

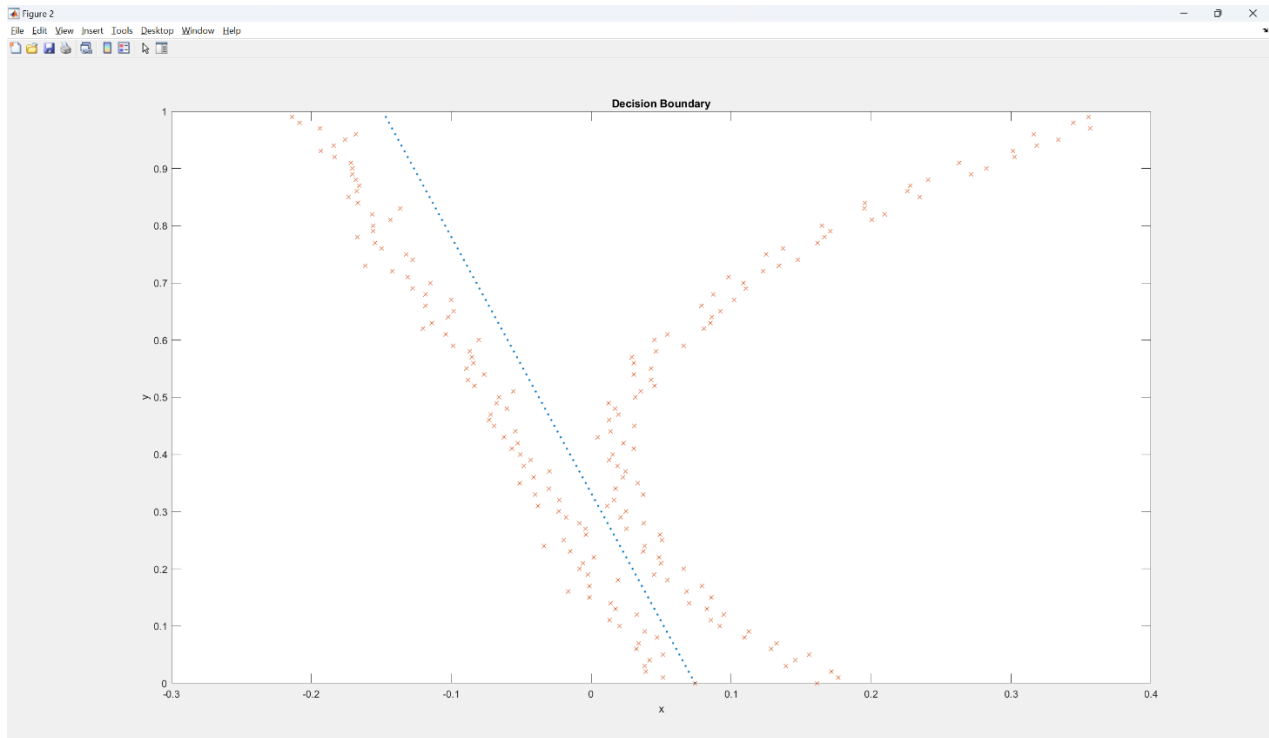
## HW2

### Q1

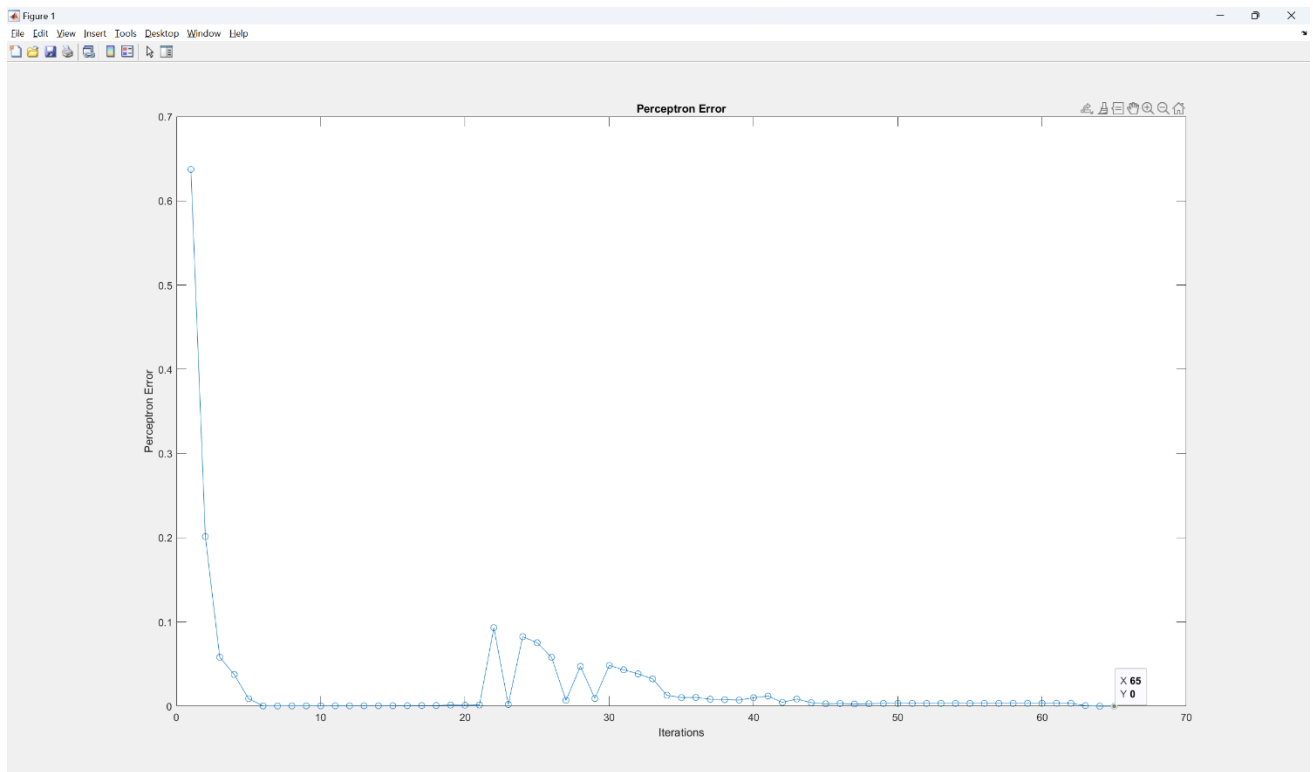
This project implemented linear perceptron using stochastic gradient descent. The following are results generated from a successful run (65 iterations).

When converged, both binary classification error and perceptron error reaches zero (the minimal).

