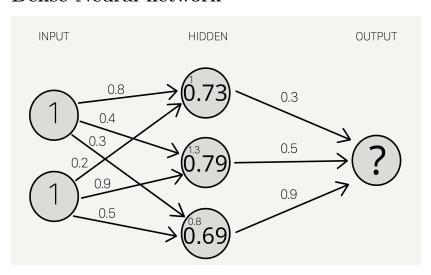
Dense Neural network



Instructions

- Complete the forward computation, given that the activation function is a sigmoid: $\frac{1}{1+e^{-x}}$.
- Calculate the mean square error $(E\left[(\hat{\theta}-\theta)^2\right])$ of the model, given that the expected output is 1.
- Determine the contribution of each node to the error.
- Update the weights using backpropagation, with the derivative of the sigmoid function given by $\operatorname{sig}'(x) = \operatorname{sig}(x)(1 \operatorname{sig}(x))$ and a learning rate $\lambda = 1$.
- Perform the forward pass with the updated weights and draw conclusions from the results.
- Identify if we applied gradient descent or stochastic gradient descent.
- Explain the difference between gradient descent with momentum and without momentum.

Solution

Notation:

× : Matrix multiplication∘ : Hadamard product

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$$W1 \times L1 = \begin{bmatrix} 0.8 & 0.2 \\ 0.4 & 0.9 \\ 0.3 & 0.5 \end{bmatrix} \times \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 1.3 \\ 0.8 \end{bmatrix} = l2$$

$$L2 = \begin{bmatrix} sig(1) \\ sig(1.3) \\ sig(0.8) \end{bmatrix} = \begin{bmatrix} 0.73 \\ 0.79 \\ 0.69 \end{bmatrix}$$

$$W2 \times L2 = \begin{bmatrix} 0.3 & 0.5 & 0.9 \end{bmatrix} \times \begin{bmatrix} 0.73 \\ 0.79 \\ 0.69 \end{bmatrix} = \begin{bmatrix} 1.24 \end{bmatrix} = l3$$

$$L3 = sig(l3) = [sig(1.24)] = [0.78]$$

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$$\operatorname{ErrL3} = \frac{\left[(0.78 - 1)^2\right]}{1} = 0.22$$

• contribNorm(W2^T)=
$$\begin{bmatrix} \frac{0.3}{0.3+0.5+0.9} \\ \frac{0.5}{0.3+0.5+0.9} \\ \frac{0.9}{0.3+0.5+0.9} \end{bmatrix} = \begin{bmatrix} 0.18 \\ 0.29 \\ 0.53 \end{bmatrix}$$

$$\begin{aligned} & \text{ErrL2= contribNorm}(W2^T) \times \text{ErrL3} = \begin{bmatrix} 0.04 \\ 0.06 \\ 0.11 \end{bmatrix} \\ & \text{contribNorm}(W1^T) = \begin{bmatrix} \frac{0.8}{0.8+0.2} & \frac{0.4}{0.4+0.9} & \frac{0.3}{0.3+0.5} \\ \frac{0.2}{0.8+0.2} & \frac{0.9}{0.4+0.9} & \frac{0.5}{0.3+0.5} \end{bmatrix} = \begin{bmatrix} 0.8 & 0.31 & 0.375 \\ 0.2 & 0.61 & 0.625 \end{bmatrix} \\ & \text{ErrL1= contribNorm}(W1^T) \times \text{ErrL2} = \begin{bmatrix} 0.06 \\ 0.11 \end{bmatrix} \end{aligned}$$

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$$\operatorname{sig'(l3)=L3\circ(1-L3)=[0.78](1-[0.78])=[0.17]}$$

