specific)):
                    if i[j] != specific[j]:
                        general[j][j] = specific[j]
                    else:
                        general[j][j] = "?"

    print("\nStep " + str(data.index(i)) + " of Candidate Elimination Algorithm")
    print(specific)
    print(general)

gh = [] # gh = general Hypothesis
for i in general:
    for j in i:
        if j != '?':
            gh.append(i)
            break
print("\nFinal Specific hypothesis:\n", specific)
print("\nFinal General hypothesis:\n", gh)

```

```

Step 0 of Candidate Elimination Algorithm
['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Step 1 of Candidate Elimination Algorithm
['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Step 2 of Candidate Elimination Algorithm
['Sunny', 'Warm', '?', 'Strong', 'Warm', 'Same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Step 3 of Candidate Elimination Algorithm
['Sunny', 'Warm', '?', 'Strong', 'Warm', 'Same']
[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', 'Same']]

Step 4 of Candidate Elimination Algorithm
['Sunny', 'Warm', '?', 'Strong', '?', '?']
[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Final Specific hypothesis:
['Sunny', 'Warm', '?', 'Strong', '?', '?']

Final General hypothesis:
[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?']]

```

```

[ ] def learn(concepts, target):
    specific_h = concepts[0].copy()
    general_h = [['?' for i in range(len(specific_h))] for i in range(len(specific_h))]
    print("Step 0:")
    print("Specific Hypothesis: ", specific_h)
    print("General Hypothesis: ", general_h)
    print("-----")
    for i, h in enumerate(concepts):
        if target[i] == "Yes":
            for x in range(len(specific_h)):
                if h[x] != specific_h[x]:
                    specific_h[x] = '?'
                    general_h[x][x] = '?'
        if target[i] == "No":
            for x in range(len(specific_h)):
                if h[x] != specific_h[x]:
                    general_h[x][x] = specific_h[x]
                else:
                    general_h[x][x] = '?'
    print("Step", i+1, ":")
    print("Specific Hypothesis: ", specific_h)
    print("General Hypothesis: ", general_h)
    print("-----")
    indices = [i for i, val in enumerate(general_h) if val == ['?', '?', '?', '?', '?', '?']]
    for i in indices:
        general_h.remove(['?', '?', '?', '?', '?', '?'])
    return specific_h, general_h

s_final, g_final = learn(concepts, target)
print("Final S:", s_final, sep="\n")
print("Final G:", g_final, sep="\n")

```

```

Step 0:
Specific Hypothesis: [['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']]
General Hypothesis: [[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]]
-----
Step 1:
Specific Hypothesis: [['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']]
General Hypothesis: [[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]]
-----
Step 2:
Specific Hypothesis: [['Sunny' 'Warm' '?' 'Strong' 'Warm' 'Same']]
General Hypothesis: [[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]]
-----
Step 3:
Specific Hypothesis: [['Sunny' 'Warm' '?' 'Strong' 'Warm' 'Same']]
General Hypothesis: [[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?', 'Same']]]
-----
Step 4:
Specific Hypothesis: [['Sunny' 'Warm' '?' 'Strong' '?' '?']]
General Hypothesis: [[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]]
-----
Final S:
['Sunny' 'Warm' '?' 'Strong' '?' '?'']
Final G:
[['Sunny', '?', '?', '?', '?', '?'], ['?', 'Warm', '?', '?', '?', '?']]

```

SECOND DATASET:

example	citations	size	inLibrary	price	editions	buy
1	some	small	no	affordable	many	no
2	many	big	no	expensive	one	yes
3	some	big	always	expensive	few	no
4	many	medium	no	expensive	many	yes
5	many	small	no	affordable	many	yes

CREATING CSV FILE:

finds_1BM20CS066

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	A	B	C	D	E	F
1	citation	size	inLibrary	price	editions	buy
2	some	small	no	affordable	many	no
3	many	big	no	expensive	one	yes
4	some	big	always	expensive	few	no
5	many	medium	no	expensive	many	yes
6	many	small	noo	affordable	many	yes
7						
8						

```

from google.colab import drive
drive.mount('/content/drive')

Mounted at /content/drive

[ ] import numpy as np
import pandas as pd

[ ] data = pd.DataFrame(data=pd.read_csv('/content/finds_1BM20CS066 - Sheet1.csv'))
print(data,"\n")

  citation  size inLibrary  price editions  buy
0   some  small      no affordable  many   no
1   many   big      no  expensive   one   yes
2   some   big  always  expensive   few   no
3   many medium      no  expensive  many   yes
4   many  small      noo affordable  many   yes

[ ] concepts = np.array(data.iloc[:,0:-1])
print("The attributes are: ",concepts)

The attributes are: [['some' 'small' 'no' 'affordable' 'many']
['many' 'big' 'no' 'expensive' 'one']
['some' 'big' 'always' 'expensive' 'few']
['many' 'medium' 'no' 'expensive' 'many']
['many' 'small' 'noo' 'affordable' 'many']]

[ ] target = np.array(data.iloc[:,-1])
print("\n The target is: ",target)

The target is: ['no' 'yes' 'no' 'yes' 'yes']

```

```
[ ] def learn(concepts, target):
    specific_h = concepts[0].copy()
    print("\n Initialization of specific_h and general_h")
    print(specific_h)
    general_h = [["?" for i in range(len(specific_h))] for i in
range(len(specific_h))]
    print(general_h)
    for i, h in enumerate(concepts):
        if target[i] == "yes":
            for x in range(len(specific_h)):
                if h[x] != specific_h[x]:
                    specific_h[x] = '?'
                    general_h[x][x] = '?'
            print(specific_h)
        print(specific_h)
        if target[i] == "no":
            for x in range(len(specific_h)):
                if h[x] != specific_h[x]:
                    general_h[x][x] = specific_h[x]
            else:
                general_h[x][x] = '?'
        print("\n Steps of Candidate Elimination Algorithm",i+1)
        print(specific_h)
        print(general_h)
        indices = [i for i, val in enumerate(general_h) if val ==
['?', '?', '?', '?', '?', '?']]
        for i in indices:
            general_h.remove(['?', '?', '?', '?', '?', '?'])
    return specific_h, general_h
s_final, g_final = learn(concepts, target)
```

Initialization of specific_h and general_h

```
['some' 'small' 'no' 'affordable' 'many']
[['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?']]
['some' 'small' 'no' 'affordable' 'many']
```

Steps of Candidate Elimination Algorithm 1

```
['some' 'small' 'no' 'affordable' 'many']
[['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?']]
['?' 'small' 'no' 'affordable' 'many']
['?' '?' 'no' 'affordable' 'many']
['?' '?' 'no' 'affordable' 'many']
['?' '?' 'no' '?' 'many']
['?' '?' 'no' '?' '?']
['?' '?' 'no' '?' '?']
```

Steps of Candidate Elimination Algorithm 2

```
['?' '?' 'no' '?' '?']
[['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?']]
['?' '?' 'no' '?' '?']
```

Steps of Candidate Elimination Algorithm 3

```
['?' '?' 'no' '?' '?']
[['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', 'no', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?']]
['?' '?' 'no' '?' '?']
['?' '?' 'no' '?' '?']
['?' '?' 'no' '?' '?']
['?' '?' 'no' '?' '?']
['?' '?' 'no' '?' '?']
['?' '?' 'no' '?' '?']
```

Steps of Candidate Elimination Algorithm 4

