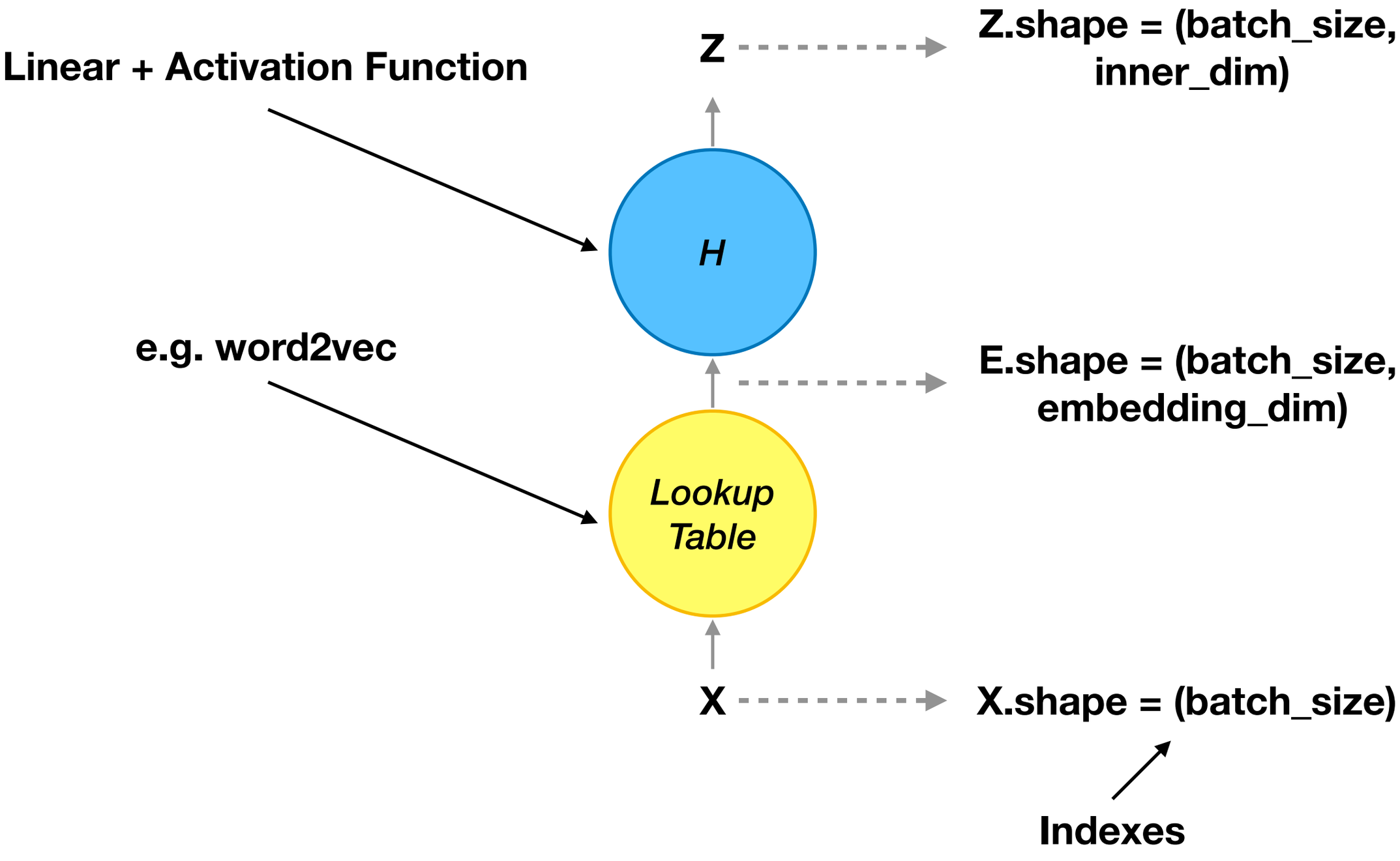
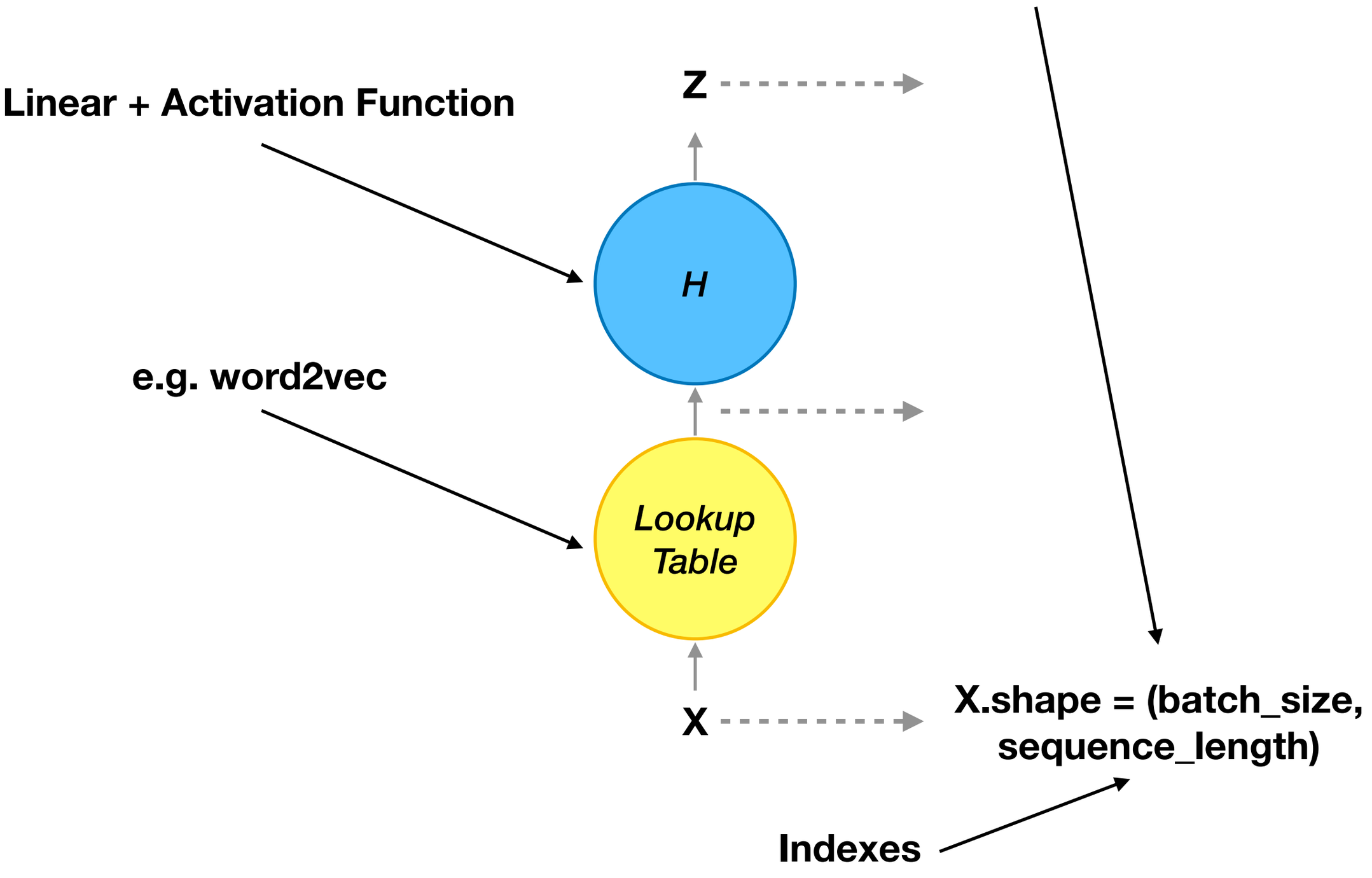
Recurrent Neural Network

Neural Network



Neural Network

What if we have different lengths?



Padding

[Мама, мыла, раму]

[Покупать, новый, телефон, затратно]

[Вау]

[Мне, очень, не, нравится ваш, банк]

↓

max_sequence_length = 8

Depend of your dataset statistics

↓

[Мама, мыла, раму, PAD, PAD, PAD, PAD, PAD]

[Покупать, новый, телефон, затратно, PAD, PAD, PAD, PAD]

[Вау, PAD, PAD, PAD, PAD, PAD, PAD, PAD]

[Мне, очень, не, нравится, ваш, банк, PAD, PAD]

Padding

[Мама, мыла, раму, PAD, PAD, PAD, PAD, PAD]

[Покупать, новый, телефон, затратно, PAD, PAD, PAD, PAD]

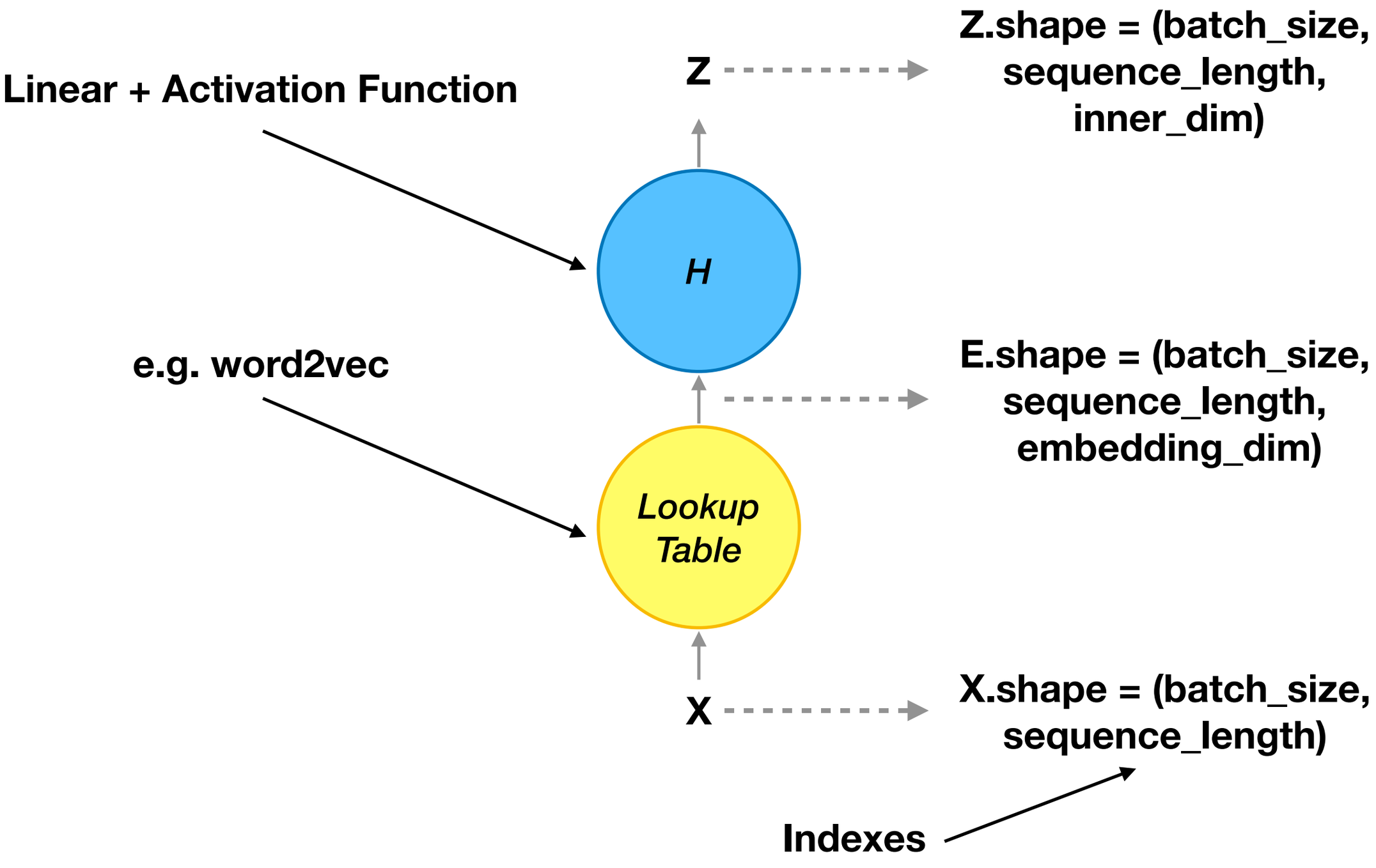
[Вау, PAD, PAD, PAD, PAD, PAD, PAD, PAD]

[Мне, очень, не, нравится, ваш, банк, PAD, PAD]

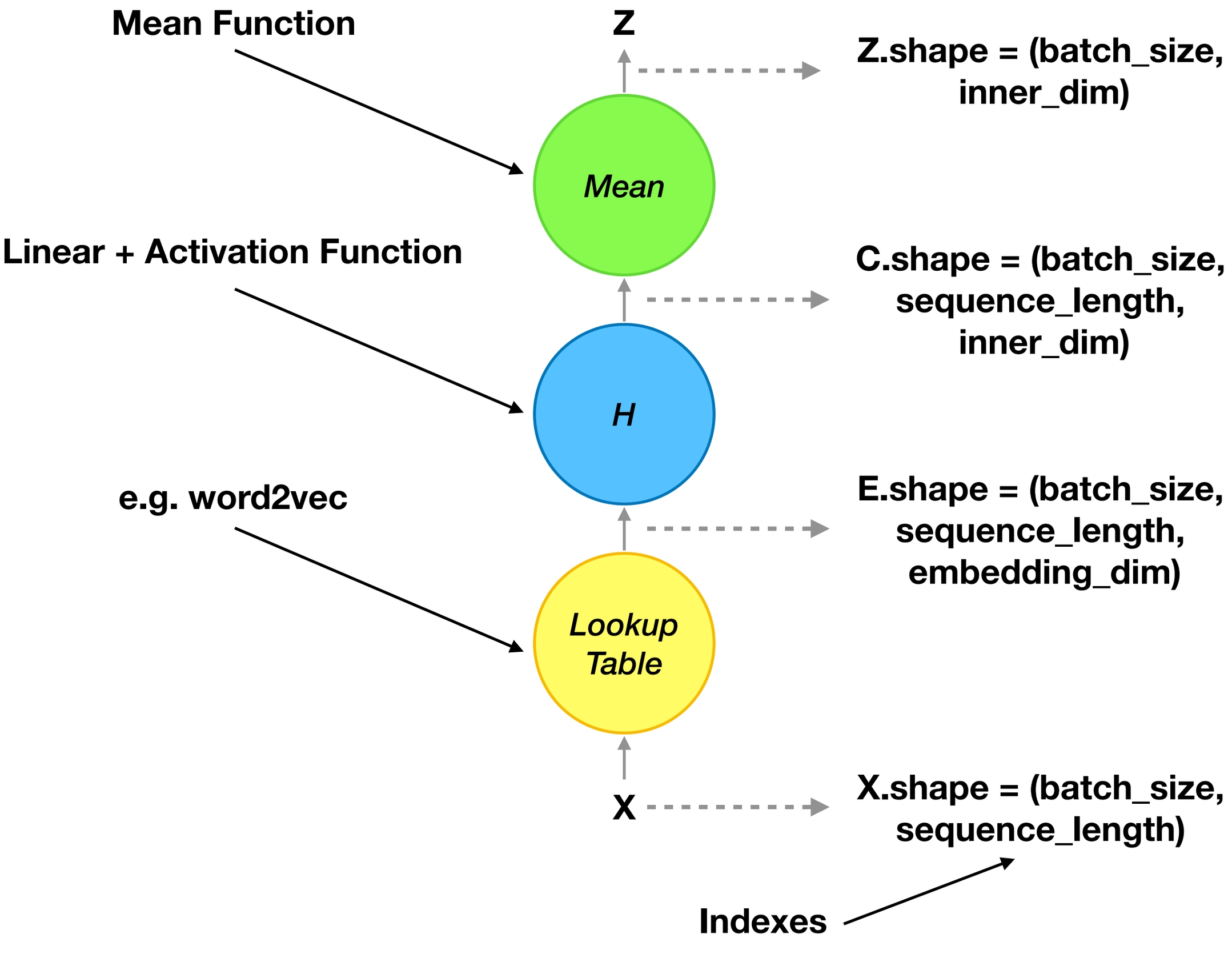
Indexing | **Collect word2index vocabulary**

