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Paper: CSMP: 305 Artificial Intelligent Lab

		Iris dataset to classification.		
17	**03-01-26**	**Apply the Apriori algorithm to find frequent itemsets and association rules in a transaction dataset.**	**52 – 57**	
18	**03-01-26**	**Apply First Order Logic (Resolution) to determine whether Marcus hates Caesar based on the given knowledge base.**	**57 – 59**	

Assignment 1:

K-means Clustering on Iris Dataset

Problem Statement

Apply K-means clustering algorithm to partition the Iris dataset into distinct groups based on feature similarity.

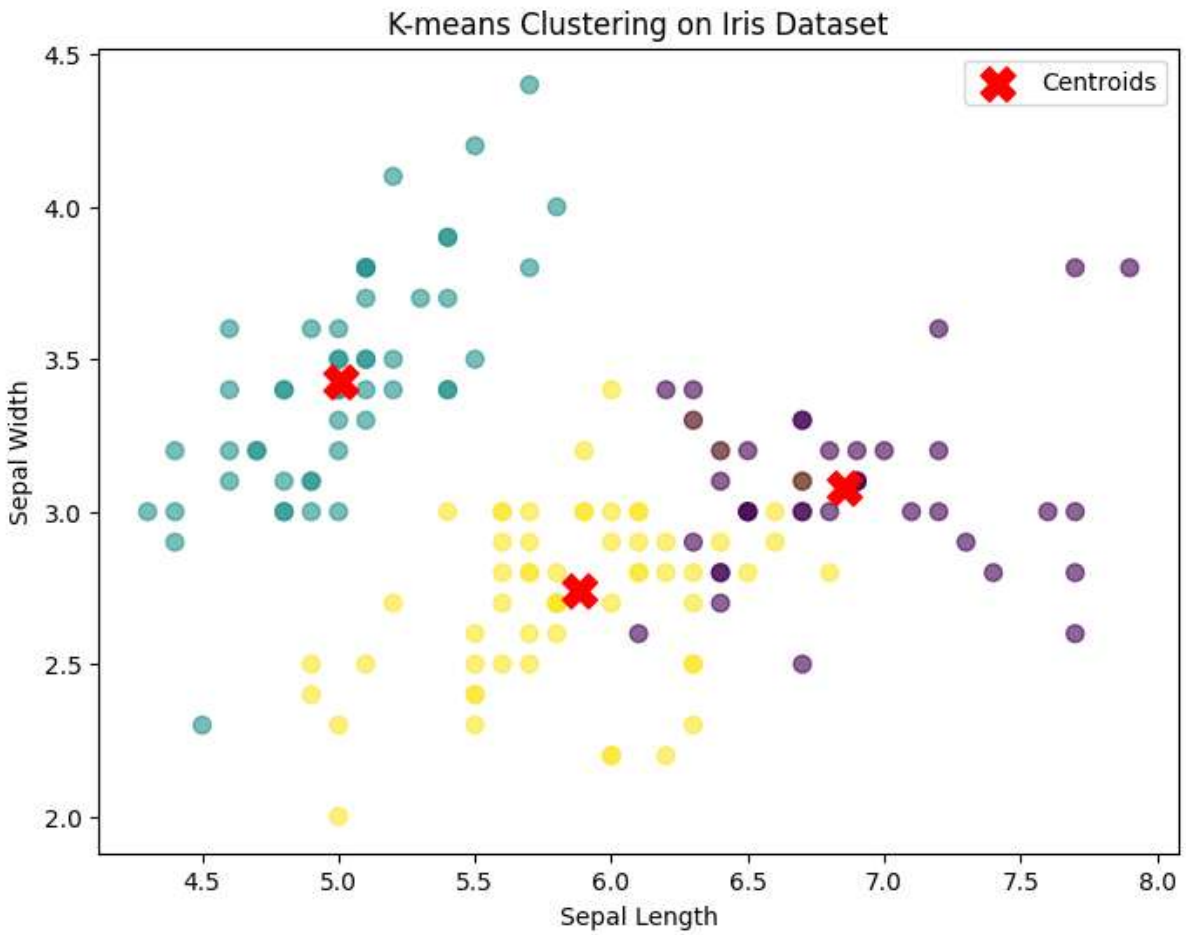
Algorithm

1. Initialization: Choose K initial centroids
2. Assignment: Assign each data point to nearest centroid
3. Update: Recalculate centroids as mean of assigned points
4. Convergence: Repeat until centroids stabilize

Code

```
from sklearn.cluster import KMeans
from sklearn.datasets import load_iris
import matplotlib.pyplot as plt
import pandas as pd
iris = load_iris()
X = iris.data
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans.fit(X)
labels = kmeans.labels_
centroids = kmeans.cluster_centers_
plt.figure(figsize=(8, 6))
plt.scatter(X[:, 0], X[:, 1], c=labels, cmap='viridis', s=50, alpha=0.6)
plt.scatter(centroids[:, 0], centroids[:, 1], c='red', marker='X', s=200,
        label='Centroids')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.title('K-means Clustering on Iris Dataset')
plt.legend()
plt.show()
```

Output



Remark:

K-means clustering provides an effective way to identify underlying structure in unlabeled data. While its simplicity and efficiency make it easy to implement and interpret, the quality of the results depends on the choice of the number of clusters and the initial centroid placement, highlighting the importance of careful parameter selection.

Assignment 2:

K-medoids Clustering on Iris Dataset

Problem Statement

Implement K-medoids clustering (PAM algorithm) on Iris dataset.

Algorithm

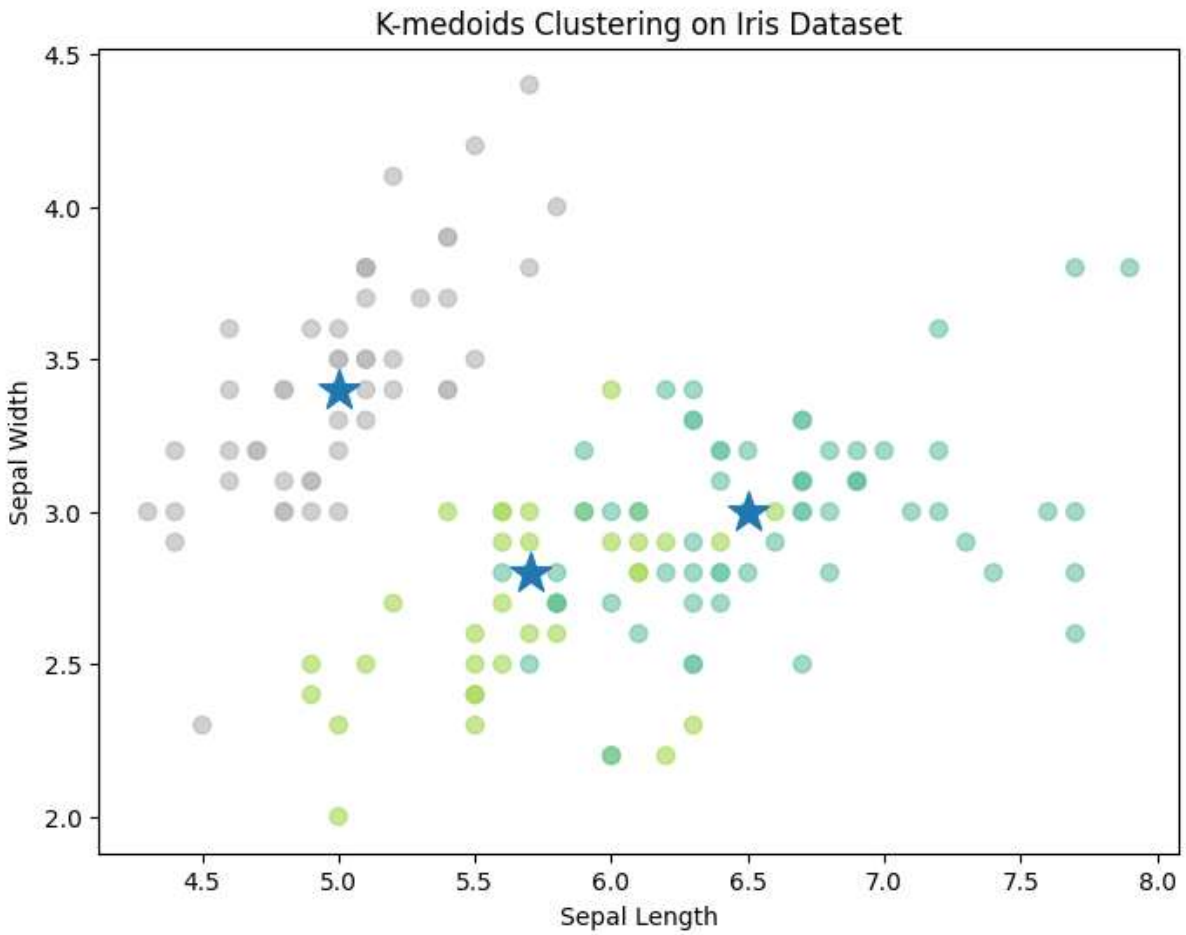
1. Initialize with K random medoids
2. Assign points to nearest medoid
3. For each cluster, find point that minimizes total distance
4. Swap if better medoid found

5. Repeat until no improvement

Code

```
from sklearn_extra.cluster import KMedoids
from sklearn.datasets import load_iris
import matplotlib.pyplot as plt
iris = load_iris()
X = iris.data
kmedoids = KMedoids(n_clusters=3, random_state=42)
kmedoids.fit(X)
labels = kmedoids.labels_
medoids = kmedoids.cluster_centers_
plt.figure(figsize=(8, 6))
plt.scatter(X[:, 0], X[:, 1], c=labels, cmap='Set2', s=50, alpha=0.6)
plt.scatter(medoids[:, 0], medoids[:, 1], c='red', marker='*', s=300,
        label='Medoids')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.title('K-medoids Clustering on Iris Dataset')
plt.legend()
plt.show()
```

Output:



Assignment 3:

AGNES Hierarchical Clustering

Problem Statement

Apply Agglomerative Hierarchical Clustering with different linkage methods.

