NLP-101-Introduction

Advanced NLP

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Session Agenda

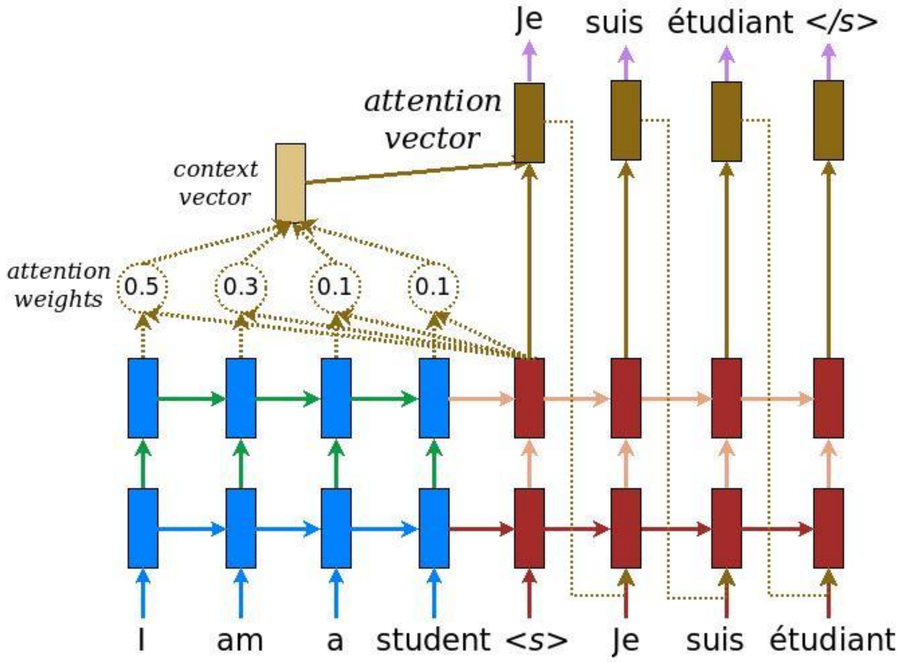
- NMT evaluation
- seq2seq tasks (summarization, question answering)
- Transformers
  - GPT, BERT, T5
- Transfer learning
- Knowledge distillation

NMT Recap

NMT Recap

NMT

- NMT is a form of a seq2seq problem.
- An encoder grasps info from input
- A decoder generates the translation
- An attention layer helps the decoder focus on important pieces from the input
- Each decoder output is reused to generate the following output.



NMT Evaluation

BLEU (BiLingual Evaluation Understudy)

NMT Evaluation

- Compare predicted translation (candidate) to the reference one (from a human)
- Ranges from 0 to 1, 1 is the best.
- It tries to find how many words from candidate appear in the reference.
- It doesn't consider semantic meaning or sentence structure.
- You can think of it as a precision metric for the translation.

BLEU (BiLingual Evaluation Understudy)

NMT Evaluation

candidate	I	I	am	I	
reference 1	Younes	said	I	am	hungry
reference 2	He	said	I	am	hungry
	Count:	**1**			

source

BLEU (BiLingual Evaluation Understudy)

NMT Evaluation

candidate	I	I	am	I	
reference 1	Younes	said	I	am	hungry
reference 2	He	said	I	am	hungry

Count: **2**

source

BLEU (BiLingual Evaluation Understudy)

NMT Evaluation

candidate	I	I	am	I	
reference 1	Younes	said	I	am	hungry
reference 2	He	said	I	am	hungry

Count: **3**

source

BLEU (BiLingual Evaluation Understudy)

NMT Evaluation

candidate	I	I	am	I	
reference 1	Younes	said	I	am	hungry
reference 2	He	said	I	am	hungry

Count: **4**

source

BLEU (BiLingual Evaluation Understudy)

NMT Evaluation

candidate	I	I	am	I	
reference 1	Younes	said	I	am	hungry
reference 2	He	said	I	am	hungry

Count: **4 / len(text) = 4/4 = 1**

source

BLEU modified

NMT Evaluation

candidate	I	I	am	I	
reference 1	Younes	said	I	am	hungry
reference 2	He	said	I	am	hungry

Count: **1**

source

BLEU modified

NMT Evaluation

candidate	I	I	am	I	
reference 1	Younes	said		am	hungry
reference 2	He	said		am	hungry

Count: **1**

source

BLEU modified

NMT Evaluation

candidate	I	I	am	I	
reference 1	Younes	said		am	hungry
reference 2	He	said		am	hungry

Count: **2**

source

BLEU modified

NMT Evaluation

candidate	I	I	am	I	
reference 1	Younes	said			hungry
reference 2	He	said			hungry
	Count:	**2**			

source

BLEU modified

NMT Evaluation

candidate	I	I	am	I	
reference 1	Younes	said			hungry
reference 2	He	said			hungry

Count: **2 / len(text) = 2/4 = 0.5**

source

ROUGE-N Score

NMT Evaluation

- Recall-Oriented Understudy for Gisting Evaluation.
- Compare the reference to predicted translation (candidate) .
- Ranges from 0 to 1, 1 is the best.
- It tries to find how many words from reference appear in the candidate.
- It doesn't consider semantic meaning or sentence structure.
- You can think of it as a recall metric for the translation.

ROUGE-N Score

NMT Evaluation

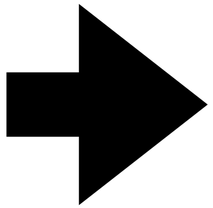
candidate	I	I	am	I	
reference 1	Younes	said	I	am	hungry
reference 2	He	said	I	am	hungry
	Count 1:	**2/5**		**Count 2:**	**2/5**

source

F1 score
NMT Evaluation

candidate	I	I	am	I	
reference 1	Younes	said	I	am	hungry
reference 2	He	said	I	am	hungry

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$



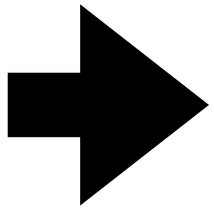
$$F1 = 2 \times \frac{BLEU \times ROUGE\text{-}N}{BLEU + ROUGE\text{-}N}$$

source

F1 score
NMT Evaluation

candidate	I	I	am	I	
reference 1	Younes	said	I	am	hungry
reference 2	He	said	I	am	hungry

$$F1 = 2 \times \frac{BLEU \times ROUGE-N}{BLEU + ROUGE-N}$$



$$F1 = 2 \times \frac{0.5 \times 0.4}{0.5 + 0.4} = \frac{4}{9} \approx 0.44$$

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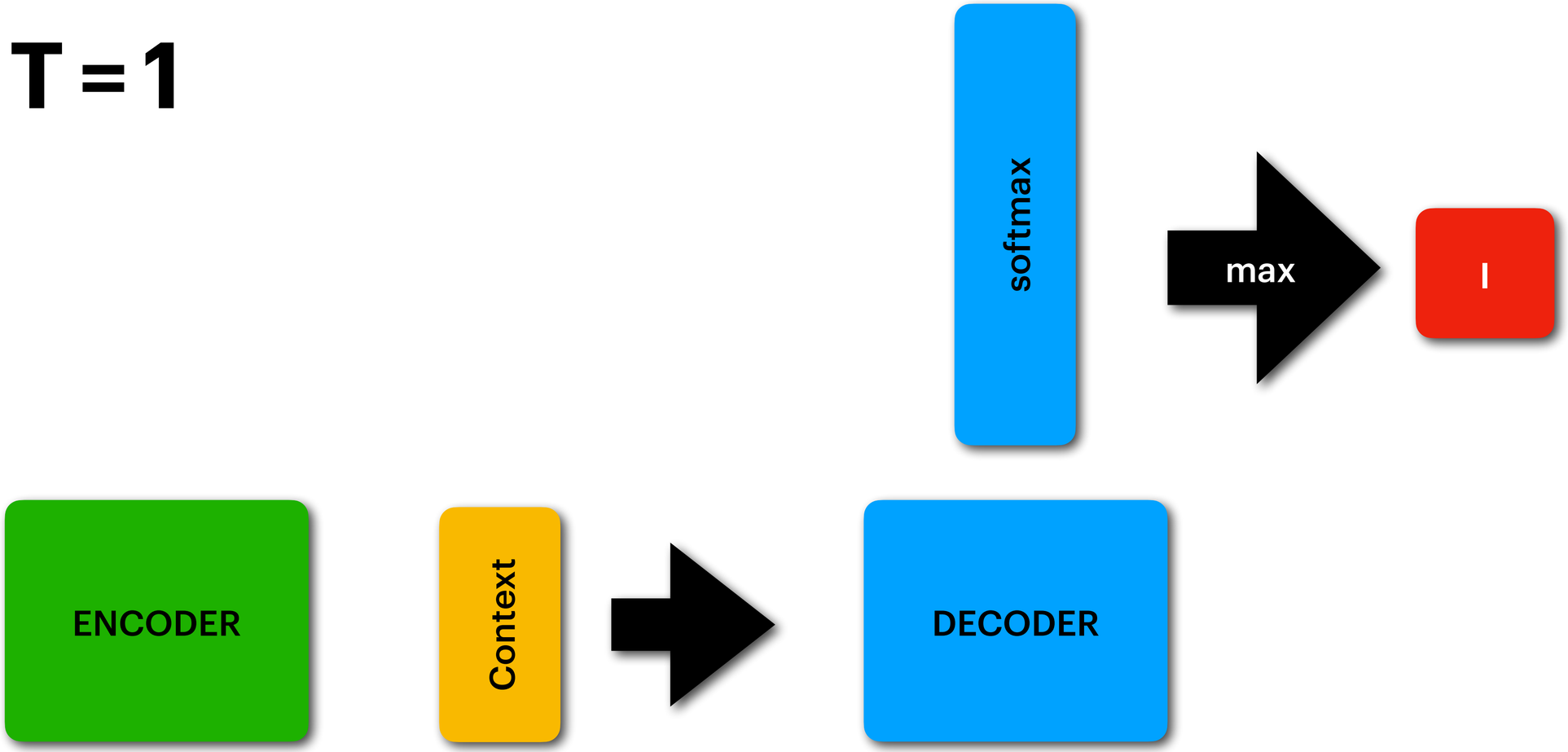
Back to decoder

