

# Training RNNs

IN RNN: Back Propagation Through Time (BPTT).

$$\bar{S}_t = \Phi(\bar{x}_t \cdot W_x + \bar{S}_{t-1} \cdot W_s)$$

e.g.,  $\bar{S}_t = \tanh(\bar{x}_t \cdot W_x + \bar{S}_{t-1} \cdot W_s)$

$$\bar{y}_t = \underset{\substack{\downarrow \\ \text{Softmax}}}{\sigma}(\bar{S}_t \cdot W_y)$$

$$E_t = (\bar{d}_t - \bar{y}_t)^2 \quad \text{error function is MSE}$$

How does BPTT work?

$$t=3$$

$$E_3 = (\bar{d}_3 - \bar{y}_3)^2$$

$\downarrow$        $\hookrightarrow$  Calculated output  
desired  
output

but we also need info from  $t=2$  and  $t=1$ .

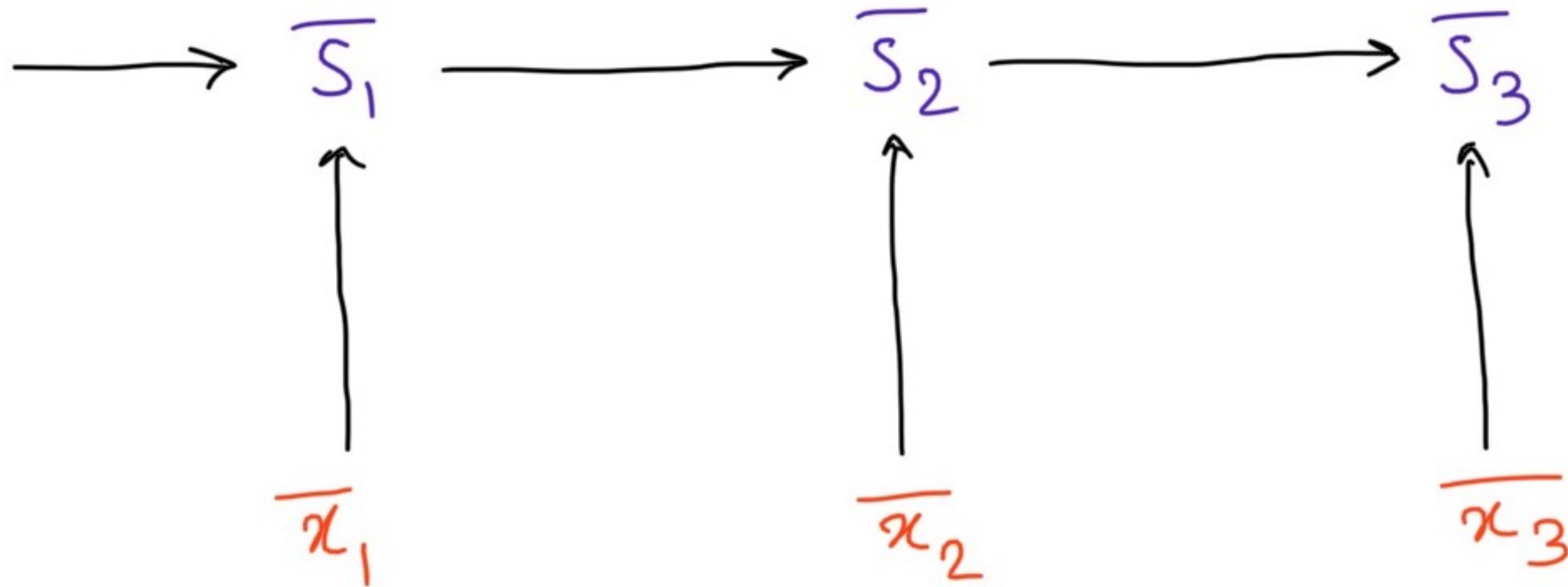


$$W_y$$

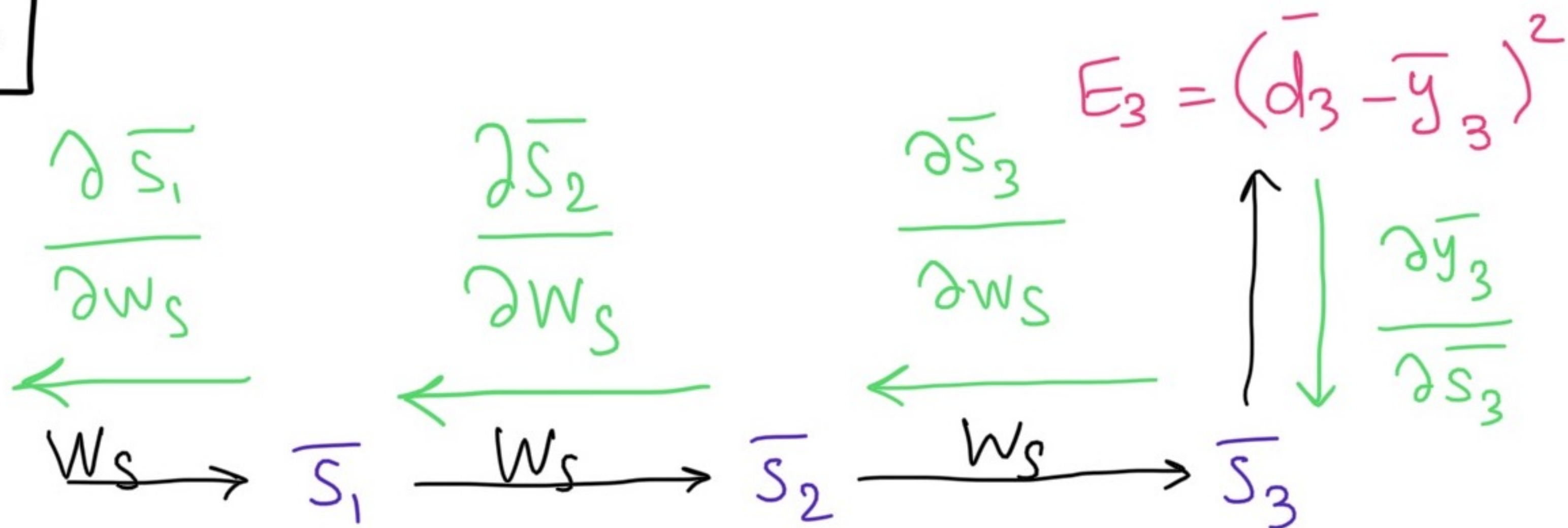
$$\frac{\partial E_3}{\partial W_y} = \frac{\partial E_3}{\partial \bar{y}_3} \cdot \frac{\partial \bar{y}_3}{\partial W_y}$$

$$E_3 = (\bar{d}_3 - \bar{y}_3)^2$$

$\uparrow$   
 $W_y$   
 $\downarrow$   
 $\frac{\partial \bar{y}_3}{\partial W_y}$



