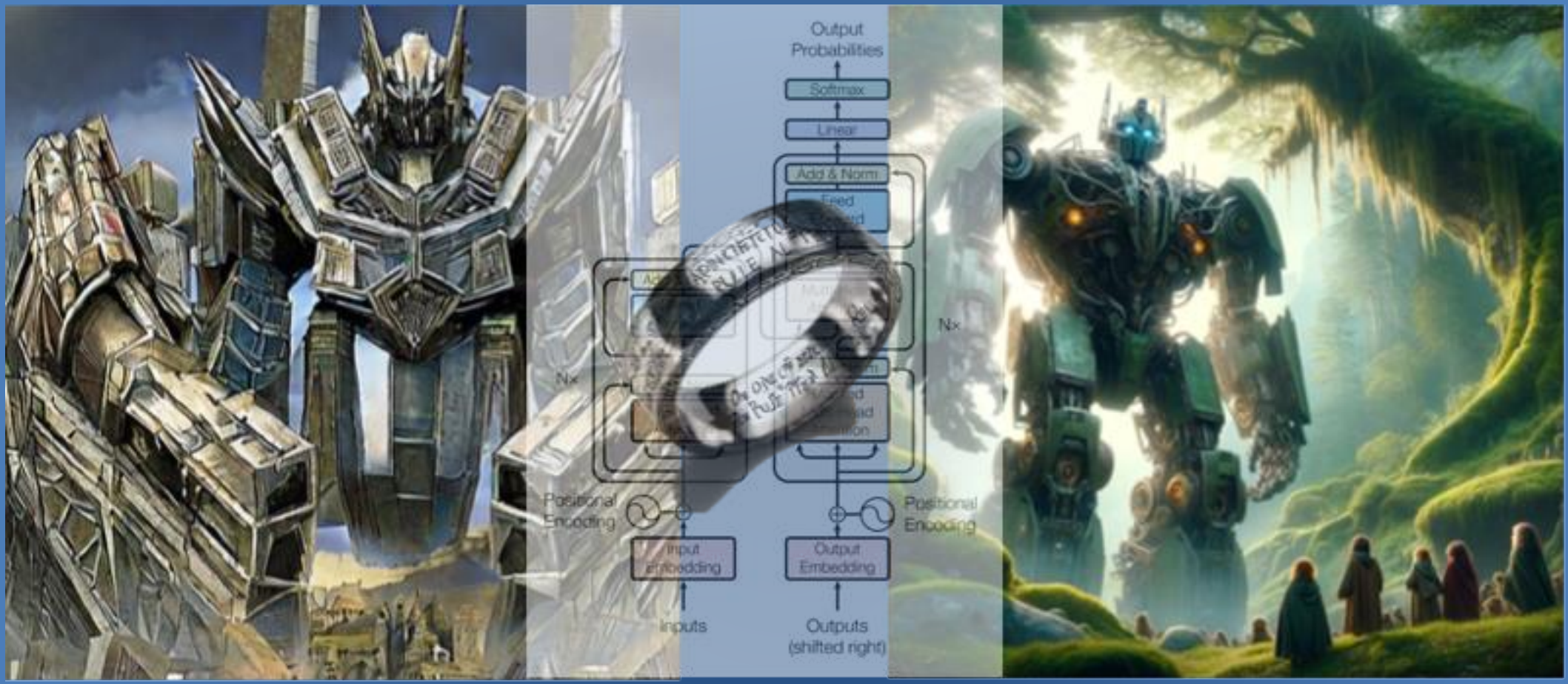
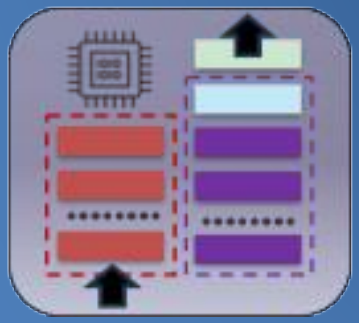


Image: Transformers: ' ...and one 'architecture' to rule them all' – Juxtaposition by Raeid Saqur (2024).



Transformers

CSC401/2511 – Natural Language Computing – Fall 2024

Gerald Penn, Sean Robertson & Raeid Saqur

Lecture 7

University of Toronto

Transformer networks

- Breakout paper: Vaswani et al. (2017) Attention is all you need.
- **Core idea**: replace recurrent connections with attention

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.

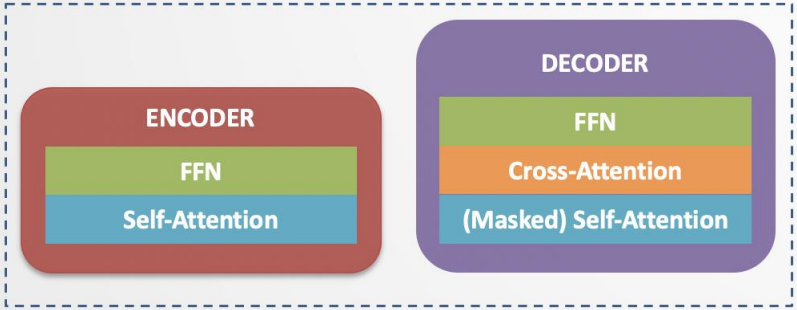
Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [15]	23.75			
Deep-Att + PosUnk [32]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [31]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [8]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [26]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
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	**$3.3 \cdot 10^{18}$**	
Transformer (big)	**28.4**	**41.0**	$2.3 \cdot 10^{19}$	

[1] Vaswani, Ashish, et al. "Attention is all you need." *NeuIPS* (2017).

Transformer networks (abstract)

Core Idea

Now two kinds of attention



- Encoder uses self-attention

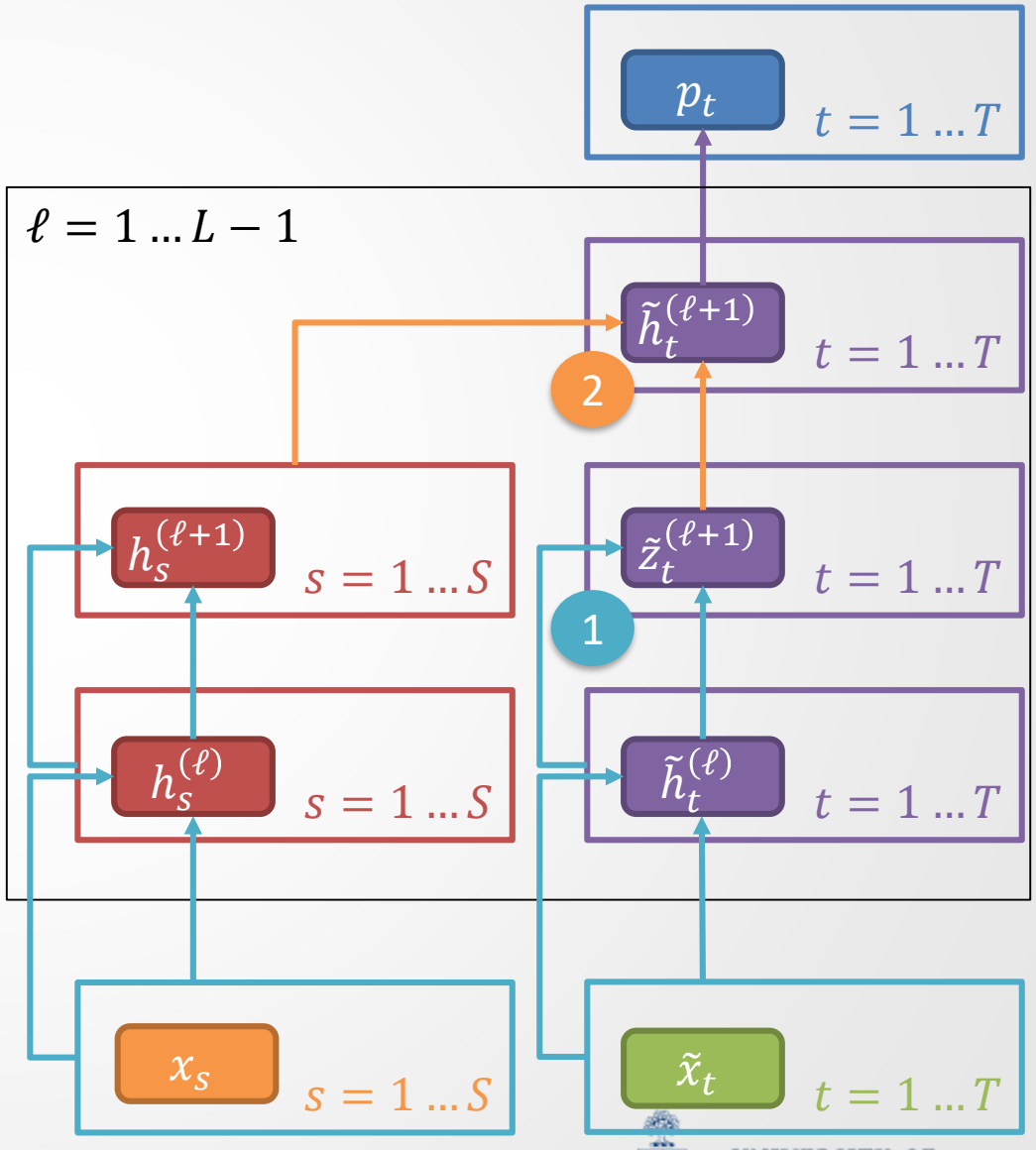
$$h_s^{(\ell+1)} \leftarrow Att_{Enc}\left(h_s^{(\ell)}, h_{1:S}^{(\ell)}\right)$$

Decoder uses 1. self-attention*

$$\tilde{z}_t^{(\ell+1)} \leftarrow Att_{Dec1}\left(\tilde{h}_t^{(\ell)}, \tilde{h}_{1:t}^{(\ell)}\right)$$

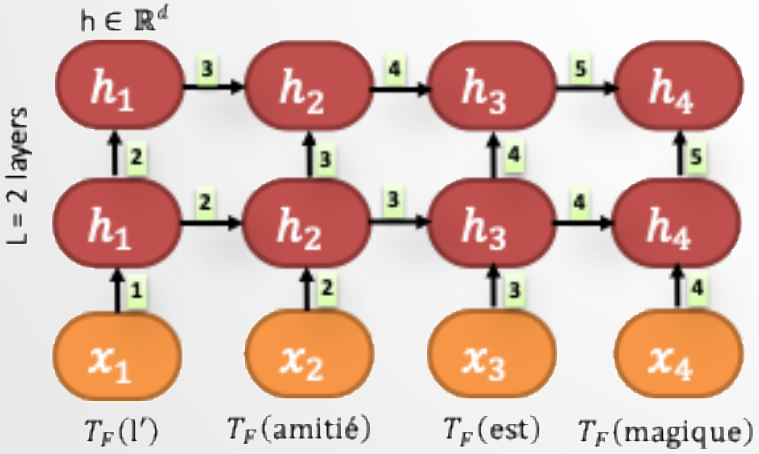
then 2. attention with encoder

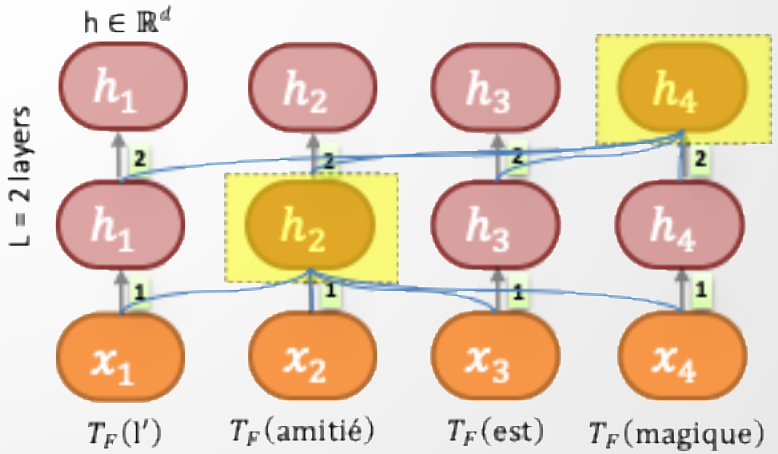
$$\tilde{h}_t^{(\ell+1)} \leftarrow Att_{Dec2}\left(\tilde{z}_t^{(\ell+1)}, h_{1:S}^{(\ell+1)}\right)$$



Transformer motivations

- Limitations of recurrent connections: long-term dependencies, lack of parallelizability, interaction distance (steps to distant tokens).
- Attention allows access to entire sequence
- Lots of computation can be shared, parallelized across sequence indices. Identical layers: [self, cross]-attention, feed-forward w/ tricks
- There are more *avant-garde* applications to other domains





Source sentence (French): *L' amitié est magique*
Target sentence (English): *Friendship is magic*

