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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.

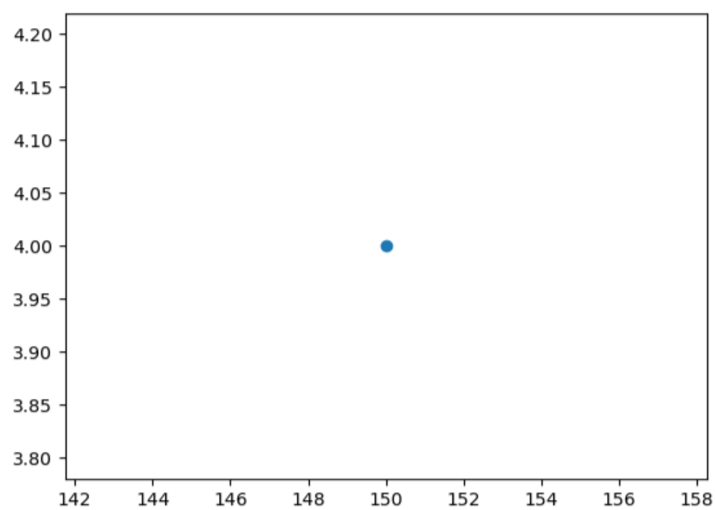
In [32]:
```
import numpy as np
np.bincount(iris.target)
```

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

In [42]:
```
import matplotlib.pyplot as plt

plt.scatter(n_samples,n_features)
```

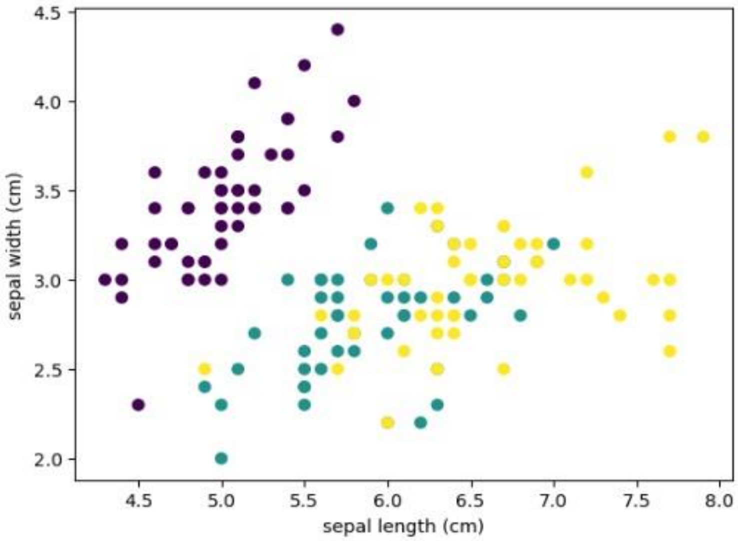
Out[42]:
```
<matplotlib.collections.PathCollection at 0x1d1c8c45550>
```




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, ?, ?>

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# Lab Program 1
## Find S algorithm

Dataset : enjoysports. csv file

| Sample | Sky | Air temp | Humidity | Wind | Water | Forcast | enjoy sports? |
|---|---|---|---|---|---|---|---|
| 1) | Sunny | warm | normal | Strong | warm | Same | Yes + |
| 2) | Sunny | warm | high | Strong | warm | Same | Yes + |
| 3) | Sunny | cold | high | Strong | warm | Same | No - |
| 4) | Sunny | warm | high | Strong | warm | same | Yes + |

* Find S algorithm: Is a basic-concept-learning algo in ML.

* It finds what is most-specific hypothesis that fits all the "Positive" examples.

* This algo starts with the most specific hypothesis and moves to the most general hypothesis.

? → accepts any value General.
Ø → accepts No value. specific (value)
MGD → (?? ? ?) accepts everything.
MSD → (Ø Ø Ø Ø) accepts None → Null.

initial hypo : { Ø, Ø, Ø, Ø }

iteration 1 h1 = < 'Sunny', 'warm', 'normal', 'strong', 'warm' 'same' > +ve
iteration 2 h2 = < 'Sunny', 'warm', 'high', 'strong', 'warm', 'same'
iteration 3 h3 = < 'Raing', 'cold', 'high', 'strong', 'warm', 'change' >
iteration 4 h4 = < 'Sunny', 'warm', 'high', 'Strong', 'cool', 'Change' >.
(Not considered)

1) Initialize 'h' to the most specific hypo in H.