Decoding output

NMT

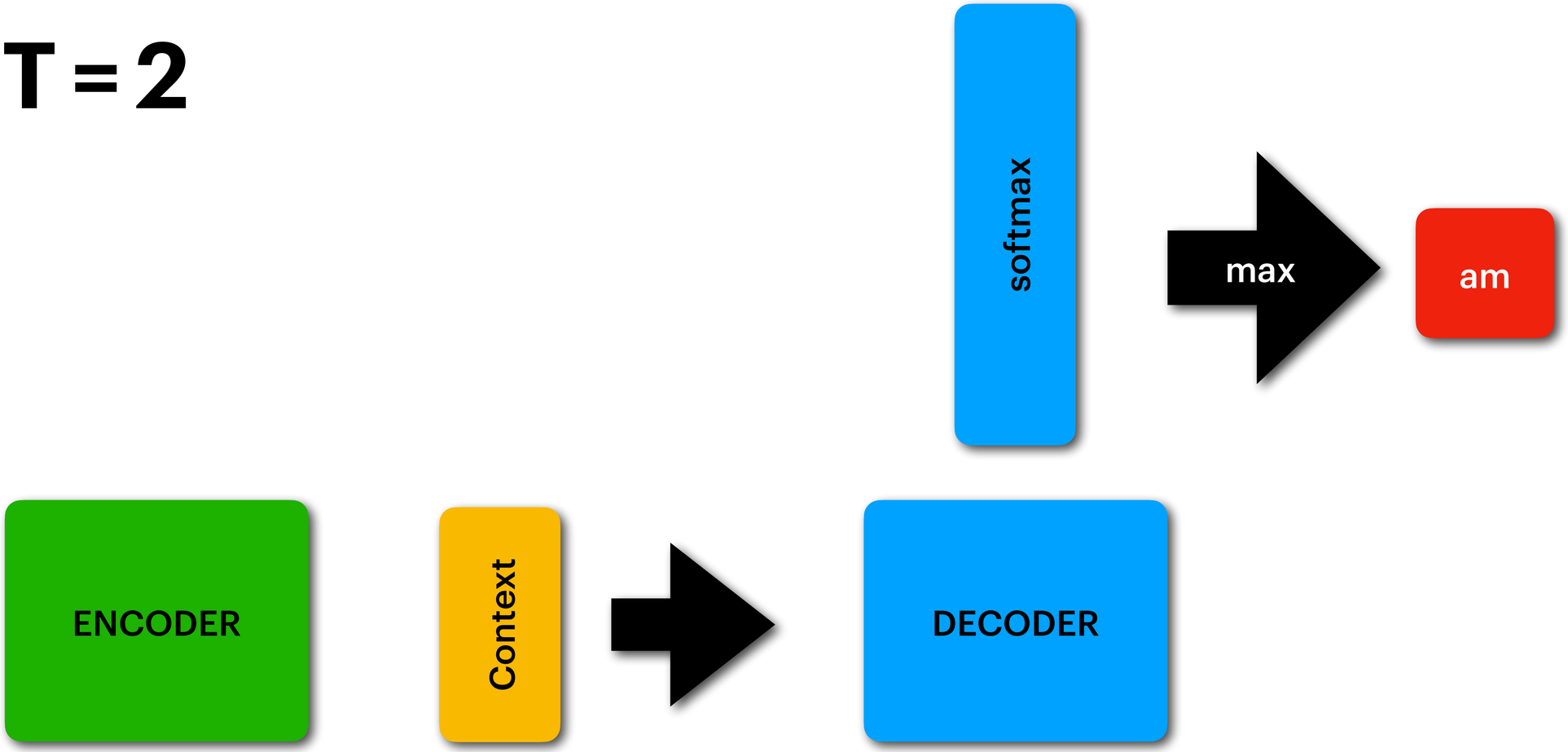
T = 1



Decoding output

NMT

T = 2

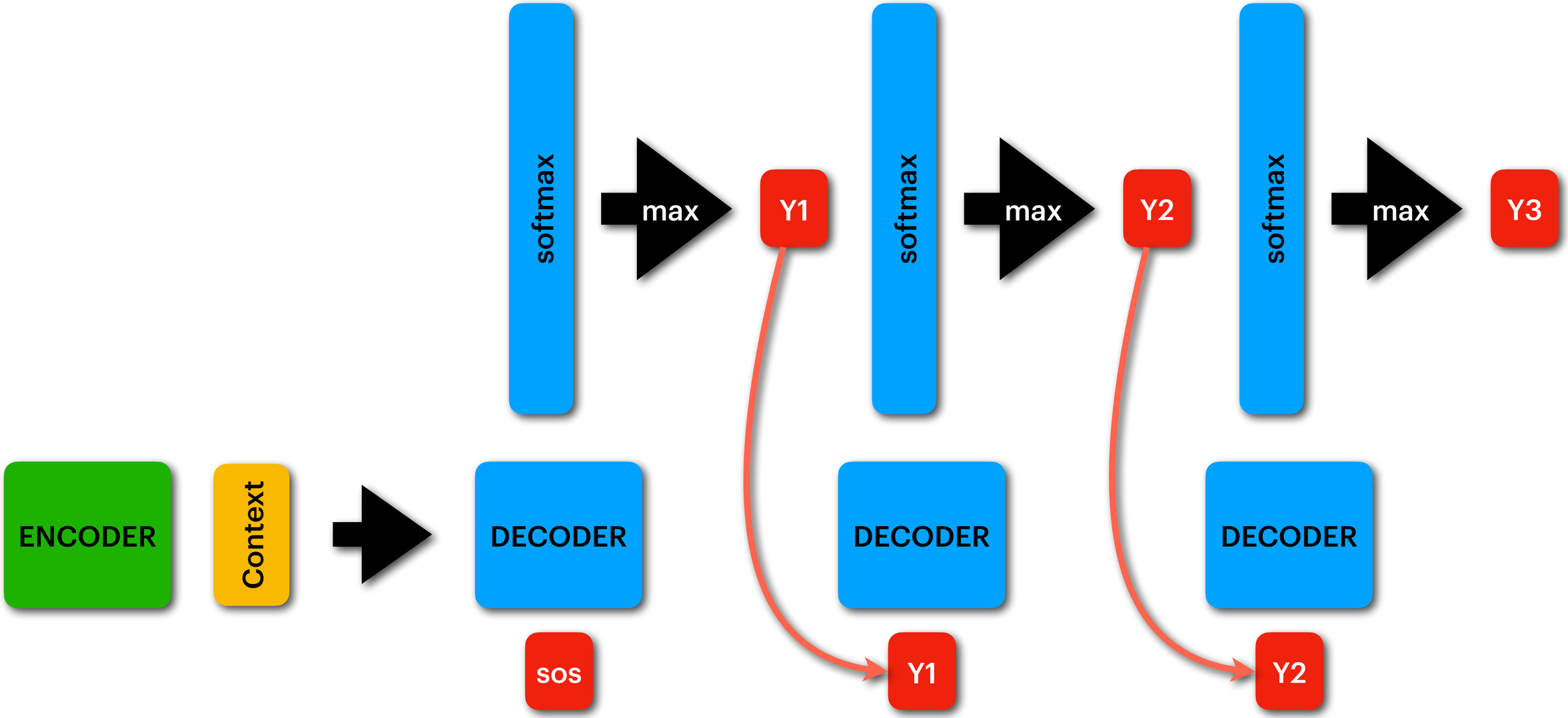


je suis étudiant

I

Greedy decoding

NMT



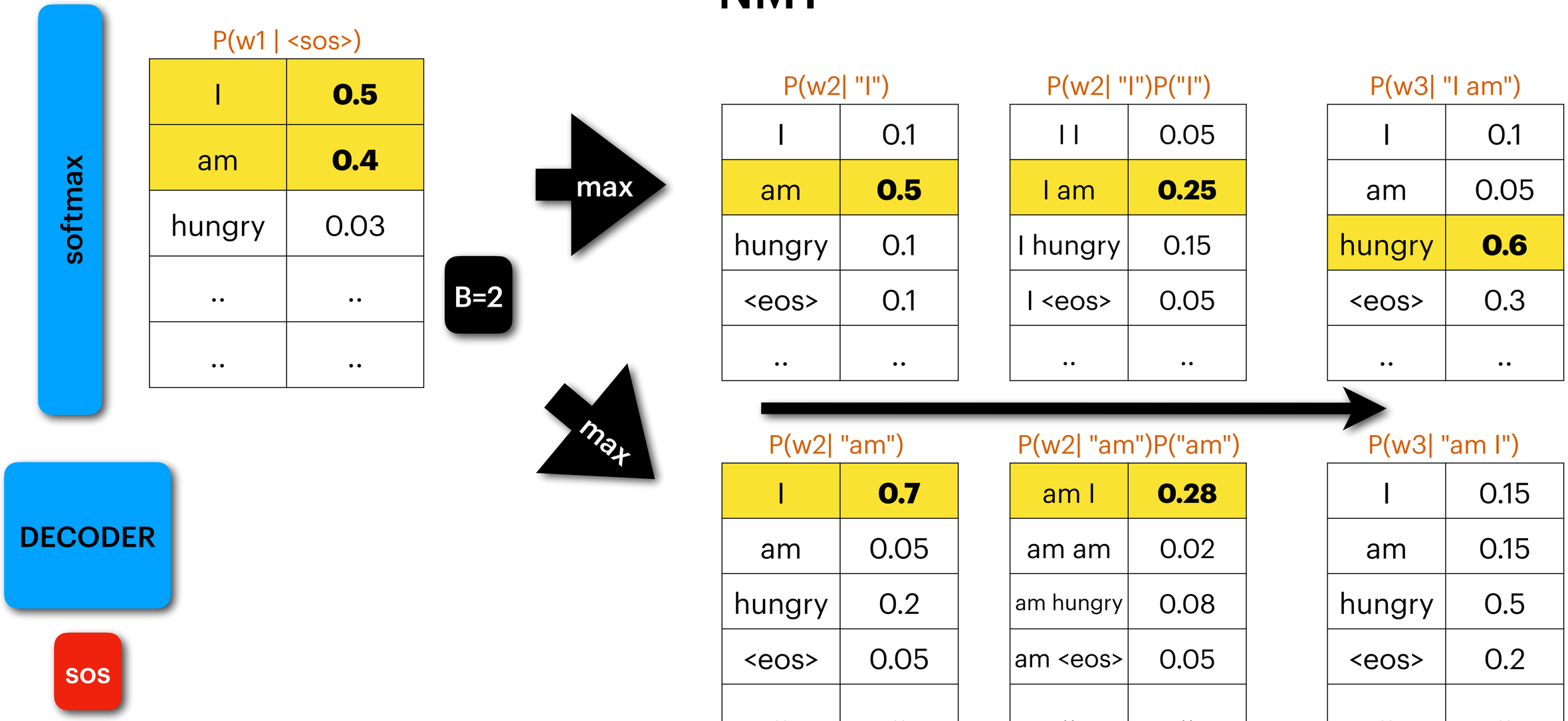
Beam Search

NMT

- Greedy decoding select the best word at each step, but this doesn't mean it is the best word overall.
- Beam search tries different paths and choose the best overall.
- Beam search with enough window helps pick the best word according to past words not just word.

Beam Search

NMT



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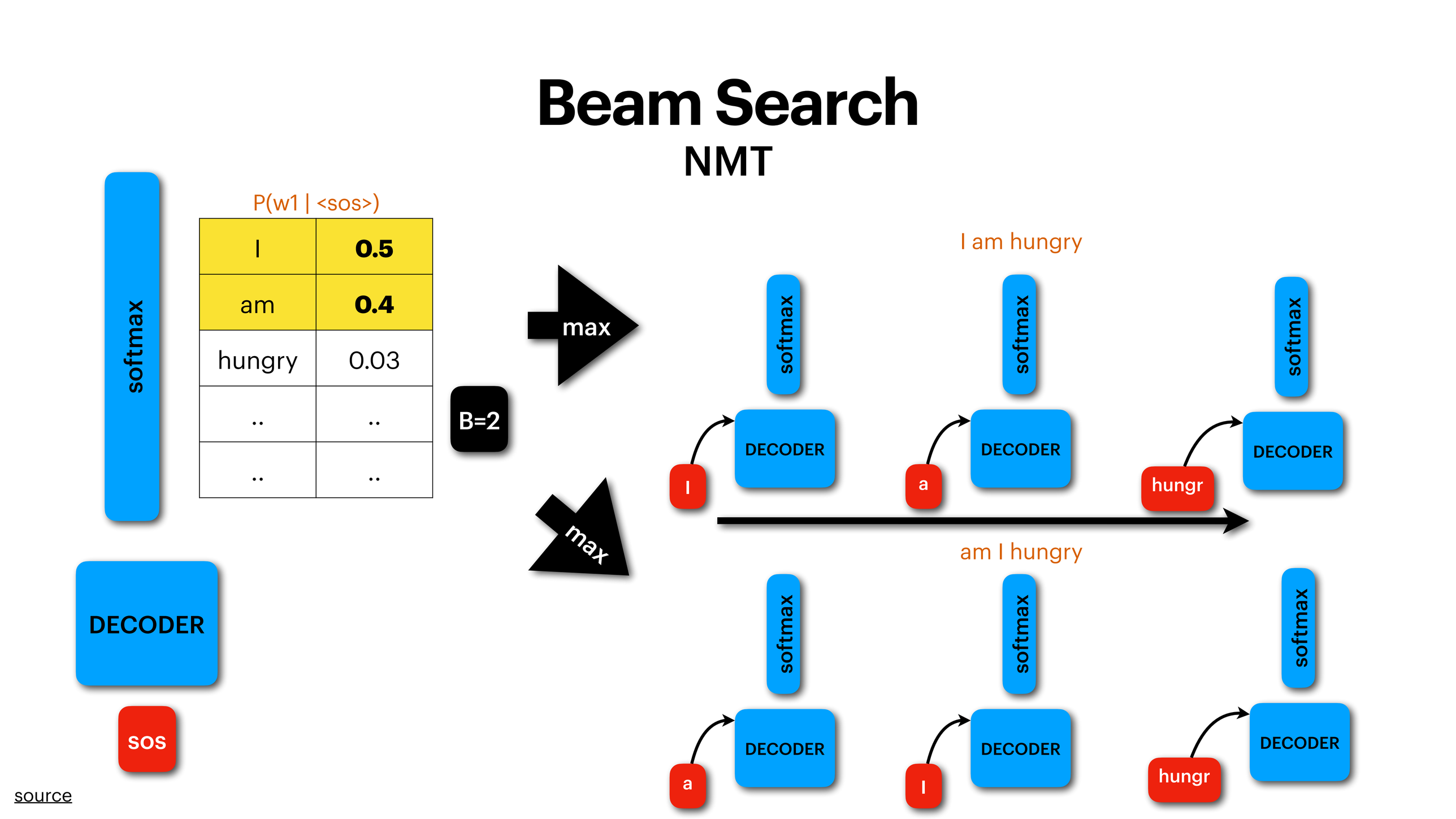
Beam Search

NMT



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Conclusion

NMT

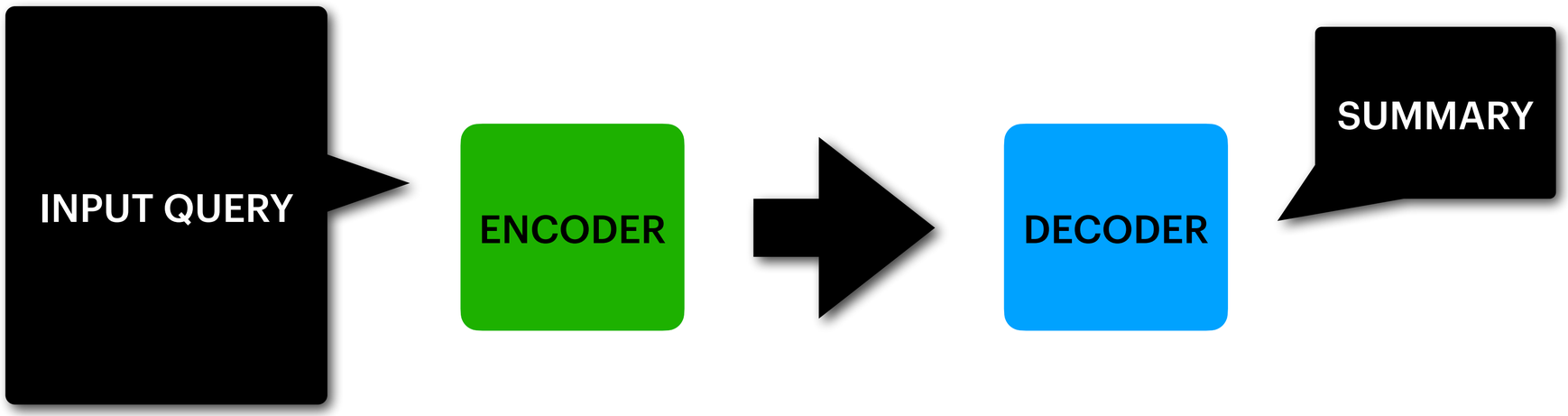
- NMT is a seq2seq problem.
- We use BLEU score, ROUGE-N and more metrics to assess the translation.
- Beam search is used to find the best overall translation with the higher overall probability.

More on seq2seq

Text Summarization

seq2seq

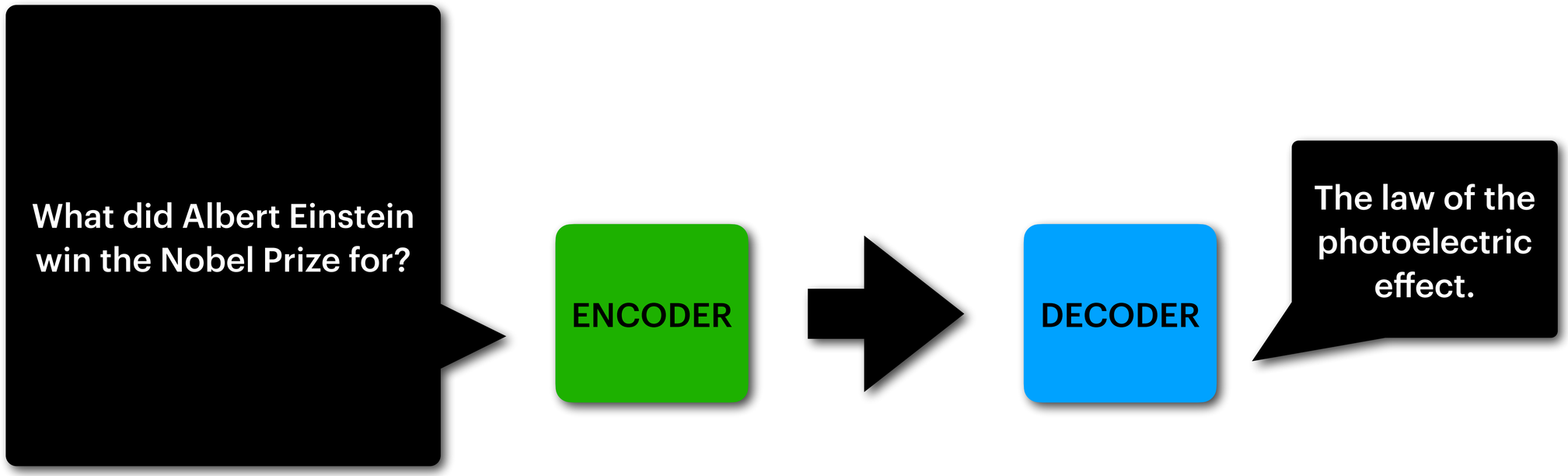
- In summarization task the output sequence is the summary for the input context.
- We can use BLEU and ROUGE to assess the summarization.
- Attention is very useful here too.



Question Answering

seq2seq

- Open-Domain QA is a form of tasks where the model is only given a question and is required to answer it with no context



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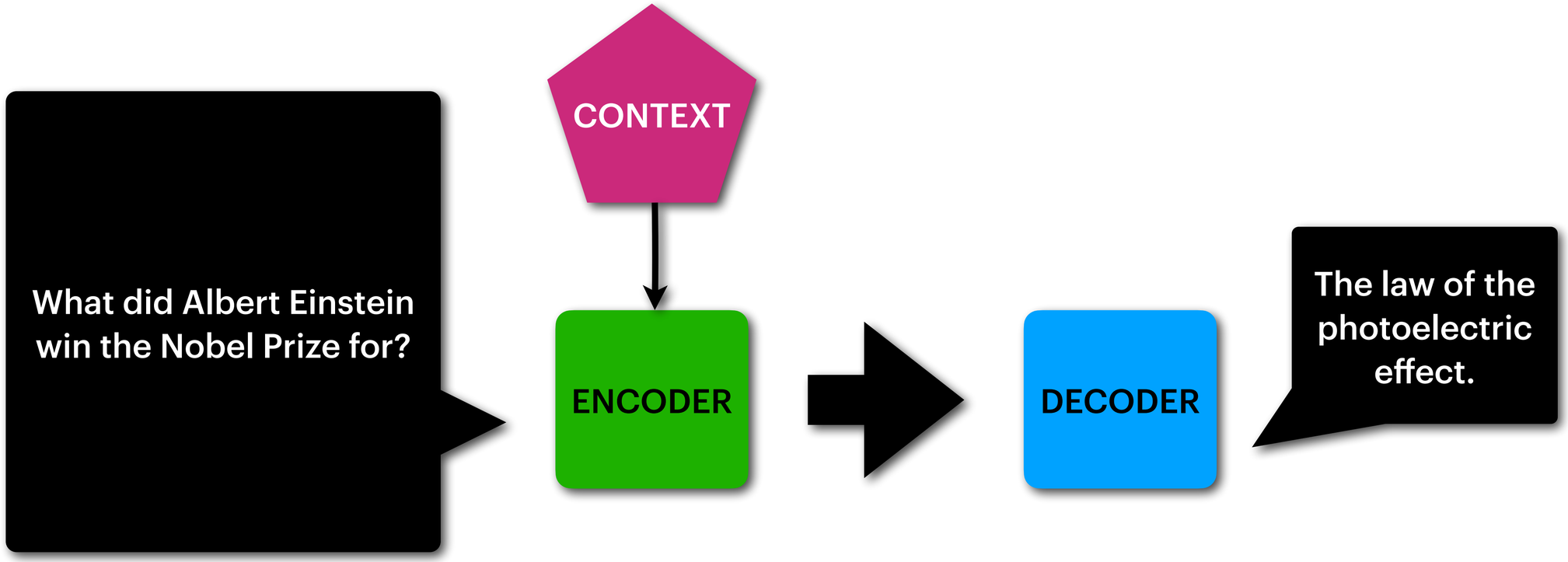
Question Answering

seq2seq

- Reading comprehension QA is a task where a context is provided to the model.



