Lecture 25: Transformers

NLP Lectures: Part 4 of 4

Harvard IACS

CS109B

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Outline

- Recap
- Transformers
  - BERT
  - GPT-2
  - Concerns
- Summary

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First, we learned about **language models (LMs)**

$P($"What is the weather today?"$)$

$P($"What is the whether two day?"$)$

$P($"What is the whether too day?"$)$

Being able to correctly estimate the likelihood of sentences is useful for many other tasks

First, we learned about **language models (LMs)**

Auto-complete

Text Generation

Machine Translation

Text Classification

Speech Recognition

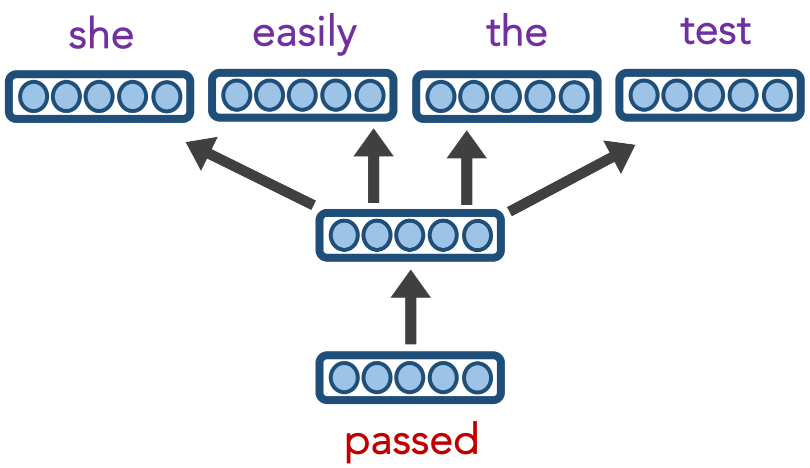
Being able to correctly estimate the likelihood

of sentences is useful for many other tasks

Next, we learned about **word embeddings**

TYPE-BASED

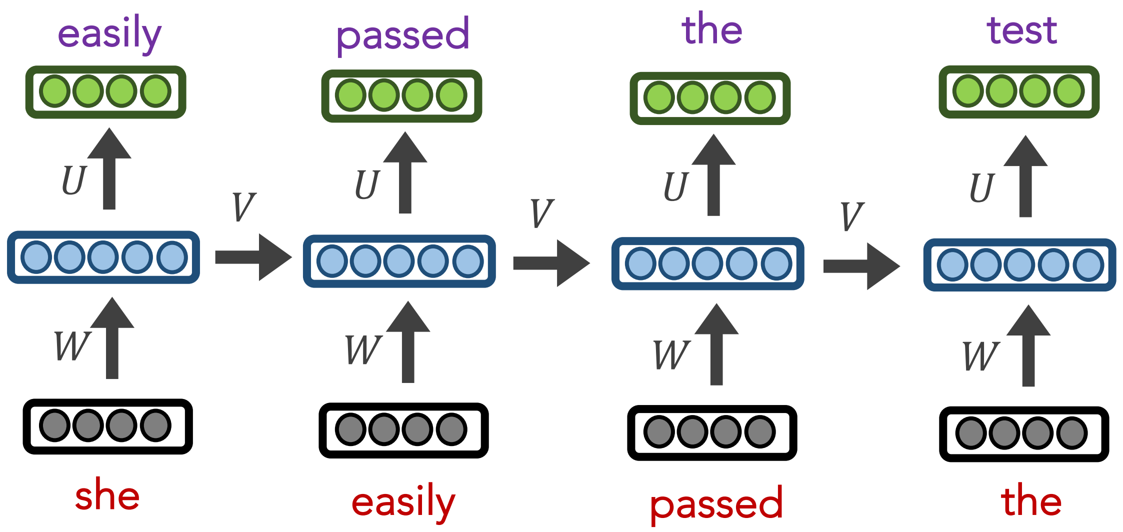
a single, global word embedding for each word, independent of its context.



word2vec (skip-gram)

TOKEN-BASED

contextualized embeddings are distinct for every occurrence of a word, completely dependent on its context



Bidirectional LSTM

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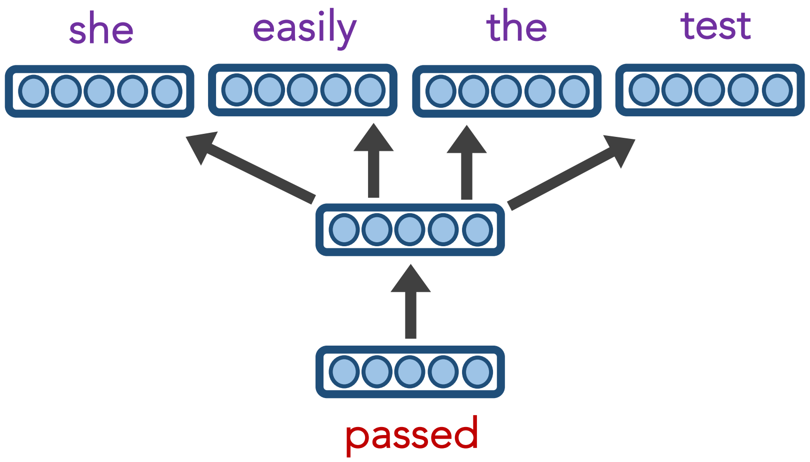

word2vec (skip-gram)

- These models **output** embeddings we can save to a file and use however we wish
- We then create a **separate model** that uses these embeddings
- Kind of limiting
- Often inferior, as of 2015

Next, we learned about **word embeddings**

- These models are trained on a **specific task** (e.g., LM, text classification, etc)
- The hidden layer(s) contains the *"meaning"* and are very useful
- We can extract those embeddings if we wish, or grab the learned weights and re-use for another task
- Dominating NLP from 2015 - present

TOKEN-BASED

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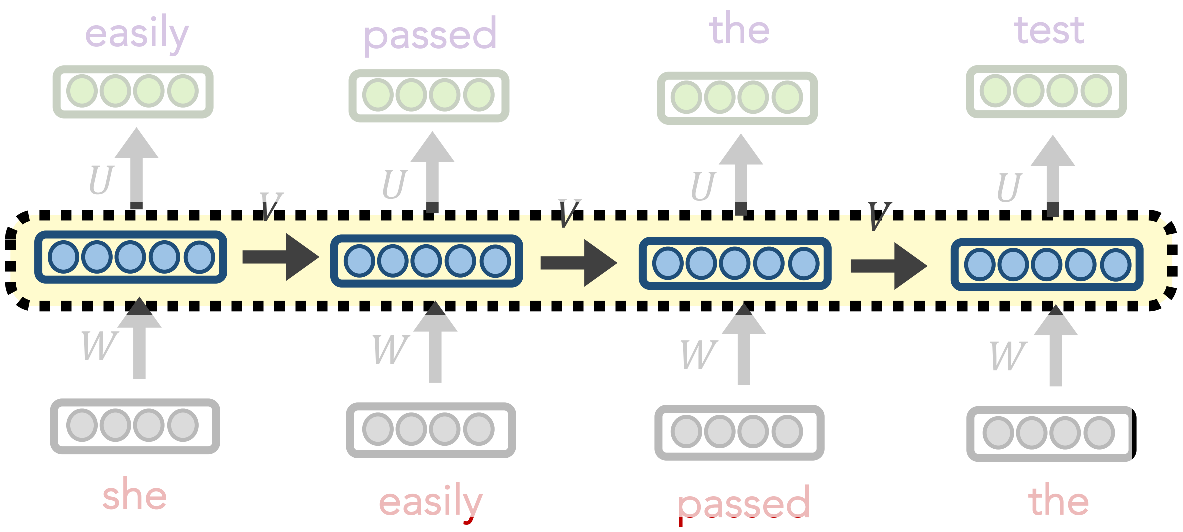


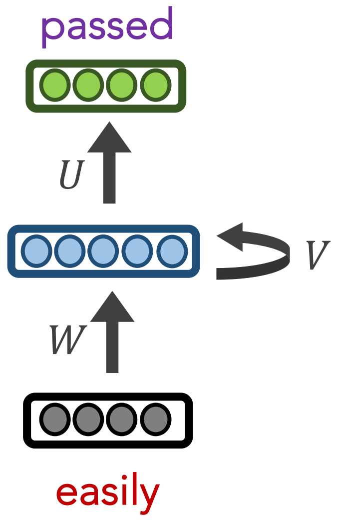
Bidirectional LSTM

Next, we learned about **word embeddings**

- LSTMs are amazing but ultimately only look at 1 word at a time, sequentially
- Sure, they maintain long-term memory, but they are short-sighted in terms of knowing what to hold onto and how to weight each input

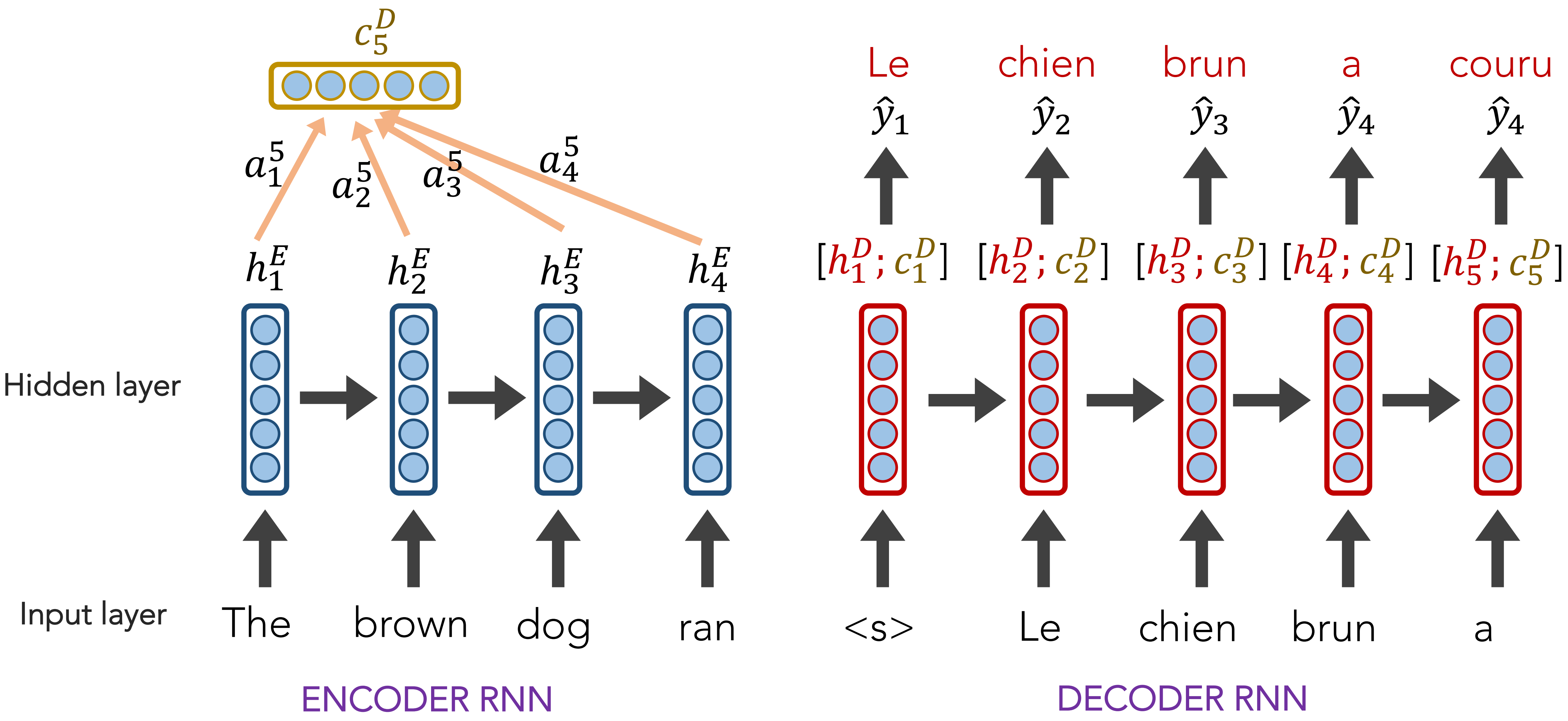
TOKEN-BASED

contextualized embeddings are distinct for every occurrence of a word, completely dependent on its context



Bidirectional LSTM

Next, we learned about **seq2seq** and **Attention**



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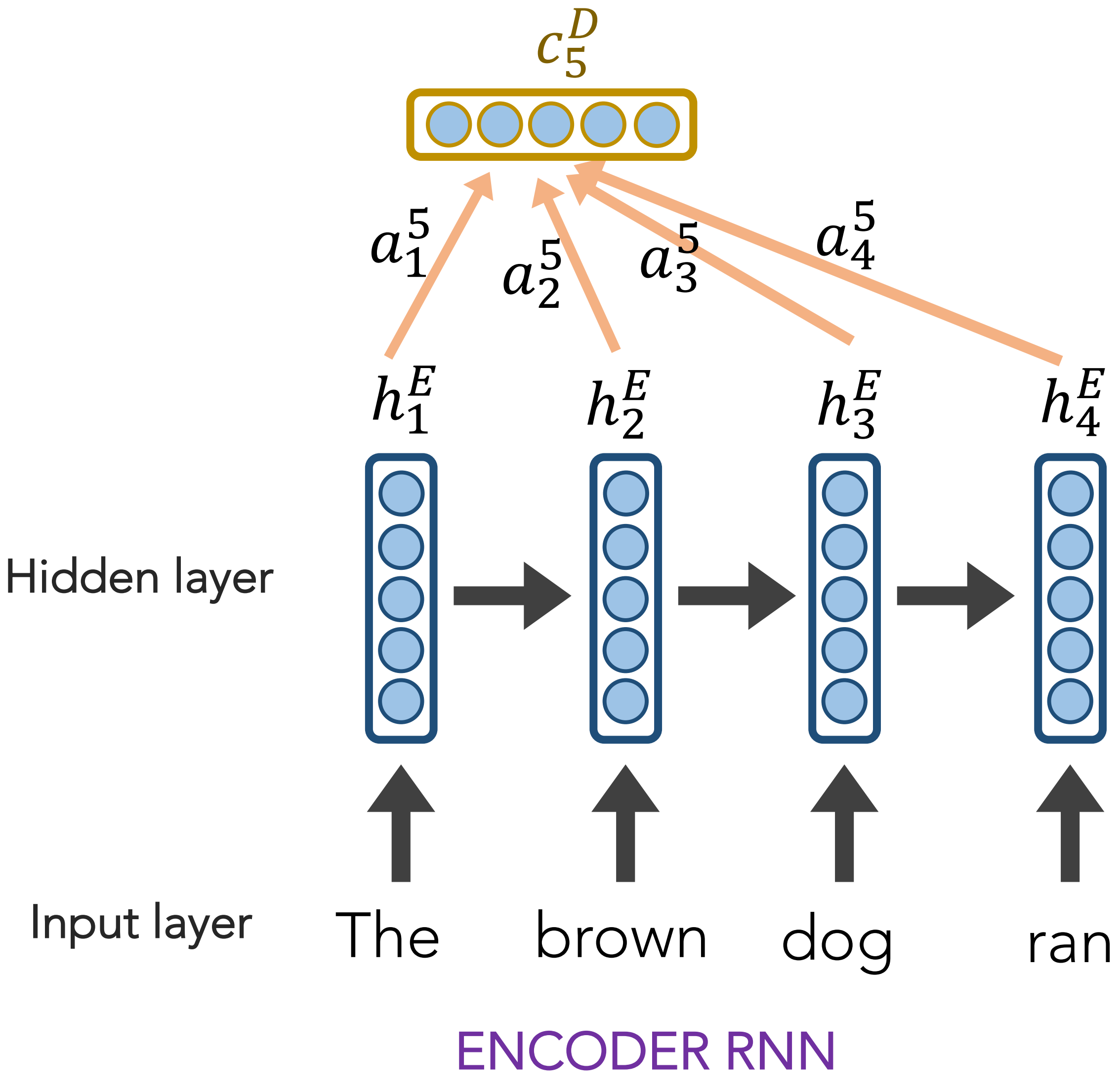

- Revolutionary idea
- Decoder has access to all input words and appropriately focuses on select parts
- It's conditioned on the current word we're *decoding*

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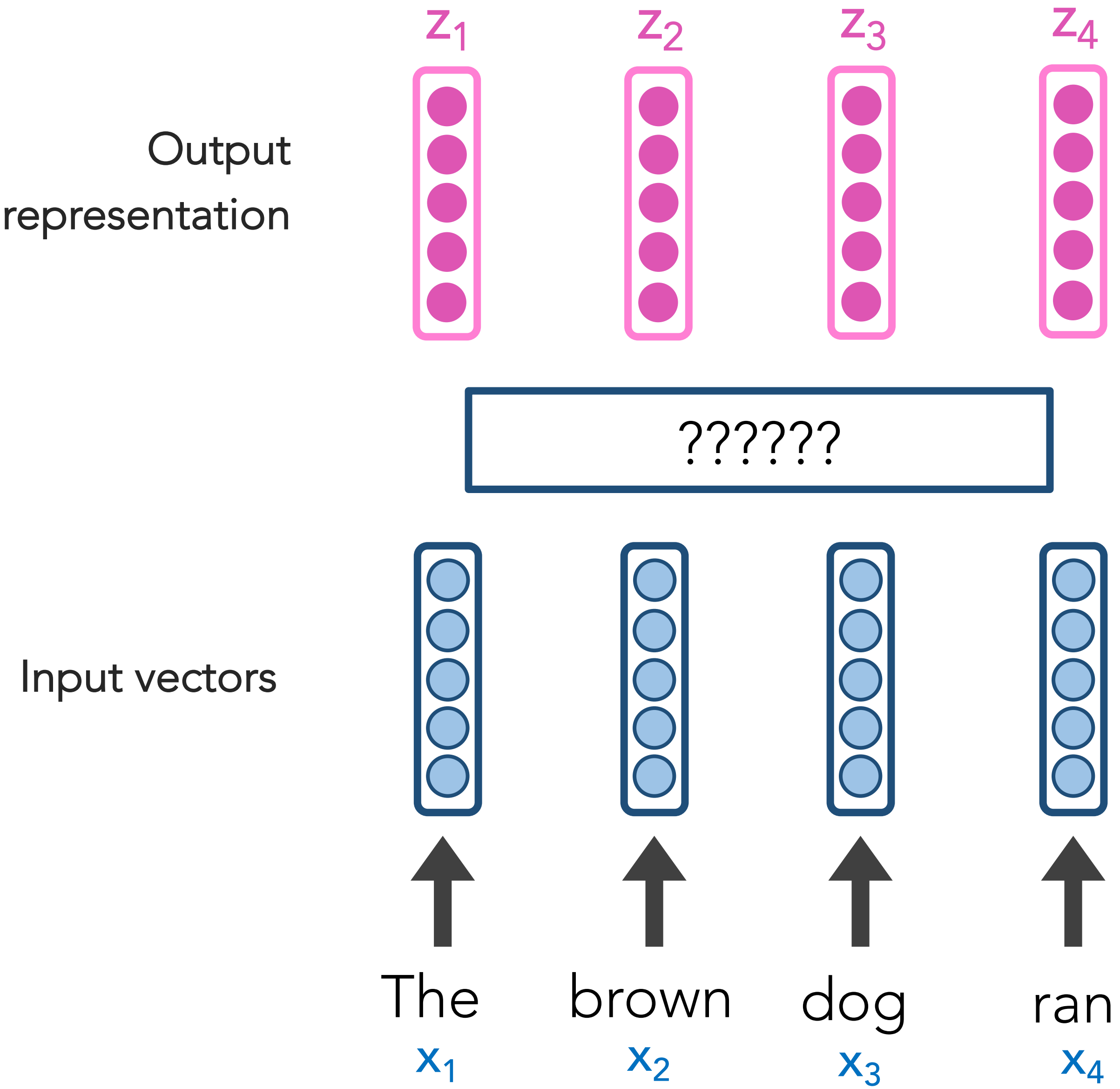
Goals

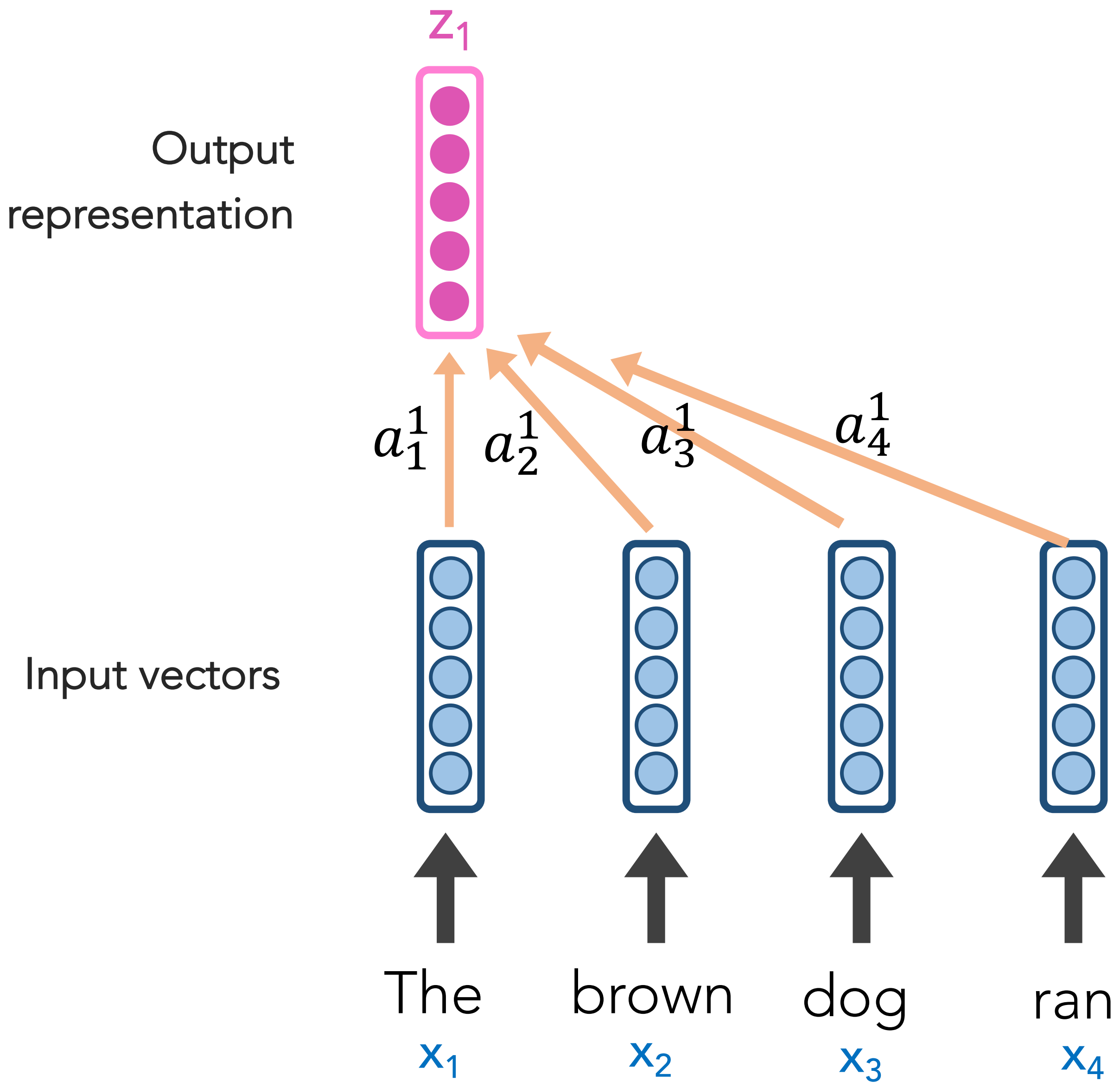
- Each word in a sequence to be transformed into a rich, abstract **representation** (context embedding) based on the weighted sums of the other words in the same sequence (akin to deep CNN layers)
- Inspired by Attention, we want each word to determine, “how much should I be influenced by each of my neighbors”
- Want positionality

Self-Attention



Self-Attention's goal is to create great representations, z_i, of the input

Self-Attention



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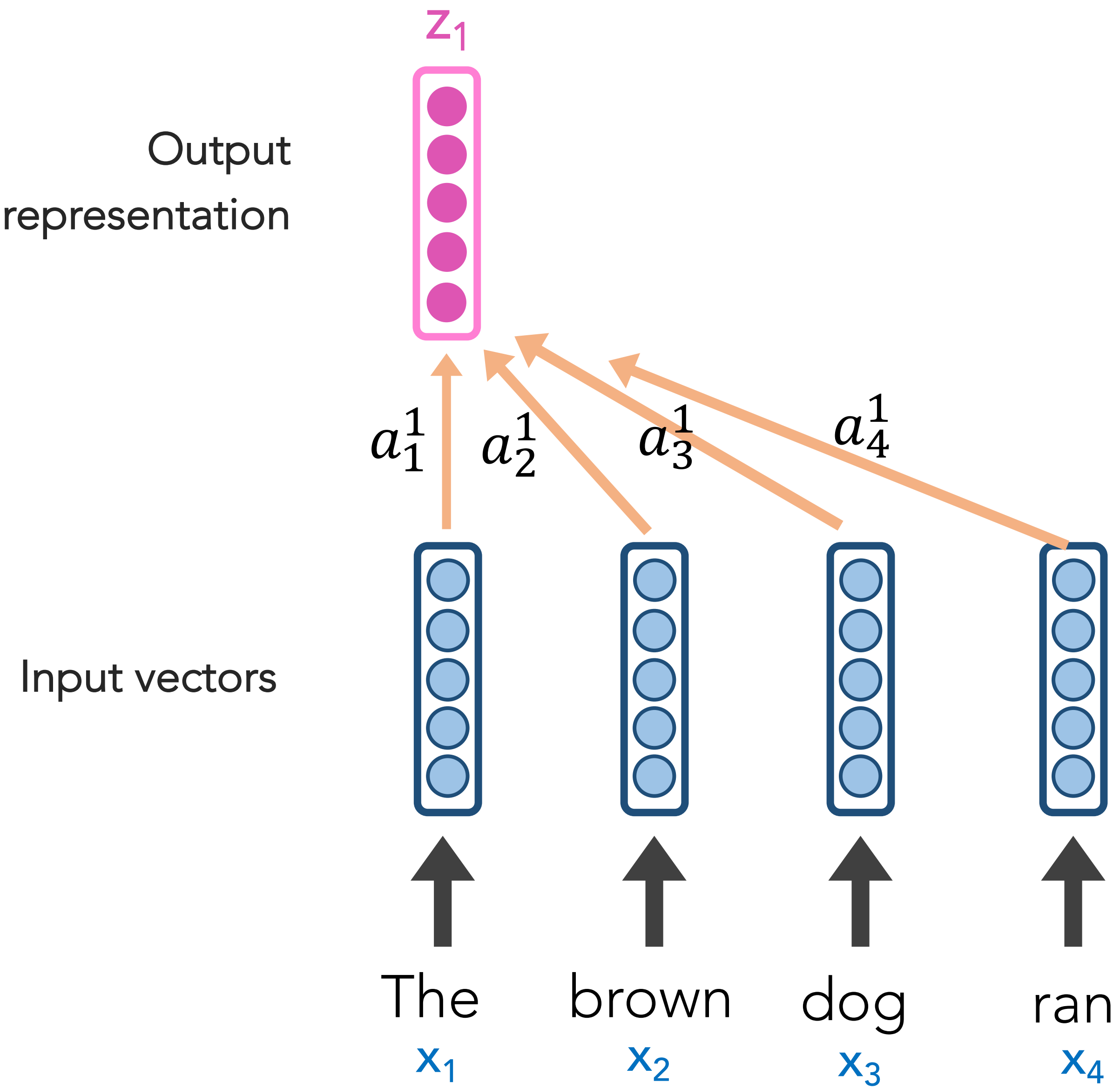
z_1 will be based on a weighted contribution of x_1, x_2, x_3, x_4

Self-Attention

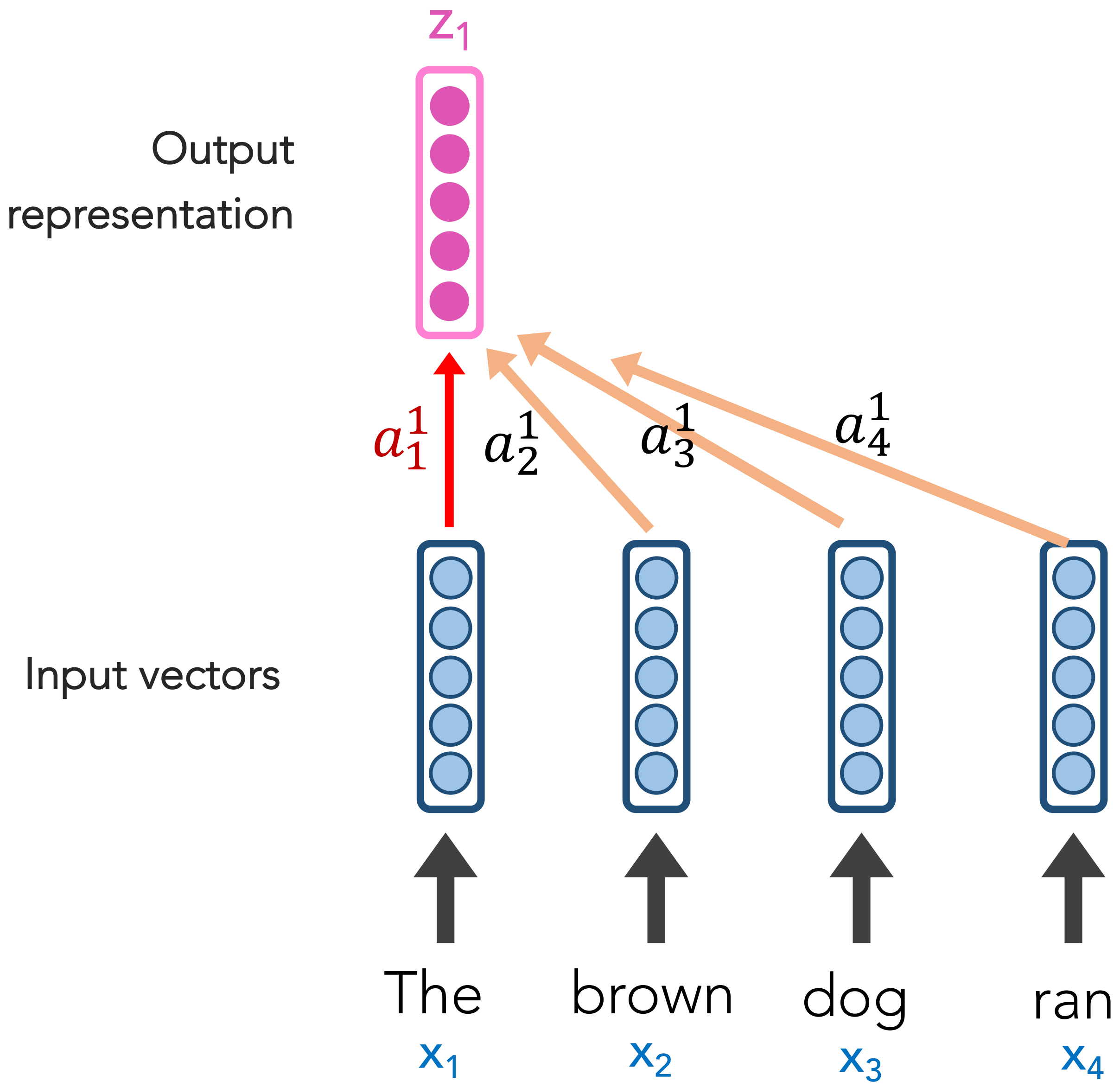


Self-Attention's goal is to create great representations, z_i, of the input

z_1 will be based on a weighted contribution of x_1, x_2, x_3, x_4

a_i^1 is "just" a weight. More is happening under the hood, but it's effectively weighting *versions* of x_1, x_2, x_3, x_4

Self-Attention



Under the hood, each x_i has 3 small, associated vectors.

