

**B.M.S. COLLEGE OF ENGINEERING BENGALURU**

Autonomous Institute, Affiliated to VTU



Lab Record

**Machine Learning**

*Submitted in partial fulfillment for the 6<sup>th</sup> Semester Laboratory*

Bachelor of Technology  
in  
Computer Science and Engineering

*Submitted by:*

**Ajay Mittur**

**1BM18CS006**

Department of Computer Science and Engineering  
B.M.S. College of Engineering  
Bull Temple Road, Basavanagudi, Bangalore 560 019  
Mar-June 2021

**B.M.S. COLLEGE OF ENGINEERING**  
**DEPARTMENT OF COMPUTER SCIENCE AND**  
**ENGINEERING**



***CERTIFICATE***

This is to certify that the Machine Learning (20CS6PCMAL) laboratory has been carried out by **Ajay Mittur (1BM18CS006)** during the 6<sup>th</sup> Semester Mar-June-2021.

Signature of the Faculty Incharge:

NAME OF THE FACULTY:

Department of Computer Science and Engineering  
B.M.S. College of Engineering, Bangalore

## Contents

Lab Program	Unit #	Program Details
1	1	Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples.
2	1	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.
3	1	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.
4	3	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
5	3	Write a program to construct a Bayesian network considering training data. Use this model to make predictions.
6	3	Apply k-Means algorithm to cluster a set of data stored in a .CSV file.
7	3	Apply EM algorithm to cluster a set of data stored in a .CSV file. Compare the results of k-Means algorithm and EM algorithm.
8	4	Write a program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions.
9	4	Implement the Linear Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.
10	4	Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

## Program 1: Find S Algorithm

```
In [ ]: # Interactive

len_x = int(input('enter no. of samples: '))
x = []
attrib = input('enter attributes: ').split()
n_attrib = len(attrib)
for i in range(len_x):
    X = input(f'enter sample {i}: ').split()
    x.append(X)
y = []
for i in range(len_x):
    Y = input(f'output for sample {i} (true/false): ')
    Y = Y.lower()
    y.append(True if Y == 'true' else False)
```

```
In [4]: # Read from csv

import pandas as pd
import numpy as np

data = pd.read_csv("data.csv")
print(data)
x = np.array(data)[:,-1]
y = np.array(data)[:,-1]
len_x = len(x)
print(x)
print(y)

temp    time is_holiday result
0  hot  afternoon      yes    True
1  hot   morning       no    False
2  cold afternoon      yes    True
[['hot' 'afternoon' 'yes']
 ['hot' 'morning' 'no']
 ['cold' 'afternoon' 'yes']]
[True False True]
```

```
In [7]: def findSAlgo(x, y, len_x):
        h = x[0] # initial generalization

        for i in range(1, len_x):
            if not y[i]:
                continue

            for j, attrib in enumerate(x[i]):
                if h[j] != attrib:
                    h[j] = '?'

        return h
```

```
In [8]: findSAlgo(x, y, len_x)
```

```
Out[8]: array(['?', 'afternoon', 'yes'], dtype=object)
```

## Program 2: Candidate Elimination Algorithm

```
In [1]: import numpy as np
import pandas as pd
```

```
In [2]: data = pd.read_csv('../input/enjoysport/enjoysport.csv')
X = data.to_numpy()[0:, :-1]
y = data.to_numpy()[0:, -1]
```

```
In [3]: def candidateElimination(X, y):
    n_attrib = len(X[0])
    specific_h = ['0' for _ in range(n_attrib)]
    general_h = [['?' for _ in range(n_attrib)] for _ in range(n_attrib)]

    print('----- Iteration 0 -----')
    print(f'Specific Boundary: {specific_h}')
    print(f'General Boundary: {general_h}')
    print()

    specific_h = X[0].copy()

    for i, x in enumerate(X):
        print(f'----- Iteration {i + 1} -----')
        print(f'Instance {i + 1}: {x} \t Target: {y[i]}')

        if y[i] == 'yes':
            for j in range(n_attrib):
                if x[j] != specific_h[j]:
                    specific_h[j] = '?'
                    general_h[j][j] = '?'
        else:
            for j in range(n_attrib):
                if x[j] != specific_h[j]:
                    general_h[j][j] = specific_h[j]
                else:
                    general_h[j][j] = '?'

        print(f'Specific Boundary: {specific_h}')
        print(f'General Boundary: {general_h}')
        print()

    general_h = [h for h in general_h if h != ['?' for _ in range(n_attrib)]]

    print('----- Result -----')
    print(f'Specific Boundary: {specific_h}')
    print(f'General Boundary: {general_h}')
    print()

    return list(specific_h), list(general_h)
```

In [4]: candidateElimination(X, y)

```
===== Iteration 0 =====
Specific Boundary: ['0', '0', '0', '0', '0', '0']
General Boundary: [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?']]

===== Iteration 1 =====
Instance 1: ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']      Target: yes
Specific Boundary: ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
General Boundary: [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?']]

===== Iteration 2 =====
Instance 2: ['sunny' 'warm' 'high' 'strong' 'warm' 'same']      Target: yes
Specific Boundary: ['sunny' 'warm' '?' 'strong' 'warm' 'same']
General Boundary: [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?']]

===== Iteration 3 =====
Instance 3: ['rainy' 'cold' 'high' 'strong' 'warm' 'change']      Target: no
Specific Boundary: ['sunny' 'warm' '?' 'strong' 'warm' 'same']
General Boundary: [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', 'same']]

===== Iteration 4 =====
Instance 4: ['sunny' 'warm' 'high' 'strong' 'cool' 'change']      Target: yes
Specific Boundary: ['sunny' 'warm' '?' 'strong' '?' '?']
General Boundary: [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

===== Result =====
Specific Boundary: ['sunny' 'warm' '?' 'strong' '?' '?']
General Boundary: [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

Out[4]: (['sunny', 'warm', '?', 'strong', '?', '?'],  
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']])

## Program 3: Decision Tree (ID3)

```
In [62]: import numpy as np
import pandas as pd
eps = np.finfo(float).eps
from numpy import log2 as log
```

```
In [63]: df = pd.read_csv('../input/playtennis/playtennis.csv')
df
```

```
Out[63]:
```

	outlook	temperature	humidity	wind	play
0	sunny	hot	high	weak	no
1	sunny	hot	high	strong	no
2	overcast	hot	high	weak	yes
3	rain	mild	high	weak	yes
4	rain	cool	normal	weak	yes
5	rain	cool	normal	strong	no
6	overcast	cool	normal	strong	yes
7	sunny	mild	high	weak	no
8	sunny	cool	normal	weak	yes
9	rain	mild	normal	weak	yes
10	sunny	mild	normal	strong	yes
11	overcast	mild	high	strong	yes
12	overcast	hot	normal	weak	yes
13	rain	mild	high	strong	no

