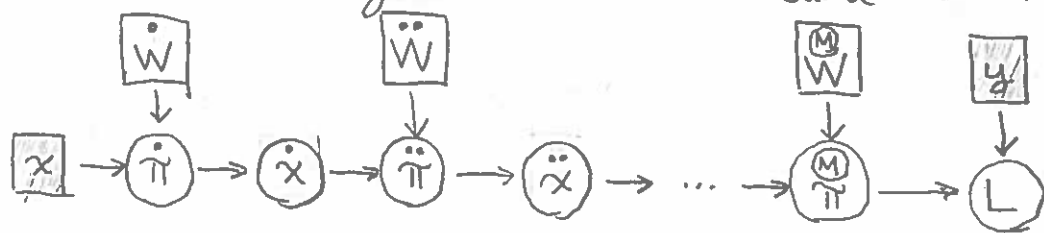
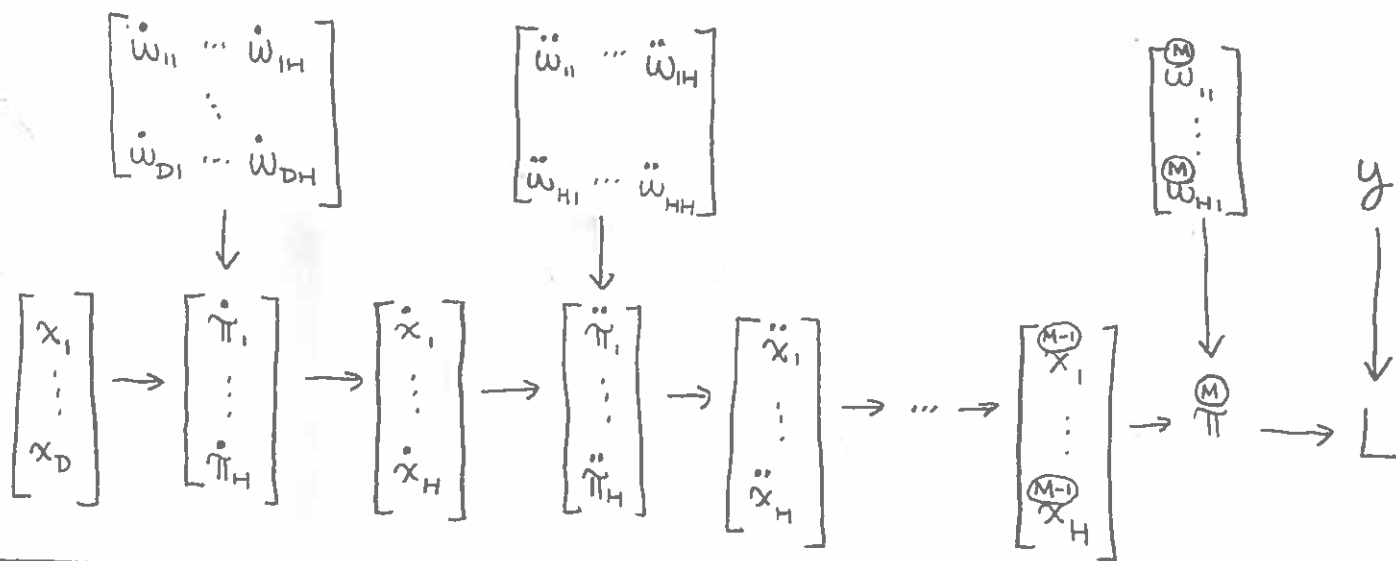


# BACKPROPAGATION: A MATRIX FORMULATION

① Recall the  $M$ -layer feedforward neural network:



which, more explicitly representing the matrices and vectors, looks like:



② The major computational step of backpropagation is to compute

$$\frac{\partial \pi^{(M)}}{\partial \pi_j^{(m)}} = a'(\pi_j^{(m)}) \sum_{h=1}^H w_{hj}^{(m+1)} \cdot \frac{\partial \pi^{(M)}}{\partial \pi_h^{(m+1)}}$$

for each  $m \in \{1, \dots, M-1\}$  and  $j \in \{1, \dots, H\}$ .

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③ This is quite a lot of computation!

M layers

└ H variables of the form  $\pi_j^{(m)}$  (per layer)

└ H terms to sum over (per variable)

So it is order  $O(MH^2)$ .

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④ Generally, when faced with quadratic computation (or cubic in this case), it's useful to investigate whether the computation can be expressed as a matrix computation. This is because:

(a) there are libraries that are heavily optimized (like Torch) to do matrix operations quickly

(b) many computers have specialized hardware (called Graphics Processing Units, or GPUs) for matrix computation.

