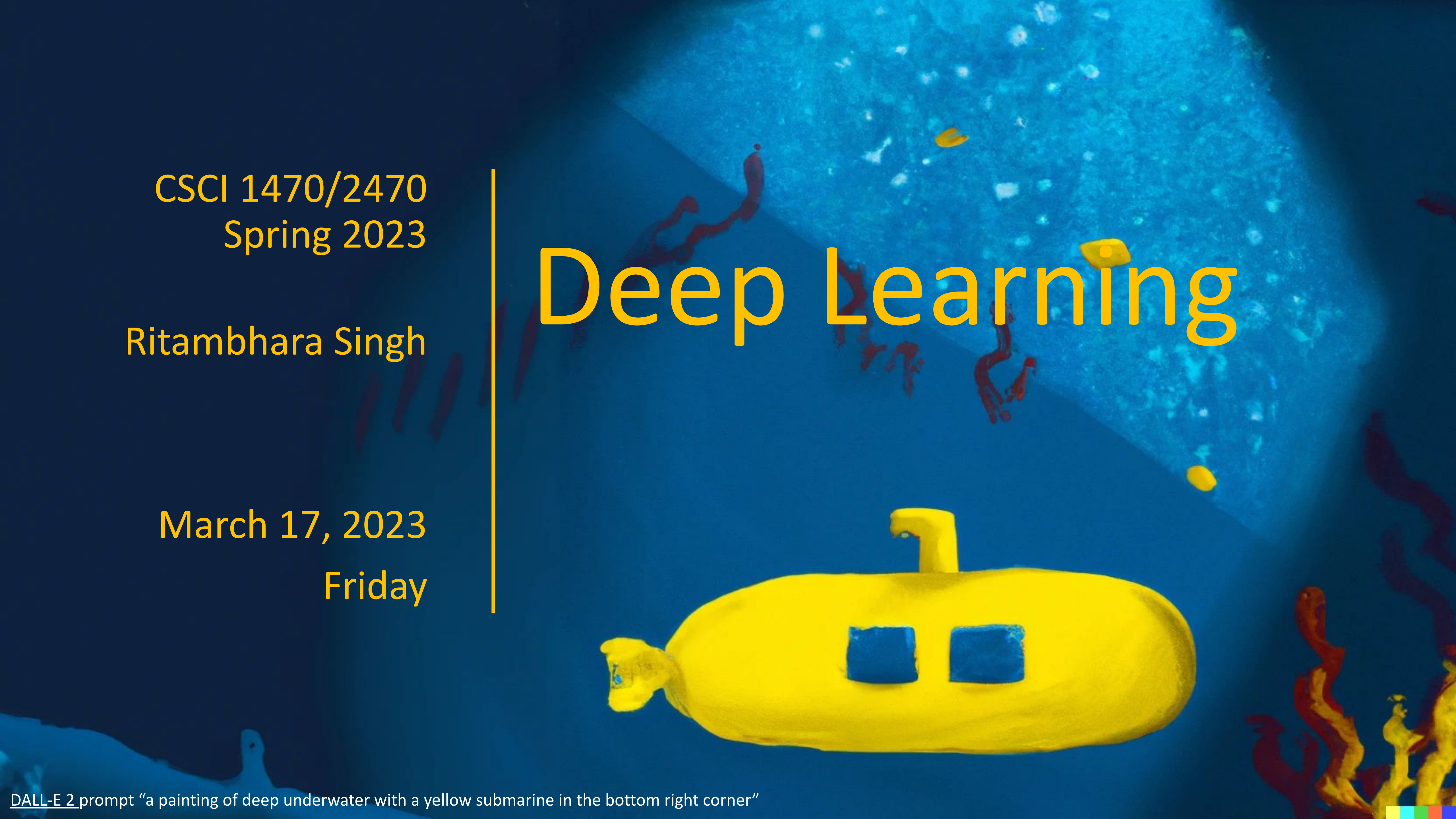
CSCI 1470/2470
Spring 2023

Ritambhara Singh

March 17, 2023
Friday

Deep Learning



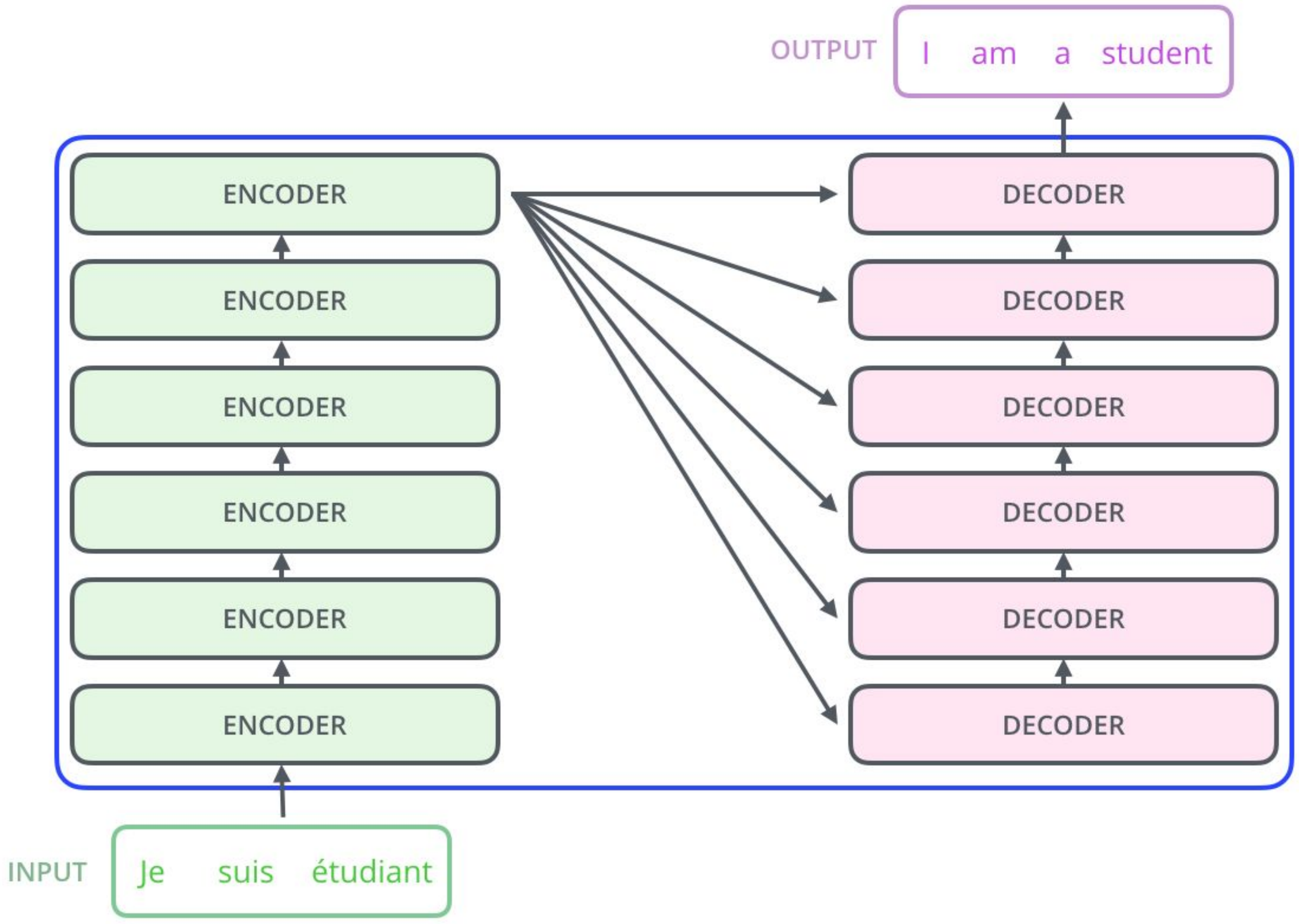
DALL-E 2 prompt “a painting of deep underwater with a yellow submarine in the bottom right corner”

Course announcements

- Project proposals **due today at 6pm EST!**
- No labs next week! ☺️
- No class on March 24 (Friday)! ☺️
- Finish mid-semester feedback and get 2 extra late days! ☺️

Review: Transformer Model Overview

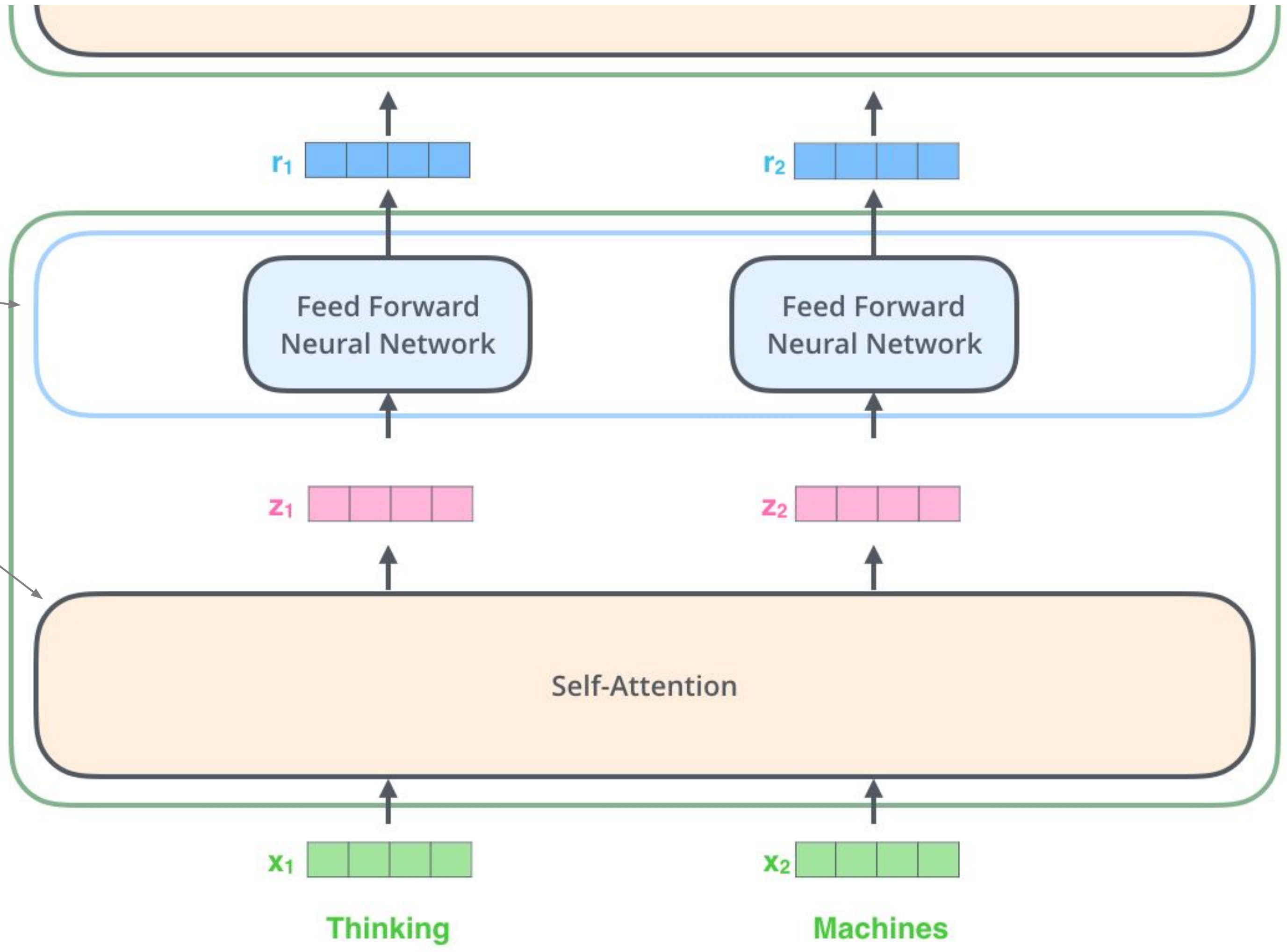
- The Transformer model breaks down into Encoder and Decoder blocks.
- At a high level, similar to the seq2seq architecture we've seen already…
- …but there are no recurrent nets inside the Encoder and Decoder blocks!
- For better performance, often stack multiple Encoder and Decoder blocks (deeper network)



Alammar, Jay (2018). The Illustrated Transformer [Blog post]. Retrieved from https://jalammar.github.io/illustrated-transformer/

Review: Encoder Block Map

- Encoder block breaks down into two main parts: Self-Attention, and Feed Forward layers.



