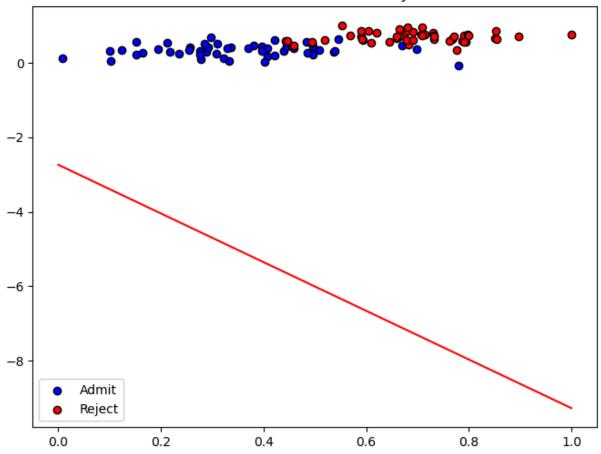
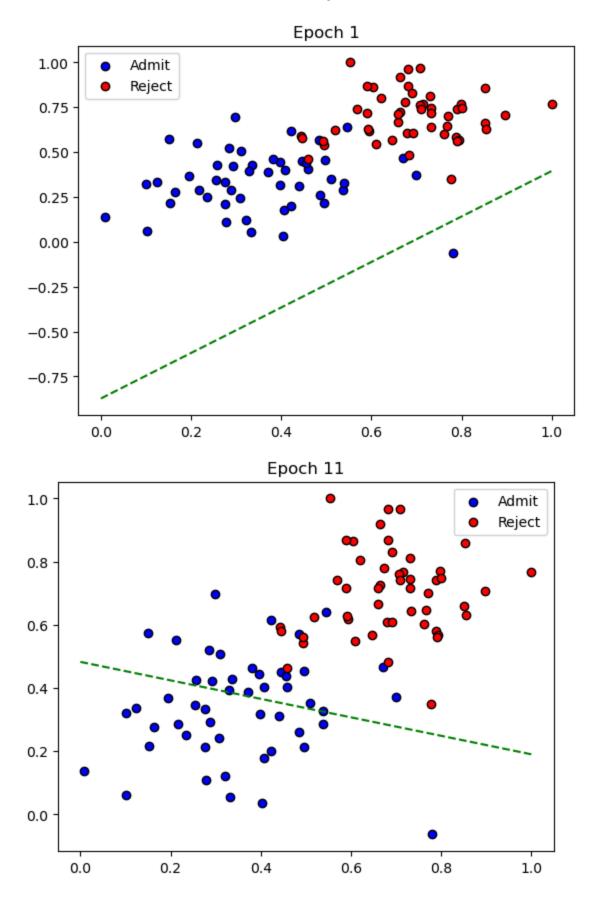
```
In [31]: import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         # Load the data
         data = pd.read csv('data.csv', header=None, names=['x1', 'x2', 'label'])
         X = np.array(data[['x1', 'x2']])
         Y = np.array(data['label'])
In [33]: def step function(t):
             return 1 if t >= 0 else 0
         def predict(x, weights, bias):
             return step_function(np.dot(weights, x) + bias)
         def plot_points(data):
             admitted = data[data['label'] == 1]
             rejected = data[data['label'] == 0]
             plt.scatter(admitted['x1'], admitted['x2'], color='blue', edgecolor='k',
             plt.scatter(rejected['x1'], rejected['x2'], color='red', edgecolor='k',
             plt.legend()
         def plot decision boundary(weights, bias, color='q--'):