2) For each positive training instance 'x' each attribute constraint ai in h if the constraint ai is set satisfied by 'x' then do nothing. else replace ai in h by the next more general constraint that is required by 'x' hypothese h.

3) Output hypothesis h.

Program

```
import csv
def updateHypothesis(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 = []
    with open ("Desktop FindS.csv", 'r') as file:
        reader = csv.reader (file)
        print ("Data:")
        data.append (row)
        print (row)
    if data:
        for x in data
        if x[-1].upper() == "Yes" : x.pop()
        updateHypothesis(x,h)
    print ("\n Hypothesis :", h)
```

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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 | | | | | | | |

FINDS_1BM20CS066.ipynb

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

```python
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).
```

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

Double-click (or enter) to edit

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

```python
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
```

```python
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']]
```

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

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

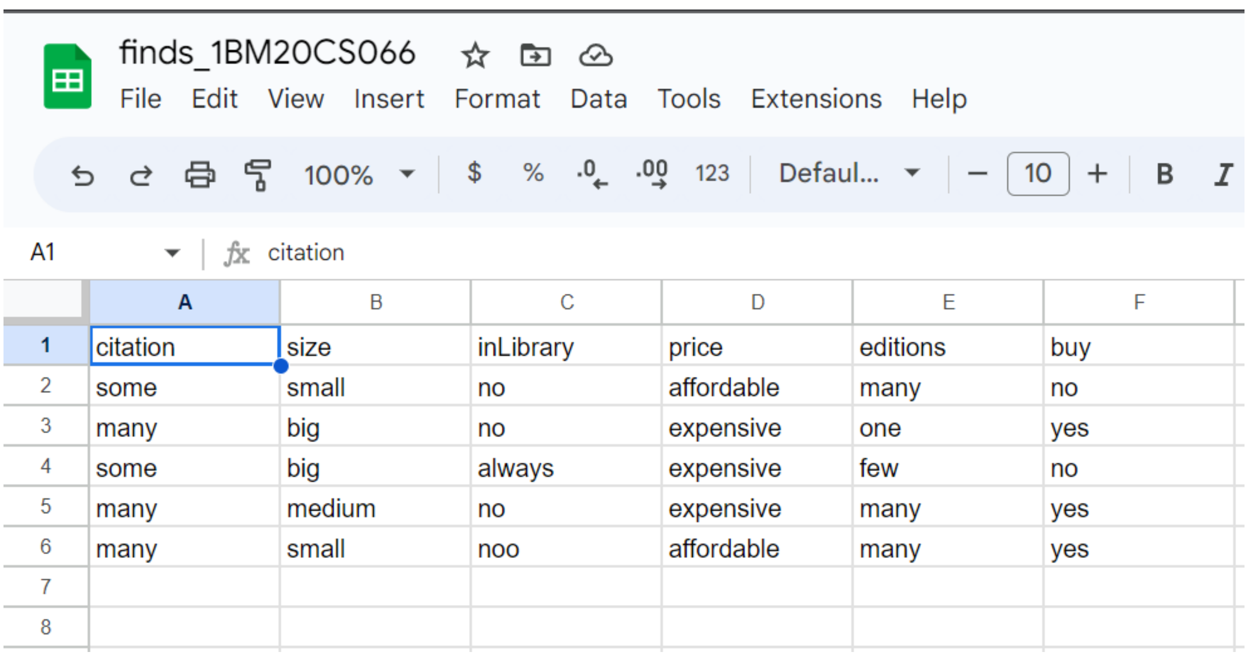
```
[ ]  def findS(c,t):
         for i, val in enumerate(t):
             if val == "Yes":
                 specific_hypothesis = c[i].copy()
                 break

         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




| | 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/finds_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.

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## Lab Program 2
## Candidate Elimination Algorithm

| Example | Sky | Air temp | Humidity | Wind | Water |
|---|---|---|---|---|---|
| 1 | Sunny | warm | Normal | Strong | warm |
| 2 | Sunny | warm | high | strong | warm |
| 3 | Raing | cold | high | strong | warm |
| 4 | Sunny | warm | high | strong. | cool. |

| forcast | Enjoy sport |
|---|---|
| Same | Yes +ve |
| Same | Yes +ve |
| Change | No -ve |
| Change | Yes. +ve |

Target variable.
6 attributes | candidate
concept learning

gives out binary results.
Considers both negative and Positive values.

To find consistent hypothesis for a given solution of training example
most General $G_0 = < ?, ?, ?, ?, ?, ? >$
Most Specific $S_0 = < \phi, \phi, \phi, \phi, \phi, \phi >$
Start from Generic Boundary,
first takes generic attribute values.
Whenever matches retain generic values if hypothesis matches expected is +ve and outcome +ve.

$G_1 = G_0$

Null value in $S_0$ is replaced by $S_1$.

$S_0 = < \phi \phi \phi \phi \phi \phi >$

No match → negative classification

* All question marks match with example, hence +ve classification. Target variable = +ve ⇒ GB

* All null values doesn't match, hence -ve Classifier. But expected = +ve classifier, therefore it is inconsistent hypothesis. When inconsist exist write next general hypothesis that is:

→ Replace Null values by 1st examples.

I) $G_1$ = < ?, ?, ?, ?, ?, ? >
$S_1$ = < Sunny, warm, Normal, Strong, warm, same >

II) $G_1$ = < ? ? ? ? ? ? >
Consider prev generic hypothesis.
$S_2 = G_1$
if generic +ve → retain
if match retain
if Target value -ve → Start from S
if Target value +ve → Start from G

$S_2$ = < Sunny, warm, ?, Strong, warm, same >

* GB, all ? matches with $S_1$, hence +ve Classification and exped.

* SB, when inconsistency make it General (?)

Target value

III) $S_3$ = < Sunny, warm, ?, Strong, warm, same > -ve
$G_3$ = { < Sunny, ?, ?, ?, ?, ? > }.

* Since all values are generic in Previous hypothesis, only Posible when example is +ve. and if there exists inconsistency, then all hypothesis which are Consistent with all the training examples seen now.

* ? match with all the attribute but expected -ve, hence inconsistency.

* All hypothesis which are consistent till now.

→ To do that, consider 1 ? at a time.

Program

