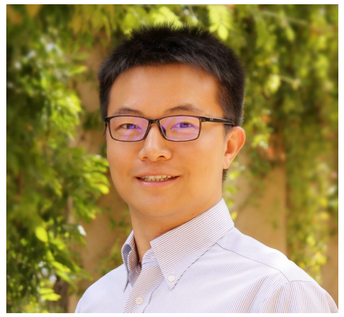
MIT HAN LAB

EfficientML.ai Lecture 12 Transformer and LLM

Part I



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Distinguished Scientist, NVIDIA

@SongHan_MIT

Large Language Model

ChatGPT

GPT-4

JI Please make a syllabus for a course titled "TinyML and Efficient Deep Learning Computing".

Course Syllabus: "TinyML and Efficient Deep Learning Computing"

Course Overview:
This course provides an in-depth exploration of the principles and practices of designing, developing, and deploying efficient deep learning models suitable for resource-constrained environments, with a special emphasis on TinyML (Tiny Machine Learning) applications for edge devices.

Course Objectives:
By the end of this course, students will be able to:

1. Understand the challenges and limitations of deploying deep learning models on edge and embedded devices.
2. Implement model quantization, pruning, and knowledge distillation techniques to optimize model size and computational efficiency.
3. Design, train, and deploy TinyML models tailored for specific edge computing applications.
4. Evaluate trade-offs between model accuracy, size, power consumption, and latency.

Prerequisites:

- Fundamental understanding of deep learning and neural networks.
- Basic programming knowledge in Python.
- Familiarity with TensorFlow or PyTorch.

Week-by-Week Breakdown:

Week 1: Introduction to TinyML and Edge Computing

- The landscape of edge computing
- Introduction to TinyML
- Challenges and opportunities in edge AI

Week 2: Efficient Neural Network Architectures

- MobileNets, EfficientNet, and other compact architectures
- Design principles for resource-efficient networks

Week 3: Model Compression Techniques I

- Quantization: Introduction, types, and benefits
- Post-training quantization vs. quantization-aware training

Week 4: Model Compression Techniques II

- Model pruning: Weight pruning, channel pruning, structured pruning
- Knowledge distillation: Basics and techniques

Week 5: Hardware Considerations for TinyML

- Overview of edge AI hardware
- Hardware accelerators and NPUs
- Understanding latency, throughput, and power trade-offs

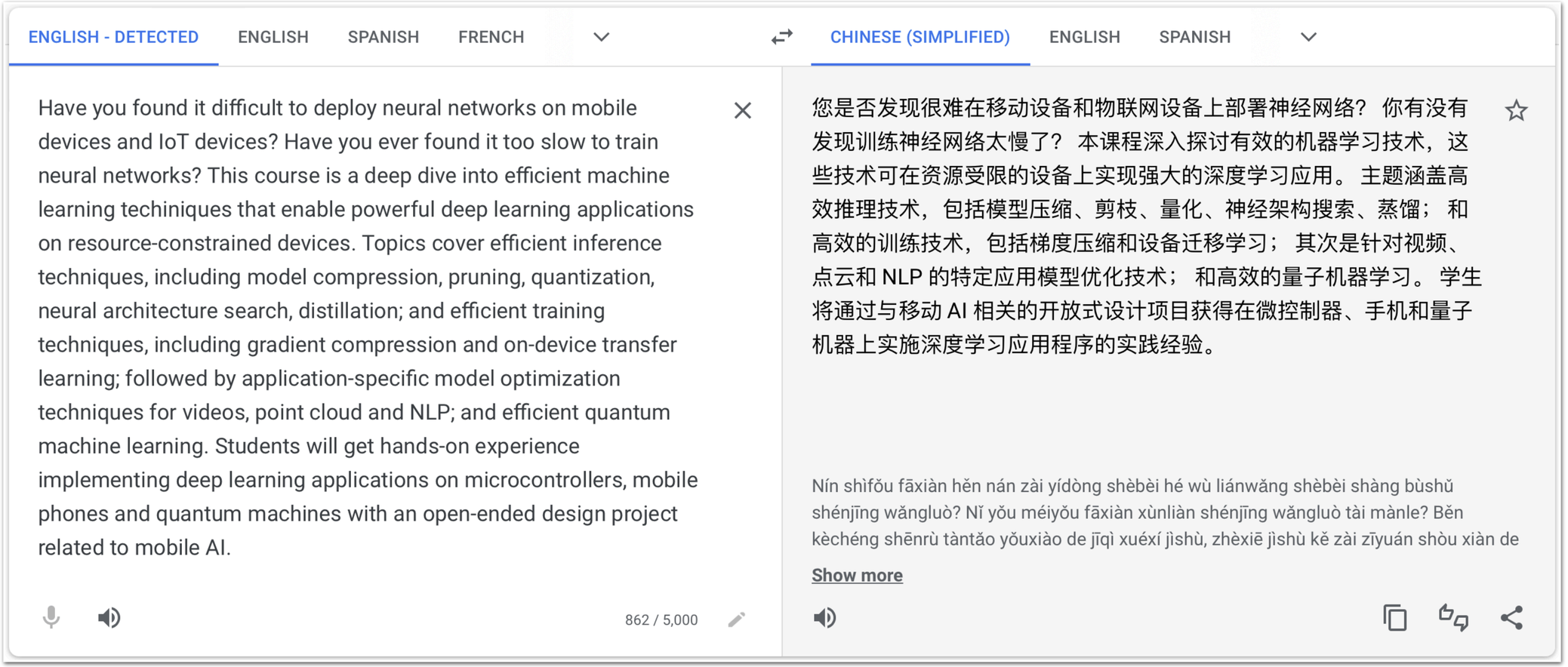
Week 6: TinyML Frameworks and Tools

- Introduction to TensorFlow Lite (TFLite)

Image credit: https://www.gorgias.com/blog/chatbot-vs-live-chat

Large Language Model

Google Translate



https://translate.google.com/

Large Language Model

GitHub Copilot

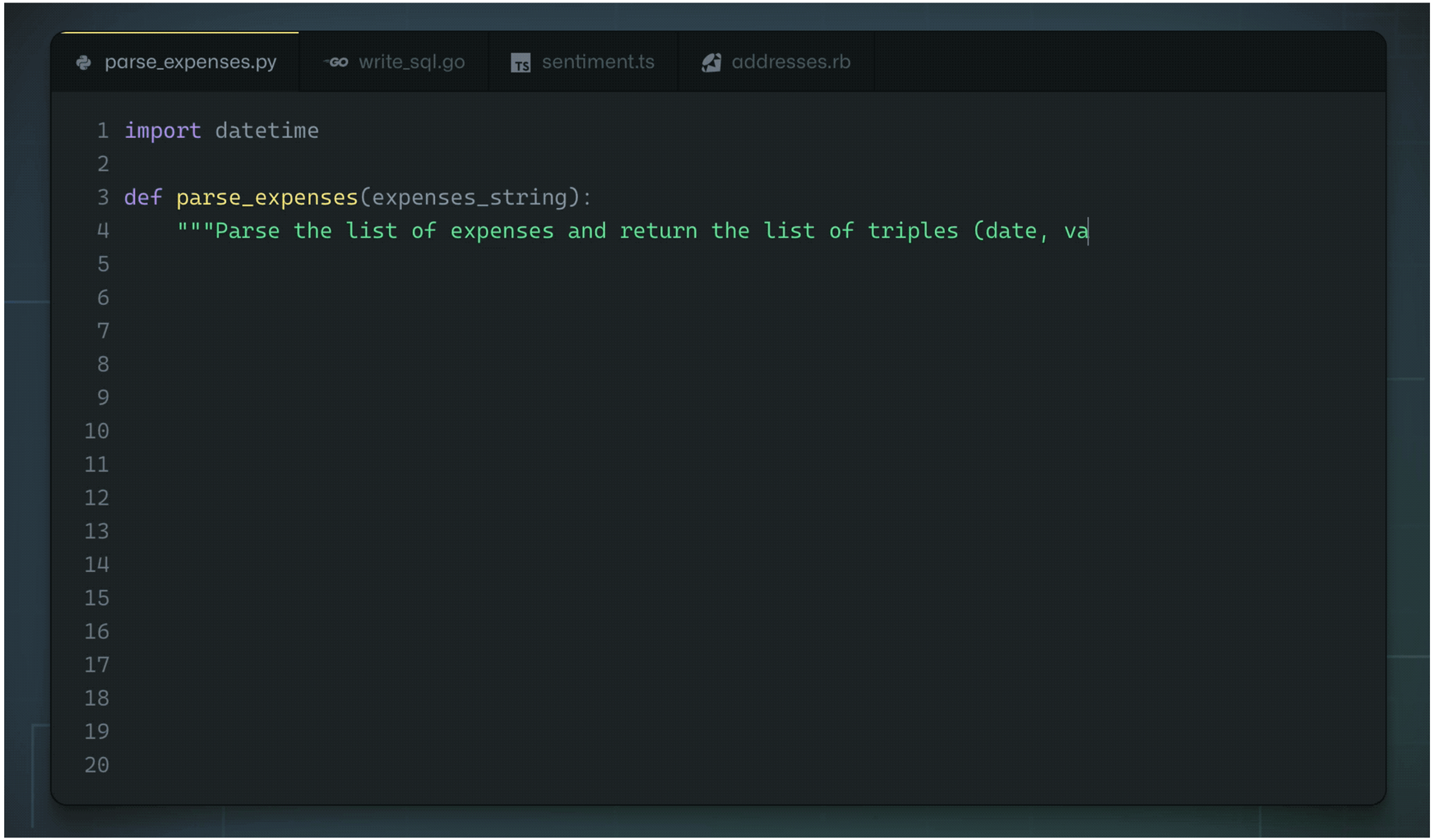
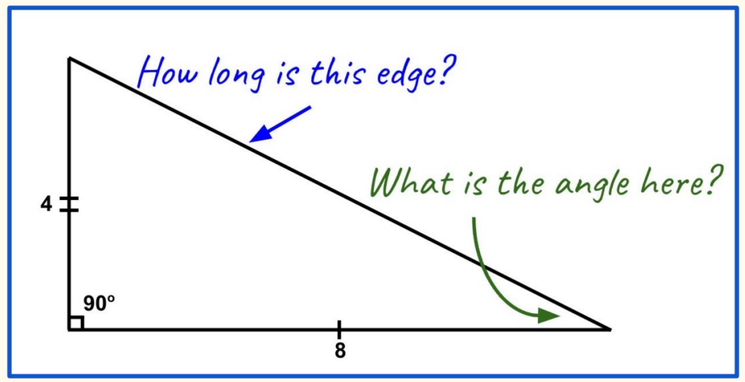


Image credit: https://techcrunch.com/2021/06/29/github-previews-new-ai-tool-that-makes-coding-suggestions/

Multi-modal LLM

Personal assistant w/ visual input

Answer the question in the following figure. Provide intermediate steps.



GPT-4V:

To find the length of the blue arrowed edge, we can use the Pythagorean theorem since we have a right triangle. The theorem states that $a^2 + b^2 = c^2$, where a and b are the two legs of the right triangle and c is the hypotenuse. Plugging in the values we have, we get:

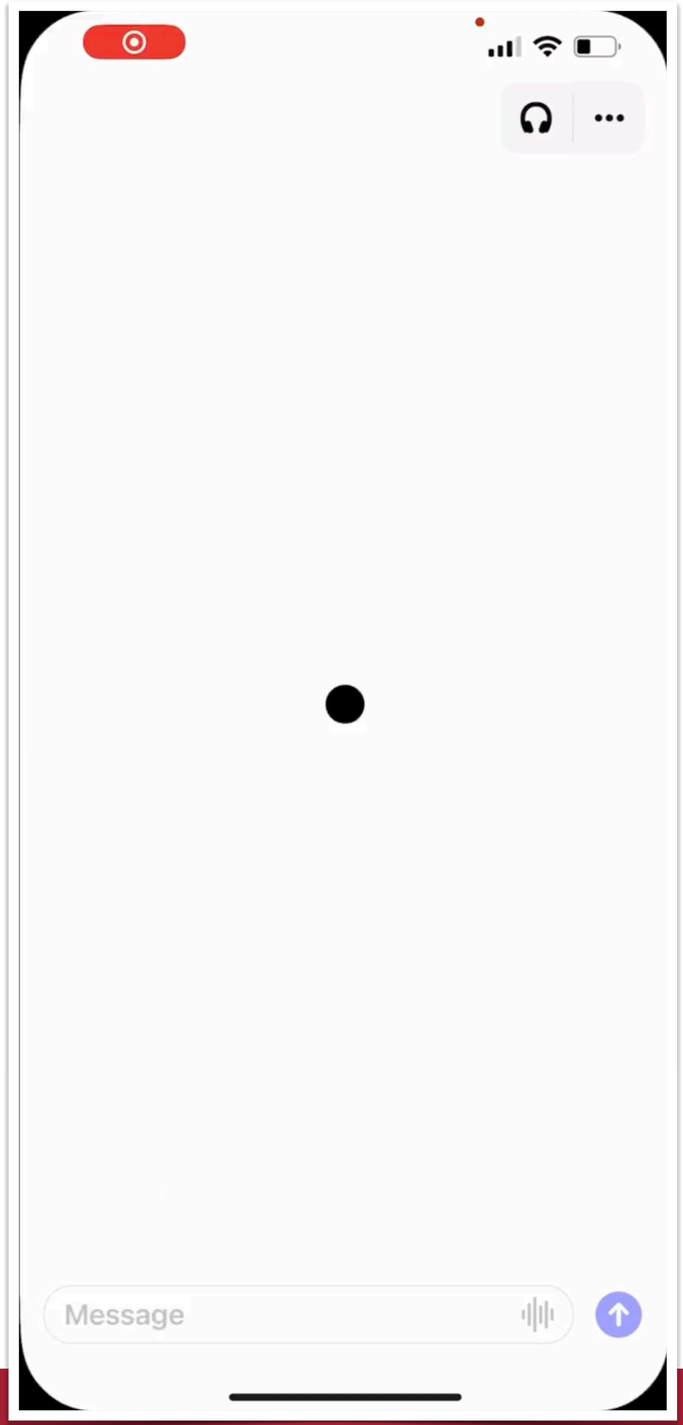
$4^2 + 8^2 = c^2$ $16 + 64 = c^2$ $80 = c^2$ $\sqrt{80} = c$ $8.94 \approx c$

Therefore, the length of the blue arrowed edge is approximately 8.94.

To find the angle at the green arrow, we can use the tangent function since we have the opposite and adjacent sides of the angle. The tangent function states that tanθ = opposite/adjacent. Plugging in the values we have, we get:

tanθ = 4/8 tanθ = 1/2 θ = tan^-1(1/2) θ ≈ 26.57°

Therefore, the angle at the green arrow is approximately 26.57°.

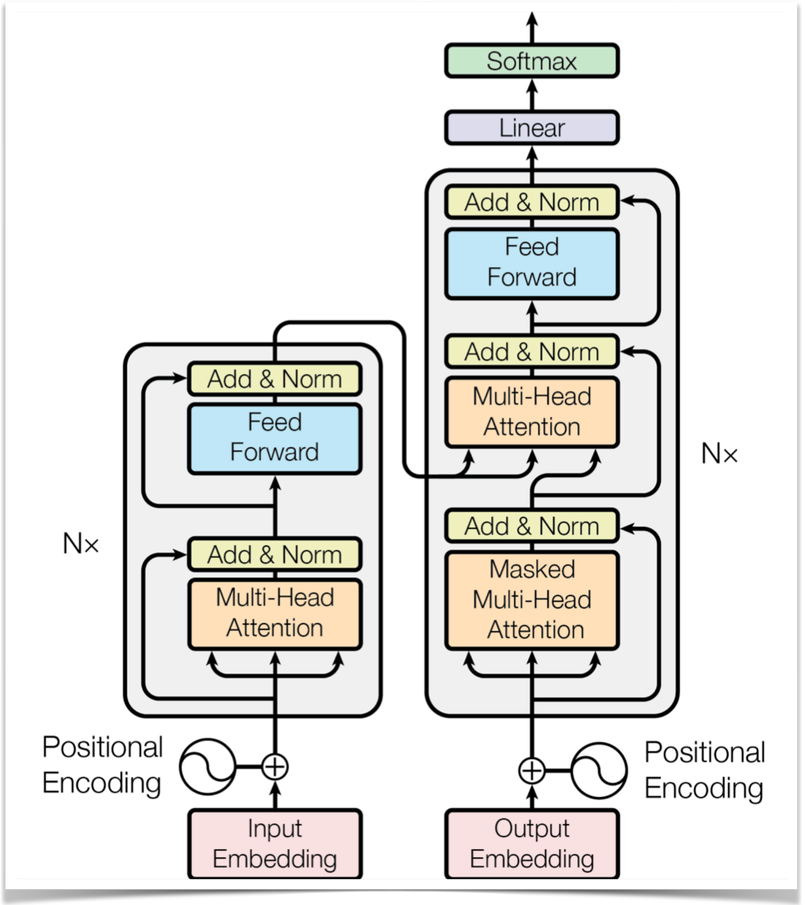


https://openai.com/blog/chatgpt-can-now-see-hear-and-speak

Lecture Plan

Today, we will cover:

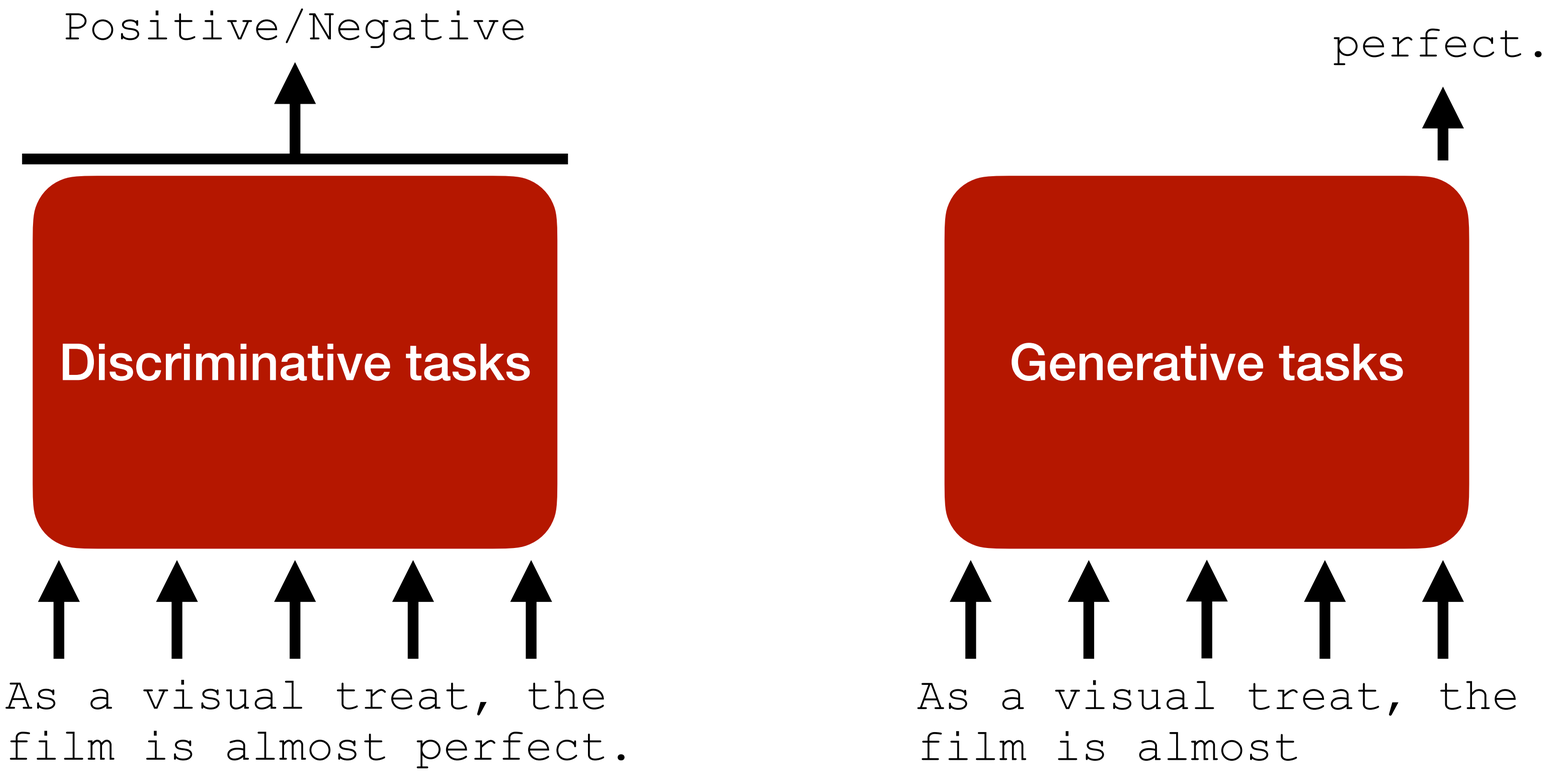
1. Transformer basics
2. Transformer design variants
3. Large language models (LLMs)
4. Advanced topics, multi-modal LLM



I. Transformer Basics

Revisit: NLP Tasks

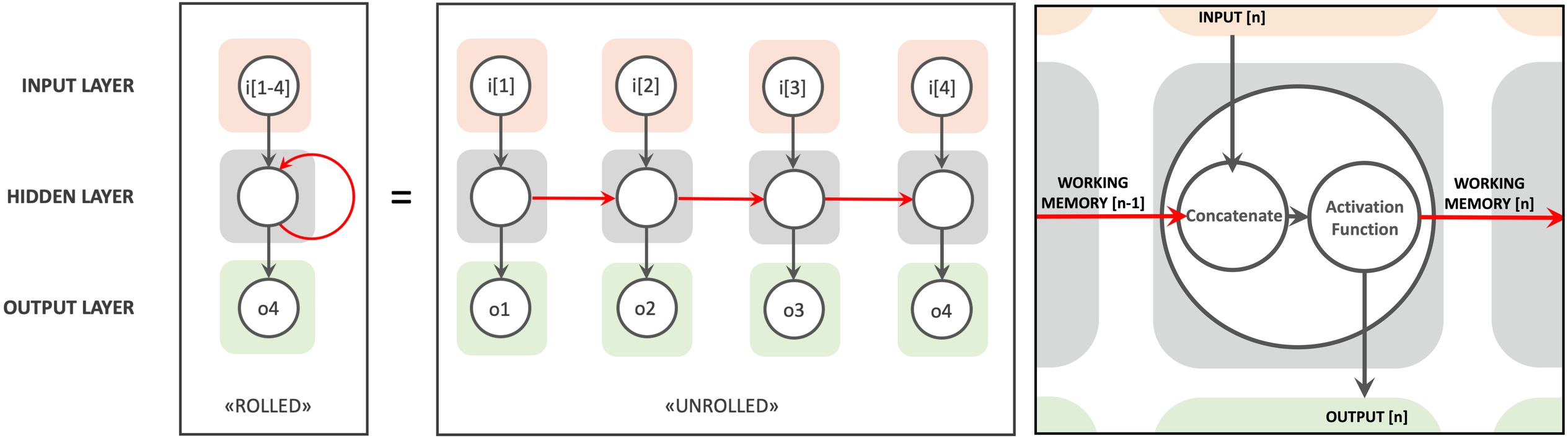
- **Discriminative tasks** (e.g., sentiment analysis, text classification, textual Entailment)
- **Generative tasks** (e.g., language modeling, machine translation, summarization)



Pre-Transformer Era

Recurrent Neural Networks (RNNs)

- The "working memory" struggles to retain **long-term** dependancies (can be solved by LSTM).
- There is **dependency** across tokens, limiting the scalability.

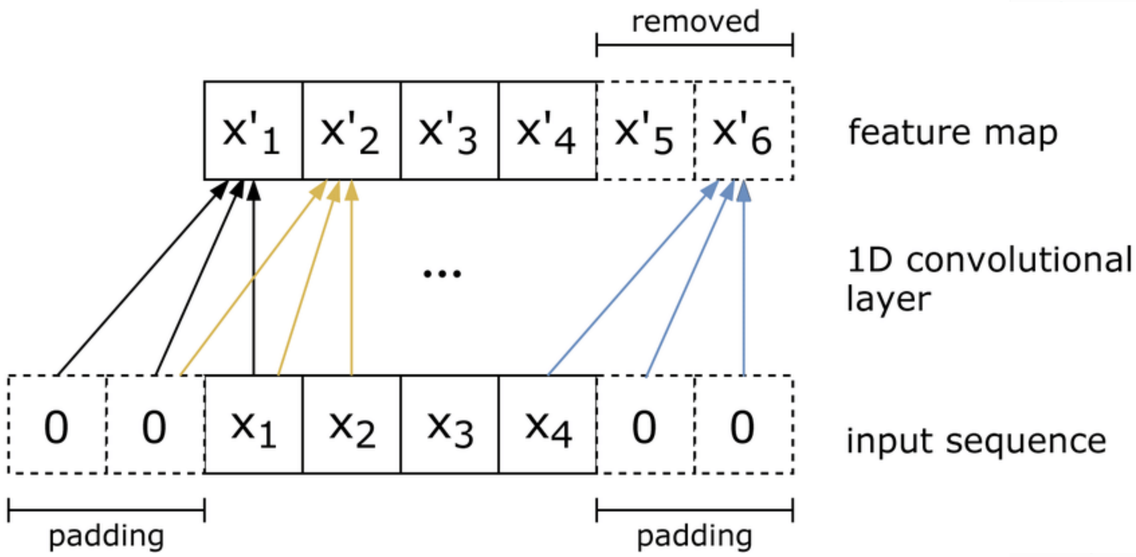


Content credit: https://www.bouvet.no/bouvet-deler/explaining-recurrent-neural-networks

Pre-Transformer Era

Convolutional Neural Networks (CNNs)

- No dependency between tokens, leading to **better scalability**.
- **Limited context information**, resulting in worse modeling capability.