For example, x_1 has:

- Query $\mathbf{q}_i$
- Key $\mathbf{k}_i$
- Value $\mathbf{v}_i$

Self-Attention

Step 1: Our Self-Attention Head I has just 3 weight matrices W_q, W_k, W_v in total. These same 3 weight matrices are multiplied by each x_i to create all vectors:

$$q_i = w_q x_i$$

$$k_i = w_k x_i$$

$$v_i = w_v x_i$$

Under the hood, each x_i has 3 small, associated vectors. For example, x_1 has:

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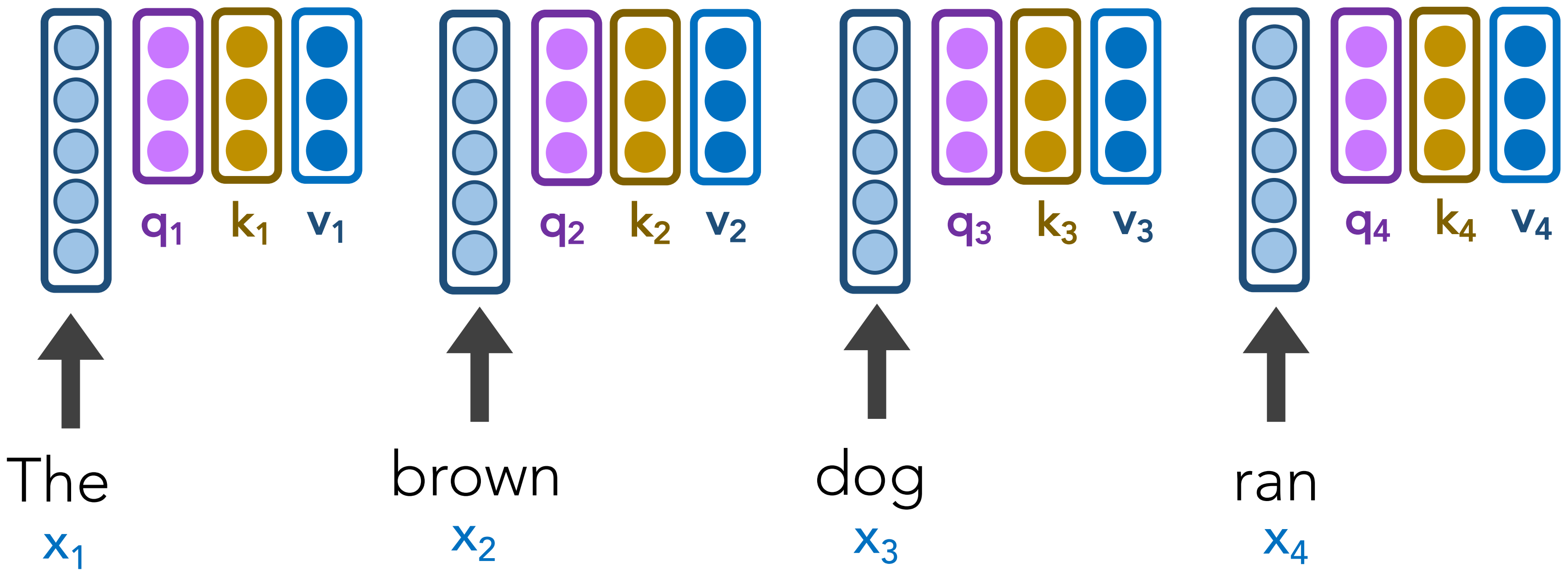
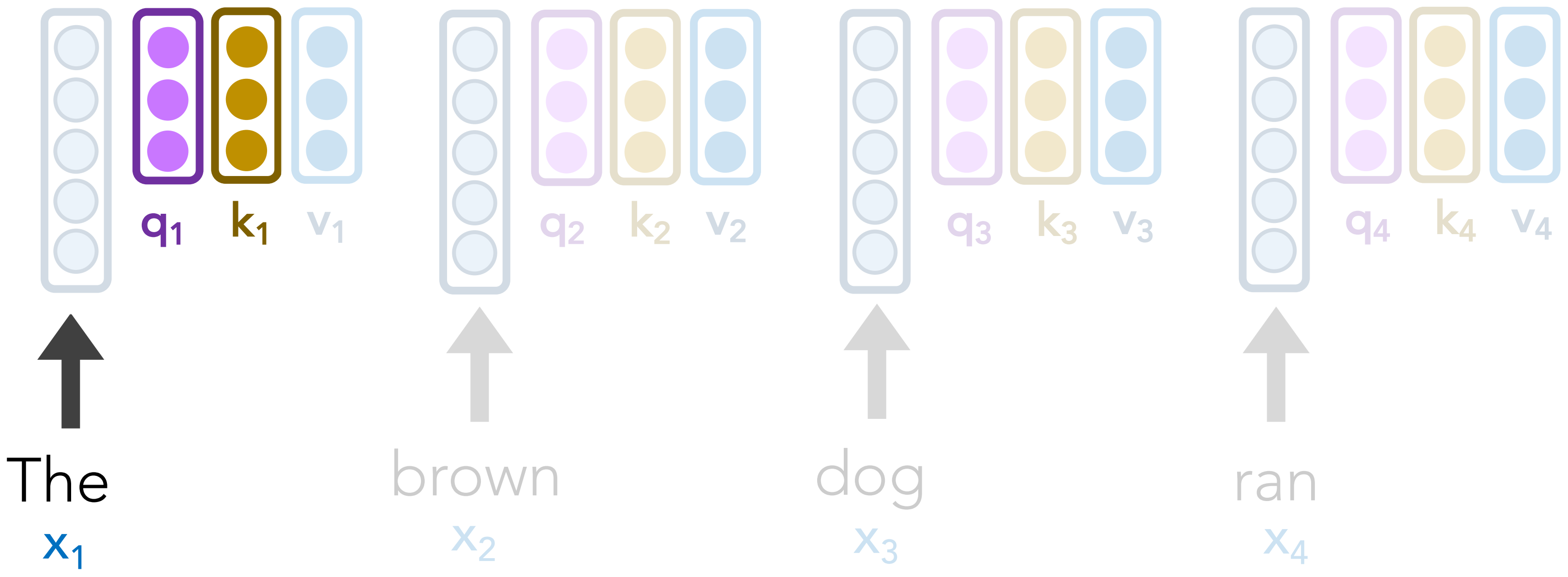


Self-Attention

Step 2: For word x_1, let's calculate the scores s_1, s_2, s_3, s_4, which represent how much attention to pay to each respective "word" v_i

$s_1 = q_1 \cdot k_1 = 112$

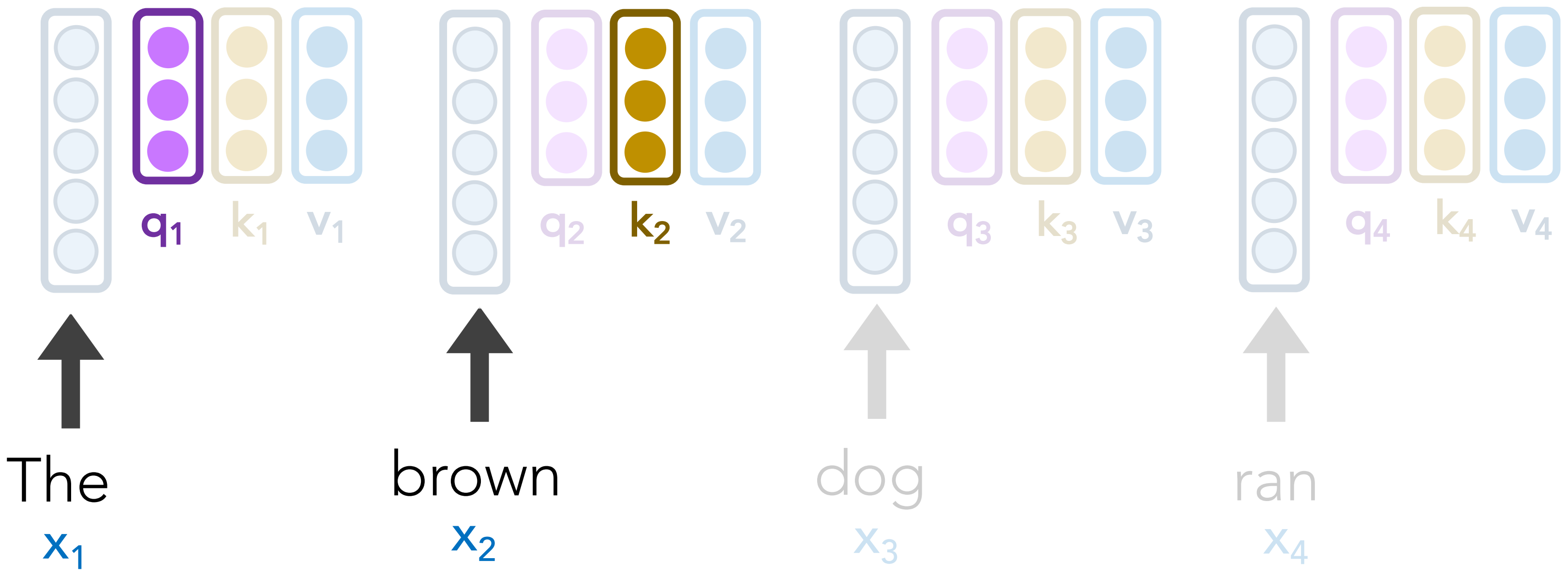


Self-Attention

Step 2: For word x_1, let's calculate the scores s_1, s_2, s_3, s_4, which represent how much attention to pay to each respective "word" v_i

$s_2 = q_1 \cdot k_2 = 96$

$s_1 = q_1 \cdot k_1 = 112$



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Step 2: For word x_1, let's calculate the scores s_1, s_2, s_3, s_4, which represent how much attention to pay to each respective "word" v_i

$s_3 = q_1 \cdot k_3 = 16$

$s_2 = q_1 \cdot k_2 = 96$

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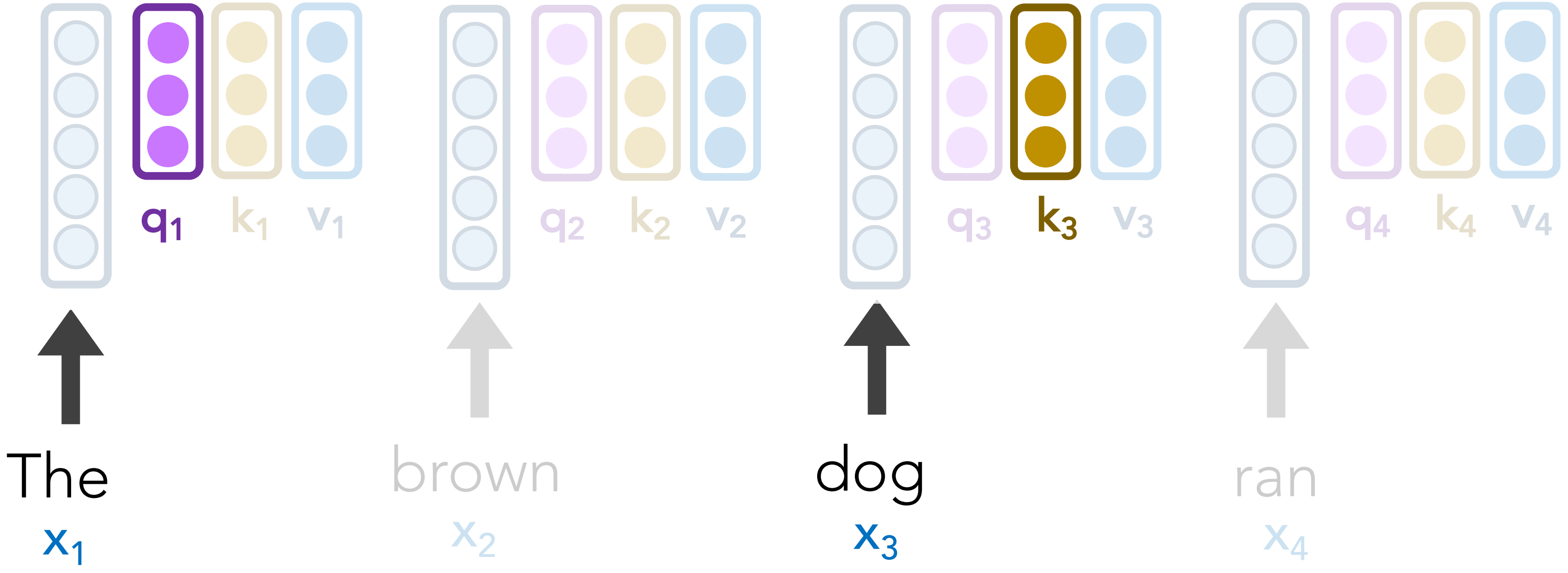


Self-Attention

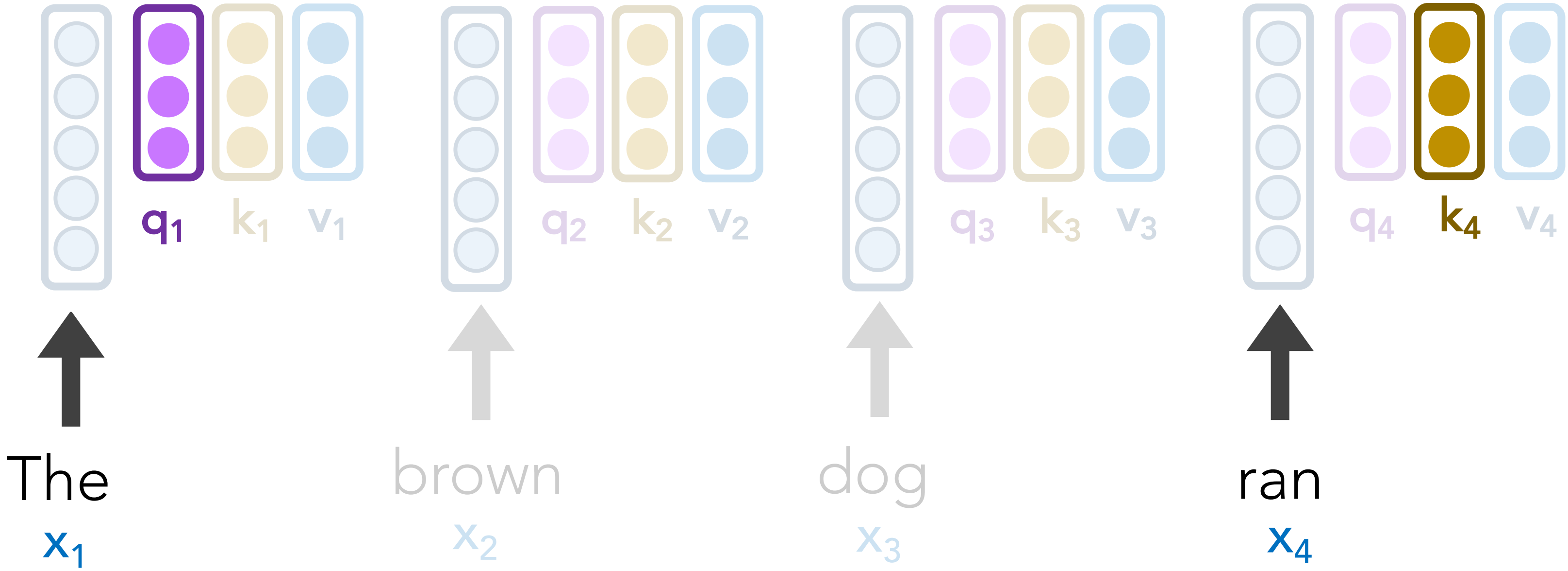
Step 2: For word x_1, let's calculate the scores s_1, s_2, s_3, s_4, which represent how much attention to pay to each respective "word" v_i

$s_4 = q_1 \cdot k_4 = 8$

$s_3 = q_1 \cdot k_3 = 16$

$s_2 = q_1 \cdot k_2 = 96$

$s_1 = q_1 \cdot k_1 = 112$



Self-Attention

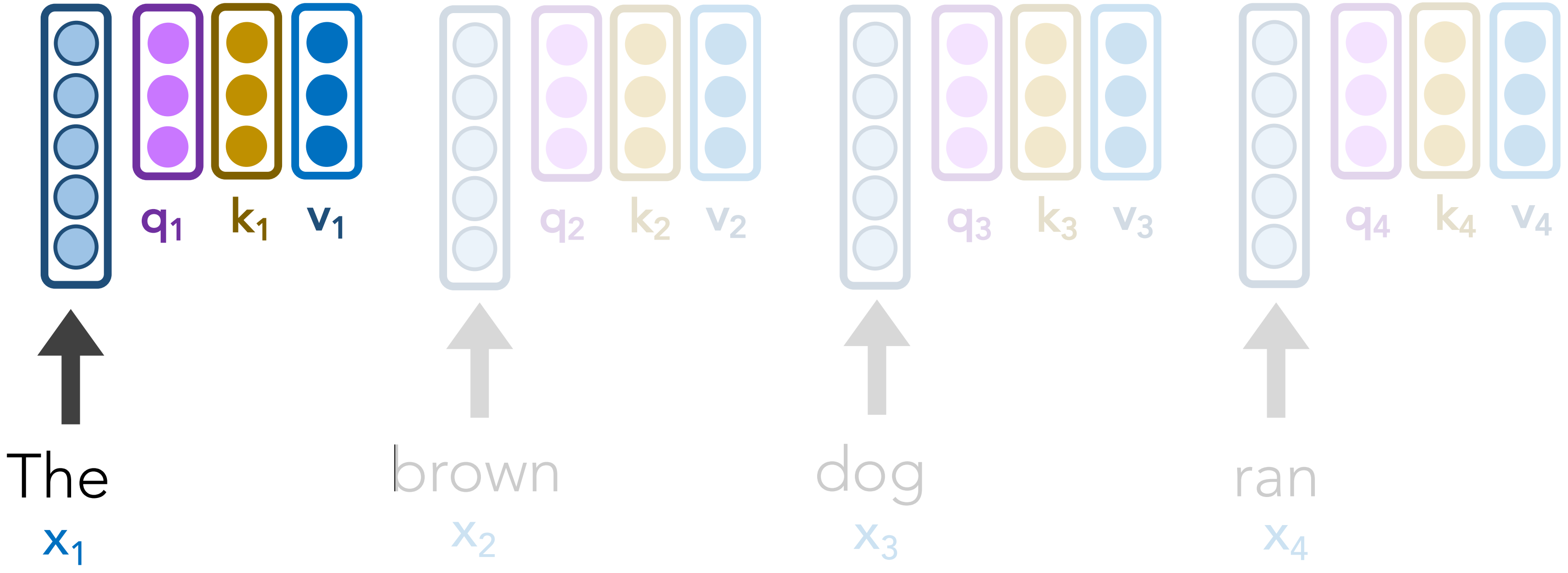
Step 3: Our scores s_1, s_2, s_3, s_4 don't sum to 1. Let's divide by $\sqrt{len(k_i)}$ and softmax it

$s_4 = q_1 \cdot k_4 = 8$ $\qquad a_4 = \sigma(s_4/8) = 0$

$s_3 = q_1 \cdot k_3 = 16$ $\qquad a_3 = \sigma(s_3/8) = .01$

$s_2 = q_1 \cdot k_2 = 96$ $\qquad a_2 = \sigma(s_2/8) = .12$

$s_1 = q_1 \cdot k_1 = 112$ $\qquad a_1 = \sigma(s_1/8) = .87$



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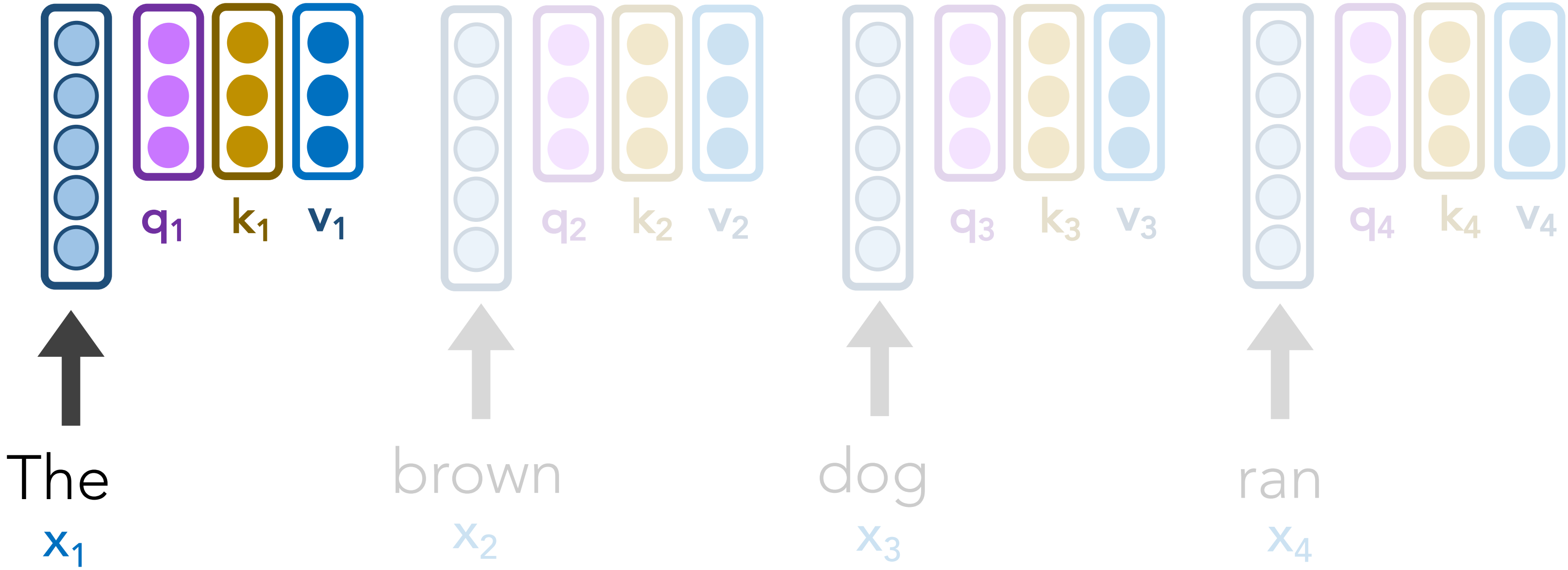
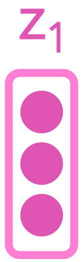
Instead of these a_i values directly weighting our original x_i word vectors, they directly weight our v_i vectors.



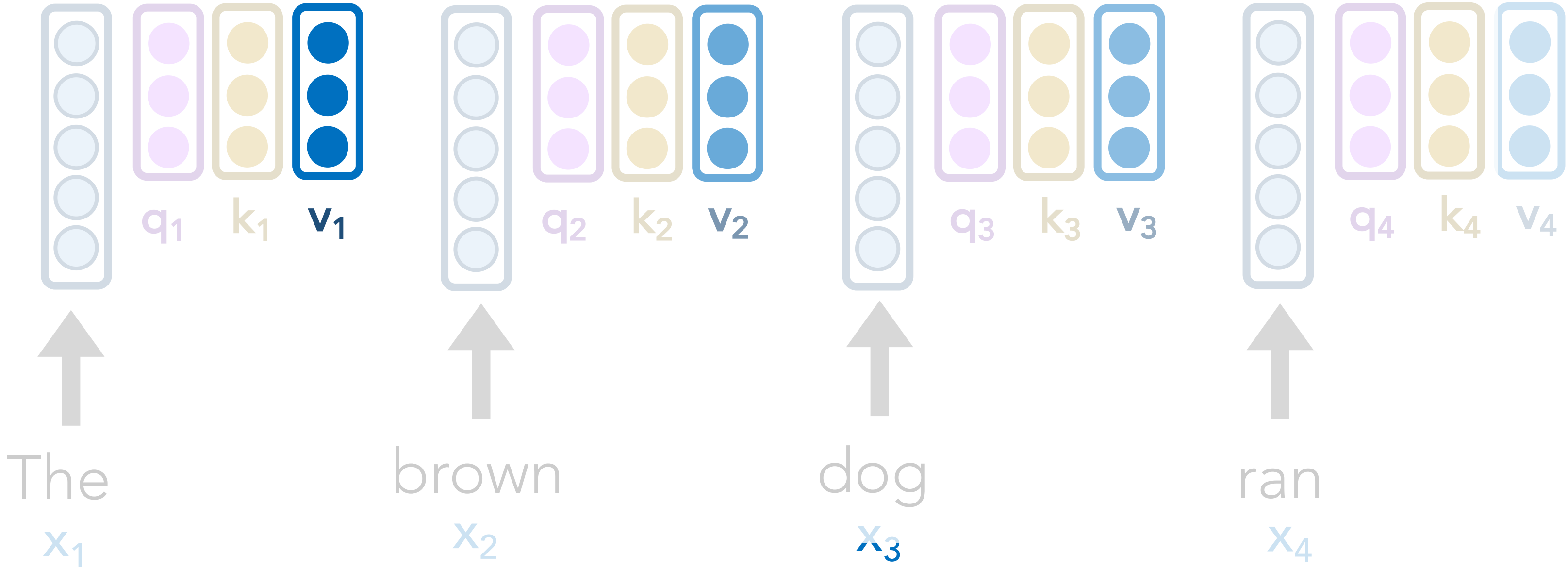
Self-Attention

Step 4: Let's weight our v_i vectors and simply sum them up!



