Recurrent Neural Networks

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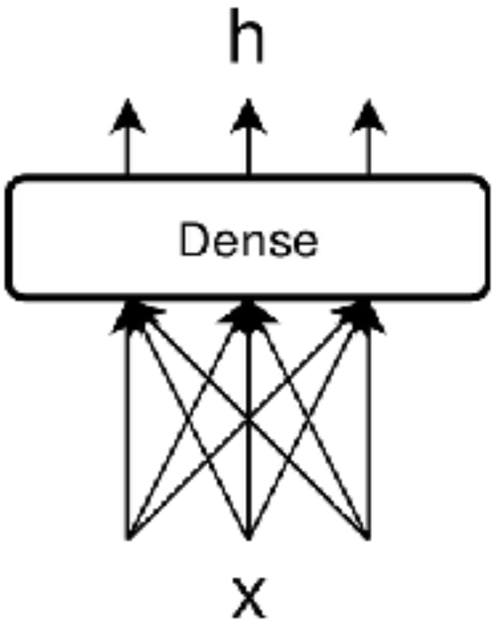
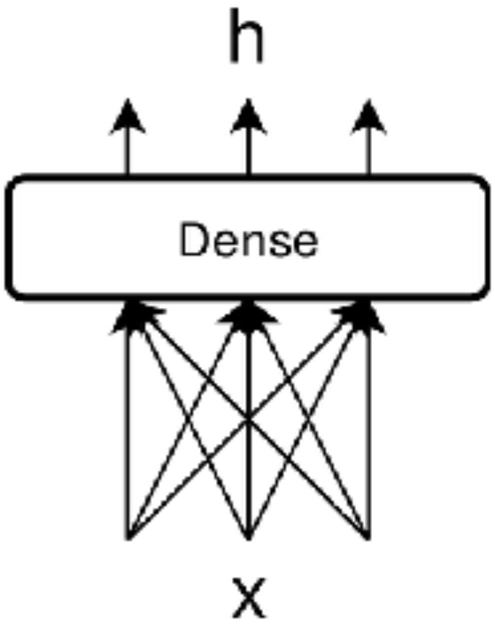
Dense Layers



