

# CSC413/2516 Lecture 8: Transformers and Autoregressive models

Jimmy Ba and Bo Wang

a.k.a. Attention is All You Need!

a.k.a. Good bye, RNN!

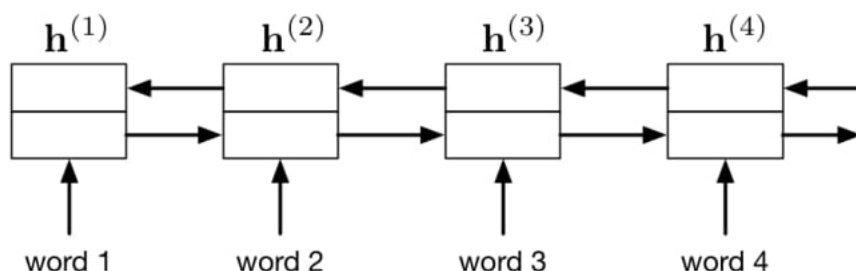


# Overview

- We have seen a few RNN-based sequence prediction models.
- It is still challenging to generate long sequences, when the decoders only has access to the final hidden states from the encoder.
  - Machine translation: it's hard to summarize long sentences in a single vector, so let's allow the decoder peek at the input.
  - Vision: have a network glance at one part of an image at a time, so that we can understand what information it's using
- We also introduced **attention** coupled with RNN that drastically improves the performance on the long sequences.

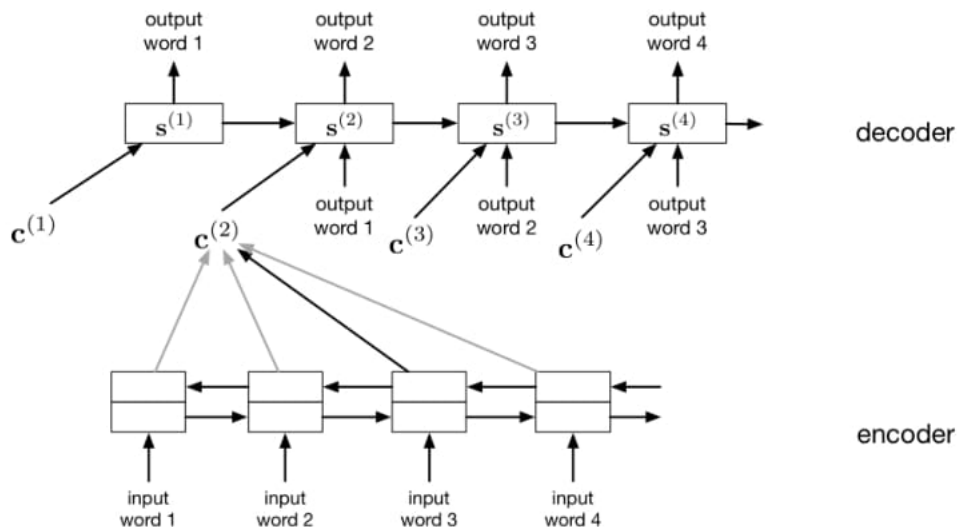
# Overview: Attention-Based Machine Translation

- The model has both an encoder and a decoder. The encoder computes an **annotation** of each word in the input.
- It takes the form of a **bidirectional RNN**. This just means we have an RNN that runs forwards and an RNN that runs backwards, and we concatenate their hidden vectors.
  - The idea: information earlier or later in the sentence can help disambiguate a word, so we need both directions.
  - The RNN uses an LSTM-like architecture called gated recurrent units.



# Overview: Attention-Based Machine Translation

- The decoder network is also an RNN. Like the encoder/decoder translation model, it makes predictions one word at a time, and its predictions are fed back in as inputs.
- The difference is that it also receives a **context vector**  $c^{(t)}$  at each time step, which is computed by attending to the inputs.



# Overview: Attention-Based Machine Translation

- The context vector is computed as a weighted average of the encoder's annotations.

$$\mathbf{c}^{(i)} = \sum_j \alpha_{ij} \mathbf{h}^{(j)}$$

- The attention weights are computed as a softmax, where the inputs depend on the annotation and the decoder's state:

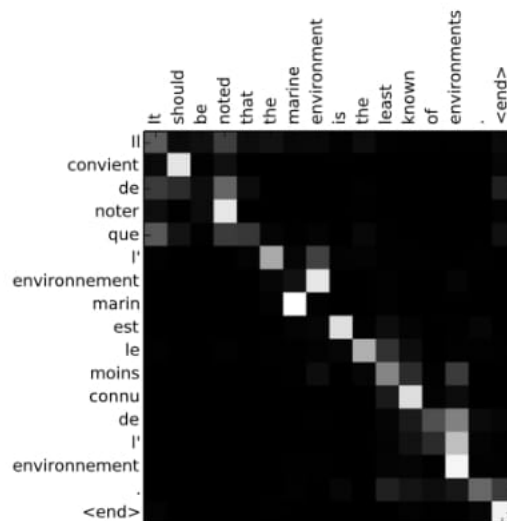
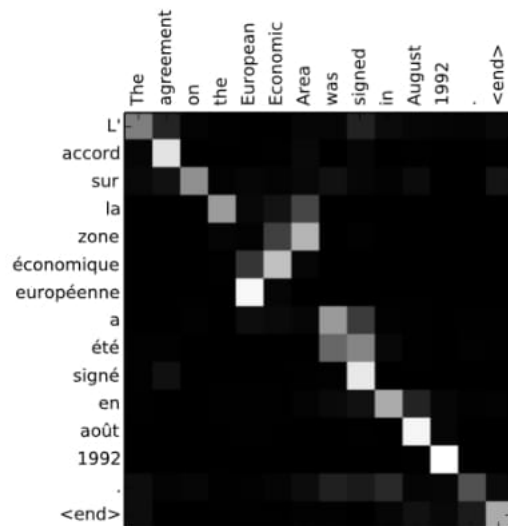
$$\alpha_{ij} = \frac{\exp(\tilde{\alpha}_{ij})}{\sum_{j'} \exp(\tilde{\alpha}_{ij'})}$$

$$\tilde{\alpha}_{ij} = f(\mathbf{s}^{(i-1)}, \mathbf{h}^{(j)})$$

- Note that the attention function,  $f$  depends on the annotation vector, rather than the position in the sentence. This means it's a form of **content-based addressing**.
  - My language model tells me the next word should be an adjective.  
Find me an adjective in the input.

# Overview: Attention-Based Machine Translation

- Here's a visualization of the attention maps at each time step.



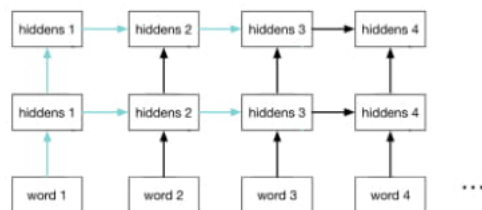
- Nothing forces the model to go linearly through the input sentence, but somehow it learns to do it.
  - It's not perfectly linear — e.g., French adjectives can come after the nouns.

# Limitations of Attention in RNN

1. It is hard to generalize to long sequences.
2. It is difficult to parallel the computing.
3. It does not fully exploit the contextual information.

# Attention is All You Need (Transformers)

- We would like our model to have access to the entire history at the hidden layers.
- Previously we achieve this by having the recurrent connections.





# Attention is All You Need (Transformers)

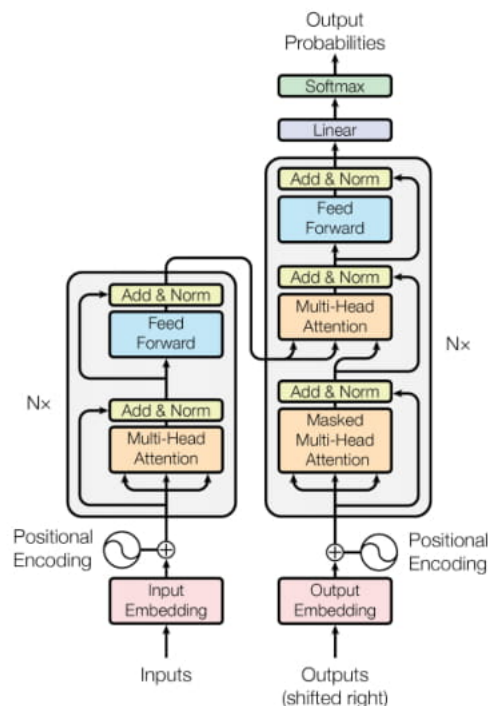
- We would like our model to have access to the entire history at the hidden layers.
- Previously we achieve this by having the recurrent connections.



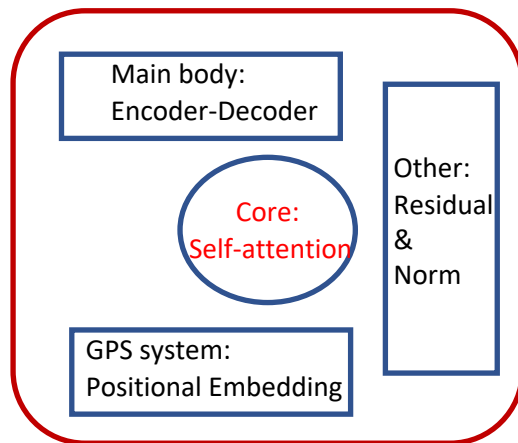
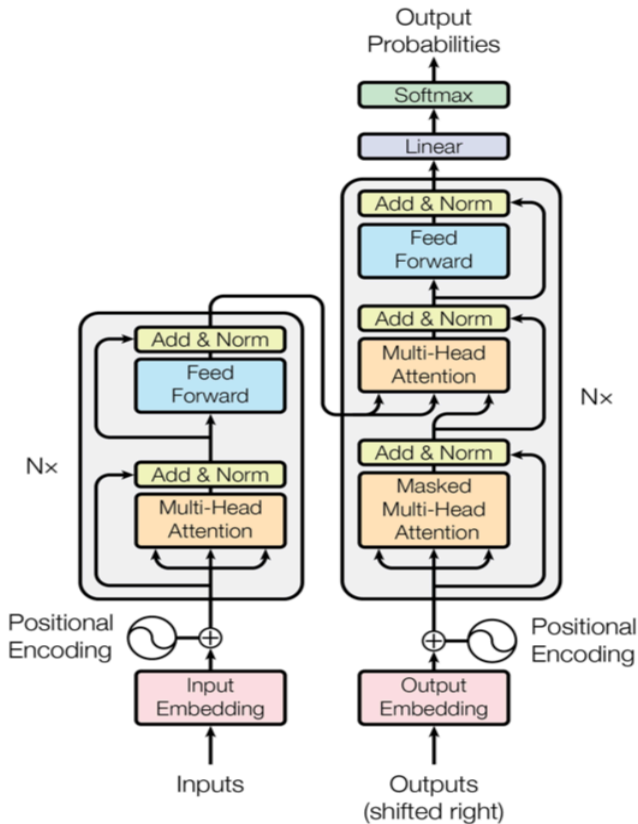
- **Core idea:** use attention to aggregate the context information by attending to one or a few important inputs from the past history.

# Attention is All You Need

- We will now study a very successful neural network architecture for machine translation in the last few years:  
*Vaswani, Ashish, et al. "Attention is all you need." Advances in Neural Information Processing Systems. 2017.*
- “**Transformer**” has a encoder-decoder architecture similar to the previous sequence-to-sequence RNN models.
  - except all the recurrent connections are replaced by the attention modules.