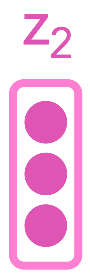
$$z_1 = a_1 \cdot v_1 + a_2 \cdot v_2 + a_3 \cdot v_3 + a_4 \cdot v_4$$

$$= 0.87 \cdot v_1 + 0.12 \cdot v_2 + 0.01 \cdot v_3 + 0 \cdot v_4$$

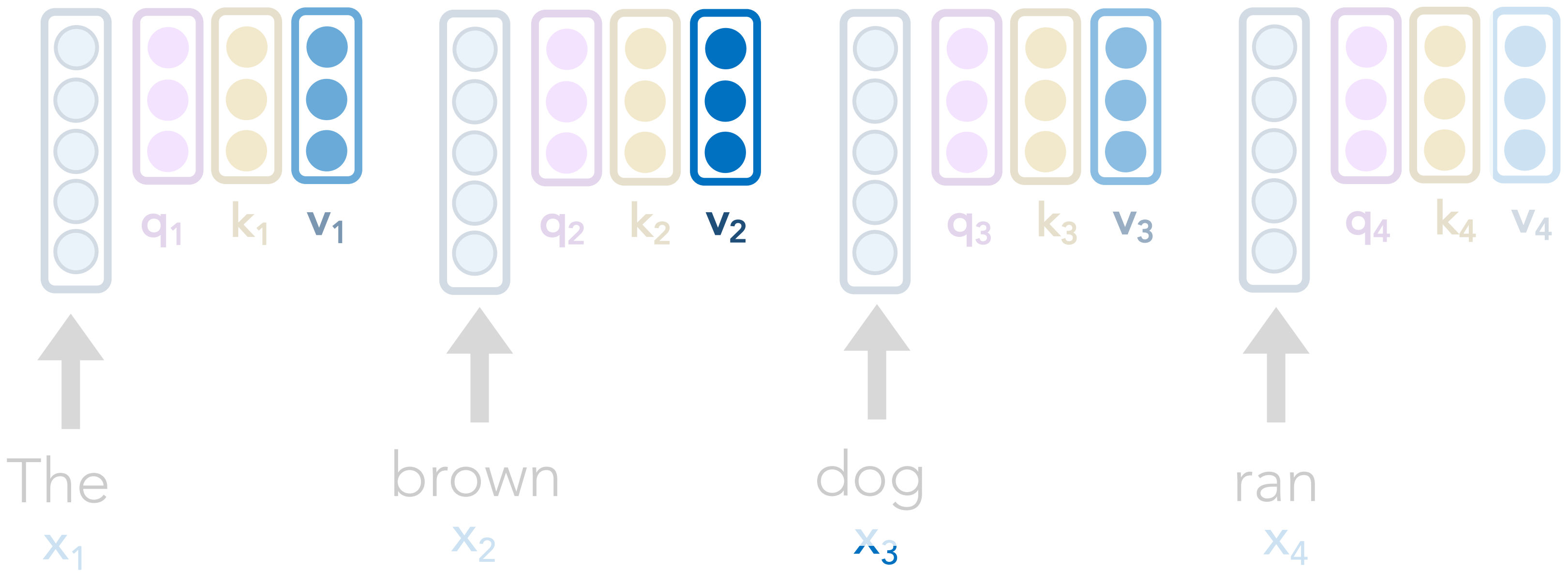


Self-Attention

Step 5: We repeat this for all other words, yielding us with great, new z_i representations!



$$z_2 = a_1 \cdot v_1 + a_2 \cdot v_2 + a_3 \cdot v_3 + a_4 \cdot v_4$$



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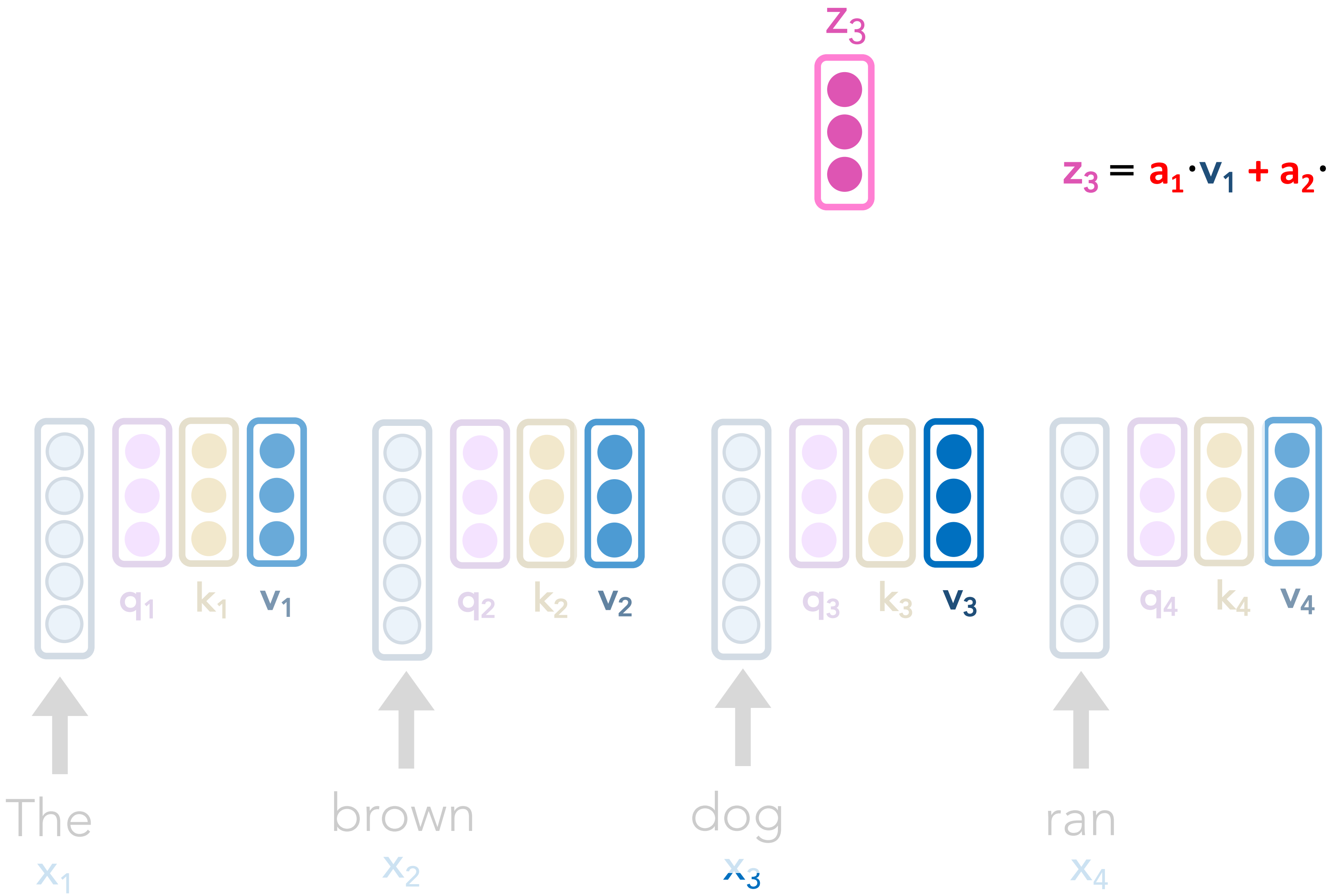
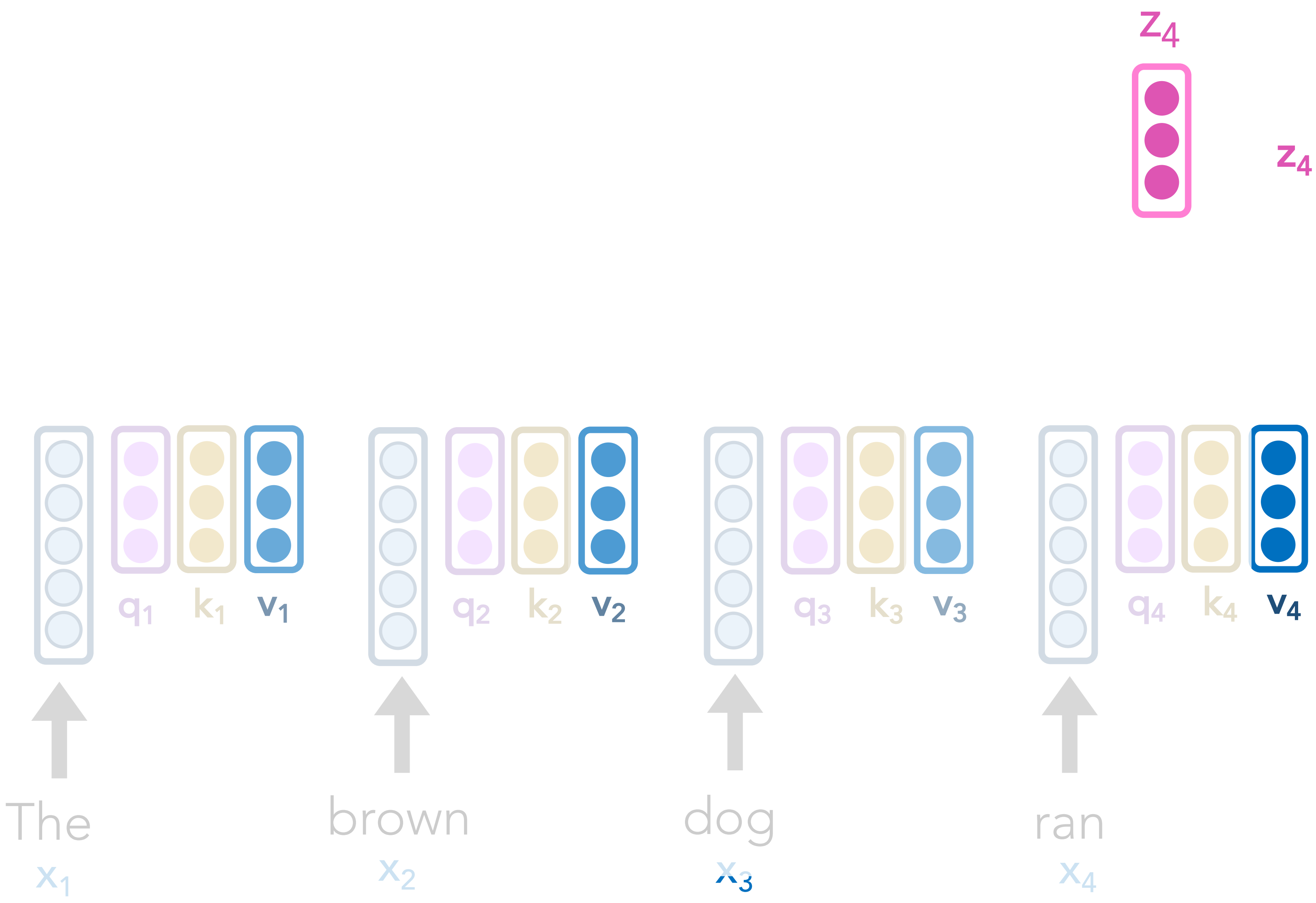


$$z_3 = a_1 \cdot v_1 + a_2 \cdot v_2 + a_3 \cdot v_3 + a_4 \cdot v_4$$

Self-Attention

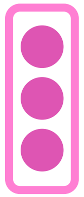
Step 5: We repeat this for all other words, yielding us with great, new z_i representations!

$$z_4 = a_1 \cdot v_1 + a_2 \cdot v_2 + a_3 \cdot v_3 + a_4 \cdot v_4$$



Let's illustrate another example:

z_2



$$z_2 = a_1 \cdot v_1 + a_2 \cdot v_2 + a_3 \cdot v_3 + a_4 \cdot v_4$$

Remember, we use the same 3 weight matrices W_q, W_k, W_v as we did for computing z_1.

This gives us q_2, k_2, v_2

Self-Attention

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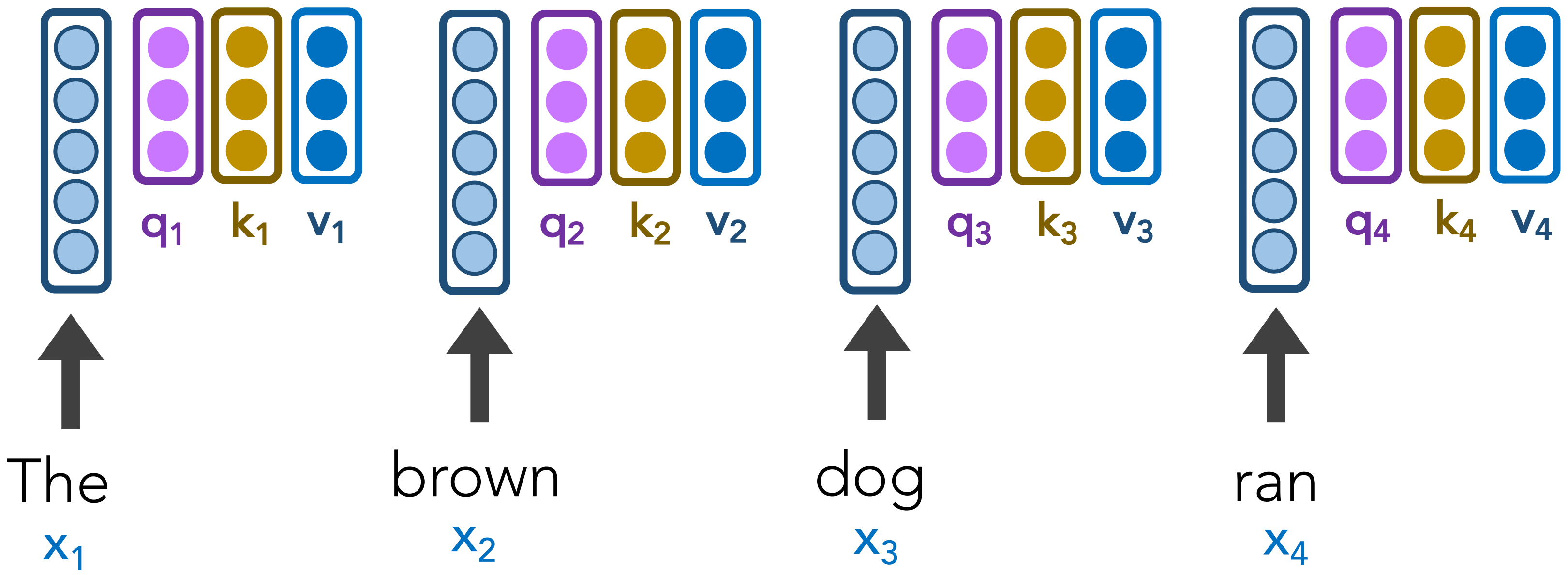
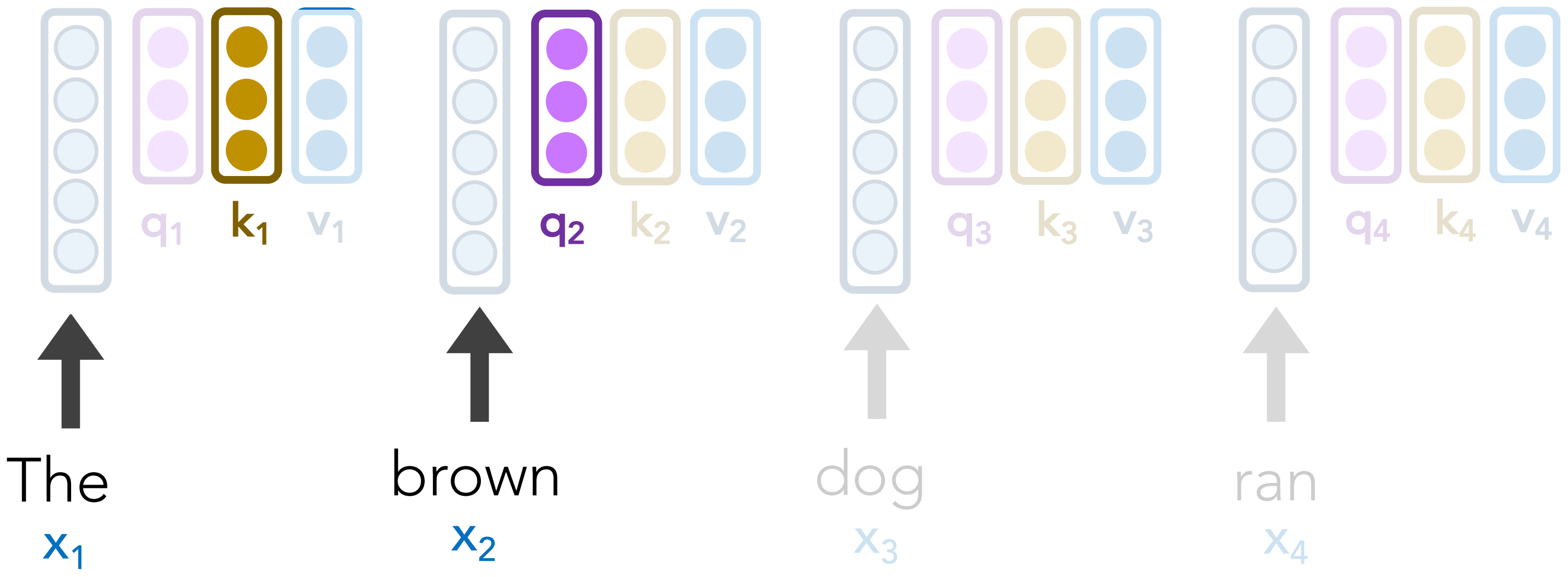


Self-Attention

Step 2: For word x_2, let's calculate the scores s_1, s_2, s_3, s_4, which represent how much attention to pay to each respective "word" v_i

$s_1 = q_2 \cdot k_1 = 92$



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Step 2: For word x_2, let's calculate the scores s_1, s_2, s_3, s_4, which represent how much attention to pay to each respective "word" v_i

$s_2 = q_2 \cdot k_2 = 124$

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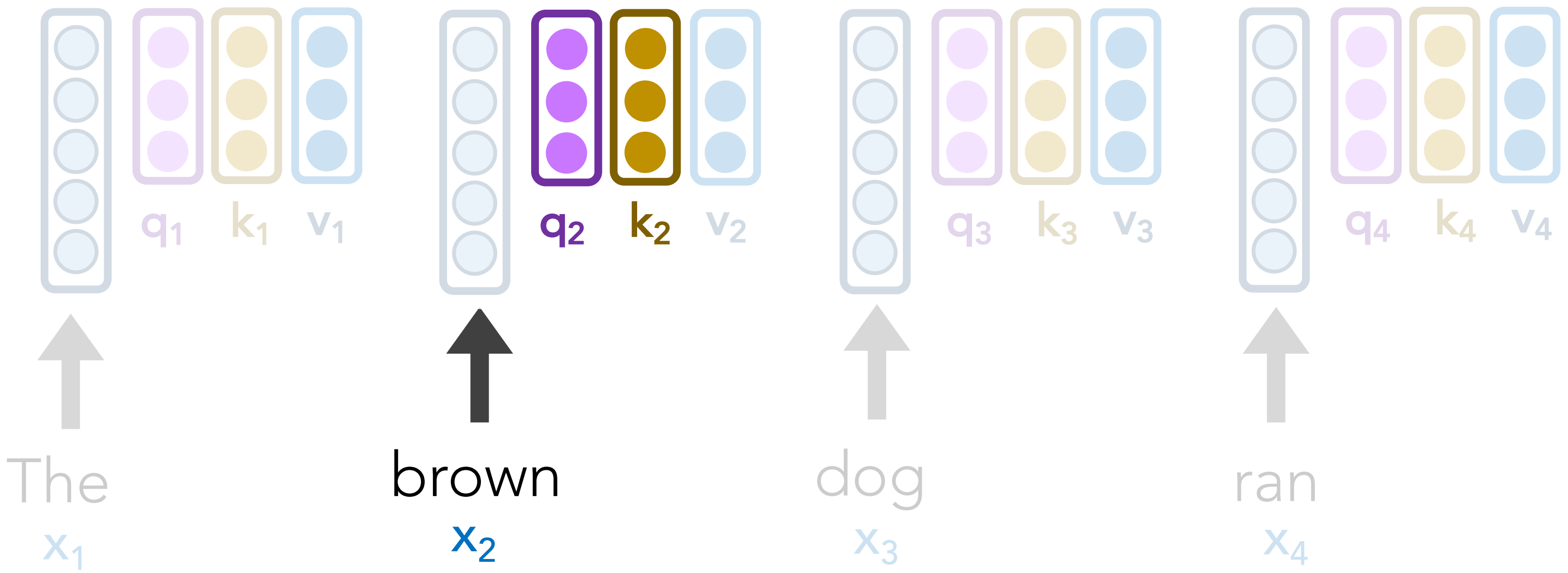

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Step 2: For word x_2, let's calculate the scores s_1, s_2, s_3, s_4, which represent how much attention to pay to each respective "word" v_i

$s_3 = q_2 \cdot k_3 = 22$

$s_2 = q_2 \cdot k_2 = 124$

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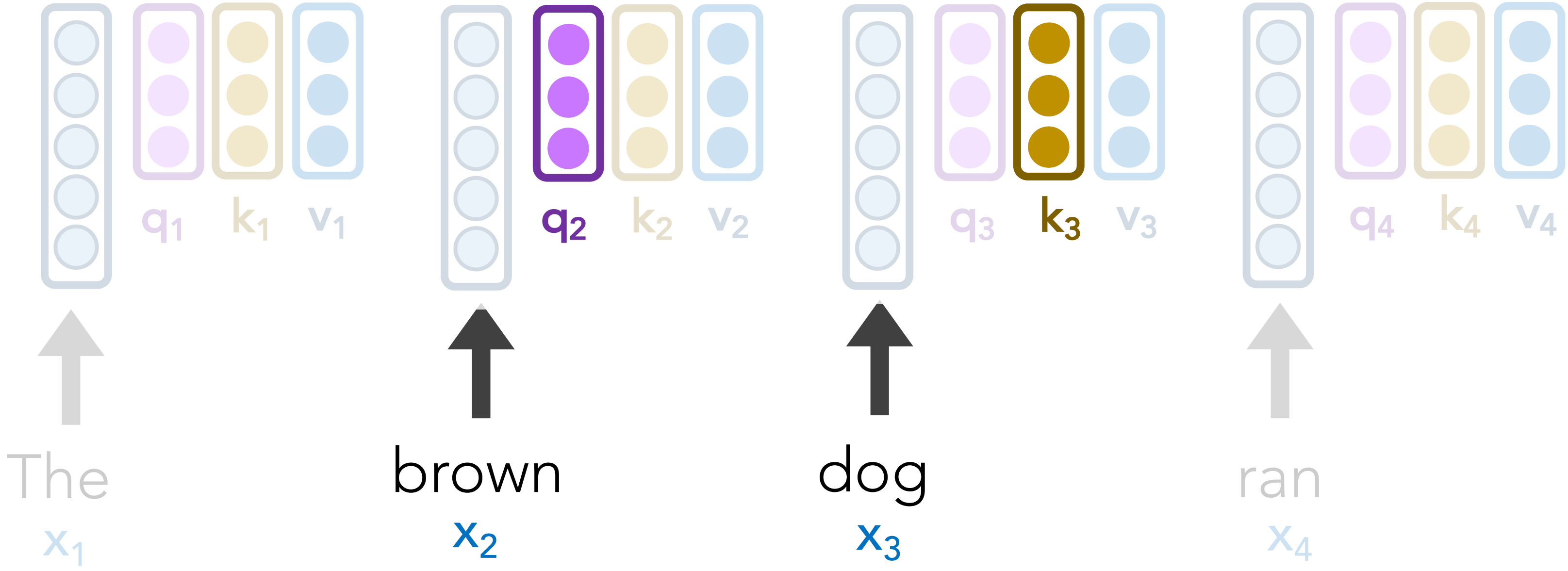

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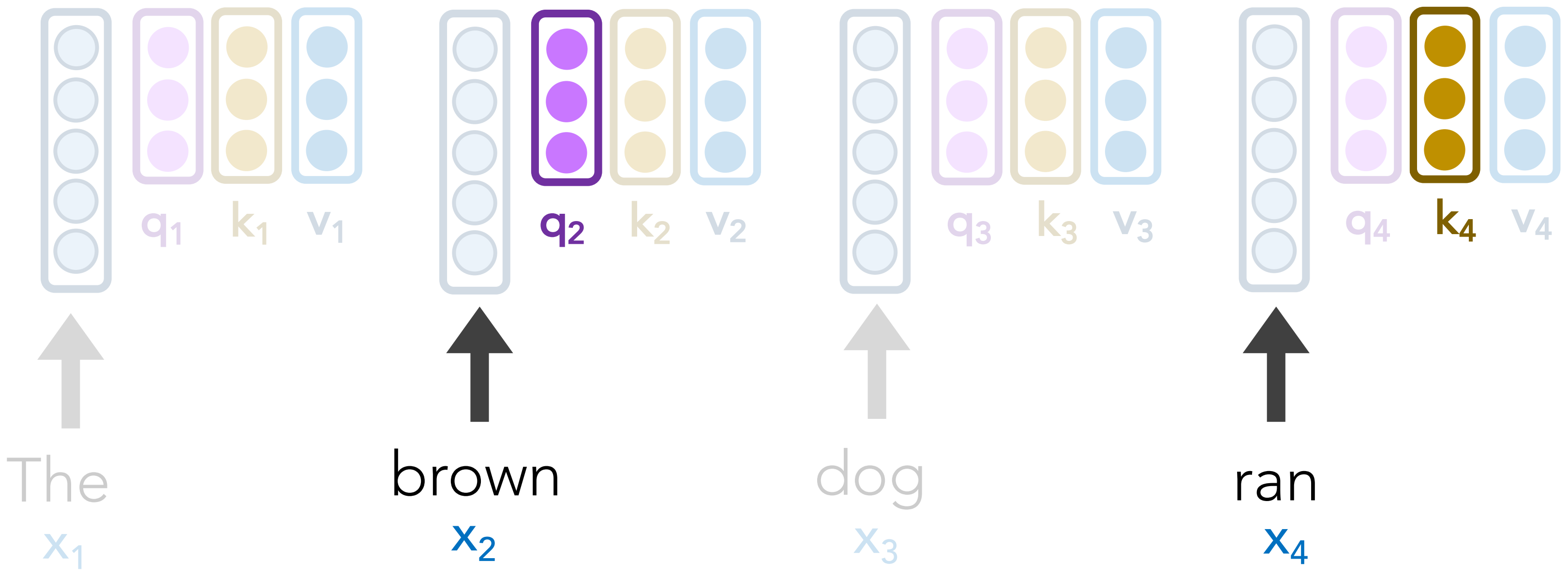

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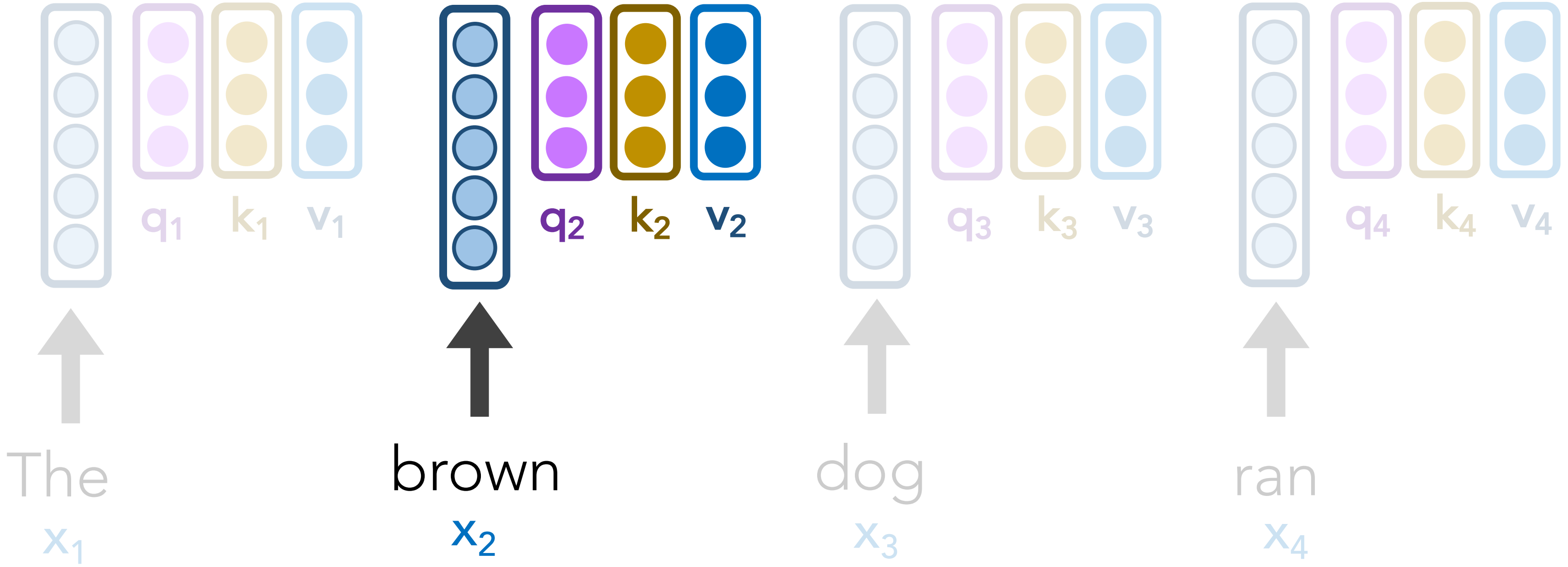

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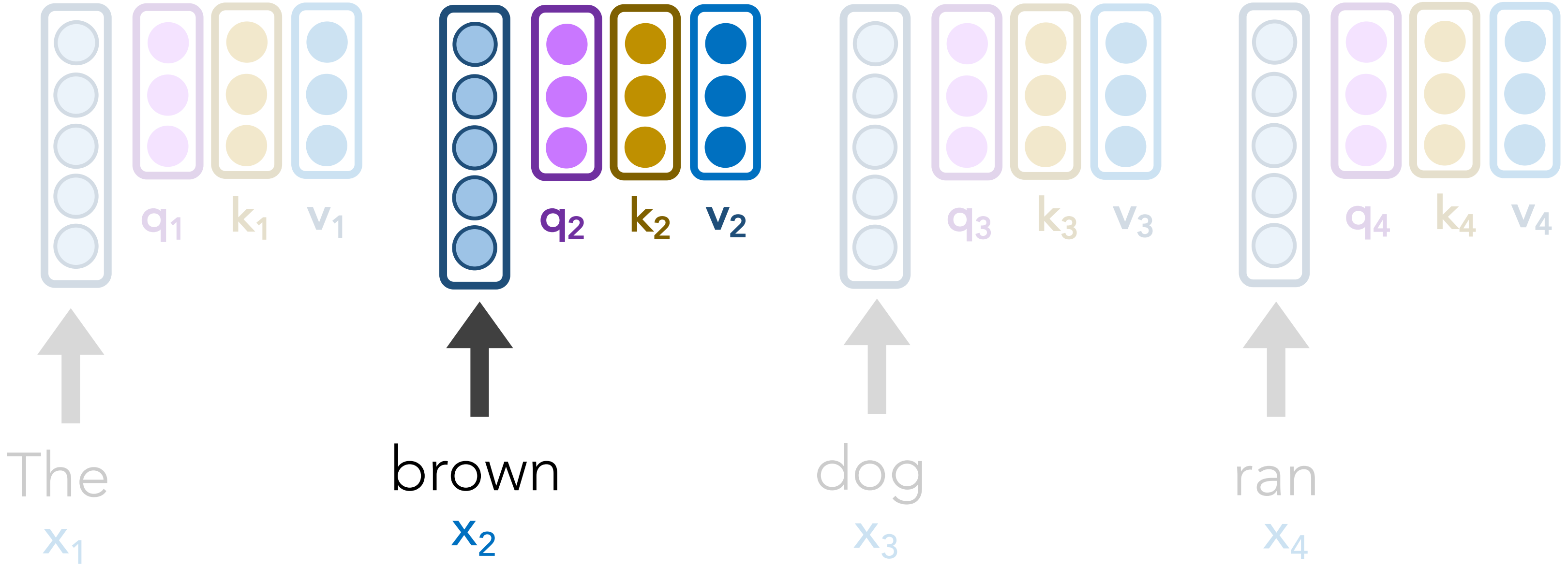

