Neural Network Language Models & BERT

Mittul Singh

Language Model Applications

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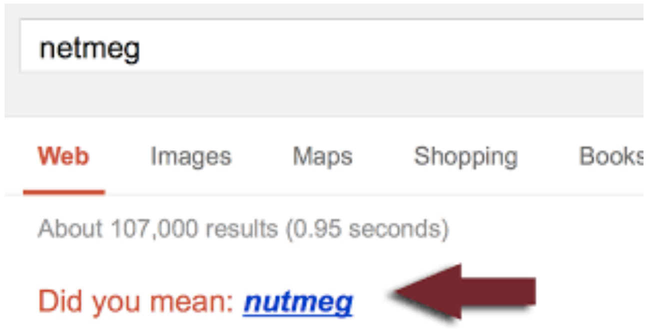
- Spelling correction, text input
    - Search Query Completion



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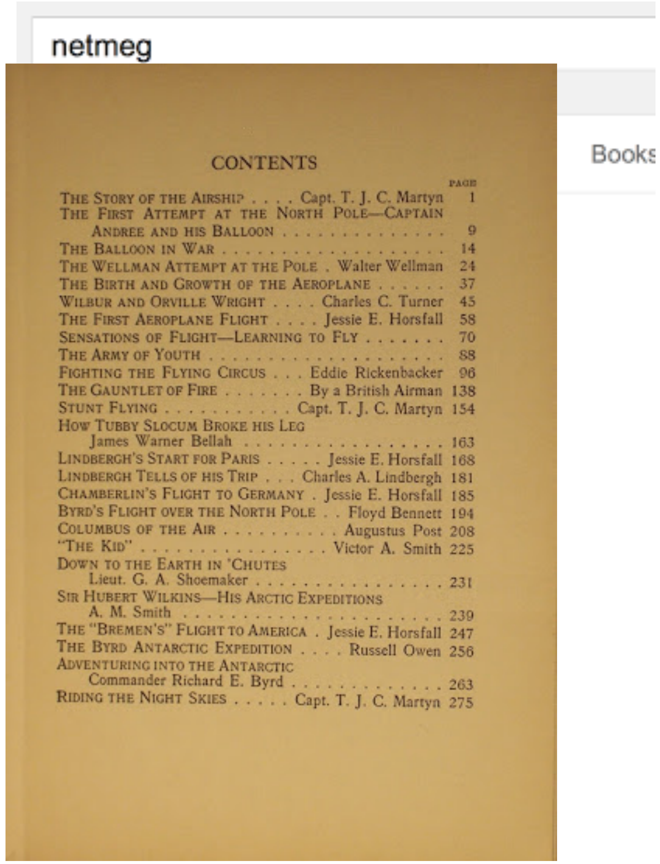

CONTENTS

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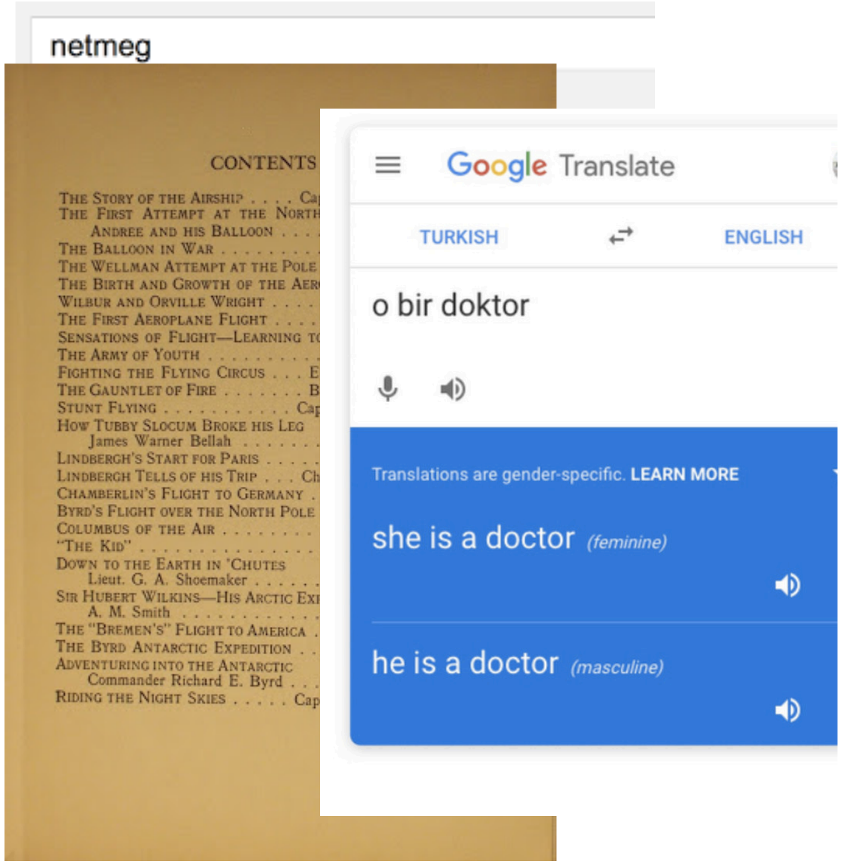

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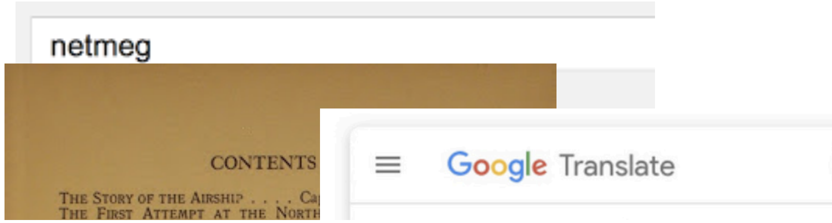

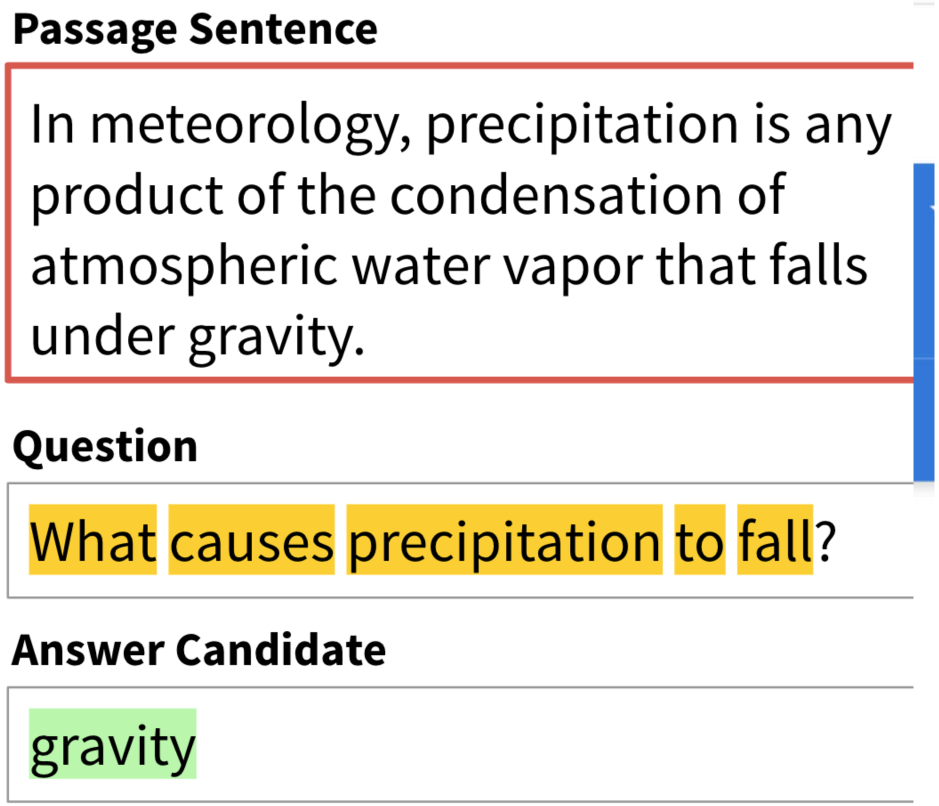

Language Model Applications

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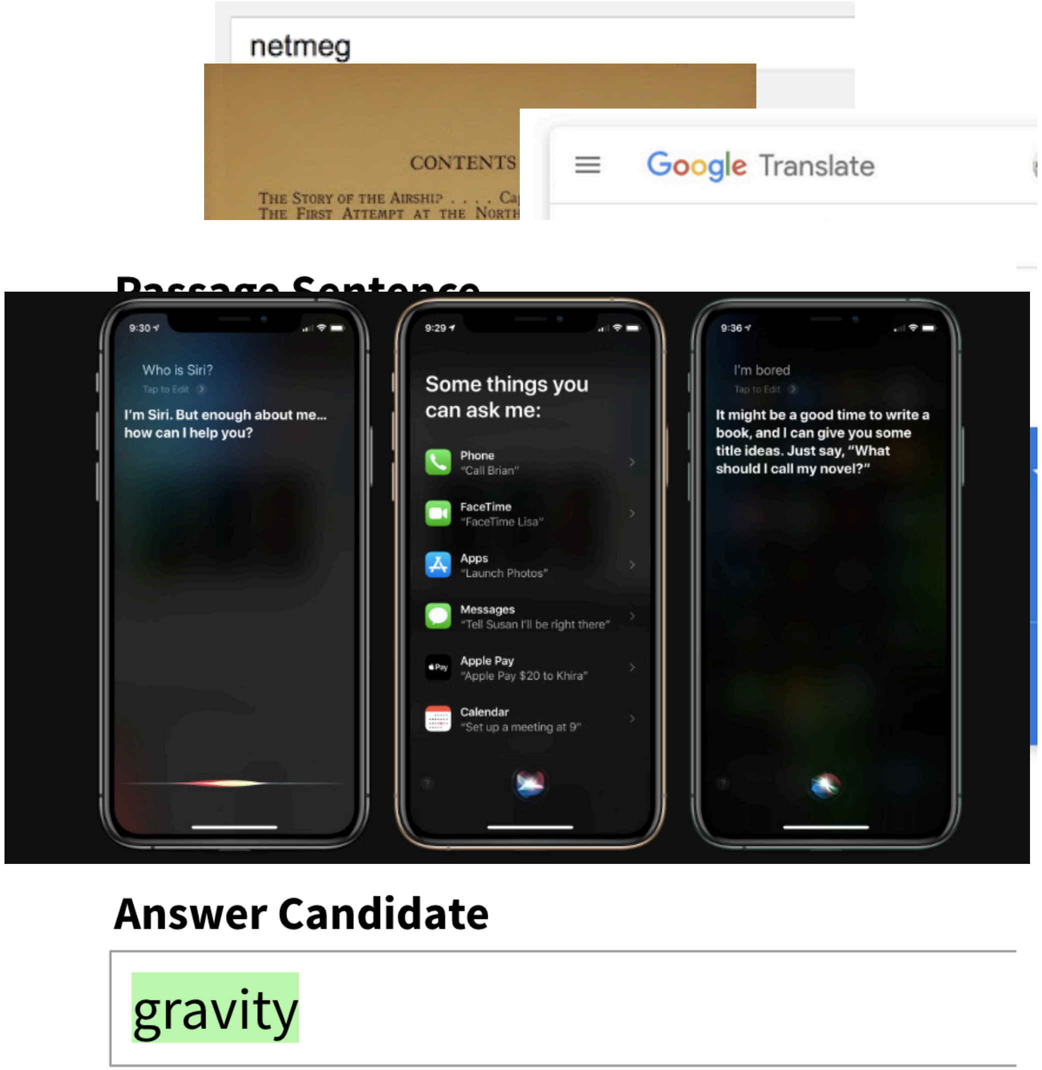
- Statistical machine translation
- Information retrieval
  - Question Answering
- Automatic speech recognition
- …



Recap: N-gram Language Models

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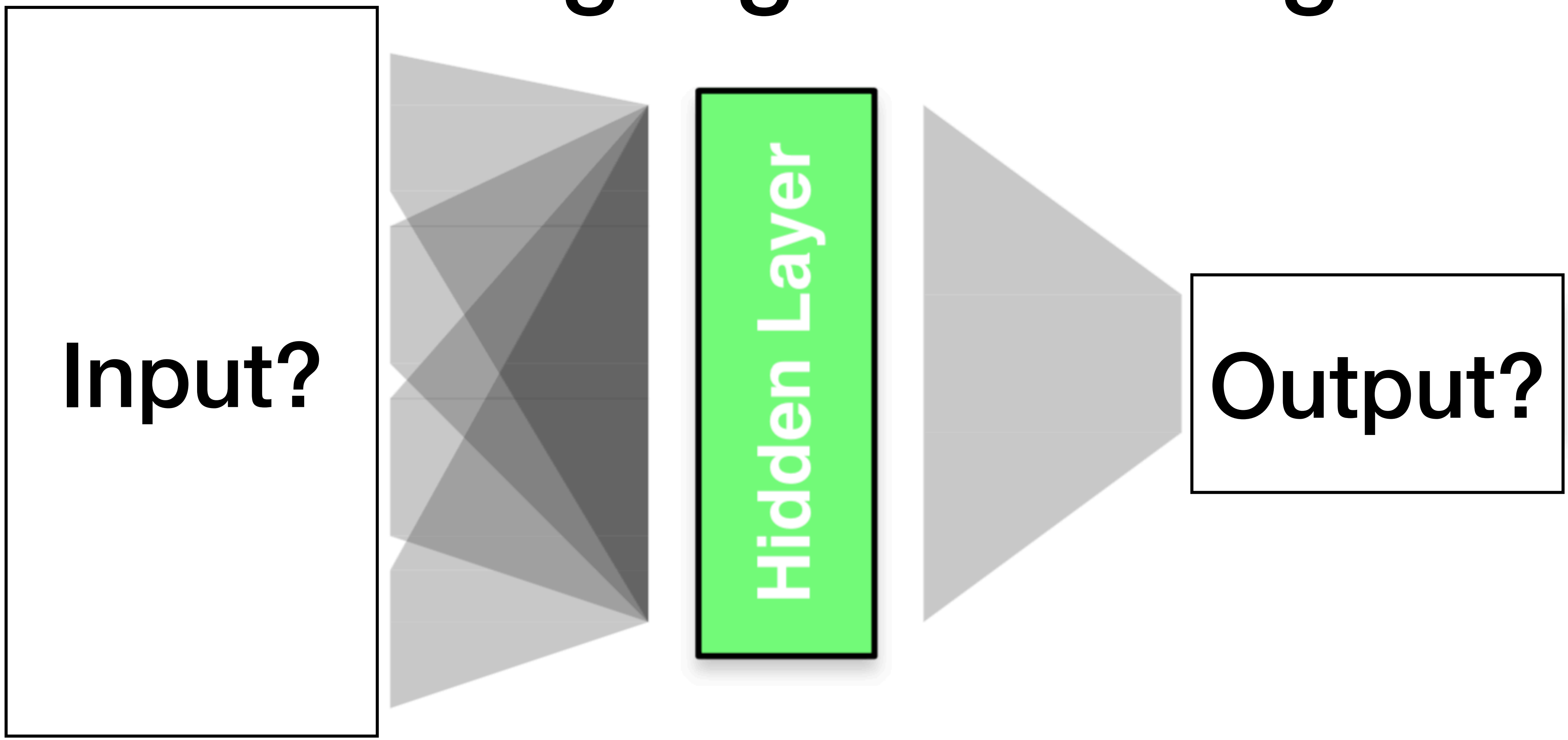
- We wanted to calculate

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

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

Neural Network Classifier for Language Modelling



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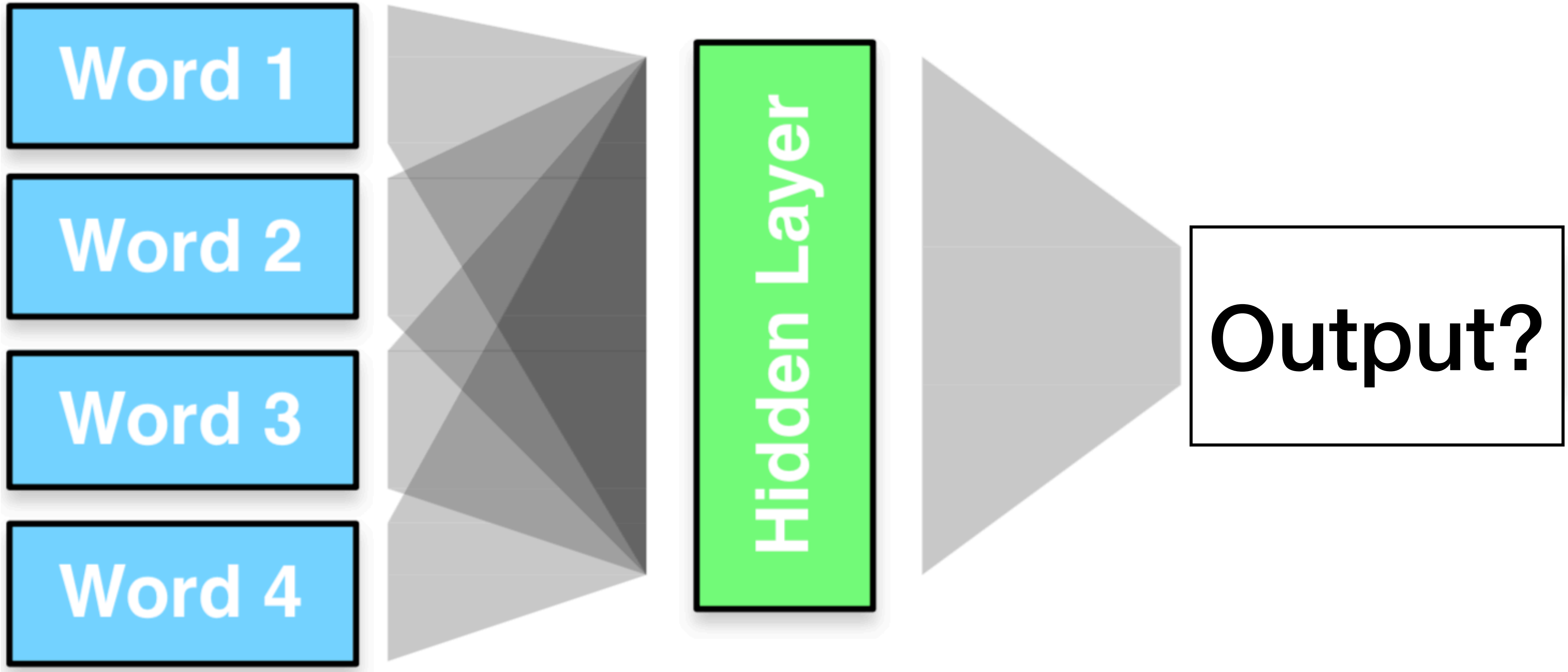

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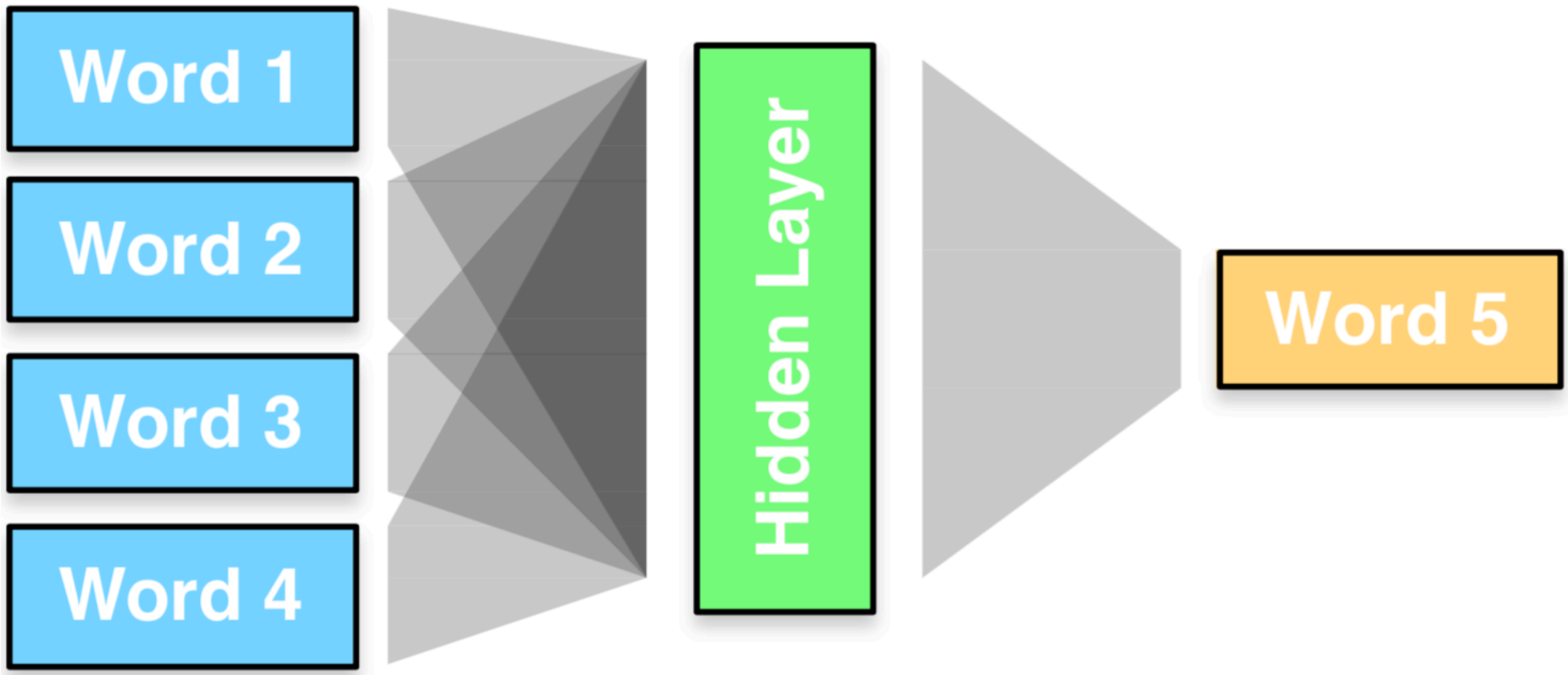

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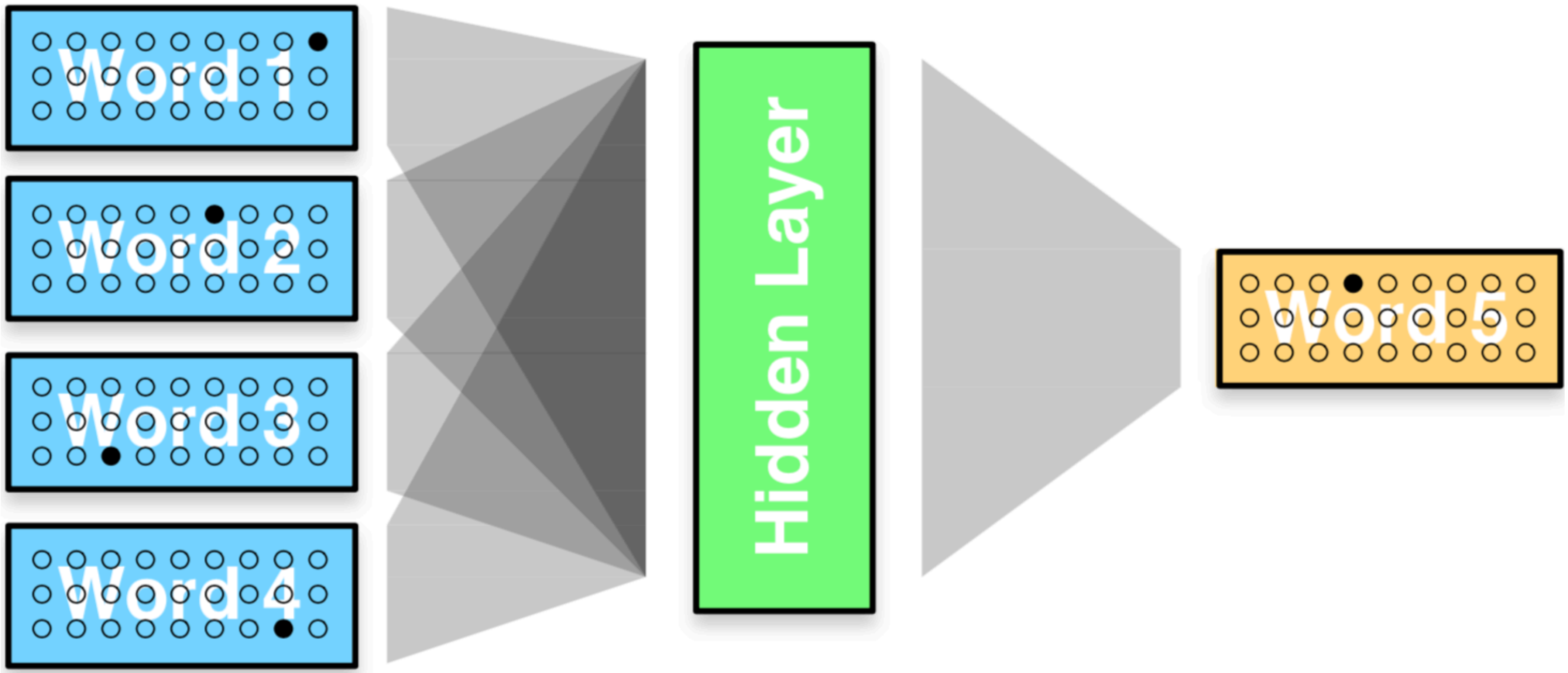
Representing Words