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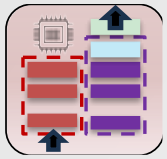
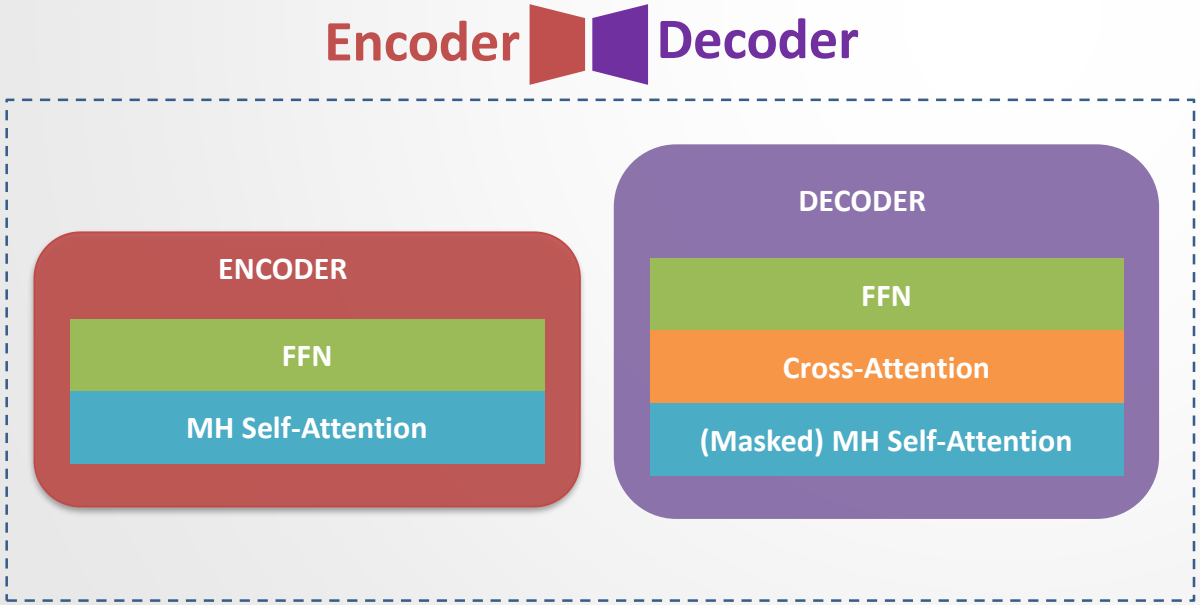
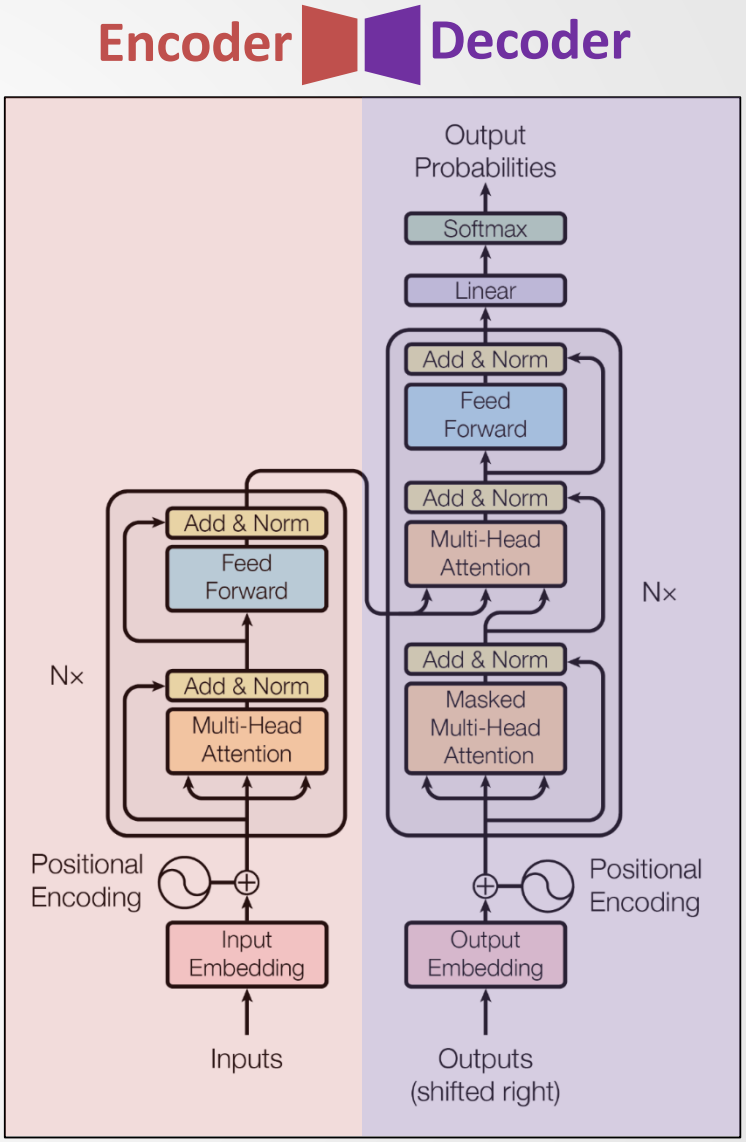


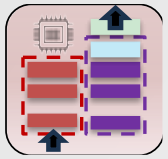
Transformer Architecture

- Architecture diagram from Vaswani[1]
- Building blocks:
  1. Encoder
  2. Decoder



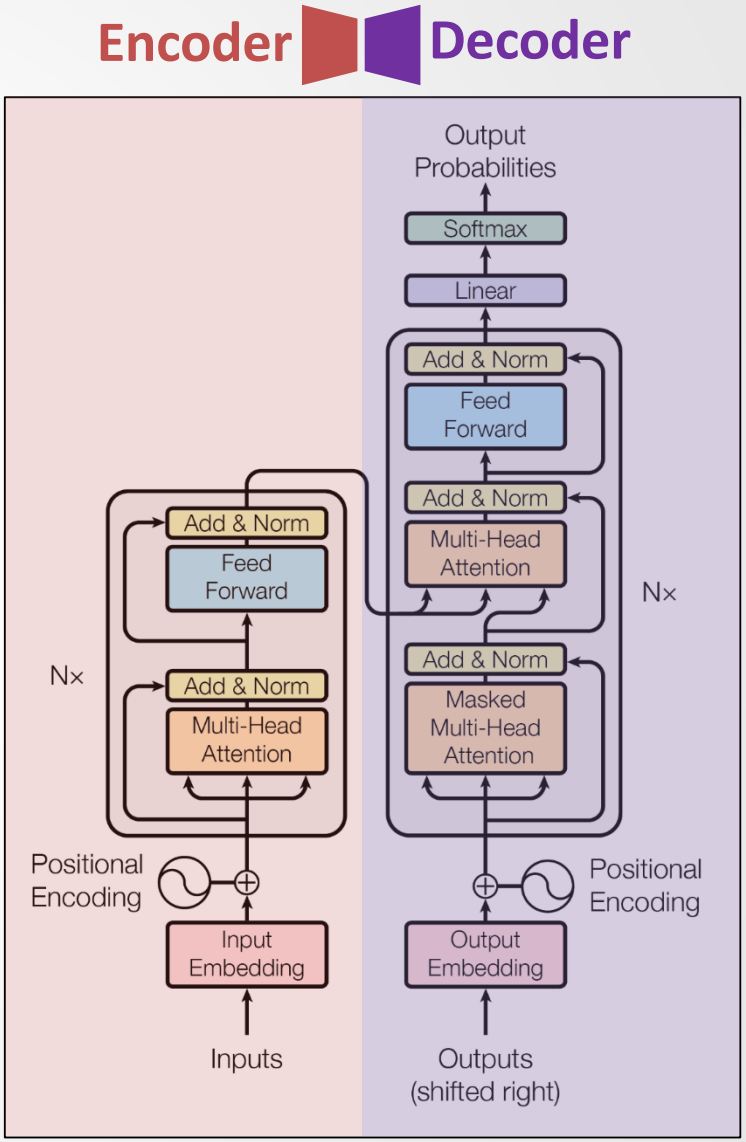


[1] Vaswani, Ashish, et al. "Attention is all you need." *NeurIPS* (2017).



Transformer Architecture

- Architecture diagram from Vaswani[1]
- Building blocks:
  1. Encoder
  2. Decoder
- Main components within building blocks:
  - Attention mechanisms:
    - single and multi-head attention
    - self, cross, and masked attention
  - Feed-forward MLPs (FFN)
  - Layer normalization (LN)
  - Positional encodings (PE)
  - Residual connections

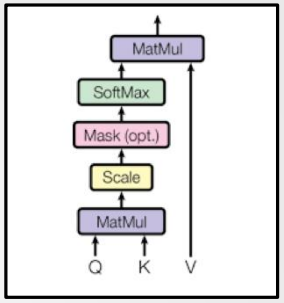


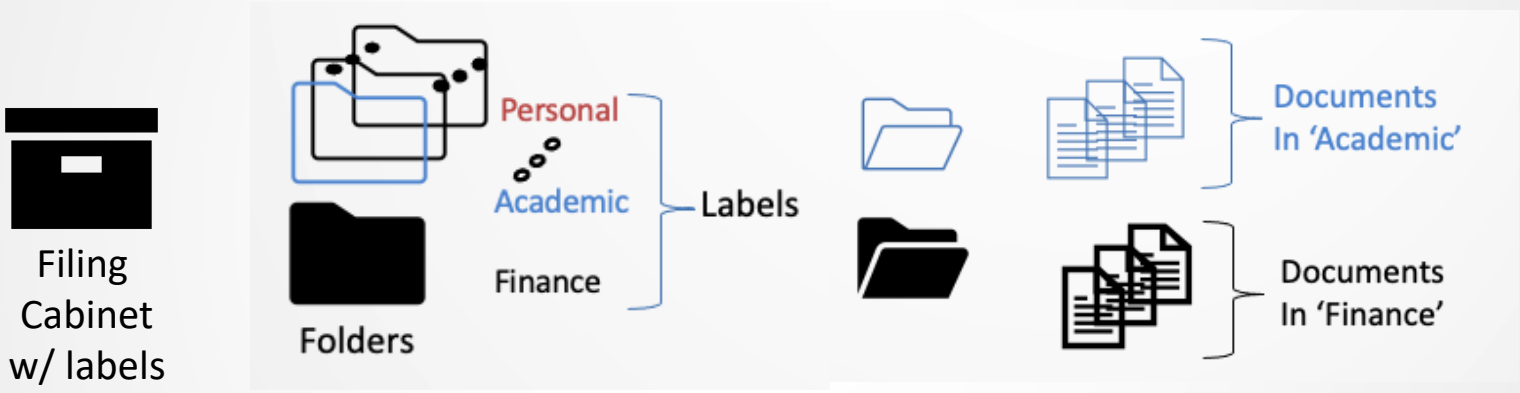
[1] Vaswani, Ashish, et al. "Attention is all you need." *NeuIPS* (2017).

Transformer Attention(Q,K,V) : Intuition

In the classical roboquity era (2100-2250 AD), humans in designated zones/zoos are only allowed *filing cabinets* and *paper documents* to store information.

ACORN has been terminated, and UofT students' info (financial, academic, personal) retrieval works as follows:





K Keys

V Values

Similarity Measure

Dot Product Attention

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

Q Queries

q1 What is the student's current academic standing?

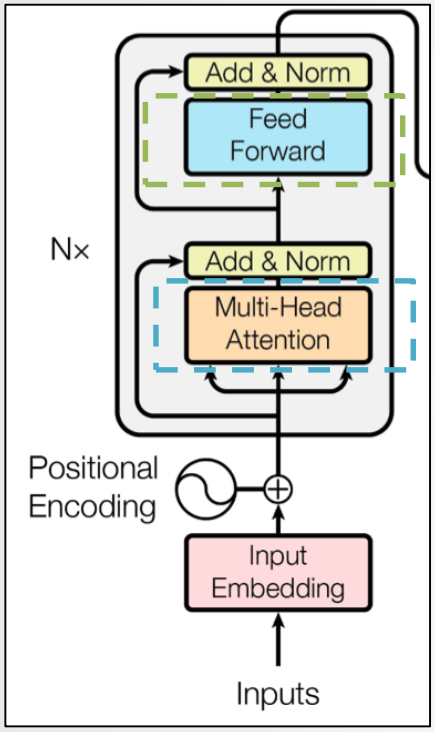
q2 What is the student's current financial status?

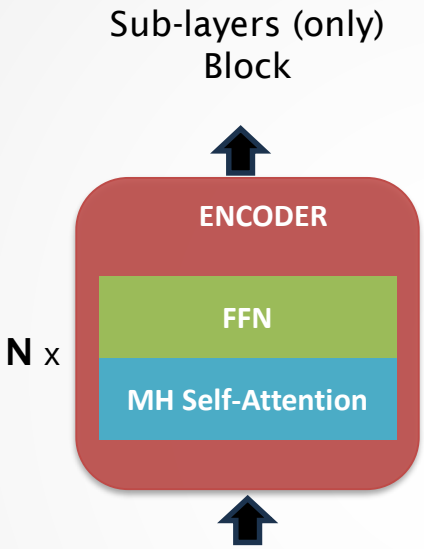
q3 What is the student's residency status in Canada?

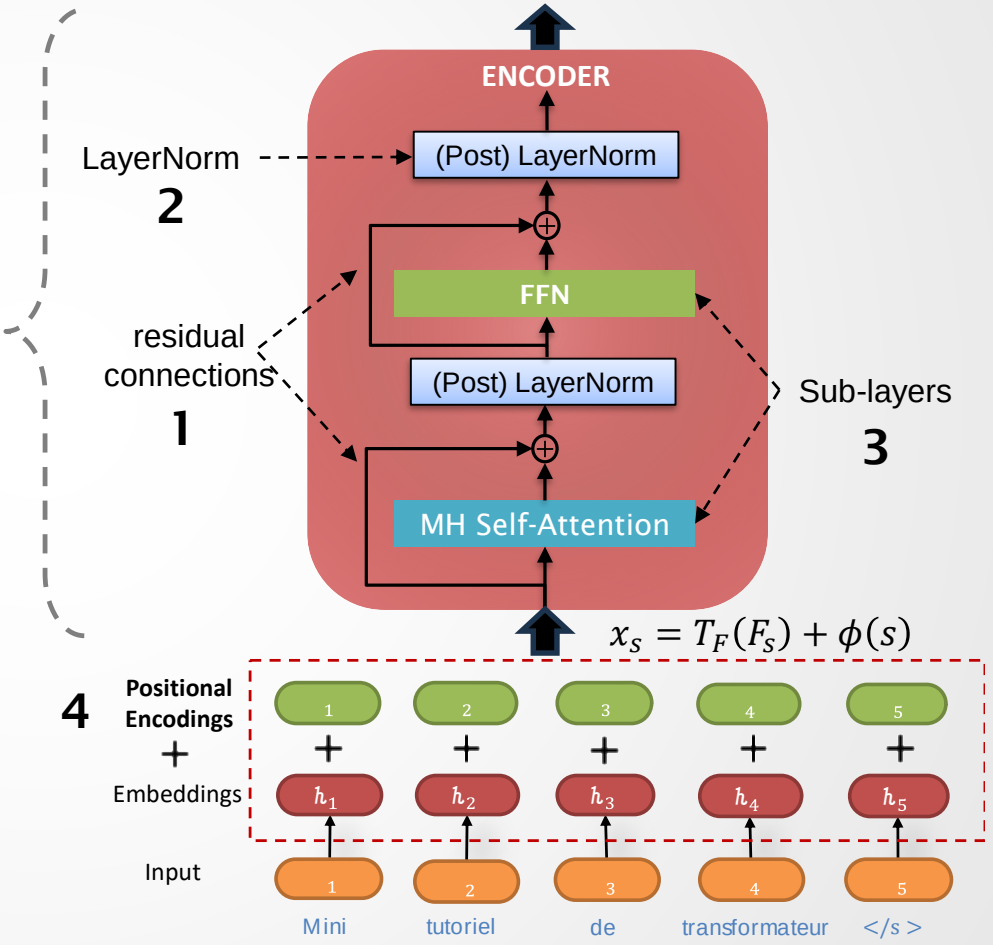
Transformer Encoder

F_S: Mini tutoriel de transformateur

Encoder Decoder E_T:Tiny transformer tutorial

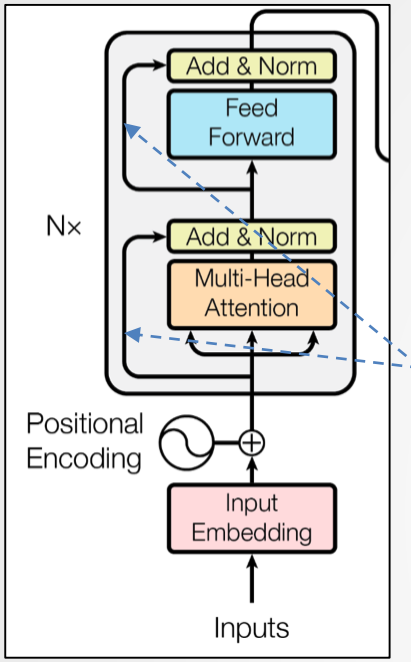


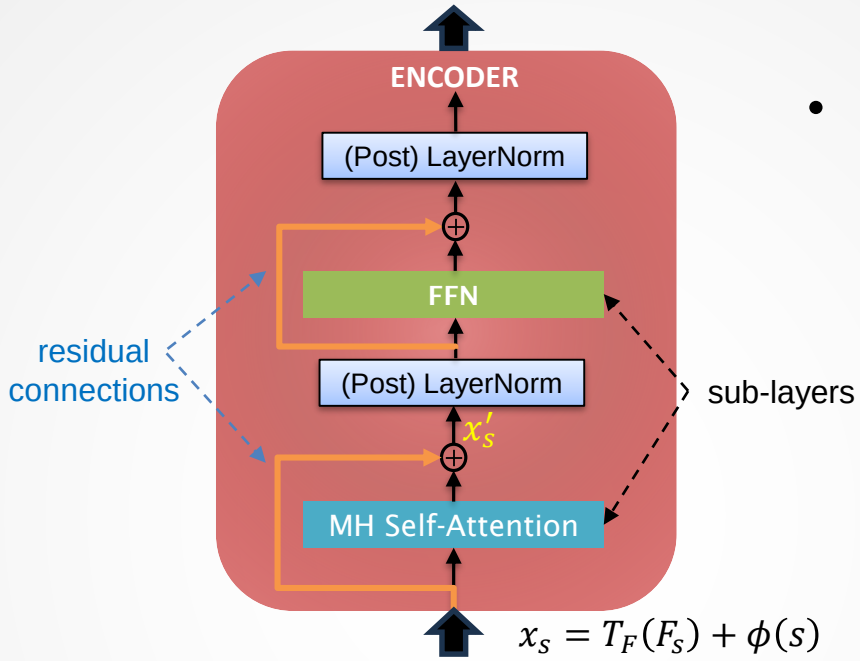




- **Plan**: discuss building blocks:
  1. Residual connections
  2. LayerNorm
  3. Attention and FFN sub-layers
  4. Positional encodings

Residual Connections





- Idea from computer vision[1]

$$x_{l+1} = \mathcal{F}(x_l) + x_l$$

+ Helps smoothen loss curvature allowing better backprop.

