CO542 - Neural Networks and Fuzzy Systems

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Lab 01: Introduction to Perceptron

Task 01: Manual vs. Library Implementation of a Perceptron

In [1]:

```
# import libs
import numpy as np
from sklearn.linear_model import Perceptron
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
```

In [2]:

```
# Step 1: Define the Dataset
# Define input and output for the AND Gate
X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
y = np.array([0, 0, 0, 1])
```

In [3]:

```
# Step 2: Manual Implementation of Perceptron
def step_function(x):
    return 1 if x >= 0 else 0

def perceptron_training(X, y, learning_rate=0.1, epochs=10):
    weights = np.zeros(X.shape[1])
    bias = 0
    for _ in range(epochs):
        for i in range(len(X)):
            activation = np.dot(X[i], weights) + bias
            prediction = step_function(activation)

            error = y[i] - prediction
            weights += learning_rate * error * X[i]
            bias += learning_rate * error

    return weights, bias

# Train manually
weights, bias = perceptron_training(X, y)

print("Manual Weights:", weights)
print("Manual Bias:", bias)
```

```
Manual Weights: [0.2 0.1]
Manual Bias: -0.20000000000000004
```

In [4]:

```
# Step 3: Ready-Made Implementation using sklearn
model = Perceptron(max_iter=1000, eta0=0.1, random_state=42)
model.fit(X, y)
```

```
print("Sklearn Weights:", model.coef_)
print("Sklearn Bias:", model.intercept_)
```

```
Sklearn Weights: [[0.2 0.2]]
Sklearn Bias: [-0.2]
```

In [5]:

```
# Step 4: Compare Results
# Predictions
manual_predictions = [step_function(np.dot(x, weights) + bias) for x in X]

sklearn_predictions = model.predict(X)

print("Manual Predictions:", manual_predictions)
print("Sklearn Predictions:", sklearn_predictions)
```

```
Manual Predictions: [0, 0, 0, 1]
Sklearn Predictions: [0 0 0 1]
```

Questions

Q1. What are the similarities and differences between manual implementation and Sklearn's model?

Similarities

- Functionality: Both implementations successfully learn the AND gate behavior and produce the correct output: [0, 0, 0, 1].
- Activation function: Both use a step function to determine the output (i.e., output is 1 if activation ≥ 0, else 0).
- Learning rule: Both apply the perceptron learning algorithm, adjusting weights based on the error (error = y - prediction).

Differences

- Weight initialization:
  - Manual: Starts with all weights set to zero.
  - Sklearn: Initializes weights randomly or with small non-zero values (controlled by random_state).
- Training mechanism:
  - Manual: Uses online learning, updating weights after each training example and runs for a fixed number of epochs.
  - Sklearn: Uses batch updates internally, with data shuffling, and automatically stops if convergence is reached.
- Convergence and optimization:
  - Manual: Does not check for convergence; training may continue unnecessarily.
  - Sklearn: Efficiently detects convergence and stops early, saving time.
- Flexibility and features:
  - Manual: Basic and minimal, useful for educational purposes.

- Sklearn: Offers additional features such as regularization, different learning rate schedules, and integration with pipelines.

Q2. Why is it beneficial to use libraries like sklearn in practice?

- Efficiency: Highly optimized code performs better and trains faster, especially on large datasets.
- Reliability: Reduces the chance of implementation errors (e.g., incorrect updates, wrong bias handling).
- Scalability: Easily scales from small problems (like AND gates) to large, real-world datasets and models.

Task 02: Logical Gate Classification

In [6]:

```
# Define a logic gate input and output for AND, OR, NOT, XOR
and_input = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
and_output = np.array([0, 0, 0, 1])

or_input = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
or_output = np.array([0, 1, 1, 1])

not_input = np.array([[0], [1]])
not_output = np.array([1, 0])

xor_input = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
xor_output = np.array([0, 1, 1, 0])
```

In [7]:

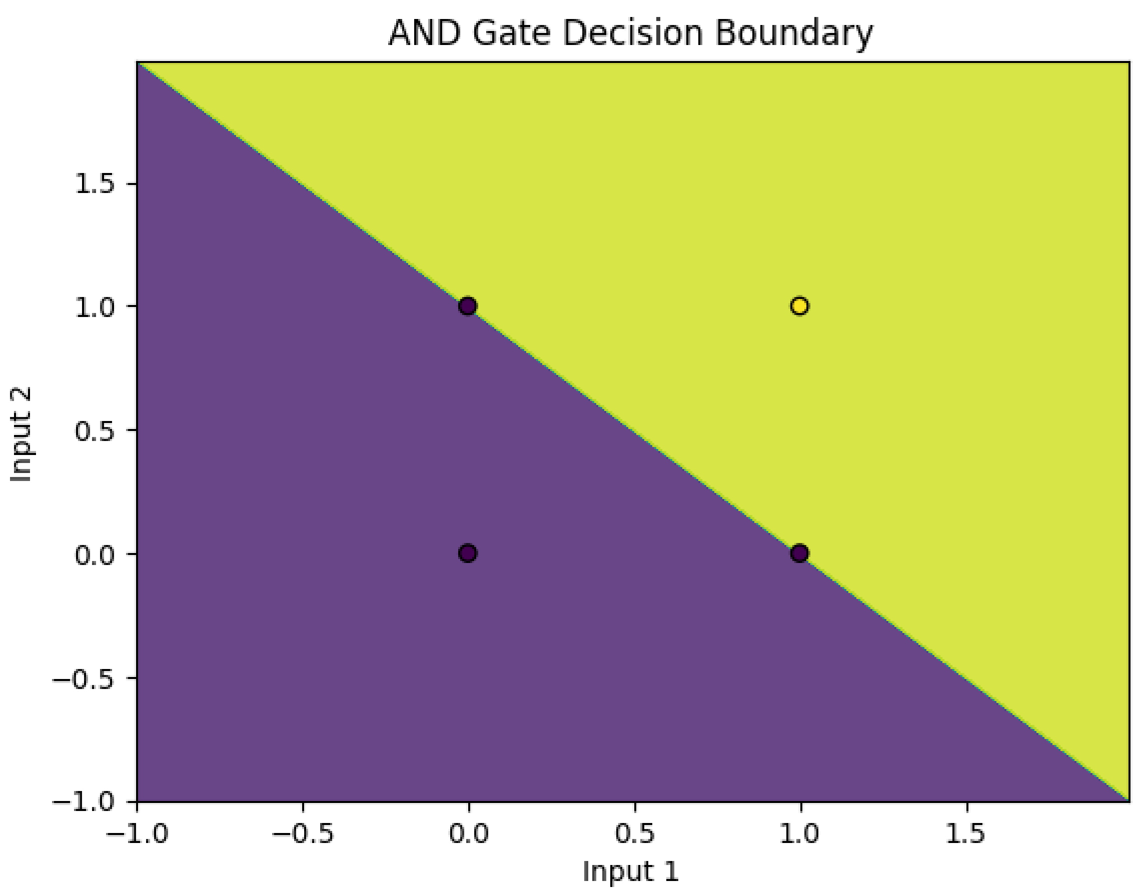
```
# define a function to train the perceptron for different gates
# X - input data, y - output data, gate_type - type of gate (AND, OR, NOT, XOR)
def train(X, y, gate_type="AND"):
    model = Perceptron(max_iter=1000, eta0=0.1, random_state=42)
    model.fit(X, y)

    y_pred = model.predict(X)
    print(f"{gate_type} Gate - Accuracy: {accuracy_score(y, y_pred):.2f}")

    if X.shape[1] == 2:
        x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
        y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1

        xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
                             np.arange(y_min, y_max, 0.01))

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

        plt.contourf(xx, yy, Z, alpha=0.8)
        plt.scatter(X[:, 0], X[:, 1], c=y, edgecolor='k')
        plt.title(f"{gate_type} Gate Decision Boundary")
        plt.xlabel('Input 1')
        plt.ylabel('Input 2')
        plt.show()

    elif X.shape[1] == 1:
        # For NOT gate (1 feature)
        x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
```

```
        x_plot = np.linspace(x_min, x_max, 100).reshape(-1, 1)
        y_plot = model.predict(x_plot)

        plt.plot(x_plot, y_plot, color='blue', linewidth=2)
        plt.scatter(X[:, 0], y, color='red', edgecolor='k')
        plt.title(f"{gate_type} Gate Decision Boundary")
        plt.xlabel('Input')
        plt.ylabel('Output')
        plt.ylim(-0.5, 1.5)
        plt.grid(True)
        plt.show()

    else:
        print("Unsupported input dimension for plotting.")

    return model
```

