

2021/02/09

Exercise 3

Given an input $\mathbf{x} \in \mathbb{R}^2$, a weight vector $\mathbf{w} \in \mathbb{R}^2$ and a bias $b_0 \in \mathbb{R}$, draw the computational graph for the computation of the mean squared error $L = MSE(\hat{y}, y)$ of a prediction $\hat{y} = \sigma(\mathbf{w}^T \mathbf{x} + b_0)$ with respect to the true value y ; σ is the sigmoid function.

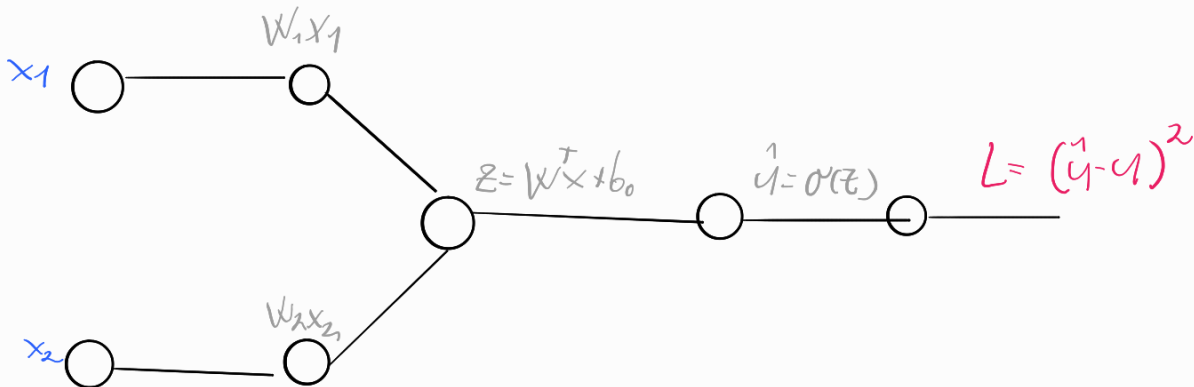
Consider the following values for $\mathbf{x}, \mathbf{w}, b_0$ and y :

$$\mathbf{x} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \quad \mathbf{w} = \begin{bmatrix} \frac{4}{5} \\ \frac{7}{5} \end{bmatrix}, \quad b_0 = \frac{3}{5}, \quad y = 1, \quad (3)$$

and the MSE function $L = (\hat{y} - y)^2$. Report the corresponding values on the computational graph.

Explain how the backpropagation method can be used to compute the gradient of L with respect to the inputs.

Draw the computational graph for the computation of the gradient and calculate the gradients values for each edge and node in the computational gradient graph.



$$\begin{aligned} x_1 &= 1 & z &= \frac{4}{5} + \frac{7}{5} + \frac{3}{5} = \frac{14}{5} \\ x_2 &= 1 & \hat{y} &= \sigma\left(\frac{14}{5}\right) \approx 0,94 \\ w_1 x_1 &= \frac{4}{5} \cdot 1 & L &= (0,94 - 1)^2 = 0,06 \approx 0,003 \\ w_2 x_2 &= \frac{7}{5} \cdot 1 \end{aligned}$$

Forward Pass

Backpropagation derive $\dot{v} = \frac{\partial L}{\partial v}$

$$\frac{\partial L}{\partial \hat{y}} = 2(\hat{y} - y) = 2(0,94 - 1) = -0,12$$

$$\frac{\partial \hat{y}}{\partial z} = \sigma(z) (1 - \sigma(z)) = \hat{y} (1 - \hat{y}) = 0,05$$

$$\frac{\partial L}{\partial z} = \frac{\partial L}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial z} = -0,12 \cdot 0,05 = -0,06$$

$$\frac{\partial z}{\partial w_1} = x_1 = 1 \rightarrow \frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial z} \cdot \frac{\partial z}{\partial w_1} = -0,06$$

$$\frac{\partial z}{\partial w_2} = x_2 = 1 \rightarrow \frac{\partial L}{\partial w_2} = \frac{\partial L}{\partial z} \cdot \frac{\partial z}{\partial w_2} = -0,06$$

$$L = (\hat{y} - y)^2$$

$$\uparrow \frac{\partial L}{\partial \hat{y}} = 2(\hat{y} - y)$$

$$\hat{y} = \sigma(z)$$

$$\uparrow \frac{\partial \hat{y}}{\partial z} = \sigma(z) (1 - \sigma(z))$$

$$z = w^T x + b_0$$

$$\begin{array}{c} \nearrow \frac{\partial z}{\partial w_1} = x_1 \\ w_1 \end{array} \quad \begin{array}{c} \frac{\partial z}{\partial w_2} = x_2 \\ w_2 \end{array} \quad \begin{array}{c} \nearrow \frac{\partial z}{\partial b_0} = 1 \\ b_0 \end{array}$$