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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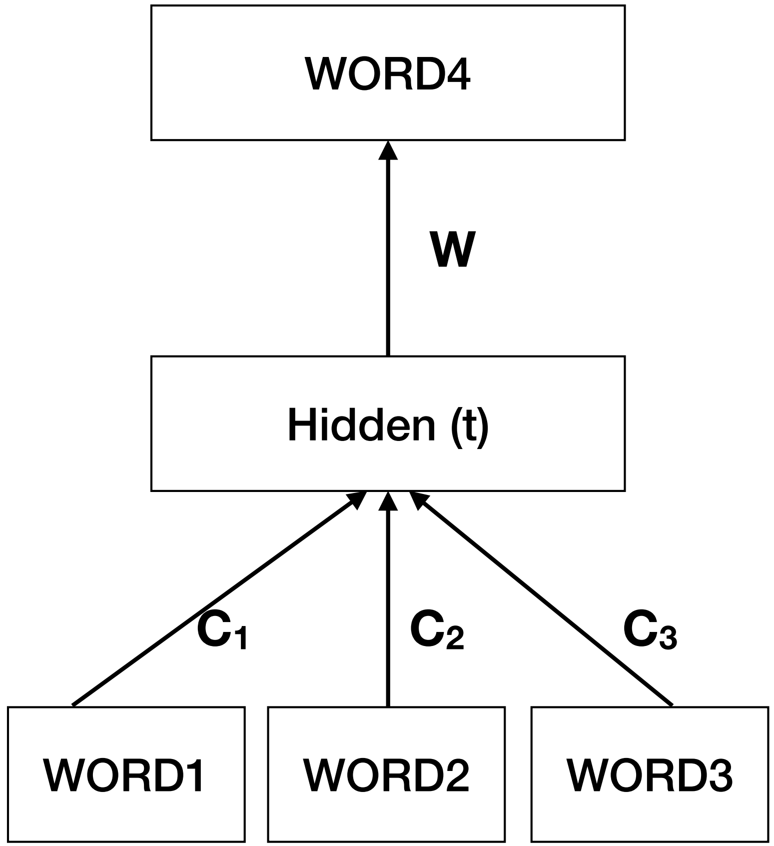
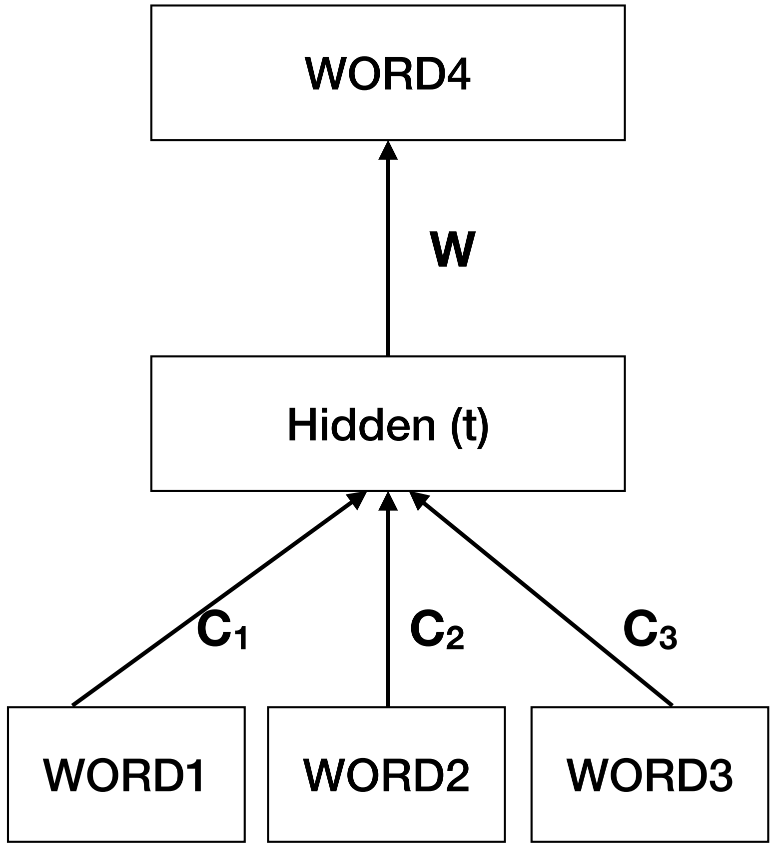
Feedforward Neural Network LM (FFNN)



FFNN

Feedforward Neural Network LM (FFNN)

- Loop through the entire corpus



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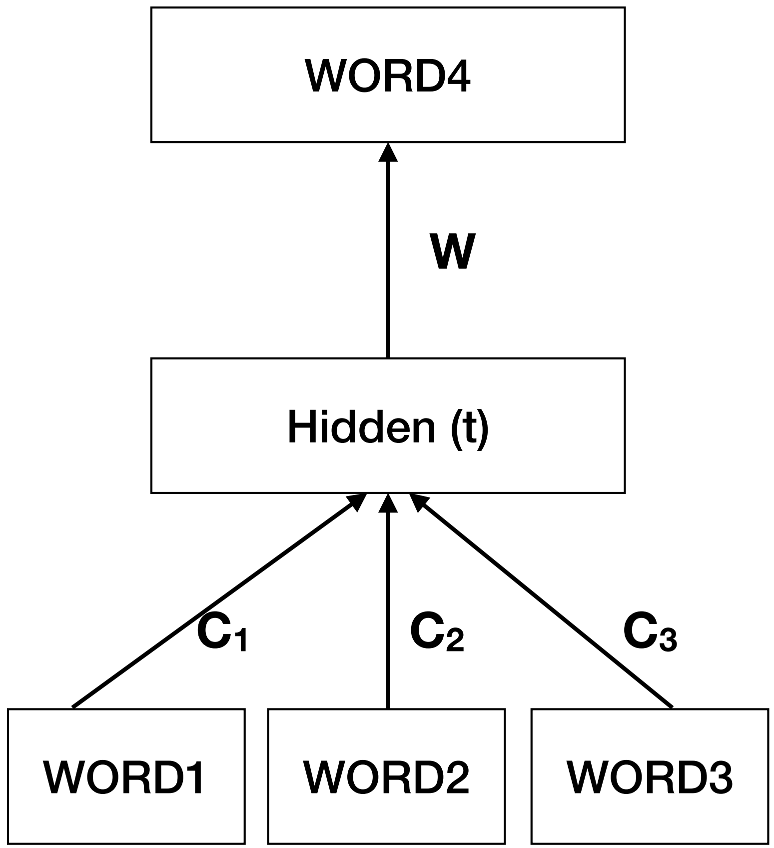

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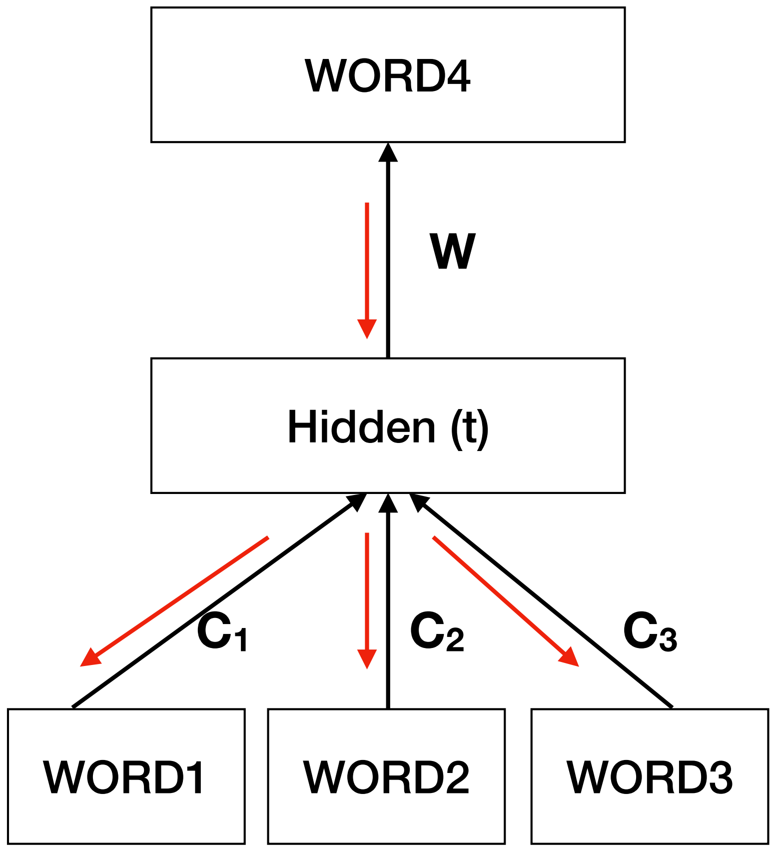
- Loop through the entire corpus
- Calculate error or loss (cross-entropy loss)
- Propagate the error through network to update the weight matrices



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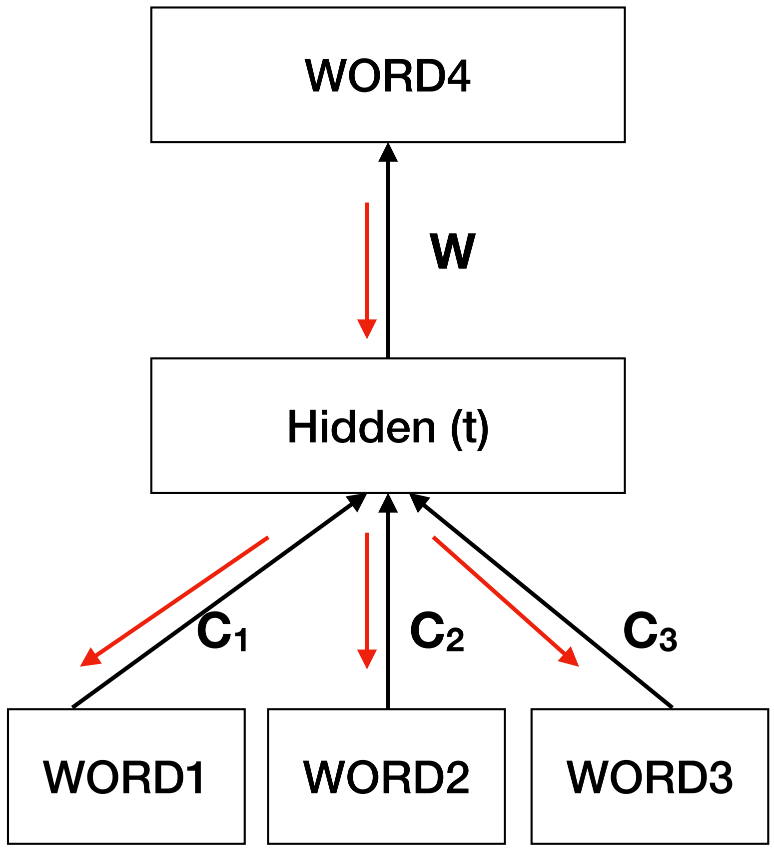
Feedforward Neural Network LM (FFNN)

- 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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- 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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- Training Speed

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Feedforward: Long-term information

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

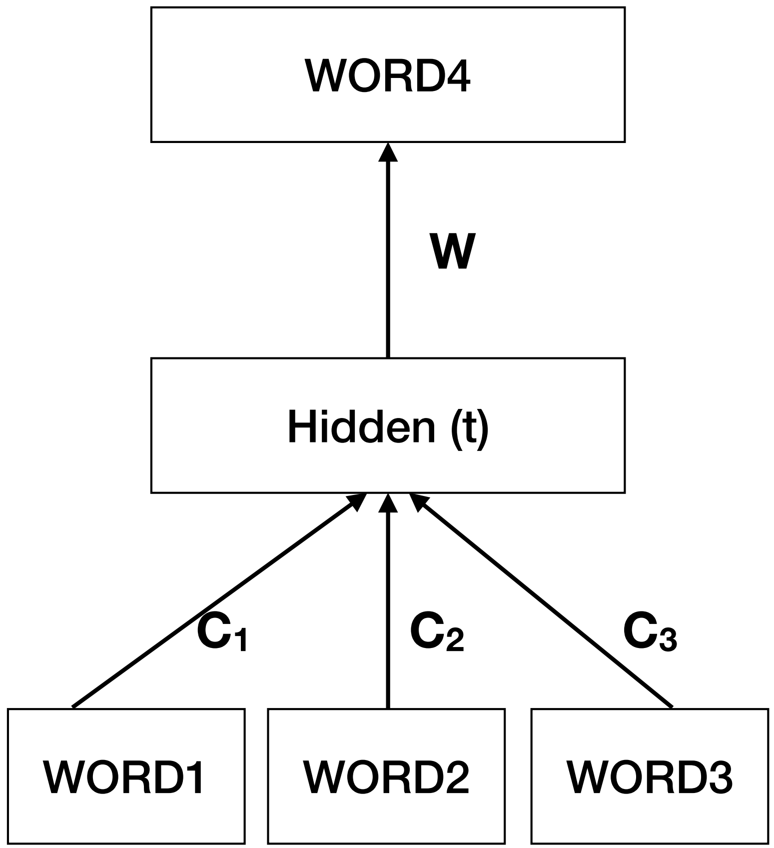
Feedforward: Long-term information

- “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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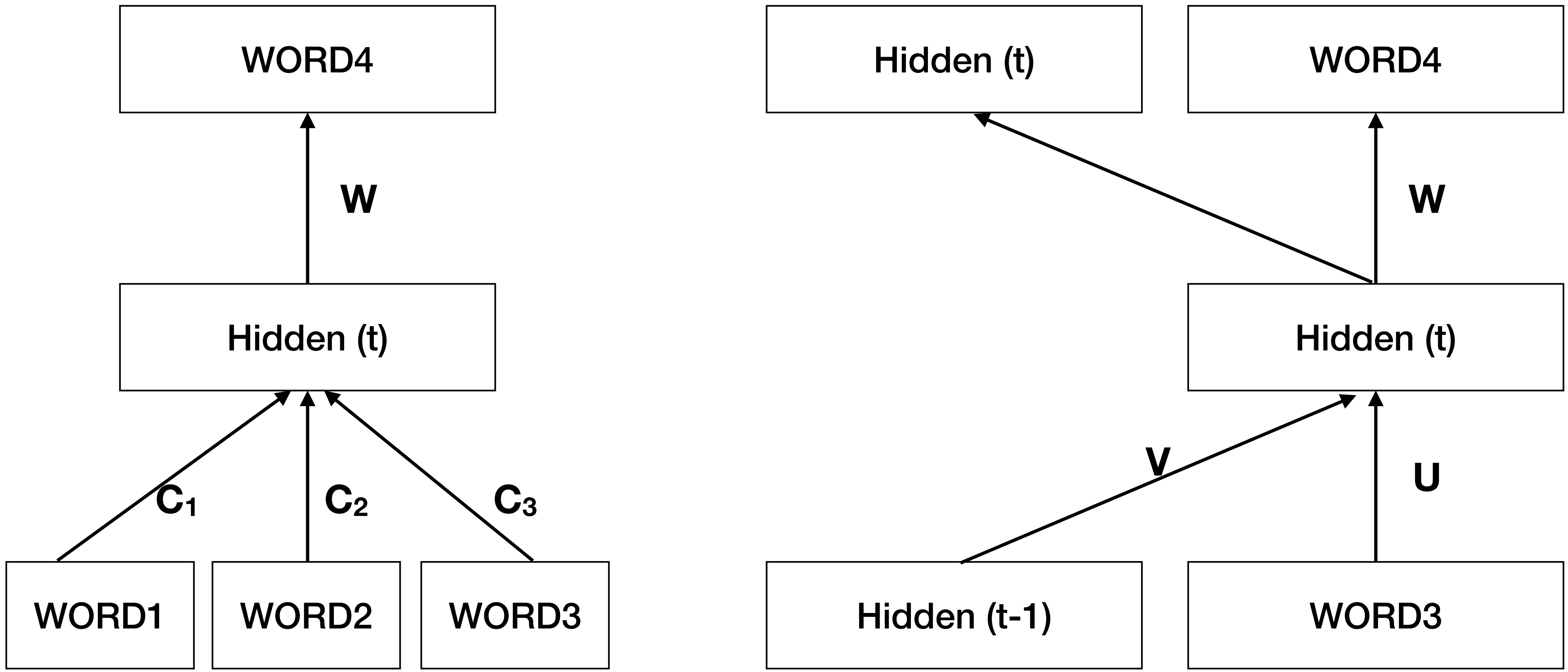

FFNN

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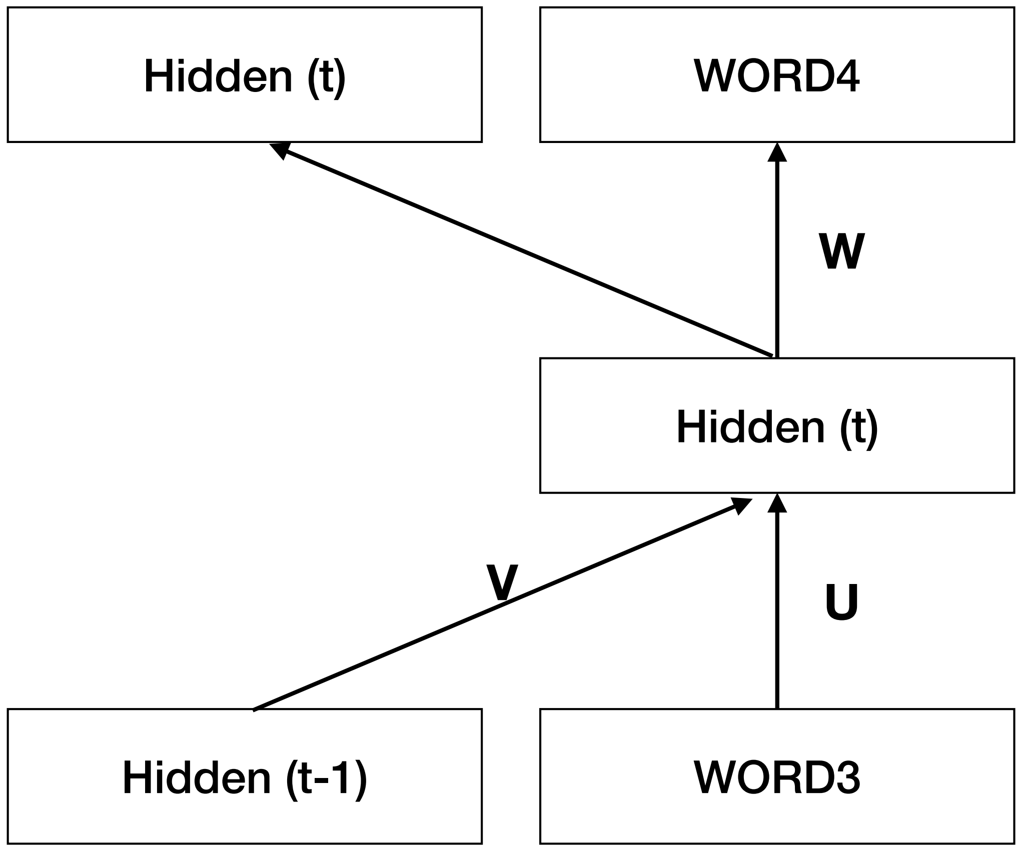

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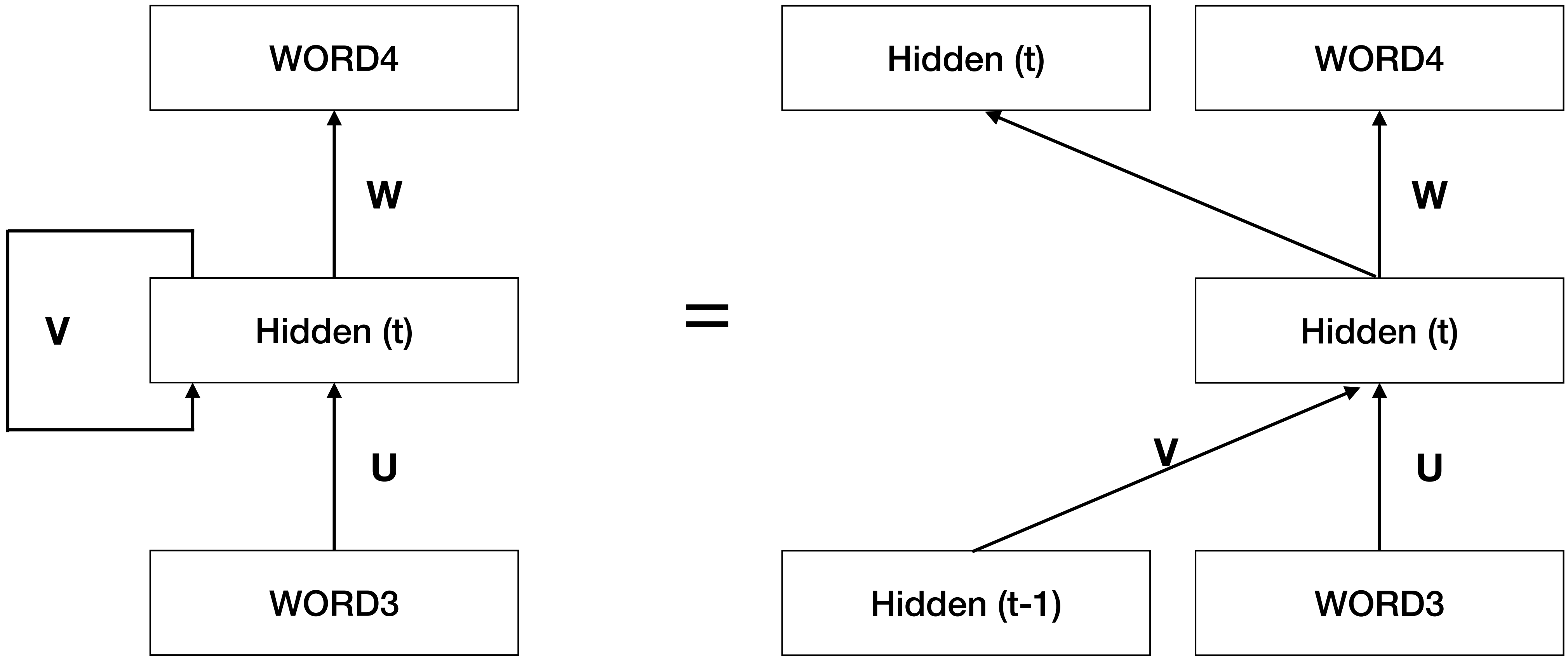
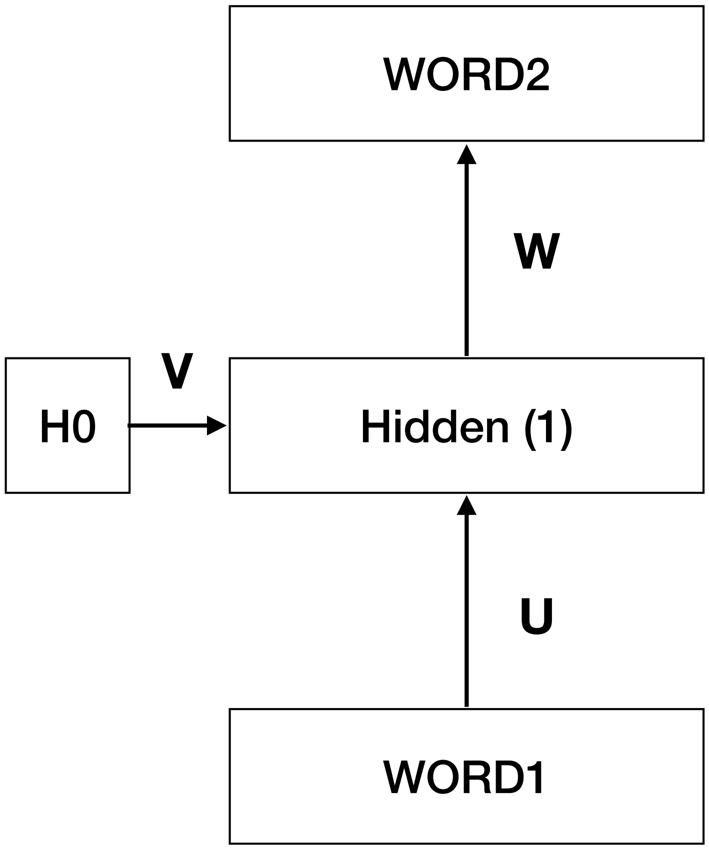
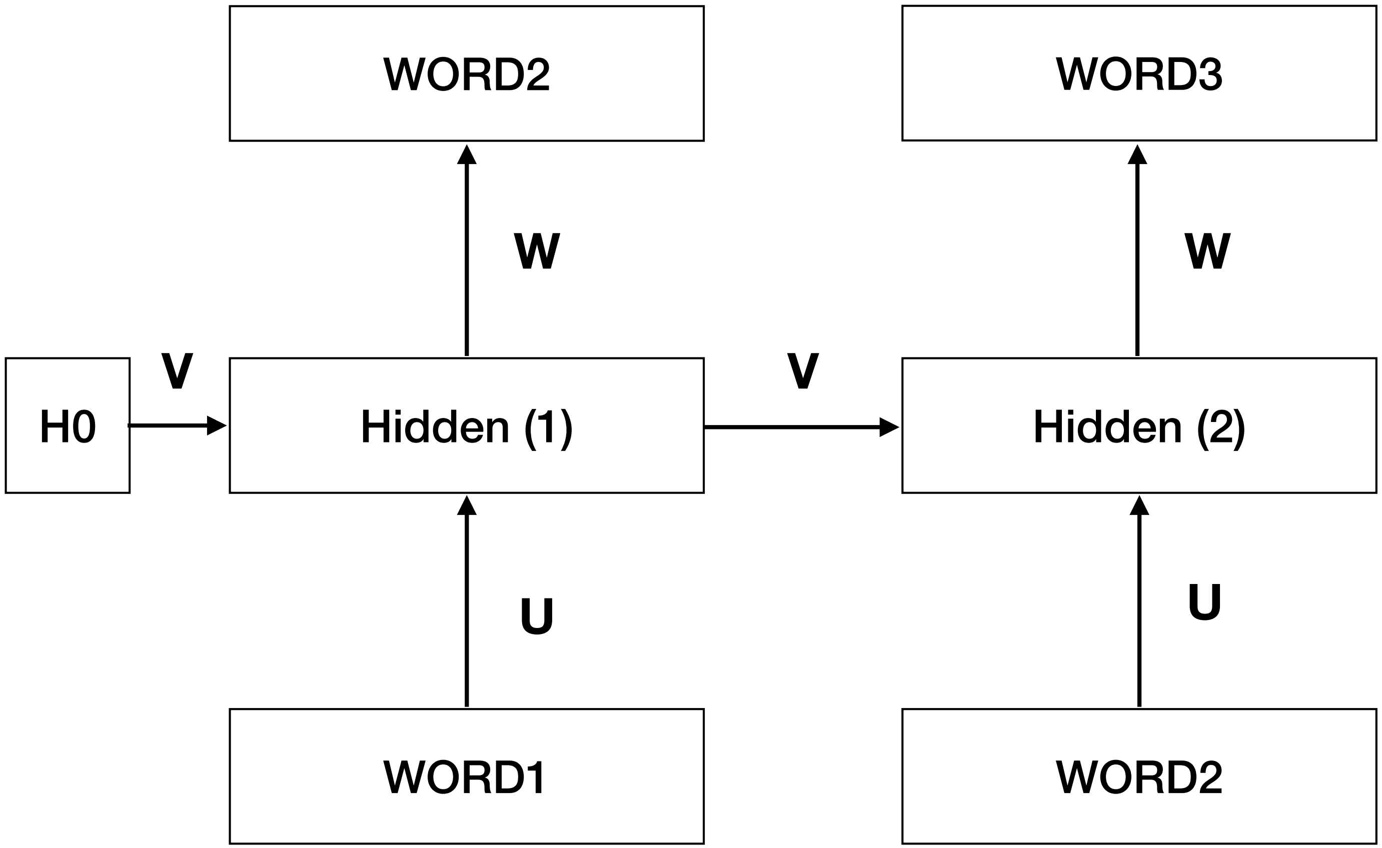