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RNN Limitations

RNN Limitations

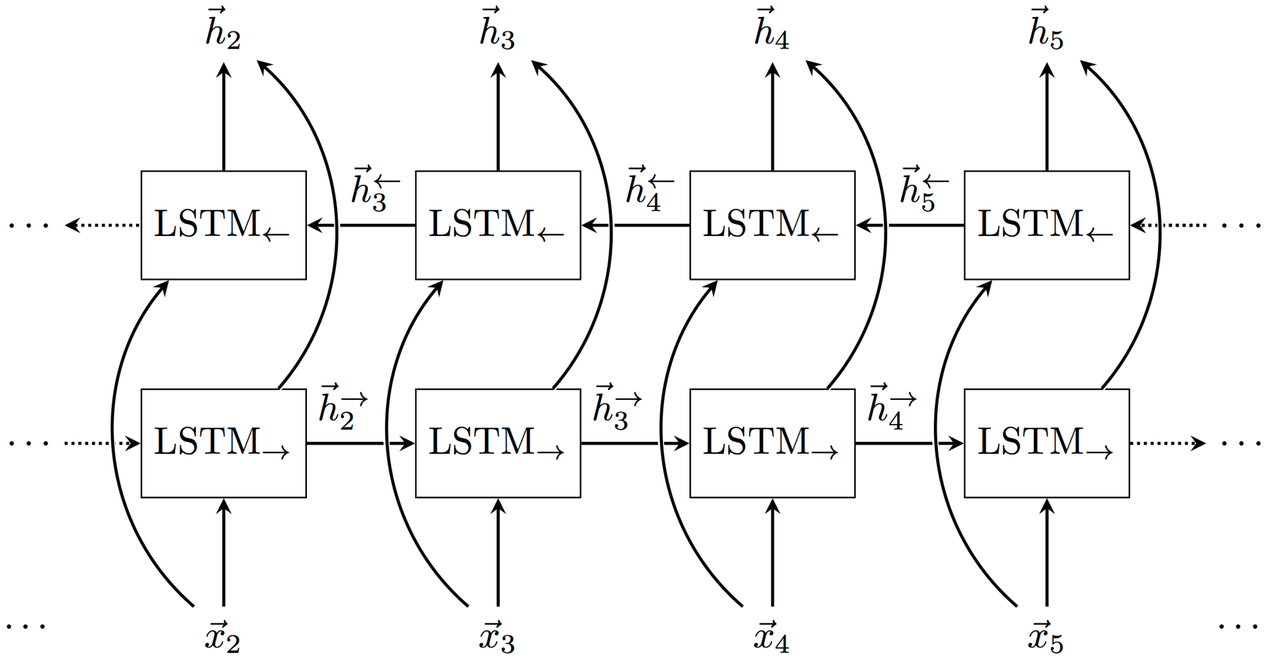
seq2seq

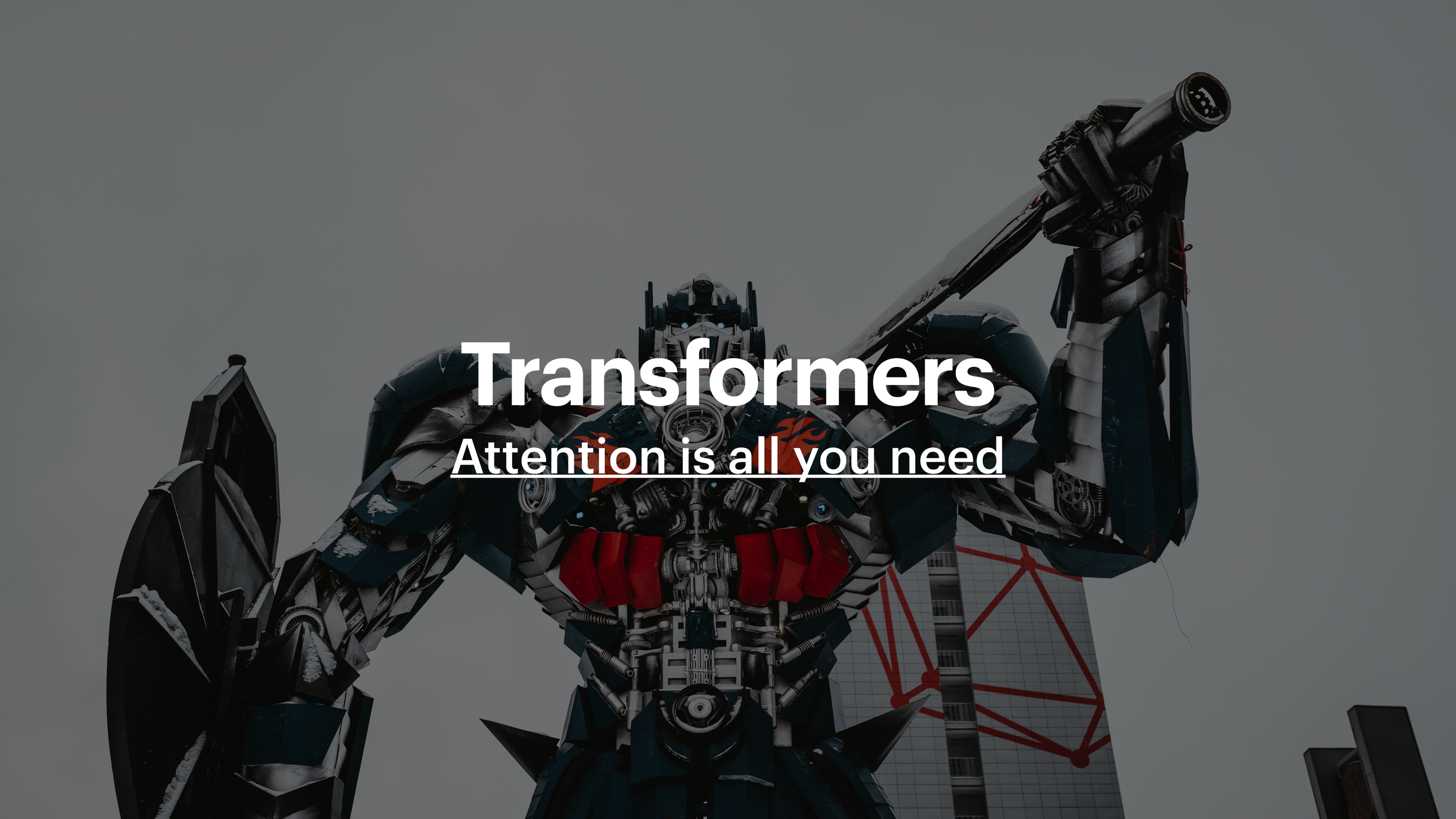
- Information bottleneck happens when the encoder tries to fit all info in one vector.
- Hard to parallelize due to sequential nature.
- Can't see both direction (even in BiDirectional) as every direction network sees in one direction only.

Bi-directional RNN

seq2seq

- This is considered as one layer but in facts two LSTMs are in work here.
- Every LSTM sees in one direction and can't see the whole sentence while encoding.




Transformers
Attention is all you need

What is a transformer

Transformers

- Transformer model was introduced by Google in the very famous paper Attention is all you need.
- The model is built based on attention and got rid of RNNs.
- Transformer model reshaped the NLP industry as it enabled a way to optimize large model by parallelizing model operations and making use of GPUs/TPUs.
- The original paper introduced the transformer in NMT task and had a better BLEU score than all previous SOTA models.

What is a transformer

Transformers

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

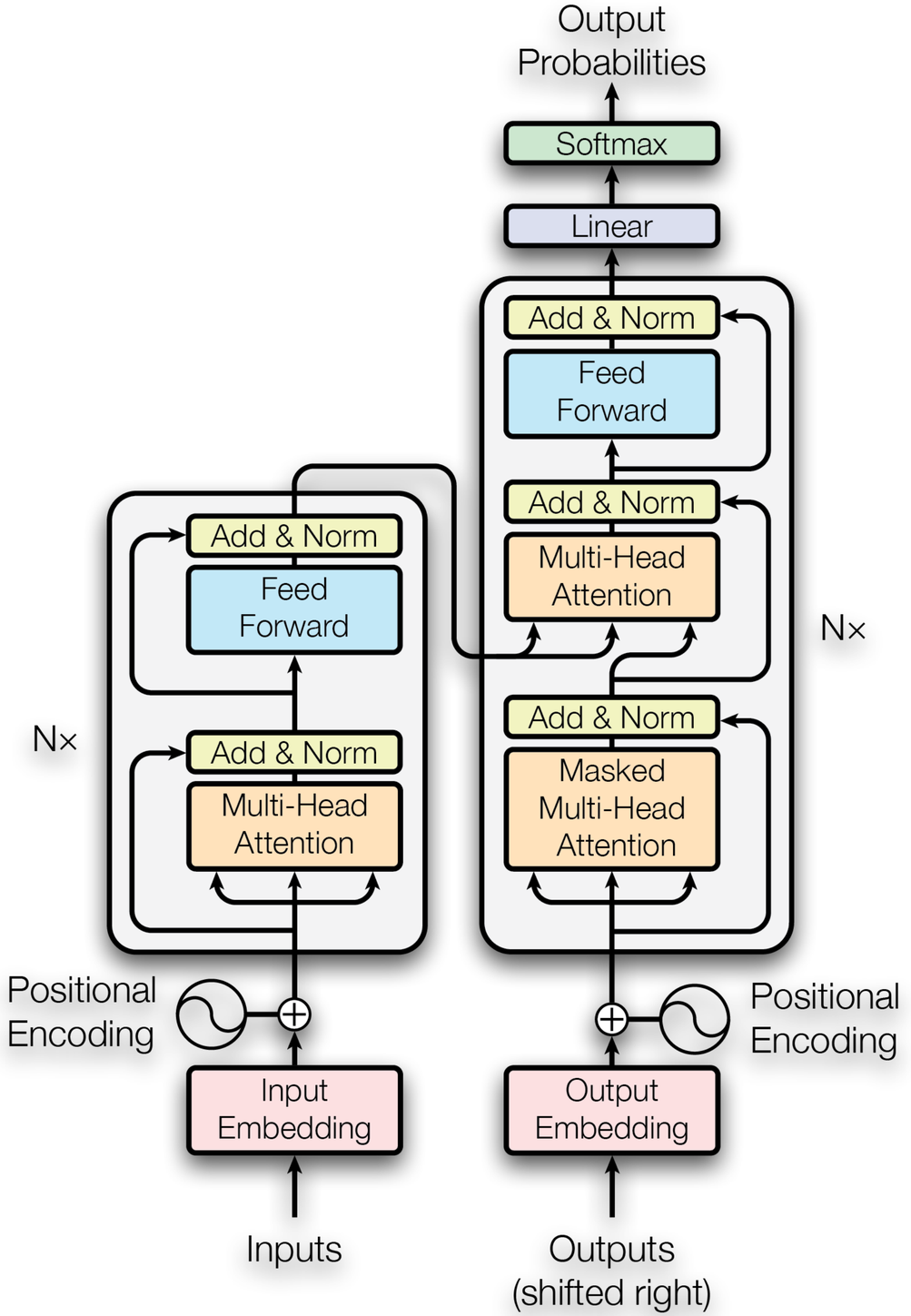
Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
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	**$3.3 \cdot 10^{18}$**	
Transformer (big)	**28.4**	**41.8**	$2.3 \cdot 10^{19}$	

source

Architecture

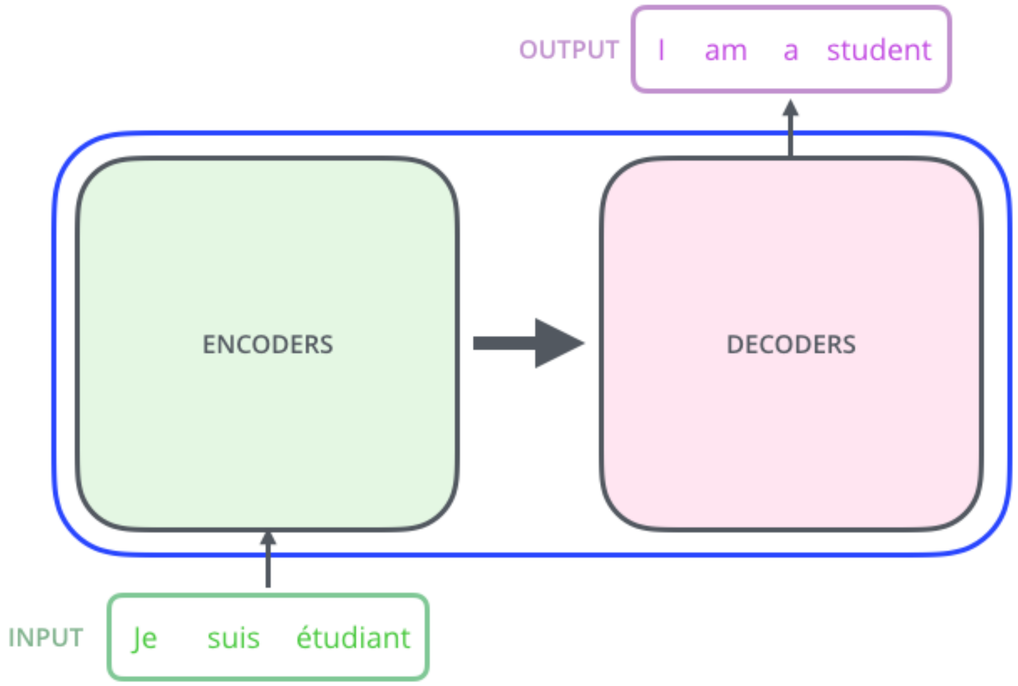
Transformer

- Positional encoding is used to addresses the position.
- Multi-head attention is used to learn context of words.
- All the components can be parallelized and thus make use of large hardware/data.



How it works
Transformer

- The main idea is the same here, seq2seq model
- An encoder and a decoder are used to generate context and generate translation.
- Attention is the core building block



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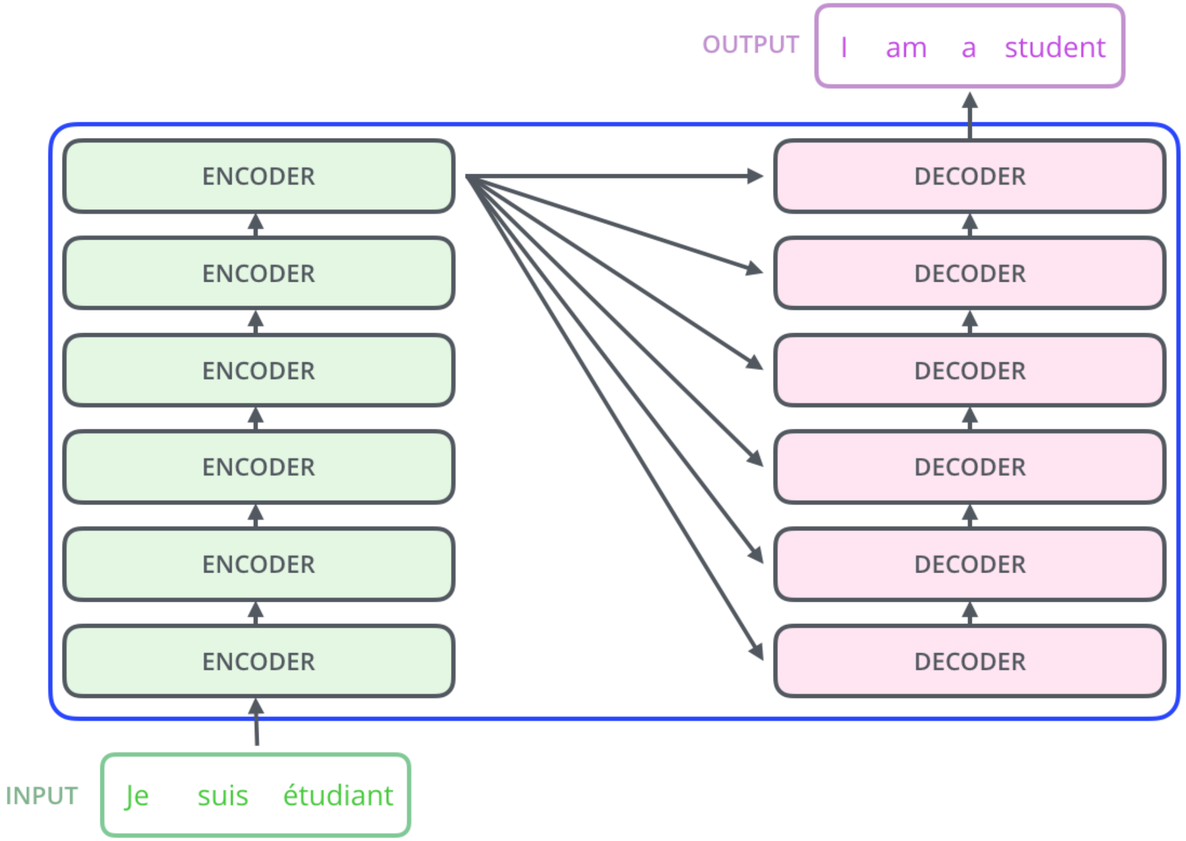
How it works
Transformer

- encoder and decoder are a stack of multiple ones (6 layers in the original paper)



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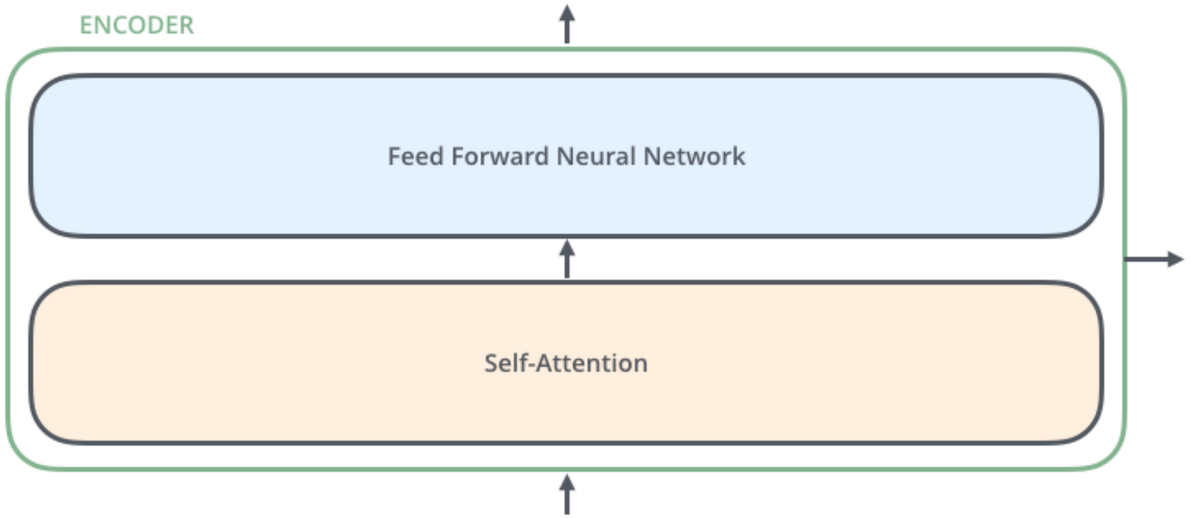
How it works
Transformer

- The encoder itself consists of a **self-attention** layer and a FCN.
- **self-attention** layer helps the encoder look at other words in the input sentence as it encodes a specific word.



