

# Neural Networks and Deep Learning: Exercises

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February 10, 2020

# Contents

<b>1</b>	<b>Using Neural Networks to Recognize Handwritten Digits</b>	<b>2</b>
<b>2</b>	<b>The Backpropagation Algorithm</b>	<b>5</b>
2.1	The Backpropagation Equations . . . . .	5
2.2	Backpropagation Applied to Gradient Descent . . . . .	6
<b>3</b>	<b>Improving the Way Neural Networks Learn</b>	<b>7</b>
3.1	The Cross-Entropy Cost Function . . . . .	7
3.1.1	Deriving the Cross-Entropy Function . . . . .	9
3.2	Softmax . . . . .	9

# Chapter 1

## Using Neural Networks to Recognize Handwritten Digits

**Exercise 1.1.** Consider a network of perceptrons. Suppose that we multiply all weights and biases by a positive constant  $c > 0$ . Show that the behaviour of the network does not change.

*Solution.* First consider a single perceptron. Assume that weights and bias are  $w_1, \dots, w_n$  and  $b$ , respectively. Then  $\sum_i w_i \cdot x_i + b$  and  $c \cdot (\sum_i w_i \cdot x_i + b)$  have exactly the same sign and hence multiplying the weights and the bias by  $c$  will not change the behaviour of this single perceptron. Now if all perceptrons in a network have their weights and biases multiplied by  $c > 0$ , then each individual perceptron behaves as before and hence the network behaves as before. ■

**Exercise 1.2.** Suppose that we have network of perceptrons with a chosen input value  $x$ . We won't need the actual input value, we just need the input to have been fixed. Suppose the weights and biases are such that all  $w \cdot x + b \neq 0$  for the input  $x$  to any particular perceptron in the network. Now replace all the perceptrons in the network by sigmoid neurons, and multiply the weights and biases of the network by a positive constant  $c > 0$ . Show that in the limit as  $c \rightarrow \infty$ , the behaviour of this network of sigmoid neurons is exactly the same as the network of perceptrons. How can this fail when  $w \cdot x + b = 0$  for one of the perceptrons?

*Solution.* As in the previous exercise, first consider a single perceptron in the network. When this is replaced by a sigmoid neuron, and we let  $c \rightarrow \infty$ ,  $c \cdot (w \cdot x + b)$  tends to either  $+\infty$  or  $-\infty$  depending on whether  $w \cdot x + b$  is positive or negative. The upshot is that the output of the sigmoid neuron matches that of the perceptron it replaced. Thus when every sigmoid neuron behaves as the perceptron it replaced, the network as a whole behaves similarly.

This works as long as  $w \cdot x + b \neq 0$ . If this is zero, the output of the sigmoid neuron is “stuck” at  $1/2$  irrespective of the value of  $c$ , while the perceptron outputs a 0. The outputs do not match and the behaviour of the sigmoid network may be different. ■

**Exercise 1.3.** There is a way of determining the bitwise representation of a digit by adding an extra layer to the three-layer network given in the book. The extra layer converts the

output of the previous layer in binary representation. Find a set of weights and biases for the new output layer. Assume that the first three layers of neurons are such that the correct output in the third layer (i.e., the old output layer) has activation at least 0.99, and incorrect outputs have activation less than 0.01.

*Solution.* Label the neurons of the third layer (the old output layer) as  $0, 1, \dots, 9$  and the neurons from the new output layer as  $0', 1', 2', 3'$  with the interpretation that neuron  $0'$  is the least significant bit and  $3'$  is the most significant bit of the number represented by the output layer. The weight of the connection between the  $i$ th neuron from the third layer and the  $j$ th neuron of the output layer is  $w_{ij}$ , where  $i \in \{0, \dots, 9\}$  and  $j \in \{0', 1', 2', 3'\}$ . The bias of the  $j$ th output neuron is  $b_j$ . Denote the output of the  $i$ th neuron from the third layer as  $x_i$ . Then the input to the final layer may be represented as:

$$\begin{pmatrix} z_0 \\ z_1 \\ z_2 \\ z_3 \end{pmatrix} = \begin{pmatrix} w_{00} & w_{10} & \dots & w_{90} & b_0 \\ w_{01} & w_{11} & \dots & w_{91} & b_1 \\ w_{02} & w_{12} & \dots & w_{92} & b_2 \\ w_{03} & w_{13} & \dots & w_{93} & b_3 \end{pmatrix} \begin{pmatrix} x_0 \\ \vdots \\ x_9 \\ 1 \end{pmatrix}$$