             x \text{ vals} = \text{np.array}([0, 1])
             y_vals = -(weights[0] * x_vals + bias) / weights[1]
             plt.plot(x_vals, y_vals, color)
In [35]: def train_perceptron(X, Y, learning_rate=0.1, num_epochs=65):
             weights = np.random.rand(2)
             bias = np.random.rand()
             plt.figure(figsize=(8, 6))
             plot points(data)
             plot decision boundary (weights, bias, 'r-')
             plt.title("Initial Decision Boundary")
             plt.show()
             for epoch in range(num epochs):
                  for i in range(len(X)):
                     x = X[i]
                     y = Y[i]
                      y_hat = predict(x, weights, bias)
                      error = y - y_hat
                      weights [0] += learning rate * error * x[0]
                      weights[1] += learning_rate * error * x[1]
                      bias += learning rate * error
                  if epoch % 10 == 0:
                      plot points(data)
                      plot_decision_boundary(weights, bias, 'g--')
                      plt.title(f"Epoch {epoch + 1}")
                      plt.show()
             plot_points(data)
```

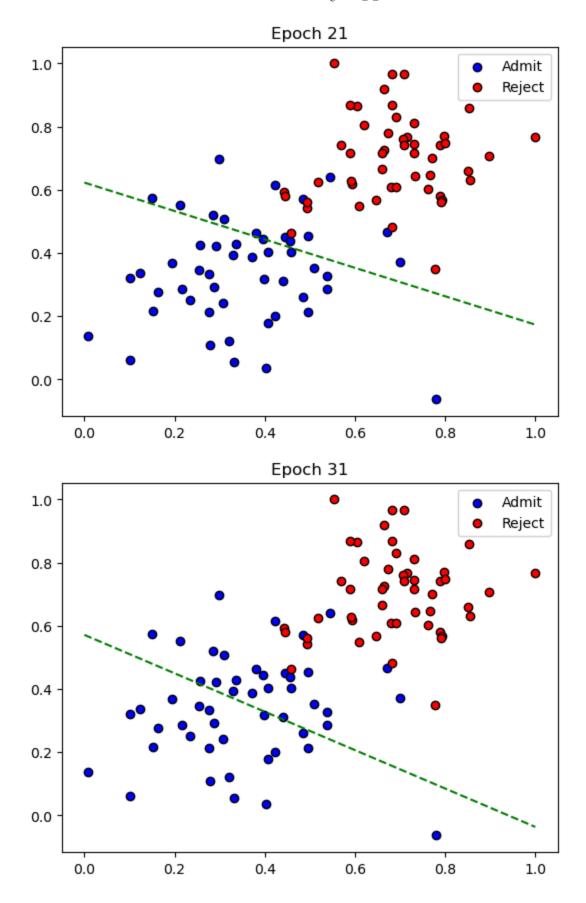
```
plot_decision_boundary(weights, bias, 'k-')
plt.title("Final Decision Boundary")
plt.show()

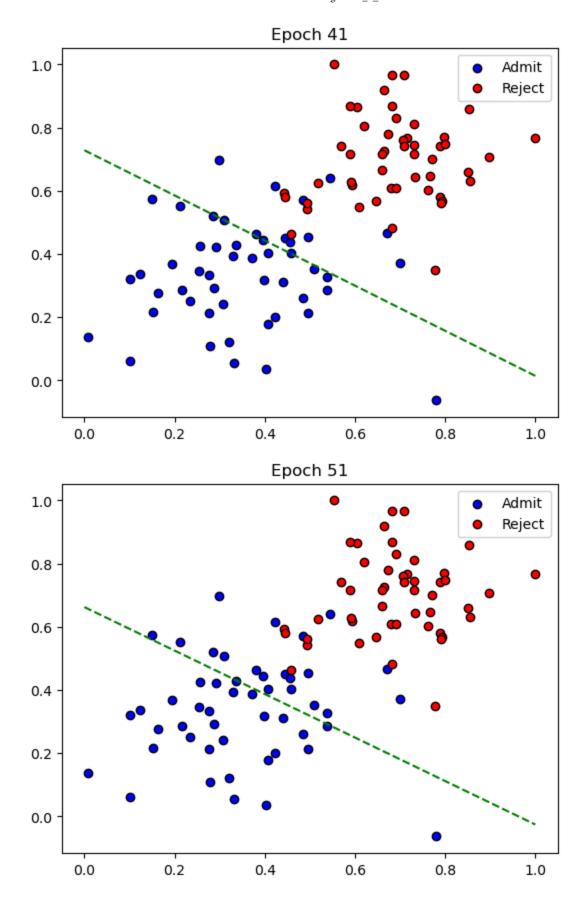
train_perceptron(X, Y)
```

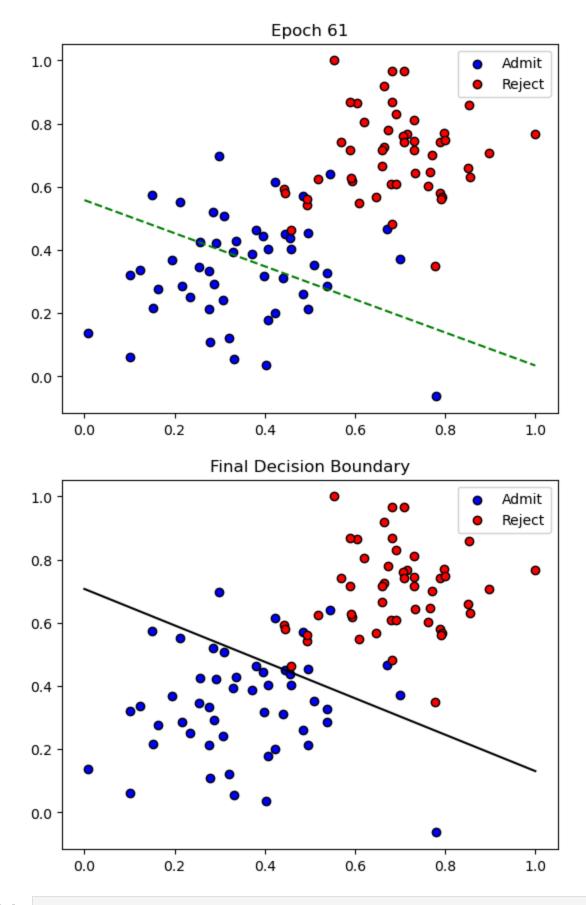
Initial Decision Boundary









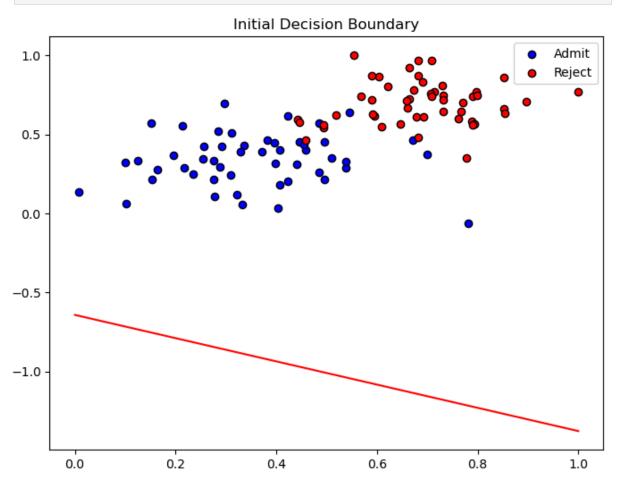


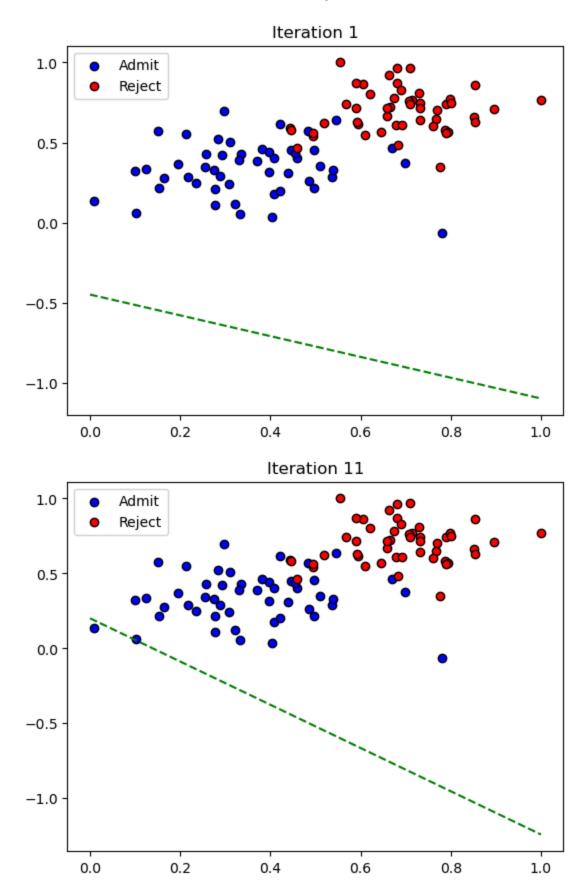
In []:

```
In [11]: import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         data = pd.read_csv('data.csv', header=None, names=['x1', 'x2', 'label'])
         X = np.array(data[['x1', 'x2']])
         Y = np.array(data['label'])