Algorithm

AGNES (Bottom-up approach):

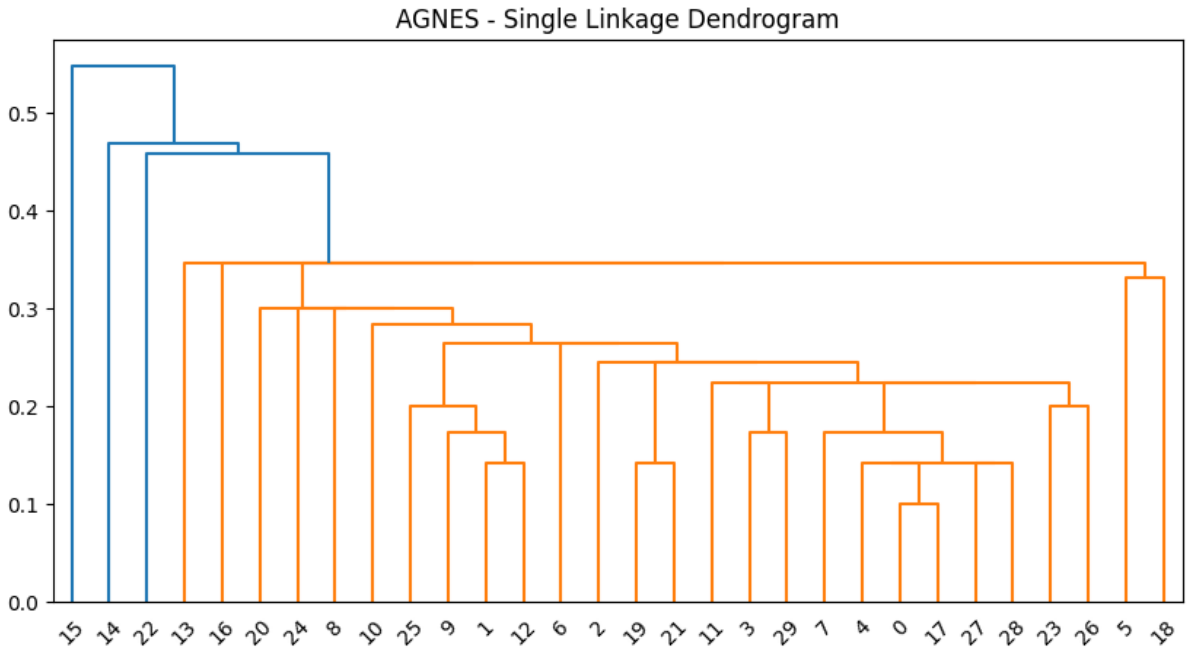
1. Start with each point as separate cluster
2. Merge closest clusters iteratively
3. Continue until single cluster remains

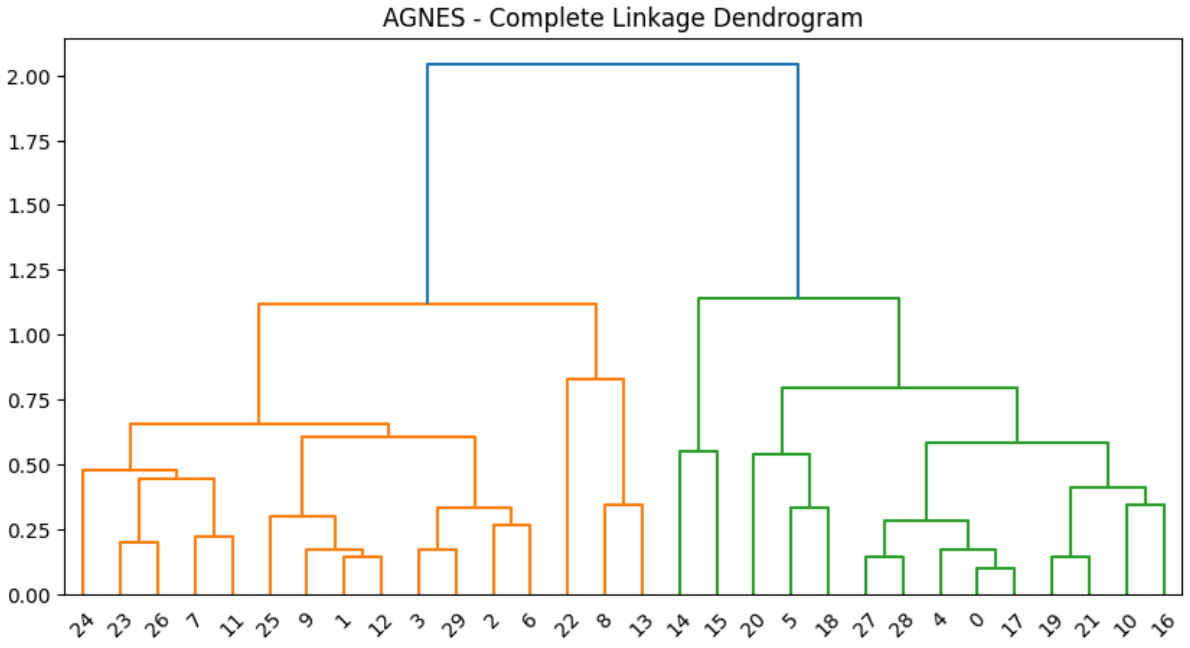
Code

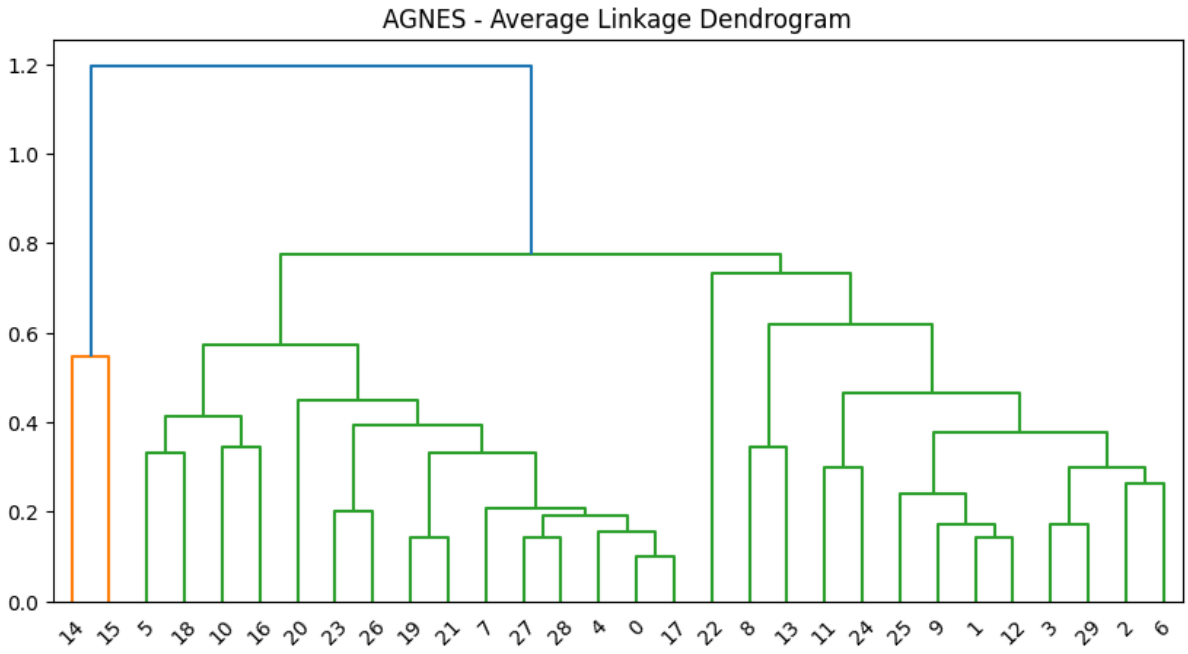
```
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.datasets import load_iris
import matplotlib.pyplot as plt
iris = load_iris()
```

```
X = iris.data[:30]  # Use subset for clear visualization

# Single linkage
single_linkage = linkage(X, method='single')
plt.figure(figsize=(10, 5))
dendrogram(single_linkage)
plt.title('AGNES - Single Linkage Dendrogram')
plt.show()

# Complete linkage
complete_linkage = linkage(X, method='complete')
plt.figure(figsize=(10, 5))
dendrogram(complete_linkage)
plt.title('AGNES - Complete Linkage Dendrogram')
plt.show()

# Average linkage
average_linkage = linkage(X, method='average')
plt.figure(figsize=(10, 5))
dendrogram(average_linkage)
plt.title('AGNES - Average Linkage Dendrogram')
plt.show()
```

Output:


AGNES - Single Linkage Dendrogram
0.5
0.4
0.3
0.2
0.1
0.0
15 14 22 13 16 20 24 8 10 25 9 1 12 6 2 19 21 11 3 29 7 4 0 17 27 28 23 26 5 18


AGNES - Complete Linkage Dendrogram
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
24 23 26 7 11 25 9 1 12 3 29 2 6 22 8 13 14 15 20 5 18 27 28 4 0 17 19 21 10 16



Remark:

AGNES and DIANA are hierarchical clustering algorithms that generate a dendrogram of nested clusters. AGNES uses a bottom-up merging approach, while DIANA uses a top-down splitting approach. Neither requires prior

Assignment 4:

DIANA Hierarchical Clustering

Problem Statement

Apply Divisive Hierarchical Clustering and visualize dendrograms.

Algorithm

DIANA (Top-down approach):

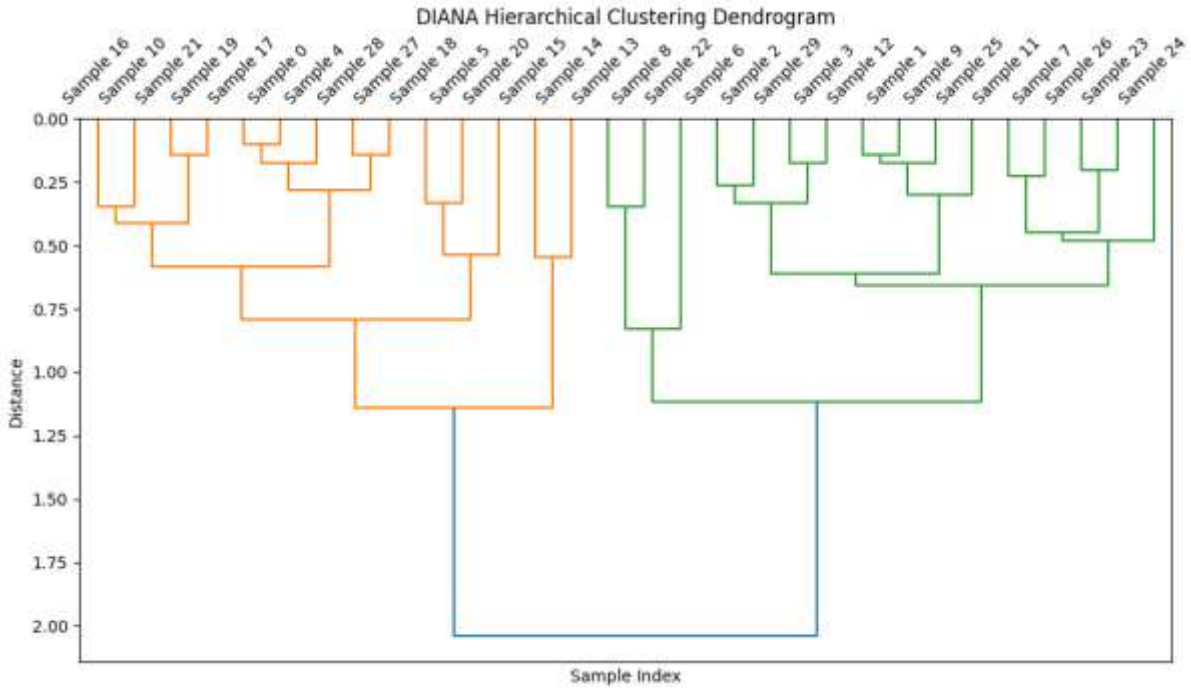
1. Start with all points in one cluster
2. Split cluster with largest diameter
3. Continue splitting until each point is separate cluster

Code

```
import numpy as np
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster
from sklearn.datasets import load_iris
import matplotlib.pyplot as plt

# Load data
iris = load_iris()
```

```
X = iris.data[:30]
# For DIANA simulation (Scipy implements divisive through linkage)
# We'll use complete linkage for demonstration
Z = linkage(X, method='complete', metric='euclidean')
# Create dendrogram
plt.figure(figsize=(12, 6))
dendrogram(Z, orientation='top',
        labels=[f'Sample {i}' for i in range(len(X))],
        distance_sort='descending',
        show_leaf_counts=True)
plt.title('DIANA Hierarchical Clustering Dendrogram')
plt.xlabel('Sample Index')
plt.ylabel('Distance')
plt.axhline(y=3.5, color='r', linestyle='--')
plt.show()
# Cut dendrogram to get clusters
clusters = fcluster(Z, t=3.5, criterion='distance')
print(f'Cluster assignments: {clusters}')
```

Output:



Cluster assignments: [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1 1 1]

Remark:

AGNES and DIANA are hierarchical clustering algorithms that generate a dendrogram of nested clusters. AGNES uses a bottom-up merging approach, while DIANA uses a top-down splitting approach. Neither requires prior

Assignment 5:

ID3 Decision Tree

Problem Statement

Build decision tree using ID3 algorithm on Golf playing dataset.