$$W_s$$

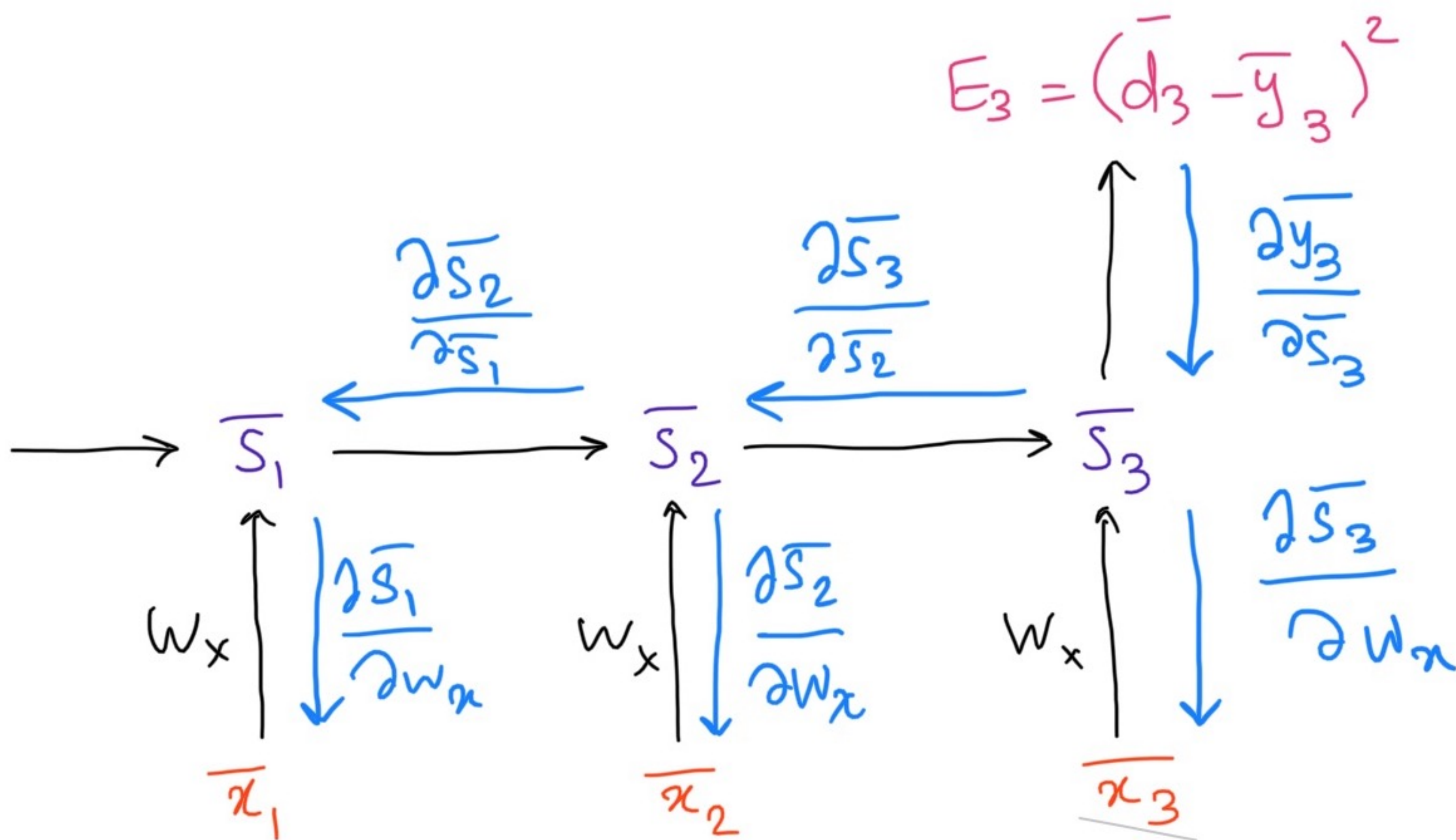


$$\begin{aligned} \frac{\partial E_3}{\partial W_s} &= \frac{\partial E_3}{\partial \bar{y}_3} \cdot \frac{\partial \bar{y}_3}{\partial \bar{s}_3} \cdot \frac{\partial \bar{s}_3}{\partial W_s} \\ &+ \frac{\partial E_3}{\partial \bar{y}_3} \cdot \frac{\partial \bar{y}_3}{\partial \bar{s}_3} \cdot \frac{\partial \bar{s}_3}{\partial \bar{s}_2} \cdot \frac{\partial \bar{s}_2}{\partial W_s} \\ &+ \frac{\partial E_3}{\partial \bar{y}_3} \cdot \frac{\partial \bar{y}_3}{\partial \bar{s}_3} \cdot \frac{\partial \bar{s}_3}{\partial \bar{s}_2} \cdot \frac{\partial \bar{s}_2}{\partial \bar{s}_1} \cdot \frac{\partial \bar{s}_1}{\partial W_s} \end{aligned}$$



$$\text{More generally: } \frac{\partial E_N}{\partial W_S} = \sum_{i=1}^N \frac{\partial E_N}{\partial \bar{y}_N} \cdot \frac{\partial \bar{y}_N}{\partial \bar{s}_i} \cdot \frac{\partial \bar{s}_i}{\partial W_S}$$

$$W_x$$



$$\frac{\partial E_3}{\partial W_x} = \frac{\partial E_3}{\partial \bar{y}_3} \cdot \frac{\partial \bar{y}_3}{\partial \bar{s}_3} \cdot \frac{\partial \bar{s}_3}{\partial W_x}$$

