2. Back-propagation Algorithm

Bookmark this page

Exercises due Mar 29, 2023 08:59 -03 Completed

Back-propagation Algorithm

0:00 / 0:00 1.0x

Video

Download video file

Transcripts

Download SubRip (.srt) file

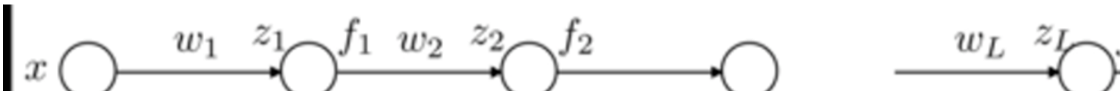
Download Text (.txt) file

Once we set up the architecture of our (feedforward) neural network, our goal will be t
that minimize our loss function. We will use the **stochastic gradient descent algorithm**
Lecture 4 and revisited in lecture 5) to carry out the optimization.

This involves computing the gradient of the loss function with respect to the weight pa

Since the loss function is a long chain of compositions of activation functions with the
entering at different stages, we will break down the computation of the gradient into di
chain rule; this way of computing the gradient is called the back-propagation algorithm

In the following problems, we will explore the main step in the stochastic gradient desc
training the following simple neural network from the video:



Gradient Descent Update

1/1 point (graded)

Let η be the learning rate for the stochastic gradient descent algorithm.

Recall that our goal is to tune the parameters of the neural network so as to minimize th
of the following is the appropriate update rule for the paramter w_1 in the stochastic gra

☑ $w_1 \leftarrow w_1 - \eta \cdot \nabla_{w_1} \mathcal{L}(y, f_L)$

☐ $w_1 \leftarrow w_1 + \eta \cdot \nabla_{w_1} \mathcal{L}(y, f_L)$

☐ $w_1 \leftarrow \eta \cdot \nabla_{w_1} \mathcal{L}(y, f_L)$

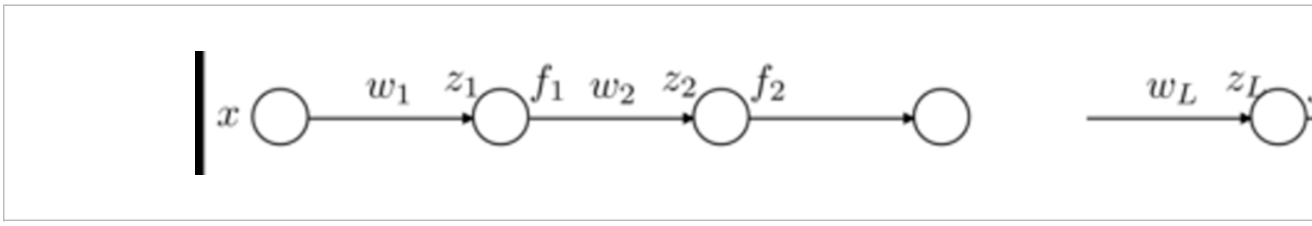
☐ $w_1 \leftarrow -\eta \cdot \nabla_{w_1} \mathcal{L}(y, f_L)$

✓

Submit You have used 1 of 2 attempts

Recursive Expression - Part I

1/1 point (graded)



As above, let $\mathcal{L}(y, f_L)$ denote the loss function as a function of the predictions f_L and the

$$\begin{aligned} z_1 &= x w_1 \\ \text{for } i = 2 \ldots L: \quad z_i &= f_{i-1} w_i \quad \text{where } f_{i-1} = f(z_{i-1}). \end{aligned}$$

Let $\delta_i = \dfrac{\partial \mathcal{L}}{\partial z_i}$.

The first step to updating any weight w is to calculate $\dfrac{\partial \mathcal{L}}{}$

✓

Submit You have used 2 of 2 attempts

Recursive Expression - Part II

1/1 point (graded)

As above, let $\mathcal{L}(y, f_L)$ denote the loss function as a function of the predictions f_L and the

.

In this problem, we derive a recurrence relation between δ_i and δ_{i+1}

Assume that f is the hyperbolic tangent function:

$$\begin{aligned} f(x) &= \tanh(x) \\ f'(x) &= (1 - \tanh^2(x)). \end{aligned}$$

Which of the following option is the correct expression for δ_1 in terms of δ_2?

● $\delta_1 = (1 - f_1^2) \cdot w_2 \cdot \delta_2$

○ $\delta_1 = (1 - f_1^2) \cdot w_1 \cdot \delta_2$

○ $\delta_1 = (1 - f_2^2) \cdot w_2 \cdot \delta_2$

○ $\delta_2 = (1 - f_1^2) \cdot w_2 \cdot \delta_1$

✓

Submit You have used 2 of 2 attempts

Final Expression of the Gradient

1/1 point (graded)

● $\frac{\partial \mathcal{L}}{\partial w_1} = x(1 - f_1^2)(1 - f_2^2)\cdots(1 - f_L^2)w_2w_3\cdots w_L(2(f_L - y))$

○ $\frac{\partial \mathcal{L}}{\partial w_1} = xw_2w_3\cdots w_L(2(f_L - y))$

✓

Submit You have used 1 of 2 attempts

Discussion

Previous

Next

Topic: Unit 3. Neural networks (2.5 weeks):Lecture 9. Feedforward Neural Networks, Back Propagation, and Stochastic Gradient Descent (SGD) / 2. Back-propagation Algorithm