```
In [64]: def find_entropy(df):
    Class = df.keys()[-1]
    entropy = 0
    values = df[Class].unique()
    for value in values:
        fraction = df[Class].value_counts()[value]/len(df[Class])
        entropy += -fraction*np.log2(fraction)
    return entropy

def find_entropy_attribute(df, attribute):
    Class = df.keys()[-1]
    target_variables = df[Class].unique()
    variables = df[attribute].unique()
    entropy2 = 0
    for variable in variables:
        entropy = 0
        for target_variable in target_variables:
            num = len(df[attribute][df[attribute]==variable][df[Class] ==target_variable])
            den = len(df[attribute][df[attribute]==variable])
```

```

        fraction = num/(den+eps)
        entropy += -fraction*log(fraction+eps)
        fraction2 = den/len(df)
        entropy2 += -fraction2*entropy
    return abs(entropy2)

def find_winner(df):
    Entropy_att = []
    IG = []
    for key in df.keys()[:-1]:
        IG.append(find_entropy(df)-find_entropy_attribute(df,key))
    return df.keys()[:-1][np.argmax(IG)]

def get_subtable(df, node,value):
    return df[df[node] == value].reset_index(drop=True)

def buildTree(df,tree=None):
    Class = df.keys()[:-1]
    node = find_winner(df)
    attValue = np.unique(df[node])
    if tree is None:
        tree={}
        tree[node] = {}

    for value in attValue:

        subtable = get_subtable(df,node,value)
        clValue,counts = np.unique(subtable['play'],return_counts=True)

        if len(counts)==1:
            tree[node][value] = clValue[0]
        else:
            tree[node][value] = buildTree(subtable)

    return tree

```

```

In [65]: t = buildTree(df)
         t

```

```

Out[65]: {'outlook': {'overcast': 'yes',
                      'rain': {'wind': {'strong': 'no', 'weak': 'yes'}}},
          'sunny': {'humidity': {'high': 'no', 'normal': 'yes'}}}

```

```

In [ ]:

```



## Program 4: Naïve Bayes Classifier

```
In [1]: import csv
import random
import math
```

```
In [2]: def load_csv(filename):
    lines = csv.reader(open(filename, "r"));
    dataset = list(lines)
    for i in range(len(dataset)):
        dataset[i] = [float(x) for x in dataset[i]]
    return dataset

def split_dataset(dataset, splitratio):
    trainsize = int(len(dataset) * splitratio);
    trainset = []
    copy = list(dataset);
    while len(trainset) < trainsize:
        index = random.randrange(len(copy));
        trainset.append(copy.pop(index))
    return [trainset, copy]

def separate_by_class(dataset):
    separated = {}
    for i in range(len(dataset)):
        vector = dataset[i]
        if (vector[-1] not in separated):
            separated[vector[-1]] = []
        separated[vector[-1]].append(vector)
    return separated

def mean(numbers):
    return sum(numbers)/float(len(numbers))

def std_dev(numbers):
    avg = mean(numbers)
    variance = sum([pow(x-avg,2) for x in numbers])/float(len(numbers)-1)
    return math.sqrt(variance)

def summarize(dataset):
    summaries = [(mean(attribute), std_dev(attribute)) for attribute in zip(*dataset)];
    del summaries[-1]
    return summaries

def summarize_by_class(dataset):
    separated = separate_by_class(dataset);
    summaries = {}
    for classvalue, instances in separated.items():
        summaries[classvalue] = summarize(instances)
    return summaries

def calculate_probability(x, mean, stdev):
    exponent = math.exp(-(math.pow(x-mean,2)/(2*math.pow(stdev,2))))
    return (1 / (math.sqrt(2*math.pi) * stdev)) * exponent

def calculate_class_probabilities(summaries, inputvector):
    probabilities = {}
```

```

    for classvalue, classsummaries in summaries.items():
        probabilities[classvalue] = 1
    for i in range(len(classsummaries)):
        mean, stdev = classsummaries[i]
        x = inputvector[i]
        probabilities[classvalue] *= calculate_probability(x, mean, stdev)
    return probabilities

def predict(summaries, inputvector):
    probabilities = calculate_class_probabilities(summaries, inputvector)
    bestLabel, bestProb = None, -1
    for classvalue, probability in probabilities.items():
        if bestLabel is None or probability > bestProb:
            bestProb = probability
            bestLabel = classvalue
    return bestLabel

def get_predictions(summaries, testset):
    predictions = []
    for i in range(len(testset)):
        result = predict(summaries, testset[i])
        predictions.append(result)
    return predictions

def get_accuracy(testset, predictions):
    correct = 0
    for i in range(len(testset)):
        if testset[i][-1] == predictions[i]:
            correct += 1
    return (correct/float(len(testset))) * 100.0

```

```

In [3]: splitratio = 0.67
dataset = load_csv('../input/pimaIndiansDiabetes.csv/pima-indians-diabetes.csv');

trainingset, testset = split_dataset(dataset, splitratio)

print(f'Split {len(dataset)} rows into train={len(trainingset)} and test={len(testset)} rows')

summaries = summarize_by_class(trainingset);
predictions = get_predictions(summaries, testset)
accuracy = get_accuracy(testset, predictions)

print(f'Accuracy of the classifier is :{accuracy}%')

```

```

Split 768 rows into train=514 and test=254 rows
Accuracy of the classifier is :64.96062992125984%

```

In [ ]:

## Program 5: Bayesian Network

```
In [1]: import numpy as np
import pandas as pd
import csv
!pip install pgmpy
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.models import BayesianModel
from pgmpy.inference import VariableElimination