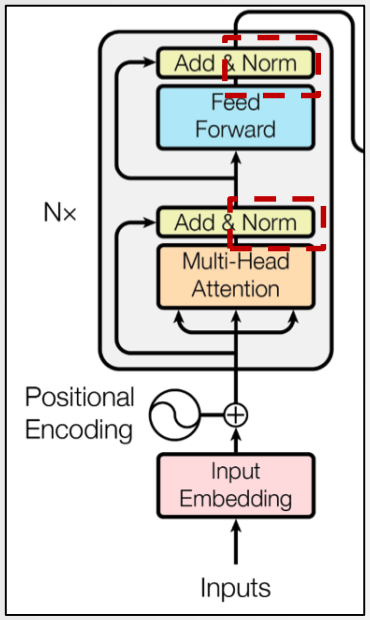
- Problem: NNs struggle to learn the identity function mapping
- Solution: Add back the input embeddings to the sub-layer's output moving up

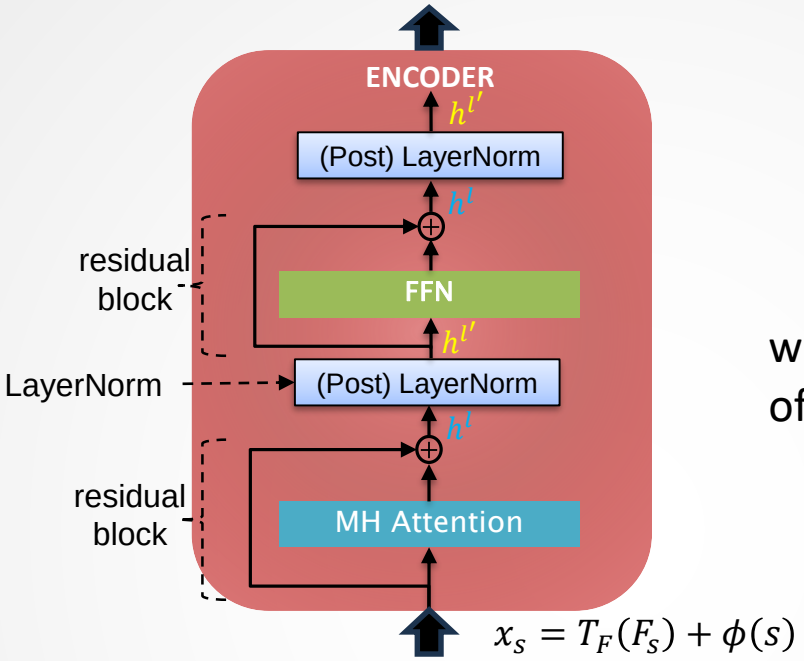
$$x'_s = Sublayer(x_s) + x_s$$

- *Analogy*: think of the noisy-channel analogy. Helps address forgetting past information by passing through a signal without distortion.

[1] He, Kaiming, et al. "Deep residual learning for image recognition." *CVPR*. 2016.

Layer Normalization: default (Post-) LN





$$h^{l\prime} = LayerNorm(h^l) = \gamma\left(\frac{h^l - \mu^l}{\sigma^l}\right) + \beta$$

where μ, σ are mean and std. dev. of features in h^l. γ, β are scale, bias params.

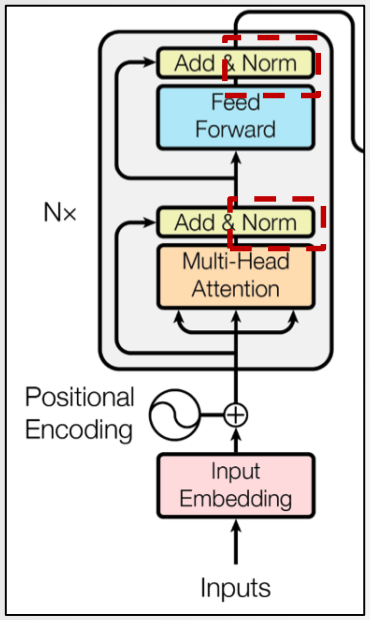
$$\mu = \frac{1}{d}\sum_{k=1}^{d} h_k^l$$

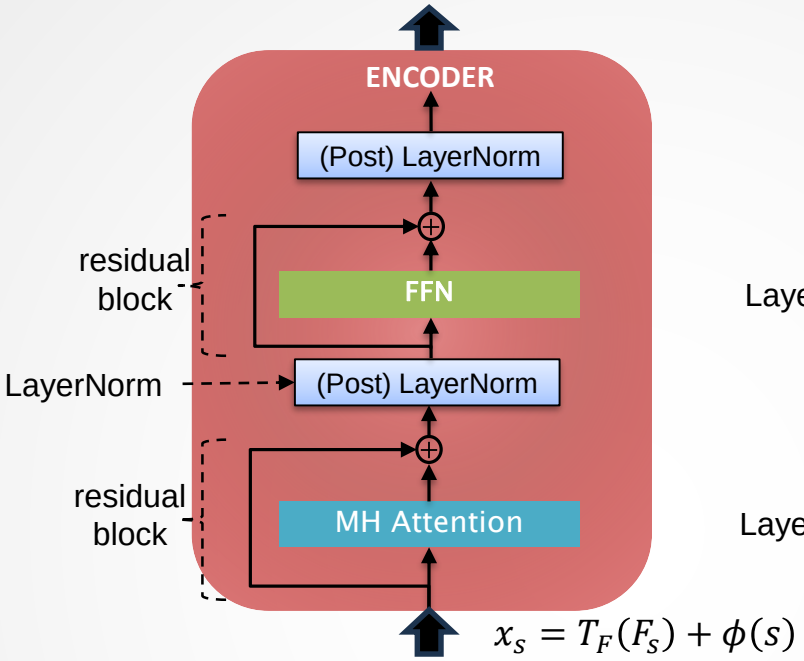
$$\sigma^2 = \frac{1}{d}\sum_{k=1}^{d} \left(h_k^l - \mu\right)^2$$

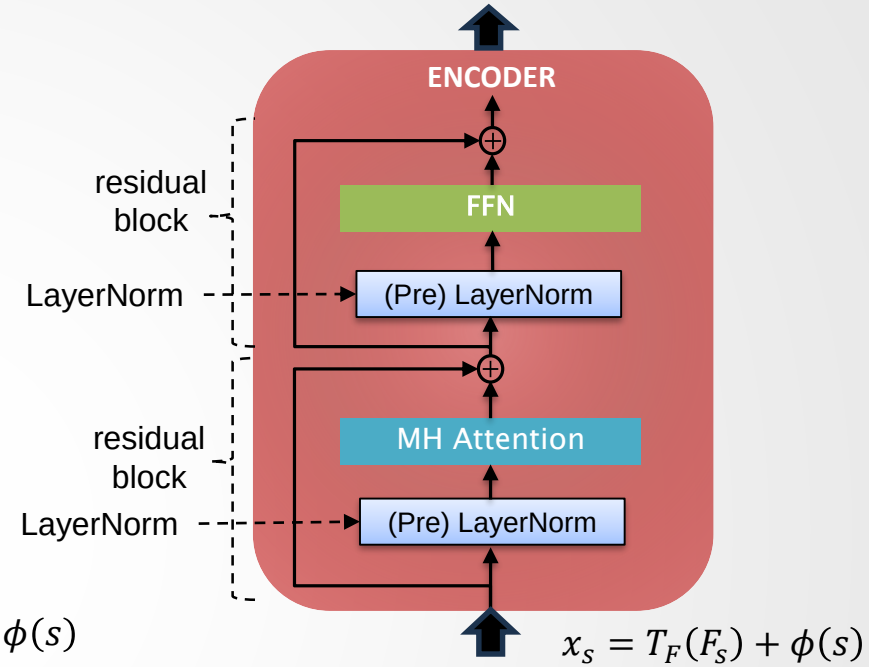
- Layer Normalization[1]:
  - **Normalize** input layer's distribution to 0 mean and 1 standard deviation.
  - Removes uninformative variation in layer's features

[1] Ba, Jimmy Lei, Jamie Ryan Kiros, and Geoffrey E. Hinton. "Layer normalization. 2016" [link]
[2] Xiong, Ruibin, et al. "On layer normalization in the transformer architecture." *ICML*. PMLR, 2020. [link]

Layer Normalization Variant: Pre-LN





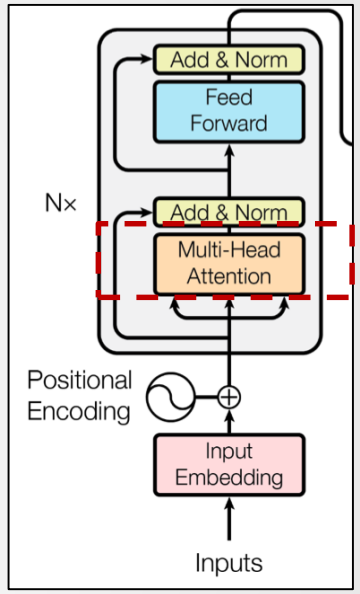


- Layer Normalization[1]: two popular variants
  - *Post layer normalization* (Post-LN): original Transformer model: requires learning rate warm-up due to initial instability of large output gradients.
  - *Pre layer normalization* (**Pre-LN**): puts layer-norm within the residual block. Allows removing warm-up stage. More stable training initialization.

[1] Ba, Jimmy Lei, Jamie Ryan Kiros, and Geoffrey E. Hinton. "Layer normalization." 2016 [No NLP; no pre- vs. post-]
[2] Xiong, Ruibin, et al. "On layer normalization in the transformer architecture." *ICML*. PMLR, 2020

Transformer Encoder - Self Attention

- Recall our discussion of attention in transformer LMs
- Steps:
  1. Calculate the query, key, and value for each token
     - Attention of each query (q_i) against all the keys ($k_{1:j}$)
  2. Calculate the **attention score** between query and keys
  3. **Normalize** the attention scores by applying softmax
  4. Calculate values by taking a **weighted sum**



$$q_i = W^Q x_i$$
$$k_i = W^K x_i$$
$$v_i = W^V x_i$$

$$a_{i,j} = score(q_i, k_j)$$
$$a_{i,j} = q_i . k_j$$
$$a_{i,j} = \frac{q_i . k_j}{\sqrt{d_k}}$$

$$\alpha_{i,j} = softmax(a_{i,1:K})$$
$$\alpha_{i,j} = \frac{exp^{(a_{i,j})}}{\sum_{k=1}^{K} exp^{(a_{i,k})}}$$

$$c_i = \sum_j \alpha_{i,j} v_j$$

[1] Vaswani, Ashish, et al. "Attention is all you need." *NeurIPS* (2017).

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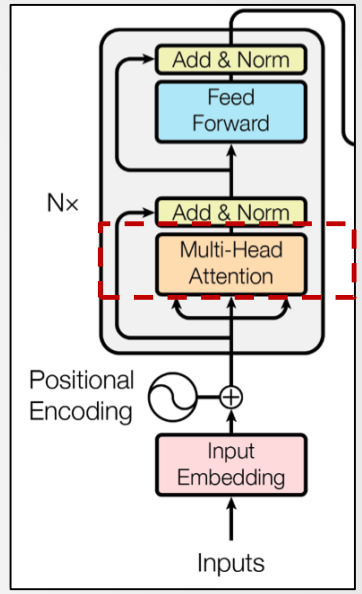


