Neural Network Language Models

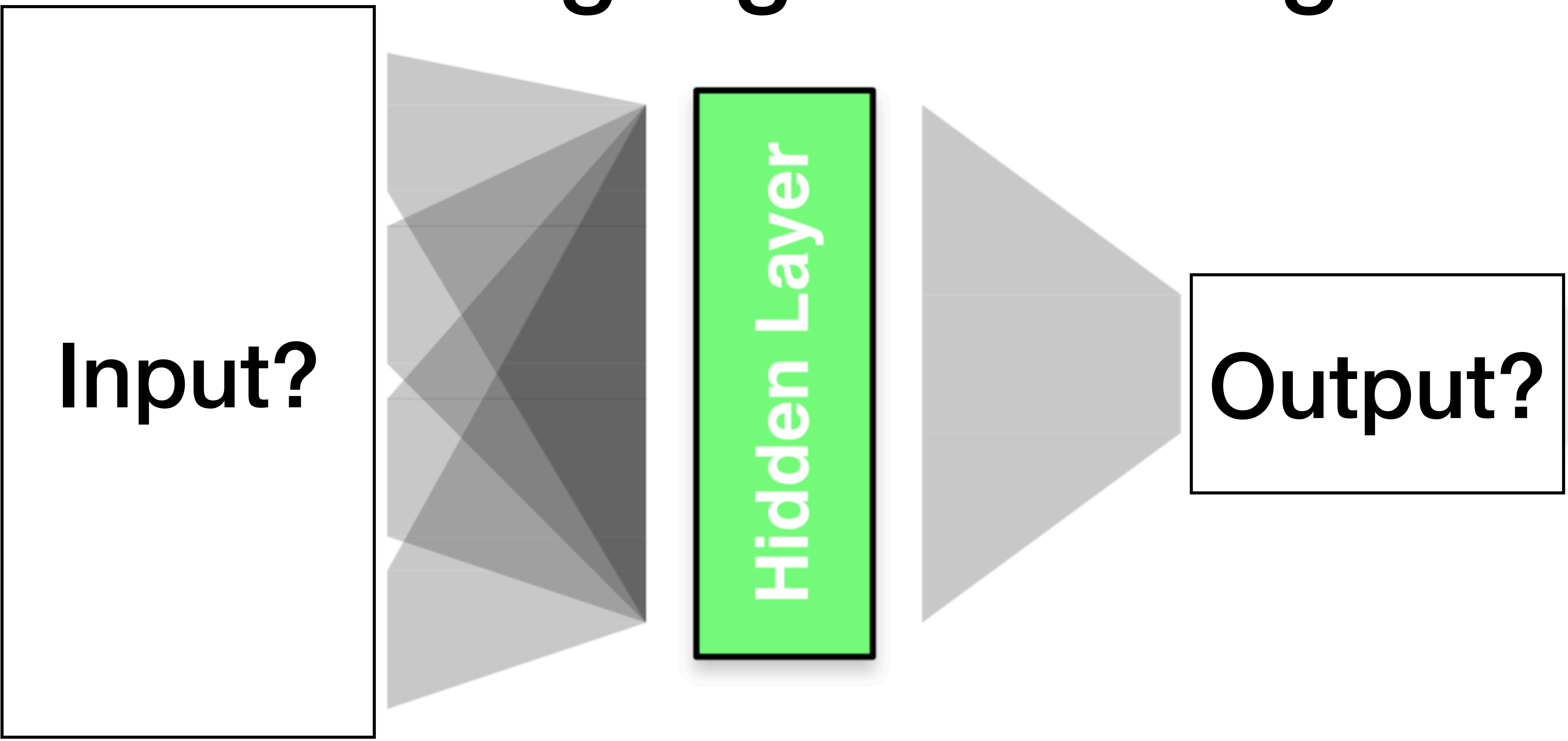
Mittul Singh

Recap: N-gram Language Models

- N-gram language model

$$P(w_i|w_{i-1}, w_{i-2}, w_{i-3}, w_{i-4})$$

Neural Network Classifier for Language Modelling



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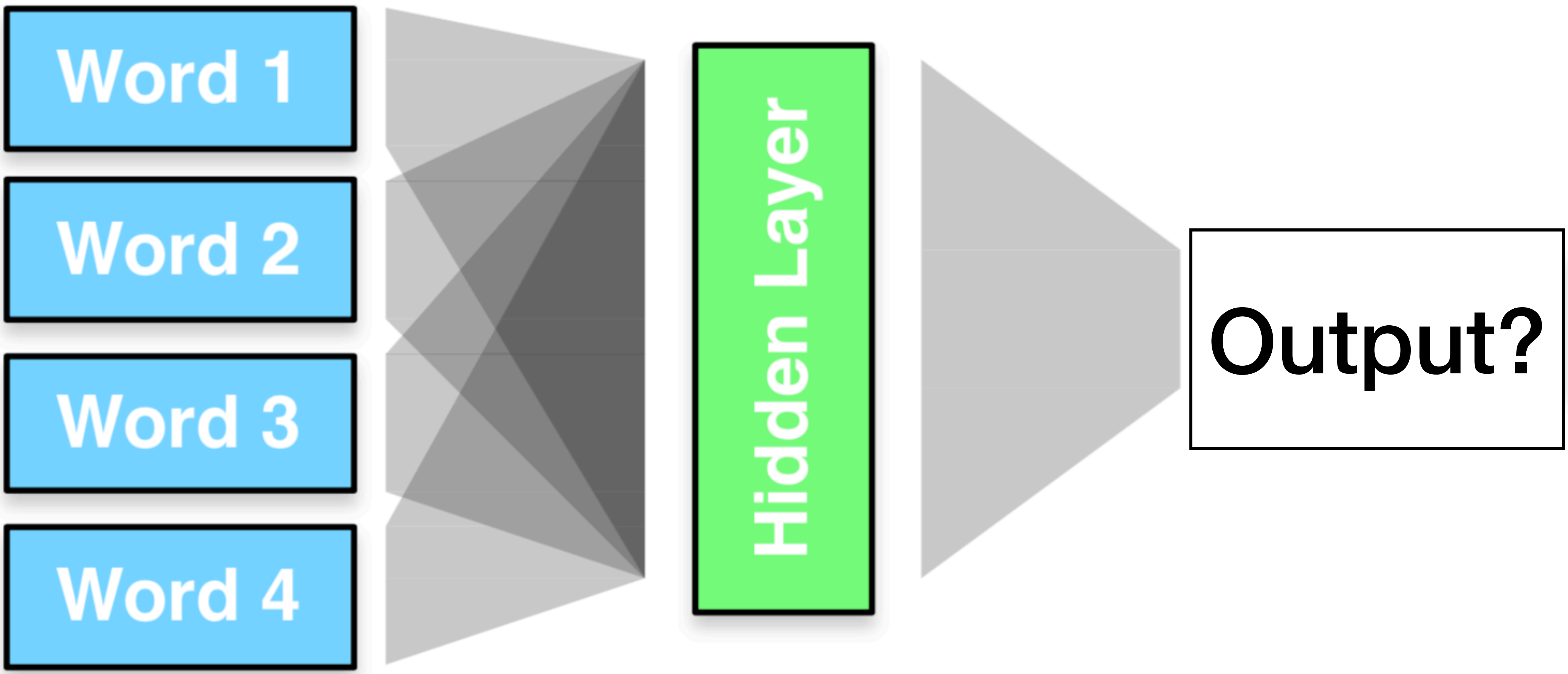

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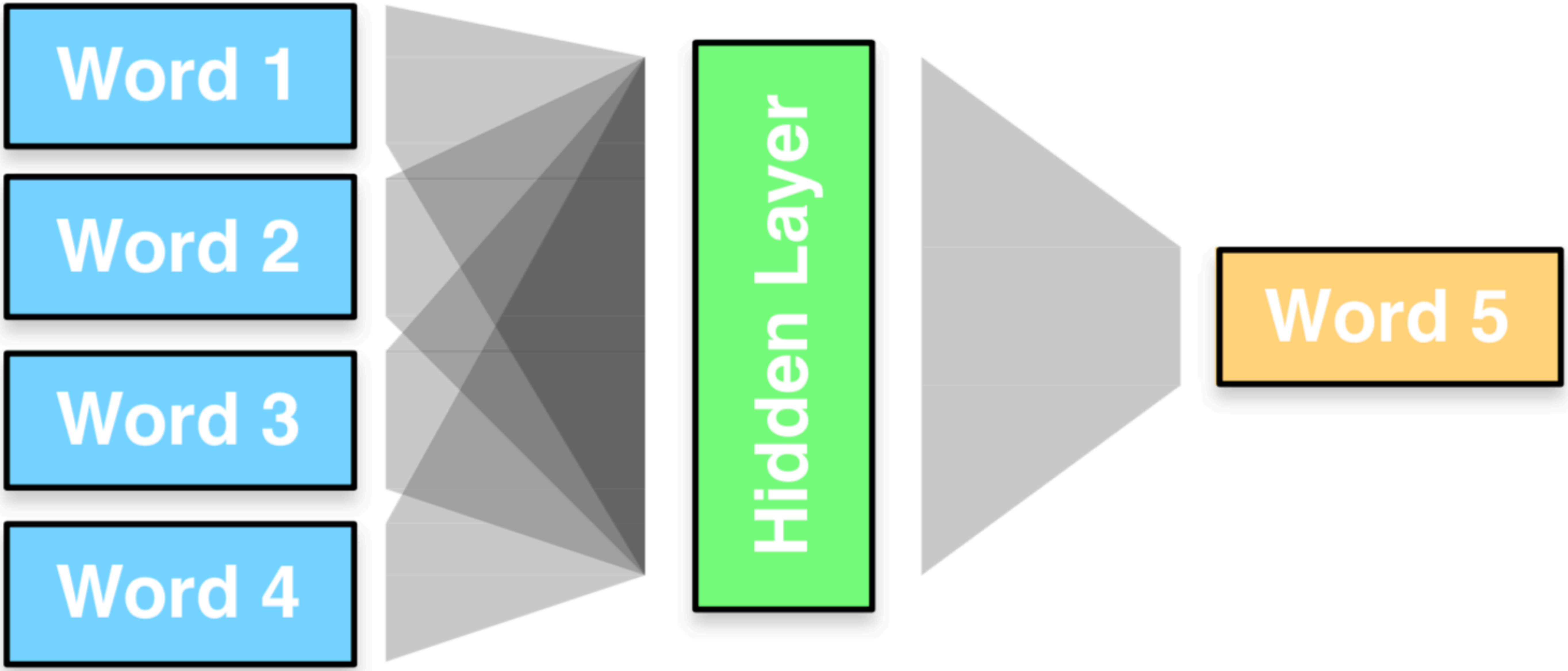

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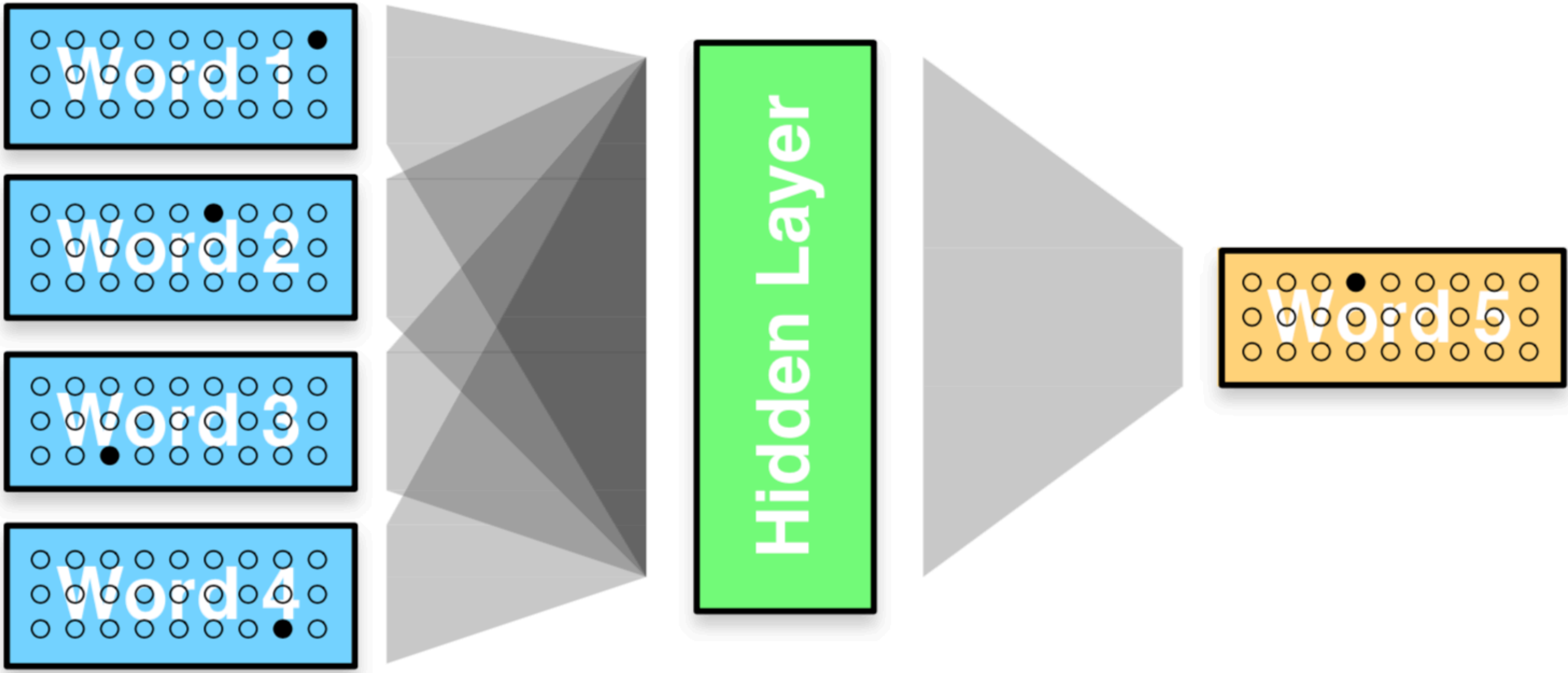
Representing Words

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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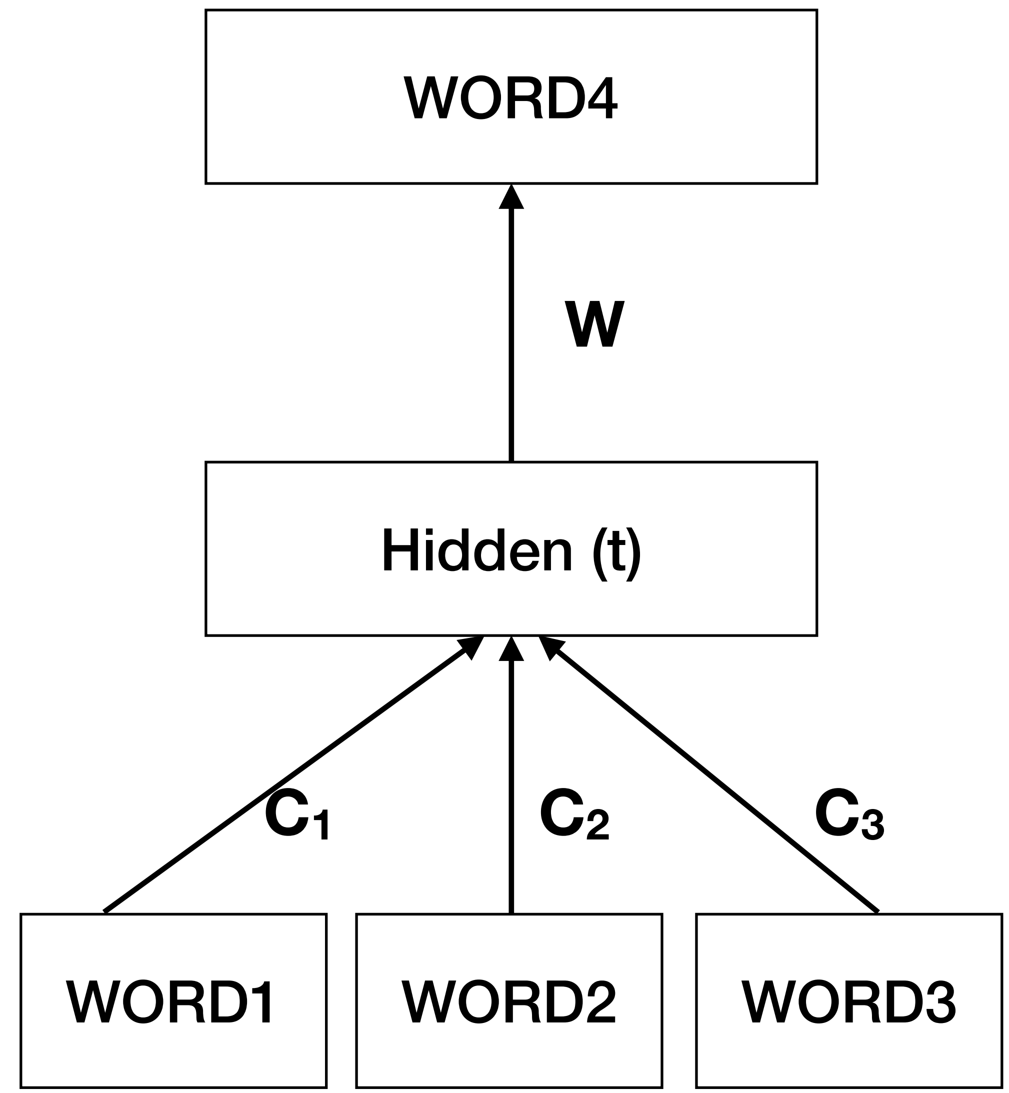
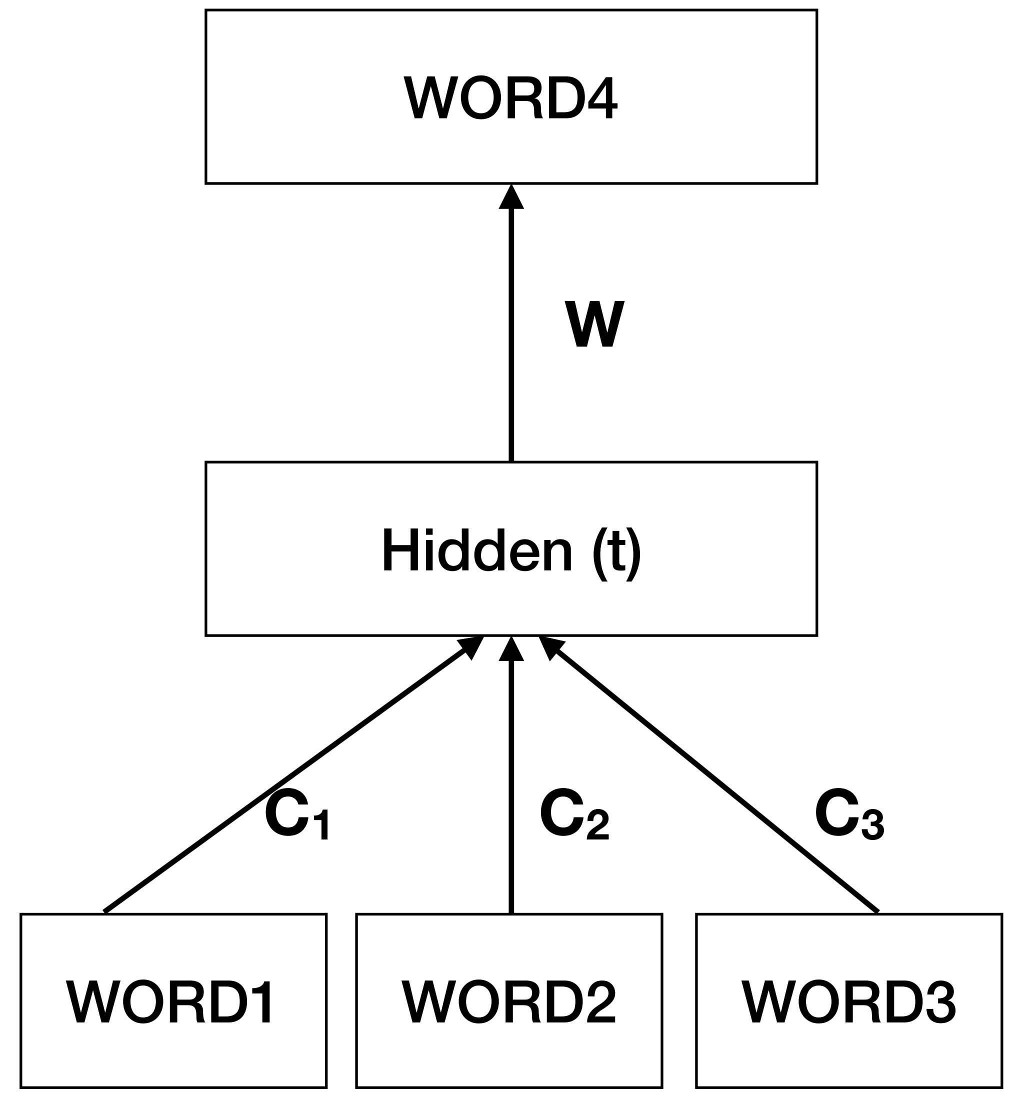
Feedforward Neural Network LM (FFNN)



FFNN

Feedforward Neural Network LM (FFNN)

