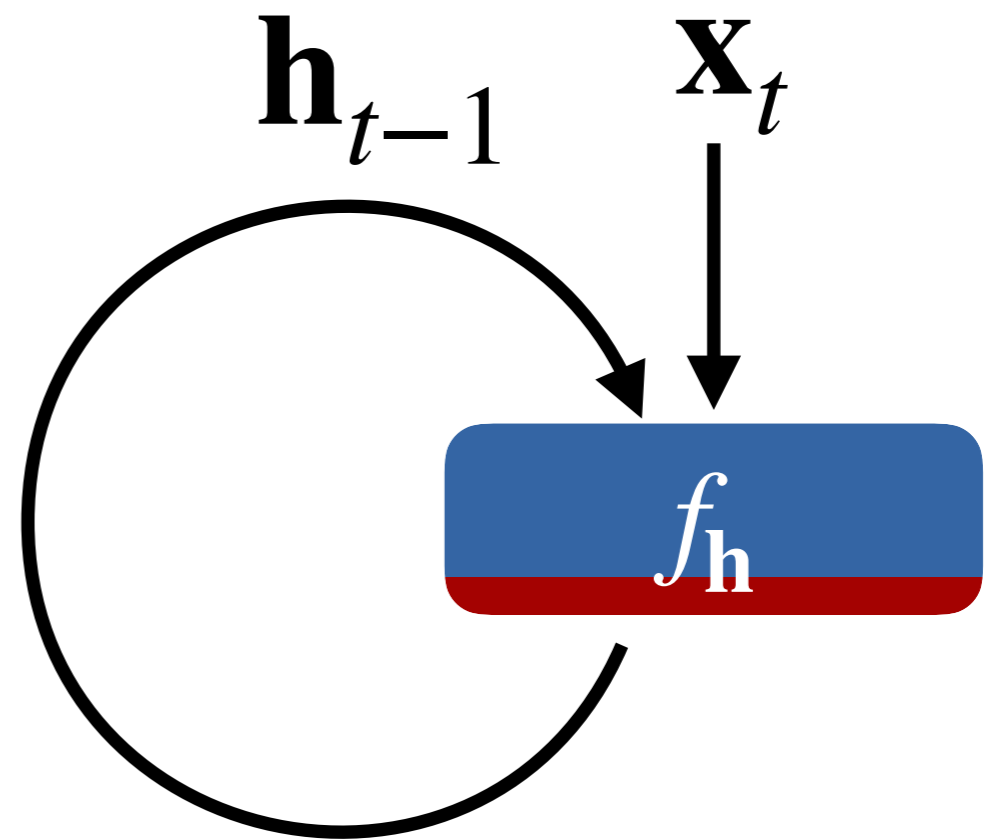


# Training recurrent networks

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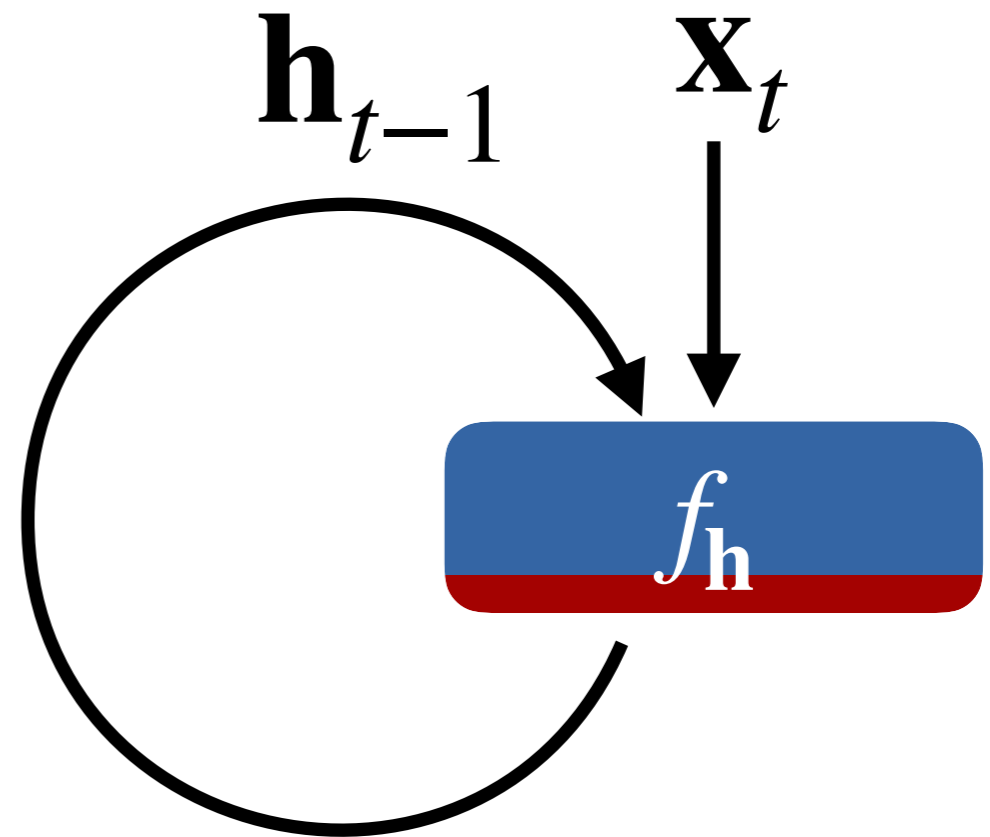
# Recurrent Networks