```
import numpy as np
import Pandas as pd.
data = Pd. DataFrame (data=pd.read_csv(enjoysport.csv))
Concepts = np.array (data.iloc [:, 0, -1])
print (Concepts)
target = np.array(data.iloc[:0, -1]).
print (general_h)
print (specific_h) .
```

—— x ——

$X_4$ (+)

$S_4$ = < ?, large, light, ?, thick >

$G_4$ = < ? ? light, ? ? > , < ? ? ? ? thick >

Dataset

| Size | Trunk | Fuel economy | No of Passengers | Type | Target value. |
|---|---|---|---|---|---|
| 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 |

$G_0$ = < ?, ?, ?, ?, ? >

$S_0$ = < $\phi$, $\phi$, $\phi$, $\phi$, $\phi$ >

$S_1$ = < small, available, high, 4, economy >

$G_1$ = < ?, ?, ?, ?, ? >

$S_2$ = < Small, ? high, 4, economy >

$G_2$ = { < small, ?, ?, ?, ? > ; < ?, ?, high, ?, ? > ;
{ < ?, ?, ? 4, ? > ; < ? ? ? ? economy. }

S3 = < small , ? , high, 4, economy >

G3 = < small, ?, ?, ?, ? > ; < ?, ?, high, ?, ? > ;
< ? ? ? 4 ? > ; < ? ? ? ? economy >.

S4 = < ?, ?, high, 4, economy >

G4 = { < ?, ?, high, ?, ? > ; < ?, ?, ?, 4, ? > ;
< ? ? ? ? economy >.

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CREATING CSV FILE:

enjoysport.csv

File Edit View Insert Format Data Tools Extensions Help

|   | 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
```

```python
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', '?', '?', '?', '?']]
```

[ ]

```python
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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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']
```

