

Problem 1

(1)

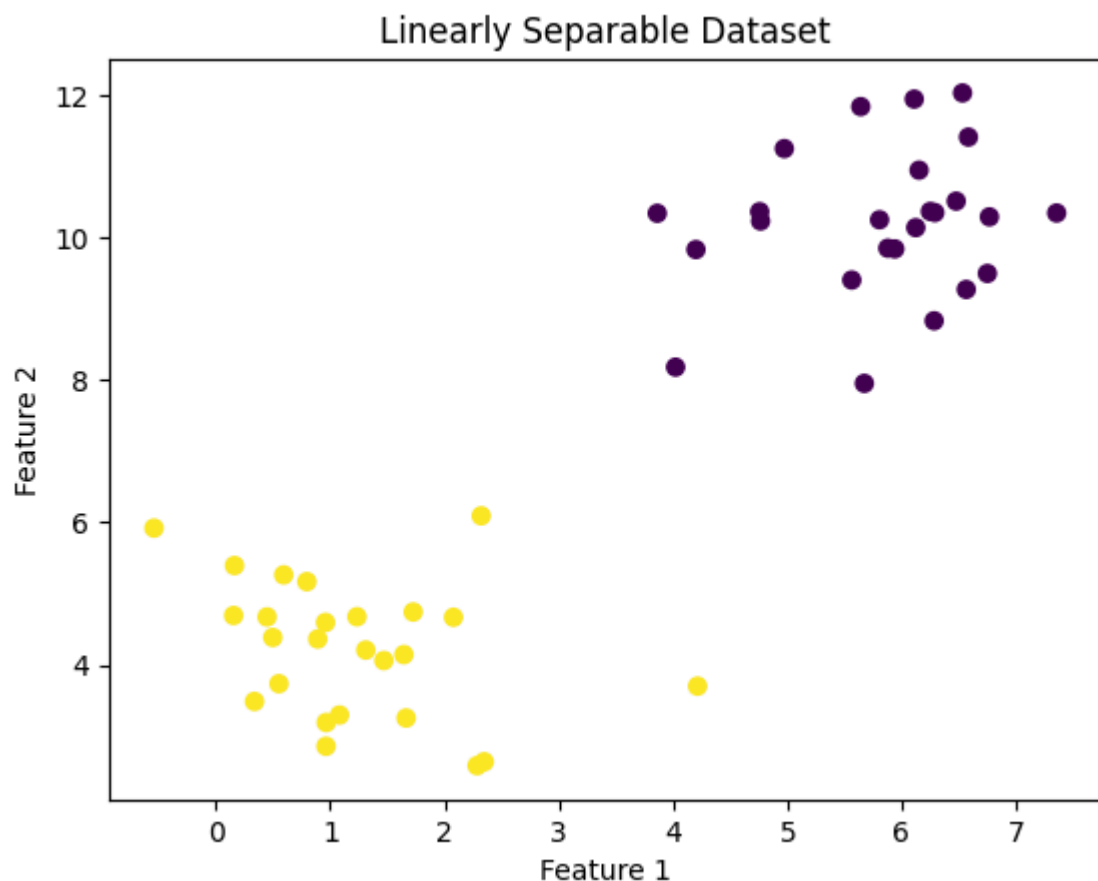
```
In [1]: import numpy as np
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.model_selection import train_test_split

np.random.seed(42)

x, y = datasets.make_blobs(n_samples = 50, centers = 2, n_features = 2,
                           center_box = (0, 10), cluster_std = 1, random_
y = np.where(y == 0, -1, 1)

plt.scatter(x[:, 0], x[:, 1], c = y)
plt.title('Linearly Separable Dataset')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.4
```