- Processes a sequence
- Feedback connections

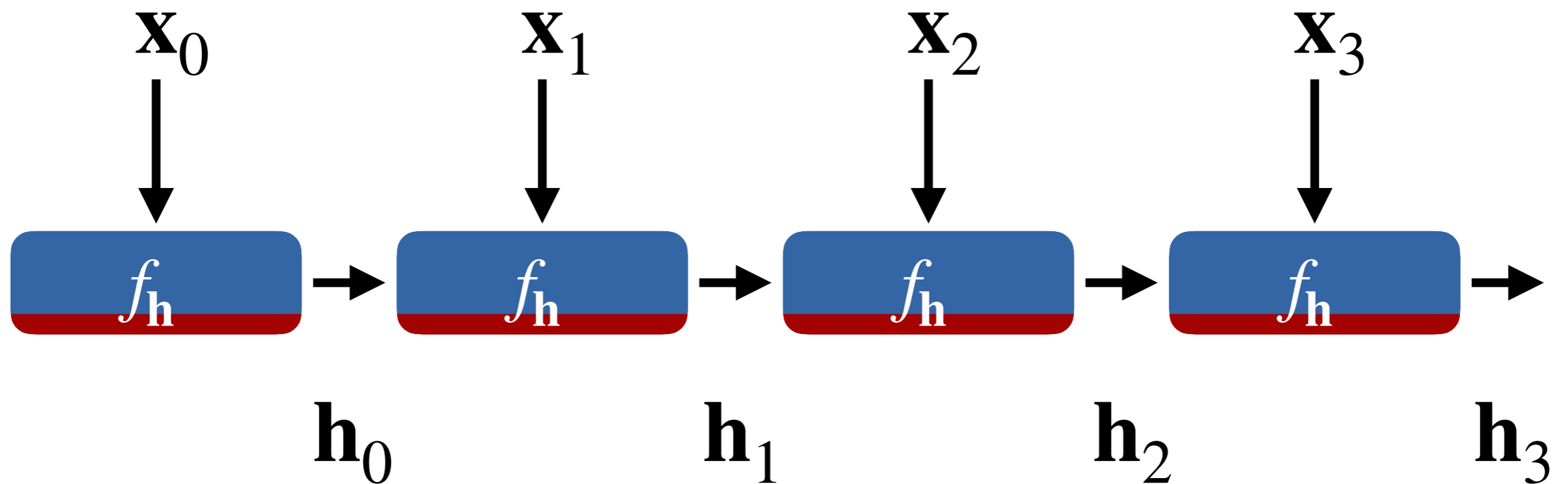


# How do we train RNNs?

- No longer a simple forward and backward pass
- Cycles

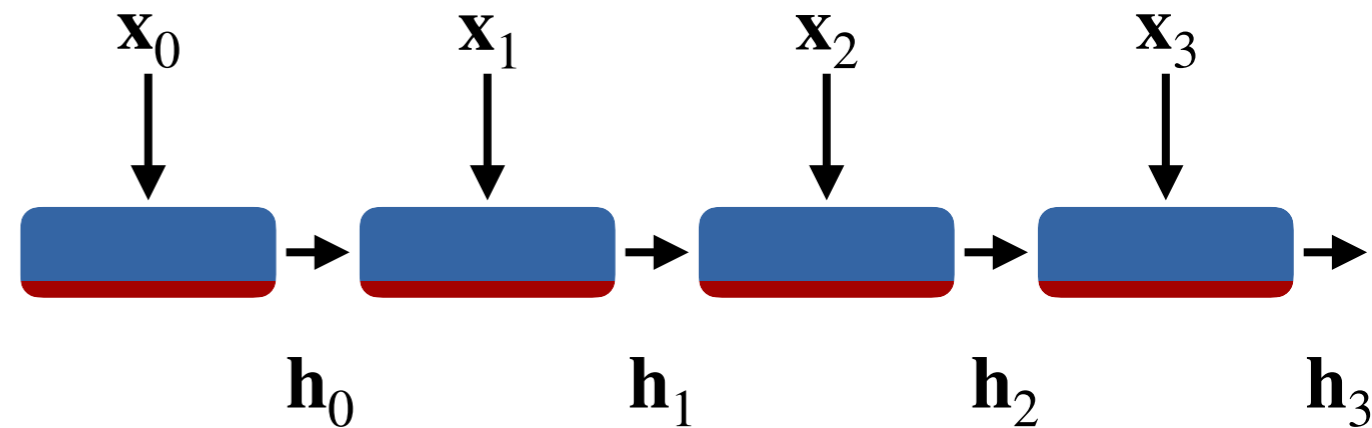


