

1. We mentioned in the lecture that the perceptron (pp. 8 of back propagation) with a loss function of  $J(\mathbf{w}) = |z_k d_k| - z_k d_k$  can be trained with the following updating rule:

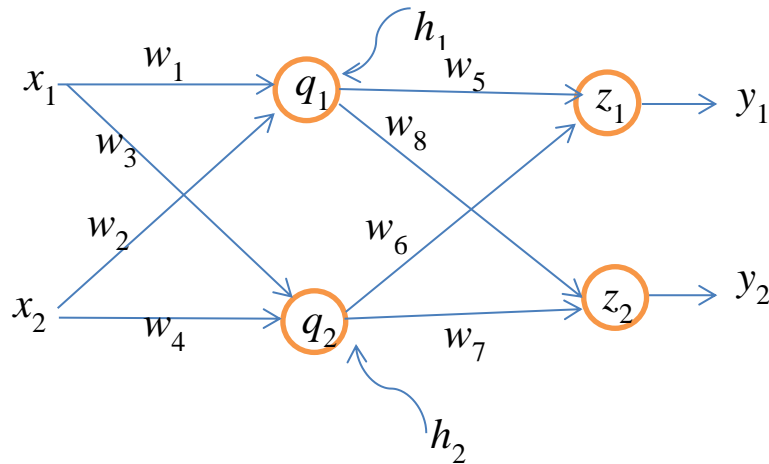
$$\mathbf{w}(k+1) = \mathbf{w}(k) + \begin{cases} 0, & \text{if } z_k d_k > 0 \\ \eta \mathbf{x}_k d_k, & \text{otherwise} \end{cases}$$

Show that this algorithm is directly derived from the stochastic gradient descent algorithm.

2. For the neural network given below, let  $w_1 = 2.0$ ,  $w_2$  to  $w_8$  be 1.0,  $d_1 = 1.0$ ,  $d_2 = 0.0$ ,  $\eta = 0.1$ ,  $x_1 = 1.0$ , and  $x_2 = -1.0$ . The activation function from  $q_1$  to  $h_1$  and  $q_2$  to  $h_2$  is ReLU, the activation function at the output nodes is linear (i.e.,  $y = z$ ), and the cost function is

$$J = \frac{1}{2} \sum_{i=1}^2 (y_i - d_i)^2.$$

- (i) Find  $y_1$  and  $y_2$  (forward computation).
- (ii) Find the value of  $\Delta w_1 = \eta \frac{\partial J}{\partial w_1}$  by using the BP algorithm.



3. Prove the following statement: The derivative of the softmax activation function has the following form

$$\frac{\partial}{\partial z_i} y_\ell = \begin{cases} y_\ell(1 - y_\ell), & \text{if } i = \ell \\ -y_\ell y_i, & \text{if } i \neq \ell \end{cases}$$

4. Reproduce the MSE plot on pp. 9 of the 23\_Cost functions. The input is 1.0, initial weight  $w = 2.0$ , bias  $b = 2.0$ ,  $\eta = 0.15$ , and desired output is 0.0. Because this problem is simple, you can manually compute the updating equations for  $w(k+1)$  and  $b(k+1)$ , and write a hard-coded program without using a library, such as Keras.

5. Implement a perceptron with the learning rule given in Problem 1 to classify the classes of virginica and Versicolor in the Iris dataset. Use a bias term in the perceptron to make it a linear binary classifier. As usual, take 70% of the samples as the training set and then report the average accuracy after 10 trials. You need to determine a suitable value of  $\eta$  and the number of training epochs.