Attention is all you need

Paper by Vaswani et al, 2017

Presented by Andreas Munk, Curtis Huebner, Martin Wang
Background

- In machine translation, conventional approach is to use a seq2seq encoder-decoder network.
- Sequential data modelled using RNNs or LSTMs, as seen in class.

However, this has limitations!

Difficult to take into account long term dependencies:

- Makes the model hard to parallelize. (inefficient)
- Efficiency and performance drops for longer sentences (sequences).

Fig 2, *Neural Machine Translation by Jointly learning to align and translate*, (Bahdanau et al), ICLR 2015
“Classic” attention - was shown in lecture

- Neural Machine translation by Jointly learning to align and translate

Attention intuition: Think of it as a weighted sum of inputs, where the weights are learnt through a simple neural network.

- When decoding, we take a weighted sum of all the encoder inputs so far, and pass it into the decoder hidden state.
- This lets us **selectively** use past state information, and helps utilize long term dependencies.
More on the “classic” attention approach

Classic Encoder-Decoder:

\[ h_t = f(x_t, h_{t-1}) \]

\[ c = q(h_1, \ldots, h_{T_x}) \]

\[ p(y_t \mid \{y_1, \ldots, y_{t-1}\}, c) = g(y_{t-1}, s_t, c), \]

Classic attention:

\[ p(y_i \mid y_1, \ldots, y_{i-1}, x) = g(y_{i-1}, s_i, c_i), \]

Notice, we have \(c_i\) now:

\[ c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j, \quad \alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}, \]

\[ h_j = \begin{bmatrix} h_j^T; h_j^T \end{bmatrix}^T. \]

Equations from *Neural Machine Translation by Jointly learning to align and translate*, (Bahdanau et al), ICLR 2015
"Classic" attention - diagram from lecture 9 slides

Previous work, non-attention based

- Previous work has tried to address the challenges mentioned previously regarding long-term dependencies.
- Bytenet (Kalchbrenner et al, 2017)
- ConvS2S (Gehring et al, 2017)

Both of these models use CNN’s for encoding and decoding, eliminating the need for recurrence (RNN, LSTM)

- Enables parallelization
- Intuitively, similar to attention
- Still hard to take into account long term dependencies
Transformer Intuition

● In classic attention, during the decoding process, we weight all the encoder hidden states. Can this be extended? Turns out it can.

● **We can eliminate recurrence altogether.**

● In seq2seq, we “unrolled” a recurrent network. When we started to decode, the “last hidden state of the encoder” included information about the long-term dependencies in the sequence. (this was passed through the recurrent encoder)

● Now, instead of using recurrent hidden states, we use attention. The crucial difference is that each output prediction word is its own “prediction problem”
More intuition

● Didn’t the old network also use attention **alongside** recurrence?
● Yes - but this paper introduces a more sophisticated attention mechanism - multi-headed attention: the idea that we have multiple passes of attention, and then combine them.

Andreas will now talk about these in detail
Architecture - The Transformer

- Similar to the encoder-decoder network (Sutskever, Ilya; Vinyals, Oriol; Le, Quoc V. Sequence to sequence learning with neural networks. In: Advances in neural information processing systems. 2014. p. 3104-3112)
- Encoder-decoder is a mapping:

\[(x_1, \ldots, x_n) \rightarrow (z_1, \ldots, z_n) \rightarrow (y_1, \ldots, y_m)\]

"le chat est noir" <EOS>  
\[02 85 03 12 99 \]

"the cat is black" <SOS>  
\[00 42 82 16 04 \]

"the cat is black" <EOS>  
\[42 82 16 04 99 \]

Scaled Dot-Product Attention


\[ Q \in \mathbb{R}^{q \times k} \quad K \in \mathbb{R}^{k \times l} \quad V \in \mathbb{R}^{l \times v} \]

We choose the dimensions \( q, k, \) and \( v. \) \( l \) is the number of elements to attend to.
Dot product attention

\[
\text{Attention}(Q, K, V) = \text{softmax} \left( \frac{QK}{\sqrt{k}} \right) V
\]

- Weighted sum over elements to attend to
- Scaling to counteract saturating the softmax function, leading to small gradients.