RNN

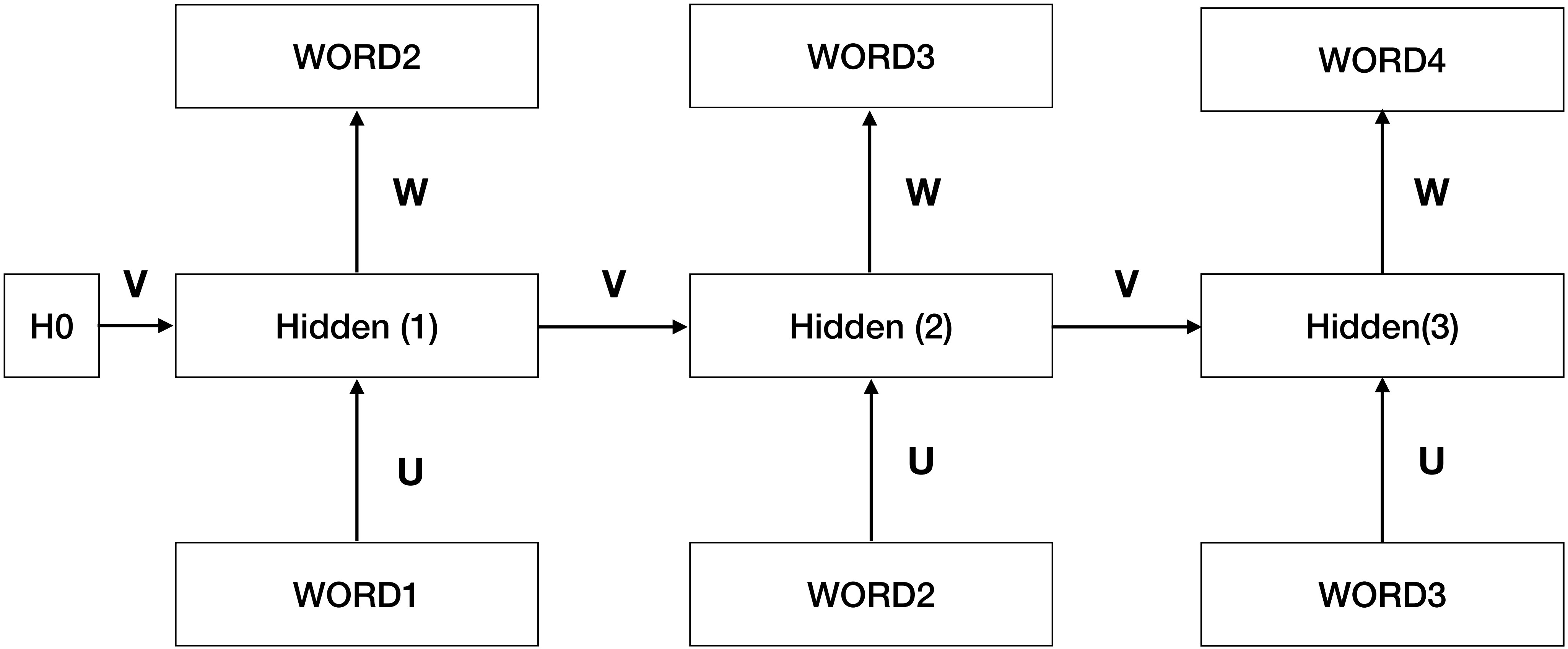
RNN: Timestep 1



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*."

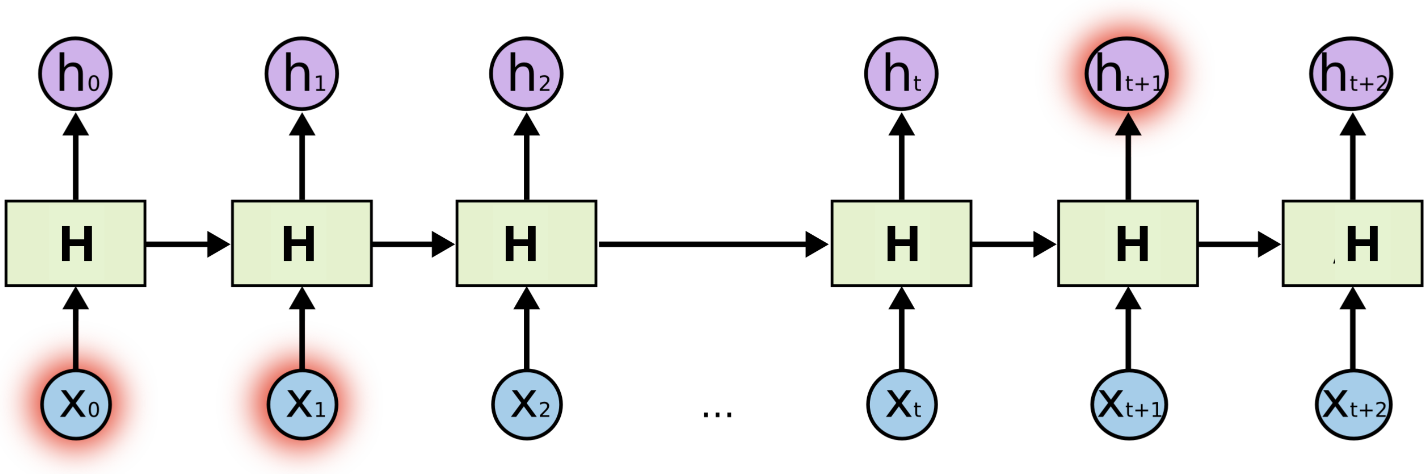
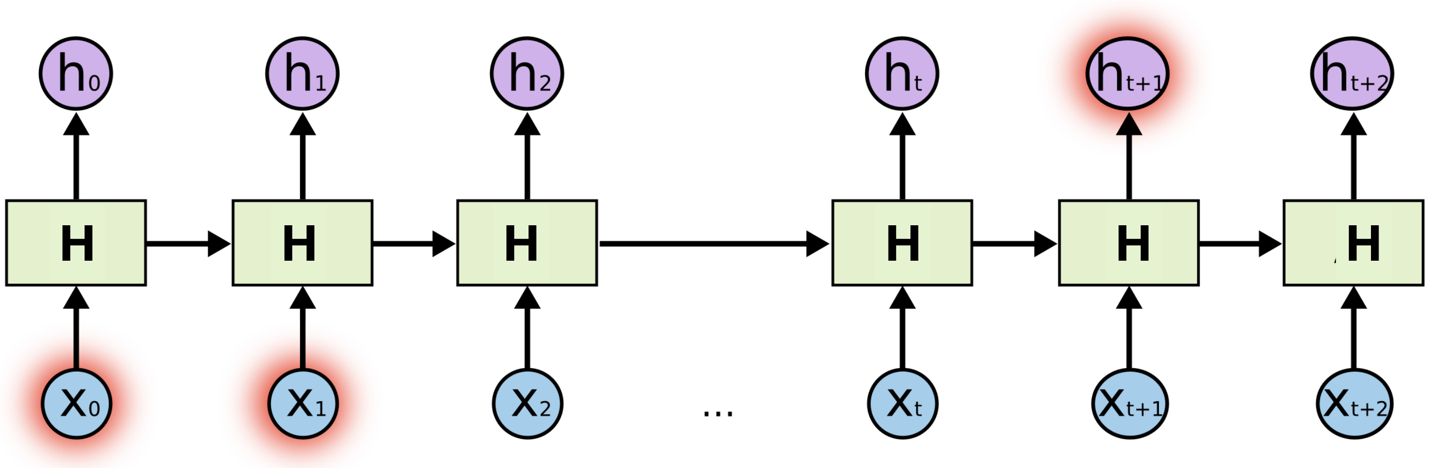


Image: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

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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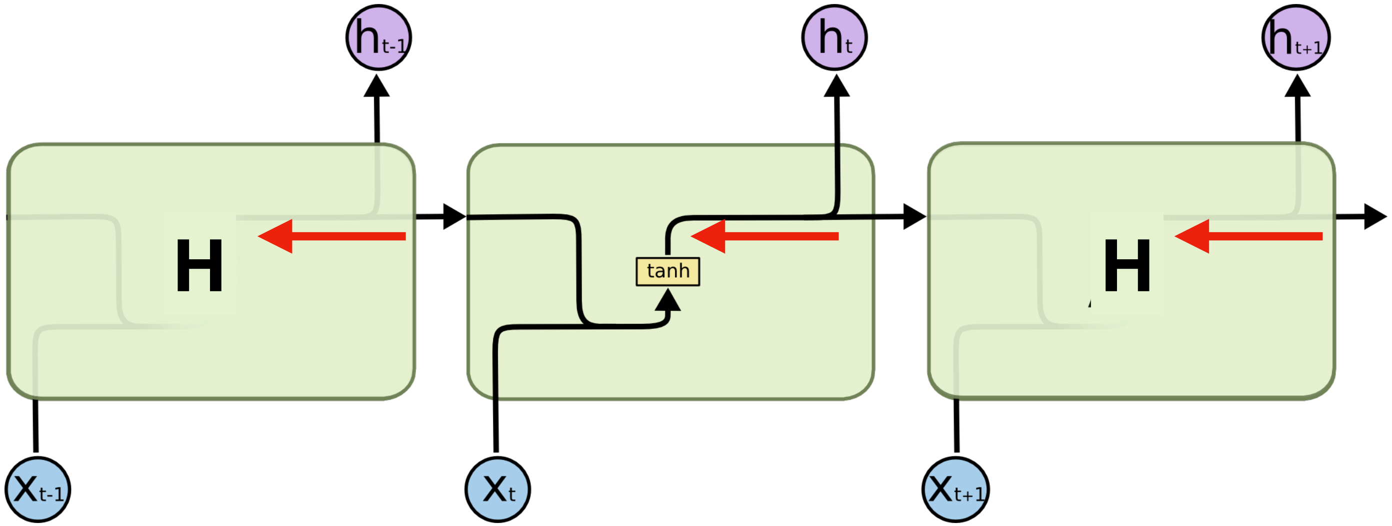
RNN



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

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

RNNs don’t do long-distance well

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- Gradients greater than 1 become exponentially large over time (the exploding gradient problem)*

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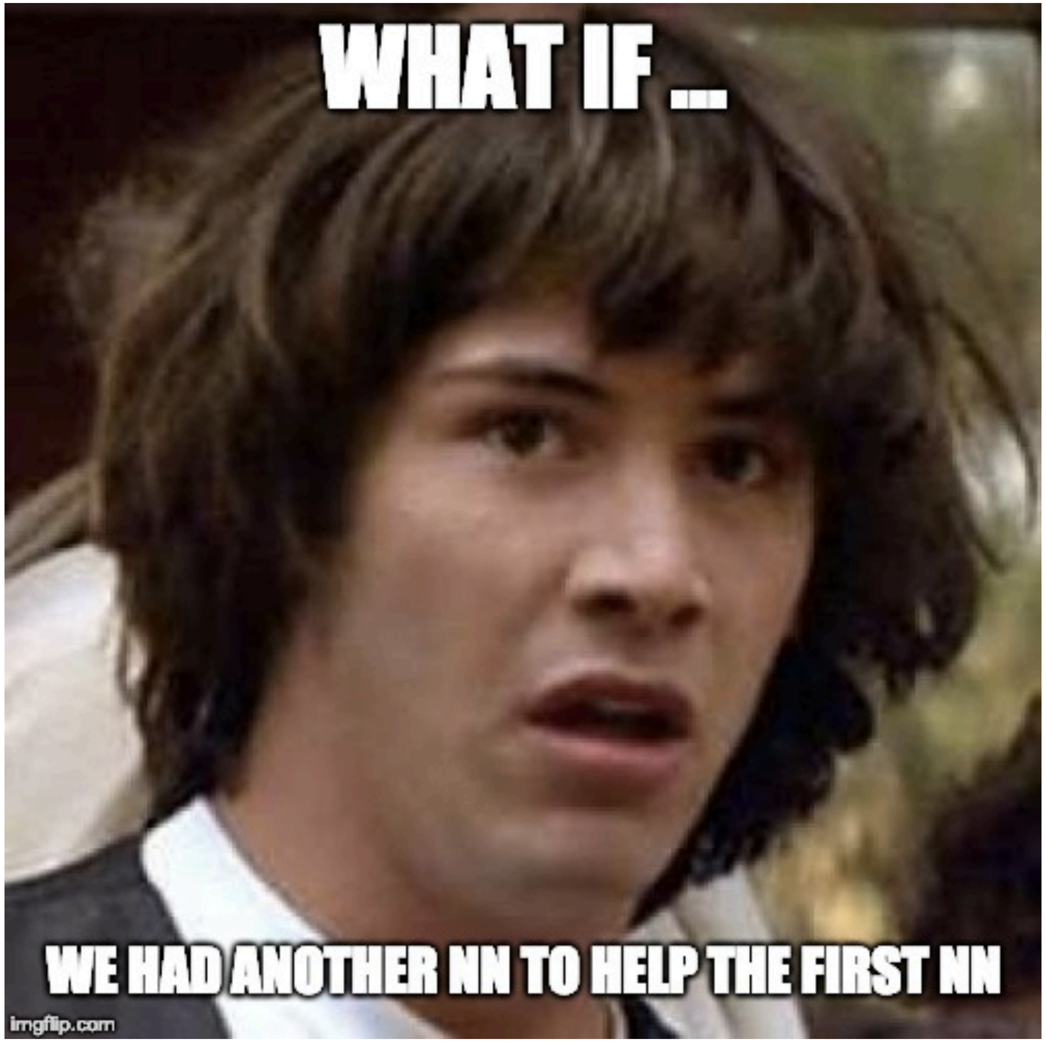
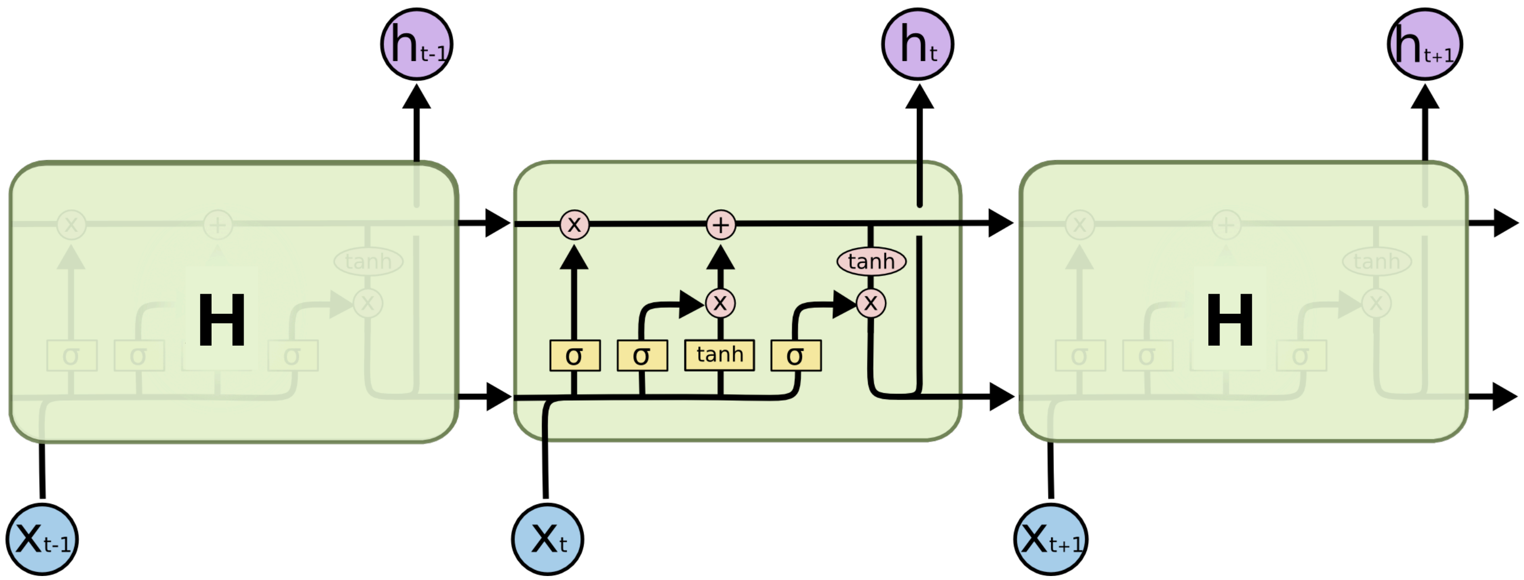
- Gradients greater than 1 become exponentially large over time (the exploding gradient problem)*
- This leads to training instability, and bad results
- Sequence Modeling: https://www.deeplearningbook.org/contents/rnn.html

* 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

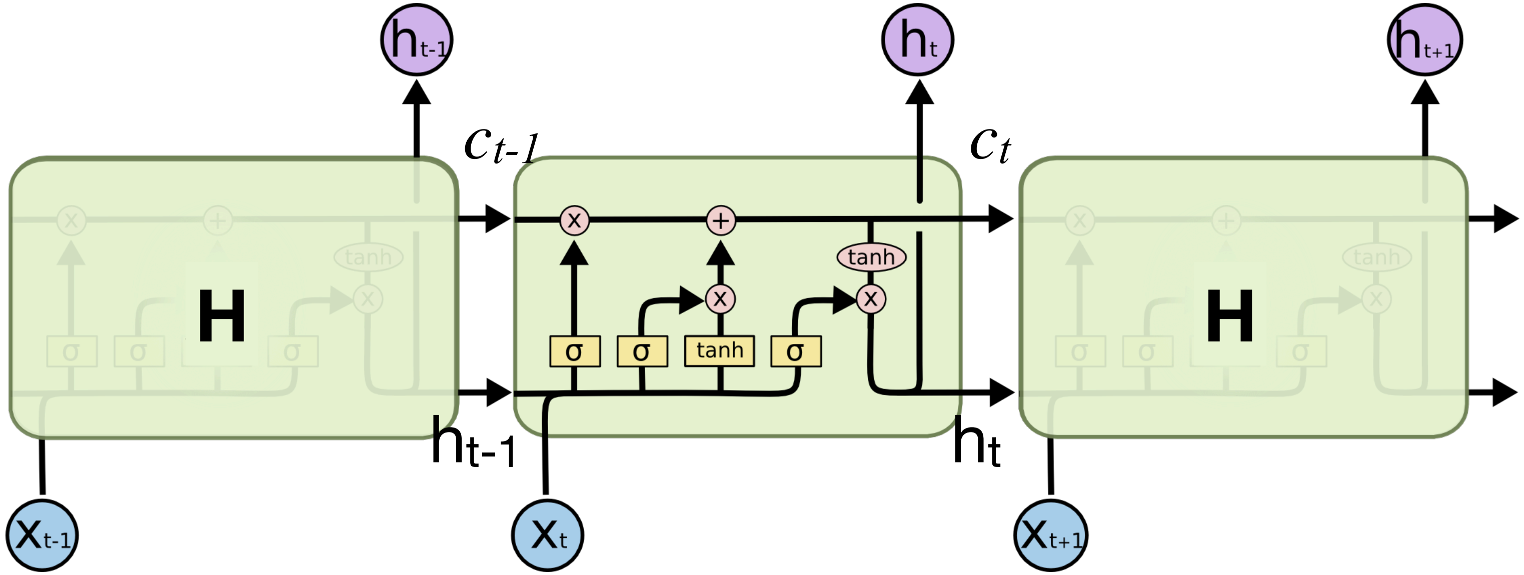
Long-Short Term Memory



- Lets add another neural network help the first network learn long-term dependencies
- 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