$$h = f(Wx + b)$$

Dense Layers

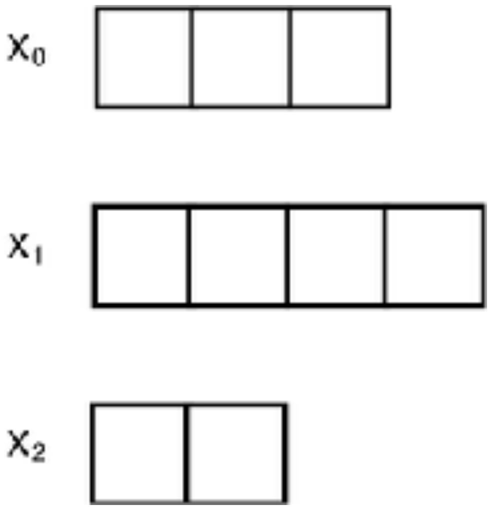


H x 1 H x N H x 1

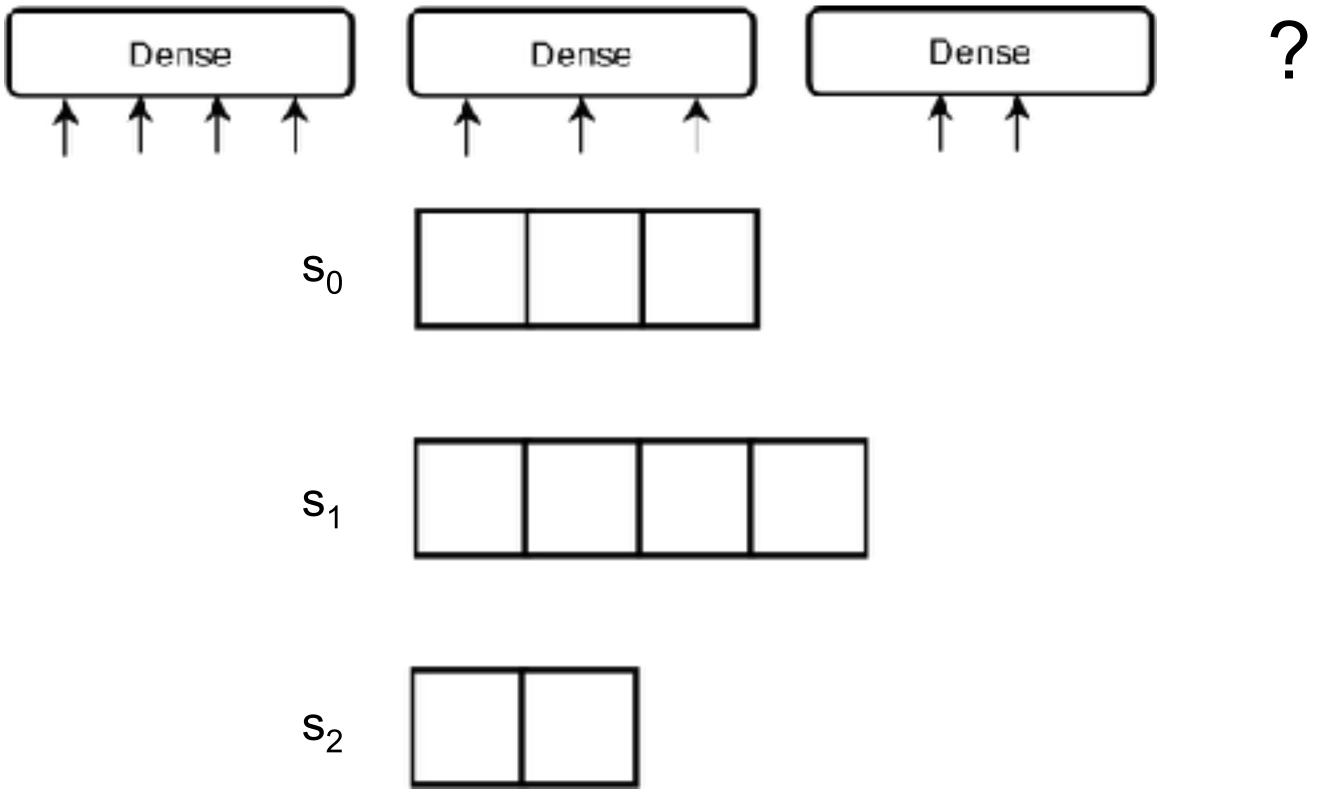
$$h = f(Wx + b)$$

N x 1

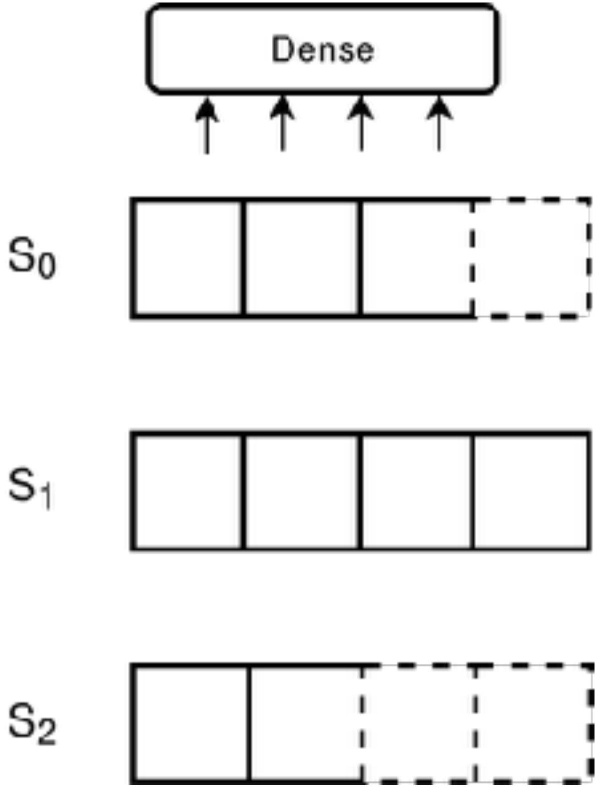
Variable sequence length



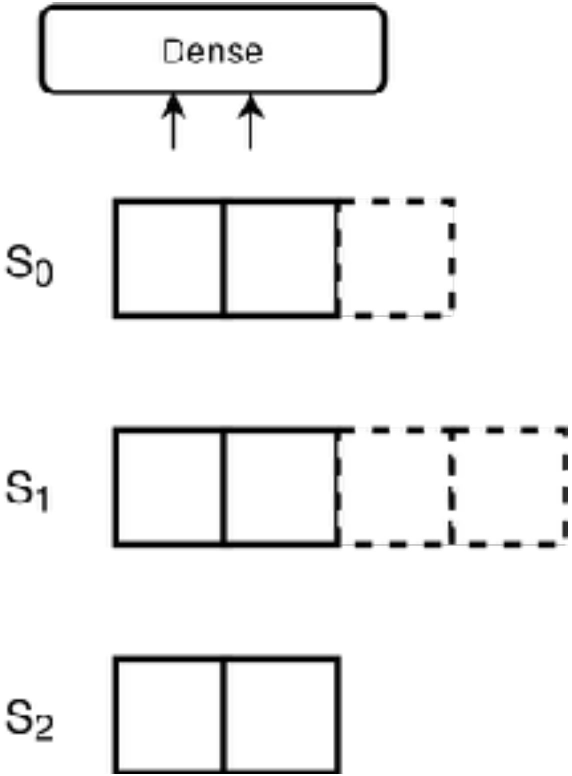
Variable sequence length



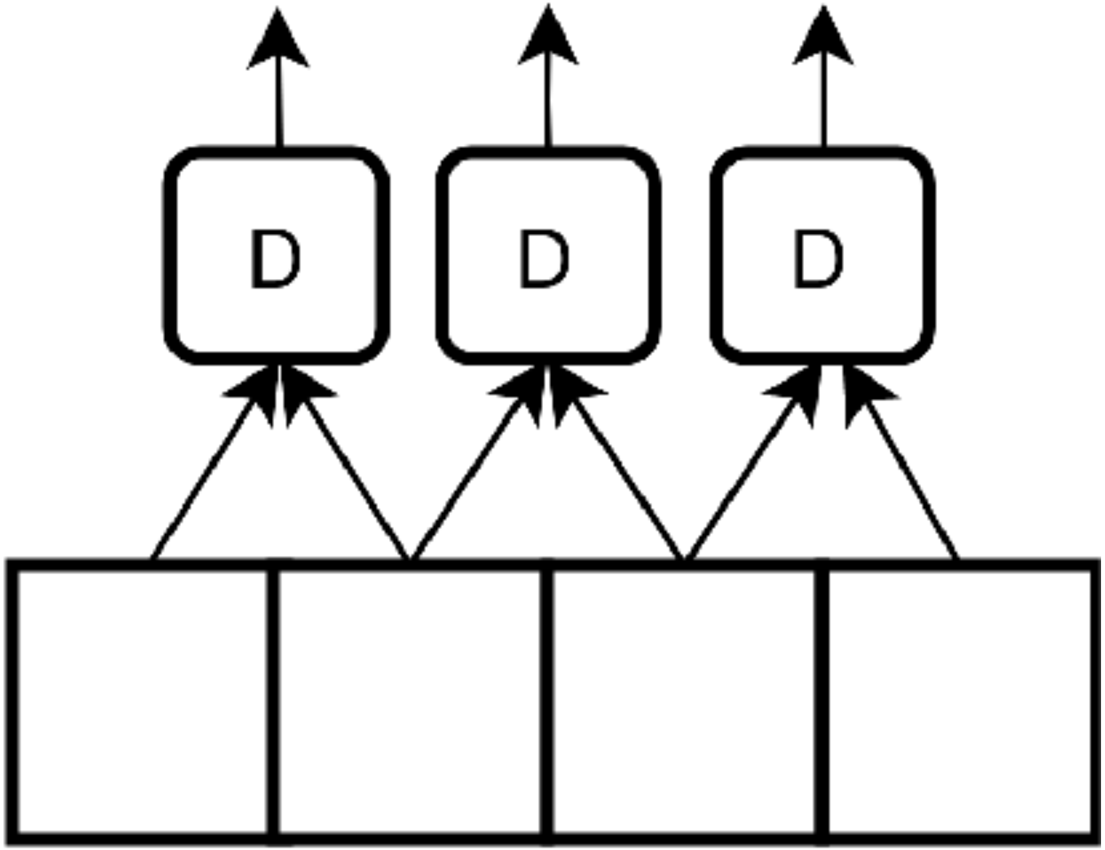
Variable sequence length

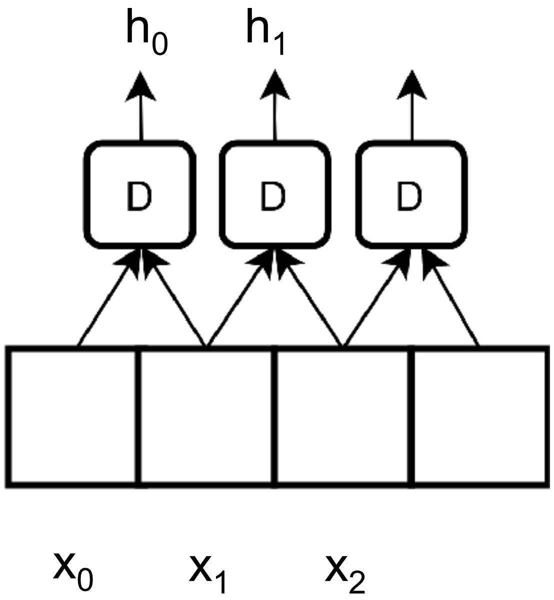


Variable sequence length

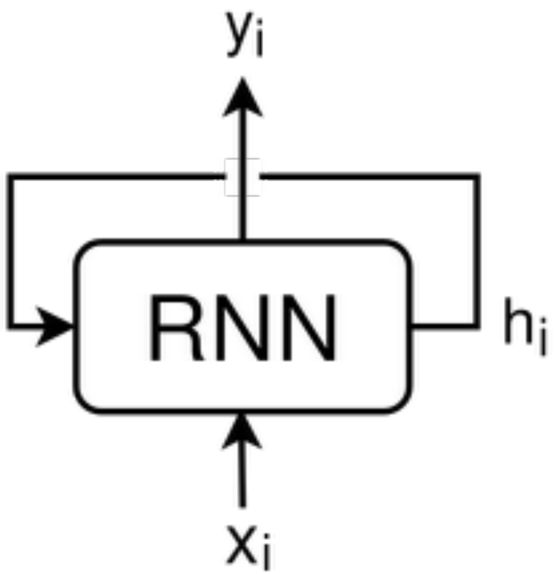


Convolutional Neural Networks



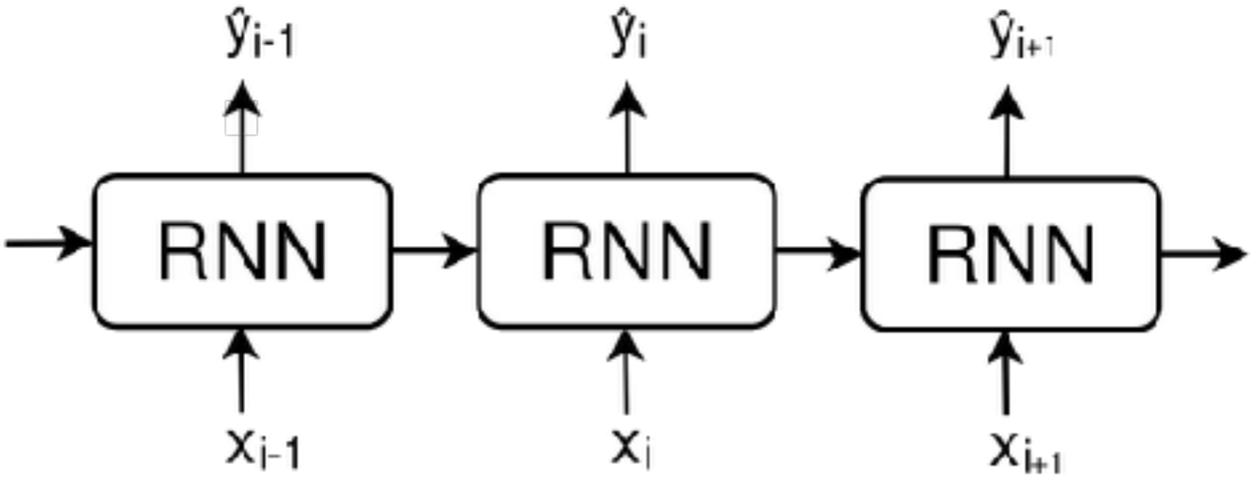

h_0
h_1
D
D
D
x_0
x_1
x_2

Recurrent neural network



$$h_i = f_h(Wx_i + Vh_{i-1} + b_h) \qquad \hat{y}_i = f_y(Uh_i + b_y)$$

Recurrent neural network



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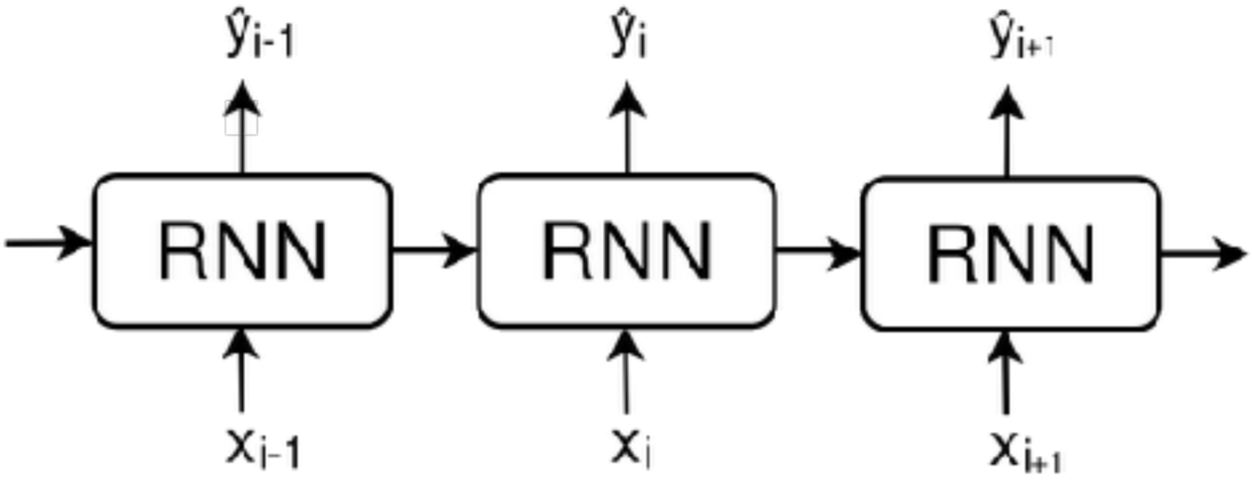
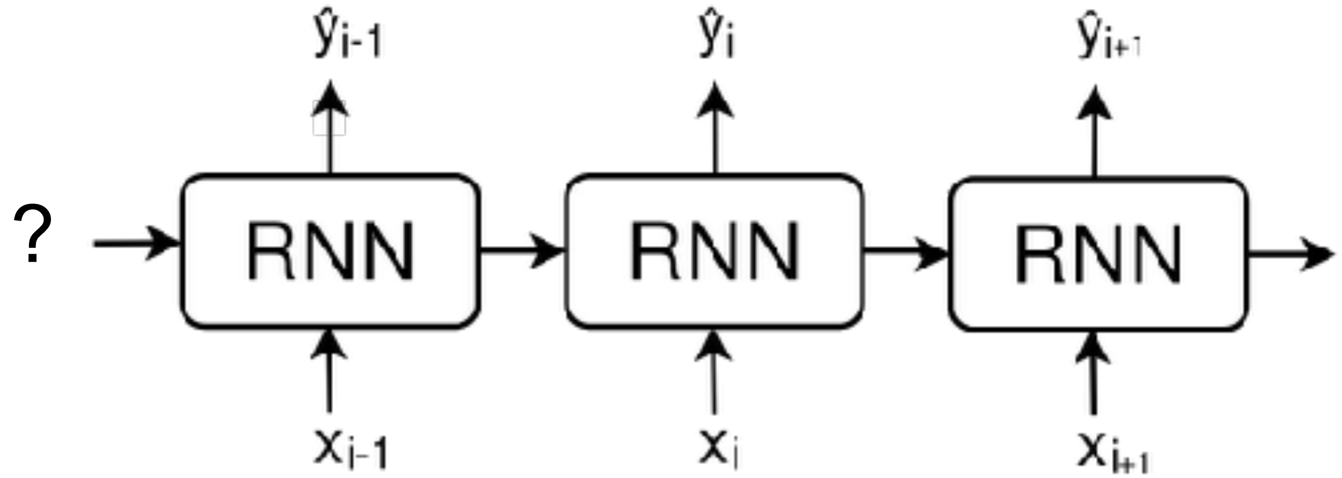
Recurrent neural network