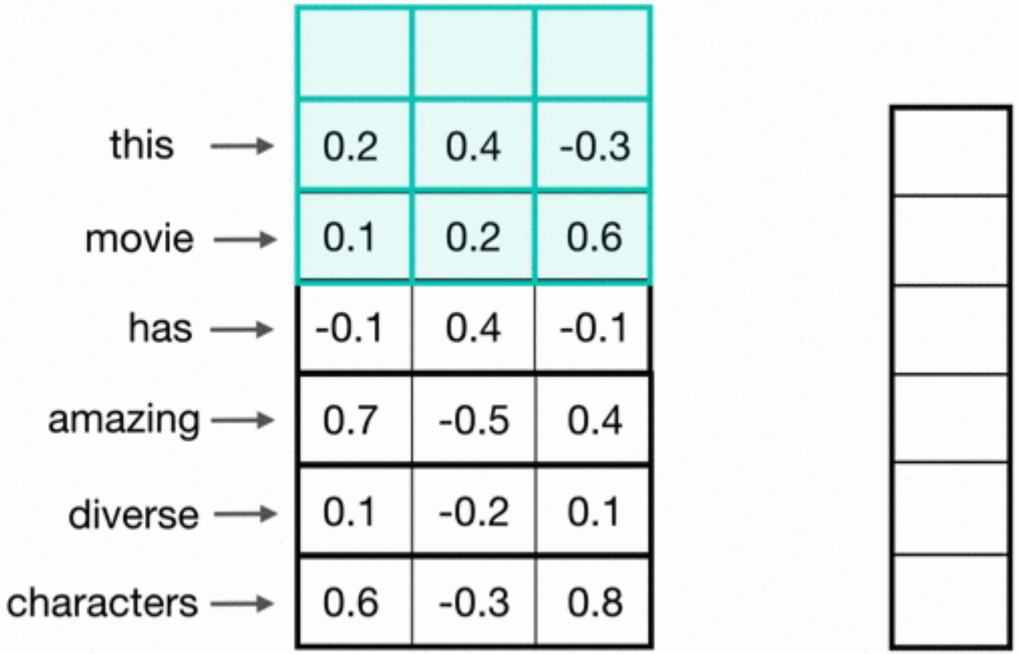
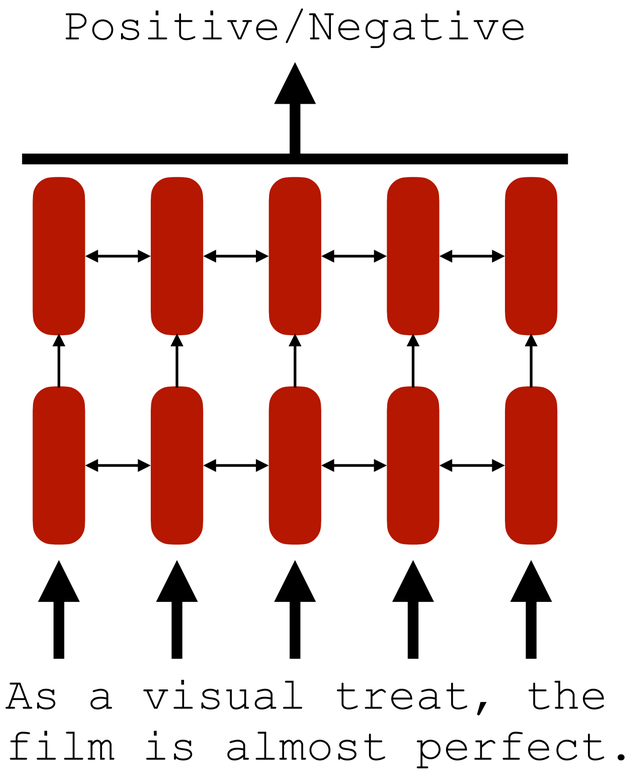


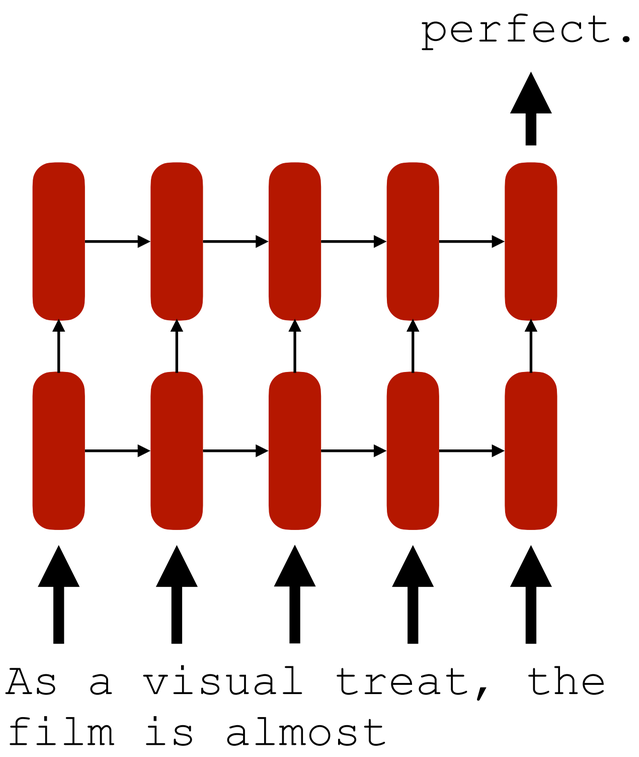
Image credit: https://cezannec.github.io/CNN_Text_Classification/

Pre-Transformer Era

NLP with RNN/LSTM

- **Bi-directional** RNNs for discriminative tasks (encoding)
- **Uni-directional** RNNs for generative tasks (decoding)

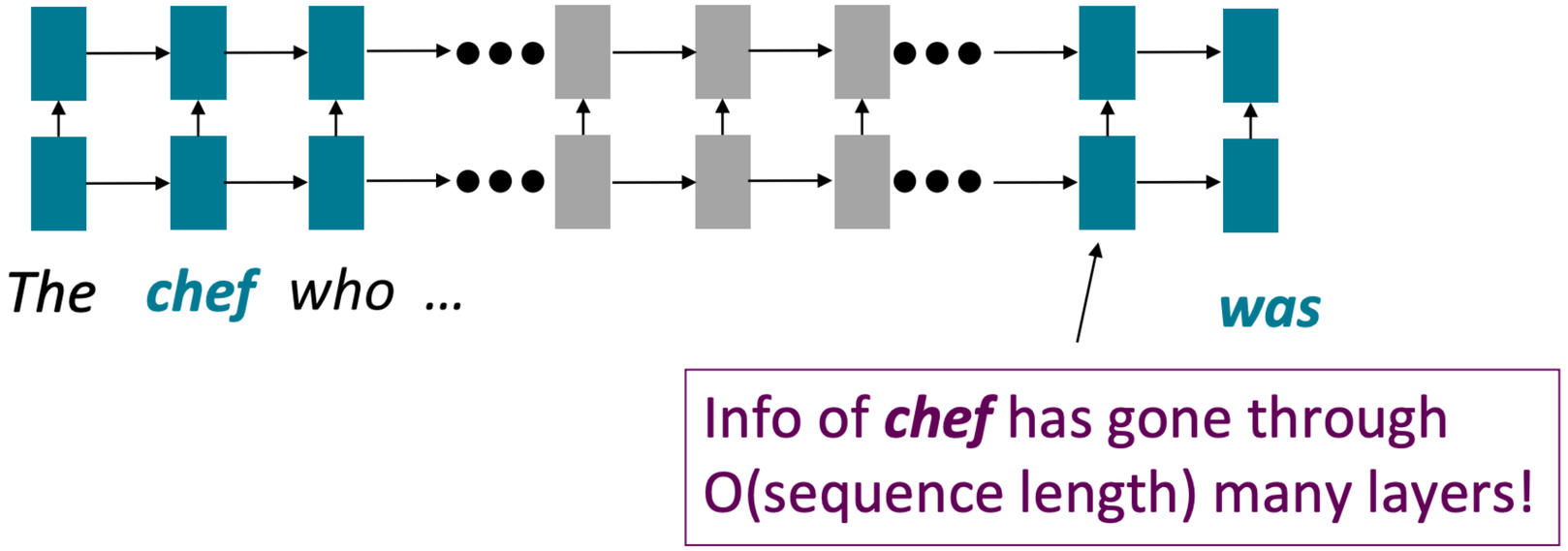




Pre-Transformer Era

Problem with RNNs/LSTMs

- **Hard to model long-term relationships**
  - It takes O(seq_len) steps to model the interaction between two tokens
  - Images have locality; but languages may not have locality:

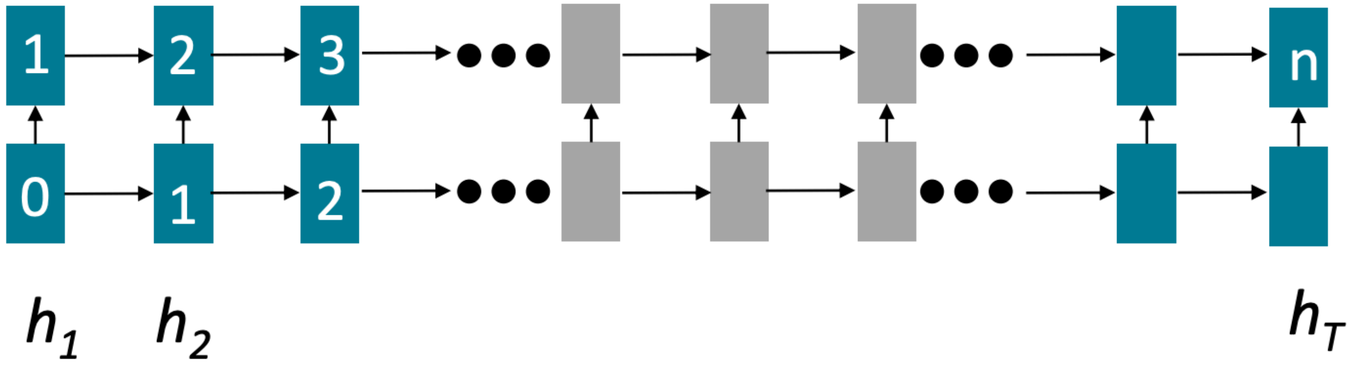


https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture08-transformers.pdf

Pre-Transformer Era

Problem with RNNs/LSTMs

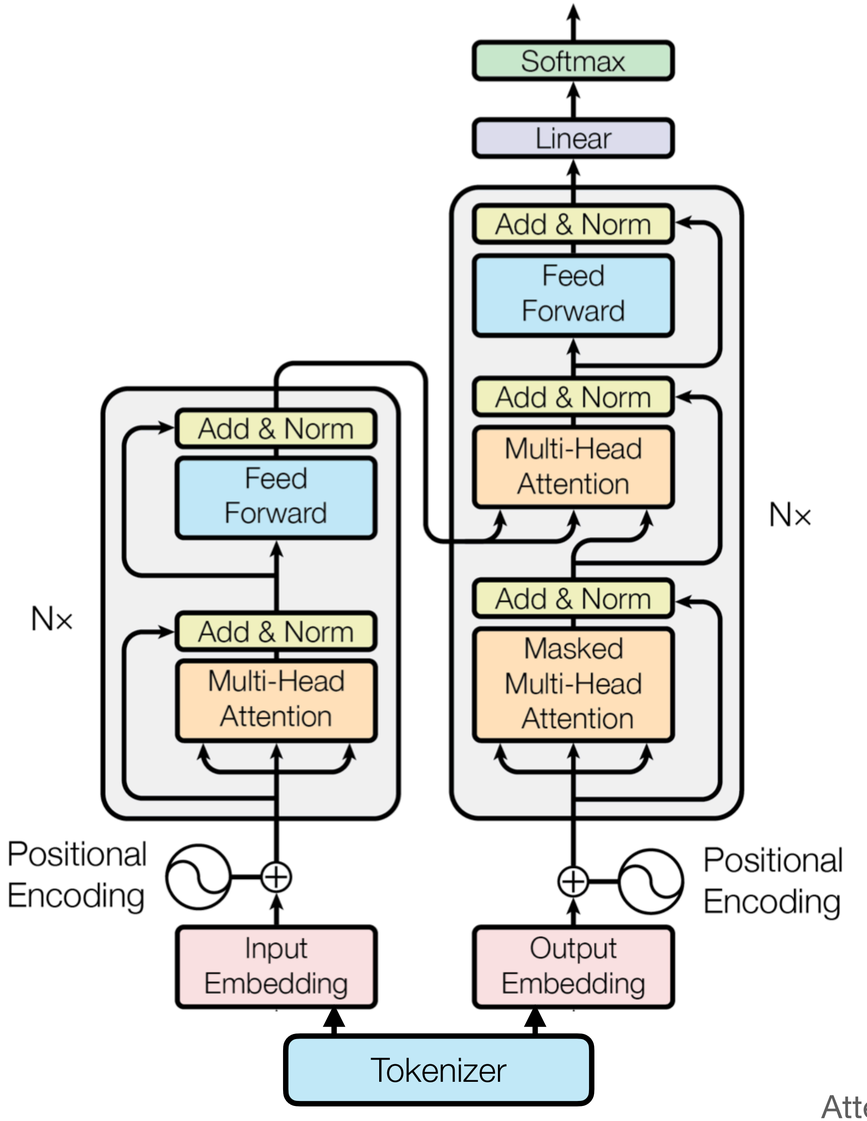
- **Hard to model long-term relationships**
- **Limited training parallelism**
  - The states are strictly dependent on earlier states
  - It takes *n* steps to get state *n*



Numbers indicate min # of steps before a state can be computed

https://web.stanford.edu/class/cs224n/slides/cs224n-2023-lecture08-transformers.pdf

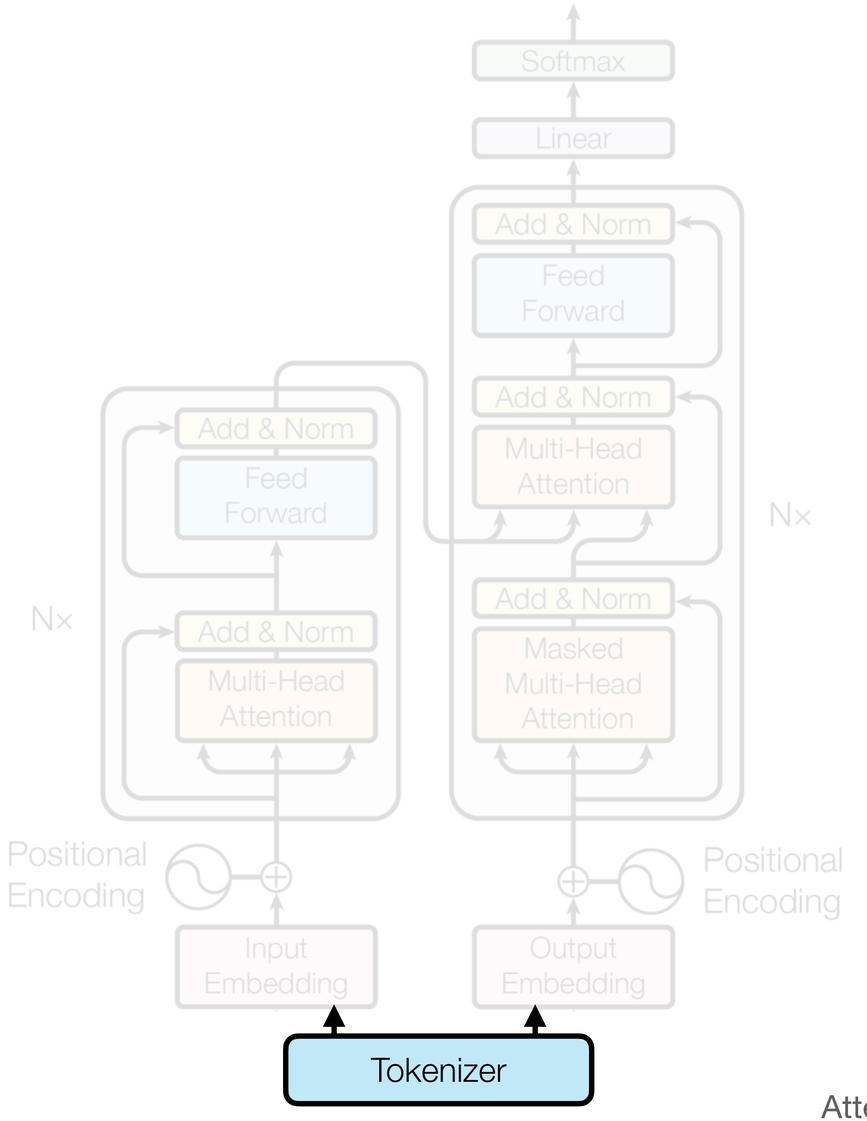
Transformer



- Tokenize words (word -> tokens)
- Map tokens into embeddings
- Embeddings go through Transformer blocks
  - Multi-Head Attention (MHA)
  - Feed-Forward Network (FFN)
  - LayerNorm
  - Residual connection
- Positional encoding
- Final prediction with Linear head

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

Transformer



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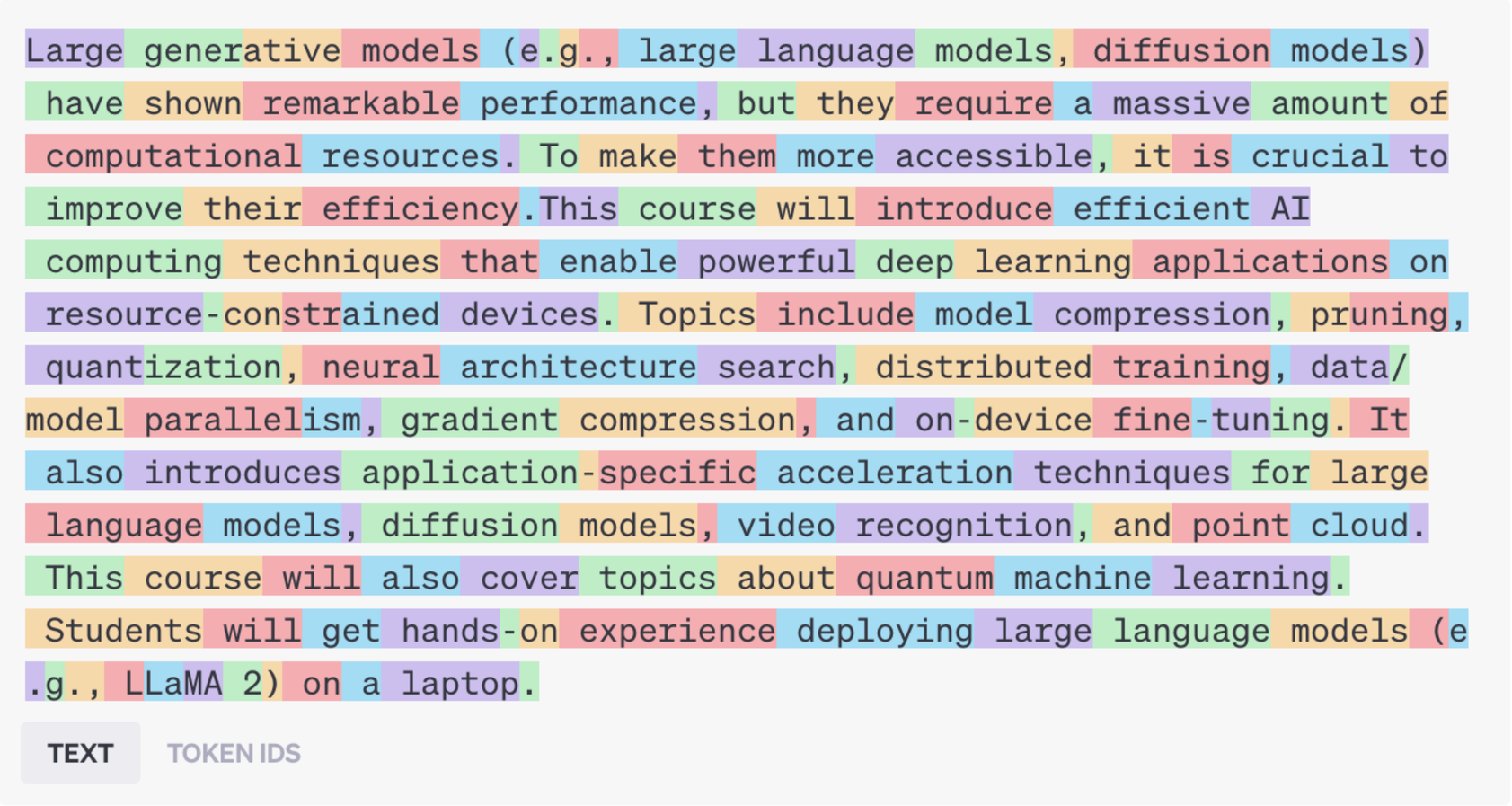
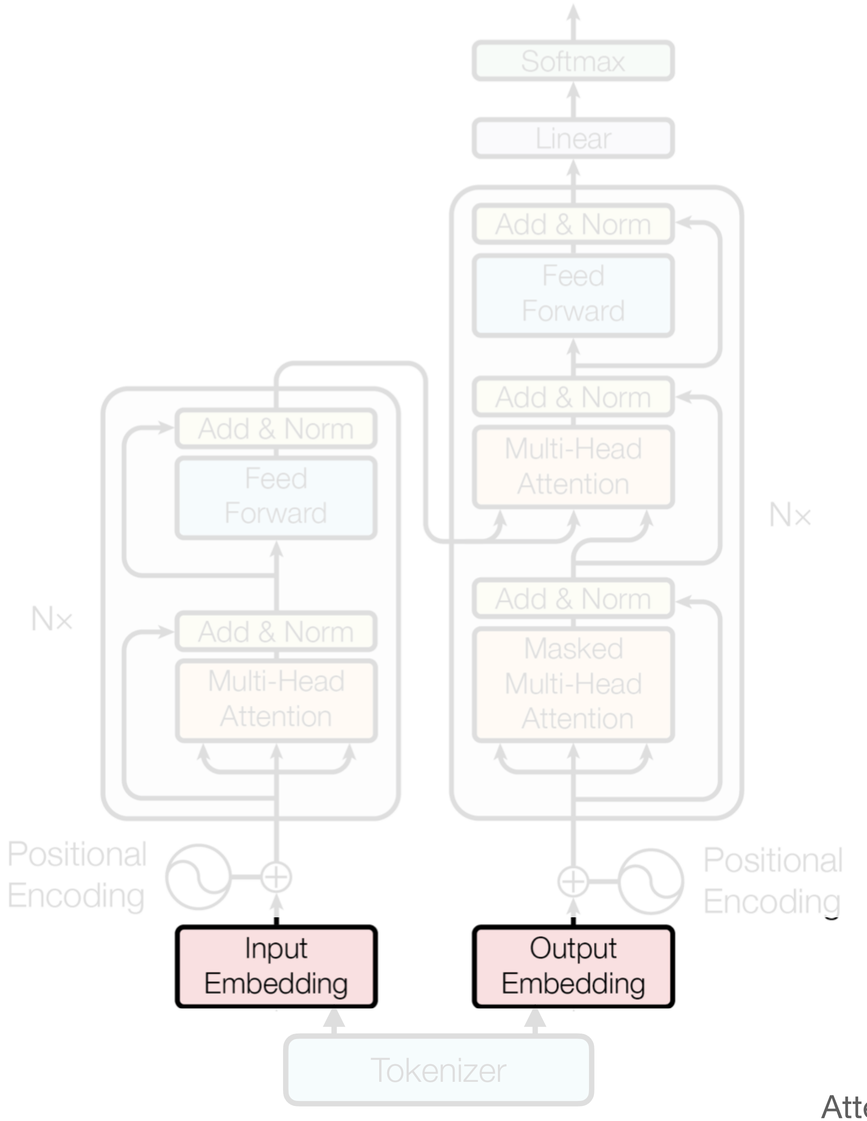
Tokenization

- A tokenizer maps a word to one/multiple tokens:
- **110 words** => **162 tokens**



https://platform.openai.com/tokenizer

Transformer



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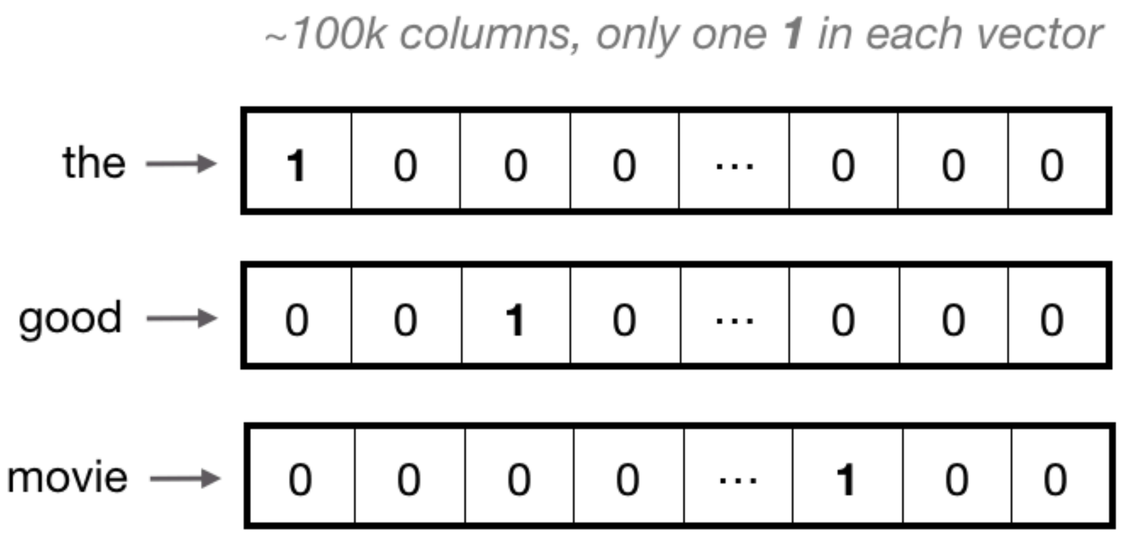
Attention Is All You Need [Vaswani *et al.*, 2017]

Word Representation

One-Hot Encoding

- **Key idea**: Representing each word as a vector that has as many values in it as there are words in the vocabulary. Each column in a vector represents one possible word in a vocabulary.



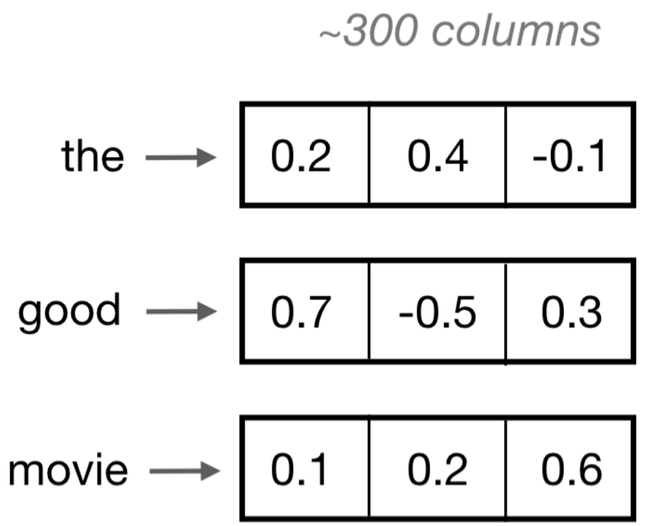
- For **large vocabularies**, these vectors can get very **long**, and they contain all 0's except for one value. This is considered a very sparse representation.

Content credit: https://cezannec.github.io/CNN_Text_Classification/

Word Representation

Word Embedding

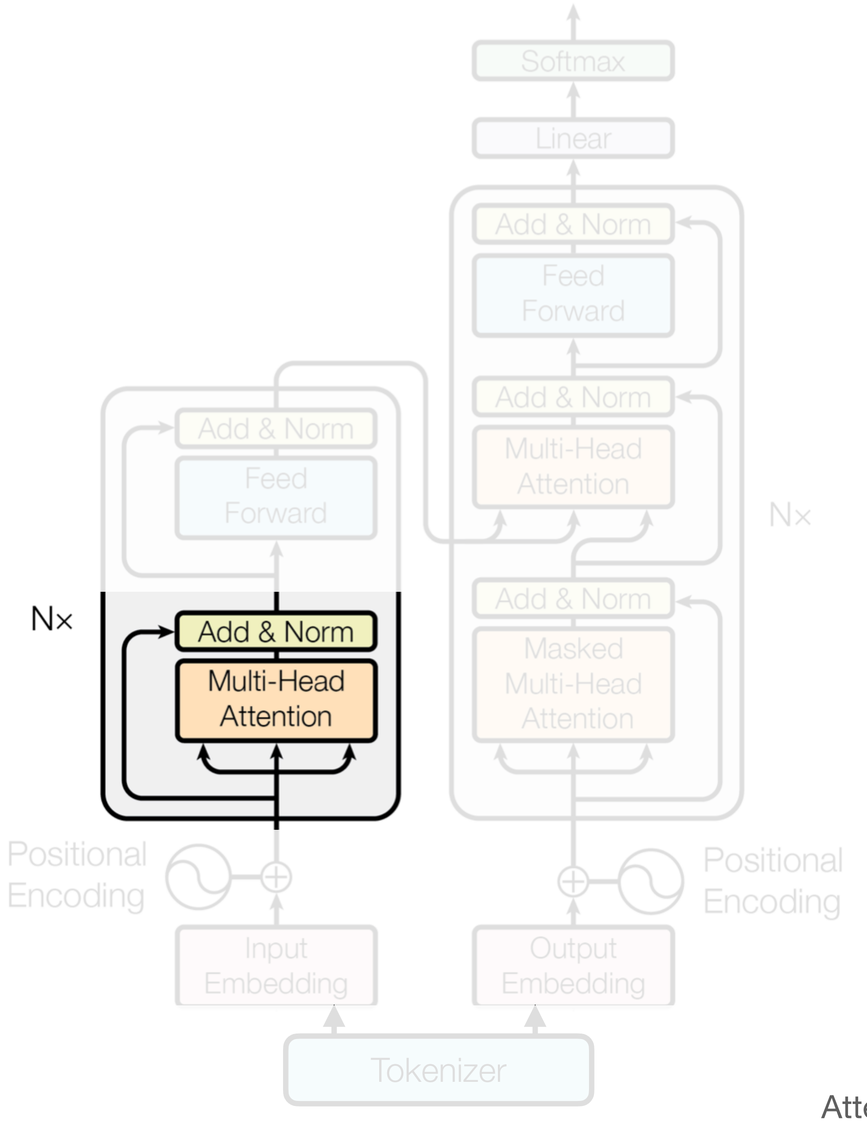
- **Key idea**: Map the word index to a **continuous** word embedding through a **look-up table**.



- The word embedding can be trained **end-to-end** with the model for the downstream tasks.
  - Popular pre-trained word embeddings: Word2Vec, GloVe.