- Loop through the entire corpus



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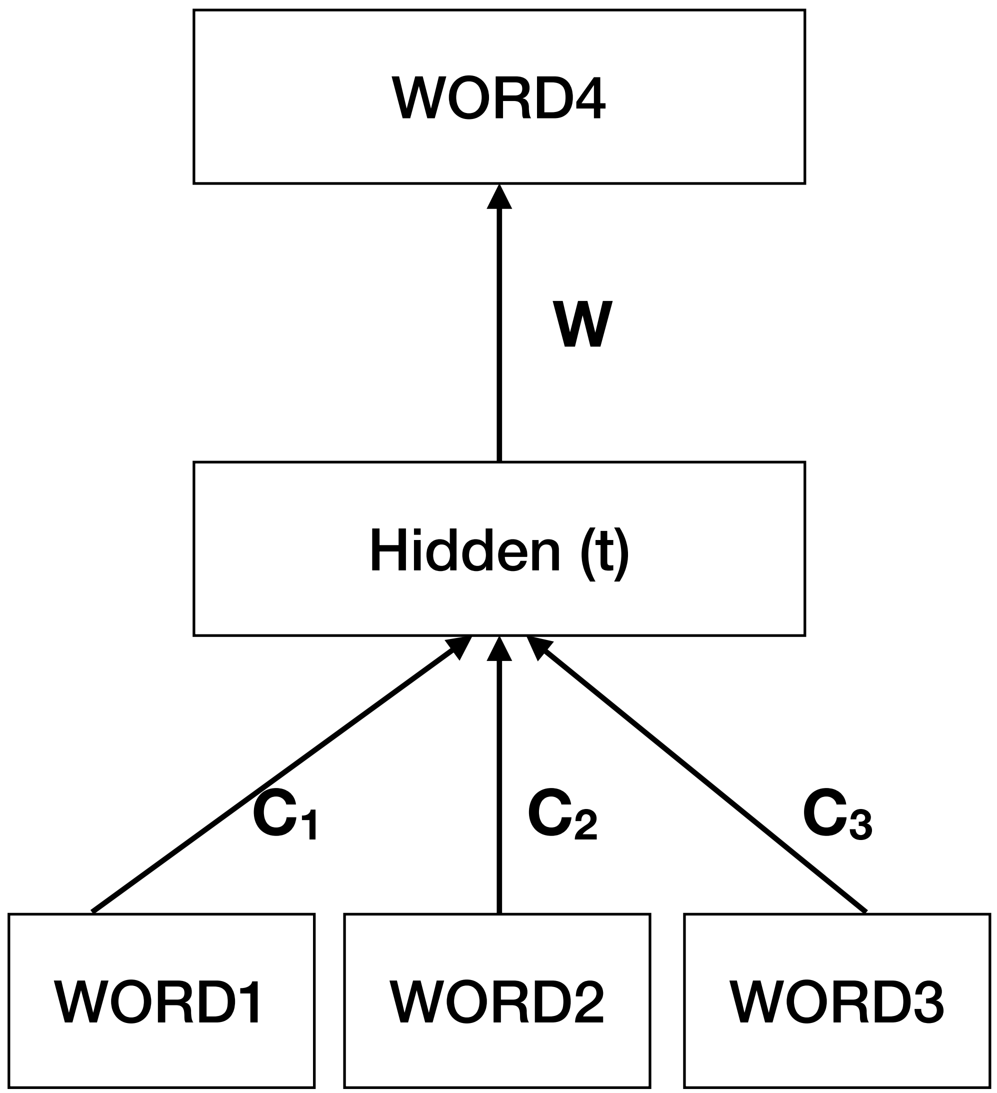

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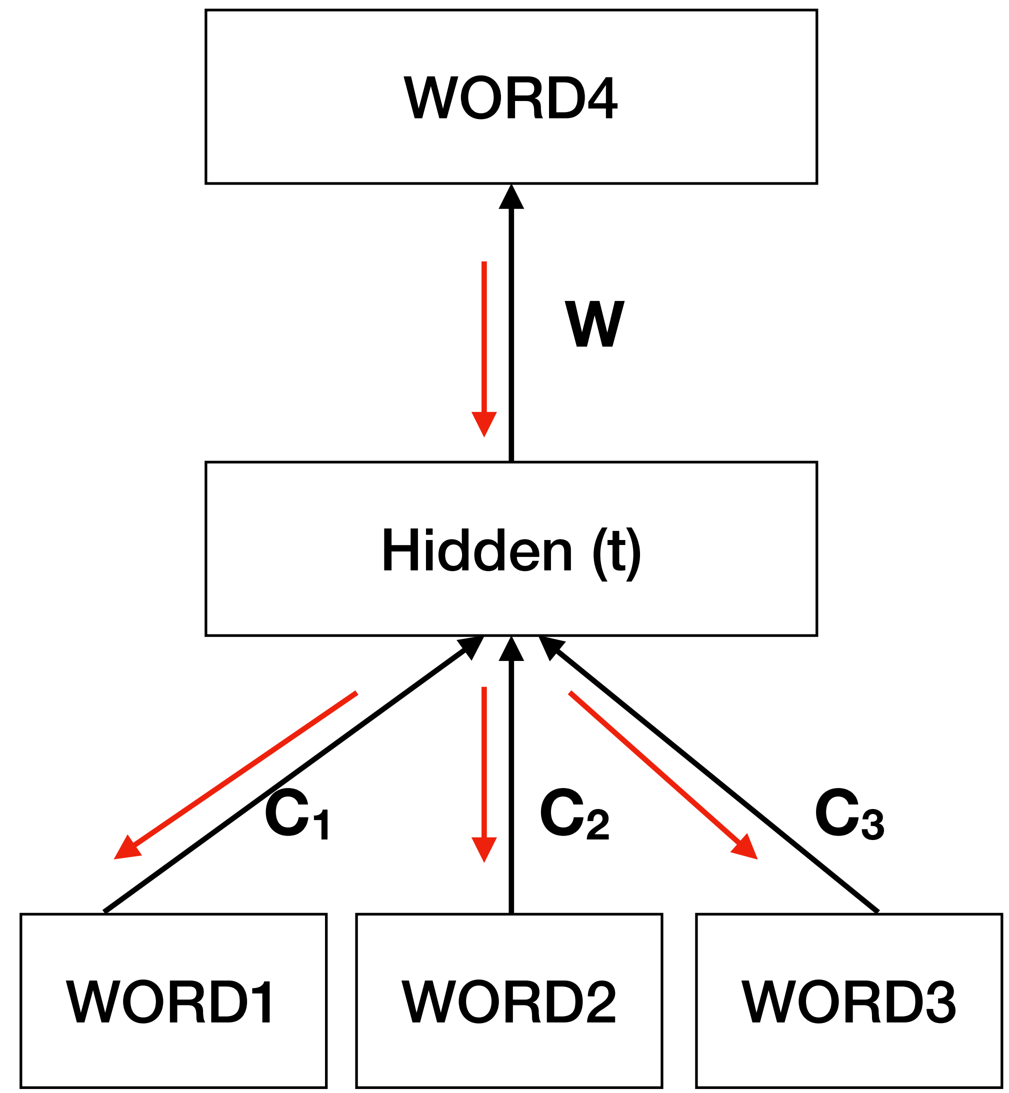
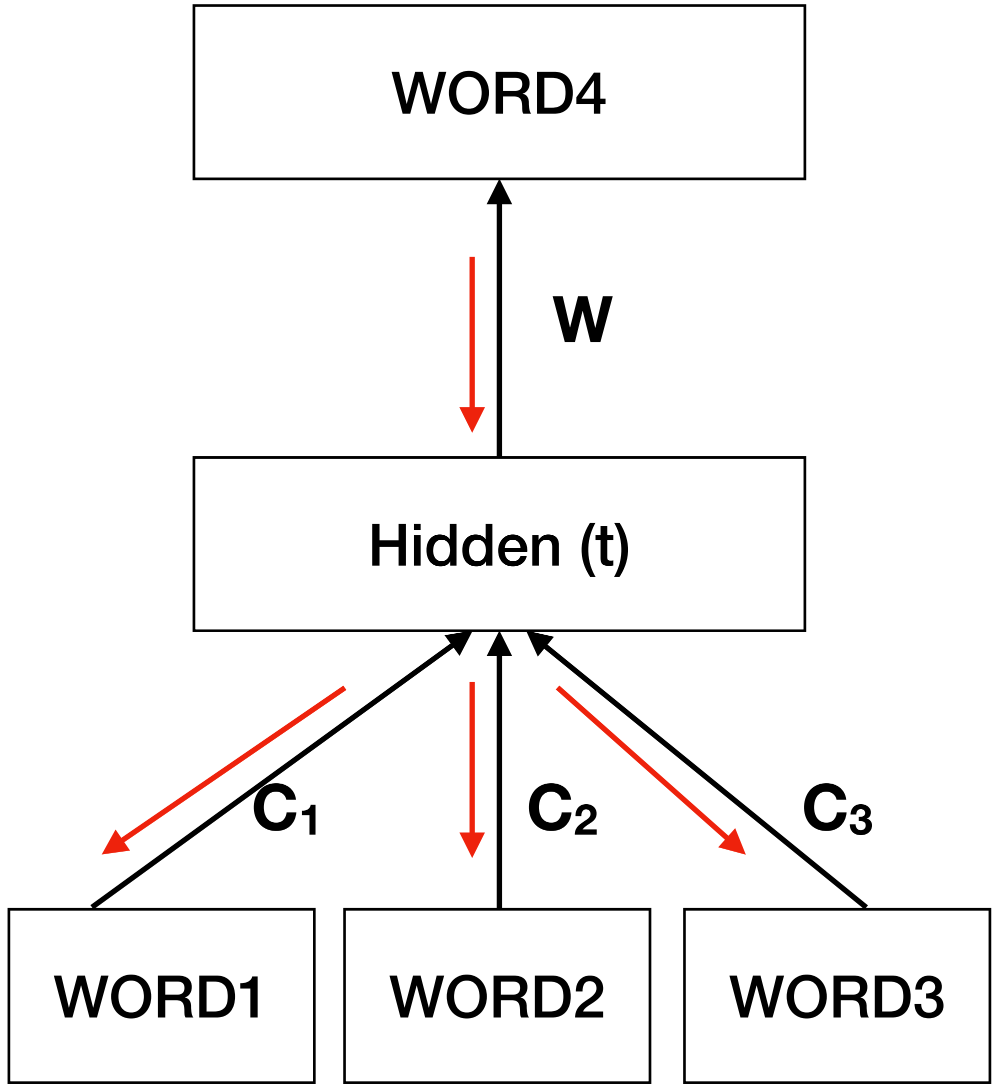
- Propagate the error through network to update the weight matrices



FFNN

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 ________.”

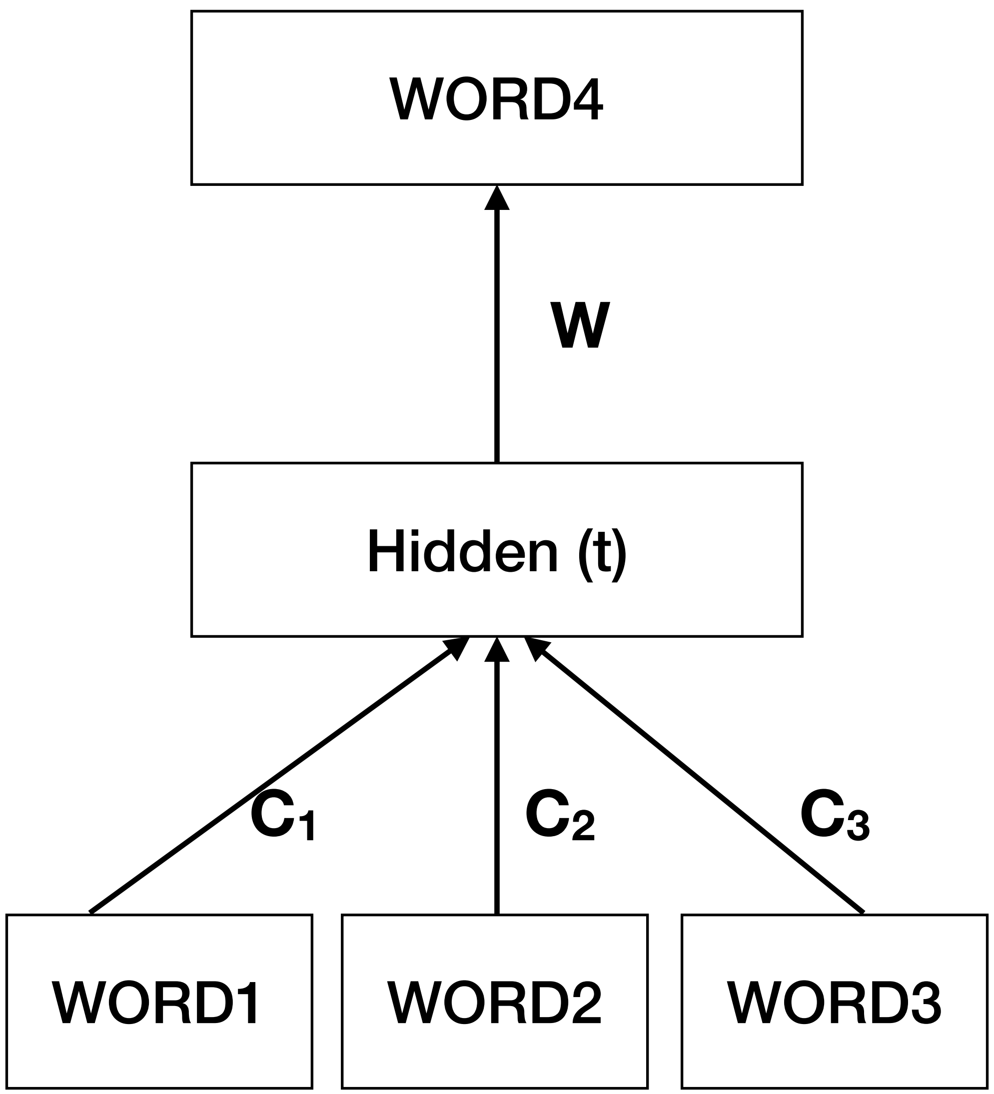
Feedforward: Long-term information

- “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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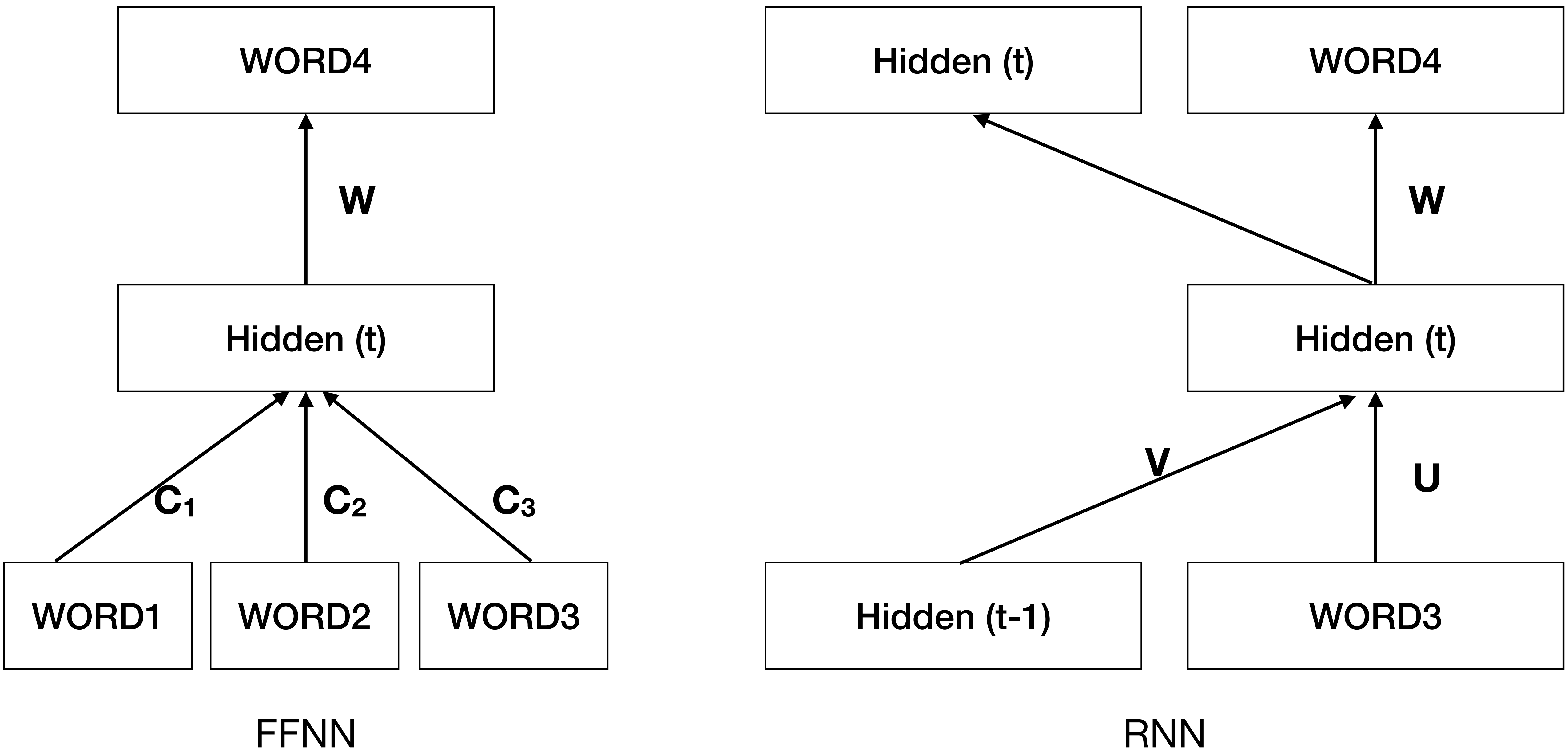

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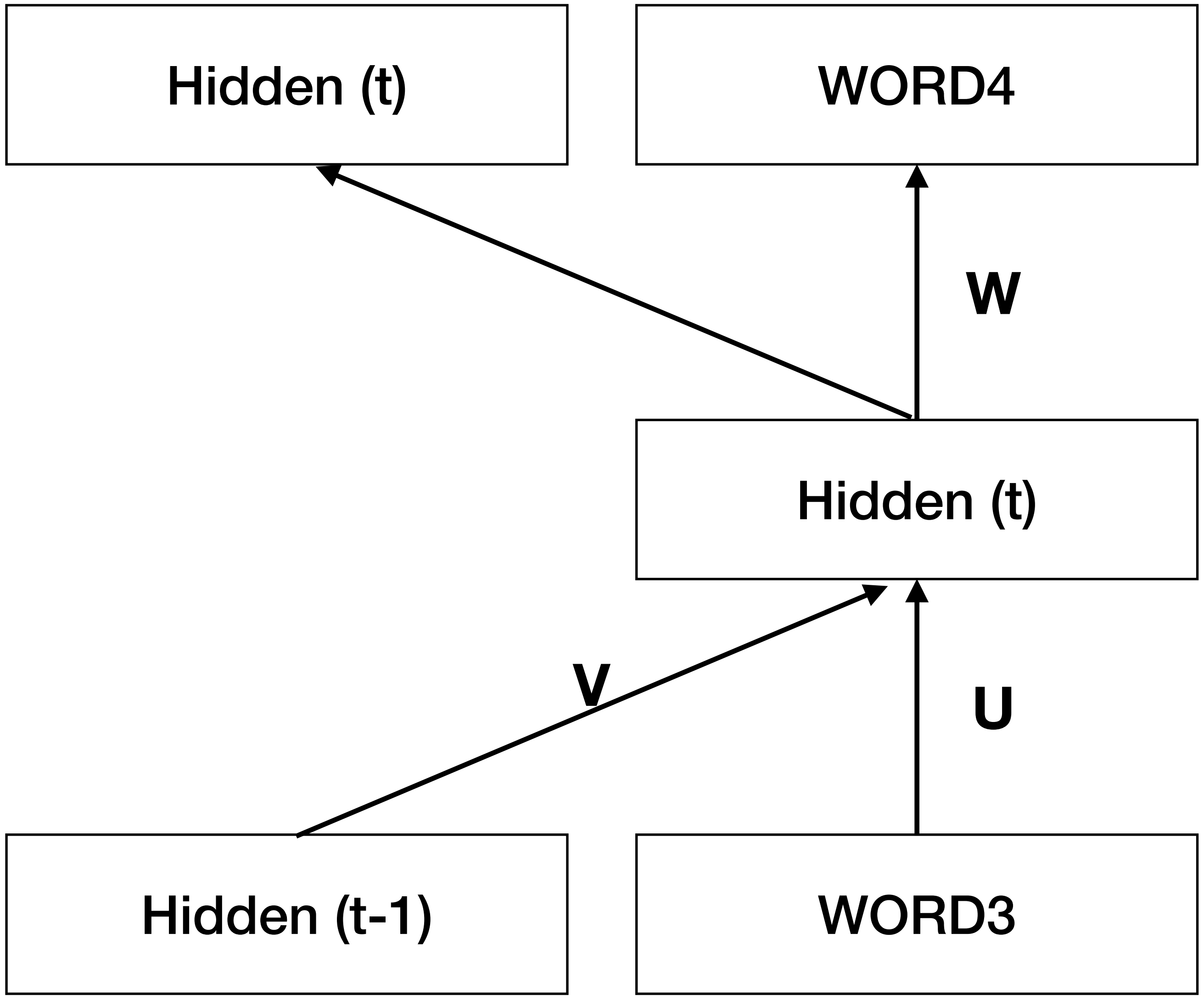

