VISVESVARAYA TECHNOLOGICAL UNIVERSITY

“JnanaSangama”, Belgaum -590014, Karnataka.

LAB REPORT
on

MACHINE LEARNING
(20CS6PCMAL)

Submitted by

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in partial fulfillment for the award of the degree of
BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
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C ERTIFICATE

This is to certify that the Lab work entitled "**MACHINE LEARNING**" carried out by **Sudeshna Bhushan (1BM19CS189),** who is a 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

Course Outcome

CO1	Ability to apply the different learning algorithms.
CO2	Ability to analyse the learning techniques for a given dataset.
CO3	Ability to design a model using machine learning to solve a problem.
CO4	Ability to conduct practical experiments to solve problems using appropriate machine learning techniques.

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

In [1]:

```python
import csv

def findS(dataset, hypothesis):
    for i in range(len(dataset)):
        if dataset[i][-1] == 'yes':
            print('The tuple', i+1, 'is a positive instance.')
            for j in range(len(hypothesis)):
                if hypothesis[j] == '0'  or dataset[i][j] == hypothesis[j]:
                    hypothesis[j] = dataset[i][j]
                else:
                    hypothesis[j] = '?'
            print('The hypothesis for traning tuple',i+1,'and instance',j+1, 'is:', hypothesis)
        elif dataset[i][-1] == 'no':
            print('The tuple', i+1, 'is a negative instance.')
            print('The hypothesis for traning tuple',i+1, 'is:', hypothesis)
    return hypothesis


def main():

    dataset = []
    with open('FindS-CSV.csv', 'r') as csvfile:
        next(csvfile)
        for row in csv.reader(csvfile):
            dataset.append(row)
        print(dataset)
    hypothesis = ['0']*len(dataset[0])
    print('The Initial hypothesis:', hypothesis)
    hypothesis = findS(dataset, hypothesis)
    print('Final Hypothesis: ', hypothesis)

if __name__ == "__main__":
    main()
```

```
[['sunny', 'warm', 'normal', 'strong', 'warm', 'same', 'yes'], ['sunny', 'warm', 'high', 'strong', 'warm', 'same', 'yes'], ['rainy', 'col
d', 'high', 'strong', 'warm', 'change', 'no'], ['sunny', 'warm', 'high', 'strong', 'cool', 'change', 'yes']]
The Initial hypothesis: ['0', '0', '0', '0', '0', '0', '0']
The tuple 1 is a positive instance.
The hypothesis for traning tuple 1 and instance 7 is: ['sunny', 'warm', 'normal', 'strong', 'warm', 'same', 'yes']
The tuple 2 is a positive instance.
The hypothesis for traning tuple 2 and instance 7 is: ['sunny', 'warm', '?', 'strong', 'warm', 'same', 'yes']
The tuple 3 is a negative instance.
The hypothesis for traning tuple 3 is: ['sunny', 'warm', '?', 'strong', 'warm', 'same', 'yes']
The tuple 4 is a positive instance.
The hypothesis for traning tuple 4 and instance 7 is: ['sunny', 'warm', '?', 'strong', '?', '?', 'yes']
Final Hypothesis:  ['sunny', 'warm', '?', 'strong', '?', '?', 'yes']
```

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]:

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


data = pd.read_csv('Candidate-Elimination.csv')
d = np.array(data.iloc[:,0:-1])
print("\nInstances are:\n",d)
target = np.array(data.iloc[:,-1])
print("\nTarget Values are: ",target)
```

```
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']
```

In [2]:

```python
def learn(d, target):
    specific_h = d[0].copy()
    print("\nSpecific Hypothesis: ", specific_h)
    general_h = [["?" for i in range(len(specific_h))] for i in range(len(specific_h))]
    print("\nGeneric Hypothesis: ",general_h)

    for i, h in enumerate(d):
        print("\nIteration", 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 Hypothesis after ", i+1, "Instance is ", specific_h)
        print("Generic Hypothesis 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
```

In [3]:

```python
specific, general = learn(d, target)

print("Final Specific Hypothesis: ", '<', ', '.join(specific),'>')
print("Final General Hypothesis: ")
for i in general:
    print('<', ', '.join(i),'>, ')
```

```
Specific Hypothesis:  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']

Generic Hypothesis:  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?',
'?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

