Transformers

Attention Is All You Need

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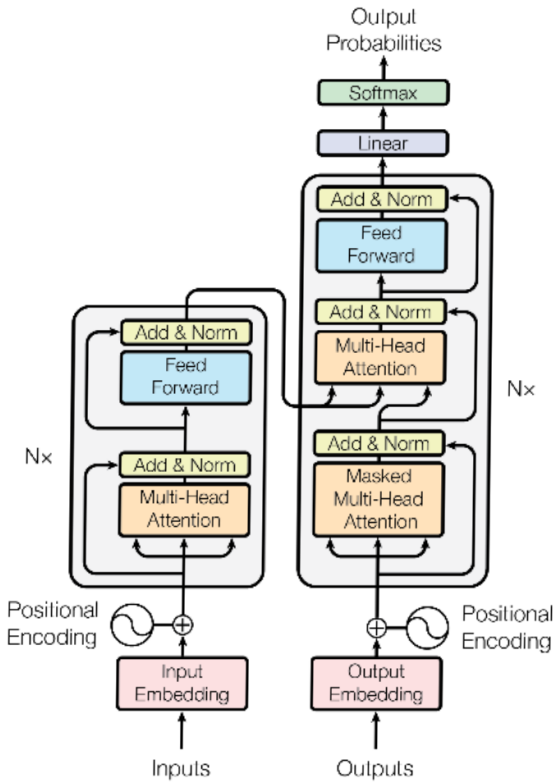
Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.



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Bag Of Words

I had a **good** day
I had a **great** day
I had a **had** day

	I	had	a	good	great	day
I	1	0	0	0	0	0
had	0	1	0	0	0	0
a	0	0	1	0	0	0
good	0	0	0	1	0	0
great	0	0	0	0	1	0
day	0	0	0	0	0	1

Embedding space

Word Embedddings

happy	0.5	0.45	0.76
sad	0.45	0.45	0.82
red	0.01	0.9	0.2

Pretrained embeddings can be downloaded using libraries like FastText

Positional Encoding

Impart positional information to the vectors

Sara's **dog** is cute
Sara is cute like a **dog**

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

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

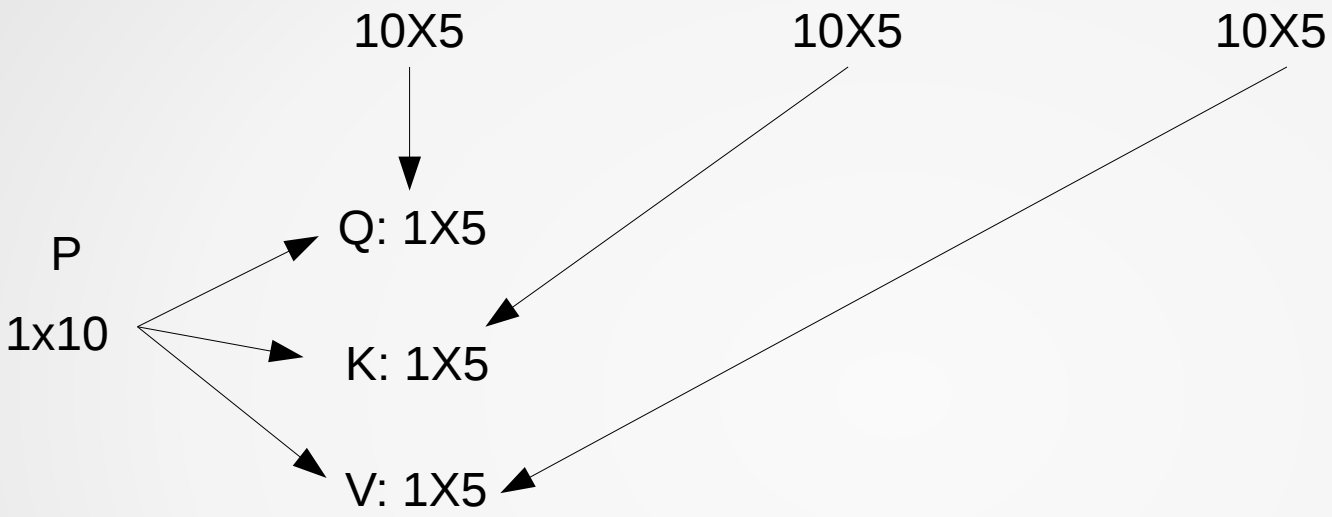
So far .....

