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MACHINE LEARNING LAB OBSERVATION

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 [8]: from sklearn.datasets import load_iris
        iris=load_iris()

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],

In [5]: type(iris)

Out[5]: function

In [12]: iris.keys()

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.

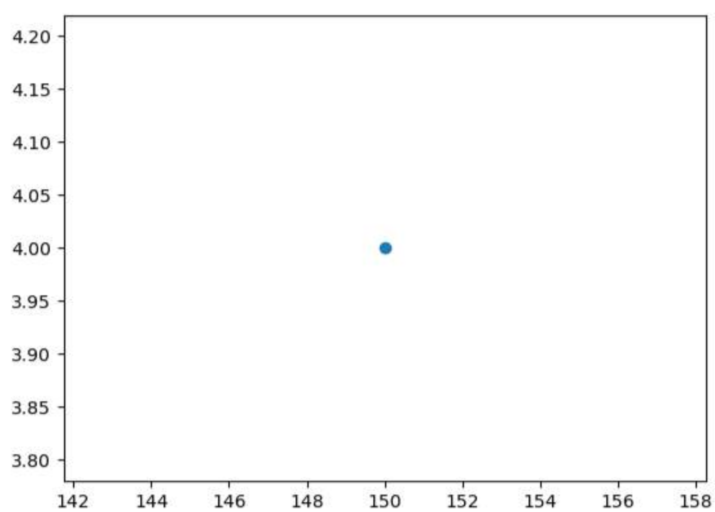
In [32]:
```
import numpy as np
np.bincount(iris.target)
```

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>
```

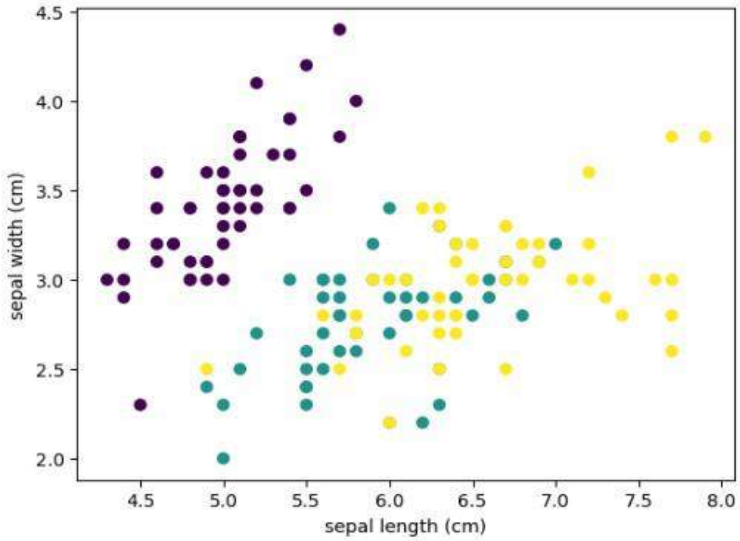


Scattered graph: with first two features (septal width vs septal length)
The three colors represents three different classes respectively.

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', 'proa
nthocyanins', '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-(Ø, Ø, Ø, Ø, Ø, Ø)

1. First training example X1=< Sunny, Warm. Normal, Strong Warm Same>. EnjoySport=+ve Observing.The first trainin example, it is clear that hypothesis h is too specific. None of the "Ø" constraints in h are satisfied by this example, so each is replaced by the next more general constraint that fits the example h1 = < Sunny, Warm, Normal, Strong Warm, Same>.

2.Consider the second training example x2 < Sunny, Warm, High, Strong, Warm, Same>. 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 h2 =< Sunny, Warm, ?, Strong,Warm, Same>

3. Consider the third training example x3< Rainy, Cold, High, Strong, Warm. Change EnjoySport ve. The FIND-S algorithm simply ignores every negative example. So the hypothesis remain as before, so 13=< Sunny, Warm, ?, Strong, Warm, Same>

4. Consider the fourth training example x4 <Sunny, Warm, High. Strong. Cool, Change, EnjoySport +ve. The fourth example leads to a further generalization of h as h4=< Sunny, Warm, ?, Strong, ?, ?>

5. So the final hypothesis is < Sunny, Warm, ?, Strong, ?, ?>

5/4/23

find -S algorithm

1) Initialize 'h' to most specific hypothesis in H
$h = \{\phi, \phi, \phi \ldots\}$

2) for each positive training instance 'x'
for each attribute constraint a_i in h
if constraint a_i is satisfied by 'x'
then do nothing
else
replace a_i in h by next
more general constraint that is replaced
by 'x'
$h, H = \{h_1, h_2, h_3, h_4\}$

3) Output hypothesis h.

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Q) Implement and demonstrate FIND S algorithm for finding most specific hypothesis