(2)

```
In [2]: def batch_perceptron(x_train, y_train, learning_rate=0.001,
                             epochs=100, batch_size=x_train.shape[0]):
    w = np.array([1, 1])
    b = 1

    errors = []
    b_history = []
    w_history = []

    for _ in range(epochs):
        missed = []
        num_error = 0

        for i in range(batch_size):
            if y_train[i] * (np.dot(x_train[i], w) + b) <= 0:
                missed.append((x_train[i], y_train[i]))
                num_error += 1

        for x_i, y_i in missed:
            w = w + learning_rate * y_i * x_i
            b = b + learning_rate * y_i

        errors.append(num_error)
        w_history.append(w.copy())
        b_history.append(b)

        if num_error == 0:
            break

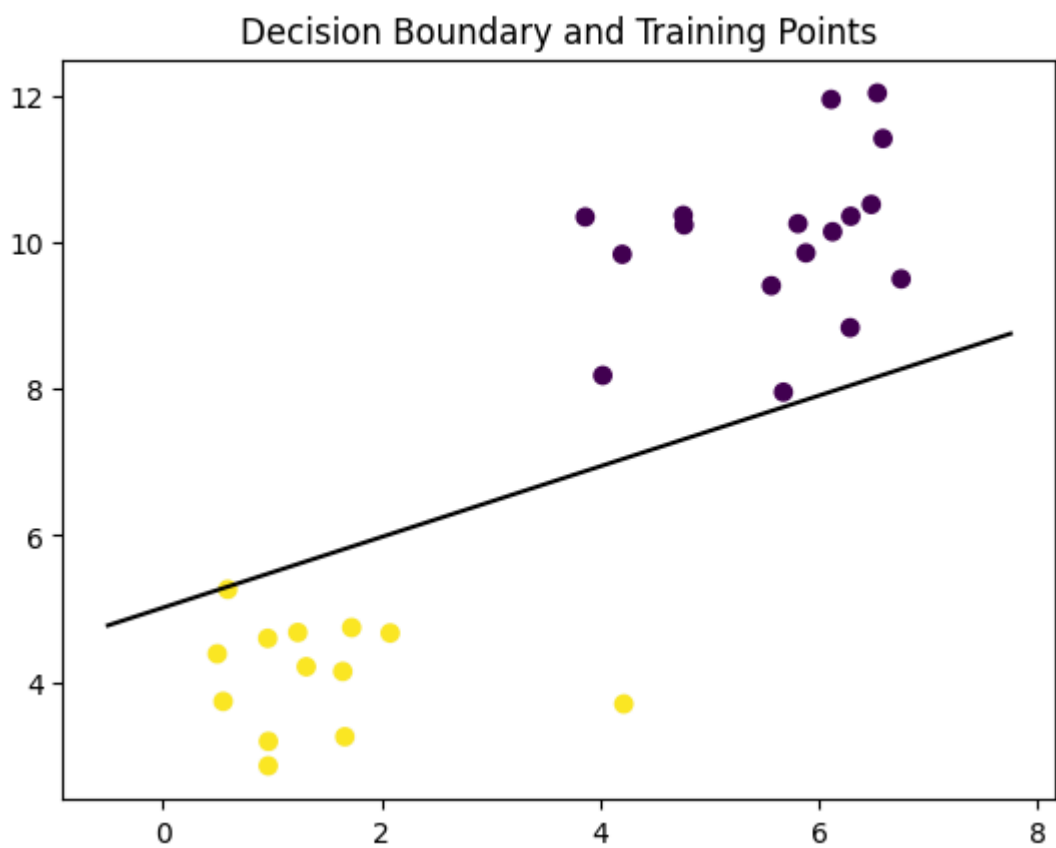
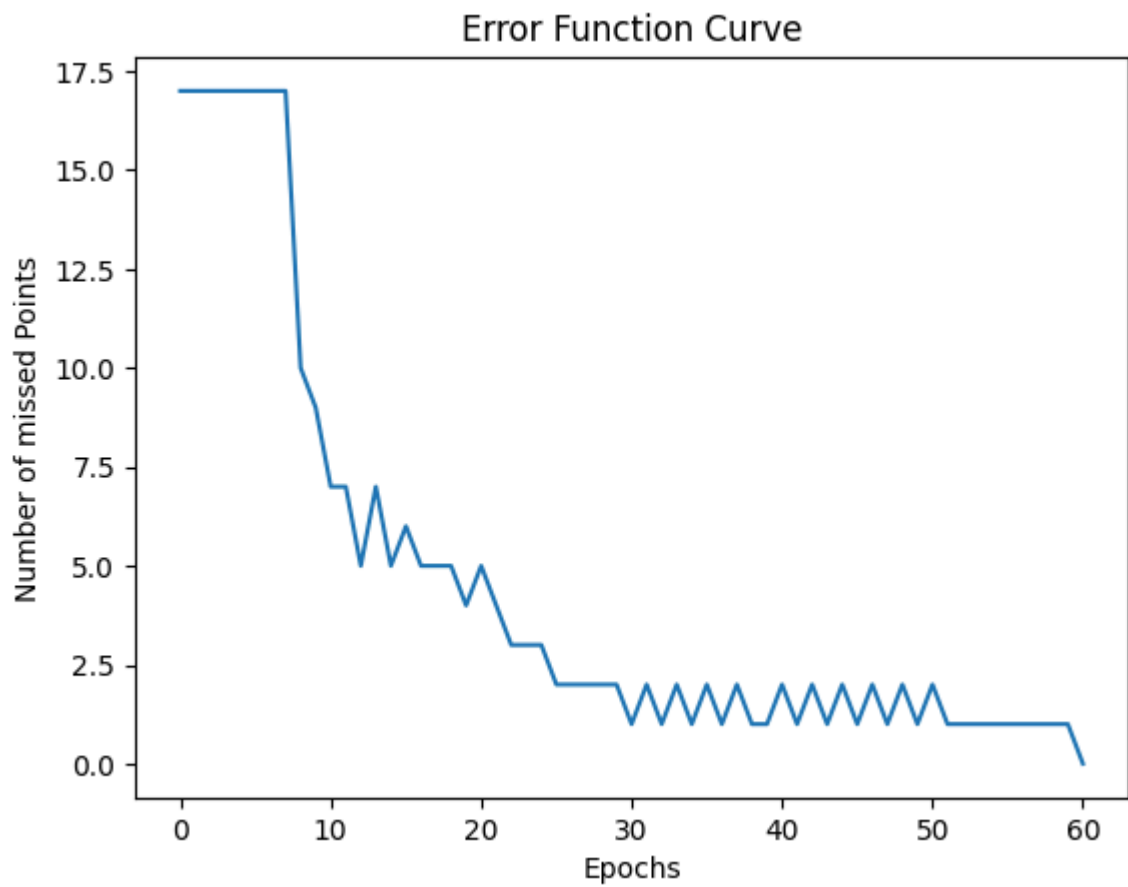
    return w, b, errors, w_history, b_history

w, b, errors, w_history, b_history = batch_perceptron(x_train, y_train)

plt.figure("Figure 1")
plt.plot(errors)
plt.xlabel('Epochs')
plt.ylabel('Number of missed Points')
plt.title('Error Function Curve')
plt.show()

x_min, x_max = x_train[:, 0].min() - 1, x_train[:, 0].max() + 1
y_min_line = -(b + w[0] * x_min) / w[1]
y_max_line = -(b + w[0] * x_max) / w[1]

plt.figure("Figure 2")
plt.plot([x_min, x_max], [y_min_line, y_max_line], 'k-', label='Decision
plt.scatter(x_train[:, 0], x_train[:, 1], c=y_train)
plt.title('Decision Boundary and Training Points')
plt.show()
```

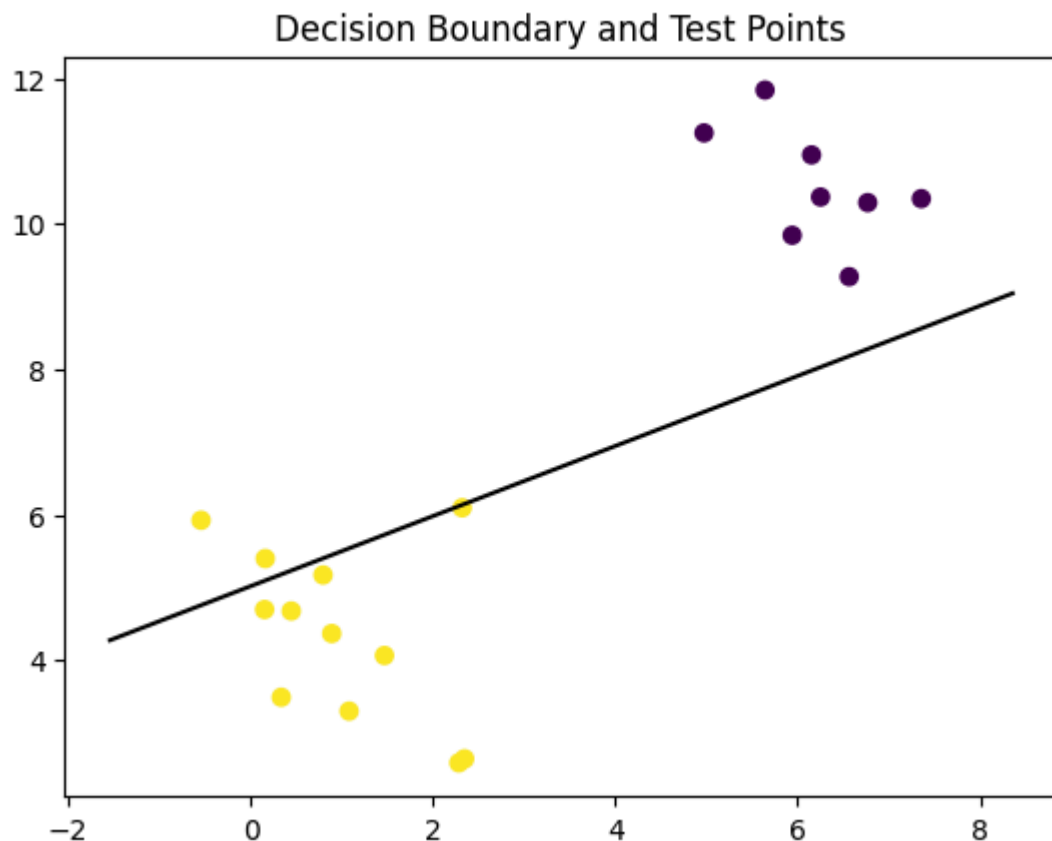


(3)

```
In [3]: def run_perceptron(x, w, b):  
        return np.where(np.dot(x, w) + b > 0, 1, -1)  
  
y_pred = run_perceptron(x_test, w, b)  
  
accuracy = np.mean(y_pred == y_test)  
error_rate = 1 - accuracy  
  
print(f"Batch Perceptron Accuracy: {accuracy * 100:.2f}%")  
print(f"Batch Perceptron Error rate: {error_rate * 100:.2f}%")  
  
x_min, x_max = x_test[:, 0].min() - 1, x_test[:, 0].max() + 1  
y_min_line = -(b + w[0] * x_min) / w[1]  
y_max_line = -(b + w[0] * x_max) / w[1]  
  
plt.plot([x_min, x_max], [y_min_line, y_max_line], 'k-', label='Decision  
plt.scatter(x_test[:, 0], x_test[:, 1], c = y_test)  
plt.title('Decision Boundary and Test Points')  
plt.show()
```