# Disassemble the Transformers

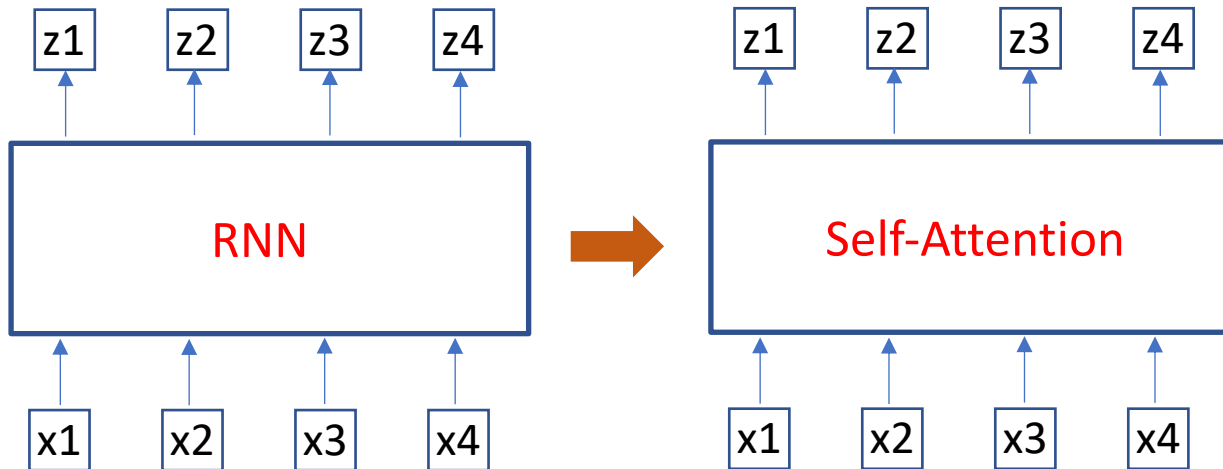


# The core of Transformers: Self-attention layer

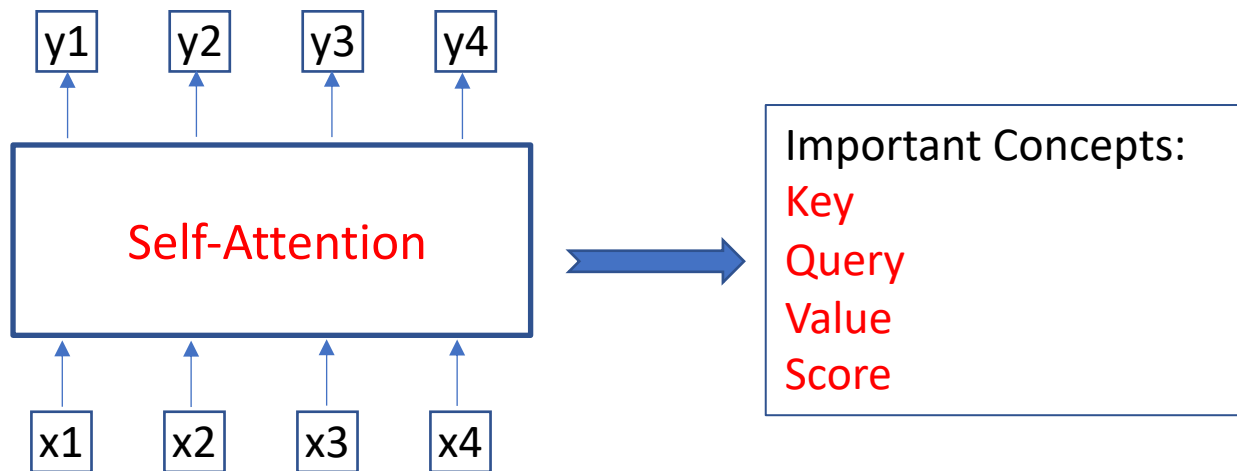
## Sequence-to-Sequence Modeling

### Key Difference:

1.  $z$  is obtained based on the whole input sequence
2.  $z$  can be computed parallelly



# The core of Transformers: Self-attention layer



# Example Time: Self-attention layer

## Step1: Calculate Queries, Keys, Values

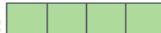
Input

Thinking


Machines

Embedding

$x_1$  

$x_2$  

Queries


$q_1$  


$q_2$  

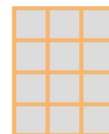


$W_Q$

Keys

$k_1$  

$k_2$  



$W_K$

Values

$v_1$  

$v_2$  



$W_V$

Source: [Jay Alammar](#)

# Example Time: Self-attention layer

## How to understand the queries, keys and values in attention?

The key/value/query formulation of attention is from the paper [Attention Is All You Need](#).

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How should one understand the queries, keys, and values

The key/value/query concepts come from retrieval systems. For example, when you type a query to search for some video on Youtube, the search engine will map your **query** against a set of **keys** (video title, description etc.) associated with candidate videos in the database, then present you the best matched videos (**values**).

The attention operation turns out can be thought of as a retrieval process as well, so the key/value/query concepts also apply here. (BTW the above example is just a toy system for illustration, in practice search engines and recommendation systems are much more complex.)

<https://stats.stackexchange.com/questions/421935/what-exactly-are-keys-queries-and-values-in-attention-mechanisms>

# Example Time: Self-attention layer

Step2: Calculate 'Scaled Dot-Product Attention' scores

Input

Embedding

Queries

Keys

Values

Score

Divide by 8 (  $\sqrt{d_k}$  )

Softmax

Thinking

$x_1$  

$q_1$  

$k_1$  

$v_1$  

$q_1 \cdot k_1 = 112$

14

0.88

Machines

$x_2$  

$q_2$  

$k_2$  

$v_2$  

$q_1 \cdot k_2 = 96$

12

0.12

Source: [Jay Alammar](#)



# Example Time: Self-attention layer

## Step3: Calculate the output of self-attention layer

Input

Embedding

Queries

Keys

Values

Score

Divide by 8 (  $\sqrt{d_k}$  )

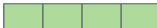
Softmax

Softmax

X  
Value

Sum

Thinking

$x_1$  

$q_1$  

$k_1$  

$v_1$  

$q_1 \cdot k_1 = 112$

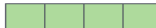
14

0.88

$v_1$  

$z_1$  

Machines

$x_2$  

$q_2$  

$k_2$  

$v_2$  

$q_2 \cdot k_2 = 96$

12

0.12

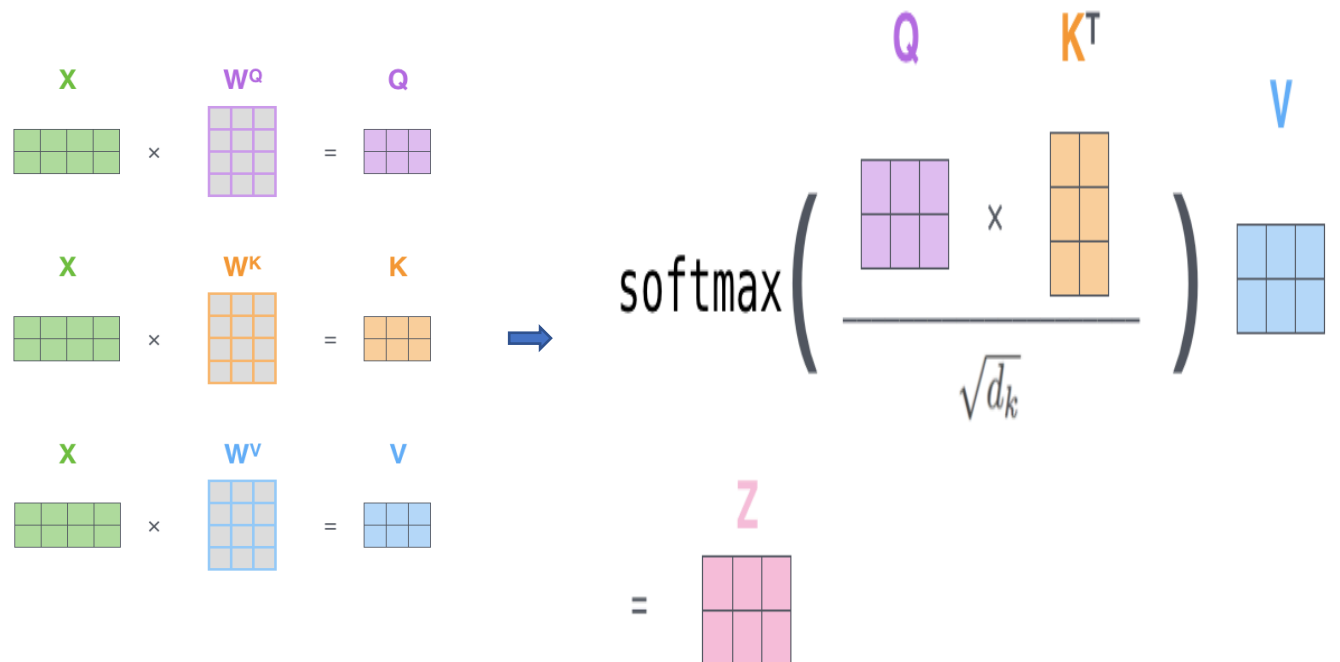
$v_2$  

$z_2$  

Source: [Jay Alammar](#)

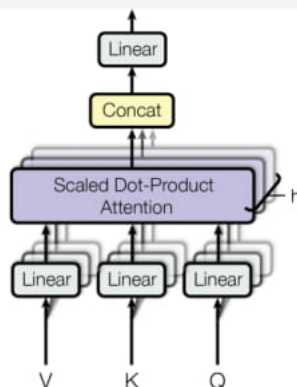
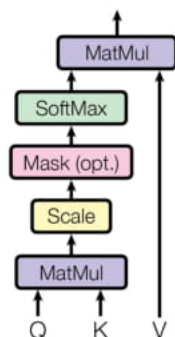
# Example Time: Self-attention layer

## Matrix Form of Self-Attention



Source: [Jay Alammar](#)

# Attention is All You Need



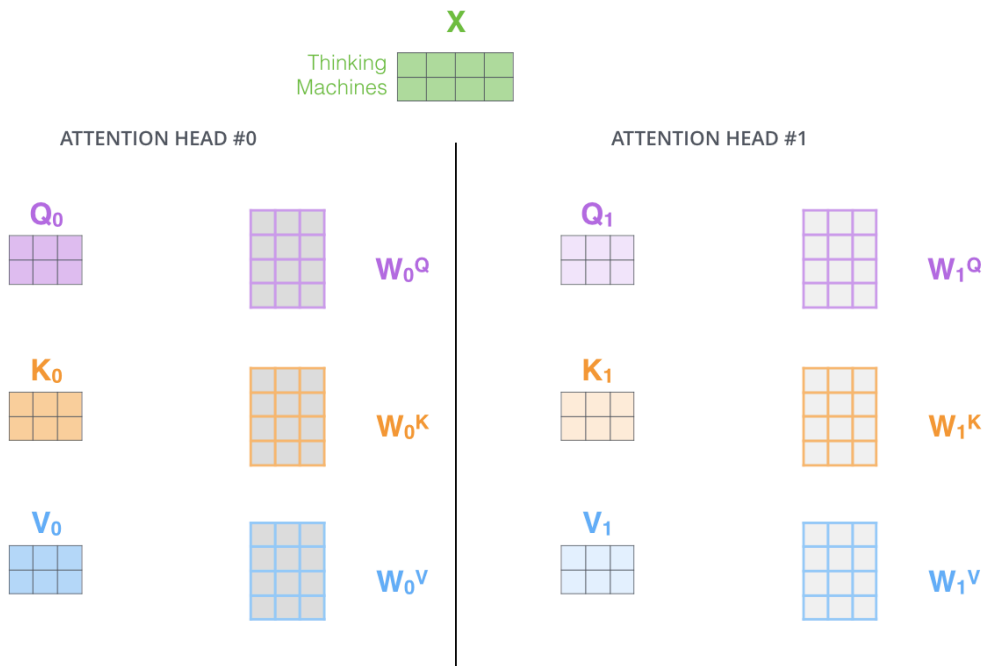
- The Scaled Dot-Product Attention attends to one or few entries in the input key-value pairs.
  - Humans can attend to many things simultaneously.
- The idea: apply Scaled Dot-Product Attention multiple times on the linearly transformed inputs.