```
['?' '?' 'no' '?' '?']
[['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', 'no', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?']]
['?' '?' 'no' '?' '?']
['?' '?' 'no' '?' '?']
['?' '?' 'no' '?' '?']
['?' '?' 'no' '?' '?']
['?' '?' 'no' '?' '?']
['?' '?' 'no' '?' '?']
```

Steps of Candidate Elimination Algorithm 5

```
['?' '?' 'no' '?' '?']
[['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?']]
```

```
print("\nFinal Specific_h:", s_final, sep="\n")
print("\nFinal General_h:", g_final, sep="\n")
```

Final Specific_h:

```
['?' '?' '?' '?' '?']
```

Final General_h:

```
[['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?']]
```

Program 4: Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.

Day	Outlook	Temperature	Humidity	Wind	PlayTennis
D1	Sunny	Hot	High	Weak	No
D2	Sunny	Hot	High	Strong	No
D3	Overcast	Hot	High	Weak	Yes
D4	Rain	Mild	High	Weak	Yes
D5	Rain	Cool	Normal	Weak	Yes
D6	Rain	Cool	Normal	Strong	No
D7	Overcast	Cool	Normal	Strong	Yes
D8	Sunny	Mild	High	Weak	No
D9	Sunny	Cool	Normal	Weak	Yes
D10	Rain	Mild	Normal	Weak	Yes
D11	Sunny	Mild	Normal	Strong	Yes
D12	Overcast	Mild	High	Strong	Yes
D13	Overcast	Hot	Normal	Weak	Yes
D14	Rain	Mild	High	Strong	No

ALGORITHM:

- Create a Root node for the tree
- If all Examples are positive, Return the single-node tree Root, with label = +
- If all Examples are negative, Return the single-node tree Root, with label = -
- If Attributes is empty, Return the single-node tree Root, with label = most common value of Target_attribute in Examples
- Otherwise Begin
 - $A \leftarrow$ the attribute from Attributes that best* classifies Examples
 - The decision attribute for Root $\leftarrow A$
 - For each possible value, v_i , of A,
 - Add a new tree branch below Root, corresponding to the test $A = v_i$
 - Let $Examples_{v_i}$ be the subset of Examples that have value v_i for A
 - If $Examples_{v_i}$ is empty
 - Then below this new branch add a leaf node with label = most common value of Target_attribute in Examples
 - Else below this new branch add the subtree $ID3(Examples_{v_i}, Target_attribute, Attributes - \{A\})$
 - End
 - Return Root

v = Temp

$G(S, \text{Temp})$

$$= E(S) - \left[\frac{4}{14} \times E(2+, 2-) + \frac{6}{14} \times E(4+, 2-) + \frac{4}{14} \times E(3+, 1-) \right]$$

$$= 0.9402 - \left[\frac{4}{14} \left(-\frac{2}{4} \log\left(\frac{2}{4}\right) + \left(-\frac{2}{4} \log\left(\frac{2}{4}\right)\right) + \frac{6}{14} \left(\left(-\frac{4}{6} \log\left(\frac{4}{6}\right) + \left(-\frac{2}{6} \log\left(\frac{2}{6}\right)\right) \right) + \frac{4}{14} \left(-\frac{3}{4} \log\left(\frac{3}{4}\right) + \left(-\frac{1}{4} \log\left(\frac{1}{4}\right) \right) \right) \right]$$

$$= 0.9402 - \left[0.679269 + \frac{4}{14} \left(-\frac{3}{4} \log\left(\frac{3}{4}\right) - \frac{1}{4} \log\left(\frac{1}{4}\right) \right) \right]$$

$$= 0.9402 - 0.9110$$

$$= 0.0291$$

outdoor



$$\text{Entropy}(S) = -P_0 \log_2(P_0) - P_1 \log_2(P_1)$$

$$= -\frac{9}{14} \log_2\left(\frac{9}{14}\right) - \frac{5}{14} \log_2\left(\frac{5}{14}\right)$$

$$= 0.9402$$

If Entropy is

1 \rightarrow 50% - 50%

0 \rightarrow Biased

0-1 \rightarrow

Information gain $G(S, A)$ ^{whole dataset} each attribute A

$$= E(S) - \sum_{v \in A} \frac{|S_v|}{|S|} E(S_v)$$

Outlook

$$= E(S) - \sum \frac{|S_v|}{|S|} E(S_v)$$

$$= E(S) - \left[\frac{5}{14} \times E(\text{outlook} = \text{Sunny}) + \frac{4}{14} \times E(\text{outlook} = \text{Overcast}) + \frac{5}{14} \times E(\text{outlook} = \text{Rain}) \right]$$

$$= E(S) - \left[\frac{5}{14} \times E(2+, 3-) + \frac{4}{14} \times E(4+, 0-) + \frac{5}{14} \times E(3+, 2-) \right]$$

$$= E(S) - \left[\frac{5}{14} \times \left(-\frac{2}{5} \log_2 \frac{2}{5} - \frac{3}{5} \log_2 \frac{3}{5} \right) + \frac{4}{14} \times \left(-\frac{4}{4} \log_2 \frac{4}{4} - \frac{0}{4} \log_2 \frac{0}{4} \right) + \frac{5}{14} \times \left(-\frac{3}{5} \log_2 \frac{3}{5} - \frac{2}{5} \log_2 \frac{2}{5} \right) \right] = 0.2467$$

0.151
0.048

PAGE NO:
DATE:

v = Humidity

$g(s, \text{Humidity})$

$$= 0.9402 - \left[\frac{3}{14} \log \left(\frac{3}{14} \right) + \frac{2}{14} \times \left(-\frac{3}{7} \log \left(\frac{3}{7} \right) - \frac{4}{7} \log \frac{4}{7} \right) + \frac{9}{14} \times \left(-\frac{6}{7} \log \frac{6}{7} - \frac{1}{7} \log \frac{1}{7} \right) \right]$$

$$= 0.9402 - (0.7884)$$

$$= 0.1517$$

v = Wind

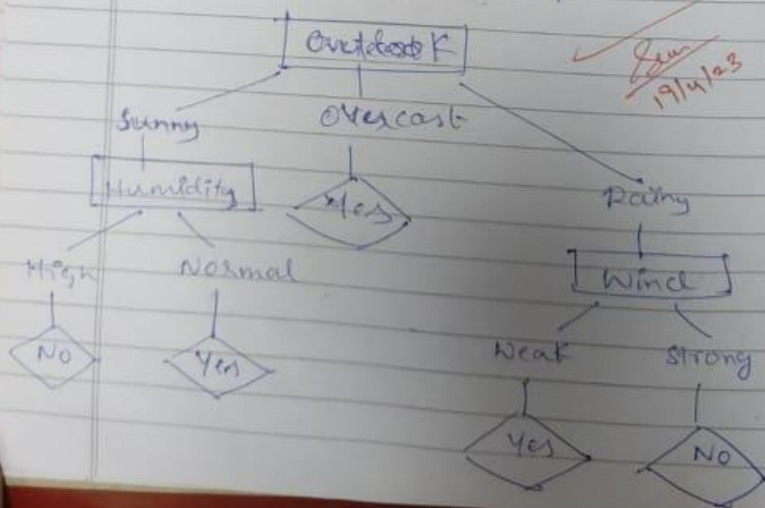
$g(s, \text{Wind})$

$$= 0.9402 - \left[\frac{8}{14} \times \left(-\frac{6}{8} \log \frac{6}{8} - \frac{2}{8} \log \frac{2}{8} \right) + \frac{6}{14} \times \left(-\frac{3}{6} \log \frac{3}{6} - \frac{3}{6} \log \frac{3}{6} \right) \right]$$

$$= 0.9402 - 0.89215$$

$$= 0.0480$$

v	outlook	Temp	Humidity	Wind
$g(s, v)$	0.2467	0.0291	0.1517	0.0480





1BM20CS066_ID3



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A1



outlook

	A	B	C	D	E
1	outlook	temperture	humidity	wind	play tennis
2	sunny	hot	high	weak	no
3	sunny	hot	high	strong	no
4	overcast	hot	high	weak	yes
5	rain	mild	high	weak	yes
6	rain	cool	normal	weak	yes
7	rain	cool	normal	strong	no
8	overcast	cool	normal	strong	yes
9	sunny	mild	high	weak	no
10	sunny	cool	normal	weak	yes
11	rain	mild	normal	weak	yes
12	sunny	mild	normal	strong	yes
13	overcast	mild	high	strong	yes
14	overcast	hot	normal	weak	yes
15	rain	mild	high	strong	no
16					



Files



{x}



sample_data



1BM20CS066_ID3.csv

<>



Disk 84.31 GB available

+ Code + Text