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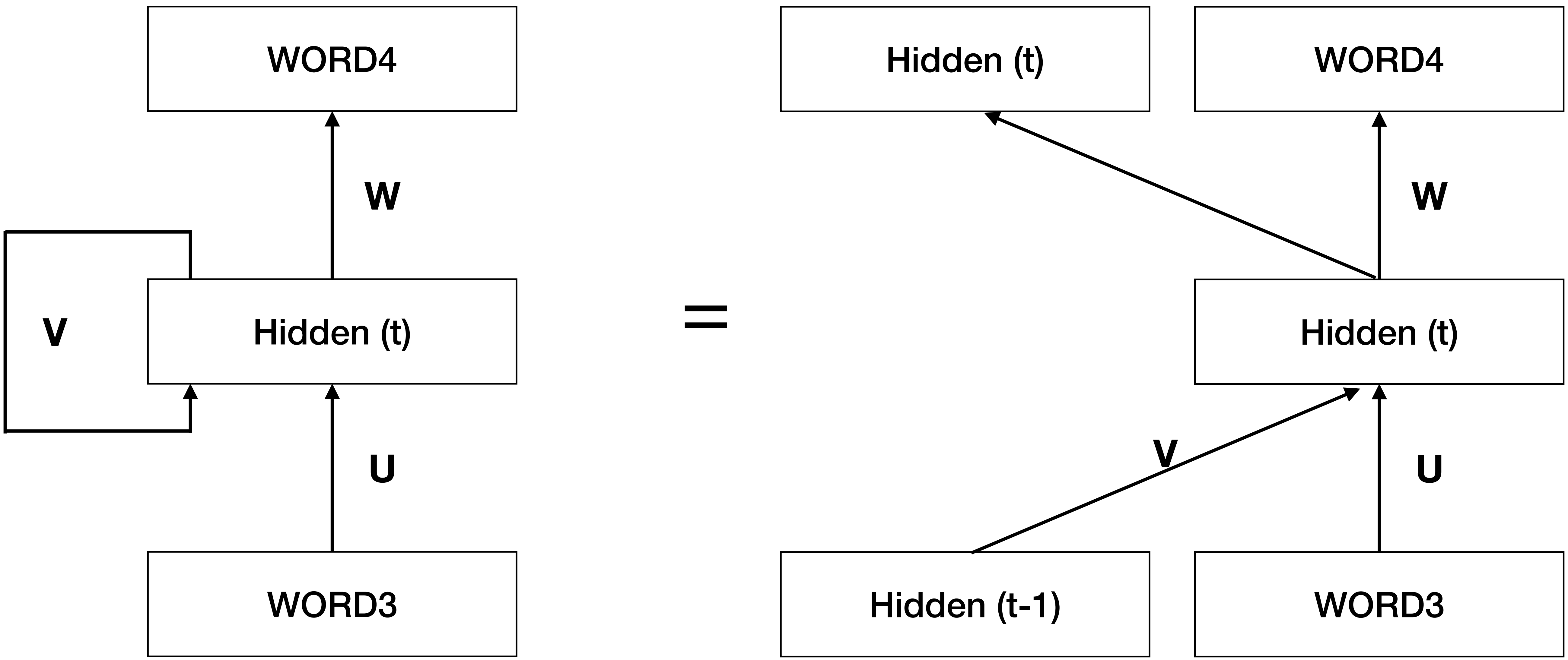
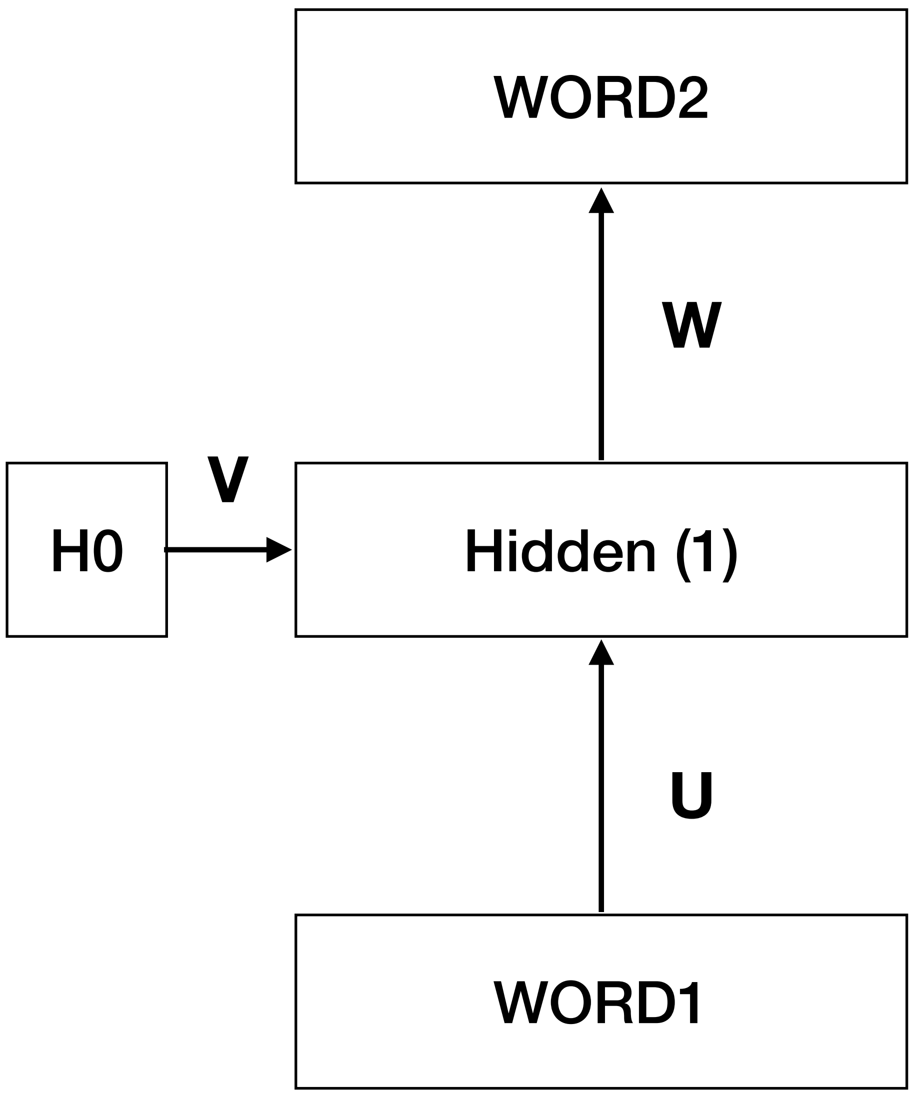
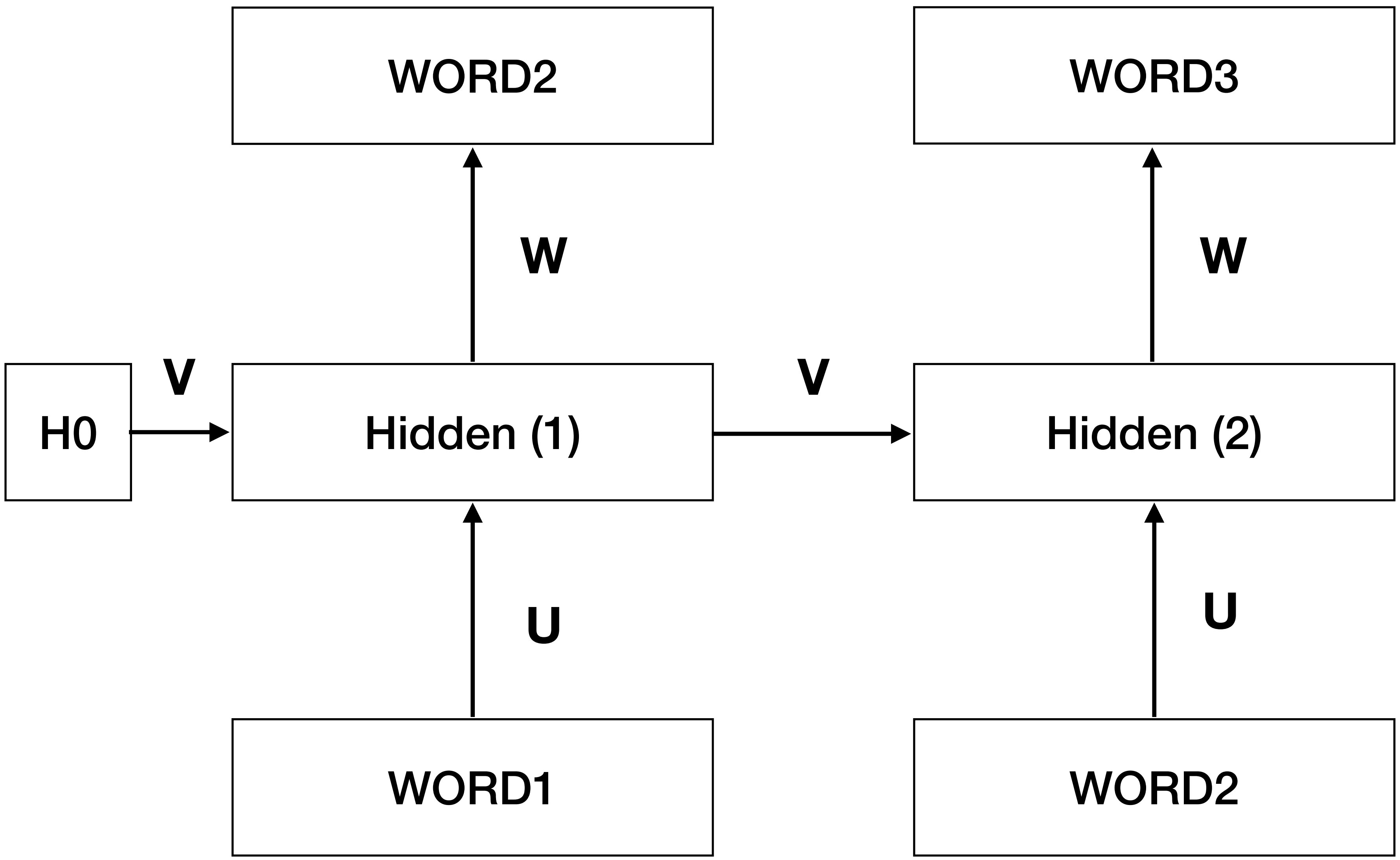


RNN

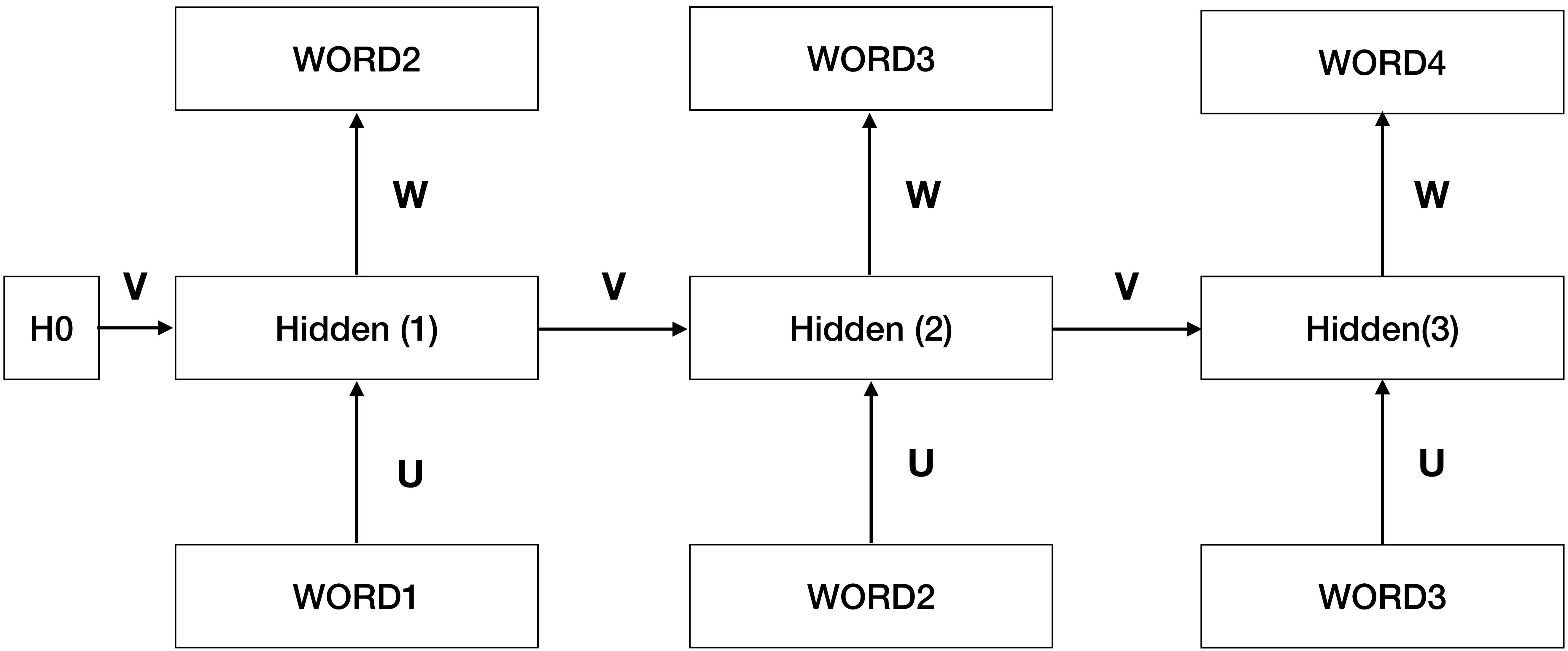
RNN: Timestep 1



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_."

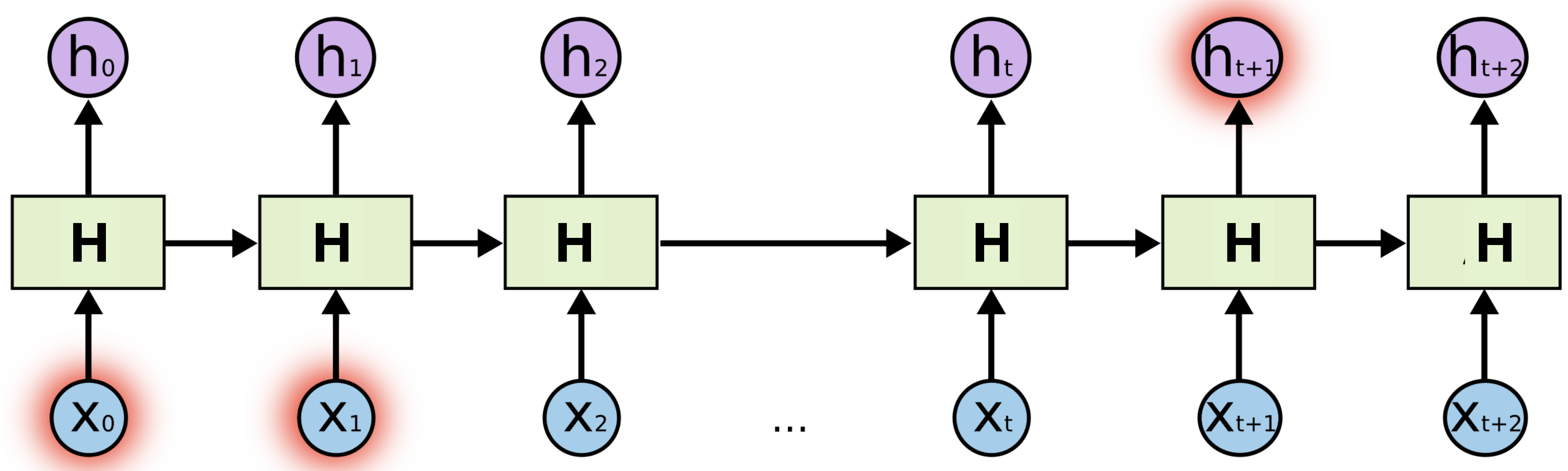
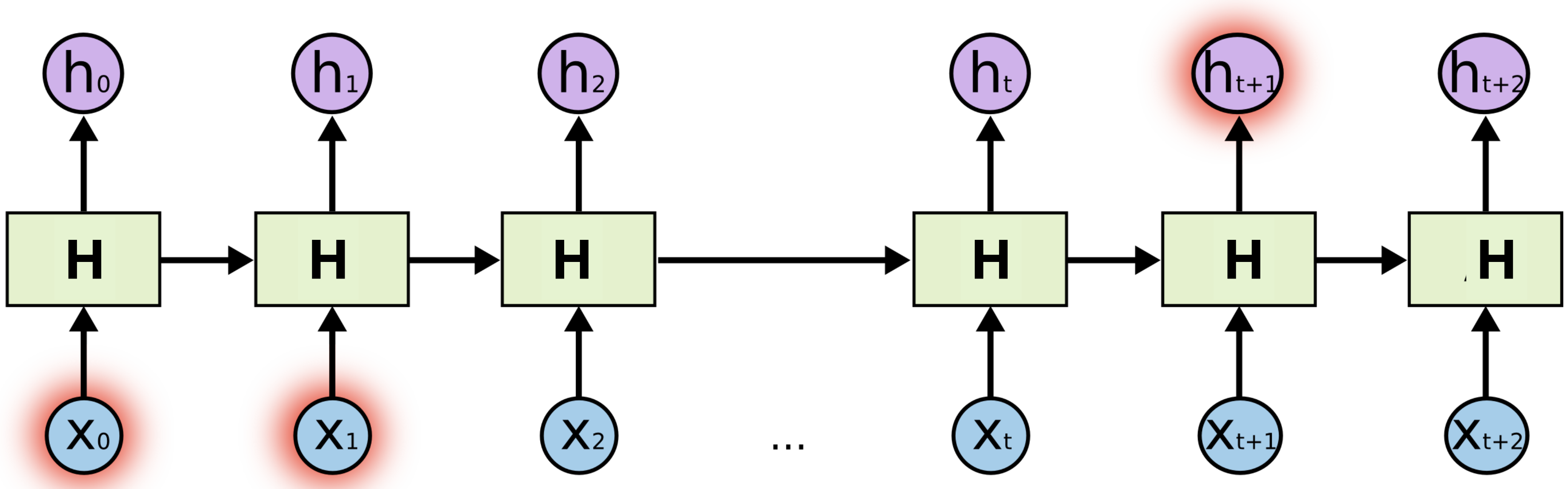


Image: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

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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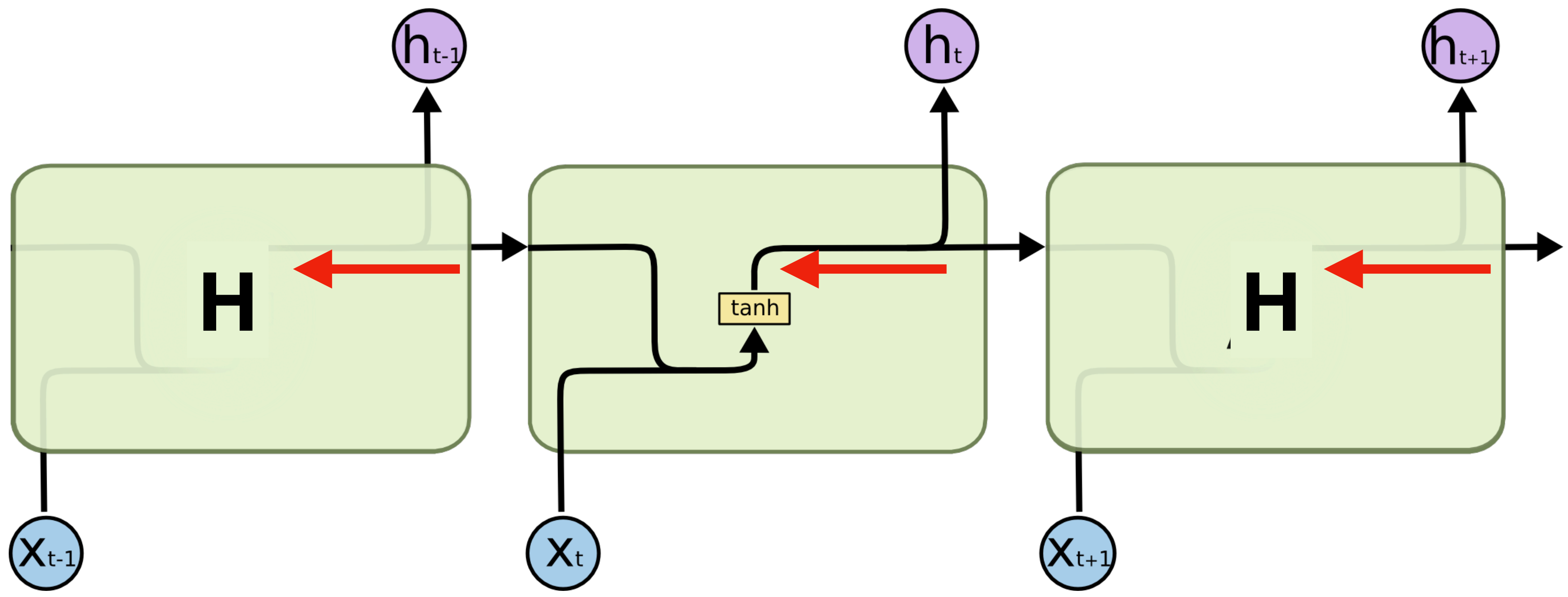
RNN



- 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

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- Sequence Modeling: https://www.deeplearningbook.org/contents/rnn.html

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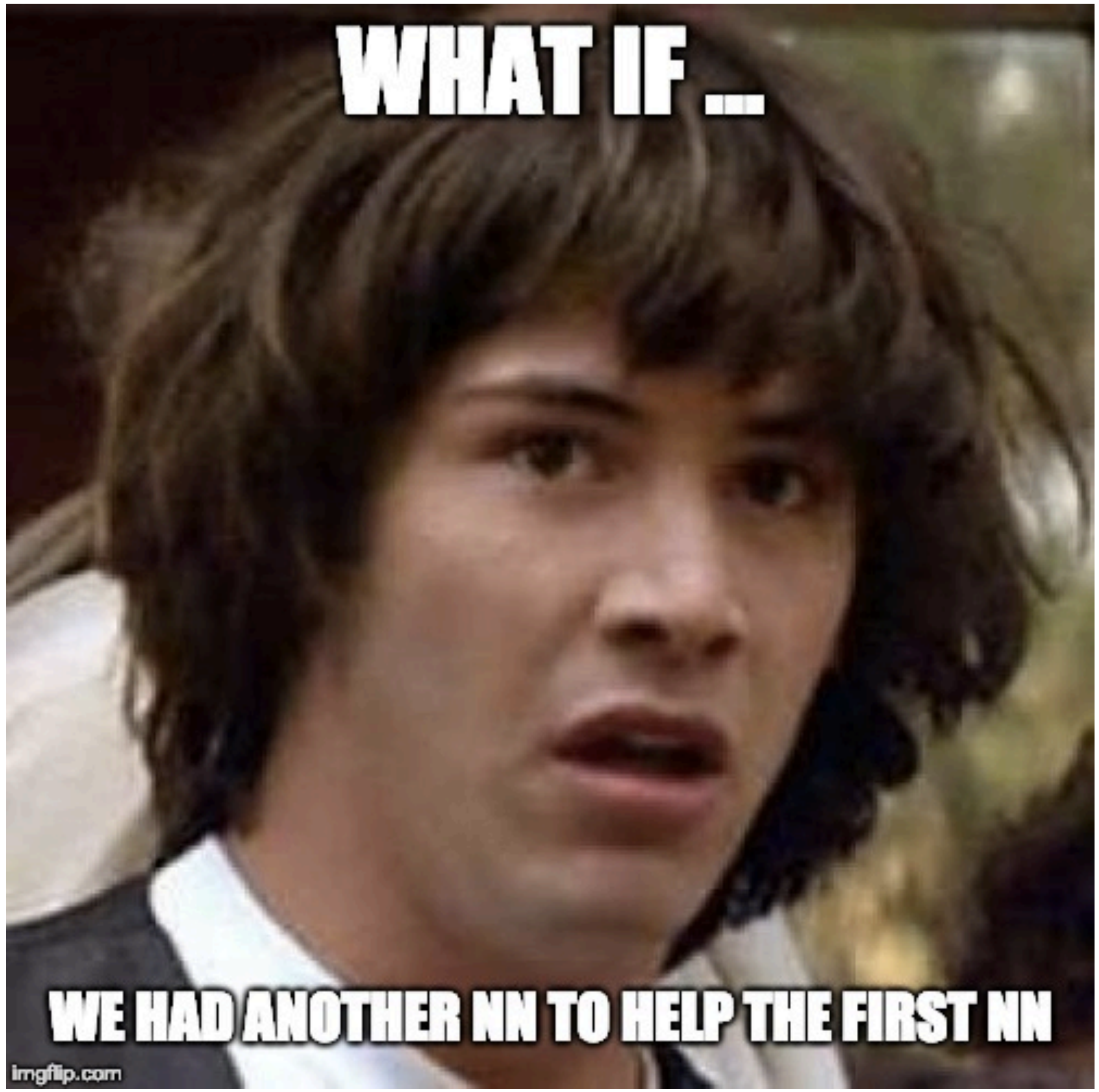
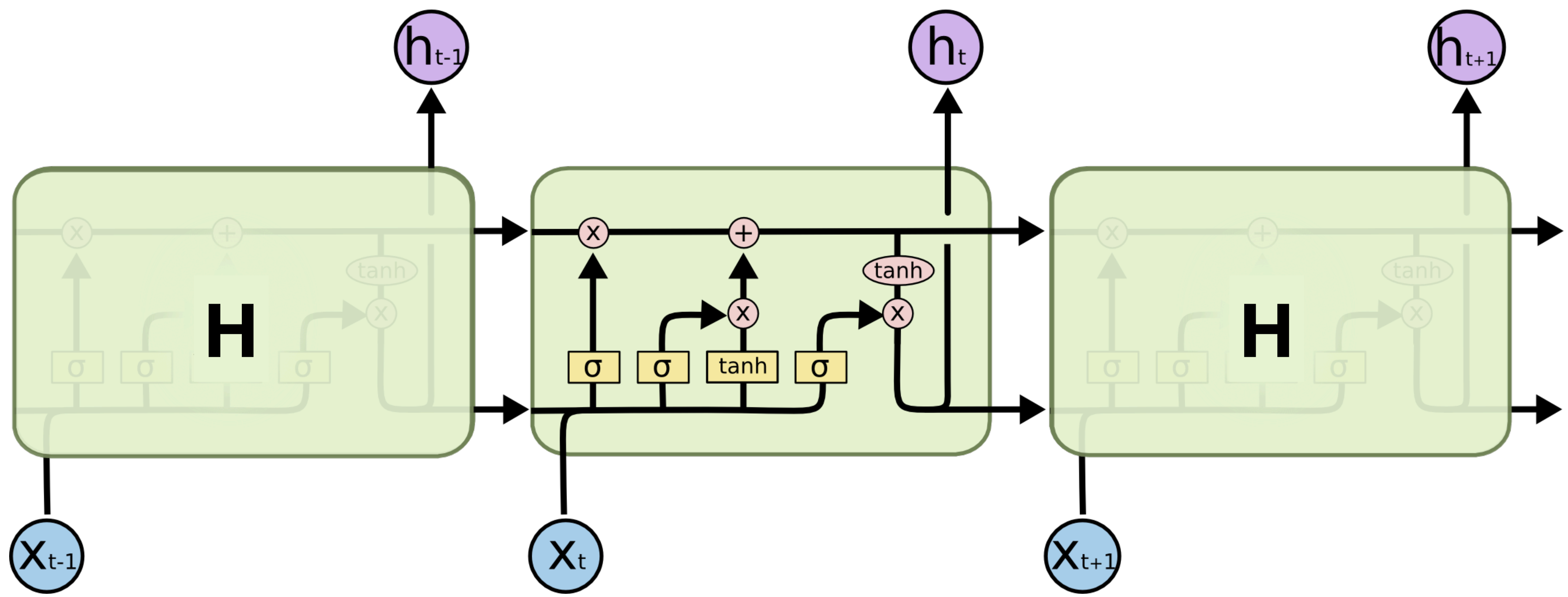