Collecting pgmpy
  Downloading pgmpy-0.1.14-py3-none-any.whl (331 kB)
    |#####| 331 kB 3.0 MB/s
Requirement already satisfied: pandas in /opt/conda/lib/python3.7/site-packages (from pgmpy) (1.2.3)
Requirement already satisfied: scikit-learn in /opt/conda/lib/python3.7/site-packages (from pgmpy) (0.24.1)
Requirement already satisfied: scipy in /opt/conda/lib/python3.7/site-packages (from pgmpy) (1.5.4)
Requirement already satisfied: torch in /opt/conda/lib/python3.7/site-packages (from pgmpy) (1.7.0)
Requirement already satisfied: tqdm in /opt/conda/lib/python3.7/site-packages (from pgmpy) (4.59.0)
Requirement already satisfied: joblib in /opt/conda/lib/python3.7/site-packages (from pgmpy) (1.0.1)
Requirement already satisfied: pyparsing in /opt/conda/lib/python3.7/site-packages (from pgmpy) (2.4.7)
Requirement already satisfied: statsmodels in /opt/conda/lib/python3.7/site-packages (from pgmpy) (0.12.2)
Requirement already satisfied: networkx in /opt/conda/lib/python3.7/site-packages (from pgmpy) (2.5)
Requirement already satisfied: numpy in /opt/conda/lib/python3.7/site-packages (from pgmpy) (1.19.5)
Requirement already satisfied: decorator>=4.3.0 in /opt/conda/lib/python3.7/site-packages (from networkx->pgmpy) (4.4.2)
Requirement already satisfied: python-dateutil>=2.7.3 in /opt/conda/lib/python3.7/site-packages (from pandas->pgmpy) (2.8.1)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.7/site-packages (from pandas->pgmpy) (2021.1)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.7/site-packages (from python-dateutil>=2.7.3->pandas->pgmpy) (1.15.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /opt/conda/lib/python3.7/site-packages (from scikit-learn->pgmpy) (2.1.0)
Requirement already satisfied: patsy>=0.5 in /opt/conda/lib/python3.7/site-packages (from statsmodels->pgmpy) (0.5.1)
Requirement already satisfied: future in /opt/conda/lib/python3.7/site-packages (from torch->pgmpy) (0.18.2)
Requirement already satisfied: typing_extensions in /opt/conda/lib/python3.7/site-packages (from torch->pgmpy) (3.7.4.3)
Requirement already satisfied: dataclasses in /opt/conda/lib/python3.7/site-packages (from torch->pgmpy) (0.6)
Installing collected packages: pgmpy
Successfully installed pgmpy-0.1.14

In [2]: heartDisease = pd.read_csv('../input/heartdisease/heart.csv')
heartDisease = heartDisease.replace('?',np.nan)

print('Sample instances from the dataset are given below')
print(heartDisease.head())
print('\n Attributes and datatypes')
print(heartDisease.dtypes)

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

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 [3]: model = BayesianModel([('age','heartdisease'),('sex','heartdisease'),('exang','heartdisease'),('cp','heartdisease'),
('heartdisease','restecg'),('heartdisease','chol')])
```

```
In [4]: print('\nLearning CPD using Maximum likelihood estimators')
model.fit(heartDisease,estimator=MaximumLikelihoodEstimator)
```

```
print('\nInferencing with Bayesian Network:')
HeartDiseasetest_infer = VariableElimination(model)
```

Learning CPD using Maximum likelihood estimators

Inferencing with Bayesian Network:

```
In [5]: print('\n1.Probability of HeartDisease given evidence = restecg :')
q1=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'restecg':1})
print(q1)

print('\n2.Probability of HeartDisease given evidence = cp :')
q2=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'cp':2})
print(q2)
```

```
Finding Elimination Order: : 0%|          | 0/5 [00:00<?, ?it/s]
0%|          | 0/5 [00:00<?, ?it/s]
Finding Elimination Order: : 100%|██████████| 5/5 [00:00<00:00, 480.98it/s]

Eliminating: age: 0%|          | 0/5 [00:00<?, ?it/s]
Eliminating: sex: 0%|          | 0/5 [00:00<?, ?it/s]
Eliminating: chol: 0%|          | 0/5 [00:00<?, ?it/s]
Eliminating: exang: 100%|██████████| 5/5 [00:00<00:00, 92.85it/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

2.Probability of HeartDisease given evidence = cp :

```
Finding Elimination Order: : 0%| | 0/5 [00:00<?, ?it/s]
0%| | 0/5 [00:00<?, ?it/s]
Eliminating: age: 0%| | 0/5 [00:00<?, ?it/s]
Eliminating: sex: 0%| | 0/5 [00:00<?, ?it/s]
Eliminating: chol: 0%| | 0/5 [00:00<?, ?it/s]
Eliminating: exang: 0%| | 0/5 [00:00<?, ?it/s]
Eliminating: restecg: 100%|██████████| 5/5 [00:00<00:00, 227.41it/s]
```

heartdisease	phi(heartdisease)
heartdisease(0)	0.3610
heartdisease(1)	0.2159
heartdisease(2)	0.1373
heartdisease(3)	0.1537
heartdisease(4)	0.1321

---

In [ ]:

---

## Program 6: K-Means (Iris Dataset)

```
In [1]: from sklearn import datasets
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.cluster import KMeans
from sklearn.metrics import accuracy_score, confusion_matrix
```