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

```
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 ← 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

Date
Page 9

Decision Tree - Play Glof

1)

| Day | Outlook | Temp | Humidity | Wind | Play |
| --- | --- | --- | --- | --- | --- |
| 1 | Sunny | Hot | high | weak | No |
| 2 | Sunny | Hot | high | Strong | No |
| 3 | Overcast | Hot | high | weak | Yes |
| 4 | Rain | Mild | high | weak | Yes |
| 5 | Rain | cool | Normal | weak | Yes |
| 6 | Rain | Cool | Normal. | Strong | No |
| 7 | Overcast | cool | Normal | Strong | Yes |
| 8 | Sunny | Mild | high | weak | No |
| 9 | Sunny | Cool | Normal | Weak | Yes |
| 10 | Rain | Mild | Normal | weak | Yes |
| 11 | Sunny | Mild. | Normal | strong | Yes |
| 12 | Overcast | Mild | high | Strong | Yes |
| 13 | Overcast | hot | Normal | weak | Yes. |
| 14 | Rain | mild. | High. | Strong. | No |

$= \left(-9/14(-0.6374)\right) + \left(-5/14(-1.9854)\right)$

$= (0.941)$

Information Gain: $G(S, A, T)$

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

$$\text{Entropy}(S) = -P_{\oplus} \log_2 P_{\oplus} - P_{\ominus} \log_2 P_{\ominus}$$

$$G(S, temp) = E(S) - \left[ \frac{4}{14} * E(temp = hot) + \frac{6}{14} * E(temp = Mild) + \frac{9}{14} * E(temp = cool) \right]$$

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

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

$$\left[ \frac{9}{14} * \left( \frac{-3}{4} \log_2 \frac{3}{4} \right) + \left( \frac{-1}{4} \log_2 \frac{1}{4} \right) \right]$$

$$= 0.94 - 0.969$$

$$= \boxed{0.029}$$

$$G(S, Humidity) = 0.151 \quad Entropy(S)$$

$$= -(7|14) entropy(S_{high}) - (7|14) entropy(S_{normal})$$

$$= 9.40 - (7|14) .985 - (7|14) .592$$

$$= \boxed{0.0489}$$

Bw 19/4/23

$$G(S, Wind) = Entropy(S) - (8|14) entropy(S_{weak}) - (6|14) entropy(S_{strong})$$

$$= 0.940 - (8|14) 0.811 - (6|14) 1$$

$$= \boxed{0.48}$$

Algorithm

ID3 (Example, Target-attribute, attribute)

* Create a root node for the tree.

* If all examples are +ve,
  return the singlenode tree
  Root with label = +ve.

* If all examples are -ve,
  return the singlenode tree
  Root with label = -ve.

* Otherwise Begin,

→ A ← the attribute from attributes that best* Classifies examples.

→ The decision attribute for root ← A

→ Add a new tree-branch below root, corresponding to the test A = Vi

→ Let example Vi, be the subset of example that have values Vi from A.

→ If example Vi, that is empty.

• Then a below this new branch at a leaf node with label S' most Common value of Target-attribute in example.

→ Else, below this new branch add the subtree ID3 (examples vi, target_attribute, attribute - {A})

* end

* Return Root.

O/p Seen
17/5/23.

1BM20CS066_ID3

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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 | | | | | |

ID3.ipynb

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Files

..

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]
```python
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]
```python
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 | | |

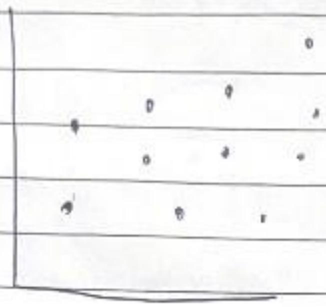
**ALGORITHM:**

- 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.

# Linear Regression

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

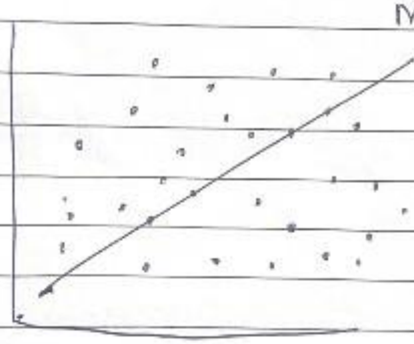
$$b_1 = \frac{n(\sum_i xy) - (\sum_i x)(\sum_i y)}{n(\sum_i x^2) - (\sum_i x)^2}.$$



$Y = mx + C.$

$m = 1.2873$

$C = 9.908.$



A straight-line equation involving slope $(dy/dx)$ and Y-intercept

$Y = mx + C.$

$y =$ dependent value of $x$.

$Y = b_1 x_i + b_0.$

$Y_i$ = Predicted Y value for observation

$b_0$ = Estimate of Regression intercept.

$b_1$ = Estimate of regression slope.

$x_i$ = Input.

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

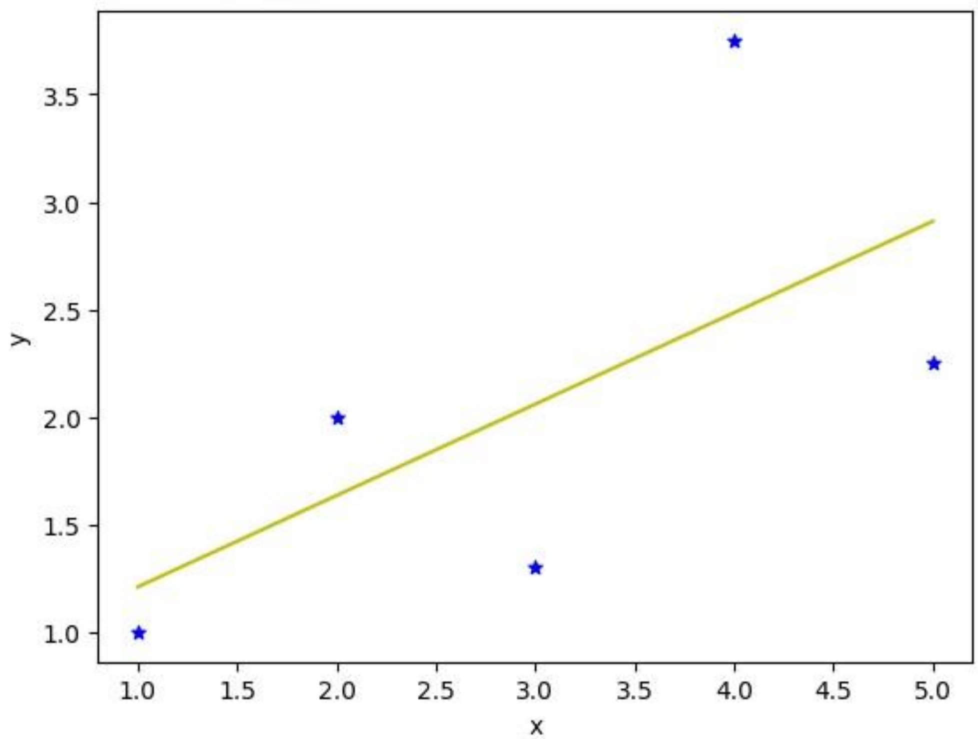
```
[ ]  def plot_regression_line(x, y, b):

