The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms. Experiments on two machine translation tasks show these models to be superior in quality.

The Transformer is the first transduction model relying entirely on self-attention to compute representations of its input and output. It can reach a new state of the art in translation quality after being trained for as little as twelve hours on eight P100 GPUs. In the following sections, we will describe the Transformer, motivate self-att attention and discuss its advantages over other models.

The Transformer follows this overall architecture using stacked self-attention and point-wise, fully connected layers for both the encoder and decoder, shown in the left and right halves of Figure 1. The encoder is composed of a stack of N= 6 identical layers. Each layer has two sub-layers. We employ a residual connection around each of the sub-layer, followed by layer normalization.

The attention function can be described as mapping a query and a set of key-value pairs to an output. The two most commonly used attention functions are additive attention [2], and dot-product (multi- plicative) attention. We call our particular attention "Scaled Dot-Product Attention" (Figure 2) Multi-head Attention consists of several attention layers running in parallel.

Each position in the encoder can attend to all positions in the previous layer. Each of the layers in our encoder and decoder contains a fully-connected feed-forward network. We use learned embeddings to convert the input and output tokens to vectors of dimension dmodel. We also use the usual learned linear transfor- mation and softmax function.

Self-attention layers are faster than recurrent layers when the sequence is small. We train our models on the standard WMT 2014 English-French dataset. Training regime performs different semantic analyses for different sentences. We inspect attention distributions from our models and discuss examples in the appendix.

We trained our models on one machine with 8 NVIDIA P100 GPUs. Each training step took about 0.4 seconds. The big models were trained for 300,000 steps for 3.5 days. We varied the learning rate over the course of training, according to the formula: lrate =d–0.5 model·min(step_num) (3)

Table 2 summarizes our results and compares our translation quality and training costs to other model architectures from the literature. All metrics are on the English-to-German translation development set, newstest2013. We used beam search as described in the previous section, but no checkpoint averaging. We observe that reducing the attention key size dkhurts model quality.

The Transformer is the first sequence transduction model based entirely on attention. It can be trained significantly faster than architectures based on non recurrent or convolutional layers. In the former task, our best model outperforms even all previously reported ensembles. We are excited about the future of attention-based models and plan to apply them to other tasks.

Arxiv preprint arXiv:1705.03122v2 , 2017. Can active memory replace attention? In Advances in Neural Information Processing Systems, (NIPS) , 2016. In International Conference on Learning Representations (ICLR) - 2016.

This week's issue of the arXiv is the first in a series of articles on the topic of machine translation. In this issue, we look at how to multi-task neural networks for sequence to sequence learning. We also look at a way to prevent neural networks from overfitting with a simple dropout.

Figure 3: An example of the attention mechanism following long-distance dependencies in the encoder self-attention in layer 5 of 6. Attentions here shown only for the word ‘making’ Different colors represent different heads. Note that the attentions that are very sharp are apparently involved in anaphora resolution.

The attention heads exhibit behaviour that seems related to the structure of the sentence. We give two such examples above, from two different heads from the encoder self-attention at layer 5 of 6.15. The heads clearly learned to perform different tasks.