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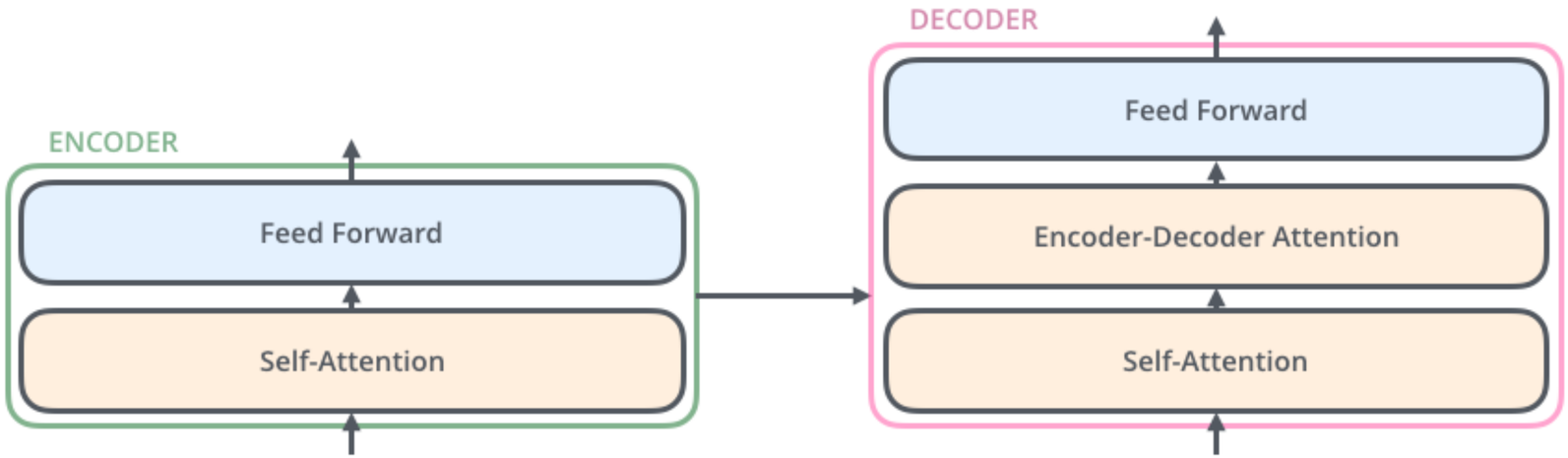
How it works
Transformer

- Decoder is the same as encoder with and addition of an attention layer that helps it focusing on important parts from the encoder.



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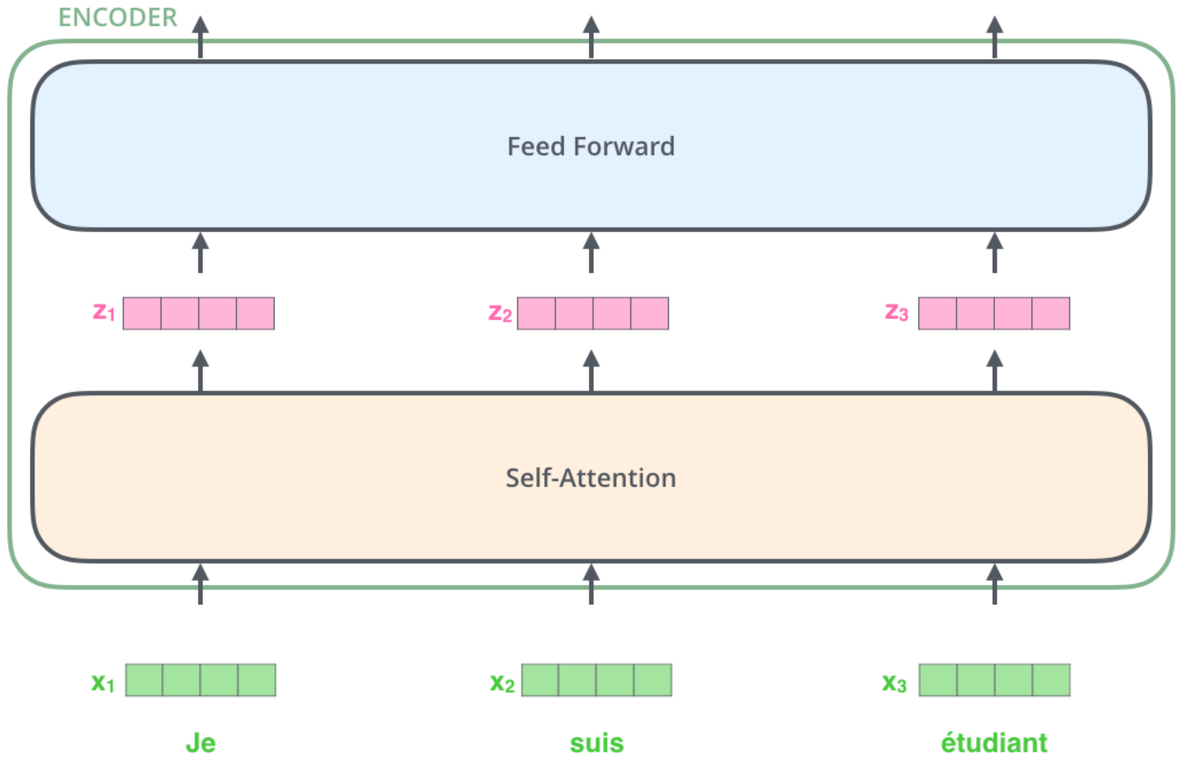
How it works
Transformer

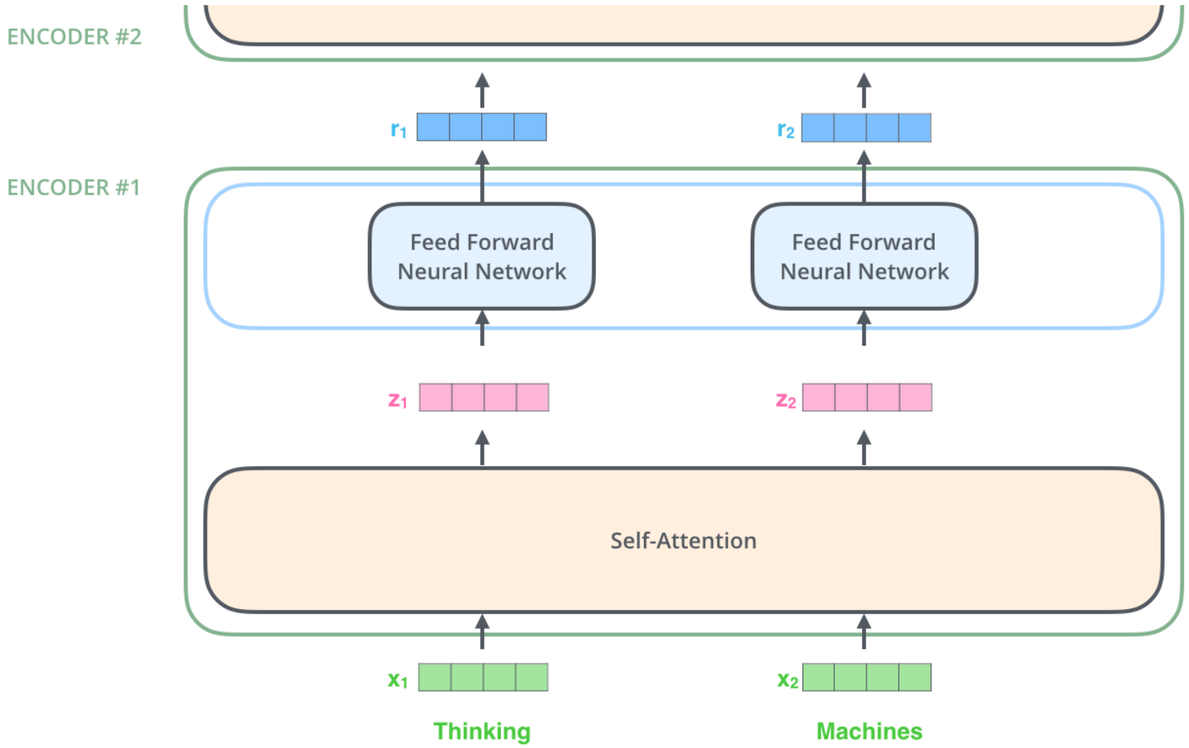
- The first encoder input is the word embeddings for the input words.
- Words enters in form of vectors (embeddings)



source

How it works
Transformer

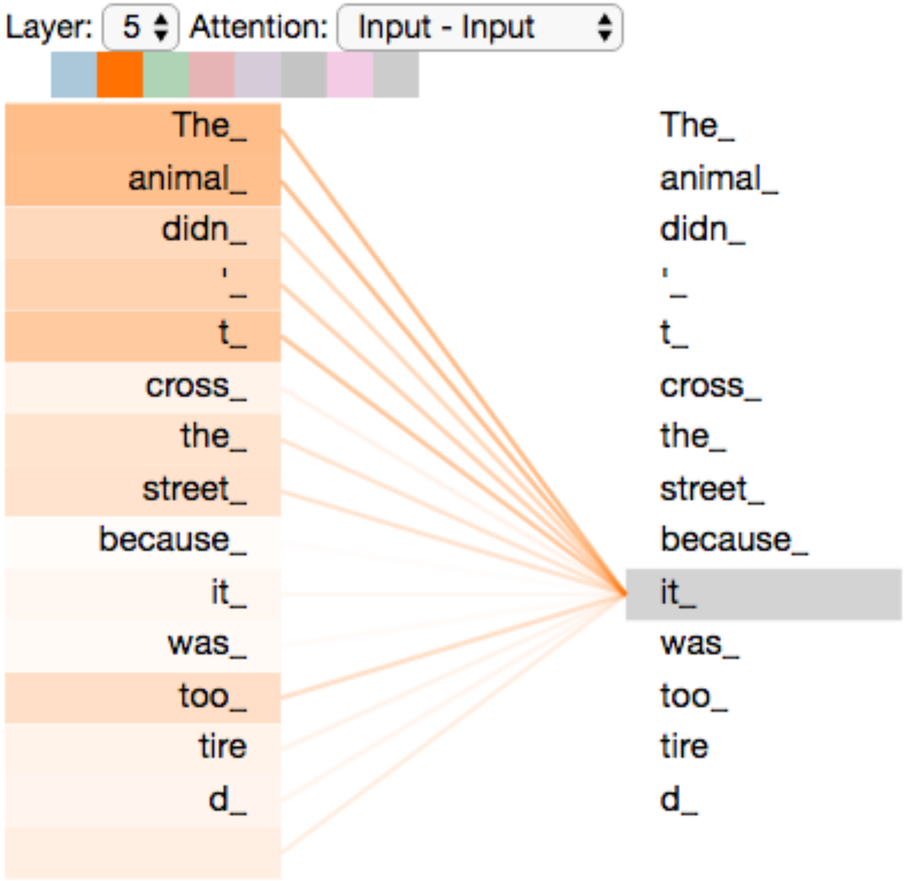
- following encoders input is the output of the previous encoders.
- You can see already each word goes to it's own path, **no dependency** is required between each word and it's previous one, which makes it easy to parallelize this model.



source

Self-Attention
Transformer

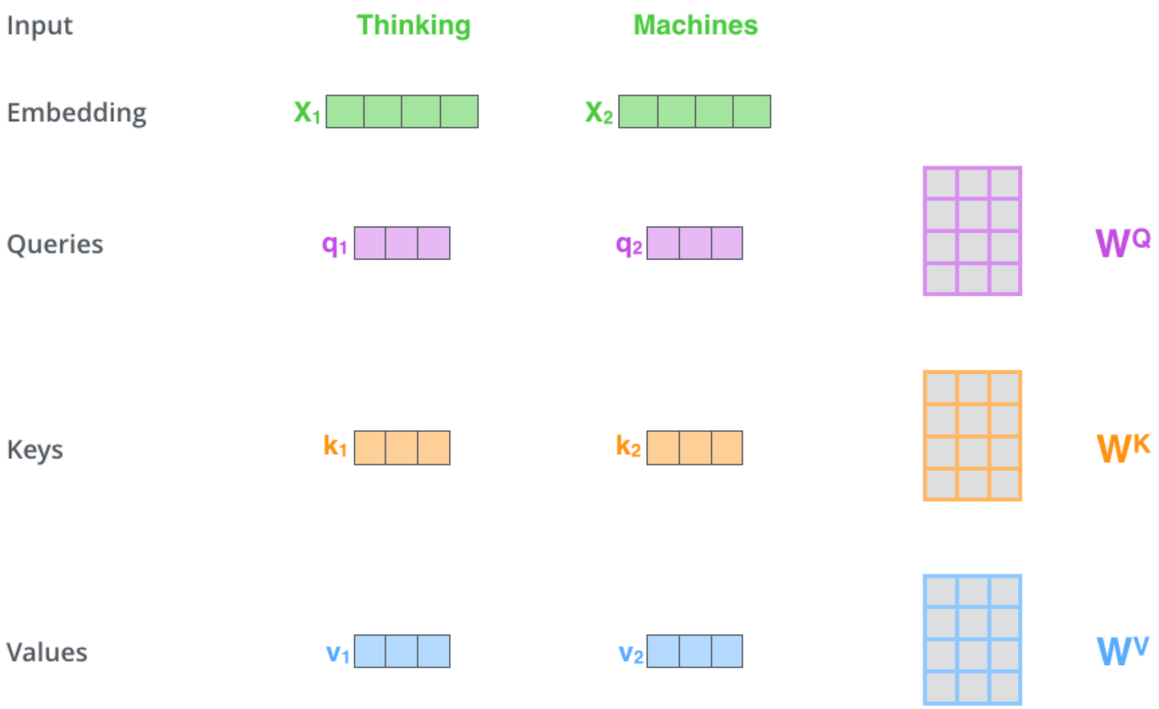
- self attention allows the model to look at other positions in the input sequence for clues that can help lead to a better encoding for this word.
- It help changing the meaning/ representation of the word based on it's context.