In [13]: def sigmoid(x):
             return 1 / (1 + np.exp(-x))
         def log loss(y, y hat):
             epsilon = 1e-9 # To prevent log(0)
             return -y * np.log(y_hat + epsilon) - (1 - y) * np.log(1 - y_hat + epsilon)
         def predict_prob(x, weights, bias):
             return sigmoid(np.dot(weights, x) + bias)
         def predict(x, weights, bias):
             return 1 if predict prob(x, weights, bias) \geq 0.5 else 0
         def plot points(data):
             admitted = data[data['label'] == 1]
             rejected = data[data['label'] == 0]
             plt.scatter(admitted['x1'], admitted['x2'], color='blue', edgecolor='k',
             plt.scatter(rejected['x1'], rejected['x2'], color='red', edgecolor='k',
             plt.legend()
         def plot decision boundary(weights, bias, color='q--'):
             x \text{ vals} = \text{np.array}([0, 1])
             y_vals = -(weights[0] * x_vals + bias) / weights[1]
             plt.plot(x vals, y vals, color)
In [15]: def train_gradient_descent(X, Y, learning_rate=0.01, num_iterations=100):
             weights = np.random.rand(2)
             bias = np.random.rand()
             losses = []
             plt.figure(figsize=(8, 6))
             plot points(data)
             plot_decision_boundary(weights, bias, 'r-')
             plt.title("Initial Decision Boundary")
             plt.show()
             for iteration in range(num_iterations):
                  total loss = 0
                  for i in range(len(X)):
                     x = X[i]
                     v = Y[i]
                      y_hat = predict_prob(x, weights, bias)
                      error = y - y_hat
                      weights[0] += learning_rate * error * x[0]
                      weights[1] += learning_rate * error * x[1]