Batch Perceptron Accuracy: 90.00%

Batch Perceptron Error rate: 10.00%



(4)

```
In [4]: def sequential_perceptron(x_train, y_train, learning_rate=0.001, epochs=1000):
    w = np.array([1, 1])
    b = 1
    weights = []

    for _ in range(epochs):
        for i in range(x_train.shape[0]):
            if y_train[i] * (np.dot(x_train[i], w) + b) <= 0:
                w = w + learning_rate * y_train[i] * x_train[i]
                b = b + learning_rate * y_train[i]
                weights.append((w.copy(), b))

        predictions = np.sign(np.dot(x_train, w) + b)
        if np.all(predictions == y_train):
            break

    return w, b, weights

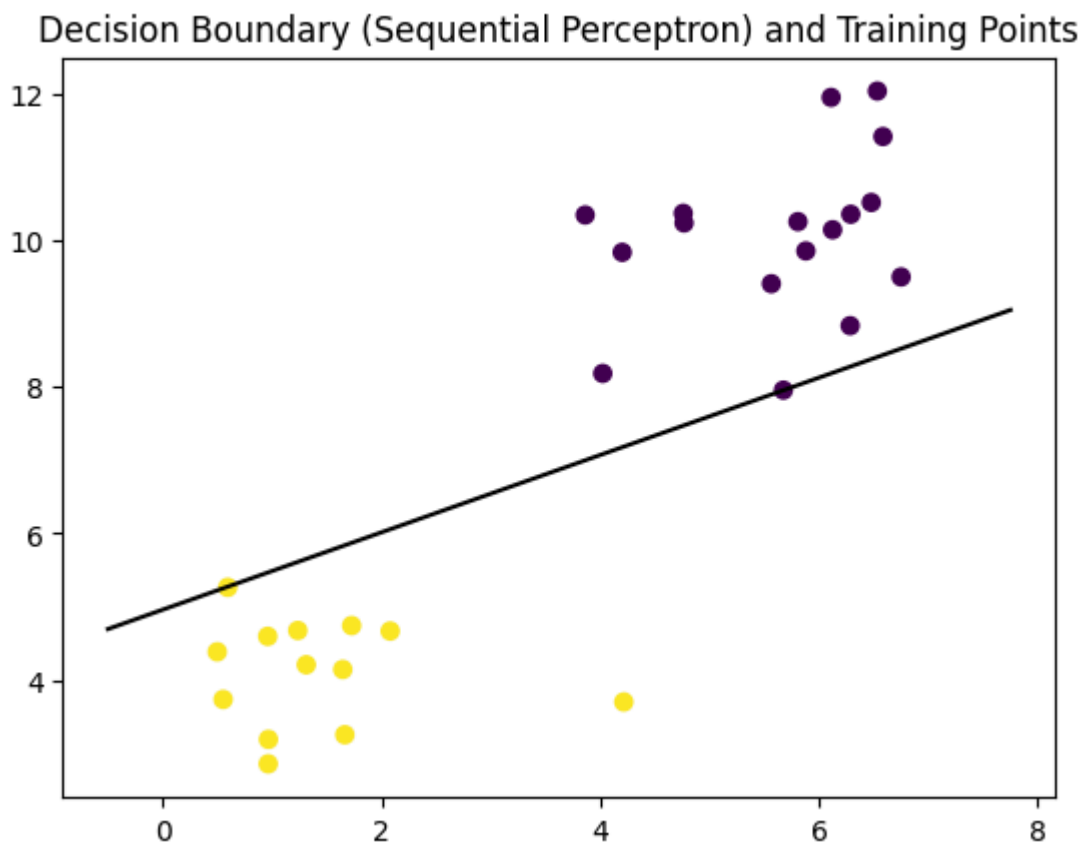
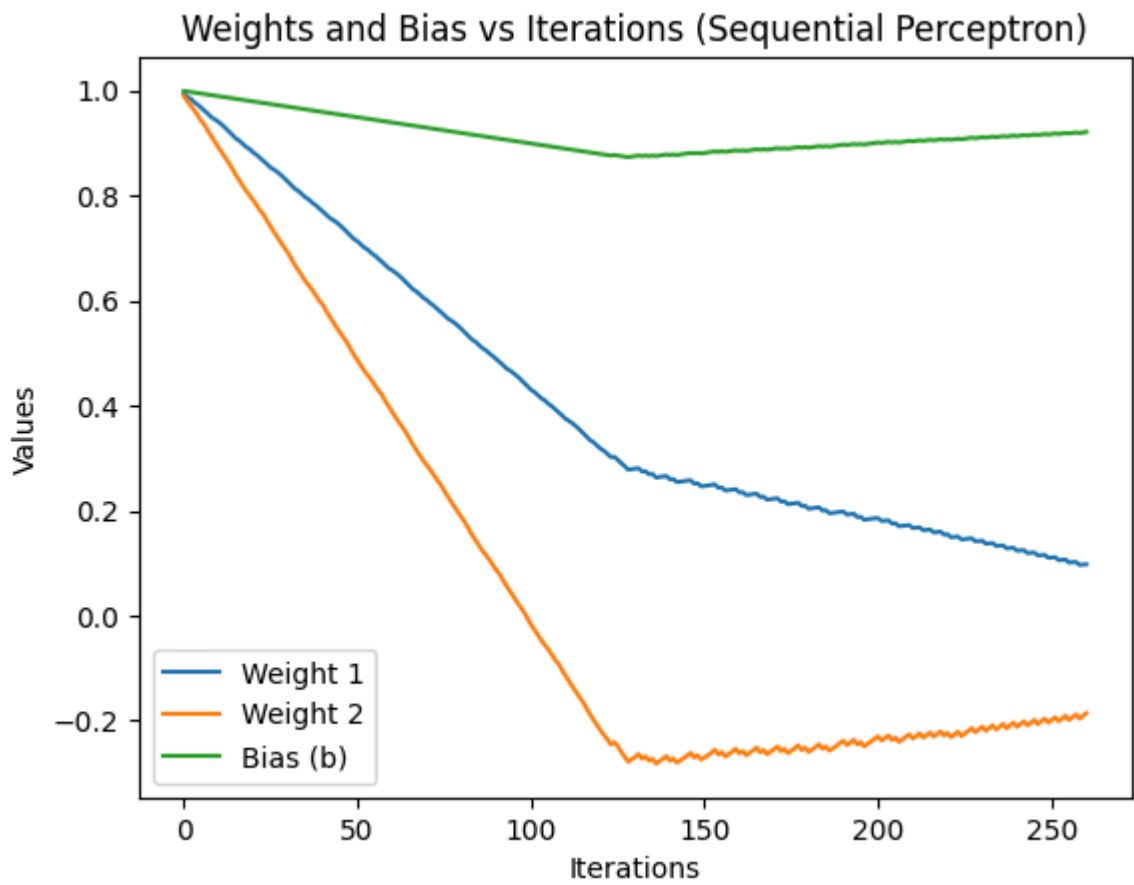
w, b, w_h = sequential_perceptron(x_train, y_train)

weights_array = np.array([np.append(w, b) for w, b in w_h])

plt.figure("Figure 1")
plt.plot(weights_array[:, 0], label="Weight 1")
plt.plot(weights_array[:, 1], label="Weight 2")
plt.plot(weights_array[:, 2], label="Bias (b)")
plt.xlabel('Iterations')
plt.ylabel('Values')
plt.title('Weights and Bias vs Iterations (Sequential Perceptron)')
plt.legend()
plt.show()

x_min, x_max = x_train[:, 0].min() - 1, x_train[:, 0].max() + 1
y_min_line_seq = -(b + w[0] * x_min) / w[1]
y_max_line_seq = -(b + w[0] * x_max) / w[1]

plt.figure("Figure 2")
plt.plot([x_min, x_max], [y_min_line_seq, y_max_line_seq],
        'k-', label='Decision Boundary')
plt.scatter(x_train[:, 0], x_train[:, 1], c=y_train)
plt.title('Decision Boundary (Sequential Perceptron) and Training Points')
plt.show()
```



