Neural Network Language Models & Large Language Models

Mittul Singh

Neural Network Language Models & their subclass: Large Language Models

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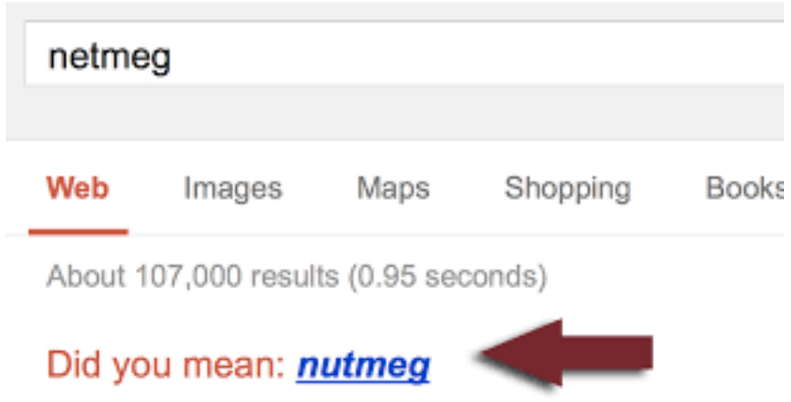
Language Model Applications

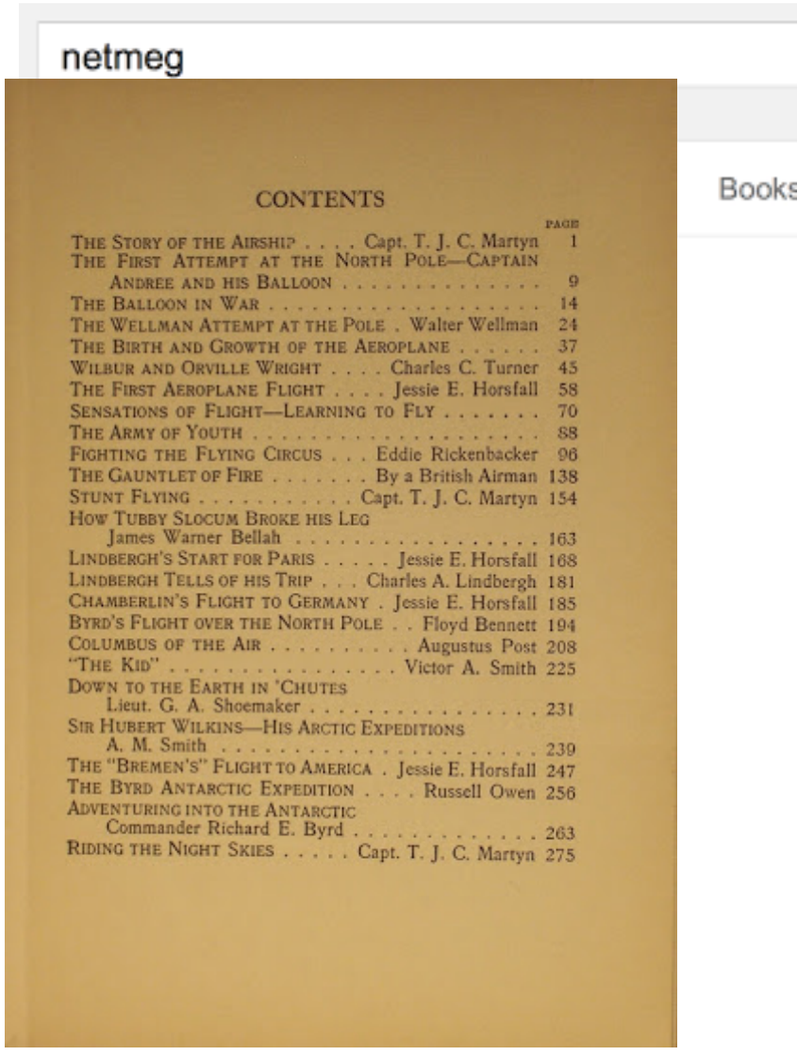
Language Model Applications

- Spelling correction, text input
    - Search Query Completion



Language Model Applications

- Spelling correction, text input
  - Search Query Completion
- Optical character recognition
  - e.g. scanning old books



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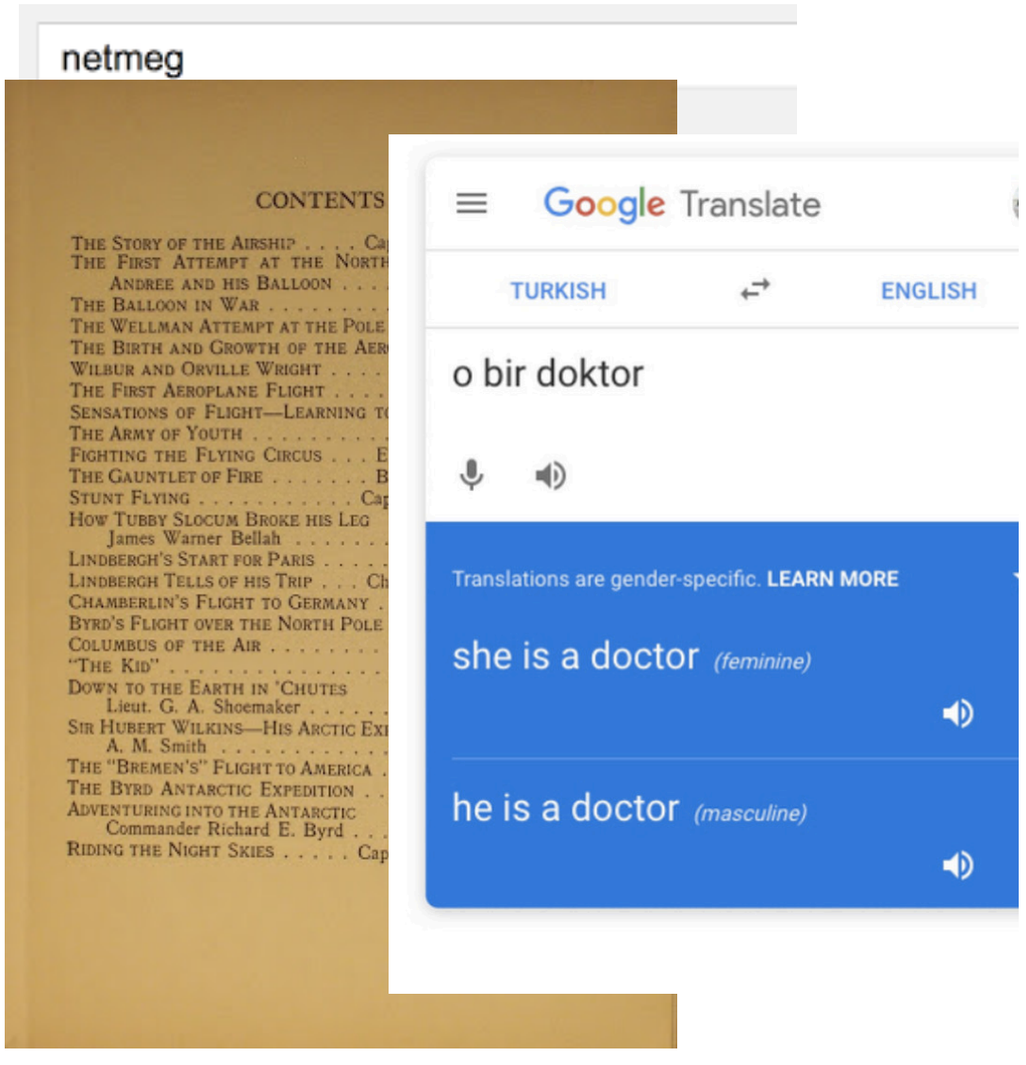

Language Model Applications

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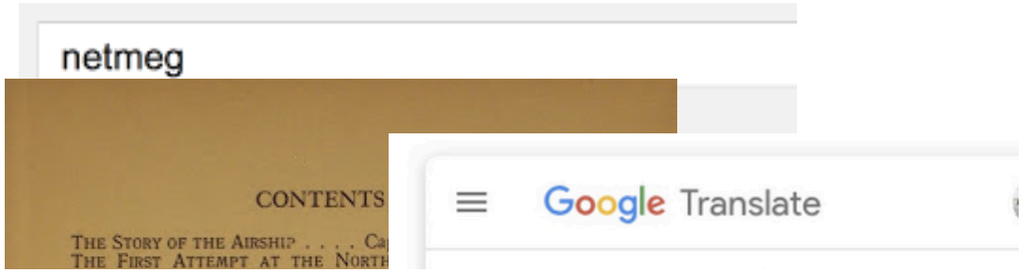
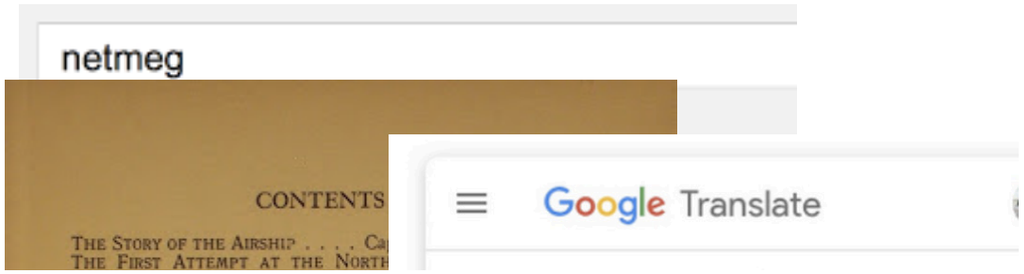
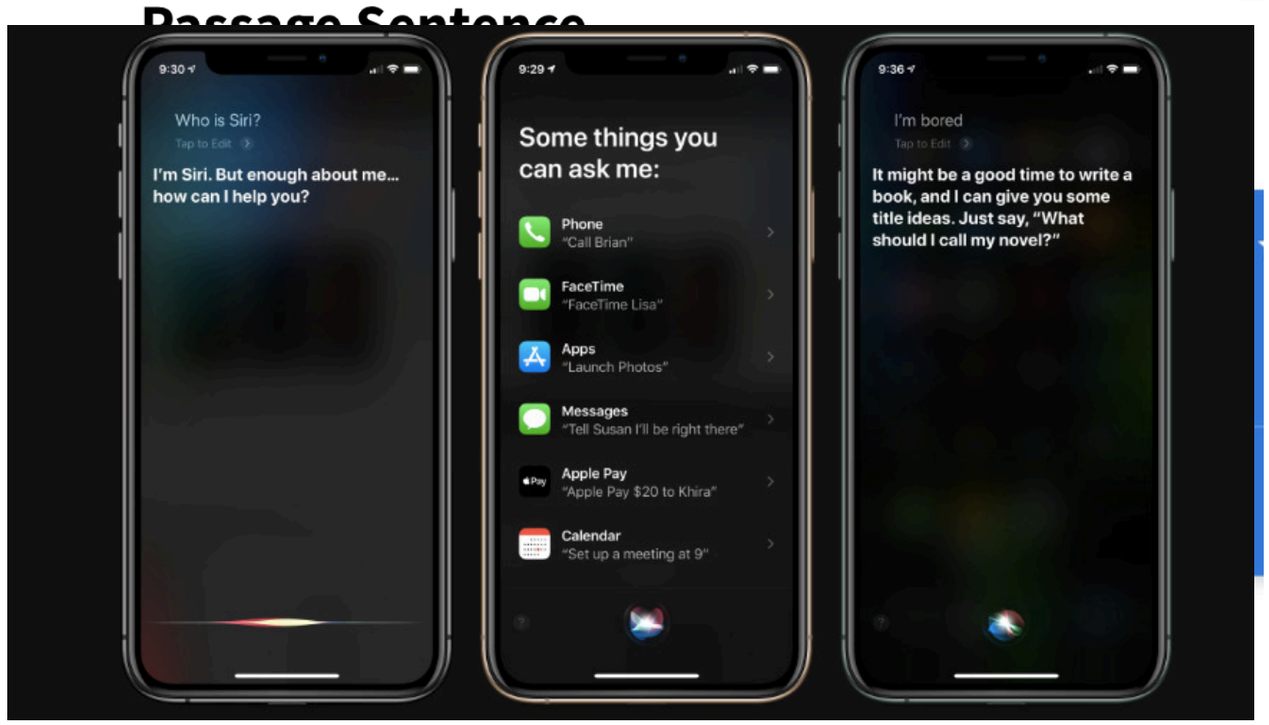
- Information retrieval
  - Question Answering



Language Model Applications

- Spelling correction, text input
  - Search Query Completion
- Optical character recognition
  - e.g. scanning old books
- 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

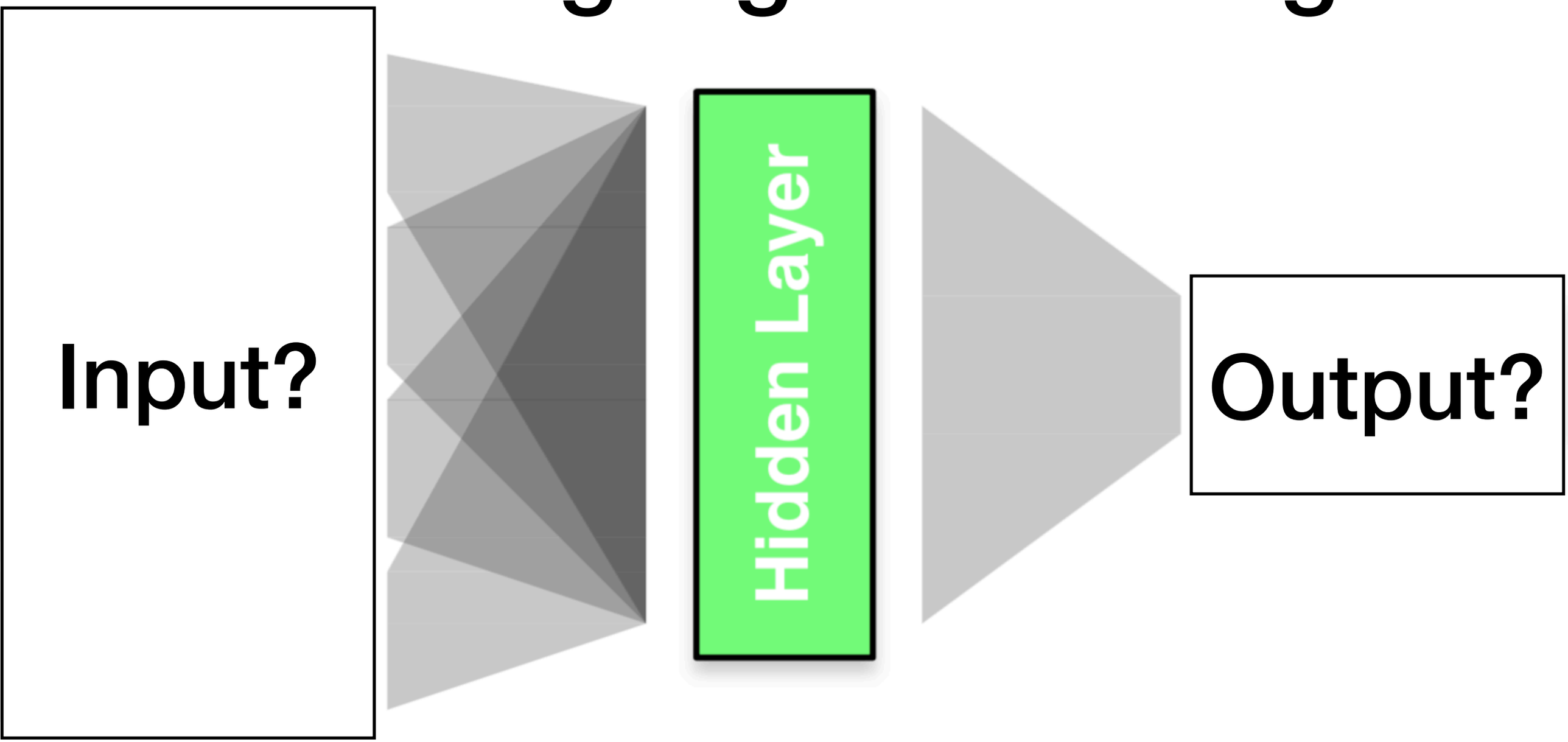

Image: http://mt-class.org/jhu/slides/lecture-nn-lm.pdf

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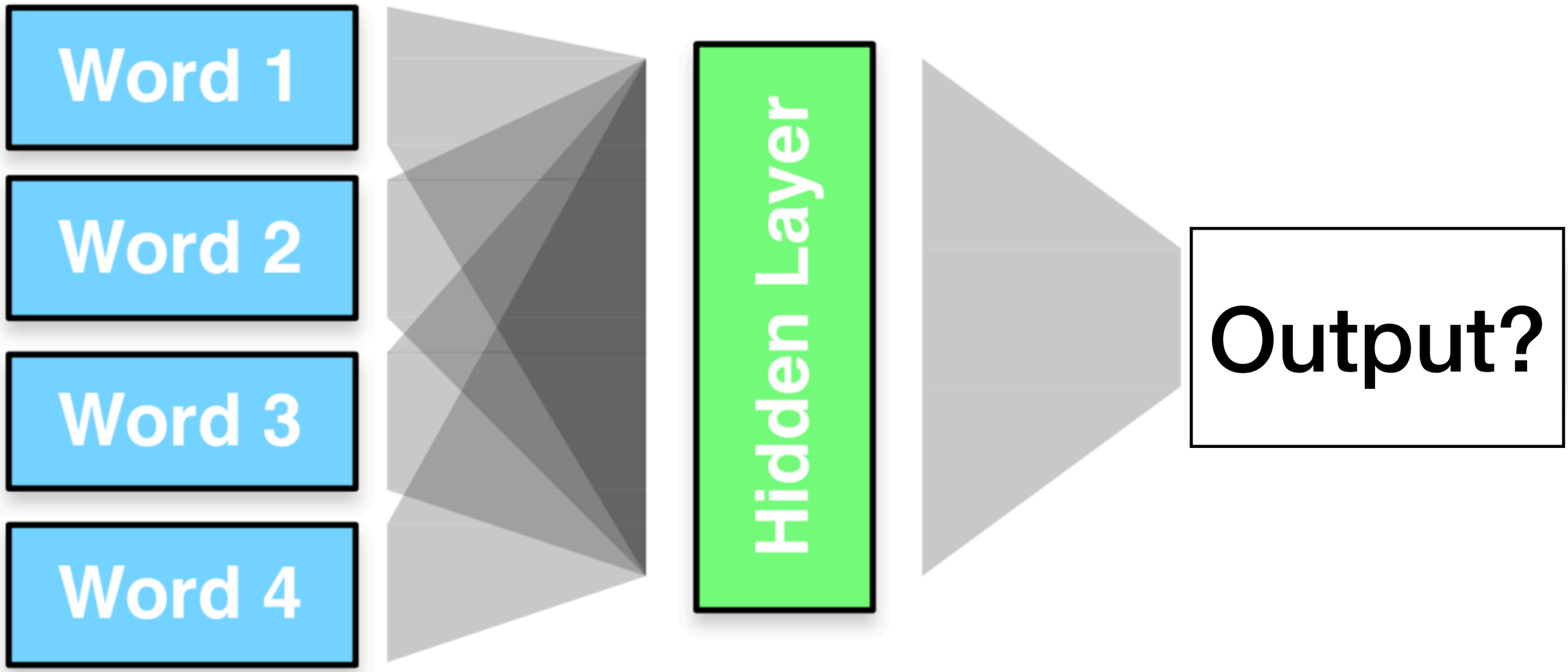

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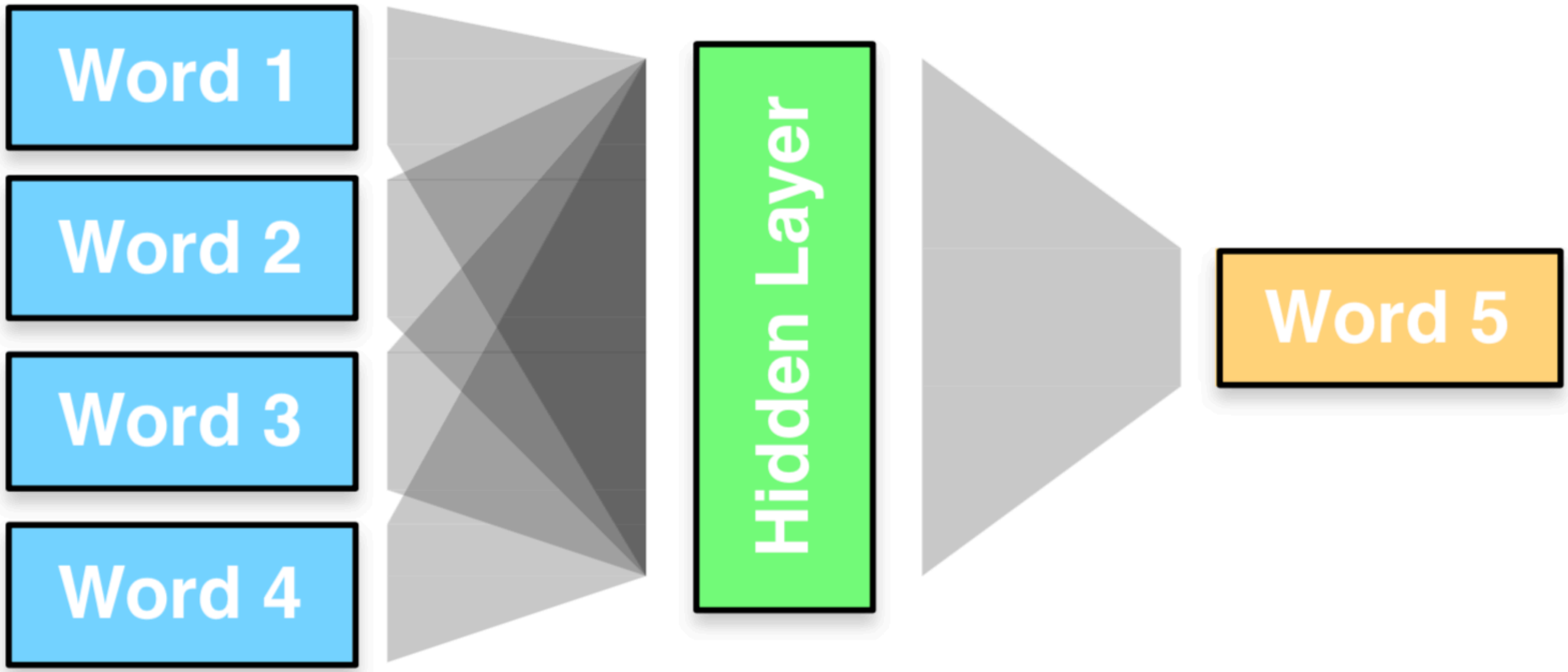

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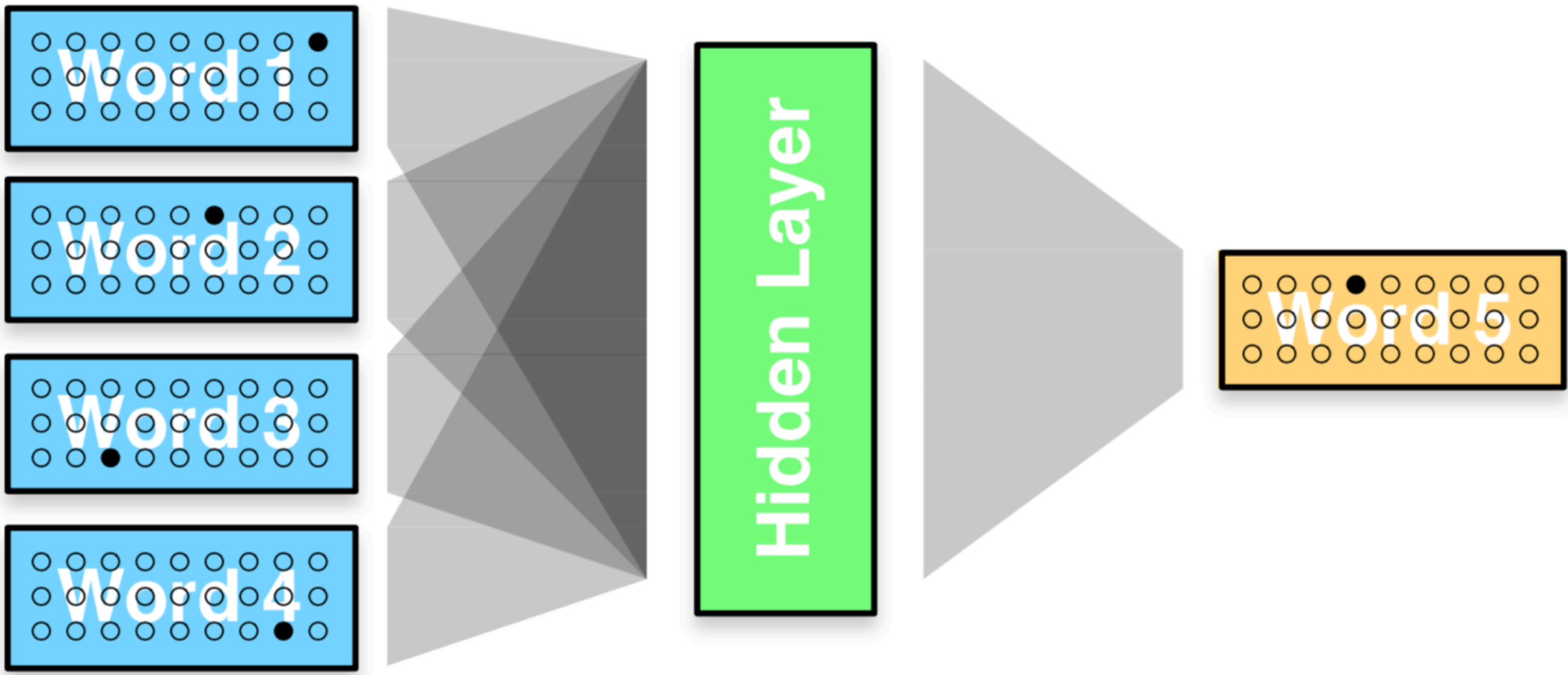
Second Sketch



