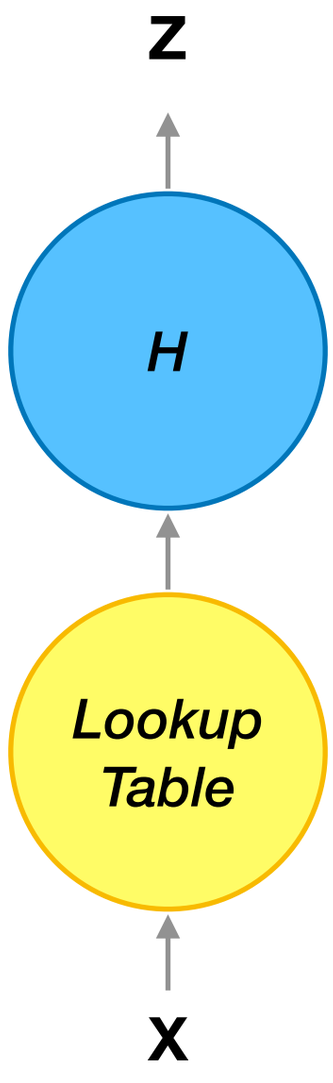
Recurrent Neural Network

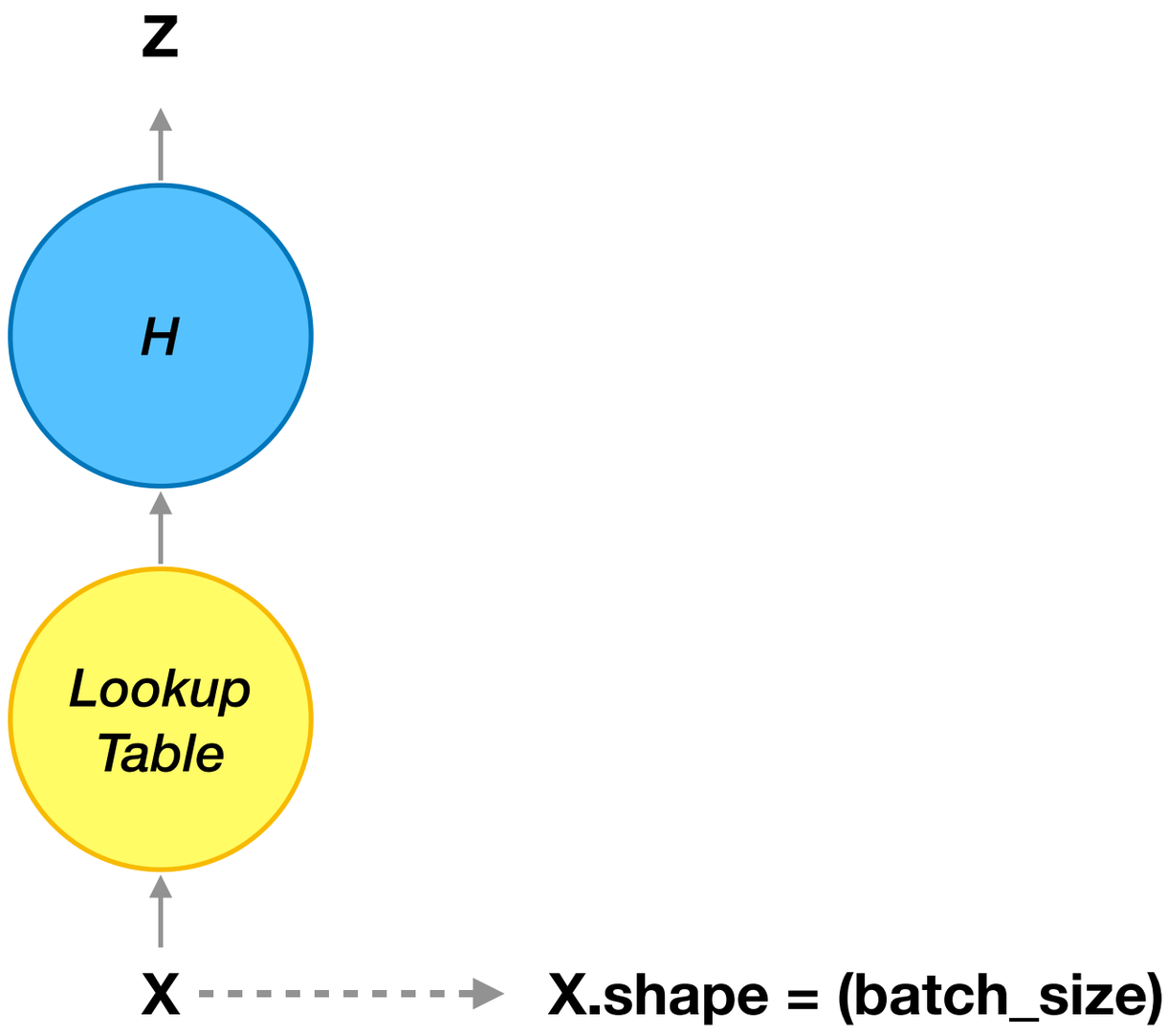
Boris Zubarev

@bobazooba

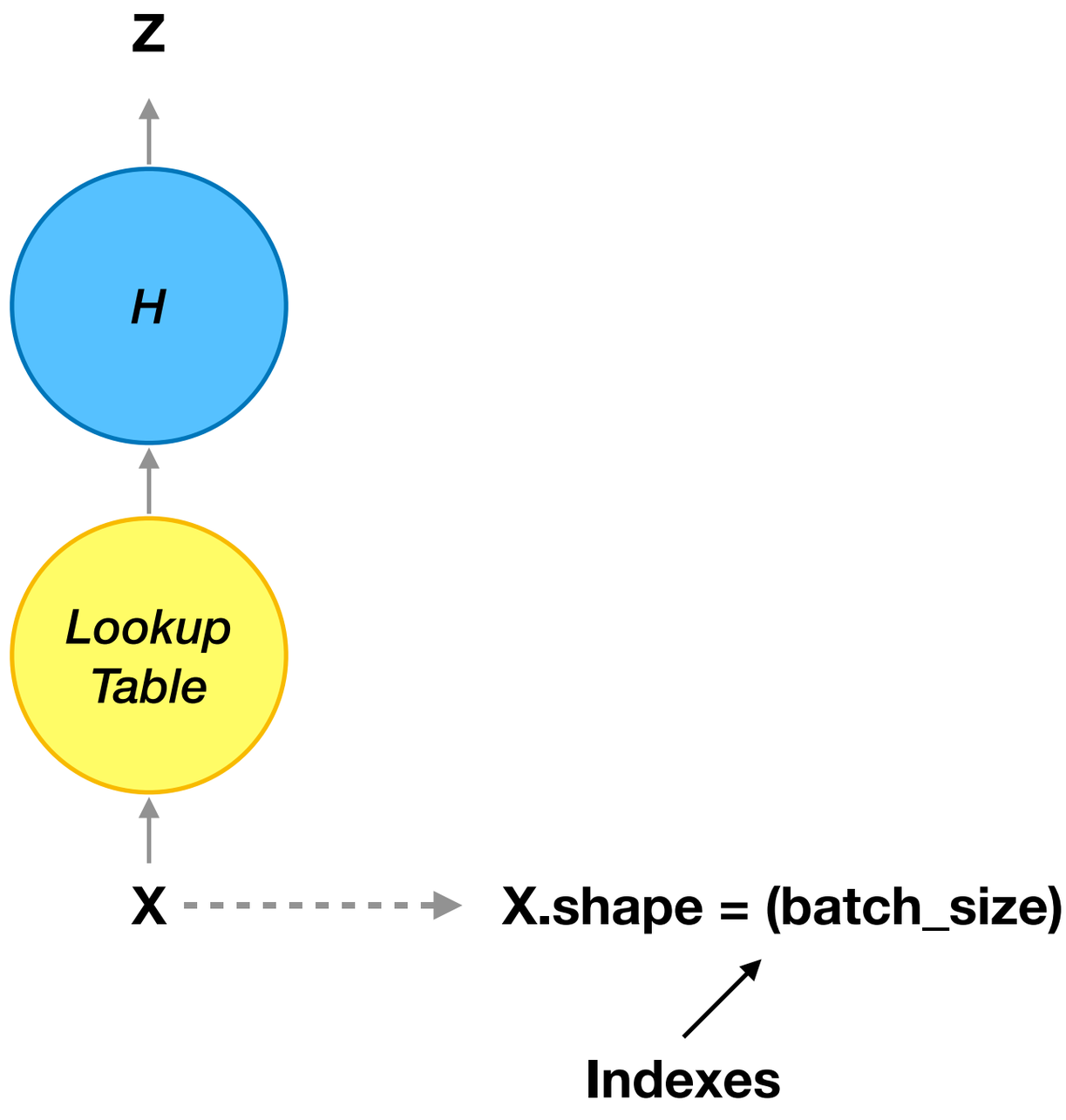
Neural Network



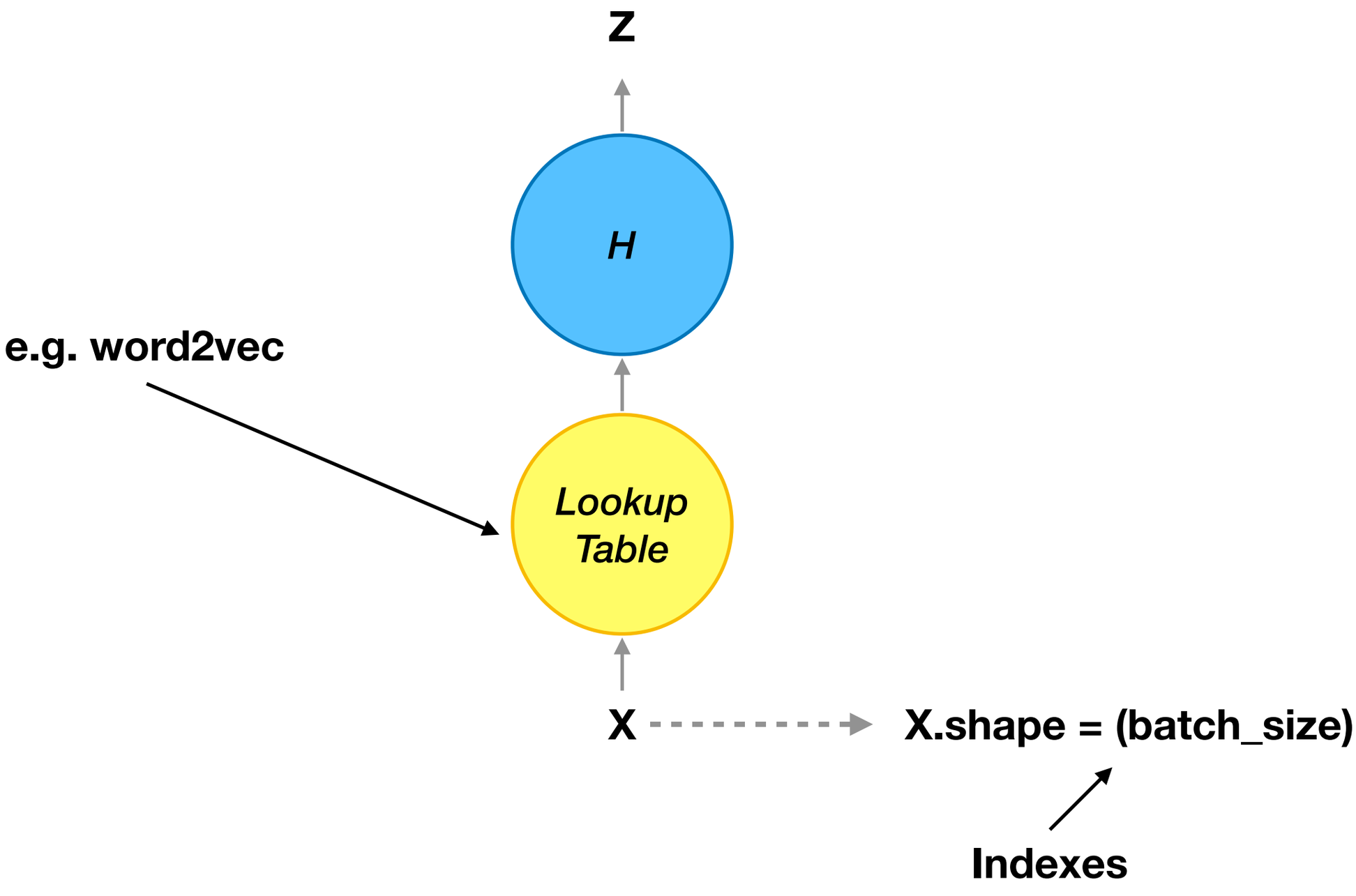
Neural Network



Neural Network



Neural Network



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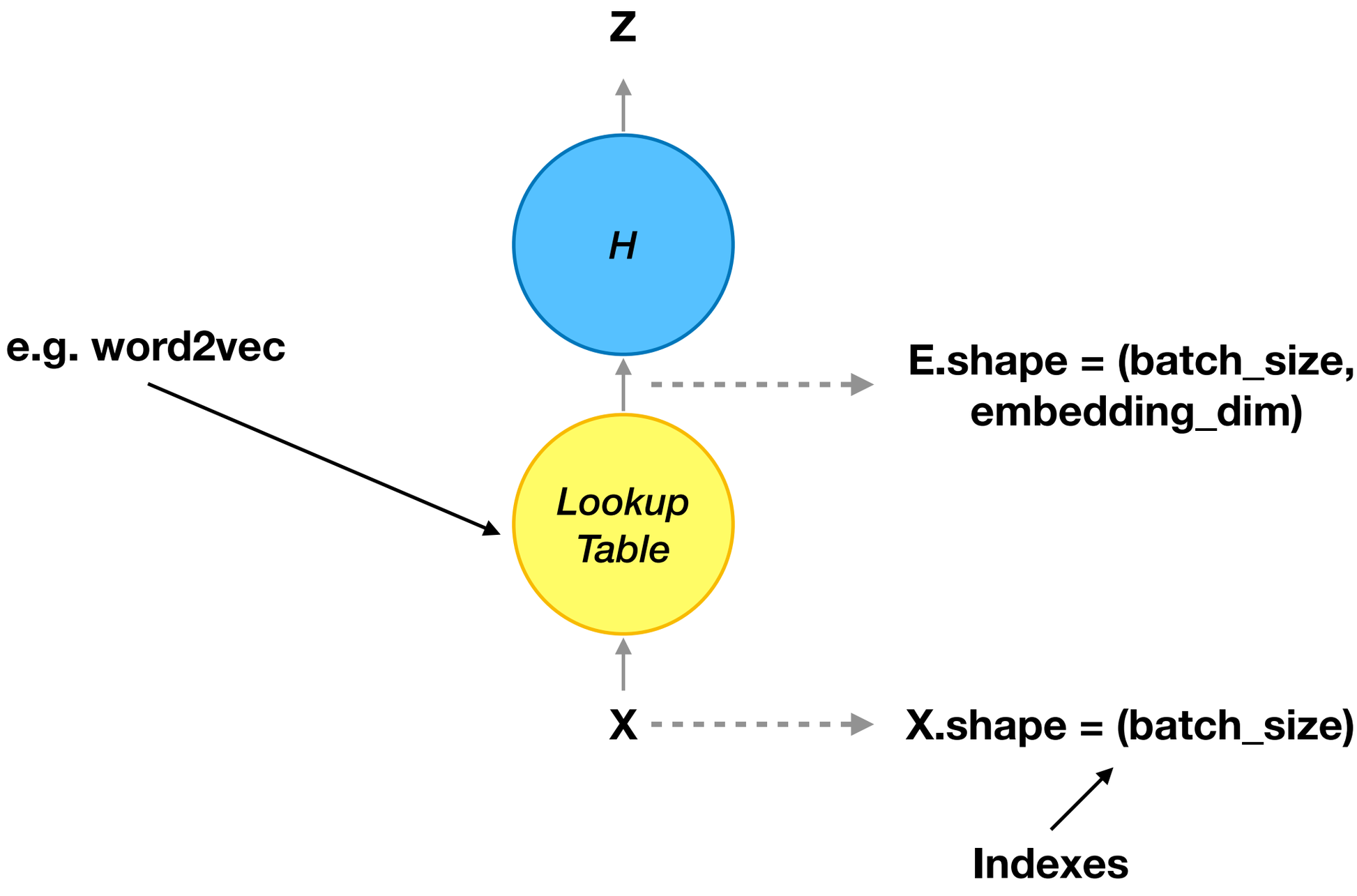
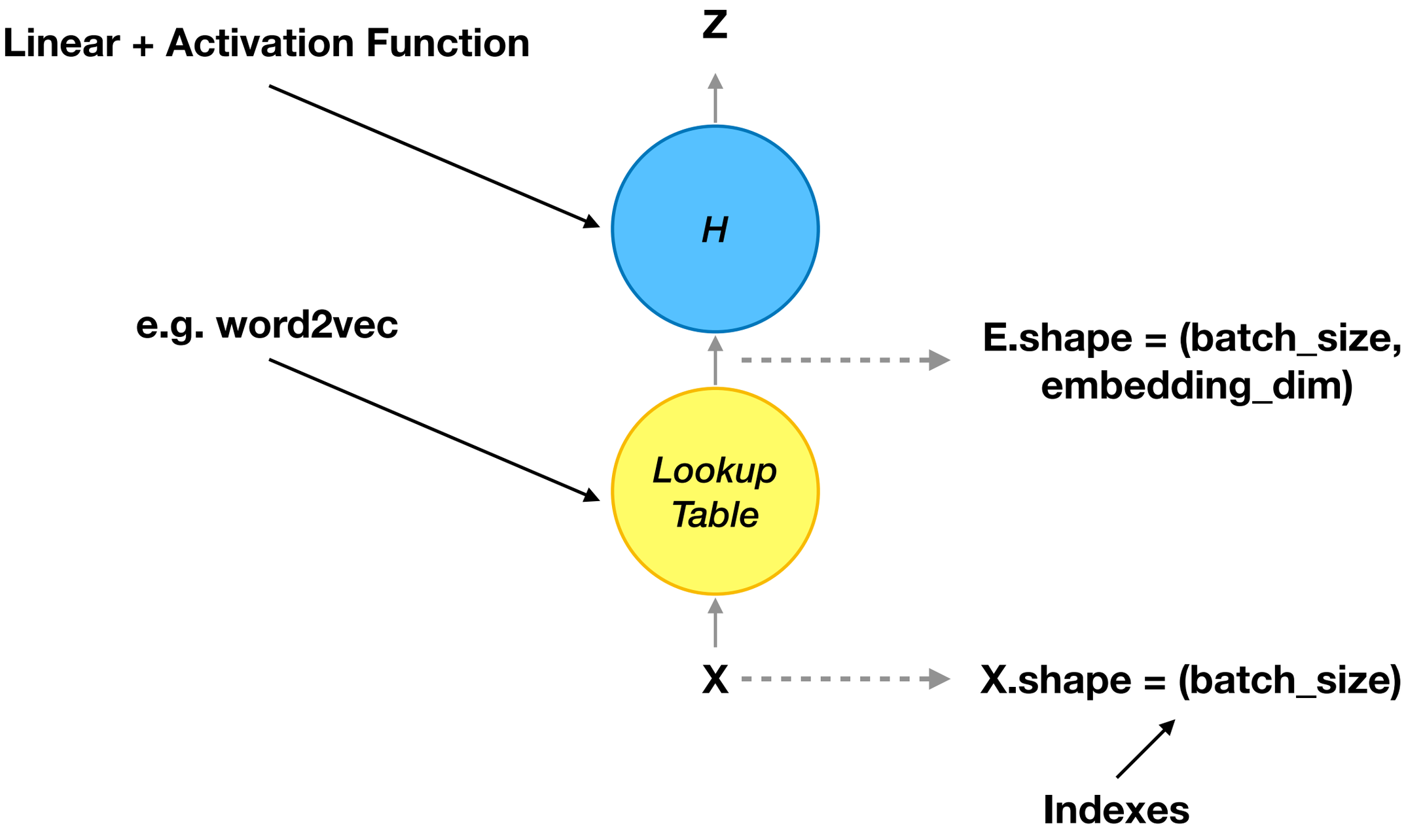


Neural Network



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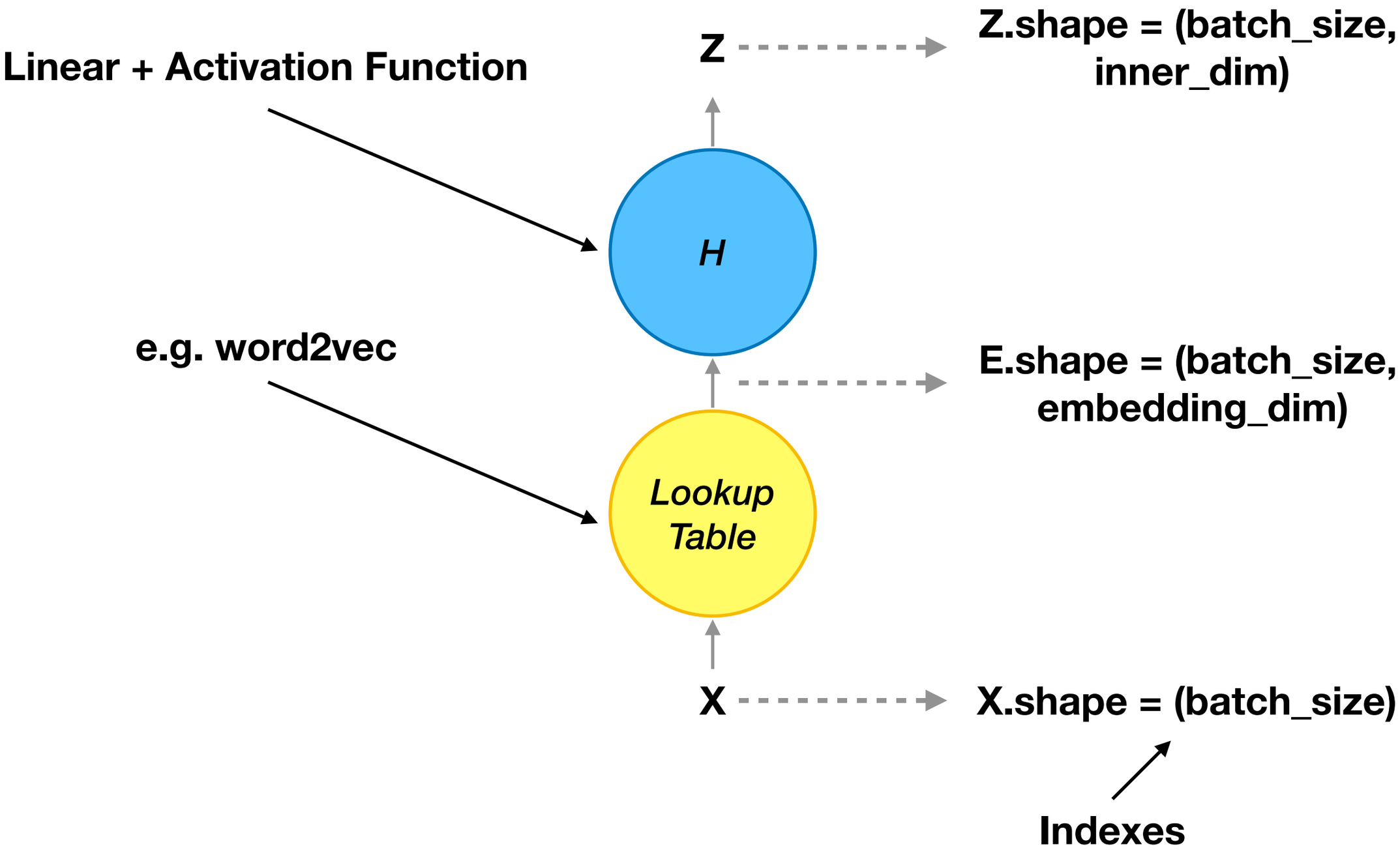
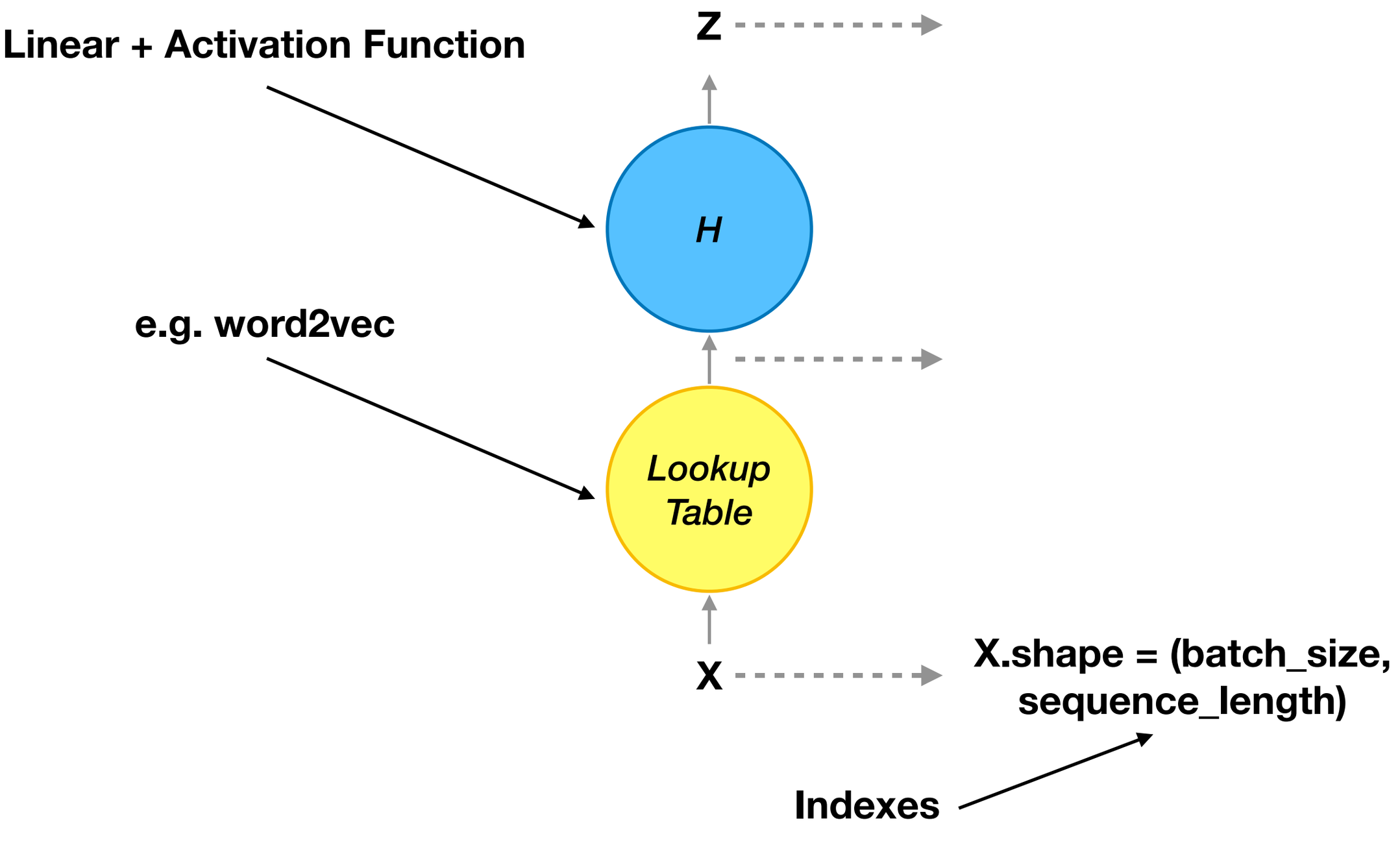
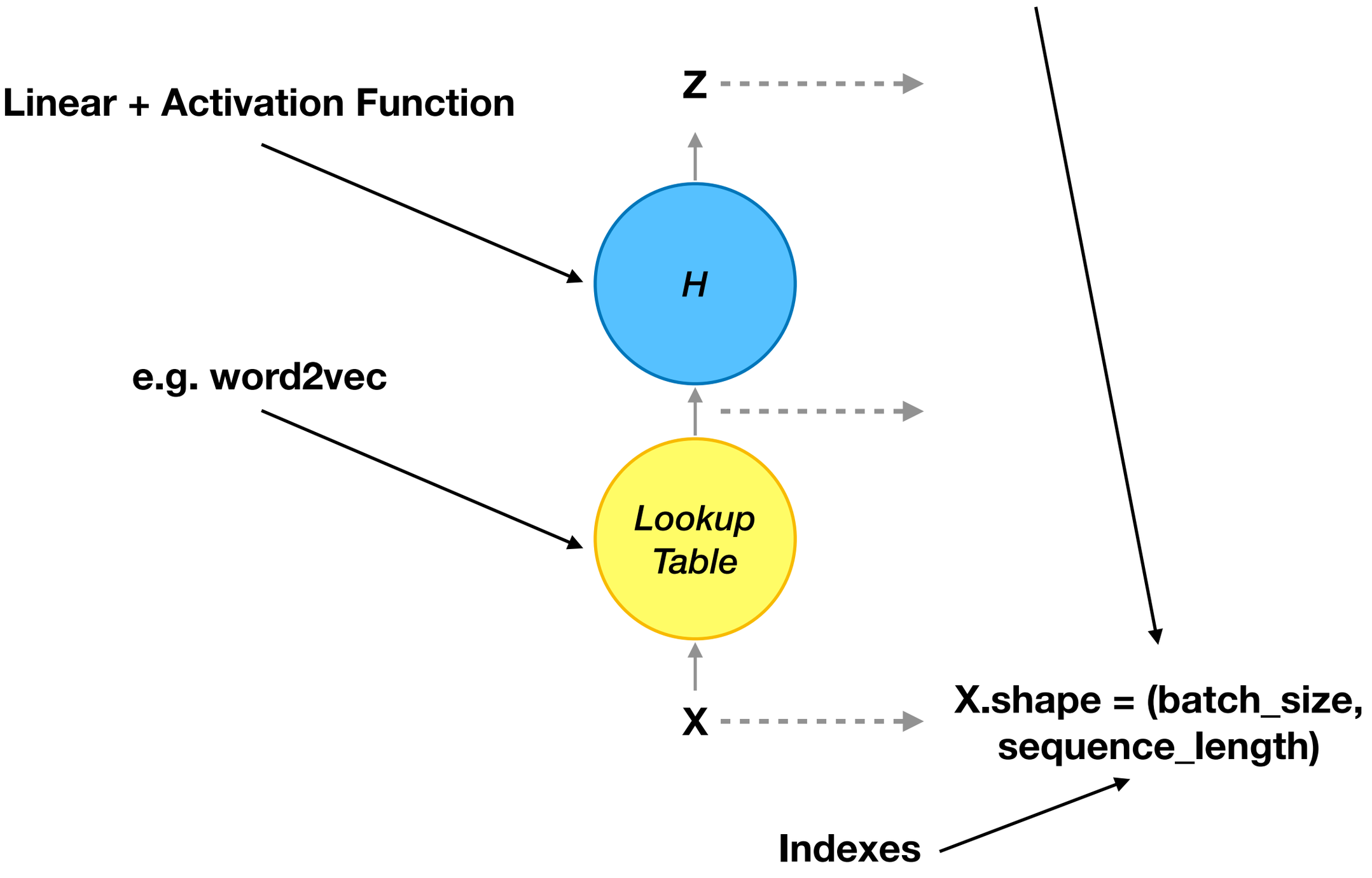


Neural Network



Neural Network

What if we have different lengths?



Padding

[Мама, мыла, раму]

[Покупать, новый, телефон, затратно]

[Вау]

[Мне, очень, не, нравится ваш, банк]

Padding

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[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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[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]

Padding

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

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

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

Indexing → **Collect word2index vocabulary**

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
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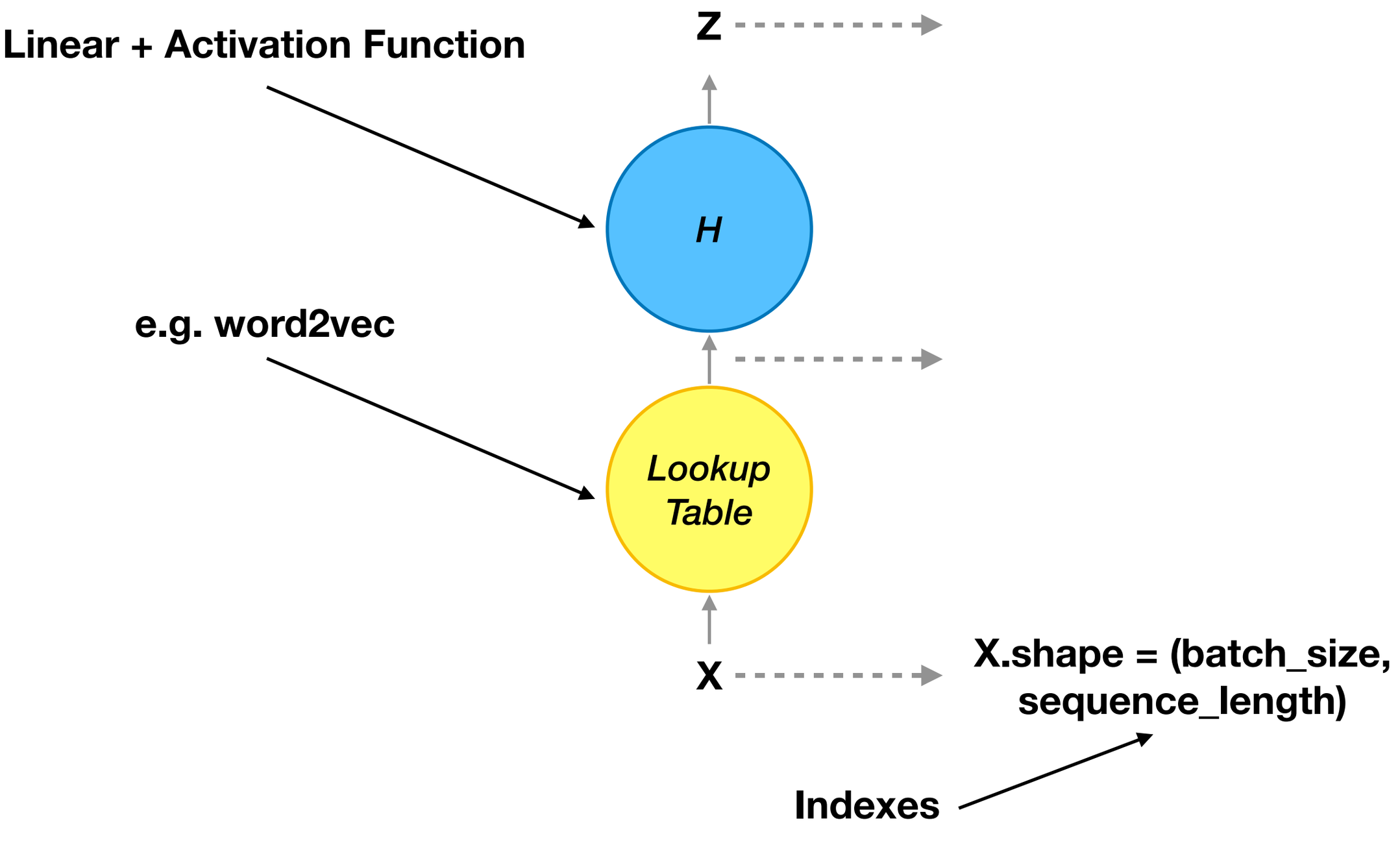
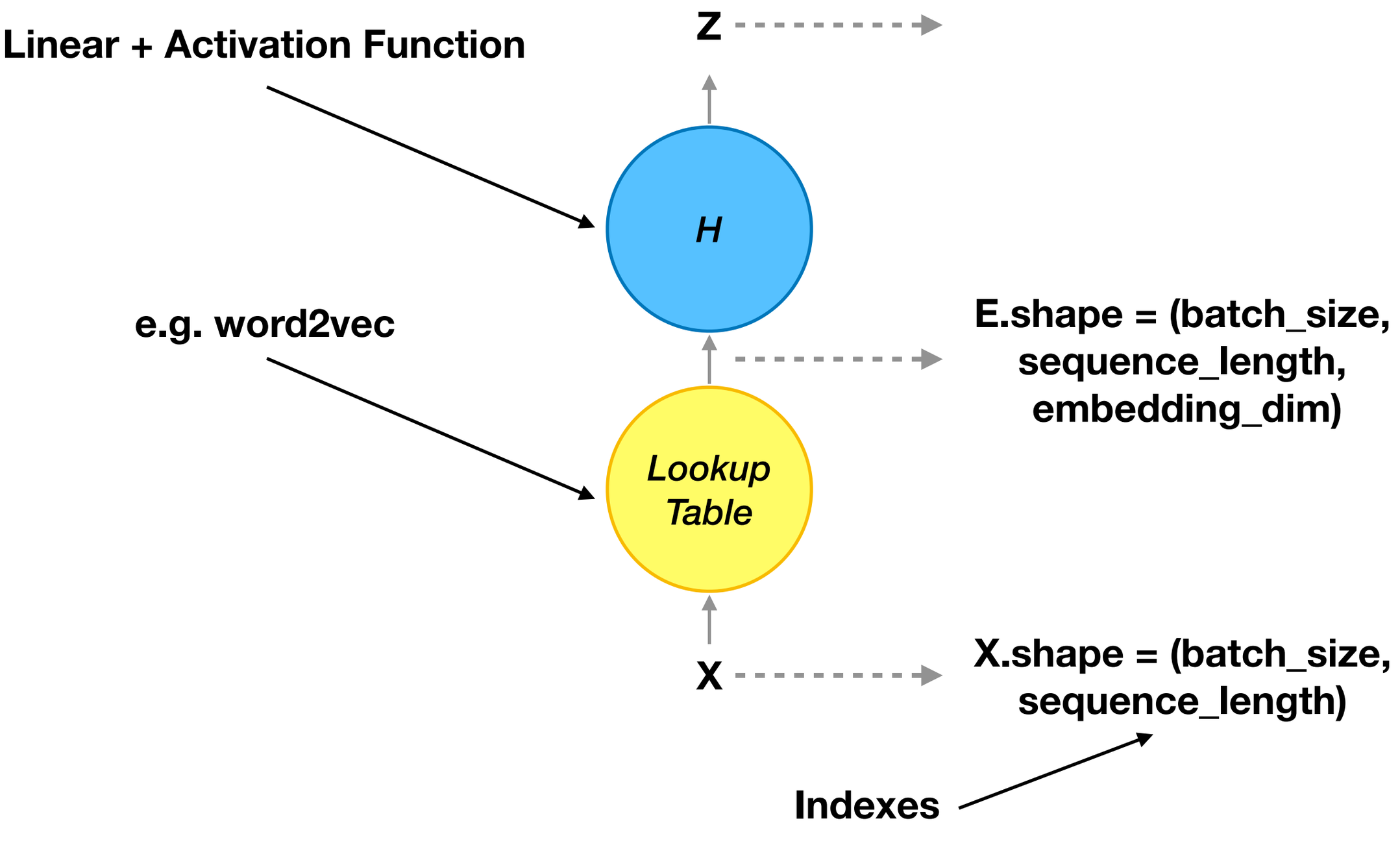
Neural Network