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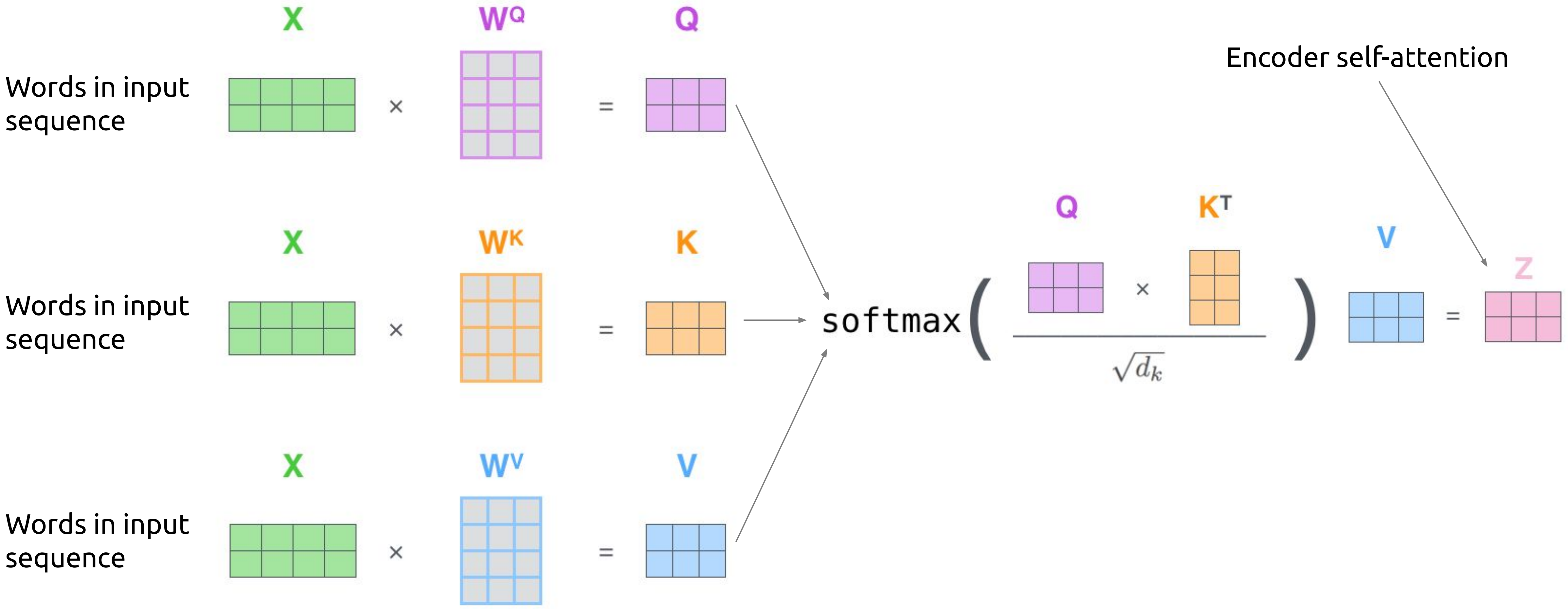
Review: Encoder Self-Attention



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Today's goal – learn about other components of Transformers and scaling of deep learning models

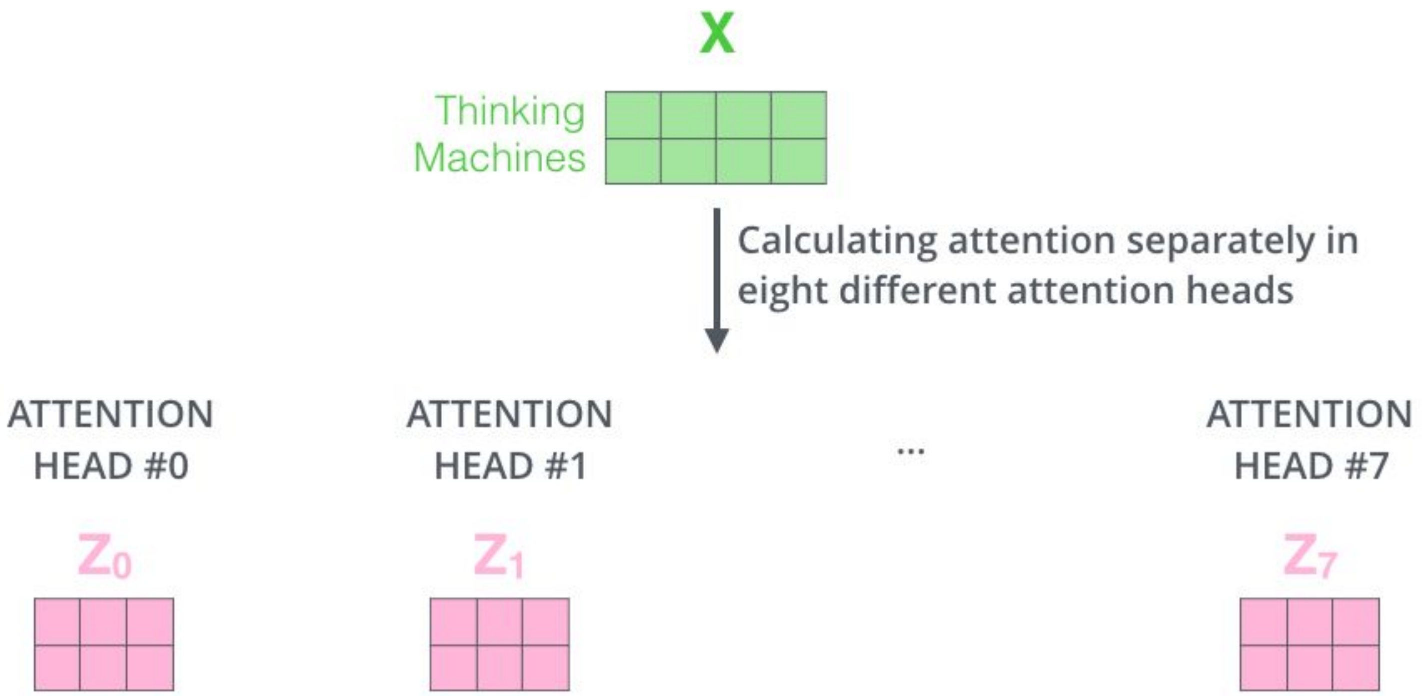
(1) Multi-headed attention and other improvements

(2) Decoder details

(3) Scaling deep learning models

Multi-head Attention

- Multi-head Attention is used to improve the performance of regular self-attention.
- We compute self-attention as before some number of times. Call these “attention heads”.
- The size of the attention heads are smaller than when just using regular self-attention.



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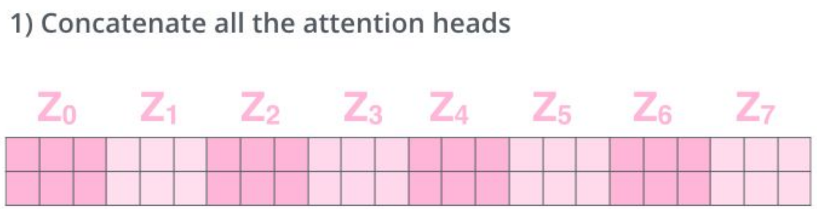
Multi-head Attention

Multi-head Attention



To get one set of attention vectors, we concatenate all the heads and apply a linear layer in order to get **Z.**

Alammar, Jay (2018). The Illustrated Transformer [Blog post]. Retrieved from https://jalammar.github.io/illustrated-transformer/

Multi-head Attention

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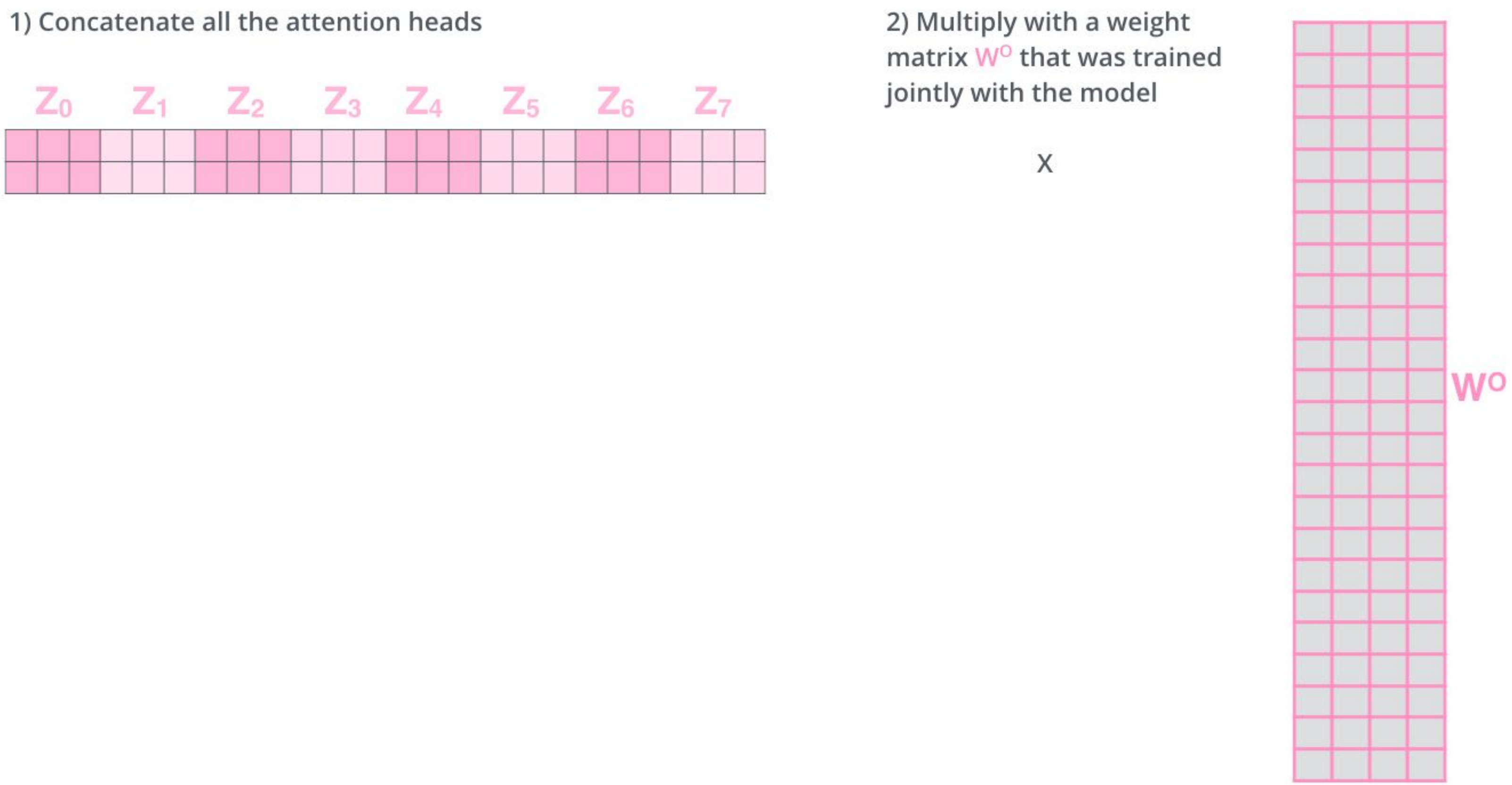

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Multi-head Attention

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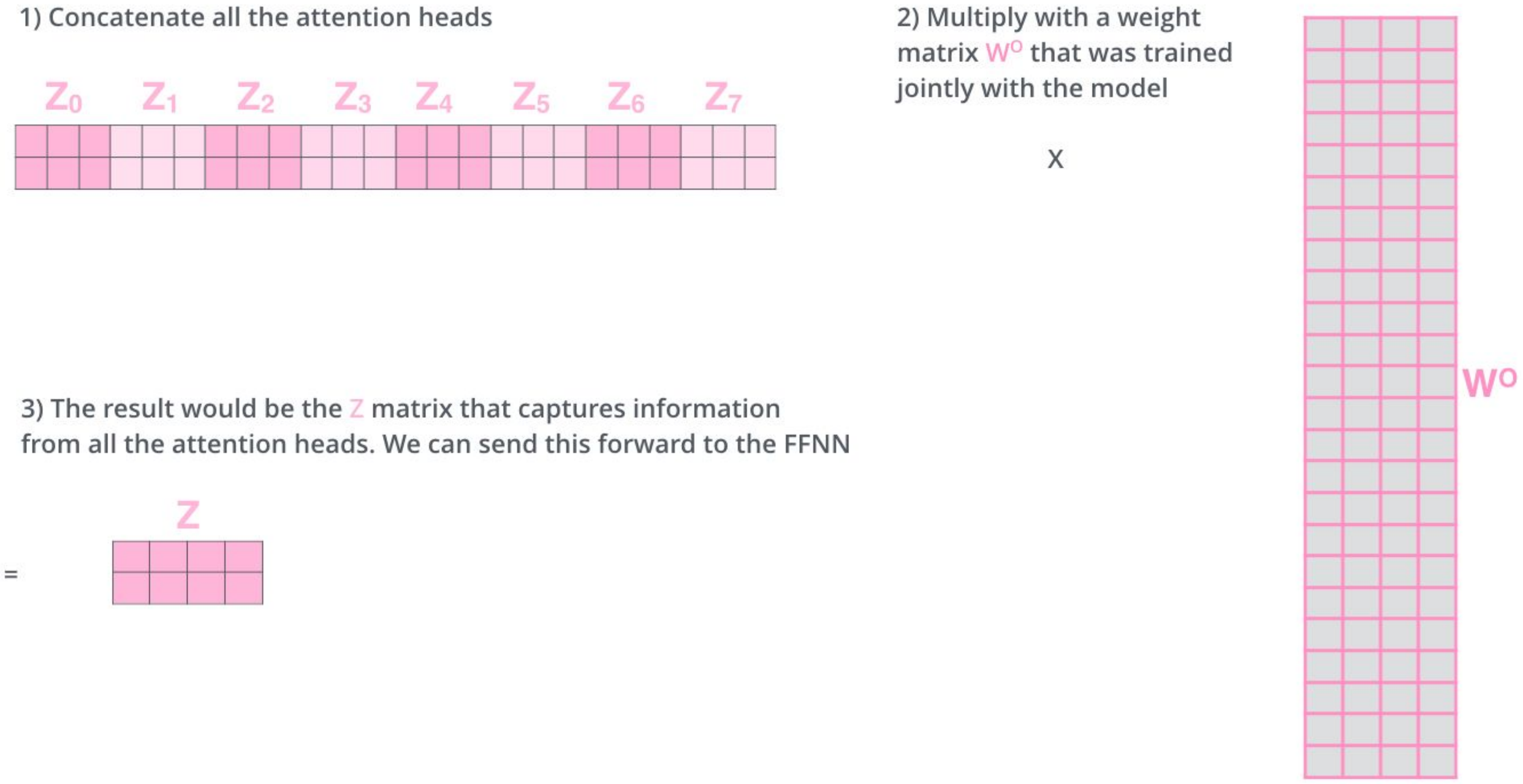

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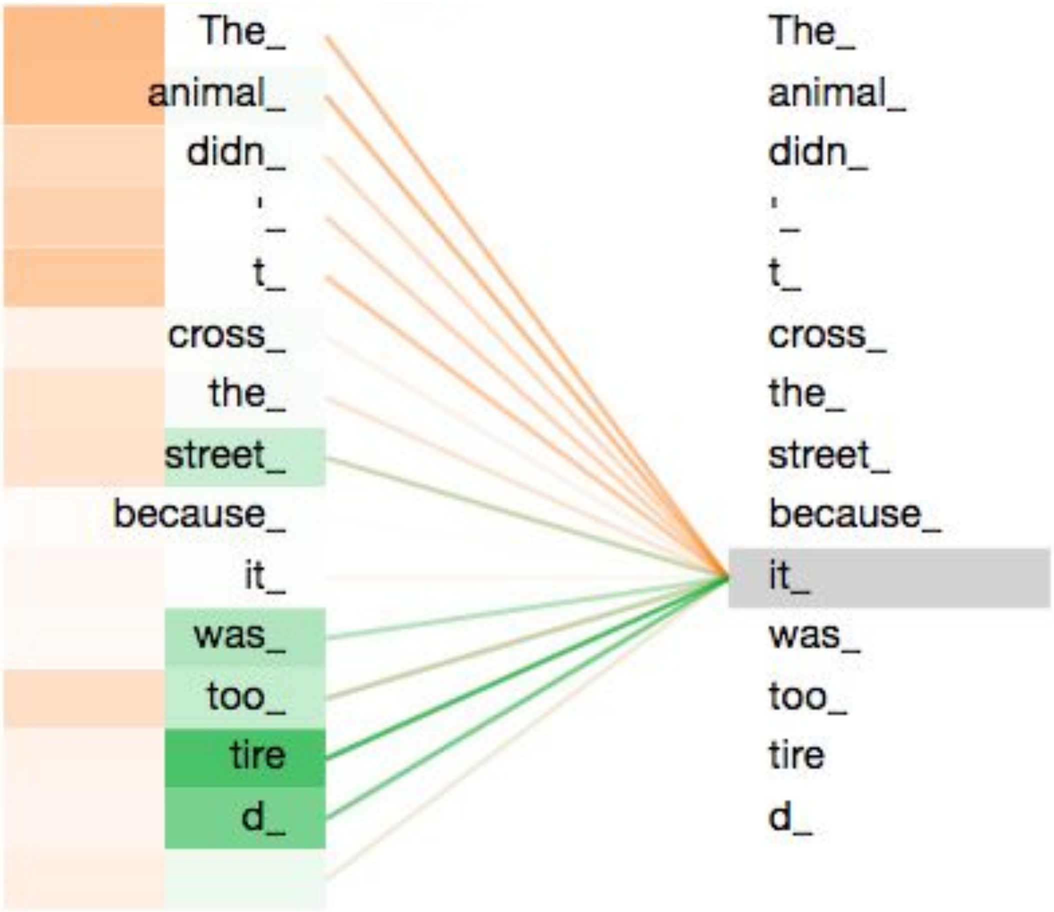
Multi-head Attention Visualized

Multiple heads allow for each head to learn different relationships between words in the sentence.