source

Self-Attention
Transformer

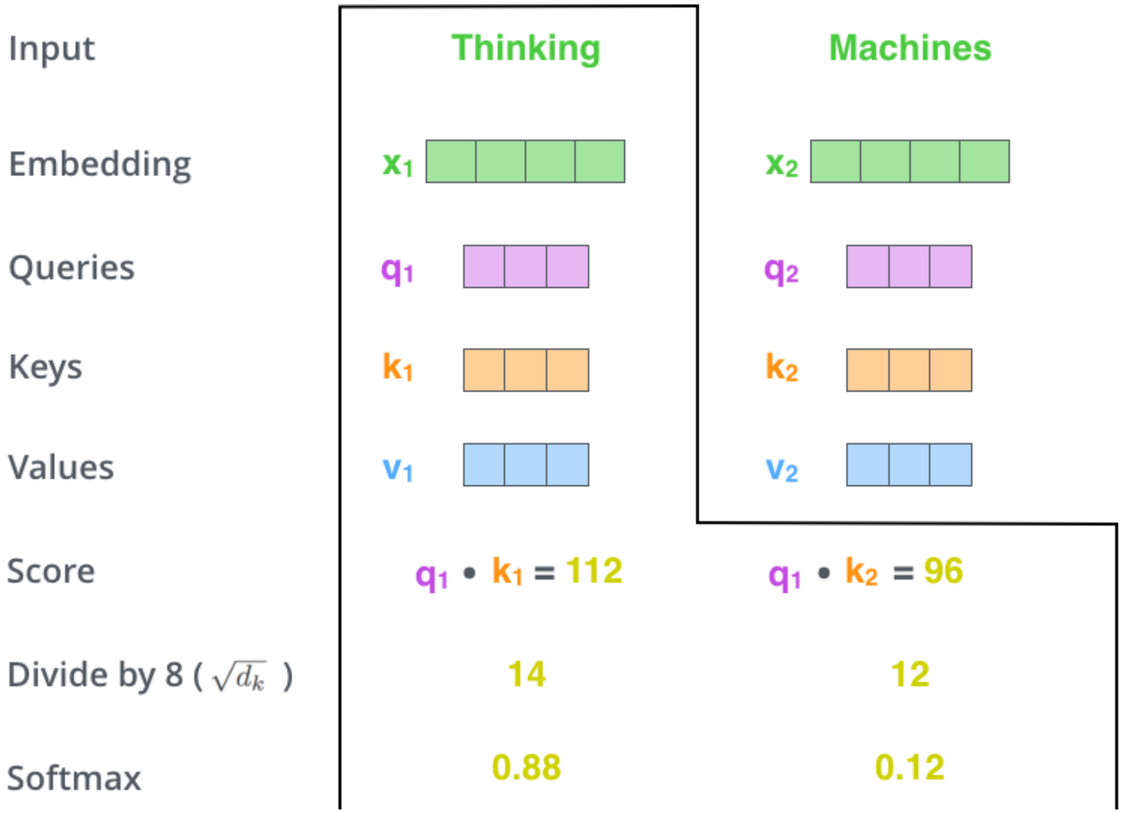
- It works by creating three vectors for each word.
- Query, key and value.
- Each one is created by a weights matrix that is learnable.
- multiplying **x** by and **W** generates the corresponding vector.



source

Self-Attention
Transformer

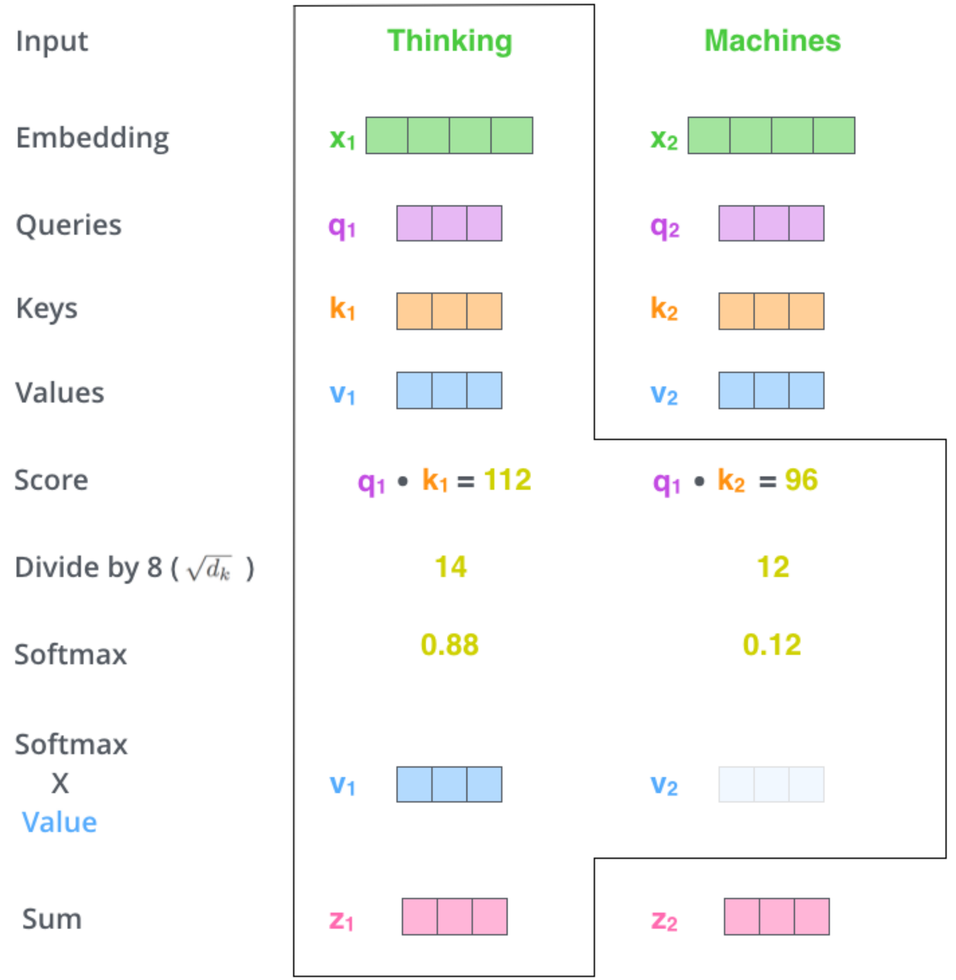
- To calculate self-attention for first word "Thinking" we multiply it's **Query** vector by all the **Key** vectors of every token to get a score.
- The score is then normalized and softmax-ed to get the weight of each key word w.r.t the query word.



source

Self-Attention
Transformer

- The **Value** vectors are then scaled by the score and summed per word.
- What we did for the first word is done for every single word, producing a **Z** vector for every word that carries meaning of it.



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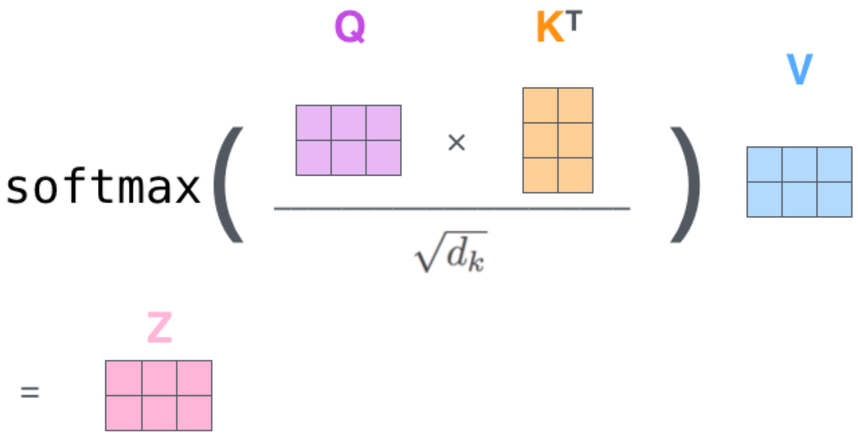
Self-Attention
Transformer

- The previous operations can be calculated as matrix multiplication as follows.



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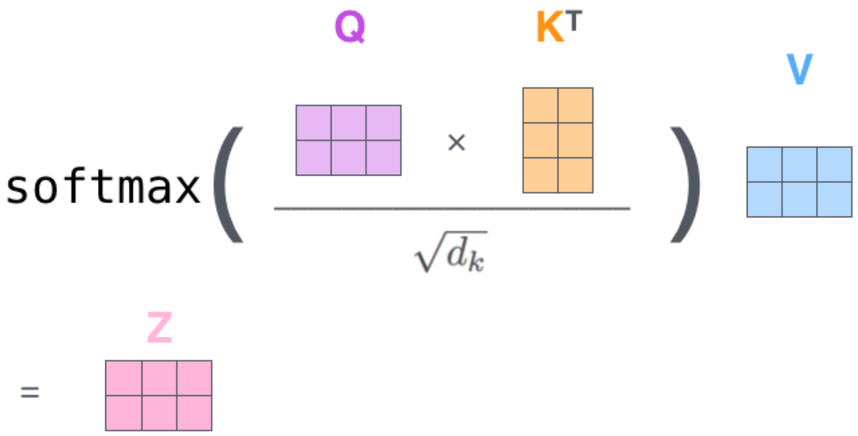
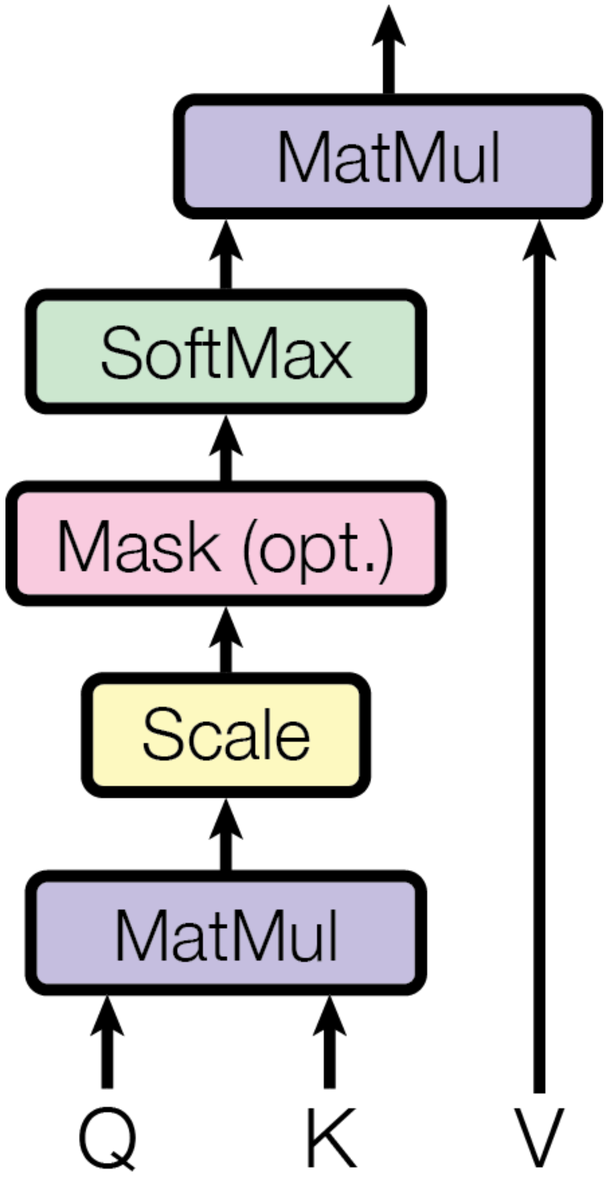
Self-Attention
Transformer

- Another annotation for the self-attention mechanism.





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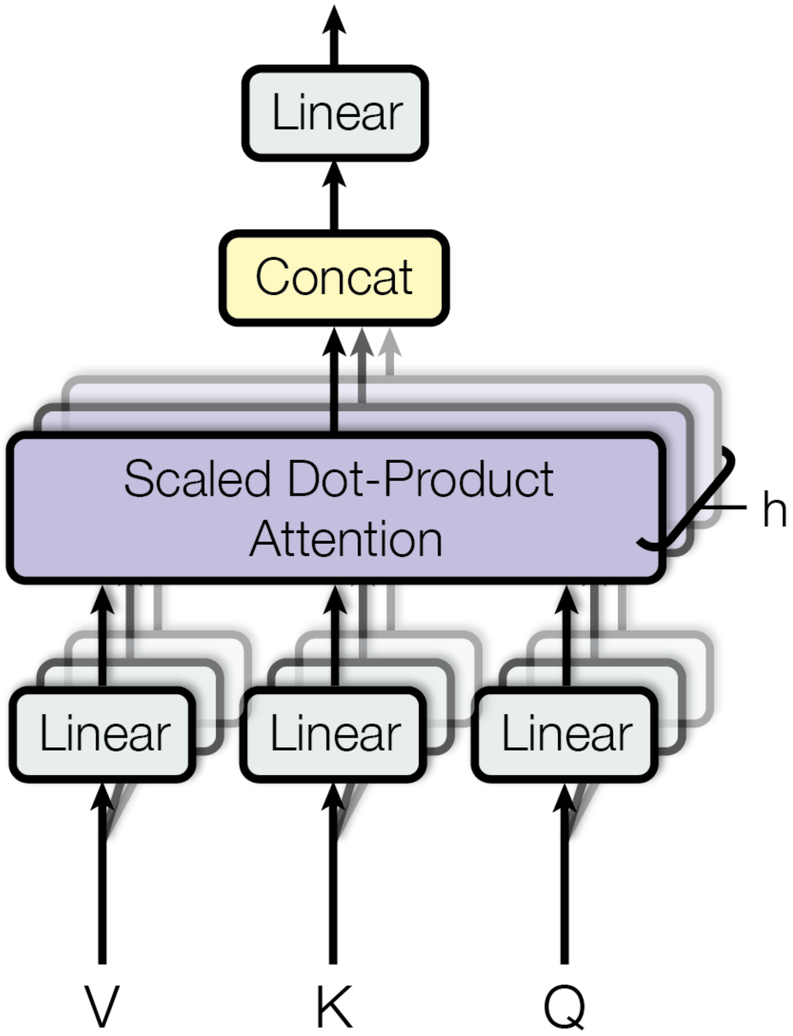
Self-Attention
Transformer

- A multi-headed attention is used.
- This enables multiple representation space for the features.
- Think of it as more layers in NN, it adds more learning space to the model.



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Self-Attention
Transformer

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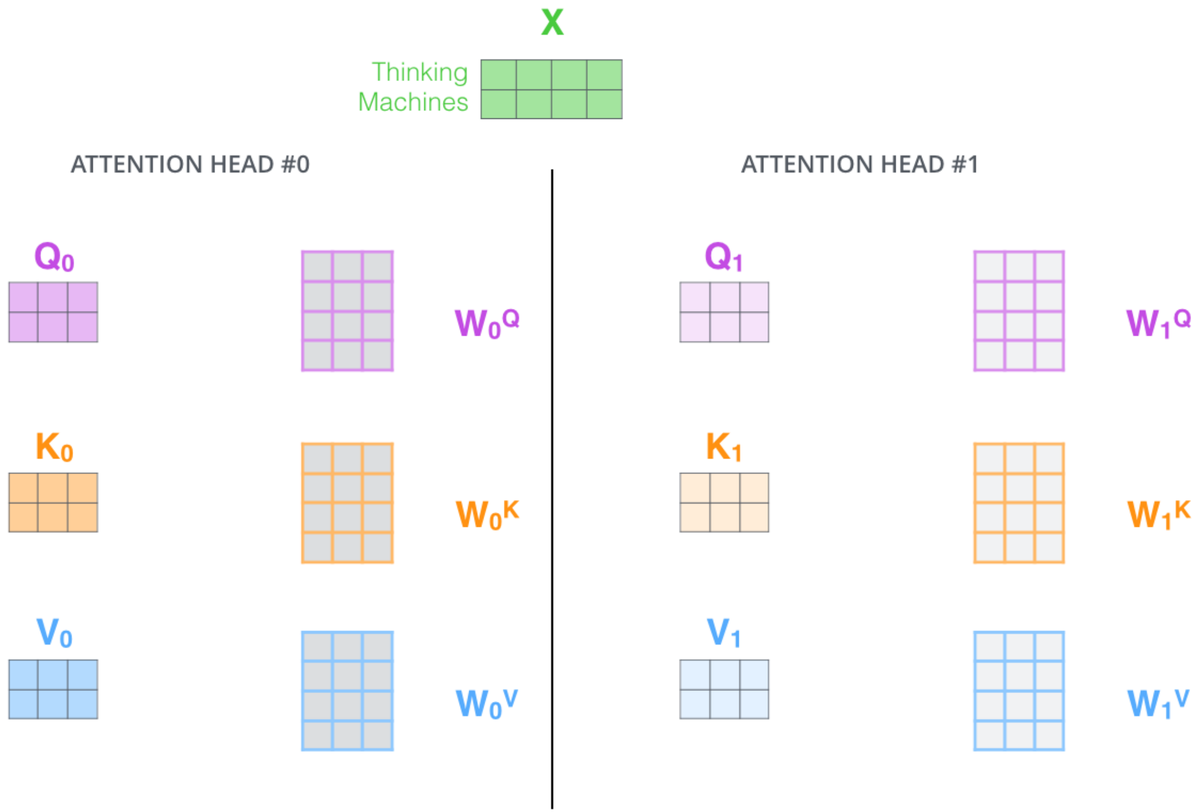

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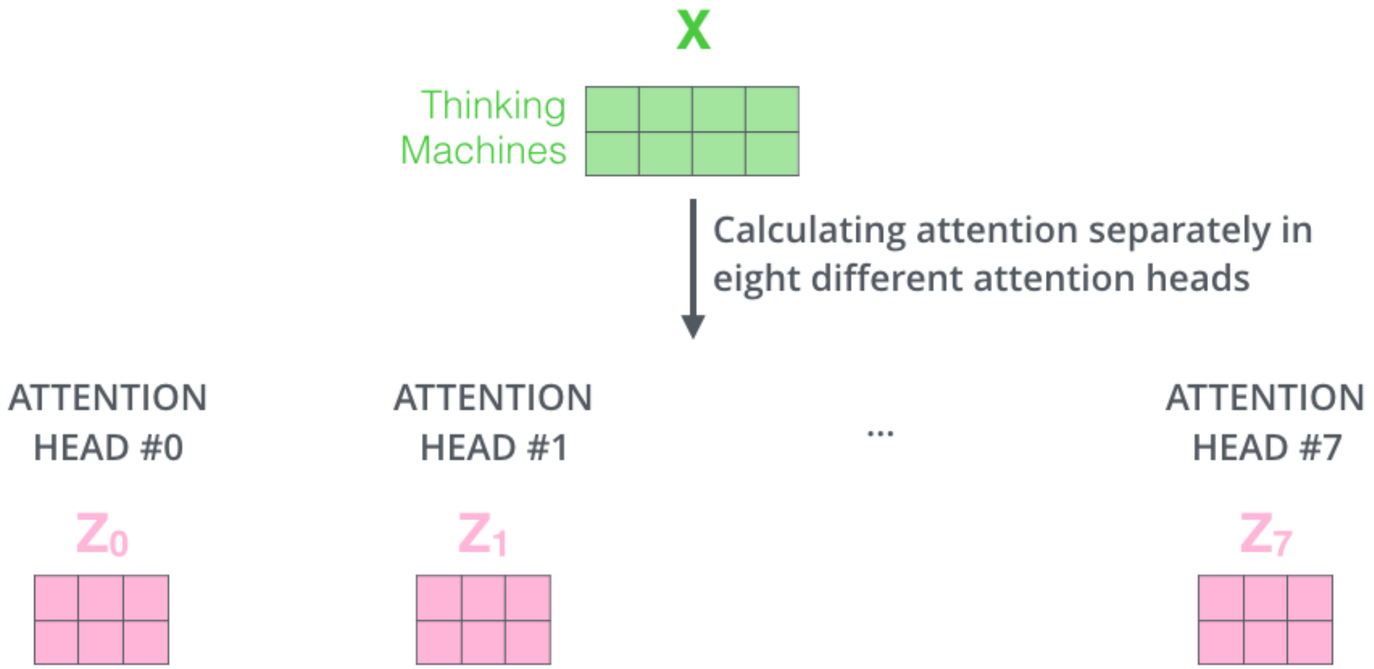
Self-Attention
Transformer

- each head generate a different **z** vector.