34	2	3	0	0	0	0	0
64	23	1515	45	0	0	0	0
55	0	0	0	0	0	0	0
36	43	22	7	124	356	0	0

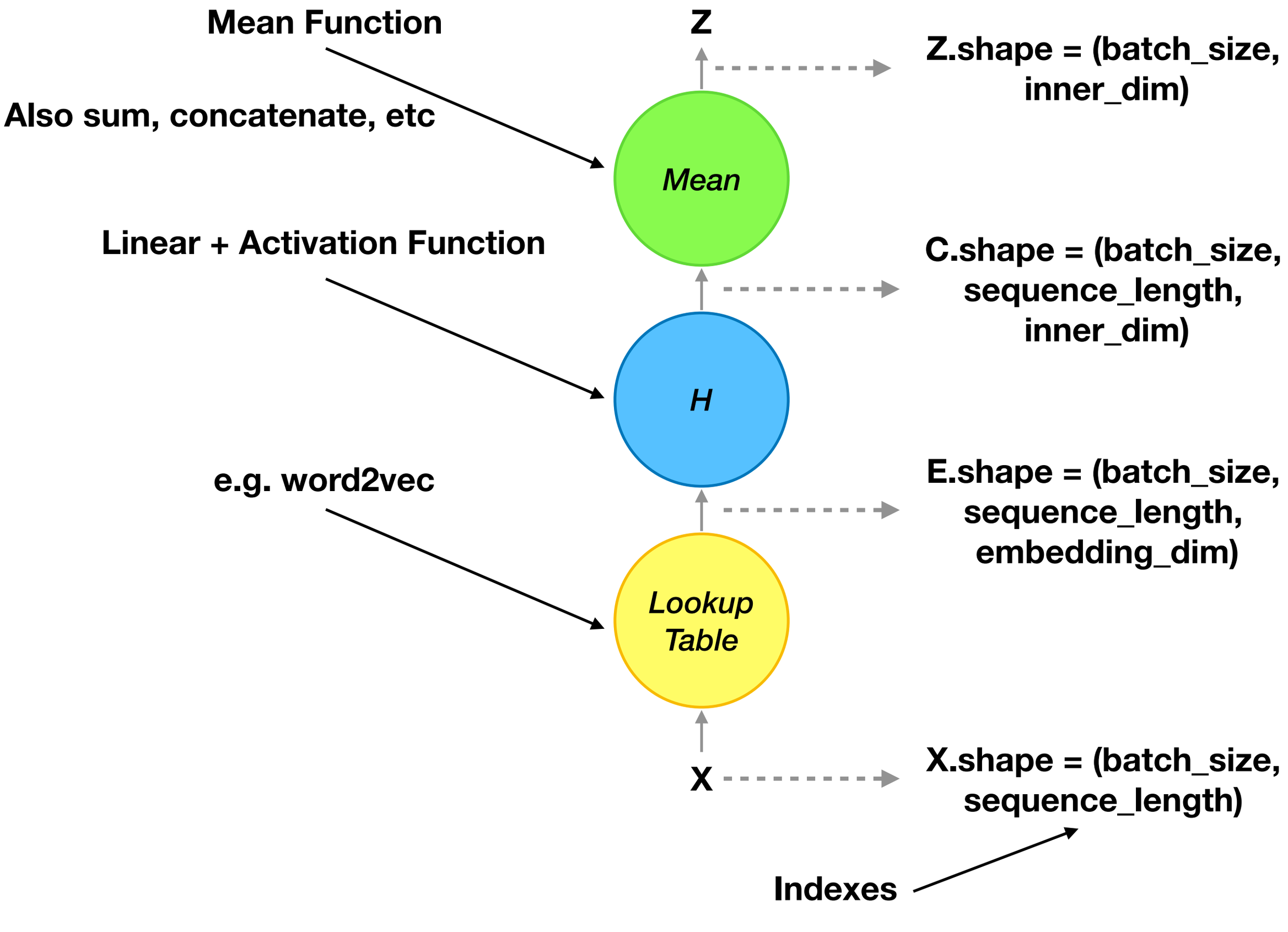
Neural Network



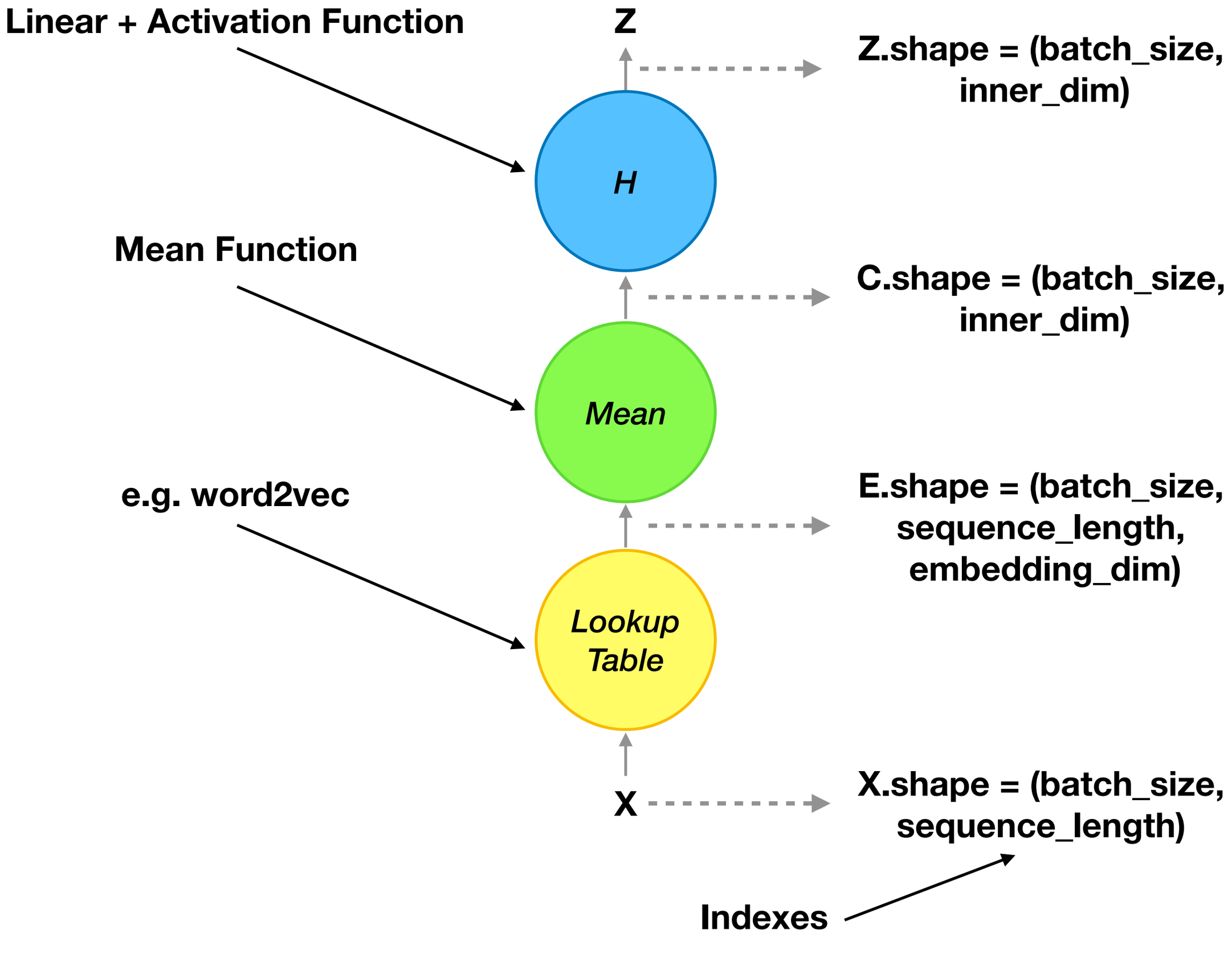
Neural Network



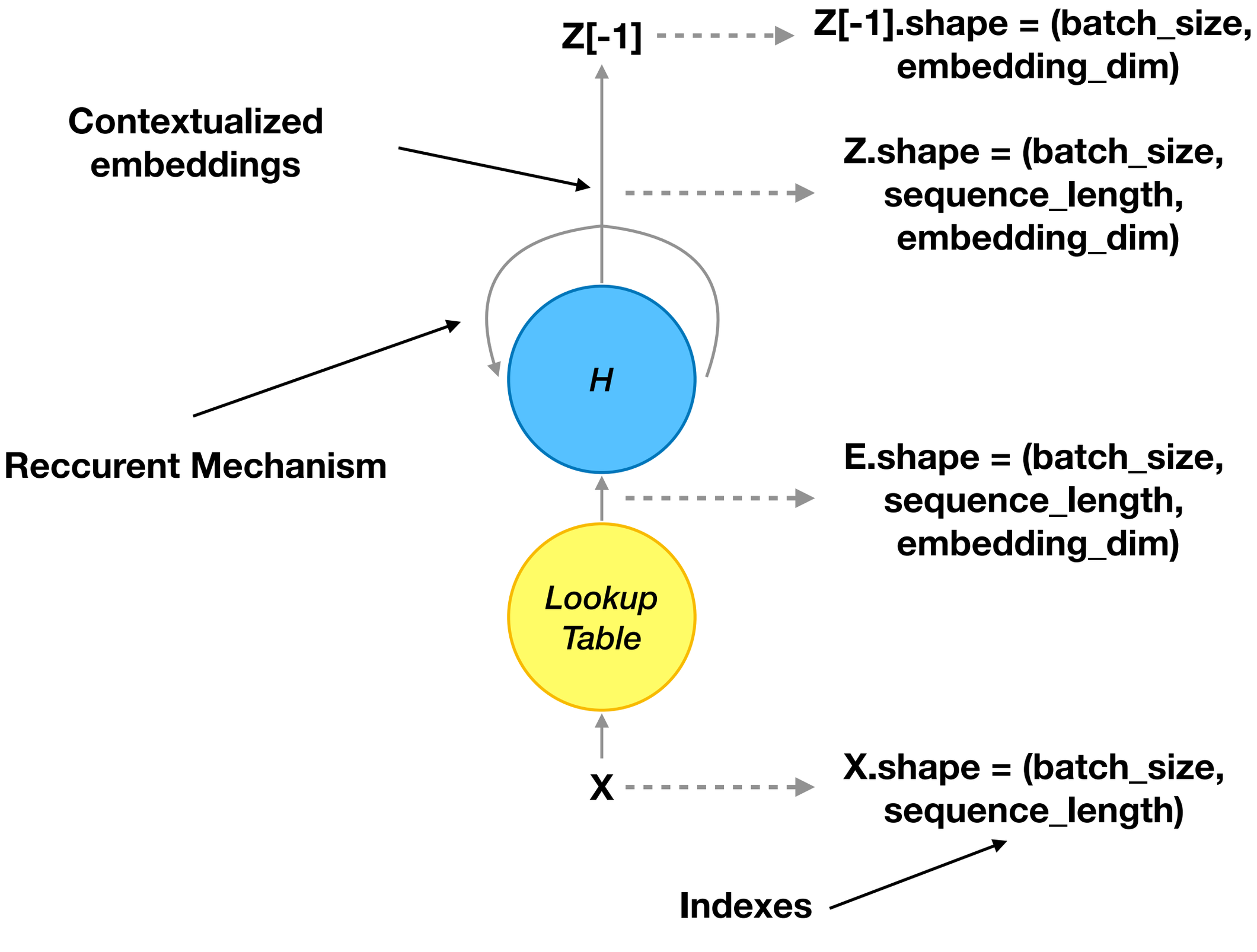
Neural Network



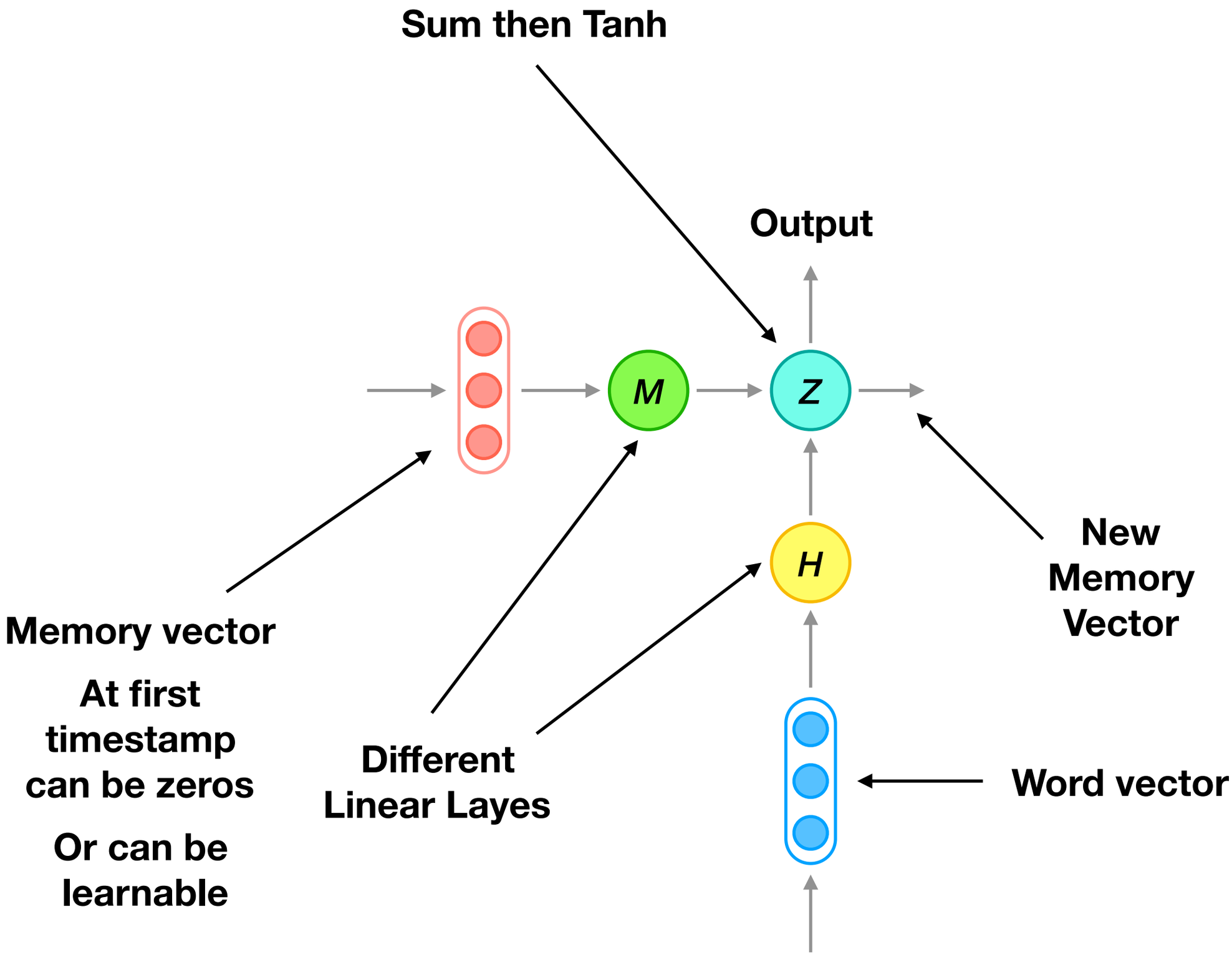
Neural Network



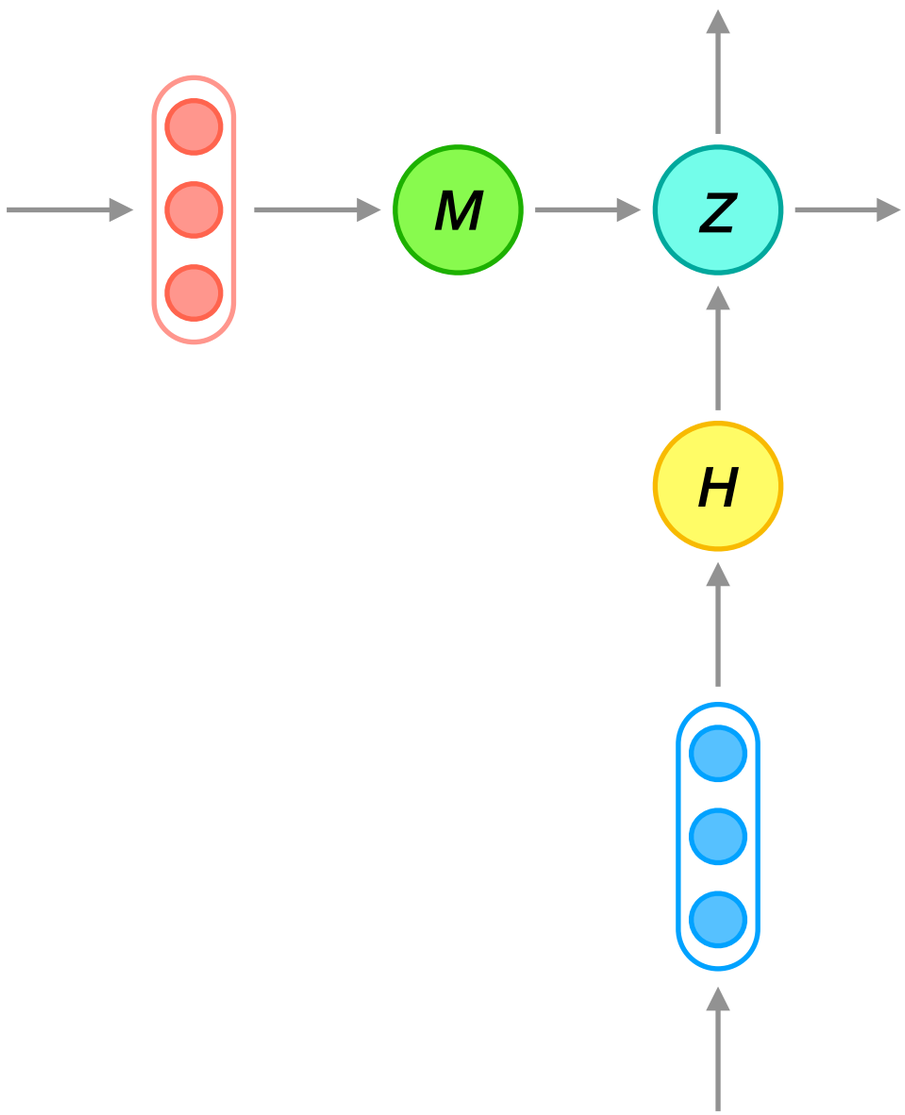
Recurrent Neural Network



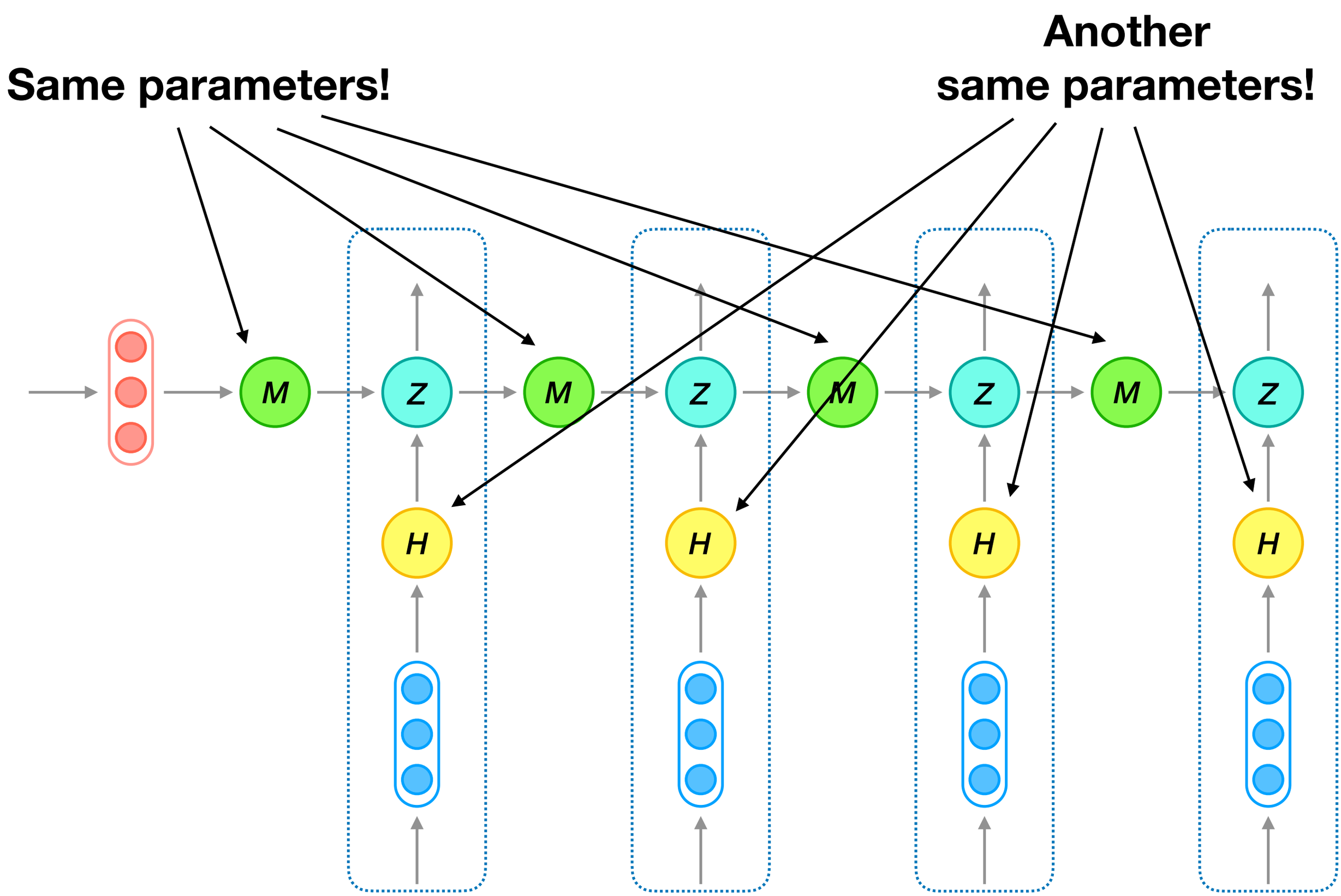
Reccurent Cell



Reccurent Mechanism



Reccurent Mechanism



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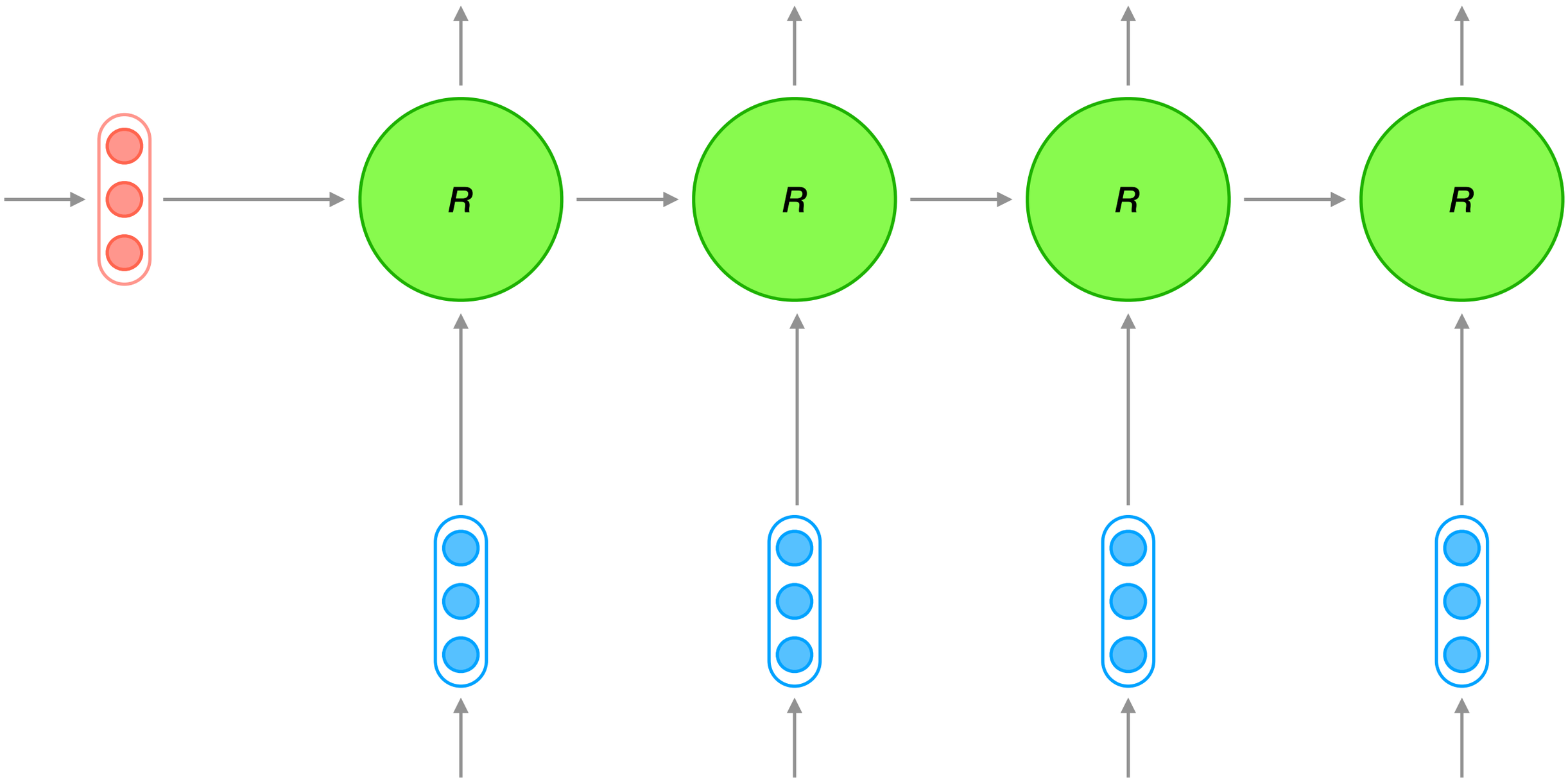

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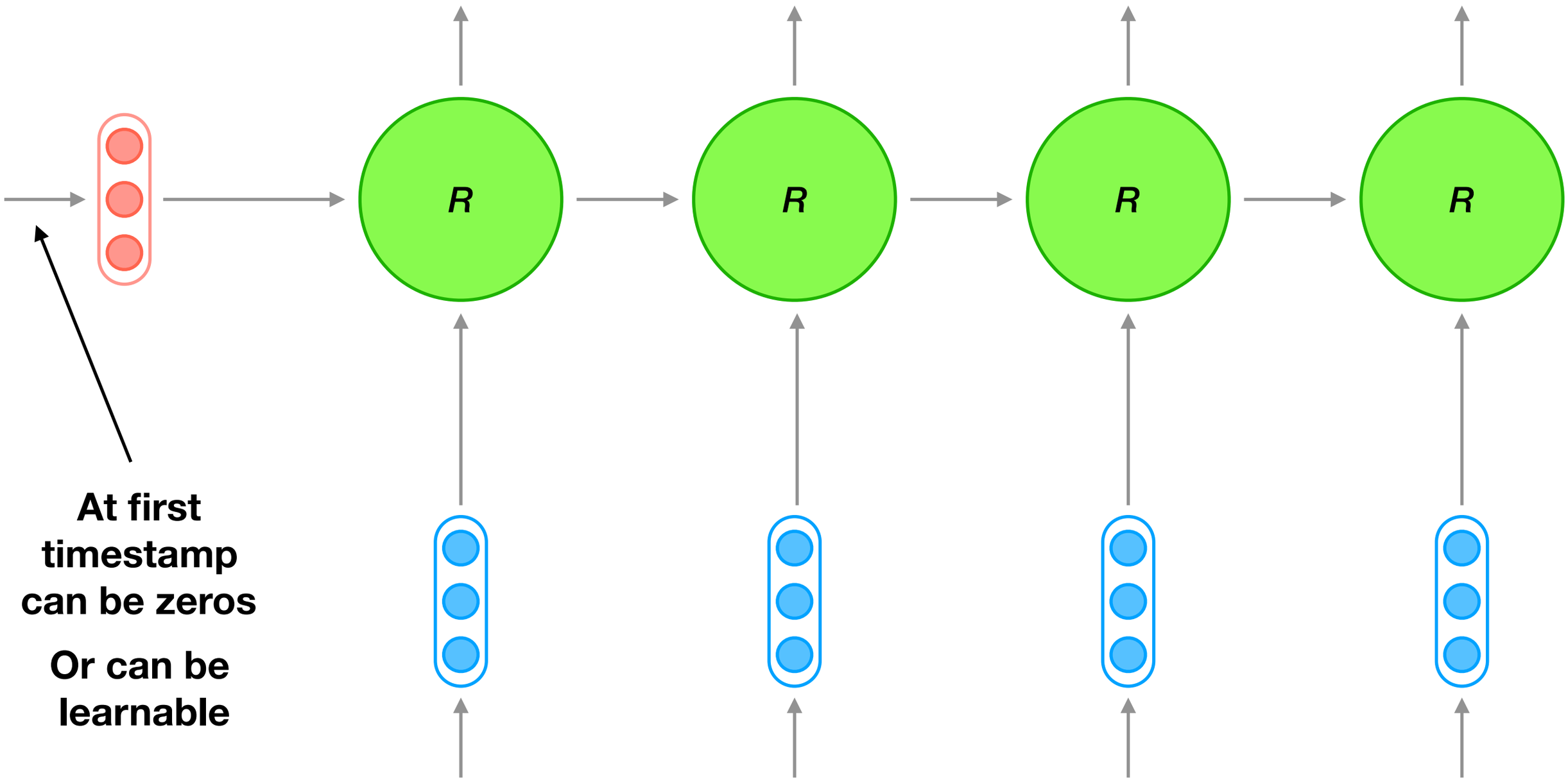
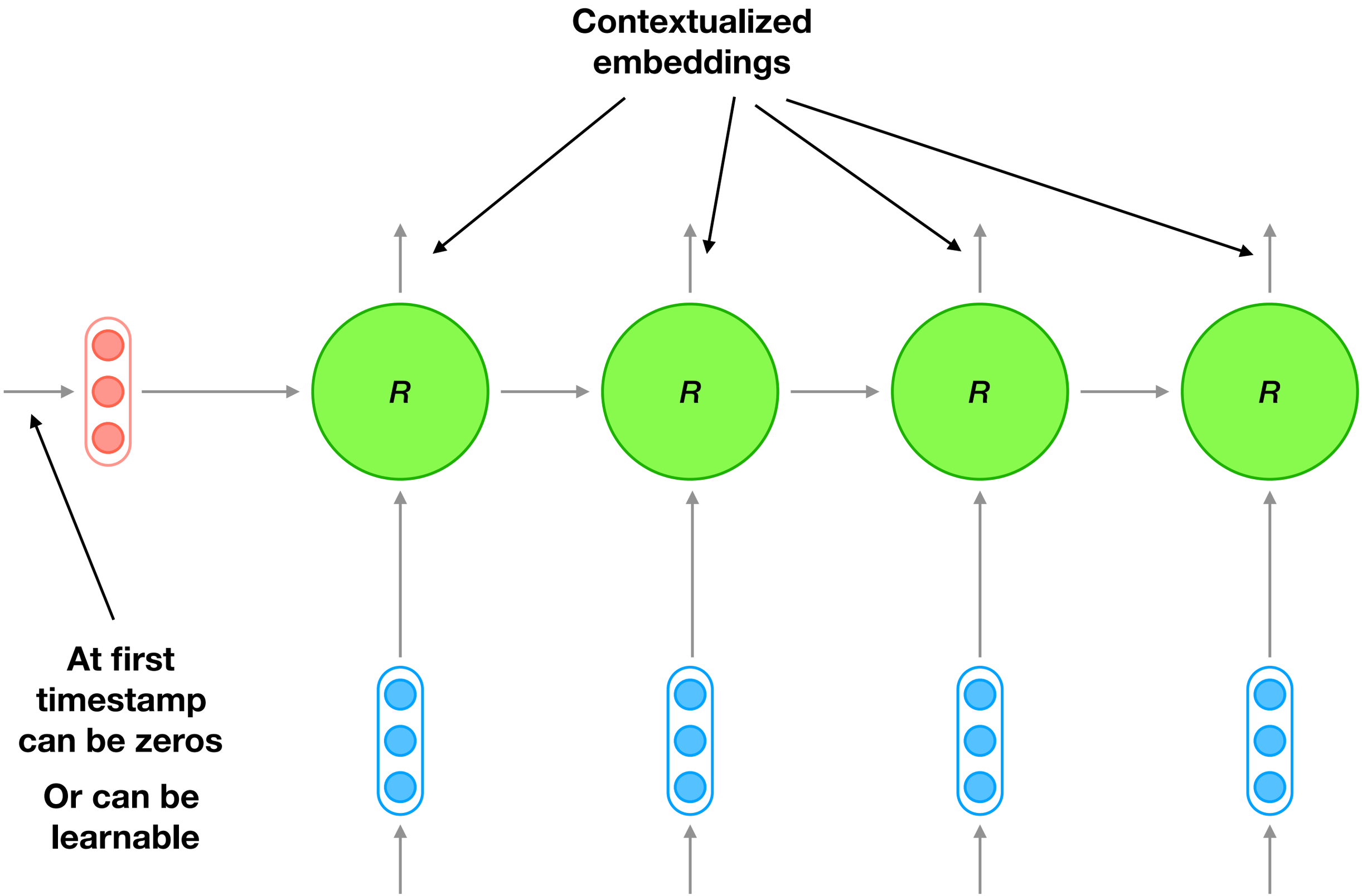
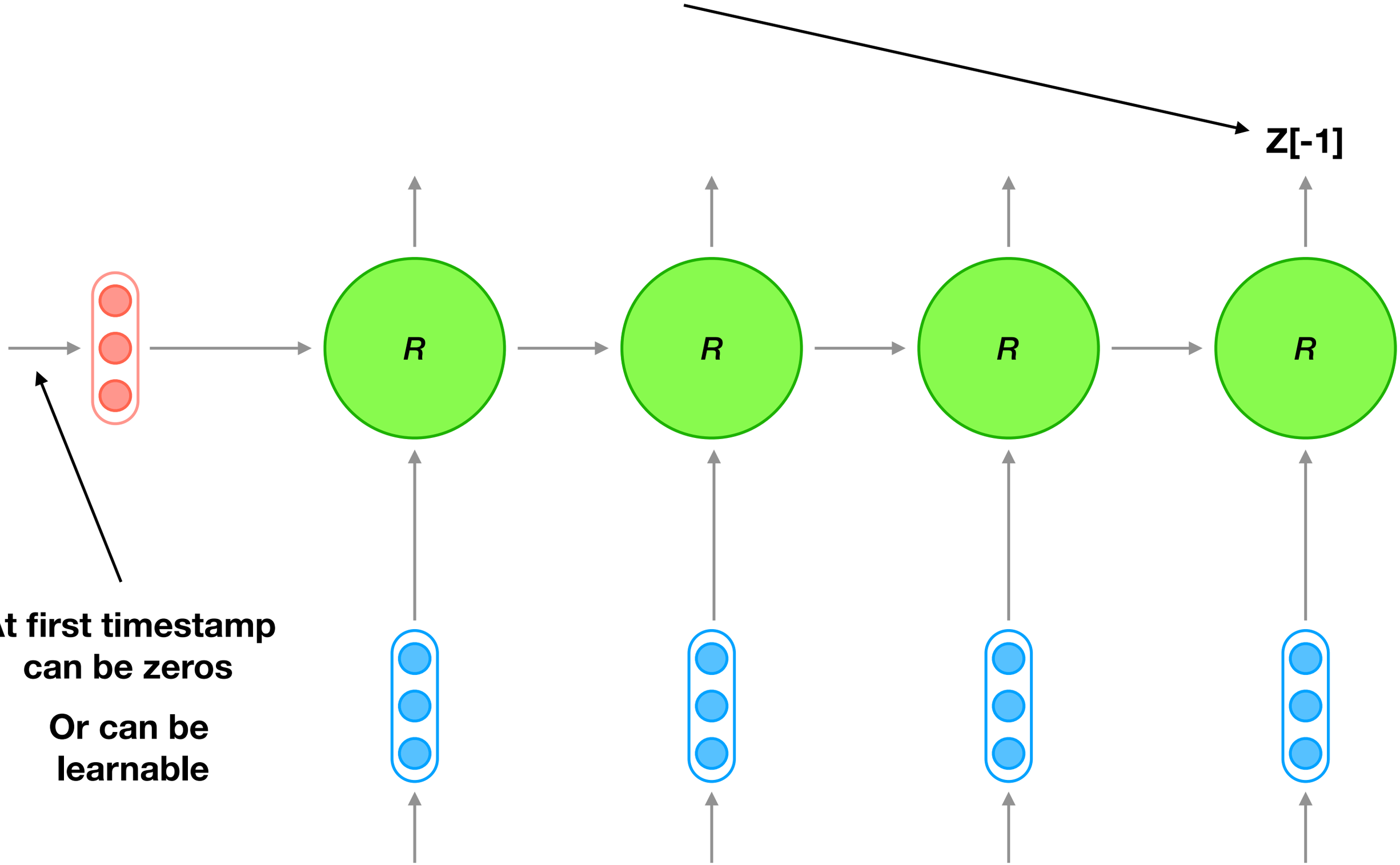


Reccurent Mechanism

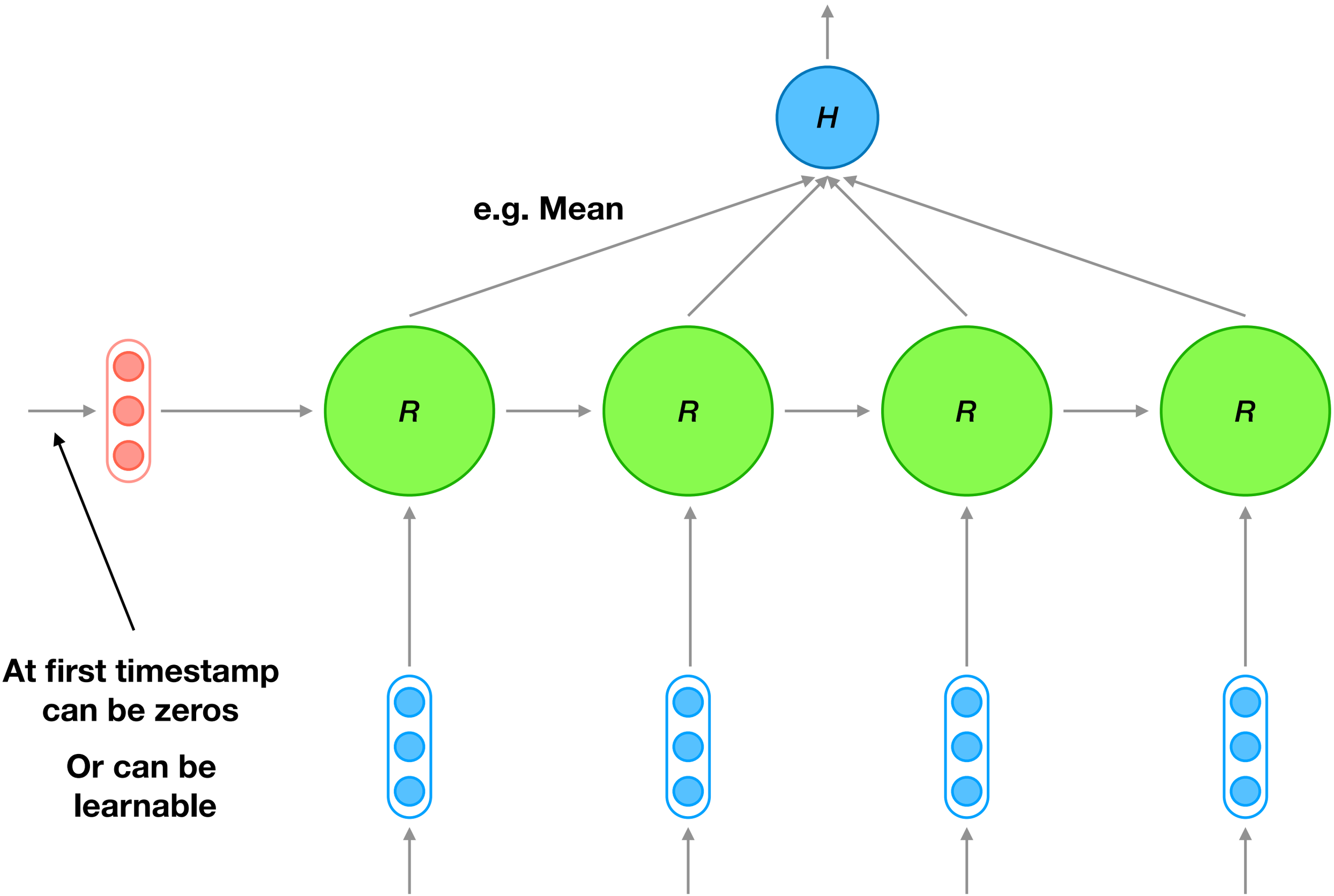


Reccurent Mechanism

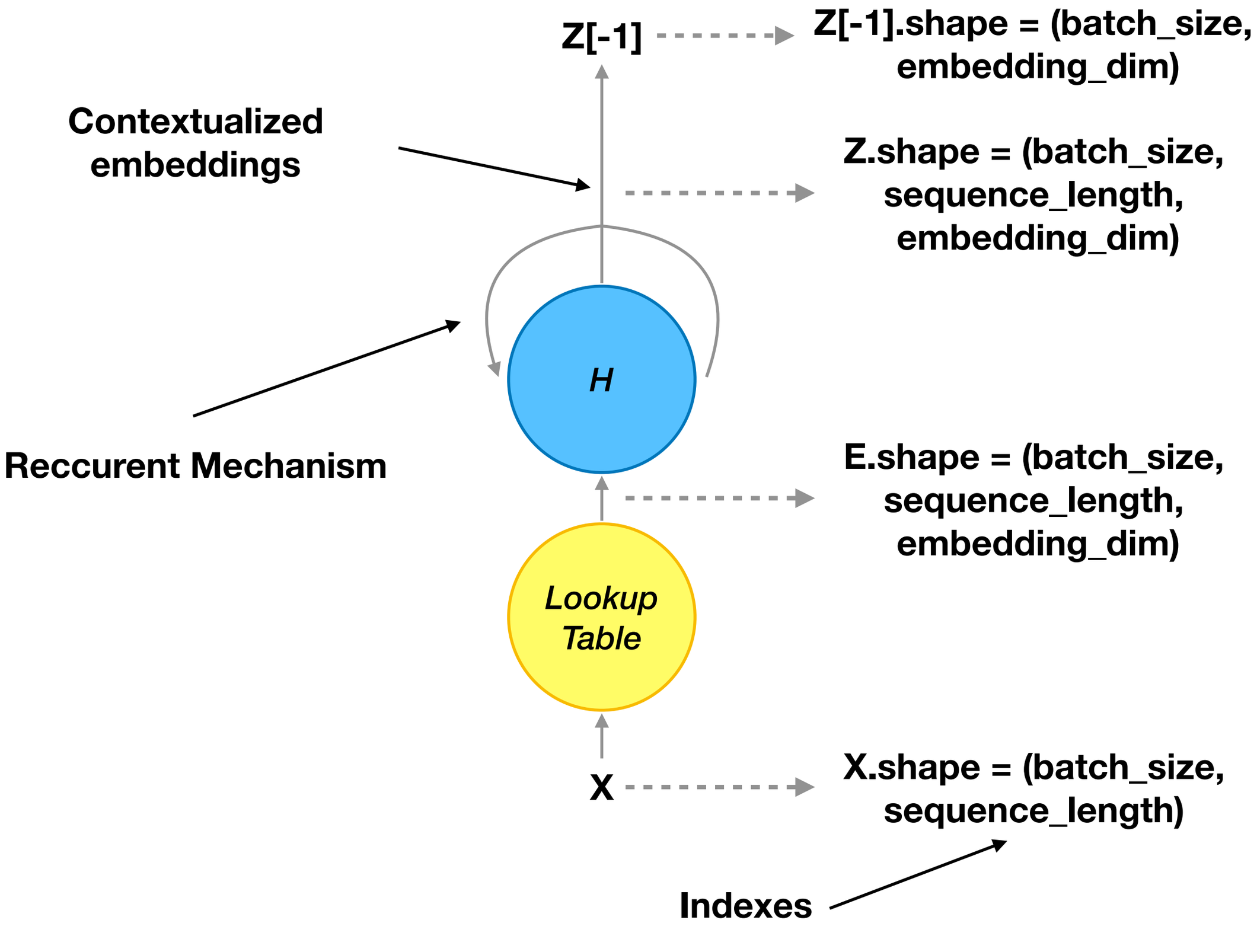
Now we can take last vector from sequence



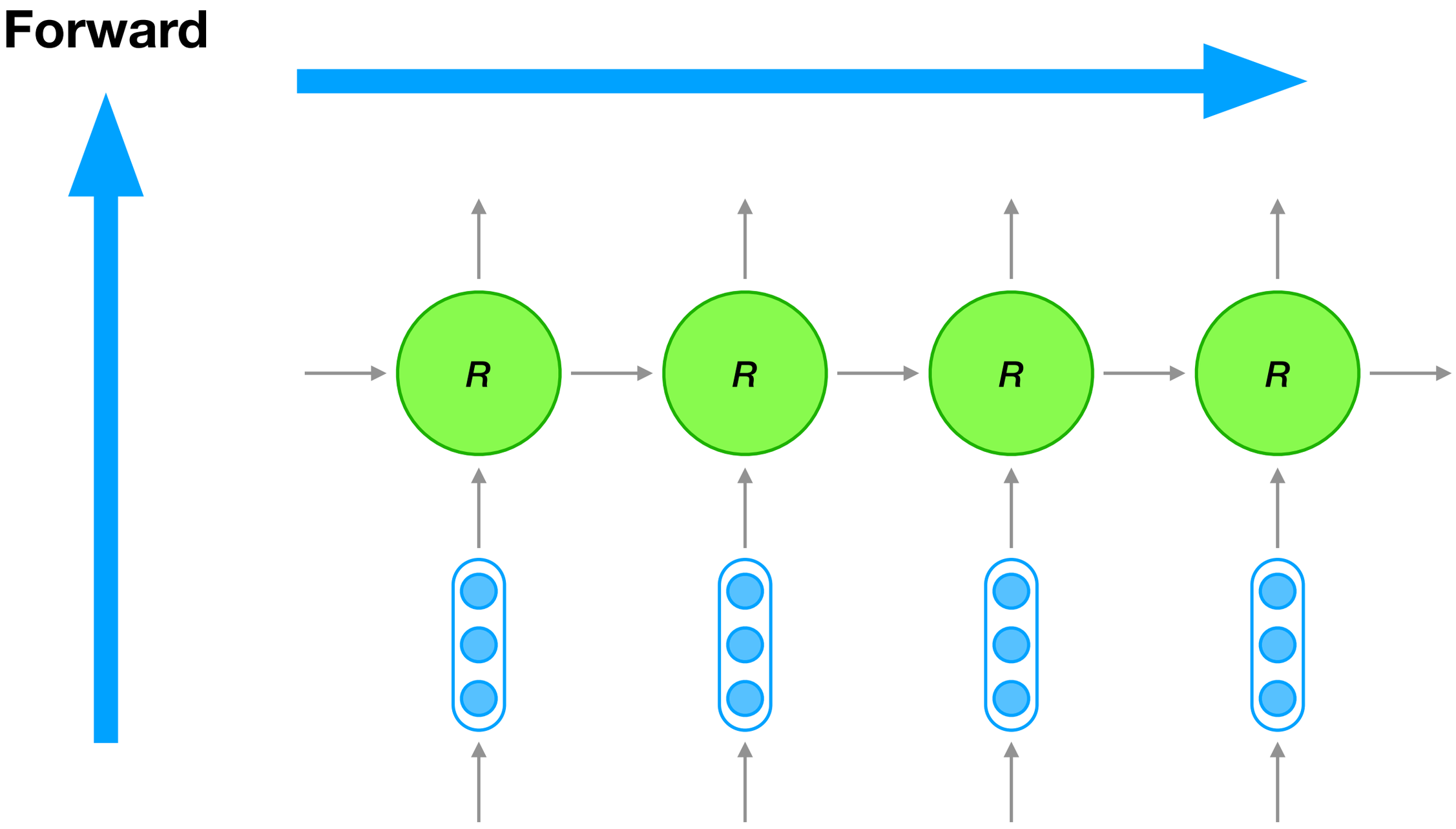
Reccurent Mechanism



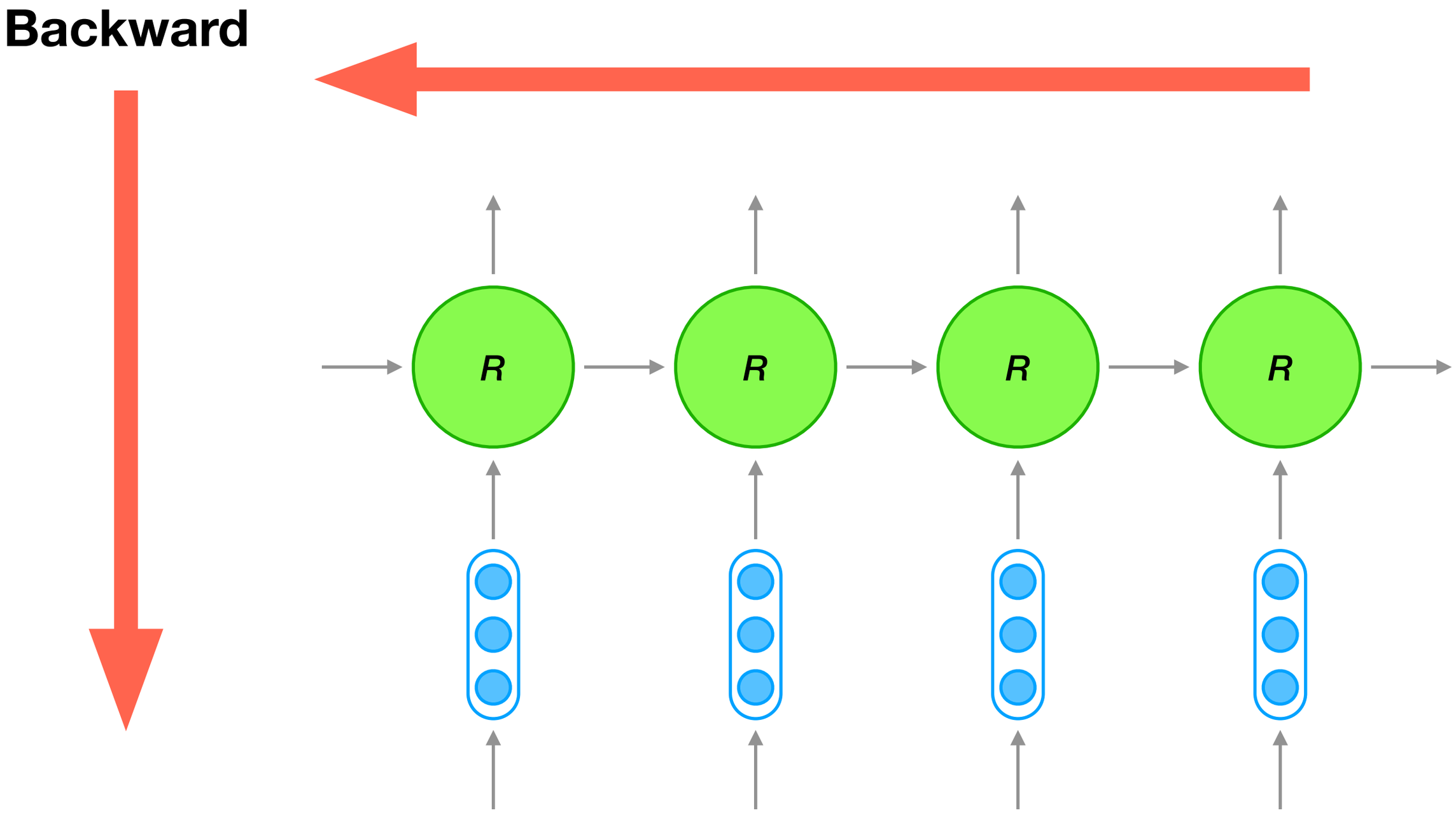
Recurrent Neural Network



BPTT

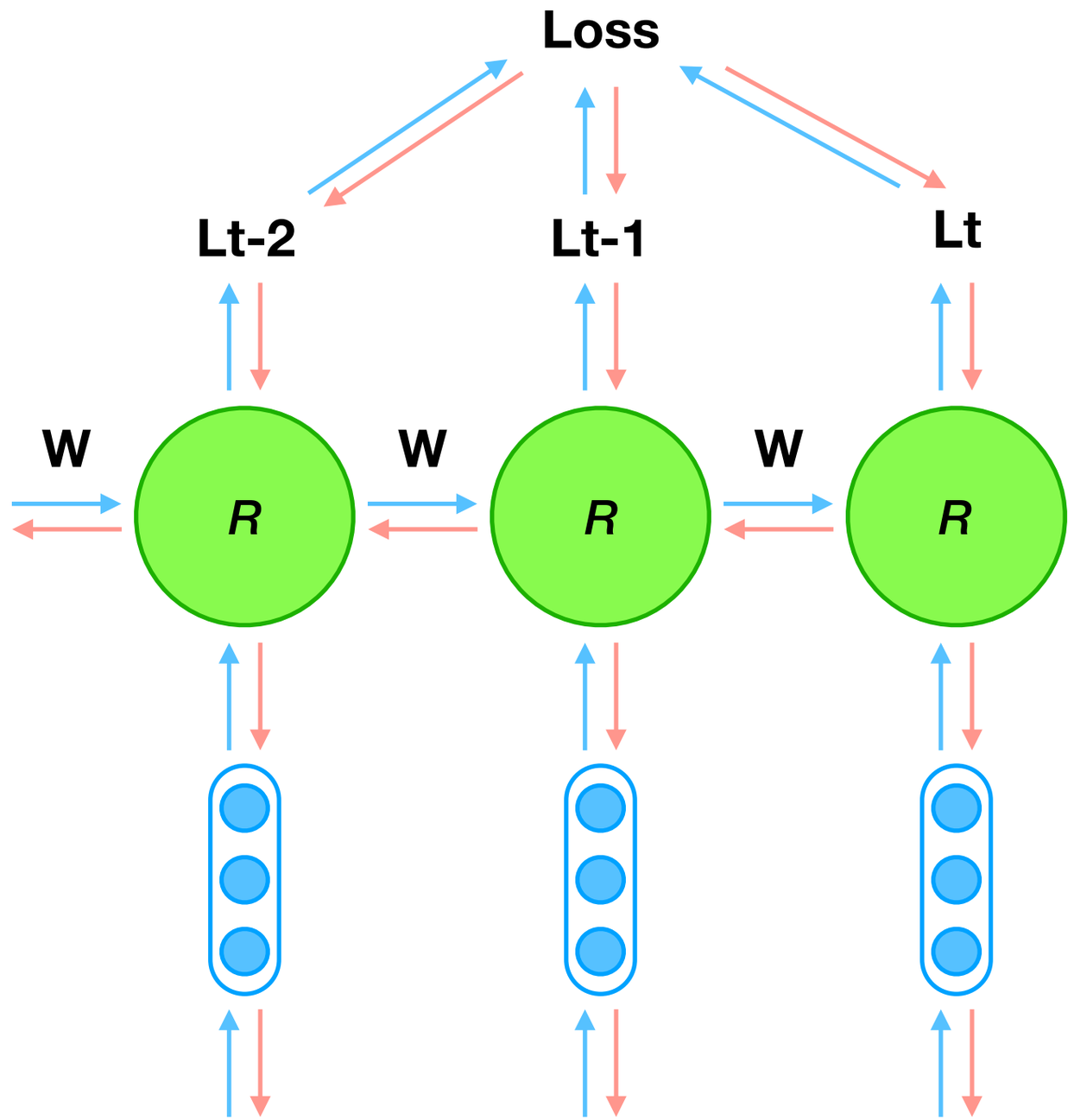


BPTT



BPTT

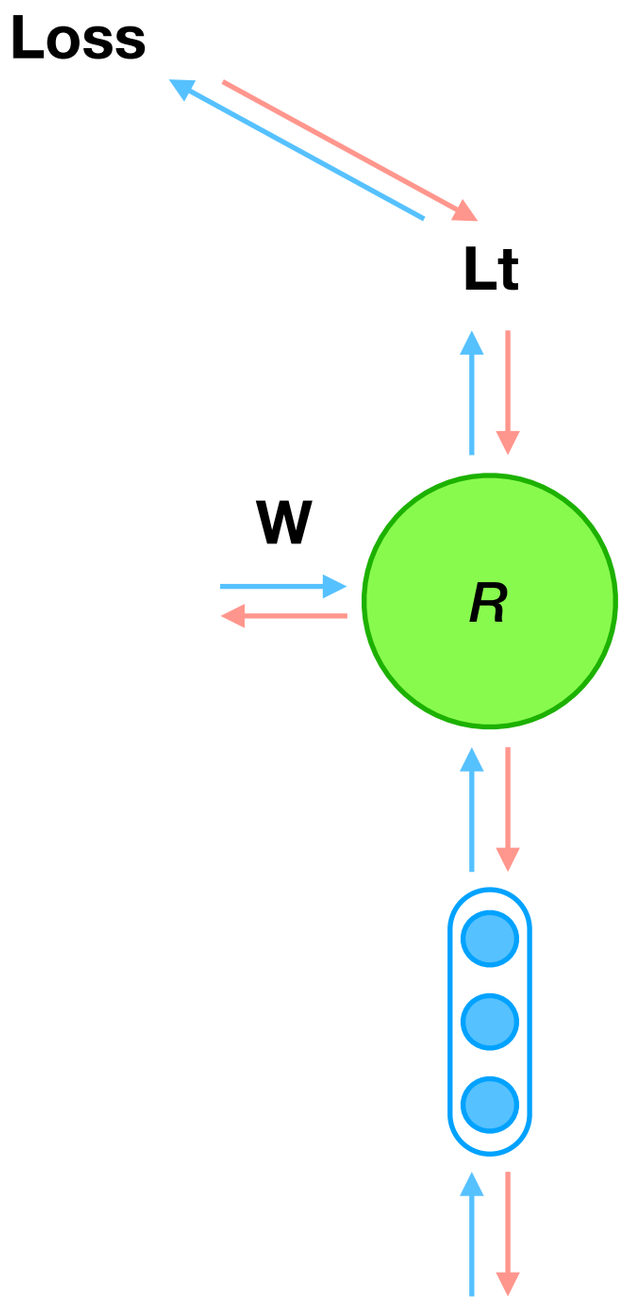
$$\frac{\partial L}{\partial W} = \sum_{i=0}^{T} \frac{\partial L_i}{\partial W}$$



BPTT

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

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



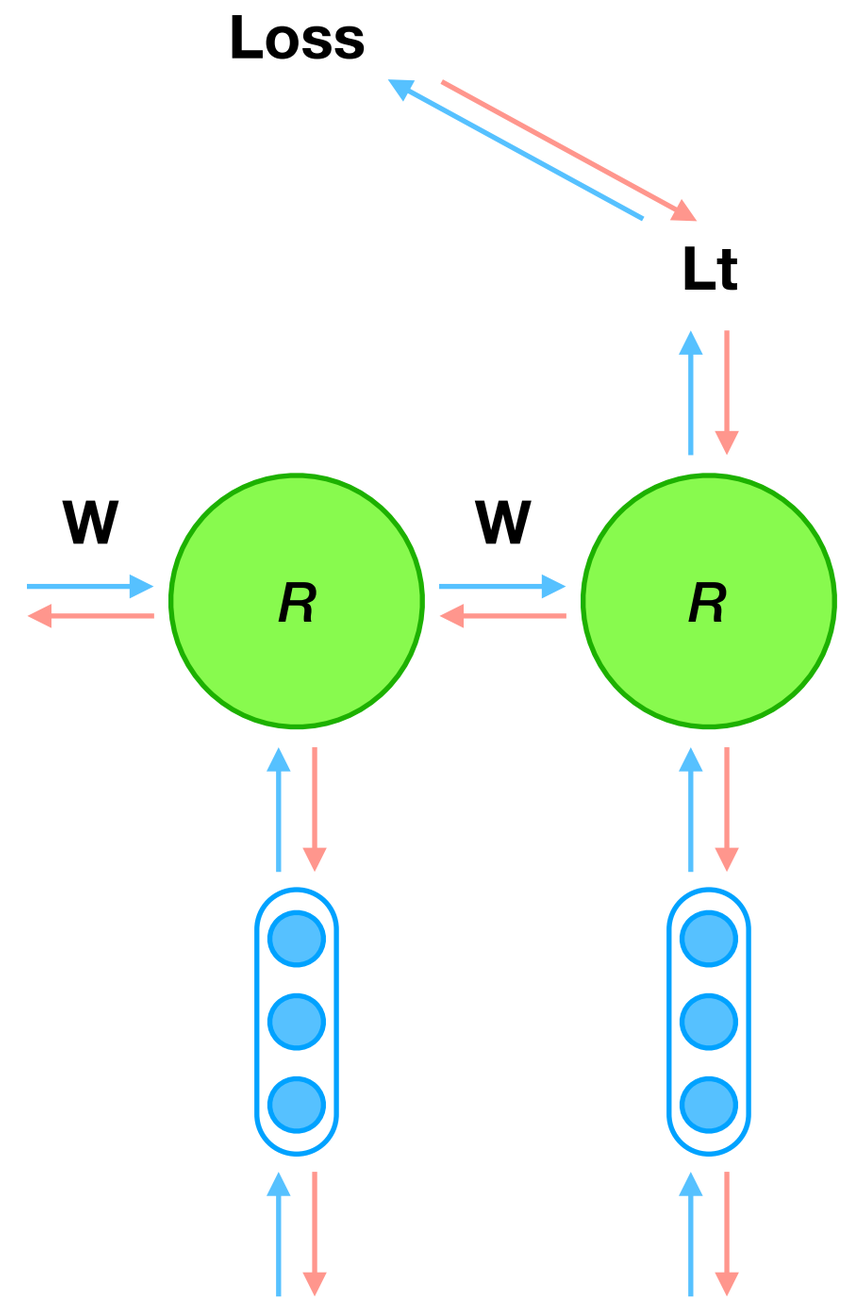
BPTT

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

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

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

This is NOT the only dependence!



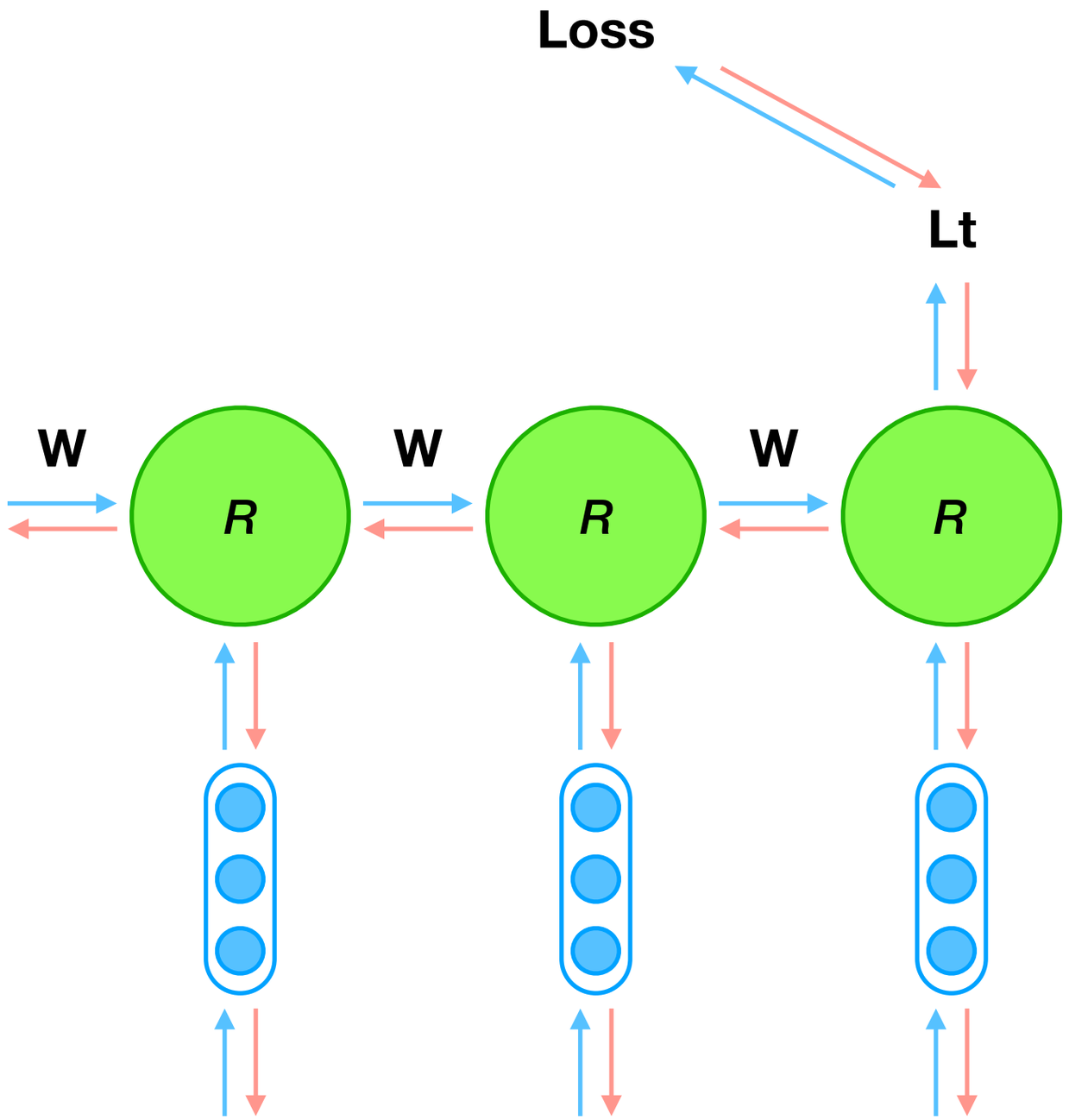
BPTT

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

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

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

This is NOT the only dependence!



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

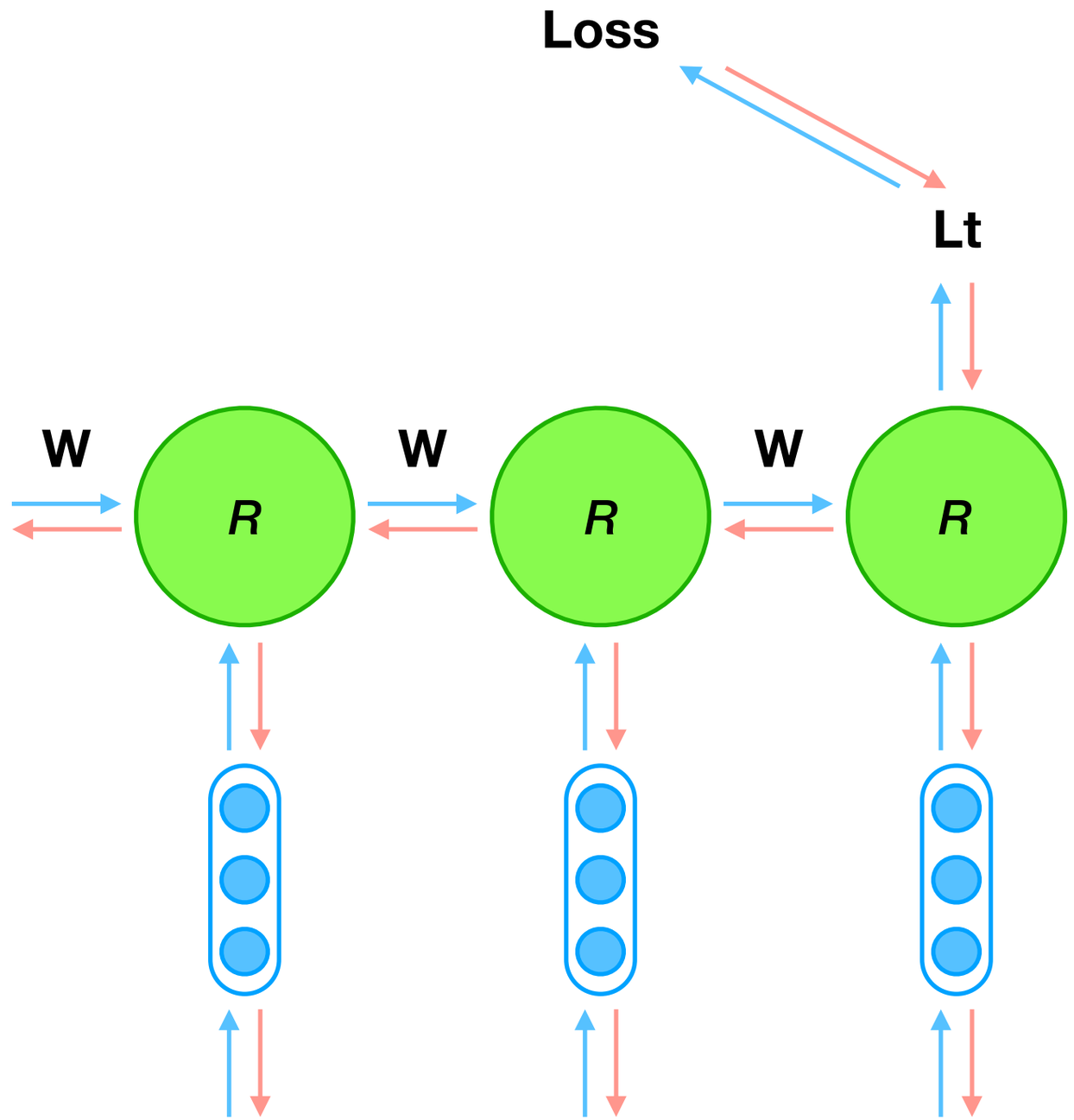
BPTT

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

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

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

This is NOT the only dependence!



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

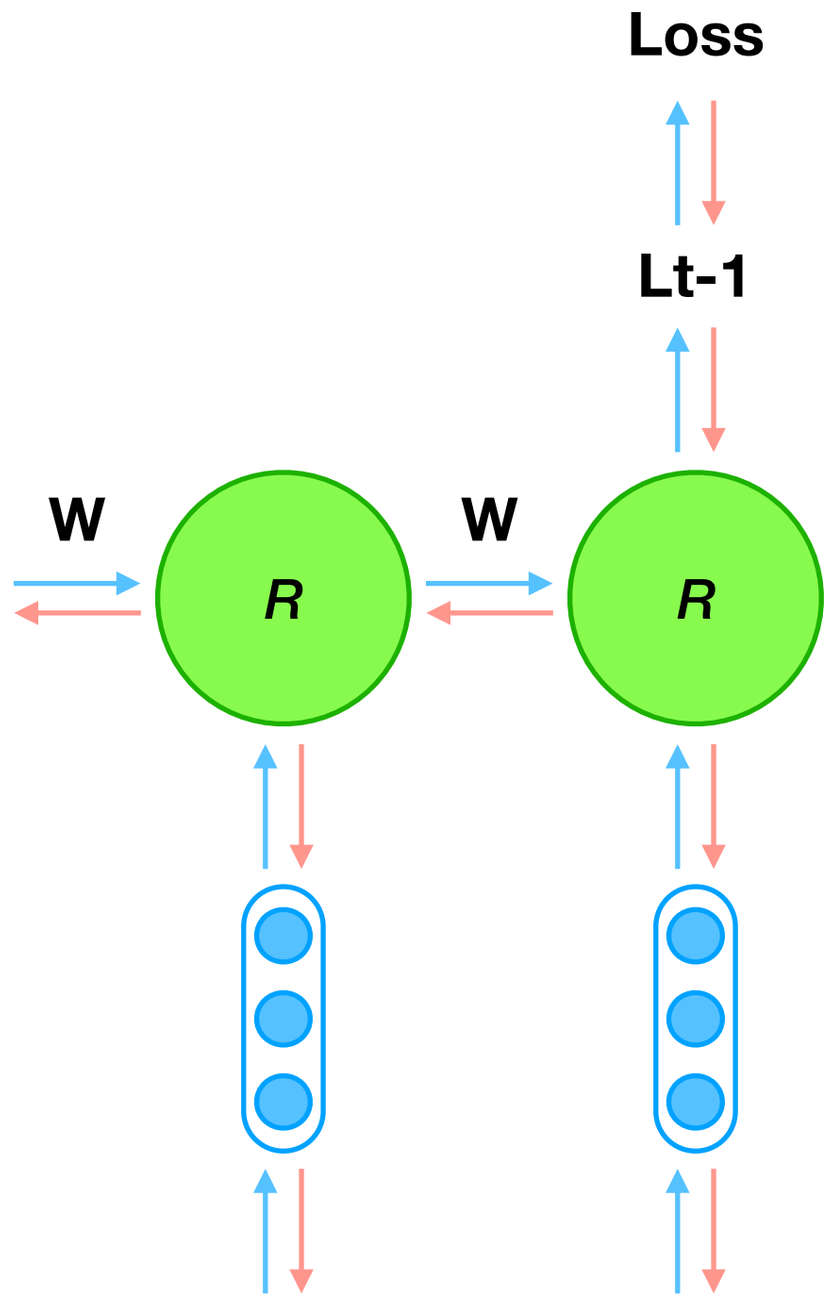
BPTT

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

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

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

This is NOT the only dependence!



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

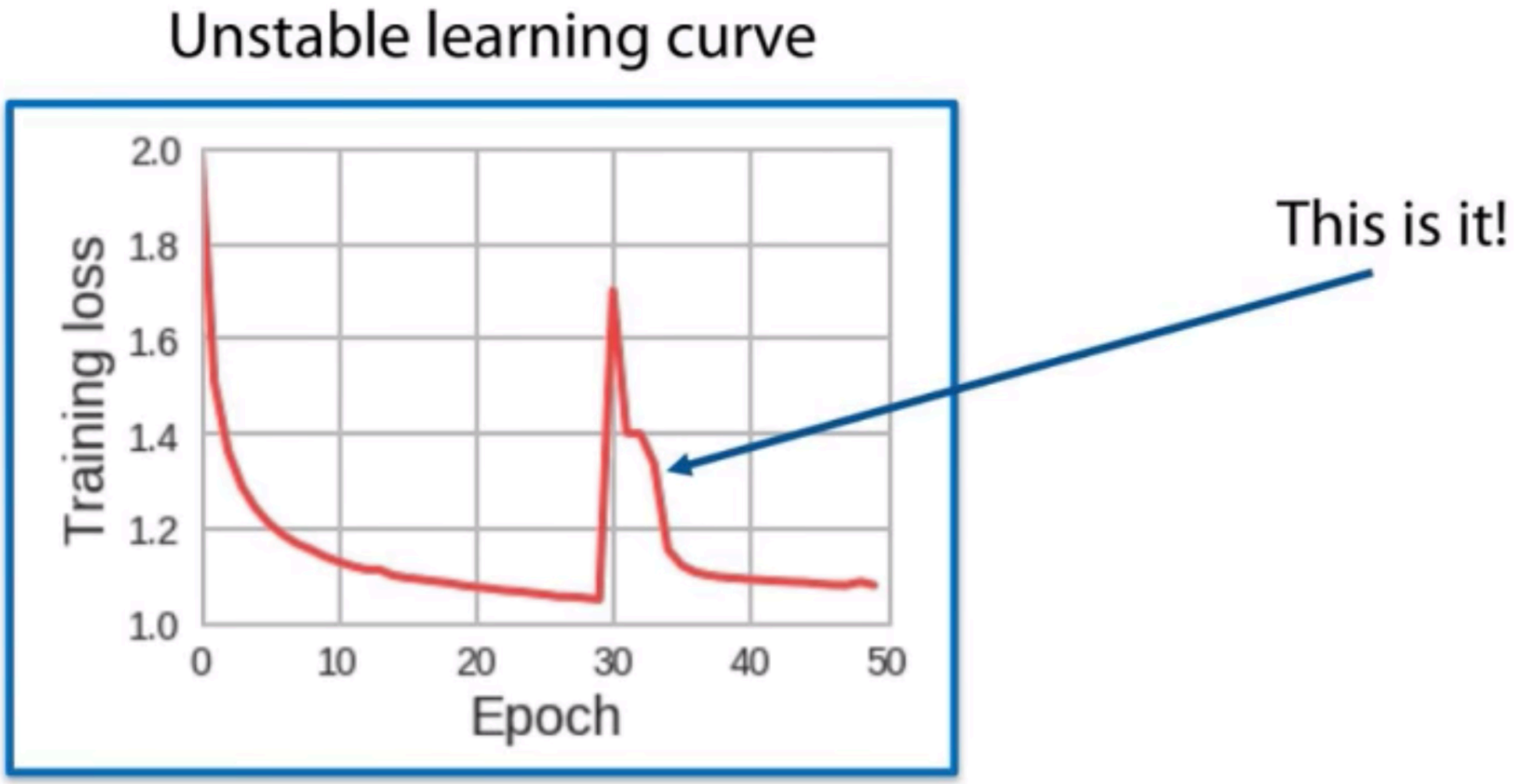
Gradients

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

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

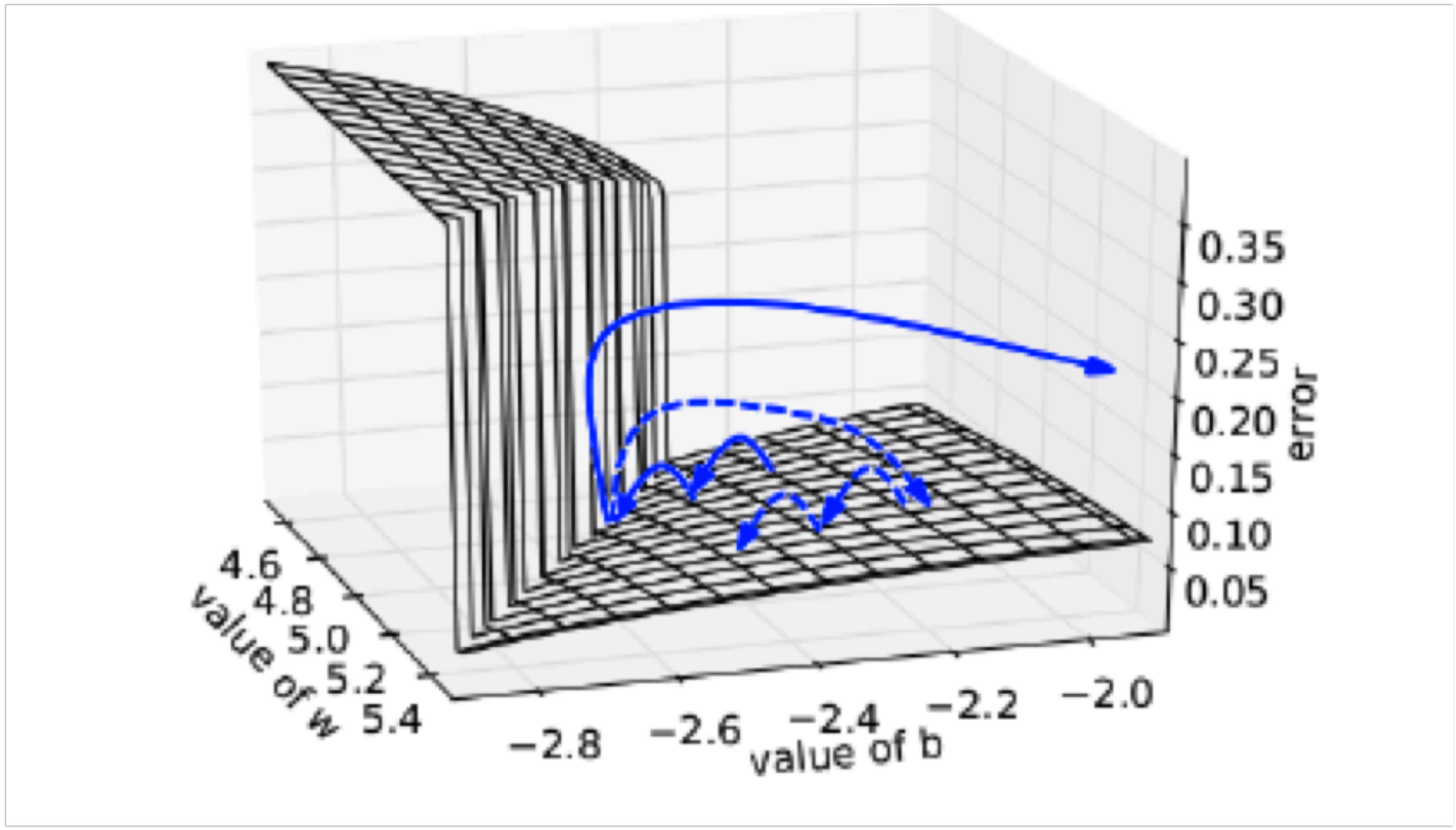
$$\left\| \frac{\partial h_i}{\partial h_{i-1}} \right\|_2 > 1 \quad \Rightarrow \quad \text{Exploding gradients}$$

Exploding gradients



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

Exploding gradients



Gradient Clipping

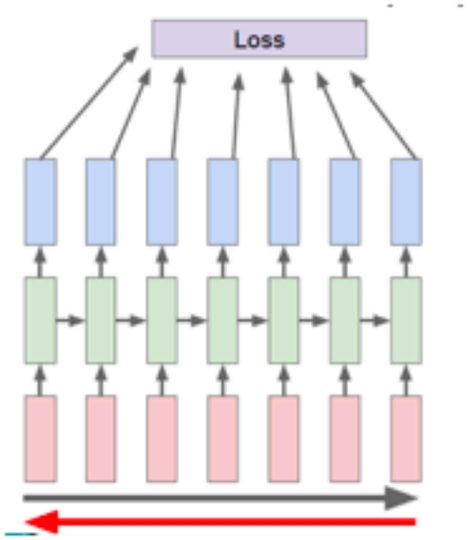
Gradient $g = \frac{\partial L}{\partial \theta}$, θ - all the network parameters

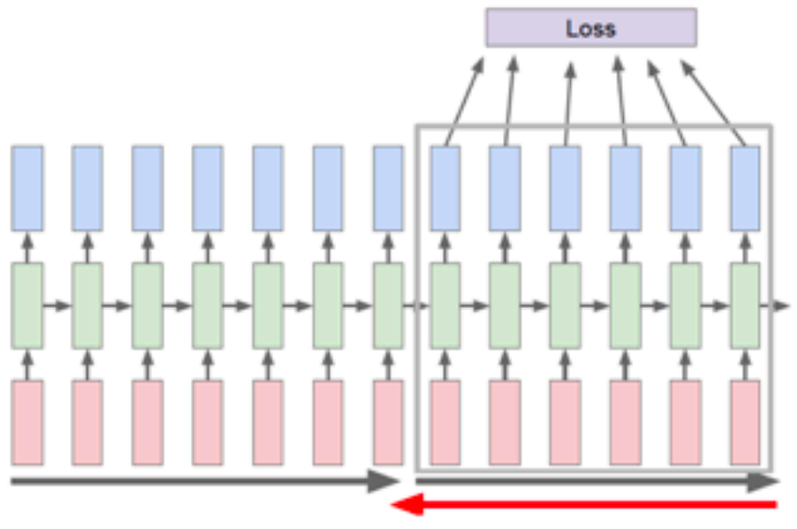
If $||g||$> threshold:

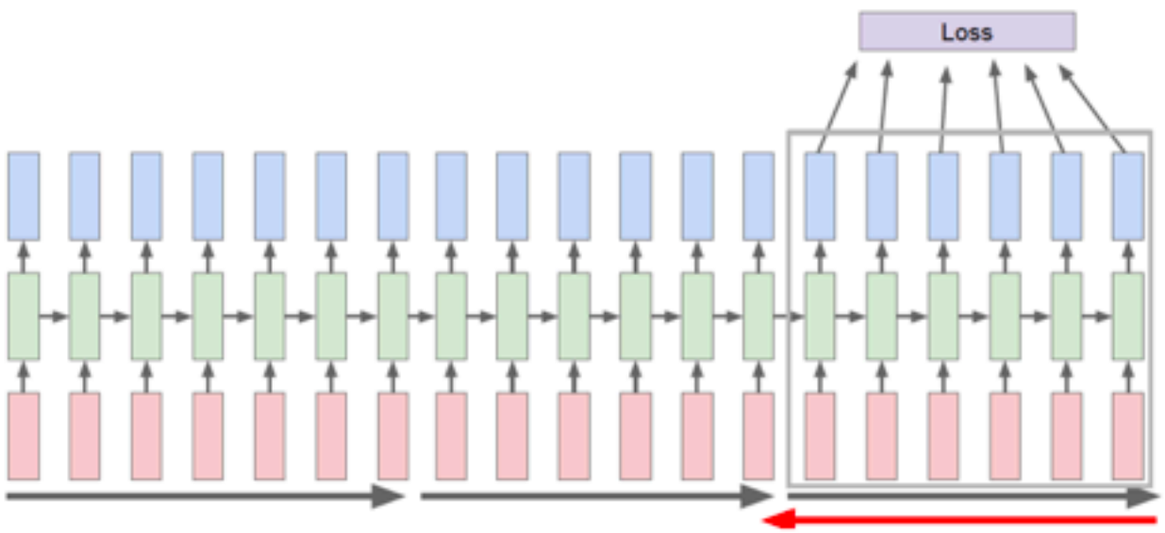
$$g \leftarrow \frac{threshold}{\|g\|} g$$

Simple but still very effective!

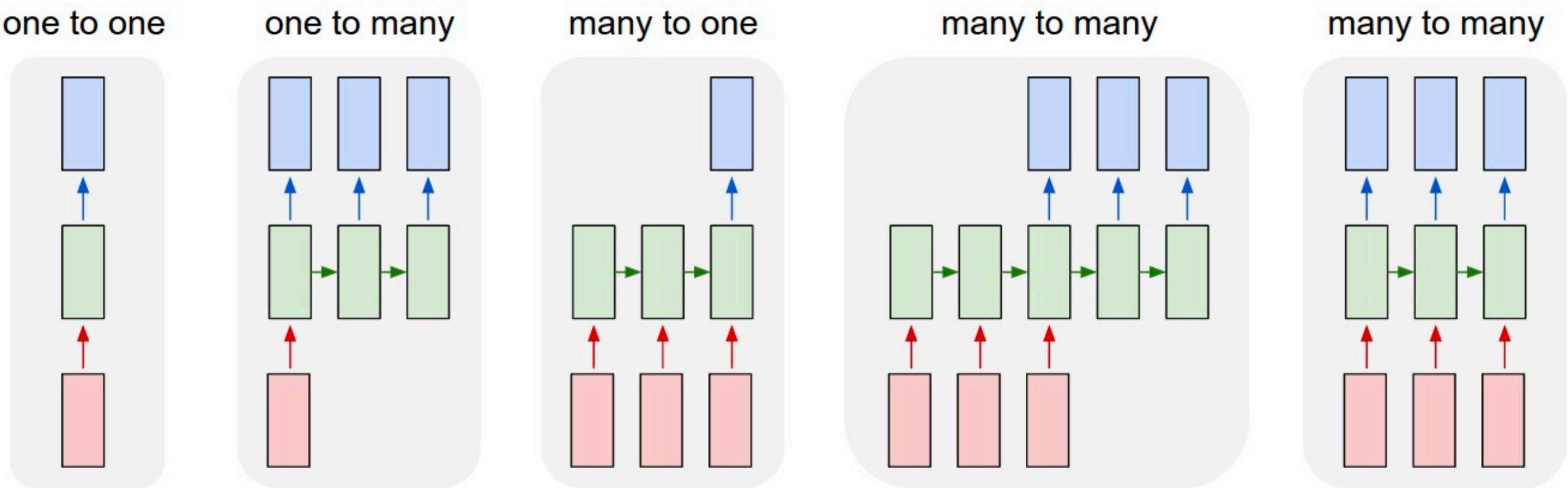
Truncated BPTT



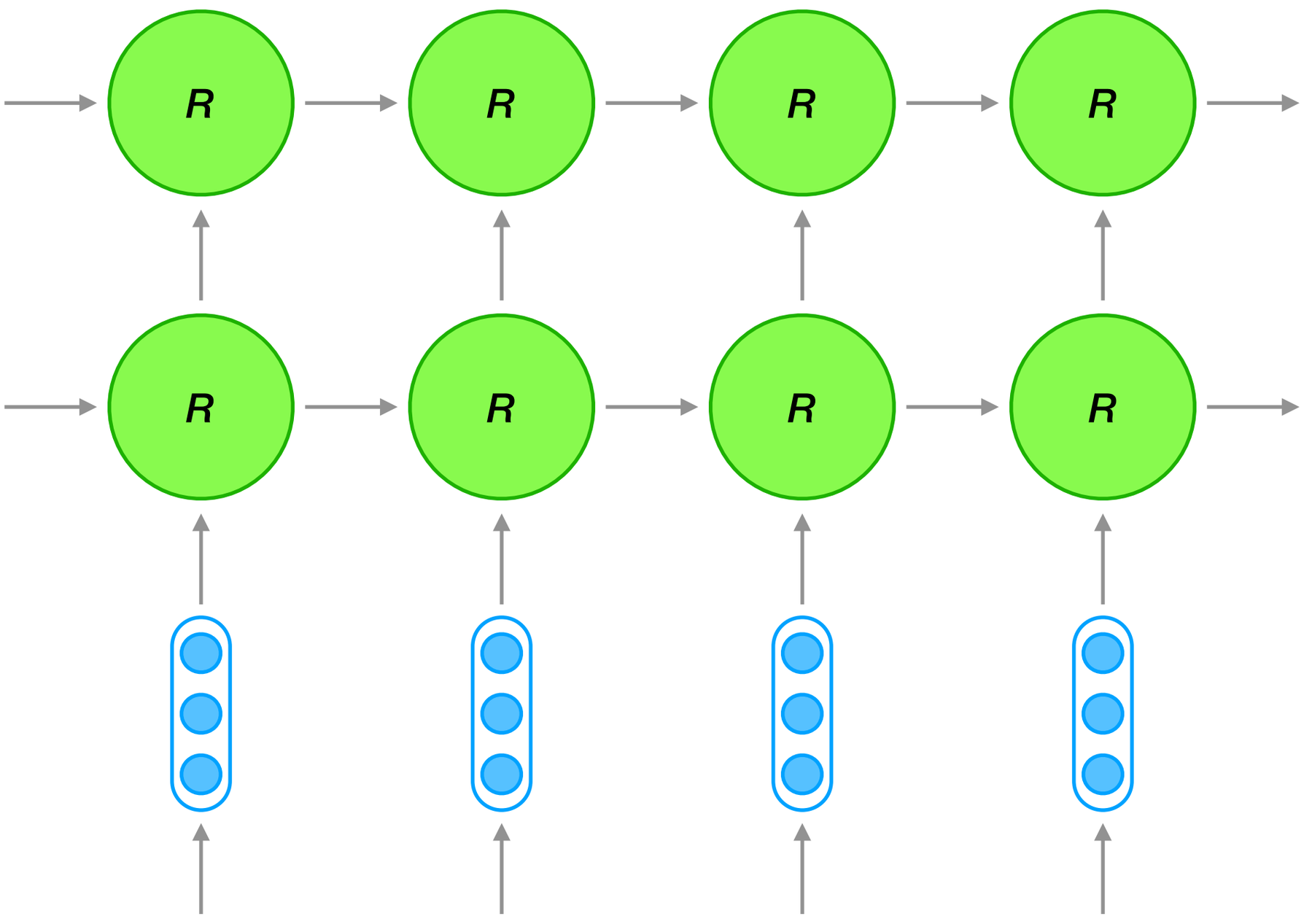




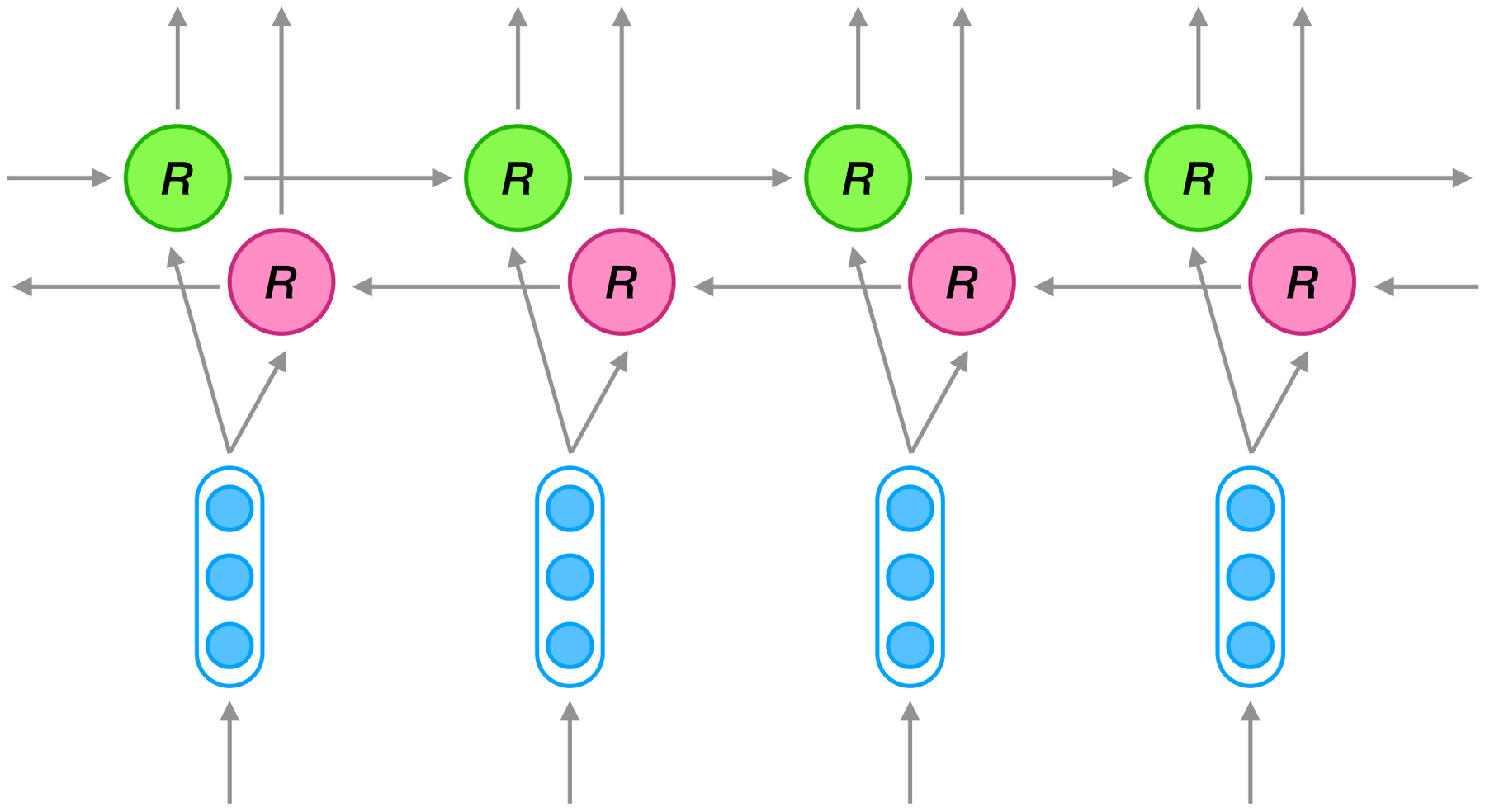
Recurrent Neural Network



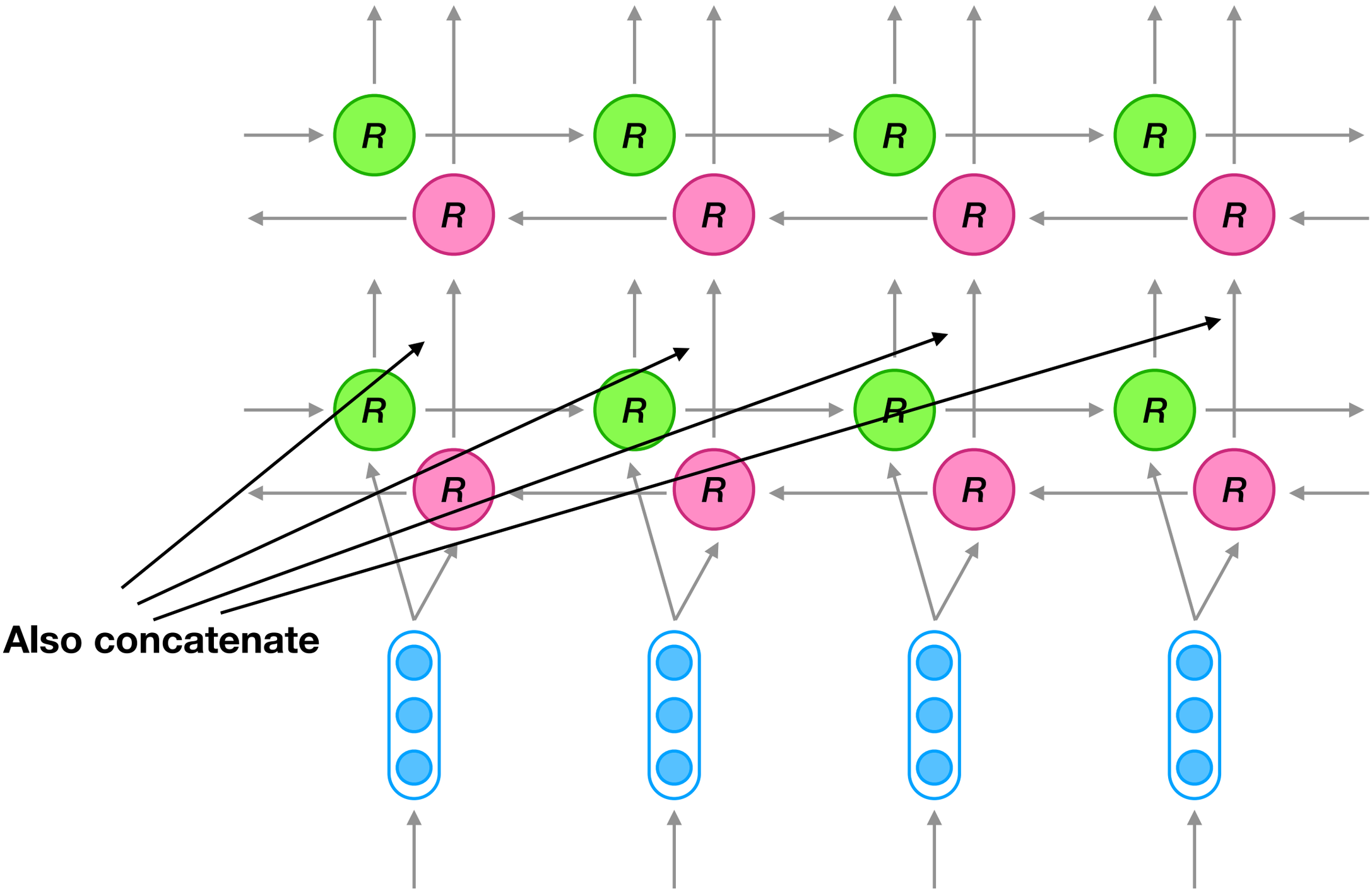
Deeper



Bidirectional



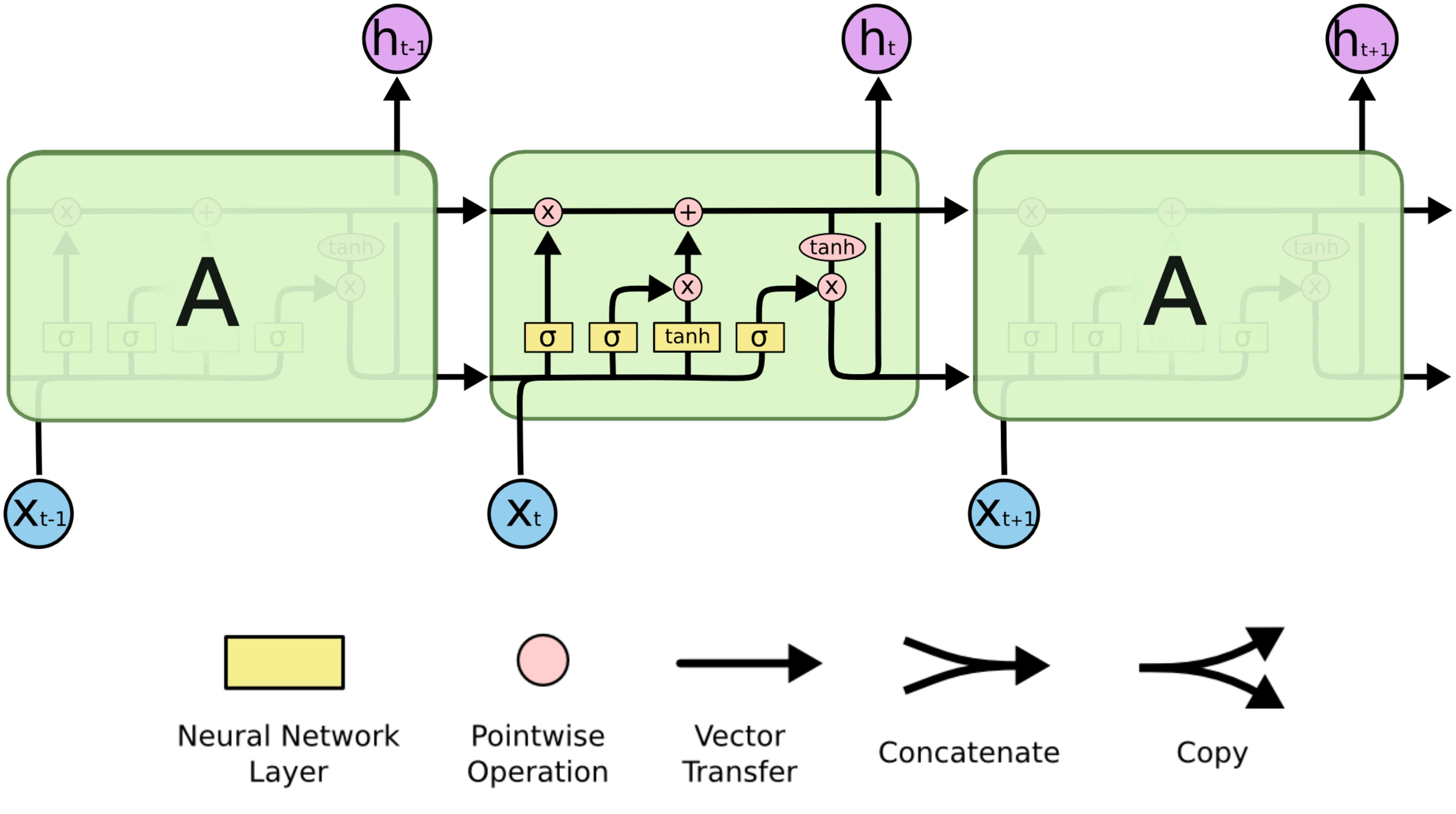
Deeper Bidirectional



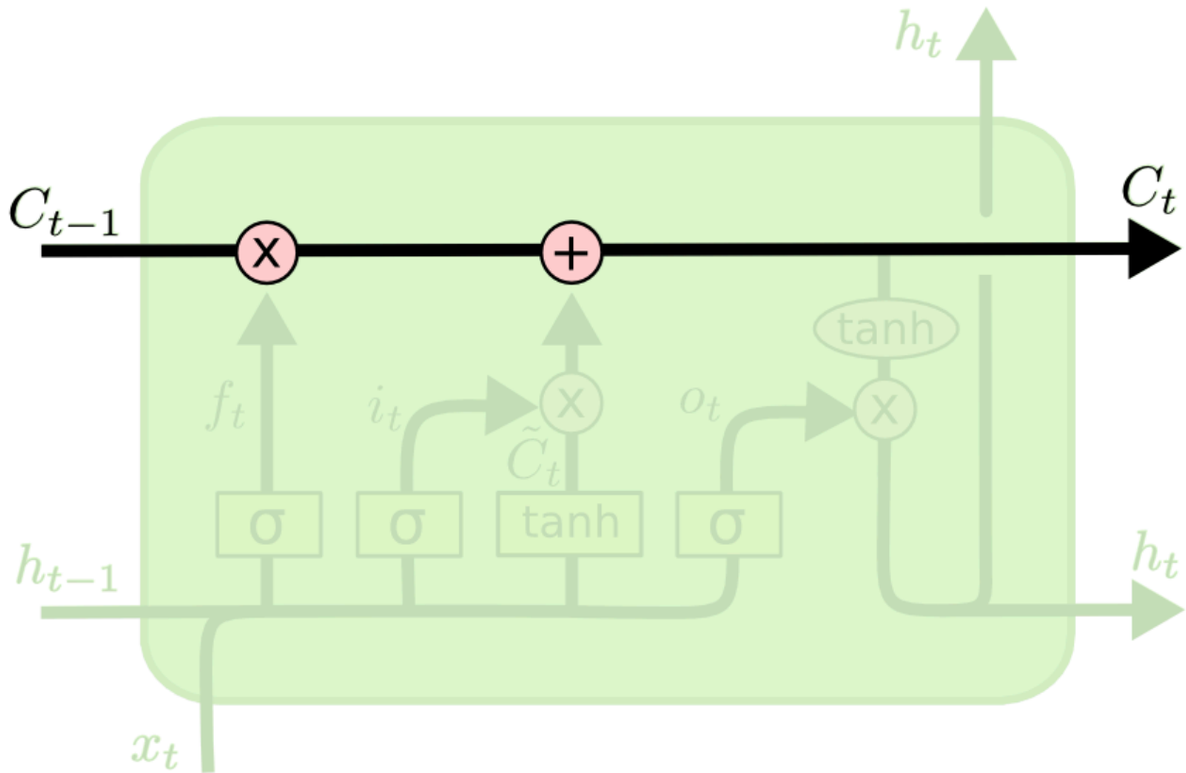
Bidirectional

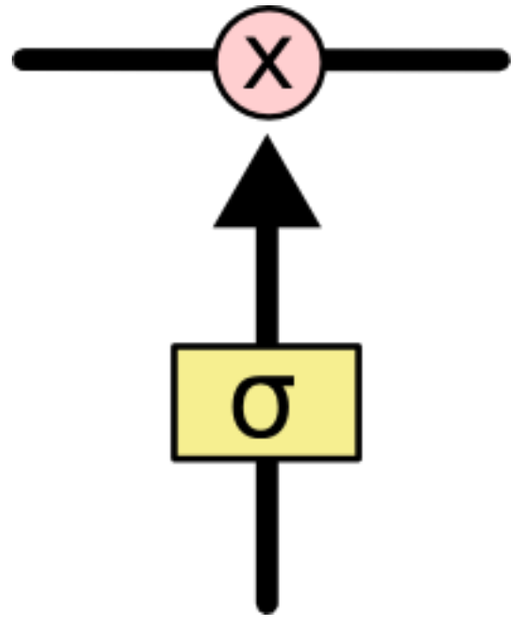
Source	<START>	The	poor	don’t	have	any	money	<END>
Forward	<START>	The	poor	don’t	have	any	money	<END>
Backward	<END>	money	any	have	don’t	poor	The	<START>

Long Short Term Memories

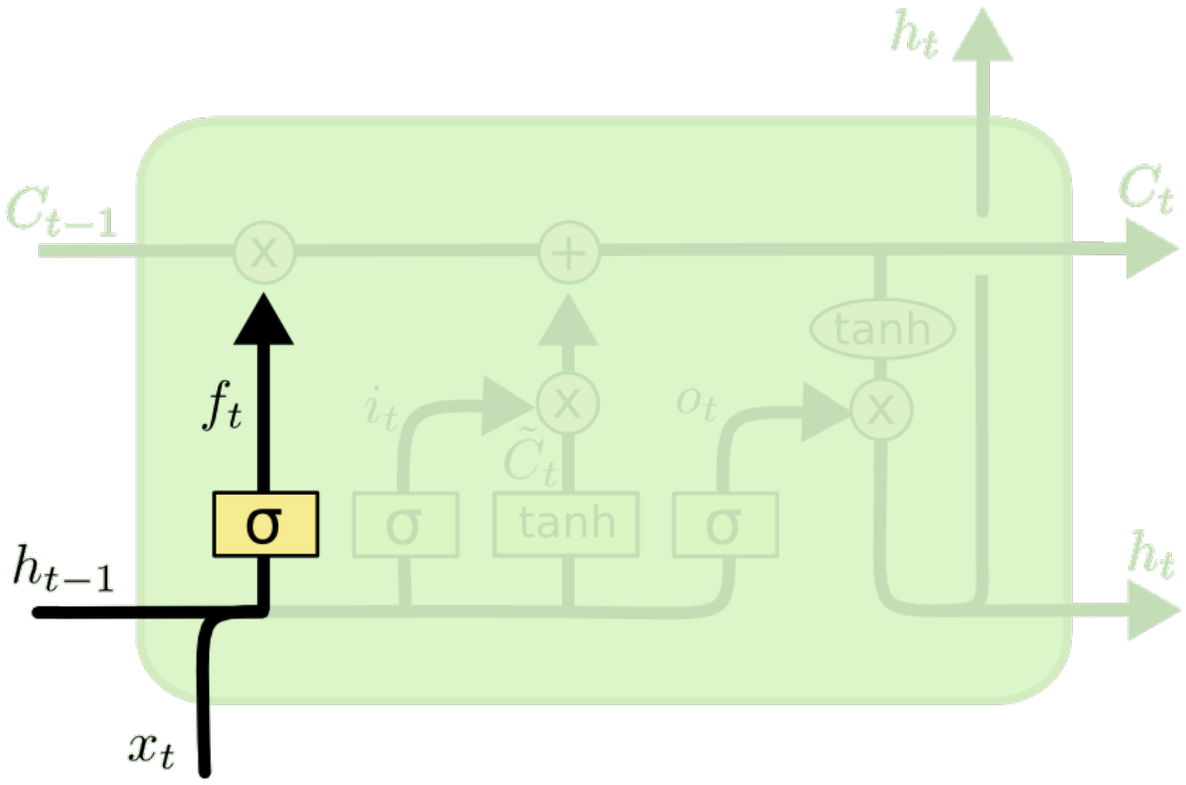


Long Short Term Memories



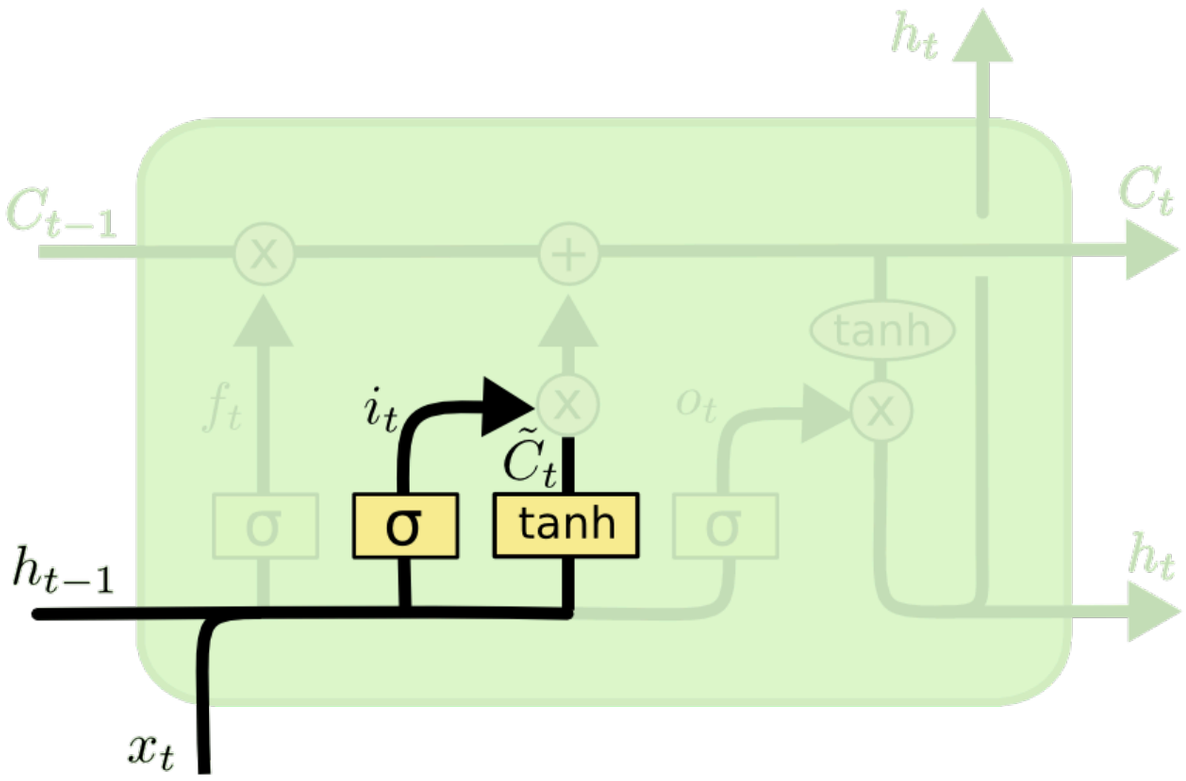


Long Short Term Memories



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

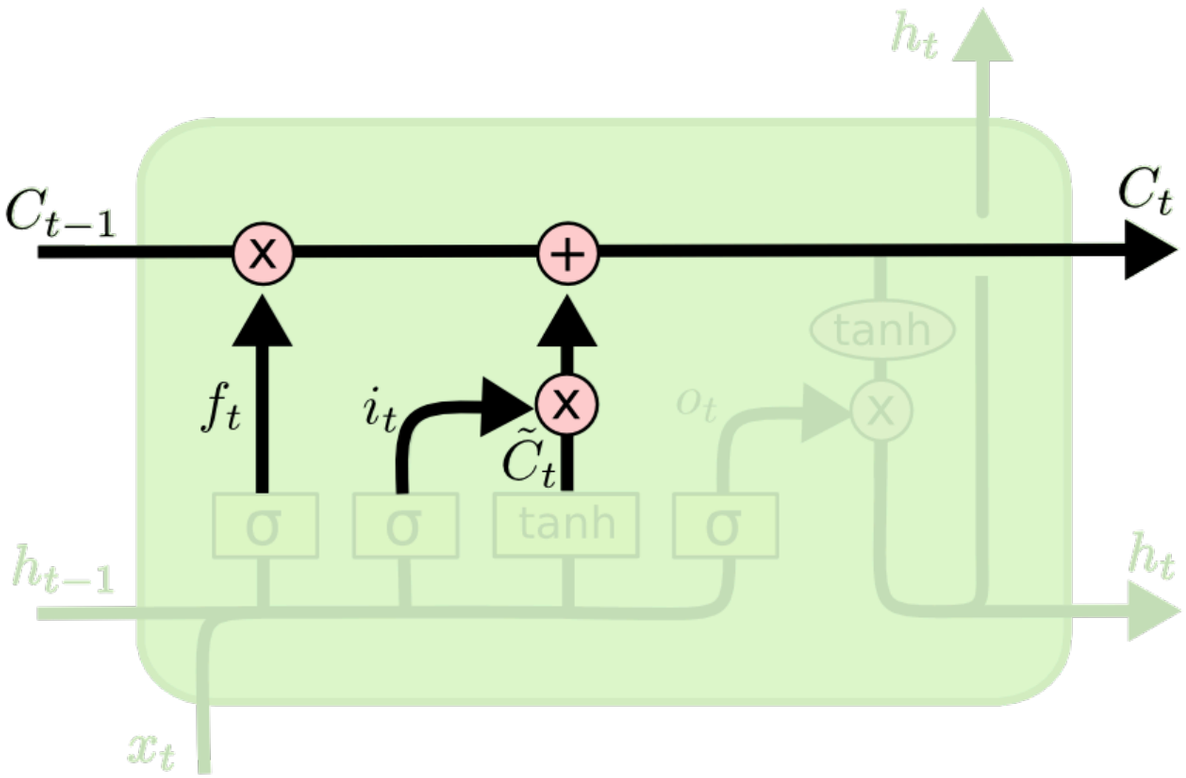
Long Short Term Memories



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$$

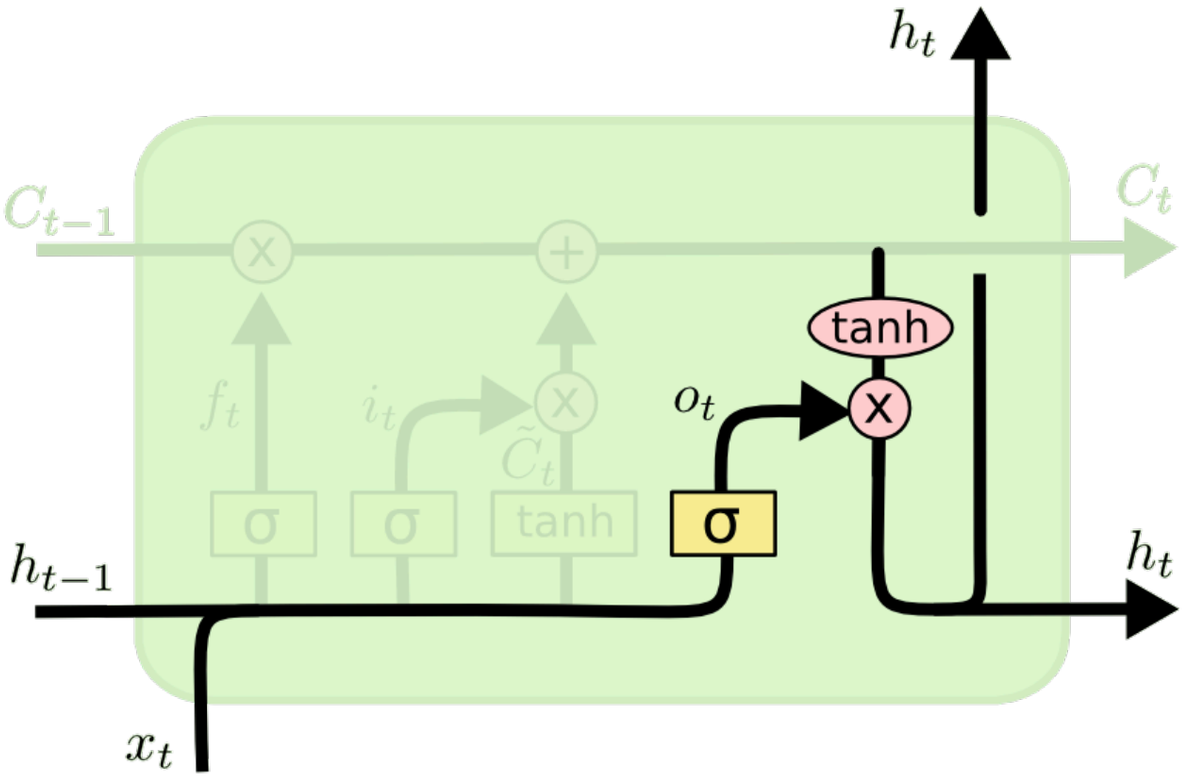
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

Long Short Term Memories



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

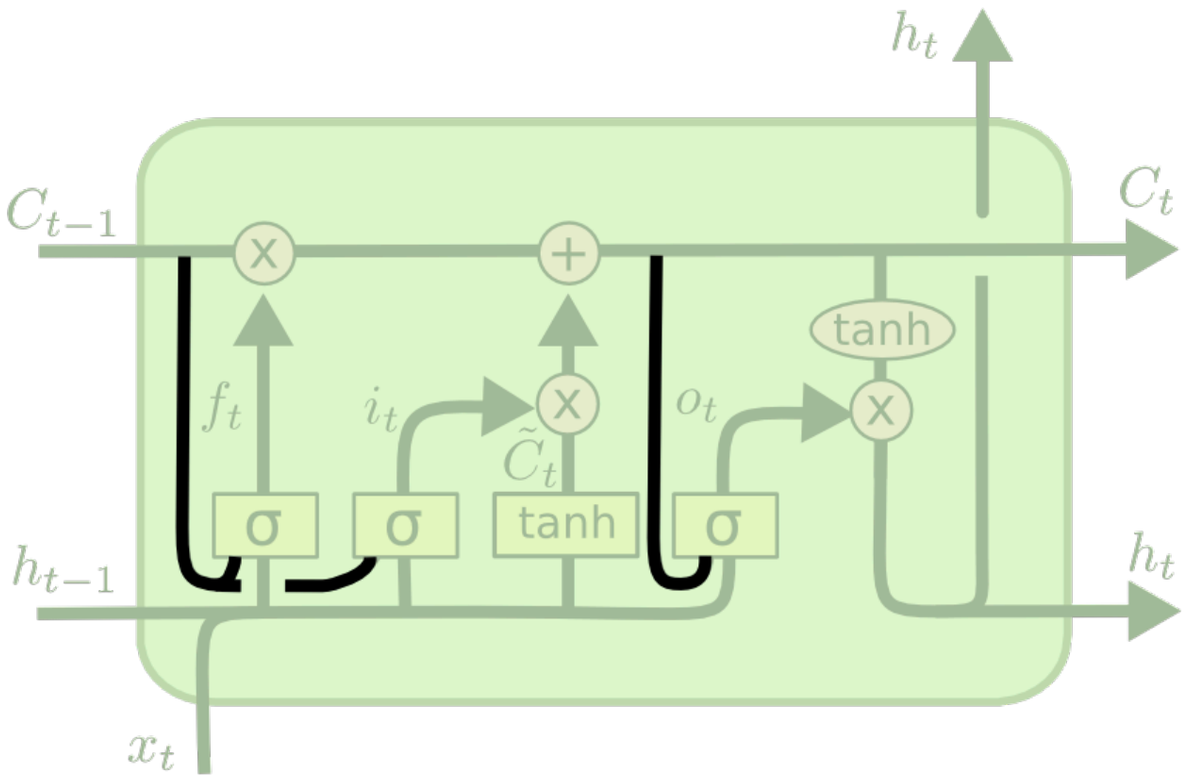
Long Short Term Memories



$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

Long Short Term Memories

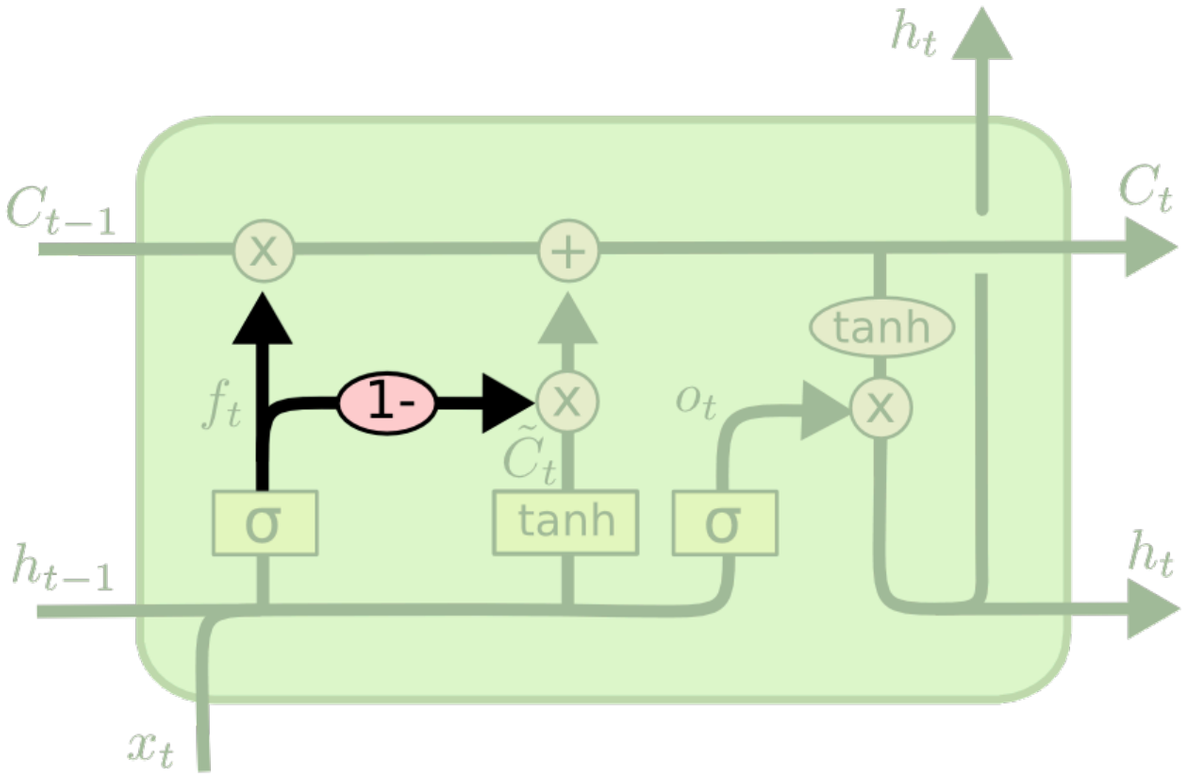


$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_f\right)$$

$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_i\right)$$

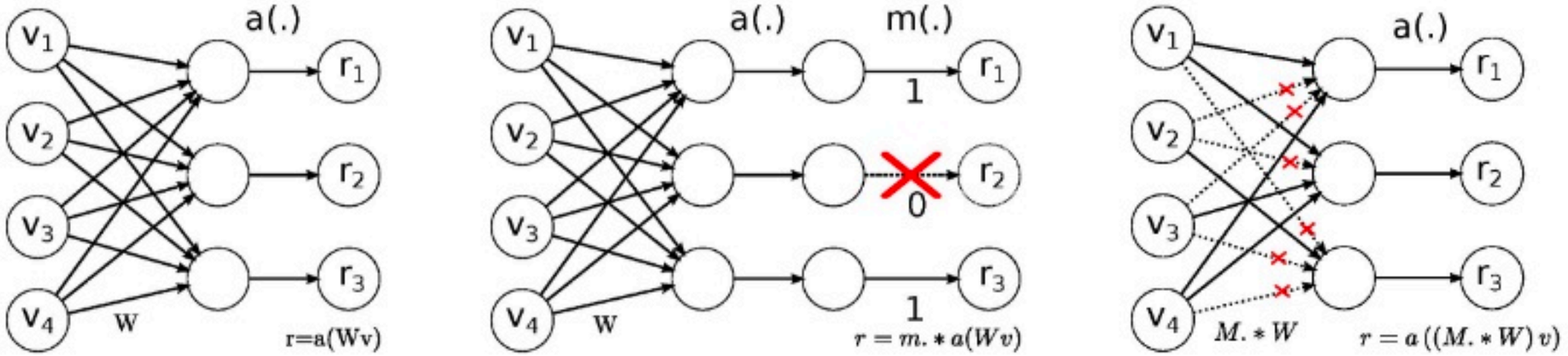
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \; + \; b_o\right)$$

Long Short Term Memories



$$C_t = f_t * C_{t-1} + (1 - \boldsymbol{f_t}) * \tilde{C}_t$$

Dropout in RNN



No-Drop Network

DropOut Network

DropConnect Network

Layer Normalization

Batch Normalization → **Layer Normalization**

$$\mu_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij}$$
$$\sigma_j^2 = \frac{1}{m}\sum_{i=1}^{m}(x_{ij} - \mu_j)^2$$
$$\hat{x_{ij}} = \frac{x_{ij} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}}$$

$$\mu_i = \frac{1}{m}\sum_{j=1}^{m} x_{ij}$$
$$\sigma_i^2 = \frac{1}{m}\sum_{j=1}^{m}(x_{ij} - \mu_i)^2$$
$$\hat{x_{ij}} = \frac{x_{ij} - \mu_i}{\sqrt{\sigma_i^2 + \epsilon}}$$