```
[53] import math
import csv
```

```
[55] def load_csv(filename):
    lines=csv.reader(open(filename,"r"))
    dataset = list(lines)
    headers = dataset.pop(0)
    return dataset,headers
```

```
[56] class Node:
    def __init__(self,attribute):
        self.attribute=attribute
        self.children=[]
        self.answer=""
```

```
def subtables(data,col,delete):
    dic={}
    coldata=[row[col] for row in data]
    attr=list(set(coldata))

    counts=[0]*len(attr)
    r=len(data)
    c=len(data[0])
    for x in range(len(attr)):
        for y in range(r):
            if data[y][col]==attr[x]:
                counts[x]+=1

    for x in range(len(attr)):
        dic[attr[x]]=[[0 for i in range(c)] for j in range(counts[x])]
        pos=0
        for y in range(r):
            if data[y][col]==attr[x]:
                if delete:
                    del data[y][col]
                dic[attr[x]][pos]=data[y]
                pos+=1
    return attr,dic
```

```

[58] def entropy(S):
    attr=list(set(S))
    if len(attr)==1:
        return 0

    counts=[0,0]
    for i in range(2):
        counts[i]=sum([1 for x in S if attr[i]==x])/(len(S)*1.0)

    sums=0
    for cnt in counts:
        sums+=-1*cnt*math.log(cnt,2)
    return sums

```

```

[59] def compute_gain(data,col):
    attr,dic = subtables(data,col,delete=False)

    total_size=len(data)
    entropies=[0]*len(attr)
    ratio=[0]*len(attr)

    total_entropy=entropy([row[-1] for row in data])
    for x in range(len(attr)):
        ratio[x]=len(dic[attr[x]])/(total_size*1.0)
        entropies[x]=entropy([row[-1] for row in dic[attr[x]]])
        total_entropy-=ratio[x]*entropies[x]
    return total_entropy

```

```

[60] def build_tree(data,features):
    lastcol=[row[-1] for row in data]
    if(len(set(lastcol))==1:
        node=Node("")
        node.answer=lastcol[0]
        return node

    n=len(data[0])-1
    gains=[0]*n
    for col in range(n):
        gains[col]=compute_gain(data,col)
    split=gains.index(max(gains))
    node=Node(features[split])
    fea = features[:split]+features[split+1:]

    attr,dic=subtables(data,split,delete=True)

    for x in range(len(attr)):
        child=build_tree(dic[attr[x]],fea)
        node.children.append((attr[x],child))
    return node

```

```

def print_tree(node,level):
    if node.answer!="":
        print("  "*level,node.answer)
        return

    print("  "*level,node.attribute)
    for value,n in node.children:
        print("  "*(level+1),value)
        print_tree(n,level+2)

```

```
✓ [62] def classify(node,x_test,features):  
0s     if node.answer!="":  
        print(node.answer)  
        return  
    pos=features.index(node.attribute)  
    for value, n in node.children:  
        if x_test[pos]==value:  
            classify(n,x_test,features)
```

```
✓ [63]  
0s dataset,features=load_csv("1BM20CS066_ID3.csv")  
    node1=build_tree(dataset,features)  
  
    print("The decision tree for the dataset using ID3 algorithm is")  
    print_tree(node1,0)  
    testdata,features=load_csv("1BM20CS066_ID3.csv")  
  
    for xtest in testdata:  
        print("The test instance:",xtest)  
        print("The label for test instance:")  
        classify(node1,xtest,features)
```

```
✓ 0s ▶ The decision tree for the dataset using ID3 algorithm is  
    outlook  
    rain  
    wind  
    weak  
    yes  
    strong  
    no  
    sunny  
    humidity  
    high  
    no  
    normal  
    yes  
    overcast  
    yes
```

The test instance: ['sunny', 'hot', 'high', 'weak', 'no']
The label for test instance:
no
The test instance: ['sunny', 'hot', 'high', 'strong', 'no']
The label for test instance:
no
The test instance: ['overcast', 'hot', 'high', 'weak', 'yes']
The label for test instance:
yes
The test instance: ['rain', 'mild', 'high', 'weak', 'yes']
The label for test instance:
yes
The test instance: ['rain', 'cool', 'normal', 'weak', 'yes']
The label for test instance:
yes
The test instance: ['rain', 'cool', 'normal', 'strong', 'no']
The label for test instance:
no
The test instance: ['overcast', 'cool', 'normal', 'strong', 'yes']
The label for test instance:
yes
The test instance: ['sunny', 'mild', 'high', 'weak', 'no']
The label for test instance:
no
The test instance: ['sunny', 'cool', 'normal', 'weak', 'yes']
The label for test instance:
yes
The test instance: ['rain', 'mild', 'normal', 'weak', 'yes']
The label for test instance:
yes
.
The test instance: ['sunny', 'mild', 'normal', 'strong', 'yes']
The label for test instance:
yes
The test instance: ['overcast', 'mild', 'high', 'strong', 'yes']
The label for test instance:
yes
The test instance: ['overcast', 'hot', 'normal', 'weak', 'yes']
The label for test instance:
yes
The test instance: ['rain', 'mild', 'high', 'strong', 'no']
The label for test instance:
no

PROGRAM 5: Simple linear regression program

Dataset used:

	A	B
1	x	y
2	1	1
3	2	2
4	3	1.3
5	4	3.75
6	5	2.25
7		

ALGORITHM:

- The main function to calculate values of coefficients
- Initialize the parameters.
- Predict the value of a dependent variable by giving an independent variable.
- Calculate the error in prediction for all data points.
- Calculate partial derivatives w.r.t a_0 and a_1 .
- Calculate the cost for each number and add them.
- Update the values of a_0 and a_1 .

Linear Regression

- 1) Reading & Understanding the data
- 2) Visualizing the data (Exploratory data Analysis)
- 3) Find \bar{x}, \bar{y}
- 4) Find m, c using

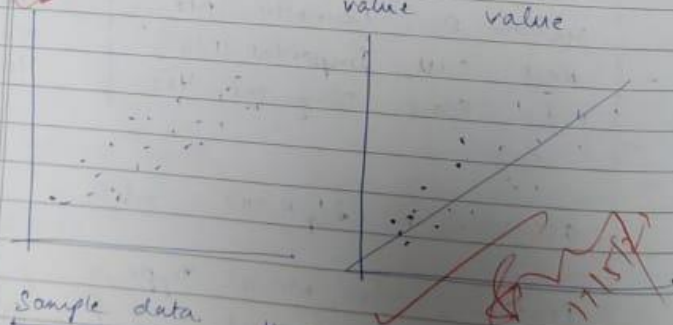
$$m = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

$$c = \bar{y} - m\bar{x} \quad (c = -4.150, m = 1.210)$$

Minimize the error, using loss function

$$L(x) = \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

Actual value Predicted value



Sample data

x	y
5.1101	17.592
5.5277	8.1302
8.5186	13.662

x - experience

y - salary (in K)

