

2. Neural Network Basics (2)

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3. $\frac{\partial J}{\partial x}$?

$$\begin{cases} J = CE(y, \hat{y}) \\ \hat{y} = \text{softmax}(hW_2 + b_2) \\ h = \sigma(xW_1 + b_1) \end{cases} \quad \begin{array}{l} \nearrow \text{let's say this as } z_2 \\ \nwarrow \end{array}$$

$$\frac{\partial (CE(y, \hat{y}))}{\partial x} = \frac{\partial (CE(y, \hat{y}))}{\partial z_2} \cdot \frac{\partial z_2}{\partial x}$$

$$= (\hat{y} - y) \cdot \frac{\partial z_2}{\partial x} \quad (\because \text{softmax})$$

$$= (\hat{y} - y) \cdot \frac{\partial z_2}{\partial h} \cdot \frac{\partial h}{\partial x}$$

$$= (\hat{y} - y) W_2^T \cdot \frac{\partial h}{\partial x}$$

$$= \left[(\hat{y} - y) W_2^T \right] \circ \left[h(1-h) \right] \cdot W_1^T \quad : M \times D_x$$

$$(cf) \quad \begin{cases} y, \hat{y} : M \times D_y \\ x : M \times D_x \\ W_1 : D_x \times H \\ b_1 : 1 \times H \\ h : M \times H \\ W_2 : H \times D_y \\ b_2 : 1 \times D_y \end{cases}$$

4. # of params?

$$\begin{aligned} & n(W_1) + n(W_2) + n(b_1) + n(b_2) \\ &= (D_x \times H) + (H \times D_y) + (H) + (D_y) \end{aligned}$$

5. (programming part - sigmoid implementation)

6. (programming part - gradient checker)

< Central difference approximations >

$$f'(x) \approx \frac{f(x+h) - f(x-h)}{2h}$$

매우 작은 $h > 0$ 를 이용해 gradient를 수치적으로 근사가능.

근사할 때 chain rule을 써서 gradient와

차이값을 계산해서 gradient를 써서 구현한지 여부를 check가능.

7. (programming part - neural net)