

# Machine Learning Course 2024 Spring: Homework 3

April 28, 2024

## 1 Problem 1

Consider the following multi-layer neural network (Figure 1) which includes an input layer, one hidden layer, and an output layer, containing  $d, n, q$  neurons respectively. The parameters between the input layer and the hidden layer are  $\mathbf{W}_1 \in \mathbb{R}^{d \times n}$ ,  $\mathbf{b}_1 \in \mathbb{R}^n$ , and the parameters between the hidden layer and the output layer are  $\mathbf{W}_2 \in \mathbb{R}^{n \times q}$ ,  $\mathbf{b}_2 \in \mathbb{R}^q$ . Where  $\mathbf{W}_1, \mathbf{W}_2$  are the weight matrices and  $\mathbf{b}_1, \mathbf{b}_2$  are the bias vectors.

Let us first compute the forward propagation. Let  $\mathbf{x} = [x_1, x_2, \dots, x_d]^\top \in \mathbb{R}^d$  be the input. The hidden layer is computed as follows:

$$\mathbf{h} = \mathbf{W}_1^\top \mathbf{x} + \mathbf{b}_1 \in \mathbb{R}^n \quad (1.1)$$

Then the ReLU activation function is applied to Eq.(1.1):

$$\mathbf{a} = \text{ReLU}(\mathbf{h}) \in \mathbb{R}^n \quad (1.2)$$

The output layers' activation is obtained using the following transformation

$$\mathbf{z} = \mathbf{W}_2^\top \mathbf{a} + \mathbf{b}_2 \in \mathbb{R}^q \quad (1.3)$$

Finally, the soft-max function is applied to Eq.(1.3) to obtain the probability for each category.

$$\hat{\mathbf{y}} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \vdots \\ \hat{y}_q \end{bmatrix} = \text{Softmax}(\mathbf{z}) = \begin{bmatrix} \text{Softmax}(z_1) \\ \text{Softmax}(z_2) \\ \vdots \\ \text{Softmax}(z_q) \end{bmatrix} = \begin{bmatrix} \frac{\exp(z_1)}{\sum_{k=1}^q \exp(z_k)} \\ \frac{\exp(z_2)}{\sum_{k=1}^q \exp(z_k)} \\ \vdots \\ \frac{\exp(z_q)}{\sum_{k=1}^q \exp(z_k)} \end{bmatrix} \in \mathbb{R}^q \quad (1.4)$$

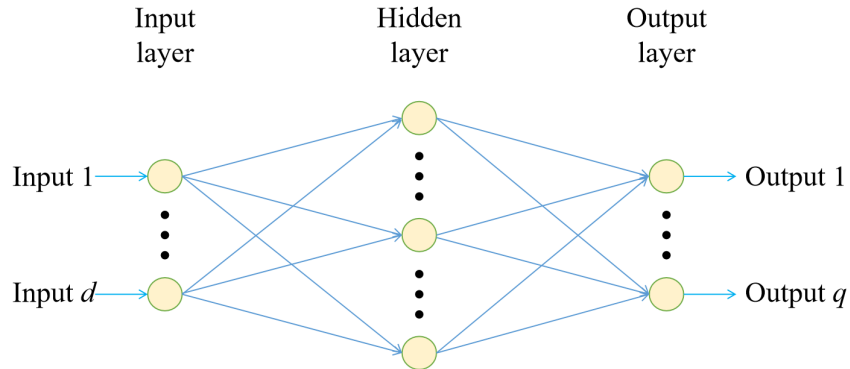


Figure 1: Neural Network

Here,  $\hat{y}_i, z_i$  is the  $i$ -th element of  $\hat{\mathbf{y}}, \mathbf{z}$ , and  $\hat{\mathbf{y}}$  is the predicted output by the feed-forward neural network.

Your task is to compute the derivatives of the Cross-Entropy loss function given in Eq.(1.5) with respect to  $\mathbf{W}_1, \mathbf{W}_2, \mathbf{b}_1, \mathbf{b}_2$  by hand, i.e.,

$$\frac{\partial \text{Loss}}{\partial \mathbf{W}_1}, \frac{\partial \text{Loss}}{\partial \mathbf{W}_2}, \frac{\partial \text{Loss}}{\partial \mathbf{b}_1}, \frac{\partial \text{Loss}}{\partial \mathbf{b}_2}. \quad (1.5)$$

$$\text{Loss} = - \sum_{i=1}^q y_i^s \ln(\hat{y}_i).$$

Here,  $y_i^s = (1 - \epsilon)y_i + \frac{\epsilon}{q}$  is the soft label via label smoothing, where  $\epsilon$  is a small constant.  $y_i \in \{0, 1\}$  is the ground-truth indicator,  $\hat{y}_i$  is the  $i$ -th element of  $\hat{\mathbf{y}}$ .

Show all the intermediate derivative computation steps. You might benefit from making a rough schematic of the back-propagation process.

## 2 Problem 2

Consider a simple practical case with only one input instance:  $\mathbf{x} = [0, 2]^\top \in \mathbb{R}^2, \mathbf{y} = [1, 0, 0]^\top \in \mathbb{R}^3; d = 2, n = 3$  and  $q = 3$ . The initial values of the parameters are listed below:

$$\begin{aligned}
\mathbf{W}_1 &= \begin{bmatrix} -5 & 2 & 2 \\ -5 & 2 & -1 \end{bmatrix} \in \mathbb{R}^{2 \times 3}, & \mathbf{b}_1 &= \begin{bmatrix} -3 \\ -2 \\ -3 \end{bmatrix} \in \mathbb{R}^3, \\
\mathbf{W}_2 &= \begin{bmatrix} 3 & -4 & 1 \\ -2 & -4 & -2 \\ -4 & -2 & 3 \end{bmatrix} \in \mathbb{R}^{3 \times 3}, & \mathbf{b}_2 &= \begin{bmatrix} 4 \\ 5 \\ 5 \end{bmatrix} \in \mathbb{R}^3.
\end{aligned} \tag{2.1}$$

Your task is to compute the updated value of the parameters  $\mathbf{W}_1$ ,  $\mathbf{W}_2$ ,  $\mathbf{b}_1$ , and  $\mathbf{b}_2$  after one step of Gradient Descent ( $\theta^{t+1} \leftarrow \theta^t - \eta \cdot \nabla_{\theta} \text{Loss}$ ) for  $\epsilon = 0.3$  and  $\eta = 0.1$ .

Use the intermediate computation you derived from Problem 1. You might benefit from performing the feed-forward process first and then the back-propagation process. You can use a calculator or write code to do the calculations.