(5)

```
In [5]: y_pred_seq = run_perceptron(x_test, w, b)

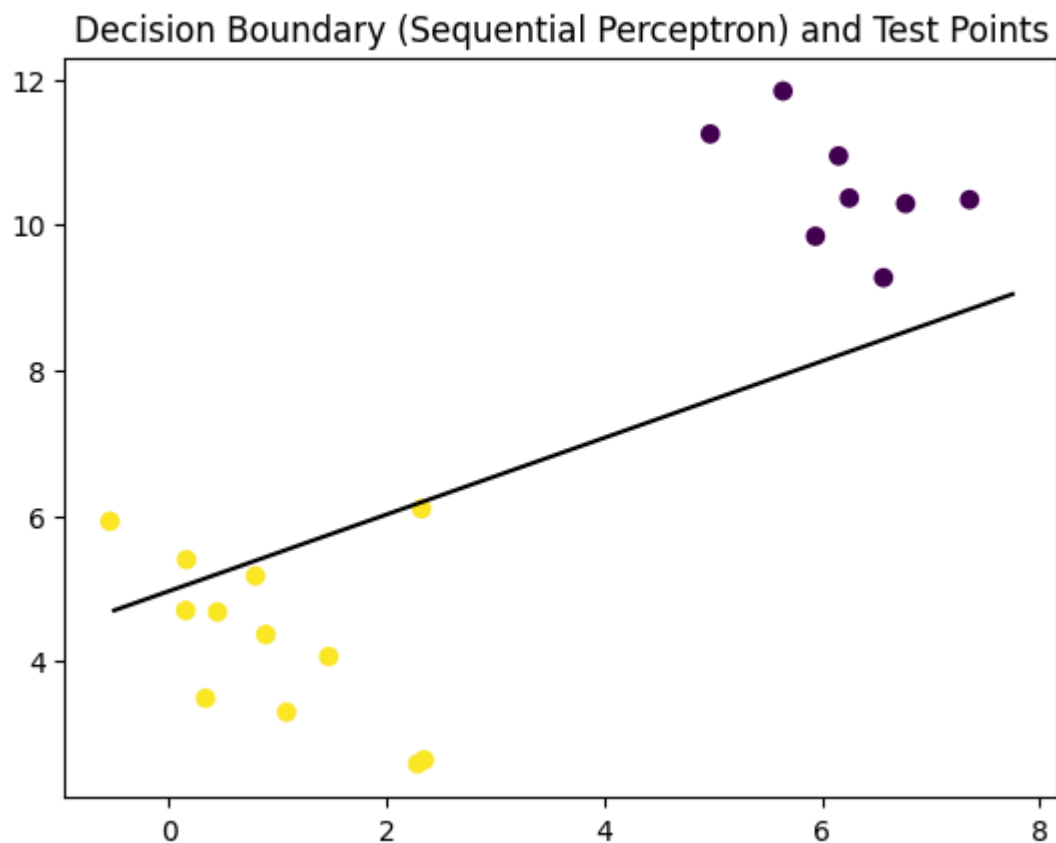
accuracy_seq = np.mean(y_pred_seq == y_test)
error_rate_seq = 1 - accuracy_seq

print(f"Sequential Perceptron Accuracy: {accuracy_seq * 100:.2f}%")
print(f"Sequential Perceptron Error Rate: {error_rate_seq * 100:.2f}%")

x_min, x_max = x_train[:, 0].min() - 1, x_train[:, 0].max() + 1
y_min_line = -(b + w[0] * x_min) / w[1]
y_max_line = -(b + w[0] * x_max) / w[1]

plt.plot([x_min, x_max], [y_min_line, y_max_line], 'k-', label='Decision
plt.scatter(x_test[:, 0], x_test[:, 1], c = y_test)
plt.title('Decision Boundary (Sequential Perceptron) and Test Points')
plt.show()
```

