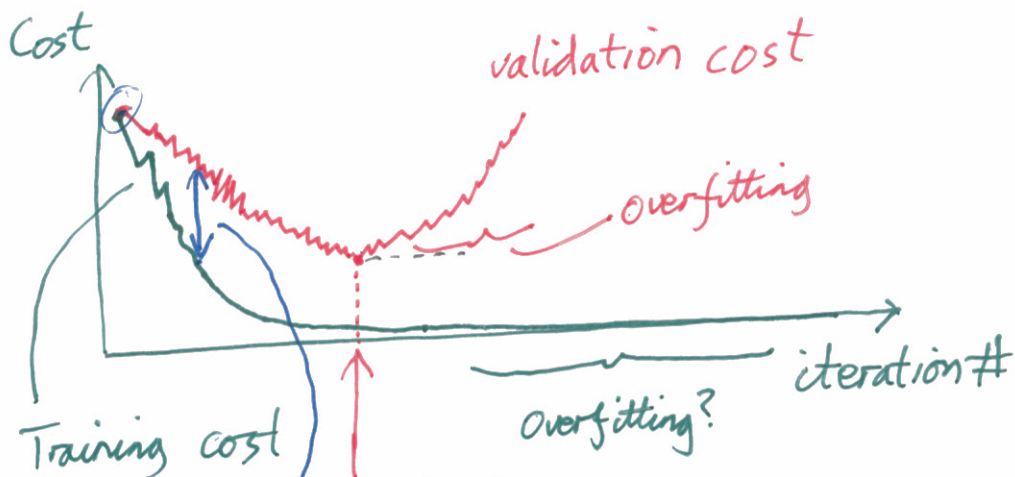


Regularization — Early-stopping

Could do L2 regularization

Set λ ... cross-validate



want this model.

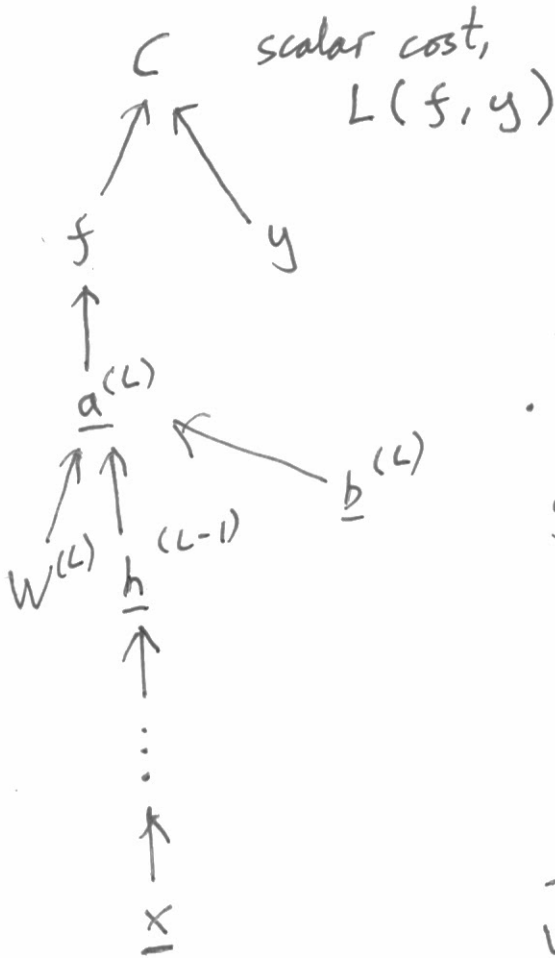
(val. error - train error)

is not "overfittingness"

\Rightarrow do not use for model comparison

Getting gradients - Reverse-mode differentiation

"Backpropagation"



Graph
DAG

Strategy:

- For every intermediate θ

$$\text{get } \bar{\theta} = \frac{\partial C}{\partial \theta}$$

$$\bar{f} = \frac{\partial C}{\partial f}$$

$$\bar{a}_i^{(L)} = \frac{\partial C}{\partial a_i^{(L)}}$$

$$\bar{W}_{ij}^{(L)} = \frac{\partial C}{\partial W_{ij}^{(L)}}$$

Start at end of computation graph

Example: $c = (f - y)^2$

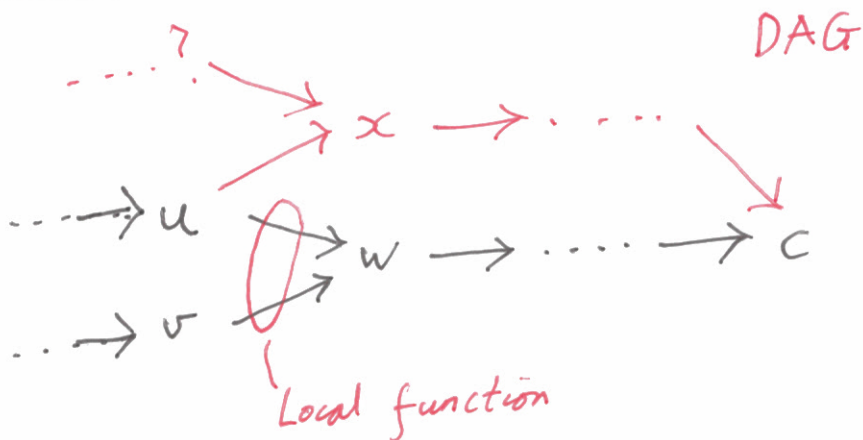
$$\bar{f} = \frac{\partial c}{\partial f} = 2(f - y)$$

