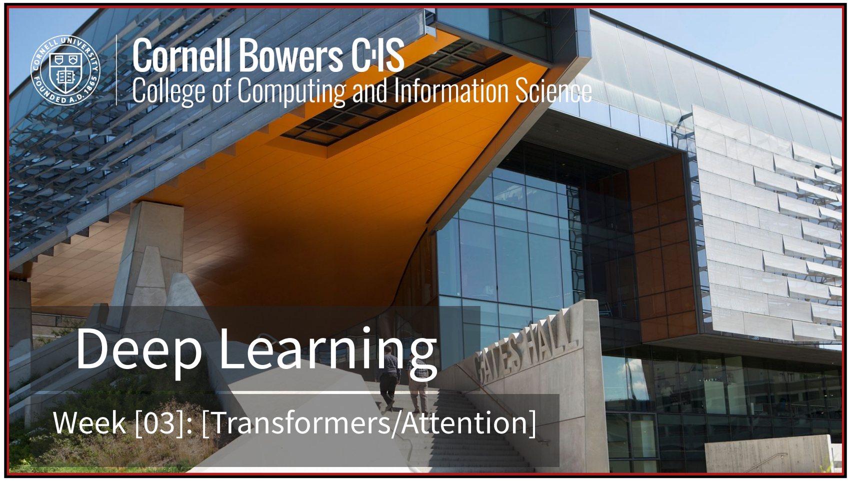
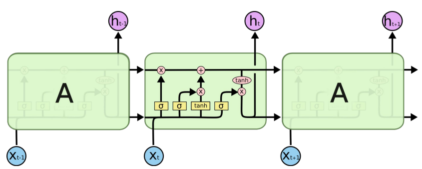


Logistics

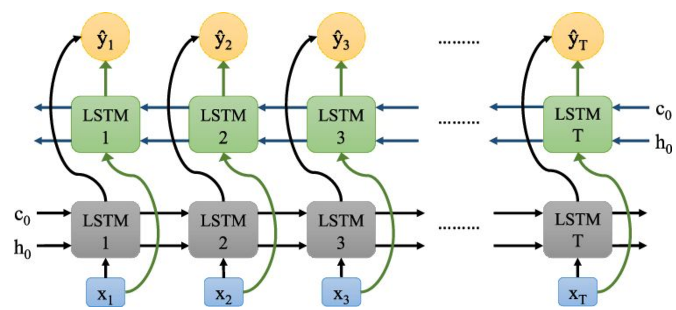
- HW2 is out
- We have a feedback form (due Friday February 23)
- Tuesday 10am office hours might change
- We will talking about projects on Thursday
  - HW3 will be a shorter

Previously: Using LSTMs to solve sequence problems

- Process sequences one element at a time.
- Maintain a 'memory' (cell state) to capture information about previous steps.
- Mitigates the RNN vanishing gradient problem
- Suitable for time series, speech, text, and other sequential data.



Bidirectional LSTM



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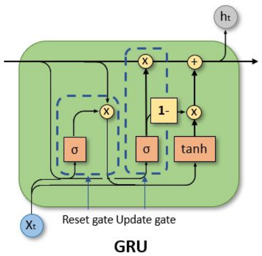
Gated recurrent units (GRUs)



$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z)$$
$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r)$$
$$\hat{h}_t = \phi(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h)$$
$$h_t = (1 - z_t) \odot \hat{h}_t + z_t \odot h_{t-1}$$

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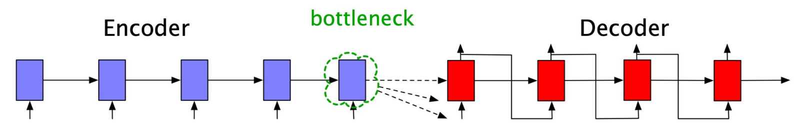
Bottleneck Problem

- All the information about the source sequence must be stored in a single vector
  - How to translate a long paragraph?
  - How to summarize long articles?



https://web.stanford.edu/~jurafsky/slp3/

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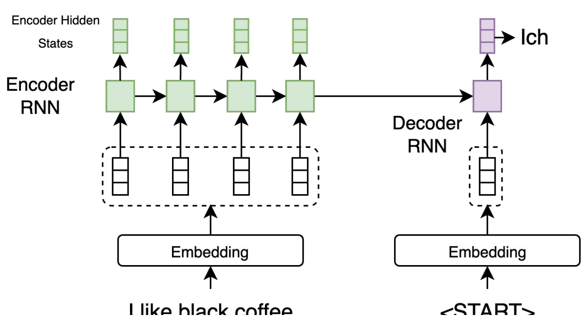
RNN for Machine Translation