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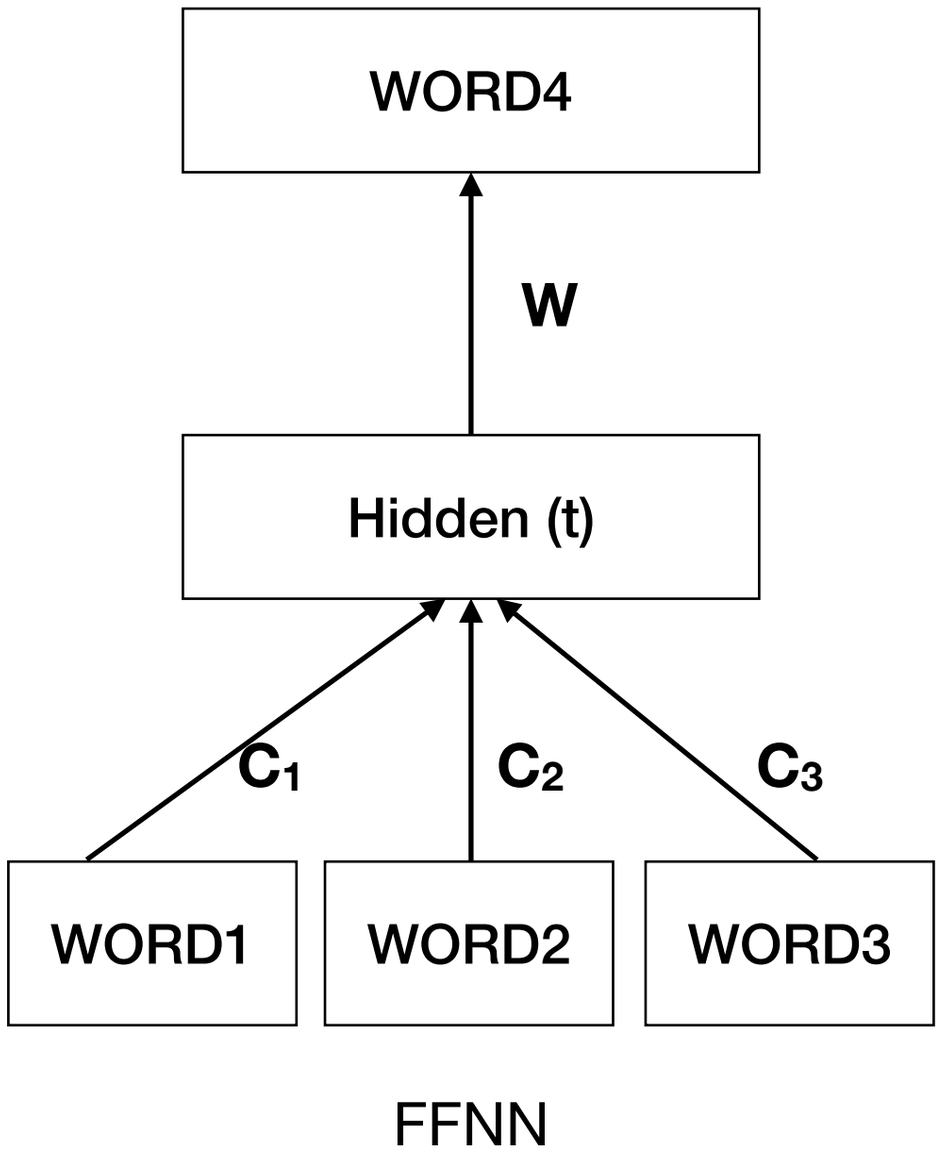
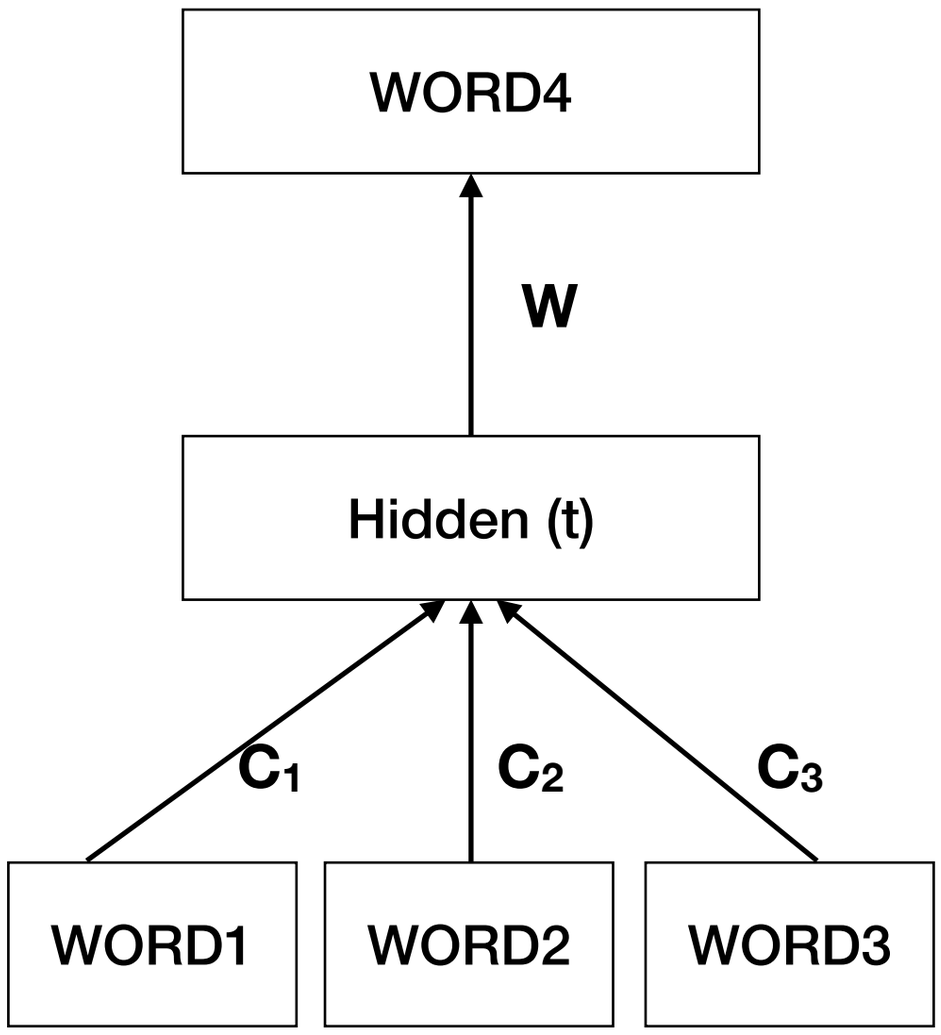
Feedforward Neural Network LM (FFNN)



FFNN

Feedforward Neural Network LM (FFNN)

- Loop through the entire corpus



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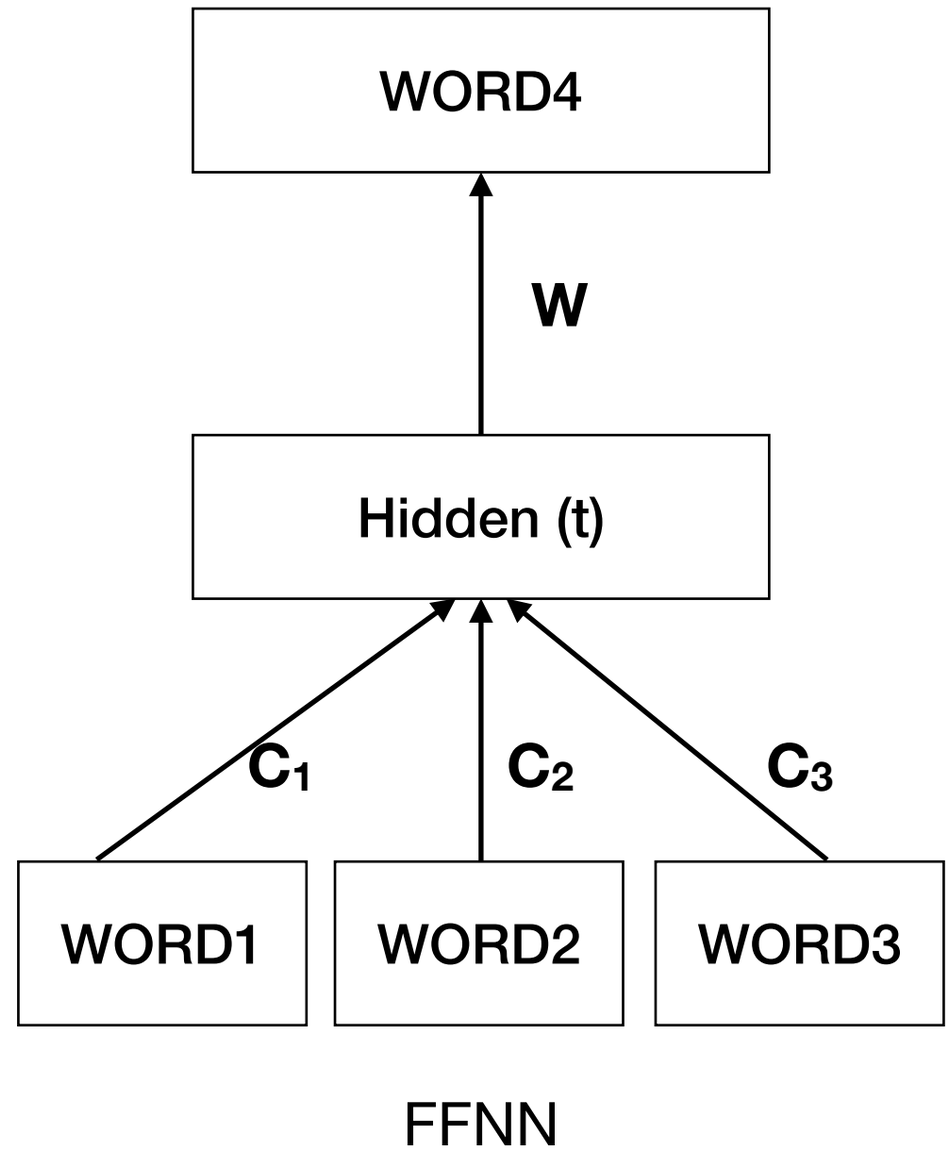
Feedforward Neural Network LM (FFNN)

- Loop through the entire corpus

- Calculate error or loss (cross-entropy loss)



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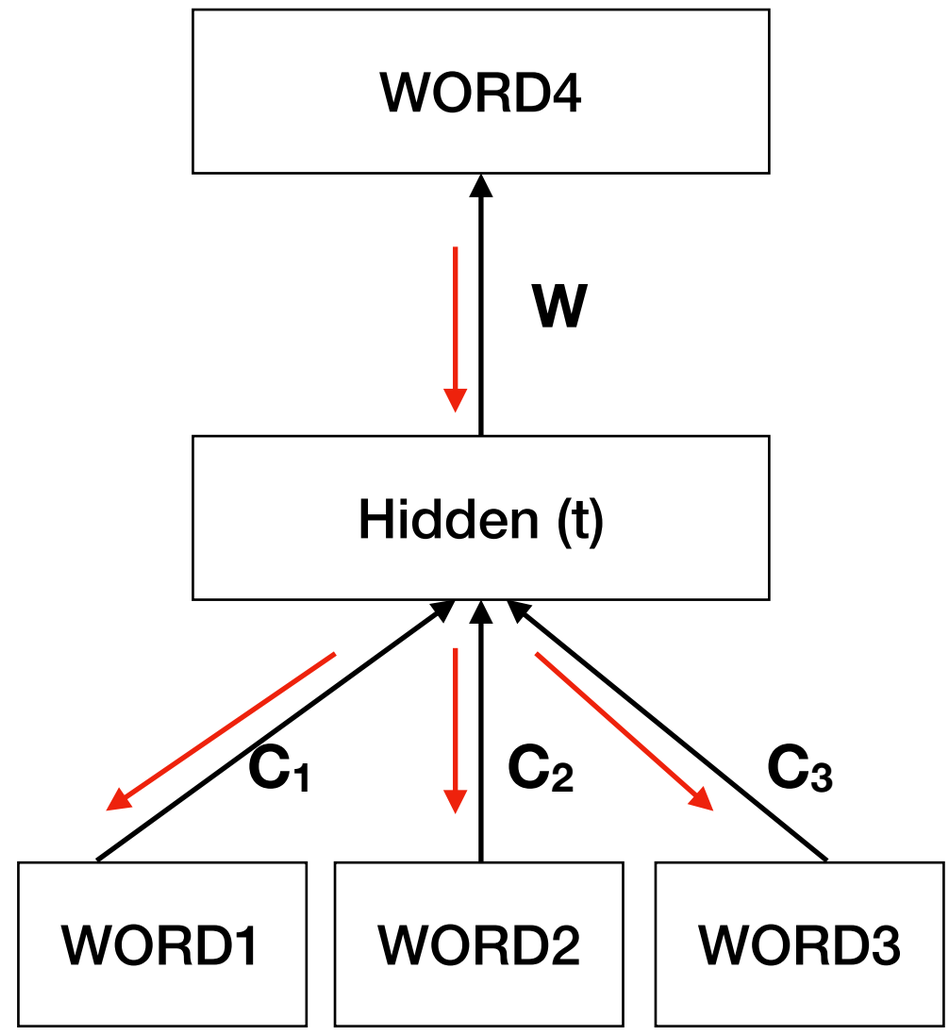
Feedforward Neural Network LM (FFNN)

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



FFNN

Feedforward Neural Network LM (FFNN)

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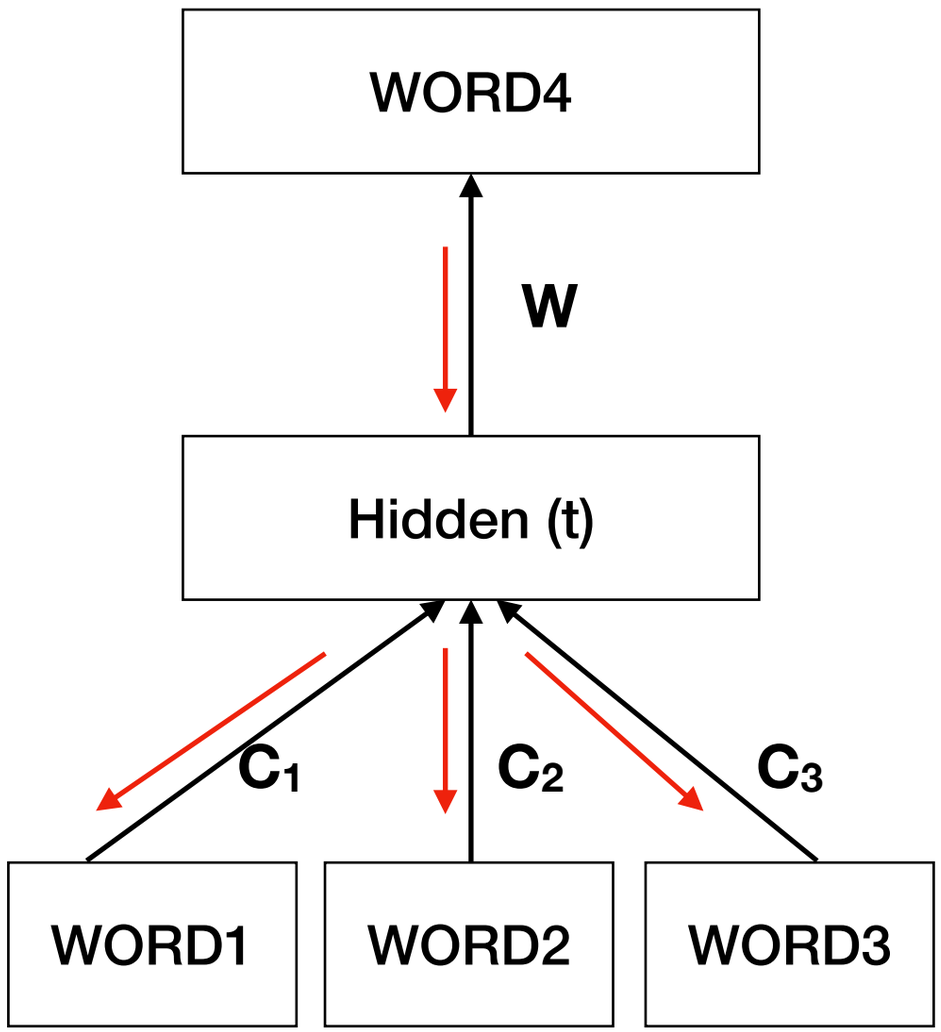
- Propagate the error through network to update the weight matrices
- Back Propagation



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 running in a room

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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 _____.”

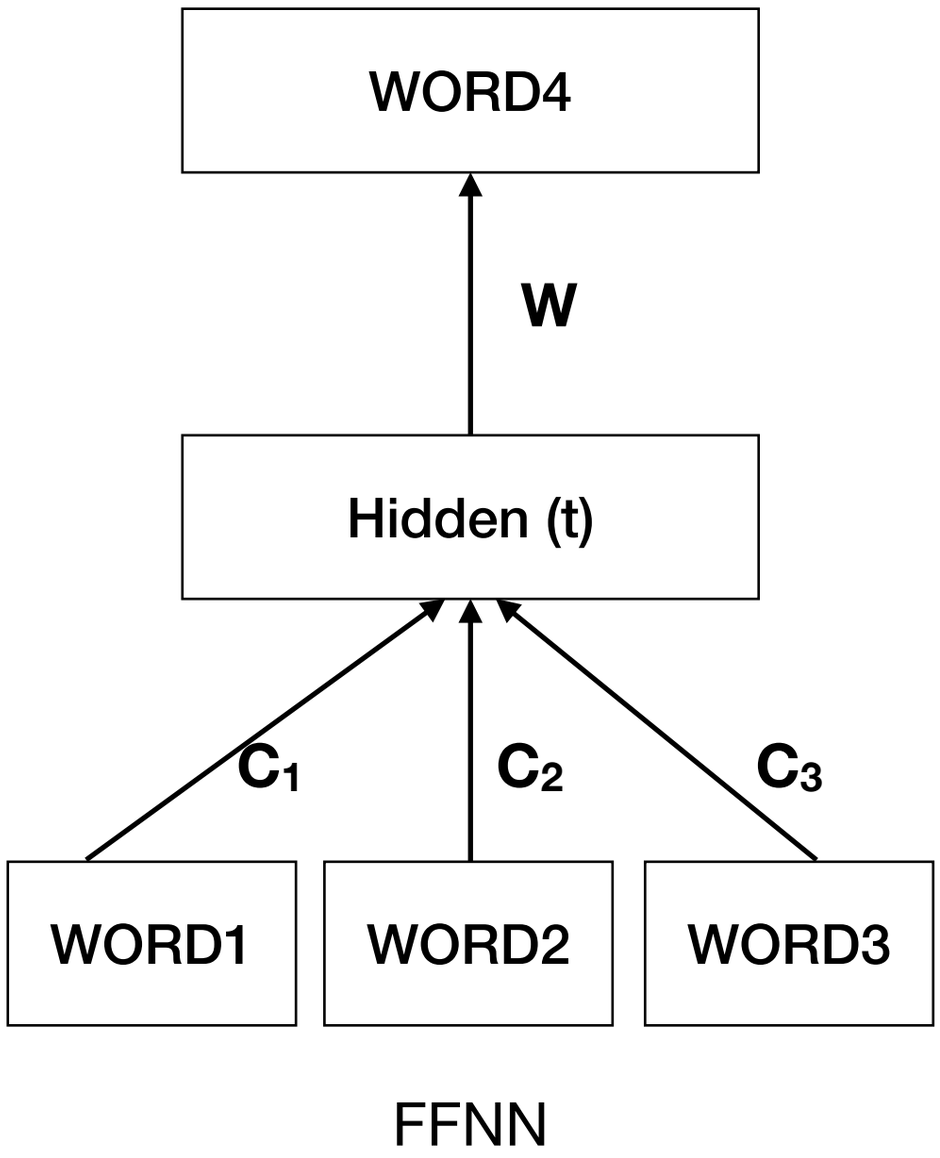
Feedforward: Long-term information

- “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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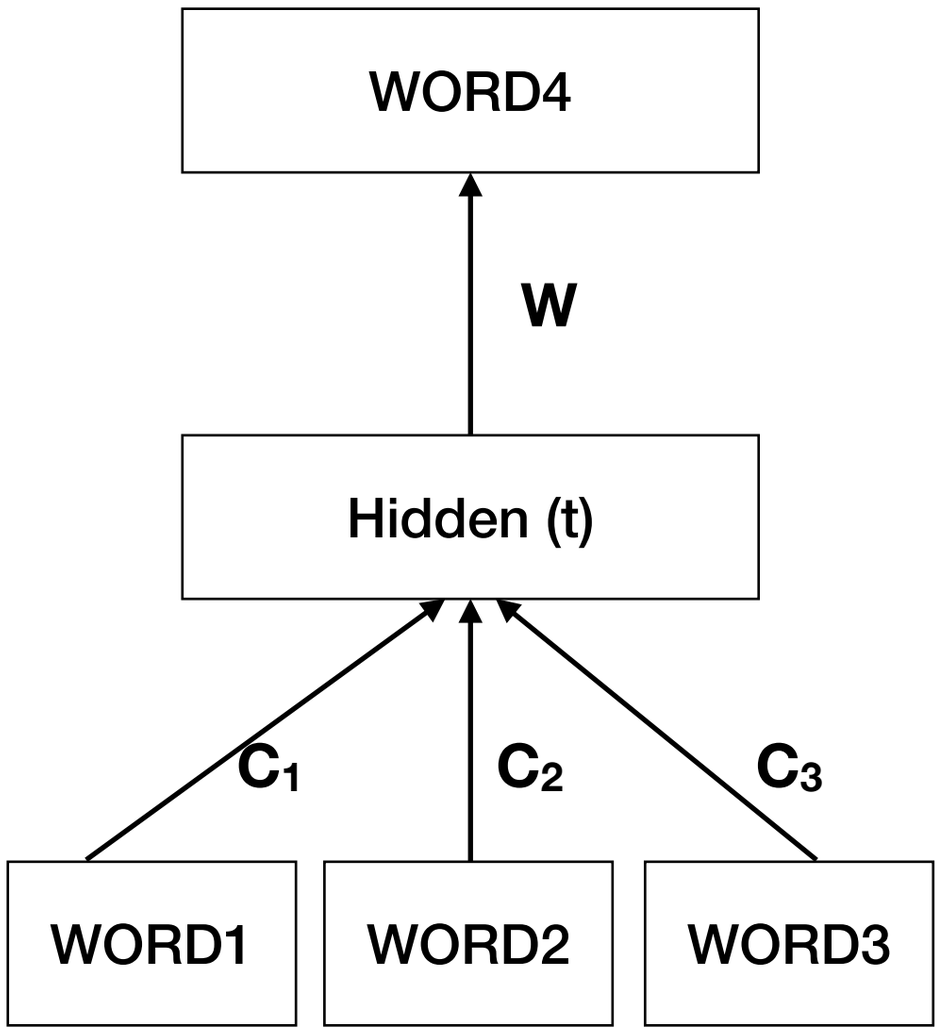
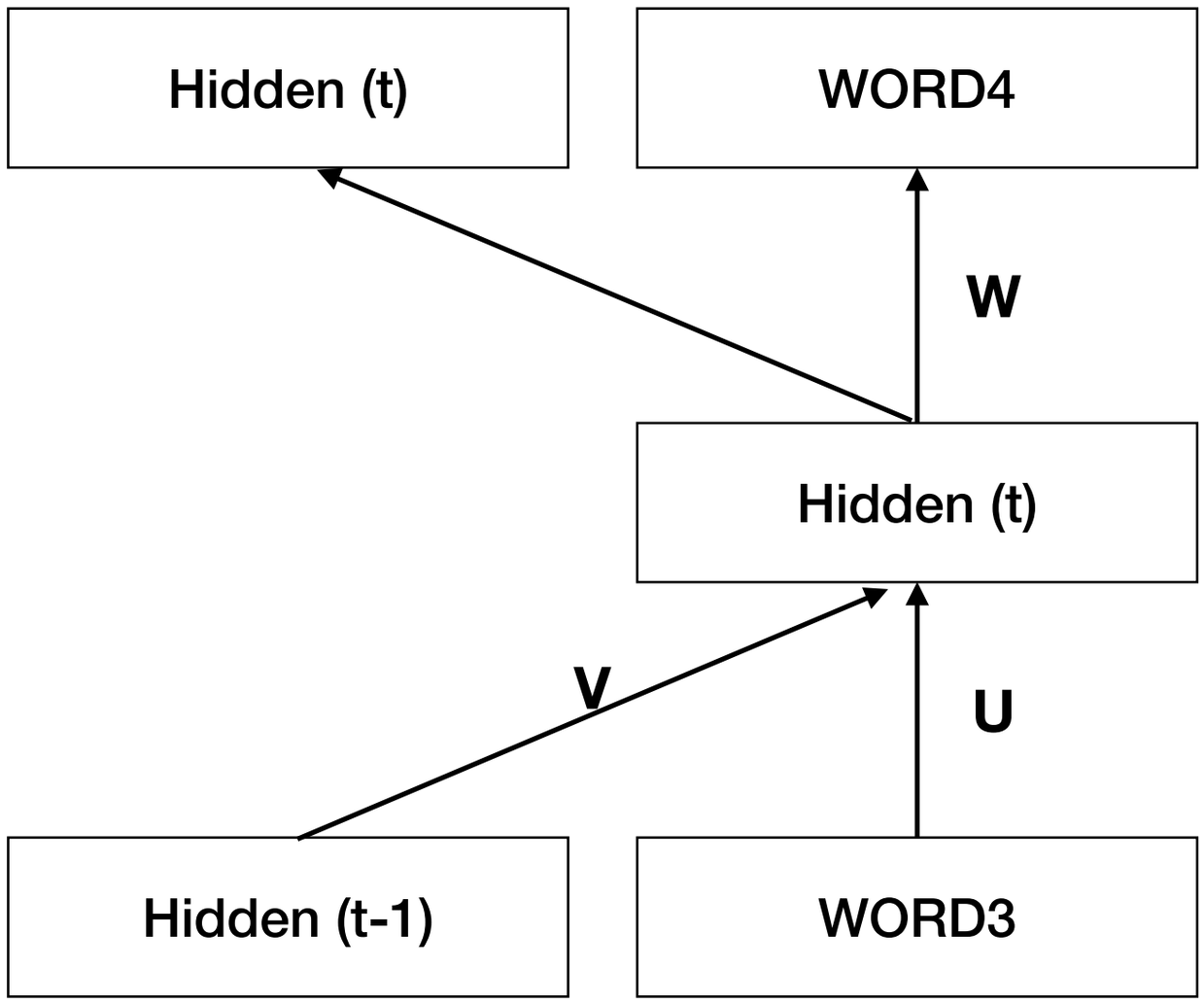