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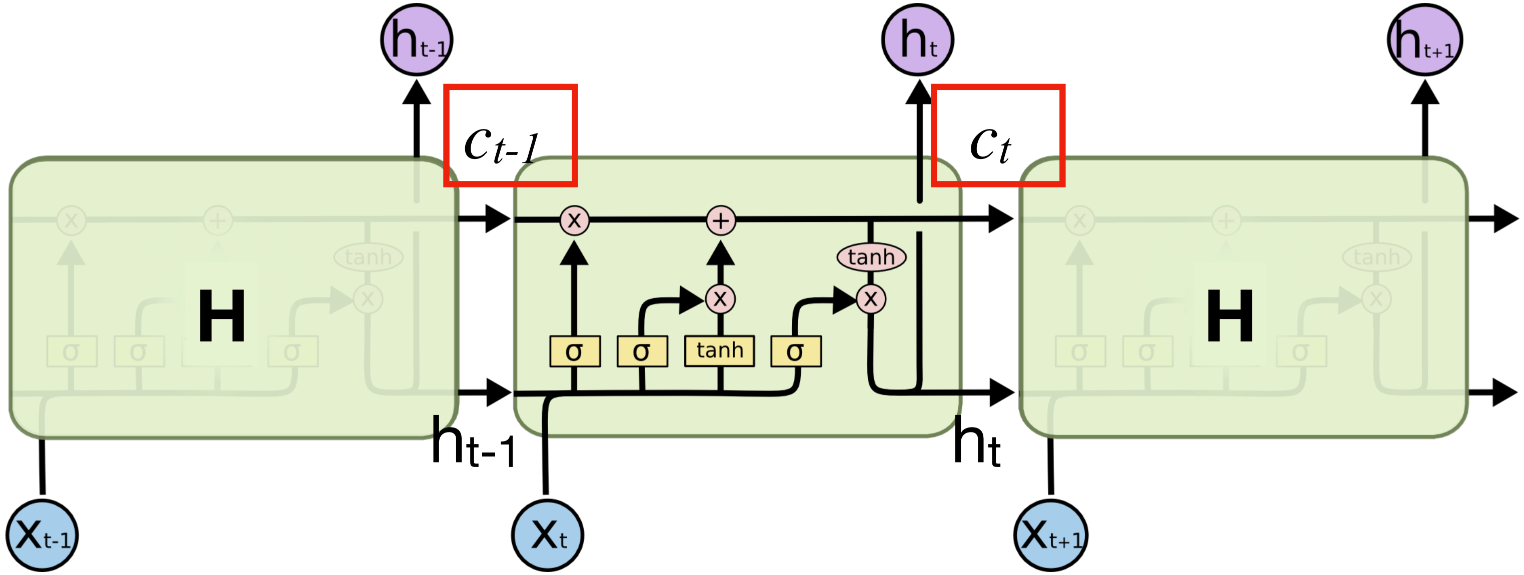
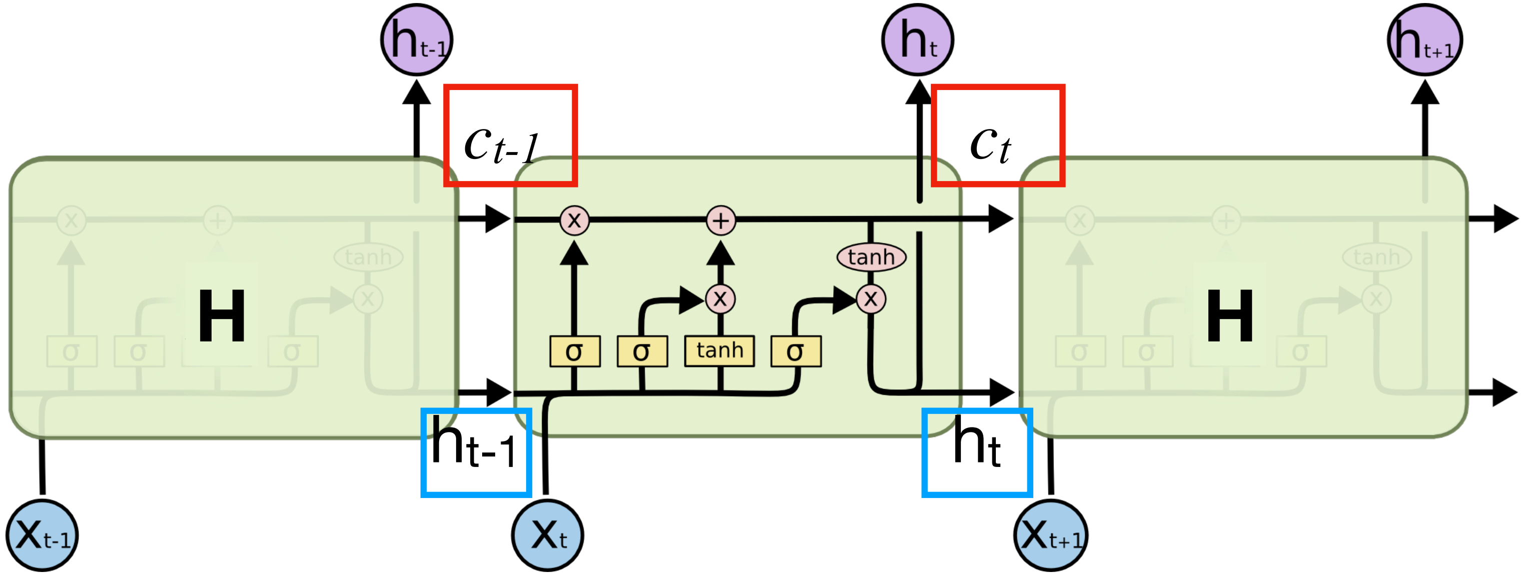


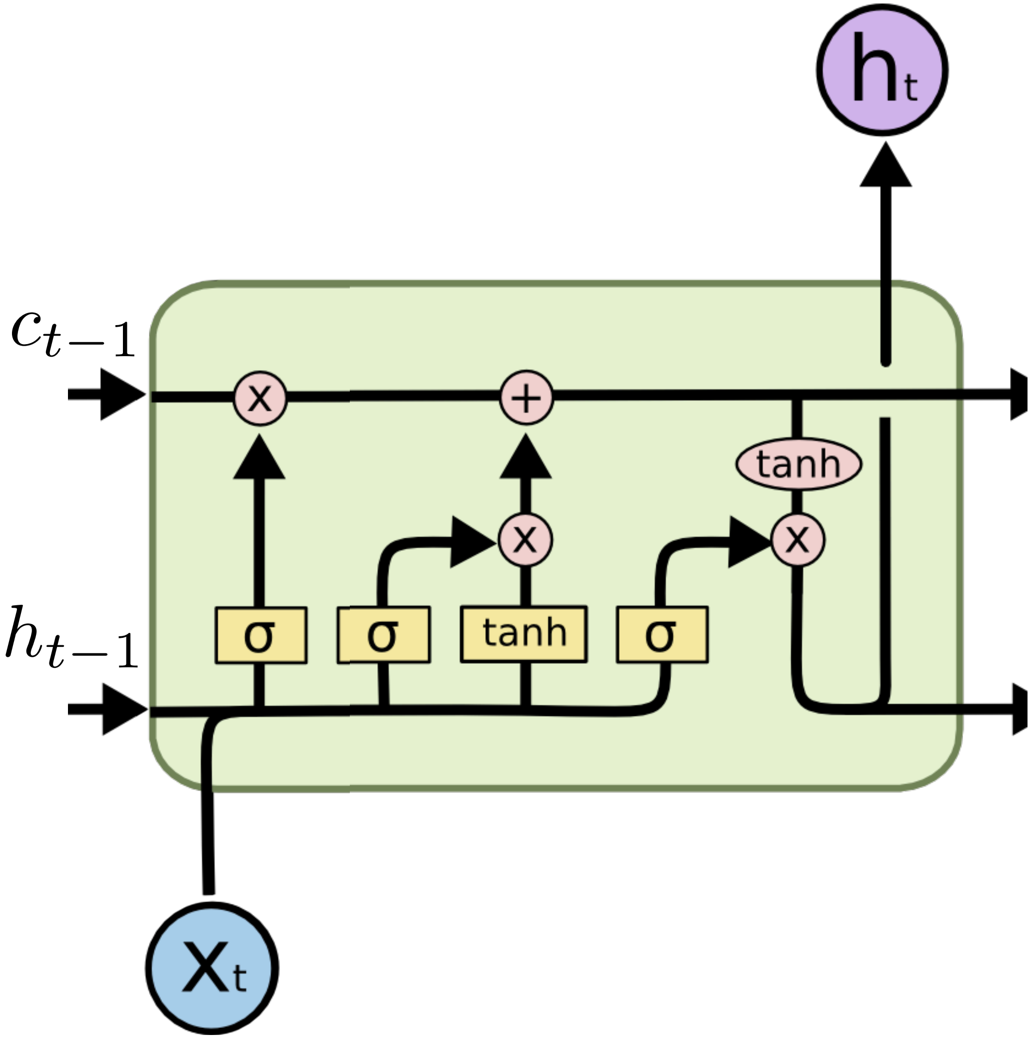
- Global State $\boxed{c}$ captures global information at the document/ sentence level

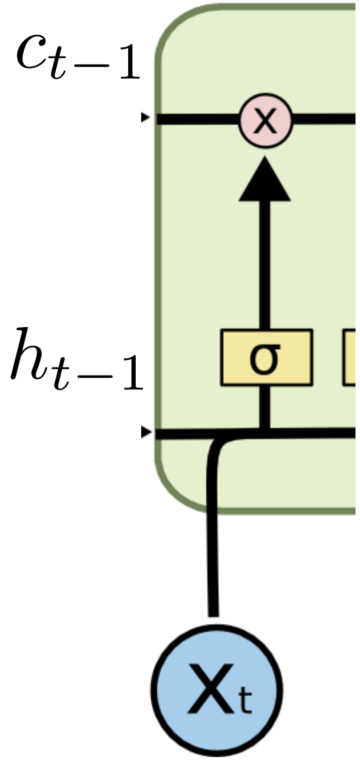
LSTM: States



- Global State c captures global information at the document/ sentence level

- LSTM hidden state h_t interacts with this global state to predict the next word


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



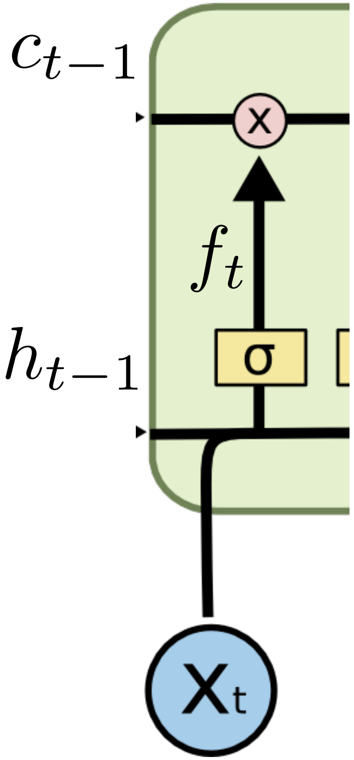
σ sigmoid function

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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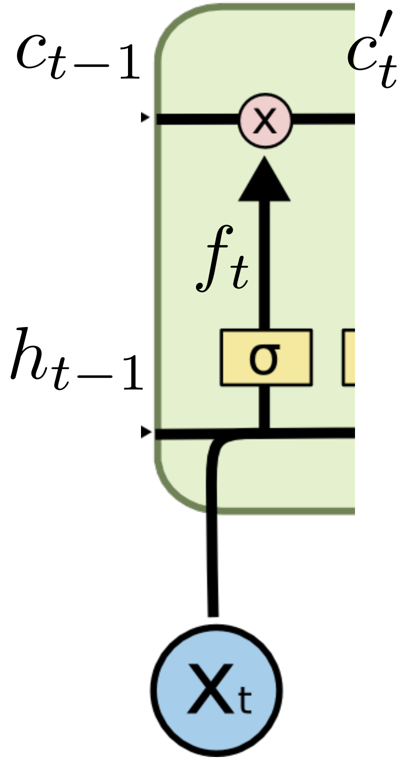

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x_t	input at current timestamp

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

Exercise 1

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

- 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

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

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- calculate: c'_t

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

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

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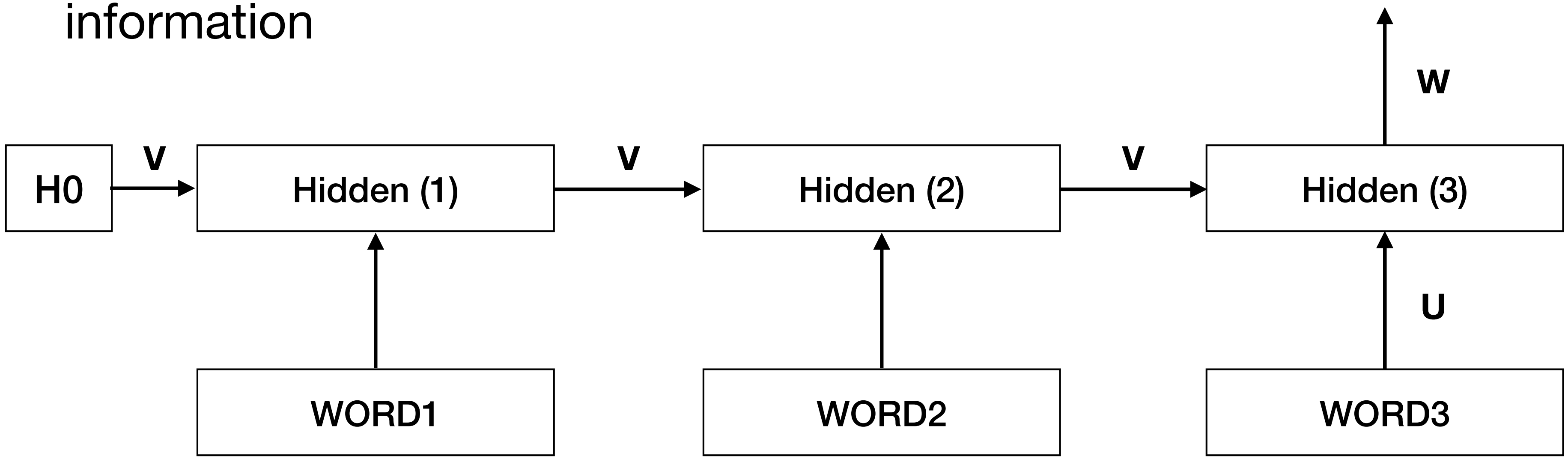
$$w_f[h_{t-1}, x_t] + b_f = [1 \quad 1] \times \begin{bmatrix} 1 \\ 0.2 \end{bmatrix} = [1.2]$$

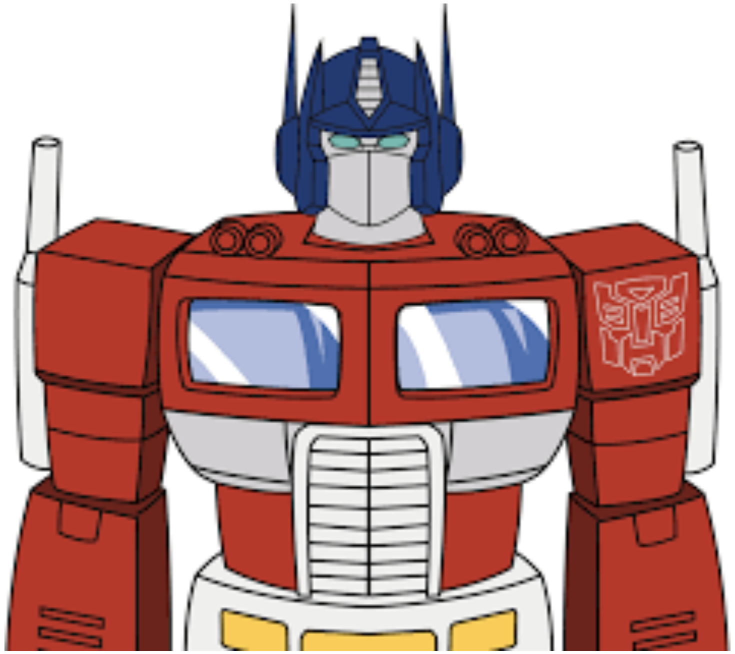
$$f_t = [\sigma(1.2)] = [0.77]$$

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

LSTM Problems

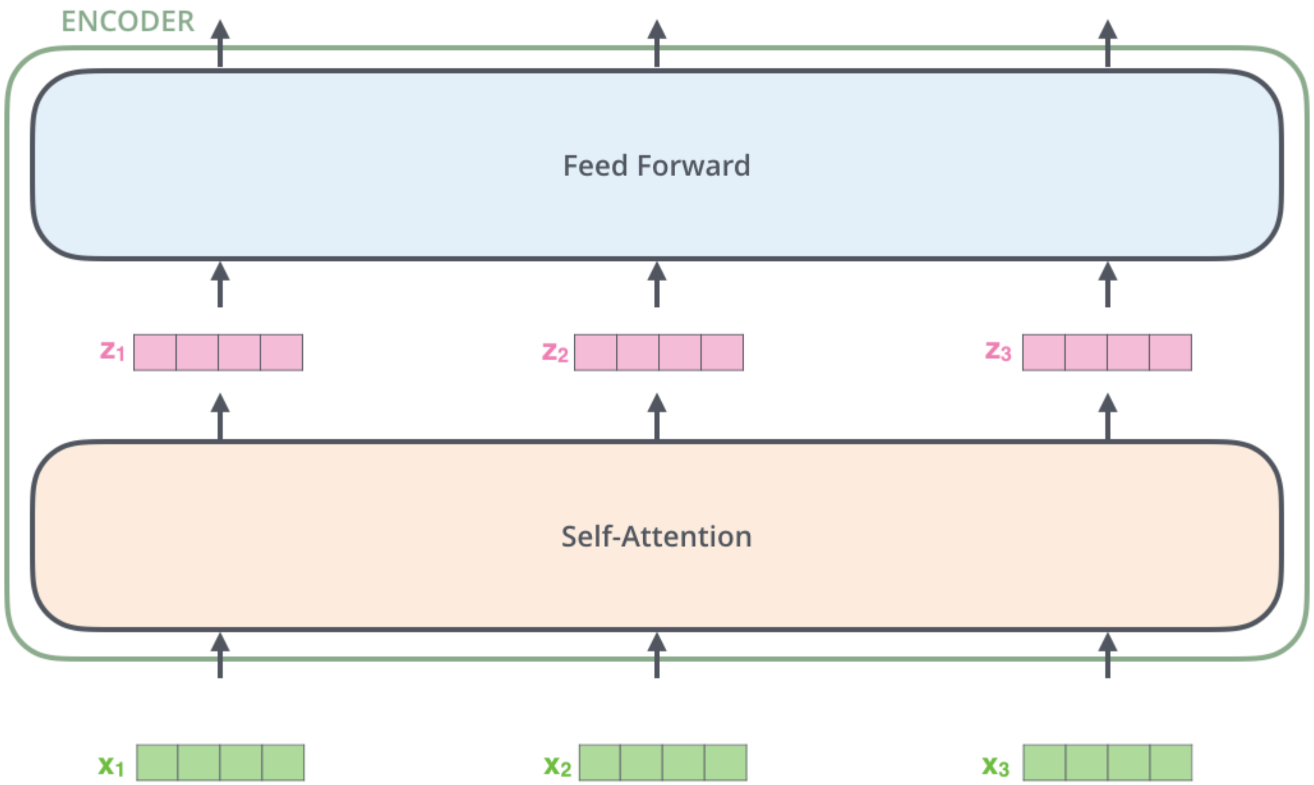
- Forget gate: removes information from the Global Cell state (C)
  - this information might be be useful at a later stage
- Implicit representation of long-term information
  - Cell state and previous hidden state summarise the prior information





Transformers for Language Modelling

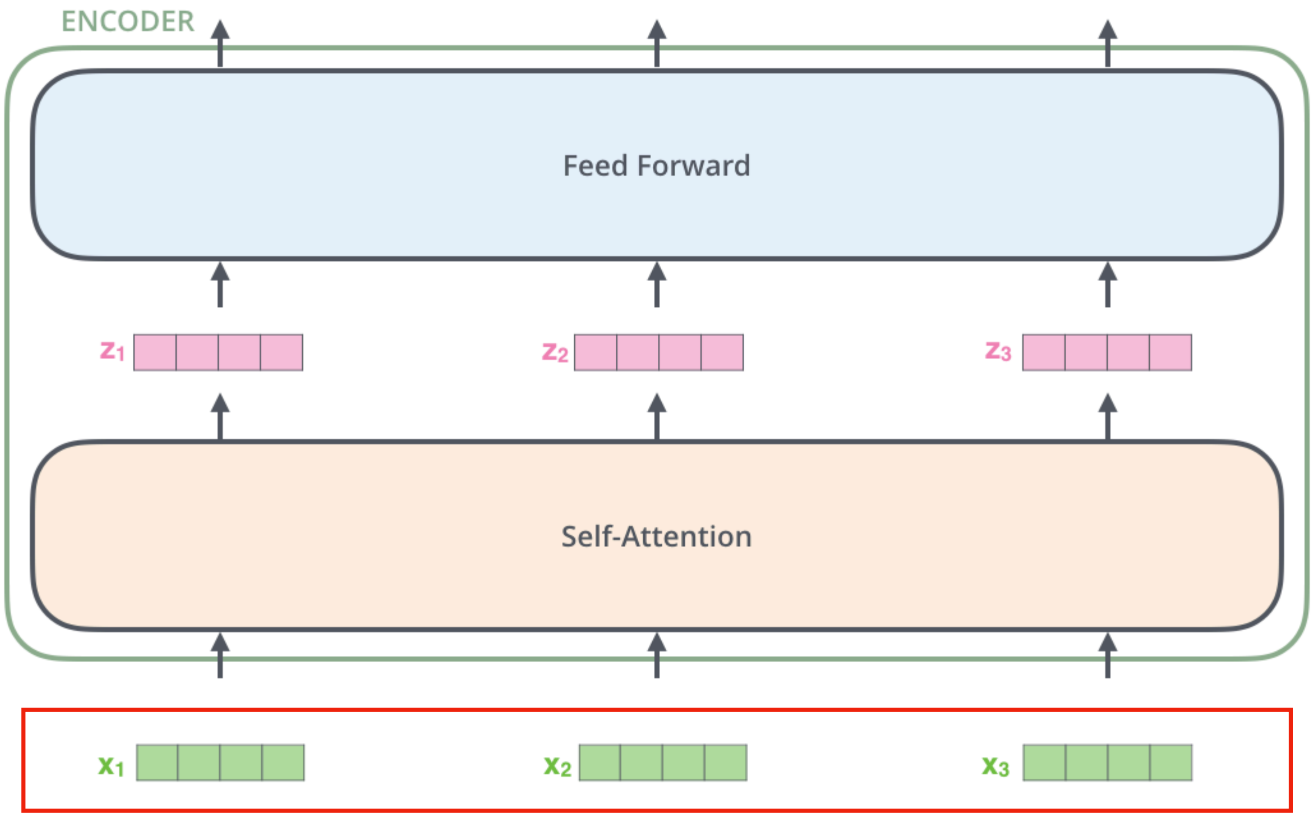
Transformers: Simplified



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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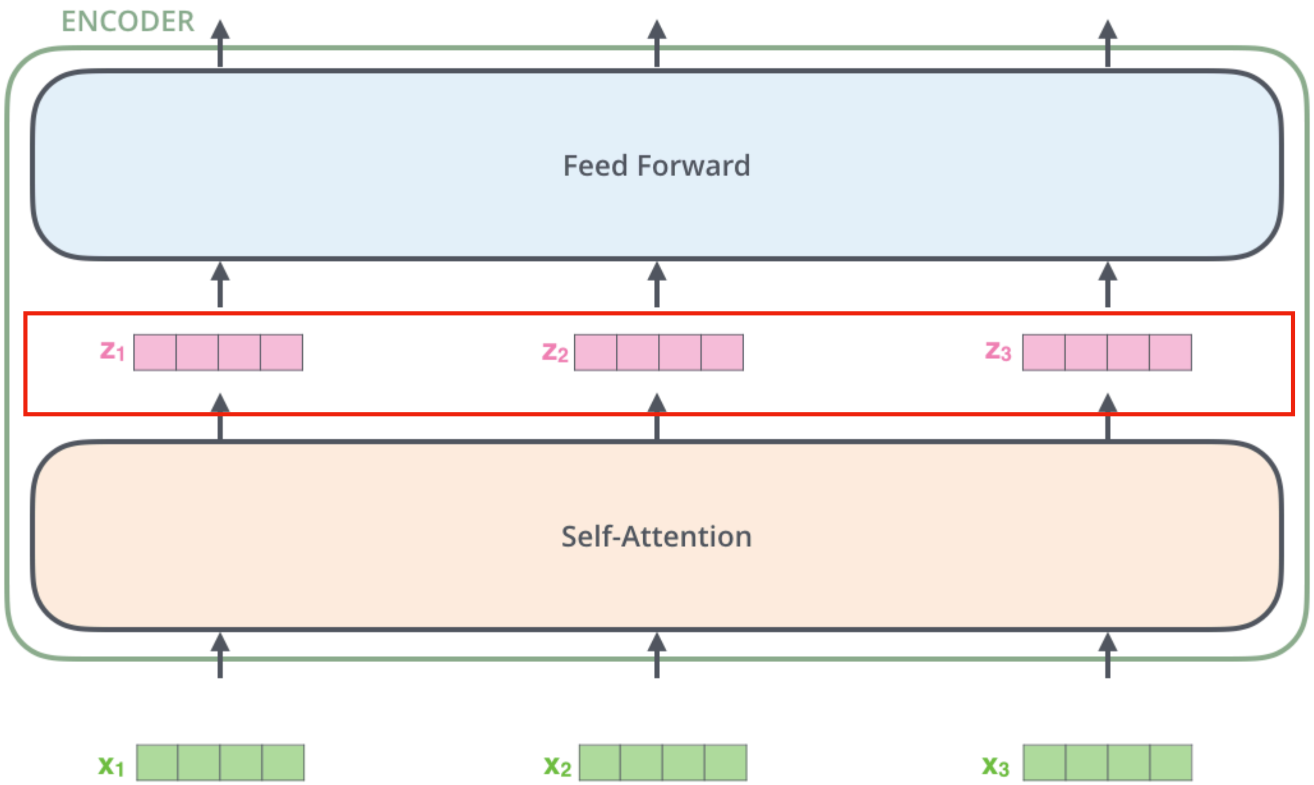