Would be nice if we could "look back" at previous hidden states



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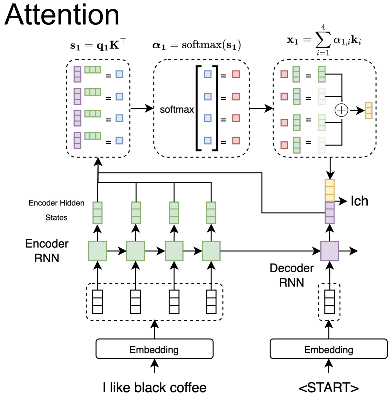
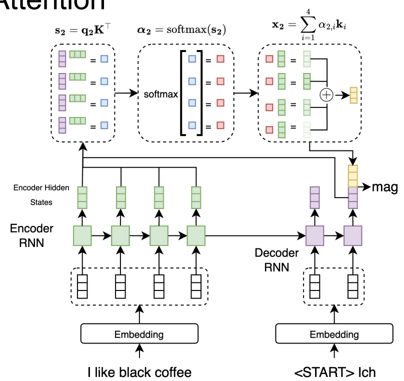
RNN with Attention

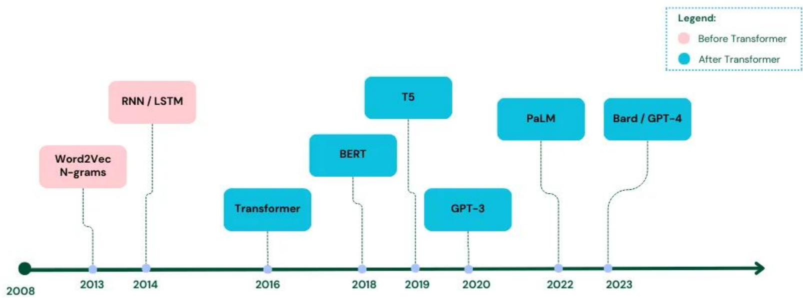


RNN with Attention



Discuss: What are limitations of such sequence to sequence models? Hint: Think about runtime.

Language Modelling History



https://medium.com/@kirudang/language-model-history-before-and-after-transformer-the-ai-revolution-bedc7948a130

Self-Attention

A bat flew out of the dugout, startling the baseball player and making him drop his bat.

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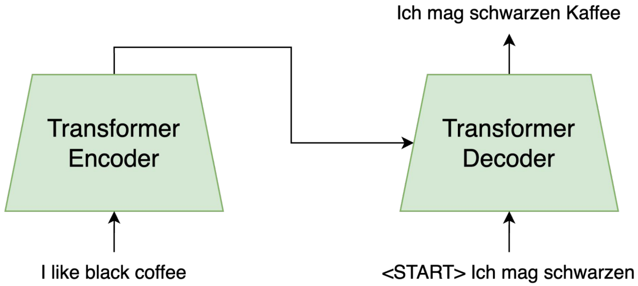
Transformer Architecture

Introduced for seq2seq tasks like Machine translation, summarization, question answering, etc.



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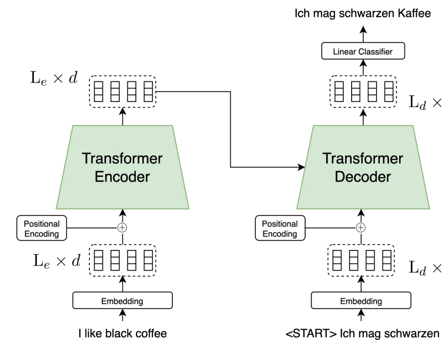
Transformer Architecture



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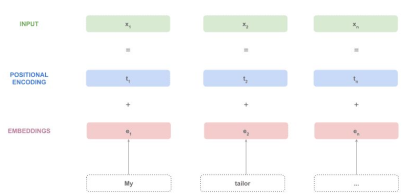
Input Embeddings