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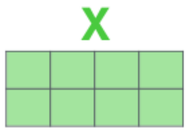
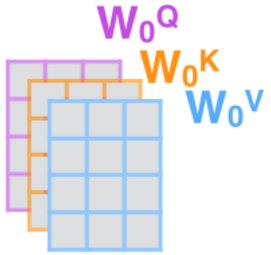
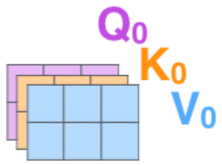
Self-Attention

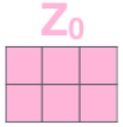
Transformer

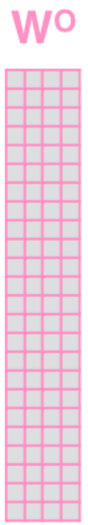
Thinking
Machines

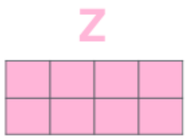




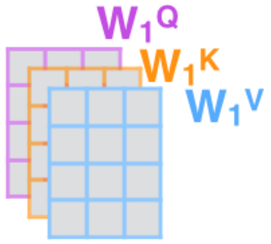


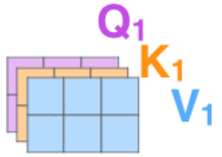


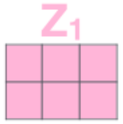


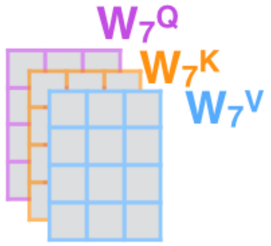


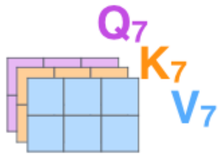
* In all encoders other than #0,
we don't need embedding.
We start directly with the output
of the encoder right below this one

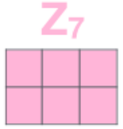








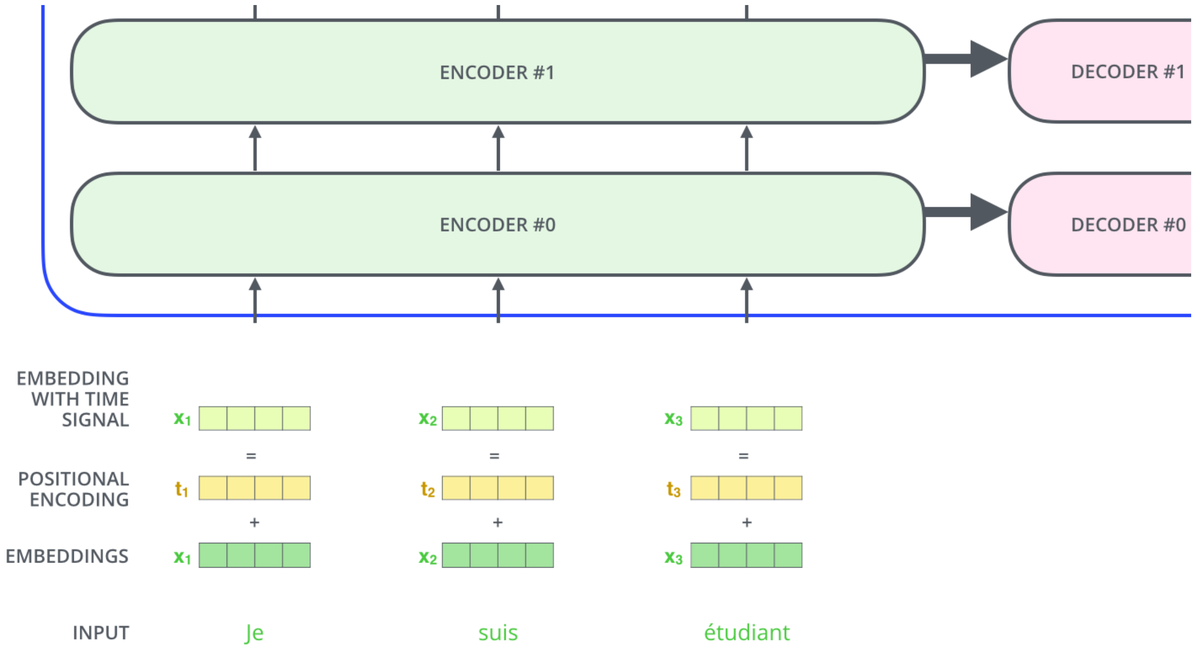




source

Positional Encoding
Transformer

- To get a sense of position, we add a positional encoder to give the model a way to know if words are close to each.
- The positional encodings follow a specific pattern.



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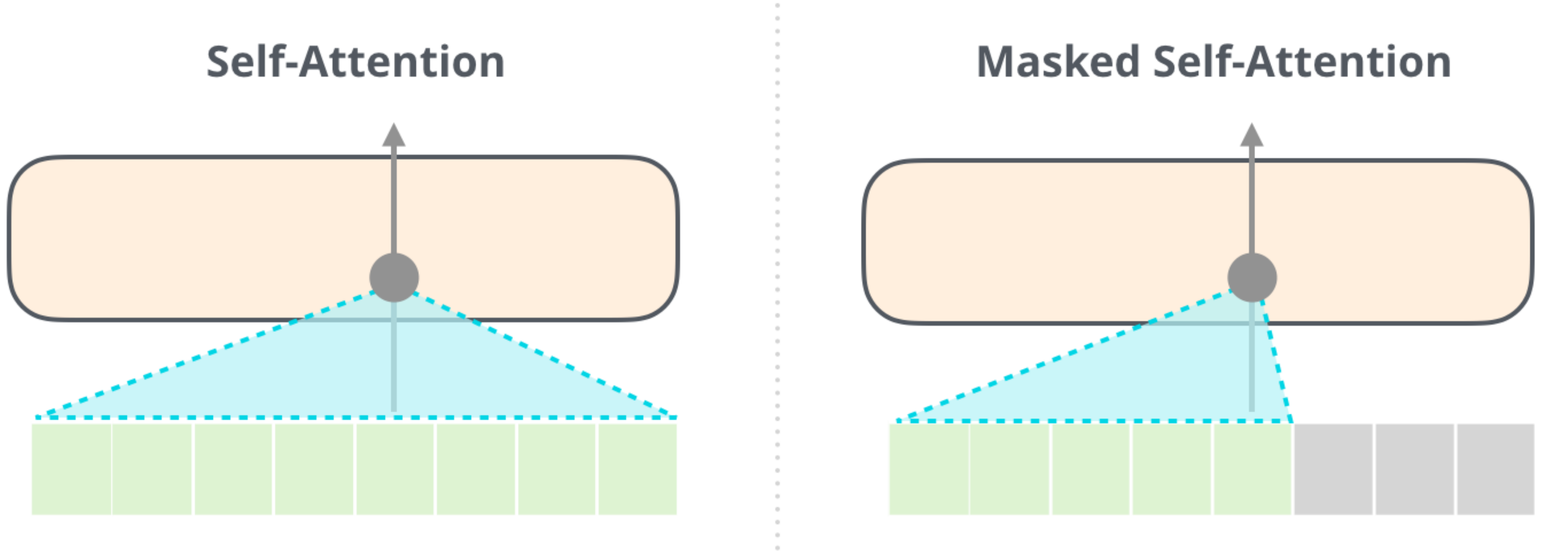
Decoder
Transformer

- The decoder works exactly as the encoder expect for the mask.
- Every future token is masked so the decoder can't attend to future tokens while training, as they won't be available in inference.



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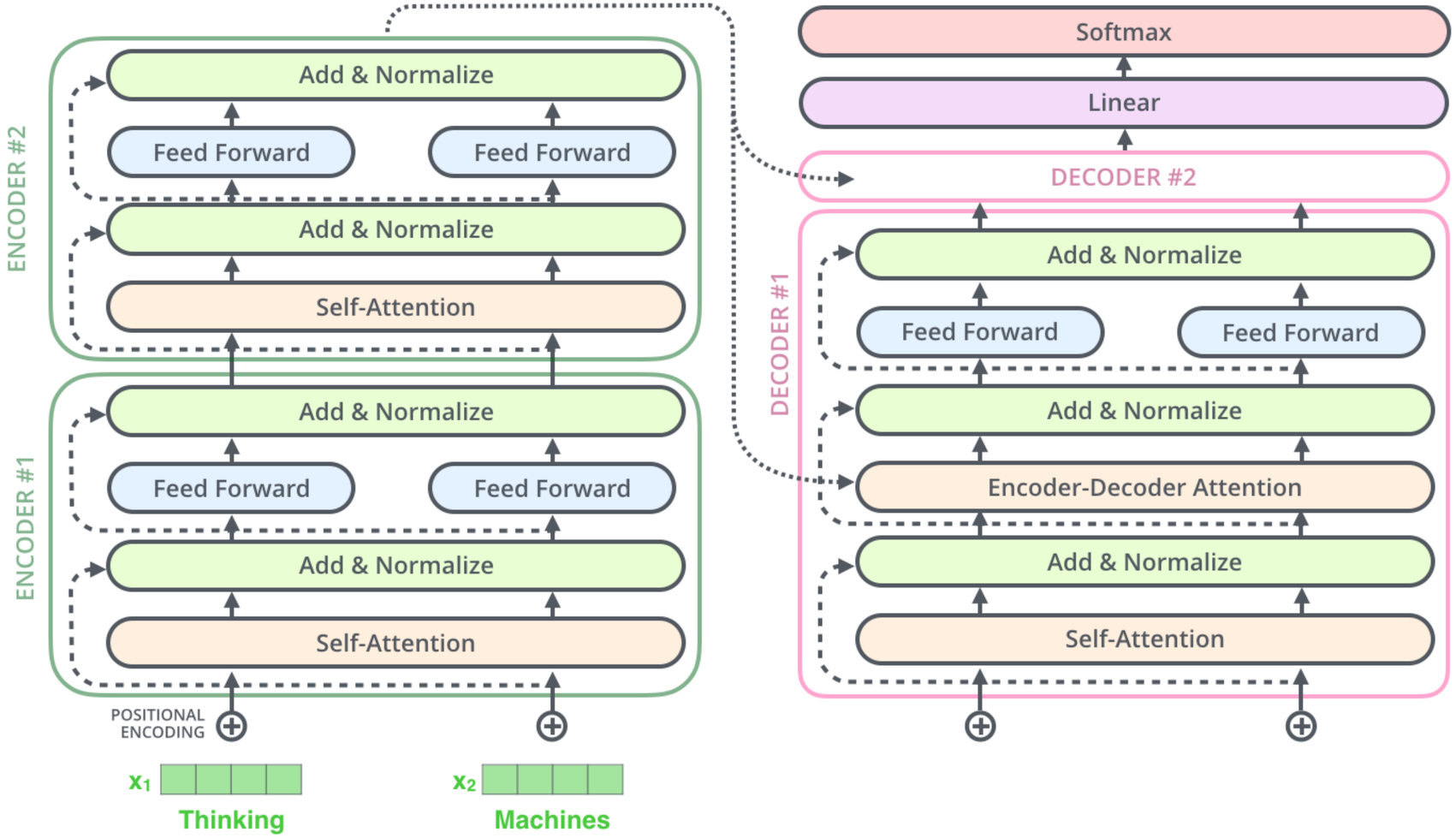
Decoder

Transformer



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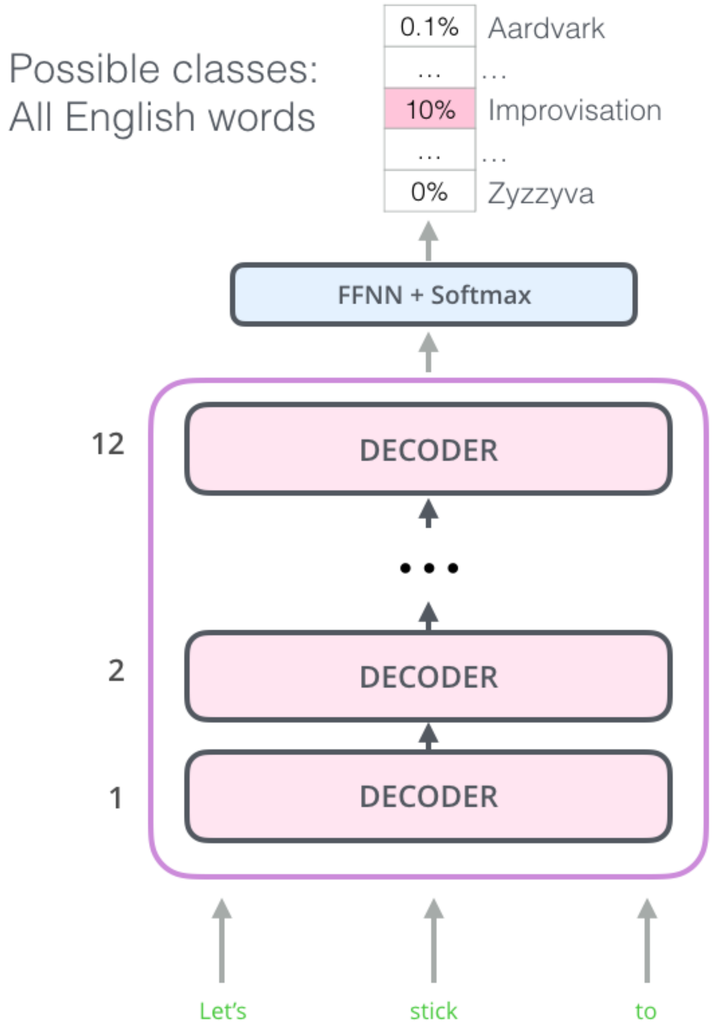
The dawn of transformers

OpenAI: GPT
Transformers

- It uses a stack of 12 decoder unit.
- No encoder is used.
- It trains on language modeling task.
- The objective is to predict the next word.