```
[ ] import numpy as np
import matplotlib.pyplot as plt
```

```
[ ] def plot_regression_line(x, y, b):

    plt.scatter(x, y, color = "m",
                marker = "o", s = 30)

    y_pred = b[0] + b[1]*x

    plt.plot(x, y_pred, color = "g")

    plt.xlabel('x CO-EFF')
    plt.ylabel('y CO-EFF')

    plt.show()
```

```
[ ] def estimate_coef(x, y):

    n = np.size(x)

    m_x = np.mean(x)
    m_y = np.mean(y)

    SS_xy = np.sum(y*x) - n*m_y*m_x
    SS_xx = np.sum(x*x) - n*m_x*m_x

    b_1 = SS_xy / SS_xx
    b_0 = m_y - b_1*m_x

    return (b_0, b_1)
```

```
▶ def plot_regression_line(x, y, b):
    plt.scatter(x, y, color = "b",
                marker = "*", s = 30)

    y_pred = b[0] + b[1]*x

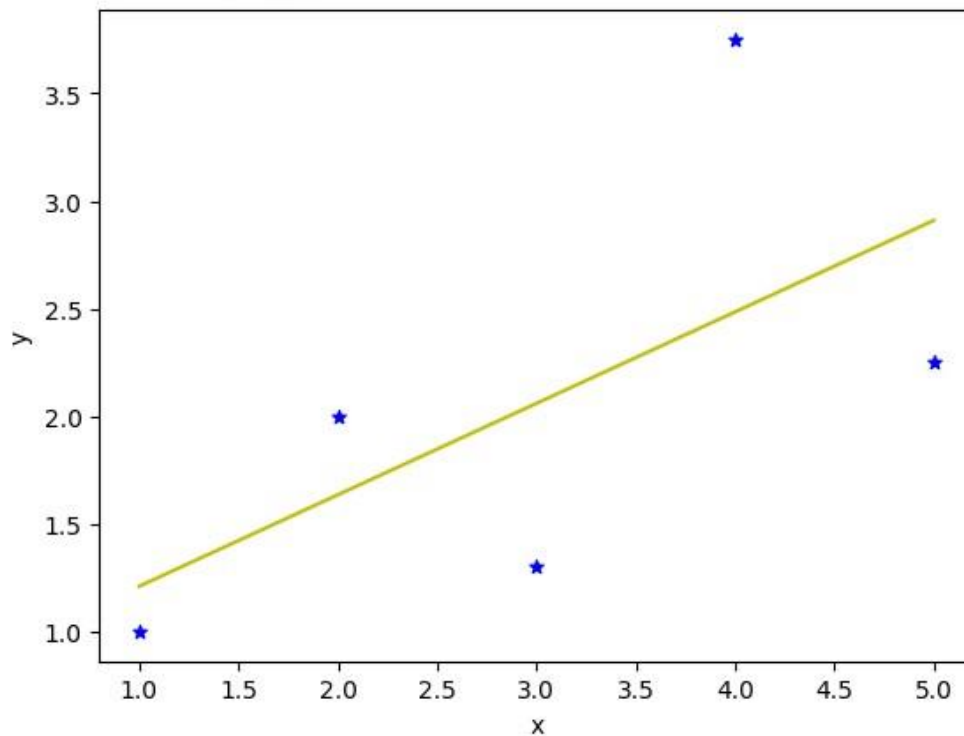
    plt.plot(x, y_pred, color = "y")

    plt.xlabel('x')
    plt.ylabel('y')

    plt.show()
```

```
def main():  
  
    x = np.array([1,2,3,4,5])  
    y = np.array([1,2,1.3,3.75,2.25])  
  
    b = estimate_coef(x, y)  
    print("Estimated coefficients:\nb_0 = {} \nb_1 = {}".format(b[0], b[1]))  
  
    plot_regression_line(x, y, b)  
  
if __name__ == "__main__":  
    main()
```

Estimated coefficients:
b_0 = 0.7850000000000001
b_1 = 0.42499999999999966



Conclusion:

This model is not appropriate for this model. All the points of this dataset are away from the prediction line.

Program 6: Write a program to implement the naïve Bayesian classifier for a sample training data set stored as a .CSV file. Compute the accuracy of the classifier, considering few test data sets.

Data set used:

	A	B
1	outlook	play
2	rainy	Yes
3	sunny	Yes
4	overcast	Yes
5	overcast	Yes
6	sunny	No
7	rainy	Yes
8	sunny	Yes
9	overcast	Yes
10	rainy	No
11	sunny	No
12	sunny	Yes
13	rainy	No
14	overcast	Yes
15	overcast	Yes

Algorithm:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Formula for naive bayes classifier is as follows →

1. Convert the given dataset into frequency tables.
2. Generate Likelihood table by finding the probabilities of given features.
3. Now, use Bayes theorem to calculate the posterior probability.
4. Test accuracy of the result and visualizing the test set result.

The screenshot shows a Jupyter Notebook titled '1BM20CS066_NBC.ipynb'. The left sidebar displays the file explorer with a folder named 'sample_data' containing a file '1BM20CS066_NBC.csv'. The main area contains two code cells. The first cell (index 7) imports necessary libraries: numpy, math, csv, and pdb. The second cell (index 9) defines two functions: 'read_data(filename)' which reads a CSV file and returns metadata and training data, and 'splitDataset(dataset, splitRatio)' which splits the dataset into training and testing sets based on the provided ratio.