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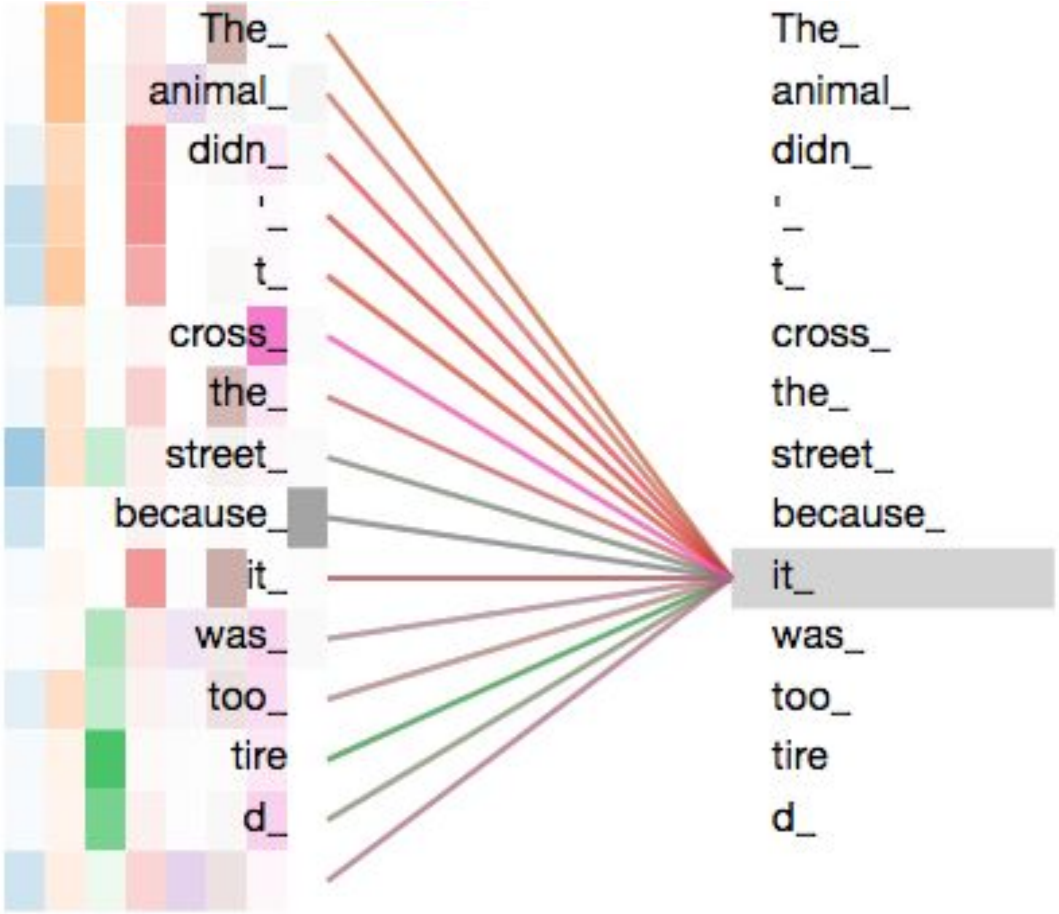
Multi-head Attention Visualized

Multiple heads allow for each head to learn different relationships between words in the sentence.

These relationships become more difficult to interpret with many heads.

Visualizer tool:
https://colab.research.google.com/github/tensorflow/tensor2tensor/blob/master/tensor2tensor/notebooks/hello_t2t.ipynb



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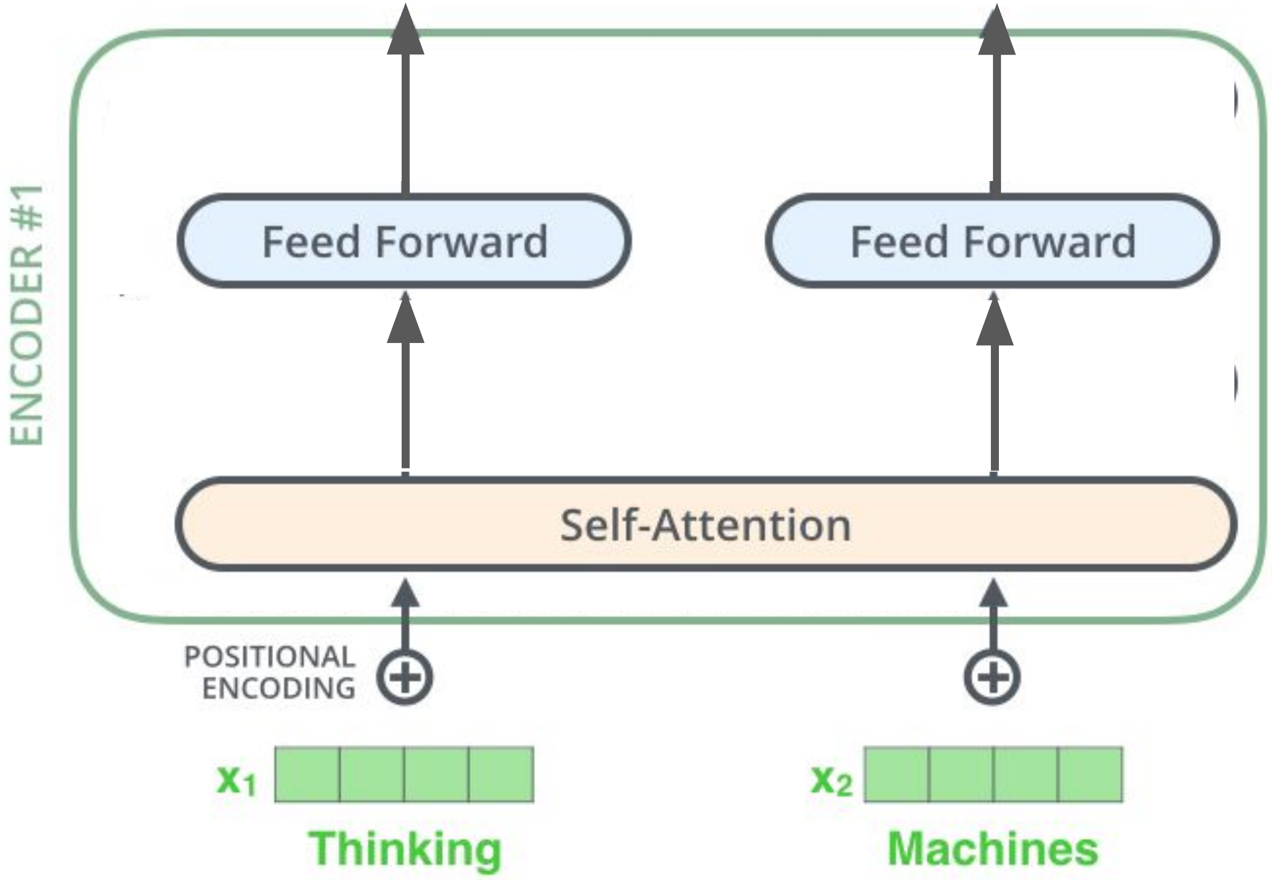
Extra Performance Improvements

- **Recap:** This is the current state of our encoder block



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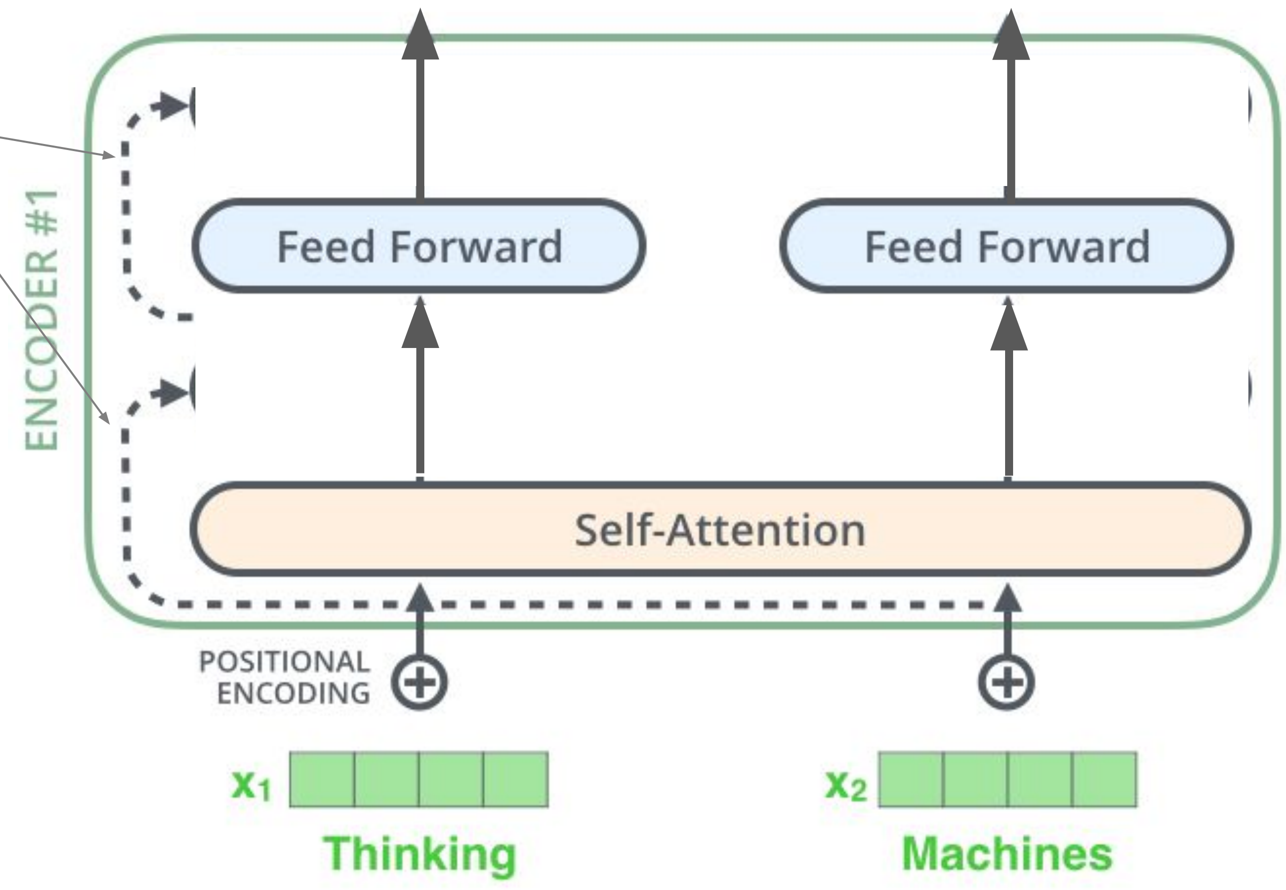
Extra Performance Improvements

- **Residual Connections**

Do you remember when we talked about these?