Vectorized notation:

$$Q = XW^Q$$
$$K = XW^K$$
$$V = XW^V$$

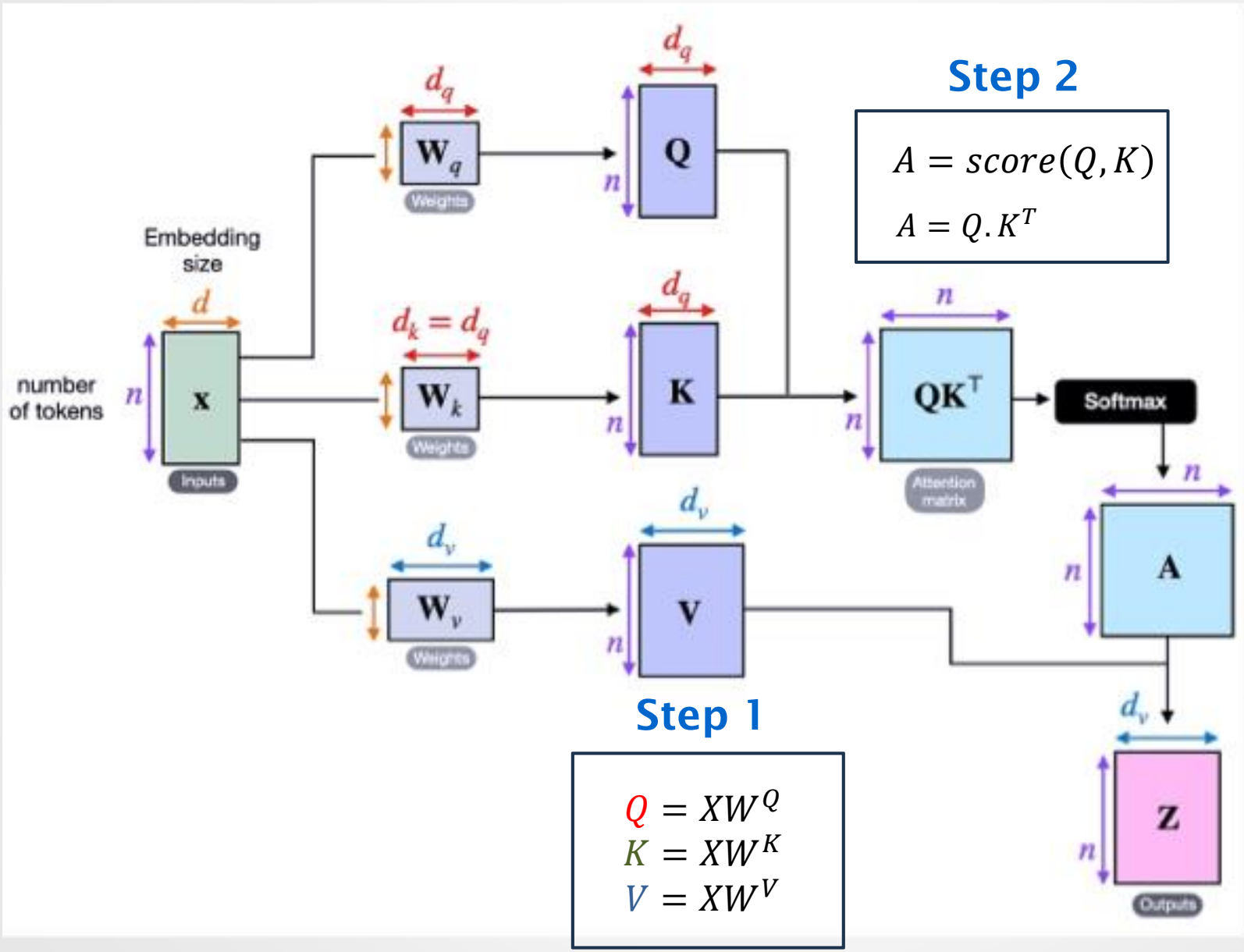
$$A = score(Q, K)$$
$$A = Q.K^T$$
$$A = \frac{Q.K^T}{\sqrt{d_k}}$$

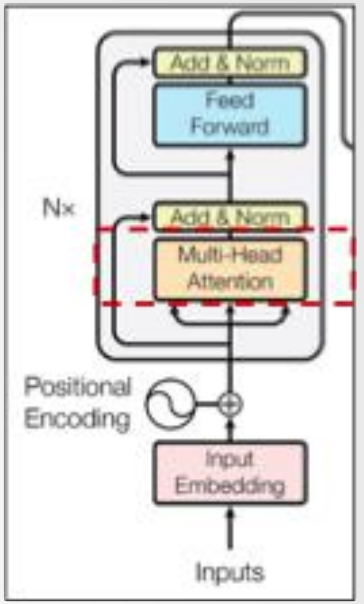
$$\mathrm{A} = softmax(A)$$
$$\mathrm{A} = softmax(\frac{QK^T}{\sqrt{d_k}})$$

$$Z = \mathrm{A}.V$$

[1] Vaswani, Ashish, et al. "Attention is all you need." *NeuIPS* (2017).

Transformer Encoder - Self Attention





[1] Vaswani, Ashish, et al. "Attention is all you need." *NeuIPS* (2017).

Multi-head Self Attention (MHA)

- As alluded to earlier, multi-head attention (MHA) jointly attends to information from different representation subspaces at different positions

$$MHA(Q, K, V) = Concat(head_1, \dots, head_h)W^O$$
$$where\ head_i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right)$$

And projections are parameter matrices:

$$W_i^Q \in \mathbb{R}^{d_{model} \times d_k}$$
$$W_i^K \in \mathbb{R}^{d_{model} \times d_k}$$
$$W_i^V \in \mathbb{R}^{d_{model} \times d_v}$$

$$W^O \in \mathbb{R}^{hd_v \times d_{model}}$$

$$d_k = d_v = \frac{d_{model}}{h}$$

[1] Vaswani, Ashish, et al. "Attention is all you need." *NeurIPS* (2017).

Feed-forward (FFN) layers

- Attention only **re-weighs** the **value** **vectors**
- We still need more degrees of freedom (and *non-linearity)* to learn
- The feed-forward layer(s) (**FFN**) provide these non-linearities to attention layer outputs
- Specifically, each output x undergoes two (layer) linear transformations with a ReLU activation in between. Pointwise:

$$FFN(x_i) = \max(0, xiW_1 + b_1)\, W_2 + b_2$$

$$z_i = \sum_j \alpha_{i,j} v_j$$

- FFN sub-layer is applied to each token pos. separately and identically
- Given x, a sequence of tokens $(x_1, \ldots, x_S)$:

$$FFN(x) = ReLU(xW_1 + b_1)\, W_2 + b_2$$

$$Z = \mathrm{A}.V$$

where W_1, W_2, b_1 *and* b_2 are parameters

[1] Vaswani, Ashish, et al. "Attention is all you need." *NeurIPS* (2017).

Position (in)dependence

- To a great extent, attention is agnostic to order
  - For permutation vector v on $(1,2,\ldots,V)$:

$$Att(a, b_v) = Att(a, b_{1:V})$$

- But *word order* **matters** in language
- **Solution**: encode position in input:

$$x_s = T_F(F_s) + \phi(s)$$

Recap: Transformer Architecture

- Architecture diagram from Vaswani[1]
- Building blocks:
  - ☑ 1. Encoder
  - 2. **Decoder**
- Main components within building blocks:
  - Attention mechanisms:
    - ☑ single and multi-head attention
      - self, **cross, and masked attention**
  - ☑
    - Feed-forward MLPs (FFN)
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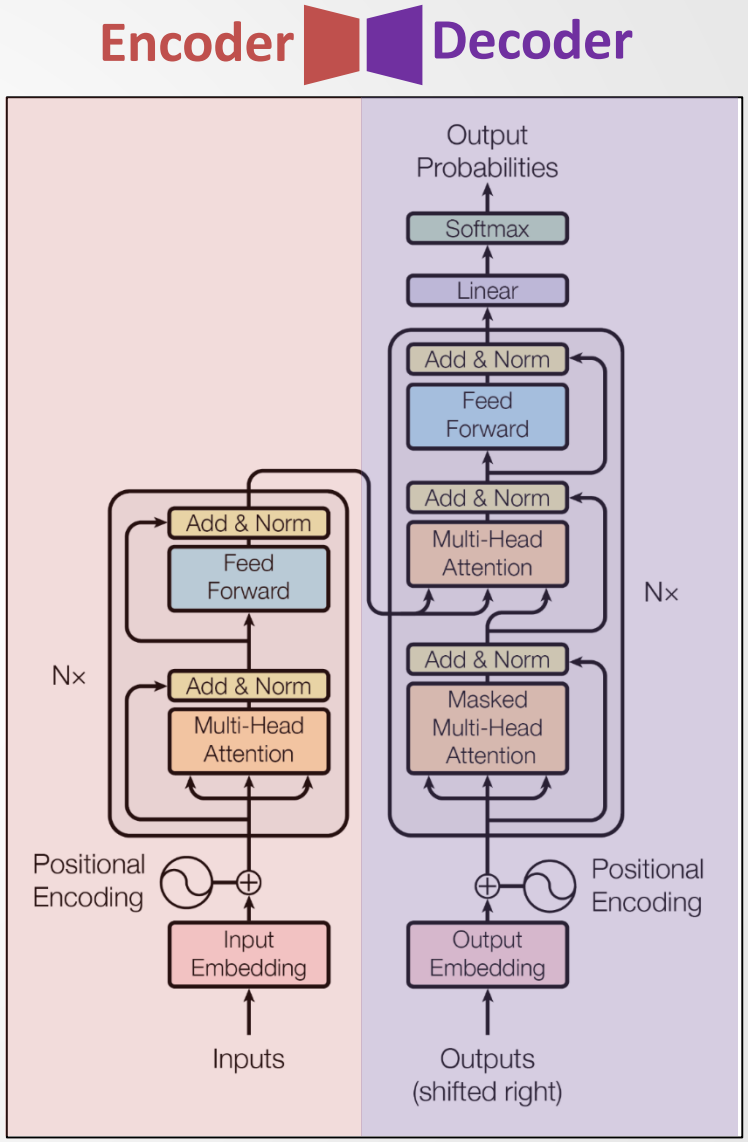
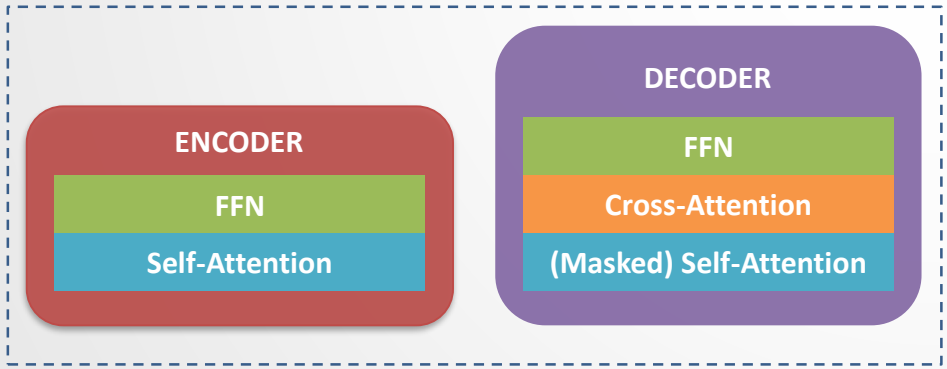
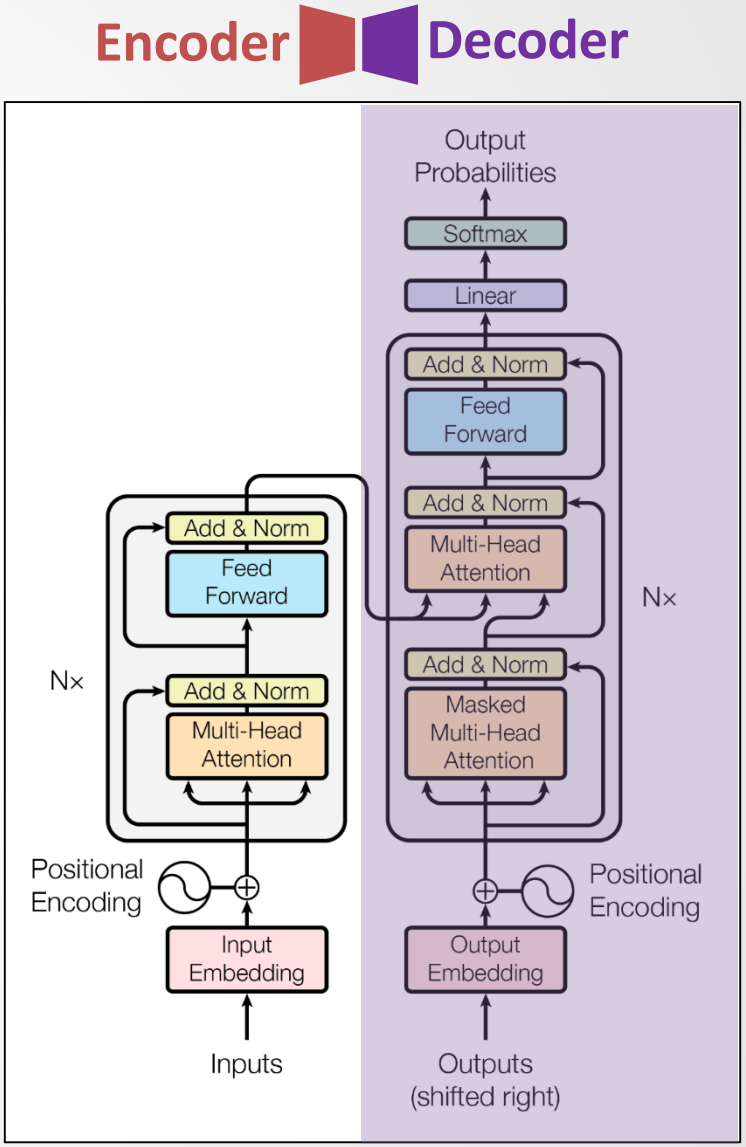
    - Positional encodings (PE)
    - Residual connections



Next block: Transformer Decoder

- Layer normalization, residual connections, FFNs are identical to the encoder block
- Thus, we focus on remaining:
  - Masked/Causal self-attention sub-layer
  - Cross-attention

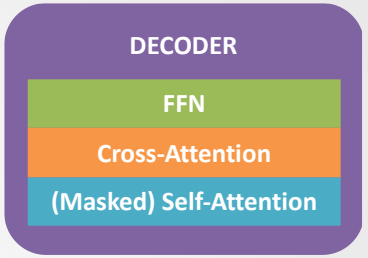


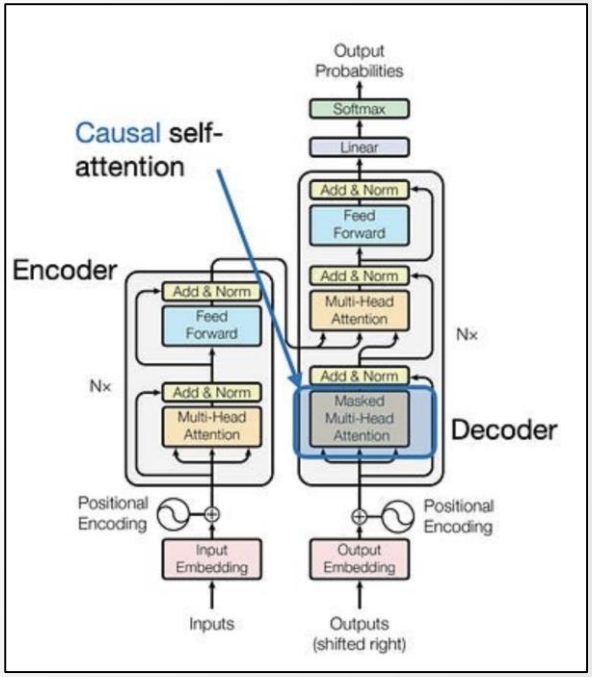


[1] Vaswani, Ashish, et al. "Attention is all you need." *NeurIPS* (2017).

Decoder – Masked Self-Attention

- Masked (Multi-head) self-attention:
  - Enforce auto-regressive language modeling objective. The decoder cannot peek and pay attention to the (unknown) future words
  - **Solution**: use a *look-ahead mask M,* by setting attention scores of future tokens to –inf.



