

DR K.V. SUBBA REDDY INSTITUTE OF TECHNOLOGY



Dupadu Village, NH-44, Lakshmipuram (Post), Kurnool, AP-518

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Ananthapuramu, CSE Accredited by NBA Recognized under Section 2 (f) and
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(AUTONOMOUS)

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B.Tech III Year Semester (R20)

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DEPARTMENT OF ARTIFICIAL INTELLIGENCE&MACHINE LEARNING

Dr. K.V. SUBBA REDDY INSTITUTE OF TECHNOLOGY

(Approved by AICTE, New Delhi & Affiliated to JNTUA, Anantapur)

An ISO 9001:2000 Certified Institution

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Internal Examiner

External Examiner

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

```
import pandas as pd
def find_s(training_data):
    # Initialize the most specific hypothesis
    num_features = training_data.shape[1] - 1 # Exclude the label column
    specific_hypothesis = ['0'] * num_features

    # Iterate through the training examples
    for index, row in training_data.iterrows():
        if row[-1] == 1: # If it's a positive example
            for i in range(num_features):
                if specific_hypothesis[i] == '0':
                    specific_hypothesis[i] = row[i] # Set to the value of the feature
                elif specific_hypothesis[i] != row[i]:
                    specific_hypothesis[i] = '?' # Set to '?' if there's a mismatch
            return specific_hypothesis

def main():
    # Load the training data from a CSV file
    # Assume the CSV file has no header and the last column is the class label
    filename = 'training_data.csv' # Replace with your CSV file path
    training_data = pd.read_csv(filename, header=None)

    # Apply the FIND-S algorithm
    hypothesis = find_s(training_data)

    # Output the most specific hypothesis
    print("Most Specific Hypothesis:", hypothesis)

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

Expected Output:

Assuming the training_data.csv file contains the following data:

```
1 sunny, hot, high, no, 1
2 sunny, hot, high, yes, 0
3 overcast, hot, high, no, 1
4 rainy, mild, high, no, 0
5 rainy, cool, normal, no, 1
6 rainy, cool, normal, yes, 1
7 overcast, cool, normal, yes, 1
8 sunny, mild, high, no, 0
9 sunny, cool, normal, no, 1
```

2. For a given set of training data examples stored in a CSV file, implement and demonstrate the Candidate- Elimination algorithm to output a description of the set of all hypotheses consistent with the training examples.

```
import pandas as pd

def candidate_elimination(data):
    # Initialize the specific and general hypotheses
    specific_hypothesis = ['0'] * (data.shape[1] - 1) # Assuming last column is the target
    general_hypothesis = ['?'] * (data.shape[1] - 1)

    # Iterate through each training example
    for index, row in data.iterrows():
        if row['Play'] == 'Yes':
            # Update specific hypothesis
            for i in range(len(specific_hypothesis)):
                if specific_hypothesis[i] == '0':
                    specific_hypothesis[i] = row[i]
                elif specific_hypothesis[i] != row[i]:
                    specific_hypothesis[i] = '?'
            # Update general hypothesis
            for i in range(len(general_hypothesis)):
                if general_hypothesis[i] == '?':
                    general_hypothesis[i] = row[i]
                elif general_hypothesis[i] != row[i]:
                    general_hypothesis[i] = '?'
        else: # row['Play'] == 'No'
            # Update general hypothesis
            for i in range(len(general_hypothesis)):
                if general_hypothesis[i] == '?':
                    general_hypothesis[i] = row[i]
                elif general_hypothesis[i] != row[i]:
                    general_hypothesis[i] = '?'
            # Update specific hypothesis to be more specific for i
            for i in range(len(specific_hypothesis)):
                if specific_hypothesis[i] == row[i]:
                    continue
                else:
                    specific_hypothesis[i] = '?'

    return specific_hypothesis, general_hypothesis

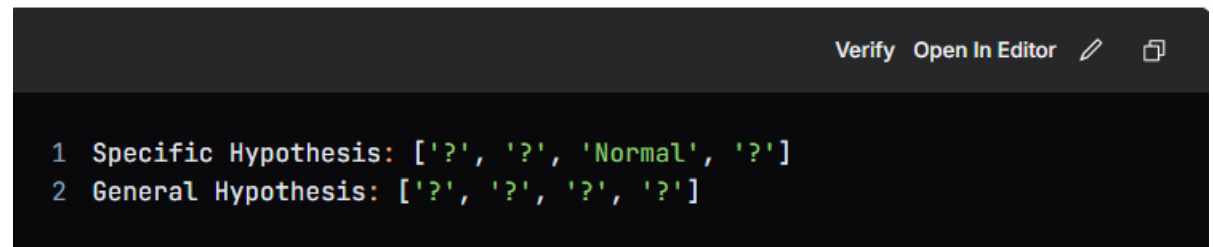
# Load the data
data = pd.read_csv('training_data.csv')