FFNN



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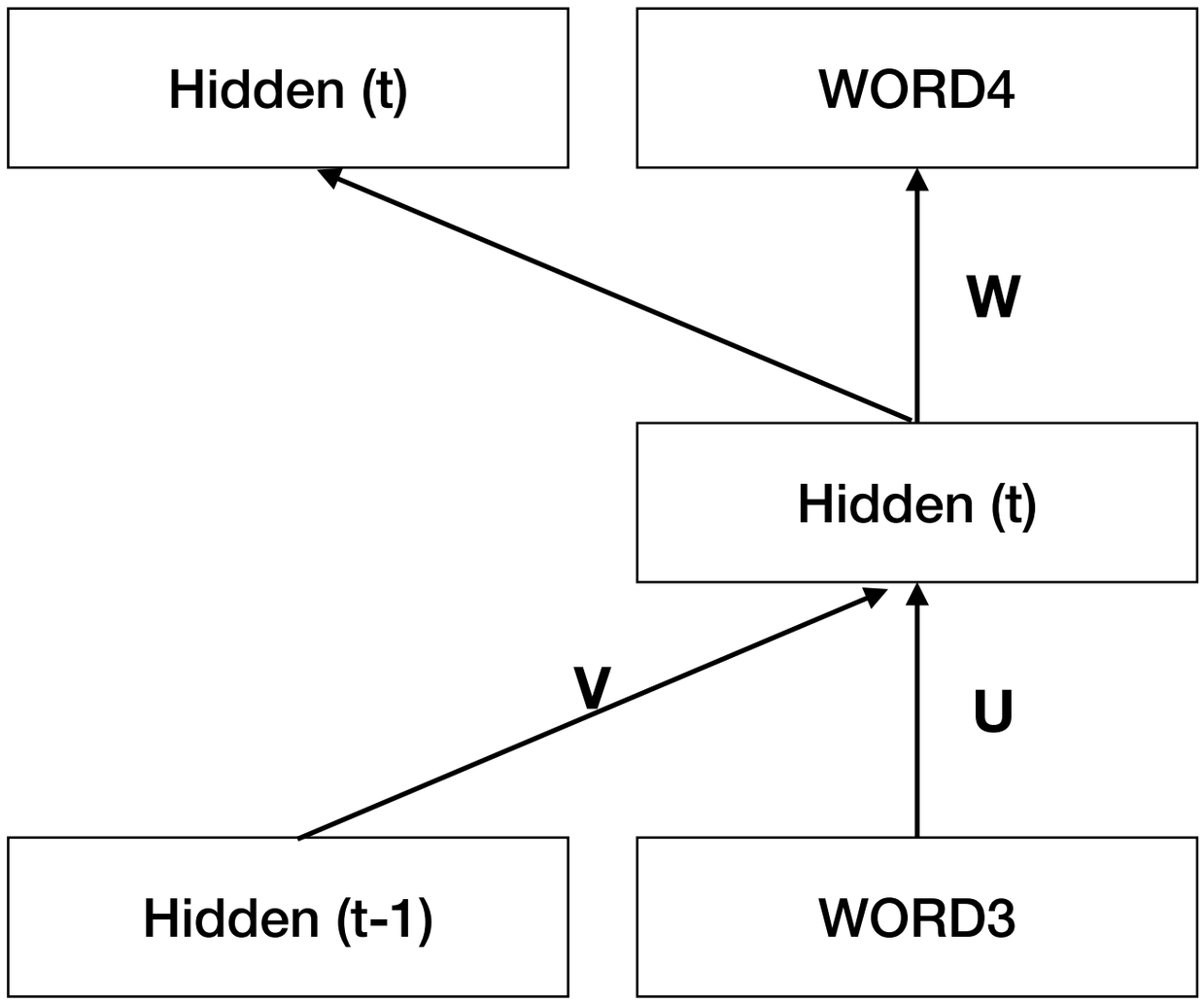

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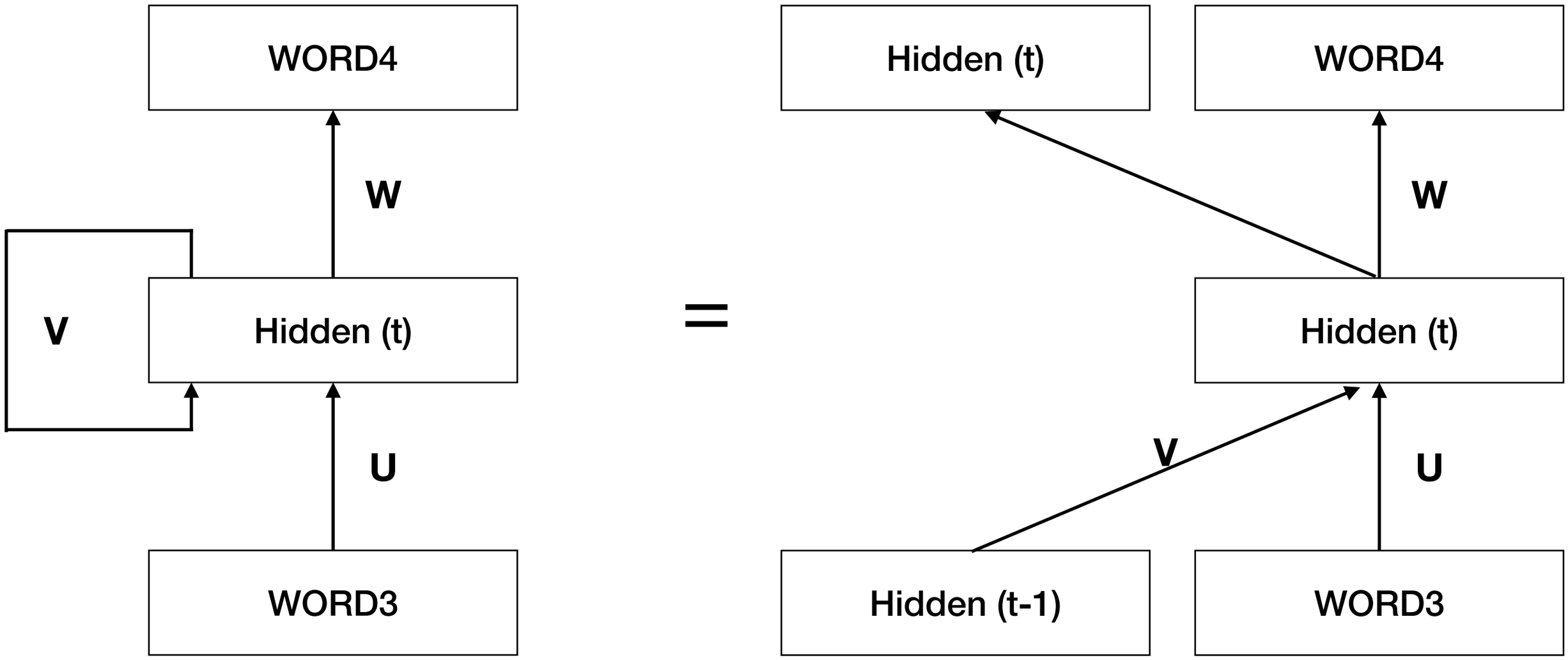
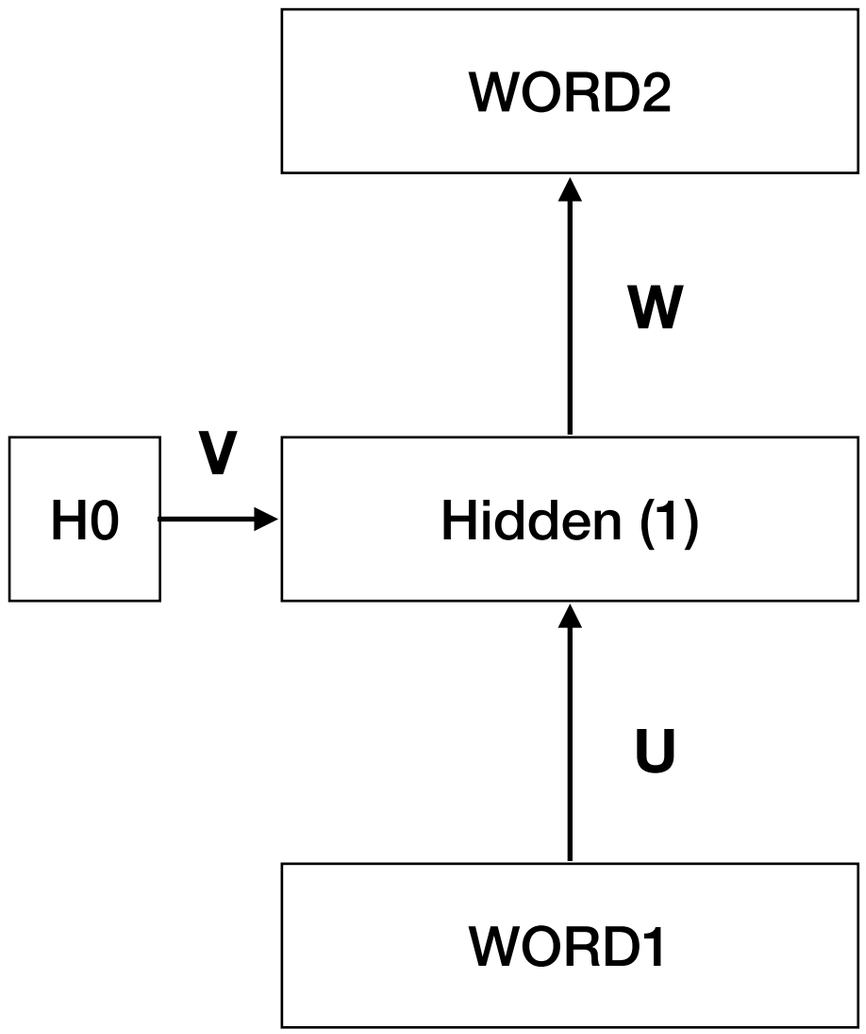
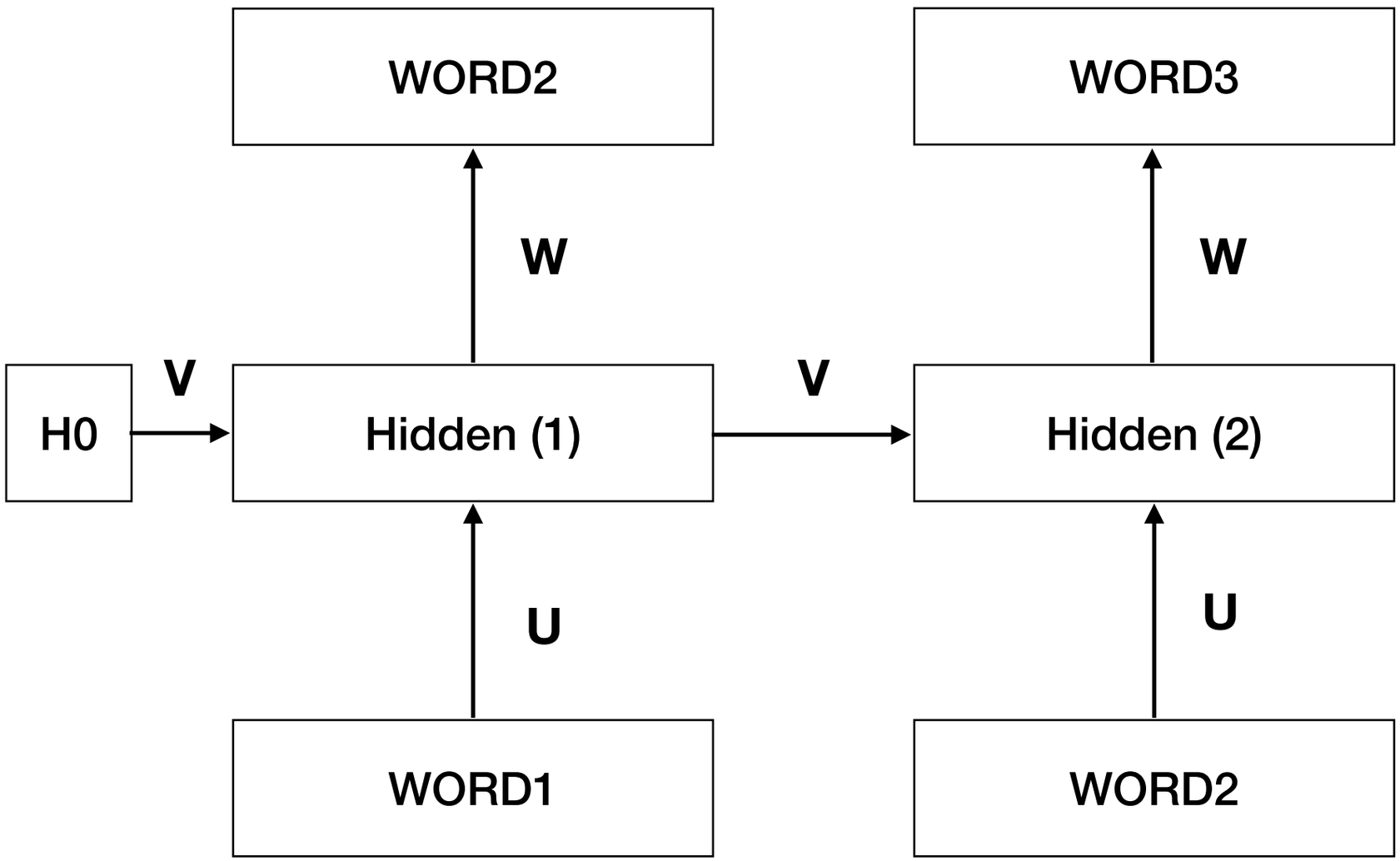


RNN

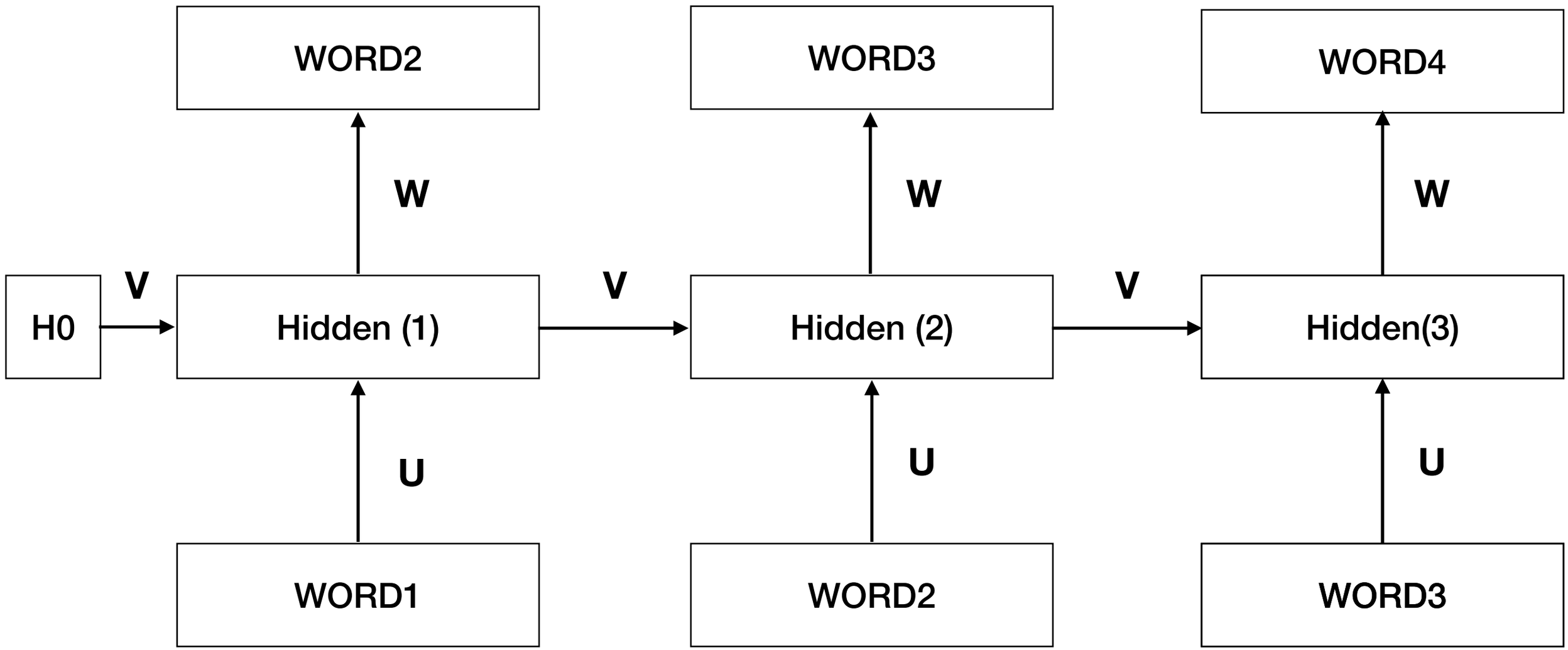
RNN: Timestep 1



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*.”

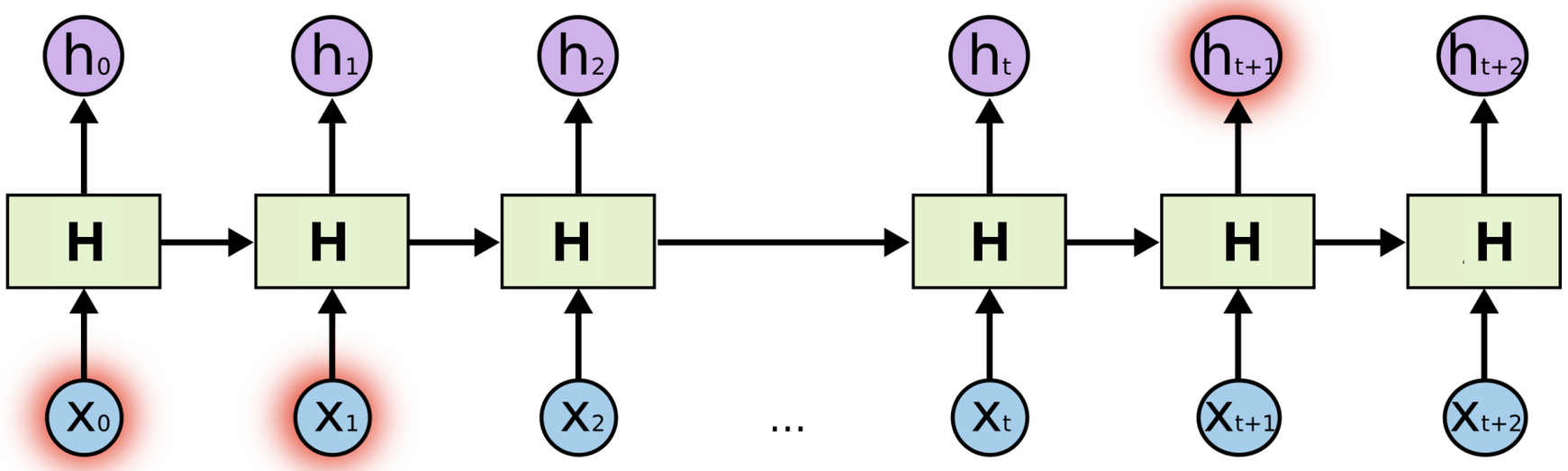
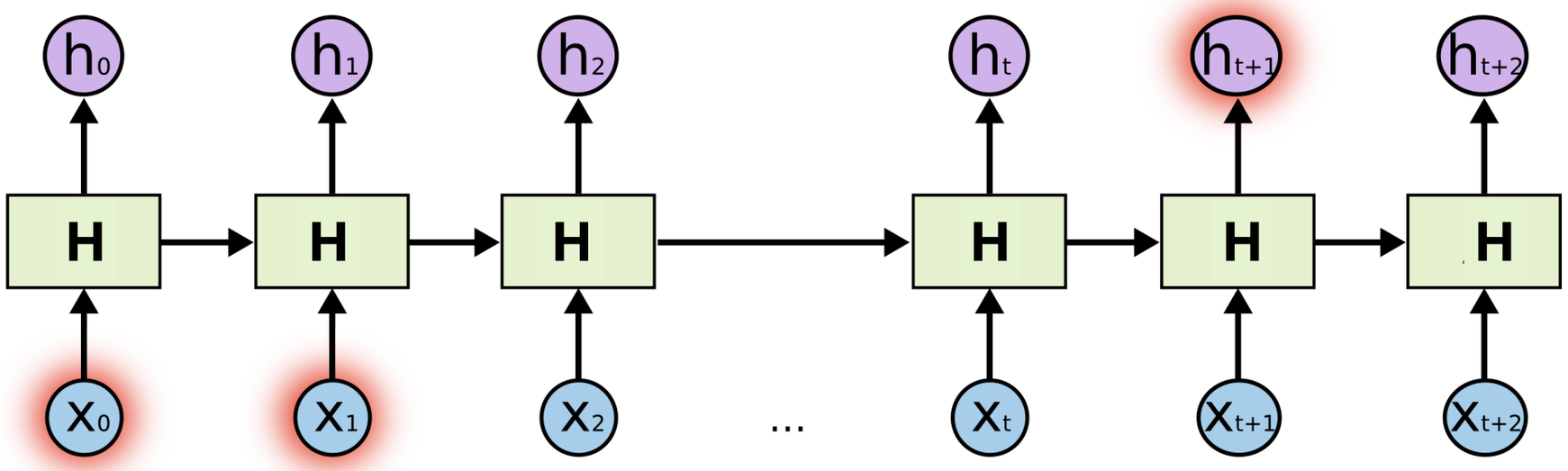


Image: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

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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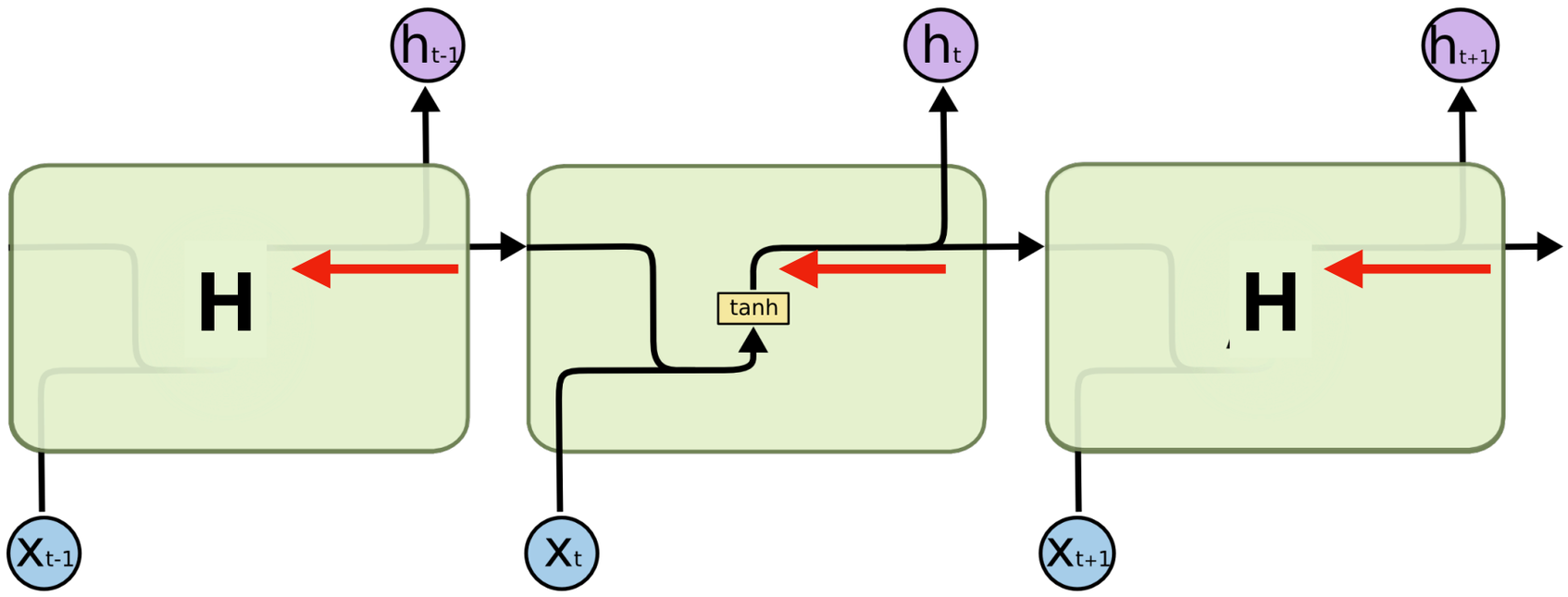

