

## Week 8 Neural Net

define neural net: Rather than placing basis functions by hand,  
pick the family of basis functions, “learn” the locations and any other  
parameters from data

Regularization: L2, L1, input noise (data aug), dropout, batch norm, skip connection,  
early stopping

Train more epoch: could be seen as model getting more complex (weights larger,  
decision boundary more complex)  
train & val loss w.r.t epoch VS # of parameters

### Adaptive unit:

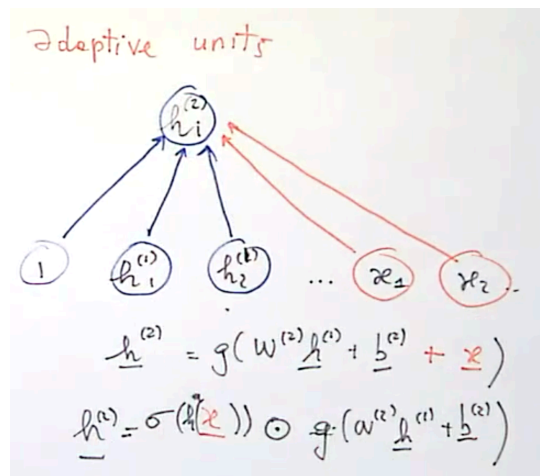
Skip connection but put  $x$  inside activation (make sure dimension match)

=> input participate into this transformation

e.g. hidden units depends on input; want input being processed by all hidden  
layers

OR:

=> input activate the layer (set layer as 1 or 0 using sigmoid)

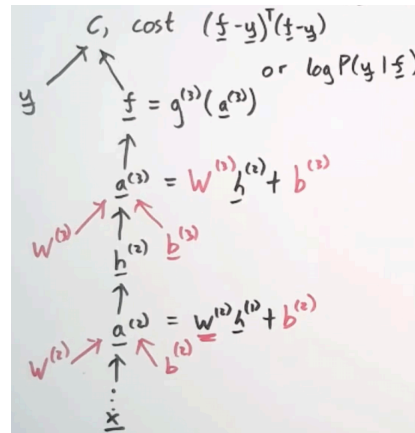
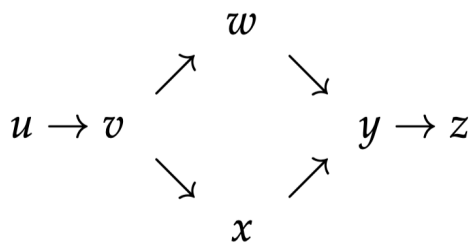


### Forward Prop:

have a Directed Acyclic Graph (DAG), e.g.:

OR right graph: Cost  $C$  depends on training labels  $y$  & neural net functions  $f$   
activation  $a$  depends on  $w$  and  $b$ ...

$$z = \exp(\sin(u^2) \log(u^2))$$



Forward derivative  $\theta^{\cdot}$ : any intermediate quantity  $\theta$  w.r.t leftmost element  $u$   
 from left to right  
 = derivatives of the elementary function used at that stage \* already computed value (use the chain rule)

$$\dot{\theta} = \frac{\partial \theta}{\partial u}$$

### Back Prop:

from right to left  
 any intermediate quantity  $\theta$  **w.r.t final value  $z$**   
 use the chain rule (this = derivative of current function \* already calculated)

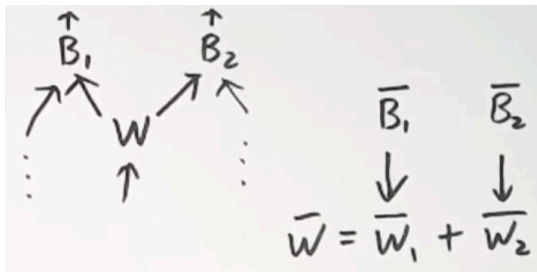
$$\bar{\theta} = \frac{\partial z}{\partial \theta}$$

If  $Z$  is a matrix:

derivative of cost  $c$  (final element) w.r.t every elements  $i, j$  in matrix  $Z$   
 (or represent derivative via matrices)

$$\bar{Z}_{ij} = \frac{\partial c}{\partial Z_{ij}}$$

when have multiple children (to final cost  $C$ ) (e.g. at point  $v$ )  
 do BP individually, add those up



Forward derivative at rightmost node = backward derivative at leftmost node

$$\dot{z} = \bar{u} = \frac{\partial z}{\partial u}$$

**Goal** of BP: Neural net fitting wants derivative of final cost  $c$ , w.r.t all free parameters in the graph  $(a, h, w, b)$ ,

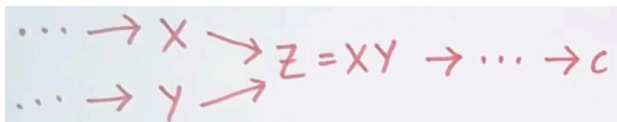
s.t. we could optimize those parameters

**Computationally efficient:** get derivative of the cost w.r.t everything, with only the cost of evaluating the NN 2-3 times

forward prob: have to perturb (change a bit) each parameter one at a time, have to re evaluate cost w.r.t every parameters one a a time

Efficient BP for matrix

For  $Z = XY$ :



General equation for matrix BP:

$$\bar{X}_{ij} = \frac{\partial c}{\partial X_{ij}} = \sum_{m,n} \underbrace{\frac{\partial c}{\partial Z_{mn}}}_{\bar{Z}_{mn}} \underbrace{\frac{\partial Z_{mn}}{\partial X_{ij}}}_{\delta_{im} Y_{jn}} = \sum_n \bar{Z}_{in} \underbrace{Y_{jn}}_{(Y^T)_{nj}}$$

But if breaking down one element of output matrix  $Z$ , = one row of  $X$  \* one column of  $Y$

since derivative w.r.t  $X_{ij}$ , only the  $j$ th term involving the  $j$ th column of  $X$  is relevant (underlined, not constant as long as  $m=i$ ; this term = chronic delta)  
all other terms are constant w.r.t  $X_{ij}$

$$\begin{aligned} z_{mn} &= \sum_p X_{mp} y_{pn} \\ &= X_{m1} y_{1n} + X_{m2} y_{2n} + \dots \\ &\quad \dots \underbrace{X_{mj} y_{jn}}_{\delta_{im} y_{jn}} + \dots \end{aligned}$$

so BP partial derivative = computational cost of one element of output matrix,

$$\boxed{\bar{X} = \bar{Z} Y^T}$$

$M \times P \quad M \times N \quad N \times P$

Other rules:(memorize!)

matrix product:  $C = AB \Rightarrow \bar{A} = \bar{C} B^T$  and  $\bar{B} = A^T \bar{C}$ ,

matrix addition:  $C = A + B \Rightarrow \bar{A} = \bar{C}$  and  $\bar{B} = \bar{C}$ ,

$C = AB^T \Rightarrow \bar{A} = \bar{C} B$  and  $\bar{B} = \bar{C}^T A$ ,