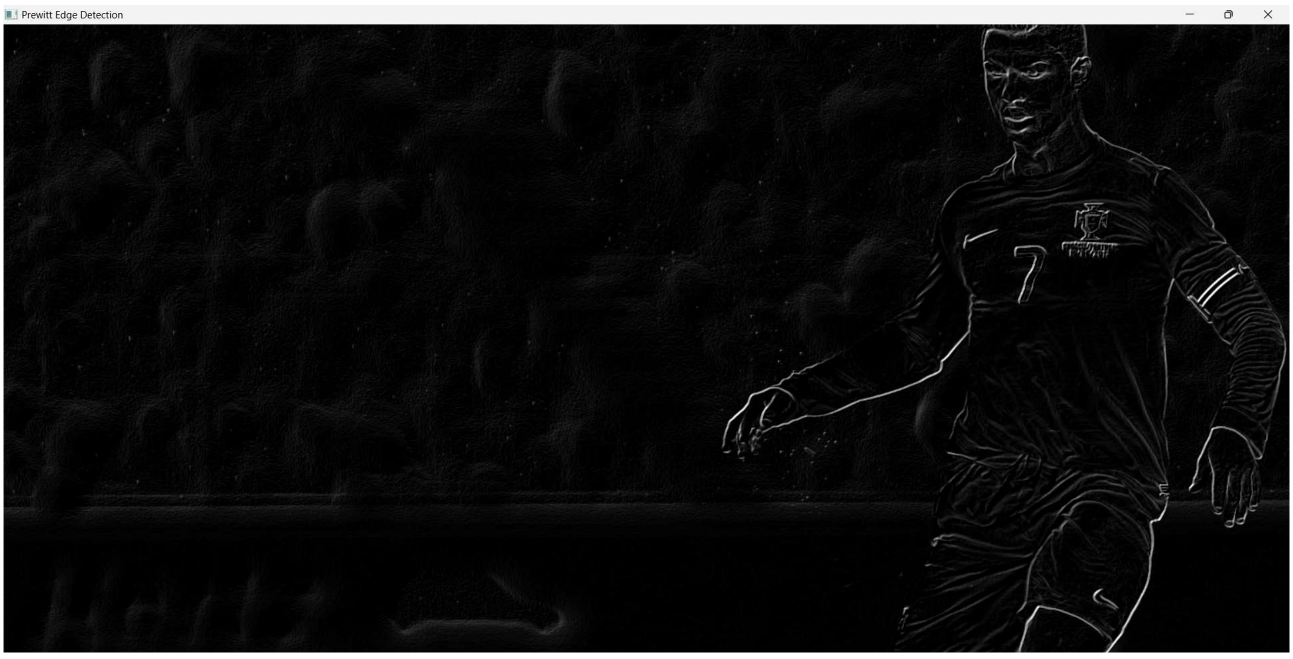
1.Program to show the edge detection using python programming

1. **Prewitt Edge Detection**

```
import cv2
import numpy as np

# Read the image
img = cv2.imread('cr7.jpg', 0)

# Apply Prewitt edge detection
prewittx = cv2.filter2D(img, -1, np.array([[-1, 0, 1], [-1, 0, 1], [-1, 0, 1]]))
prewitty = cv2.filter2D(img, -1, np.array([[-1, -1, -1], [0, 0, 0], [1, 1, 1]]))
prewitt = cv2.addWeighted(prewittx, 0.5, prewitty, 0.5, 0)

# Display the result
cv2.imshow('Prewitt Edge Detection', prewitt)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

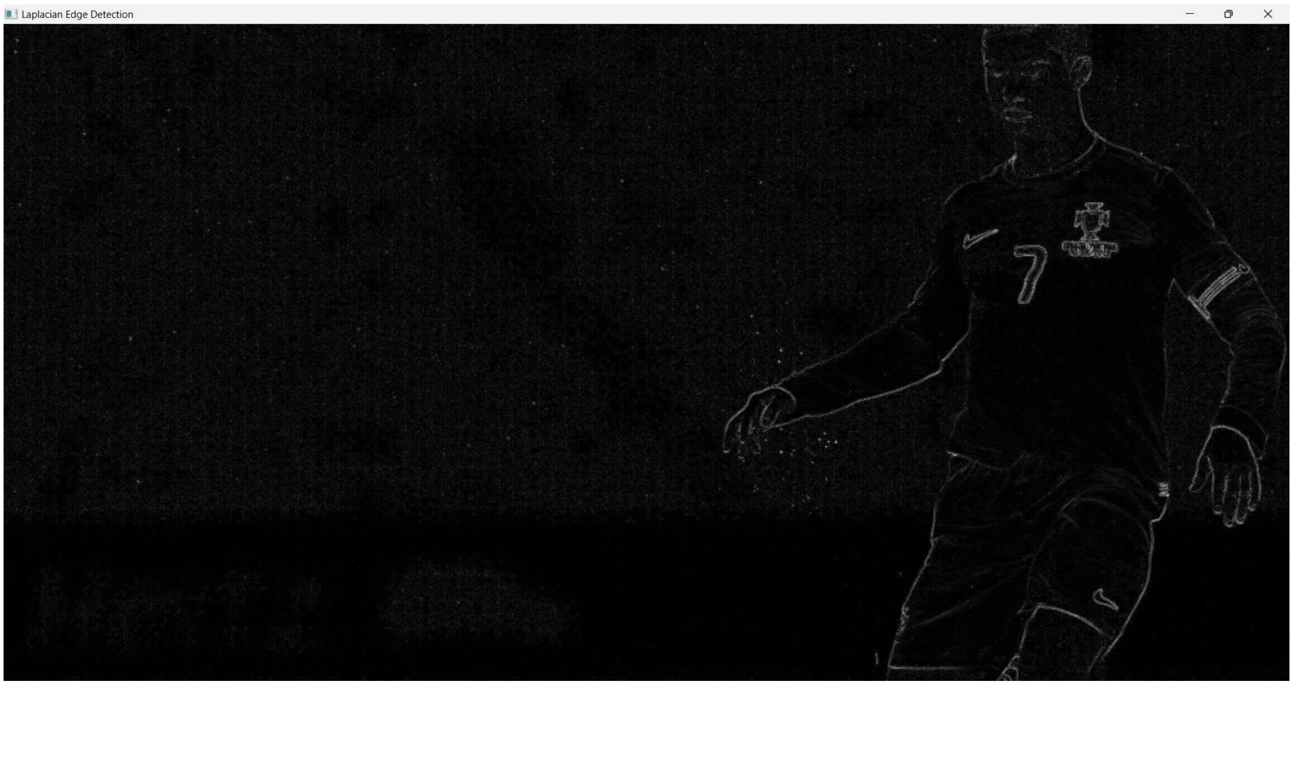
Output:



2.**Laplacian Edge Detection**