### Dataset

```
In [2]: iris = datasets.load_iris()
iris
```

```
Out[2]: {'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],
                        [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],
                        [4.8, 3.4, 1.9, 0.2],
                        [5. , 3. , 1.6, 0.2],
                        [5. , 3.4, 1.6, 0.4],
                        [5.2, 3.5, 1.5, 0.2],
                        [5.2, 3.4, 1.4, 0.2],
                        [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],
                        ...])
```

```

1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 4, 4, 4, 4, 4, 4, 4, 4,
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]),
'frame': None,
'target_names': array(['setosa', 'versicolor', 'virginica'], dtype='<U10'),
'DESCR': '._iris_dataset:\n\nIris plants dataset\n-----\n\n**Data Set Characteristics:**\n\n      Num
ber of Instances: 150 (50 in each of three classes)\n      Number of Attributes: 4 numeric, predictive attributes and t
he class\n      Attribute Information:\n          - sepal length in cm\n          - sepal width in cm\n          - petal leng
th in cm\n          - petal width in cm\n          - class:\n          - Iris-Setosa\n          - Iris-Versico
lour\n          - Iris-Virginica\n          \n      Summary Statistics:\n\n      =====
=====
\n      Min Max Mean SD Class Correlation\n      =====
=====
\n      sepal length: 4.3 7.9 5.84 0.83 0.7826\n      sepal width:
2.0 4.4 3.05 0.43 -0.4194\n      petal length: 1.0 6.9 3.76 1.76 0.9490 (high!)\n      petal width:
0.1 2.5 1.20 0.76 0.9565 (high!)\n      =====
=====
\n      Mis
sing Attribute Values: None\n      Class Distribution: 33.3% for each of 3 classes.\n      Creator: R.A. Fisher\n      Do
nor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)\n      Date: July, 1988\n\nThe famous Iris database, first used by
Sir R.A. Fisher. The dataset is taken\nfrom Fisher's paper. Note that it's the same as in R, but not as in the UCI\n
Machine Learning Repository, which has two wrong data points.\n\nThis is perhaps the best known database to be found i
n the\npattern recognition literature. Fisher's paper is a classic in the field and\nis referenced frequently to thi
s day. (See Duda & Hart, for example.) The\ndata set contains 3 classes of 50 instances each, where each class refer
s to a\ntype of iris plant. One class is linearly separable from the other 2; the\nlatter are NOT linearly separable
from each other.\n\n.. topic:: References\n\n      - Fisher, R.A. "The use of multiple measurements in taxonomic problem
s"\n      Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to\n      Mathematical Statistics" (John W
iley, NY, 1950).\n      - Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysis.\n      (Q327.D83) Joh
n Wiley & Sons. ISBN 0-471-22361-1. See page 218.\n      - Dasarthy, B.V. (1980) "Nosing Around the Neighborhood: A Ne
w System\n      Structure and Classification Rule for Recognition in Partially Exposed\n      Environments". IEEE Trans
actions on Pattern Analysis and Machine\n      Intelligence, Vol. PAMI-2, No. 1, 67-71.\n      - Gates, G.W. (1972) "The R
educed Nearest Neighbor Rule". IEEE Transactions\n      on Information Theory, May 1972, 431-433.\n      - See also: 1988
MLC Proceedings, 54-64. Cheeseman et al's AUTOCLASS II\n      conceptual clustering system finds 3 classes in the dat
a.\n      - Many, many more ...',
'feature_names': ['sepal length (cm)',
'sepal width (cm)',
'petal length (cm)',
'petal width (cm)'],
'filename': '/opt/conda/lib/python3.7/site-packages/sklearn/datasets/data/iris.csv'}

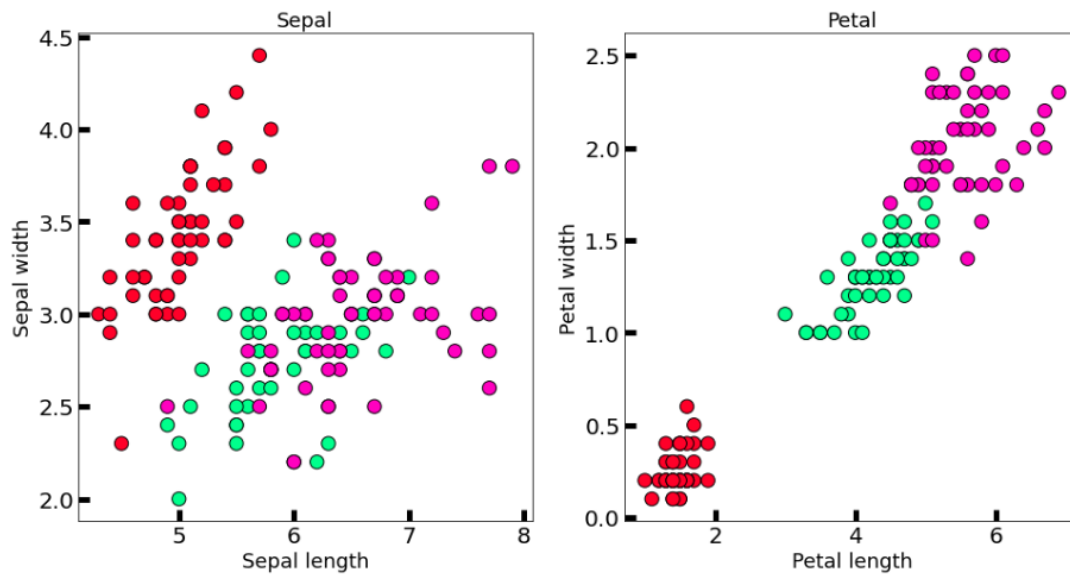
```

```

In [3]: sepal_X = iris.data[:, :2]
petal_X = iris.data[:, 2:]
y = iris.target
categories = len(iris.target_names)

fig, axes = plt.subplots(1, 2, figsize=(16,8))
axes[0].scatter(sepal_X[:, 0], sepal_X[:, 1], c=y, cmap='gist_rainbow', edgecolor='k', s=150)
axes[1].scatter(petal_X[:, 0], petal_X[:, 1], c=y, cmap='gist_rainbow', edgecolor='k', s=150)
axes[0].set_xlabel('Sepal length', fontsize=18)
axes[0].set_ylabel('Sepal width', fontsize=18)
axes[1].set_xlabel('Petal length', fontsize=18)
axes[1].set_ylabel('Petal width', fontsize=18)
axes[0].tick_params(direction='in', length=10, width=5, colors='k', labelsz=20)
axes[1].tick_params(direction='in', length=10, width=5, colors='k', labelsz=20)
axes[0].set_title('Sepal', fontsize=18)
axes[1].set_title('Petal', fontsize=18)
plt.show()

```



## Model

```
In [4]: model_sepal = KMeans(n_clusters=3)
model_sepal.fit(sepal_X)
model_petal = KMeans(n_clusters=3)
model_petal.fit(petal_X)
```

```
Out[4]: KMeans(n_clusters=3)
```

## Analysis

```
In [5]: def plot_centers(sepal_centers, petal_centers):
plt.scatter([point[0] for point in sepal_centers], [point[1] for point in sepal_centers])
plt.title('Sepal KMeans Centers')
plt.show()
```



```

plt.title('Petal KMeans Centers')
plt.show()

def plot_actualvpredicted(X, y, predicted, part):
    fig, axes = plt.subplots(1, 2, figsize=(16,8))
    axes[0].scatter(X[:, 0], X[:, 1], c=y, cmap='gist_rainbow', edgecolor='k', s=150)
    axes[1].scatter(X[:, 0], X[:, 1], c=predicted, cmap='jet', edgecolor='k', s=150)
    axes[0].set_xlabel(f'{part} length', fontsize=18)
    axes[0].set_ylabel(f'{part} width', fontsize=18)
    axes[1].set_xlabel(f'{part} length', fontsize=18)
    axes[1].set_ylabel(f'{part} width', fontsize=18)
    axes[0].tick_params(direction='in', length=10, width=5, colors='k', labelsiz=20)
    axes[1].tick_params(direction='in', length=10, width=5, colors='k', labelsiz=20)
    axes[0].set_title('Actual', fontsize=18)
    axes[1].set_title('Predicted', fontsize=18)
    plt.show()

def plot_confusion(accuracy, confusion, part):
    print(f'{part} Accuracy: {accuracy}')

    fig, ax = plt.subplots()
    im = ax.imshow(confusion)

    ax.set_xticks(range(categories))
    ax.set_yticks(range(categories))
    ax.set_xticklabels(iris.target_names)
    ax.set_yticklabels(iris.target_names)

    plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
             rotation_mode="anchor")

    for i in range(categories):
        for j in range(categories):
            text = ax.text(j, i, confusion[i, j],
                           ha="center", va="center", color="w")

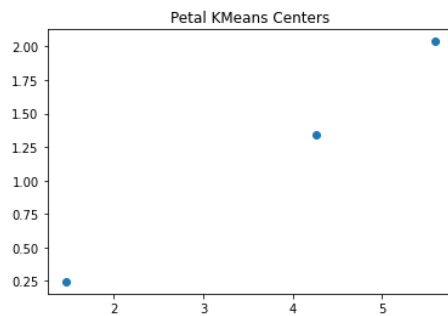
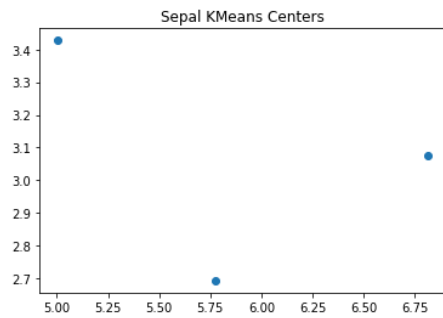
    ax.set_title(f'{part} Confusion Matrix (Actual / Predicted)')
    fig.tight_layout()
    plt.show()

