TTIC 31230, Fundamentals of Deep Learning

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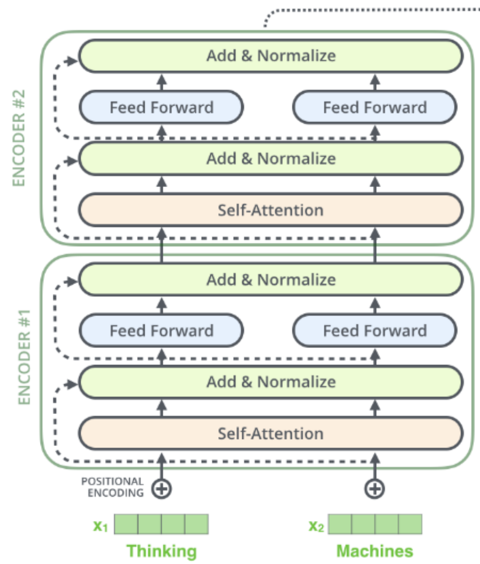
The Transformer Part I

The Transformer

Attention is All You Need, Vaswani et al., June 2017

The Transformer has now essentially replaced RNNs and is now used in speech, protein folding and vision.

Vector Sequences



Each layer in the Transformer has shape $L[T, J]$ where t ranges over the position in the input sequence and j ranges over neurons at that position (and omitting the batch index).

This is the same shape as layers in an RNN — a sequence of vectors $L[t, J]$.

Parallel Layer Computation

However, in the transformer we can compute the layer $L_{\ell+1}[T, J]$ from $L_\ell[T, J]$ in parallel.

This is an important difference from RNNs which compute sequentially over time.

In this respect the transformer is more similar to a CNN than to an RNN.

Self-Attention

The fundamental innovation of the transformer is the self-attention layer.

For each position t in the sequence we compute an attention over the other positions in the sequence.

Transformer Heads

There is an intuitive analogy between this soft graph and a dependency parse tree.

In a dependency parse edges are typically labeled with grammatical roles such as "subject-of" or "object-of".

The self attention layers of the transformer we have "heads" which can be viewed as labels for dependency edges.

Self attention constructs a tensor $\alpha[k, t_1, t_2]$ — the strength of the attention weight (edge weight) from t_1 to t_2 with head (label) k.

Query-Key Attention

For each head k and position t we compute a key vector and a query vector with dimension I typically smaller than dimension J.

$$\begin{aligned}
\mathrm{Query}_{\ell+1}[k,t,I] &= W^{Q}_{\ell+1}[k,I,J]L_{\ell}[t,J] \\
\mathrm{Key}_{\ell+1}[k,t,I] &= W^{K}_{\ell+1}[k,I,J]L_{\ell}[t,J] \\
\alpha_{\ell+1}[k,t_1,t_2] &= \operatorname*{softmax}_{t_2} \frac{1}{\sqrt{I}}\,\mathrm{Query}_{\ell+1}[k,t_1,I]\mathrm{Key}_{\ell+1}[k,t_2,I]
\end{aligned}$$

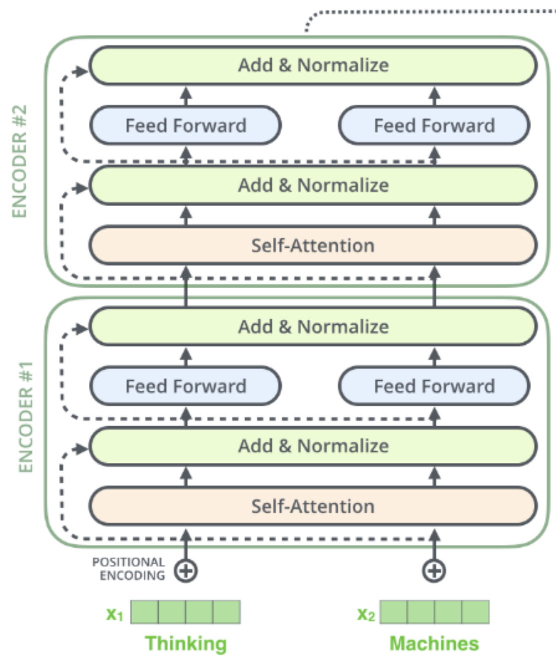
Computing the Output

$$\begin{aligned}
\mathrm{Value}_{\ell+1}[k,t,I] &= W^V_{\ell+1}[k,I,J]L_\ell[t,J] \\
h^1_{\ell+1}[k,t,I] &= \alpha[k,t,T]\mathrm{Value}[k,T,I] \\
h^2_{\ell+1}[t,C] &= h^1_{\ell+1}[0,t,I];\cdots;h^1_{\ell+1}[K-1,t,I] \\
L_{\ell+1}[t,J] &= W^0_{\ell+1}[J,C]h^2[t,C]
\end{aligned}$$

Here semicolon denotes vector concatenation.

The Transformer Layer

Each "transformer layer" consists of six "sublayers" the first of which is the self-attention layer.



Jay Alammar's blog

The other layers are discussed in the next unit.

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