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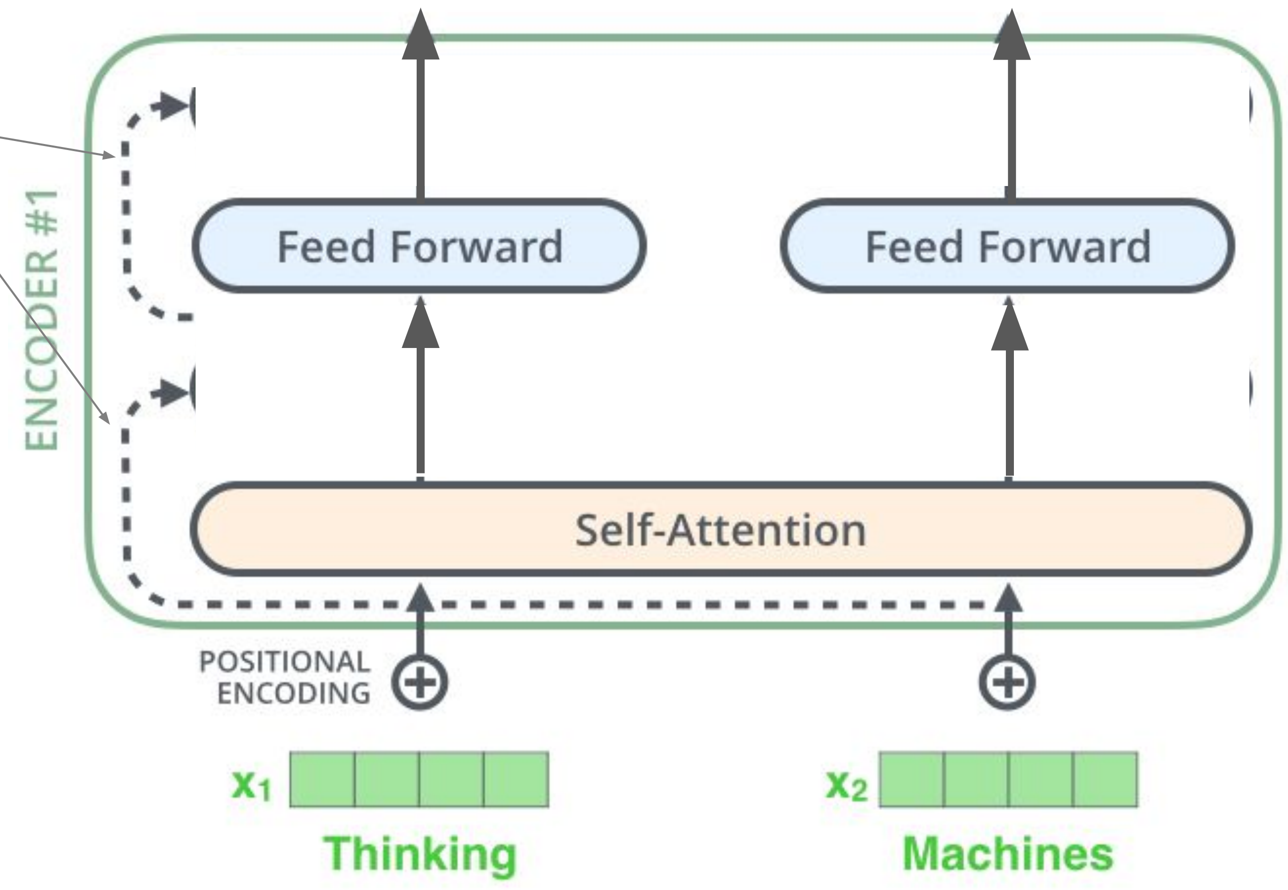
Extra Performance Improvements

- **Residual Connections:** Just like in CNN architectures, transformer models make use of skip connections to negate vanishing gradients.



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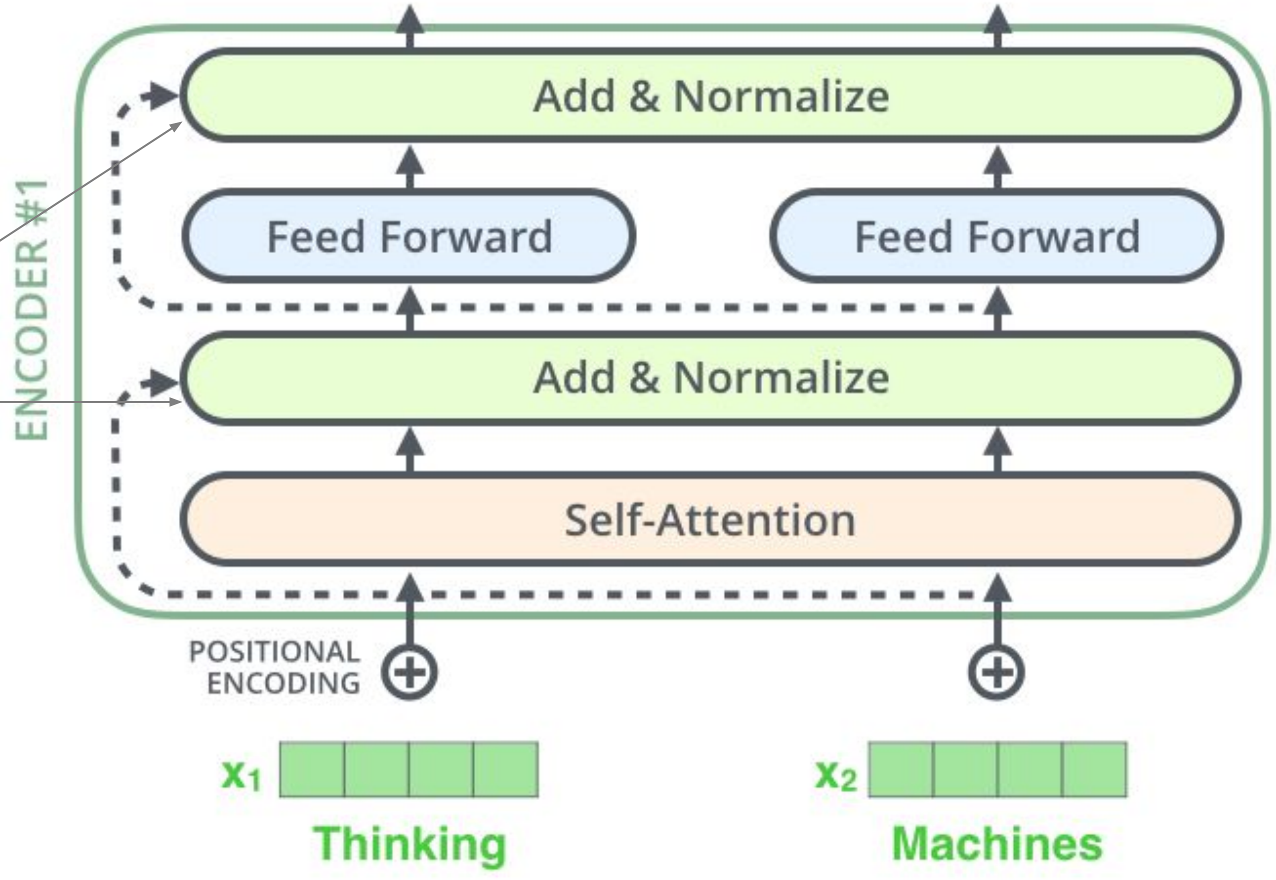
Extra Performance Improvements

- **Residual Connections:** Just like in CNN architectures, transformer models make use of skip connections to negate vanishing gradients.

- **LayerNorm:** Similar to Batch Normalization, improves convergence time.



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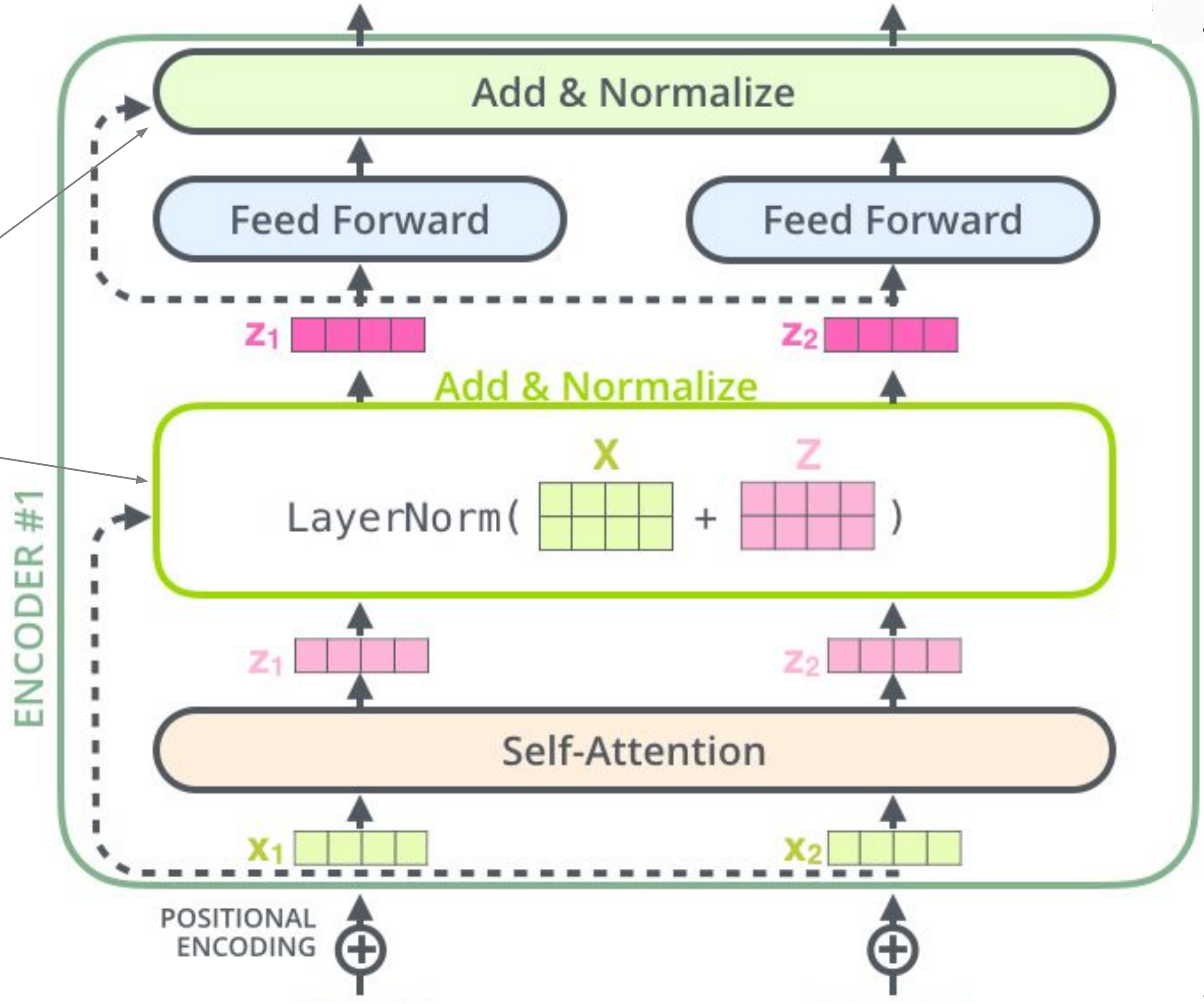
Any questions?

Extra Performance Improvements

- **Residual Connections:** Just like in CNN architectures, transformer models make use of skip connections to negate vanishing gradients.
- **LayerNorm:** Similar to Batch Normalization, improves convergence time.

We combine the residual connection and self-attention layer by adding them together.



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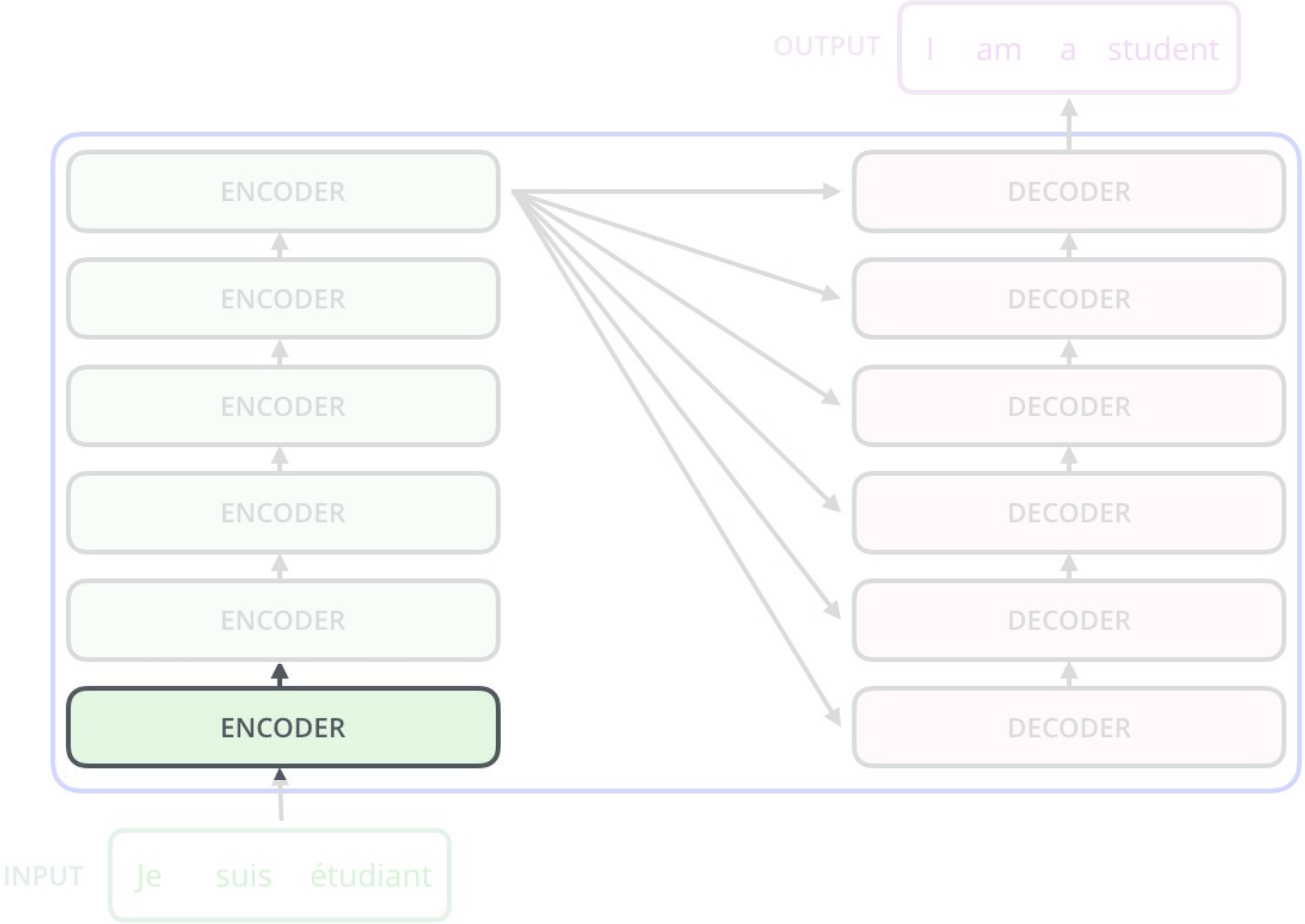
Transformer Model Overview