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



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



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



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


Final Specific Hypothesis:  < sunny, warm, ?, strong, ?, ? >
Final General Hypothesis:
< 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 [4]:
```python
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)


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 [5]:
```python
dataset,features=load_csv("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("id3.csv")

for xtest in testdata:
    print("The test instance:",xtest)
    print("The label for test instance:",end="   ")
    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: ['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
```

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

In [1]:

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

In [2]:

```python
data = pd.read_csv('/content/dataset.csv')
data.head()
```

Out[2]:

	PlayTennis	Outlook	Temperature	Humidity	Wind
0	No	Sunny	Hot	High	Weak
1	No	Sunny	Hot	High	Strong
2	Yes	Overcast	Hot	High	Weak
3	Yes	Rain	Mild	High	Weak
4	Yes	Rain	Cool	Normal	Weak

In [3]:

```python
y = list(data['PlayTennis'].values)
X = data.iloc[:,1:].values
print(f'Target Values: {y}')
print(f'Features: \n{X}')
```

```
Target Values: ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes',  File display  'No']
Features:
[['Sunny' 'Hot' 'High' 'Weak']
 ['Sunny' 'Hot' 'High' 'Strong']
 ['Overcast' 'Hot' 'High' 'Weak']
 ['Rain' 'Mild' 'High' 'Weak']
 ['Rain' 'Cool' 'Normal' 'Weak']
 ['Rain' 'Cool' 'Normal' 'Strong']
 ['Overcast' 'Cool' 'Normal' 'Strong']
 ['Sunny' 'Mild' 'High' 'Weak']
 ['Sunny' 'Cool' 'Normal' 'Weak']
 ['Rain' 'Mild' 'Normal' 'Weak']
 ['Sunny' 'Mild' 'Normal' 'Strong']
 ['Overcast' 'Mild' 'High' 'Strong']
 ['Overcast' 'Hot' 'Normal' 'Weak']
 ['Rain' 'Mild' 'High' 'Strong']]
```

In [4]:

```python
y_train = y[:8]
y_val = y[8:]
X_train = X[:8]
X_val = X[8:]
print(f"Number of instances in training set: {len(X_train)}")
print(f"Number of instances in testing set: {len(X_val)}")
```

```
Number of instances in training set: 8
Number of instances in testing set: 6
```

In [5]:

```python
class NaiveBayesClassifier:
    def __init__(self, X, y):
        self.X, self.y = X, y
        self.N = len(self.X)
        self.dim = len(self.X[0])
        self.attrs = [[] for _ in range(self.dim)]
        self.output_dom = {}
        self.data = []
        for i in range(len(self.X)):
            for j in range(self.dim):
                if not self.X[i][j] in self.attrs[j]:
                    self.attrs[j].append(self.X[i][j])
            if not self.y[i] in self.output_dom.keys():
                self.output_dom[self.y[i]] = 1
            else:
                self.output_dom[self.y[i]] += 1
            self.data.append([self.X[i], self.y[i]])
    def classify(self, entry):
        solve = None
        max_arg = -1
        for y in self.output_dom.keys():
            prob = self.output_dom[y]/self.N
            for i in range(self.dim):
                cases = [x for x in self.data if x[0][i] == entry[i] and x[1] == y]
                n = len(cases)
                prob *= n/self.N
            if prob > max_arg:
                max_arg = prob
                solve = y
        return solve
```

In [6]:

```python
nbc = NaiveBayesClassifier(X_train, y_train)
total_cases = len(y_val)
good = 0
bad = 0
predictions = []
for i in range(total_cases):
    predict = nbc.classify(X_val[i])
    predictions.append(predict)
    if y_val[i] == predict:
        good += 1
    else:
        bad += 1
print('Predicted values:', predictions)
print('Actual values:', y_val)
print()
print('Total number of testing instances in the dataset:', total_cases)
print('Number of correct predictions:', good)
print('Number of wrong predictions:', bad)
print()
print('Accuracy of Bayes Classifier:', good/total_cases)
```

```
Predicted values: ['No', 'Yes', 'No', 'Yes', 'Yes', 'No']
Actual values: ['Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No']

Total number of testing instances in the dataset: 6
Number of correct predictions: 4
Number of wrong predictions: 2

Accuracy of Bayes Classifier: 0.6666666666666666
```

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

In [7]:
```
import numpy as np
import pandas as pd
import csv
```

In [8]:
```
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.models import BayesianModel
from pgmpy.inference import VariableElimination
```

In [9]:
```
heartDisease = pd.read_csv('heart.csv')
heartDisease = heartDisease.replace('?',np.nan)

print('Sample instances from the dataset are given below')
print(heartDisease.head())
```