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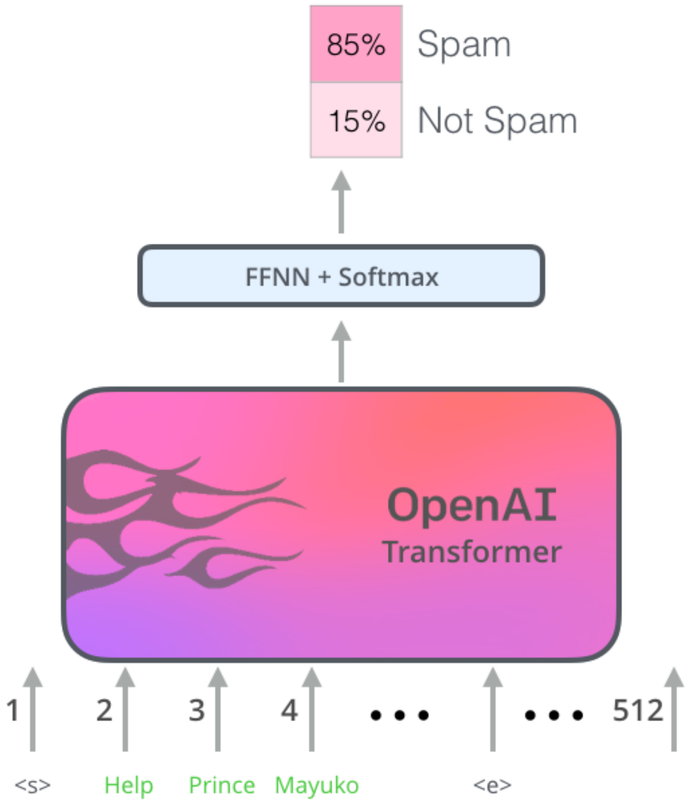
OpenAI: GPT
Transformers

- The model is then used in downstream tasks.
- The decoder has a drawback, it can't attend to future tokens.



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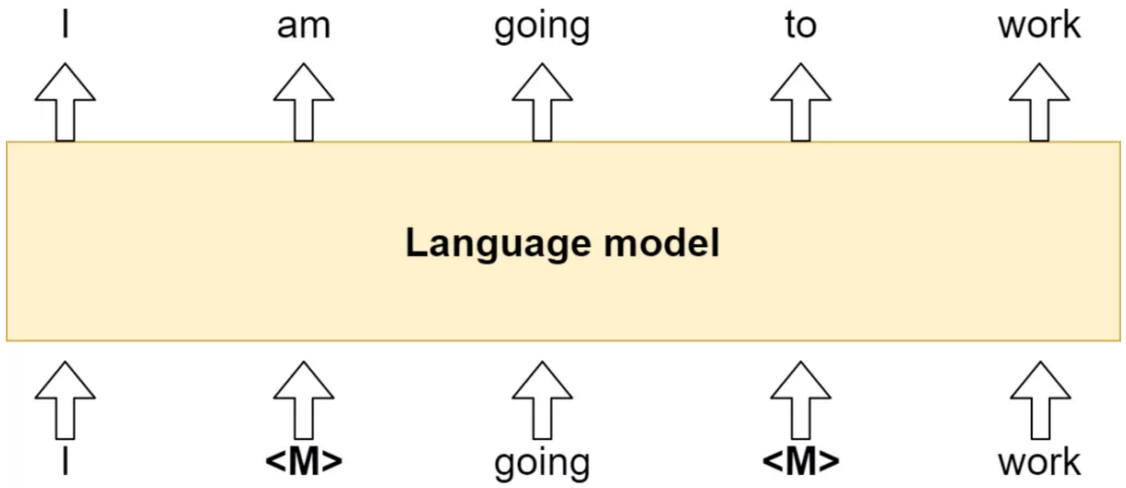
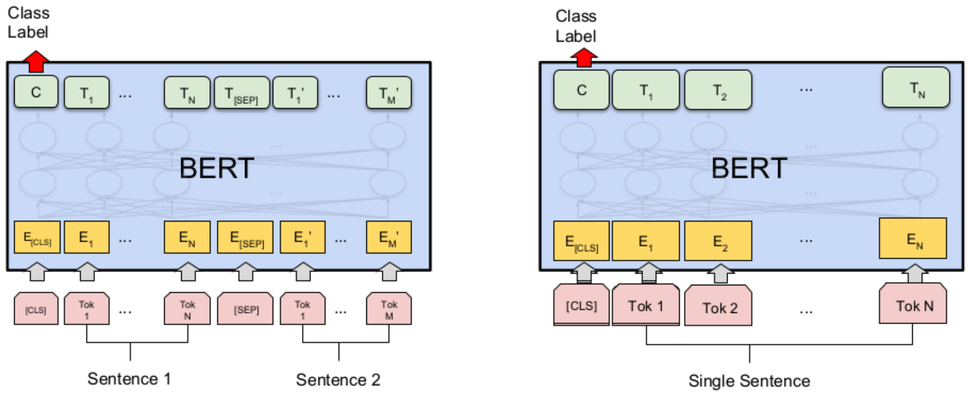
Google: BERT
Transformers

- Uses encoder instead of decoder.
- Trained on masked language modeling task, BERT objective is to predict masked token.



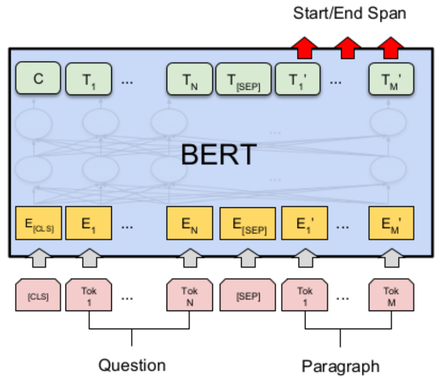
Google: BERT
Transformers

- BERT can be used for almost every NLP task

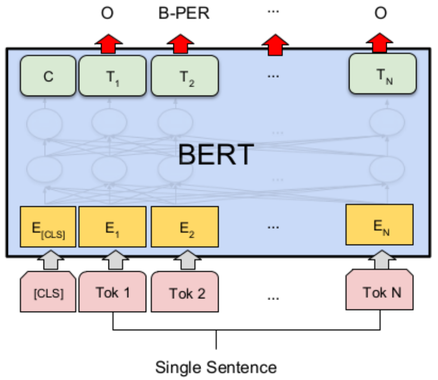


(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

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



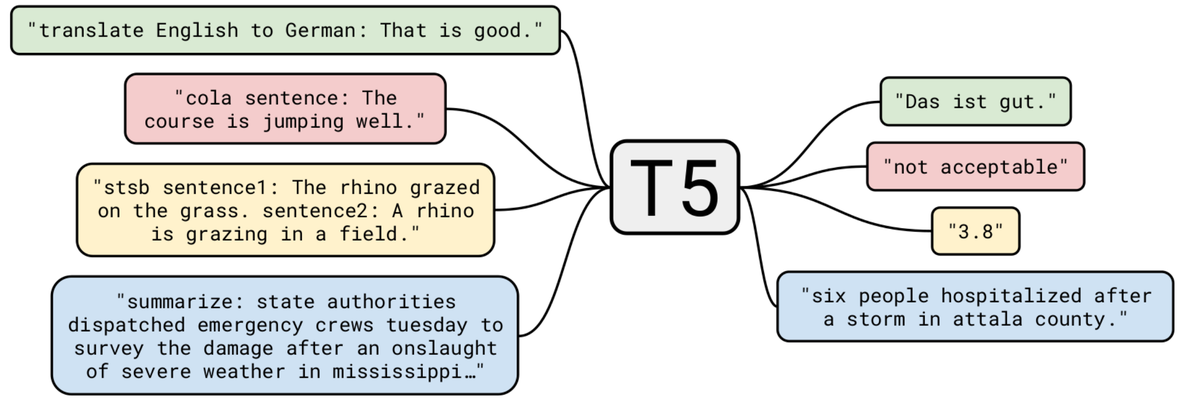
(c) Question Answering Tasks: SQuAD v1.1



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

Google: T5
Transformers

- T5 was introduced by Google in early 2020, it's an encoder-decoder architecture.
- The model was trained on the Colossal Clean Crawled Corpus (C4) which is a huge corpus covering differing kind of tasks.
- The objective of the model is to fill the blank.



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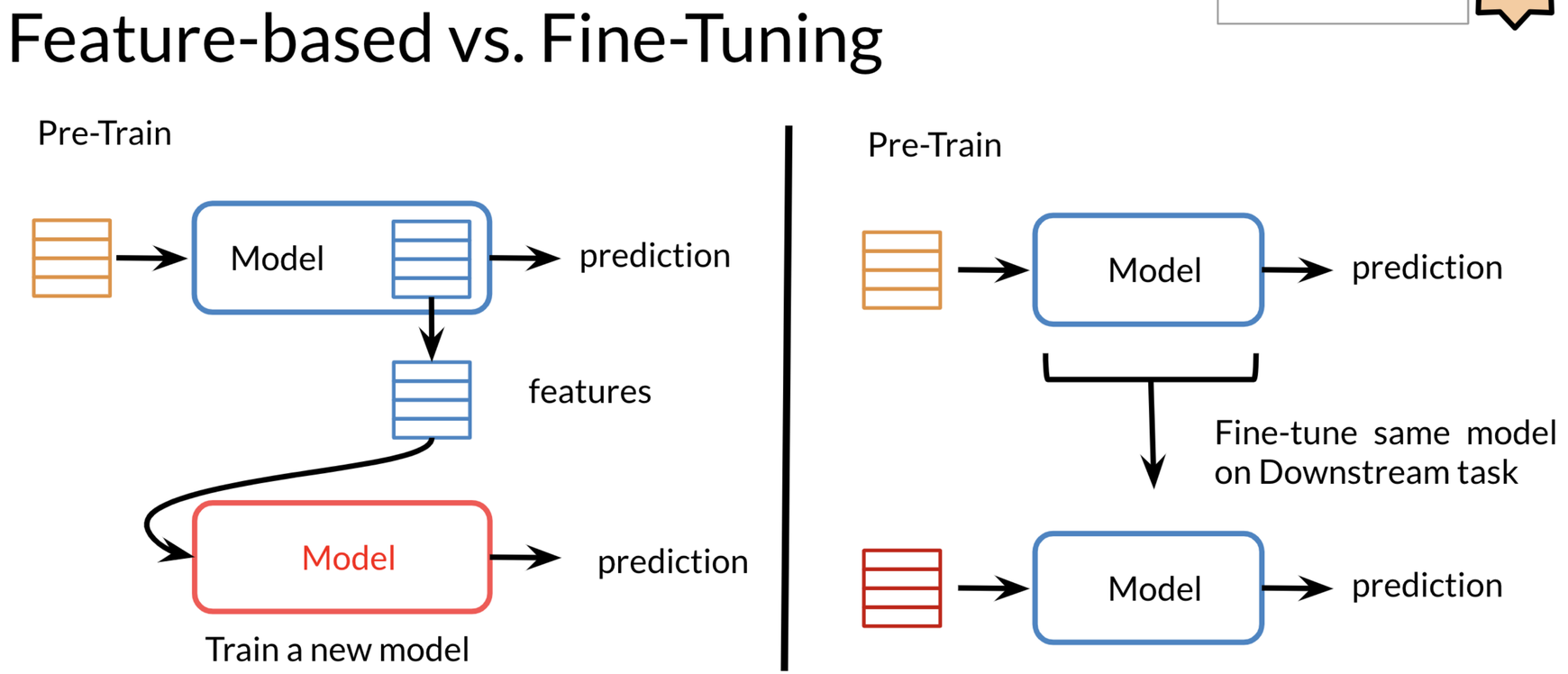
Transfer Learning

Feature-based vs Fine-Tuning

Transfer Learning

Transfer 1



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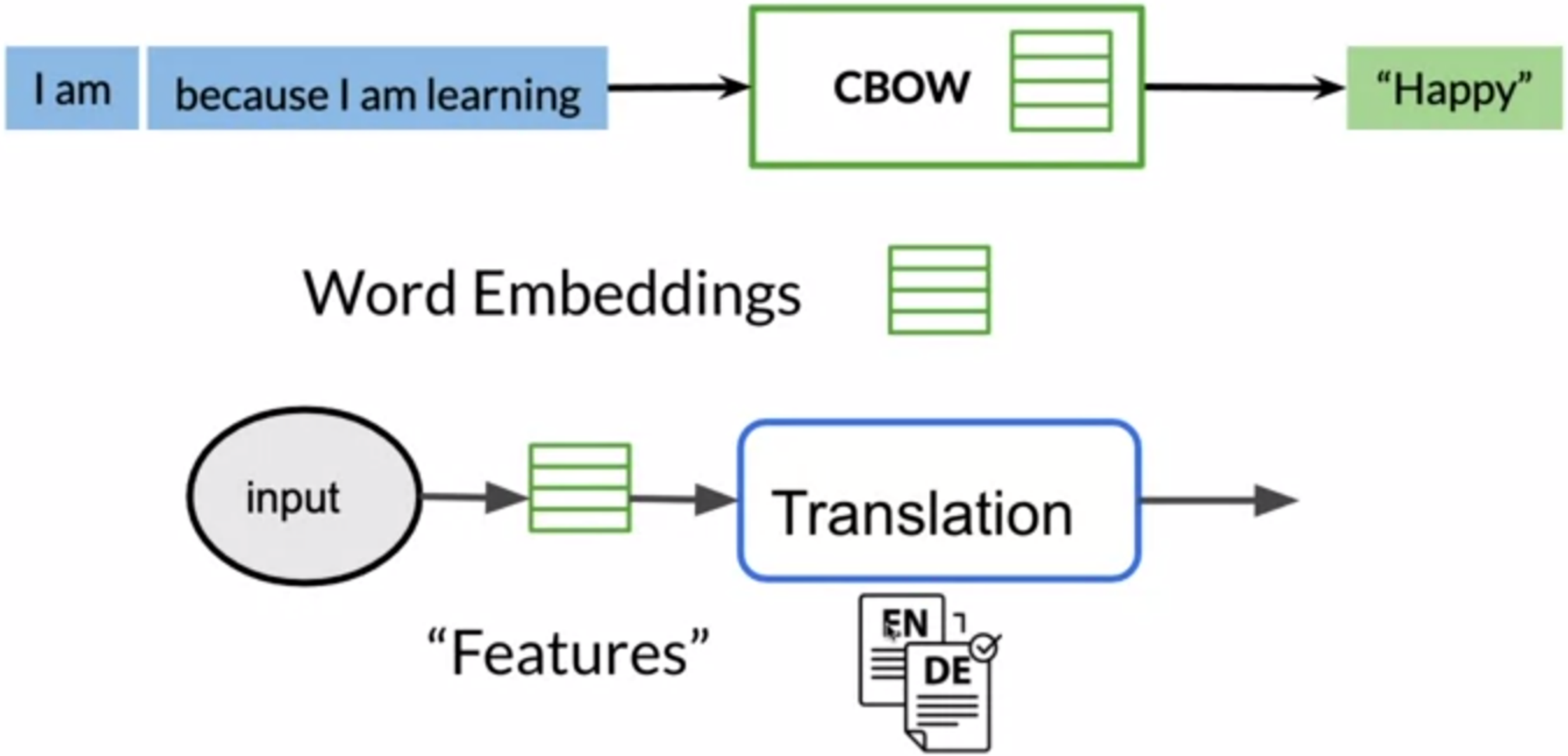
Feature-based

Transfer Learning



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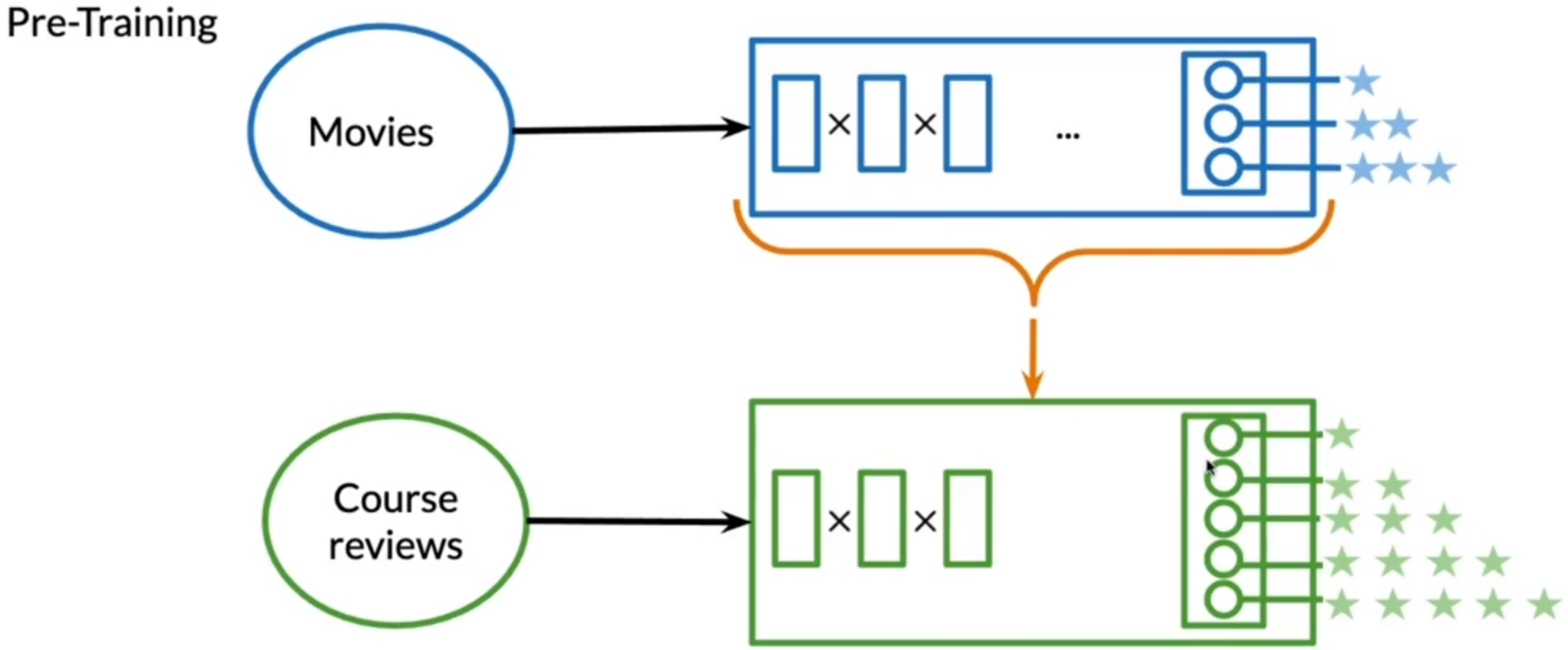
Fine-Tuning
Transfer Learning



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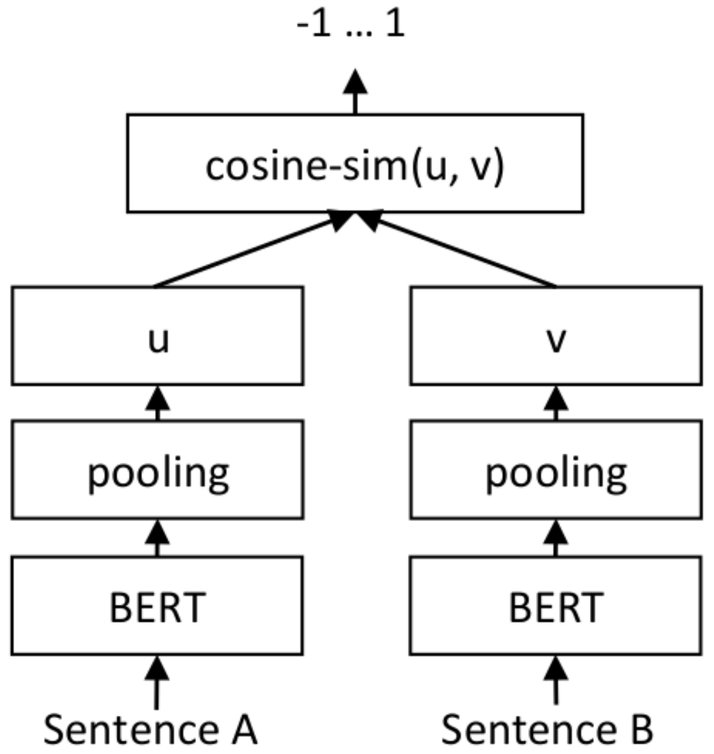
Siamese Network

Transfer Learning

- We can use Siamese Network to fine-tune a model on a specific domain.
- This architecture is very useful in sentence similarity tasks.
- We can transfer model knowledge to new domains.



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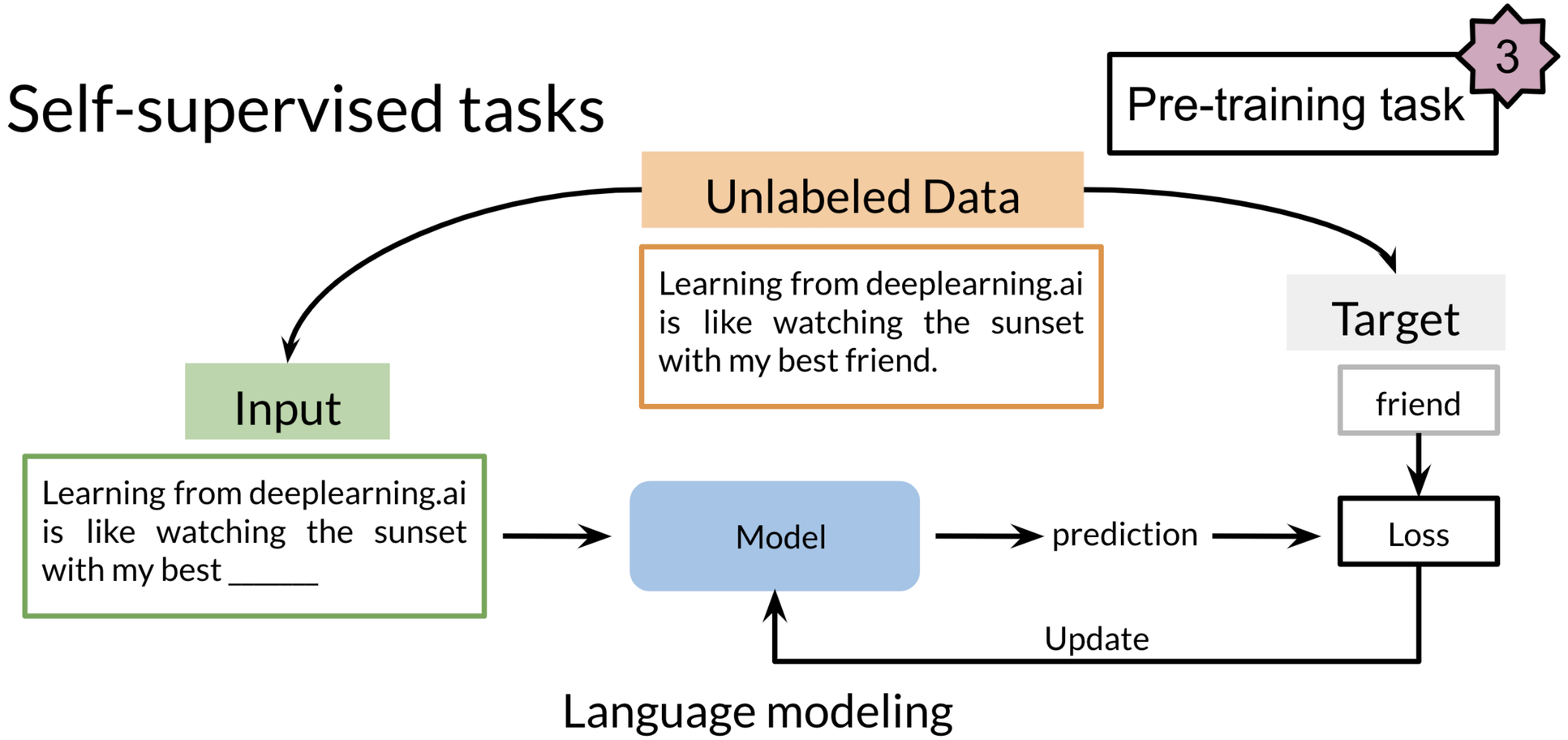
Self Supervised Learning

Self-Supervised learning

Transfer Learning



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Knowledge Distillation

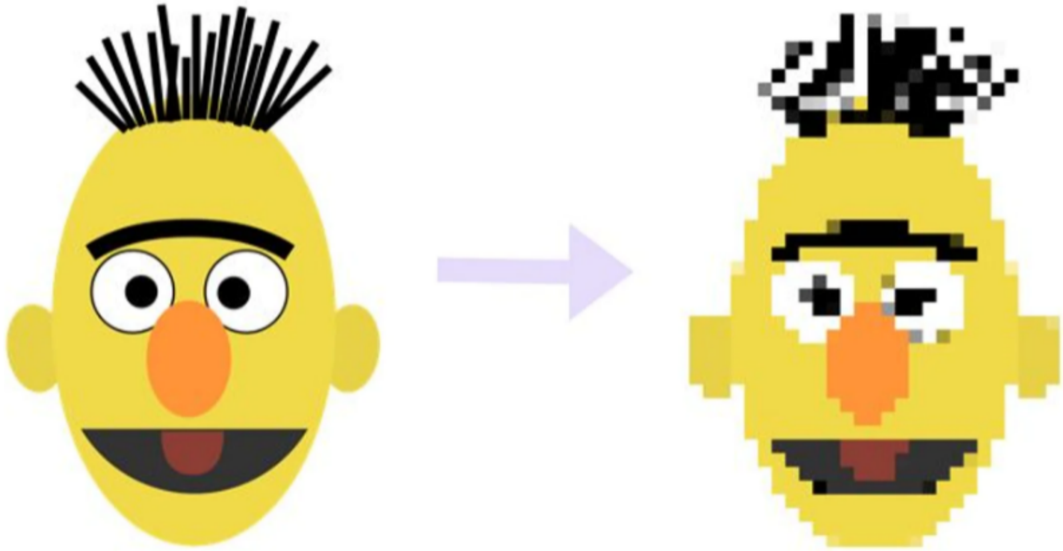
Transformers limitations

Knowledge Distillation

- Transformer based models are huge in terms of compute power and memory consumption.
- They need GPUs to offer a reasonable inference time.
- We can reduce the number of parameters (weights), or reduce the precision of them for example going from **float64** to **float16**.

Quantization
Knowledge Distillation

- Quantization works by reducing the precision of the weights to 8-bits.
- This significantly reduce memory usage of the model but also the accuracy of the model.
- The trade-off most of the time is worth it.



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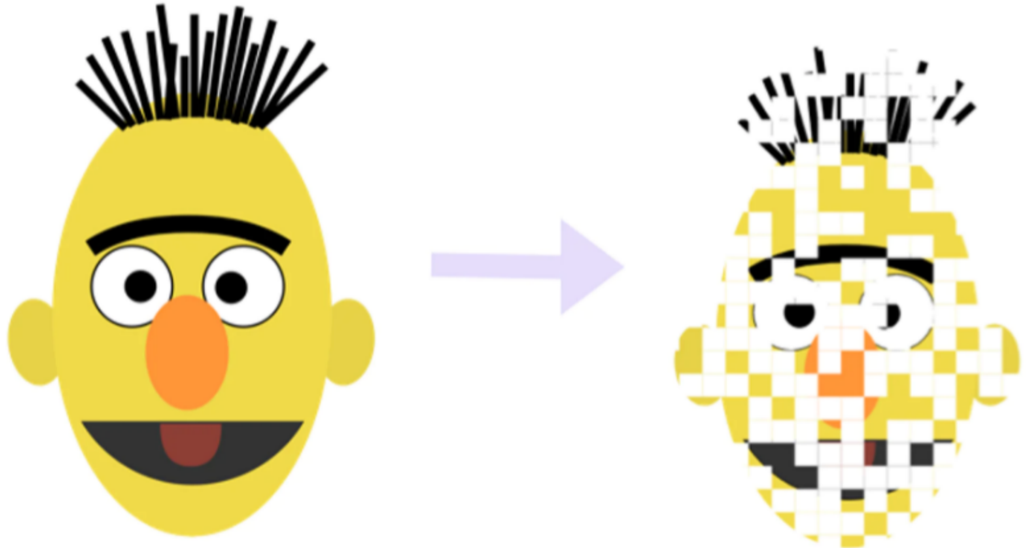
Pruning
Knowledge Distillation

- Pruning remove some weights that is very insignificant.
- The importance of the weight is decided based on it's value, when it is close to 0 it's not important.
- The enhancement depends on the sparse matrix implementation that you use.
- Also some pruning techniques removes neurons or even a complete weight matrix (like remove an attention head)



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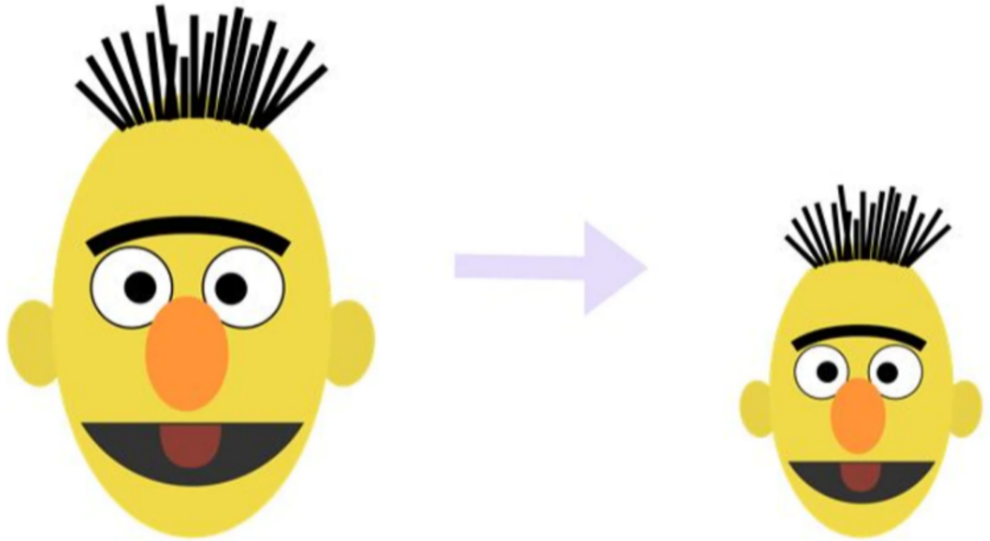
Knowledge distillation

Knowledge Distillation

- After training a big and slow model (the teacher), a smaller model (the student) is trained to mimic the teacher's behavior - whether its outputs or its internal data representations.
- The student trains to copy the knowledge of teacher.
- The loss of the model is a cross-entropy over the soft targets (probabilities of the teachers) not the hard targets.



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HuggingFace

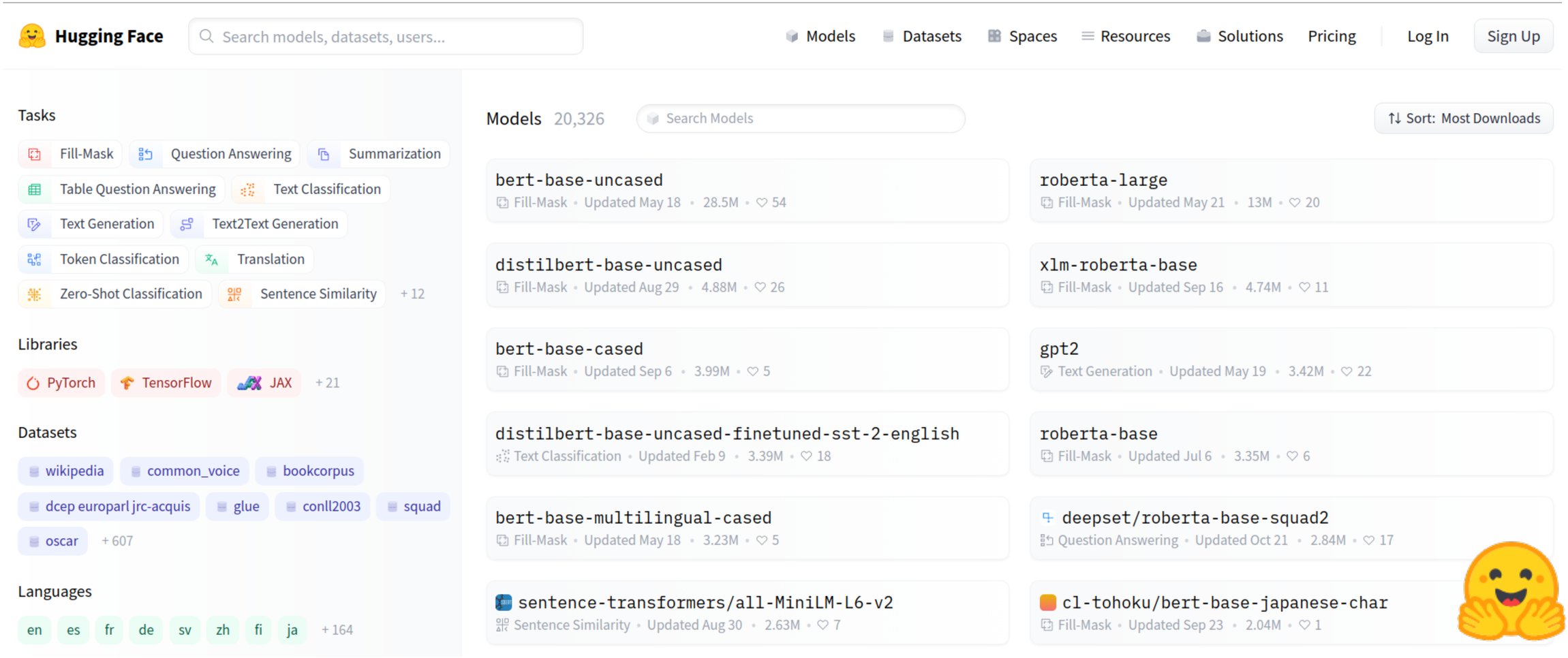
HF Hub

HuggingFace

- HF is an open source community with a hub for wide range of pre-trained deep learning models.
- HF also provide wide range of datasets for lots of tasks.
- transformers, datasets are the most famous libraries huggingface has provided.

HF Hub

HuggingFace



Notebooks - 1

Transformers introduction

Notebooks - 2

Sentence Transformers

Notebooks - 3

ONNX

Questions ?

Thank you !