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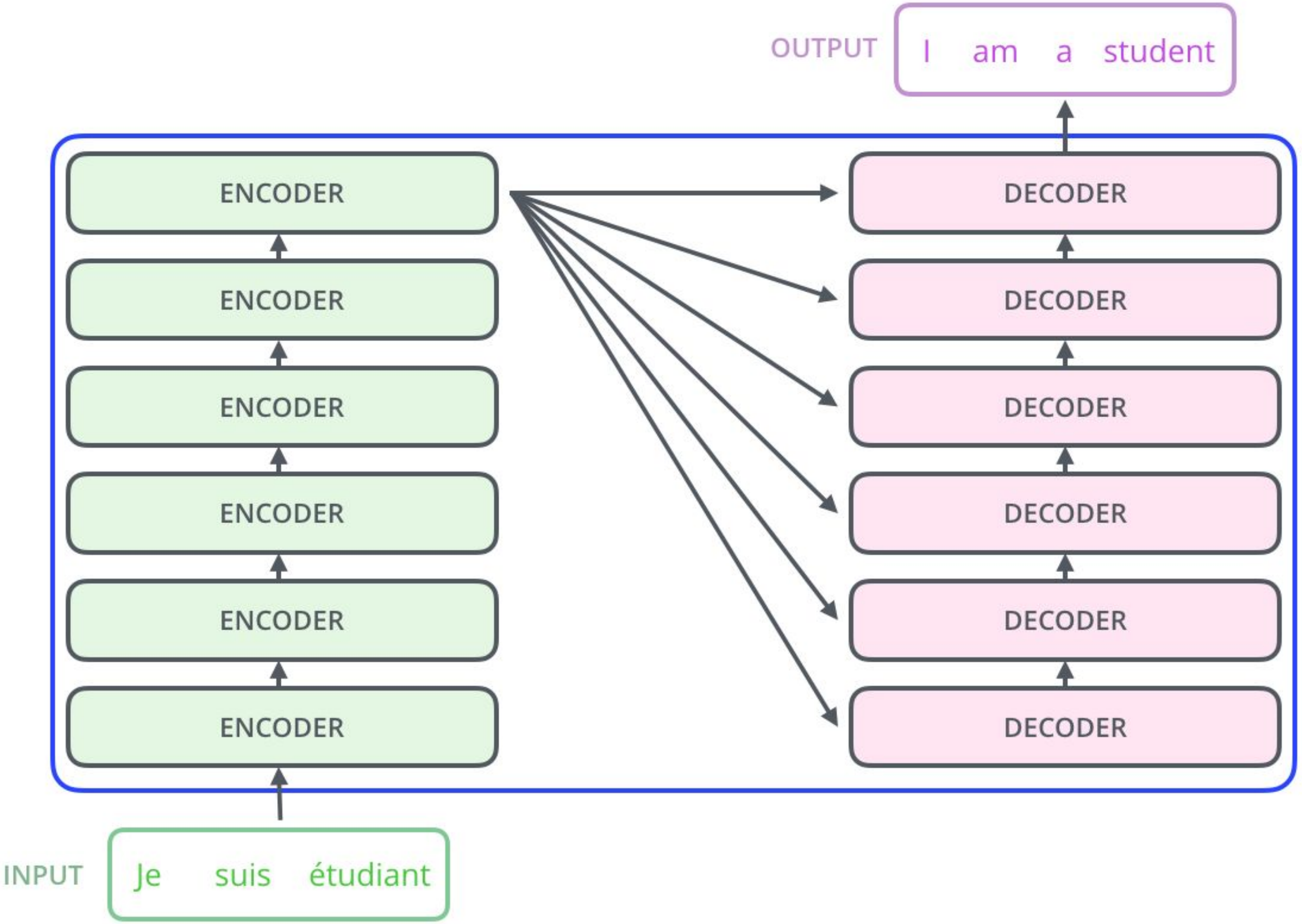
Transformer Model Overview



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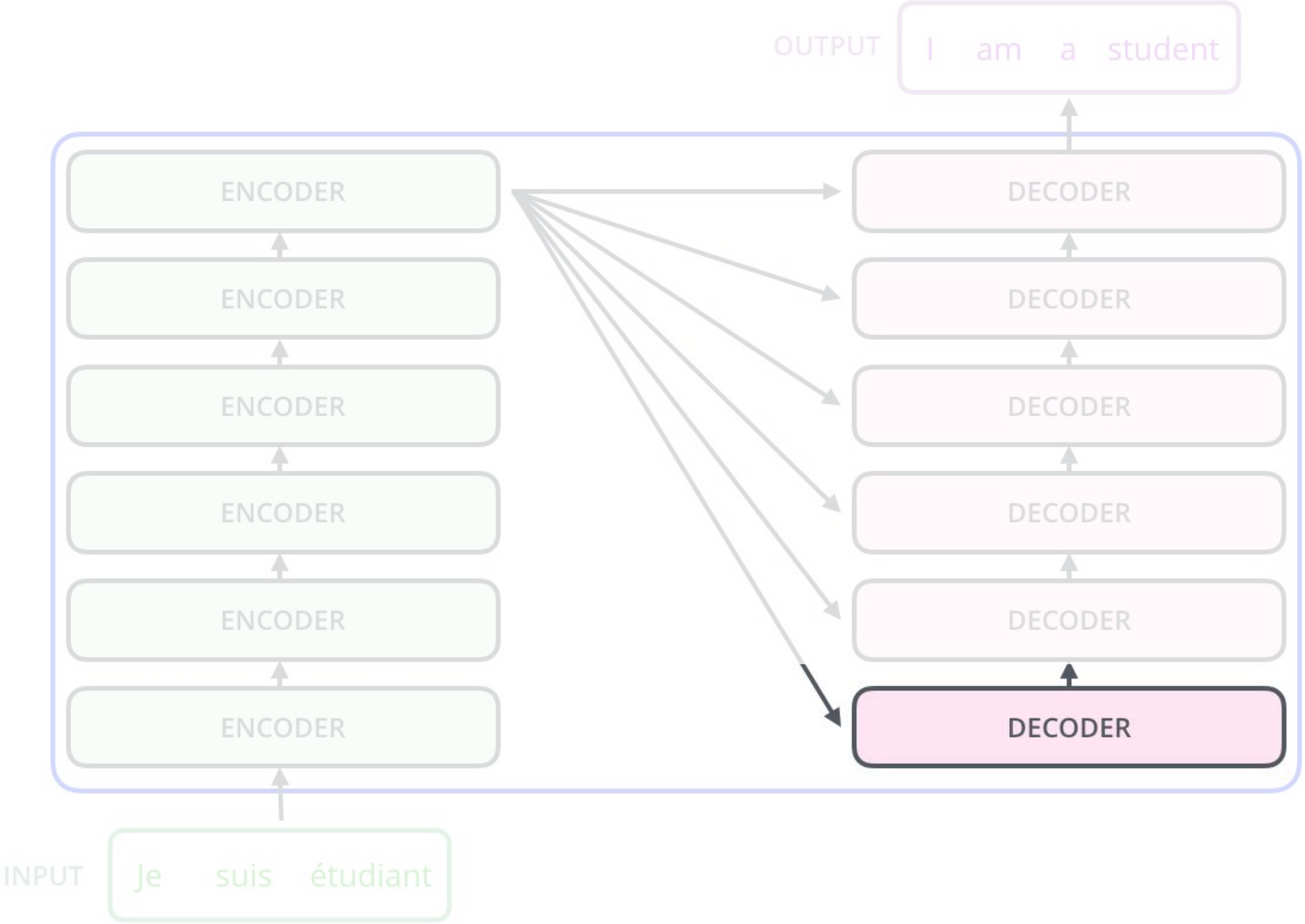
Transformer Model Overview

- Now let's look under the hood of a Decoder block



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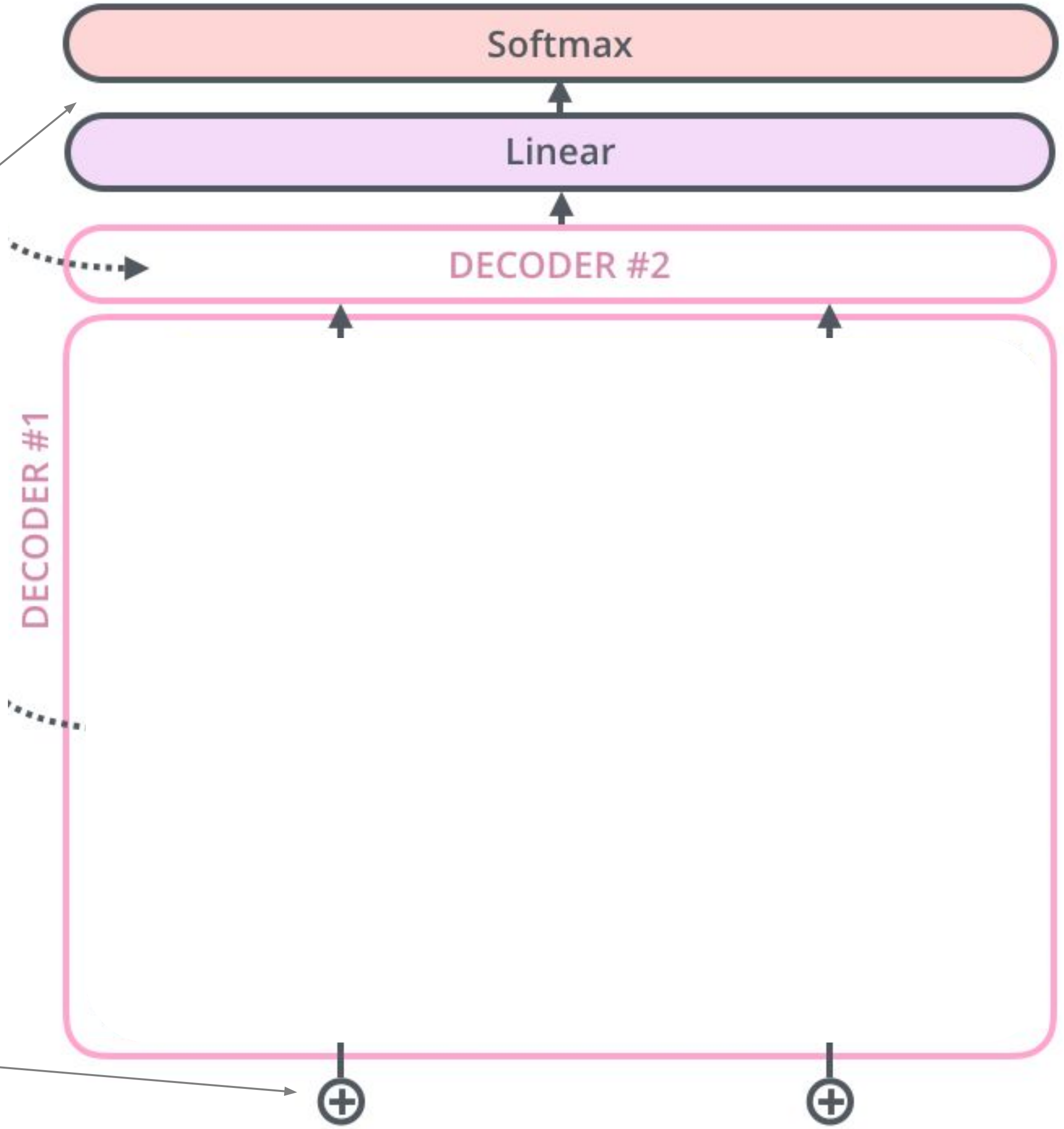
Decoder Block

Ultimately, decoder terminates in a linear + softmax to predict a probability distribution over the next word in the target language (same as with seq2seq model)

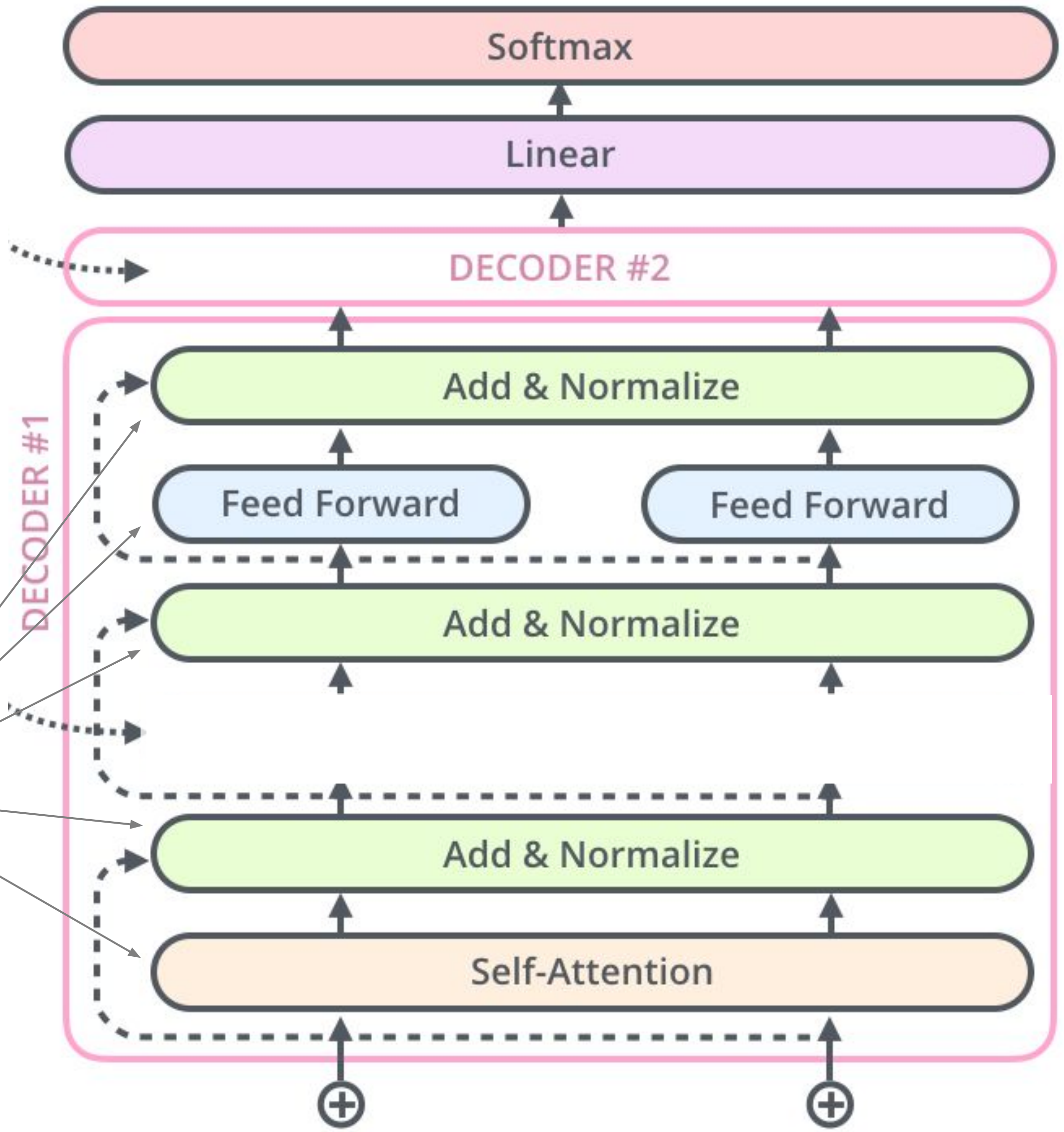


Like in other seq2seq models, the decoder receive the target sequence shifted back by one step as input.

