## Assignment 2

By Brandon Young and Ruicheng Wu

# 1 problem 1

#### 2.1 a.

We claim the provided tree correctly categorize the provided example since every example can be inducted from this decision tree. Like GPA above 3.6 is P and below 3.3 is N, then with publication P,otherwise check University Rank, Only rank 2 will be P,other ranks are N. And recommendation doesn't matter.

#### 2.2 b.

#### Step I

$$I(\frac{6}{12},\frac{6}{12})=1$$

GPA: [3.9, 4.0] 3(PPP), (3.2, 3.9) 5(PPPNN), [3.0, 3.2] 4(NNNN)

University: Rank 1— 5(PPPNN), Rank 2— 3(PPN) , Rank 3— 4(PNNN)

Publication: Yes 5(PPPNN), No 7(PPPNNNN)

Recommendation: good 8(PPPPNNN), normal 4(PNNN)

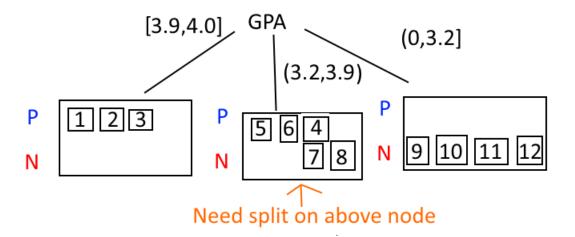
$$\begin{array}{l} Gain(GPA) = 1 - \left[\frac{3}{12} B(\frac{3}{3}) + \frac{5}{12} B(\frac{3}{5}) + \frac{4}{12} B(\frac{0}{4})\right] = 1 - \left[0.0 + 0.404562747689 + 0.0\right] \\ = 0.595437252311 \end{array}$$

Gain(University)=1-
$$\left[\frac{5}{12} \text{ B}\left(\frac{3}{5}\right) + \frac{3}{12} \text{ B}\left(\frac{2}{3}\right) + \frac{4}{12} \text{ B}\left(\frac{1}{4}\right)\right]$$
= 1- $\left[0.404562747689 + 0.229573958514 + 0.270426041486\right] = 0.095437252395$ 

Gain(Publication)=1-[
$$\frac{5}{12}$$
 B( $\frac{3}{5}$ )+ $\frac{7}{12}$  B( $\frac{3}{7}$ )]=1-[0.404562747689+0.574716412687]=0.020720839624

Gain(Recommendation)= 
$$1-\left[\frac{8}{12} \text{ B}(\frac{5}{8})+\frac{4}{12} \text{ B}(\frac{1}{4})\right]=1-\left[0.636289335283+0.270426041486\right]=0.093284623231$$

So we pick GPA as the best Gain attribute in this level



### Step II

$$I(\frac{2}{5}, \frac{3}{5}) = 0.970950594455$$

University: Rank 1— 2(PN), Rank 2— 1(P) , Rank 3— 2(PN)

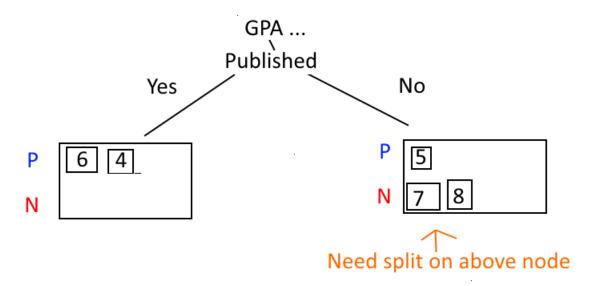
Publication: Yes 2(PP), No 3(PNN)Recommendation: good 5(PPPNN)

Gain(University)=
$$0.970950594455$$
- $\left[\frac{2}{5} \text{ B}\left(\frac{1}{2}\right) + \frac{1}{5} \text{ B}\left(\frac{1}{1}\right) + \frac{2}{5} \text{ B}\left(\frac{1}{2}\right)\right]$ =  $0.970950594455$ - $\left[0.4 + 0.0 + 0.4\right] = 0.170950594455$ 

