ARTIFICIAL NEURAL NETWORKS

Exercise Set 1

Antonio Peters

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Exercise 1.1.1

1.1 [1] (a)

 $f(x) = ax^2 + bx + c$ Let $\bar{v} = [ax_1^2 + bx_1 + c, ..., ax_n^2 + bx_n + c]$ Let $\bar{y} = [y_1, y_2, ..., y_n]$ Minimize $\bar{e} = \bar{v} - \bar{y} = [(ax_1^2 + bx_1 + c - y_1), ..., (ax_n^2 + bx_n + c - y_n)]$ We need to minimize $||\bar{e}||$ or equivalently minimize $S = ||\bar{e}||^2$. Therefore $S = \sum_{i=1}^n (x_i^2 + bx_i + c - y_i)^2$, the sum of square errors needs to be minimized.

Set:

$$\frac{\partial S}{\partial a} = \sum_{i=1}^{n} 2(ax_i^2 + bx_i + c - y_i)x_i^2 = 0$$

$$\frac{\partial S}{\partial b} = \sum_{i=1}^{n} 2(ax_i^2 + bx_i + c - y_i)x_i = 0$$

$$\frac{\partial S}{\partial c} = \sum_{i=1}^{n} 2(ax_i^2 + bx_i + c - y_i) = 0$$
(1)

Which is equivalent to:

$$(\sum_{i=1}^{n} x_i^4)a + (\sum_{i=1}^{n} x_i^3)b + (\sum_{i=1}^{n} x_i^2)c = \sum_{i=1}^{n} x_i^2 y_i$$

$$(\sum_{i=1}^{n} x_i^3)a + (\sum_{i=1}^{n} x_i^2)b + (\sum_{i=1}^{n} x_i)c = \sum_{i=1}^{n} x_i y_i$$

$$(\sum_{i=1}^{n} x_i^2)a + (\sum_{i=1}^{n} x_i)b + \sum_{i=1}^{n} c = \sum_{i=1}^{n} y_i$$

$$(2)$$

Which becomes:

$$\begin{bmatrix} \sum_{i=1}^{n} x_{i}^{4} & \sum_{i=1}^{n} x_{i}^{3} & \sum_{i=1}^{i} x_{i}^{2} \\ \sum_{i=1}^{n} x_{i}^{3} & \sum_{i=1}^{n} x_{i}^{2} & \sum_{i=1}^{i} x_{i} \\ \sum_{i=1}^{n} x_{i}^{2} & \sum_{i=1}^{i} x_{i} & n \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} x_{i}^{2} y_{i} \\ \sum_{i=1}^{n} x_{i} y_{i} \\ \sum_{i=1}^{n} y_{i} \end{bmatrix}$$
(3)

Which can be represented by:

$$A\bar{b} = C \tag{4}$$

And our coefficients can be found by solving:

$$\bar{b} = C/A \tag{5}$$

1.2 [1] (b)

See $q1_1b.m$ and quadreg.m

1.3 [2] (a)

$$f(x) = M(1 - e^{-kx})$$
 Let $\bar{v} = [M(1 - e^{-kx_1}), ..., M(1 - e^{-kx_n})]$ Let $\bar{y} = [y_1, y_2, ..., y_n]$ Minimize $\bar{e} = \bar{v} - \bar{y} = [(M(1 - e^{-kx_1}) - y_1), ..., (M(1 - e^{-kx_n}) - y_n)]$ We need to minimize $\|\bar{g}\|$ or equivalently minimize $S = \|\bar{g}\|^2$

We need to minimize $||\bar{e}||$ or equivalently minimize $S = ||\bar{e}||^2$. Therefore $S = \sum_{i=1}^{n} (M(1 - e^{-kx_i}) - y_i)^2$, the sum of square errors needs to be minimized.

Set:

$$\frac{\partial S}{\partial M} = \sum_{i=1}^{n} 2(M(1 - e^{-kx_i}) - y_i)(1 - e^{-kx_i}) = 0$$

$$\frac{\partial S}{\partial k} = \sum_{i=1}^{n} 2(M(1 - e^{-kx_i}) - y_i)Mx_ie^{-kx_i} = 0$$
(6)

Which is equivalent to:

$$\sum_{i=1}^{n} (M - Me^{-kx_i} - y_i)(1 - e^{-kx_i}) = 0$$

$$\sum_{i=1}^{n} (M - Me^{-kx_i} - y_i)Mx_ie^{-kx_i} = 0$$
(7)

Which can be simplified to:

$$\sum_{i=1}^{n} M(1 - 2e^{-kx_i} - e^{-2kx_i}) = y_i e^{-kx_i} + y_i$$

$$\sum_{i=1}^{n} M - Me^{-kx_i} = y_i$$
(8)

M and k are clearly not separable to separate the equations into a set of matrix equations, therefore, there is no explicit solution.