Alammar, Jay (2018). The Illustrated Transformer [Blog post]. Retrieved from https://jalammar.github.io/illustrated-transformer/

Decoder Block

What else do we need here?



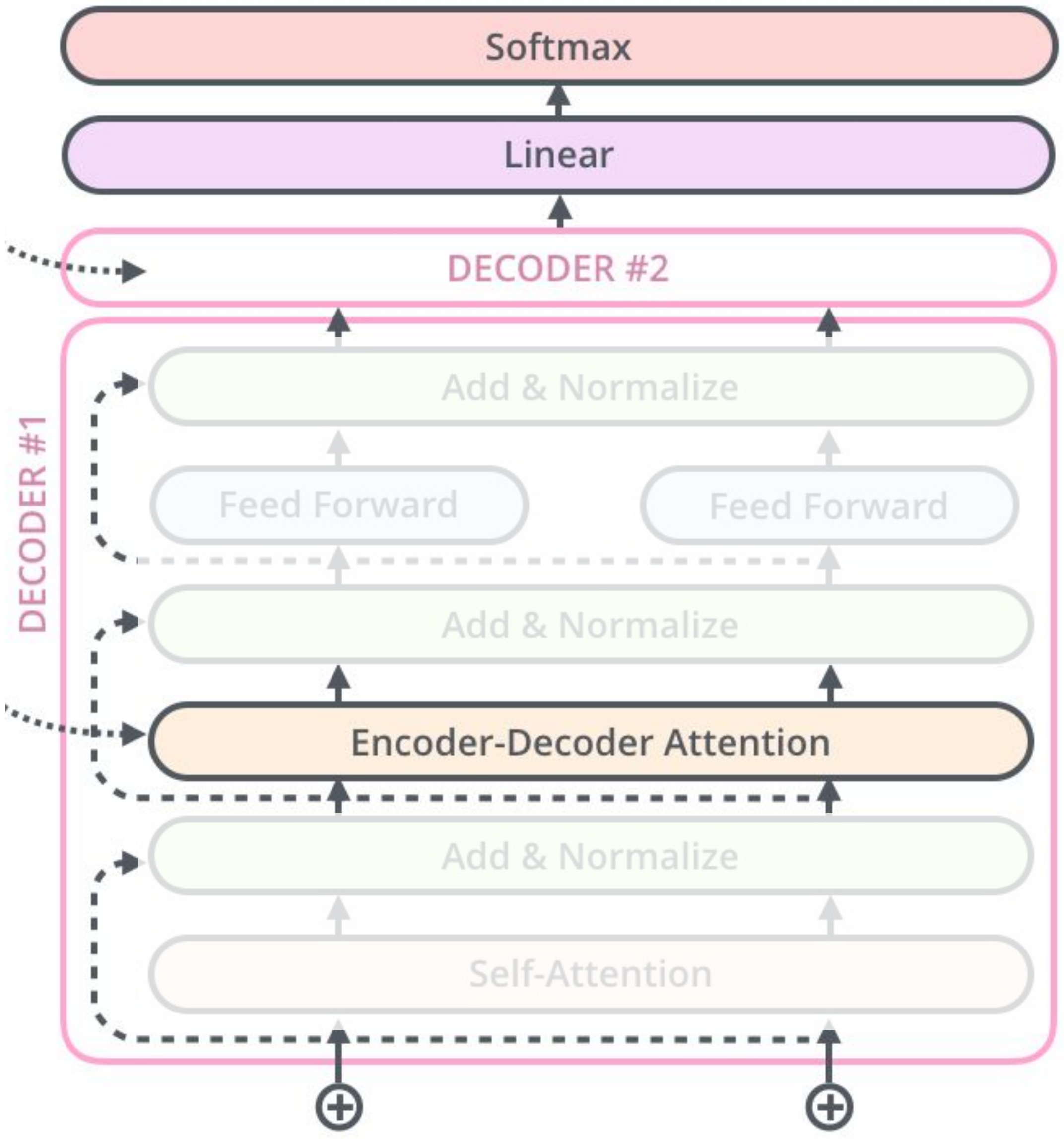
Self-attention, LayerNorm, and Feed Forward layers are identical to the Encoder block versions.

Alammar, Jay (2018). The Illustrated Transformer [Blog post]. Retrieved from https://jalammar.github.io/illustrated-transformer/

Decoder Block

What's Encoder-Decoder Attention?

- The part that says "how much should each *output* word pay attention to each input word"
- Analogous to the 'weighted average of LSTM states' that we pass to each decoder step in the seq2seq model



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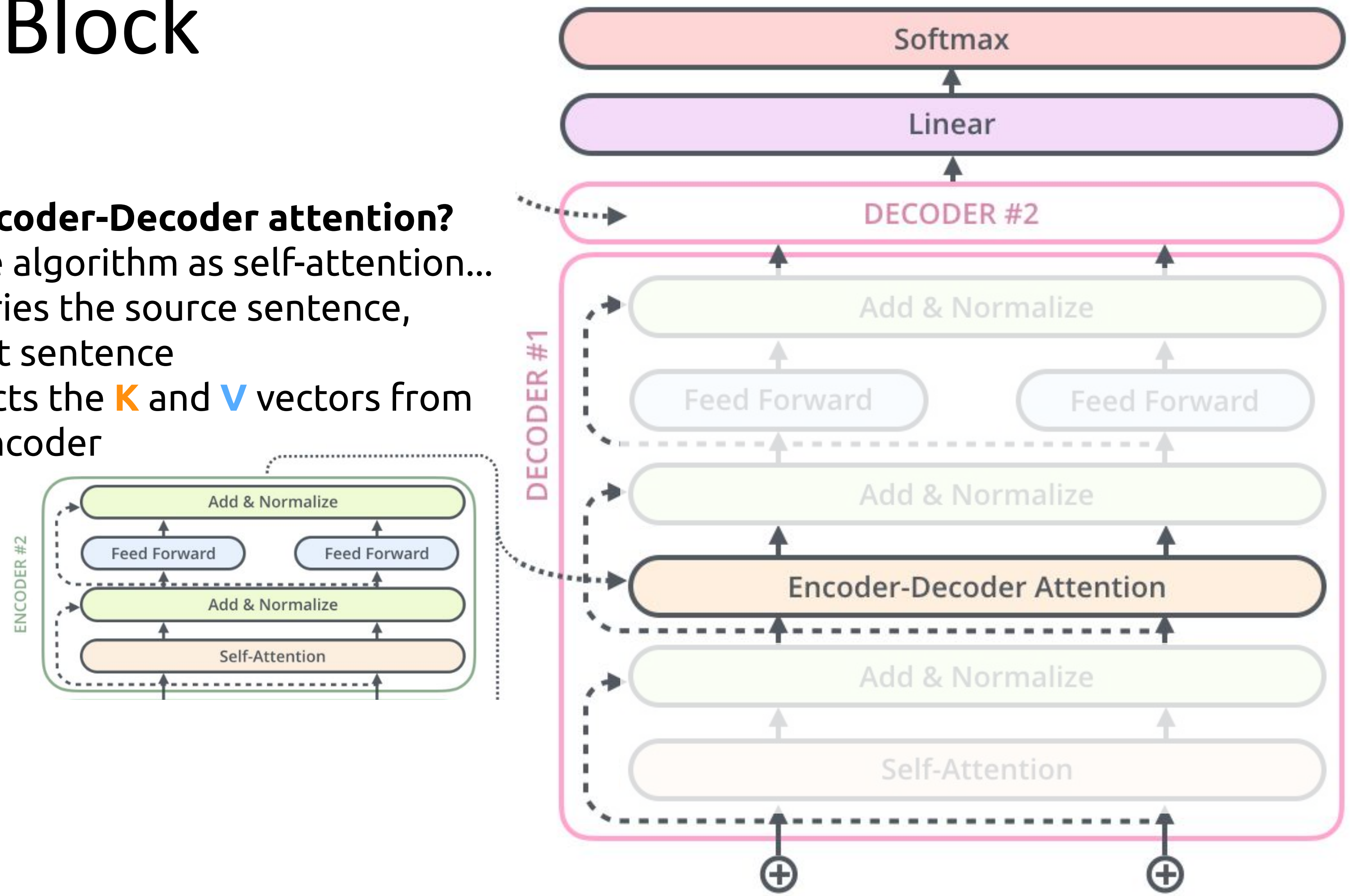
Decoder Block

How to implement Encoder-Decoder attention?

- It's exactly the same algorithm as self-attention...
- ...except that it queries the source sentence, instead of the target sentence
- Specifically, it extracts the K and V vectors from the output of the encoder



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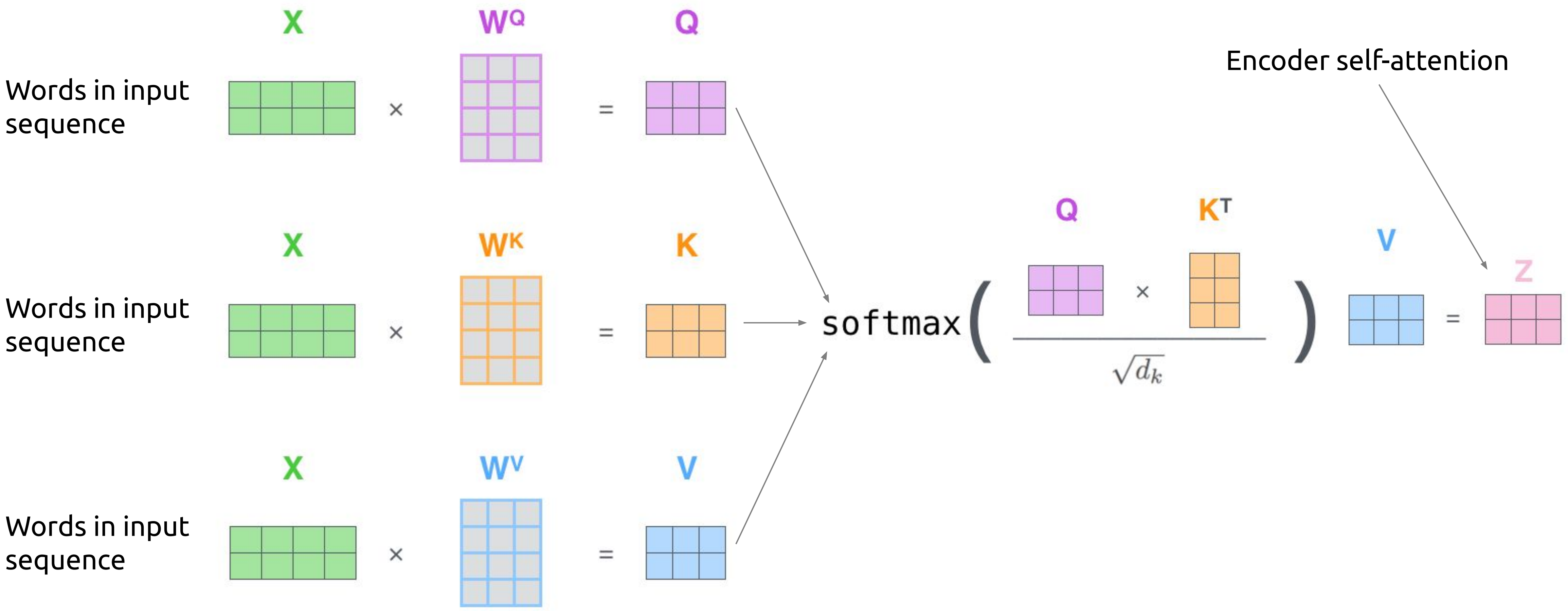
Encoder Self-Attention

What do we change for Encoder-Decoder attention?

What will be our query?
What will be our keys and values?



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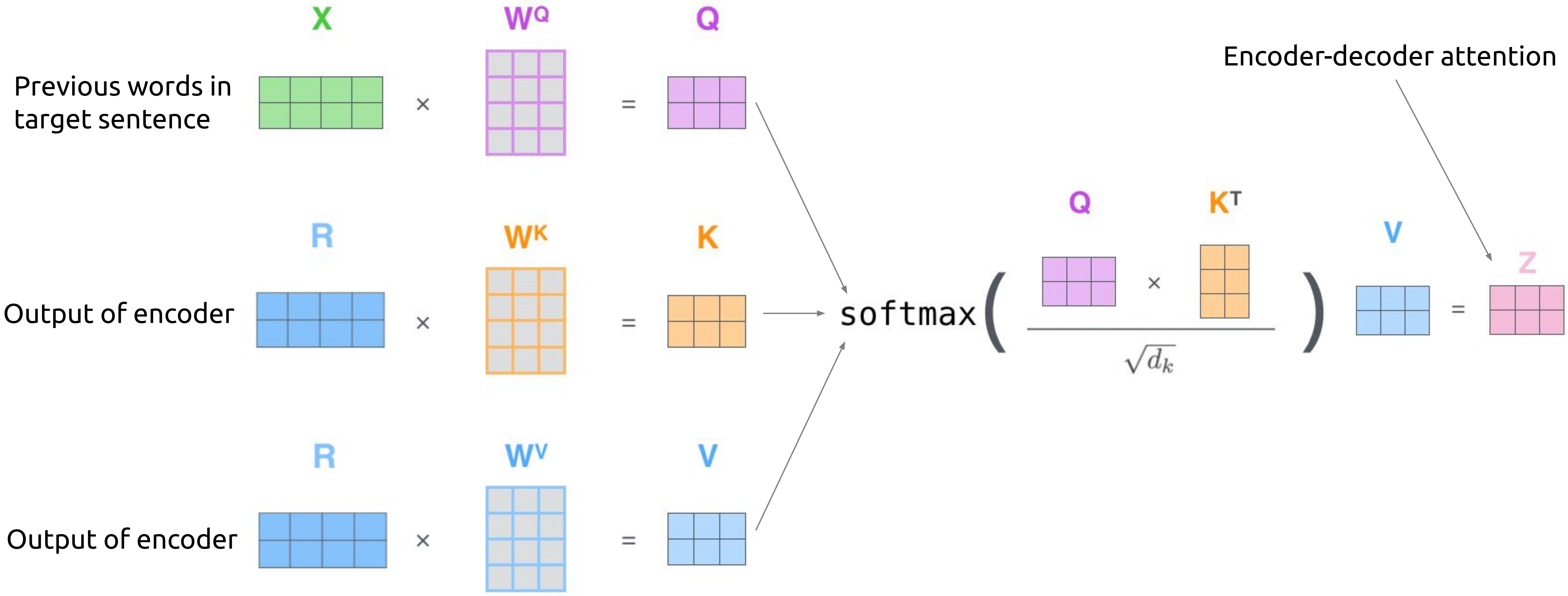
Encoder-Decoder Attention