Content credit: https://cezannec.github.io/CNN_Text_Classification/

Transformer



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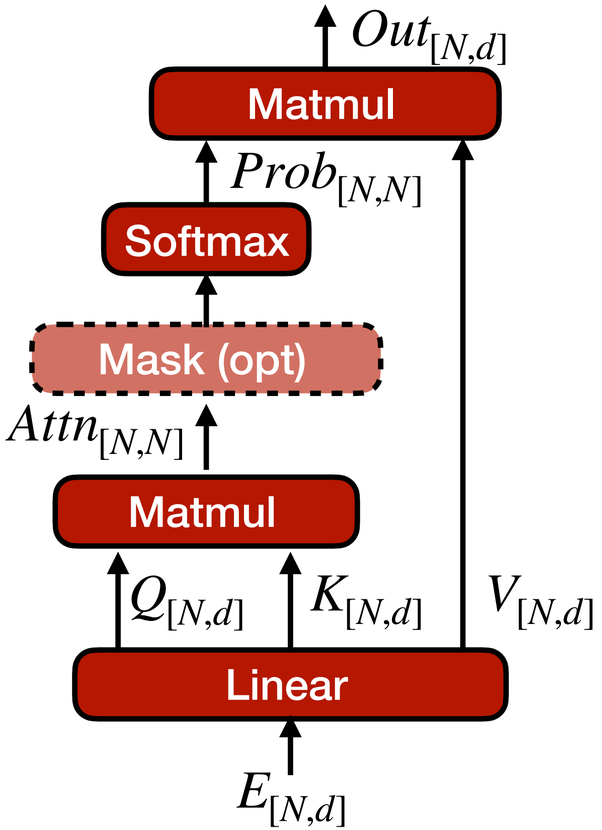
Attention Is All You Need [Vaswani *et al.*, 2017]

Self-Attention

- Project the embedding E into query, key, and value (Q, K, V)

- The Query-Key-Value design is analogous to a retrieval system (let's take YouTube search as an example)
  - Query: text prompt in the search bar
  - Key: the titles/descriptions of videos
  - Value: the corresponding videos

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

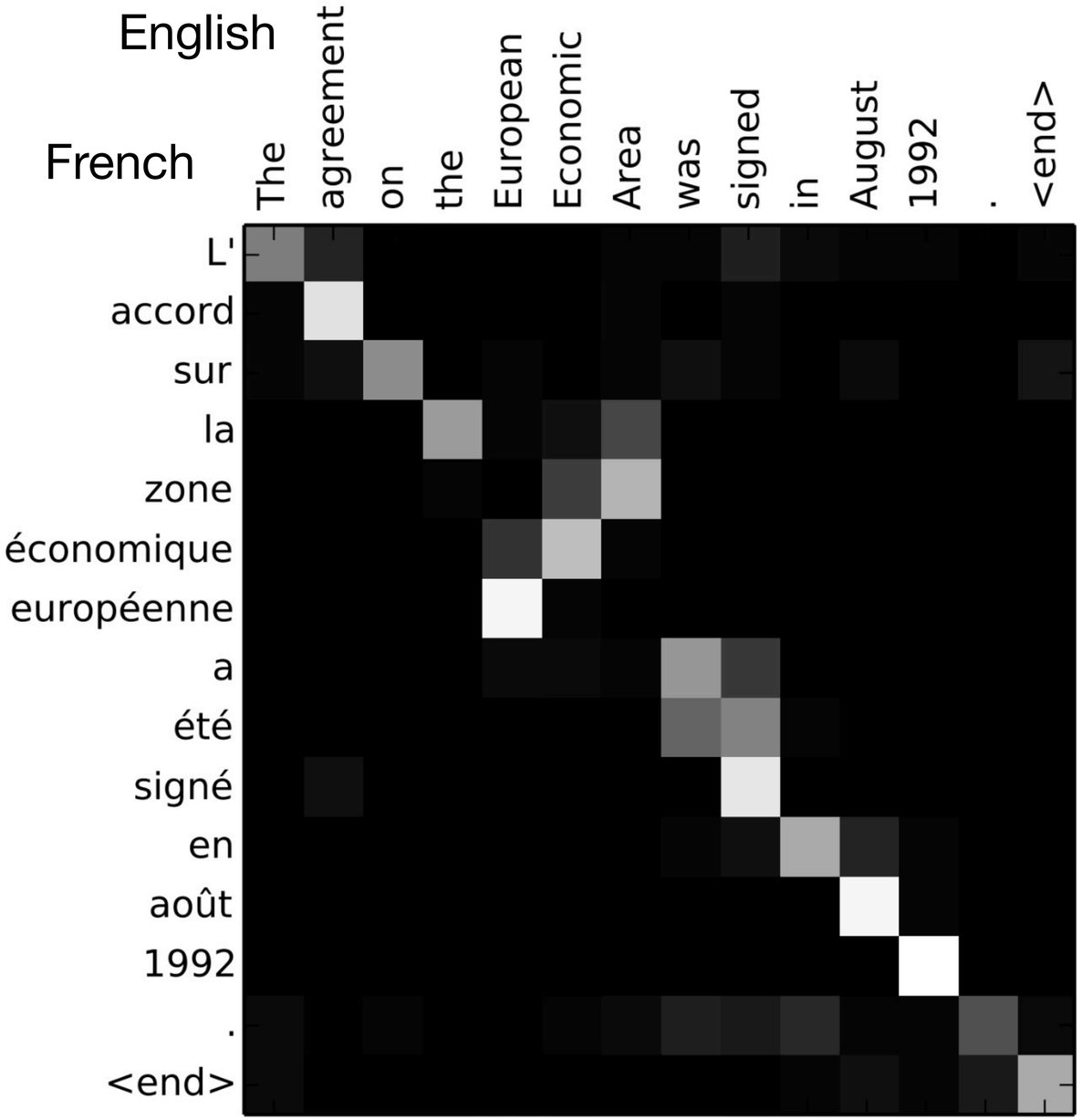


- Multiply Q and K to get the inner product (normalize by $\sqrt{d}$)
- Pass through Softmax to get the attention weights of shape $N \times N$
  - The attention computation has $O(N^2)$ complexity!
- Multiply attention weights with V to get the output

Content credit: https://stats.stackexchange.com/questions/421935/what-exactly-are-keys-queries-and-values-in-attention-mechanisms

Self-Attention

- Example of attention matrix from machine translation
- The attention mechanism finds the correspondence between words



Example from Greg Durrett

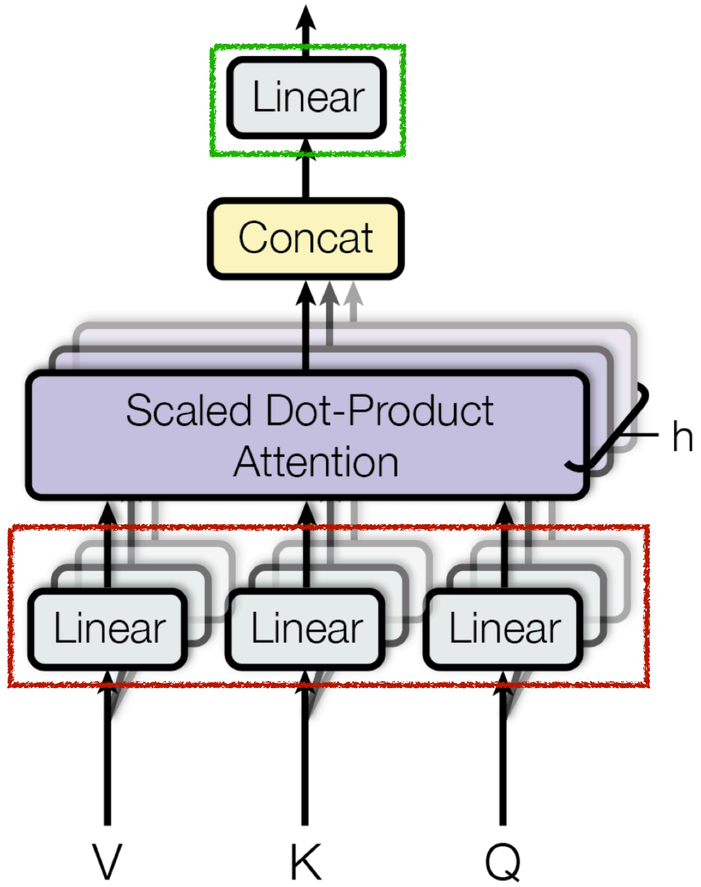
Multi-Head Attention (MHA)

Each head captures different semantics

- We need different attention maps to capture different semantic relationships
- Multi-head attention models different attention functionalities by having $H > 1$ heads (parallel branches of QKV attention)
- The final output is concatenated and goes through a linear projection to merge the features

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, ..., \text{head}_\text{h})W^O$$

$$\text{where head}_\text{i} = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$$

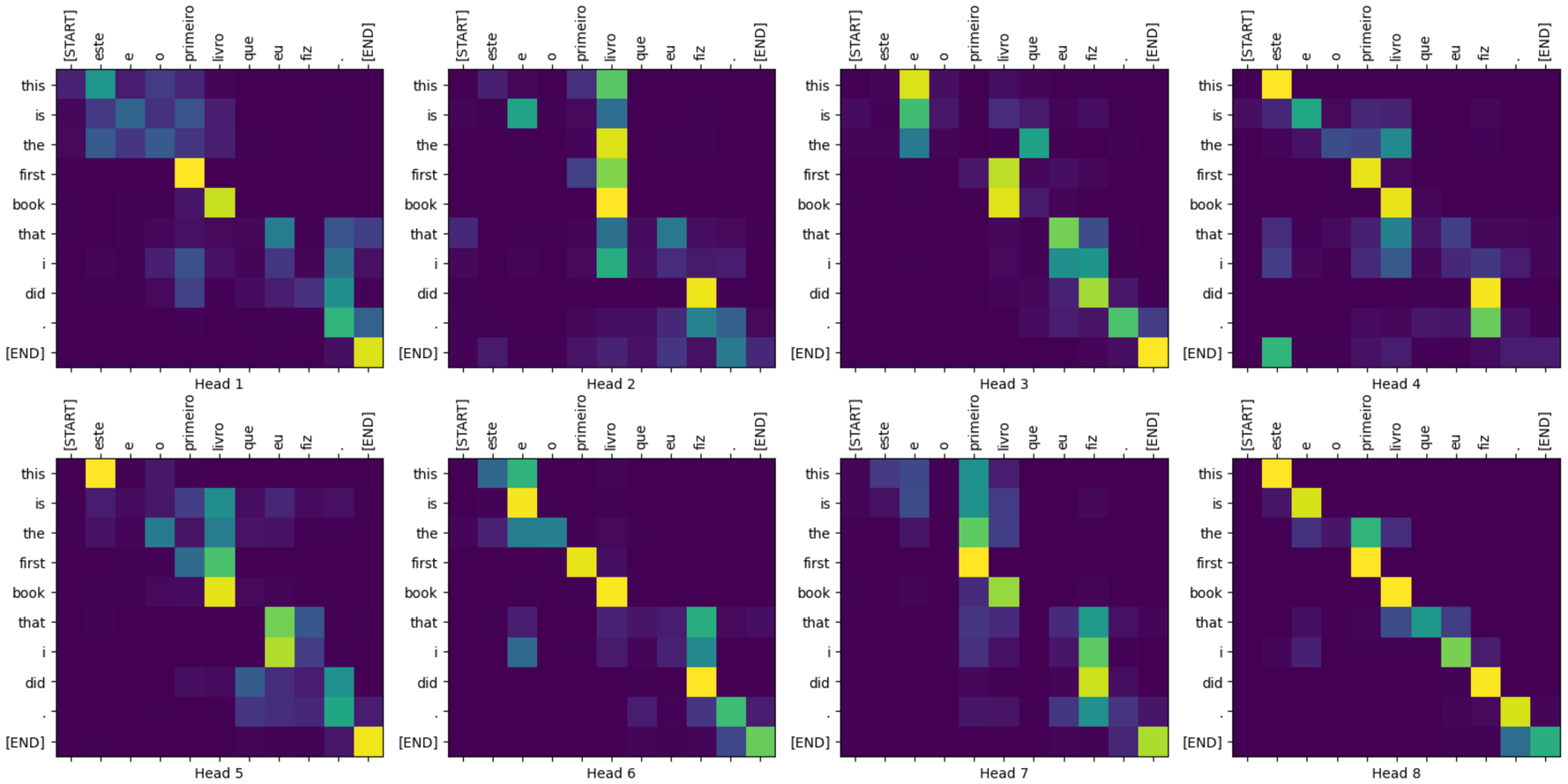


Content credit: https://cezannec.github.io/CNN_Text_Classification/

Multi-Head Attention (MHA)

Each head captures different semantics

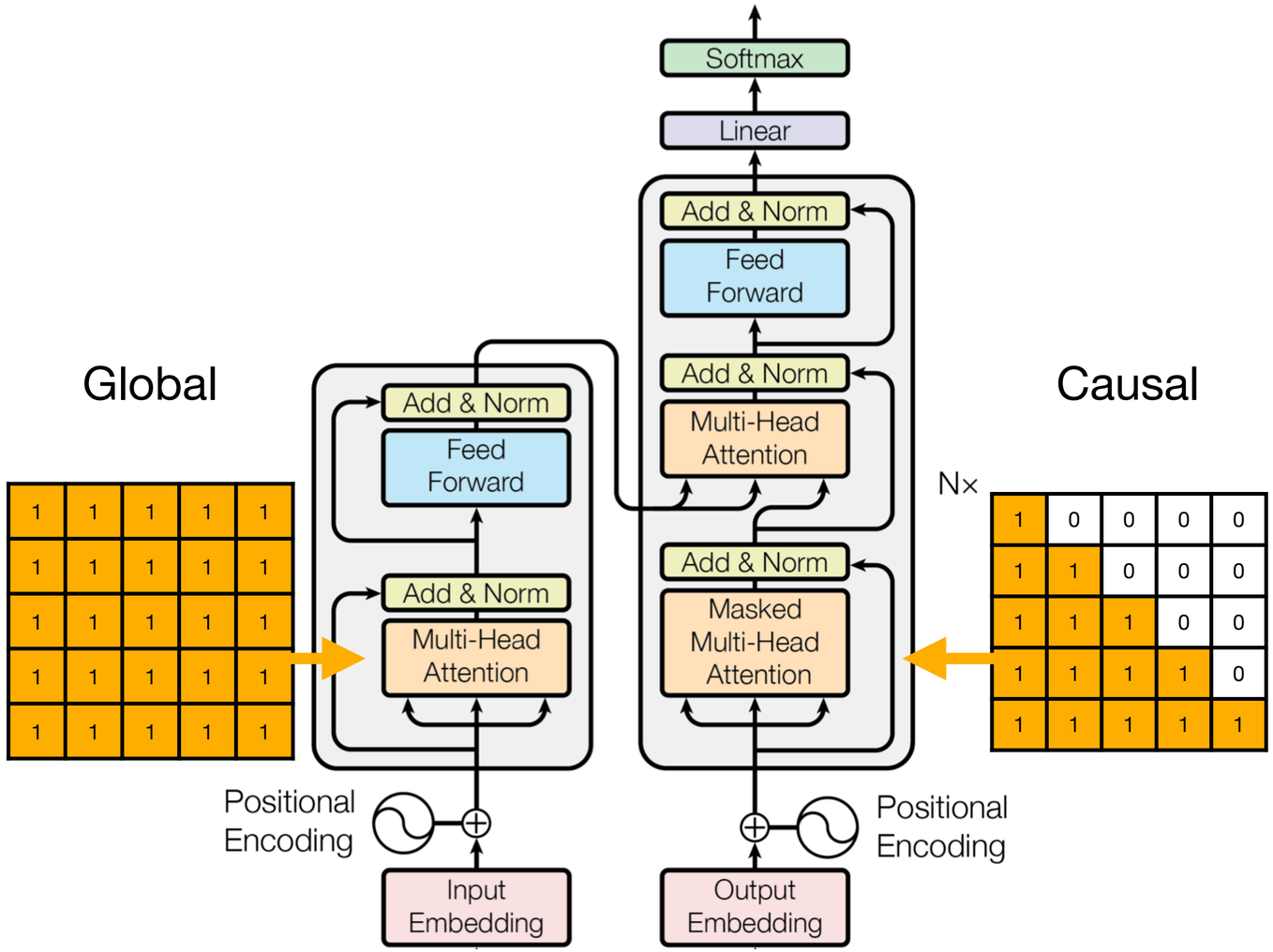
- Visualization from different heads



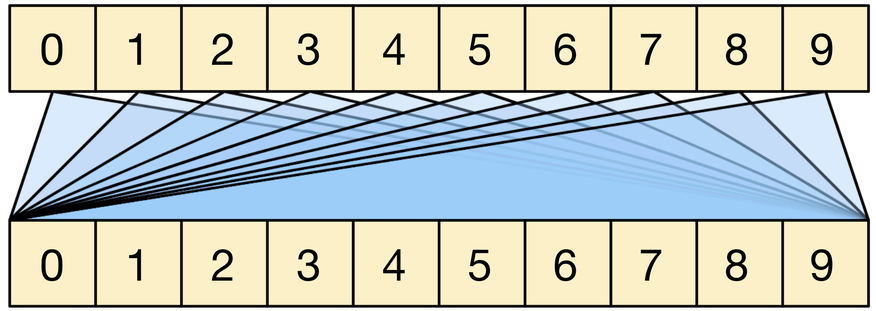
https://www.tensorflow.org/text/tutorials/transformer

Attention Masking

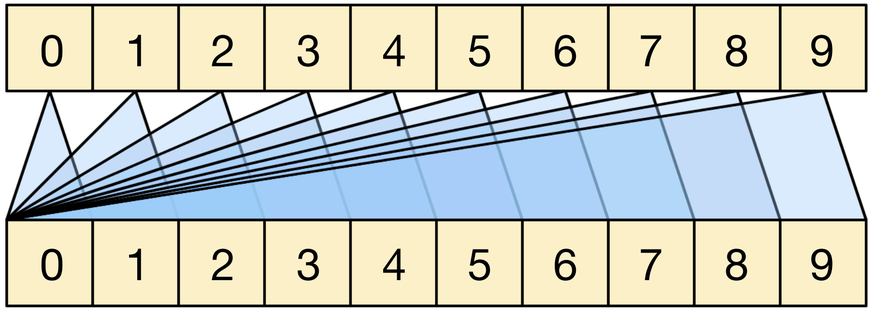
Casual/masked language modeling



- Global self attention layer



- Causal self attention layer



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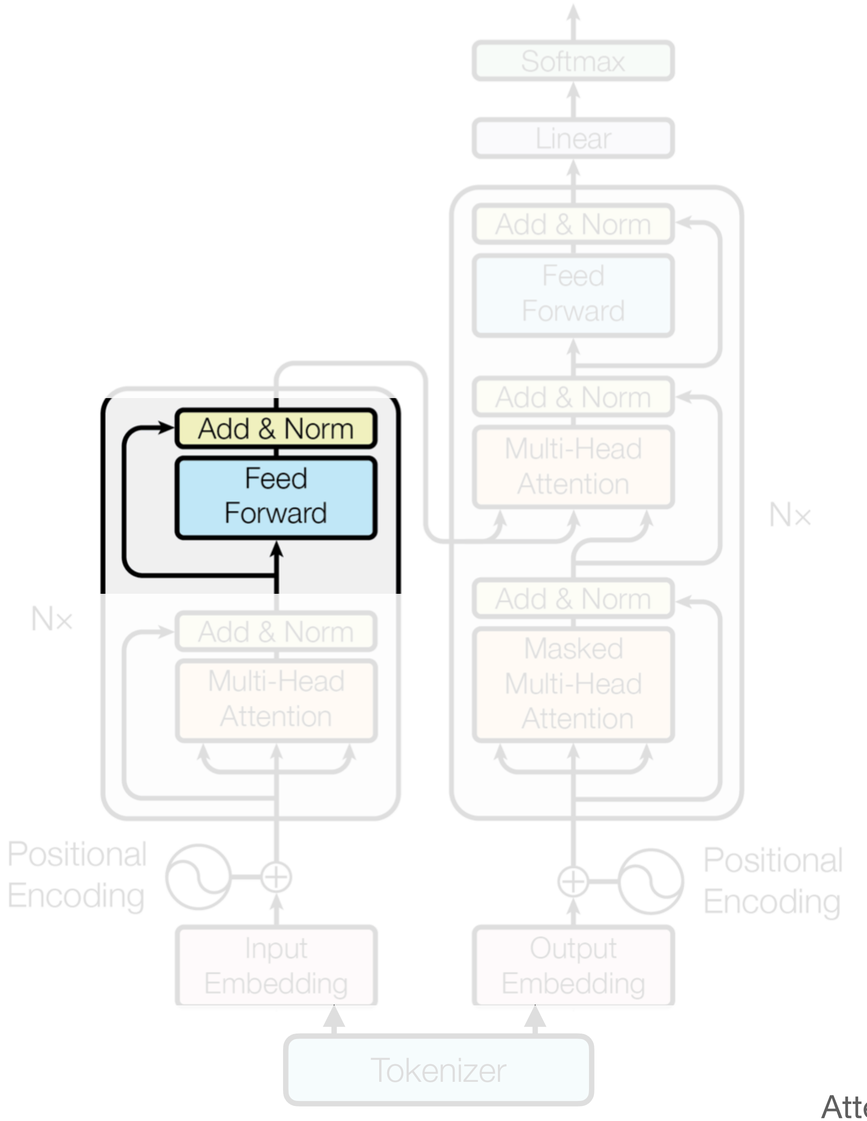
Transformer



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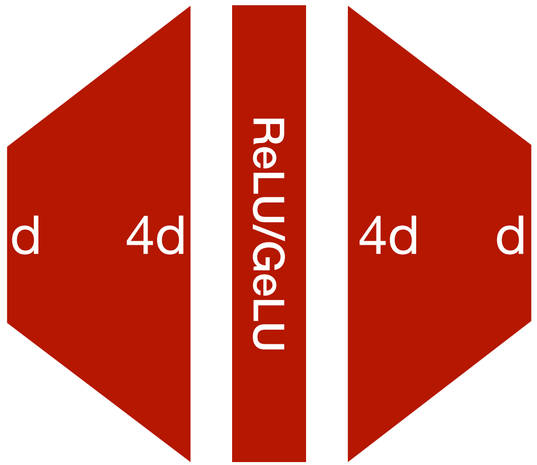
Attention Is All You Need [Vaswani *et al.*, 2017]

Feed-Forward Network (FFN)

- Self-attention models relationships **between** tokens, but there is no **element-wise** non-linearity
- Add a feed-forward network (FFN) to help with feature modeling
- The vanilla implementation is a two-layer MLP with a larger hidden state size (**inverted bottleneck**) and ReLU/GeLU **activation**

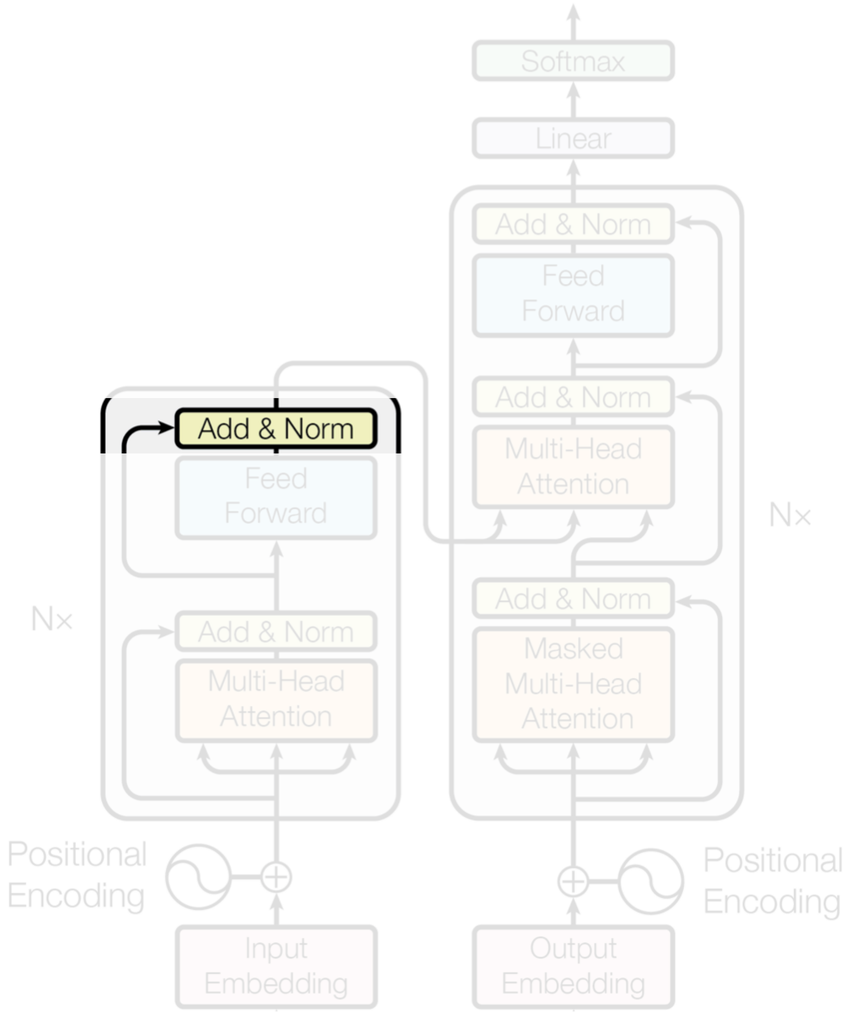
$$\mathrm{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$



- Later we are going to visit several design variants

Model	#L	#H	d_{model}	LR	Batch
125M	12	12	768	$6.0e{-4}$	0.5M
350M	24	16	1024	$3.0e{-4}$	0.5M
1.3B	24	32	2048	$2.0e{-4}$	1M
2.7B	32	32	2560	$1.6e{-4}$	1M
6.7B	32	32	4096	$1.2e{-4}$	2M
13B	40	40	5120	$1.0e{-4}$	4M
30B	48	56	7168	$1.0e{-4}$	4M
66B	64	72	9216	$0.8e{-4}$	2M
175B	96	96	12288	$1.2e{-4}$	2M

Transformer



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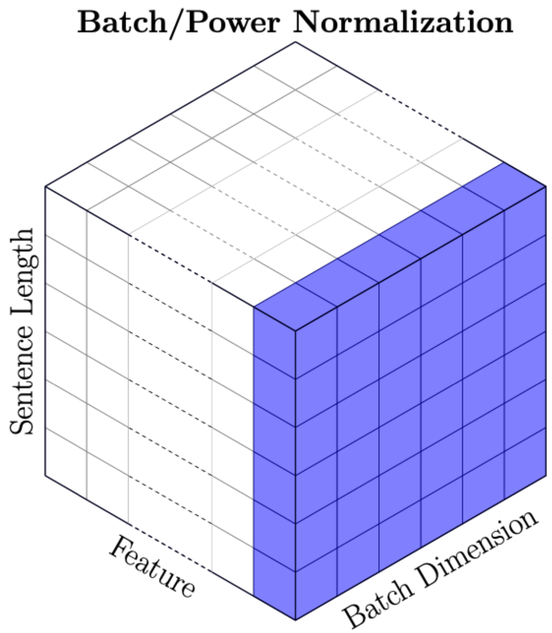
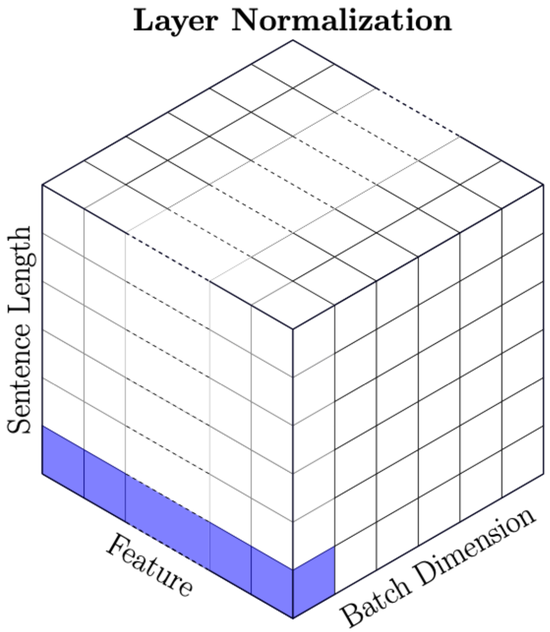
Layer Normalization (LN)

- Unlike BatchNorm (BN) in CNNs, Transformers use **LayerNorm (LN)**
- LN performs normalization for each token's embedding, then applies a learnable affine transformation