In [8]:

```
# Train and visualize the AND gate
train(and_input, and_output)
```

```
AND Gate - Accuracy: 1.00
```



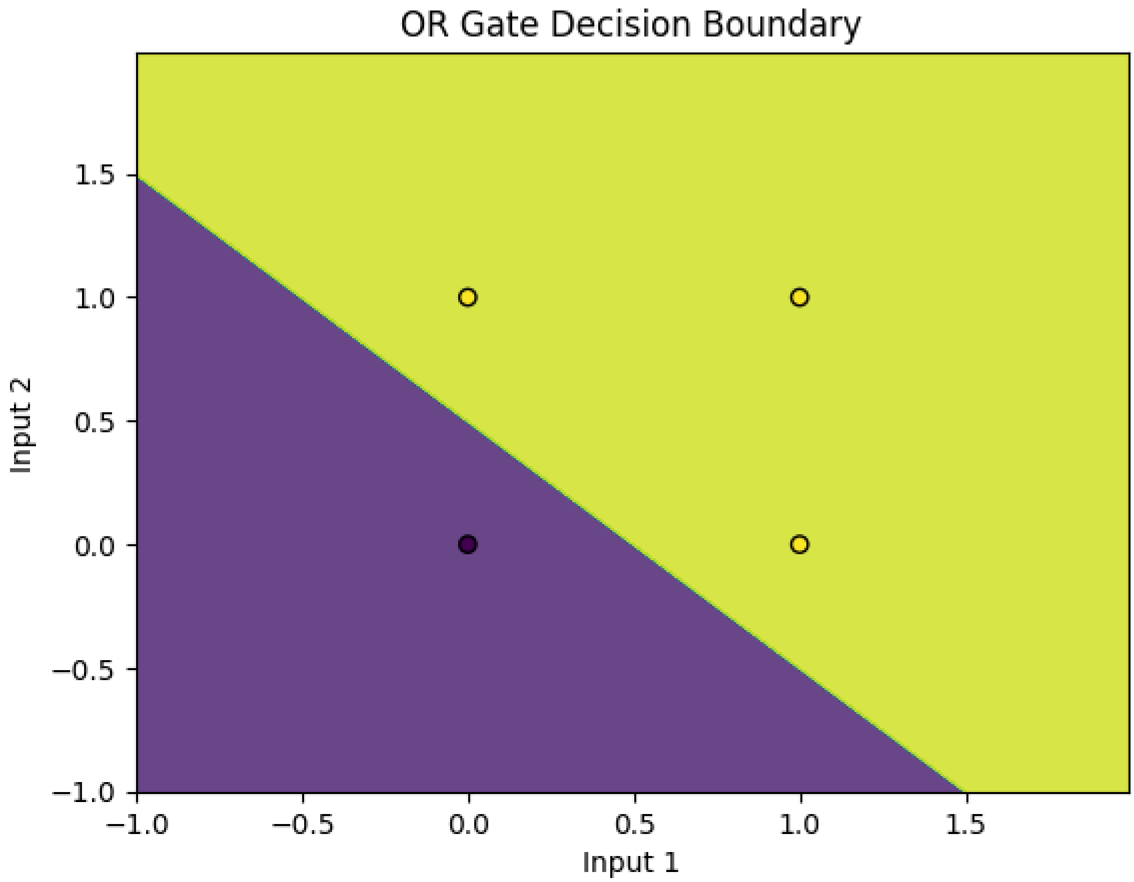
Out[8]:

```
▾ Perceptron
Perceptron(eta0=0.1, random_state=42)
```

In [9]:

```
# Train and visualize the OR gate
train(or_input, or_output, gate_type="OR")
```

```
OR Gate - Accuracy: 1.00
```