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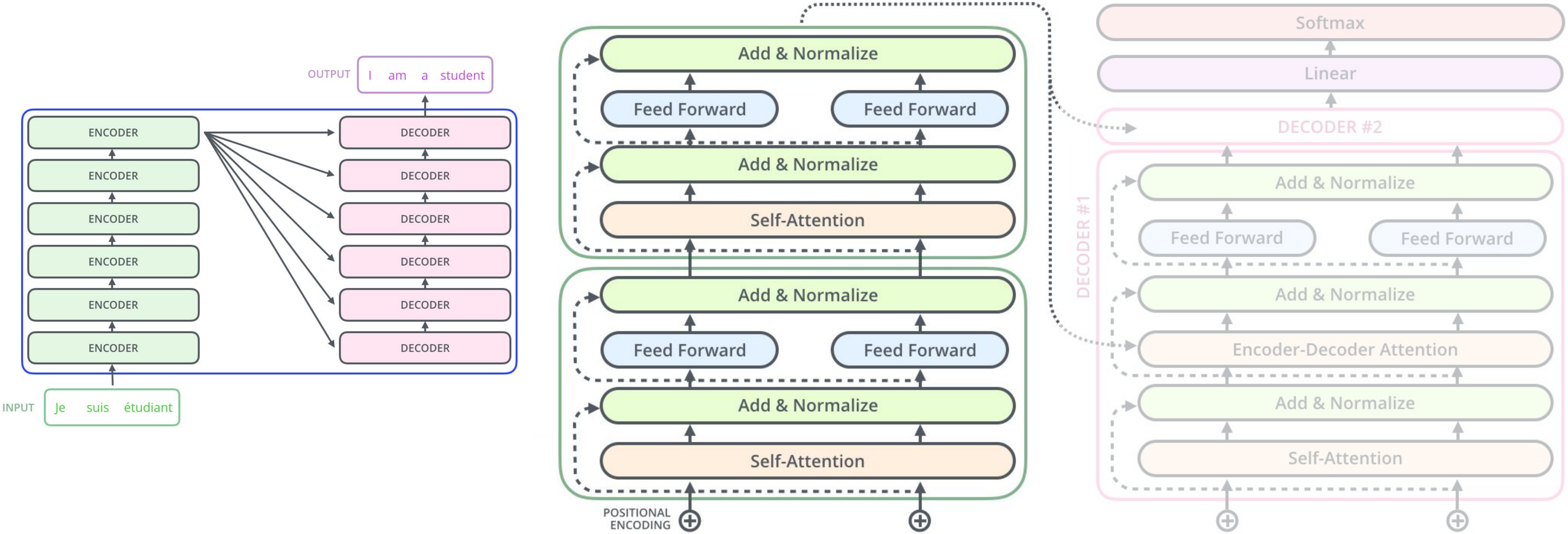
Encoders and Decoders Together



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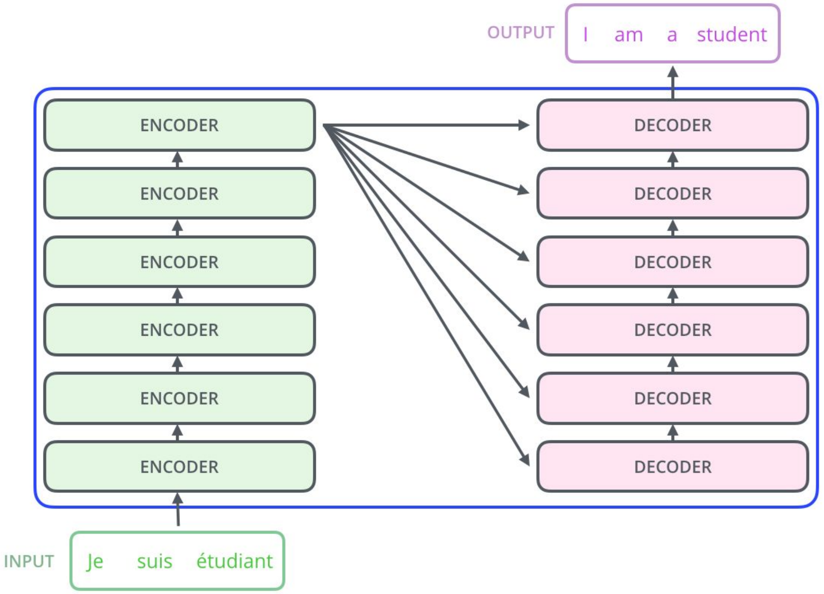
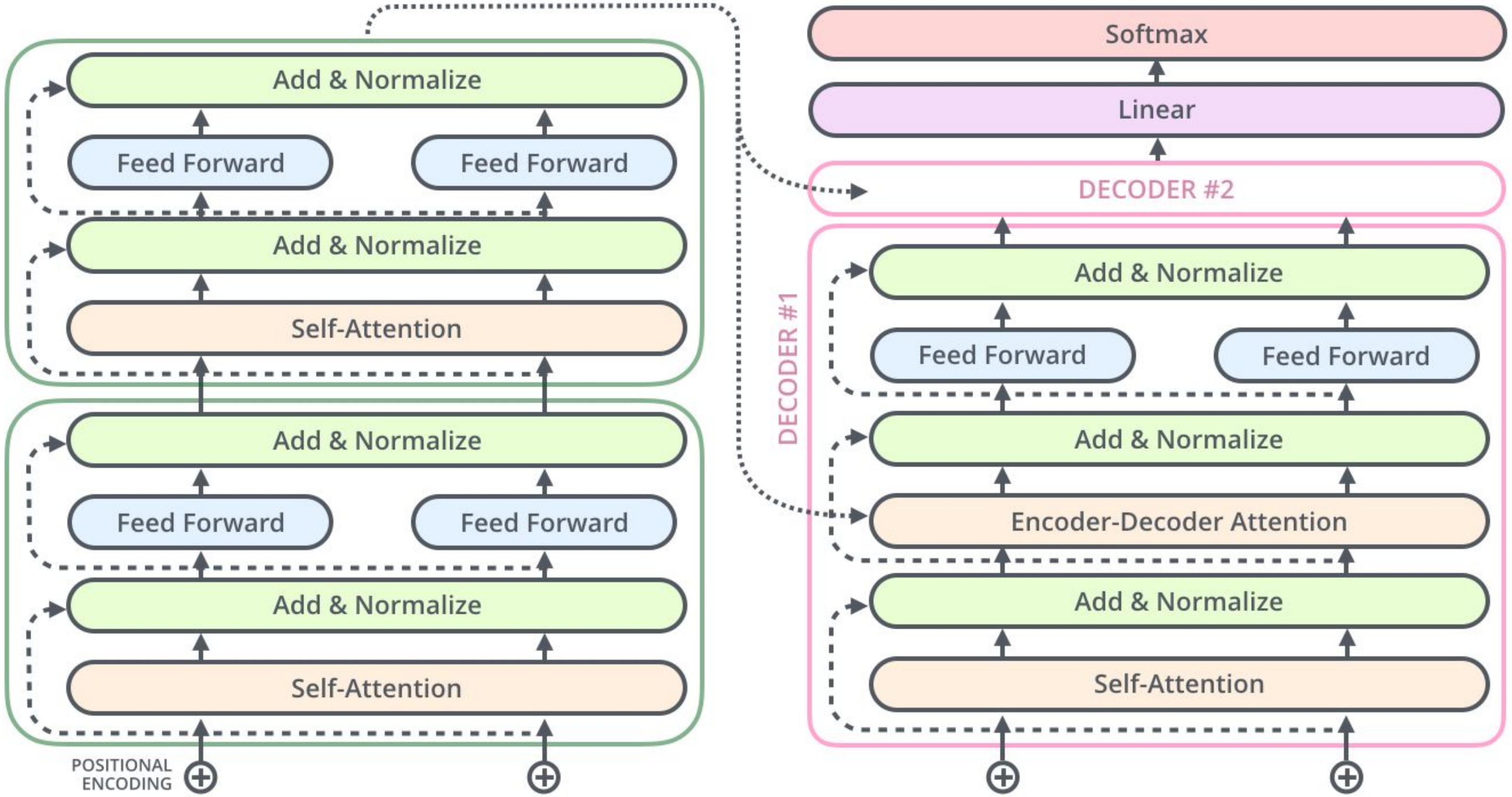
Any questions?

Encoders and Decoders Together





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Side-note: Masking

Implementing the decoder side of self-attention uses ***masking**.*

Masking is a technique used to nullify certain words before they are passed to the model to prevent the model from seeing them.

The reason for this stems from the fact that for the decoder, we would like to pass the entire sequence of *previous* words.

In practice, it is a lot easier to instead pass it the entire sequence, and mask out all of the words that the model isn't allowed to see.

Your next assignment (transformer part)

i.e. why you shouldn't be scared, even though the architecture we just described is pretty complicated...

Transformers part in Assignment 5

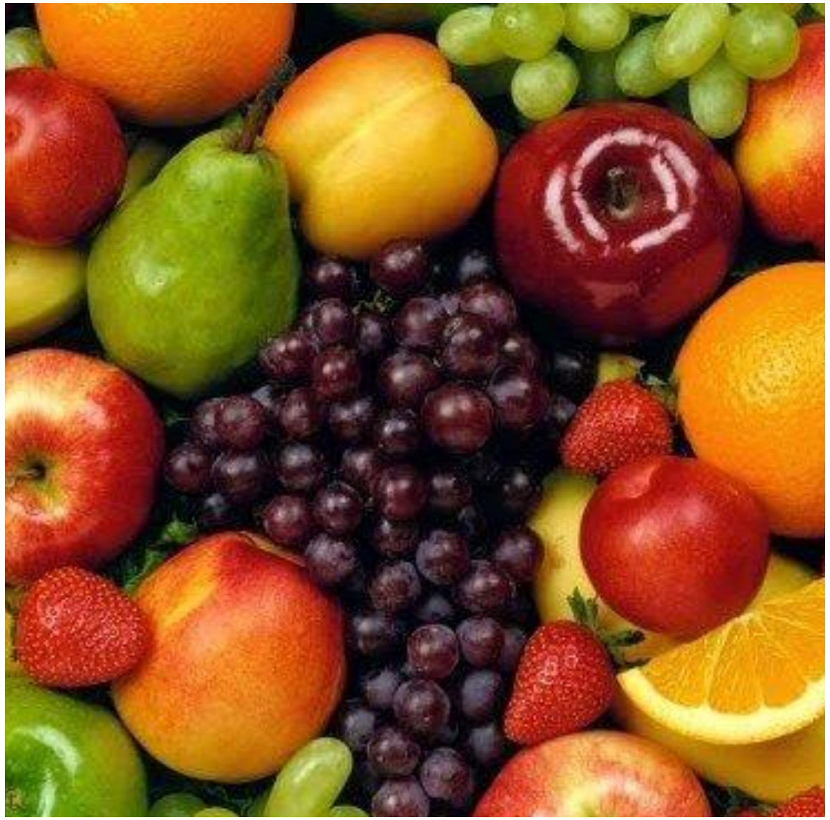
You will be implementing part of the transformer network (decoder) yourselves as part of the next assignment!

Specifically, you will be asked to implement the *Self-Attention* portion of the pipeline.

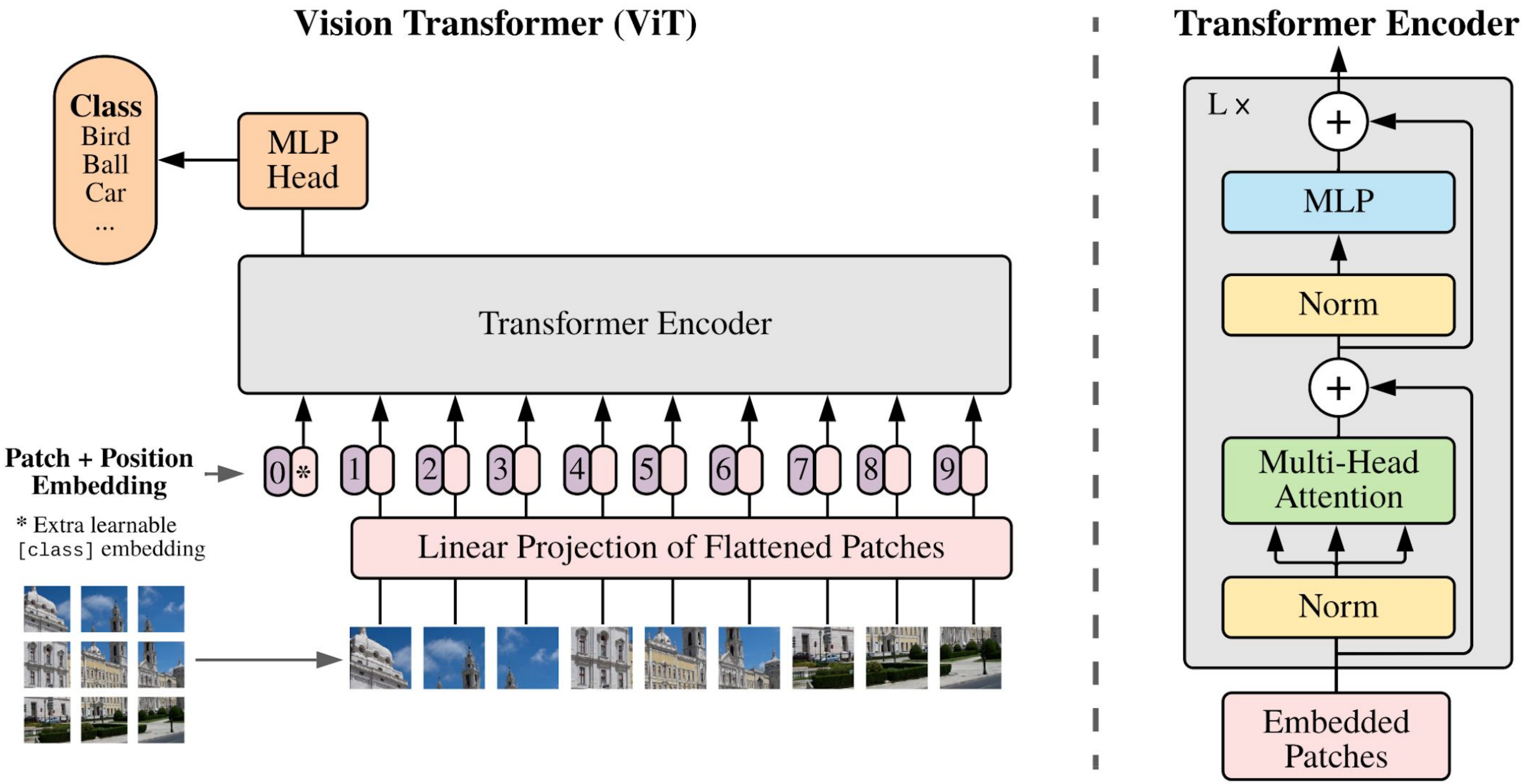
For 2470 students, you will also be required to implement *Multi-headed* attention that uses your implementation of *Self-Attention*

Can we use Transformers for Image classification?