```
import cv2
import numpy as np

# Read the image
img = cv2.imread('cr7.jpg', 0)

# Apply Laplacian edge detection
laplacian = cv2.Laplacian(img, cv2.CV_64F)

# Convert to uint8 format
laplacian = np.uint8(np.absolute(laplacian))

# Display the result
cv2.imshow('Laplacian Edge Detection', laplacian)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

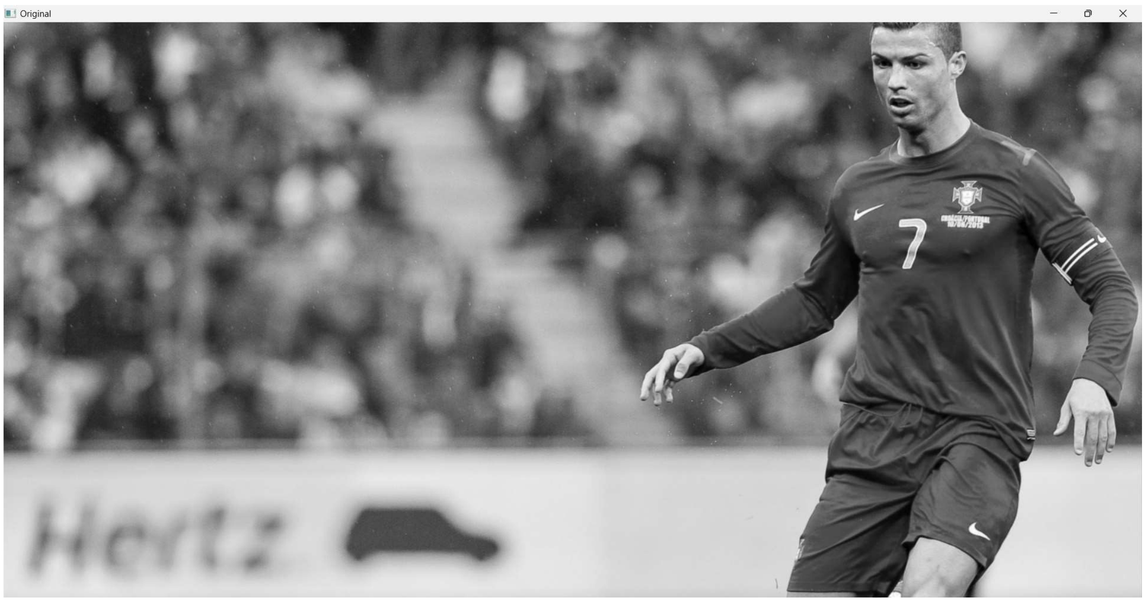
Output:

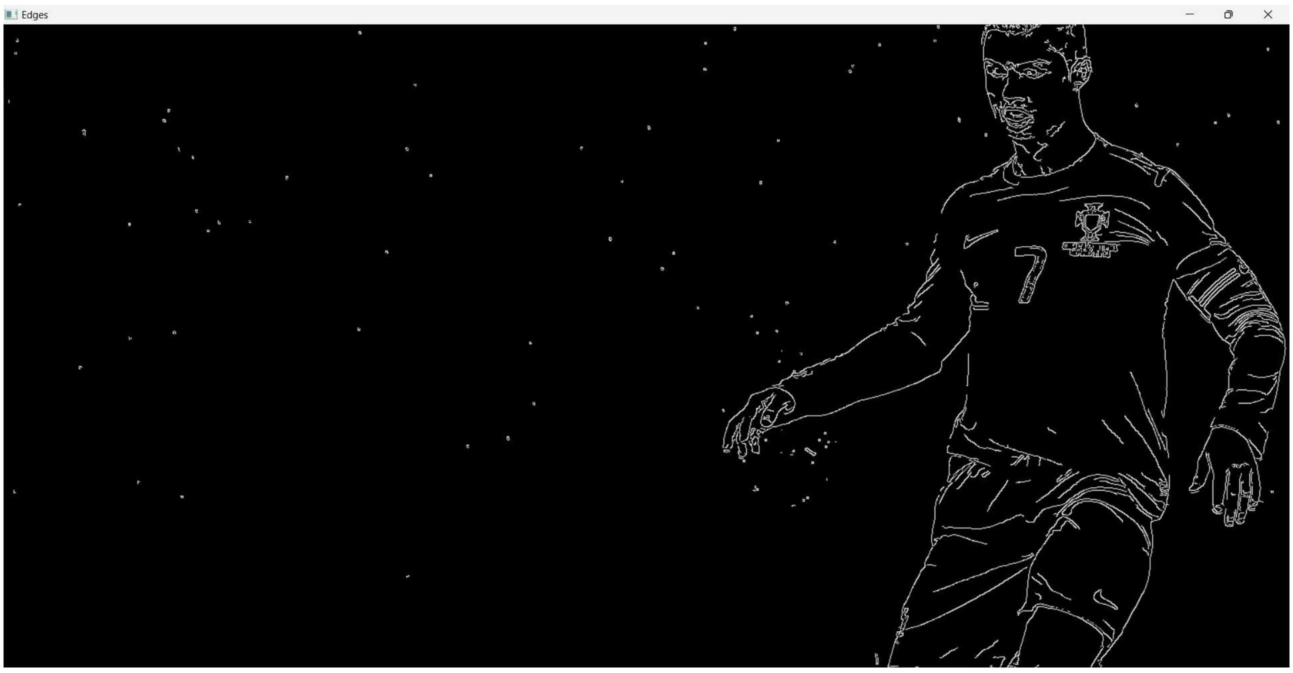


3.**Canny Edge Program**

```
import cv2
# Load image in grayscale
img = cv2.imread('cr7.jpg', 0)
# Apply Canny edge detection
edges = cv2.Canny(img, 100, 200)
# Display original image and edges
cv2.imshow('Original', img)
cv2.imshow('Edges', edges)
# Wait for a key press and close all windows
cv2.waitKey(0)
cv2.destroyAllWindows()
```

Output:



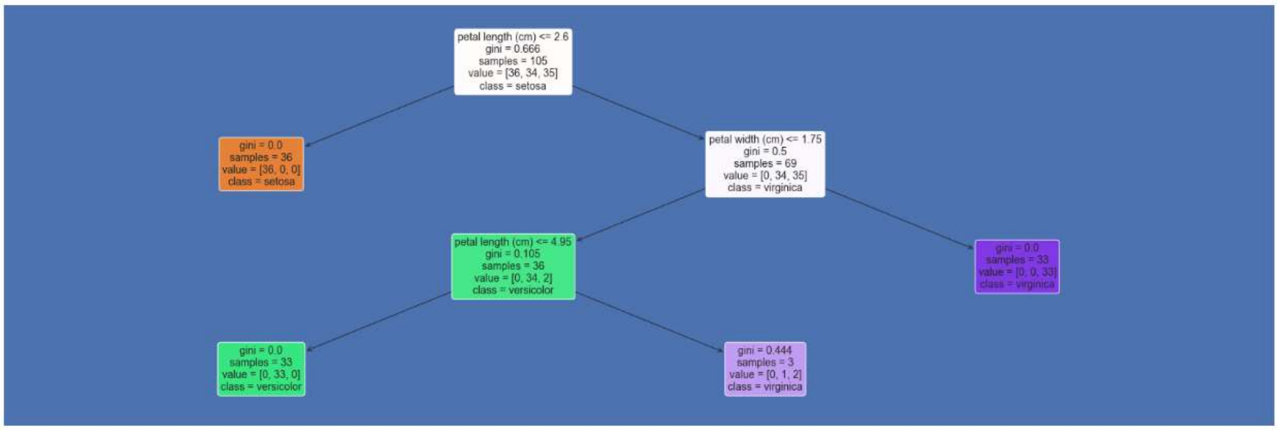


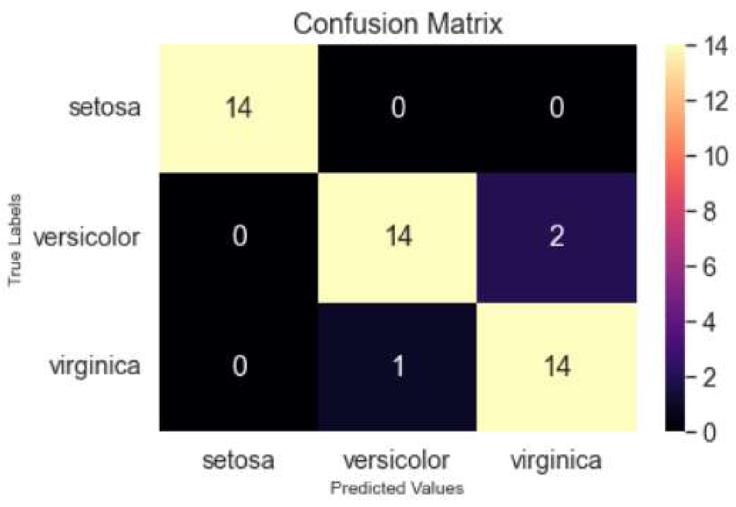
2.Write a program to implement decision tree algorithm.

```
 import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import metrics
import seaborn as sns
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn import tree
from sklearn.metrics import accuracy_score

# Loading the dataset
iris = load_iris()
#converting the data to a pandas dataframe
data = pd.DataFrame(data = iris.data, columns = iris.feature_names)

#data=pd.read_csv('Iris.csv')
#creating a separate column for the target variable of iris dataset
data['Species'] = iris.target

#replacing the categories of target variable with the actual names of the species
target = np.unique(iris.target)
target_n = np.unique(iris.target_names)
target_dict = dict(zip(target, target_n))
data['Species'] = data['Species'].replace(target_dict)

# Separating the independent dependent variables of the dataset
x = data.drop(columns = "Species")
y = data["Species"]
names_features = x.columns
target_labels = y.unique()

# Splitting the dataset into training and testing datasets
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3, random_state = 93)

# Importing the Decision Tree classifier class from sklearn
from sklearn.tree import DecisionTreeClassifier

# Creating an instance of the classifier class
dtc = DecisionTreeClassifier(max_depth = 3, random_state = 93)

# Fitting the training dataset to the model
dtc.fit(x_train, y_train)

# Plotting the Decision Tree
plt.figure(figsize = (30, 10), facecolor = 'b')
Tree = tree.plot_tree(dtc, feature_names = names_features, class_names = target_labels, rounded =
True, filled = True, fontsize = 14)
plt.show()
y_pred = dtc.predict(x_test)
```

```
# Finding the confusion matrix
confusion_matrix = metrics.confusion_matrix(y_test, y_pred)
matrix = pd.DataFrame(confusion_matrix)
axis = plt.axes()
sns.set(font_scale = 1.3)
plt.figure(figsize = (10,7))

# Plotting heatmap
sns.heatmap(matrix, annot = True, fmt = "g", ax = axis, cmap = "magma")
axis.set_title('Confusion Matrix')
axis.set_xlabel("Predicted Values", fontsize = 10)
axis.set_xticklabels([''] + target_labels)
axis.set_ylabel( "True Labels", fontsize = 10)
axis.set_yticklabels(list(target_labels), rotation = 0)
plt.show()


accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

Output:





```
<Figure size 720x504 with 0 Axes>

Accuracy: 0.9333333333333333
```

3.Program to implement Find S algorithm.

```
import numpy as np
import pandas as pd

data = pd.read_csv('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 generic_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 Boundary 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")
```

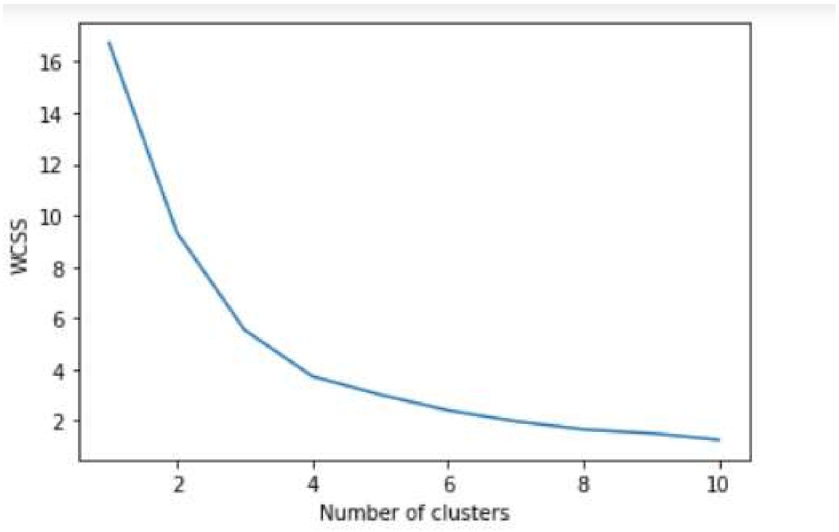
```
Instances are:
 [['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
 ['Sunny' 'Warm' 'High' 'Strong' 'Warm' 'Same']
 ['Rainy' 'Cold' 'High' 'Strong' 'Warm' 'Change']
 ['Sunny' 'Warm' 'High' 'Strong' 'Cool' 'Change']]

Target Values are:  [1 1 0 1]

Initialization of specific_h and generic_h

Specific Boundary:  ['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']

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

Instance 1 is  ['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
Specific Boundary after  1 Instance is  ['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
Generic Boundary after  1 Instance is  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
'?'], ['?', '?', '?', '?', '?', '?']]
```

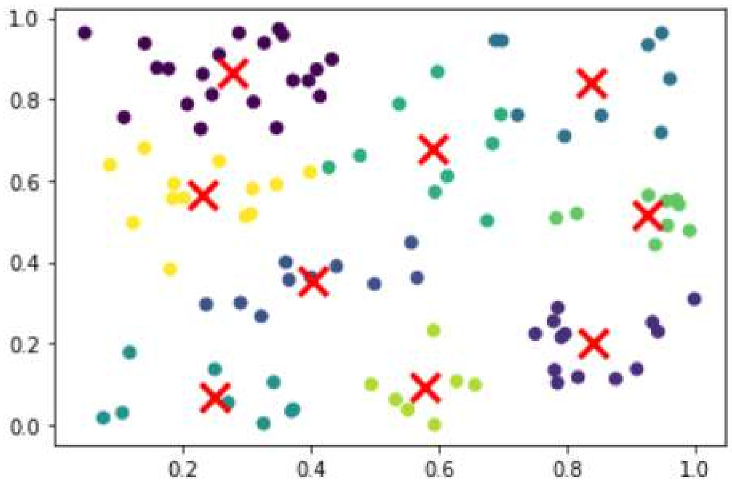
```
Instance 2 is  ['Sunny' 'Warm' 'High' 'Strong' 'Warm' 'Same']
Specific Boundary after  2 Instance is  ['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
Generic Boundary after  2 Instance is  []



Instance 3 is  ['Rainy' 'Cold' 'High' 'Strong' 'Warm' 'Change']
Specific Boundary after  3 Instance is  ['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
Generic Boundary after  3 Instance is  []



Instance 4 is  ['Sunny' 'Warm' 'High' 'Strong' 'Cool' 'Change']
Specific Boundary after  4 Instance is  ['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
Generic Boundary after  4 Instance is  []


Final Specific_h:
['Sunny' 'Warm' 'Normal' 'Strong' 'Warm' 'Same']
Final General_h:
[]
```

4.Program to implement K-means clustering.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

# Generate random data
X = np.random.rand(100, 2)

# Initialize empty list for WCSS
wcss = []

# Loop through number of clusters from 1 to 10
for i in range(1, 11):
    # Initialize KMeans object
    kmeans = KMeans(n_clusters=i)

    # Fit KMeans object to the data
    kmeans.fit(X)

    # Append WCSS to list
    wcss.append(kmeans.inertia_)

# Plot WCSS vs. number of clusters
plt.plot(range(1, 11), wcss)
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()

# Initialize KMeans object with optimal number of clusters
k = np.argmin(np.diff(wcss, 2)) + 2
kmeans = KMeans(n_clusters=k)

# Fit KMeans object to the data
kmeans.fit(X)

# Get cluster centers and labels
centers = kmeans.cluster_centers_
labels = kmeans.labels_

# Plot data points and cluster centers
plt.scatter(X[:, 0], X[:, 1], c=labels)
plt.scatter(centers[:, 0], centers[:, 1], marker='x', s=200, linewidths=3, color='r')
plt.show()
```

