VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

Machine Learning

Submitted by

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in partial fulfillment for the award of the degree of
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in
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Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled "**Machine Learning**" carried out by **Neha Cathrin (1BM19CS099),** who is bonafide student of **B. M. S. College of Engineering.** It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum during the year 2022. The Lab report has been approved as it satisfies the academic requirements in respect of a **Machine Learning-(20CS6PCMAL)** work prescribed for the said degree.

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Index Sheet

1.Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples

In [7]:

```
import pandas as pd
import numpy as np
data = pd.read_csv("data.csv")
print(data)
d = np.array(data)[:,:-1]
target = np.array(data)[:,-1]
def train(c,t):
    for i, val in enumerate(t):
        if val == "yes":
            sh = c[i].copy()
            break;
    for i, val in enumerate(c):
        if t[i] == "yes":
            for x in range(len(sh)):
                if val[x] != sh[x]:
                    sh[x] = "?"
                else:
                    pass
    return sh

print(train(d,target))
```

```
      time weather temperature company humidity    wind goes
0  morning   sunny        warm     yes     mild  strong  yes
1  evening   rainy        cold      no     mild  normal   no
2  morning   sunny    moderate     yes   normal  normal  yes
3  evening   sunny        cold     yes     high  strong  yes
['?' 'sunny' '?' 'yes' '?' '?']
```

In [ ]:

2.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.

In [1]:

```
import numpy as np
import pandas as pd

data = pd.read_csv(r"C:\Users\admin\Downloads\enjoysport.csv")
concepts = np.array(data.iloc[:,0:-1])
print("\nInstances are:\n",concepts)
target = np.array(data.iloc[:,-1])
print("\nTarget Values are: ",target)

def learn(concepts, target):
    specific_h = concepts[0].copy()
    print("\nInitialization of specific_h and genearal_h")
    print("\nSpecific Boundary: ", specific_h)
    general_h = [["?" for i in range(len(specific_h))] for i in range(len(specific_h))]
    print("\nGeneric Boundary: ",general_h)

    for i, h in enumerate(concepts):
        print("\nInstance", i+1 , "is ", h)
        if target[i] == "yes":
            print("Instance is Positive ")
            for x in range(len(specific_h)):
                if h[x]!= specific_h[x]:
                    specific_h[x] ='?'
                    general_h[x][x] ='?'

        if target[i] == "no":
            print("Instance is Negative ")
            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("Specific Bundary after ", i+1, "Instance is ", specific_h)
        print("Generic Boundary after ", i+1, "Instance is ", general_h)
        print("\n")

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

```
Instances 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 Values are:  ['yes' 'yes' 'no' 'yes']

Initialization of specific_h and genearal_h

Specific Boundary:  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']

Generic Boundary:  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Instance 1 is  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
Instance is Positive
Specific Bundary after  1 Instance is  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
Generic Boundary after  1 Instance is  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?',
'?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]



Instance 2 is  ['sunny' 'warm' 'high' 'strong' 'warm' 'same']
Instance is Positive
Specific Bundary after  2 Instance is  ['sunny' 'warm' '?' 'strong' 'warm' 'same']
Generic Boundary after  2 Instance is  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?',
'?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]



Instance 3 is  ['rainy' 'cold' 'high' 'strong' 'warm' 'change']
Instance is Negative
Specific Bundary after  3 Instance is  ['sunny' 'warm' '?' 'strong' 'warm' 'same']
Generic Boundary after  3 Instance is  [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?',
'?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', 'same']]


 Instance 4 is  ['sunny' 'warm' 'high' 'strong' 'cool' 'change']
 Instance is Positive
 Specific Bundary after  4 Instance is  ['sunny' 'warm' '?' 'strong' '?' '?']
 Generic Boundary after  4 Instance is  [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?',
 '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]


 Final Specific_h:
 ['sunny' 'warm' '?' 'strong' '?' '?']
 Final General_h:
 [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

3.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

In [1]:

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

In [2]:

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

In [3]:

```
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
```

In [4]:

```
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
```

In [6]:

```
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
```

In [7]:

```
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
```

In [8]:

```
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)
```

In [9]:

```
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)
```

In [10]:

```
dataset,features=load_csv("data.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("test.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
   overcast
     yes
   sunny
     Humidity
       high
         no
       normal
         yes
   rain
     Wind
       strong
         no
       weak
         yes
The test instance: ['rain', 'cool', 'normal', 'strong']
The label for test instance:
no
The test instance: ['sunny', 'mild', 'normal', 'strong']
The label for test instance:
yes
```

4.Write a program to implement the naive Bayesian classifier for a sample training data set stored as a .CSV file. Compute the accuracy of the classifier, considering few test data samples

In [1]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn import metrics
```

In [2]:

```
df = pd.read_csv("input_data.csv")
col_names = ['num_preg', 'glucose_conc', 'diastolic_bp', 'thickness', 'insulin', 'bmi', 'diab_pred', 'age']
predicted_class = ['diabetes']
```

In [3]:

```
X = df[col_names].values
y = df[predicted_class].values
print(df.head)
xtrain,xtest,ytrain,ytest=train_test_split(X,y,test_size=0.4)

print ('\n the total number of Training Data :',ytrain.shape)
print ('\n the total number of Test Data :',ytest.shape)
```

```
<bound method NDFrame.head of      num_preg  glucose_conc  diastolic_bp  thickness  insulin   bmi  \
0           6           148            72         35        0  33.6
1           1            85            66         29        0  26.6
2           8           183            64          0        0  23.3
3           1            89            66         23       94  28.1
4           0           137            40         35      168  43.1
..        ...           ...           ...        ...      ...   ...
763        10           101            76         48      180  32.9
764         2           122            70         27        0  36.8
765         5           121            72         23      112  26.2
766         1           126            60          0        0  30.1
767         1            93            70         31        0  30.4

     diab_pred  age  diabetes
0        0.627   50         1
1        0.351   31         0
2        0.672   32         1
3        0.167   21         0
4        2.288   33         1
..         ...  ...       ...
763      0.171   63         0
764      0.340   27         0
765      0.245   30         0
766      0.349   47         1
767      0.315   23         0

[768 rows x 9 columns]>

 the total number of Training Data : (460, 1)

 the total number of Test Data : (308, 1)
```

In [4]:

```
clf = GaussianNB().fit(xtrain,ytrain.ravel())
predicted = clf.predict(xtest)
predictTestData= clf.predict([[6,148,72,35,0,33.6,0.627,50]])
print('\n Confusion matrix')
print(metrics.confusion_matrix(ytest,predicted))

print('\n Accuracy of the classifier is',metrics.accuracy_score(ytest,predicted))

print('\n The value of Precision', metrics.precision_score(ytest,predicted))

print('\n The value of Recall', metrics.recall_score(ytest,predicted))

print("Predicted Value for individual Test Data:", predictTestData)
```

```
 Confusion matrix
[[160  41]
 [ 47  60]]

 Accuracy of the classifier is 0.7142857142857143

 The value of Precision 0.594059405940594

 The value of Recall 0.5607476635514018
Predicted Value for individual Test Data: [1]
```

```
[ ]:
```

5.Write a program to construct a Bayesian network considering training data. Use this model to make predictions.