$$\text{MultiHead}(Q, K, V) = \text{concat}(\mathbf{c}_1, \dots, \mathbf{c}_h) W^O,$$

$$\mathbf{c}_i = \text{attention}(QW_i^Q, KW_i^K, VW_i^V).$$

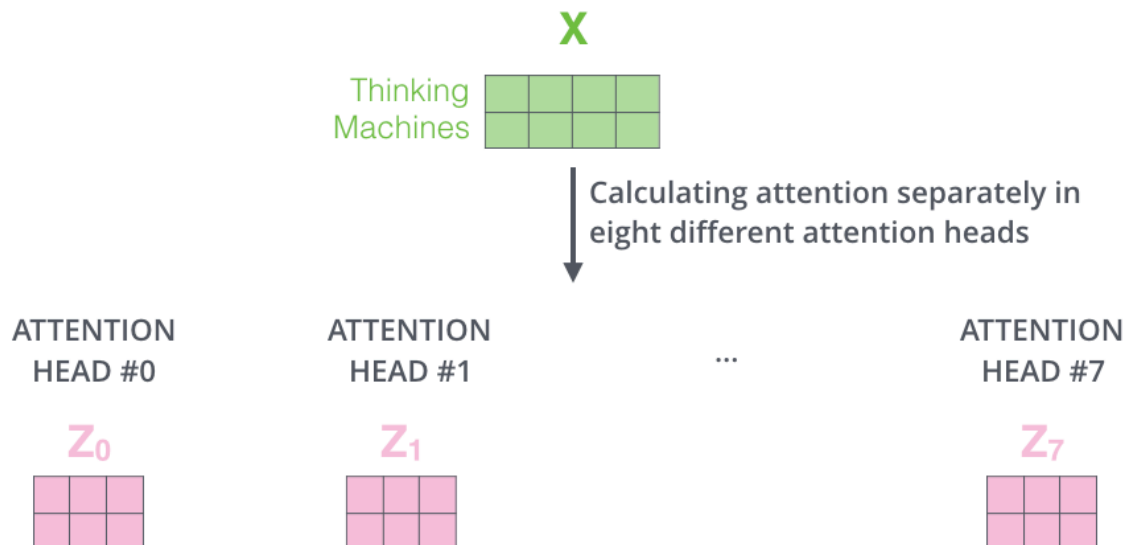
# A bit of extension: Multi-Head Attention

The beast with multiple heads --- Step 1 : Calculate multiple keys, queries, and values



# A bit of extension: Multi-Head Attention

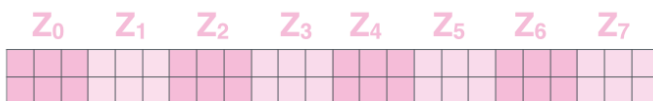
The beast with multiple heads --- Step 2 : Calculate multiple attentions



# A bit of extension: Multi-Head Attention

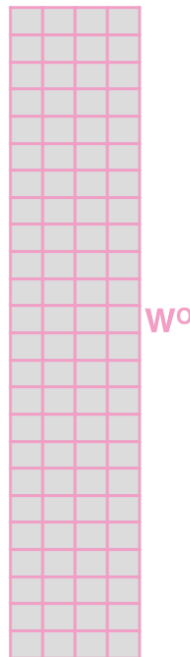
## The beast with multiple heads --- Step 3 : Concatenate and Compress

1) Concatenate all the attention heads



2) Multiply with a weight matrix  $W^O$  that was trained jointly with the model

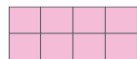
X



3) The result would be the  $Z$  matrix that captures information from all the attention heads. We can send this forward to the FFNN

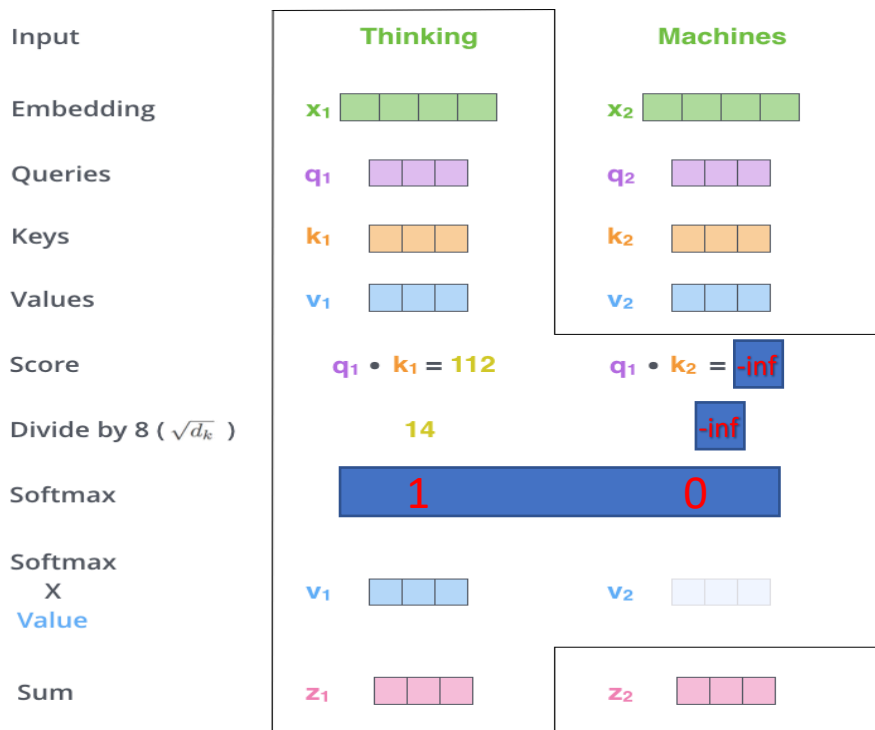
$Z$

=



# A bit more of extension: Masked Multi-Head Attention

Sometimes you don't want to attend to future sequences, just mask them.



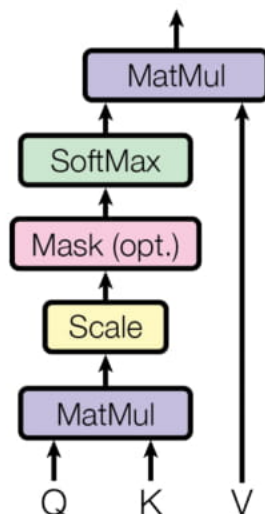
## Summary: Self-attention layer

- In general, Attention mappings can be described as a function of a query and a set of key-value pairs.
- Transformers use a "Scaled Dot-Product Attention" to obtain the context vector:

$$\mathbf{c}^{(t)} = \text{attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_K}}\right) V,$$

scaled by square root of the key dimension  $d_K$ .

- Invalid connections to the future inputs are masked out to preserve the autoregressive property.

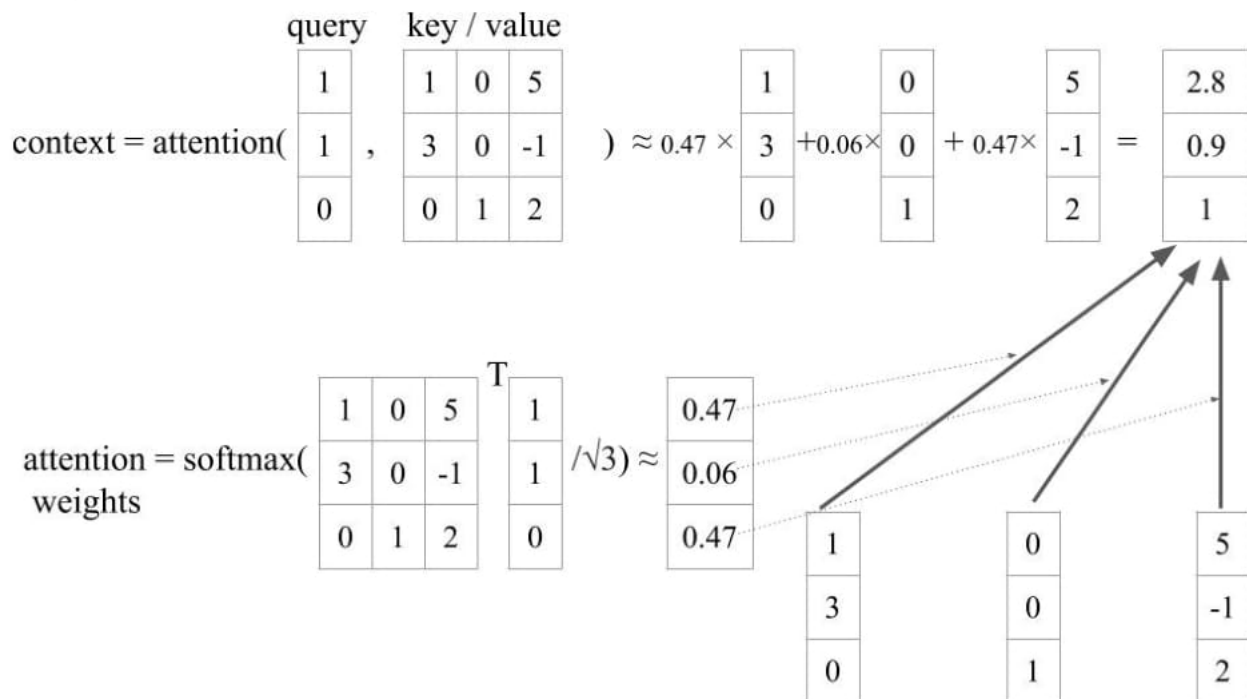




# More Example: Scaled Dot-Product

$$\mathbf{c}^{(t)} = \text{attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_K}}\right) V$$

Scale the un-normalized attention weights by the square root of the vector length:



## More Example: Different Keys

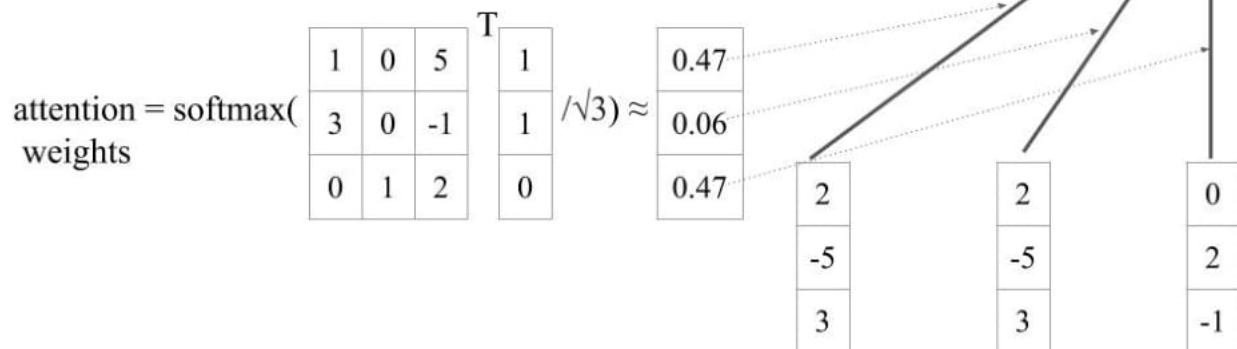
$$\mathbf{c}^{(t)} = \text{attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_K}}\right) V$$