```
Sample instances from the dataset are given below
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  slope  \
0   63    1   1       145   233    1        2      150      0      2.3      3
1   67    1   4       160   286    0        2      108      1      1.5      2
2   67    1   4       120   229    0        2      129      1      2.6      2
3   37    1   3       130   250    0        0      187      0      3.5      3
4   41    0   2       130   204    0        2      172      0      1.4      1

  ca thal  heartdisease
0  0    6             0
1  3    3             2
2  2    7             1
3  0    3             0
4  0    3             0
```

In [10]:
```
print('\n Attributes and datatypes')
print(heartDisease.dtypes)
```

```
 Attributes and datatypes
age               int64
sex               int64
cp                int64
trestbps          int64
chol              int64
fbs               int64
restecg           int64
thalach           int64
exang             int64
oldpeak         float64
slope             int64
ca               object
thal             object
heartdisease      int64
dtype: object
```

In [11]:
```
model= BayesianModel([('age','heartdisease'),('sex','heartdisease'),('exang','heartdisease'),('cp','heartdisease'),('heartdisease','restec
print('\nLearning CPD using Maximum likelihood estimators')
model.fit(heartDisease,estimator=MaximumLikelihoodEstimator)

print('\n Inferencing with Bayesian Network:')
```

```
Learning CPD using Maximum likelihood estimators

 Inferencing with Bayesian Network:
```

In [12]:
```
HeartDiseasetest_infer = VariableElimination(model)

print('\n 1. Probability of HeartDisease given evidence= restecg')
q1=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'restecg':1})
print(q1)
```

```
Finding Elimination Order: : 100%|| 5/5 [00:00<00:00, 2500.78it/s]
Eliminating: chol: 100%|| 5/5 [00:00<00:00, 185.63it/s]
 1. Probability of HeartDisease given evidence= restecg
+-----------------+---------------------+
| heartdisease    |   phi(heartdisease) |
+=================+=====================+
| heartdisease(0) |              0.1012 |
+-----------------+---------------------+
| heartdisease(1) |              0.0000 |
+-----------------+---------------------+
| heartdisease(2) |              0.2392 |
+-----------------+---------------------+
| heartdisease(3) |              0.2015 |
+-----------------+---------------------+
| heartdisease(4) |              0.4581 |
+-----------------+---------------------+
```

In [13]:
```
print('\n 2. Probability of HeartDisease given evidence= cp ')
q2=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'cp':2})
print(q2)
```

```
Finding Elimination Order: : 100%|| 5/5 [00:00<00:00, 2507.06it/s]
Eliminating: restecg: 100%|| 5/5 [00:00<00:00, 179.06it/s]
 2. Probability of HeartDisease given evidence= cp
+-----------------+---------------------+
| heartdisease    |   phi(heartdisease) |
+=================+=====================+
| heartdisease(0) |              0.3610 |
+-----------------+---------------------+
| heartdisease(1) |              0.2159 |
+-----------------+---------------------+
| heartdisease(2) |              0.1373 |
+-----------------+---------------------+
| heartdisease(3) |              0.1537 |
+-----------------+---------------------+
| heartdisease(4) |              0.1321 |
+-----------------+---------------------+
```

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

In [2]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import pandas as pd
import numpy as np
from itertools import cycle, islice
```

In [3]:
```
from google.colab import drive
drive.mount("/content/drive")
```

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

In [4]:
```
data = pd.read_csv('/content/drive/MyDrive/minute_weather.csv')
```

In [5]:
```
data.shape
```

Out[5]:
```
(1587257, 13)
```

In [6]:
```
data.head()
```

Out[6]:

	rowID	hpwren_timestamp	air_pressure	air_temp	avg_wind_direction	avg_wind_speed	max_wind_direction	max_wind_speed	min_wind_direction	min_wind_speed
0	0	2011-09-10 00:00:49	912.3	64.76	97.0	1.2	106.0	1.6	85.0	1.0
1	1	2011-09-10 00:01:49	912.3	63.86	161.0	0.8	215.0	1.5	43.0	0.2
2	2	2011-09-10 00:02:49	912.3	64.22	77.0	0.7	143.0	1.2	324.0	0.3
3	3	2011-09-10 00:03:49	912.3	64.40	89.0	1.2	112.0	1.6	12.0	0.7
4	4	2011-09-10 00:04:49	912.3	64.40	185.0	0.4	260.0	1.0	100.0	0.1