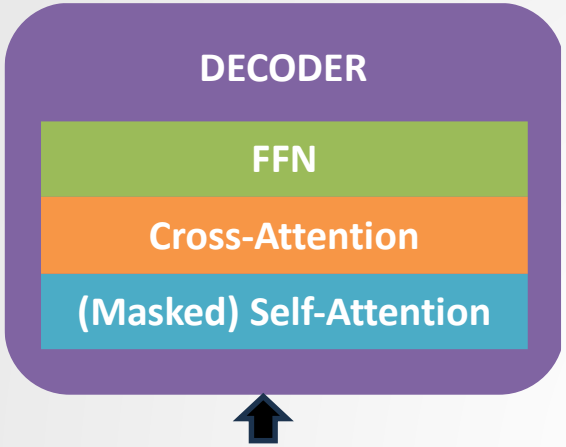


$$\begin{array}{c} \\ a^Q \\ b^Q \\ c^Q \\ D^Q \end{array} \begin{array}{c} \begin{array}{cccc} a^K & b^K & c^K & D^K \end{array} \\ \begin{bmatrix} 0 & -\infty & -\infty & -\infty \\ 0 & 0 & -\infty & -\infty \\ 0 & 0 & 0 & -\infty \\ 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

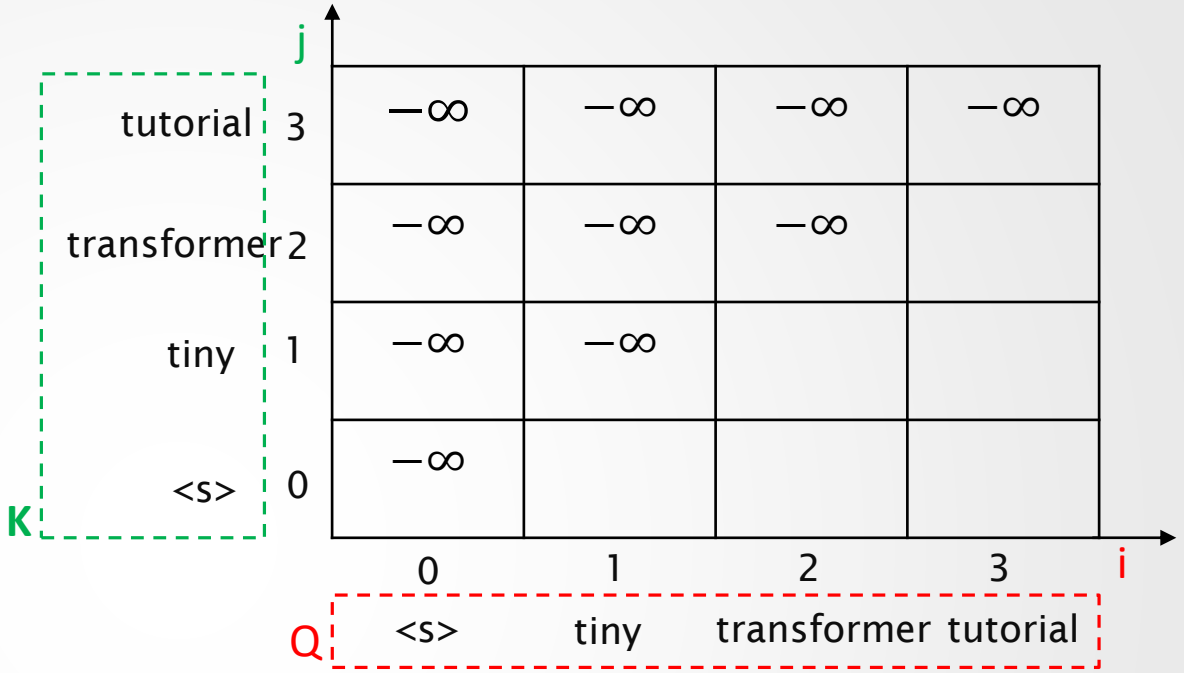
$$a_{ij} = \begin{cases} q_i^T . k_j, j < i \\ -\infty, j \geq i \end{cases}$$

[1] Vaswani, Ashish, et al. "Attention is all you need." *NeurIPS* (2017).

Decoder – Masked Self-Attention



E_T: <s> tiny transformer tutorial



Recall

$$a_{i,j} = score(q_i, k_j)$$

or,

$$A = score(Q, K)$$

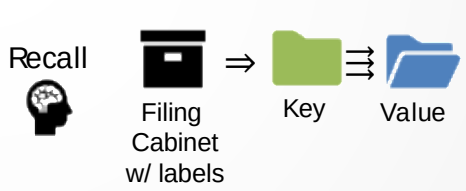
[1] Vaswani, Ashish, et al. "Attention is all you need." *NeurIPS* (2017).

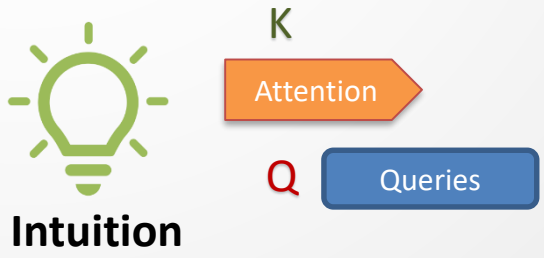
Encoder-Decoder (Cross) Attention

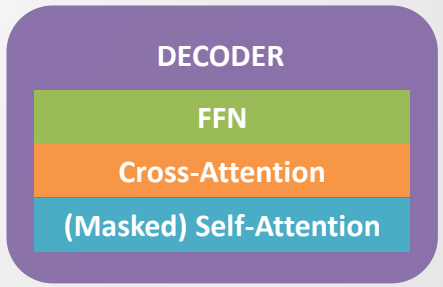
- In self-attention: Q, K and V have same source (tokens)
- **Cross attention** is encoder <> decoder attention between output vectors
- Using our running example and notation:
  - Let $h_1, \ldots, h_S$ be encoder output vectors, where $h_i \in \mathbb{R}^{d_k}$
  - Let $\tilde{h}_1, \ldots, \tilde{h}_T$ be decoder output vectors, where $\tilde{h}_i \in \mathbb{R}^{d_q}$

- Then, keys and values: K and V comes from encoder (or, *memory*):
  - $k_i = K h_i \,,\; v_i = V h_i$

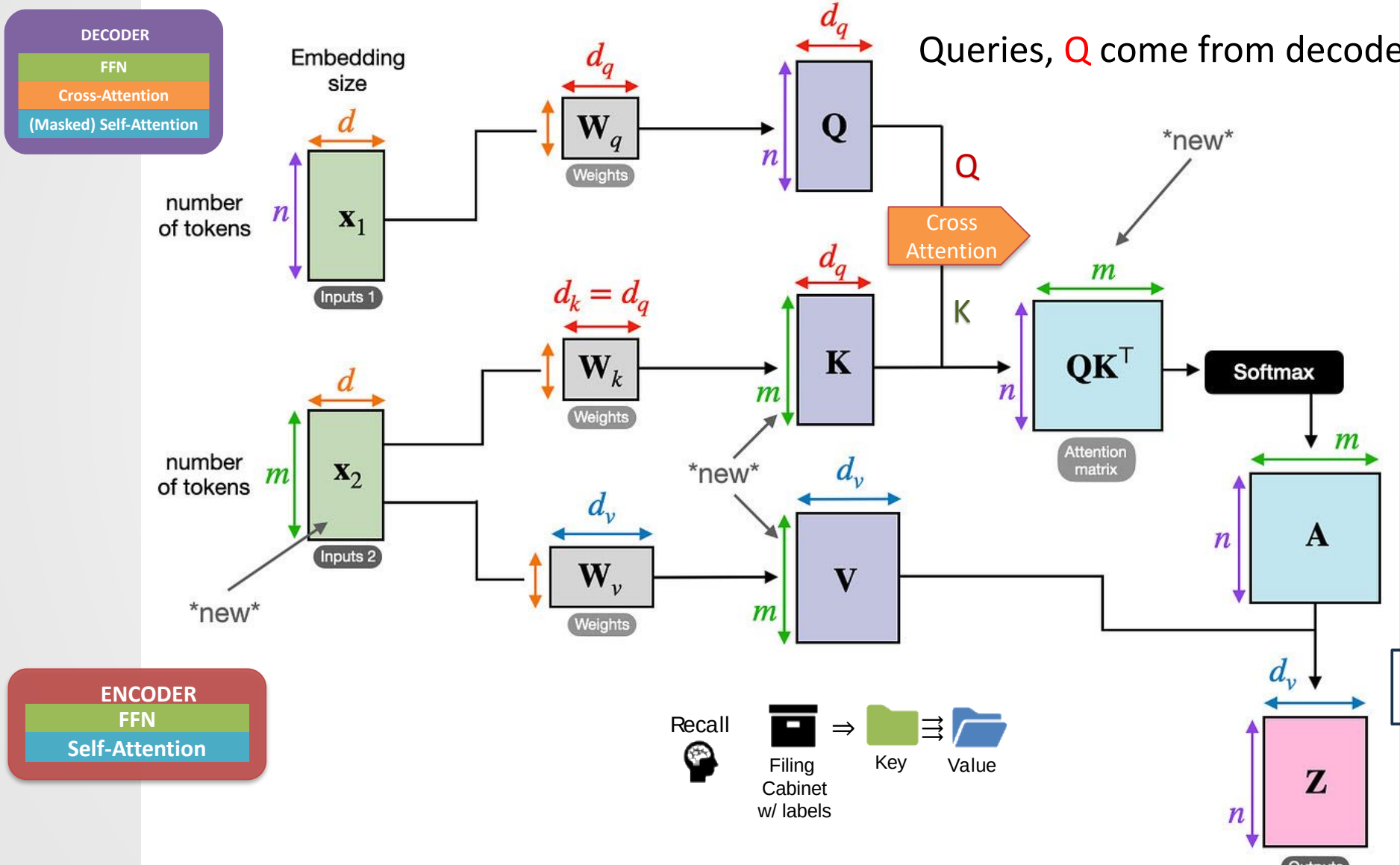
- Queries, Q comes from decoder:
  - $q_i = Q \tilde{h}_i$



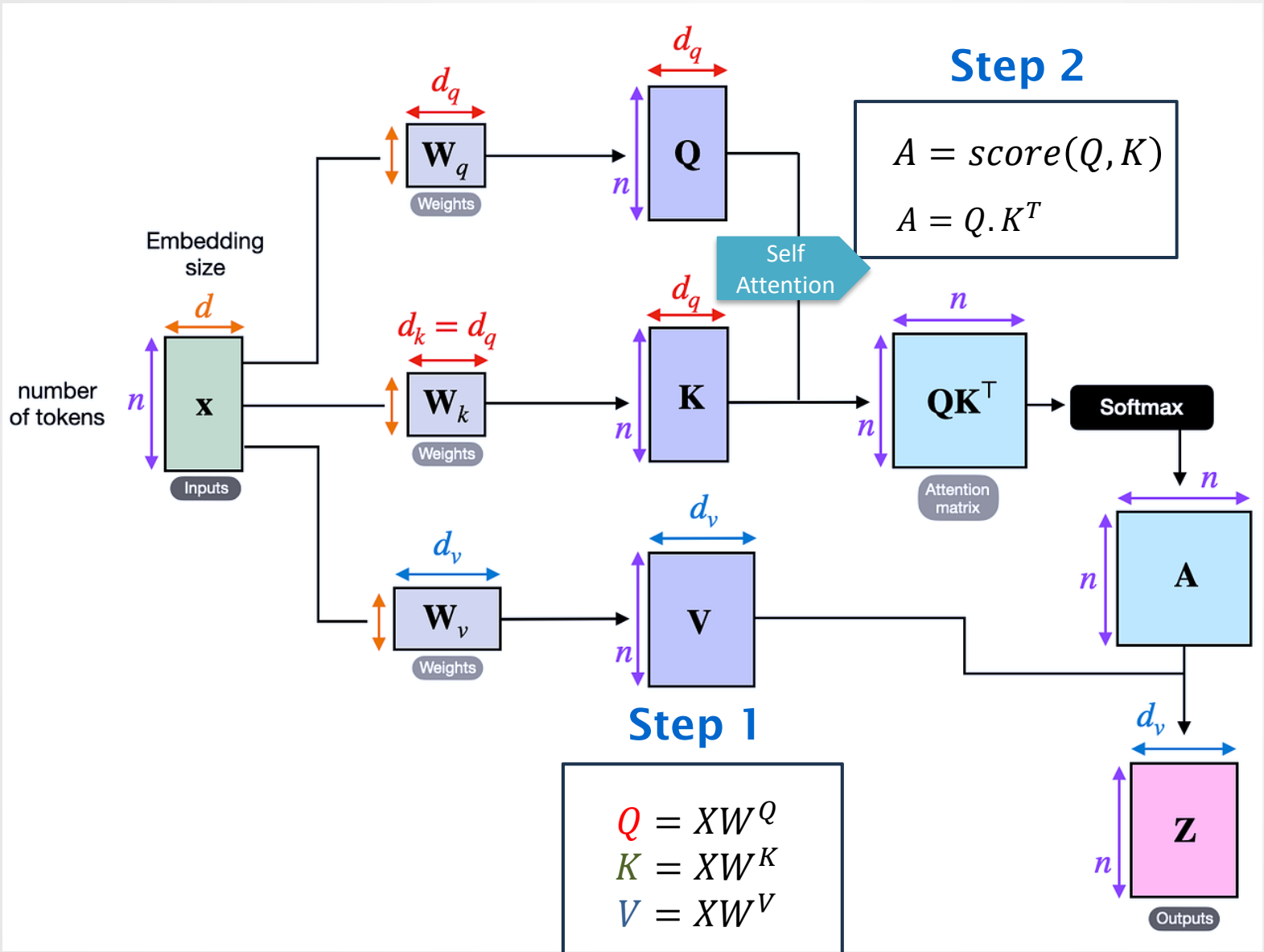


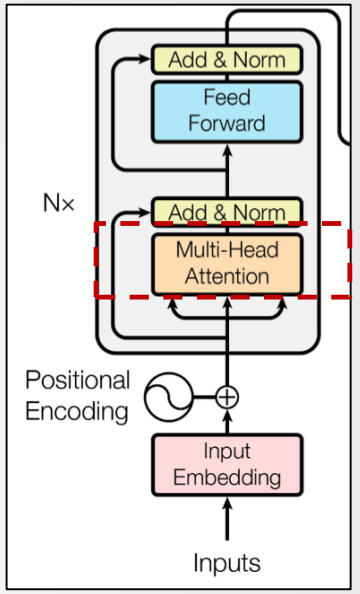


Encoder-Decoder (Cross) Attention



(Compare) Encoder - Self Attention





[1] Vaswani, Ashish, et al. "Attention is all you need." *NeuIPS* (2017).

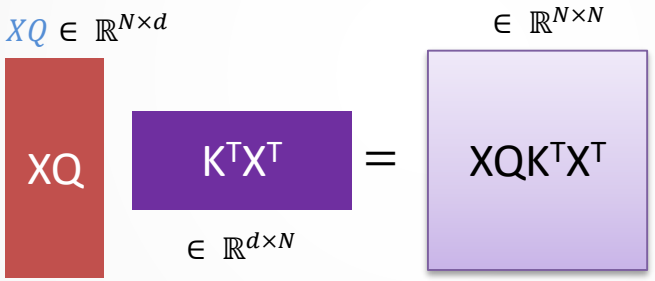
Recap

- We have now covered all the primitives you need for building a transformer!
- All of these equations look abstract, but not to worry …
- Assignment 2 was designed for you to implement all these concepts into a working MT model of your own.