Multiple (50-90) such layers in a Transformer LM

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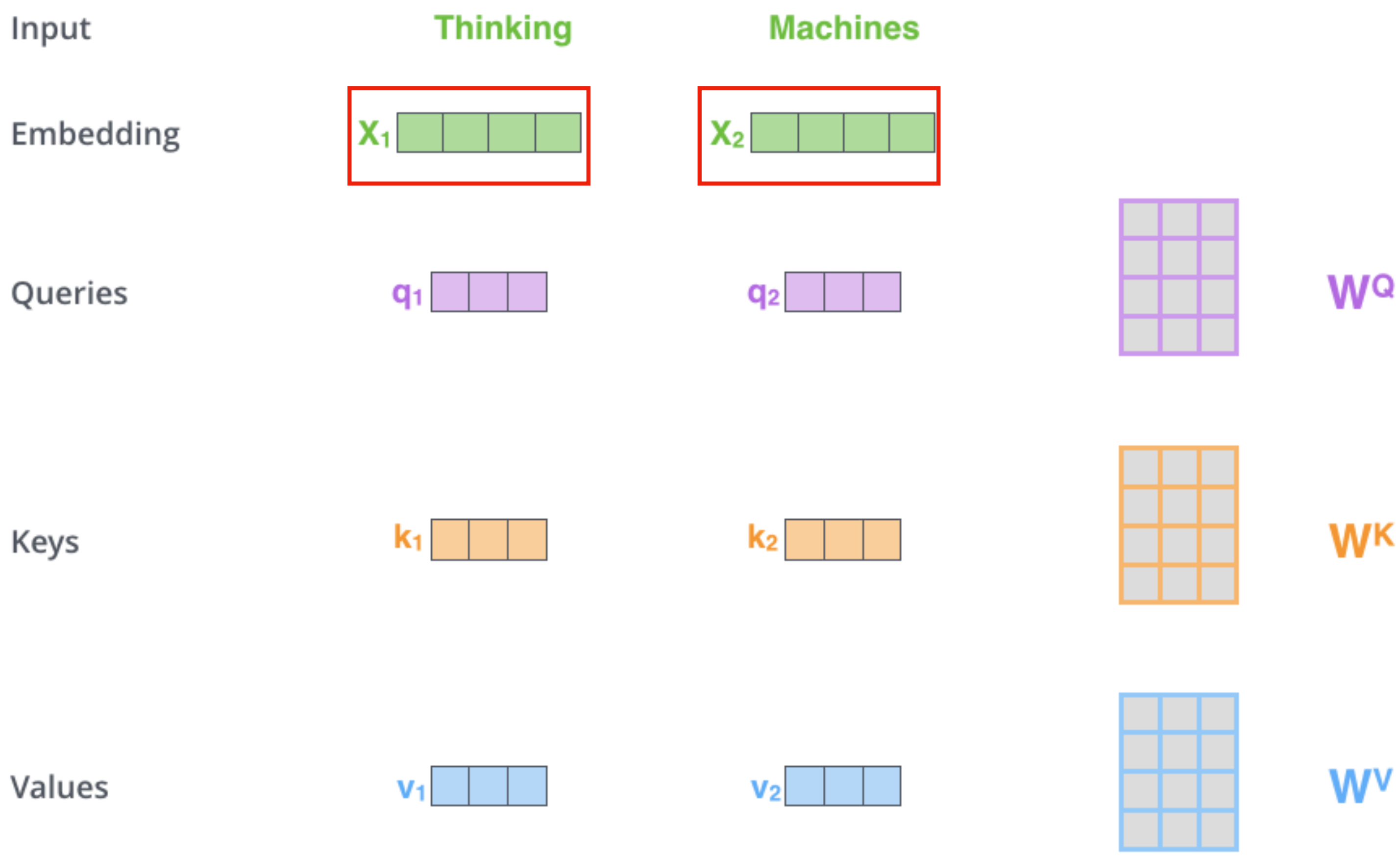
Self-Attention

- 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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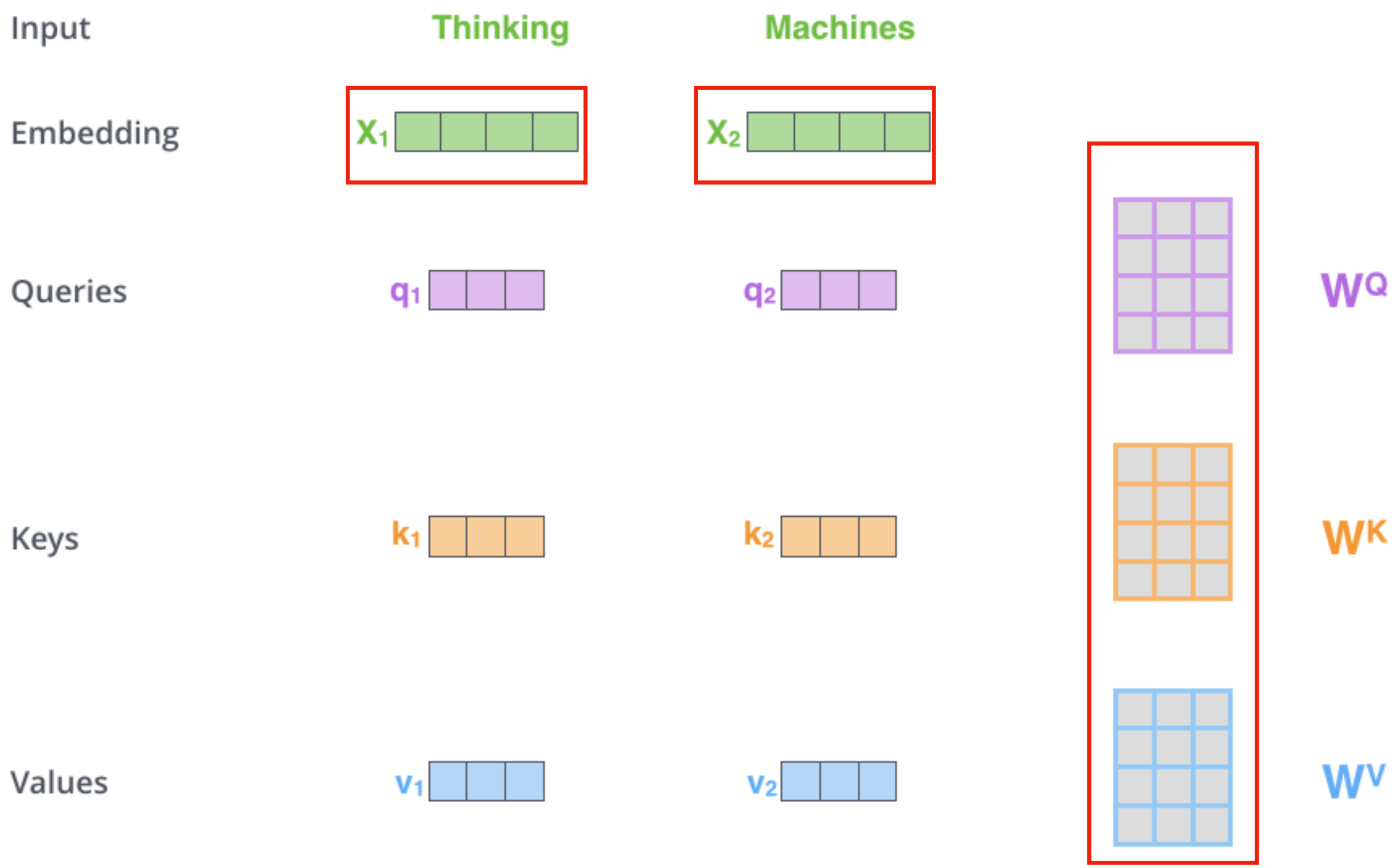
Self-Attention: Step 0



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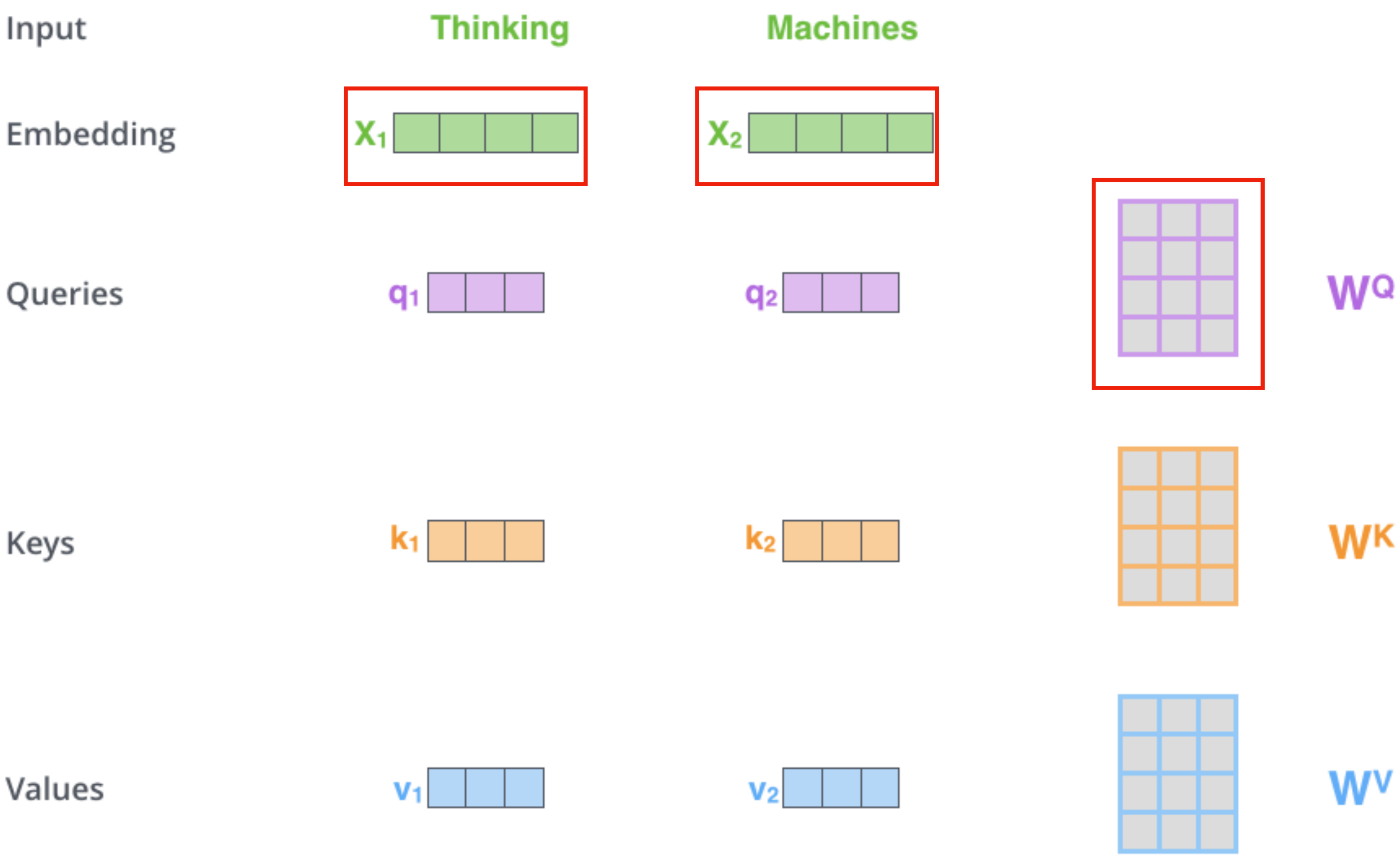
Self-Attention: Step 0



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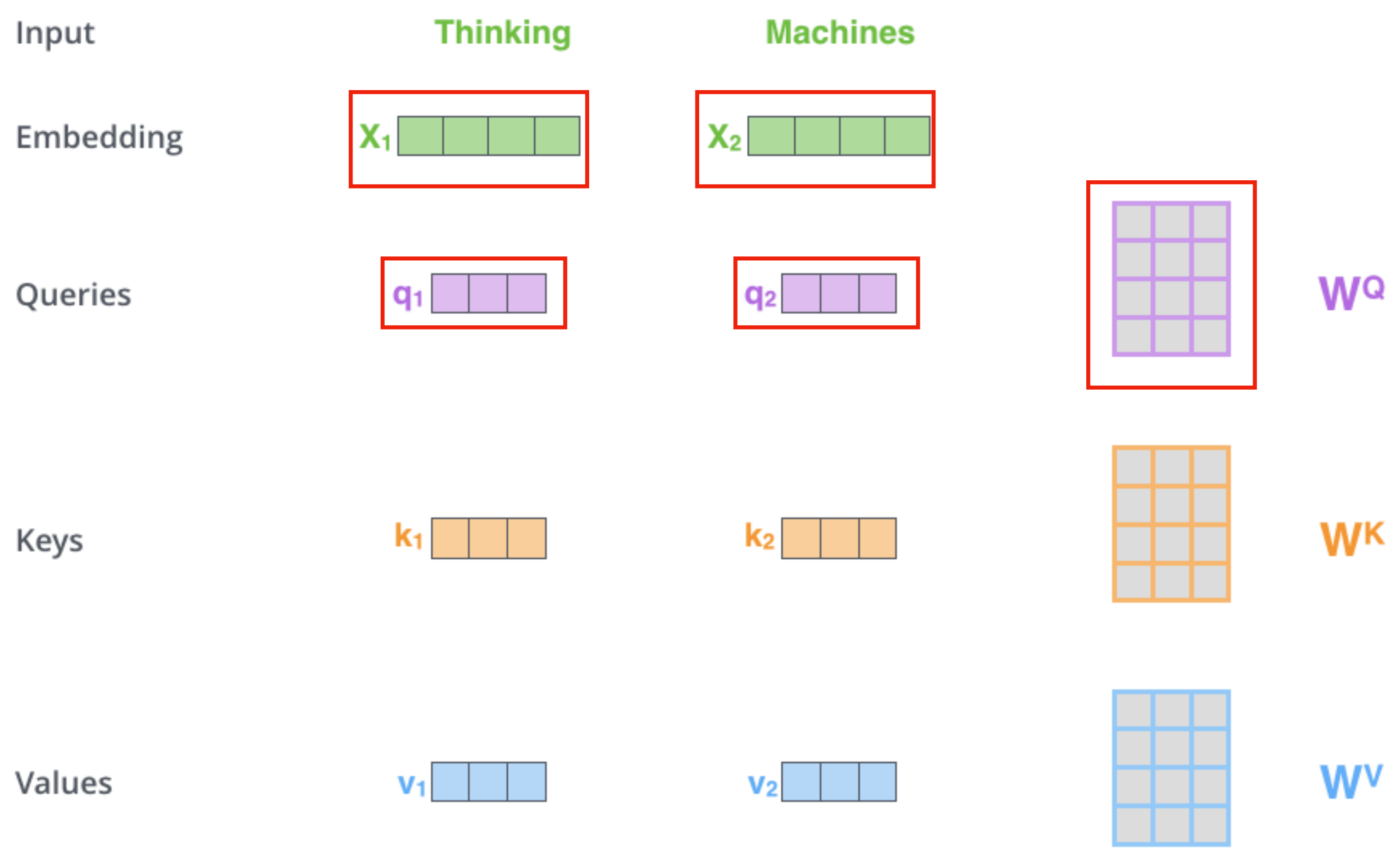
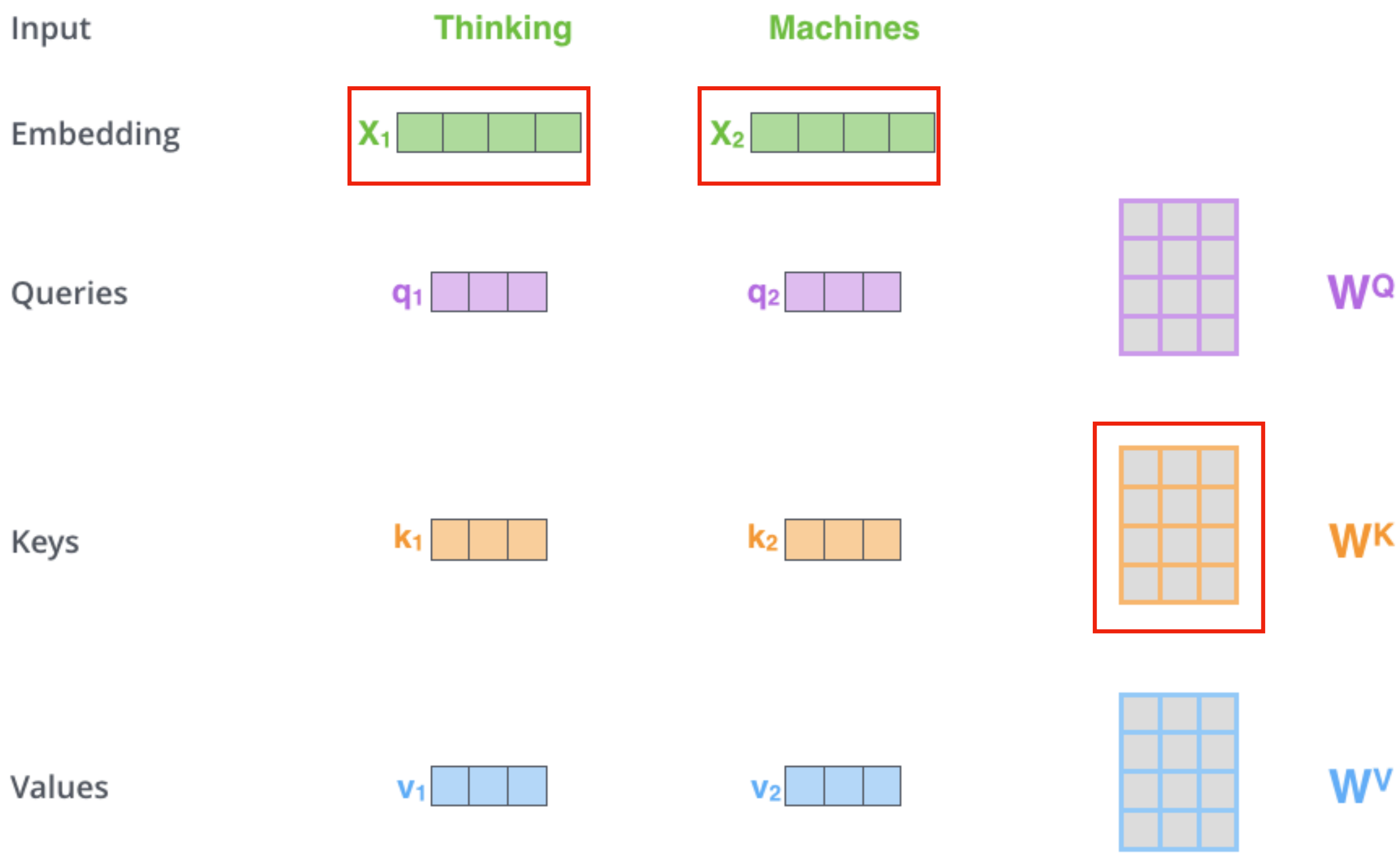
Self-Attention: Step 0



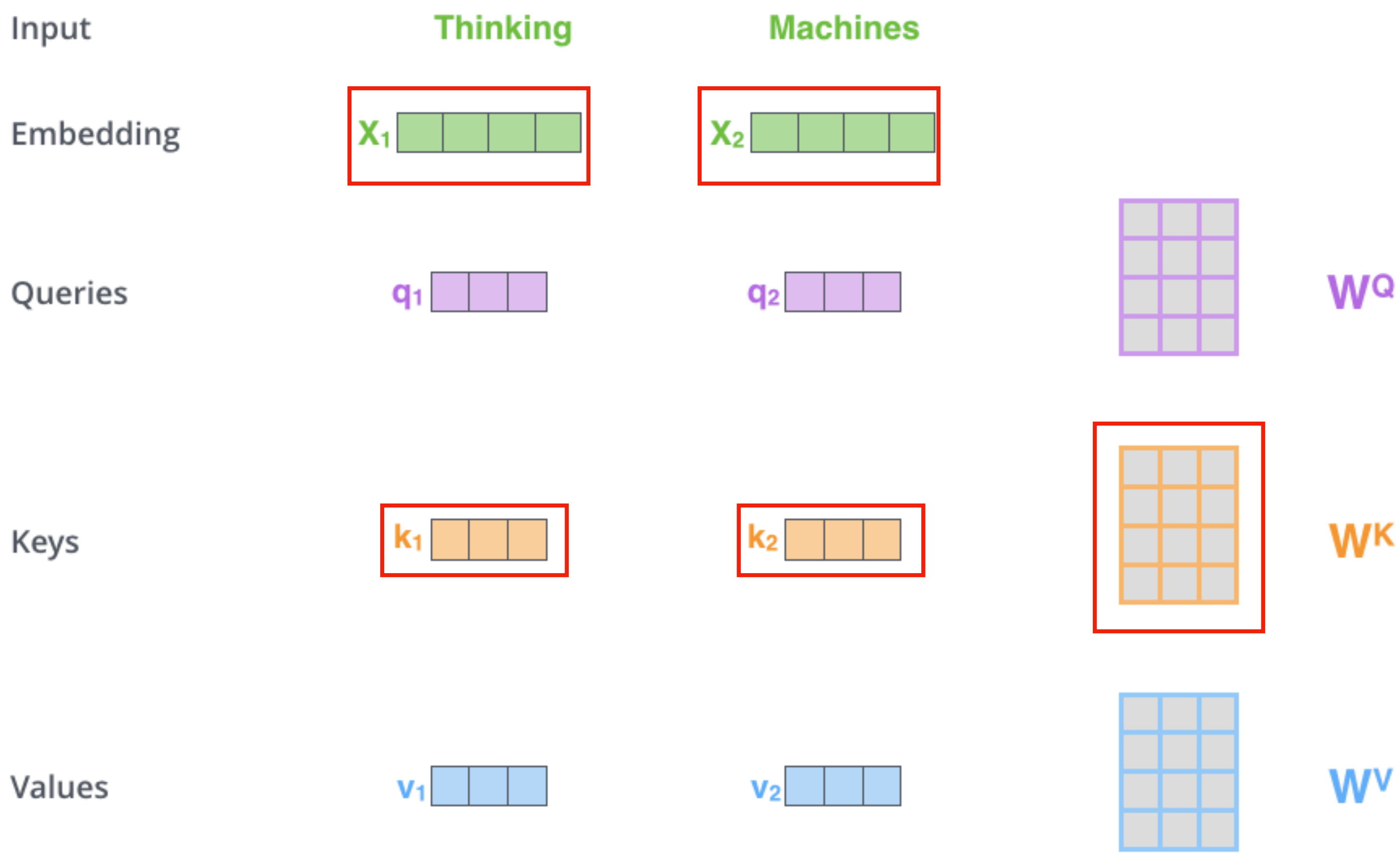
Credit: http://jalammar.github.io/illustrated-transformer/

Self-Attention: Step 0



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

Self-Attention: Step 0



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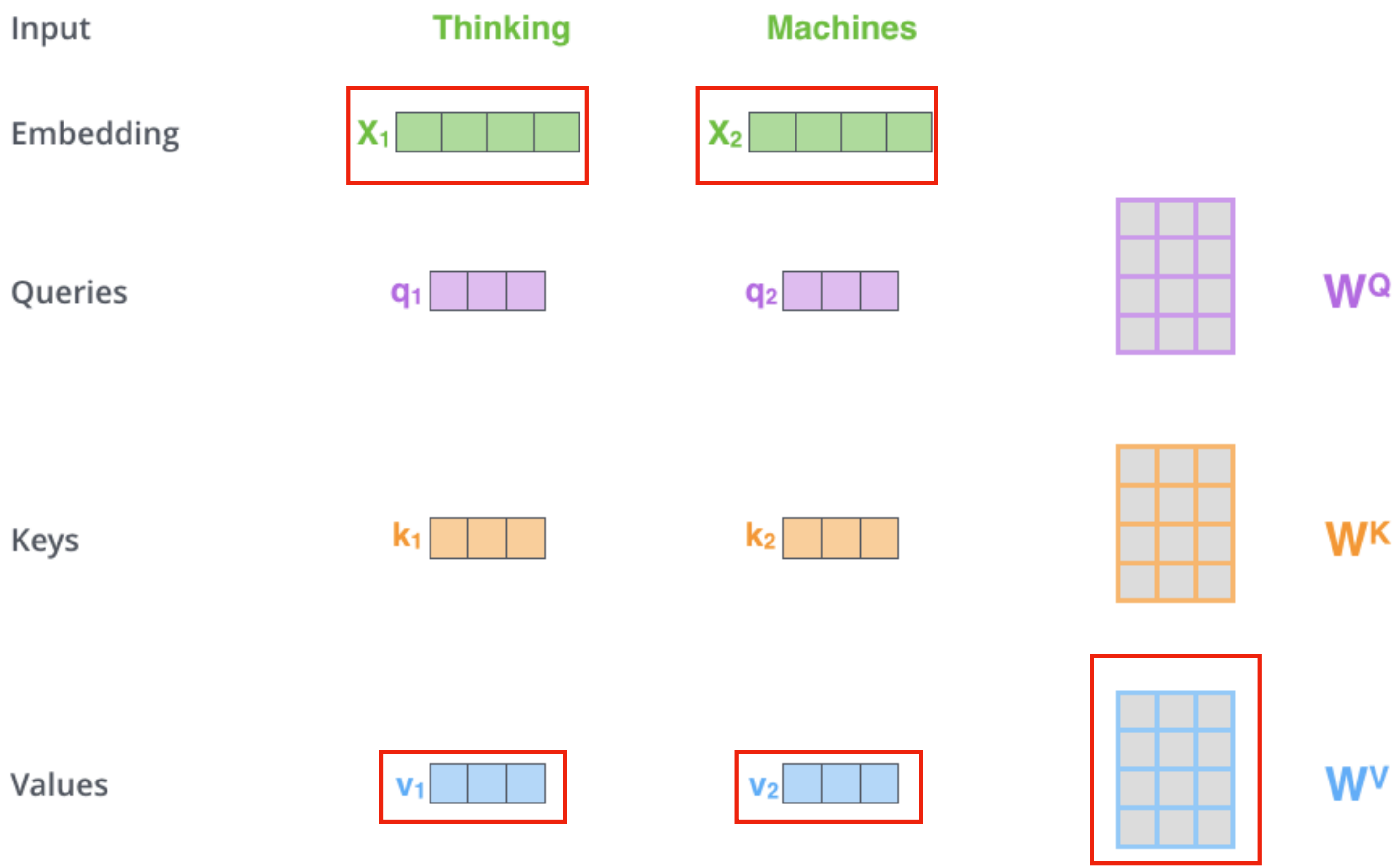
Self-Attention: Step 0