- Error (red arrow) is passed through a chain of hidden states

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

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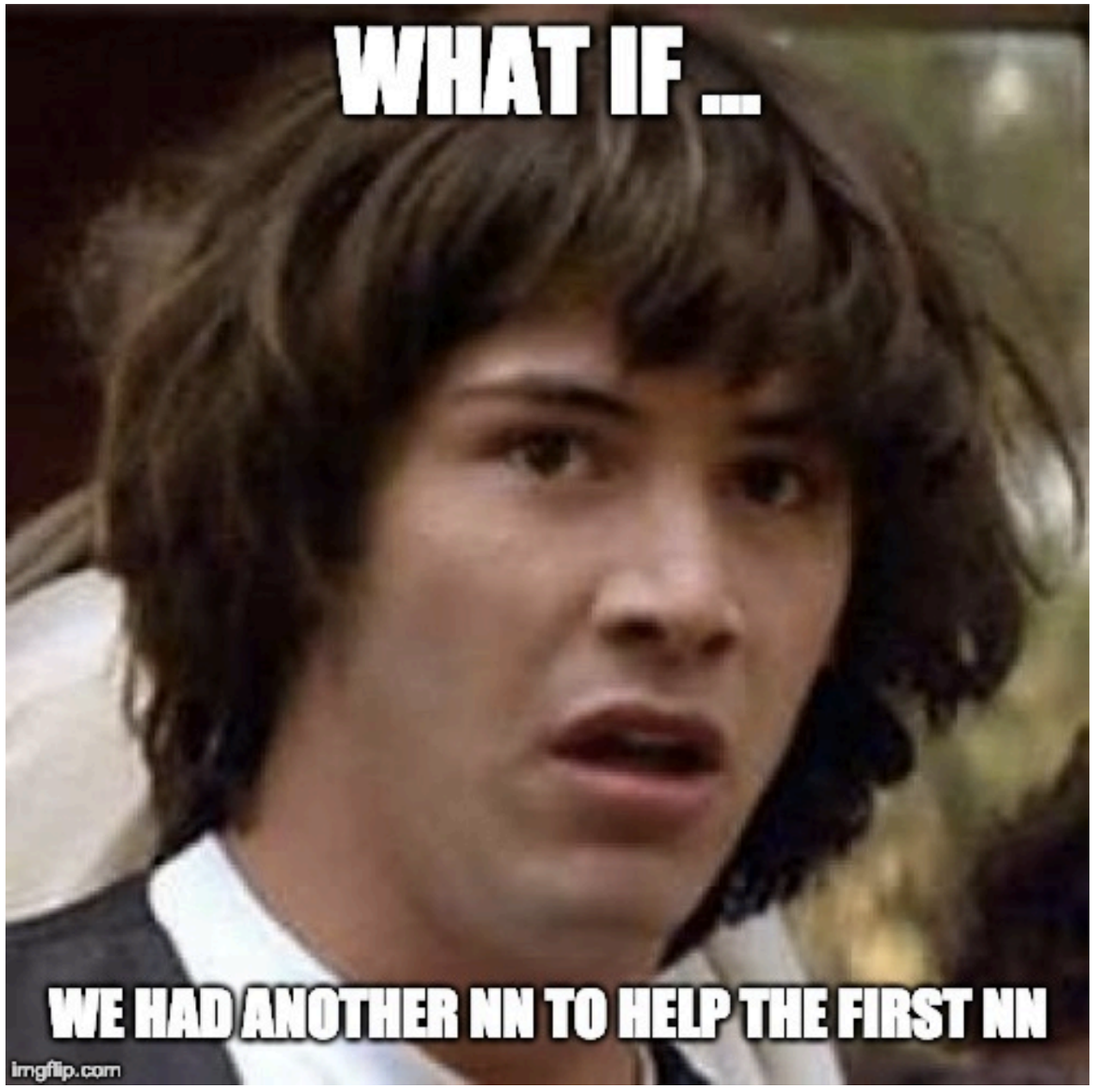
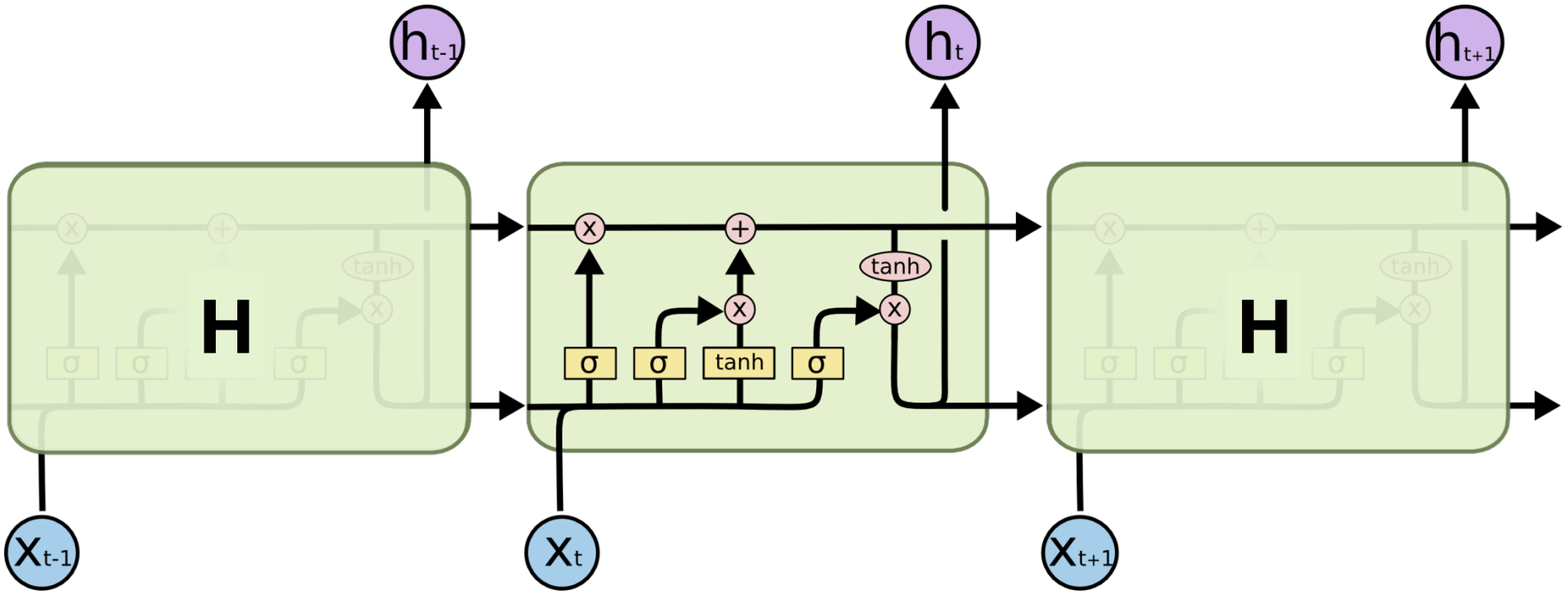

WHAT IF ...
WE HAD ANOTHER NN TO HELP THE FIRST NN
imgflip.com

Long-Short Term Memory



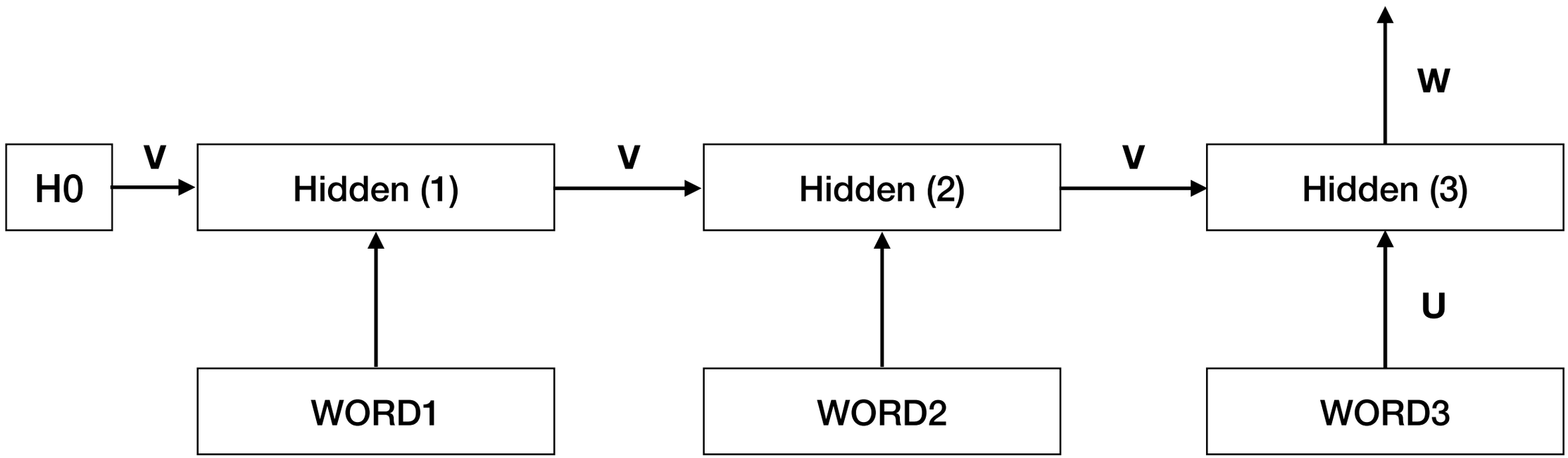
- Lets add another neural network help the first network learn long-term dependencies

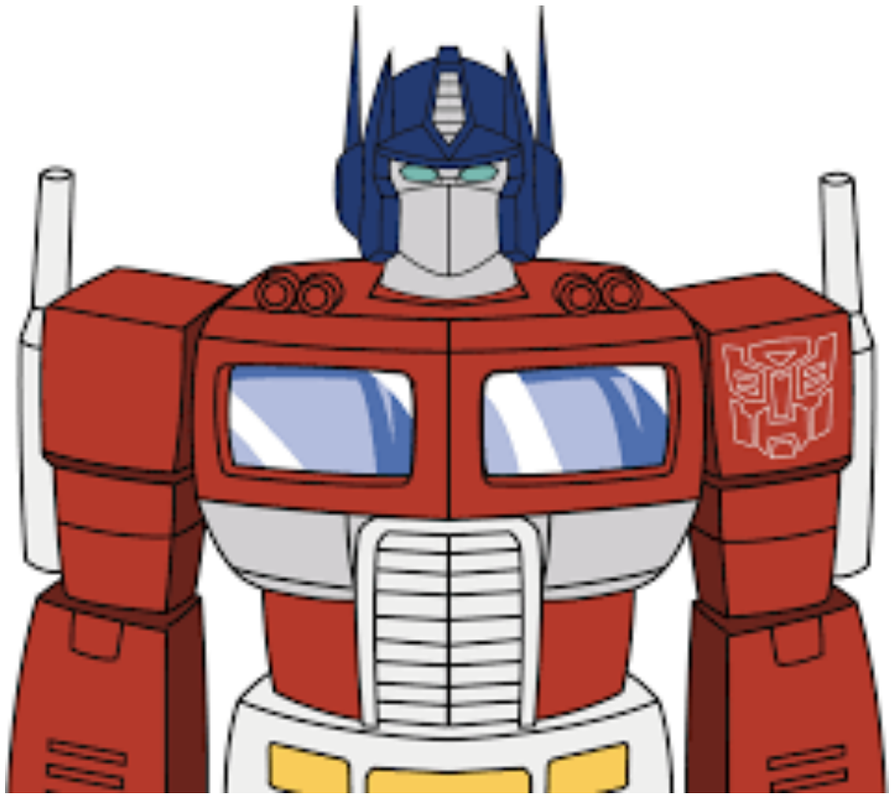
- That's basically what we do when we add more weight matrices to a neural network

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

LSTM Problems

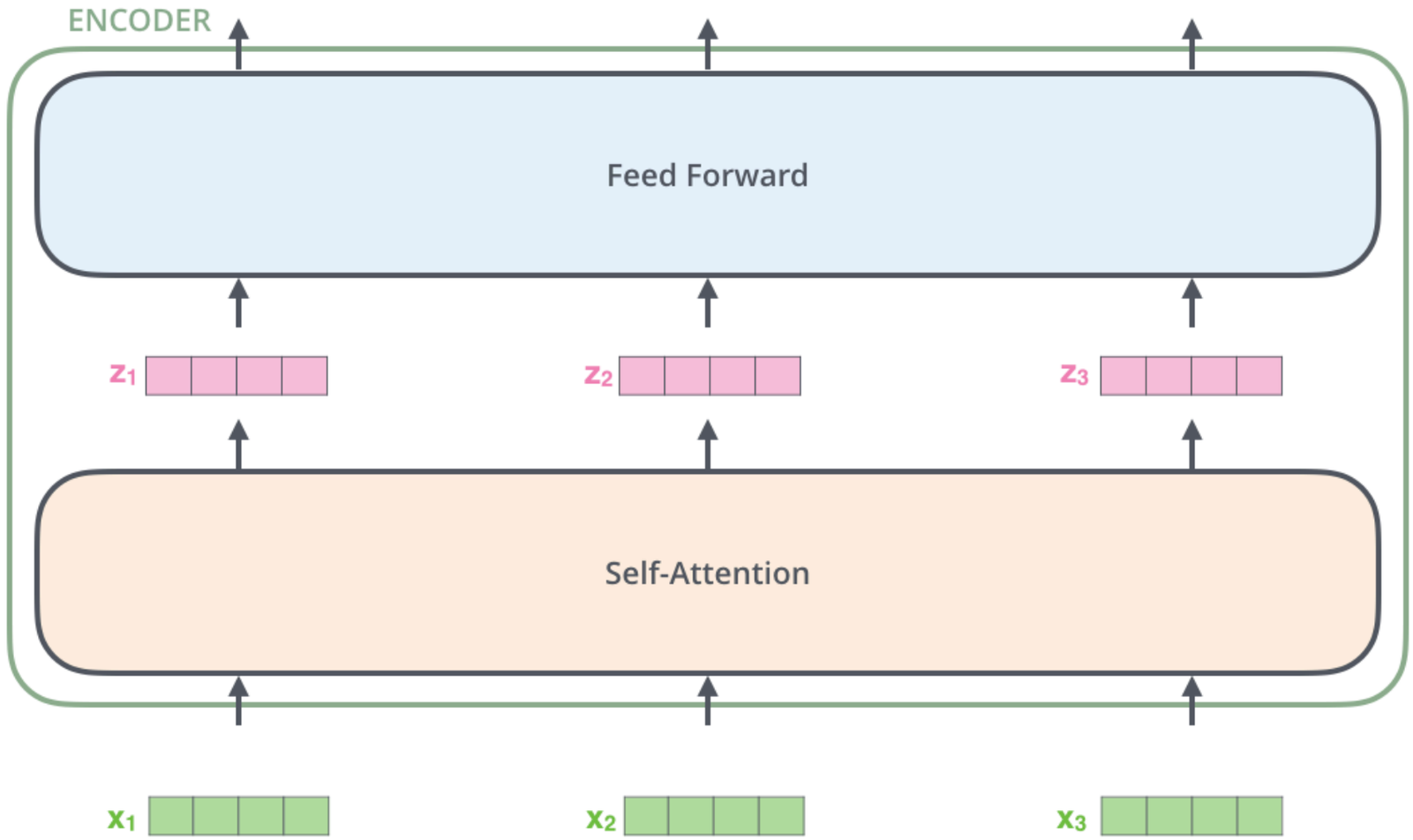
- Implicit representation of long-term information
  - Cell state and previous hidden state summarise the prior information





Transformers for Language Modelling

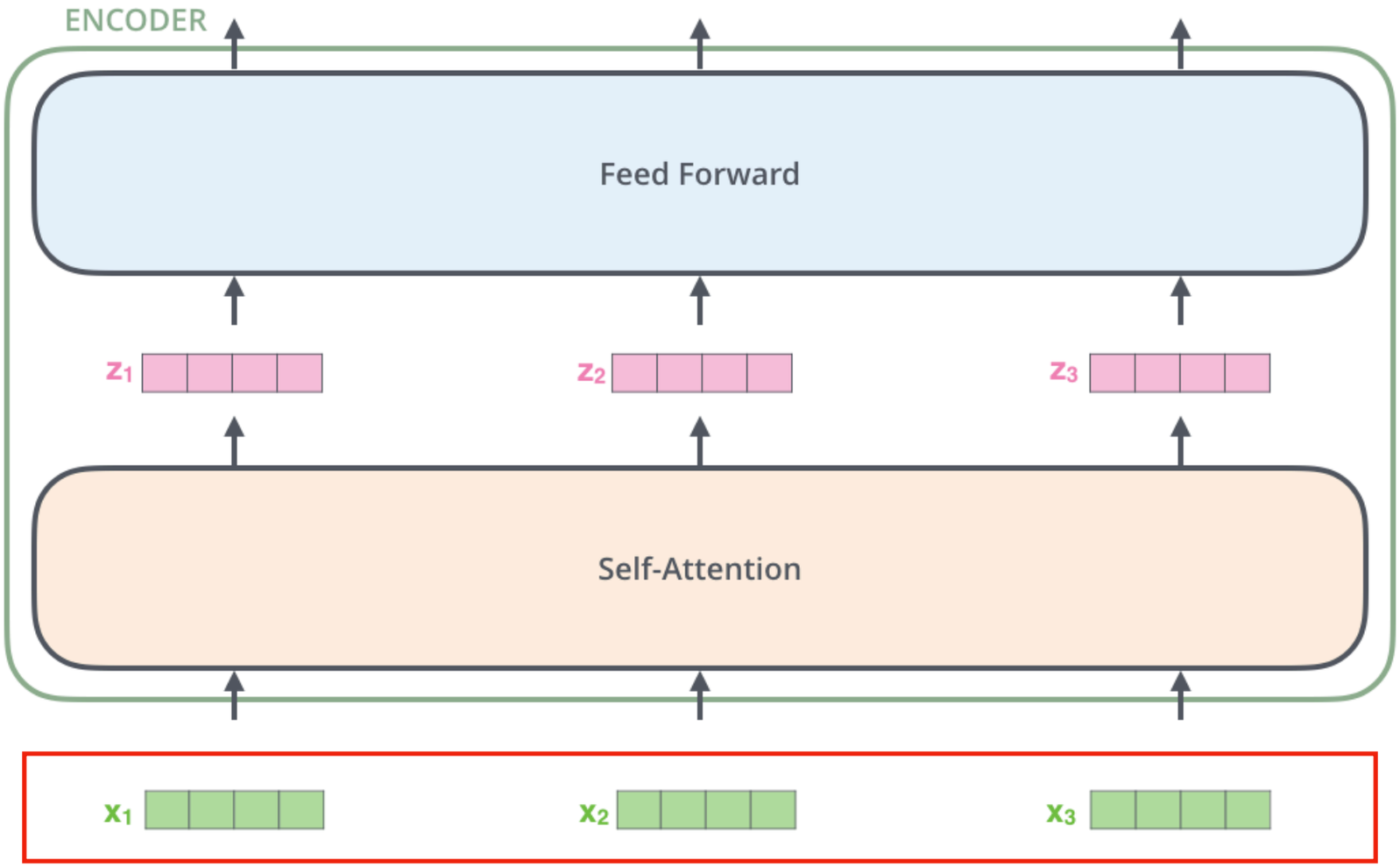
Transformers: Simplified



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

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

Transformers: Simplified



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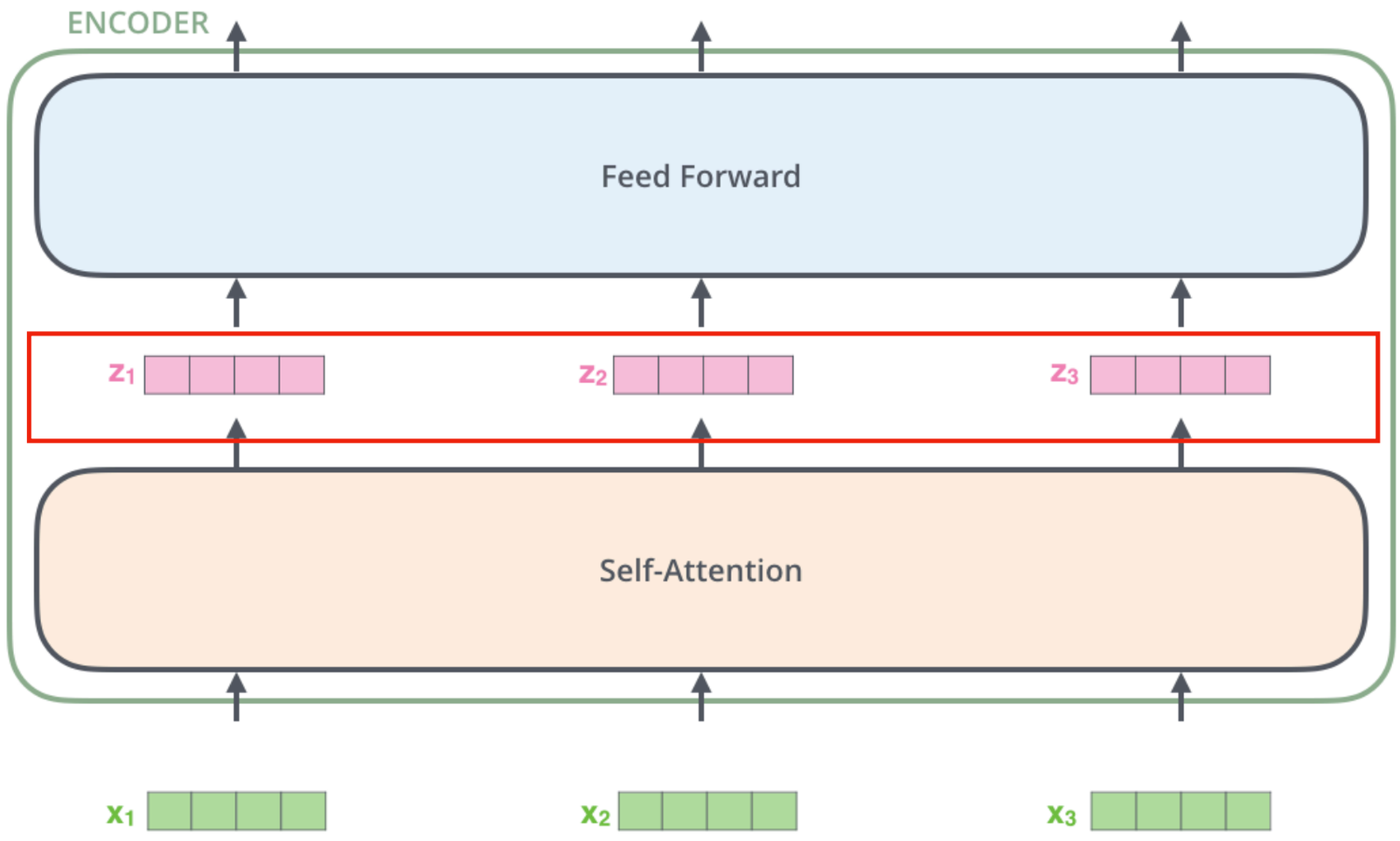

Multiple (50-90) such layers in a Transformer LM

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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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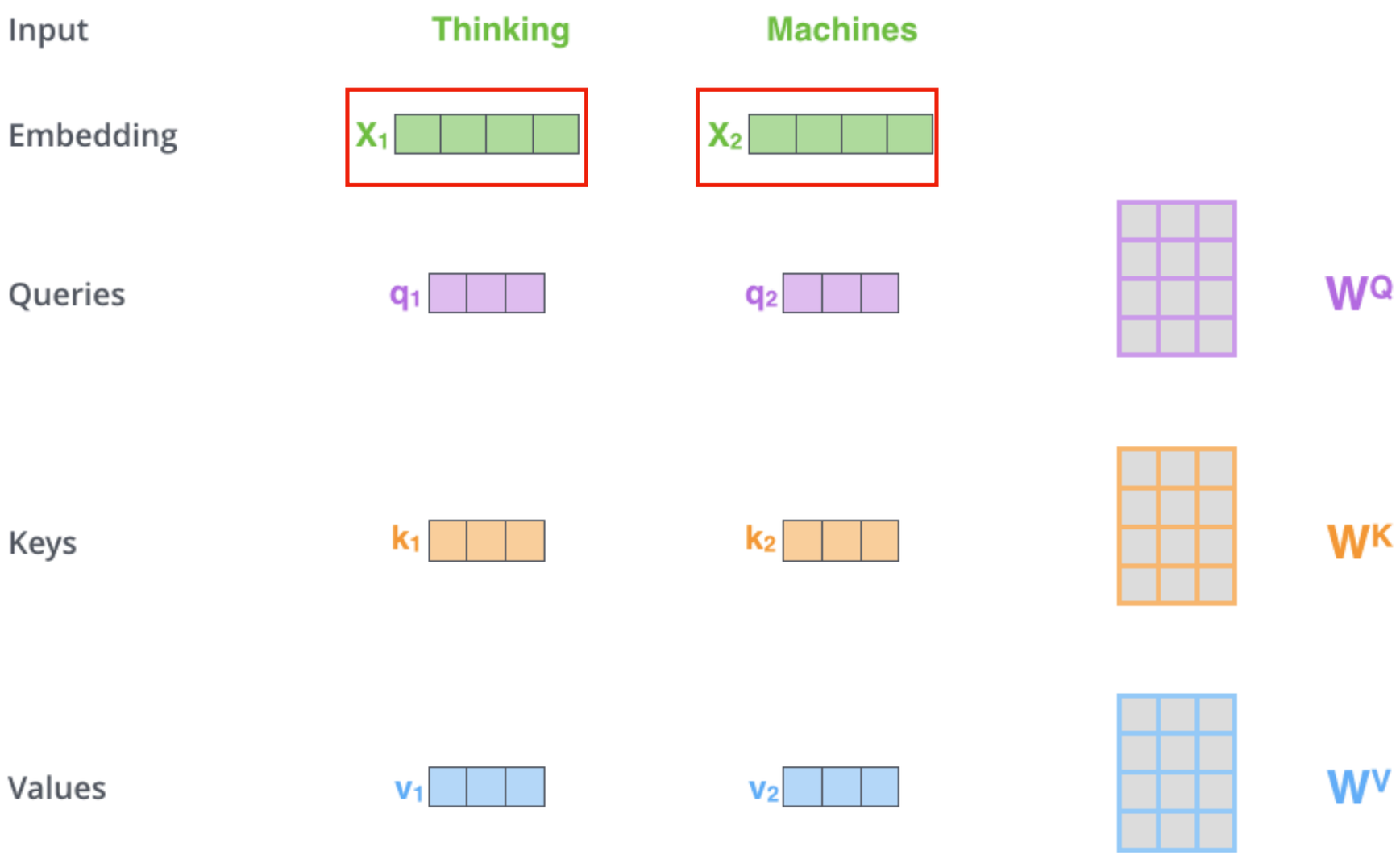
Self-Attention: Step 0