Neural Network



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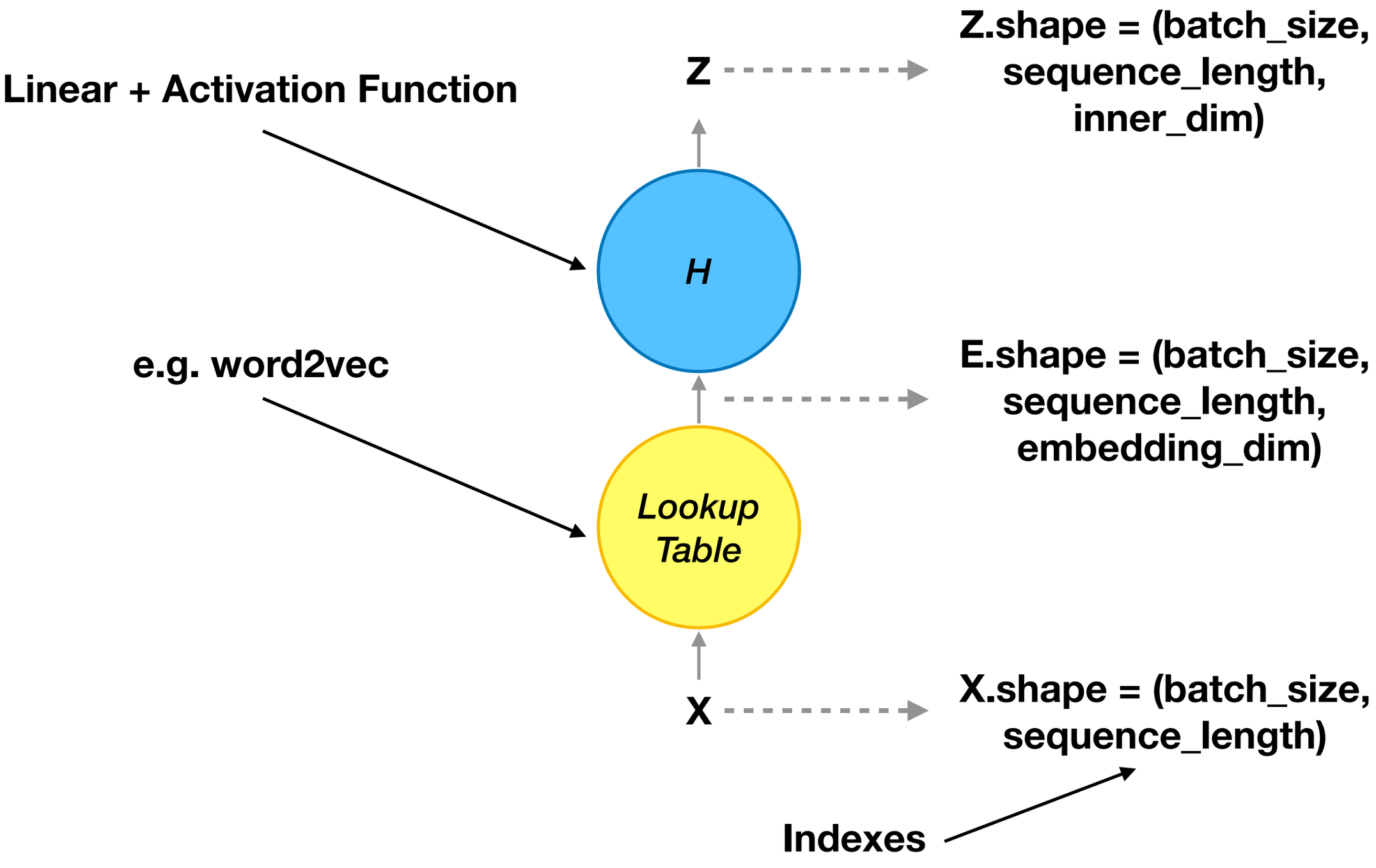

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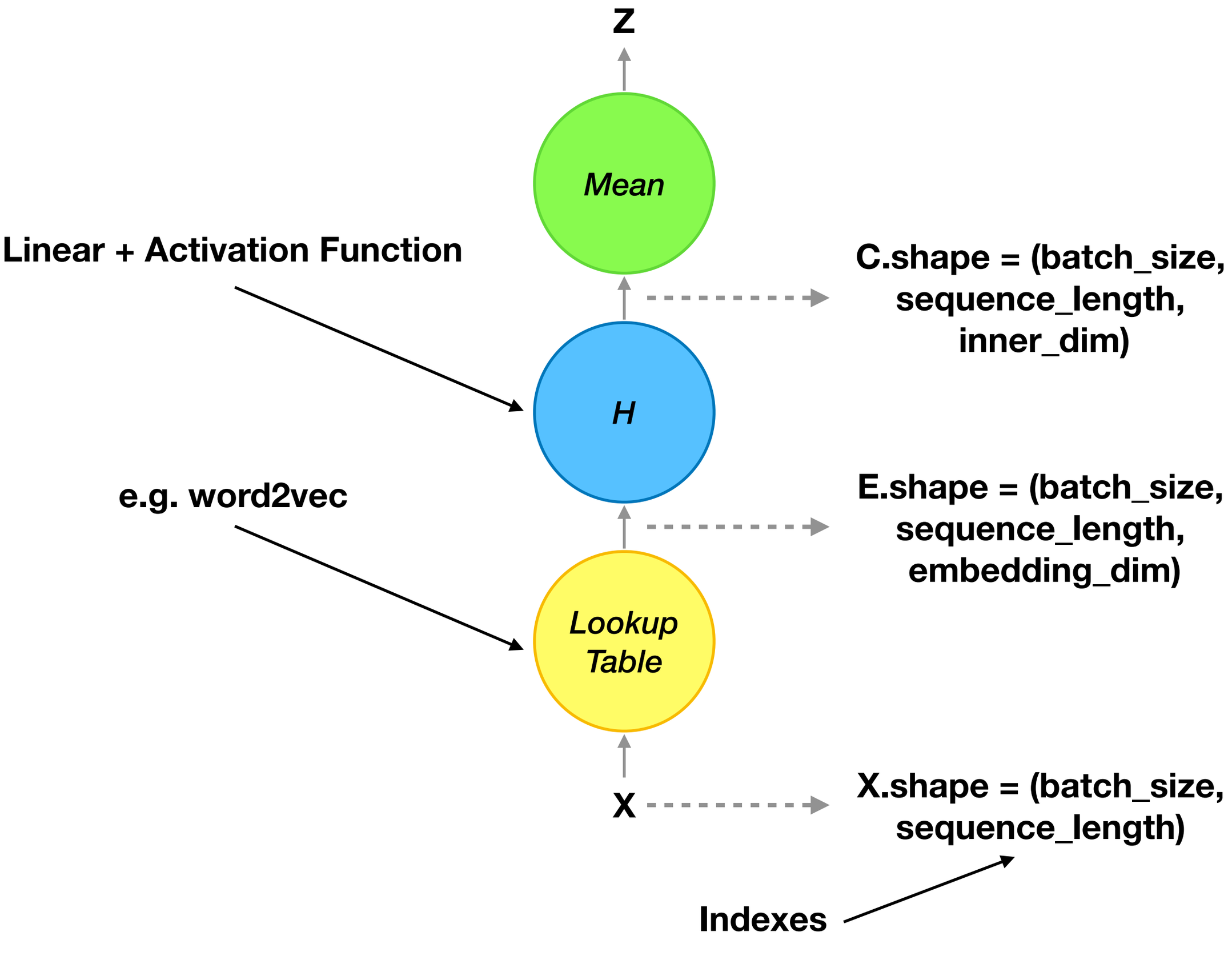

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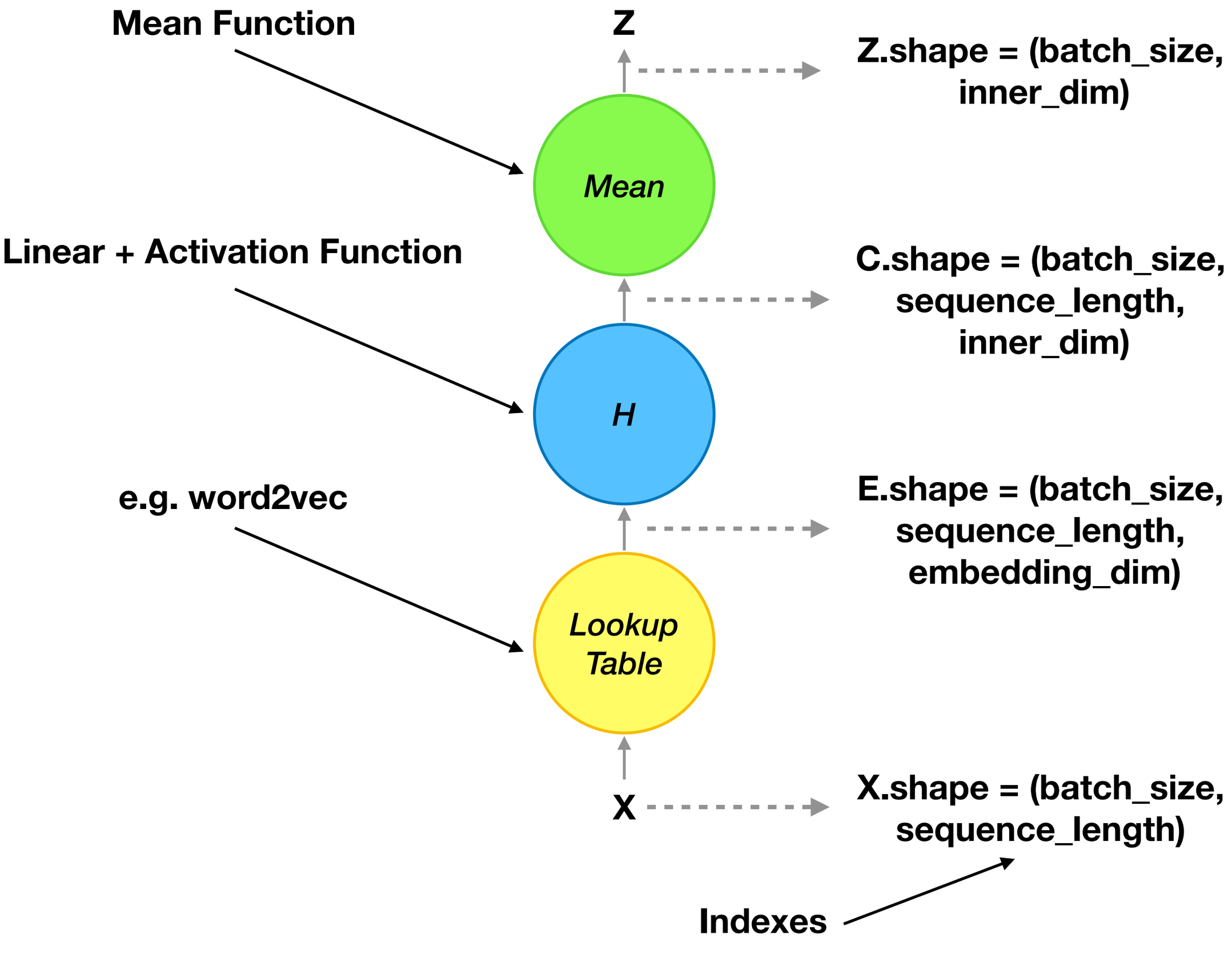

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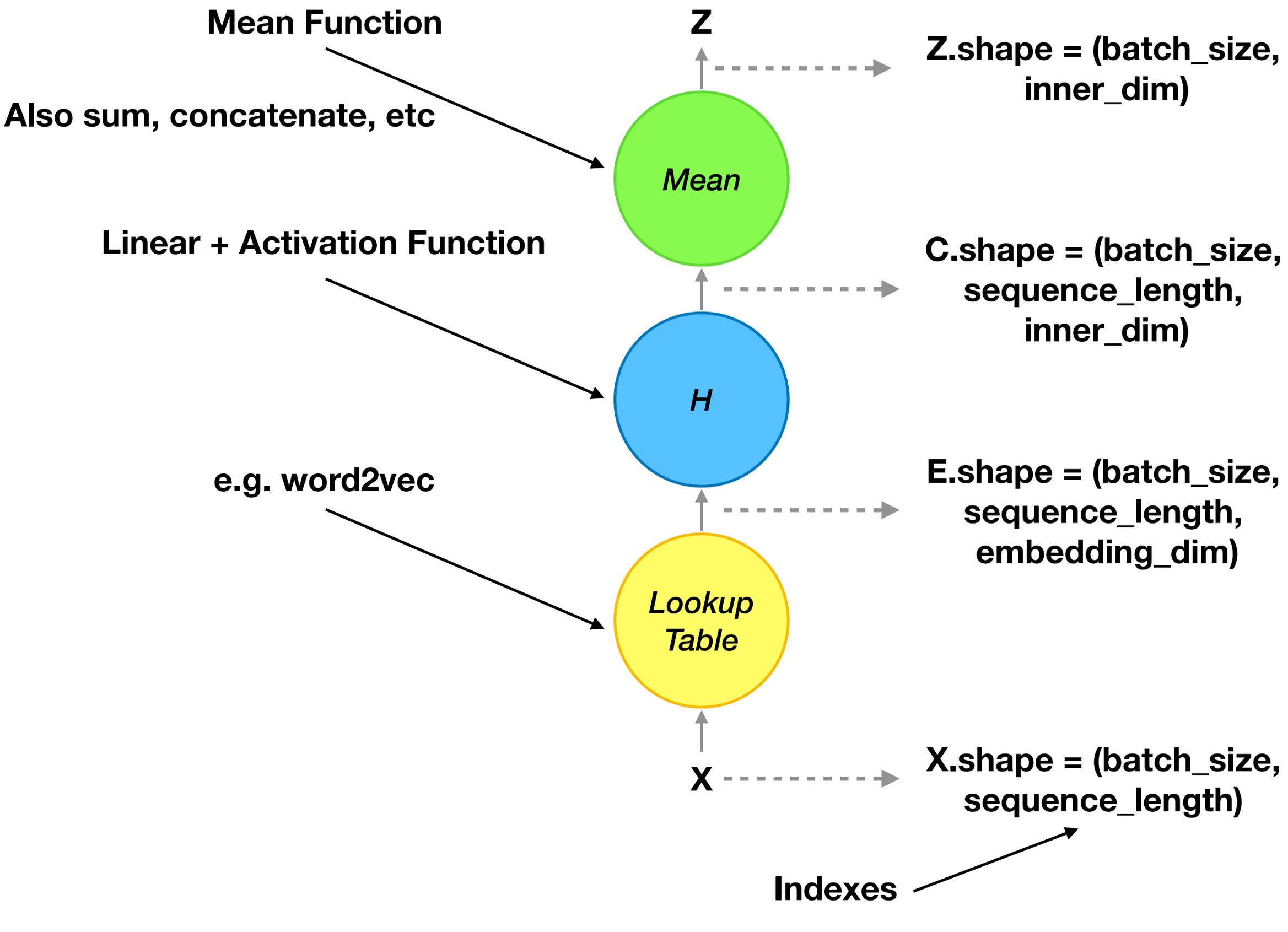

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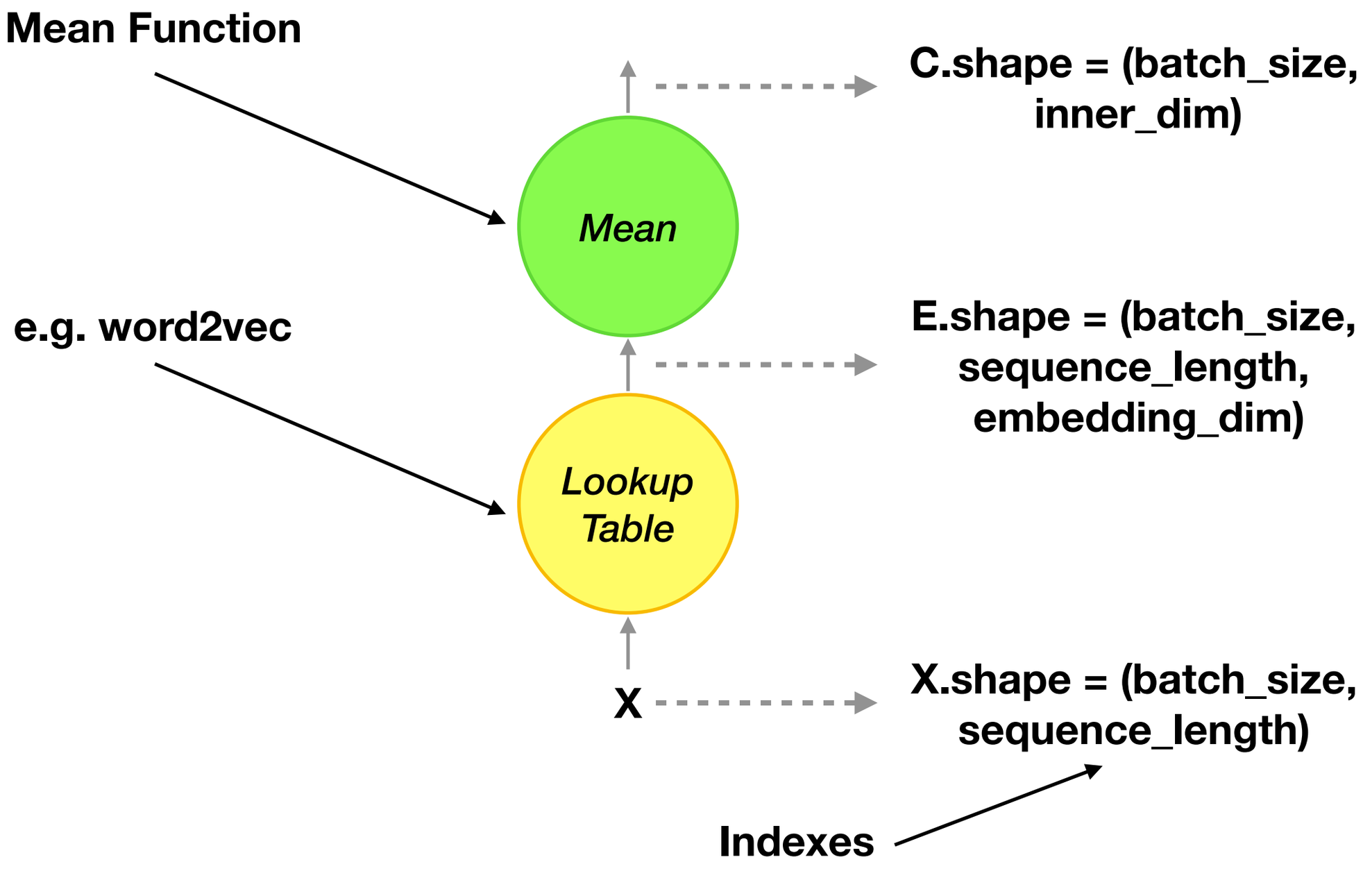

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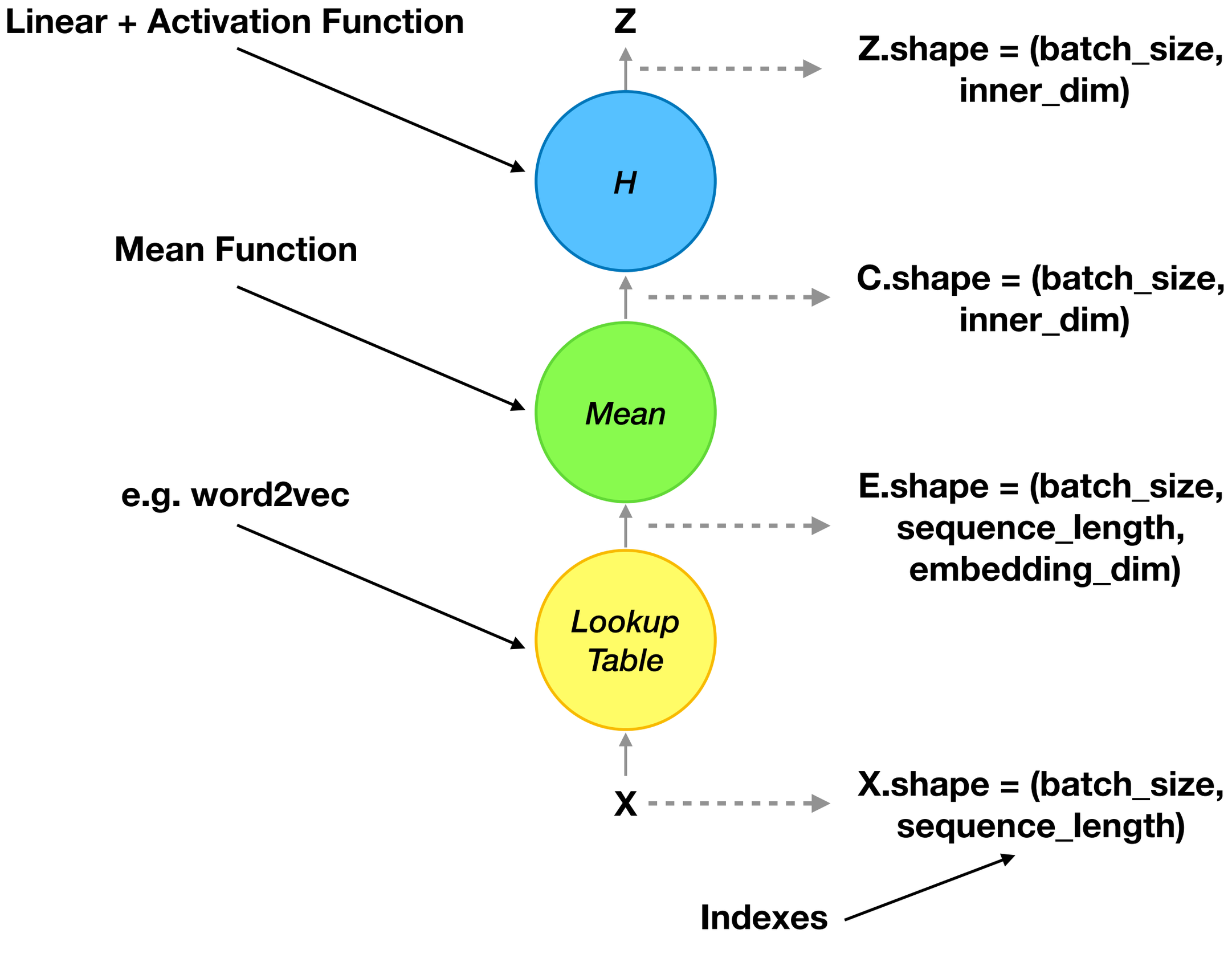
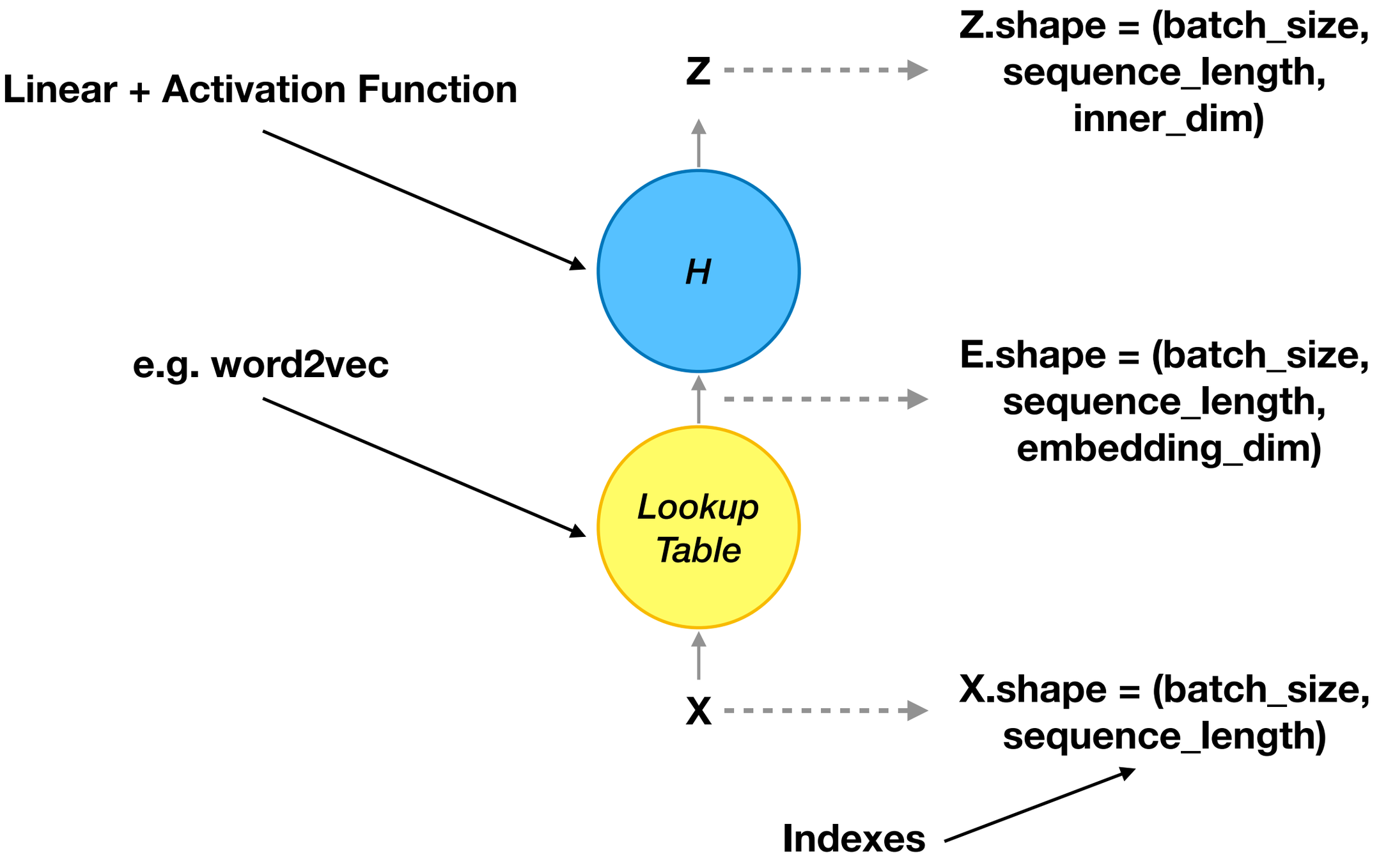
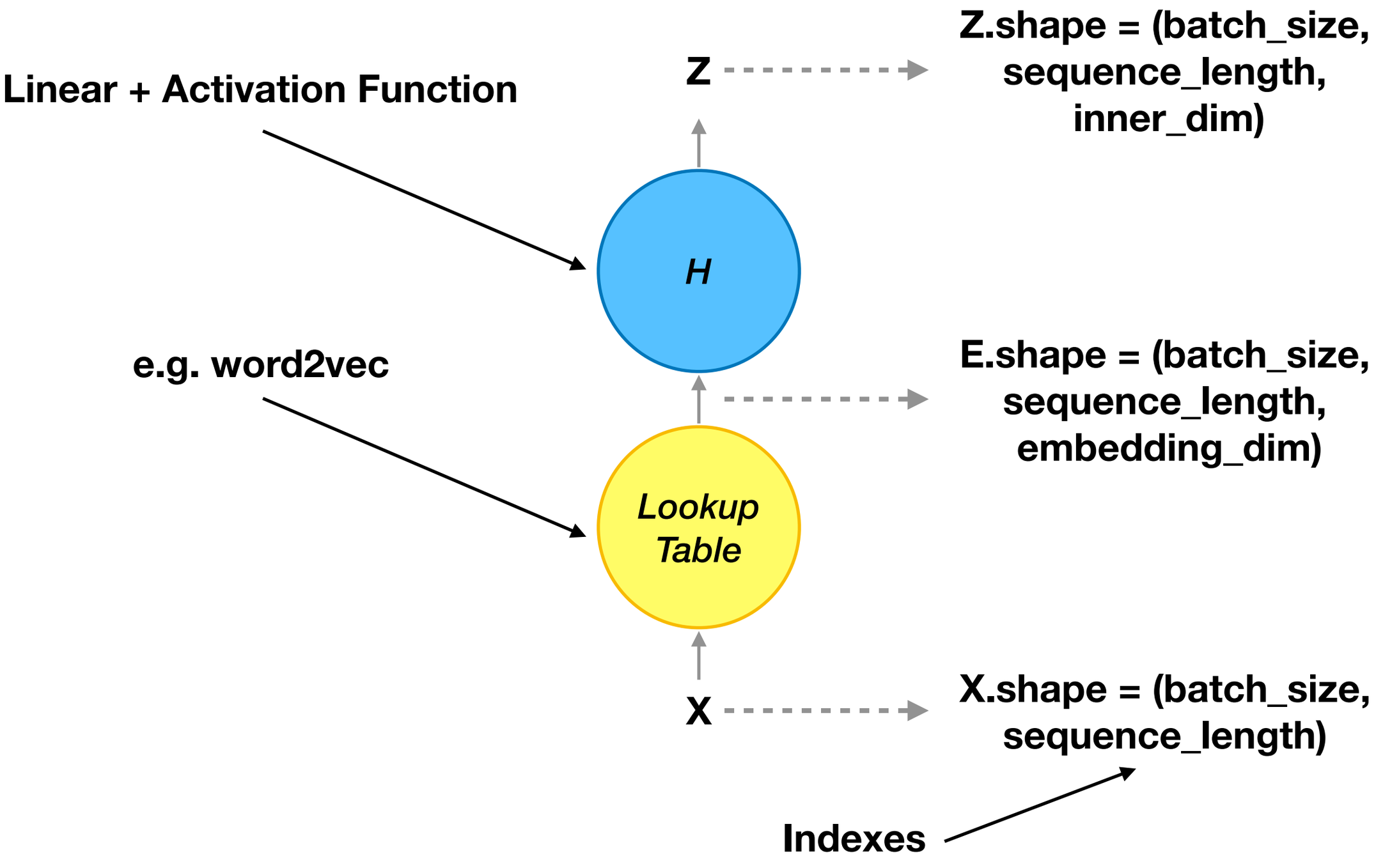


Recurrent Neural Network



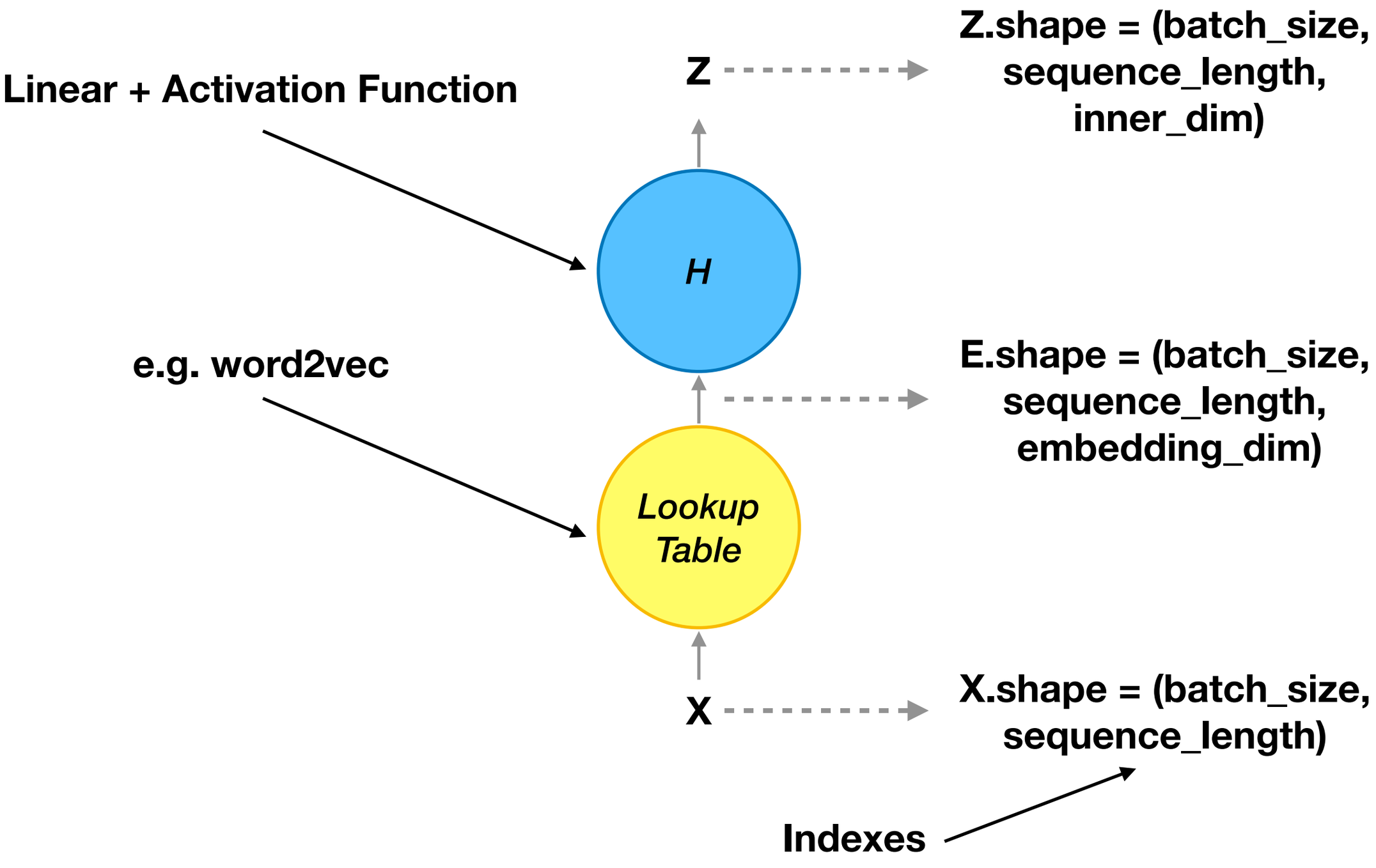
Recurrent Neural Network

Maybe we can take last token?

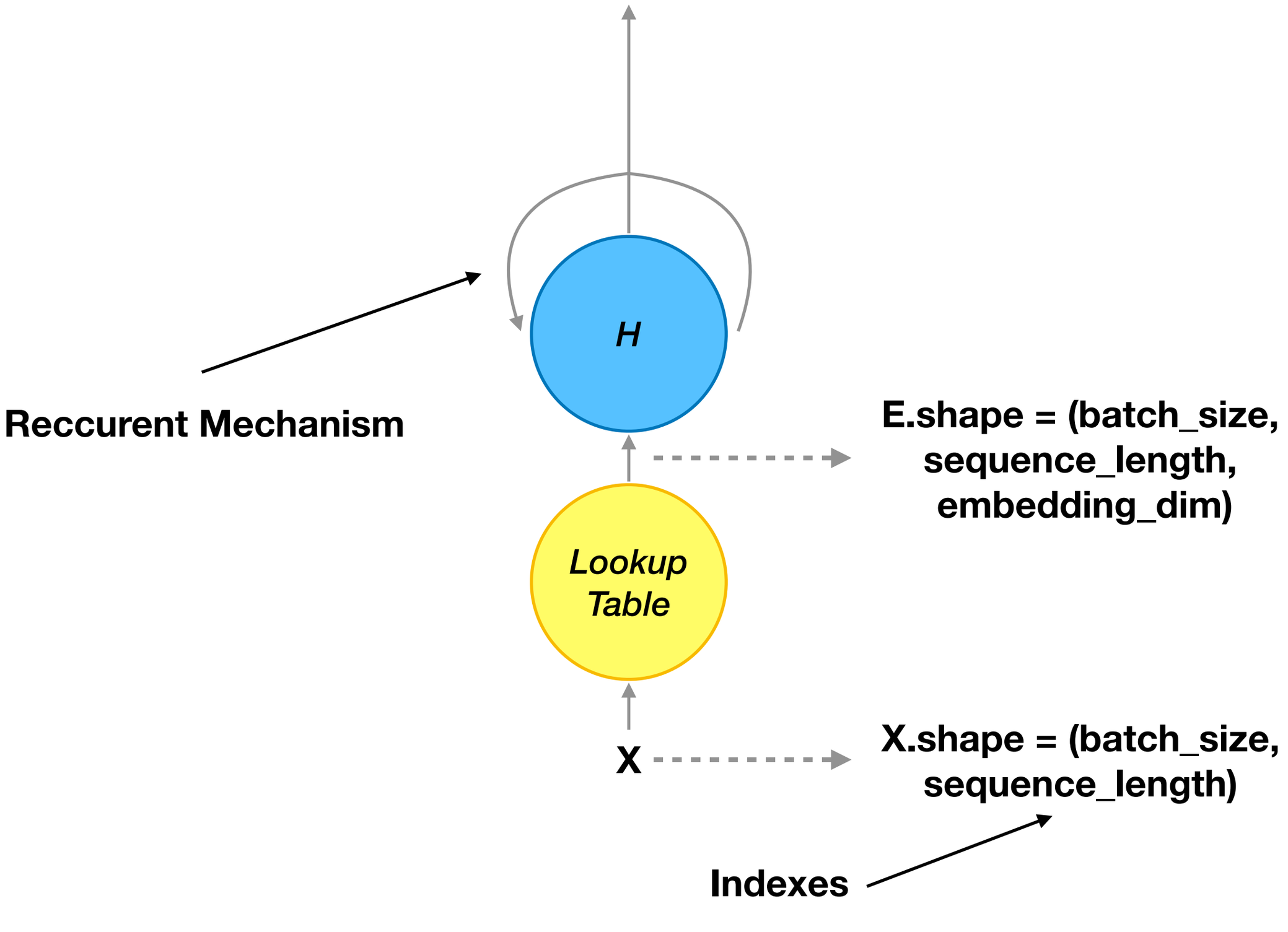


Recurrent Neural Network

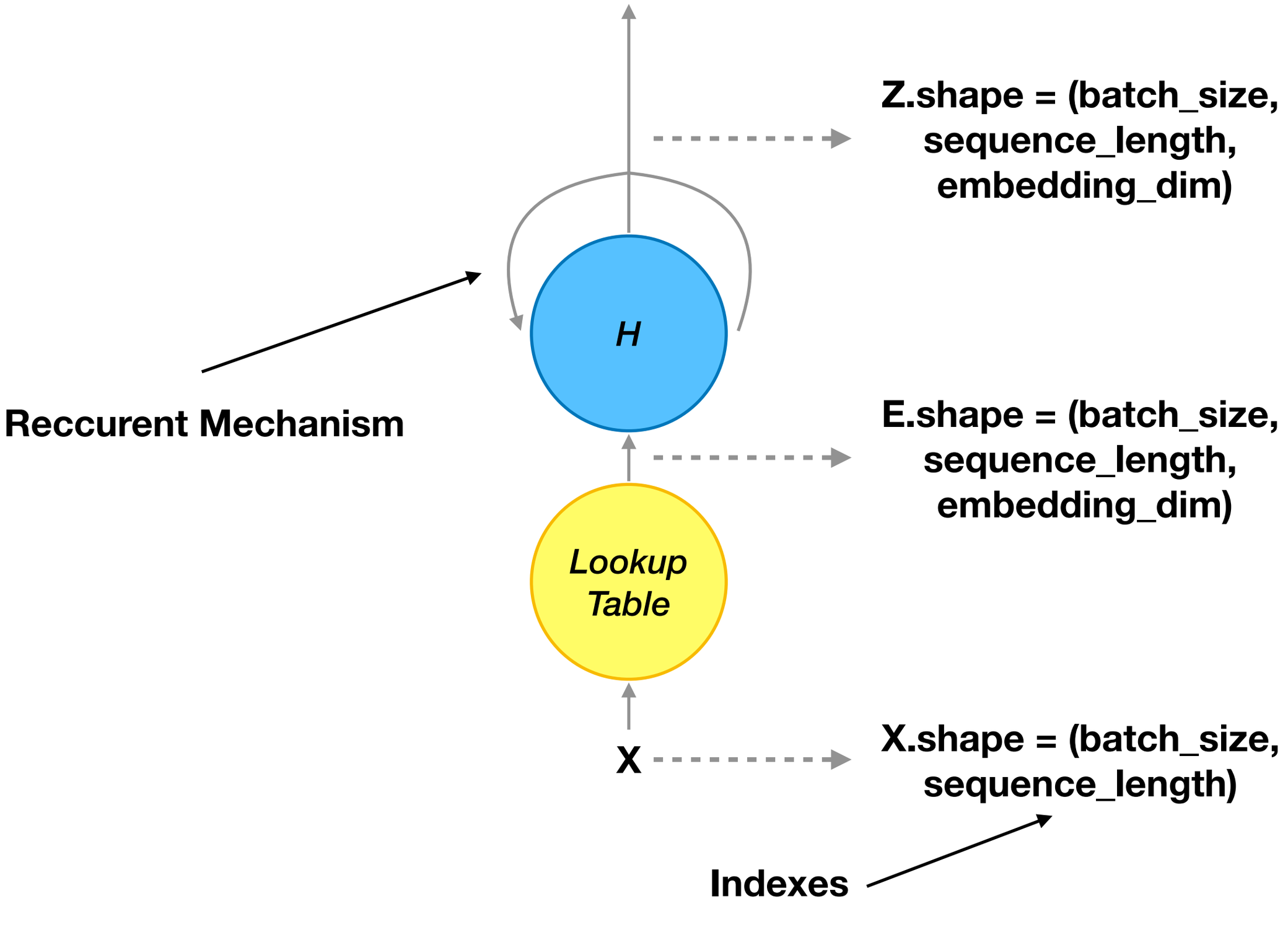
No, because we don’t have information about whole sentence



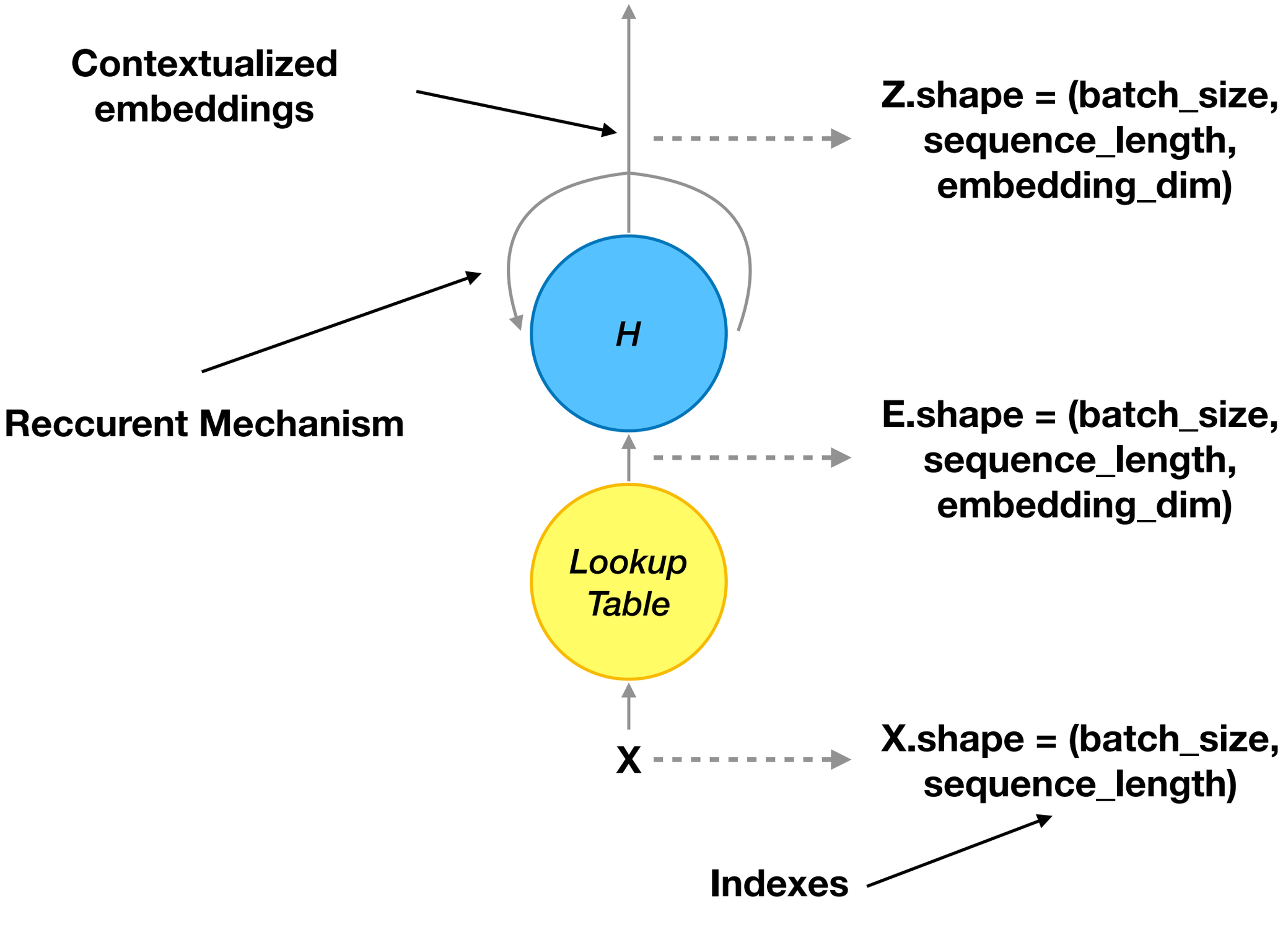
Recurrent Neural Network



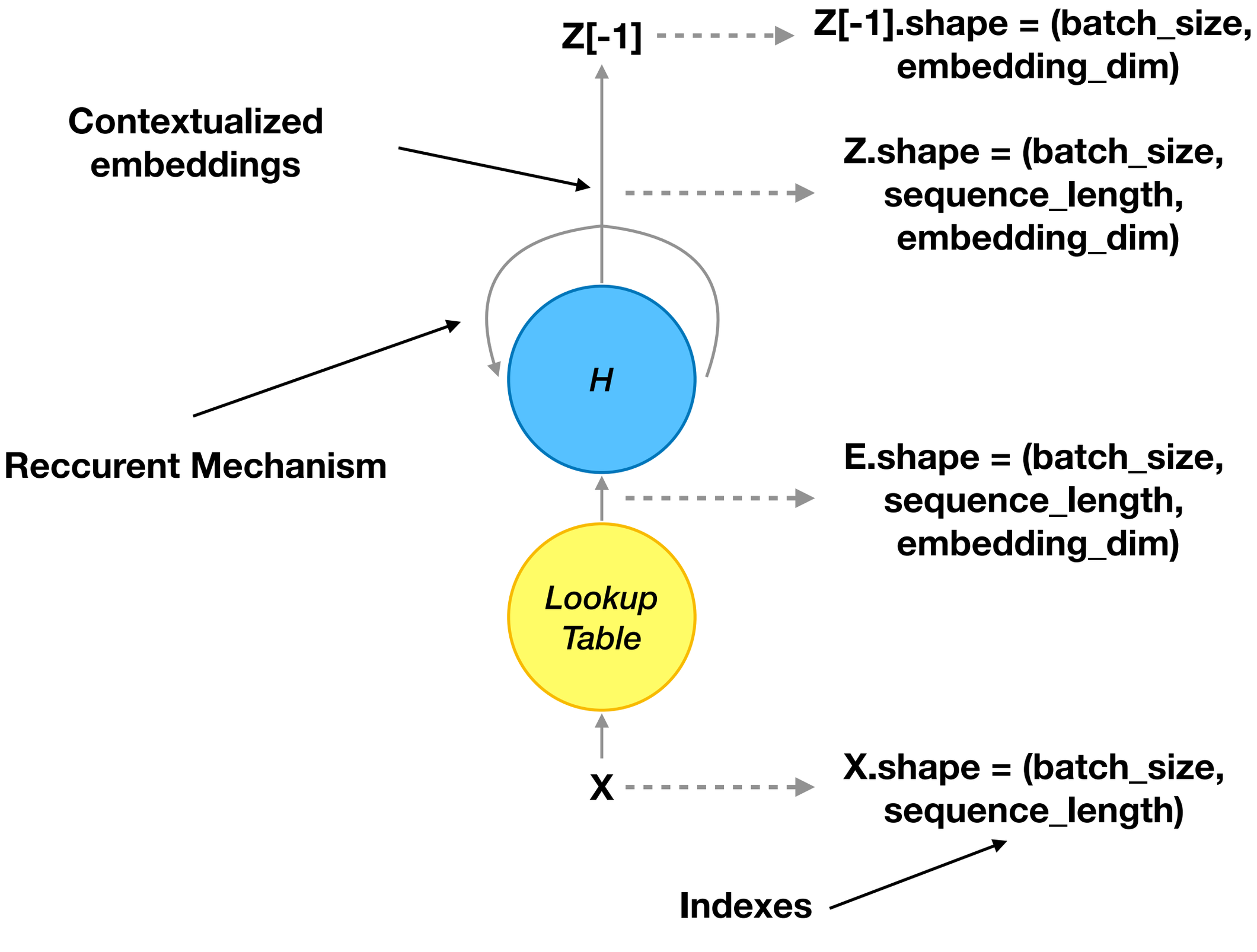
Recurrent Neural Network



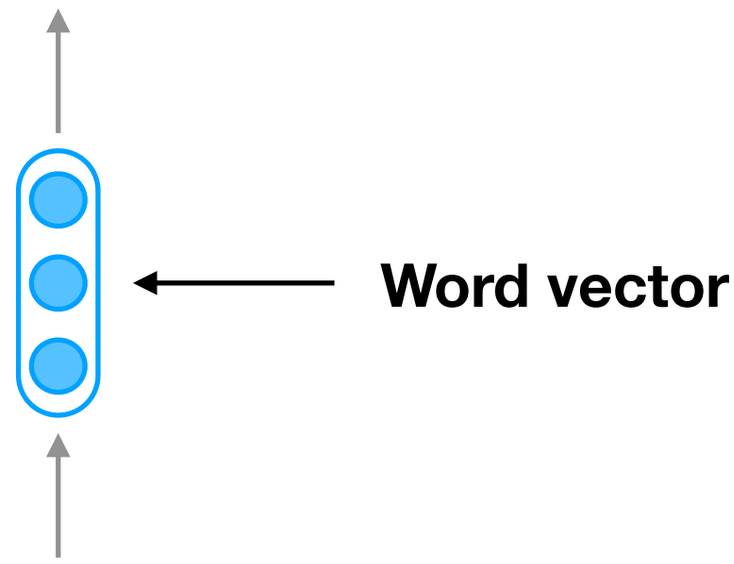
Recurrent Neural Network



Recurrent Neural Network



Reccurent Cell



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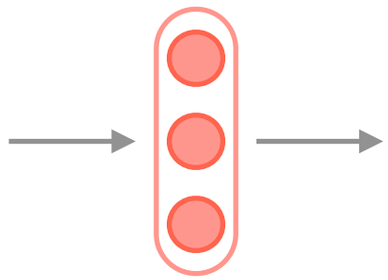

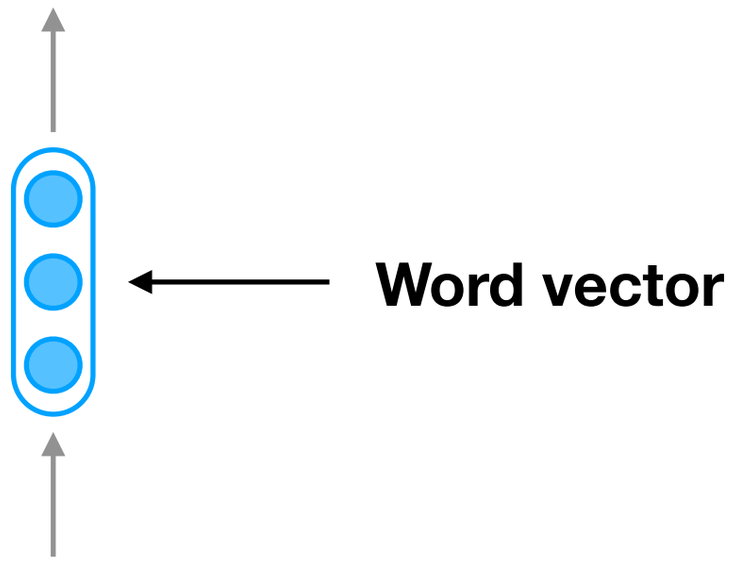

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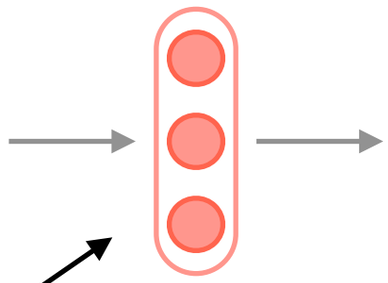
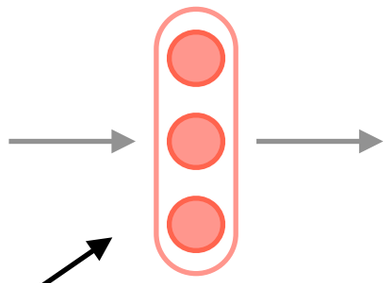


Memory vector

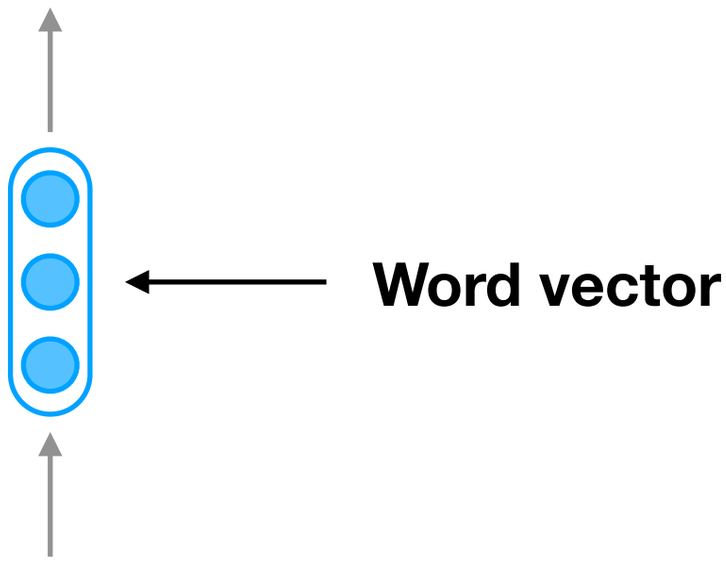
Word vector

Reccurent Cell

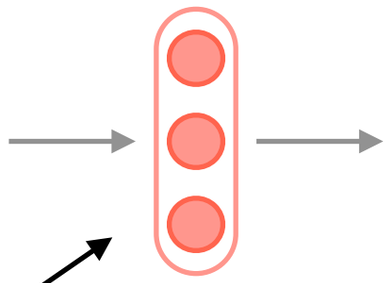


Memory vector

At first timestamp can be zeros



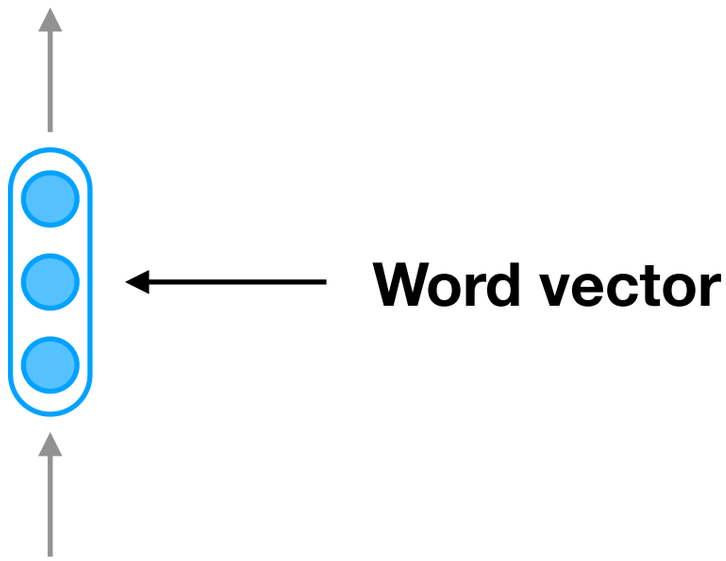
Reccurent Cell



Memory vector

At first timestamp can be zeros

Or can be learnable



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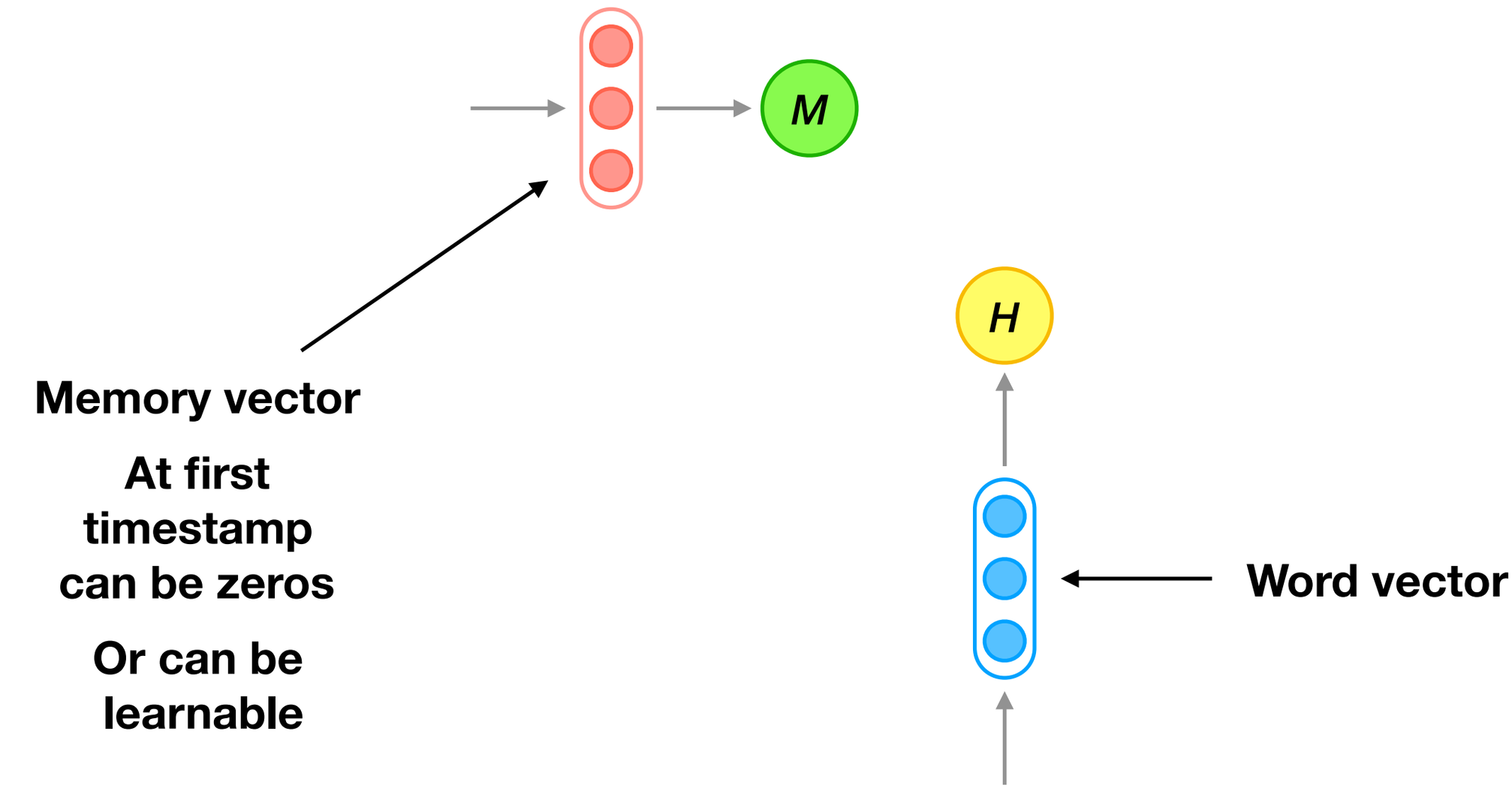

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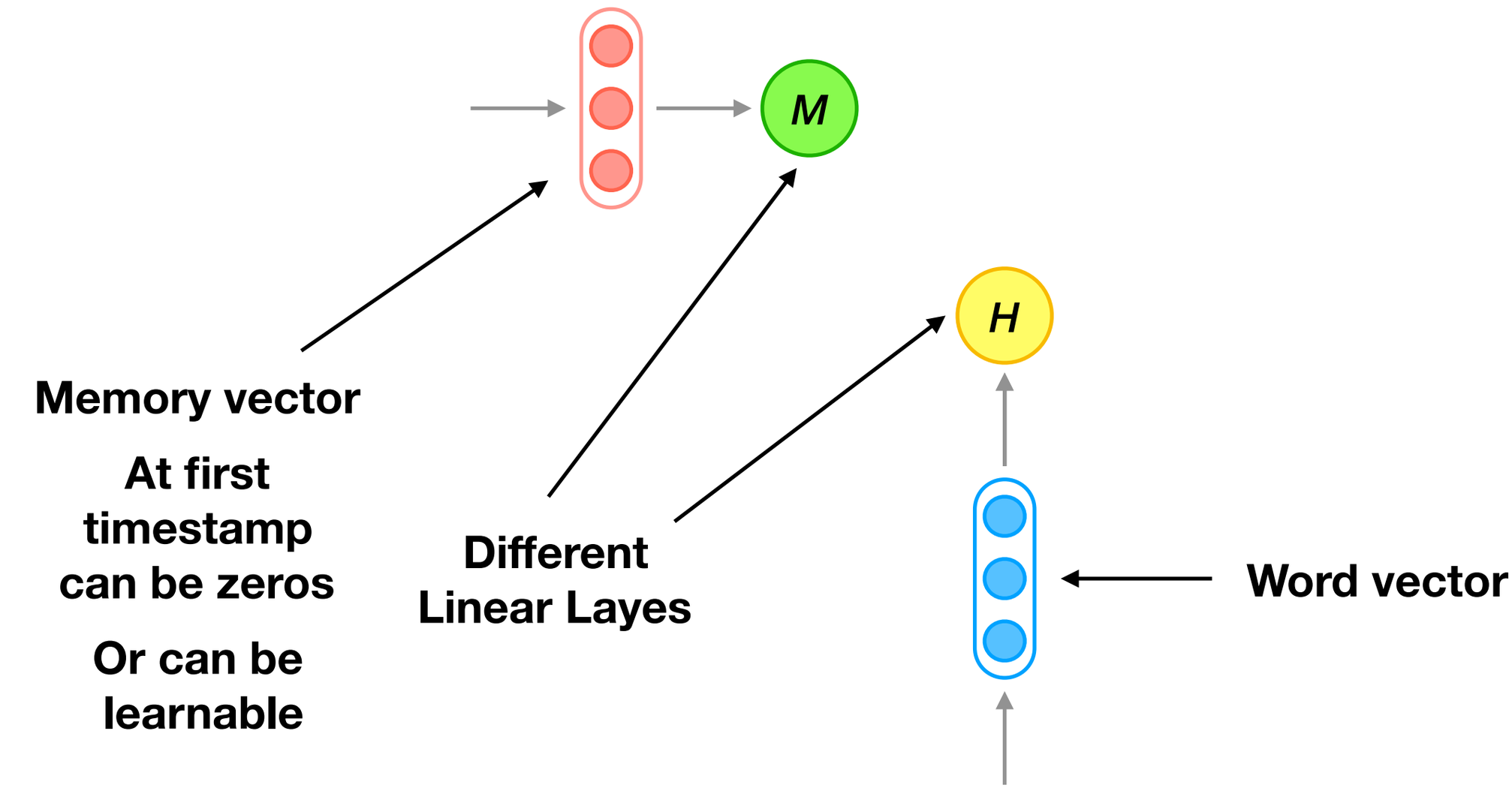

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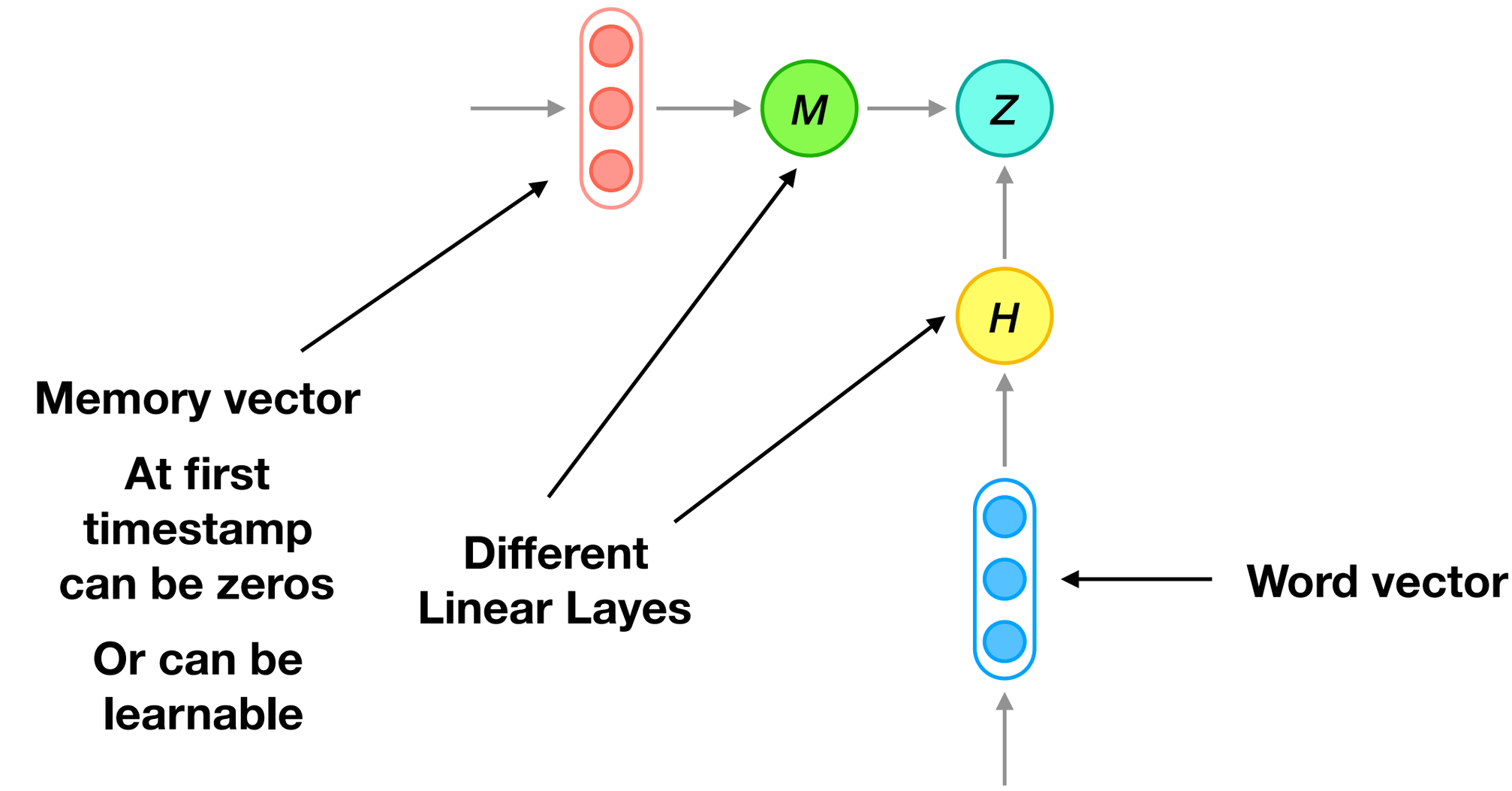

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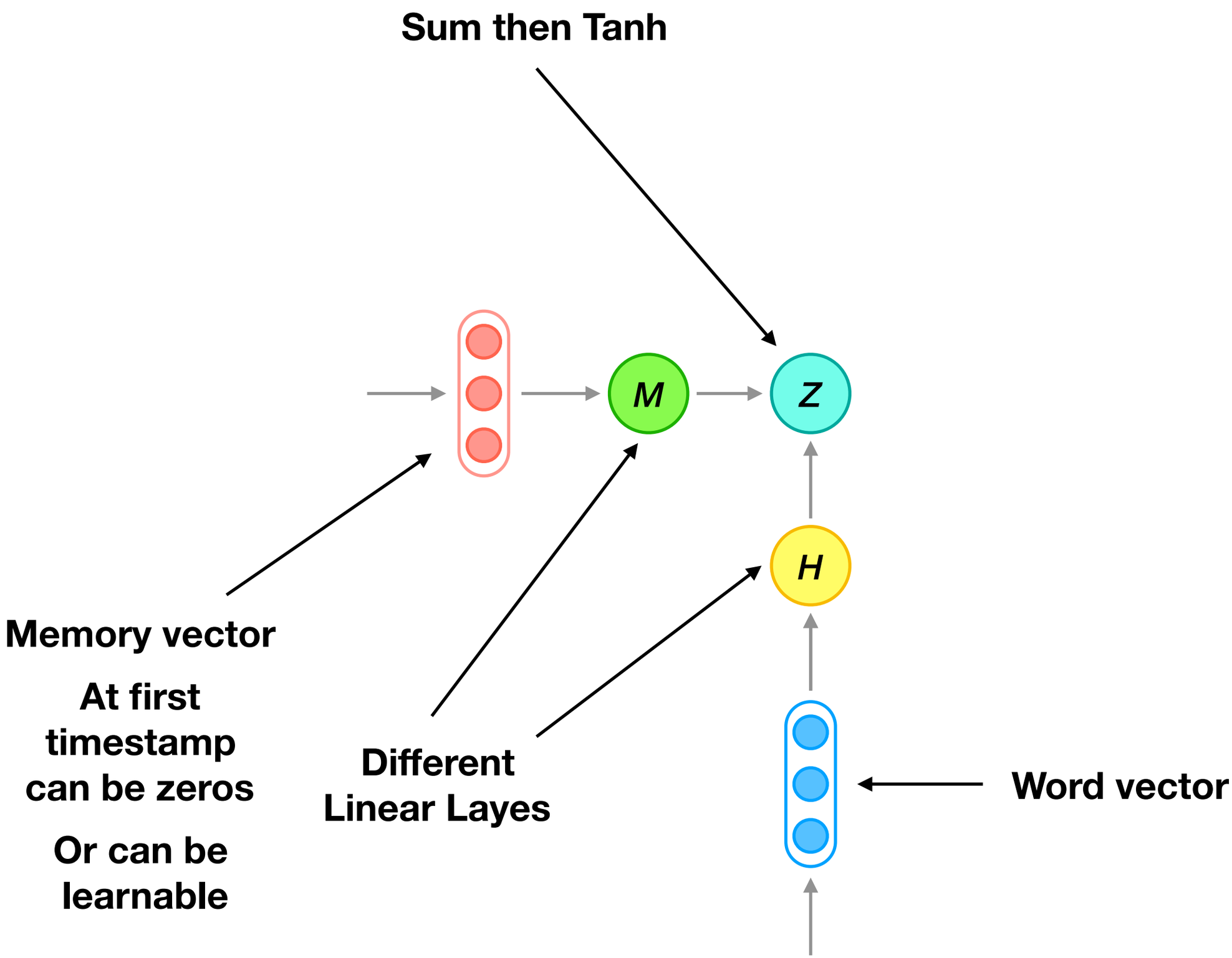

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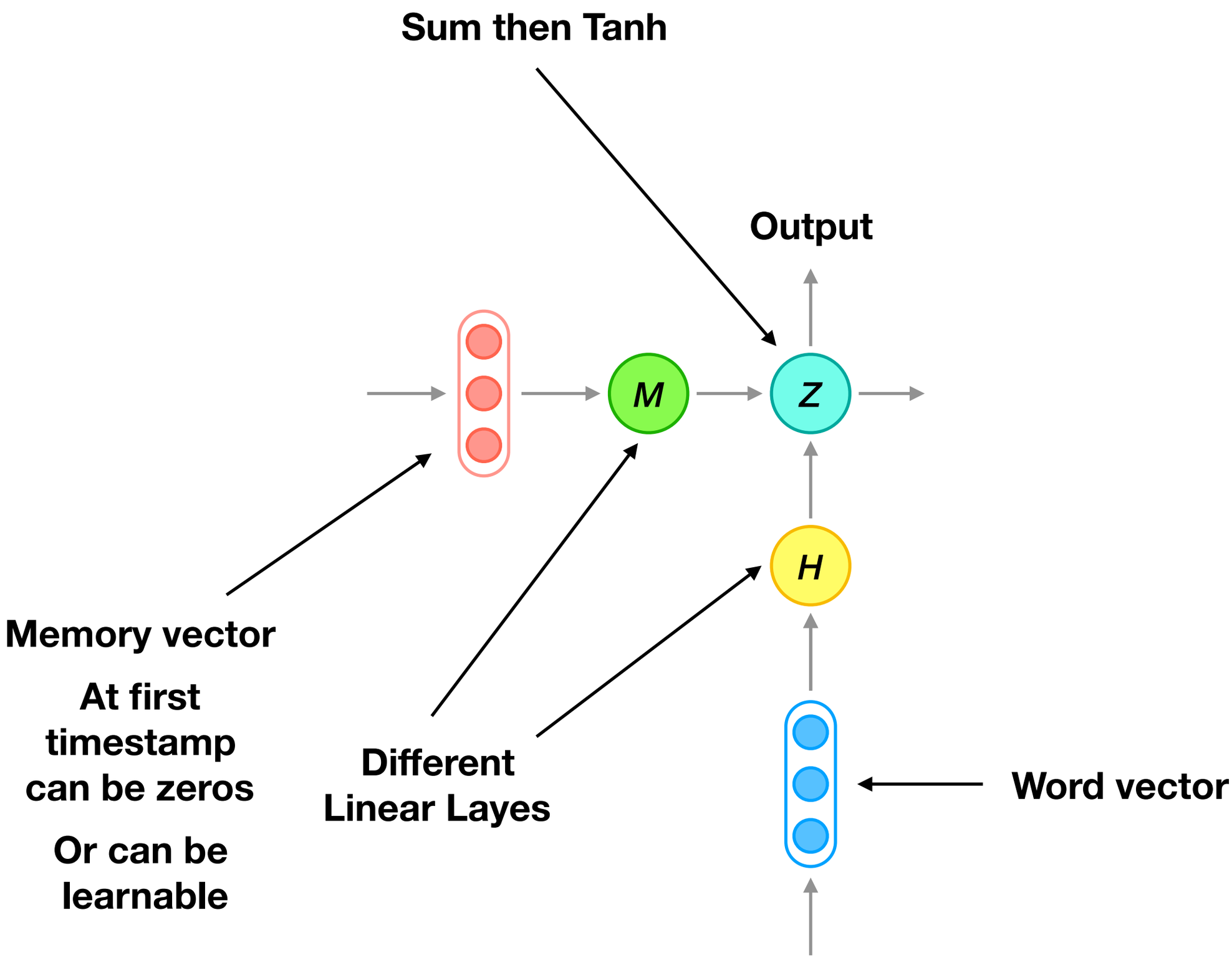

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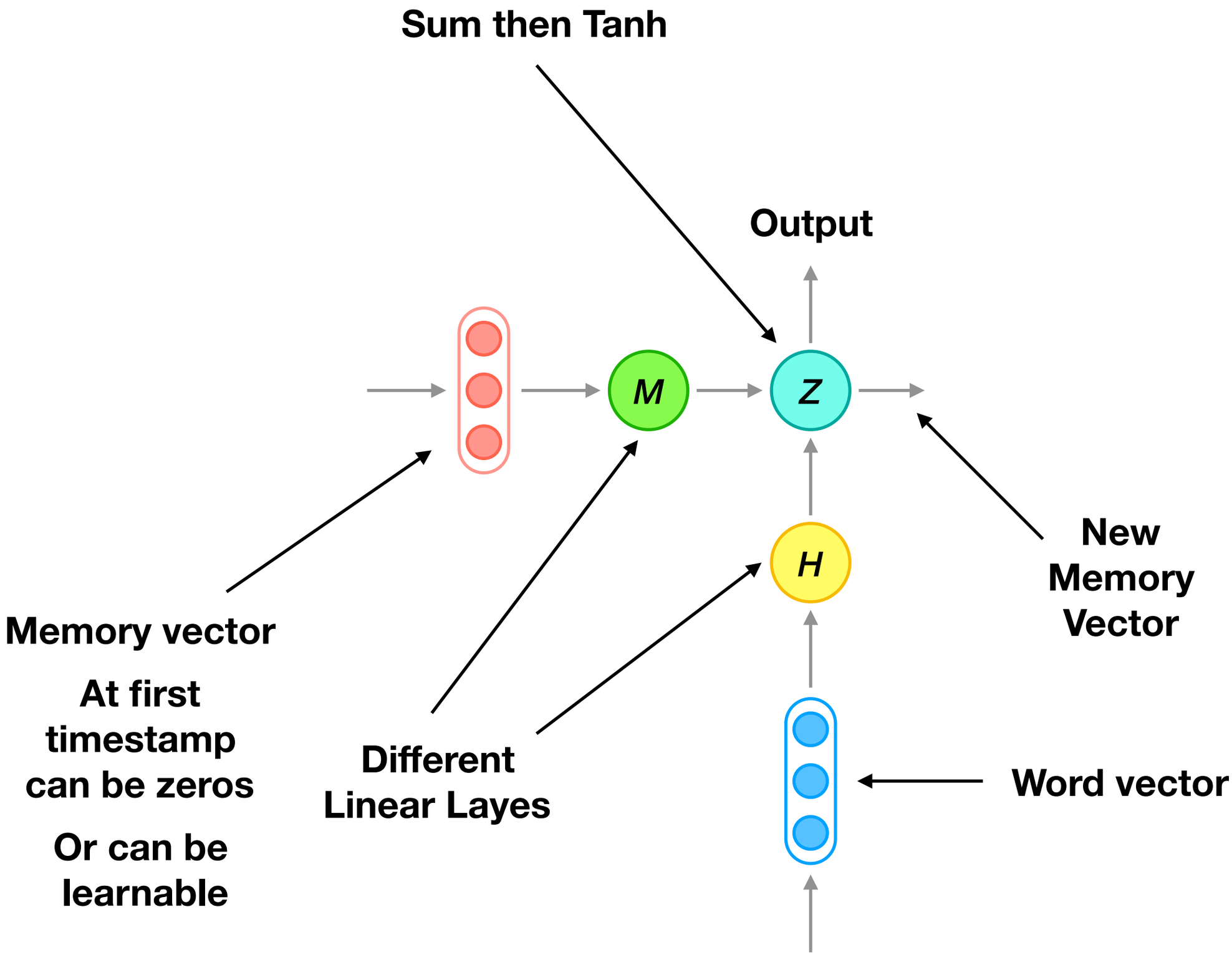
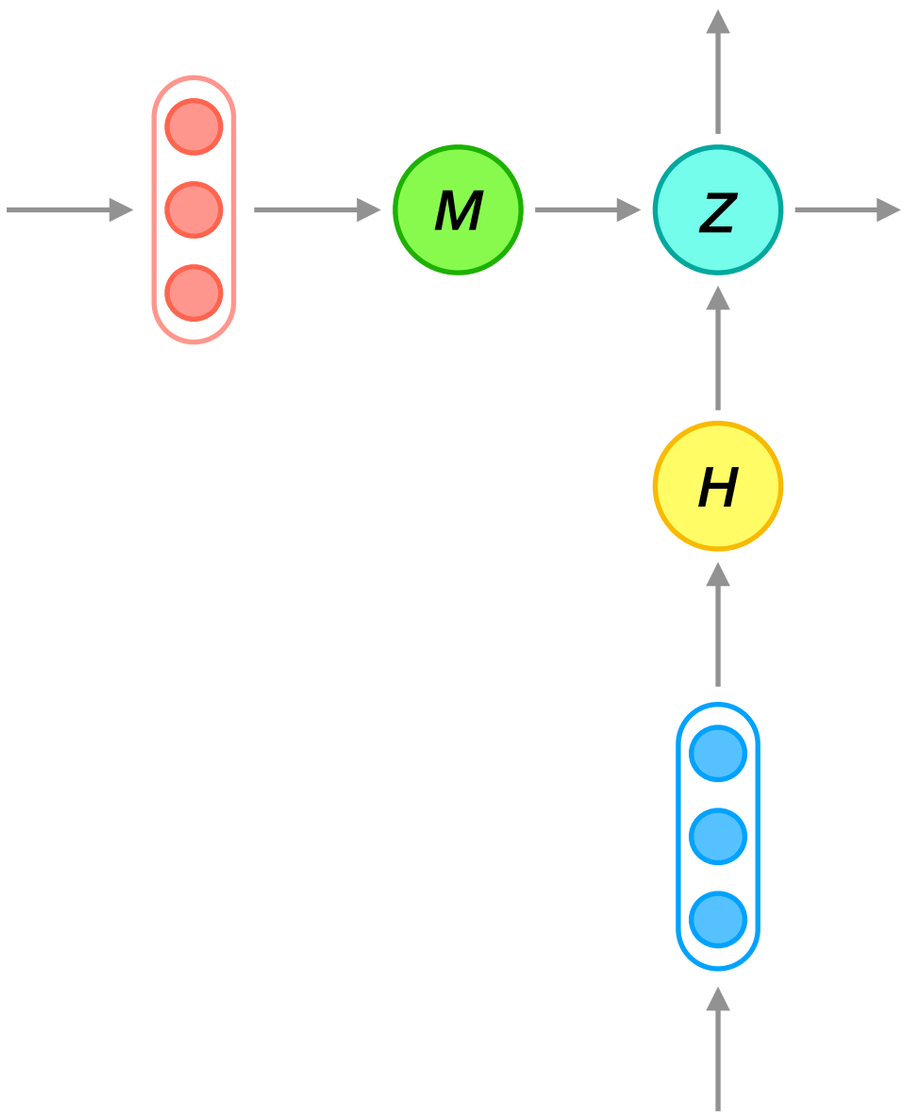
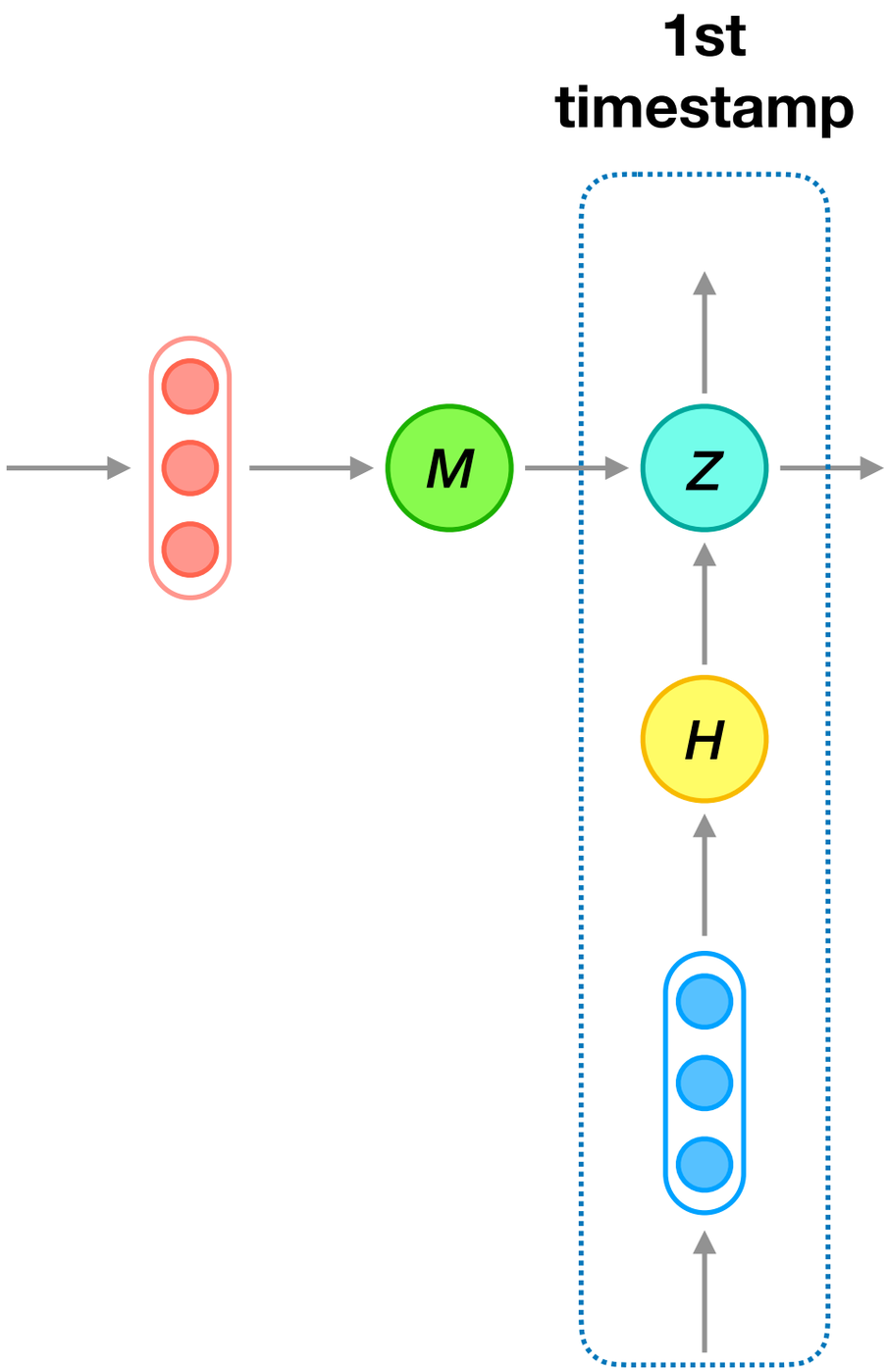


Reccurent Mechanism



Reccurent Mechanism



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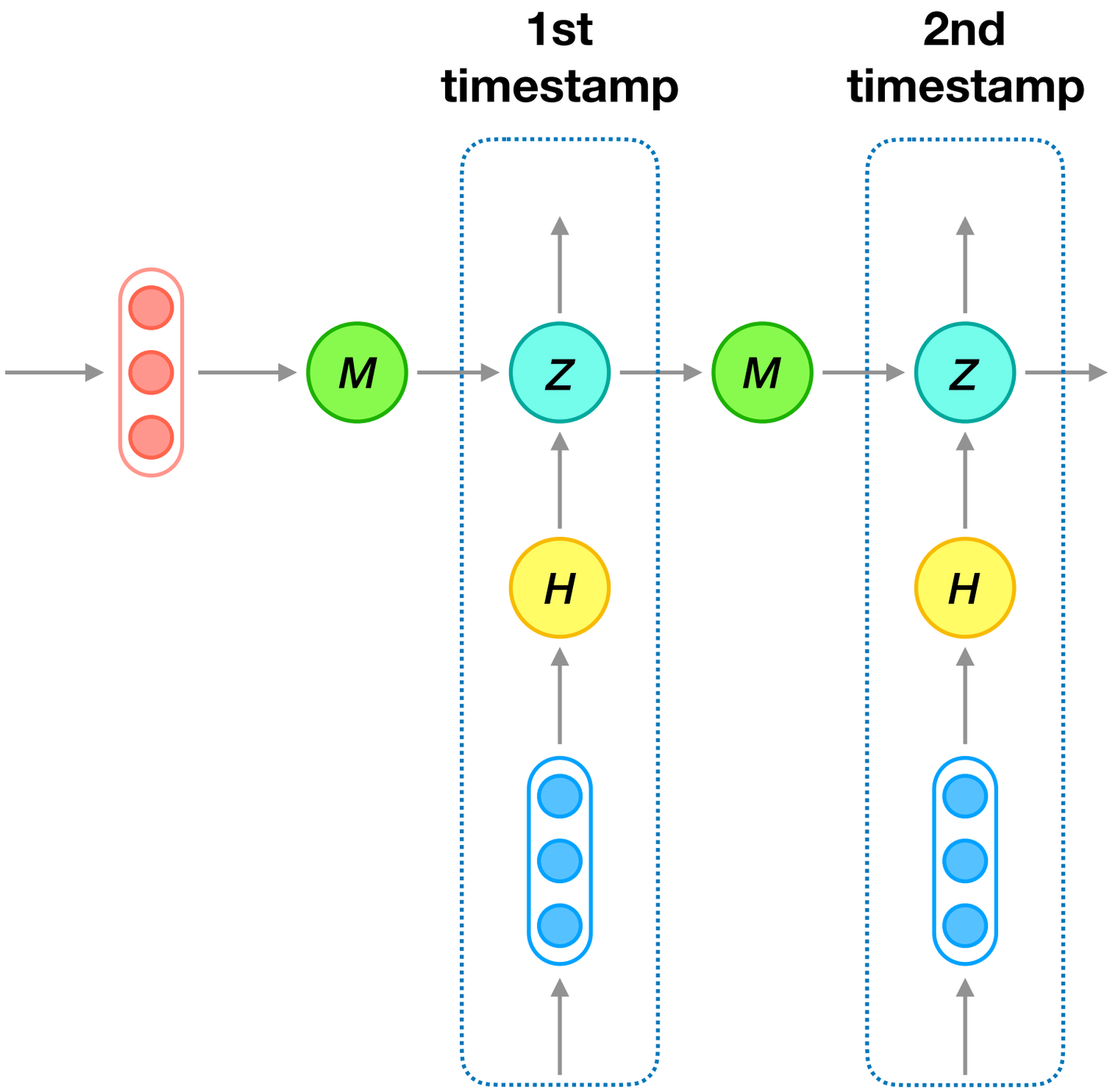

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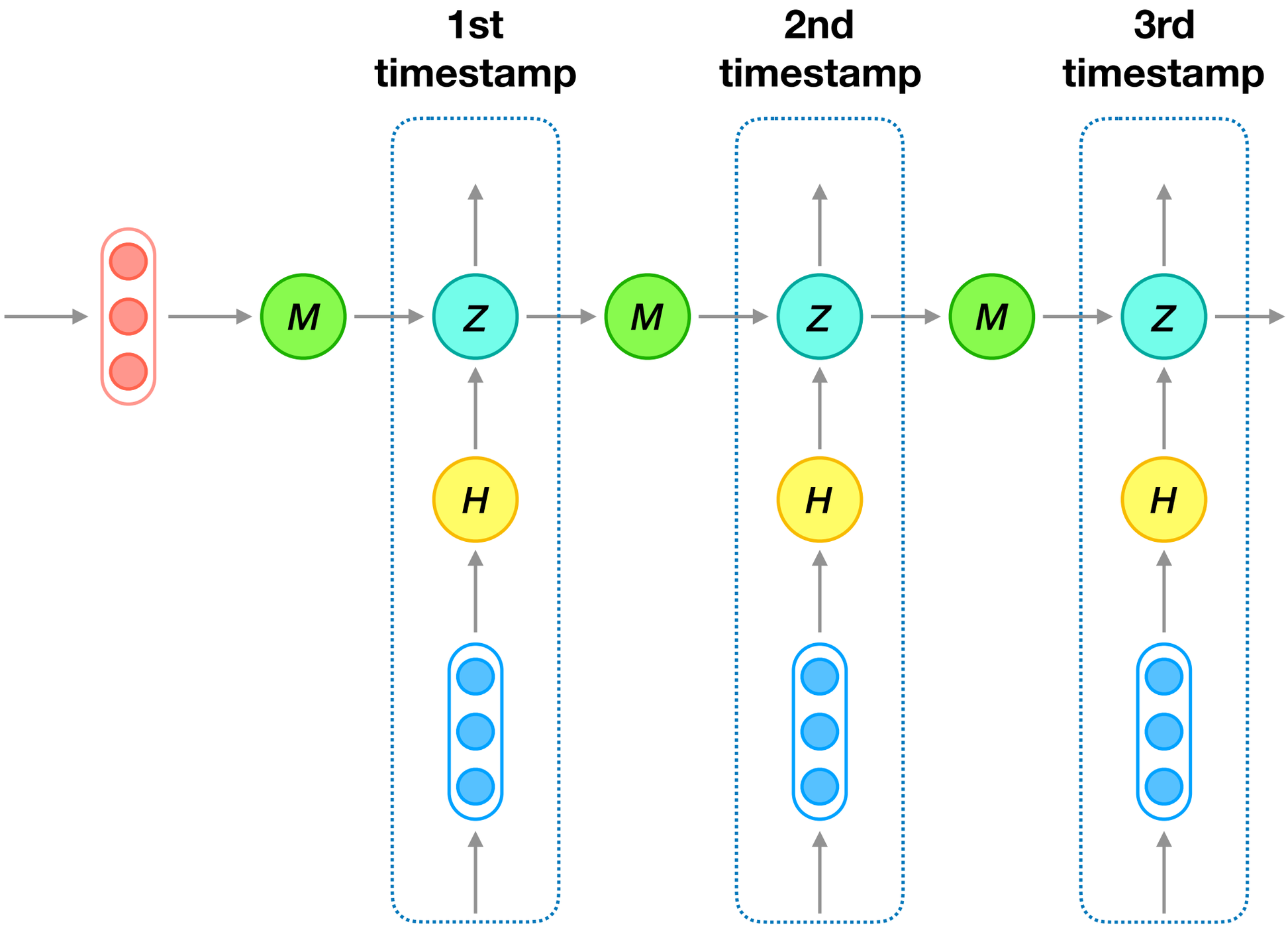

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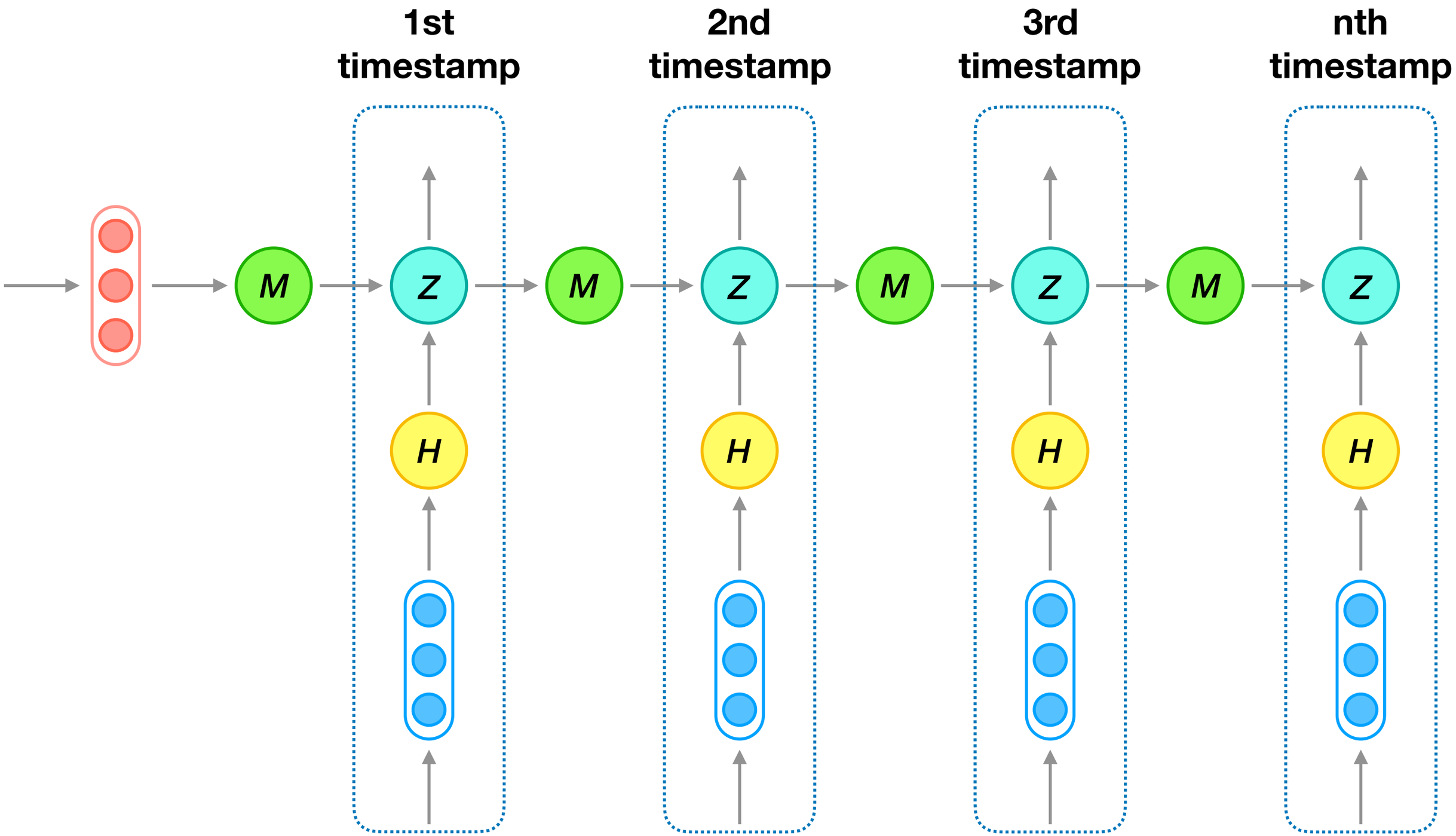

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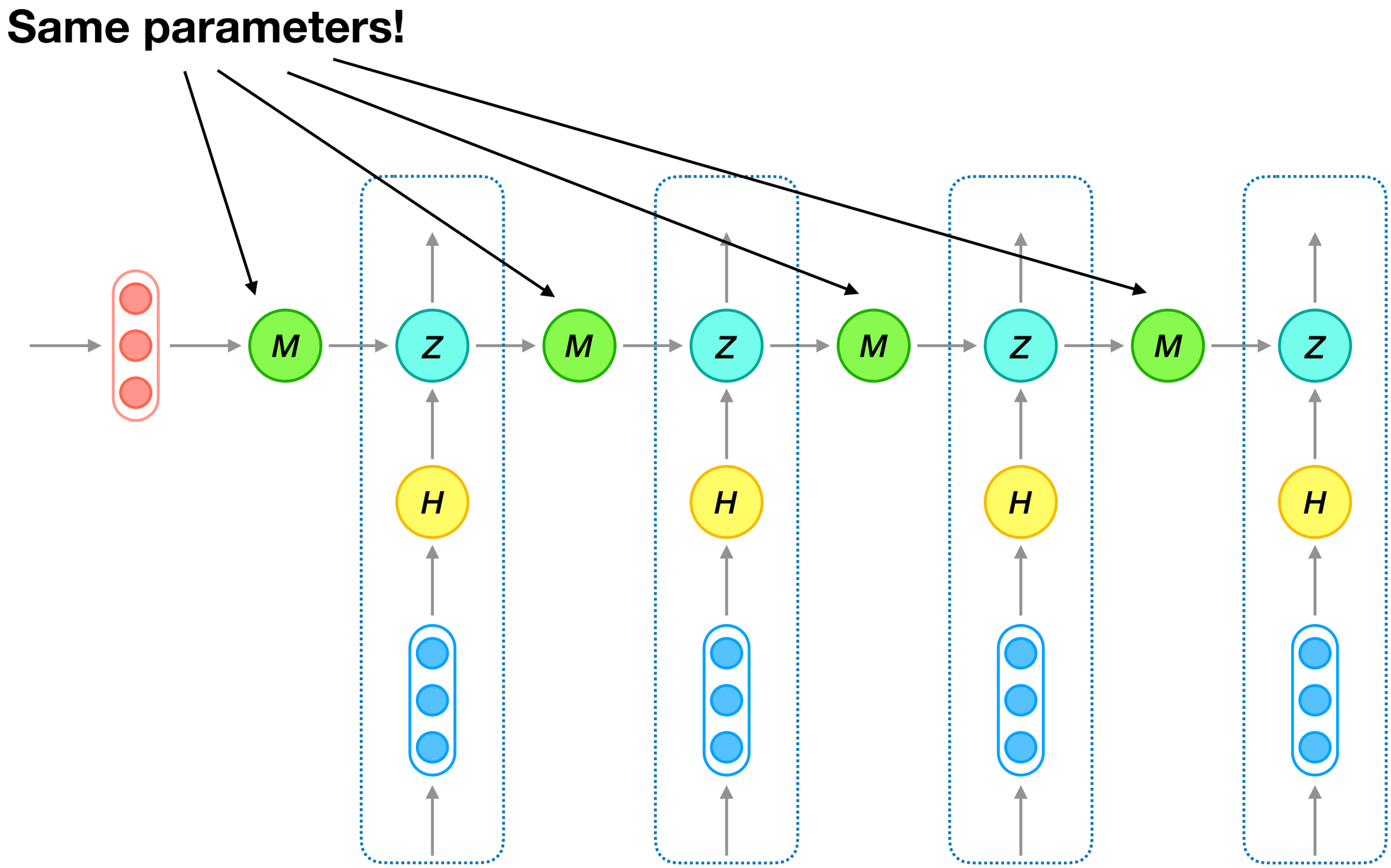

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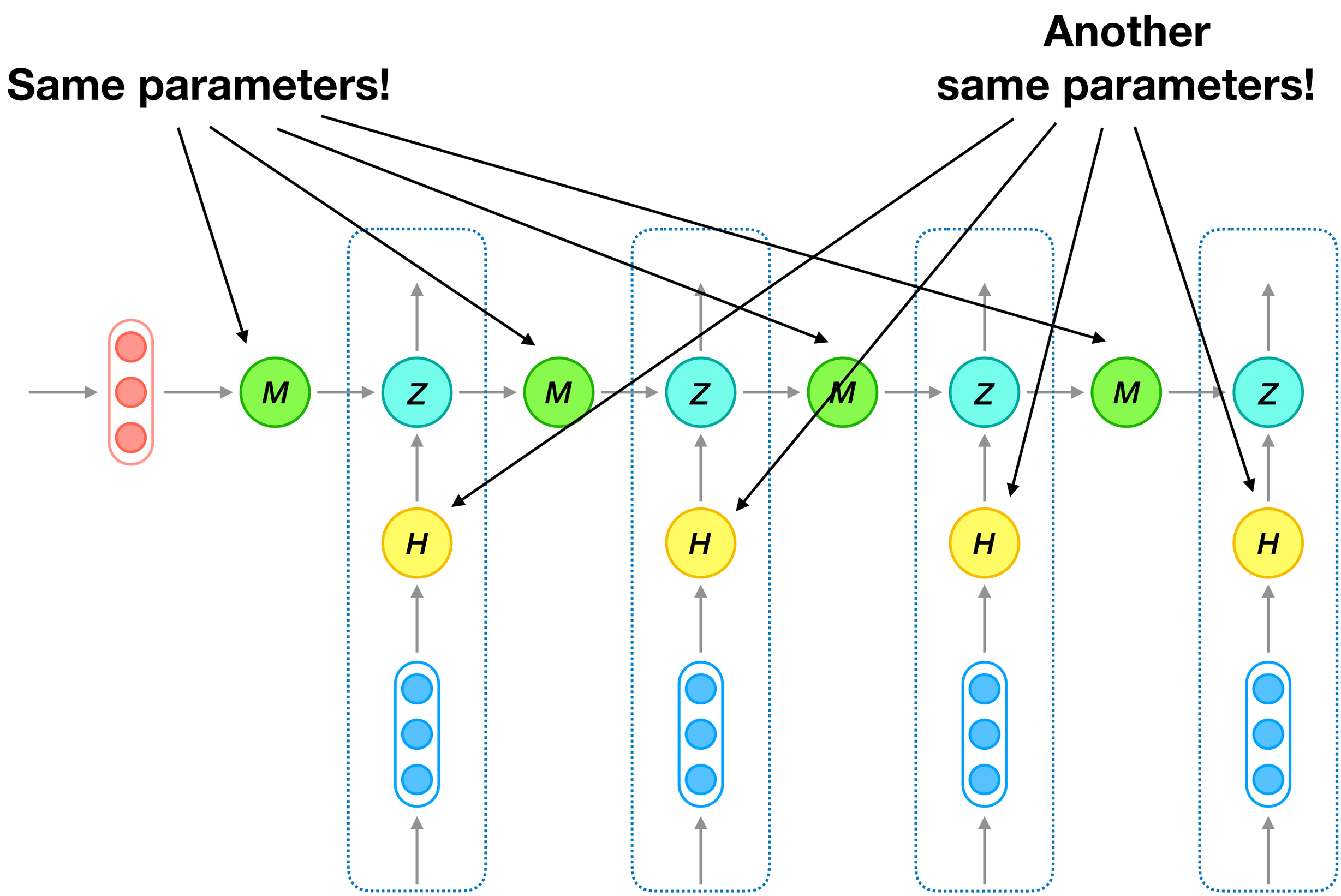

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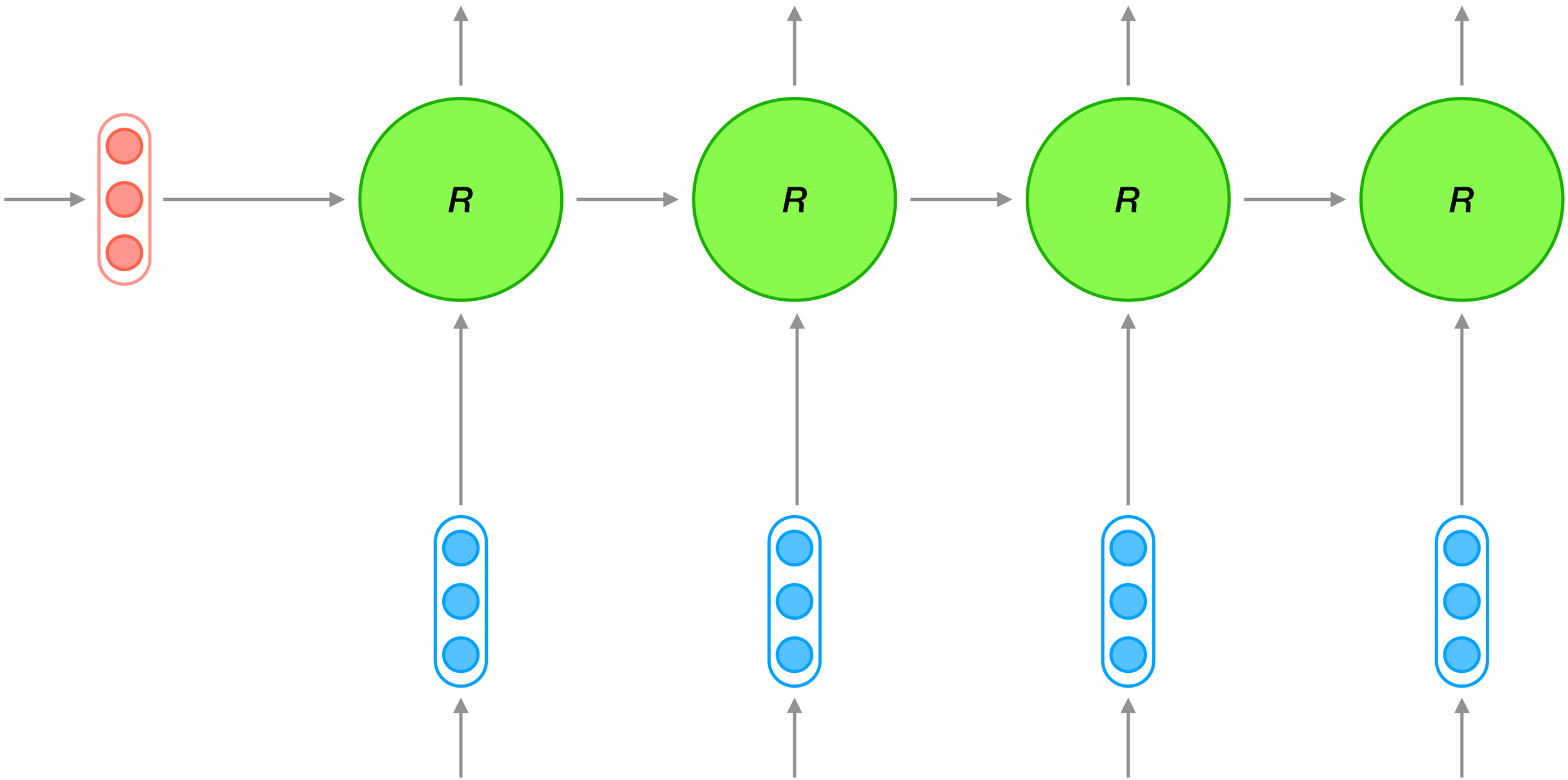
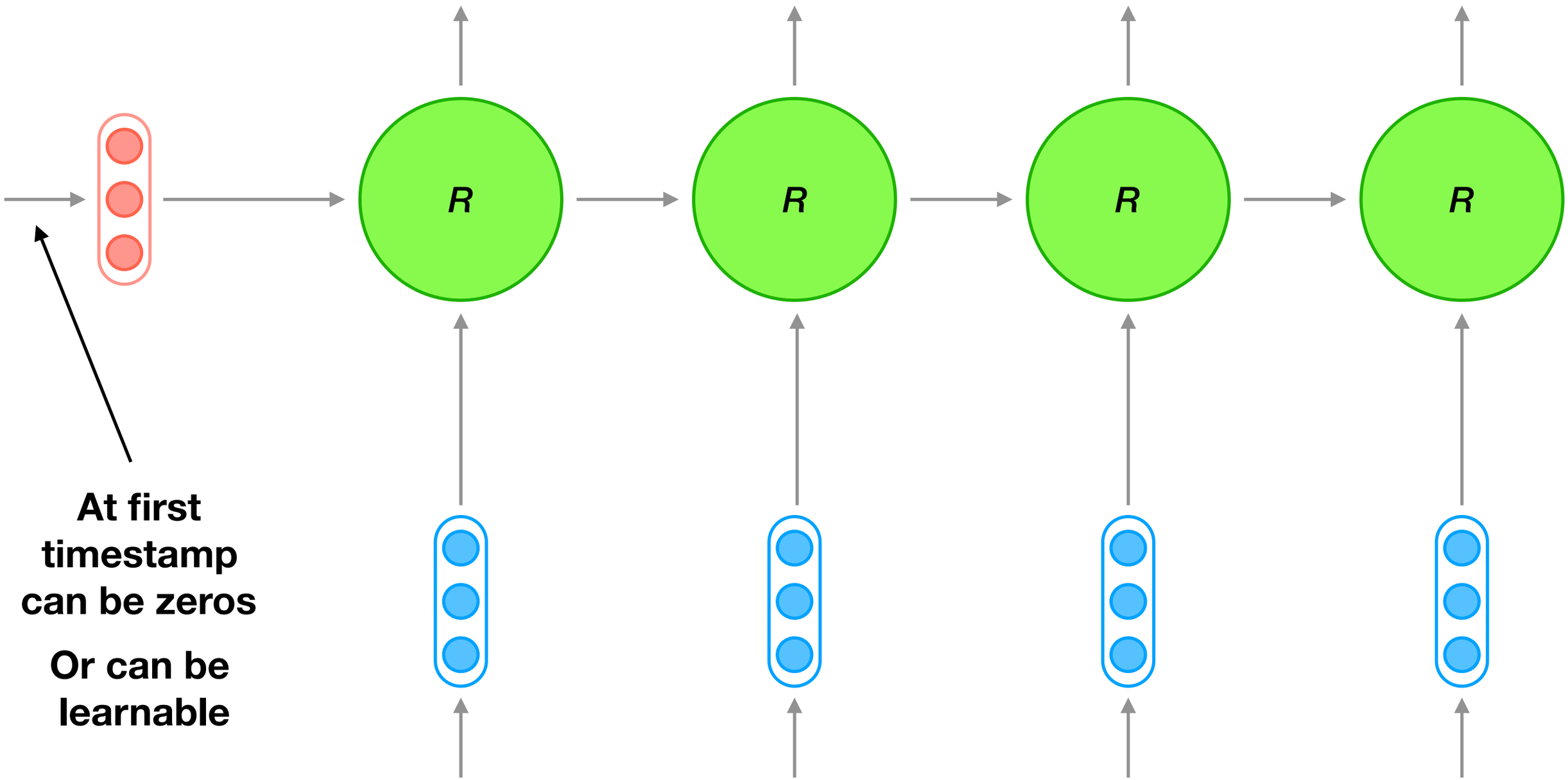
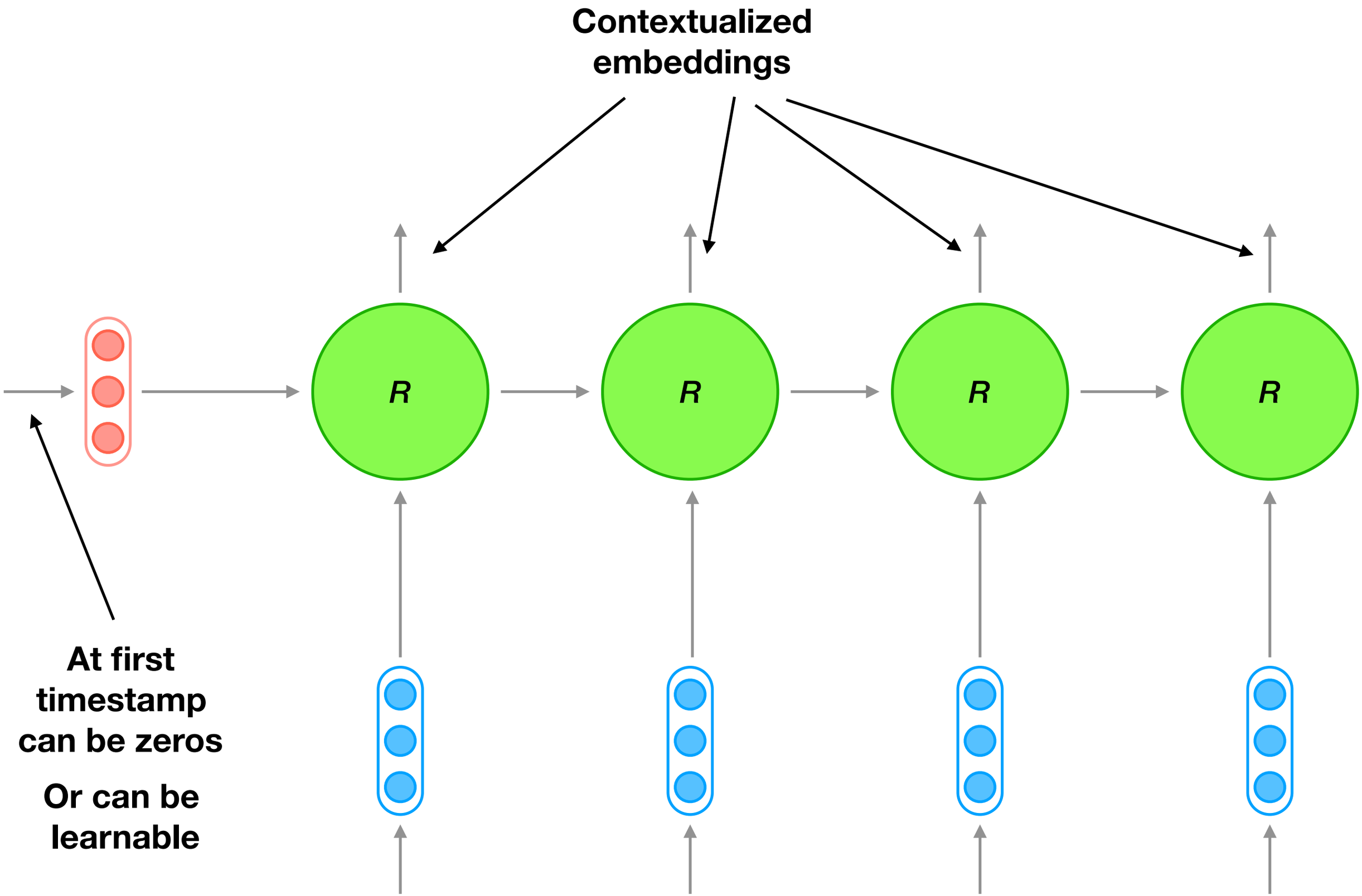


Reccurent Mechanism

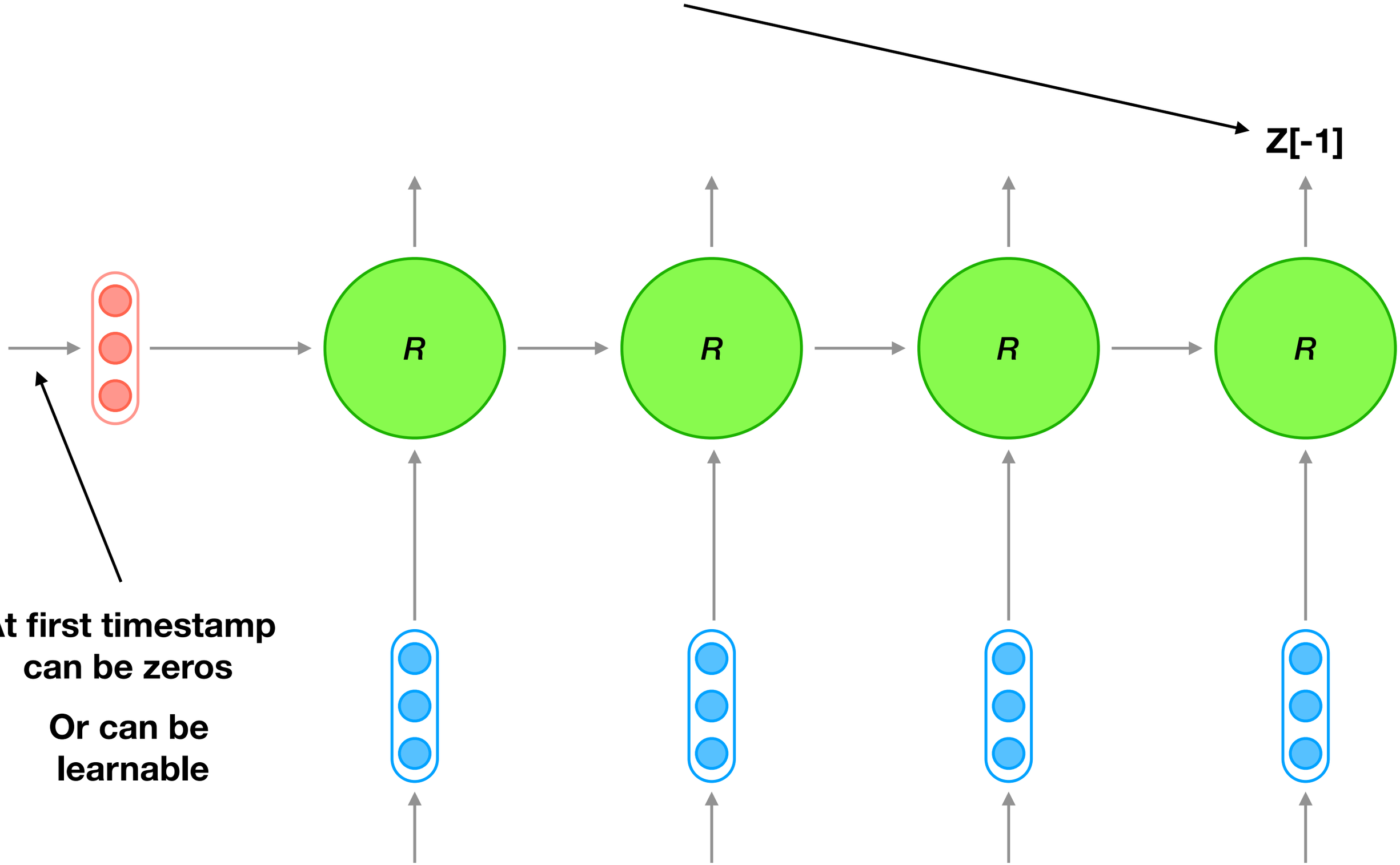


Reccurent Mechanism

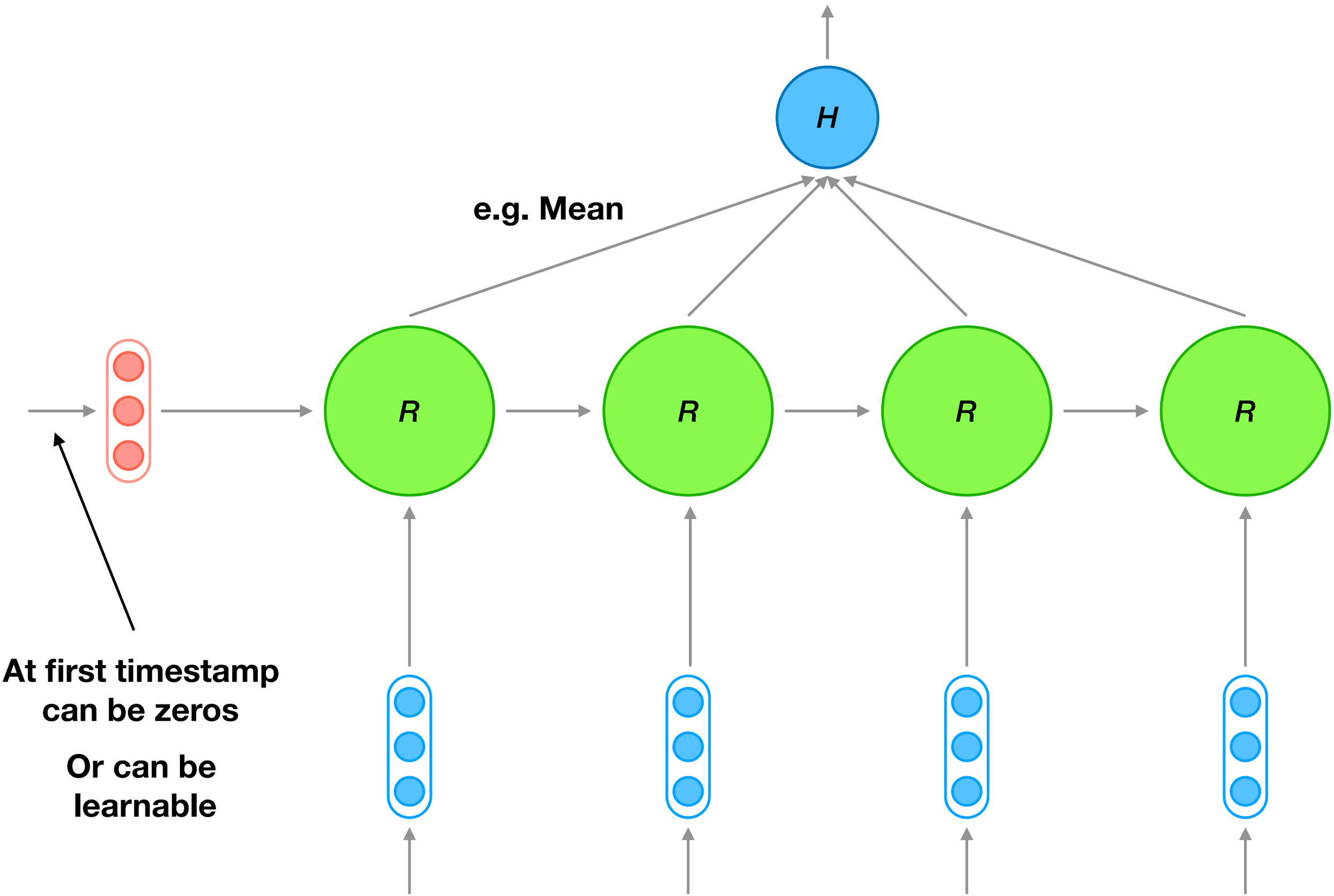


Reccurent Mechanism

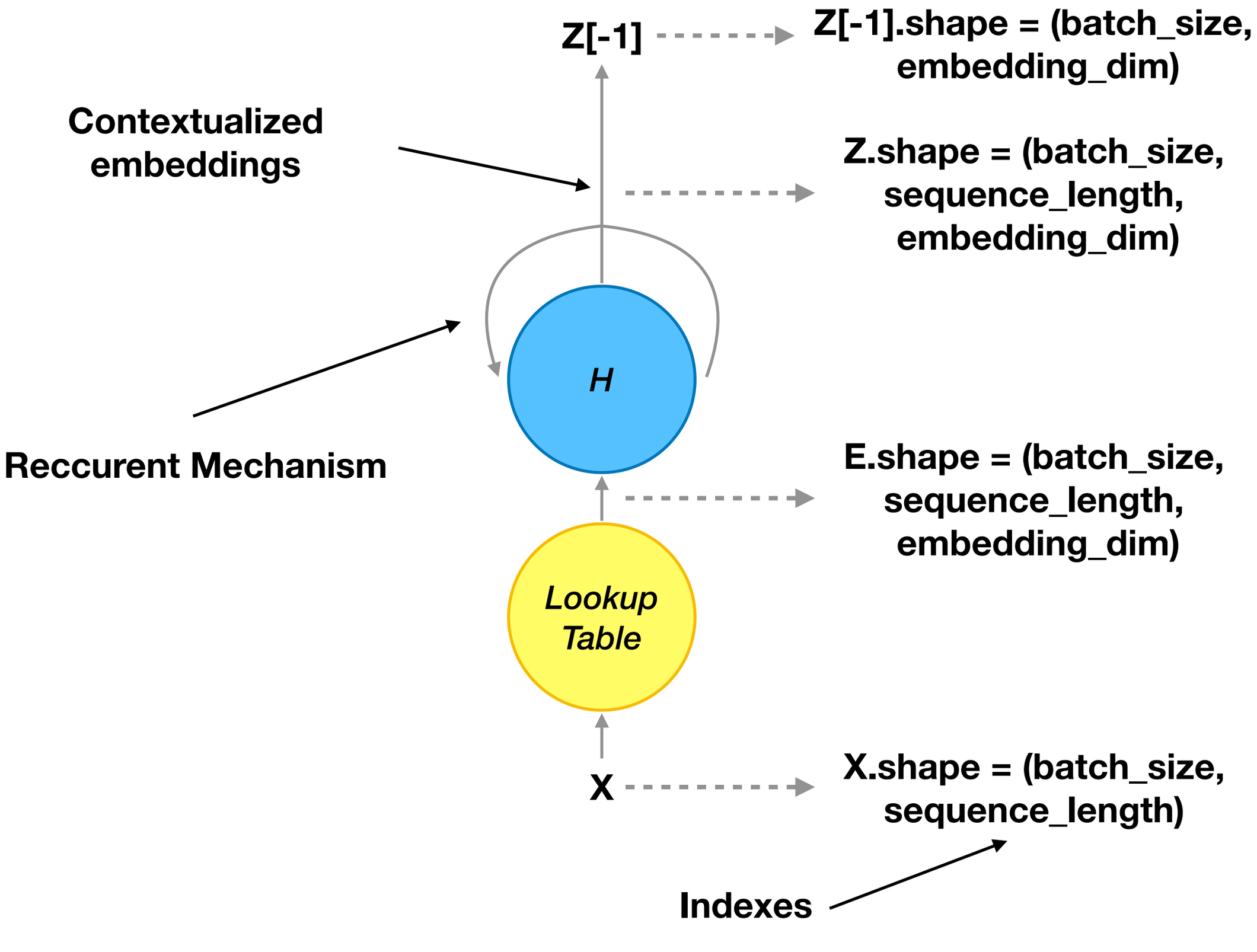
Now we can take last vector from sequence



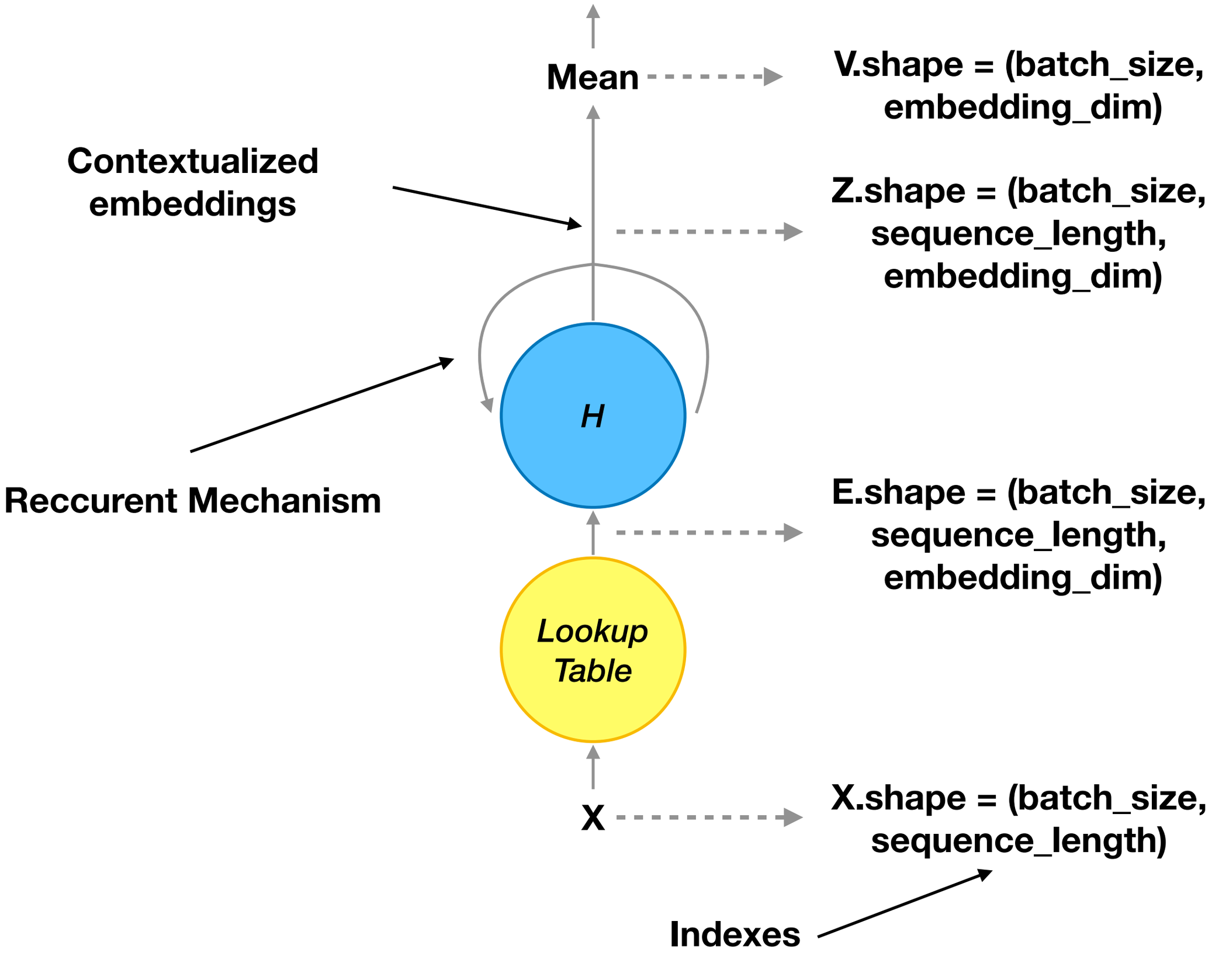
Reccurent Mechanism



Recurrent Neural Network



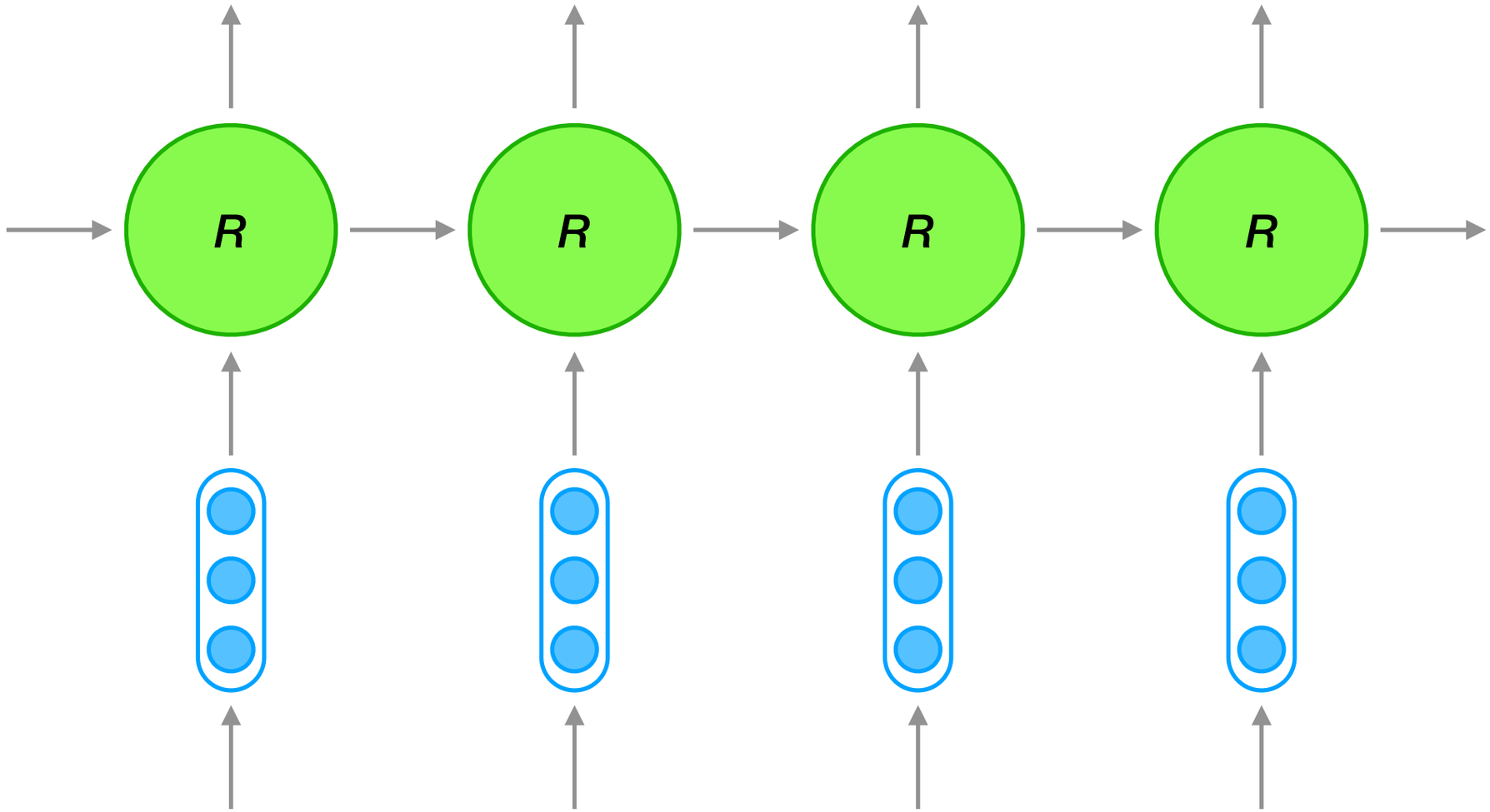
Recurrent Neural Network



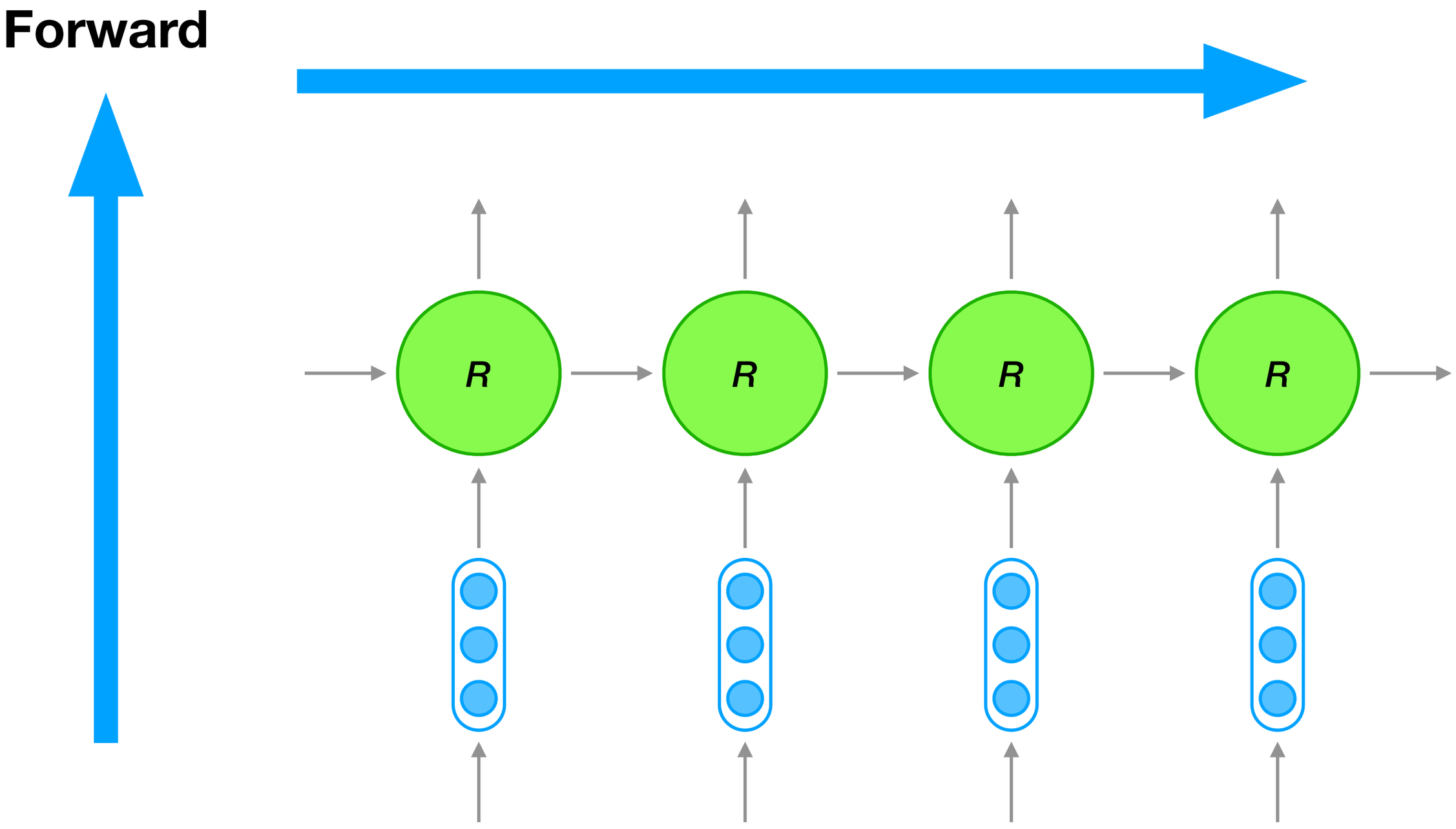
```python
class RNNCell(nn.Module):

    def __init__(self, in_features, hidden_features):

        super().__init__()

        self.in_features = in_features
        self.hidden_features = hidden_features

        self.input_linear = nn.Linear(in_features=in_features, out_features=hidden_features)
        self.memory_linear = nn.Linear(in_features=hidden_features, out_features=hidden_features)

    def init_memory(self, batch_size):

        return torch.zeros((batch_size, self.hidden_features))

    def forward(self, x, memory=None):

        if memory is None:
            memory = self.init_memory(batch_size=x.shape[0])

        x = torch.tanh(self.input_linear(x) + self.memory_linear(memory))

        memory = x

        return x, memory
```

```python
class RNN(nn.Module):

    def __init__(self, rnn_cell, output_last=False):

        super().__init__()

        self.rnn_cell = rnn_cell

        self.output_last = output_last

    def forward(self, x, memory=None):

        if memory is None:
            memory = self.rnn_cell.init_memory(batch_size=x.shape[0])

        hiddens = []

        for timestamp in range(x.size(1)):
            current_timestamp = x[:, timestamp, :]
            current_hidden, memory = self.rnn_cell(current_timestamp, memory)
            hiddens.append(current_hidden.unsqueeze(1))

        if self.output_last:
            return hiddens[-1].squeeze()

        hiddens = torch.cat(hiddens, dim=1)

        return hiddens
```

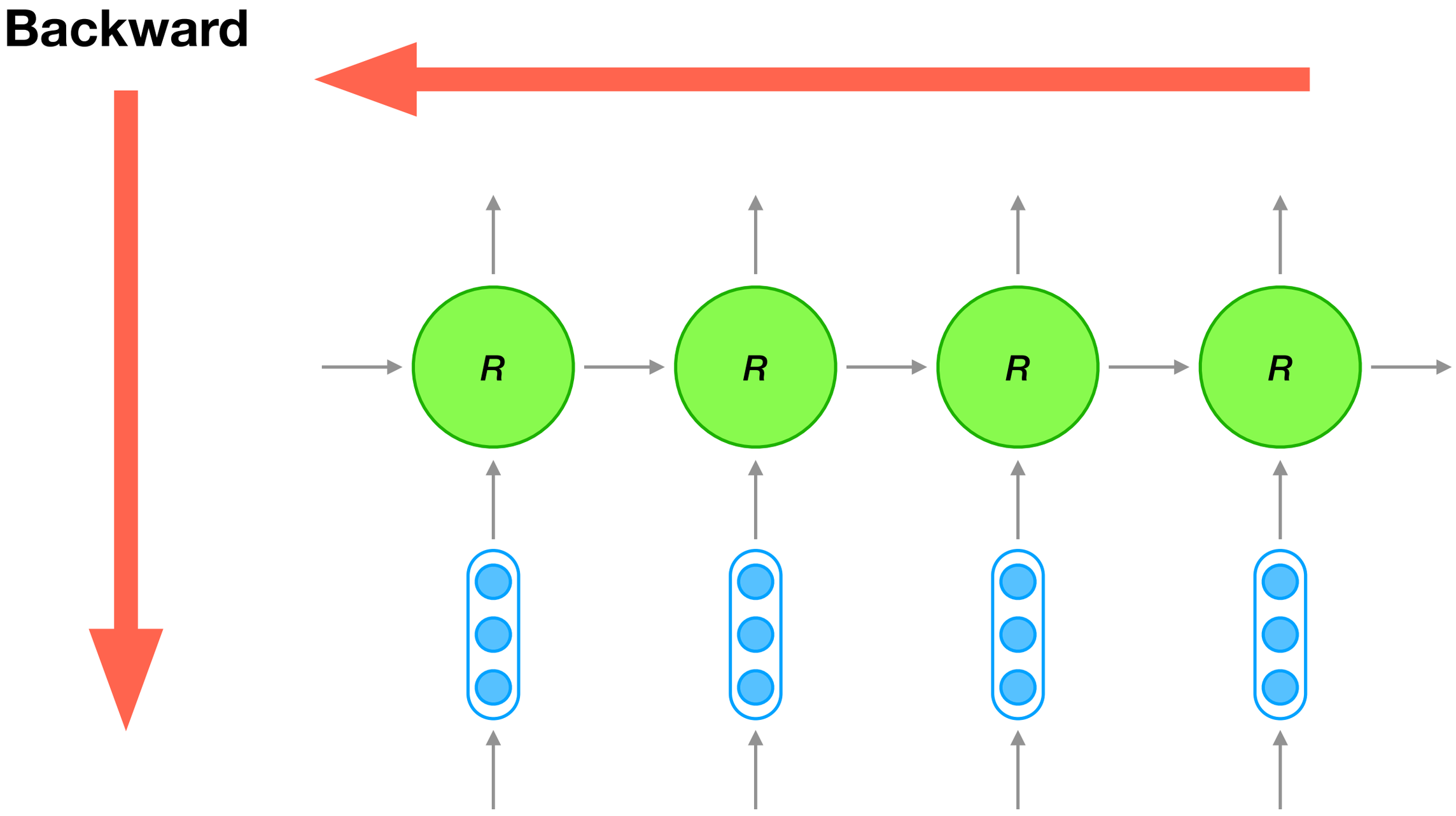
BPTT



BPTT



BPTT



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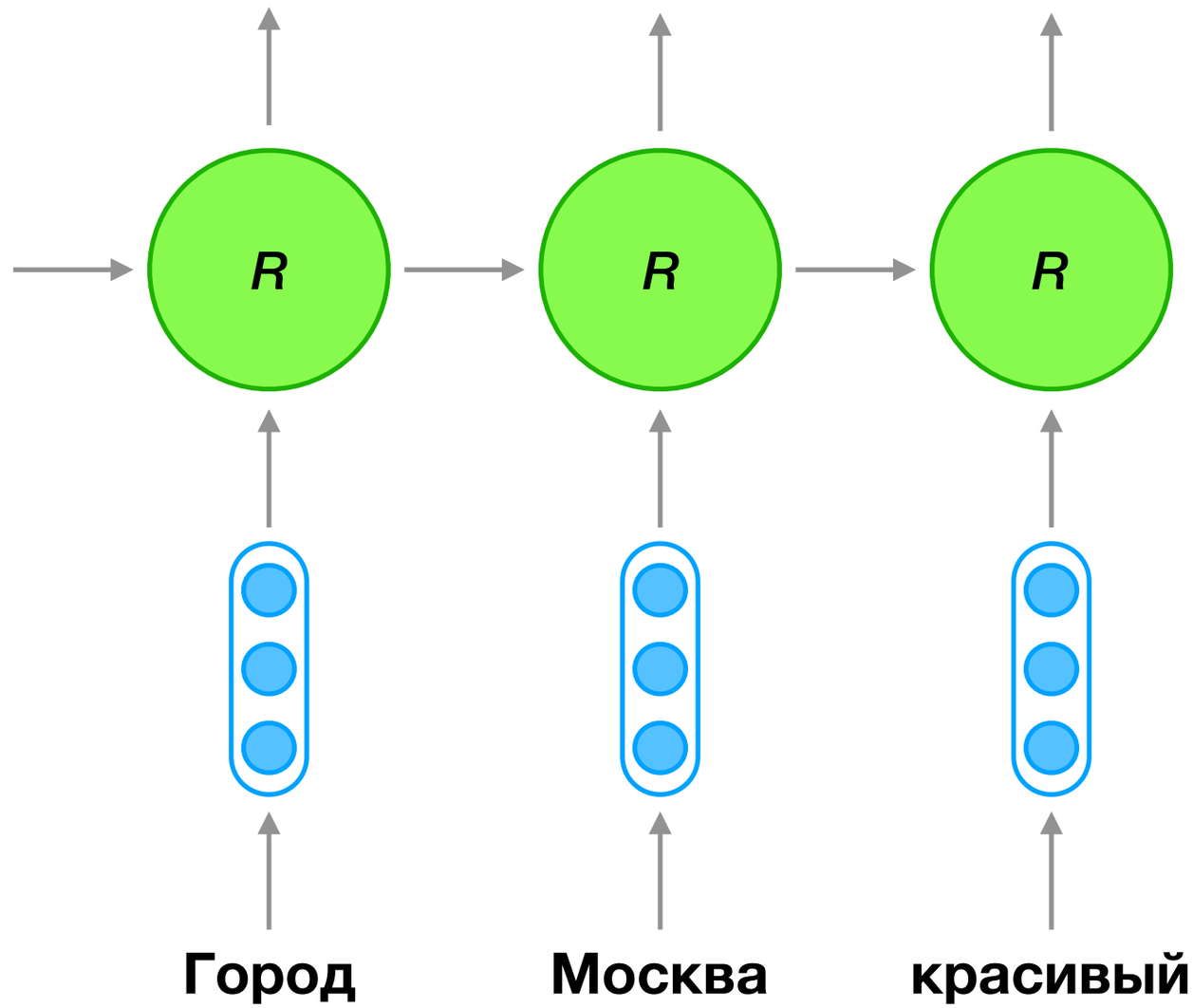

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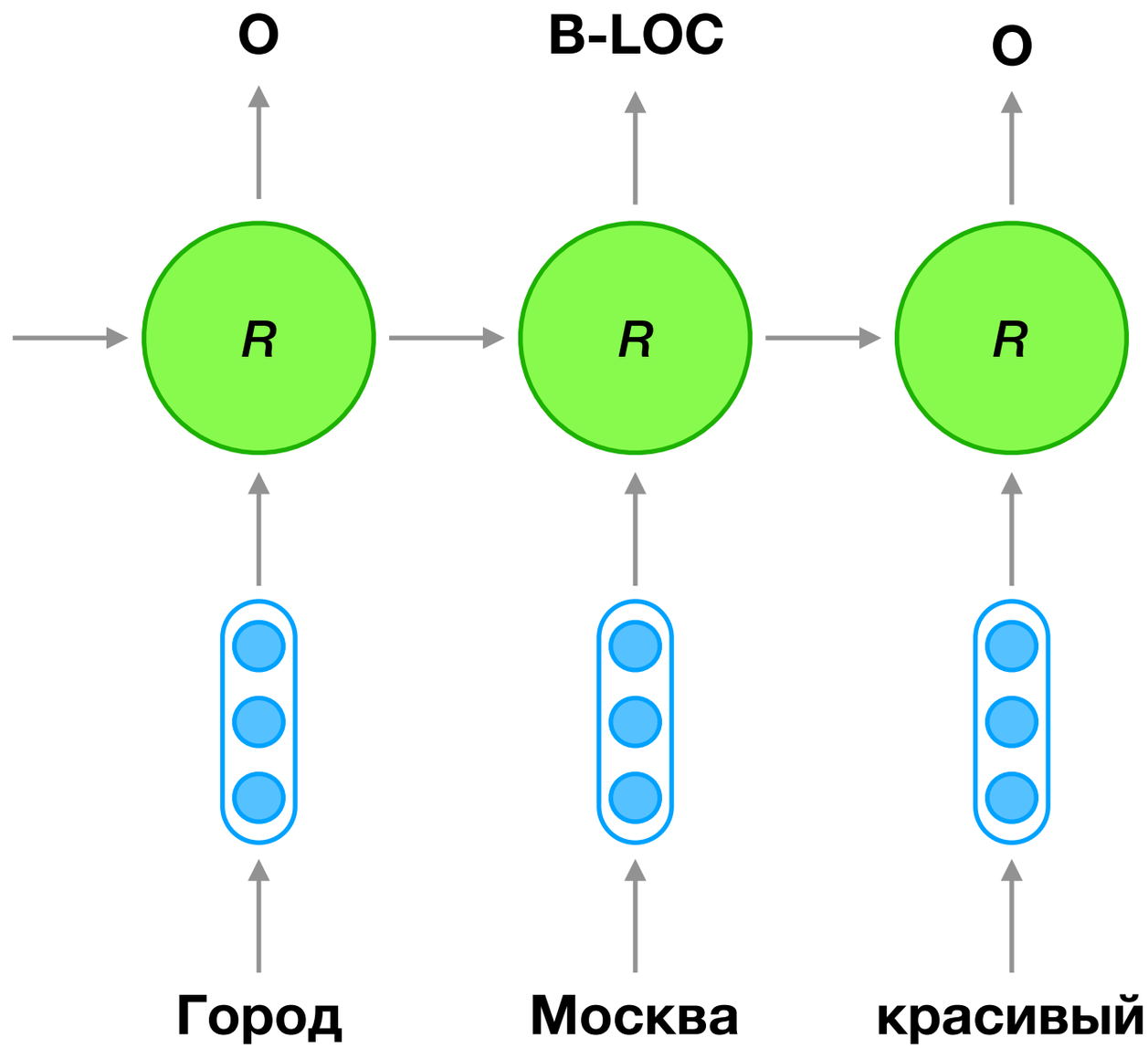
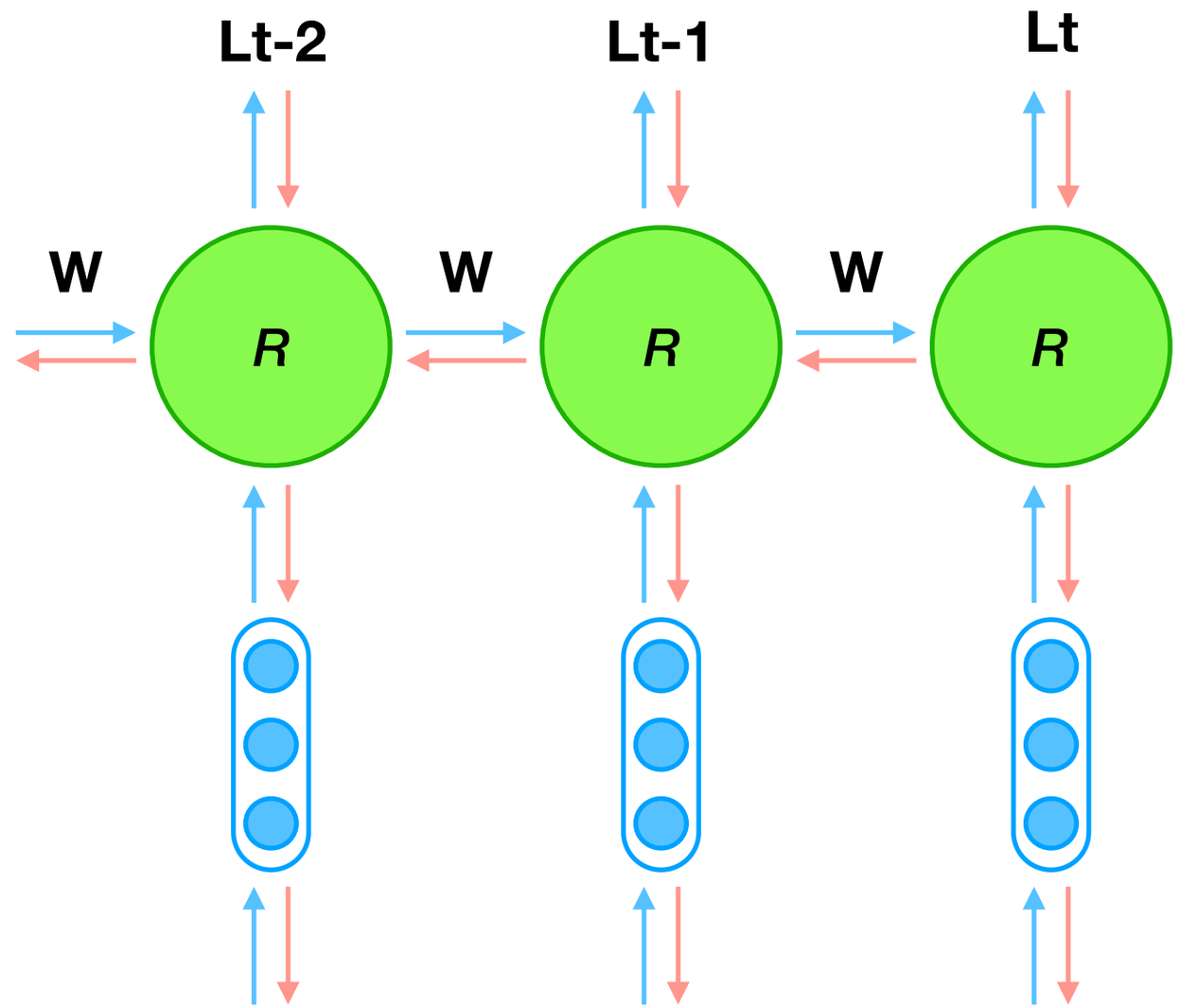
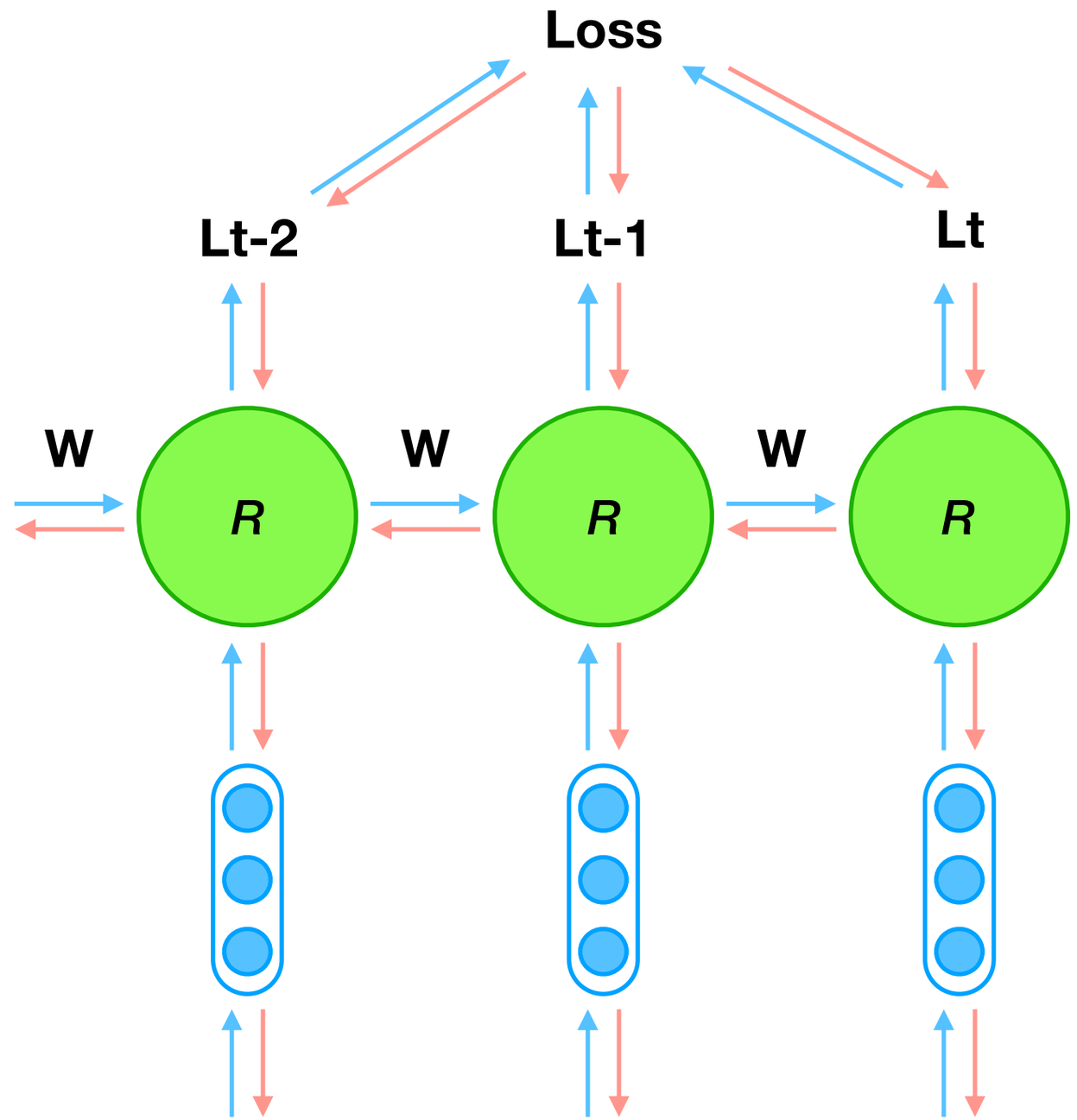


BPTT

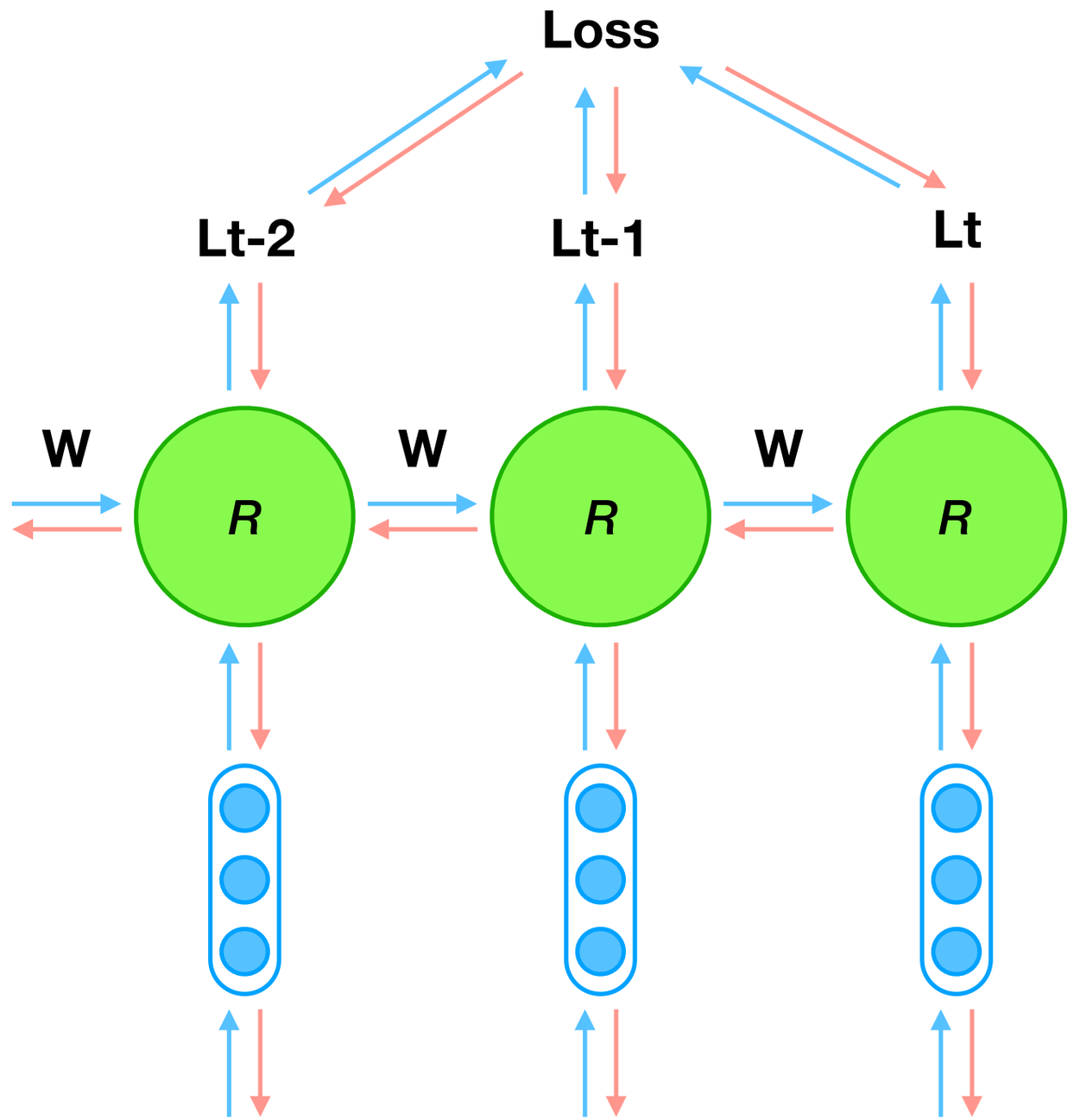


BPTT



BPTT

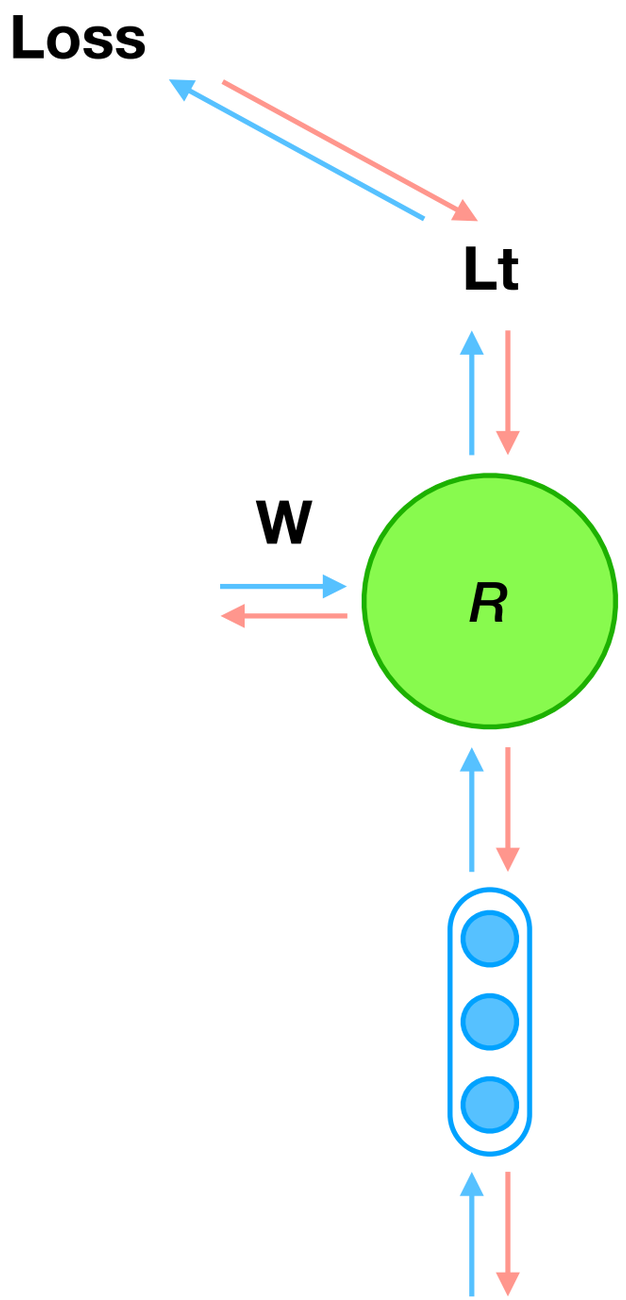
$$\frac{\partial L}{\partial W} = \sum_{i=0}^{T} \frac{\partial L_i}{\partial W}$$



BPTT

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

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



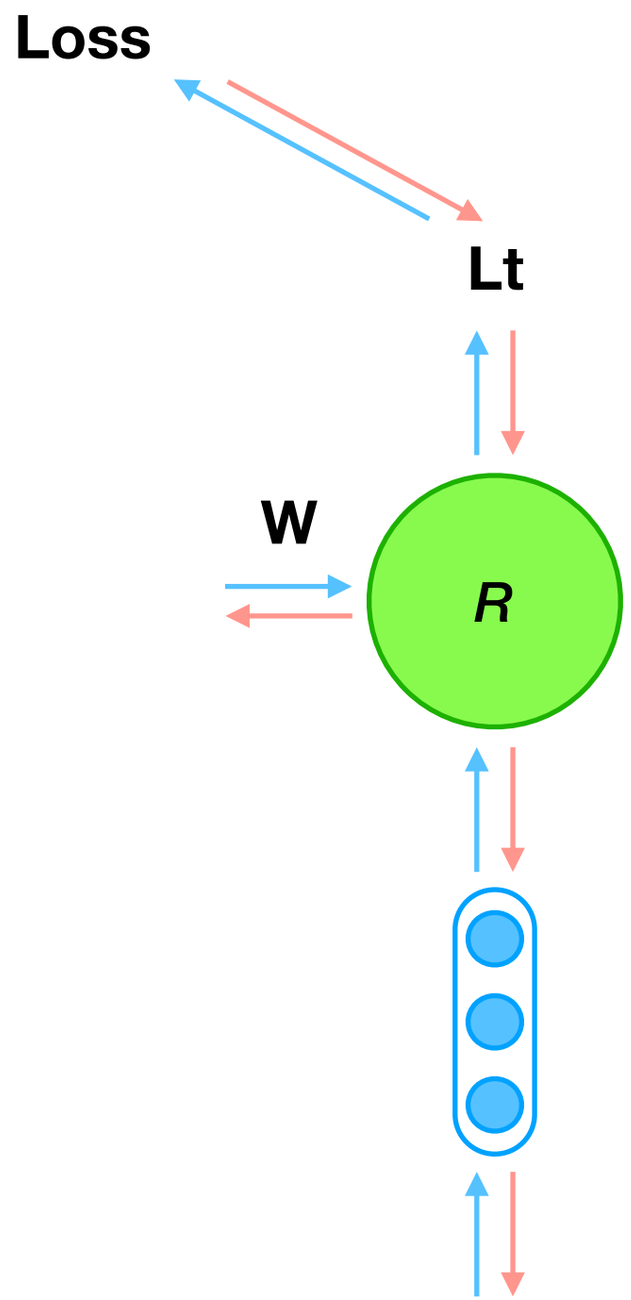
BPTT

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

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

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

This is NOT the only dependence!



BPTT

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

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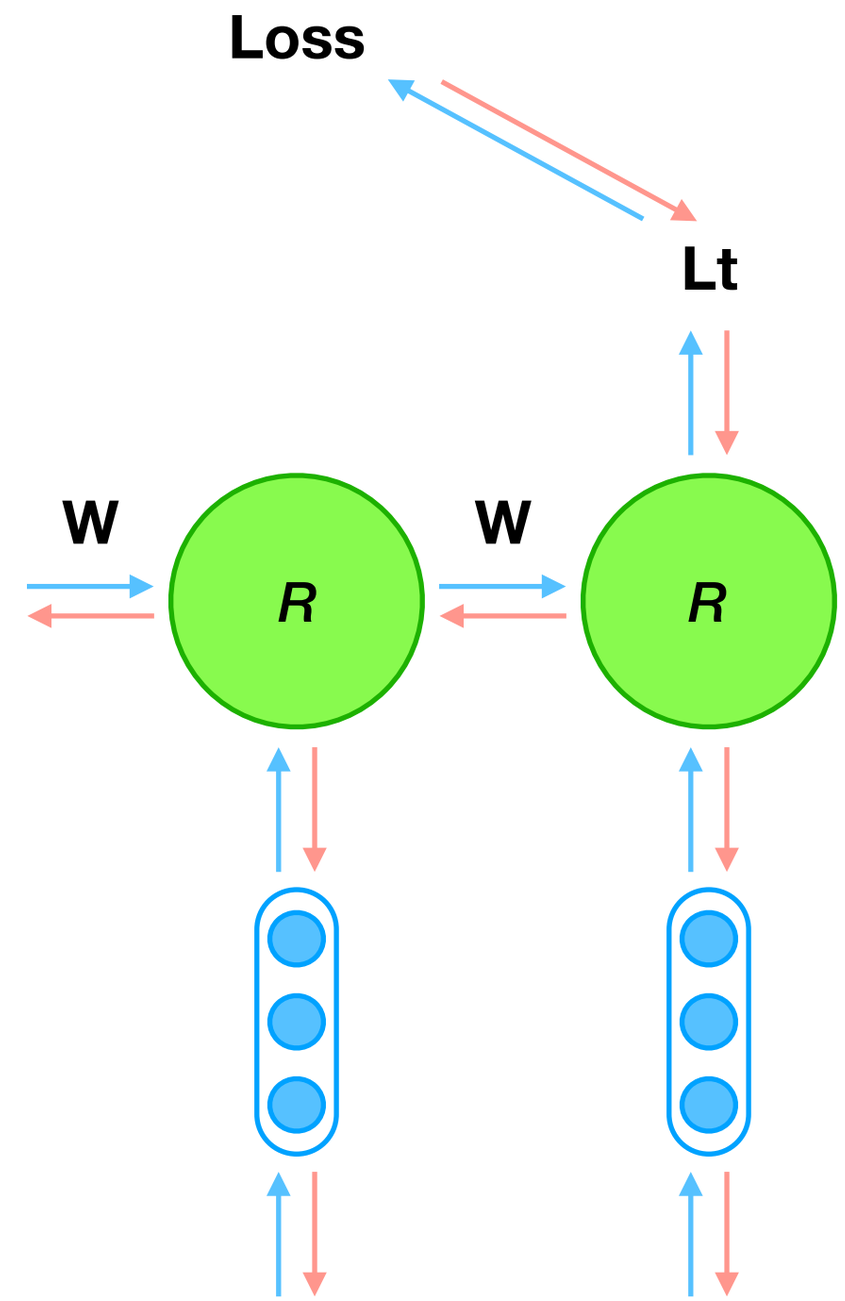

BPTT

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

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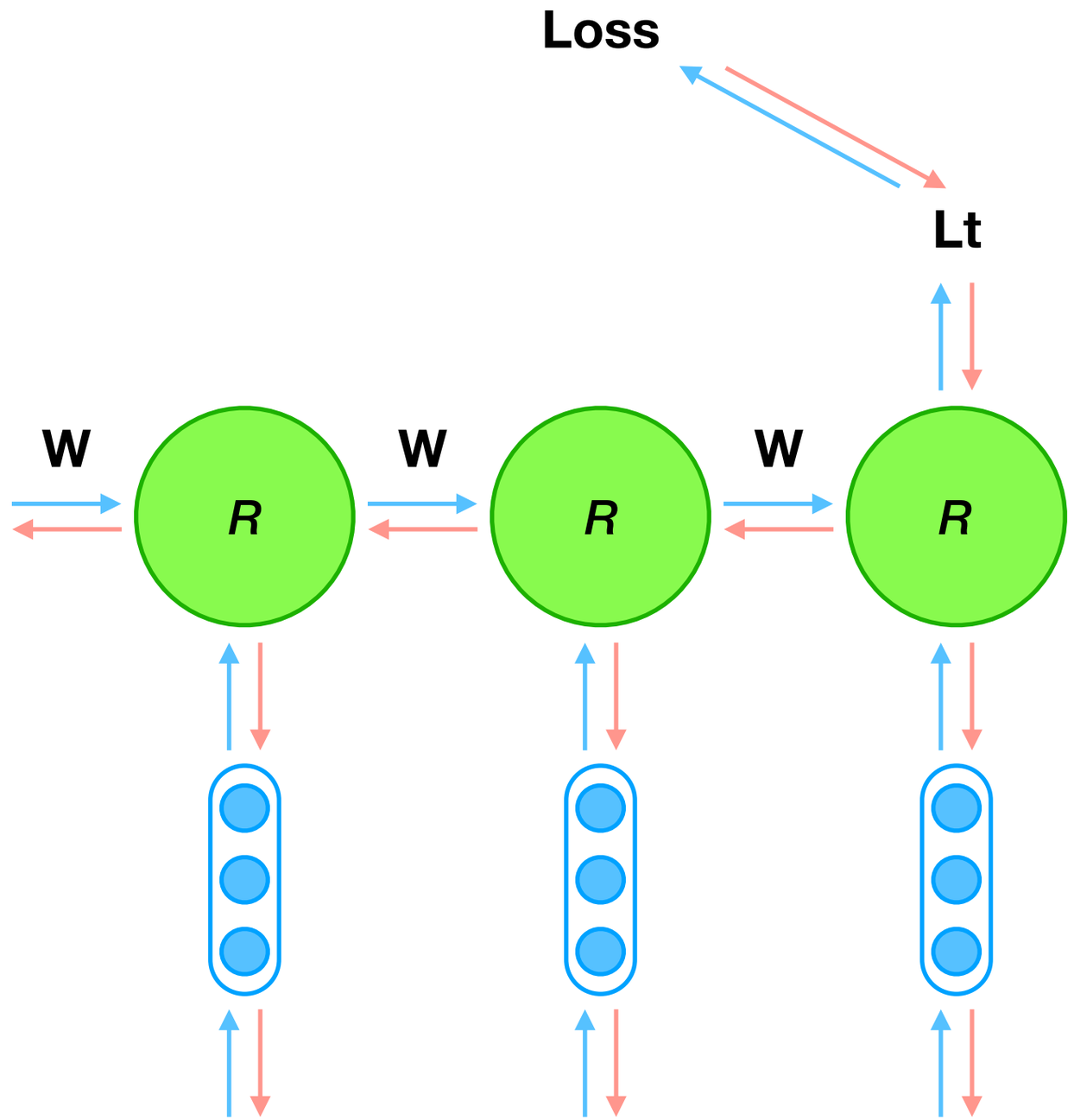


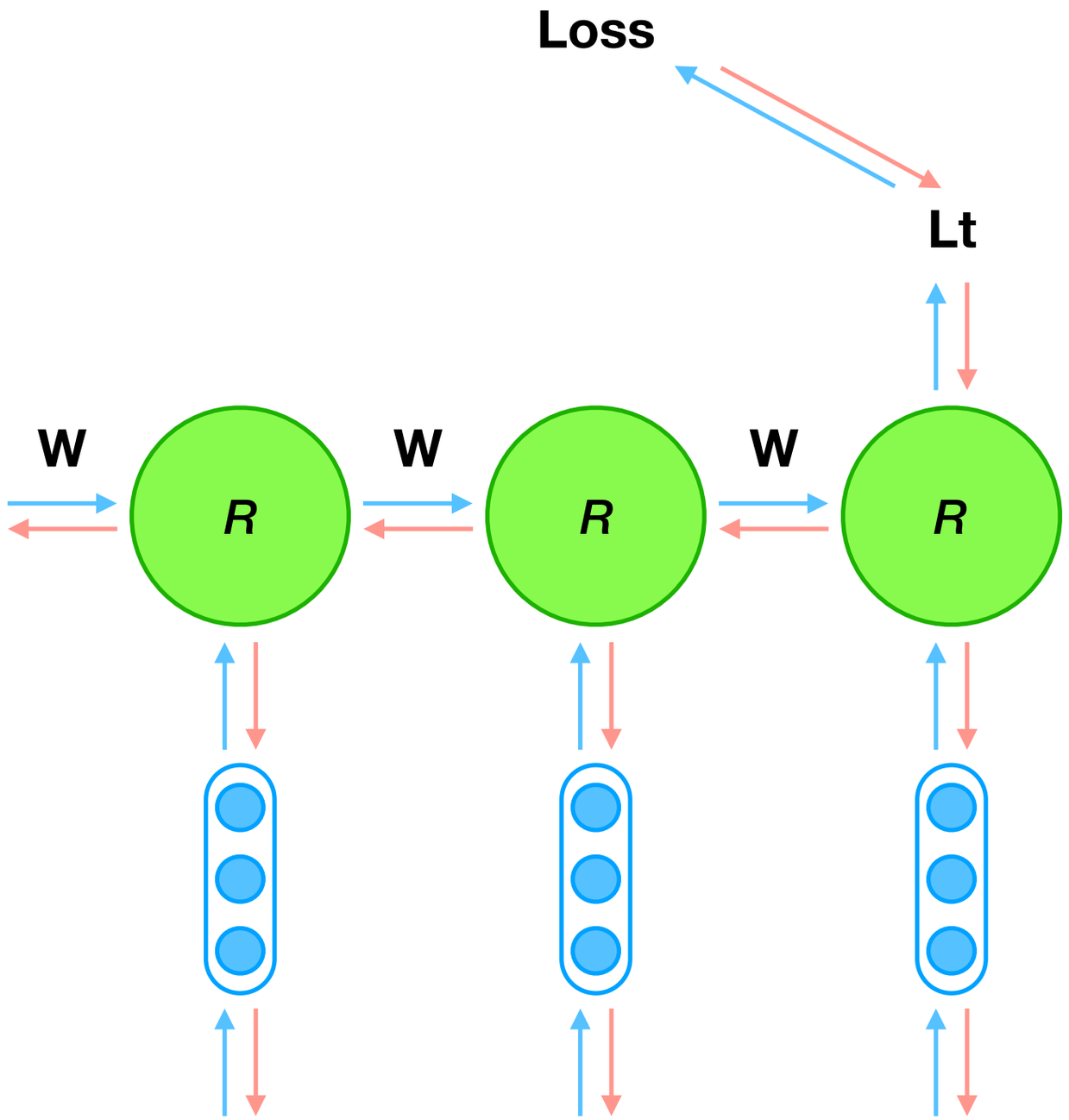
BPTT

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

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

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

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

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

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

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

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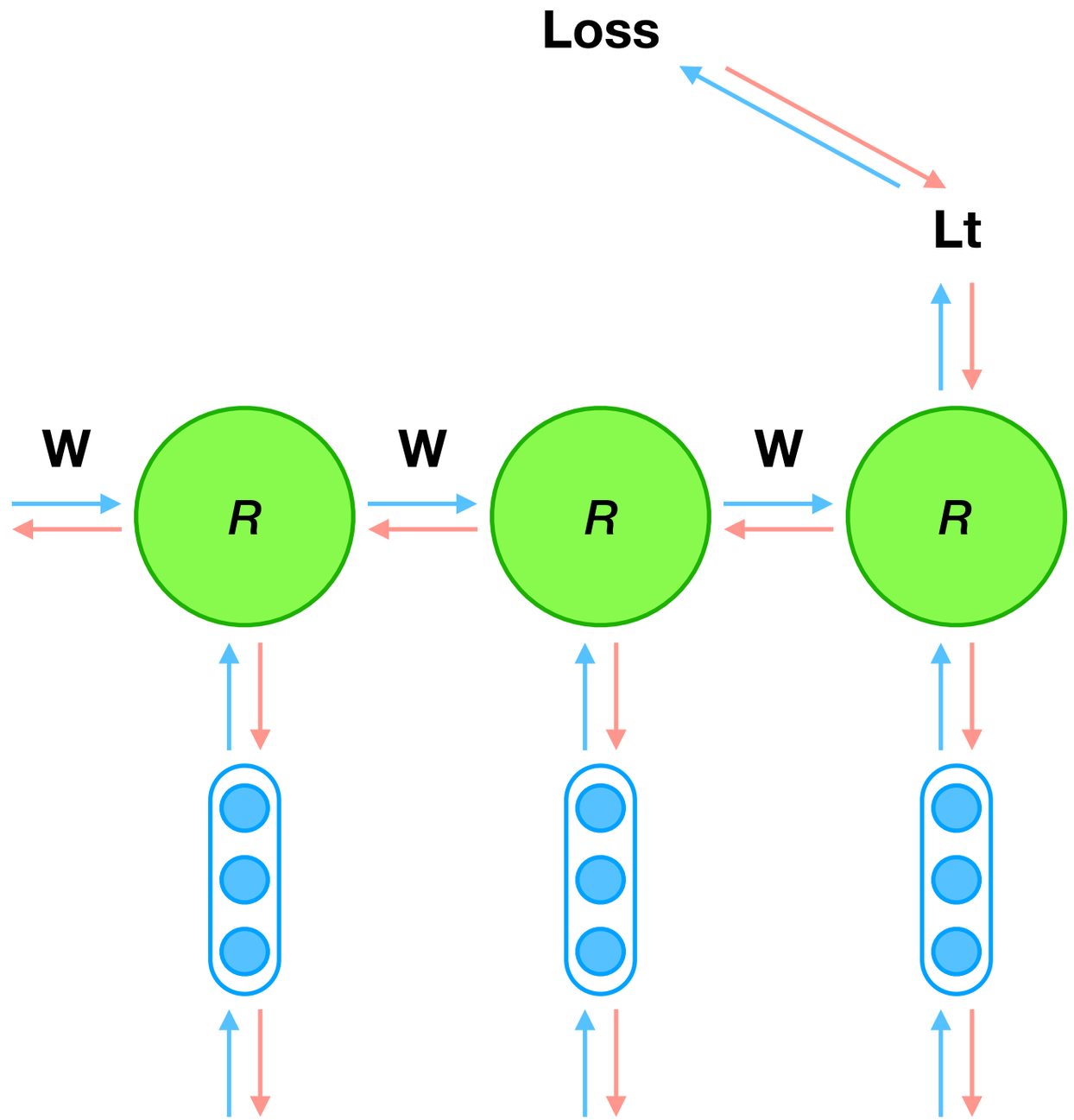


$$\frac{\partial L_t}{\partial W} = \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \left[\sum_{k=0}^{t} \left(\prod_{i=k+1}^{t} \frac{\partial h_i}{\partial h_{i-1}} \right) \frac{\partial h_k}{\partial W} \right]$$

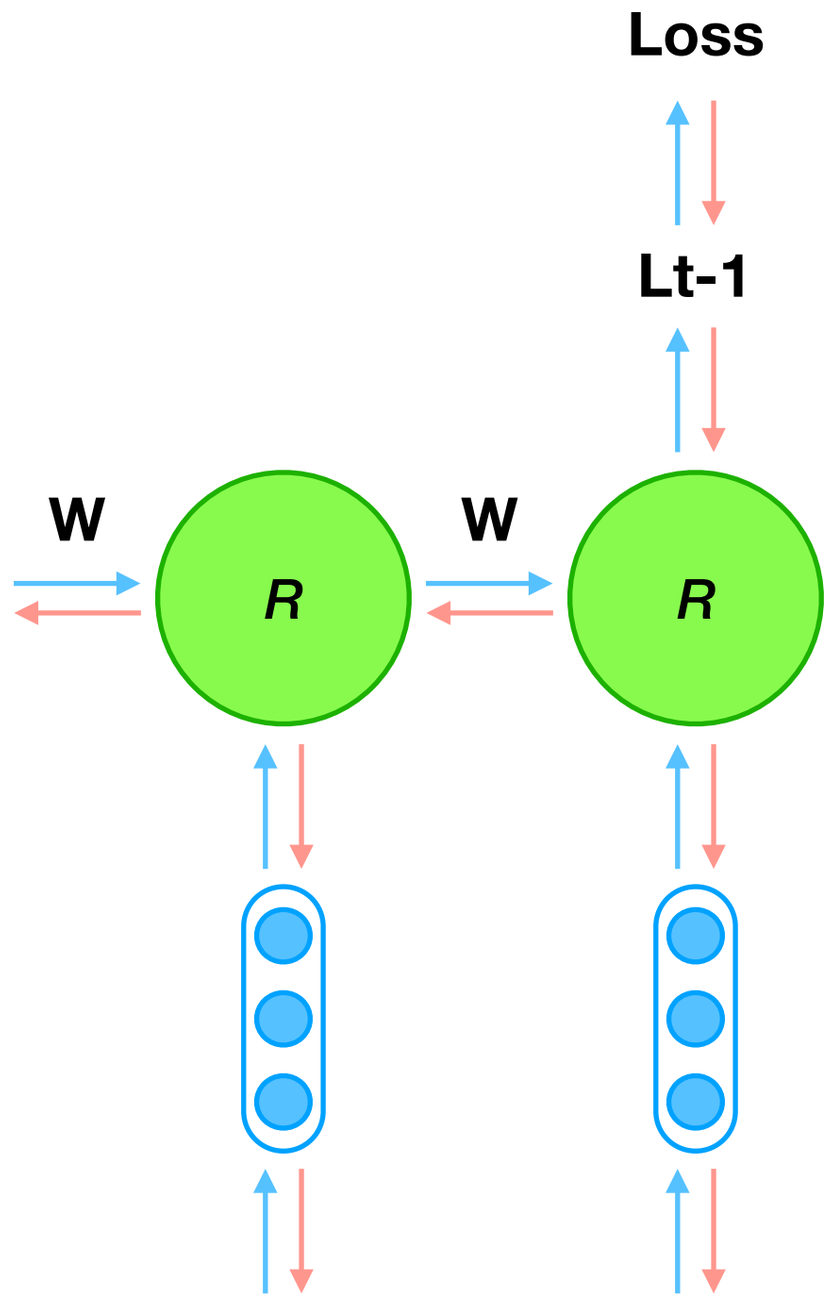
BPTT

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

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

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

This is NOT the only dependence!



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

BPTT

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

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

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

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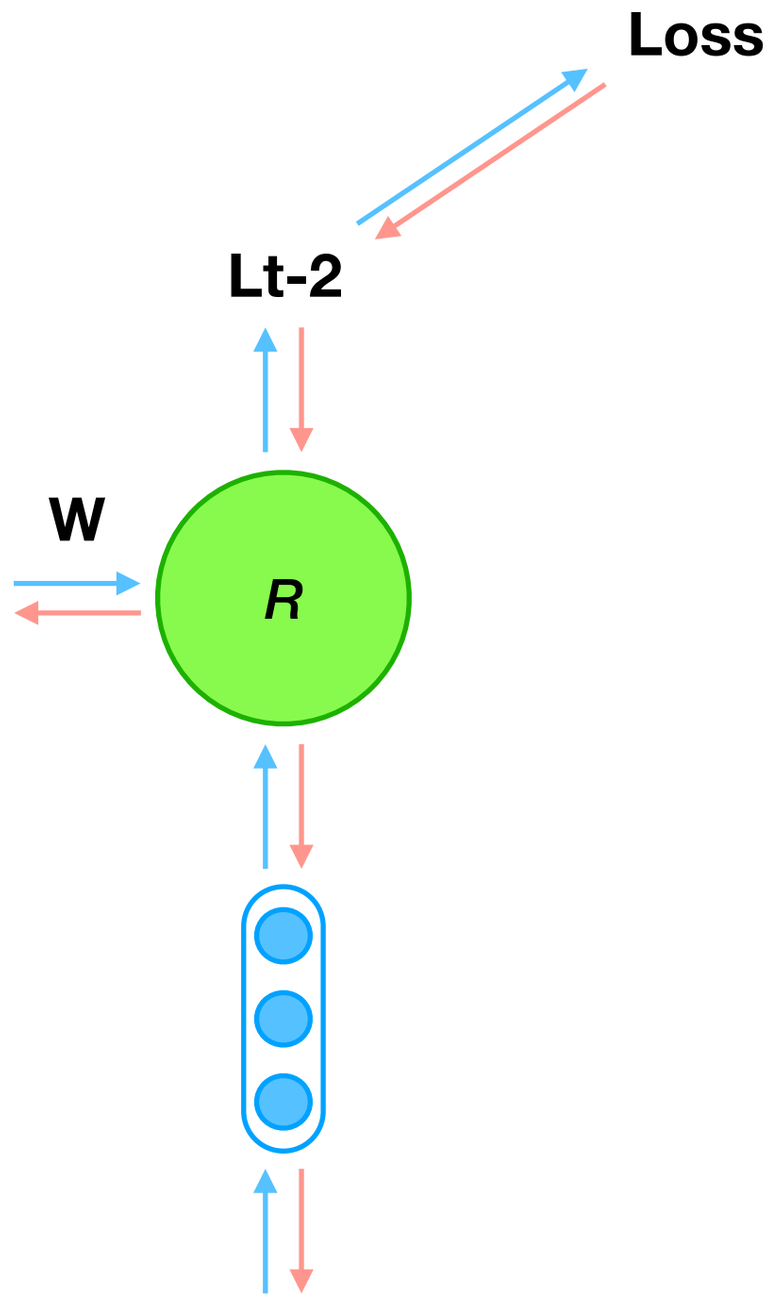


$$\frac{\partial L_t}{\partial W} = \frac{\partial L_t}{\partial \hat{y}_t} \frac{\partial \hat{y}_t}{\partial h_t} \sum_{k=0}^{t} \left(\prod_{i=k+1}^{t} \frac{\partial h_i}{\partial h_{i-1}} \right) \frac{\partial h_k}{\partial W}$$

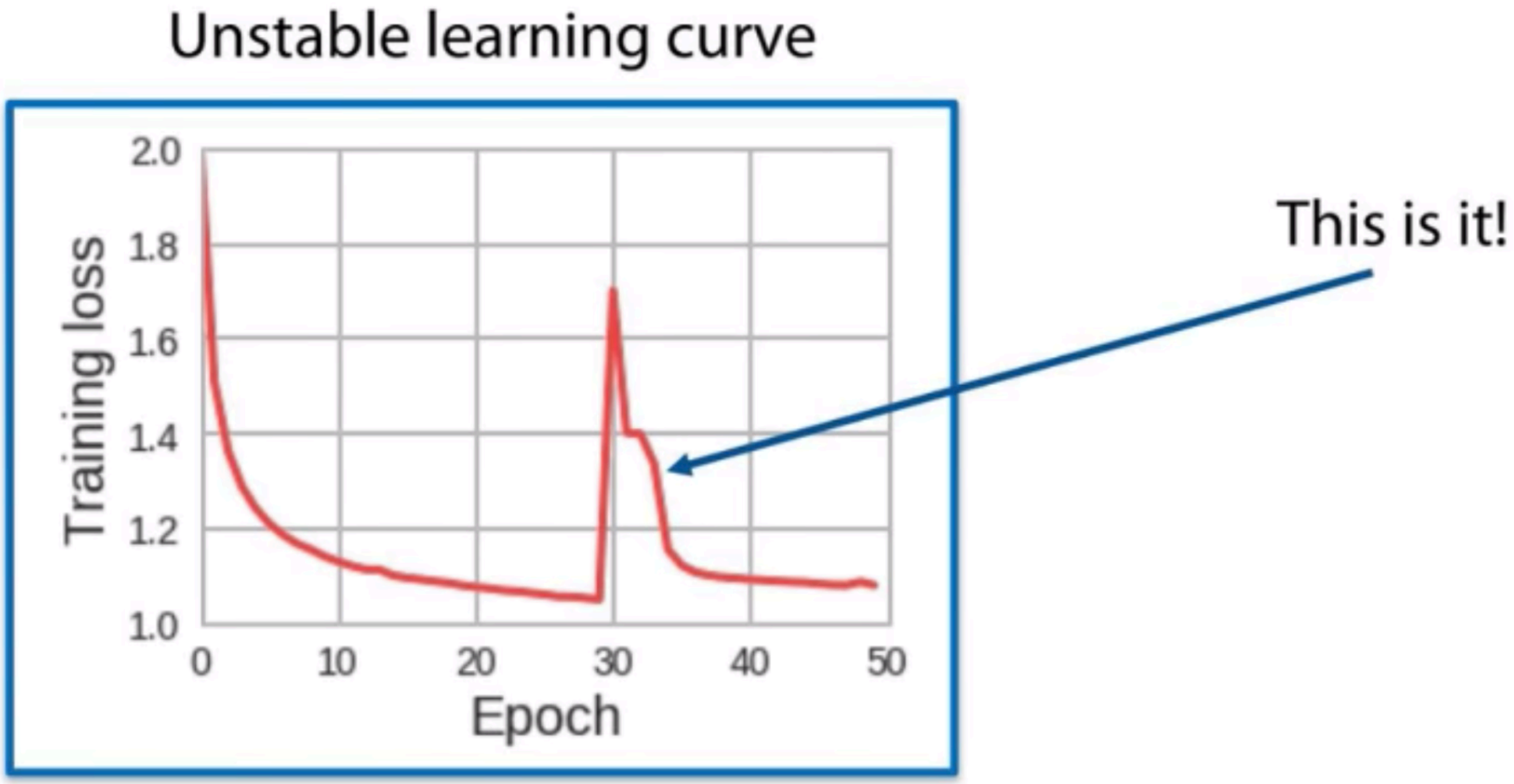
Gradients

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

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

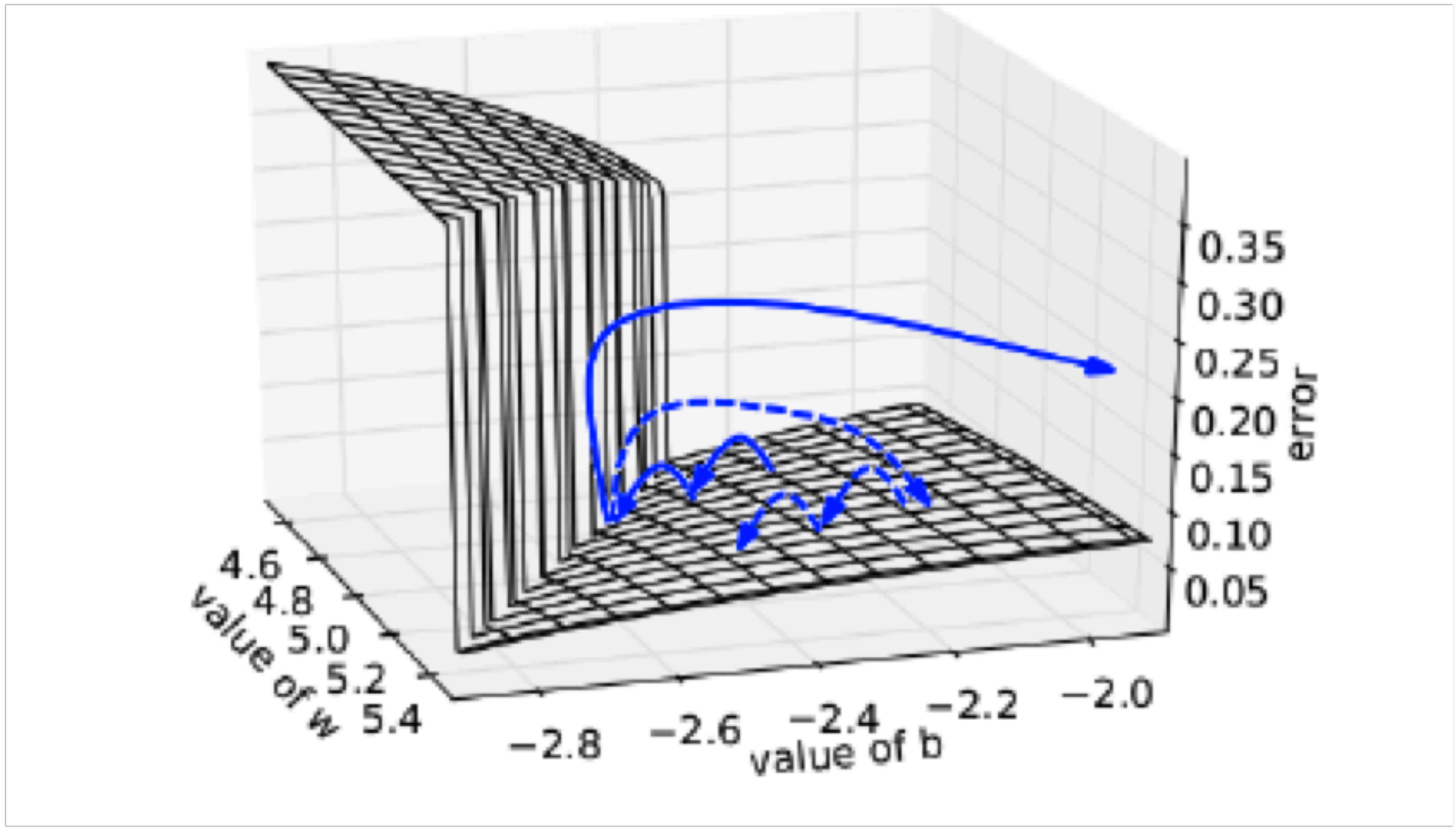
$$\left\| \frac{\partial h_i}{\partial h_{i-1}} \right\|_2 > 1 \quad \Rightarrow \quad \text{Exploding gradients}$$

Exploding gradients



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

Exploding gradients



Gradient Clipping

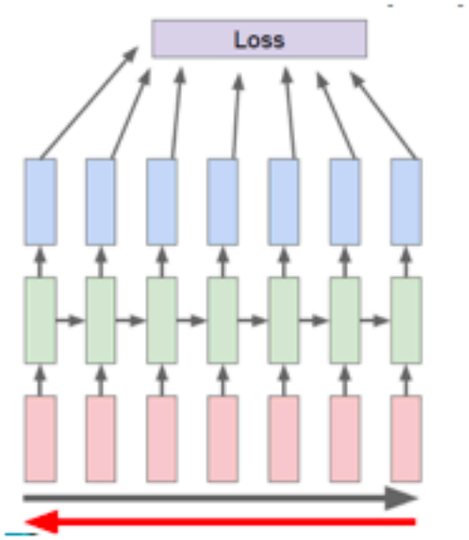
Gradient $g = \frac{\partial L}{\partial \theta}$, θ - all the network parameters

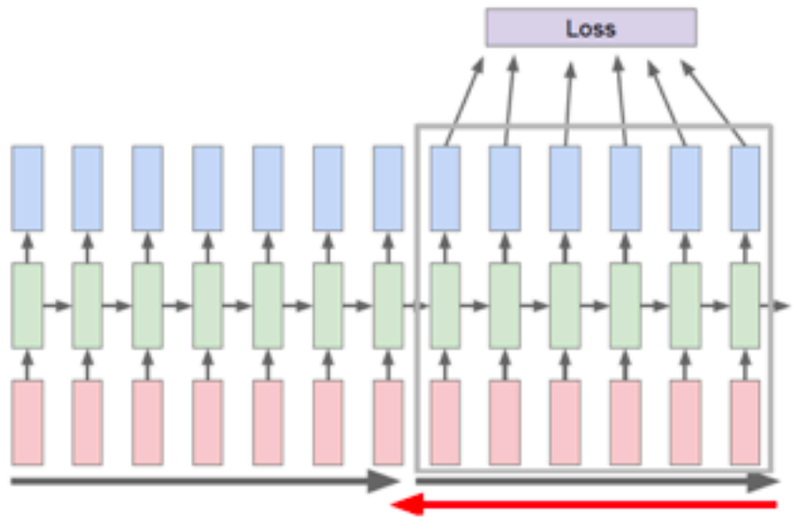
If $||g||$> threshold:

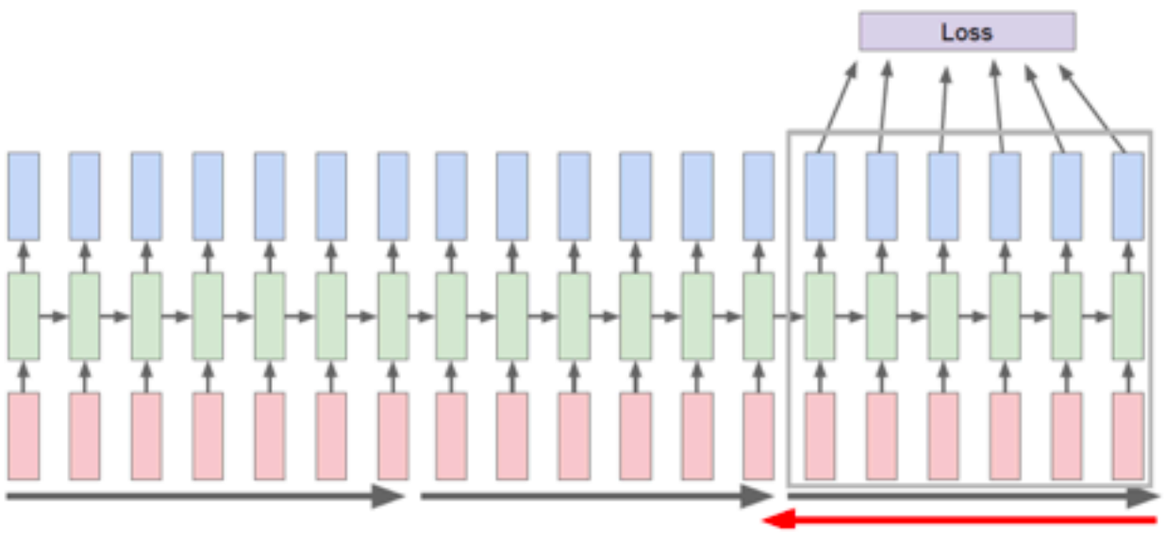
$$g \leftarrow \frac{threshold}{\|g\|} g$$

Simple but still very effective!

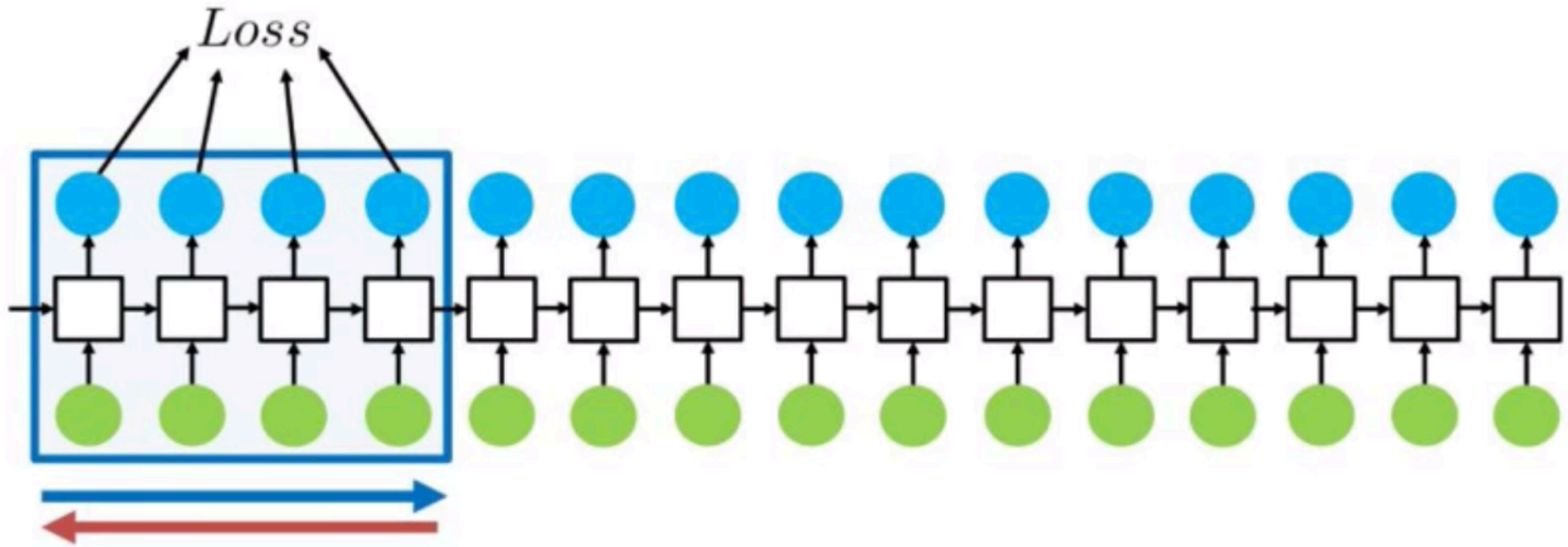
Truncated BPTT







Truncated BPTT



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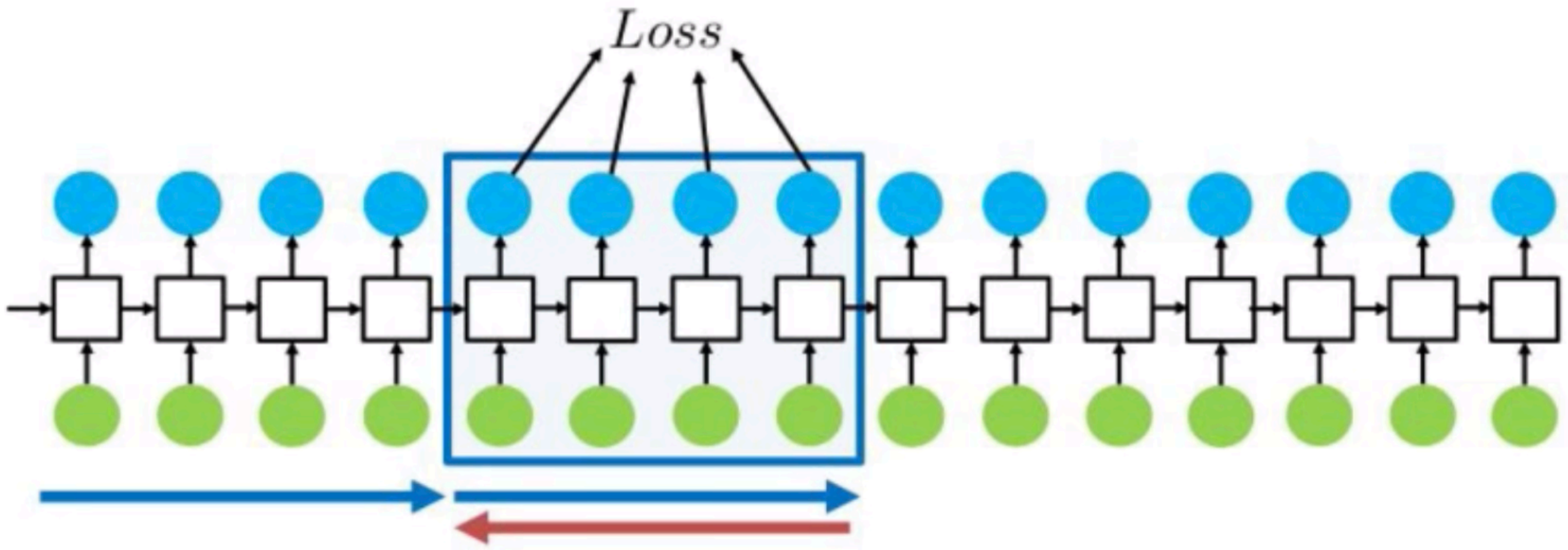
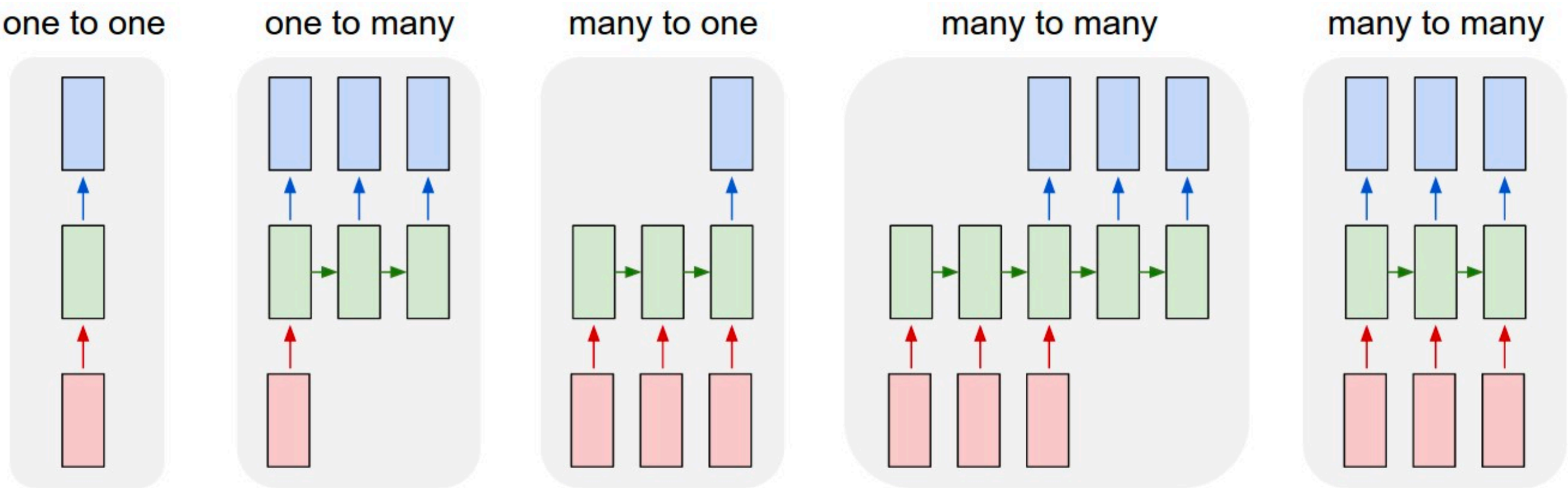
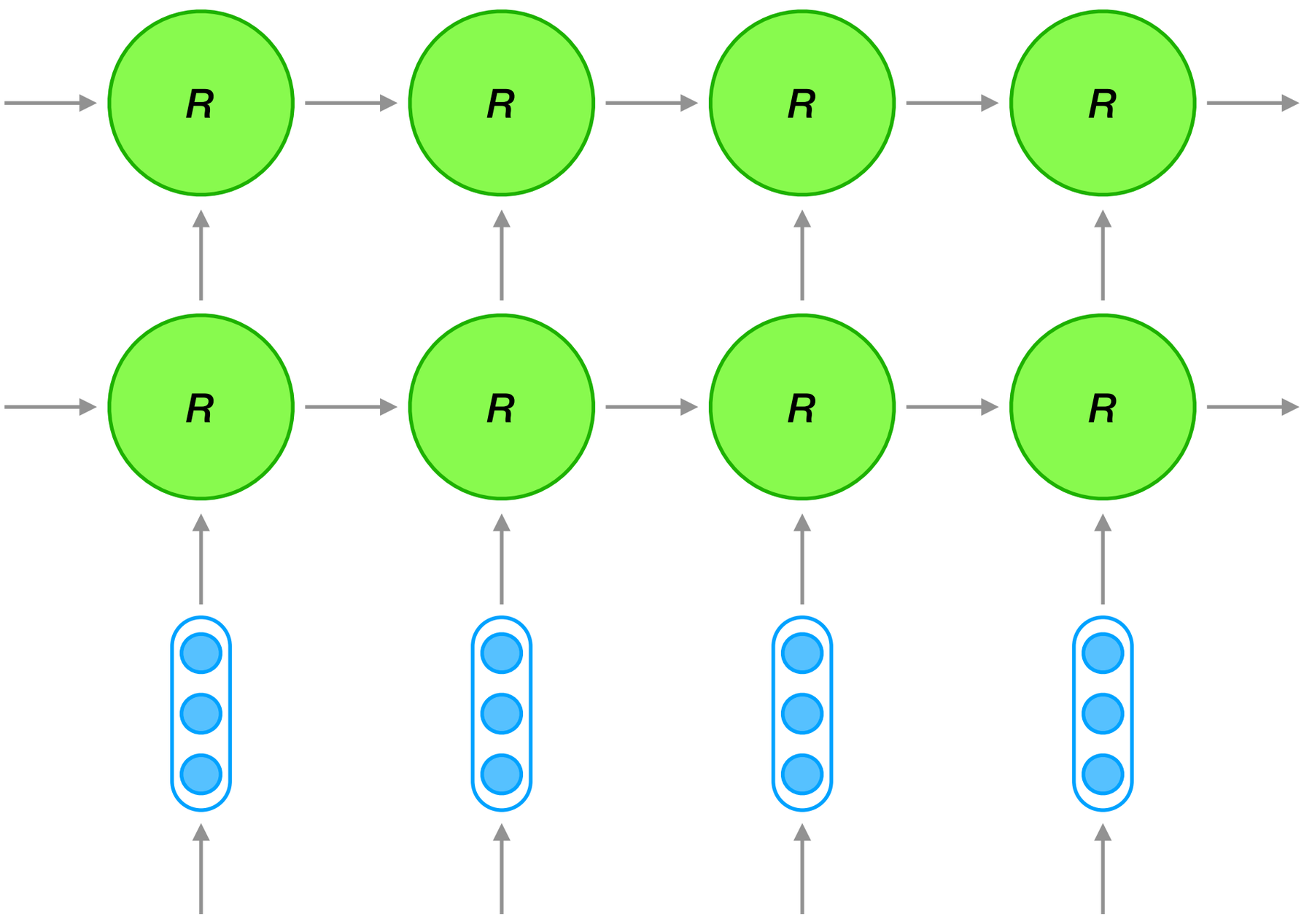


Recurrent Neural Network

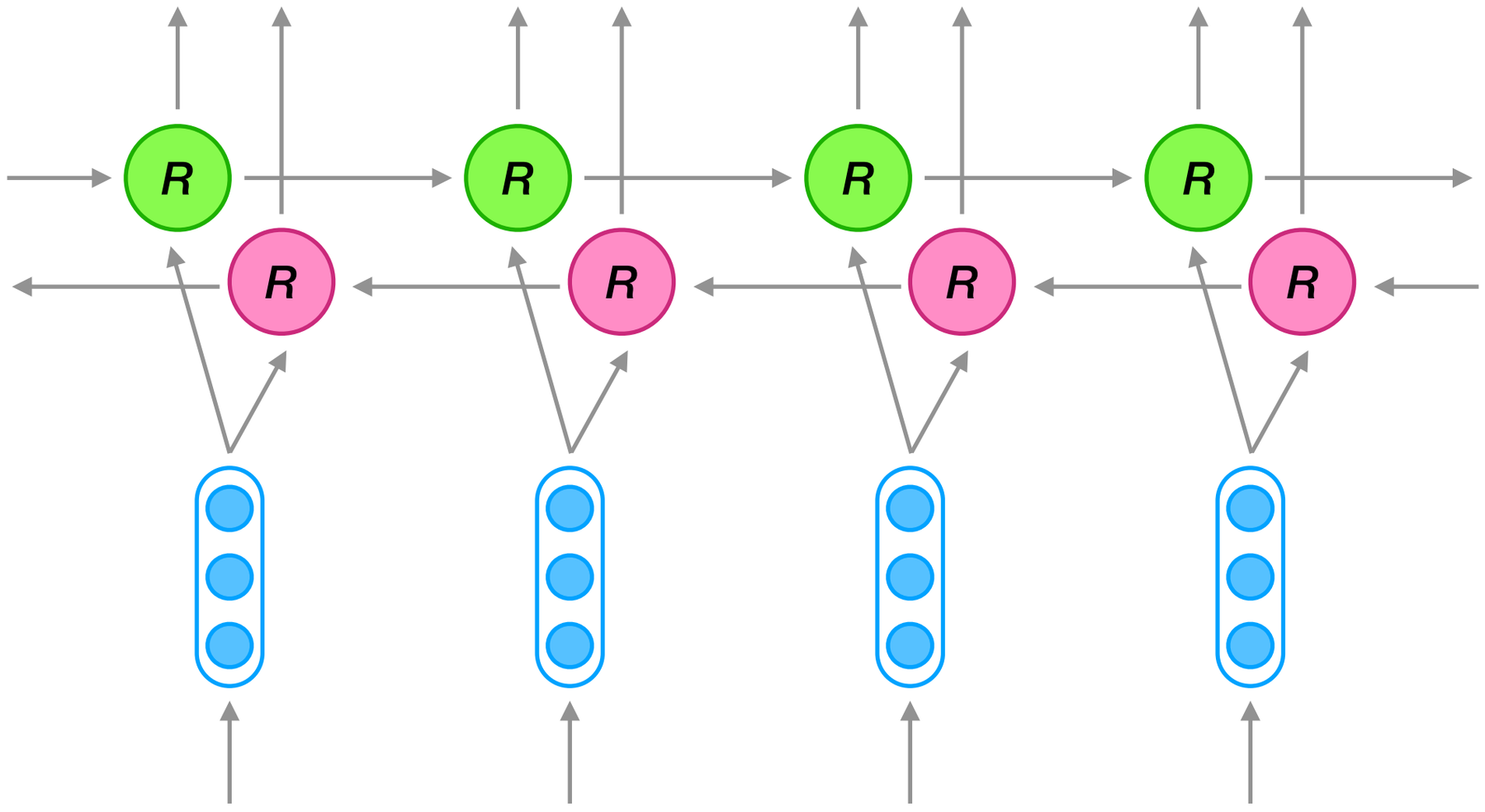
Recurrent Neural Network



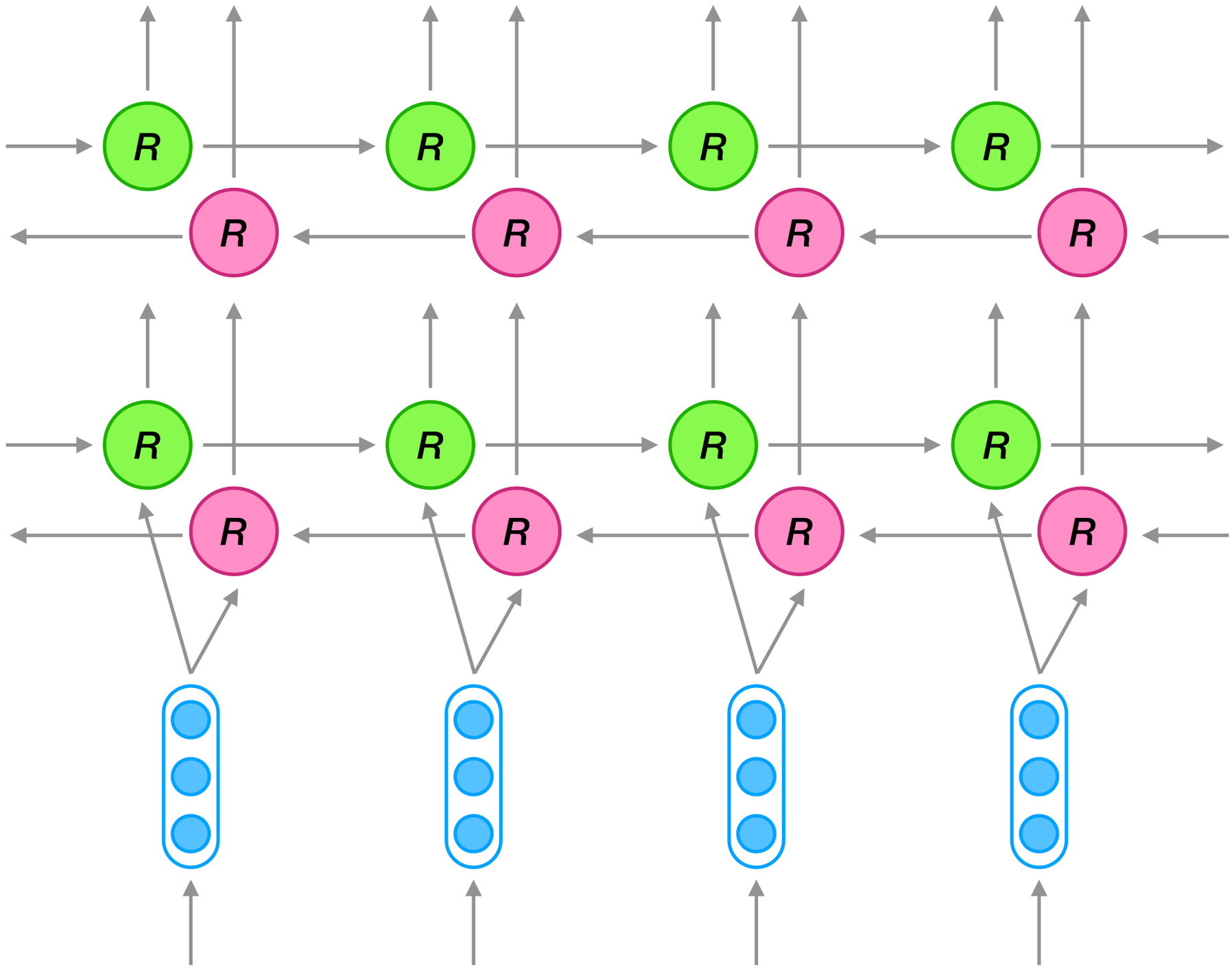
Deeper



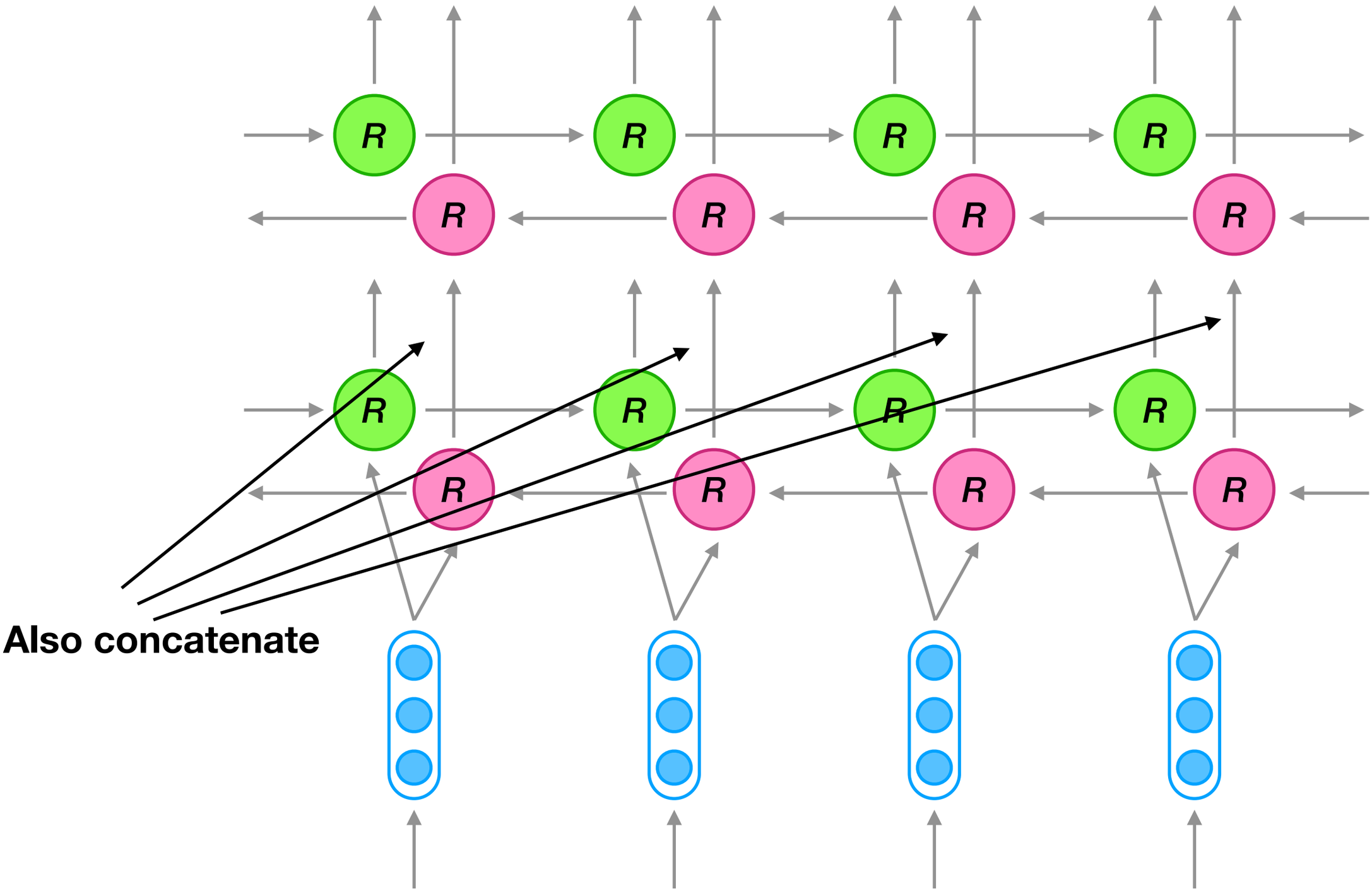
Bidirectional



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		

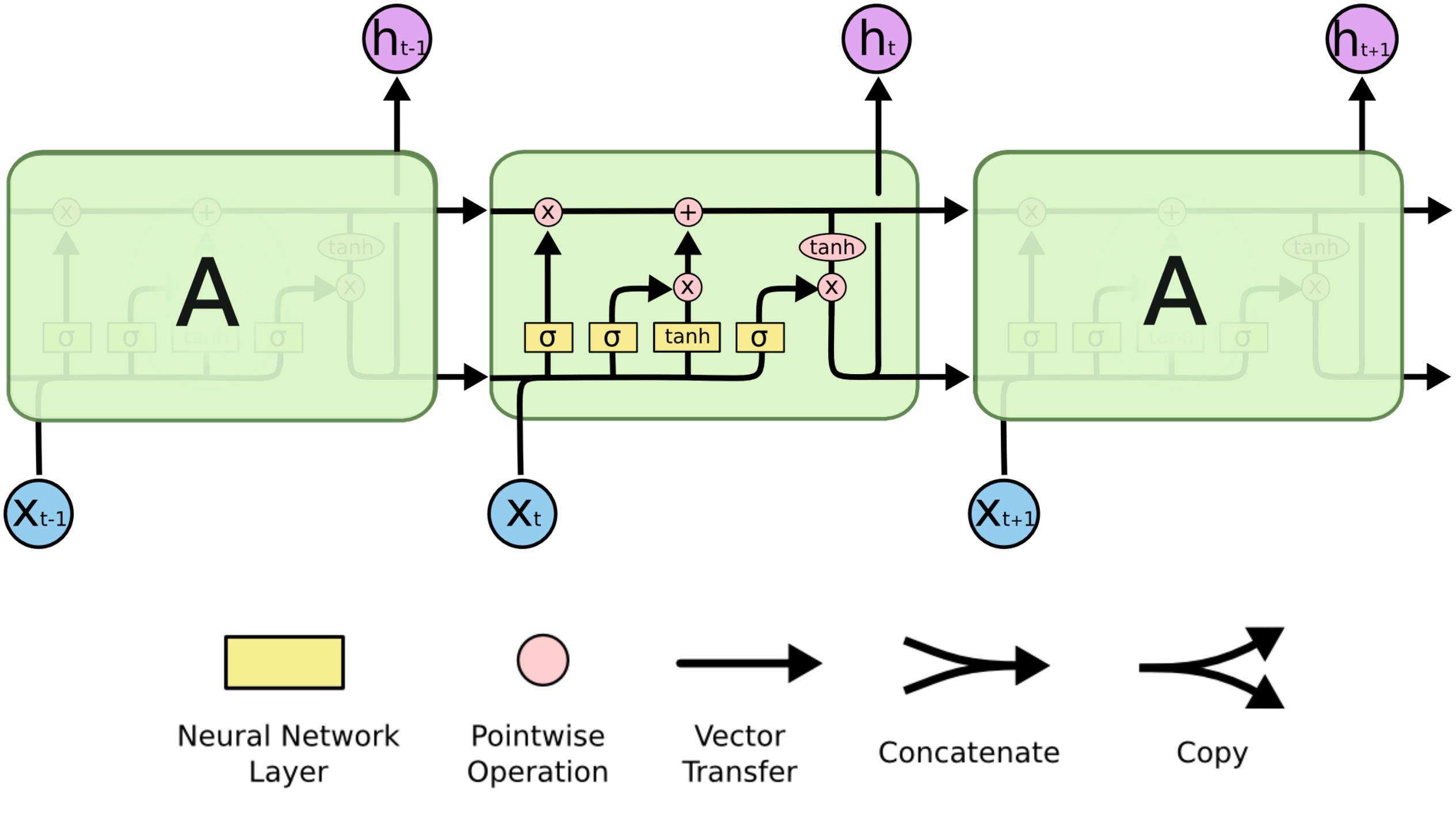
Bidirectional

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	

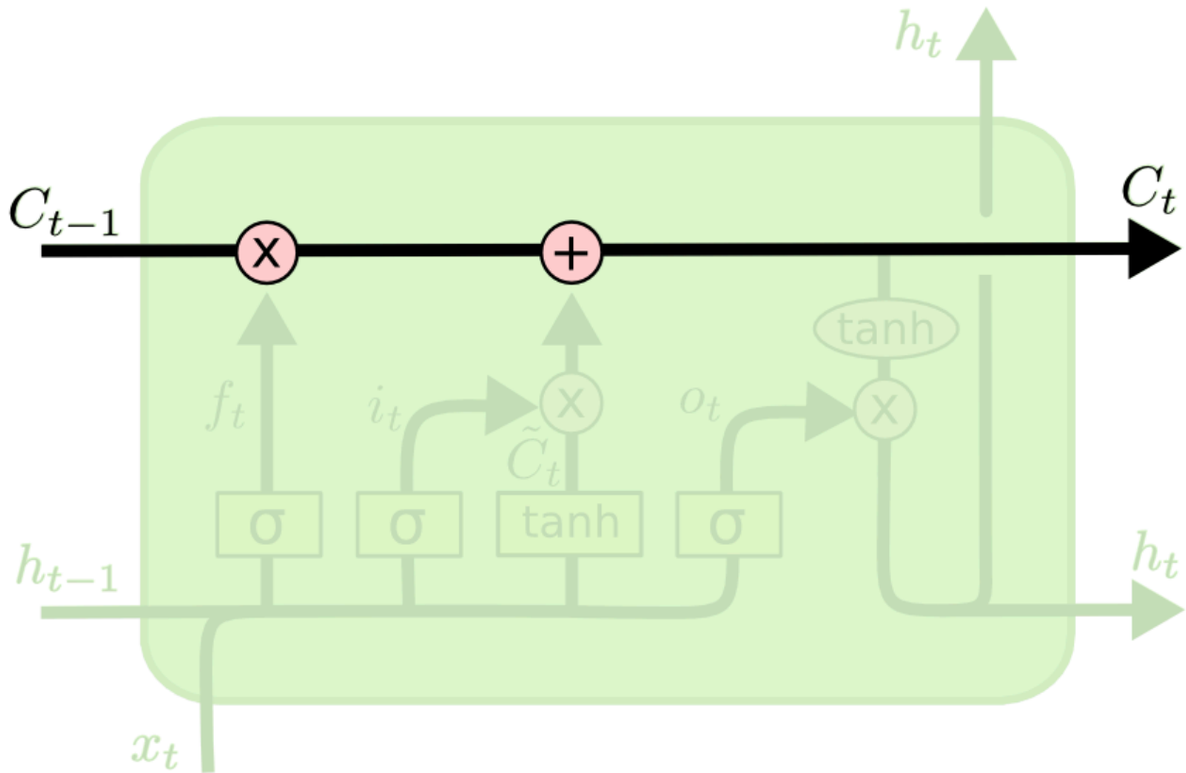
Bidirectional

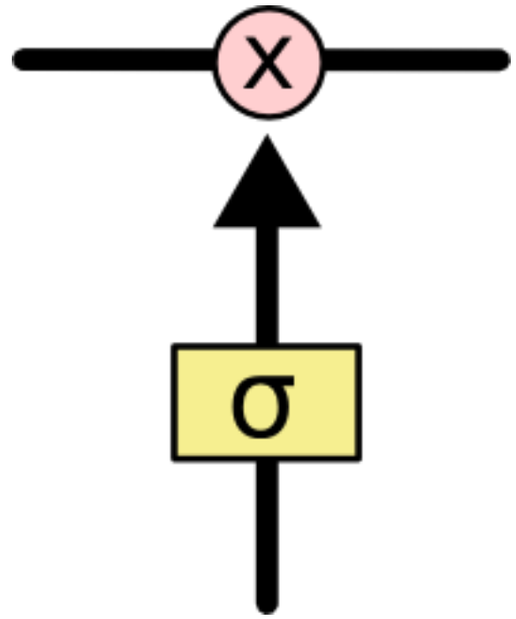
Source	<START>	The	poor	don’t	have	any	money	<END>
Forward	<START>	The	poor	don’t	have	any	money	<END>
Backward	<END>	money	any	have	don’t	poor	The	<START>

Long Short Term Memories

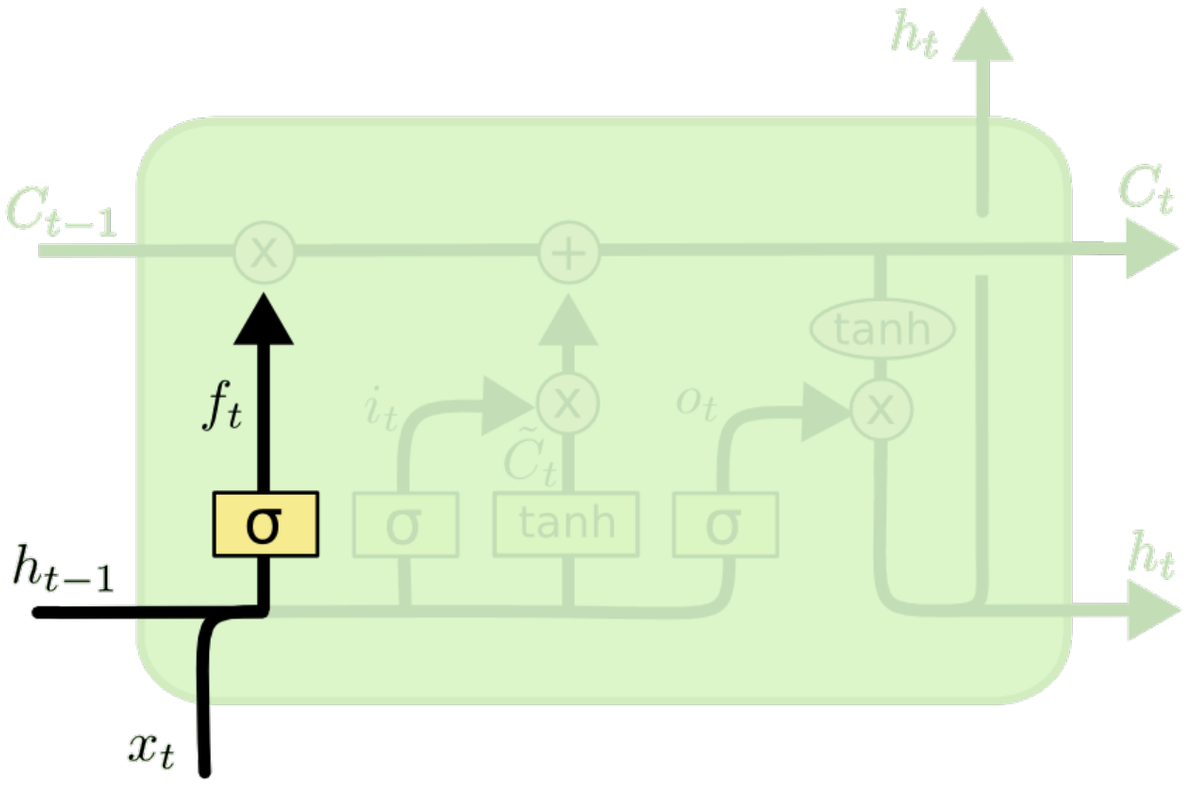


Long Short Term Memories



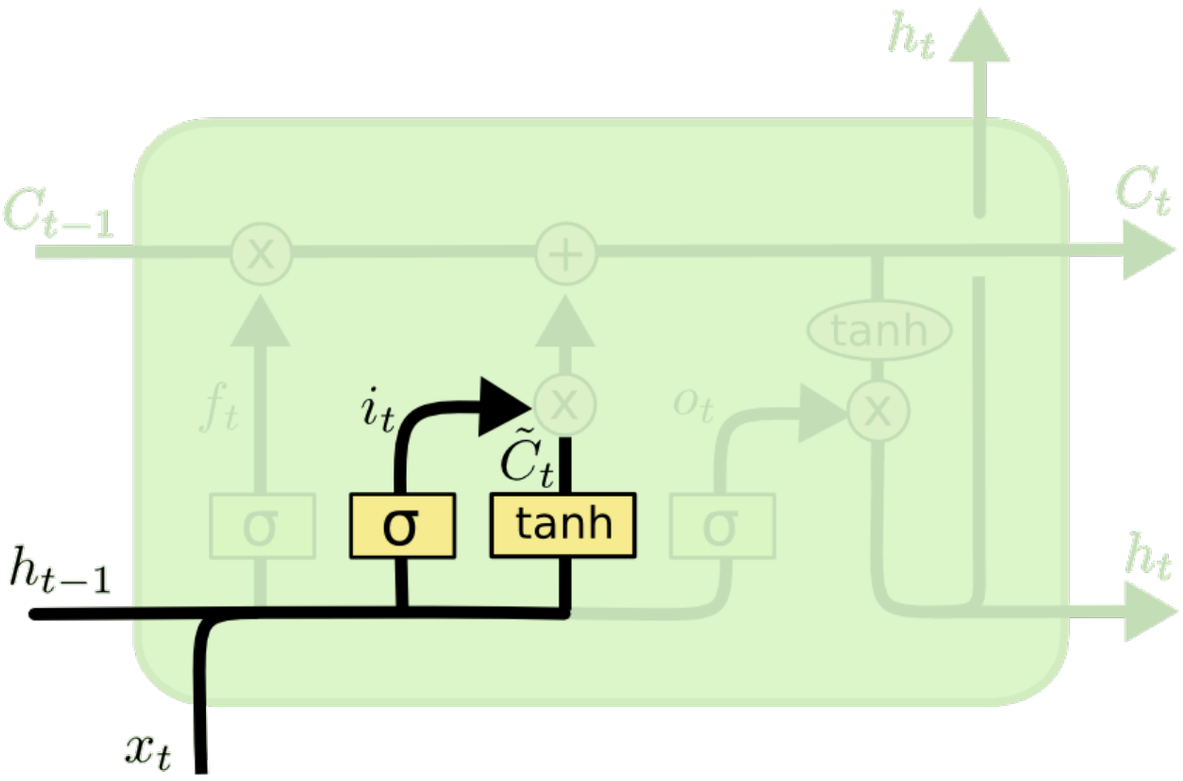


Long Short Term Memories



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

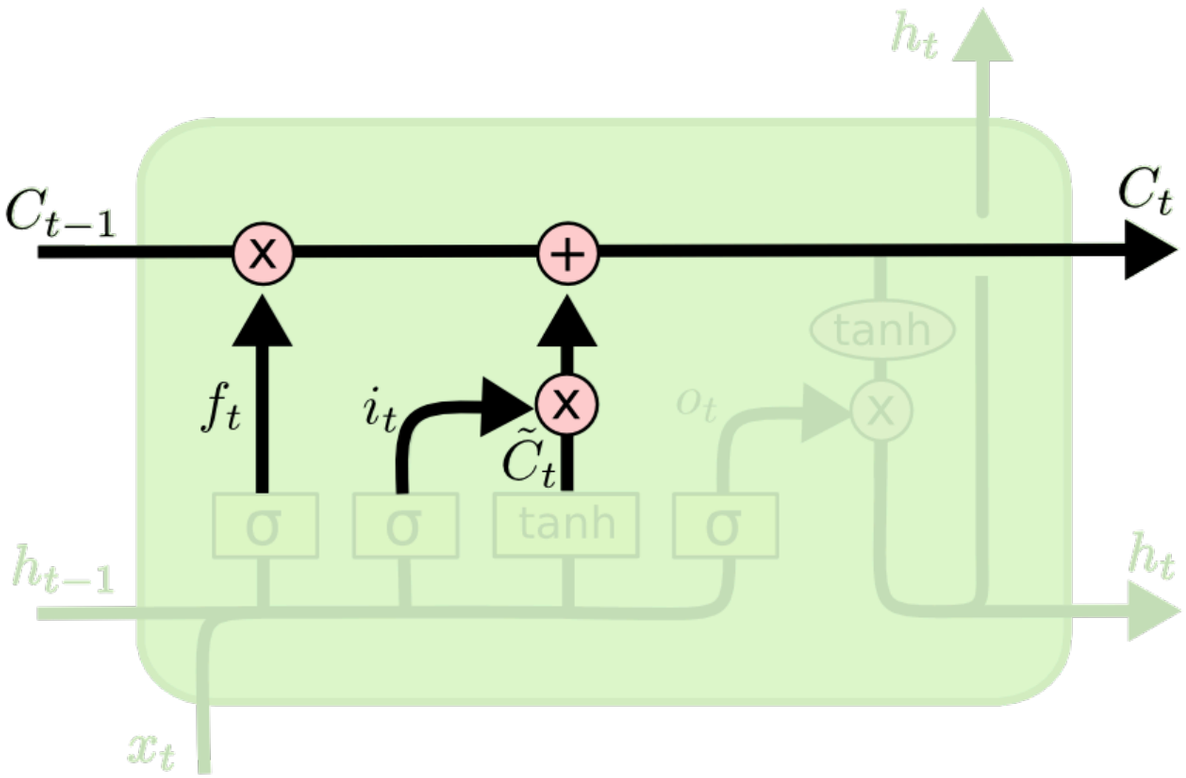
Long Short Term Memories



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

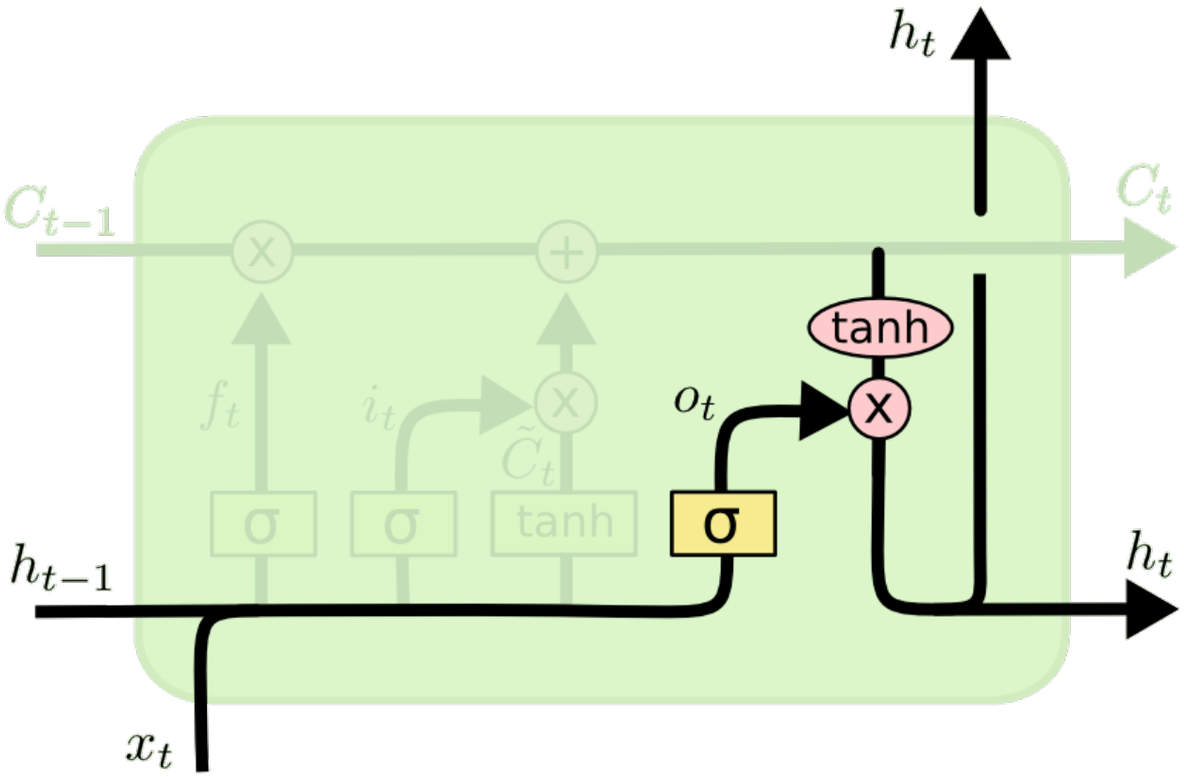
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$$

Long Short Term Memories



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

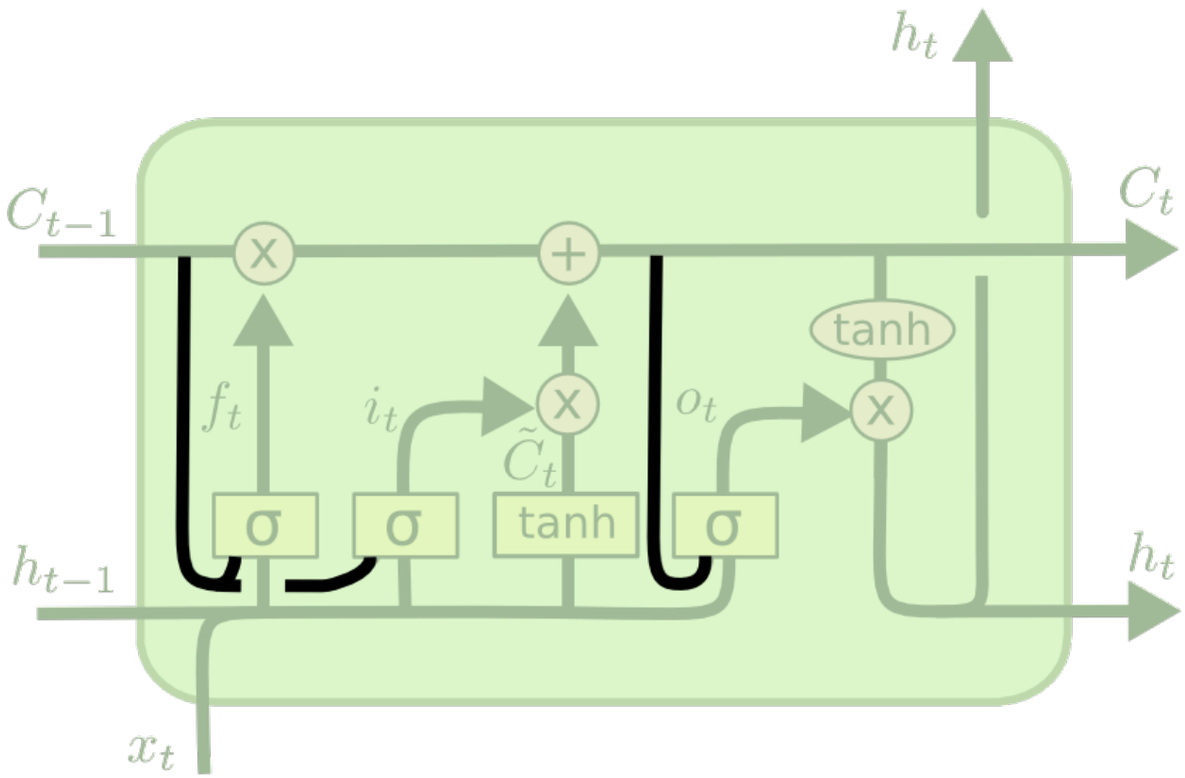
Long Short Term Memories



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

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

Long Short Term Memories

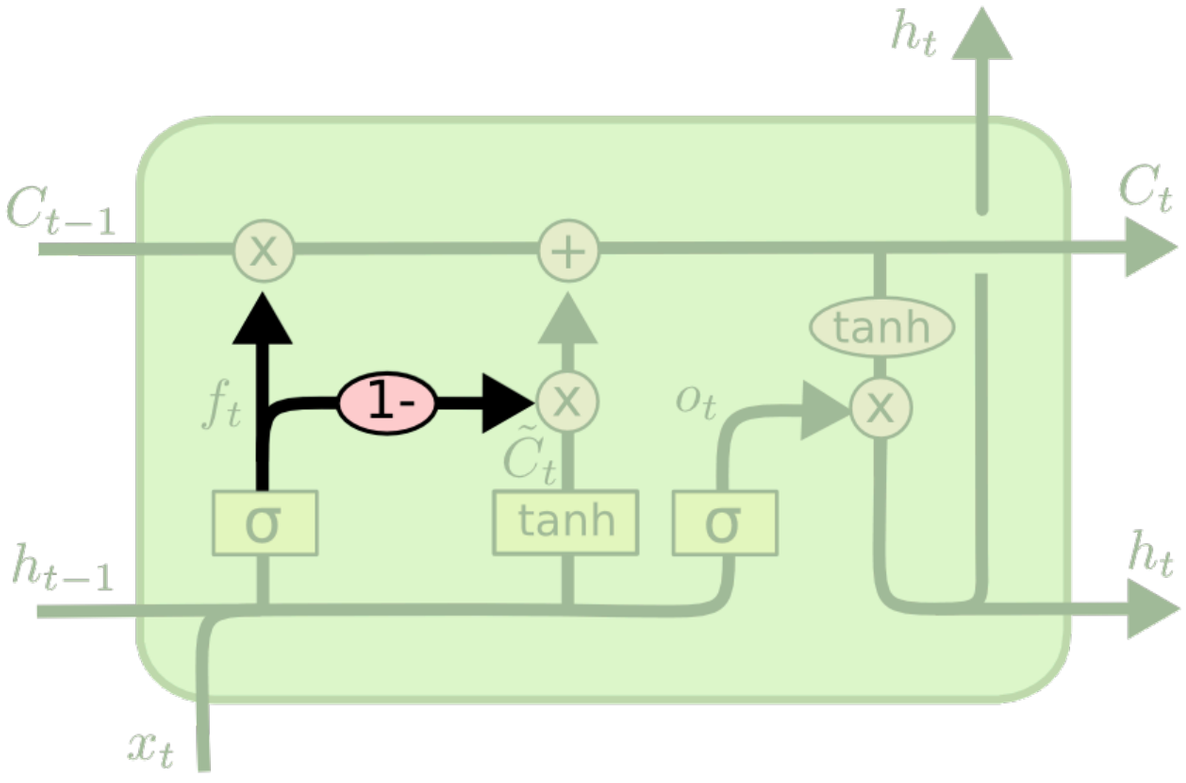


$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \; + \; b_f\right)$$

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

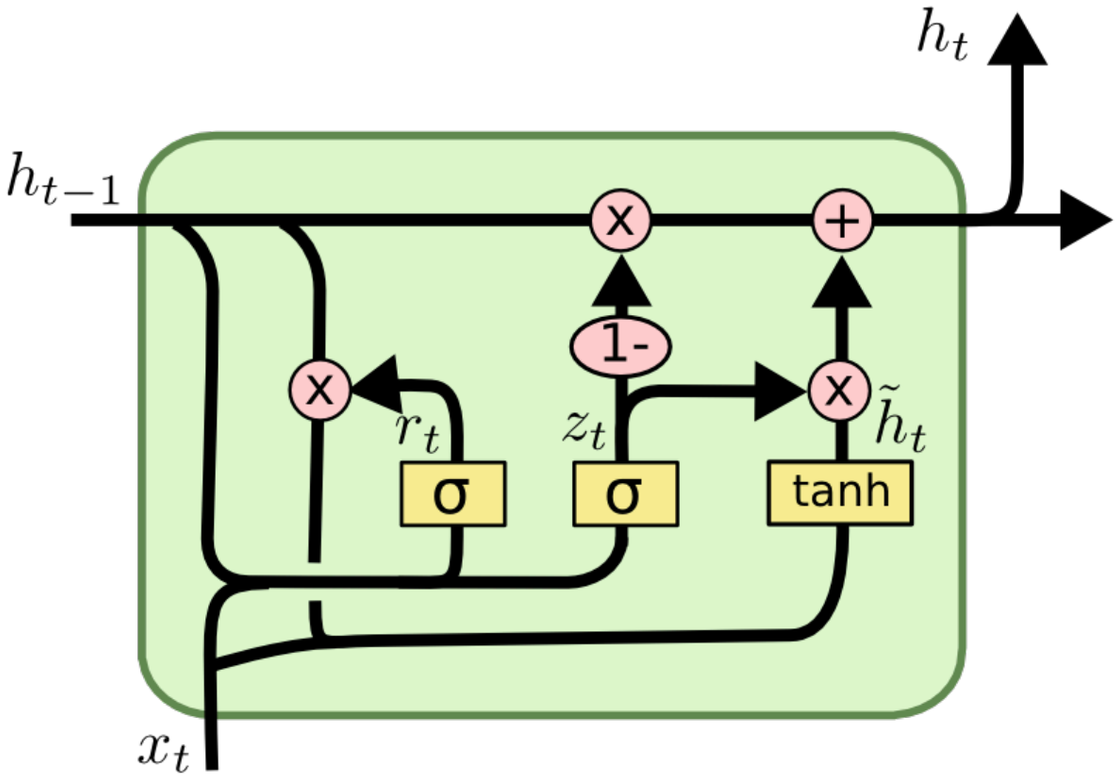
$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \; + \; b_o\right)$$

Long Short Term Memories



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

Gated Recurrent Unit



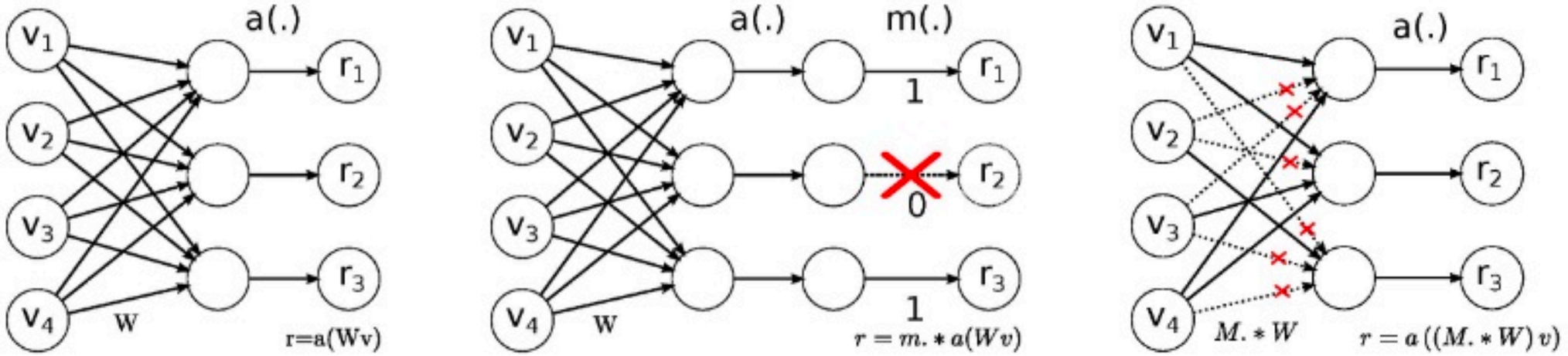
$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

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

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

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

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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$$\mu_i = \frac{1}{m}\sum_{j=1}^{m} x_{ij}$$
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Layer Normalization

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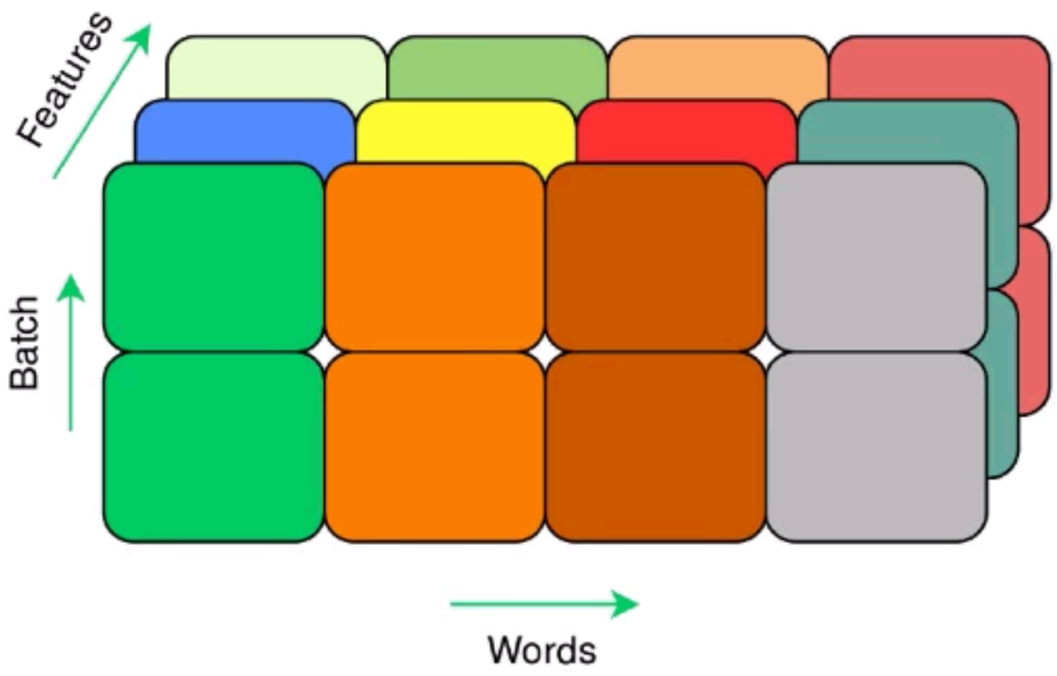
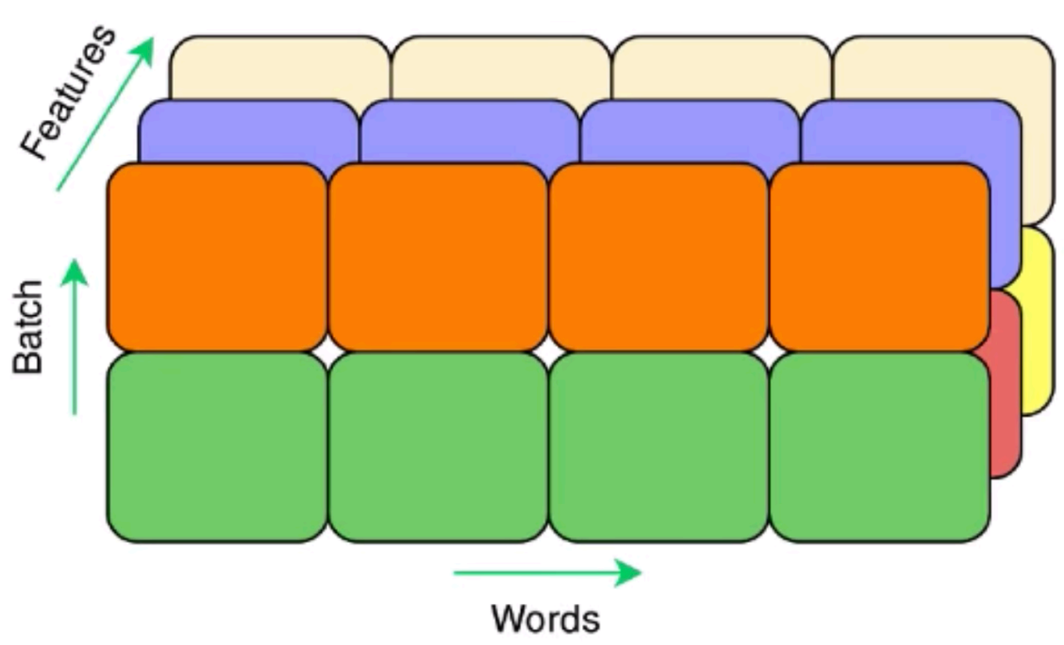
$$\hat{x_{ij}} = \frac{x_{ij} - \mu_i}{\sqrt{\sigma_i^2 + \epsilon}}$$





Thanks for your Attention!

Boris Zubarev

@bobazooba