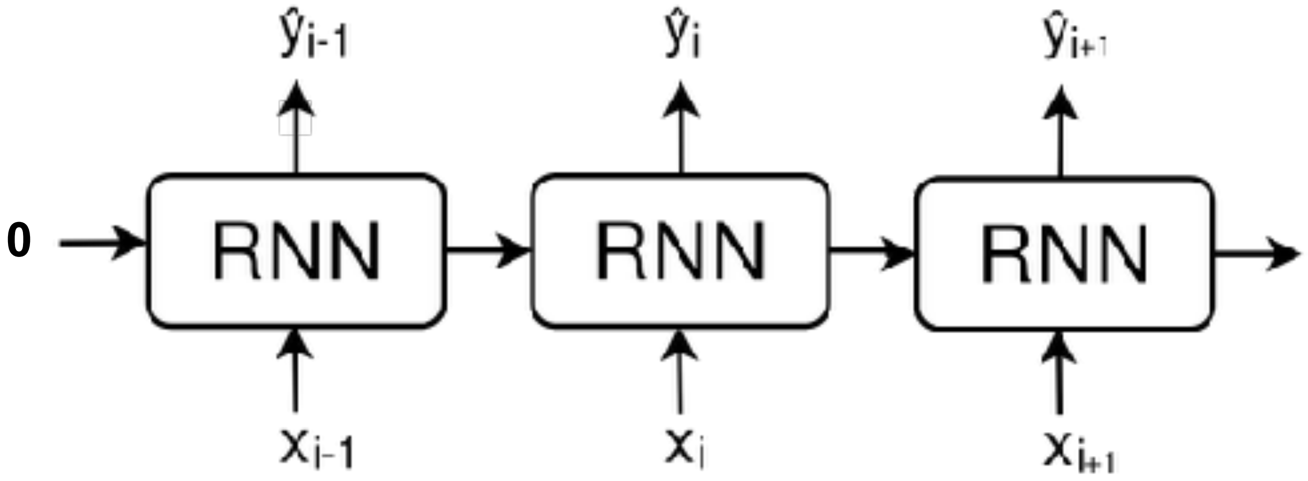
$$h_i = f_h(\overset{H \times N}{W} \underset{N \times 1}{x_i} + \overset{H \times H}{V} \underset{H \times 1}{h_{i-1}} + \underset{H \times 1}{b_h}) \qquad \hat{y}_i = f_y(U h_i + b_y)$$

Recurrent neural network initial states



$$h_i = f_h(Wx_i + Vh_{i-1} + b_h) \qquad \hat{y}_i = f_y(Uh_i + b_y)$$

Recurrent neural network initial states



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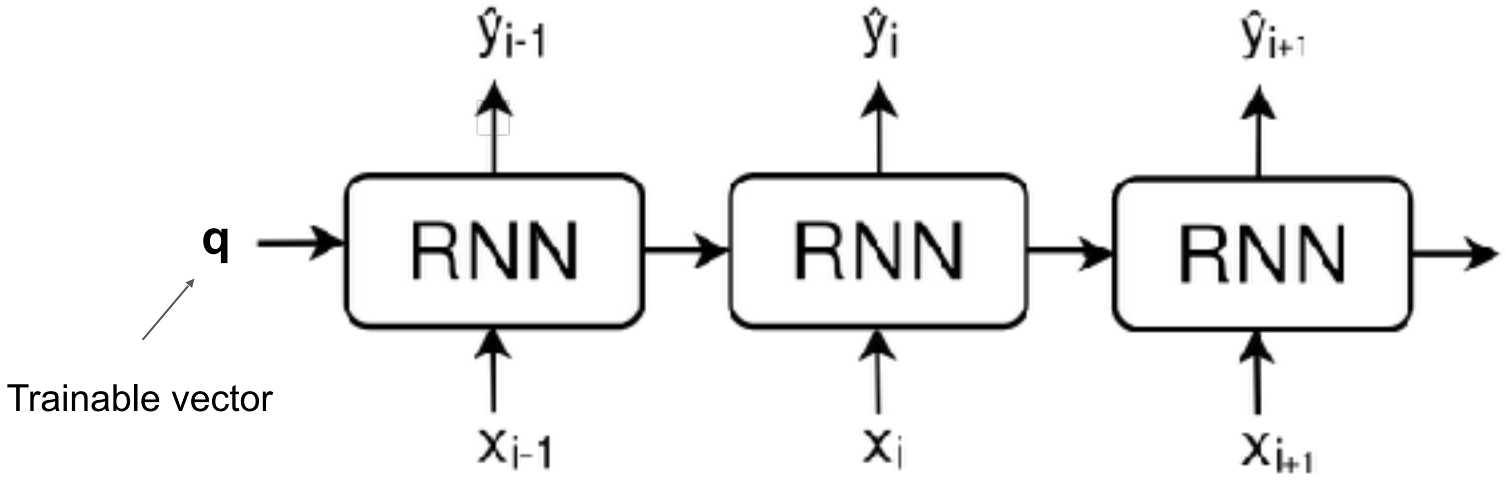
Recurrent neural network initial states

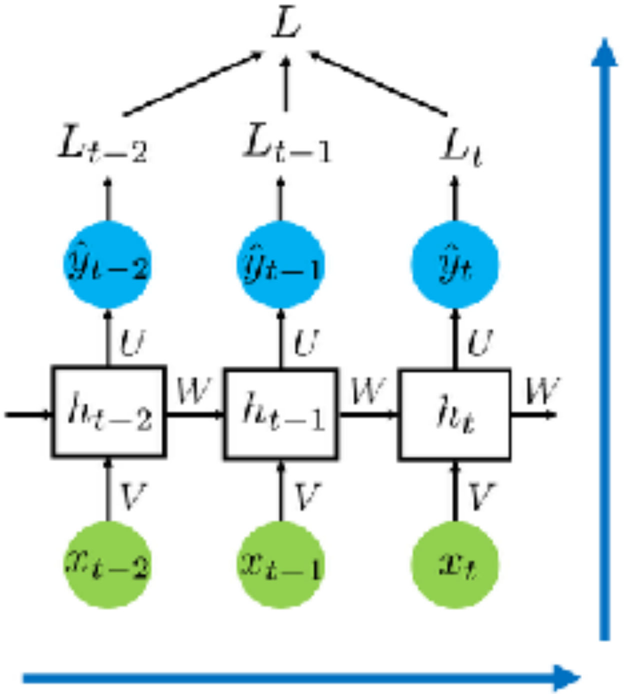


$$h_i = f_h(Wx_i + Vh_{i-1} + b_h) \qquad \hat{y}_i = f_y(Uh_i + b_y)$$

Backpropagation through time

Forward pass:

$h_t,\ \hat{y}_t,\ L_t,\ L$



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Backpropagation through time

Forward pass:

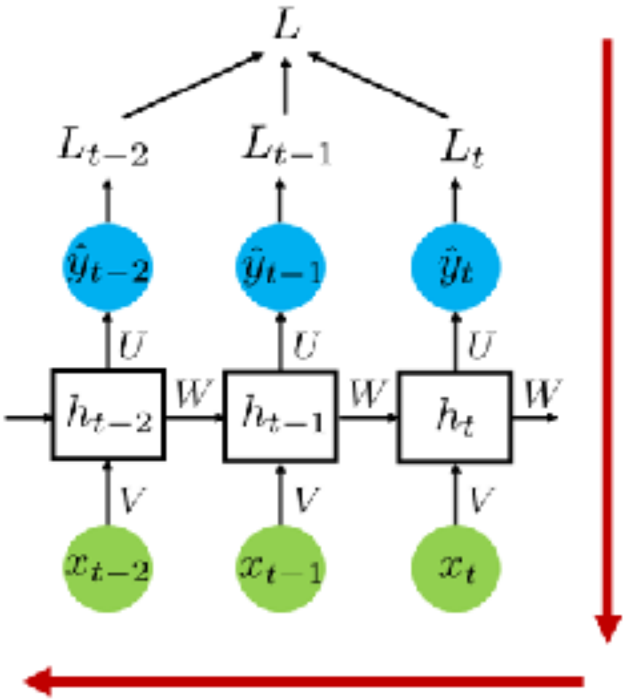
$$h_t,\ \hat{y}_t,\ L_t,\ L$$

Backward pass:

$$\frac{\partial L}{\partial U}, \frac{\partial L}{\partial V}, \frac{\partial L}{\partial W},$$

$$\frac{\partial L}{\partial b_x}, \frac{\partial L}{\partial b_h}$$

We backpropagate through layers and time



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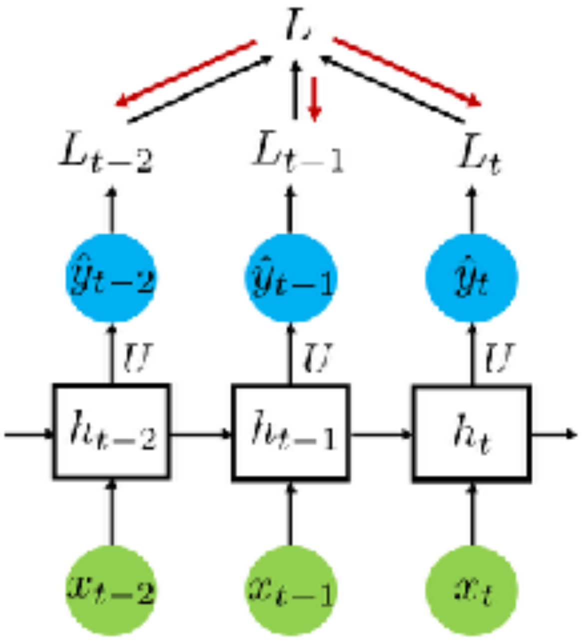
Backpropagation through time

$$\frac{\partial L}{\partial U} = \sum_{i=0}^{T} \frac{\partial L_i}{\partial U}$$



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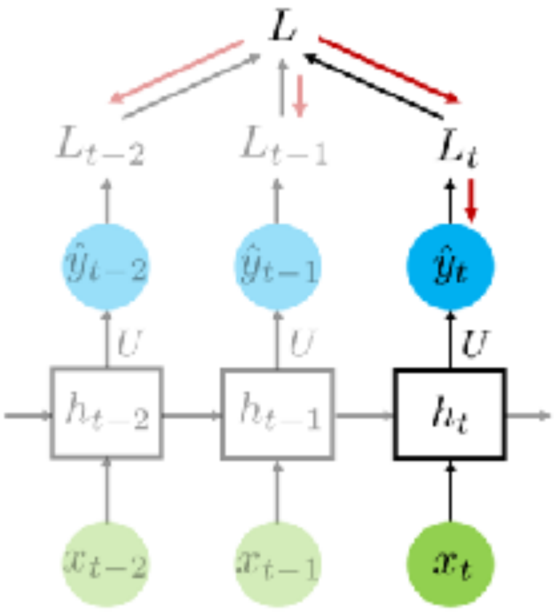
Backpropagation through time

$$\frac{\partial L}{\partial U} = \sum_{i=0}^{T} \frac{\partial L_i}{\partial U}$$

$$\frac{\partial L_t}{\partial U} = \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial U}$$

$$\hat{y}_t = f_y(\boxed{U} h_t + b_y)$$

this is the only dependence



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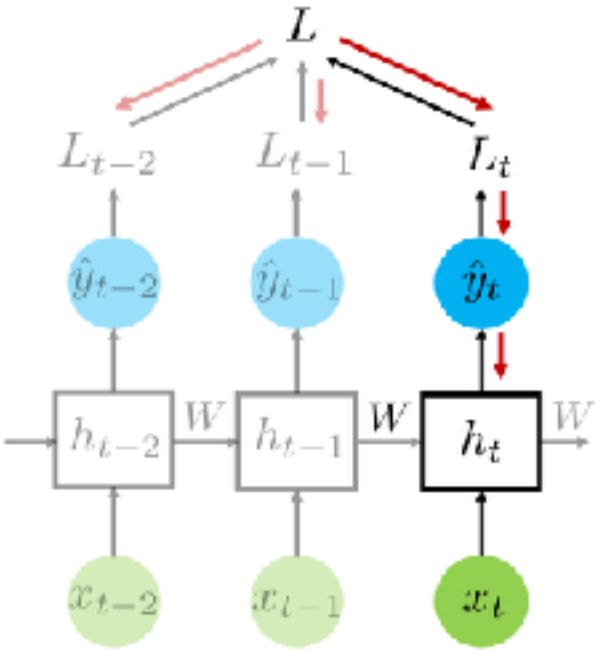
Backpropagation through time

$$\frac{\partial L}{\partial W} = \sum_{i=0}^{T} \frac{\partial L_i}{\partial W}$$

$$\frac{\partial L_t}{\partial W} = \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \frac{\partial h_t}{\partial W}$$



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Backpropagation through time

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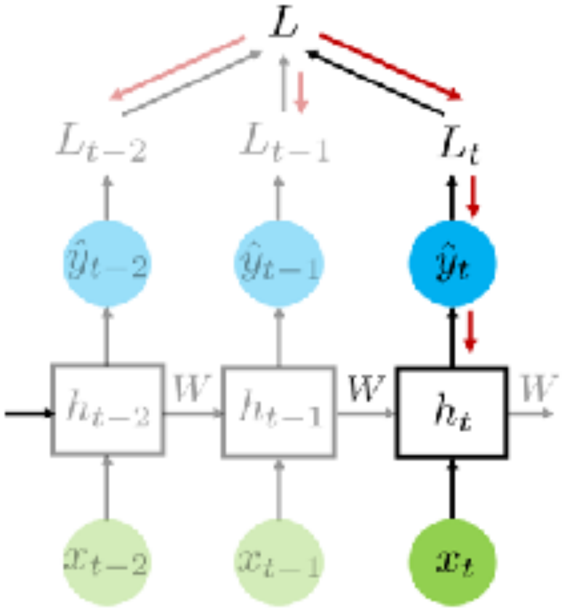
$$h_t = f_h(Vx_t + \boxed{W} h_{t-1} + b_h)$$

This is NOT the only dependence!



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Backpropagation through time

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$$h_t = f_h(V x_t + \boxed{W} h_{t-1} + b_h)$$

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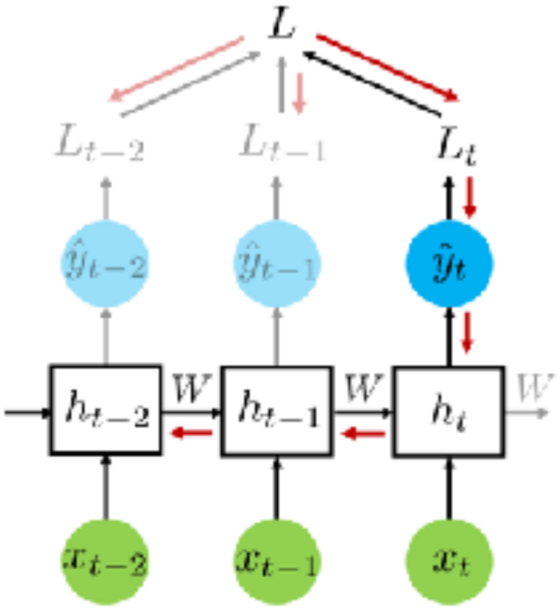

$$\frac{\partial L_t}{\partial W} = \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \boxed{\left(\frac{\partial h_t}{\partial W} + \frac{\partial h_t}{\partial h_{t-1}} \frac{\partial h_{t-1}}{\partial W} + \dots \right)}$$

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Backpropagation through time

$$\frac{\partial L}{\partial W} = \sum_{i=0}^{T} \frac{\partial L_i}{\partial W}$$

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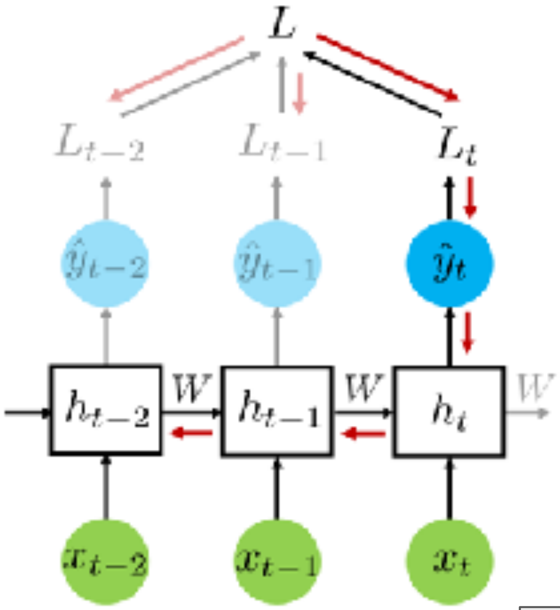

$$\frac{\partial L_t}{\partial W} = \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \boxed{\left(\frac{\partial h_t}{\partial W} + \frac{\partial h_t}{\partial h_{t-1}} \frac{\partial h_{t-1}}{\partial W} + \dots \right)}$$

$$\boxed{f(x, y(x)) = \frac{\partial f}{\partial x} + \frac{\partial f}{\partial y} \frac{\partial y}{\partial x}}$$

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Backpropagation through time

$$\frac{\partial L}{\partial W} = \sum_{i=0}^{T} \frac{\partial L_i}{\partial W}$$

$$\frac{\partial L_t}{\partial W} = \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \frac{\partial h_t}{\partial W}$$