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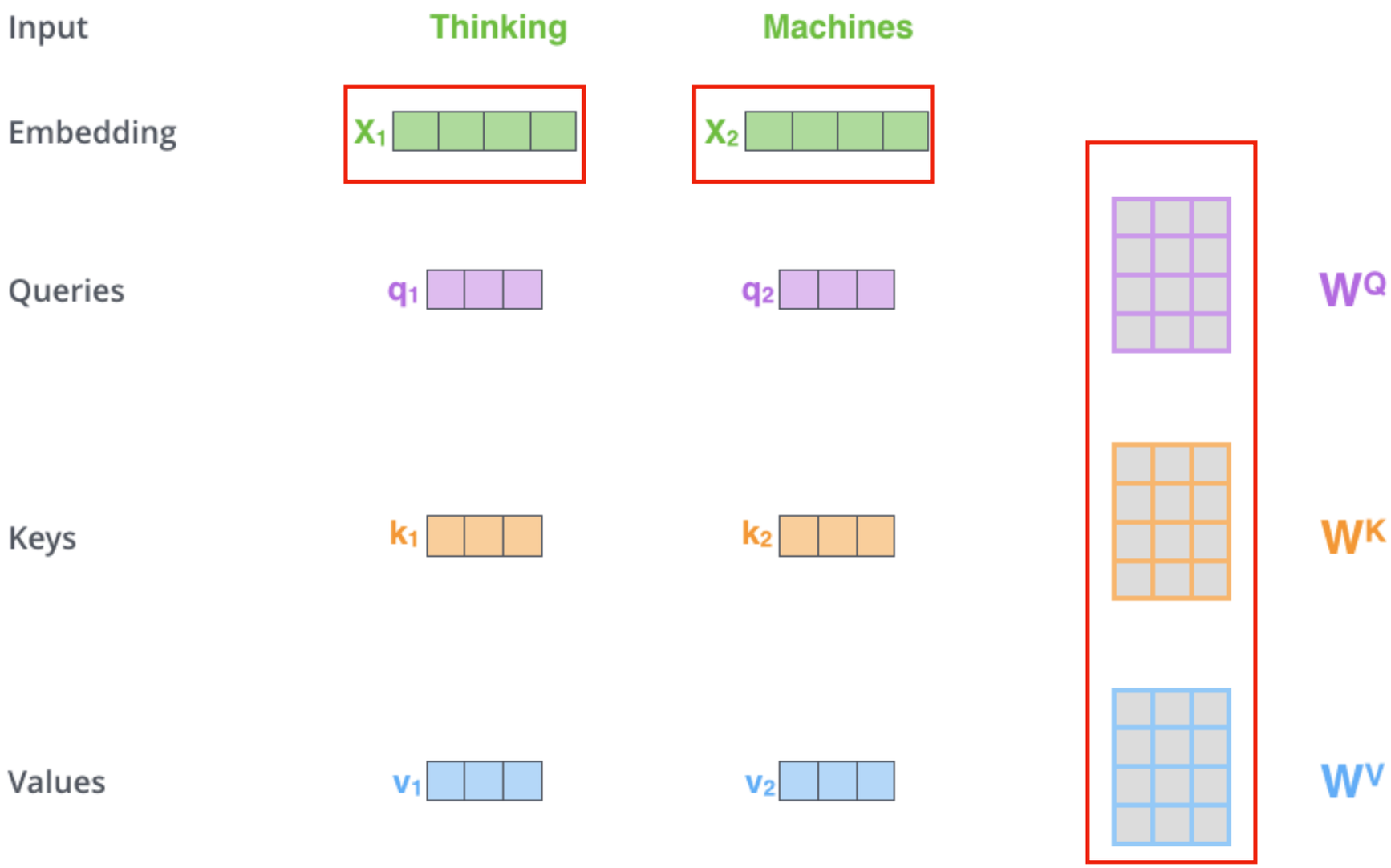

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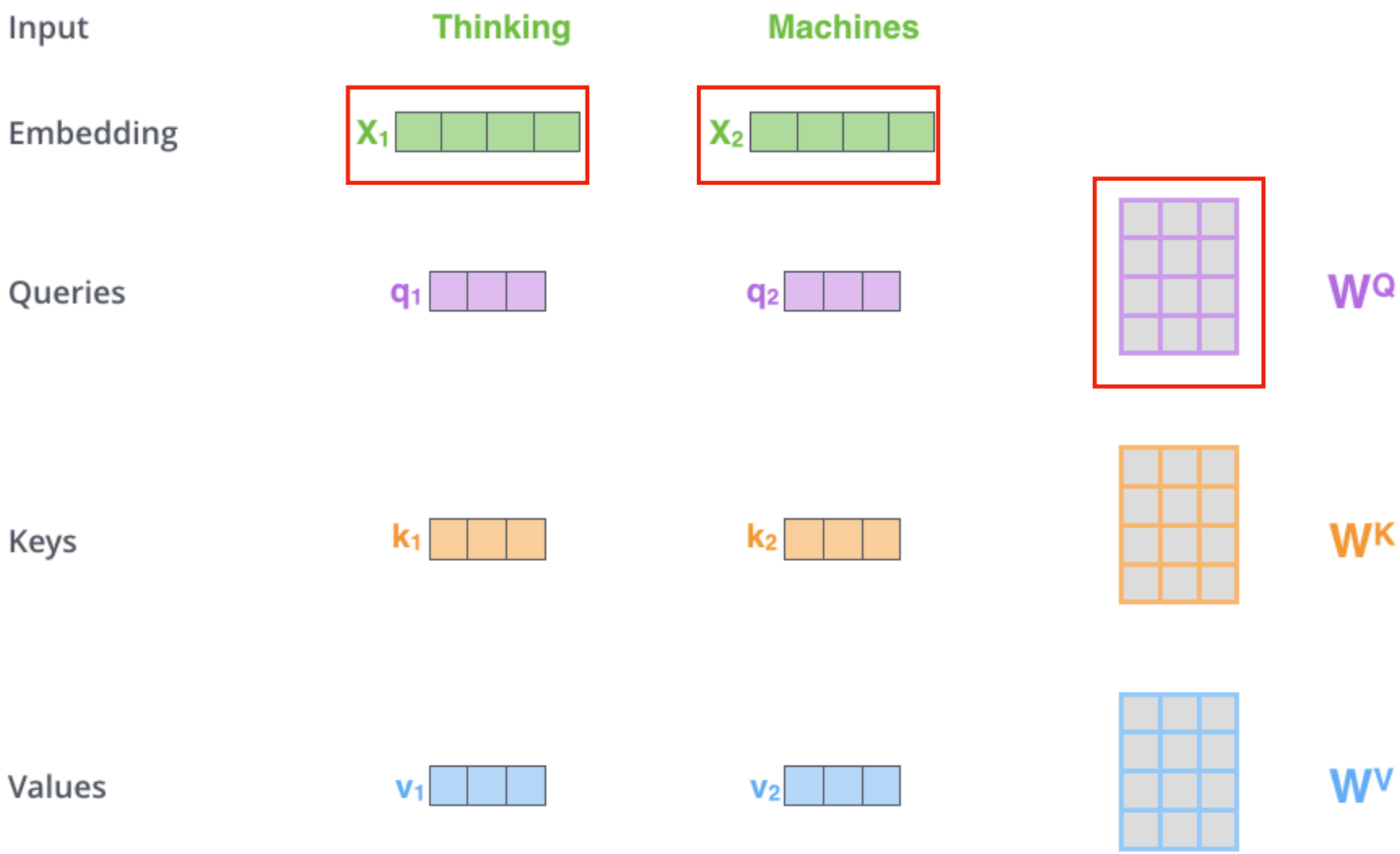

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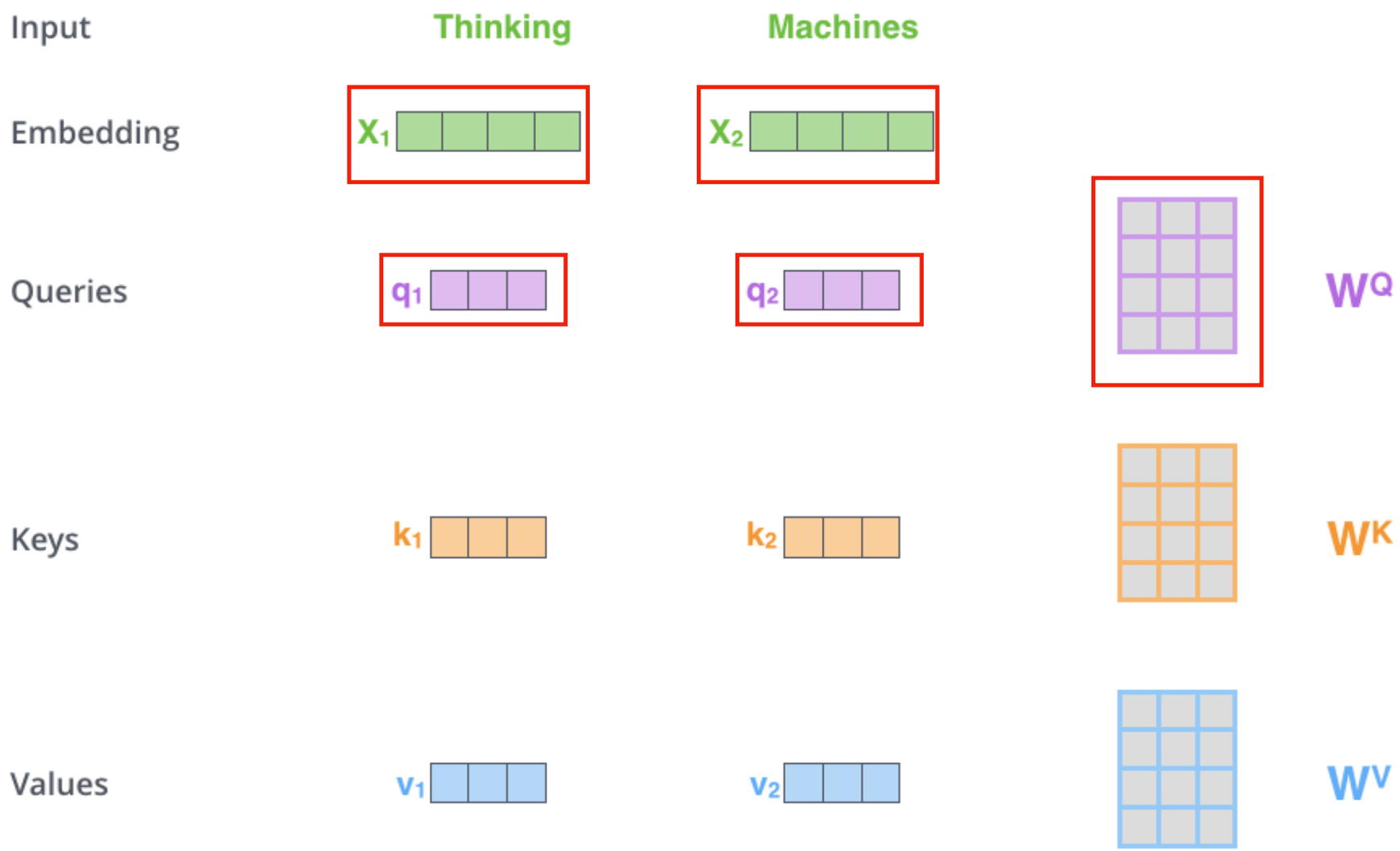

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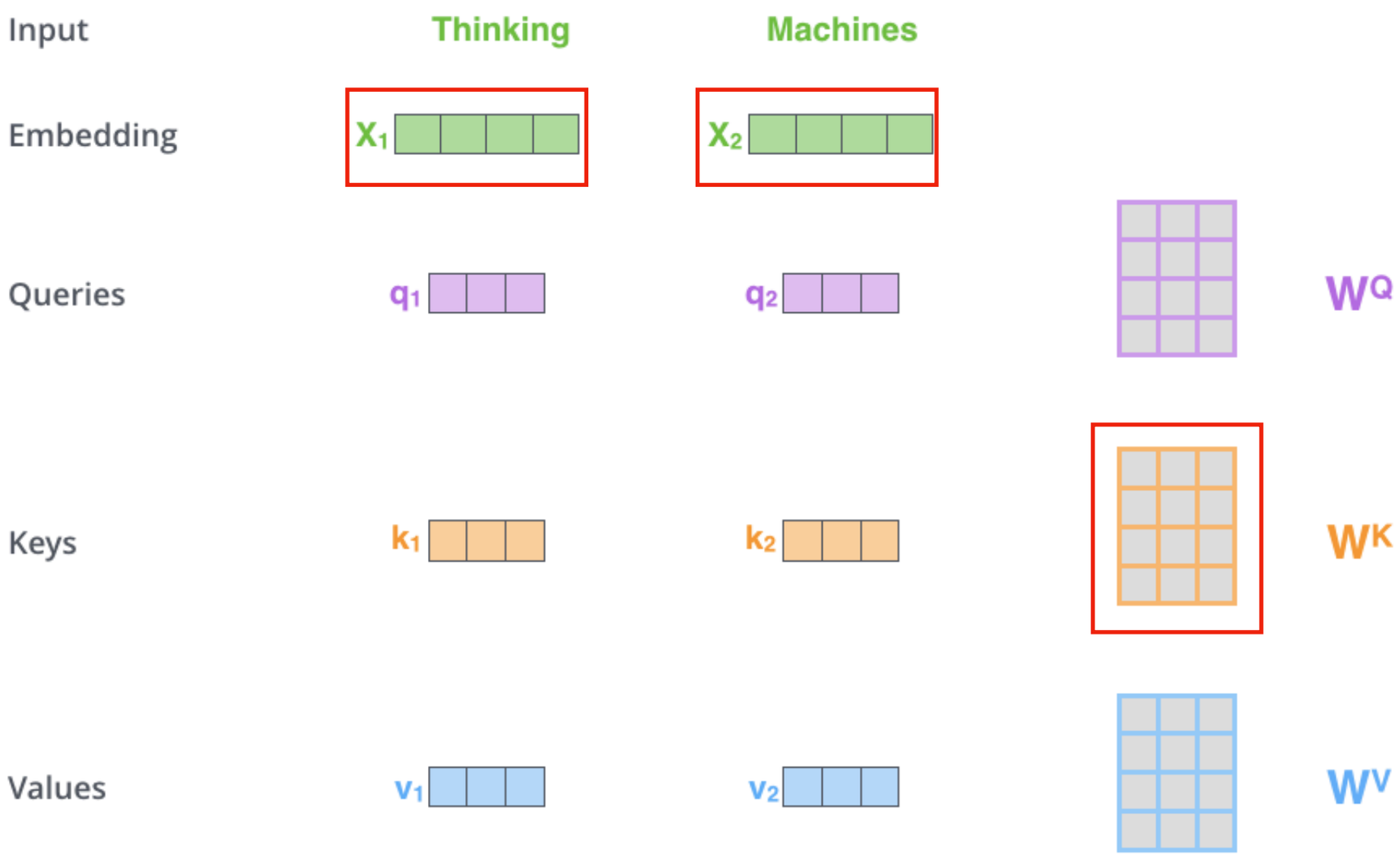
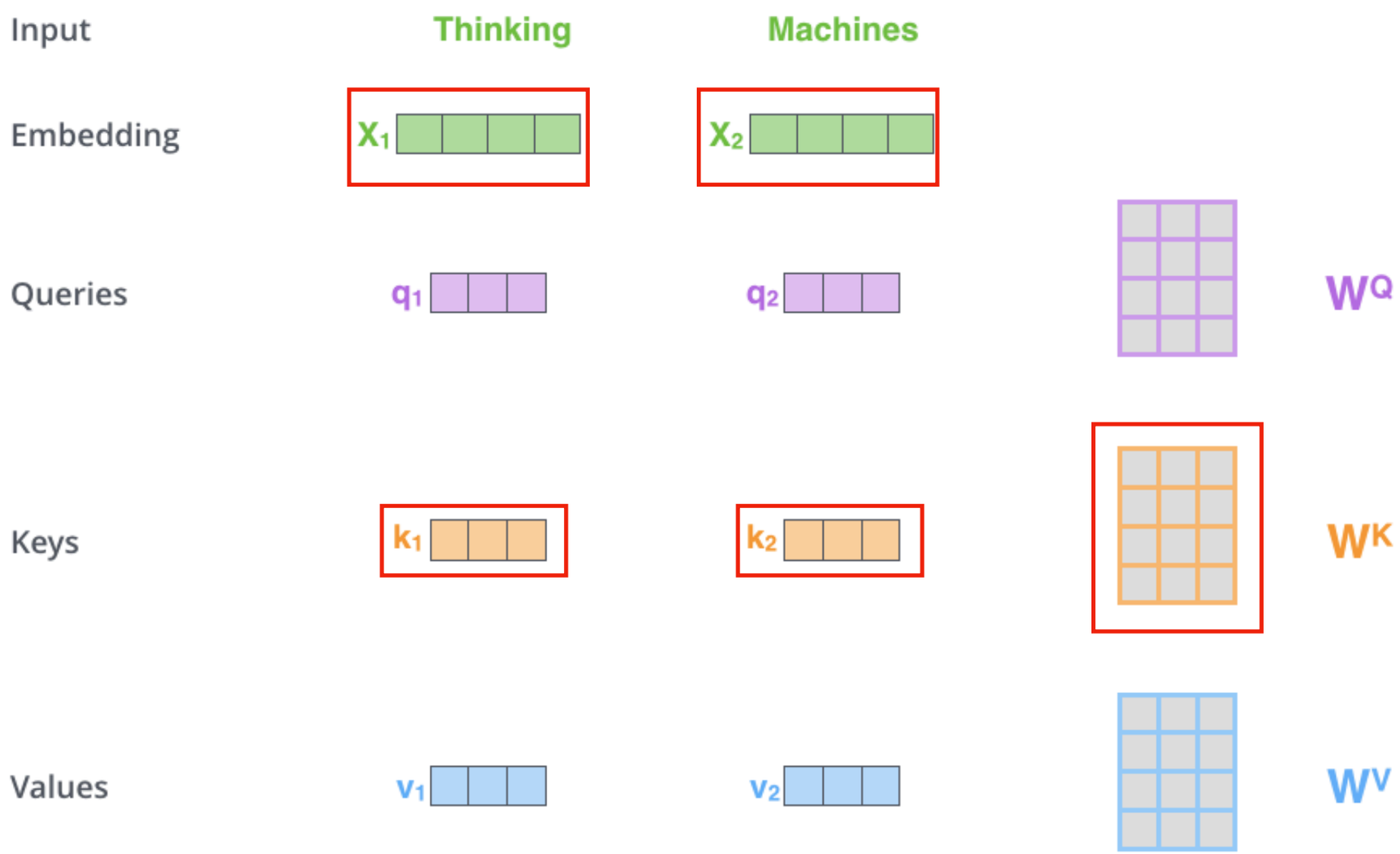
Self-Attention: Step 0



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

Self-Attention: Step 0



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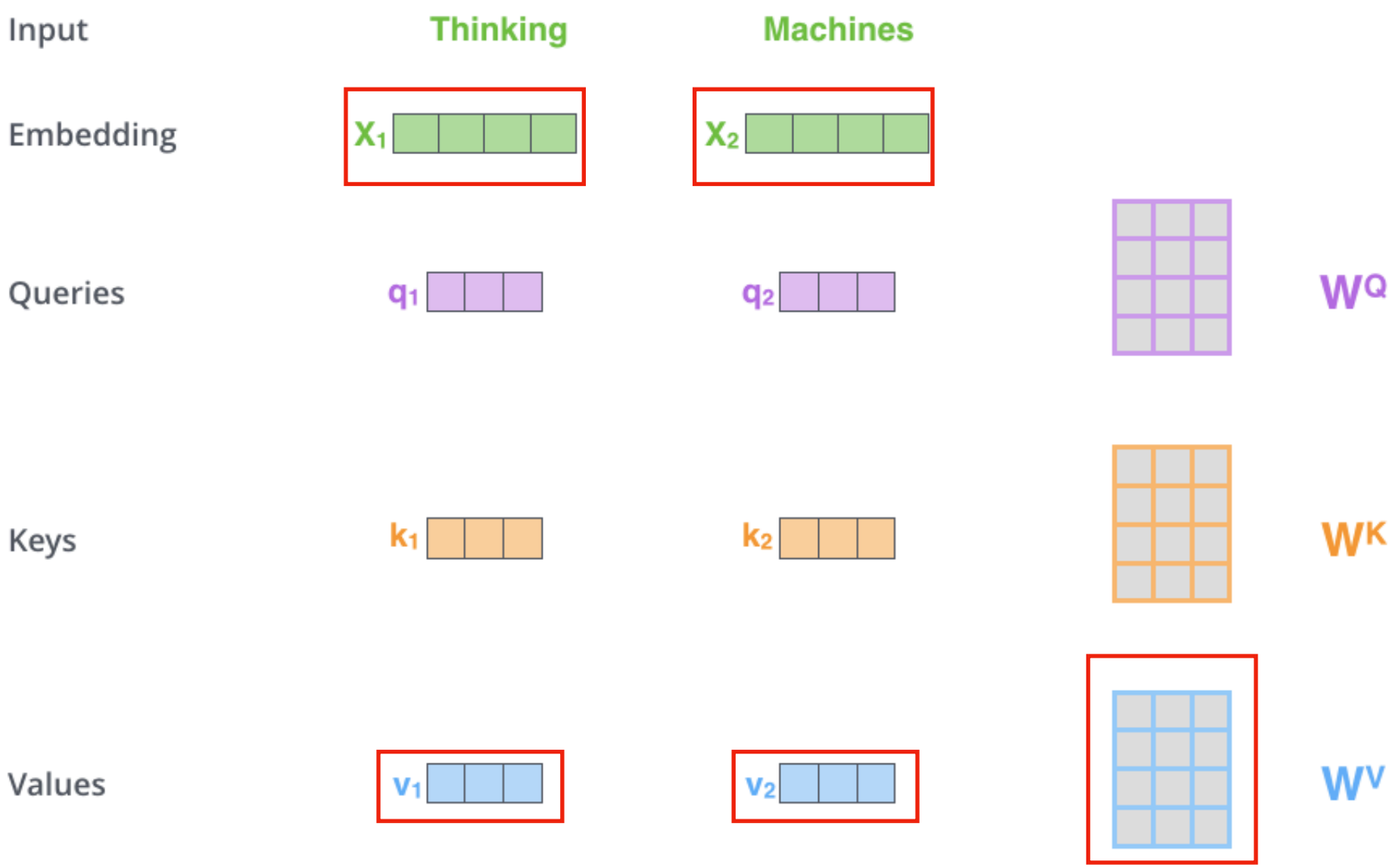

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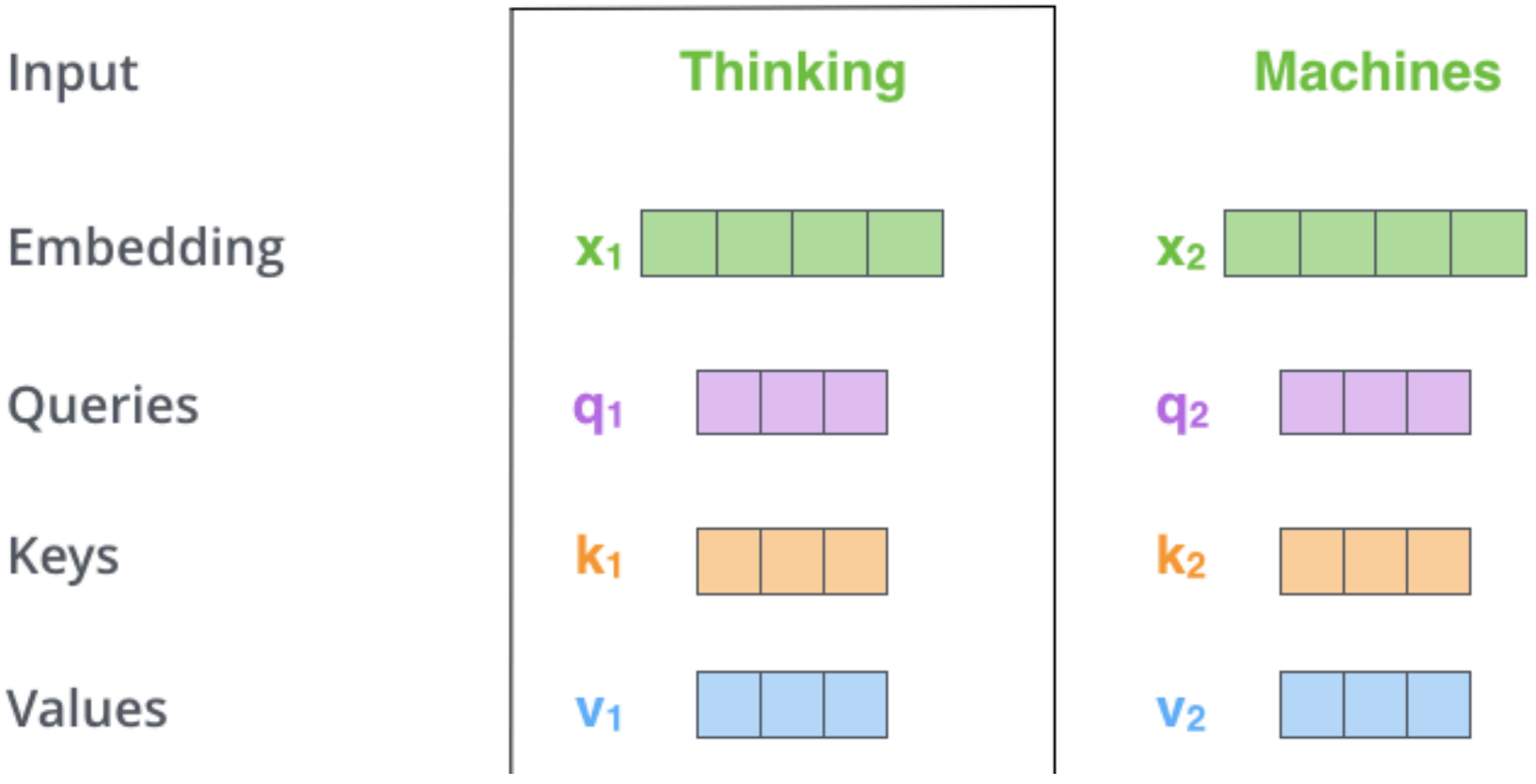
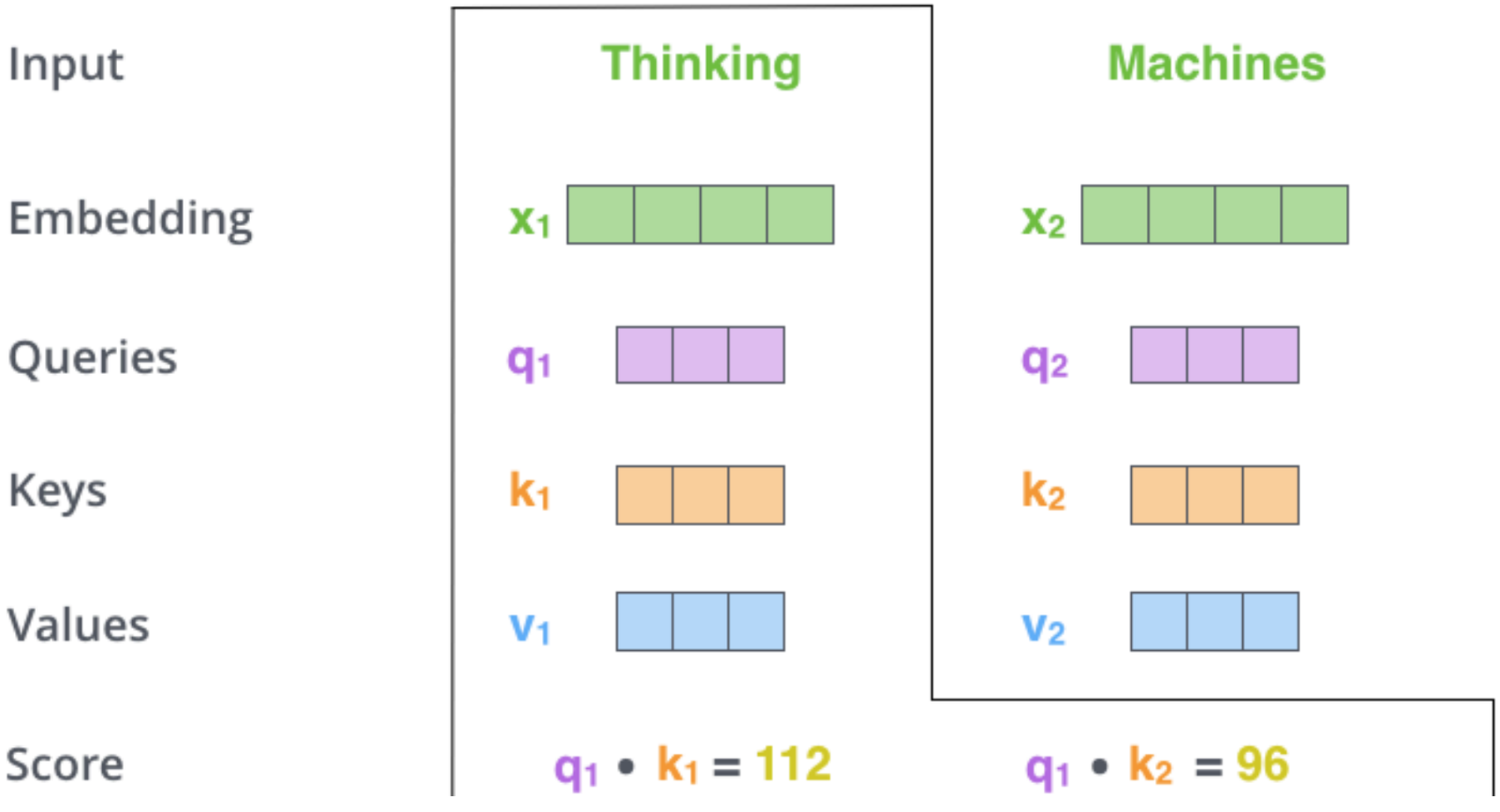
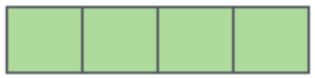
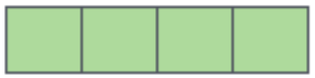
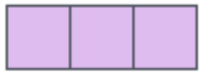
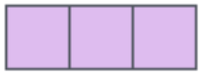
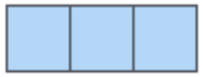
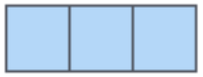