```
import csv
def update hypothesis (x, h)
  if h = = [ ]
    return x
  for i in range (0, len (h) ];
    if x[i], upper ()! = h[i]. upper ();
      h[i] = '?'
  return h
if _name_ = = "_main_":
  data = [ ]
  h = [ ]
  # reading csv file
  with open ("Desktop/find S.csv", 'r') as file
  reader = csv. reader (file)
    print ("Data")
  for row in reader.
    data.append (row)
    print (row)

  if data :
    for x in data
    if x[-1] . upper () = = "yes" . x.pop()
      h = update hypothesis (x, h)
        print ("H:", h)
```

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o/p

CREATING CSV FILE:

A1 fx 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							

+ Code + Text Connect

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

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

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
[ ] 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

100% $ % .0 .00 123 Defaul... 10 B I

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						

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

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

```
Mounted at /content/drive
```

```python
path ="/content/finds_1BM20CS066 - Sheet1.csv"
```

```python
data = pd.read_csv(path)
```

```python
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
```

```python
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']]
```

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

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

\+ Code + Text

```python
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.

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⇒ Candidate Elimination Algorithm

Initialize G to set of maximally general hypothesis in H
Initialize ~~A~~ S to 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 generalization 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 any other hypothesis in S

~~of~~ 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~~ member of S is more specific than h
- Remove from G any hypothesis that is less general than ~~an~~ another hypothesis in G

size	tank	fuel Economy	No. of passengers	Type	Target
Small	Available	High	4	economy	Y
Big	Available	low	2	Sports	N
Small	Available	High	4	economy	Y
Small	Not available	low	2	Sports	N
medium	Available	High	4	economy	Y

So = ⟨ø, ø, ø, ø, ø⟩
Go = ⟨?, ?, ?, ?, ?⟩

+ve S1 = Small, available, high, 4, economy
G1 = ?, ?, ?, ?, ?

-ve S_2 = Small, available, high, 4, economy
G_2 = (Small, ?, ?, ?, ?), (?, ?, high, ?, ?)
(?, ?, ?, 4, ?) (?, ?, ?, ? economy)

+ve S_3 = Small, available, high, 4, economy
G_3 = (Small, ?, ?, ?, ?) (?, ?, high, ?, ?)
(?, ?, ? 4, ?) (?, ?, ?, ?, economy)

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-ve S_4 = Small, available, high, 4, economy
G_4 = (?, ?, high, ?, ?)(?, ?, ? 4, ?) (?, ?, ?, ?, economy)
(Small, ?, ?, ? economy)

+ve S_5 = ?, available high, 4, economy
G_5 = (?, ?, high ? ?)(? ? ?, 4, ?) (? ? ? ? economy)

12/4/23

CREATING CSV FILE:

enjoysport.csv

	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.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:

File Edit View Insert Format Data Tools Extensions Help

100% $ % .0 .00 123 Defaul... 10 B I

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						

```
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']
```

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

 Steps of Candidate Elimination Algorithm 5
['?' '?' '?' '?' '?']
[['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?']]
```

```python
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

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

sample.