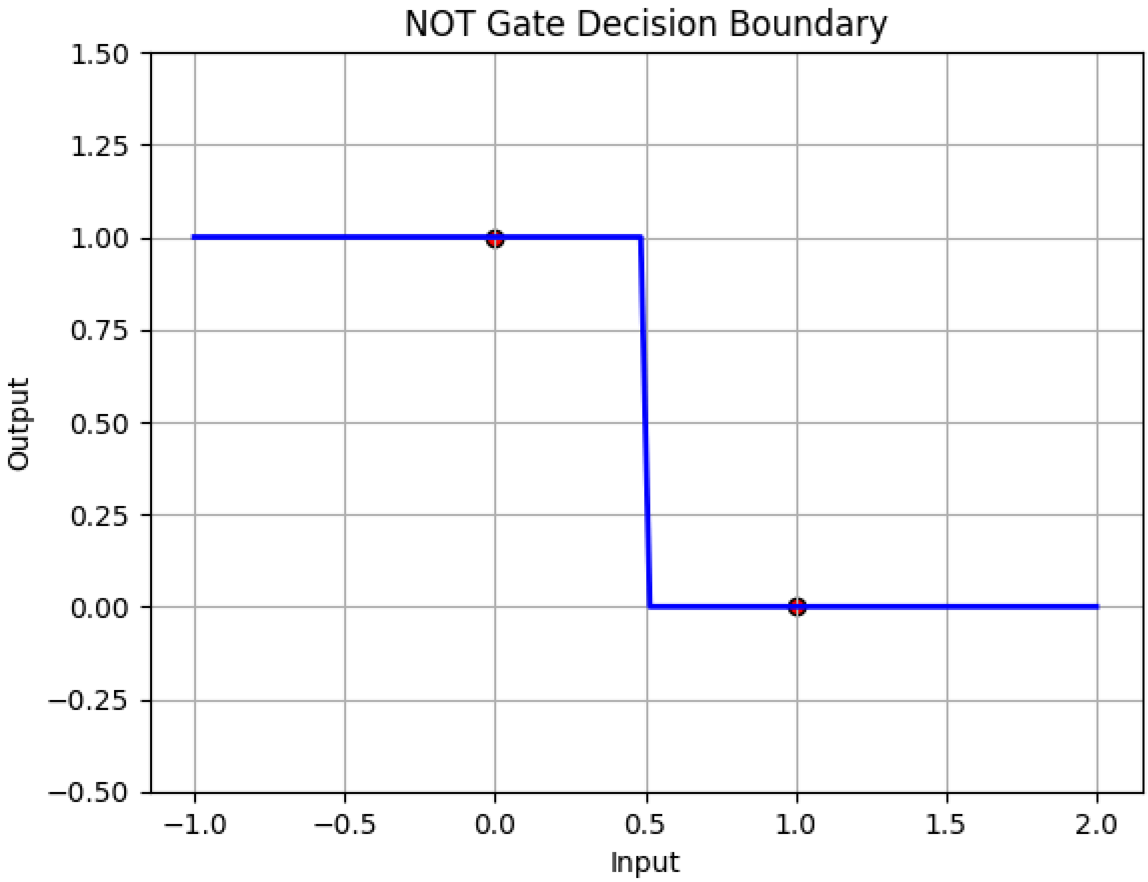
Out[9]:

```
▾ Perceptron

Perceptron(eta0=0.1, random_state=42)
```

In [10]:

```
# Train and visualize the NOT gate
train(not_input, not_output, gate_type="NOT")
```

```
NOT Gate - Accuracy: 1.00
```