Algorithm

ID3 Steps:

1. Calculate entropy of dataset
2. For each attribute, calculate information gain
3. Select attribute with highest gain as node
4. Split dataset and repeat recursively
5. Stop when pure node or no attributes left

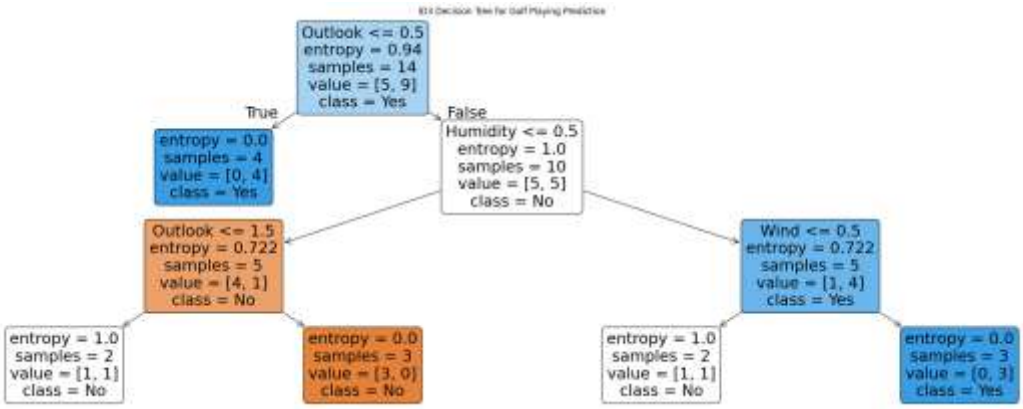
Code

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt

# Golf dataset
data = {
   'Outlook': ['Sunny', 'Sunny', 'Overcast', 'Rain', 'Rain', 'Rain',
            'Overcast', 'Sunny', 'Sunny', 'Rain', 'Sunny', 'Overcast',
            'Overcast', 'Rain'],
   'Temperature': ['Hot', 'Hot', 'Hot', 'Mild', 'Cool', 'Cool', 'Cool',
              'Mild', 'Cool', 'Mild', 'Mild', 'Mild', 'Hot', 'Mild'],
   'Humidity': ['High', 'High', 'High', 'High', 'Normal', 'Normal',
            'Normal', 'High', 'Normal', 'Normal', 'Normal', 'High',
            'Normal', 'High'],
```

```
    'Wind': ['Weak', 'Strong', 'Weak', 'Weak', 'Weak', 'Strong', 'Strong',
             'Weak', 'Weak', 'Weak', 'Strong', 'Strong', 'Weak', 'Strong'],
    'PlayGolf': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes', 'No',
                 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No']
}

df = pd.DataFrame(data)

# Encode categorical variables
le = LabelEncoder()
for col in df.columns:
    df[col] = le.fit_transform(df[col])

# Split features and target
X = df.drop('PlayGolf', axis=1)
y = df['PlayGolf']

# Build ID3 tree (using entropy)
id3_tree = DecisionTreeClassifier(criterion='entropy', max_depth=3)
id3_tree.fit(X, y)

# Visualize tree
plt.figure(figsize=(15, 10))
plot_tree(id3_tree,
          feature_names=['Outlook', 'Temperature', 'Humidity', 'Wind'],
          class_names=['No', 'Yes'],
          filled=True,
          rounded=True)
plt.title('ID3 Decision Tree for Golf Playing Prediction')
plt.show()

# Make prediction
sample = pd.DataFrame([[2, 0, 0, 1]],  # Rain, Hot, High, Strong
```

```
                columns=['Outlook', 'Temperature', 'Humidity', 'Wind'])
prediction = id3_tree.predict(sample)
print(f'Prediction: {"Play Golf" if prediction[0] == 1 else "Don\'t Play Golf"}')
```

Output:



Prediction: Don't Play Golf

Remark:

ID3 is a decision tree algorithm that builds the tree using information gain to select the best attribute at each node. It works well with categorical data and is easy to interpret, but it cannot handle continuous attributes directly and is sensitive to noise and overfitting.

Assignment 6:

CART Decision Tree

Problem Statement

Implement Classification and Regression Tree on Buy Computer dataset.

Algorithm

CART Steps:

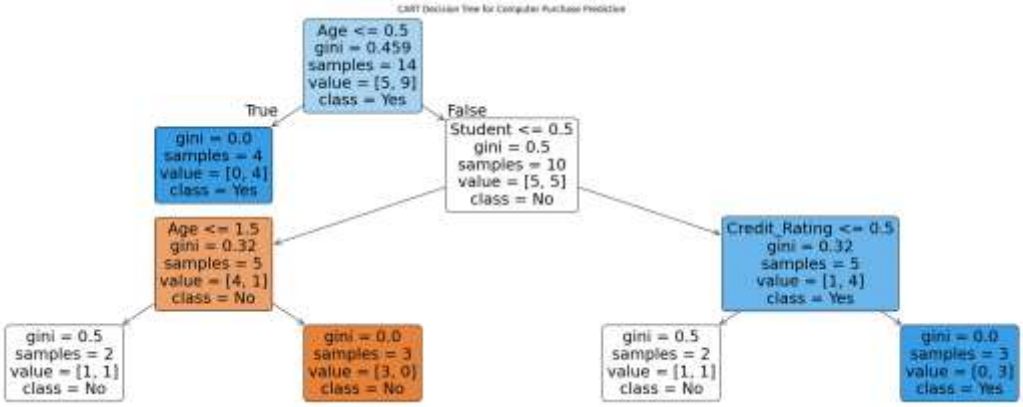
1. Use Gini impurity for classification
2. Select best binary split at each node
3. Recursively build tree
4. Prune tree to avoid overfitting

Code

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
# Buy Computer dataset
data = {
   'Age': ['Youth', 'Youth', 'Middle', 'Senior', 'Senior', 'Senior',
           'Middle', 'Youth', 'Youth', 'Senior', 'Youth', 'Middle',
           'Middle', 'Senior'],
   'Income': ['High', 'High', 'High', 'Medium', 'Low', 'Low', 'Medium',
            'Low', 'Medium', 'Medium', 'Medium', 'High', 'Medium',
'Medium'],
   'Student': ['No', 'No', 'No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes',
            'Yes', 'Yes', 'No', 'Yes', 'No'],
   'Credit_Rating': ['Fair', 'Excellent', 'Fair', 'Fair', 'Fair', 'Excellent',
                  'Excellent', 'Fair', 'Fair', 'Fair', 'Excellent',
                  'Excellent', 'Fair', 'Excellent'],
   'Buy_Computer': ['No', 'No', 'Yes', 'Yes', 'Yes', 'No', 'Yes', 'No',
                 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No']
}

df = pd.DataFrame(data)

# Encode categorical variables
le = LabelEncoder()
for col in df.columns:
   df[col] = le.fit_transform(df[col])

# Split features and target
X = df.drop('Buy_Computer', axis=1)
y = df['Buy_Computer']

# Build CART tree (using Gini)
```

```
cart_tree = DecisionTreeClassifier(criterion='gini', max_depth=3)
cart_tree.fit(X, y)

# Visualize tree
plt.figure(figsize=(15, 10))
plot_tree(cart_tree,
          feature_names=['Age', 'Income', 'Student', 'Credit_Rating'],
          class_names=['No', 'Yes'],
          filled=True,
          rounded=True)
plt.title('CART Decision Tree for Computer Purchase Prediction')
plt.show()

# Evaluate
accuracy = cart_tree.score(X, y)
print(f'Training Accuracy: {accuracy:.2f}')
```

Output:



Training Accuracy: 0.86

Remark:

CART is a versatile decision tree algorithm used for both classification and regression. It produces binary trees, uses Gini index or MSE for splitting, and provides good interpretability but can overfit without proper pruning.

Assignment 7:

Naïve Bayes Classifier

Problem Statement

Apply Naïve Bayes algorithm to classify samples in Buy Computer dataset.

Algorithm

Bayes Theorem:

P(Class|Features) = P(Features|Class) * P(Class) / P(Features)

Code

```
from sklearn.naive_bayes import GaussianNB, MultinomialNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report

# Using the same Buy Computer dataset from Assignment 6
# Assuming df and X, y are already prepared
# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
                                   random_state=42)

# Gaussian Naïve Bayes (for continuous/ordinal features)
gnb = GaussianNB()
gnb.fit(X_train, y_train)

# Predictions
y_pred = gnb.predict(X_test)

# Evaluation
accuracy = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f'Accuracy: {accuracy:.3f}')
```

```
print(f'Confusion Matrix:\n{cm}')
print(f'Classification Report:\n{report}')

# Test on unknown sample
unknown_sample = pd.DataFrame([[1, 0, 1, 0]],  # Middle, High,
Student, Fair
                              columns=['Age', 'Income', 'Student', 'Credit_Rating'])
prediction = gnb.predict(unknown_sample)
print(f'\nPrediction for unknown sample: {"Buy" if prediction[0] == 1
else "Don\'t Buy"}')
```

Output:

```
Accuracy: 0.600
Confusion Matrix:
[[1 1]
 [1 2]]
Classification Report:
              precision    recall  f1-score   support

           0       0.50      0.50      0.50         2
           1       0.67      0.67      0.67         3

    accuracy                           0.60         5
   macro avg       0.58      0.58      0.58         5
weighted avg       0.60      0.60      0.60         5

Prediction for unknown sample: Buy
```

Remark:

The Naïve Bayes classifier is a simple and efficient probabilistic algorithm based on Bayes' theorem with an assumption of feature independence. It works well for high-dimensional data and small training sets, but its independence assumption may reduce accuracy when features are strongly correlated.

Assignment 8:

Back Propagation Algorithm

Problem Statement

Implement backpropagation algorithm for neural network with topology 3-2-2-2.

