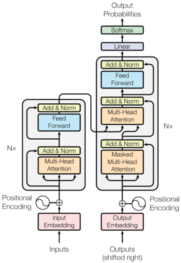
Transformer

The Decoder



Learning goals

- Understand Masked Self-Attention and the role of causality in decoding
- Understand the connection between the encoder and the decoder

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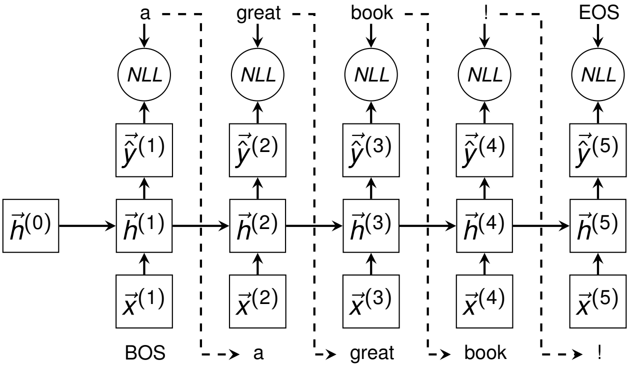
- `https://slds-lmu.github.io/dl4nlp/`

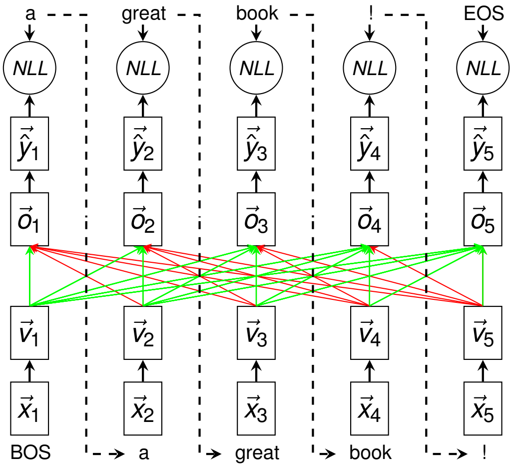
RNNS FOR AUTOREGRESSIVE LM & DECODING

- In autoregressive language modeling, or in the decoder of a sequence-to-sequence model, the task is to always predict the next word
- In an RNN, a given state $\vec{h}^{(j)}$ depends on past inputs $x^{(1)} \dots x^{(j)}$
- Thus, the RNN is unable to “cheat”:



SELF-ATTENTION FOR AR LM & DECODING

- With attention, all $\vec{o}_j$ depend on all $\vec{v}_{j'}$ (and by extension, all $\vec{x}_{j'}$).
- This means that the model can easily cheat by looking at future words (red connections)



MASKED SELF-ATTENTION

- So when we use self-attention for language modeling or in a sequence-to-sequence decoder, we have to prevent $\vec{o}_j$ from attending to any $\vec{v}_{j'}$ where $j' > j$.
- **Question:** How can we do that?
- Remember:

$$\vec{o}_j = \sum_{j'=1}^{J} \alpha_{j,j'} \vec{v}_{j'}$$

$$\alpha_{j,j'} = \frac{\exp(e_{j,j'})}{\sum_{j''=1}^{J} \exp(e_{j,j''})}$$

  - By hardcoding $e_{j,j'} = -\infty$ when $j' > j$ (in practice, "∞" is just a large constant)
  - That way, $\exp(e_{j,j'}) = \alpha_{j,j'} = 0$, so $\vec{v}_{j'}$ has no impact on $\vec{o}_j$

PARALLELIZED MASKED SELF-ATTENTION

- Step 1: Calculate $\vec{E}$ like we usually would
- Step 1B:

$$\vec{E}^{\text{masked}} = \vec{E} \odot \vec{M} + \infty \vec{M} - \infty; \qquad m_{j,j'} = \begin{cases} 1 & \text{if } j' \leq j \\ 0 & \text{otherwise} \end{cases}$$

- Example:

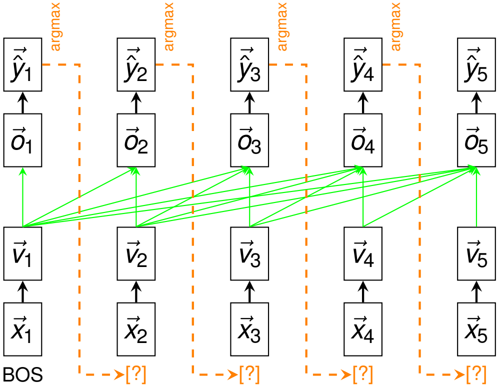
$$\vec{E} = \begin{bmatrix} e_{1,1} & e_{1,2} & e_{1,3} \\ e_{2,1} & e_{2,2} & e_{2,3} \\ e_{3,1} & e_{3,2} & e_{3,3} \end{bmatrix}; \qquad \vec{M} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