If we have \underline{f} and \underline{y} , $c = \sum_n (f_n - y_n)^2$
 $N \times 1$ $N \times 1$

$$\frac{\partial c}{\partial f_m} = 2(f_m - y_m)$$

$$\bar{\underline{f}} = 2(\underline{f} - \underline{y})$$

We combine local propagation rules



Assume we have $\bar{w} = \frac{\partial c}{\partial w}$

Want $\bar{u} = \frac{\partial c}{\partial u}$, $\bar{v} = \frac{\partial c}{\partial v}$

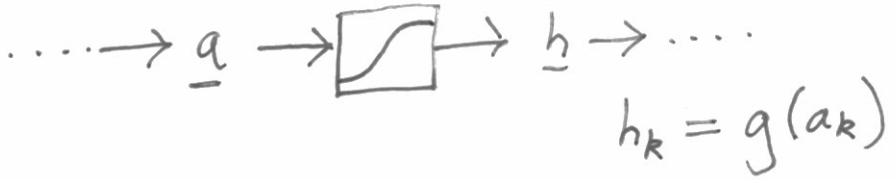
Chain rule

$$\bar{u} = \frac{\partial c}{\partial u} = \underbrace{\frac{\partial c}{\partial w}}_{\bar{w}} \underbrace{\frac{\partial w}{\partial u}}_{\text{Derivative of local function}}$$

$$+ \underbrace{\bar{x}}_{\text{Deriv. local function}} \underbrace{\frac{\partial c}{\partial x}}_{\text{local function}} \underbrace{\frac{\partial x}{\partial u}}_{\text{local function}}$$

Derivative of local function
Depends on u, v, and/or w

Elementwise Functions



$$\bar{a}_k = \frac{\partial c}{\partial a_k} = \frac{\partial c}{\partial h_k} \frac{\partial h_k}{\partial a_k}$$

$$= \bar{h}_k g'(a_k)$$

$$\underline{\bar{a}} = \underline{\bar{h}} \odot g'(\underline{a})$$

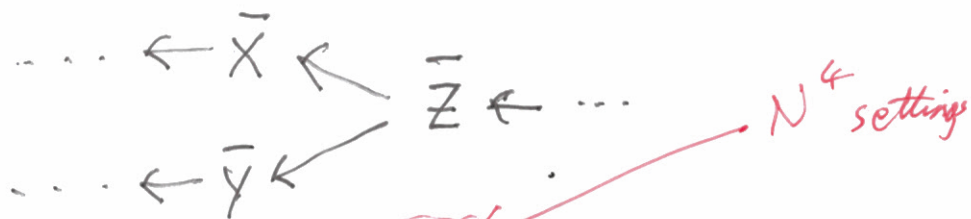
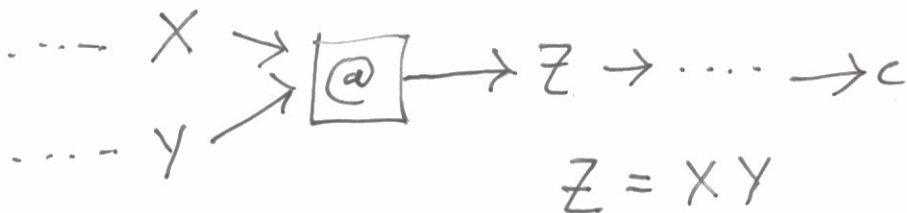
Hadamard
product

\nearrow
* Python
* Matlab

Example: Matrix Multiplication

$N \times N$ matrix, N^2 numbers in matrix

$O(N^3)$, ~~$O(N^4)$~~ , ~~$O(N^k)$~~
 ~~$350 \leq 3$~~
 ~~3.2~~



$$\frac{\partial c}{\partial X_{ij}} = \sum_{m,n} \frac{\partial c}{\partial Z_{mn}} \frac{\partial Z_{mn}}{\partial X_{ij}} = \sum_n \bar{Z}_{in} Y_{jn}$$

$\underbrace{\quad}_{\bar{Z}_{mn}} \quad \underbrace{\quad}_{\delta_{mi} Y_{jn}} \quad \underbrace{\quad}_{(Y^T)_{nj}}$

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

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

$$Z_{mn} = \sum_p X_{mp} Y_{pn}$$

$$= X_{m1} Y_{1n} + X_{m2} Y_{2n} + \dots$$

$$\dots \underbrace{X_{mj} Y_{jn}} + \dots$$

$$\begin{array}{ccc} Z & = & X \quad Y \\ M \times N & & M \times P \quad P \times N \end{array}$$

$$\begin{array}{ccc} \bar{Y} & = & X^T \bar{Z} \\ P \times N & & P \times M \quad M \times N \end{array}$$