When the key and the value vectors are different:

$$\text{context} = \text{attention}\left(\begin{array}{|c|} \hline \text{query} \\ \hline \begin{array}{|c|} \hline 1 \\ \hline \end{array} \\ \hline \end{array}, \begin{array}{|c|} \hline \text{key} \\ \hline \begin{array}{|c|c|c|} \hline 1 & 0 & 5 \\ \hline \end{array} \\ \hline \end{array}, \begin{array}{|c|} \hline \text{value} \\ \hline \begin{array}{|c|c|c|} \hline 2 & 2 & 0 \\ \hline \end{array} \\ \hline \end{array}\right) \approx 0.47 \times \begin{array}{|c|} \hline 2 \\ \hline \end{array} + 0.06 \times \begin{array}{|c|} \hline 2 \\ \hline \end{array} + 0.47 \times \begin{array}{|c|} \hline 0 \\ \hline \end{array} = \begin{array}{|c|} \hline 1.06 \\ \hline \end{array}$$

$$\begin{array}{|c|} \hline 1 \\ \hline \end{array} \approx 0.47 \times \begin{array}{|c|} \hline -5 \\ \hline \end{array} + 0.06 \times \begin{array}{|c|} \hline -5 \\ \hline \end{array} + 0.47 \times \begin{array}{|c|} \hline 2 \\ \hline \end{array} = \begin{array}{|c|} \hline -1.71 \\ \hline \end{array}$$

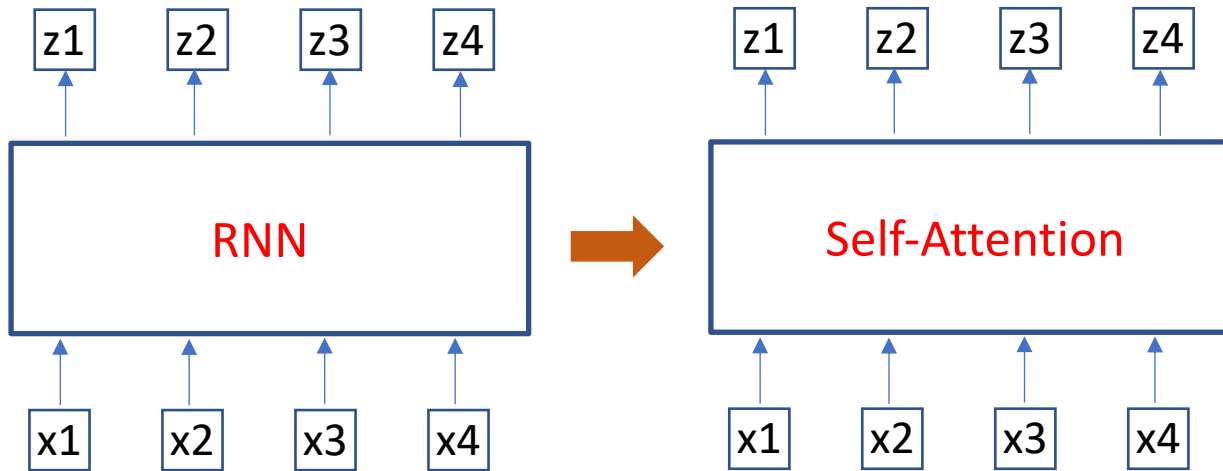
$$\begin{array}{|c|} \hline 0 \\ \hline \end{array} \approx 0.47 \times \begin{array}{|c|} \hline 3 \\ \hline \end{array} + 0.06 \times \begin{array}{|c|} \hline 3 \\ \hline \end{array} + 0.47 \times \begin{array}{|c|} \hline -1 \\ \hline \end{array} = \begin{array}{|c|} \hline 1.12 \\ \hline \end{array}$$



# The core of Transformers: Self-attention layer

## Key Takeaway:

1. Self-attention learns how/where to attend within the whole input sequences.
2. Self-attention can be computed parallelly
3.  $F(S) = F(R) * (1 + \epsilon_{pi})$



# GPS system: Positional Encoding

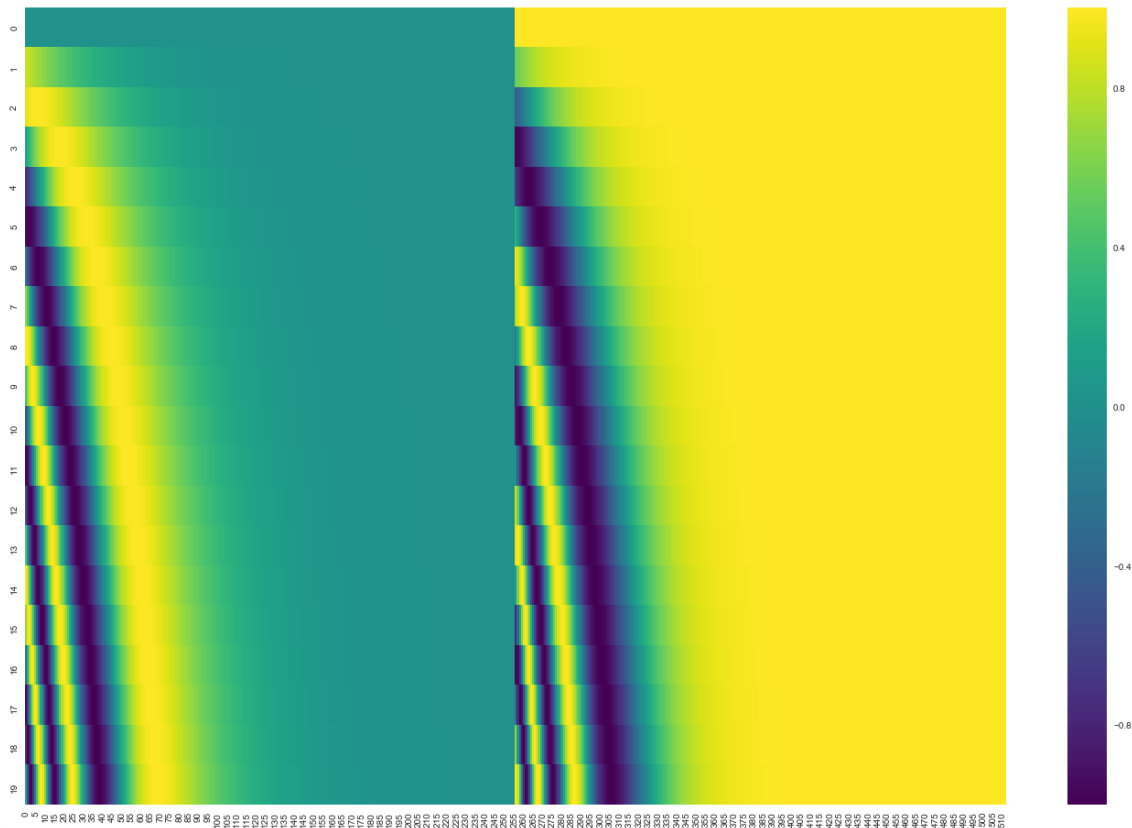
- Unlike RNNs and CNNs encoders, the attention encoder outputs do not depend on the order of the inputs. (Why?)
- The order of the sequence conveys important information for the machine translation tasks and language modeling.
- The idea: add positional information of a input token in the sequence into the input embedding vectors.

$$PE_{pos,2i} = \sin(pos/10000^{2i/d_{emb}}),$$

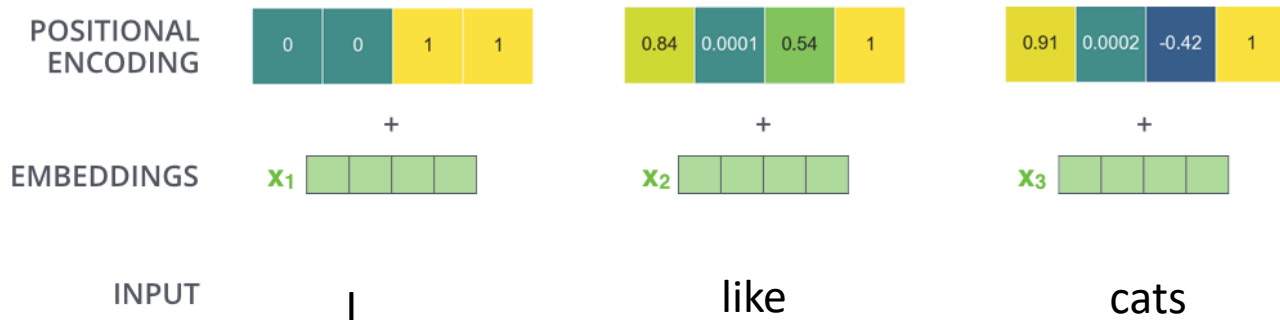
$$PE_{pos,2i+1} = \cos(pos/10000^{2i/d_{emb}}),$$

- The final input embeddings are the concatenation of the learnable embedding and the positional encoding.