- Replace tokens with continuous vectors
- Made up of two components:
  - token embeddings
  - positional encoding depends on position and dimension index as follows:

$$PE_{(pos,2i)} = sin(\frac{pos}{10000^{2i/d_{\text{model}}}})$$

$$PE_{(pos,2i+1)} = cos(\frac{pos}{10000^{2i/d_{\text{model}}}})$$



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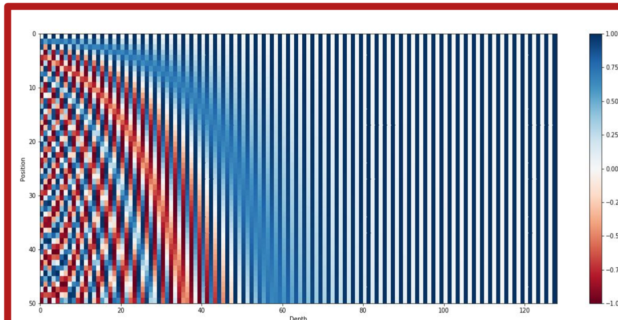
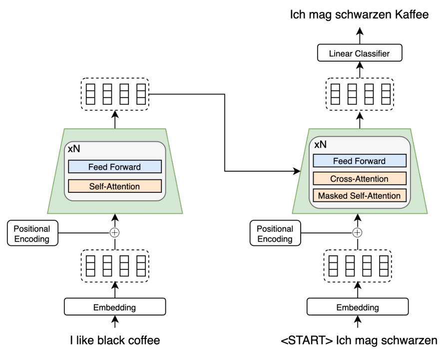
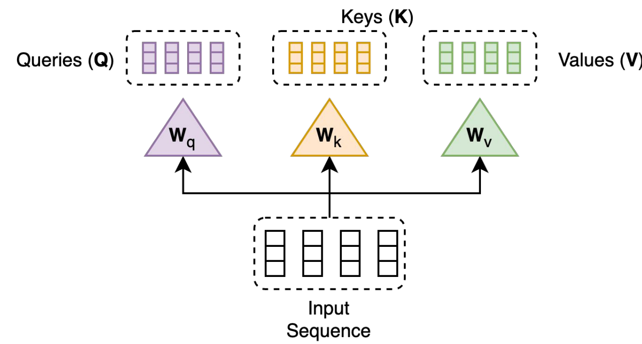
Example Positional Encoding



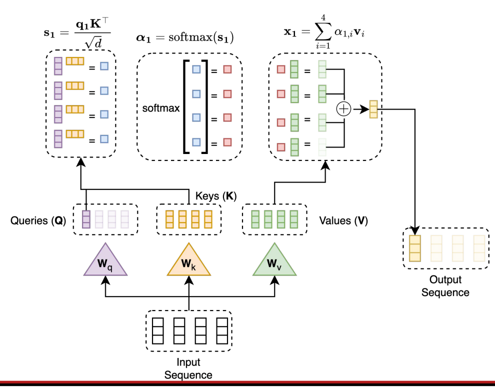
Transformer Architecture



Self-Attention



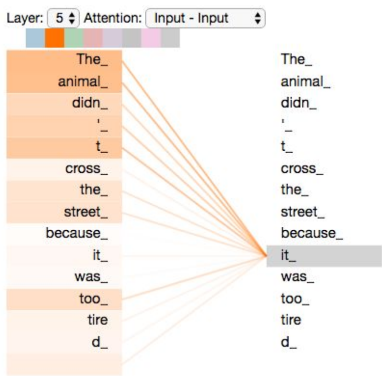
Self-Attention



Self-Attention: General Formula

$$Attention(Q, K, V) = Softmax(\frac{QK^T}{d_k})V$$

Self-attention



Discuss:

- Q, K, V are all (n x d) matrices. Consider have an input of shape b x n x d.
- What is the shape of QK^T?
  - What does this matrix represent?
- What is the shape of the final output?
  - What does this matrix represent?

$$Attention(Q,K,V) = Softmax(\frac{QK^T}{d_k})V$$

Multi-Head Attention

What if I want to pay attention to different things at the same time!?

Content-based — This is my big red dog, Clifford.

Description-based — This is my big red dog, Clifford.

Reference-based — This is my big red dog, Clifford.

What's useful depends on the task. How do I pick what to do?