```
!pip install pgmpy
```

```
Requirement already satisfied: pgmpy in c:\programdata\anaconda3\lib\site-packages (0.1.18)
Requirement already satisfied: pyparsing in c:\programdata\anaconda3\lib\site-packages (from pgmpy) (3.0.4)
Requirement already satisfied: statsmodels in c:\programdata\anaconda3\lib\site-packages (from pgmpy) (0.12.2)
Requirement already satisfied: scikit-learn in c:\programdata\anaconda3\lib\site-packages (from pgmpy) (0.24.2)
Requirement already satisfied: torch in c:\programdata\anaconda3\lib\site-packages (from pgmpy) (1.11.0)
Requirement already satisfied: tqdm in c:\programdata\anaconda3\lib\site-packages (from pgmpy) (4.62.3)
Requirement already satisfied: joblib in c:\programdata\anaconda3\lib\site-packages (from pgmpy) (1.1.0)
Requirement already satisfied: pandas in c:\programdata\anaconda3\lib\site-packages (from pgmpy) (1.3.4)
Requirement already satisfied: networkx in c:\programdata\anaconda3\lib\site-packages (from pgmpy) (2.6.3)
Requirement already satisfied: numpy in c:\programdata\anaconda3\lib\site-packages (from pgmpy) (1.20.3)
Requirement already satisfied: scipy in c:\programdata\anaconda3\lib\site-packages (from pgmpy) (1.7.1)
Requirement already satisfied: python-dateutil>=2.7.3 in c:\programdata\anaconda3\lib\site-packages (from pandas->pgmpy) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in c:\programdata\anaconda3\lib\site-packages (from pandas->pgmpy) (2021.3)
Requirement already satisfied: six>=1.5 in c:\programdata\anaconda3\lib\site-packages (from python-dateutil>=2.7.3->pandas->pgmpy) (1.16.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\programdata\anaconda3\lib\site-packages (from scikit-learn->pgmpy) (2.2.0)
Requirement already satisfied: patsy>=0.5 in c:\programdata\anaconda3\lib\site-packages (from statsmodels->pgmpy) (0.5.2)
Requirement already satisfied: typing-extensions in c:\programdata\anaconda3\lib\site-packages (from torch->pgmpy) (3.10.0.2)
Requirement already satisfied: colorama in c:\programdata\anaconda3\lib\site-packages (from tqdm->pgmpy) (0.4.4)
```

```
from pgmpy.models import BayesianModel
from pgmpy.models import BayesianNetwork
from pgmpy.factors.discrete import TabularCPD
from pgmpy.inference import VariableElimination
```

```
cancer_model = BayesianNetwork([('Pollution', 'Cancer'),
                              ('Smoker', 'Cancer'),
                              ('Cancer', 'Xray'),
                              ('Cancer', 'Dyspnoea')])
print('Bayesian network nodes:')
print('\t', cancer_model.nodes())
print('Bayesian network edges:')
print('\t', cancer_model.edges())
```

```python
cpd_poll = TabularCPD(variable='Pollution', variable_card=2,
                      values=[[0.9], [0.1]])
cpd_smoke = TabularCPD(variable='Smoker', variable_card=2,
                       values=[[0.3], [0.7]])
cpd_cancer = TabularCPD(variable='Cancer', variable_card=2,
                        values=[[0.03, 0.05, 0.001, 0.02],
                                [0.97, 0.95, 0.999, 0.98]],
                        evidence=['Smoker', 'Pollution'],
                        evidence_card=[2, 2])
cpd_xray = TabularCPD(variable='Xray', variable_card=2,
                      values=[[0.9, 0.2], [0.1, 0.8]],
                      evidence=['Cancer'], evidence_card=[2])
cpd_dysp = TabularCPD(variable='Dyspnoea', variable_card=2,
                      values=[[0.65, 0.3], [0.35, 0.7]],
                      evidence=['Cancer'], evidence_card=[2])
cancer_model.add_cpds(cpd_poll, cpd_smoke, cpd_cancer, cpd_xray, cpd_dysp)
print('Model generated bt adding conditional probability distribution(cpds)')

# Checking if the cpds are valid for the model.
print('Checking for Correctness of model:', end='')
print(cancer_model.check_model())
```

```
Model generated bt adding conditional probability distribution(cpds)
Checking for Correctness of model:True
```

```python
'''print('All local dependencies are as follows')
cancer_model.get_independencies()
'''

print('Displaying CPDs')
print(cancer_model.get_cpds('Pollution'))
print(cancer_model.get_cpds('Smoker'))
print(cancer_model.get_cpds('Cancer'))
print(cancer_model.get_cpds('Xray'))
print(cancer_model.get_cpds('Dyspnoea'))
```