# GPS system: Positional Encoding

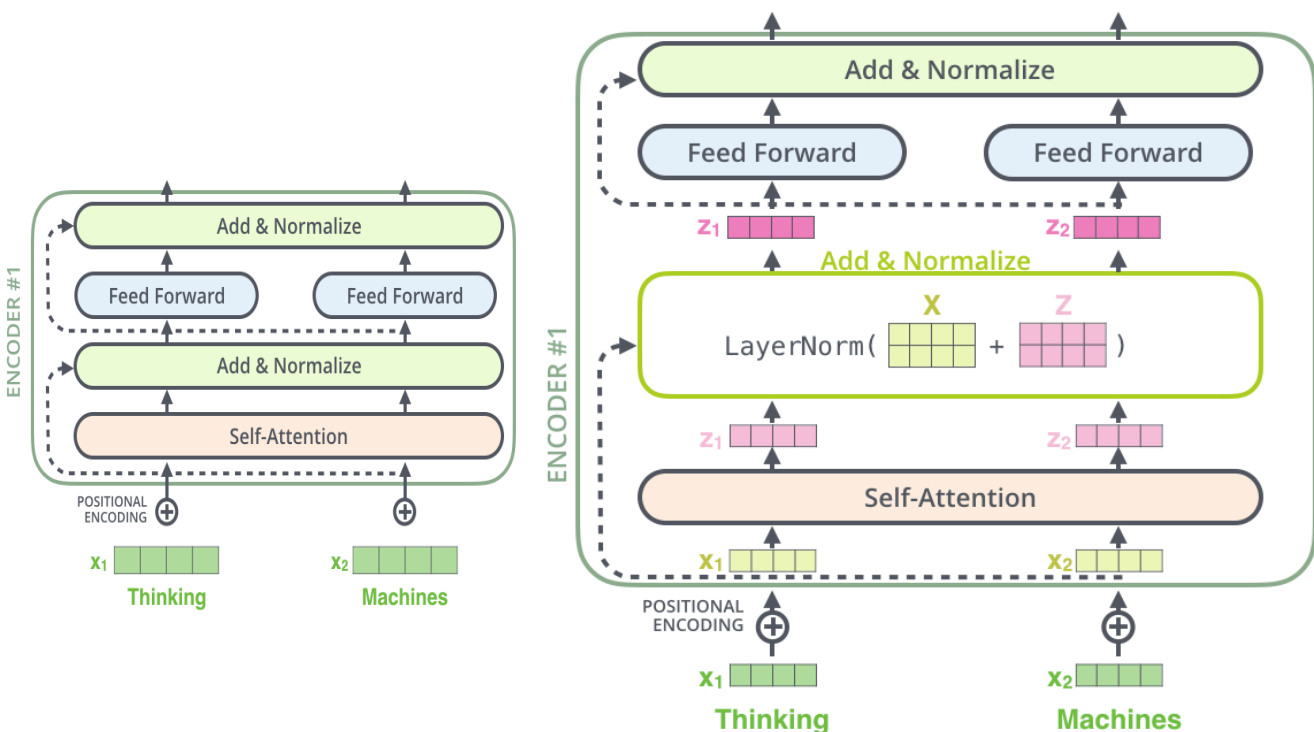


# GPS system: Positional Encoding

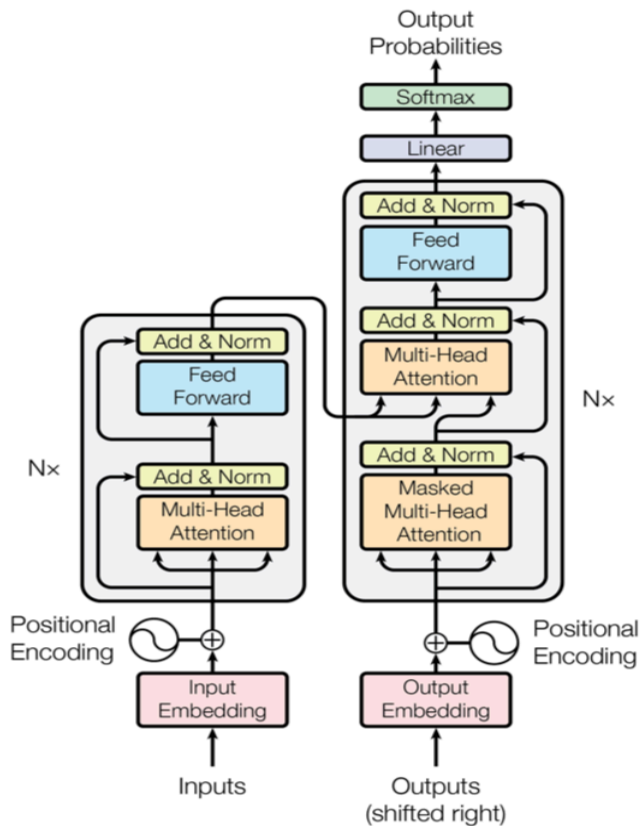


A real example of positional encoding with a toy embedding size of 4

# Nothing Fancy: Skip Connections and Normalization

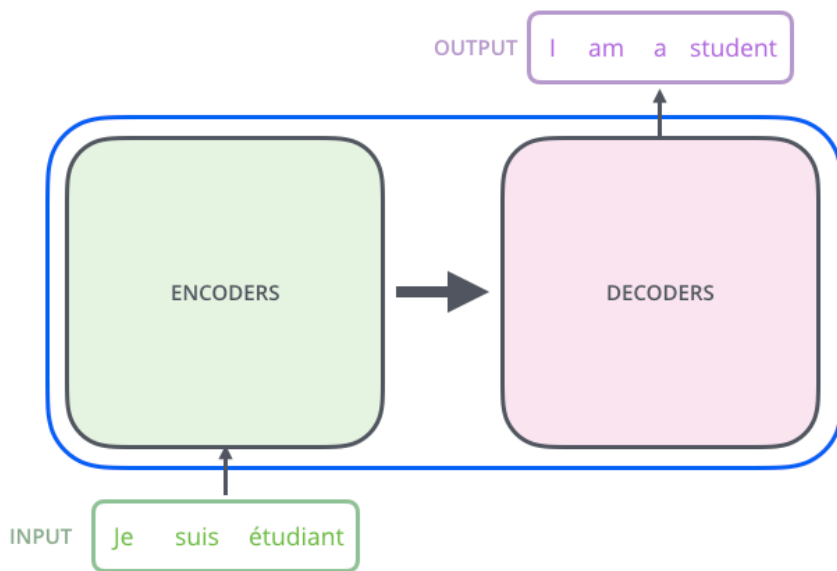


# Let's assemble the transformer!

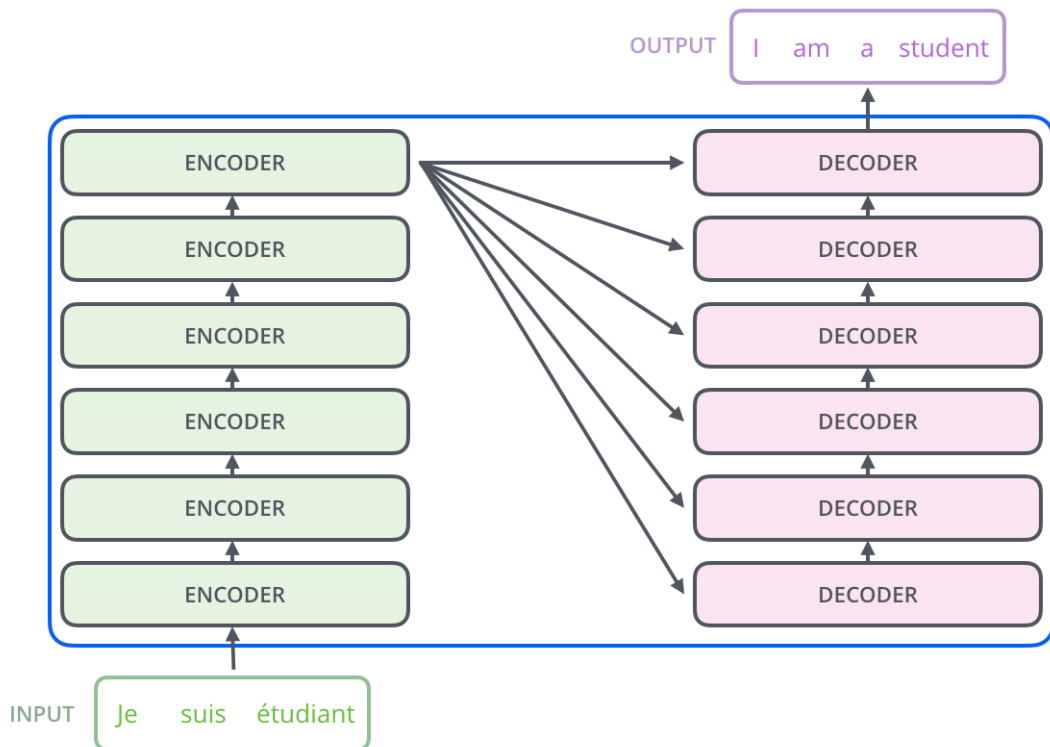




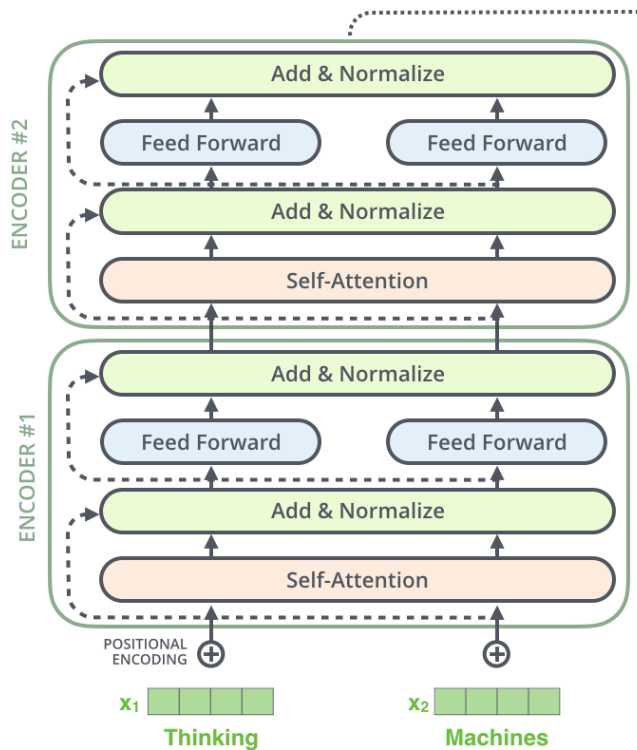
# Main Body: Encoder-Decoder



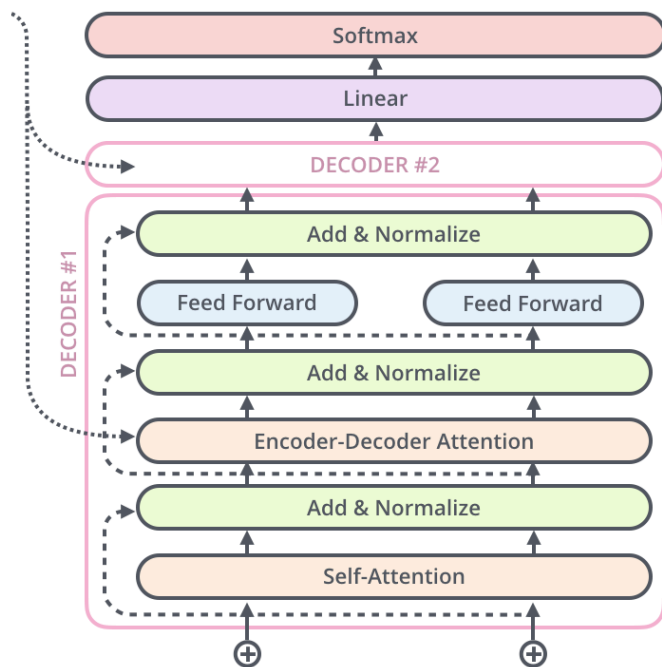
# Main Body: Encoder-Decoder



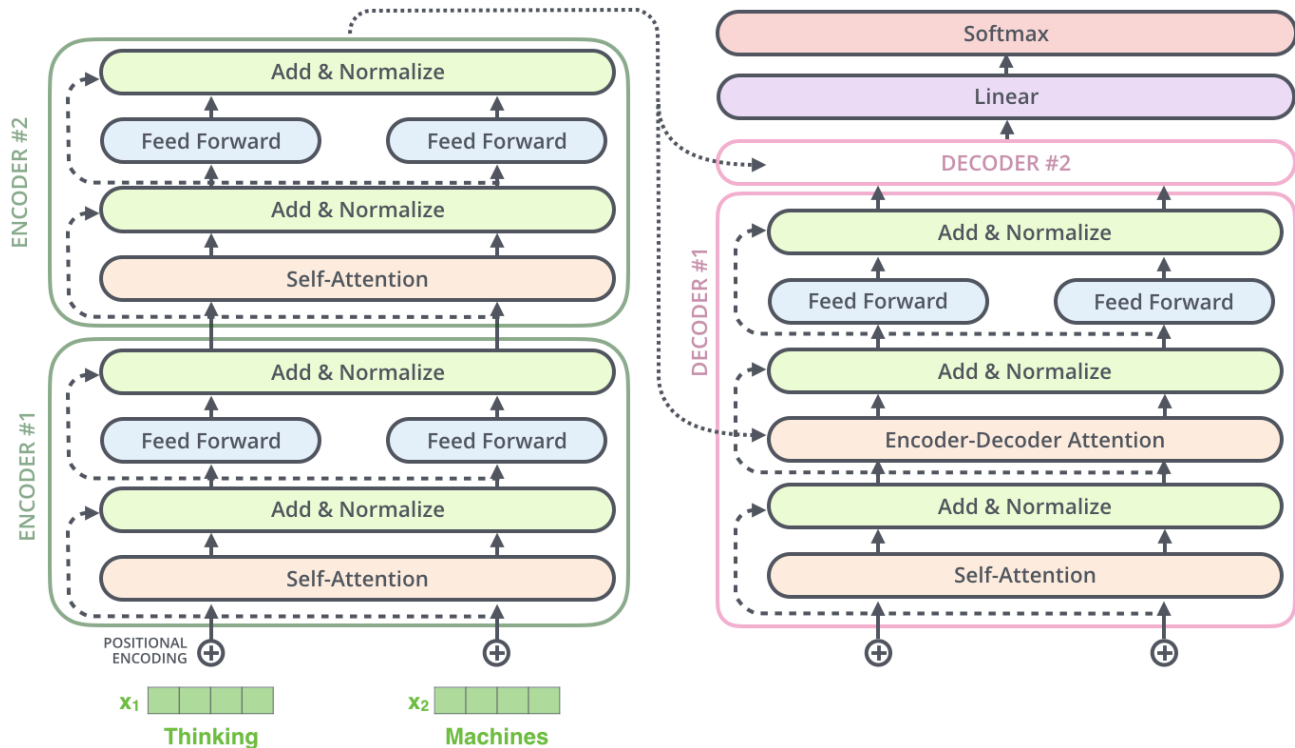
# Encoder



# Decoder



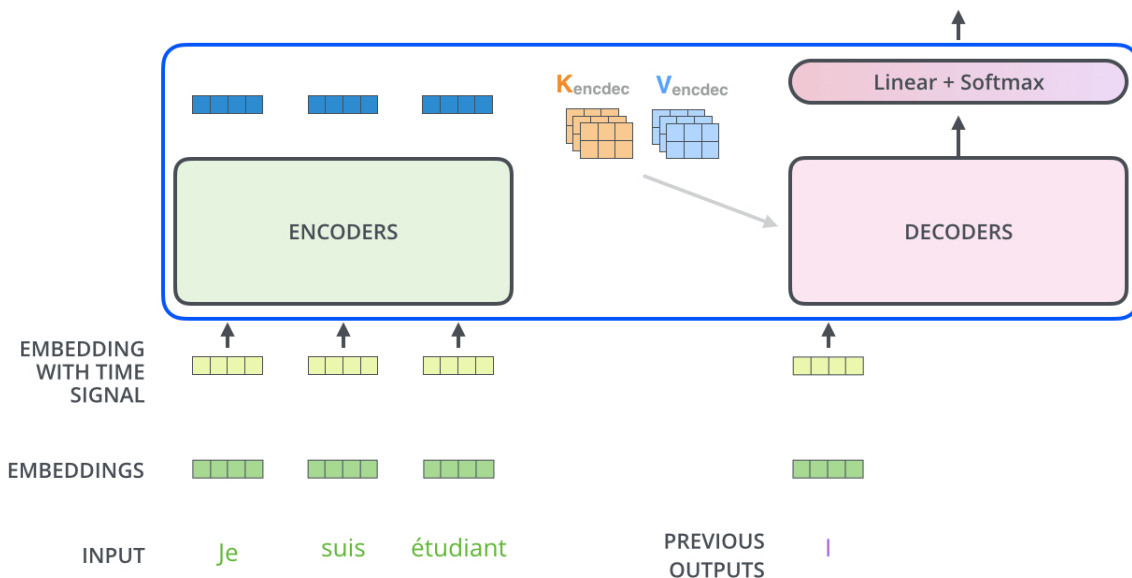
# Main Body: Encoder-Decoder



# Main Body: Encoder-Decoder Training

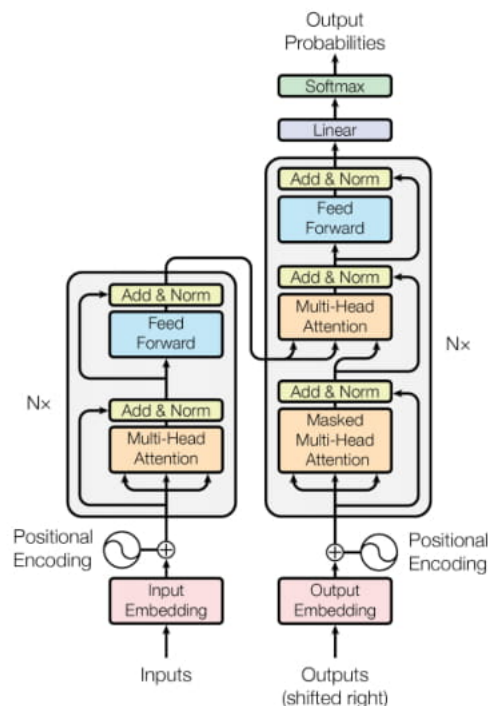
Decoding time step: 1 2 3 4 5 6

OUTPUT |



# Transformer Machine Translation

- Transformer has a encoder-decoder architecture similar to the previous RNN models.
  - except all the recurrent connections are replaced by the attention modules.
- The transformer model uses N stacked self-attention layers.
- Skip-connections help preserve the positional and identity information from the input sequences.



# Transformer Machine Translation

- BLEU scores of state-of-the-art models on the WMT14 English-to-German translation task

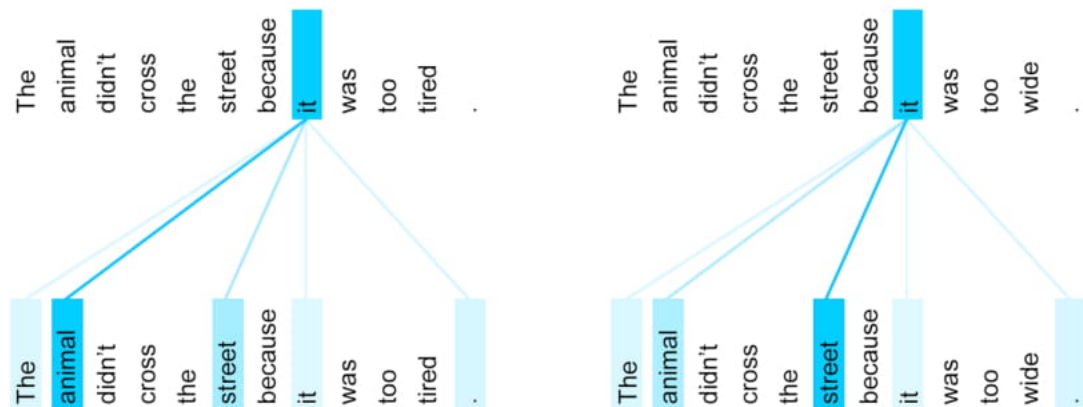
Translation Model	Training time	BLEU (diff. from MOSES)
<a href="#">Transformer</a> (large)	3 days on 8 GPU	<b>28.4</b> <b>(+7.8)</b>
<a href="#">Transformer</a> (small)	1 day on 1 GPU	24.9   (+4.3)
<a href="#">GNMT + Mixture of Experts</a>	1 day on 64 GPUs	26.0   (+5.4)