In [7]:
```
#data sampling
sampled_df = data[(data['rowID'] % 10) == 0]
sampled_df.shape
```

Out[7]:
```
(158726, 13)
```

In [8]:
```
sampled_df.describe().transpose()
```

Out[8]:

	count	mean	std	min	25%	50%	75%	max
rowID	158726.0	793625.000000	458203.937509	0.00	396812.5	793625.00	1190437.50	1587250.00
air_pressure	158726.0	916.830161	3.051717	905.00	914.8	916.70	918.70	929.50
air_temp	158726.0	61.851589	11.833569	31.64	52.7	62.24	70.88	99.50
avg_wind_direction	158680.0	162.156100	95.278201	0.00	62.0	182.00	217.00	359.00
avg_wind_speed	158680.0	2.775215	2.057624	0.00	1.3	2.20	3.80	31.90
max_wind_direction	158680.0	163.462144	92.452139	0.00	68.0	187.00	223.00	359.00
max_wind_speed	158680.0	3.400558	2.418802	0.10	1.6	2.70	4.60	36.00
min_wind_direction	158680.0	166.774017	97.441109	0.00	76.0	180.00	212.00	359.00
min_wind_speed	158680.0	2.134664	1.742113	0.00	0.8	1.60	3.00	31.60
rain_accumulation	158725.0	0.000318	0.011236	0.00	0.0	0.00	0.00	3.12
rain_duration	158725.0	0.409627	8.665523	0.00	0.0	0.00	0.00	2960.00
relative_humidity	158726.0	47.609470	26.214409	0.90	24.7	44.70	68.00	93.00

In [9]:
```
sampled_df[sampled_df['rain_accumulation'] == 0].shape
```

Out[9]:
```
(157812, 13)
```

In [10]:
```
sampled_df[sampled_df['rain_duration'] == 0].shape
```

Out[10]:
```
(157237, 13)
```

In [11]:
```
del sampled_df['rain_accumulation']
del sampled_df['rain_duration']
```

In [12]:
```
rows_before = sampled_df.shape[0]
sampled_df = sampled_df.dropna()
rows_after = sampled_df.shape[0]
```

In [13]:

Out[13]: 46

In [14]:

```
sampled_df.columns
```

In [15]:

```
features = ['air_pressure', 'air_temp', 'avg_wind_direction', 'avg_wind •n«d', 'm • =Snd_dSr«vtSon', 'm•• w;nN • «d','relariwe_fi.—;ai,y
```

In [17]:

In [18]:

```
select df
```

Out[18]:

	air_pressure	air_temp	avg_wind_direction	avg_wind_speed	max_wind_direction	max_wind_speed	relative_humidity
10	912.3	62.24	144.0	1.2	167.0	1.8	38.5
20	912.2	63.32	1DD.D	2.0	122.0	2.b	68.2
				US	âd1D		
1587210	915.9	75.56	2âD.D			1.3	

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7
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8

1S0BB0 s x 7 columns

In [19]:

Out[19]:

```
array([[-1.48456281,  0.24544455, -0.68385323, ..., -0.62153592,
       [-1.48456281,  0.03247142, -0.19055941, ...,  0.03826701,
        -0.66171726, -0.34710804],
       [-1.51733167,  0.12374562, -0.65236639, ..., -0.44847286,
       [-0.30488381,
        -0.JO30+01T,
       [-0.30488381,
        -0.62037434,
        1.15619654, 1.9dF5SJ2d,          ...,  2.0393087 ,
        0.01538018],
        1.12776181,  2.06599745, ..., -1.67073075,
        -0.69711J47]]}
```

```
mnNml -     c.*it{z]
```

```
       [-0.7245782 ,  0.51194369,  0.17191124, -0.58229578,  0.34128394,
        0.67243274, -0.15J29I94].
        1.98322667,  0.53830956,
       -0.63899948, -1.67791749,
```

```
[-0.16372869,  0.86324348, -1.31172732,
 -0.6047306 , -0.64119682],
[ 0.25182364, -0.99684608,  0.65839645, -0.58942801, -1.16773268,
                                       -0.54672097,
 -6. 1248 +112,                        1 1 *62 T 6 23 ],                    •*.Z51t2£S6.
[ 0.23422959,                          0.32038874,  1.88815273, -0.65179307,

[ 0.68752537,  0.48036551,  0.28249096,
 -0.54507948, -0.76332259],
[- .S9D42211, -1.20432314,  0.37675641,

[ 1.36796382, -0.08175169, -1.20532878, -0.05333267, -1.073853  ,
```