WHAT IF ...
WE HAD ANOTHER NN TO HELP THE FIRST NN
imgflip.com

Long-Short Term Memory

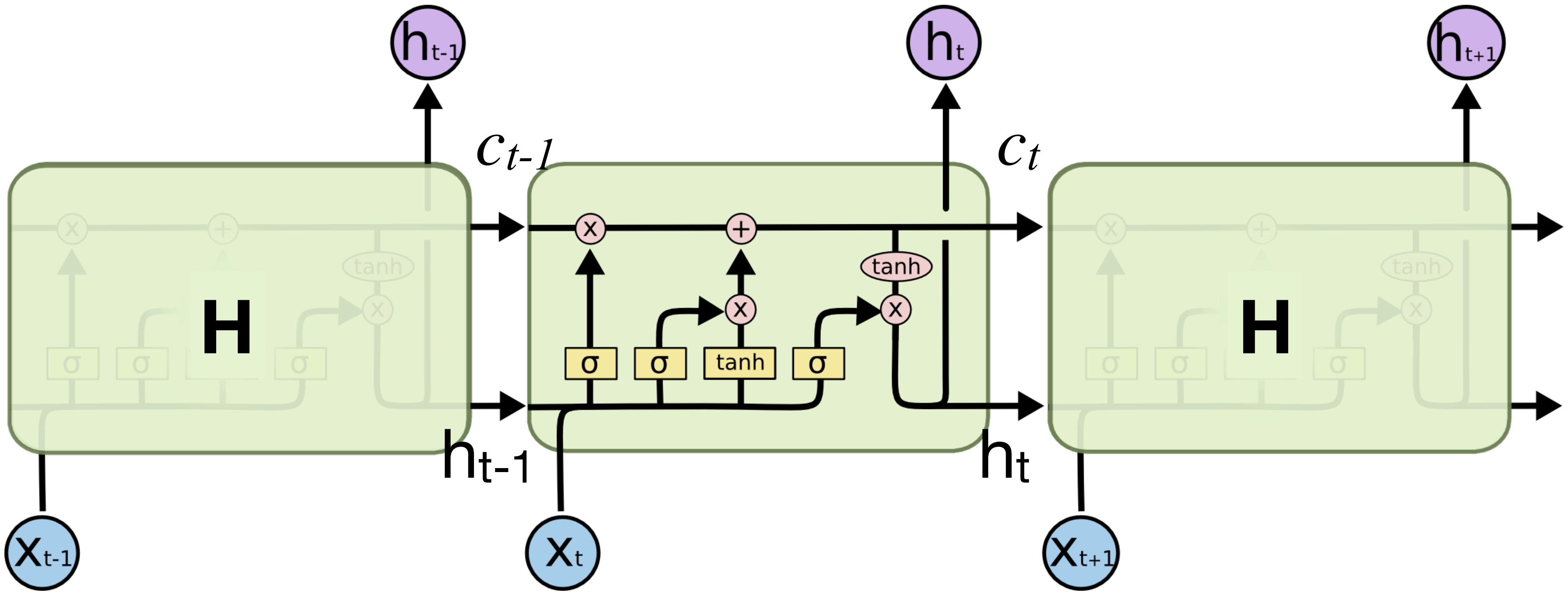


- Lets add another neural network help the first network learn long-distance relationships

- 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



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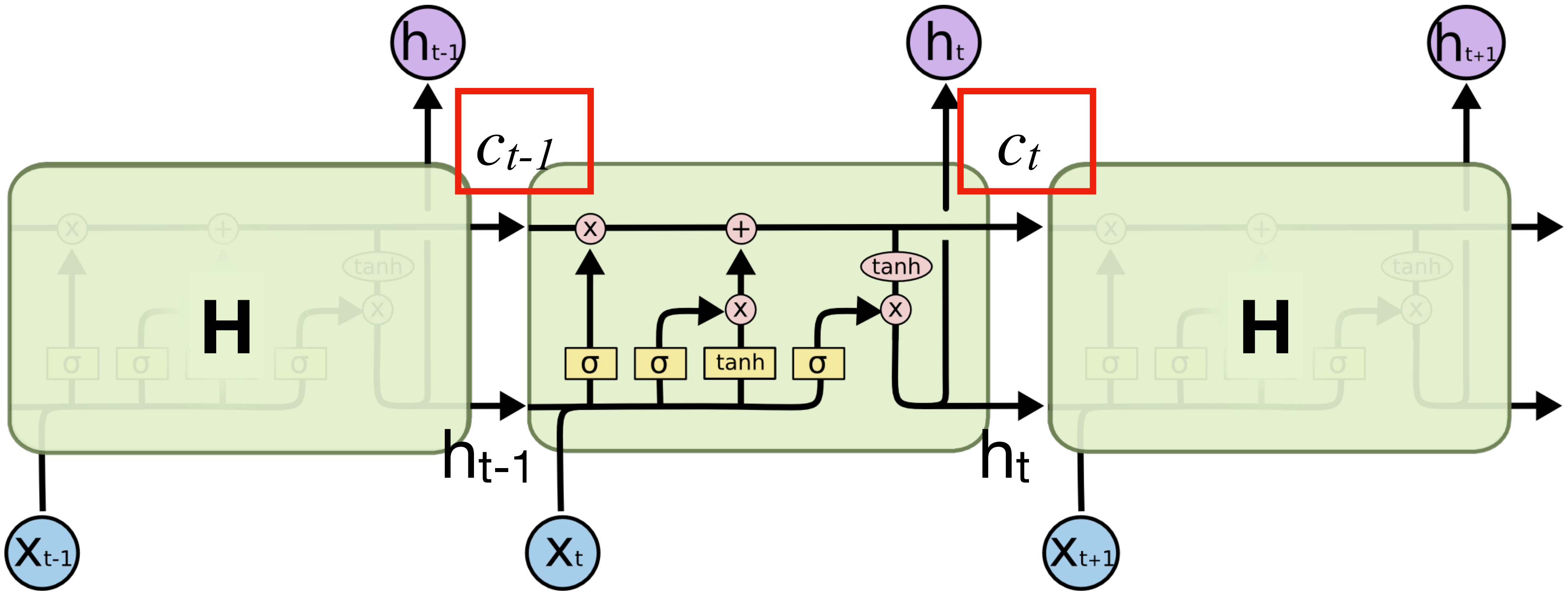
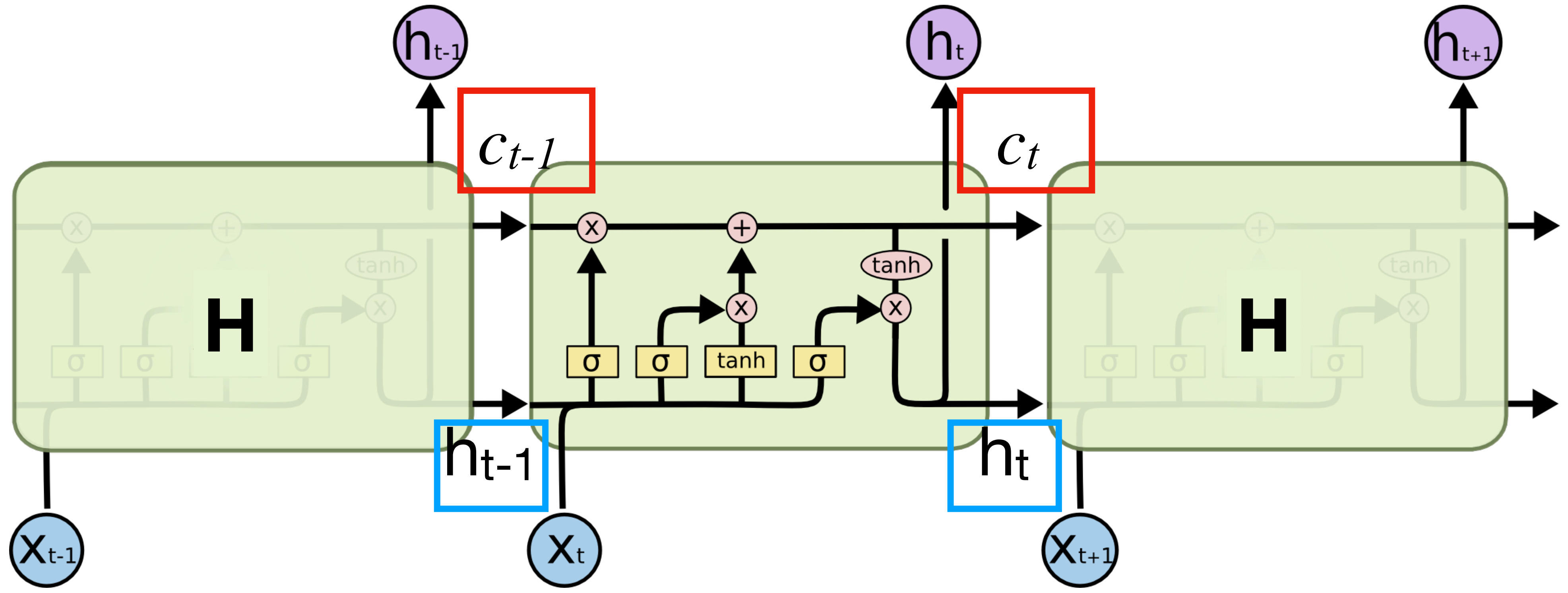


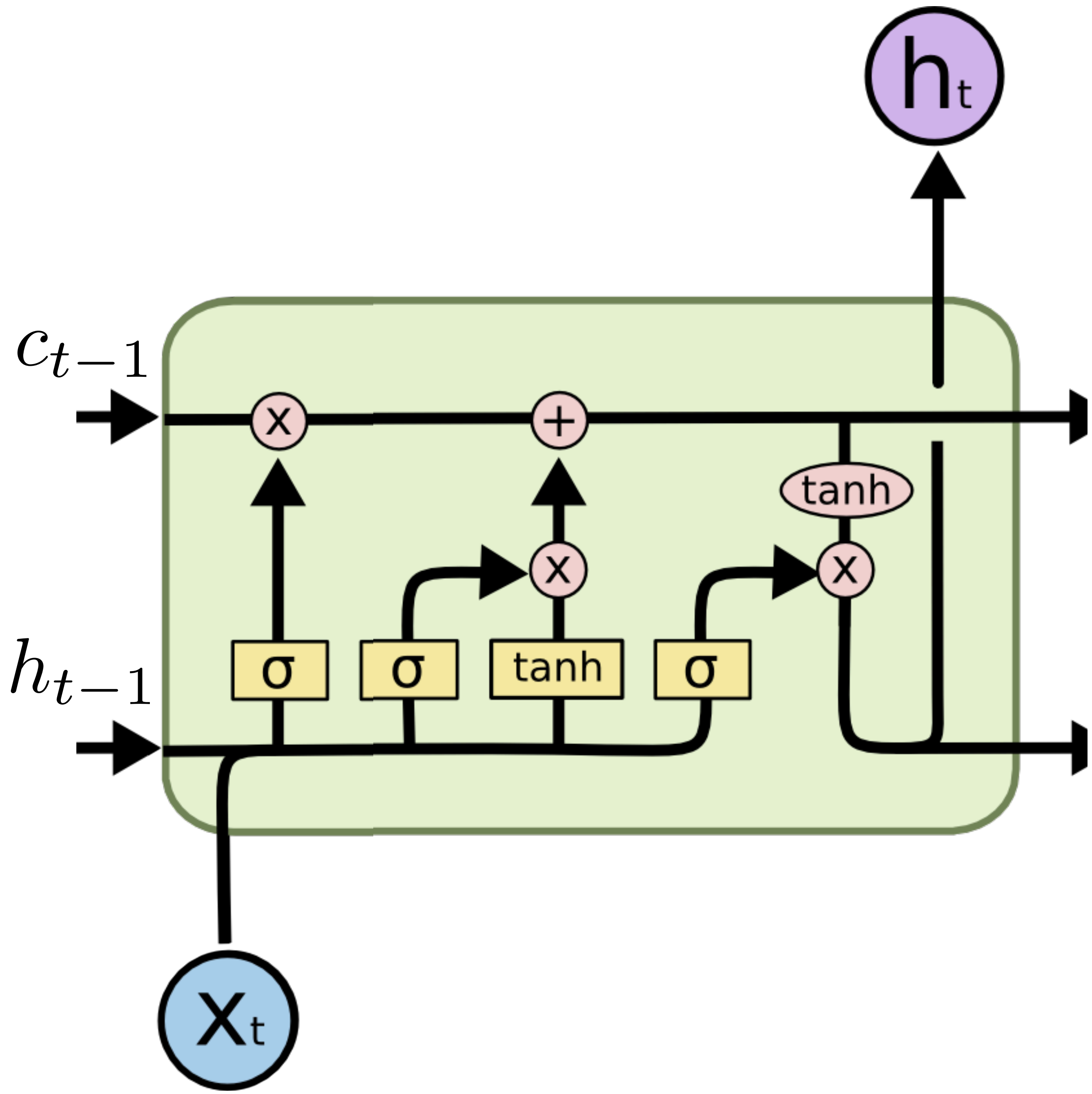
- Global State c captures global information at the document/ sentence level

LSTM: States

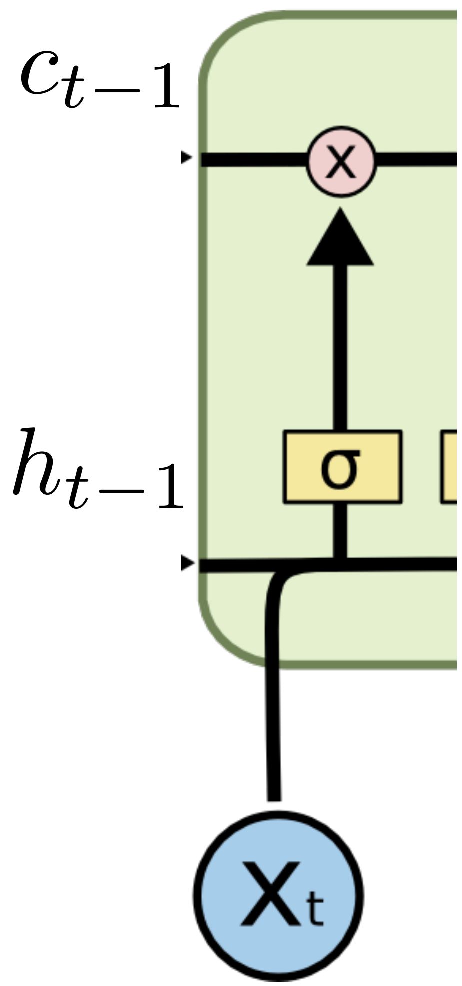


- Global State c captures global information at the document/ sentence level

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



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



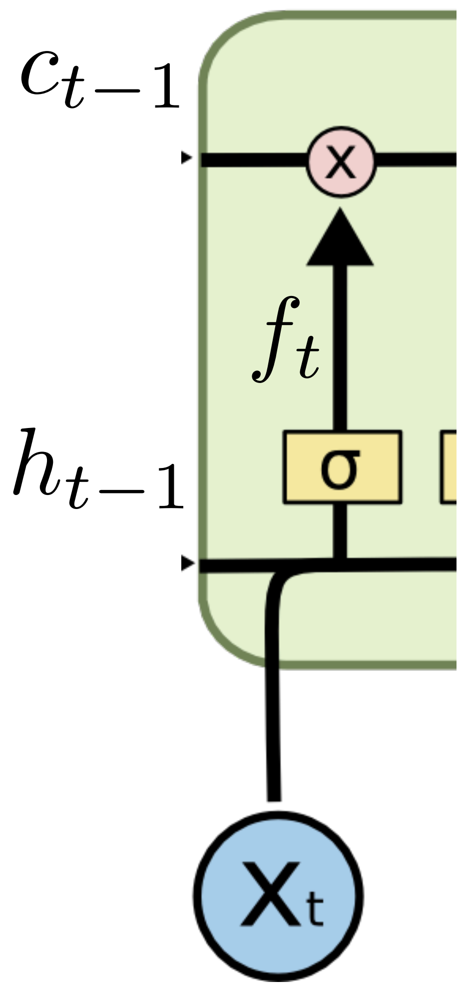
σ sigmoid function

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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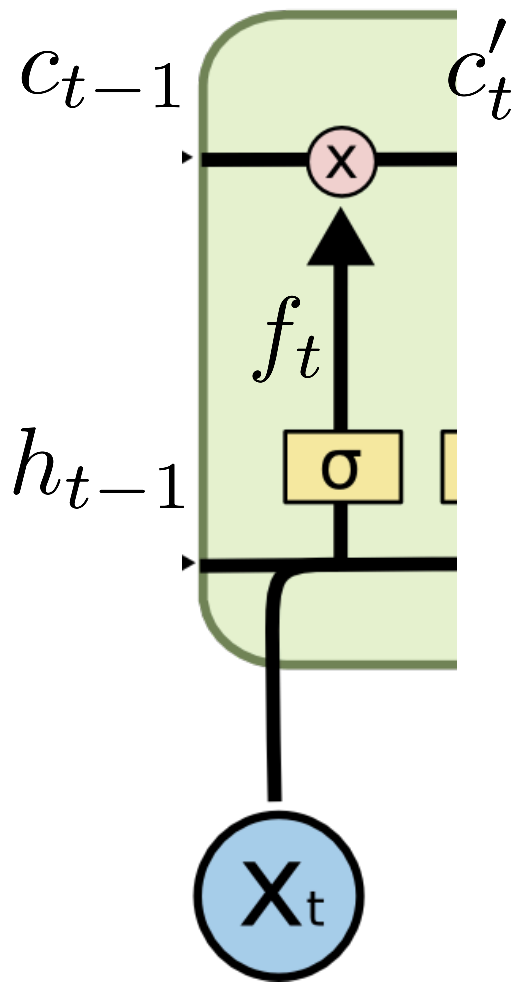

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- weights and bias

  $w_f = [1 \quad 1]$

  $b_f = 0$

- σ : sigmoid fn * : pointwise multiplication
- h_{t-1} = [1], c_{t-1} = [2], x_t = [0.2]
- calculate: c'_t