Output:

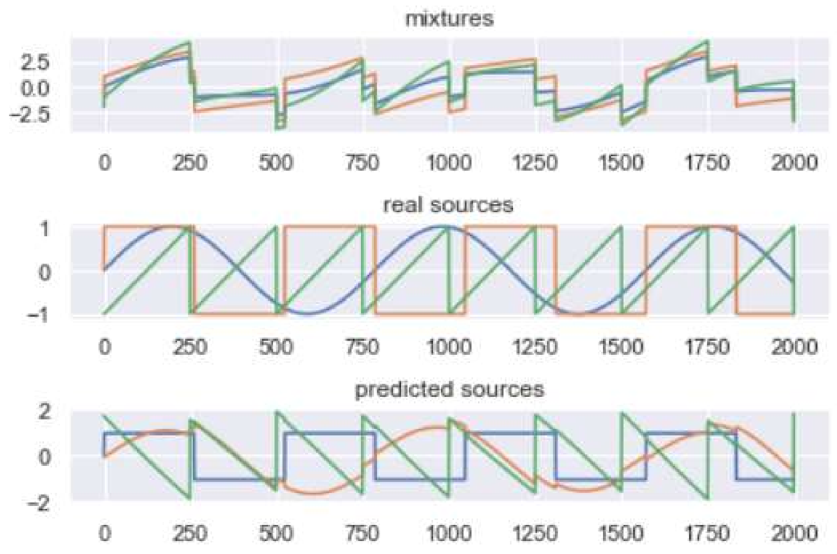

WCSS
Number of clusters
16
14
12
10
8
6
4
2
2
4
6
8
10


1.0
0.8
0.6
0.4
0.2
0.0
0.2
0.4
0.6
0.8
1.0

5.Program to implement Independent Component Analysis.

```
import numpy as np
np.random.seed(0)
from scipy import signal
from scipy.io import wavfile
from matplotlib import pyplot as plt
import seaborn as sns
sns.set(rc={'figure.figsize':(11.7,8.27)})
def g(x):
    return np.tanh(x)
def g_der(x):
    return 1 - g(x) * g(x)
def center(X):
 X = np.array(X)
 mean = X.mean(axis=1, keepdims=True)
 return X- mean
def whitening(X):
 cov = np.cov(X)
 d, E = np.linalg.eigh(cov)
 D = np.diag(d)
 D_inv = np.sqrt(np.linalg.inv(D))
 X_whiten = np.dot(E, np.dot(D_inv, np.dot(E.T, X)))
 return X_whiten
def calculate_new_w(w, X):
 w_new = (X * g(np.dot(w.T, X))).mean(axis=1) - g_der(np.dot(w.T,
 X)).mean() * w
 w_new /= np.sqrt((w_new ** 2).sum())
 return w_new
def ica(X, iterations, tolerance=1e-5):
    X = center(X)
    X = whitening(X)
    components_nr = X.shape[0]
    W = np.zeros((components_nr, components_nr), dtype=X.dtype)
    for i in range(components_nr):
        w = np.random.rand(components_nr)
        for j in range(iterations):
            w_new = calculate_new_w(w, X)
            if i >= 1:
                w_new -= np.dot(np.dot(w_new, W[:i].T), W[:i])
            distance = np.abs(np.abs((w * w_new).sum()) - 1)
            w = w_new
            if distance < tolerance:
                break
        W[i, :] = w
    S = np.dot(W, X)
    return S
def plot_mixture_sources_predictions(X, original_sources, S):
    fig = plt.figure()
    plt.subplot(3, 1, 1)
    for x in X:
        plt.plot(x)
    plt.title("mixtures")
    plt.subplot(3, 1, 2)
    for s in original_sources:
        plt.plot(s)
    plt.title("real sources")
    plt.subplot(3,1,3)
    for s in S:
        plt.plot(s)
    plt.title("predicted sources")
    fig.tight_layout()
    plt.show()
def mix_sources(mixtures, apply_noise=False):
    for i in range(len(mixtures)):
        max_val = np.max(mixtures[i])
        if max_val > 1 or np.min(mixtures[i]) < 1:
            mixtures[i] = mixtures[i] / (max_val / 2) - 0.5
    X = np.c_[[mix for mix in mixtures]]
    if apply_noise:
        X += 0.02 * np.random.normal(size=X.shape)
    return X
n_samples = 2000
time = np.linspace(0, 8, n_samples)
s1 = np.sin(2 * time) # sinusoidal
s2 = np.sign(np.sin(3 * time)) # square signal
s3 = signal.sawtooth(2 * np.pi * time) # saw tooth signal

X = np.c_[s1, s2, s3]
A = np.array(([[1, 1, 1], [0.5, 2, 1.0], [1.5, 1.0, 2.0]]))
X = np.dot(X, A.T)
X = X.T
S = ica(X, iterations=1000)
plot_mixture_sources_predictions(X, [s1, s2, s3], S)
```

Output:

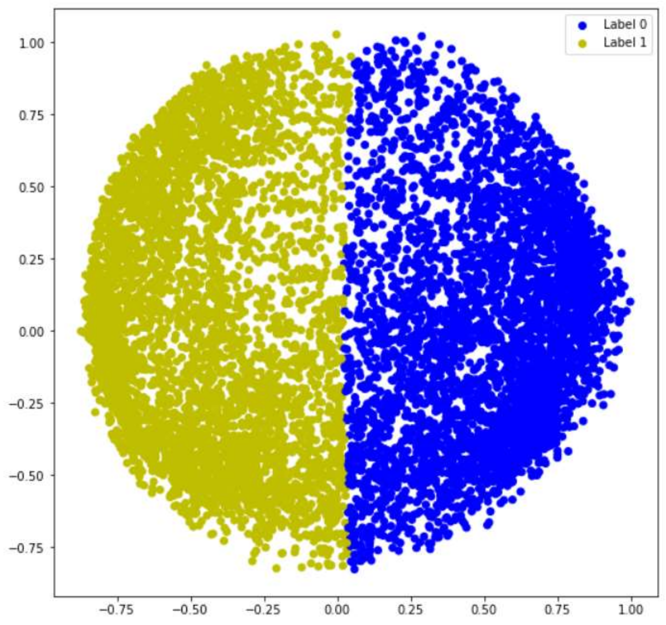


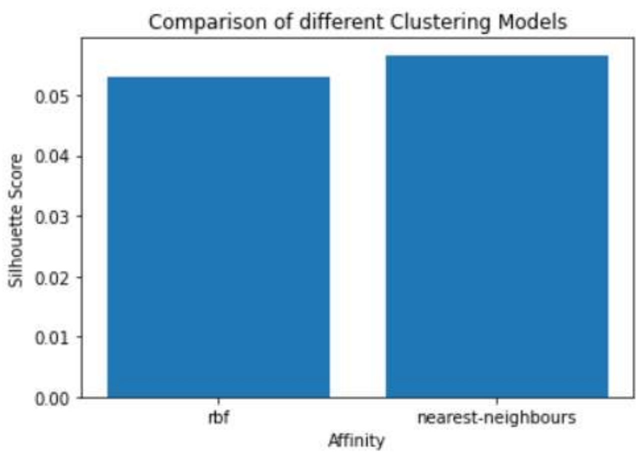
6.Program to implement Special Clustering.

```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import SpectralClustering
from sklearn.preprocessing import StandardScaler, normalize
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score

# Loading the data
X = pd.read_csv('CC GENERAL.csv')

# Dropping the CUST_ID column from the data
X = X.drop('CUST_ID', axis = 1)

# Handling the missing values if any
X.fillna(method ='ffill', inplace = True)

X.head()
# Preprocessing the data to make it visualizable

# Scaling the Data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Normalizing the Data
X_normalized = normalize(X_scaled)

# Converting the numpy array into a pandas DataFrame
X_normalized = pd.DataFrame(X_normalized)
# Reducing the dimensions of the data
pca = PCA(n_components = 2)
X_principal = pca.fit_transform(X_normalized)
X_principal = pd.DataFrame(X_principal)
X_principal.columns = ['P1', 'P2']
X_principal.head()
# Building the clustering model
spectral_model_rbf = SpectralClustering(n_clusters = 2, affinity ='rbf')

# Training the model and Storing the predicted cluster labels
labels_rbf = spectral_model_rbf.fit_predict(X_principal)
# Building the label to colour mapping
colours = {}
colours[0] = 'b'
colours[1] = 'y'

# Building the colour vector for each data point
cvec = [colours[label] for label in labels_rbf]

# Plotting the clustered scatter plot

b = plt.scatter(X_principal['P1'], X_principal['P2'], color ='b');
```

```
y = plt.scatter(X_principal['P1'], X_principal['P2'], color ='y');

plt.figure(figsize =(9, 9))
plt.scatter(X_principal['P1'], X_principal['P2'], c = cvec)
plt.legend((b, y), ('Label 0', 'Label 1'))
plt.show()
# Building the clustering model
spectral_model_nn = SpectralClustering(n_clusters = 2, affinity ='nearest_neighbors')

# Training the model and Storing the predicted cluster labels
labels_nn = spectral_model_nn.fit_predict(X_principal)
# List of different values of affinity
affinity = ['rbf', 'nearest-neighbours']

# List of Silhouette Scores
s_scores = []

# Evaluating the performance
s_scores.append(silhouette_score(X, labels_rbf))
s_scores.append(silhouette_score(X, labels_nn))

print(s_scores)
# Plotting a Bar Graph to compare the models
plt.bar(affinity, s_scores)
plt.xlabel('Affinity')
plt.ylabel('Silhouette Score')
plt.title('Comparison of different Clustering Models')
plt.show()
```

Output:



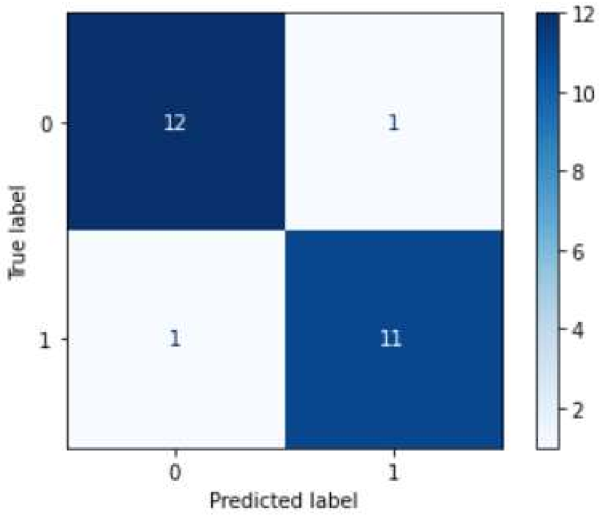


```
[0.05300611480757429, 0.05667039590382262]
```