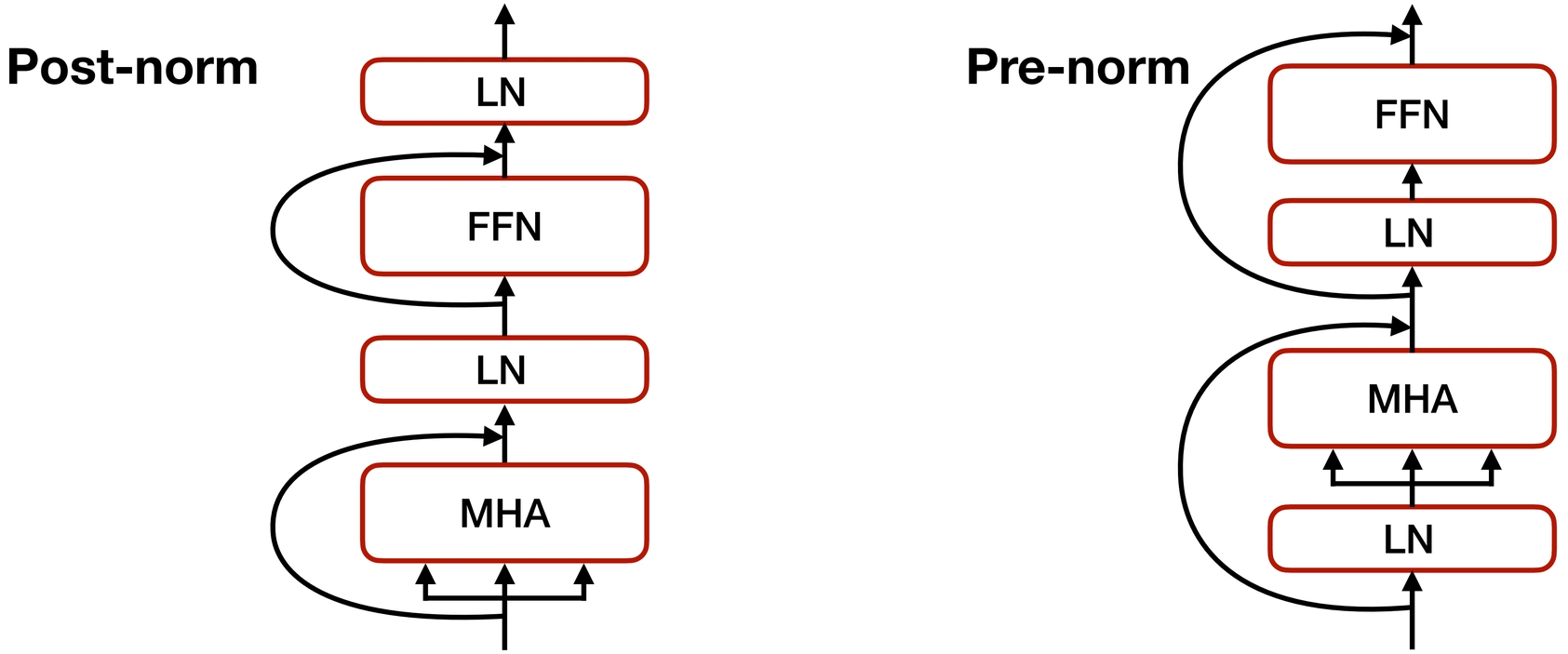


$$y = \frac{x - \mathrm{E}[x]}{\sqrt{\mathrm{Var}[x] + \epsilon}} * \gamma + \beta$$

Image credit: http://proceedings.mlr.press/v119/shen20e/shen20e.pdf

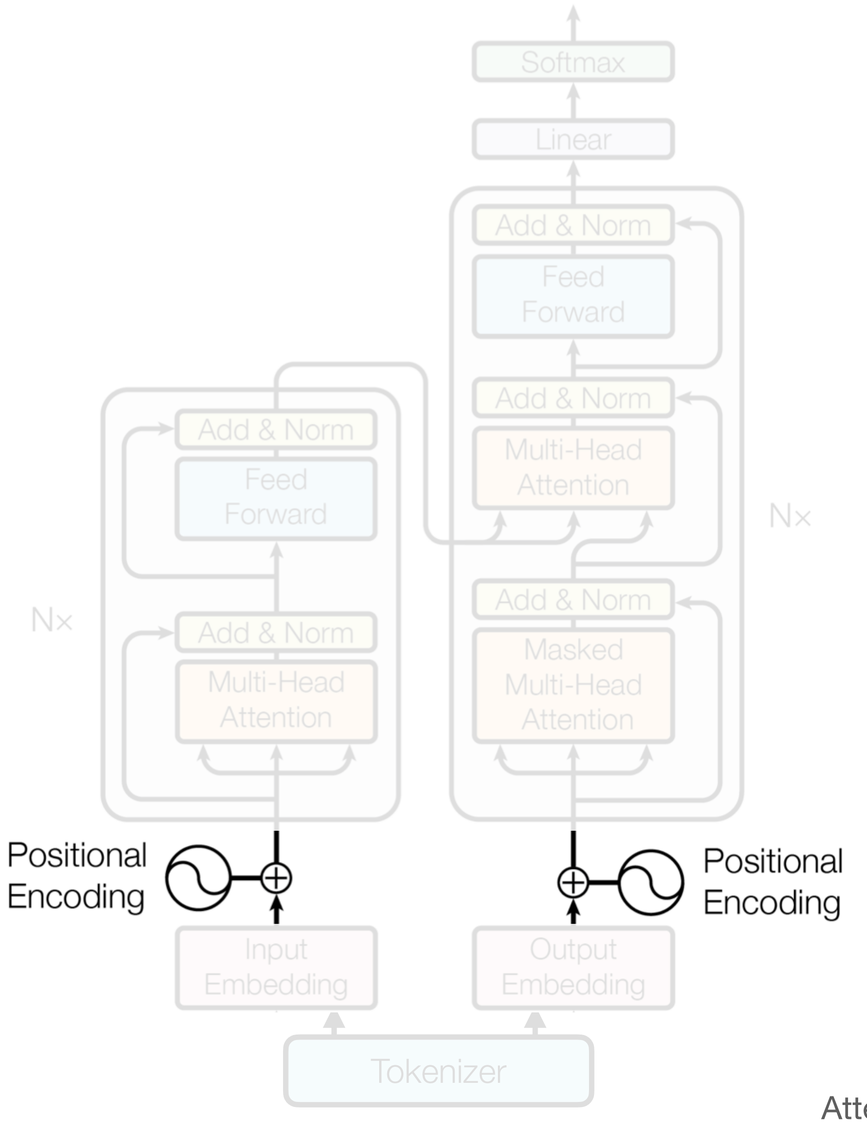
Transformer Block

- Now we put everything together to build a Transformer block
- We add LayerNorm and Residual Connections for training stability
- **Note**: the pre-norm design is more popular now due to better training stability



https://pytorch.org/docs/stable/generated/torch.nn.LayerNorm.html

Transformer



- Tokenize words (word -> tokens)
- Map tokens into embeddings
- Embeddings go through transformer blocks
  - Multi-Head Attention (MHA)
  - Feed-Forward Network (FFN)
  - LayerNorm
  - Residual connection
- Positional encoding
- Final prediction with linear head

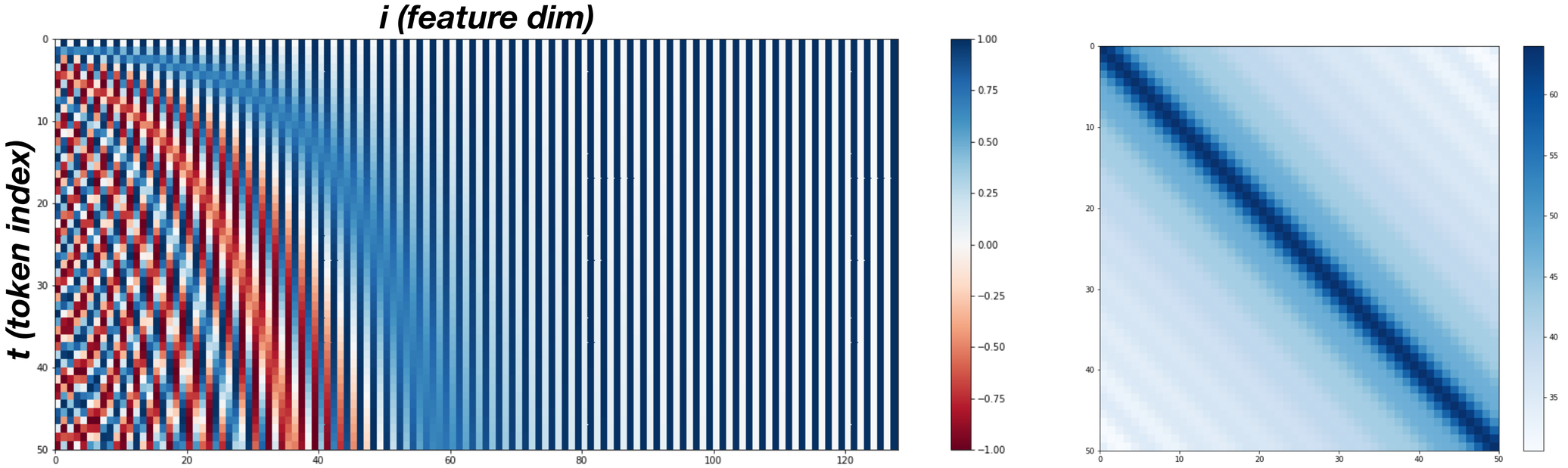
- **Problem**: attention and FFN do not differentiate the **order** of the input tokens (unlike convolutions)
  - Set encoding (bad) instead of sequence encoding (good)
- **Solution: Positional encoding!**

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

Position Encoding (PE)

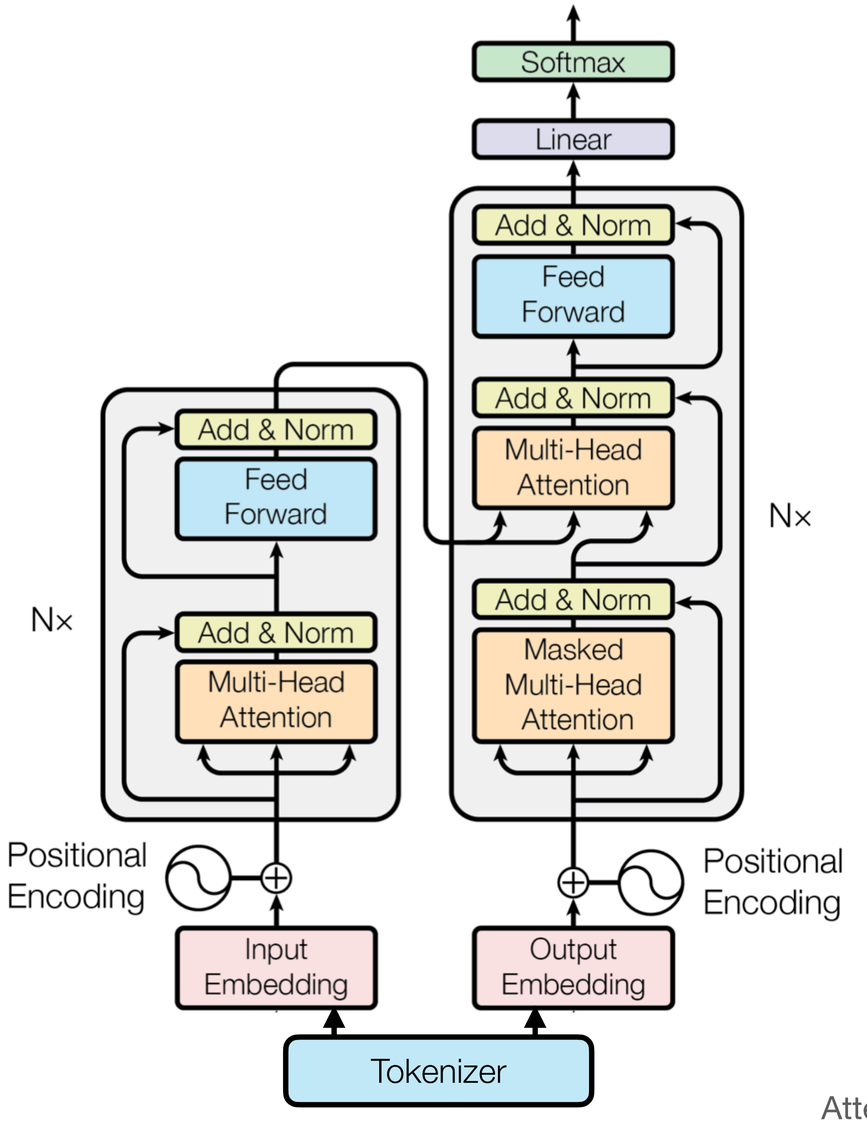
- Positional encoding provides positional information.
  - **Unique** encoding for each word's position in a sentence.
  - Each element is a function of t (i.e., index, absolute PE)
  - Added to the raw word embedding to fuse in positional information

$$\overrightarrow{p_t}^{(i)} = f(t)^{(i)} := \begin{cases} \sin(\omega_k . t), & \text{if } i = 2k \\ \cos(\omega_k . t), & \text{if } i = 2k+1 \end{cases} \qquad \omega_k = \frac{1}{10000^{2k/d}}$$



Content credit: https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

Putting it together



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

Results

Neural Machine Translation (NMT)

Model	BLEU		Training Cost (FLOPs)	
	EN-DE	EN-FR	EN-DE	EN-FR
ByteNet [18]	23.75			
Deep-Att + PosUnk [39]		39.2		$1.0 \cdot 10^{20}$
GNMT + RL [38]	24.6	39.92	$2.3 \cdot 10^{19}$	$1.4 \cdot 10^{20}$
ConvS2S [9]	25.16	40.46	$9.6 \cdot 10^{18}$	$1.5 \cdot 10^{20}$
MoE [32]	26.03	40.56	$2.0 \cdot 10^{19}$	$1.2 \cdot 10^{20}$
Deep-Att + PosUnk Ensemble [39]		40.4		$8.0 \cdot 10^{20}$
GNMT + RL Ensemble [38]	26.30	41.16	$1.8 \cdot 10^{20}$	$1.1 \cdot 10^{21}$
ConvS2S Ensemble [9]	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**	**41.8**	$2.3 \cdot 10^{19}$	

- Transformer surpasses all previously published models and ensembles, at a fraction of the training cost of any of the competitive models.
- BLEU measures the similarity of the machine-translated text to a set of reference translations.

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

II. Transformer Design Variants

Transformer Design Variants

Improved designs after the initial transformer paper

- Most designs from the initial Transformer paper have been widely used by the community
- Nonetheless, people proposed various alternative designs. For example:
  - Encoder-decoder (T5), encoder-only (BERT), decoder-only (GPT)
  - Absolute positional encoding -> Relative positional encoding
  - KV cache optimizations:
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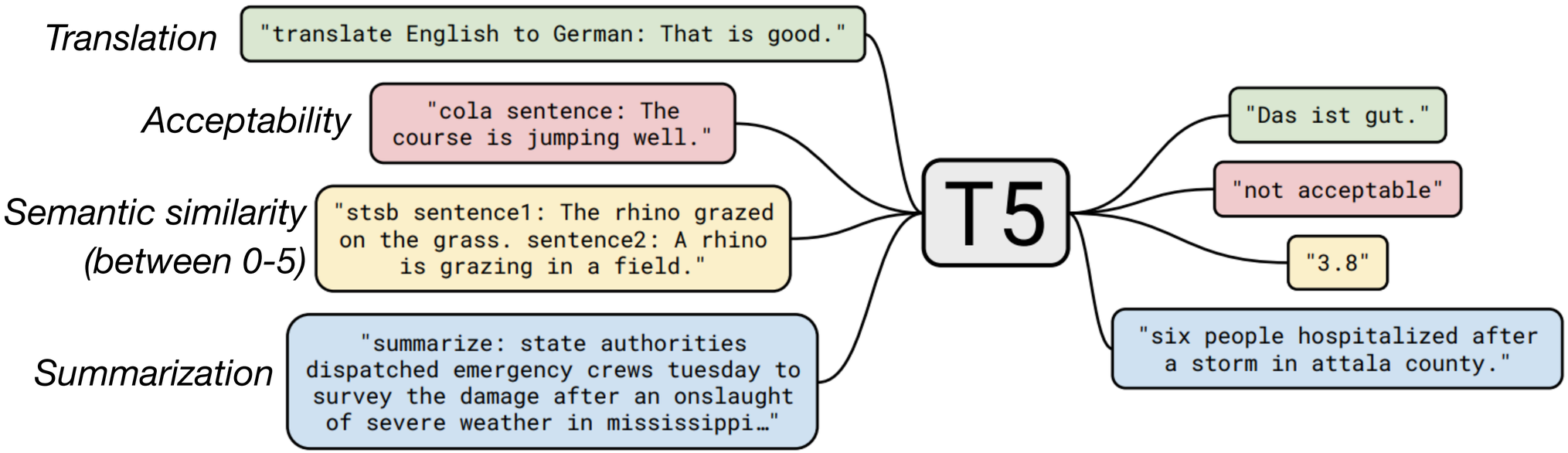
Encoder-Decoder

- The original Transformer is an Encoder-Decoder architecture
- T5 offers a unified text-to-text model for transfer learning on various NLP tasks



Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer [Raffel *et al.*, 2019]

Encoder-Decoder

- The original Transformer is an Encoder-Decoder architecture
- T5 offers a unified text-to-text model for transfer learning on various NLP tasks
- The **prompt** is fed to the encoder, the decoder generates the **answer**.

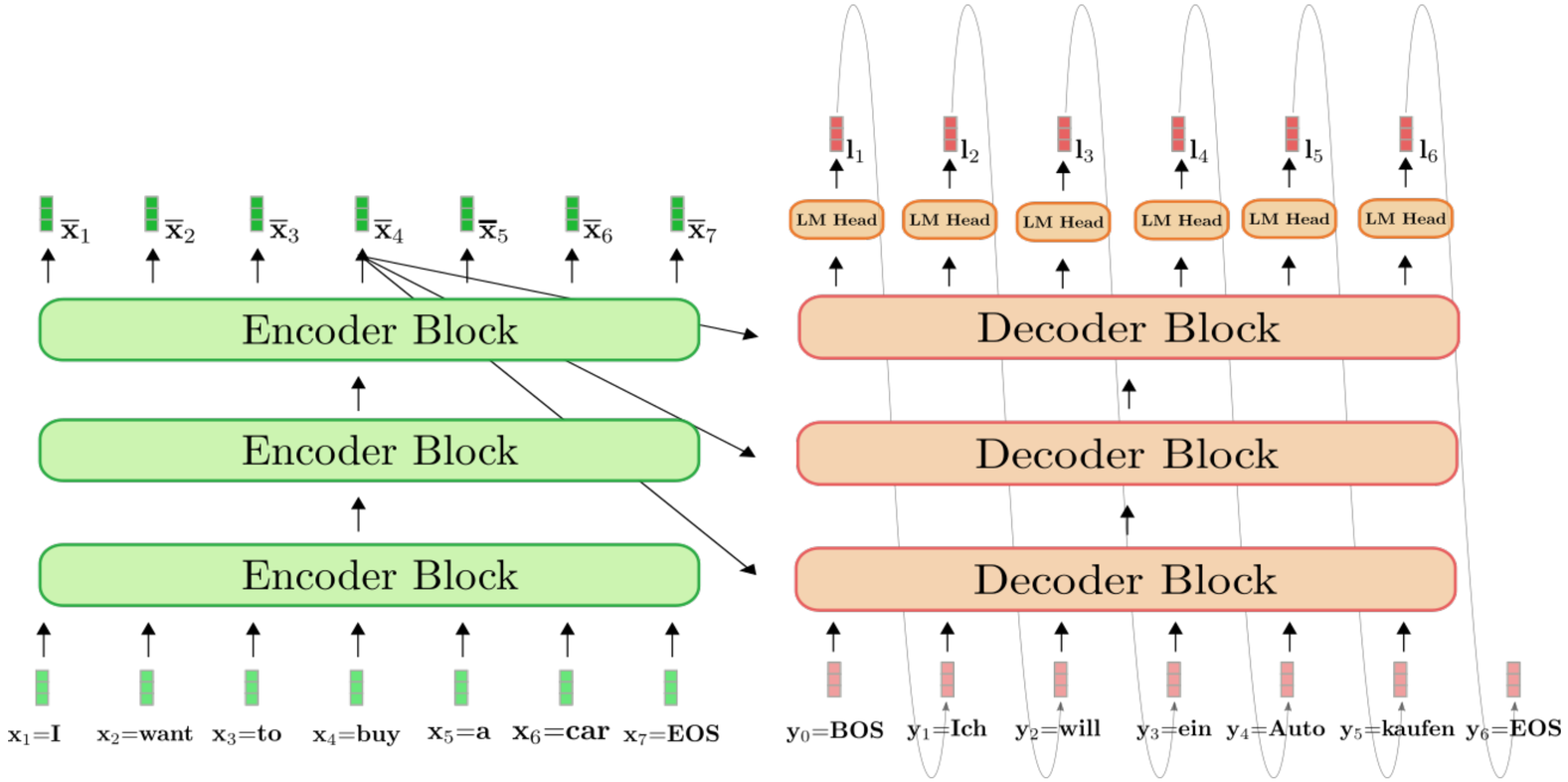


Image credit: https://huggingface.co/blog/encoder-decoder

Encoder-only (BERT)

Attention mask:

1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1

Bidirectional Encoder Representations from Transformers (BERT)

- BERT is an **encoder-only** language model
- Two pre-training objectives
  - Task #1: **Masked Language Model (MLM)**
    - Mask some percentage (15%) of the input tokens at random; train model to predict masked tokens
  - Task #2: **Next Sentence Prediction (NSP)**
    - Whether sentence B is the next sentence of sentence A (less used)
- The pre-trained model is fine-tuned to downstream tasks

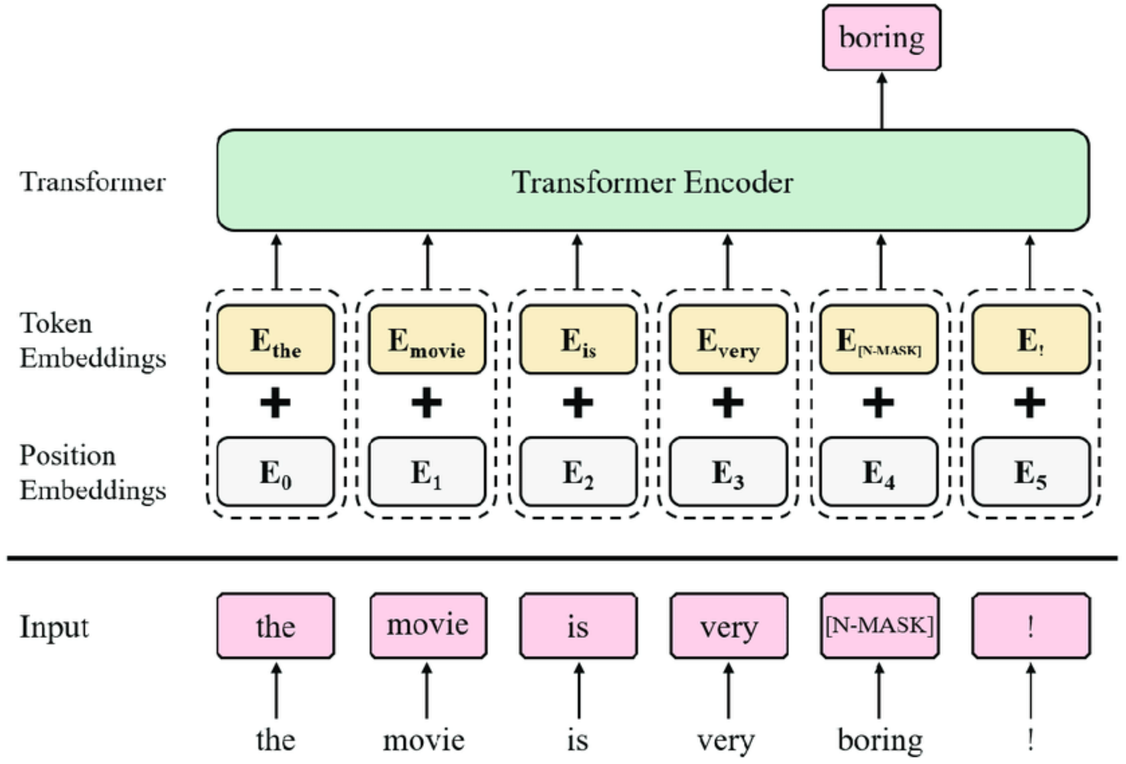


Image credit: https://www.mdpi.com/2073-8994/11/11/1393/htm

BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding [Devlin *et al.*, 2018]

Decoder-only (GPT)

Generative Pre-trained Transformer (GPT)

- GPT is a **decoder-only** language model
- Pre-training objective:
  - Next word prediction

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

- For smaller models (GPT-2), the pre-trained model is fine-tuned to downstream tasks
- Larger model can run in zero-shot/ few-shot

Attention mask:

1	0	0	0	0
1	1	0	0	0
1	1	1	0	0
1	1	1	1	0
1	1	1	1	1

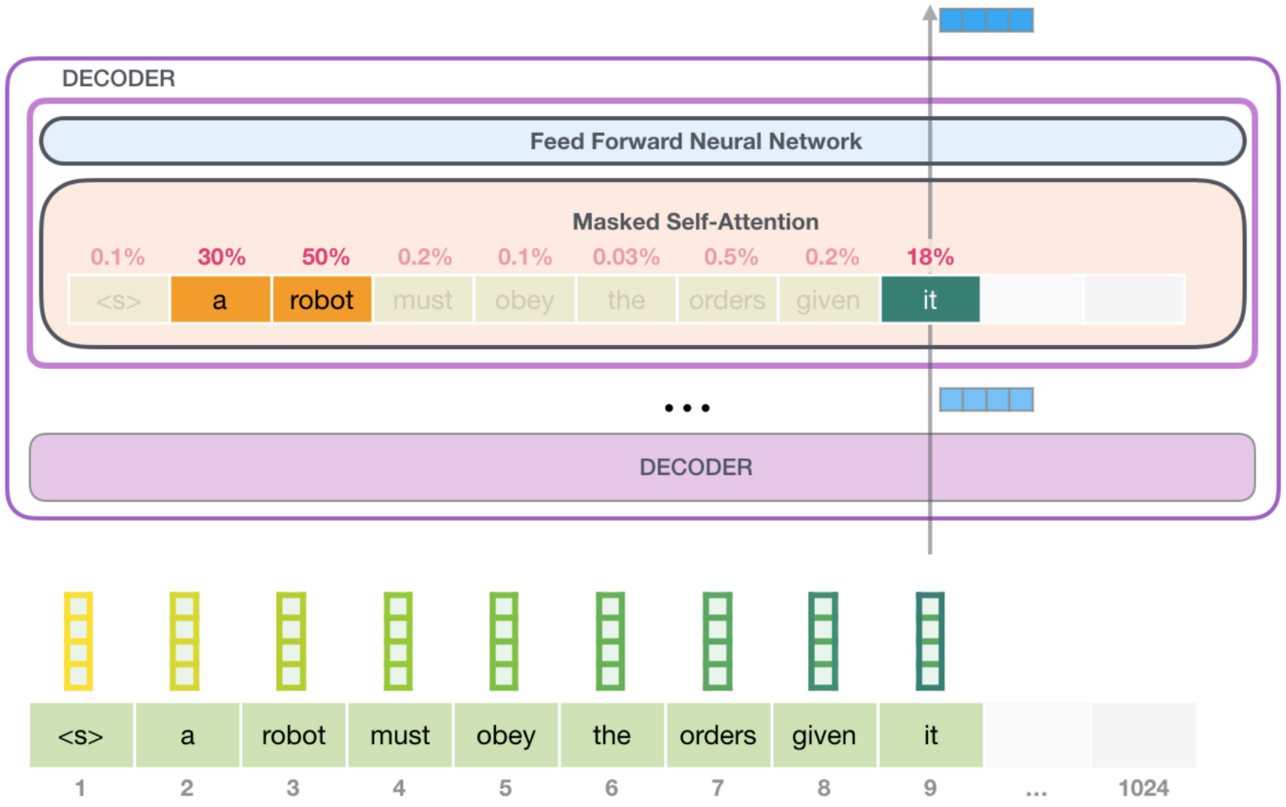


Image credit: https://jalammar.github.io/illustrated-gpt2/

Improving Language Understanding by Generative Pre-Training [Radford *et al.*, 2018]

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Absolute / Relative Positional Encoding

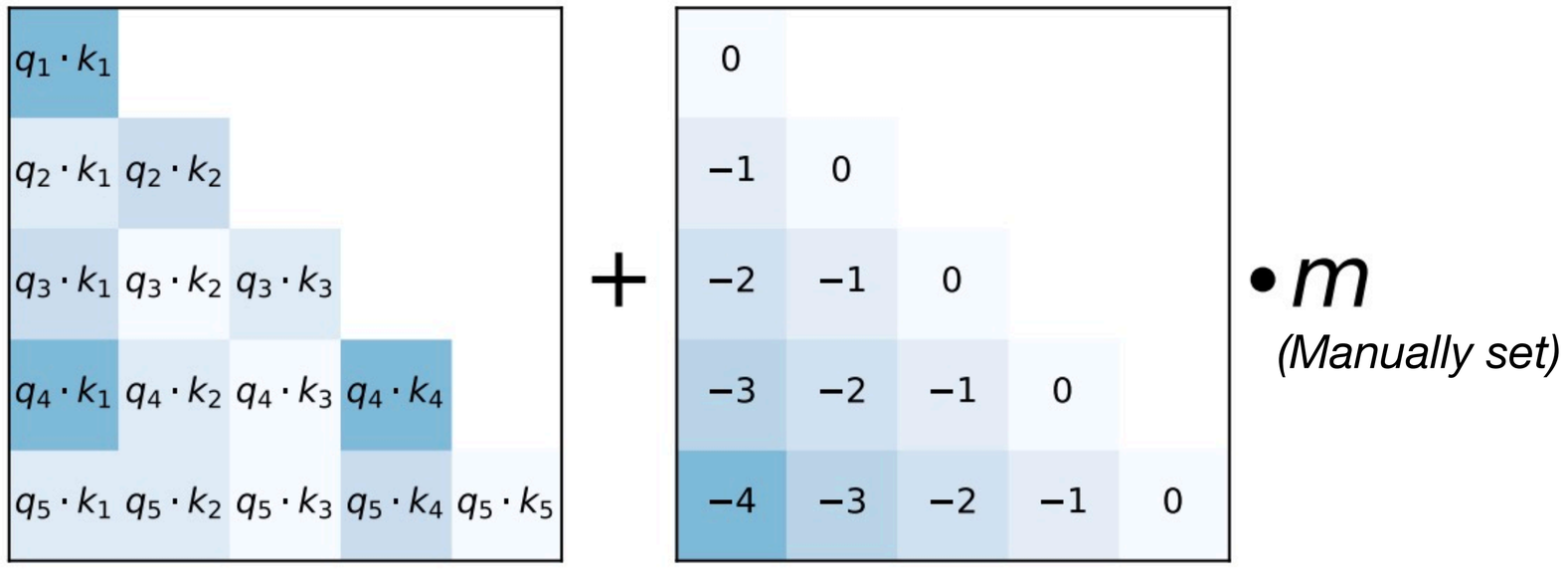
Comparing absolute/relative positional encoding

- **Absolute positional encoding** fuses the positional information into the input embeddings (thus Q/K/V). The information is propagated through the entire Transformer.
- **Relative positional encoding** provides relative distance information by impacting the attention scores (either adding a bias or modifying queries and keys), not V.
  - **Advantage**: generalize to sequence length not seen during training, i.e., train short, test long (does not always apply)

Relative Positional Encoding

Attention with Linear Biases (ALiBi)

- The idea is to change the positional encoding to be only related to **relative distance**, but not the **absolute index**, with the hope that it can be “train short, test long”.
- ALiBi proposed to **add an offset to the attention matrix** (defined as the relative distance) instead of adding it to the input token embeddings.