Sequential Perceptron Accuracy: 90.00%
Sequential Perceptron Error Rate: 10.00%



(6):

```
In [6]: learning_rates = [0.1, 0.01, 0.001]
methods = ['Batch', 'Sequential']

for method in methods:
    for lr in learning_rates:
        if method == 'Sequential':
            w, b, w_h = sequential_perceptron(x_train, y_train, learning_

            weights_array = np.array([np.append(w, b) for w, b in w_h])

            plt.plot(weights_array[:, 0], label="Weight 1")
            plt.plot(weights_array[:, 1], label="Weight 2")
            plt.plot(weights_array[:, 2], label="Bias (b)")
            plt.xlabel('Iterations')
            plt.ylabel('Values')
            plt.title(f'Weights and Bias vs Iterations ({method} Perceptr
            plt.legend()
            plt.show()

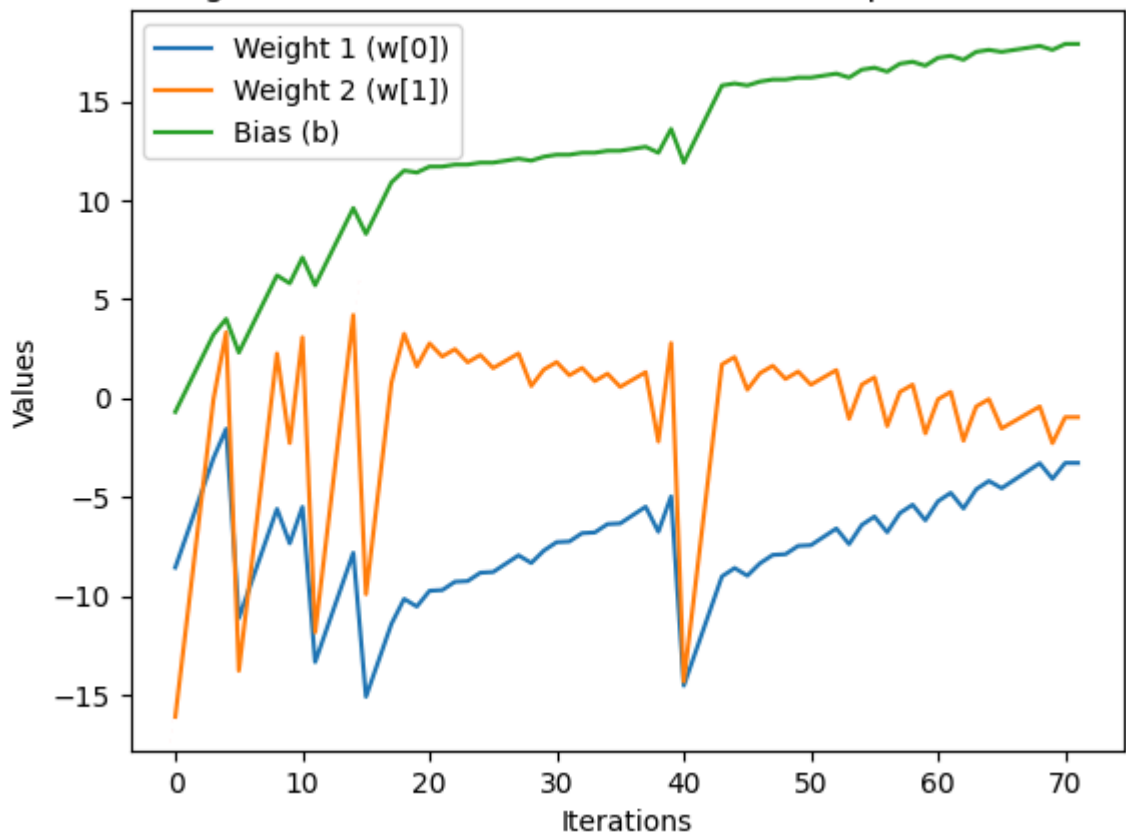
        else:
            w, b, errors, w_history, b_history = batch_perceptron(x_train
                                                                    y_train

            w_history = np.array(w_history)
            b_history = np.array(b_history)

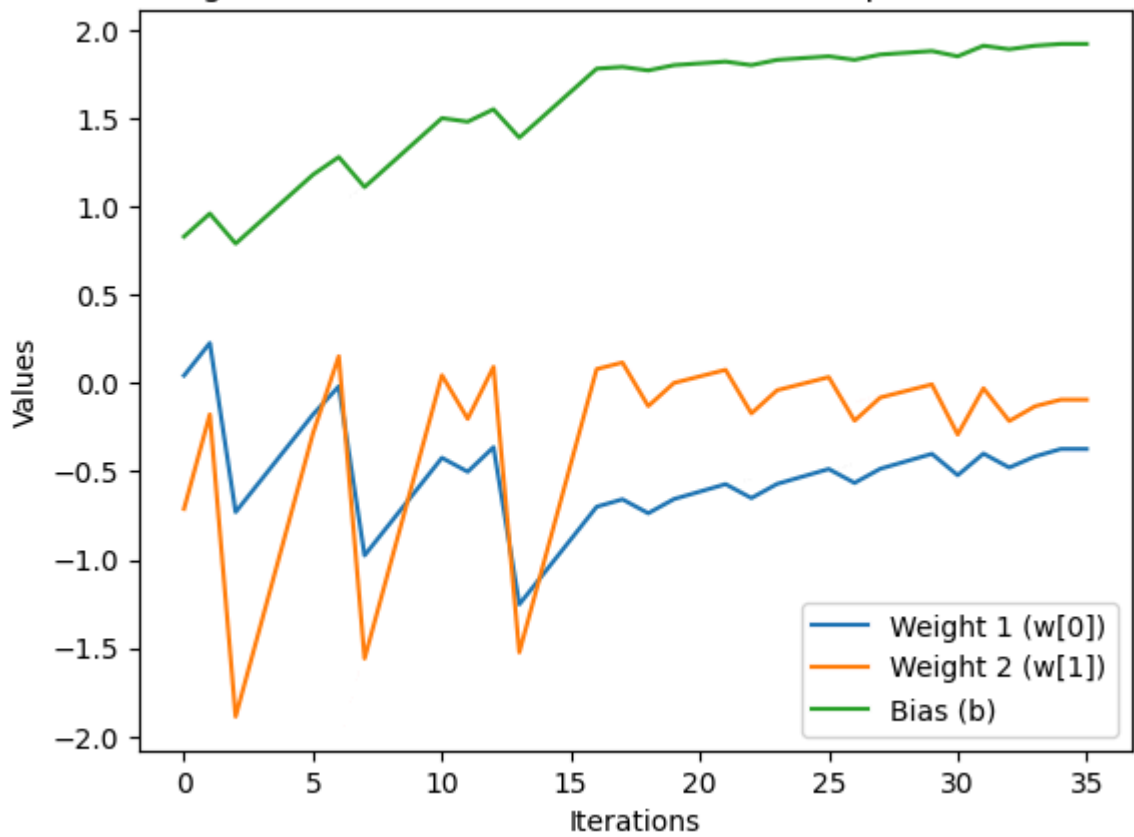
            plt.plot(w_history[:, 0], label='Weight 1 (w[0])')
            plt.plot(w_history[:, 1], label='Weight 2 (w[1])')
            plt.plot(b_history, label='Bias (b)')

            plt.xlabel('Iterations')
            plt.ylabel('Values')
            plt.title(f'Weights and Bias vs Iterations ({method} Perceptr
            plt.legend()
            plt.show()
```