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 ← the attribute from Attributes that best* classifies Examples
- The decision attribute for Root ← 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* $_{vi}$, be the subset of Examples that have value v_i for *A*
- If *Examples* $_{vi}$, 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* $_{vi}$, Targe_tattribute, Attributes – {A}))
- End
- Return Root

19/4/23

⇒ Decision Tree

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

$$= 0.94$$

$$Entropy(S) = -P_+ \log_2 P_+ - P_\ominus \log_2 P_\ominus$$

Information Gain $G(S, A)$

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

G(S, outlook)

$$\Rightarrow E(S) - [\,5/14 * E(\text{outlook} = \text{sunny}) + 4/14 * E(\text{outlook} = \text{overcast}) + 5/14 * E(\text{outlook} = \text{rain})\,]$$

$$= E(S) - [[\,5/14 * E(2+, 3-)\,] + 4/14 * E(4+, 0-)\,] + 5/14 * E(3+, 2-)\,]$$

$$= E(S) - [\,(5/14 * \left(-\tfrac{2}{5}\log_2\tfrac{2}{5}\right) + \left(-\tfrac{3}{5}\log_2\tfrac{3}{5}\right)\,] + \left(\tfrac{4}{14} * \left(-\tfrac{4}{4}\log_2\tfrac{4}{4}\right) + \left(-\tfrac{0}{4}\log_2\tfrac{0}{4}\right)\right] + \left(\tfrac{5}{14} * \left(-\tfrac{3}{5}\log_2\tfrac{3}{5}\right) + \left(-\tfrac{2}{5}\log_2\tfrac{2}{5}\right)\right]$$

~~0.86~~

$$= 0.247$$

Date:

G(S, Temperature) ⇒

Temp

Hot = 4 (2+, 2-)

mild = 6 (4+, 2-)

cool = 4 (3+, 1-)

$$\Rightarrow E(S) - \left[\left(\frac{4}{14} * E\ \text{Hot}\right) + \left(\frac{6}{14} * E\ \text{mild}\right) + \frac{4}{14} * E(\text{cool})\right]$$

$$\Rightarrow E(S) - \left[\frac{4}{14} * \left(-\frac{2}{4}\log_2\frac{2}{4}\right) + \left(-\frac{2}{4}\log_2\frac{2}{4}\right)\right.$$

$$\frac{6}{14} * \left(-\frac{4}{6}\log_2\frac{4}{6}\right) + \left(-\frac{2}{6}\log_2\frac{2}{6}\right)$$

$$+ \frac{4}{14} * \left(-\frac{3}{4}\log_2\frac{3}{4}\right) + \left(-\frac{1}{6}\log_2 + \frac{1}{6}\right)$$

$$\Rightarrow 0.029$$

Page No.:
Date:

YOUVA

G(S, Humidity)

High(3+, 4-)

Normal(6+, 1-)

$$\Rightarrow E(S) - \left[\frac{7}{14} * \left(-\frac{3}{7}\log_2 \frac{3}{7}\right) + \left(-\frac{4}{7}\log_2 \frac{4}{7}\right)\right]$$

$$+ \frac{7}{14} * \left(-\frac{6}{7}\log_2 \frac{6}{7}\right) + \left(-\frac{1}{7}\log_2 \frac{1}{7}\right)\Big]$$

$$= 0.152$$

G(S, wind)

Weak(6+, 2-)

Strong(4+, 2-)

$$\Rightarrow E(S) - \left[\frac{8}{14} * \left(\frac{-6}{8}\log_2 \frac{6}{8}\right) + \left(\frac{-2}{8}\log_2 \frac{2}{8}\right)\right]$$

$$+ \frac{6}{14} * \left(\frac{-4}{8}\log_2 \frac{4}{8}\right) + \left(\frac{-2}{6}\log_2 \frac{2}{6}\right)\Big]$$

$$= 0.048$$

Elpha
19/4/23

3/5/23

⇒ ID3 Algorithm

ID3 (Examples, Target_attributes, Attributes)

- Create a Root node for tree
- If all Examples are positive, Return single node tree Root with label = +
- If all Examples are negative, Return single-node tree Root with label = -
- If attribute is empty, Return single-node tree Root, with label = most common value of Target_attribute in example

- Otherwise begin
  - A ← attribute from attribute from Attributes best classifies Examples
  - the decision attribute for Root ← A
  - for each possible value, v_i, of A,
    - Add new tree branch below Root, corresponding to test $A = v_i$
    - let Examples v_i be 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 subtree ID3 (Examples v_i, Target_attributes, Attributes - {A}))
- End
- Return Root

8

3/5/23

A1 fx 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					

ntime Tools Help All changes saved

\+ 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]
```python
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]
```python
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]
```python
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):
    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]
```
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)
```

```
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 a0 and a1.
- Calculate the cost for each number and add them.
- Update the values of a0 and a1.