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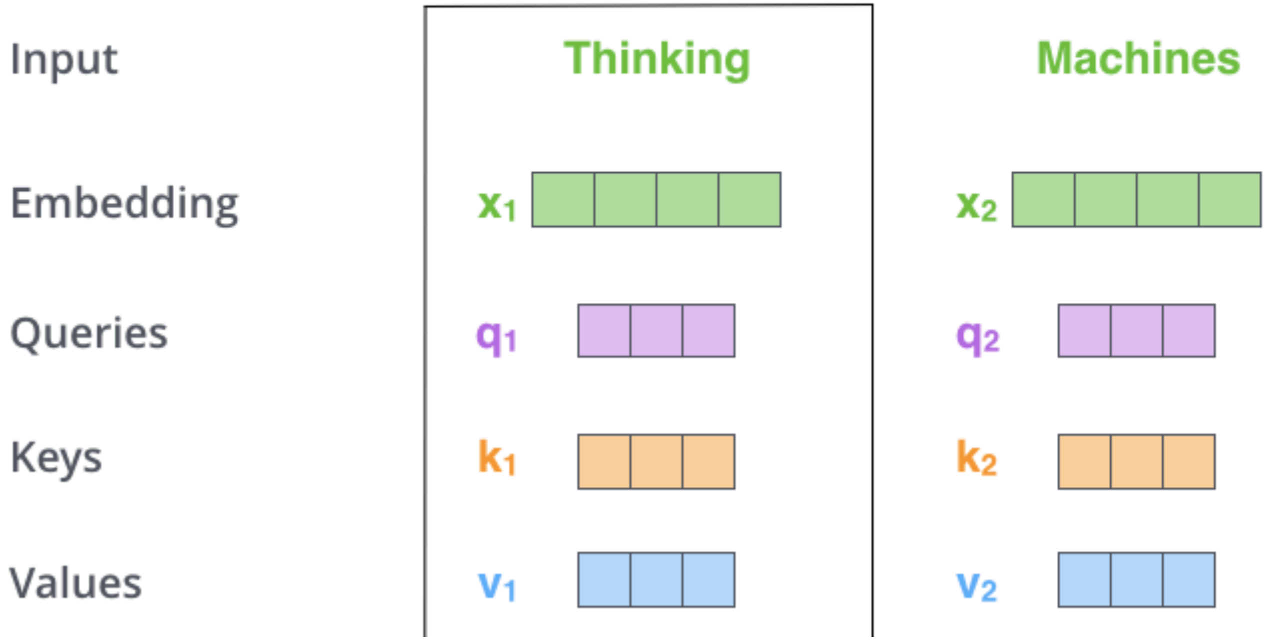
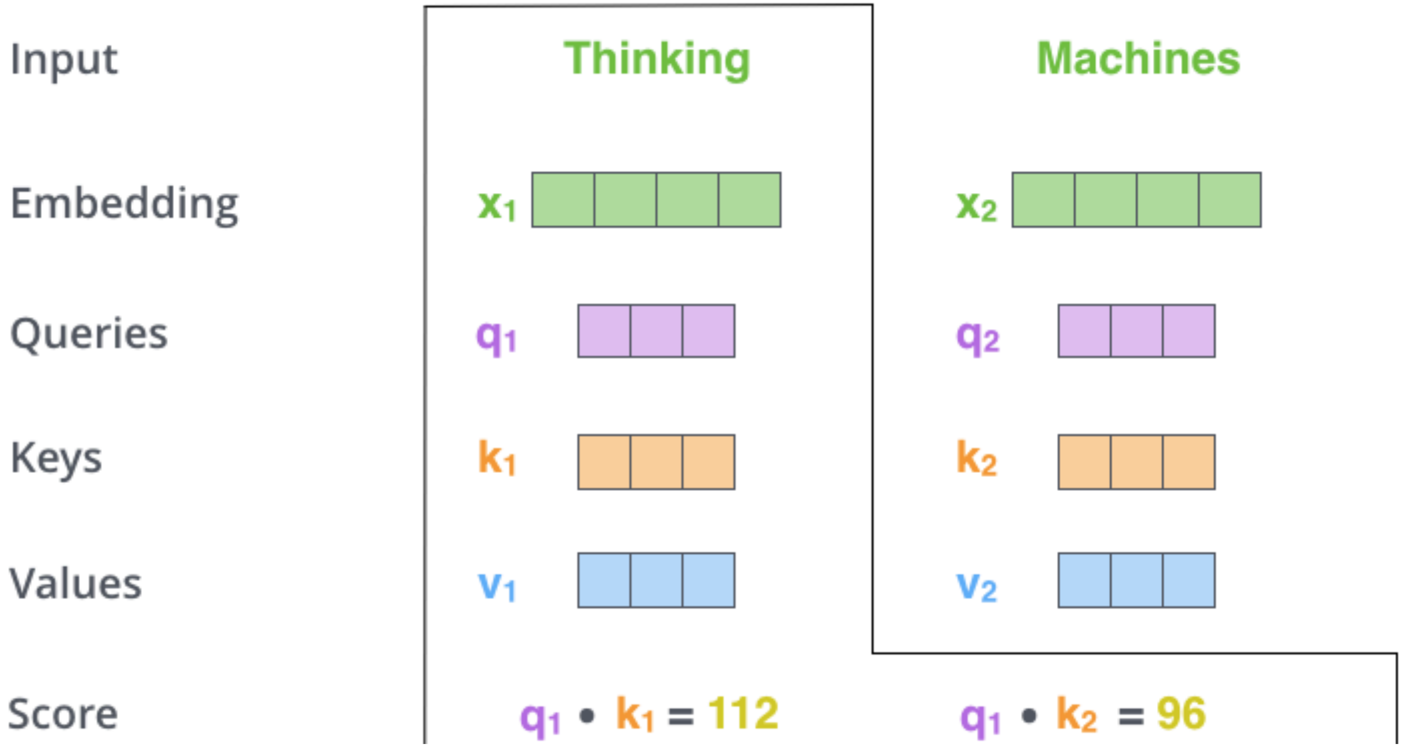
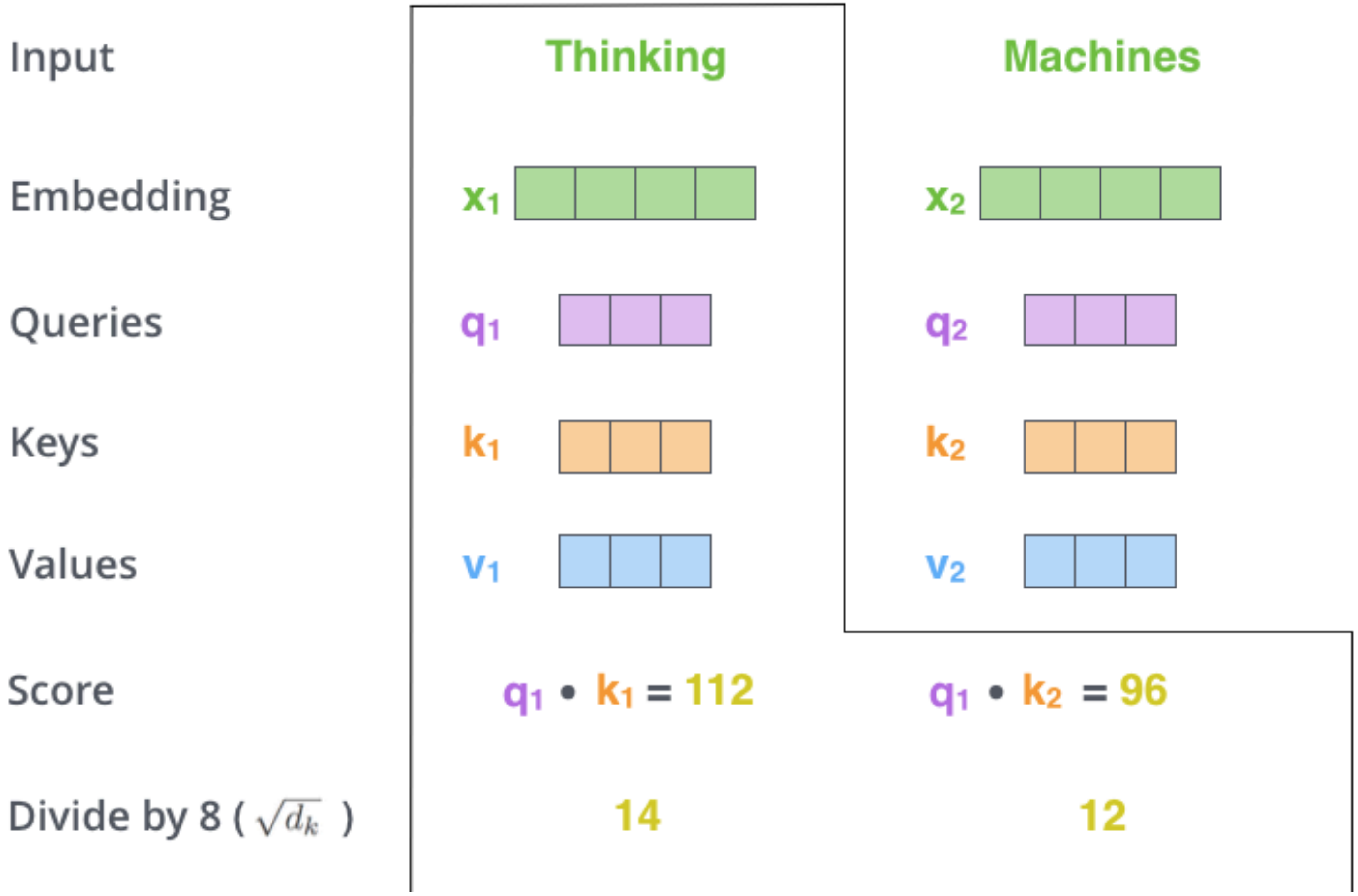
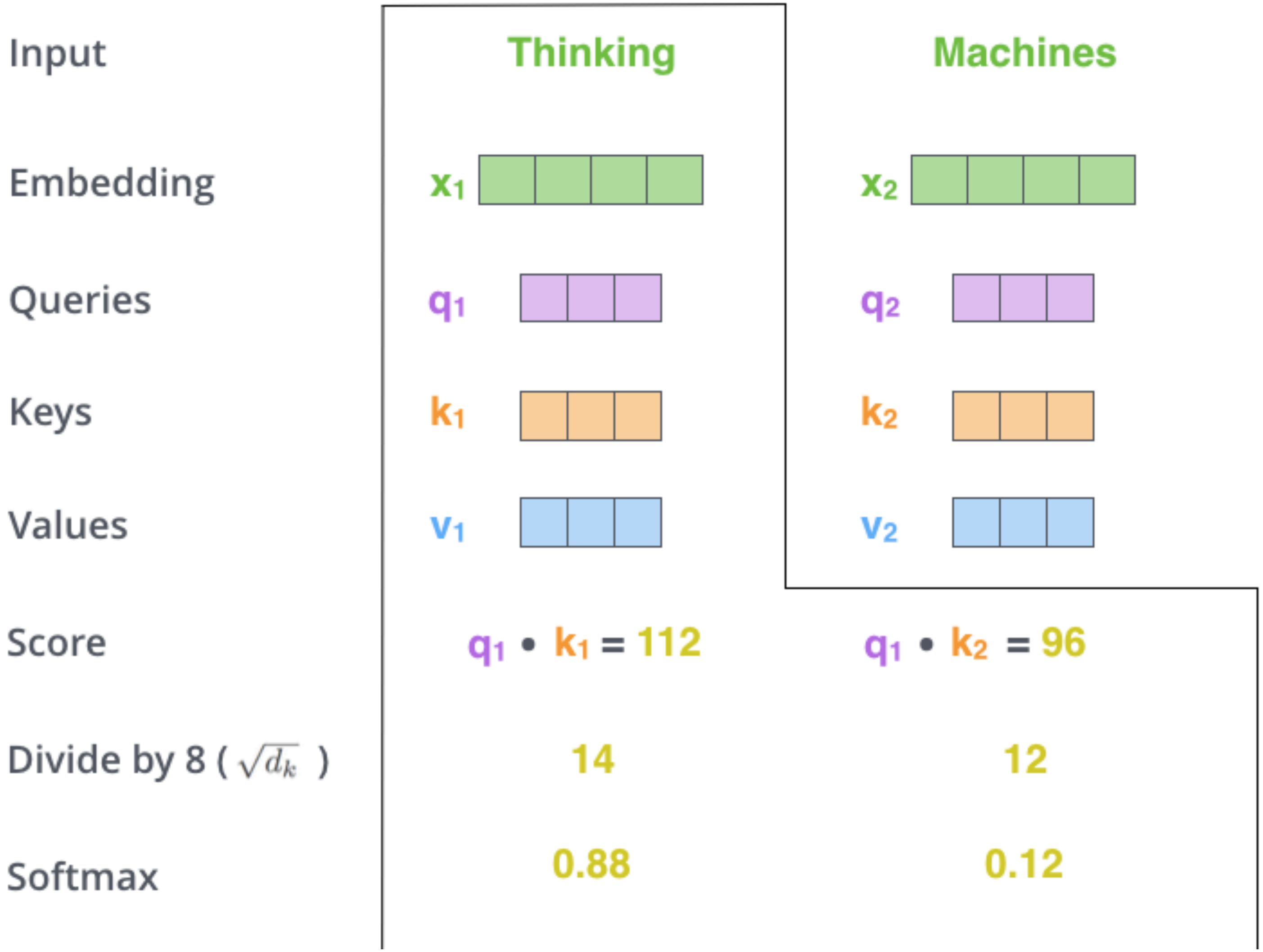


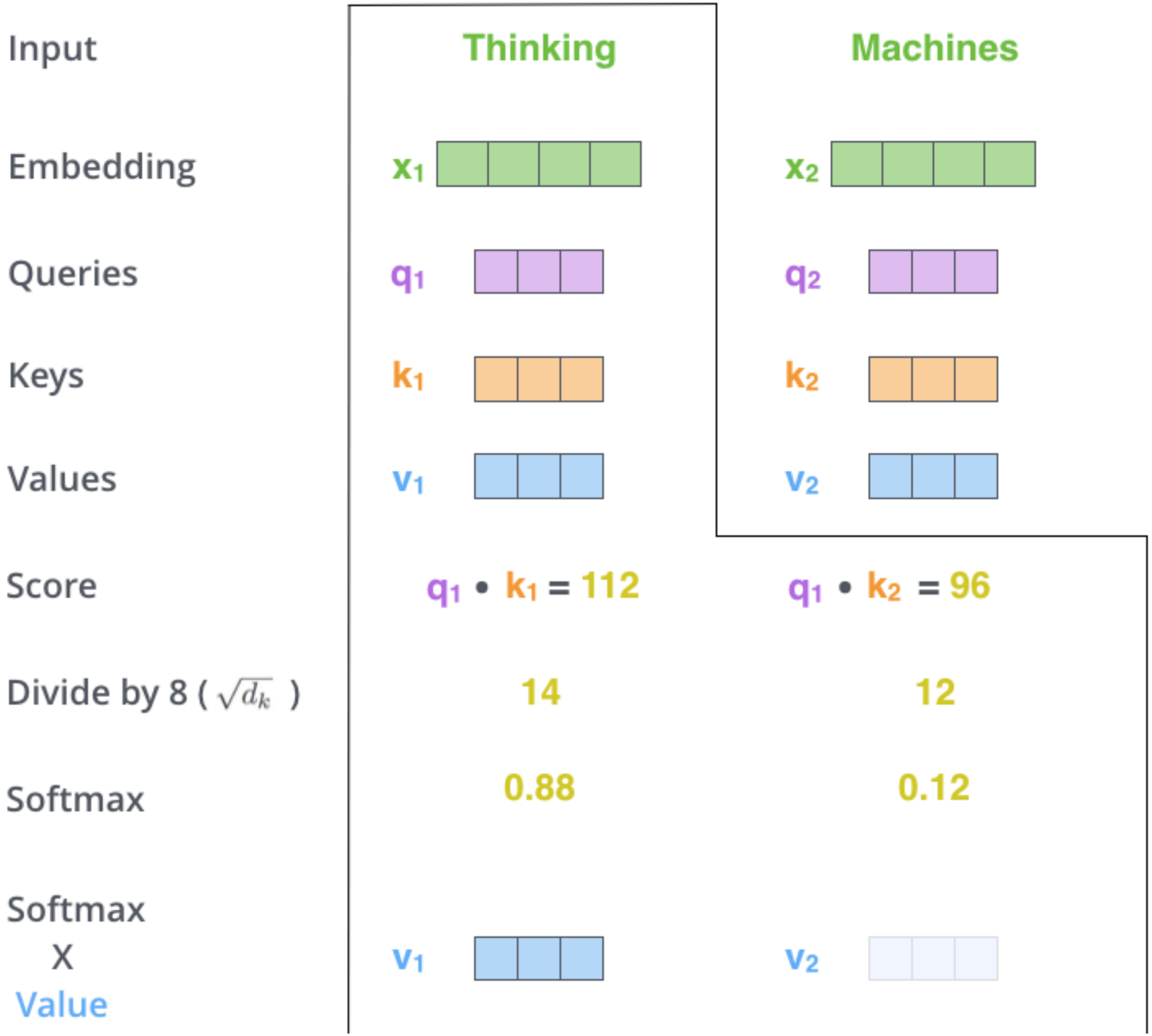
Input
Thinking
Machines
Embedding
x1
x2
Queries
q1
q2
Keys
k1
k2
Values
v1
v2

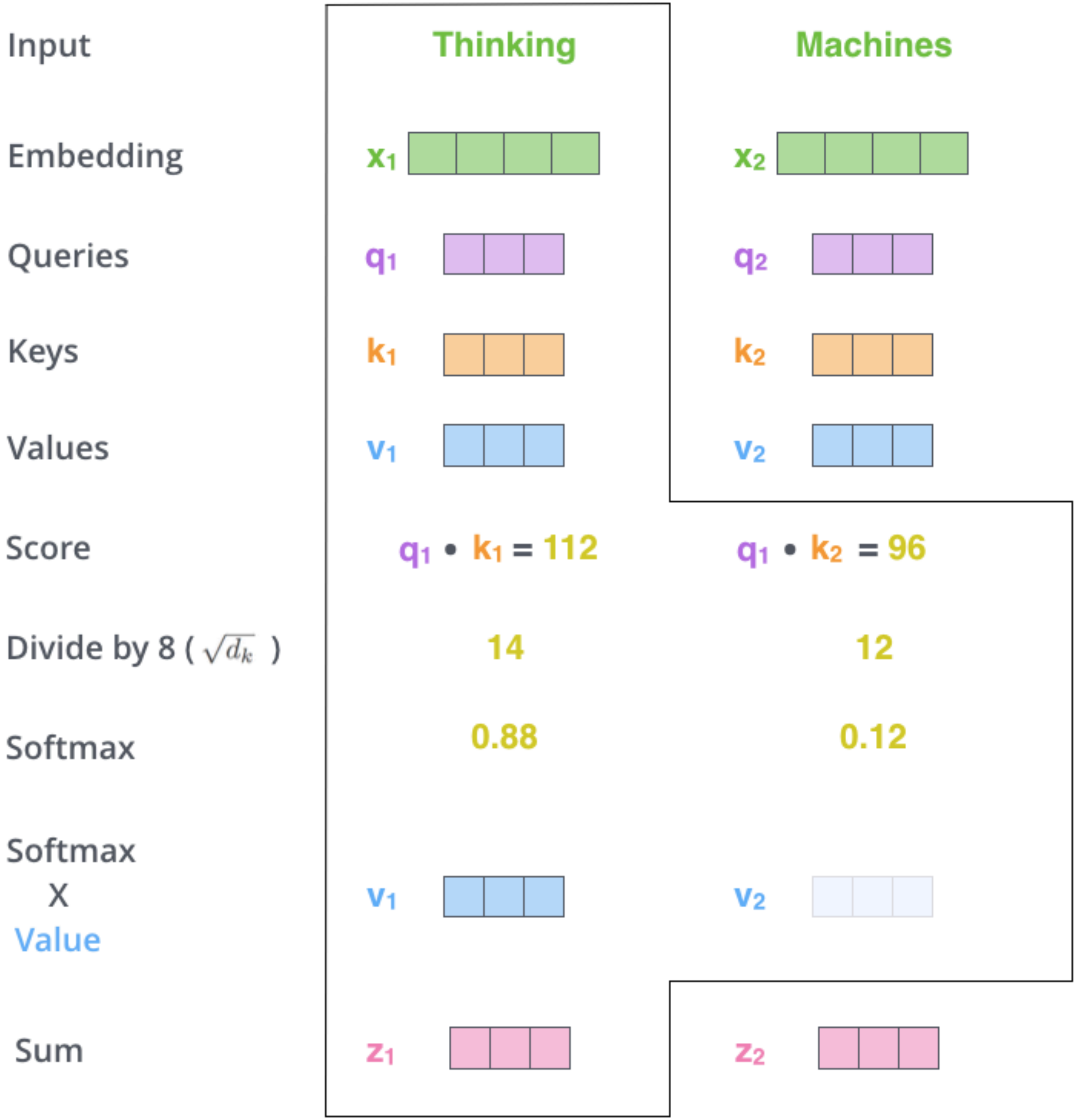

Input
Thinking
Machines
Embedding
x1
x2
Queries
q1
q2
Keys
k1
k2
Values
v1
v2
Score
q1 • k1 = 112
q1 • k2 = 96



Input
Thinking
Machines
Embedding
x_1
x_2
Queries
q_1
q_2
Keys
k_1
k_2
Values
v_1
v_2
Score
$q_1 \bullet k_1 = 112$
$q_1 \bullet k_2 = 96$
Divide by 8 ($\sqrt{d_k}$)
14
12