```
[7] import numpy as np
import math
import csv
import pdb

def read_data(filename):
    with open(filename, 'r') as csvfile:
        datareader = csv.reader(csvfile)
        metadata = next(datareader)
        traindata = []
        for row in datareader:
            traindata.append(row)
    return (metadata, traindata)

[9] def splitDataset(dataset, splitRatio):
    trainSize = int(len(dataset) * splitRatio)
    trainSet = []
    testset = list(dataset)
    i = 0
    while len(trainSet) < trainSize:
        trainSet.append(testset.pop(i))
    return [trainSet, testset]
```



```
def classify(data,test):
```

```

    total_size = data.shape[0]
    print("\n")
    print("training data size=",total_size)
    print("test data size=",test.shape[0])

    countYes = 0
    countNo = 0
    probYes = 0
    probNo = 0
    print("\n")
    print("target    count    probability")

    for x in range(data.shape[0]):
        if data[x,data.shape[1]-1] == 'Yes':
            countYes +=1
        if data[x,data.shape[1]-1] == 'No':
            countNo +=1

    probYes=countYes/total_size
    probNo= countNo / total_size

    print('Yes',"\\t",countYes,"\\t",probYes)
    print('No',"\\t",countNo,"\\t",probNo)

    prob0 =np.zeros((test.shape[1]-1))
    prob1 =np.zeros((test.shape[1]-1))
    accuracy=0
    print("\n")
    print("instance prediction  target")

    for t in range(test.shape[0]):
        for k in range (test.shape[1]-1):
            count1=count0=0
            for j in range (data.shape[0]):
                #how many times appeared with no
                if test[t,k] == data[j,k] and data[j,data.shape[1]-1]=='No':
                    count0+=1
                #how many times appeared with yes
                if test[t,k]==data[j,k] and data[j,data.shape[1]-1]=='Yes':
                    count1+=1

            prob0[k]=count0/countNo
            prob1[k]=count1/countYes

        probno=probNo
        probyes=probYes
        for i in range(test.shape[1]-1):
            probno=probno*prob0[i]
            probyes=probyes*prob1[i]
        if probno>probyes:
            predict='No'
        else:
            predict='Yes'

        print(t+1,"\\t",predict,"\\t    ",test[t,test.shape[1]-1])
        if predict == test[t,test.shape[1]-1]:
            accuracy+=1
    final_accuracy=(accuracy/test.shape[0])*100
    print("accuracy",final_accuracy,"%")
    return
```

```

metadata,traindata= read_data("/content/1BM20CS066_NBC.csv")
splitRatio=0.6
trainingset, testset=splitDataset(traindata, splitRatio)
training=np.array(trainingset)
print("\n The Training data set are:")
for x in trainingset:
    print(x)

testing=np.array(testset)
print("\n The Test data set are:")
for x in testing:
    print(x)
classify(training,testing)

```

output:

The Training data set are:

```

['rainy', 'Yes']
['sunny', 'Yes']
['overcast', 'Yes']
['overcast', 'Yes']
['sunny', 'No']
['rainy', 'Yes']
['sunny', 'Yes']
['overcast', 'Yes']

```

The Test data set are:

```

['rainy' 'No']
['sunny' 'No']
['sunny' 'Yes']
['rainy' 'No']
['overcast' 'Yes']
['overcast' 'Yes']

```

training data size= 8

test data size= 6

target	count	probability
Yes	7	0.875
No	1	0.125

instance	prediction	target
1	Yes	No
2	Yes	No
3	Yes	Yes
4	Yes	No
5	Yes	Yes
6	Yes	Yes

accuracy 50.0 %

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Naive Bayes Classifier

- 1) Convert the dataset into a frequency table
- 2) Create likelihood table by finding probabilities
- 3) Use the naive Bayesian equation to calculate the posterior probability

$$P(h|d) = \frac{P(d|h) P(h)}{P(d)}$$

Data set	Car dataset	Target
Red	Sports Domestic	Yes
Red	Sports Domestic	No
Yellow	Sports Imported	Yes

Training	Target	Predicted
Yellow, SUV, Imported, Yes	Yes	No
Yellow, SUV, Domestic, No	No	No
Red, SUV, Imported, No	No	No
Red, Sports, Imported, Yes	Yes	Yes

10

accuracy = $\frac{3}{4} \times 100 = 75\%$

Features: Color, Model, Type

Target: Sold or not

17/5/23

Program 7:K- means clustering

Algorithm:

Initialize k means with random values

For a given number of iterations:

Iterate through items:

Find the mean closest to the item by calculating the euclidean distance of the item with each of the means

Assign item to mean

Update mean by shifting it to the average of the items in that cluster

Dataset:

Kmeans_1BM20CS066.csv ×			
1 to 22 of 22 entries Filter			
1	Name	Age	Income(\$)
2	Rob	27	70000
3	Michael	29	90000
4	Mohan	29	61000
5	Ismail	28	60000
6	Kory	42	150000
7	Gautam	39	155000
8	David	41	160000
9	Andrea	38	162000
10	Brad	36	156000
11	Angelina	35	130000
12	Donald	37	137000
13	Tom	26	45000
14	Arnold	27	48000
15	Jared	28	51000
16	Stark	29	49500
17	Ranbir	32	53000
18	Dipika	40	65000
19	Priyanka	41	63000
20	Nick	43	64000
21	Alia	39	80000
22	Sid	41	82000
21	Abdul	39	58000

Show 25 ▼ per page

✓
2s

```
[1] import pandas as pd
from sklearn.cluster import KMeans
from sklearn.preprocessing import MinMaxScaler
from matplotlib import pyplot as plt
%matplotlib inline
```

✓
0s

```
3 df = pd.read_csv('/content/Kmeans_1BM20CS066.csv')
df.head(10)
```



	1	Name	Age	Income(\$)
0	2	Rob	27	70000
1	3	Michael	29	90000
2	4	Mohan	29	61000
3	5	Ismail	28	60000
4	6	Kory	42	150000
5	7	Gautam	39	155000
6	8	David	41	160000
7	9	Andrea	38	162000
8	10	Brad	36	156000
9	11	Angelina	35	130000



✓
0s

```
[4] scaler = MinMaxScaler()
scaler.fit(df[['Age']])
df[['Age']] = scaler.transform(df[['Age']])

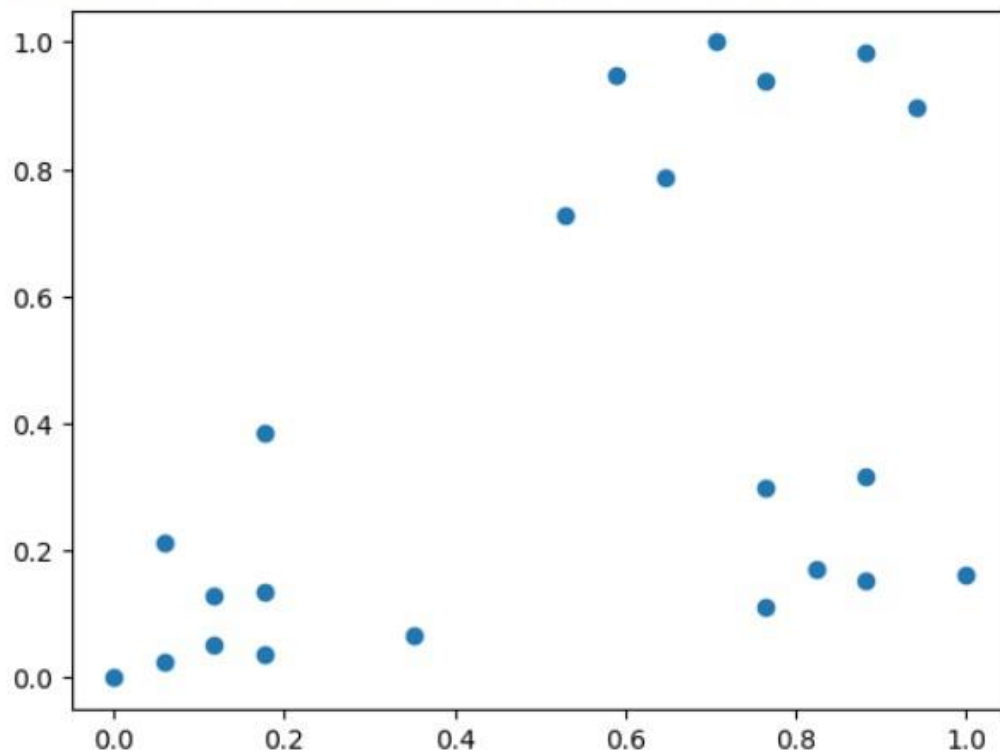
scaler.fit(df[['Income($)']])
df[['Income($)']] = scaler.transform(df[['Income($)']])
df.head(10)
```

	1	Name	Age	Income(\$)
0	2	Rob	0.058824	0.213675
1	3	Michael	0.176471	0.384615
2	4	Mohan	0.176471	0.136752
3	5	Ismail	0.117647	0.128205
4	6	Kory	0.941176	0.897436
5	7	Gautam	0.764706	0.940171
6	8	David	0.882353	0.982906
7	9	Andrea	0.705882	1.000000
8	10	Brad	0.588235	0.948718
9	11	Angelina	0.529412	0.726496