# Solution: unrolling through time



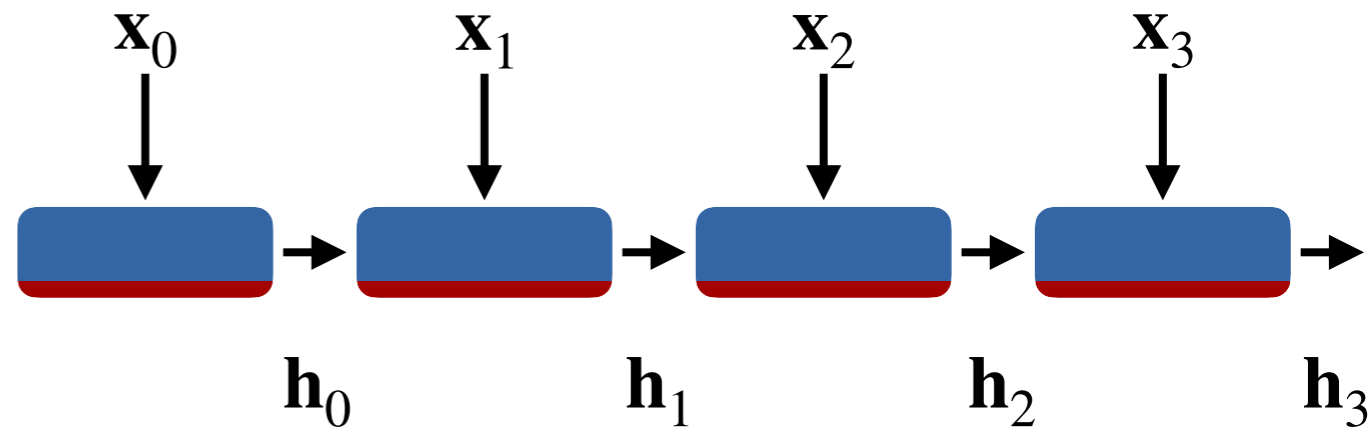
# Unrolling through time

- Unrolled RNN (T steps)
  - Feed forward network
  - Shared parameters
- Trained with backprop