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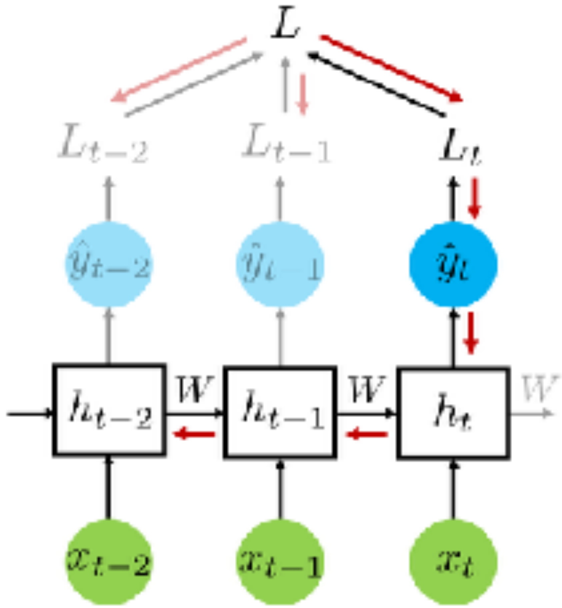

$$\frac{\partial L_t}{\partial W} = \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \boxed{\sum_{k=0}^{t} \left(\prod_{i=k+1}^{t} \frac{\partial h_i}{\partial h_{i-1}} \right) \frac{\partial h_k}{\partial W}}$$

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Vanishing and exploding grads

$$\frac{\partial L_t}{\partial W} \propto \sum_{k=0}^{t} \left(\prod_{i=k+1}^{t} \frac{\partial h_i}{\partial h_{i-1}} \right) \frac{\partial h_k}{\partial W}$$

$$\left\| \frac{\partial h_i}{\partial h_{i-1}} \right\|_2 < 1 \Rightarrow \text{Vanishing gradients}$$

$$\left\| \frac{\partial h_i}{\partial h_{i-1}} \right\|_2 > 1 \Rightarrow \text{Exploding gradients}$$

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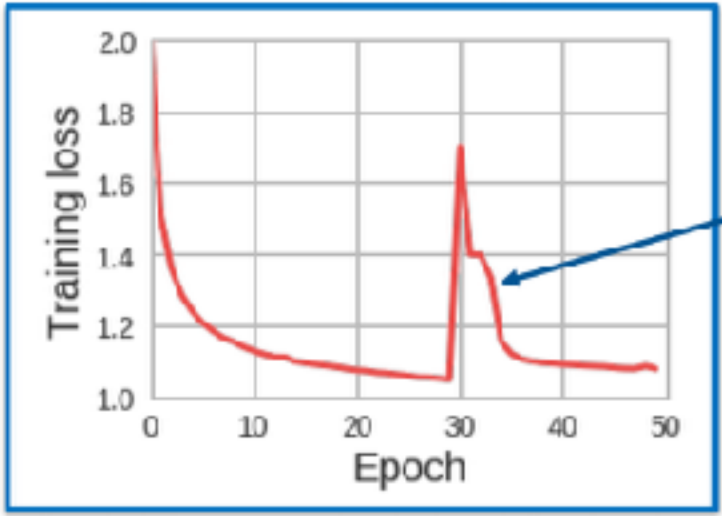
Exploding gradients: detection

Unstable learning curve



This is it!

If the gradients contain NaNs you end up with NaNs in the weights

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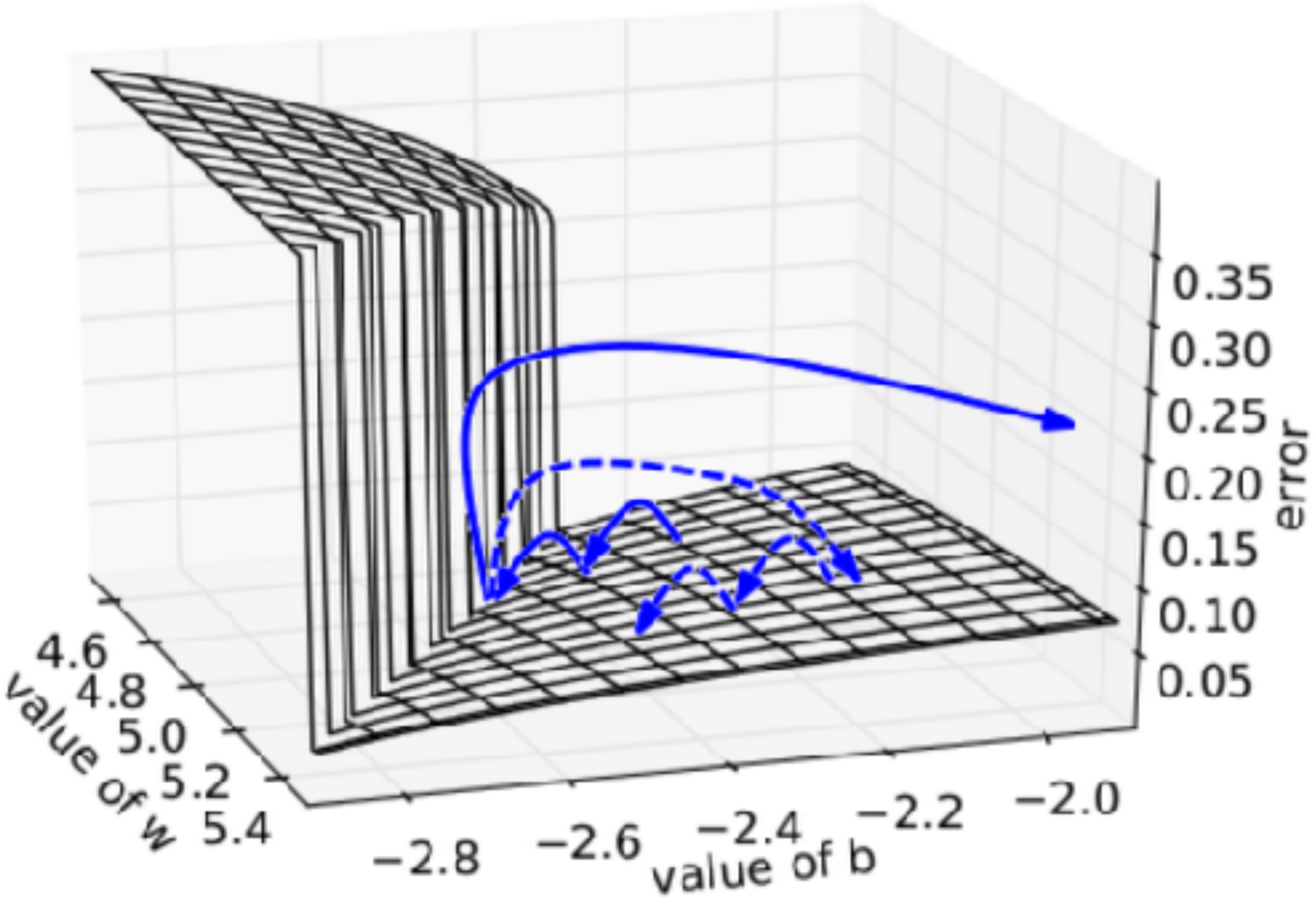

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Gradient clipping

Gradient $g = \frac{\partial L}{\partial \theta}$, θ - all the network parameters

If $||g||>$ threshold:

$$g \leftarrow \frac{threshold}{||g||} g$$

Simple but still very effective!

[Pascanu et al., 2012]

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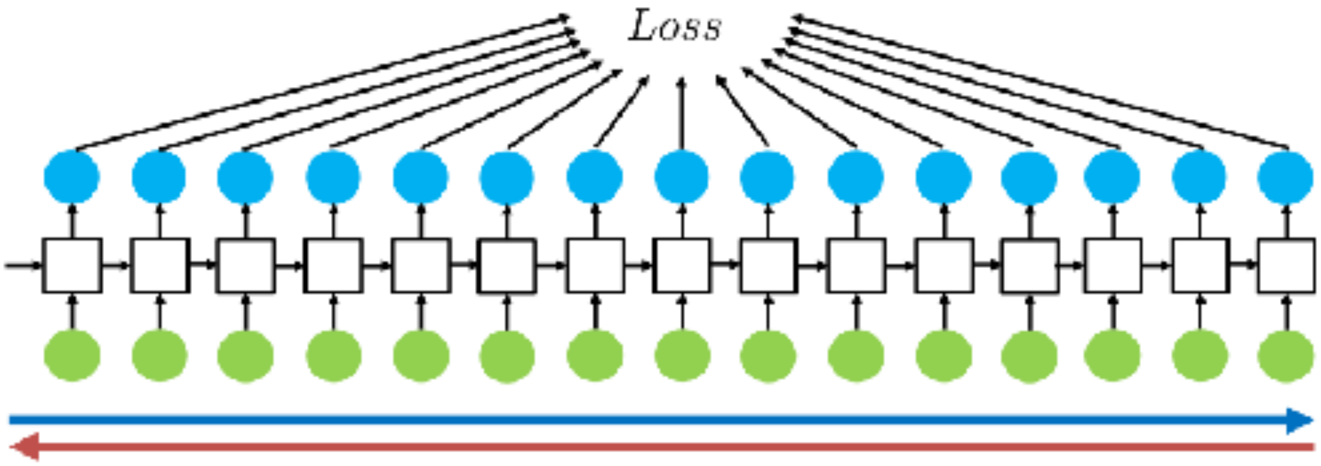
Truncated BPTT