       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()
```

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

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.

1BM20CS066_NBC.ipynb

File Edit View Insert Runtime Tools Help All changes saved

Files

sample_data

1BM20CS066_NBC.csv

+ 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 %
```

# Naive Baye's

Training Dataset

Color Type Origin Stolen.

[Red, Sports, domestic, Yes]
[Red, Sports, Domestic, No]  Size = 6
[Red, Sports, Domestic, Yes]
[Yellow, Sports, Domestic, No]
[Yellow, Sports, Imported, Yes]
[Yellow, SUV, Imported, No]

Test Data Set.

| Color | Type | Origin | Stolen. |
|---|---|---|---|
| Yellow | SUV | imported | Yes |
| Yellow | SUV | Domestic | No |
| Red | SUV | Imported | No |
| Red | Sports | Imported | Yes. |

Size = 4

| Target | Count | Probability. |
|---|---|---|
| Yes | 3 | 1/2 |
| No | 3 | 1/2 |

| Instance | Prediction | Target. |
|---|---|---|
| 1 | No | Yes |
| 2 | No | No |
| 3 | No | No |
| 4 | Yes | Yes. |

Accuracy : 75.0%

$$P(h|D) = \frac{P(D|h) \cdot P(h)}{P(D)}$$

$P(h|D)$ = Posterior Probability

$P(h)$ = Prior Probability

$P(D)$ = Probability over data set

$P(D|h)$ = Current Probability.

O/p - [illegible]

12/5/23

## 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

# K-means Algorithm

① Select the number K to decide the number of clusters.

② select random K points or centroids.

③ Assign each data point to their closest centroid which will form the Predefined K cluster.

④ Calculate the variance and new place centroid of each cluster.

⑤ Repeat the third steps, which means re-assign each datapoint to new closest centroid

⑥ If any re-assignment occurs, go to step 4 else FINISH

⑦ Model is ready.

GMM - Gausian Mixture model.