Now we would like  $z_0$  to be 1 when the number is 1, 3, 5, 7, 9 and 0 otherwise. To be able to do this, first set

$$w_{10} = w_{30} = w_{50} = w_{70} = w_{90} = +1$$

and the remaining weights of the inputs to  $0'$  to  $-1$ . Set  $b_0 = 0$ . Now if the third layer represents  $k \in \{1, 3, 5, 7, 9\}$ , we would have  $w_{k0} > 0.99$  and  $w_{j0} < 0.01$  for all  $j \neq k$ . With these weights, we would have  $z_0 > 0.99 - 9 \times 0.01 = 0.90$ . If the third layer represents a number  $k \notin \{1, 3, 5, 7, 9\}$ , then  $z_0 < -0.99 + 9 \times 0.01 = -0.90$ . We can amplify this phenomenon by multiplying all these weights by a large positive constant. This would lead the sigmoid neuron  $0'$  to output a 1 for the digits 1, 3, 5, 7, 9 and a 0 for the remaining digits.

We can use a similar strategy for the remaining neurons of the fourth layer. For example, the second most significant bit  $1'$  must be a 1 for the digits 2, 3, 6, 7, 9 and a 0 for the remaining digits. We would then set

$$w_{21} = w_{31} = w_{61} = w_{71} = w_{91} = +1$$

and the remaining weights to  $-1$ . The bias  $b_1$  is set to 0. ■

**Exercise 1.4.** Let  $C(v_1, \dots, v_m): \mathbb{R}^m \rightarrow \mathbb{R}$  be a differentiable function. Then  $\Delta C \approx \nabla C \cdot \Delta v$ . Constrain  $\|\Delta v\| = \epsilon$ , where  $\epsilon > 0$  is a small fixed real. Show that the choice of  $\Delta v$  that minimizes  $\nabla C \cdot \Delta v$  is  $\Delta v = -\eta \nabla C$ , where  $\eta = \epsilon / \|\nabla C\|$ .

*Solution.* The Cauchy-Schwarz inequality tells us that

$$\begin{aligned} |C_{v_1}^{(1)} \Delta v_1 + \dots + C_{v_m}^{(1)} \Delta v_m| &\leq \left( (C_{v_1}^{(1)})^2 + \dots + (C_{v_m}^{(1)})^2 \right)^{1/2} \left( (\Delta v_1)^2 + \dots + (\Delta v_m)^2 \right)^{1/2} \\ &= \|\nabla C\| \cdot \epsilon, \end{aligned}$$

where  $C_{v_i}^{(1)} = \frac{\partial C}{\partial v_i}$ . Since the right-hand side is a positive number no matter what the values of the partial derivatives  $C_{v_i}^{(1)}$  and the changes  $\Delta v_i$  in the values of the variables, the smallest

possible value of the left-hand side is  $-\|\nabla C\| \cdot \epsilon$ . Since we are trying to minimize  $\Delta C$  which is approximated by the left-hand side, the goal is to find values for the  $\Delta v_i$  such that minimizes the left-hand side. Observe that when we set  $\Delta v_i := -\epsilon \cdot \frac{\nabla C}{\|\nabla C\|}$  for all  $1 \leq i \leq m$ , then the left-hand side indeed equals the said minimum value. Hence it must be that this setting of the  $\Delta v_i$ s is the optimum. ■

# Chapter 2

## The Backpropagation Algorithm

### 2.1 The Backpropagation Equations

Before we describe anything, we briefly recap notation. We let  $C$  denote the cost function and  $\sigma$  the activation function of the neurons.

1.  $w_{jk}^l$  is the weight of the link between the  $j$ th neuron in layer  $l$  and the  $k$ th neuron in layer  $l - 1$ .
2.  $b_j^l$  is the bias of neuron  $j$  in layer  $l$ .
3.  $z_j^l$  is the weighted input to neuron  $j$  in layer  $l$ .
4.  $a_j^l = \sigma(z_j^l)$  is the activation of neuron  $j$  in layer  $l$ .
5.  $\delta_j^l := \partial C / \partial z_j^l$  is the “error” of neuron  $j$  in layer  $l$ .

Using this notation, we may write the weighted output to neuron  $j$  in the  $l$ th layer as:

$$z_j^l = \sum_k w_{jk}^l a_k^{l-1} + b_j^l = \sum_k w_{jk}^l \sigma(z_k^{l-1}) + b_j^l,$$

where the index  $k$  runs over all neurons in layer  $l - 1$  and  $2 \leq l \leq L$ . Symbols such as  $w^l$ ,  $b^l$ ,  $a^l$  without subscripts refer to either matrices or vectors as the case may be. For example,  $w^l$  refers to the matrix whose  $(j, k)$ th element is  $w_{jk}^l$ . This matrix has as many rows as there are neurons in the  $l$ th layer and as many columns as there are neurons in layer  $l - 1$ . The symbol  $b^l$  refers to the vector of biases  $b_j^l$  of the neurons in layer  $l$ ; similarly,  $a^l$  refers to the vector of activations  $a_j^l$  of the neurons in layer  $l$ .