 $\operatorname{NewW2}^T = \operatorname{W2}^T + \lambda \operatorname{L2} \times (\operatorname{ErrL3\circ sig'(l3)})^T$

$$= \begin{bmatrix} 0.3 \\ 0.5 \\ 0.9 \end{bmatrix} + \lambda \begin{bmatrix} 0.73 \\ 0.79 \\ 0.69 \end{bmatrix} ([0.22] \circ [0.17])^{T}$$

$$= \begin{bmatrix} 0.3 \\ 0.5 \\ 0.9 \end{bmatrix} + \lambda \begin{bmatrix} 0.73 * 0.04 \\ 0.79 * 0.04 \\ 0.69 * 0.04 \end{bmatrix}$$

$$= \begin{bmatrix} 0.3 \\ 0.5 \\ 0.9 \end{bmatrix} + \lambda \begin{bmatrix} 0.03 \\ 0.03 \\ 0.03 \end{bmatrix}$$

$$= \begin{bmatrix} 0.33 \\ 0.53 \\ 0.93 \end{bmatrix}$$

$$\begin{split} & \operatorname{sig'(l2)} = \operatorname{L2\circ(1\text{-}L2)} = \begin{bmatrix} 0.20 \\ 0.17 \\ 0.23 \end{bmatrix} \\ & \operatorname{NewW1}^T = \operatorname{W1}^T + \lambda \operatorname{L1} \times (\operatorname{ErrL2\circ\operatorname{sig'(l2)}})^T \\ &= \begin{bmatrix} 0.8 & 0.4 & 0.3 \\ 0.2 & 0.9 & 0.5 \end{bmatrix} + \lambda \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{pmatrix} 0.04 \\ 0.06 \\ 0.11 \end{pmatrix} \circ \begin{bmatrix} 0.20 \\ 0.17 \\ 0.23 \end{bmatrix})^T \\ &= \begin{bmatrix} 0.8 & 0.4 & 0.3 \\ 0.2 & 0.9 & 0.5 \end{bmatrix} + \lambda \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 0.04 * 0.20 \\ 0.06 * 0.17 \\ 0.11 * 0.23 \end{bmatrix}^T \\ &= \begin{bmatrix} 0.8 & 0.4 & 0.3 \\ 0.2 & 0.9 & 0.5 \end{bmatrix} + \lambda \begin{bmatrix} 1 \\ 1 \end{bmatrix} \begin{bmatrix} 0.01 & 0.01 & 0.03 \end{bmatrix} \\ &= \begin{bmatrix} 0.8 & 0.4 & 0.3 \\ 0.2 & 0.9 & 0.5 \end{bmatrix} + \lambda \begin{bmatrix} 0.01 & 0.01 & 0.03 \\ 0.01 & 0.01 & 0.03 \end{bmatrix} = \begin{bmatrix} 0.81 & 0.41 & 0.33 \\ 0.21 & 0.91 & 0.53 \end{bmatrix} \end{split}$$

$$NewW1*L1 = \begin{bmatrix} 0.81 & 0.21\\ 0.41 & 0.91\\ 0.33 & 0.53 \end{bmatrix} \times \begin{bmatrix} 1\\1 \end{bmatrix} = \begin{bmatrix} 1.02\\1.32\\0.86 \end{bmatrix} = l2$$

$$\text{L2=} \begin{bmatrix} sig(1.02) \\ sig(1.32) \\ sig(0.86) \end{bmatrix} = \begin{bmatrix} 0.73 \\ 0.79 \\ 0.70 \end{bmatrix}$$

$$\begin{bmatrix} sig(0.86) \end{bmatrix} \quad \begin{bmatrix} 0.70 \end{bmatrix}$$
NewW2*L2= $\begin{bmatrix} 0.33 & 0.53 & 0.93 \end{bmatrix} \times \begin{bmatrix} 0.73 \\ 0.79 \\ 0.70 \end{bmatrix} = \begin{bmatrix} 1.31 \end{bmatrix} = l3$

$$L3 = sig(13) = 0.79$$

We have successfully improved the prediction accuracy by reducing the error from $(0.78 - 1)^2 = 0.05$ to $(0.79 - 1)^2 = 0.04$.

- Gradient descent was used because the batch size is 1. It is not stochastic because it does not rely on batch sampling.
- Gradient Descent with Momentum includes an extra term called momentum, which is a fraction of the previous weight update, this fraction is determined by the momentum factor β . This smooths out the updates, accelerates convergence, and reduces oscillations by enabling the algorithm to maintain its direction and build up speed along the most promising path.