```
plt.scatter(df['Age'], df['Income($)'])
```

```
<matplotlib.collections.PathCollection at 0x7f43820d1a50>
```

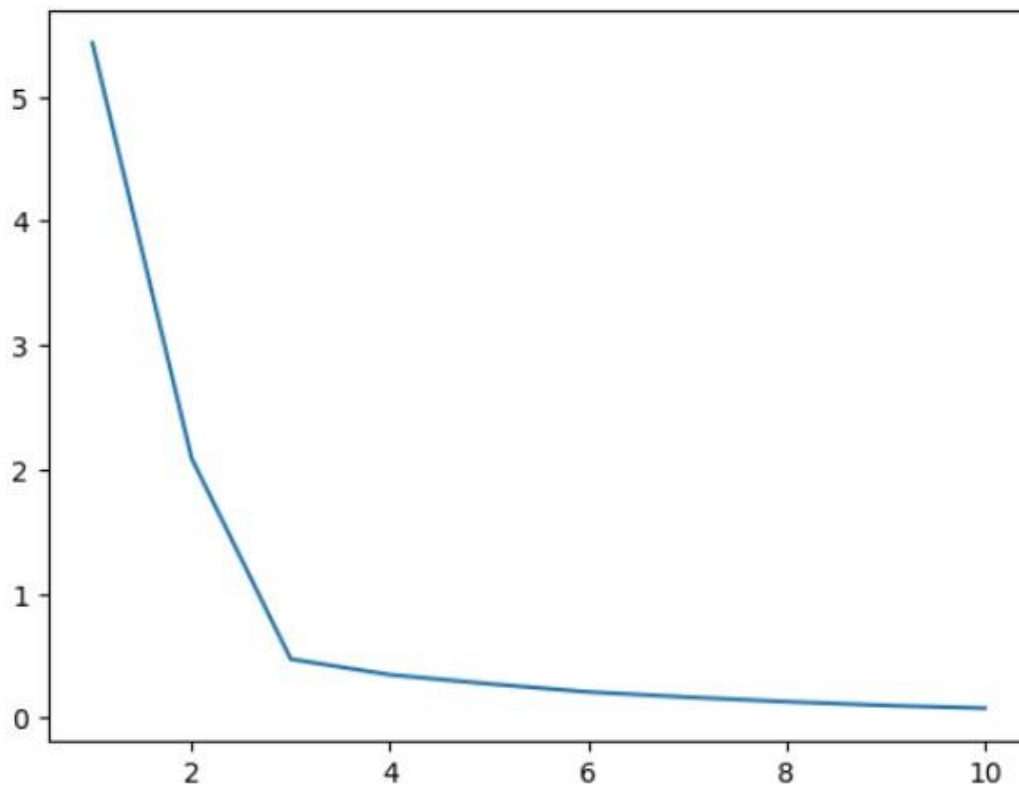


```
k_range = range(1, 11)
sse = []
for k in k_range:
    kmc = KMeans(n_clusters=k)
    kmc.fit(df[['Age', 'Income($)']])
    sse.append(kmc.inertia_)
sse
```

```
array([5.434011511988178,
       2.091136388699078,
       0.4750783498553096,
       0.3491047094419566,
       0.2798062931046179,
       0.2203764169077067,
       0.1685851223602976,
       0.13265419827245162,
       0.1038375258660356,
       0.08510915216361345])
```

```
plt.xlabel = 'Number of Clusters'
plt.ylabel = 'Sum of Squared Errors'
plt.plot(k_range, sse)
```

[<matplotlib.lines.Line2D at 0x7f438004a6e0>]



```
[8] km = KMeans(n_clusters=3)
km
```

KMeans
KMeans(n_clusters=3)

```
y_predict = km.fit_predict(df[['Age', 'Income($)']])
y_predict
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of 'n_init' will change from 10 to 'auto' in 1.4. Set the value of
warnings.warn(
array([1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2],
      dtype=int32)
```

```
[10] df['cluster'] = y_predict
df.head()
```

	1	Name	Age	Income(\$)	cluster
0	2	Rob	0.058824	0.213675	1
1	3	Michael	0.176471	0.384615	1
2	4	Mohan	0.176471	0.136752	1
3	5	Ismail	0.117647	0.128205	1
4	6	Kory	0.941176	0.897436	0

```
[11] df0 = df[df.cluster == 0]
df0
```

	1	Name	Age	Income(\$)	cluster
4	6	Kory	0.941176	0.897436	0
5	7	Gautam	0.764706	0.940171	0
6	8	David	0.882353	0.982906	0
7	9	Andrea	0.705882	1.000000	0
8	10	Brad	0.588235	0.948718	0
9	11	Angelina	0.529412	0.726496	0

```
✓ [12] df1 = df[df.cluster == 1]
0s df1
```

	1	Name	Age	Income(\$)	cluster
0	2	Rob	0.058824	0.213675	1
1	3	Michael	0.176471	0.384615	1
2	4	Mohan	0.176471	0.136752	1
3	5	Ismail	0.117647	0.128205	1
11	13	Tom	0.000000	0.000000	1
12	14	Arnold	0.058824	0.025641	1
13	15	Jared	0.117647	0.051282	1
14	16	Stark	0.176471	0.038462	1
15	17	Ranbir	0.352941	0.068376	1



```
✓ [13] df2 = df[df.cluster == 2]
0s df2
```

	1	Name	Age	Income(\$)	cluster
16	18	Dipika	0.823529	0.170940	2
17	19	Priyanka	0.882353	0.153846	2
18	20	Nick	1.000000	0.162393	2
19	21	Alia	0.764706	0.299145	2
20	22	Sid	0.882353	0.316239	2
21	21	Abdul	0.764706	0.111111	2

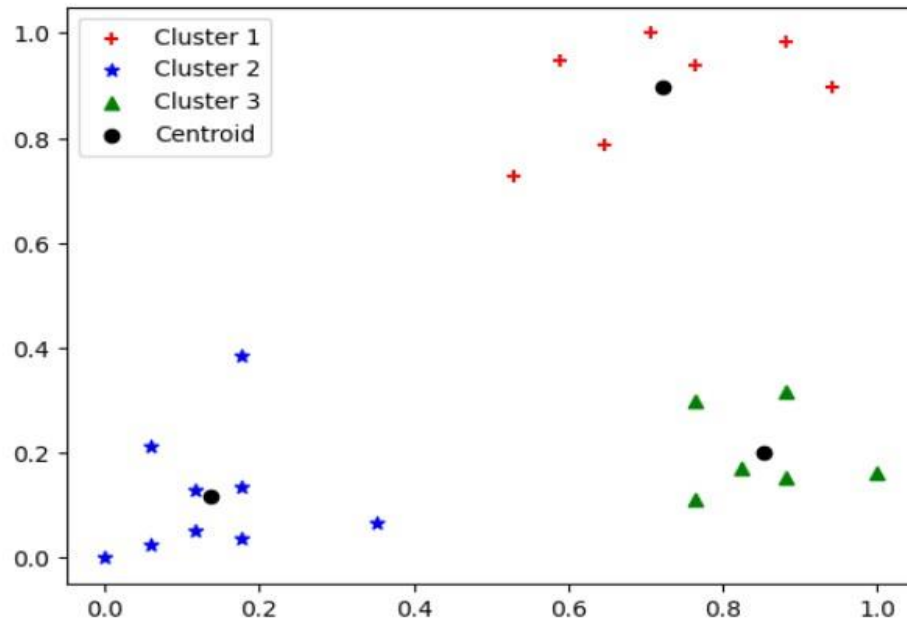