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

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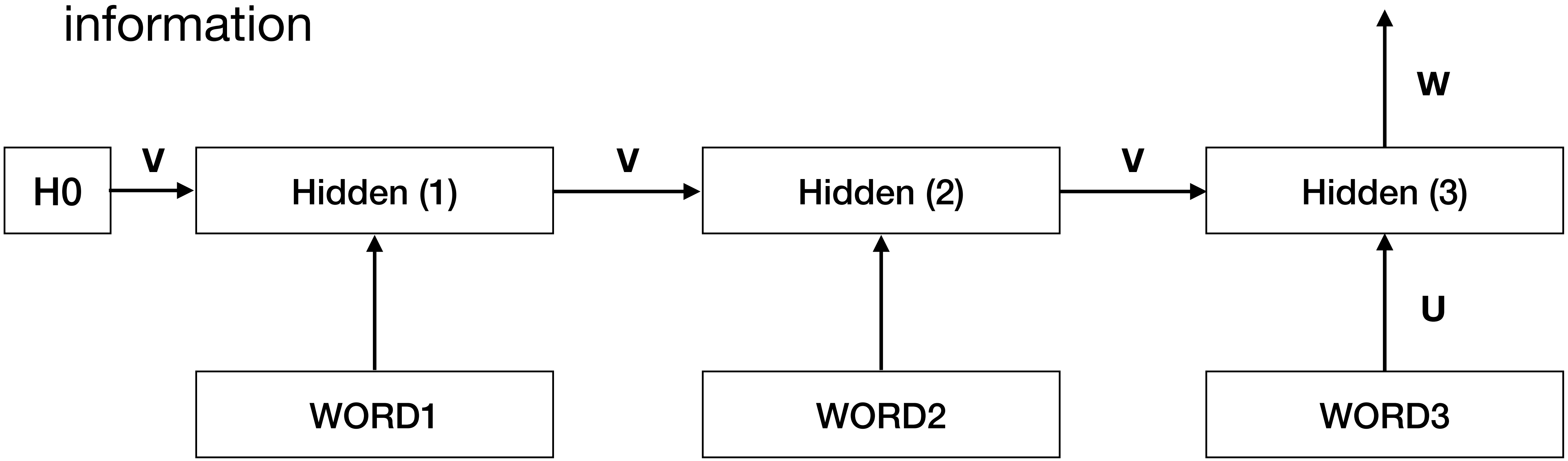
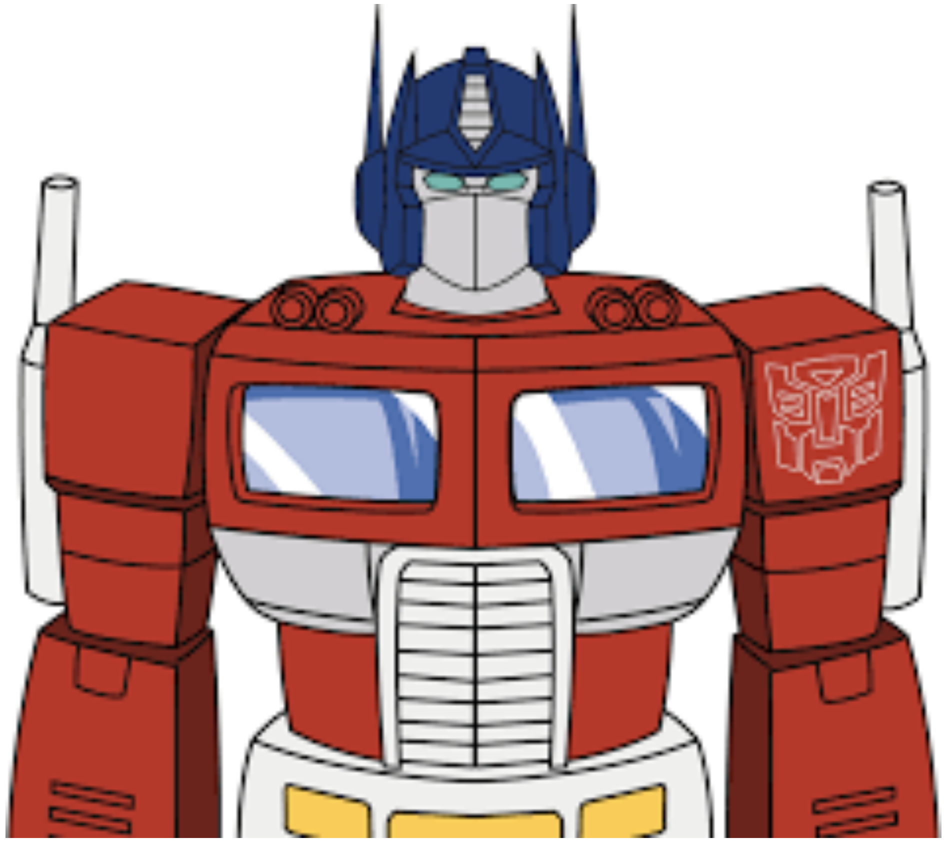
$$f_t = [\sigma(1.2)] = [0.77]$$

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

LSTM Problems

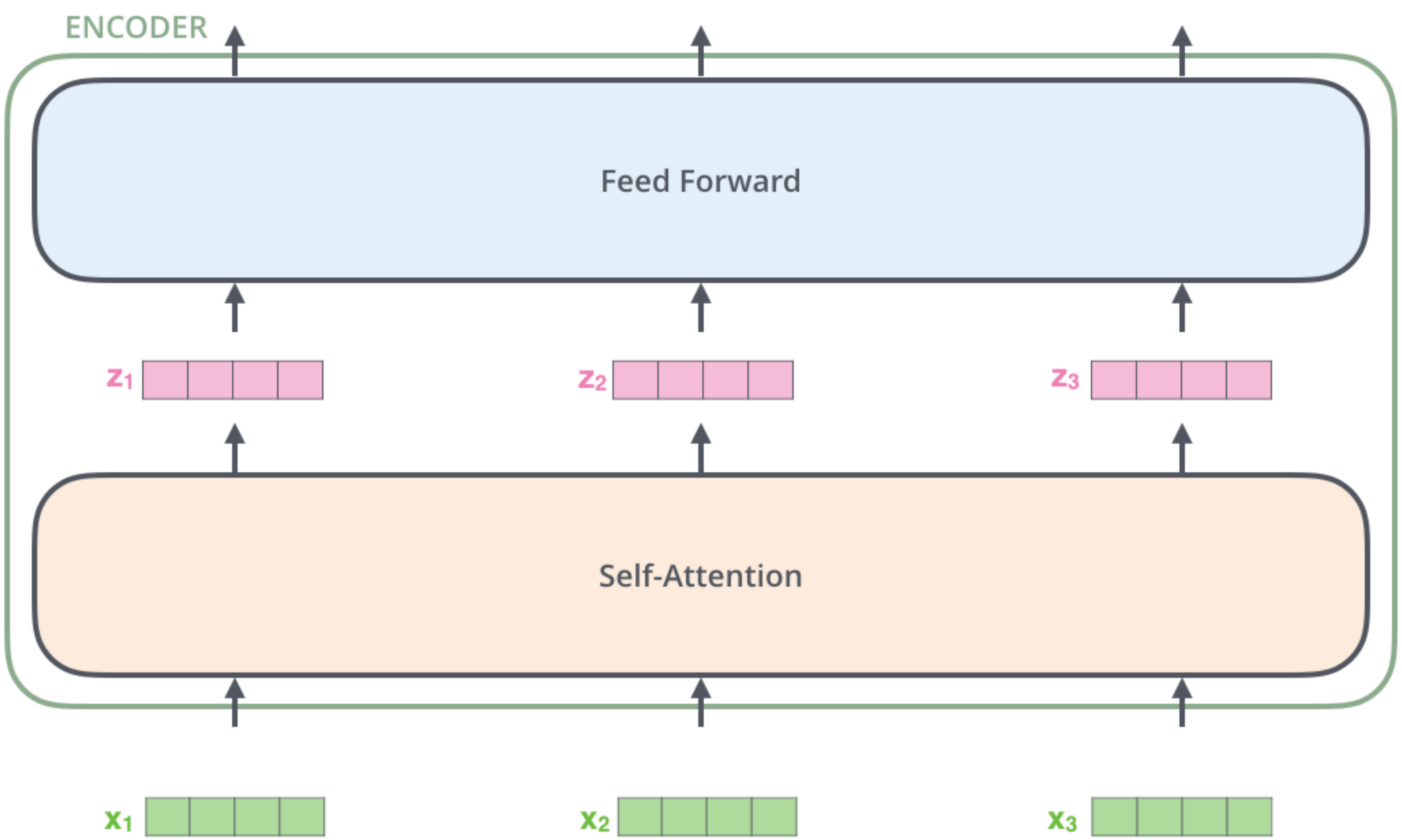
- Forget gate: removes information from the Global Cell state (*C*)
  - this information might be be useful at a later stage
- Implicit representation of long-term information
  - Cell state and previous hidden state summarise the prior information





Transformers for Language Modelling

Transformers: Simplified



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

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

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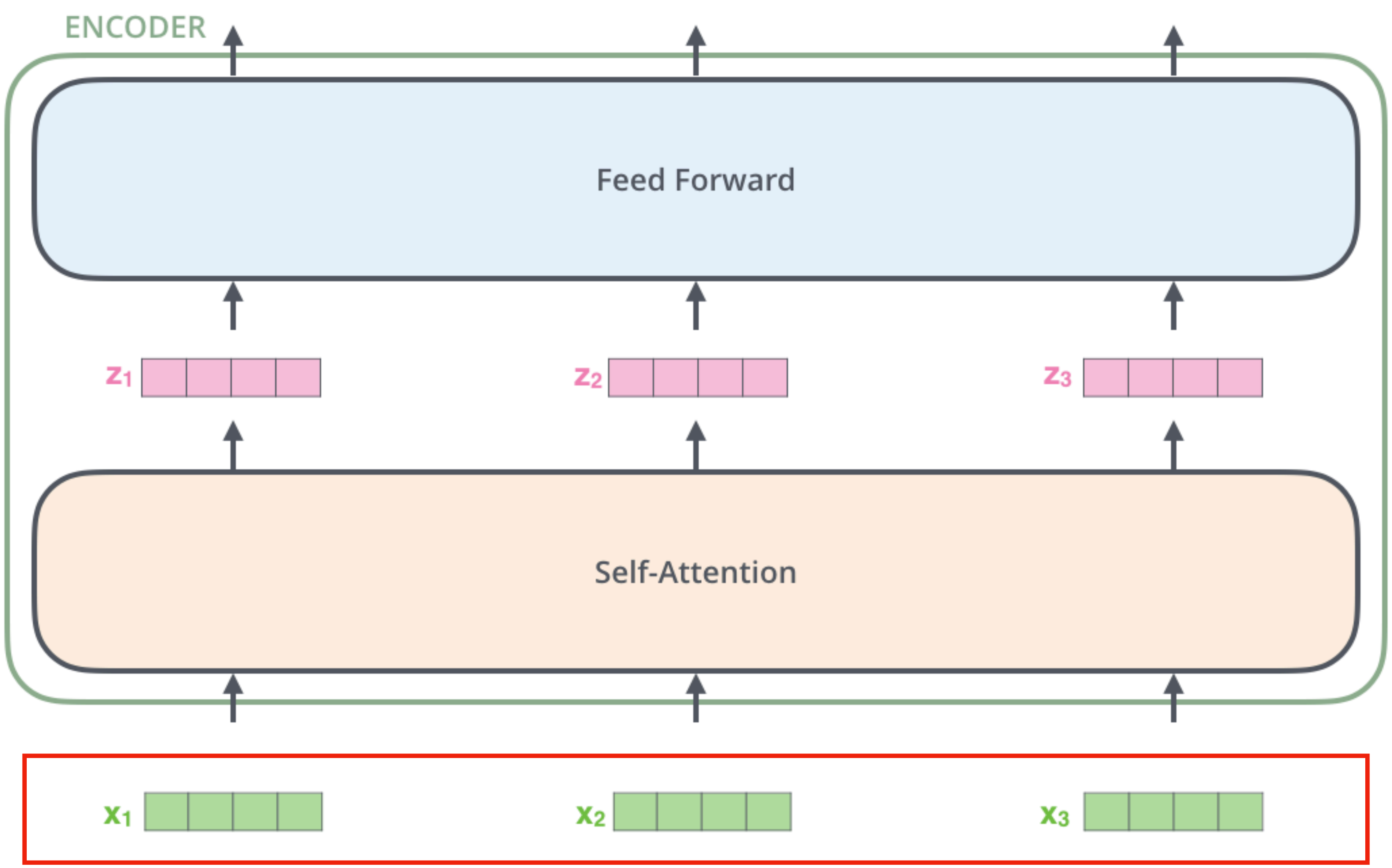

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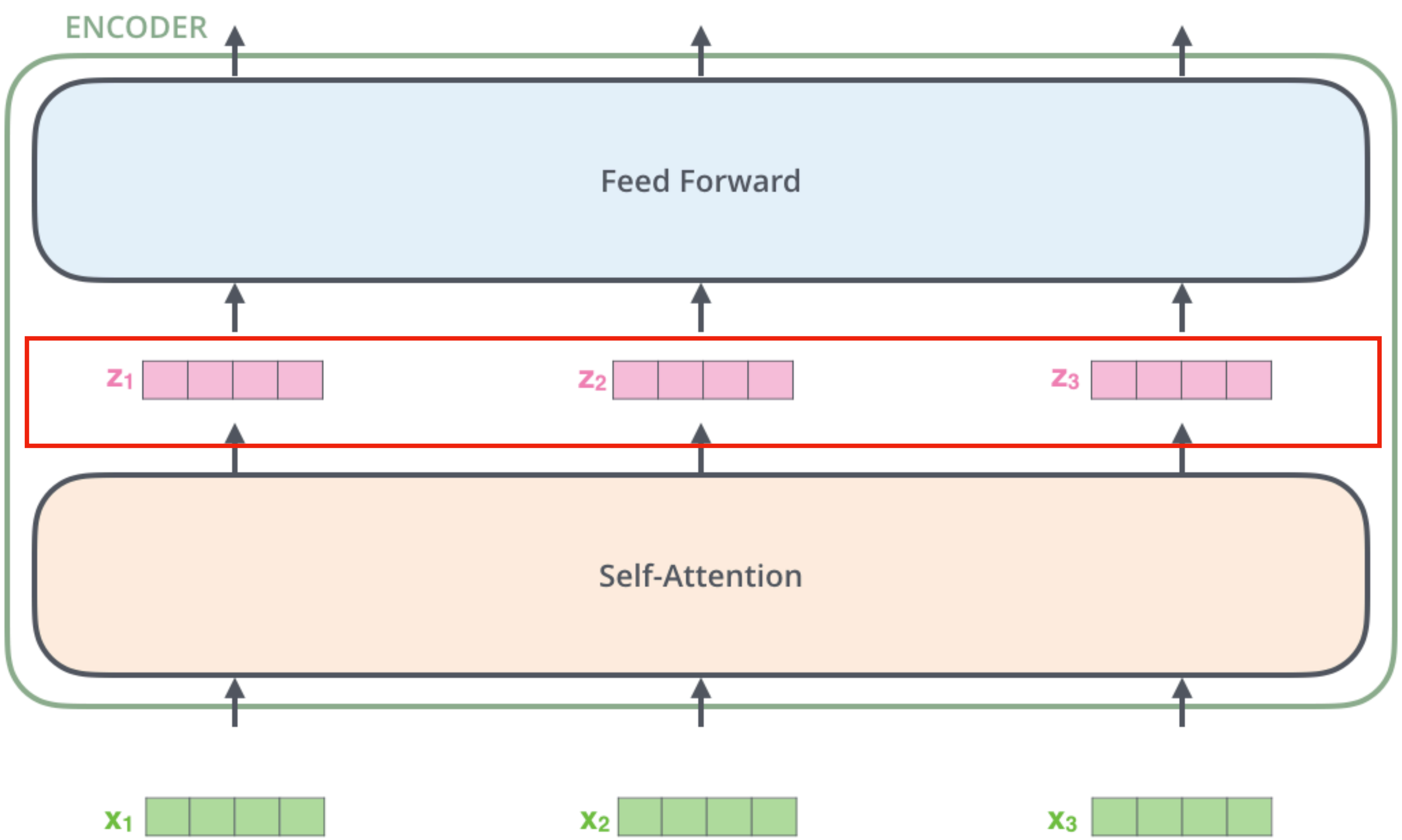

Multiple (50-90) such layers in a Transformer LM

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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"

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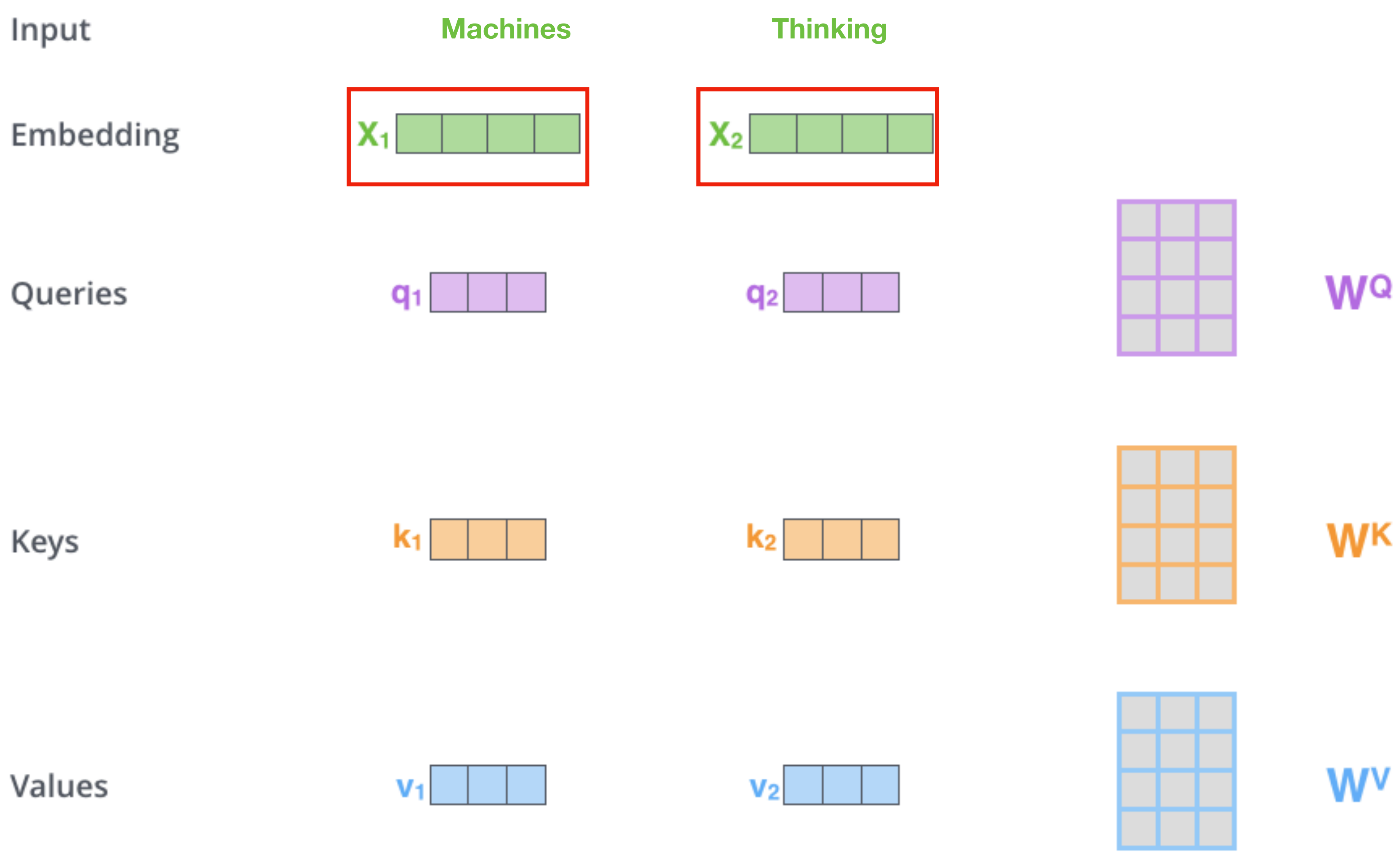
Self-Attention: Step 0



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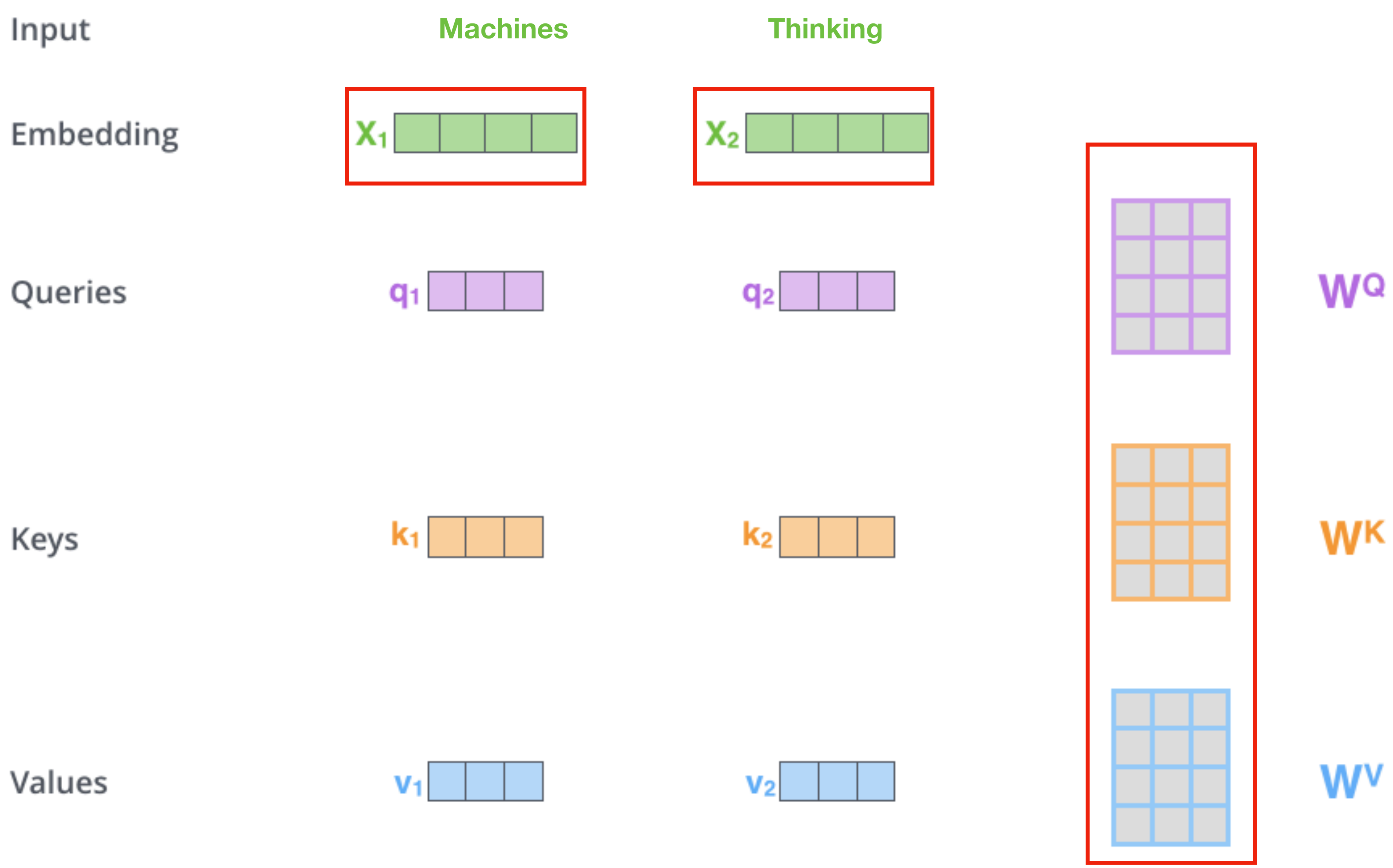