For each word

Embedding (vector)
+
Positional Encoding (operation)
=
Context with position info

To be done for both encoder and decoder

Queries, Keys and Values

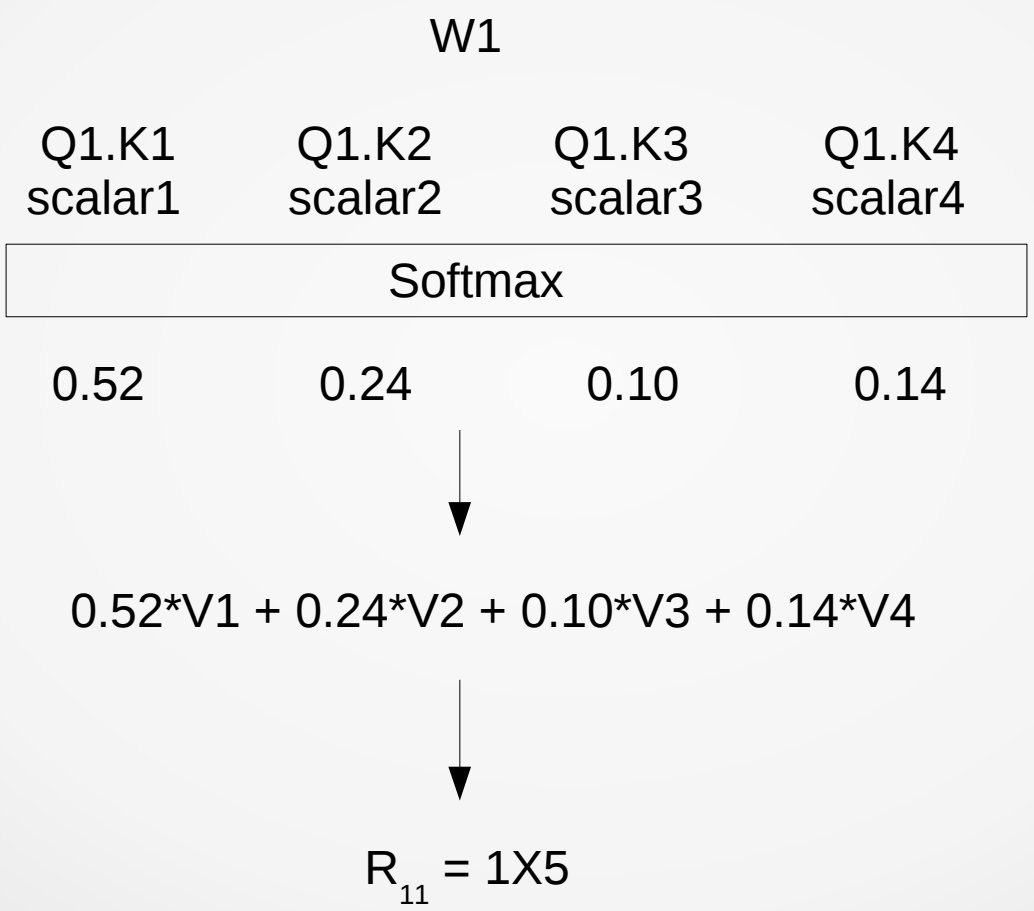


Do the same for all word vectors
(Let's assume a 4 word sentence)

Queries, Keys and Values

	Word1	Word2	Word3	Word4
Positionally Encoded Vectors	P1	P2	P3	P4
Queries	Q1	Q2	Q3	Q4
Keys	K1	K2	K3	K4
Values	V2	V2	V3	V4