```
Displaying CPDs
+---------------+-----+
| Pollution(0)  | 0.9 |
+---------------+-----+
| Pollution(1)  | 0.1 |
+---------------+-----+
+-----------+-----+
| Smoker(0) | 0.3 |
+-----------+-----+
| Smoker(1) | 0.7 |
+-----------+-----+
+-----------+--------------+--------------+--------------+--------------+
| Smoker    | Smoker(0)    | Smoker(0)    | Smoker(1)    | Smoker(1)    |
+-----------+--------------+--------------+--------------+--------------+
| Pollution | Pollution(0) | Pollution(1) | Pollution(0) | Pollution(1) |
+-----------+--------------+--------------+--------------+--------------+
| Cancer(0) | 0.03         | 0.05         | 0.001        | 0.02         |
+-----------+--------------+--------------+--------------+--------------+
| Cancer(1) | 0.97         | 0.95         | 0.999        | 0.98         |
+-----------+--------------+--------------+--------------+--------------+
+---------+-----------+-----------+
| Cancer  | Cancer(0) | Cancer(1) |
+---------+-----------+-----------+
| Xray(0) | 0.9       | 0.2       |
+---------+-----------+-----------+
| Xray(1) | 0.1       | 0.8       |
+---------+-----------+-----------+
+-------------+-----------+-----------+
| Cancer      | Cancer(0) | Cancer(1) |
+-------------+-----------+-----------+
| Dyspnoea(0) | 0.65      | 0.3       |
+-------------+-----------+-----------+
| Dyspnoea(1) | 0.35      | 0.7       |
+-------------+-----------+-----------+
```

```python
cancer_infer = VariableElimination(cancer_model)
print('\nInferencing with Bayesian Network')

print('\nProbability of Cancer given Smoker')
q = cancer_infer.query(variables=['Cancer'], evidence={'Smoker': 1})
print(q)

print('\nProbability of Cancer given Smoker, Pollution')
q = cancer_infer.query(variables=['Cancer'], evidence={'Smoker': 1,'Pollution': 1})
print(q)
```

```
Inferencing with Bayesian Network

Probability of Cancer given Smoker
  0%|          | 0/1 [00:00<?, ?it/s]
  0%|          | 0/1 [00:00<?, ?it/s]
+-----------+---------------+
| Cancer    |   phi(Cancer) |
+===========+===============+
| Cancer(0) |        0.0029 |
+-----------+---------------+
| Cancer(1) |        0.9971 |
+-----------+---------------+

Probability of Cancer given Smoker, Pollution
0it [00:00, ?it/s]
0it [00:00, ?it/s]
+-----------+---------------+
| Cancer    |   phi(Cancer) |
+===========+===============+
| Cancer(0) |        0.0200 |
+-----------+---------------+
| Cancer(1) |        0.9800 |
+-----------+---------------+
```

6.Apply k-Means algorithm to cluster a set of data stored in a .CSV file.

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

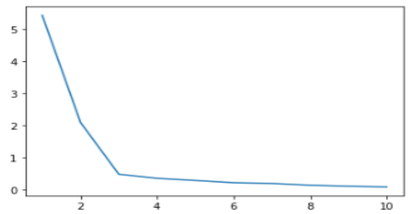
```
df = pd.read_csv('income.csv')
df.head(10)
```

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

```
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)
```

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

```
[<matplotlib.lines.Line2D at 0x7f23cb541c10>]
```



Therefore, the elbow point is 3

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

```
KMeans(n_clusters=3)
```

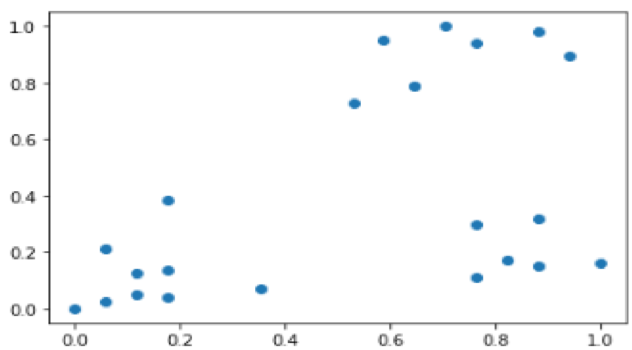
```
y_predict = km.fit_predict(df[['Age', 'Income($)']])
y_predict
```

```
array([0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2],
      dtype=int32)
```

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

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

```
<matplotlib.collections.PathCollection at 0x7f23ce044f10>
```



Finding Elbow Point

```
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
```

```
[5.434011511988179,
 2.091136388699078,
 0.4750783498553097,
 0.3491047094419566,
 0.2818479744366238,
 0.21055478995472496,
 0.18752738899206242,
 0.13265419827245162,
 0.10188787724979426,
 0.08026197041664467]
```

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

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