Multi-Head Attention

- The Scaled Dot-Product Attention attends to one or few entries in the input key-value pairs.
- Idea: apply Scaled Dot-Product Attention multiple times on the linearly transformed inputs.

$$\mathrm{MultiHead}(Q,K,V) = \mathrm{Concat}(\mathrm{head_1}, ..., \mathrm{head_h})W^O$$
$$\text{where } \mathrm{head_i} = \mathrm{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

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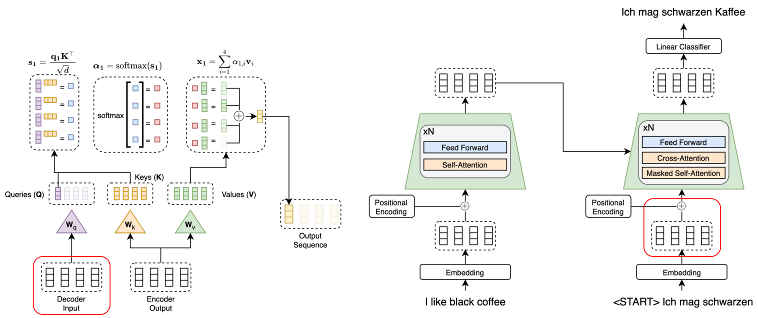
Cross-Attention



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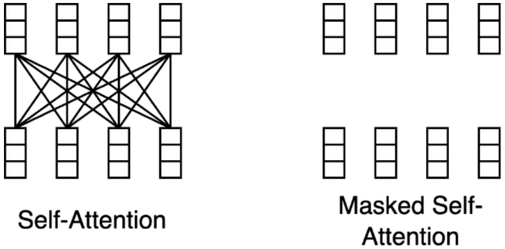
Self-Attention vs. Masked Self-Attention



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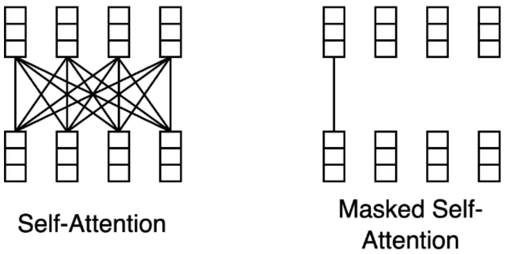
Self-Attention vs. Masked Self-Attention



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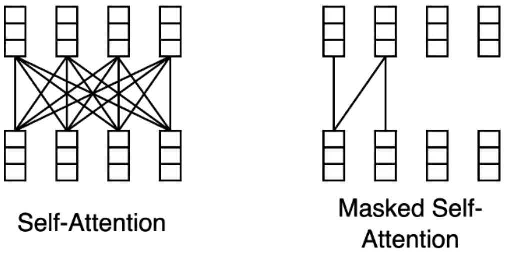
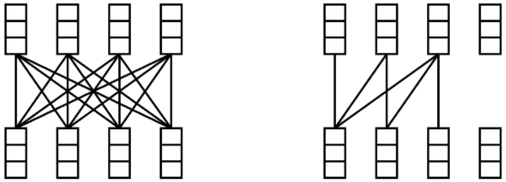
Self-Attention vs. Masked Self-Attention



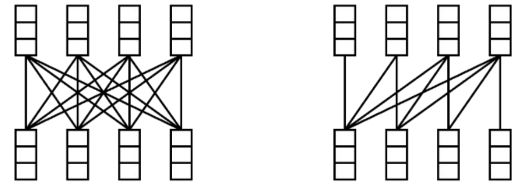
Self-Attention vs. Masked Self-Attention



Self-Attention

Masked Self-Attention

Self-Attention vs. Masked Self-Attention



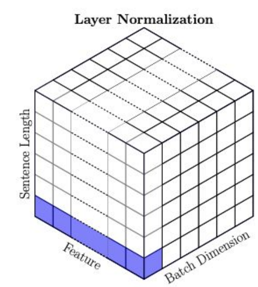
Self-Attention

Masked Self-Attention

Point-wise Feed-forward Networks

- Purpose
  - Applies non-linear transformations to the output of the attention layer
- Equation
  - $FFN(x) = max(0, xW_1 + b_1)W_2 + b_2$
    - where W and b are learned weights and biases
- These FFN is applied separately to each position

Layernorm



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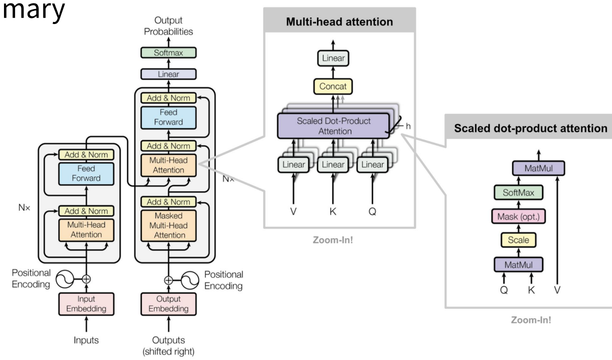
Summary



