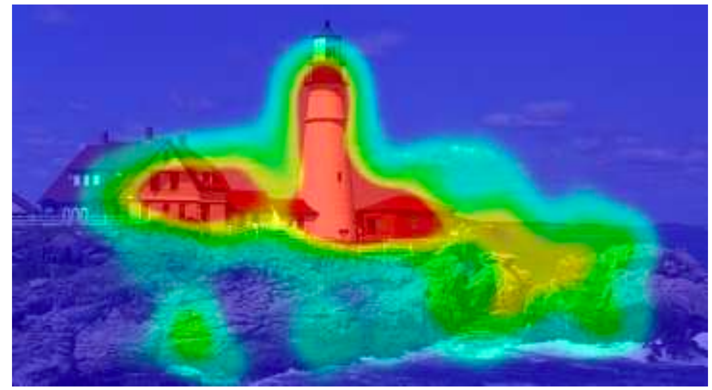
CS480/680
Lecture 19: July 10, 2019

Attention and Transformer Networks

[Vaswani et al., Attention is All You Need, *NeurIPS*, 2017]

Attention

- Attention in Computer Vision
  - 2014: Attention used to highlight important parts of an image that contribute to a desired output



- Attention in NLP
  - 2015: Aligned machine translation
  - 2017: Language modeling with **Transformer networks**

Sequence Modeling

Challenges with RNNs

- Long range dependencies
- Gradient vanishing and explosion
- Large # of training steps
- Recurrence prevents parallel computation

Transformer Networks

- Facilitate long range dependencies
- No gradient vanishing and explosion
- Fewer training steps
- No recurrence that facilitate parallel computation

Attention Mechanism

- Mimics the retrieval of a **value** v_i for a **query** q based on a **key** k_i in database
- Picture

$$attention(q, \boldsymbol{k}, \boldsymbol{v}) = \sum_i similarity(q, k_i) \times v_i$$

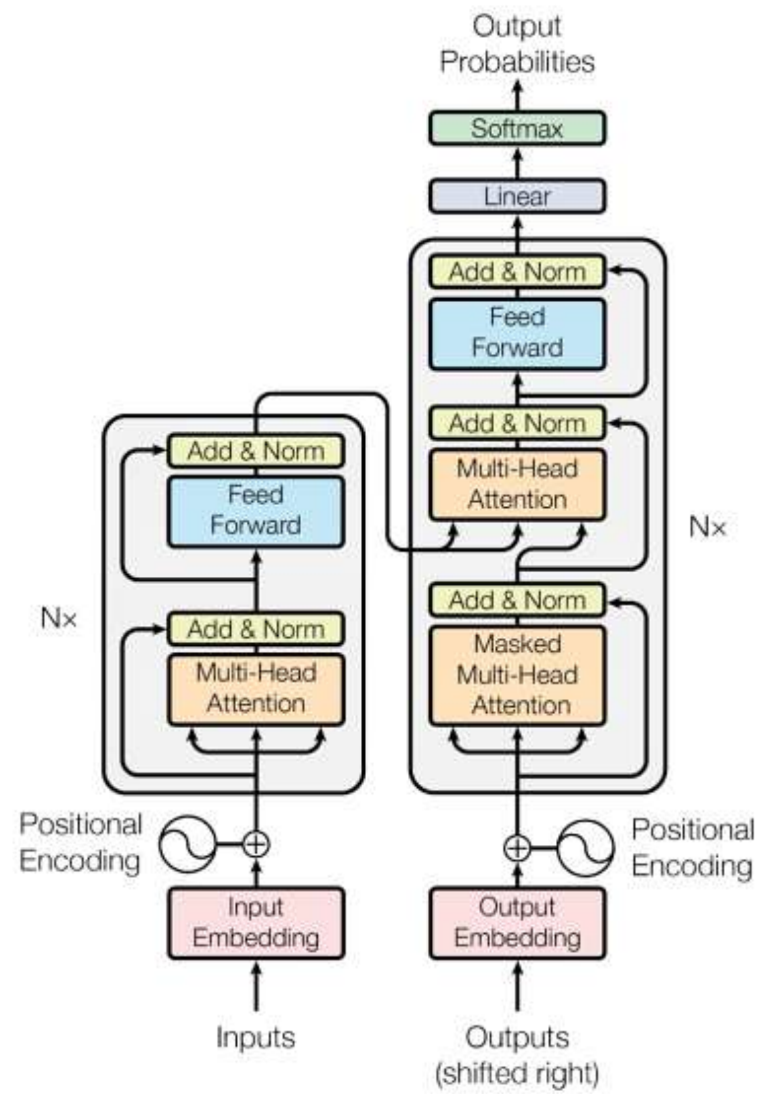
Attention Mechanism

- Neural architecture

- Example: machine translation
  - Query: s_{i-1} (hidden vector for $i-1^{th}$ output word)
  - Key: h_j (hidden vector for j^{th} input word)
  - Value: h_j (hidden vector for j^{th} input word)

Transformer Network

- Vaswani et al., (2017) Attention is all you need.
- Encoder-decoder based on attention (no recurrence)



Multihead attention

- Multihead attention: compute multiple attentions per query with different weights

$$multihead(Q, K, V) = W^O concat(head_1, head_2, \dots, head_h)$$
$$head_i = attention\left(W_i^Q Q, W_i^K K, W_i^V V\right)$$
$$attention(Q, K, V) = softmax\left(\frac{Q^T K}{\sqrt{d_k}}\right) V$$

Masked Multi-head attention

- Masked multi-head attention: multi-head where some values are masked (i.e., probabilities of masked values are nullified to prevent them from being selected).
- When decoding, an output value should only depend on previous outputs (not future outputs). Hence we mask future outputs.