With this notation in hand, we may write the backpropagation equations as:

$$\begin{aligned}
 \delta^L &= \nabla_{a^L} C \odot \sigma'(z^L) \\
 \delta^l &= ((w^{l+1})^\top \delta^{l+1}) \odot \sigma'(z^l) \\
 \frac{\partial C}{\partial b_j^l} &= \delta_j^l \\
 \frac{\partial C}{\partial w_{jk}^l} &= a_k^{l-1} \delta_j^l
 \end{aligned} \tag{2.1}$$

## 2.2 Backpropagation Applied to Gradient Descent

The backpropagation procedure calculates the gradient of the cost function  $C$  with respect to a single input example. To make use of backprop in the context of stochastic gradient descent, we need to take the mean of the gradient computed over all examples in a mini batch. Let's suppose that we have a mini batch with  $m$  examples  $x_1, \dots, x_m$ .

1. For each training example  $x$ , set the input activation  $a^1(x)$  and perform the following steps:
  - (a) **Feedforward.** For  $2 \leq l \leq L$ , set  $z^l(x) = w^l a^{l-1}(x) + b^l$  and  $a^l(x) = \sigma(z^l(x))$ .
  - (b) **Output Error.** Calculate  $\delta^L(x) = \nabla_{a^L} C(x) \odot \sigma'(z^L(x))$ .
  - (c) **Backprop.** For  $L-1 \leq l \leq 2$ ,  $\delta^l(x) = ((w^{l+1})^\top \delta^{l+1}(x)) \odot \sigma'(z^l(x))$ .
  - (d) **Gradients.** Calculate  $\frac{\partial C}{\partial b_j^l}(x) = \delta_j^l(x)$  and  $\frac{\partial C}{\partial w_{jk}^l}(x) = a_k^{l-1} \delta_j^l(x)$ .
2. **Gradient Descent.** For  $L \leq l \leq 2$ , set  $w^l = w^l - \frac{\eta}{m} \sum_x \delta^l(x) (a^{l-1}(x))^\top$  and  $b^l = b^l - \frac{\eta}{m} \sum_x \delta^l(x)$ .

# Chapter 3

## Improving the Way Neural Networks Learn

### 3.1 The Cross-Entropy Cost Function

**Exercise 3.1.** Show that the cross-entropy function is minimized when  $\sigma(z) = y$  for all inputs.

*Solution.* The cross-entropy function is defined as:

$$C = -\frac{1}{m} \sum_{i=1}^m [y_i \ln(a_i) + (1 - y_i) \ln(1 - a_i)],$$

where the  $y_i$ s are fixed and the  $a_i$ s are the “variables.” Now  $\partial C / \partial a_i$  is given by:

$$\frac{\partial C}{\partial a_i} = \frac{1}{m} \frac{a_i - y_i}{a_i(1 - a_i)}.$$

At an extremum point of  $C$ , each component of the gradient  $\nabla_a C$  will be zero. This happens when  $a_i = y_i$  for all  $1 \leq i \leq m$ .

As a side note, the function  $H(y) = -[y \ln(y) + (1 - y) \ln(1 - y)]$  for  $y \in (0, 1)$  is called the binary entropy function and behaves as shown in Figure 3.1. ■

**Exercise 3.2.** Partial derivatives of the cross-entropy cost function in multi-layer networks.

*Solution.* The cross-entropy function for a single training example  $x$  for the last layer  $L$  of the network is defined as:

$$C(x) = -\sum_j [y_j \ln(a_j^L) + (1 - y_j) \ln(1 - a_j^L)],$$

where the sum is over all neurons  $j$  in layer  $L$ . To recap notation,

$$a_j^L = \sigma(z_j^L) = \sum_k w_{jk}^L a_k^{L-1} + b_j^L.$$





Figure 3.1: The Binary Entropy Function

For this training example  $x$ ,

$$\begin{aligned} \frac{\partial C(x)}{\partial z_j^L} &= -\frac{y_j}{a_j^L} \cdot \sigma'(z_j^L) + \frac{1-y_j}{1-a_j^L} \cdot \sigma'(z_j^L) \\ &= \frac{-y_j + y_j a_j^L + a_j^L - y_j a_j^L}{a_j^L(1-a_j^L)} \cdot \sigma'(z_j^L) \\ &= a_j^L - y_j. \end{aligned}$$

The last equality follows since  $\sigma'(z_j^L) = a_j^L(1-a_j^L)$ .