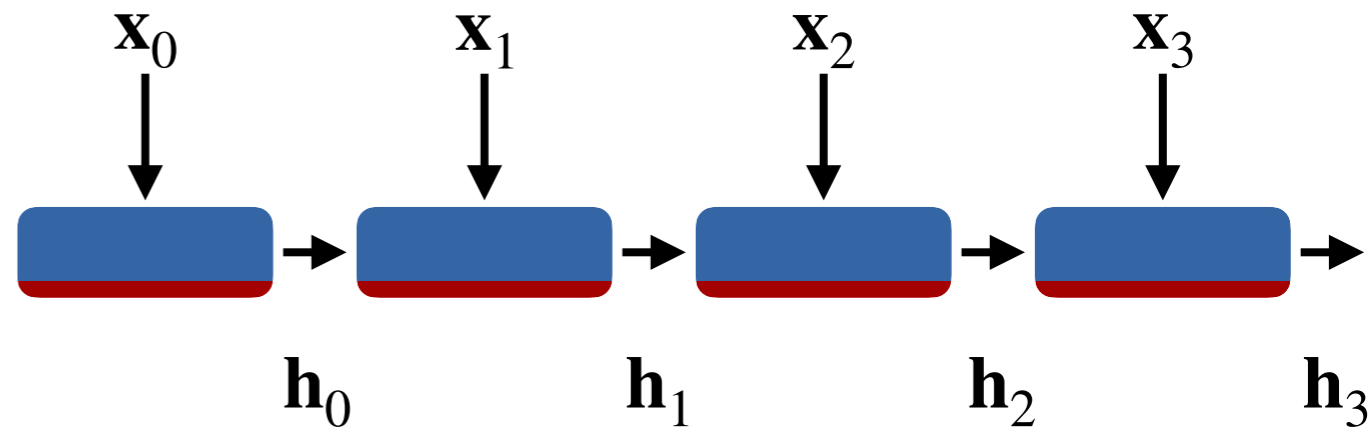
# Unrolling through time - Issues

- Long unrolling
- Computationally expensive
- Vanishing or exploding gradients



# Computation

- Solution (hack)
  - Cut RNN after n steps
    - Set  $h=0$
  - Works well in practice