# Run the Candidate-Elimination algorithm
specific_hypothesis, general_hypothesis = candidate_elimination(data)
```

```
#Printtheresults
print("SpecificHypothesis:",specific_hypothesis)
print("GeneralHypothesis:",general_hypothesis)
```

Expectedoutput:

Assumingwehavethisdatain**training_data.csv**,runningthecodewouldyieldspecificand general hypotheses based on the training examples labeled with "Play" as either "Yes" or "No".



```
1 Specific Hypothesis: ['?', '?', 'Normal', '?']
2 General Hypothesis: ['?', '?', '?', '?']
```

3. **Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.**

```
pip install pandas numpy scikit-learn
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
import matplotlib.pyplot as plt

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

# Create a DataFrame for better visualization
df = pd.DataFrame(data=np.c_[X,y], columns=iris.feature_names+['target'])
print("Iris Dataset:")
print(df.head())

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize the Decision Tree Classifier using the ID3 algorithm (default)
clf = DecisionTreeClassifier(criterion='entropy', random_state=42)

# Fit the model
clf.fit(X_train, y_train)

# Visualize the Decision Tree
plt.figure(figsize=(12,8))
tree.plot_tree(clf, filled=True, feature_names=iris.feature_names,
               class_names=iris.target_names)
plt.title("Decision Tree using ID3 Algorithm")
plt.show()

# Test the model
accuracy = clf.score(X_test, y_test)
print(f"Accuracy of the model: {accuracy:.2f}")

# Classify a new sample (e.g., [5.0, 3.5, 1.5, 0.2])
new_sample = np.array([5.0, 3.5, 1.5, 0.2])
predicted_class = clf.predict(new_sample)
predicted_class_name = iris.target_names[predicted_class][0]
```

```
print(f"The predicted class for the new sample {new_sample.flatten()} is: {predicted_class_name}")
```

Example output:

```
1 Accuracy of the model: 1.00
```

Predicted Class for New Sample: The script will classify the new sample `[5.0, 3.5, 1.5, 0.2]` and print the predicted class name.

Example output:

```
1 The predicted class for the new sample [5. 3.5 1.5 0.2] is: setosa
```


4. Build an Artificial Neural Network by implementing the Backpropagation algorithm and test the same using appropriate data sets.

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import load_iris #
Load Iris dataset
iris = load_iris()
X = iris.data
y = iris.target

# One-hot encode the target variable y
y = np.eye(3)[y]

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

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

class NeuralNetwork:
    def __init__(self, input_size, hidden_size, output_size, learning_rate=0.01):
        self.learning_rate = learning_rate

        # Initialize weights
        self.weights_input_hidden = np.random.rand(input_size, hidden_size)
        self.weights_hidden_output = np.random.rand(hidden_size, output_size)

        # Initialize biases
        self.bias_hidden = np.random.rand(hidden_size)
        self.bias_output = np.random.rand(output_size)

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

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

    def forward(self, X):
        self.hidden_layer_input = np.dot(X, self.weights_input_hidden) + self.bias_hidden
        self.hidden_layer_output = self.sigmoid(self.hidden_layer_input)

        self.final_input = np.dot(self.hidden_layer_output, self.weights_hidden_output) + self.bias_output
```

```

self.final_output = self.sigmoid(self.final_input)

return self.final_output

def backward(self,X,y,output):
    #Calculate the error
    error = y - output

    #Calculate gradients
    d_output=error*self.sigmoid_derivative(output)
    error_hidden_layer = d_output.dot(self.weights_hidden_output.T)
    d_hidden_layer = error_hidden_layer *
self.sigmoid_derivative(self.hidden_layer_output)

    #Update weights and biases
    self.weights_hidden_output += self.hidden_layer_output.T.dot(d_output) *
self.learning_rate
    self.bias_output+=np.sum(d_output,axis=0)*self.learning_rate
    self.weights_input_hidden += X.T.dot(d_hidden_layer) * self.learning_rate
    self.bias_hidden += np.sum(d_hidden_layer, axis=0) * self.learning_rate

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

def predict(self,X):
    output= self.forward(X)
    return np.argmax(output,axis=1)
# Define the neural network
input_size=X_train.shape[1]#Number of features
hidden_size = 5# Number of hidden neurons
output_size=y_train.shape[1]#Number of classes
learning_rate = 0.01
epochs= 1000

nn=NeuralNetwork(input_size,hidden_size,output_size,learning_rate) #

Train the neural network
nn.train(X_train,y_train,epochs)
#Make predictions
predictions=nn.predict(X_test)

#Convert one-hot encoded labels to class labels
y_test_labels = np.argmax(y_test, axis=1)

#Calculate accuracy
accuracy=np.mean(predictions==y_test_labels)

