

# 5/30: Neural Networks (part 1: very basics) Later p2: adv. NN

Recap: Linear Model: Lin Reg, logistic Reg, Perceptron

p3: recurrent

net = linear dot product

$$\langle x, w \rangle$$

$$\text{Error} = \text{OBJ}(w)$$

output  
 $\uparrow$   
 $f(\text{net})$

$$\text{net} = \sum_{d=1}^D x^d w^d$$

NEURON



- $w$  = model weights
- $f$  = linear / identity  $\Rightarrow$  output is linear
  - Lin Reg, - Percep.

- $f$  non linear
  - ex  $f$  = sigmoid / logistic

GD:  $\frac{\partial \text{Error}}{\partial w} \Rightarrow$  update weights to improve Error "back-propagate"  $\Rightarrow$  output  $\neq$  linear the error to weights

Stack of neurons : output of layer = input to next layer.

$t = \text{true labels}$

Error

$$(Z_k - t_k)^2$$

$$Z_k = f(\text{net}_k)$$

$$Z_1 = f(\text{net}_1)$$

layer 2  $\text{net}_1 = \langle y \cdot w_1 \rangle$

$\dots \text{net}_2 = \langle y \cdot w_2 \rangle$

$\text{net}_e = \langle y \cdot w_e \rangle$

$w$  Matrix  
 $w_{kj}$  (k layer, j layer)

$$y_i = f(\text{net}_i)$$

$$y_j = f(\text{net}_j)$$

$$y_H = f(\text{net}_H)$$

layer 1  $\text{net} = \langle x w_1 \rangle$

$\dots \text{net}_j = \langle x \cdot w_j \rangle$

$\dots \text{net}_H = \langle x \cdot w_H \rangle$

$w$  Matrix  
 $w_{ji}$  (layer j, layer i)

$H$  neurons  
index by  $j$



GD update: Error  $\Rightarrow$  update weights

• Start at the top (Error - top layer)  $\frac{\partial \text{Error}}{\partial w} \Rightarrow$  update  $w$  top layer

• move to second layer (from top) backpropagate Error  $\Rightarrow$  update  $w$  on second layer

Simple Network (input - hidden - output layers - error)

OBJ  $J = \frac{1}{2} \sum_k (t_k - z_k)^2 = \sum_k (t_k - f(\text{net}_k))^2 = \sum_k (t_k - f(y \cdot w_k))^2$

top layer

• update weights at top layer  $w_{kj}$

$$\frac{\partial J}{\partial w_{kj}} = \frac{\partial J}{\partial \text{net}_k} \cdot \frac{\partial \text{net}_k}{\partial w_{kj}} = \frac{\partial J}{\partial z_k} \cdot \frac{\partial z_k}{\partial \text{net}_k} \cdot \frac{\partial (y \cdot w_k)}{\partial w_{kj}}$$

$$= (z_k - t_k) \cdot \boxed{\frac{\partial f}{\partial \text{net}_k}} \cdot y_j$$

$f'(\text{net}_k)$

$f =$  non linear activator

GD update

$w_{kj}(\text{new}) = w_{kj} - \overset{\text{learn rate}}{\lambda} (z_k - t_k) f'(\text{net}_k) \cdot y_j$

• update the bottom layer  $w_{ji}$

$$\frac{\partial J}{\partial w_{ji}} = \frac{\partial J}{\partial y_j} \cdot \frac{\partial y_j}{\partial \text{net}_j} \cdot \boxed{\frac{\partial \text{net}_j}{\partial w_{ji}}} \quad \frac{\partial (x \cdot w_j)}{\partial w_{ji}}$$

$$\frac{\partial \frac{1}{2} \left[ \sum_k (t_k - z_k)^2 \right]}{\partial y_j} \quad \downarrow \quad f'(\text{net}_j) \quad \downarrow \quad x_i$$

$$- \sum_k (t_k - z_k) \cdot \boxed{\frac{\partial z_k}{\partial \text{net}_k}} \cdot \boxed{\frac{\partial \text{net}_k}{\partial y_j}} \cdot \frac{\partial (y \cdot w_k)}{\partial y_j} \quad f'(\text{net}_j) \cdot x^i$$

$$\quad \quad \quad f'(\text{net}_k) \quad \quad \quad = w_{jk}^k$$

$$- \left[ \sum_k (t_k - z_k) f'(\text{net}_k) \cdot w_{jk}^k \right] \quad \cdot \quad f'(\text{net}_j) \cdot x^i$$

GD update  $w_{ji}(\text{new}) = w_{ji} + \lambda \left[ \sum_k (t_k - z_k) f'(\text{net}_k) w_{jk}^k \right] \cdot f'(\text{net}_j) \cdot x^i$