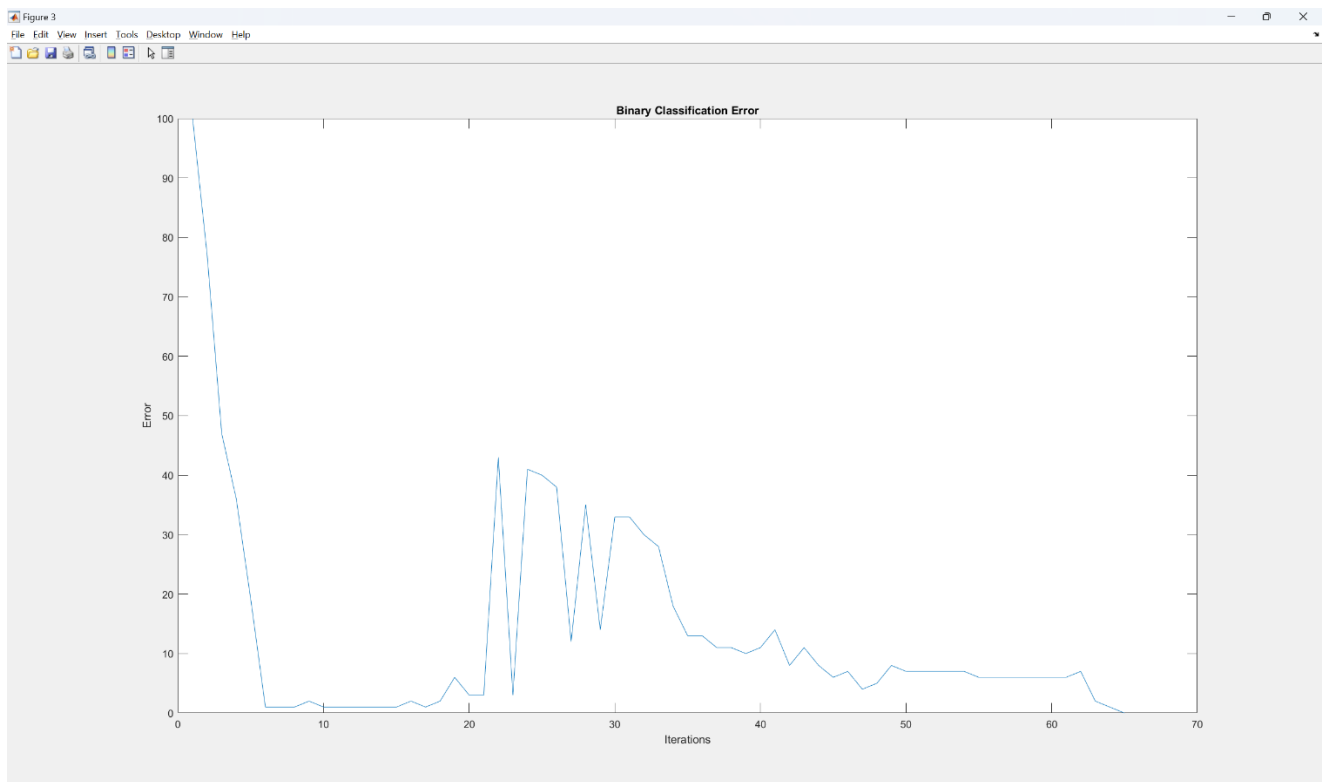
**Decision Boundary**



## Perceptron Error



## Binary Classification Error



## Code Screenshot

### Perceptron.m

```
1 function [theta, iterations,x, Errors, Risk] = Perceptron(Data)
2     theta = rand(3,1) ; %3 1
3     t = 1;
4     y = Data(:,3); %200 1
5     x = [ones(200,1) Data(:,[1,2])]; %200 3
6     Errors = [];
7     Risk = [];
8     err = 10;
9     while (err~=0)
10         xx = [zeros(200,3)]; %miss classified x, reset
11         yy = [zeros(200,1)]; %miss classified y, reset
12         err = 0;
13         temp = theta;
14         k = 1;
15         for i = 1:length(Data)
16             if(y(i) * (x(i,:) * theta) <= 0)
17                 xx(k,:) = x(i,:);
18                 yy(k,:) = y(i);
19                 k = k+1;
20                 err= err + 1;
21                 %disp(xx);
22             else
23                 err = err + 0;
24             end
25             Errors(t) = err;
26         end
27         if size(xx)>0 %calculate risk
28             Risk(t) = (-1/length(yy))*sum(yy .* (xx * theta));
29         end
30         for i = 1:length(Data) %update theta
31             if(y(i) * (x(i,:) * theta) <= 0)
32                 theta = theta + (y(i) .* x(i,:))';
33             end
34         end
35         t = t+1;
36     end
37     iterations = t-1;
38 end
```

## Main.m

```
.m  Perceptron.m  T
load data3.mat
[Theta, Iterations, x, Errors, Risk] = Perceptron(data);

% Perceptron error - iteration plot
figure
plot(1:length(Risk), Risk, '-o');
xlabel("Iterations");
ylabel("Perceptron Error")
title('Perceptron Error');

% Linear decision boundary plot
figure;
A = -(Theta(2)/Theta(3)) * x(:,2) - (Theta(1)/Theta(3));
B = x(:,2);
plot(A,B, '.');
hold on
plot (x(:,3), x(:,2), 'x');
xlabel("x");
ylabel("y");
title('Decision Boundary');

%Binary classification error plot
figure;
plot (1:length(Errors), Errors);
title('Binary Classification Error');
xlabel("Iterations");
ylabel("Error")
```