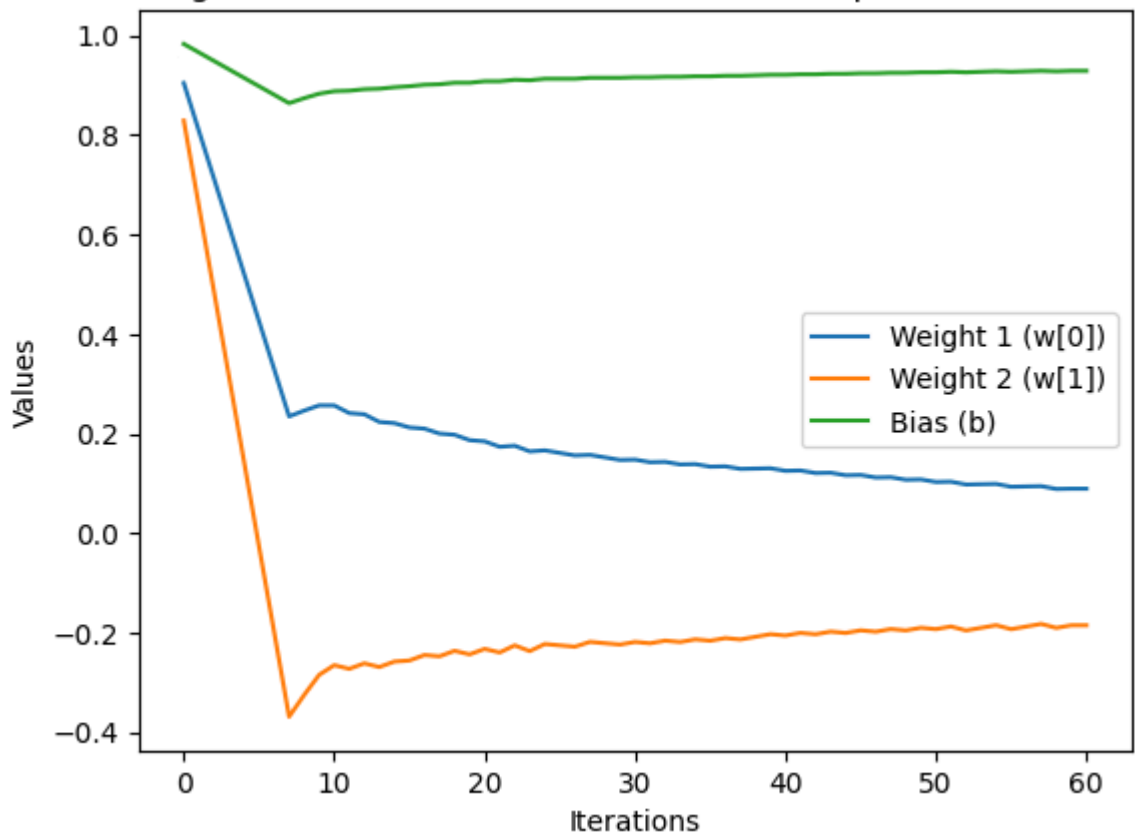

Weights and Bias vs Iterations (Batch Perceptron, LR=0.1)



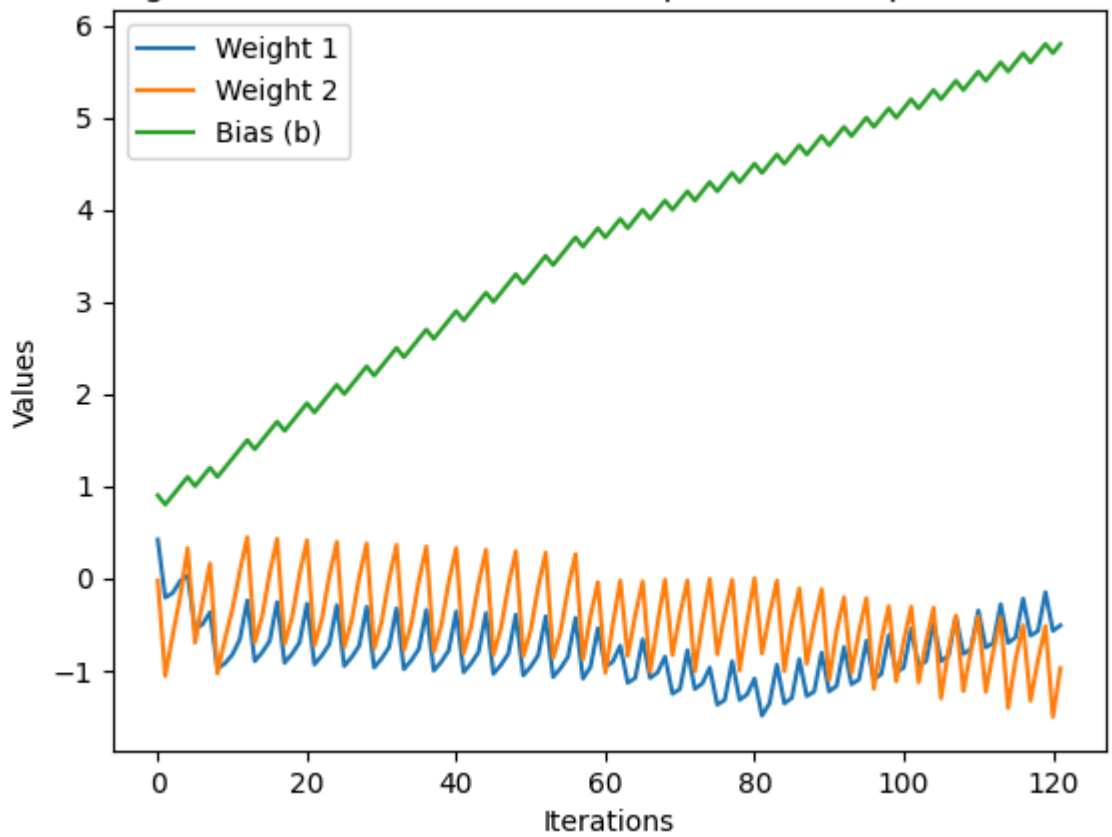
Weights and Bias vs Iterations (Batch Perceptron, LR=0.01)