Train Short, Test Long: Attention with Linear Biases Enables Input Length Extrapolation [Press *et al.*, 2021]

Relative Positional Encoding

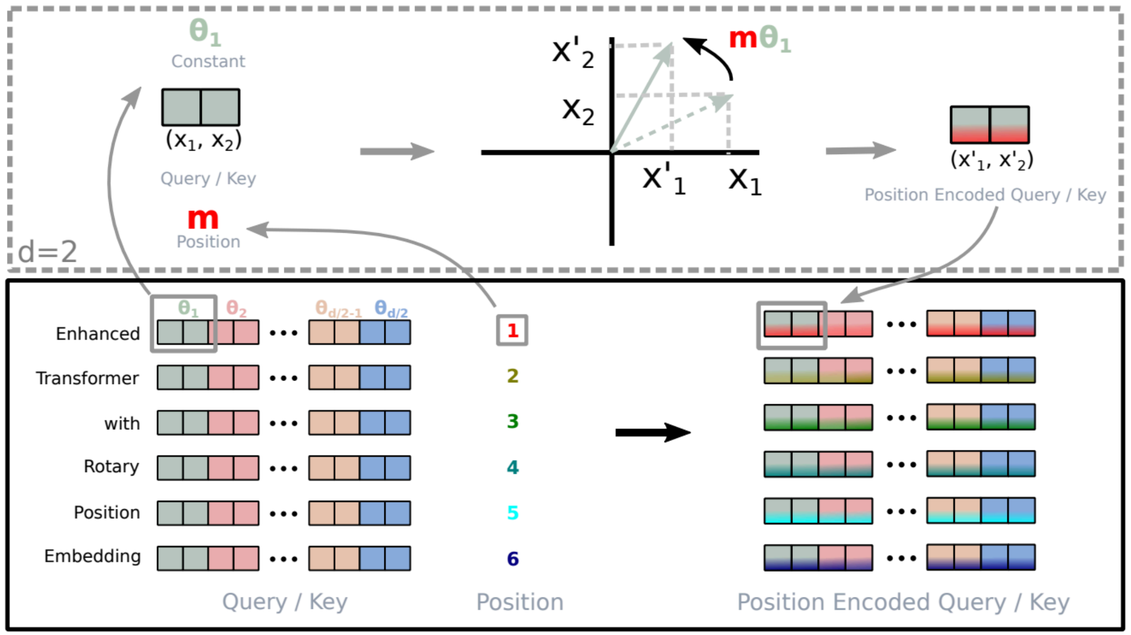
Rotary Positional Embedding (RoPE)

- A popular implementation for relative positional embedding (used in LLaMA)
- Rotate the embeddings in 2D space:
  - Split an embedding of dimension d into $d/2$ pairs, each pair considered as a 2D coordinate
  - Apply rotation according to the position m

We need a big enough number to distinguish more tokens

$$\Theta = \{\theta_i = \boxed{10000}^{-2(i-1)/d}, i \in [1, 2, ..., d/2]\}$$

$$\begin{aligned}
\text{RoPE}(x, m) &= xe^{mi\varepsilon} \\
\langle \text{RoPE}(q_j, m), \text{RoPE}(k_j, n) \rangle &= \langle q_j e^{mi\varepsilon}, k_j e^{ni\varepsilon} \rangle \\
&= q_j k_j e^{mi\varepsilon} \overline{e^{ni\varepsilon}} \\
&= q_j k_j e^{(m-n)i\varepsilon} \\
&= \text{RoPE}(q_j k_j, m - n)
\end{aligned}$$



- The phase angle of the inner product of two complex vectors is the phase difference between the two complex vectors (thus m-n)

RoFormer: Enhanced Transformer with Rotary Position Embedding [Su *et al.*, 2021]

Relative Positional Encoding

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- Rotate the embeddings in 2D space:
  - Split an embedding of dimension d into $d/2$ pairs, each pair considered as a 2D coordinate
  - Apply rotation according to the position m
- The general form:

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

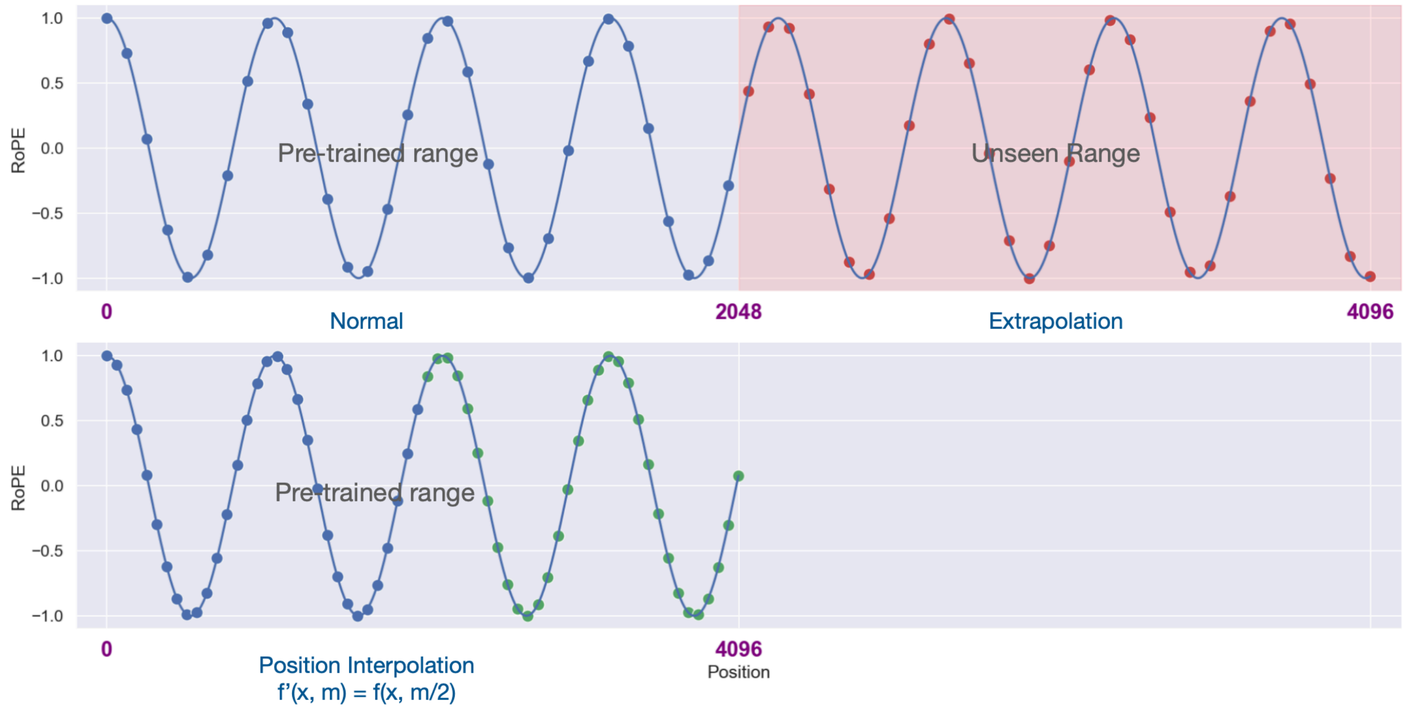
$$\boldsymbol{R}^d_{\Theta,m} = \begin{pmatrix} \cos m\theta_1 & -\sin m\theta_1 & 0 & 0 & \cdots & 0 & 0 \\ \sin m\theta_1 & \cos m\theta_1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cos m\theta_2 & -\sin m\theta_2 & \cdots & 0 & 0 \\ 0 & 0 & \sin m\theta_2 & \cos m\theta_2 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & \cos m\theta_{d/2} & -\sin m\theta_{d/2} \\ 0 & 0 & 0 & 0 & \cdots & \sin m\theta_{d/2} & \cos m\theta_{d/2} \end{pmatrix}$$

RoFormer: Enhanced Transformer with Rotary Position Embedding [Su *et al.*, 2021]

Relative Positional Embedding

Advantage of RoPE: extending the context window

- LLM is usually trained with a context length constraint (e.g., 2k for LLaMA, 4k for Llama-2, 8k for GPT-4) and fails with a larger context length
- We can extend the context length support by **interpolating** RoPE PE (i.e., use a smaller θ_i)
- Extend the context length of LLaMA from 2k to 32k



$m \in [0, 2048 * 2), \quad \theta_i' = \theta_i$ ✗

$m \in [0, 2048 * 2), \quad \theta_i' = \theta_i / 2$ ✓

Extending Context Window of Large Language Models via Position Interpolation [Chen et al., 2023]

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KV Cache Optimizations

The KV cache could be large with long context

- During Transformer decoding (GPT-style), we need to store the **K**eys and **V**alues of **all previous** tokens so that we can perform the attention computation, namely the **KV cache**
  - Only need the **current** query token

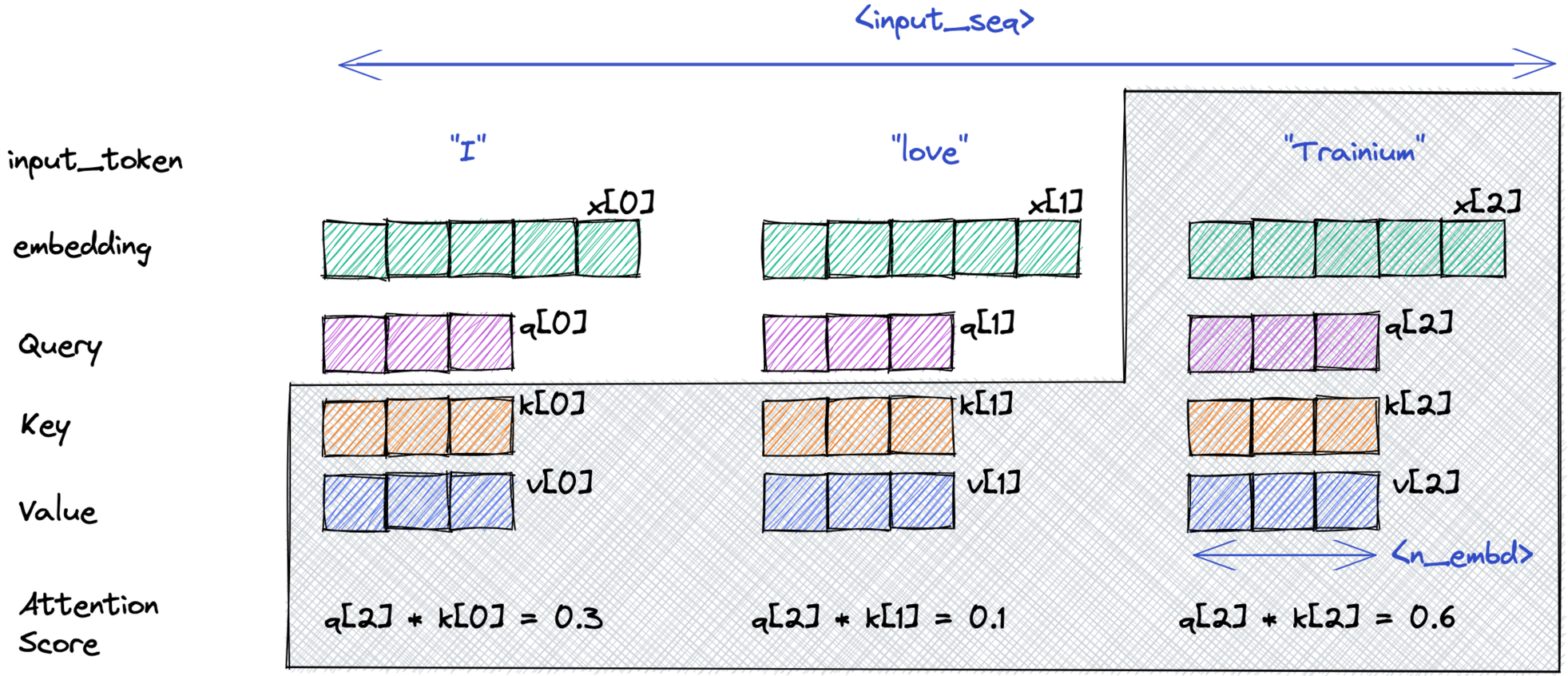

Image credit: https://awsdocs-neuron.readthedocs-hosted.com/en/latest/general/appnotes/transformers-neuronx/generative-llm-inference-with-neuron.html

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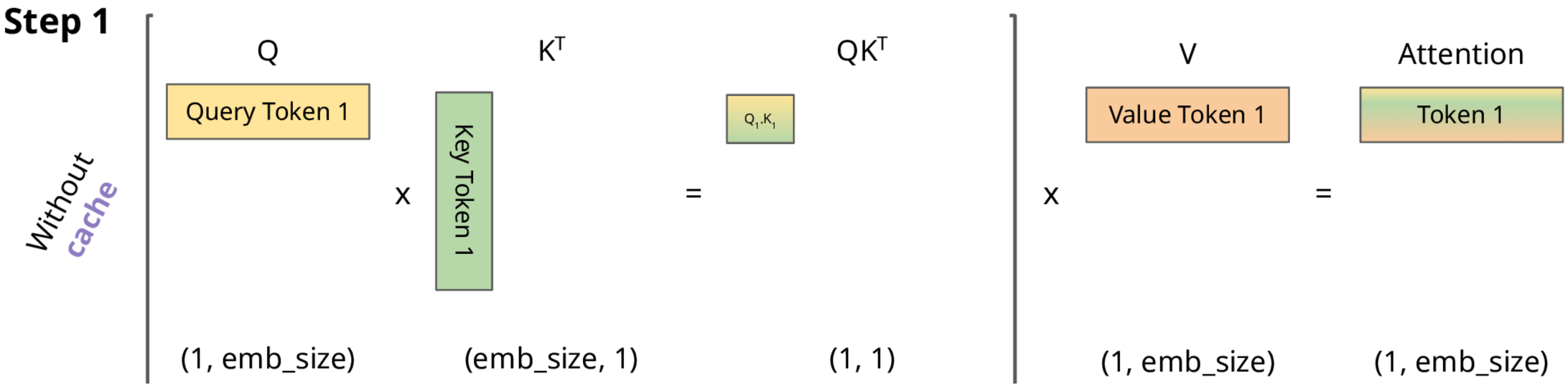

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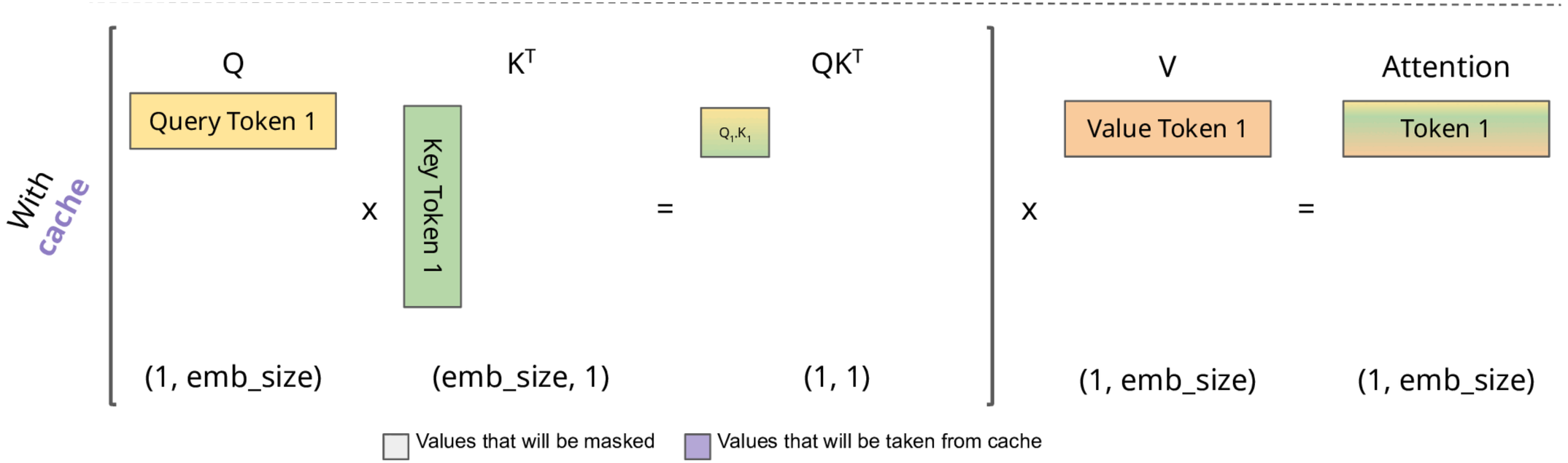

Image credit: https://medium.com/@joaolages/kv-caching-explained-276520203249

KV Cache Optimizations

The KV cache could be large with long context

- We can calculate the memory required to store the KV cache:
- Llama-2-7B, KV cache size =

$$\underbrace{BS}_{minibatch} * \underbrace{32}_{layers} * \underbrace{32}_{heads} * \underbrace{128}_{n_{emd}} * \underbrace{N}_{length} * \underbrace{2}_{K\&V} * \overbrace{2\text{bytes}}^{fp16} = 512\text{KB} \times BS \times N$$

- Llama-2-13B, KV cache size =

$$\underbrace{BS}_{minibatch} * \underbrace{40}_{layers} * \underbrace{40}_{heads} * \underbrace{128}_{n_{emd}} * \underbrace{N}_{length} * \underbrace{2}_{K\&V} * \overbrace{2\text{bytes}}^{fp16} = 800\text{KB} \times BS \times N$$

- Llama-2-70B (if using MHA), KV cache size =

$$\underbrace{BS}_{minibatch} * \underbrace{80}_{layers} * \underbrace{64}_{kv-heads} * \underbrace{128}_{n_{emd}} * \underbrace{N}_{length} * \underbrace{2}_{K\&V} * \overbrace{2\text{bytes}}^{FP16} = 2.5\text{MB} \times BS \times N$$

https://www.databricks.com/blog/llm-inference-performance-engineering-best-practices

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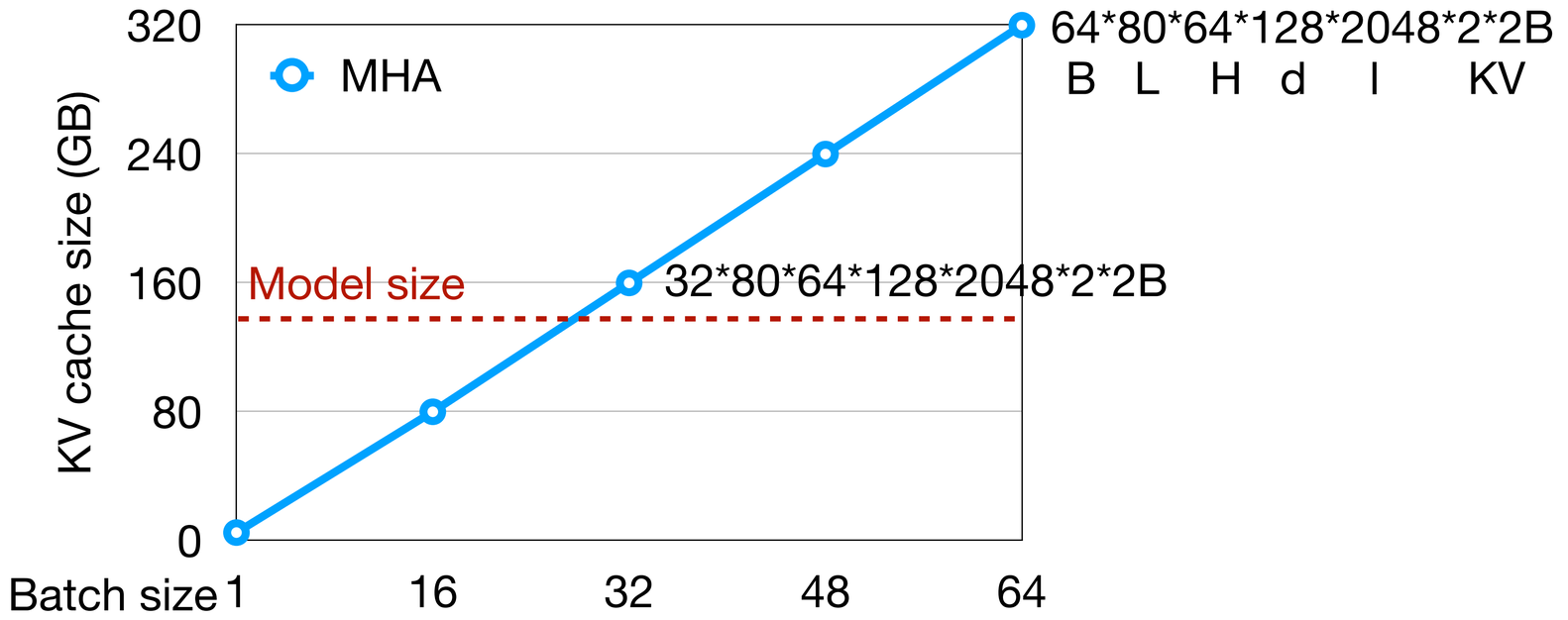
- bs=1, n_seq=512: 1.25GB
- bs=1, n_seq=4096 : 10GB (~ a paper)
- bs=16, n_seq=4096: 160GB (requires two A100 GPU!)

https://www.databricks.com/blog/llm-inference-performance-engineering-best-practices

KV Cache Optimizations

The KV cache could be large with long context

- Now, we calculate the KV cache size under $N = 2048$ different batch sizes
  - The KV cache size goes quickly larger than the model weights



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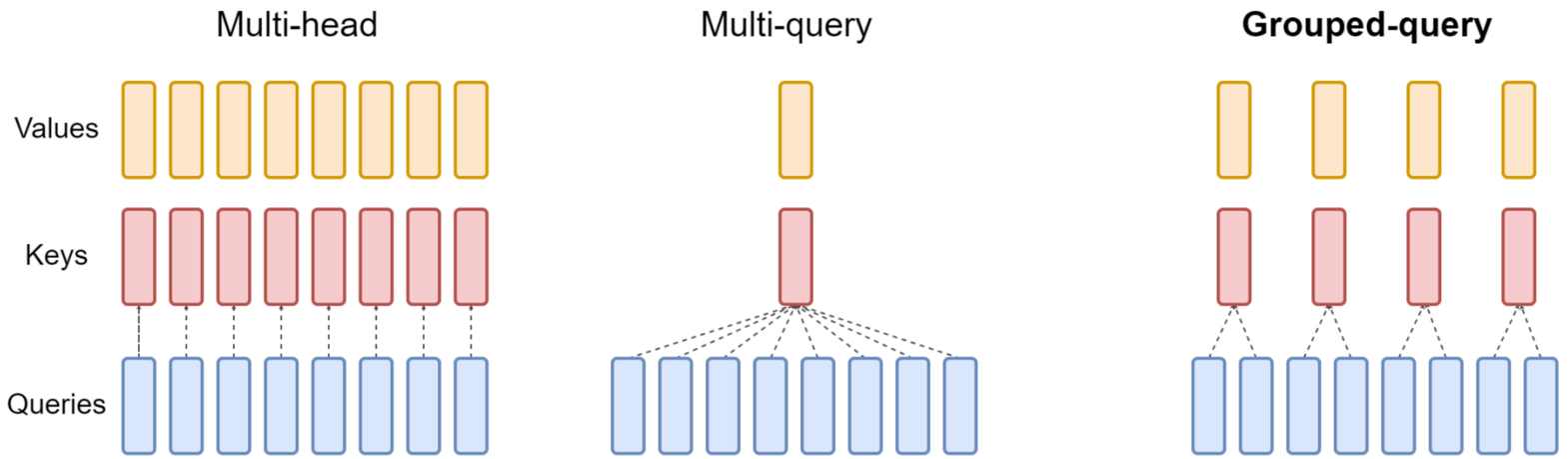
Multi-Query Attention

Reduce the KV cache memory usage with MQA/GQA

- Reducing the KV cache size by reducing #`kv-heads`
  - Multi-head attention (MHA): N heads for query, N heads for key/value
  - Multi-query attention (MQA): N heads for query, 1 heads for key/value
  - Grouped-query attention (GQA): N heads for query, G heads for key/value (typically $G = N/8$)



Fast Transformer Decoding: One Write-Head is All You Need [Shazeer *et al.*, 2019]
GQA: Training Generalized Multi-Query Transformer Models from Multi-Head Checkpoints [Ainslie *et al.*, 2023]