Self - Attention

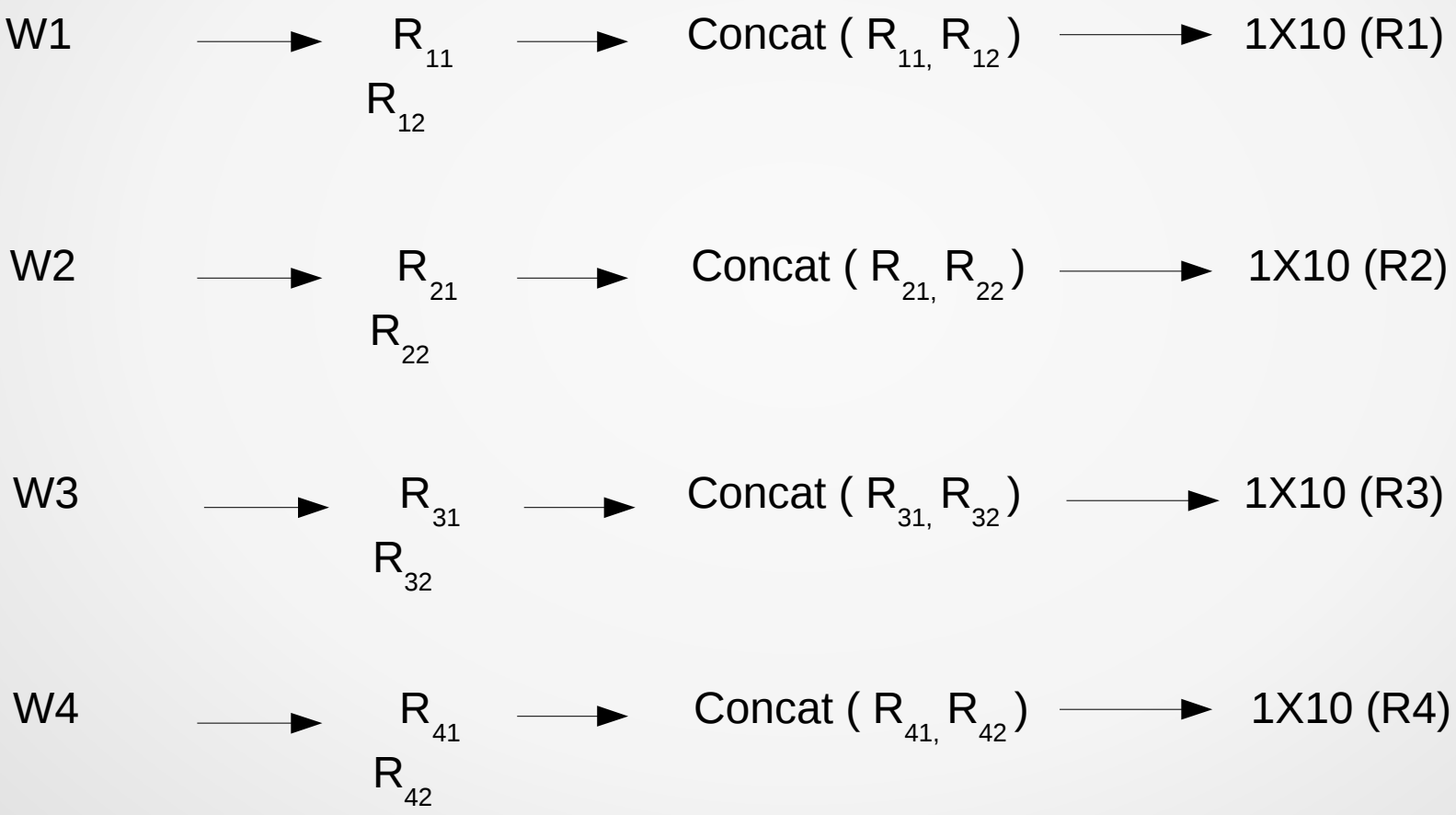


Self - Attention

- Computes attention vector for each word

The day was good	0.7	0.6	0.54	0.32	0.43
The day was good	0.8	0.9	0.6	0.5	0.4
The day was good	.43	0.52	0.76	0.54	0.32
The day was good	0.45	0.23	0.54	0.67	0.49

