

Lecture 10

Back propagation

Sol 1, 2, 3

Q1: 11:30 Thu 2/12

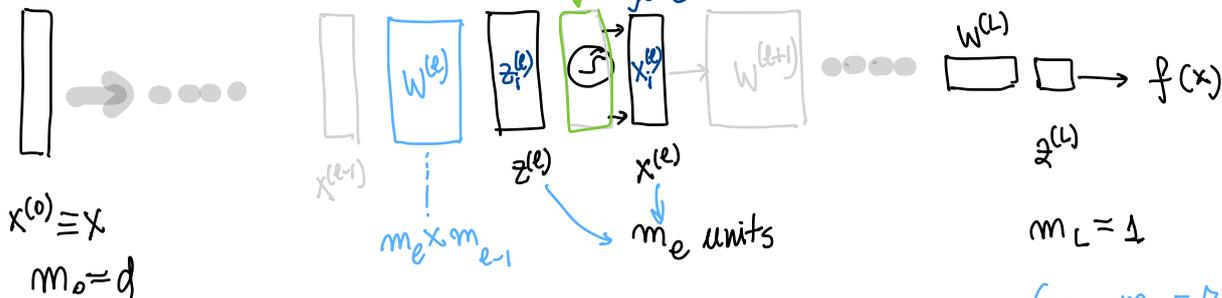
15 min

LIV-2 TPosted

[HW 4 out]

Backpropagation

Training a multi-layer network



Parameters $W = \{ W^{(1)}, \dots, W^{(L)} \}$ to train

Data $\mathcal{D} = \{ (x^i, y^i), i = 1:n \}$

TRAIN: by Gradient Descent on loss \mathcal{L}

1. Init W with small random values

2. for $t = 1, 2, \dots$
 $W \leftarrow W - \eta \frac{\partial \mathcal{L}(W^t)}{\partial W}$
step size η

$$W_{ij}^{(l)} \sim N(0, \sigma^2 \frac{1}{m_l})$$

σ^2 small

(or $m_L = r$ for r -way classification)

y_i, x_i^j ← training ex. i

$x_i^{(l)}$ ← layer l

x_i^j units

$x^{(0)}_i$ = input value
 2nd attribute
 i th example

Single unit (layer L)

$$z \equiv f \equiv w^{(L)T} \cdot x^{(L)}$$

$$W = \{w\} \quad w \in \mathbb{R}^d$$

$$d = \frac{1}{2} (y - f_w(x))^2 \quad \Rightarrow \quad \frac{\partial d}{\partial f} = f - y = -(y - f)$$

target - output

other d : $y \rightarrow y_*$
 $f \Rightarrow \varphi_{\text{out}}(z)$

$$\frac{\partial d}{\partial f} = -(y_* - \varphi_{\text{out}}) \Rightarrow f = \varphi_{\text{out}}(z)$$

Chain Rule:

$$n=1 \quad (x, y) = \mathcal{D}$$

$$\frac{\partial f}{\partial z} = \varphi'_{\text{out}}(z)$$

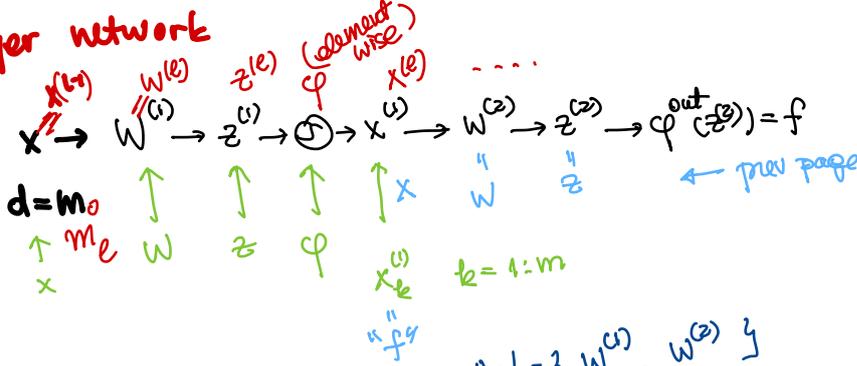
$$\frac{\partial z}{\partial w} = x$$

$$z = w^T x$$

$$\frac{\partial z}{\partial x} = w$$

$$\frac{\partial d}{\partial w} = \frac{\partial d}{\partial f} \cdot \frac{\partial f}{\partial z} \cdot \frac{\partial z}{\partial w} = -(y_* - \varphi_{\text{out}}) \cdot \varphi'_{\text{out}}(z) \cdot x$$

2 layer network



Chain Rule:

$$\frac{\partial f}{\partial z^{(2)}} = \phi'_{out}(z^{(2)})$$

$$\frac{\partial z^{(2)}}{\partial W^{(2)}} = X^{(1)}$$

$$\frac{\partial z^{(2)}}{\partial X^{(1)}} = W^{(2)}$$

$$z = W^T x$$

$$\frac{\partial L}{\partial W^{(2)}} = \frac{\partial L}{\partial f} \cdot \frac{\partial f}{\partial z^{(2)}} \cdot \frac{\partial z^{(2)}}{\partial W^{(2)}} = -(y_{\text{tar}} - \phi_{out}) \cdot \phi'_{out}(z^{(2)}) \cdot X^{(1)}$$

$$\frac{\partial x_k^{(1)}}{\partial z_k^{(1)}} = \phi'(z_k^{(1)})$$

$$\frac{\partial x_k^{(1)}}{\partial z_k^{(1)}} = \phi'(z_k^{(1)}) \in \mathbb{R}^m$$

$$z_k^{(1)} = W_k^{(1)T} x^{(0)}$$

row k of $W^{(1)}$

$$\frac{\partial z_k^{(1)}}{\partial x_k^{(0)}} = W_k^{(1)}$$

$$\frac{\partial z_k^{(1)}}{\partial x^{(0)}} = X^{(0)}$$

$$\Rightarrow \frac{\partial L}{\partial W_k^{(2)}} = \frac{\partial L}{\partial f} \left[\frac{\partial f}{\partial x_k^{(1)}} \right] \frac{\partial x_k^{(1)}}{\partial z_k^{(1)}} \cdot \frac{\partial z_k^{(1)}}{\partial W_k^{(2)}} = -(y_{\text{tar}} - \phi_{out}) \phi'_{out}(z^{(2)}) \cdot \phi'(z_k^{(1)}) \cdot W_k^{(2)}$$

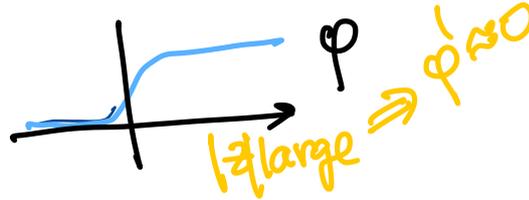
NEW

$$\frac{\partial f}{\partial x^{(l+1)}}$$

$$\frac{\partial f}{\partial x^{(l)}} = \frac{\partial f}{\partial x^{(l+1)}} \cdot \frac{\partial x^{(l+1)}}{\partial x^{(l)}}$$

$$\frac{\partial x_j^{(l+1)}}{\partial x^{(l)}} = \phi'(z_j^{(l+1)}) \cdot \frac{\partial z_j^{(l+1)}}{\partial x^{(l)}} = \phi'(z_j^{(l+1)}) \cdot W_j^{(l+1)}$$

$$z_j^{(l+1)} = W_j^{(l+1)T} \cdot x^{(l)}$$



$|\phi'| \text{ large} \Rightarrow \phi'$