```
✓ [14] km.cluster_centers_
s
array([[0.72268908, 0.8974359 ],
       [0.1372549 , 0.11633428],
       [0.85294118, 0.2022792 ]])
```



```
[17] p1 = plt.scatter(df0['Age'], df0['Income($)', marker='+', color='red')
p2 = plt.scatter(df1['Age'], df1['Income($)', marker='*', color='blue')
p3 = plt.scatter(df2['Age'], df2['Income($)', marker='^', color='green')
c = plt.scatter(km.cluster_centers_[0], km.cluster_centers_[1], color='black')
plt.legend((p1, p2, p3, c),
           ('Cluster 1', 'Cluster 2', 'Cluster 3', 'Centroid'))
```

<matplotlib.legend.Legend at 0x7f437d4c73a0>



Program 8: KNN ALGORITHM

Dataset used: Iris dataset

Algorithm:

- Select the number K of the neighbor
- Calculate the Euclidean distance of K number of neighbors
- Take the K nearest neighbors as per the calculated Euclidean distance.
- Among these k neighbors, count the number of the data points in each category.
- Assign the new data points to that category for which the number of the neighbor is maximum.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

def most_common(lst):
    return max(set(lst), key=lst.count)

def euclidean(point, data):
    # Euclidean distance between points a & data
    return np.sqrt(np.sum((point - data)**2, axis=1))

class KNeighborsClassifier:
    def __init__(self, k=5, dist_metric=euclidean):
        self.k = k
        self.dist_metric = dist_metric

    def fit(self, X_train, y_train):
        self.X_train = X_train
        self.y_train = y_train

    def predict(self, X_test):
        neighbors = []
        for x in X_test:
            distances = self.dist_metric(x, self.X_train)
            y_sorted = [y for _, y in sorted(zip(distances, self.y_train))]
            neighbors.append(y_sorted[:self.k])
        return list(map(most_common, neighbors))
```



```
def evaluate(self, X_test, y_test):
    y_pred = self.predict(X_test)
    accuracy = sum(y_pred == y_test) / len(y_test)
    return accuracy

iris = datasets.load_iris()
X = iris['data']
y = iris['target']

# Split data into train & test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Preprocess data
ss = StandardScaler().fit(X_train)
X_train, X_test = ss.transform(X_train), ss.transform(X_test)

# Test knn model across varying ks
accuracies = []
ks = range(1, 30)
for k in ks:
    knn = KNeighborsClassifier(k=k)
    knn.fit(X_train, y_train)
    accuracy = knn.evaluate(X_test, y_test)
    accuracies.append(accuracy)

# Visualize accuracy vs. k
fig, ax = plt.subplots()
ax.plot(ks, accuracies)
ax.set(xlabel="k",
       ylabel="Accuracy",
       title="Performance of knn")
plt.show()
```

KNN

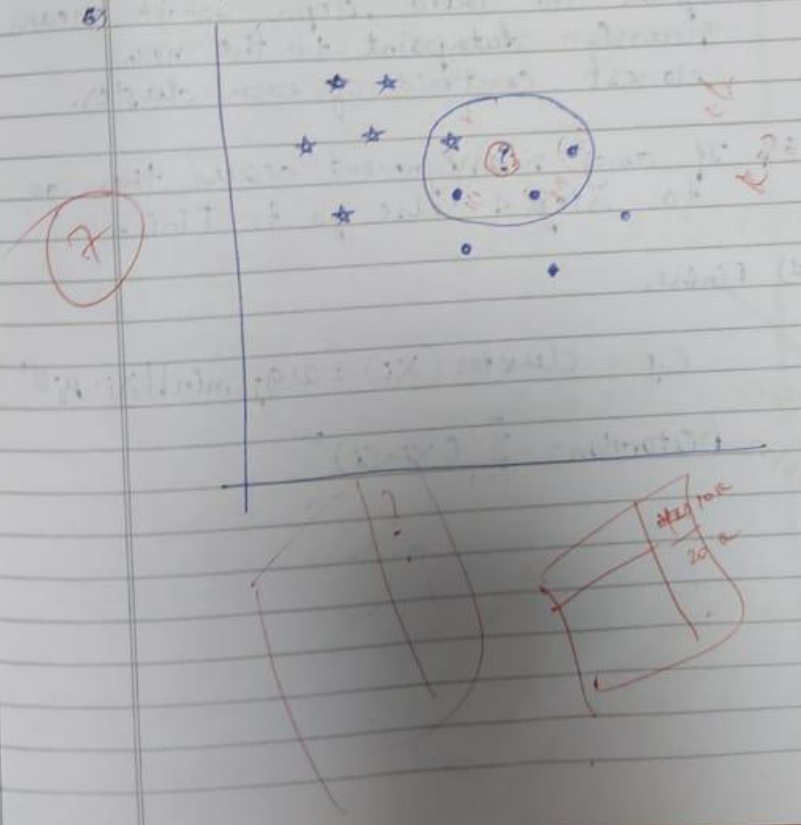
K-Nearest Neighbour

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Algorithm

- 1) Select the number K of the neighbours
- 2) Calculate the euclidean distance of K number of neighbours
- 3) Take the K nearest neighbours as per the calculated euclidean distance
- 4) Among these K neighbours, count the number of data points in each category
- 5) Assign the new data points to that category for which the number of the neighbour is maximum

Other
Steps



Program 9: Apply EM algorithm to cluster a set of data stored in a .CSV file. Compare the results of k-Means algorithm and EM algorithm.

Algorithm for k means clustering:

- Initialize k means with random values
- For a given number of iterations:
 - Iterate through items:
 - Find the mean closest to the item by calculating the euclidean distance of the item with each of the means
 - Assign item to mean
 - Update mean by shifting it to the average of the items in that clusters

Algorithm for EM algorithm:

- The very first step is to initialize the parameter values. Further, the system is provided with incomplete observed data with the assumption that data is obtained from a specific model.
 - This step is known as Expectation or E-Step, which is used to estimate or guess the values of the missing or incomplete data using the observed data. Further, E-step primarily updates the variables.
 - This step is known as Maximization or M-step, where we use complete data obtained from the 2nd step to update the parameter values. Further, M-step primarily updates the hypothesis.
 - The last step is to check if the values of latent variables are converging or not.