Multi Head Attention



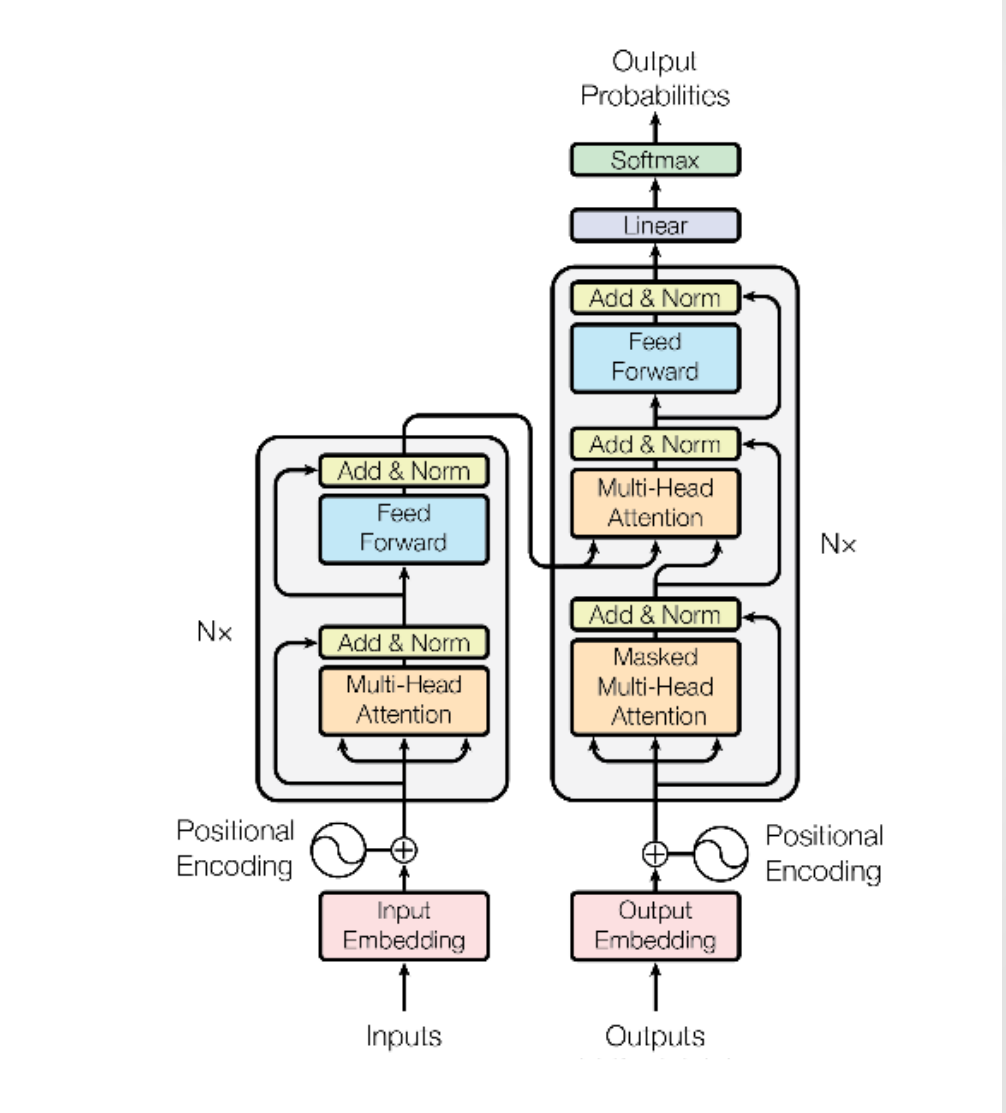
Projection

$$\underset{1\times10}{[\ R\ ]}\ \underset{10\times10}{[\ W_0\ ]} = \underset{1\times10}{[\ Pr\ ]}$$

Layer Normalisation

P is the positionally encoded vector fed into the self-attention layer

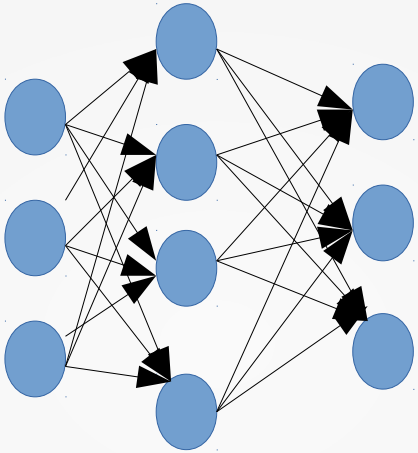
Layer Normalisation (P + Pr)



Feed Forward, Add and Normalize

Pr_i

Input size = size of a P_r vector



Output is same size as Input

Layer Normalization (Pr_i + $Ouput_i$)