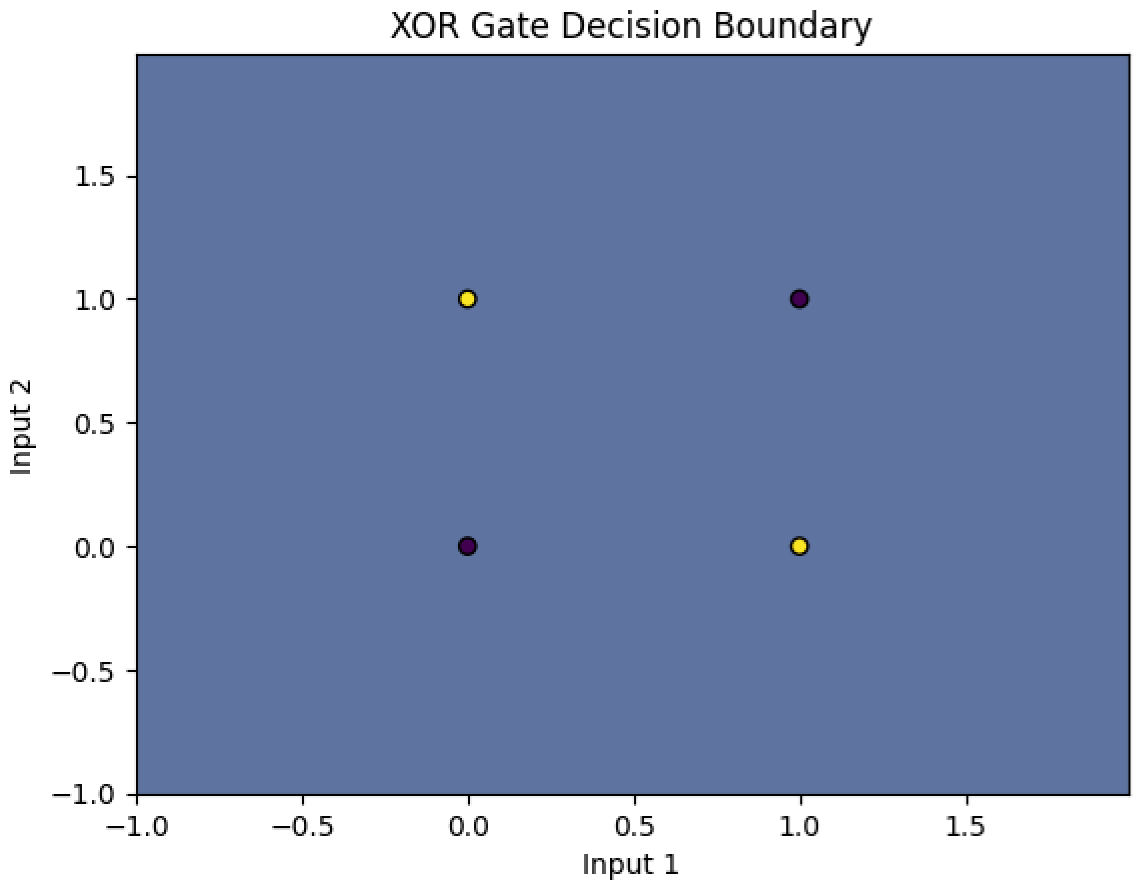
Out[10]:

```
▾ Perceptron
Perceptron(eta0=0.1, random_state=42)
```

In [11]:

```
# Train and visualize the XOR gate
train(xor_input, xor_output, gate_type="XOR")
```

```
XOR Gate - Accuracy: 0.50
```



Out[11]:

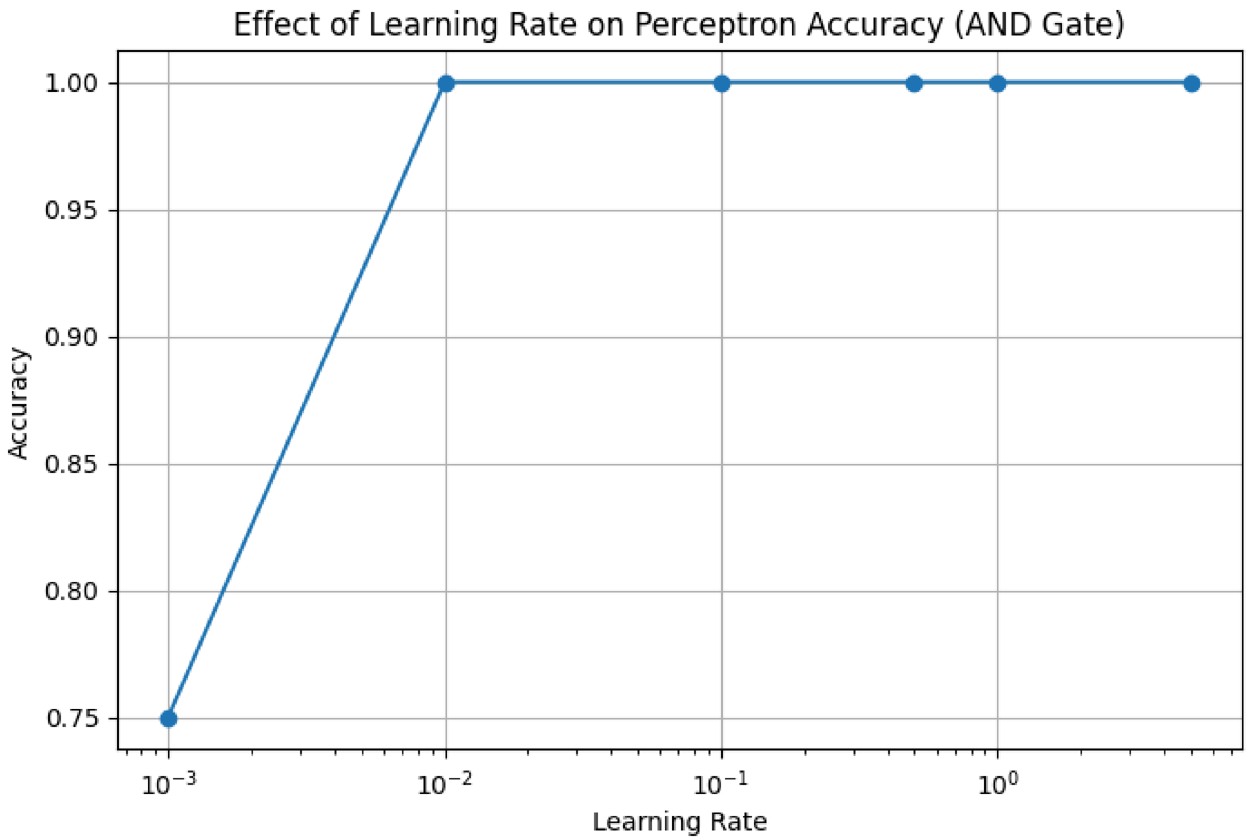
```
Perceptron
Perceptron(eta0=0.1, random_state=42)
```

In [ ]:

```
# Learning rates to test
learning_rates = [0.001, 0.01, 0.1, 0.5, 1.0, 5.0]
accuracies = []

# Train and record accuracy for each learning rate
for lr in learning_rates:
    model = Perceptron(max_iter=1000, eta0=lr, random_state=42)
    model.fit(X, y)
    y_pred = model.predict(X)
    acc = accuracy_score(y, y_pred)
    accuracies.append(acc)
    print(f"Learning Rate: {lr}, Accuracy: {acc:.2f}")

# Plotting learning rate vs. accuracy
plt.figure(figsize=(8, 5))
plt.plot(learning_rates, accuracies, marker='o', linestyle='-')
plt.title('Effect of Learning Rate on Perceptron Accuracy (AND Gate)')
plt.xlabel('Learning Rate')
plt.ylabel('Accuracy')
plt.xscale('log')
plt.grid(True)
plt.show()
```

```
Learning Rate: 0.001, Accuracy: 0.75
Learning Rate: 0.01, Accuracy: 1.00
Learning Rate: 0.1, Accuracy: 1.00
```

```
Learning Rate: 0.5, Accuracy: 1.00
Learning Rate: 1.0, Accuracy: 1.00
Learning Rate: 5.0, Accuracy: 1.00
```



Questions

Why does a single-layer perceptron fail for certain logic gates, and which ones?

A single-layer perceptron can only solve problems that are linearly separable. This means it can successfully learn logic gates like AND, OR, and NOT because their outputs can be separated by a straight line (or a hyperplane in higher dimensions).

However, it fails for the XOR gate. The XOR gate's outputs cannot be separated by a single straight line, there is no linear boundary that divides the true and false outputs for XOR. Therefore, a single-layer perceptron cannot learn the XOR function.

Logic Gate	Linearly Separable	Perceptron Success?
AND	Yes	Yes
OR	Yes	Yes
NOT	Yes	Yes
XOR	No	No

How does adjusting the learning rate affect the perceptron’s performance?

- Low learning rate: Training progresses slowly and requires more epochs to converge, but the weight updates are stable and less likely to overshoot the optimal solution.