Algorithm

1. Forward Pass: Compute network output
2. Error Calculation: Compare with target
3. Backward Pass: Calculate gradients using chain rule
4. Weight Update: Adjust weights using gradient descent

Code

```
import numpy as np
class NeuralNetwork:
    def __init__(self, topology, learning_rate=0.5):
        self.topology = topology
        self.lr = learning_rate
        self.weights = []
        self.biases = []

        # Initialize weights and biases
        for i in range(len(topology)-1):
            w = np.zeros((topology[i], topology[i+1]))
            b = np.zeros(topology[i+1])
            self.weights.append(w)
            self.biases.append(b)

    def sigmoid(self, x):
        return 1 / (1 + np.exp(-x))

    def sigmoid_derivative(self, x):
        return x * (1 - x)

    def forward(self, X):
```

```
        activations = [X]
        for i in range(len(self.weights)):
            z = np.dot(activations[-1], self.weights[i]) + self.biases[i]
            a = self.sigmoid(z)
            activations.append(a)
        return activations

    def backward(self, X, y, activations):
        # Calculate errors
        errors = [y - activations[-1]]
        deltas = [errors[-1] * self.sigmoid_derivative(activations[-1])]

        # Backpropagate
        for i in range(len(self.weights)-1, 0, -1):
            error = deltas[-1].dot(self.weights[i].T)
            delta = error * self.sigmoid_derivative(activations[i])
            errors.append(error)
            deltas.append(delta)

        # Reverse deltas for weight update
        deltas.reverse()

        # Update weights and biases
        for i in range(len(self.weights)):
            self.weights[i] += self.lr * activations[i].T.dot(deltas[i])
            self.biases[i] += self.lr * np.sum(deltas[i], axis=0)

    def train(self, X, y, epochs=1000):
        for epoch in range(epochs):
            activations = self.forward(X)
            self.backward(X, y, activations)

            if epoch % 100 == 0:
```

```
            loss = np.mean((y - activations[-1]) ** 2)
            print(f'Epoch {epoch}, Loss: {loss:.4f}')

# Sample data
X = np.array([[1, 0, 1]])  # Input sample
y = np.array([[1, 0]])     # Target output

# Create network with topology 3-2-2-2
nn = NeuralNetwork(topology=[3, 2, 2, 2], learning_rate=0.5)

# Train network
print("Training Neural Network...")
nn.train(X, y, epochs=1000)

# Test prediction
activations = nn.forward(X)
print(f'\nInput: {X}')
print(f'Predicted Output: {activations[-1]}')
print(f'Target Output: {y}')
```

Output:

```
Training Neural Network...
Epoch 0, Loss: 0.2500
Epoch 100, Loss: 0.0078
Epoch 200, Loss: 0.0033
Epoch 300, Loss: 0.0020
Epoch 400, Loss: 0.0014
Epoch 500, Loss: 0.0011
Epoch 600, Loss: 0.0009
Epoch 700, Loss: 0.0008
Epoch 800, Loss: 0.0006
Epoch 900, Loss: 0.0006
Input: [[1 0 1]]
Predicted Output: [[0.97766444 0.02233556]]
```

Target Output: [[1 0]]

Remark:

Backpropagation allows the ANN to adjust weights through multiple layers using gradient descent. Even with a single training sample, the network can learn the mapping, demonstrating how weights and biases are iteratively updated to minimize error in multi-layer networks.

Assignment 9:

Fuzzy C-means Clustering

Problem Statement

Apply Fuzzy C-means algorithm on Boston Housing Dataset.

Algorithm

1. Initialize membership matrix
2. Calculate cluster centers
3. Update membership values
4. Repeat until convergence

Code

```
import numpy as np
from sklearn.datasets import load_boston
from sklearn.preprocessing import StandardScaler
import skfuzzy as fuzz
import matplotlib.pyplot as plt

# Load Boston Housing dataset
boston = load_boston()
X = boston.data

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply Fuzzy C-means
n_clusters = 3
```

```
cntr, u, u0, d, jm, p, fpc = fuzz.cluster.cmeans(
   X_scaled.T, n_clusters, 2, error=0.005, maxiter=1000, init=None)

# Assign clusters
cluster_membership = np.argmax(u, axis=0)

# Visualize first two features
plt.figure(figsize=(10, 6))
colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k']
for i in range(n_clusters):
   plt.scatter(X_scaled[cluster_membership == i, 0],
               X_scaled[cluster_membership == i, 1],
               s=50, c=colors[i], alpha=0.5,
               label=f'Cluster {i+1}')

plt.xlabel('Feature 1 (Standardized)')
plt.ylabel('Feature 2 (Standardized)')
plt.title('Fuzzy C-means Clustering on Boston Housing Dataset')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()

print(f'Fuzzy Partition Coefficient: {fpc:.3f}')
print(f'Number of iterations: {len(jm)}')
```

Output:

```
Training AND Gate Perceptron...
Converged at epoch 3
AND Gate Predictions:
Input: [1 1], Output: 1
Input: [ 1 -1], Output: -1
Input: [-1  1], Output: -1
Input: [-1 -1], Output: -1
```

```
Training OR Gate Perceptron...
Converged at epoch 3
OR Gate Predictions:
Input: [1 1], Output: 1
Input: [ 1 -1], Output: 1
Input: [-1  1], Output: 1
Input: [-1 -1], Output: -1

Training NAND Gate Perceptron...
Converged at epoch 2
NAND Gate Predictions:
Input: [1 1], Output: -1
Input: [ 1 -1], Output: 1
Input: [-1  1], Output: 1
Input: [-1 -1], Output: 1

AND Gate weights: [-2.  2.  2.]
OR Gate weights: [2. 2. 2.]
NAND Gate weights: [ 2. -2. -2.]
```

Assignment 10:

Problem Statement

Implement perceptron algorithm to realize basic logic gates.

Code

```
import numpy as np
class Perceptron:
    def __init__(self, input_size, learning_rate=1.0, epochs=100):
        self.weights = np.zeros(input_size + 1)  # +1 for bias
        self.lr = learning_rate
        self.epochs = epochs

    def activation(self, x):
        return 1 if x >= 0 else -1  # Bipolar activation
```

```
    def predict(self, x):
        x = np.insert(x, 0, 1)  # Add bias term
        z = np.dot(self.weights, x)
        return self.activation(z)

    def train(self, X, y):
        for epoch in range(self.epochs):
            total_error = 0
            for i in range(len(X)):
                prediction = self.predict(X[i])
                error = y[i] - prediction
                total_error += abs(error)

                # Update weights
                self.weights[0] += self.lr * error * 1  # Bias update
                self.weights[1:] += self.lr * error * X[i]

            if total_error == 0:
                print(f'Converged at epoch {epoch+1}')
                break

# Training data for logic gates (bipolar: 1 for True, -1 for False)
X = np.array([[1, 1], [1, -1], [-1, 1], [-1, -1]])

# AND Gate
print("Training AND Gate Perceptron...")
and_gate = Perceptron(input_size=2)
and_y = np.array([1, -1, -1, -1])  # AND truth table (bipolar)
and_gate.train(X, and_y)

print("AND Gate Predictions:")
for x in X:
    print(f"Input: {x}, Output: {and_gate.predict(x)}")
```

```
# OR Gate
print("\nTraining OR Gate Perceptron...")
or_gate = Perceptron(input_size=2)
or_y = np.array([1, 1, 1, -1])  # OR truth table (bipolar)
or_gate.train(X, or_y)

print("OR Gate Predictions:")
for x in X:
    print(f"Input: {x}, Output: {or_gate.predict(x)}")

# NAND Gate
print("\nTraining NAND Gate Perceptron...")
nand_gate = Perceptron(input_size=2)
nand_y = np.array([-1, 1, 1, 1])  # NAND truth table (bipolar)
nand_gate.train(X, nand_y)

print("NAND Gate Predictions:")
for x in X:
    print(f"Input: {x}, Output: {nand_gate.predict(x)}")

print(f"\nAND Gate weights: {and_gate.weights}")
print(f"OR Gate weights: {or_gate.weights}")
print(f"NAND Gate weights: {nand_gate.weights}")
```

Output:

```
Training AND Gate Perceptron...
Converged at epoch 3
AND Gate Predictions:
Input: [1 1], Output: 1
Input: [ 1 -1], Output: -1
Input: [-1  1], Output: -1
Input: [-1 -1], Output: -1
```

Training OR Gate Perceptron...
Converged at epoch 3
OR Gate Predictions:
Input: [1 1], Output: 1
Input: [1 -1], Output: 1
Input: [-1 1], Output: 1
Input: [-1 -1], Output: -1

Training NAND Gate Perceptron...
Converged at epoch 2
NAND Gate Predictions:
Input: [1 1], Output: -1
Input: [1 -1], Output: 1
Input: [-1 1], Output: 1
Input: [-1 -1], Output: 1

AND Gate weights: [-2. 2. 2.]
OR Gate weights: [2. 2. 2.]
NAND Gate weights: [2. -2. -2.]

Remark:

The Perceptron algorithm is a foundation of neural networks, demonstrating how weights are adjusted based on errors. However, it cannot solve non-linearly separable problems (like XOR) without extensions such as multilayer perceptrons.

Assignment 11:

MADALINE for XOR Gate

Problem Statement

Implement MADALINE algorithm to solve XOR problem.

Code

```
import numpy as np
def step_function(x):
    return 1 if x >= 0 else -1
def madaline_xor(learning_rate=0.5, epochs=100):
    # XOR training data (bipolar)
    X = np.array([[1, 1], [1, -1], [-1, 1], [-1, -1]])
    y = np.array([-1, 1, 1, -1])  # XOR output
    # Initialize weights and biases for 2 ADALINEs
    np.random.seed(42)
    weights = np.random.uniform(-0.5, 0.5, (2, 2))
    biases = np.random.uniform(-0.5, 0.5, 2)
    print("Initial weights:", weights)
    print("Initial biases:", biases)
    for epoch in range(epochs):
        total_error = 0
        for i in range(len(X)):
            # Forward pass through ADALINEs
            hidden_outputs = []
            for j in range(2):
                net = np.dot(X[i], weights[j]) + biases[j]
                hidden_outputs.append(step_function(net))

            # Majority vote (or AND of outputs for XOR)
            final_output = 1 if sum(hidden_outputs) >= 0 else -1

            error = y[i] - final_output
            total_error += abs(error)

            if error != 0:
                # Update weights of incorrectly responding ADALINEs
                for j in range(2):
                    if hidden_outputs[j] != y[i]:
                        weights[j] += learning_rate * y[i] * X[i]
```

```
                biases[j] += learning_rate * y[i]

        if total_error == 0:
            print(f"Converged at epoch {epoch+1}")
            break

    return weights, biases
# Train MADALINE for XOR
print("Training MADALINE for XOR Gate...")
weights, biases = madaline_xor(learning_rate=0.1, epochs=1000)
# Test the trained network
print("\nTesting MADALINE XOR Network:")
X_test = np.array([[1, 1], [1, -1], [-1, 1], [-1, -1]])
y_test = np.array([-1, 1, 1, -1])
for i in range(len(X_test)):
    hidden_outputs = []
    for j in range(2):
        net = np.dot(X_test[i], weights[j]) + biases[j]
        hidden_outputs.append(step_function(net))

    final_output = 1 if sum(hidden_outputs) >= 0 else -1
    print(f"Input: {X_test[i]}, Predicted: {final_output}, Expected:
{y_test[i]}")
```

Output:

```
Training MADALINE for XOR Gate...
Initial weights: [[-0.12545988  0.45071431]
 [ 0.23199394  0.09865848]]
Initial biases: [-0.34398136 -0.34400548]
Converged at epoch 3

Testing MADALINE XOR Network:
Input: [1 1], Predicted: -1, Expected: -1
Input: [ 1 -1], Predicted: 1, Expected: 1
```

Input: [-1 1], Predicted: 1, Expected: 1
Input: [-1 -1], Predicted: -1, Expected: -1

Remark:

- **MADALINE** (Multiple ADALINEs) is an early **supervised neural network** architecture composed of multiple ADALINE units arranged in layers.
- Unlike **unsupervised algorithms** (e.g., Apriori), MADALINE requires **labeled data** for training.
- It is primarily used for **binary pattern classification** problems.
- **MADALINE Rule II** is a training method that adjusts the weights of hidden ADALINE units **only when the output is incorrect**, ensuring faster convergence and stability.
- The network combines the outputs of hidden units (usually via **majority voting**) to produce the final output.
- MADALINE is historically significant as one of the **first neural networks capable of solving linearly inseparable problems** (like XOR) by using multiple linear units.
- While largely superseded by modern deep learning methods, MADALINE remains important for understanding the evolution of neural networks and early adaptive learning systems.