```
df1 = df[df.cluster == 1]
df1
```

	Name	Age	Income($)	cluster
4	Kory	0.941176	0.897436	1
5	Gautam	0.764706	0.940171	1
6	David	0.882353	0.982906	1
7	Andrea	0.705882	1.000000	1
8	Brad	0.588235	0.948718	1
9	Angelina	0.529412	0.726496	1
10	Donald	0.647059	0.786325	1

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

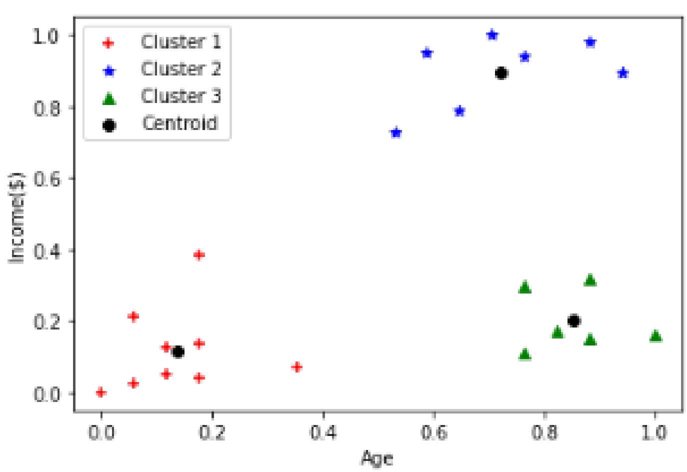
	Name	Age	Income($)	cluster
16	Dipika	0.823529	0.170940	2
17	Priyanka	0.882353	0.153846	2
18	Nick	1.000000	0.162393	2
19	Alia	0.764706	0.299145	2
20	Sid	0.882353	0.316239	2
21	Abdul	0.764706	0.111111	2

```
km.cluster_centers_
```

```
array([[0.1372549 , 0.11633428],
       [0.72268908, 0.8974359 ],
       [0.85294118, 0.2022792 ]])
```

```
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($)'], marker='^', color='green')
c = plt.scatter(km.cluster_centers_[:,0], km.cluster_centers_[:,1], color='black')
plt.xlabel('Age')
plt.ylabel('Income($)')
plt.legend((p1, p2, p3, c),
           ('Cluster 1', 'Cluster 2', 'Cluster 3', 'Centroid'))
```

```
<matplotlib.legend.Legend at 0x7f23cb75d910>
```

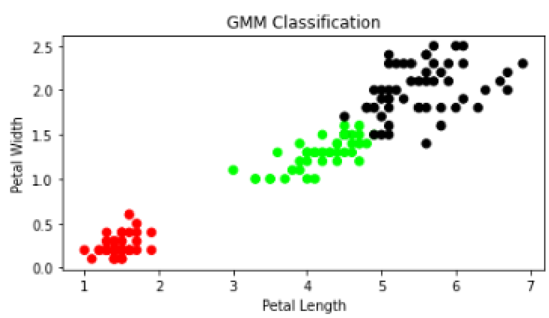


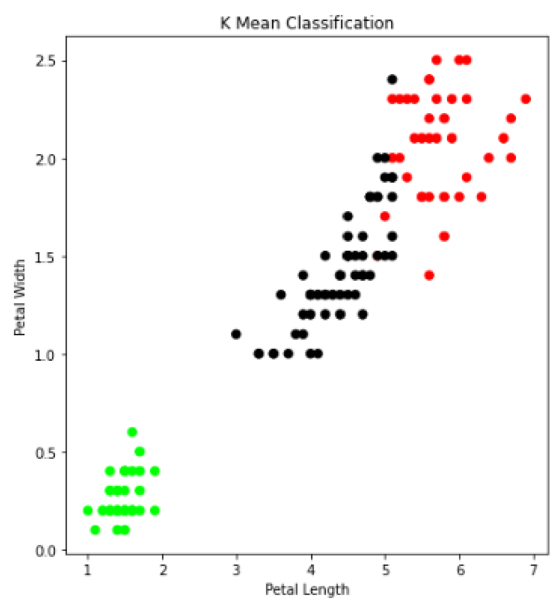
7.Apply EM algorithm to cluster a set of data stored in a .CSV file. Compare the results of k-Means algorithm and EM algorithm.