7.program to implement confusion matrix.

```
from sklearn.metrics import confusion_matrix, plot_confusion_matrix
import matplotlib.pyplot as plt
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

# Generate random data
X, y = make_classification(random_state=0)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)

# Train a logistic regression classifier on the training data
clf = LogisticRegression(random_state=0)
clf.fit(X_train, y_train)

# Predict the labels for the testing data
y_pred = clf.predict(X_test)

# Calculate the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix
plot_confusion_matrix(clf, X_test, y_test, cmap=plt.cm.Blues)
plt.show()
```

Output:



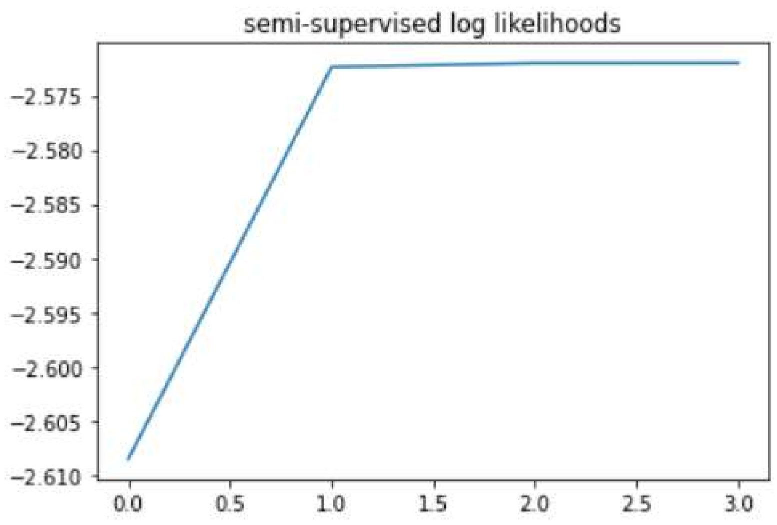
8.Program to implement Expectation-Maximization Algorithm(EM)

```
import numpy as np
import pandas as pd
from scipy import stats
from scipy.special import logsumexp
from sklearn.mixture import GaussianMixture
from matplotlib import pyplot as plt


def GMM_sklearn(x, weights=None, means=None, covariances=None):
    model = GaussianMixture(n_components=2,
                            covariance_type='full',
                            tol=0.01,
                            max_iter=1000,
                            weights_init=weights,
                            means_init=means,
                            precisions_init=covariances)
    model.fit(x)
    print("\nscikit learn:\n\tphi: %s\n\tmu_0: %s\n\tmu_1: %s\n\tsigma_0: %s\n\tsigma_1: %s"
            % (model.weights_[1], model.means_[0, :], model.means_[1, :], model.covariances_[0, :],
model.covariances_[1, :]))
    return model.predict(x), model.predict_proba(x)[:,1]


def get_random_psd(n):
    x = np.random.normal(0, 1, size=(n, n))
    return np.dot(x, x.transpose())


def initialize_random_params():
    params = {'phi': np.random.uniform(0, 1),
            'mu0': np.random.normal(0, 1, size=(2,)),
            'mu1': np.random.normal(0, 1, size=(2,)),
            'sigma0': get_random_psd(2),
            'sigma1': get_random_psd(2)}
    return params


def learn_params(x_labeled, y_labeled):
    n = x_labeled.shape[0]
    phi = x_labeled[y_labeled == 1].shape[0] / n
    mu0 = np.sum(x_labeled[y_labeled == 0], axis=0) / x_labeled[y_labeled == 0].shape[0]
    mu1 = np.sum(x_labeled[y_labeled == 1], axis=0) / x_labeled[y_labeled == 1].shape[0]
    sigma0 = np.cov(x_labeled[y_labeled == 0].T, bias= True)
    sigma1 = np.cov(x_labeled[y_labeled == 1].T, bias=True)
    return {'phi': phi, 'mu0': mu0, 'mu1': mu1, 'sigma0': sigma0, 'sigma1': sigma1}


def e_step(x, params):
    np.log([stats.multivariate_normal(params["mu0"], params["sigma0"]).pdf(x),
            stats.multivariate_normal(params["mu1"], params["sigma1"]).pdf(x)])
    log_p_y_x = np.log([1-params["phi"], params["phi"]])[np.newaxis, ...] + \
                np.log([stats.multivariate_normal(params["mu0"], params["sigma0"]).pdf(x),
            stats.multivariate_normal(params["mu1"], params["sigma1"]).pdf(x)]).T
    log_p_y_x_norm = logsumexp(log_p_y_x, axis=1)
    return log_p_y_x_norm, np.exp(log_p_y_x - log_p_y_x_norm[..., np.newaxis])


def m_step(x, params):
    total_count = x.shape[0]
    _, heuristics = e_step(x, params)
    heuristic0 = heuristics[:, 0]
    heuristic1 = heuristics[:, 1]
    sum_heuristic1 = np.sum(heuristic1)
    sum_heuristic0 = np.sum(heuristic0)
    phi = (sum_heuristic1/total_count)
    mu0 = (heuristic0[..., np.newaxis].T.dot(x)/sum_heuristic0).flatten()
    mu1 = (heuristic1[..., np.newaxis].T.dot(x)/sum_heuristic1).flatten()
    diff0 = x - mu0
    sigma0 = diff0.T.dot(diff0 * heuristic0[..., np.newaxis]) / sum_heuristic0
    diff1 = x - mu1
    sigma1 = diff1.T.dot(diff1 * heuristic1[..., np.newaxis]) / sum_heuristic1
    params = {'phi': phi, 'mu0': mu0, 'mu1': mu1, 'sigma0': sigma0, 'sigma1': sigma1}
    return params


def get_avg_log_likelihood(x, params):
    loglikelihood, _ = e_step(x, params)
    return np.mean(loglikelihood)


def run_em(x, params):
    avg_loglikelihoods = []
    while True:
        avg_loglikelihood = get_avg_log_likelihood(x, params)
        avg_loglikelihoods.append(avg_loglikelihood)
        if len(avg_loglikelihoods) > 2 and abs(avg_loglikelihoods[-1] - avg_loglikelihoods[-2]) <
0.0001:
            break
        params = m_step(x_unlabeled, params)
    print("\tphi: %s\n\tmu_0: %s\n\tmu_1: %s\n\tsigma_0: %s\n\tsigma_1: %s"
            % (params['phi'], params['mu0'], params['mu1'], params['sigma0'], params['sigma1']))
    _, posterior = e_step(x_unlabeled, params)
    forecasts = np.argmax(posterior, axis=1)
    return forecasts, posterior, avg_loglikelihoods
```

```
if __name__ == '__main__':
    data_unlabeled = pd.read_csv('unlabeled.csv')
    x_unlabeled = data_unlabeled[["x1", "x2"]].values

    # Unsupervised learning
    print("unsupervised: ")
    random_params = initialize_random_params()
    unsupervised_forecastsforecasts, unsupervised_posterior, unsupervised_loglikelihoods =
run_em(x_unlabeled, random_params)
    print("total steps: ", len(unsupervised_loglikelihoods))
    plt.plot(unsupervised_loglikelihoods)
    plt.title("unsupervised log likelihoods")
    plt.savefig("unsupervised.png")
    plt.close()

    # Semi-supervised learning
    print("\nsemi-supervised: ")
    data_labeled = pd.read_csv('labeled.csv')
    x_labeled = data_labeled[["x1", "x2"]].values
    y_labeled = data_labeled["y"].values
    learned_params = learn_params(x_labeled, y_labeled)
    semisupervised_forecasts, semisupervised_posterior, semisupervised_loglikelihoods =
run_em(x_unlabeled, learned_params)
    print("total steps: ", len(semisupervised_loglikelihoods))
    plt.plot(semisupervised_loglikelihoods)
    plt.title("semi-supervised log likelihoods")
    plt.savefig("semi-supervised.png")

    # Compare the forecats with Scikit-learn API
    learned_params = learn_params(x_labeled, y_labeled)
    weights = [1 - learned_params["phi"], learned_params["phi"]]
    means = [learned_params["mu0"], learned_params["mu1"]]
    covariances = [learned_params["sigma0"], learned_params["sigma1"]]
    sklearn_forecasts, posterior_sklearn = GMM_sklearn(x_unlabeled, weights, means, covariances)

    output_df = pd.DataFrame({'semisupervised_forecasts': semisupervised_forecasts,
                              'semisupervised_posterior': semisupervised_posterior[:, 1],
                              'sklearn_forecasts': sklearn_forecasts,
                              'posterior_sklearn': posterior_sklearn})

    print("\n%s%% of forecasts matched." % (output_df[output_df["semisupervised_forecasts"] ==
output_df["sklearn_forecasts"]].shape[0] /output_df.shape[0] * 100))
```