Forward pass through the entire sequence to compute the loss

Backward pass through the entire sequence to compute the gradient

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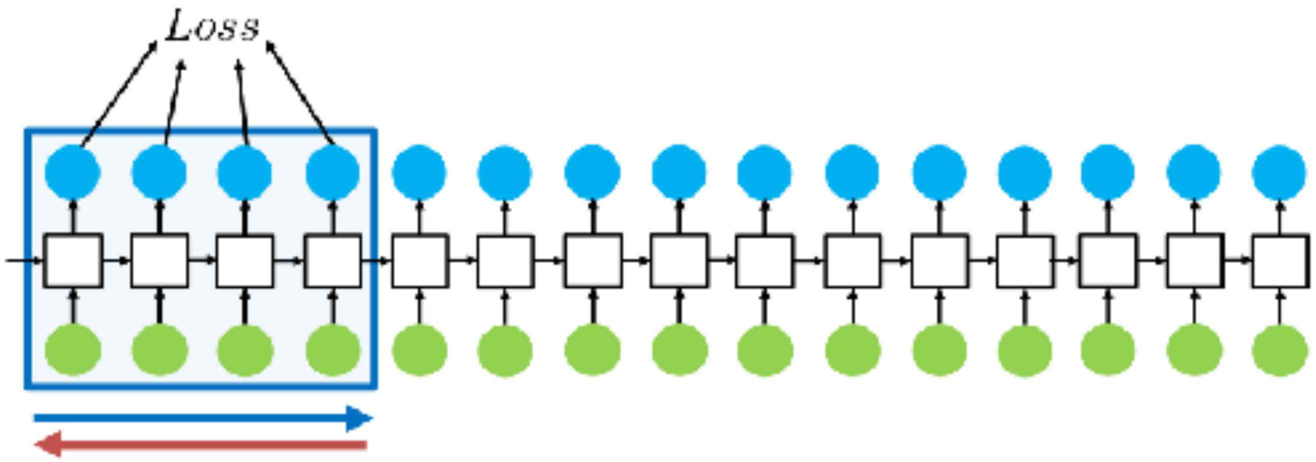
Truncated BPTT



Carry hidden states forward in time forever, but only backpropagate for some smaller number of steps.

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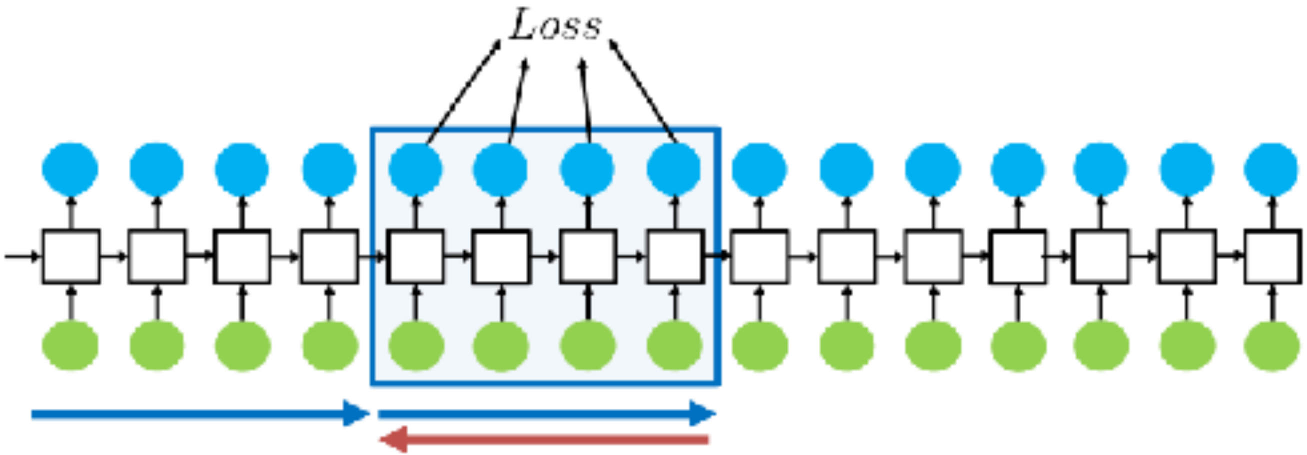
Truncated BPTT



Truncated BPTT is much faster but it doesn't come without a price! Dependencies longer than the chunk size don't affect the training but at least they still work at forward pass.

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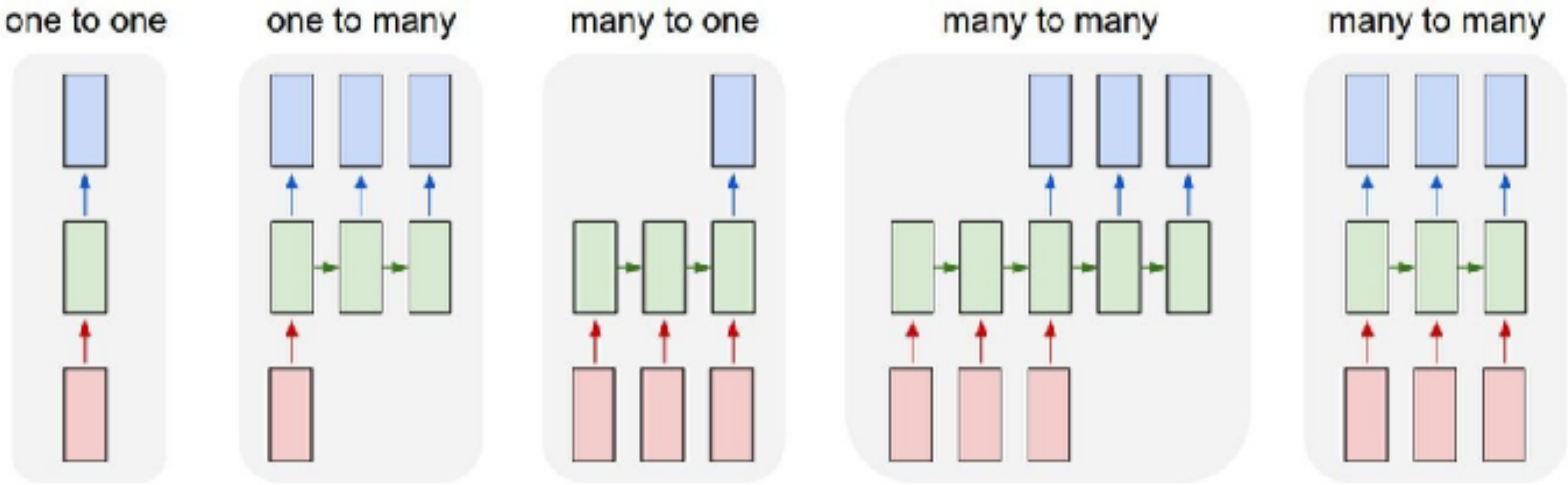
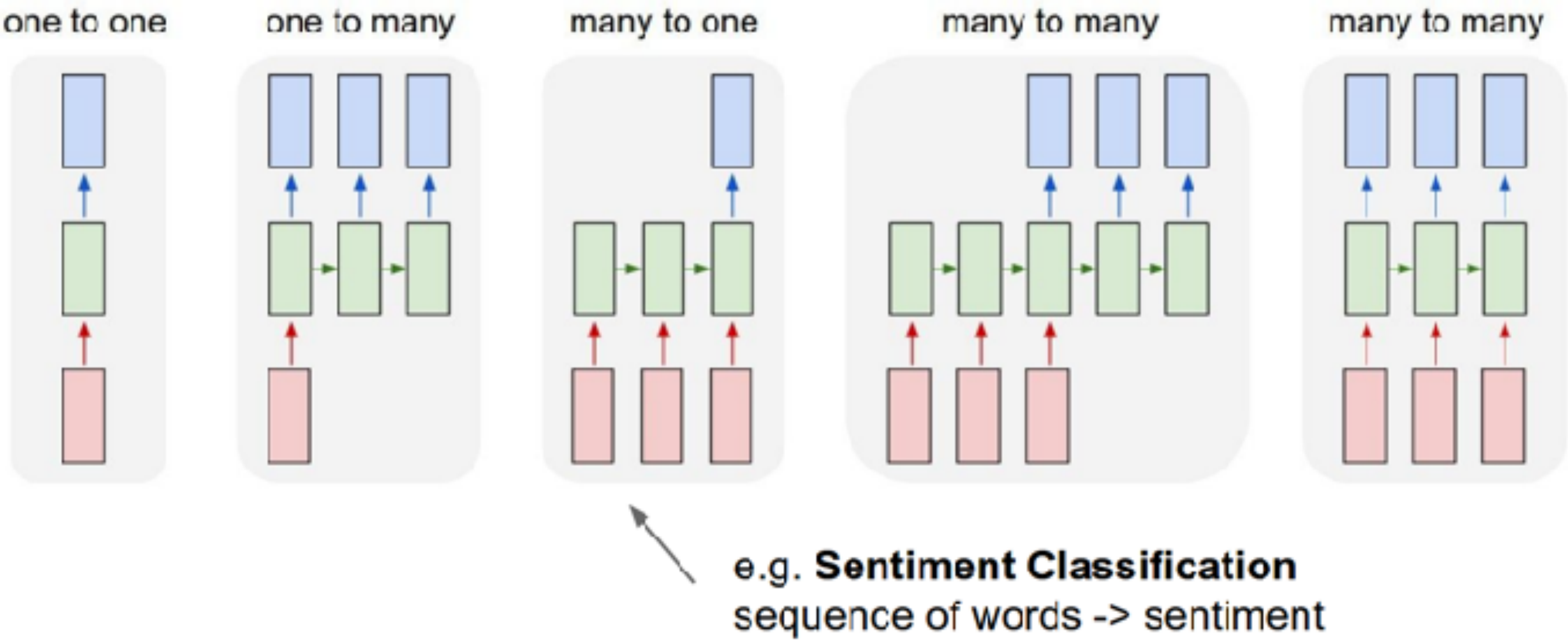
Types of tasks