17/5/22

⇒ Linear Regression

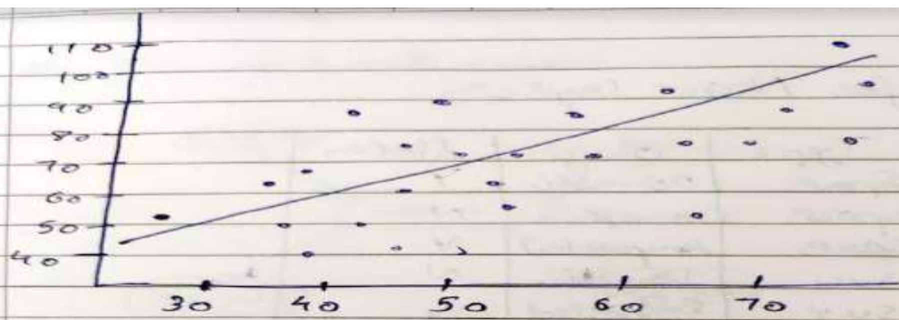
1. Reading and understanding data
2. Visualizing data (Exploratory Data analysis)
3. Data preparation
4. Splitting data into training and test sets
5. Building linear model
6. Residual analysis of train data
7. Making predictions using final model and evaluation

$$\hat{y}_i = b_1 x_i + b_0$$

$$b_0 = \frac{(\Sigma y)(\Sigma x^2) - (\Sigma(x))(\Sigma xy)}{n(\Sigma x^2) - (\Sigma x)^2}$$

$$b_1 = \frac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{n(\Sigma x^2) - (\Sigma x)^2}$$

```
num + = (x[i] - x_mean) * y[i] - Y_mean ]
den + = (x[i] - x_mean) ** 2
m = num/den
c = Y_mean - m * x_mean.
```



O/P seen
12/6/23

Dataset

Years of experience	Salary
1.1	39343
1.3	46205
1.5	37731
2	43525
2.2	39891
2.9	56642
3	60150
3.2	54445
3.2	64445

```python
import numpy as np
import matplotlib.pyplot as plt
```

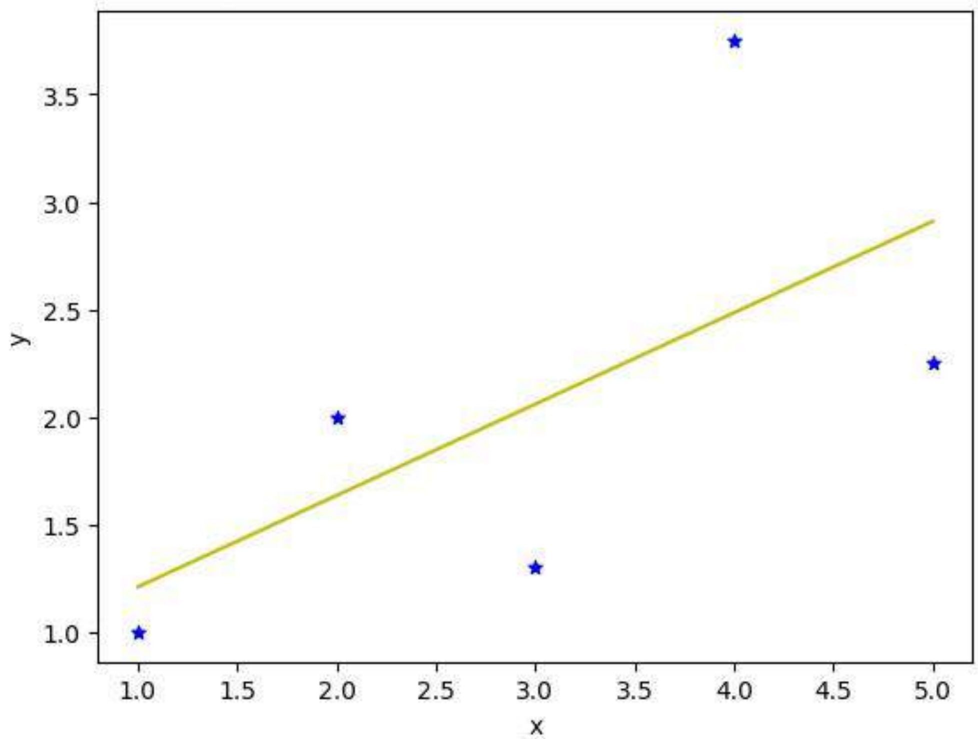
```python
def plot_regression_line(x, y, b):

  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()
```

```python
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)
```

```python
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()
```

```python
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 = 0.785000000000001
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 tes 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:

Formula for naive bayes classifier is as follows → $P(A|B)= \dfrac{P(B|A)P(A)}{P(B)}$

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.

untime Tools Help All changes saved

+ Code + Text