Self-Attention

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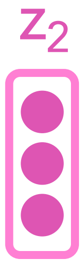
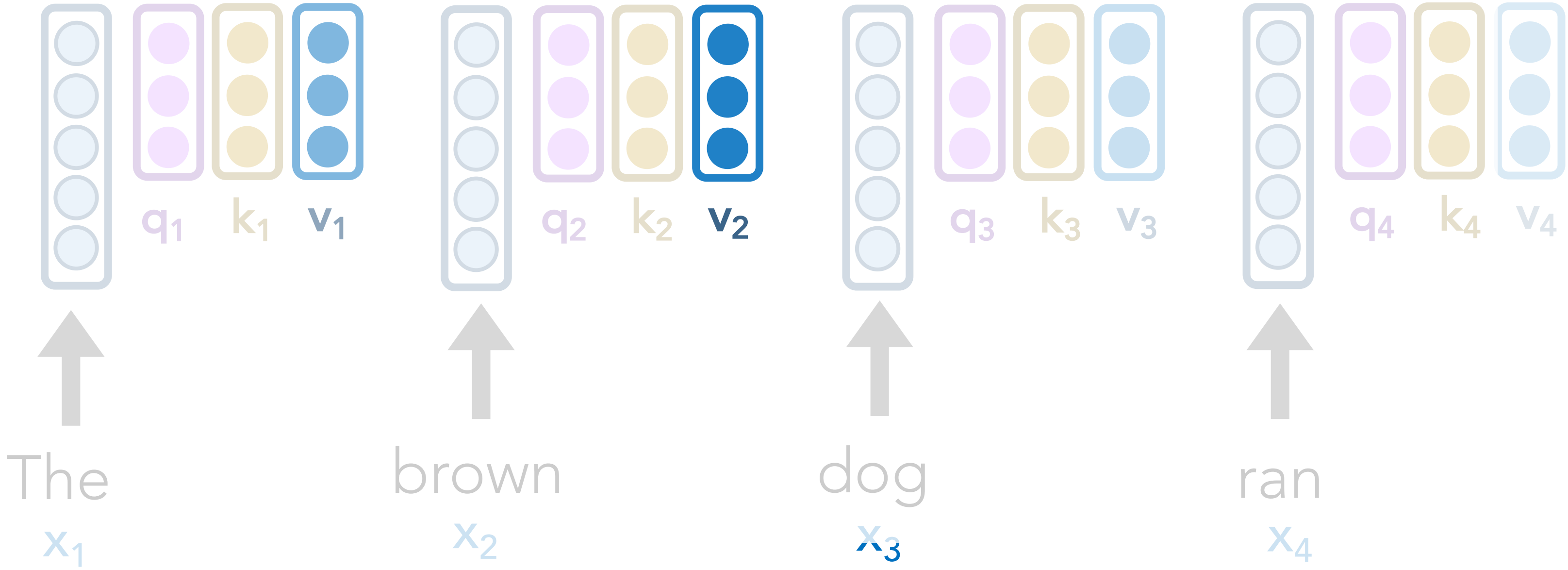


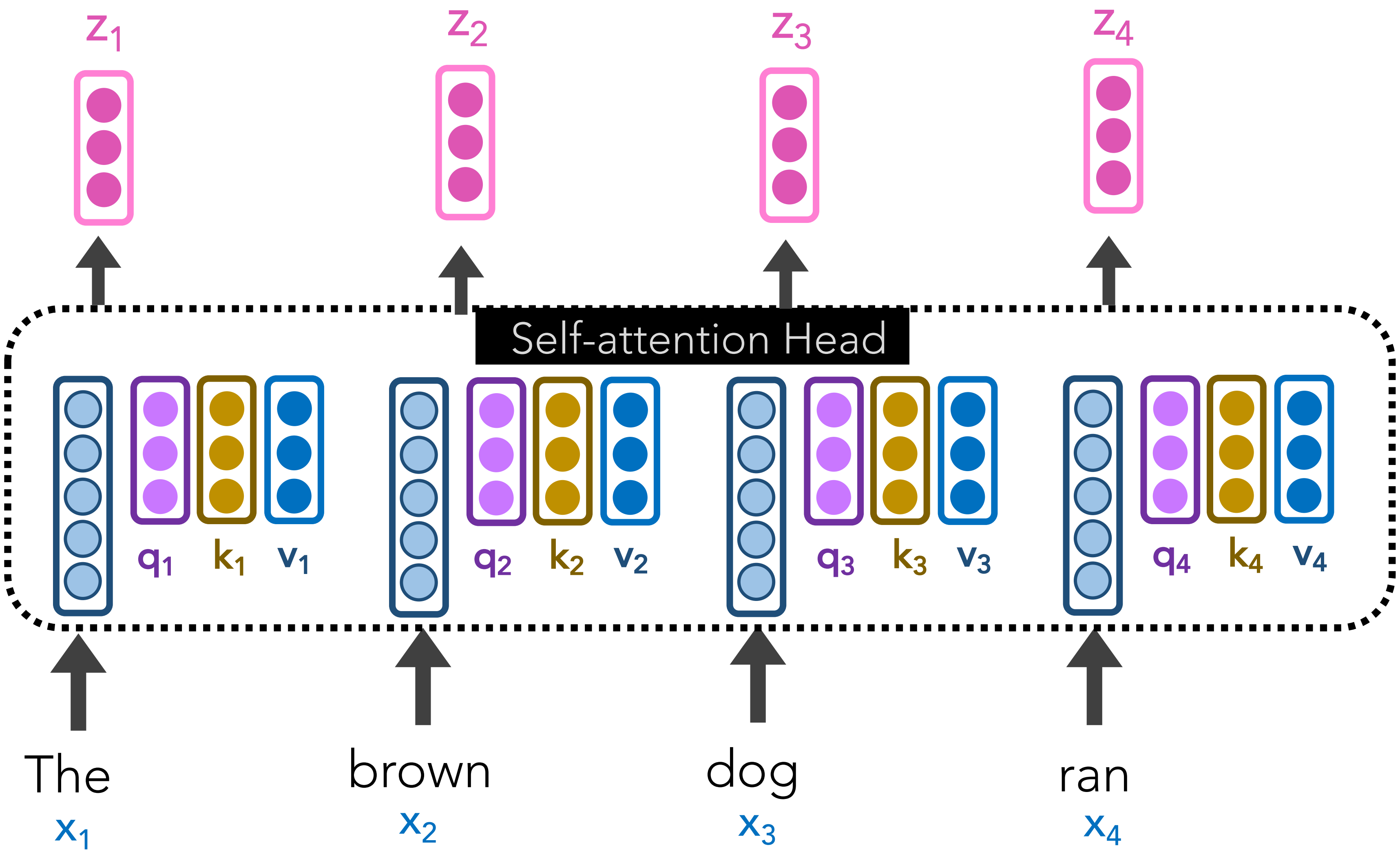
$$z_2 = a_1 \cdot v_1 + a_2 \cdot v_2 + a_3 \cdot v_3 + a_4 \cdot v_4$$

$$= 0.08 \cdot v_1 + 0.91 \cdot v_2 + 0.01 \cdot v_3 + 0 \cdot v_4$$



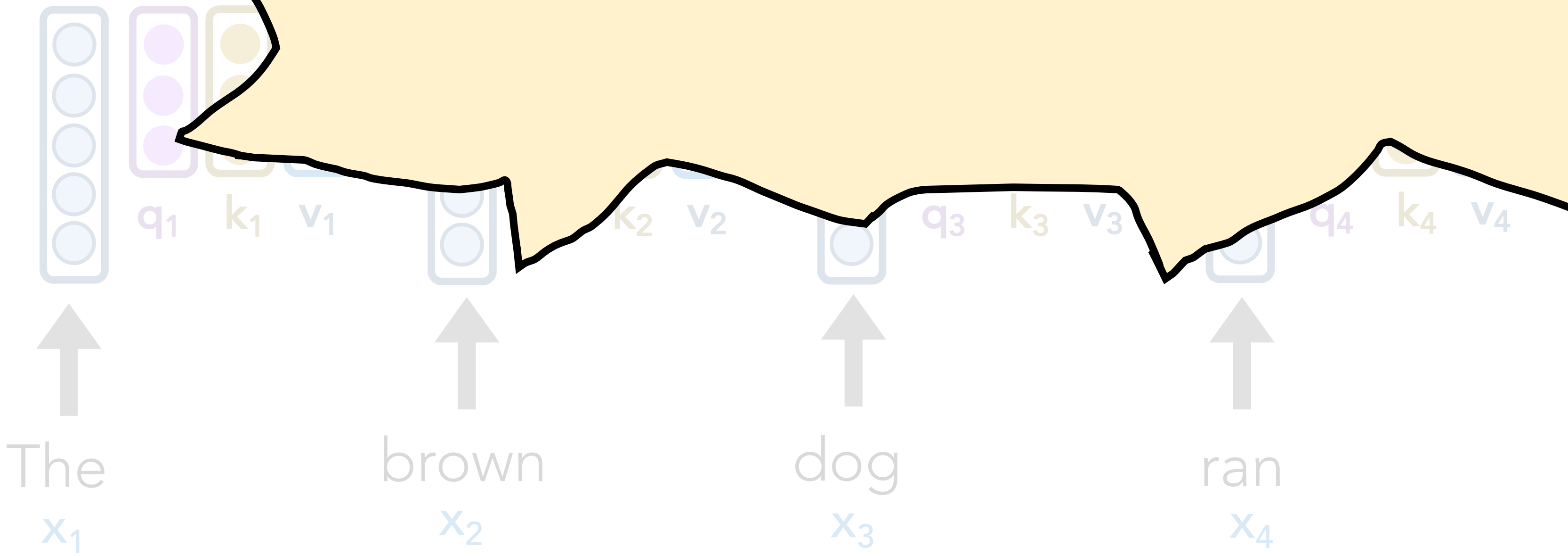
Self-Attention

Tada! Now we have great, new representations z_i via a self-attention head



Takeaway:

Self-Attention is powerful; allows us to create great, context-aware representations



Self-Attention may seem strikingly like Attention in seq2seq models

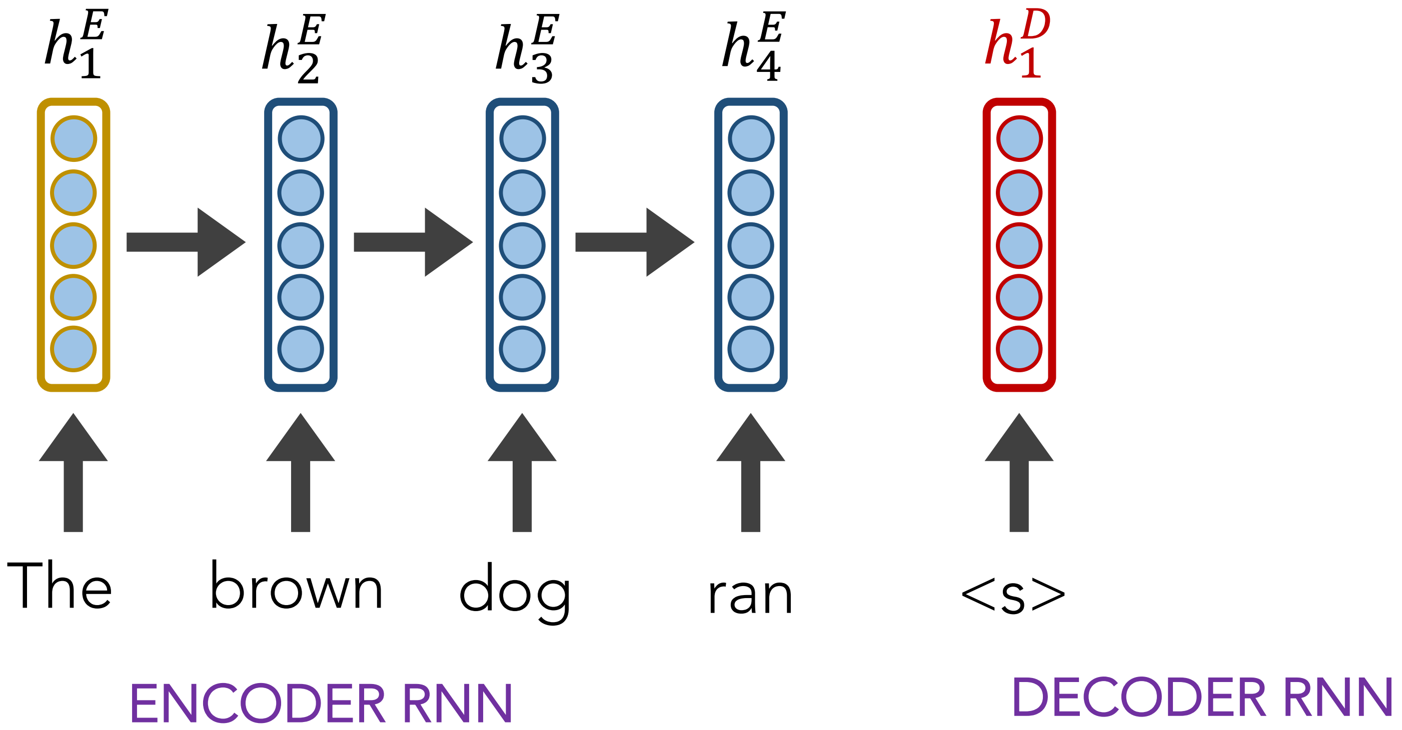
$$s_4 = h_1^D * h_4^E \qquad a_4 = \sigma(s_4)$$

$$s_3 = h_1^D * h_3^E \qquad a_3 = \sigma(s_3)$$

$$s_2 = h_1^D * h_2^E \qquad a_2 = \sigma(s_2)$$

$$s_1 = h_1^D * h_1^E \qquad a_1 = \sigma(s_1)$$

Attention



$s_4 = h_1^D * h_4^E$ $a_4 = \sigma(s_4)$

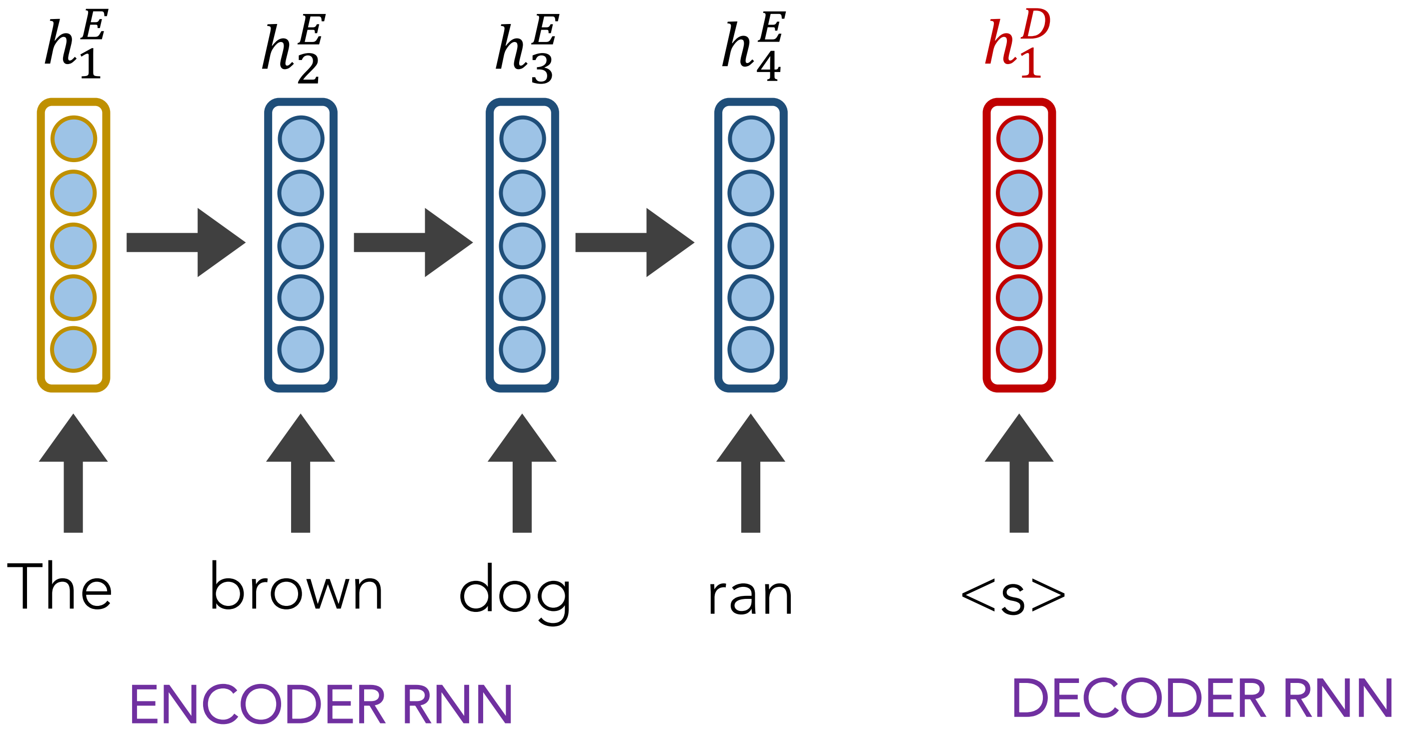
$s_3 = h_1^D * h_3^E$ $a_3 = \sigma(s_3)$

$s_2 = h_1^D * h_2^E$ $a_2 = \sigma(s_2)$

$s_1 = h_1^D * h_1^E$ $a_1 = \sigma(s_1)$

We multiply each encoder's hidden layer by its a_i^1 attention weights to create a context vector c_1^D

Attention



Attention

$s_4 = h_1^D * h_4^E$ $a_4 = \sigma(s_4)$

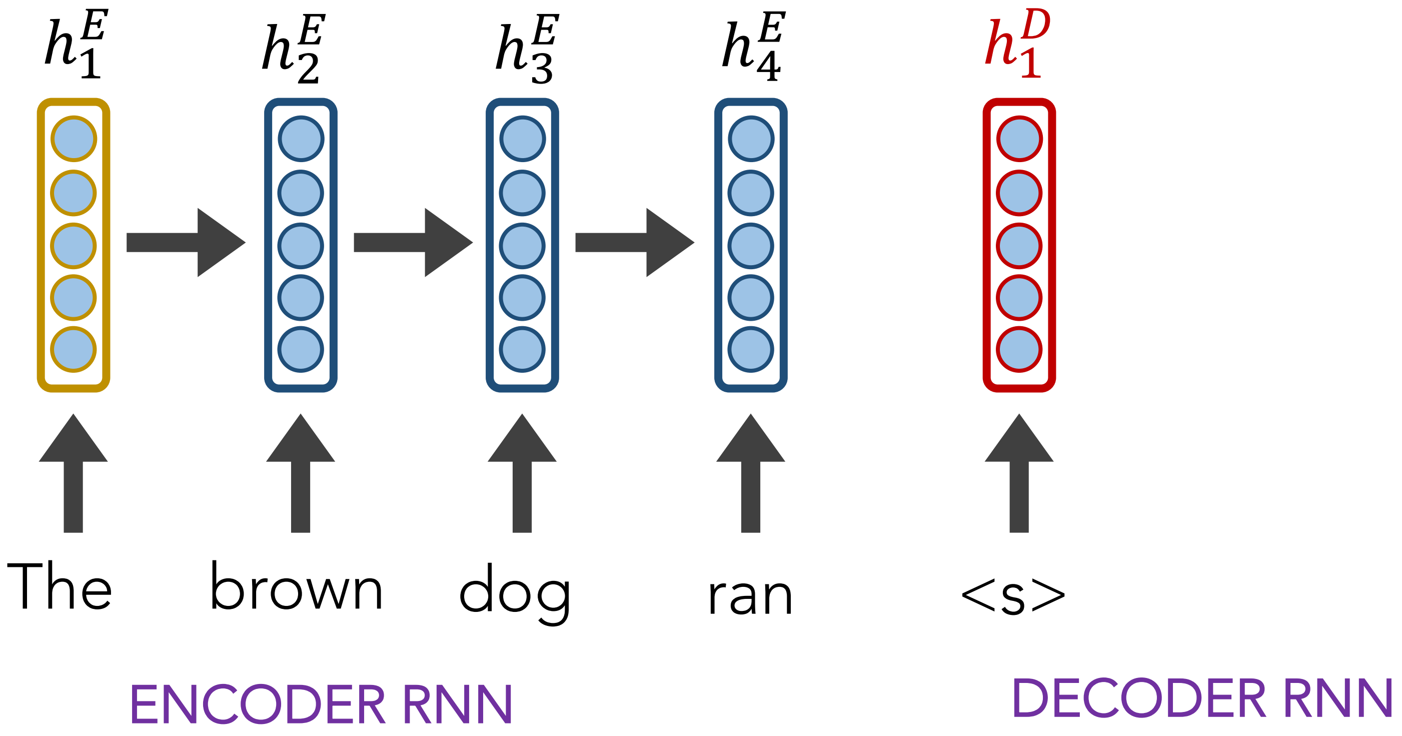
$s_3 = h_1^D * h_3^E$ $a_3 = \sigma(s_3)$

$s_2 = h_1^D * h_2^E$ $a_2 = \sigma(s_2)$

$s_1 = h_1^D * h_1^E$ $a_1 = \sigma(s_1)$

We multiply each encoder's hidden layer by its a_i^1 attention weights to create a context vector c_1^D

$$c_1^D = a_1 \cdot h_1^E + a_2 \cdot h_2^E + a_3 \cdot h_3^E + a_4 \cdot h_4^E$$



$s_4 = q_2 \cdot k_4$

$s_3 = q_2 \cdot k_3$

$s_2 = q_2 \cdot k_2$

$s_1 = q_2 \cdot k_1$

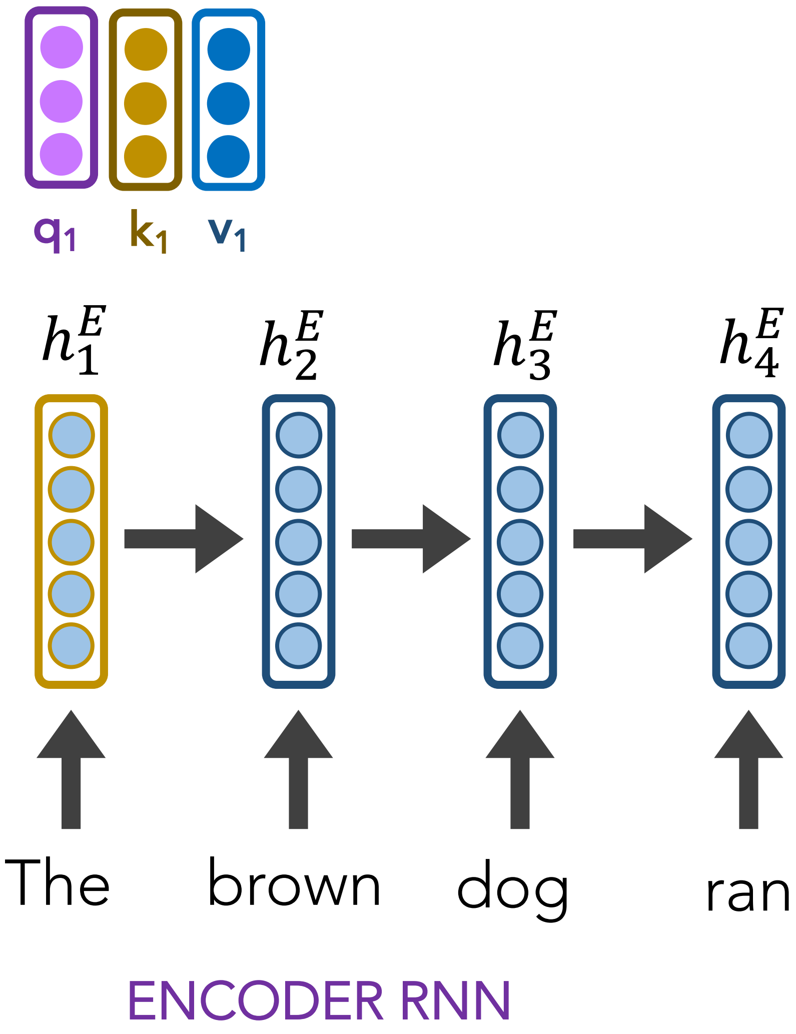
$a_4 = \sigma(s_4/8)$

$a_3 = \sigma(s_3/8)$

$a_2 = \sigma(s_2/8)$

$a_1 = \sigma(s_1/8)$

Self-Attention



We multiply each word's value vector by its a_i^1 attention weights to create a better vector z_1

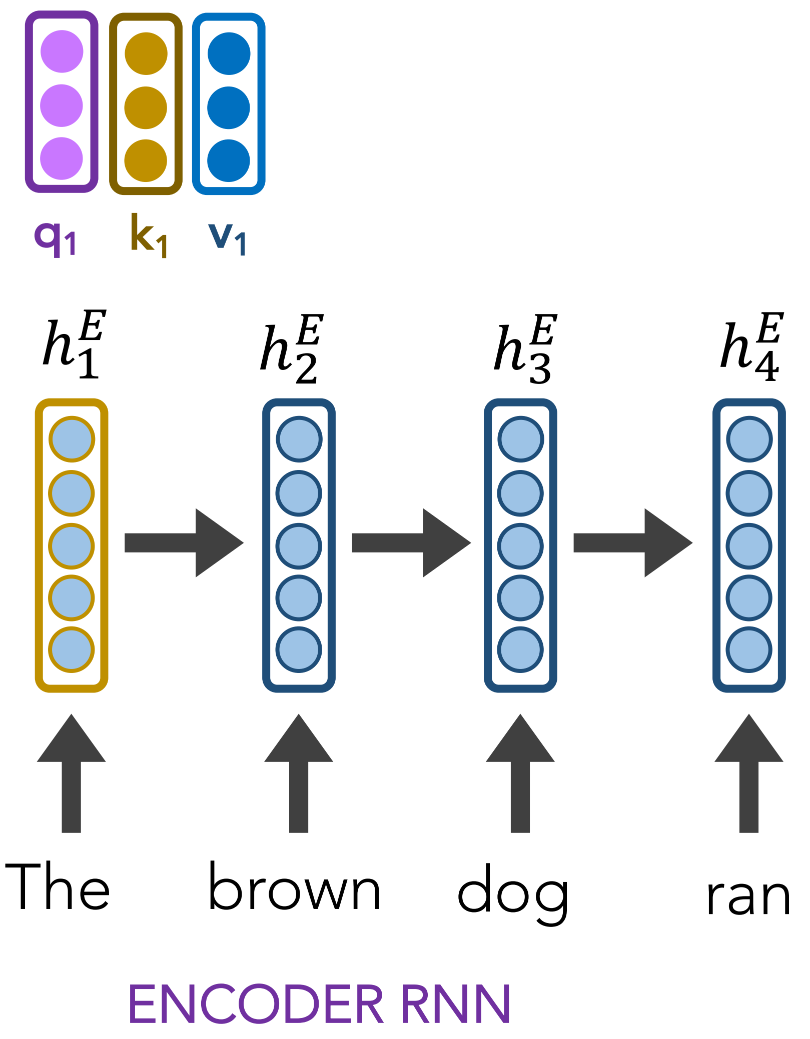
$$z_1 = a_1 \cdot v_1^E + a_2 \cdot v_2^E + a_3 \cdot v_3^E + a_4 \cdot v_4^E$$

Self-Attention

Self-Attention	Attention	Description
q_i	h_i^D	the probe
k_i	h_i^E	item being compared
v_i	h_i^E	item being weighted

vector by its a_i^1 attention weights to create a better vector z_1

$$z_1 = a_1 \cdot v_1^E + a_2 \cdot v_2^E + a_3 \cdot v_3^E + a_4 \cdot v_4^E$$



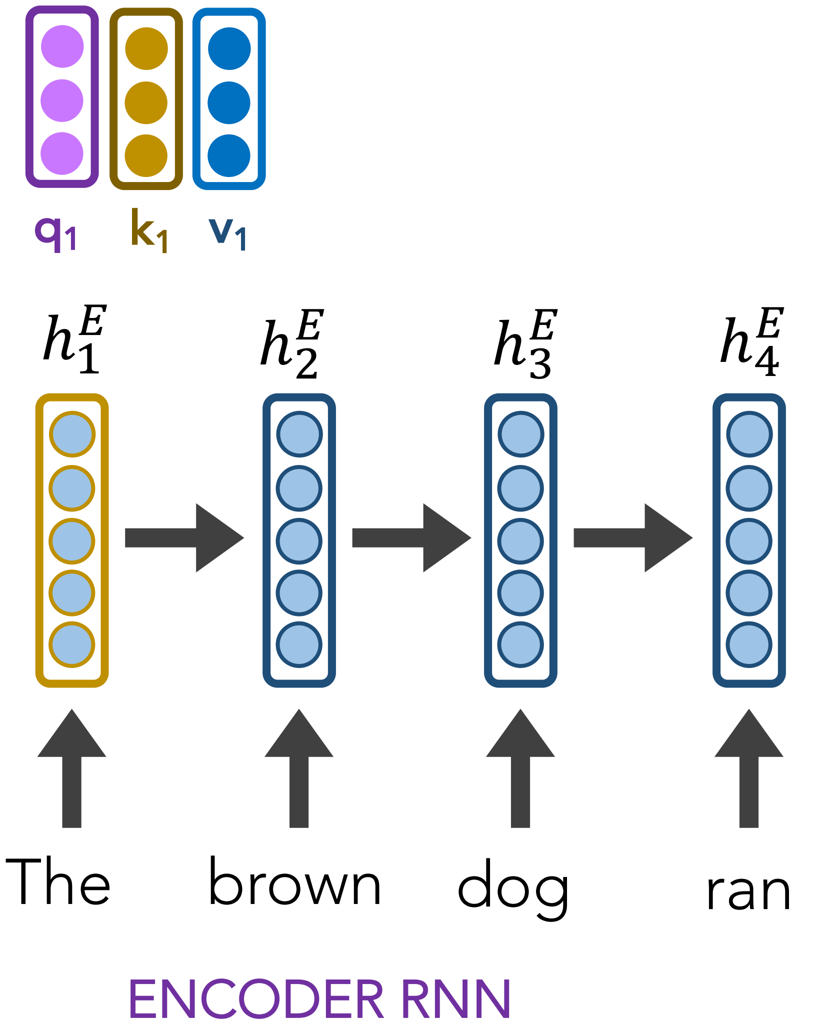
Self-Attention	Attention	Description
q_i	h_i^D	the probe
k_i	h_i^E	item being compared
v_i	h_i^E	item being weighted

All of these are like surrogates/proxies/abstractions.