<a href="#">ConvS2S</a> (FB)	18 days on 1 GPU	25.1   (+4.5)
<a href="#">GNMT</a>	1 day on 96 GPUs	24.6   (+4.0)

Vaswani, Ashish, et al. "Attention is all you need." Advances in Neural Information Processing Systems. 2017.



# Transformer Machine Translation

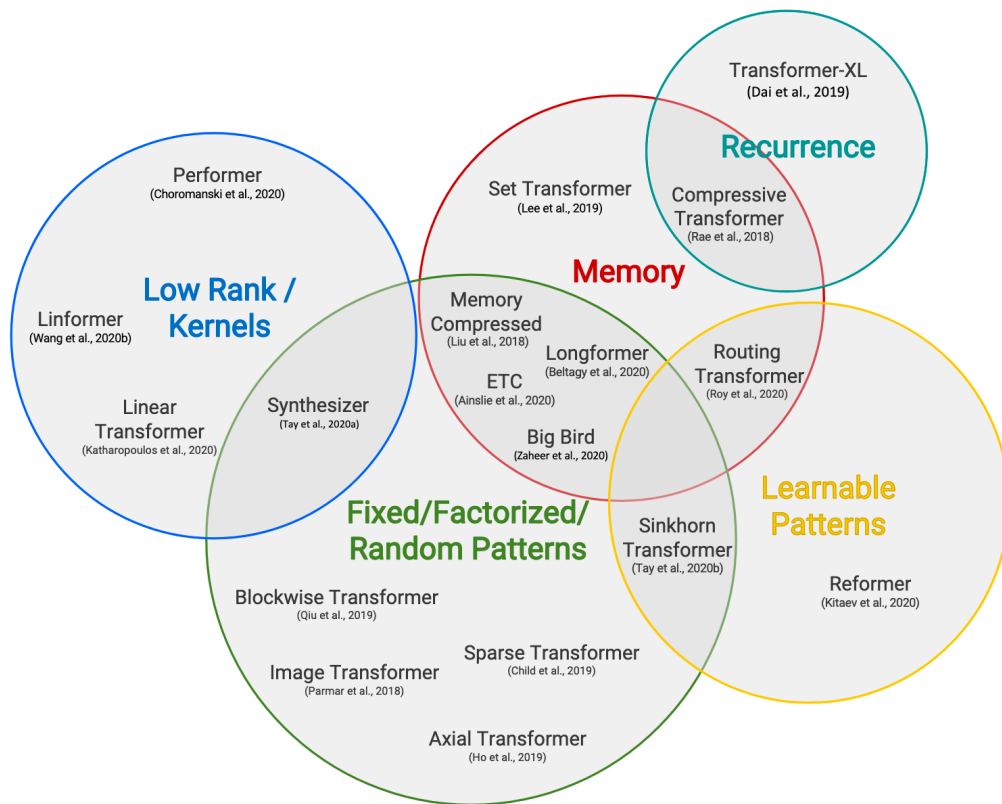
- Self-attention layers learnt "it" could refer to different entities in the different contexts.



- Visualization of the 5th to 6th self-attention layer in the encoder.

<https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html>

# Transformer Machine Translation



# After the break

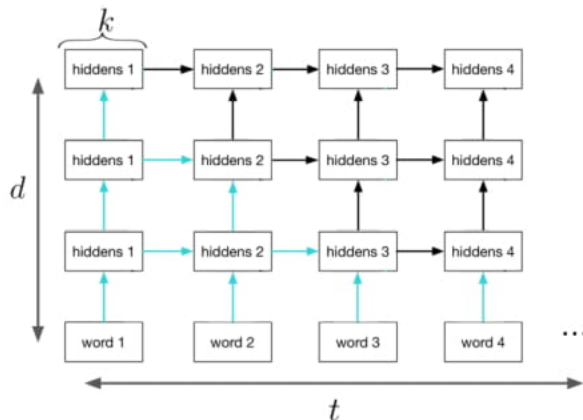
After the break: **Computational Cost**

# Computational Cost and Parallelism

- There are a few things we should consider when designing an RNN.
- Computational cost:
  - **Number of connections.** How many add-multiply operations for the forward and backward pass.
  - **Number of time steps.** How many copies of hidden units to store for Backpropagation Through Time.
  - **Number of sequential operations.** The computations cannot be parallelized. (The part of the model that requires a for loop).
- **Maximum path length across time:** the shortest path length between the first encoder input and the last decoder output.
  - It tells us how easy it is for the RNN to remember / retrieve information from the input sequence.

# Computational Cost and Parallelism

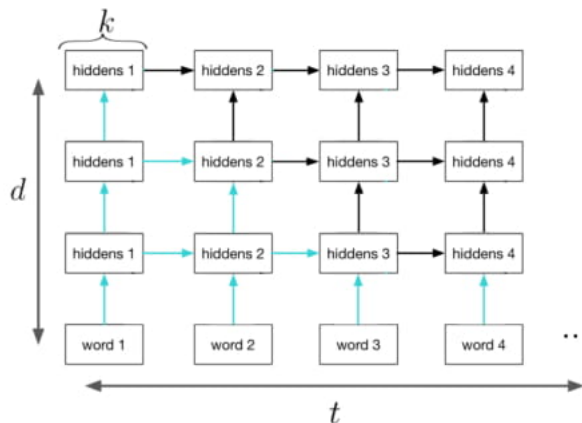
- Consider a standard  $d$  layer RNN from Lecture 7 with  $k$  hidden units, training on a sequence of length  $t$ .



