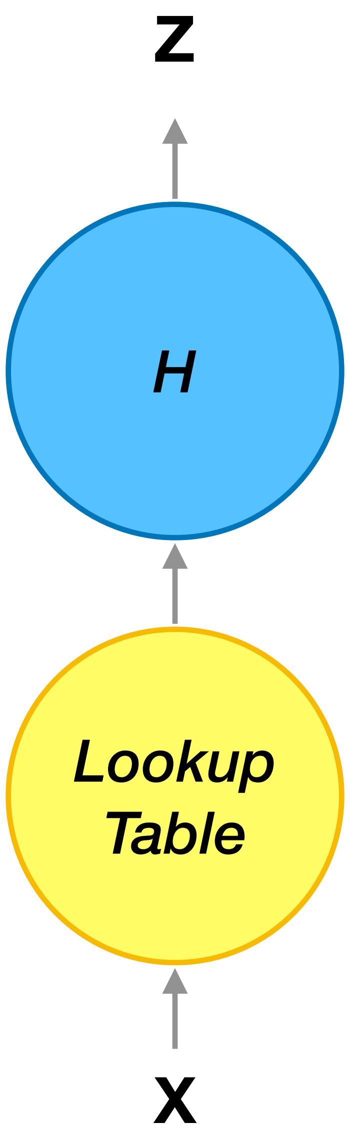
Recurrent Neural Network

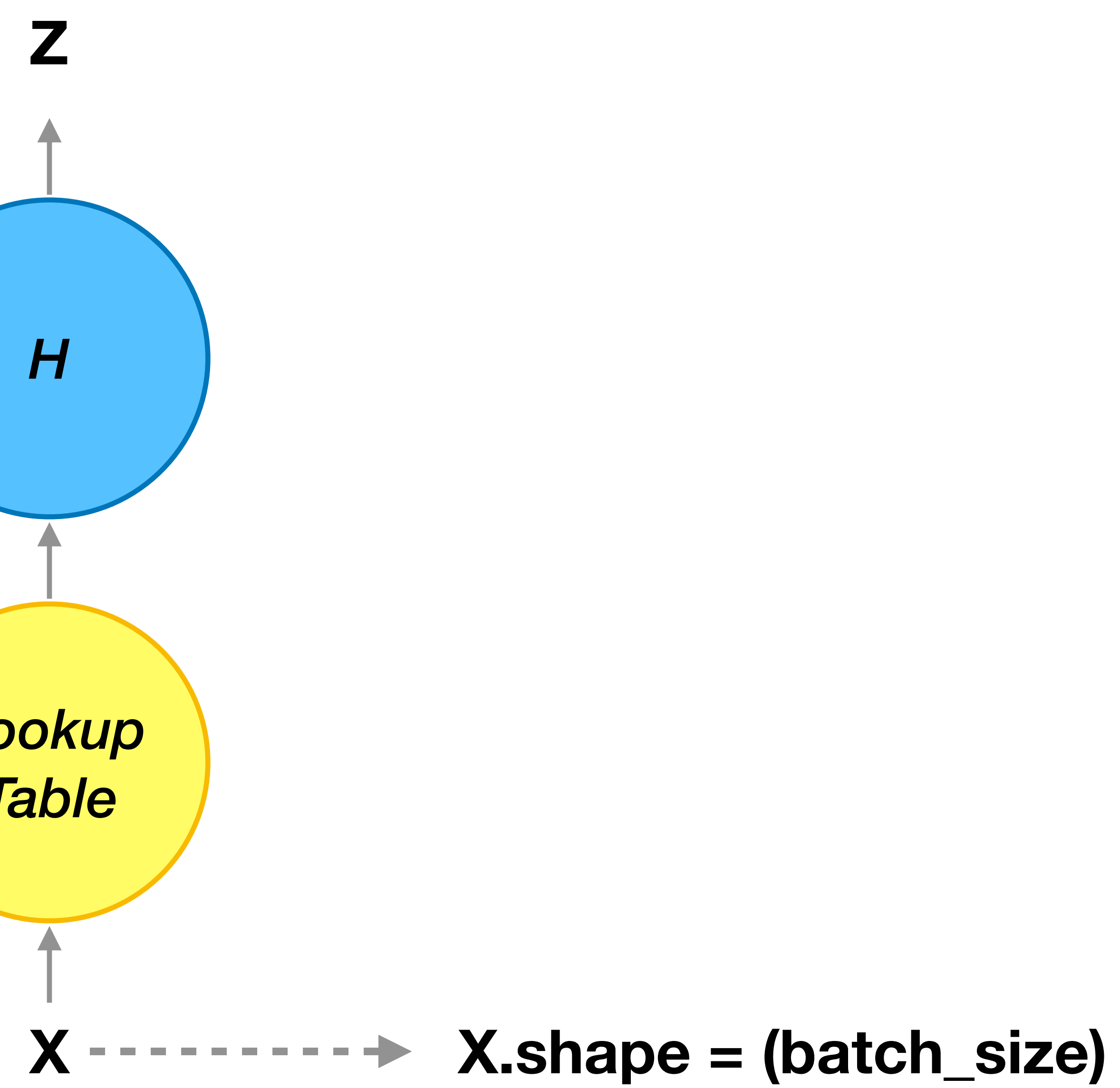
Boris Zubarev

@bobazooba

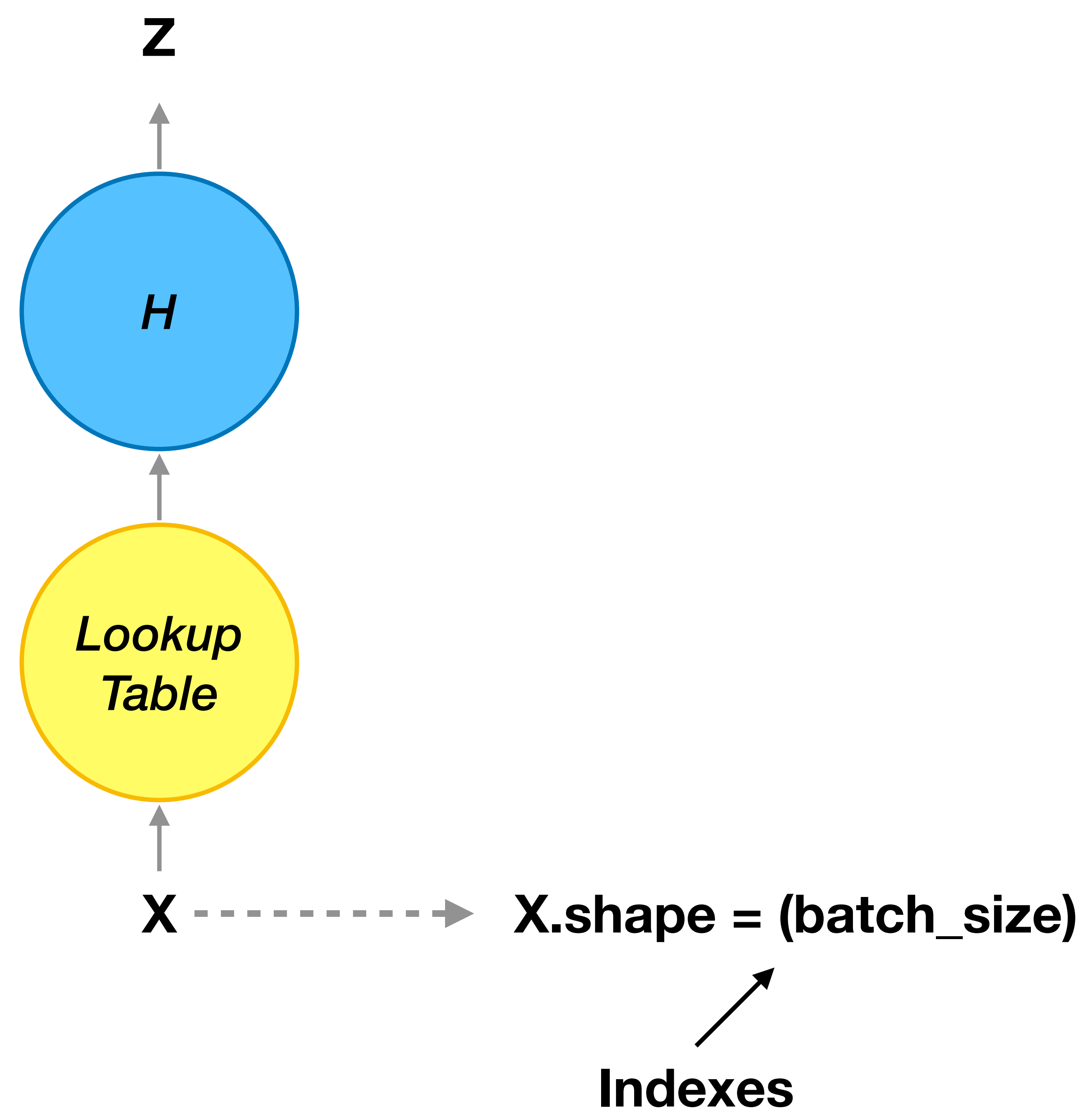
Neural Network



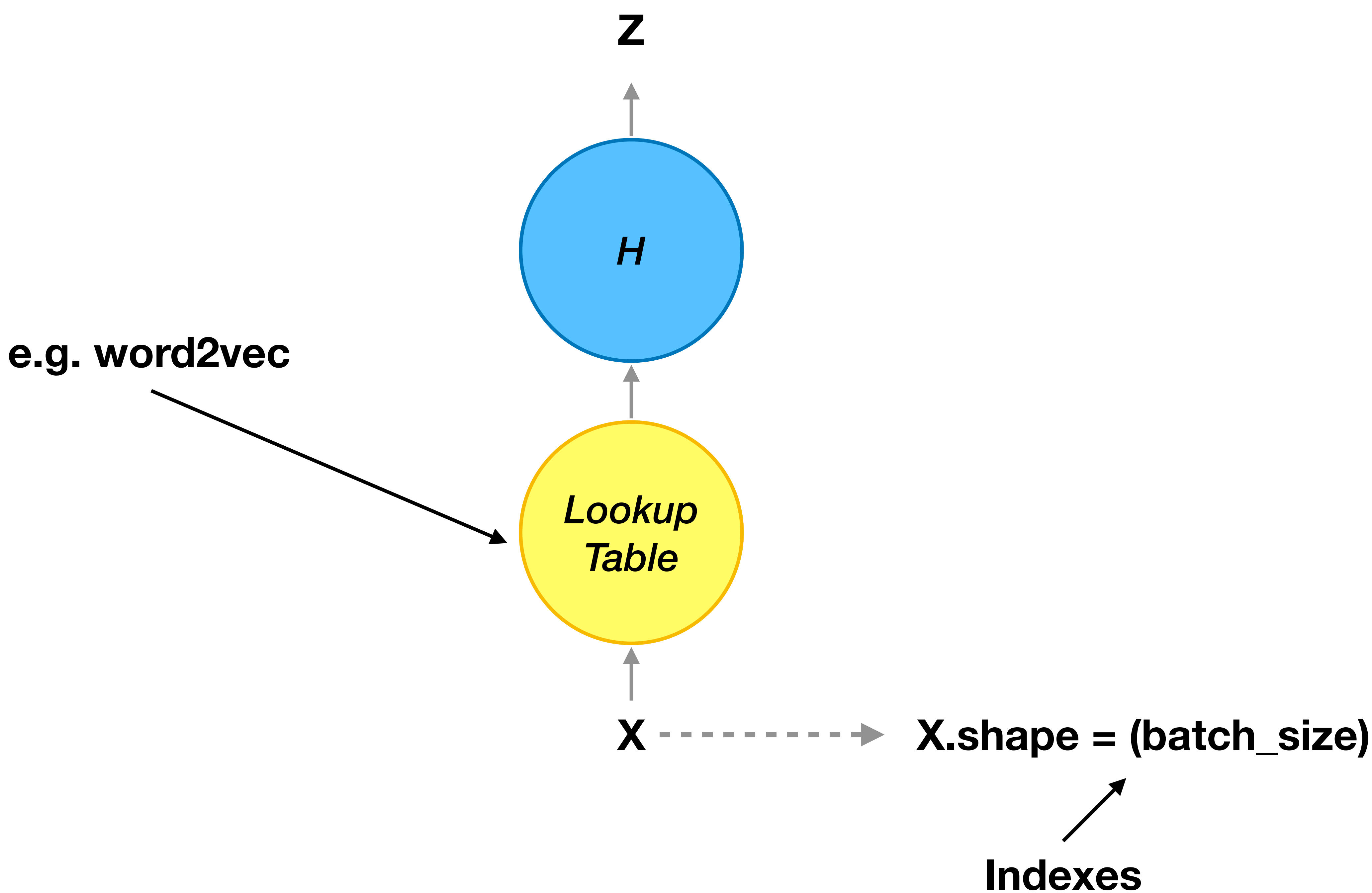
Neural Network



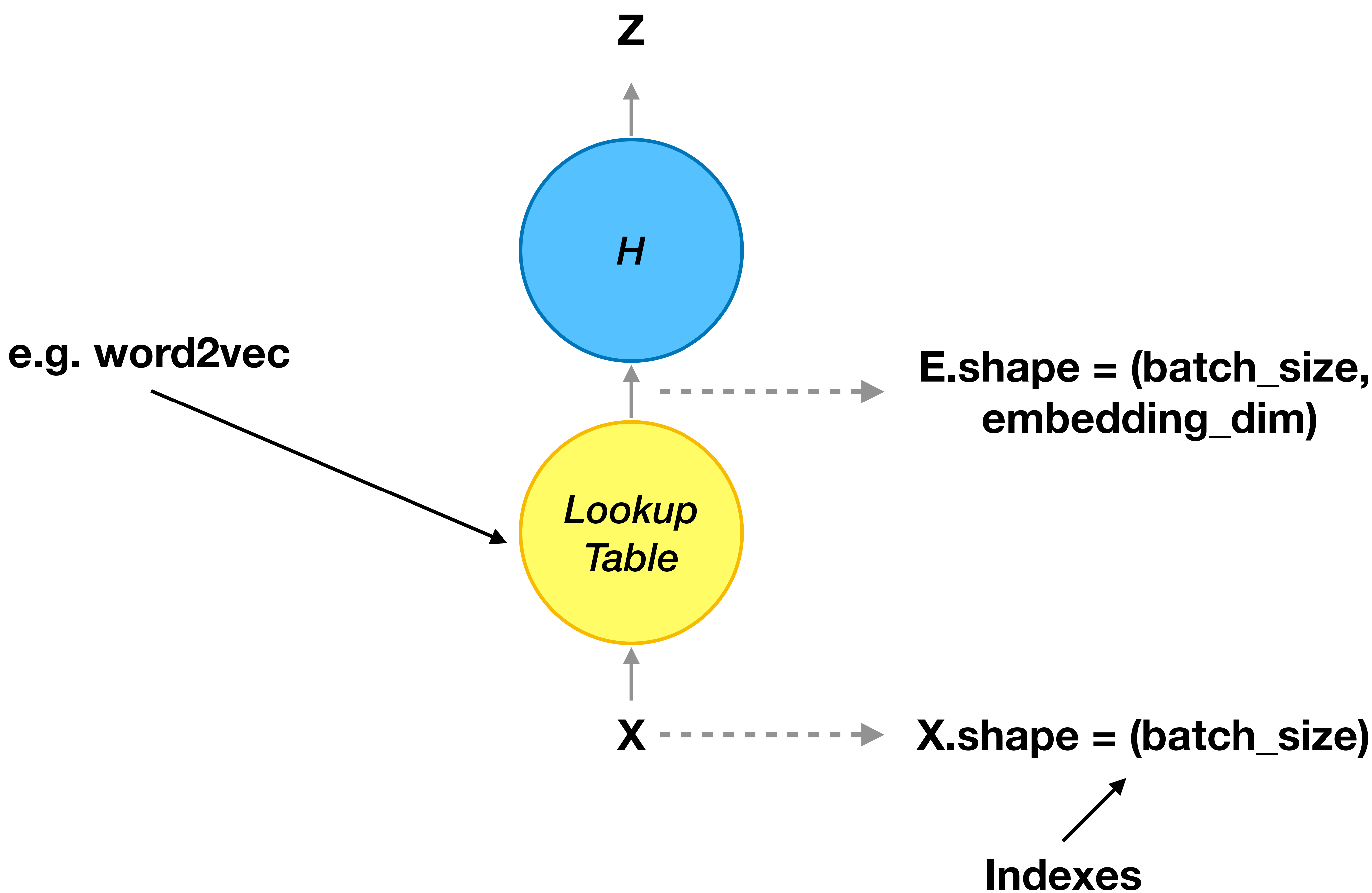
Neural Network



Neural Network



Neural Network



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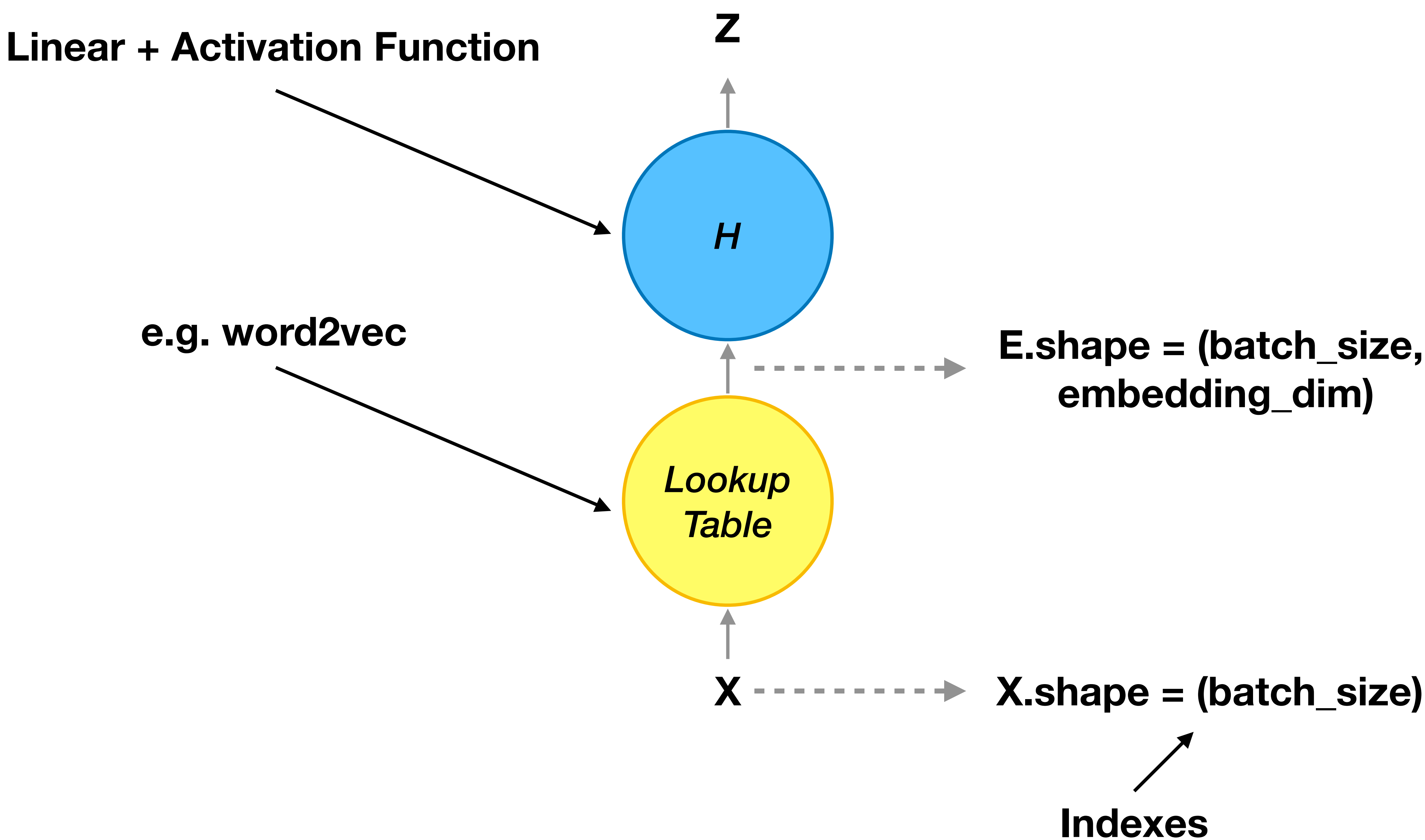
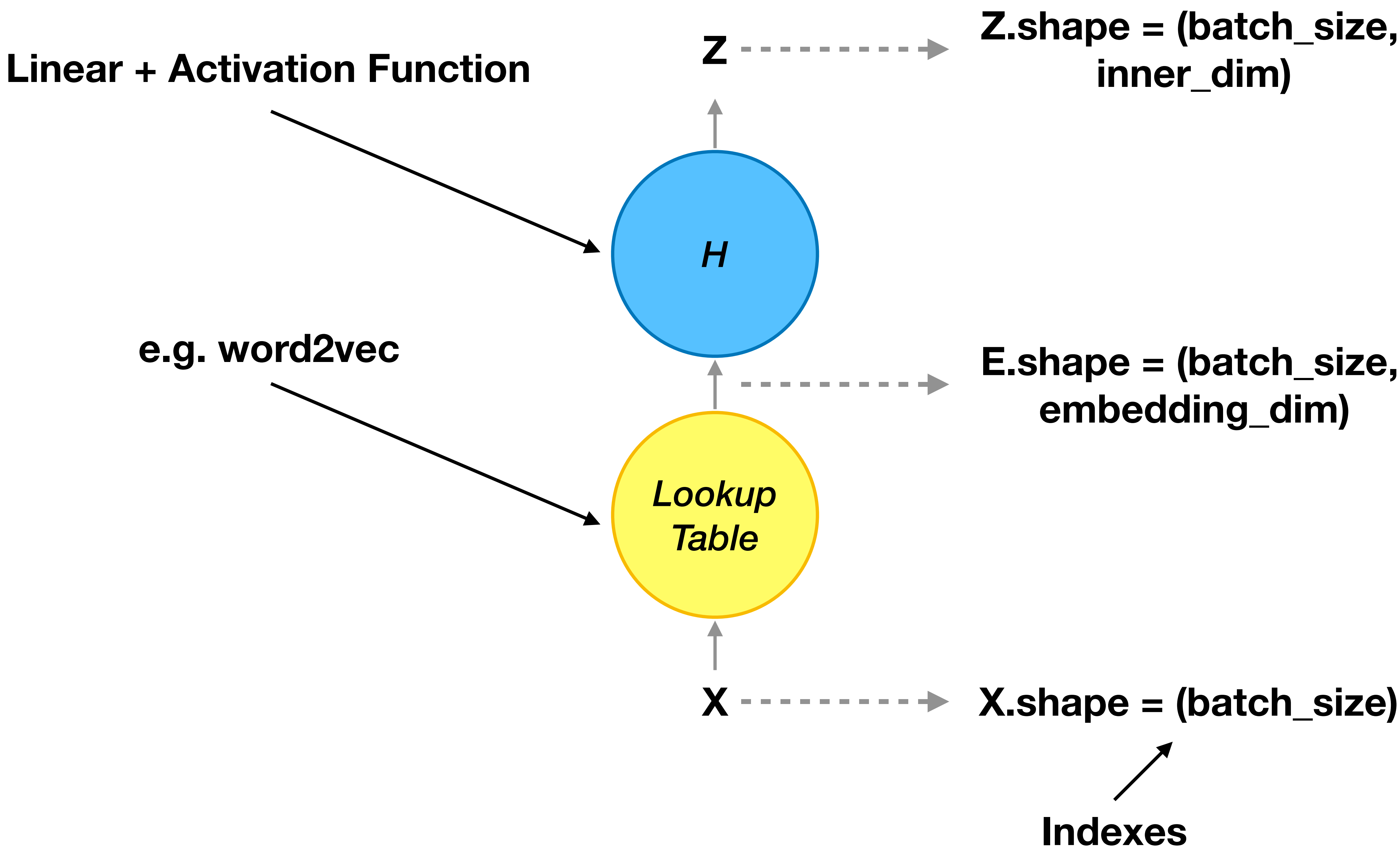
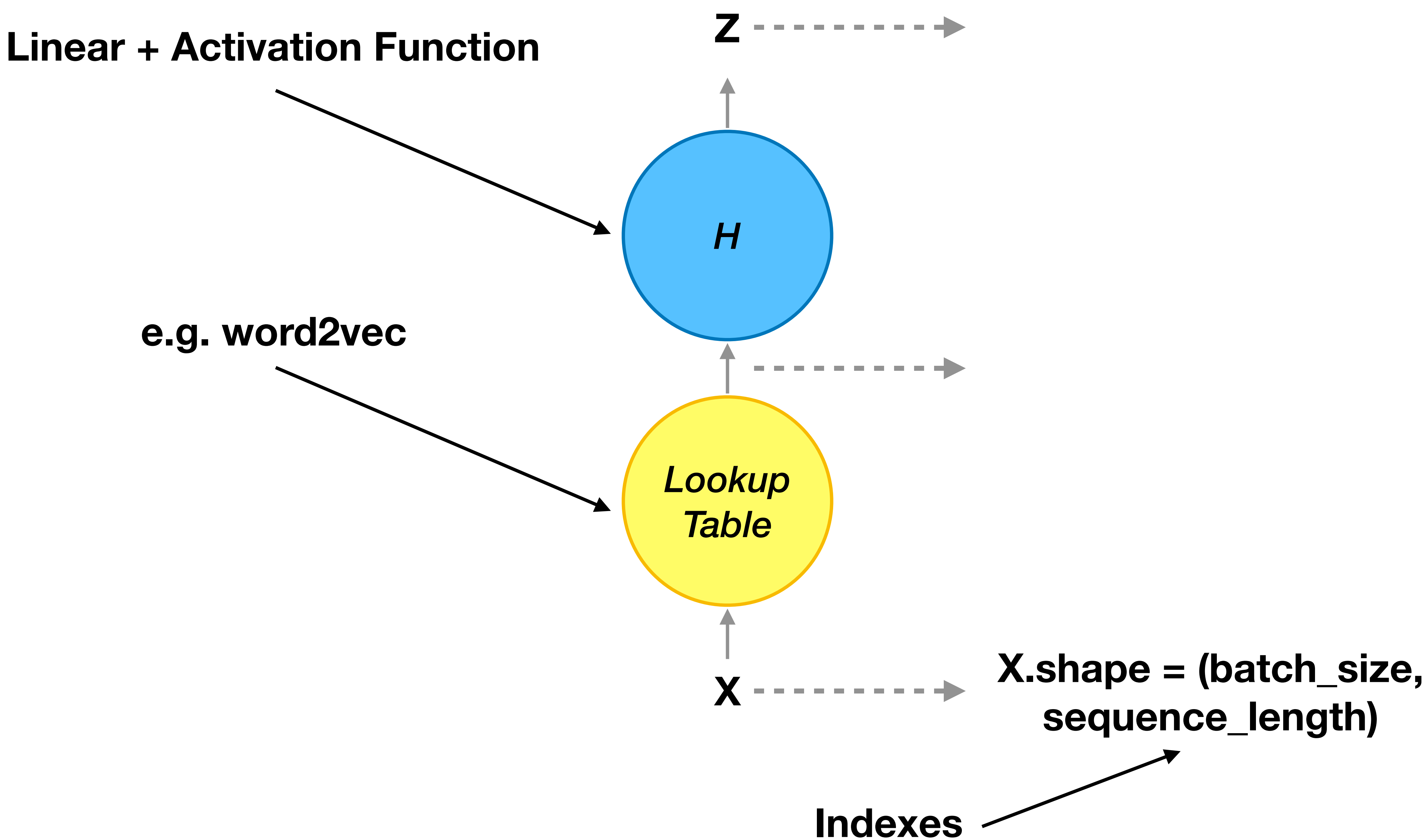


Neural Network

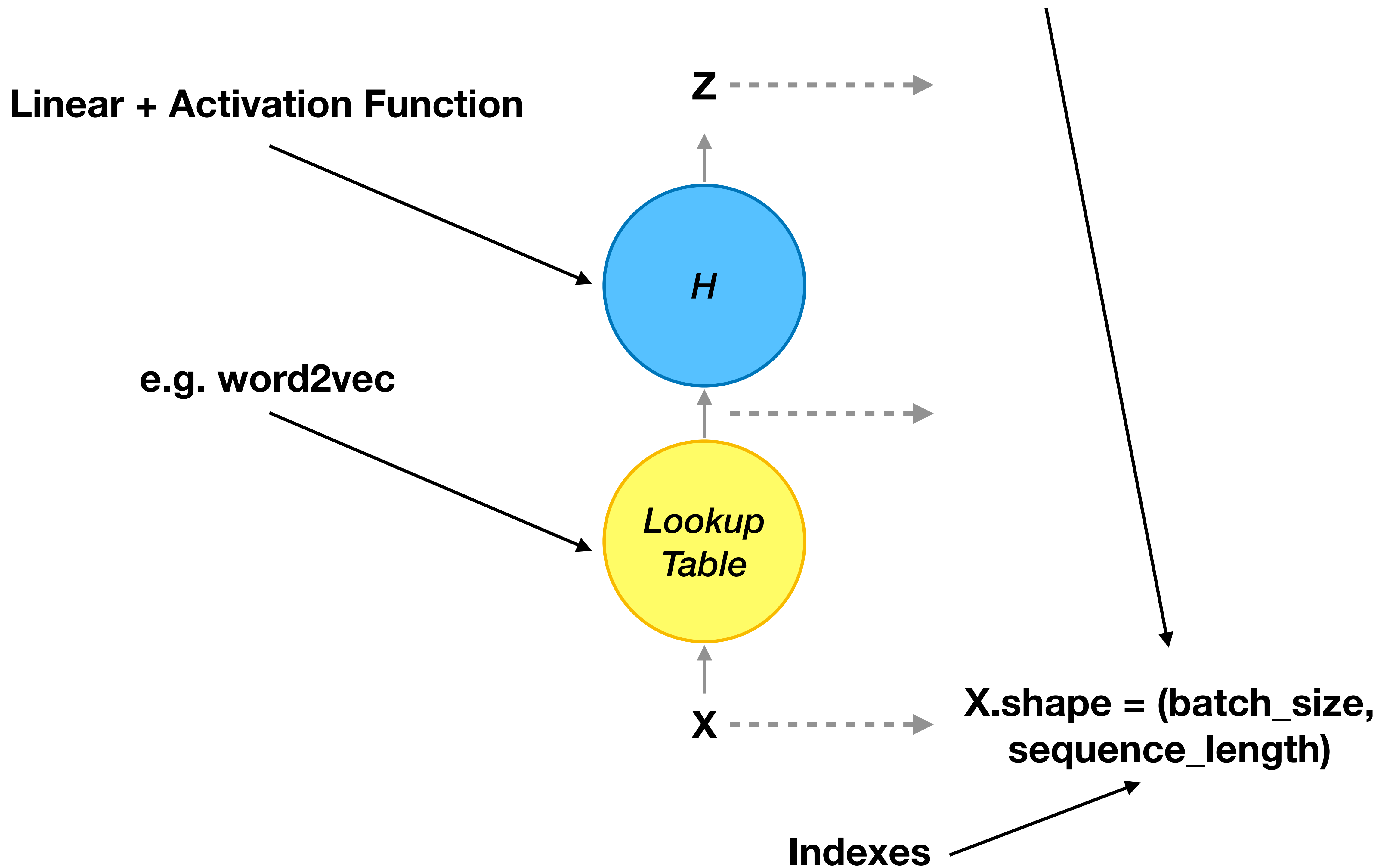


Neural Network



Neural Network

What if we have different lengths?



Padding

[Мама, мыла, раму]

[Покупать, новый, телефон, затратно]

[Вау]

[Мне, очень, не, нравится ваш, банк]

Padding

[Мама, мыла, раму]

[Покупать, новый, телефон, затратно]

[Вау]

[Мне, очень, не, нравится ваш, банк]

max_sequence_length = 8

Depend of your dataset statistics

Padding

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[Покупать, новый, телефон, затратно]

[Вау]

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↓

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]

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

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

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Indexing ↓ **Collect word2index vocabulary**

Padding

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

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

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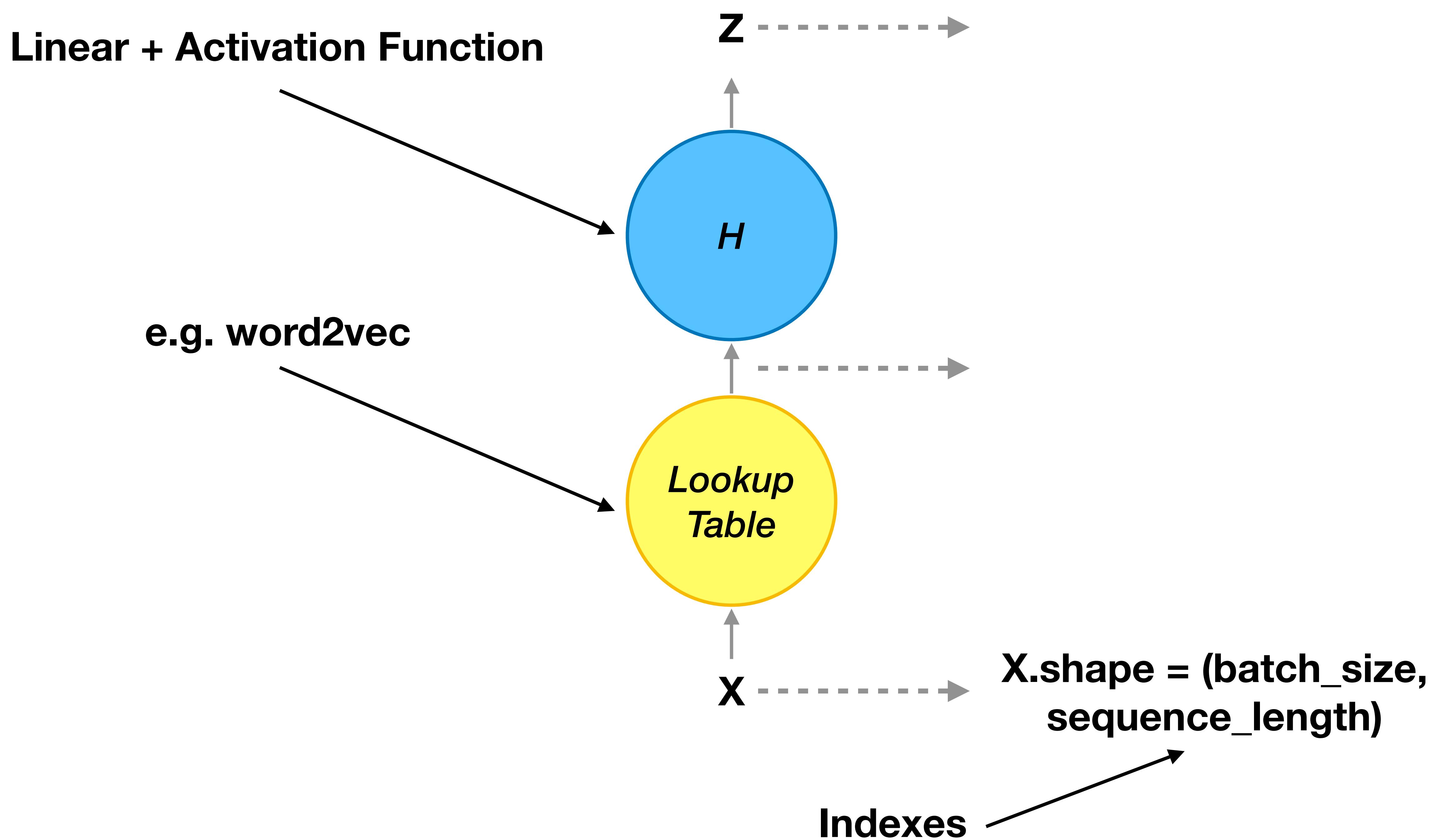
[Мне, очень, не, нравится, ваш, банк, PAD, PAD]

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



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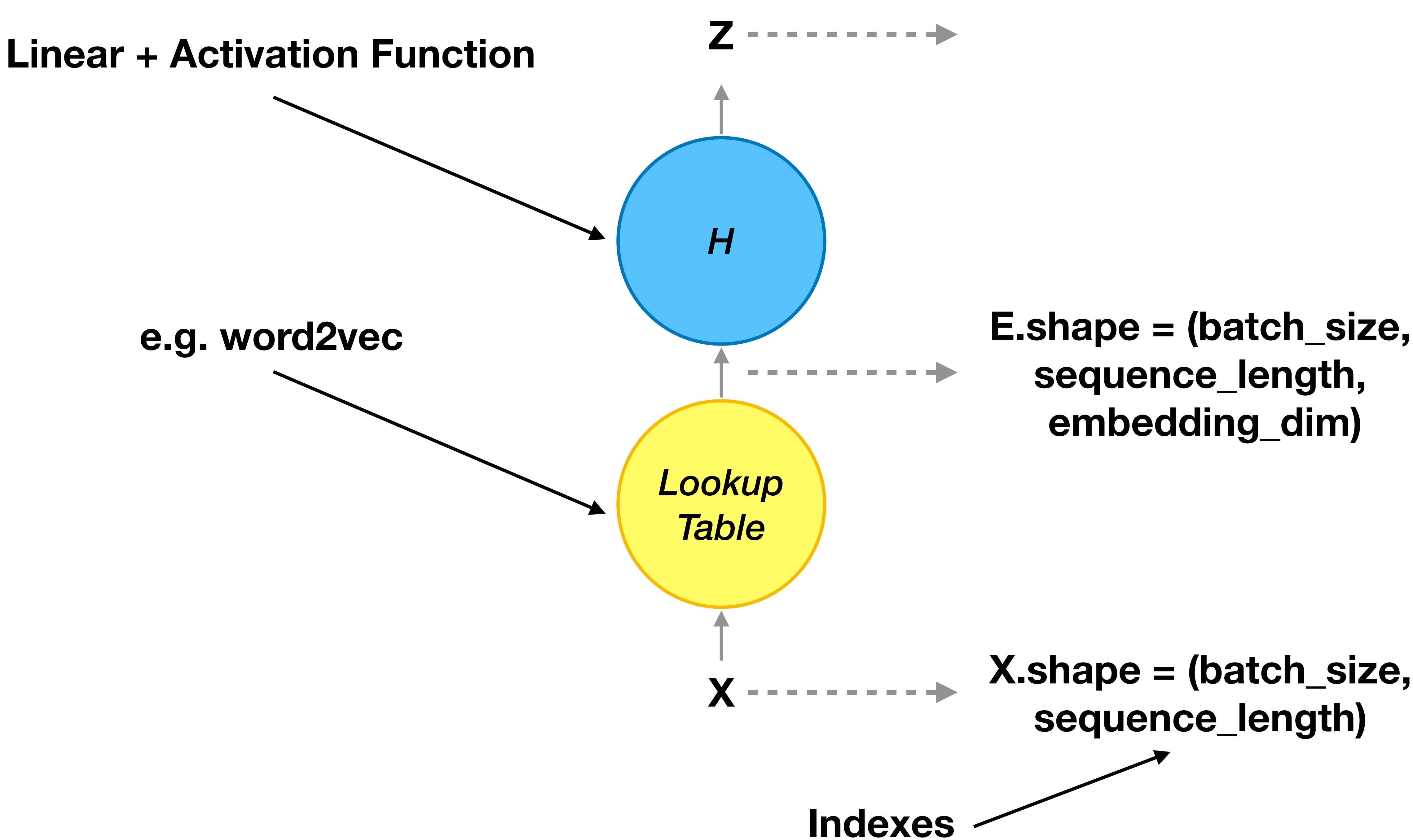

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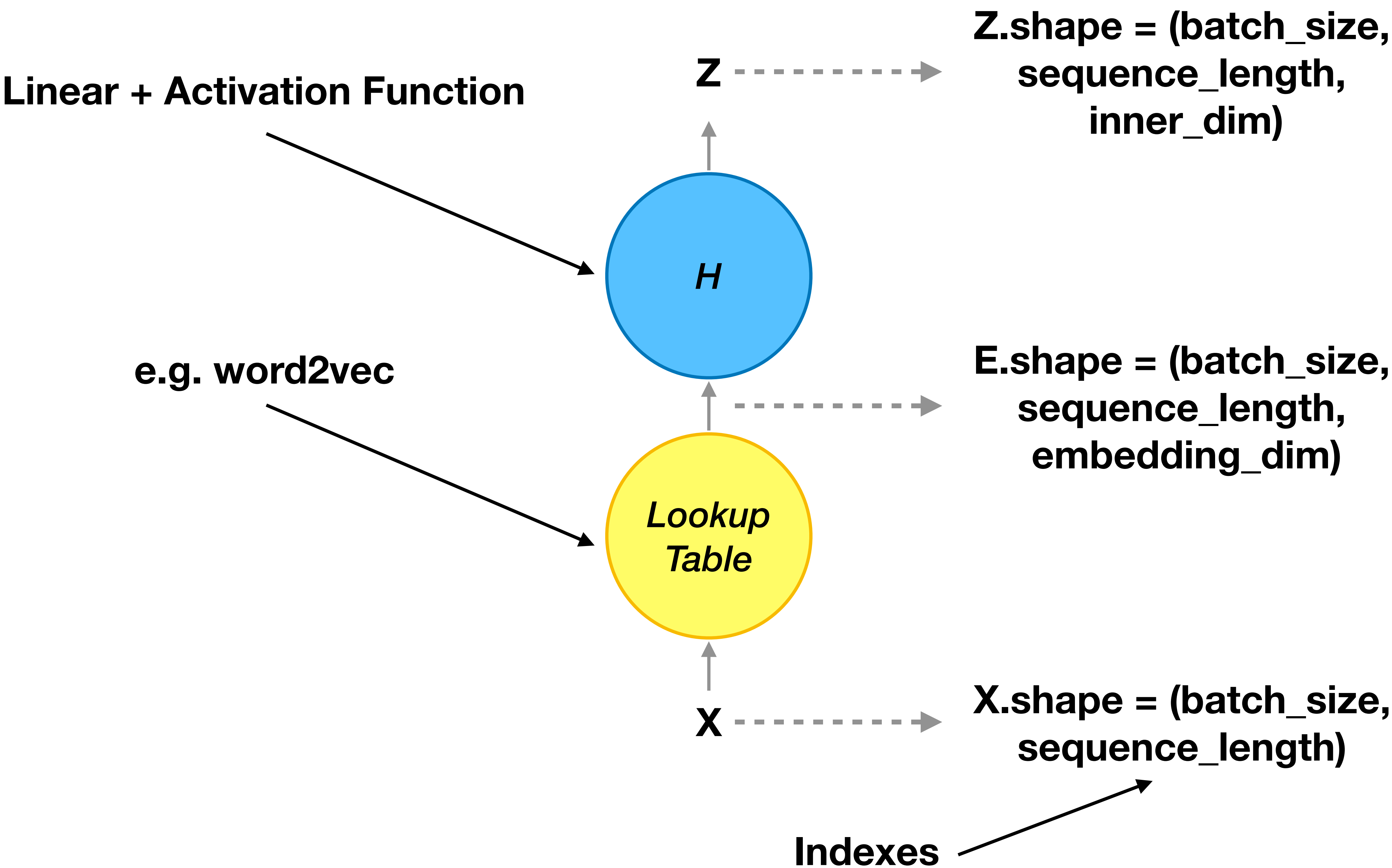

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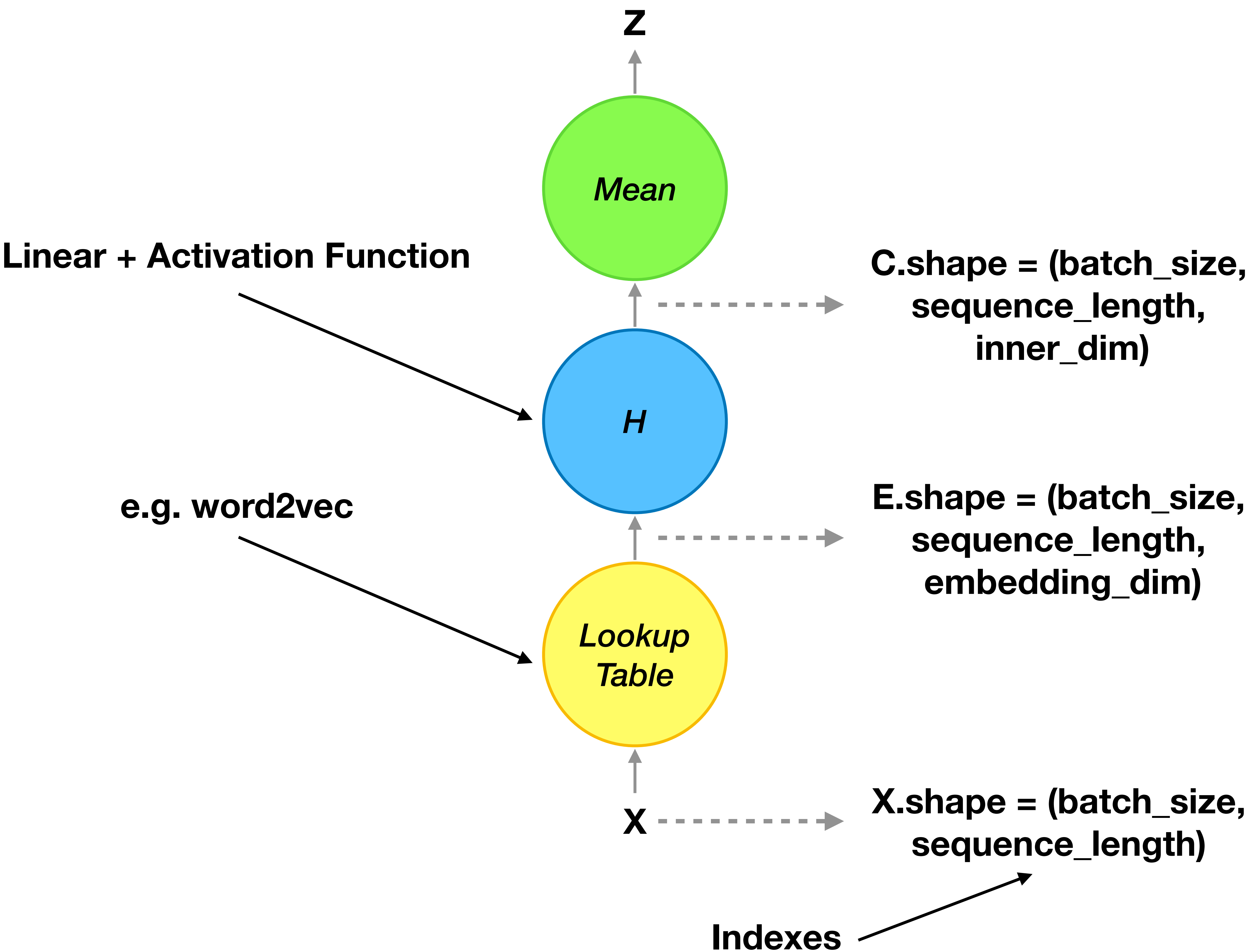

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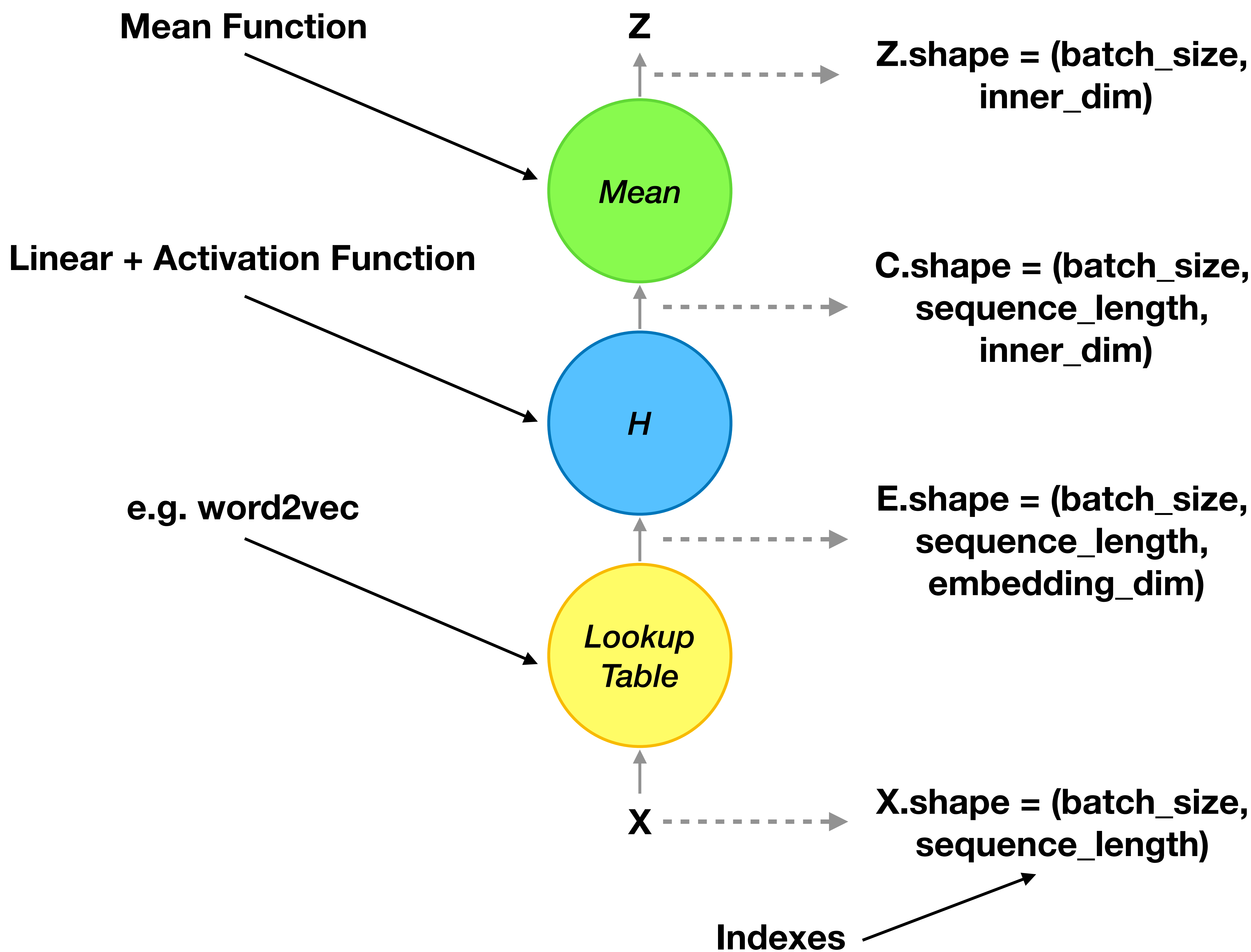

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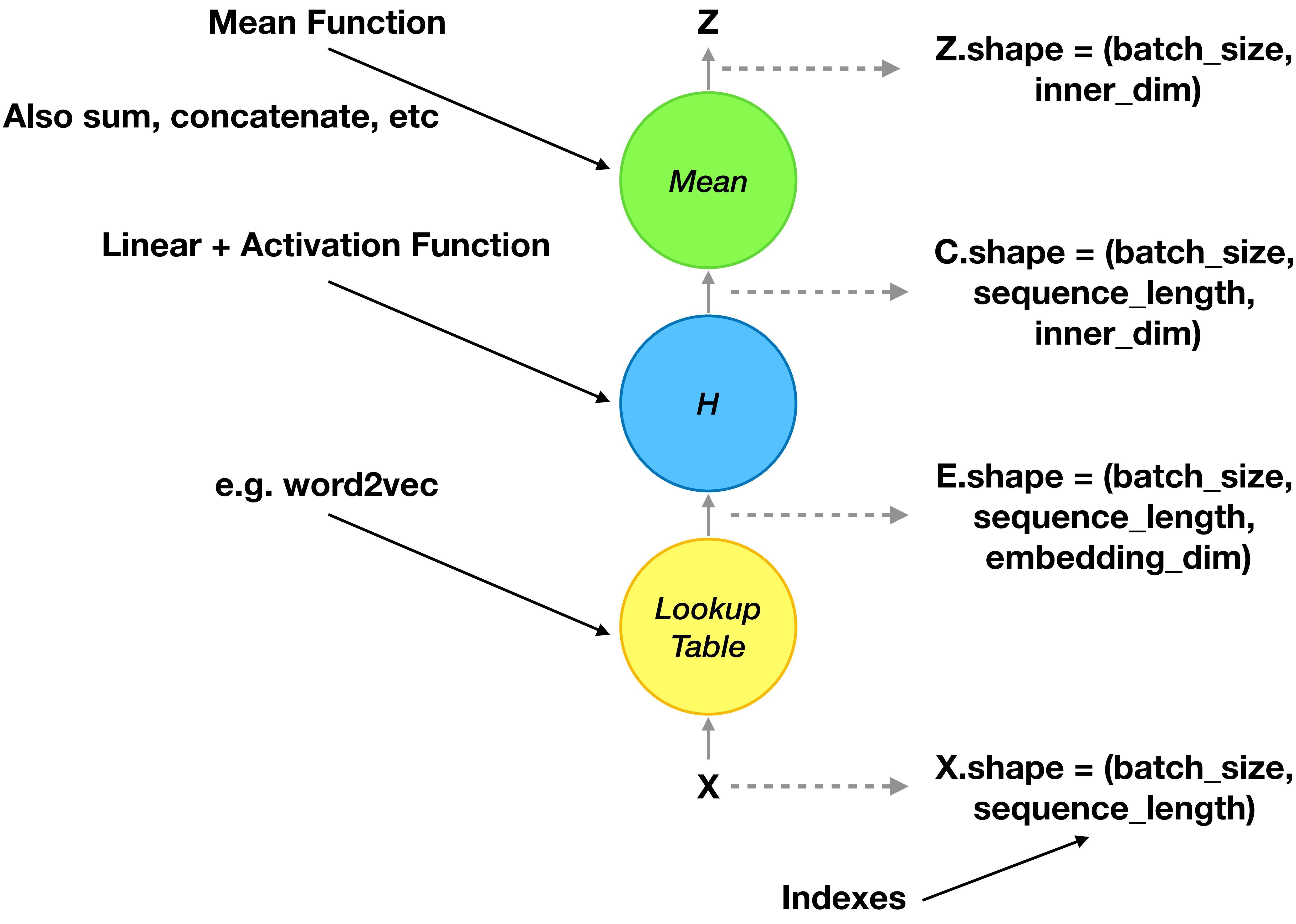

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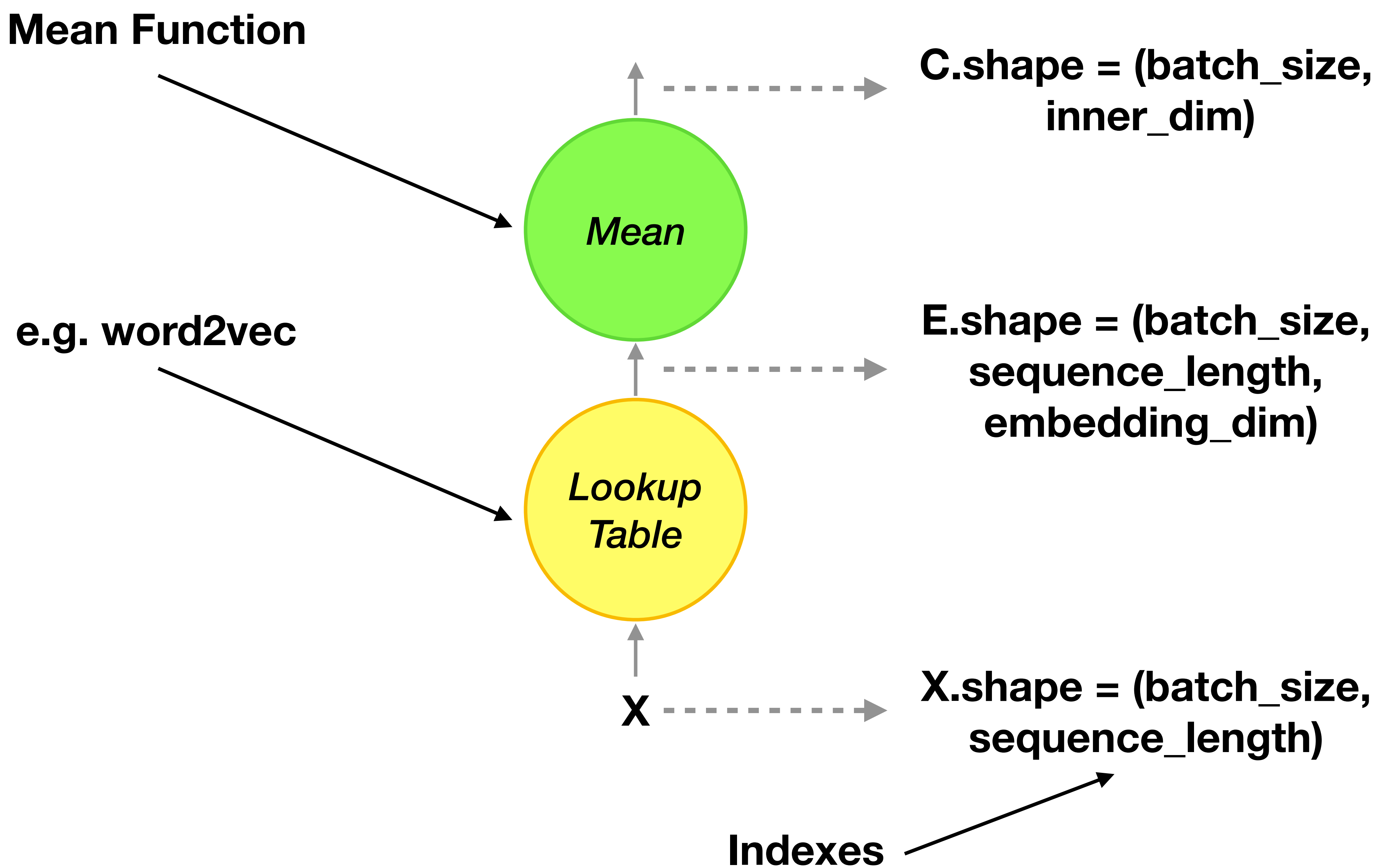

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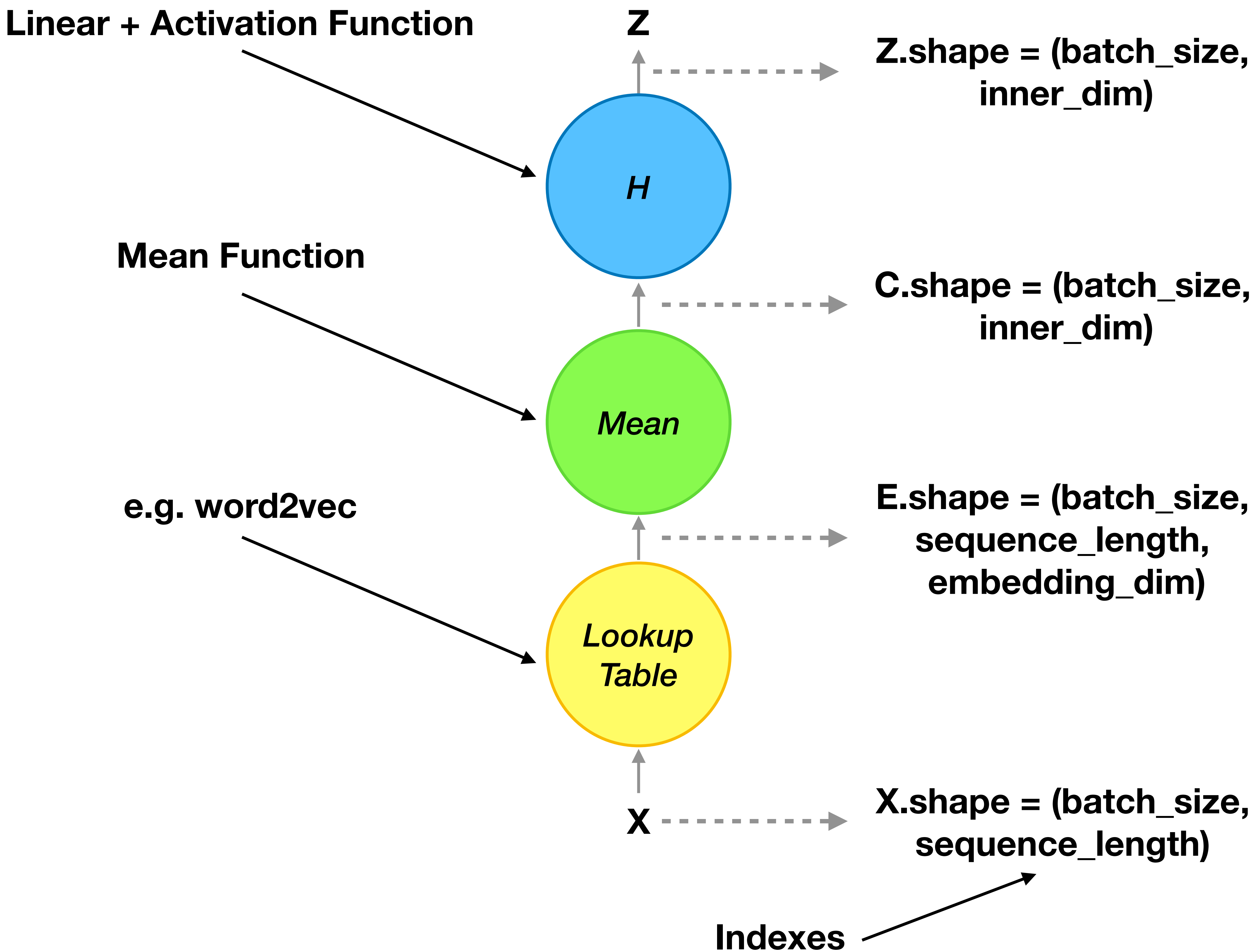
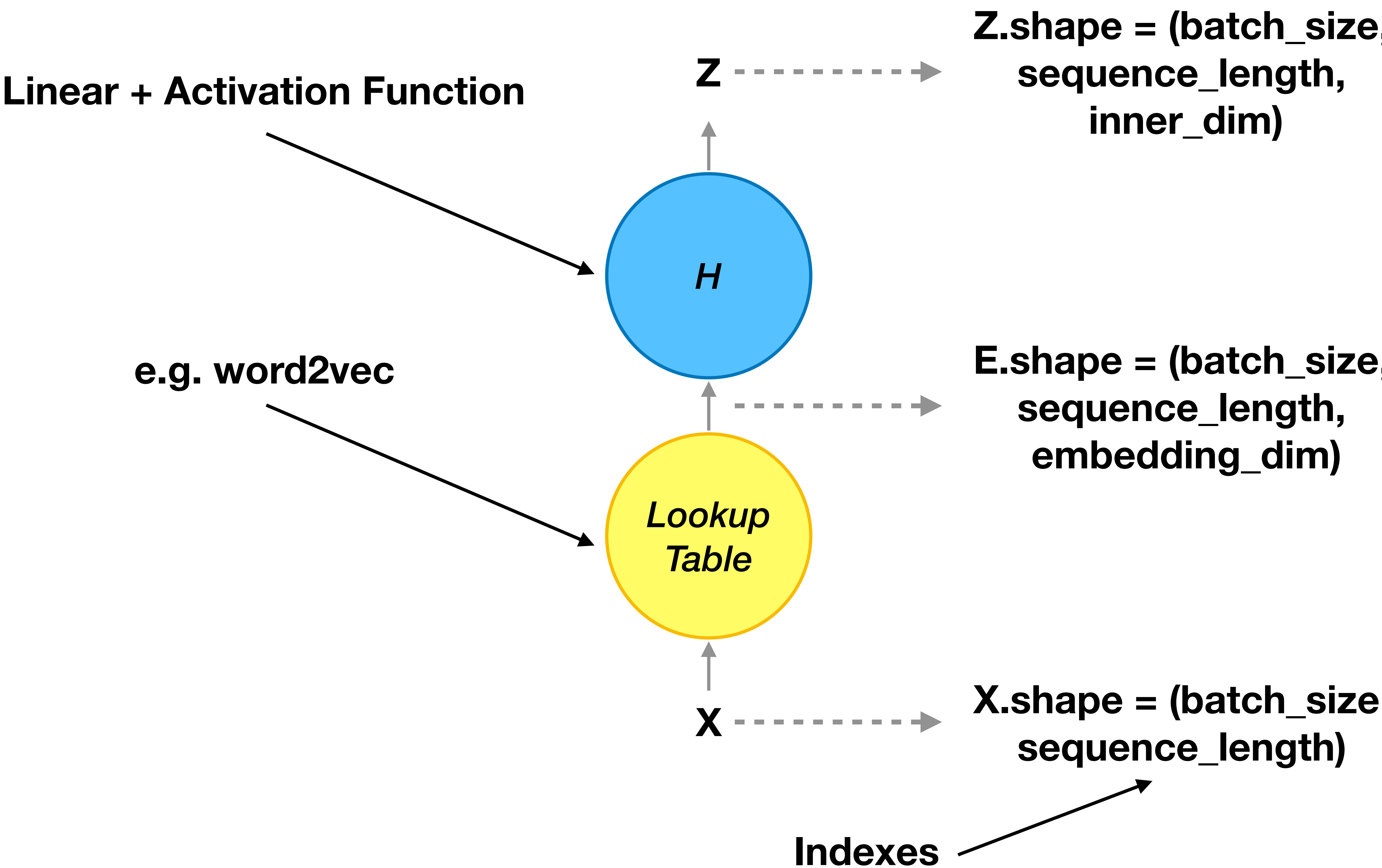
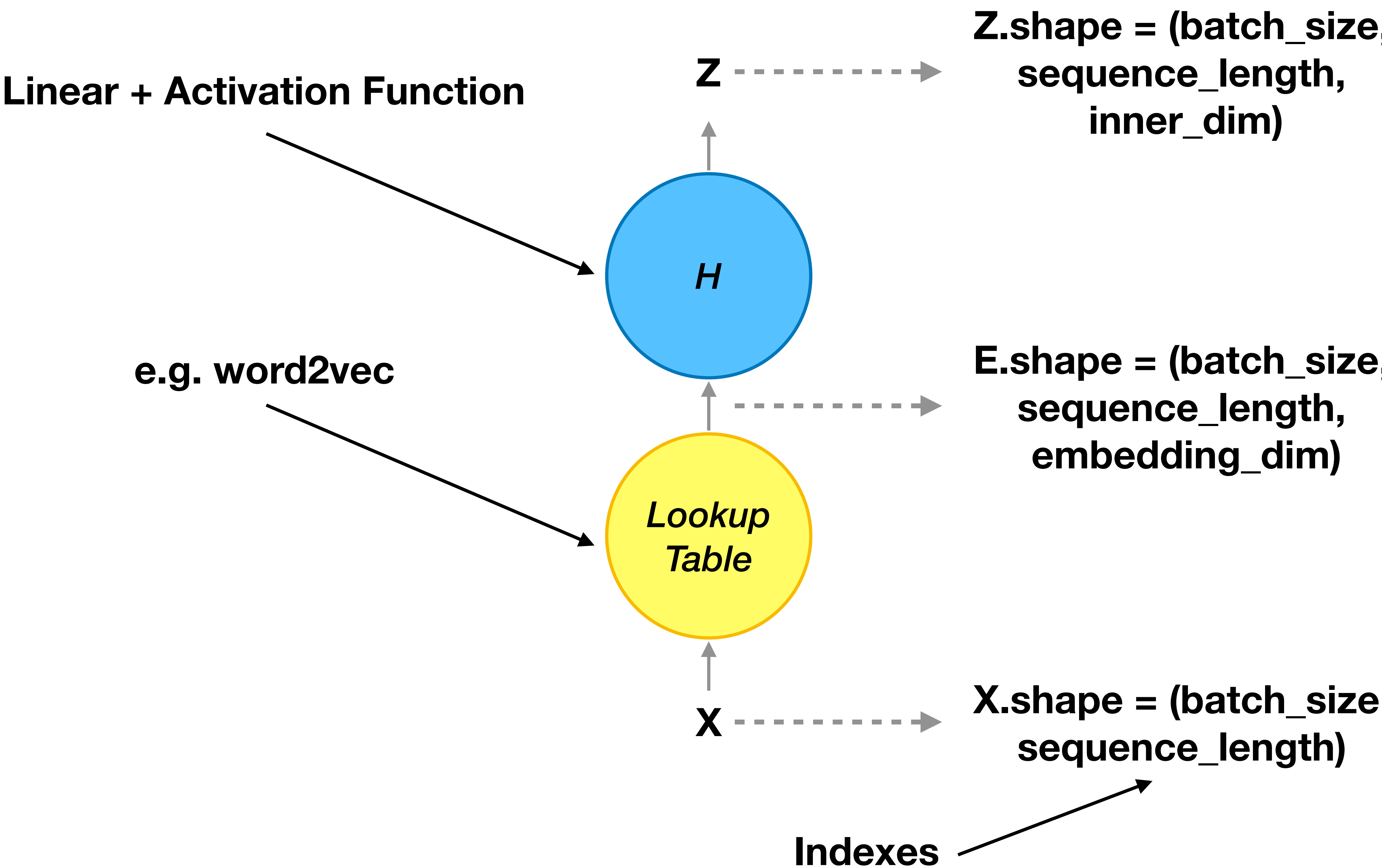


Recurrent Neural Network



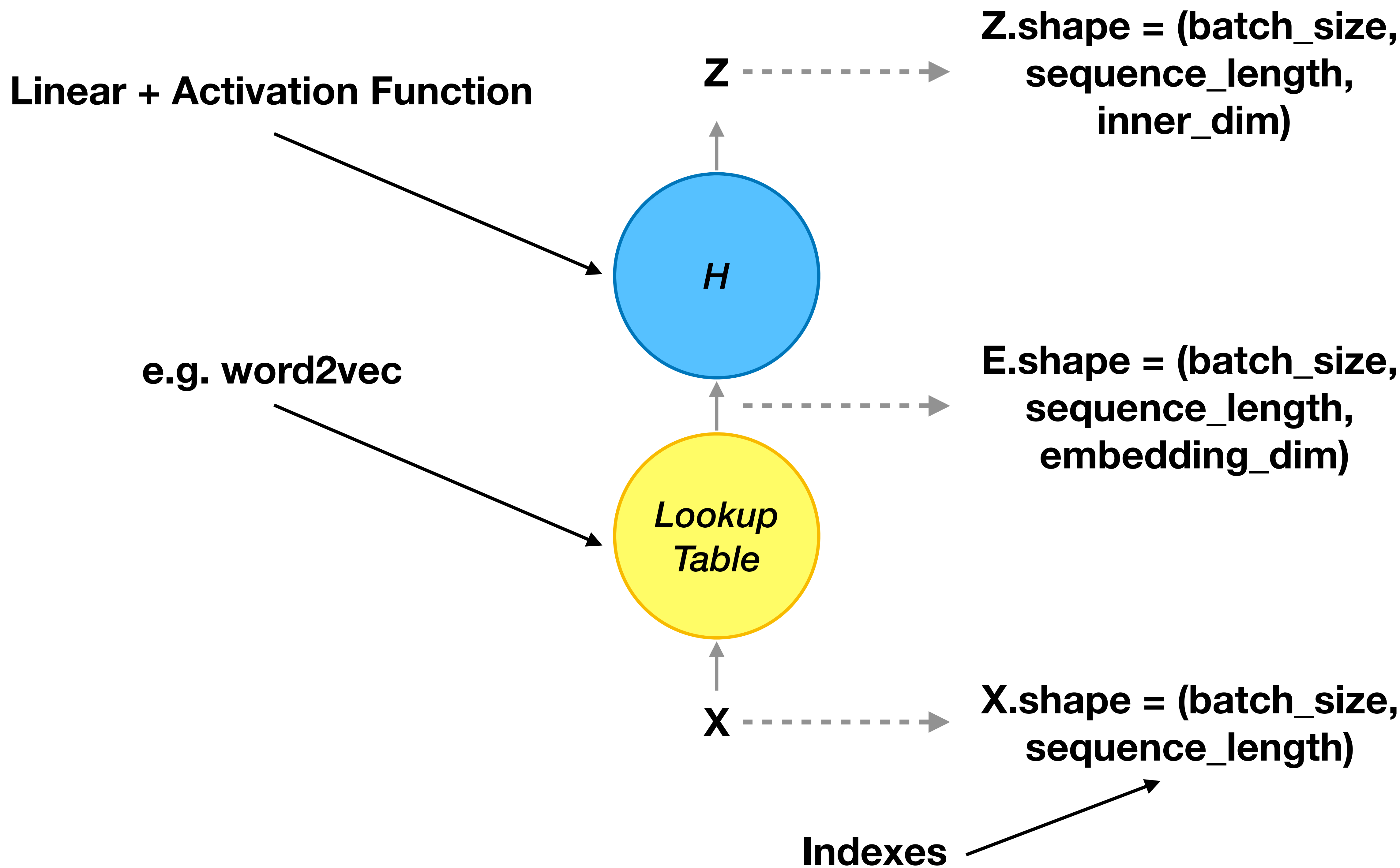
Recurrent Neural Network

Maybe we can take last token?

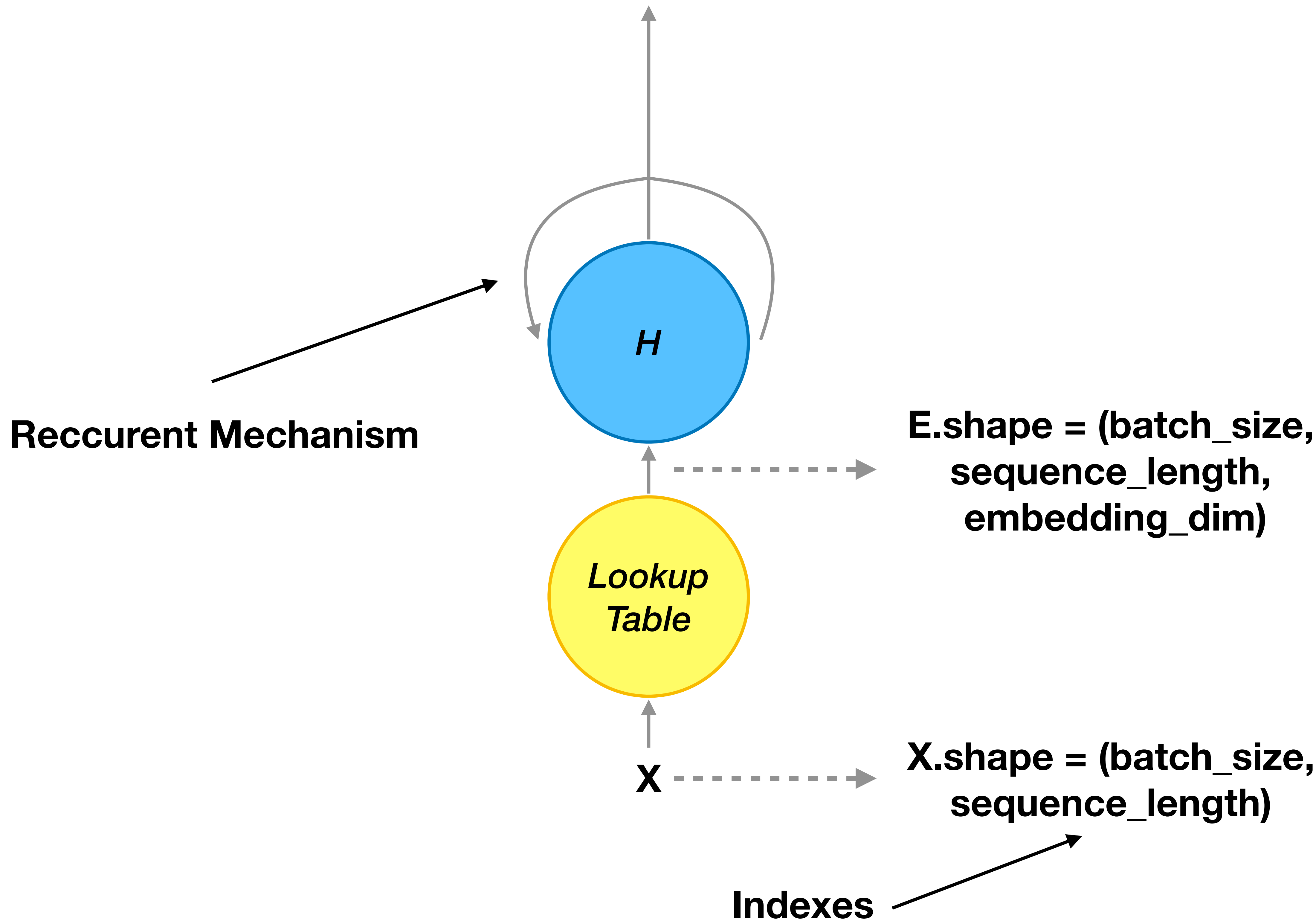


Recurrent Neural Network

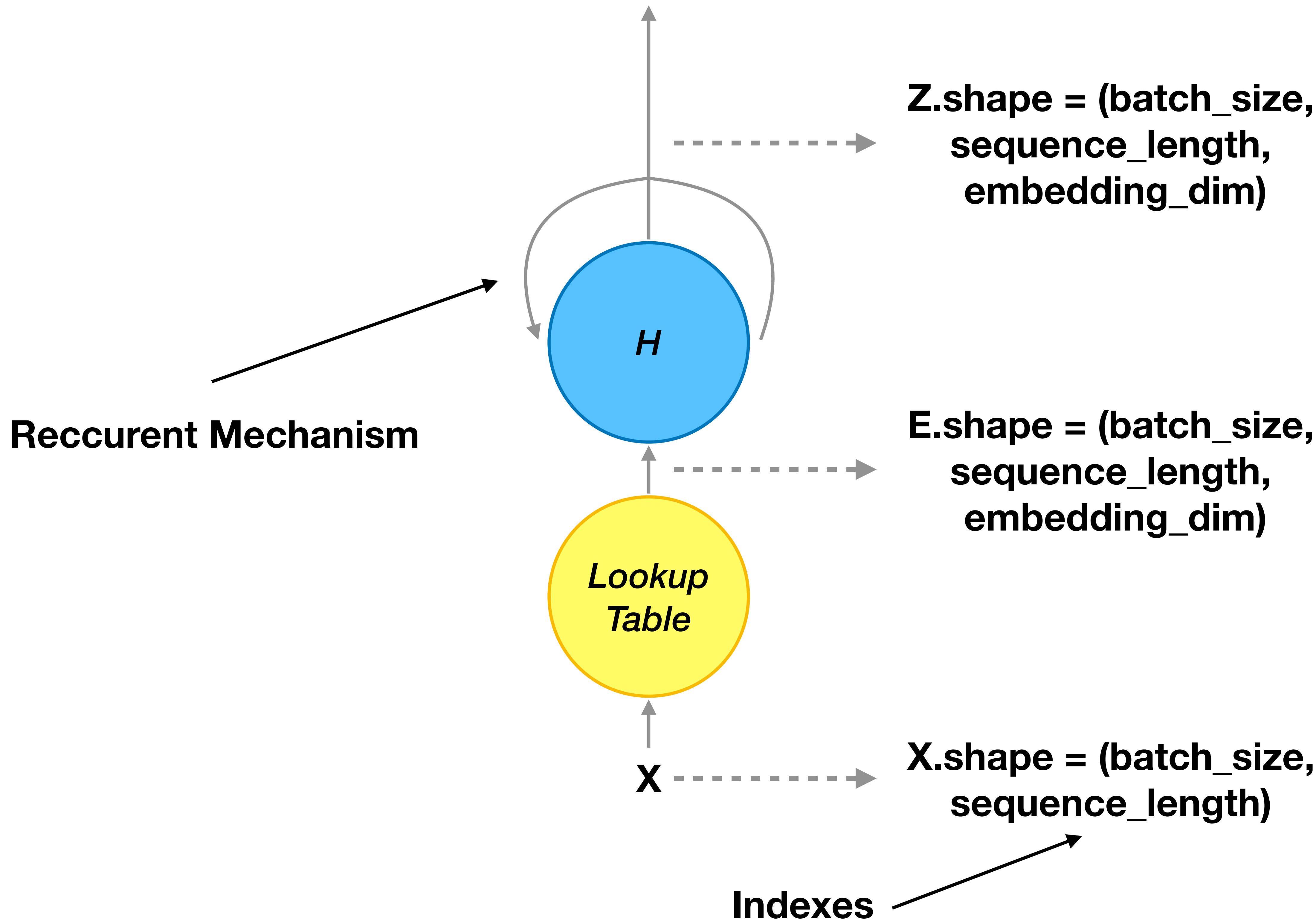
No, because we don't have information about whole sentence



Recurrent Neural Network



Recurrent Neural Network



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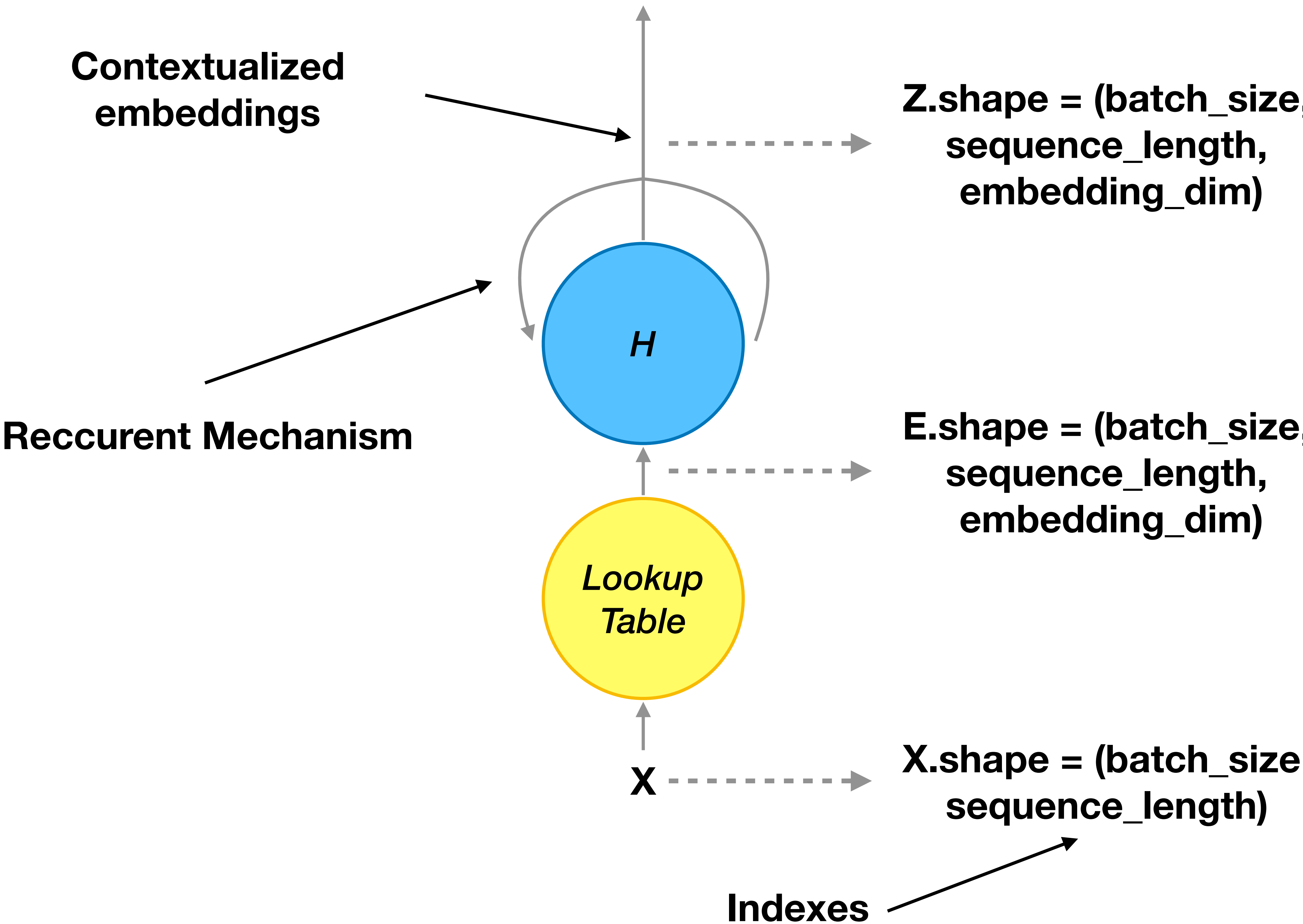
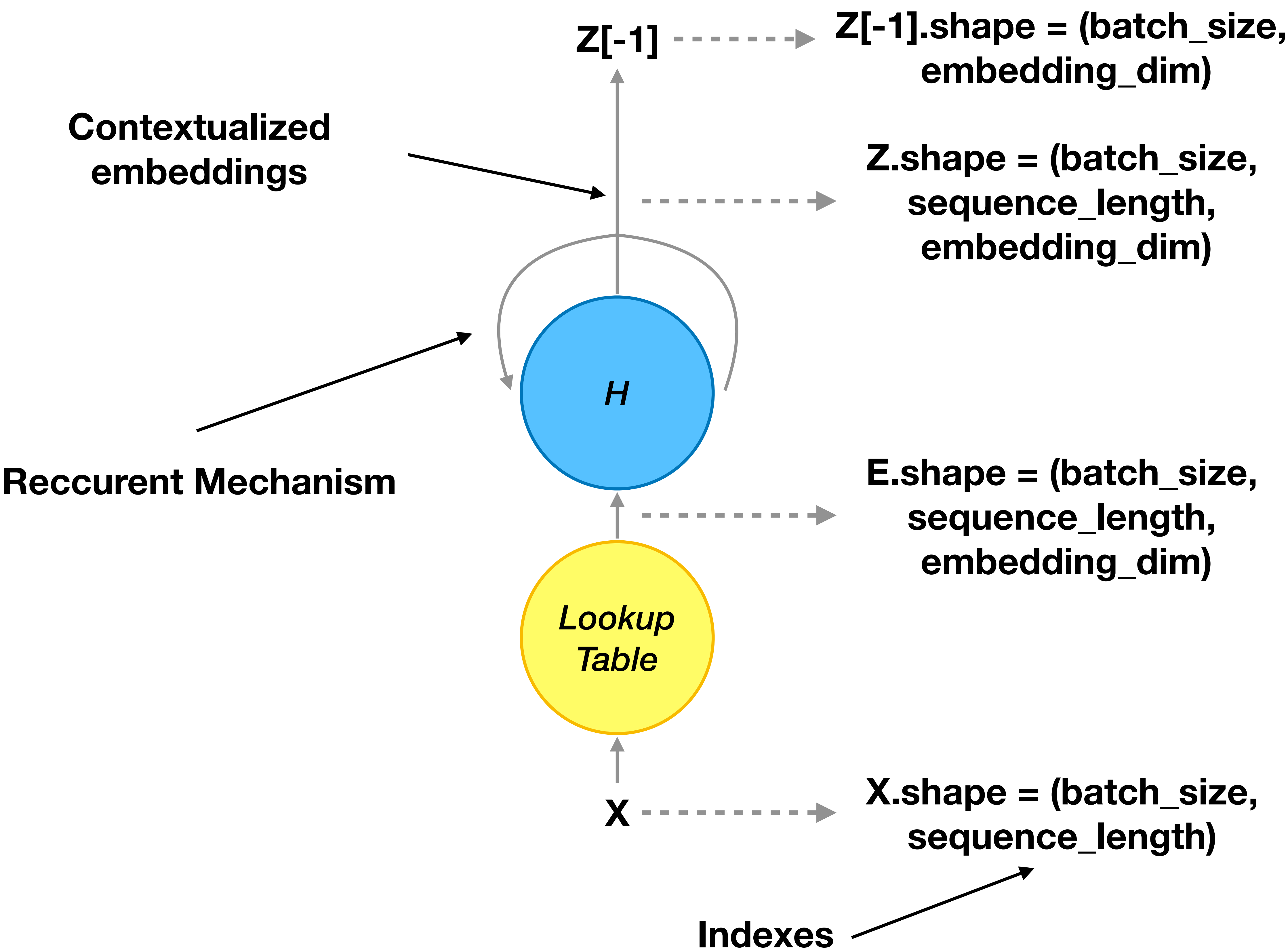
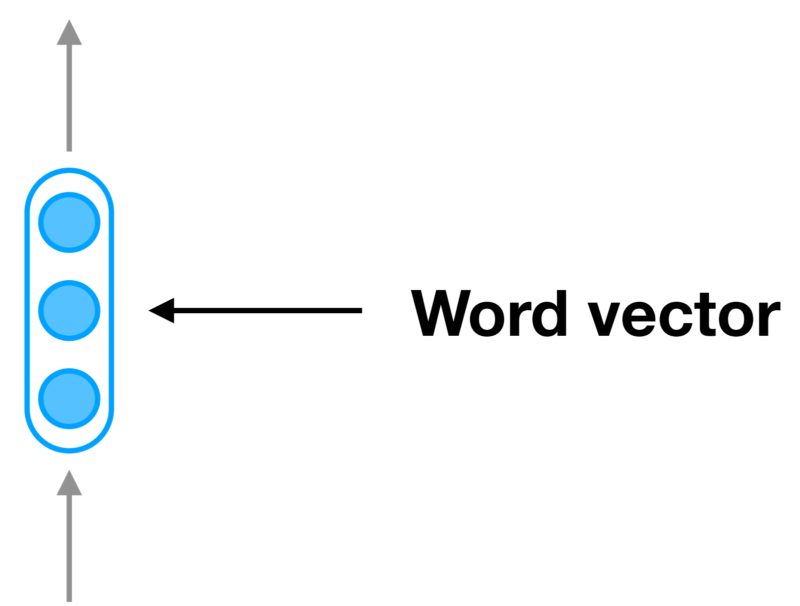


Recurrent Neural Network



Reccurent Cell



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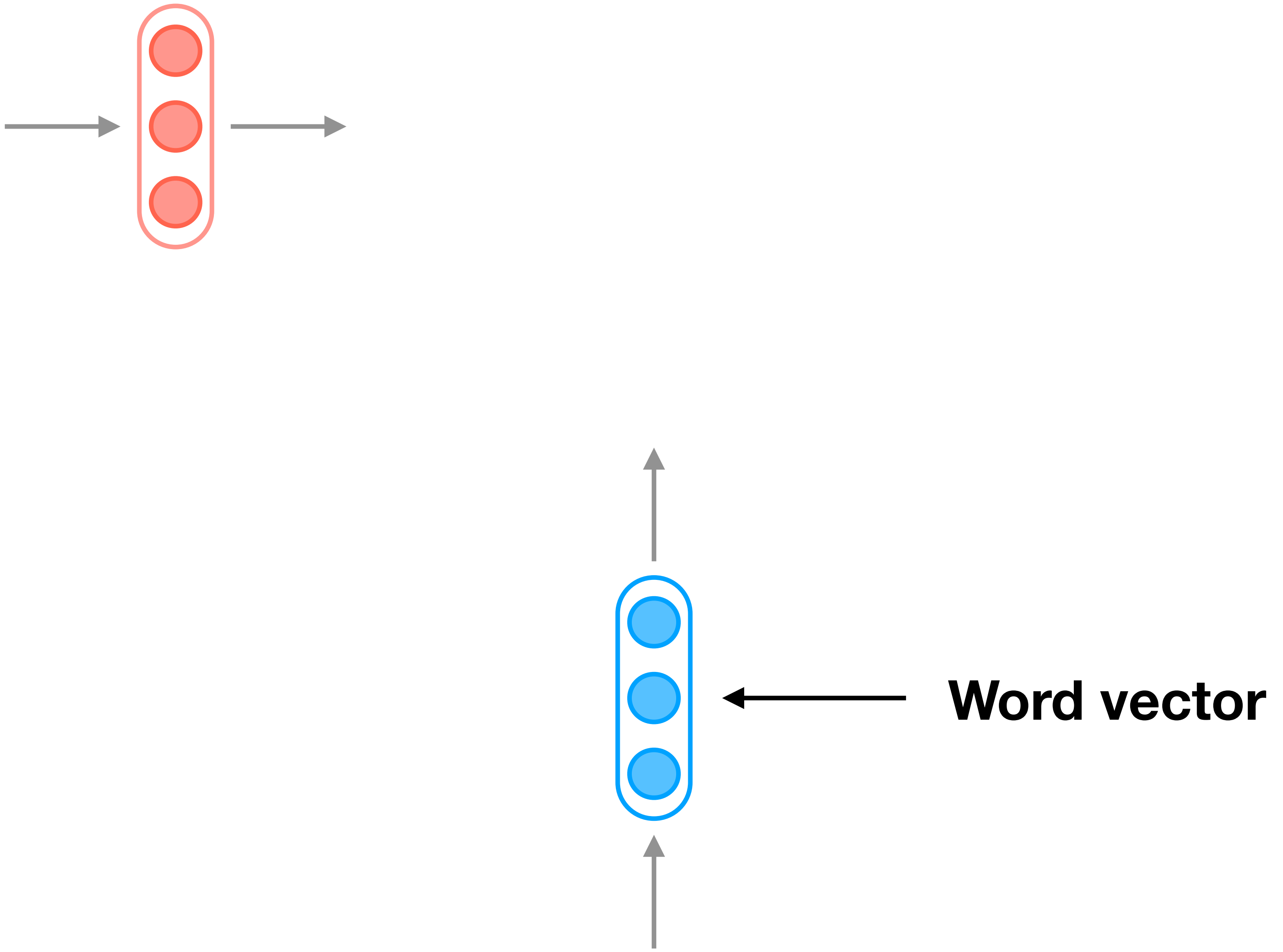

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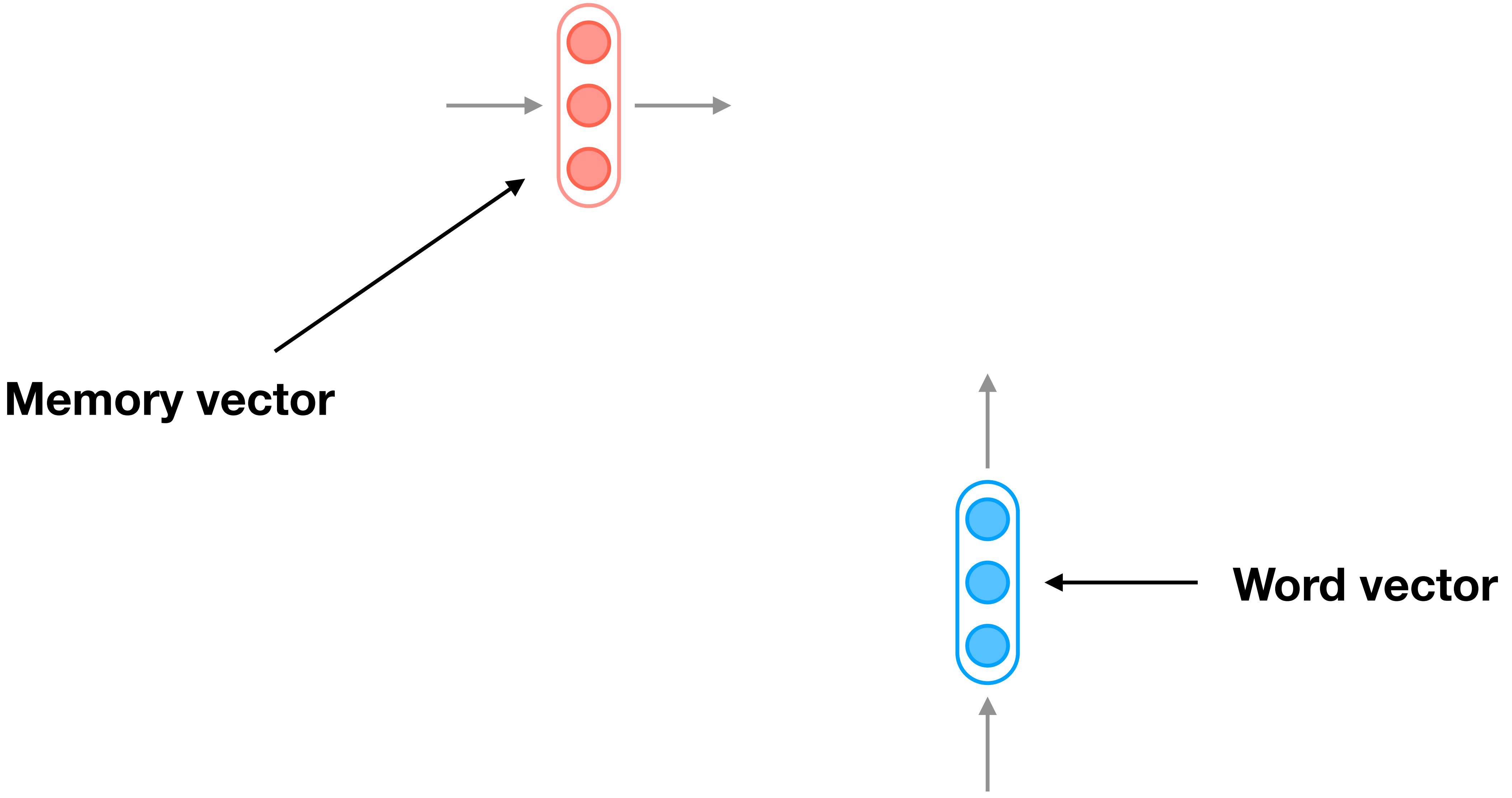

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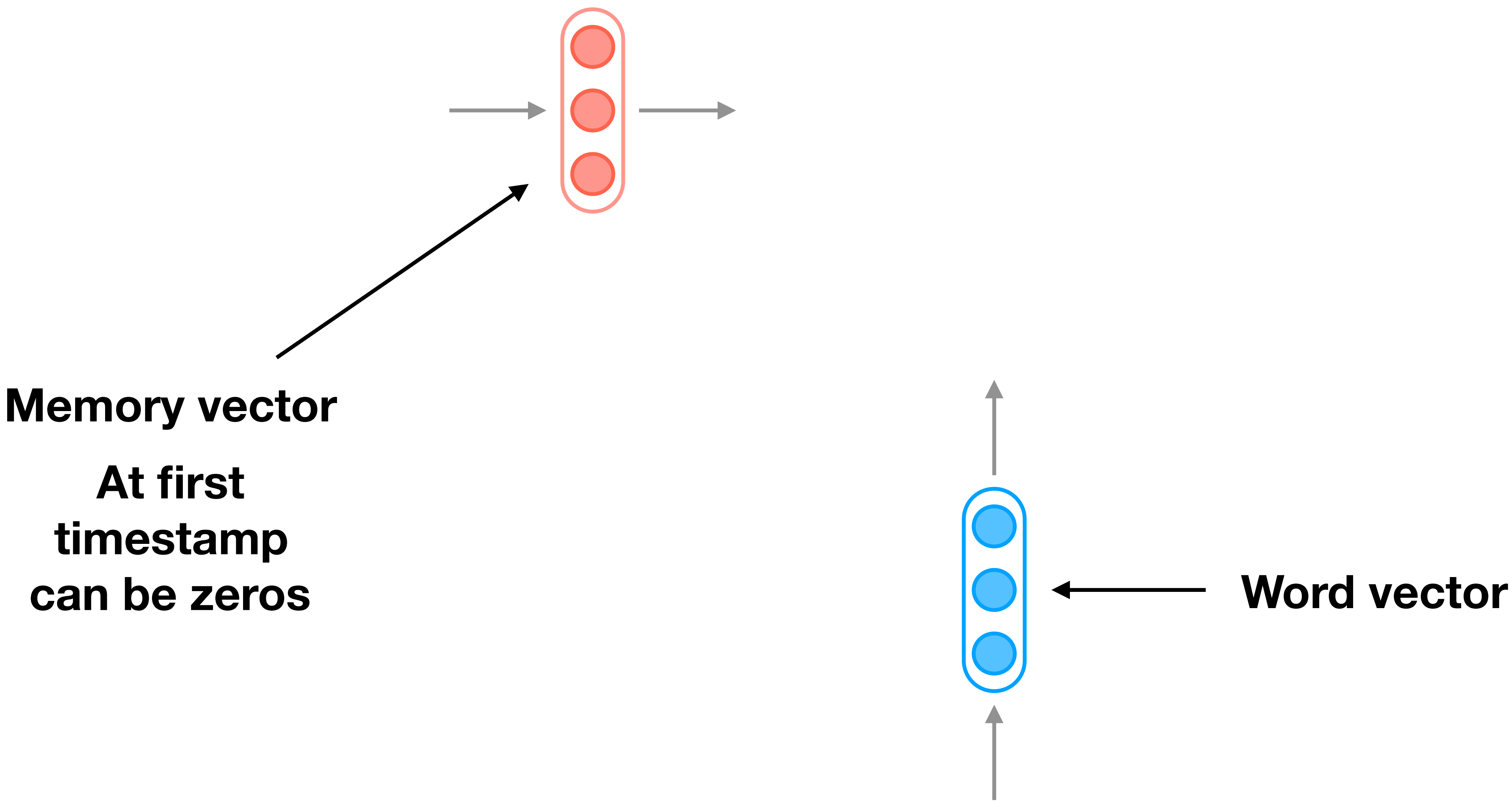

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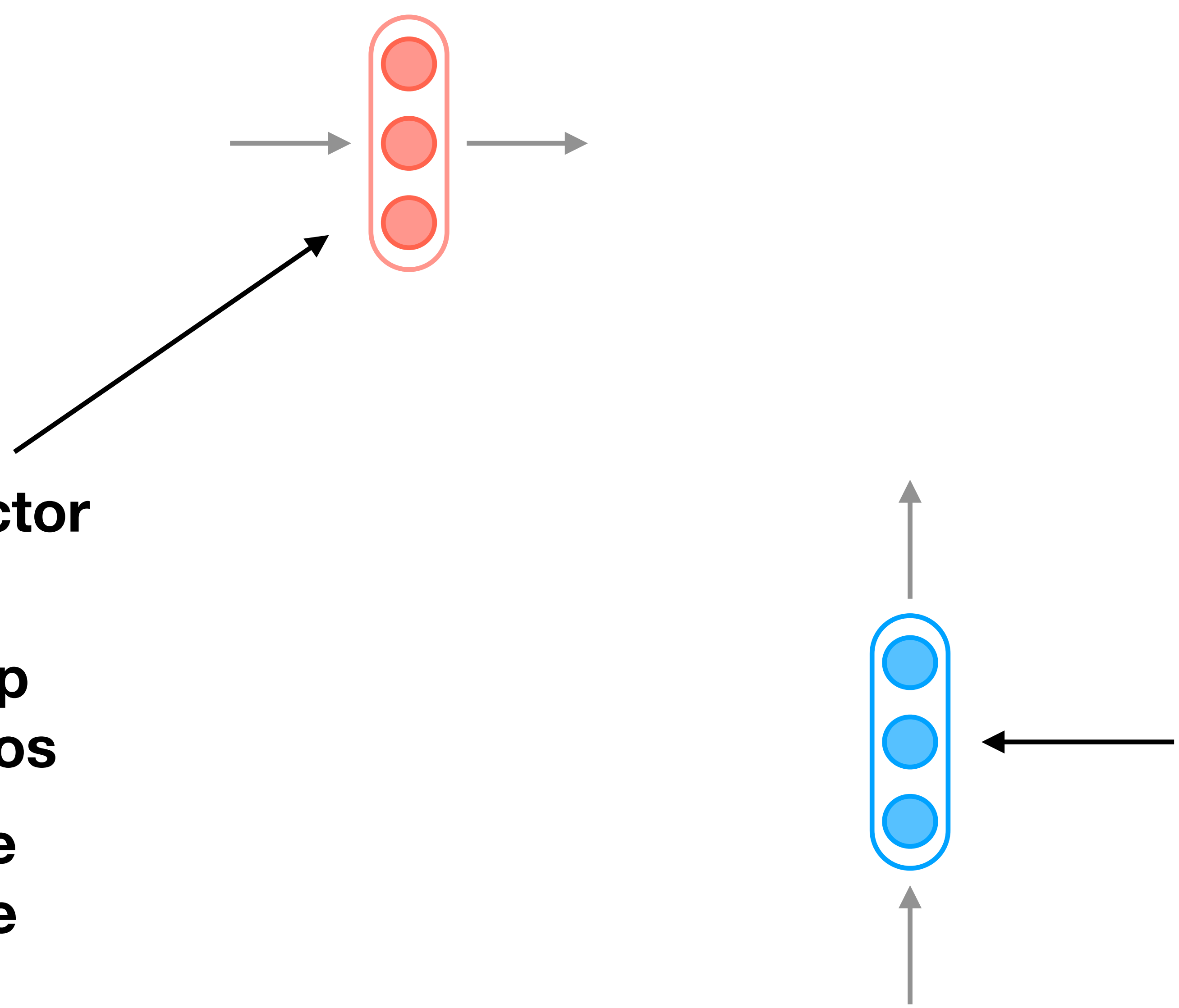

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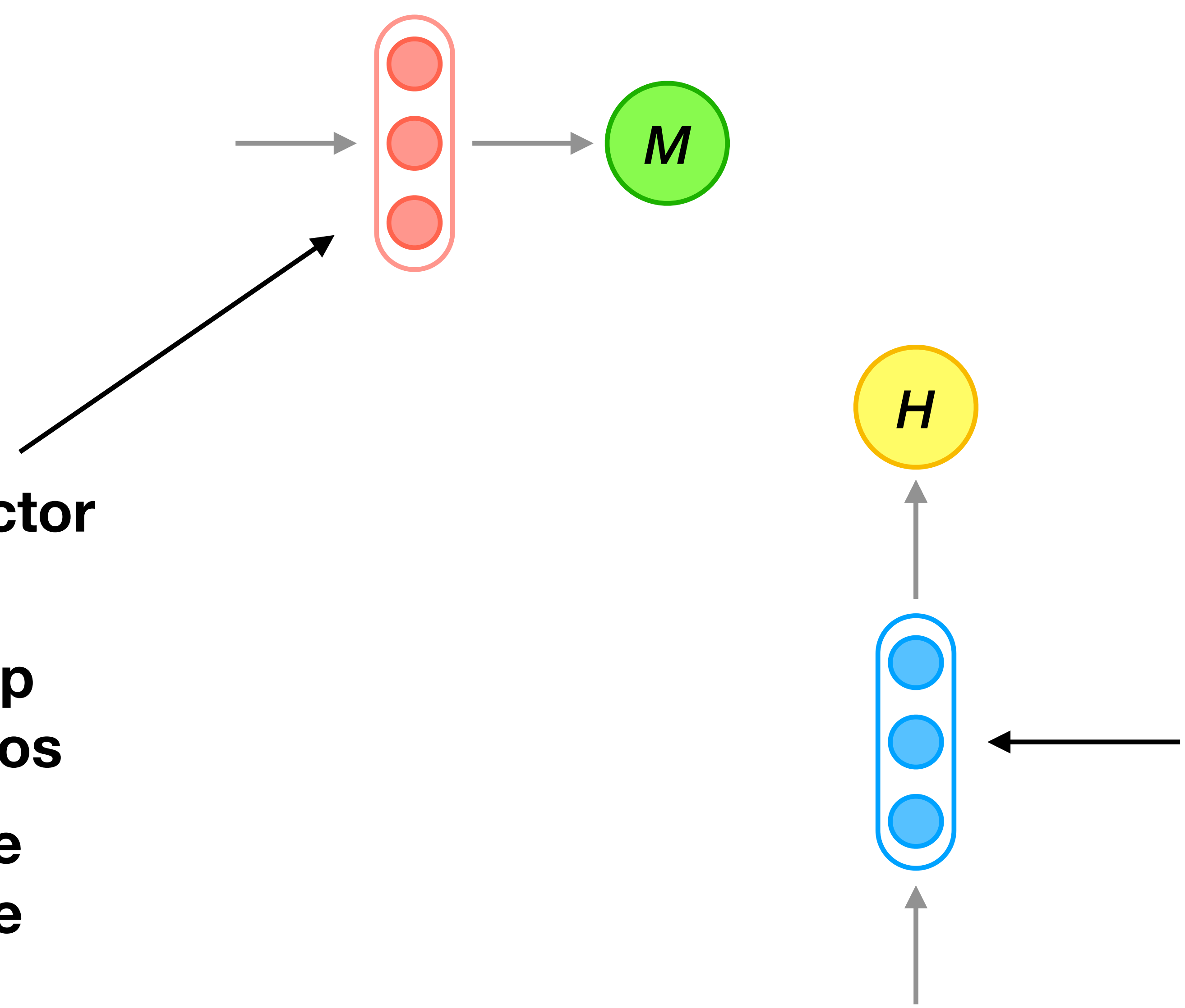


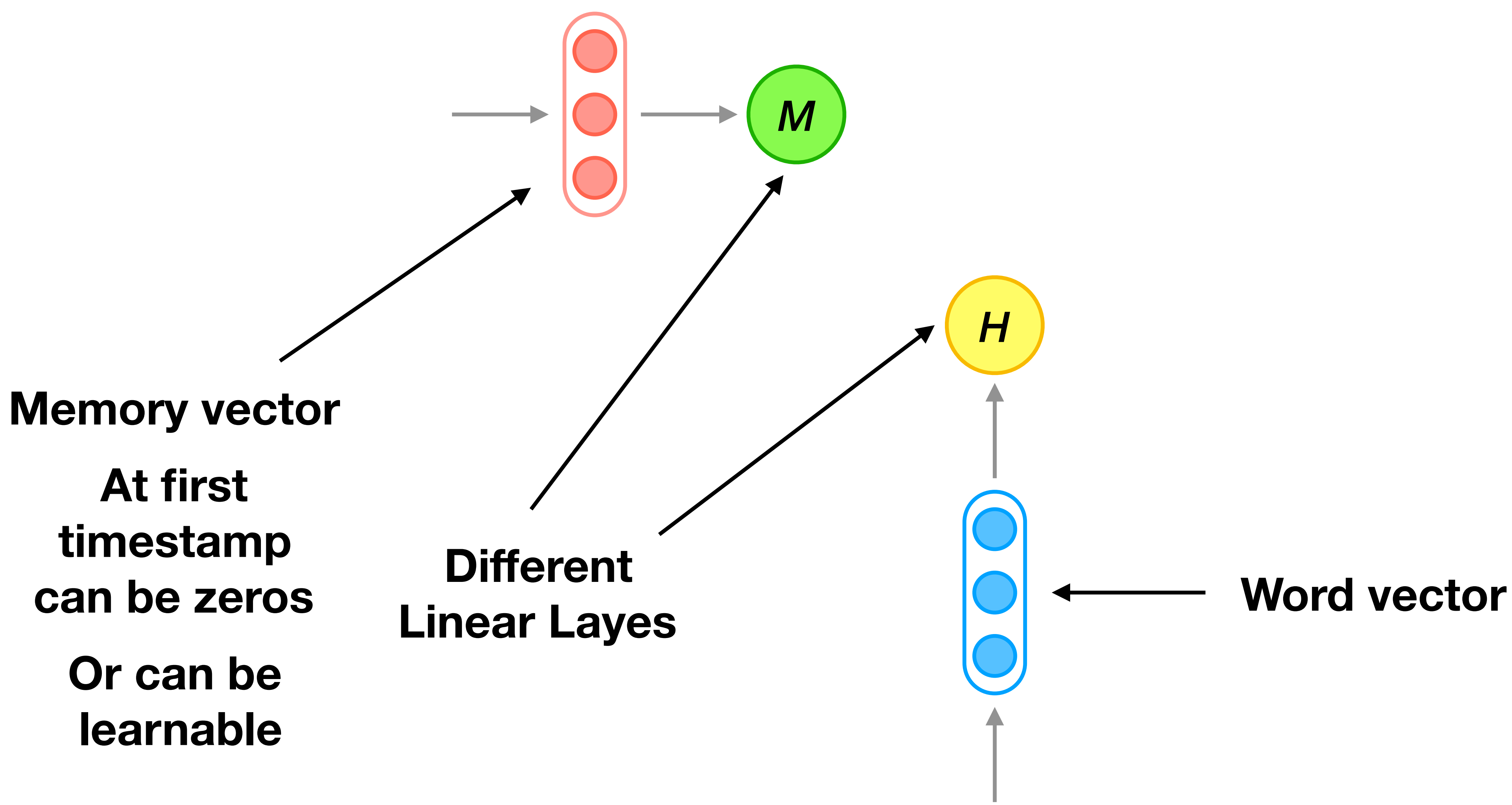
Memory vector

At first timestamp can be zeros

Or can be learnable

Word vector

Reccurent Cell



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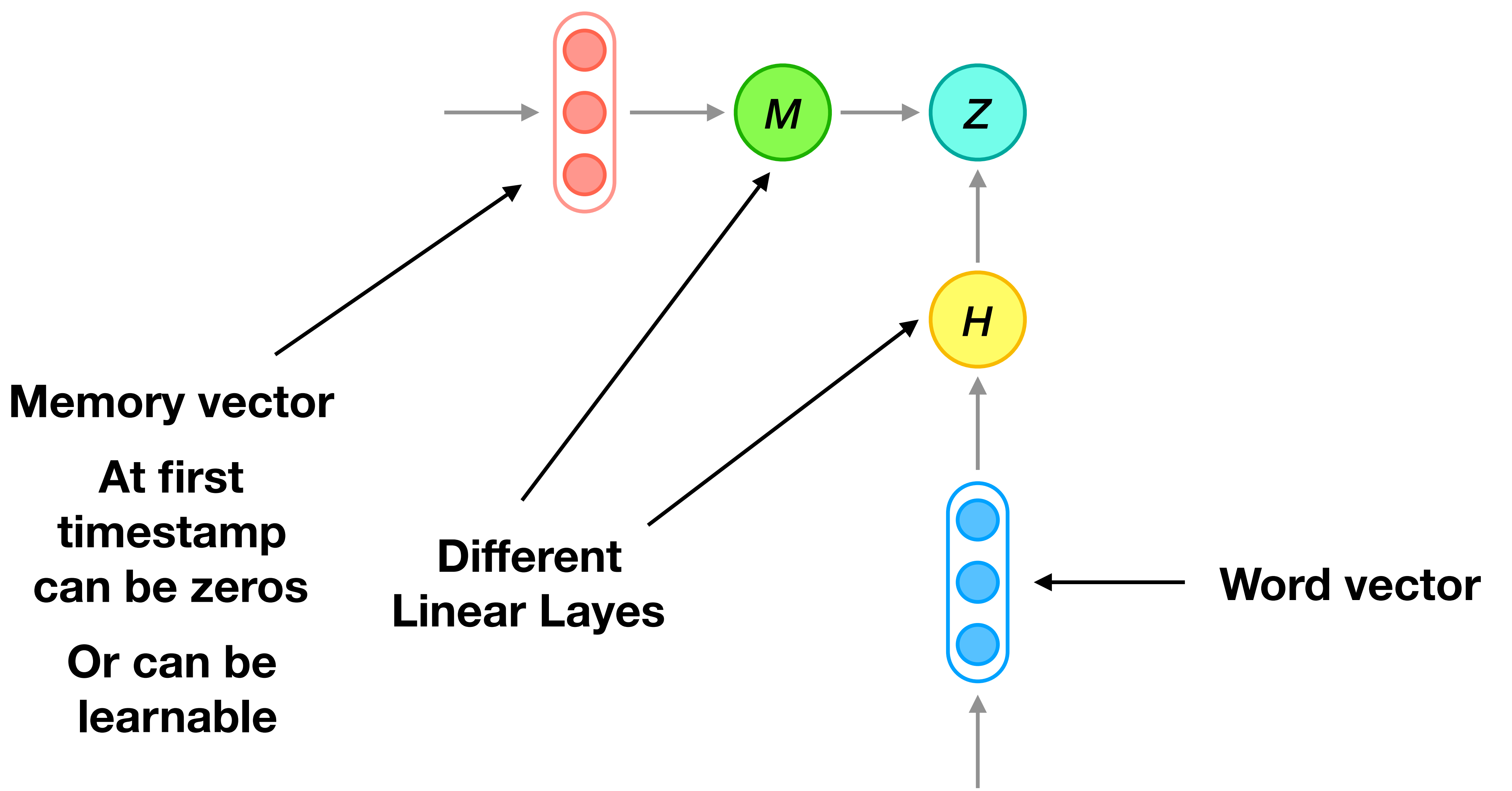

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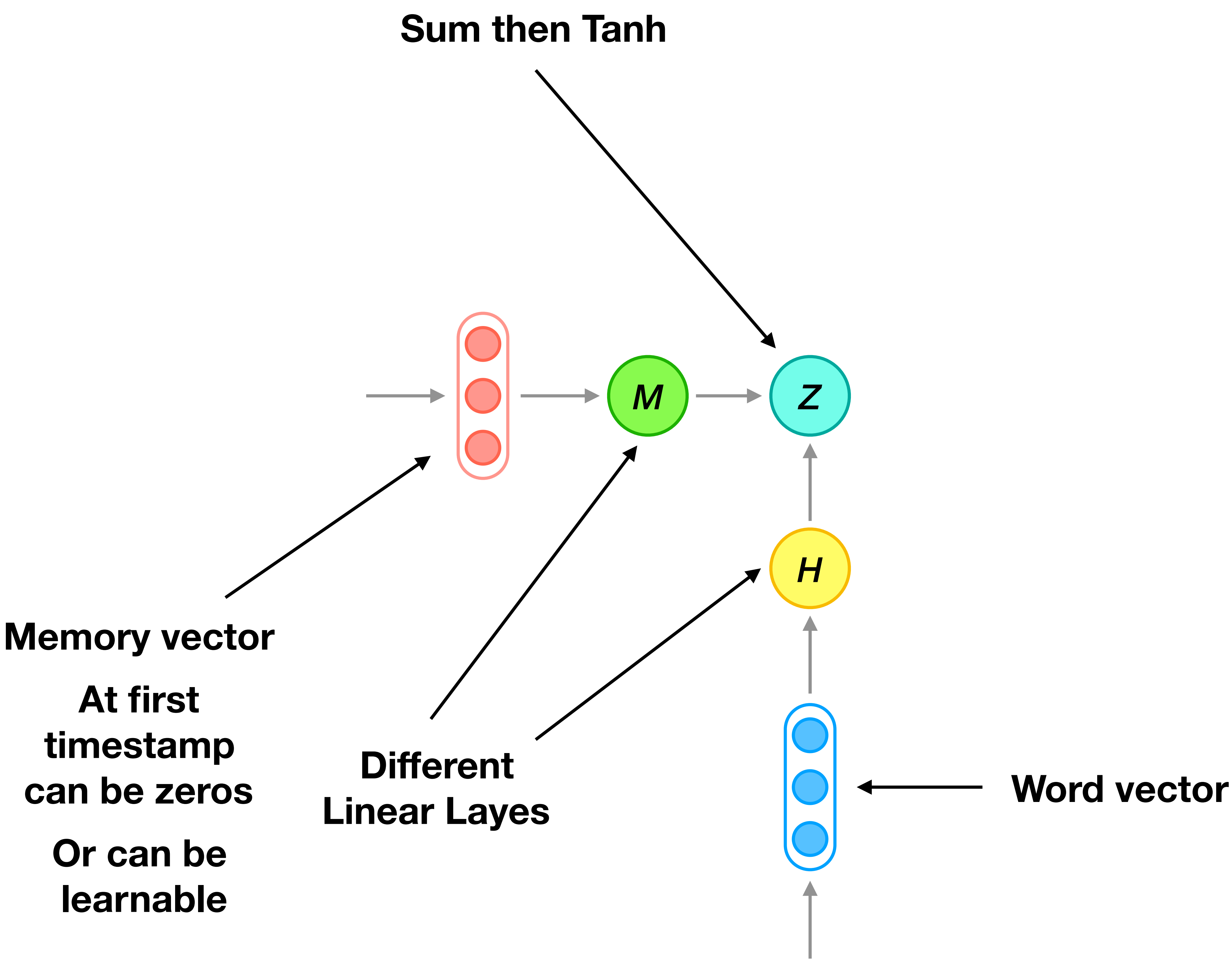

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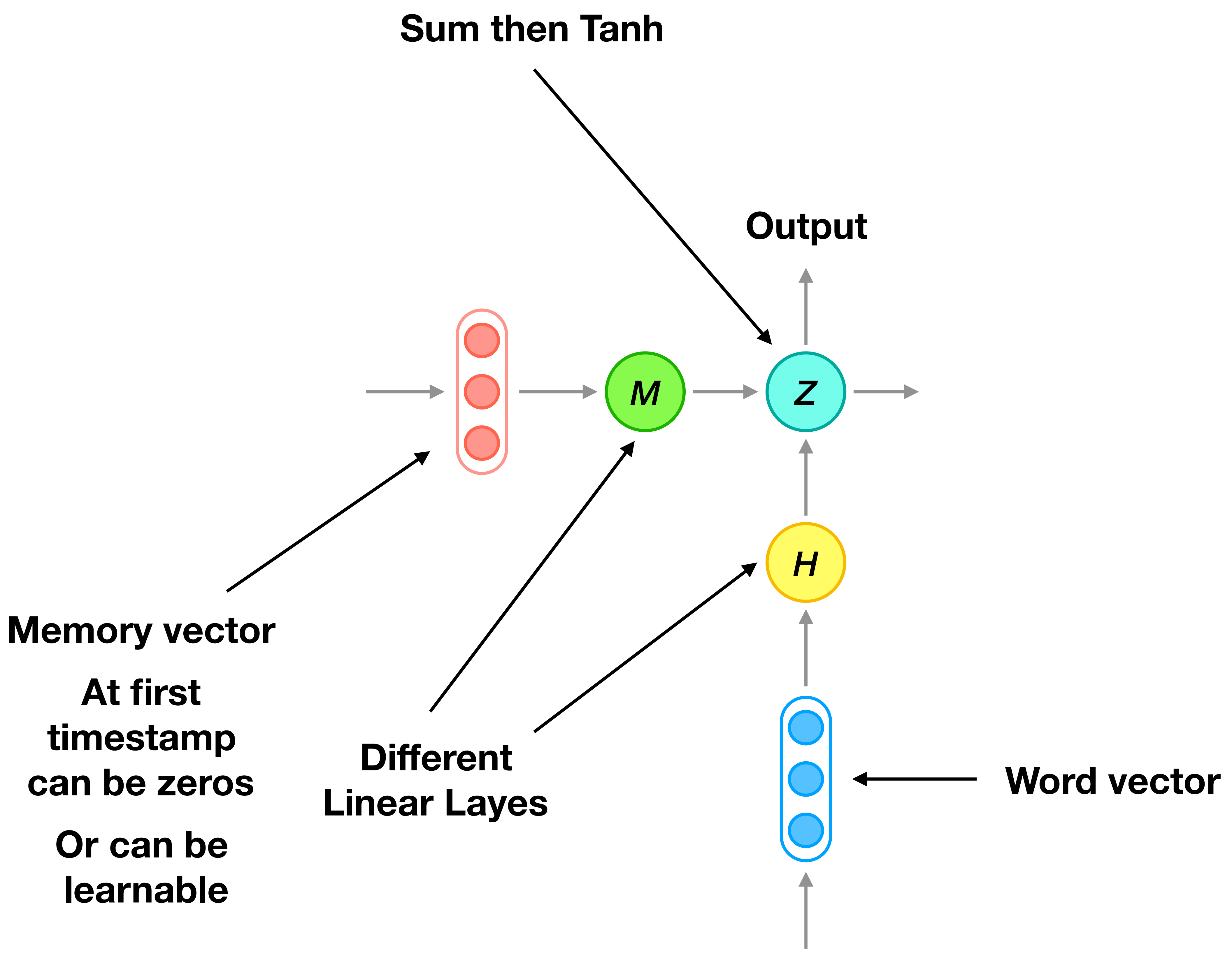

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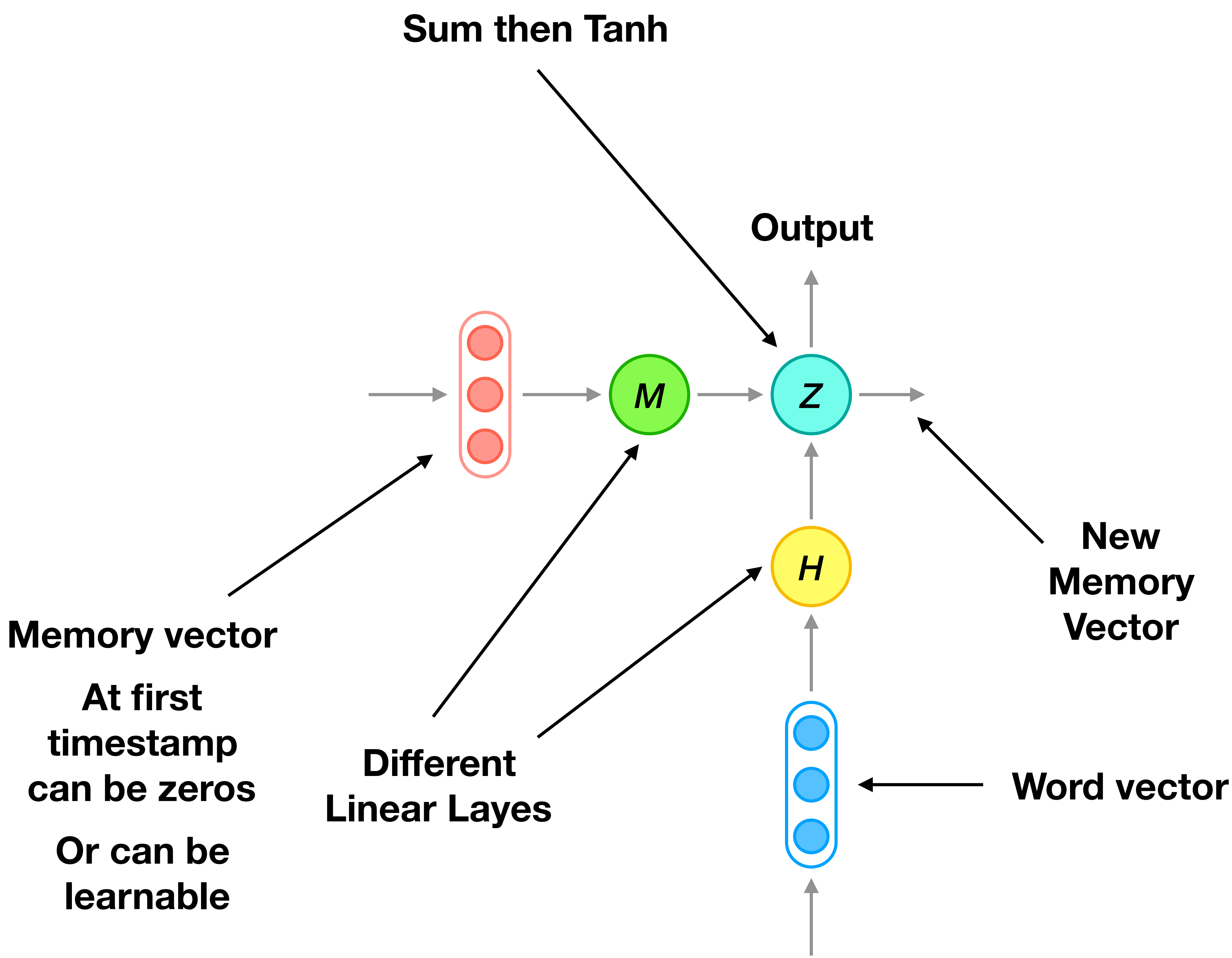
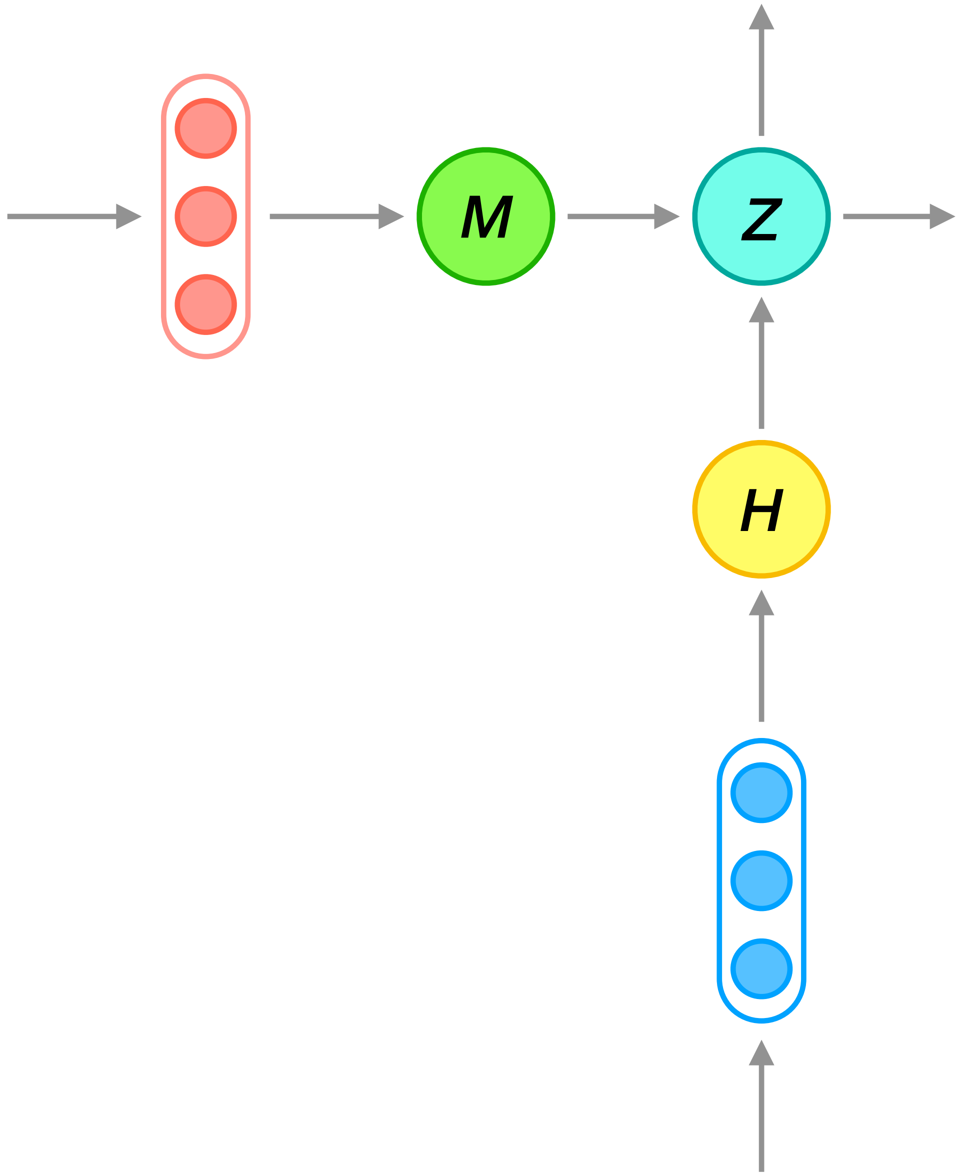


Reccurent Mechanism



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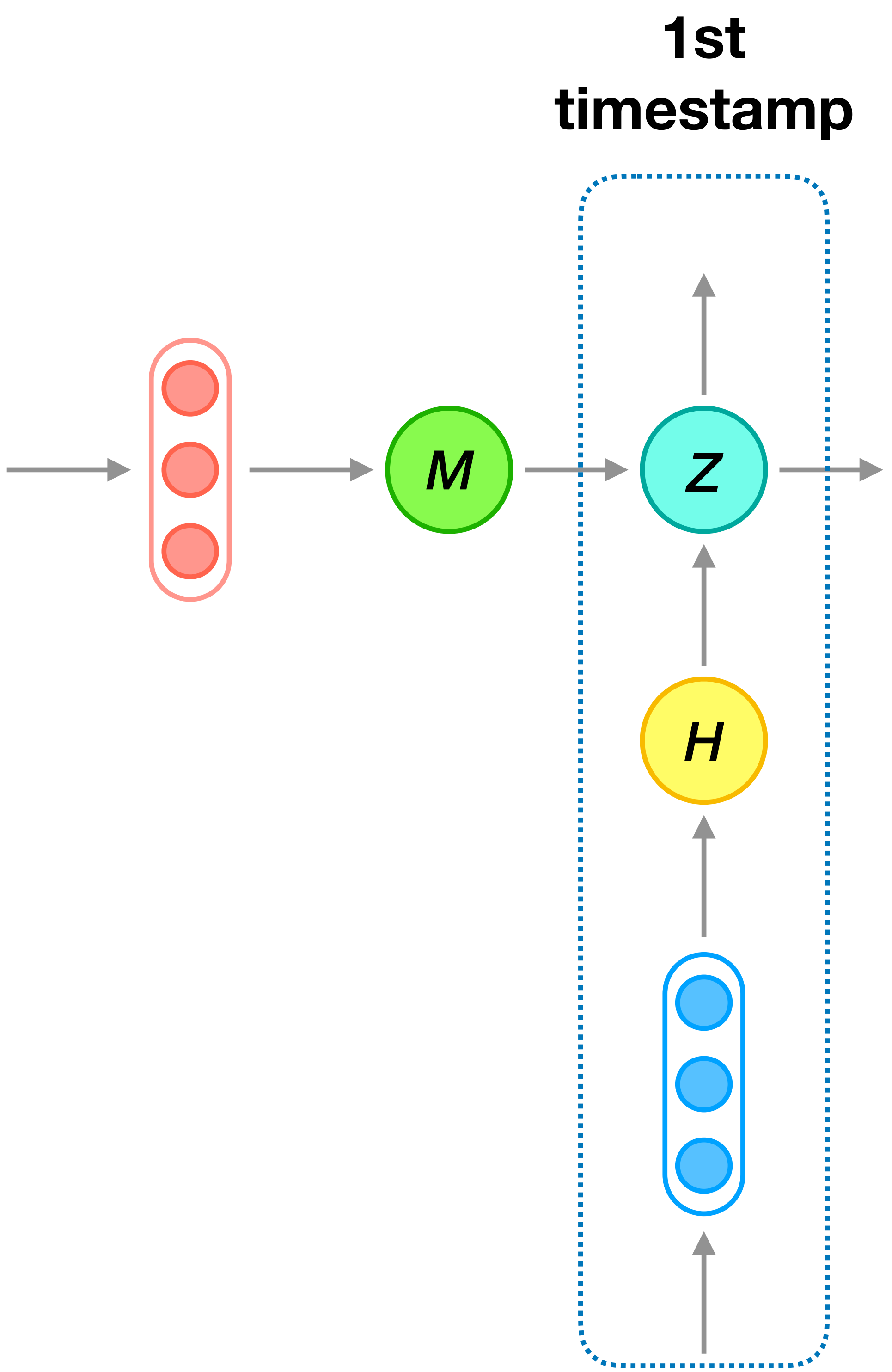

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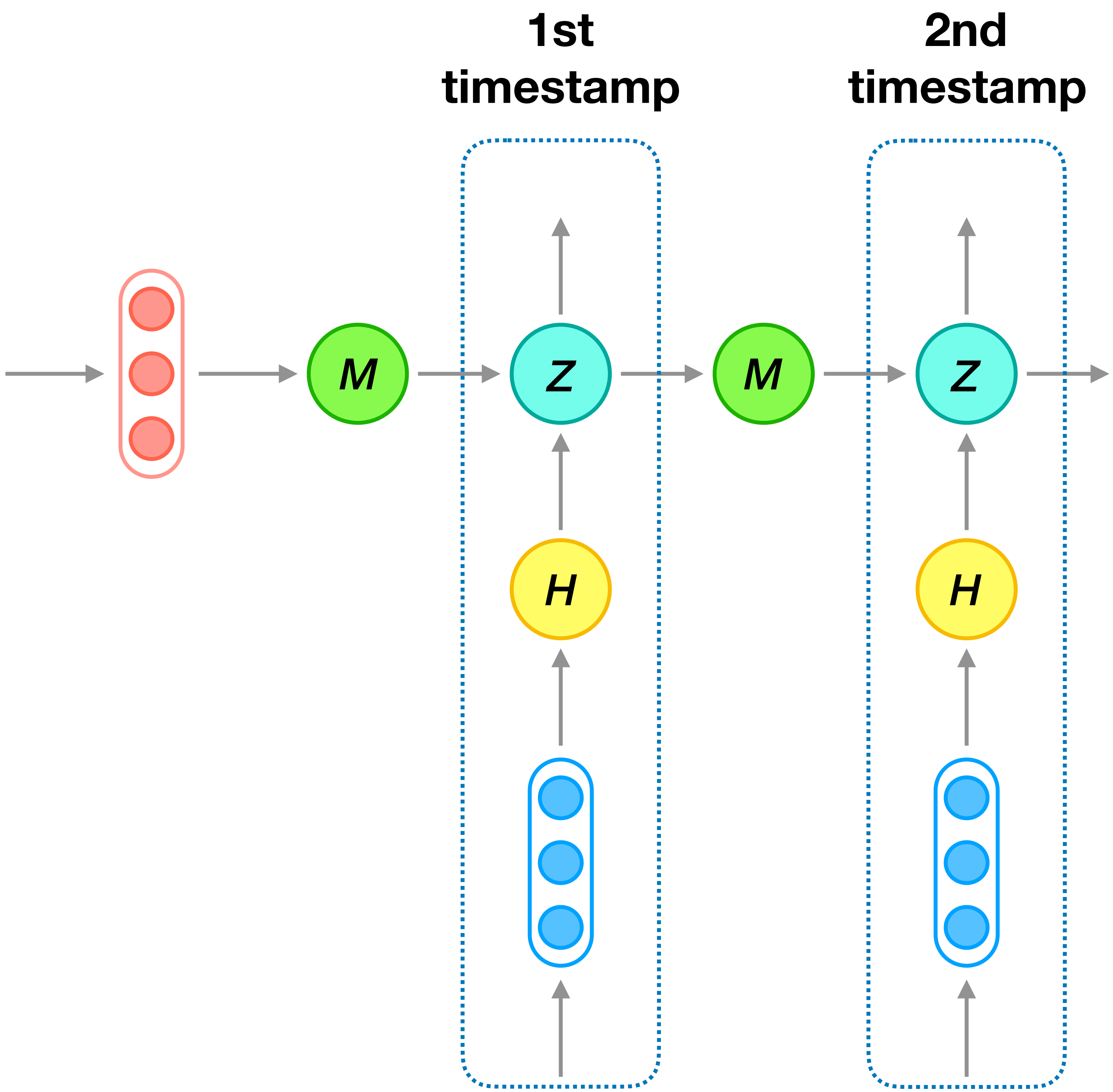

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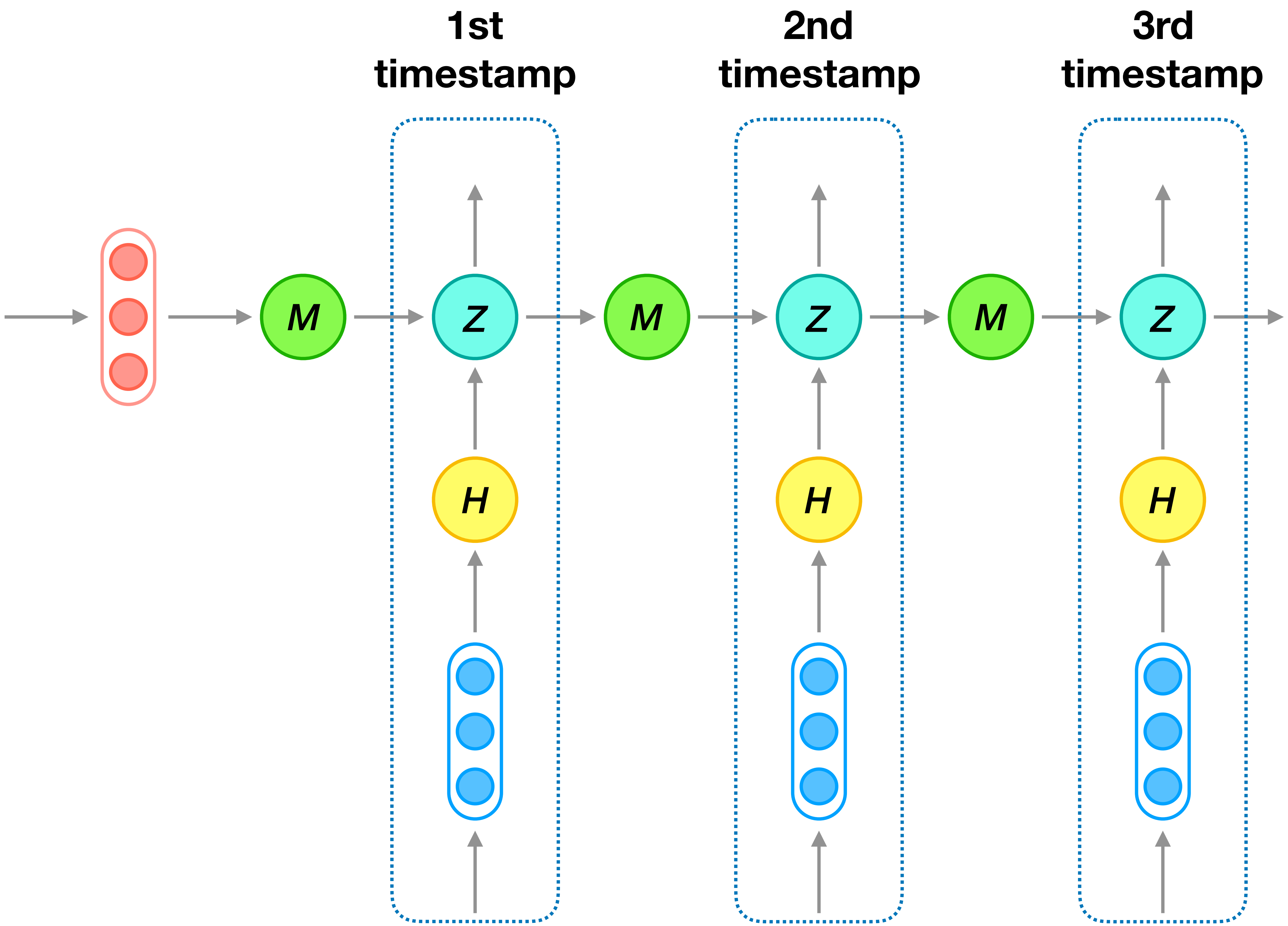

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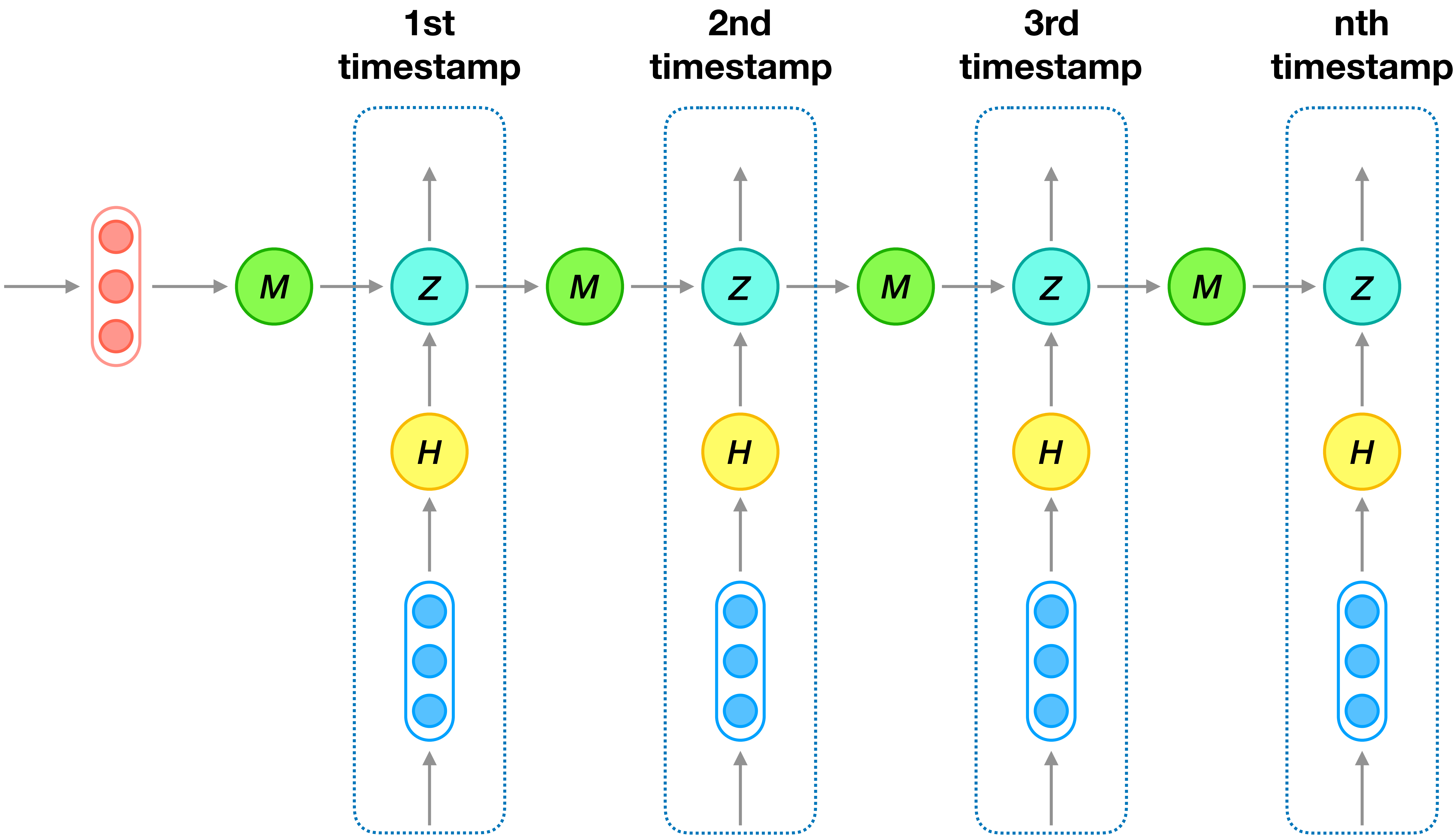

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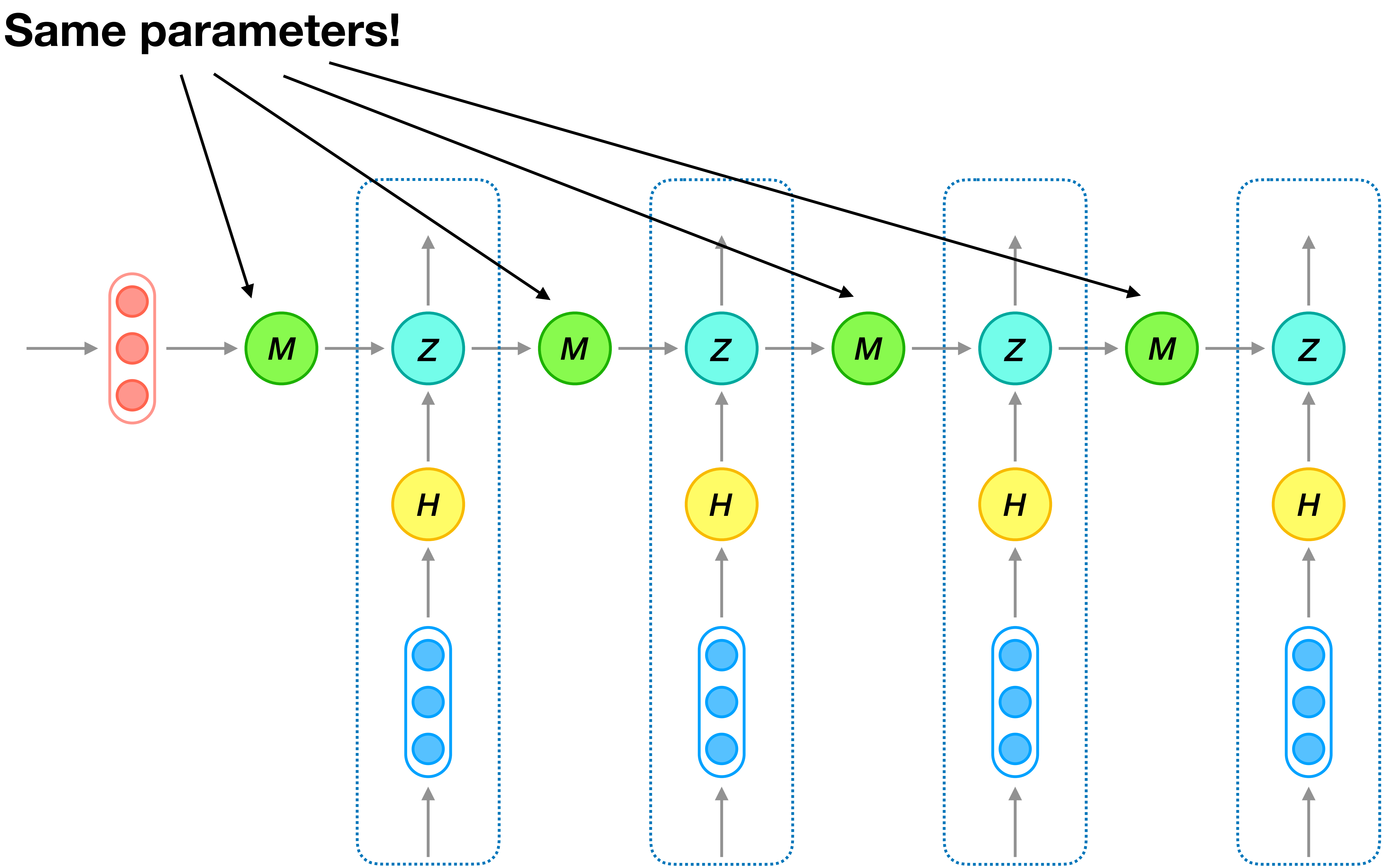

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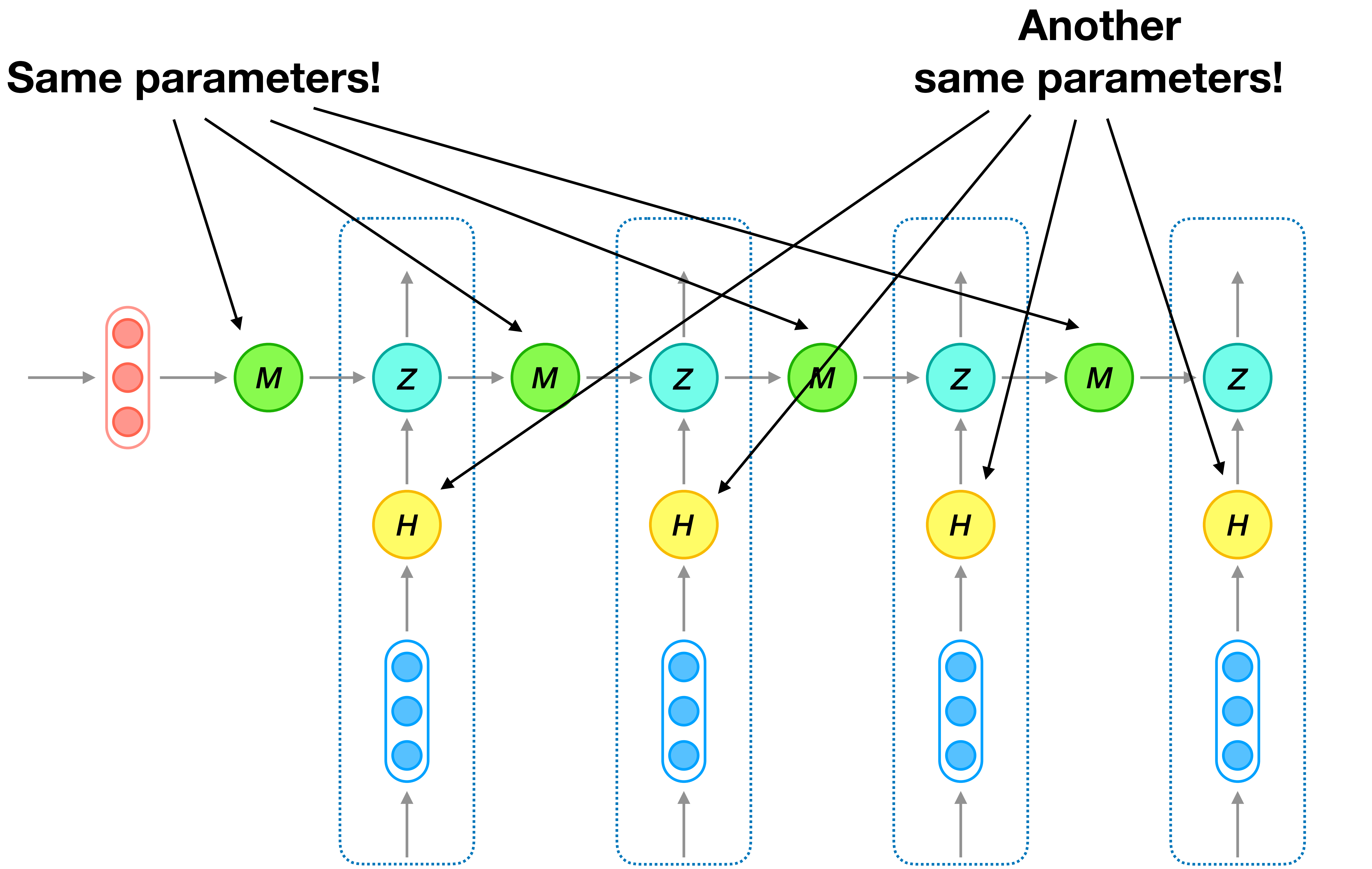

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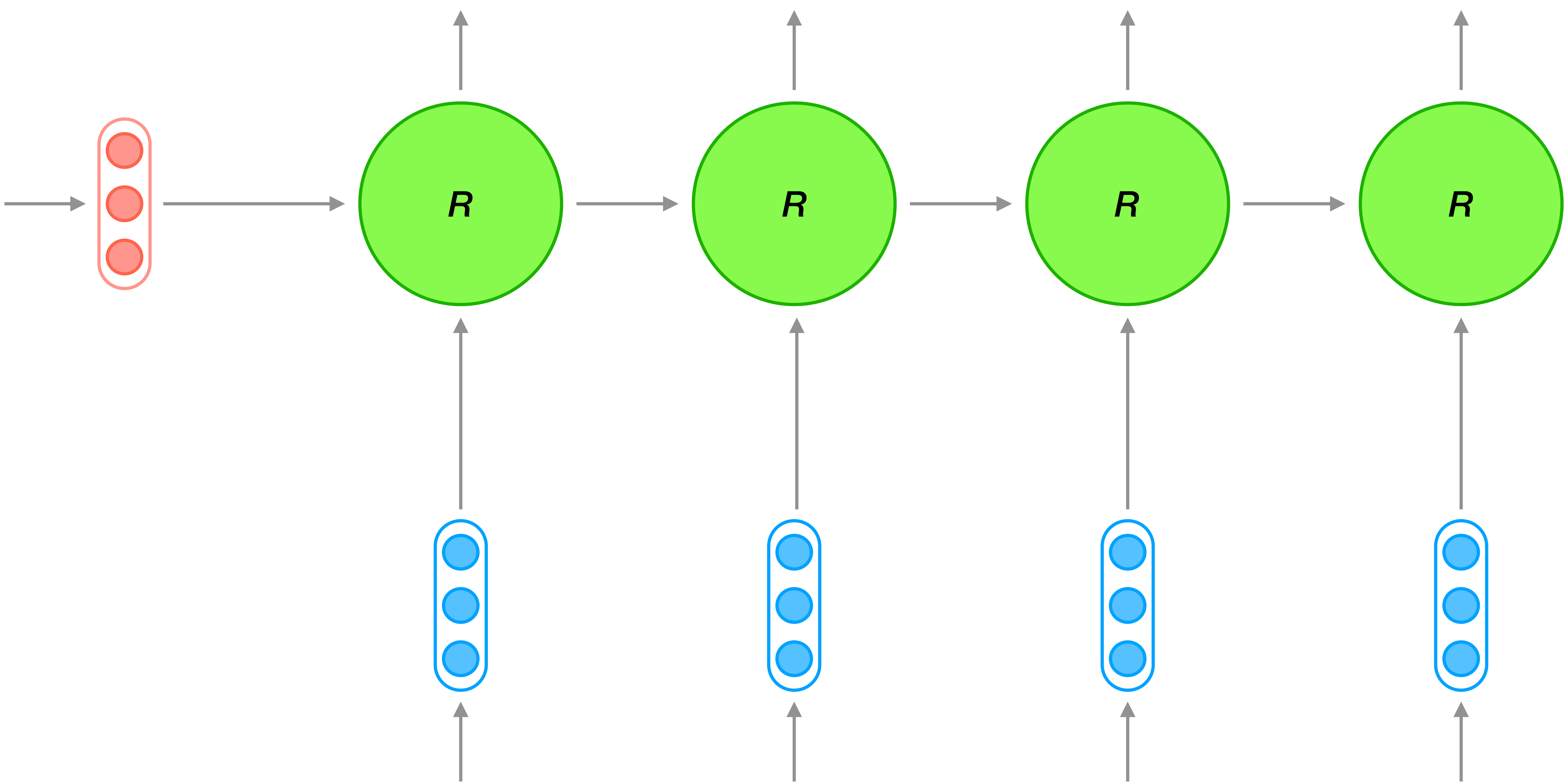

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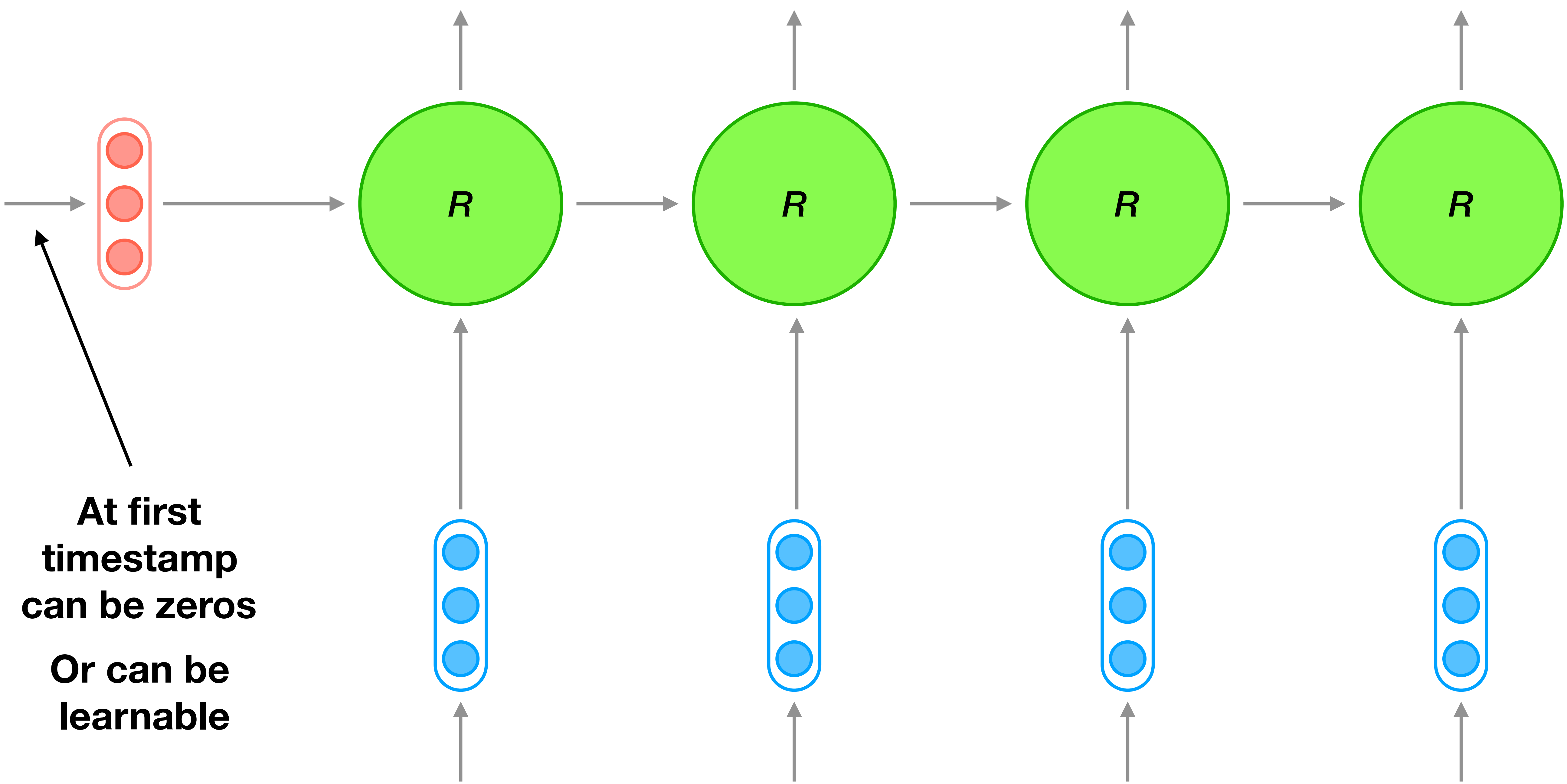
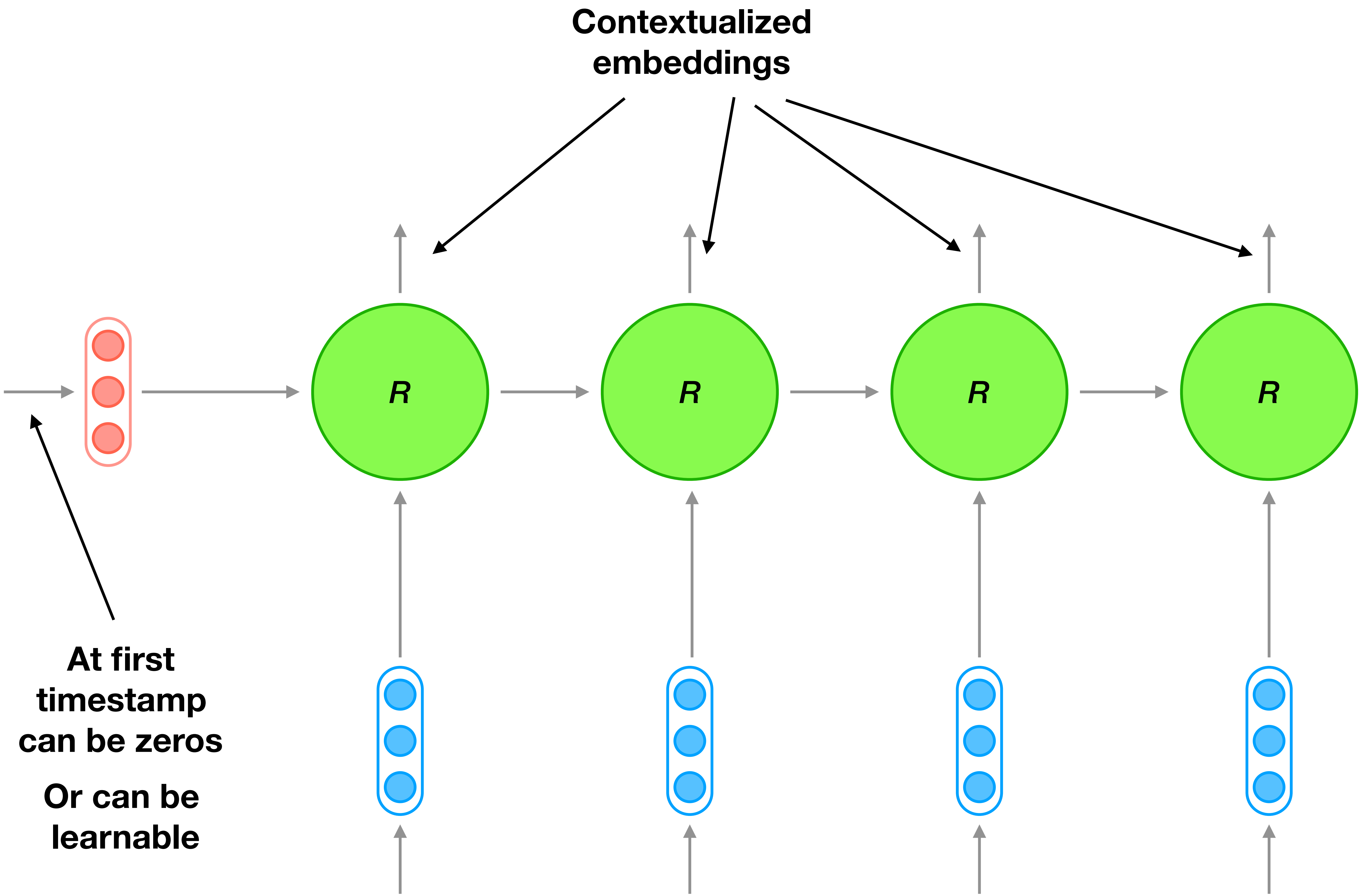


At first timestamp can be zeros

Or can be learnable

Reccurent Mechanism



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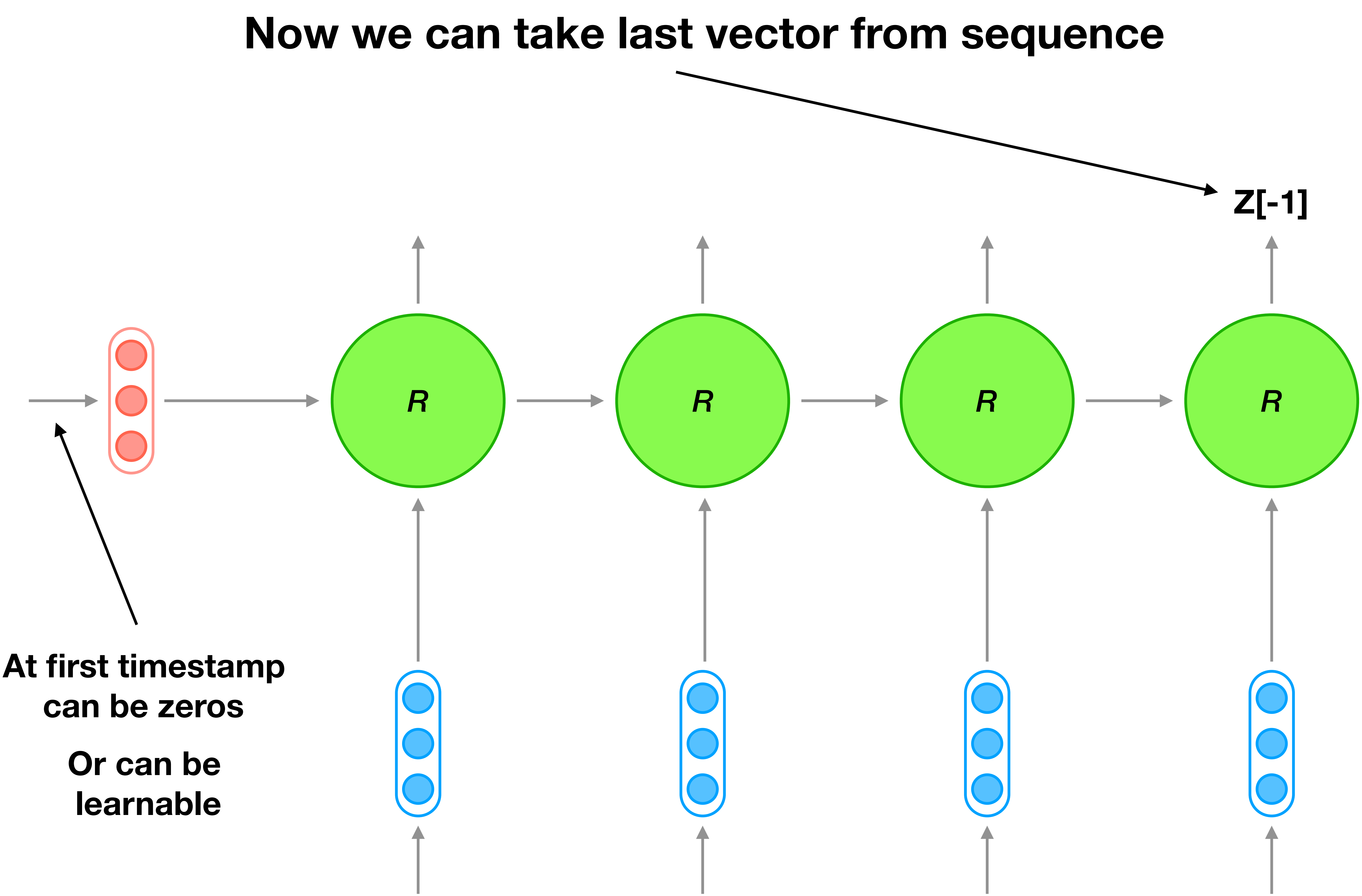

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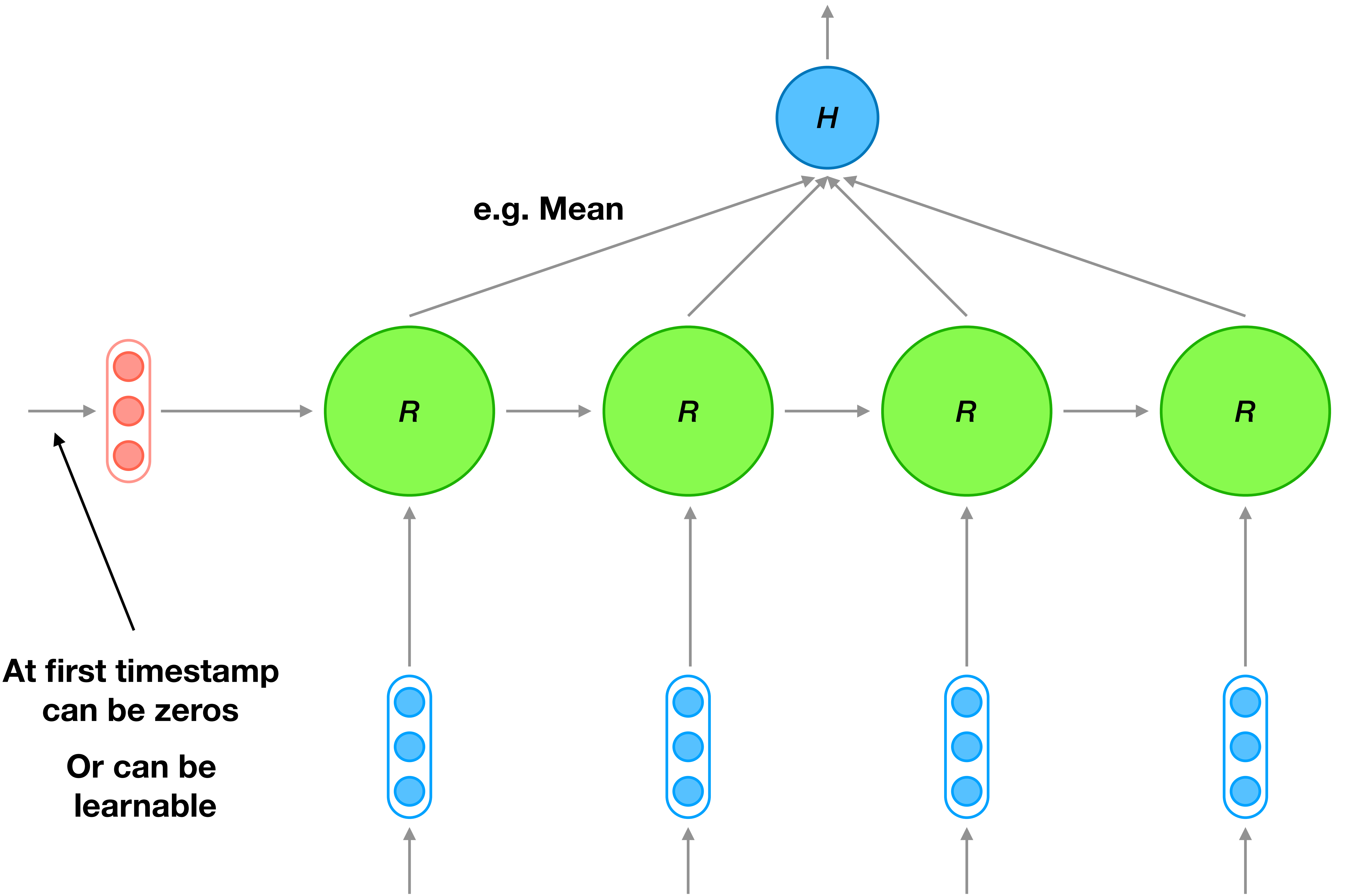
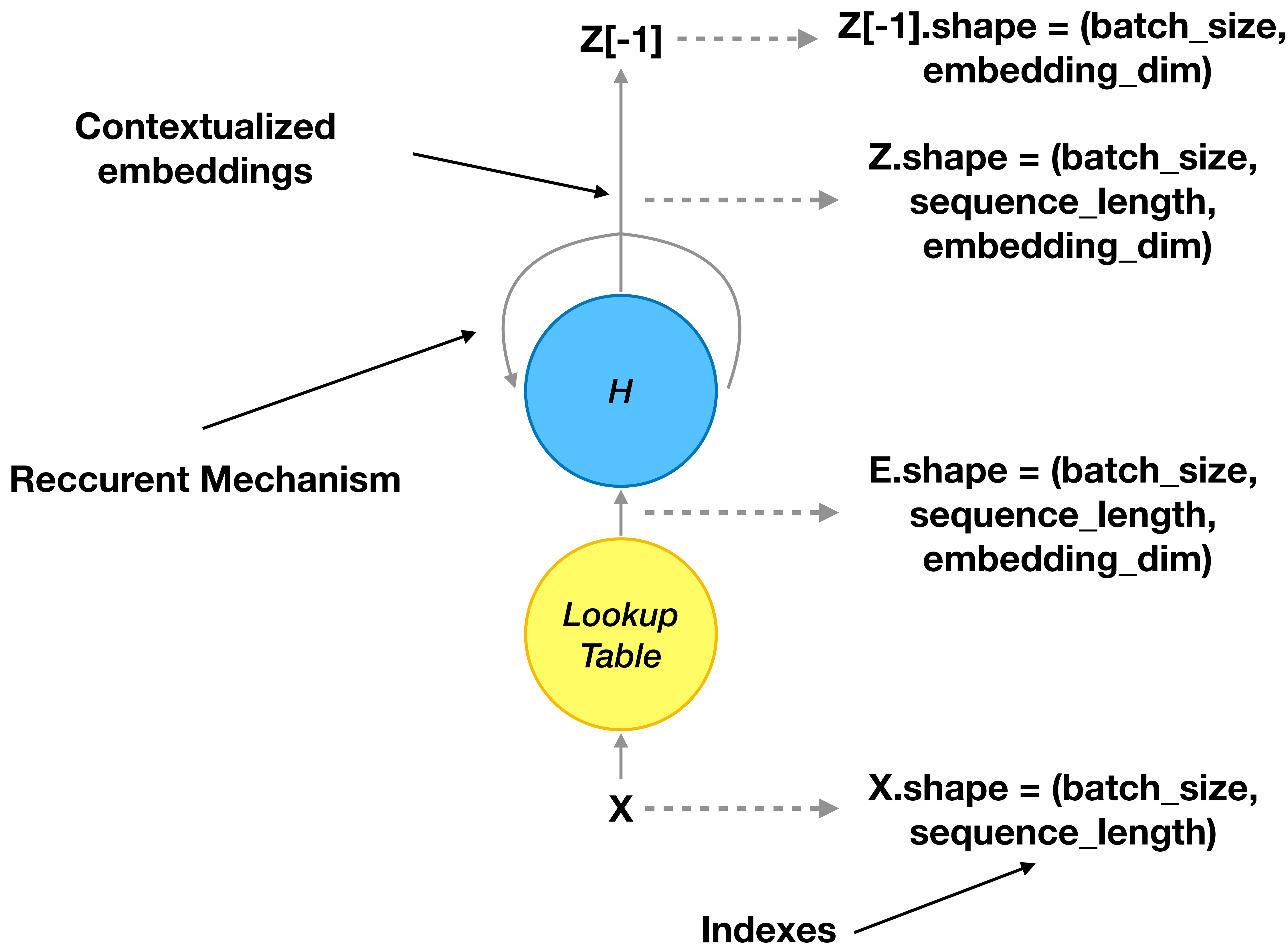


Recurrent Neural Network



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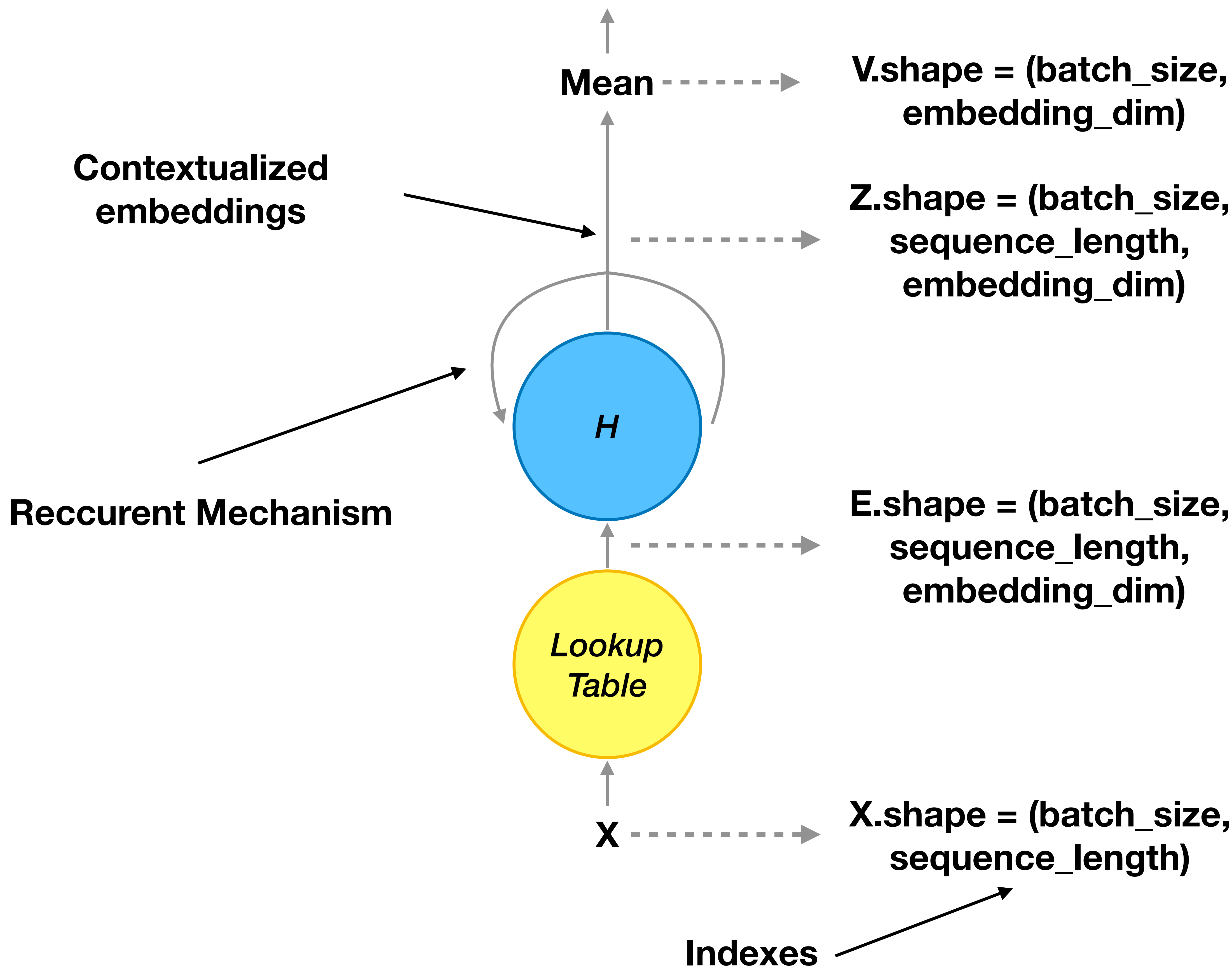
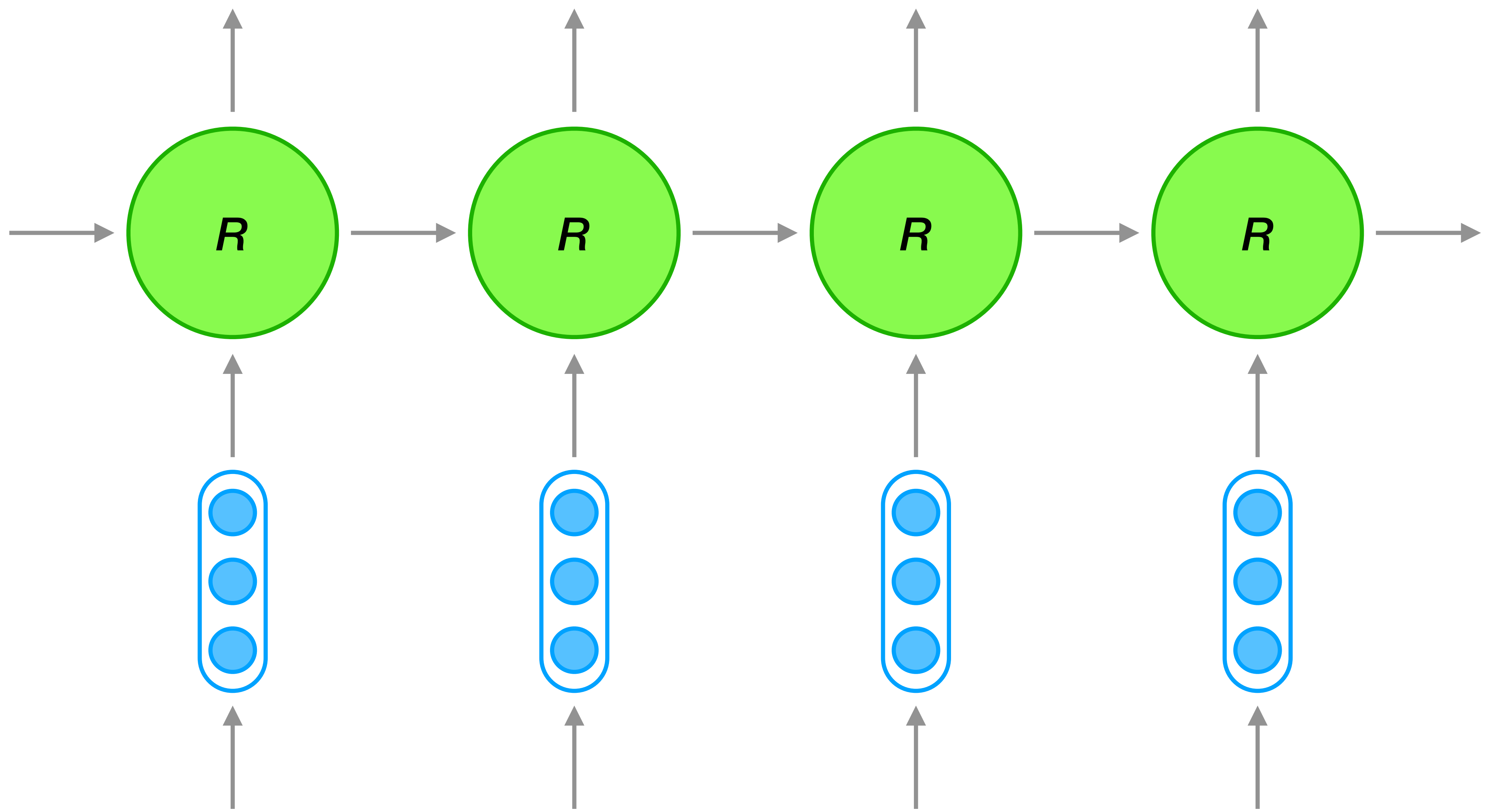


BPTT



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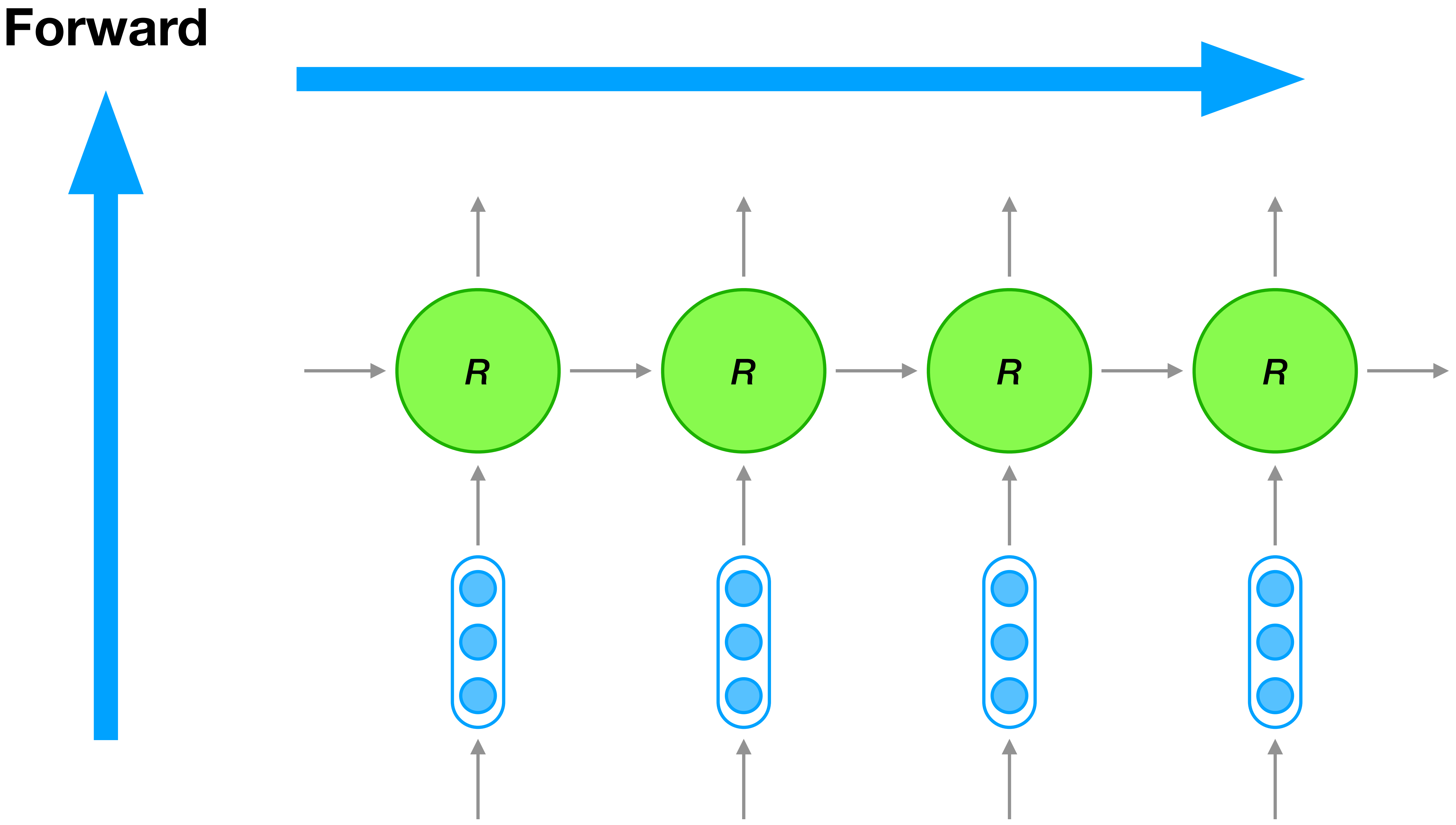

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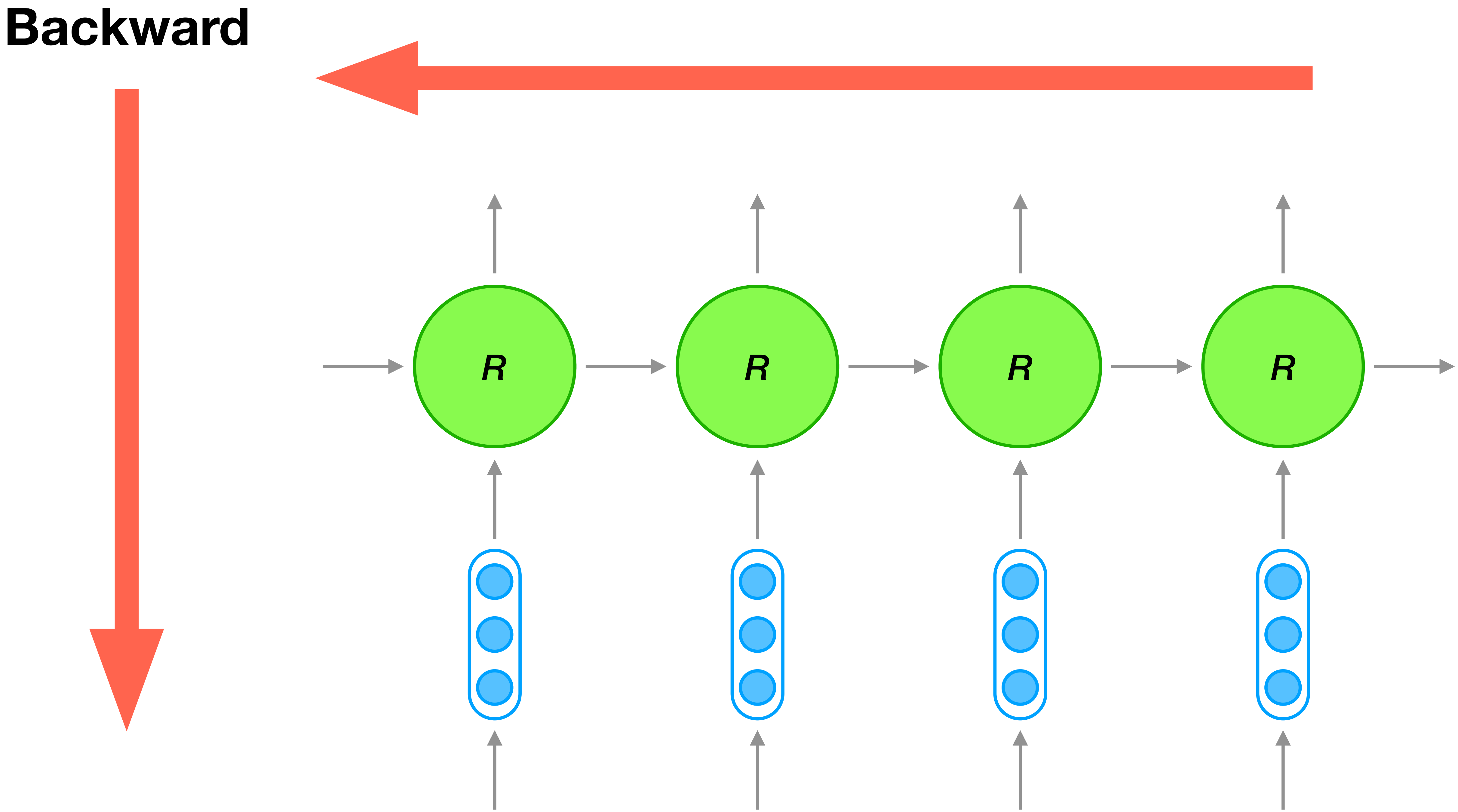

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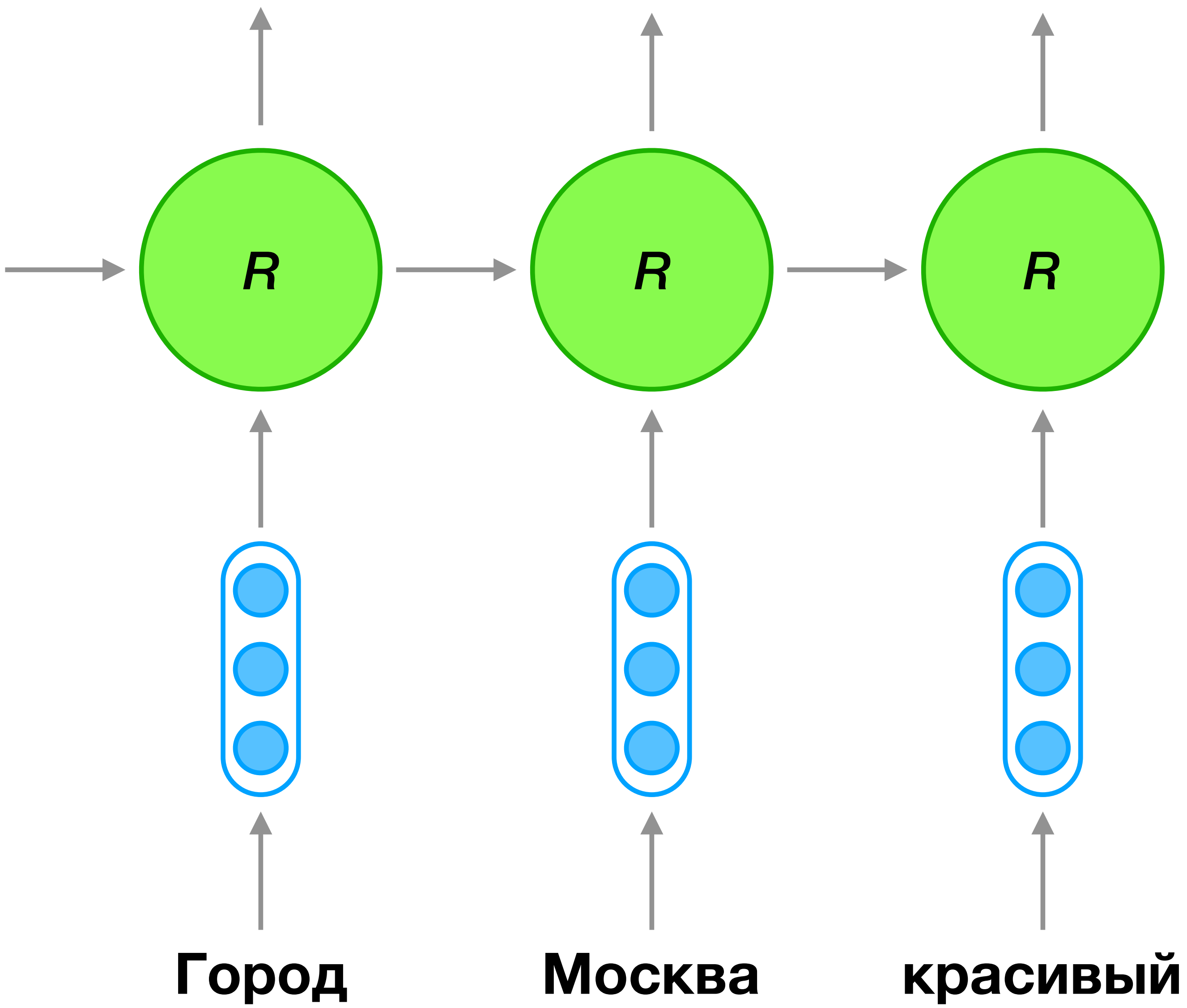

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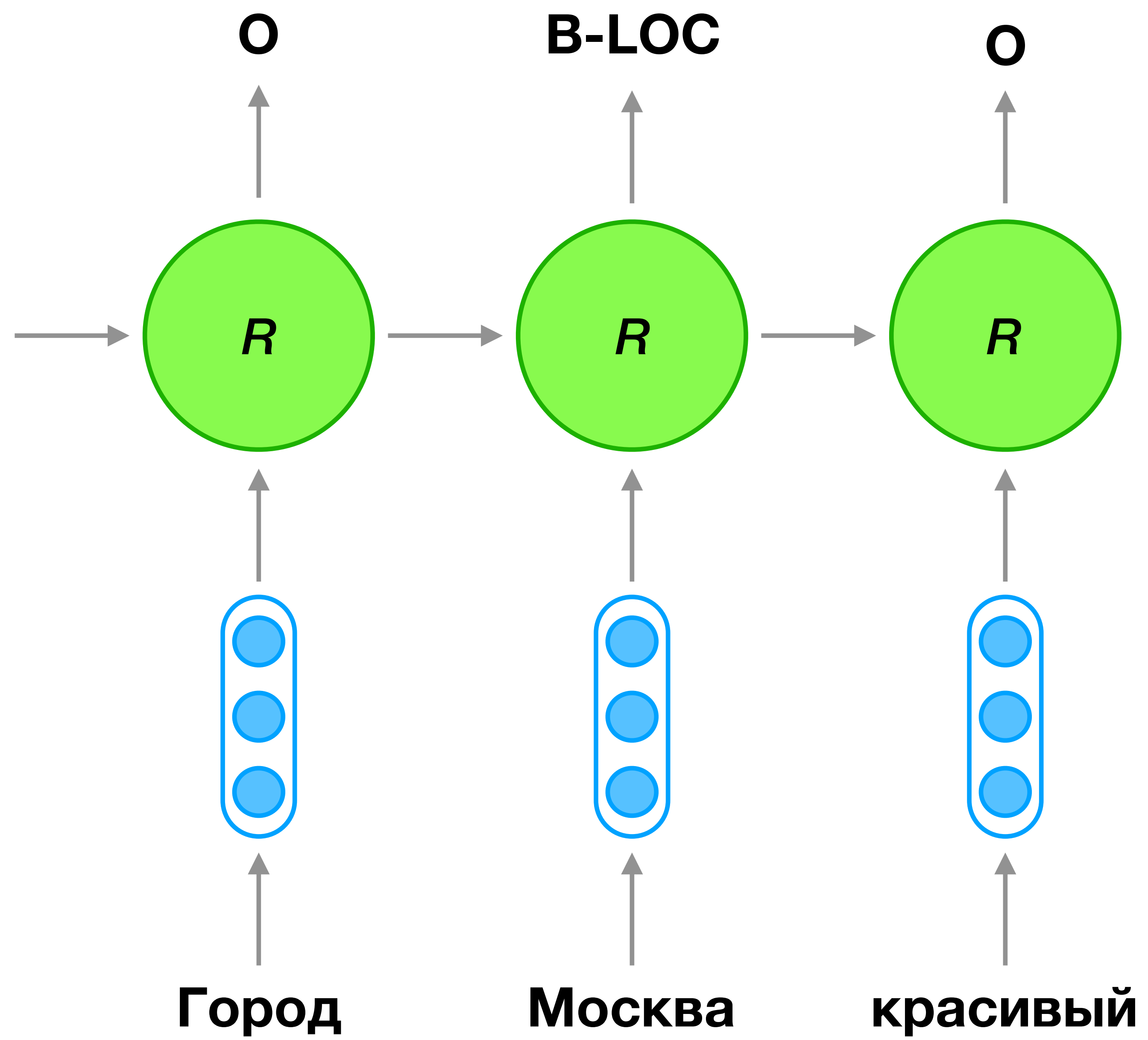

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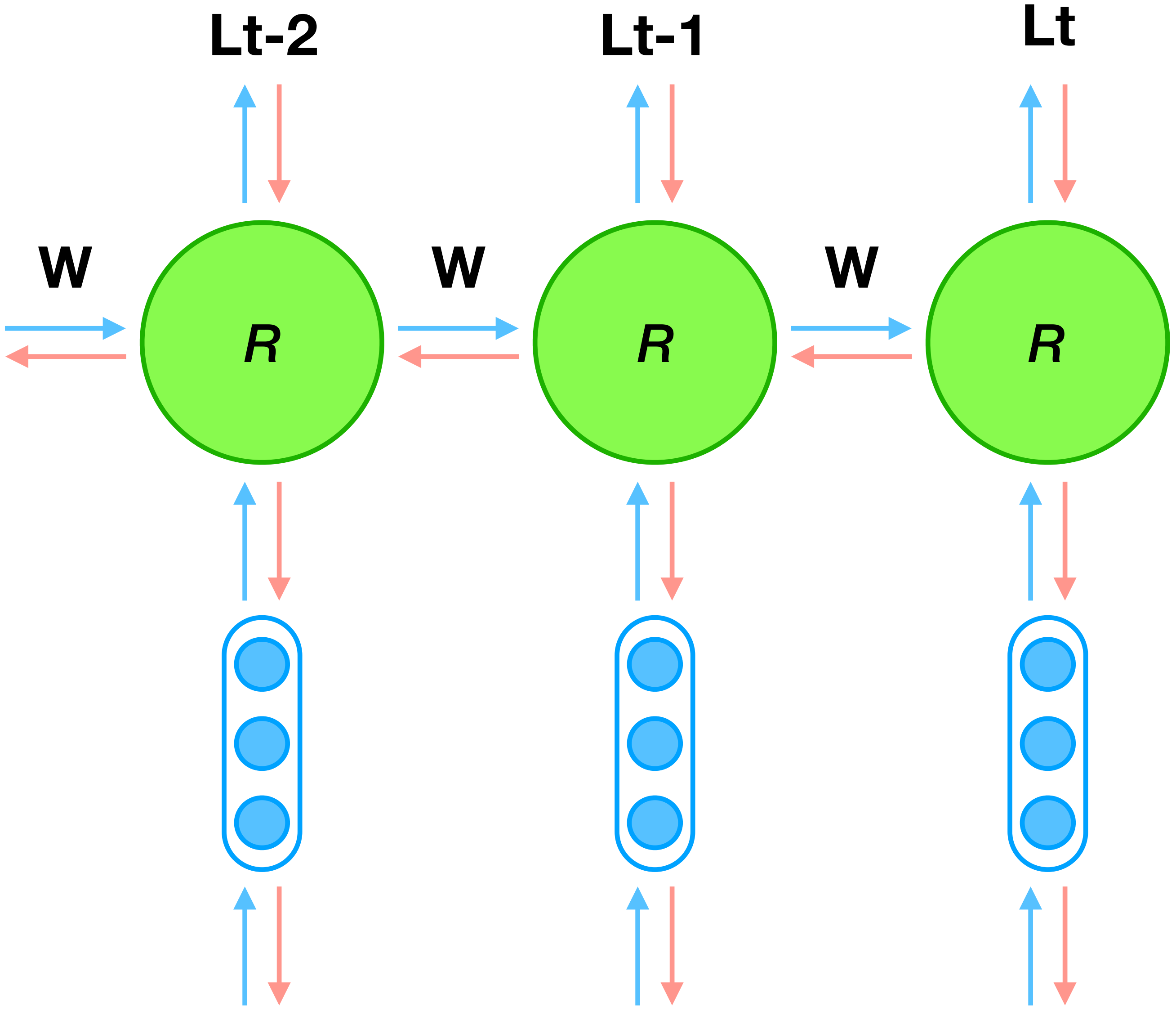

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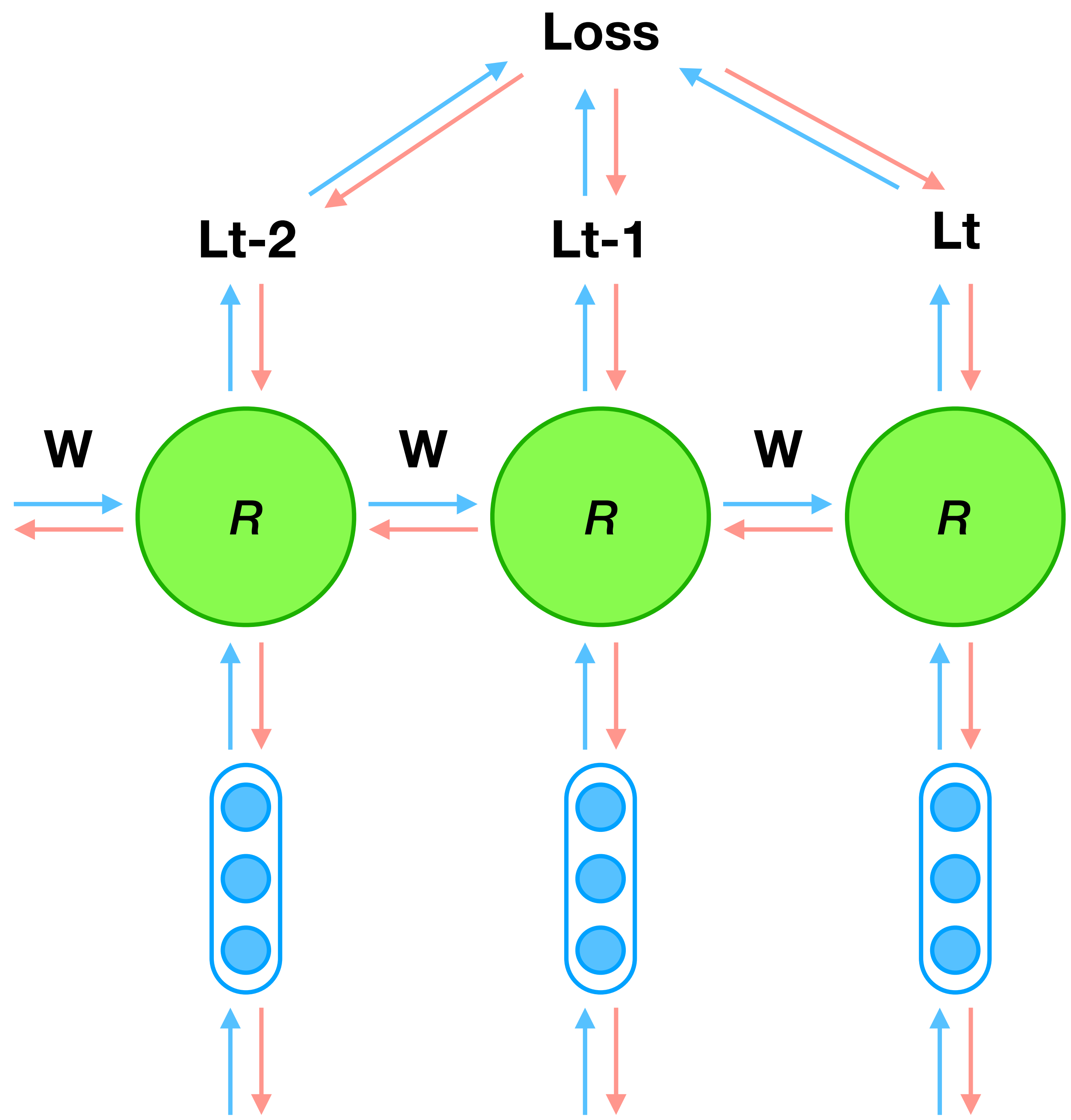
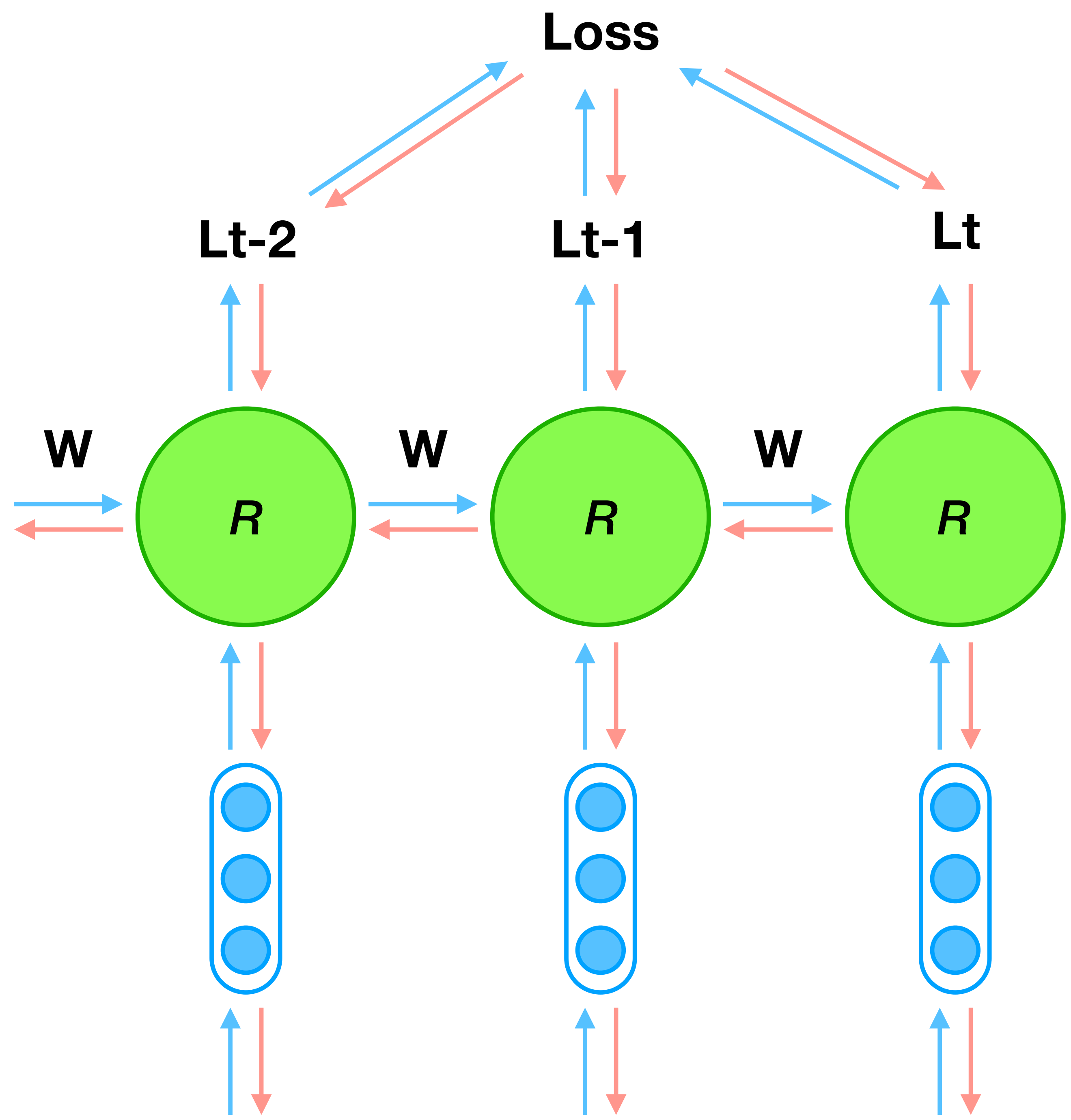


BPTT

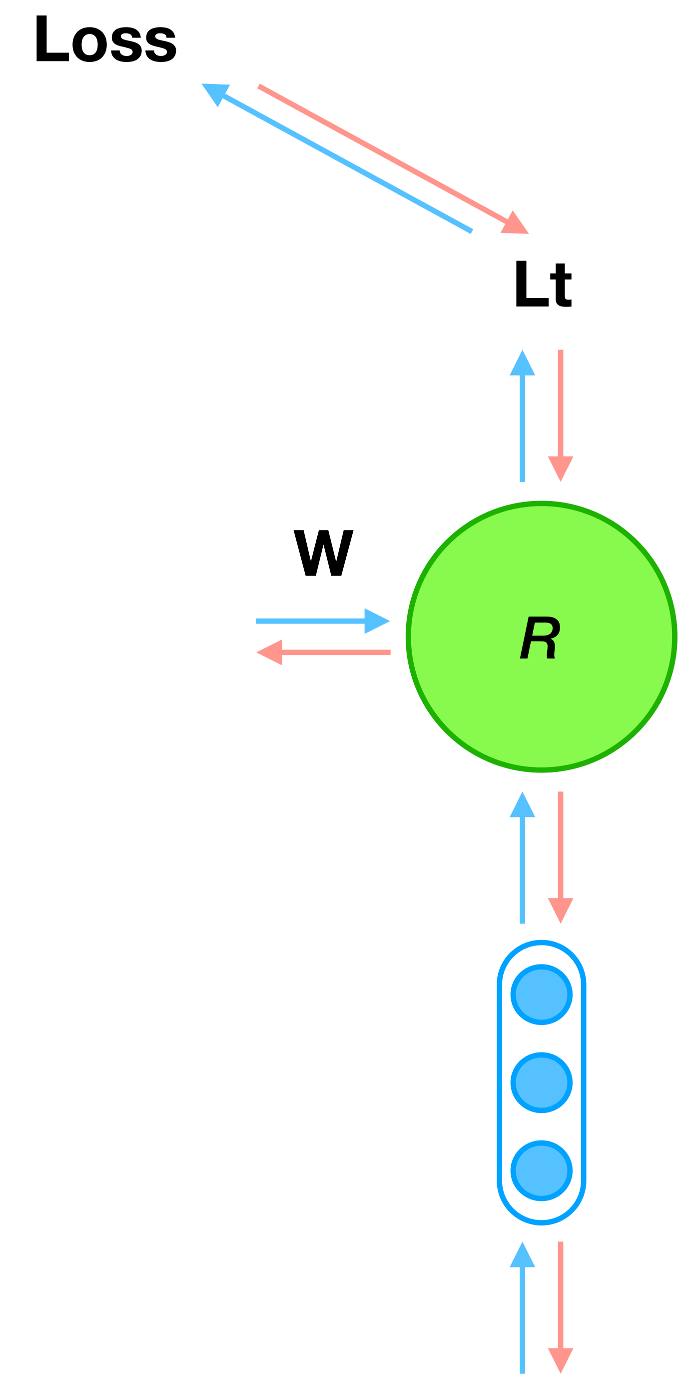
$$\frac{\partial L}{\partial W} = \sum_{i=0}^{T} \frac{\partial L_i}{\partial W}$$



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

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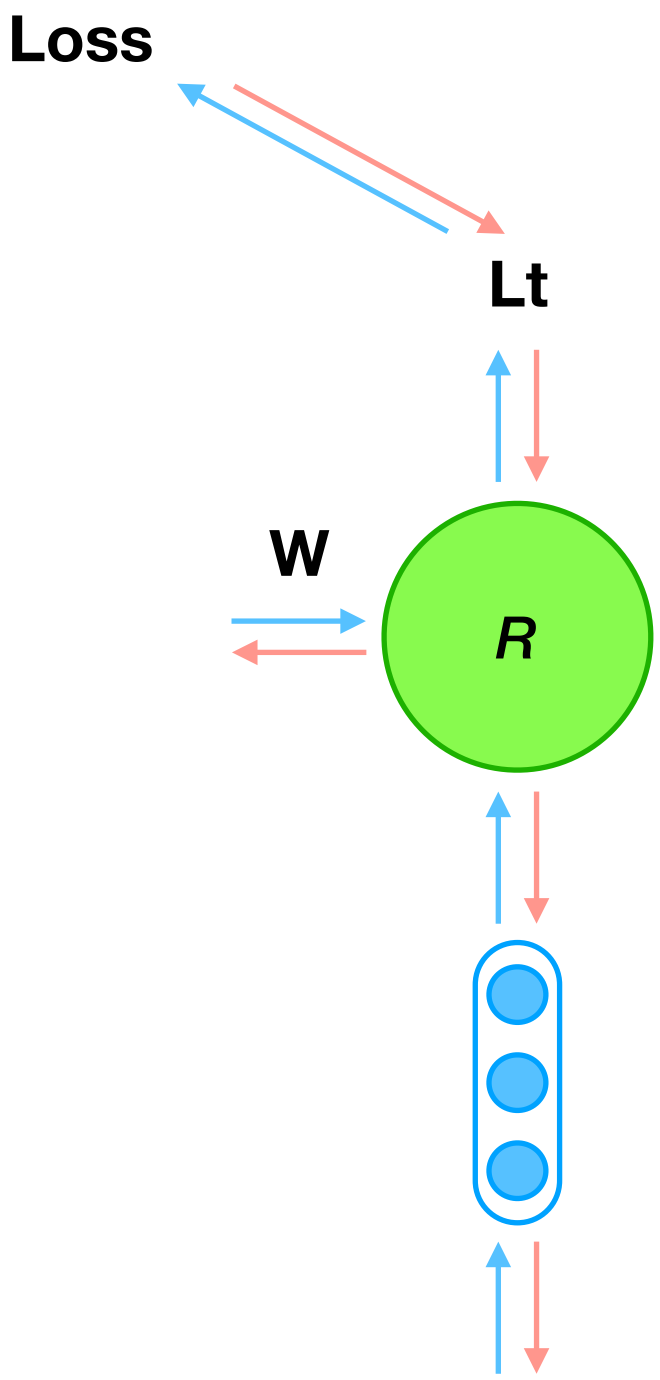
$$h_t = f_h(Vx_t + \boxed{W} h_{t-1} + b_h)$$

This is NOT the only dependence!



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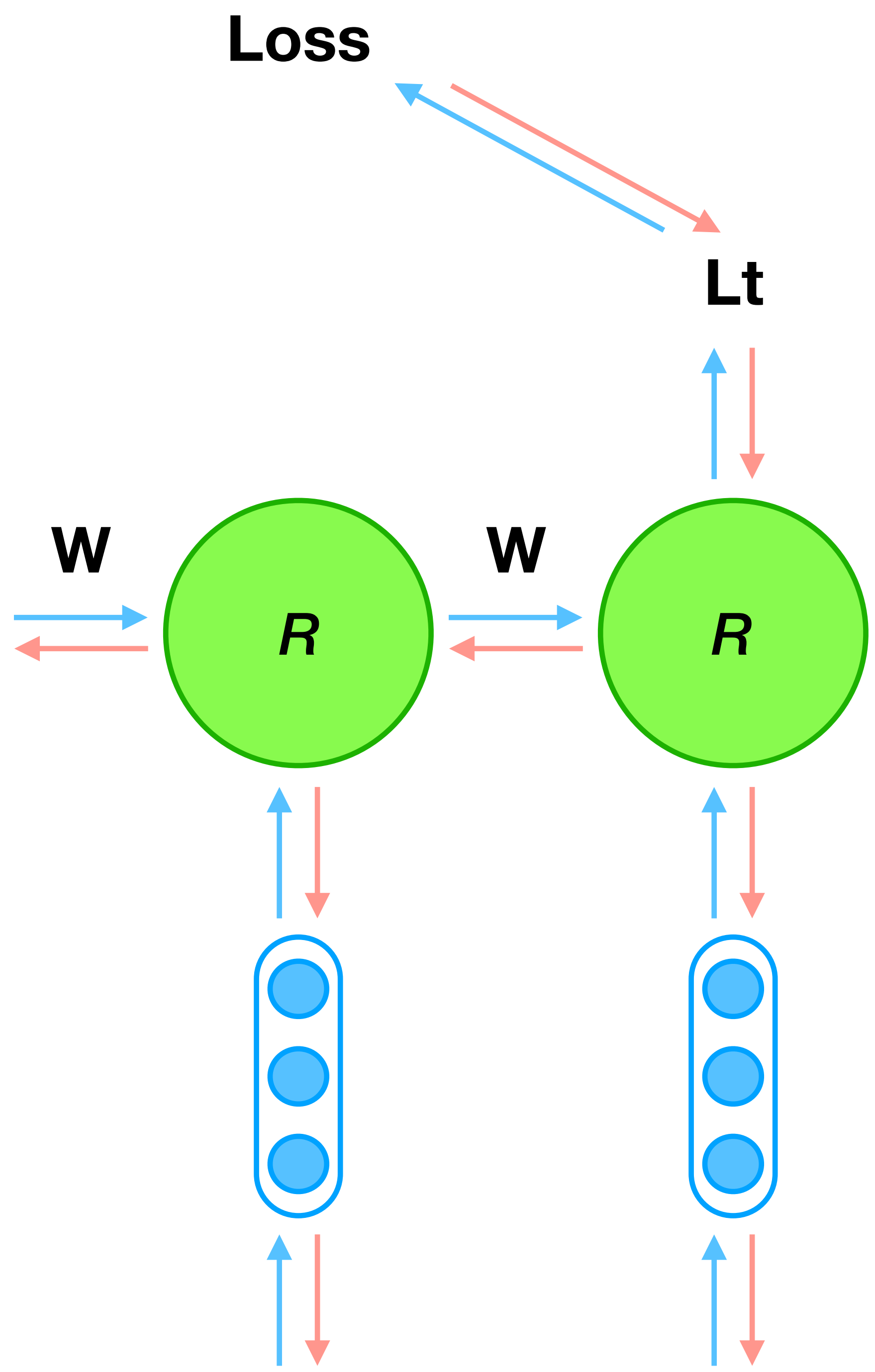

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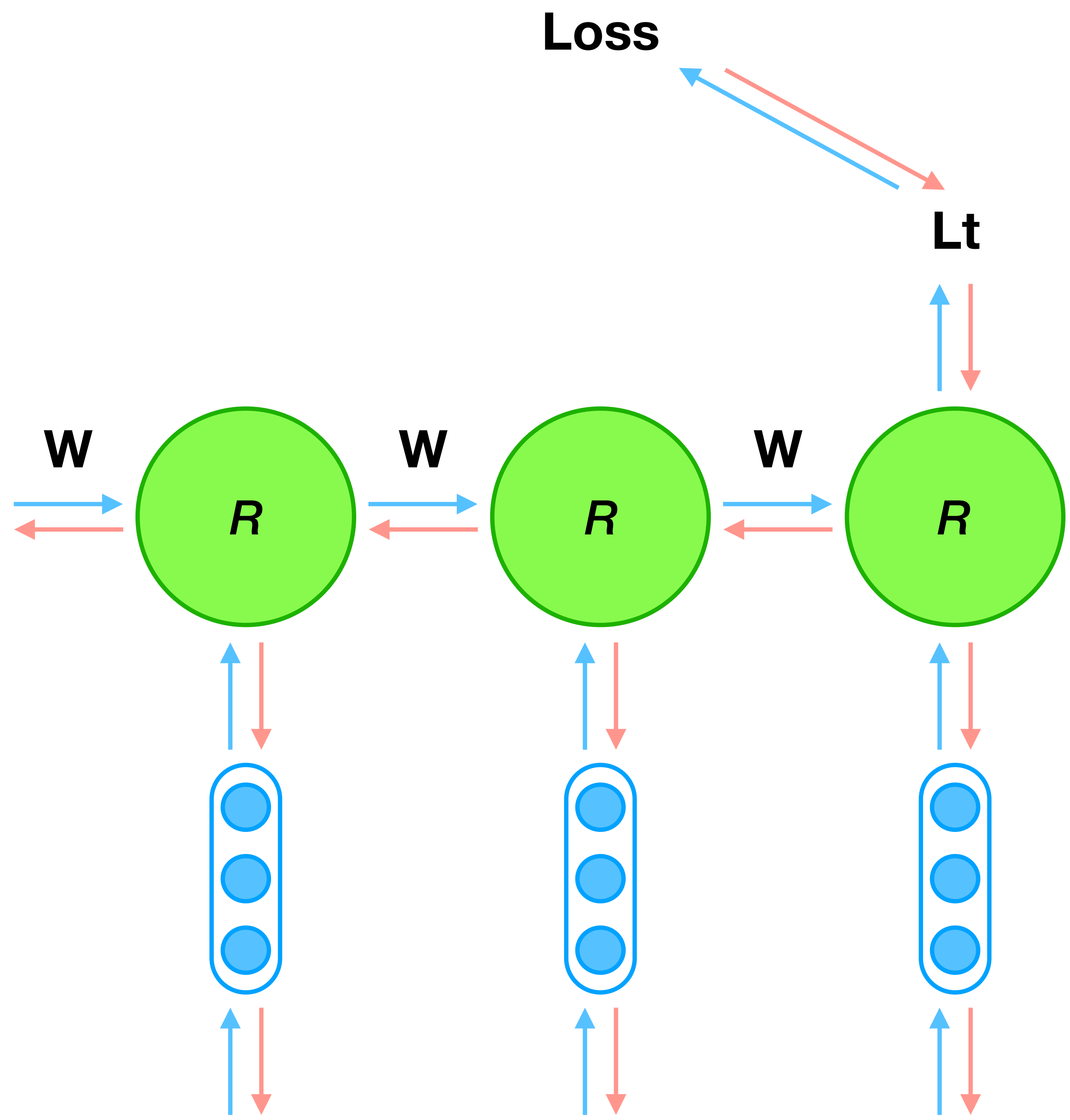


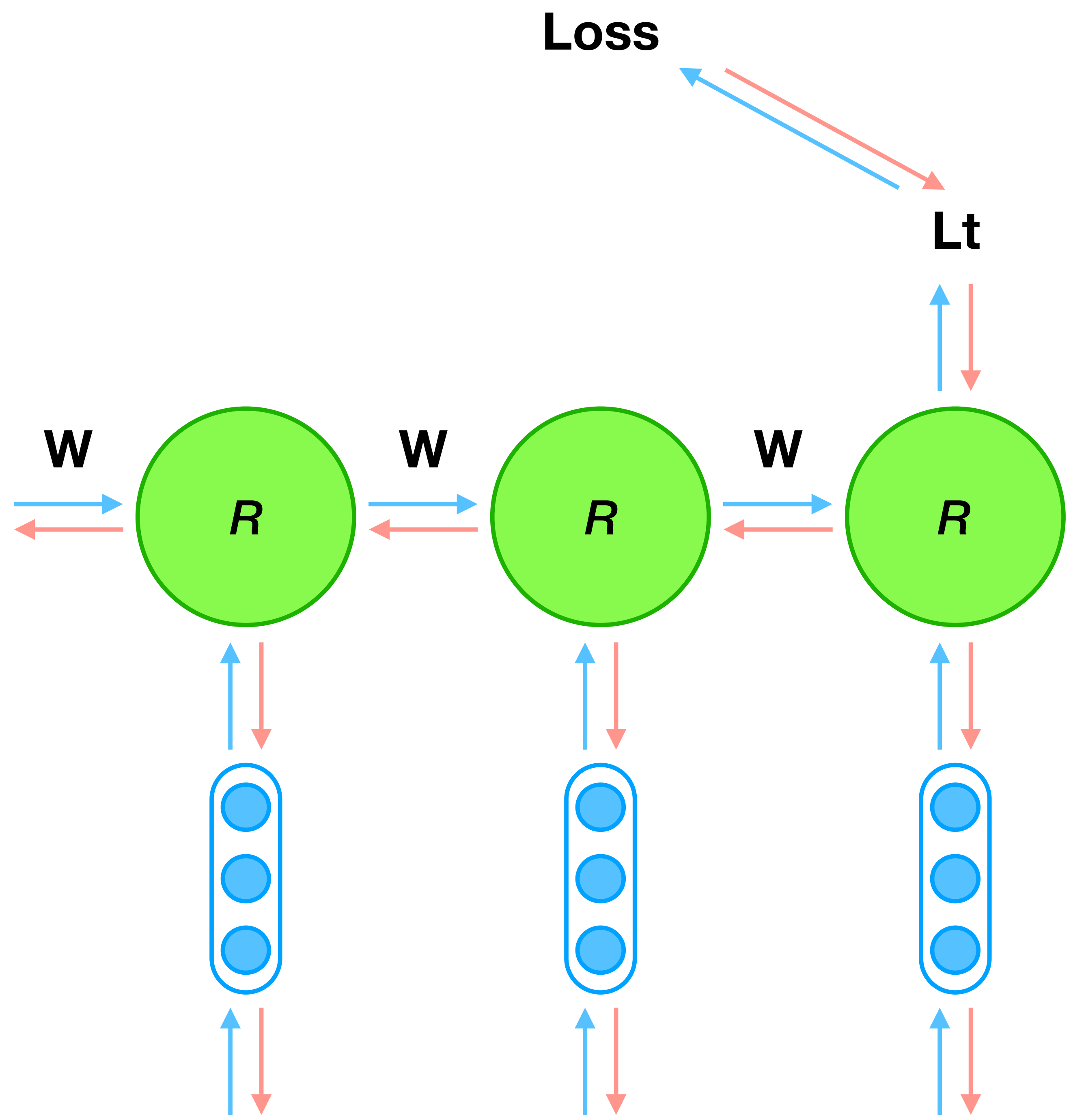
BPTT

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

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

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

This is NOT the only dependence!



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

BPTT

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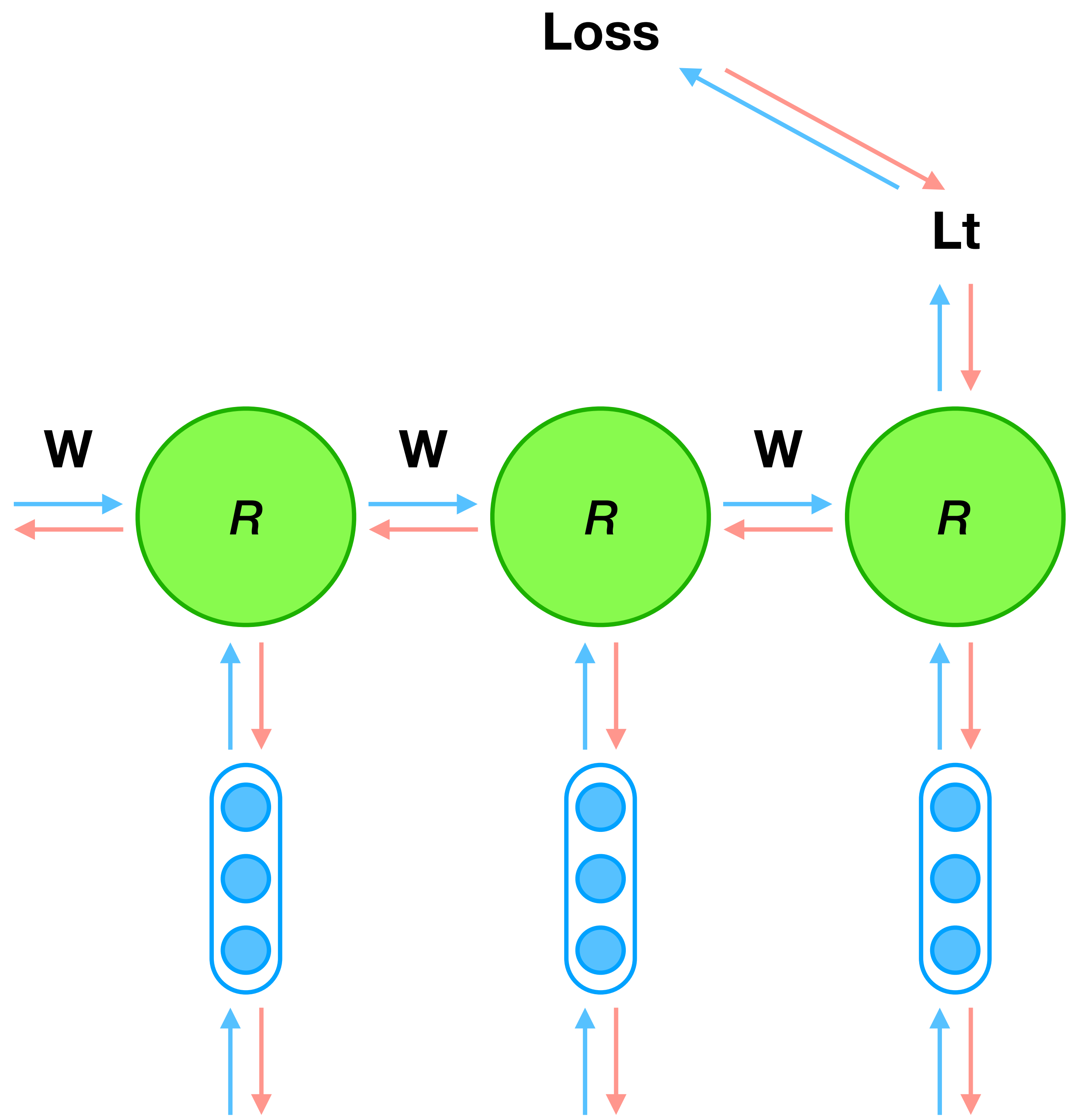

$$\frac{\partial L_t}{\partial W} = \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \boxed{\sum_{k=0}^{t} \left(\prod_{i=k+1}^{t} \frac{\partial h_i}{\partial h_{i-1}} \right) \frac{\partial h_k}{\partial W}}$$

BPTT

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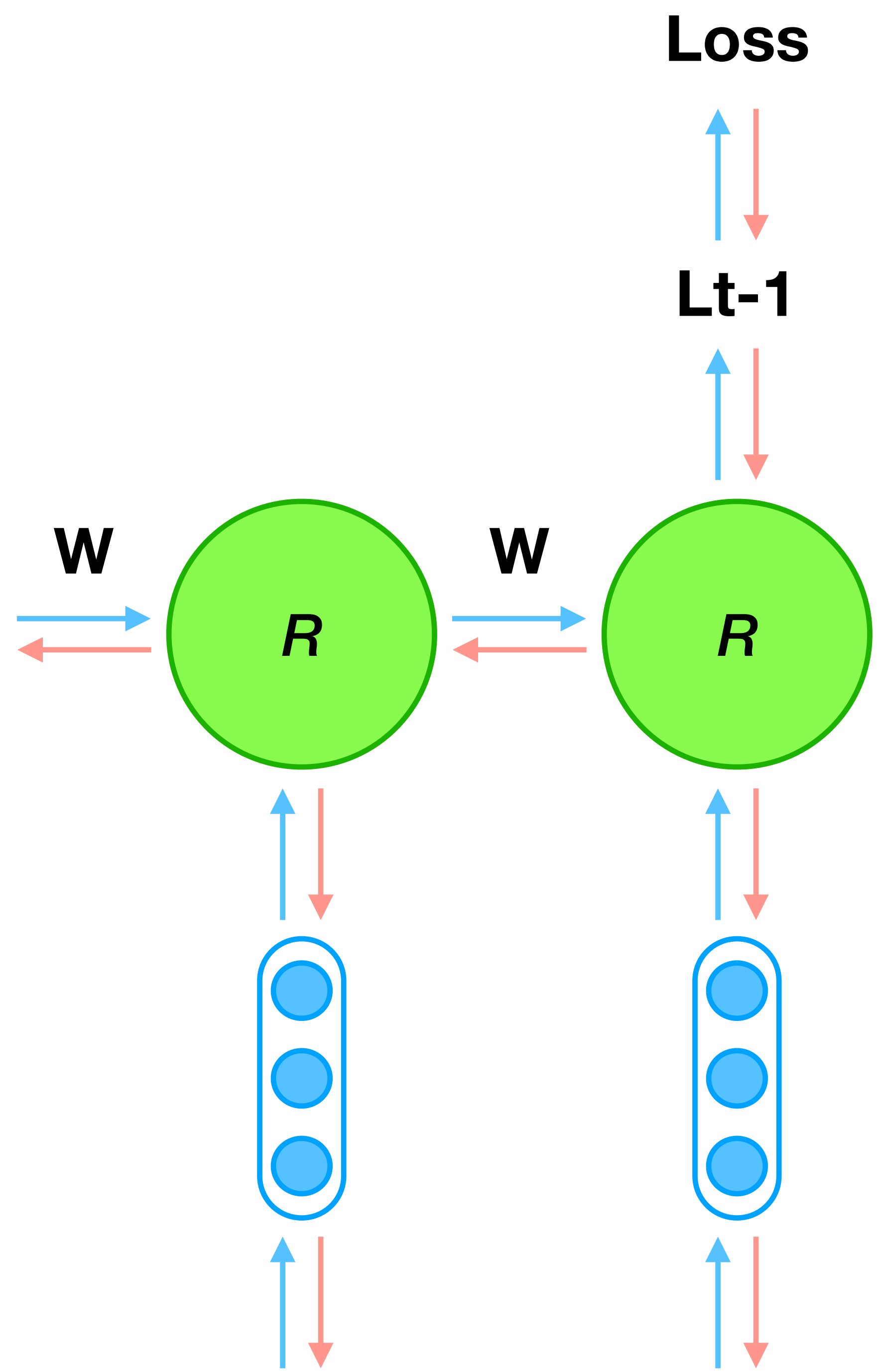

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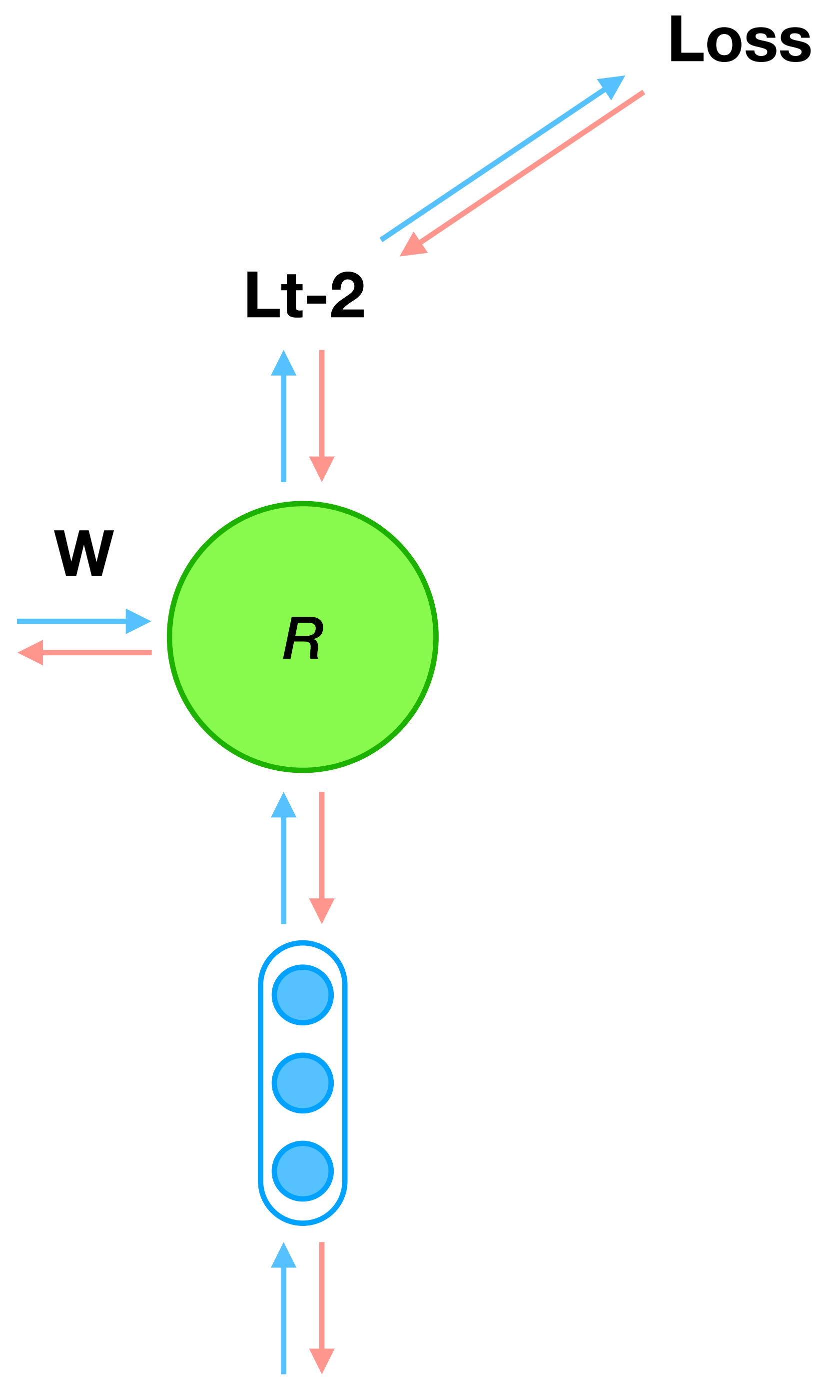


$$\frac{\partial L_t}{\partial W} = \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \boxed{\sum_{k=0}^{t} \left(\prod_{i=k+1}^{t} \frac{\partial h_i}{\partial h_{i-1}} \right) \frac{\partial h_k}{\partial W}}$$

Gradients

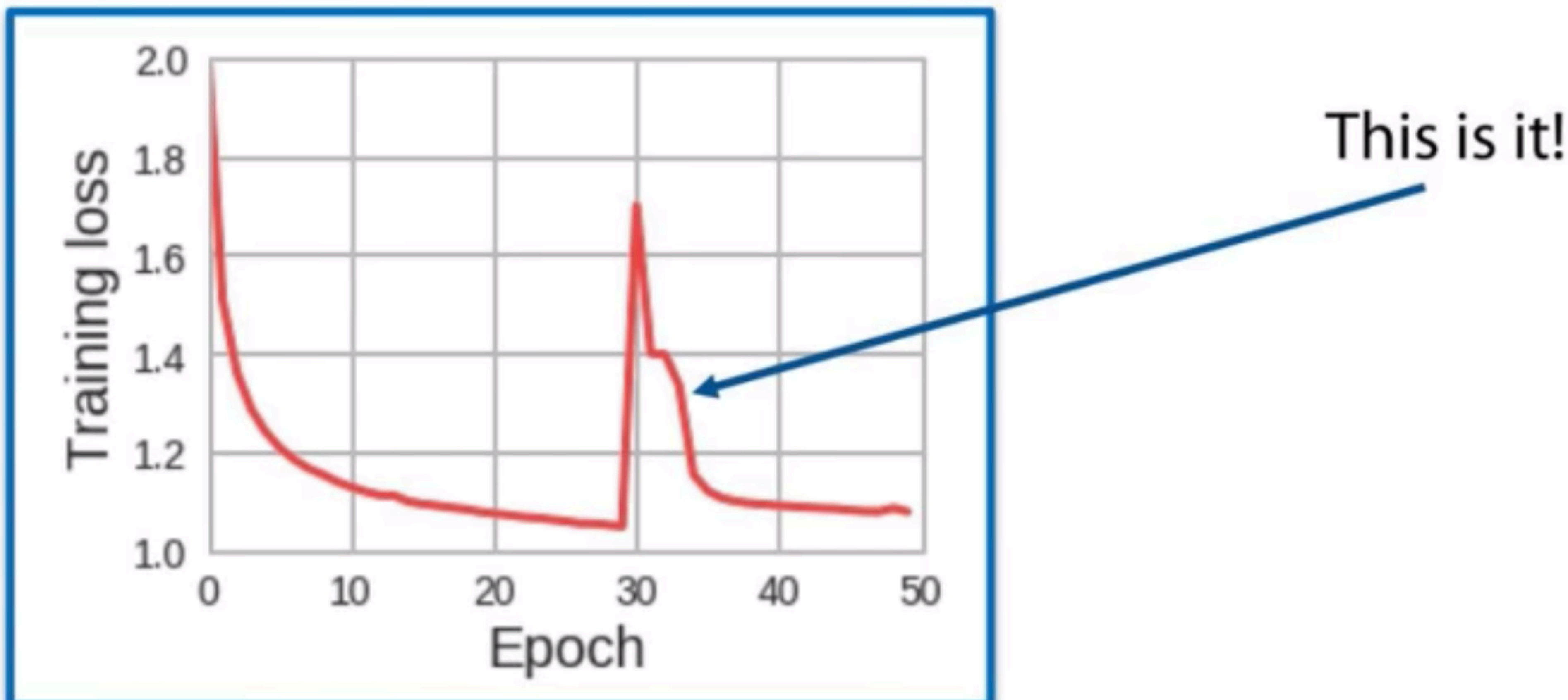
$$\frac{\partial L_t}{\partial W} \propto \sum_{k=0}^{t} \left(\prod_{i=k+1}^{t} \frac{\partial h_i}{\partial h_{i-1}} \right) \frac{\partial h_k}{\partial W}$$

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

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

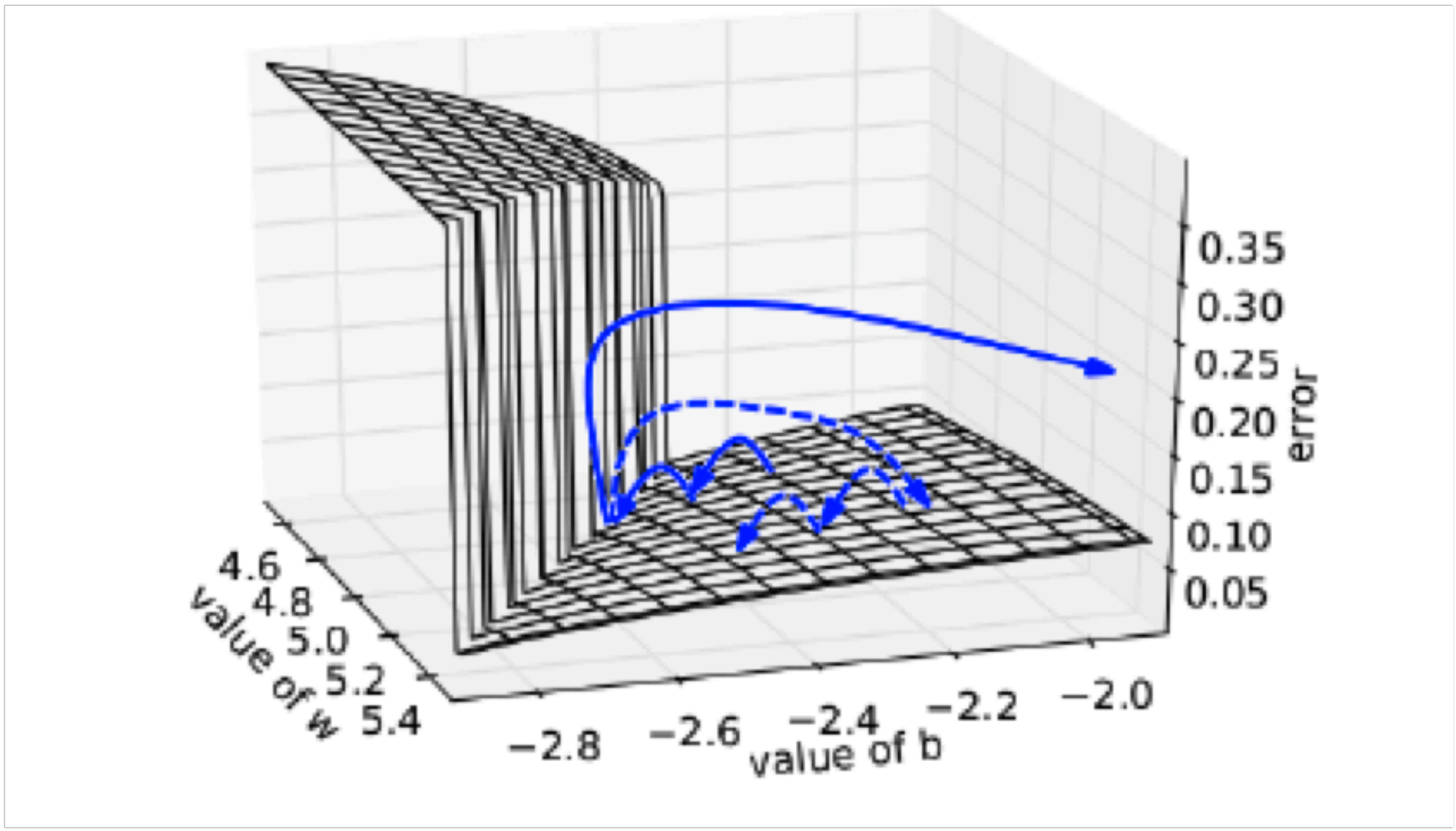
Exploding gradients

Unstable learning curve



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

Exploding gradients



Gradient Clipping

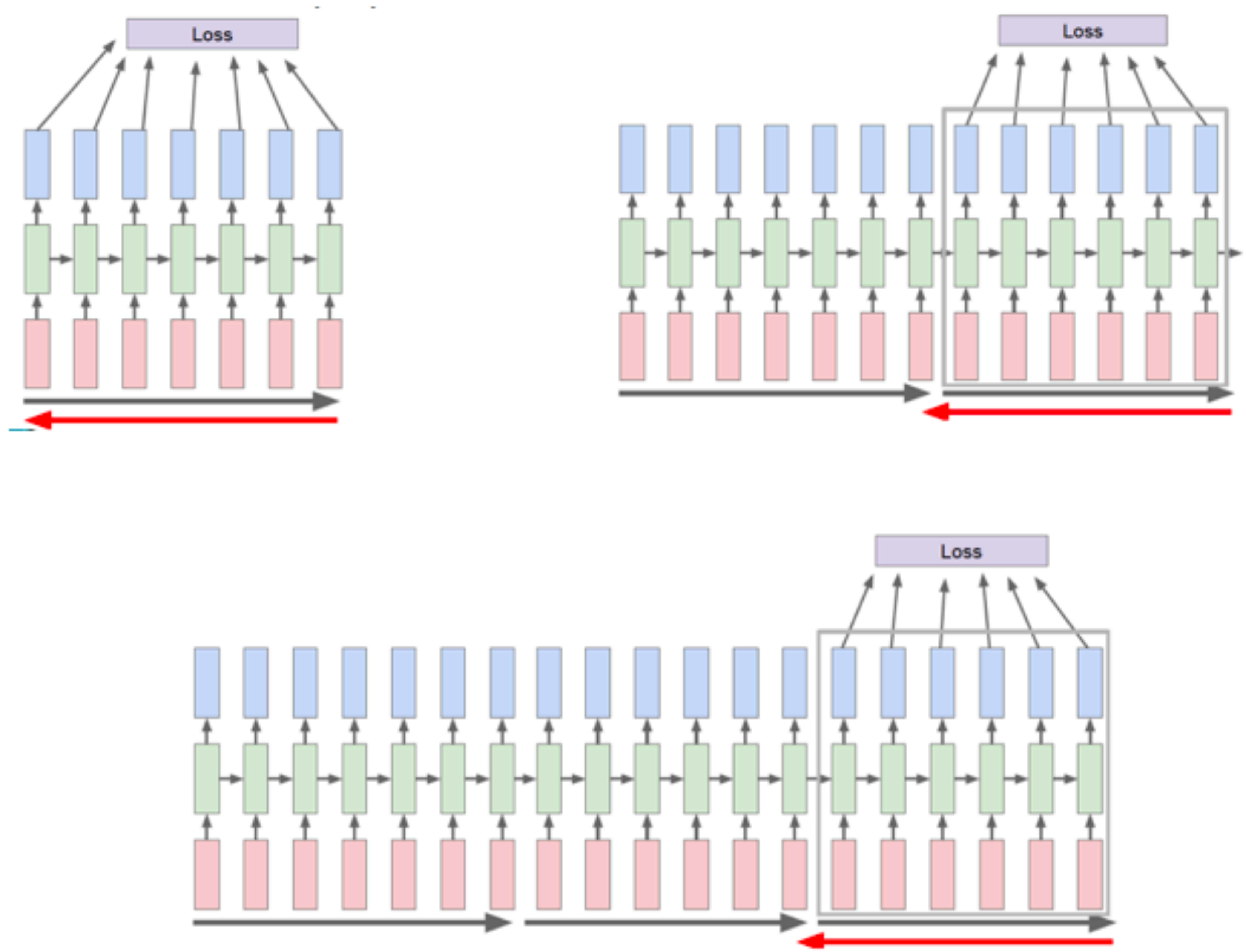
Gradient $g = \frac{\partial L}{\partial \theta}$, θ - all the network parameters

If $||g||$> threshold:

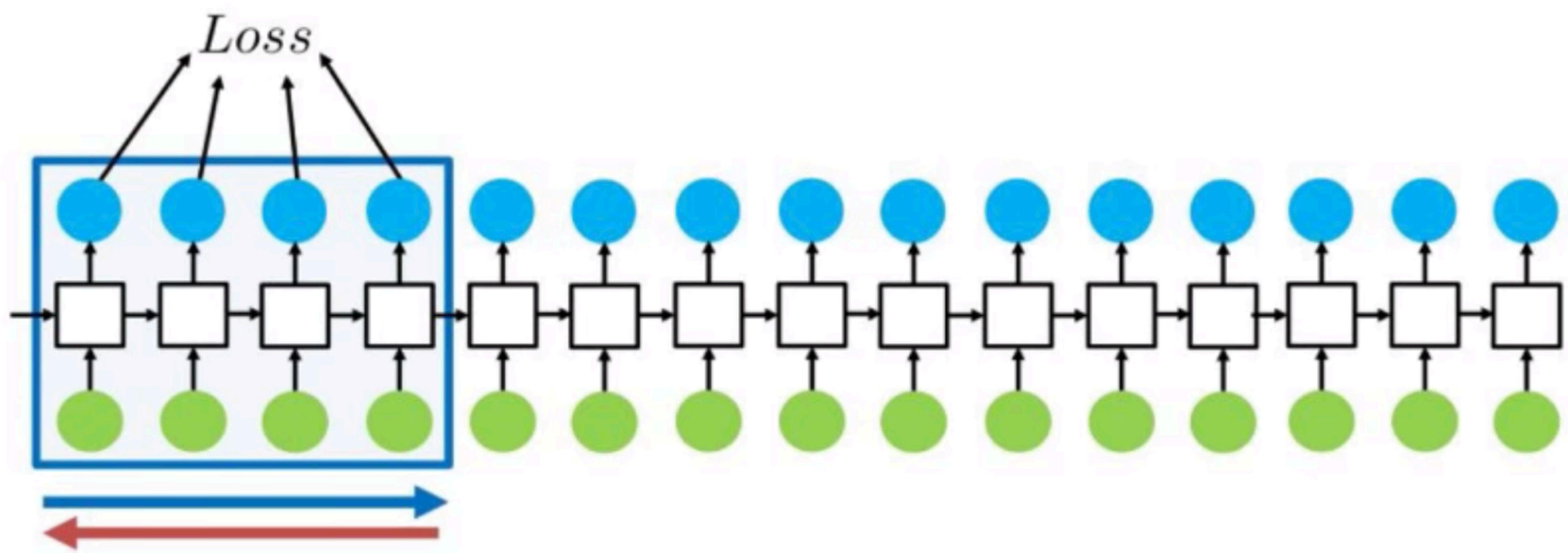
$$g \leftarrow \frac{threshold}{||g||} g$$

Simple but still very effective!

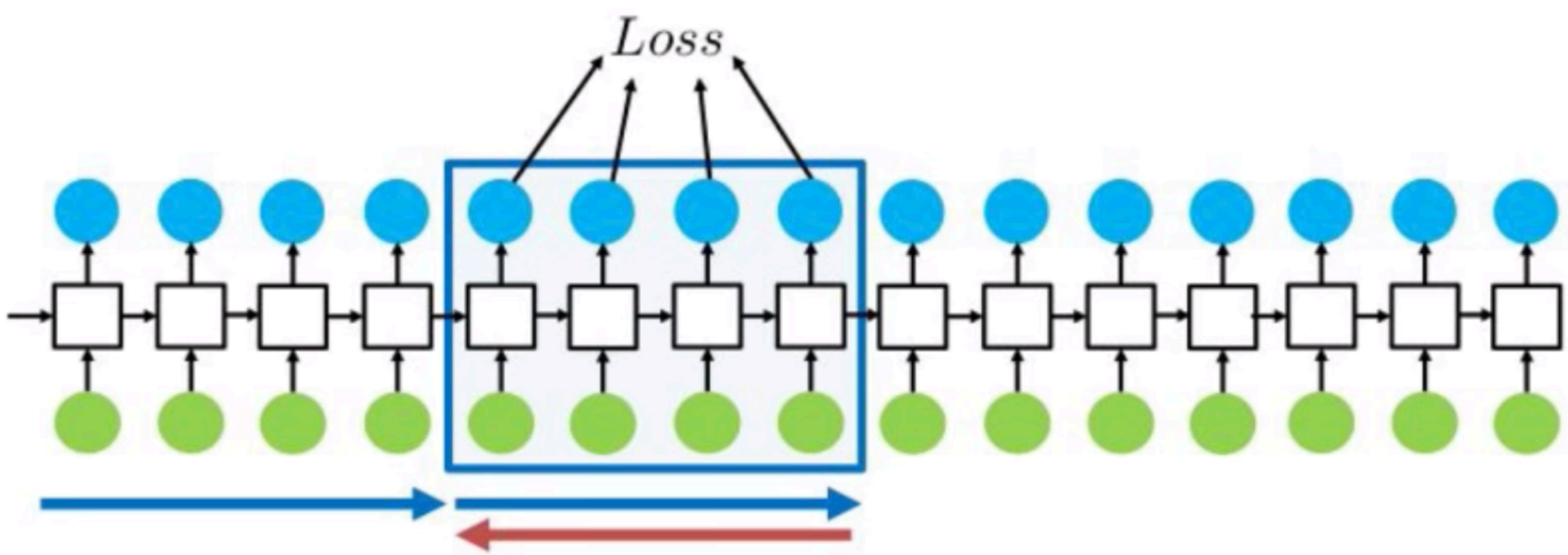
Truncated BPTT



Truncated BPTT



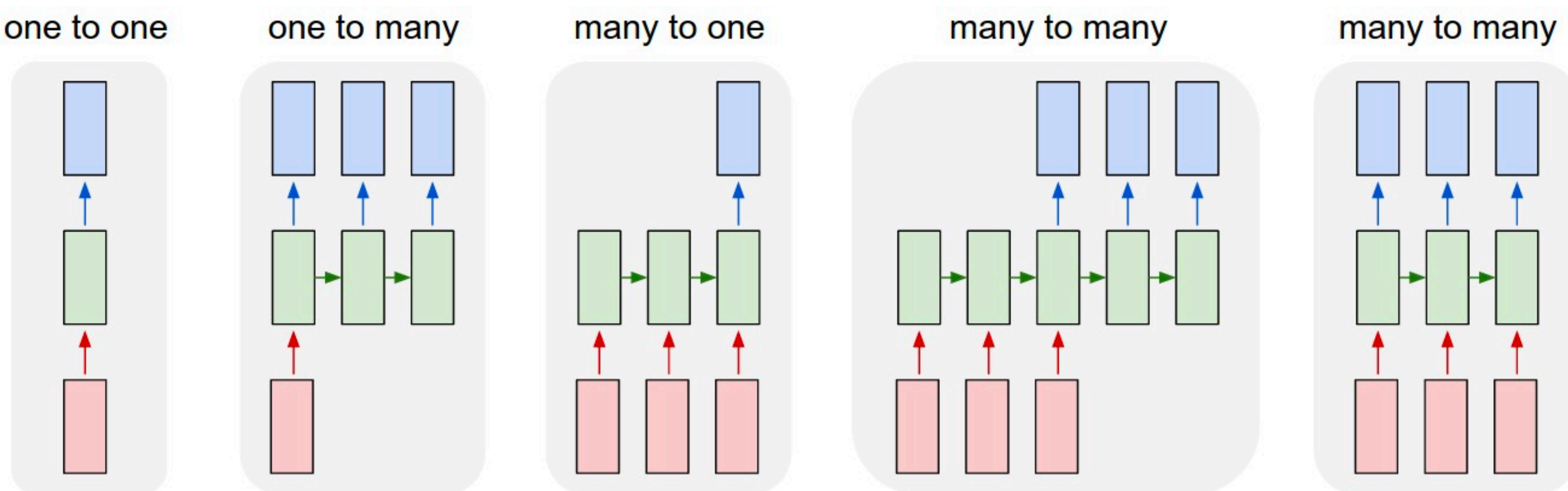
Truncated BPTT



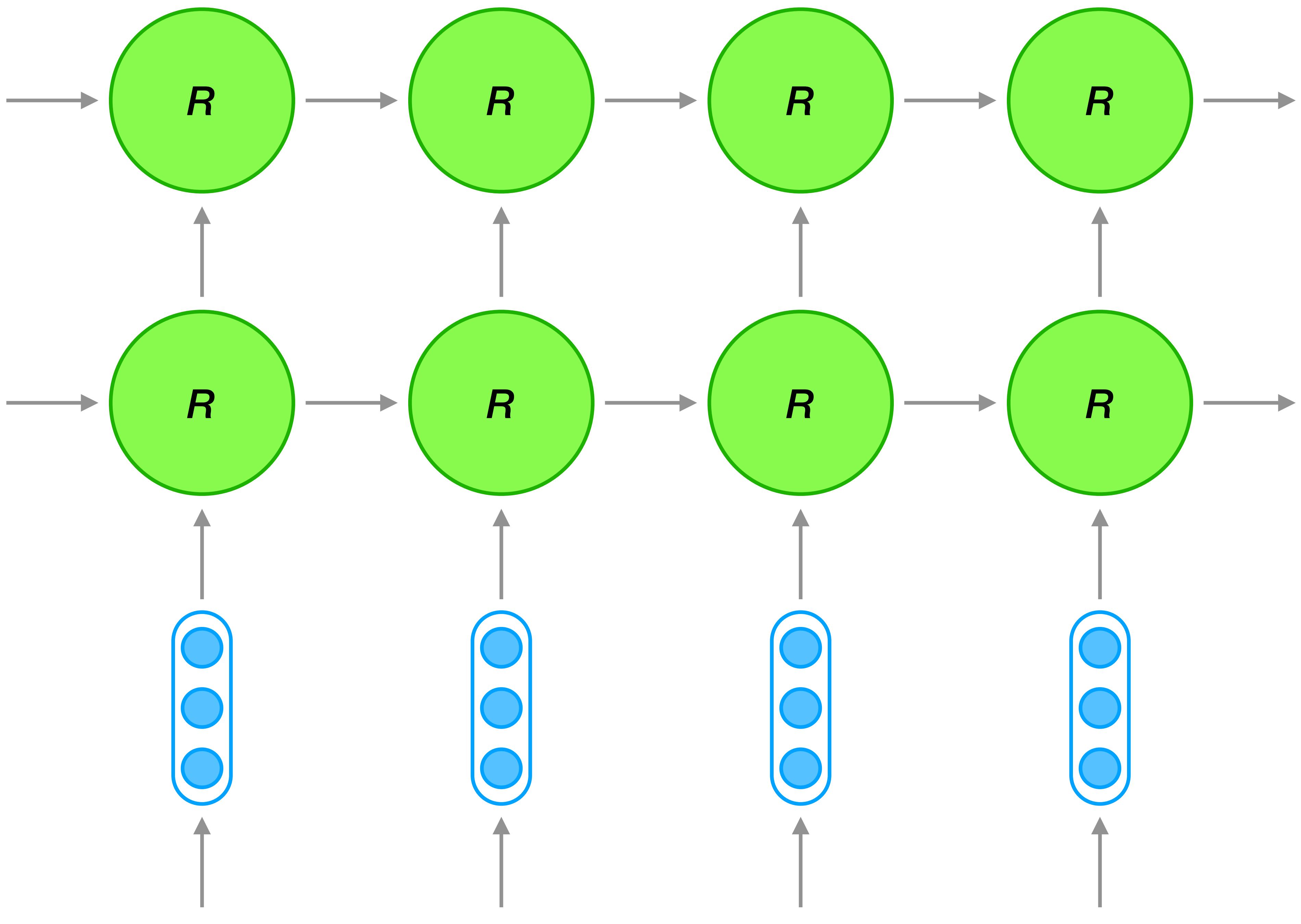
Recurrent Neural Network

+ -

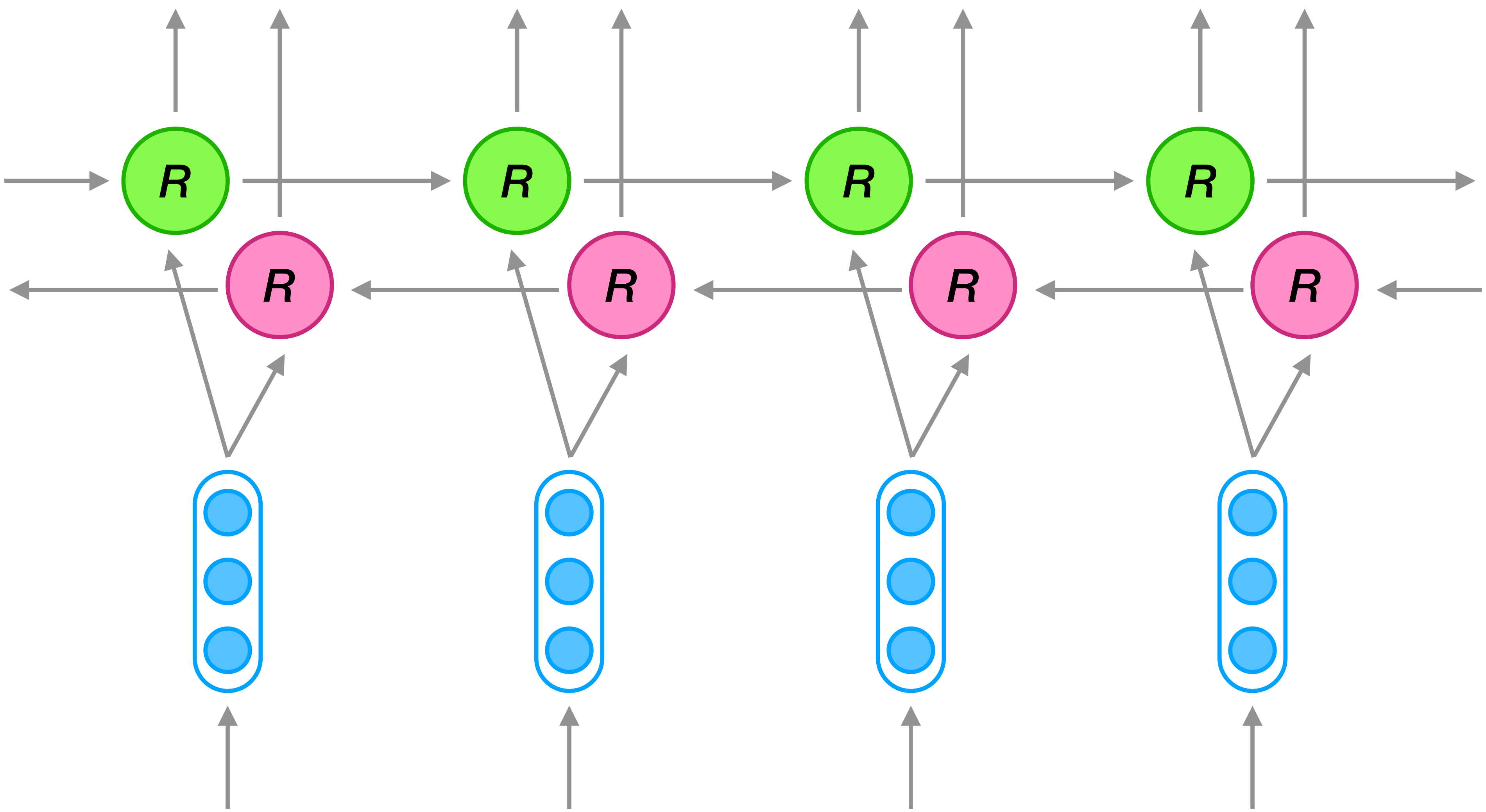
Recurrent Neural Network



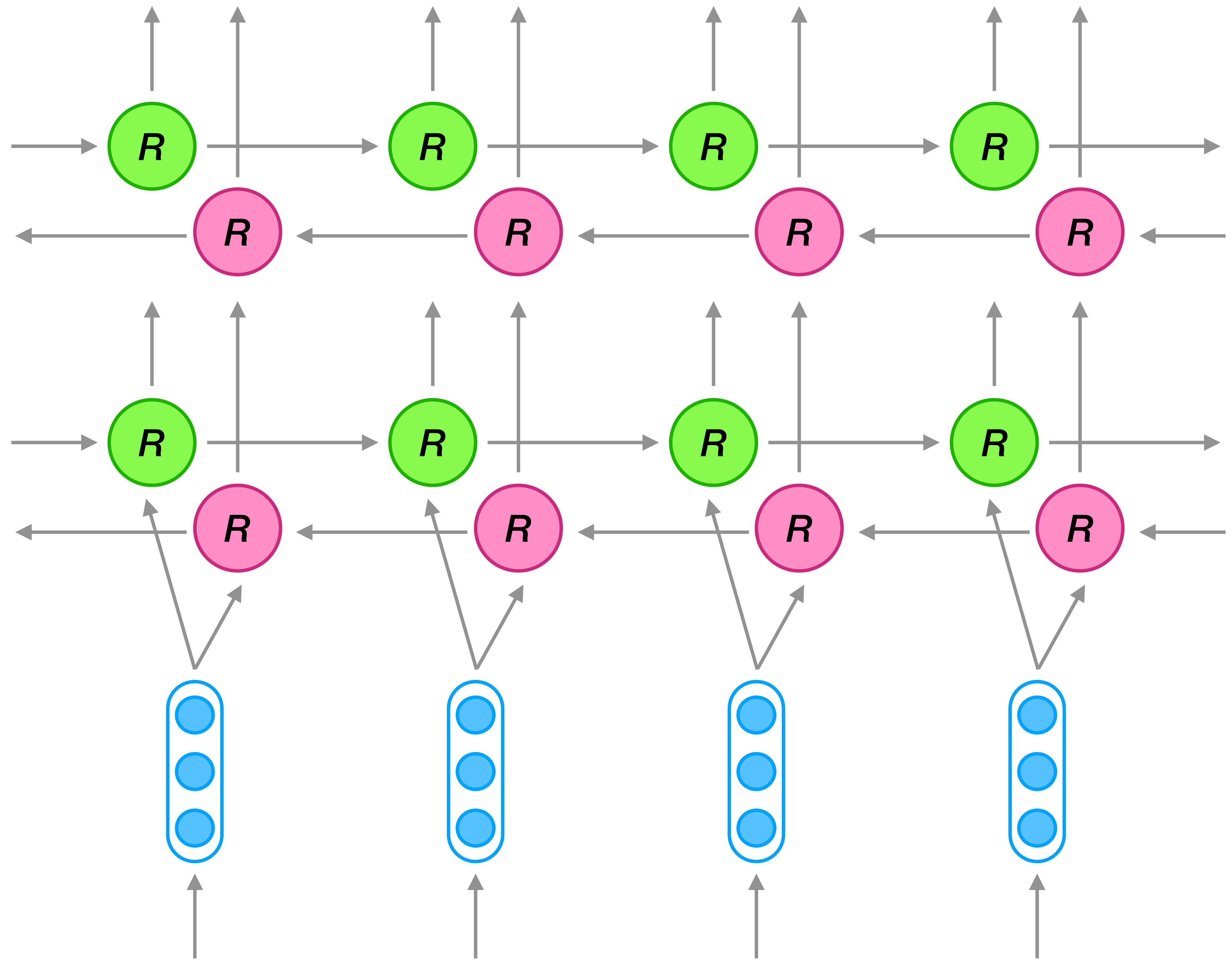
Deeper



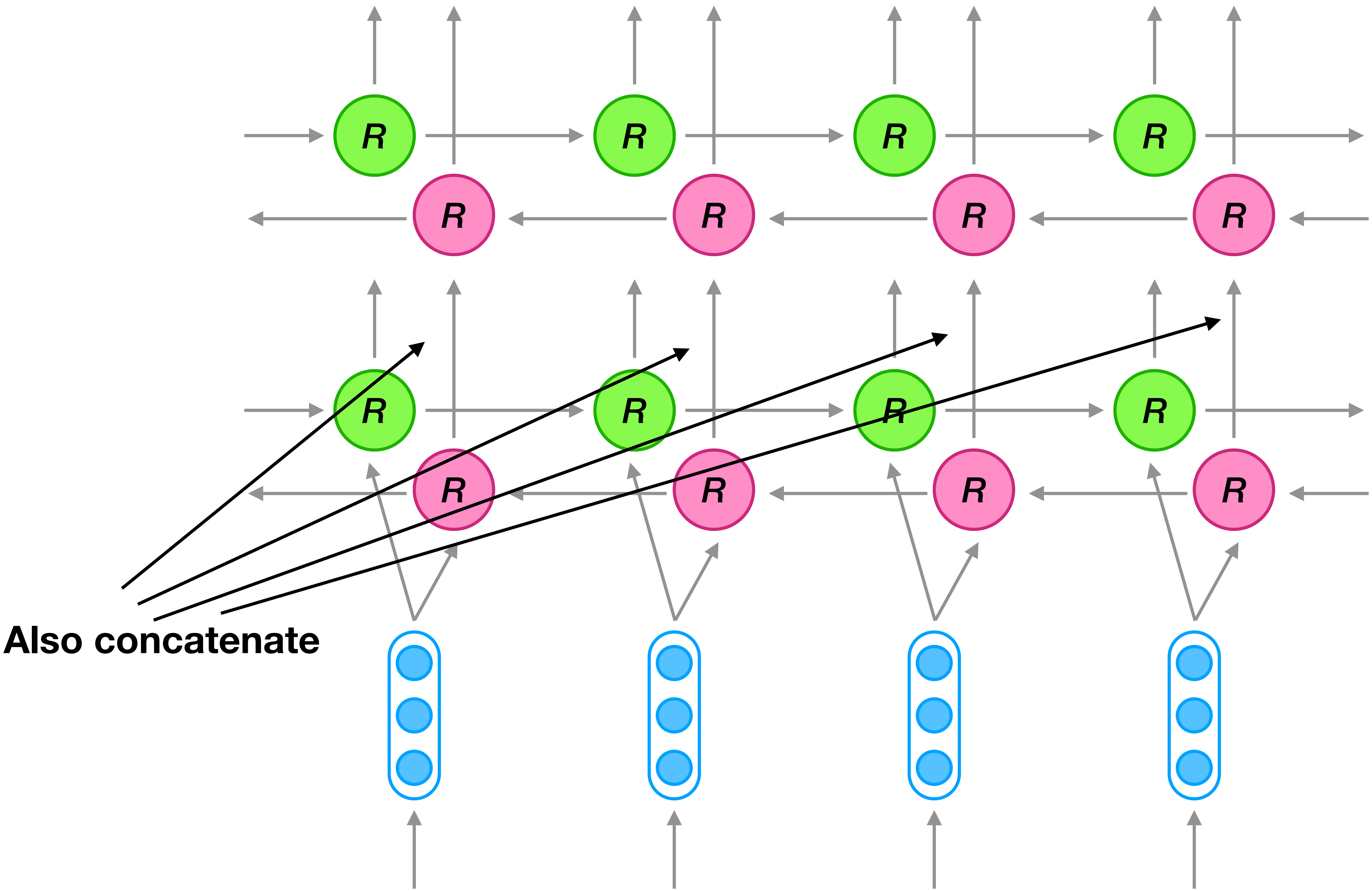
Bidirectional



Deeper Bidirectional



Deeper Bidirectional



Bidirectional

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

Bidirectional

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

Bidirectional

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

Bidirectional

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

Bidirectional

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

Bidirectional

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

Bidirectional

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

Bidirectional

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

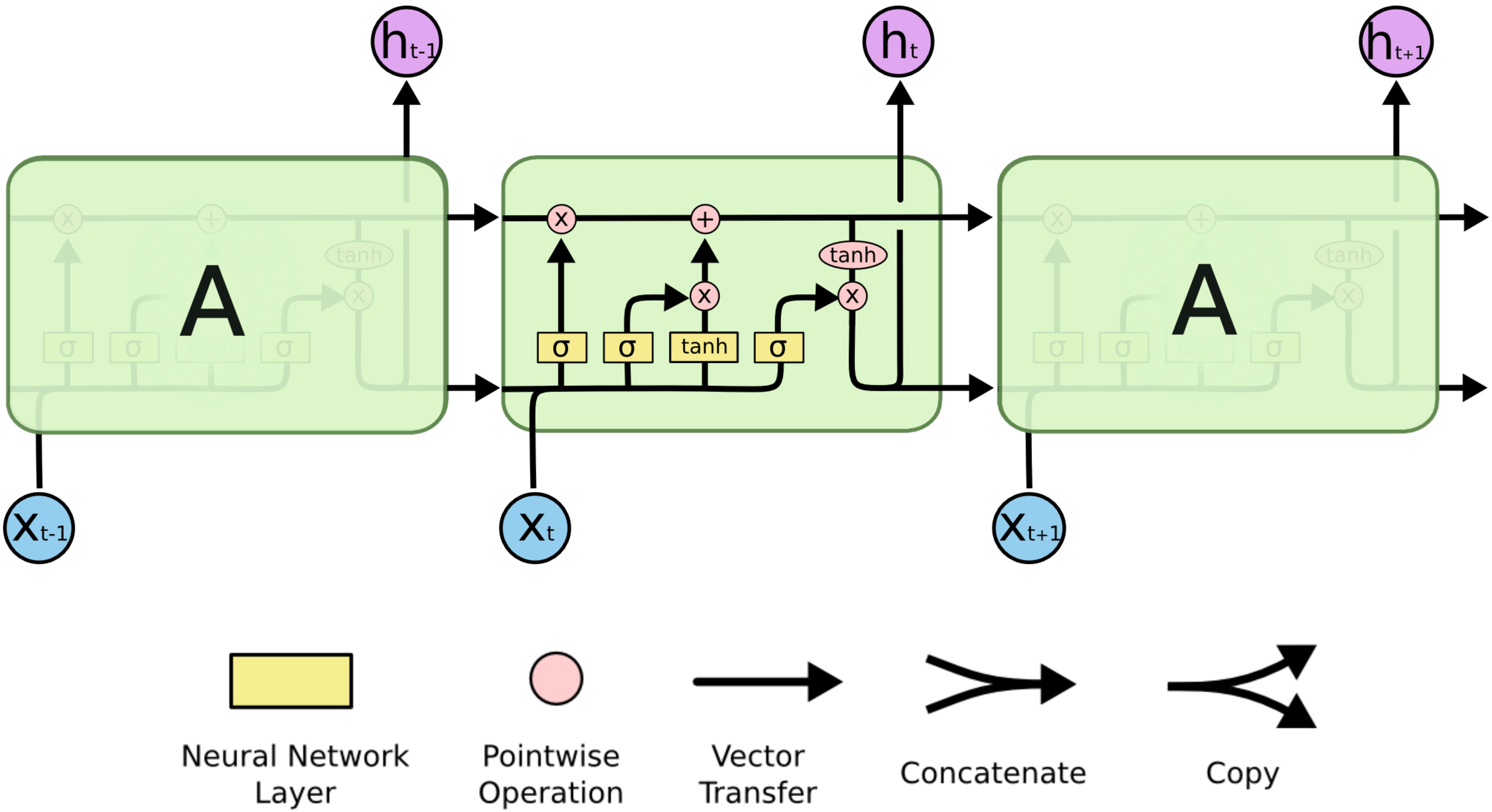
Bidirectional

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

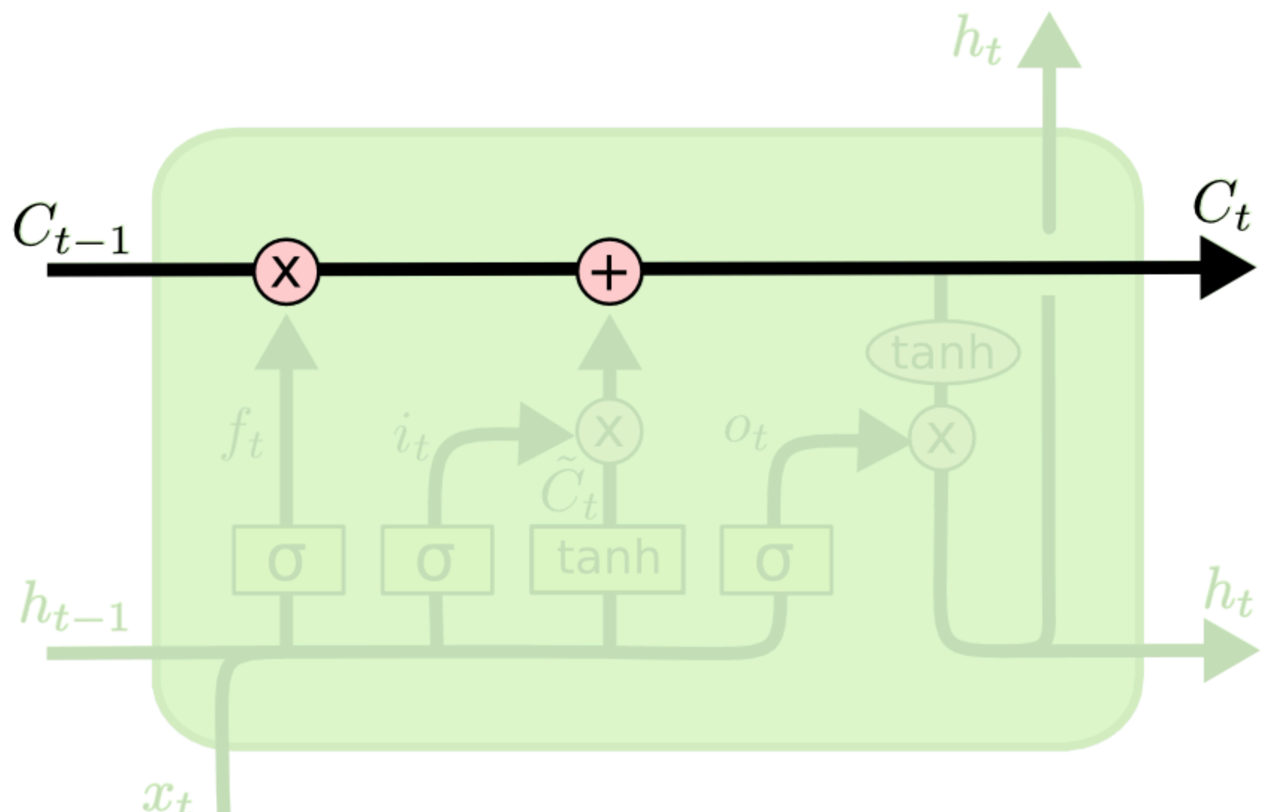
Bidirectional

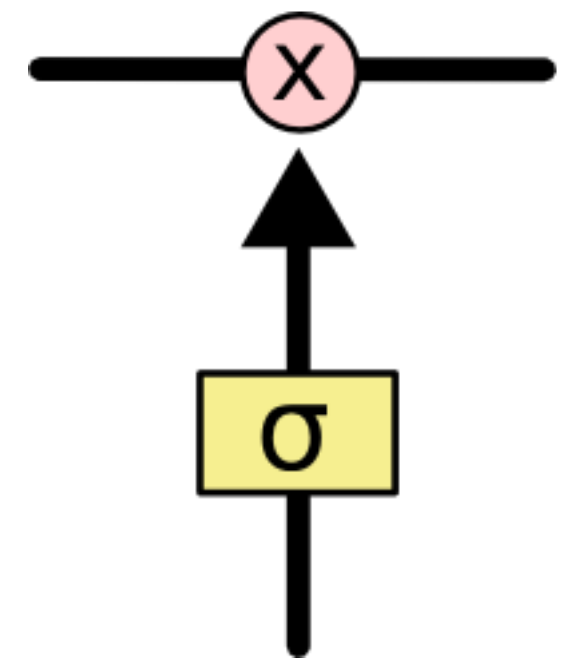
Source	<START>	The	poor	don't	have	any	money	<END>
Forward	<START>	The	poor	don't	have	any	money	<END>
Backward	<END>	money	any	have	don't	poor	The	<START>

Long Short Term Memories

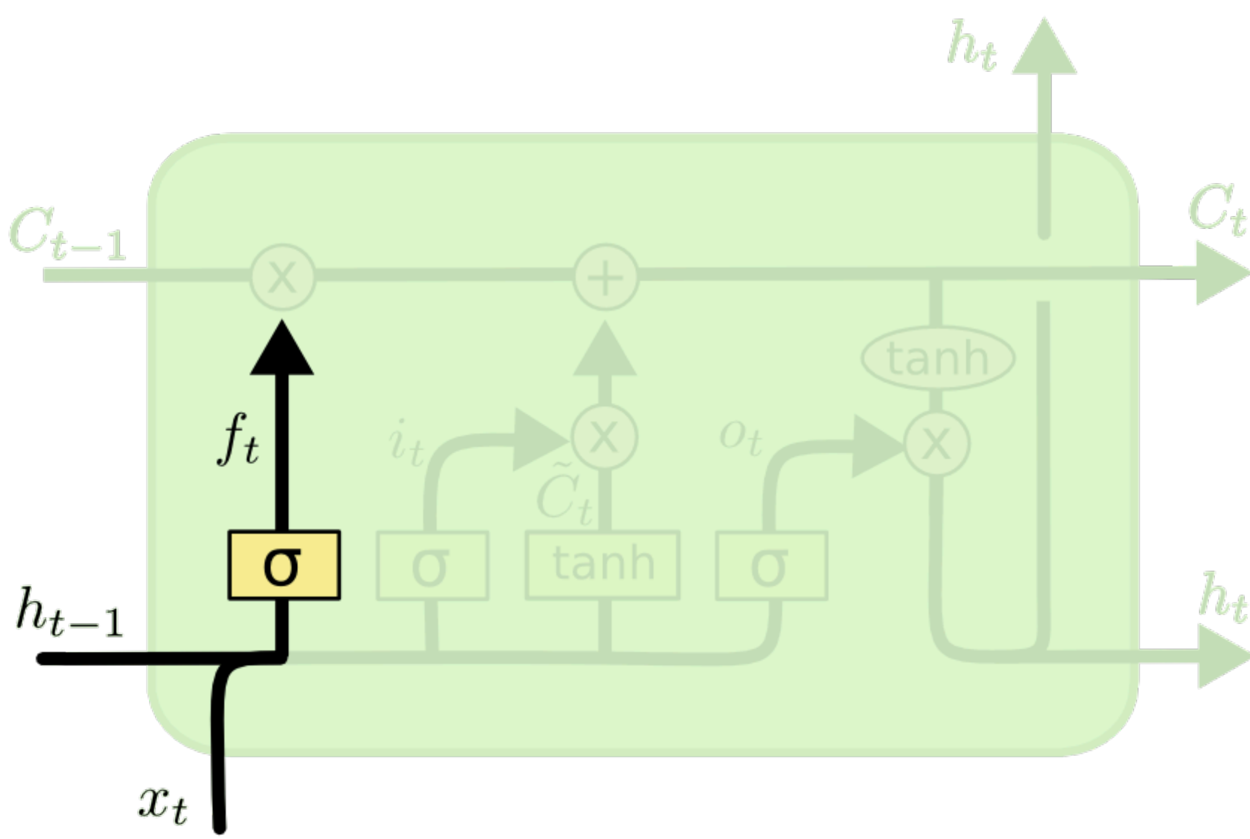


Long Short Term Memories



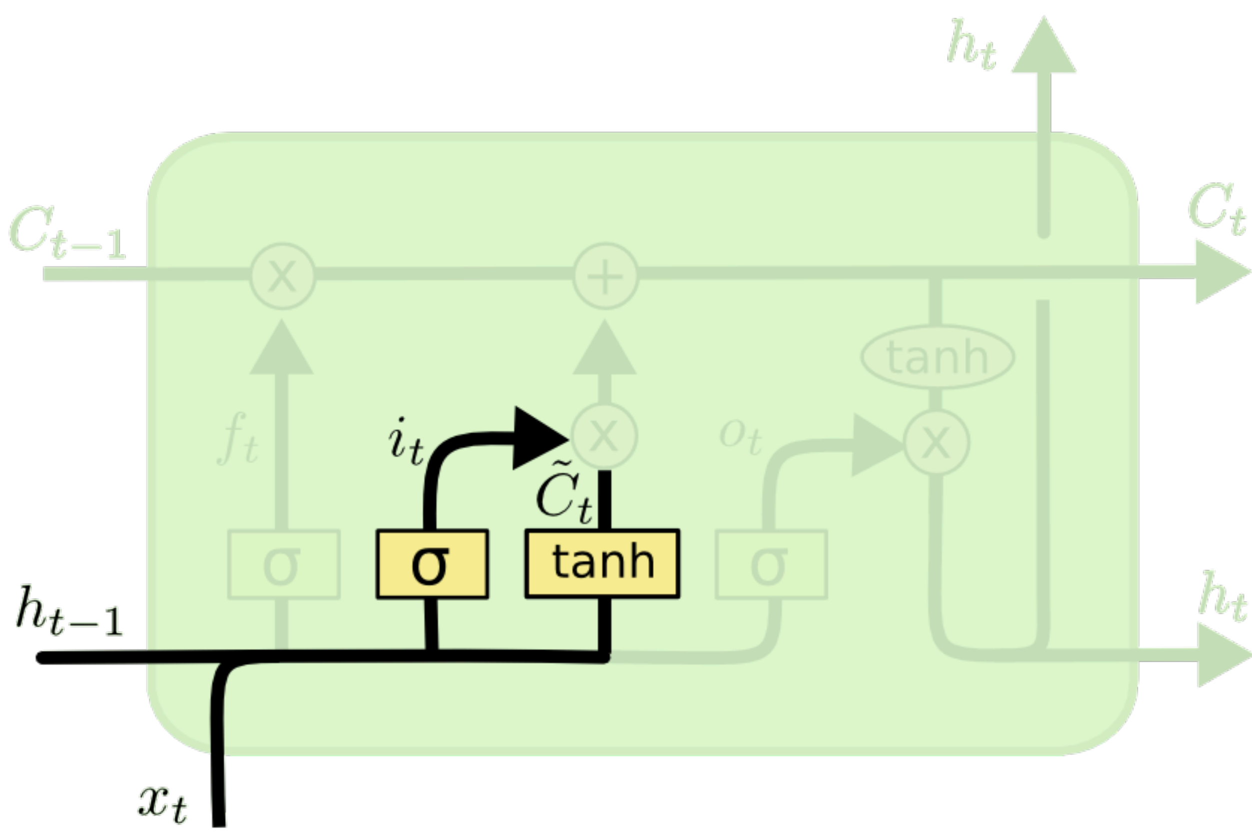


Long Short Term Memories



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

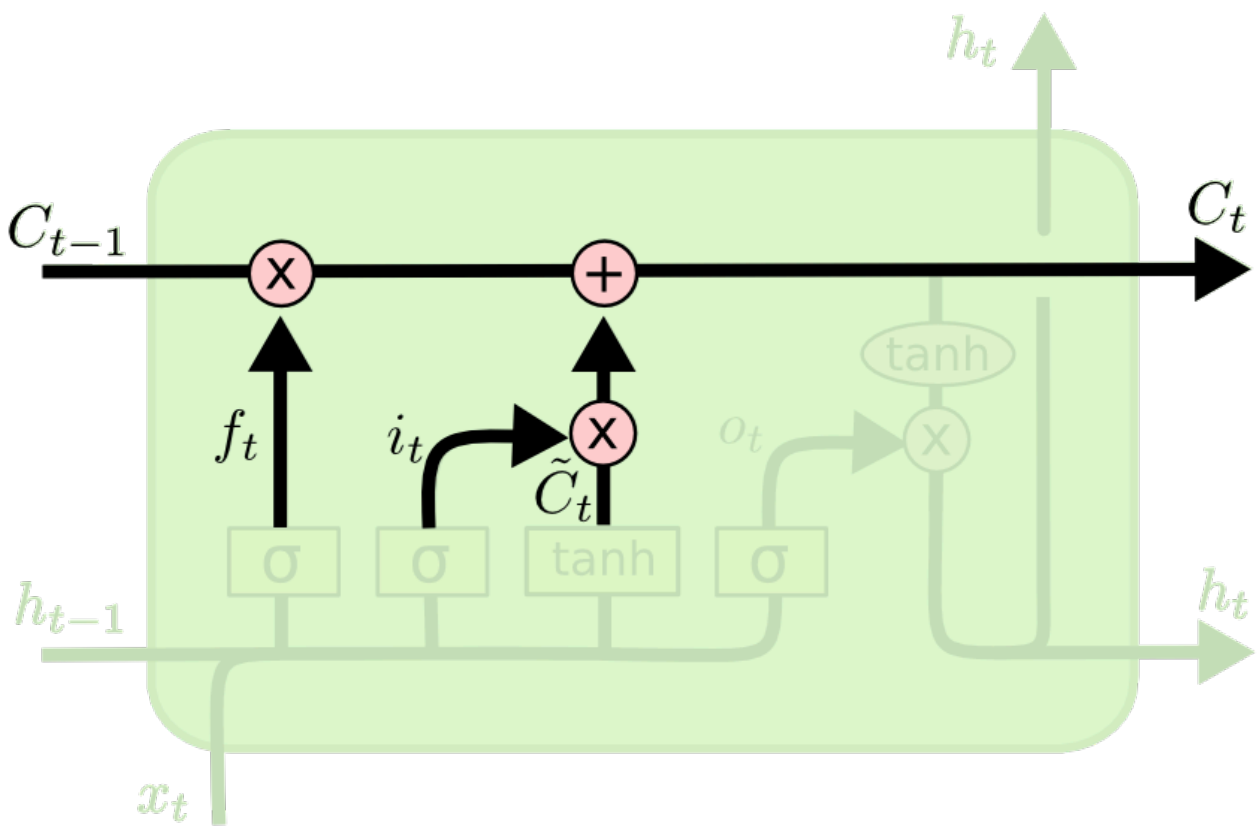
Long Short Term Memories



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

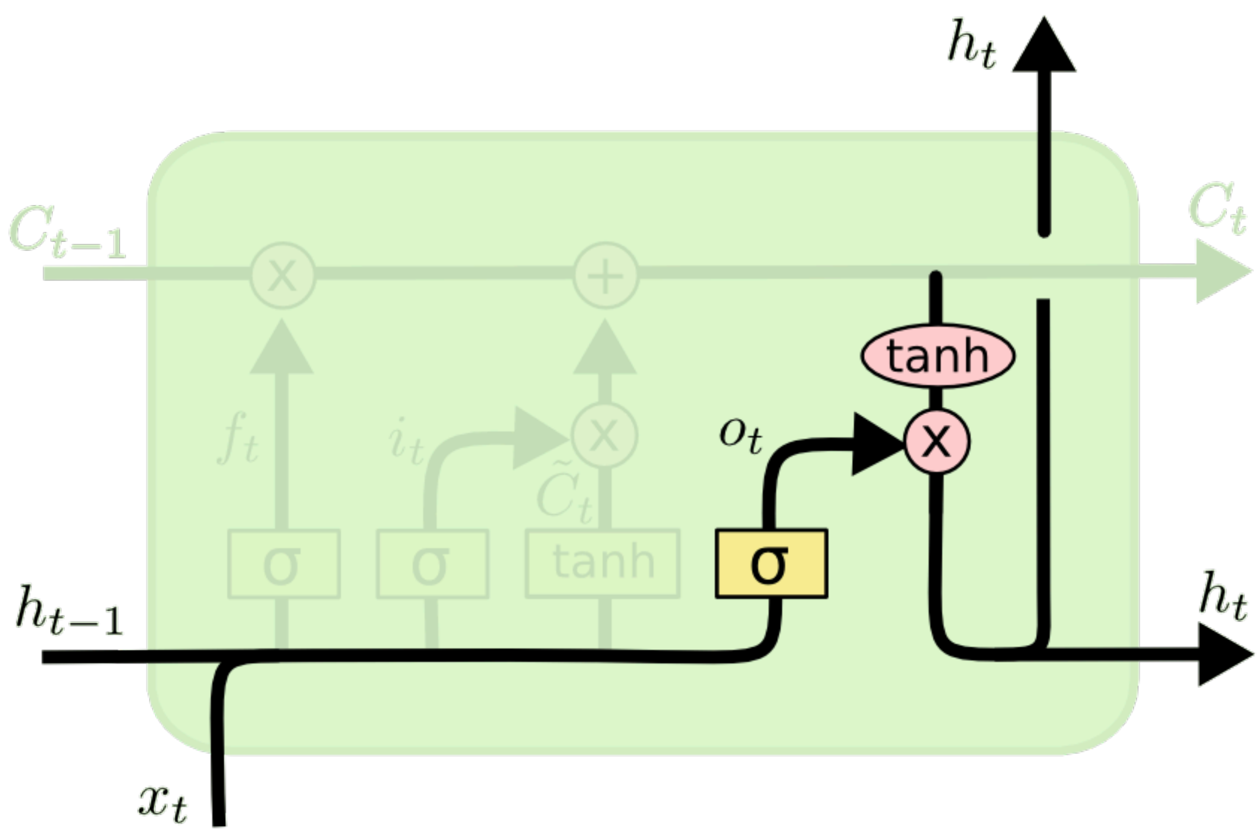
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

Long Short Term Memories



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

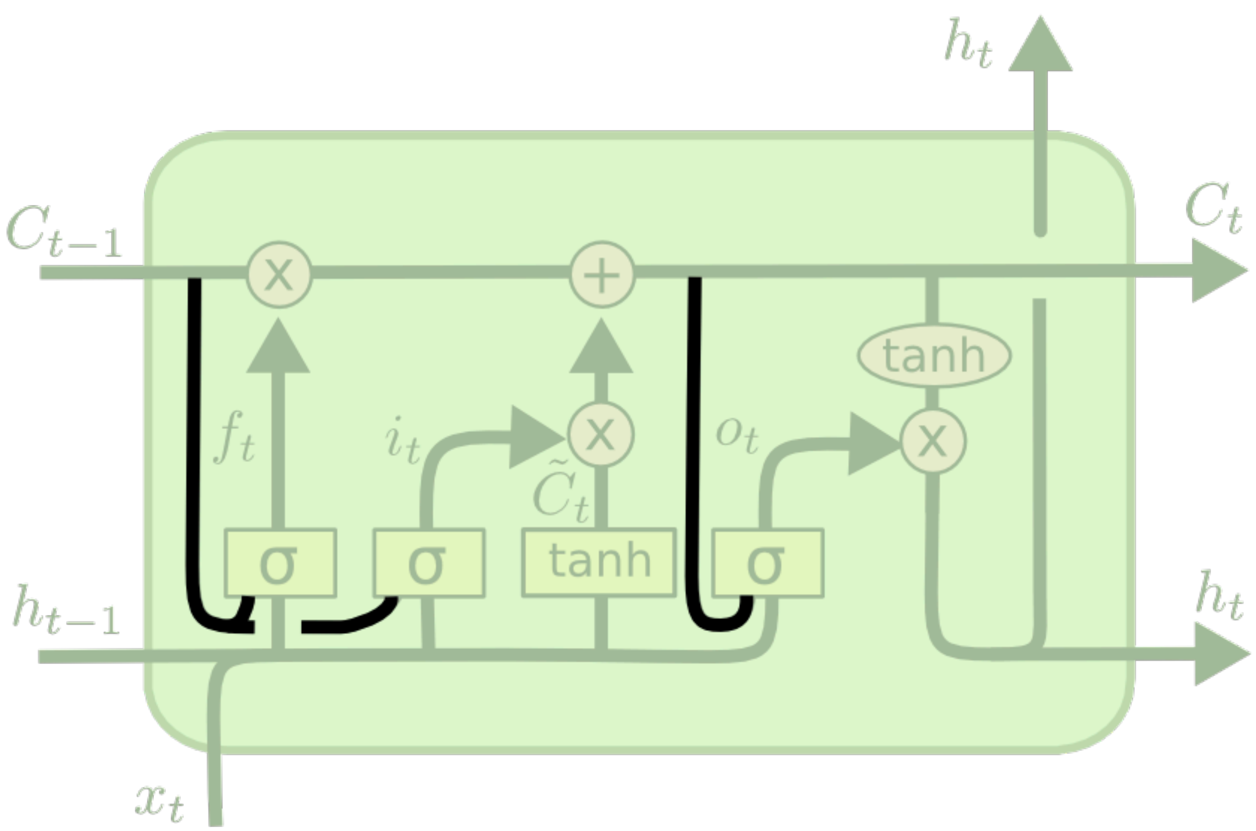
Long Short Term Memories



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

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

Long Short Term Memories

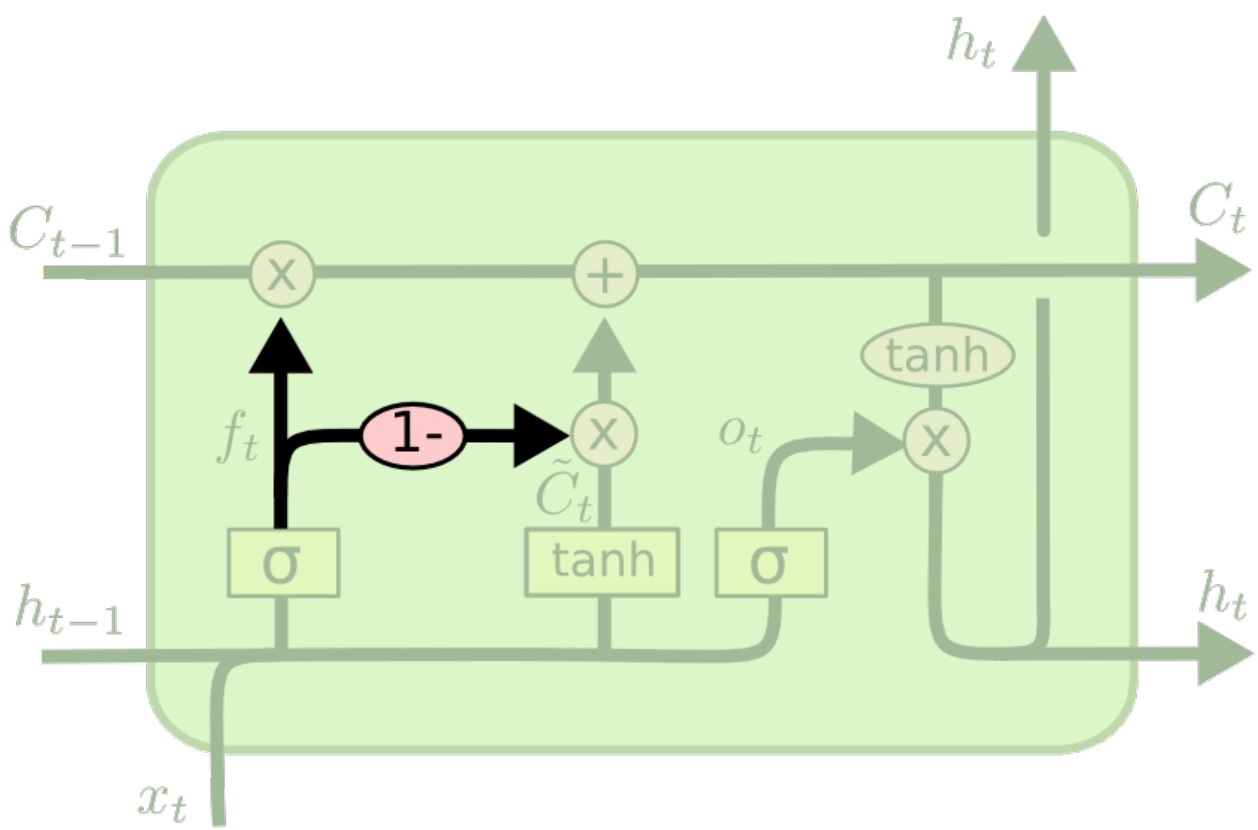


$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \ + \ b_f\right)$$

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

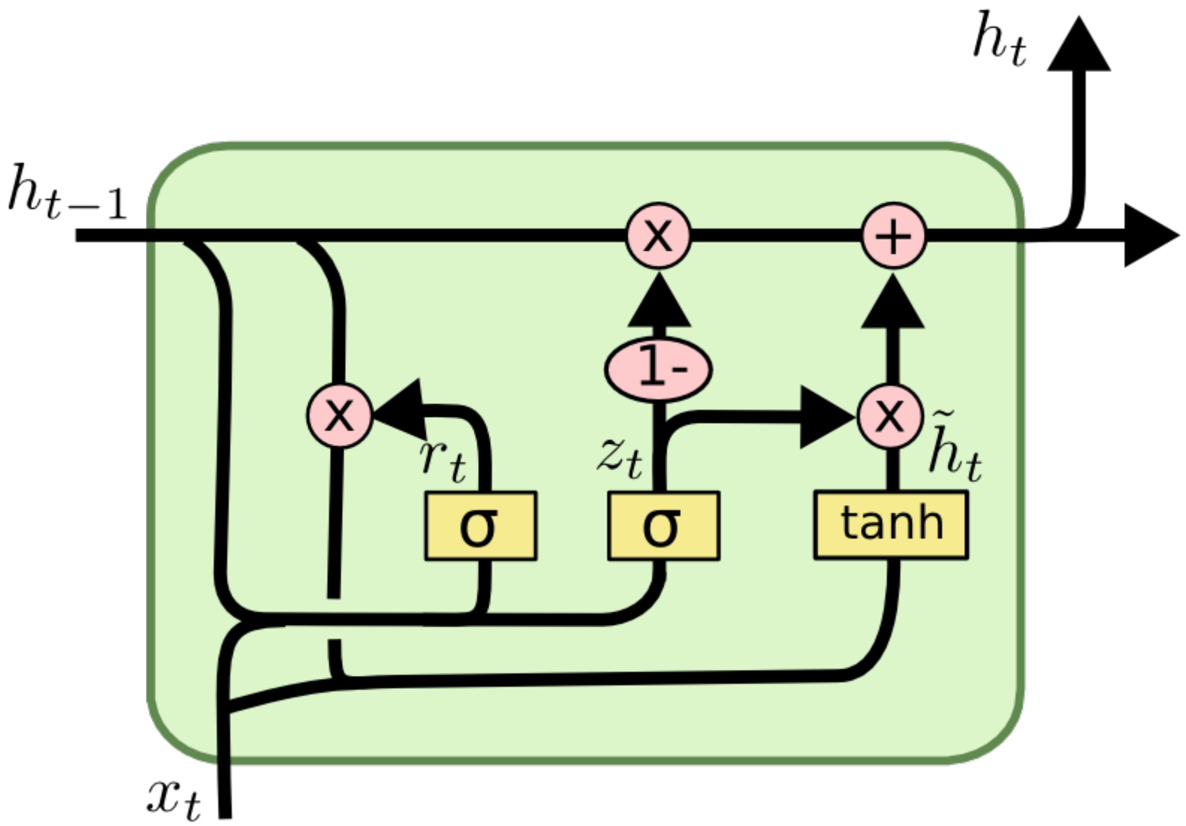
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \ + \ b_o\right)$$

Long Short Term Memories



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

Gated Recurrent Unit



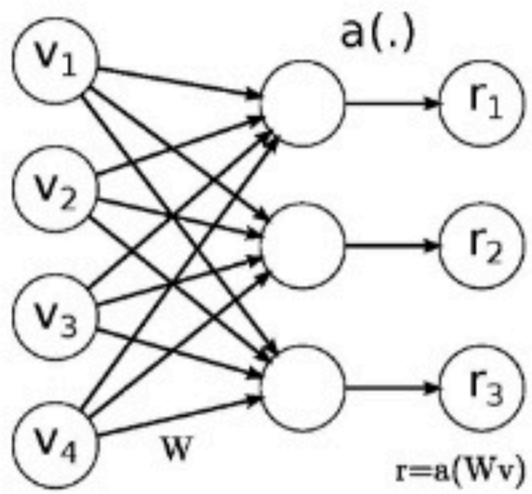
$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

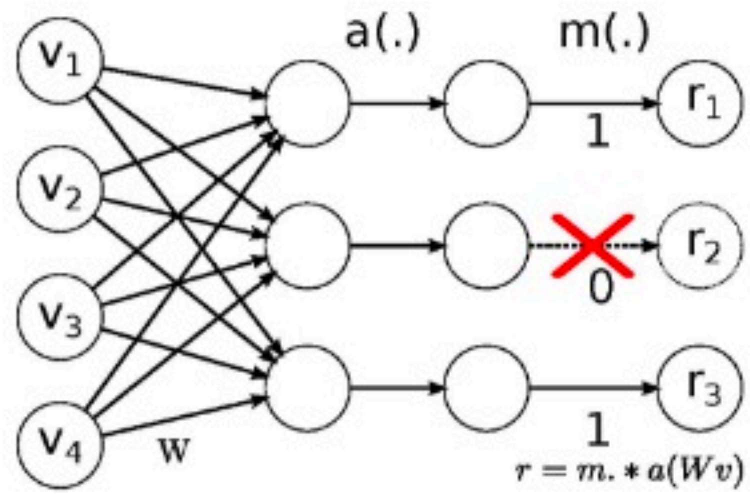
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

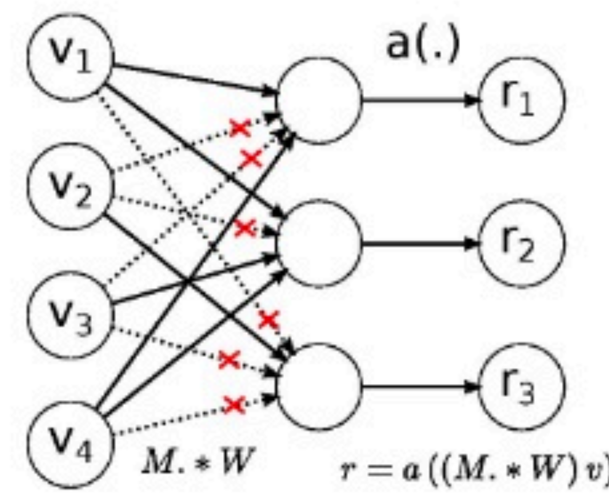
Dropout in RNN



No-Drop Network



DropOut Network



DropConnect Network

Layer Normalization

Batch Normalization

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

Layer Normalization

Batch Normalization → **Layer Normalization**

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Layer Normalization

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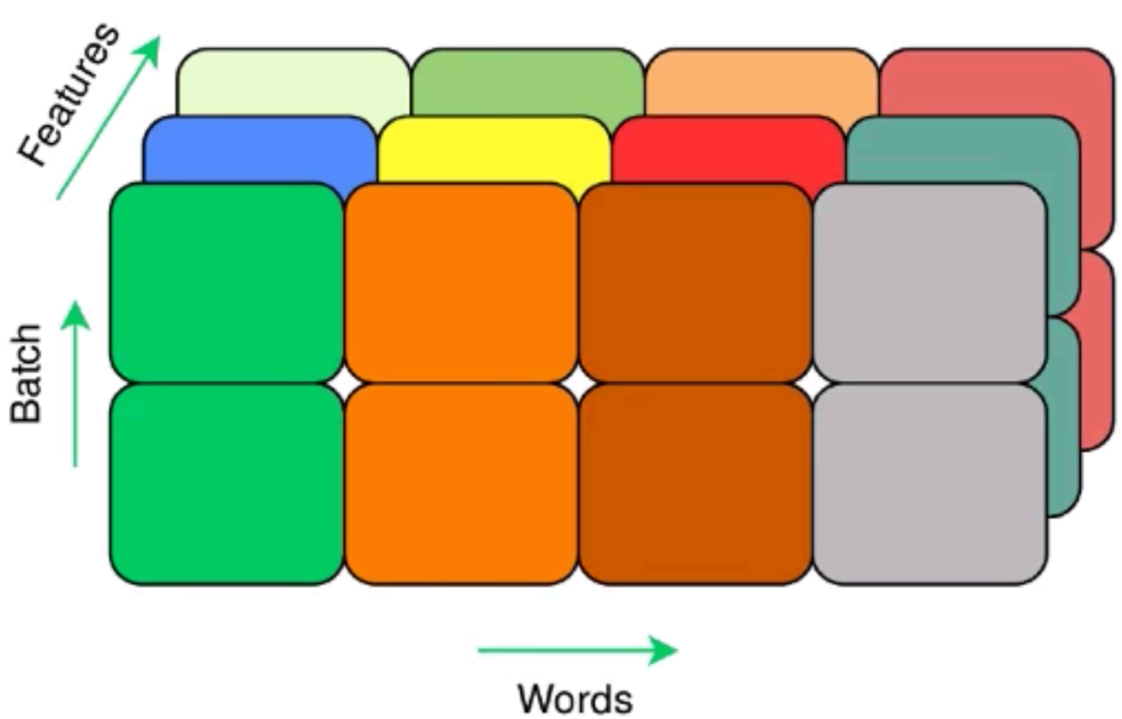

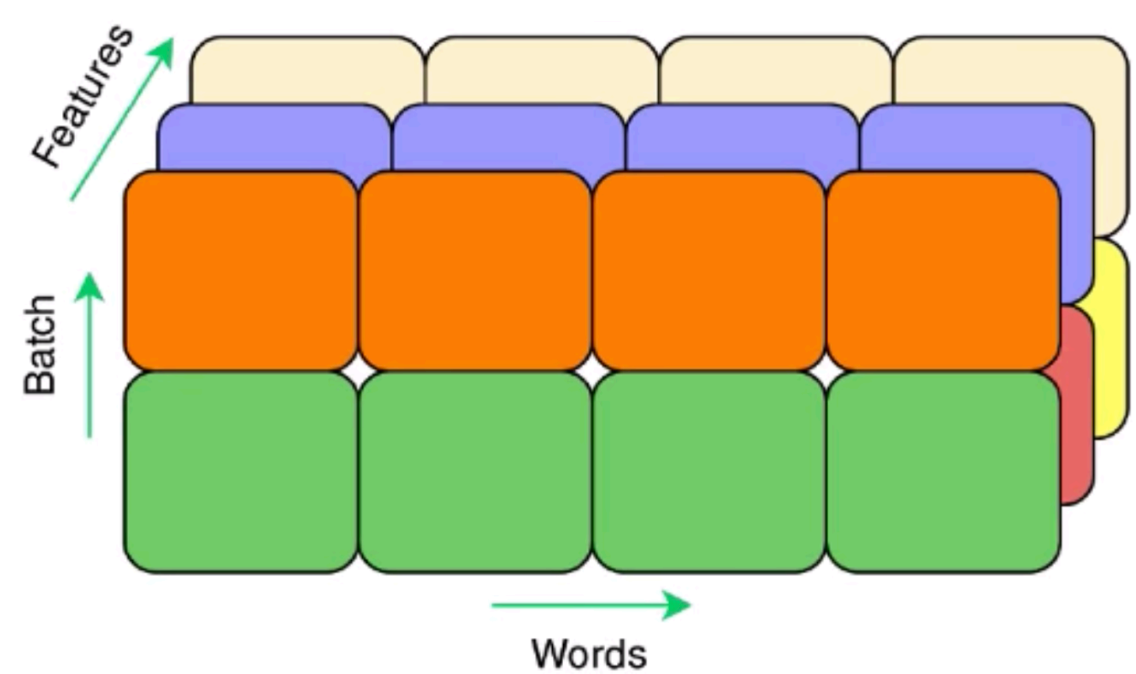

Thanks for your Attention!

Boris Zubarev

@bobazooba