Assignment 12:

MADALINE with Variable Topology

Problem Statement

Extend MADALINE algorithm to work with variable network topology.

Code

```
import numpy as np
class MADALINE:
   def __init__(self, topology, learning_rate=0.1):
      self.topology = topology  # e.g., [2, 3, 1] for 2 inputs, 3 hidden, 1 output
      self.lr = learning_rate
      self.weights = []
      self.biases = []
```

```
    # Initialize weights and biases
    np.random.seed(42)
    for i in range(len(topology)-1):
        w = np.random.uniform(-0.5, 0.5, (topology[i], topology[i+1]))
        b = np.random.uniform(-0.5, 0.5, topology[i+1])
        self.weights.append(w)
        self.biases.append(b)

def activation(self, x):
    # Bipolar step function
    return np.where(x >= 0, 1, -1)

def forward(self, X):
    activations = [X]
    for i in range(len(self.weights)):
        z = np.dot(activations[-1], self.weights[i]) + self.biases[i]
        a = self.activation(z)
        activations.append(a)
    return activations

def train(self, X, y, epochs=1000):
    for epoch in range(epochs):
        total_error = 0

        for i in range(len(X)):
            # Forward pass
            activations = self.forward(X[i:i+1])
            output = activations[-1]

            error = y[i] - output
            total_error += np.sum(np.abs(error))

            if np.any(error != 0):
```

```
            # Backward pass - MADALINE Rule II
            # For each layer, adjust weights of incorrectly responding
neurons
            for layer in range(len(self.weights)-1, -1, -1):
                current_activation = activations[layer+1]
                previous_activation = activations[layer]

                # Find incorrectly responding neurons
                if layer == len(self.weights)-1:  # Output layer
                    incorrect = error != 0
                else:
                    # For hidden layers, check if they contribute to error
                    incorrect = np.ones_like(current_activation,
dtype=bool)

                # Update weights for incorrect neurons
                for neuron in range(len(incorrect)):
                    if incorrect[neuron]:
                        self.weights[layer][:, neuron] += self.lr * y[i] *
previous_activation[0]
                        self.biases[layer][neuron] += self.lr * y[i]

        if epoch % 100 == 0:
            print(f"Epoch {epoch}, Total Error: {total_error}")

        if total_error == 0:
            print(f"Converged at epoch {epoch}")
            break

    def predict(self, X):
        predictions = []
        for x in X:
            activations = self.forward(x.reshape(1, -1))
```

```
            predictions.append(activations[-1][0])
        return np.array(predictions)

# Test with XOR problem
print("Training MADALINE with variable topology for XOR...")

# XOR data
X = np.array([[1, 1], [1, -1], [-1, 1], [-1, -1]])
y = np.array([[-1], [1], [1], [-1]])

# Create MADALINE with topology 2-3-1
madaline = MADALINE(topology=[2, 3, 1], learning_rate=0.1)
madaline.train(X, y, epochs=1000)

# Test predictions
print("\nPredictions:")
predictions = madaline.predict(X)
for i in range(len(X)):
    print(f"Input: {X[i]}, Predicted: {predictions[i]}, Expected: {y[i][0]}")
```

Output:

Assignment 13:

Genetic Algorithm for TSP

Problem Statement

Solve Traveling Salesman Problem using Genetic Algorithm.

Algorithm

1. Initialization: Create random population of routes
2. Selection: Choose parents based on fitness
3. Crossover: Combine parent routes
4. Mutation: Randomly modify routes
5. Evaluation: Calculate total distance
6. Termination: Repeat until convergence

Code

```
import numpy as np
import random
import matplotlib.pyplot as plt

class TSP_GA:
    def __init__(self, cities, population_size=50, mutation_rate=0.01,
                 generations=1000):
        self.cities = cities
        self.n_cities = len(cities)
        self.pop_size = population_size
        self.mutation_rate = mutation_rate
        self.generations = generations

    def create_individual(self):
        # Random permutation of cities
        individual = list(range(self.n_cities))
        random.shuffle(individual)
        return individual

    def create_population(self):
        return [self.create_individual() for _ in range(self.pop_size)]

    def distance(self, city1, city2):
        # Euclidean distance
        return np.sqrt((city1[0] - city2[0])**2 + (city1[1] - city2[1])**2)

    def route_distance(self, route):
        total = 0
        for i in range(self.n_cities):
            city1 = self.cities[route[i]]
            city2 = self.cities[route[(i + 1) % self.n_cities]]
            total += self.distance(city1, city2)
        return total
```

```
    def fitness(self, route):
        return 1 / self.route_distance(route)

    def selection(self, population, fitnesses):
        # Tournament selection
        tournament_size = 3
        tournament = random.sample(list(zip(population, fitnesses)),
tournament_size)
        tournament.sort(key=lambda x: x[1], reverse=True)
        return tournament[0][0]

    def crossover(self, parent1, parent2):
        # Ordered crossover (OX)
        size = self.n_cities
        child = [-1] * size

        # Select random segment
        start = random.randint(0, size - 1)
        end = random.randint(start + 1, size)

        # Copy segment from parent1
        child[start:end] = parent1[start:end]

        # Fill remaining from parent2
        pointer = 0
        for i in range(size):
            if child[i] == -1:
                while parent2[pointer] in child:
                    pointer += 1
                child[i] = parent2[pointer]
                pointer += 1
```

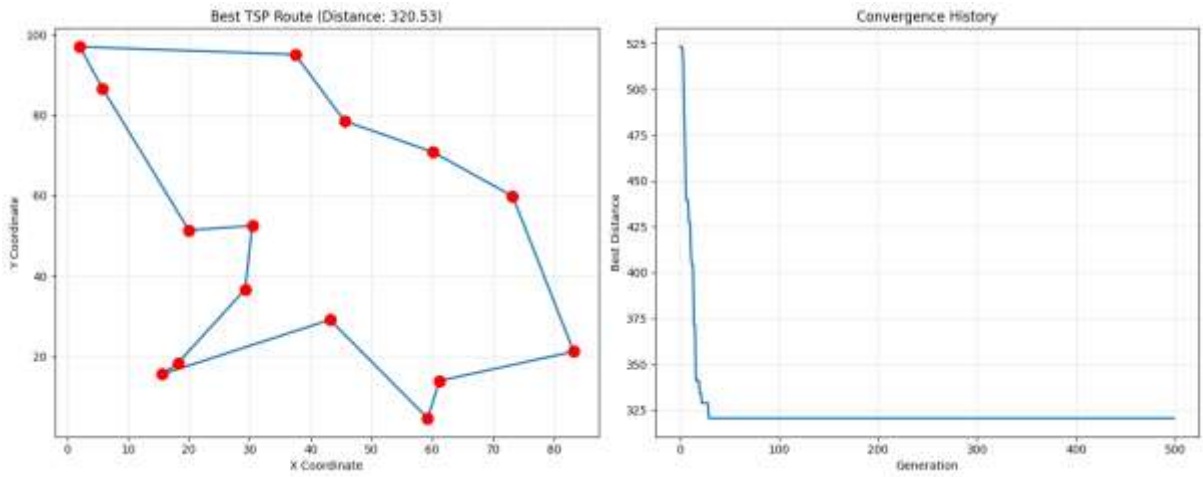
```
    return child

def mutate(self, individual):
    # Swap mutation
    if random.random() < self.mutation_rate:
        i, j = random.sample(range(self.n_cities), 2)
        individual[i], individual[j] = individual[j], individual[i]
    return individual

def evolve(self):
    population = self.create_population()
    best_distance = float('inf')
    best_route = None
    history = []

    for gen in range(self.generations):
        # Calculate fitness
        fitnesses = [self.fitness(ind) for ind in population]

        # Find best
        distances = [self.route_distance(ind) for ind in population]
        min_dist = min(distances)
        idx = distances.index(min_dist)

        if min_dist < best_distance:
            best_distance = min_dist
            best_route = population[idx]

        history.append(best_distance)

        # Create new population
        new_population = [best_route]  # Elitism
```

```
            while len(new_population) < self.pop_size:
                parent1 = self.selection(population, fitnesses)
                parent2 = self.selection(population, fitnesses)
                child = self.crossover(parent1, parent2)
                child = self.mutate(child)
                new_population.append(child)

            population = new_population

            if gen % 100 == 0:
                print(f"Generation {gen}: Best Distance =
{best_distance:.2f}")

        return best_route, best_distance, history

# Generate random cities
np.random.seed(42)
n_cities = 15
cities = np.random.rand(n_cities, 2) * 100

# Solve TSP with GA
print("Solving TSP using Genetic Algorithm...")
tsp_solver = TSP_GA(cities, population_size=100,
mutation_rate=0.02,
                    generations=500)
best_route, best_distance, history = tsp_solver.evolve()

print(f"\nBest route distance: {best_distance:.2f}")
print(f"Best route: {best_route}")

# Visualization
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))
```

```
# Plot best route
route_coords = cities[best_route]
route_coords = np.vstack([route_coords, route_coords[0]])  # Return
to start

ax1.plot(route_coords[:, 0], route_coords[:, 1], 'o-', linewidth=2)
ax1.scatter(cities[:, 0], cities[:, 1], c='red', s=100, zorder=5)
ax1.set_title(f'Best TSP Route (Distance: {best_distance:.2f})')
ax1.set_xlabel('X Coordinate')
ax1.set_ylabel('Y Coordinate')
ax1.grid(True, alpha=0.3)

# Plot convergence
ax2.plot(history, linewidth=2)
ax2.set_title('Convergence History')
ax2.set_xlabel('Generation')
ax2.set_ylabel('Best Distance')
ax2.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```

Ouput:

```
Solving TSP using Genetic Algorithm...
Generation 0: Best Distance = 523.15
Generation 100: Best Distance = 320.53
Generation 200: Best Distance = 320.53
Generation 300: Best Distance = 320.53
Generation 400: Best Distance = 320.53
Best route distance: 320.53
Best route: [6, 10, 14, 9, 2, 7, 11, 8, 13, 3, 5, 0, 12, 4, 1]
```



Assignment 14:

SVM on Iris Dataset

Problem Statement

Apply Support Vector Machine for classification on Iris dataset.

Code

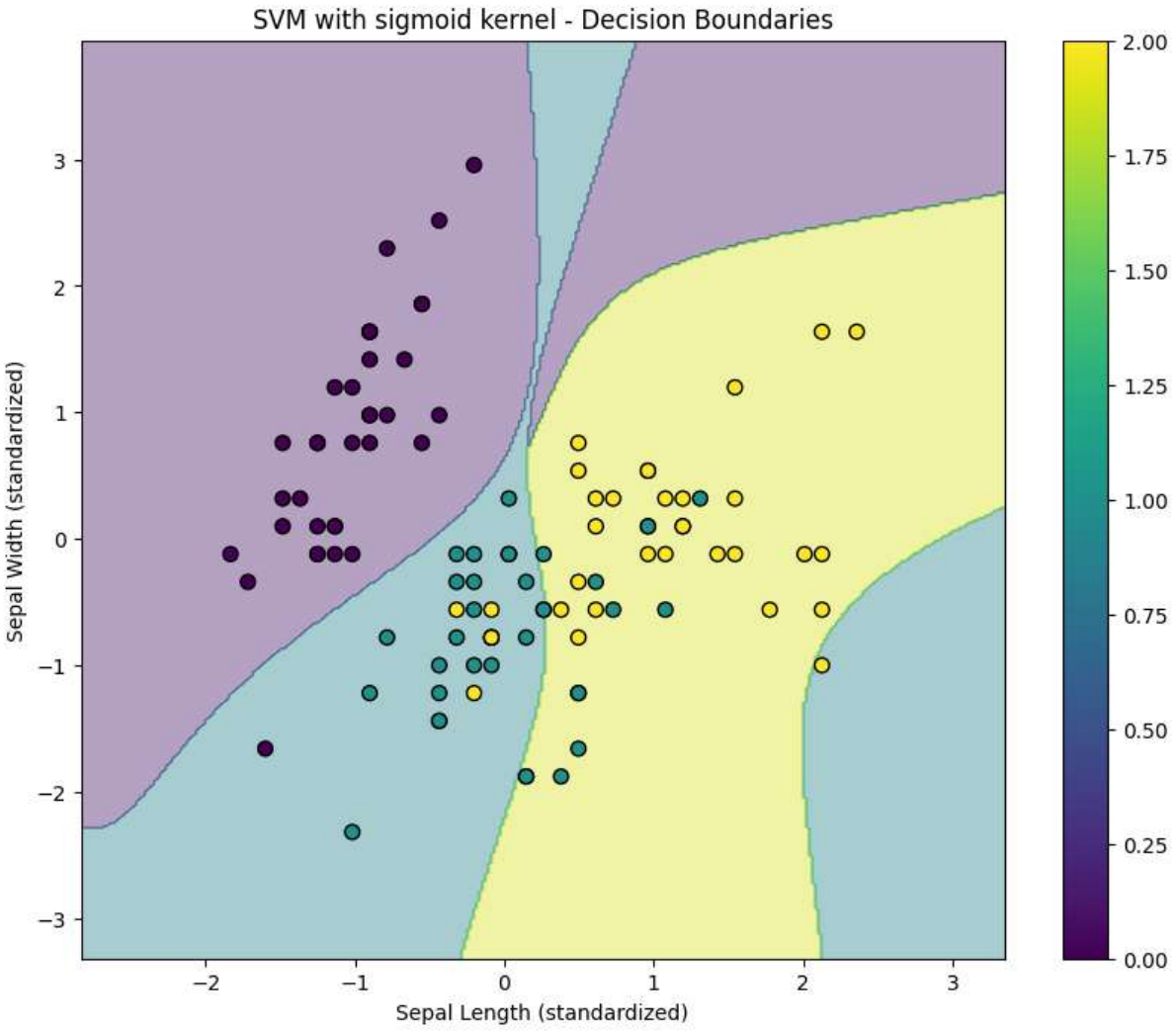
```
from sklearn import svm
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
import matplotlib.pyplot as plt
import numpy as np

# Load Iris dataset
iris = load_iris()
X = iris.data[:, :2]  # Use only first two features for visualization
y = iris.target

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
                                    random_state=42,
                                    stratify=y)
```

```
# Standardize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train SVM with different kernels
kernels = ['linear', 'poly', 'rbf', 'sigmoid']
results = {}

for kernel in kernels:
    print(f"\nTraining SVM with {kernel} kernel...")

    # Create and train SVM
    clf = svm.SVC(kernel=kernel, gamma='scale', C=1.0,
random_state=42)
    clf.fit(X_train_scaled, y_train)

    # Predictions
    y_pred = clf.predict(X_test_scaled)

    # Evaluation
    accuracy = accuracy_score(y_test, y_pred)
    cm = confusion_matrix(y_test, y_pred)
    report = classification_report(y_test, y_pred,
target_names=iris.target_names)

    results[kernel] = {
        'model': clf,
        'accuracy': accuracy,
        'confusion_matrix': cm,
        'report': report
    }
```

```
    print(f"Accuracy: {accuracy:.3f}")
    print(f"Confusion Matrix:\n{cm}")

# Visualization for best kernel
best_kernel = max(results, key=lambda k: results[k]['accuracy'])
best_model = results[best_kernel]['model']

print(f"\nBest kernel: {best_kernel} with accuracy:
{results[best_kernel]['accuracy']:.3f}")

# Create mesh grid for decision boundary
h = 0.02  # Step size in mesh
x_min, x_max = X_train_scaled[:, 0].min() - 1, X_train_scaled[:,
0].max() + 1
y_min, y_max = X_train_scaled[:, 1].min() - 1, X_train_scaled[:,
1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                     np.arange(y_min, y_max, h))

# Predict for each point in mesh
Z = best_model.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

# Plot decision boundary
plt.figure(figsize=(10, 8))
plt.contourf(xx, yy, Z, alpha=0.4, cmap='viridis')
plt.scatter(X_train_scaled[:, 0], X_train_scaled[:, 1], c=y_train,
            cmap='viridis', s=50, edgecolors='k')
plt.xlabel('Sepal Length (standardized)')
plt.ylabel('Sepal Width (standardized)')
plt.title(f'SVM with {best_kernel} kernel - Decision Boundaries')
plt.colorbar()
plt.show()
```

Output:

```
Training SVM with linear kernel...
Accuracy: 0.689
Confusion Matrix:
[[15  0  0]
 [ 0  9  6]
 [ 0  8  7]]

Training SVM with poly kernel...
Accuracy: 0.689
Confusion Matrix:
[[14  1  0]
 [ 0 15  0]
 [ 0 13  2]]

Training SVM with rbf kernel...
Accuracy: 0.689
Confusion Matrix:
[[15  0  0]
 [ 0  9  6]
 [ 0  8  7]]

Training SVM with sigmoid kernel...
Accuracy: 0.778
Confusion Matrix:
[[15  0  0]
 [ 0  8  7]
 [ 0  3 12]]

Best kernel: sigmoid with accuracy: 0.778
```



Remark:

SVM is a supervised learning algorithm that finds the optimal hyperplane to classify data with maximum margin.

Assignment 15:

KNN on Iris Dataset

Problem Statement

Implement K-Nearest Neighbors algorithm for classification.

Code

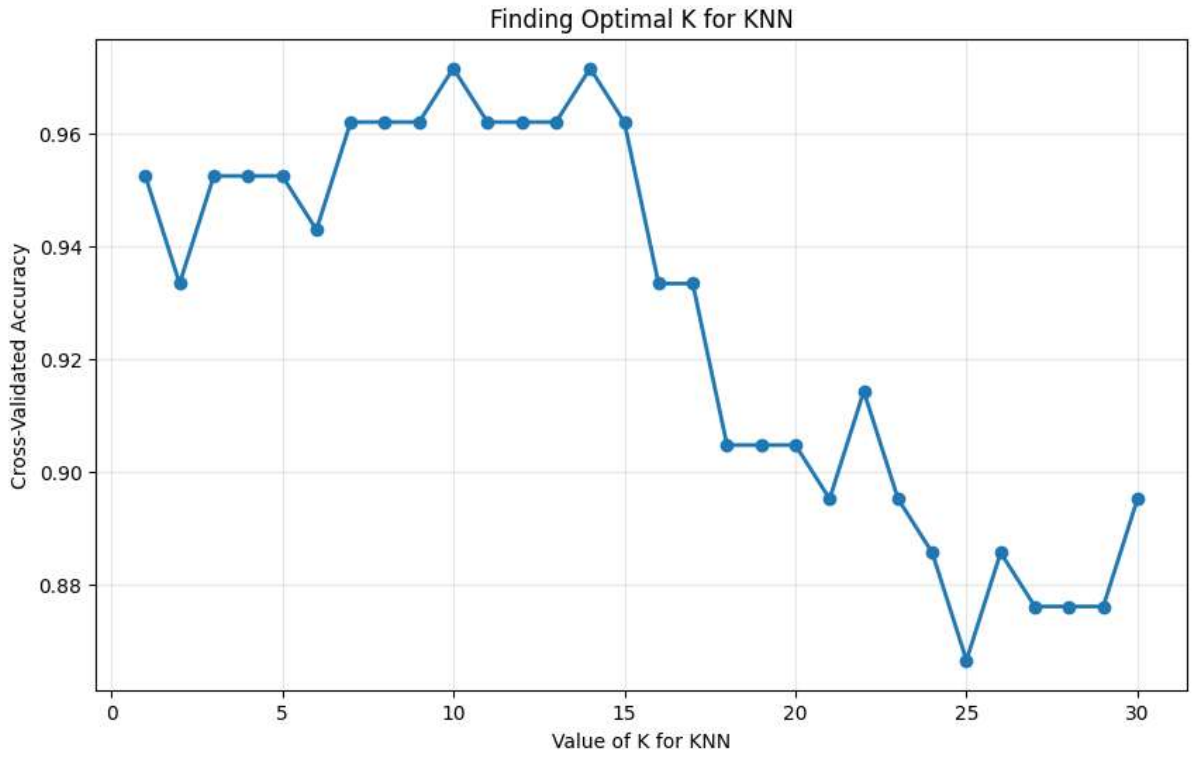
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split,
cross_val_score
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
import matplotlib.pyplot as plt
import numpy as np

# Load dataset
iris = load_iris()
X = iris.data
y = iris.target

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
                                    random_state=42,
                                    stratify=y)

# Standardize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Find optimal k using cross-validation
k_range = range(1, 31)
k_scores = []

for k in k_range:
   knn = KNeighborsClassifier(n_neighbors=k)
   scores = cross_val_score(knn, X_train_scaled, y_train, cv=5,
scoring='accuracy')
   k_scores.append(scores.mean())

# Plot accuracy vs k
plt.figure(figsize=(10, 6))
plt.plot(k_range, k_scores, 'o-', linewidth=2)
```

```
plt.xlabel('Value of K for KNN')
plt.ylabel('Cross-Validated Accuracy')
plt.title('Finding Optimal K for KNN')
plt.grid(True, alpha=0.3)
plt.show()

# Best k
best_k = k_range[np.argmax(k_scores)]
print(f"Optimal K: {best_k} with accuracy: {max(k_scores):.3f}")

# Train with best k
knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train_scaled, y_train)

# Predictions
y_pred = knn.predict(X_test_scaled)

# Evaluation
accuracy = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred,
target_names=iris.target_names)

print(f"\nTest Accuracy: {accuracy:.3f}")
print(f"Confusion Matrix:\n{cm}")
print(f"Classification Report:\n{report}")

# Test on new sample
new_sample = np.array([[5.1, 3.5, 1.4, 0.2]])  # Setosa sample
new_sample_scaled = scaler.transform(new_sample)
prediction = knn.predict(new_sample_scaled)
print(f"\nNew sample prediction: {iris.target_names[prediction[0]]}")
```

```
# Distance-based visualization for first two features
plt.figure(figsize=(10, 8))
plt.scatter(X_train_scaled[:, 0], X_train_scaled[:, 1], c=y_train,
        cmap='viridis', s=50, alpha=0.6, label='Training data')

# Plot test points with predictions
colors = ['red', 'green', 'blue']
for i in range(len(X_test_scaled)):
   plt.scatter(X_test_scaled[i, 0], X_test_scaled[i, 1],
            c=colors[y_pred[i]], marker='*', s=200,
            edgecolors='black', linewidth=1.5)

plt.xlabel('Feature 1 (standardized)')
plt.ylabel('Feature 2 (standardized)')
plt.title(f'KNN Classification (K={best_k})')
plt.legend(['Training Data', 'Test Predictions'])
plt.grid(True, alpha=0.3)
plt.show()
```