- High learning rate: The perceptron learns faster but may overshoot the optimal weights, leading to instability or failure to converge.
- Appropriate learning rate: Ensures efficient and stable convergence. For example, a learning rate of 0.1 provided good results for the AND, OR, and NOT gates.

Task 03: Effect of Outliers on Training

In [ ]:
```
# Step 1: Generate Data
# Generate two Gaussian distributions
class1 = np.random.multivariate_normal([2, 2], [[1, 0], [0, 1]], 100)
class2 = np.random.multivariate_normal([5, 5], [[1, 0], [0, 1]], 100)

# Add an outlier
class2 = np.vstack([class2, [10, 10]])

# Labels
X = np.vstack([class1, class2])
y = np.hstack([np.ones(100), -np.ones(101)])
```

In [14]:
```
# Step 2: Train the Perceptron
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=4

model = Perceptron(max_iter=1000, eta0=0.1, random_state=42)

model.fit(X_train, y_train)
```

Out[14]:
```
▾ Perceptron
Perceptron(eta0=0.1, random_state=42)
```

In [15]:
```
# Step 3: Evaluate
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)

print("Accuracy:", accuracy)
```

```
Accuracy: 0.9836065573770492
```

Questions

How does the presence of outliers affect training time and accuracy?

- The perceptron model achieved 98.36% accuracy despite the presence of an outlier, showing reasonable resilience.
- Outliers generally:
  - Increase training time as the model struggles to converge on a clean boundary.
  - Shift the decision boundary, leading to less optimal separation for the majority of data.
  - Decrease generalization performance, especially on test data that follows the original distribution.

What strategies can be used to mitigate the effect of outliers?

- Data Preprocessing
  - Remove extreme data points using statistical techniques like z-score or interquartile range (IQR).
  - Use anomaly detection algorithms to flag and possibly exclude unusual data points.
- Algorithm Modifications
  - Add regularization terms to penalize large weight updates caused by outliers.
  - Use modified perceptron algorithms that introduce margin-based constraints.
  - Apply robust models like RANSAC, which iteratively fits models excluding suspected outliers.
- Alternative Approaches
  - Switch to more robust classifiers like support vector machines with soft margins.
  - Use ensemble techniques like bagging or boosting to minimize the impact of single outlier points.
  - Apply weighted learning to reduce the importance of samples that deviate significantly from the majority.

Task 04: Real-World Classification

In [21]:
```
# Step 1: Load the Dataset
from sklearn.datasets import load_digits
from sklearn.preprocessing import StandardScaler
```

In [22]:
```
digits = load_digits()

mask = (digits.target == 0) | (digits.target == 1)

X = digits.data[mask]
y = digits.target[mask]

scaler = StandardScaler()

X = scaler.fit_transform(X)
```

In [23]:
```
# Step 2: Train the Perceptron
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=4
model = Perceptron(max_iter=1000, eta0=0.1, random_state=42)
model.fit(X_train, y_train)
```