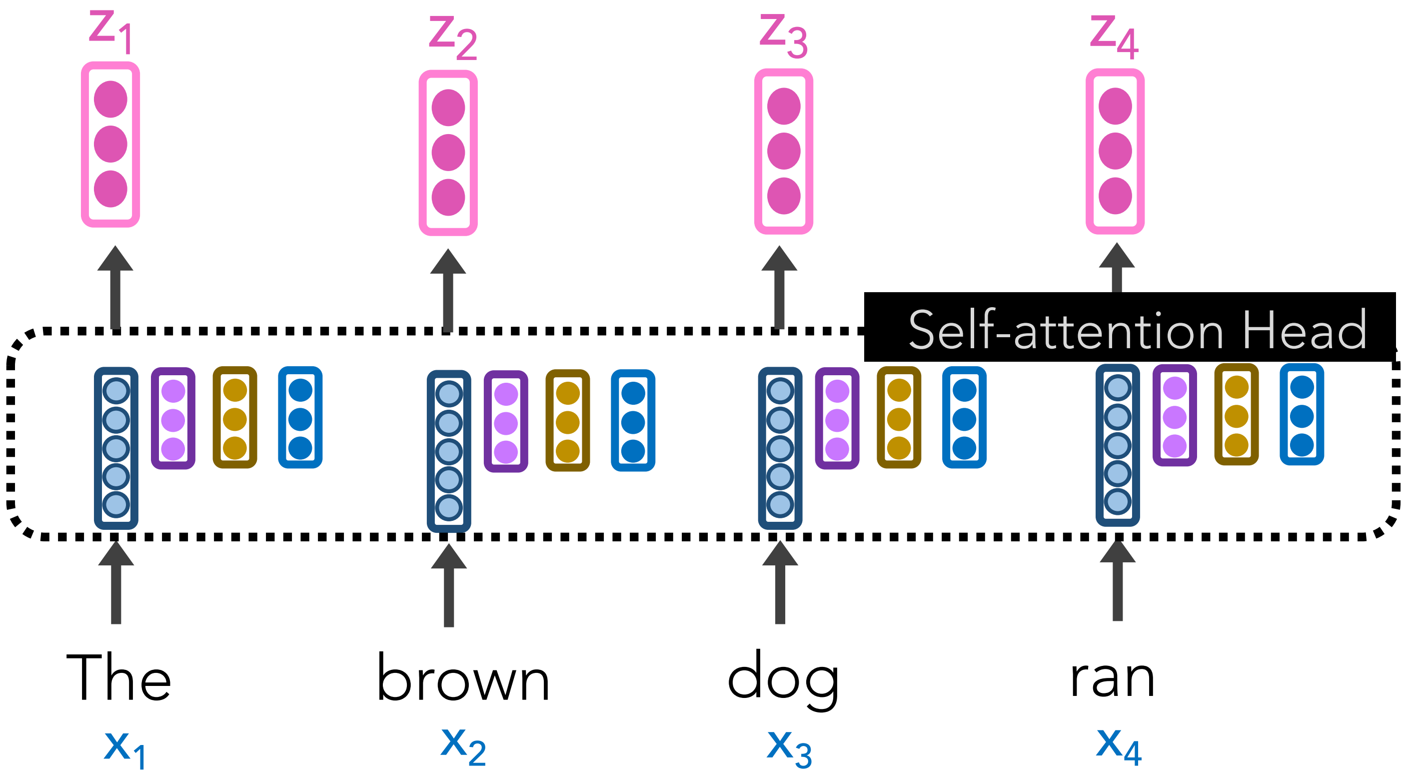
This provides flexibility and fewer constraints.

More room for rich abstractions.

Self-Attention

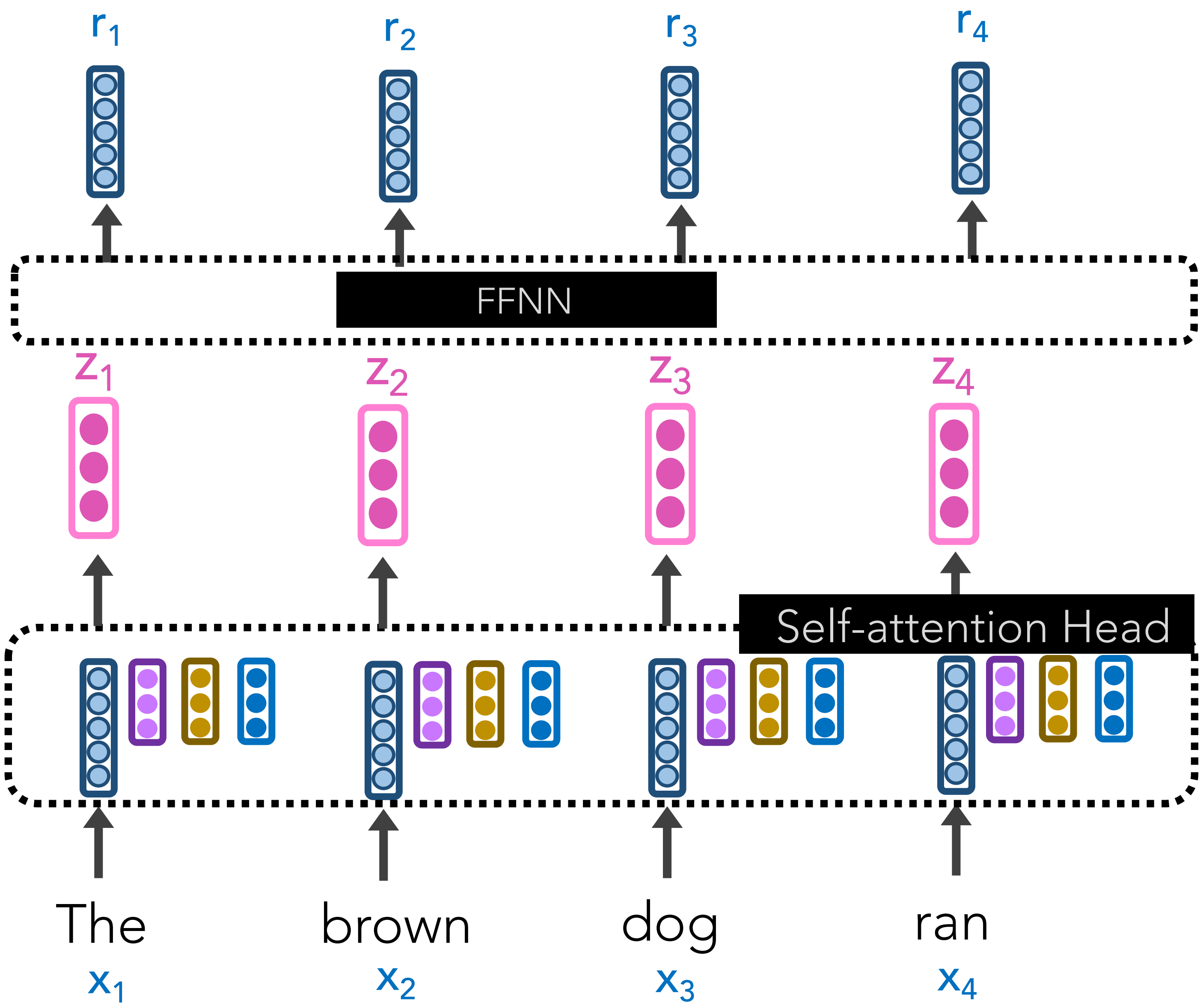


Self-Attention



Let's further pass each z_i through a FFNN

Self-Attention + FFNN



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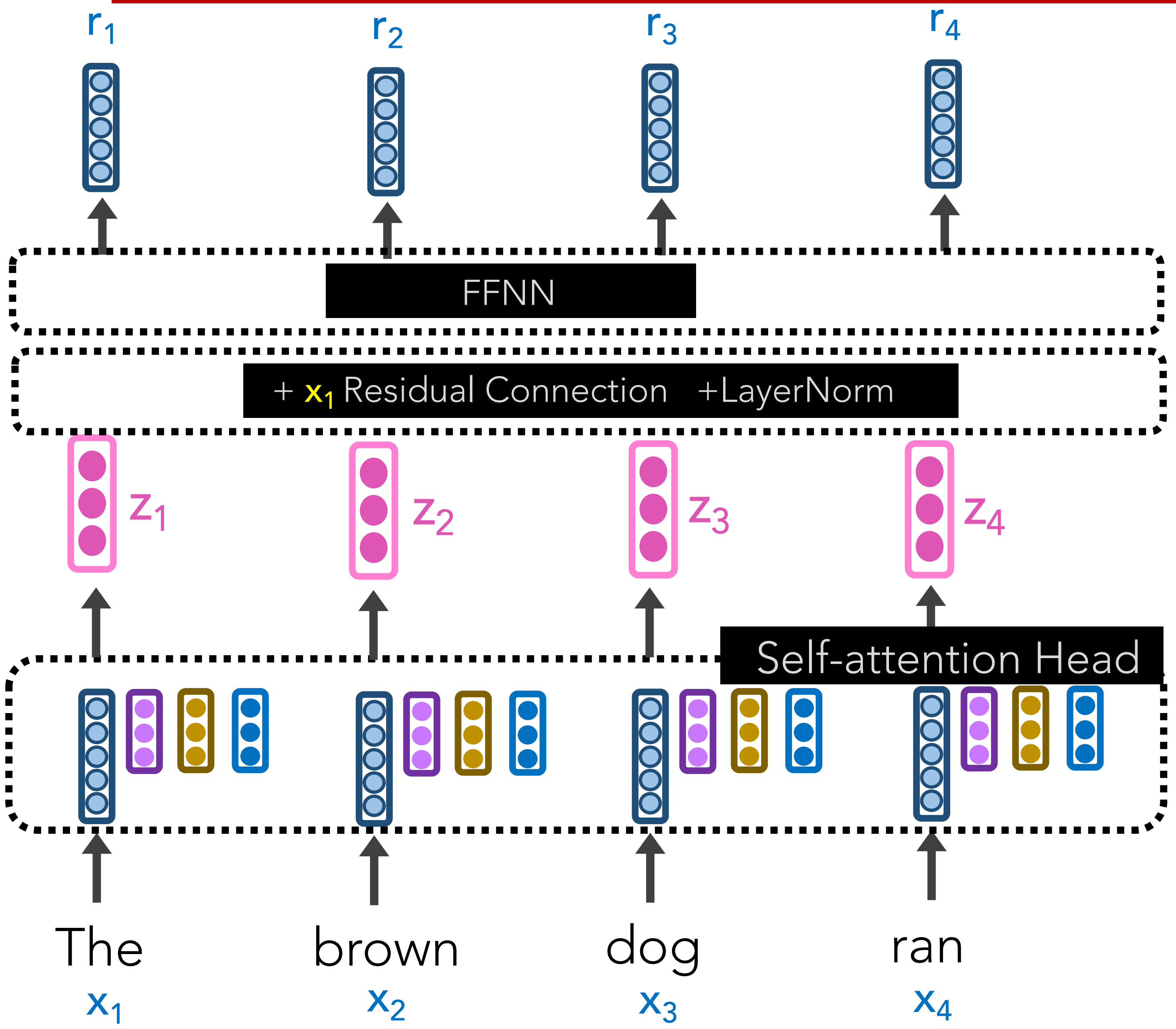
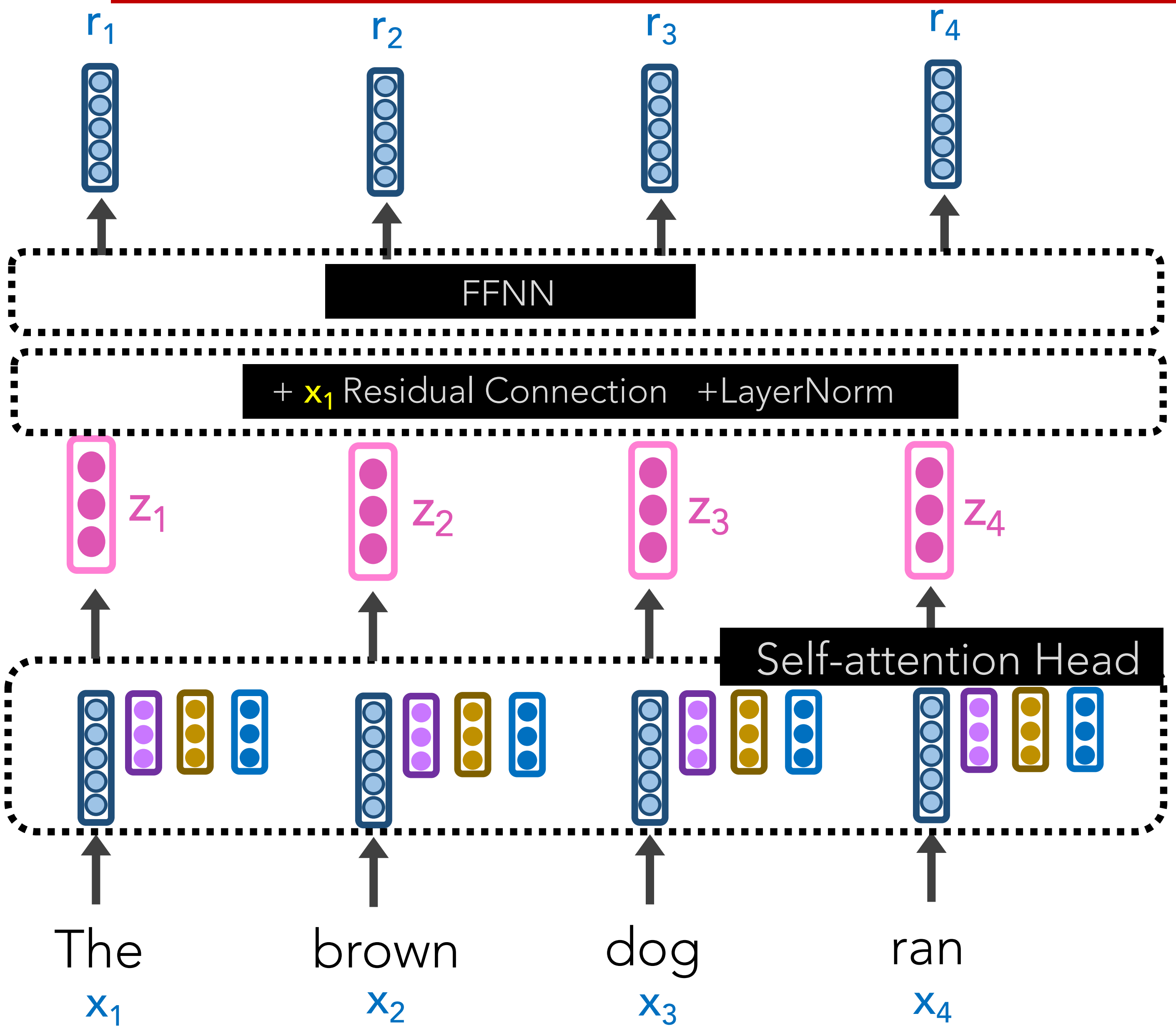


Let's further pass each z_i through a FFNN

We concat w/ a residual connection to help ensure relevant info is getting forward passed.

We perform LayerNorm to stabilize the network and allow for proper gradient flow.

Self-Attention + FFNN



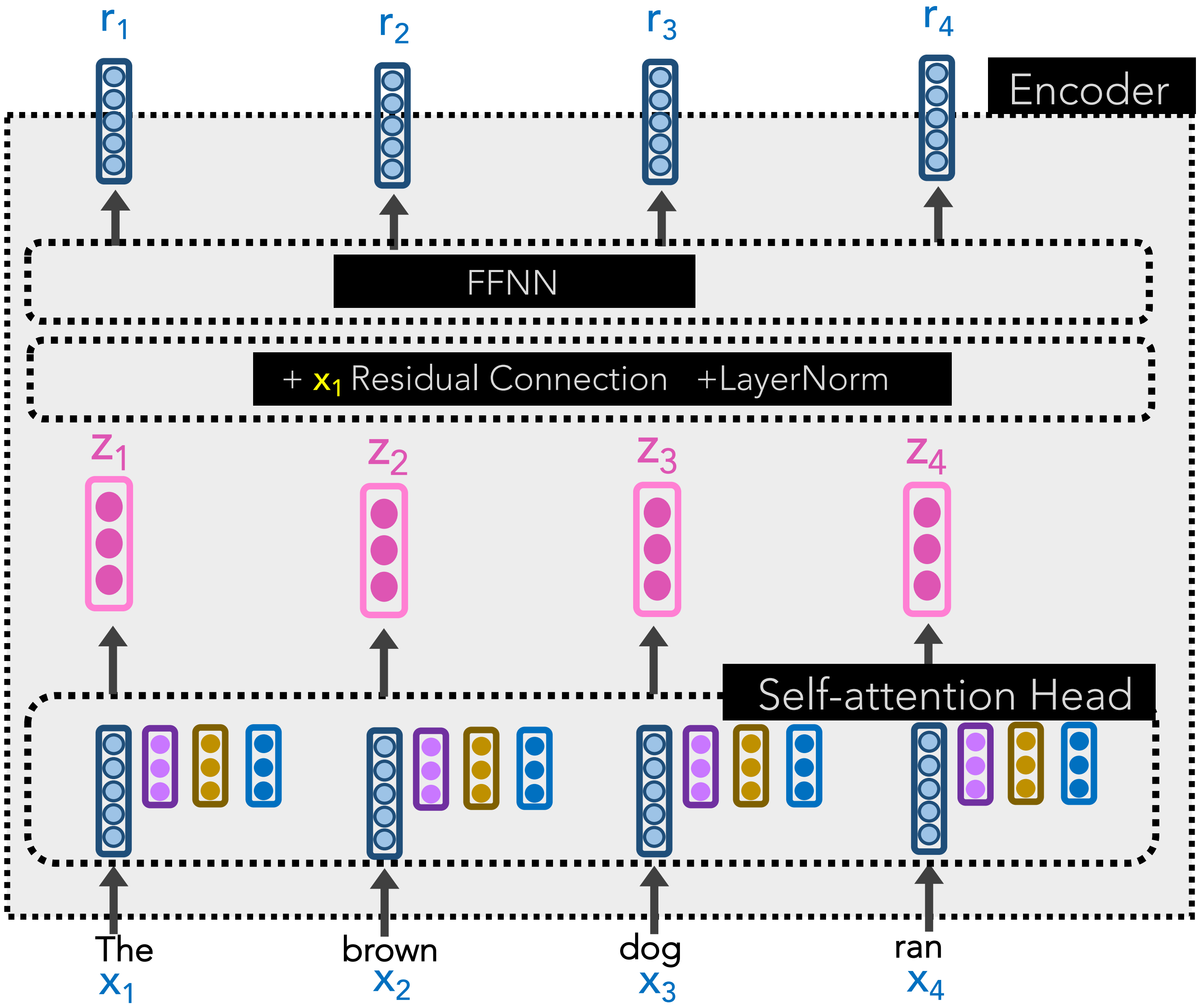
Let's further pass each z_i through a FFNN

We concat w/ a residual connection to help ensure relevant info is getting forward passed.

We perform LayerNorm to stabilize the network and allow for proper gradient flow.

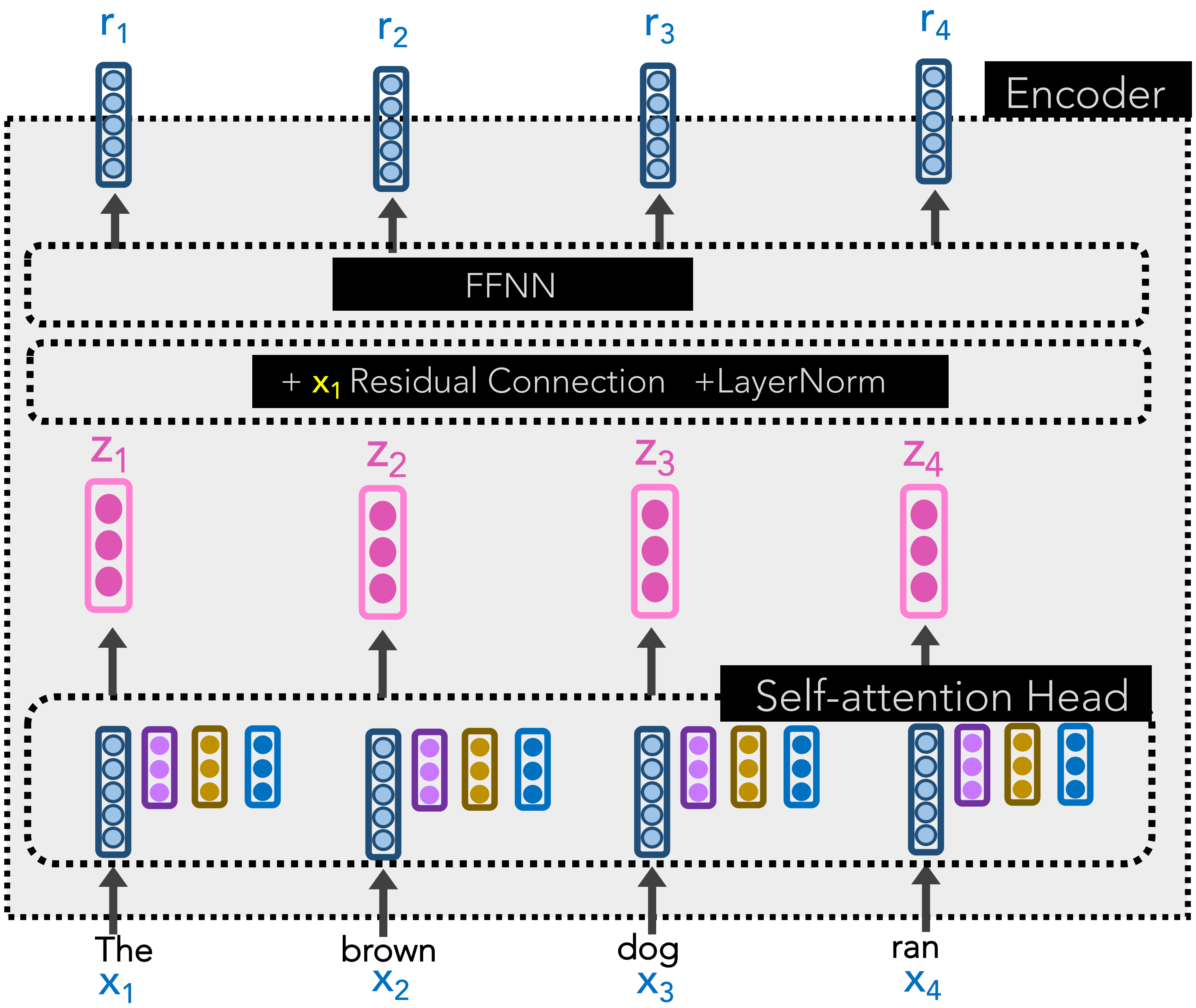
Each z_i can be computed in parallel, unlike LSTMs!

Transformer Encoder



Yay! Our r_i vectors are our new representations, and this entire process is called a **Transformer Encoder**

Transformer Encoder



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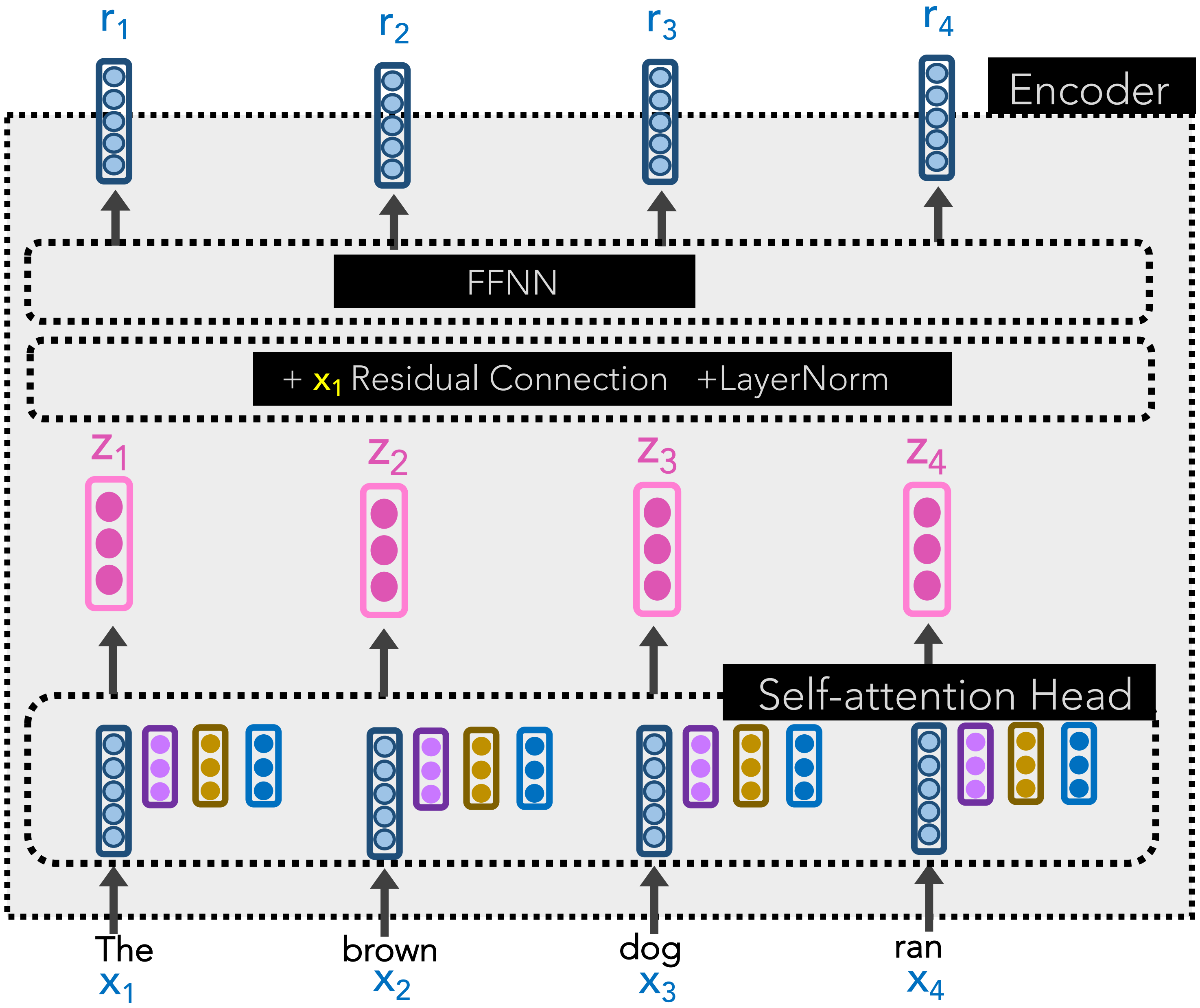
Problem: there is no concept of positionality. Words are weighted as if a "bag of words"

Transformer Encoder



Yay! Our r_i vectors are our new representations, and this entire process is called a **Transformer Encoder**

Problem: there is no concept of positionality. Words are weighted as if a "bag of words"

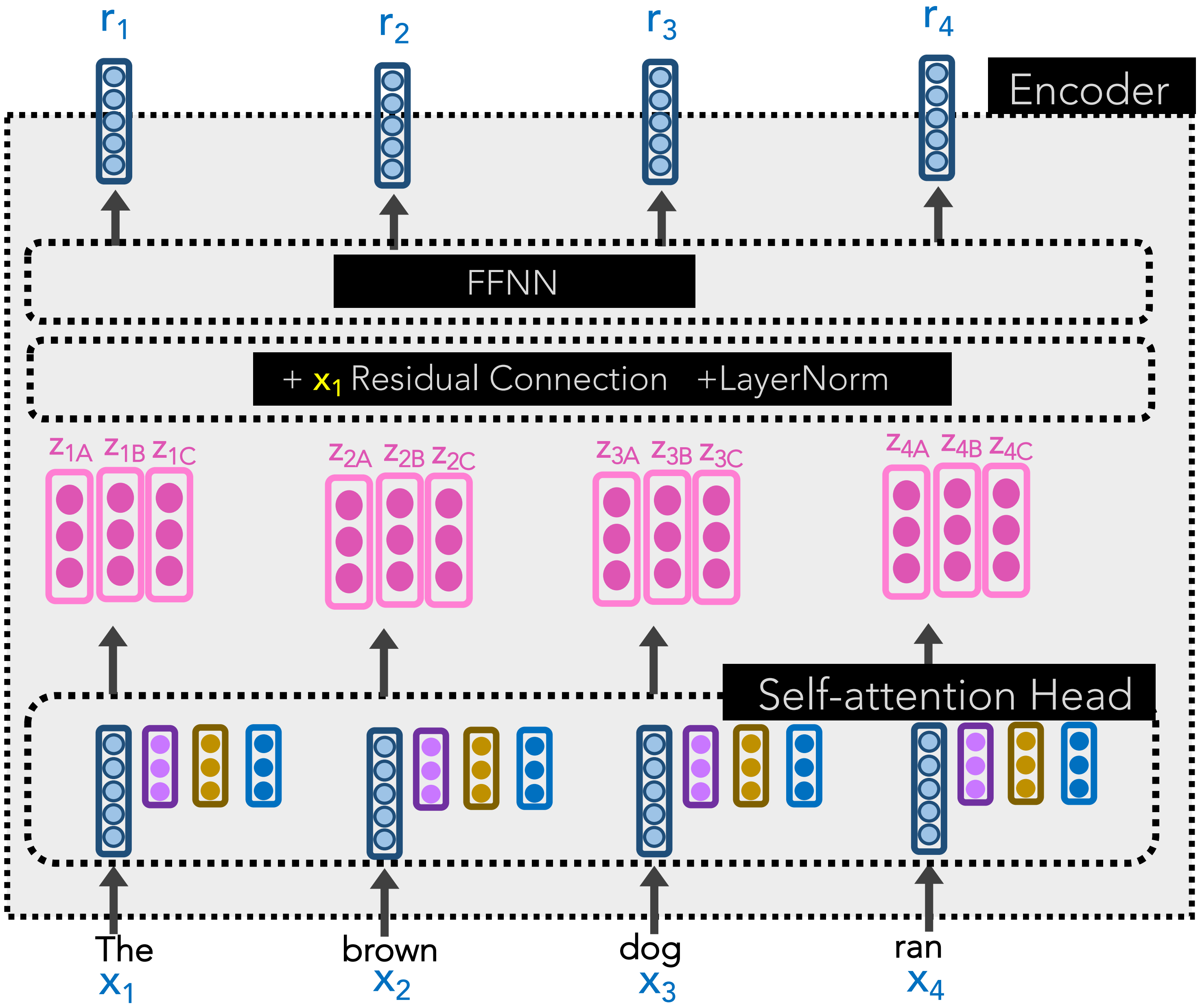
Solution: append each input word x_i with a positional encoding: $\sin(i)\ \cos(i)$

A Self-Attention Head has just one set of query/key/value weight matrices w_q, w_k, w_v

Words can relate in many ways, so it's restrictive to rely on just one Self-Attention Head in the system.