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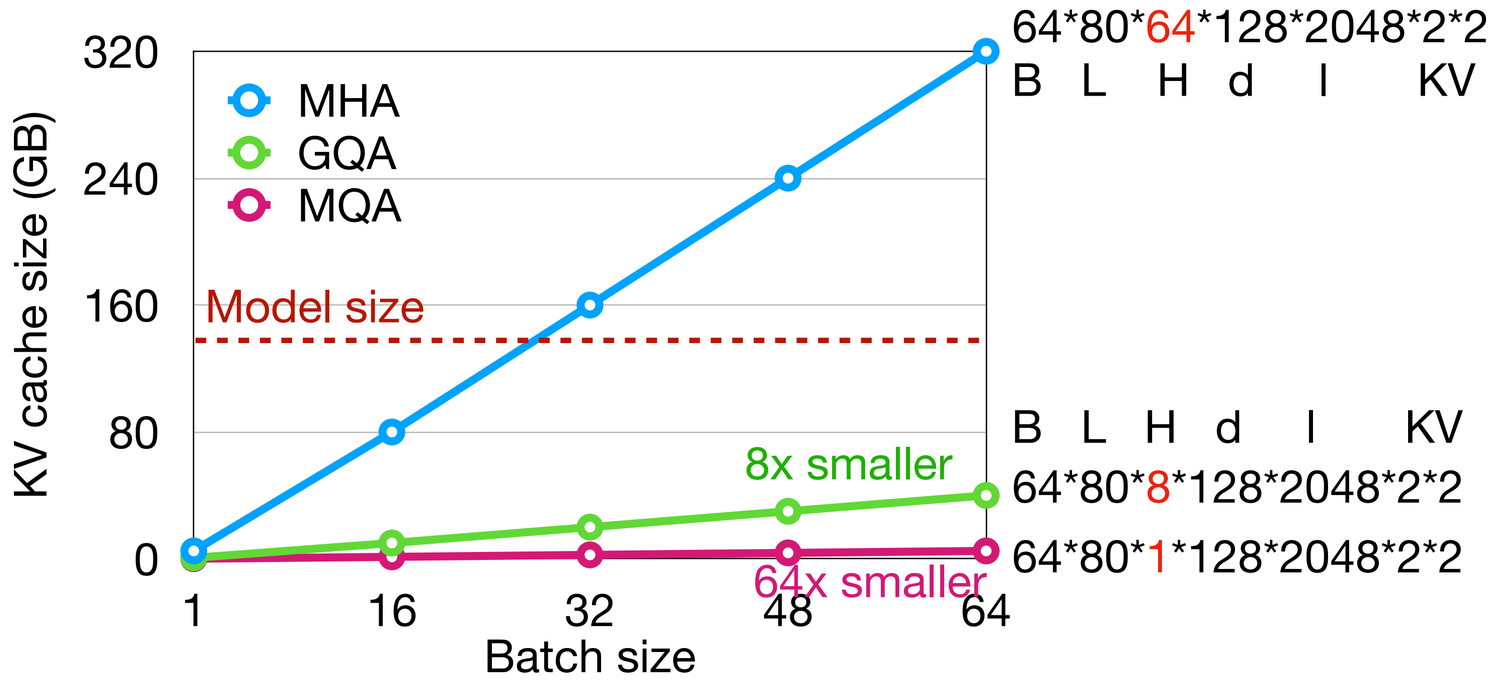

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- GQA matches the accuracy of MHA under a large model size

	BoolQ	PIQA	SIQA	Hella-Swag	ARC-e	ARC-c	NQ	TQA	MMLU	GSM8K	Human-Eval
MHA	**71.0**	**79.3**	48.2	75.1	71.2	**43.0**	12.4	44.7	**28.0**	4.9	**7.9**
MQA	70.6	79.0	47.9	74.5	71.6	41.9	**14.5**	42.8	26.5	4.8	7.3
GQA	69.4	78.8	**48.6**	**75.4**	**72.1**	42.5	14.0	**46.2**	26.9	**5.3**	**7.9**

Llama-2, 30B, 150B tokens

Llama 2: Open Foundation and Fine-Tuned Chat Models [Touvron et al., 2023]

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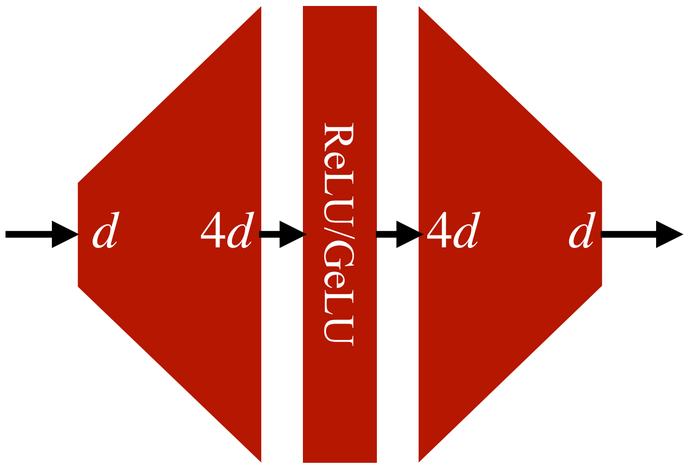
Gated Linear Units (GLU)

Improving over FFN

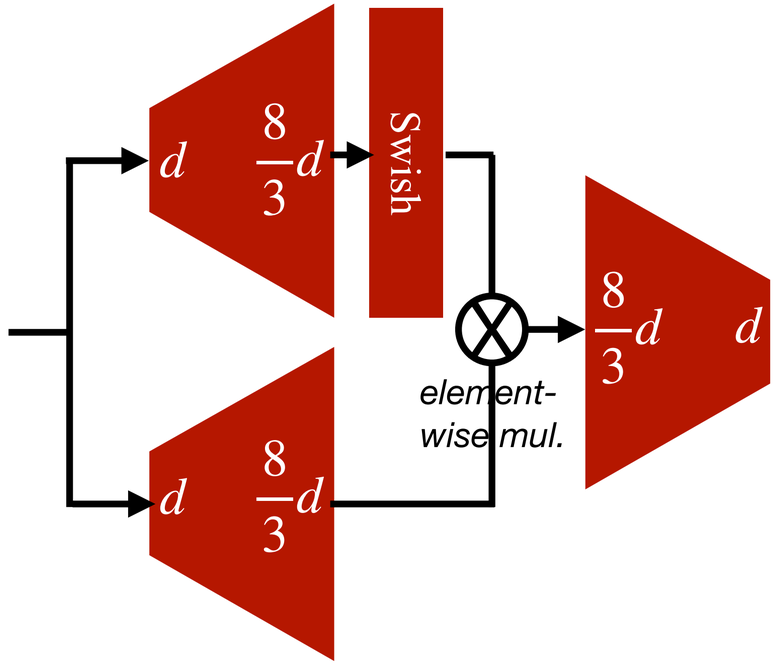
- Replacing the vanilla FFN with GLU improves Transformers

$$\mathrm{FFN}_{\mathrm{SwiGLU}}(x, W, V, W_2) = (\mathrm{Swish}_1(xW) \otimes xV)W_2$$

FFN



SwiGLU



PPL results

Training Steps	65,536	524,288
$\mathrm{FFN}_{\mathrm{ReLU}}$ (*baseline*)	1.997 (0.005)	1.677
$\mathrm{FFN}_{\mathrm{GELU}}$	1.983 (0.005)	1.679
$\mathrm{FFN}_{\mathrm{Swish}}$	1.994 (0.003)	1.683
$\mathrm{FFN}_{\mathrm{GLU}}$	1.982 (0.006)	1.663
$\mathrm{FFN}_{\mathrm{Bilinear}}$	1.960 (0.005)	1.648
$\mathrm{FFN}_{\mathrm{GEGLU}}$	**1.942** (0.004)	**1.633**
$\mathrm{FFN}_{\mathrm{SwiGLU}}$	**1.944** (0.010)	**1.636**
$\mathrm{FFN}_{\mathrm{ReGLU}}$	1.953 (0.003)	1.645

GLU Variants Improve Transformer [Shazeer, 2020]

Gated Linear Units (GLU)

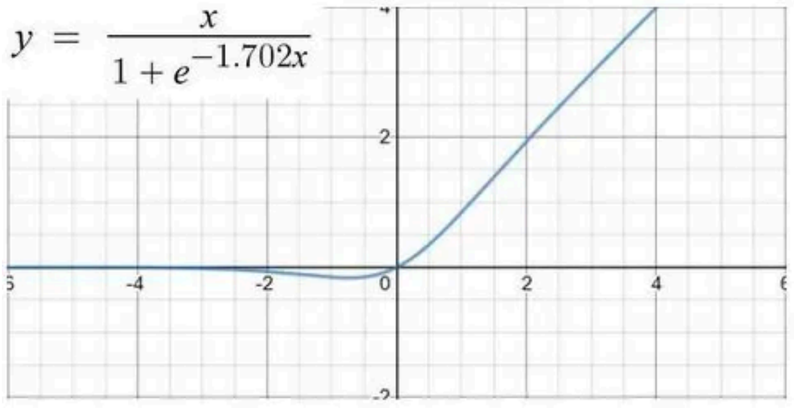
Improving over FFN

- Replacing the vanilla FFN with GLU improves Transformers

$$\mathrm{FFN}_{\mathrm{SwiGLU}}(x, W, V, W_2) = (\mathrm{Swish}_1(xW) \otimes xV)W_2$$

- Equation of activation functions

GeLU



Swish

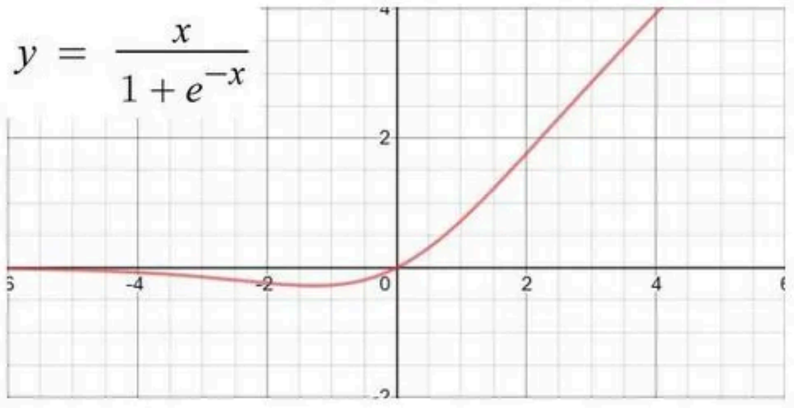


Image credit: https://towardsdatascience.com/on-the-disparity-between-swish-and-gelu-1ddde902d64b

PPL results

Training Steps	65,536	524,288
$\mathrm{FFN}_{\mathrm{ReLU}}(baseline)$	1.997 (0.005)	1.677
$\mathrm{FFN}_{\mathrm{GELU}}$	1.983 (0.005)	1.679
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$\mathrm{FFN}_{\mathrm{ReGLU}}$	1.953 (0.003)	1.645

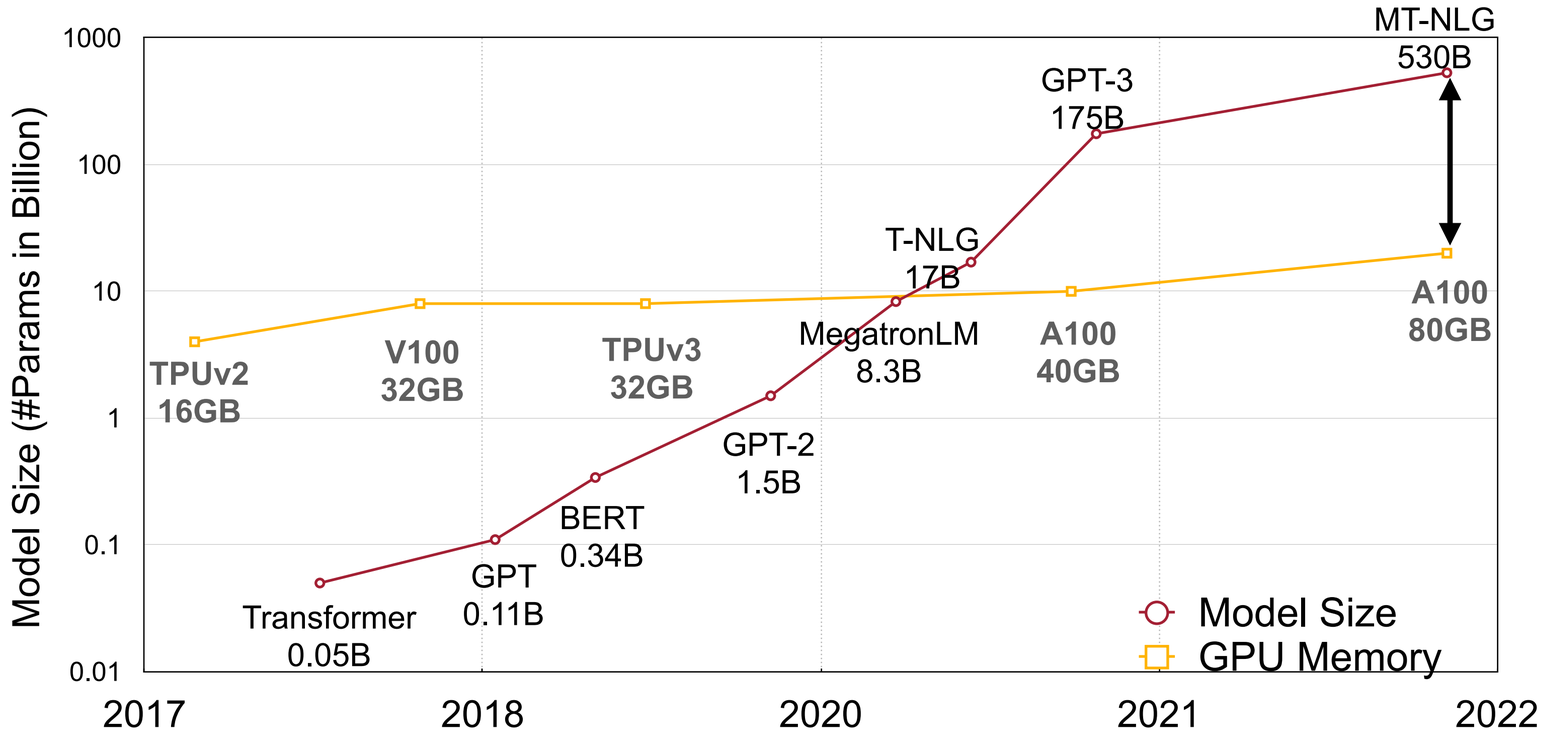
Searching for Activation Functions [Ramachandran et al., 2020]
Gaussian Error Linear Units (GELUs) [Hendrycks and Gimpel, 2016]

III. Large language models (LLMs)

Large Language Models (LLMs)

The growing trend of scaling up

- LLMs are scaled-up transformers models trained on large language corpus (natural language, code, etc.)

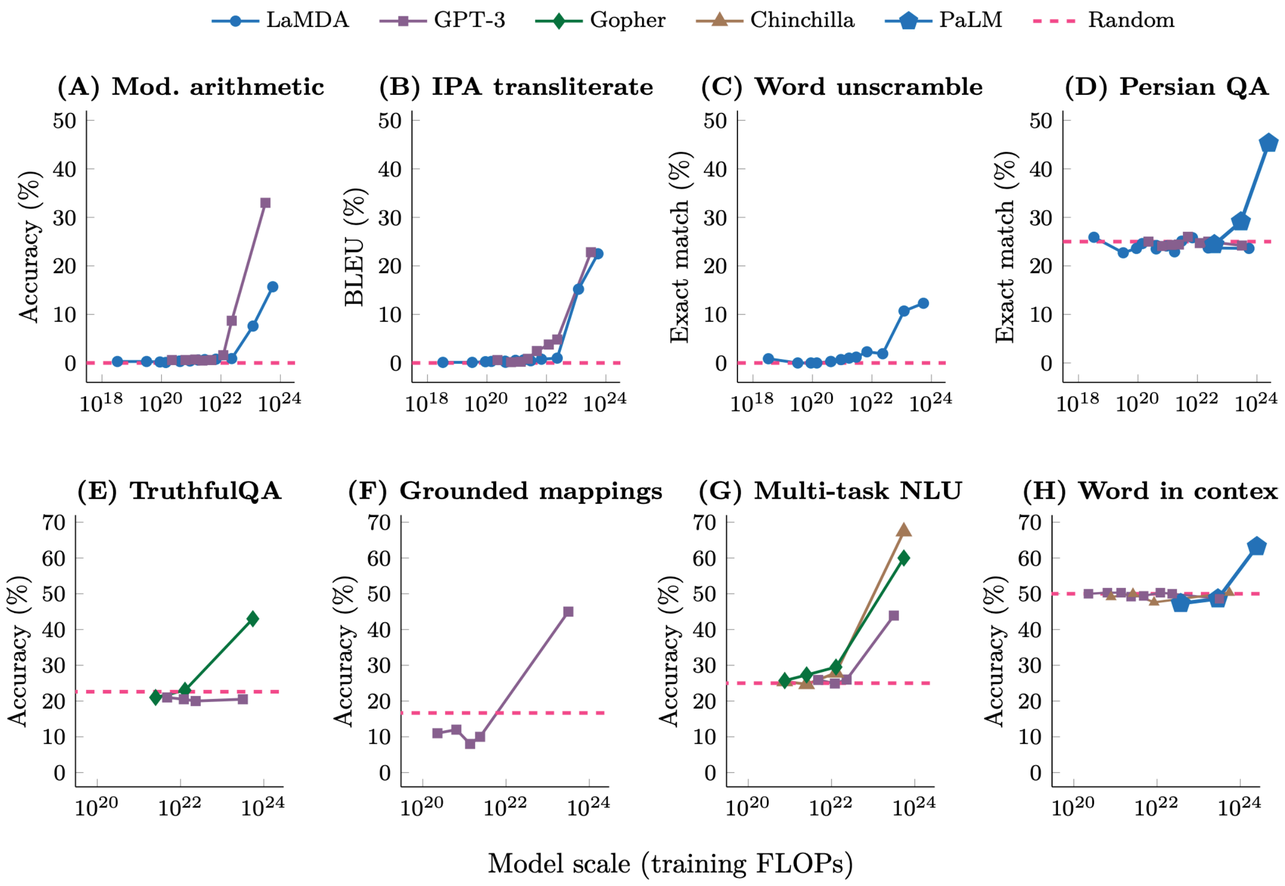


SmoothQuant: Accurate and Efficient Post-Training Quantization for Large Language Models [Xiao *et al.*, 2022]

Scaling Up Unlocks More Capabilities

The “emergent” abilities

- LLMs exhibit some “emergent” abilities that are only available with a large enough model size



(a) Modified arithmetic

```
In the following lines, the symbol -> represents a simple mathematical operation.
100 + 200 -> 301
1 + 1 -> 3
2 + 2 -> 5
```

(c) Word unscrambling

```
Input: The word hte is a scrambled version of the English word
Output: the
Input: The word sohpto is a scrambled version of the English word
Output: photos
```

Emergent Abilities of Large Language Models [Wei *et al.*, 2022]

GPT-3

Scaling up Transformers to be few-shot learners (in-context learning)

- Traditional NLP pipeline:
  - Pretraining
  - **Fine-tuning** on downstream tasks

Language Models are Few-Shot Learners [Brown *et al.*, 2020]

GPT-3

Scaling up Transformers to be few-shot learners (in-context learning)

- Scaled-up LLM (175B) can generalize to new tasks **w/o** fine-tuning by either
  - **Zero-shot**: answer questions given task descriptions
  - **Few-shot**: learn with demonstrations

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

```
1  Translate English to French:        ← task description
2  cheese =>                           ← prompt
```

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

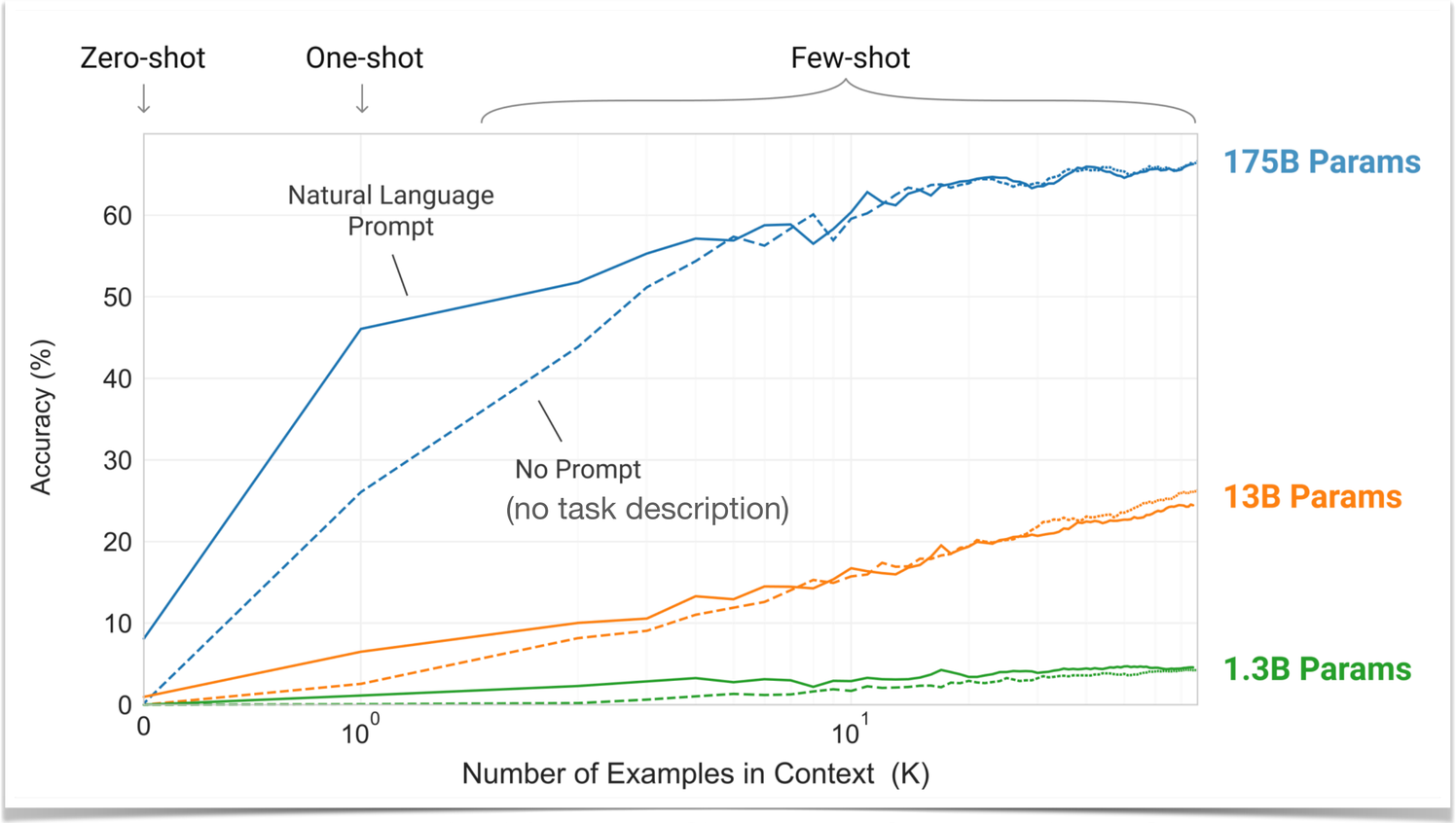
```
1  Translate English to French:        ← task description
2  sea otter => loutre de mer          ← examples
3  peppermint => menthe poivrée        ←
4  plush girafe => girafe peluche      ←
5  cheese =>                           ← prompt
```

Language Models are Few-Shot Learners [Brown *et al.*, 2020]

GPT-3

Scaling up Transformers to be few-shot learners (in-context learning)

- Scaled-up LLM (175B) can generalize to new tasks **w/o** fine-tuning by either
  - **Larger** models can more **effectively** utilize few-shot demonstrations
  - With more demonstrations, the no-prompt accuracy catches up with the task-prompted accuracy

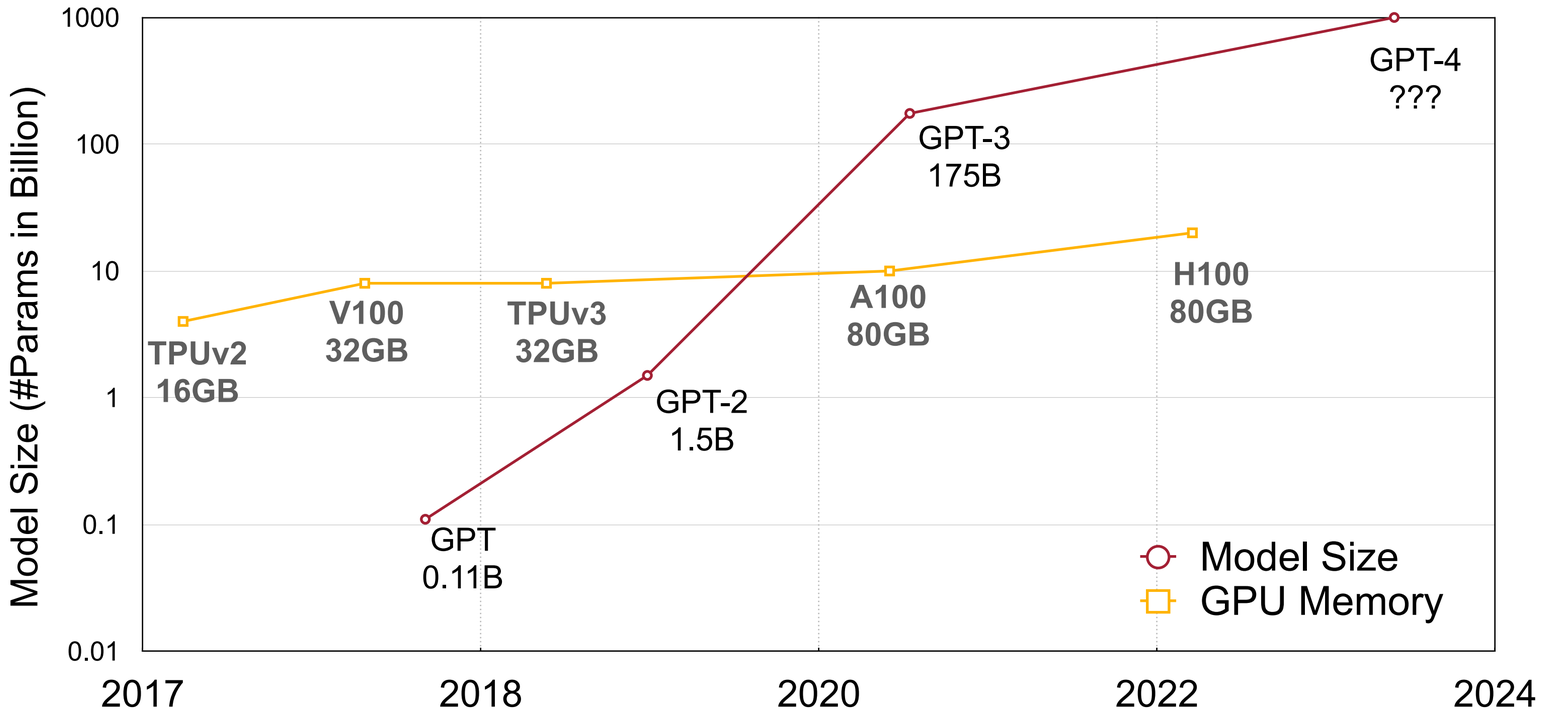


Language Models are Few-Shot Learners [Brown *et al.*, 2020]

GPT Family

The history of scaling for GPT models

- GPT-1 (2018): 117 million
- GPT-2 (2019): 1.5B
- GPT-3 (2020): 175B
- GPT-4 (2023): ???