e.g. **Image Captioning**
image -> sequence of words

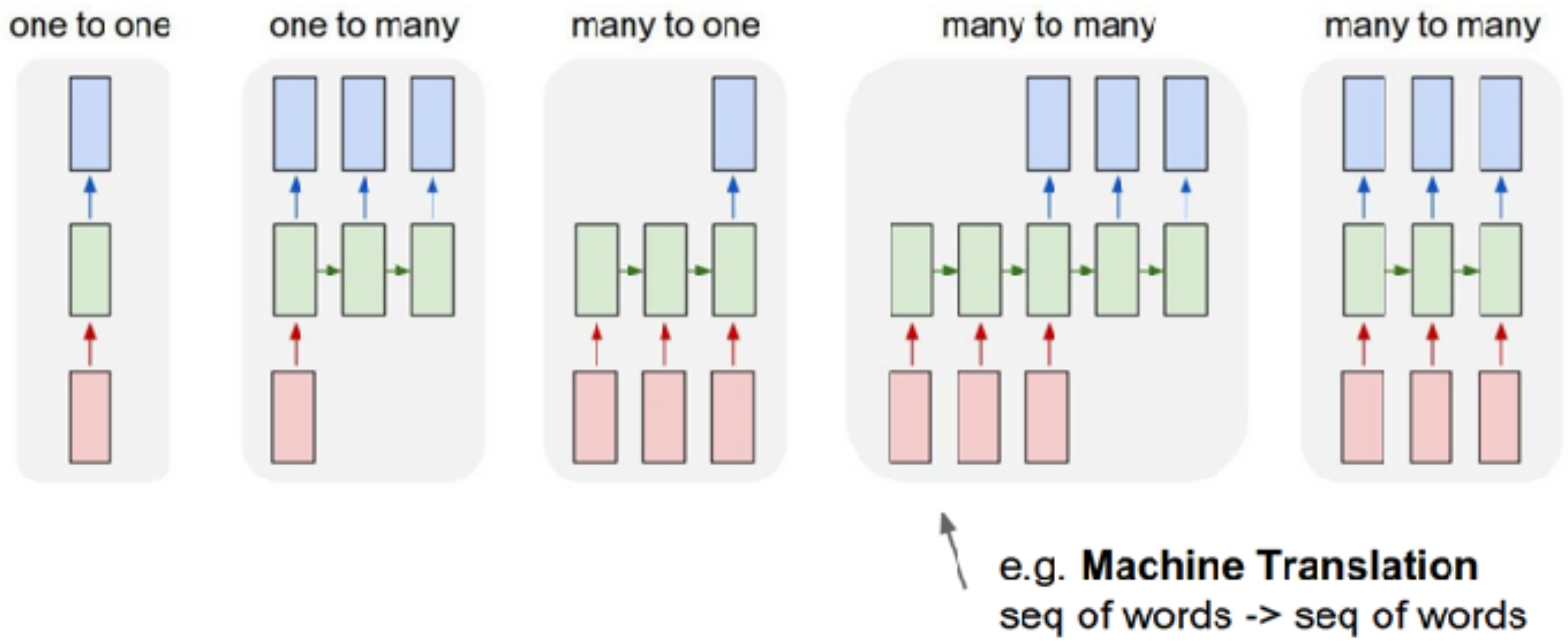
Stanford [CS234n]

Types of tasks



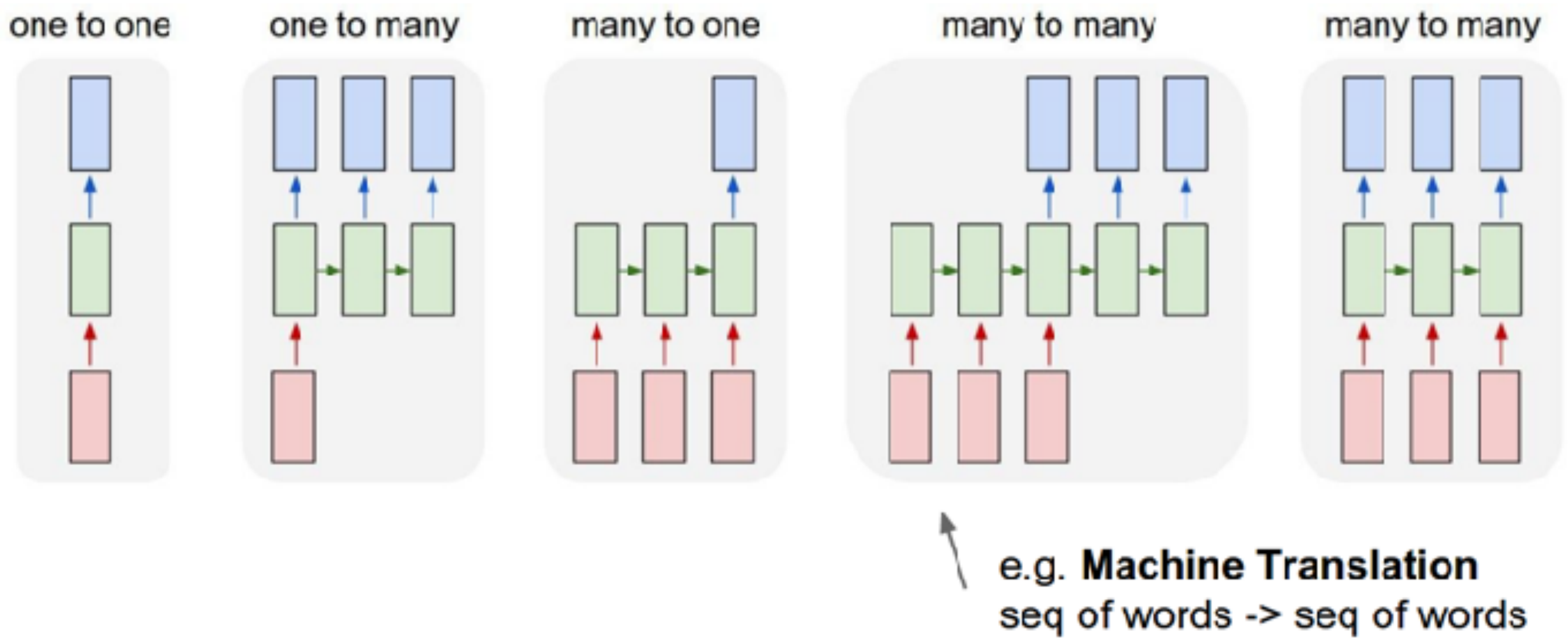
Stanford CS234n

Types of tasks



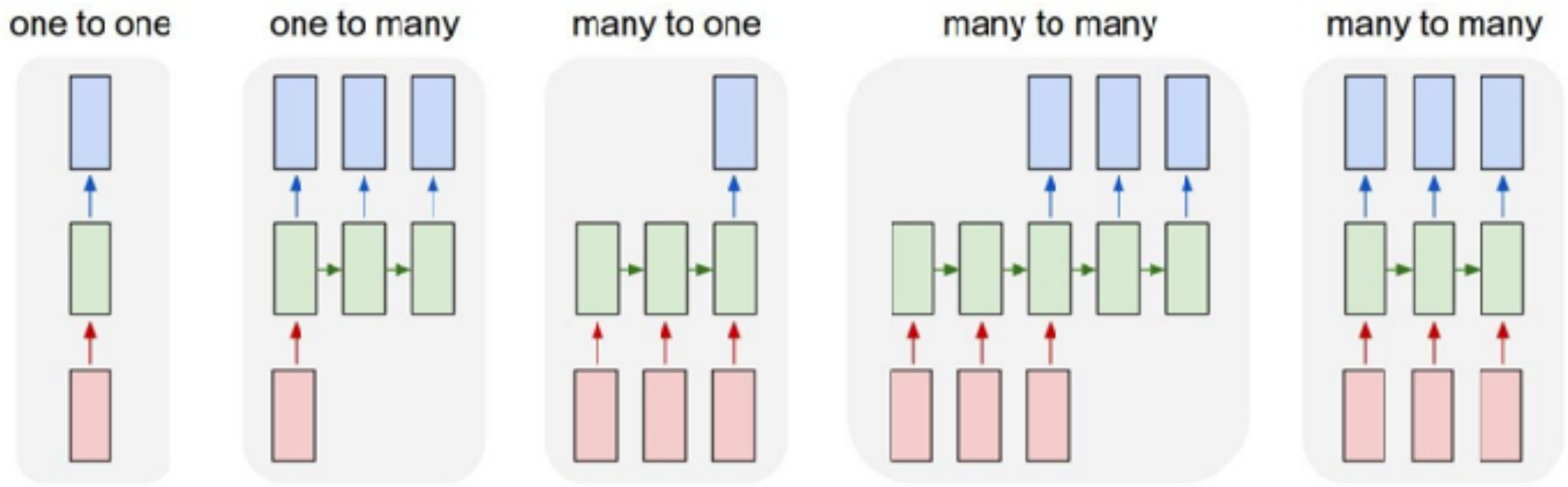
Stanford CS234n

Types of tasks



Stanford [CS234n]