```
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('GMM 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:  0.09333333333333334
The Confusion matrixof K-Mean:  [[ 0 50  0]
 [ 2  0 48]
 [36  0 14]]
The accuracy score of EM:  0.9666666666666667
The Confusion matrix of EM:  [[50  0  0]
 [ 0 45  5]
 [ 0  0 50]]
```





8.Write a program to implement k-Nearest Neighbor algorithm to classify the iris data set. Print both correct and wrong predictions.

```python
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import datasets

iris=datasets.load_iris()

x = iris.data
y = iris.target

print ('sepal-length', 'sepal-width', 'petal-length', 'petal-width')
print(x)
print('class: 0-Iris-Setosa, 1- Iris-Versicolour, 2- Iris-Virginica')
print(y)

x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.3)

#To Training the model and Nearest nighbors K=5
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(x_train, y_train)

#To make predictions on our test data
y_pred=classifier.predict(x_test)

print('Confusion Matrix')
print(confusion_matrix(y_test,y_pred))
print('Accuracy Metrics')
print(classification_report(y_test,y_pred))
```

```
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.  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]
```

```
class: 0-Iris-Setosa, 1- Iris-Versicolour, 2- Iris-Virginica
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
Confusion Matrix
[[21  0  0]
 [ 0 10  1]
 [ 0  1 12]]
Accuracy Metrics
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        21
           1       0.91      0.91      0.91        11
           2       0.92      0.92      0.92        13

    accuracy                           0.96        45
   macro avg       0.94      0.94      0.94        45
weighted avg       0.96      0.96      0.96        45
```

9.Implement the Linear Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

In [2]:
```
dataset = pd.read_csv('salary_data.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, 1].values
```

In [3]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=1/3, random_state=0)
```

In [4]:
```
# Fitting Simple Linear Regression to the Training set
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[4]:
```
LinearRegression()
```

In [5]:
```
# Predicting the Test set results
y_pred = regressor.predict(X_test)
```

In [6]:
```
# Visualizing the Training set results
viz_train = plt
viz_train.scatter(X_train, y_train, color='red')
viz_train.plot(X_train, regressor.predict(X_train), color='blue')
viz_train.title('Salary VS Experience (Training set)')
viz_train.xlabel('Year of Experience')
viz_train.ylabel('Salary')
viz_train.show()
```

In [7]:

```
# Visualizing the Test set results
viz_test = plt
viz_test.scatter(X_test, y_test, color='red')
viz_test.plot(X_train, regressor.predict(X_train), color='blue')
viz_test.title('Salary VS Experience (Test set)')
viz_test.xlabel('Year of Experience')
viz_test.ylabel('Salary')
viz_test.show()
```

In [ ]:

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

```
from numpy import *
from os import listdir
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np1
import numpy.linalg as np
from scipy.stats.stats import pearsonr
```

```
def kernel(point,xmat, k):
 m,n = np1.shape(xmat)
 weights = np1.mat(np1.eye((m)))
 for j in range(m):
    diff = point - X[j]
    weights[j,j] = np1.exp(diff*diff.T/(-2.0*k**2))
 return weights
```

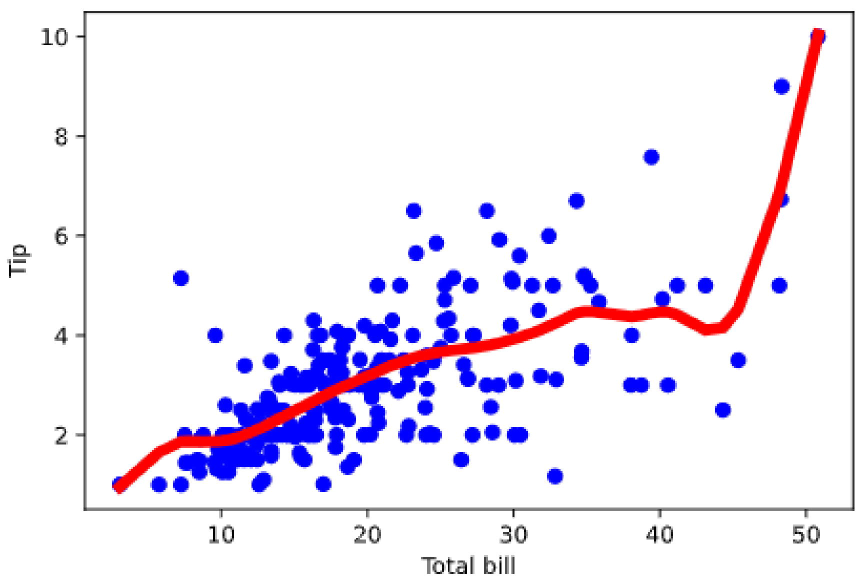
```
def localWeight(point,xmat,ymat,k):
 wei = kernel(point,xmat,k)
 W = (X.T*(wei*X)).I*(X.T*(wei*ymat.T))
 return W
```