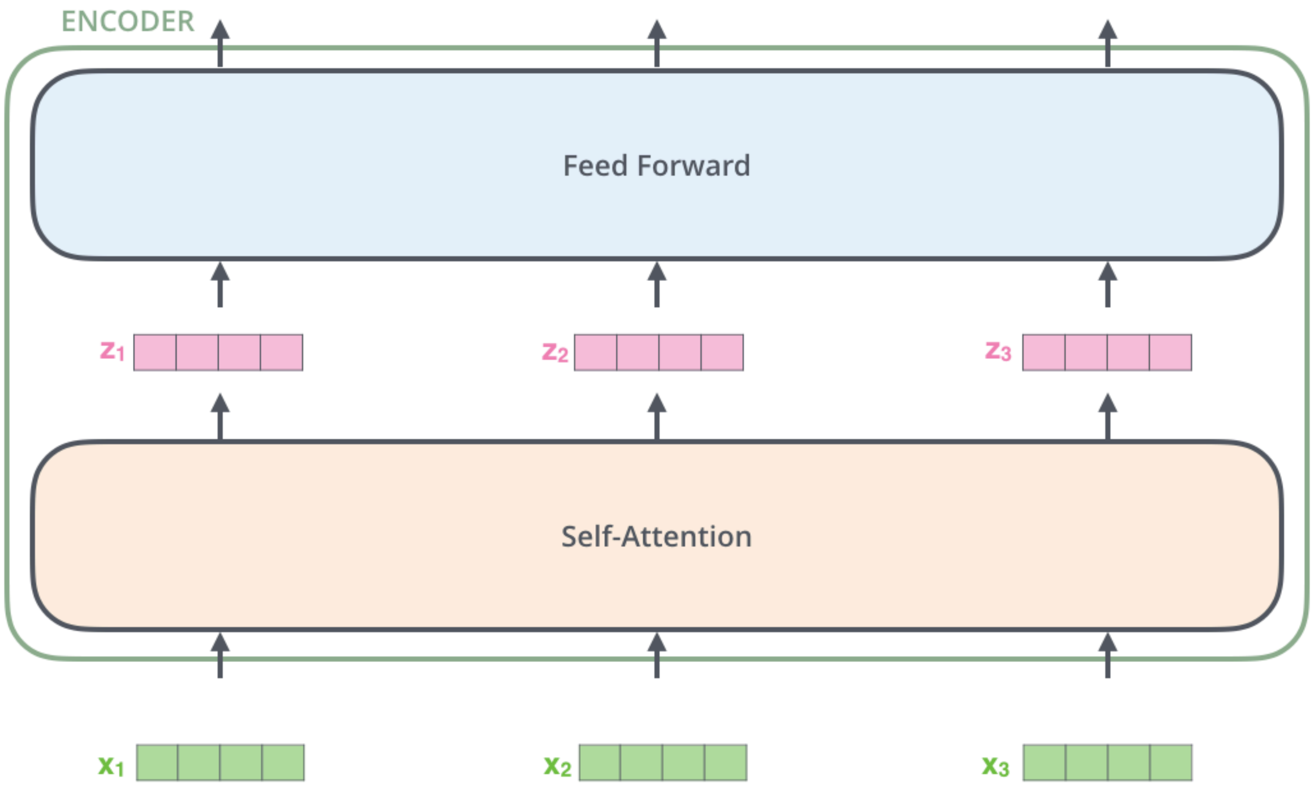

Input
Thinking
Machines
Embedding
x_1
x_2
Queries
q_1
q_2
Keys
k_1
k_2
Values
v_1
v_2
Score
$q_1 \bullet k_1 = 112$
$q_1 \bullet k_2 = 96$
Divide by 8 ($\sqrt{d_k}$)
14
12
Softmax
0.88
0.12


Input
Thinking
Machines
Embedding
x_1
x_2
Queries
q_1
q_2
Keys
k_1
k_2
Values
v_1
v_2
Score
$q_1 \bullet k_1 = 112$
$q_1 \bullet k_2 = 96$
Divide by 8 ($\sqrt{d_k}$)
14
12
Softmax
0.88
0.12
Softmax
X
Value
v_1
v_2



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

Self-Attention

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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 2

- “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”
- 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>

z = [0.24   0.55]

Input	Computers	are	thinking	machines
Embedding				
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				
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				

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·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 √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]
Score	q·k	0.7	0.21	-0.49	0.98
Divide by √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]	$\boxed{[0.7\ 0.7]}$
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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]	$\boxed{[0.7\ 0.7]}$
Keys		[0.2 0.8]	[-0.2 0.5]	$\boxed{[-0.3\ -0.4]}$	[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	$\boxed{-0.49}$	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]	$\boxed{[-0.2\ 0.5]}$	[-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]
Score	q·k	0.7	$\boxed{0.21}$	-0.49	0.98
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]	$\boxed{[0.7\ 0.7]}$
Keys		$\boxed{[0.2\ 0.8]}$	[-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]	$\boxed{[0.7\ 0.7]}$
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 √2($\sqrt{d_k}$)				
Softmax				
Softmax X Value				
Sum				

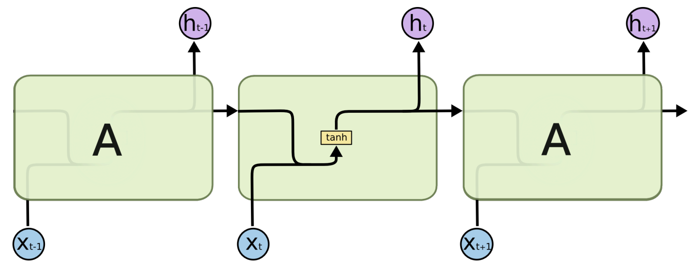
Input		Computers	are	thinking	machines
Embedding		[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	$\boxed{[0.7\ 0.7]}$
Keys		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Values		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Score	q·k	0.7	0.21	-0.49	0.98
Divide by $\sqrt{2}$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

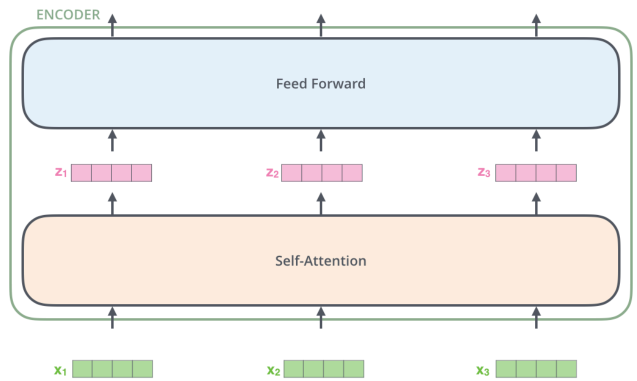
		Computers	are	thinking	machines
Input		Computers	are	thinking	machines
Embedding		[1 0 0 0]	[0 1 0 0]	[0 0 1 0]	[0 0 0 1]
Queries		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	$\boxed{[0.7\ 0.7]}$
Keys		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Values		[0.2 0.8]	[-0.2 0.5]	[-0.3 -0.4]	[0.7 0.7]
Score	q·k	0.7	0.21	-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					

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]
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					[0.23 0.54]

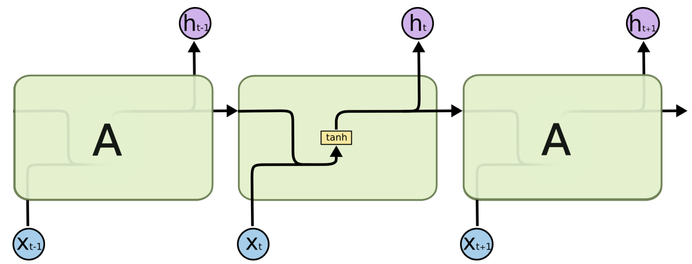
Transformers for Language Modelling

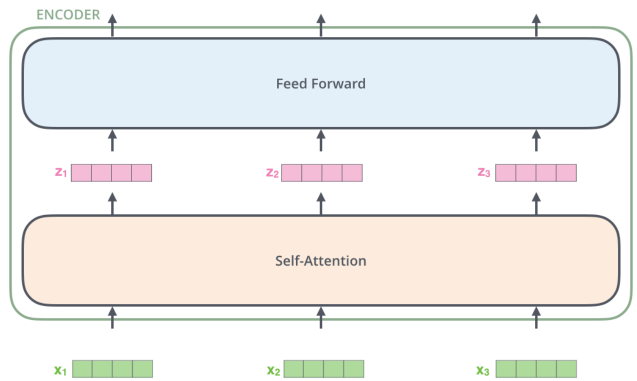




Transformers for Language Modelling

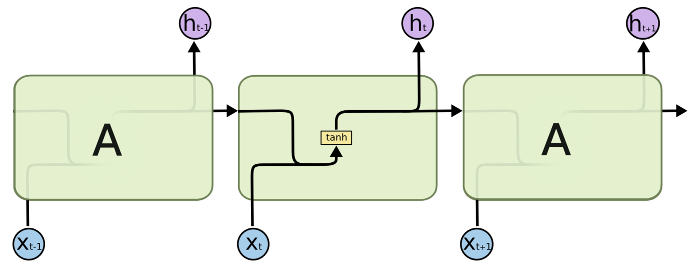
- RNNs: Process tokens one-by-one

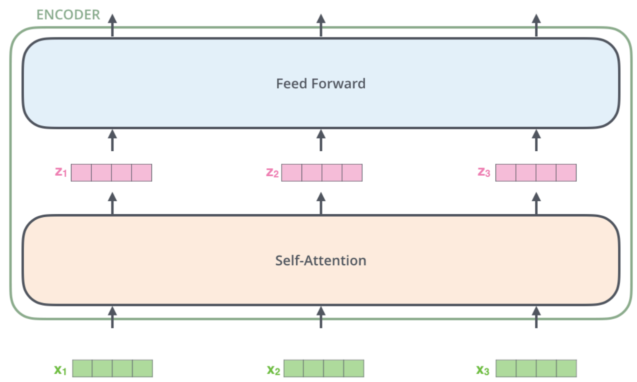




Transformers for Language Modelling

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





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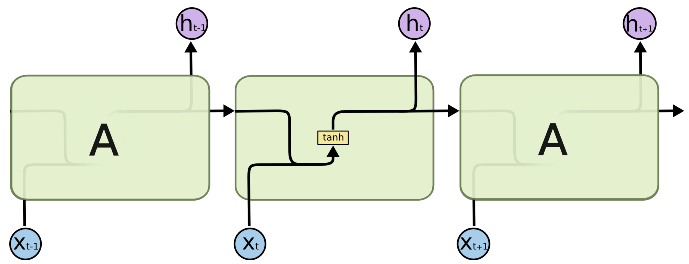
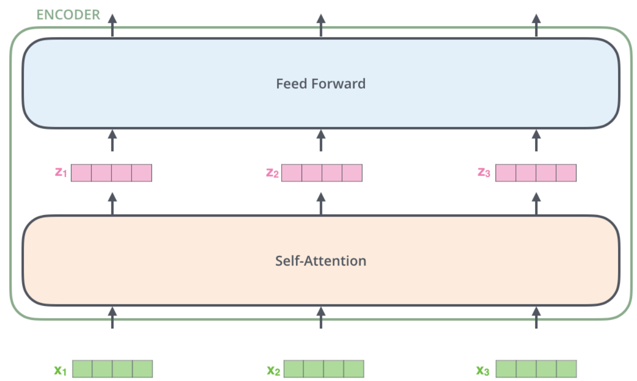


- Transformers LM: Process a segment of tokens



Transformers for Language Modelling

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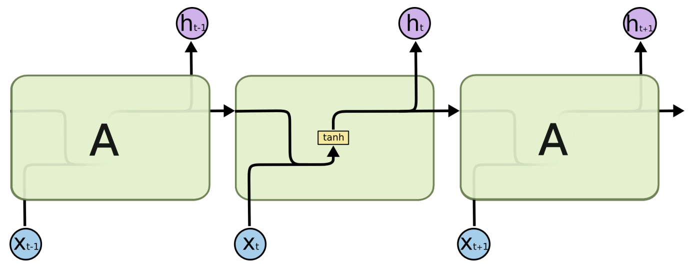
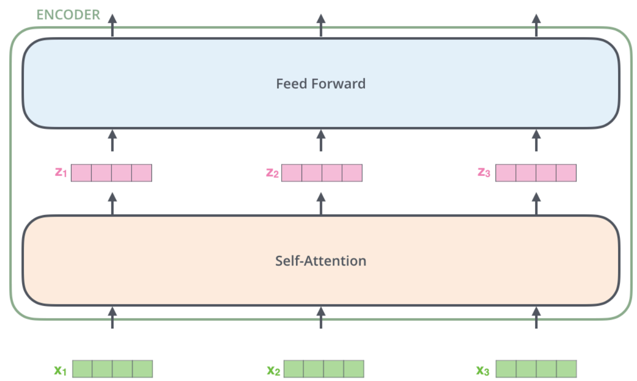


- Transformers LM: Process a segment of tokens
  - Dependencies within the segment



Transformers for Language Modelling

- RNNs: Process tokens one-by-one
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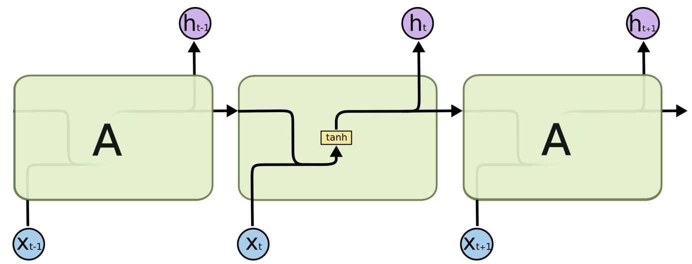
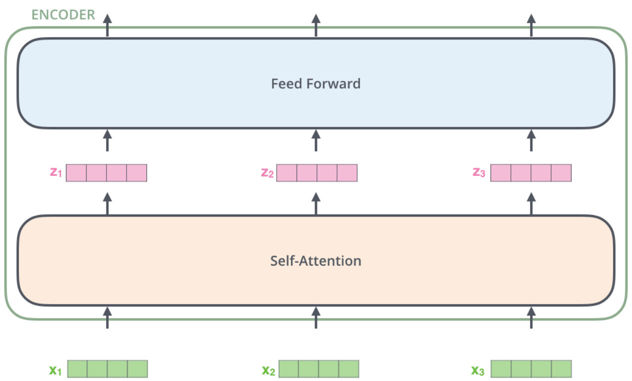
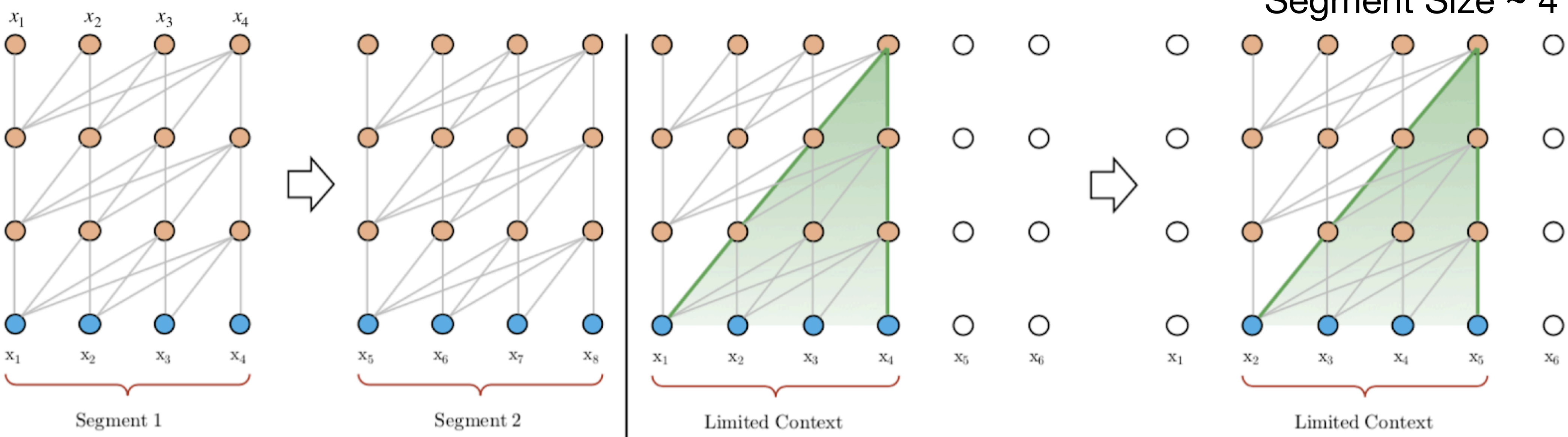


- Transformers LM: Process a segment of tokens
  - Dependencies within the segment
  - Within segment position is given by the positional encoding



Transformer LM processing of Segments

Segment Size ~ 4

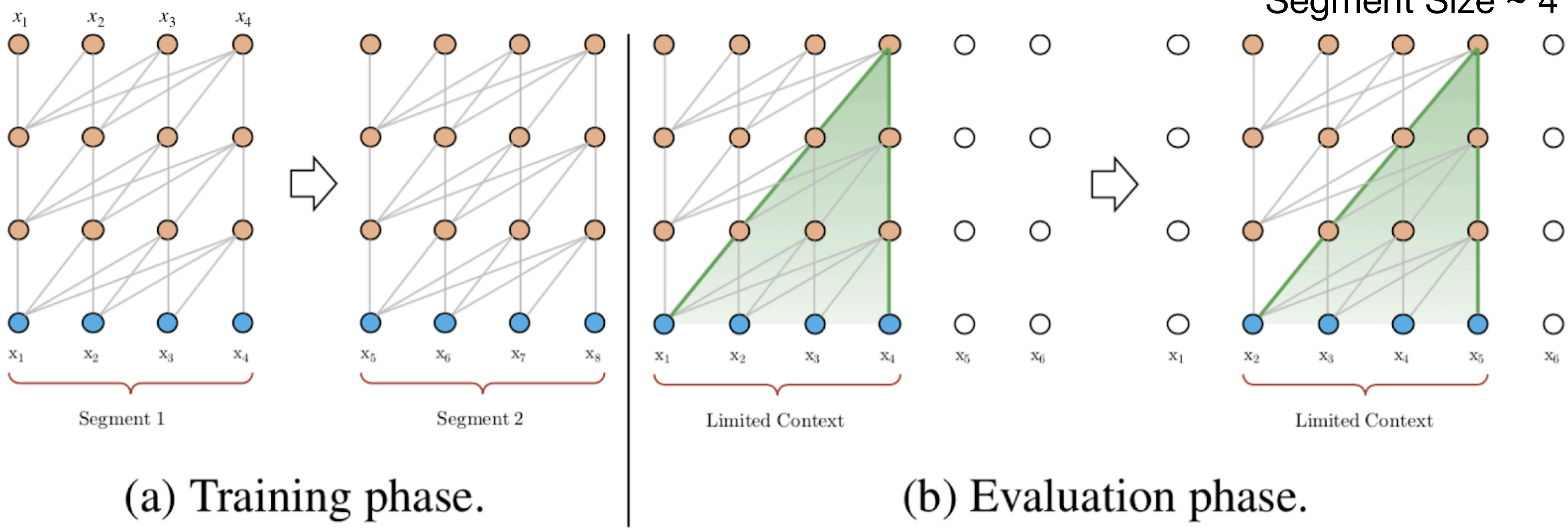


(a) Training phase. (b) Evaluation phase.

Dai et al., 2019

Transformer LM processing of Segments

Segment Size ~ 4

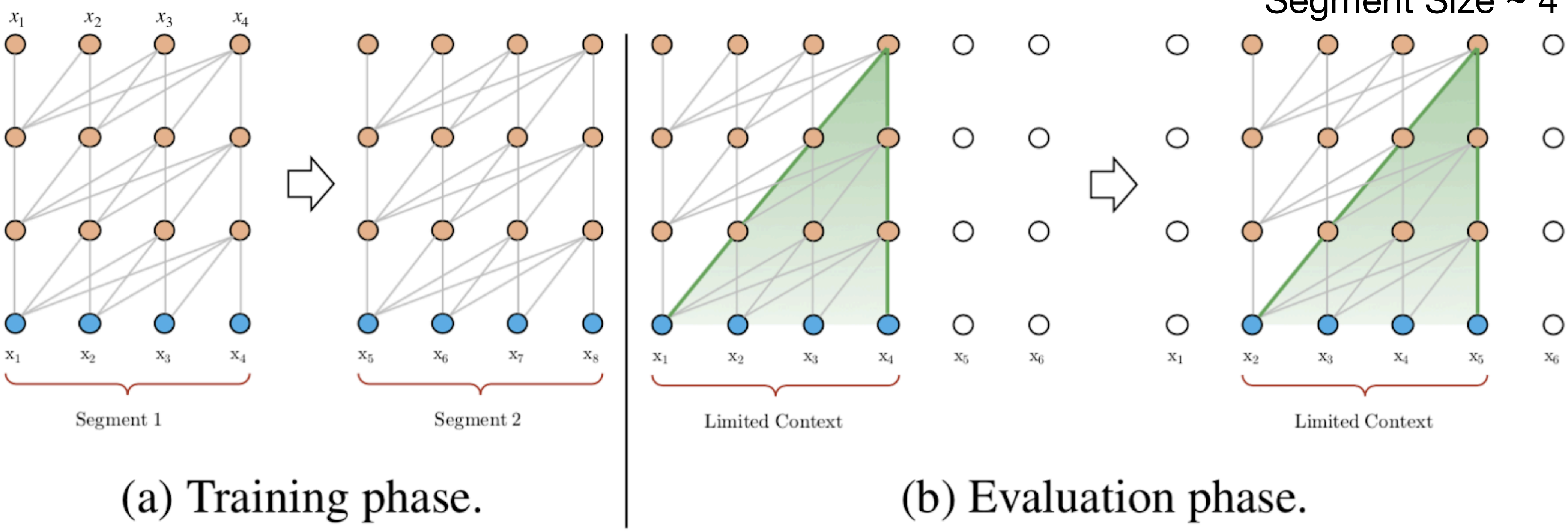


Dai et al., 2019

- 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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- Aim to **pretrain** general purpose representations

BERT: Bidirectional Encoder Representations from Transformers

- 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

BERT: Bidirectional Encoder Representations from Transformers

- 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
- Welcome BERT!

Transformers for Language Modelling

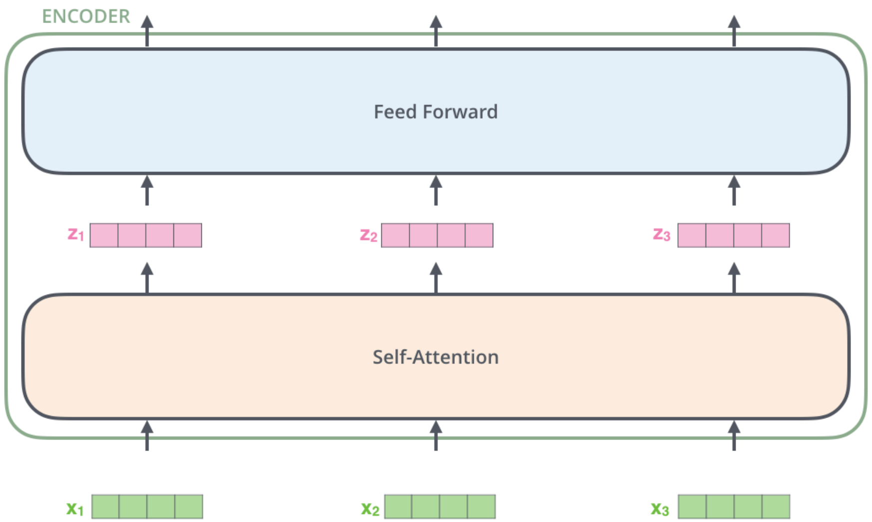
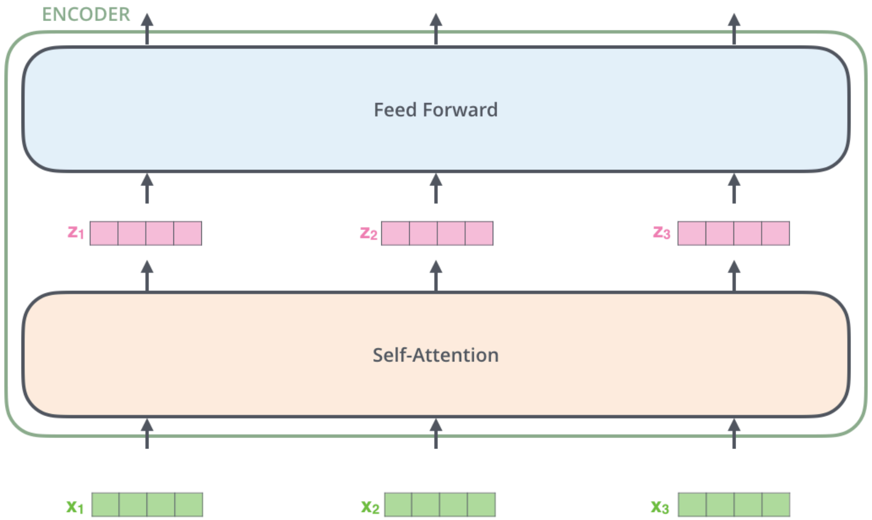


Image Credit: https://arxiv.org/pdf/1706.03762.pdf
Content Credit:TransformerXL Explained & Al-Rfou et al. 2018

Transformers for Language Modelling

- Transformers LM



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Transformers for Language Modelling