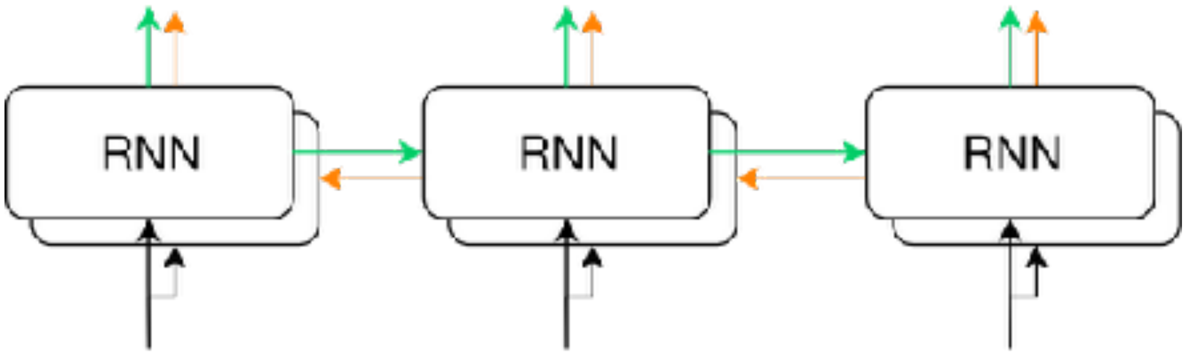
Types of tasks



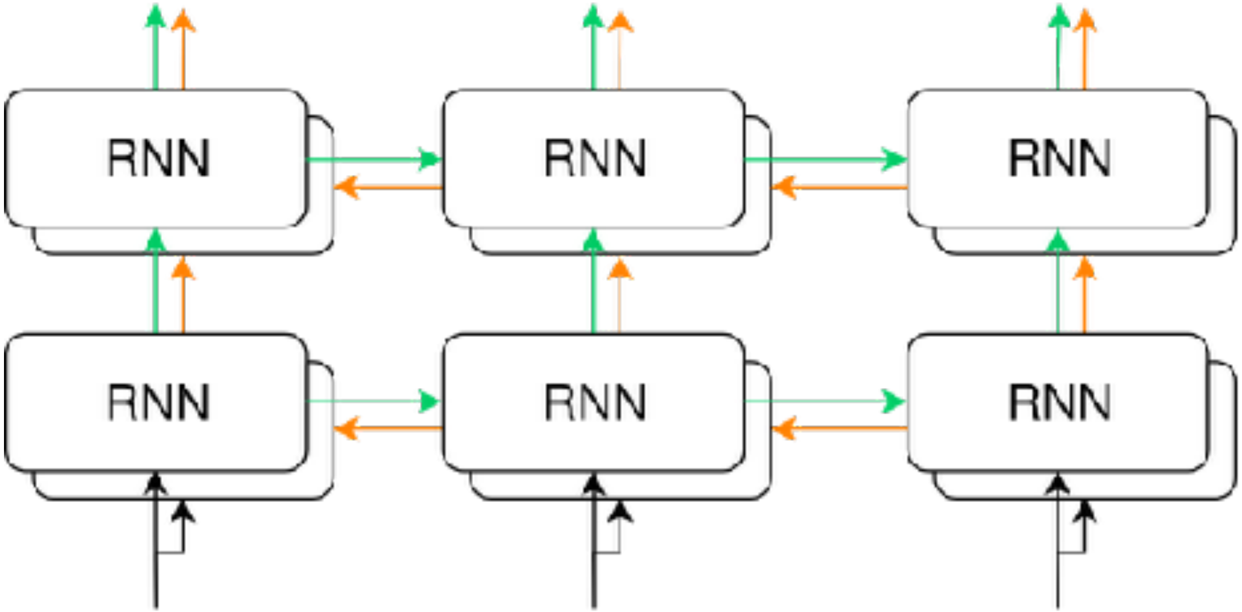
e.g. **POS tagging**,
sequence of tokens to sequence of tags

Stanford CS234n

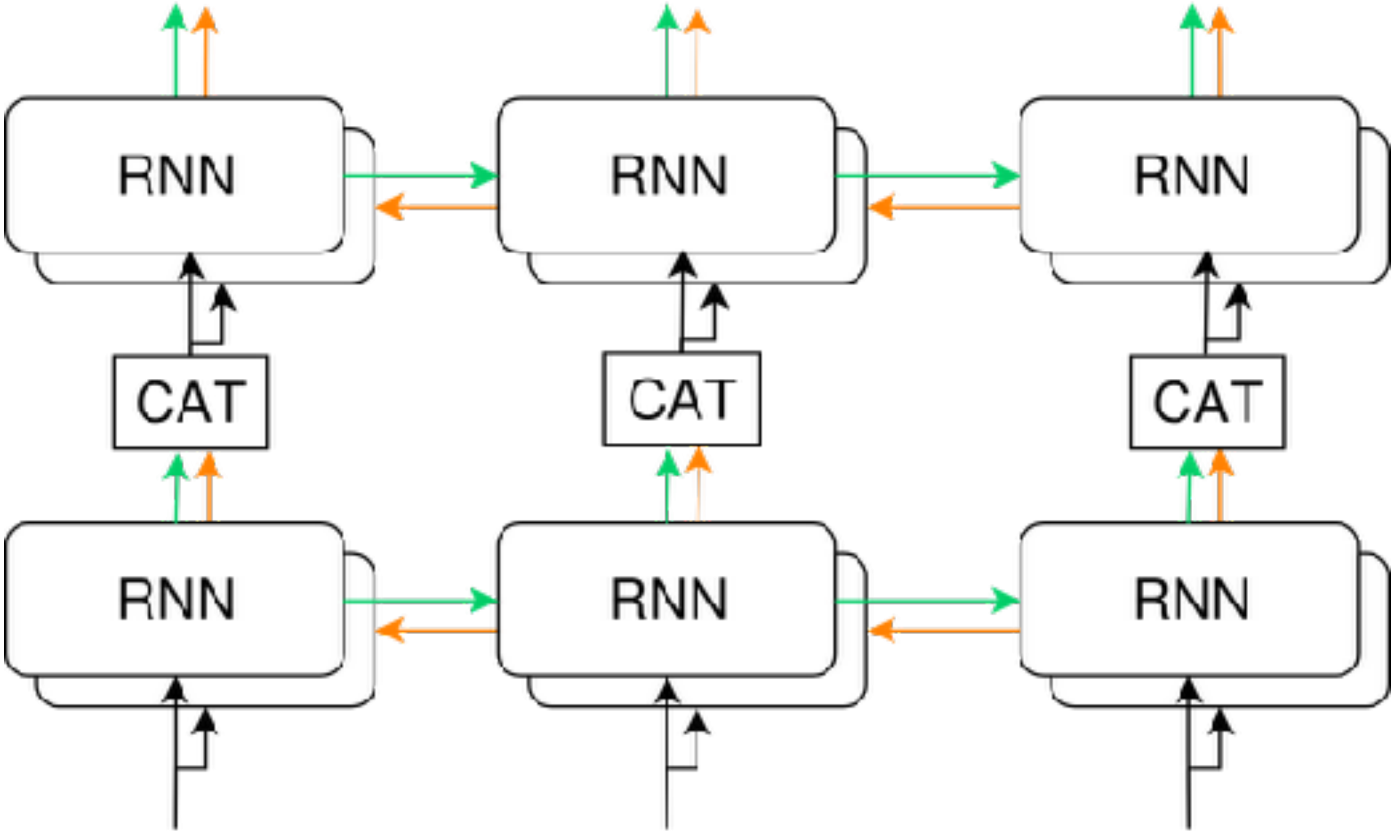
Bi-Directional RNN



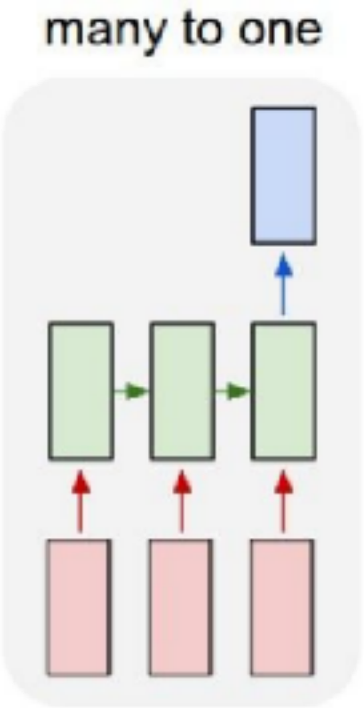
Stacked Bi-Directional RNN

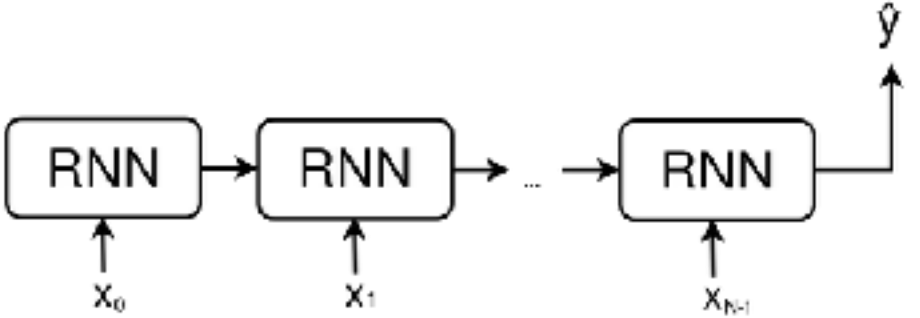


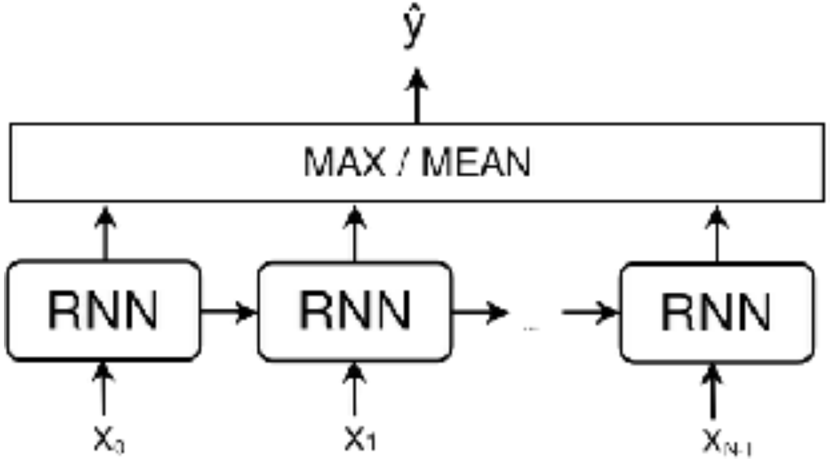
Stacked Bi-Directional RNN with Concatenation



Aggregation methods







Spasibo