## Q2.1

$$\begin{aligned}
 E &= -(t_i \log(x_i) + (1-t_i) \log(1-x_i)) \\
 x_i &= \frac{1}{1+e^{-s_i}} \quad s_i = \gamma_j' w_{ji} \\
 \frac{\partial E}{\partial w} &= \frac{\partial E}{\partial x} \cdot \frac{\partial x}{\partial s} \cdot \frac{\partial s}{\partial w} \\
 \frac{\partial E}{\partial x} &= -t_i \log(x_i)' - (1-t_i) \log(1-x_i)' = -\frac{t_i}{x_i} + \frac{1-t_i}{1-x_i} = \frac{x_i - t_i}{x_i(1-x_i)} \\
 \frac{\partial x}{\partial s} &= \frac{\partial}{\partial s} [ (1+e^{-s})^{-1} ] = (-1)(1+e^{-s})^{-2} \cdot (-e^{-s}) = x_i(1-x_i) \\
 \frac{\partial s}{\partial w} &= \gamma_j' w_{ji} + \gamma_j w_{ji}' = \gamma_j \\
 \frac{\partial E}{\partial w} &\Rightarrow (x_i - t_i) \gamma_j
 \end{aligned}$$

## Q2.2

$$\begin{aligned}
 \frac{dE}{ds} &= \frac{\partial E}{\partial x} \cdot \frac{dx}{ds} \\
 \textcircled{1} i \neq c \quad \frac{\partial x_i}{\partial s_c} &= \frac{\partial}{\partial s_c} \left( \frac{e^{s_i}}{e^{s_c} + \sum_{c \neq i} e^{s_c}} \right) = -x_i \cdot x_c \\
 \textcircled{2} i = c \quad \frac{\partial x_i}{\partial s_c} &= x_i(1-x_i) \\
 \Rightarrow \frac{dE}{ds} &= -\frac{\partial}{\partial s} \left[ \gamma_i \log(x_i) + \sum_{c \neq i} \gamma_c \log(x_c) \right] \\
 &= -\frac{\gamma_i}{x_i} \cdot \frac{\partial x_i}{\partial s_i} - \sum_{c \neq i} \frac{\gamma_c}{x_c} \cdot \frac{\partial x_c}{\partial s_i} = x_i - \gamma_i
 \end{aligned}$$

Q3

$$H = - \sum_{k=1}^N p_k \ln(p_k)$$

$$J(p) = \sum p_k \ln(p_k) - \lambda_0 (\sum p_k - 1)$$

$$\frac{\partial J}{\partial p_k} = 1 + \ln(p_k) - \lambda_0 = 0$$

$$\Rightarrow \ln(p_k) = 1 - \lambda_0$$

$$p_k = e^{1-\lambda_0}$$

$$\text{Therefore: } \sum p_k = 1 = \sum e^{1-\lambda_0}$$

$$\Rightarrow \sum e^{1-\lambda_0} = 1$$

$$e^{1-\lambda_0} (N-1) = 1$$

$$e^{1-\lambda_0} = \frac{1}{N-1}$$

$$-\lambda_0 + 1 = \ln \frac{1}{N-1}$$

$$\lambda_0 = 1 - \ln \frac{1}{N-1}$$

$$\Rightarrow p_k = e^{1-\lambda_0}$$

$$p_k = e^{1 - (1 - \ln \frac{1}{N-1})}$$

$$p_k = e^{\ln \frac{1}{N-1}}$$

$$p_k = \frac{1}{N-1}$$

#### Q4

##### **Solution:**

For three points, Let A, B, C be  $(1,0)$ ,  $(0,1)$ ,  $(-1,0)$  in a Cartesian coordinate system. Label two of these points positive, an axis-aligned square with these two points as its corners can shatter and classify the three points correctly. Therefore, the VC-dimension is at least three. For four points, Let A be the highest point on y-axis, B be the lowest point on y-axis, C be the leftmost point on x-axis, D be the rightmost point on x-axis. Assume  $d_{AB}$  is greater than  $d_{CD}$ , without losing generality. When A and B are positive, C and D cannot be labeled negative. Therefore, the VC-dimension of axis-aligned square is 3.