# Vanishing and exploding gradients – Simple example

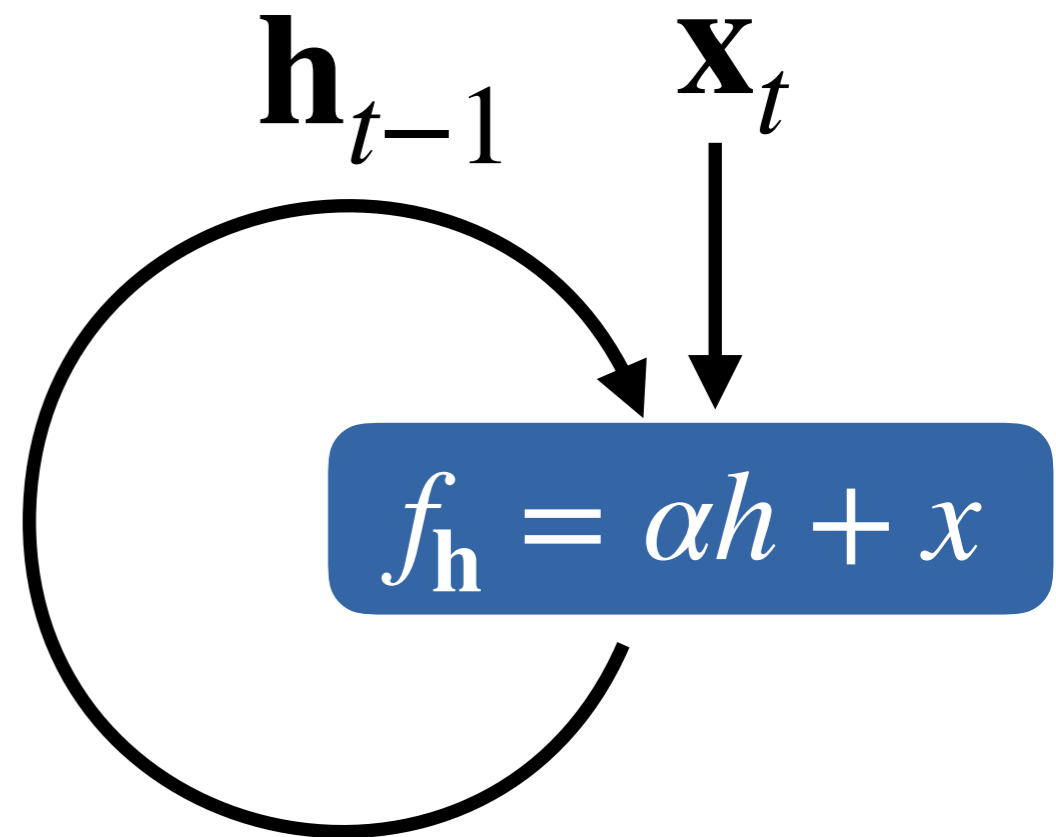
- Linear RNN

- $\mathbf{h}_t = \alpha \mathbf{h}_{t-1} + \mathbf{x}_t$

- For large  $t$

- $a > 1 \quad \frac{\partial}{\partial \mathbf{x}_0} \mathbf{h}_t = \alpha^t \rightarrow \infty$

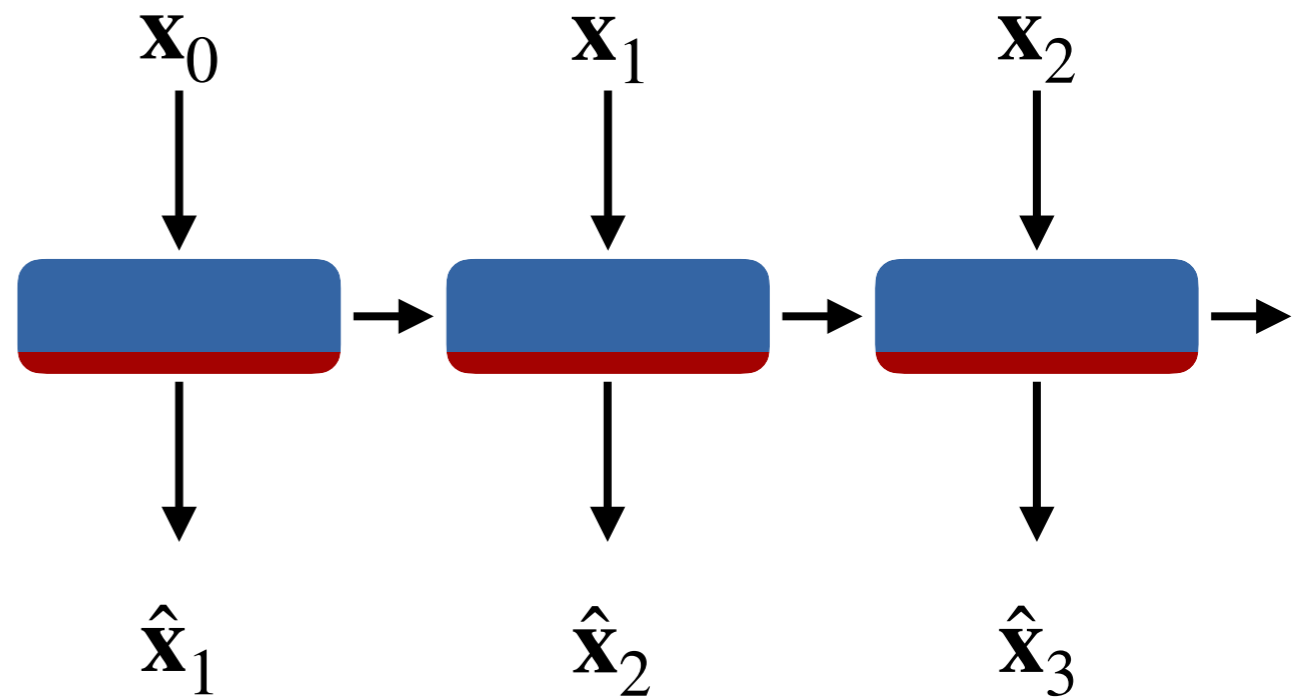
- $a < 1 \quad \frac{\partial}{\partial \mathbf{x}_0} \mathbf{h}_t = \alpha^t \rightarrow 0$





# Preventing vanishing and exploding gradients

- Generative models
- Use ground truth inputs



# Preventing vanishing and exploding gradients

- Exploding gradients

- Gradient clipping

$$\nabla \ell' = \nabla \ell \min \left( 1, \frac{\epsilon}{|\nabla \ell|} \right)$$

- Vanishing gradients

- Different RNN structure