Tasks	Section	Class	criterion	Max mark	Sub-Total	File
1	Building Blocks	LayerNorm	:forward	2		*a2_transformer_model.py*
2		MultiHeadAttention	:attention	4		
3			:forward	5		
4		FeedForwardLayer	:forward	1	12	
5	Architecture	TransformerEncoderLayer	:pre_layer_norm_forward	2		
6			:post_layer_norm_forward	1		
7		TransformerDecoderLayer	:__init__	4		
8			:pre_layer_norm_forward	2		
9			:post_layer_norm_forward	2		
10		TransformerDecoder	:forward	3		
11		TransformerEncoderDecoder	:create_pad_mask	1		
12			:create_causal_mask	2		
13			:forward	3	20	
15			:greedy_decode	5		

Transformers - Drawbacks

- Attention's **quadratic** computation **cost**
  - Function of sequence length N, and token dimension d
  - Computing all token pairs mean the function grows quadratically with N, $O(N^2 d)$ unlike RNNs: $O(Nd)$



- Can you see why this could be the biggest hurdle for increasing a transformer LM's **context length** (i.e., the size of input it can process)?

Transformers - Drawbacks

- Context (input) size limitation:
  - Dimension d in modern LLMs are ~>3K
  - If length of one sentence is ~10-30 word tokens, then computation scales with 10^2-30^2 times d
  - Thus, many encoders set a bound on N (usually 500-700 tokens)
  - But, some people want **N** to be much larger, e.g., processing a document (N > 10K) at one go (instead of chunking by N for every call)

- Active research area: improving the quadratic cost of attention, like self-attention with linear complexity[1]
  - + Roformer, flash attention, sliding-window etc.

[1] Wang, Sinong, et al. "Linformer: Self-attention with linear complexity." (2020).

Transformers - Drawbacks

- Other drawbacks / improvement areas:
  - **Positional encoding representations**:
    - Do we need absolute indices to represent position?

$$f_{t:t\in\{q,k,v\}}(\boldsymbol{x}_i, i) := \boldsymbol{W}_{t:t\in\{q,k,v\}}(\boldsymbol{x}_i + \boldsymbol{p}_i)$$

  - Slew of variants proposed to the (sinusoidal, absolute) positional encoding we saw

- General trend:
  - Move towards **relative position encoding**
  - E.g. Relative linear position attention [Shaw et al. 2018]

$$f_q(\boldsymbol{x}_m) := \boldsymbol{W}_q\boldsymbol{x}_m$$
$$f_k(\boldsymbol{x}_n, n) := \boldsymbol{W}_k(\boldsymbol{x}_n + \tilde{\boldsymbol{p}}_r^k)$$
$$f_v(\boldsymbol{x}_n, n) := \boldsymbol{W}_v(\boldsymbol{x}_n + \tilde{\boldsymbol{p}}_r^v)$$

where $\tilde{\boldsymbol{p}}_r^k, \tilde{\boldsymbol{p}}_r^v \in \mathbb{R}^d$ are trainable relative position embeddings

Relative distance between pos. m and n

$$r = clip(m - n, r_{min}, r_{max})$$

[Aside] Rotary Position Embeddings

- RoPE – perhaps the most common in modern LLMs
  - Encodes absolute position with a rotation matrix
  - RoPE + Transformer = **RoFormer**

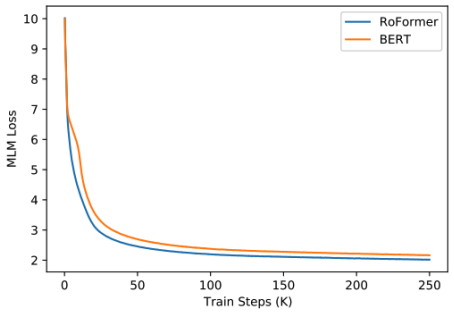
$$f_{\{q,k\}}(\boldsymbol{x}_m, m) = \boldsymbol{R}^d_{\Theta,m}\boldsymbol{W}_{\{q,k\}}\boldsymbol{x}_m$$

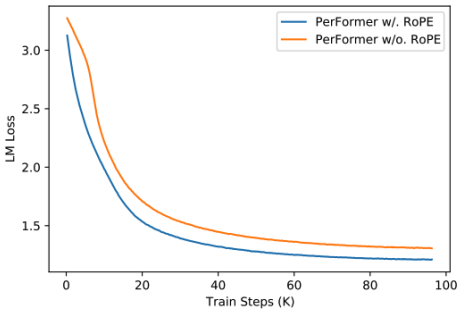
$$f_{\{q,k\}}(\boldsymbol{x}_m, m) = \begin{pmatrix} \cos m\theta & -\sin m\theta \\ \sin m\theta & \cos m\theta \end{pmatrix} \begin{pmatrix} W^{(11)}_{\{q,k\}} & W^{(12)}_{\{q,k\}} \\ W^{(21)}_{\{q,k\}} & W^{(22)}_{\{q,k\}} \end{pmatrix} \begin{pmatrix} x^{(1)}_m \\ x^{(2)}_m \end{pmatrix}$$

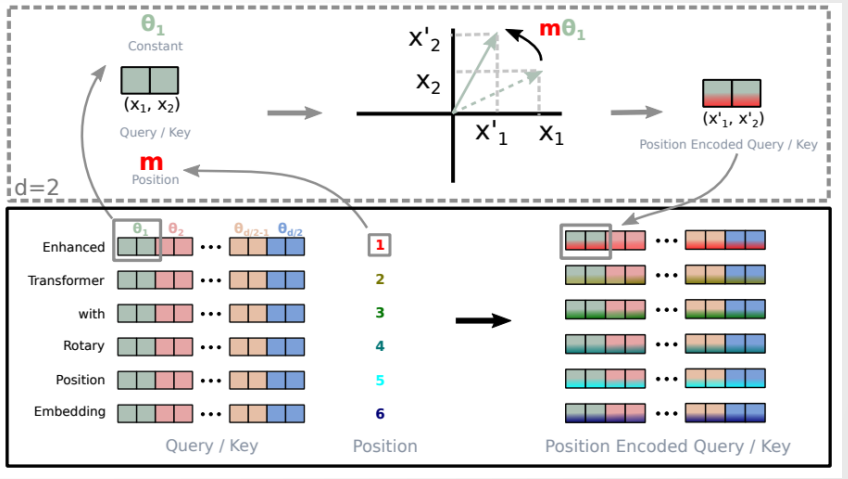
Model	BLEU
Transformer-baseVaswani et al. [2017]	27.3
RoFormer	**27.5**

Table 2: Comparing RoFormer and BERT by fine tuning on downstream GLEU tasks.

Model	MRPC	SST-2	QNLI	STS-B	QQP	MNLI(m/mm)
BERTDevlin et al. [2019]	88.9	93.5	90.5	85.8	71.2	84.6/83.4
RoFormer	**89.5**	90.7	88.0	**87.0**	**86.4**	80.2/79.8



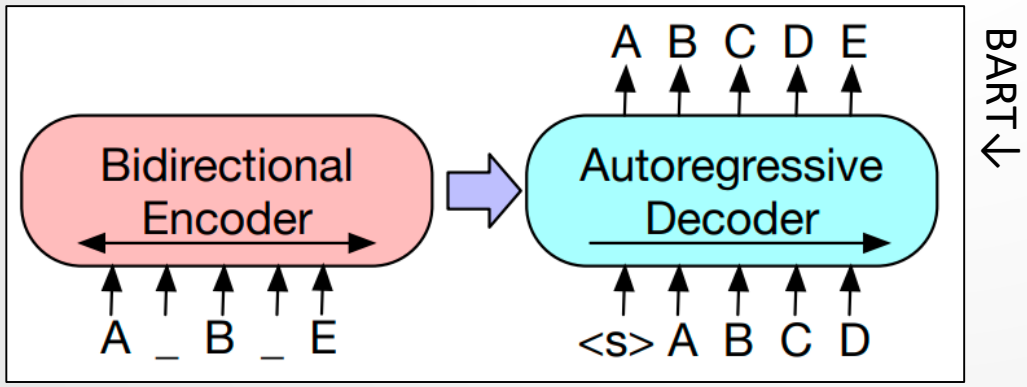


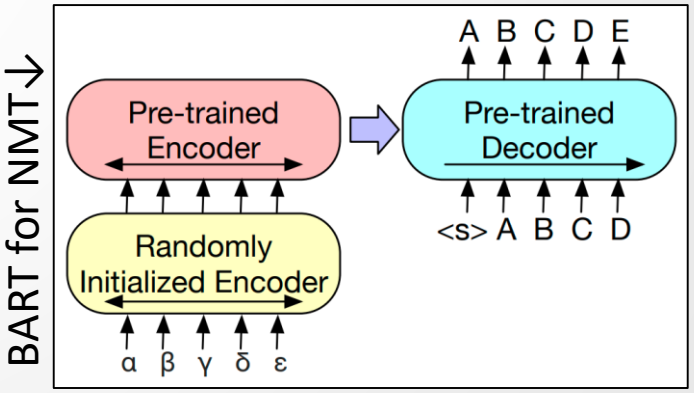


[1] **RoPE**: Su, Jianlin, et al. "Roformer: Enhanced transformer with rotary position embedding." (2021)

Aside – BERT → BART → NMT

- Explosion of variants to BERT
- Pretrained BERT language model used to re-score/fine-tune downstream NLP tasks
- BART (Lewis *et al*, 2020) adds the decoder back to BERT, keeping the BERT objective
- Add some source language layers on top to train for NMT





Lewis, Mike, et al. "Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension." (2019). link.

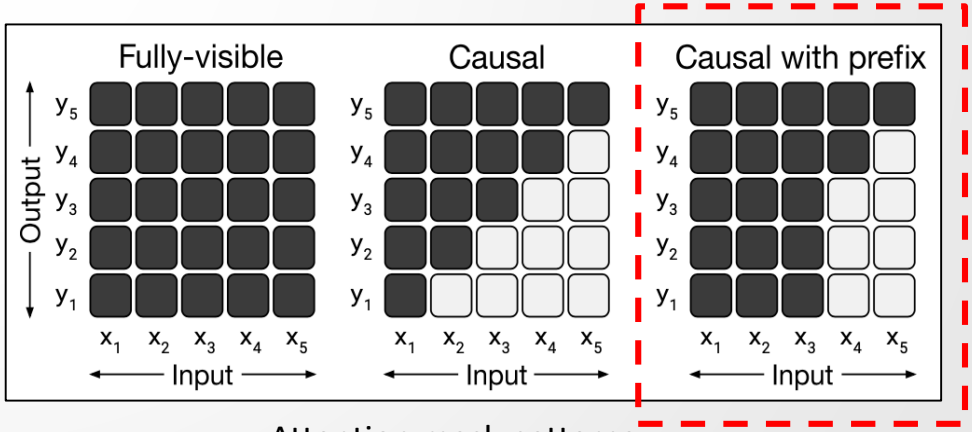
T5: Text-to-Text Transfer Transformer

A transformer refined with extensive scientific testing

- T5 is an unified framework that casts all NLP problems into a '*text-to-text*' format.
- Architecturally (almost) identical to the original Transformer (Vaswani et al., 2017).
- Draws from a systematic study comparing pre-training objectives, architectures, unlabeled data sets, transfer approaches, and other factors on dozens of language understanding tasks.
- Introduces and uses a new curated **dataset**: "*Colossal Clean Crawled Corpus*" (**C4**) for training.

Distinguishing features:

- Consistent, task-invariant MLE training objective.
- Self-attention "mask" with prefix.
- Unsupervised "denoising" training objectives: ***span corruption*** (conceptually same to MLM, mask 'spans' instead of words).



Attention mask patterns

1. Raffel et al. "Exploring the limits of transfer learning with a unified text-to-text transformer." (2020).

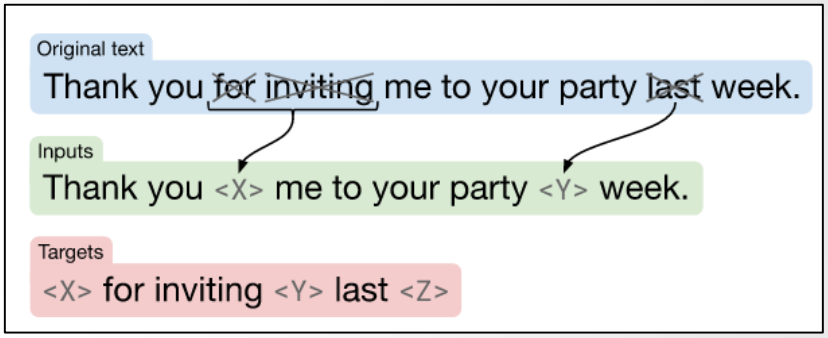
T5: Text-to-Text Transfer Transformer

Example Task: English to German (En-De) translation:

Input sentence: "*That is good.*"
Target: "*Das ist gut.*"

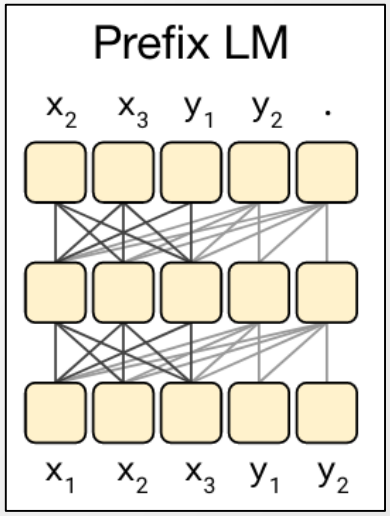
- **Training:** task specification is imbued by prepending task prefix to the input sequence. Model trained on next sequence prediction over the concatenated input sequence:

  "*translate En-De: That is good. Target: Das ist gut.*"



Input/Output format for training denoising objective

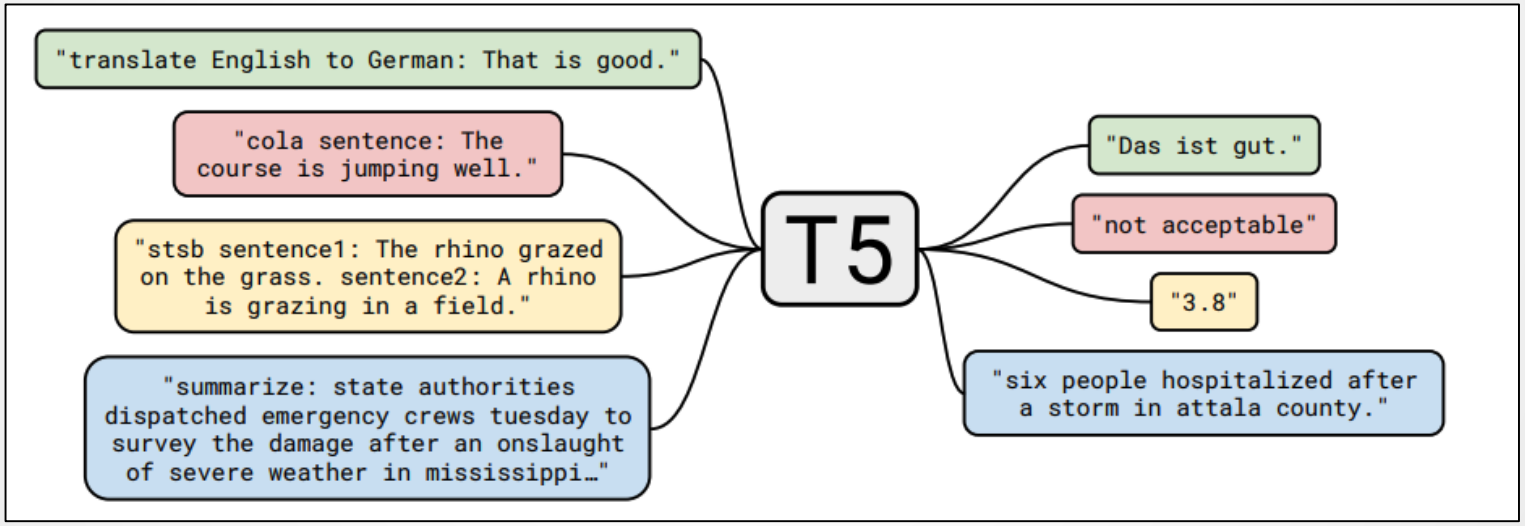
- For prediction, the model is fed **prefix**:
  - "*translate En-De: That is good. Target:*"
- For **classification** tasks, the model predicts a single word corresponding to the target label.
- E.g. MNLI task of entailment prediction:
  - "*mnli premise: I hate pigeons. hypothesis: I am hostile to pigeons. entailment.* "
- Model predicts label: {"entailment", "neutral", "contradiction"}.