$$+ \frac{\partial E_3}{\partial \bar{y}_3} \cdot \frac{\partial \bar{y}_3}{\partial \bar{s}_3} \cdot \frac{\partial \bar{s}_3}{\partial \bar{s}_2} \cdot \frac{\partial \bar{s}_2}{\partial W_x}$$

$$+ \frac{\partial E_3}{\partial \bar{y}_3} \cdot \frac{\partial \bar{y}_3}{\partial \bar{s}_3} \cdot \frac{\partial \bar{s}_3}{\partial \bar{s}_2} \cdot \frac{\partial \bar{s}_2}{\partial \bar{s}_1} \cdot \frac{\partial \bar{s}_1}{\partial W_x}$$



More generally:

$$\frac{\partial E_N}{\partial W_x} = \sum_{i=1}^N \frac{\partial E_N}{\partial \bar{y}_N} \cdot \frac{\partial \bar{y}_N}{\partial \bar{s}_i} \cdot \frac{\partial \bar{s}_i}{\partial W_x}$$

- for training: updating weights every  $N$  steps  
mini-batch
- what happens if we have too many steps?  
up to 8-10 steps, this BPTT works,  
but beyond that, the vanishing gradient  
problem happens.  $\rightarrow$  LSTM is born!

• Gradient clipping:  $\rightarrow$  avoiding Exploding Gradient Problem.

At each timestep  $t$ :

$$\delta = \frac{\partial y}{\partial w_{ij}} > \text{threshold?}$$

If so, normalize the gradient.