```

```

In [6]: sepal_centers = model_sepal.cluster_centers_
        petal_centers = model_petal.cluster_centers_
        plot_centers(sepal_centers, petal_centers)

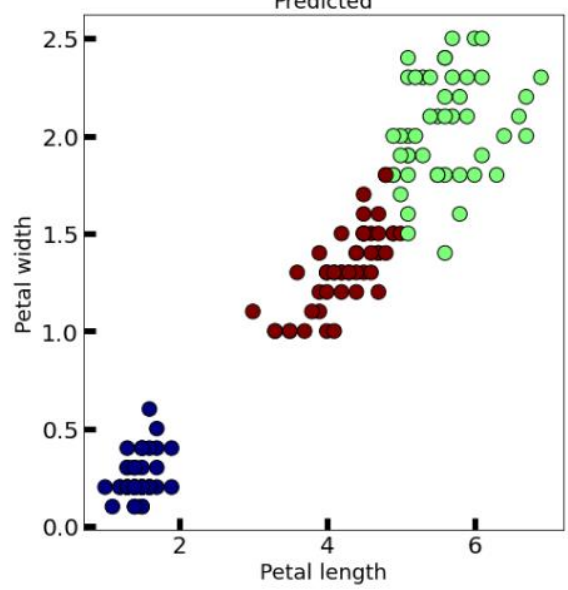
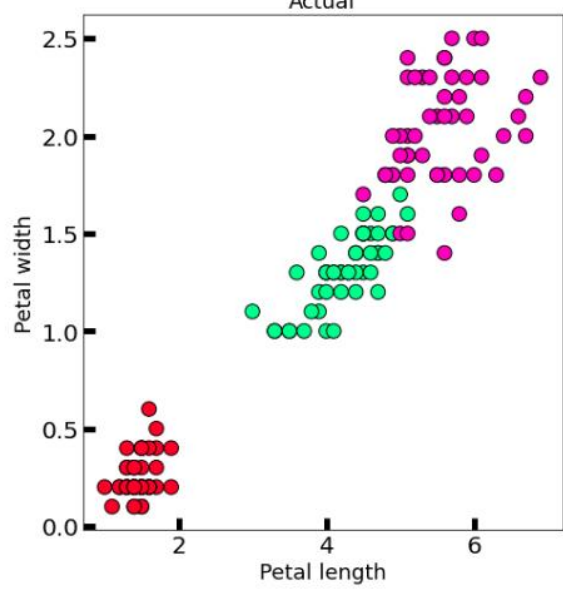
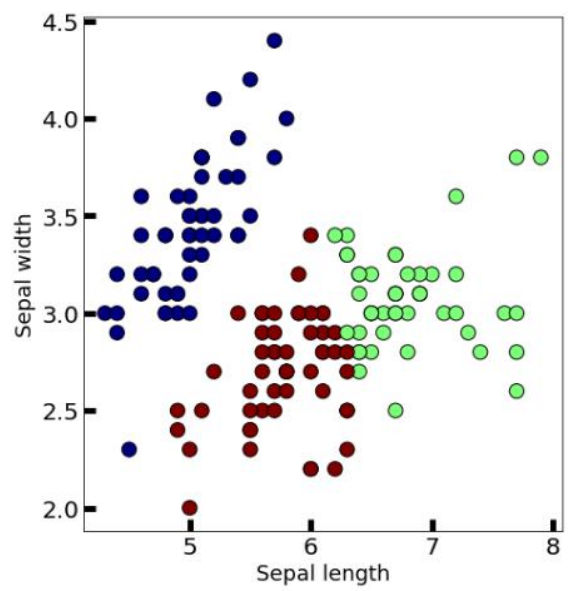
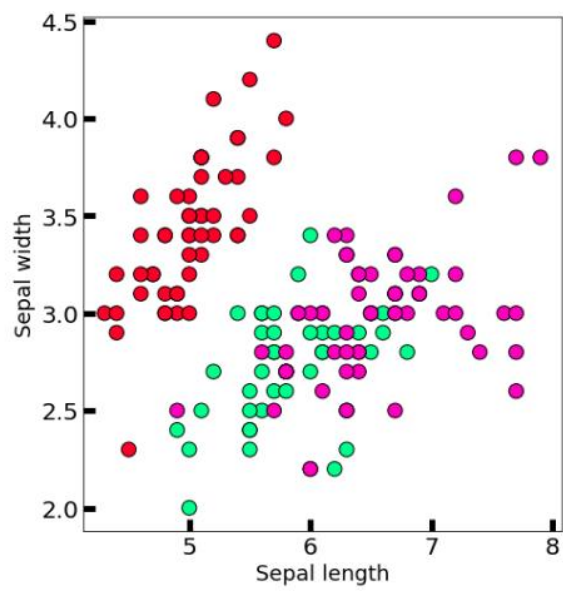
```



```
In [7]: sepal_labels = model_sepal.labels_
petal_labels = model_petal.labels_
print(sepal_labels, petal_labels, sep='\n')

[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 2 1 2 1 2 1 2 2 2 2 2 2 1 2 2 2 2 2 2 2
 1 1 1 1 2 2 2 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 1 1 1 1 2 1 1 1
 1 1 2 2 1 1 1 1 2 1 2 1 2 1 1 2 2 1 1 1 1 1 2 2 1 1 1 2 1 1 1 2 1
 1 2]
[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 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 1 2 2 2 2 2 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 2 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1
 1 1]
```

```
In [8]: plot_actualvpredicted(sepal_X, y, sepal_labels, 'Sepal')
plot_actualvpredicted(petal_X, y, petal_labels, 'Petal')
```