Let's create Multi-headed Self-Attention

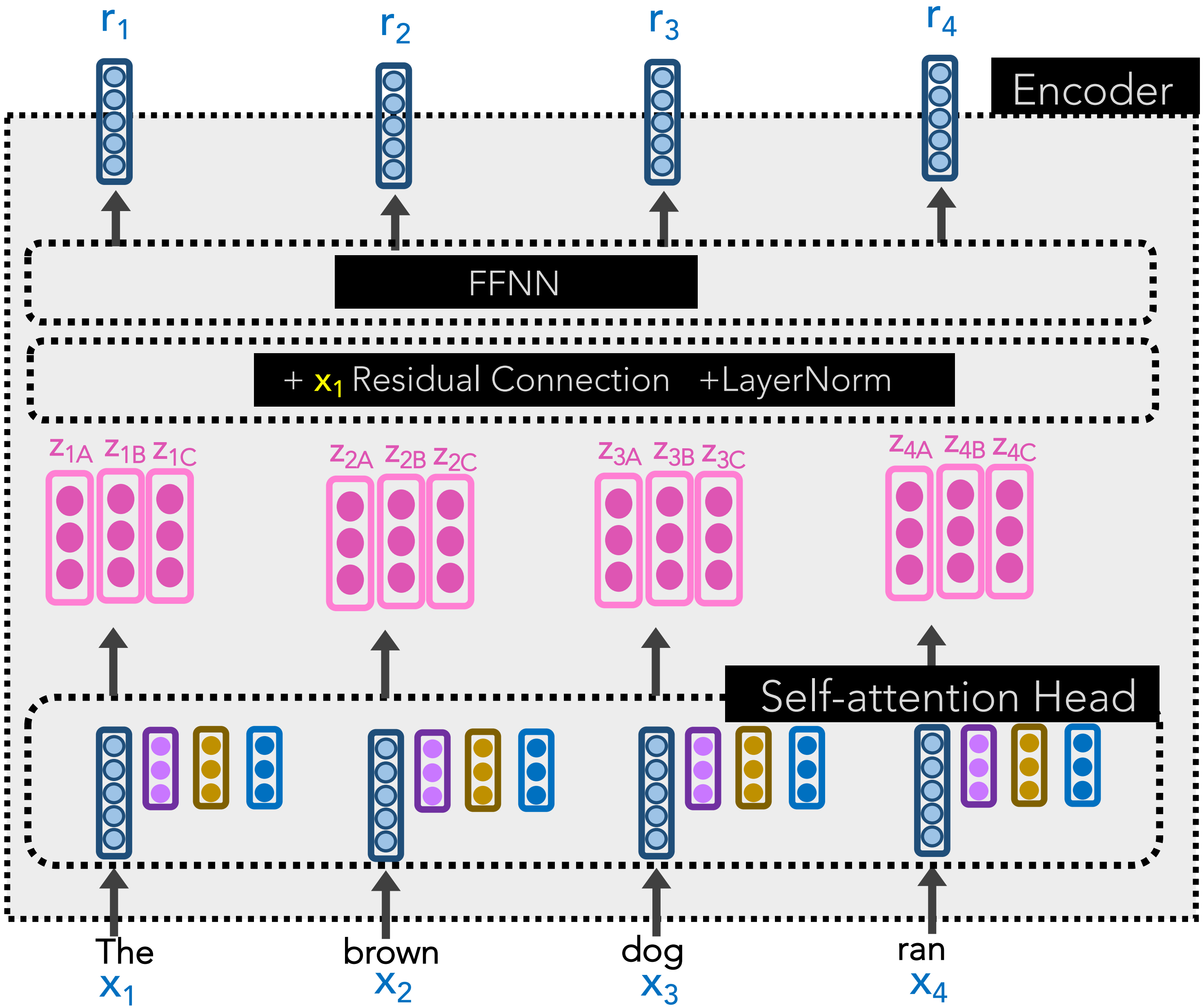
Transformer Encoder



Each Self-Attention Head produces a z_i vector.

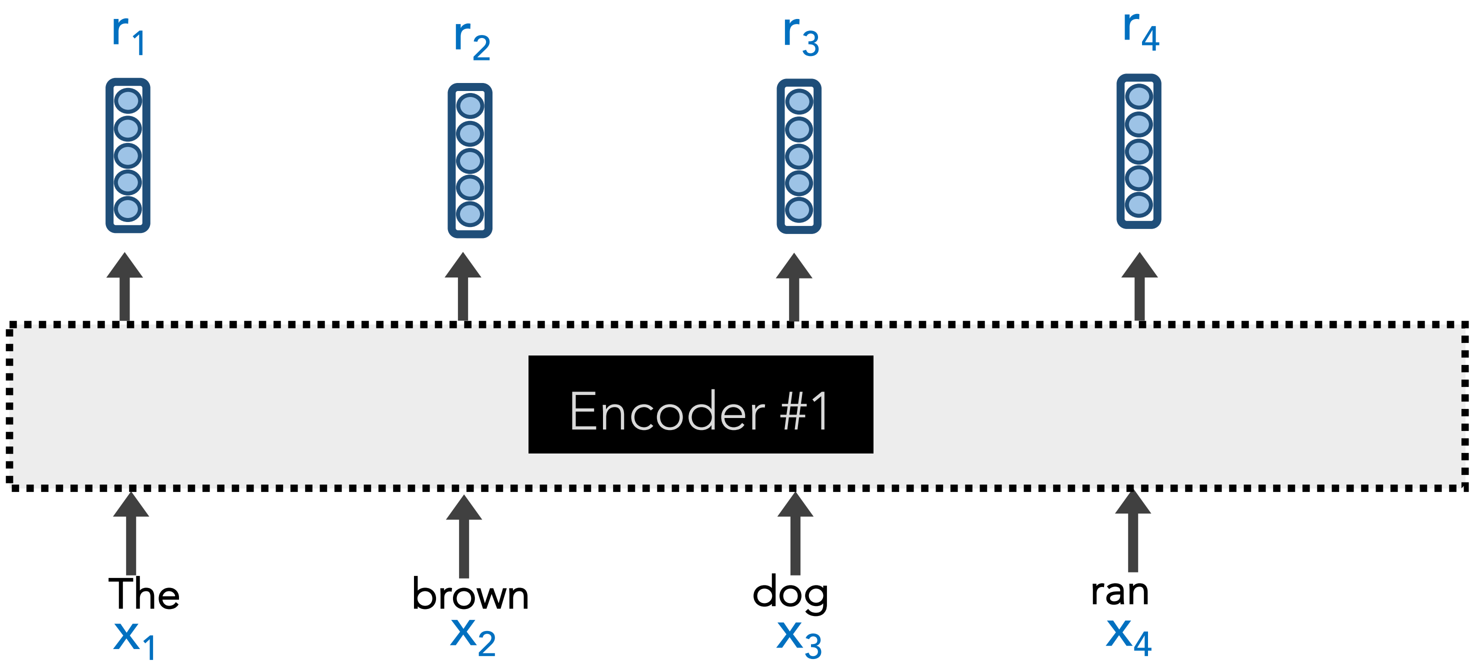
We can, in parallel, use multiple heads and concat the z_i's.

Transformer Encoder



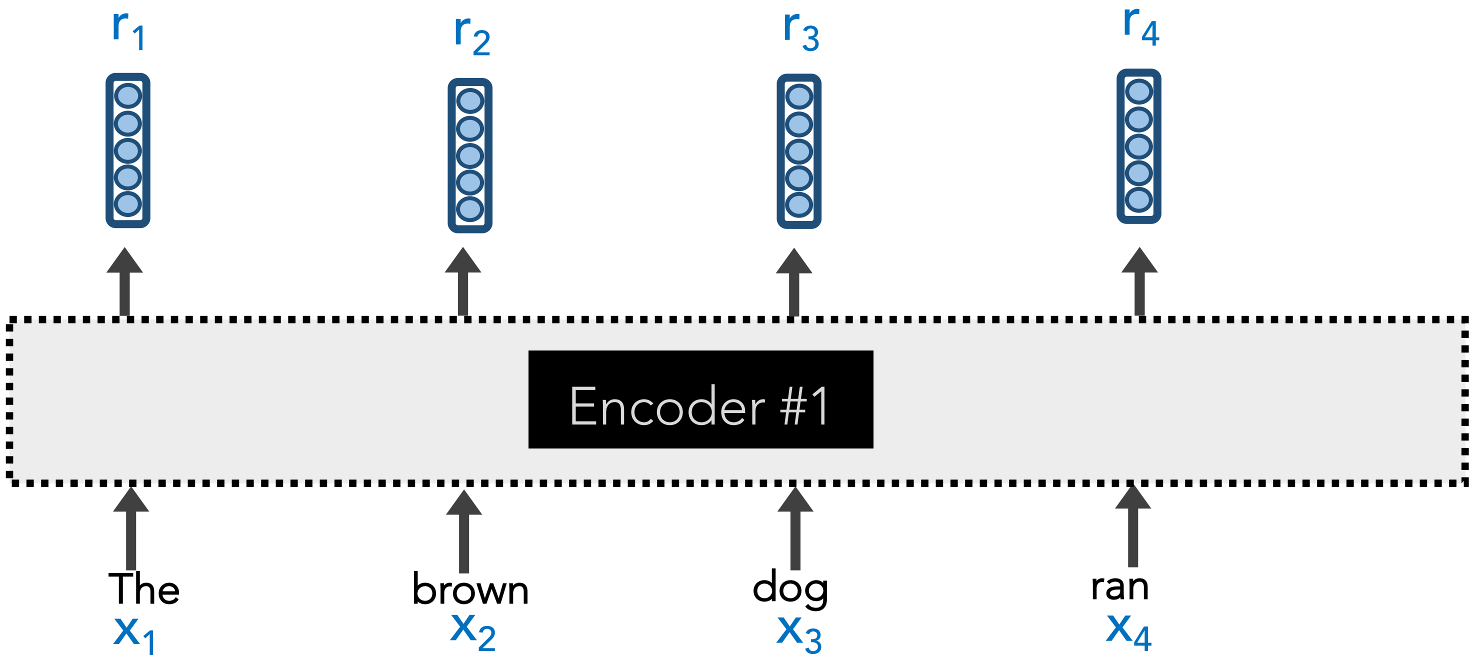
To recap: all of this looks fancy, but ultimately it's just producing a very good **contextualized embedding** r_i of each word x_i

Transformer Encoder



To recap: all of this looks fancy, but ultimately it's just producing a very good **contextualized embedding** r_i of each word x_i

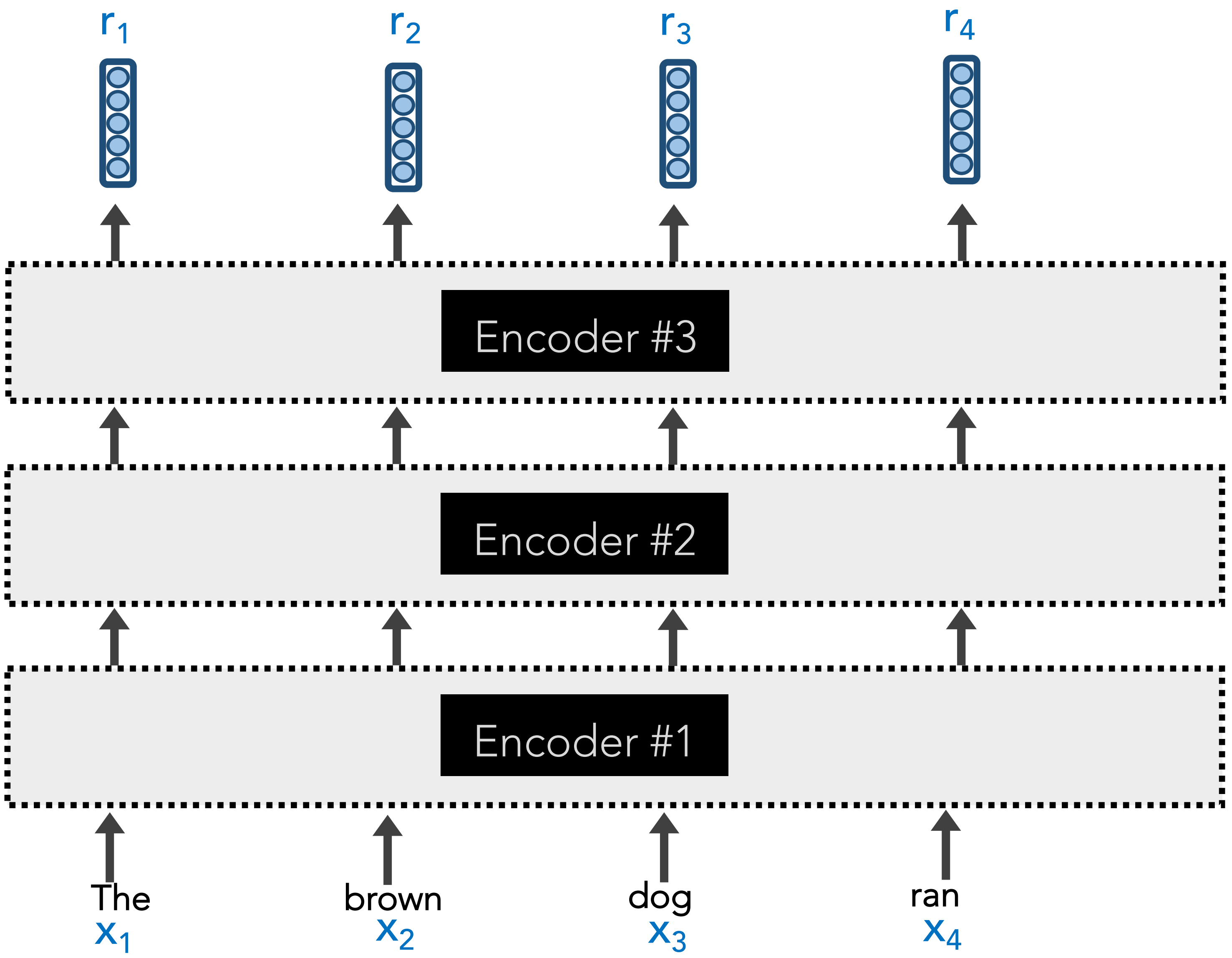
Transformer Encoder



To recap: all of this looks fancy, but ultimately it's just producing a very good **contextualized embedding** r_i of each word x_i

Why stop with just 1 Transformer Encoder? We could stack several!

Transformer Encoder

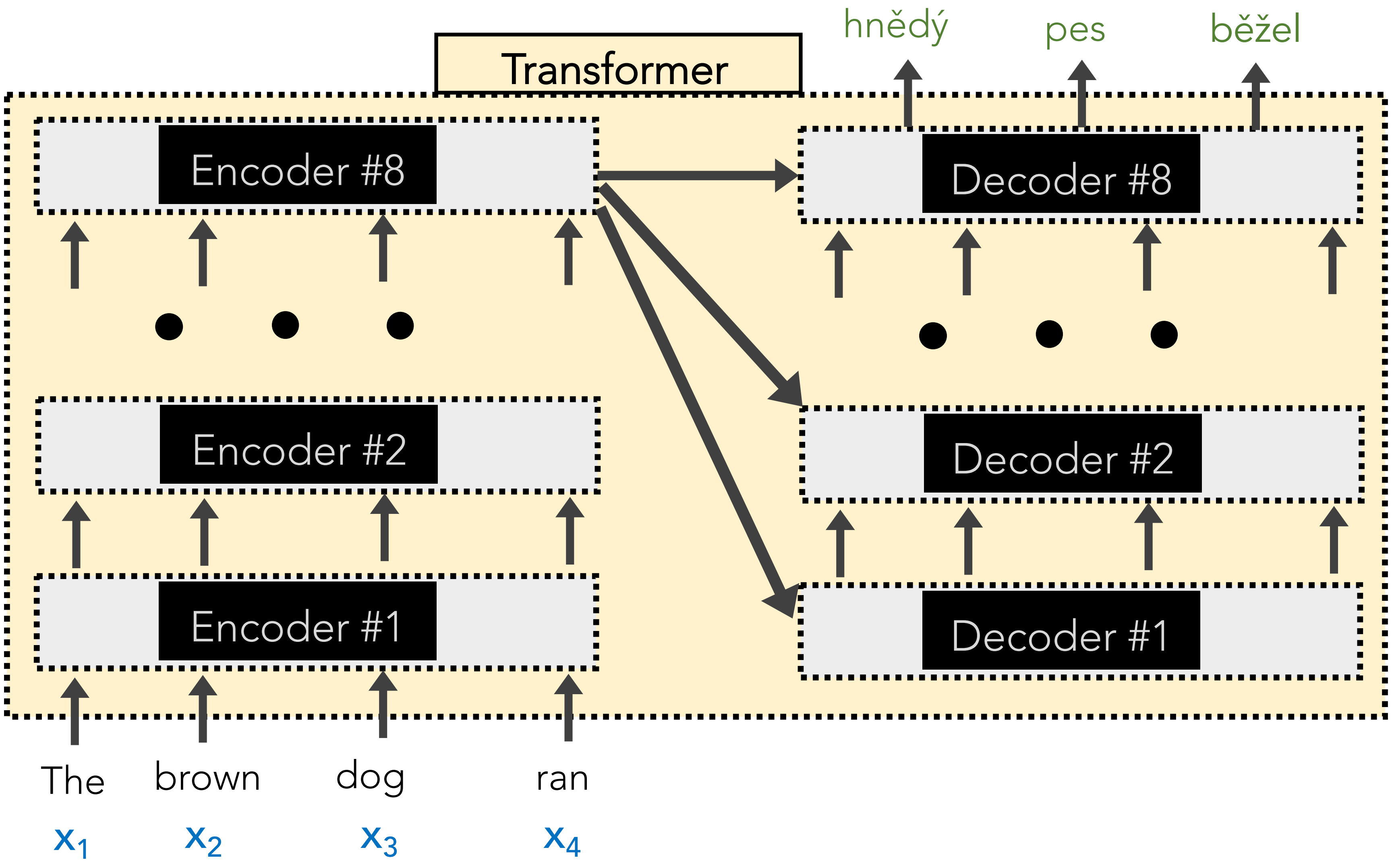


To recap: all of this looks fancy, but ultimately it's just producing a very good **contextualized embedding** r_i of each word x_i

Why stop with just 1 Transformer Encoder? We could stack several!

The original Transformer model was intended for Machine Translation, so it had Decoders, too

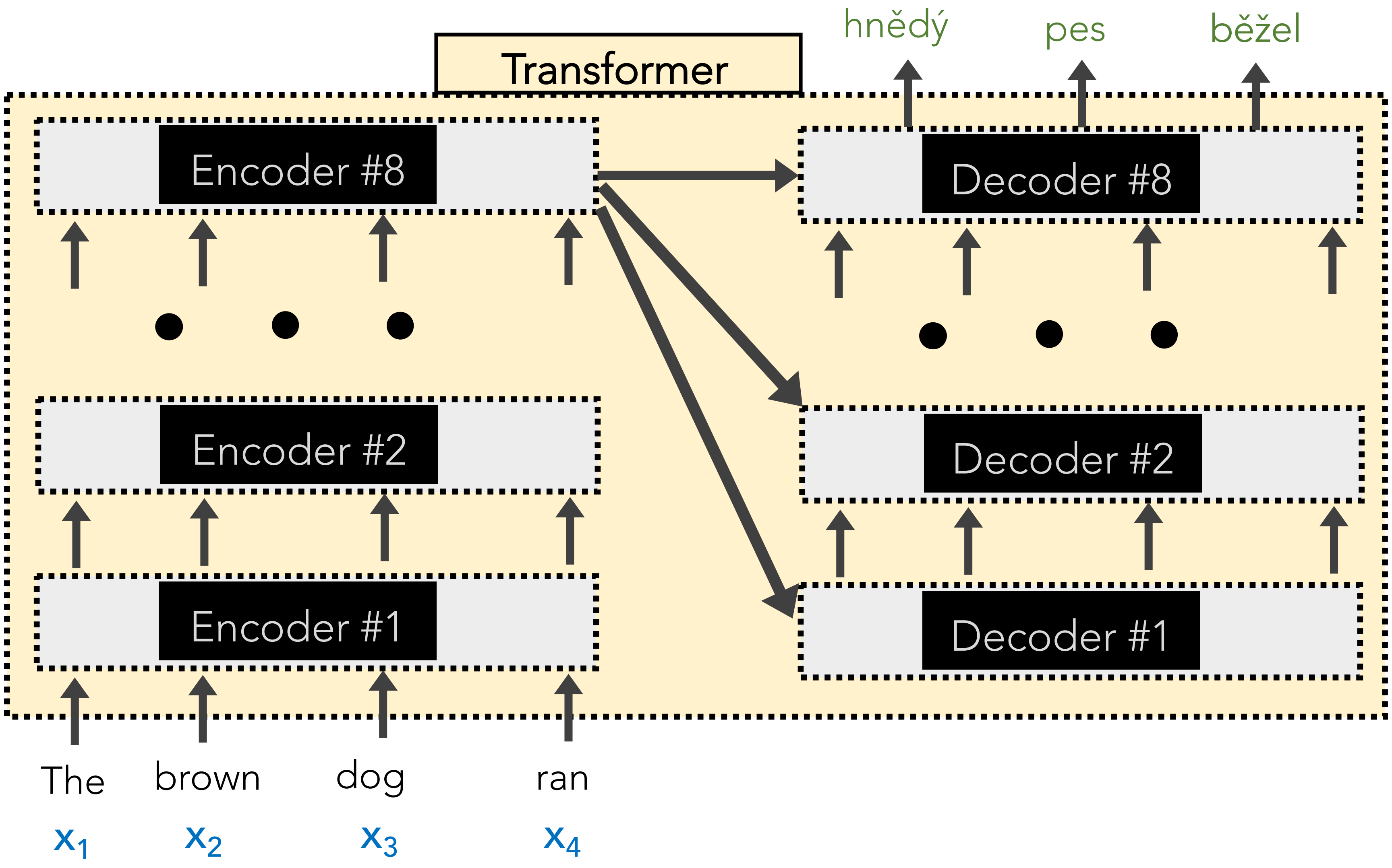
Transformer Encoders and Decoders



Transformer Encoders produce **contextualized embeddings** of each word

Transformer Decoders generate new sequences of text

Transformer Encoders and Decoders

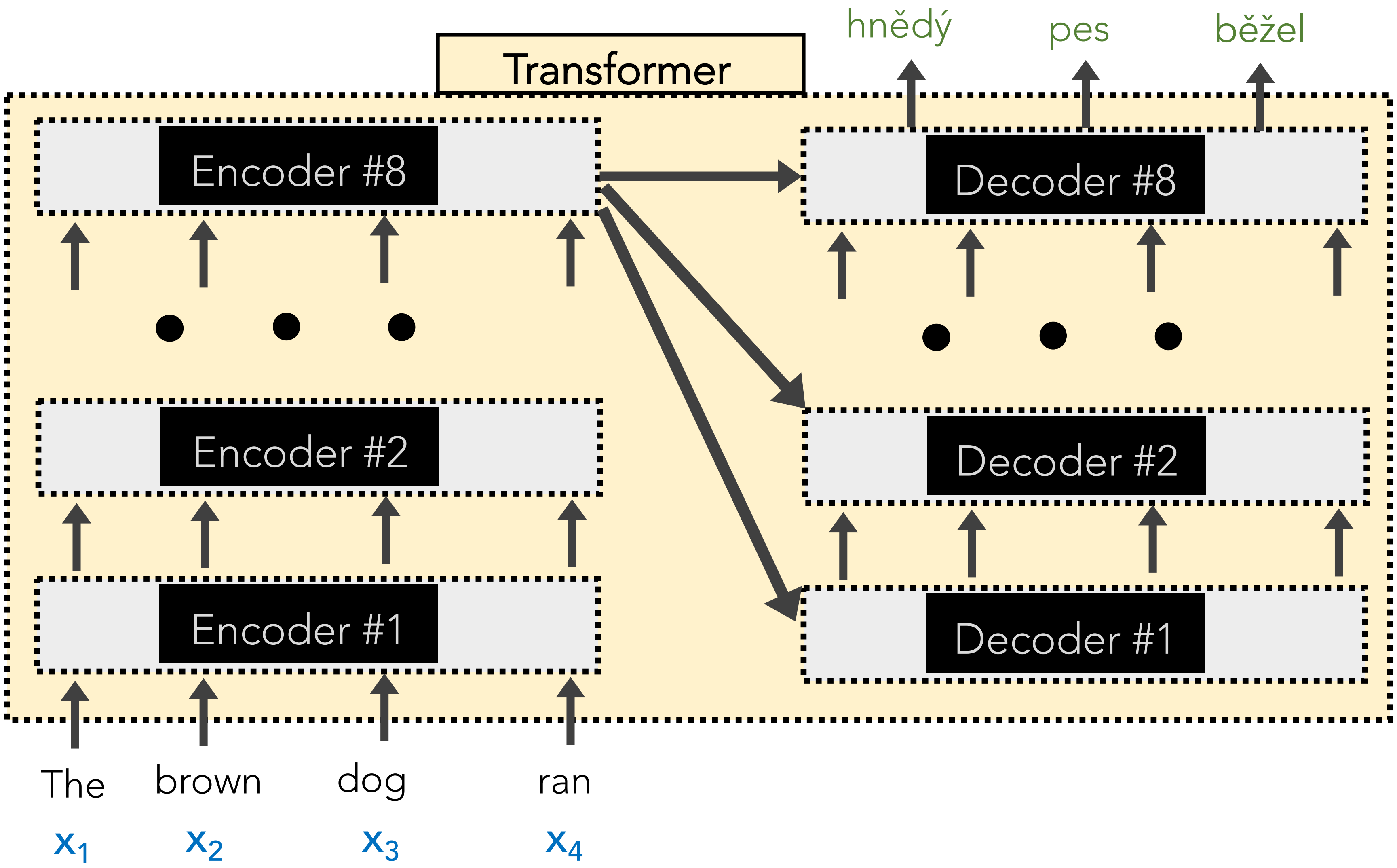


NOTE

Transformer Decoders are identical to the Encoders, except they have an additional Attention Head in between the Self-Attention and FFNN layers.

This additional Attention Head focuses on parts of the encoder's representations.

Transformer Encoders and Decoders

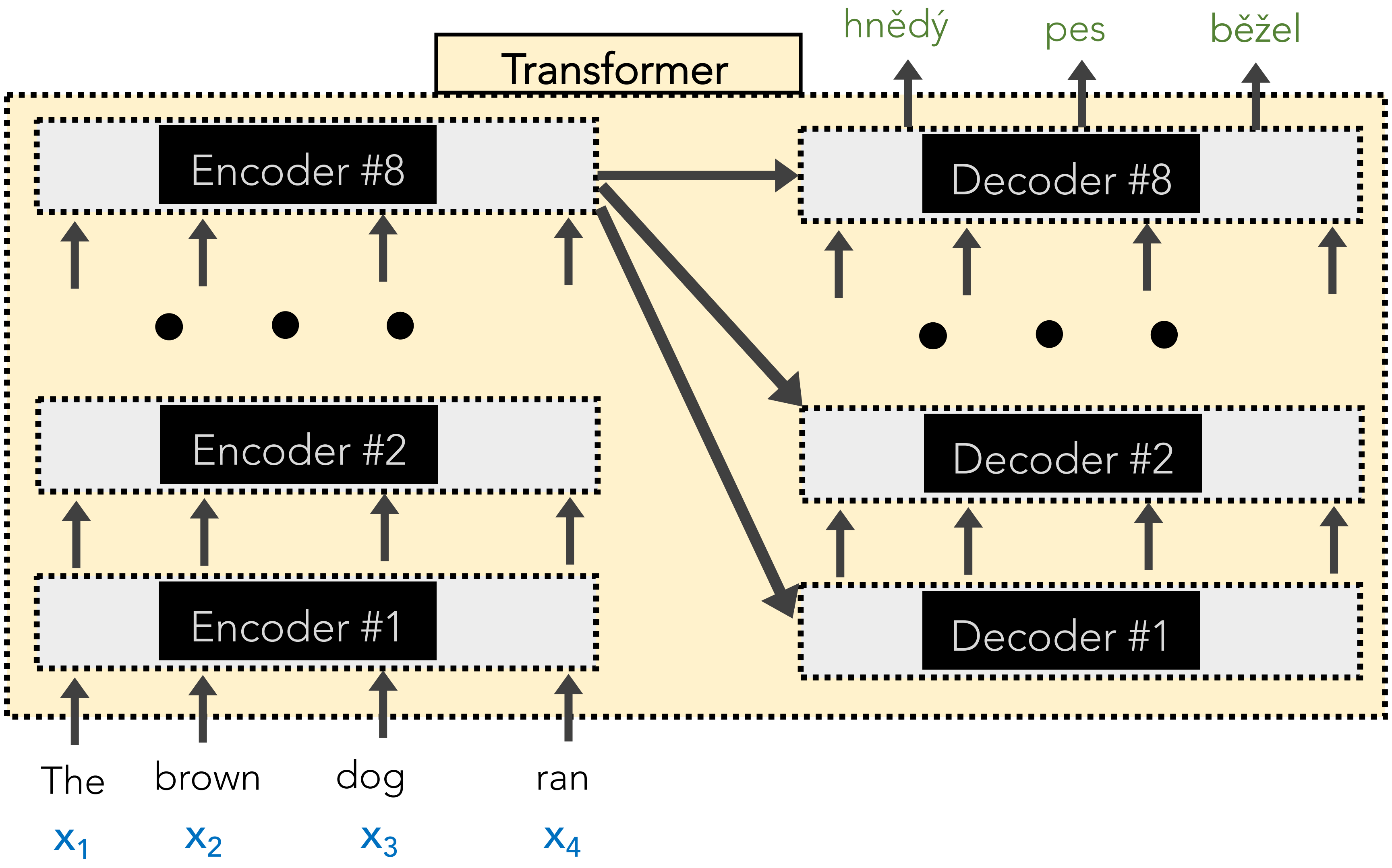


NOTE

The query vector for a Transformer Decoder's Attention Head (not Self-Attention Head) is from the output of the previous decoder layer.

However, the key and value vectors are from the Transformer Encoders' outputs.