```
[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]
```

```python
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
```

```python
            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
```

```python
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 %
```

1/5/23

⇒ Naive Bayesian classifier

1. Convert data set into frequency table
2. Create likelihood table by finding probability
3. use Naive Bayesian equation to calculate posterior probability

Bayes theorem to calculate posterior probability of each candidate hypothesis is h map is an MAP hypothesis

Provided

$$h_{map} = \underset{h \in H}{\arg\max}\ P(h/D)$$

$$= \arg\max \frac{P(D/h)\ P(h)}{P(D)}$$

$$= \arg\max P(D/h)\ P(h)$$

Bayes theorem stated as

$$P(h/D) = \frac{P(D/h)\ P(h)}{P(D)}$$

Where

$P(h/D)$ is probability of hypothesis h given data D. This is called posterior probability.

$P(D/h)$ is probability of data d given hypothesis h was true

$P(h)$ is probability of hypothesis h being true. This is called prior probability of h.

$P(D)$ is probability of data. This called prior probability of D.

dataset for Naive Bayesian.

Color	Type	Origin	Stolen
Red	Sports	Domestic	Y
Red	Sports	Domestic	N
Red	Sports	Imported	Y
yellow	SUV	Domestic	N
yellow	SUV	Imported	Y
yellow	SUV	Domestic	N
yellow	SUV	Imported	N
yellow	Sports	Imported	Y

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:

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

⇒ K-Means Algorithm

Step 1:
Select ~~number~~ number K to decide no. of clusters

Step 2:
Select random K points or centroids

Step 3:
Assign each data point to their closest centroid, which will form predefined K clusters.

Step 4:
Calculate variance and place new centroid of each cluster

Step 5:
Repeat step 3 steps which means reassign each data point to new closest centroid of each cluster.

Step 6:
If any reassignment occurs, go to step-4 else go to finish.

Step-7:
Model is ready.

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

[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

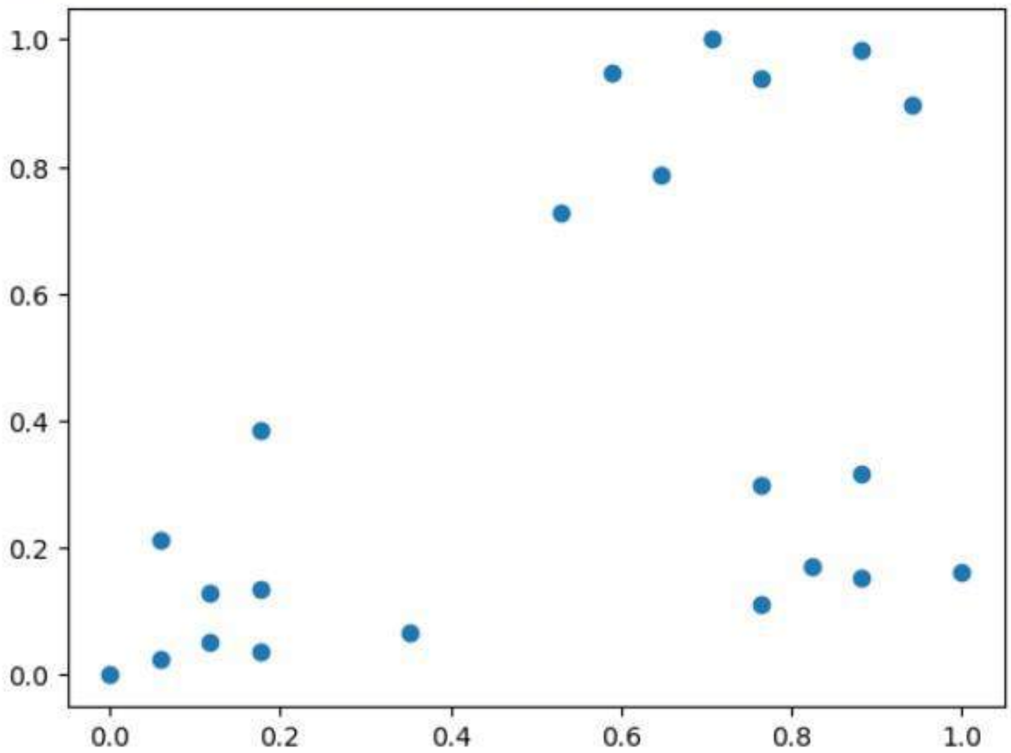
[4]
```
scaler = MinMaxScaler()
scaler.fit(df[['Age']])
df[['Age']] = scaler.transform(df[['Age']])