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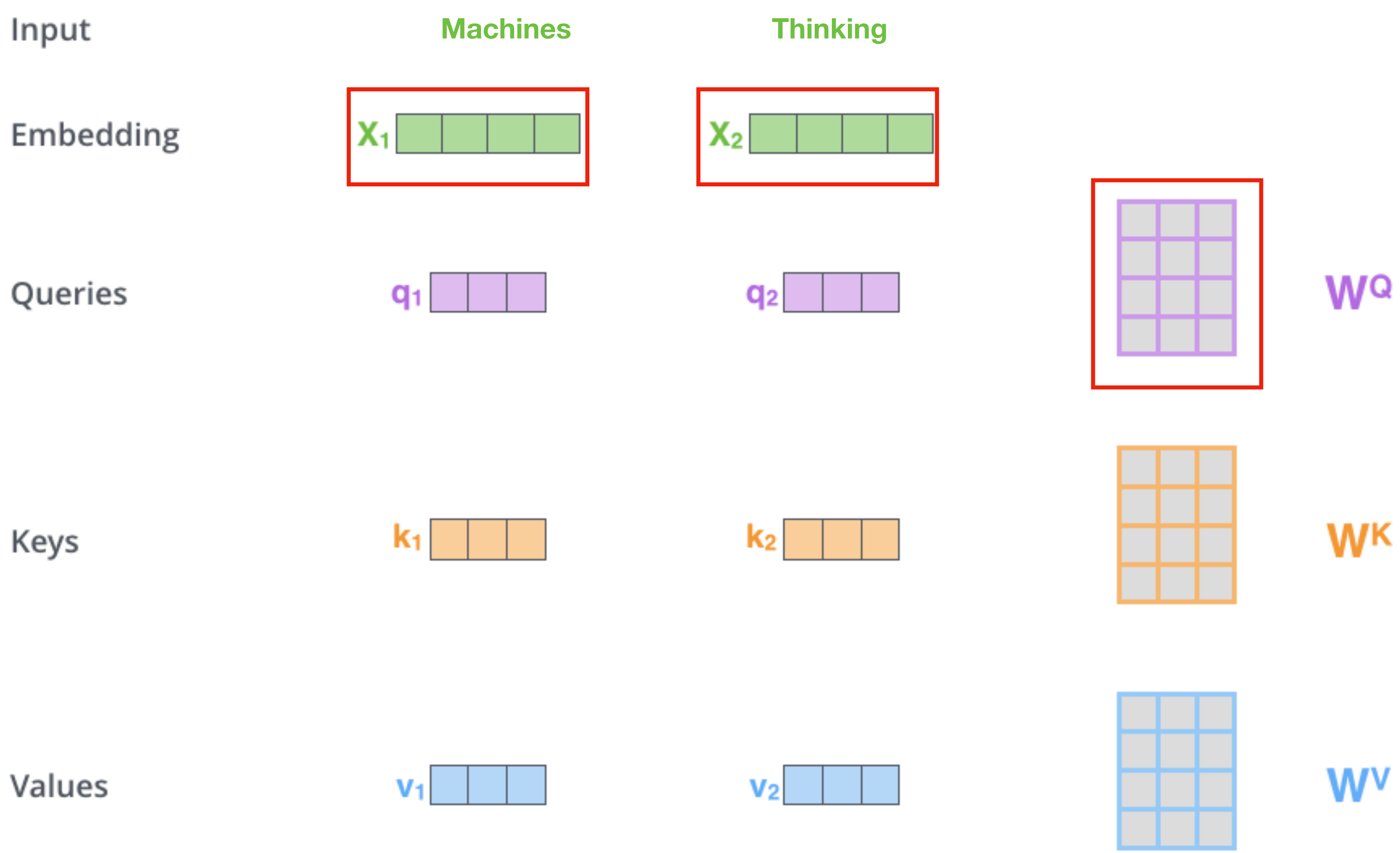

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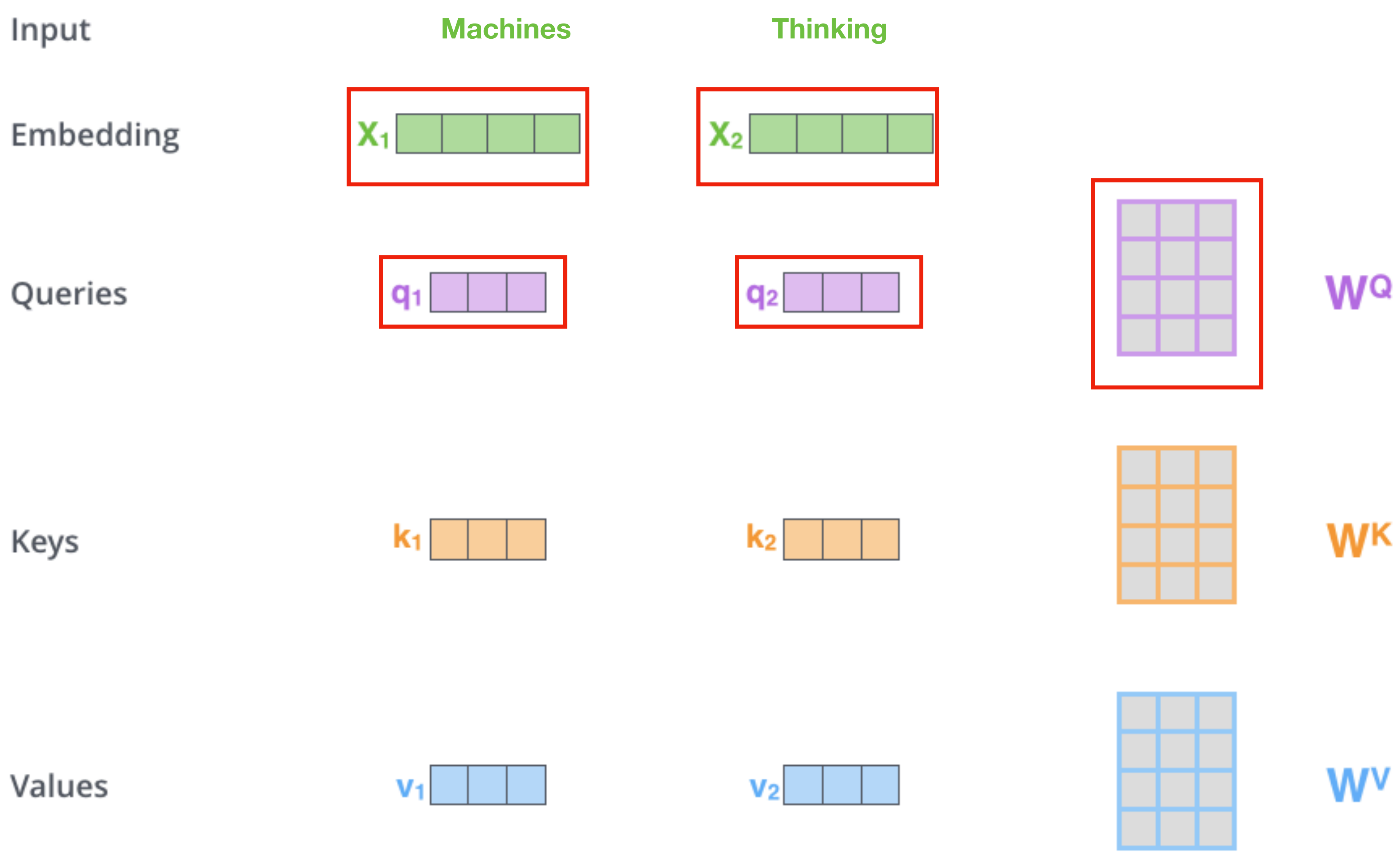

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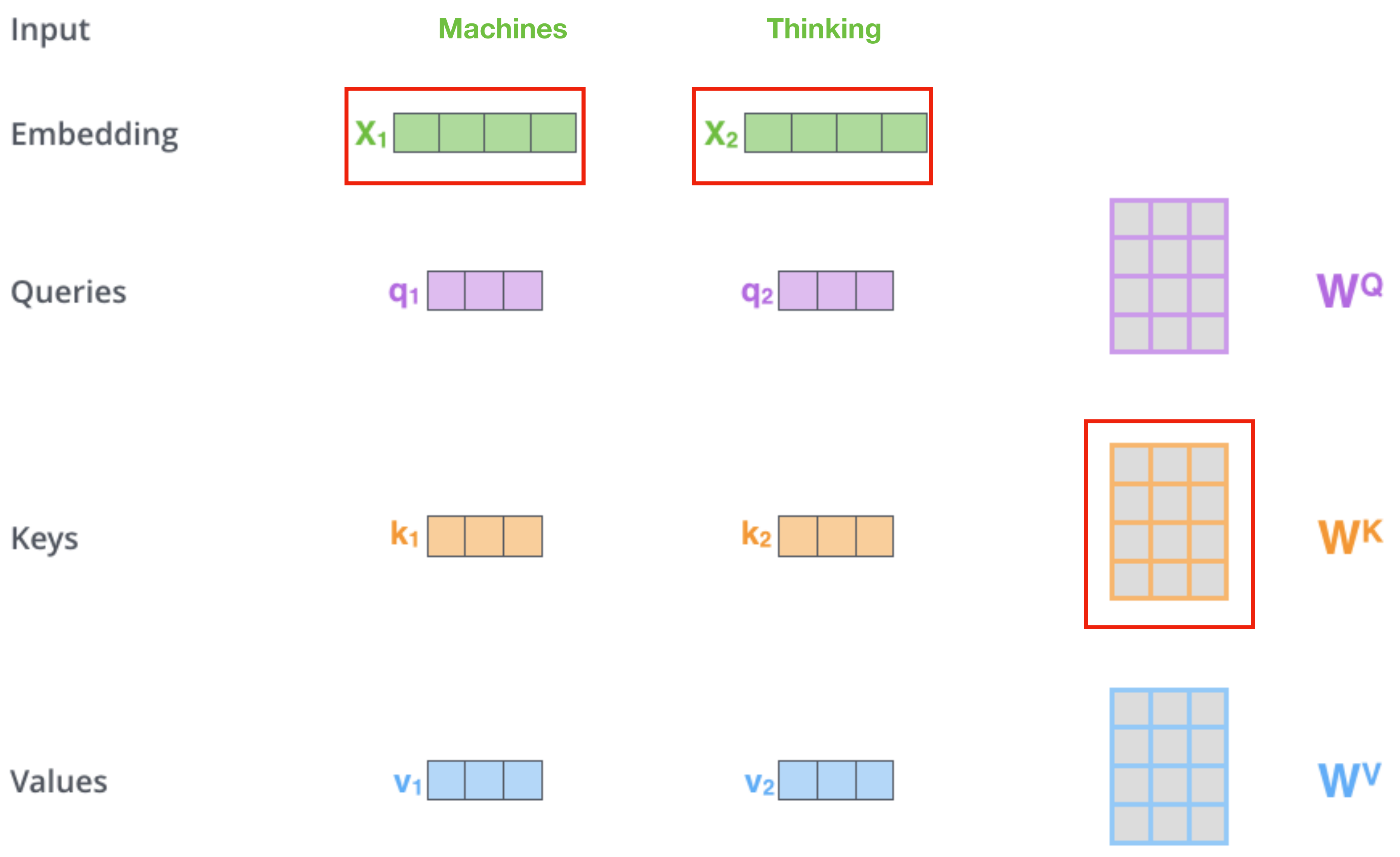

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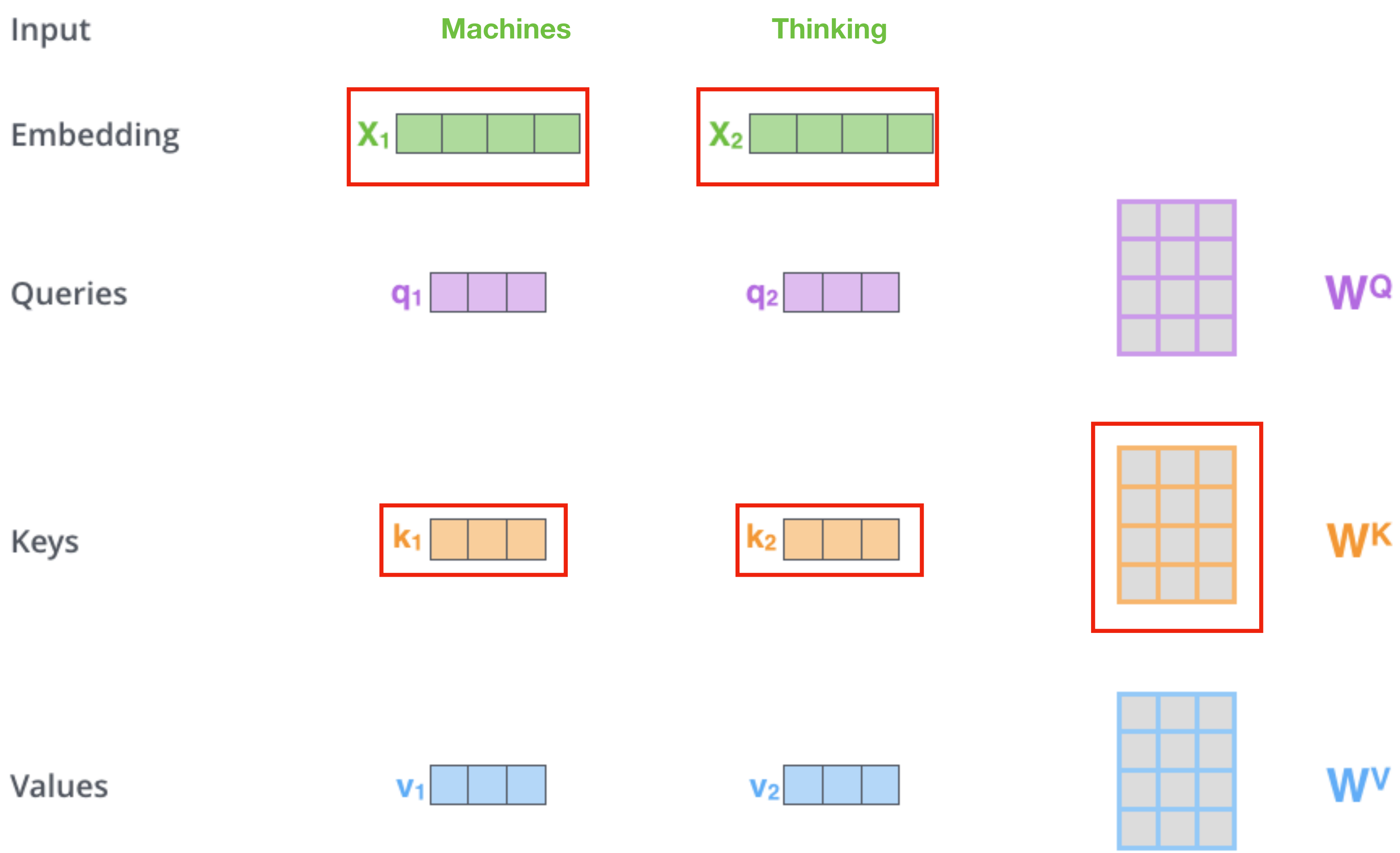

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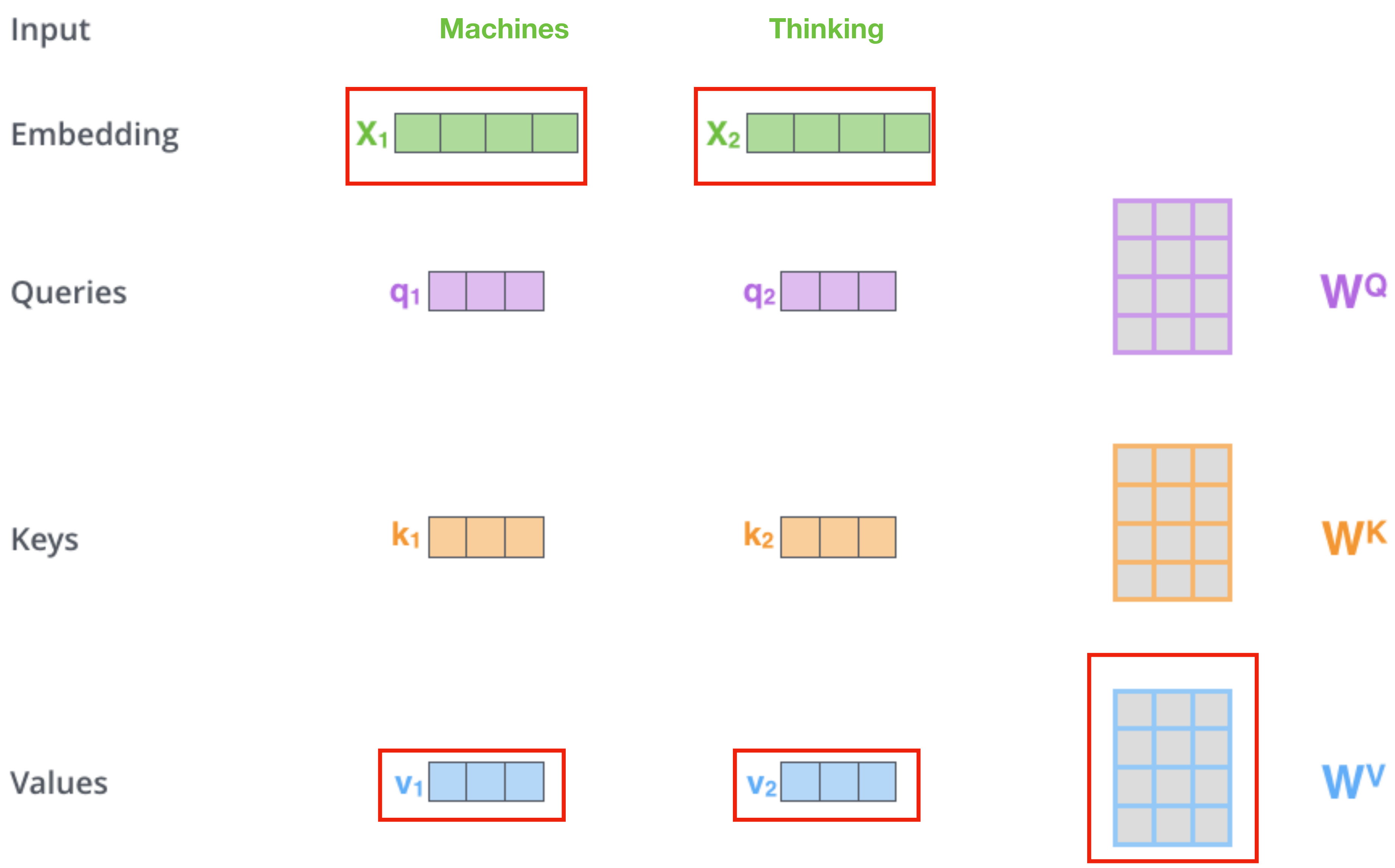

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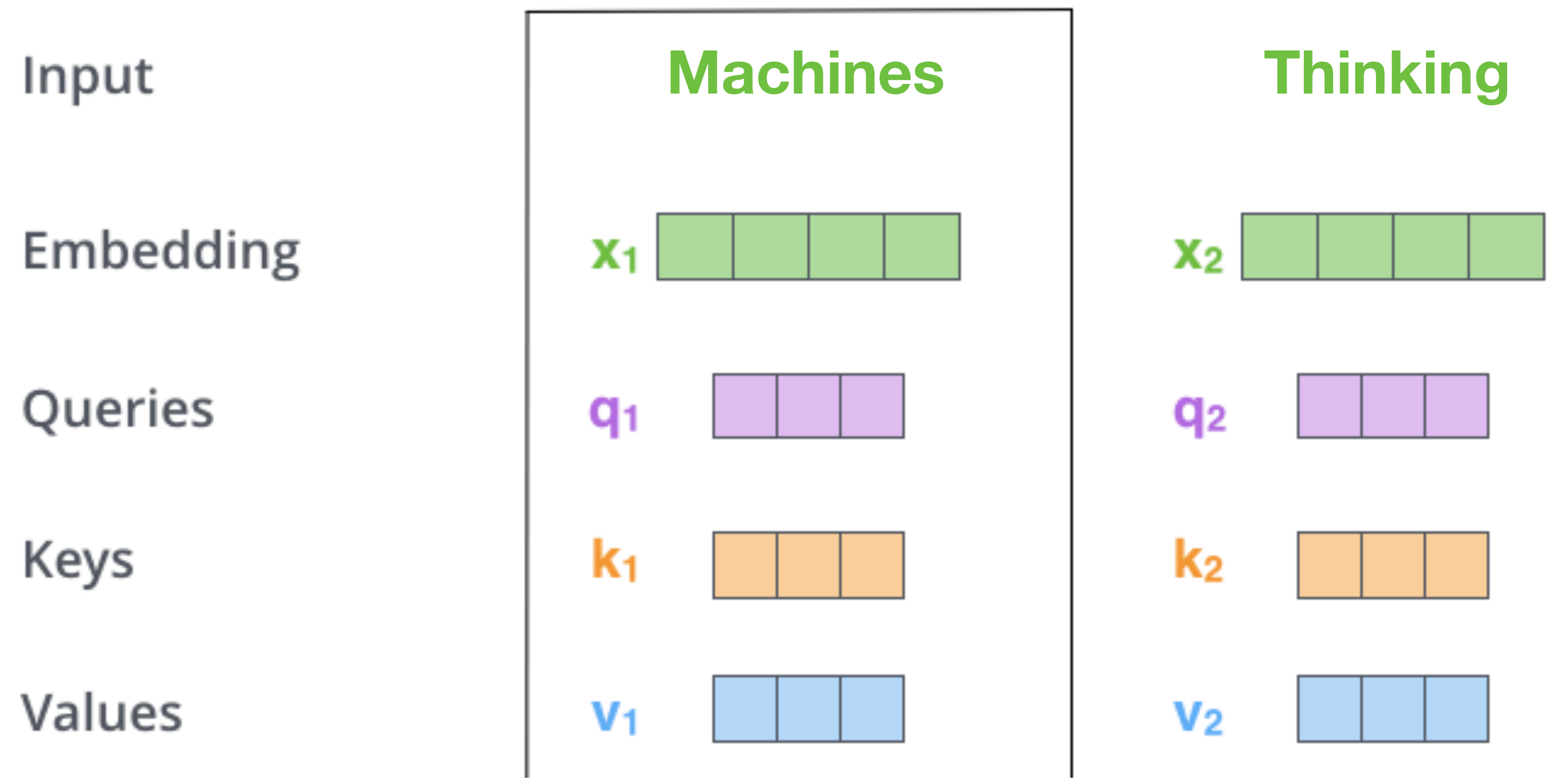
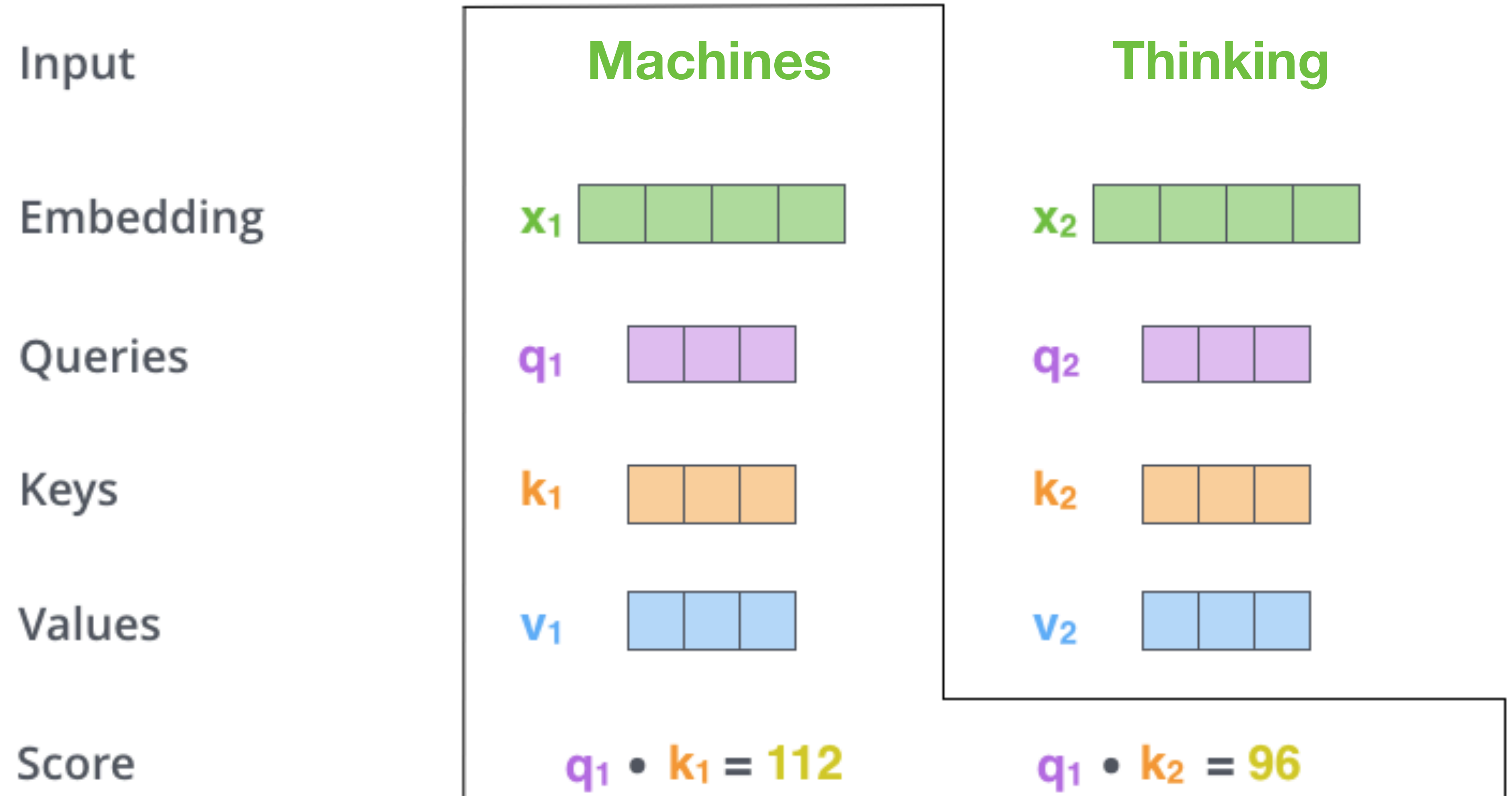