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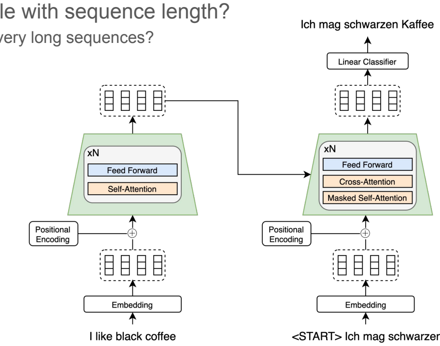
Discuss:

- How does the transformer scale with sequence length?
  - Any problems with applying it to very long sequences?



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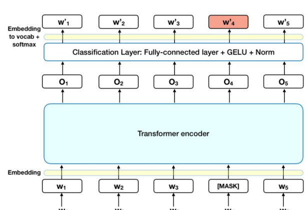
BERT (Bidirectional Encoder Representations from Transformers)

- Bidirectional Context
- Pre-trained on the language, and then fine-tuned



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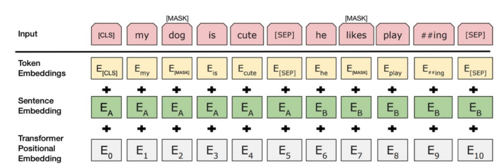
BERT - Input Representation

Input:

- Use 30,000 WordPiece vocabulary on input.
- Each token is sum of three embeddings



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Training

- Masked Language Modelling
  - Mask out k% of the input words, and then predict the masked words
  - the man went to the store to [MASK] a [MASK] of milk
  - What can you use as a loss function?

- Next sentence prediction
  - To learn relationships between sentences, predict whether Sentence B is actual sentence that
  - proceeds Sentence A, or a random sentence

Sentence A = `The man went to the store.`
Sentence B = `He bought a gallon of milk.`
Label = `IsNextSentence`

Sentence A = `The man went to the store.`
Sentence B = `Penguins are flightless.`
Label = `NotNextSentence`

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Model Details

- Data: Wikipedia (2.5B words) + BookCorpus (800M words)
- Batch Size: 131,072 words (1024 sequences * 128 length or 256 sequences * 512 length)
- Training Time: 1M steps (~40 epochs)
- Optimizer: AdamW, 1e-4 learning rate, linear decay
- BERT-Base: 12-layer, 768-hidden, 12-head, 110M params
- BERT-Large: 24-layer, 1024-hidden, 16-head, 340M params
- Trained on 4x4 or 8x8 TPU slice for 4 days

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Demo

https://huggingface.co/google-bert/bert-large-cased?text=Paris+is+the+capital+of+%5BMASK%5D.

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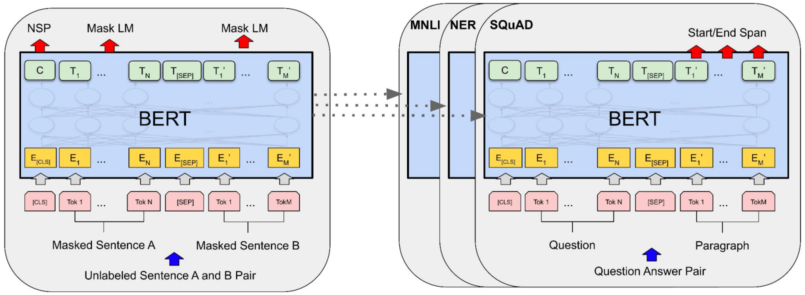
Pre-training to Fine-tuning Pipeline



Pre-training Fine-Tuning

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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**

https://arxiv.org/pdf/1810.04805.pdf

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Self-supervised Learning

- Labels are generated automatically, no human labeling process
- Benefits
  - Scales well
  - Cost-Efficient
  - Flexible
- Challenges
  - Larger datasets are required
  - More compute is necessary

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Review

- LSTMs/GRUs are recurrent
- Self-attention can effectively replace recurrence in sequence-to-sequence models
- Transformers use self-attention and are parallelizable
- Pre-training using self-supervised learning help train large models that learn very good representations