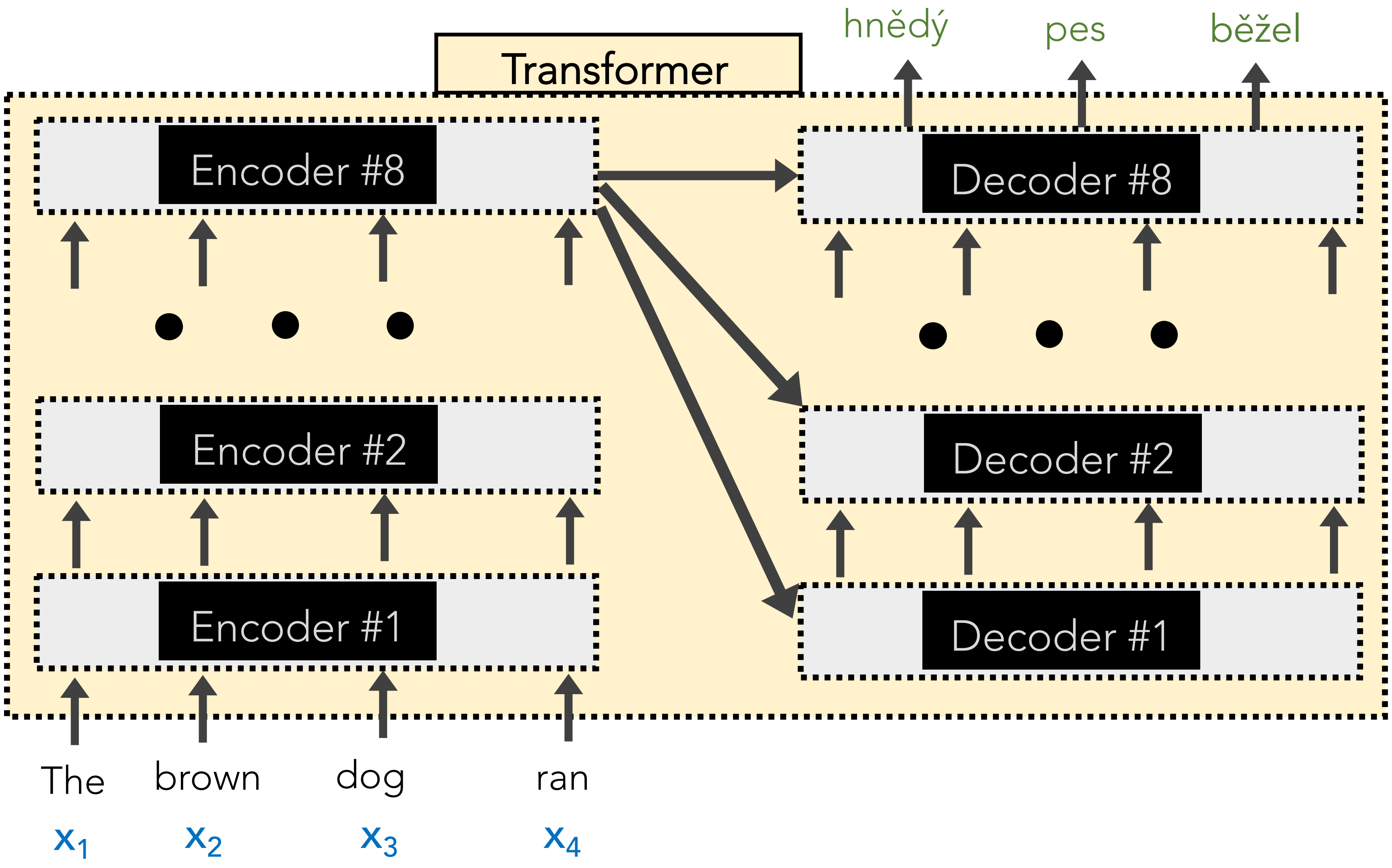
Transformer Encoders and Decoders



NOTE

The query, key, and value vectors for a Transformer Decoder's **Self-Attention Head** (not Attention Head) are all from the previous decoder layer.

Transformer Encoders and Decoders



IMPORTANT

The Transformer Decoders have positional embeddings, too, just like the Encoders.

Critically, each position is only allowed to attend to the previous indices. This *masked* Attention preserves it as being an auto-regressive LM.

Loss Function: cross-entropy (predicting translated word)

Training Time: ~4 days on (8) GPUs

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

Machine Translation results: state-of-the-art (at the time)

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	

Machine Translation results: state-of-the-art (at the time)

You can train to translate from Language A to Language B.

Then train it to translate from Language B. to Language C.

Then, without training, it can translate from Language A to Language C

- What if we don’t want to decode/translate?
- Just want to perform a particular task (e.g., classification)
- Want even more robust, flexible, rich representation!
- Want positionality to play a more explicit role, while not being restricted to a particular form (e.g., CNNs)

Outline

- Recap
- Transformers
  - BERT
  - GPT-2
  - Concerns
- Summary

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BERT

Bidirectional Encoder Representations from Transformers

BERT

Bidirectional **E**ncoder **R**epresentations from **T**ransformers

Like *Bidirectional LSTMs*, let's look in **both** directions

BERT

Bidirectional **E**ncoder **R**epresentations from **T**ransformers

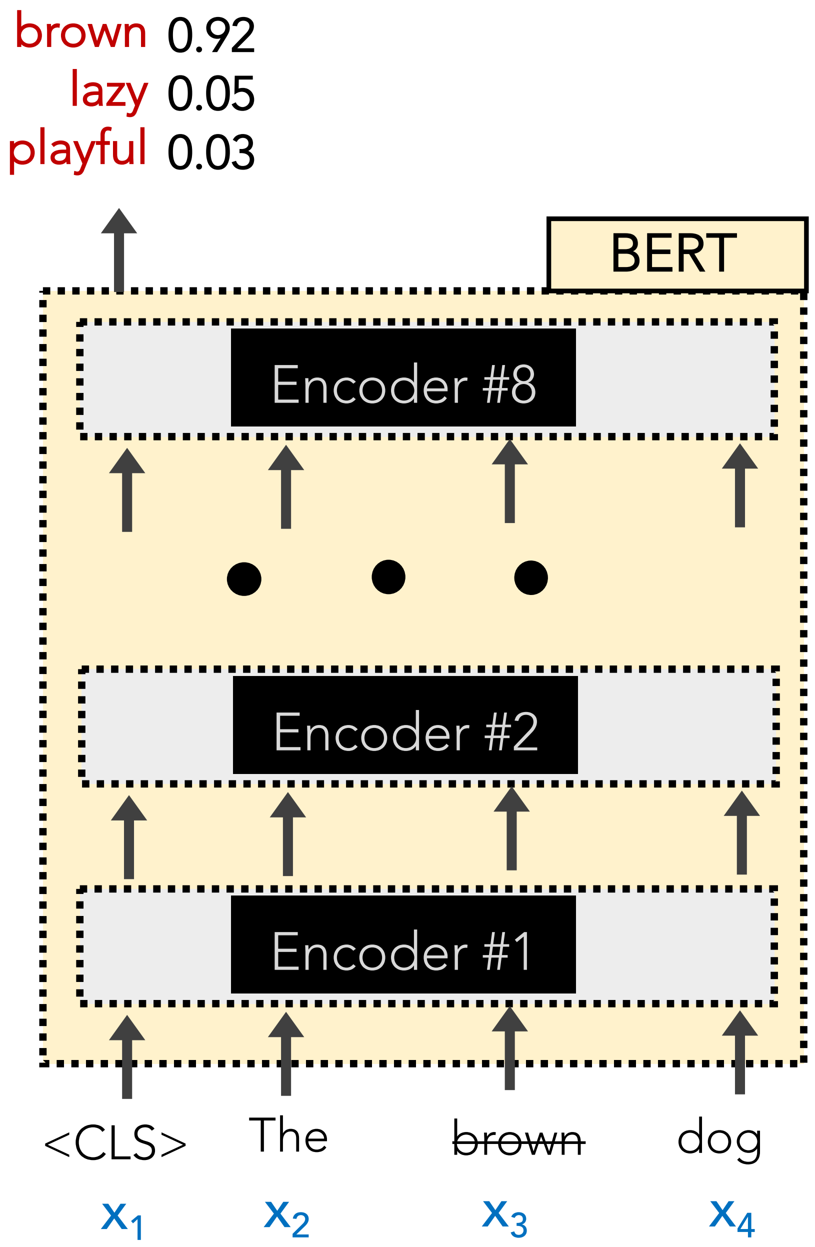
Let's only use Transformer *Encoders*, no Decoders

BERT

Bidirectional Encoder Representations from Transformers

It's a language model that builds rich representations

BERT



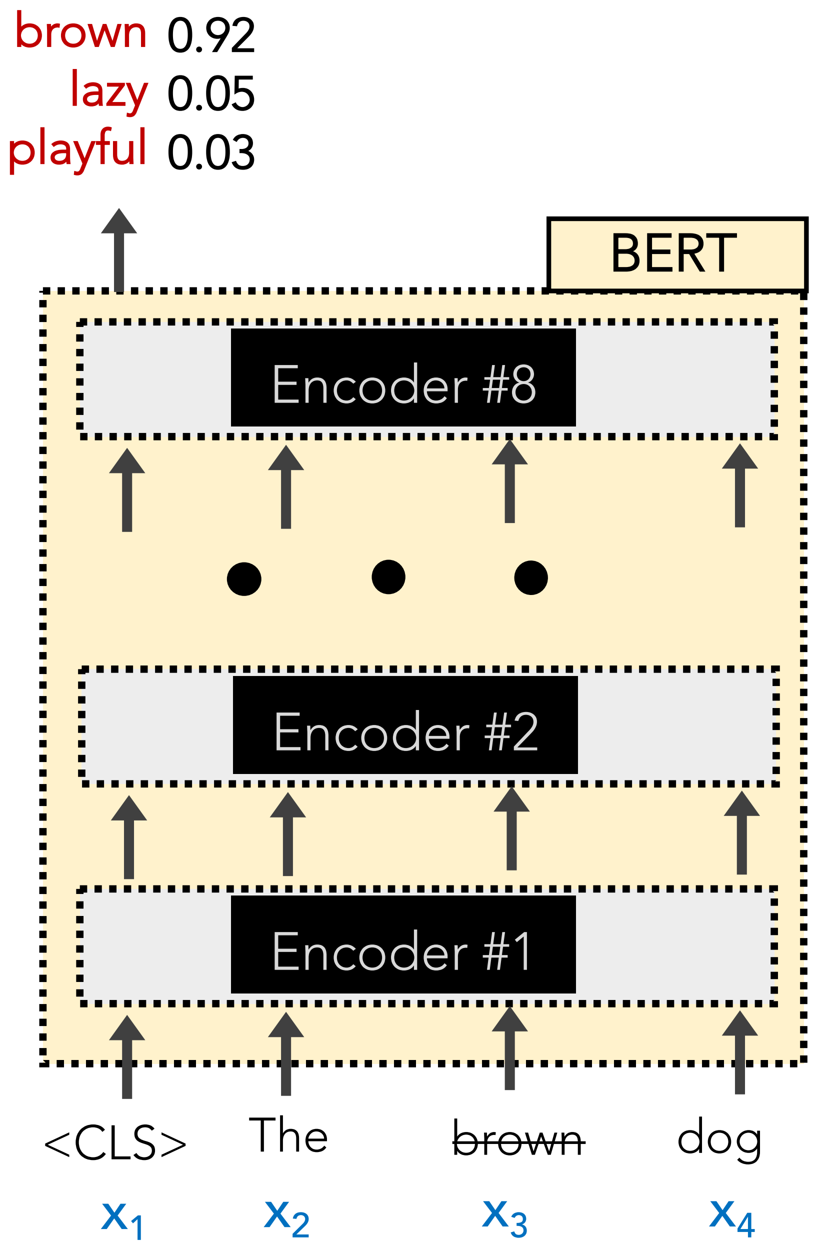
BERT has 2 training objectives:

1. Predict the **Masked word** (a la CBOW)

15% of all input words are randomly masked.

- 80% become [MASK]
- 10% become revert back
- 10% become are deliberately corrupted as wrong words

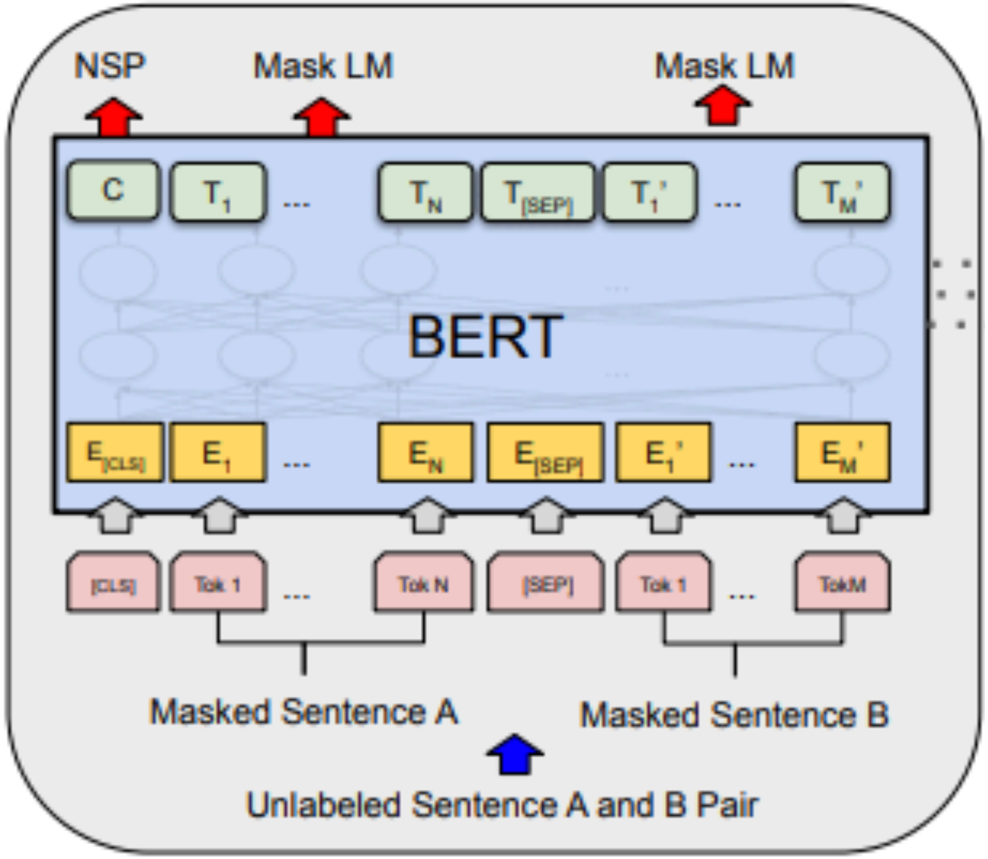
BERT



BERT has 2 training objectives:

2. Two sentences are fed in at a time. Predict the if the second sentence of input truly follows the first one or not.

BERT



Pre-training

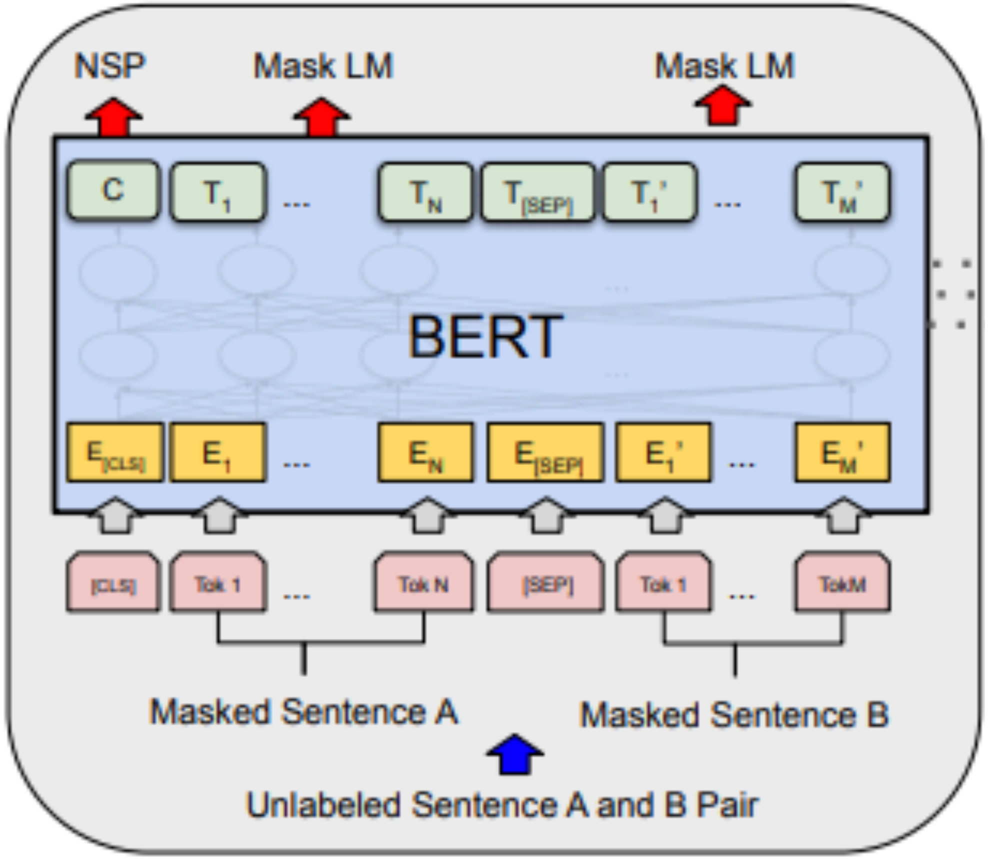
Every two sentences are separated by a <SEP> token.

50% of the time, the 2nd sentence is a randomly selected sentence from the corpus.

50% of the time, it truly follows the first sentence in the corpus.

Source: original BERT paper: https://arxiv.org/pdf/1810.04805.pdf

BERT



Pre-training

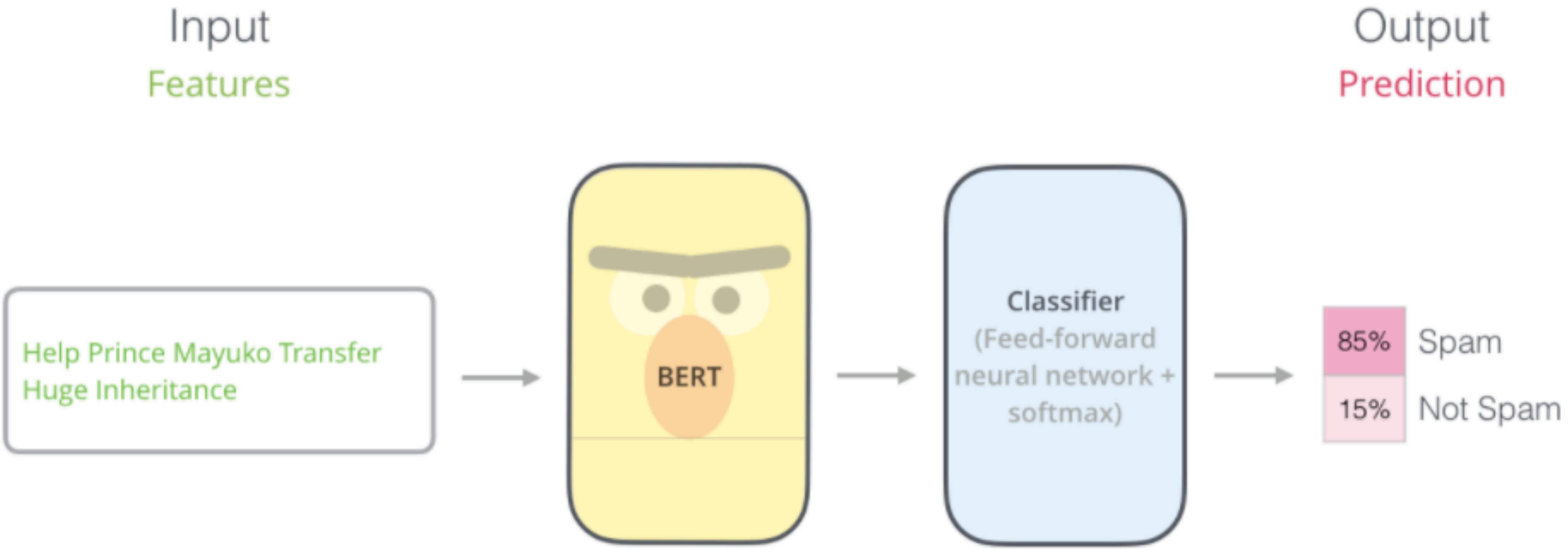
NOTE: BERT also embeds the inputs by their WordPiece embeddings.

WordPiece is a sub-word tokenization learns to merge and use characters based on which pairs maximize the likelihood of the training data if added to the vocab.

Source: original BERT paper: https://arxiv.org/pdf/1810.04805.pdf

BERT

Most of the time, people use BERT to fine-tune on a separate task



Picture: https://jalammar.github.io/illustrated-bert/

BERT

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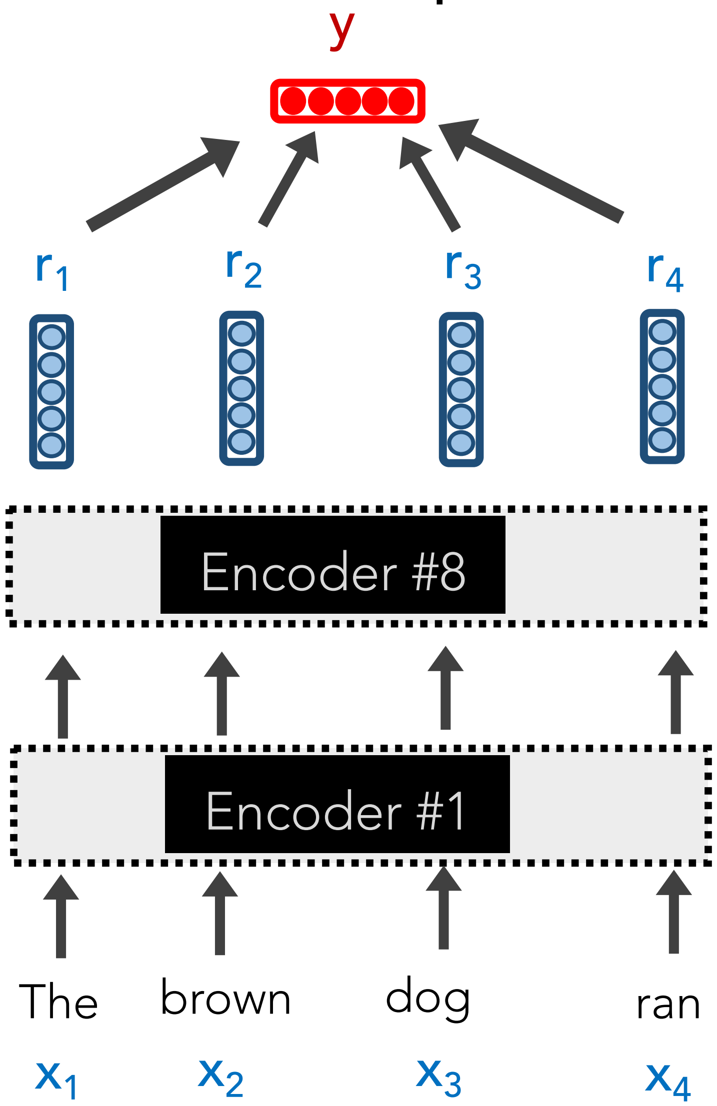

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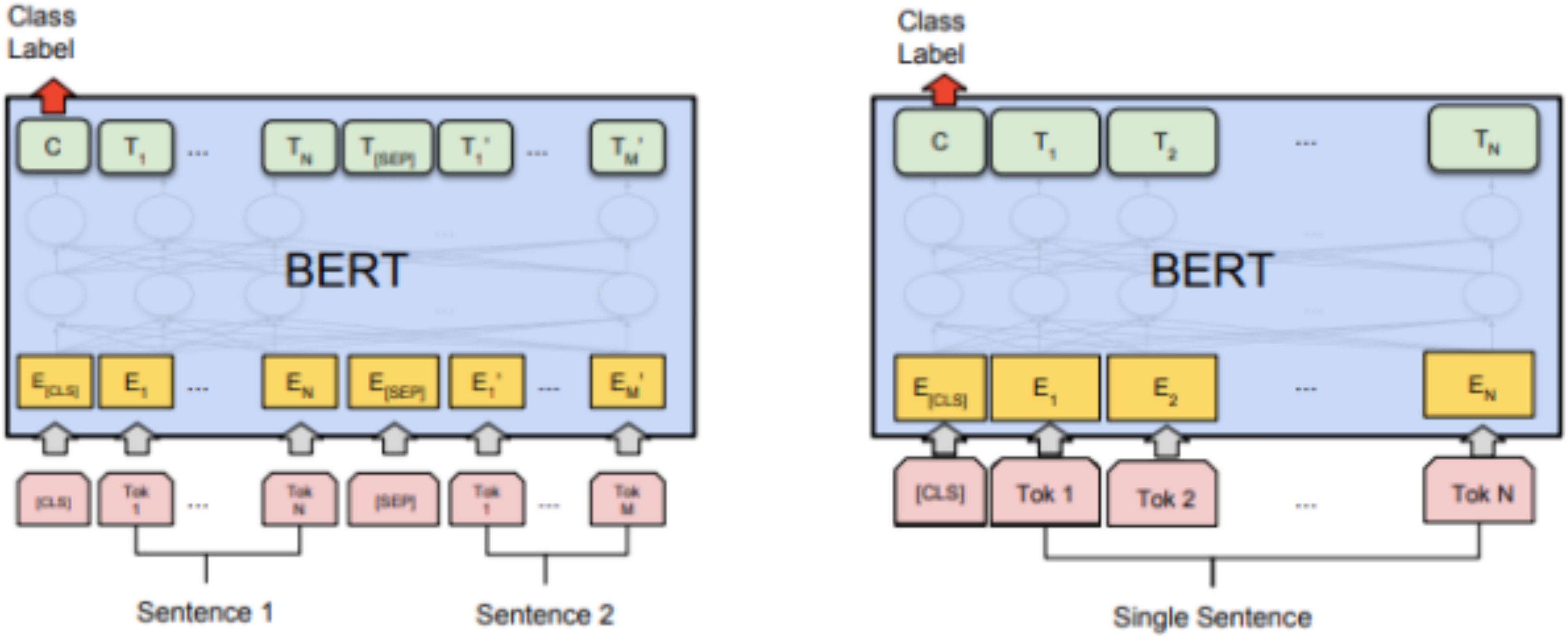


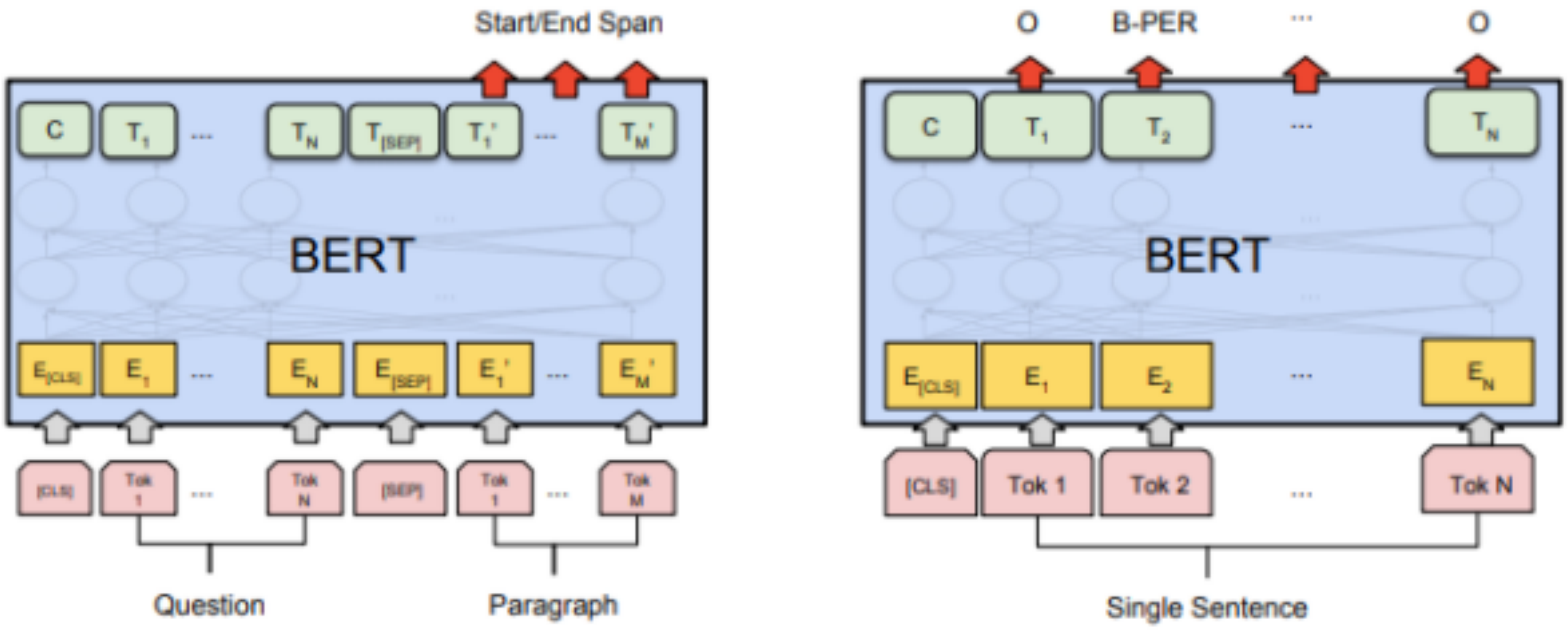
(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