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>
```

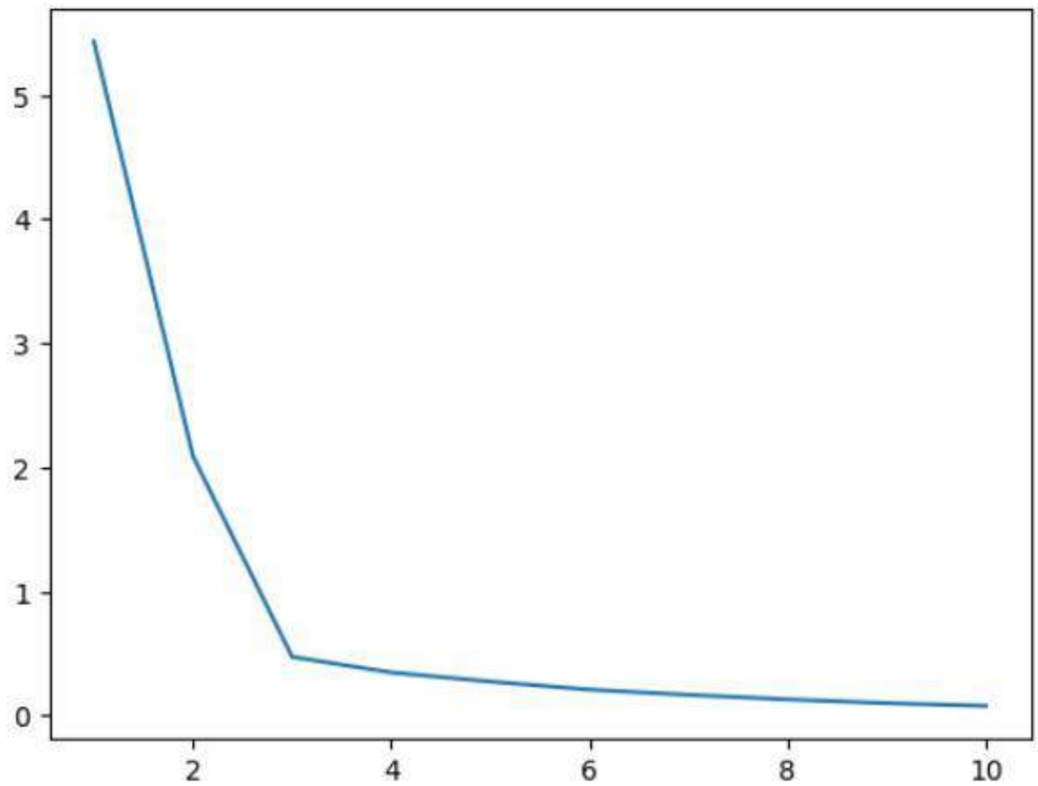



