

# Deep Learning Homework 1

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## 1 Perceptrons

- (a) Given that  $d = 2$ , the perceptron activation rule can be rewritten as:

$$\begin{aligned} y &= \begin{cases} 1 & \text{if } \sum_{i=0}^2 w_i x_i \geq 0 \\ 0 & \text{else} \end{cases} \\ &= \begin{cases} 1 & \text{if } w_2 x_2 + w_1 x_1 + w_0 \geq 0 \\ 0 & \text{else} \end{cases} \end{aligned}$$

If we're looking for the decision boundary we simply need to find at what point  $y = 0$ , which occurs when our summation is less than 0, therefore we can find the decision boundary at:

$$w_2 x_2 + w_1 x_1 + w_0 = 0$$

Which we can write in slope intercept form assuming  $x_2 = y(x)$  and  $x_1 = x$ :

$$\begin{aligned} x_2 &= -\frac{w_1}{w_2} x_1 + \left(-\frac{w_0}{w_2}\right) \\ y(x) &= -\frac{w_1}{w_2} x + \left(-\frac{w_0}{w_2}\right) \end{aligned}$$

- (b) Given we can represent the discriminant function as

$$y(x) = w^T x + w_0$$

We can take a geometric representation of this equation to notice that  $w$  would be normal to the line. Therefore, if we consider  $x$  to be some point on the line, then the normal distance can be given by:

$$l = \frac{w^T x}{\|w\|}$$

Where  $w^T = y(x) - w_0 = 0 - w_0 = -w_0$  from the discriminant function, giving us:

$$l = \frac{-w_0}{\|w\|}$$

- (c) We will define  $\alpha$  as the learning rate,  $t$  as the teacher output, and  $y$  as the expected output. The update equation can be expressed as:

$$w_j^{(r+1)} = w_j^{(r)} + \alpha * (t - y) * x_i$$

(d)

$x_1$	$x_2$	Output	Teacher	$w_0$	$w_1$	$w_2$
0	1	1	0	0	0	0
0	0	0	1	-1	0	-1
1	0	1	0	0	0	-1
0	0	0	1	-1	-1	-1
0	0	1	1	0	-1	-1

- (e) No, the solution is not unique, a weight vector of (0, -2, -2) would also be a sufficient perceptron that satisfies the truth table.

## 2 Logistic Regression

$$\begin{aligned}
E(w) &= - \sum_{n=1}^N \{t^n \ln(y^n) + (1 - t^n) \ln(1 - y^n)\} \\
&= - \sum_{n=1}^N \left\{ t^n \ln \left( \frac{1}{1 + e^{-w_j x_j^n}} \right) + (1 - t^n) \ln \left( 1 - \frac{1}{1 + e^{-w_j x_j^n}} \right) \right\} \\
&= - \sum_{n=1}^N \left\{ t^n \ln 1 - t^n \ln(1 + e^{-w_j x_j^n}) + (1 - t^n) \ln \left( \frac{1 + e^{-w_j x_j^n} - 1}{1 + e^{-w_j x_j^n}} \right) \right\} \\
&= - \sum_{n=1}^N \left\{ t^n \ln 1 - t^n \ln(1 + e^{-w_j x_j^n}) + (1 - t^n) \ln \left( \frac{e^{-w_j x_j^n}}{1 + e^{-w_j x_j^n}} \right) \right\} \\
&= - \sum_{n=1}^N \left\{ t^n \ln 1 - t^n \ln(1 + e^{-w_j x_j^n}) + (1 - t^n) \ln e^{-w_j x_j^n} - (1 - t^n) \ln 1 + e^{-w_j x_j^n} \right\} \\
&= - \sum_{n=1}^N \left\{ t^n \ln 1 + (1 - t^n) \ln e^{-w_j x_j^n} - \ln(1 + e^{-w_j x_j^n}) \right\} \\
&= - \sum_{n=1}^N \left\{ t^n \ln 1 - (1 - t^n) w_j x_j^n - \ln(1 + e^{-w_j x_j^n}) \right\} \\
&= - \sum_{n=1}^N \left\{ t^n \ln 1 - w_j x_j^n + t^n w_j x_j^n - \ln(1 + e^{-w_j x_j^n}) \right\} \\
\frac{\partial E(w)}{\partial w_j} &= - \sum_{n=1}^N \left\{ -x_j^n + t^n x_j^n - \frac{1}{1 + e^{-w_j x_j^n}} * e^{-w_j x_j^n} * -x_j^n \right\} \\
&= - \sum_{n=1}^N \left\{ (t^n - 1) x_j^n + \frac{e^{-w_j x_j^n}}{1 + e^{-w_j x_j^n}} * x_j^n \right\} \\
&= - \sum_{n=1}^N \left\{ \left( t^n + \frac{e^{-w_j x_j^n}}{1 + e^{-w_j x_j^n}} - 1 \right) x_j^n \right\} \\
&= - \sum_{n=1}^N \left\{ \left( t^n + \frac{e^{-w_j x_j^n} - (1 + e^{-w_j x_j^n})}{1 + e^{-w_j x_j^n}} \right) x_j^n \right\} \\
&= - \sum_{n=1}^N \left\{ \left( t^n - \frac{1}{1 + e^{-w_j x_j^n}} \right) x_j^n \right\} \\
&= - \sum_{n=1}^N (t^n - y^n) x_j^n \\
-\frac{\partial E(w)}{\partial w_j} &= \sum_{n=1}^N (t^n - y^n) x_j^n
\end{aligned}$$