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  - Unidirectional

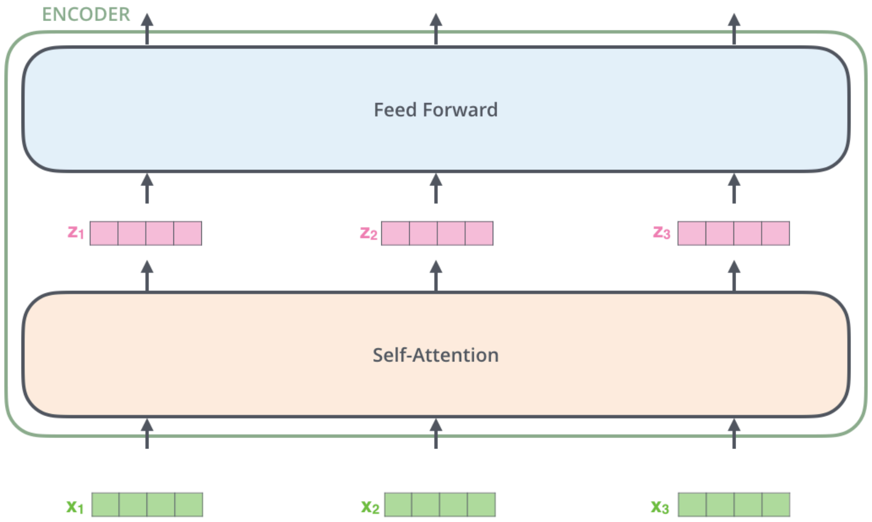

Image Credit: https://arxiv.org/pdf/1706.03762.pdf
Content Credit: TransformerXL Explained & Al-Rfou et al. 2018

Transformers for Language Modelling

- Transformers LM
  - Unidirectional
  - Segment of tokens

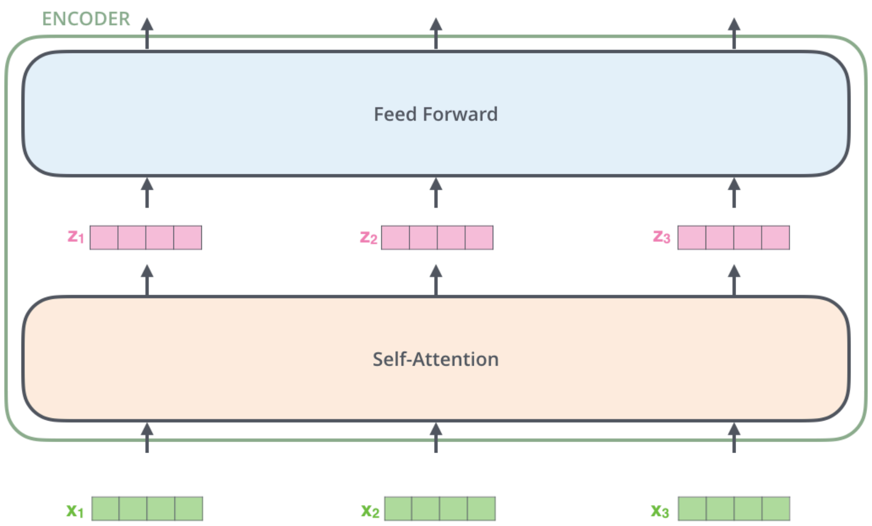

Image Credit: https://arxiv.org/pdf/1706.03762.pdf
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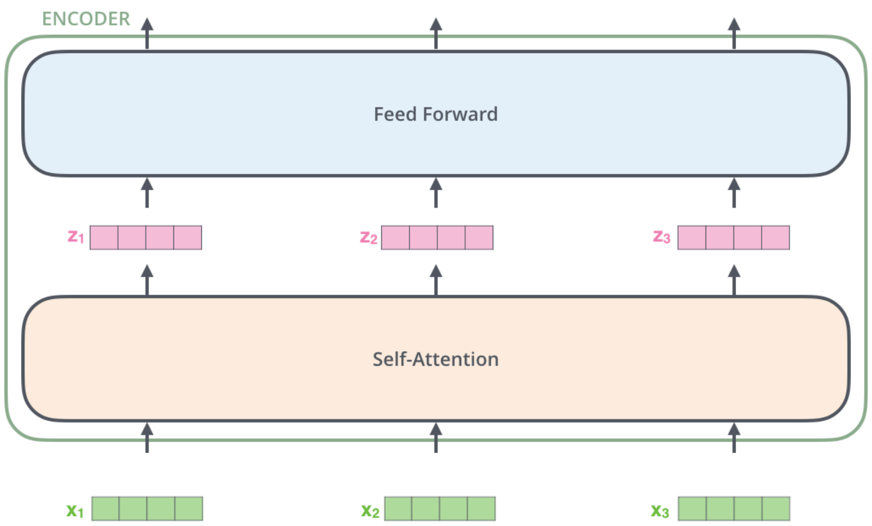
Transformers for Language Modelling

- Transformers LM
    - Unidirectional
    - Segment of tokens
- Language Models predict the next word



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Encoder Representations

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

Traditionally,

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- Language models are mostly used as unidirectional tools
- 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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BERT: Learning Setup

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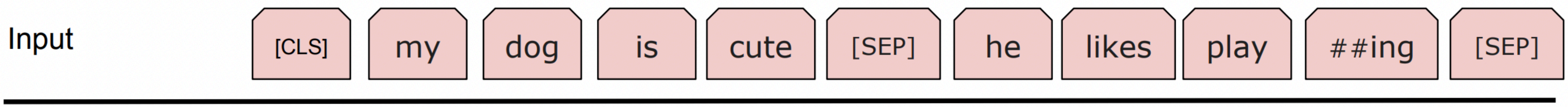
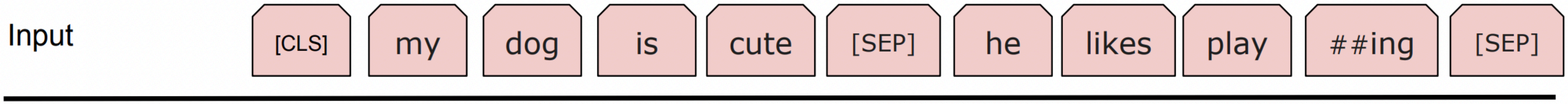
    - Takes lots and lots of sentences
    - Self-supervision
        - Masked LM
        - Next Sentence Prediction
- Finetune
    - Supervised using target task

Masked LM

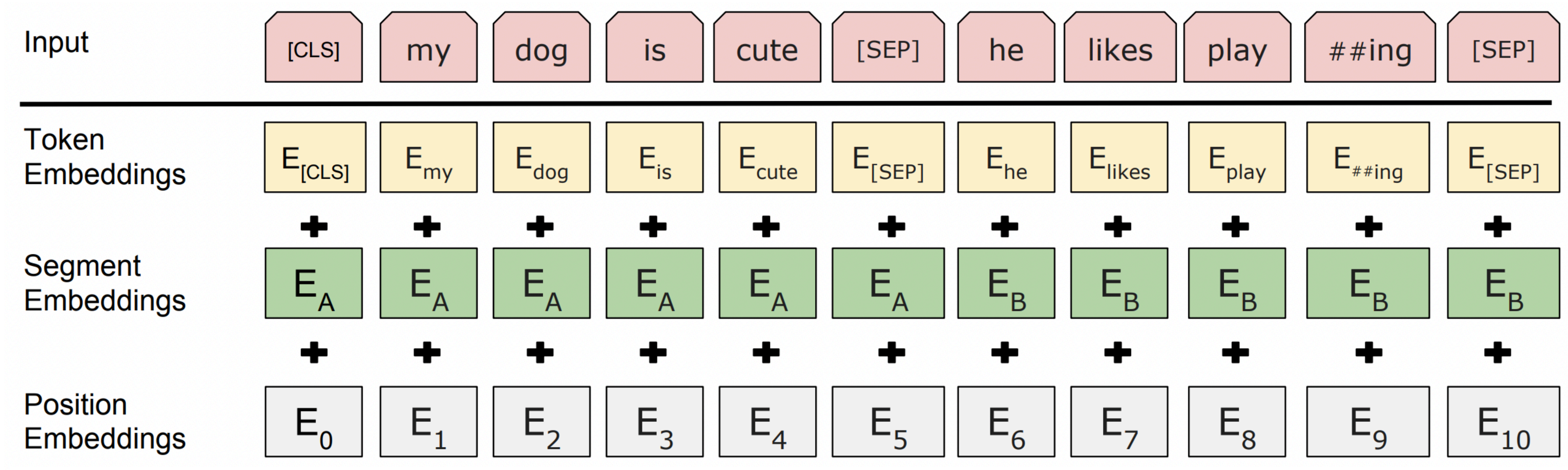


Masked LM



- Use specialised tokens CLS, SEP

Masked LM



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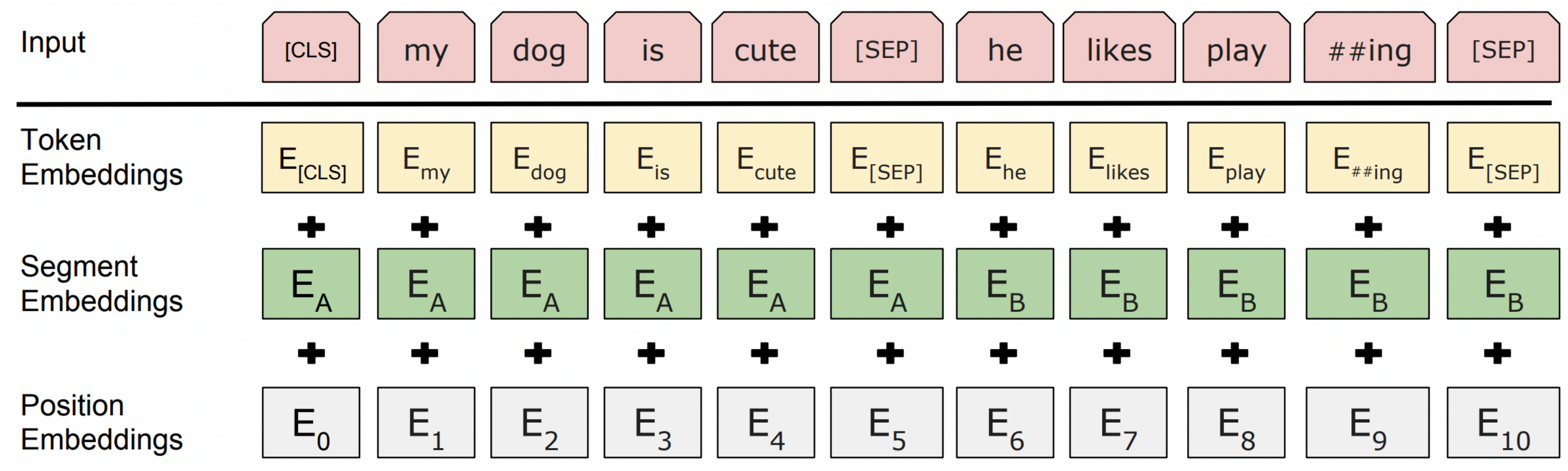
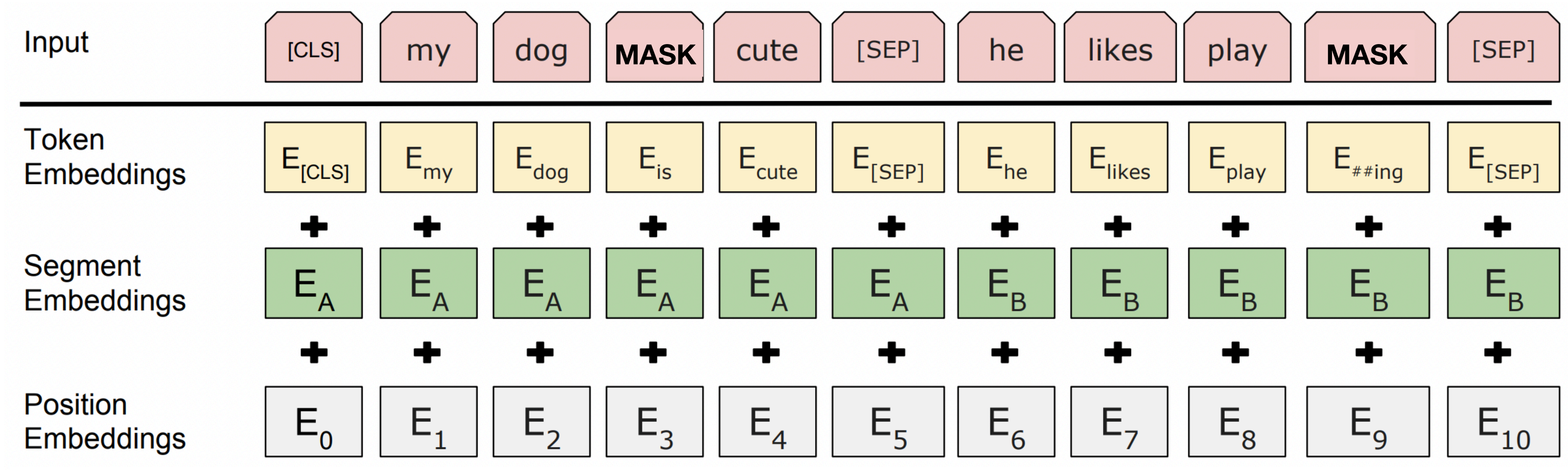


- Use specialised tokens CLS, SEP
- 15% of the tokens are randomly masked

Masked LM



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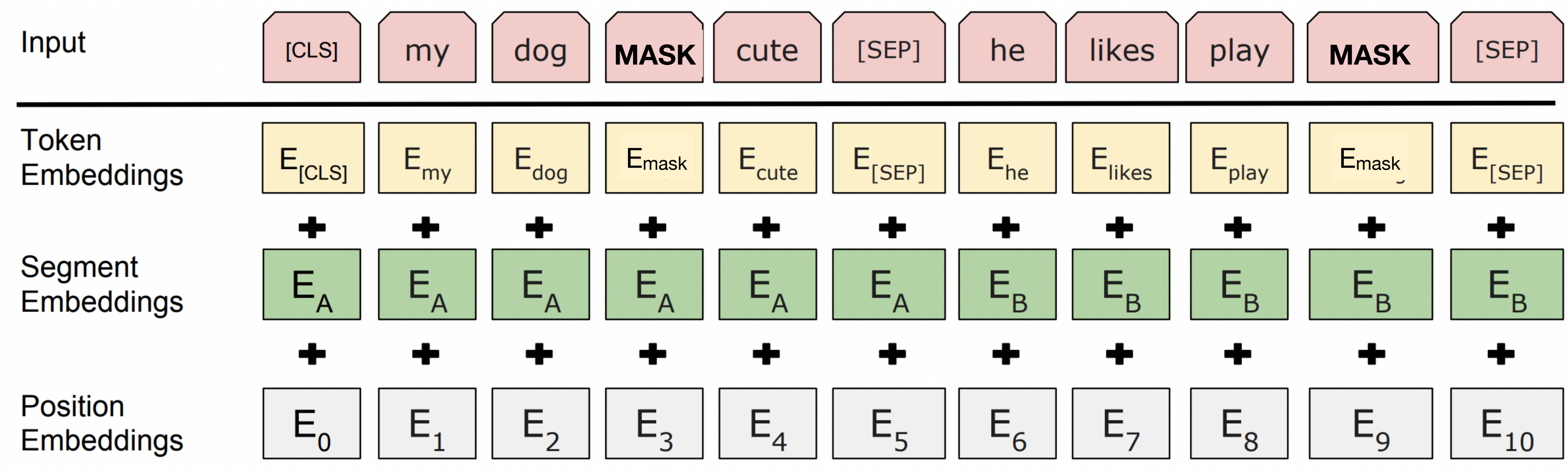

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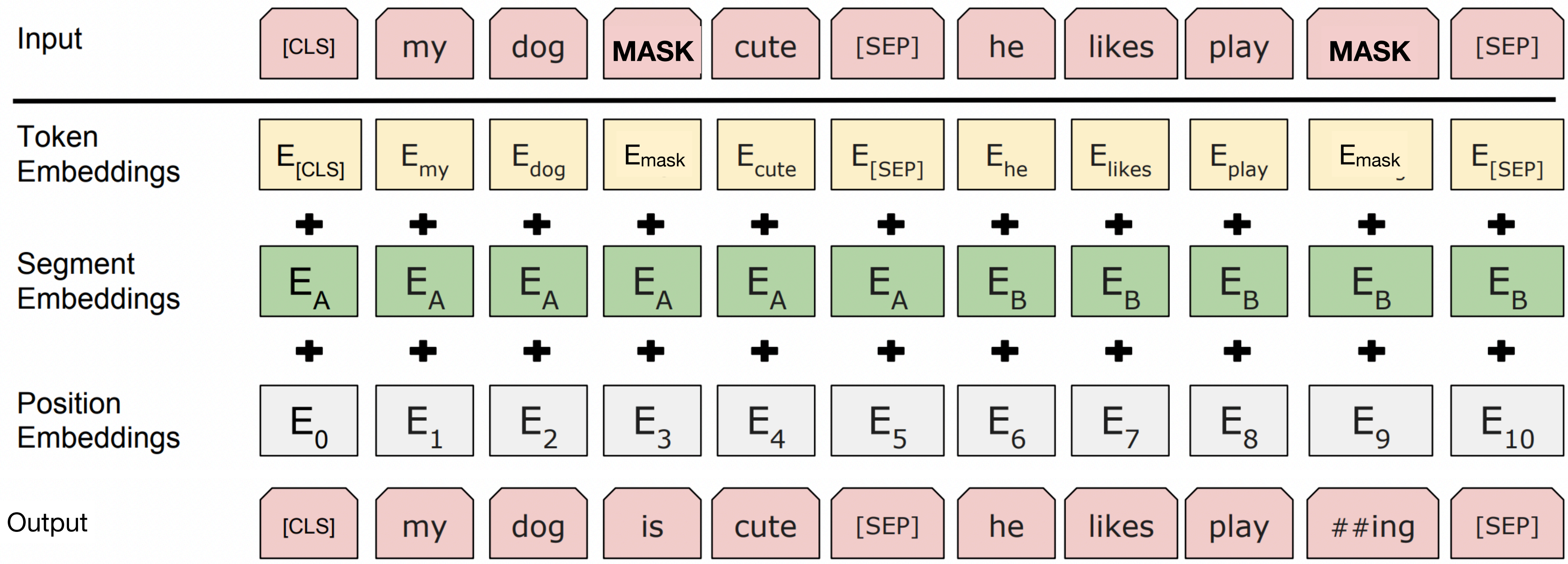

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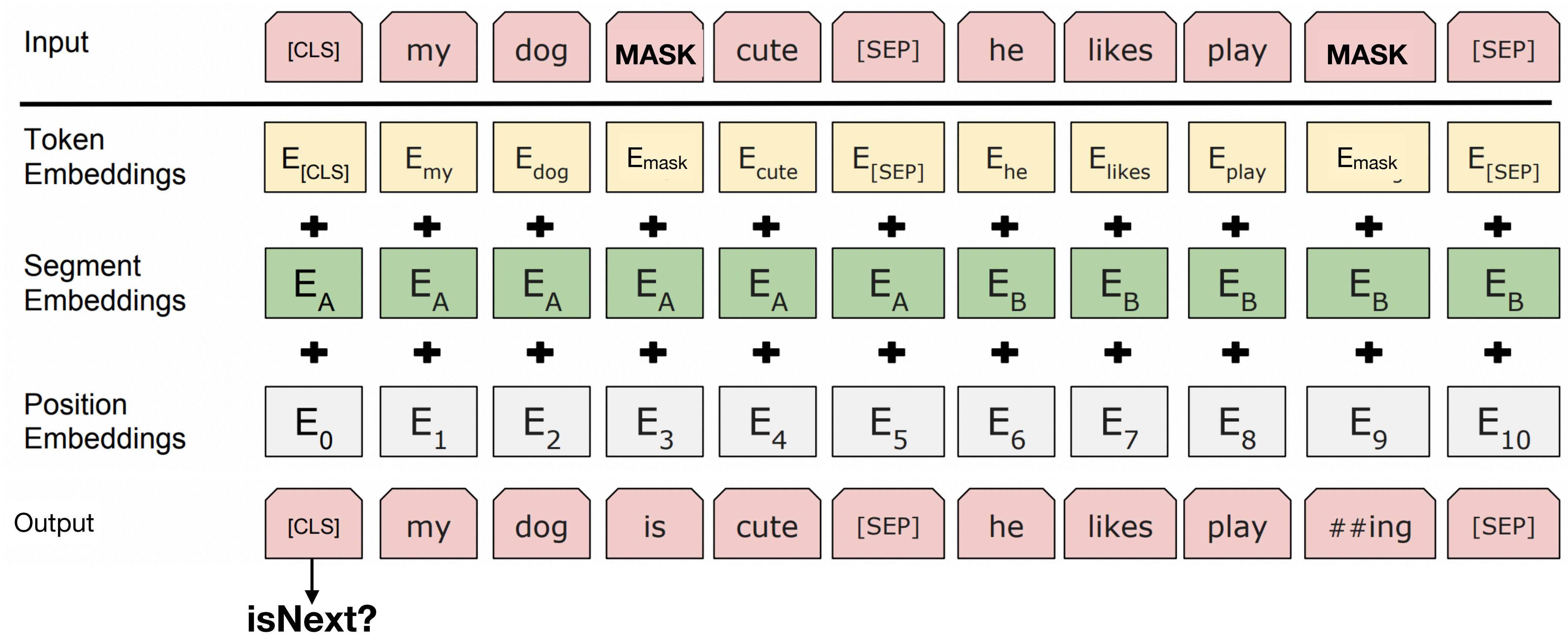
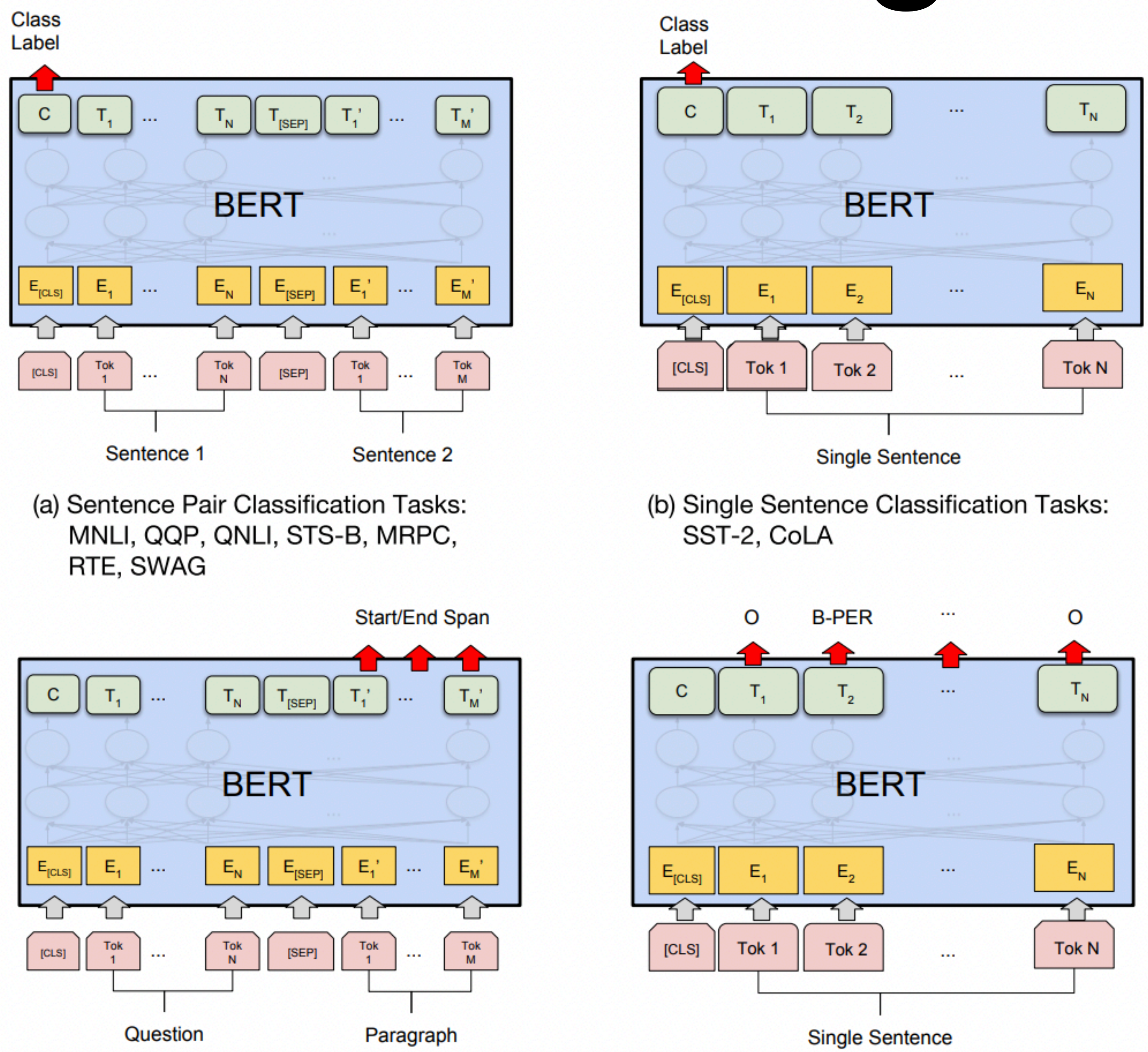
Next Sentence Prediction



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

Fine-tuning



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

(b) Single Sentence Classification Tasks: SST-2, CoLA

(c) Question Answering Tasks: SQuAD v1.1

(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]

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