1.4 [2] (b and c)

See $q1_2b.m$

$\mathbf{2}$

See q2.m and r2.m

$$q1_1_b.m \to r2 = 0.996$$

$$q1_2_b.m \to r2 = 1$$

3 Exercise 1.6.1

See layer1.m

4 Exercise 2.1.1

4.1 [1]

We seek:

$$\begin{bmatrix} 0 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 \end{bmatrix} \to \begin{bmatrix} 0 & 0 & 0 & 1 \end{bmatrix} \tag{9}$$

Therefore, we need:

$$(0,0) \to 0$$

 $(0,1) \to 0$
 $(1,0) \to 0$
 $(1,1) \to 1$ (10)

Which can be derived to:

$$hardlim(W\begin{pmatrix} 0\\0 \end{pmatrix} + b) = 0$$

$$hardlim(W\begin{pmatrix} 0\\1 \end{pmatrix} + b) = 0$$

$$hardlim(W\begin{pmatrix} 1\\0 \end{pmatrix} + b) = 0$$

$$hardlim(W\begin{pmatrix} 1\\1 \end{pmatrix} + b) = 1$$

$$(11)$$

or:

$$W\begin{pmatrix} 0\\0 \end{pmatrix} + b < 0$$

$$W\begin{pmatrix} 0\\1 \end{pmatrix} + b < 0$$

$$W\begin{pmatrix} 1\\0 \end{pmatrix} + b < 0$$

$$W\begin{pmatrix} 1\\1 \end{pmatrix} + b > 0$$

$$(12)$$

Assuming a Weighting of (1,1), any bias between 1 and 2 will give us the needed result, in this case, a bias of 1.1 was used. See q4.m for results.

4.2 [2]

We seek:

$$\begin{bmatrix} 0 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 \end{bmatrix} \to \begin{bmatrix} 1 & 0 & 0 & 1 \end{bmatrix} \tag{13}$$

Therefore, we need:

$$(0,0) \to 1$$

 $(0,1) \to 0$
 $(1,0) \to 0$
 $(1,1) \to 1$ (14)

Which can be derived to:

$$hardlim(W \begin{pmatrix} 0 \\ 0 \end{pmatrix} + b) = 1$$

$$hardlim(W \begin{pmatrix} 0 \\ 1 \end{pmatrix} + b) = 0$$

$$hardlim(W \begin{pmatrix} 1 \\ 0 \end{pmatrix} + b) = 0$$

$$hardlim(W \begin{pmatrix} 1 \\ 1 \end{pmatrix} + b) = 1$$

$$(15)$$

or:

$$W\begin{pmatrix} 0\\0 \end{pmatrix} + b > 0$$

$$W\begin{pmatrix} 0\\1 \end{pmatrix} + b < 0$$

$$W\begin{pmatrix} 1\\0 \end{pmatrix} + b < 0$$

$$W\begin{pmatrix} 1\\1 \end{pmatrix} + b > 0$$

$$(16)$$

Again assuming a weighting of (1,1) there does not exist a bias which will produce this result, this is due to the fact that the problem is not linearly separable, meaning that a straight line does not exist which can separate the data.

5

5.1 (a)

$$a = f(n) = tansig(n) = \frac{sinh(n)}{cosh(n)}$$

$$= \frac{\frac{e^{n} - e^{-n}}{2}}{\frac{e^{n} + e^{-n}}{2}} = \frac{e^{n} - e^{-n}}{e^{n} + e^{-n}}$$
(17)

The derivative is therefore:

$$\dot{a} = \dot{f}(n) = \frac{d}{dn} \frac{e^n - e^{-n}}{e^n + e^{-n}} \tag{18}$$

By the quotient rule:

$$\frac{d}{dx}\left(\frac{f\left(x\right)}{g\left(x\right)}\right) = \frac{\frac{d}{dx}f\left(x\right)g\left(x\right) - f\left(x\right)\frac{d}{dx}g\left(x\right)}{g^{2}\left(x\right)} \tag{19}$$

This equates to:

$$\frac{(e^{n} + e^{-n})(e^{n} + e^{-n}) - (e^{n} - e^{-n})(e^{n} - e^{-n})}{(e^{n} + e^{-n})^{2}}$$

$$= \frac{(e^{n} + e^{-n})^{2} - (e^{n} - e^{-n})^{2}}{(e^{n} + e^{-n})^{2}}$$

$$= \frac{(e^{n} + e^{-n})^{2}}{(e^{n} + e^{-n})^{2}} - \frac{(e^{n} - e^{-n})^{2}}{(e^{n} + e^{-n})^{2}}$$

$$= 1 - a^{2}$$
(20)

5.2 (b)

$$a = f(n) = log sig(n) = \frac{1}{1 + e^{-n}}$$
 (21)

The derivative is therefore:

$$\dot{a} = \dot{f}(n) = \frac{d}{dn} \frac{1}{1 + e^{-n}}
= \left(-\frac{1}{1 + e^{-n}} \right) (-e^{-n})
= \frac{e^{-n}}{(1 + e^{-n})^2}
= \frac{1 + e^{-n} - 1}{(1 + e^{-n})^2}
= \frac{1 + e^{-n}}{(1 + e^{-n})^2} - \frac{1}{(1 + e^{-n})^2}
= \frac{1}{1 + e^{-n}} - \frac{1}{(1 + e^{-n})^2}
= a - a^2 = (1 - a)a$$
(22)

5.3 (c)

For a:

$$a = 0 (n) tansig(n);$$

 $dot_f = 1 - a(n)^2;$

For b:

$$a = 0 (n) logsig(n);$$

 $dot_f = (1 - a(n)) *a(n);$