[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)
```

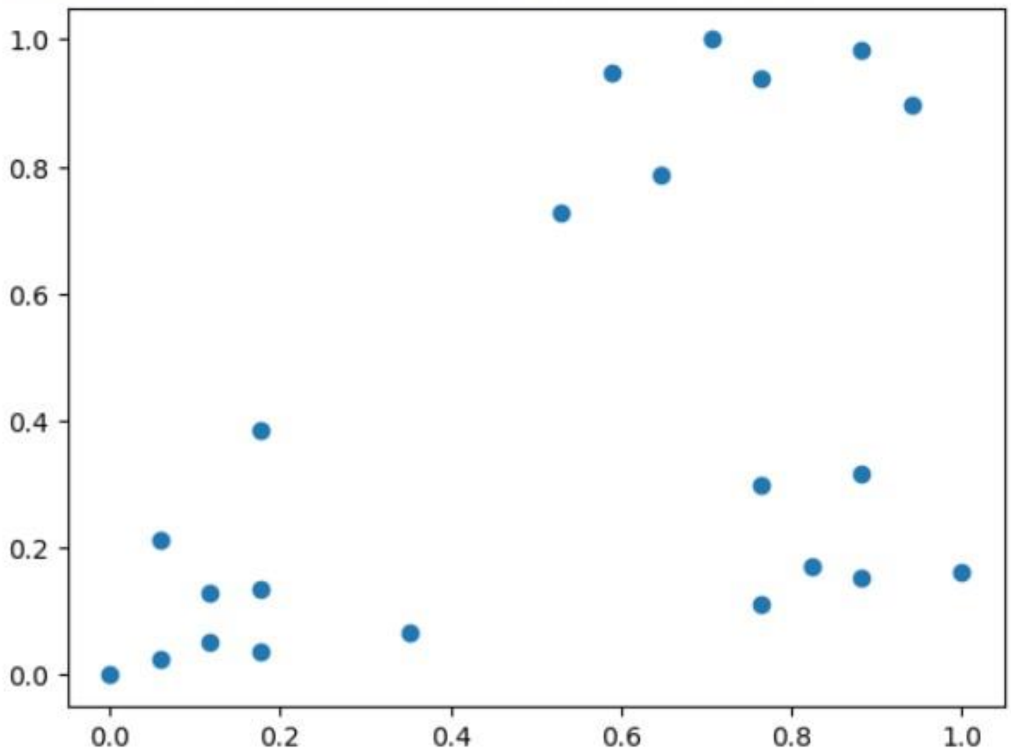
| | 1 | Name | Age | Income($) |
|---|---|---|---|---|
| 0 | 2 | Rob | 27 | 70000 |
| 1 | 3 | Michael | 29 | 90000 |
| 2 | 4 | Mohan | 29 | 61000 |
| 3 | 5 | Ismail | 28 | 60000 |
| 4 | 6 | Kory | 42 | 150000 |
| 5 | 7 | Gautam | 39 | 155000 |
| 6 | 8 | David | 41 | 160000 |
| 7 | 9 | Andrea | 38 | 162000 |
| 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>
```

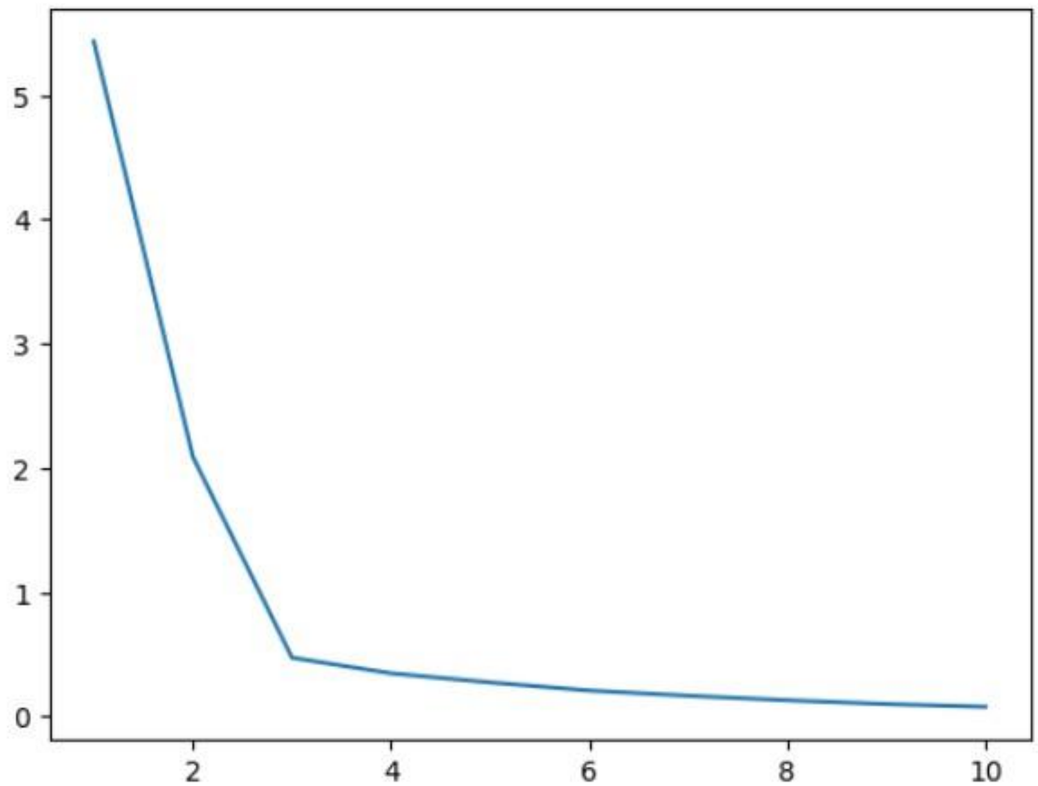


```
k_range = range(1, 11)
sse = []
for k in k_range:
    kmc = KMeans(n_clusters=k)
    kmc.fit(df[['Age', 'Income($)']])
    sse.append(kmc.inertia_)
sse
```

```
  warnings.warn(
[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>]
```




```python
[8] 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)
```

```python
[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 |