Dataset: Iris dataset

```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import sklearn.metrics as sm
import pandas as pd
import numpy as np

iris = datasets.load_iris()

X = pd.DataFrame(iris.data)
X.columns = ['Sepal_Length', 'Sepal_Width', 'Petal_Length', 'Petal_Width']

y = pd.DataFrame(iris.target)
y.columns = ['Targets']

model = KMeans(n_clusters=3)
model.fit(X)

plt.figure(figsize=(14,7))

colormap = np.array(['red', 'lime', 'black'])
```



```

# Plot the Original Classifications
plt.subplot(1, 2, 1)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y.Targets], s=40)
plt.title('Real Classification')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')

# Plot the Models Classifications
plt.subplot(1, 2, 2)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[model.labels_], s=40)
plt.title('K Mean Classification')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
print('The accuracy score of K-Mean: ', sm.accuracy_score(y, model.labels_))
print('The Confusion matrix of K-Mean: ', sm.confusion_matrix(y, model.labels_))

from sklearn import preprocessing
scaler = preprocessing.StandardScaler()
scaler.fit(X)
xsa = scaler.transform(X)
xs = pd.DataFrame(xsa, columns = X.columns)
#xs.sample(5)

from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=3)
gmm.fit(xs)

y_gmm = gmm.predict(xs)
#y_cluster_gmm

```

```

plt.subplot(2, 2, 3)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y_gmm], s=40)
plt.title('EM Classification')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')

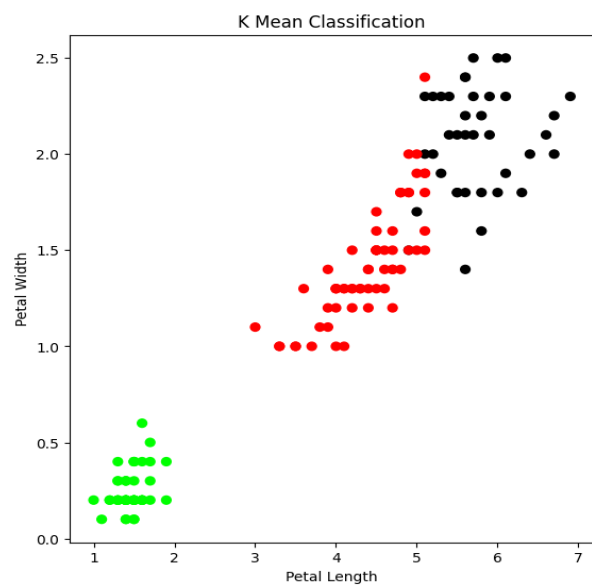
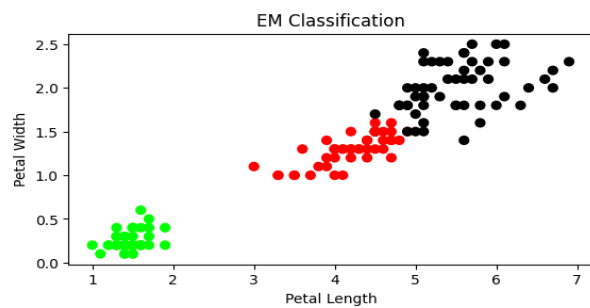
print('The accuracy score of EM: ', sm.accuracy_score(y, y_gmm))
print('The Confusion matrix of EM: ', sm.confusion_matrix(y, y_gmm))

```

```

The accuracy score of K-Mean: 0.24
The Confusion matrix of K-Mean: [[ 0 50  0]
 [48  0  2]
 [14  0 36]]
The accuracy score of EM: 0.3333333333333333
The Confusion matrix of EM: [[ 0 50  0]
 [45  0  5]
 [ 0  0 50]]

```

EM-Algorithm

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Algorithm

- 1) Given a set of incomplete data, consider a set of starting parameters
- 2) Expectation step (E-step): Using available data, guess (estimate) the values of the missing data
- 3) Maximization step (M-step): Complete the data generated after expectation (E) step in order to update the parameters.
- 4) Repeat 2 & 3 until converges

E step formula

$$Q(\theta, \theta^t) = \sum_{i=1}^n \sum_y p(y | x_i, \theta^t) \log P(x_i, y | \theta)$$

M step formula.

$$\theta^{(t+1)} = \arg \max_{\theta} Q(\theta, \theta^t)$$

①

Program 10: Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select the appropriate data set for your experiment and draw graphs.

Algorithm:

1. F is approximated near X_q using a linear function:

$$\hat{f}(x) = w_0 + \sum_{u=1}^k w_u K_u(d(x_u, x))$$

2. Minimize the squared error:

$$E_3(x_q) \equiv \frac{1}{2} \sum_{x \in k \text{ nearest nbrs of } x_q} (f(x) - \hat{f}(x))^2 K(d(x_q, x))$$

$$\Delta w_j = \eta \sum_{x \in k \text{ nearest nbrs of } x_q} K(d(x_q, x)) (f(x) - \hat{f}(x)) a_j(x)$$

3. It is weighted because the contribution of each training example is weighted by its distance from the query point.

Dataset: tip.csv



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

```
[ ] def kernel(point,xmat, k):
    m,n = np.shape(xmat)
    weights = np.mat(np.eye((m)))
    for j in range(m):
        diff = point - X[j]
        weights[j,j] = np.exp(diff*diff.T/(-2.0*k**2))
    return weights
```

```
[ ] def localWeight(point,xmat,yamat,k):
    wei = kernel(point,xmat,k)
    W = (X.T*(wei*X)).I*(X.T*(wei*yamat.T))
    return W
```

```

▶ def localWeightRegression(xmat,ymat,k):
    m,n = np.shape(xmat)
    ypred = np.zeros(m)
    for i in range(m):
        ypred[i] = xmat[i]*localWeight(xmat[i],xmat,ymat,k)
    return ypred

```

```

[ ] def graphPlot(X,ypred):
    sortindex = X[:,1].argsort(0)
    xsort = X[sortindex][:,0]
    fig = plt.figure()
    ax = fig.add_subplot(1,1,1)
    ax.scatter(bill,tip, color='green')
    ax.plot(xsort[:,1],ypred[sortindex], color = 'red', linewidth=5)
    plt.xlabel('Total bill')
    plt.ylabel('Tip')
    plt.show();

```

```

▶ data = pd.read_csv('/content/tips.csv')
bill = np.array(data.total_bill)
tip = np.array(data.tip)

mbill = np.mat(bill)
mtip = np.mat(tip)
m= np.shape(mbill)[1]
one = np.mat(np.ones(m))
X = np.hstack((one.T,mbill.T))

# increase k to get smooth curves
ypred = localWeightRegression(X,mtip,3)
graphPlot(X,ypred)

```

Locally Weighted Regression

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DATE: _____

Algorithm

- 1) Read the given data sample to x and the curve (linear or non linear) to y
- 2) Set the value for smoothing parameter or Free parameter say σ
- 3) Set the bias/Point of interest set x_0 which is a subset of x
- 4) Determine the weight matrix using
$$W(x, x_0) = e^{-\frac{(x - x_0)^2}{2\sigma^2}}$$
- 5) Determine the value of model term parameter β using
$$\hat{\beta}(x_0) = (x^T W x)^{-1} x^T W y$$
- 6) Prediction = $x_0^T \hat{\beta}$