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5) So let's see whether we can compute all the partial derivatives  $\frac{\partial \pi^{(M)}}{\partial \pi_j^{(m)}}$  at a given layer  $m$

via matrix computation.

$$\frac{\partial \pi^{(M)}}{\partial \pi^{(m)}} = \begin{bmatrix} \frac{\partial \pi^{(M)}}{\partial \pi_1^{(m)}} \\ \vdots \\ \frac{\partial \pi^{(M)}}{\partial \pi_H^{(m)}} \end{bmatrix} = \begin{bmatrix} a'(\pi_1^{(m)}) \sum_{h=1}^H w_{h1}^{(m+1)} \cdot \frac{\partial \pi^{(M)}}{\partial \pi_h^{(m+1)}} \\ \vdots \\ a'(\pi_H^{(m)}) \sum_{h=1}^H w_{hH}^{(m+1)} \cdot \frac{\partial \pi^{(M)}}{\partial \pi_h^{(m+1)}} \end{bmatrix}$$

remember that  $x \odot y$  is the elementwise product of two equal-size vectors  $x$  and  $y$



$$= \begin{bmatrix} a'(\pi_1^{(m)}) \\ \vdots \\ a'(\pi_H^{(m)}) \end{bmatrix} \odot \begin{bmatrix} \sum_{h=1}^H w_{h1}^{(m+1)} \cdot \frac{\partial \pi^{(M)}}{\partial \pi_h^{(m+1)}} \\ \vdots \\ \sum_{h=1}^H w_{hH}^{(m+1)} \cdot \frac{\partial \pi^{(M)}}{\partial \pi_h^{(m+1)}} \end{bmatrix}$$

"Hadamard" product

$$= a'(\pi^{(m)}) \odot \begin{bmatrix} w_{11}^{(m+1)} & \dots & w_{1H}^{(m+1)} \\ \vdots & \ddots & \vdots \\ w_{H1}^{(m+1)} & \dots & w_{HH}^{(m+1)} \end{bmatrix}^T \begin{bmatrix} \frac{\partial \pi^{(M)}}{\partial \pi_1^{(m+1)}} \\ \vdots \\ \frac{\partial \pi^{(M)}}{\partial \pi_H^{(m+1)}} \end{bmatrix}$$

$$= a'(\pi^{(m)}) \odot W^{(m+1)T} \frac{\partial \pi^{(M)}}{\partial \pi^{(m+1)}}$$

Success!

# BACKPROPAGATION: A MATRIX FORMULATION

⑥ This means we can re-express backpropagation's step (a):

BACKPROPAGATION:

(a) for  $m$  in  $\{M-1, \dots, 1\}$ :

$$\text{compute } \frac{\partial \pi^{(M)}}{\partial \pi^{(m)}} = a'(\pi^{(m)}) \odot W^{(m+1)T} \frac{\partial \pi^{(M)}}{\partial \pi^{(m+1)}}$$

$$(b) \frac{\partial L}{\partial w_{ij}^{(m)}} = \frac{\partial L}{\partial \pi^{(M)}} \cdot x_i^{(m-1)} \cdot \frac{\partial \pi^{(M)}}{\partial \pi_j^{(m)}}$$

⑦ While we're on a roll, let's try to matrixify step (b):

$$\frac{\partial L}{\partial w^{(m)}} = \begin{bmatrix} \frac{\partial L}{\partial w_{11}^{(m)}} & \dots & \frac{\partial L}{\partial w_{1n}^{(m)}} \\ \vdots & \ddots & \vdots \\ \frac{\partial L}{\partial w_{n1}^{(m)}} & \dots & \frac{\partial L}{\partial w_{nn}^{(m)}} \end{bmatrix} = \begin{bmatrix} \frac{\partial L}{\partial \pi^{(M)}} x_1^{(m-1)} \frac{\partial \pi^{(M)}}{\partial \pi_1^{(m)}} & \dots & \frac{\partial L}{\partial \pi^{(M)}} x_1^{(m-1)} \frac{\partial \pi^{(M)}}{\partial \pi_n^{(m)}} \\ \vdots & \ddots & \vdots \\ \frac{\partial L}{\partial \pi^{(M)}} x_n^{(m-1)} \frac{\partial \pi^{(M)}}{\partial \pi_1^{(m)}} & \dots & \frac{\partial L}{\partial \pi^{(M)}} x_n^{(m-1)} \frac{\partial \pi^{(M)}}{\partial \pi_n^{(m)}} \end{bmatrix}$$

$$= \frac{\partial L}{\partial \pi^{(M)}} \cdot \begin{bmatrix} x_1^{(m-1)} \\ \vdots \\ x_n^{(m-1)} \end{bmatrix} \begin{bmatrix} \frac{\partial \pi^{(M)}}{\partial \pi_1^{(m)}} \\ \vdots \\ \frac{\partial \pi^{(M)}}{\partial \pi_n^{(m)}} \end{bmatrix}^T$$

$$= \frac{\partial L}{\partial \pi^{(M)}} \cdot x^{(m-1)} \cdot \left( \frac{\partial \pi^{(M)}}{\partial \pi^{(m)}} \right)^T$$

hurray!



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⑧ This gives us a matrix formulation of backpropagation:

BACKPROPAGATION:

[ ] for  $m$  in  $\{M-1, \dots, 1\}$ :

(a) compute  $\frac{\partial \pi^{(M)}}{\partial \pi^{(m)}} = a'(\pi^{(m)}) \odot W^{(m+1)T} \frac{\partial \pi^{(M)}}{\partial \pi^{(m+1)}}$

(b) compute  $\frac{\partial L}{\partial w^{(m)}} = \frac{\partial L}{\partial \pi^{(M)}} \cdot x^{(m-1)} \cdot \left( \frac{\partial \pi^{(M)}}{\partial \pi^{(m)}} \right)^T$