$$attention(Q,K,V) = softmax\left(\frac{Q^T K}{\sqrt{d_k}}\right)V$$

$$maskedAttention(Q,K,V) = softmax\left(\frac{Q^T K + M}{\sqrt{d_k}}\right)V$$

where M is a mask matrix of 0's and $-\infty$'s

Other layers

- Layer normalization:
  - Normalize values in each layer to have 0 mean and 1 variance
  - For each hidden unit h_i compute $h_i \leftarrow \frac{g}{\sigma}(h_i - \mu)$
    where g is a variable, $\mu = \frac{1}{H}\sum_{i=1}^{H} h_i$ and $\sigma = \sqrt{\frac{1}{H}\sum_{i=1}^{H}(h_i - \mu)^2}$
  - This reduces "covariate shift" (i.e., gradient dependencies between each layer) and therefore fewer training iterations are needed

- Positional embedding
  - Embedding to distinguish each position

$$PE_{position,2i} = \sin(position/10000^{2i/d})$$
$$PE_{position,2i+1} = \cos(position/10000^{2i/d})$$

Comparison

- Attention reduces sequential operations and maximum path length, which facilitates long range dependencies

Table 1: Maximum path lengths, per-layer complexity and minimum number of sequential operations for different layer types. n is the sequence length, d is the representation dimension, k is the kernel size of convolutions and r the size of the neighborhood in restricted self-attention.

Layer Type	Complexity per Layer	Sequential Operations	Maximum Path Length
Self-Attention	$O(n^2 \cdot d)$	$O(1)$	$O(1)$
Recurrent	$O(n \cdot d^2)$	$O(n)$	$O(n)$
Convolutional	$O(k \cdot n \cdot d^2)$	$O(1)$	$O(log_k(n))$
Self-Attention (restricted)	$O(r \cdot n \cdot d)$	$O(1)$	$O(n/r)$

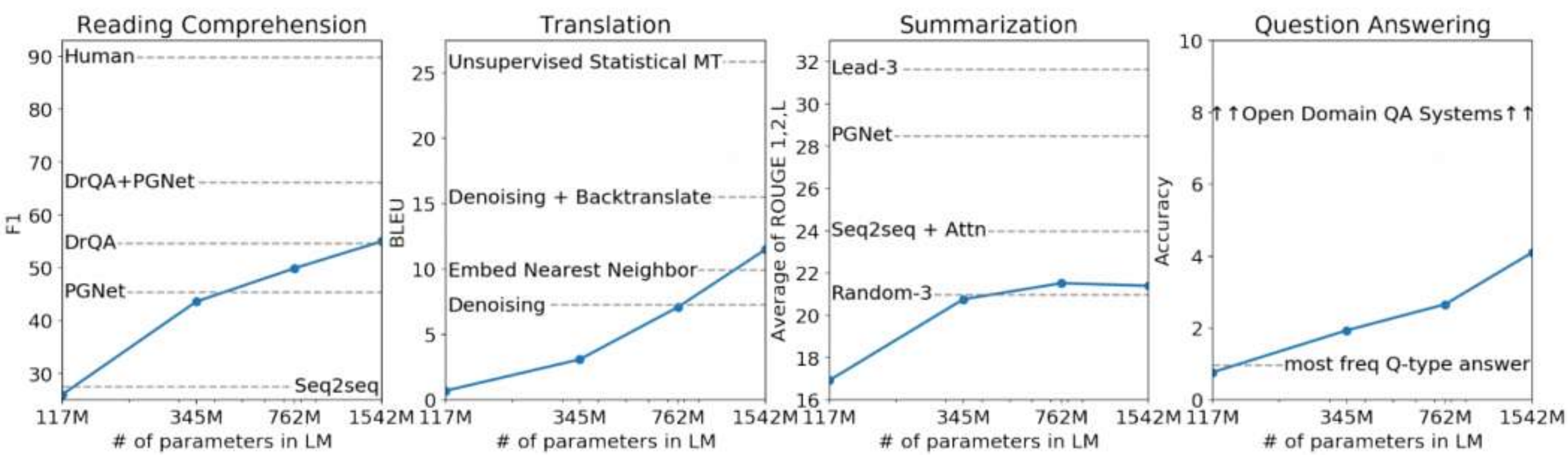
Results

Table 2: The Transformer achieves better BLEU scores than previous state-of-the-art models on the English-to-German and English-to-French newstest2014 tests at a fraction of the training cost.

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [15]	23.75			
Deep-Att + PosUnk [32]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [31]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [8]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [26]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [32]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [31]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [8]	26.36	**41.29**	$7.7 \cdot 10^{19}$	$1.2 \cdot 10^{21}$
Transformer (base model)	27.3	38.1	$\mathbf{3.3 \cdot 10^{18}}$	
Transformer (big)	**28.4**	**41.0**	$2.3 \cdot 10^{19}$	

GPT and GPT-2

- Radford et al., (2018) Language models are unsupervised multitask learners
  - Decoder transformer that predicts next word based on previous words by computing $P(x_t|x_{1..t-1})$
  - SOTA in "zero-shot" setting for 7/8 language tasks (where zero-shot means no task training, only unsupervised language modeling)



BERT (Bidirectional Encoder Representations from Transformers)

- Devlin et al., (2019) BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding
  - Decoder transformer that predicts a missing word based on surrounding words by computing $P(x_t|x_{1..t-1,t+1..T})$
  - Mask missing word with masked multi-head attention
  - Improved state of the art on 11 tasks

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**