Input
Embedding
Queries
Keys
Values
Machines
Thinking
x1
x2
q1
q2
k1
k2
v1
v2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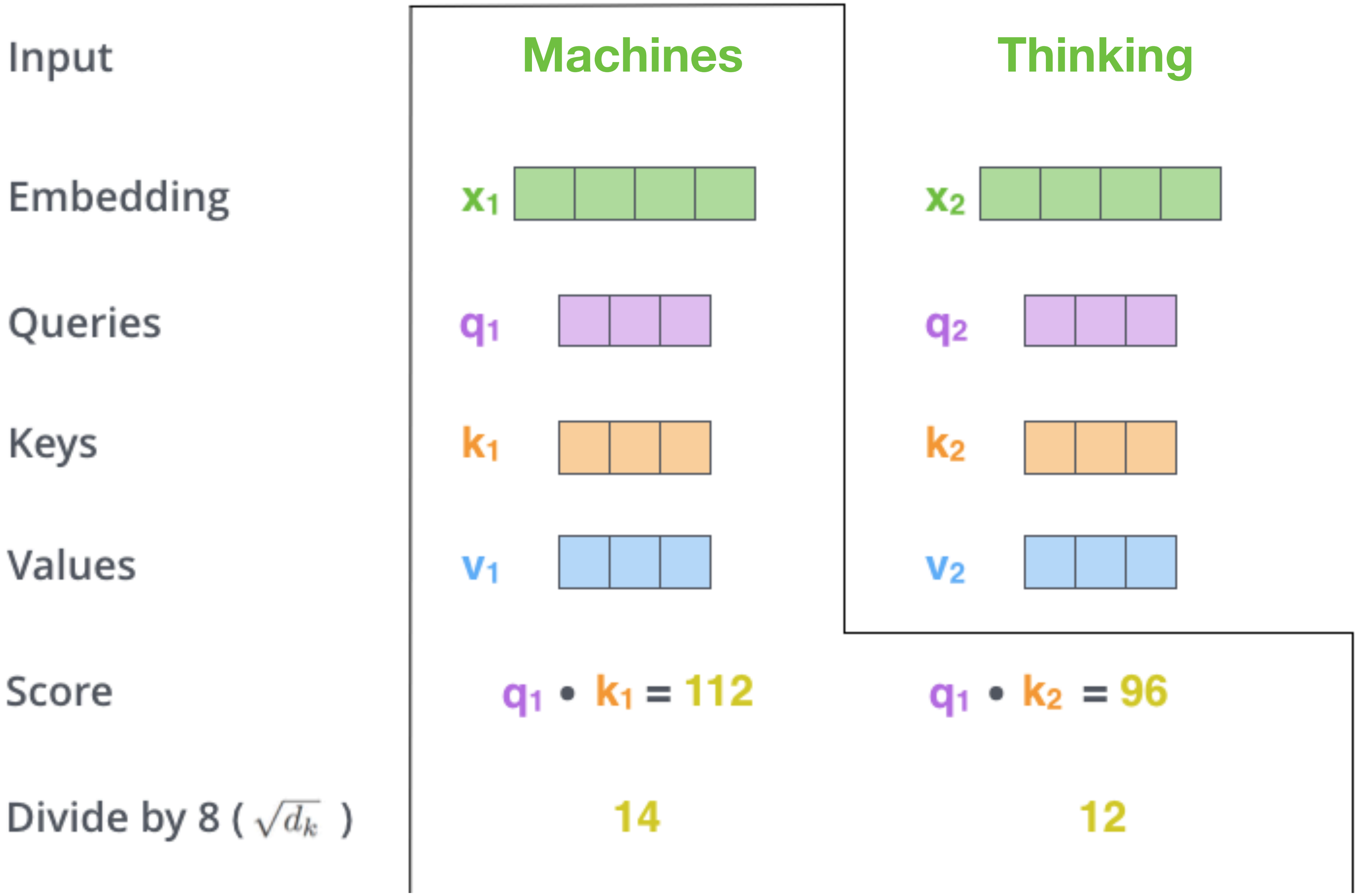
Score
q1 • k1 = 112
q1 • k2 = 96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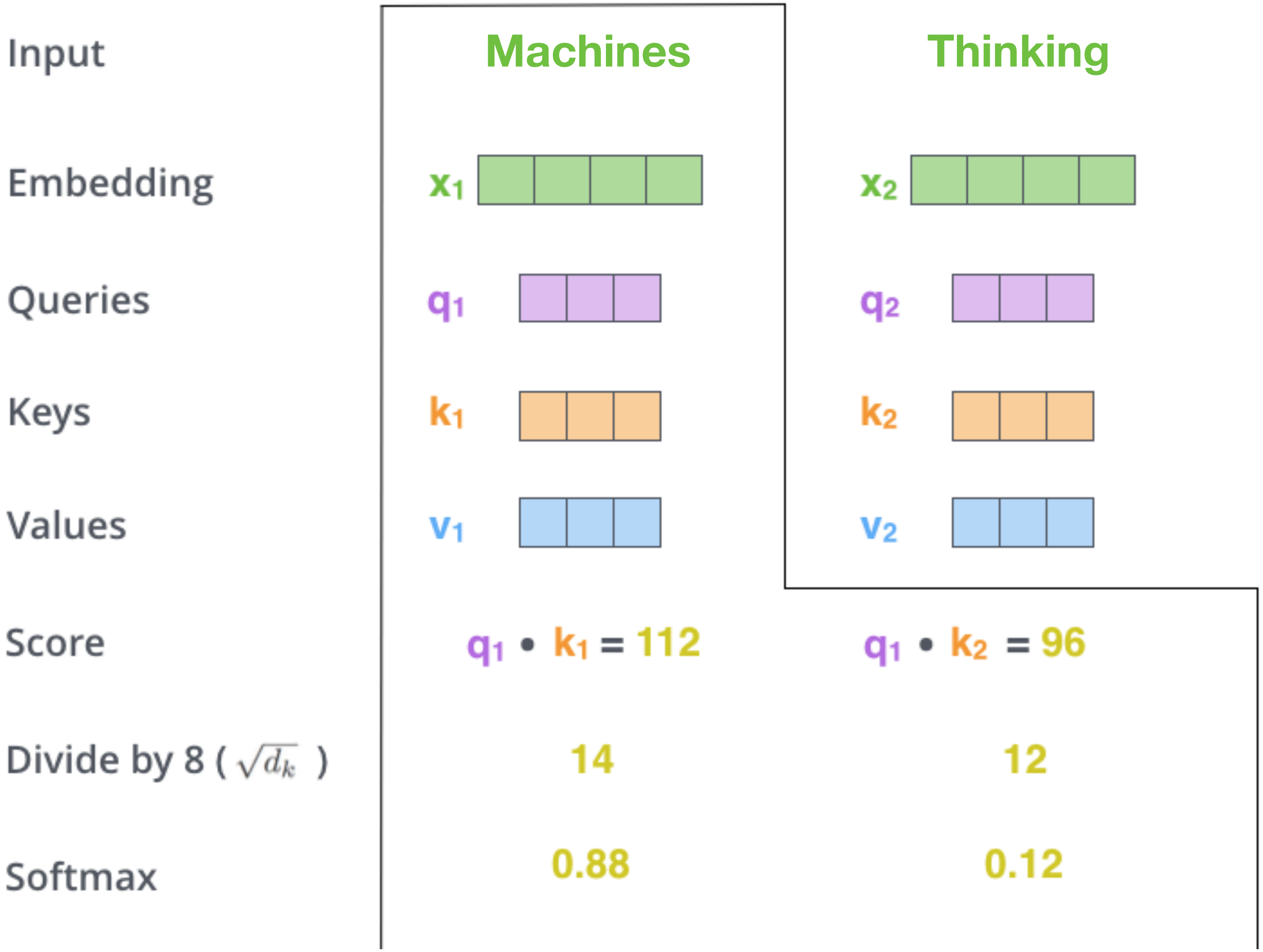
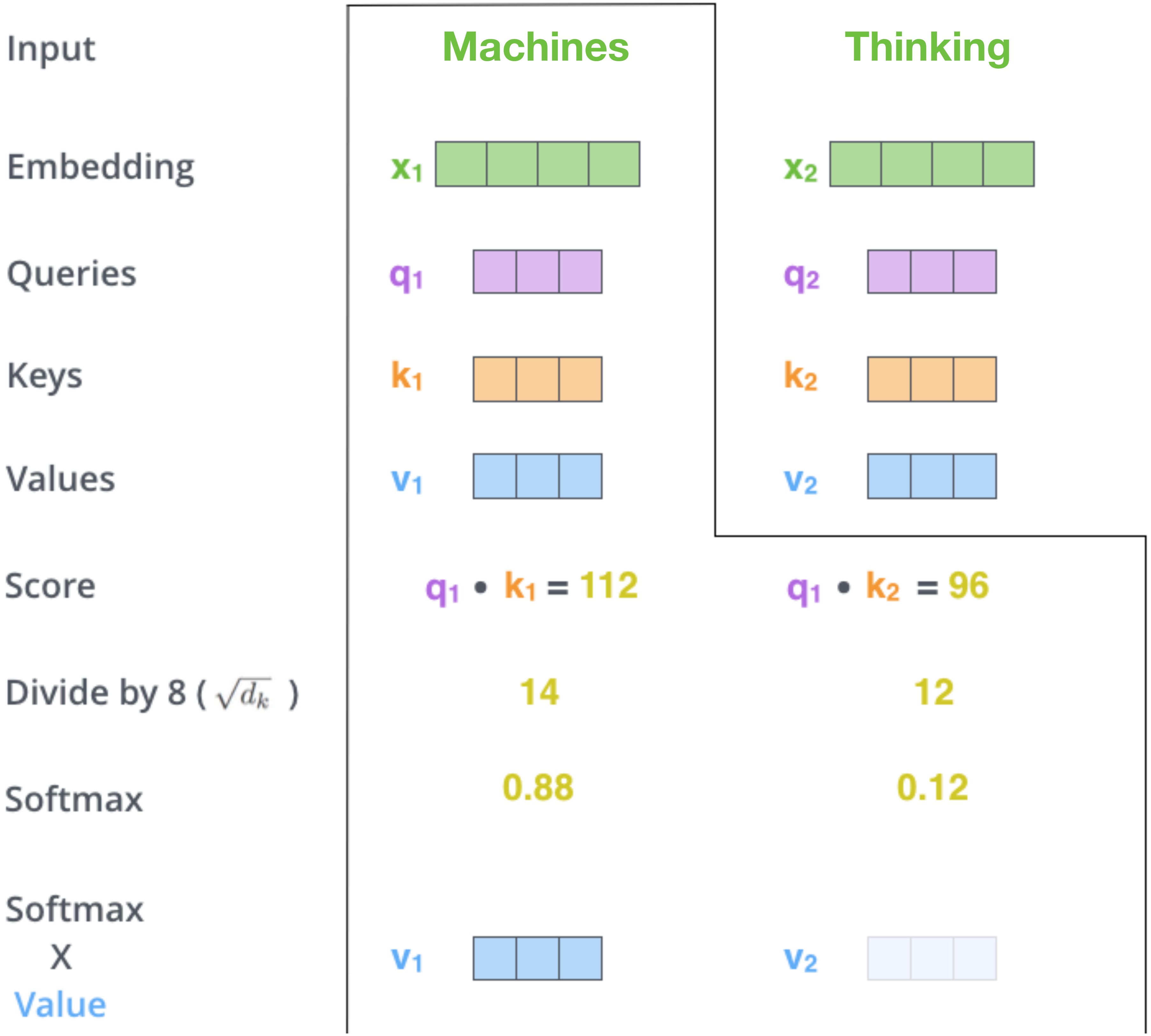
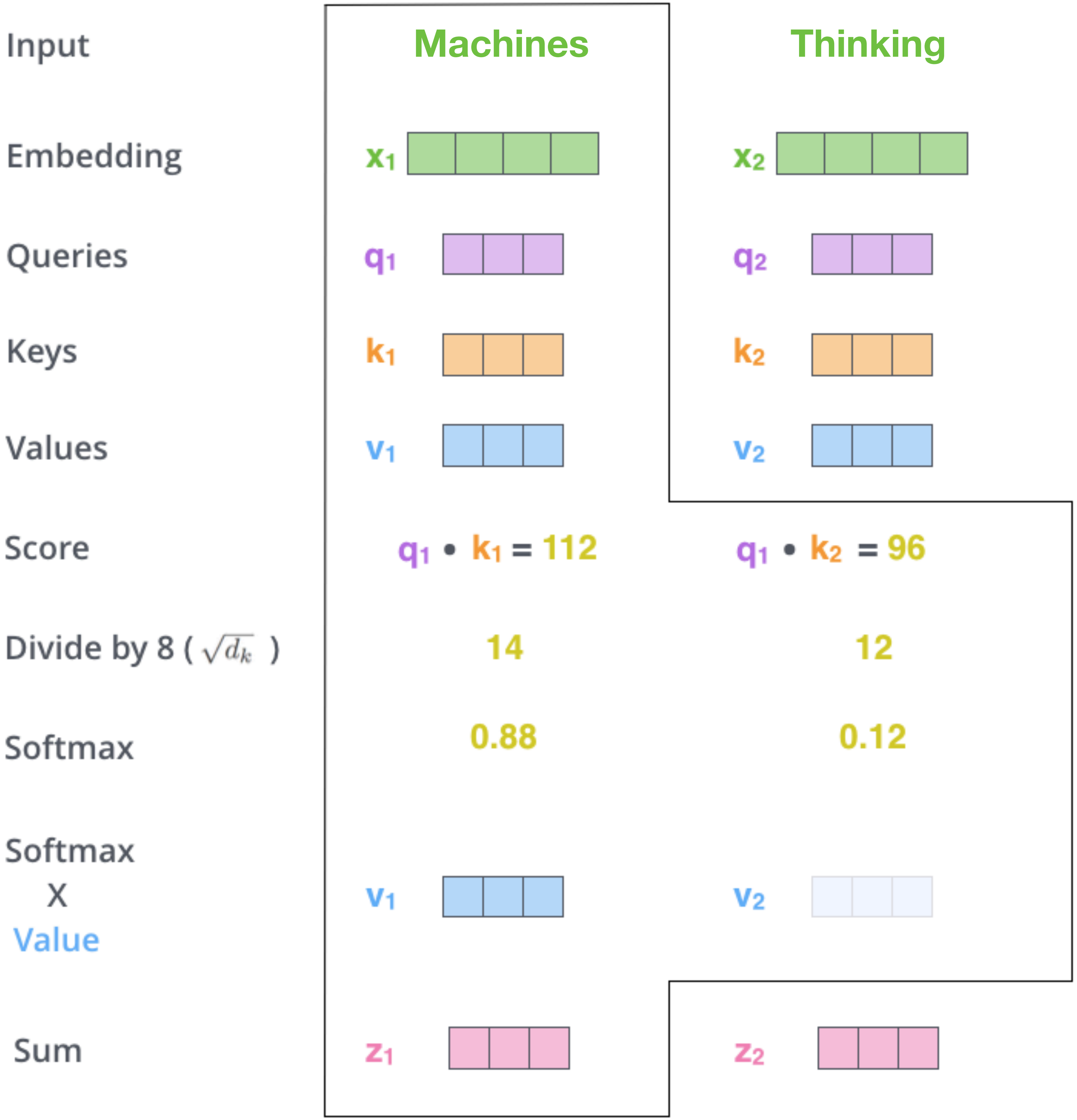
Score
q1 • k1 = 112
q1 • k2 = 96
Divide by 8 ($\sqrt{d_k}$)
14
12

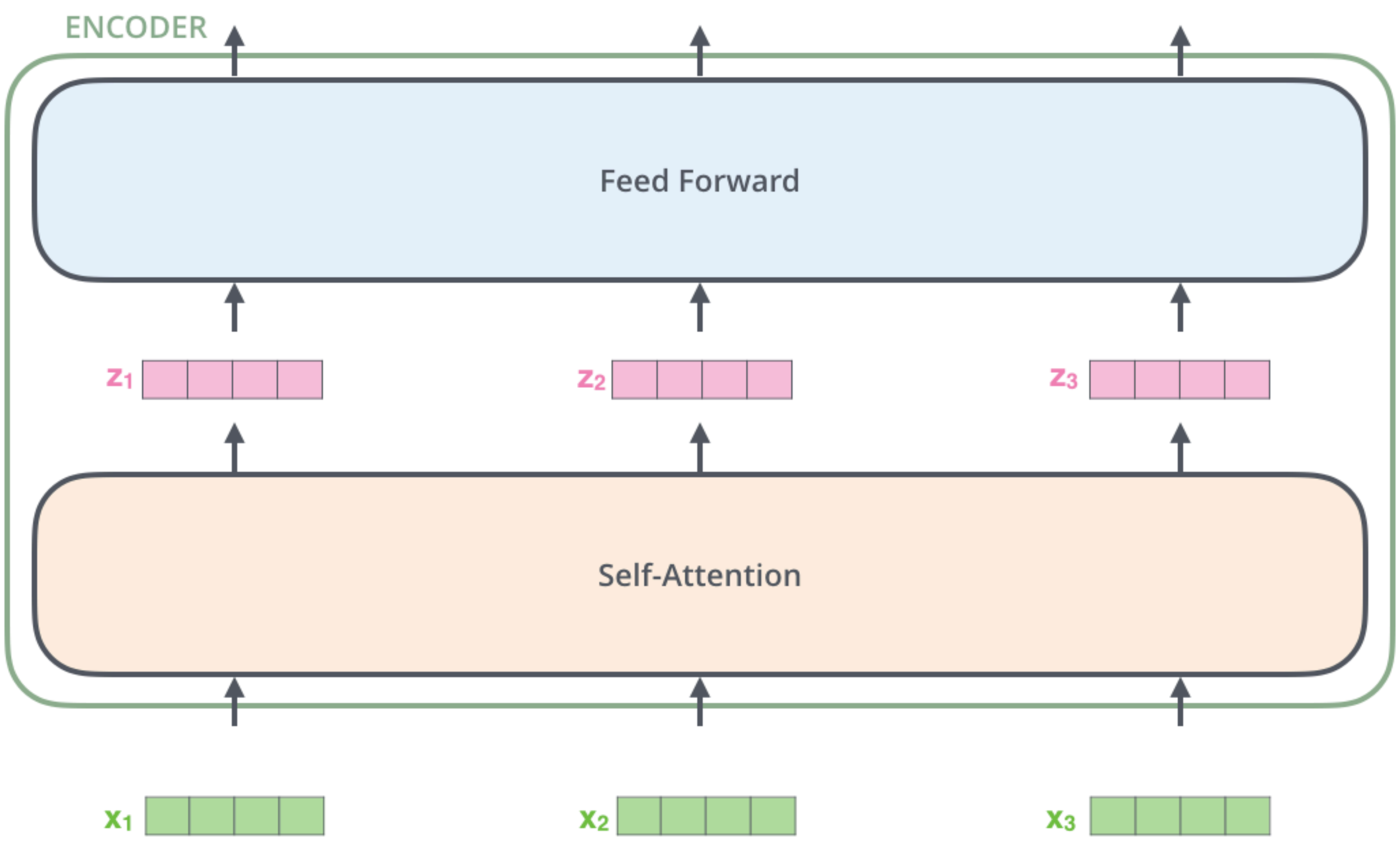

Input
Machines
Thinking
Embedding
x1
x2
Queries
q1
q2
Keys
k1
k2
Values
v1
v2
Score
q1 • k1 = 112
q1 • k2 = 96
Divide by 8 ($\sqrt{d_k}$)
14
12
Softmax
0.88
0.12