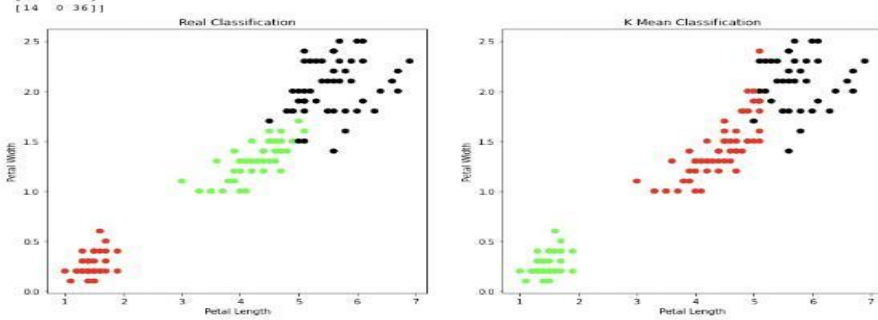
7. Apply EM algorithm to cluster a set of data stored in a .CSV file. Compare the results of k-Means algorithm and EM algorithm.

In [1]:
```
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
```

In [2]:
```
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']
```

In [3]:
```
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_))
```

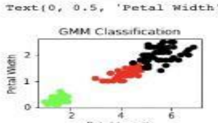
```
The accuracy score of K-Mean:  0.24
The Confusion matrixof K-Mean:  [[ 0 50  0]
 [48  0  2]
 [14  0 36]]
```



In [4]:
```
from sklearn import preprocessing
scaler = preprocessing.StandardScaler()
scaler.fit(X)
xsa = scaler.transform(X)
xs = pd.DataFrame(xsa, columns = X.columns)
```

In [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')
```

Out[5]:
```
Text(0, 0.5, 'Petal Width')
```



In [6]:
```
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 EM:  0.3333333333333333
The Confusion matrix of EM:  [[ 0 50  0]
 [45  0  5]
 [ 0  0 50]]
```

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

```python
from sklearn import datasets
```

```
pr*nt l’:eral ?«r.g:h'. ’:«pn1 wiz:h’, ’gctnl lcr.gtu’, ’r«tzi
width'} print(x)
print{’-ia*s: o 1ri: 6s:o«z 1 iris ver:i-odour, z ml Virjir.icz
print{y)
```

```
»cpal-long:h repel-wrath pct f-1cng:b ps:*1-width

[4.9 3.  1.4 0.2]

[4.6 3.1 1.5 0.2]
[5.  3.6 1.4 0.2]


[5.  3.4 1.5 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]

[4.3 3.  1.1 0.1]

[5.7 4.4 1.5 0.4]
[5.4 3.9 1.3 0.4]
[5.1 3.5 1.4 0.3]

[5.1 3.8 1.5 0.3]
[5.4 3.4 1.7 0.2]
[5.1 3.7 1.5 0.4]
[4.6 3.6 1.  0.2]
[5.1 3.3 1.7 0.5]

[5.  3.  1.6 0.2]
[5.  3.4 1.6 0.4]

[5.2 3.4 1.4 0.2]
[4.7 3.2 1.6 0.2]

[5.4 3.4 1.5 0.4]
[5.2 4.1 1.5 0.1]

[4.9 3.1 1.5 0.2]
[5.  3.2 1.2 0.2]

[4.9 3.6 1.4 0.1]
[4.4 3.  1.3 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]

[5.1 3.8 1.9 0.4]


[4.6 3.2 1.4 0.2]
[5.3 3.7 1.5 0.2]

[7.  3.2 4.7 1.4]


[5.5 2.3 4.  1.3]
[6.5 2.8 4.6 1.5]

[6.3 3.3 4.7 1.6]
[4.9 2.4 3.3 1. ]
[6.6 2.9 4.6 1.3]

[5.  2.  3.5 1. ]

[6.  2.2 4.  1. ]

[5.6 2.9 3.6 1.3]

[5.6 3.  4.5 1.5]

[6.2 2.2 4.5 1.5]