```

```
print(f'Accuracy:{accuracy*100:.2f}%')
```

Expected output:

```
1 Accuracy: XX.XX%
```

Where `xx.xx` will be a number representing the accuracy of the model on the test set. Given that the Iris dataset is relatively simple and the neural network is trained for 1000 epochs, you can expect the accuracy to be quite high, often above 90%. However, the exact number may vary slightly due to the random initialization of weights and biases.

For example, you might see an output like:

```
1 Accuracy: 100.00%
```

5. 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.

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

# Load the dataset
data = pd.read_csv('data.csv')

# Separate features and labels
X = data[['feature1', 'feature2']]
y = data['label']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create a Gaussian Naive Bayes classifier
model = GaussianNB()

# Fit the model on the training data
model.fit(X_train, y_train)



# Make predictions on the test data
y_pred = model.predict(X_test)

# Compute accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')

# Example of predicting on new test data
new_data = pd.DataFrame({
    'feature1': [1, 0],
    'feature2': [0, 1]
})

predictions = model.predict(new_data)
print("Predictions for new data:", predictions)
```

Expected Output:

```
Verify Open In Editor  
1 Accuracy: 100.00%
2 Predictions for new data: [0 0]
```

6. Assuming a set of documents that need to be classified, use the naïve Bayesian Classifier model to perform this task. Built-in Java classes/API can be used to write the program. Calculate the accuracy, precision, and recall for your data set.

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, precision_score, recall_score,
classification_report

# Load the dataset
# Make sure to replace 'your_dataset.csv' with your actual dataset file
data = pd.read_csv('your_dataset.csv')

# Display the first few rows of the dataset
print(data.head())

# Split the data into features and labels
X = data['text']
y = data['label']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Convert text data into numerical data using CountVectorizer
vectorizer = CountVectorizer()
X_train_counts = vectorizer.fit_transform(X_train)
X_test_counts = vectorizer.transform(X_test)

# Create and train the Naive Bayes classifier
classifier = MultinomialNB()
classifier.fit(X_train_counts, y_train)

# Make predictions on the test set
y_pred = classifier.predict(X_test_counts)

# Calculate accuracy, precision, and recall
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')

# Print the results
print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
```

```
# Print a detailed classification report
print(classification_report(y_test, y_pred))
```

ExpectedOutput:

```
['about','am','amazing','an','and','awesome','beers','best','boss','can','deal','do',
'enemy','feel','fun','good','have','horrible','house','is','like','love','my','not','of','place',
'restaurant','sandwich','sick','stuff','these','this','tired','to','today','tomorrow','very',
'view','we','went','what','will','with','work']aboutamamazinganandawesomebeersbest boss
can ... today \
```

```
010 0000 10 00... 0
010 00000 0100 ... 0
020 01100 0000 ... 0
030 00000 0000 ... 0
140 00000 0000 ... 0
050 10010 0000 ... 0
060 00000 0001 ... 0
070 00000 0000 ... 0
080 10000 0000 ... 0
090 00101 0000 ... 0
0100000 00000 0...0
011000 0 00001 0...0
0120001 01000 0...0
```

