Neural Machine Translation

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Part 1: Positional Encoding

Attention is all you need

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Vaswani+ arXiv:1706.03762v4 Jun 2017

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- Any questions?

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- Output sequence of symbols: $(o_1, o_2, \ldots, o_m)$

Layer Normalization

Ba+ arXiv 2016

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$$\mathbf{h}_t^{\ell} = W_{hh}\mathbf{h}_t^{\ell-1} + W_{xh}\mathbf{x}_t$$

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$$\mu^\ell = \frac{1}{H}\sum_{i=1}^{H} a_i^\ell$$

- Take the variance of **a**

$$\sigma^\ell = \sqrt{\frac{1}{H}\sum_{i=1}^{H}(a_i^\ell - \mu^\ell)^2}$$

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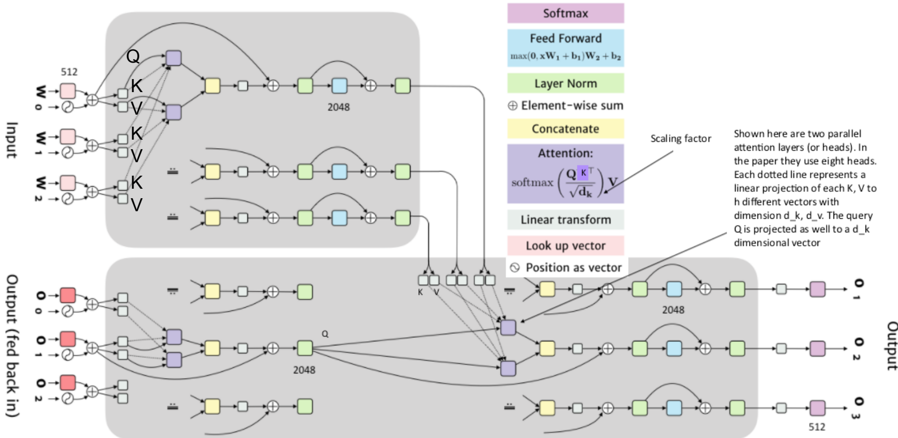
- The normalization terms make it invariant to re-scaling all of the summed inputs to a layer
- Results in much more stable hidden-to-hidden dynamics

Attention is all you need

Figure modified from one made by J. Kummerfeld



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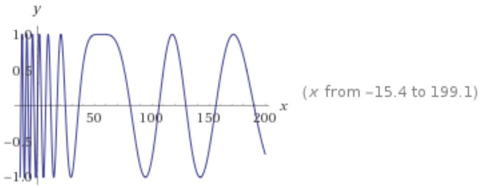
- **Positional encoding** which is a vector of the same length as the word representation. Depends only on position in the input.

$$f(pos, dim) = sin(\frac{pos}{10000^{\frac{2dim}{d_w}}})$$



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- They use a new formula for adjusting the learning rate.
- They use dropout in several places and label smoothing for regularization