Gain(Publication)=0.970950594455-[ $\frac{3}{5}$ B( $\frac{1}{3}$ )+ $\frac{2}{5}$ B( $\frac{2}{2}$ )]=0.970950594455-[0.550977500433+0.0]= 0.419973094022

Gain(Recommendation)=0.970950594455- $\left[\frac{5}{5} B\left(\frac{3}{5}\right)\right]$ =0.970950594455- $\left[0.970950594455+0.0+0.0\right]$ = 0

So we pick Publication as the best Gain attribute in this level



## Step III

$$I(\frac{1}{3}, \frac{2}{3}) = 0.918295834054$$

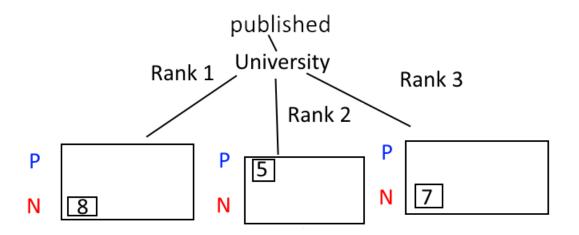
 $I(\frac{1}{3}, \frac{2}{3})$ =0.918295834054 University: Rank 1 — 1(N),Rank 2 — 1(P), Rank 3 — 1(N)

Recommendation: good 3(PNN)

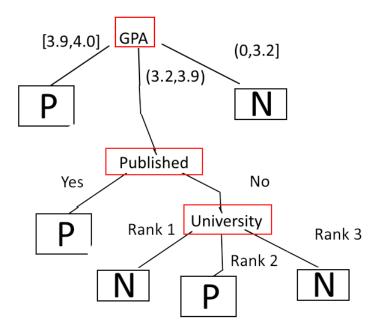
 $Gain(University) = 0.918295834054 - \left[\frac{1}{3} B(\frac{0}{1}) + \frac{1}{3} B(\frac{1}{1}) + \frac{1}{3} B(\frac{0}{1})\right] = 0.918295834054 - \left[\frac{1}{3} B(\frac{0}{1}) + \frac{1}{3} B(\frac$ [0.0+0.0+0.0] = 0.918295834054

Gain(Recommendation)=0.918295834054-[
$$\frac{3}{3}$$
 B( $\frac{1}{3}$ )]=0.918295834054-[0.918295834054]= 0

So we pick University as the best Gain attribute in this level



And the final tree to be returned is

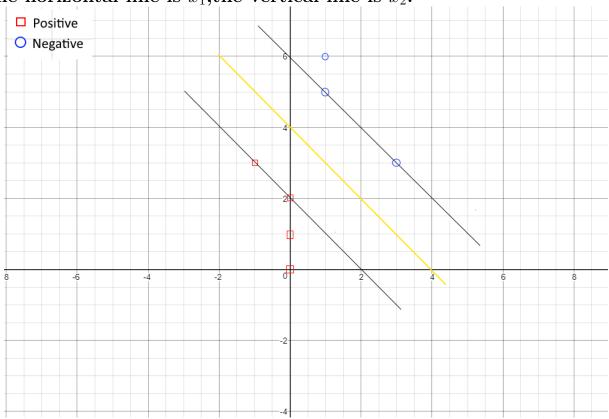


### 2.3 c.

The decision tree we got from b. is same from the provided one. This is not coincidence, it is believed both tree is generated by applying the decision tree algorithm.

#### 3.1 a.

The horizontal line is  $x_1$ , the vertical line is  $x_2$ .



### 3.2 b.

 $s_1:(1,5)$  ,  $s_2:(-1,3)$  , w:(1,1), So decision boundary is: y=(1,1)x-4 Assume there is (a,a) for  $w^T,$  we will have

$$a + 5a + b = -1$$

$$-a + 3a + b = 1$$

Solve those equations for:

$$a = -0.5, b = 2$$

So we have  $w^T: (-0.5, -0.5)$  and b: 2 for parameters. We can confirm the max Margin is  $\frac{2}{||w^T||} = \frac{2}{(\frac{\sqrt{2}}{2})} = 2\sqrt{2}$ , which verifies with the distance between  $s_1: (1,5)$ ,  $s_2: (-1,3)$ ,  $\sqrt{(1-(-1))^2+(5-3)^2} = 2\sqrt{2}$ .