```python
[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]
     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 |

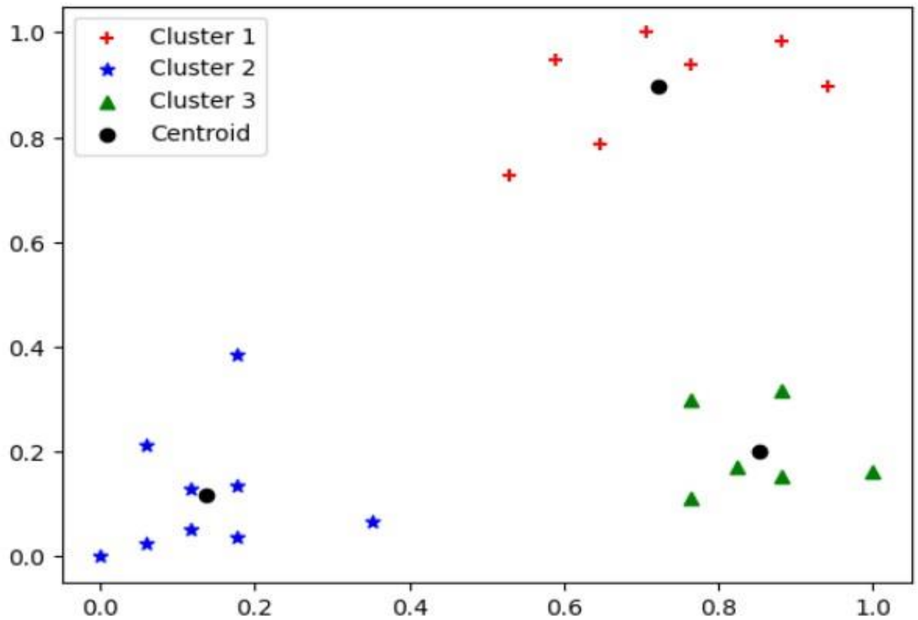
```
[13] df2 = df[df.cluster == 2]
     df2
```