```
def localWeightRegression(xmat,ymat,k):
 m,n = np1.shape(xmat)
 ypred = np1.zeros(m)
 for i in range(m):
    ypred[i] = xmat[i]*localWeight(xmat[i],xmat,ymat,k)
 return ypred
```

```
# load data points
data = pd.read_csv('tips.csv')
bill = np1.array(data.total_bill)
tip = np1.array(data.tip)
```

```
#preparing and add 1 in bill
mbill = np1.mat(bill)
mtip = np1.mat(tip) # mat is used to convert to n dimesiona to 2 dimensional array form
m= np1.shape(mbill)[1]
# print(m) 244 data is stored in m
one = np1.mat(np1.ones(m))
X= np1.hstack((one.T,mbill.T)) # create a stack of bill from ONE
#print(X)
#set k here
ypred = localWeightRegression(X,mtip,2)
SortIndex = X[:,1].argsort(0)
xsort = X[SortIndex][:,0]
```

```
fig = plt.figure()
ax = fig.add_subplot(1,1,1)
ax.scatter(bill,tip, color='blue')
ax.plot(xsort[:,1],ypred[SortIndex], color = 'red', linewidth=5)
plt.xlabel('Total bill')
plt.ylabel('Tip')
plt.show()
```



```python
def local_regression(x0, X, Y, tau):# add bias term
    x0 = np.r_[1, x0] # Add one to avoid the loss in information
    X = np.c_[np.ones(len(X)), X]
    # fit model: normal equations with kernel
    xw = X.T * radial_kernel(x0, X, tau) # XTranspose * W
    beta = np.linalg.pinv(xw @ X) @ xw @ Y #@ Matrix Multiplication or Dot Product
    # predict value
    return x0 @ beta # @ Matrix Multiplication or Dot Product for prediction
```

```python
def radial_kernel(x0, X, tau):
    return np.exp(np.sum((X - x0) ** 2, axis=1) / (-2 * tau * tau))
# Weight or Radial Kernal Bias Function
```

```python
n = 1000
# generate dataset
X = np.linspace(-3, 3, num=n)
print("The Data Set ( 10 Samples) X :\n",X[1:10])
Y = np.log(np.abs(X ** 2 - 1) + .5)
print("The Fitting Curve Data Set (10 Samples) Y :\n",Y[1:10])
# jitter X
X += np.random.normal(scale=.1, size=n)
print("Normalised (10 Samples) X :\n",X[1:10])
domain = np.linspace(-3, 3, num=300)
print(" Xo Domain Space(10 Samples) :\n",domain[1:10])
```

```
The Data Set ( 10 Samples) X :
 [-2.99399399 -2.98798799 -2.98198198 -2.97597598 -2.96996997 -2.96396396
 -2.95795796 -2.95195195 -2.94594595]
The Fitting Curve Data Set (10 Samples) Y :
 [2.13582188 2.13156806 2.12730467 2.12303166 2.11874898 2.11445659
 2.11015444 2.10584249 2.10152068]
Normalised (10 Samples) X :
 [-2.95983905 -2.77699311 -3.06439147 -3.15903005 -3.19868861 -3.00406048
 -2.9445708  -2.87933746 -2.94253902]
 Xo Domain Space(10 Samples) :
 [-2.97993311 -2.95986622 -2.93979933 -2.91973244 -2.89966555 -2.87959866
 -2.85953177 -2.83946488 -2.81939799]
```