Input
Thinking
Machines
Embedding
x_1
x_2
Queries
q_1
q_2
Keys
k_1
k_2
Values
v_1
v_2


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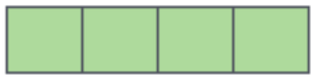
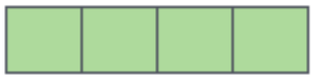
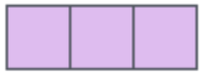
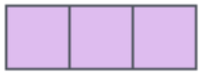
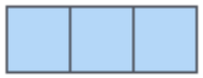
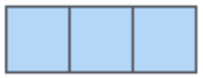
Divide by 8 ($\sqrt{d_k}$)	14	12

Input	Thinking	Machines
Embedding	x_1 	x_2 
Queries	q_1 	q_2 
Keys	k_1 	k_2 
Values	v_1 	v_2 
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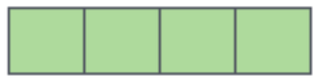
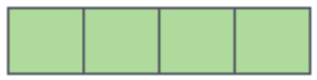
Softmax	0.88	0.12

	Thinking	Machines
Input		
Embedding	x_1 	x_2 
Queries	q_1 	q_2 
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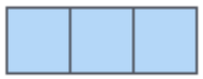
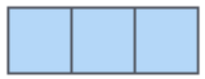
Values	v_1 	v_2 
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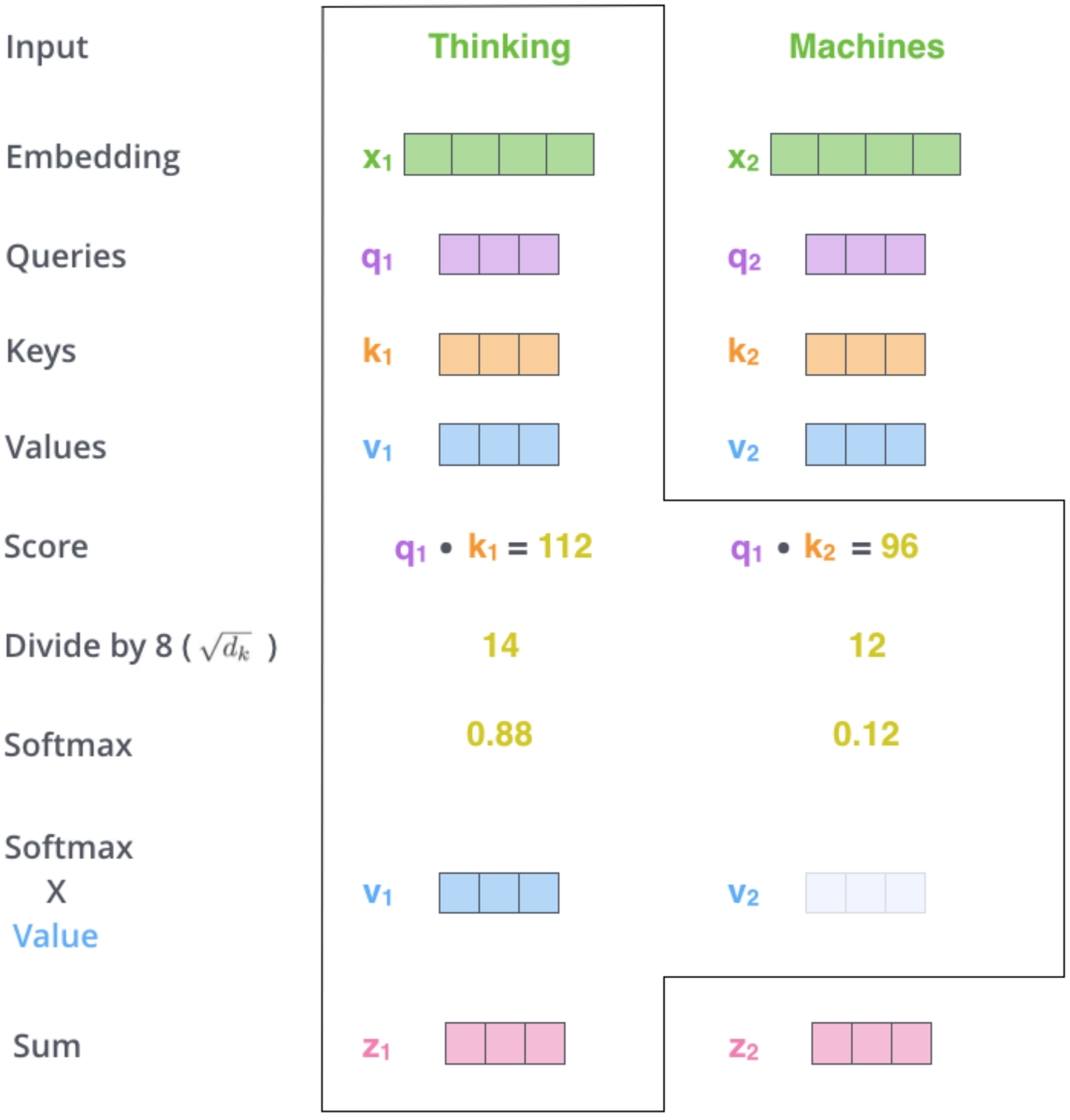
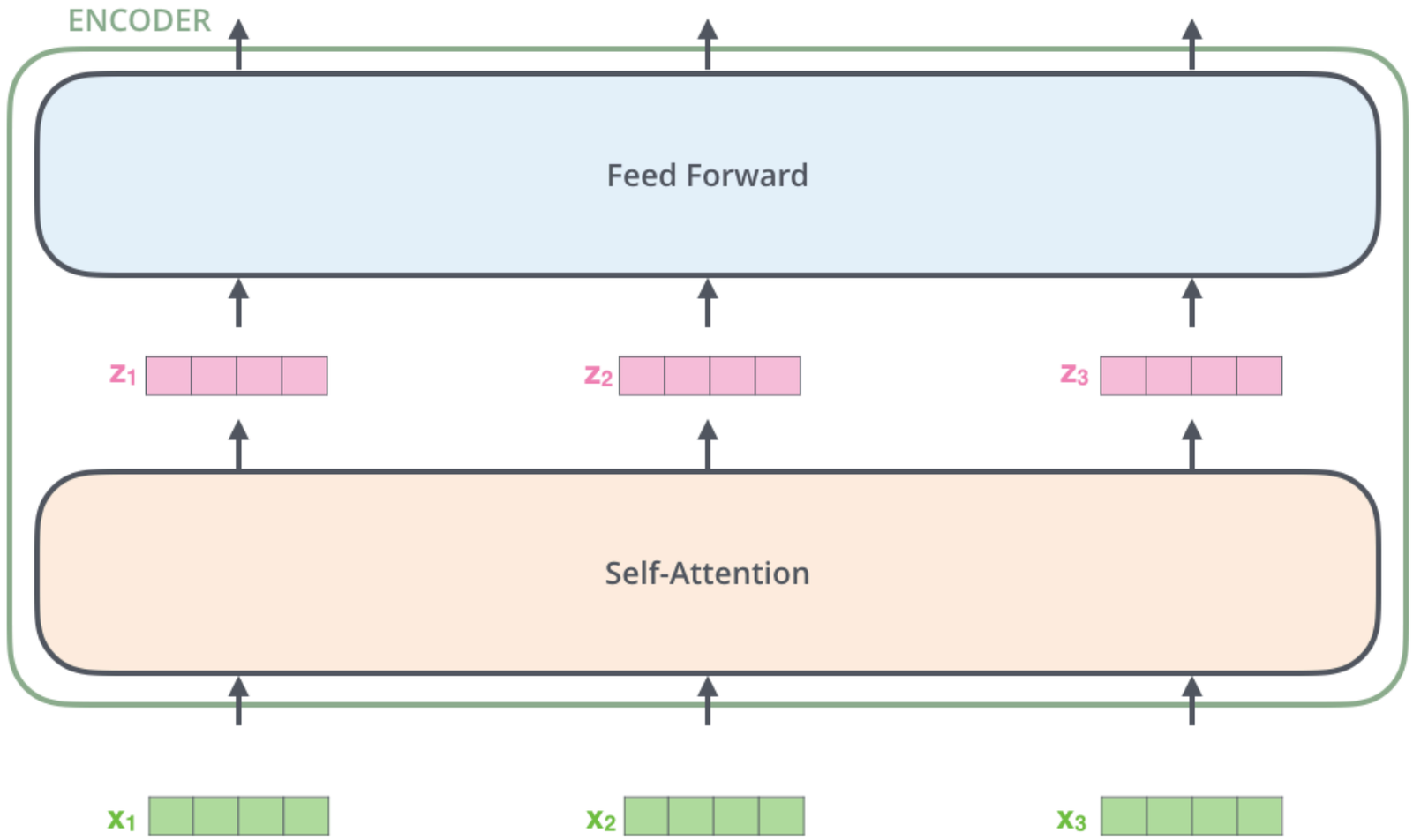


Credit: http://jalammar.github.io/illustrated-transformer/

Transformers: Simplified



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Self-Attention

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- 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]
- Softmax

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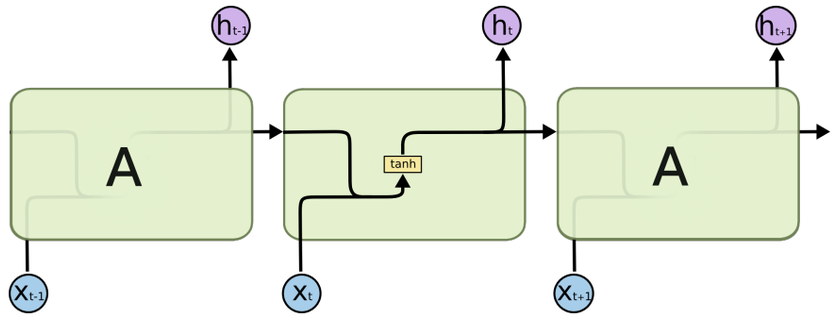
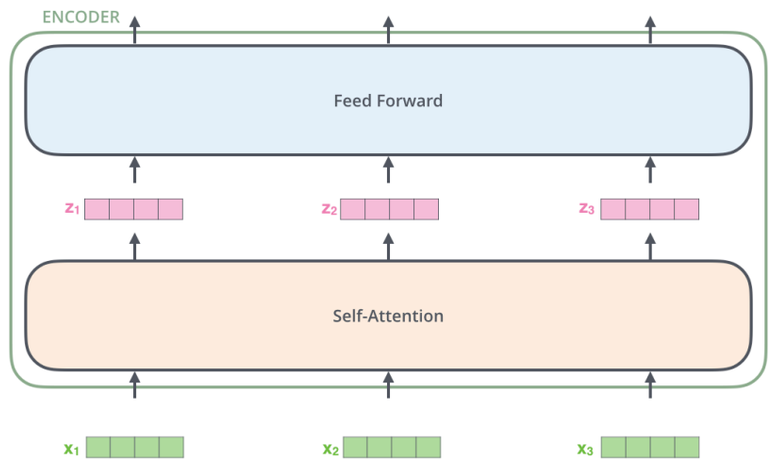
z = [0.24 0.55]

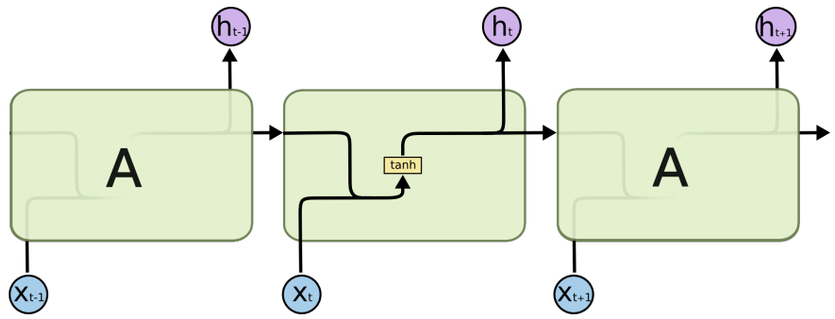
Transformers for Language Modelling

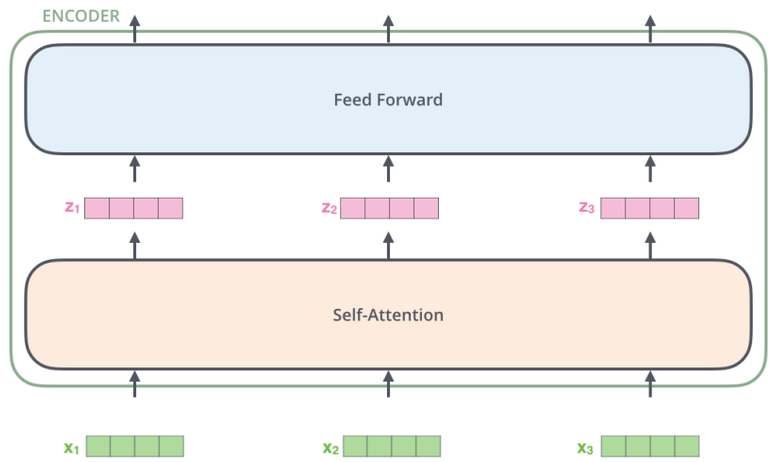




Transformers for Language Modelling

- RNNs: Process tokens one-by-one





Transformers for Language Modelling

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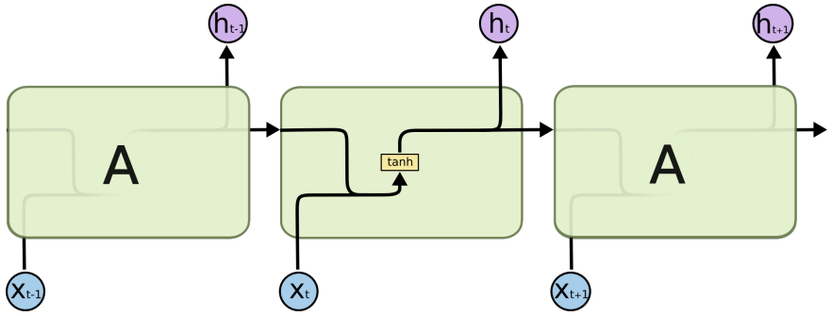

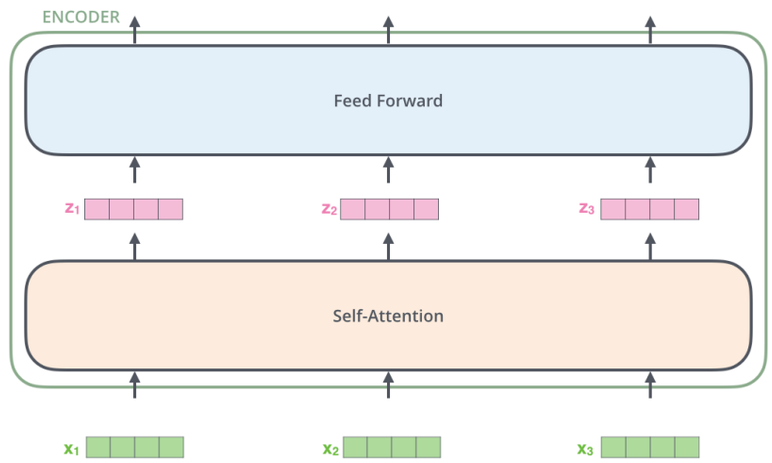

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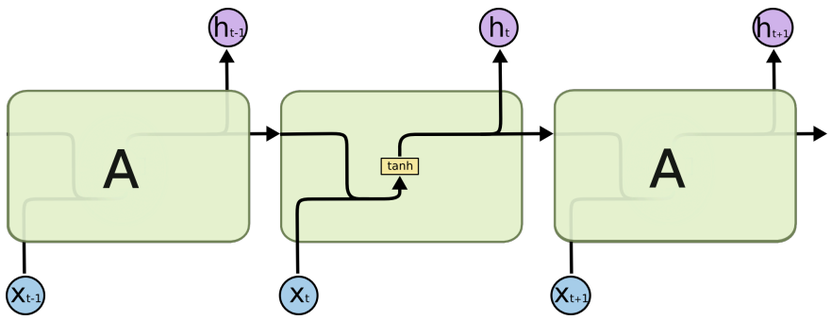
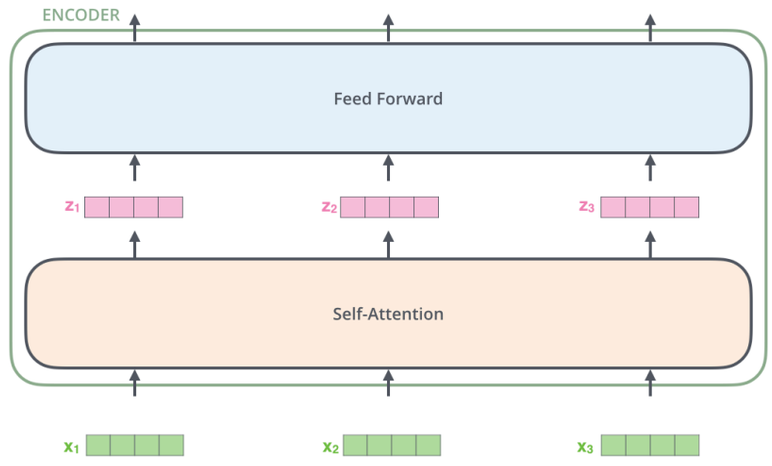


- Transformers LM: Process a segment of tokens



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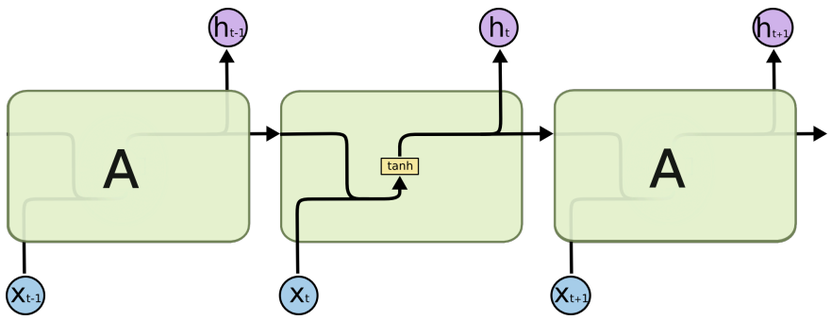

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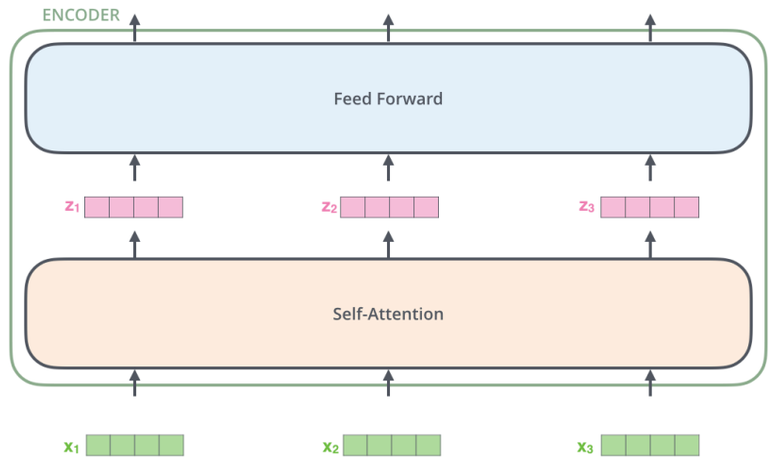

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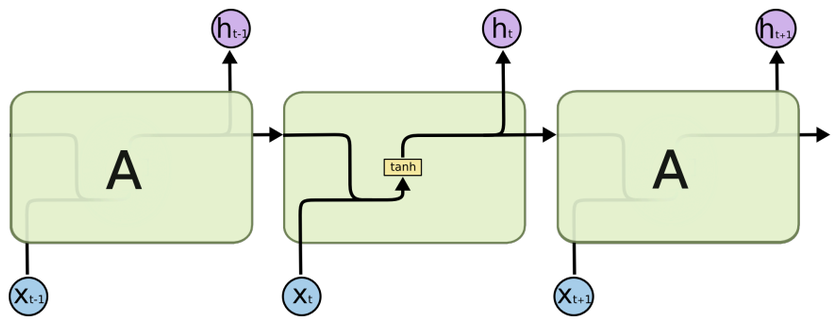

- Transformers LM: Process a segment of tokens
  - Dependencies within the segment
  - Within segment position is given by the positional encoding

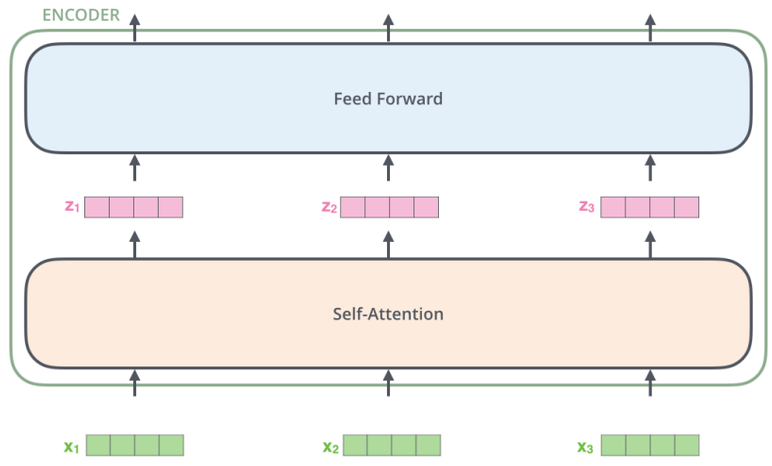

Image credit: https://towardsml.com/2019/09/17/bert-explained-a-complete-guide-with-theory-and-tutorial/ [Jacob Devlin et al 2018]

BERT: Bidirectional Encoder Representations from Transformers

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- Welcome BERT!