| | 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 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.

```python
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))
```

```python
    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 Algorithm

* For each given training example $(x, f(x))$, add the example to the list training examples to the list training examples Classification algorithm.

* Given a query instance $x_q$ to be classified,
  Let $x_1 --- x_k$ denote the K instances from training examples that are nearest to $x_q$.

* Return

$$\hat{f}(x_q) \leftarrow \frac{\sum_{i=1}^{n} f(x_i)}{K}.$$

~~Sepal~~

Output.

Sepal-length sepal-width petal-length Petal-width

[[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]
[5.0 3.6 1.4 0.2]
. . . . .
. . . . .
[6.2 3.4 5.4 2.3]
[5.9.3 5.1 1.8]]

Class : 0-Iris-sentosa, 1-Iris Versicolor, 2-Iris-virginica

[000 --- 00111 --- 11222 --- 22]

Confusion Matrix

[[20 0 0]
[0 10 0]
[0 1 14]]

Accuracy Metrics

| | Precision | Recall | f1-score | support |
|---|---|---|---|---|
| 0 | 1.00 | 1.00 | 1.00 | 20 |
| 1 | 0.91 | 1.00 | 0.95 | 10 |
| 2 | 1.00 | 0.93 | 0.97 | 15 |
| avg/total | 0.98 | 0.98 | 0.98 | 45 |

O/p seen
7/6/23

**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.

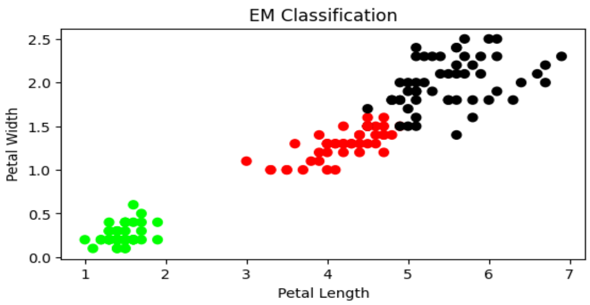
Dataset: Iris dataset

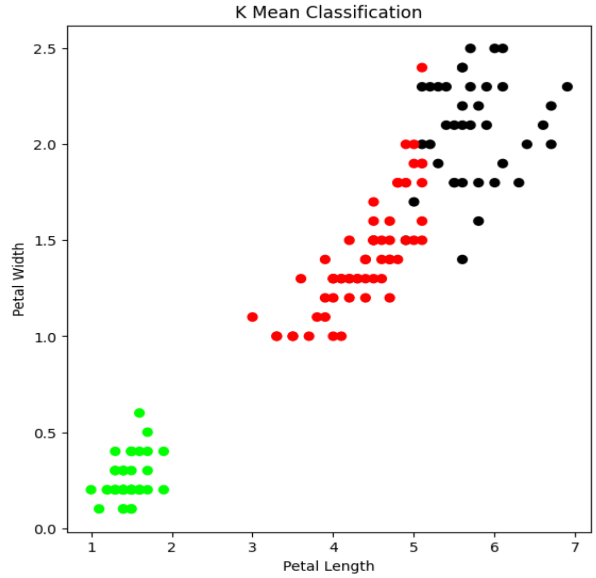
```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import sklearn.metrics as sm
import pandas as pd
import numpy as np

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
0.0
0.5
1.0
1.5
2.0
2.5
1
2
3
4
5
6
7


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

# EM- Algorithm

* Expectation step (E step) : It involves the estimation of all missing values in dataset so that after completing this step, there should not be any missing value.

* Maximize step (M-step) : This step involves the use of estimated data in E-step and updating the parameter.

* Repeat E step and M step until the convergence of value occur.

① Initialize Parameter Values. Further, the system is provided with incomplete observerd data with assumption that data is obtained from specific model.

② E-step, which is used to estimate or guess the value of the missing data using the observerd data.

③ Maximization step, where we use the complete data obtained from 2nd step to update Parameter values.

* The last step is to check if value of variables are covering or not.

* If yes, stop Process else repeat Until convergence occurs.

Euclidian distance Formula:

$$\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}$$

$x_1$ = x co-ordinate of point 1

$y_1$ = y co-ordinate of point 1

$x_2$ = x co-ordinate of pt 2

$y_2$ = y co-ordinate of pt 2

**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
```

```
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)
```

# Lab - 7 Locally weighted Regression Algorithm

1) Read the given data sample to X and the curve (linear or non linear) to Y.

2) Set the value of Smoothening Parameter of Free Parameter say $\tau$.

3) Set the bias / Point of Interest set $X_0$ which is subset of X.

4) Determine the weight matrix using:

$$W(x, x_0) = e^{\frac{-(x - x_0)^2}{2\tau^2}}$$

5) Determine the value of model term parameter $\beta$ using:

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

6) Prediction = $x_0 * \beta$;

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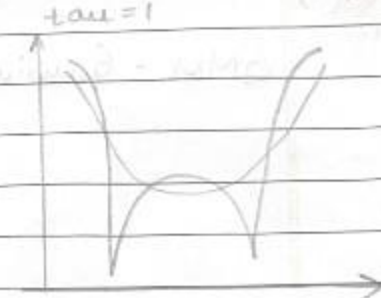
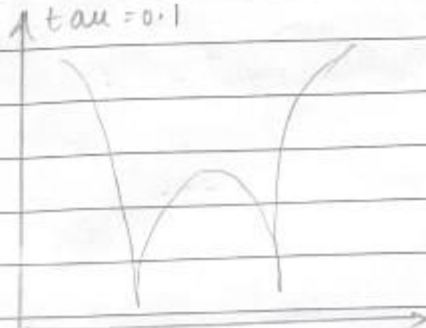
tau = 10

tau = 1



tau = 0.1



tau = 0.01