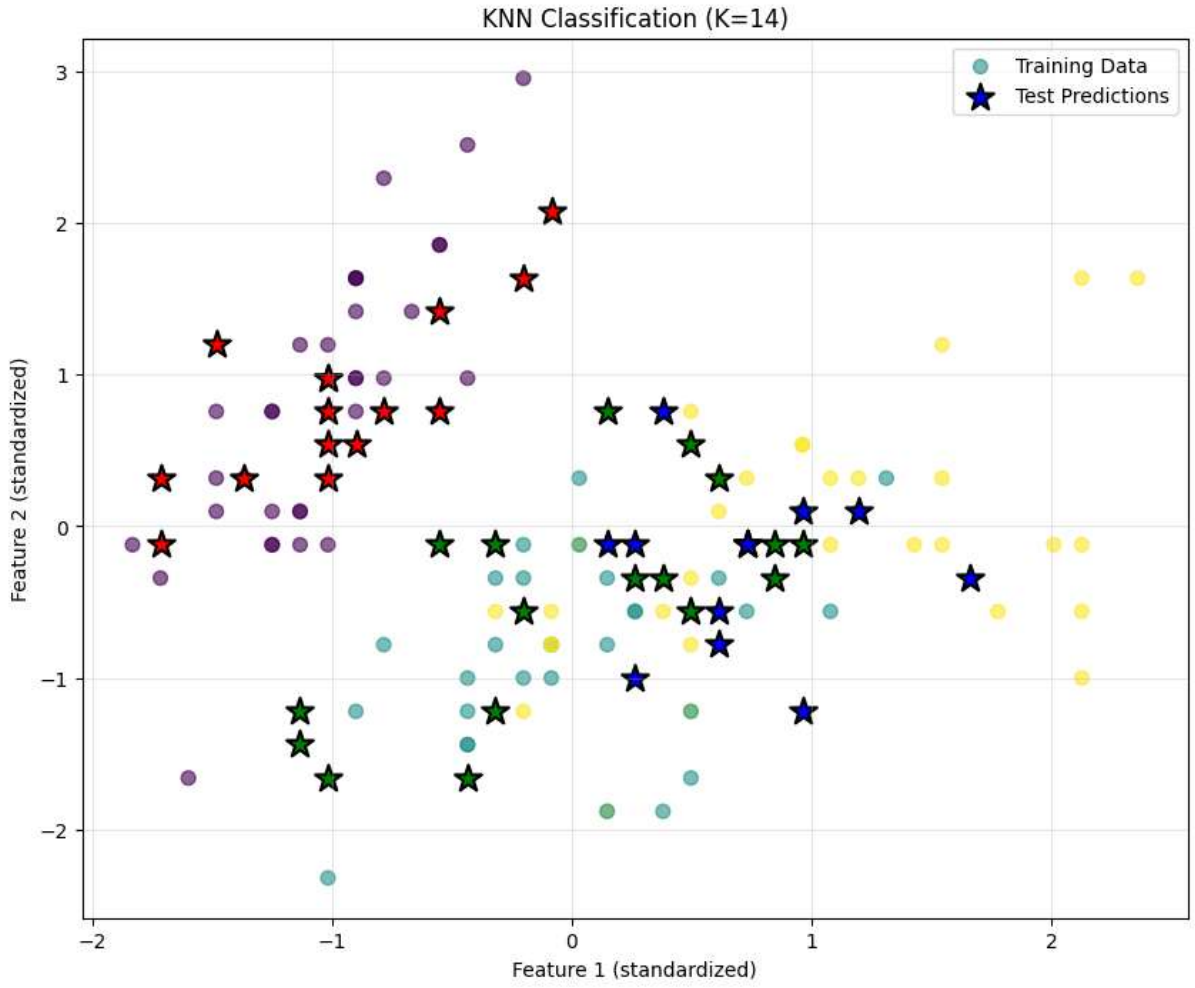
Output:



Optimal K: 14 with accuracy: 0.971
Test Accuracy: 0.956
Confusion Matrix:
[[15 0 0]
 [0 15 0]
 [0 2 13]]
Classification Report:

	precision	recall	f1-score	support
setosa	1.00	1.00	1.00	15
versicolor	0.88	1.00	0.94	15
virginica	1.00	0.87	0.93	15
accuracy			0.96	45
macro avg	0.96	0.96	0.96	45
weighted avg	0.96	0.96	0.96	45

New sample prediction: setosa



Assignment 16:

Logistic Regression on Iris Dataset

Problem Statement

Implement Logistic Regression for multi-class classification.

Code

```
from sklearn.linear_model import LogisticRegression
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import (accuracy_score, confusion_matrix,
                             classification_report, roc_curve, auc)
from sklearn.preprocessing import label_binarize
import matplotlib.pyplot as plt
import numpy as np

# Load dataset
iris = load_iris()
X = iris.data
y = iris.target

# For binary classification demonstration, use only two classes
# (Logistic Regression inherently binary, but sklearn extends to multi-class)
X = X[y != 2]
y = y[y != 2]

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
                                                    random_state=42,
                                                    stratify=y)

# Standardize features
scaler = StandardScaler()
```

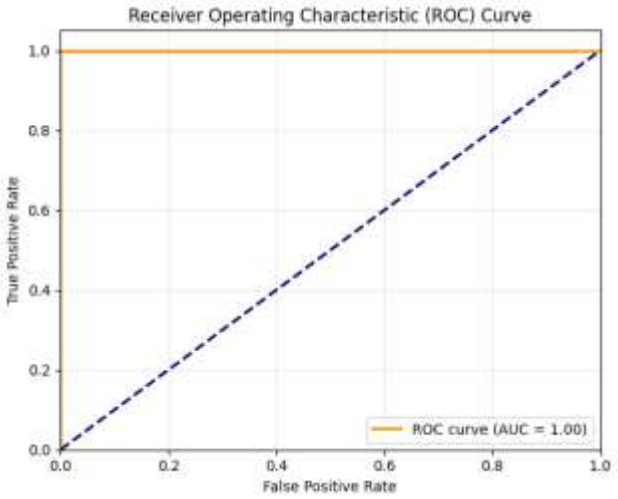
```
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train Logistic Regression
logreg = LogisticRegression(C=1.0, solver='lbfgs', max_iter=1000,
                            random_state=42)
logreg.fit(X_train_scaled, y_train)

# Get predictions and probabilities
y_pred = logreg.predict(X_test_scaled)
y_pred_proba = logreg.predict_proba(X_test_scaled)[:, 1]

# Evaluation
accuracy = accuracy_score(y_test, y_pred)
cm = confusion_matrix(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.3f}")
print(f"Confusion Matrix:\n{cm}")
print(f"Classification Report:\n{report}")

print(f"\nModel Coefficients: {logreg.coef_}")
print(f"Model Intercept: {logreg.intercept_}")

# ROC Curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(12, 5))

# Plot ROC Curve
plt.subplot(1, 2, 1)
plt.plot(fpr, tpr, color='darkorange', lw=2,
```

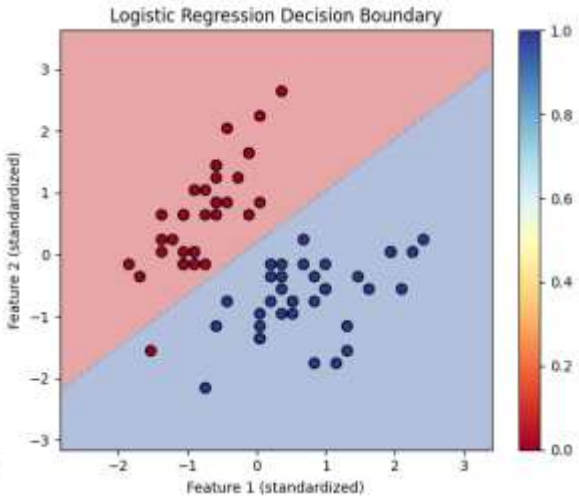
```
        label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.grid(True, alpha=0.3)

# Plot decision boundary (using first two features)
plt.subplot(1, 2, 2)
h = 0.02  # Step size
x_min, x_max = X_train_scaled[:, 0].min() - 1, X_train_scaled[:,
0].max() + 1
y_min, y_max = X_train_scaled[:, 1].min() - 1, X_train_scaled[:,
1].max() + 1
xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                     np.arange(y_min, y_max, h))

Z = logreg.predict(np.c_[xx.ravel(),
                         yy.ravel(),
                         np.zeros(xx.ravel().shape),
                         np.zeros(xx.ravel().shape)])
Z = Z.reshape(xx.shape)

plt.contourf(xx, yy, Z, alpha=0.4, cmap='RdYlBu')
plt.scatter(X_train_scaled[:, 0], X_train_scaled[:, 1], c=y_train,
           cmap='RdYlBu', s=50, edgecolors='k')
plt.xlabel('Feature 1 (standardized)')
plt.ylabel('Feature 2 (standardized)')
plt.title('Logistic Regression Decision Boundary')
plt.colorbar()
```

```
plt.tight_layout()
plt.show()

# Predict probability for new sample
new_sample = np.array([[5.1, 3.5, 1.4, 0.2]])
new_sample_scaled = scaler.transform(new_sample)
probabilities = logreg.predict_proba(new_sample_scaled)
prediction = logreg.predict(new_sample_scaled)

print(f"\nNew sample probabilities: {probabilities}")
print(f"Predicted class: {prediction[0]}")
```

Output:

```
Accuracy: 1.000
Confusion Matrix:
[[15  0]
 [ 0 15]]
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        15
           1       1.00      1.00      1.00        15

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
Model Coefficients: [[ 0.84579129 -1.00398344  1.39479409
1.4247247 ]]
Model Intercept: [0.19790844]
```





New sample probabilities: [[0.98290327 0.01709673]]
Predicted class: 0

Assignment 17:

Apriori Algorithm

Problem Statement

Find frequent itemsets and association rules using Apriori algorithm.