Transformers for Language Modelling

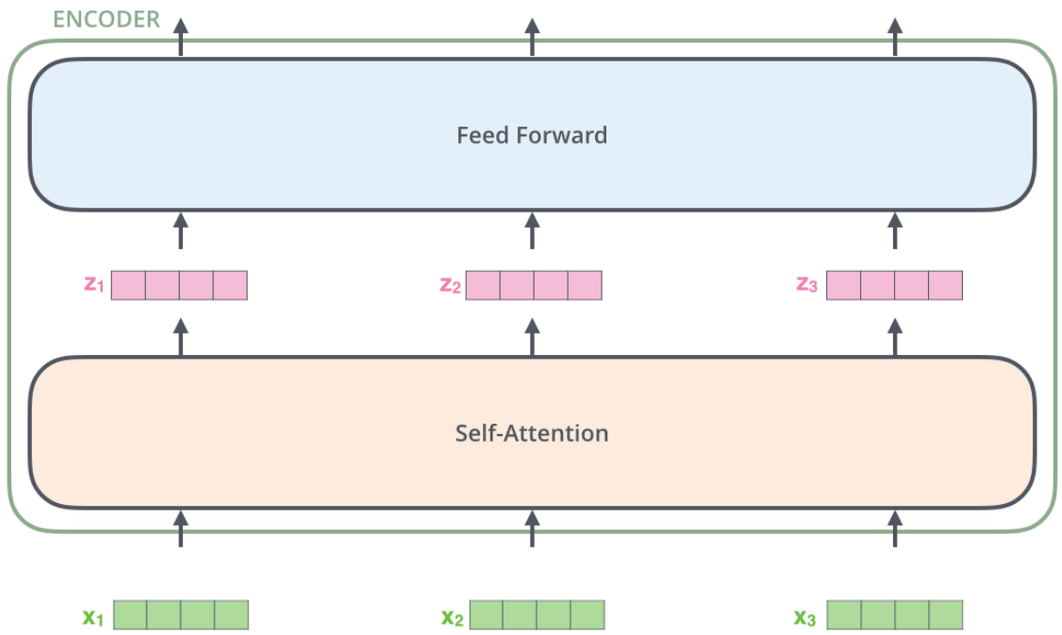
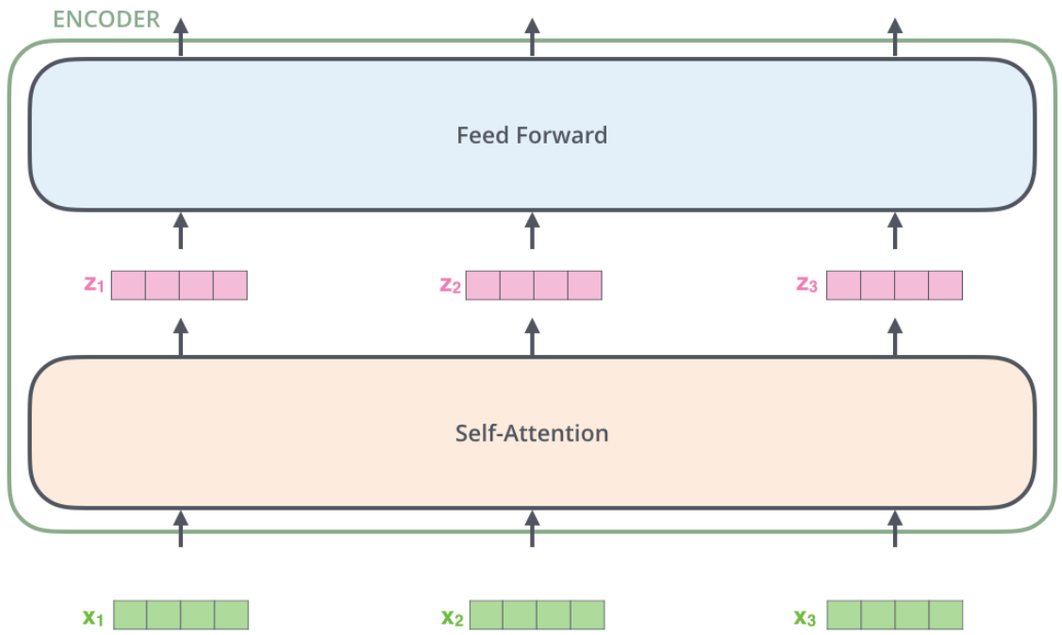


Image Credit: https://arxiv.org/pdf/1706.03762.pdf
Content Credit:TransformerXL Explained & Al-Rfou et al. 2018

Transformers for Language Modelling

- Transformers LM



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Transformers for Language Modelling

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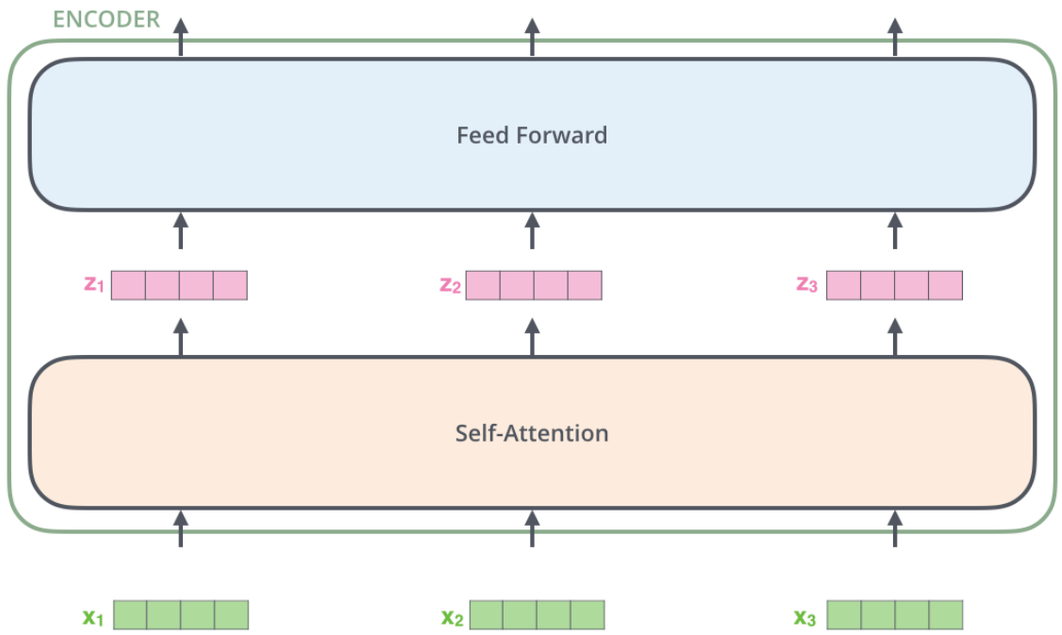
  - Unidirectional



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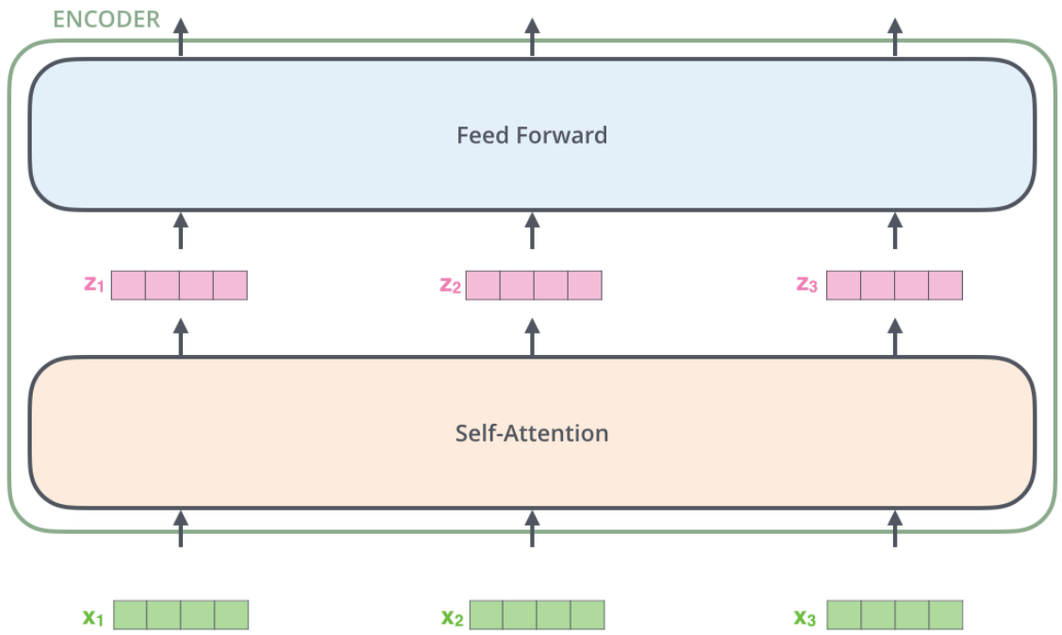
Transformers for Language Modelling

- Transformers LM
  - Unidirectional
  - Segment of tokens



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Transformers for Language Modelling

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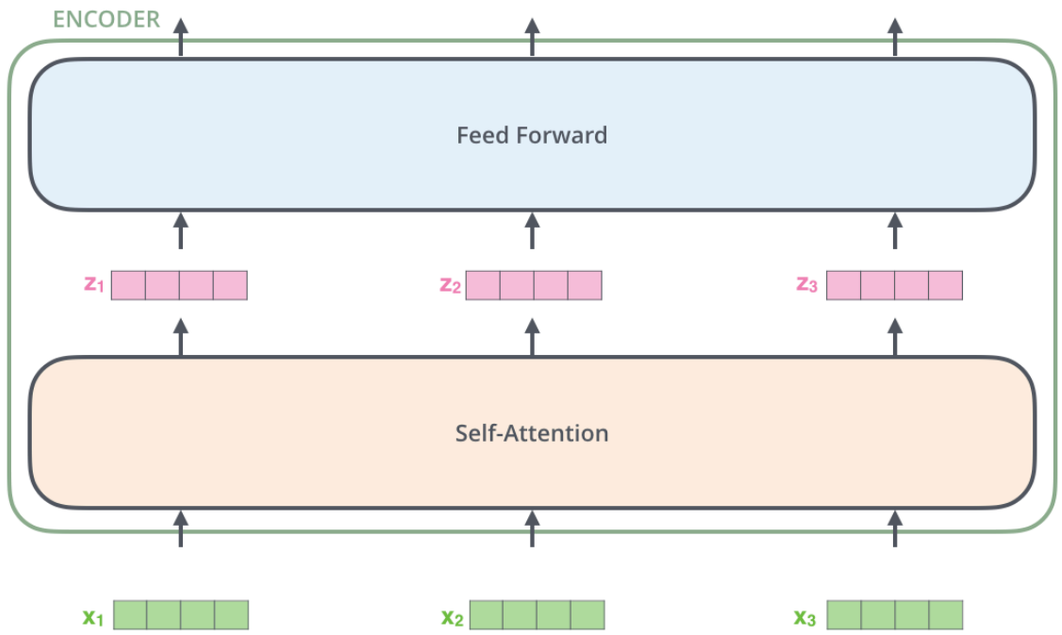
  - Unidirectional
  - Segment of tokens
  - Language Models predict the next word



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Encoder Representations

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

Traditionally,

- Language Models predict the next word

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- Language Models predict the next word
- Or loosely, they “fill in the blank” based on the context

Traditionally,

- Language Models predict the next word
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- The man went to the store and bought a _____ of shoes

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- In BERT, this bidirectionality is important to obtain good general purpose representations

BERT: Learning Setup

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- Pretraining

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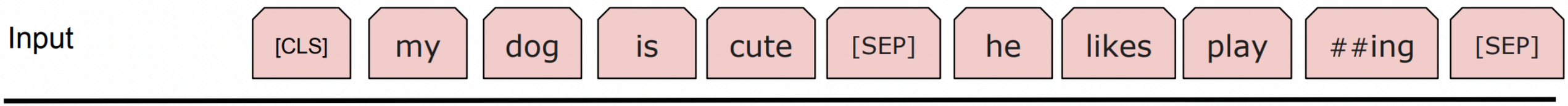
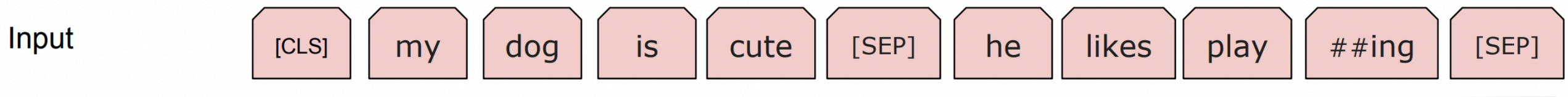
    - Masked LM (cloze task)
    - Next Sentence Prediction
- Finetune
  - Supervised using target task

Masked LM

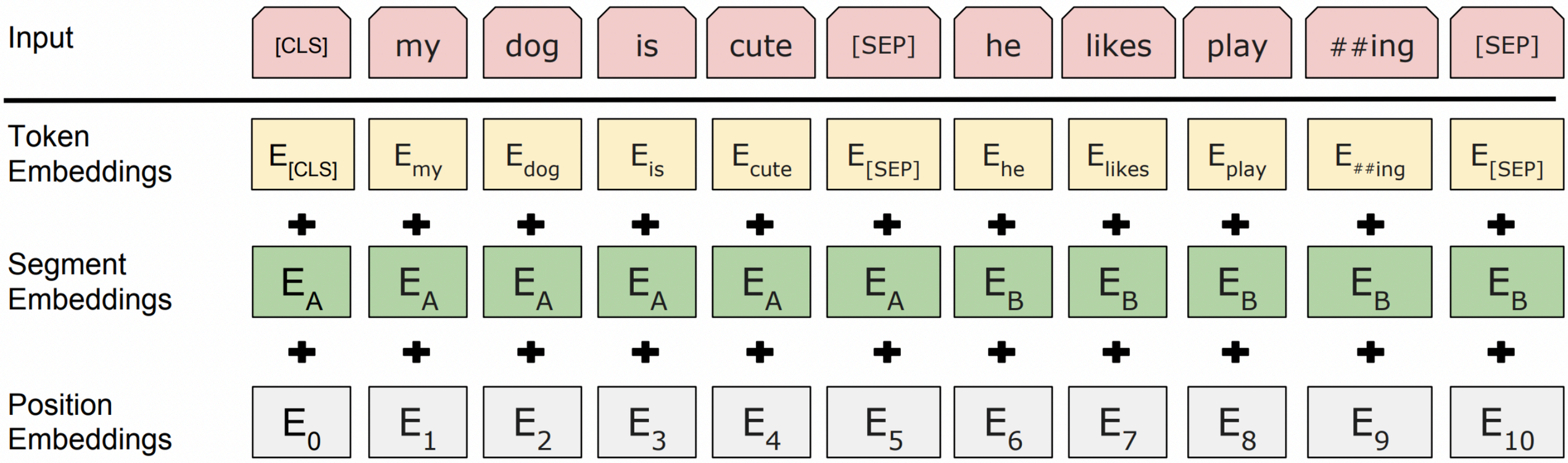


Masked LM



- Use specialised tokens CLS, SEP

Masked LM



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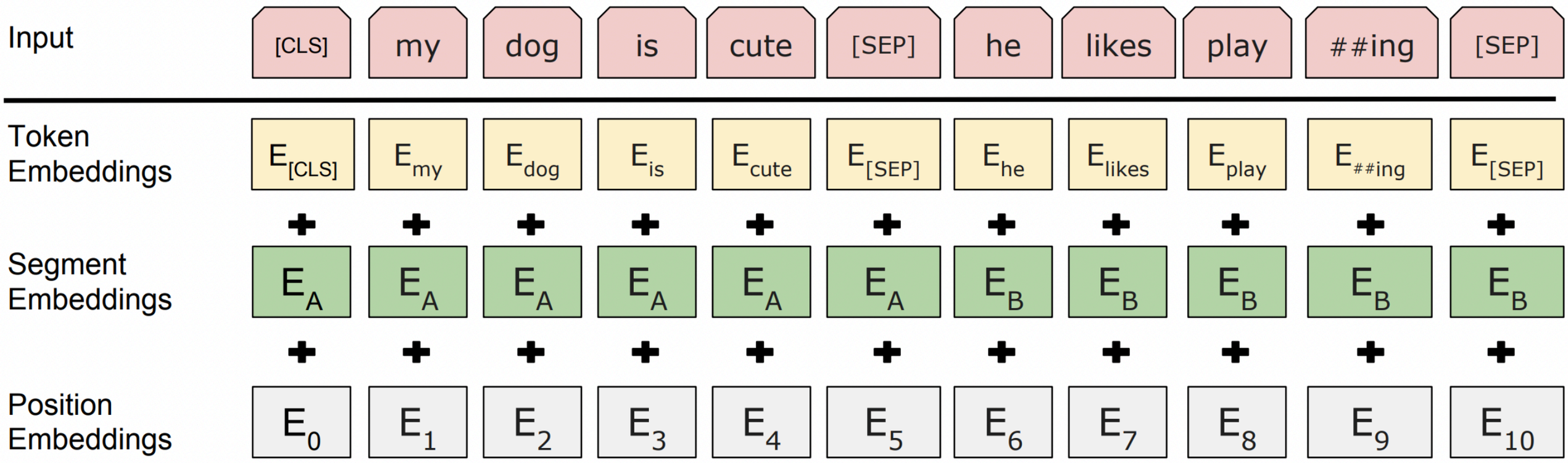

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- 15% of the tokens are randomly masked

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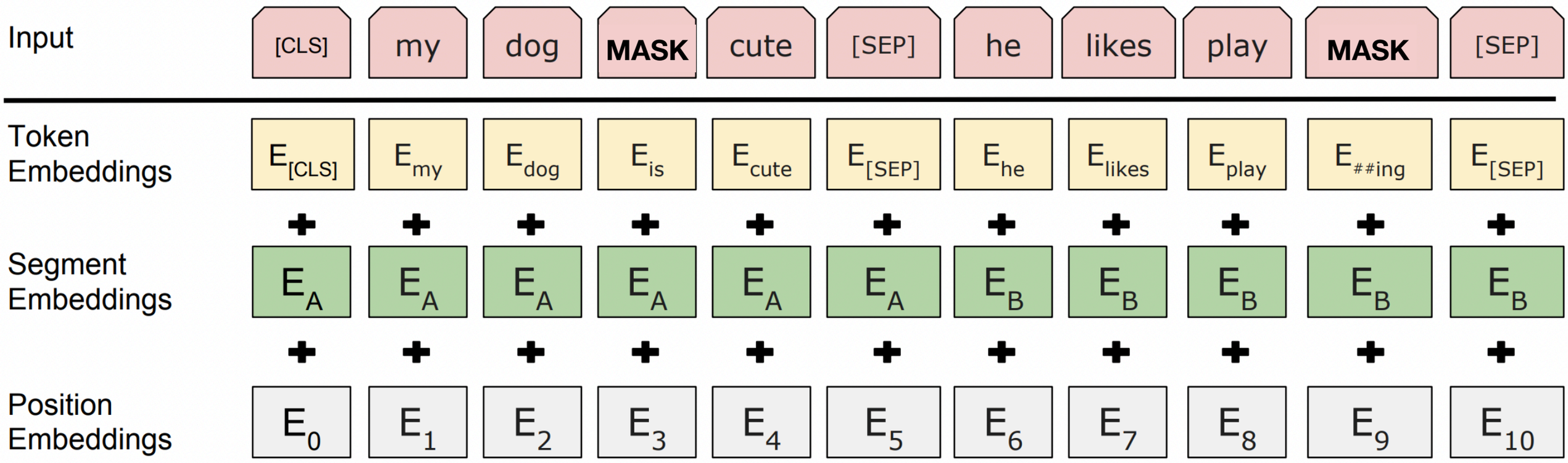

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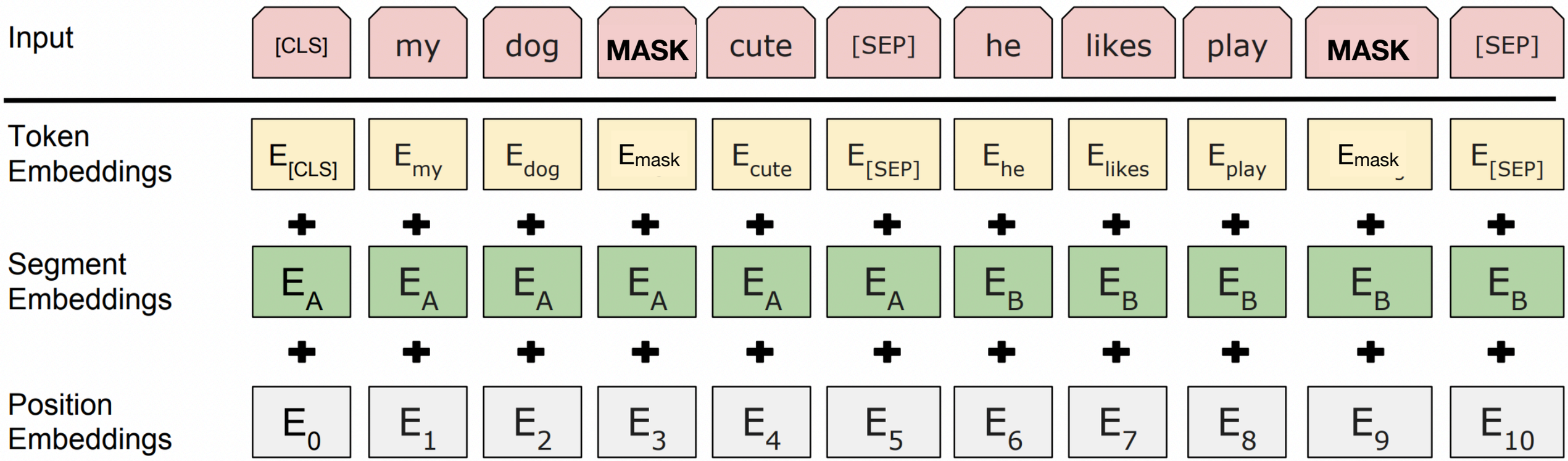

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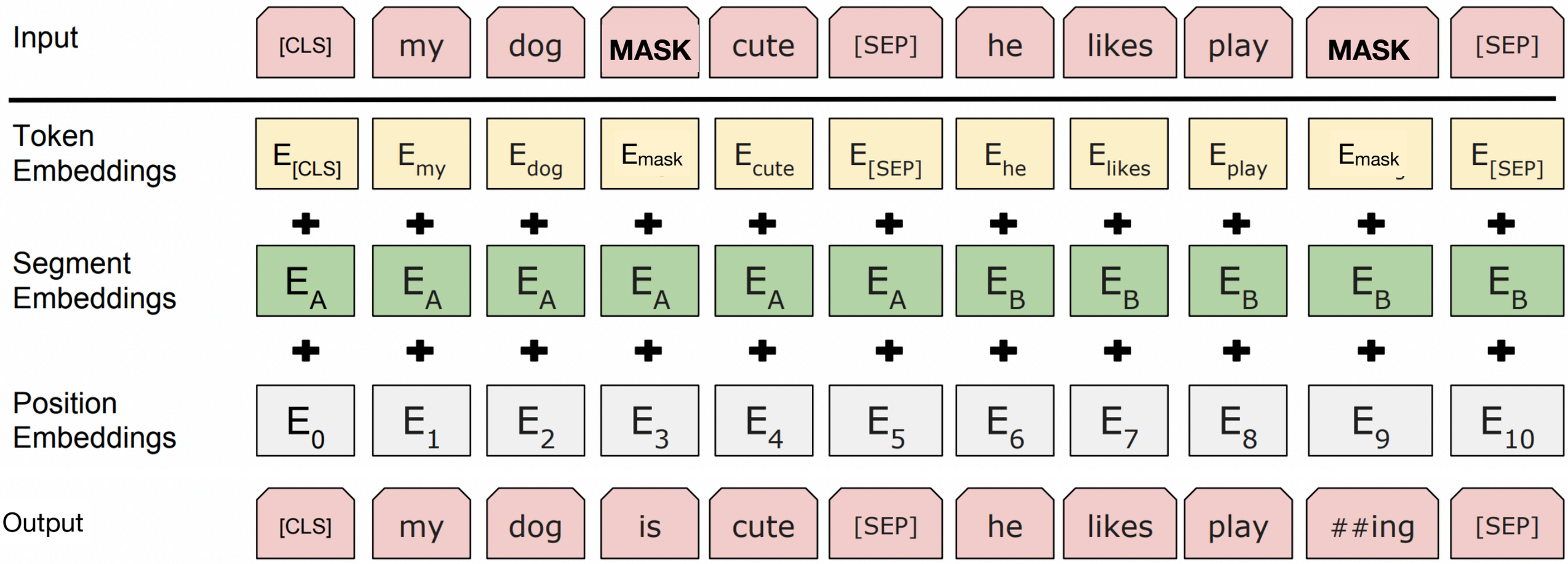