[5.9 3.2 4.8 1.8]

[6.3 2.5 4.9 1.5]

[6.4 2.9 4.3 1.3]
[6.6 3.  4.4 1.4]
[6.8 2.8 4.8 1.4]

[6.  2.9 4.5 1.5]

[5.5 2.4 3.8 1.1]

[5.8 2.7 3.9 1.2]

[5.4 3.  4.5 1.5]

[6.7 3.1 4.7 1.5]

[5.6 3.  4.1 1.3]
```

```
[5.6 3.  4.1 1.3]
[5.5 2.5 4.  1.3]
[5.5 2.6 4.4 1.2]

[5.8 2.6 4.  1.2]
[5.  2.3 3.3 1. ]
[5.6 2.7 4.2 1.3]
[5.7 3. 4.2 1.2]
[5.7 2.9 4.2 1.3]
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[5.I 2.5 J. 1.i]
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[6. J 3.J 6. 2.S]
[5.4 2.7 S.1 1.9]
[7. I 3.  S.9 2.i]
[6. J 2.9 S.6 1.8]
[€ . 5 3. 5.# 2.2]

[3.9 2.5 4.5 1.7]
[7. J 2.9 6.2 1.8]
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[€.â 3.2 S.1 J.
[6.4 2.7 S.2 1.9]
[6.8 3.  5.5 2.1]
[5.1 2.5 S. J.
[5.B 2.B S.1 J.4]
[6. a 3.2 S.2 2.3]
[6.5 3.  5.5 1.8]
[7.1 3.4 6.7 2.2]
[7.1 2.6 6.9 J.3]
[6.  2.2 S. 1.S]
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[5.6 2.4 J.9 J.
[7.1 2.4 6.7 2.
[£J 2.7 J.9 1.B]
[6.7 3.3 5.7 2.1]
[7.1 3.2 6. 1.8]
[£1 2.B 4.4 1.8]

[6.4 2.8 5.6 2.1]
[7.2 3.  5.8 1.6]
[7. 2.4 6.i 1.9]

[€. 2.4 S.£ 2.2]
[6.J 2.4 S.i 1.S]
[6 I 2.6 S.6 1.4]
[7.7 3.  6.1 2.3]
[6.3 3.4 5.6 2.4]
[6.4 3.1 5.5 1.8]

[6.9 3.1 5.4 2.1]

[0. 9 3.1 S.1 2.3]
[5.B 2.7 S.1 1.9]
[6 # 3.2 S.9 2.3]
[6.7 3.3 5.7 2.5]
[0. 7 3. S.2 2.3]
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class: 0-Iris-Setosa, 1- Iris-Versicolour, 2- Iris-Virginica
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```

```
x_train, *_teat, y_train, y_tozt - train_teat_split|n.y,test_zizo•0.1]
```

```
y red-oLazsiKier.prediot‹n_tozt*
```

t[16 a dj

a	1.aa	I.aa I.aa 0.8a	I.ba	16
1	0.82		b.9a	14
2	1.aa		d.e9	15
accuracy		6.92	0.9J	45
wrSg%tod avg	0.95		4t	0.93

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

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

In [3]:
```python
dataset = pd.read_csv('salary_dataset.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, 1].values
```

In [4]:
```python
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)
```

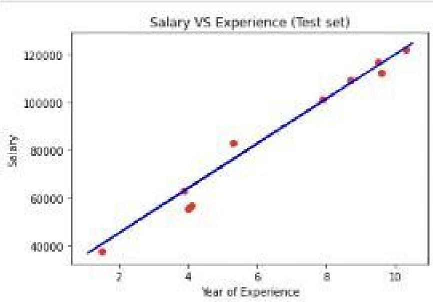
In [5]:
```python
# Fitting Simple Linear Regression to the Training set
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[5]:
```
LinearRegression()
```

In [6]:
```python
# Predicting the Test set results
y_pred = regressor.predict(X_test)
```

In [7]:
```python
# 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 [8]:
```python
# 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()
```



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.

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

In [3]:
```
dataset = pd.read_csv('salary_dataset.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, 1].values
```

In [4]:
```
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 [5]:
```
# Fitting Simple Linear Regression to the Training set
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[5]:
```
LinearRegression()
```

In [6]:
```
# Predicting the Test set results
y_pred = regressor.predict(X_test)
```

In [7]:
```
# 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 [8]:
```
# 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()
```