Code

```
import pandas as pd
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules
import matplotlib.pyplot as plt

# Sample transaction dataset
transactions = [
    ['Milk', 'Bread', 'Butter'],
    ['Bread', 'Butter', 'Eggs'],
    ['Milk', 'Bread', 'Eggs', 'Butter'],
    ['Bread', 'Eggs'],
    ['Milk', 'Eggs'],
    ['Milk', 'Bread', 'Eggs'],
    ['Bread'],
    ['Milk', 'Bread', 'Butter', 'Eggs'],
    ['Milk', 'Bread'],
    ['Butter', 'Eggs']
```

```
]

# Convert to one-hot encoded DataFrame
te = TransactionEncoder()
te_ary = te.fit(transactions).transform(transactions)
df = pd.DataFrame(te_ary, columns=te.columns_)

print("Transaction Dataset (One-hot encoded):")
print(df)

# Find frequent itemsets with min_support = 0.3
frequent_itemsets = apriori(df, min_support=0.3,
use_colnames=True)
frequent_itemsets['length'] =
frequent_itemsets['itemsets'].apply(lambda x: len(x))

print("\nFrequent Itemsets:")
print(frequent_itemsets.sort_values('support', ascending=False))

# Generate association rules
rules = association_rules(frequent_itemsets, metric="confidence",
min_threshold=0.6)

print("\nAssociation Rules (confidence >= 0.6):")
print(rules[['antecedents', 'consequents', 'support', 'confidence',
'lift']])

# Filter strong rules (lift > 1.2 and confidence > 0.7)
strong_rules = rules[(rules['lift'] > 1.2) & (rules['confidence'] > 0.7)]

print("\nStrong Association Rules (lift > 1.2, confidence > 0.7):")
print(strong_rules[['antecedents', 'consequents', 'support',
'confidence', 'lift']])
```

```
# Visualization
plt.figure(figsize=(12, 5))

# Support vs Confidence scatter plot
plt.subplot(1, 2, 1)
plt.scatter(rules['support'], rules['confidence'], alpha=0.5,
c=rules['lift'],
          cmap='viridis', s=rules['lift']*100)
plt.colorbar(label='Lift')
plt.xlabel('Support')
plt.ylabel('Confidence')
plt.title('Association Rules: Support vs Confidence')
plt.grid(True, alpha=0.3)

# Top 10 rules by lift
plt.subplot(1, 2, 2)
top_rules = rules.sort_values('lift', ascending=False).head(10)
rule_labels = [f"{set(rule.antecedents)} → {set(rule.consequents)}"
             for _, rule in top_rules.iterrows()]
y_pos = range(len(rule_labels))

plt.barh(y_pos, top_rules['lift'], color='skyblue')
plt.yticks(y_pos, rule_labels)
plt.xlabel('Lift')
plt.title('Top 10 Association Rules by Lift')
plt.tight_layout()

plt.show()

# Generate actionable insights
print("\nActionable Insights from Association Rules:")
for idx, rule in strong_rules.iterrows():
```

```
    antecedents = set(rule['antecedents'])
    consequents = set(rule['consequents'])
    support = rule['support']
    confidence = rule['confidence']
    lift = rule['lift']

    print(f"\nRule: {antecedents} → {consequents}")
    print(f"  Support: {support:.2%} | Confidence: {confidence:.2%} |
Lift: {lift:.2f}")
    print(f"  Insight: Customers who buy {antecedents} are
{confidence:.0%} likely to also buy {consequents}")
    if lift > 1.5:
        print(f"  Action: Consider placing {antecedents} and
{consequents} close together")
```

Output:

Transaction Dataset (One-hot encoded):

	Bread	Butter	Eggs	Milk
0	True	True	False	True
1	True	True	True	False
2	True	True	True	True
3	True	False	True	False
4	False	False	True	True
5	True	False	True	True
6	True	False	False	False
7	True	True	True	True
8	True	False	False	True
9	False	True	True	False

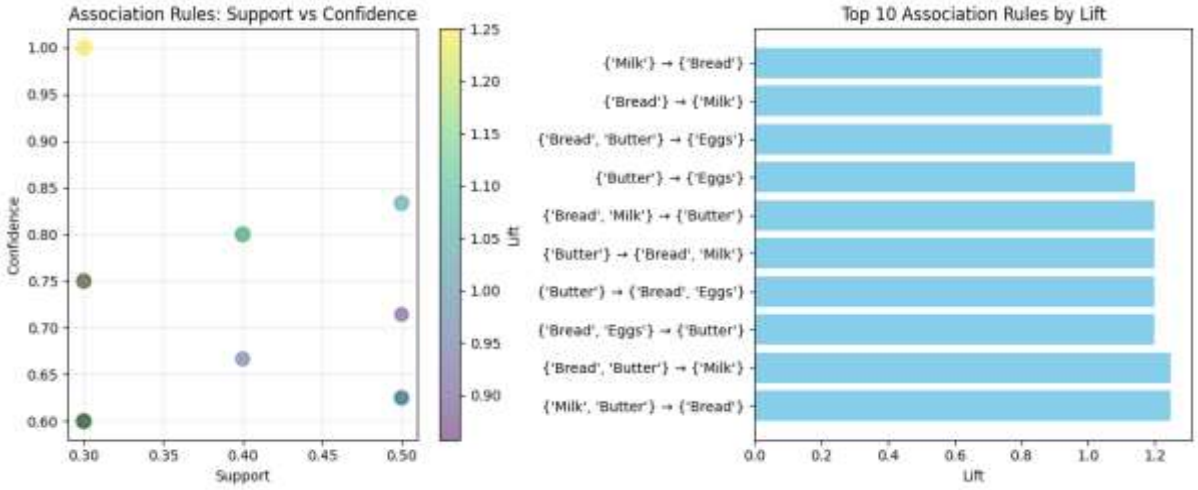
Frequent Itemsets:

	support	itemsets	length
0	0.8	(Bread)	1
2	0.7	(Eggs)	1
3	0.6	(Milk)	1

```
1      0.5            (Butter)      1
5      0.5         (Bread, Eggs)      2
6      0.5         (Bread, Milk)      2
4      0.4        (Bread, Butter)      2
7      0.4         (Eggs, Butter)      2
9      0.4          (Milk, Eggs)      2
8      0.3         (Milk, Butter)      2
10     0.3  (Bread, Eggs, Butter)      3
11     0.3  (Bread, Milk, Butter)      3
12     0.3    (Bread, Milk, Eggs)      3

Association Rules (confidence >= 0.6):
      antecedents    consequents  support  confidence     lift
0         (Butter)       (Bread)     0.4    0.800000  1.000000
1         (Bread)        (Eggs)     0.5    0.625000  0.892857
2          (Eggs)       (Bread)     0.5    0.714286  0.892857
3         (Bread)        (Milk)     0.5    0.625000  1.041667
4          (Milk)       (Bread)     0.5    0.833333  1.041667
5         (Butter)        (Eggs)     0.4    0.800000  1.142857
6         (Butter)        (Milk)     0.3    0.600000  1.000000
7          (Milk)        (Eggs)     0.4    0.666667  0.952381
8    (Bread, Eggs)      (Butter)     0.3    0.600000  1.200000
9   (Bread, Butter)        (Eggs)     0.3    0.750000  1.071429
10   (Eggs, Butter)       (Bread)     0.3    0.750000  0.937500
11        (Butter)  (Bread, Eggs)     0.3    0.600000  1.200000
12   (Bread, Milk)      (Butter)     0.3    0.600000  1.200000
13  (Bread, Butter)        (Milk)     0.3    0.750000  1.250000
14   (Milk, Butter)       (Bread)     0.3    1.000000  1.250000
15        (Butter)  (Bread, Milk)     0.3    0.600000  1.200000
16   (Bread, Milk)        (Eggs)     0.3    0.600000  0.857143
17   (Bread, Eggs)        (Milk)     0.3    0.600000  1.000000
18    (Milk, Eggs)       (Bread)     0.3    0.750000  0.937500
```

Strong Association Rules (lift > 1.2, confidence > 0.7):

	antecedents	consequents	support	confidence	lift
13	(Bread, Butter)	(Milk)	0.3	0.75	1.25
14	(Milk, Butter)	(Bread)	0.3	1.00	1.25



Assignment 18:

First Order Logic Resolution

Problem Statement

Use resolution to prove " Marcus hates Ceaser" from given axioms.

Knowledge Base

Given axioms:

Resolution Proof Example.

(a) Marcus was a man.

(b) Marcus was a Roman.

(c) All men are people.

(d) Caesar was a ruler.

(e) All Romans were either loyal to Caesar or hated him (or both).

(f) Everyone is loyal to someone.

(g) People only try to assassinate rulers they are not loyal to.

(h) Marcus tried to assassinate Caesar.Prolog Implementation

Prolog

Code:

```
% Simple working Prolog program


% Facts
```

```
man(marcus).
roman(marcus).
ruler(caesar).
tried_to_assassinate(marcus, caesar).

% Rules
person(X) :- man(X).  % All men are people

% Everyone is loyal to someone
loyal_to_someone(X) :- person(X).

% People only try to assassinate rulers they are not loyal to
% This is the key rule: if X tries to assassinate Y, then X is not loyal to Y
not_loyal(X, Y) :- tried_to_assassinate(X, Y), person(X), ruler(Y).

% All Romans were either loyal to Caesar or hated him
% Since we know Marcus tried to assassinate Caesar, he must hate
him
hates(X, caesar) :- roman(X), not_loyal(X, caesar).

% Query
query_result :-
   (hates(marcus, caesar) ->
      format('Result: Marcus hates Caesar.~nProof complete.~n')
   ;
      format('Result: Marcus does not hate Caesar.~n')
   ).

% Run the proof
:- initialization((
   write('======================================~n'),
   write('  Proof that Marcus Hates Caesar~n'),
   write('======================================~n~n'),
```

```
    write('Given:~n'),
    write('1. Marcus was a man.~n'),
    write('2. Marcus was a Roman.~n'),
    write('3. All men are people.~n'),
    write('4. Caesar was a ruler.~n'),
    write('5. All Romans were either loyal to Caesar or hated him.~n'),
    write('6. Everyone is loyal to someone.~n'),
    write('7. People only try to assassinate rulers they are not loyal
to.~n'),
    write('8. Marcus tried to assassinate Caesar.~n~n'),

    write('Proof Steps:~n~n'),

    write('Step 1: Marcus is a person (from 1 and 3).~n'),
    write('Step 2: From 8 and 7, Marcus is not loyal to Caesar.~n'),
    write('Step 3: From 2 and 5, as a Roman, Marcus must either:~n'),
    write('        a) be loyal to Caesar, OR~n'),
    write('        b) hate Caesar.~n'),
    write('Step 4: From Step 2, Marcus is not loyal to Caesar.~n'),
    write('Step 5: Therefore, from Step 3b, Marcus must hate
Caesar.~n~n'),

    query_result,

    write('~n=====================================~n')
)).
```