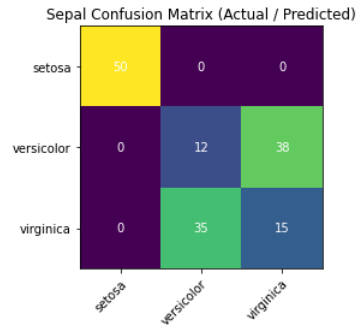


```
In [9]: sepal_accuracy = accuracy_score(y, sepal_labels)
petal_accuracy = accuracy_score(y, petal_labels)

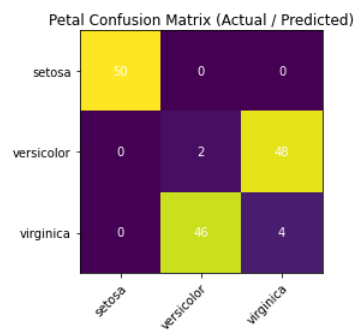
sepal_confusion = confusion_matrix(y, sepal_labels)
petal_confusion = confusion_matrix(y, petal_labels)
```

```
In [10]: plot_confusion(sepal_accuracy, sepal_confusion, 'Sepal')
plot_confusion(petal_accuracy, petal_confusion, 'Petal')
```

Sepal Accuracy: 0.5133333333333333



Petal Accuracy: 0.37333333333333335



## Program 7: EM vs K-Means (Iris Dataset)

```
In [1]: import matplotlib.pyplot as plt
import pandas as pd
from sklearn.mixture import GaussianMixture
from sklearn.metrics import accuracy_score, confusion_matrix
```

### Data

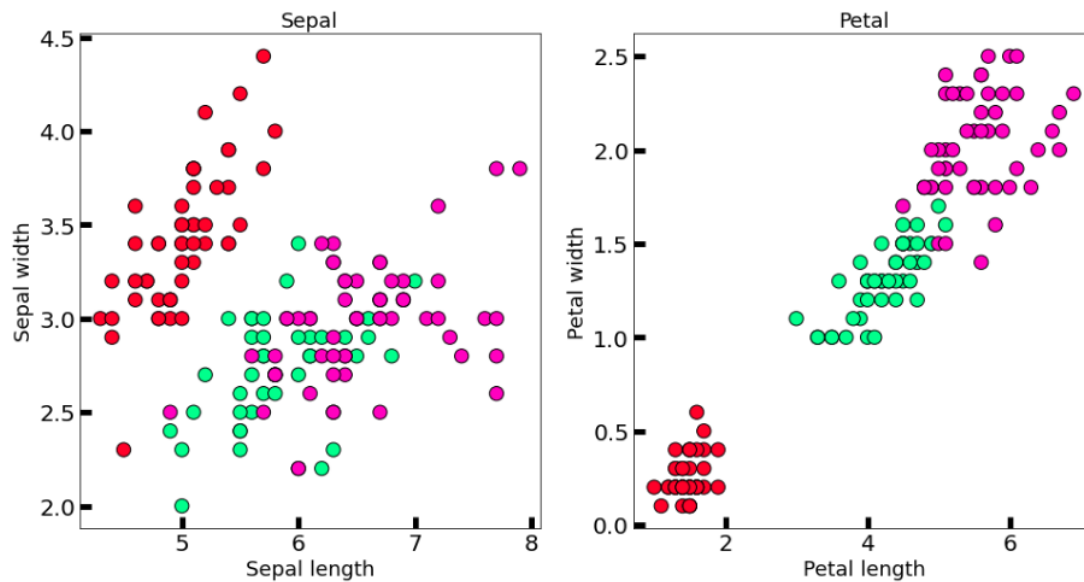
```
In [2]: data = pd.read_csv('../input/iris/Iris.csv')
data.head()
```

```
Out[2]:
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

```
In [3]: sepal_X = data[['SepalLengthCm', 'SepalWidthCm']]
petal_X = data[['PetalLengthCm', 'PetalWidthCm']]
y = data['Species'].astype("category").cat.codes
num_cat = y.nunique()
categories = data['Species'].astype("category").cat.categories
```

```
In [4]: fig, axes = plt.subplots(1, 2, figsize=(16,8))
axes[0].scatter(sepal_X.SepalLengthCm, sepal_X.SepalWidthCm, c=y, cmap='gist_rainbow', edgecolor='k', s=150)
axes[1].scatter(petal_X.PetalLengthCm, petal_X.PetalWidthCm, c=y, cmap='gist_rainbow', edgecolor='k', s=150)
axes[0].set_xlabel('Sepal length', fontsize=18)
axes[0].set_ylabel('Sepal width', fontsize=18)
axes[1].set_xlabel('Petal length', fontsize=18)
axes[1].set_ylabel('Petal width', fontsize=18)
axes[0].tick_params(direction='in', length=10, width=5, colors='k', labelsiz=20)
axes[1].tick_params(direction='in', length=10, width=5, colors='k', labelsiz=20)
axes[0].set_title('Sepal', fontsize=18)
axes[1].set_title('Petal', fontsize=18)
plt.show()
```



## Model

```
In [5]: model_sepal = GaussianMixture(n_components=3)
sepal_labels = model_sepal.fit_predict(sepal_X)
model_petal = GaussianMixture(n_components=3)
petal_labels = model_petal.fit_predict(petal_X)
```

## Analysis

```
In [6]: def plot_actuallpredicted(X, y, predicted, part):
fig, axes = plt.subplots(1, 2, figsize=(16,8))
axes[0].scatter(X[f'{part}LengthCm'], X[f'{part}WidthCm'], c=y, cmap='gist_rainbow', edgecolor='k', s=150)
axes[1].scatter(X[f'{part}LengthCm'], X[f'{part}WidthCm'], c=predicted, cmap='jet', edgecolor='k', s=150)
axes[0].set_xlabel(f'{part} length', fontsize=18)
axes[0].set_ylabel(f'{part} width', fontsize=18)
axes[1].set_xlabel(f'{part} length', fontsize=18)
axes[1].set_ylabel(f'{part} width', fontsize=18)
axes[0].tick_params(direction='in', length=10, width=5, colors='k', labelsiz=20)
axes[1].tick_params(direction='in', length=10, width=5, colors='k', labelsiz=20)
axes[0].set_title('Actual', fontsize=18)
axes[1].set_title('Predicted', fontsize=18)
plt.show()
```

```
def plot_confusion(accuracy, confusion, part):
    print(f'{part} Accuracy: {accuracy}')

    fig, ax = plt.subplots()
    im = ax.imshow(confusion)