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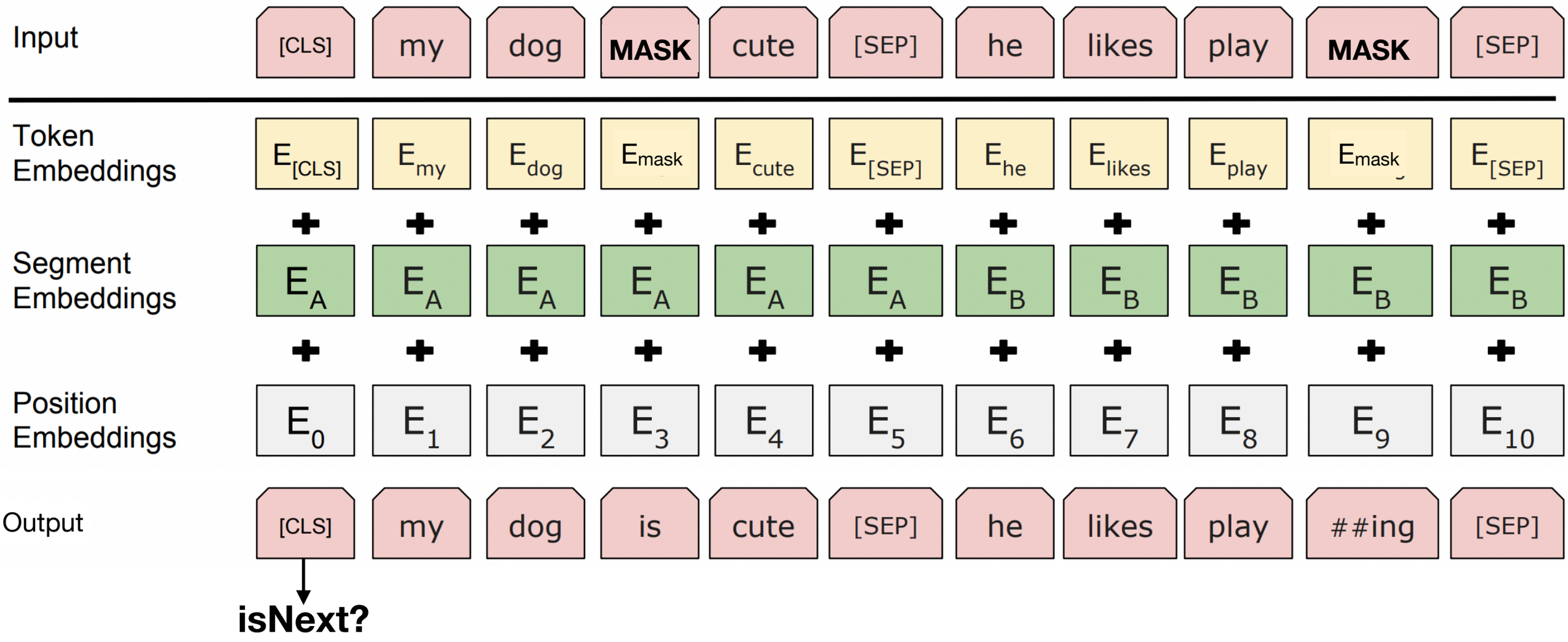
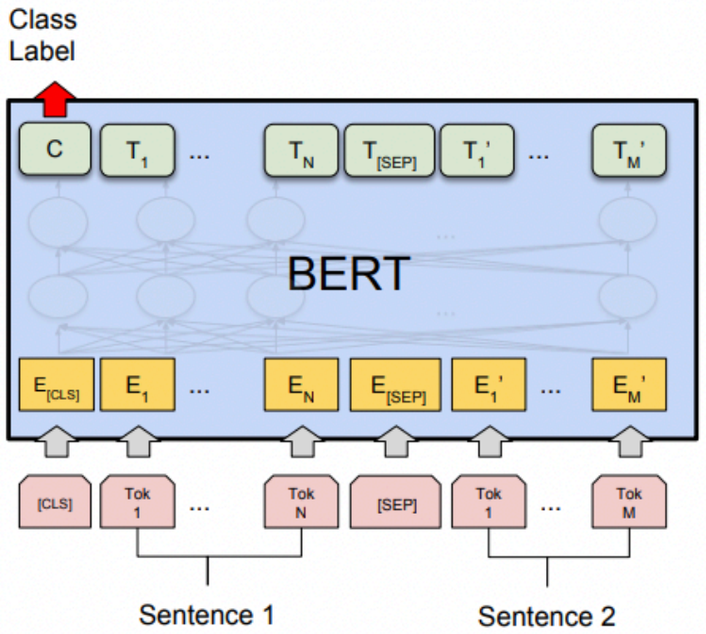
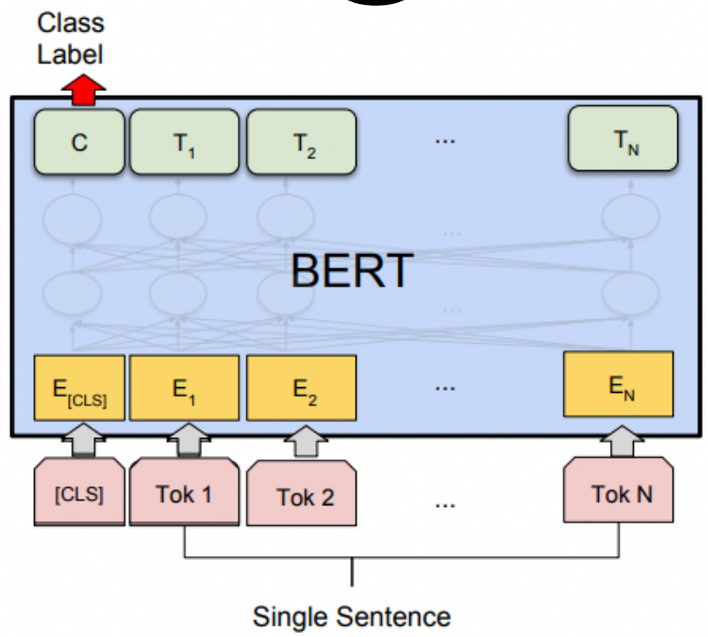


Use the CLS output embedding to predict is sentence B is the next sentence or not.

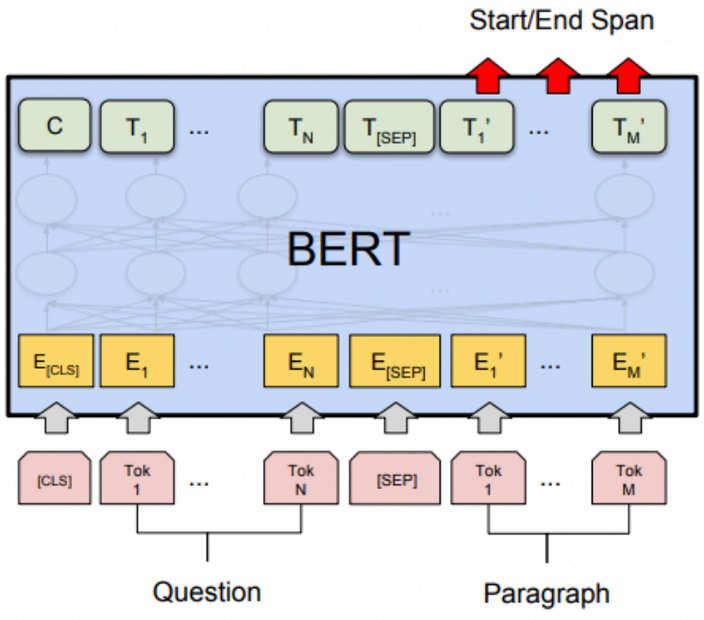
Fine-tuning



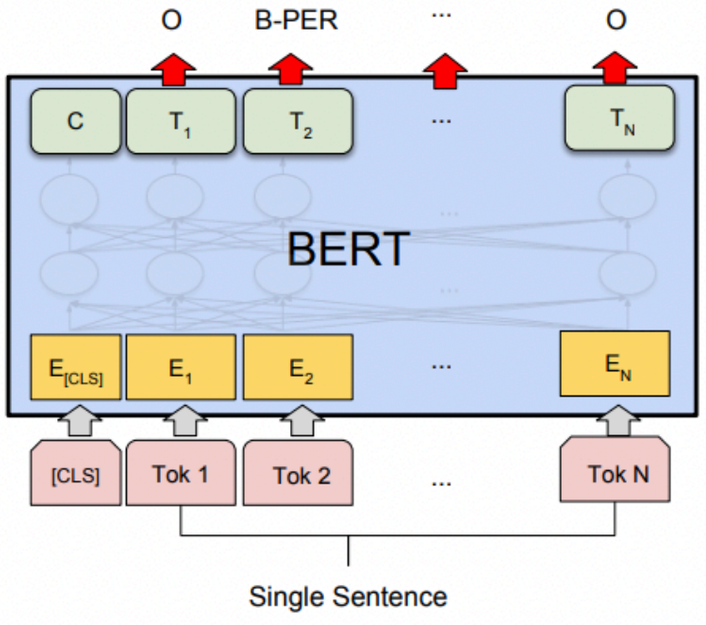
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG



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



(c) Question Answering Tasks: SQuAD v1.1



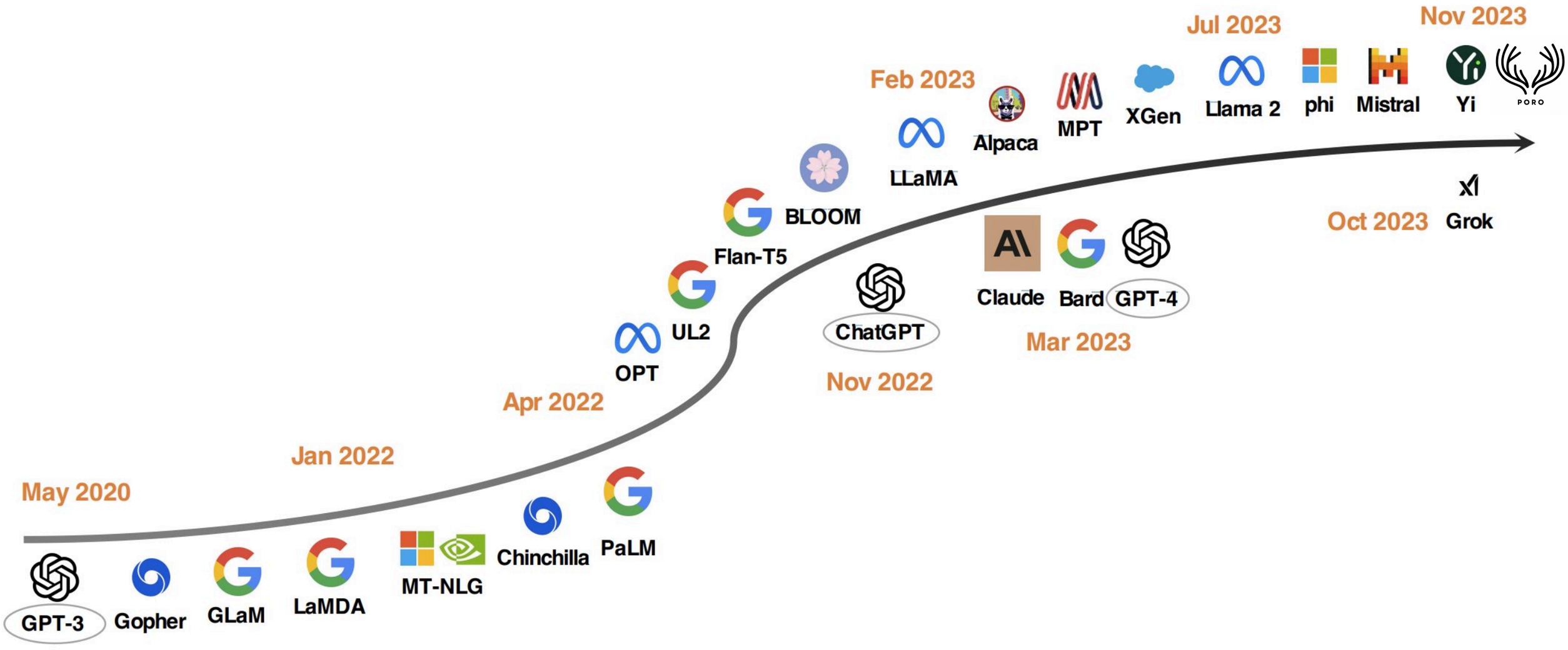
(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Glue Test Results

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
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]

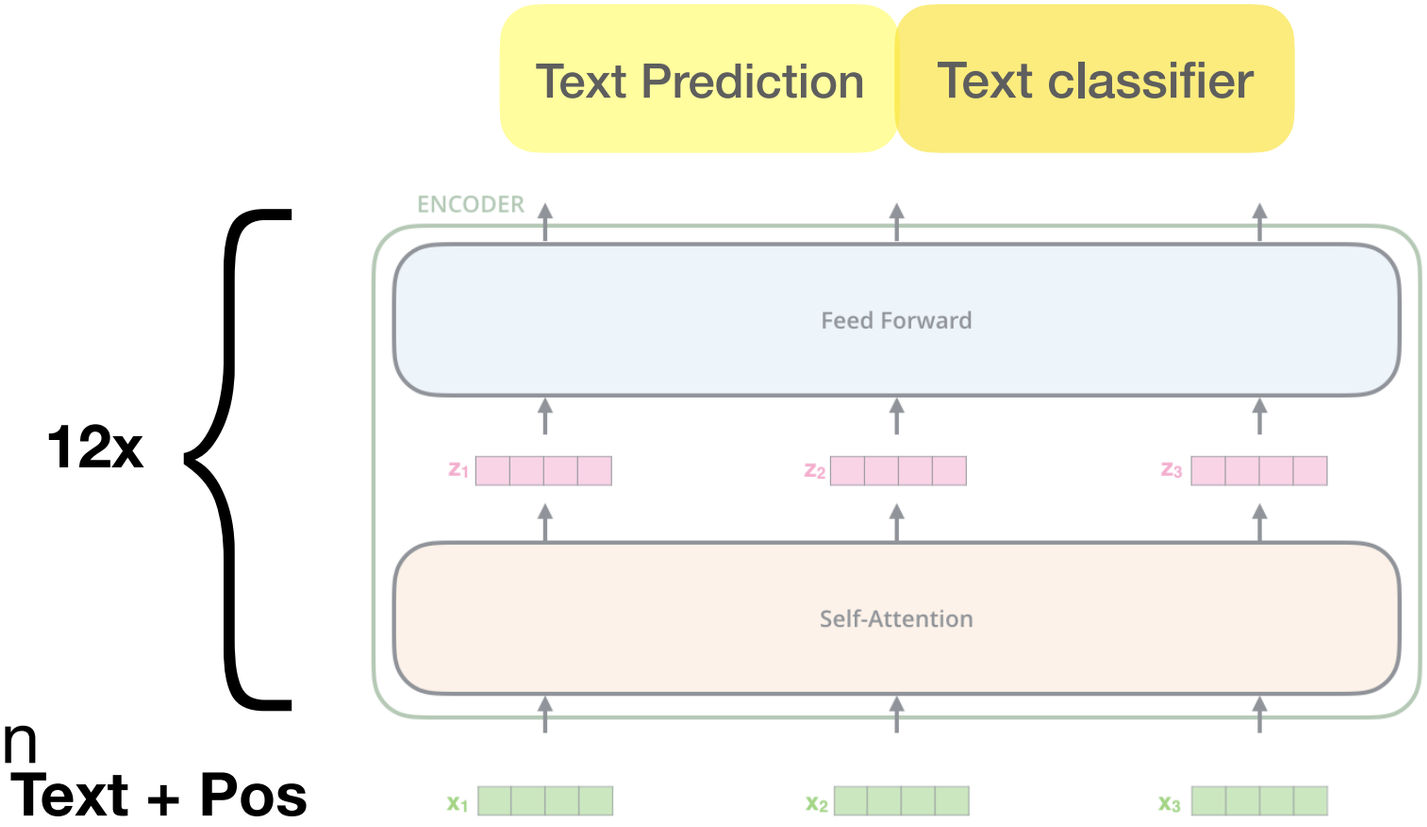
Large Language Models



CC: Adapted from slides by Dr. Stig-Arne Grönroos on ChatGPT

Generative Pretrained Transformer (GPT)

- Autoregressive
- GPT: 12 layers, 117M
- GPT-2: 48 layers, 1.5B
- GPT-3: 96 layers, 175B
- InstructGPT: GPT-3 + human feedback for a certain task
- ChatGPT: GPT-3 + human feedback for being a good chatbot



Reinforcement Learning

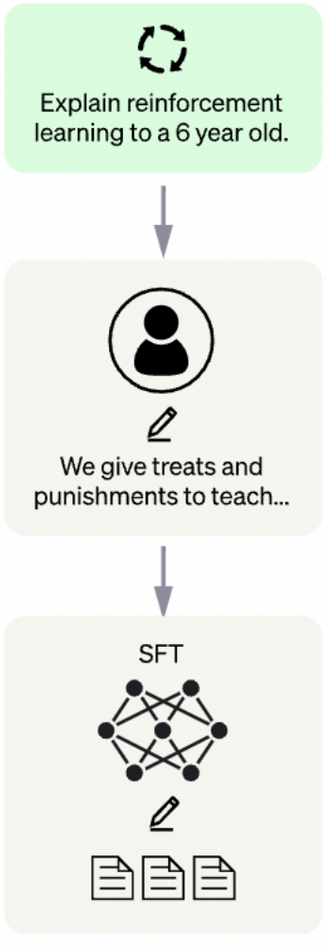
Step 1

Collect demonstration data and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

This data is used to fine-tune GPT-3.5 with supervised learning.



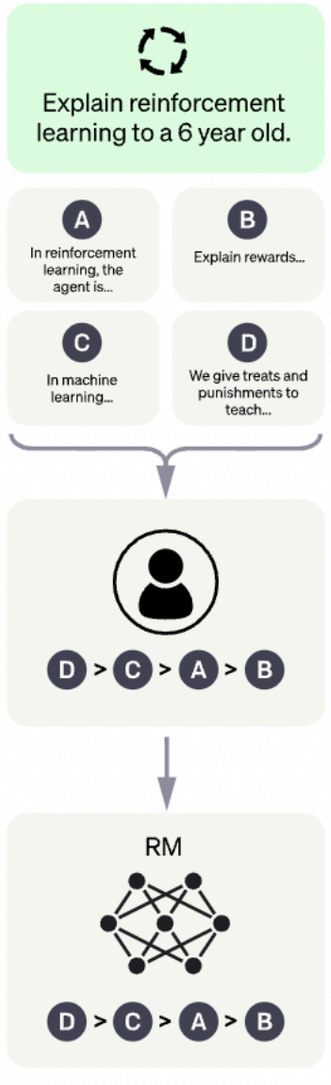
Step 2

Collect comparison data and train a reward model.

A prompt and several model outputs are sampled.

A labeler ranks the outputs from best to worst.

This data is used to train our reward model.



Step 3

Optimize a policy against the reward model using the PPO reinforcement learning algorithm.

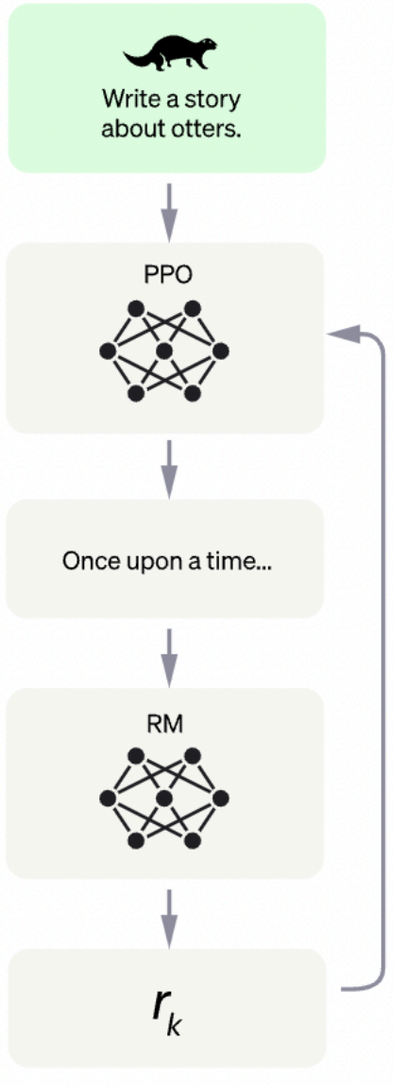
A new prompt is sampled from the dataset.

The PPO model is initialized from the supervised policy.

The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.



Performance

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- The good

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- Style transfer: write X in the style of Y

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- Improved coherence: 2048 tokens as window size vs 512 for BERT

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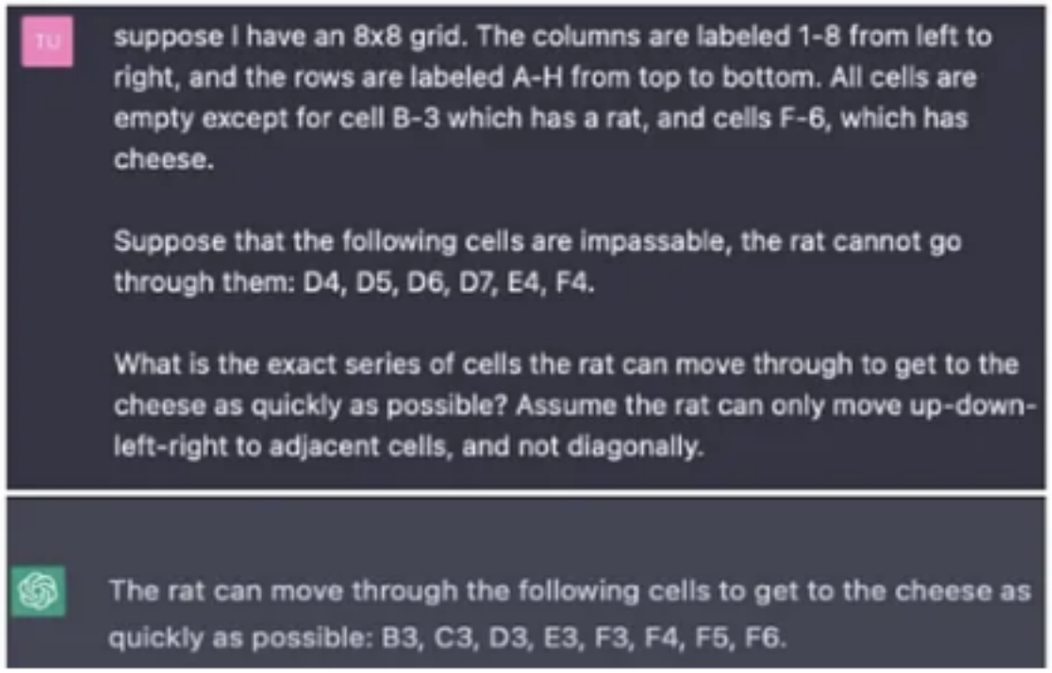
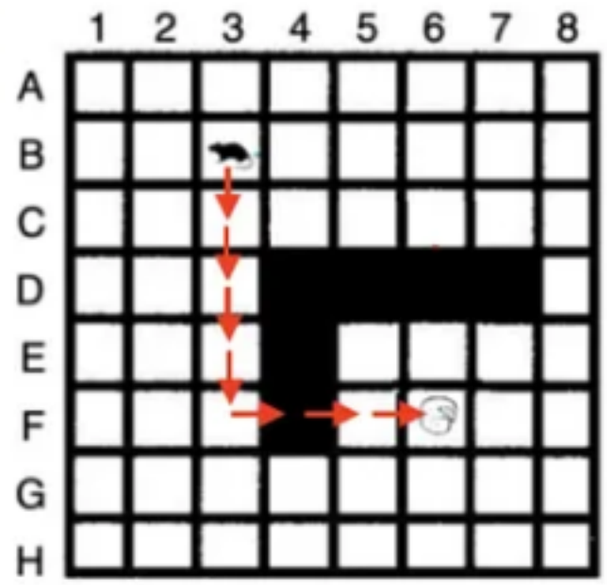
- The bad
- Logical and spatial reasoning
- Puns, word-play jokes
- The ugly
- Confidently states incorrect information

Spatial reasoning





credit: https://medium.com/@aliborji/a-categorical-archive-of-chatgpt-failures-2c888805d3c3

Evaluation

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- LLM generates text response

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- The response can be compared to a reference but also judged on its helpfulness, relevance, accuracy, depth, creativity, and level of detail

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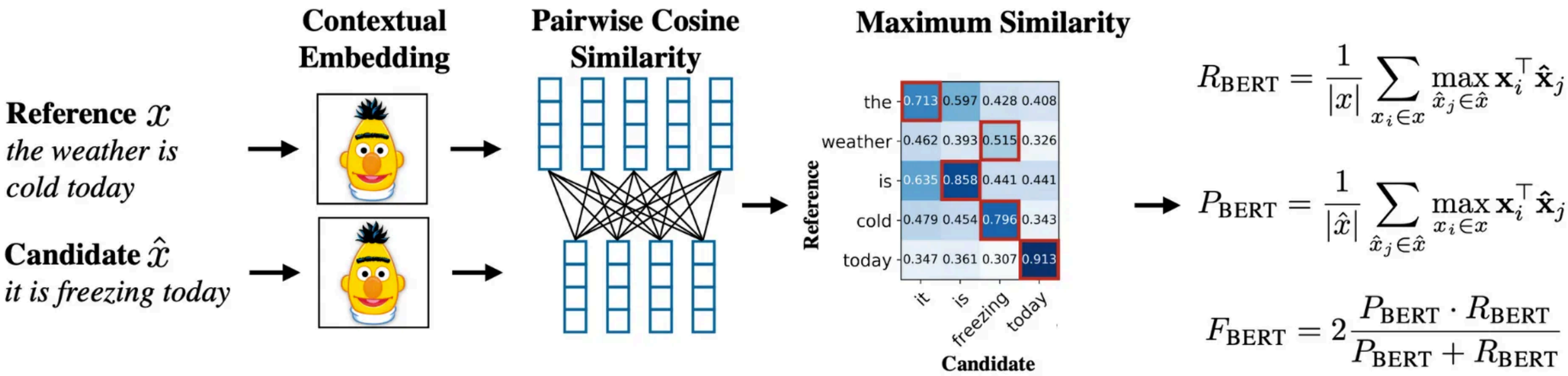
- The response can be compared to a reference but also judged on its helpfulness, relevance, accuracy, depth, creativity, and level of detail
- Automatic metrics like BERTScore can help

BERTScore



Source: Bertscore: Evaluating text generation with bert

Code for Bertscore is available at https://github.com/Tiiiger/bert score

BERTScore

- Automatic metrics like BERTScore do help but some times do not capture human preferences well

- Humans, of course, capture human preference but are slow and expensive, thus not really a scalable solution

- What if… we used an LLM as a judge

Chatbot arena

Rank	🤖 Model	⭐ Arena Elo	📊 95% CI	🗳 Votes	Organization
1	GPT-4-0125-preview	1253	+10/-11	3922	OpenAI
2	GPT-4-1106-preview	1252	+5/-6	35385	OpenAI
3	Bard (Gemini Pro)	1224	+9/-9	9081	Google
4	GPT-4-0314	1190	+5/-6	18945	OpenAI
5	GPT-4-0613	1162	+4/-5	29950	OpenAI
6	Mistral Medium	1150	+6/-7	15447	Mistral
7	Claude-1	1149	+6/-6	18189	Anthropic
8	Claude-2.0	1132	+6/-7	12131	Anthropic
9	Gemini Pro (Dev API)	1120	+7/-7	7616	Google

Summary

- NNLM:
    - RNNs
    - Transformers
        - Self Attention
        - BERT
        - ChatGPT
- Challenges
    - Long-Term Dependencies
- LLMs
    - GPTs
    - Evaluation

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

- GPT-3 paper: https://arxiv.org/abs/2005.14165

- ChatGPT: https://gist.github.com/veekaybee/6f8885e9906aa9c5408ebe5c7e870698