$$\vec{E}^{\text{masked}} = \begin{bmatrix} e_{1,1} & -\infty & -\infty \\ e_{2,1} & e_{2,2} & -\infty \\ e_{3,1} & e_{3,2} & e_{3,3} \end{bmatrix}; \qquad \vec{A}^{\text{masked}} = \begin{bmatrix} 1 & 0 & 0 \\ \alpha_{2,1} & \alpha_{2,2} & 0 \\ \alpha_{3,1} & \alpha_{3,2} & \alpha_{3,3} \end{bmatrix}$$

$$\vec{o}_1 = \vec{v}_1; \qquad \vec{o}_2 = \alpha_{2,1}\vec{v}_1 + \alpha_{2,2}\vec{v}_2; \qquad \vec{o}_3 = \alpha_{3,1}\vec{v}_1 + \alpha_{3,2}\vec{v}_2 + \alpha_{3,3}\vec{v}_3$$

AR TRANSFORMER AT INFERENCE TIME

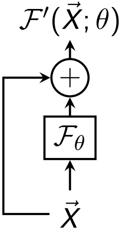
- During training (targets known): Use parallelized masked attention
- At inference time (targets unknown): Decode prediction in a loop
- Slower, but at least we don't have to worry about masking anymore



ADD. SUBTLETIES: RESIDUAL CONNECTIONS

- Let $\mathcal{F}$ be a function with parameters θ
- $\mathcal{F}$ with a residual connection:

$$\mathcal{F}'(\vec{X};\theta) = \mathcal{F}(\vec{X};\theta) + \vec{X}$$



- Benefits: Information retention (we add to $\vec{X}$ but don't replace it)

ADD. SUBTLETIES: LAYER NORMALIZATION

- Let $\theta = \{\vec{\gamma} \in \mathbb{R}^d, \vec{\beta} \in \mathbb{R}^d\}$ be trainable parameters
- Let $\vec{h} \in \mathbb{R}^d$ be an output vector of some layer (e.g., an $\vec{o}_j$ vector from an attention layer)
- Then layer normalization calculates:

$$\vec{\gamma} \odot \frac{\vec{h} - \mu}{\sigma} + \vec{\beta}$$

- where μ, σ are mean and standard deviation over the dimensions of $\vec{h}$:

$$\mu = \frac{1}{d} \sum_{i=1}^{d} h_i; \qquad \sigma = \sqrt{\frac{1}{d} \sum_{i=1}^{d} (h_i - \mu)^2}$$

- Benefits: Allows us to normalize vectors after every layer; helps against exploding activations on the forward pass
- In the Transformer, layer normalization is applied position-wise, i.e., every $\vec{o}_j$ is normalized independently

ENCODER-DECODER ATTENTION

Open question: How do we connect encoder and decoder?

Construction of one decoder block:

1. Masked (Multi-Head) Attention layer (only target sequence)
2. "Ordinary" (Multi-Head) Attention layer
   - Queries from the previous decoder layer
   - Keys, Values from the encoder output
3. Feed-Forward layer (w/ residual connections & layer norm)

$\rightarrow$ Allows the decoder to attend to *all* tokens from the input sequences (cf. Bahdanau et al. (2014) for RNNs)

THE TRANSFORMER ARCHITECTURE

(For simpler problems (e.g., classification, tagging), you would simply use the encoder.)

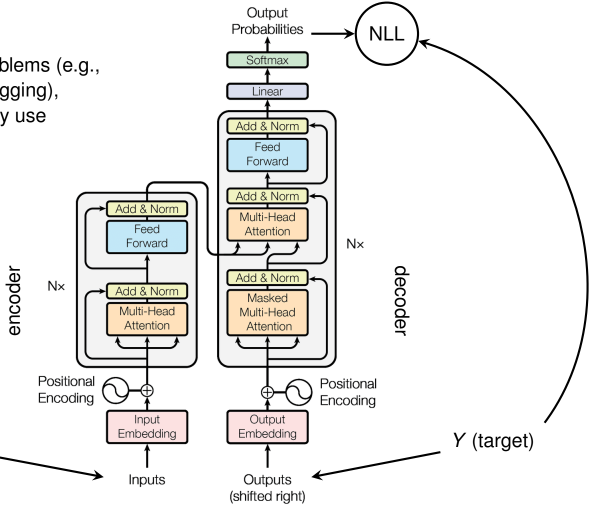


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Figure from Vaswani et al. 2017: Attention is all you need