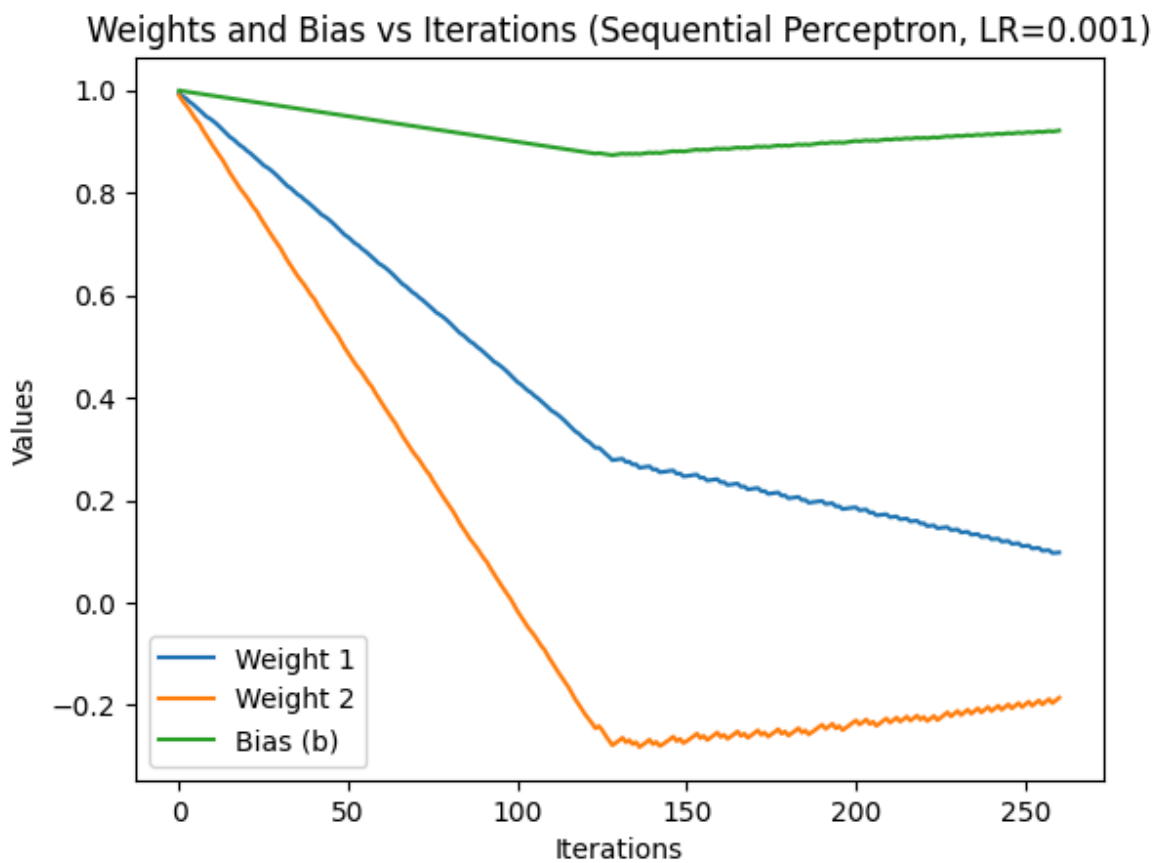
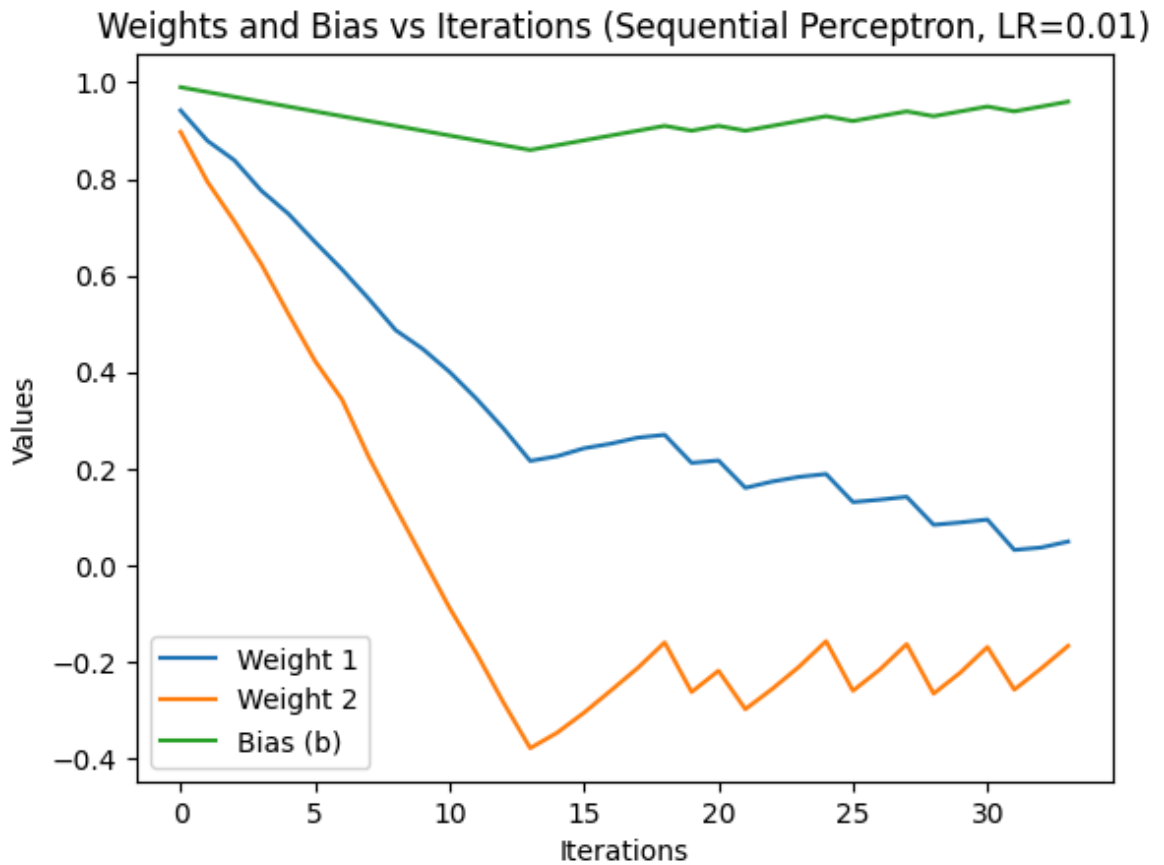


Weights and Bias vs Iterations (Batch Perceptron, LR=0.001)



Weights and Bias vs Iterations (Sequential Perceptron, LR=0.1)





For both model I chose my learning rate to be 0.001. From the plots provided above, it is clear to that if choosing learning rate to be 0.1 or 0.01, the weight vectors are hard to converge because the curve shows the zigzag pattern, which is caused by learning rate being to large. The 0.001 learning rate set has the proper converge

behavior. Although the converging speed might be slower, it's important to maintain stability and make sure that weight vector converge.

Problem 2

Part a:

```
In [7]: from sklearn.metrics import (classification_report,
                                     confusion_matrix,
                                     precision_score,
                                     recall_score,
                                     f1_score)

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.datasets import make_classification
from sklearn.metrics import accuracy_score
from sklearn.linear_model import Perceptron
import numpy as np
import matplotlib.pyplot as plt

# part a

x, y = make_classification(n_samples = 100, n_features = 2,
                           n_informative = 2, n_redundant = 0,
                           n_clusters_per_class = 1, class_sep = 2, random_state=42)

plt.scatter(x[:, 0], x[:, 1], c = y)
plt.title('Linearly Separable Dataset (sklearn)')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.4, random_state=42)

model = Perceptron()
model.fit(x_train, y_train)

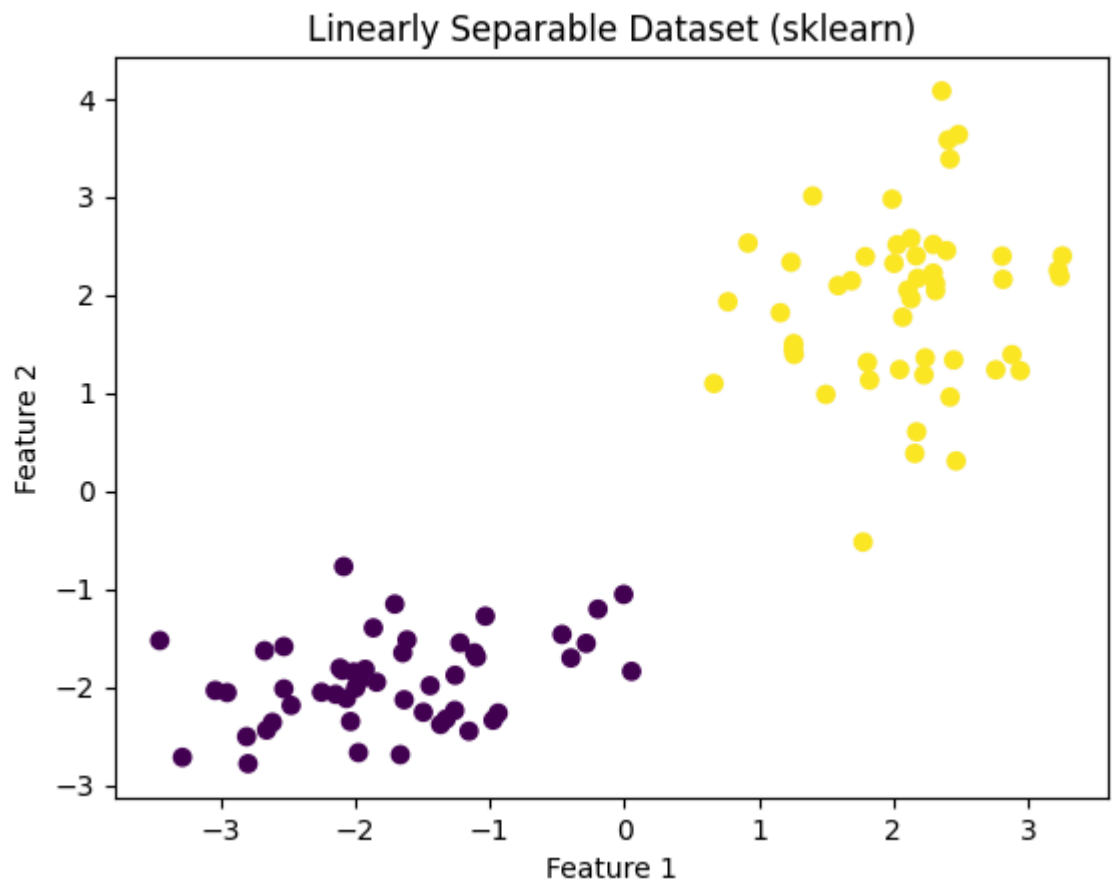
y_pred = model.predict(x_test)

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

w = model.coef_[0]
b = model.intercept_[0]

x_min, x_max = x[:, 0].min() - 1, x[:, 0].max() + 1
y_min_line = -(b + w[0] * x_min) / w[1]
y_max_line = -(b + w[0] * x_max) / w[1]

plt.plot([x_min, x_max], [y_min_line, y_max_line], 'k-', label='Decision Boundary')
plt.scatter(x_test[:, 0], x_test[:, 1], c = y_test)
plt.title('Decision Boundary (sklearn Perceptron) and Test Points')
plt.show()
```