T5: Text-to-Text Transfer Transformer

Why T5 matters?

- Unifying diverse NLP problems as one (‘*text-to-text*’) format is a **really cool idea**.
- This allows us to use the **same** model, loss function, hyperparameters etc. across a diverse set of tasks



- Remarkable transfer learning capabilities: T5 can be finetuned to answer a wide range of (open-domain) questions, retrieving factoids from its parameters

On that note – A2 BART/T5 Analysis

- **Code Demo** HuggingFace [t5_small|BART-base] NMT trained on Hansard (Fr-En)
- https://huggingface.co/docs/transformers/model_doc/bart
- https://huggingface.co/raeidsaqur/bart-base
- https://huggingface.co/raeidsaqur/mt_fr2en_hansard_t5-small

Lewis, Mike, et al. "Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension." (2019).

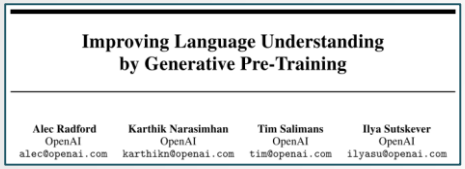
GPT SERIES

(slides borrowed from Brown et al. (2020) Language Models are Few-Shot Learners, *Arxiv* 2005.14165)

GPT: Generative Pretrained Transformers

Open AI GPT-series of models – uses multi-layer decoder only blocks

- Open AI GPT papers: GPT (2018)[1], GPT-2 (2019)[2], GPT-3 (2020)[3]



Improving Language Understanding by Generative Pre-Training

Alec Radford, OpenAI, alec@openai.com
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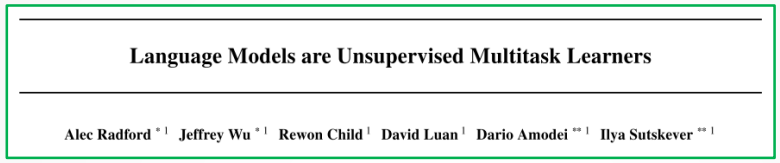
Ilya Sutskever, OpenAI, ilyasu@openai.com



Language Models are Unsupervised Multitask Learners

Alec Radford [*1] Jeffrey Wu [*1] Rewon Child [1] David Luan [1] Dario Amodei [**1] Ilya Sutskever [**1]

Language Models are Few-Shot Learners

OpenAI

- Architecturally (almost) identical – each scales (params, data) on predecessor
- Pretraining objective is classic '**language modeling**', to maximize the likelihood:

$$p(x) = \prod_{i=1}^{n} p(s_n | s_1, \ldots, s_{n-1})$$

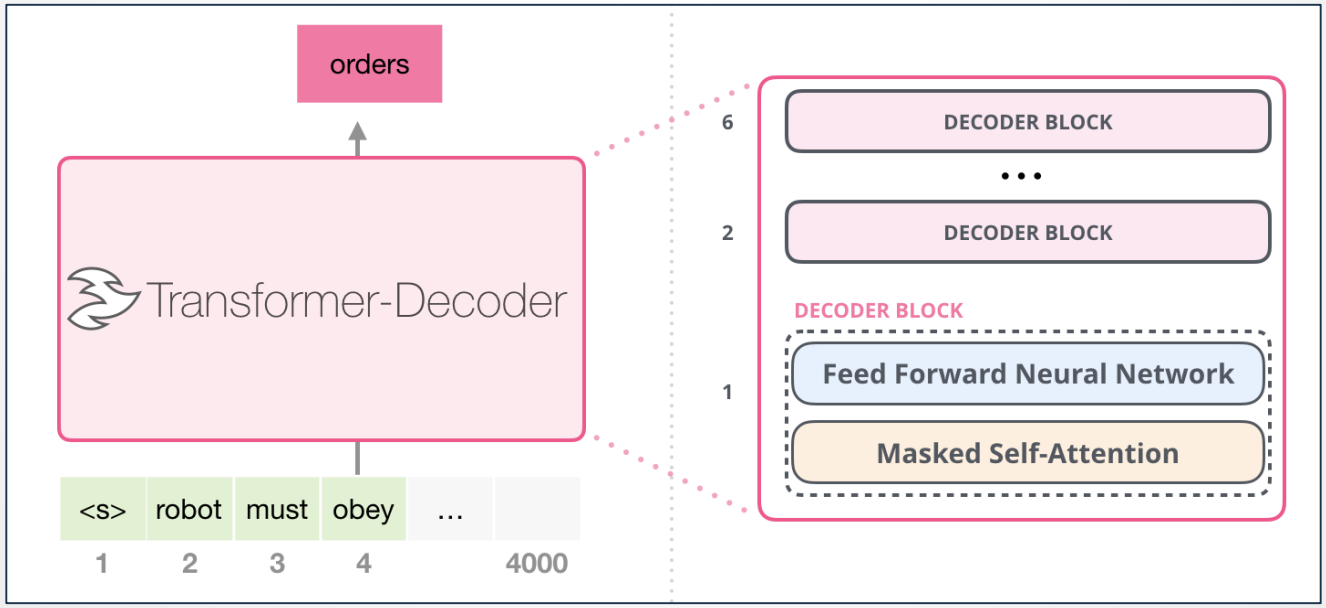
- Specifically, given an unsupervised corpus of tokens $\boldsymbol{\mu} = \{\mu_1, \ldots, \mu_n\}$, where k is context window, P is modelled using a neural network with parameters θ.

$$L_1(\mathcal{U}) = \sum_i \log P(u_i | u_{i-k}, \ldots, u_{i-1}; \Theta)$$

1. Radford, Alec, et al. "Improving language understanding by generative pre-training." (2018)
2. Radford, Alec, et al. "Language models are unsupervised multitask learners." OpenAI Blog 1.8 (2019)
3. Brown, Tom B., et al. "Language models are few-shot learners." arXiv preprint arXiv:2005.14165 (2020)

GPT: Generative Pretrained Transformers

- Distinguishing features:
  - Uses multi-layer transformer **decoder only blocks**
  - Auto-regressive generative model, does not see the future (no bi-directional awareness)
  - Like traditional LMs, outputs one token at a time



1. Radford, Alec, et al. "Improving language understanding by generative pre-training." (2018)
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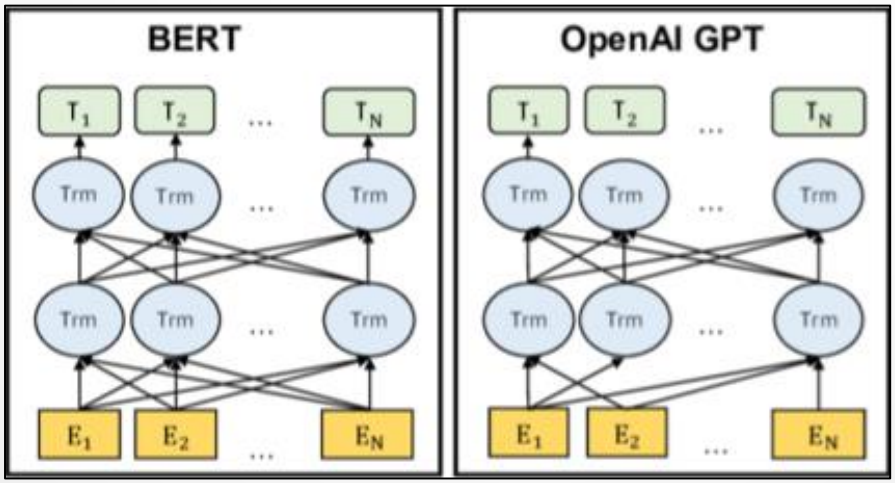
3. Brown, Tom B., et al. "Language models are few-shot learners." arXiv preprint arXiv:2005.14165 (2020)

Key architectural differences

- GPT vs. BERT-variants:
  - GPT uses ‘transformer’ blocks as *decoders*, and BERT as *encoders*.
  - Underlying (block level) ideology is same
  - GPT (later Transformer XL, XLNet) is an **autoregressive** model, BERT is not
    - At the cost of auto-regression, BERT has bi-directional context awareness.
  - GPT, like traditional LMs, outputs (predicts) one token at a time.
- Compare with T5, BART that uses encoder-decoder



[1] Radford, Alec, et al. "Improving language understanding by generative pre-training." (2018).

GPT-3 LLMs take off …

- Increasingly convincing results permeating into the public sphere and *Zeitgeist*
- In-context learning:

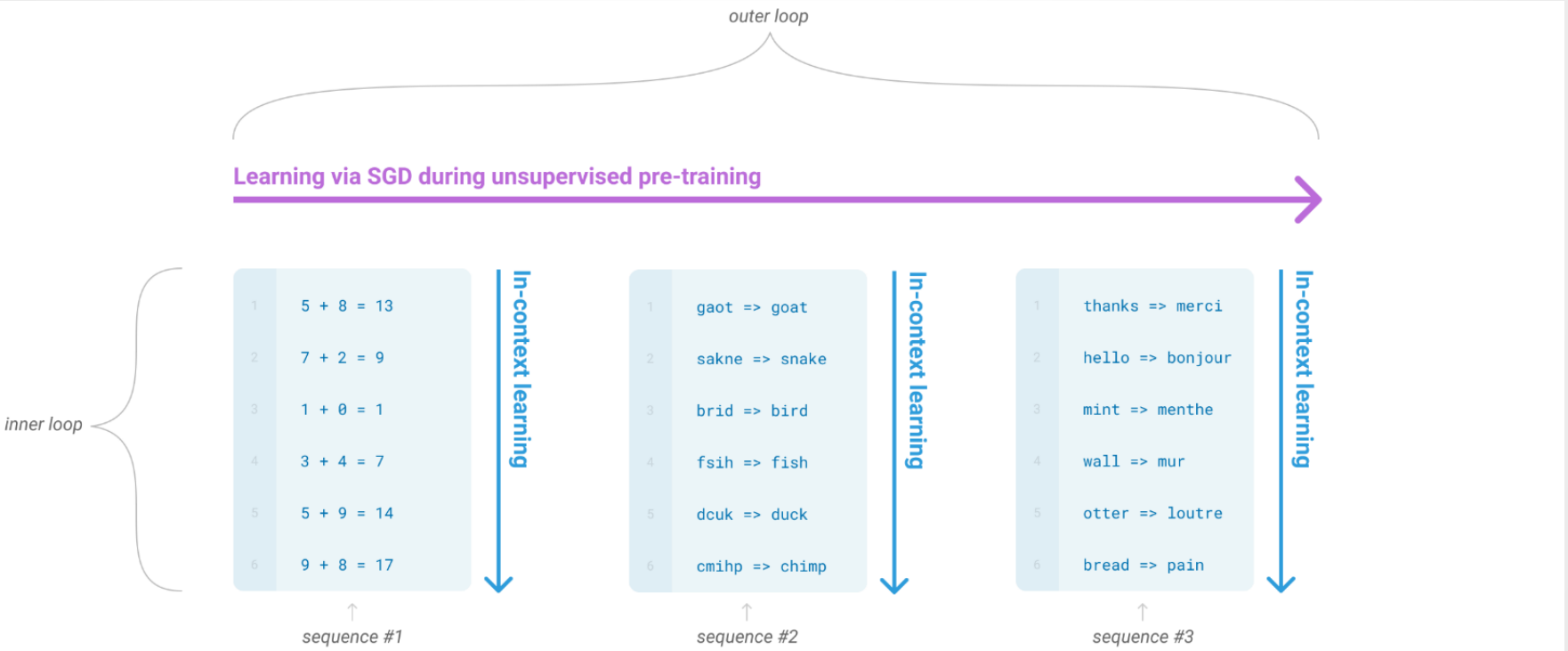


Figure 1.1: Language model meta-learning. During unsupervised pre-training, a language model develops a broad set of skills and pattern recognition abilities. It then uses these abilities at inference time to rapidly adapt to or recognize the desired task. We use the term "in-context learning" to describe the inner loop of this process, which occurs within

1. Brown, Tom B., et al. "Language models are few-shot learners." arXiv preprint arXiv:2005.14165 (2020)

GPT-3: In context learning + … prompting

- '**Prompting**' had been around as a convenience, but now a necessity …

Figure 2.1: Zero-shot, one-shot and few-shot, contrasted with traditional fine-tuning. The panels above show

1. Brown, Tom B., et al. "Language models are few-shot learners." arXiv preprint arXiv:2005.14165 (2020)

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GPT-3: In context learning + … prompting

- ‘**Prompting**’ had been around as a convenience, but now a necessity …

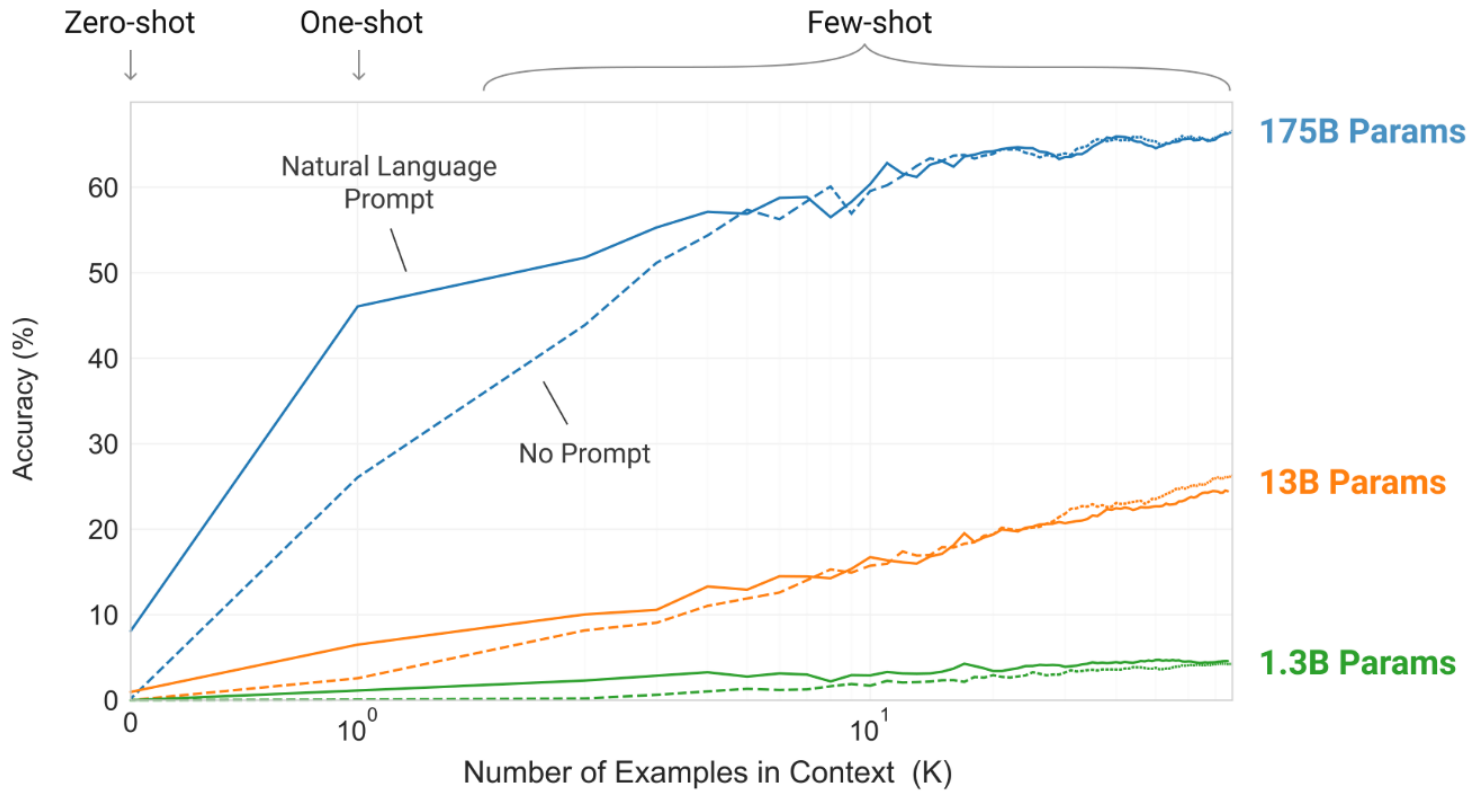


Figure 1.2: Larger models make increasingly efficient use of in-context information. We show in-context learning

1. Brown, Tom B., et al. "Language models are few-shot learners." arXiv preprint (2020)

Prompting: Chain of Thought

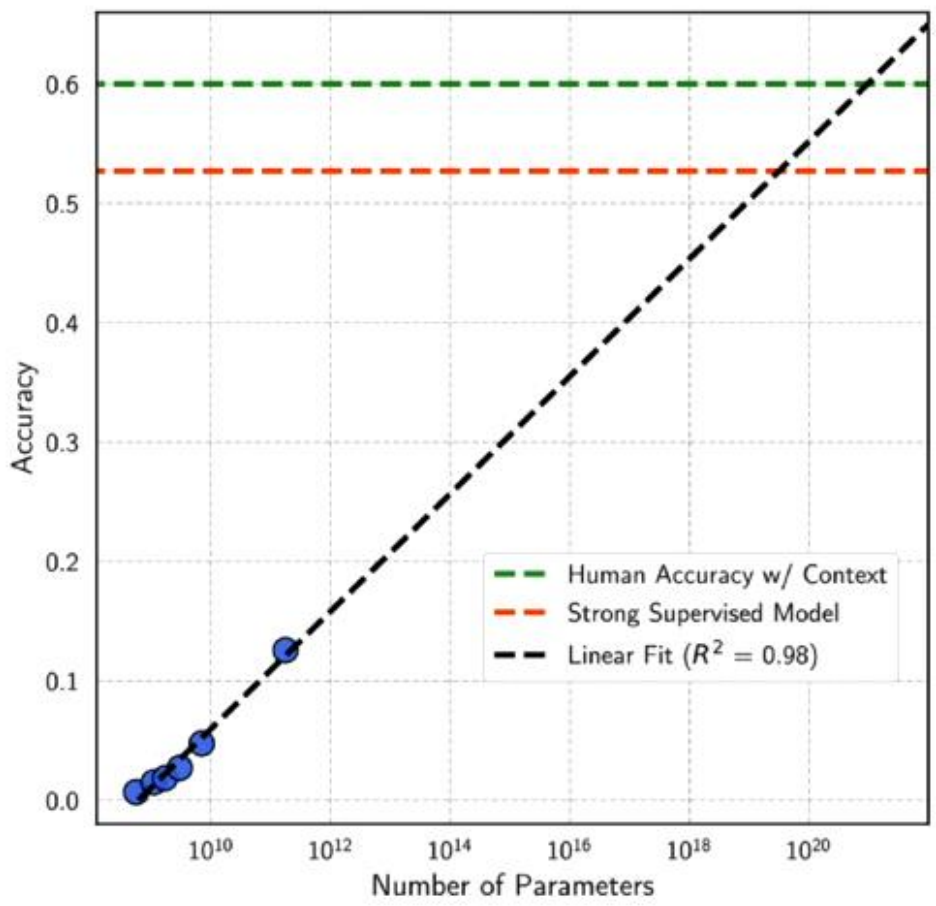
- Encourage the model to establish a logical chain of inference

CoT Prompt (0-shot with LLAMA2-70B-CHAT)	Accuracy
Let's reflect on each answer option like an operations research expert	0.487
Let's think step by step	0.518
Let's think step by step like an operations research expert	0.509
Let's use step by step inductive reasoning, given the mathematical nature of the question	0.510
Let's work by elimination	0.475
Prompt ensembling (majority vote)	0.537

- See also "least-to-most" prompting, in which the inference proceeds relative to a taxonomy or decomposition into subproblems.

ICL/Prompting vs. Fine-tuning?

- Fine-tuning is probably here to stay, however…



From "Large Language Models Struggle to Learn Long-Tail Knowledge" by Kandpal et al.

GPT-3: Results

- TL;DR: very impressive results across task domains
  - Performance (e.g. accuracy) **increases with size**
- Datasets grouped to 9 categories of downstream tasks
  - Examples: language modeling, QA, translation, Winograd, common-sense reasoning, reading comprehension, NLI etc.
  - Read the paper for details

Setting	PTB
SOTA (Zero-Shot)	35.8[a]
GPT-3 Zero-Shot	**20.5**

Table 3.1: Zero-shot results on PTB language modeling dataset. Many other common language modeling datasets are omitted because they are derived from Wikipedia or other sources which are included in GPT-3's training data. [a][RWC+19]

Turing-NLG?

Setting	LAMBADA (acc)	LAMBADA (ppl)	StoryCloze (acc)	HellaSwag (acc)
SOTA	68.0[a]	8.63[b]	**91.8**[c]	**85.6**[d]
GPT-3 Zero-Shot	**76.2**	**3.00**	83.2	78.9
GPT-3 One-Shot	**72.5**	**3.35**	84.7	78.1
GPT-3 Few-Shot	**86.4**	**1.92**	87.7	79.3

Table 3.2: Performance on cloze and completion tasks. GPT-3 significantly improves SOTA on LAMBADA while achieving respectable performance on two difficult completion prediction datasets. [a][Tur20] [b][RWC+19] [c][LDL19] [d][LCH+20]

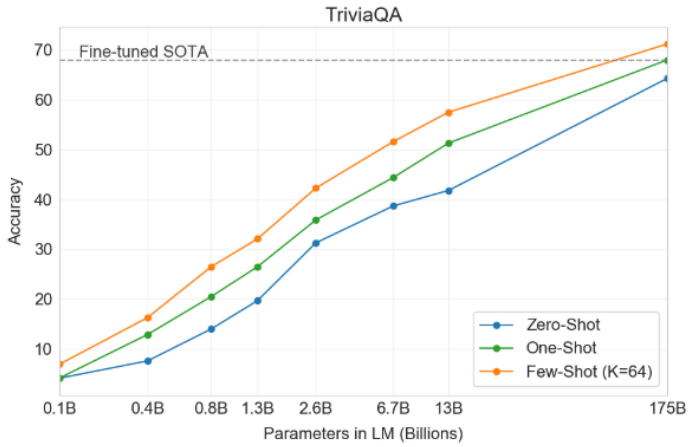


Figure 3.3: On TriviaQA GPT3's performance grows smoothly with model size, suggesting that language models continue to absorb knowledge as their capacity increases. One-shot and few-shot performance make significant gains over zero-shot behavior, matching and exceeding the performance of the SOTA fine-tuned open-domain model, RAG [LPP+20]

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DIFFERENT DIRECTIONS

Token free models

- Unlike the ubiquitous pre-trained LMs that operate on sequences of tokens corresponding to word or sub-word units, *token free models*:

  - ⊕ Operate on raw text (bytes or characters) **directly.**
  - ⊕ Removes necessity for (error-prone, complex) text preprocessing pipelines.
  - ⊖ Con: raw sequences significantly **longer than token sequences**, increases computational complexity. (Reminder: *'attention' costs are quadratic to the length of input sequence*)

1. Clark et al. "**CANINE**: Pre-training an efficient tokenization-free encoder for language representation." (2021). **link**
2. Xue et al. "**ByT5**: Towards a token-free future with pre-trained byte-to-byte models." (2022). **link**

Token free models

- Pitfalls of explicit (word, sub-word) tokenization:
  - Need for large language dependent (fixed) vocabulary mapping matrices.
  - Applies hand-engineered, costly, language-specific string tokenization/segmentation algorithms (e.g. BPE, word-piece, sentence-piece) requiring linguistic expertise.
  - Heuristic string-splitting, however nuanced, cannot capture full breadth of linguistic phenomena, (e.g. morphologically distant agglutinative, non-concatenative languages). Other examples include languages without white-space (Thai, Chinese), or that uses punctuation as letters (Hawaiian, Twi). *Fine-tuning* tokenization needs to match *pretraining* tokenization methods.
  - Brittle to noise, corruption of input (typos, adversarial manipulations). Corrupted tokens lose vocabulary coverage.

1. Clark et al. "**CANINE**: Pre-training an efficient tokenization-free encoder for language representation." (2021). **link**
2. Xue et al. "**ByT5**: Towards a token-free future with pre-trained byte-to-byte models." (2022). **link**

[Aside] Token free models - CANINE

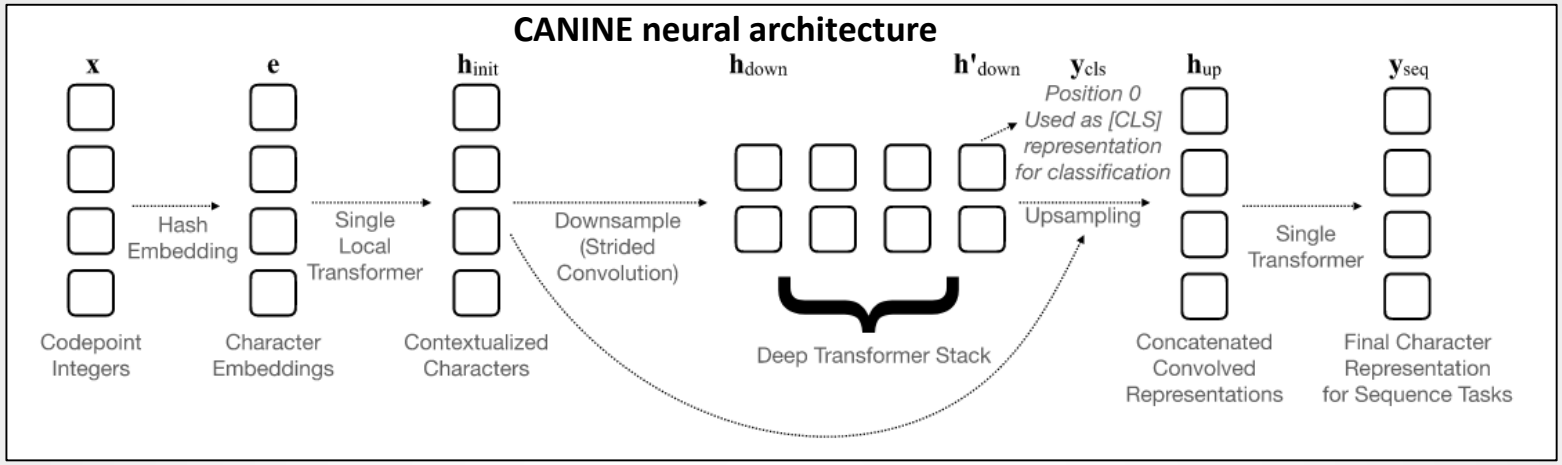
CANINE: Character Architecture with No tokenization In Neural Encoders.

- CANINE is a large language encoder with a deep transformer stack at its core.
- Inputs to the model are sequences of Unicode characters. 143,698 Unicode codepoints assigned to characters covers 154 scripts and over 900 languages!
- To avoid slowdown from increasing sequence length, it uses **stride convolutions to down-sample** input sequences to a shorter length, before the deep transformer stack to encode context.

- Three primary components:
  - Vocab free embedding technique;
  - Character-level model (CLM) with efficiency measures (up/down sampling of sequences); and
  - Perform **unsupervised** masked LM (MLM) pretraining on the CLM using variants:
    - Autoregressive character prediction
    - Subword prediction

Clark et al. "**CANINE**: Pre-training an efficient tokenization-free encoder for language representation." (2022).

[Aside] Token free models - CANINE



- The overall functional composition form uses [UP|DOWN]-sampling, and primary encoder:

$$Y_{seq} \leftarrow \text{UP}(\text{ENCODE}(\text{DOWN}\ (e)))$$ where $e \in \mathbb{R}^{n \times d}$ is an input characters sequence, and $Y_{seq} \in \mathbb{R}^{n \times d}$ is output of sequence predictions

- **Down-sampling**: $h_{init} \leftarrow \text{LOCALTRANSFORMER}(e);\ \ h_{down} \leftarrow \text{STRIDEDCONV}(h_{init}, r)$

  where $h_{down} \in \mathbb{R}^{m \times d}$ and $m = \frac{n}{r}$ is the number of downsampled positions

- **Up-sampling**: prediction require model's output layer sequence length to match input's length

$$h_{up} \leftarrow \text{CONV}(h_{init} \oplus h'_{down}, w);\qquad y_{seq} \leftarrow \text{TRANSFORMER}\ (h_{up})$$

where $\oplus$ is vector concatenation, CONV projects $\mathbb{R}^{n \times 2d}$ back to $\mathbb{R}^{n \times d}$ across a window of w characters. Applying a final transformer layer yields a final sequence representation: $Y_{seq} \in \mathbb{R}^{n \times d}$