1 Introduction

Recurrent neural networks, long short-term memory and gated recurrent neural networks have been firmly established as state of the art approaches in sequence modeling and machine translation. Recent work has achievedsignificant improvements in computational efficiency through factorization tricks. Numerousefforts have since continued to push the boundaries of recurrent language models and encoder-decoderarchitectures. The Transformer allows for significantly more parallelization and can reach a new state of the art intranslation quality after being trained for as little as twelve hours on eight P100 GPUs. The model architecture eschewing recurrence and insteadrelying entirely on an attention mechanism to draw global dependencies between input and output.

2 Background

Self-attention is an attention mechanism relating different positions of a single sequence in order to compute a representation of the sequence. In the Transformer this is reduced to a constant number of operations, albeit at the cost of reduced effective resolution. We counteract this effect with Multi-Head Attention asdescribed in section 3.2. CNN.com will feature iReporter photos in a weekly Travel Snapshots gallery. Please submit your best shots of the U.S. for next week. Visit CNN.com/Travel next Wednesday for a new gallery of snapshots. For the latest, go to CNN iReport.com.

3 Model Architecture

Most competitive neural sequence transduction models have an encoder-decoder structure. At each step the model is auto-regressive, consuming the previously generated symbols as additional input when generating the next. The Transformer follows this overall architecture using stacked self-attention and point-wise, fullyconnected layers. An attention function can be described as mapping a query and a set of key-value pairs to an output. The weight assigned to each value is computed by a compatibility function of the query with the corresponding key. Multi-Head Attention consists of severalattention layers running in parallel.

3.2.1 Scaled Dot-Product Attention

We call our particular attention "Scaled Dot-Product Attention" (Figure 2) The input consists ofqueries and keys of dimension dk, and values ofdimension dv. We compute the dot products of the query with all keys, divide each by$\sqrt{}$dk, and apply a softmax function.

3.2.2 Multi-Head Attention

Multi-head attention allows the model to jointly attend to information from different representationsubspaces at different positions. With a single attention head, averaging inhibits this. In this work we employ h= 8 parallel attention layers, or heads. For each of these we usedk=dv=dmodel/h= 64 .

3.2.3 Applications of Attention in our Model

The Transformer uses multi-head attention in three different ways. In "encoder-decoder attention" layers, the queries come from the previous decoder layer. In a self-attention layer all of the keys, valuesand queries come to the same place.

3.3 Position-wise Feed-Forward Networks

In addition to attention sub-layers, each of the layers in our encoder and decoder contains a fullyconnected feed-forward network, which is applied to each position separately and identically.

Thisconsists of two linear transformations with a ReLU activation in between.FFN(x) = max(0 , xW 1+b1)W2+b2 (2)

3.4 Embeddings and Softmax

We use learned embeddings to convert the inputtokens and output tokens to vectors of dimension dmodel. Inour model, we share the same weight matrix between the two embedding layers and the pre-softmaxlinear transformation. nis the sequence length, dis the representation dimension, kis the kernelsize of convolutions and rthe size of the neighborhood in restricted self-attention.

3.5 Positional Encoding

Since our model contains no recurrence and no convolution, in order for the model to make use of theorder of the sequence, we must inject some information about the relative or absolute position of thetokens in the sequence. To this end, we add "positional encodings" to the input embeddings at thebottoms of the encoder and decoder stacks. , and found that the twoversions produced nearly identical results. We chose the sinusoidal versionbecause it may allow the model to extrapolate to sequence lengths longer than the ones encounteredduring training. See Table 3 row (E) for more details on the results.

4 Why Self-Attention

In this section we compare various aspects of self-attention layers to the recurrent and convolu-tional layers commonly used for mapping one variable-length sequence of symbol representations. The shorter these paths between any combination of positions in the inputand output sequences, the easier it is to learn long-range dependencies. A single convolutional layer with kernel width $k < n$ does not connect all pairs of input and outputpositions. To improve computational performance for tasks involvingvery long sequences, self-attention could be restricted to considering only a neighborhood of size rinthe input sequence centered around the respective output position. This would increase the maximumpath length to O(n/r)

5 Training

This section describes the training regime for our models. This section includes the training regimes used to train the models. The training regime is described in the training section of this article. For more information on our training regime, please visit our training page. For information on training for models, visit the training page of this page.

5.1 Training Data and Batching

We trained on the standard WMT 2014 English-German dataset consisting of about 4.5 millionsentence pairs. Sentences were encoded using byte-pair encoding , which has a shared source-target vocabulary of about 37,000 tokens. For English-French, we used the significantly larger WMT2014 English- French dataset and split tokens into a 32,000 word-piecevocabulary.

5.2 Hardware and Schedule

We trained our models on one machine with 8 NVIDIA P100 GPUs. For our base models usingthe hyperparameters described throughout the paper, each training step took about 0.4 seconds. Wetrained the base models for a total of 100,000 steps or 12 hours. The big models were trained for 300,000 Steps or 3.5 days.