```

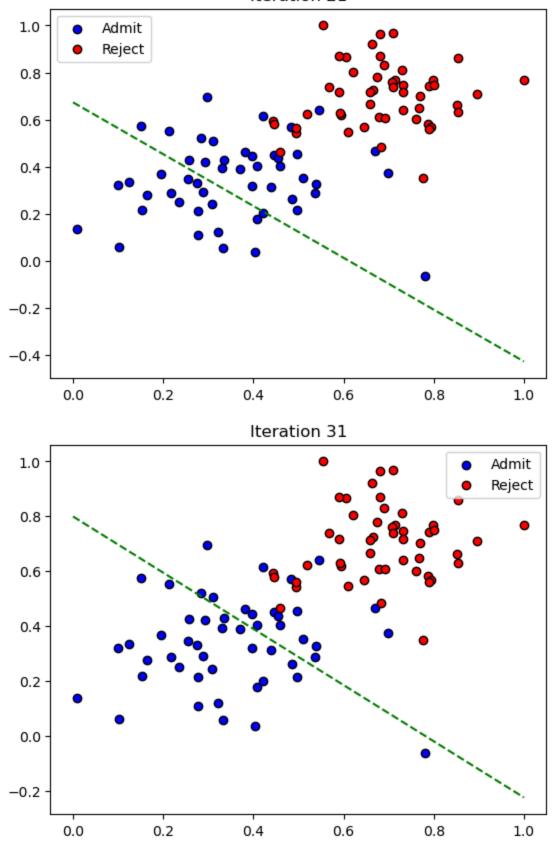
```
bias += learning_rate * error
        total_loss += log_loss(y, y_hat)
    losses.append(total_loss / len(X))
    if iteration % 10 == 0:
        plot_points(data)
        plot_decision_boundary(weights, bias, 'g--')
        plt.title(f"Iteration {iteration + 1}")
        plt.show()
plot_points(data)
plot_decision_boundary(weights, bias, 'k-')
plt.title("Final Decision Boundary After All Iterations")
plt.show()
plt.plot(range(num_iterations), losses, marker='o')
plt.title("Log Loss Over Iterations")
plt.xlabel("Iteration")
plt.ylabel("Log Loss")
plt.show()
```

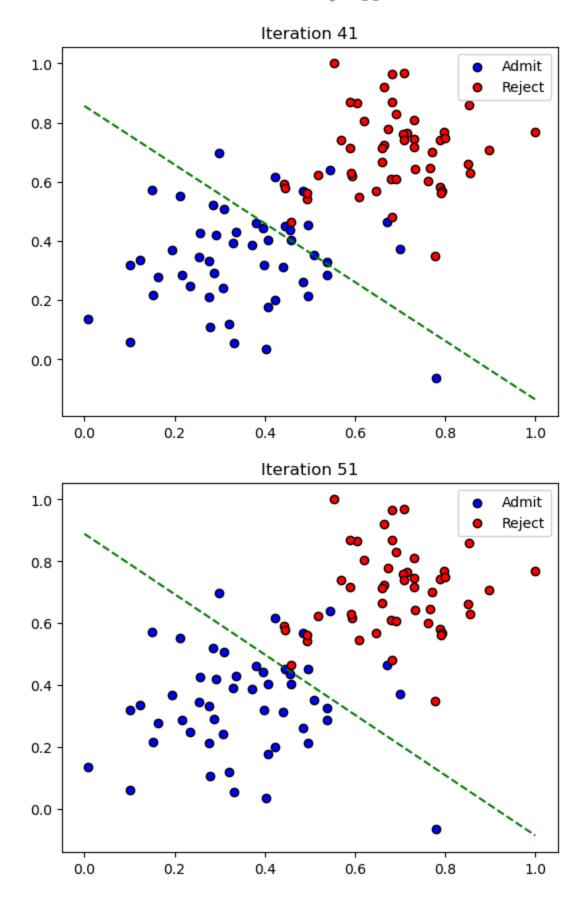
In [17]: train_gradient_descent(X, Y, learning_rate=0.01, num_iterations=100)

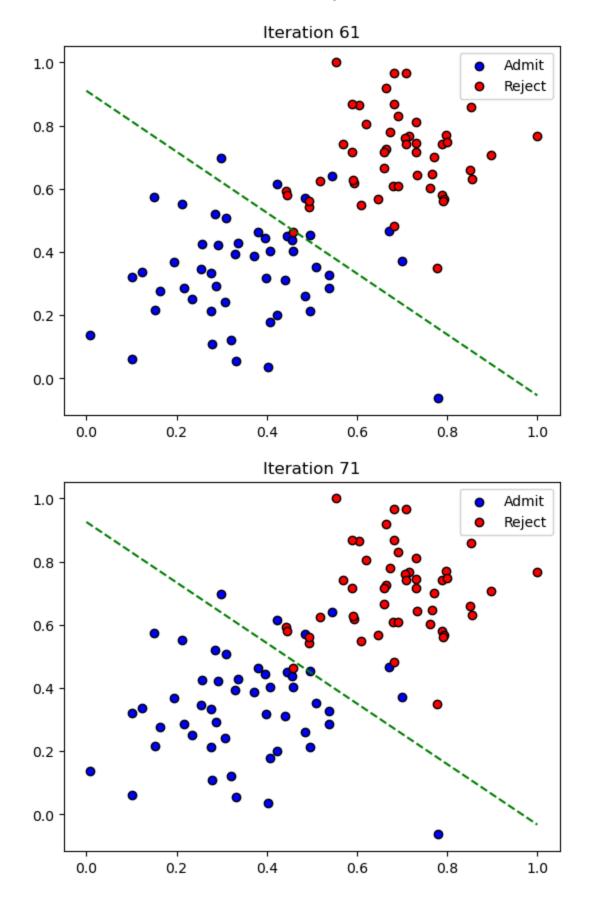


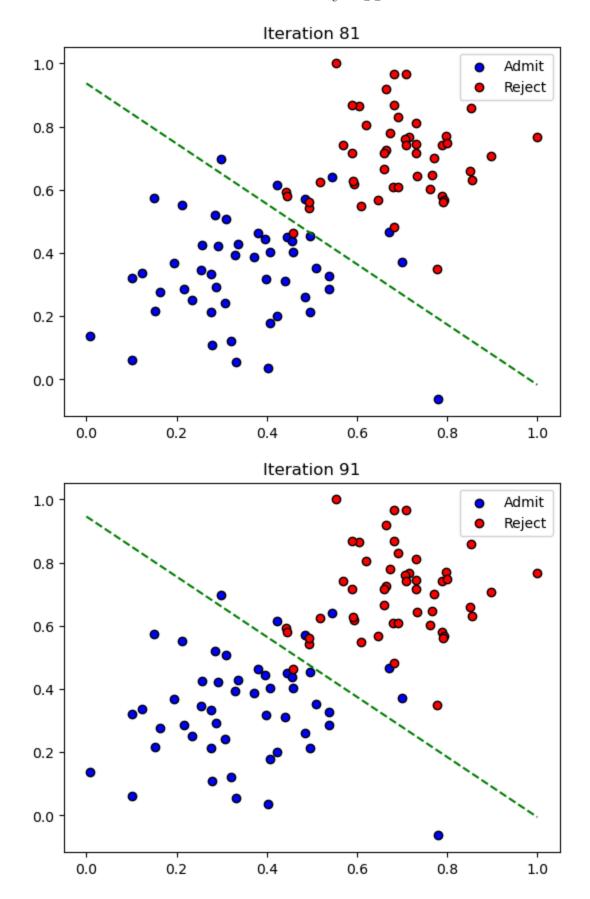


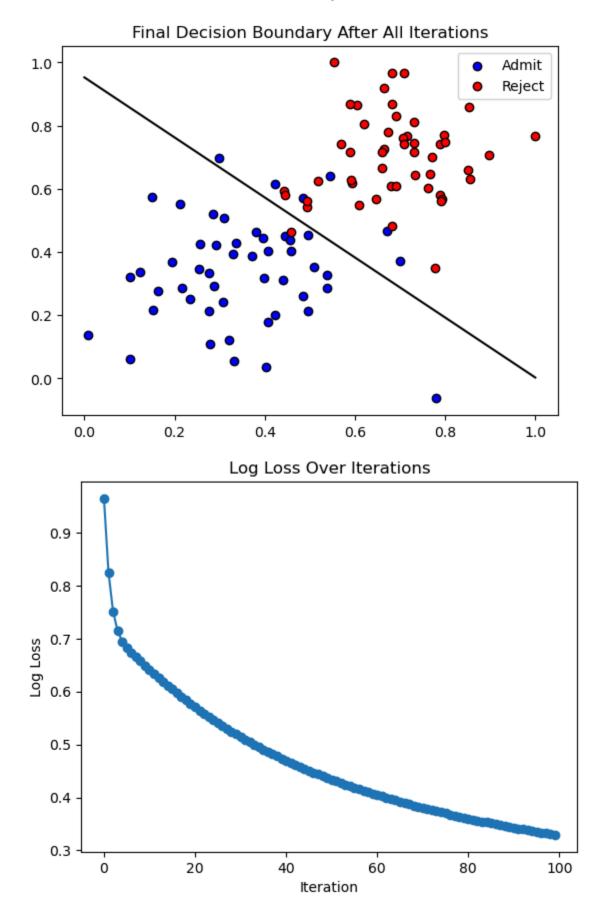












In []: