SILO AI

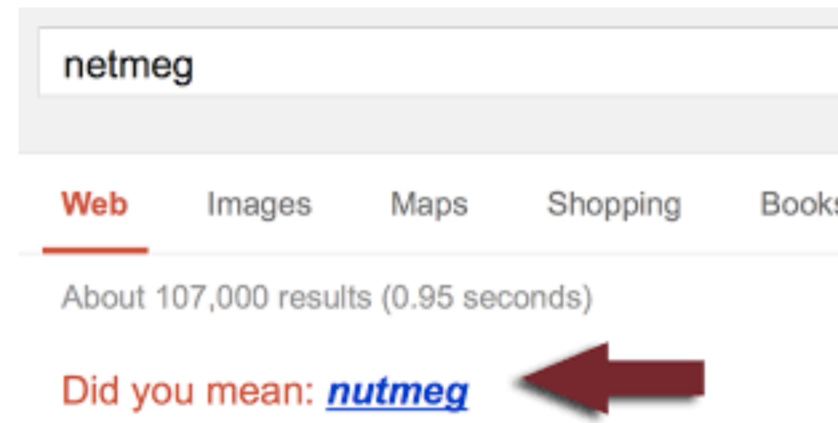
Neural Network Language Models & BERT

Mittul Singh

Language Model Applications

Language Model Applications

- Spelling correction, text input
    - Search Query Completion



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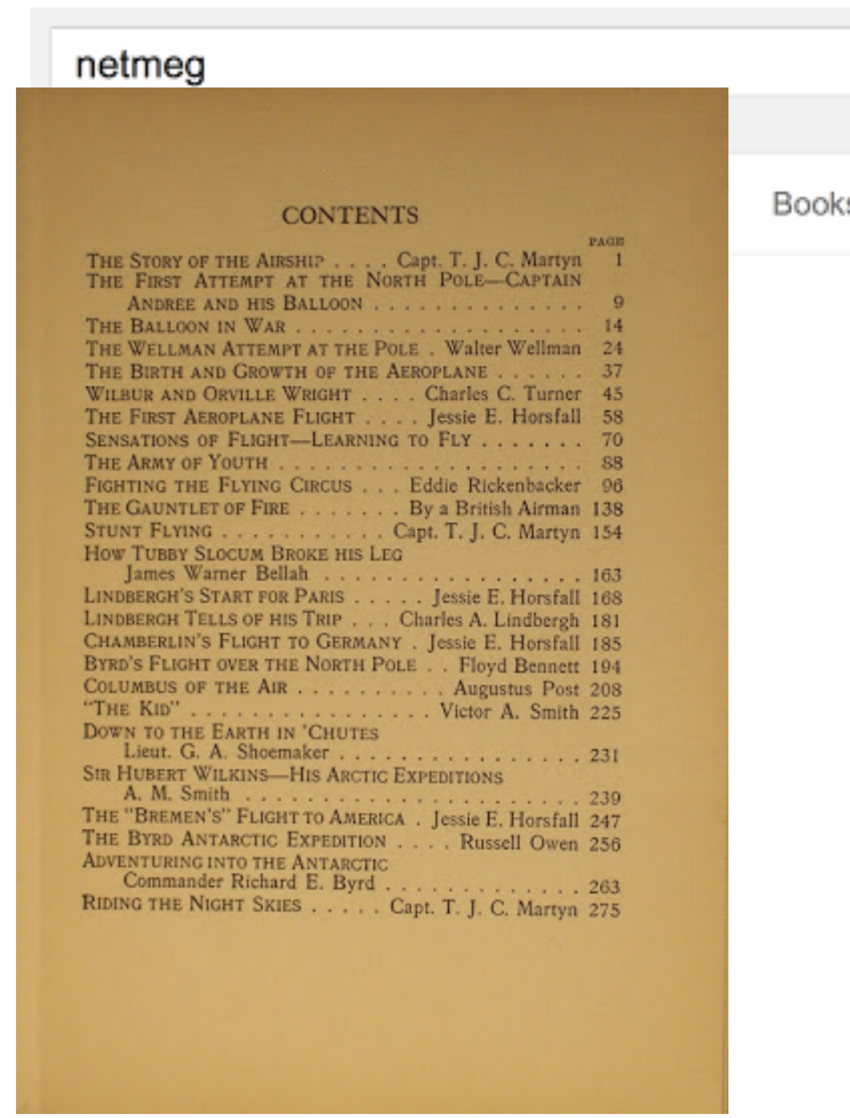

CONTENTS

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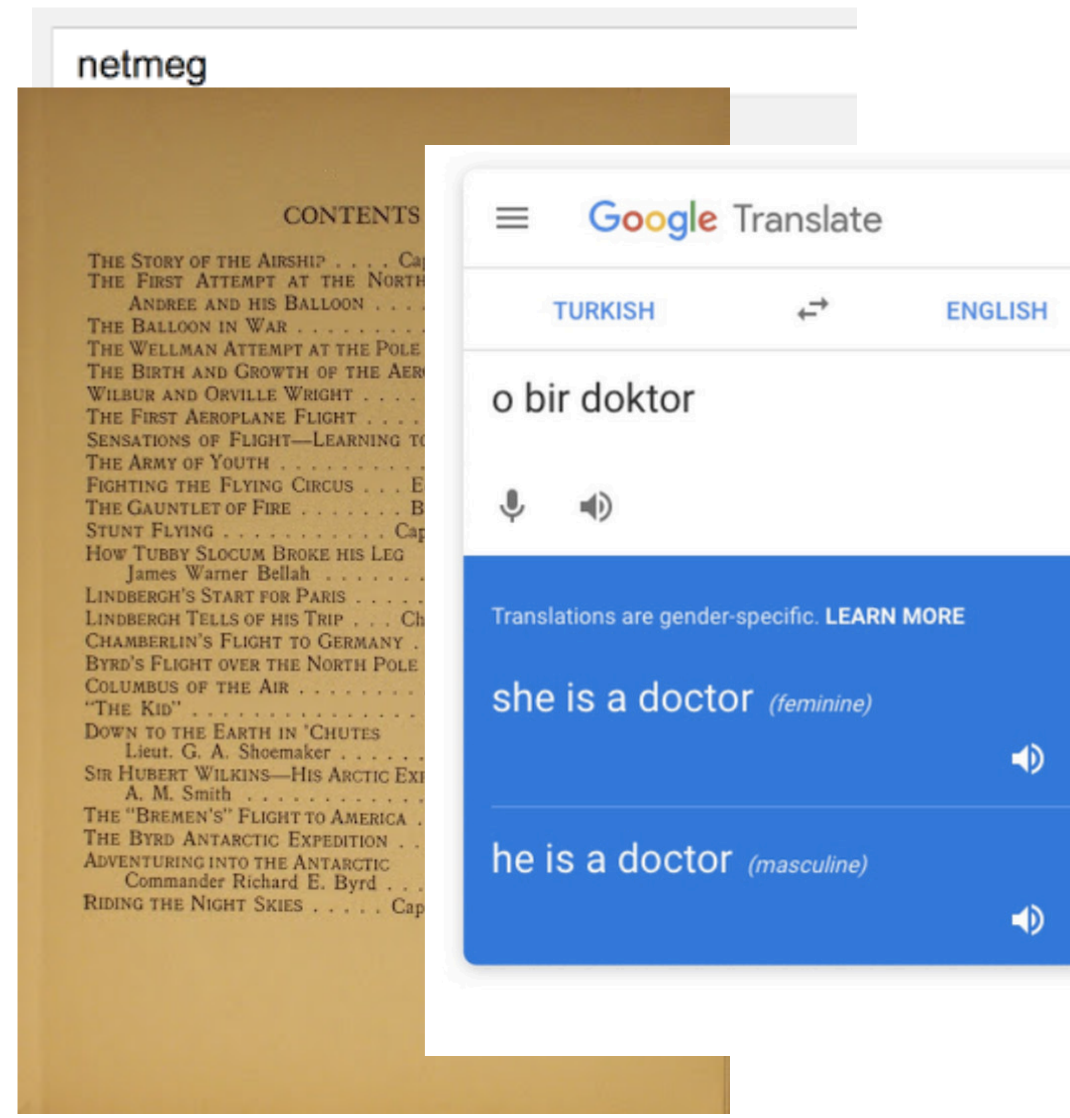

Language Model Applications

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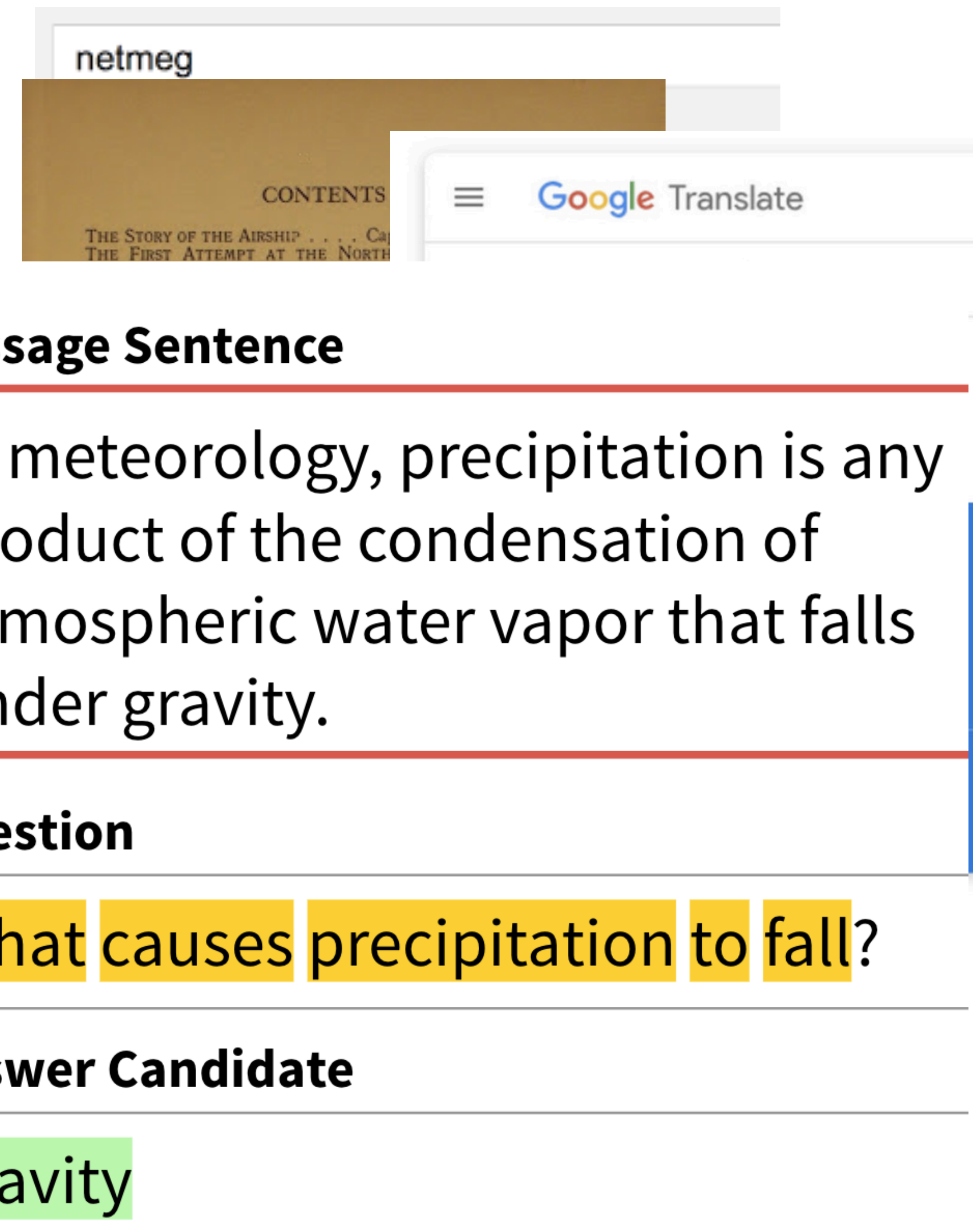
- Information retrieval
    - Question Answering



Language Model Applications

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- Optical character recognition
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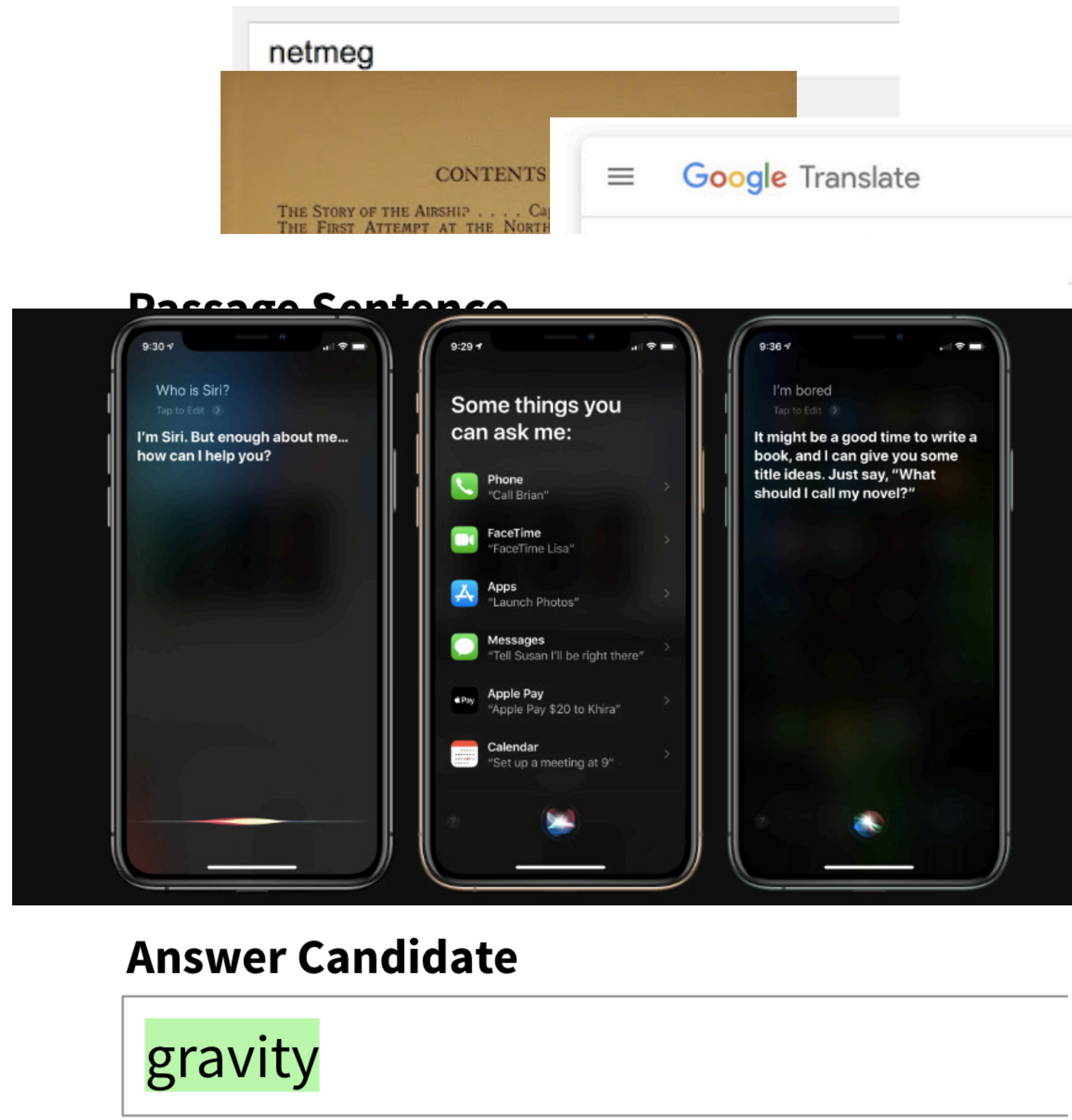
- Statistical machine translation
- Information retrieval
    - Question Answering
- Automatic speech recognition
- …



Recap: N-gram Language Models

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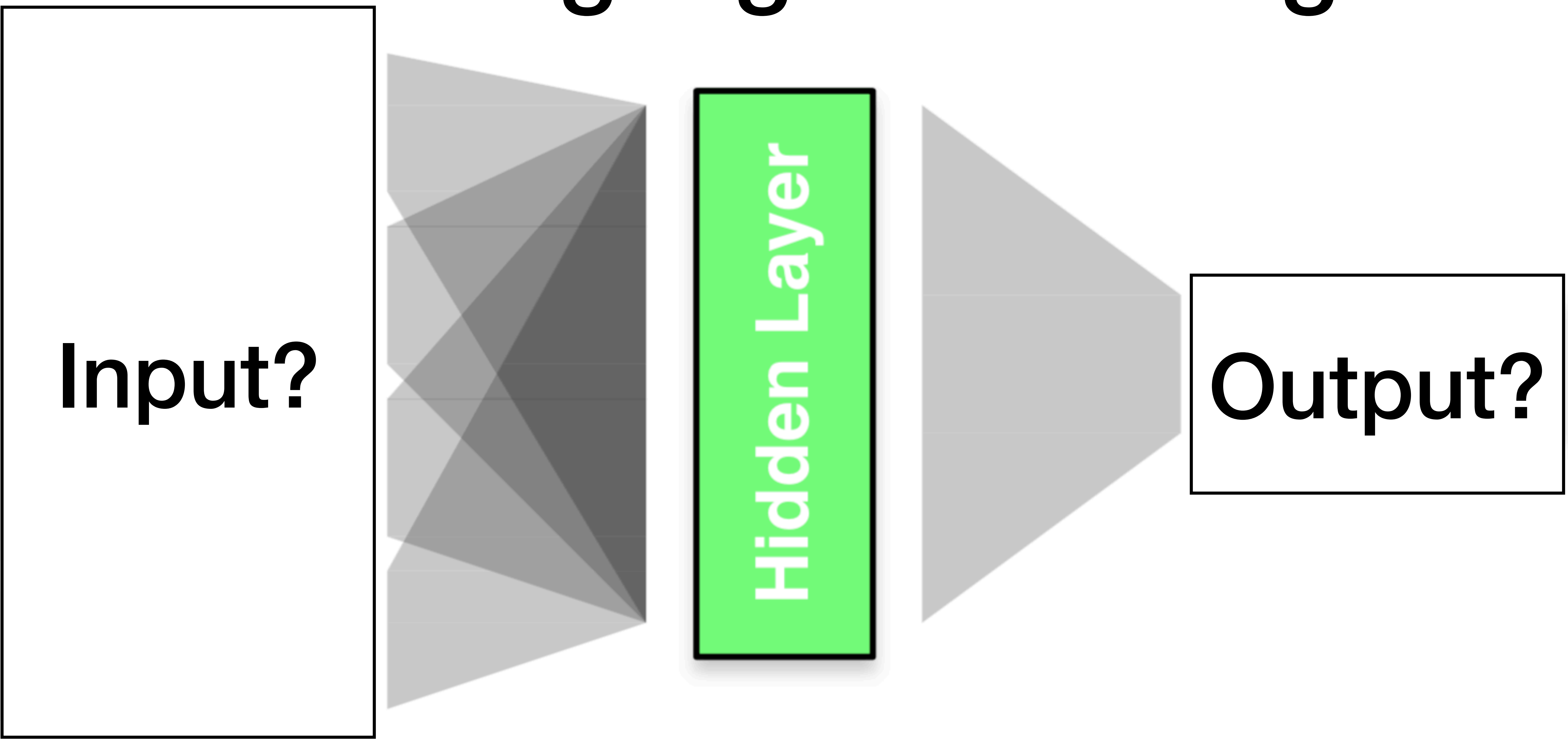
- We wanted to calculate

$$p(W) = p(w_1, w_2, \ldots, w_n) \tag{1}$$

$$p(w_i|w_{i-1}, w_{i-2}, \ldots, w_{n-1}) \approx p(w_i|w_{i-1}, w_{i-2}, w_{i-3}, w_{i-4}) \tag{2}$$

Neural Network Classifier for Language Modelling



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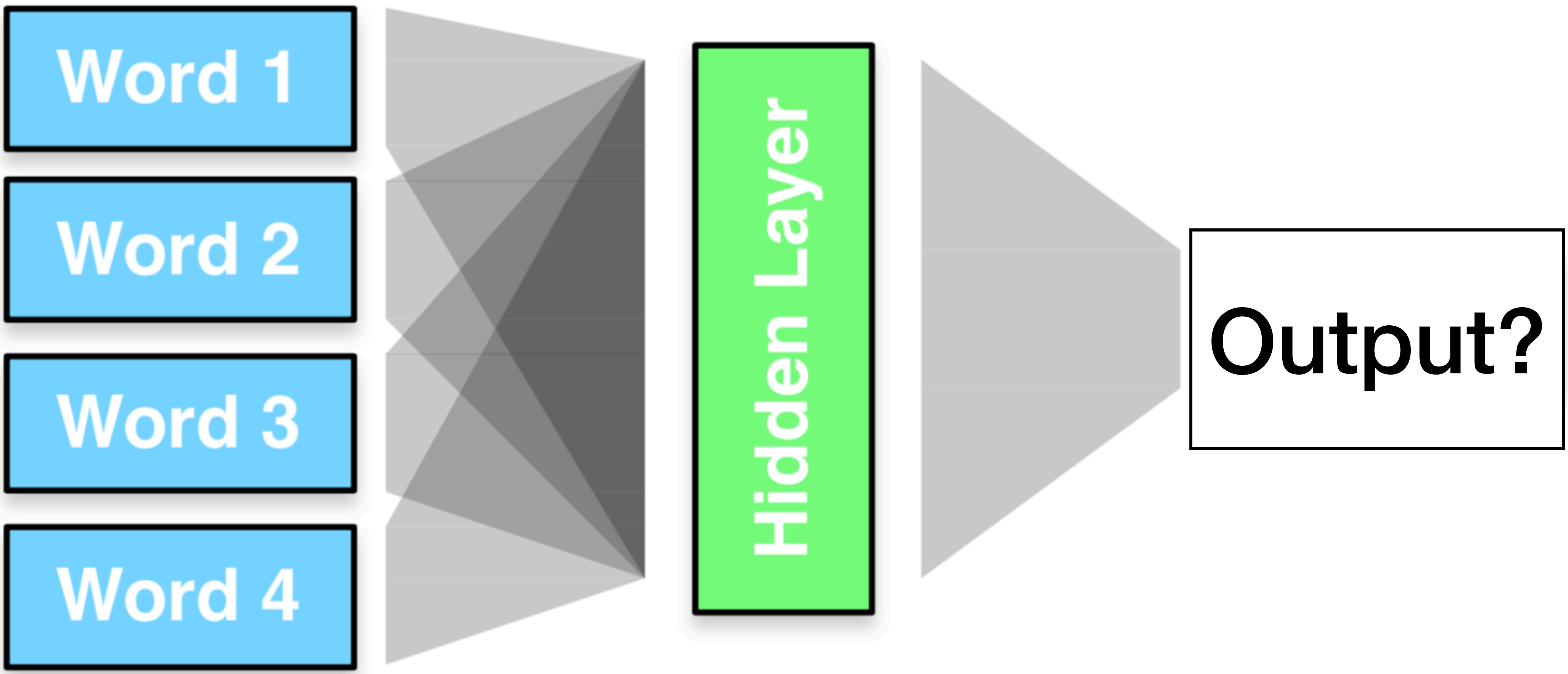
Neural Network Classifier for Language Modelling



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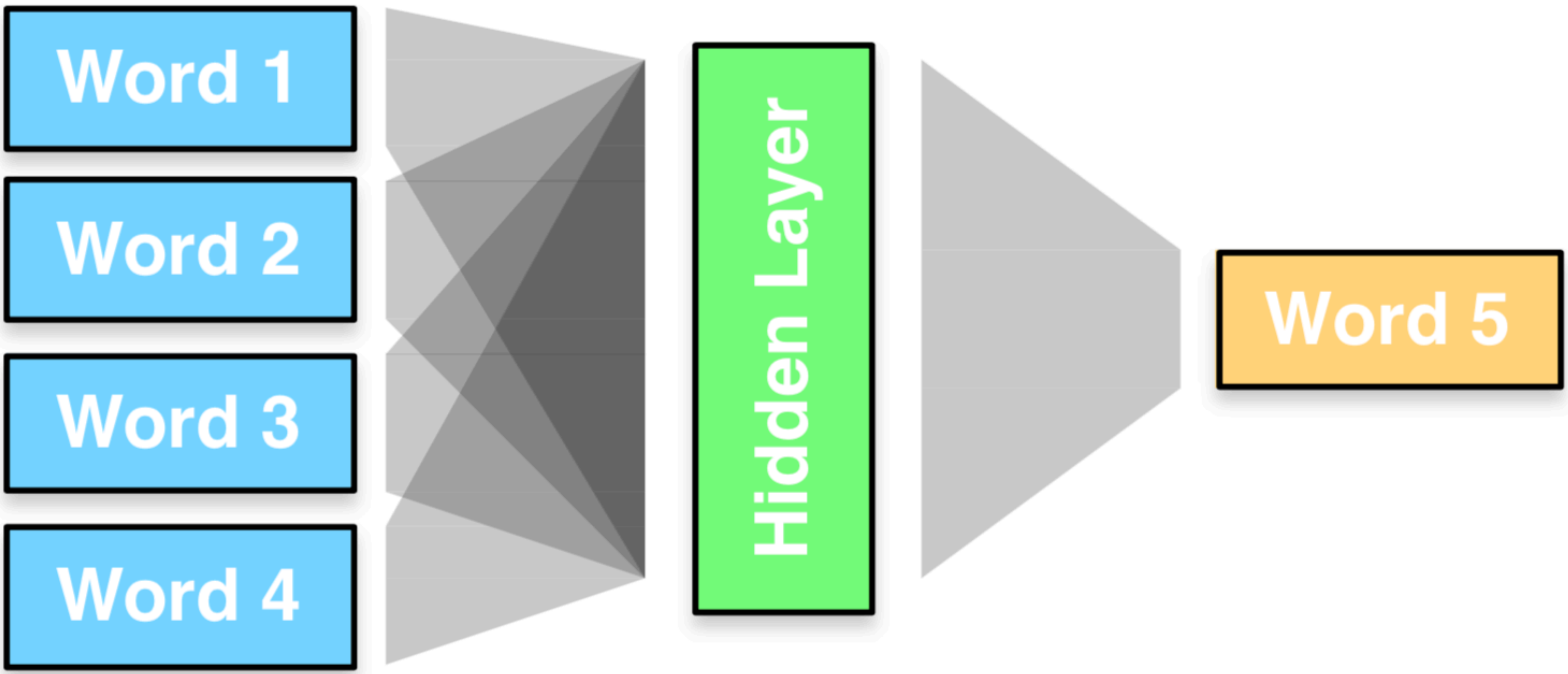

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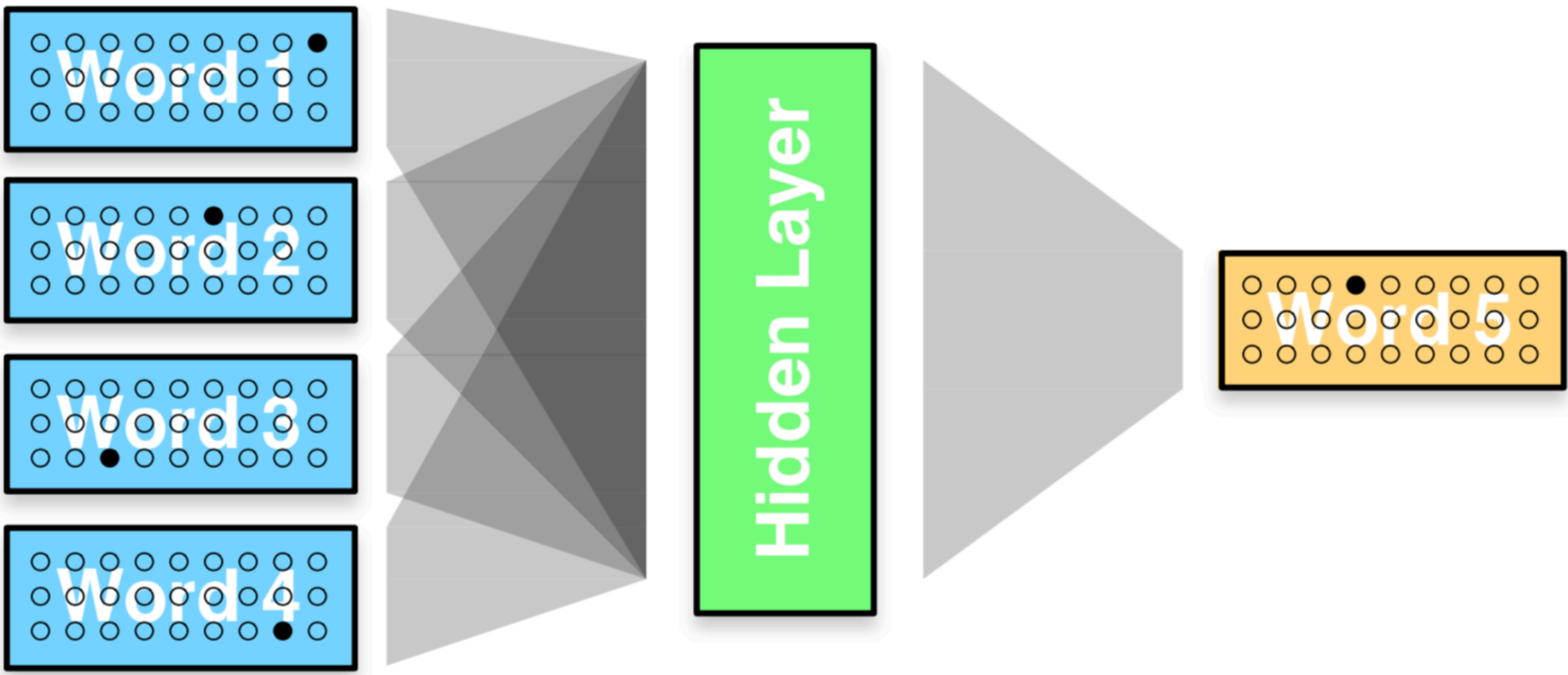
Representing Words

Representing Words

- Words are represented with one-hot vector, e.g.,
  - dog = (0, 0, 0, 1, 0, 0, …)
  - cat = (0, 0, 0, 0, 0, 1, …)
  - eat = (0, 1, 0, 0, 0, 0, …)

Second Sketch



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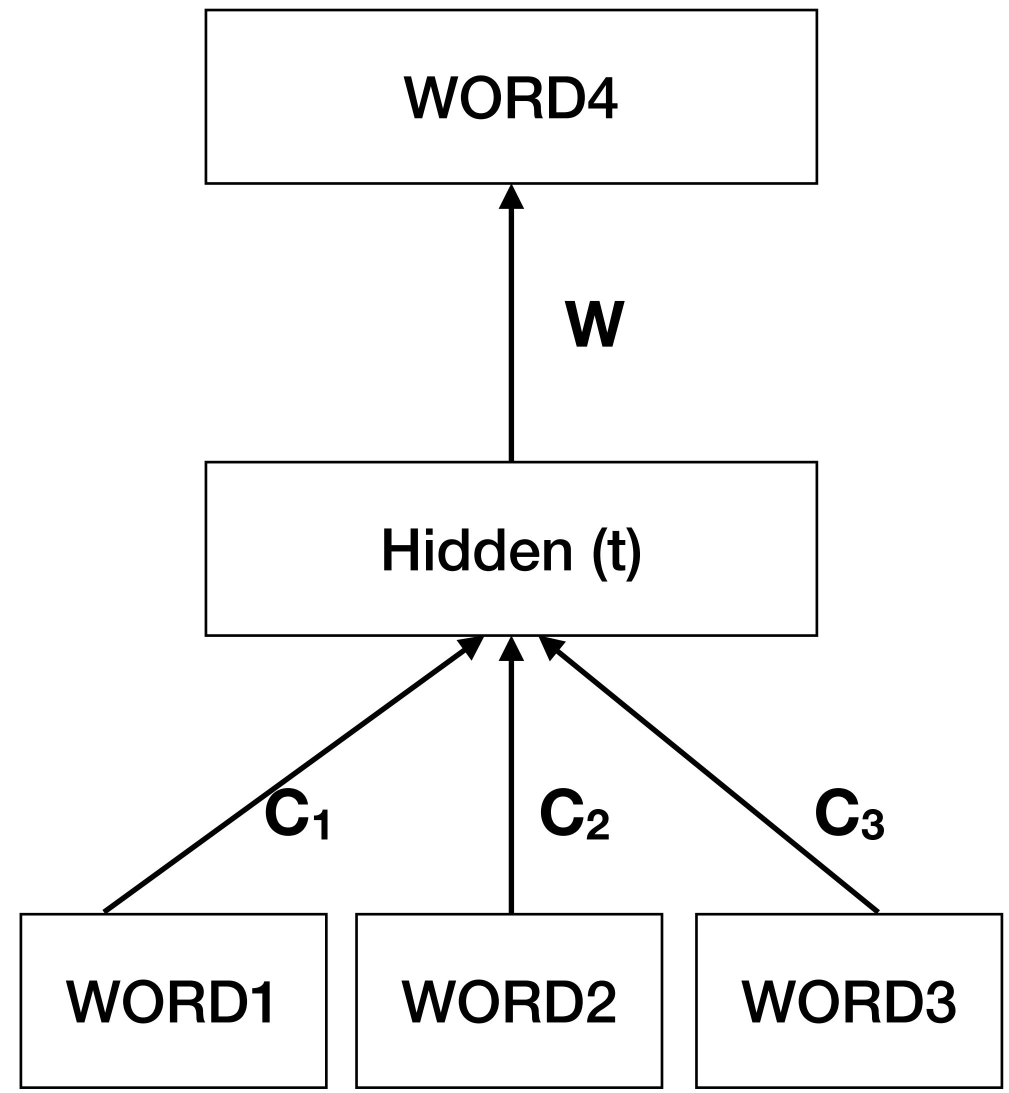
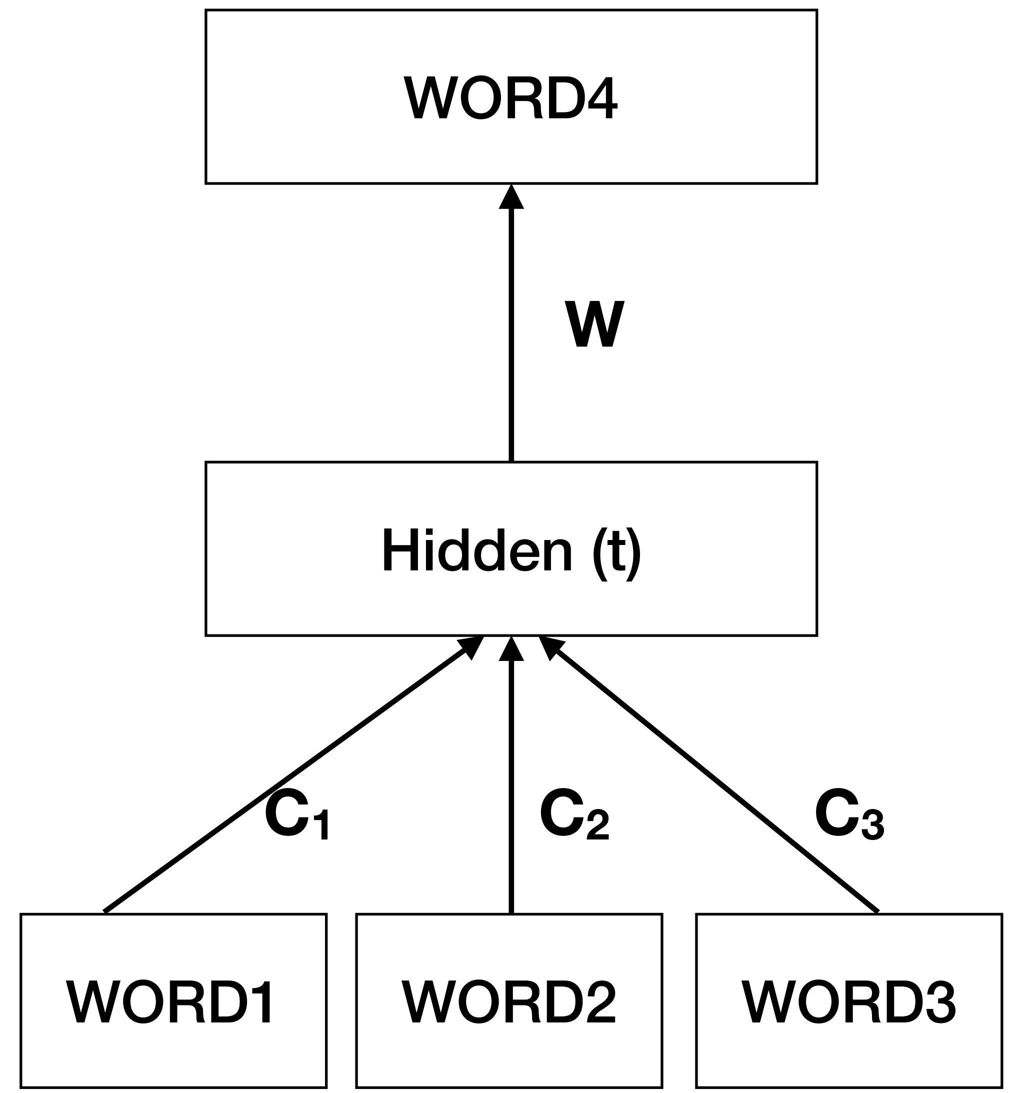
Feedforward Neural Network LM (FFNN)



FFNN

Feedforward Neural Network LM (FFNN)

- Loop through the entire corpus



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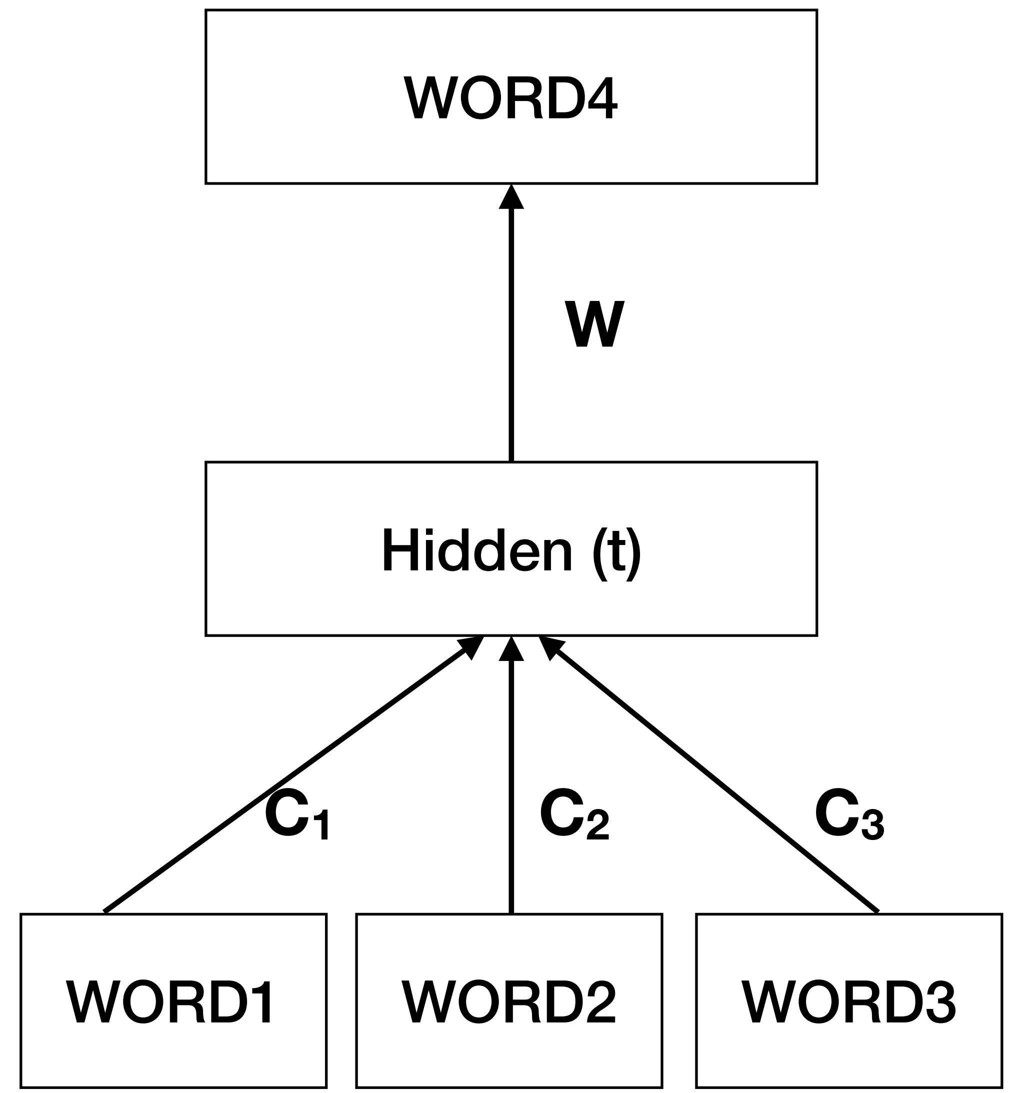
Feedforward Neural Network LM (FFNN)

- Loop through the entire corpus

- Calculate error or loss (cross-entropy loss)



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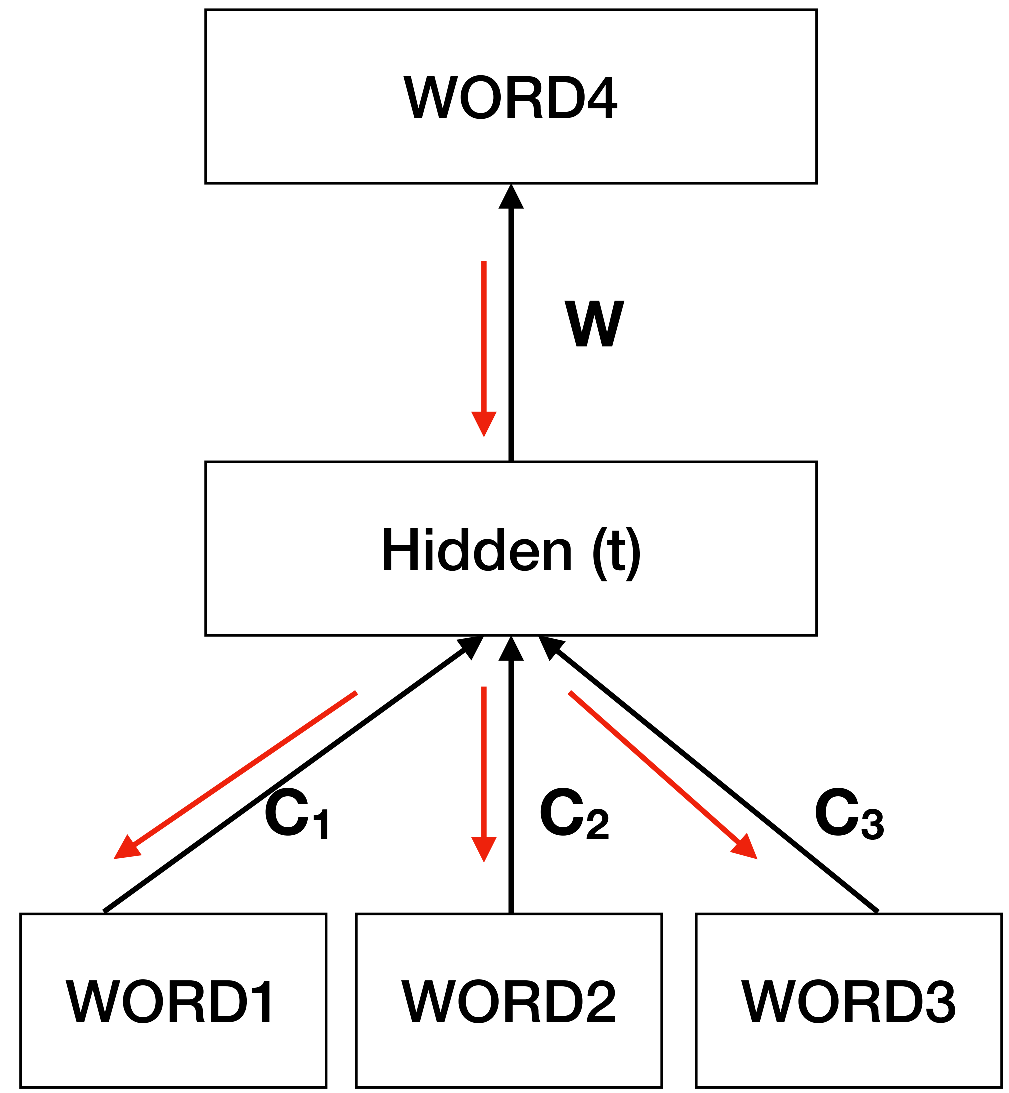
- Propagate the error through network to update the weight matrices



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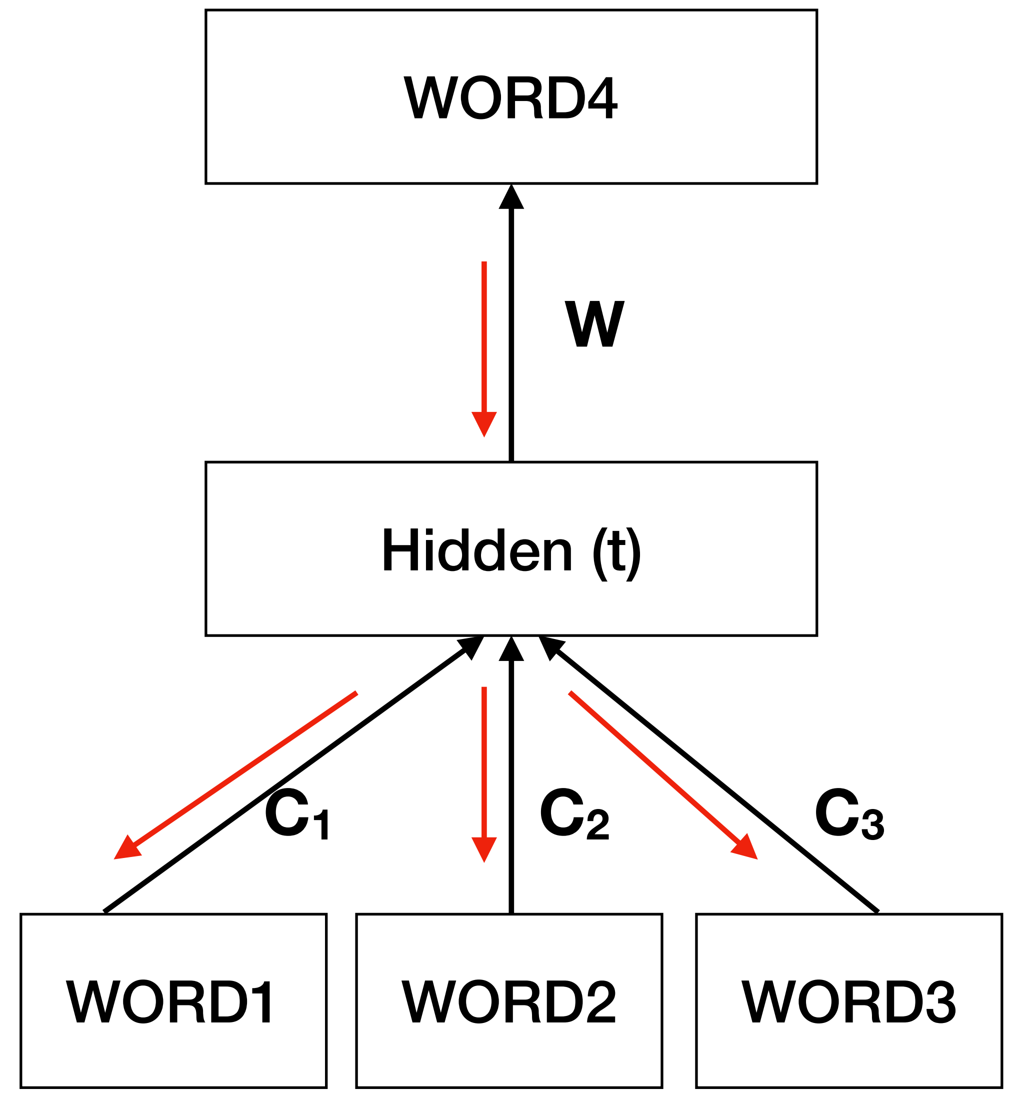
Feedforward Neural Network LM (FFNN)

- Loop through the entire corpus
- Calculate error or loss (cross-entropy loss)
- Propagate the error through network to update the weight matrices
- Back Propagation



FFNN

Why NNs for LMs

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The cat is walking in the bedroom

A dog was running in a room

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- NNLM generalizes in such a way that **similar** words have **similar** vectors

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The cat is walking in the bedroom

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- NNLM generalizes in such a way that **similar** words have **similar** vectors
- Presence of only one such sentence in the training set helps improve the probability of its combinations

Types of NNLM

- Feedforward Neural Network Language Model
- Recurrent Neural Network Language Model
- Long-Short Term Memory LM
- Transformer-based LM
- ..

NNLM: Questions

- What might be some challenges that you might face while training or applying NNLMs?

NNLMs Challenges

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- Long-Range Dependencies

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Feedforward: Long-term information

- “I grew up in France… I speak fluent ________.”

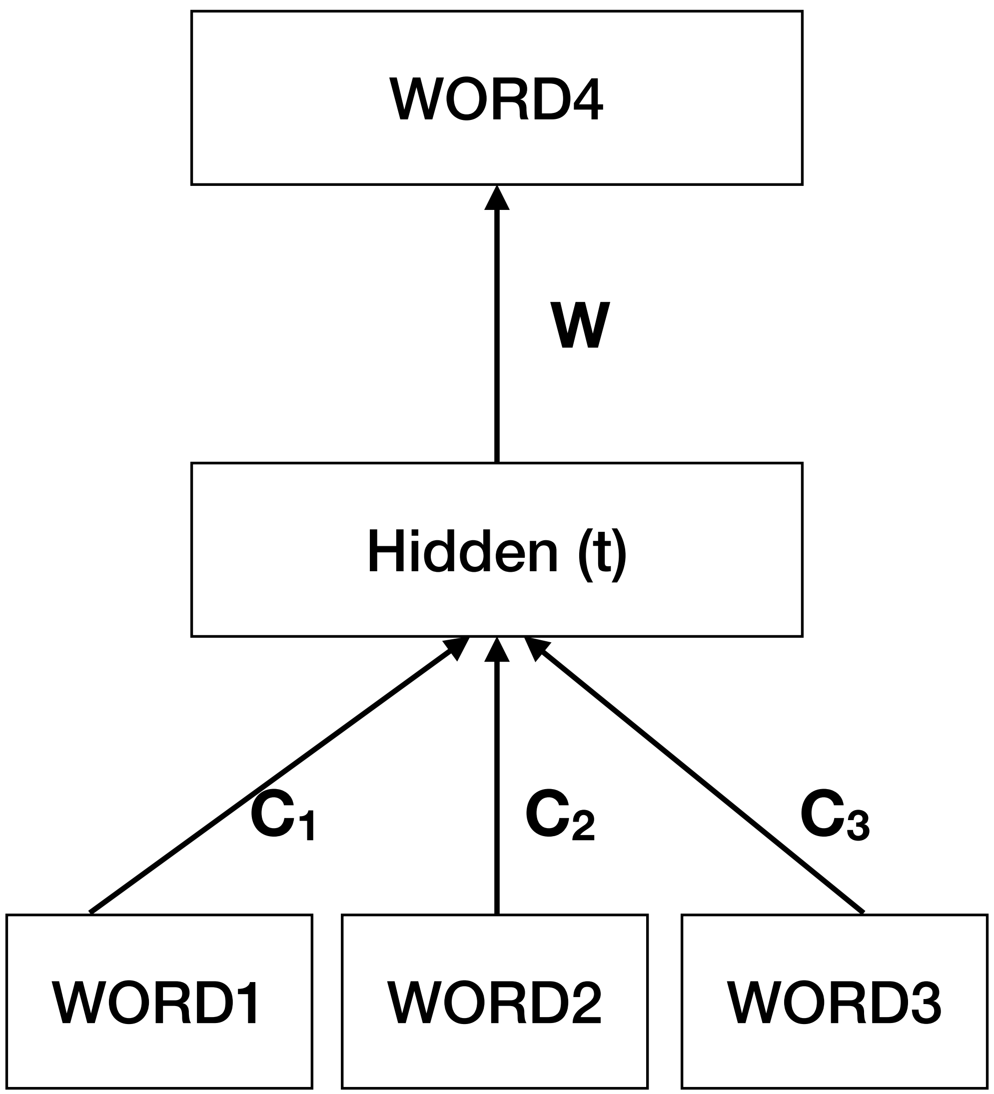
Feedforward: Long-term information

- “I grew up in France… I speak fluent ___*French*___.”

Feedforward: Long-term information

- “I grew up in France… I speak fluent _*French*_.”
- Feedforward Neural Network (FFNN) has limited context size

Recurrent Neural Networks (RNN)



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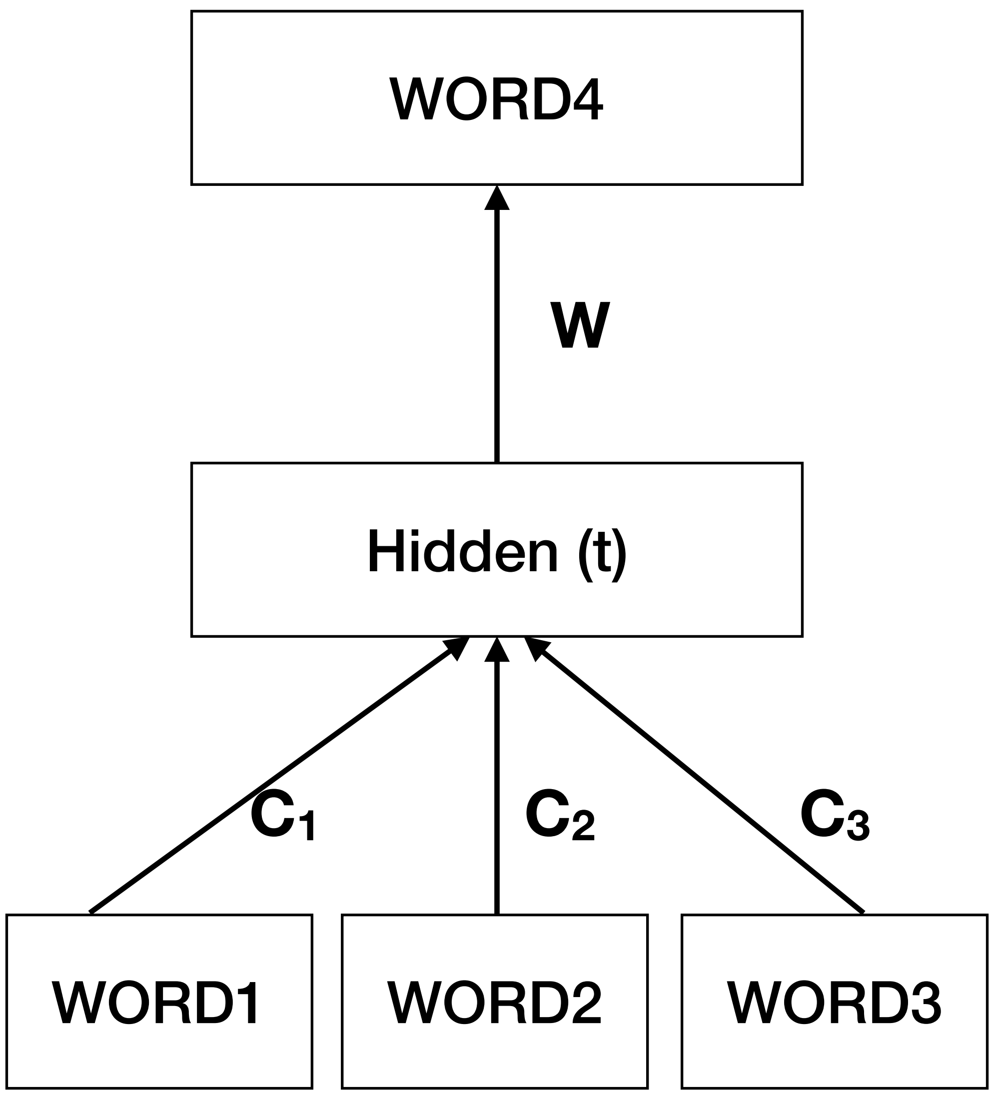

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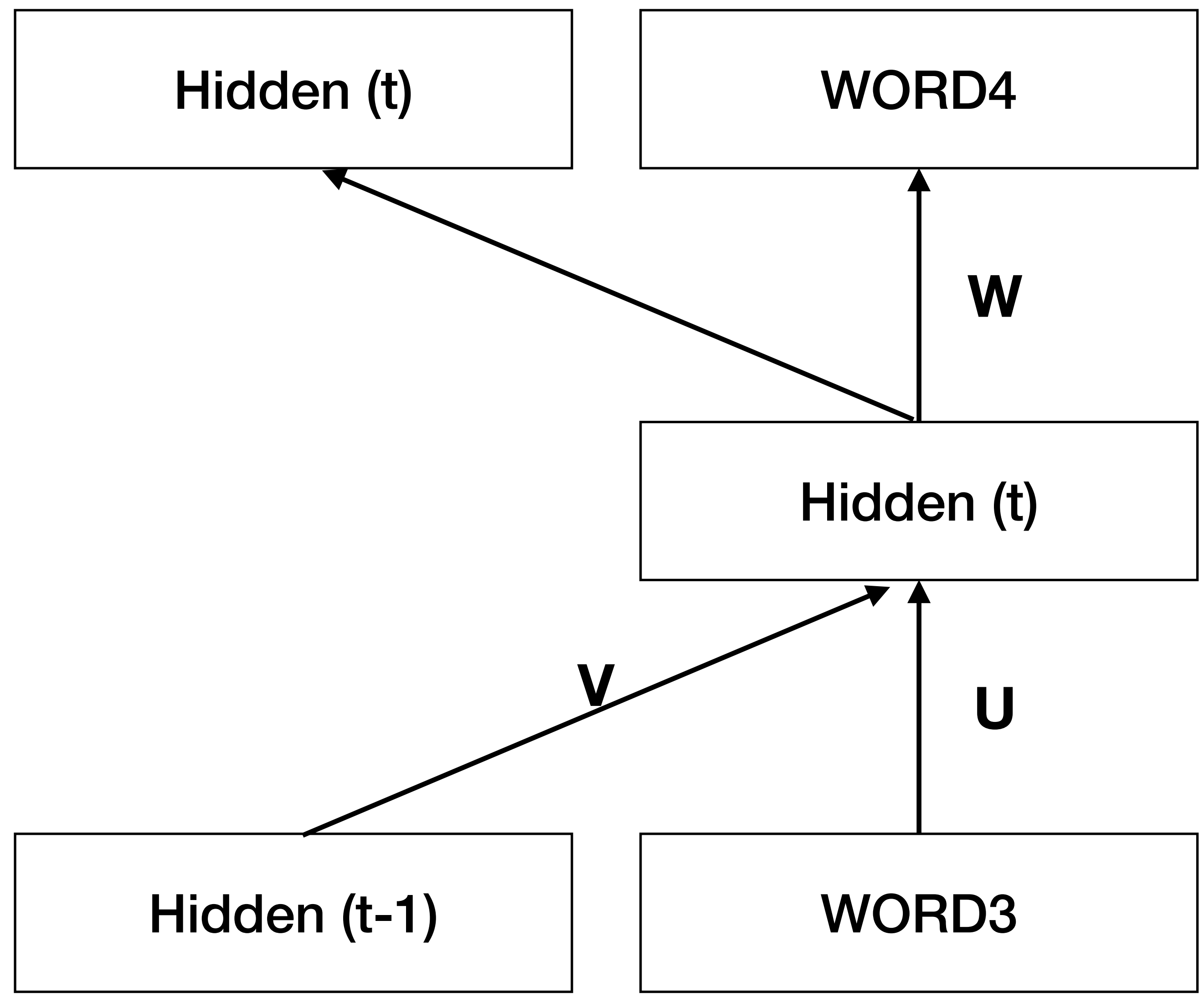

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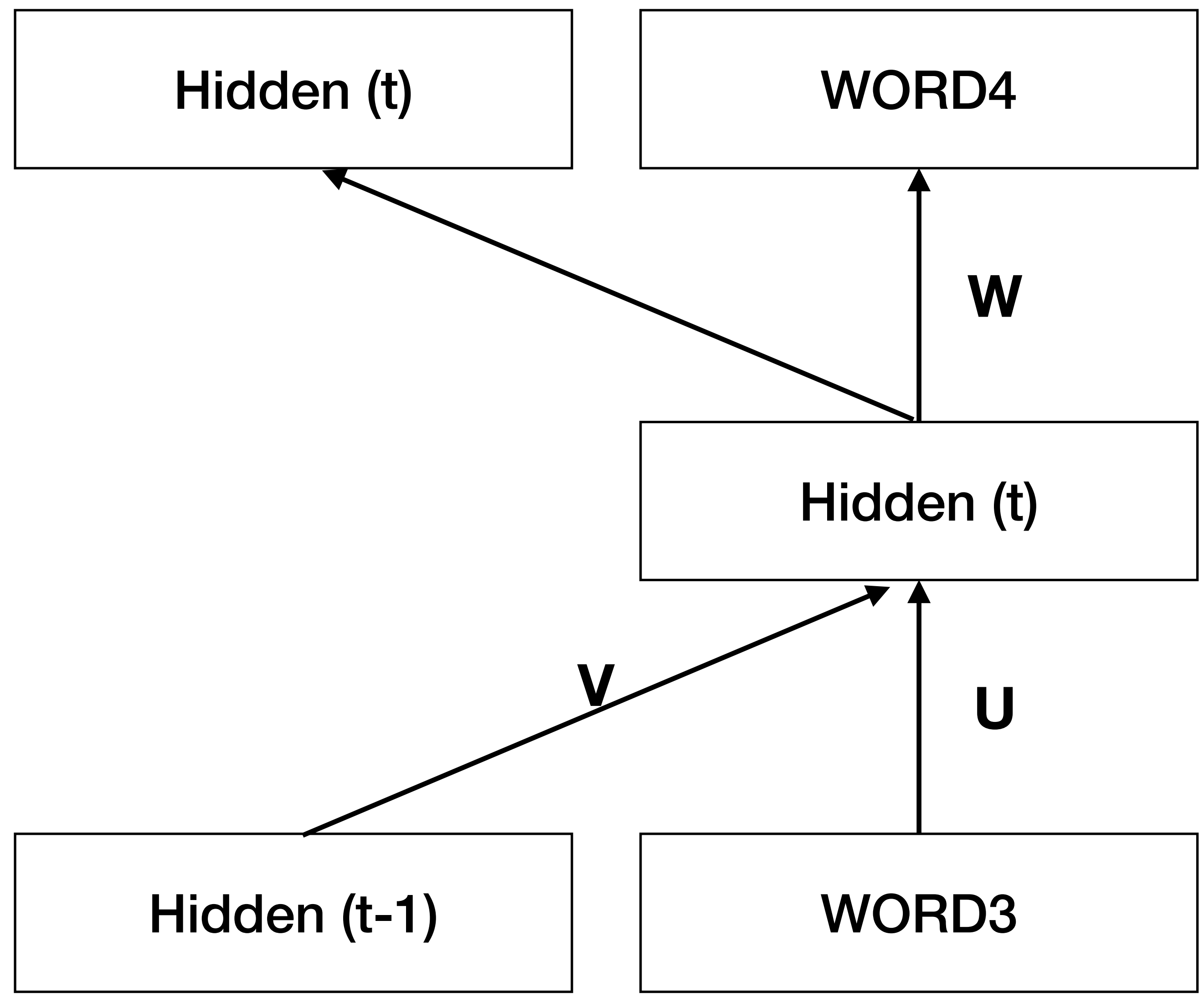

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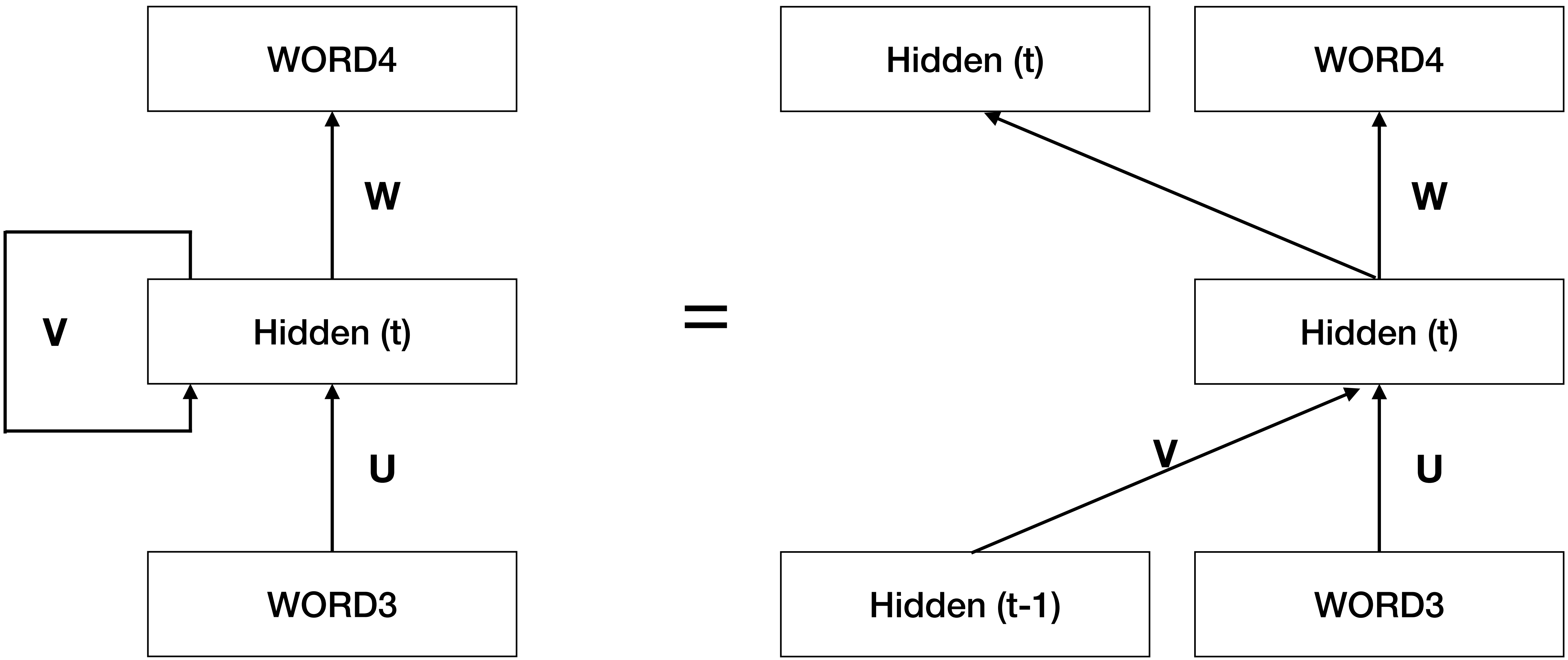
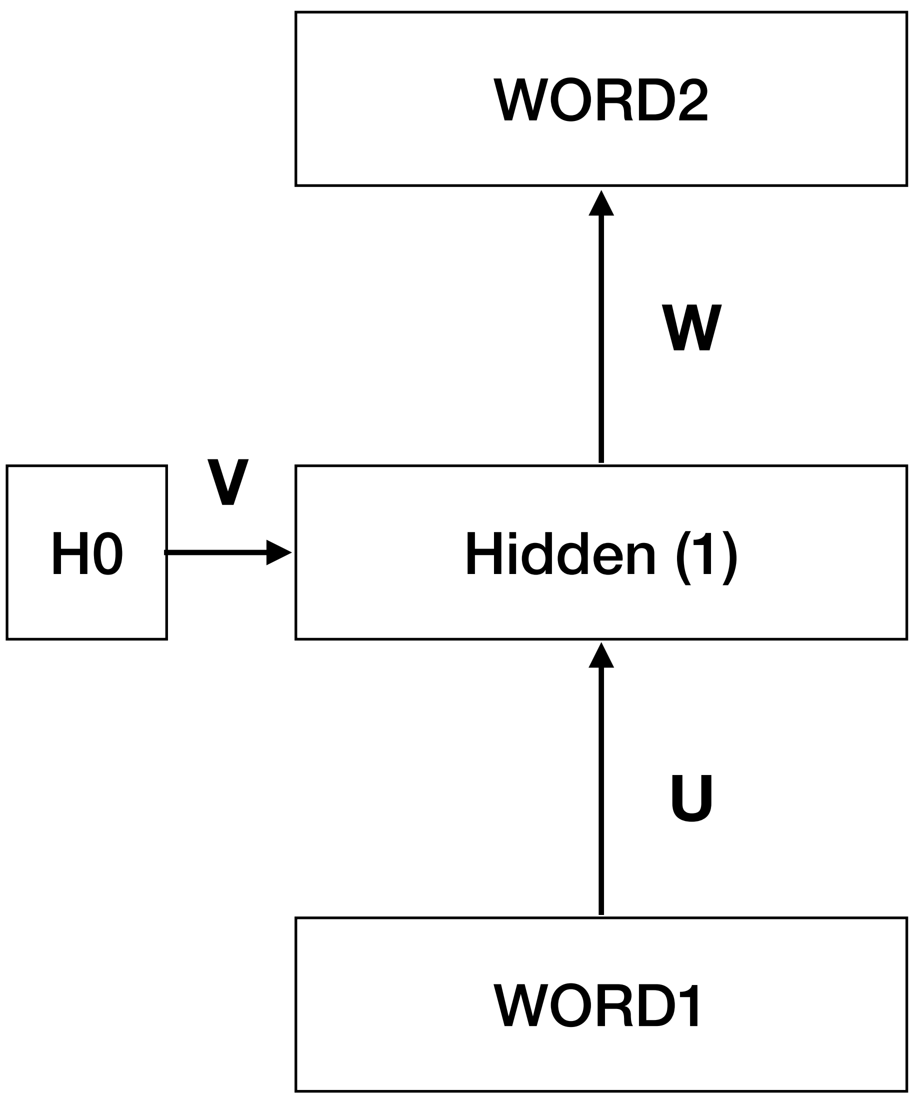
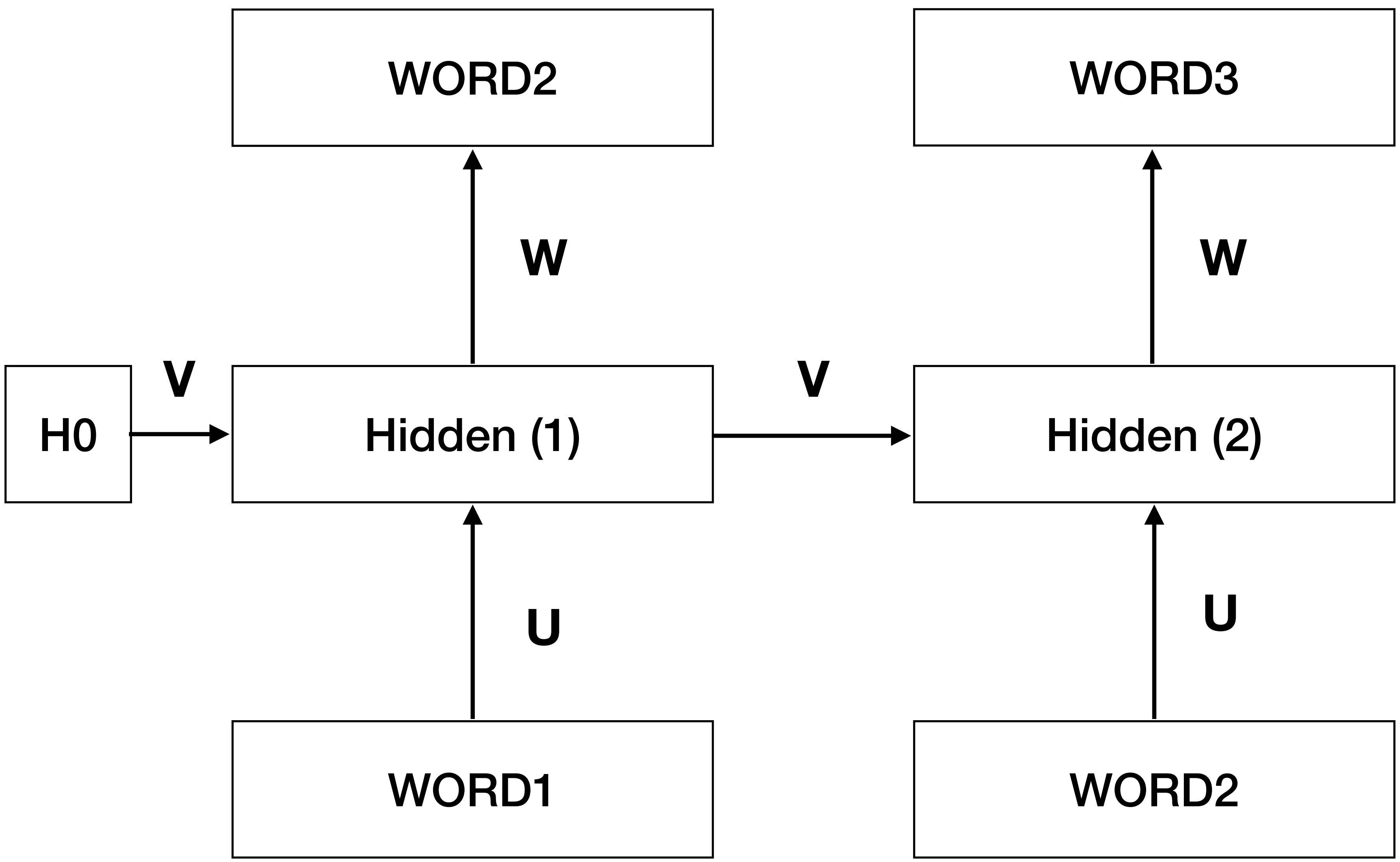


RNN

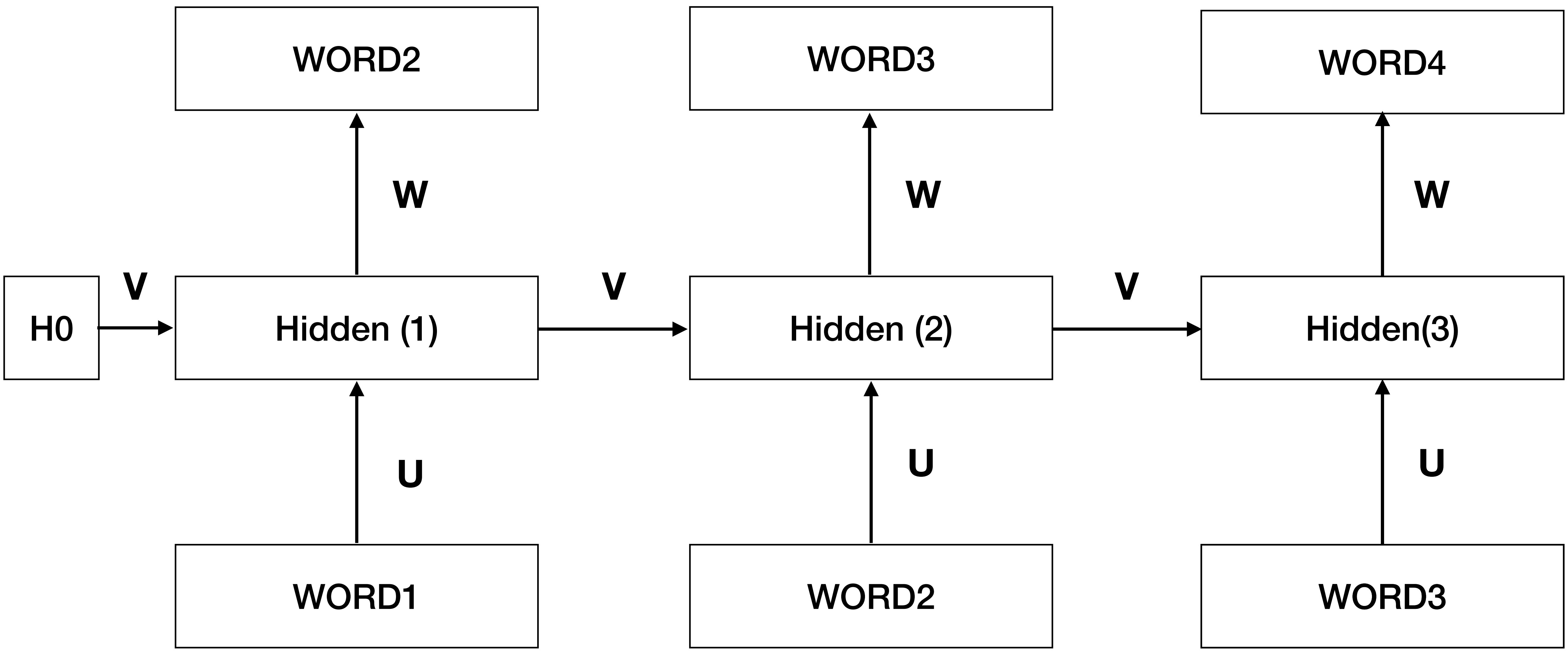
RNN: Timestep 1



RNN: Timestep 2



RNN: Timestep 3



Theoretically information from first step is available to the present timestep

RNN

- "I grew up in France… I speak fluent _*French*_."

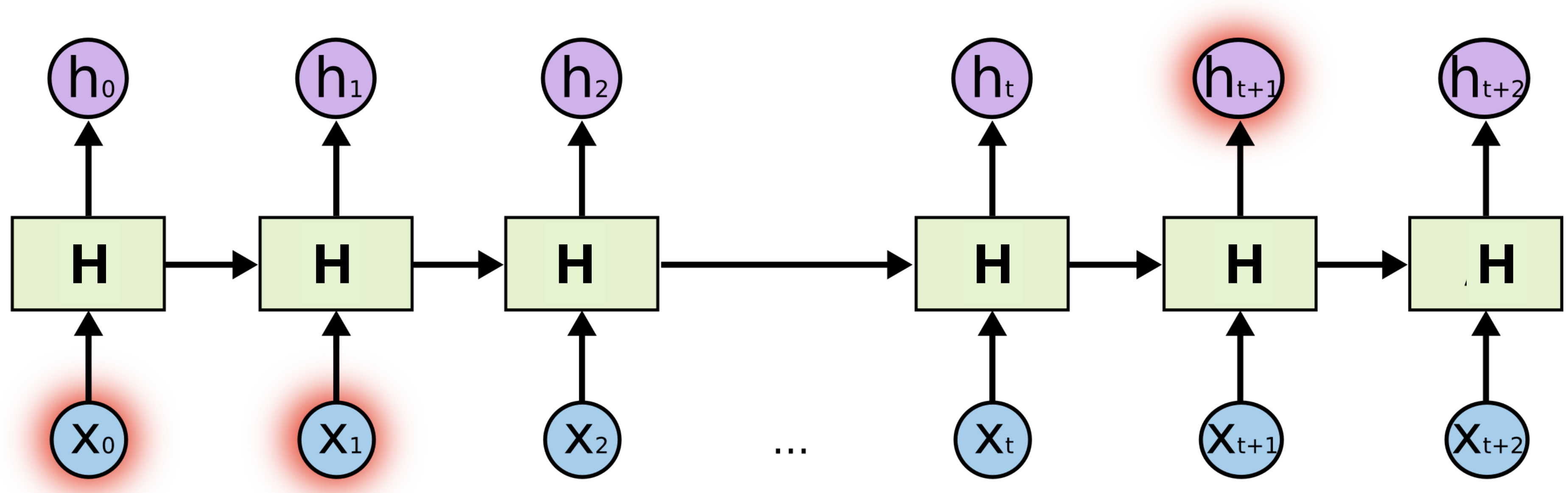
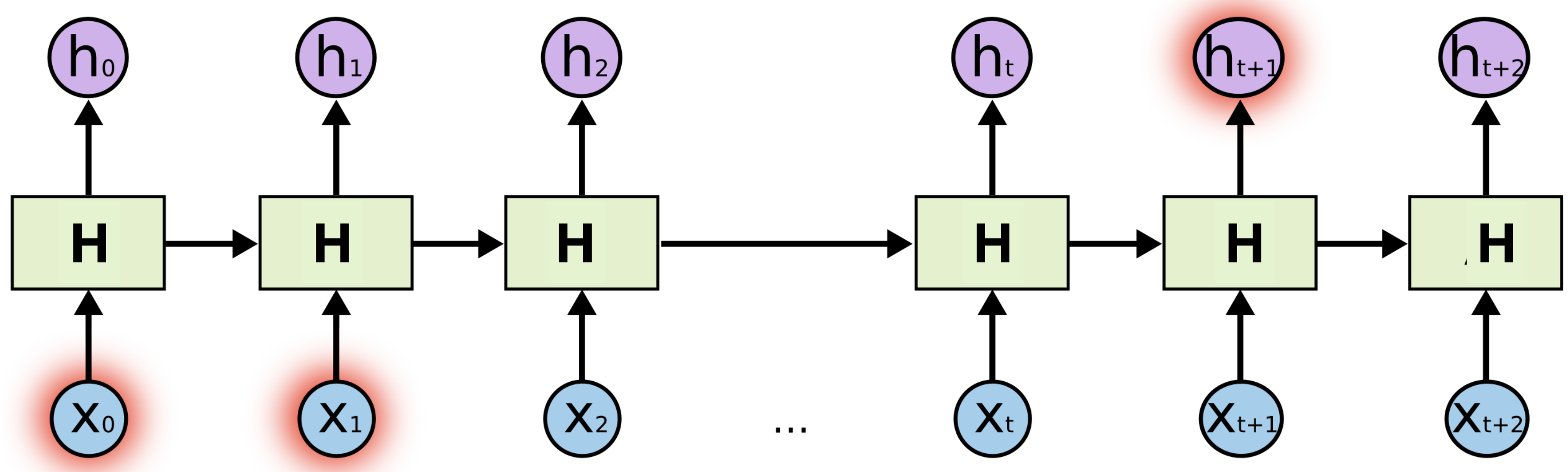


Image: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

RNN

- "I grew up in France… I speak fluent _French_."

- As the gap grows, RNNs become unable to learn to connect information



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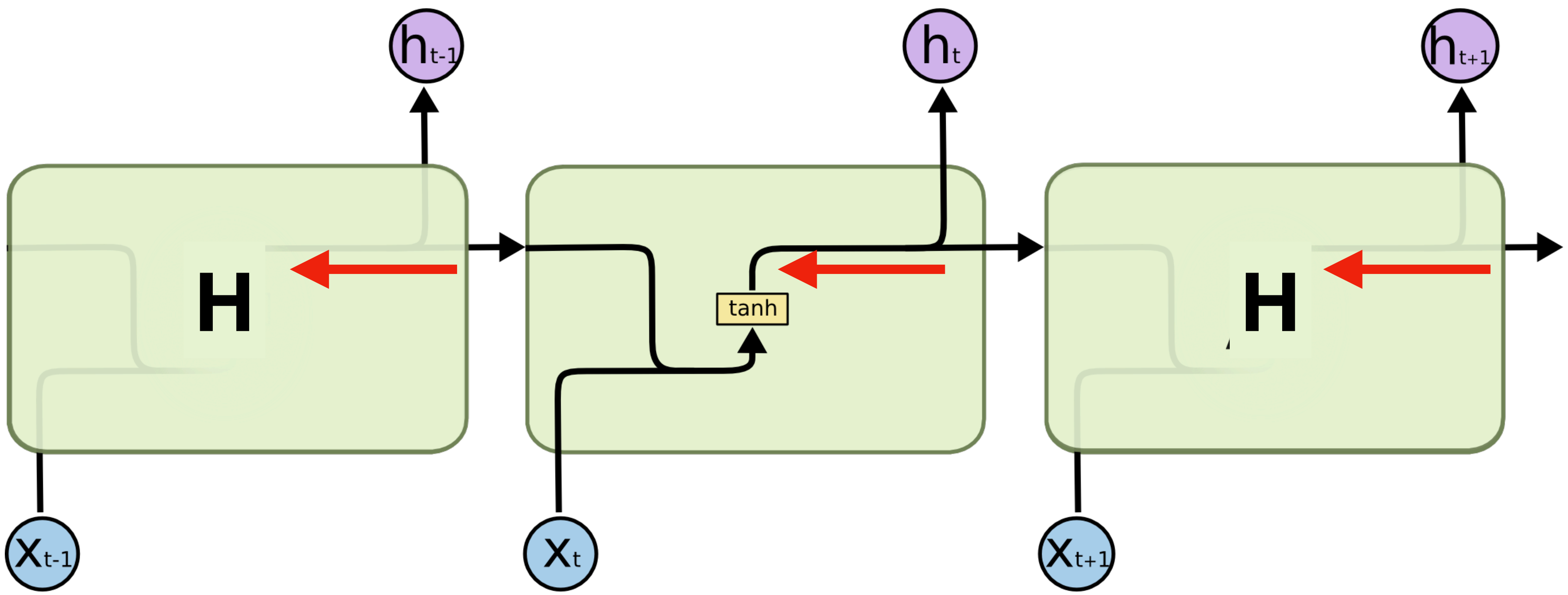
RNN



- Error (red arrow) is passed through a chain of hidden states
- Error passing through multiple of these functions can vanish

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Problems with RNN

- The main problem with RNNs is that gradients less than 1 become exponentially small over time

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* The exploding gradient problem can be alleviated by clipping large gradient values to some maximum number

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- This leads to training instability, and bad results

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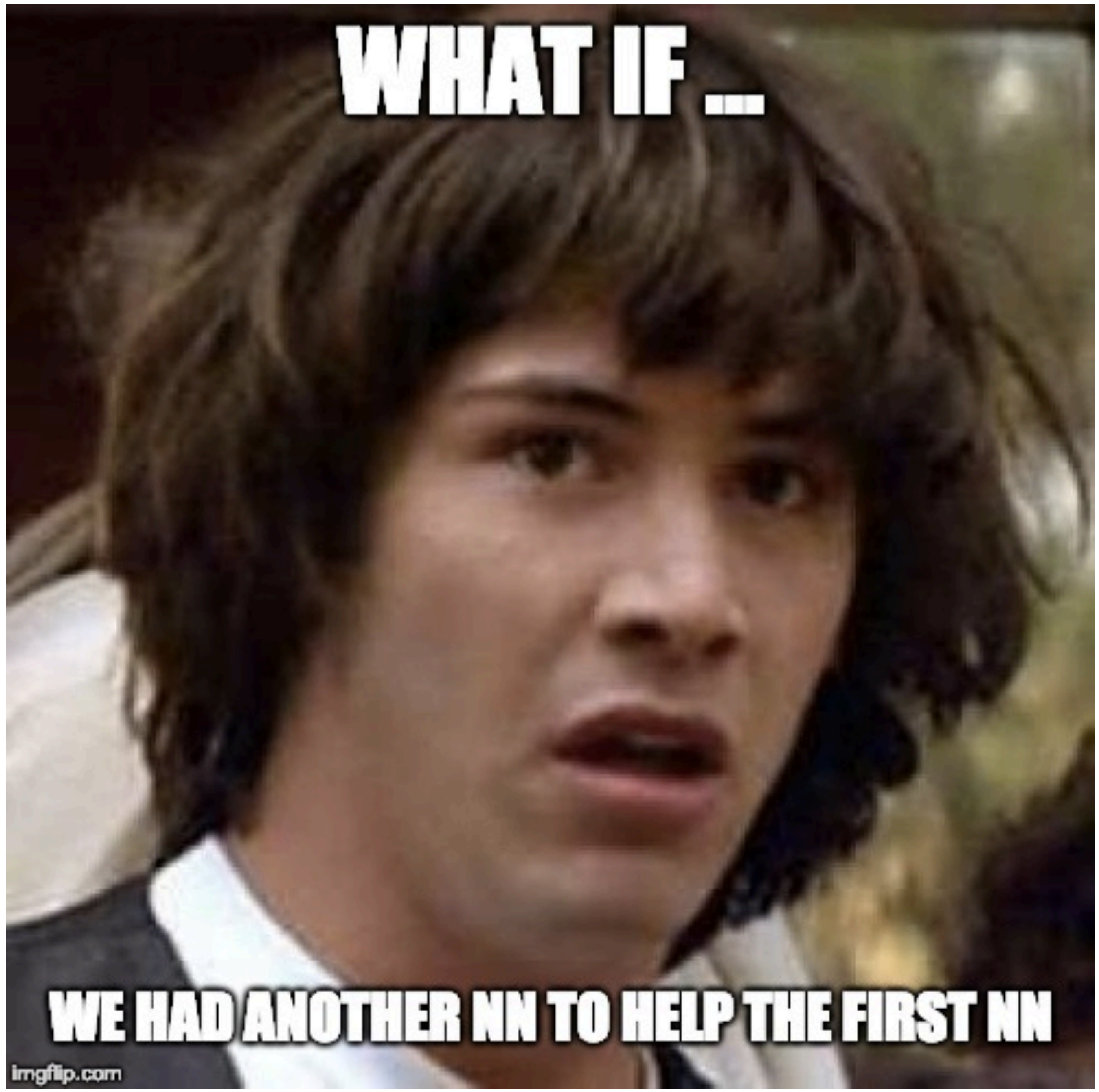
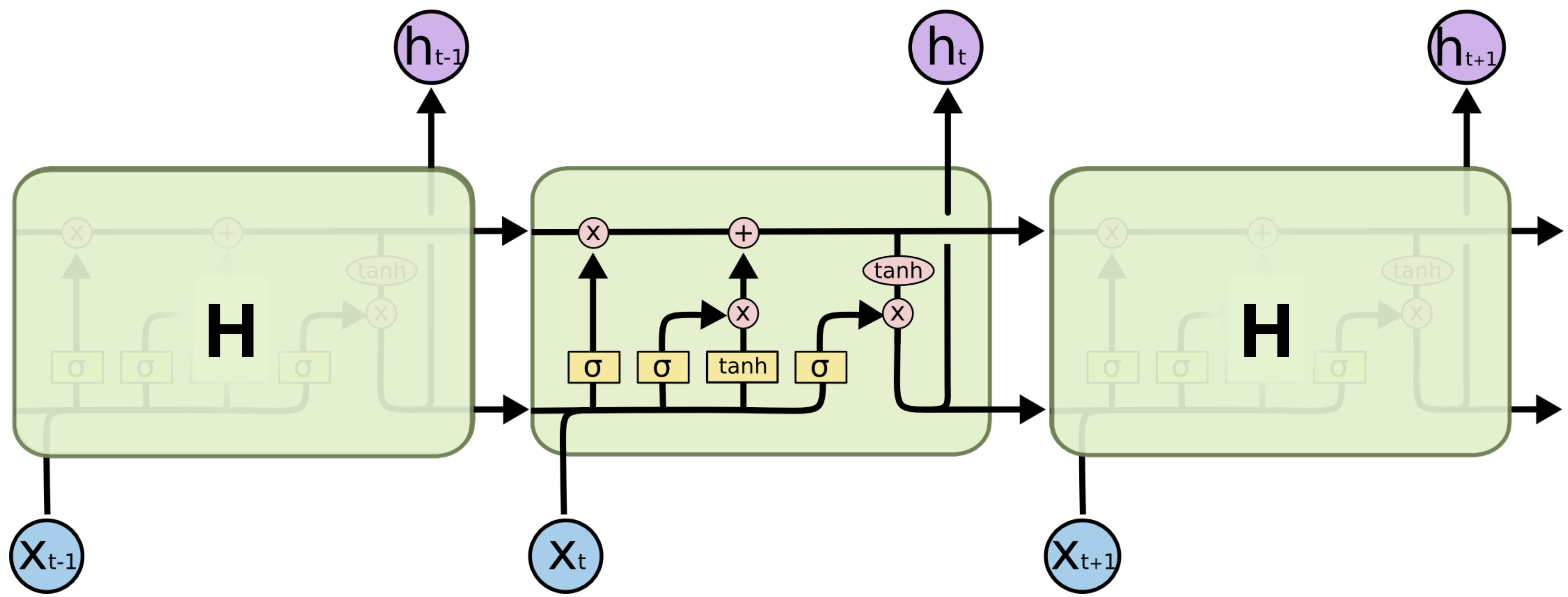
- Gradients greater than 1 become exponentially large over time (the exploding gradient problem)*
- This leads to training instability, and bad results
- Sequence Modeling: https://www.deeplearningbook.org/contents/rnn.html

* The exploding gradient problem can be alleviated by clipping large gradient values to some maximum number


WHAT IF ...
WE HAD ANOTHER NN TO HELP THE FIRST NN
imgflip.com

Long-Short Term Memory

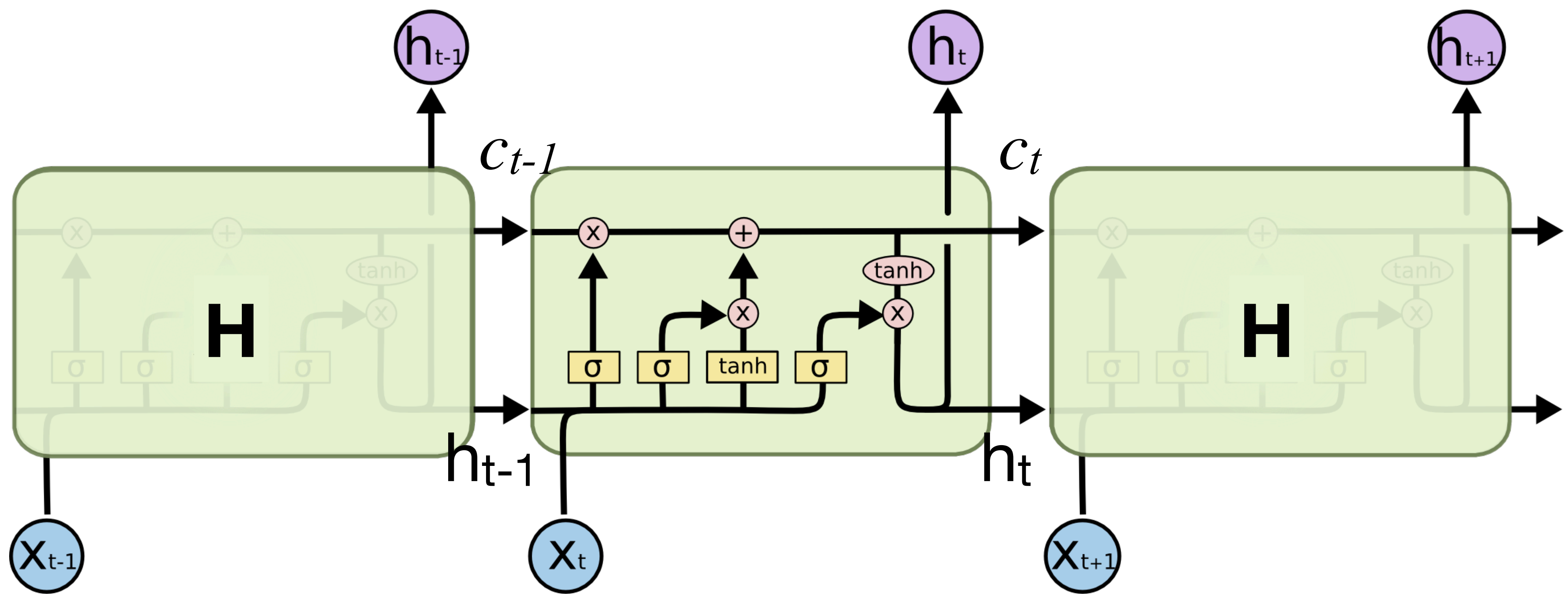


- Lets add another neural network help the first network learn long-distance relationships

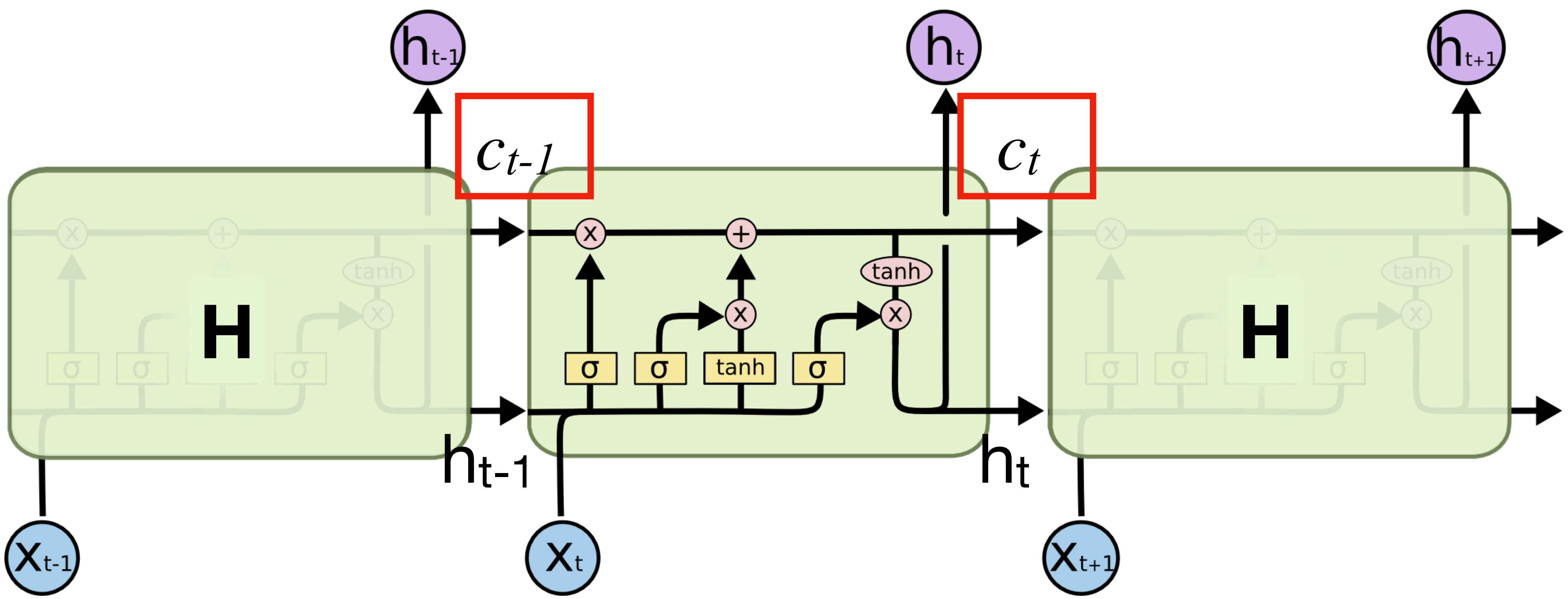
- That's basically what we do when we add more weight matrices to a neural network

Image: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM: States

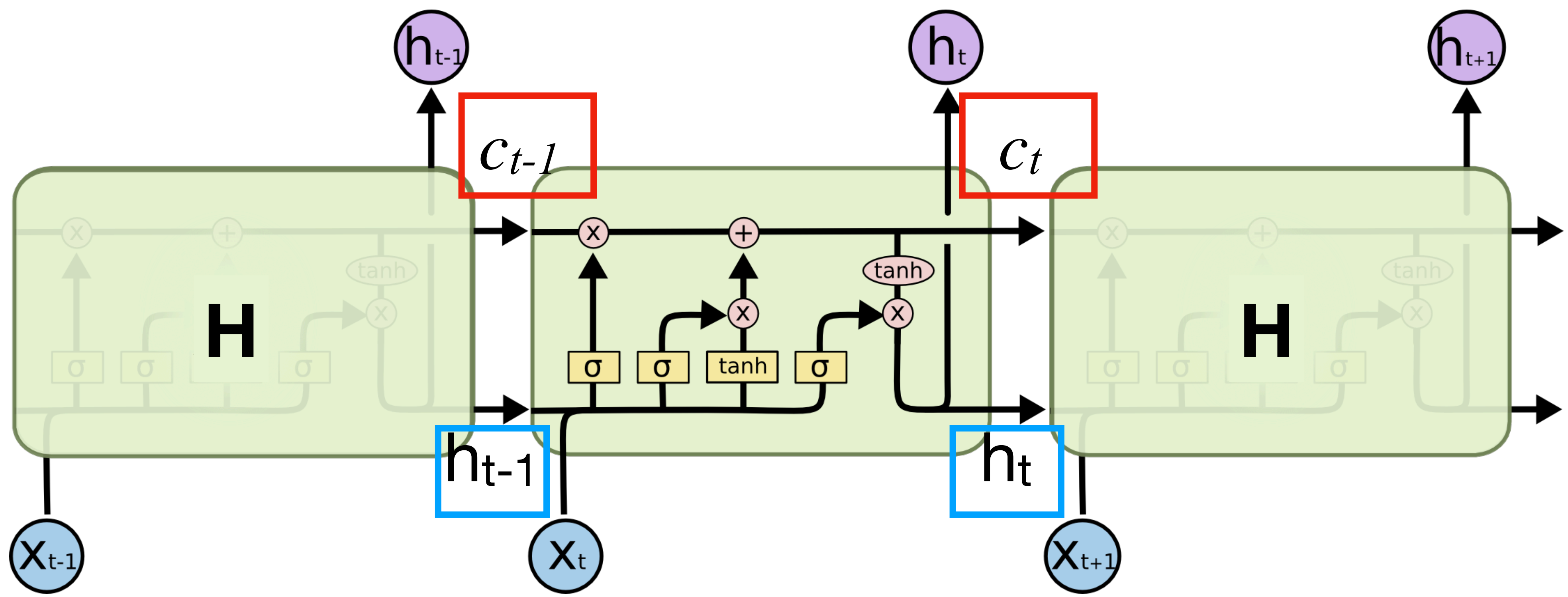


LSTM: States

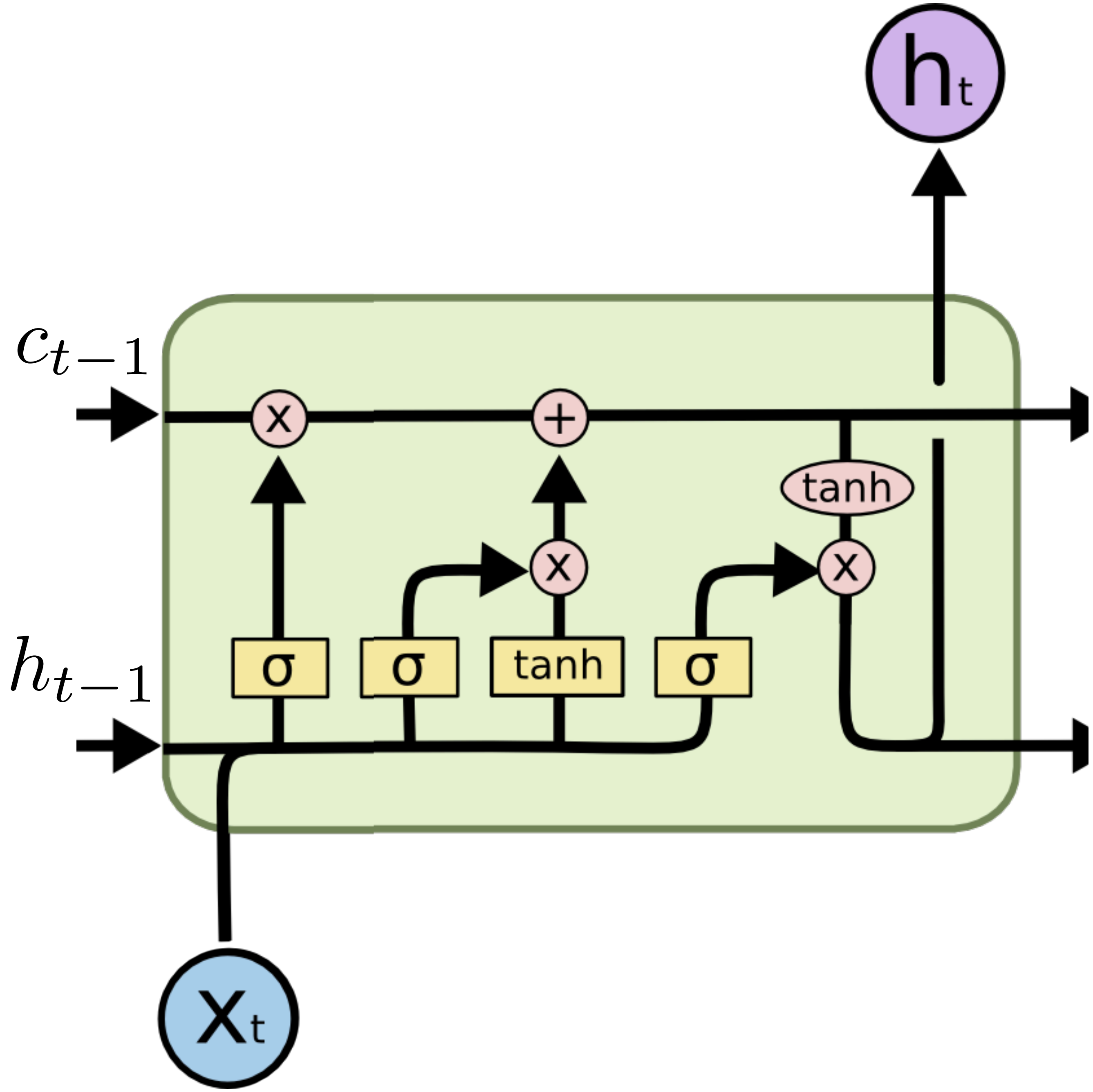


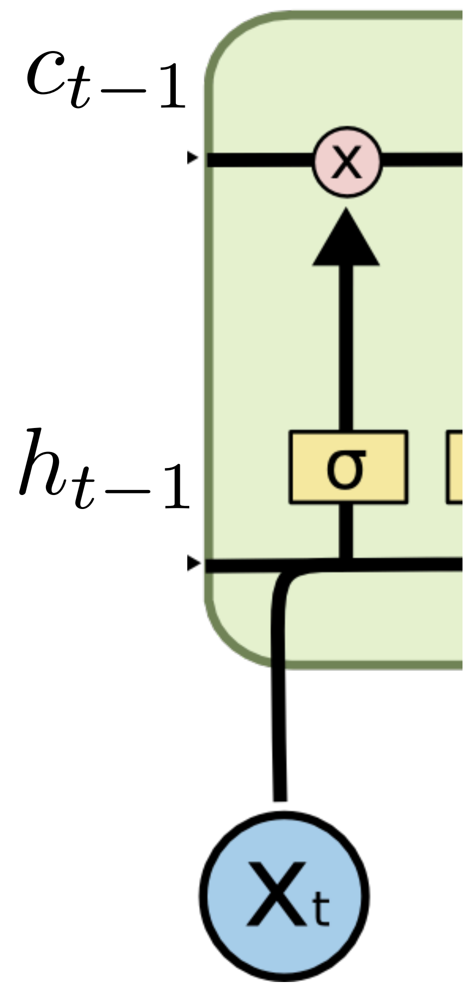
- Global State $\boxed{c}$ captures global information at the document/ sentence level

LSTM: States

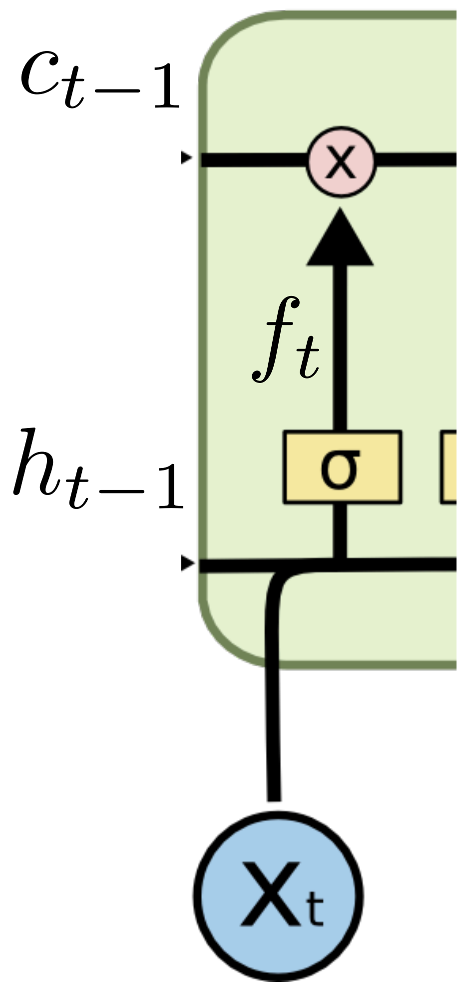


- Global State $\boxed{c}$ captures global information at the document/ sentence level
- LSTM hidden state $\boxed{h_t}$ interacts with this global state to predict the next word


c_{t-1}
h_{t-1}
h_t
x
+
tanh
x
x
σ
σ
tanh
σ
x_t



σ	sigmoid function
w_x	weight of the respective gate(x)
b_x	bias of the respective gate(x)
h_{t-1}	output of the previous LSTM
x_t	input at current timestamp



$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)$$

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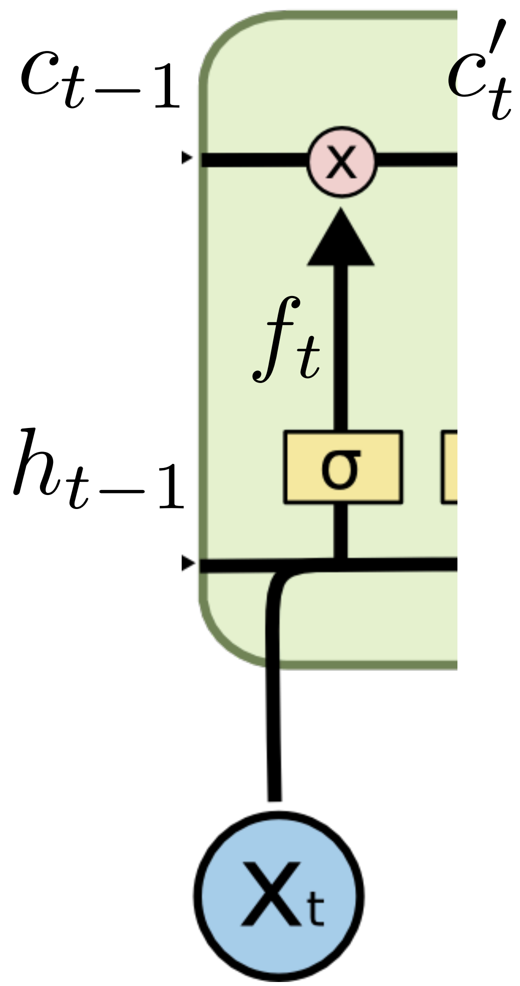

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σ sigmoid function

w_x weight of the respective gate(x)

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h_{t-1} output of the previous LSTM

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$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)$$

$$c'_t = c_{t-1} * f_t$$

- weights and bias

  $w_f = [1 \quad 1]$

  $b_f = 0$
- σ : sigmoid fn * : pointwise multiplication
- "," is vector concatenation
- h_{t-1} = [1], c_{t-1} = [2], x_t = [0.2]
- calculate: c'_t

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)$$

$$c'_t = c_{t-1} * f_t$$

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$$w_f = \begin{bmatrix} 1 & 1 \end{bmatrix}$$

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- h_{t-1} = [1], c_{t-1} = [2], x_t = [0.2]

- calculate: c'_t

$$w_f[h_{t-1}, x_t] + b_f = \begin{bmatrix} 1 & 1 \end{bmatrix} \times \begin{bmatrix} 1 \\ 0.2 \end{bmatrix} = [1.2]$$

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)$$

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$$w_f[h_{t-1}, x_t] + b_f = [1 \quad 1] \times \begin{bmatrix} 1 \\ 0.2 \end{bmatrix} = [1.2]$$

$$f_t = [\sigma(1.2)] = [0.77]$$

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)$$

$$c'_t = c_{t-1} * f_t$$

- weights and bias

$$w_f = [1 \quad 1]$$

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- calculate: c'_t

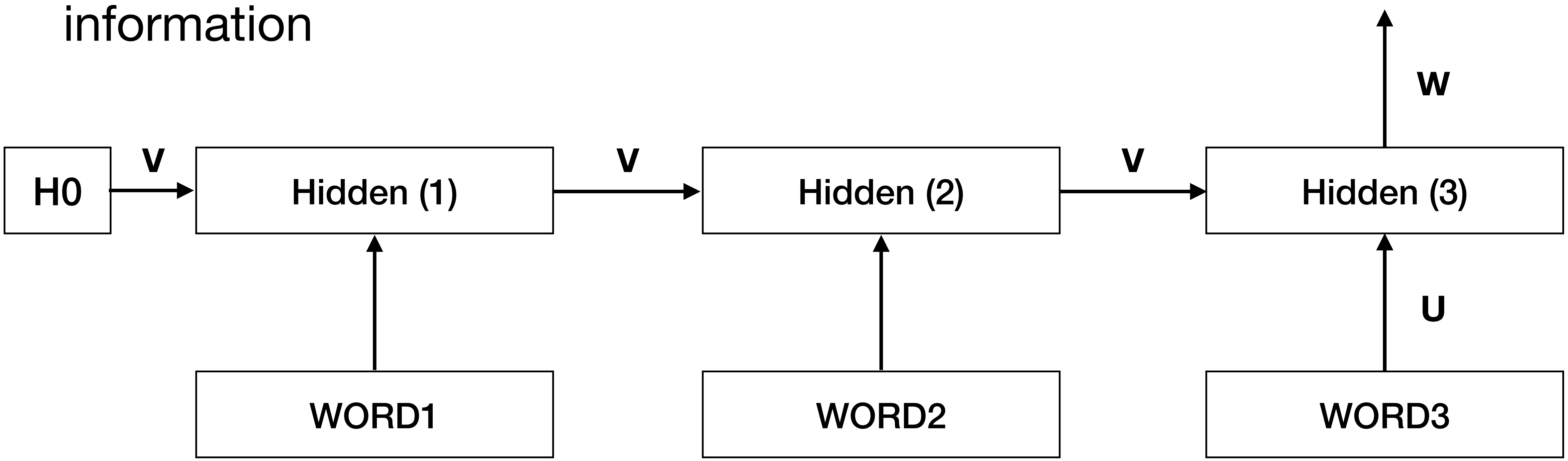
$$w_f[h_{t-1}, x_t] + b_f = [1 \quad 1] \times \begin{bmatrix} 1 \\ 0.2 \end{bmatrix} = [1.2]$$

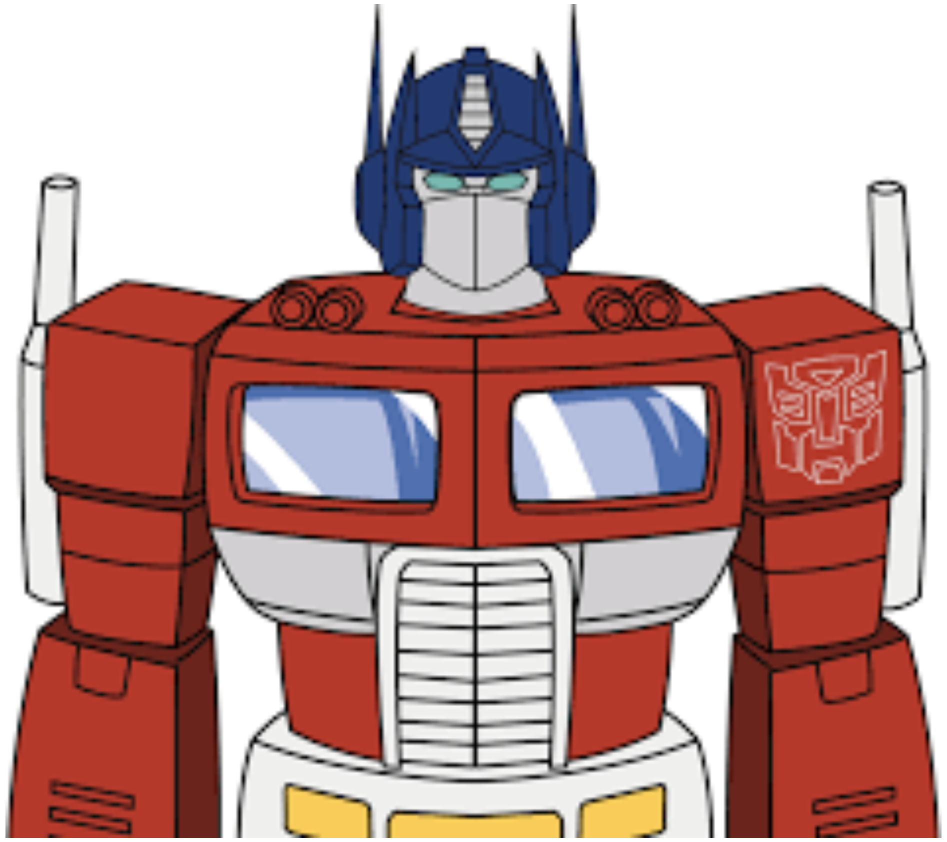
$$f_t = [\sigma(1.2)] = [0.77]$$

$$c'_t = c_{t-1} * f_t = [2] * [0.77] = [1.54]$$

LSTM Problems

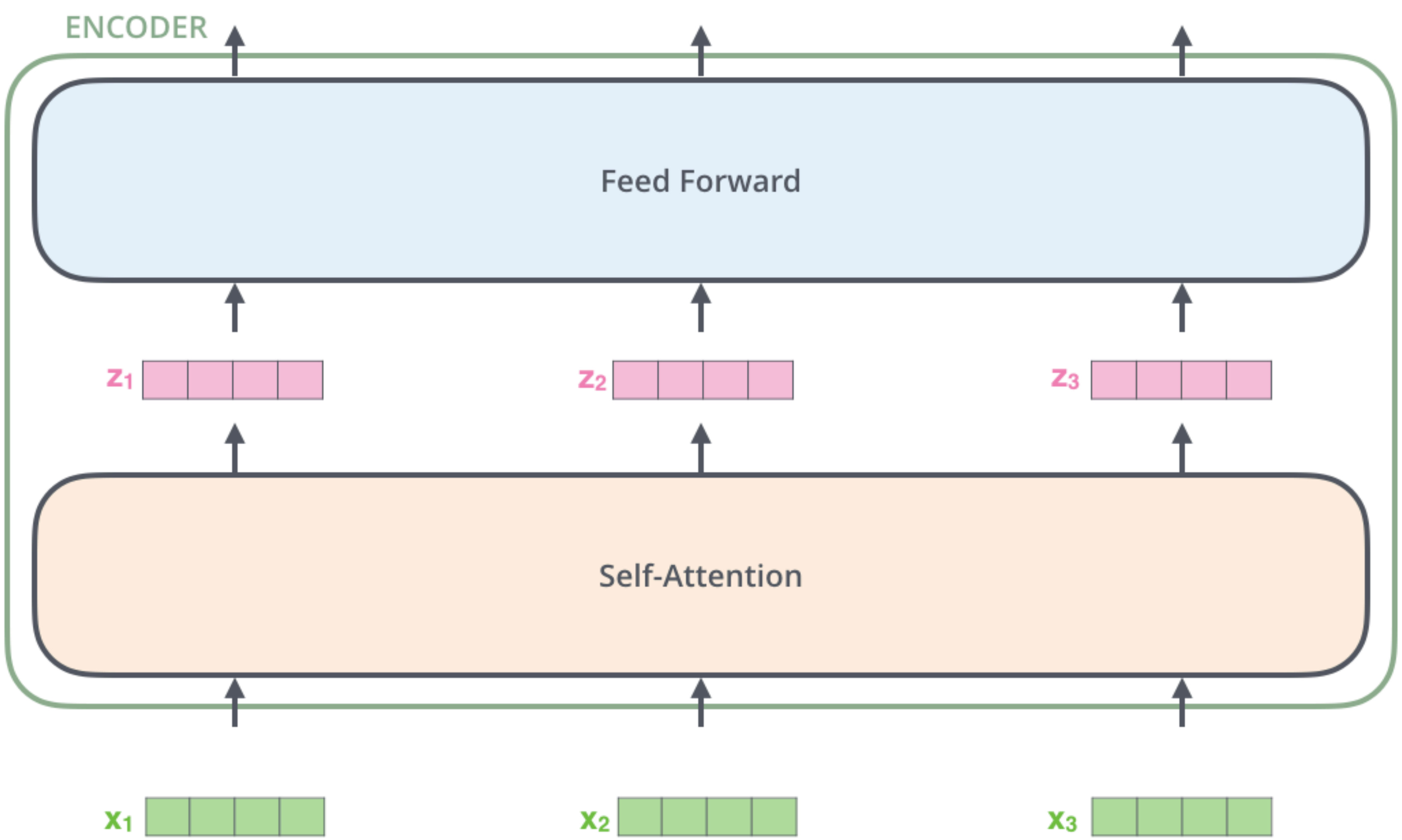
- Forget gate: removes information from the Global Cell state (C)
  - this information might be be useful at a later stage
- Implicit representation of long-term information
  - Cell state and previous hidden state summarise the prior information





Transformers for Language Modelling

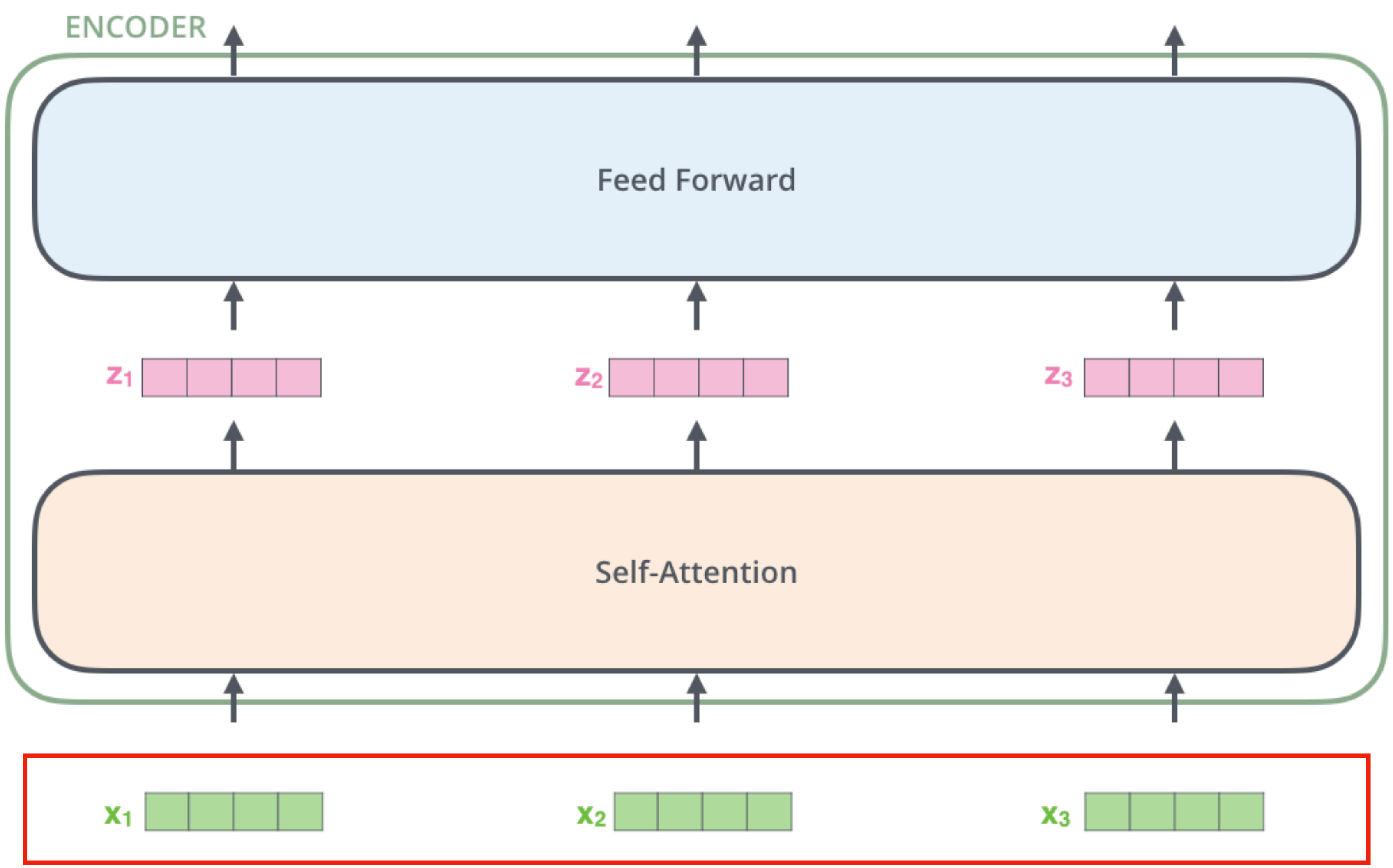
Transformers: Simplified



Multiple (50-90) such layers in a Transformer LM

Credit: http://jalammar.github.io/illustrated-transformer/

Transformers: Simplified



Multiple (50-90) such layers in a Transformer LM

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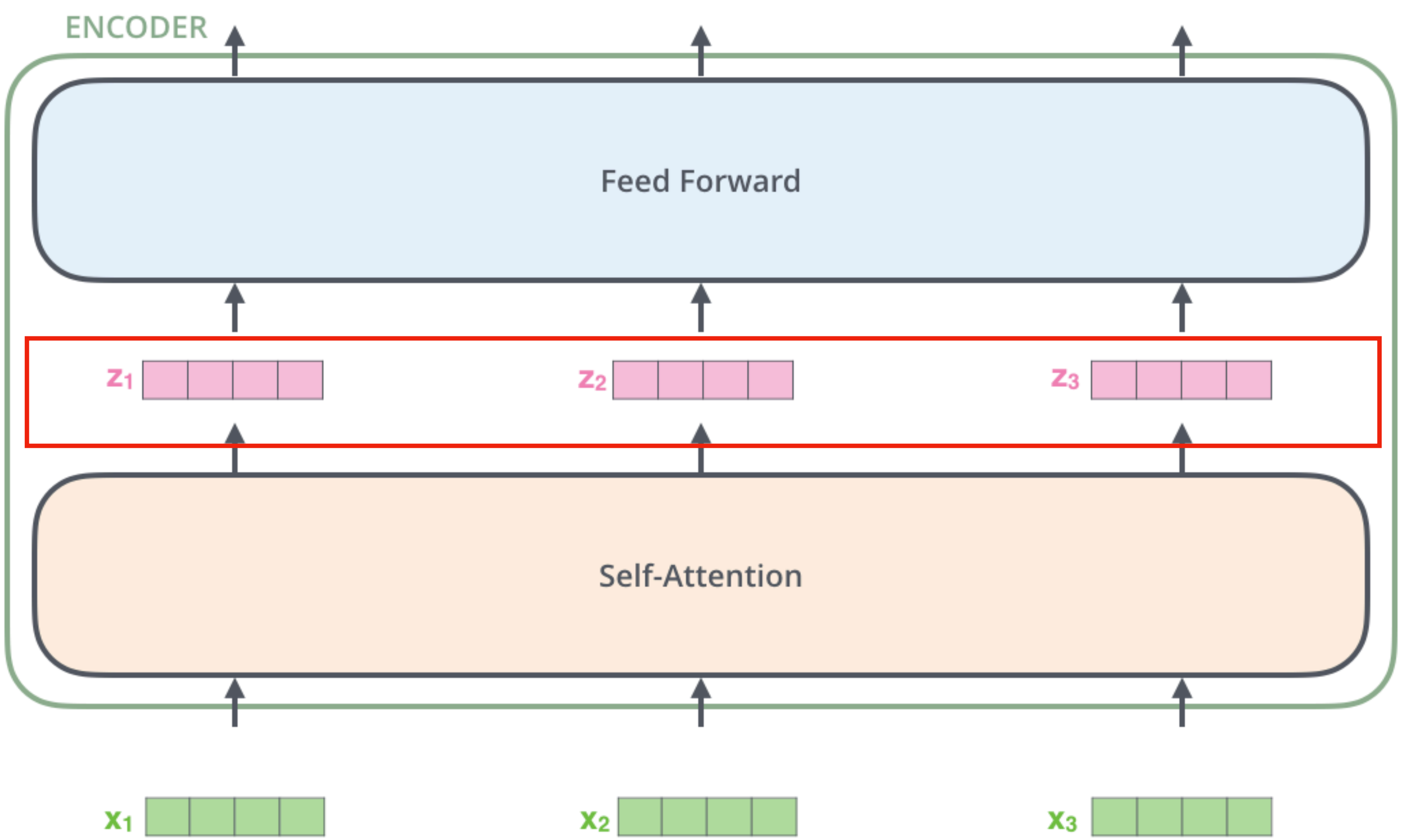

Multiple (50-90) such layers in a Transformer LM

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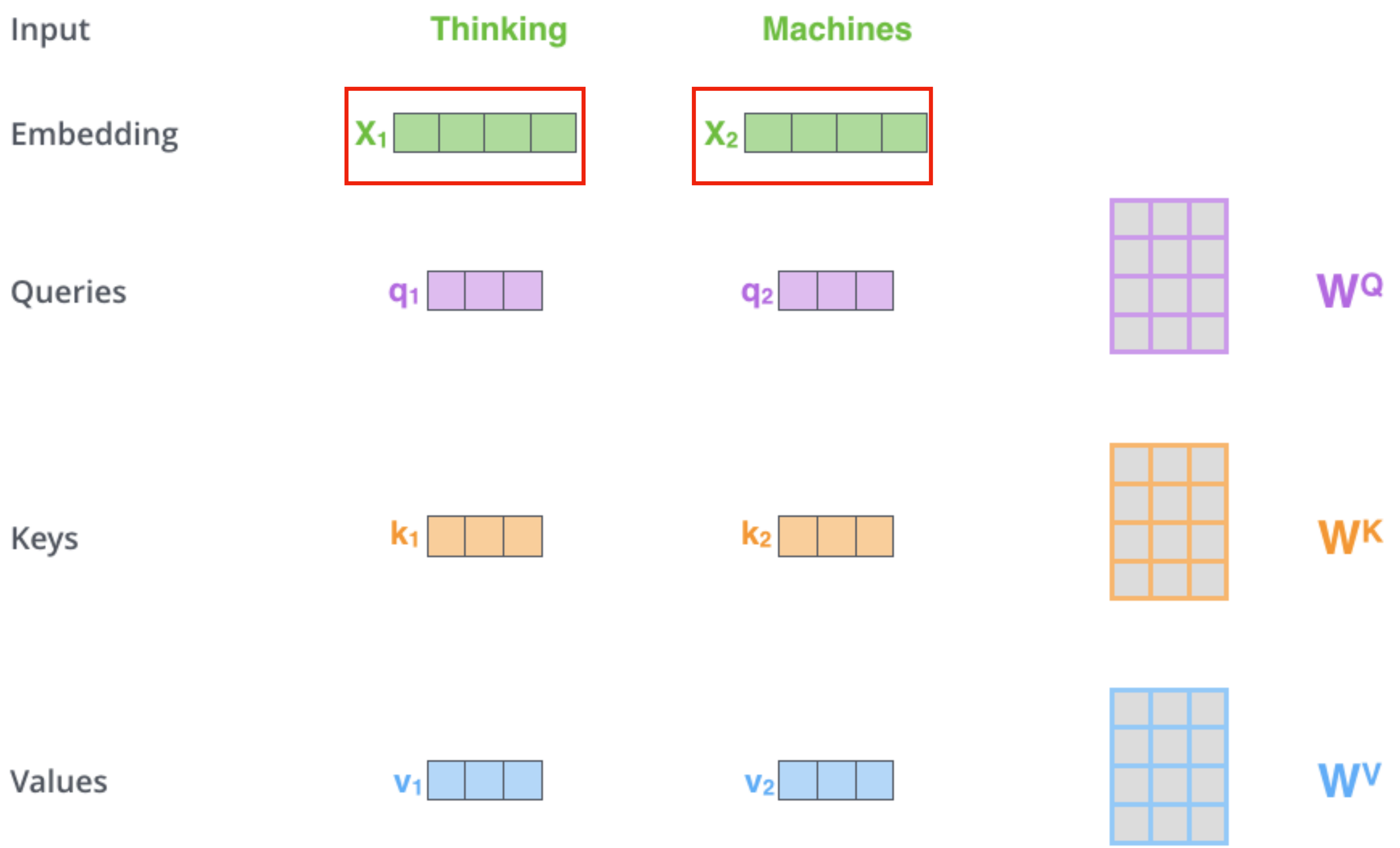
Self-Attention

- E.g. “The animal didn't cross the street because **it** was too tired”
- What does “**it**” refer to? “The animal” or “the street”
- Self-attention is the mechanism that helps LM associate:
    - “**it**” with “the animal”

Credit: http://jalammar.github.io/illustrated-transformer/

Self-Attention: Step 0



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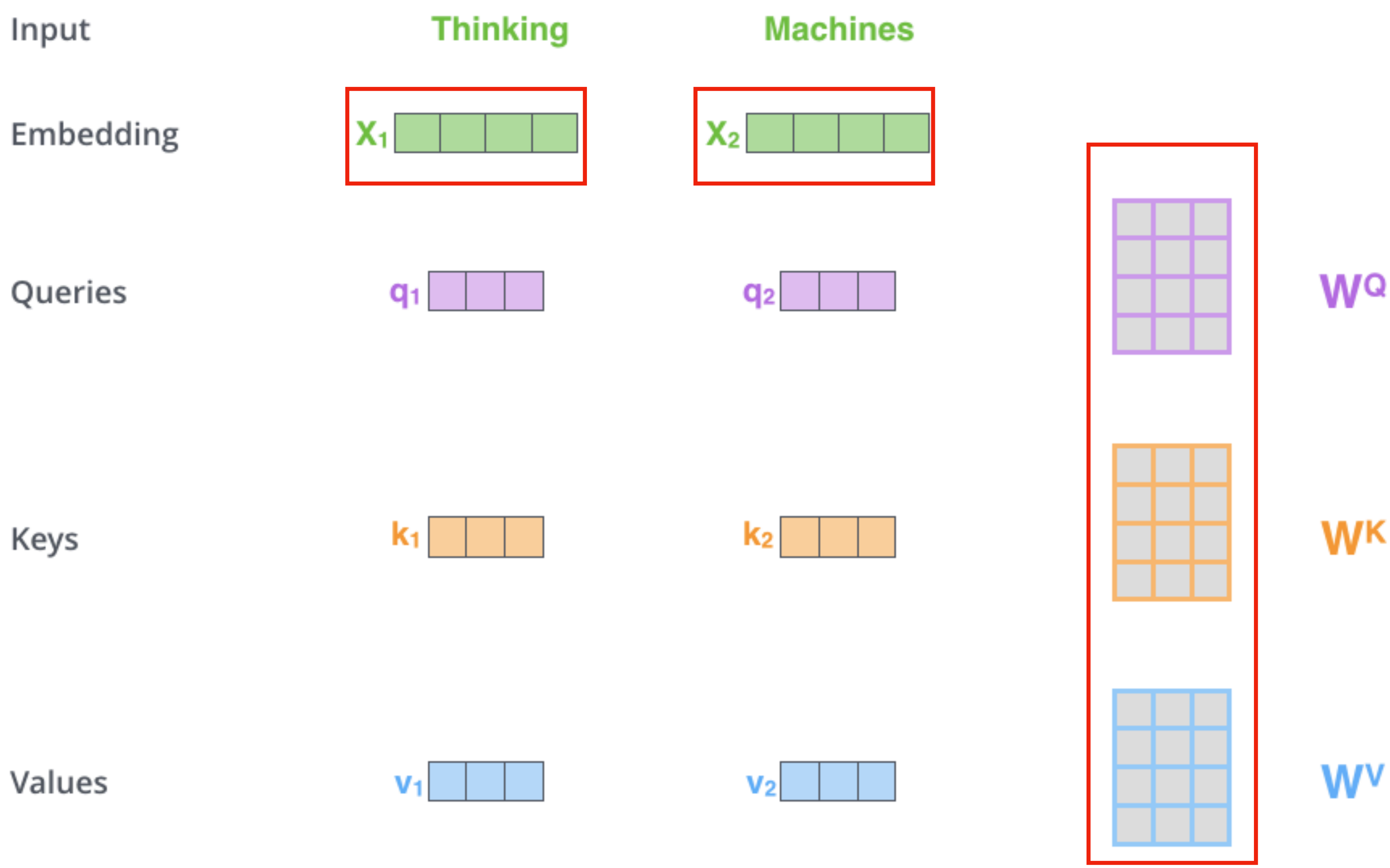
Self-Attention: Step 0



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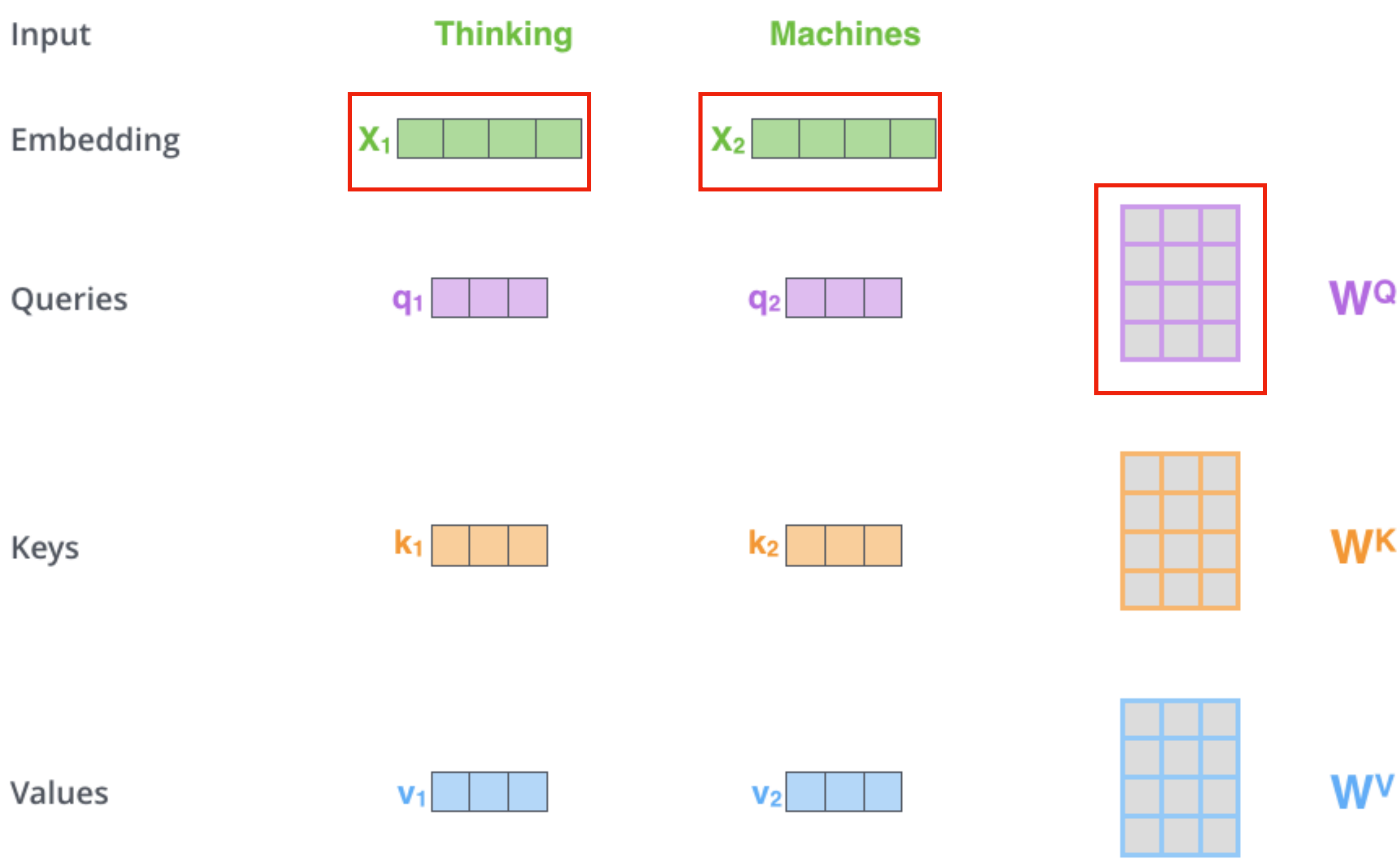

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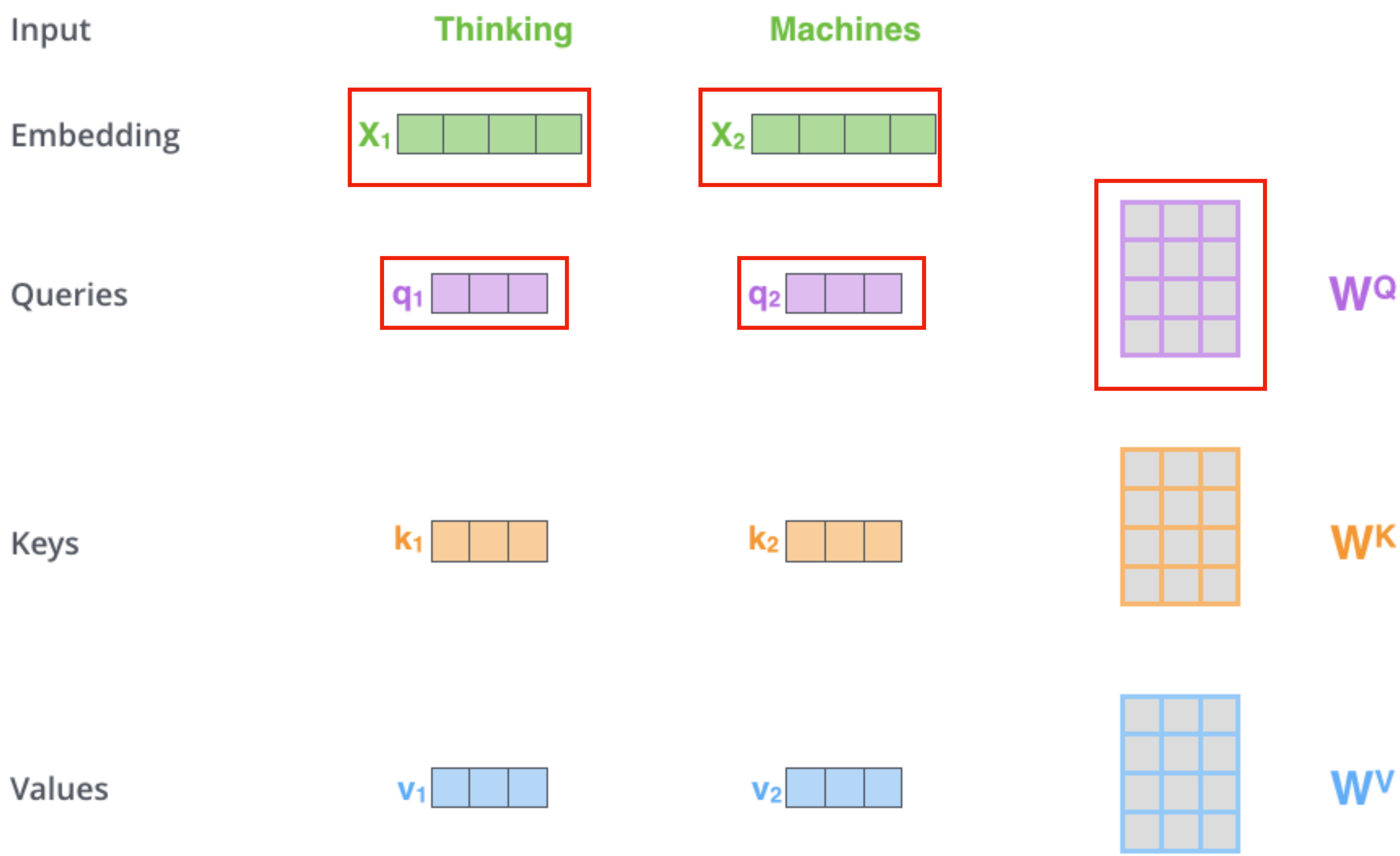
Self-Attention: Step 0



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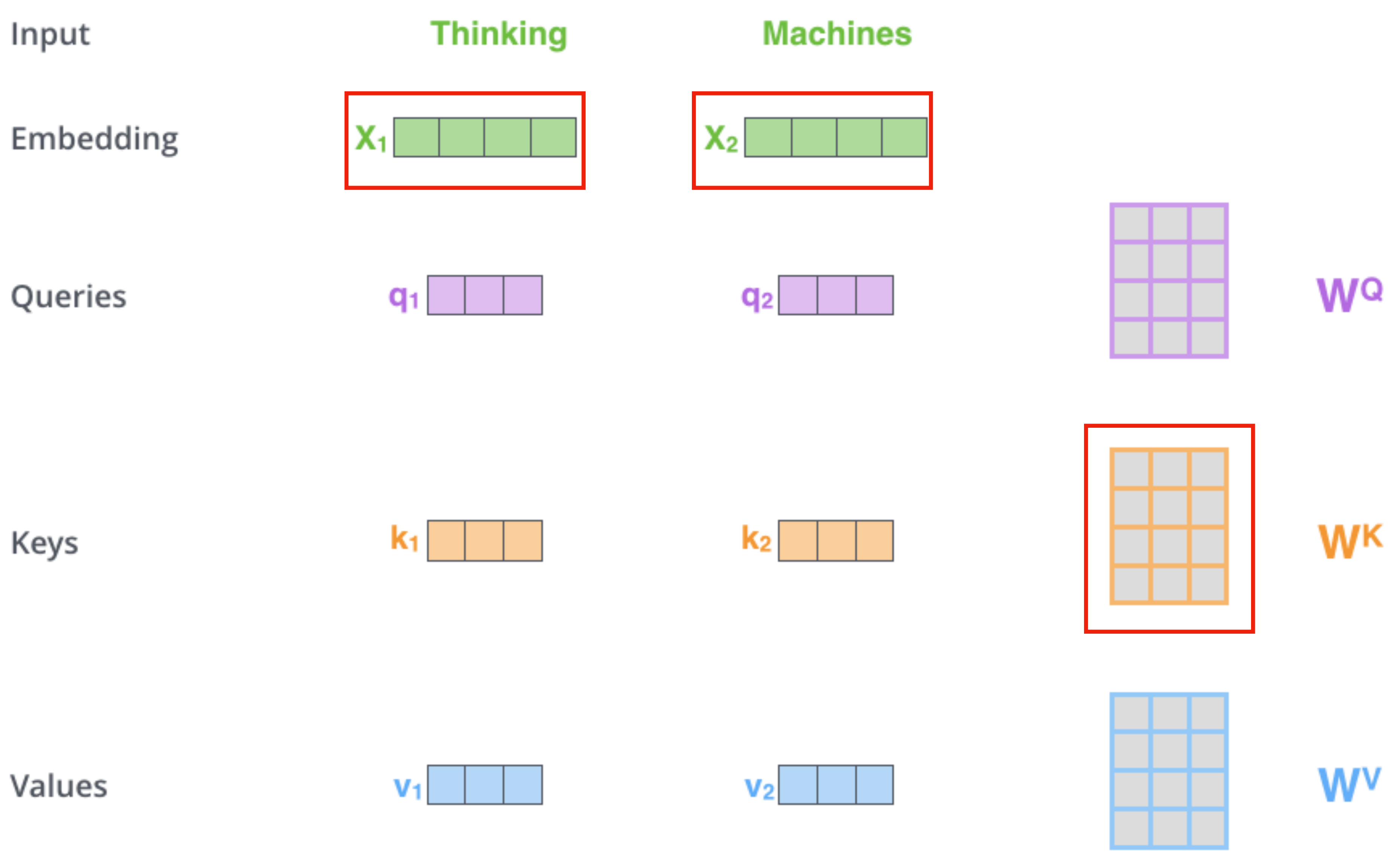

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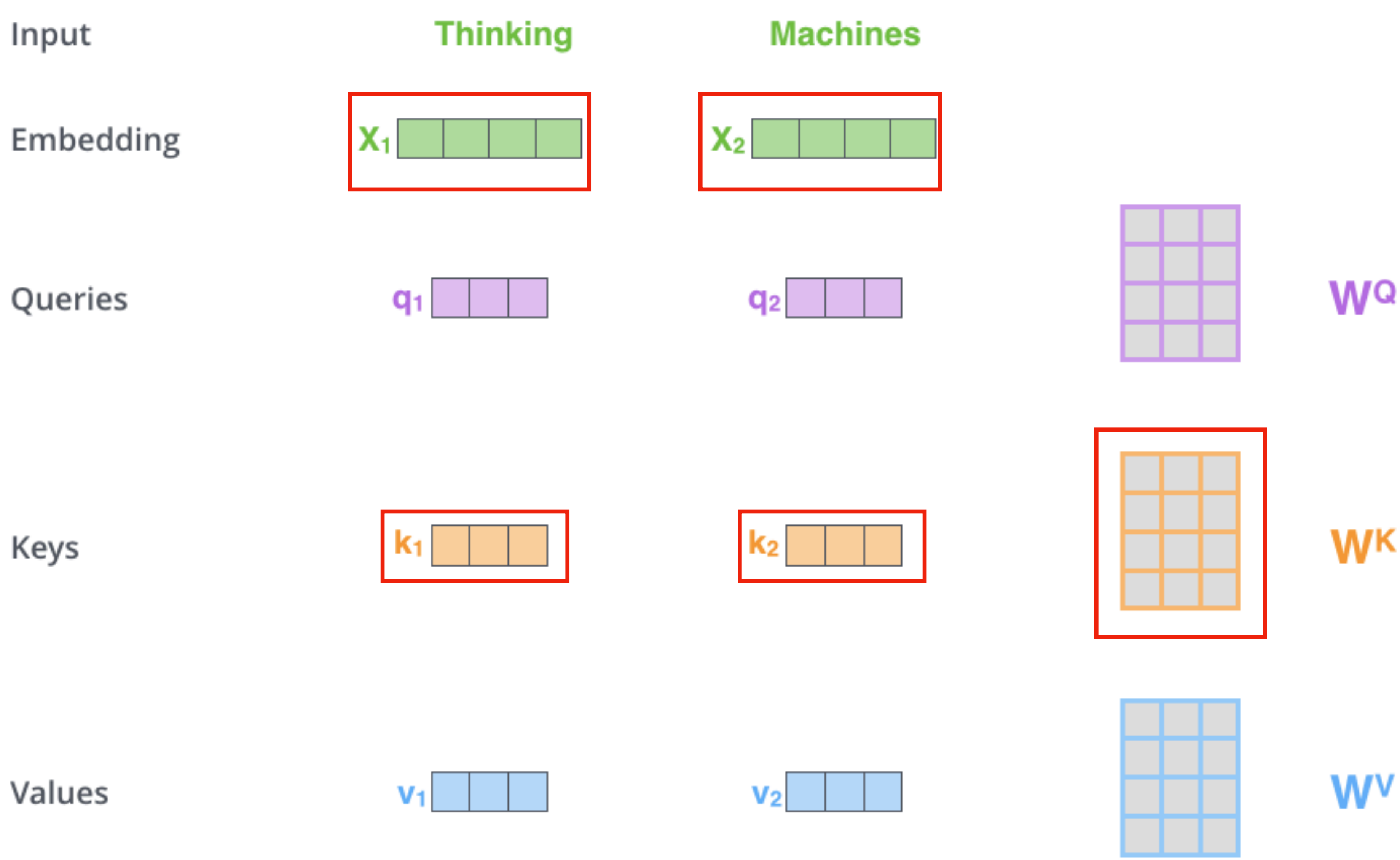

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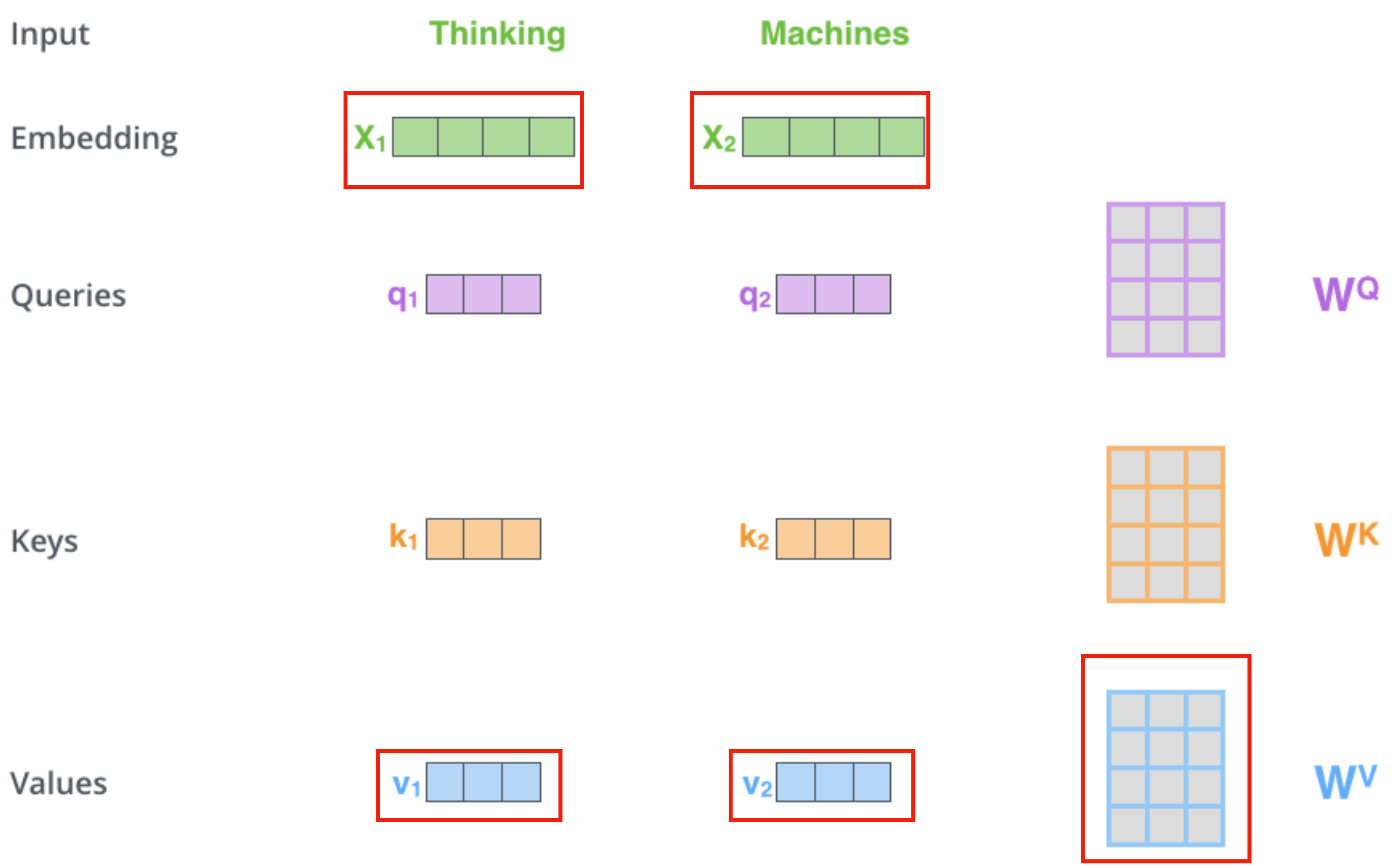
Self-Attention: Step 0



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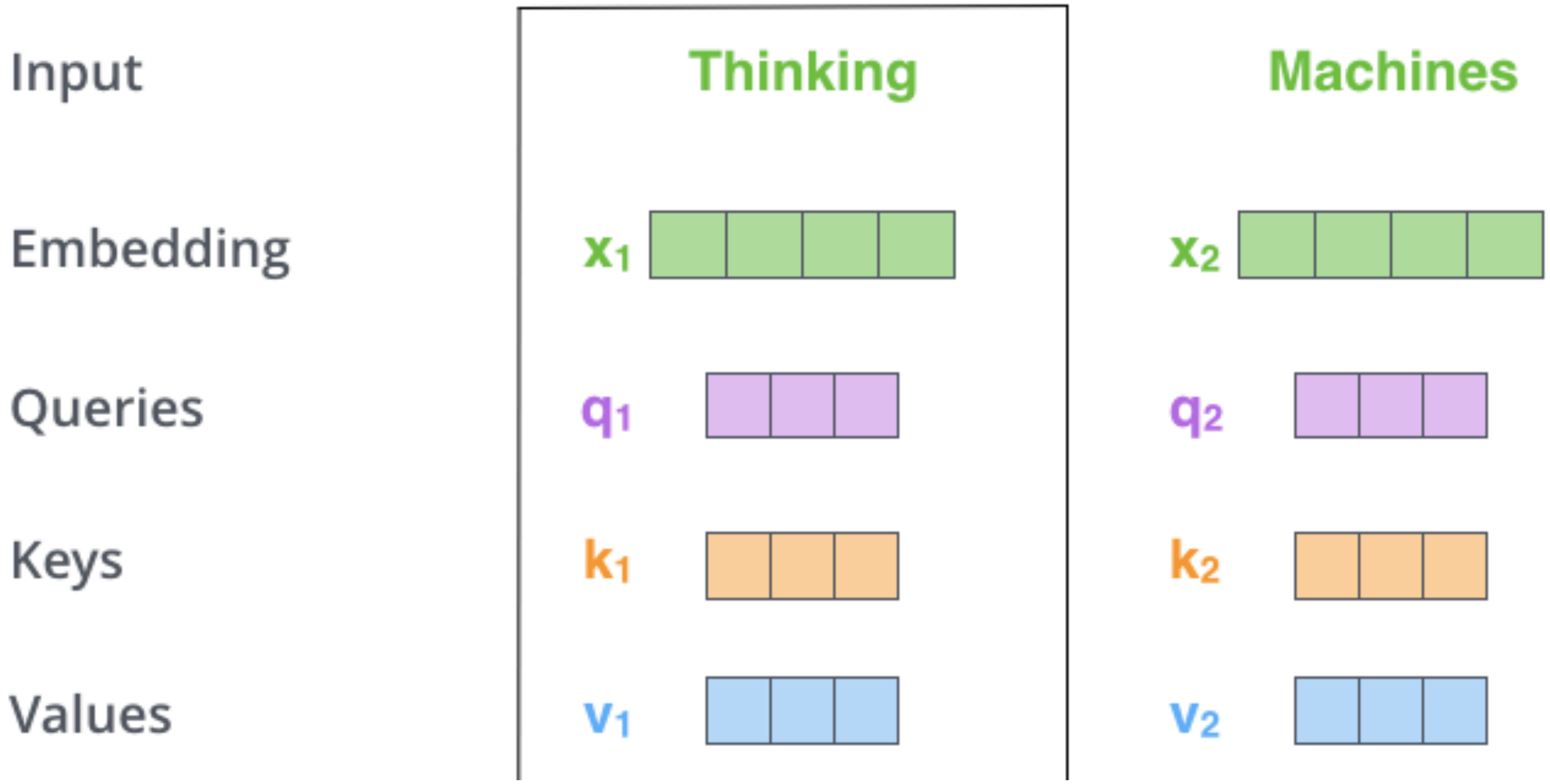
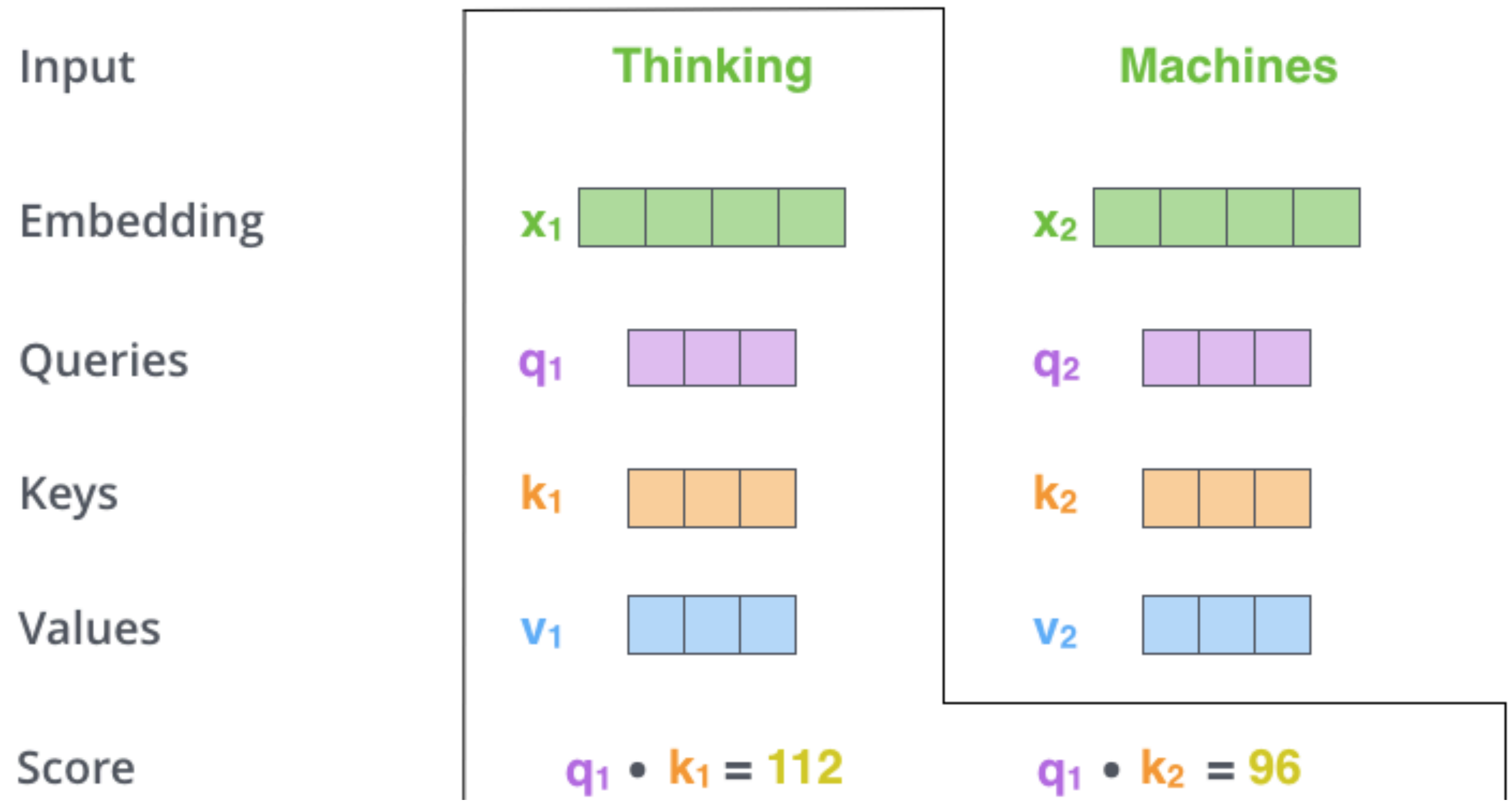
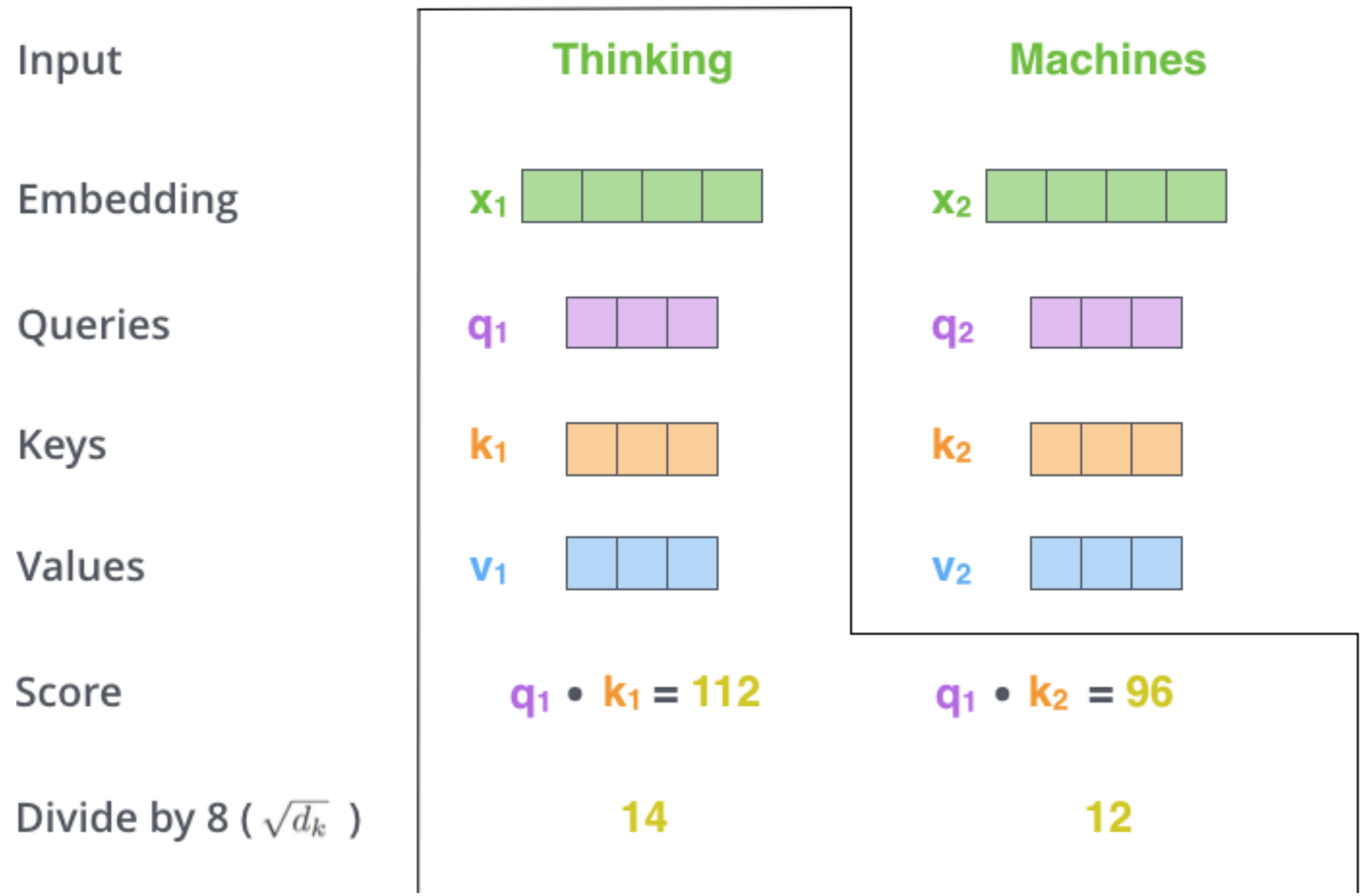
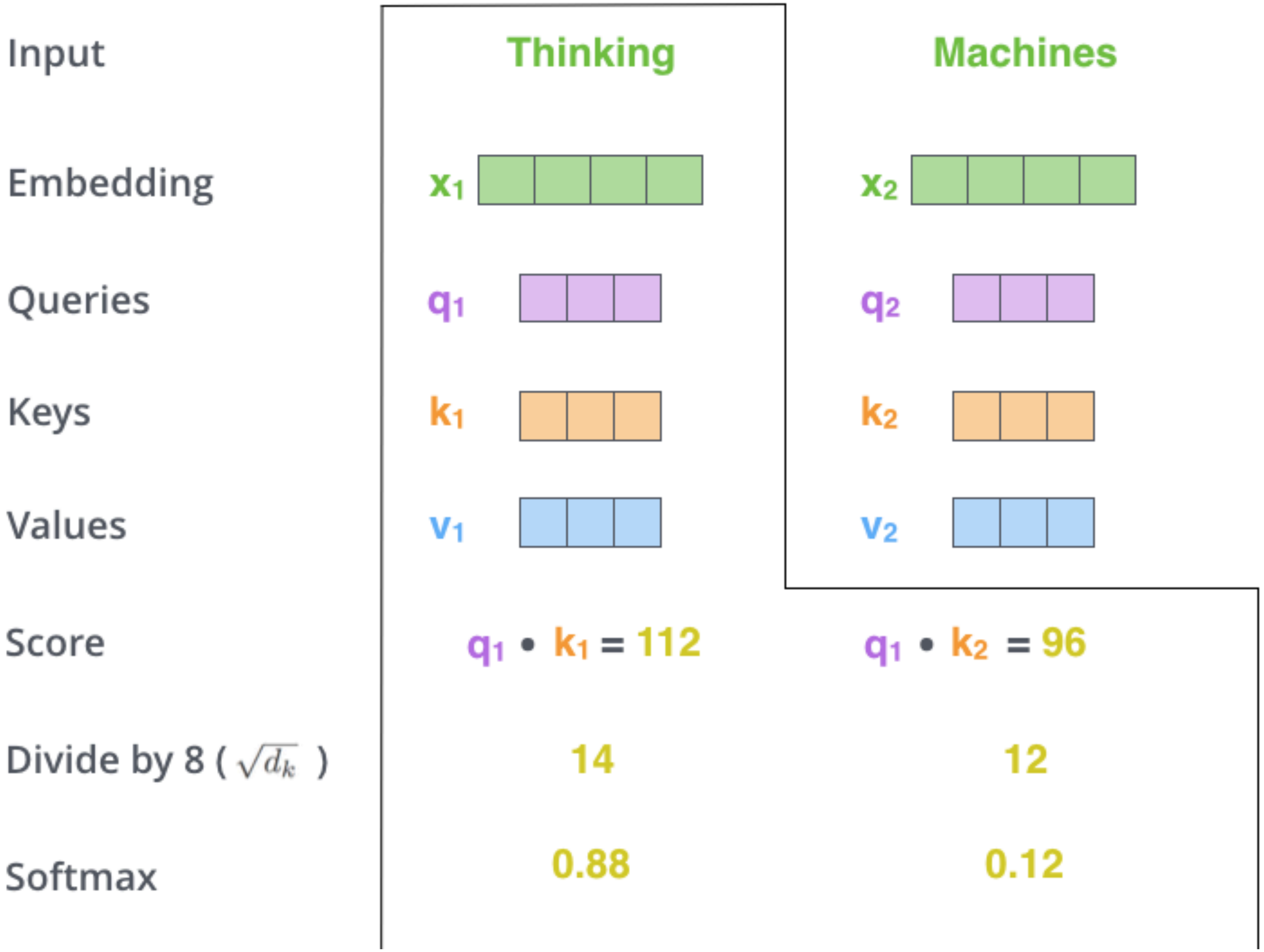
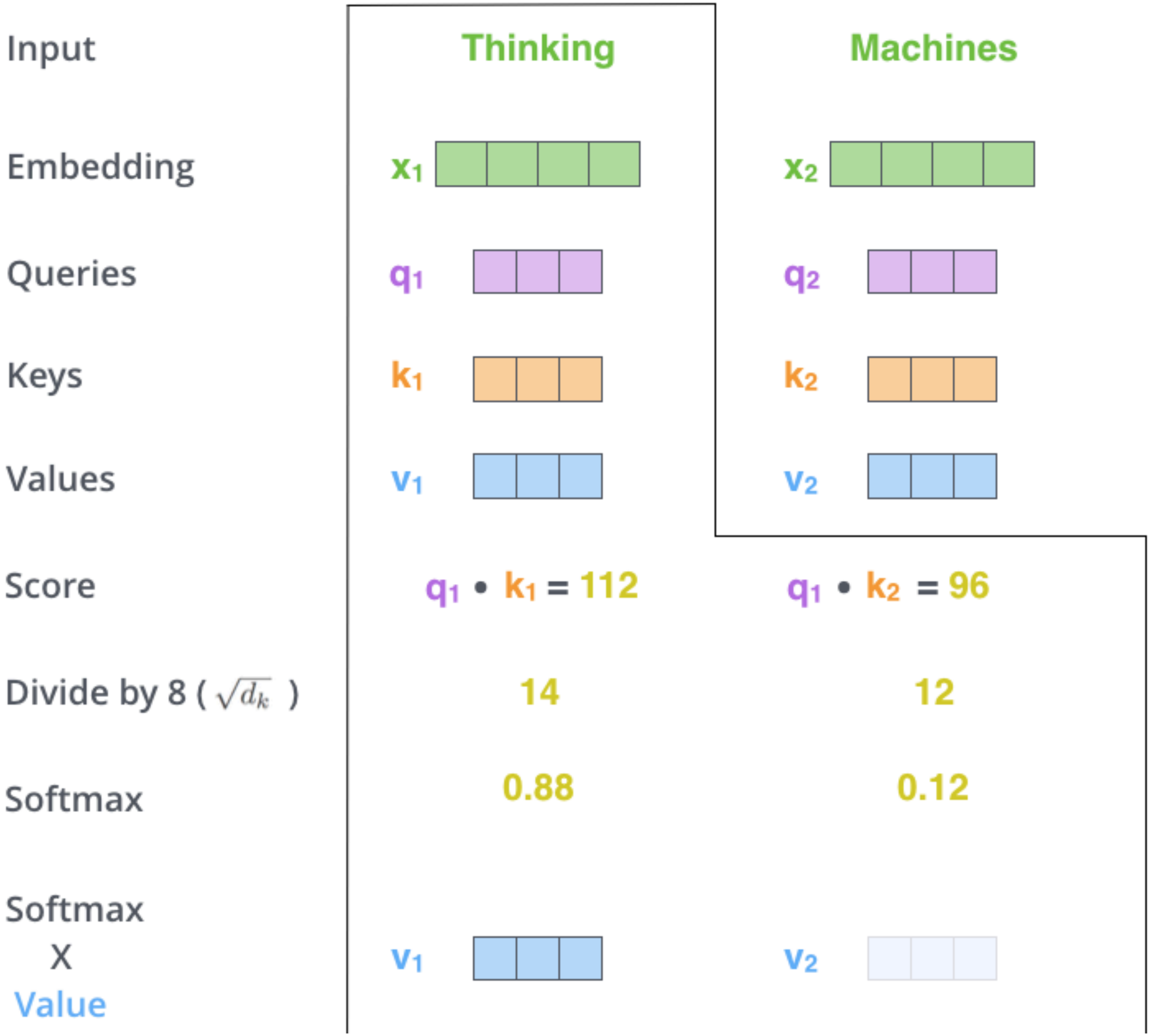

Input
Embedding
Queries
Keys
Values
Thinking
Machines
x1
x2
q1
q2
k1
k2
v1
v2


Input
Thinking
Machines
Embedding
x_1
x_2
Queries
q_1
q_2
Keys
k_1
k_2
Values
v_1
v_2
Score
$q_1 \bullet k_1 = 112$
$q_1 \bullet k_2 = 96$

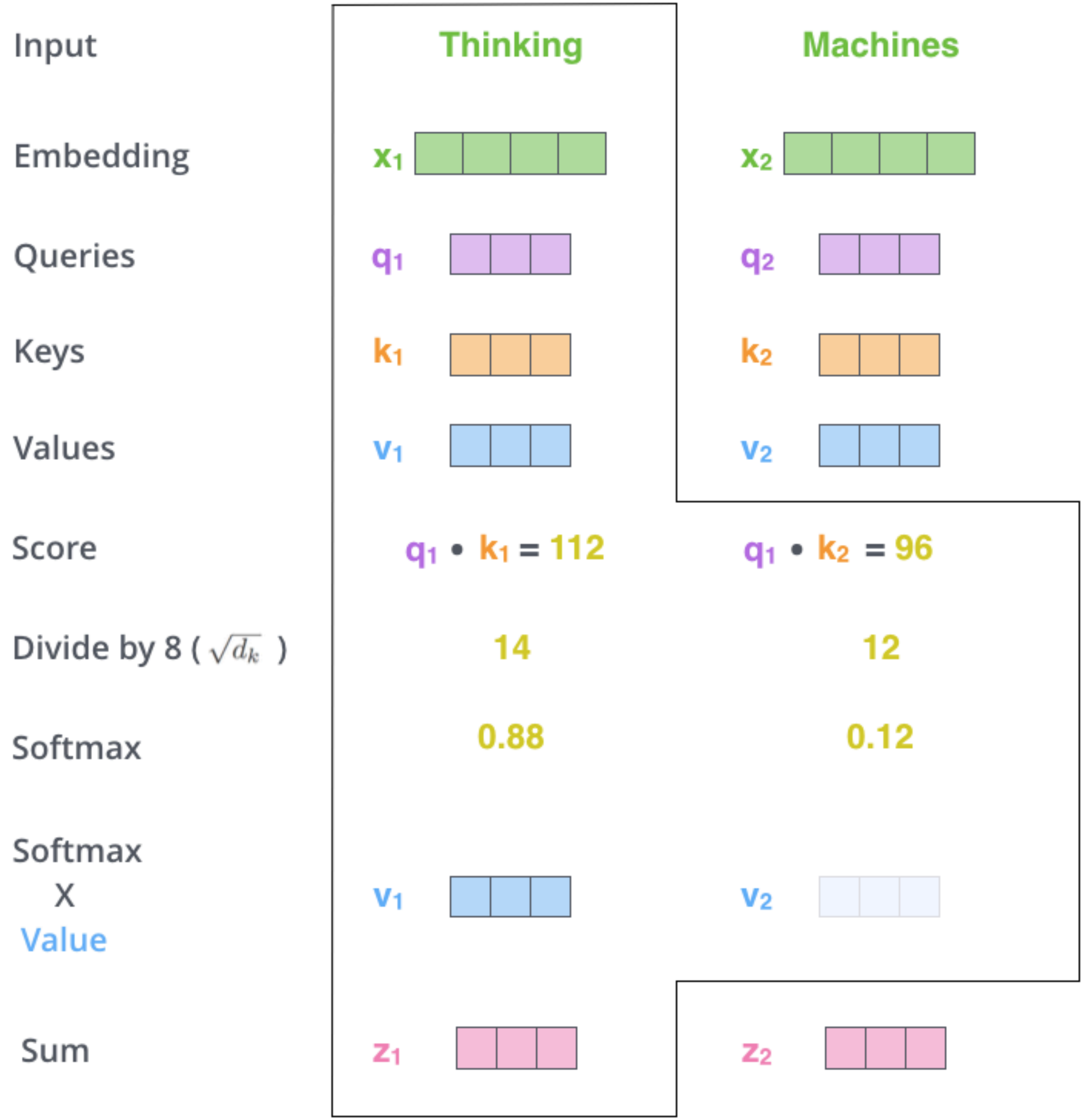

Input
Thinking
Machines
Embedding
x1
x2
Queries
q1
q2
Keys
k1
k2
Values
v1
v2
Score
q1 • k1 = 112
q1 • k2 = 96
Divide by 8 ($\sqrt{d_k}$)
14
12



Input
Thinking
Machines
Embedding
x1
x2
Queries
q1
q2
Keys
k1
k2
Values
v1
v2
Score
q1 • k1 = 112
q1 • k2 = 96
Divide by 8 ($\sqrt{d_k}$)
14
12
Softmax
0.88
0.12

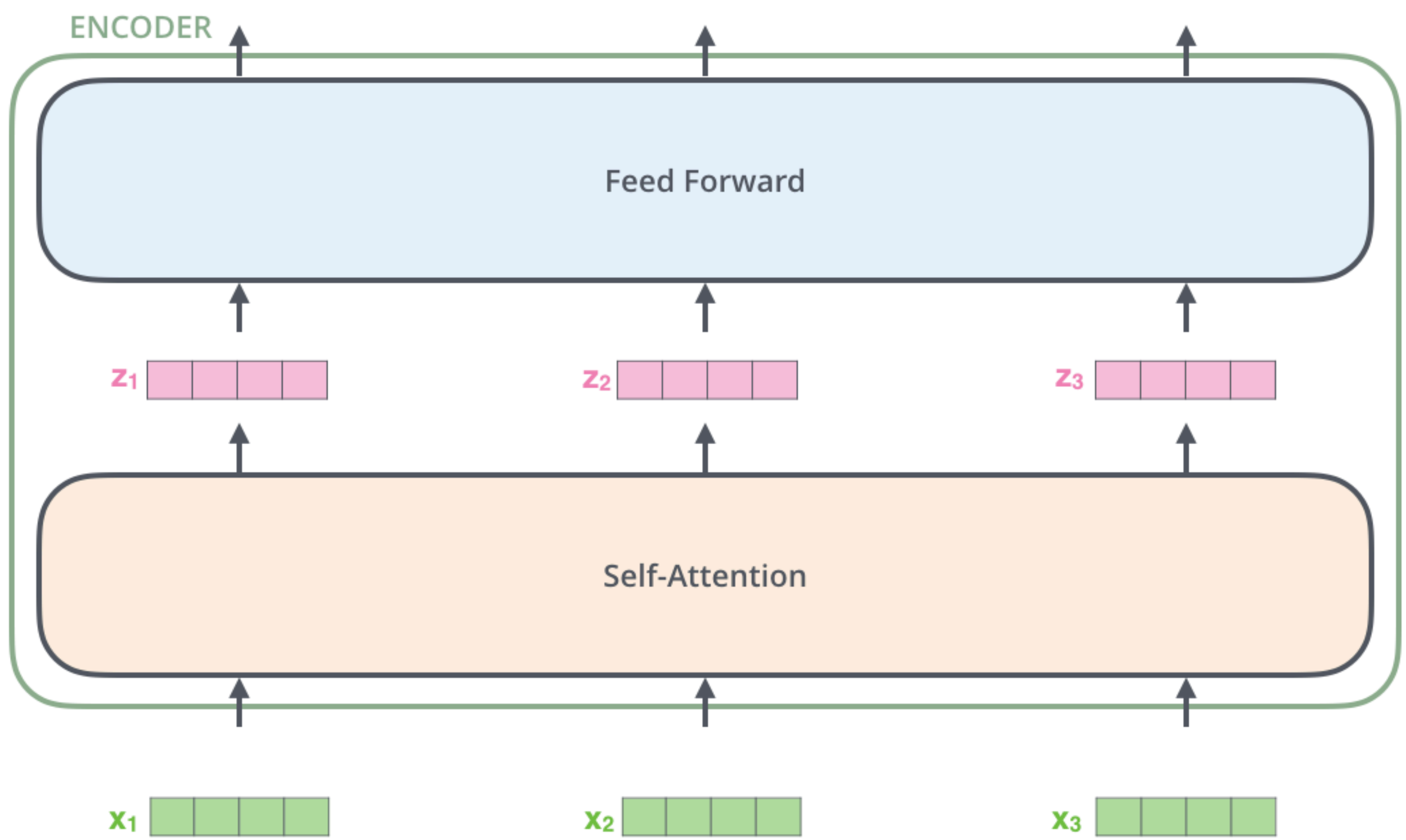


Input
Thinking
Machines
Embedding
x1
x2
Queries
q1
q2
Keys
k1
k2
Values
v1
v2
Score
q1 • k1 = 112
q1 • k2 = 96
Divide by 8 ($\sqrt{d_k}$)
14
12
Softmax
0.88
0.12
Softmax
X
Value
v1
v2



Credit: http://jalammar.github.io/illustrated-transformer/

Transformers: Simplified



Credit: http://jalammar.github.io/illustrated-transformer/

Self-Attention

- Self-Attention seems to be asking an association question

Self-Attention

- Self-Attention seems to be asking an association question
- Query ~ smaller word embedding

Self-Attention

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- Key & Value ~ Key is the hash key that maps to Value

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- The names Query, Key and Value come from retrieval parlance

Self-Attention

- Self-Attention seems to be asking an association question
- Query ~ smaller word embedding
- Key & Value ~ Key is the hash key that maps to Value
- The names Query, Key and Value come from retrieval parlance
  - you fire a query, you compare to a key vector and return the value

Self-attention: exercise

- “Computers are thinking machines”
- Compute z for machines
- Q = K = V = $\begin{bmatrix} 0.2 & 0.8 \\ -0.2 & 0.5 \\ -0.3 & -0.4 \\ 0.7 & 0.7 \end{bmatrix}$
- Computers = [1 0 0 0], are = [0 1 0 0], thinking = [0 0 1 0], machines = [0 0 0 1]
- <u>Softmax</u>

Self-attention: exercise

- “Computers are thinking machines”
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- Computers = [1 0 0 0], are = [0 1 0 0], thinking = [0 0 1 0], machines = [0 0 0 1]
- Softmax

z = [0.24   0.55]

Input	Computers	are	thinking	machines
Embedding				
Queries				
Keys				
Values				
Score	q·k			
Divide by $\sqrt{2}$ ($\sqrt{d_k}$)				
Softmax				
Softmax X Value				
Sum				

Input	Computers	are	thinking	machines
Embedding	[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries				
Keys				
Values				
Score $q \cdot k$				
Divide by $\sqrt{2}$ ($\sqrt{d_k}$)				
Softmax				
Softmax X Value				
Sum				

Input	Computers	are	thinking	machines
Embedding	[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Keys				
Values				
Score $q \cdot k$				
Divide by $\sqrt{2}$ ($\sqrt{d_k}$)				
Softmax				
Softmax X Value				
Sum				

	Computers	are	thinking	machines
Input	Computers	are	thinking	machines
Embedding	[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Keys	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Values				
Score $q \cdot k$				
Divide by $\sqrt{2}$ ($\sqrt{d_k}$)				
Softmax				
Softmax X Value				
Sum				

Input	Computers	are	thinking	machines
Embedding	[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Keys	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Values	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Score $q \cdot k$				
Divide by $\sqrt{2}$ ($\sqrt{d_k}$)				
Softmax				
Softmax X Value				
Sum				

Input		Computers	are	thinking	machines
Embedding		[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Keys		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Values		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Score	q·k	0.7	0.21	-0.49	0.98
Divide by $\sqrt{2}$ ($\sqrt{d_k}$)					
Softmax					
Softmax X Value					
Sum					

Input	Computers	are	thinking	machines
Embedding	[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	$\boxed{[0.7\ 0.7]}$
Keys	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Values	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
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Divide by $\sqrt{2}$ ($\sqrt{d_k}$)				
Softmax				
Softmax X Value				
Sum				

Input		Computers	are	thinking	machines
Embedding		[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	$\boxed{[0.7\ 0.7]}$
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Embedding		[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
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Keys		[0.2 0.8]	[-0.2 0.5]	$\boxed{[-0.3\ -0.4]}$	[0.7 0.7]
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Softmax					
Softmax X Value					
Sum					

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Input		Computers	are	thinking	machines
Embedding		[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	$\boxed{[0.7\ 0.7]}$
Keys		[0.2 0.8]	$\boxed{[-0.2\ 0.5]}$	[-0.3 -0.4]	[0.7 0.7]
Values		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
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Divide by $\sqrt{2}$ ($\sqrt{d_k}$)					
Softmax					
Softmax X Value					
Sum					

Input	Computers	are	thinking	machines
Embedding	[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	$\boxed{[0.7\ 0.7]}$
Keys	$\boxed{[0.2\ 0.8]}$	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
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Divide by $\sqrt{2}$ ($\sqrt{d_k}$)				
Softmax				
Softmax X Value				
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Embedding		[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	$\boxed{[0.7\ 0.7]}$
Keys		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
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Softmax X Value					
Sum					

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Embedding	[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	$\boxed{[0.7\ 0.7]}$
Keys	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Values	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Score q·k	0.7	0.21	-0.49	0.98
Divide by $\sqrt{2}$ ($\sqrt{d_k}$)	0.49	0.15	-0.35	0.69
Softmax				
Softmax X Value				
Sum				

		Computers	are	thinking	machines
Input		Computers	are	thinking	machines
Embedding		[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	$\boxed{[0.7\ 0.7]}$
Keys		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Values		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Score	q·k	0.7	0.21	-0.49	0.98
Divide by $\sqrt{2}$ ($\sqrt{d_k}$)		0.49	0.15	-0.35	0.69
Softmax		0.30	0.21	0.13	0.36
Softmax X Value					
Sum					

	Computers	are	thinking	machines
Input	Computers	are	thinking	machines
Embedding	[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	$\boxed{[0.7\ 0.7]}$
Keys	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Values	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Score q·k	0.7	0.21	-0.49	0.98
Divide by $\sqrt{2}$ ($\sqrt{d_k}$)	0.49	0.15	-0.35	0.69
Softmax	0.30	0.21	0.13	0.36
Softmax X Value	[0.06 0.24]	[-0.04 0.10]	[-0.04 -0.05]	[0.25 0.25]
Sum				

Input	Computers	are	thinking	machines
Embedding	[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	$\boxed{[0.7\ 0.7]}$
Keys	[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
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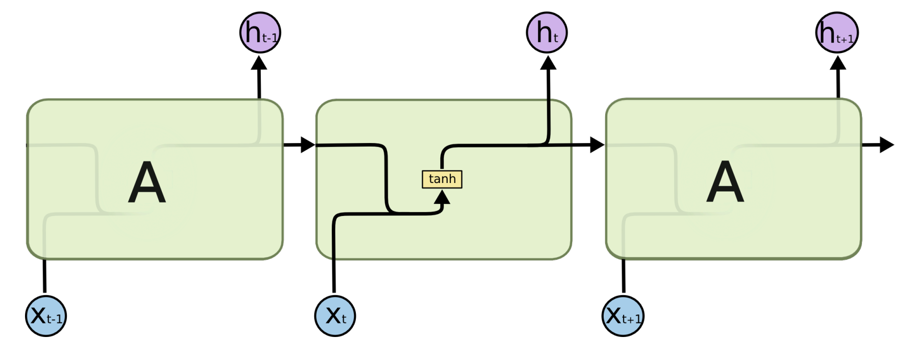
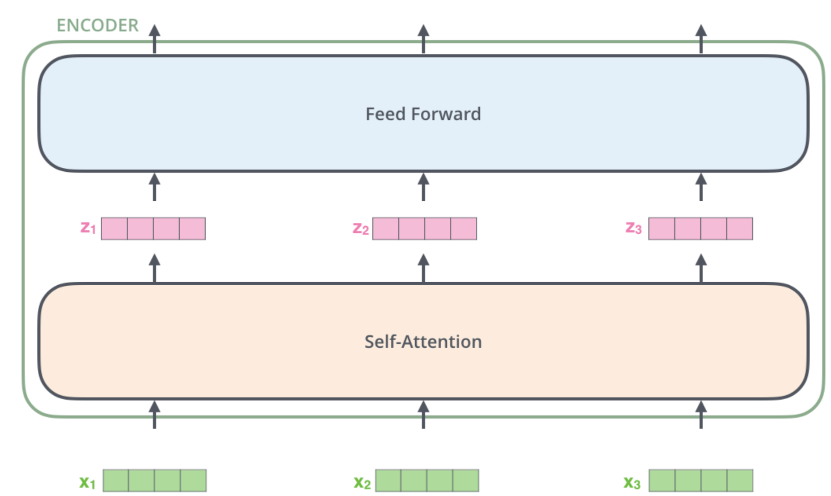
Softmax	0.30	0.21	0.13	0.36
Softmax X Value	[0.06 0.24]	[-0.04 0.10]	[-0.04 -0.05]	[0.25 0.25]
Sum				[0.23 0.54]

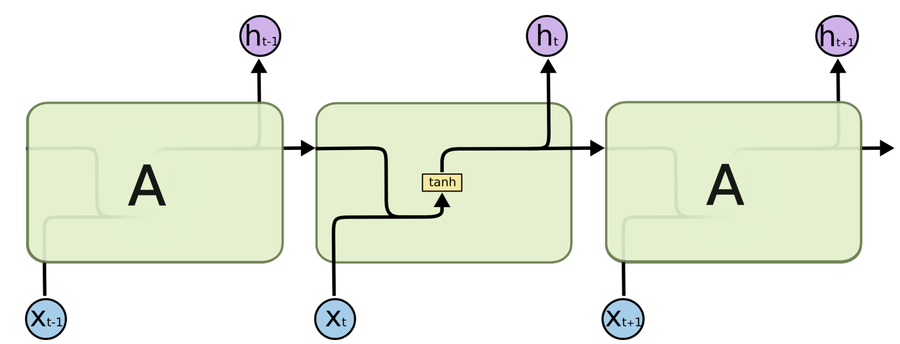
Transformers for Language Modelling

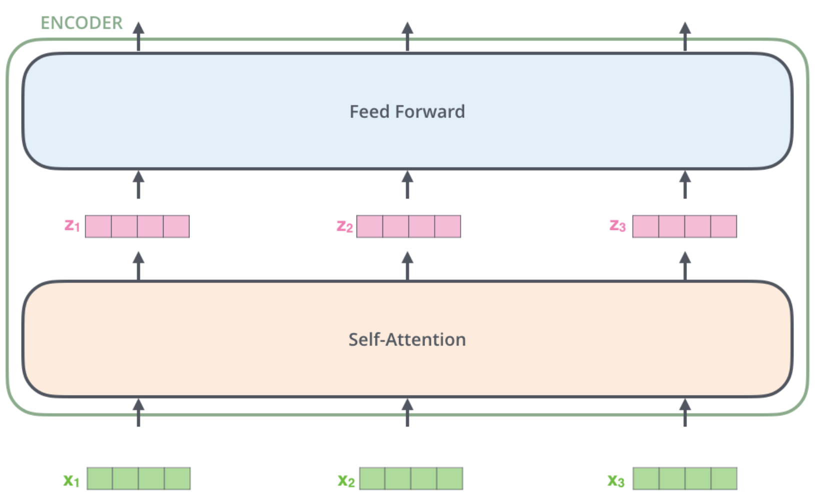




Transformers for Language Modelling

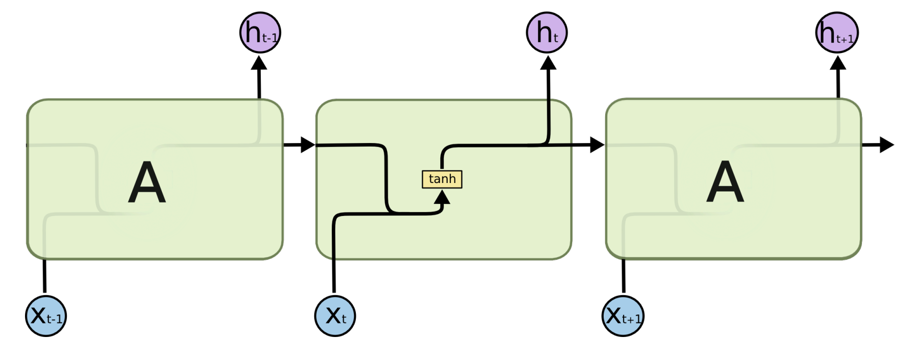
- RNNs: Process tokens one-by-one

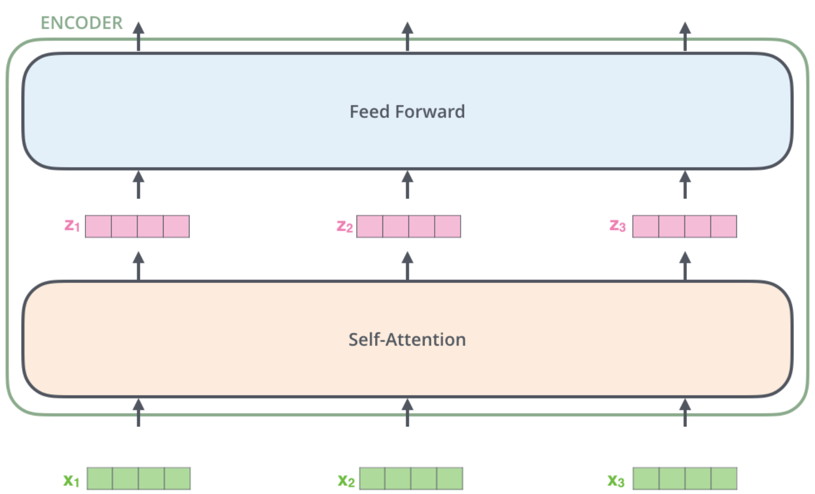




Transformers for Language Modelling

- RNNs: Process tokens one-by-one
  - Chain of dependencies built using a single token





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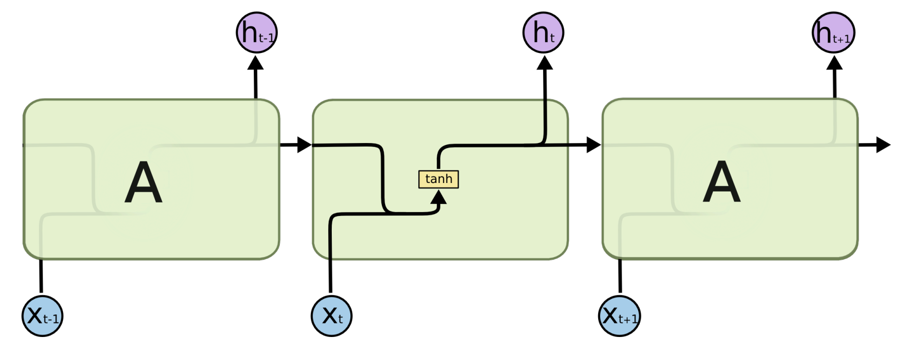
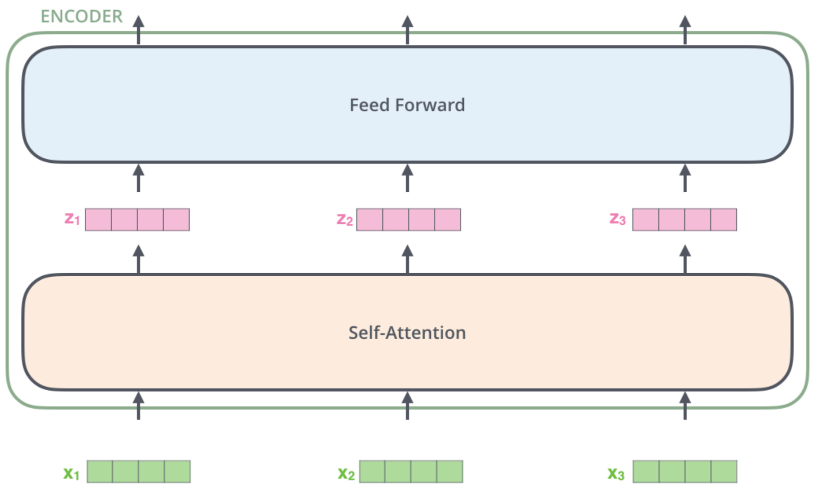


- Transformers LM: Process a segment of tokens



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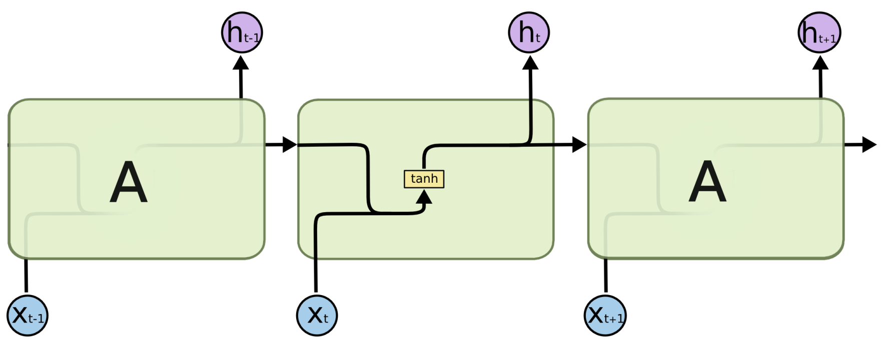

- Transformers LM: Process a segment of tokens
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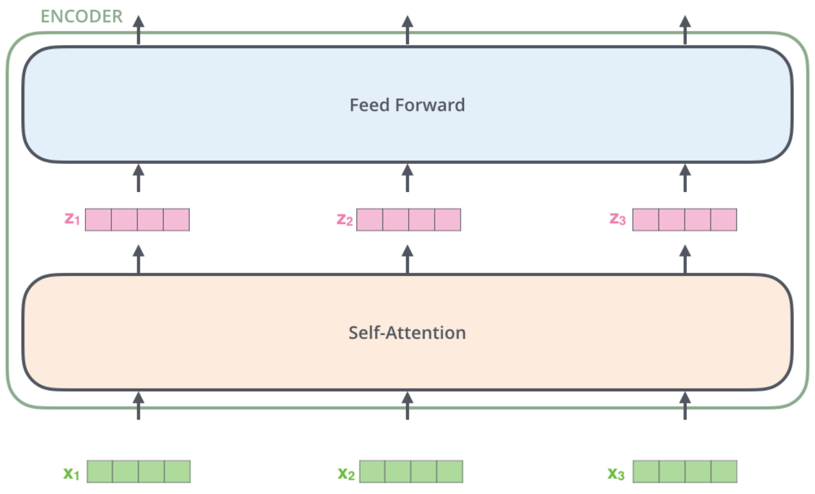

Transformers for Language Modelling

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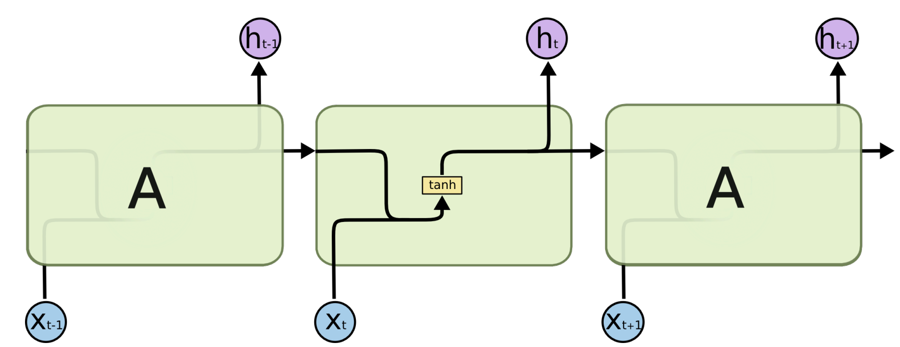
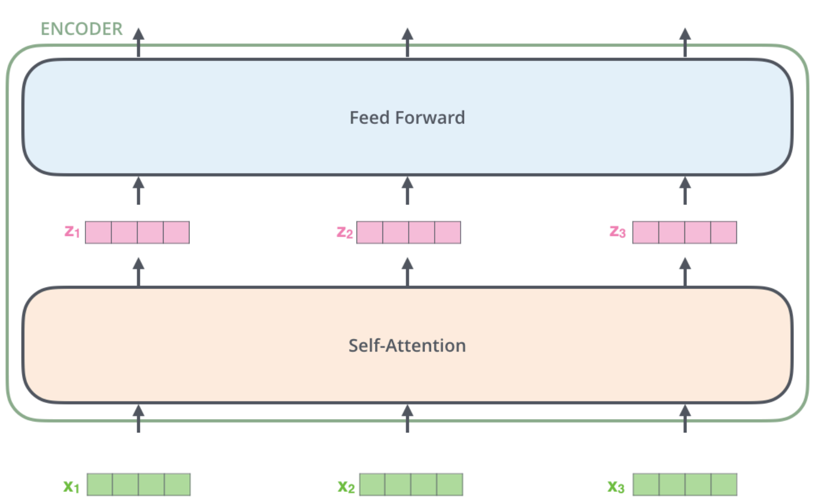
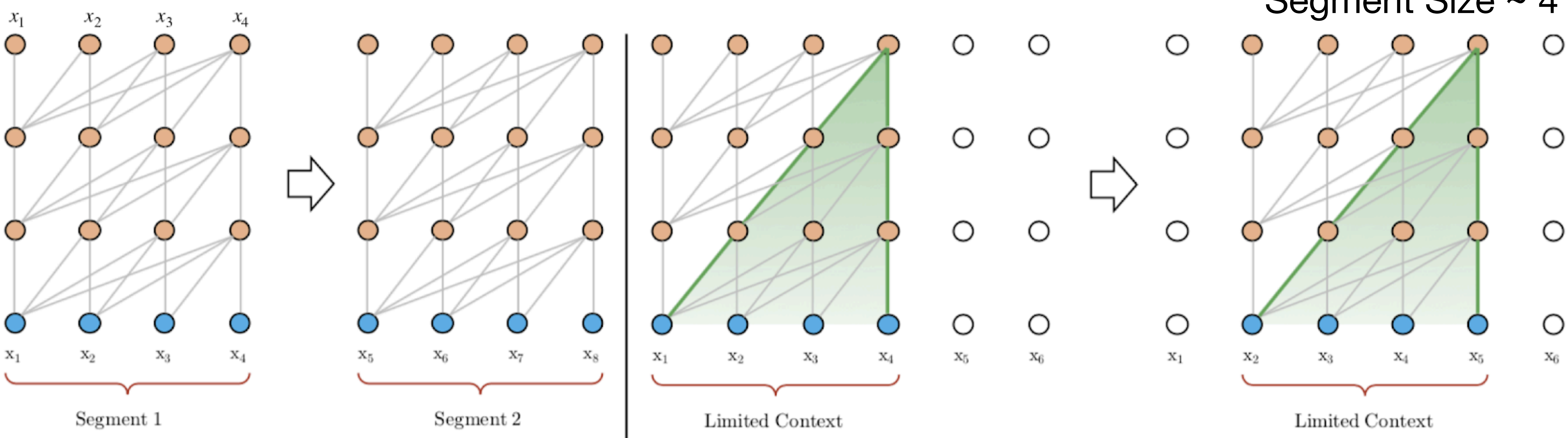


- Transformers LM: Process a segment of tokens
  - Dependencies within the segment
  - Within segment position is given by the positional encoding



Transformer LM processing of Segments

Segment Size ~ 4

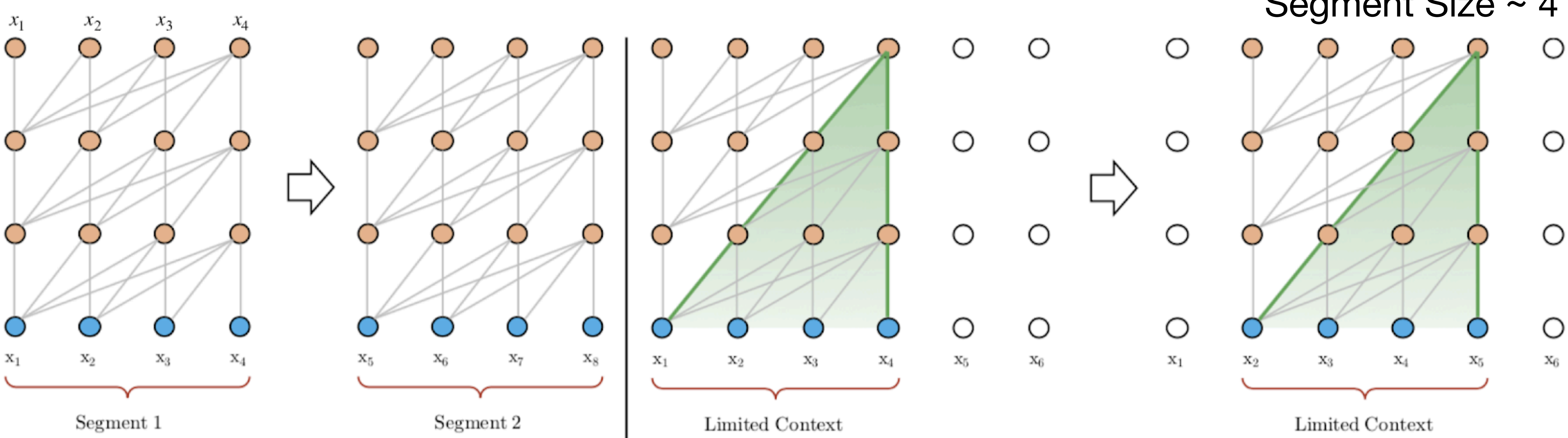


(a) Training phase. (b) Evaluation phase.

Dai et al., 2019

Transformer LM processing of Segments

Segment Size ~ 4



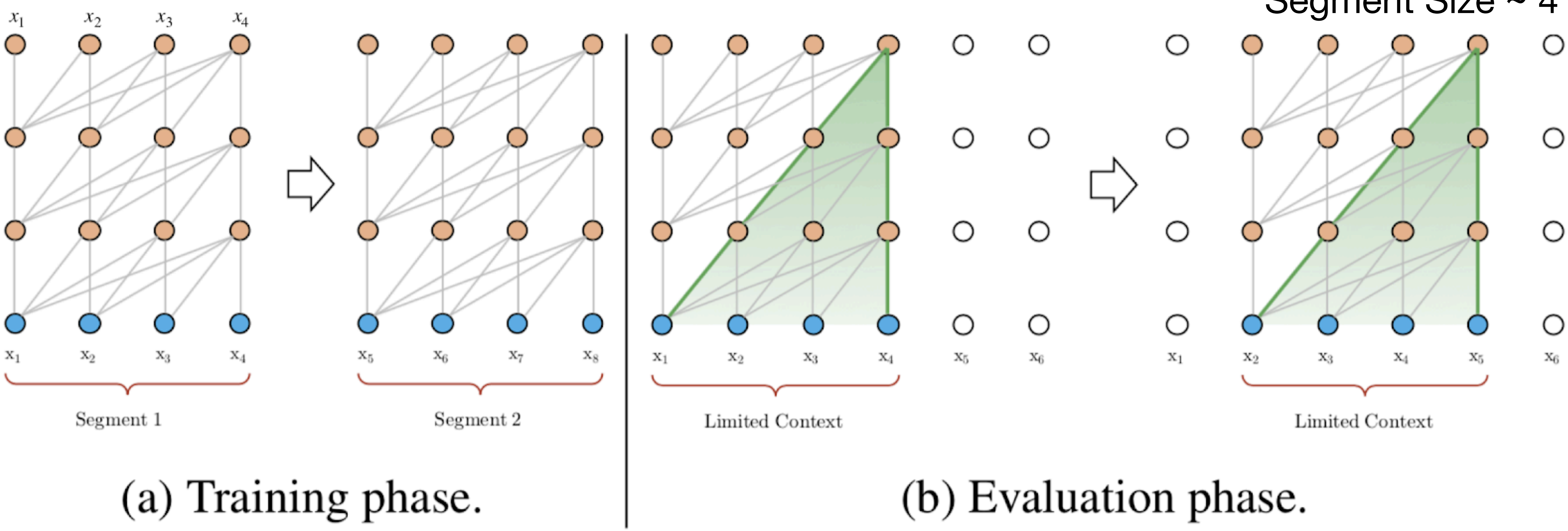
(a) Training phase. (b) Evaluation phase.

Dai et al., 2019

- Limited context-dependency
  - the model can't "use" a word that appeared several sentences ago.

Transformer LM processing of Segments

Segment Size ~ 4



Dai et al., 2019

- Limited context-dependency
  - the model can't "use" a word that appeared several sentences ago.
- Context fragmentation
  - no relationships can be leveraged across segments

[Jacob Devlin et al 2018]

Image credit: https://towardsml.com/2019/09/17/bert-explained-a-complete-guide-with-theory-and-tutorial/

BERT: Bidirectional Encoder Representations from Transformers

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- For specialised tasks like named entity recognition, question answering there is a lack of training data

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- For specialised tasks like named entity recognition, question answering there is a lack of training data
- Deep learning requires large amounts of annotated data
- Language models for general purpose representations
- Aim to **pretrain** general purpose representations
- that can be **fine-tuned** using small task-specific dataset to obtain good performance on specialised tasks

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- For specialised tasks like named entity recognition, question answering there is a lack of training data
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- Language models for general purpose representations
- Aim to **pretrain** general purpose representations
- that can be **fine-tuned** using small task-specific dataset to obtain good performance on specialised tasks
- Welcome BERT!

Transformers for Language Modelling

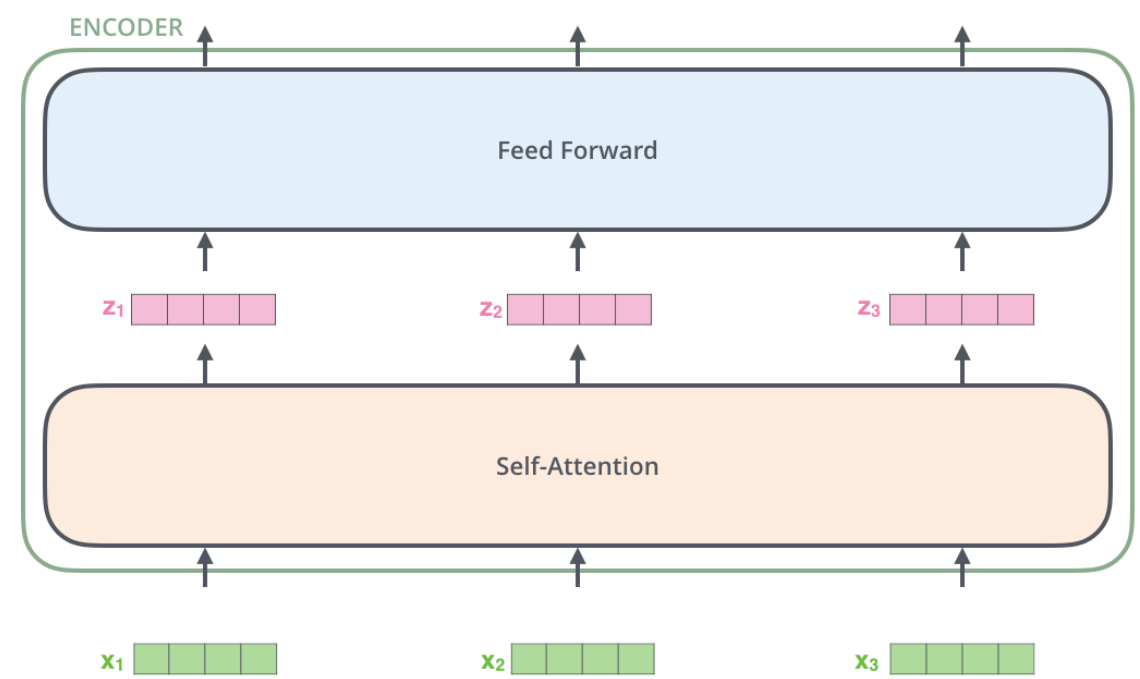
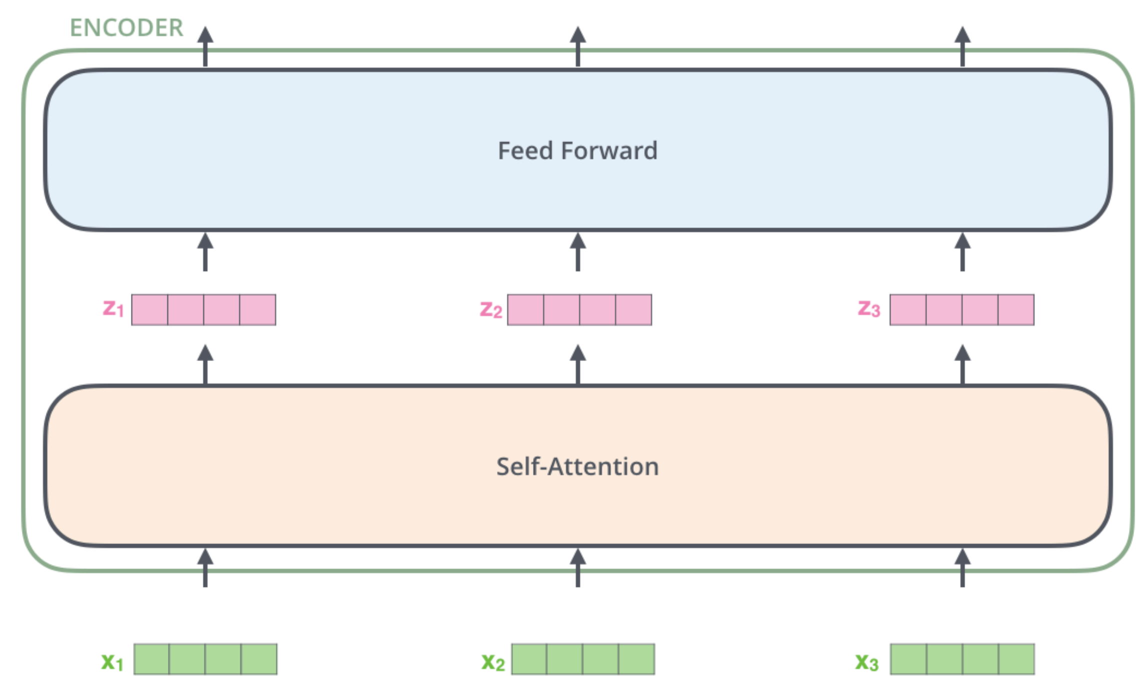


Image Credit: https://arxiv.org/pdf/1706.03762.pdf
Content Credit:TransformerXL Explained & Al-Rfou et al. 2018

Transformers for Language Modelling

- Transformers LM



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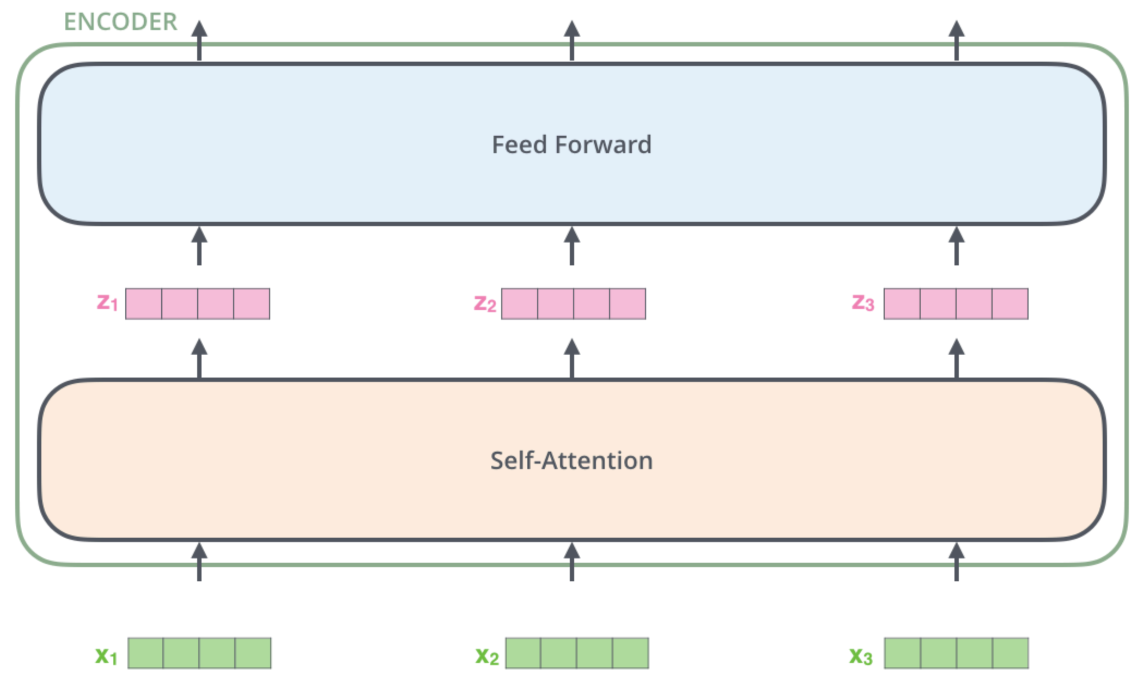

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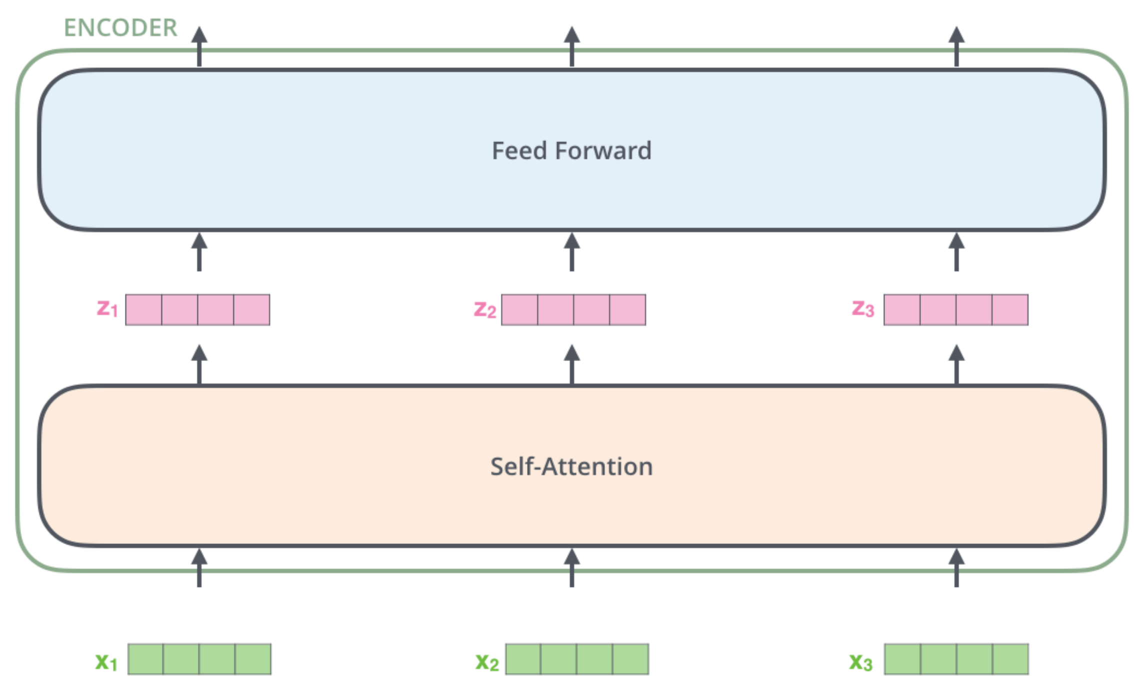

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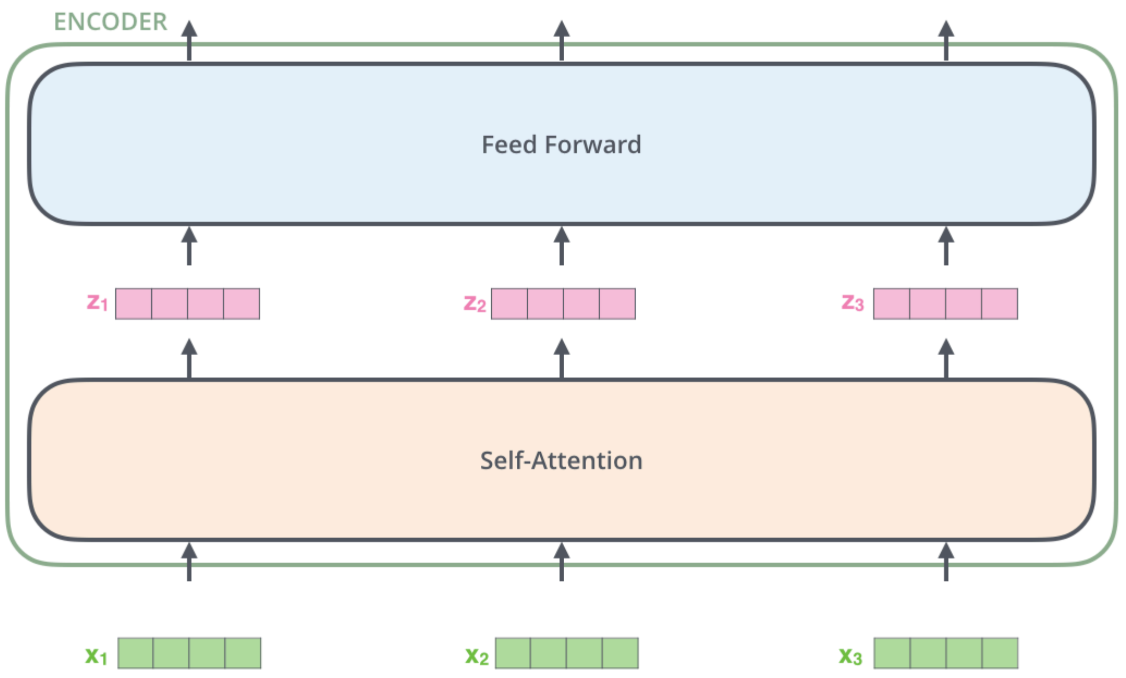

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Encoder Representations

- Require only the representations
- Forego of the output layer and only keep the encoder

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- Bidirectionality in this above example can help make a better judgement
- In BERT, this bidirectionality is important to obtain good general purpose representations

BERT: Learning Setup

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- Pretraining

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  - Takes lots and lots of sentences

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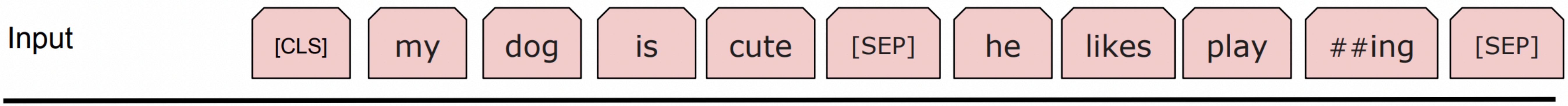
- Finetune

Masked LM



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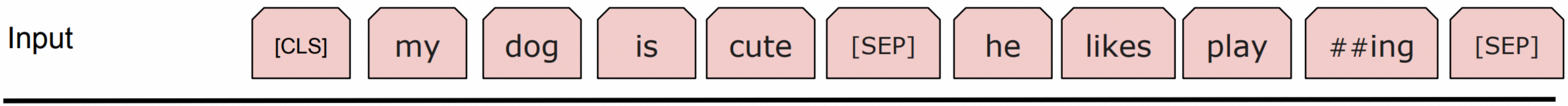
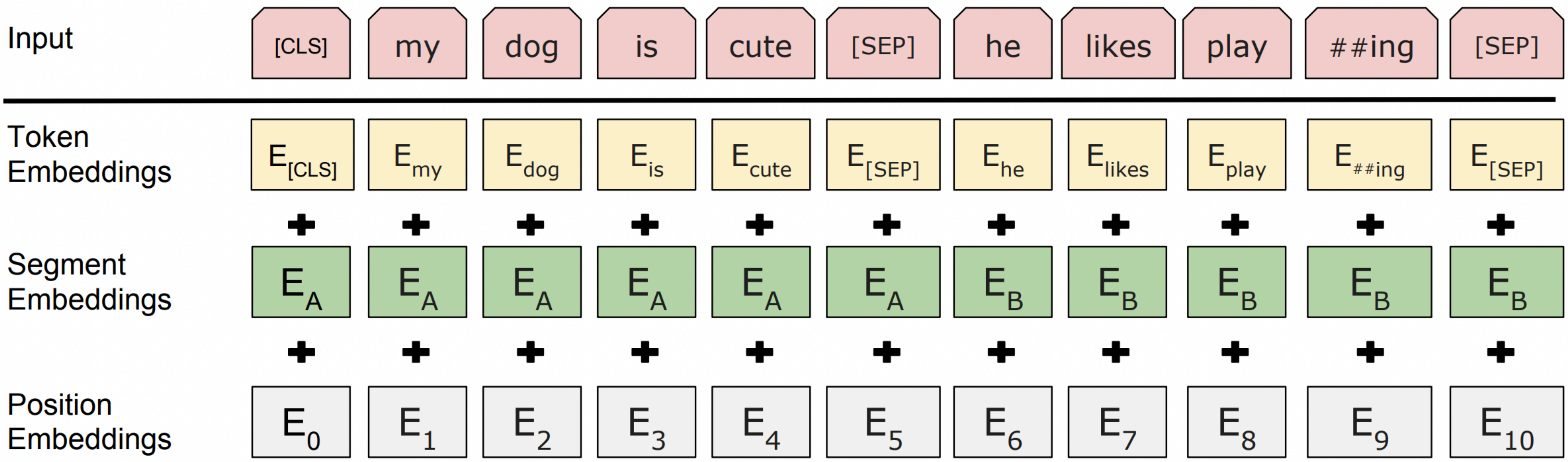


- Use specialised tokens CLS, SEP

Masked LM



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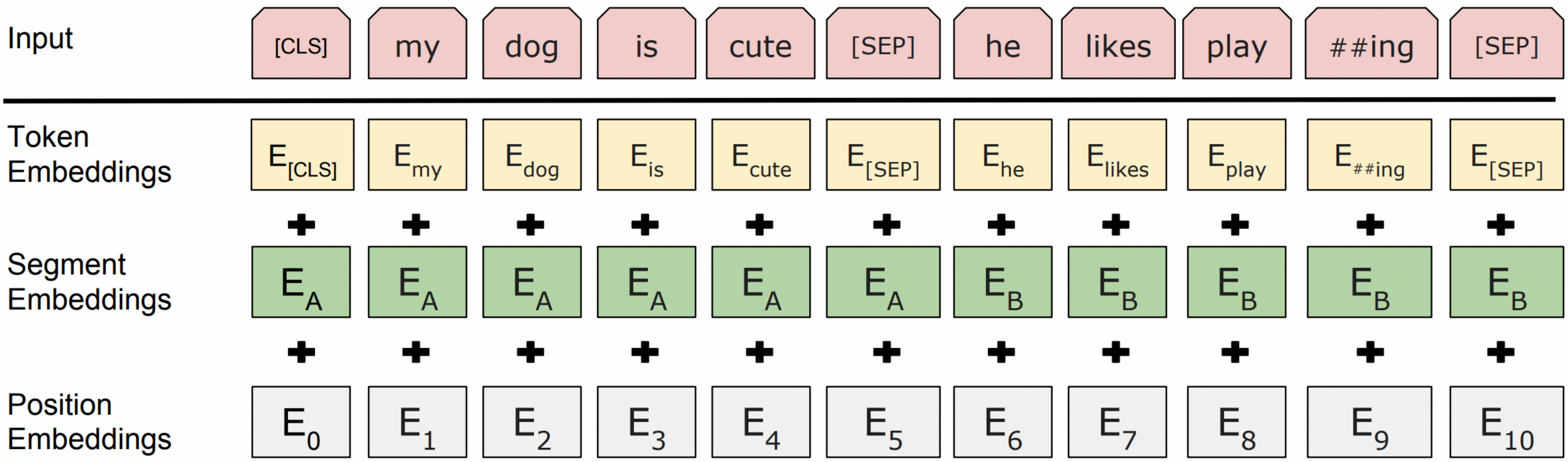

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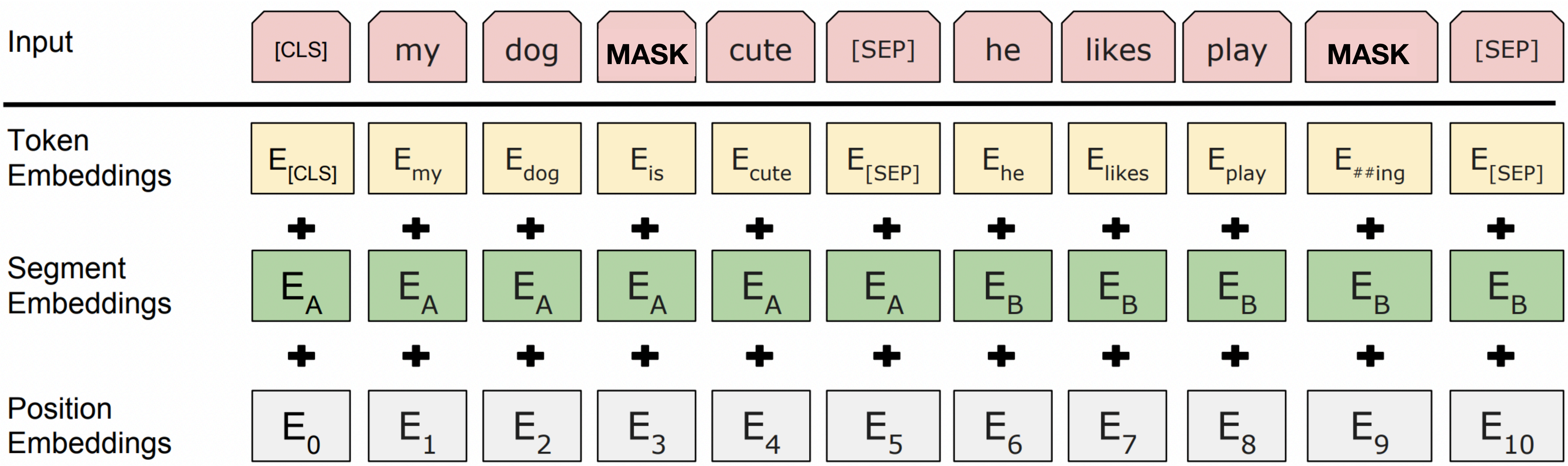

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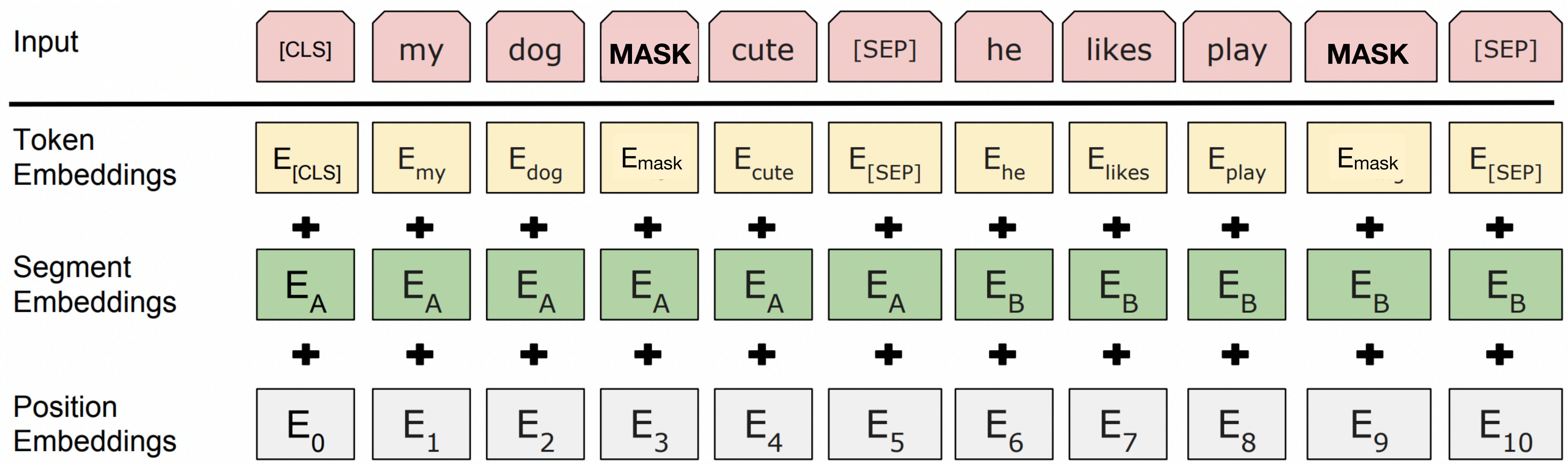

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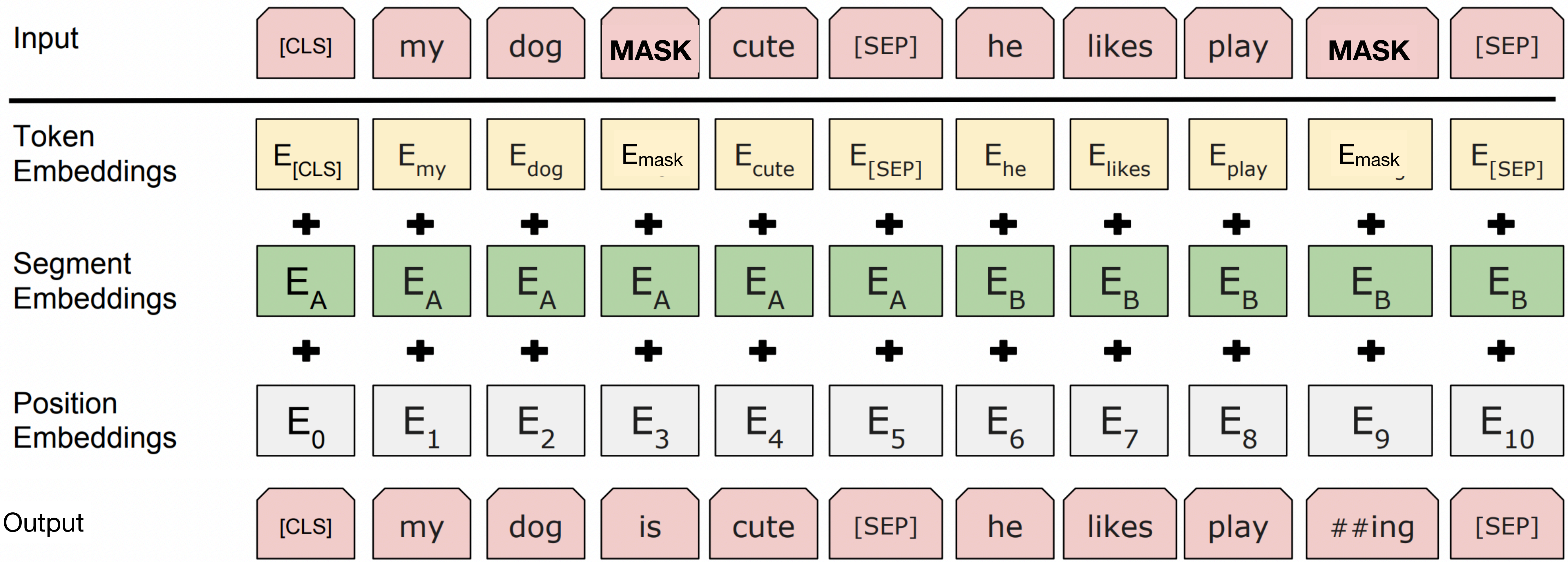

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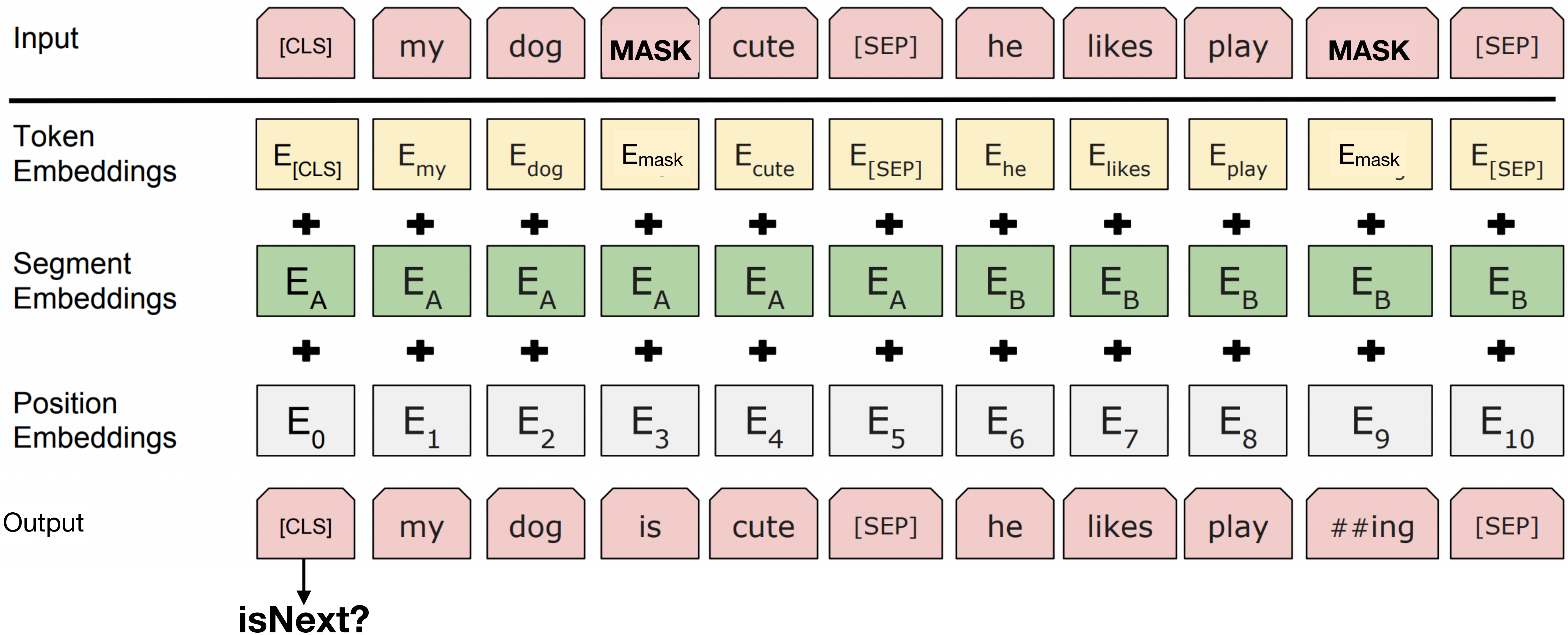
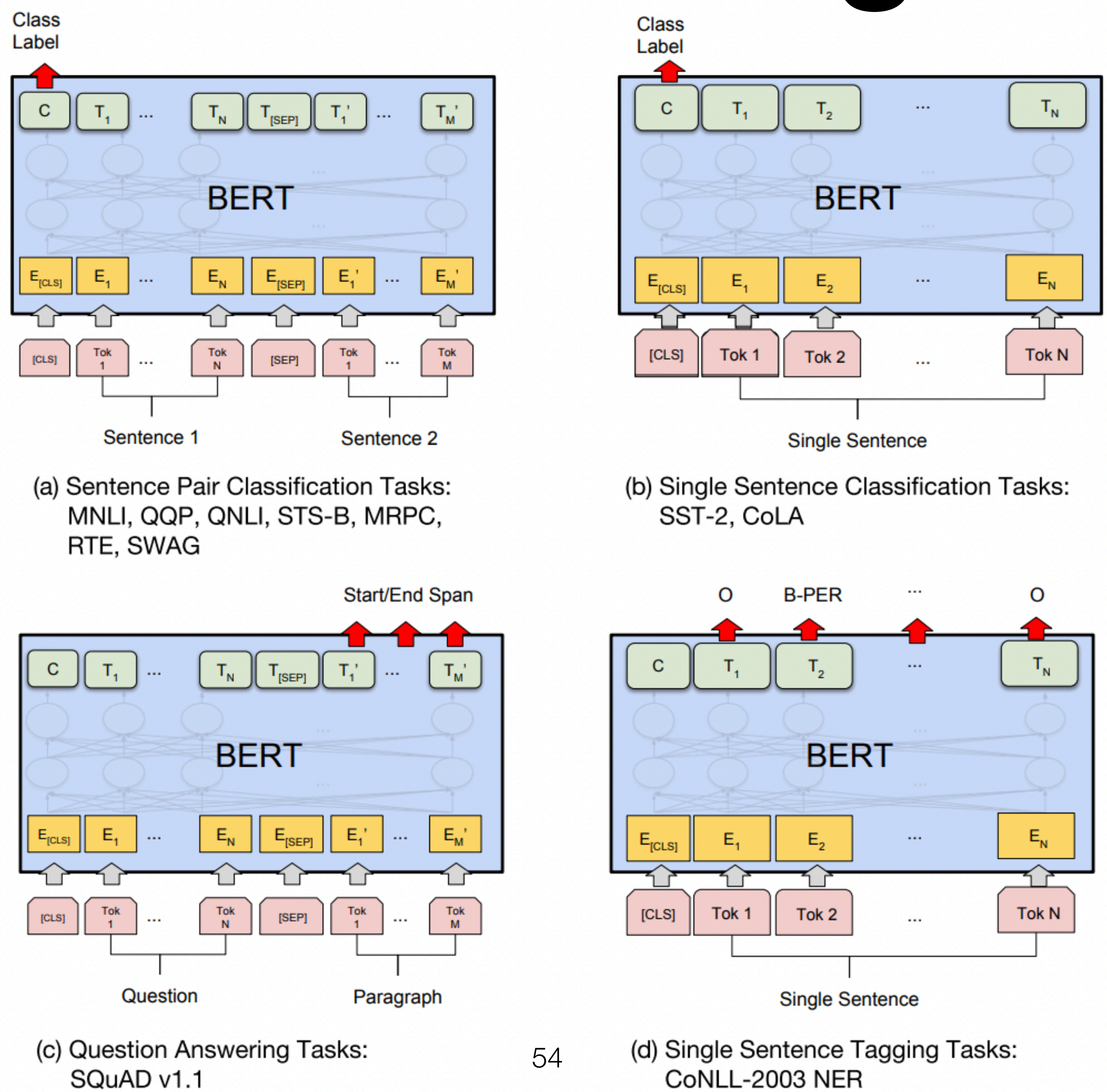
Next Sentence Prediction



Use the CLS output embedding to predict is sentence B is the next sentence or not.

Fine-tuning


Class Label
BERT
Sentence 1
Sentence 2
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG
Class Label
BERT
Single Sentence
(b) Single Sentence Classification Tasks: SST-2, CoLA
Start/End Span
BERT
Question
Paragraph
(c) Question Answering Tasks: SQuAD v1.1
O
B-PER
O
BERT
Single Sentence
(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Glue Test Results

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

[Jacob Devlin et al 2018]

Reading Task

- Read this article: https://medium.com/@samia.khalid/bert-explained-a-complete-guide-with-theory-and-tutorial-3ac9ebc8fa7c

- Prepare questions to discuss!

- Time: 10 mins

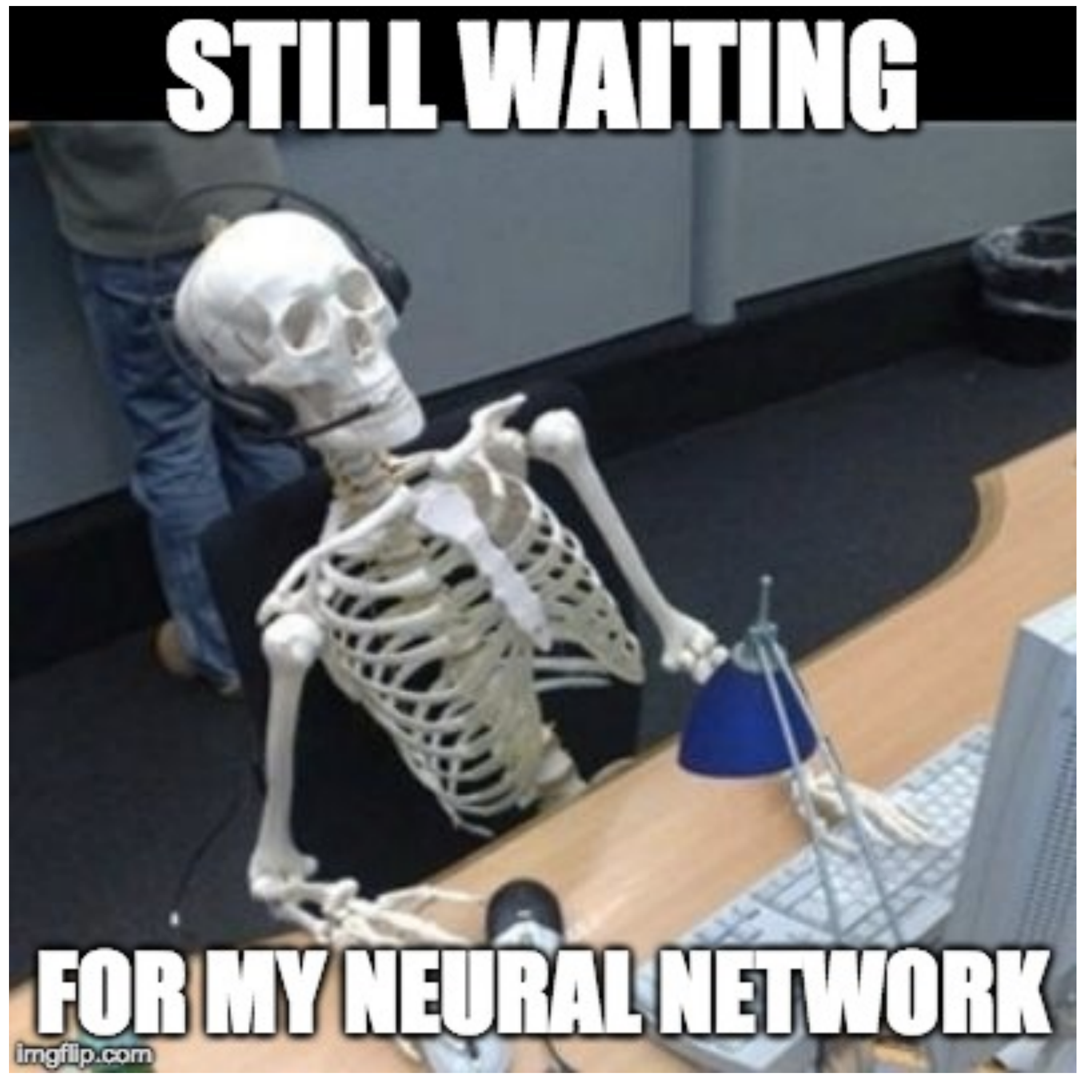
Summary

- NNLM:
  - LSTMs
  - Transformers
    - Self Attention
    - BERT
- Challenges
  - Long-Term Dependencies
  - Class-based output layer
  - Rare Words

Further Reading

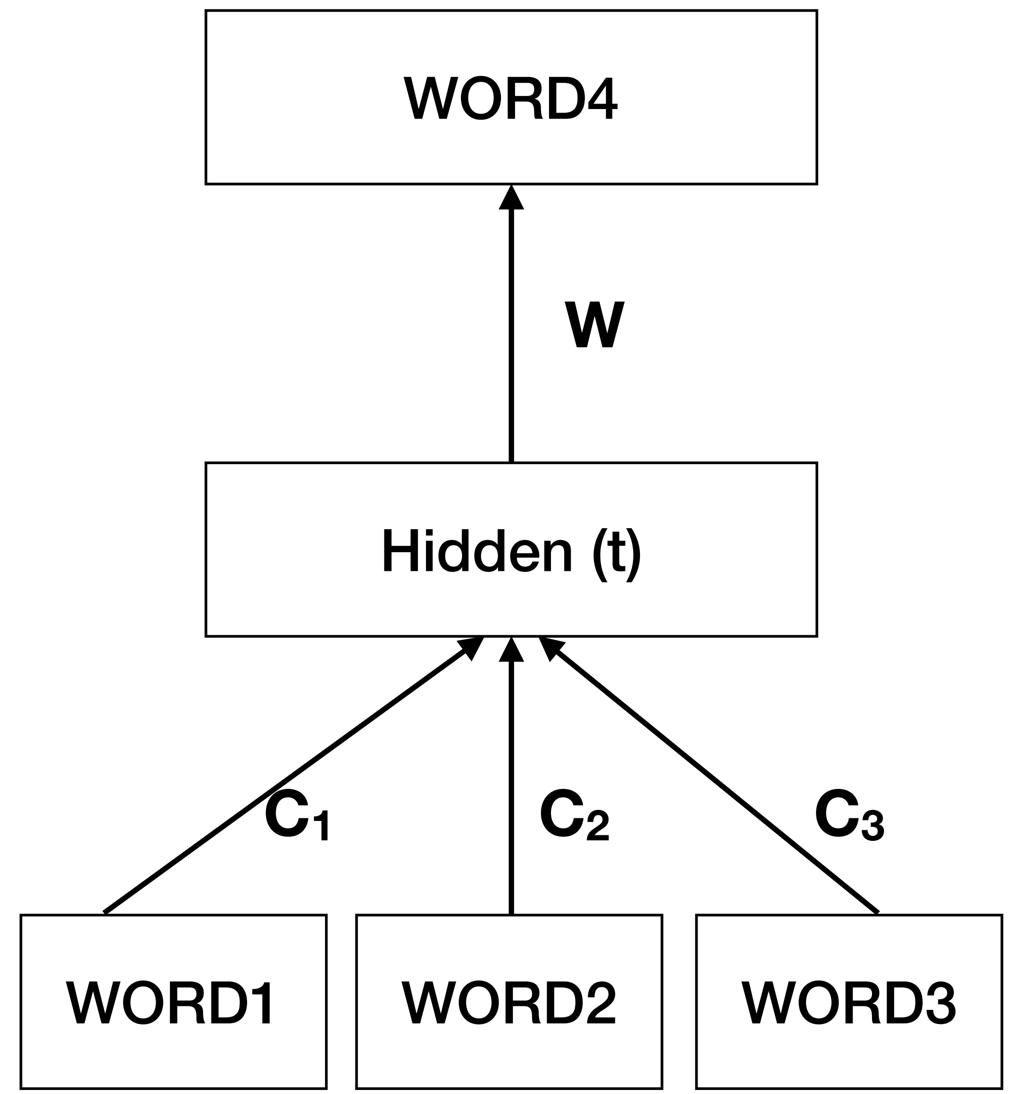
- Neural Networks and Neural Language Models: https://web.stanford.edu/~jurafsky/slp3/7.pdf

Neural Network Training



Softmax Normalization

- Slowest part of training an NNLM is softmax normalization



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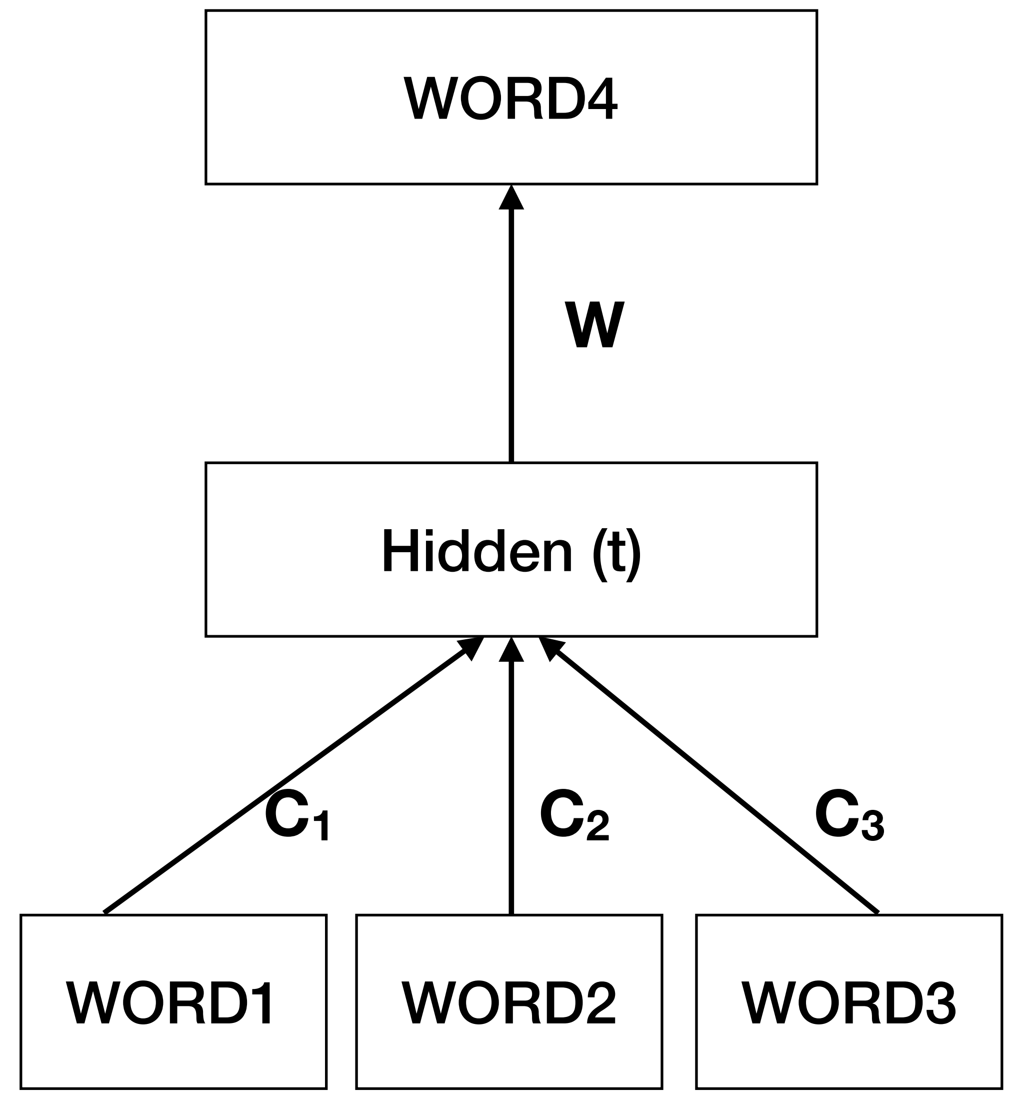

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- We must do this for every word in our training set (eg. 1M-1B), every epoch (> 10)

Class-based Output Layer

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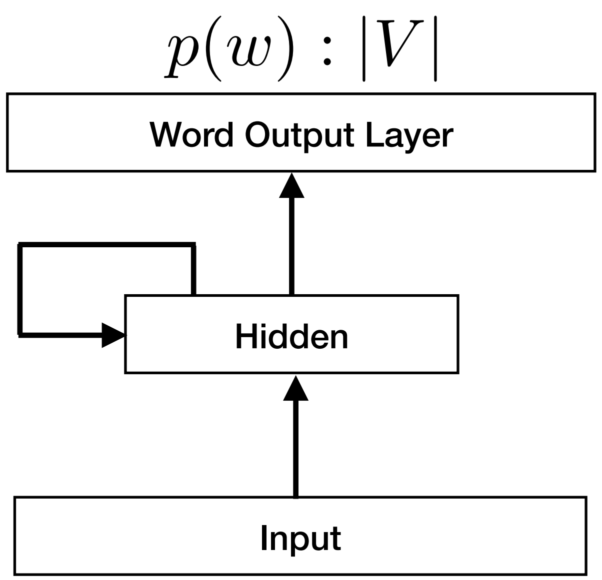

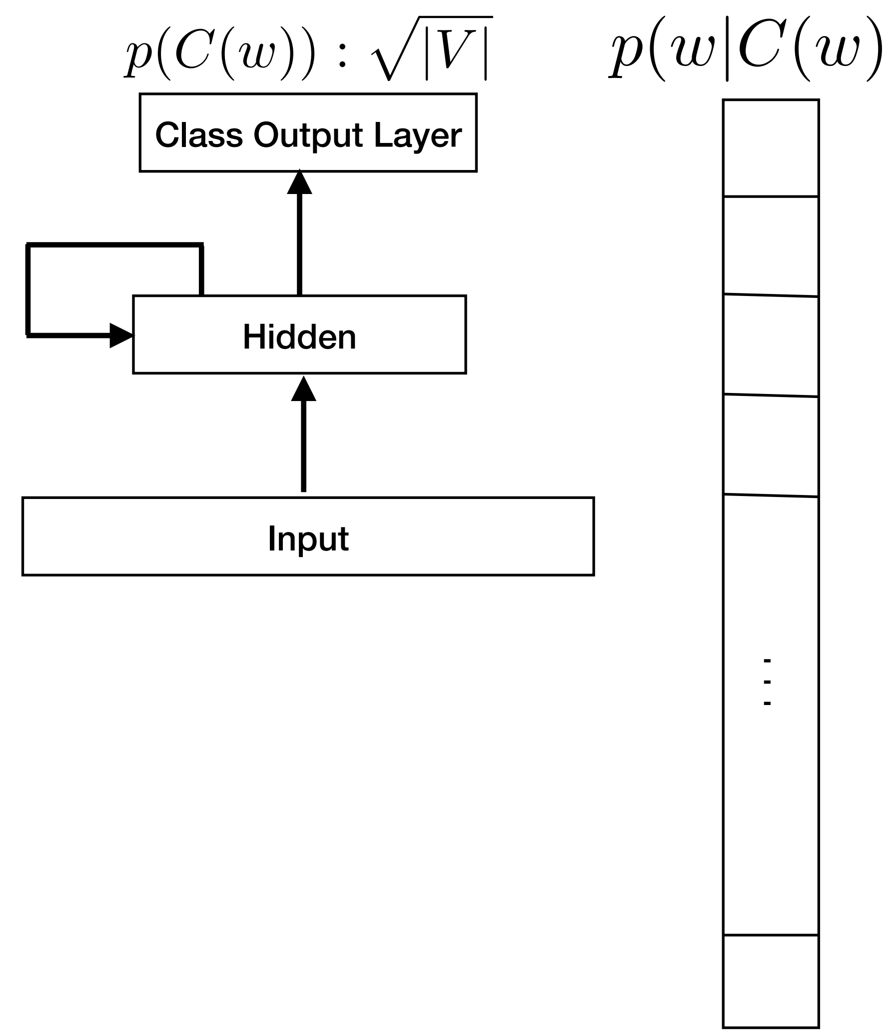

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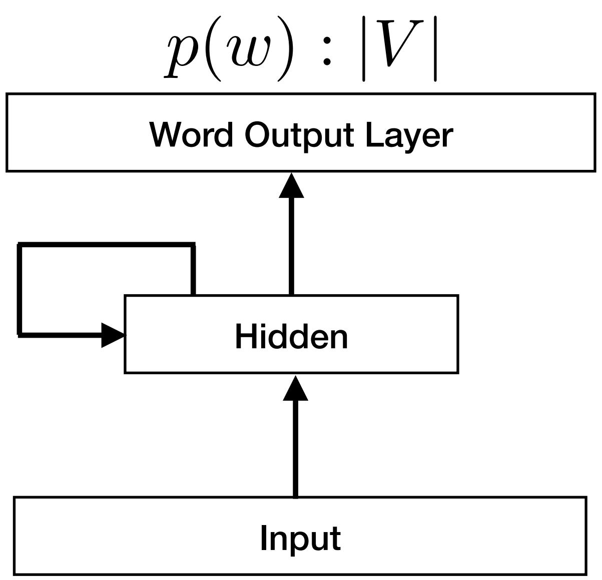

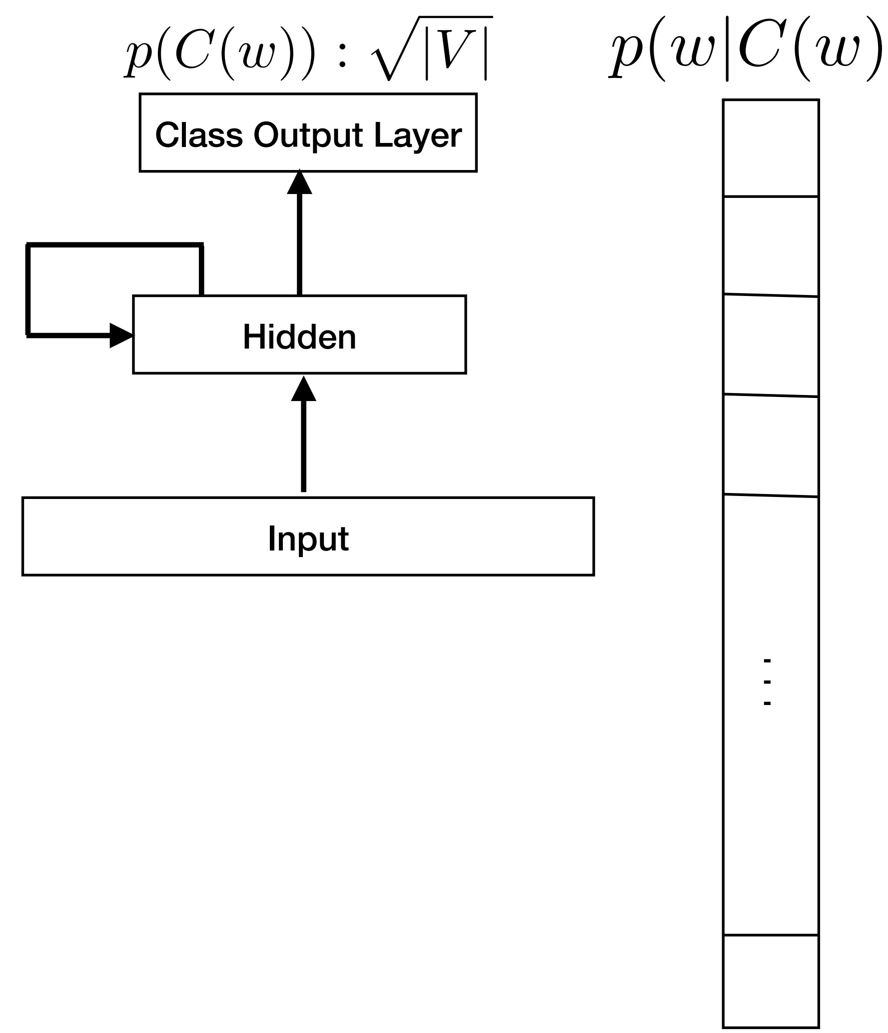

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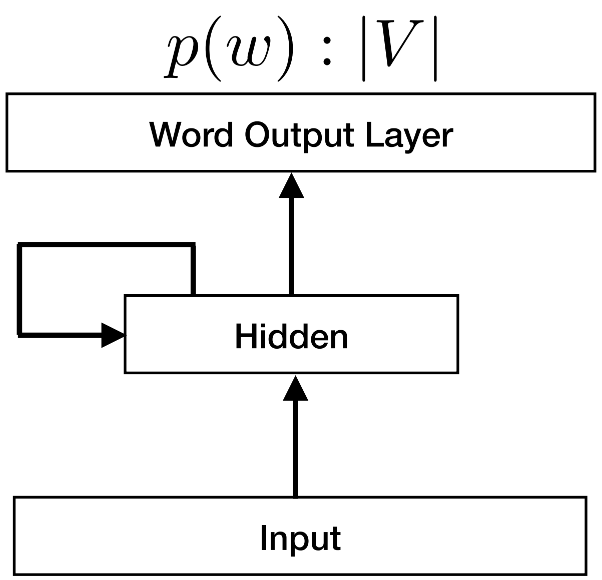

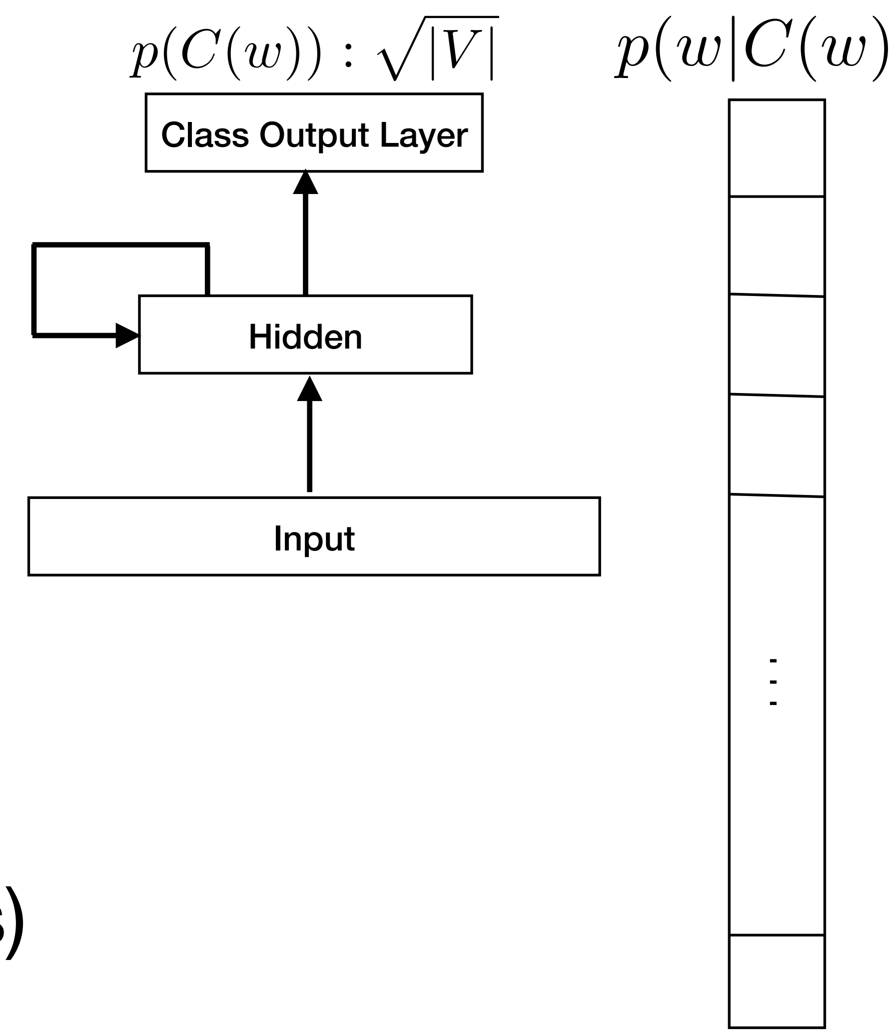

- Softmax: N × 4M (Vocabulary)

- Class-based Output: N × 2K (Classes)

Speeding up Normalization

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- Class-based Decomposition $O(\sqrt{|V|})$

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- Class-based Decomposition $O(\sqrt{|V|})$
- Noise Contrastive Estimation (NCE) $O(1)$
- Hierarchical Softmax $O(\log_2 |V|)$
- Self Normalization ensures that the normalization constant Z is close to one. Slow for training, fast for test-time queries $O(1)$

Question

- What kind of words will be tough to predict by neural network language model? And what can help the NNLM to predict these?

Rare Words

- Rare words: words which occur with low frequency
  - Out-of-Vocabulary words (OOVs: Frequency 0 in training set)
  - Frequency is 1
- Problem learning good feature vectors for such words
  - Not enough data
- A predictive system is not able handle them well
  - One would want automatic Video Subtitling Systems to predict these words as well

Rare Words

Languages	
Finnish	
Swedish	
Arabic	
English	

Rare Words

Languages	Training Set Size
Finnish	170M
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Rare Words

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Rare Words

Languages	Training Set Size	Vocabulary	Rare Words (f≤1)
Finnish	170M	4.2M	55 %
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Rare words form a large portion of the vocabulary

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- Some languages (low-resource) can have OOV rates as high as 40%

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