Part b:

```
In [8]: x, y = make_classification(n_samples = 100, n_features = 2,
                                n_informative = 2, n_redundant = 0,
                                n_clusters_per_class = 1, class_sep = 0.5,
                                flip_y = 0.1, weights = [0.9, 0.1])

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.4)

plt.scatter(x[:, 0], x[:, 1], c = y)
plt.title('Non-Linearly Separable Dataset (SKlearn)')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()

model = Perceptron()
model.fit(x_train, y_train)
y_pred = model.predict(x_test)

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
print(f'F1 Score: {f1:.2f}')

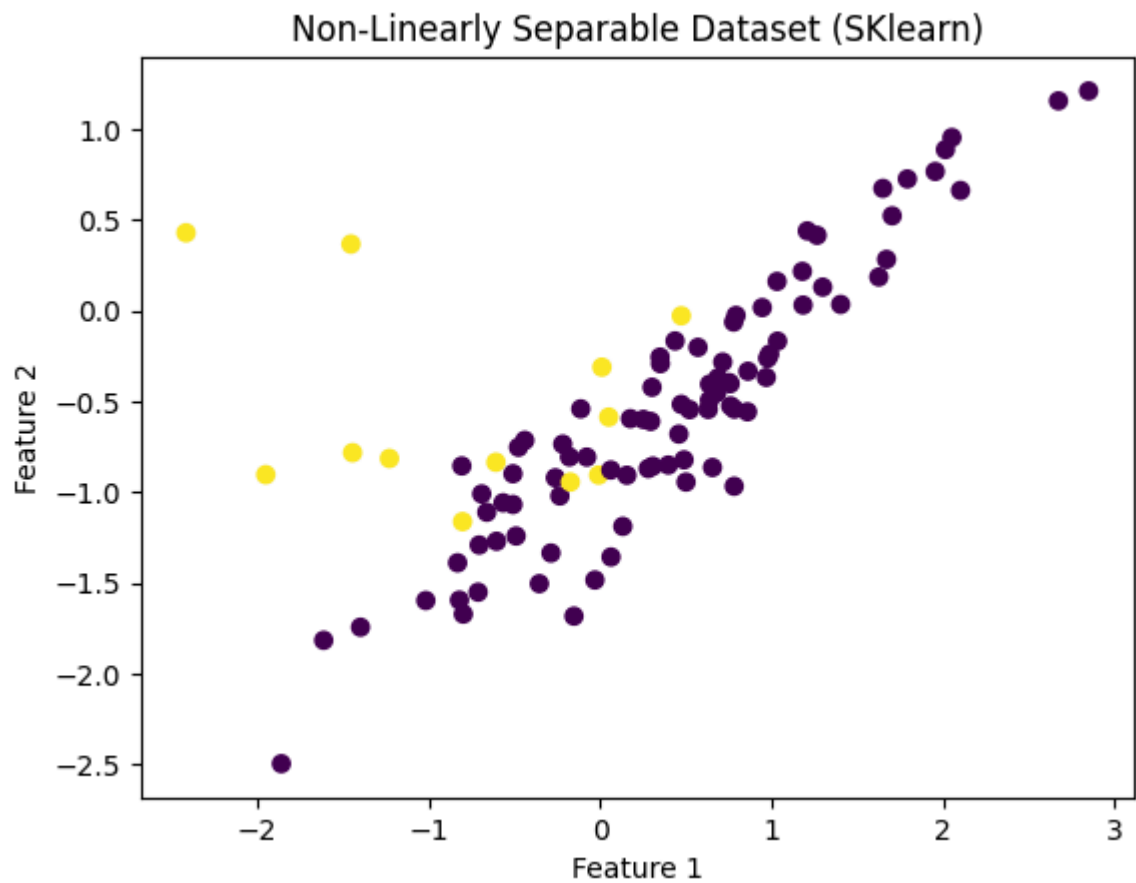
print("Classification Report:\n")
print(classification_report(y_test, y_pred))

print("Confusion Matrix:\n")
print(confusion_matrix(y_test, y_pred))

w = model.coef_[0]
b = model.intercept_[0]

x_min, x_max = x[:, 0].min() - 1, x[:, 0].max() + 1
y_min_line = -(b + w[0] * x_min) / w[1]
y_max_line = -(b + w[0] * x_max) / w[1]

plt.plot([x_min, x_max], [y_min_line, y_max_line], 'k-', label='Decision
plt.scatter(x_test[:, 0], x_test[:, 1], c = y_test)
plt.title('Decision Boundary (sklearn Perceptron) and Test Points')
plt.show()
```



Accuracy: 0.88
Precision: 0.50
Recall: 0.40
F1 Score: 0.44
Classification Report:

	precision	recall	f1-score	support
0	0.92	0.94	0.93	35
1	0.50	0.40	0.44	5
accuracy			0.88	40
macro avg	0.71	0.67	0.69	40
weighted avg	0.86	0.88	0.87	40

Confusion Matrix:

```
[[33  2]
 [ 3  2]]
```


Decision Boundary (sklearn Perceptron) and Test Points