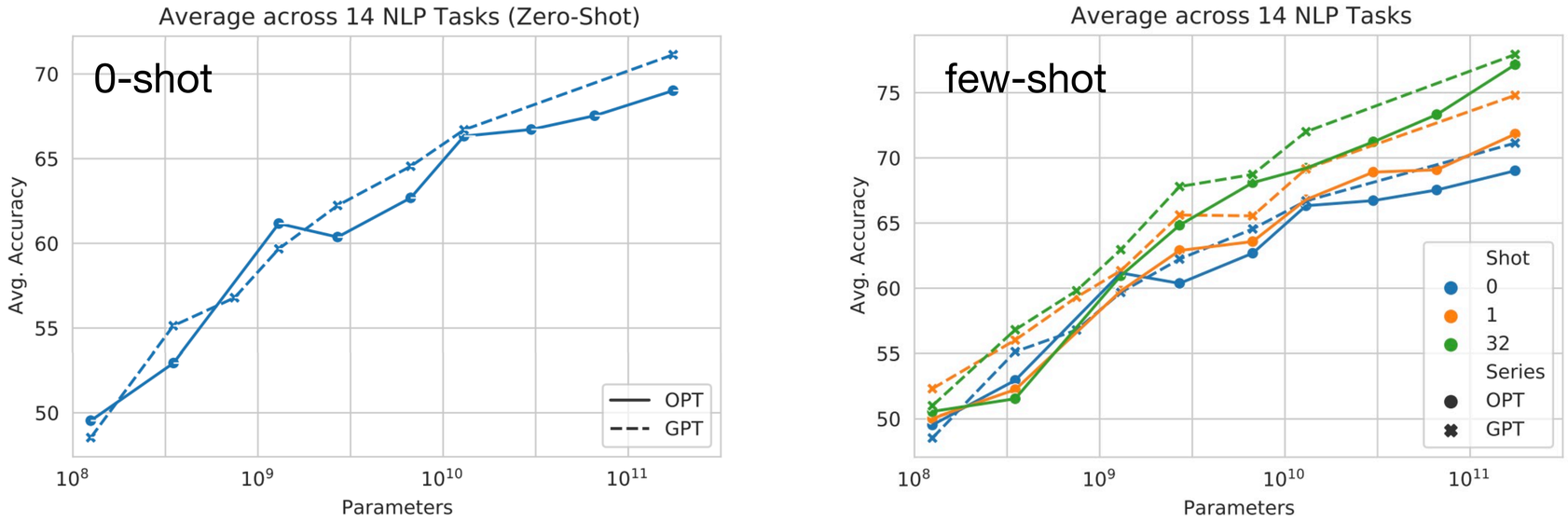


Language Models are Few-Shot Learners [Brown *et al.*, 2020]

OPT

Open Pre-trained Transformer Language Models

- Open-source pre-trained LLM from Meta
- Size: 125M/350M/1.3B/2.7B/6.7B/13B/30B/66B/175B
- Design choices: Decoder-only, Pre-norm (post-norm for 350M), ReLU activation in FFN
- 175B model: hidden dimension 12288, #heads 96, vocab size 50k, context length 2048
- Close performance compared to GPT models



OPT: Open Pre-trained Transformer Language Models [Zhang *et al.*, 2022]

BLOOM

Open Pre-trained Transformer Language Models

- Open-source pre-trained LLM from BigScience (and opensource community)
- Size: 560M/1.1B/1.7B/3B/7.1B/176B
- Design choices: Decoder-only, Pre-norm, GeLU activation in FFN, ALiBI positional embedding
- 176B model: hidden dimension 14336, #heads 112, vocab size 250k, context length 2048
- Support multi-lingual (59 languages in the corpus)

BLOOM: A 176B-Parameter Open-Access Multilingual Language Model [BigScience, 2022]

LLaMA

Significantly better opensource LLMs

- Open-source pre-trained LLM from Meta
- Size: 7B/13B/33B/65B
- Design choices: Decoder-only, Pre-norm, **SwiGLU (swish, gated linear units)**, rotary positional embedding (RoPE)
- 7B model: hidden dimension 4096, #heads 32, #layers 32, vocab size 32k, context length 2048
- 65B model: hidden dimension 8192, #heads 64, #layers 80, vocab size 32k, context length 2048
- Much better performance compared to previous opensource models

$$\mathrm{FFN}_{\mathrm{SwiGLU}}(x, W, V, W_2) = (\mathrm{Swish}_1(xW) \otimes xV)W_2$$

		BoolQ	PIQA	SIQA	HellaSwag	WinoGrande	ARC-e	ARC-c	OBQA
GPT-3	175B	60.5	81.0	-	78.9	70.2	68.8	51.4	57.6
Gopher	280B	79.3	81.8	50.6	79.2	70.1	-	-	-
Chinchilla	70B	83.7	81.8	51.3	80.8	74.9	-	-	-
PaLM	62B	84.8	80.5	-	79.7	77.0	75.2	52.5	50.4
PaLM-cont	62B	83.9	81.4	-	80.6	77.0	-	-	-
PaLM	540B	**88.0**	82.3	-	83.4	**81.1**	76.6	53.0	53.4
LLaMA	7B	76.5	79.8	48.9	76.1	70.1	72.8	47.6	57.2
	13B	78.1	80.1	50.4	79.2	73.0	74.8	52.7	56.4
	33B	83.1	82.3	50.4	82.8	76.0	**80.0**	**57.8**	58.6
	65B	85.3	**82.8**	**52.3**	**84.2**	77.0	78.9	56.0	**60.2**

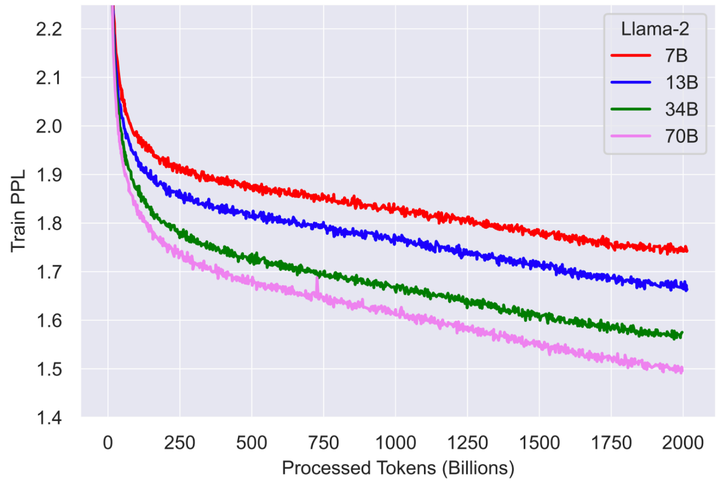
LLaMA: Open and Efficient Foundation Language Models [Touvron *et al.*, 2023]

Llama 2

Better performance from a larger training corpus

- Larger context length (2k -> 4k)
- More training tokens (1T/1.4T -> 2T, no sign of saturation yet)
- GQA for larger models (70B, 64 heads, 8 kv heads)
- Also include Llama-2-chat, an instruction-tuned version

Benchmark (shots)	GPT-3.5	GPT-4	PaLM	PaLM-2-L	LLAMA 2
MMLU (5-shot)	70.0	**86.4**	69.3	78.3	68.9
TriviaQA (1-shot)	–	–	81.4	**86.1**	85.0
Natural Questions (1-shot)	–	–	29.3	**37.5**	33.0
GSM8K (8-shot)	57.1	**92.0**	56.5	80.7	56.8
HumanEval (0-shot)	48.1	**67.0**	26.2	–	29.9
BIG-Bench Hard (3-shot)	–	–	52.3	**65.7**	51.2

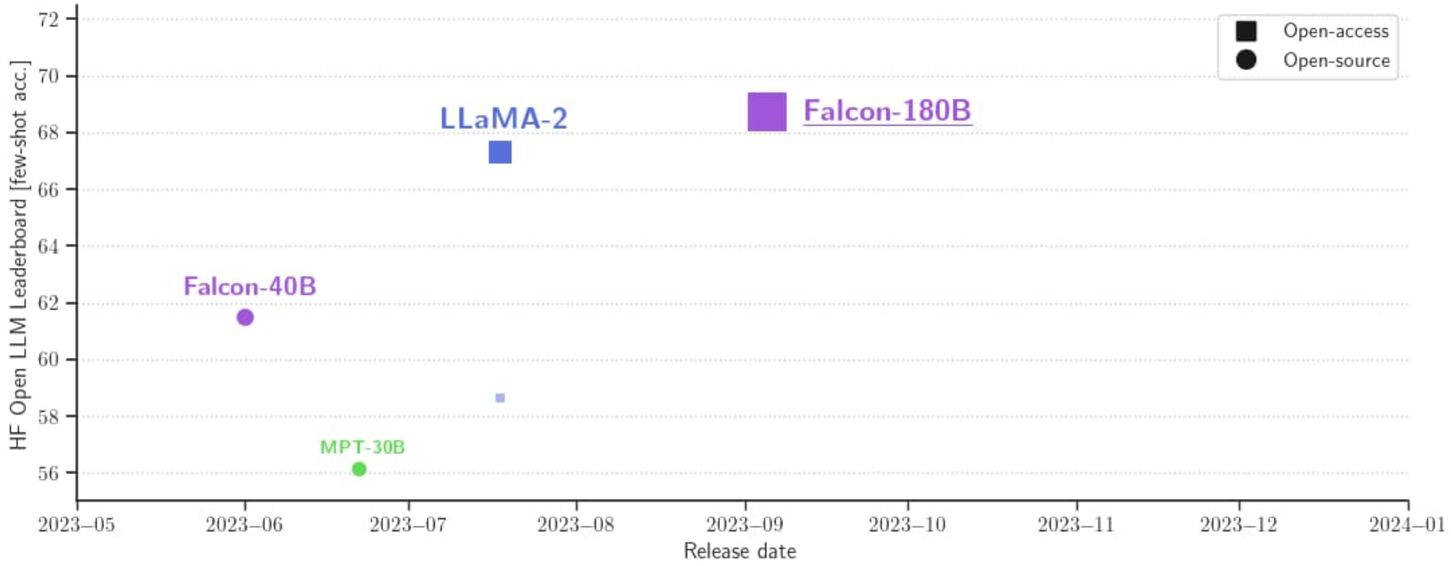


LLaMA: Open and Efficient Foundation Language Models [Touvron *et al.*, 2023]

Falcon

open-source LLM

- Size: 1.3B/7.5B/40B/**180B**
- **180B** model: hidden dimension 14848, #heads 232, #kv heads 8, #layers 80, vocab size 65k
- Comparable performance as PaLM-2 Large

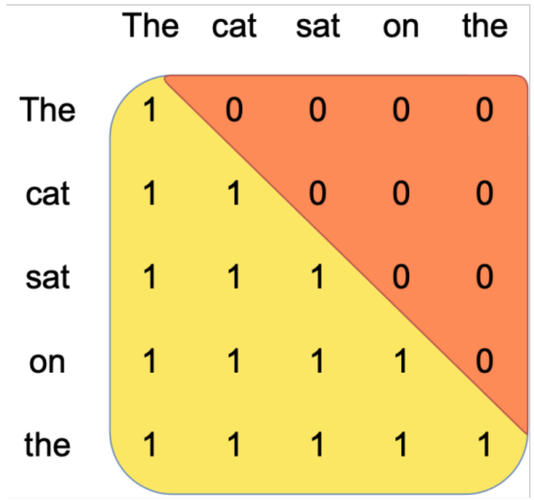


LLaMA: Open and Efficient Foundation Language Models [Touvron *et al.*, 2023]

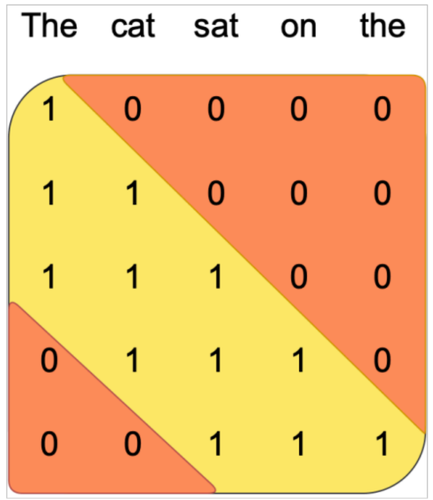
Mistral-7B

Small model with superior performance

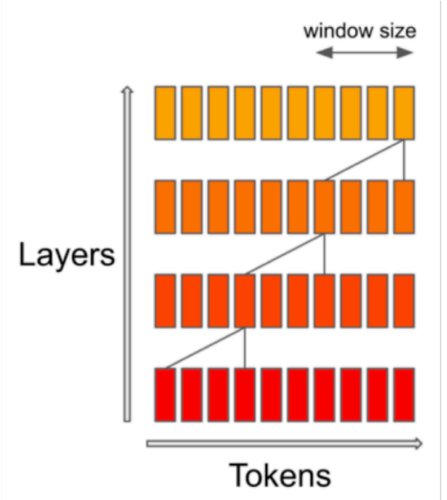
- 7B model that outperforms Llama-2-13B, Llama-34B
- hidden dimension 4096, #heads 32, #kv heads 8, #layers 32, vocab size 32k, context length 8k
- Grouped-query attention (GQA)
- **Sliding window** attention (SWA) for longer effective context length at a small cost



Vanilla Attention



Sliding Window Attention



Effective Context Length

How to scale up?

The Chinchilla Law

- We need to scale up **both** the model size and data size for training to have the best **training** computation vs. accuracy trade-off
- **Note**: the trade-off is different if we consider the **inference** computation trade-off
  - You want to train a smaller model longer to save inference costs (e.g., LLaMA)!

Parameters	FLOPs	FLOPs (in *Gopher* unit)	Tokens
400 Million	1.92e+19	1/29,968	8.0 Billion
1 Billion	1.21e+20	1/4,761	20.2 Billion
10 Billion	1.23e+22	1/46	205.1 Billion
67 Billion	5.76e+23	1	1.5 Trillion
175 Billion	3.85e+24	6.7	3.7 Trillion
280 Billion	9.90e+24	17.2	5.9 Trillion
520 Billion	3.43e+25	59.5	11.0 Trillion
1 Trillion	1.27e+26	221.3	21.2 Trillion
10 Trillion	1.30e+28	22515.9	216.2 Trillion

Llama-2 model goes beyond the #tokens by a lot (7B, 2T tokens)

Training Compute-Optimal Large Language Models [Hoffmann *et al.*, 2022]

IV. Advanced Topics

Multi-modal LLMs

Towards LLMs that can see

- GPT-4V(ision) can take visual inputs

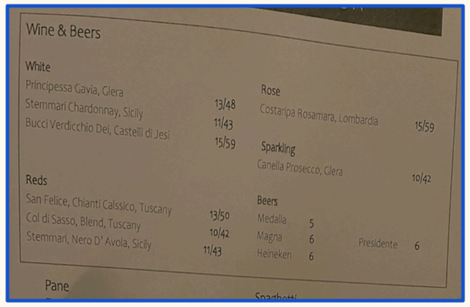
Prompt:
How much did I pay for tax?
Where is the information?

Prompt Continued

GPT-4V:
In the first receipt, you paid $3.72 for tax. The information is located at the bottom of the receipt. In the second receipt, you paid $42.23 for tax. The information is located near the bottom of the receipt, under the "Sales Tax" line. In the third receipt, you paid $4.58 for tax. The information is located at the bottom of the receipt, under the "TAX" line. In total, you paid $50.53 in tax across all three receipts.

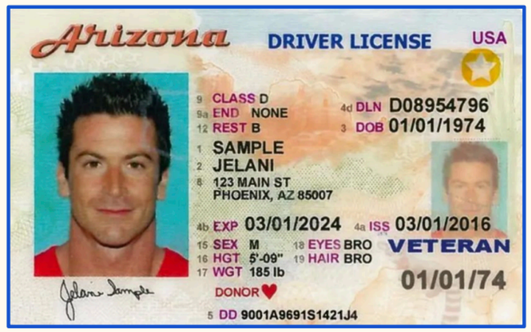
Prompt:
How much should I pay for the beer on the table according to the price on the menu?

Here is a photo of the menu.



GPT-4V:
According to the menu, the price for a Magna beer is $6. Since there are two Magna beers on the table, the total cost for the beers would be $12.

Prompt:
Please read the text in this image and return the information in the following JSON format (note xxx is placeholder, if the information is not available in the image, put "N/A" instead).
{"class": xxx, "DLN": xxx, "DOB": xxx, "Name": xxx, "Address": xxx, "EXP": xxx, "ISS": xxx, "SEX": xxx, "HGT": xxx, "WGT": xxx, "EYES": xxx, "HAIR": xxx, "DONOR": xxx}



GPT-4V:
{"class": "D", "DLN": "D08954796", "DOB": "01/01/1974", "Name": "Jelani Sample", "Address": "123 Main St, Phoenix, AZ 85007", "EXP": "03/01/2024", "ISS": "03/01/2016", "SEX": "M", "HGT": "5-09", "WGT": "185 lbs", "EYES": "BRO", "HAIR": "N/A", "DONOR": "Y"}

The Dawn of LMMs: Preliminary Explorations with GPT-4V(ision) [Yang et al., 2013]

Multi-modal LLMs

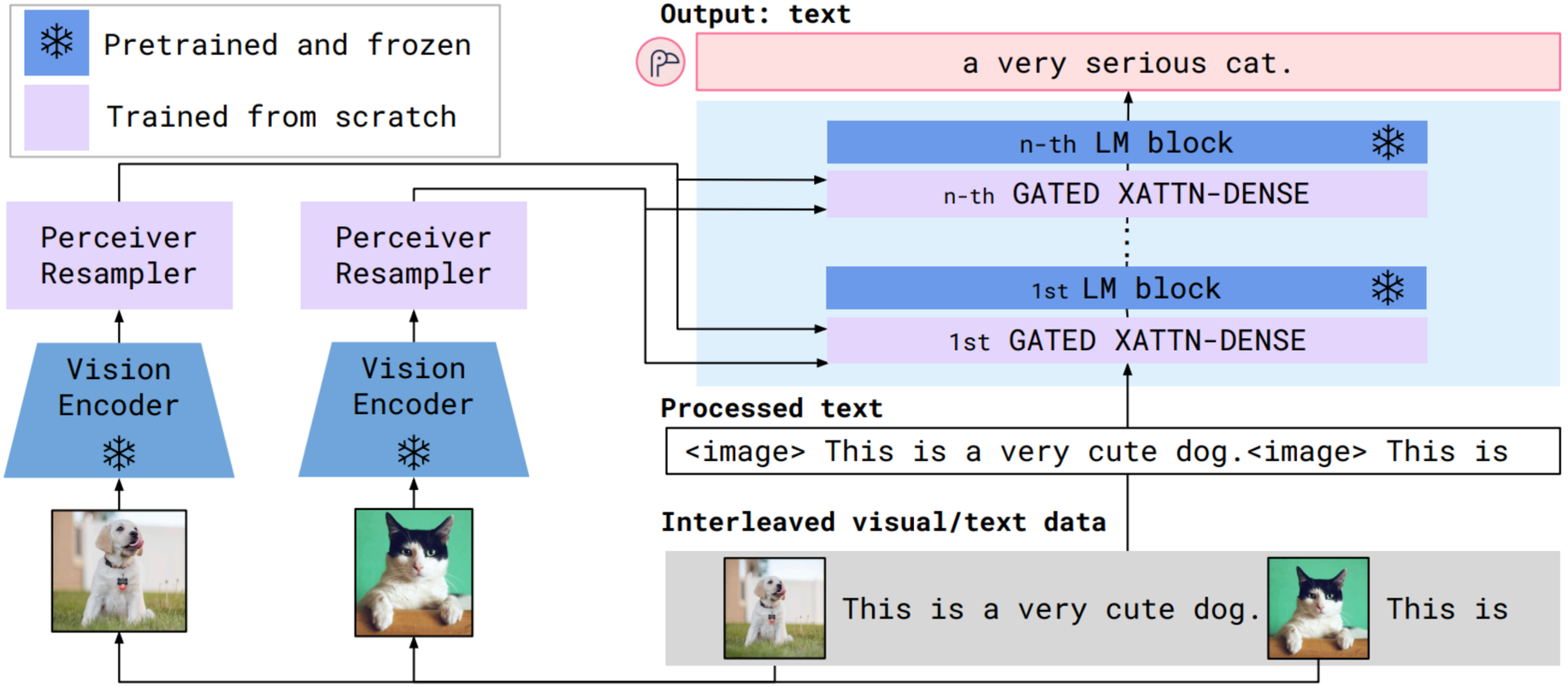
Two ways for visual language models

- Cross-attention from visual to LLM (Flamingo)
- Visual tokens as input (PaLM-E)

Flamingo

Cross-attention-based VLMs

- Pioneer work on enabling visual input support for LLMs
- LLM is frozen, added cross-attention layers to the intermediate layers of LLMs



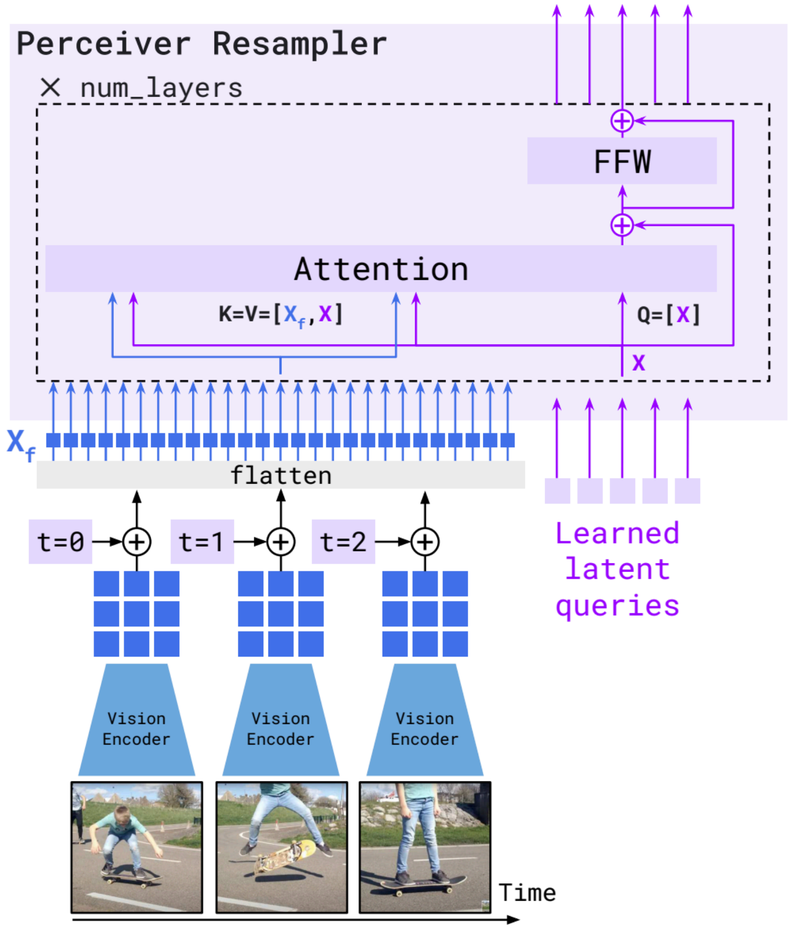
Flamingo: a Visual Language Model for Few-Shot Learning [Alayrac et al., 2022]

Flamingo

Cross-attention-based VLMs

- **Perceiver Resampler**: from varying-size large feature maps to few fixed-size visual tokens

- visual tokens: `[27, dim]`
- learned queries (Q): `[5, dim]`
- K&V: `[32, dim]`
- Attention map: `[5, 32]`
- output: `[5, dim]`



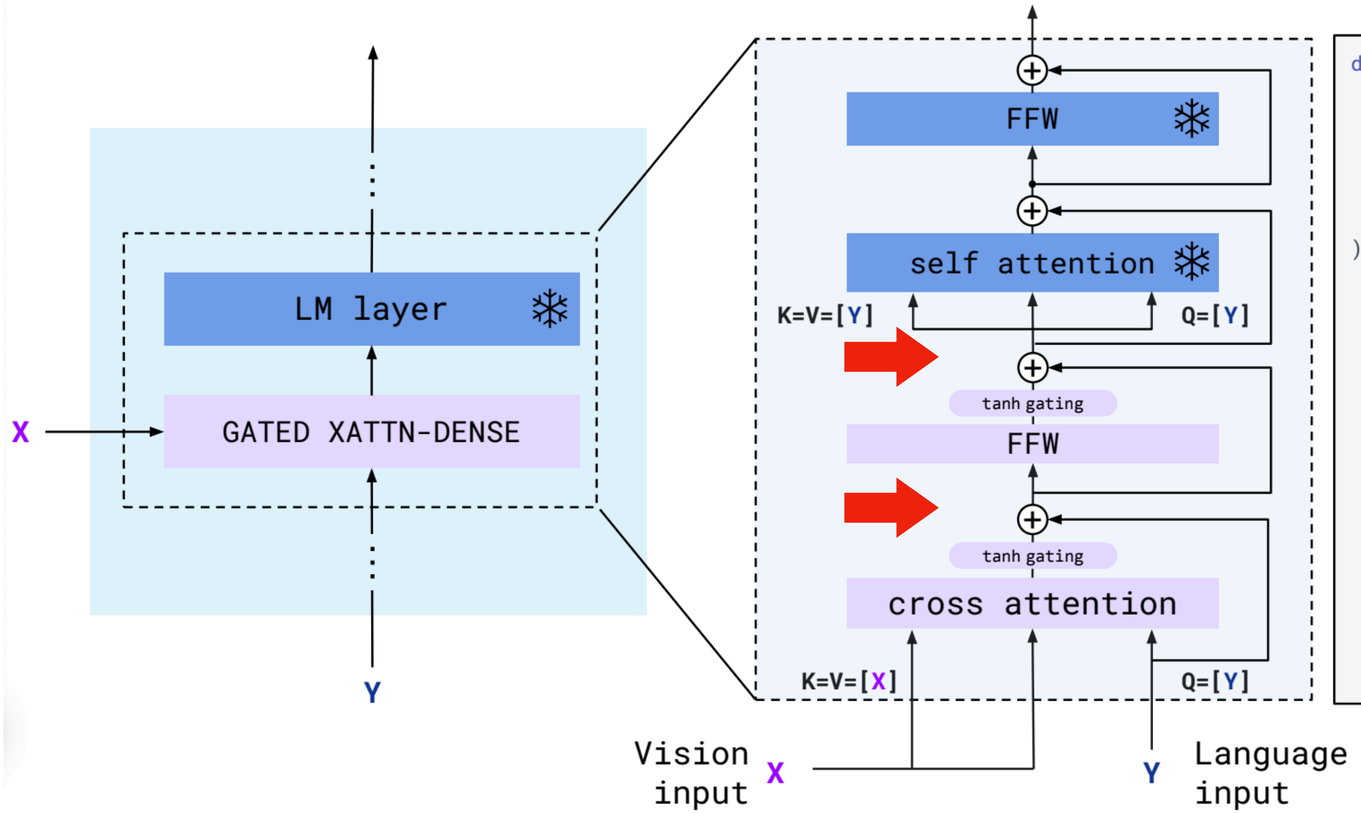

```
def perceiver_resampler(
    x_f,  # The [T, S, d] visual features (T=time, S=space)
    time_embeddings,  # The [T, 1, d] time pos embeddings.
    x,  # R learned latents of shape [R, d]
    num_layers,  # Number of layers
):
  """The Perceiver Resampler model."""

  # Add the time position embeddings and flatten.
  x_f = x_f + time_embeddings
  x_f = flatten(x_f)  # [T, S, d] -> [T * S, d]
  # Apply the Perceiver Resampler layers.
  for i in range(num_layers):
    # Attention.
    x = x + attention_i(q=x, kv=concat([x_f, x]))
    # Feed forward.
    x = x + ffw_i(x)
  return x
```

Flamingo: a Visual Language Model for Few-Shot Learning [Alayrac et al., 2022]

Flamingo

Cross-attention-based VLMs

- **Gated** cross-attention layer
  - Use a Tanh gate to control the amount of visual information




```
def gated_xattn_dense(
    y,  # input language features
    x,  # input visual features
    alpha_xattn, # xattn gating parameter – init at 0.
    alpha_dense, # ffw gating parameter – init at 0.
):
  """Applies a GATED XATTN-DENSE layer."""

  # 1. Gated Cross Attention
  y = y + tanh(alpha_xattn) * attention(q=y, kv=x)
  # 2. Gated Feed Forward (dense) Layer
  y = y + tanh(alpha_dense) * ffw(y)

  # Regular self-attention + FFW on language
  y = y + frozen_attention(q=y, kv=y)
  y = y + frozen_ffw(y)
  return y  # output visually informed language features
```

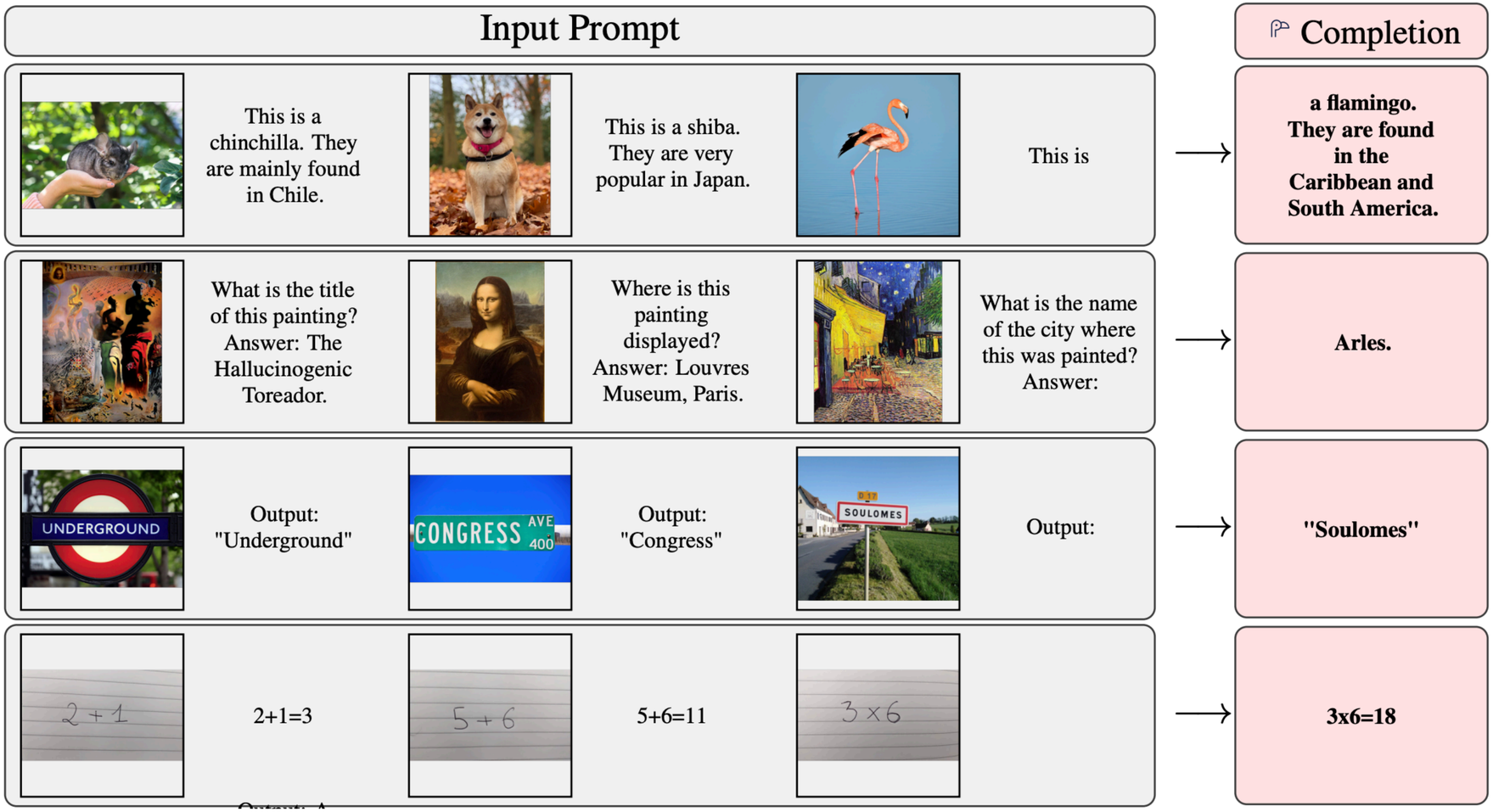
init with 0

Flamingo: a Visual Language Model for Few-Shot Learning [Alayrac et al., 2022]