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

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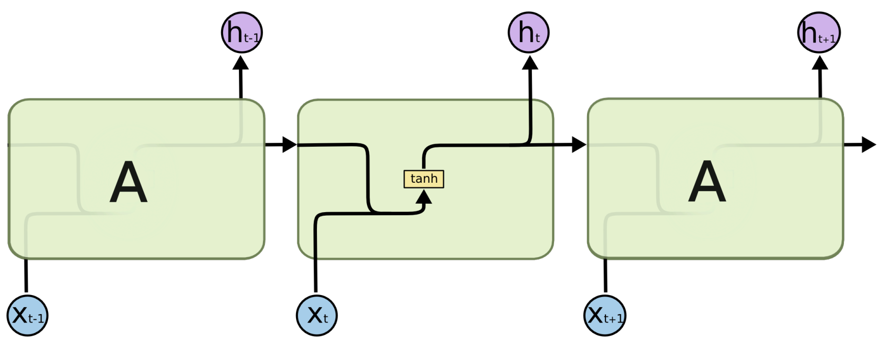
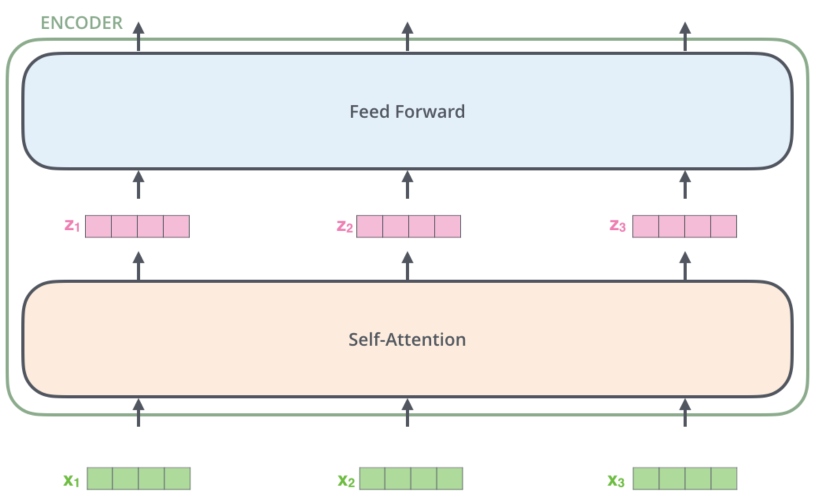
- Query ~ smaller word embedding

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

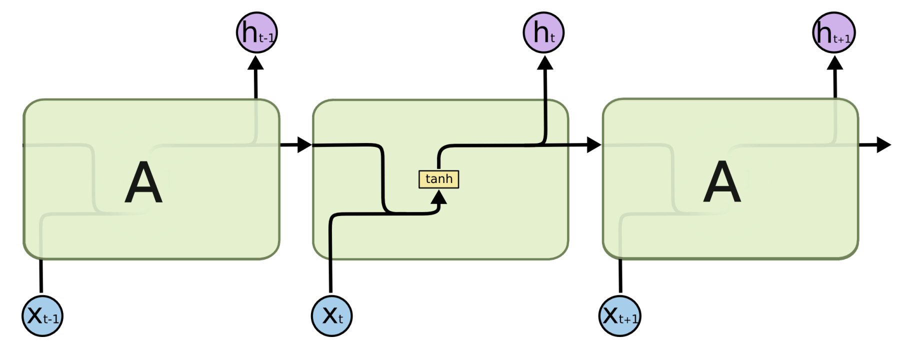
Transformers for Language Modelling

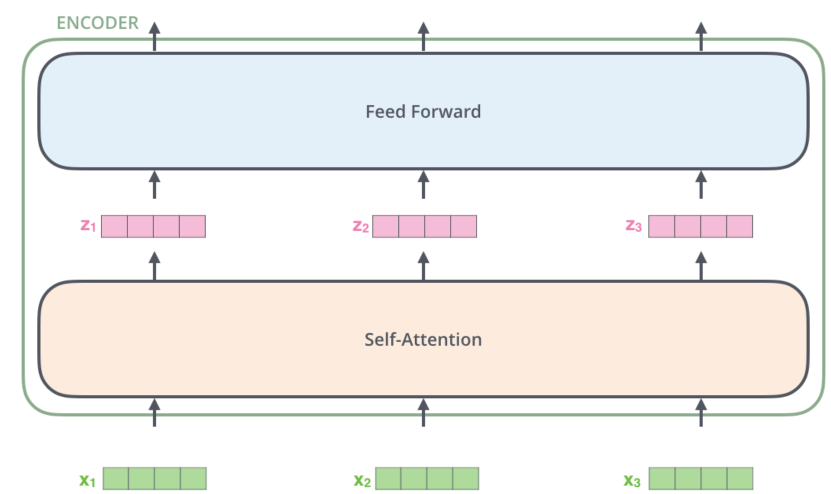




Transformers for Language Modelling

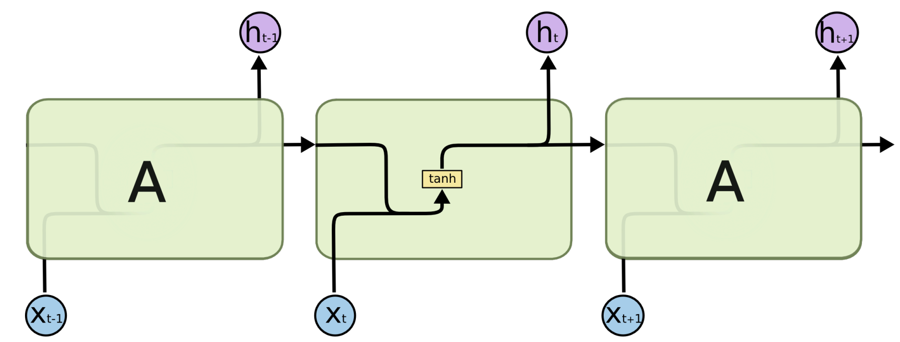
- RNNs: Process tokens one-by-one

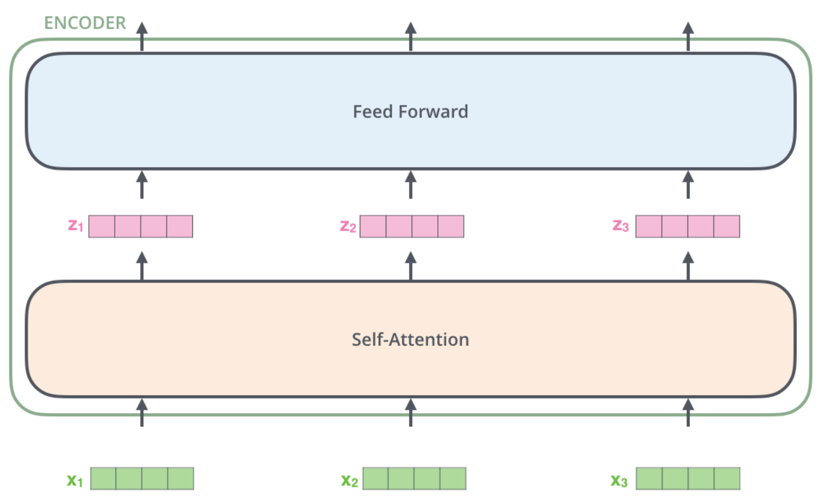




Transformers for Language Modelling

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





Transformers for Language Modelling

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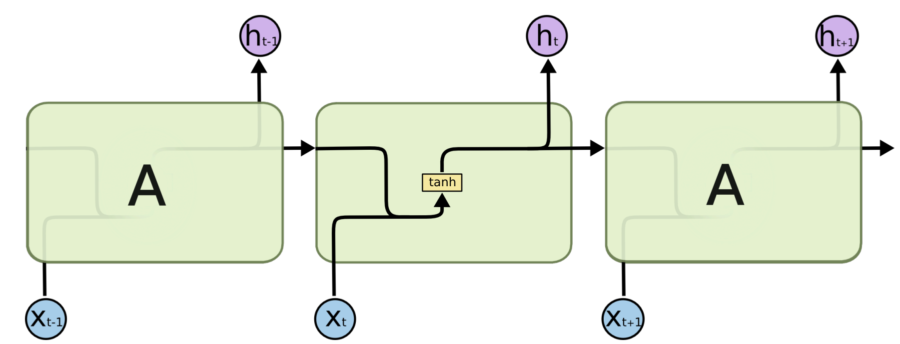
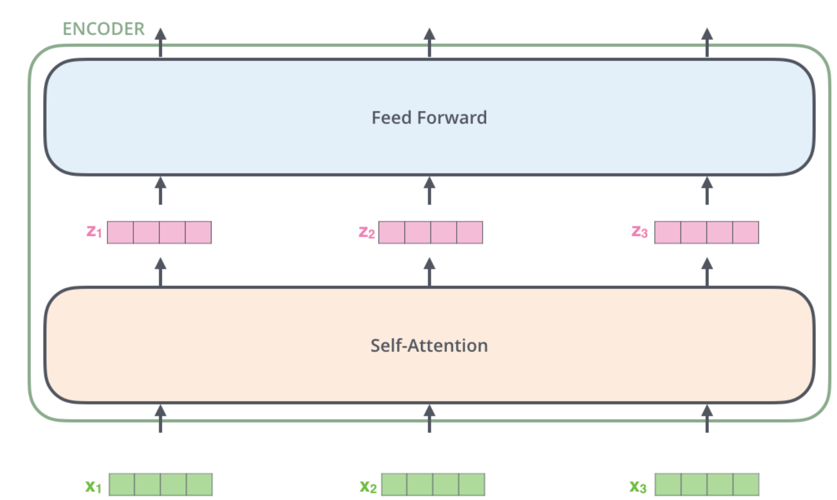


- Transformers LM: Process a segment of tokens



Transformers for Language Modelling

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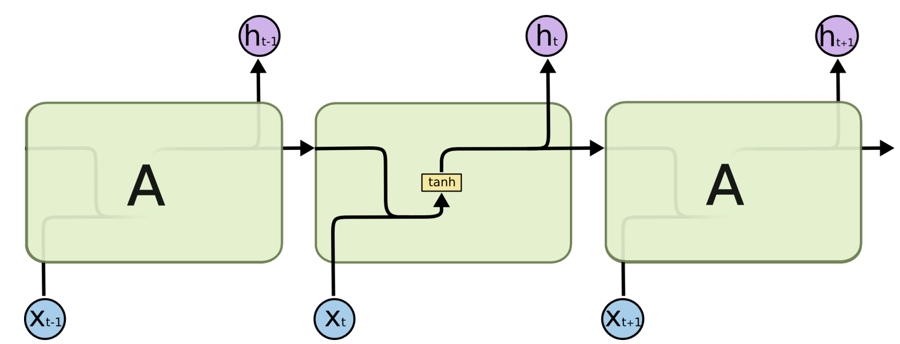
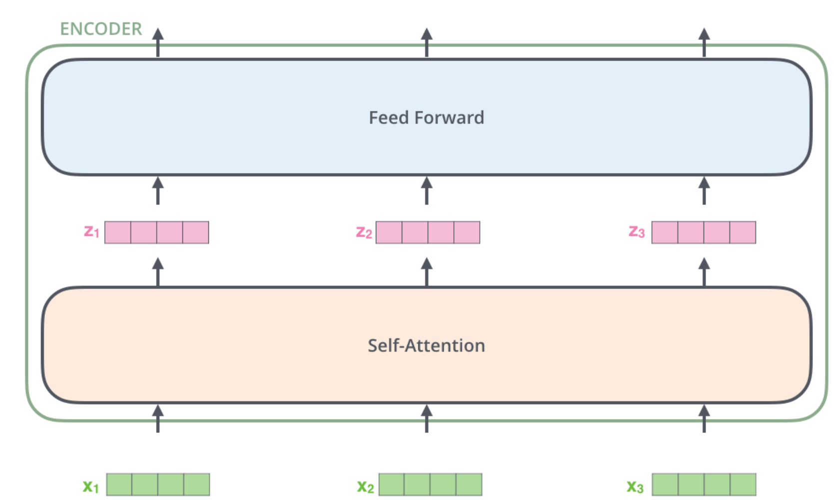
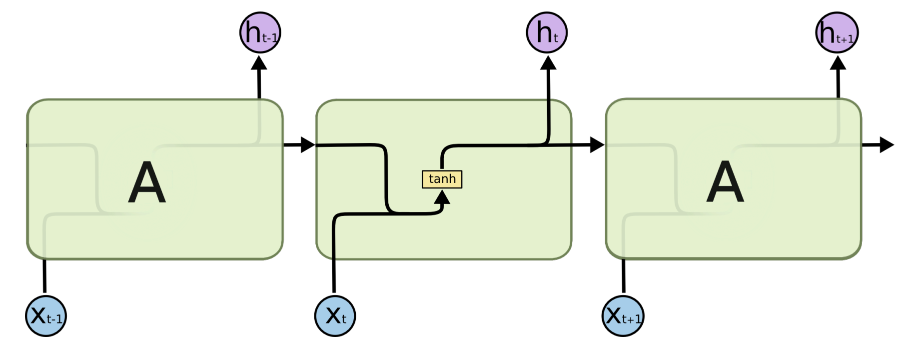


- Transformers LM: Process a segment of tokens
    - Dependencies within the segment

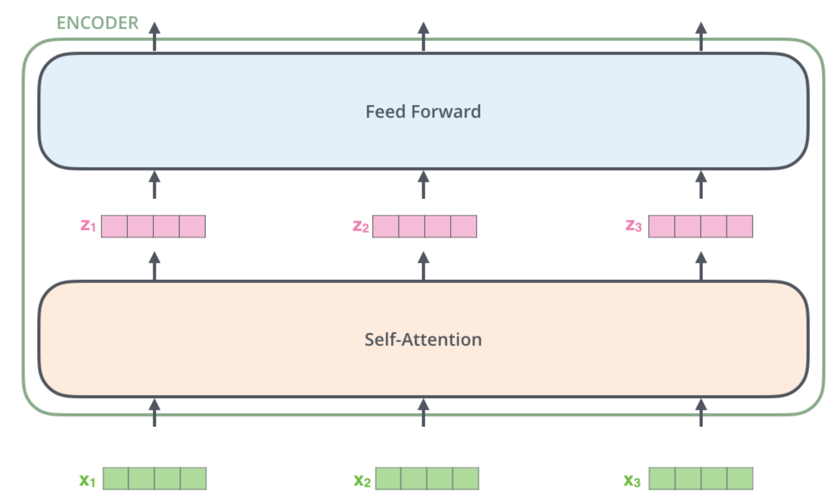


Transformers for Language Modelling

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

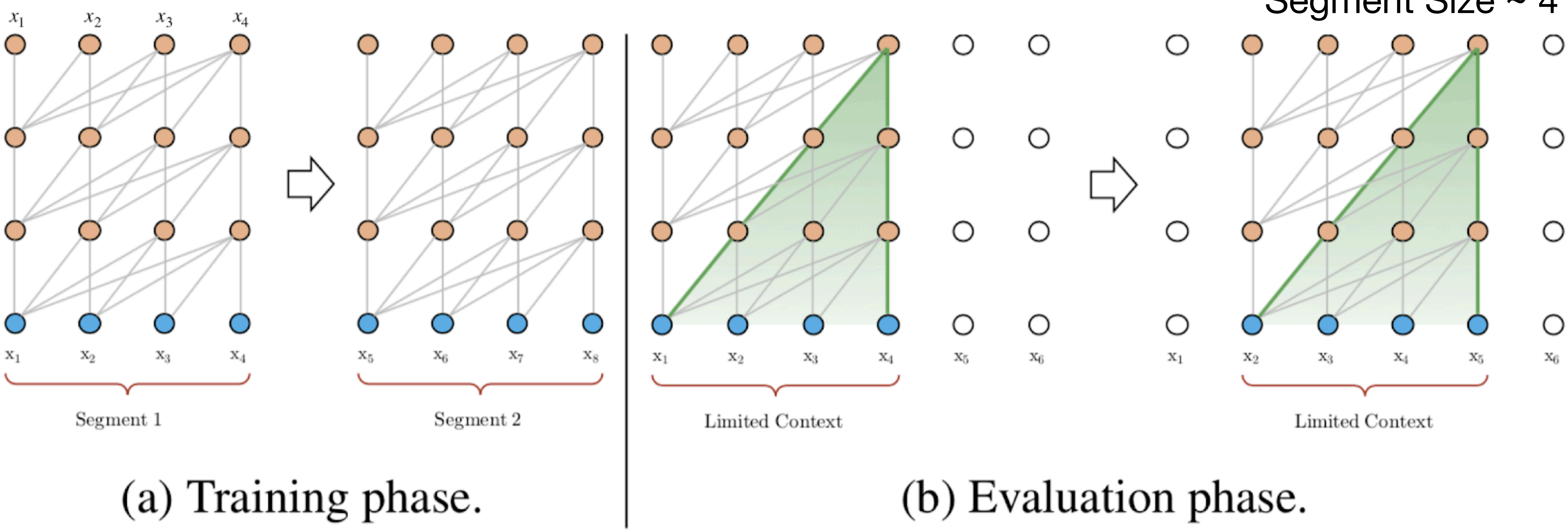


- Transformers LM: Process a segment of tokens
  - Dependencies within the segment
  - Within segment position is given by the positional encoding



Transformer LM processing of Segments

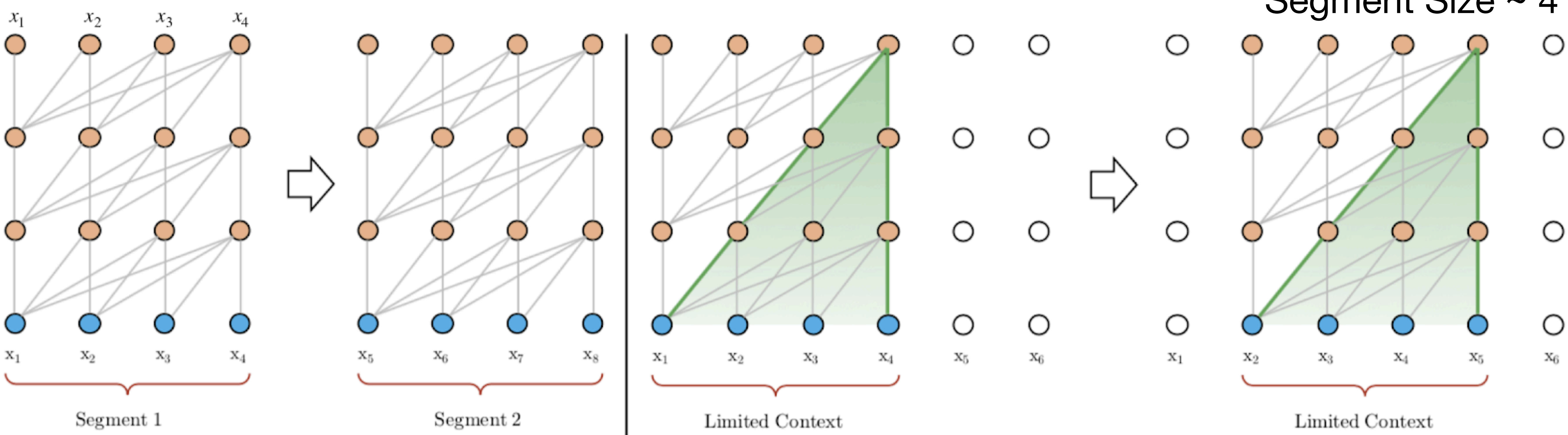
Segment Size ~ 4



Dai et al., 2019

Transformer LM processing of Segments

Segment Size ~ 4



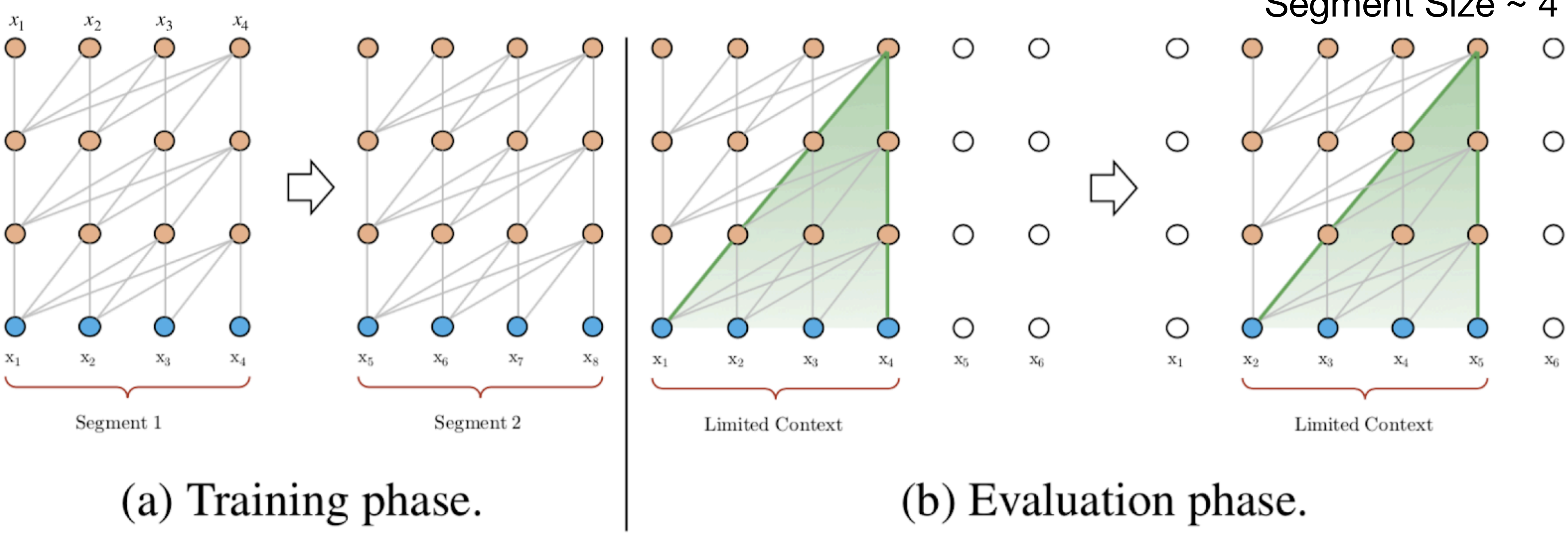
(a) Training phase. (b) Evaluation phase.

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

Summary

- NNLM:
- Challenges
  - Long-Term Dependencies
  - LSTMs
  - Transformers
    - Self Attention