5.3 Optimizer

We used the Adam optimizer to optimizer Adam optimize Adam. We used Adam optimizers for Adam, Adam and Adam.We used Adamoptimizer Adam to optimize the Adam for Adam. Used Adam optimiser Adam to Adam Adam optimized Adam. used Adam Optimizer Adam as Adam optimizing Adam. We varied the learningrate over the course of training, according to the formula:lrate =d–0.5model·min(step_num– 0.5, step _num·warmup _steps–1.5) (3) This corresponds to increasing the learning rate linearly for the first warmup _step training steps,and decreasing it thereafter proportionally to the inverse square root of the step number.

5.4 Regularization

The Transformer achieves better BLEU scores than previous state-of-the-art models. We employ three types of regularization during training:Residual Dropout We apply dropout to all models. The Transformer (base model) 27.3 38.1 3.3·1018Transformer (big) 28.4 41.8 2.3 ·1019 During training, we employed label smoothing of value ■ls= 0.1. Thishurts perplexity, as the model learns to be more unsure, but improves accuracy and BLEU score. We apply dropout to the sums of the embeddings and thepositional encodings in both the encoder and decoder stacks.

6 Results

On the WMT 2014 English-to-French translation task, our big model achieves a BLEU score of 41.0, outperforming all of the previously published single models, at less than 1/4the training cost of the previous state-of-the-art model. Training took 3.5days on 8P100 GPUs. Even our base modelsurpasses all previously published models and ensembles, at a fraction of the training costs of any of the competitive models. We trained a 4-layer transformer with dmodel = 1024 on the Wall Street Journal (WSJ) portion of thePenn Treebank. We also trained it in a semi-supervised setting,using the larger high-confidence and BerkleyParser corpora from with approximately 17M sentences. Despite the lack of task-specific tuning our model performs sur-prisingly well, yielding better results than all previously reported models. When training only on the WSJ training set of 40K sentences. when trainingonly on theWSJ trainingSet of 40k sentences. When training only for a single sentence, when training for a series of sentences, when trained for a set of multiple sentences, and so on. for a total of 40,000 sentences.

7 Conclusion

The Transformer is the first sequence transduction model based entirely onattention. It can be trained significantly faster than architectures based on recurrent or convolutional layers. We plan to extend the Transformer to problems involving input and output modalities other than text and to investigate local, restricted attention mechanisms to efficiently handle large inputs and output.

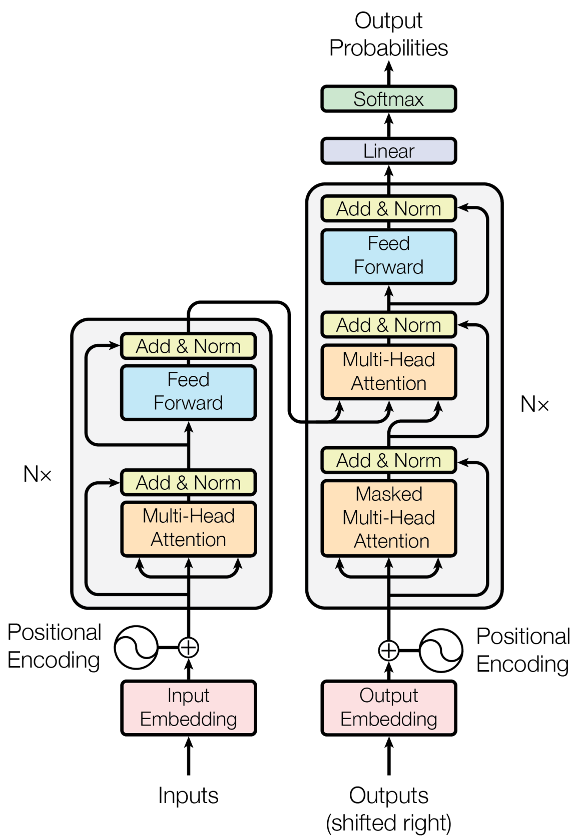

Figure 0

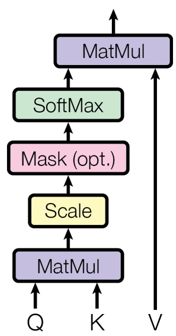

Figure 1

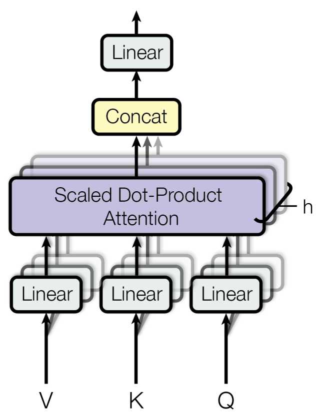

Figure 2