- There are  $k^2$  connections for each hidden-to-hidden connection. A total of  $t \times k^2 \times d$  connections.
- We need to store all  $t \times k \times d$  hidden units during training.
- Only  $k \times d$  hidden units need to be stored at test time.

# Computational Cost and Parallelism

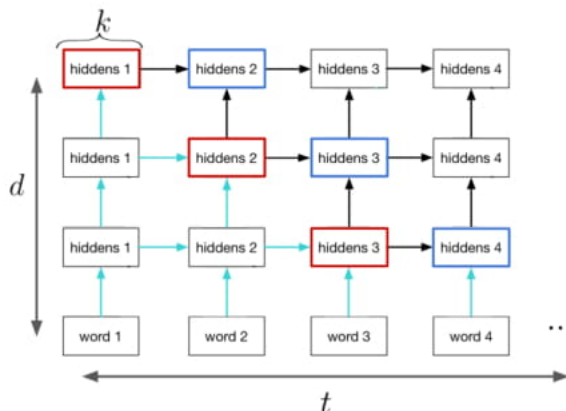
- Consider a standard  $d$  layer RNN from Lecture 7 with  $k$  hidden units, training on a sequence of length  $t$ .



- Which hidden layers can be computed in parallel in this RNN?

# Computational Cost and Parallelism

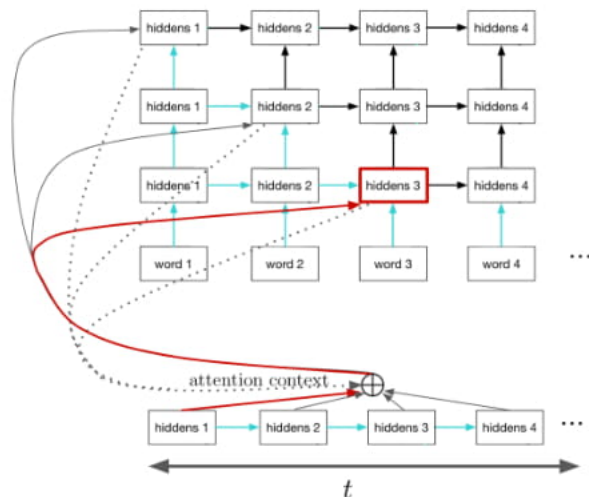
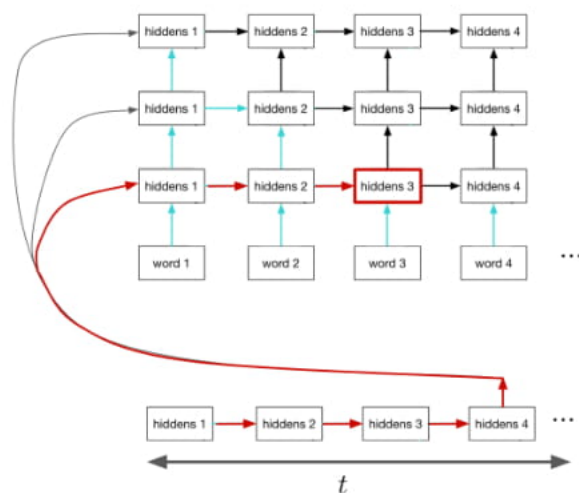
- Consider a standard  $d$  layer RNN from Lecture 7 with  $k$  hidden units, training on a sequence of length  $t$ .



- Both the input embeddings and the outputs of an RNN can be computed in parallel.
- The blue hidden units are independent given the red.
- The number of sequential operations is still proportional to  $t$ .

# Computational Cost and Parallelism

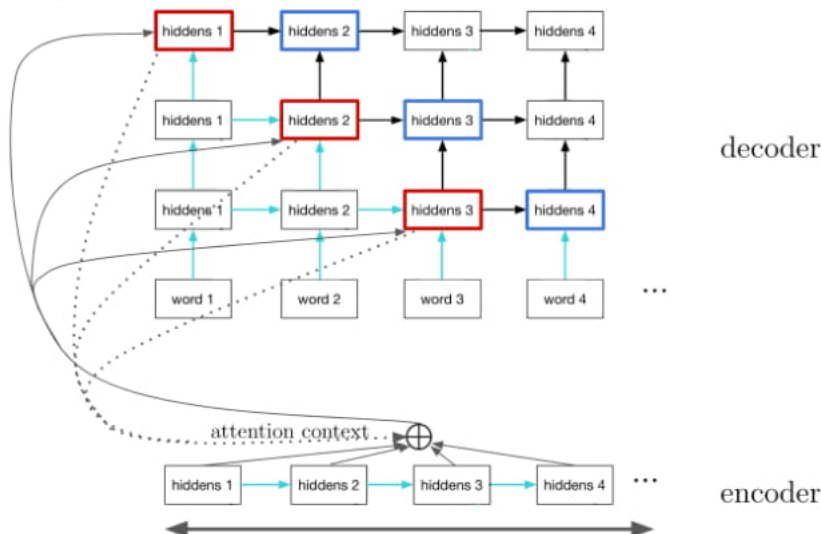
- During backprop, in the standard encoder-decoder RNN, the maximum path length across time is the number of time steps.
- Attention-based RNNs have a **constant path length** between the encoder inputs and the decoder hidden states.
  - Learning becomes easier. Why?





# Computational Cost and Parallelism

- During forward pass, attention-based RNNs achieves efficient content-based addressing at the cost of re-computing context vectors at each time step.
  - Bahdanau et. al.* computes context vector over the entire input sequence of length  $t$  using a neural network of  $k^2$  connections.
  - Computing the context vectors adds a  $t \times k^2$  cost at each time step.



# Computational Cost and Parallelism

- In summary:

- $t$ : sequence length,  $d$ : # layers and  $k$ : # neurons at each layer.

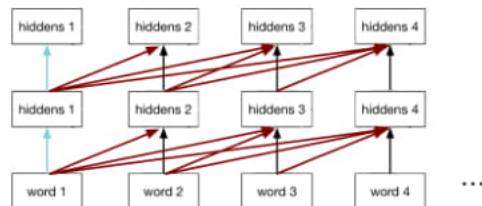
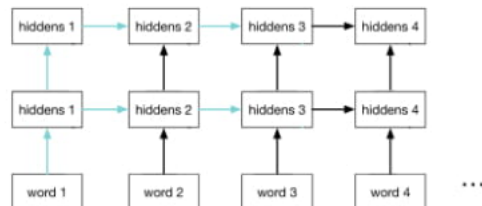
Model	training complexity	training memory	test complexity	test memory
RNN	$t \times k^2 \times d$	$t \times k \times d$	$t \times k^2 \times d$	$k \times d$
RNN+attn.	$t^2 \times k^2 \times d$	$t^2 \times k \times d$	$t^2 \times k^2 \times d$	$t \times k \times d$

- Attention needs to re-compute context vectors at every time step.
- Attention has the benefit of reducing the maximum path length between long range dependencies of the input and the target sentences.

Model	sequential operations	maximum path length across time
RNN	$t$	$t$
RNN+attn.	$t$	1

# Improve Parallelism

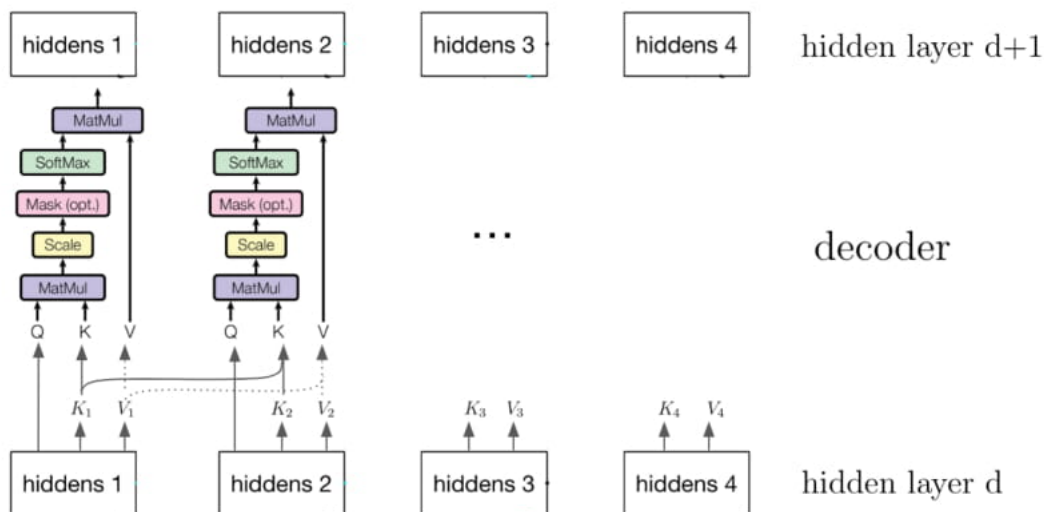
- RNNs are sequential in the sequence length  $t$  due to the number hidden-to-hidden lateral connections.
  - RNN architecture limits the parallelism potential for longer sequences.
- Improve parallelism: remove the lateral connections. We will have a deep autoregressive model, where the hidden units depends on all the previous time steps.



- Benefit: the number of sequential operations is now linear in the depth  $d$ , but is independent of the sequence length  $t$ . (usually  $d \ll t$ .)

# Computational Cost and Parallelism

- Self-attention allows the model to learn to access information from the past hidden layer, but decoding is very expensive.
- When generating sentences, the computation in the self-attention decoder grows as the sequence gets longer.



# Computational Cost and Parallelism

- t: sequence length, d: # layers and k: # neurons at each layer.

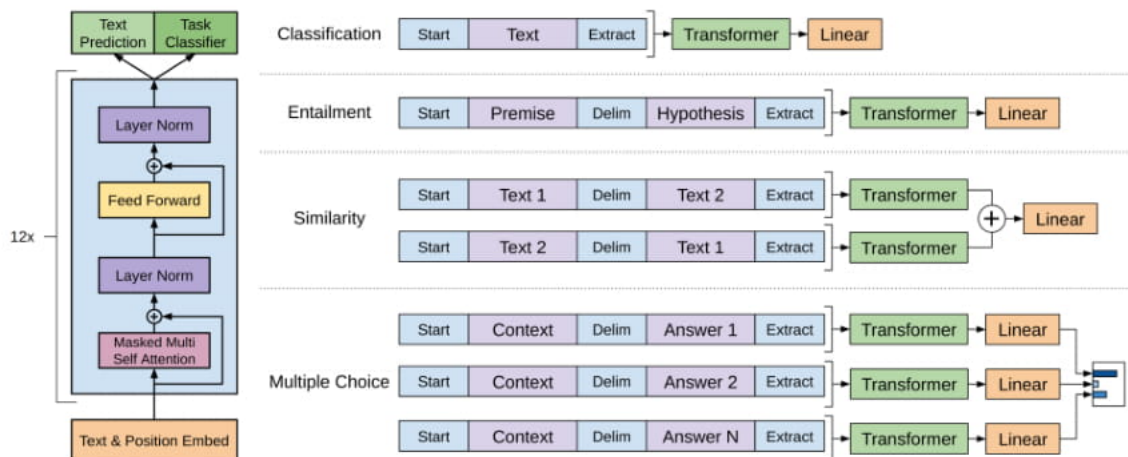
Model	training complexity	training memory	test complexity	test memory
RNN	$t \times k^2 \times d$	$t \times k \times d$	$t \times k^2 \times d$	$k \times d$
RNN+attn.	$t^2 \times k^2 \times d$	$t^2 \times k \times d$	$t^2 \times k^2 \times d$	$t \times k \times d$
transformer	$t^2 \times k \times d$	$t \times k \times d$	$t^2 \times k \times d$	$t \times k \times d$

- Transformer vs RNN:** There is a trade-off between the sequential operations and decoding complexity.
  - The sequential operations in transformers are independent of sequence length, but they are very expensive to decode.
  - Transformers can learn faster than RNNs on parallel processing hardware for longer sequences.