Output:

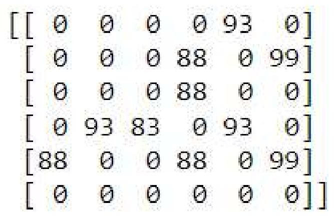
```
unsupervised:
        phi: 0.5985711658340387
        mu_0: [-1.06906401 -1.06927    ]
        mu_1: [0.96194764 0.98361038]
        sigma_0: [[0.34296075 0.28252623]
 [0.28252623 0.70705511]]
        sigma_1: [[0.74290629 0.15800099]
 [0.15800099 0.31664651]]
total steps:  24

semi-supervised:
        phi: 0.5863498817945461
        mu_0: [-1.04546727 -1.02704636]
        mu_1: [0.98763329 0.99661118]
        sigma_0: [[0.36018609 0.30853357]
 [0.30853357 0.75384027]]
        sigma_1: [[0.7196797  0.1437903 ]
 [0.1437903  0.30853791]]
total steps:  4

scikit learn:
        phi: 0.59647894226803
        mu_0: [-1.06169376 -1.0563389 ]
        mu_1: [0.96408565 0.98206315]
        sigma_0: [[0.35027155 0.29629092]
 [0.29629092 0.73083581]]
        sigma_1: [[0.74510804 0.16156928]
 [0.16156928 0.32021029]]

99.4% of forecasts matched.
```



9.Program to implement Q-learning

```
import numpy as np

# Define the reward matrix
R = np.array([[-1, -1, -1, -1, 0, -1],
              [-1, -1, -1, 0, -1, 100],
              [-1, -1, -1, 0, -1, -1],
              [-1, 0, 0, -1, 0, -1],
              [0, -1, -1, 0, -1, 100],
              [-1, 0, -1, -1, 0, 100]])

# Define the Q matrix
Q = np.zeros_like(R)

# Set the hyperparameters
alpha = 0.8
gamma = 0.95
n_episodes = 1000

# Run the Q-learning algorithm
for episode in range(n_episodes):
    state = np.random.randint(0, 6)
    while state != 5:
        action = np.random.choice(np.where(R[state, :] != -1)[0])
        next_state = action
        Q[state, action] = Q[state, action] + alpha * (R[state, action] + gamma *
np.max(Q[next_state, :]) - Q[state, action])
        state = next_state

# Print the learned Q matrix
print(Q)
```

Output:



```
[[ 0  0  0  0 93  0]
 [ 0  0  0 88  0 99]
 [ 0  0  0 88  0  0]
 [ 0 93 83  0 93  0]
 [88  0  0 88  0 99]
 [ 0  0  0  0  0  0]]
```

10. Program to implement Genetic algorithm.