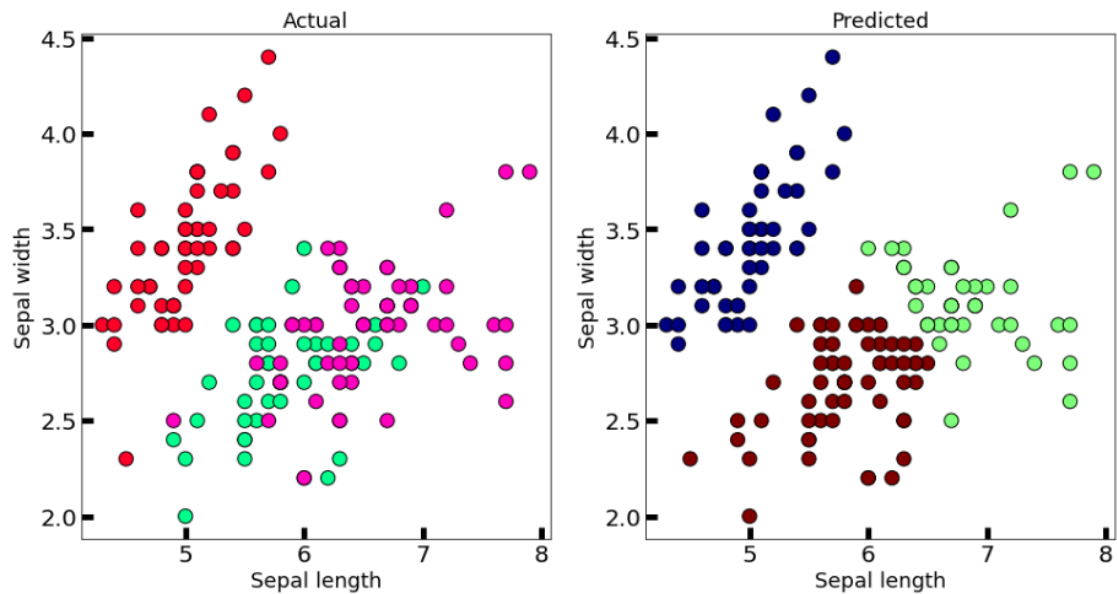
    ax.set_xticks(range(num_cat))
    ax.set_yticks(range(num_cat))
    ax.set_xticklabels(categories)
    ax.set_yticklabels(categories)

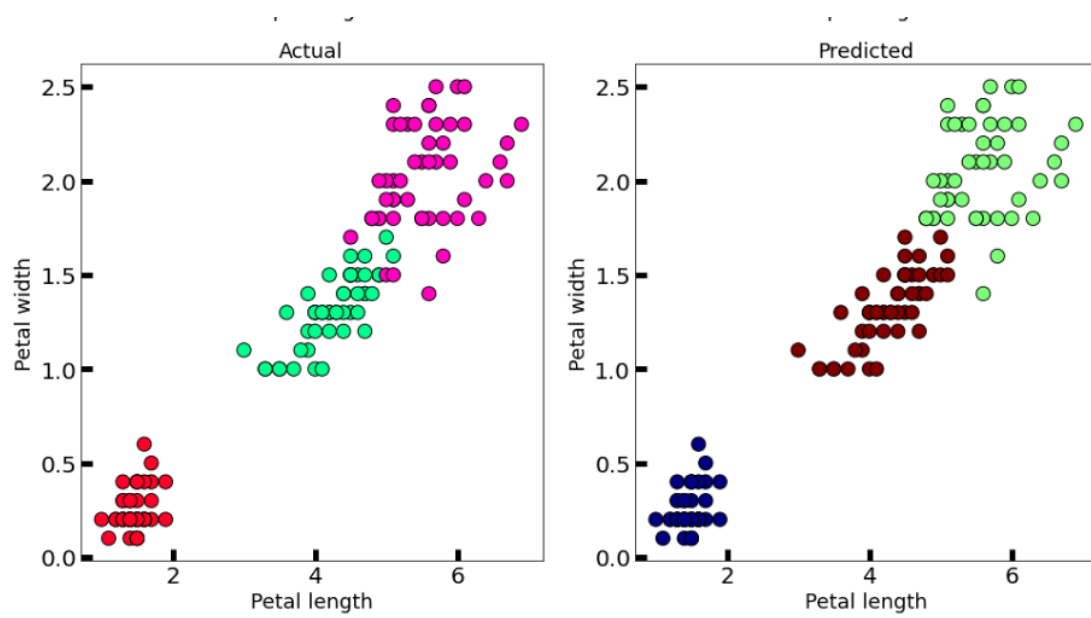
    plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
              rotation_mode="anchor")

    for i in range(num_cat):
        for j in range(num_cat):
            text = ax.text(j, i, confusion[i, j],
                           ha="center", va="center", color="w")

    ax.set_title(f'{part} Confusion Matrix (Actual / Predicted)')
    fig.tight_layout()
    plt.show()
```

```
In [7]: plot_actuallvpredicted(sepal_X, y, sepal_labels, 'Sepal')
        plot_actuallvpredicted(petal_X, y, petal_labels, 'Petal')
```





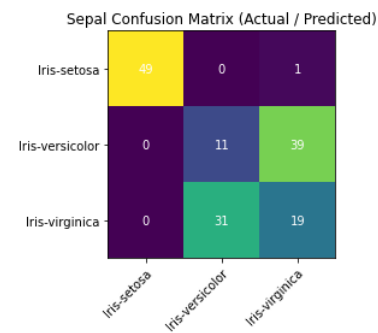
```
In [8]: sepal_accuracy = accuracy_score(y, sepal_labels)
petal_accuracy = accuracy_score(y, petal_labels)

sepal_confusion = confusion_matrix(y, sepal_labels)
petal_confusion = confusion_matrix(y, petal_labels)
```

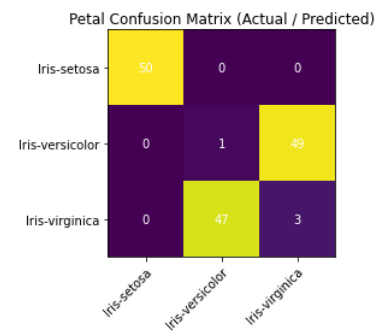


```
In [9]: plot_confusion(sepal_accuracy, sepal_confusion, 'Sepal')
        plot_confusion(petal_accuracy, petal_confusion, 'Petal')
```

Sepal Accuracy: 0.5266666666666666



Petal Accuracy: 0.36



## Comparison with K-Means

When we compare the results of the GaussianMixture model (uses EM algorithm) with that of [K-Means clustering](#) we observe that both give almost equal accuracies:

- K-Means: 0.5133333333333333 (*Sepal*) & 0.37333333333333335 (*Petal*)
- GaussianMixture: 0.5333333333333333 (*Sepal*) & 0.02 (*Petal*)

GaussianMixture performs slightly better when classified based on the *Sepal* length & width. Likewise K-Means performs slightly better when classified based on the *Petal* length & width.