Model	sequential operations	maximum path length across time
RNN	$t$	$t$
RNN+attn.	$t$	1
transformer	$d$	1

# Transformer Language Pre-training

- Similar to pre-training computer vision models on ImageNet, we can pre-train a language model for NLP tasks.
  - The pre-trained model is then fine-tuned on textual entailment, question answering, semantic similarity assessment, and document classification.



Radford, Alec, et al. "Improving Language Understanding by Generative Pre-Training." 2018.

# Transformer Language Pre-training

- Increasing the training data set and the model size has a noticeable improvement on the transformer language model. Cherry picked generated samples from *Radford, et al., 2019*:

**Context (human-written):** In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

**GPT-2:** The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Pérez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Pérez.

Pérez and his friends were astonished to see the unicorn herd. These creatures could be seen from the air without having to move too much to see them – they were so close they could touch their horns.

For the full text samples see Radford, Alec, et al. "Language Models are Unsupervised Multitask Learners," 2019.

# Transformer Language Pre-training

## Talk to Transformer

See how a modern neural network completes your text. Type a custom snippet or try one of the examples. This is a limited demo of [InferKit](#).

Custom prompt ▼

How do I best explain the powers of transformers?



Generate Another

## Completion

**How do I best explain the powers of transformers?**

I think you can make a lot of sense of them by imagining these cars in the middle of this huge, glowing energy field of energy, like you'd see in a Transformers movie. The car is the conduit that fills in the empty spaces, and the energy gives it a little extra oomph. All the effects shots that make the car seem like it's levitating, or traveling faster than normal, are actually taking advantage of this effect. A few of the car's shots also use it for its optical effect, which is pretty



# Transformer Language Pre-training

## Talk to Transformer

See how a modern neural network completes your text. Type a custom snippet or try one of the examples. This is a limited demo of [InferKit](#).

Custom prompt

Should I choose to be a professor instead of a software engineer?



Generate Another

### Completion

**Should I choose to be a professor instead of a software engineer?**

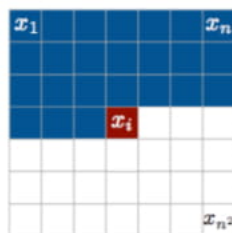
I found myself wondering if I should leave the software engineering field altogether or stay in the profession I'd always dreamed of. Did my skill set lie with teaching, or software? Maybe I should go all the way to business school, and once I'd polished up my MBA, I'd be hired as a venture capitalist and be able to make lots of money. In the meantime, I could work part time as a software engineer and on consulting projects with engineers.

# After the break

After the break: CNN for speech analysis

# Overview

- We've already looked at a few autoregressive models in this course:
  - Neural language models from Lecture 3
  - RNN language models (and decoders) from Lecture 7
  - Transformer decoders from Lecture 8
- We can push this further, and generate very long sequences.



Treat an image as a very long sequence using raster scan order



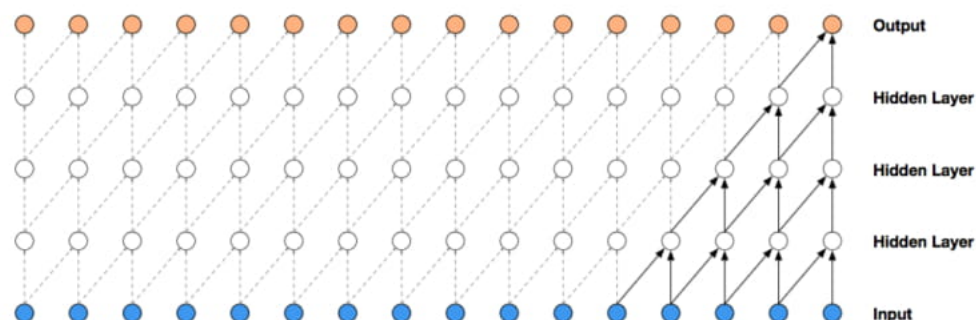
A speech signal can be represented as a waveform, with at least 16,000 samples per second.

- Problem:
  - Training an RNN to generate these sequences requires a sequential computation  $> 10,000$  time steps.
  - Transformers are too expensive to train on 10,000 time steps.

# Causal Convolution

## Idea 1: causal convolution

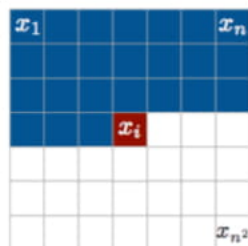
- For RNN language models, we used the training sequence as both the inputs and the outputs to the RNN.
  - We made sure the model was **causal**: each prediction depended only on inputs earlier in the sequence.
- We can do the same thing using a convolutional architecture.



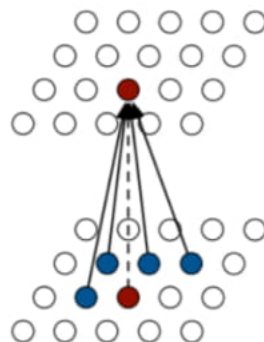
- No for loops! Processing each input sequence just requires a series of convolution operations.

# Causal Convolution

Causal convolution for images:

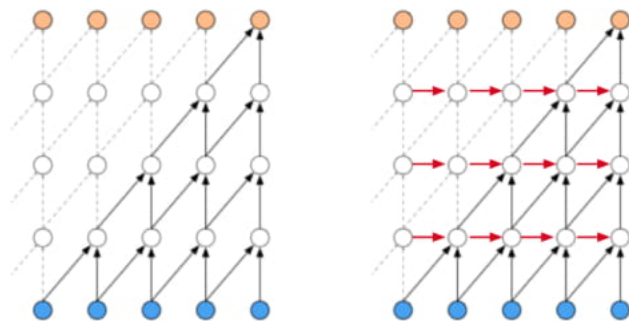


The image is treated as a very long sequence of pixels using raster scan order.



We can restrict the connectivity pattern in each layer to make it causal. This can be implemented by clamping some weights to zero.

# CNN vs. RNN



- We can turn a causal CNN into an RNN by adding recurrent connections. Is this a good idea?
  - The RNN has a memory, so it can use information from all past time steps. The CNN has a limited context.
  - But training the RNN is very expensive since it requires a for loop over time steps. The CNN only requires a series of convolutions.
  - Generating from both models is very expensive, since it requires a for loop. (Whereas generating from a GAN or a reversible model is very fast.)

# PixelCNN and PixelRNN

- Van den Oord et al., ICML 2016, “Pixel recurrent neural networks”
- This paper introduced two autoregressive models of images: the PixelRNN and the PixelCNN. Both generated amazingly good high-resolution images.
- The output is a softmax over 256 possible pixel intensities.
- Completing an image using an PixelCNN:



# PixelCNN and PixelRNN

Samples from a PixelRNN trained on ImageNet:





# Dilated Convolution

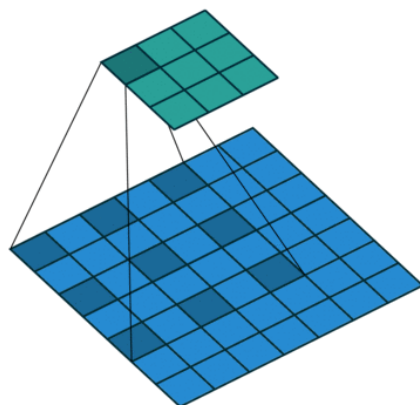
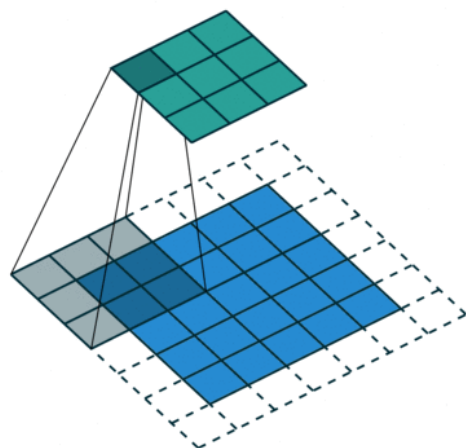
## Idea 2: dilated convolution

- The advantage of RNNs over CNNs is that their memory lets them learn arbitrary long-distance dependencies.
- But we can dramatically increase a CNN's receptive field using dilated convolution.

# Dilated Convolution

## Idea 2: dilated convolution

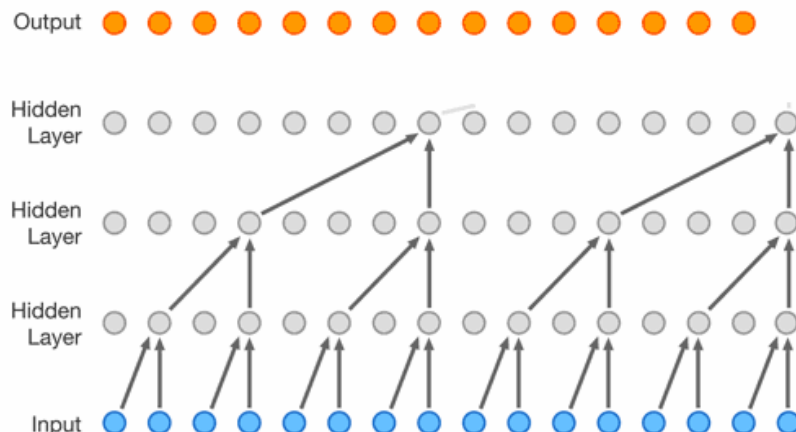
- The advantage of RNNs over CNNs is that their memory lets them learn arbitrary long-distance dependencies.
- But we can dramatically increase a CNN's receptive field using dilated convolution.



# Dilated Convolution

## Idea 2: **dilated convolution**

- The advantage of RNNs over CNNs is that their memory lets them learn arbitrary long-distance dependencies.
- But we can dramatically increase a CNN's receptive field using dilated convolution.



# WaveNet

- WaveNet is an autoregressive model for raw audio based on causal dilated convolutions.
  - van den Oord et al., 2016. "WaveNet: a generative model for raw audio".
- Audio needs to be sampled at at least 16k frames per second for good quality. So the sequences are very long.
- WaveNet uses dilations of  $1, 2, \dots, 512$ , so each unit at the end of this block as a receptive field of length 1024, or 64 milliseconds.
- It stacks several of these blocks, so the total context length is about 300 milliseconds.
- <https://deepmind.com/blog/wavenet-generative-model-raw-audio/>

## Mean Opinion Scores

### Text-to-Speech

Benefits

Demo

Key features

What's new

### Documentation

### Use cases

## Text-to-Speech

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- ✓ Personalize your communication based on user preference of voice and language

Current Best  
Non-WaveNet

WaveNet

Current Best  
Non-WaveNet

WaveNet

Current Best  
Non-WaveNet

WaveNet

Current Best  
Non-WaveNet

WaveNet

### Gartner

Google Cloud named a  
2020 Magic Quadrant  
Developer Services

Learn more

## The Bitter Lesson - Rich Sutton

The biggest lesson that can be read from 70 years of AI research is that general methods that leverage computation are ultimately the most effective, and by a large margin. The ultimate reason for this is Moore's law, or rather its generalization of continued exponentially falling cost per unit of computation.