And also we verify with given data.

 $[-1\ 3]^T\ [0\ 2]^T\ [0\ 1]^T\ [0\ 0]^T$ , plug in: All positive , so those are 1;

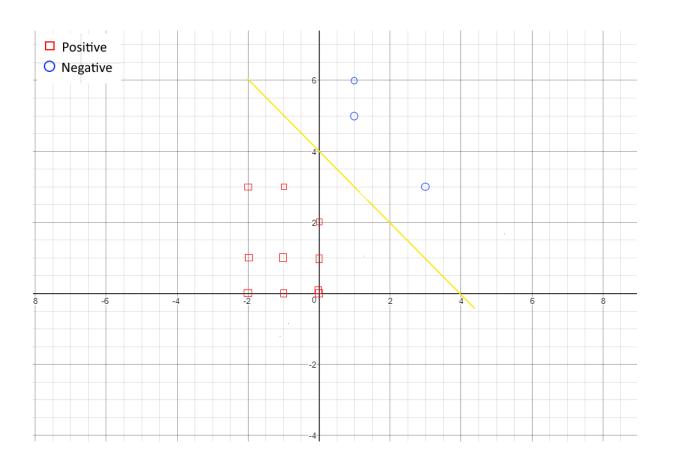
 $[1\ 5]^T\ [1\ 6]^T\ [3\ 3]^T$ , plug in: All negative, so those are -1;

#### 3.3 c.

By inspection, the new added points are not support vectors(ie. the closest points to separating line)

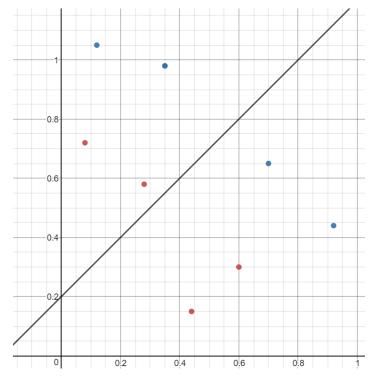
We claim the  $w^T:(-0.5,-0.5)$  and b:2 are still same to parametrize with new data.

 $[-2\ 0]^T\ [-2\ 1]^T\ [-2\ 3]^T\ [-1\ 0]^T\ [-1\ 1]^T\ [0\ 0]^T,$  plug in: All positive , so those are 1;



## 4.1 a.

The initial linear separator (line 1) is  $i_2 = -\frac{i_1}{i_2} - \frac{0.2}{i_2}$  or  $i_2 = i_1 + 0.2$ :



Assume that the points are:

- A: (0.08, 0.72)
- B: (0.28, 0.58)
- C: (0.44, 0.15)
- D: (0.6, 0.3)
- E: (0.12, 1.05)

- F: (0.35, 0.98)
- G: (0.7, 0.65)
- H: (0.92, 0.44)

where A, B, C and D are in class 1 and E, F, G and H are in class -1.

Use  $f(x) = w_1 i_1 + w_2 i_2 + 0.2$  to classify the samples. If f(x) < 0 then x is in class -1 and  $h_w(x) = 0$ . If  $f(x) \ge 0$  then x is in class 1 and  $h_w(x) = 1$ . By the initial linear separator, 4 samples are misclassified (A, B, G and H):