```
k_range = range(1, 11)
sse = []
for k in k_range:
    kmc = KMeans(n_clusters=k)
    kmc.fit(df[['Age', 'Income($)']])
    sse.append(kmc.inertia_)
sse
```

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

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

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



[8]

```python
km = KMeans(n_clusters=3)
km
```

```
▾ KMeans
KMeans(n_clusters=3)
```

```python
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, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2],
      dtype=int32)
```

[10]

```python
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]

```python
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]
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]
df2
```

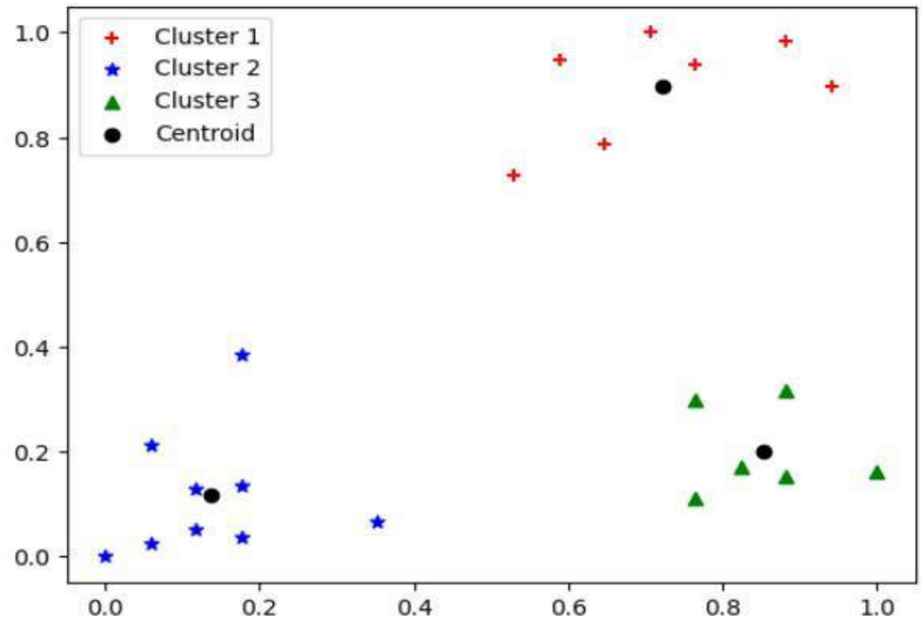
	1	Name	Age	Income($)	cluster
16	18	Dipika	0.823529	0.170940	2
17	19	Priyanka	0.882353	0.153846	2
18	20	Nick	1.000000	0.162393	2
19	21	Alia	0.764706	0.299145	2
20	22	Sid	0.882353	0.316239	2
21	21	Abdul	0.764706	0.111111	2

[14]
```
km.cluster_centers_
```

```
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

datasetAlgorithm:

- 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()
```

⇒ K - Nearest Neighbor (KNN)

Step 1:
first step of KNN, we must load training as well as test data.

Step 2:
Next, we need to choose value of k i.e nearest data points. k can be any integer

Step 3:
for each point in test data do following -

3.1 → calculate distance between test data and each row of training data with help of any method namely: Euclidean, manhattan or Hamming distance. most commonly used method is Euclidean

3.2 → Based on distance value, sort them in ascending order

3.3 → Next it will choose top k rows from sorted array

3.4 → Now, it will assign class to test point based on most frequent class of these rows

Step - 4 : End

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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.