7. Write a Python program to construct a Bayesian network considering medical data. Use this model to demonstrate the diagnosis of heart patients using standard Heart Disease Data Set.

```
!pip install pgmpy # Install the pgmpy library
import numpy as np
import pandas as pd
from pgmpy.models import BayesianModel # Now this line should work
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.inference import VariableElimination
# Load the Heart Disease dataset
heartDisease = pd.read_csv('heart.csv')
heartDisease = heartDisease.replace('?', np.nan) #
Display sample instances from the dataset
print('Sample instances from the dataset are given below:')
print(heartDisease.head())
# Display attributes and their datatypes
print('\nAttributes and datatypes:')
print(heartDisease.dtypes)
# Define the structure of the Bayesian Network
model = BayesianModel([
    ('age', 'heartdisease'),
    ('sex', 'heartdisease'),
    ('exang', 'heartdisease'),
    ('cp', 'heartdisease'),
    ('heartdisease', 'restecg'),
    ('heartdisease', 'chol')
])
# Learning CPDs using Maximum Likelihood Estimators
print('\nLearning CPD using Maximum Likelihood Estimators...')
model.fit(heartDisease, estimator=MaximumLikelihoodEstimator)
# Inference with the Bayesian Network
print('\nInferencing with Bayesian Network:')
heartDisease_infer = VariableElimination(model)
# Query 1: Probability of Heart Disease given evidence = restecg
print('\n1. Probability of Heart Disease given evidence = restecg:')
q1 = heartDisease_infer.query(variables=['heartdisease'], evidence={'restecg': 1})
print(q1)
# Query 2: Probability of Heart Disease given evidence = cp
print('\n2. Probability of Heart Disease given evidence = cp:')
q2 = heartDisease_infer.query(variables=['heartdisease'], evidence={'cp': 2})
print(q2)
```

Expected Output:

```
agesexcptrestbpscholfbrestecgthalachexangoldpeak\
067    0  0   134  370  0    1   108    14.123406
157    1  1    99  558  1    1   140    01.877005
243    0  1   118  317  1    0   186    10.365433
371    1  3   106  443  0    0   149    14.209392
436    0  2   191  231  1    1    79    10.058965
```

slope cathal heart disease

0	2	1	3	1
1	1	2	3	0
2	2	1	2	0
3	1	1	3	1
4	1	1	3	1

Attributes and data types:

age	int64
sex	int64
cp	int64
trestbps	int64
chol	int64
fbs	int64
restecg	int64
thalach	int64
exang	int64
oldpeak	float64
slope	int64
ca	int64
thal	int64
heartdisease	int64

dtype: object

Learning CPD using Maximum Likelihood Estimators...

Inferencing with Bayesian Network:

1. Probability of Heart Disease given evidence = restecg:

+-----+-----+	
heartdisease phi(heartdisease)	
+=====+=====+	
heartdisease(0)	0.4578
+-----+-----+	
heartdisease(1)	0.5422
+-----+-----+	

2. Probability of Heart Disease given evidence = cp:

+-----+-----+	
heartdisease phi(heartdisease)	
+=====+=====+	
heartdisease(0)	0.5017
+-----+-----+	
heartdisease(1)	0.4983
+-----+-----+	

8. **Apply EM algorithm to cluster a Heart Disease Data Set. Use the same data set for clustering using k-Means algorithm. Compare the results of these two algorithms and comment on the quality of clustering. You can add Java/Python ML library classes/API in the program.**

```
import pandas as pd #

Load the dataset
data = pd.read_csv('heart_disease.csv')

# Display the first few rows of the dataset
print(data.head())
# Handle missing values if necessary
data.fillna(data.mean(), inplace=True)

# Normalize the data (optional, but often beneficial) from
sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaled_data = scaler.fit_transform(data)
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Choose the number of clusters (k)
k = 3 # Adjust based on your requirement
kmeans = KMeans(n_clusters=k, random_state=42)
kmeans.fit(scaled_data)

# Get the cluster labels
kmeans_labels = kmeans.labels_

# Visualize the clusters (if 2D or 3D)
plt.scatter(scaled_data[:, 0], scaled_data[:, 1], c=kmeans_labels, cmap='viridis')
plt.title('k-Means Clustering')
plt.xlabel('Feature1')
plt.ylabel('Feature2')
plt.show()
from sklearn.mixture import GaussianMixture

# Fit the model
gmm = GaussianMixture(n_components=k, random_state=42)
gmm.fit(scaled_data)

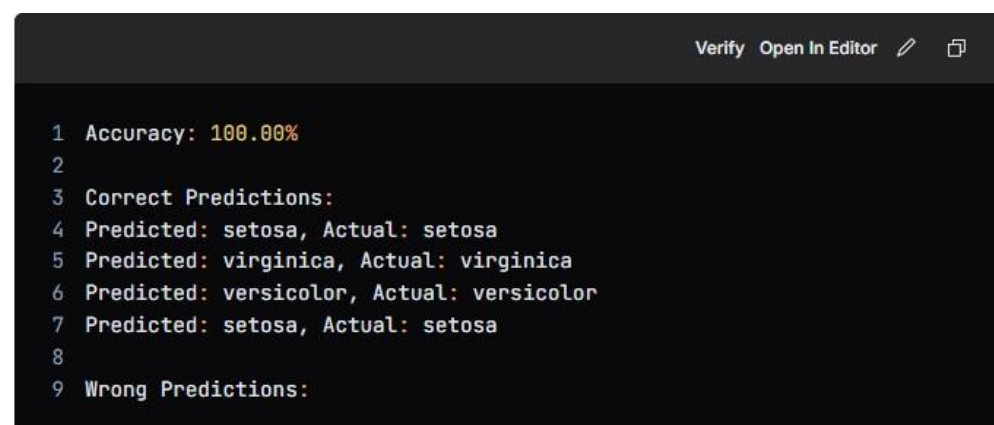
# Get the cluster labels
gmm_labels = gmm.predict(scaled_data)

# Visualize the clusters (if 2D or 3D)
plt.scatter(scaled_data[:, 0], scaled_data[:, 1], c=gmm_labels, cmap='viridis')
```