Multi-Head Attention

\[
\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O
\]

\[
\text{head}_i = \text{Attention}(QW_i^Q, W_i^K, VW_i^V)
\]

- Projection into smaller dimensions instead of the \( d_{\text{model}} = 512 \) dimensional output from previous layers
- We can consider these as intermediate embeddings
- They choose \( h = 8 \) parallel attention layers
- \( k = v = d_{\text{model}} / h = 64 \)
Positional encoding

- Sum the input/output encoding and positional encoding
- \[ PE_{(pos,2i)} = \sin(pos/10000^{2i/d_{model}}) \]
- \[ PE_{(pos,2i+1)} = \cos(pos/10000^{2i/d_{model}}) \]

Why self-attention

$n$ is sequence length, $d$ is representation dimension, $k$ convolution kernel size, and $r$ is size of neighborhood in restricted attention

<table>
<thead>
<tr>
<th>Layers Type</th>
<th>Complexity per Layer</th>
<th>Sequential Operations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Self-Attention</td>
<td>$O(n^2d)$</td>
<td>$O(1)$</td>
</tr>
<tr>
<td>Recurrent</td>
<td>$O(nd^2)$</td>
<td>$O(n)$</td>
</tr>
<tr>
<td>Convolutional</td>
<td>$O(knd^2)$</td>
<td>$O(1)$</td>
</tr>
<tr>
<td>Self-Attention (restricted)</td>
<td>$O(rnd)$</td>
<td>$O(1)$</td>
</tr>
</tbody>
</table>
Why self-attention

- Computational complexity (when sequence length is smaller than representation dimension)
  - Restricted self-attention
- Parallelization
- Long term dependencies
- Interpretability
Experiments

- The model was tested on the WMT English to German and English to French translation tasks.
  - English to German consists of 4.5M sentence pairs
  - English to French consists of 36M sentence pairs
- The model was also tested on English constituency parsing.
  - 40K sequences from the WSJ portion of the Penn Treebank dataset.
WMT EtoG and EtoF

- BLEU score used as a metric.
- Sentence to sentence translation.
- Uses label smoothing to get better BLEU scores at the cost of perplexity.

Sample sentences: “I declare resumed the session of the European Parliament adjourned on Friday 17 December 1999, and I would like once again to wish you a happy new year in the hope that you enjoyed a pleasant festive period.”

Target Translation: “Je déclare reprise la session du Parlement européen qui avait été interrompue le vendredi 17 décembre dernier et je vous renouvelle tous mes vux en espérant que vous avez passé de bonnes vacances.”
English Constituency Parsing

- Was tested to see how the architecture performs on other domains
- F1 score used to measure performance (EVALB)
- Unclear from the paper how the parse tree is generated
Ablations/Model Variations

- Evaluated on WMT EtoG
- Paper tries out various model sizes to characterize performance with different model parameters
- In general, they find that “bigger is better” but that there is an optimal # of read heads.

- | N | $d_{model}$ | $d_{ff}$ | $h$ | $d_v$ | $d_e$ | $P_{drop}$ | $\epsilon_{ts}$ | train steps | PPL (dev) | BLEU (dev) | params $\times 10^6$
- | 6 | 512 | 2048 | 8 | 64 | 64 | 0.1 | 0.1 | 100K | 4.92 | 25.8 | 65
- **(A)**
  - | 1 | 512 | 512
  - | 4 | 128 | 128
  - | 16 | 32 | 32
  - | 32 | 16 | 16 | 5.29 | 24.9
  - | 5.00 | 25.5
  - | 4.91 | 25.8
  - | 5.01 | 25.4
- **(B)**
  - | 16 | 32 | 5.16 | 25.1 | 58
  - | 5.01 | 25.4 | 60
- **(C)**
  - | 2 | 526 | 32 | 32 | 1024 | 128 | 128 | 6.11 | 23.7 | 36
  - | 4.88 | 25.3 | 50
  - | 5.19 | 25.5 | 80
  - | 5.75 | 24.5 | 28
  - | 4.66 | 26.0 | 168
  - | 5.12 | 25.4 | 53
  - | 4.75 | 26.2 | 90
- **(D)**
  - | 0.0 | 0.2 | 0.0 | 0.2 | 0.0 | 0.2 | 5.77 | 24.6
  - | 4.95 | 25.5
  - | 4.67 | 25.3
  - | 5.47 | 25.7
- **(E)**
  - | positional embedding instead of sinusoids | 4.92 | 25.7
- **big**
  - | 6 | 1024 | 4096 | 16 | 0.3 | 300K | 4.33 | 26.4 | 213