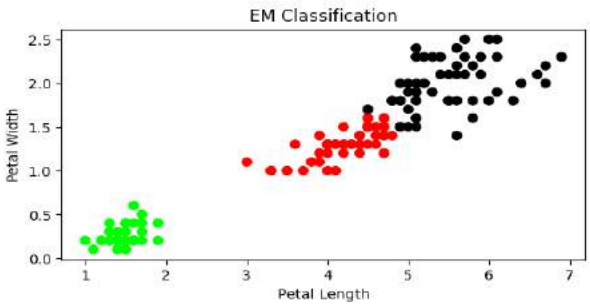
Dataset: Iris dataset

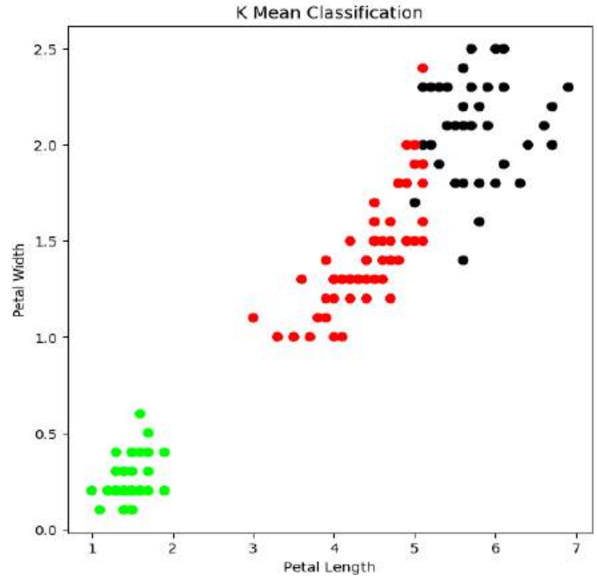
```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import sklearn.metrics as sm
import pandas as pd
import numpy as np

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 matrixof 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 matrixof 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 Classification
Petal Width
Petal Length
2.5
2.0
1.5
1.0
0.5
0.0
1
2
3
4
5
6
7


K Mean Classification
Petal Width
Petal Length
2.5
2.0
1.5
1.0
0.5
0.0
1
2
3
4
5
6
7

⇒ E-M Algorithm

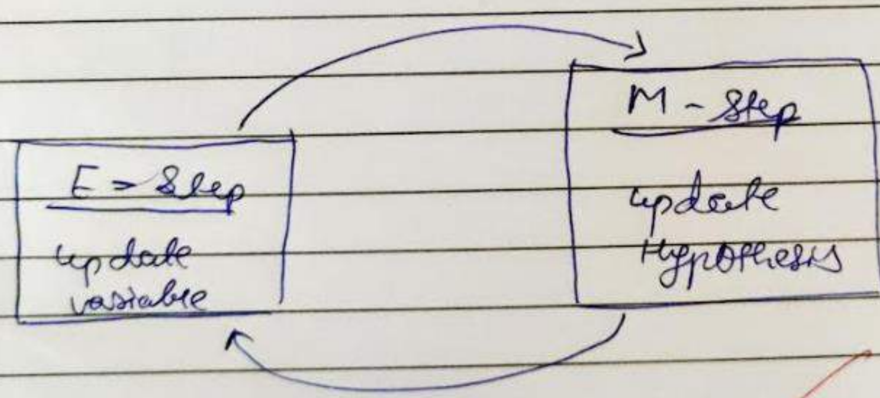
Expectation Maximization

1. Given set of incomplete data, consider a set of starting parameters.

2. Expectation step (E-step): using observed available data of dataset, estimate (guess) value of missing data

3. maximization step (M-step): complete data generated after expectation (E) step is used in order to update parameters

4. Repeat step 2 and step 3 until converge



O/P Sir
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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 Xq 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:**

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

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

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,ymat,k):
         wei = kernel(point,xmat,k)
         W = (X.T*(wei*X)).I*(X.T*(wei*ymat.T))
         return W
```

```python
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
```

```python
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();
```

```python
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

1. Read Given data Sample to X and Curve (linear or non linear) to Y

2 Set value for ~~the~~ Smoothening parameter or free parameter Say K

3. Set bias / point of interest set X0 which is subset of X

4. Determine weight matrix

$$\omega(x, x_0) = e^{-\frac{(x_0 - x_0)^2}{2k^2}}$$

5. Determine value of model term parameter

$$\hat{\beta}(x_0) = (X^T W X)^{-1} X^T W Y$$

6. prediction = X0 * β

O/p ✓ 7/6/23