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

```
import numpy as np
import pandas as pd
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
# Load the Iris dataset
iris = datasets.load_iris()
X = iris.data # Features
y = iris.target # Labels
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42) #
Create the k-NN classifier
k = 3 # You can change the value of k
knn = KNeighborsClassifier(n_neighbors=k) #
Train the classifier
knn.fit(X_train, y_train)
# Make predictions on the test set
y_pred = knn.predict(X_test)
# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')
# Print correct and wrong predictions
print("\nCorrect Predictions:")
for i in range(len(y_test)):
    if y_pred[i] == y_test[i]:
        print(f'Predicted: {iris.target_names[y_pred[i]]}, Actual: {iris.target_names[y_test[i]]}')
print("\nWrong Predictions:")
for i in range(len(y_test)):
    if y_pred[i] != y_test[i]:
        print(f'Predicted: {iris.target_names[y_pred[i]]}, Actual: {iris.target_names[y_test[i]]}')
```

Expected output:



```
Verify Open In Editor
```

```
1 Accuracy: 100.00%
2
3 Correct Predictions:
4 Predicted: setosa, Actual: setosa
5 Predicted: virginica, Actual: virginica
6 Predicted: versicolor, Actual: versicolor
7 Predicted: setosa, Actual: setosa
8
9 Wrong Predictions:
```

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

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

def locally_weighted_regression(X, y, query_point, tau):
    """Perform Locally Weighted Regression on a single query point.""" m =
    X.shape[0]
    weights = np.exp(-(X - query_point)**2, axis=1) / (2 * tau**2) W =
    np.diag(weights)

    # Calculate theta using the normal equation:  $(X.T * W * X)^{-1} * (X.T * W * y)$ 
    X_b = np.hstack((np.ones((m, 1)), X)) # Add bias term
    theta = np.linalg.inv(X_b.T @ W @ X_b) @ (X_b.T @ W @ y) return

    theta

def predict(X, y, query_points, tau):
    """Predict values for the given query points using Locally Weighted Regression.""" predictions =
    []
    for query_point in query_points:
        theta = locally_weighted_regression(X, y, query_point, tau)
        predictions.append(np.dot(np.array([1, query_point]), theta)) # Include bias term in
    prediction
    return np.array(predictions)

# Generate synthetic data
np.random.seed(42)
X = np.sort(5 * np.random.rand(80, 1), axis=0)
y = np.sin(X) + np.random.normal(0, 0.1, X.shape) # Non-linear relationship with noise

# Define query points
query_points = np.linspace(0, 5, 100)

# Perform Locally Weighted Regression
tau = 0.5 # Bandwidth parameter
predictions = predict(X, y, query_points, tau)

# Plotting the results
plt.figure(figsize=(10, 6))
plt.scatter(X, y, color='blue', label='Data Points')
plt.plot(query_points, predictions, color='red', label='Locally Weighted Regression', linewidth=2)
plt.title('Locally Weighted Regression (LWR)')
plt.xlabel('X')
plt.ylabel('y')
plt.legend()
```

```
plt.grid()  
plt.show()
```

ExpectedOutput:

