HW 1 – Machine Learning Introduction

All code are present in the github repo https://github.com/somesh-bagadiya/CMPE257-Fall23-Somesh-Bagadiya/tree/4646d5f2607 c3de5dc4a18cbf236f9d5a8366856/HW1

Task 1:

A modified version of exercise 1.3 from the textbook on the PLA weight update. w(t + 1) = w(t) + y(t)x(t)

"The weight update rule in (1.3) in the textbook has the nice interpretation that it moves in the direction of classifying x(t) correctly."

LP 1:

[LP 1] Show that $y(t) w^{T}(t) x(t) < O$

Hint: x(t) is misclassified by w(t).

Ans.

The y(t) $w^T(t)$ x(t) would be less than zero for a misclassified point because the sign of w^Tx would be the opposite of the target function, if the signs were the same the point wouldn't be a misclassified point.

For example,

x(t) is misclassified point by the vector w(t) then the sign would be -1 The target of the x(t) would be +1

Therefore, (+1) * (-1) < 0

LP 2:

[LP 2] Show that for W'final, the final hypothesis generated by the Perceptron Learning Algorithm,

assuming that the data is linearly separable, $Y_n W_{final}^T X_n > 0$ for all data points xn. Ans.

Perceptron Algorithm will stop once it correctly classifies all the points in the data set, so if we have a final weight vector i.e. W_{final} This would correctly classify all the points in the data set. y(t) $w^{T}(t)$ x(t) would be positive it the point is correctly classified.

For Example,

For some x the target is -1, and the sign(w^Tx) would also be -1 as it correctly classifies the point x. Thus, $Y_nW^T_{final}X_n > 0$.

HP:

[HP) Show that $y(t)w^{T}(t + I)x(t) > y(t)w^{T}(t)x(t)$. As far as classifying x(t) is concerned, argue that the move from w(t) to w(t + 1) is a move "in the right direction".

Show that y(t) $w^{T}(t+1)$ x(t) > y(t) $w^{T}(t)$ x(t) - - - - - - - {1} We know w(t+1) = w(t) + y(t) x(t).

$$w^{T}(t+1) = w^{T}(t) + y(t) x^{T}(t)$$

Put $w^{T}(t+1)$ in the equation 1 y(t) $[w^{T}(t) + y^{T}(t) x^{T}(t)] x(t) > y(t) w^{T}(t) x(t)$ y(t) $w^{T}(t) x(t) + [y(t) x(t)] [y(t) x^{T}(t)] > y(t) w^{T}(t) x(t)$ y(t) $w^{T}(t) x(t) + [y(t)]^{2} x^{T}(t) x(t) > y(t) w^{T}(t) x(t)$

Simplifying this we will get,

 $[y(t)]^2 x^T(t) x(t) > 0$

We know y(t) can be either -1 or 1, thus $[y(t)]^2 > 0$. We also know $x^T(t)$ x(t) is a positive definitive matrix; it is greater than 0. Hence Proved, $y(t)^2 x^T(t) x(t) > 0$ or $y(t) w^T(t+1) x(t) > y(t) w^T(t) x(t)$

Theory:

x(t) is a misclassified point and from LP 1 we know that the y(t) $w^{T}(t)$ x(t) < 0, We will update the weights to classify the point x(t) correctly. The updated weight would be w(t+1), and from LP2 we know that if a weight correctly classifies a point then y(t) $w^{T}(t)$ x(t) > 0. So, y(t) $w^{T}(t+1)$ x(t) > 0. Therefore we can say that y(t) $w^{T}(t+1)$ x(t) > y(t) $w^{T}(t)$ x(t).

TASK 2:

LP 1:

[LP I] The perceptron in two dimensions is defined as $h(x) = sign(w^Tx)$, where $w = [w0, w1, w2]^T$ and $x = [1, x1, x2]^T$. Compare the linear separator to the traditional equation of a line, i.e., X2 = mX1 + C.

Specifically, what are m and c regarding W0, W1, and W2? Ans.

$$X_2 = mX_1 + C$$
 ----- equation of line
 $-mX_1 + X_2 - C = 0$
 $mX_1 - X_2 + C = 0$
 $C + mX_1 - X_2 = 0$

We can assume W_0 , W_1 , W_2 as the coefficients of the above-mentioned equations.

 $W_0C + W_1X_1 + W_2X_2 = 0$ ------ Equation of line in term of W's $W_2X_2 = -W_1X_1 - W_0C'$

 $X_2 = (-W_1/W_2)X_1 + (-W_0/W_2)C_{----}$ In the same for form as $X_2 = mX_1 + C$ Therefore, $m = (-W_1/W_2)$ and $C = (-W_0/W_2)$

LP 2:

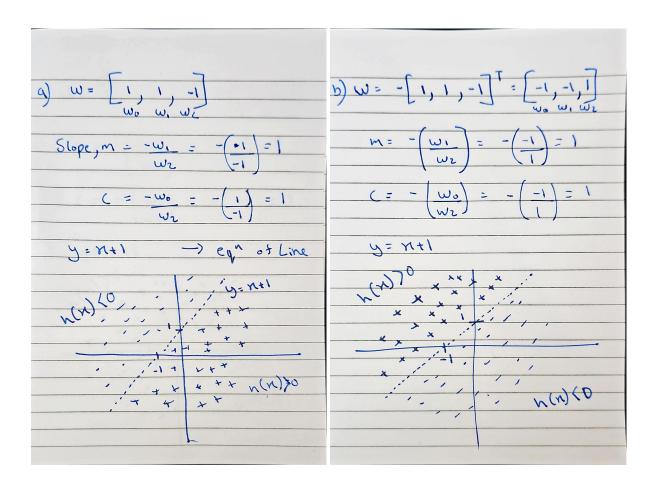
[LP 2] Without using a program, with pen and paper, draw the linear separator and the regions where

$$h(xx) = +1 \text{ and } h(xx) = -1 \text{ when:}$$

a)
$$w = [1 \ 1 - 1]^T$$

b)
$$w = -[1 \ 1 - 1]^T$$

Ans:



TASK 3:

Ans.

Refer Code HW1 New Pla.ipynb

Generated a training data of 100 points with final weights of [0.5, 0.3, 0.4].

- 1. Learning rate is 100: The rate is too high to compute a result
- 2. Learning rate is 1: The rate is too high to compute a result
- 3. Learning rate is 0.01: The rate is good enough to generate the result but I got an accuracy of only 56%
- 4. Learning rate is 0.0001: The rate is good enough to generate the result but I got an accuracy of only 56%

5. Final Learning rate is 0.052: This is the perfect learning rate at which the accuracy of the result is about 97.61%

TASK 4: Ans. Refer code HW1 Zip Data.ipynb

```
plt.scatter(intensities_dig1, symmetry_dig1, c="red", label="Digit = {}".format(dig1))
plt.scatter(intensities_dig2, symmetry_dig2, c="blue", label="Digit = {}".format(dig2))
In [136]:
                   plt.xlabel("Intensity")
plt.ylabel("Horizontal Symmetry")
                    6 plt.legend()
7 plt.show()
                                        Digit = 1
                       1.0
                                        Digit = 5
                       0.8
                   Horizontal Symmetry
                       0.6
                       0.4
                       0.2
                       0.0
                                        -0.8
                                                            -0.6
                                                                                 -0.4
                                                                                                     -0.2
                                                                                                                          0.0
                                                                            Intensity
```

I have computed the intensities of the pixels by averaging the values and then plotting it on the x axis, and i have used horizontal symmetry to plot it on the y axis.