Repeat

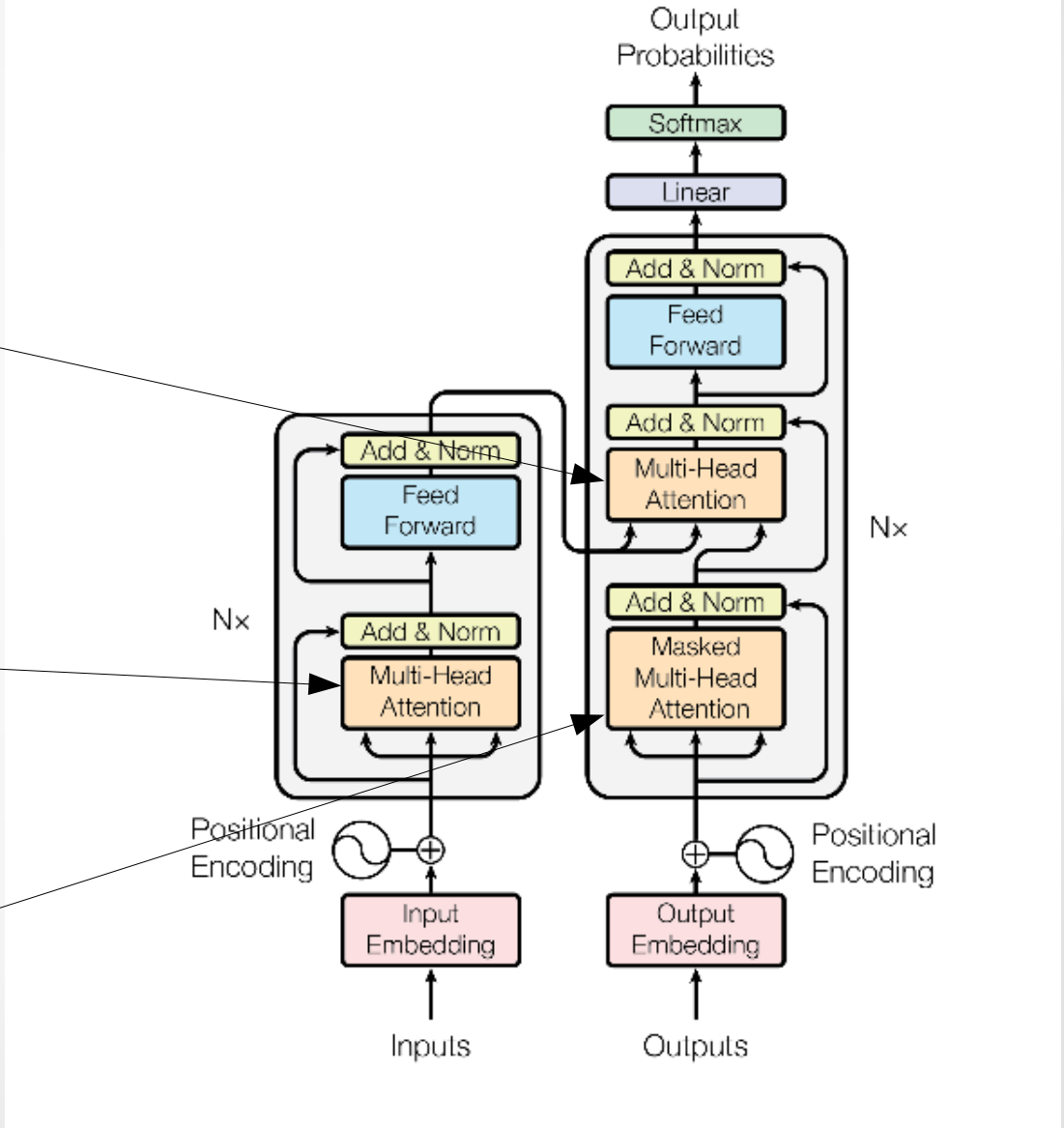
- The operations so far constitute one encoder layer.
- This output becomes the input for the next encoder layer
- Repeat process (N = 6)
- The output of the final encoder layer is used in the multi - Head attention layer of the decoder

What is being attended ?

Target Language and Source Language

Source Language and Source Language

Target Language and Target Language



Masked Self Attention in Decoder

- The generation of a word in the target language can pay attention only to the words already generated.
- Since operations are vectorized there has to be a mechanism to mask the positions for the words that will be generated afterwards.