Again, for this single training example  $x$ ,  $\partial C(x)/\partial w_{jk}^L$  is given by:

$$\begin{aligned} \frac{\partial C(x)}{\partial w_{jk}^L} &= \frac{\partial C}{\partial z_j^L} \cdot \frac{\partial z_j^L}{\partial w_{jk}^L} \\ &= (a_j^L - y_j) \cdot a_k^{L-1}. \end{aligned}$$

For  $n$  training examples, the cost function is defined as  $\frac{1}{n} \sum_x C(x)$  and this derivative is:

$$\frac{\partial C}{\partial w_{jk}^L} = \frac{1}{n} \sum_x a_k^{L-1} (a_j^L - y_j).$$

If we were to replace  $C(x)$  by the usual quadratic cost  $\frac{1}{2}(y_j - a_j^L)^2$ , then the same derivative would have been:

$$\frac{1}{n} \sum_x a_k^{L-1} (a_j^L - y_j) \cdot \sigma'(z_j^L).$$

■

### 3.1.1 Deriving the Cross-Entropy Function

Given a single neuron with  $r$  input weights  $w_1, \dots, w_r$  and bias  $b$ , and a single input  $\mathbf{x} = (x_1, \dots, x_r)^T$ , we would like the cost function  $C$  to depend on the weights and the bias as follows:

$$\frac{\partial C}{\partial w_j} = x_j(a - y) \quad (3.1)$$

$$\frac{\partial C}{\partial b} = a - y, \quad (3.2)$$

where  $a = \sigma(\sum_j w_j x_j + b)$  and  $y$  is the desired output corresponding to  $\mathbf{x}$ .

Using the chain rule, we obtain:

$$\begin{aligned} \frac{\partial C}{\partial b} &= \frac{\partial C}{\partial a} \cdot \frac{\partial a}{\partial z} \cdot \frac{\partial z}{\partial b} \\ &= \frac{\partial C}{\partial a} \cdot \sigma'(z) \\ &= \frac{\partial C}{\partial a} \cdot a(1 - a) \end{aligned} \quad (3.3)$$

From equations (3.2 and 3.3), we obtain:

$$\frac{\partial C}{\partial a} = \frac{a - y}{a(1 - a)} = \frac{1}{1 - a} - y \left( \frac{1}{1 - a} + \frac{1}{a} \right).$$

Integrating both sides wrt  $a$ , we obtain:

$$C = -[(1 - y) \ln(1 - a) + y \ln(a)] + \text{a constant}.$$

## 3.2 Softmax

Consider a classification problem, where labelled examples take the form  $(\mathbf{x}, \mathbf{y})$ , where  $\mathbf{x} \in \mathbb{R}^m$  and  $\mathbf{y} \in \{0, 1\}^J$  denotes to which of the  $J$  classes  $\mathbf{x}$  belongs to. In such cases, it makes sense to have the last layer of the neural network to have  $J$  neurons with the softmax activation:

$$\begin{aligned} z_j^L &= \sum_k w_{jk}^L a_k^{L-1} + b_j \\ a_j^L &= \frac{e^{z_j^L}}{\sum_{i=1}^J e^{z_i^L}} \end{aligned}$$

The cost associated with the input  $(\mathbf{x}, \mathbf{y})$  where  $y_r = 1$  is defined as the negative log-likelihood of the activation  $a_r^L$ :

$$C(\mathbf{x}, \mathbf{y}) = -\ln a_r^L.$$

The partial derivatives  $\partial C / \partial b_j^L$  and  $\partial C / \partial w_{jk}^L$  can be computed easily as follows. Depending on whether the index  $j$  and the class index  $r$  are the same or not, we have two cases for each partial derivative.

$$\frac{\partial C}{\partial b_r^L} = -\frac{1}{a_r^L} \cdot \left[ \frac{e^{z_r^L}}{\sum_{i=1}^J e^{z_i^L}} - \left( \frac{e^{z_r^L}}{\sum_{i=1}^J e^{z_i^L}} \right)^2 \right] = -1 + a_r^L \quad (3.4)$$

$$\frac{\partial C}{\partial b_j^L} = -\frac{1}{a_r^L} \cdot \left[ 0 - \frac{e^{z_r^L} e^{z_j^L}}{(\sum_{i=1}^J e^{z_i^L})^2} \right] = a_j^L. \quad (3.5)$$

The first equation is when the index  $r = j$  and the second when  $r \neq j$ . These two expressions can be summarized into one:

$$\frac{\partial C}{\partial b_j^L} = a_j^L - y_j. \quad (3.6)$$

Similarly, the partial derivative expression for  $\partial C / \partial w_{jk}^L$  can be written as:

$$\frac{\partial C}{\partial w_{jk}^L} = a_k^{L-1} \cdot (a_j^L - y_j). \quad (3.7)$$