Flamingo

Cross-attention-based VLMs

- In-context learning capability

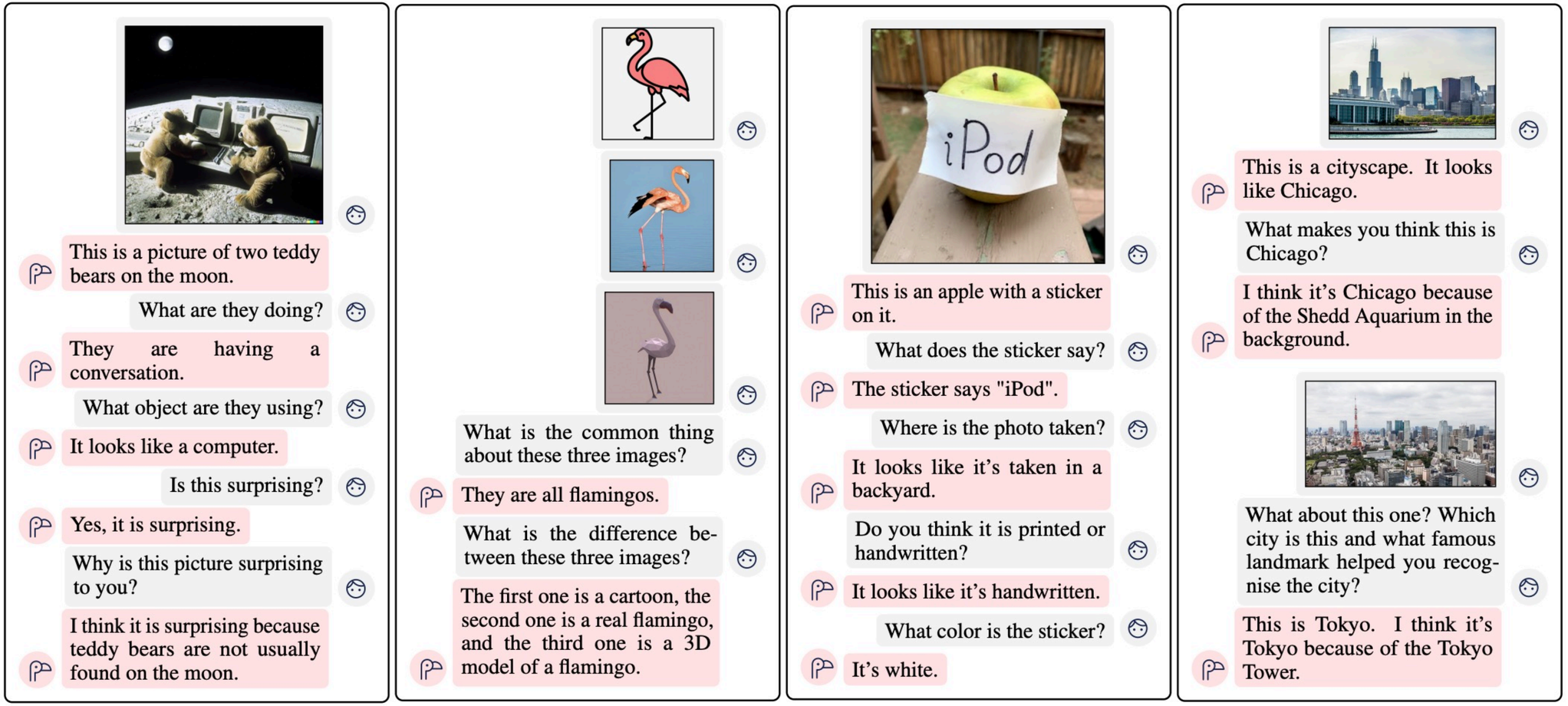


Flamingo: a Visual Language Model for Few-Shot Learning [Alayrac et al., 2022]

Flamingo

Cross-attention-based VLMs

- Visual dialogue

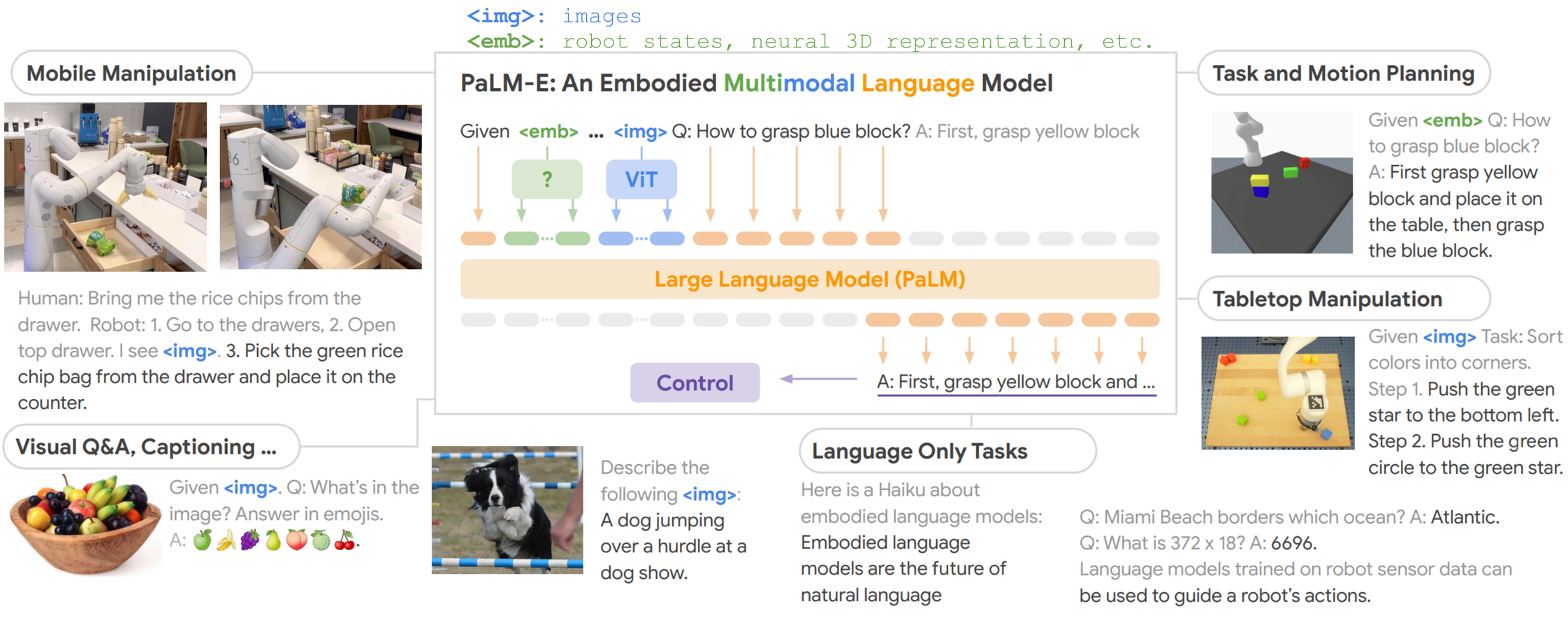


Flamingo: a Visual Language Model for Few-Shot Learning [Alayrac et al., 2022]

PaLM-E

Taking visual inputs (or other modalities) as tokens

- Support flexible modalities (e.g., visual, action)

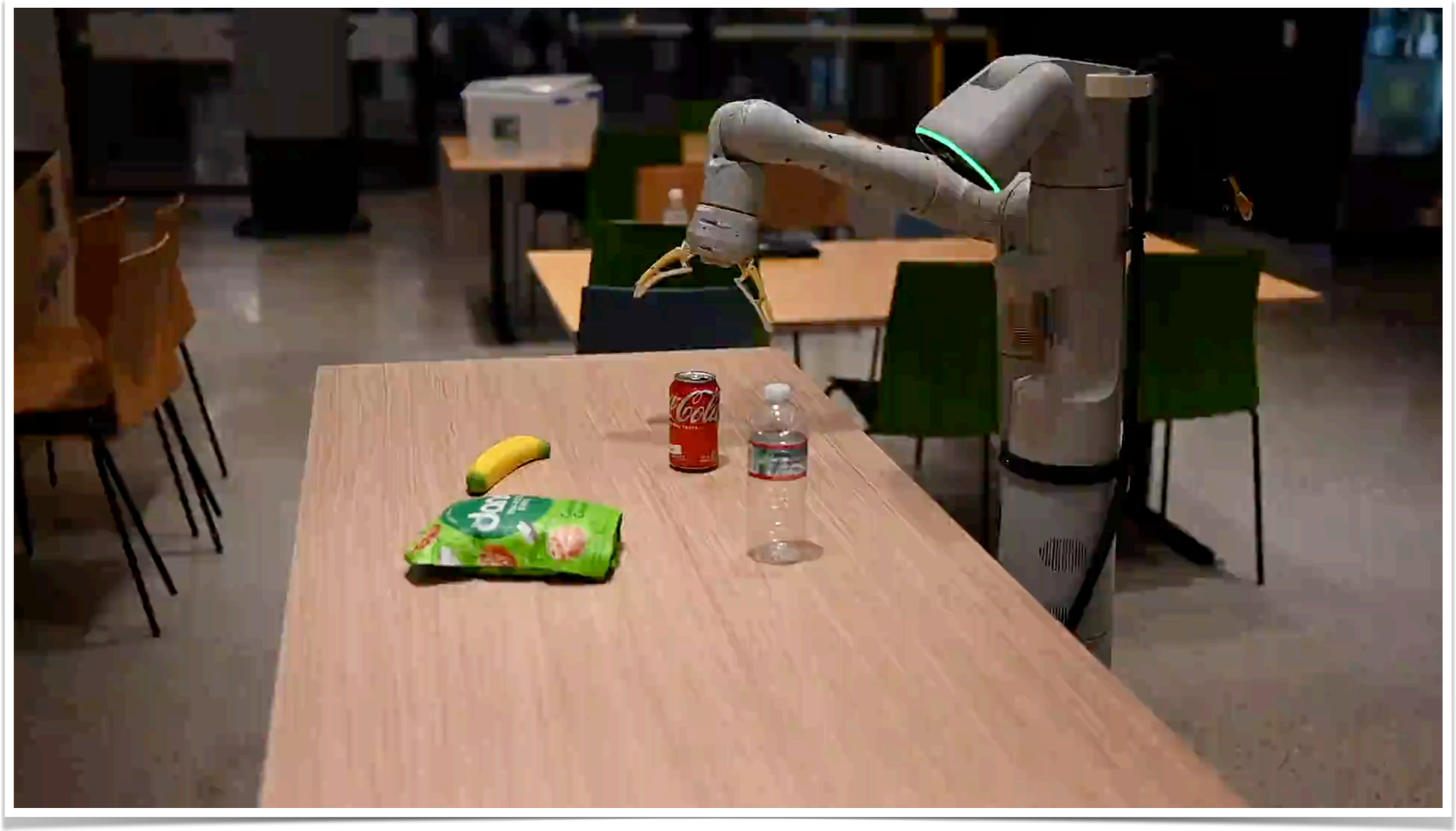


PaLM-E: An Embodied Multimodal Language Model [Driess et al., 2022]

PaLM-E -> RT-2

Taking visual inputs (or other modalities) as tokens

- Can directly output control signals



RT-2: Vision-Language-Action Models Transfer Web Knowledge to Robotic Control [Brohan et al., 2023]

Multi-modal LLMs

Applications

- *Corner case handling* in autonomous driving

image credit: https://datagen.tech/blog/how-synthetic-data-addresses-edge-cases-in-production/

Q: What is unusual about this image?

A: The unusual aspect of this image is that a chair is flying through the air on a highway, seemingly coming out of the back of a truck.

Q: What should you do if you encounter this?

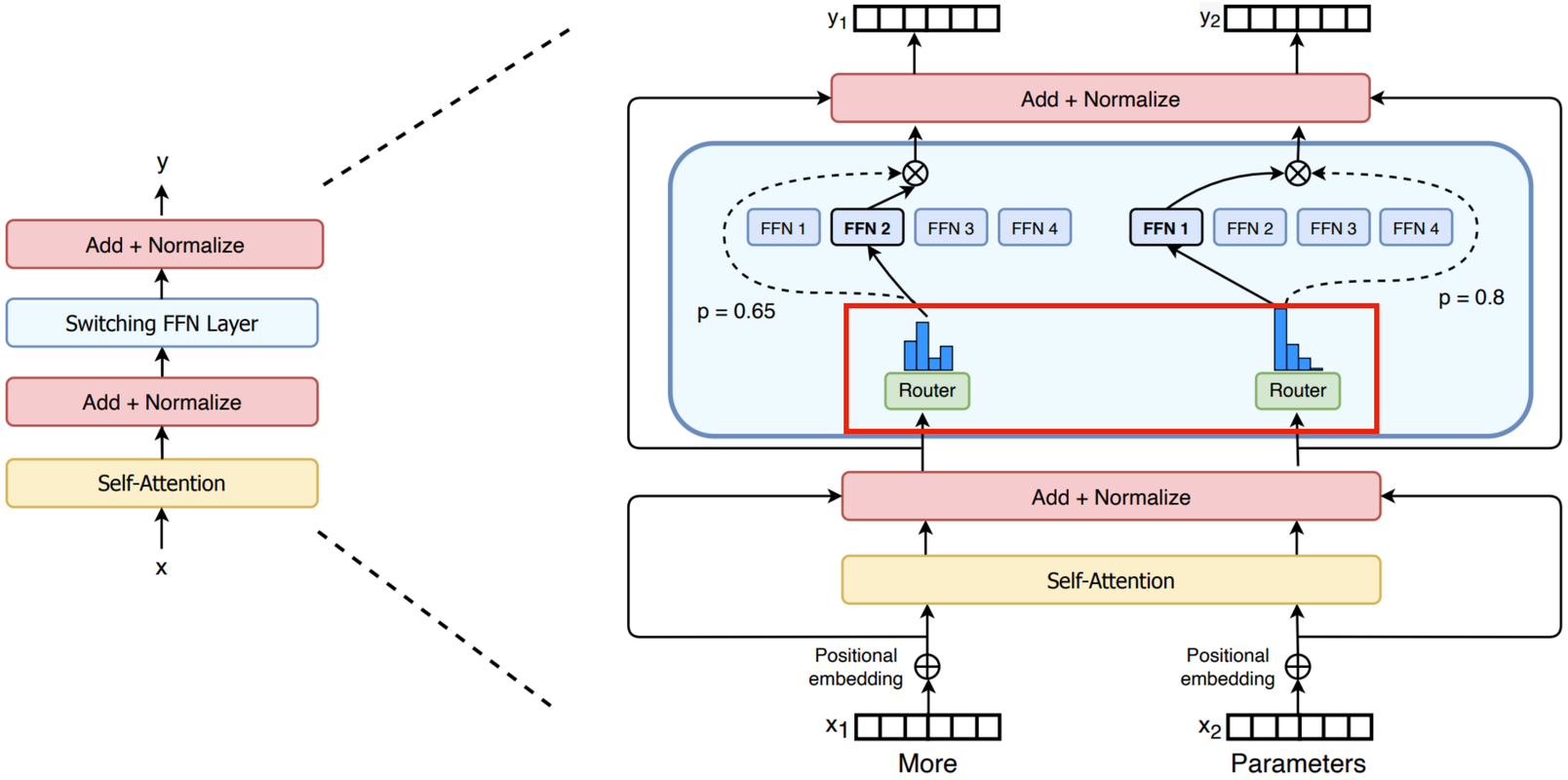
A: If you encounter this situation, you should immediately stop your vehicle and move to a safe distance from the truck and the flying chair. It is essential to avoid any potential hazards and contact the authorities to report the incident and ensure the safety of everyone involved.

Work in Progress [Lin et al., 2023]

Mixture-of-Experts (MoE)

Sparsely activated for each token

- MoE allows us to sparsely use part of the parameters for each token during inference
- It can increase the **total** amount of parameters without increasing inference costs **per token**
- A router will distribute the workload among different experts

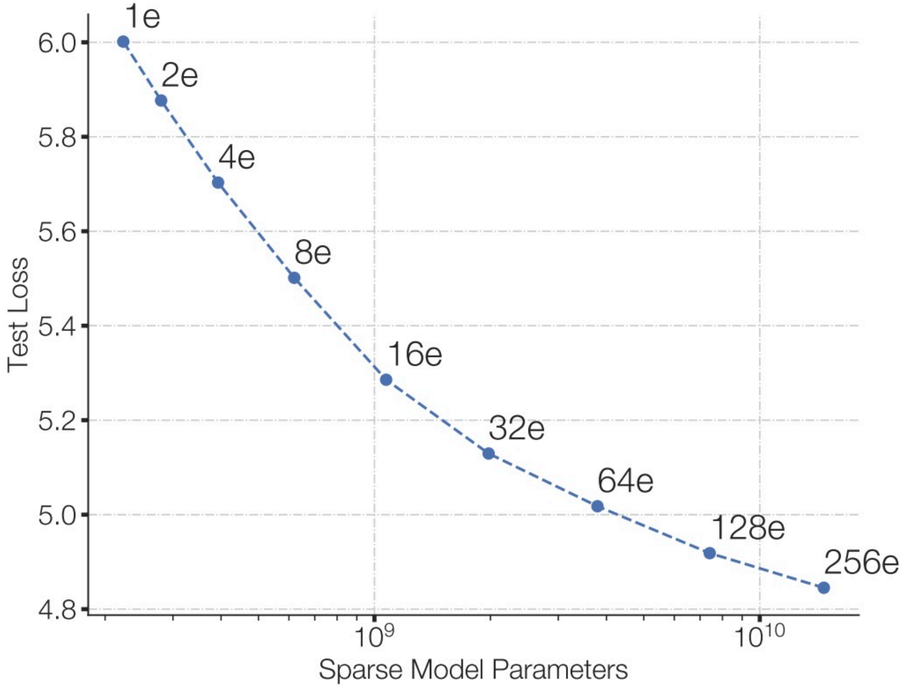


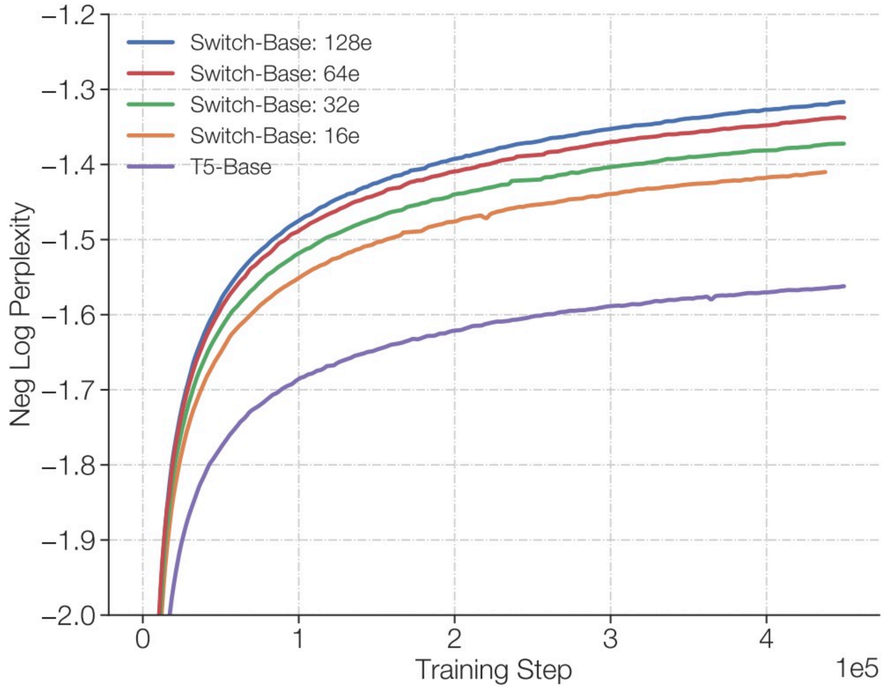
Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity [Fedus et al., 2022]

Mixture-of-Experts (MoE)

Sparsely activated for each token

- MoE allows us to use only part of the parameters for each token during inference
- It can increase the **total** amount of parameters without increasing inference costs **per token**
- A router will distribute the workload among different experts
- More experts -> larger total model size -> lower loss/better perplexity



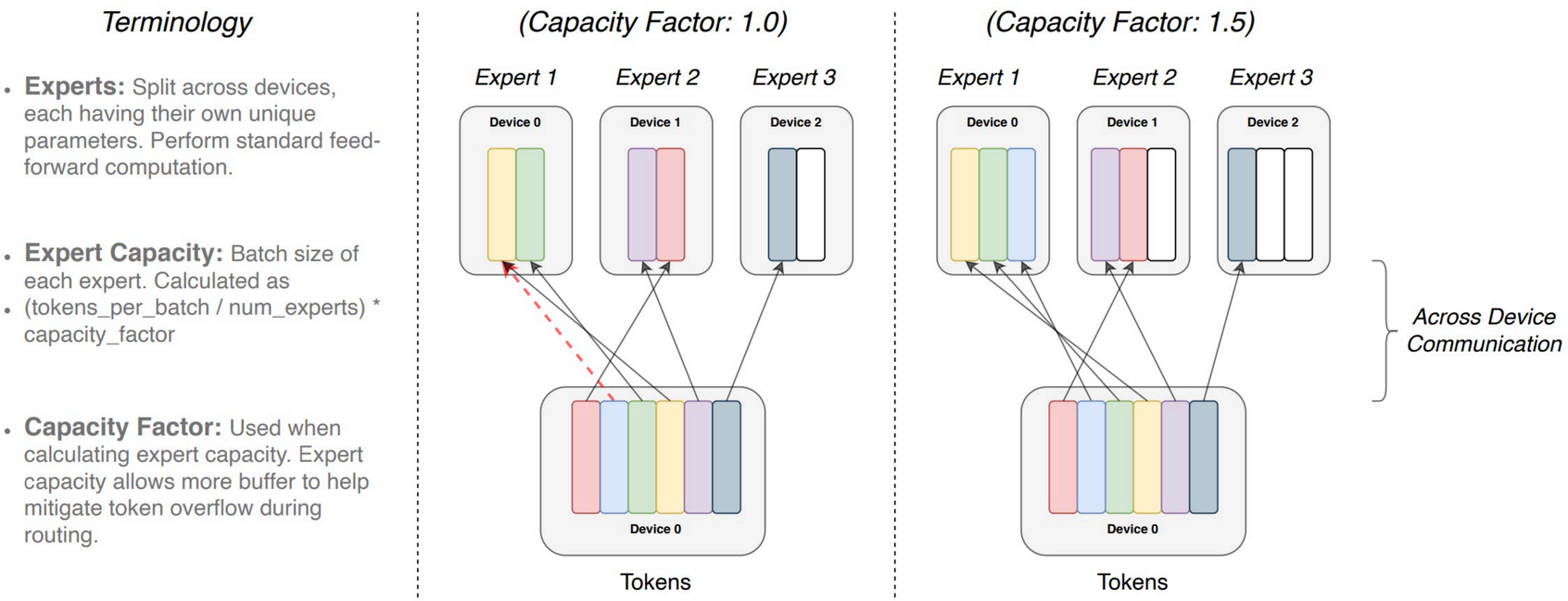


Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity [Fedus et al., 2022]

Mixture-of-Experts (MoE)

Sparsely activated for each token

- A key component of MoE is the routing function
- Capacity factor $C = \left(\frac{\text{tokens per batch}}{\text{number of experts}}\right) \times \text{capacity factor}.$
- $C = 1$, every expert can process at most 6/3*1=2 tokens; one token is skipped
- $C = 1.5$, every expert can process at most 6/3*1.5=3 tokens; slack capacity for expert 2&3

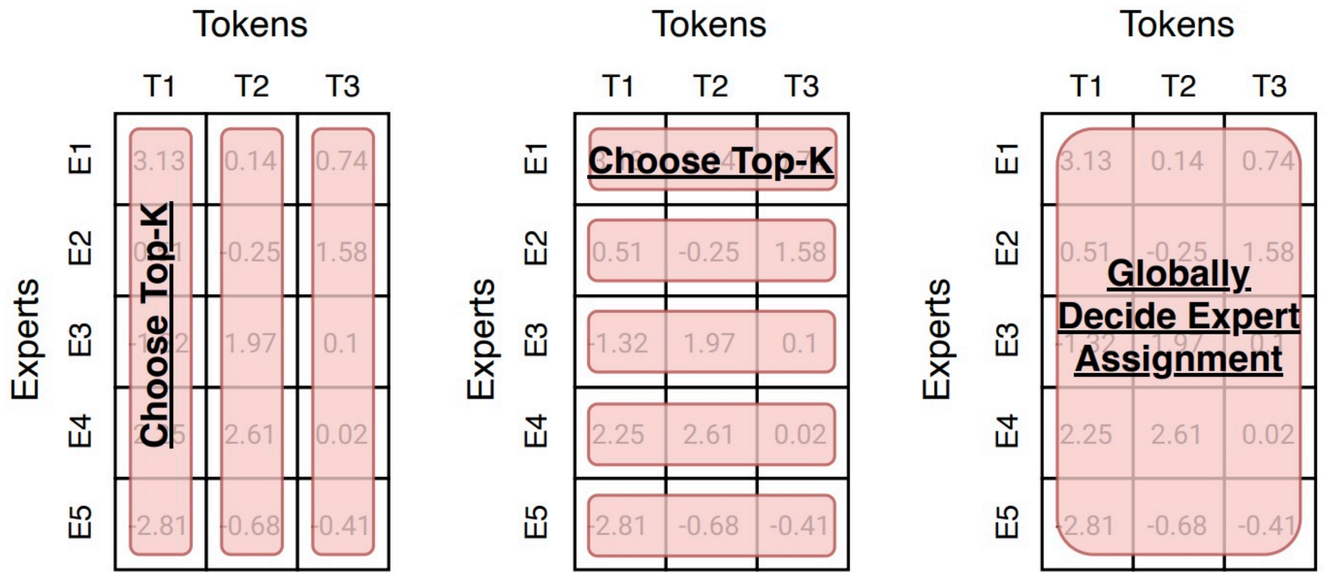


Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity [Fedus et al., 2022]

Mixture-of-Experts (MoE)

Sparsely activated for each token

- Different routing mechnisms



A Review of Sparse Expert Models in Deep Learning [Fedus et al., 2022]

TensorRT-LLM Public Release

State-of-the-art LLM serving infra from NVIDIA

Key Features

TensorRT-LLM contains examples that implement the following features.

- Multi-head Attention(MHA)
- Multi-query Attention (MQA)
- Group-query Attention(GQA)
- In-flight Batching
- Paged KV Cache for the Attention
- Tensor Parallelism
- Pipeline Parallelism
- INT4/INT8 Weight-Only Quantization (W4A16 & W8A16)
- SmoothQuant
- GPTQ
- AWQ
- FP8
- Greedy-search
- Beam-search
- RoPE

TensorRT-LLM

A TensorRT Toolbox for Large Language Models

docs latest | python 3.10.12 | cuda 12.2 | TRT 9.1 | release 0.5.0 | license Apache 2

Architecture | Results | Examples | Documentations

covered in the lecture

will introduce in next lectures

https://github.com/NVIDIA/TensorRT-LLM

Summary of Today's Lecture

In this lecture, we introduce:

1. Basics of transformers
2. Transformer design variants
3. Large language models (LLMs)
4. Advanced topics, multi-modal LLM