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### Results: WMT

<table>
<thead>
<tr>
<th>Model</th>
<th>BLEU EN-DE</th>
<th>BLEU EN-FR</th>
<th>Training Cost (FLOPs) EN-DE</th>
<th>Training Cost (FLOPs) EN-FR</th>
</tr>
</thead>
<tbody>
<tr>
<td>ByteNet [18]</td>
<td>23.75</td>
<td>39.2</td>
<td>$1.0 \cdot 10^{20}$</td>
<td></td>
</tr>
<tr>
<td>Deep-Att + PosUnk [39]</td>
<td>24.6</td>
<td>39.92</td>
<td>$2.3 \cdot 10^{19}$</td>
<td>$1.4 \cdot 10^{20}$</td>
</tr>
<tr>
<td>GNMT + RL [38]</td>
<td>25.16</td>
<td>40.46</td>
<td>$9.6 \cdot 10^{18}$</td>
<td>$1.5 \cdot 10^{20}$</td>
</tr>
<tr>
<td>ConvS2S [9]</td>
<td>26.03</td>
<td>40.56</td>
<td>$2.0 \cdot 10^{19}$</td>
<td>$1.2 \cdot 10^{20}$</td>
</tr>
<tr>
<td>MoE [32]</td>
<td>26.30</td>
<td>41.16</td>
<td>$1.8 \cdot 10^{20}$</td>
<td>$1.1 \cdot 10^{21}$</td>
</tr>
<tr>
<td>Deep-Att + PosUnk Ensemble [39]</td>
<td>26.36</td>
<td>41.29</td>
<td>$7.7 \cdot 10^{19}$</td>
<td>$1.2 \cdot 10^{21}$</td>
</tr>
<tr>
<td>ConvS2S Ensemble [9]</td>
<td>27.3</td>
<td>38.1</td>
<td></td>
<td>$3.3 \cdot 10^{18}$</td>
</tr>
<tr>
<td>Transformer (base model)</td>
<td>28.4</td>
<td>41.8</td>
<td>$2.3 \cdot 10^{19}$</td>
<td></td>
</tr>
<tr>
<td>Transformer (big)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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## Results: Constituency Parsing

<table>
<thead>
<tr>
<th>Parser</th>
<th>Training</th>
<th>WSJ 23 F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vinyals &amp; Kaiser el al. (2014) [37]</td>
<td>WSJ only, discriminative</td>
<td>88.3</td>
</tr>
<tr>
<td>Petrov et al. (2006) [29]</td>
<td>WSJ only, discriminative</td>
<td>90.4</td>
</tr>
<tr>
<td>Zhu et al. (2013) [40]</td>
<td>WSJ only, discriminative</td>
<td>90.4</td>
</tr>
<tr>
<td>Dyer et al. (2016) [8]</td>
<td>WSJ only, discriminative</td>
<td>91.7</td>
</tr>
<tr>
<td>Transformer (4 layers)</td>
<td>WSJ only, discriminative</td>
<td>91.3</td>
</tr>
<tr>
<td>Zhu et al. (2013) [40]</td>
<td>semi-supervised</td>
<td>91.3</td>
</tr>
<tr>
<td>McClosky et al. (2006) [26]</td>
<td>semi-supervised</td>
<td>92.1</td>
</tr>
<tr>
<td>Vinyals &amp; Kaiser el al. (2014) [37]</td>
<td>semi-supervised</td>
<td>92.1</td>
</tr>
<tr>
<td>Transformer (4 layers)</td>
<td>semi-supervised</td>
<td>92.7</td>
</tr>
<tr>
<td>Luong et al. (2015) [23]</td>
<td>multi-task</td>
<td>93.0</td>
</tr>
<tr>
<td>Dyer et al. (2016) [8]</td>
<td>generative</td>
<td>93.3</td>
</tr>
</tbody>
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References

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- Neural Machine Translation by Jointly Learning to Align and Translate, (Bahdanau et al) ICLR 2015
- Convolutional sequence to sequence learning (Gehring et al), 2017.