• A: 
$$(0.08) - (0.72) + 0.2 = -0.44 < 0, h_w(A) = 0$$

• B: 
$$(0.28) - (0.58) + 0.2 = -0.1 < 0, h_w(B) = 0$$

• C: 
$$(0.44) - (0.15) + 0.2 = 0.49 > 0, h_w(C) = 1$$

• D: 
$$(0.6) - (0.3) + 0.2 = 0.5 > 0, h_w(D) = 1$$

• E: 
$$(0.12) - (1.05) + 0.2 = -0.73 < 0, h_w(E) = 0$$

• F: 
$$(0.35) - (0.98) + 0.2 = -0.43 < 0, h_w(F) = 0$$

• G: 
$$(0.7) - (0.65) + 0.2 = 0.25 > 0, h_w(G) = 1$$

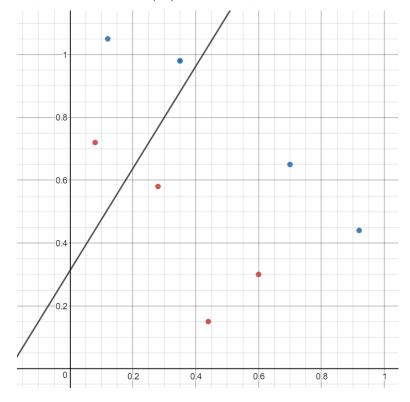
• H: 
$$(0.92) - (0.44) + 0.2 = 0.68 > 0, h_w(H) = 1$$

Let the learning rate,  $\alpha = 0.5$  and use A to update the weights. Then  $Err_A = y - h_w(A) = 1 - 0 = 1$ .

$$w'_1 \leftarrow w_1 + \alpha * Err_A * i_1$$
  
 $w'_1 \leftarrow 1 + (0.5)(1)(0.08)$   
 $w'_1 = 1.04$ 

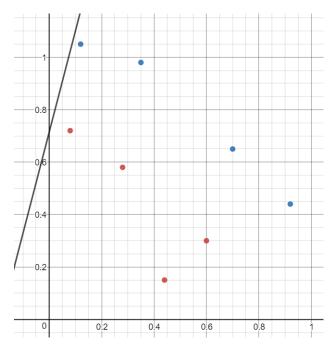
$$w_2' \leftarrow (-1) + (0.5)(1)(0.72)$$
  
 $w_2' = -0.64$ 

Hence the new weights are  $w_1 = 1.04$  and  $w_2 = -0.64$ . Line 2, then, is:  $i_2 = 1.625(i_1) + 0.3125$ , with 3 misclassified points:

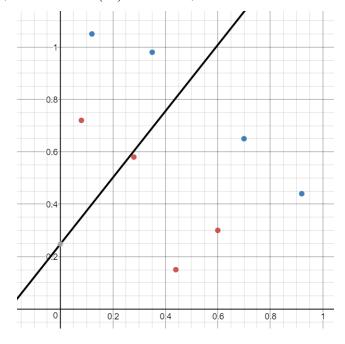


Following a similar process as above, the next few iterations generate the following plots:

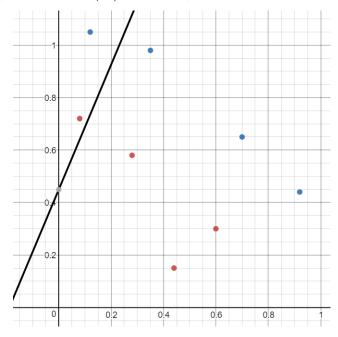
Update Line 2 with A to get  $w_1 = 1.08$ ,  $w_2 = -0.28$ . Line 3:  $i_2 = 3.857i_1 + 0.714$ , with 4 misclassified points:



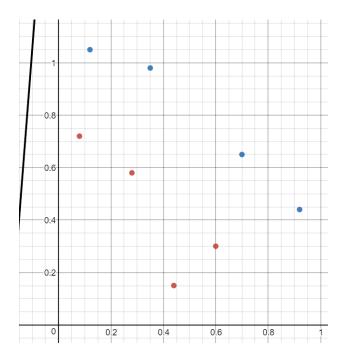
Update Line 3 with E to get  $w_1 = 1.02$ ,  $w_2 = -0.805$ . Line 4,  $i_2 = 1.267(i_1) + 0.248$ , with 3 misclassified points:



Update Line 4 with A to get  $w_1 = 1.06$ ,  $w_2 = -0.445$ . Line 5,  $i_2 = 2.382(i_1) + 0.449$ , with 4 misclassified points:



Update Line 5 with A to get  $w_1 = 1.1$ ,  $w_2 = -0.085$ . Line 6,  $i_2 = 12.941(i_1) + 2.35$ , with 4 misclassified points:

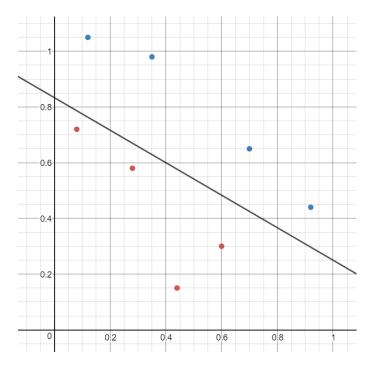


## 4.2 b.

The linear separator that achieves perfect classification (found after 172 iterations) is:

$$i_2 = -0.58333i_1 + 0.83333$$

where  $w_1 = -0.14$  and  $w_2 = -0.24$ . The line in the graph:



#### 4.3 c.

The diagram above shows only the  $i_1$  value from each sample. The dotted line represents the location of the best possible split, which is at  $i_1 = 0.65$ , with only 2 misclassified points and a 25% error.

A separator in 1D is  $w_1i_1 + w_0i_0$  or  $w_1i_1 + 0.2$  (assuming  $w_0 = 0.2$ ) which can be used to solve for  $w_1$ :

$$w_1 = -\frac{0.2}{i_1} = -\frac{0.2}{0.65} = -0.3077$$

As a result,  $w_1 = -0.3077$  is the weight that best classifies the

samples.

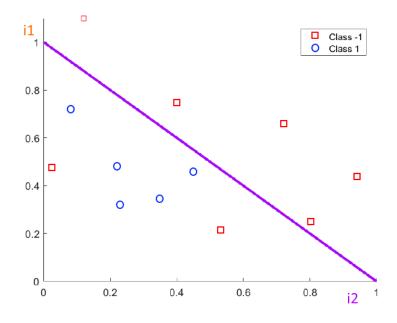
#### 5.1 a.

We define those points by inspection.

Class 1: (0.03,0.50), (0.11,1.2), (0.5,0.75), (0.54,0.23), (0.7,0.65), (0.8,0.25), (0.91,0.46); Class -1: (0.07,0.73), (0.23,0.49), (0.24,0.33), (0.35,0.35), (0.46,0.46);

The line can be observed from the graph, and we found the best single perceptron will have two unclassied points. So the minimum error will be  $\frac{2}{12} = 0.167$ ;

The formula for this dividing line is :  $1 - 1 * x_1 - 1 * x_2 = 0$ 



#### 5.2 b.

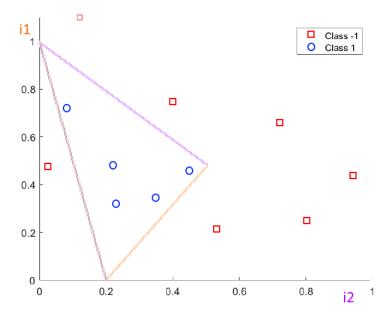
We claim that we need 3 separate lines to completely separate two classes. So we need at least 3 perceptrons to compute classification functions. We will just use 3 perceptrons for simplicity.

Formula for line 1: 
$$1 - 1 * x_1 - 1 * x_2 = 0$$

$$W_{1,0} = 1, W_{1,1} = -1, W_{1,2} = -1$$
Formula for line 2: 
$$0.2 - 1 * x_1 + 0.6 * x_2 = 0$$

$$W_{1,0} = 0.2, W_{1,1} = -1, W_{1,2} = 0.6$$
Formula for line 3: 
$$-0.2 + 1 * x_1 + 0.2 * x_2 = 0$$

$$W_{1,0} = -0.2, W_{1,1} = 1, W_{1,2} = 0.2$$



As we can see, a data point gives output as positive with all three perceptrons is class 1 and same applies to class -1. So in the next layer, we can simply apply "and" operation to the results of all three perceptrons. In that case, we only need one unit. And the output will be 1 if and only if all perceptrons in 1st layer output 1.

Hence we set

$$W_{4,0} = -2.5, W_{4,1} = 1, W_{4,2} = 1, W_{4,3} = 1$$