Out[23]:
```
▾ Perceptron
Perceptron(eta0=0.1, random_state=42)
```

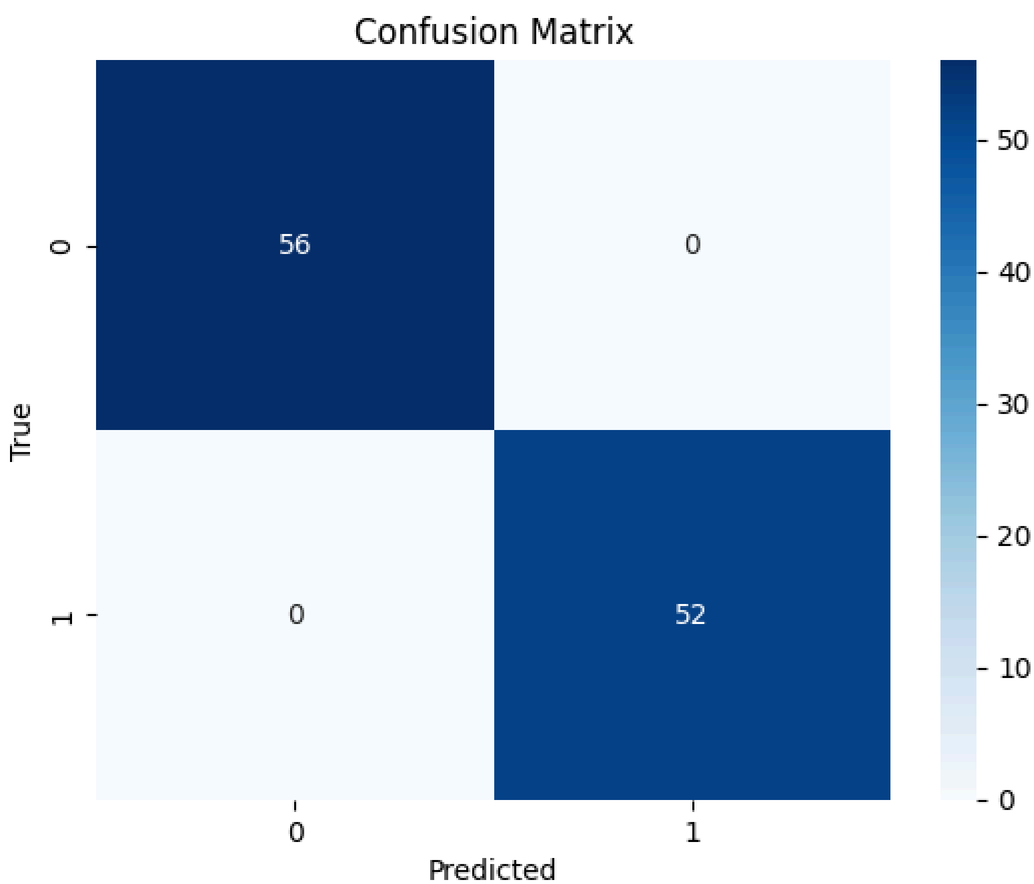
In [24]:
```
# Step 3: Evaluate Performance
from sklearn.metrics import confusion_matrix, classification_report
```

```
y_pred = model.predict(X_test)

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Confusion Matrix:
 [[56  0]
 [ 0 52]]
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        56
           1       1.00      1.00      1.00        52

    accuracy                           1.00       108
   macro avg       1.00      1.00      1.00       108
weighted avg       1.00      1.00      1.00       108
```

In [25]:

```
# Step 4: Visualize Confusion Matrix
import seaborn as sns

sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues')
plt.title("Confusion Matrix");plt.xlabel("Predicted");plt.ylabel("True")
plt.show()
```



Questions

What changes would you make to improve accuracy?

- Model Enhancements
  - **Multi-layer Neural Network**: Replace the perceptron with a multi-layer neural network (MLP) to capture non-linear patterns in digit images.
  - **Regularization**: Introduce L1 or L2 regularization (`alpha` parameter in `Perceptron`) to prevent overfitting and improve generalization.
  - **Kernel Methods**: Switch to non-linear models like `KernelPerceptron` or Support Vector Machines (SVM) with RBF or polynomial kernels for better boundary modeling.
- Data Processing Improvements
  - **Feature Selection**: Remove non-informative pixels or focus on the most active areas in the digit images.
  - **Feature Engineering**: Use shape-based features (e.g., histogram of oriented gradients, pixel transitions) that better represent digit characteristics.
  - **Dimensionality Reduction**: Apply techniques like PCA to reduce noise and emphasize key patterns.
  - **Data Augmentation**: Slightly rotate, scale, or shift digits to expand the training set and improve robustness.
- Training Optimizations
  - **Hyperparameter Tuning**: Use tools like `GridSearchCV` to optimize `eta0` , `max_iter` , and `alpha` values.
  - **Early Stopping**: Monitor performance on a validation set to stop training when accuracy plateaus.
  - **Ensemble Methods**: Use bagging or boosting to combine predictions from multiple weak models for a stronger classifier.
  - **Class Weights**: If class imbalance exists, set `class_weight='balanced'` to ensure fair treatment of both classes.
- Evaluation Strategy
  - **Cross-Validation**: Replace simple train-test split with k-fold cross-validation for a more reliable performance estimate.
  - **Error Analysis**: Visualize and analyze misclassified samples to identify systematic patterns or difficult cases.