Linear and Softmax Layer in Decoder

Will project onto the vocabulary of the target language thereby giving a probability distribution over the candidate next words.

Two ways of choosing words

- Greedy Approach
- Beam Search

Training

Feed Forward

I	there	go	am	want	come	fast	can	to	will
0.10	0.13	0.12	0.03	0.31	0.01	0.02	0.15	0.04	0.09

Target

0.	0.	0.	0.	0.	1.	0.	0.	0.	0.

Loss Function = Sum of differences
Goal is to minimize the loss function

Preprocessing and nuances

- Both german and english sentences have to be appended with eos tokens at the end

  eos = end_of_sentence

- Since this is English -> German, german sentences have to be appended with sos tokens at the beginning

  sos = start_of_sentence

- The german and english sentences have to be made of the same length else the entire thing breaks

- We do this by appending ‘padding’ tokens after eos

Inference

- The transformer is what in NLP is called a “ Language model “
- The job of a language model is to predict the next word conditioned on the previous words it has seen

- **Inference** in Machine Learning is when you use the model learned (so far) to predict (usually on test data).
- This is important when using things like BatchNorm, Dropout, etc
- There is a train( ) mode and eval mode in Pytorch( )

Linear and Softmax Layer in Decoder

Will project onto the vocabulary of the target language thereby giving a probability distribution over the candidate next words.

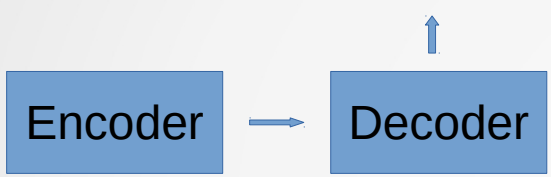
Two ways of choosing words

- Greedy Approach
- Beam Search

Inference

ran here indicates some word that we don't care about

1)



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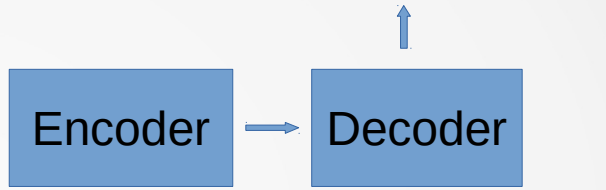

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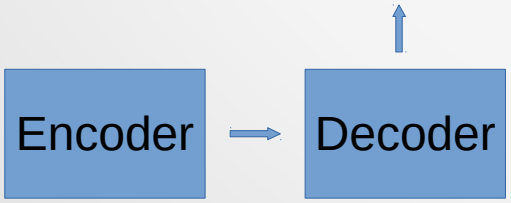

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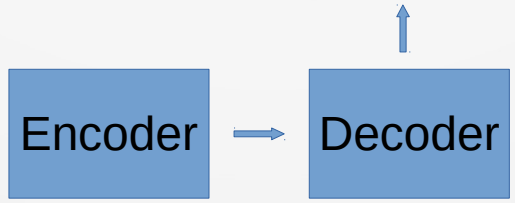
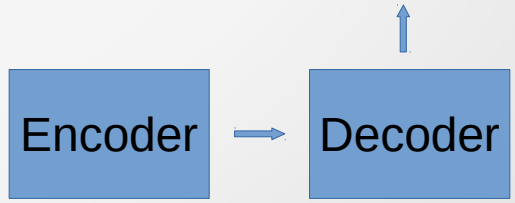


5)



Future Work

5.2 Hardware and Schedule

We trained our models on one machine with 8 NVIDIA P100 GPUs. For our base models using the hyperparameters described throughout the paper, each training step took about 0.4 seconds. We trained the base models for a total of 100,000 steps or 12 hours. For our big models,(described on the bottom line of table 3), step time was 1.0 seconds. The big models were trained for 300,000 steps (3.5 days).

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- Not possible to train
- Documentation update

Proof Of Work

https://github.com/shouvikcirca/Transformer

References

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https://arxiv.org/abs/1706.03762

The Illustrated Transformer
http://jalammar.github.io/illustrated-transformer/

Attention Is All You Need | AISC Foundational
https://www.youtube.com/watch?v=S0KakHcj_rs