```
In [ ]:
```

## Program 8: KNN (Iris Dataset)

```
In [1]: import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.model_selection import train_test_split
```

### Data

```
In [2]: data = pd.read_csv('../input/iris/Iris.csv')
```

```
In [3]: data.head()
```

```
Out[3]:
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

```
In [4]: data.describe()
```

```
Out[4]:
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

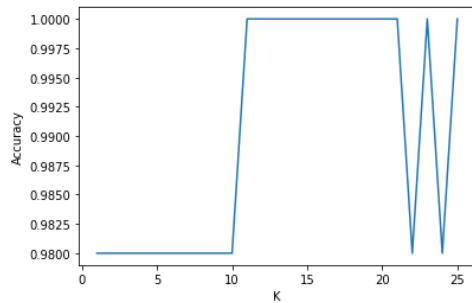
```
In [5]: X = data[['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm']]
sepal_X = data[['SepalLengthCm', 'SepalWidthCm']]
petal_X = data[['PetalLengthCm', 'PetalWidthCm']]
y = data['Species'].astype("category").cat.codes
num_cat = y.nunique()
categories = data['Species'].astype("category").cat.categories
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)
```

## Model

```
In [6]: scores = {}
scores_list = []
for k in range(1, 26):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    scores[k] = accuracy_score(y_test, y_pred)
    scores_list.append(scores[k])
```

## Analysis

```
In [7]: plt.plot(range(1, 26), scores_list)
plt.xlabel('k')
plt.ylabel('Accuracy')
plt.show()
```



```
In [8]: knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print("Confusion Matrix")
print(confusion_matrix(y_test, y_pred))
print(f"Correct Predictions: {accuracy_score(y_test, y_pred)}")
print(f"Wrong Predictions: {1 - accuracy_score(y_test, y_pred)}")
print("Accuracy Metrics: ")
print(classification_report(y_test, y_pred))
```

```
Confusion Matrix
[[19  0  0]
 [ 0 15  0]
 [ 0  1 15]]
Correct Predictions: 0.98
Wrong Predictions: 0.020000000000000018
Accuracy Metrics:
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	0.94	1.00	0.97	15
2	1.00	0.94	0.97	16
accuracy			0.98	50
macro avg	0.98	0.98	0.98	50
weighted avg	0.98	0.98	0.98	50

```
In [ ]:
```

## Program 9: Linear Regression

```
In [1]: import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

### Data

```
In [2]: df = pd.read_csv('../input/housesalesprediction/kc_house_data.csv')
```

```
In [3]: df.head()
```

```
Out[3]:
```

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0	0	0	...	7	1180
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0	0	0	...	7	2170
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0	0	0	...	6	770
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0	0	0	...	7	1050
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0	0	0	...	8	1680

5 rows x 21 columns

```
In [4]: X = np.array(df['sqft_living']).reshape(-1, 1)
y = df['price']
```

```
In [5]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)
```

### Model

```
In [6]: model = LinearRegression()
model.fit(X_train, y_train)
# model.fit(X, y)
```

```
Out[6]: LinearRegression()
```

### Analysis

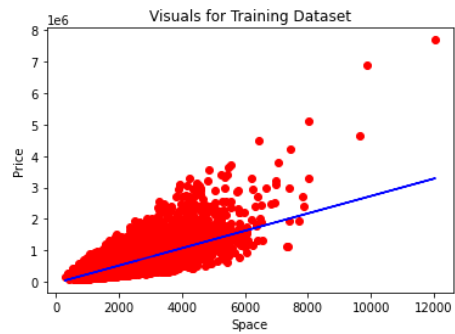
```
In [7]: y_pred = model.predict(X_test)
print(f"Mean Squared Error: {mean_squared_error(y_pred, y_test)}")
```

Mean Squared Error: 76715223988.35832

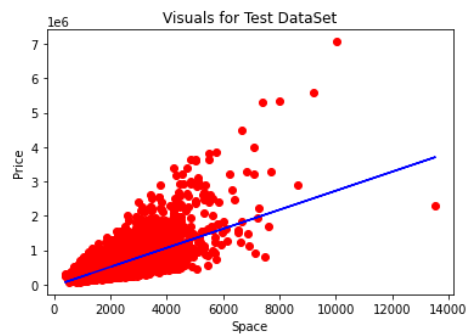
```
In [8]: #Visualizing the training Test Results
plt.scatter(X_train, y_train, color= 'red')
```

mean\_squared\_error: 1.703222550075552

```
In [8]: #Visualizing the training Test Results
plt.scatter(X_train, y_train, color= 'red')
plt.plot(X_train, model.predict(X_train), color = 'blue')
plt.title ("Visuals for Training Dataset")
plt.xlabel("Space")
plt.ylabel("Price")
plt.show()
```



```
In [9]: #Visualizing the Test Results
plt.scatter(X_test, y_test, color= 'red')
plt.plot(X_test, model.predict(X_test), color = 'blue')
plt.title("Visuals for Test DataSet")
plt.xlabel("Space")
plt.ylabel("Price")
plt.show()
```



In [ ]:

## Program 10: Locally Weighted Regression

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

### Functions

```
In [2]: # kernel smoothing function
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

# function to return local weight of eah training example
def localWeight(point, xmat, ymat, k):
    wt = kernel(point, xmat, k)
    W = (X.T * (wt*X)).I * (X.T * wt * ymat.T)
    return W

# root function that drives the algorithm
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
```

### Data

```
In [3]: #import data
data = pd.read_csv('../input/tipsdata/tips.csv')

# place them in suitable data types
colA = np.array(data.total_bill)
colB = np.array(data.tip)

mcolA = np.mat(colA)
mcolB = np.mat(colB)

m = np.shape(mcolB)[1]
one = np.ones((1, m), dtype = int)

# horizontal stacking
X = np.hstack((one.T, mcolA.T))
print(X.shape)
```

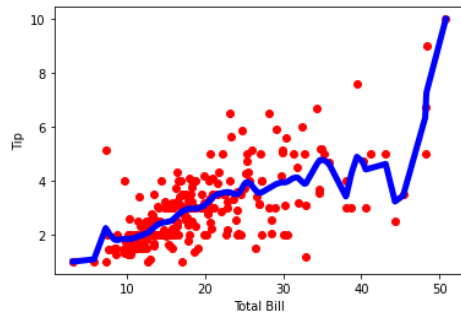
(244, 2)

## Model

```
In [4]: # predicting values using LWLR
ypred = localWeightRegression(X, mcolB, 0.8)
```

## Analysis

```
In [5]: # plotting the predicted graph
xsort = X.copy()
xsort.sort(axis=0)
plt.scatter(colA, colB, color='red')
plt.plot(xsort[:, 1], ypred[X[:, 1].argsort(0)], color='blue', linewidth=5)
plt.xlabel('Total Bill')
plt.ylabel('Tip')
plt.show()
```



```
In [ ]:
```