How?



Transformers for Image classification



An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale
ICLR 2021

Today’s goal – learn about other components of Transformers and scaling of deep learning models

(1) Multi-headed attention and other improvements

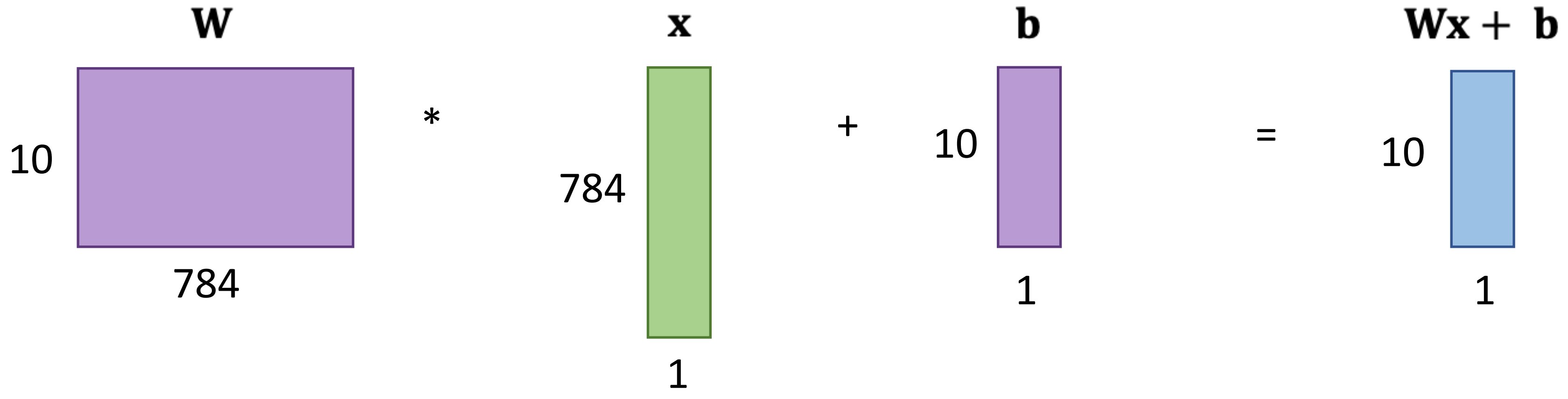
(2) Decoder details

(3) Scaling deep learning models

Your first assignments == small DL systems

MNIST digit classification

- Model size: 7850 parameters
  - 28*28*10 = 7840 weights
  - 10 biases

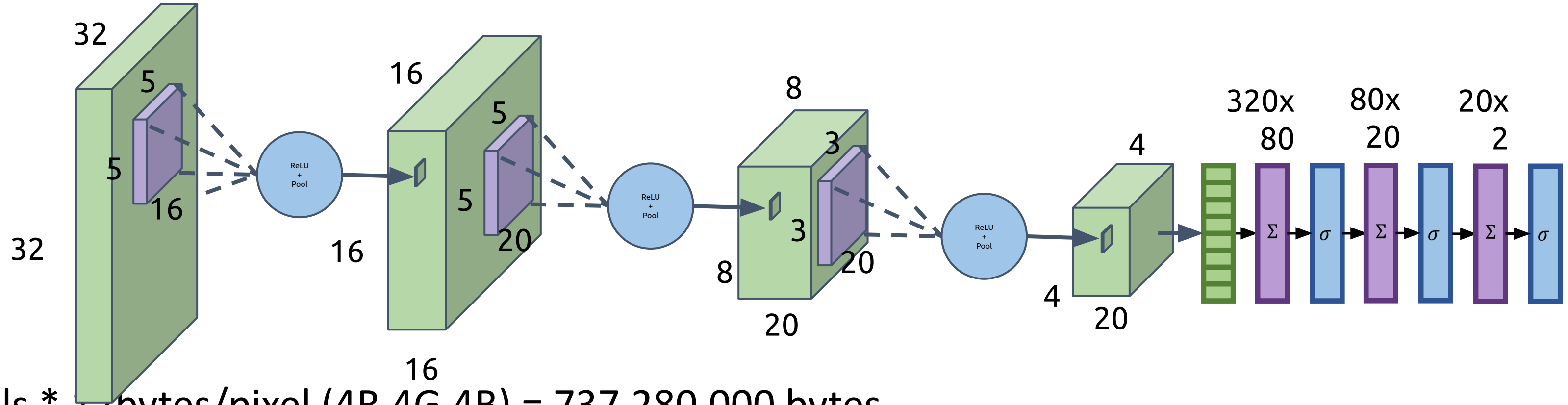


- Data size: 188.16 MB
  - 60,000 images * 28x28 pixels * 4bytes/pixel = 188,160,000 bytes

Your first assignments == small DL systems

CIFAR image classification

- Model size: 40,198 parameters
  - C1: 5*5*3*16 = 1200 weights, 16 biases
  - C2: 5*5*16*20 = 8000 weights, 20 biases
  - C3: 3*3*20*20 = 3600 weights, 20 biases
  - FC1: 320*80 = 25,600 weights, 80 biases
  - FC2: 80*20 = 1600 weights, 20 biases
  - FC3: 20*2 = 40 weights, 2 biases



- Data size: 737.28 MB
  - 60,000 images * 32x32 pixels * 12bytes/pixel (4R,4G,4B) = 737,280,000 bytes

Now, things are starting to get bigger...

question @1219

"Allocation of 122880000 exceeds 10% of free system memory." Warning

"Allocation of 10628279200 exceeds 10% of free system memory" #1079

Anonymous
3 days ago in Assignments – HW3 Language Models

PIN STAR WATCH 112 VIEWS

What solved this bug?

I think the problem is most likely because you're not batching in the test function! Since the testing dataset is quite large for this assignment, the CPU is unable to store all of the data in memory, causing a memory allocation error.

Comment Edit Delete Endorse •••

What happened, here?

Running the model on the entire dataset at once exhausts the autograder VM's system memory, causing it to crash

What to do when DL systems get ***big***

- Big = big data
- Big = big model

Scaling: Some Key Questions

- What do I do when my dataset won't fit in memory?
- Can I use multiple processors to train faster?
- Can I use multiple GPUs to train faster (or train bigger models?)
- Can I use multiple machines to train faster (or train bigger models?)

Scaling: Some Key Questions

- **What do I do when my dataset won't fit in memory?**
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Data won’t fit in memory?

- What if our dataset gets so big we can’t even load it all into memory?
- **Answer: Load, process, and discard smaller chunks of it.**
  - In Python, we don’t explicitly discard or “free” memory; the built-in garbage collector takes care of that for us.
- Typically, load the data one batch at a time.

In Tensorflow: tf.data.Dataset

TensorFlow > API > TensorFlow Core v2.3.0 > Python

tf.data.Dataset

See Stable | See Nightly

TensorFlow 1 version | View source on GitHub

Represents a potentially large set of elements.

https://www.tensorflow.org/api_docs/python/tf/data/Dataset

Example: Reading in batches of images

```
# Create a Dataset that contains all .jpg files
# in a directory
dir_path = dir_name + '/*.jpg'
dataset = tf.data.Dataset.list_files(dir_path)

# Apply a function that will read the contents of #
each file into a tensor
dataset =
dataset.map(map_func=load_and_process_image)

# Load up data in batches
dataset = dataset.batch(batch_size)

# Iterate over dataset
for i, batch in enumerate(dataset):
   # processing code goes here
```

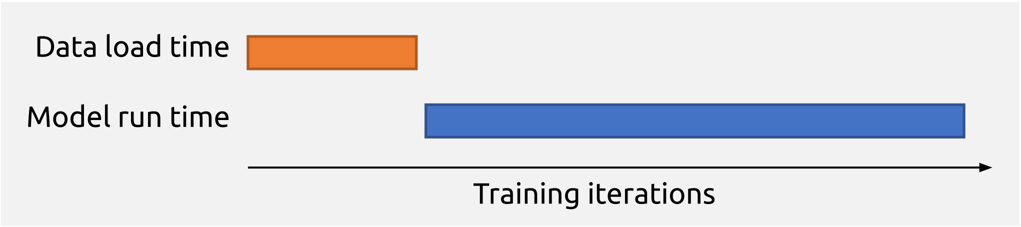
```
def load_and_process_image(file_path):
   # Load image
   image = tf.io.decode_jpeg(
      tf.io.read_file(file_path),
      channels=3)

   # Convert image to normalized float [0, 1]
   image = tf.image.convert_image_dtype(
      image,
      tf.float32)

   # Rescale data to range (-1, 1)
   image = (image - 0.5) * 2
   return image
```

Consequences of batched data loading

- Great! We can train/test on all our data without blowing out memory
- But, there's a price to pay:
  - More time loading data, in general
  - Disk is idle while model is running

What is the price?

Loading data all at once:



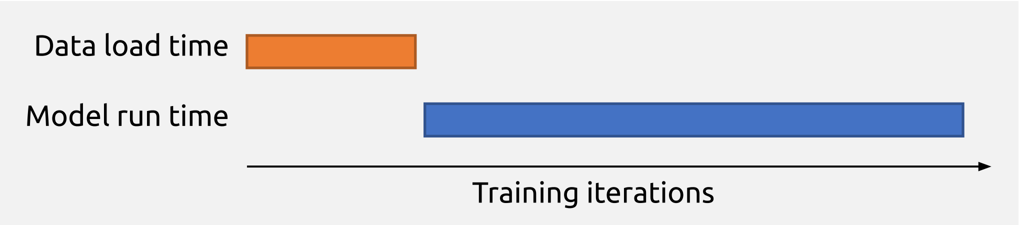
Batched data loading:

Consequences of batched data loading

- Great! We can train/test on all our data without blowing out memory
- But, there's a price to pay:
  - More time loading data, in general
  - Disk is idle while model is running
- ***What can we do about this?***

Next class!

Loading data all at once:



Batched data loading:

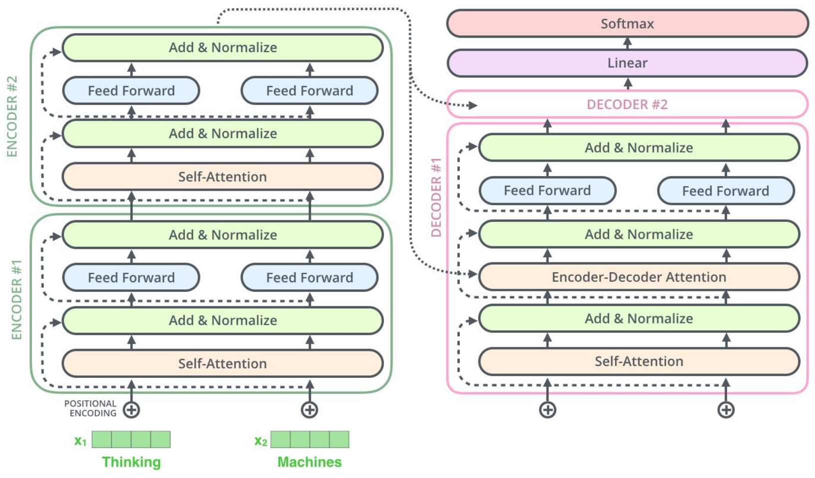
Recap

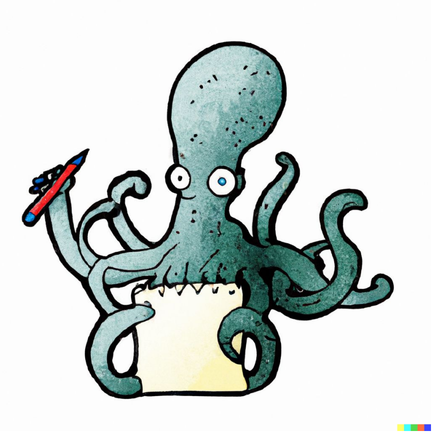
Seq-to-seq using transformers

Multi-headed attention

Residual connections + normalization

Decoder





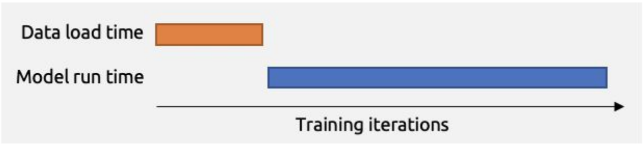
Scaling deep learning models

Data and models getting big!

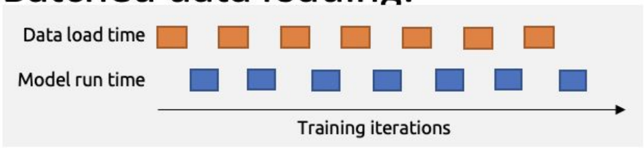
Memory and speed constraints

Batching can help! (with a price)

Loading data all at once:



Batched data loading:



Helpful Resources

Visuals for this section were taken from:
http://jalammar.github.io/illustrated-transformer/

The “Attention is All You Need” paper:

https://arxiv.org/abs/1706.03762