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

Picture: https://jalammar.github.io/illustrated-bert/

BERT

Most of the time, people use BERT to fine-tune on a separate task



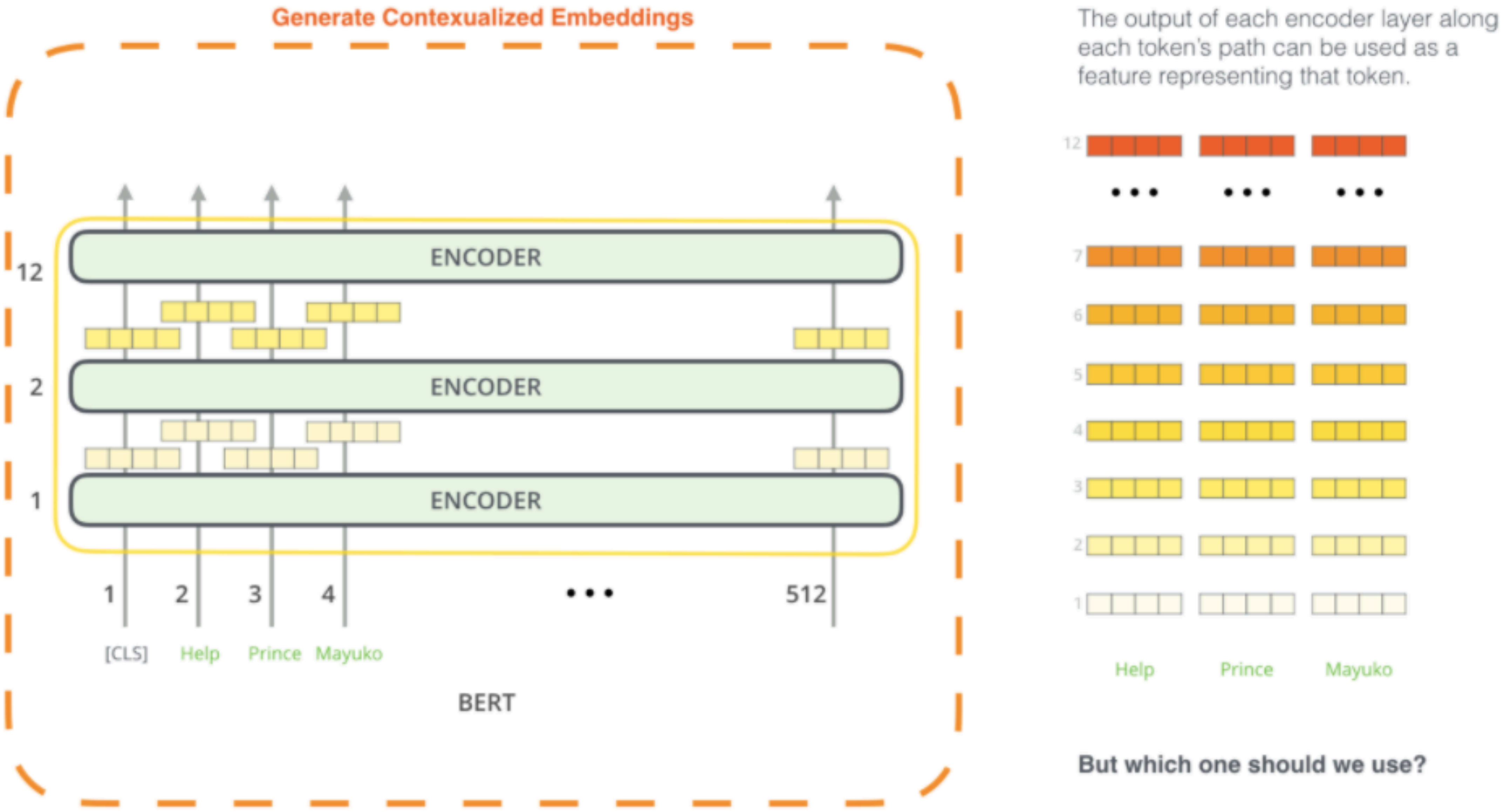
(c) Question Answering Tasks: SQuAD v1.1

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

Picture: https://jalammar.github.io/illustrated-bert/

BERT

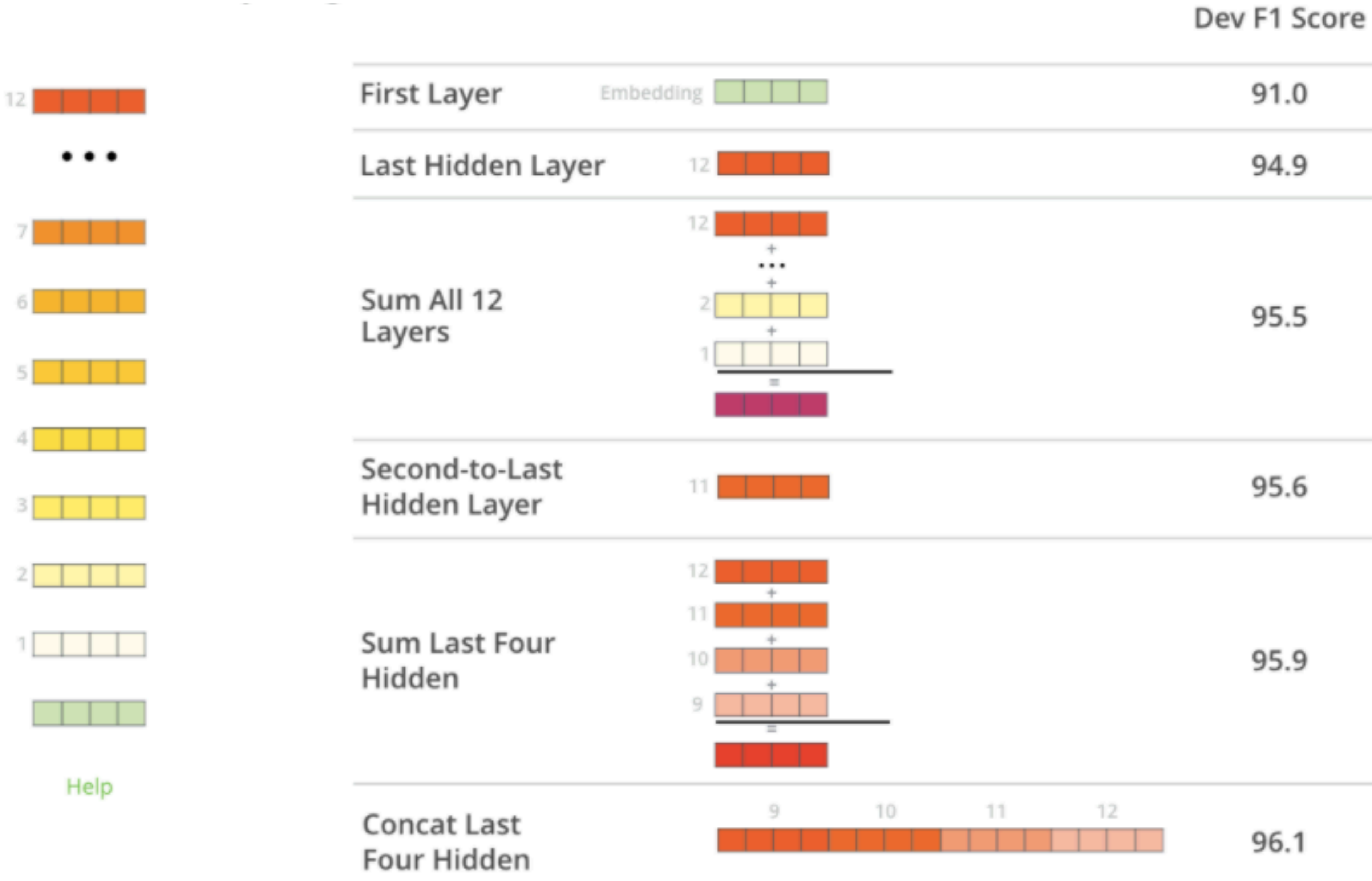
One could also extract the contextualized embeddings



Picture: https://jalammar.github.io/illustrated-bert/

BERT

Later layers have the best contextualized embeddings



Picture: https://jalammar.github.io/illustrated-bert/

BERT yields state-of-the-art (SOTA) results on many tasks

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**

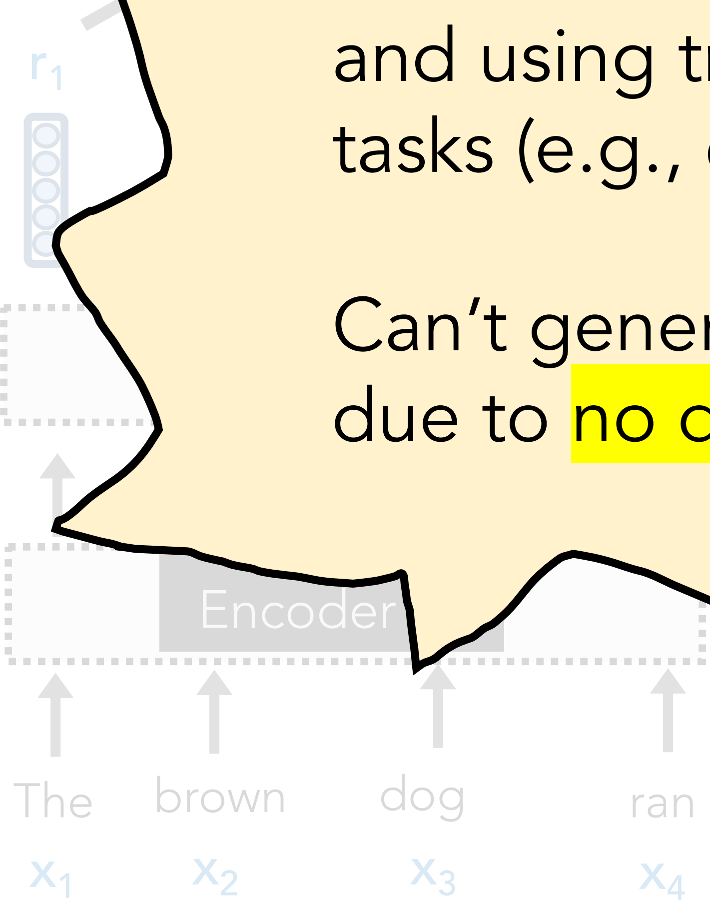
Table 1: GLUE Test results, scored by the evaluation server (https://gluebenchmark.com/leaderboard).

Source: original BERT paper: https://arxiv.org/pdf/1810.04805.pdf

Takeaway

BERT is incredible for learning **contextualized embeddings** of words and using transfer learning for other tasks (e.g., classification).

Can't generate new sentences though, due to no decoders.



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Transformer

What if we want to generate a new output sequence?

GPT-2 model to the rescue!

Generative **P**re-trained **T**ransformer 2

GPT-2 (a Transformer variant)

- GPT-2 uses only Transformer Decoders (no Encoders) to generate new sequences (from scratch or from a starting sequence)
- Oddly, there is no Attention (since there is no **Transformer Encoder** to attend to). So, there is only Self-Attention.
- As it processes each word/token, it cleverly **masks** the "future" words and conditions itself on the previous words

GPT-2 (a Transformer variant)

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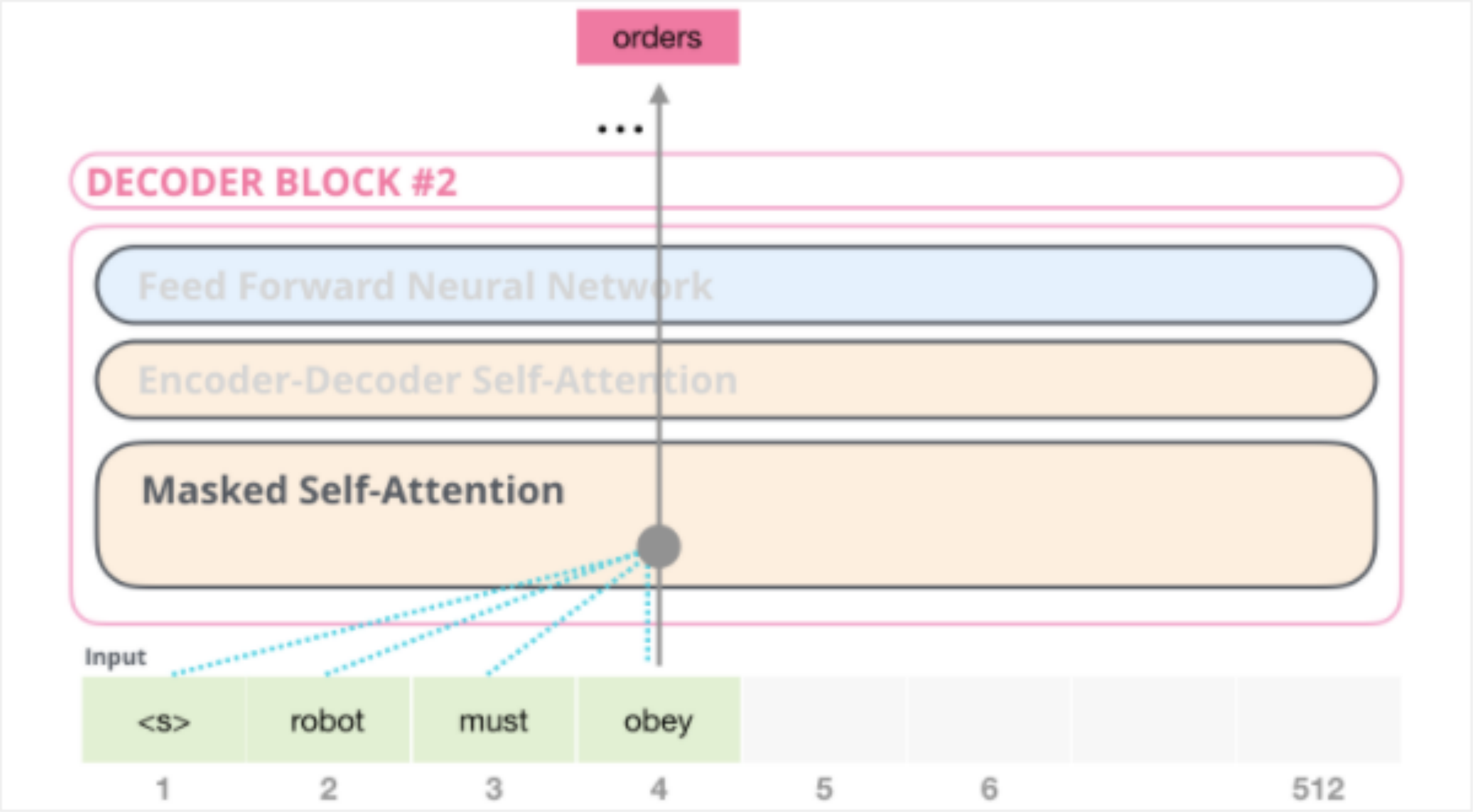

GPT-2 (a Transformer variant)

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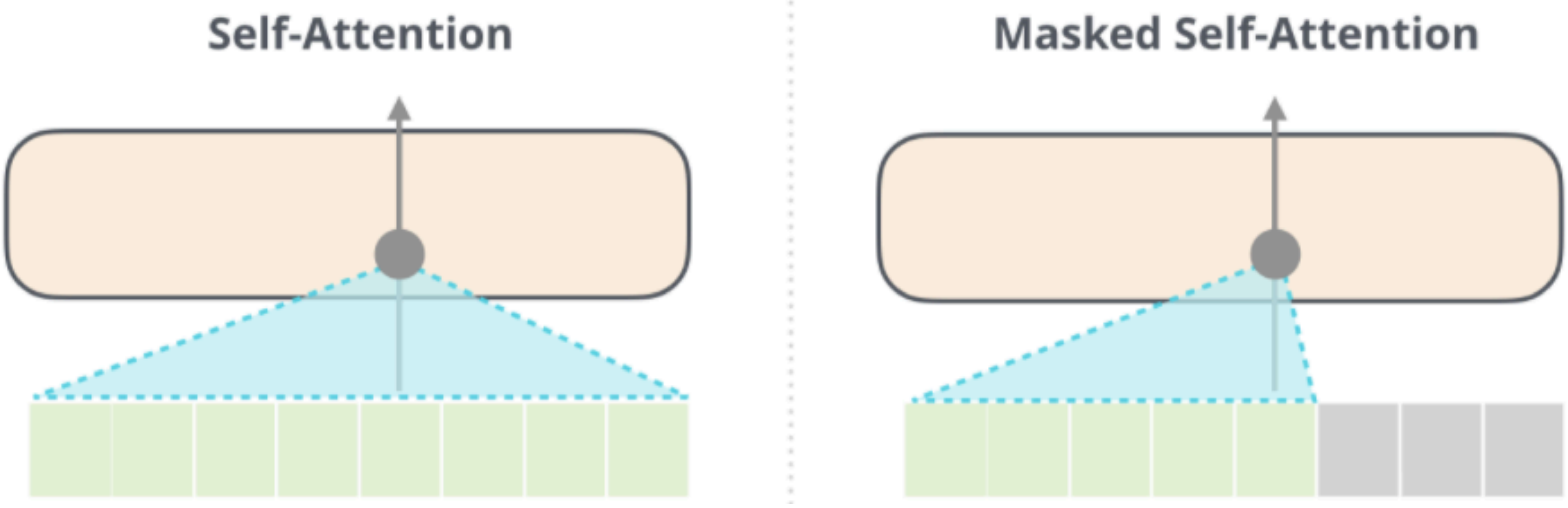

GPT-2 (a Transformer variant)

- Technically, it doesn't use words as input but Byte Pair Encodings (sub-words), similar to BERT's WordPieces.
- Includes positional embeddings as part of the input, too.
- Easy to fine-tune on your own dataset (language)

GPT-2 Results

Easy to fine-tune on your own dataset (language)

SYSTEM PROMPT (HUMAN-WRITTEN)

A train carriage containing controlled nuclear materials was stolen in Cincinnati today. Its whereabouts are unknown.

MODEL COMPLETION (MACHINE-WRITTEN, FIRST TRY)

The incident occurred on the downtown train line, which runs from Covington and Ashland stations.

In an email to Ohio news outlets, the U.S. Department of Energy said it is working with the Federal Railroad Administration to find the thief.

“The theft of this nuclear material will have significant negative consequences on public and environmental health, our workforce and the economy of our nation,” said Tom Hicks, the U.S. Energy Secretary, in a statement. “Our top priority is to secure the theft and ensure it doesn’t happen again.”
The stolen material was taken from the University of Cincinnati’s Research Triangle Park nuclear research site, according to a news release from Department officials.
The Nuclear Regulatory Commission did not immediately release any information.

GPT-2 Results

Question	Generated Answer	Correct	Probability
Who wrote the book the origin of species?	Charles Darwin	✓	83.4%
Who is the founder of the ubuntu project?	Mark Shuttleworth	✓	82.0%
Who is the quarterback for the green bay packers?	Aaron Rodgers	✓	81.1%
Panda is a national animal of which country?	China	✓	76.8%
Who came up with the theory of relativity?	Albert Einstein	✓	76.4%
When was the first star wars film released?	1977	✓	71.4%
What is the most common blood type in sweden?	A	✗	70.6%
Who is regarded as the founder of psychoanalysis?	Sigmund Freud	✓	69.3%
Who took the first steps on the moon in 1969?	Neil Armstrong	✓	66.8%
Who is the largest supermarket chain in the uk?	Tesco	✓	65.3%
What is the meaning of shalom in english?	peace	✓	64.0%
Who was the author of the art of war?	Sun Tzu	✓	59.6%
Largest state in the us by land mass?	California	✗	59.2%
Green algae is an example of which type of reproduction?	parthenogenesis	✗	56.5%
Vikram samvat calender is official in which country?	India	✓	55.6%
Who is mostly responsible for writing the declaration of independence?	Thomas Jefferson	✓	53.3%

GPT-2 Results

Language Models are Unsupervised Multitask Learners

	LAMBADA (PPL)	LAMBADA (ACC)	CBT-CN (ACC)	CBT-NE (ACC)	WikiText2 (PPL)	PTB (PPL)	enwik8 (BPB)	text8 (BPC)	WikiText103 (PPL)
SOTA	99.8	59.23	85.7	82.3	39.14	46.54	0.99	1.08	18.3
117M	**35.13**	45.99	**87.65**	**83.4**	**29.41**	65.85	1.16	1.17	37.50
345M	**15.60**	55.48	**92.35**	**87.1**	**22.76**	47.33	1.01	**1.06**	26.37
762M	**10.87**	**60.12**	**93.45**	**88.0**	**19.93**	**40.31**	**0.97**	**1.02**	22.05
1542M	**8.63**	**63.24**	**93.30**	**89.05**	**18.34**	**35.76**	**0.93**	**0.98**	**17.48**

Table 3. Zero-shot results on many datasets. No training or fine-tuning was performed for any of these results. PTB and results are from (Gong et al., 2018). CBT results are from (Bajgar et al., 2016). LAMBADA accuracy result is from (Hoang and LAMBADA perplexity result is from (Grave et al., 2016). Other results are from (Dai et al., 2019).

Takeaway:
GPT-2 is astounding for generating realistic-looking new text

Can fine-tune toward other tasks, too.

Outline

- Recap
- Transformers
  - BERT
  - GPT-2
  - Concerns
- Summary

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BERT (a Transformer variant)

BERT is trained on a lot of text data:

- BooksCorpus (800M words)
- English Wikipedia (2.5B words)

Yay, for transfer learning!

BERT-Base model has 12 transformer blocks, 12 attention heads,

110M parameters!

BERT-Large model has 24 transformer blocks, 16 attention heads,

340M parameters!

GPT-2 (a Transformer variant)

GPT-2 is:

- trained on 40GB of text data (8M webpages)!
- 1.5B parameters

GPT-3 is an even bigger version (175B parameters) of GPT-2, but isn't open-source

Yay, for transfer learning!

Concerns

There are several issues to be aware of:

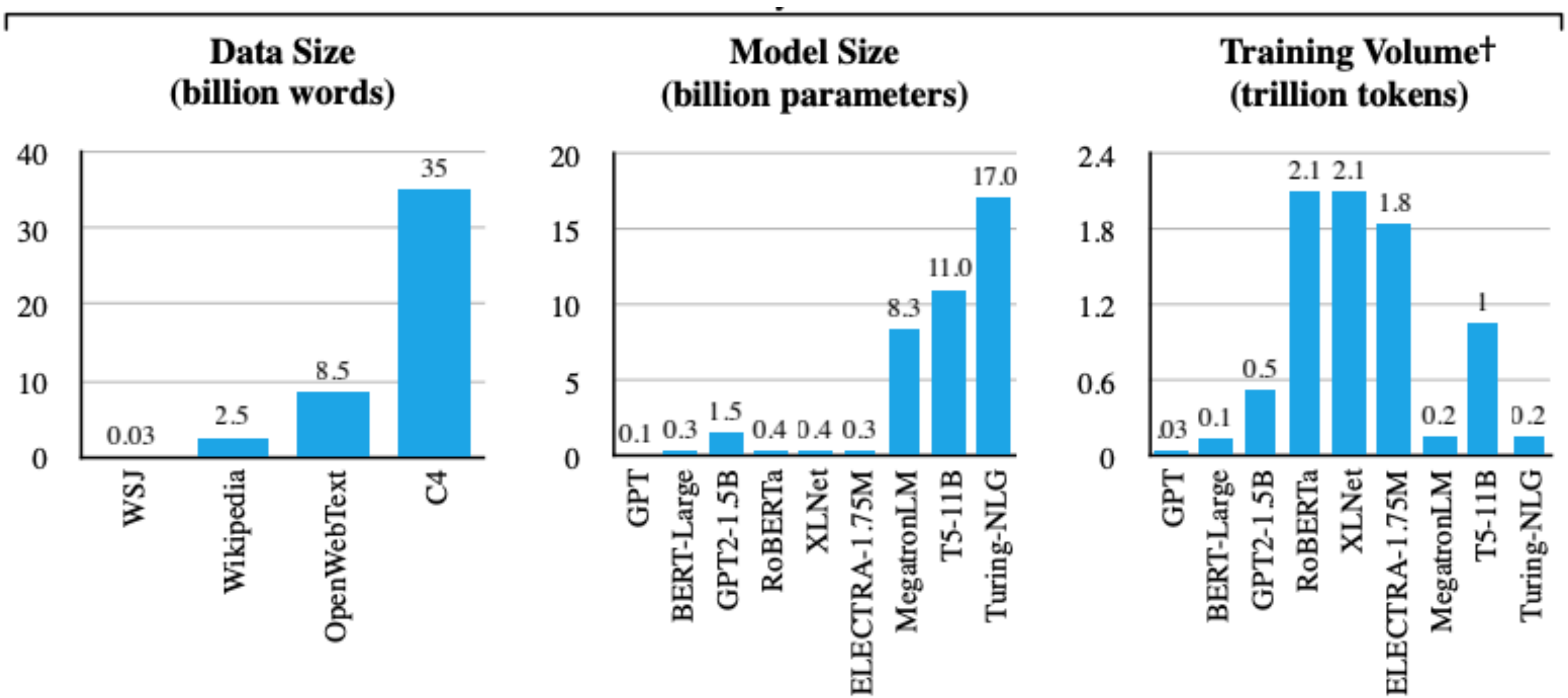
- It is very costly to train these large models. The companies who develop these models easily spend an entire month training one model, which uses incredible amounts of electricity.
- BERT alone is estimated to cost over $1M for their final models

- $2.5k - $50k (110 million parameter model)
- $10k - $200k (340 million parameter model)
- $80k - $1.6m (1.5 billion parameter model)

Source: https://arxiv.org/pdf/2004.08900.pdf

Concerns

It is very costly to train these large models.



Source: https://arxiv.org/pdf/2004.08900.pdf

Concerns

- Further, these very large language models have been shown to be biased (e.g., in terms of gender, race, sex, etc).
- Converting from one language to another often converts gender neutral pronouns to sexist stereotypes
- Using these powerful LMs comes with risks of producing such text and/or evaluating/predicting tasks based on these biased assumptions.
- People are researching how to improve this

Concerns

- As computer-generated text starts to become indistinguishable from authentic, human-generated text, consider the ethical impact of fraudulently claiming text to be from a particular author.
- If used maliciously, it can easily contribute toward the problem of Fake News

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Summary

- There has been significant NLP progress in the past few years.
- Some of the complex models are incredible, but rely on having a lot of data and computational resources (e.g., Transformers)
- With all data science and machine learning, it’s best to understand your data and task very well, clean your data, and start with a simple model (instead of jumping to the most complex model)

Summary

- NLP is incredibly fun, with infinite number of problems to work on
- I'll teach an NLP course next year (most likely Spring 2022).

Some definitions to remember

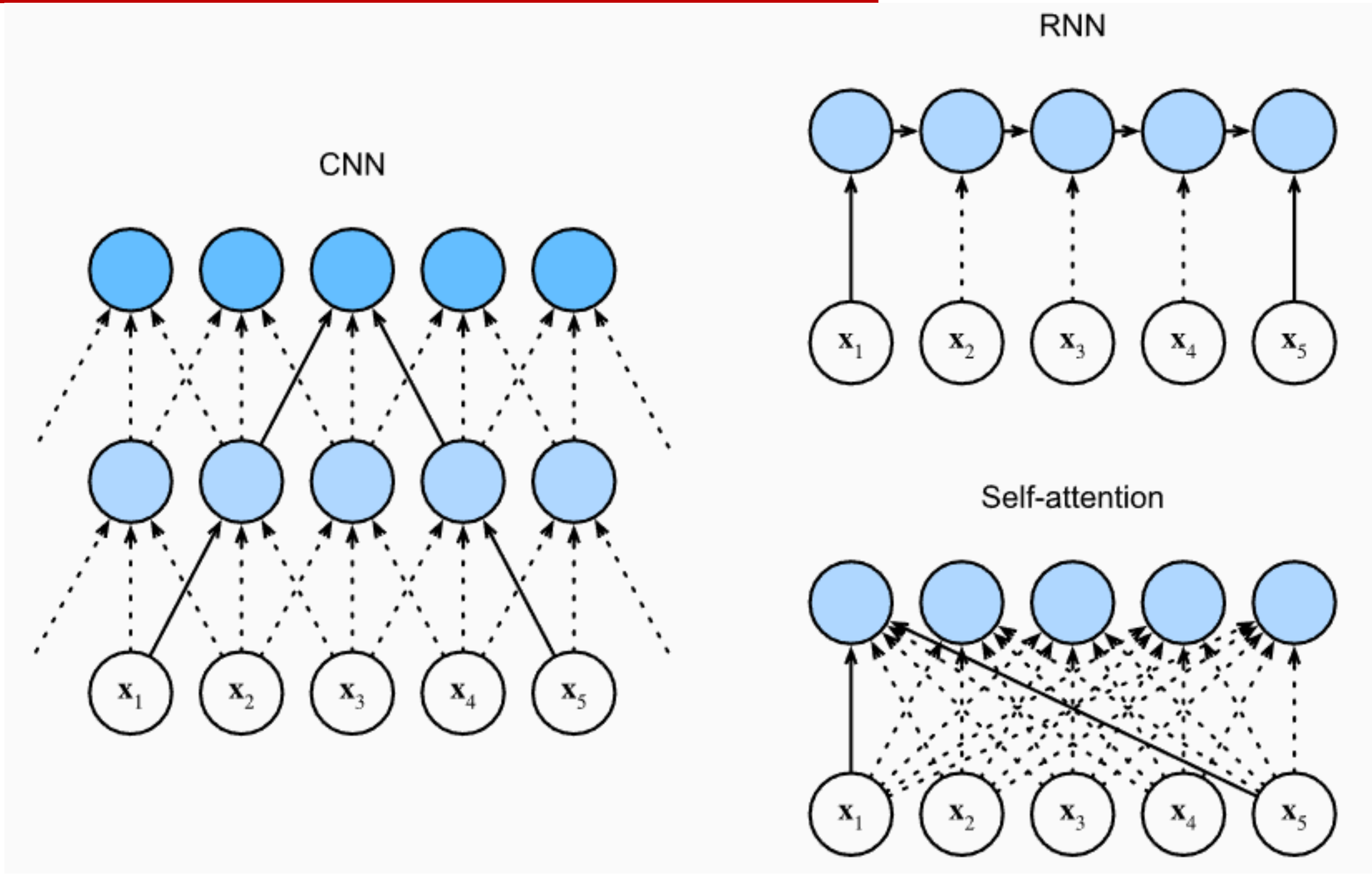
Models

- **N-gram**: count statistics; elementary sequence modelling
- **FFNN**: fixed-length context window; not ideal for sequential modelling
- **(Vanilla) RNN**: uses context; fair sequence modelling
- **LSTM**: a variant of an RNN that handles long-range context better
- **Seq2Seq**: maps 1 sequence to another (n→m sequences)
- **Attention**: determines which elements in sequence A pertain to sequence B
- **Self-Attention**: determines which elements to focus on in its own sequence A
- **Transformers**: learns excellent representation, via a seq2seq framework with self-attention and attention
    - **BERT**: Transformer <u>Encoders</u> that learn great representations and can be fine-tuned on other tasks
    - **GPT-2**: Transformer <u>Decoders</u> that generate realistic text and can be fine-tuned on other tasks

QUESTIONS?

BACKUP SLIDES

Transformer vs CNN vs RNN



Source: https://d2l.ai/chapter_attention-mechanisms/self-attention-and-positional-encoding.html#subsec-cnn-rnn-self-attention