THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

RELAXED SYSTEM LAB

Language Model Architecture

COMP4901Y

Binhang Yuan

Overview

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- What is a language model?
- Tokenization:
  - How do we represent language to machines?
- Model categorization:
  - Encoder-only, decoder-only, encoder-decoder.
- Training objectives:
  - How are large language models (LLM) trained?
- Transformer architecture:
  - The main innovation that enabled large language models.

Language Model

What Is a Language Model?

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- The classic definition of a ***language model (LM)*** is a probability distribution over sequences of tokens.
- Suppose we have a vocabulary $\mathcal{V}$ of a set of tokens.
- A language model P assigns each sequence of tokens $x_1, x_2, \dots, x_L \in \mathcal{V}$ to a probability (a number between 0 and 1): $p(x_1, x_2, \dots, x_L) \in [0,1]$.
- The probability intuitively tells us how "good" a sequence of tokens is.
  - For example, if the vocabulary is $\mathcal{V} = \{\text{ate}, \text{ball}, \text{cheese}, \text{mouse}, \text{the}\}$, the language model might assign:

$$p(\text{the}, \text{mouse}, \text{ate}, \text{the}, \text{cheese}) = 0.02$$
$$p(\text{the}, \text{cheese}, \text{ate}, \text{the}, \text{mouse}) = 0.01$$
$$p(\text{mouse}, \text{the}, \text{the}, \text{chesse}, \text{ate}\ ) = 0.0001$$

Language Model Generation

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- A language model P takes a sequence and returns a probability to assess its goodness.
- We can also generate a sequence given a language model.
- The purest way to do this is to sample a sequence $x_{1:L}$ from the language model P with probability equal to $p(x_{1:L})$ denoted:

$$x_{1:L} \sim P$$

Autoregressive Language Models

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- A common way to write the joint distribution $p(x_{1:L})$ of a sequence to $x_{1:L}$ is using the *chain rule of probablity*:

$$p(x_{1:L}) = p(x_1)p(x_2|x_1)p(x_3|x_1,x_2)\ldots p(x_L|x_{1:L-1}) = \prod_{i=1}^{L} p(x_i|x_{1:i-1})$$

- In particular, $p(x_i|x_{1:i-1})$ is a conditional probability distribution of the next token x_i given the previous tokens $x_{1:i-1}$.
- An autoregressive language model is one where each conditional distribution $p(x_i|x_{1:i-1})$ can be computed efficiently (e.g., using a feedforward neural network).

Tokenization

Tokenization

- Recall: language model P is a probability distribution over a sequence of tokens where each token comes from some vocabulary $\mathcal{V}$, e.g.,:

  [I, love, cats, and, dogs]

- Natural language doesn't come as a sequence of tokens, but as just a string (concretely, sequence of Unicode characters):

  I love cats and dogs

- A *tokenizer* converts any string into a sequence of tokens:

  I love cats and dogs $\Longrightarrow$ [I, love, cats, and, dogs]

Split by Space

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- The simplest solution is to do: `text.split(' ')`
- This doesn't work for languages such as Chinese, where sentences are written without spaces between words:
  - 我今天去了商店: [I went to the store today.]
- Then there are languages like German that have long compound words:
  - Abwasserbehandlungsanlange: [Wastewater treatment plant]
- Even in English, there are hyphenated words (e.g., father-in-law) and contractions (e.g., don't), which should get split up.

What Makes a Good Tokenization?

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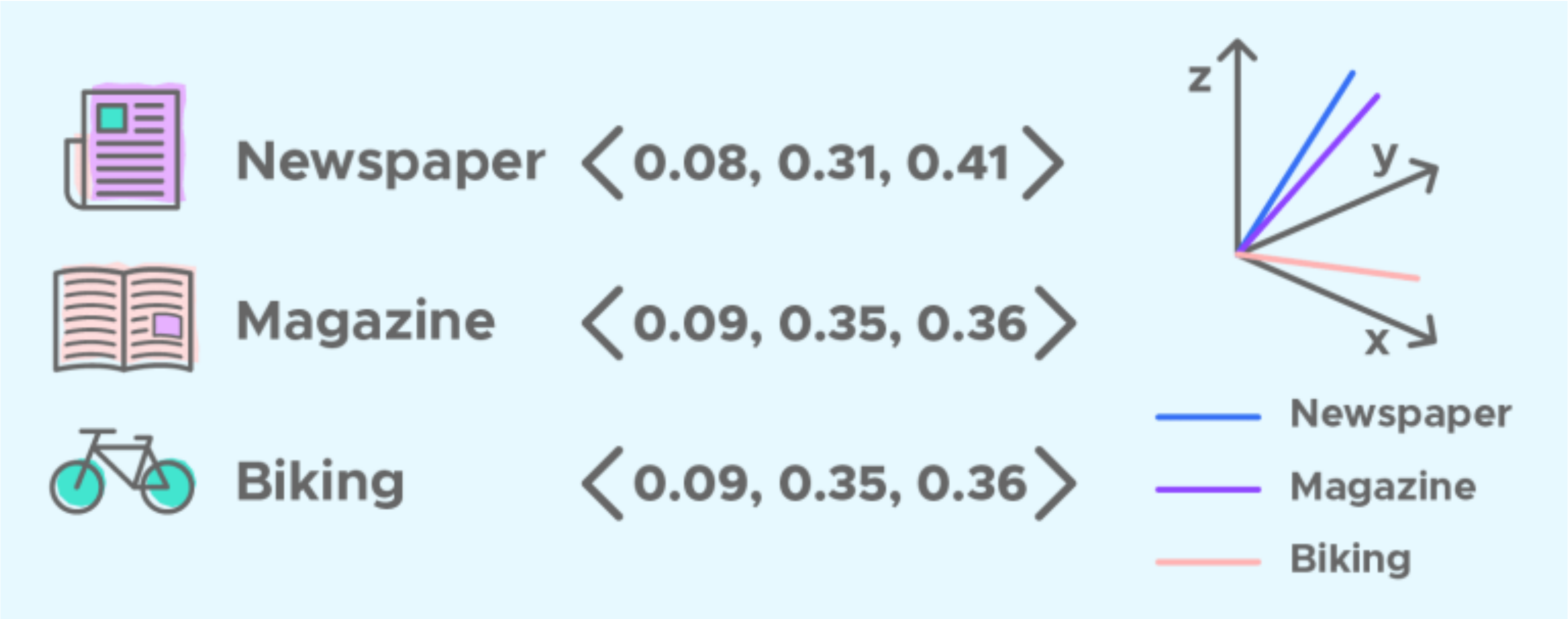
- We don't want too many tokens:
  - The extreme case characters or bytes;
  - The sequence becomes difficult to model.
- We don't want too few tokens:
  - There won't be parameter sharing between words (e.g., should mother-in-law and father-in-law be completely different)?
  - This is especially problematic for morphologically rich languages (e.g., Arabic, Turkish, etc.).
- Each token should be a linguistically or statistically meaningful unit.

Some Encoding Methods

- Byte pair encoding (BPE)
  - Start with each character as its own token and combine tokens that co-occur a lot.
  - https://arxiv.org/pdf/1508.07909.pdf
- Unigram model (SentencePiece):
  - Rather than just splitting by frequency, a more "principled" approach is to define an objective function that captures what a good tokenization looks like.
  - https://arxiv.org/pdf/1804.10959.pdf

Representation: Word as Vectors

- Tokens can be represented as number index:
  [I, love, cats, and, dogs] $\Longrightarrow$ [328, 793, 3989, 537, 3255, 269]
- But indices are also meaningless.
- Represent words in a vector space
  - Vector distance $\Longrightarrow$ similarity。



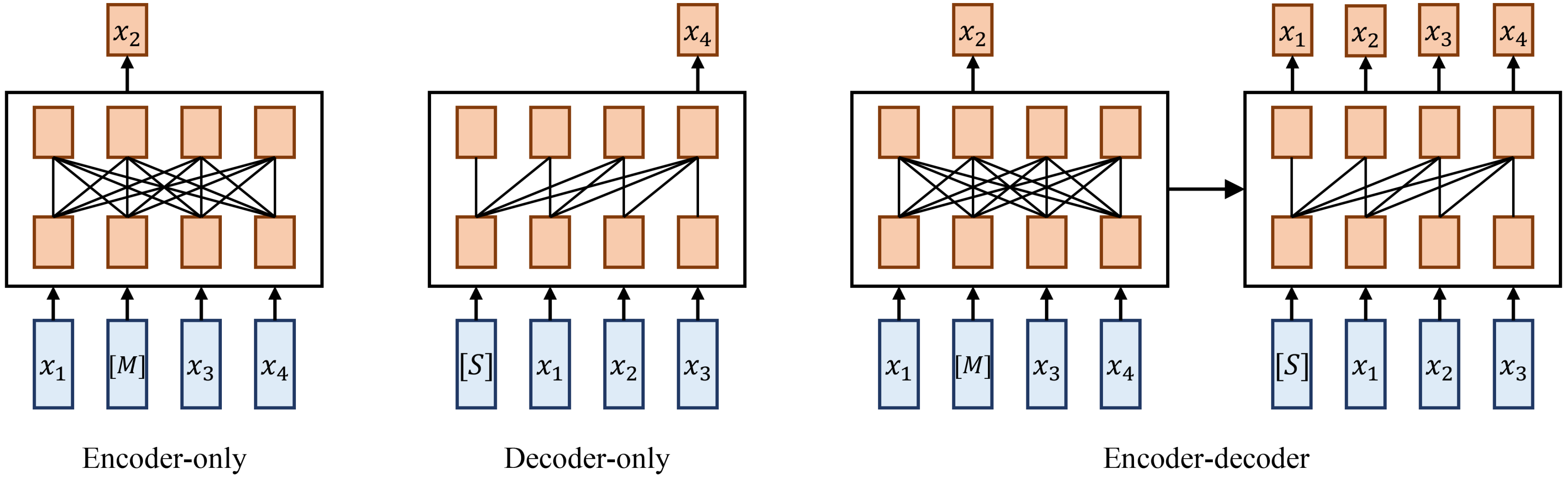
LLM Categorization

Contextual Embeddings

- Language model:
  - Associate a sequence of tokens with a corresponding sequence of contextual embeddings.
- Embedding function (analogous to a feature map for sequences):
  - $\emptyset\colon \mathcal{V}^L \rightarrow \mathbb{R}^{L\times D}$
  - A token sequence $x_{1:L}[x_1, x_2, \ldots, x_L] \in \mathcal{V}^L$
  - Map to $\emptyset(x_{1:L}) \in \mathbb{R}^{L\times D}$
- For example, if $D = 2$:
  - [I, love, cats, and, dogs] $\Longrightarrow$ [328, 793, 3989, 537, 3255, 269] $\Longrightarrow \begin{bmatrix} (0.2, 0.3) \\ (0.8, 0.7) \\ (0.2\ 0.1) \\ (0.0,0.7) \\ (0.1, 0.0) \\ (0.1, 0.4) \end{bmatrix}$

Types of language models

- Encoder-only models (BERT, RoBERTa, etc.)
- Encoder-decoder models (BART, T5, etc.)
- **Decoder-only models** (GPT-3, Llama-3, Deepseek-V3, etc.)



Encoder-only Models

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- Encoder-only models produce contextual embeddings but cannot be used directly to generate text:

$$x_{1:L} \Rightarrow \phi(x_{1:L})$$

- These contextual embeddings are generally used for classification tasks (sometimes boldly called natural language understanding tasks).
  - Example: sentiment classification: [[CLS],the,movie,was,great] ⇒ positive.
- Pros:
  - Contextual embedding for x_i can depend bidirectionally on both the left context ($x_{1:i-1}$) and the right context ($x_{i+1:L}$).
- Cons:
  - Cannot naturally generate completions.
  - Requires more ad-hoc training objectives (masked language modeling).

Decoder-only Models

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- Decoder-only models are our standard autoregressive language models.
- Given a prompt $x_{1:i}$ produces both contextual embeddings and a distribution over next tokens x_{i+1}, and recursively, over the entire completion $x_{i+1:L}$:

$$x_{1:i} \Rightarrow \emptyset(x_{1:i}), p(x_{i+1}|x_{1:i})$$

- Example: text autocomplete
  - [[CLS],the,movie,was]⇒great
- Pro:
  - Can naturally generate completions.
  - Simple training objective (maximum likelihood).
- Con:
  - Contextual embedding for x_i can only depend **unidirectionally** on both the left context ($x_{1:i-1}$).

Encoder-decoder Models

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- Encoder-decoder models can be the best of both worlds: they can use bidirectional contextual embeddings for the input $x_{1:L}$ and can generate the output $y_{1:L}$:

$$x_{1:L} \Rightarrow \emptyset(x_{1:L}), p(y_{1:L} | \emptyset(x_{1:L}))$$

- Example: table-to-text generation
  - [name,:,Clowns,|,eatType,:,coffee,shop]⇒[Clowns,is,a,coffee,shop].
- Pro:
  - Can naturally generate outputs.
- Con:
  - Requires more ad-hoc training objectives.

LLM Training Objectives

Decoder-only Model Training Objectives

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- Recall that an autoregressive language model defines a conditional distribution: $p(x_i | x_{1:i-1})$
- Define it as follows:
  - Map $x_{1:i-1}$ to contextual embedding $\emptyset(x_{1:i-1}) \in \mathbb{R}^{(i-1)\times D}$;
  - Apply an embedding matrix $E \in \mathbb{R}^{D\times|\mathcal{V}|}$ to obtain scores for each token $\emptyset(x_{1:i-1})_{i-1}E \in \mathbb{R}^{|\mathcal{V}|}$ (where $\emptyset(x_{1:i-1})_{i-1} \in \mathbb{R}^{D}$);
  - Exponentiate and normalize it to produce the distribution over x_i.
- Put them together:

$$p(x_{i+1} | x_{1:i}) = \mathrm{softmax}(\emptyset(x_{1:i})_i E)$$

Decoder-only Model Training Objectives

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- Maximum likelihood. Let θ be all the parameters of large language models.
- Let $\mathcal{D}$ be the training data consisting of a set of sequences. We can then follow the maximum likelihood principle and define the following negative log-likelihood objective function:

$$\mathcal{O}(\theta) = \sum_{x_{1:L} \in \mathcal{D}} - \log p_\theta(x_{1:L}) = \sum_{x_{1:L} \in \mathcal{D}} \sum_{i=1}^{L} - \log p_\theta(x_i | x_{1:i-1})$$

- Then we can use the SGD optimizers we have talked to optimize this loss function.

LLM Architecture Details

EmbedToken

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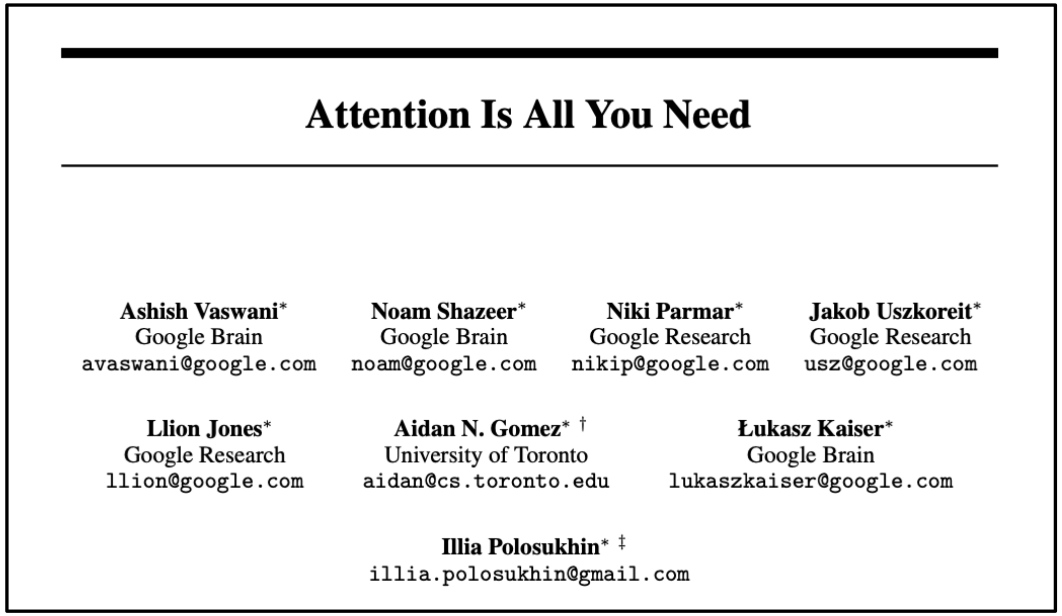
- Convert sequences of tokens into sequences of vectors.
- EmbedToken does exactly this by looking up each token in an embedding matrix $E \in \mathbb{R}^{|\mathcal{V}| \times D}$, a parameter that will be learned from data.
- $\text{EmbedToken}(x_{1:L}: \mathcal{V}^L) \rightarrow \mathbb{R}^{L \times D}$:
  - Turns each token x_i in the sequence $x_{1:L}$ into a vector $E_{x_i} \in \mathbb{R}^D$;
  - Return $\left[E_{x_1}, E_{x_2}, \ldots, E_{x_L}\right]$.
- These are *context-independent* word embeddings.
- Next the TransformerBlock(s) takes these context-independent embeddings and maps them into contextual embeddings.

TransformerBlock

- TransformerBlock(s) takes these context-independent embeddings and maps them into contextual embeddings.
- TransformerBlocks($X_{1:L}: R^{L \times D}$) $\to \mathbb{R}^{L \times D}$:
  - Process each element $X_i \in \mathbb{R}^D$ in the sequence $X_{1:L} \in R^{L \times D}$ with respect to other elements.
- TransformerBlock(s) are the building blocks of decoder-only (GPT-2, GPT-3), encoder-only (BERT, RoBERTa), and decoder-encoder (BART, T5) models.


Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com
Noam Shazeer* Google Brain noam@google.com
Niki Parmar* Google Research nikip@google.com
Jakob Uszkoreit* Google Research usz@google.com
Llion Jones* Google Research llion@google.com
Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu
Łukasz Kaiser* Google Brain lukaszkaiser@google.com
Illia Polosukhin* ‡ illia.polosukhin@gmail.com

Attention Mechanism-1

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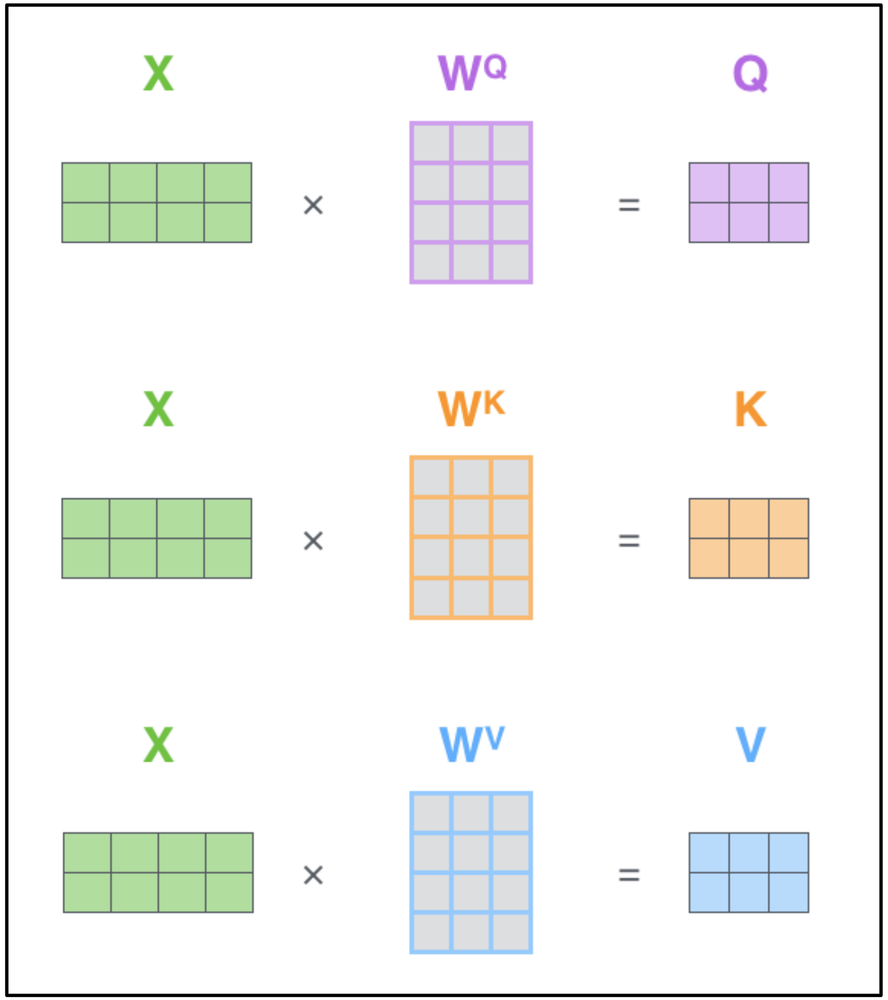
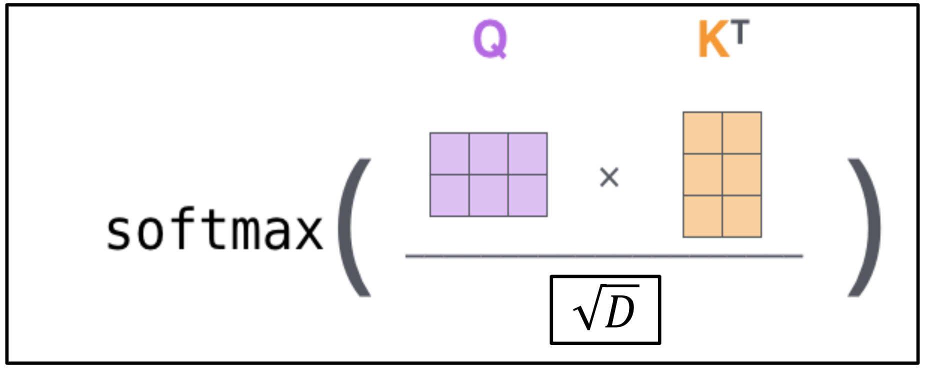
- **<u>First step</u>**: in each transformer block, for each token, we create a query vector, a key vector, and a value vector by multiplying the embedding by three weight matrices.
- Formally, for each token $X_i \in \mathbb{R}^D$:
  - Query: $Q_i = X_i \times W^Q$
  - key: $K_i = X_i \times W^K$
  - Value: $V_i = X_i \times W^V$
- In the tensor representation for sequence $X_{1:L} \in \mathbb{R}^{L \times D}$:
  - Query: $Q = Q_{1:L} = X_{1:L} \times W^Q$
  - key: $K = K_{1:L} = X_{1:L} \times W^K$
  - Value: $V = V_{1:L} = X_{1:L} \times W^V$



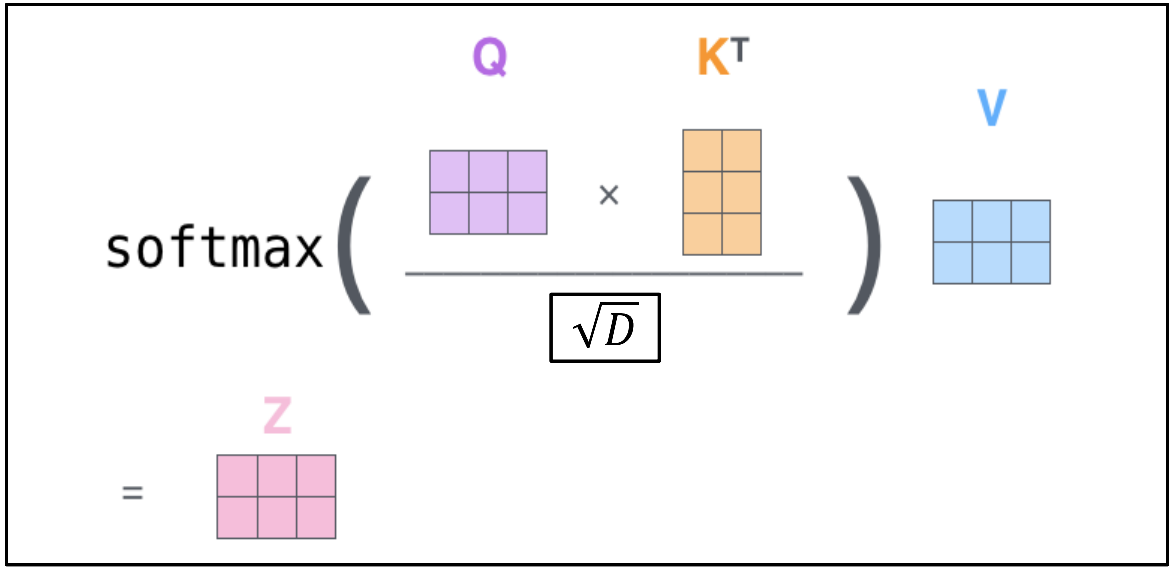
Attention Mechanism-2

- **<u>Second step</u>**: Calculate a score determining how much focus to place on other parts of the input sentence as we encode a token at a certain position.
- Calculated by:
  - Taking the dot product of the query vector with the key vector of the respective word we're scoring;
  - Divide the scores by the square root of the dimension of the key vectors;
  - Conduct a softmax operation.
- score = $\text{softmax}(\frac{QK^T}{\sqrt{D}})$



Attention Mechanism-3

- **Third step**: combine the value and the score.
  - $Z = \text{att} = \text{softmax}\left(\frac{QK^T}{\sqrt{D}}\right)V$
- **Multi-head Attention**: there can be multiple aspects (e.g., syntax, semantics) we would want to match on.
- To accommodate this, we can simultaneously have **multiple attention heads (e.g. n_H heads)** and simply combine their outputs, e.g:
  - $Z = [\text{att}^1, \text{att}^2, \ldots, \text{att}^{n_H}]$
- The attention output will be:
  - $\text{Out} = ZW^O$



Feedforward Layer

- After the attention layer, the output is put to a feed-forward neural network, then sends out the output upwards to the next encoder.
  - $\mathrm{X}'_{1:L} = \mathrm{relu}(\mathrm{Out}W^1)W^2$
  - W^1, W^2 are two weight matrices;
  - $X'_{1:L}$ is the output embedding for the current layer and the input of the next layer.
- Summarize a common weight dimension in one TransformerBlock:
  - Attention layer: $W^Q, W^K, W^V, W^O \in \mathbb{R}^{D \times D}$
  - Feedforward layer: $W^1 \in \mathbb{R}^{D \times 4D}$, $W^2 \in \mathbb{R}^{4D \times D}$

TransformerBlocks$(X \in R^{L\times D}) \rightarrow X' \in \mathbb{R}^{L\times D}$

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- L is the sequence length;
- D is the model dimension;
- Multi-head attention:
  $D = n_H \times H$
- H is the head dimension;
- n_h is the number of heads.

Computation	Input	Output
$Q = XW^Q$	$X \in \mathbb{R}^{L\times D}$, $W^Q \in \mathbb{R}^{D\times D}$	$Q \in \mathbb{R}^{L\times D}$
$K = XW^K$	$X \in \mathbb{R}^{L\times D}$, $W^K \in \mathbb{R}^{D\times D}$	$K \in \mathbb{R}^{L\times D}$
$V = XW^V$	$X \in \mathbb{R}^{L\times D}$, $W^V \in \mathbb{R}^{D\times D}$	$V \in \mathbb{R}^{L\times D}$
$[Q^1, Q^2 \dots, Q^{n_H}] = \text{Partion}_{-1}(Q)$	$Q \in \mathbb{R}^{L\times D}$	$Q^h \in \mathbb{R}^{L\times H}, h = 1, \dots n_H$
$[K^1, K^2 \dots, K^{n_H}] = \text{Partion}_{-1}(K)$	$K \in \mathbb{R}^{L\times D}$	$K^h \in \mathbb{R}^{L\times H}, h = 1, \dots n_H$
$[V^1, V^2 \dots, V^{n_H}] = \text{Partion}_{-1}(V)$	$V \in \mathbb{R}^{L\times D}$	$V^h \in \mathbb{R}^{L\times H}, h = 1, \dots n_H$
$\text{score}^h = \text{softmax}(\frac{Q^h {K^h}^T}{\sqrt{D}}), i = 1, \dots n_H$	$Q^h, K^h \in \mathbb{R}^{L\times H}$	$\text{score}^h \in \mathbb{R}^{L\times L}$
$Z^h = \text{score}^h V^h, h = 1, \dots n_H$	$\text{score}^h \in \mathbb{R}^{L\times L}, V^h \in \mathbb{R}^{L\times H}$	$Z^h \in \mathbb{R}^{L\times H}$
$Z = \text{Merge}_{-1}([Z^1, Z^2 \dots, Z^{n_H}])$	$Z^h \in \mathbb{R}^{L\times H}, h = 1, \dots n_H$	$Z \in \mathbb{R}^{L\times D}$
$\text{Out} = ZW^O$	$Z \in \mathbb{R}^{L\times D}$, $W^O \in \mathbb{R}^{D\times D}$	$\text{Out} \in \mathbb{R}^{L\times D}$
$A = \text{Out}\, W^1$	$\text{Out} \in \mathbb{R}^{L\times D}$, $W^1 \in \mathbb{R}^{D\times 4D}$	$A \in \mathbb{R}^{L\times 4D}$
$A' = \text{relu}(A)$	$A \in \mathbb{R}^{L\times 4D}$	$A' \in \mathbb{R}^{L\times 4D}$
$X' = A'W^2$	$A' \in \mathbb{R}^{L\times 4D}$, $W^2 \in \mathbb{R}^{4D\times D}$	$X' \in \mathbb{R}^{L\times D}$

Other Components

- Residual connections:
  - Instead of simply return $\text{TransformerBlock}(X_{1:L})$
  - Return: $X_{1:L} + \text{TransformerBlock}(X_{1:L})$
- Layer normalization:
  - $\text{LayerNorm}(X_{1:L}) = \alpha\frac{X_{1:L}-\mu}{\sigma} + \beta$
  - μ is the mean; σ is the standard deviation.
  - α and β are learnable parameters.

- Positional embeddings:
  - So far, the embedding of a token doesn't depend on where it occurs in the sequence, which is not sensible. ($\text{PosEmb} \in \mathbb{R}^{L\times D}$)
  - $\begin{cases} \text{PosEmb}(i, 2j) = \sin(\frac{\text{i}}{10000^{2j/D}}) \\ \text{PosEmb}(i, 2j+1) = \cos(\frac{\text{i}}{10000^{2j/D}}) \end{cases}$
  - Where $i = 1, \dots, L, j = 1, \dots, \frac{D}{2}$
  - $X_{1:L} = X_{1:L} + \text{PosEmb}$ before computing $Q_{1:L}, K_{1:L}, V_{1:L}$.

Put Them Together

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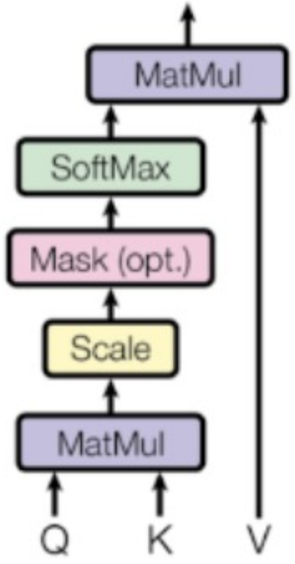
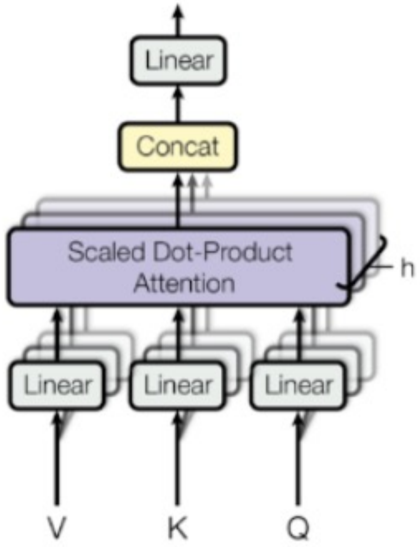
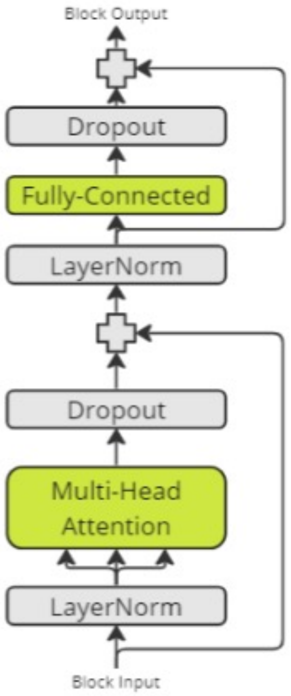


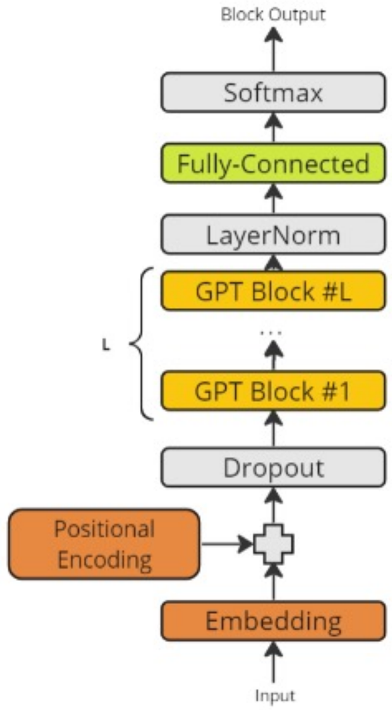
Scale Causal Attention



Multi-Head Attention



Transformer Block



GPT Model

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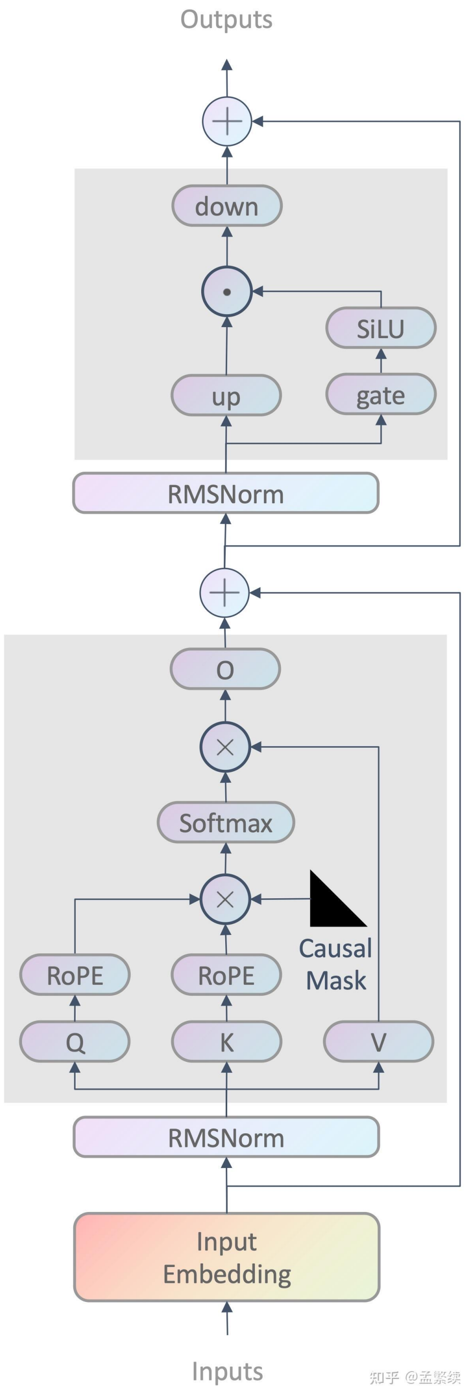
LLM Architecture Case Study

LLaMa 3

Llama-3 Block Overview

- RMSNorm (Root Mean Square Norm);
- RoPE (Rotary Position Embedding);
- GQA (Group Query Attention);
- SiLU activation function in MLP.



Llama-3 RMSNorm

- RMSNorm: $\mathrm{RMSNorm}(X_{1:L}) = \alpha \frac{X_{1:L}}{\sqrt{\mu^2+\epsilon}}$
  - μ is the mean.
  - 40% Speed-up compared with LayerNorm.

RMSNorm

CLASS torch.nn.RMSNorm(*normalized_shape*, *eps=None*, *elementwise_affine=True*, *device=None*, *dtype=None*) [SOURCE]

Applies Root Mean Square Layer Normalization over a mini-batch of inputs.

This layer implements the operation as described in the paper Root Mean Square Layer Normalization

$$y_i = \frac{x_i}{\mathrm{RMS}(x)} * \gamma_i, \quad \text{where} \quad \mathrm{RMS}(x) = \sqrt{\epsilon + \frac{1}{n}\sum_{i=1}^{n} x_i^2}$$

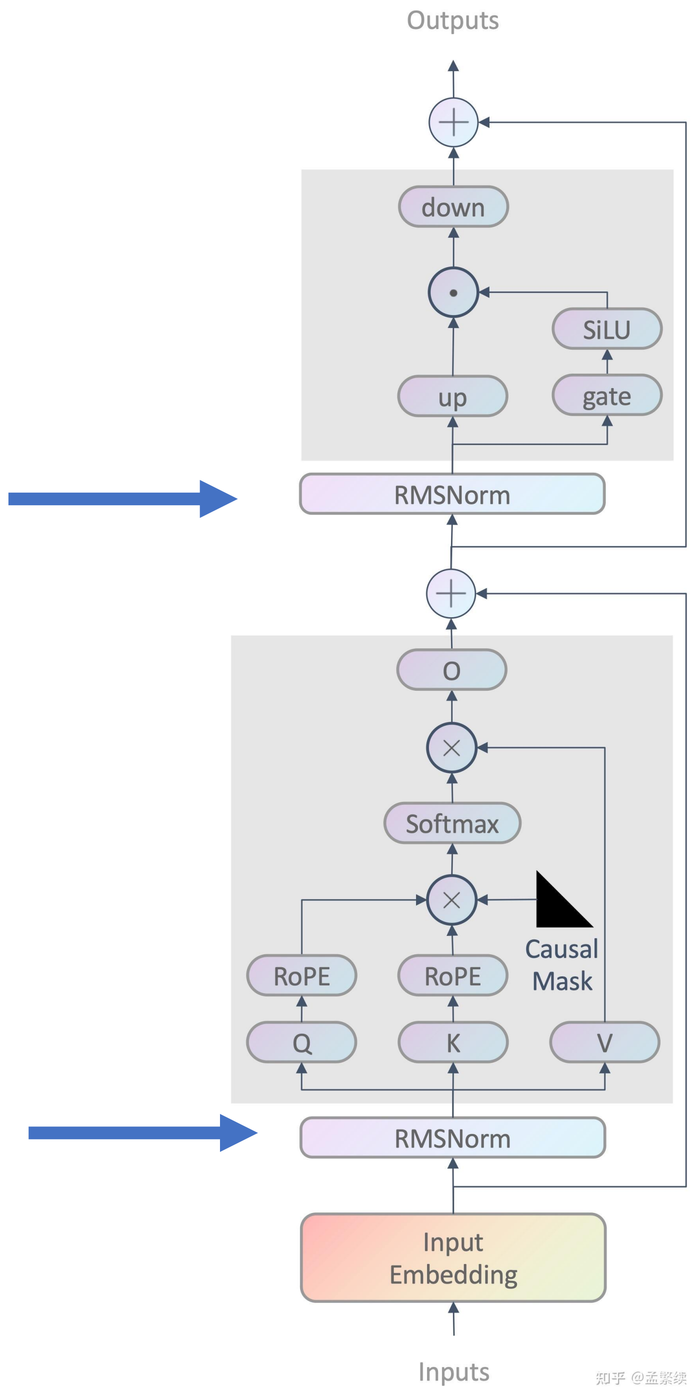
The RMS is taken over the last `D` dimensions, where `D` is the dimension of `normalized_shape`. For example, if `normalized_shape` is `(3, 5)` (a 2-dimensional shape), the RMS is computed over the last 2 dimensions of the input.

Parameters

- **normalized_shape** (*int* or *list* or *torch.Size*) – input shape from an expected input of size

  $$[* \times \text{normalized\_shape}[0] \times \text{normalized\_shape}[1] \times \ldots \times \text{normalized\_shape}[-1]]$$

  If a single integer is used, it is treated as a singleton list, and this module will normalize over the last dimension which is expected to be of that specific size.
- **eps** (*Optional*[*float*]) – a value added to the denominator for numerical stability. Default: `torch.finfo(x.dtype).eps()`
- **elementwise_affine** (*bool*) – a boolean value that when set to `True`, this module has learnable per-element affine parameters initialized to ones (for weights). Default: `True`.

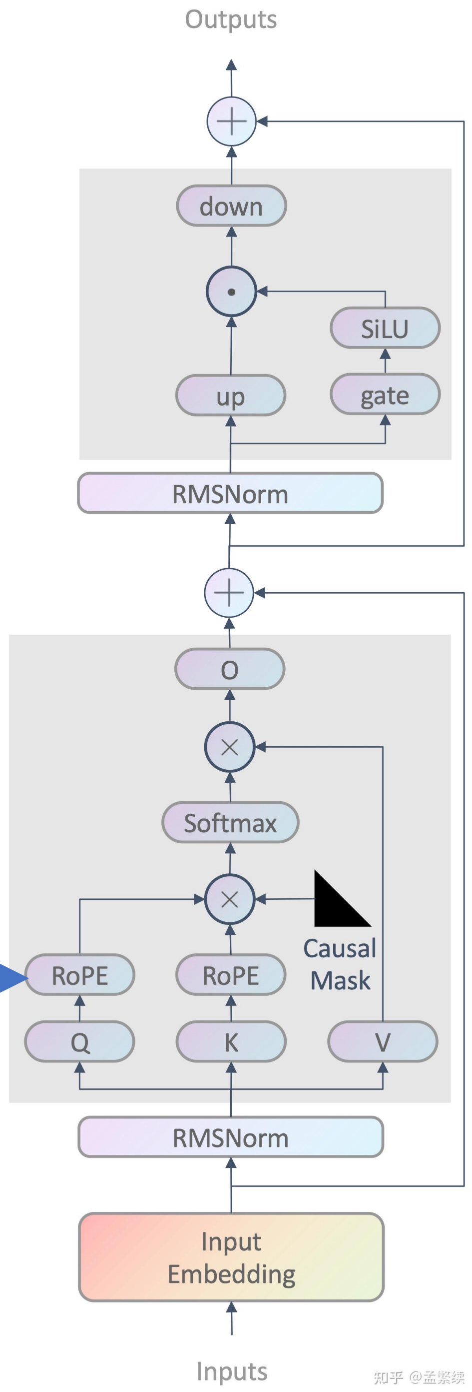


Llama-3 RoPE

- RoPE incorporates both absolute and relative positional information.
- Computation efficient implementation transform a position i:

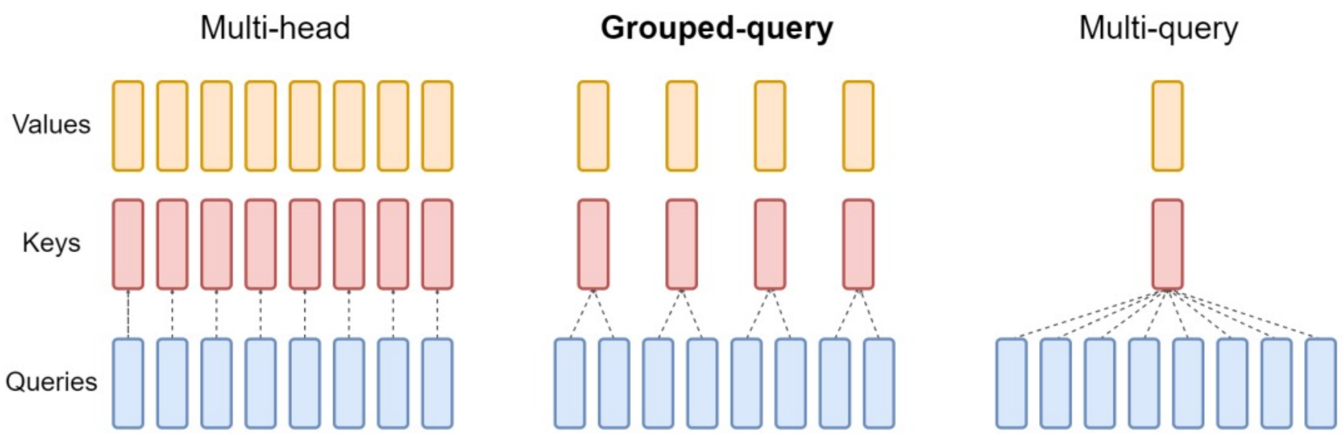
$$\begin{pmatrix} X_{i,1} \\ X_{i,2} \\ X_{i,1} \\ X_{i,1} \\ \vdots \\ X_{i,D-1} \\ X_{i,D} \end{pmatrix} \otimes \begin{pmatrix} \cos i\theta_1 \\ \cos i\theta_1 \\ \cos i\theta_2 \\ \cos i\theta_2 \\ \vdots \\ \cos i\theta_{D/2} \\ \cos i\theta_{D/2} \end{pmatrix} + \begin{pmatrix} -X_{i,2} \\ X_{i,1} \\ -X_{i,4} \\ X_{i,3} \\ \vdots \\ -X_{i,D} \\ X_{i,D-1} \end{pmatrix} \otimes \begin{pmatrix} \sin i\theta_1 \\ \sin i\theta_1 \\ \sin i\theta_2 \\ \sin i\theta_2 \\ \vdots \\ \sin i\theta_{D/2} \\ \sin i\theta_{D/2} \end{pmatrix}$$

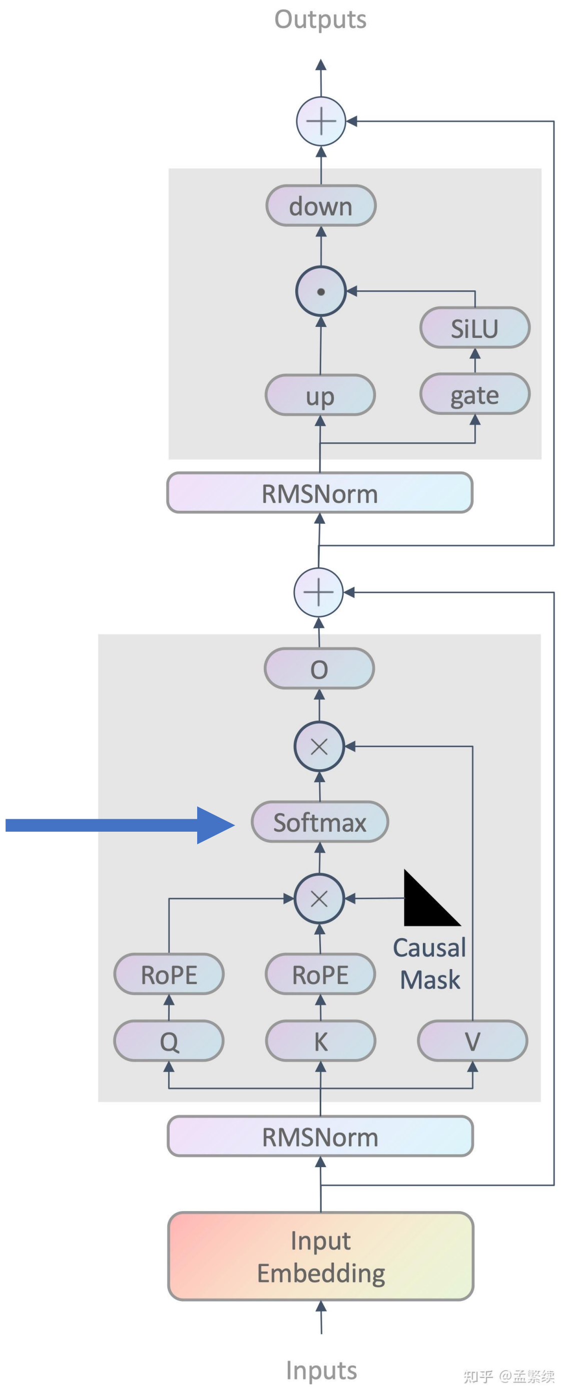
  - $\otimes$ indicates element-wise multiplication;
  - $\theta_j = 10000^{-\frac{2j}{D}}$
- https://arxiv.org/pdf/2104.09864



Llama-3 GQA

- Replace multi-head attention with grouped-query attention.

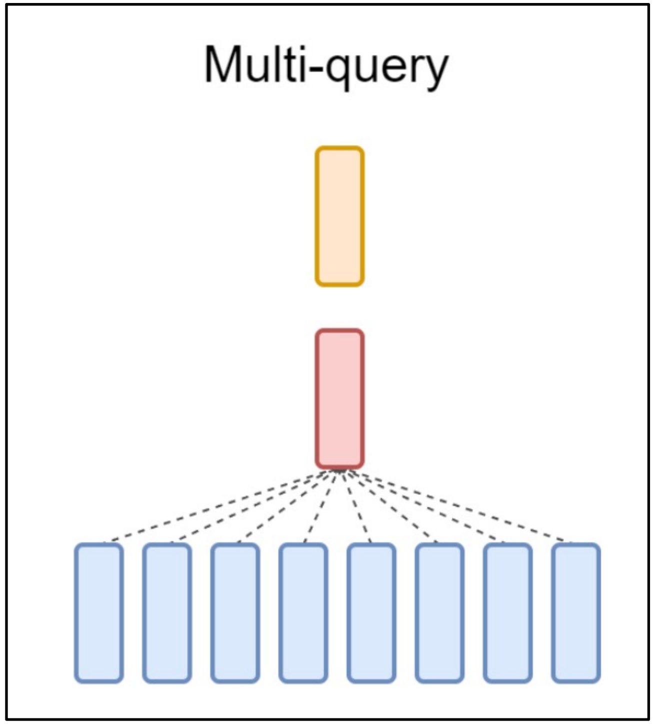




Multi-Query Attention (MQA)

- The idea is simple yet effective:
  - Use multiple query heads but only a single key and value head.

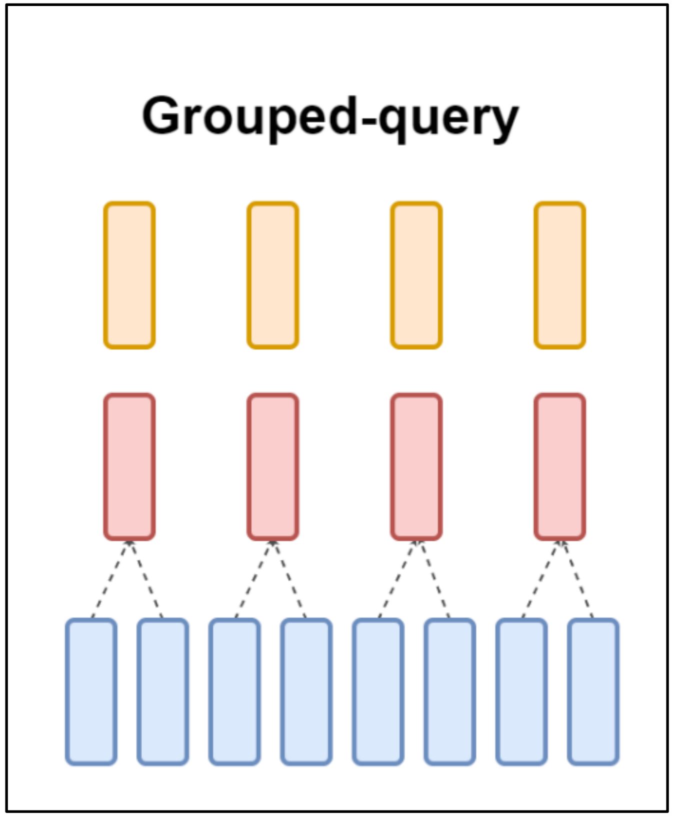
Computation	Input	Output
$Q = XW^Q$	$X \in \mathbb{R}^{L\times D}$, $W^Q \in \mathbb{R}^{D\times D}$	$Q \in \mathbb{R}^{L\times D}$
$K = XW^K$	$X \in \mathbb{R}^{L\times D}$, $W^K \in \mathbb{R}^{D\times H}$	$K \in \mathbb{R}^{L\times H}$
$V = XW^V$	$X \in \mathbb{R}^{L\times D}$, $W^V \in \mathbb{R}^{D\times H}$	$V \in \mathbb{R}^{L\times H}$
$[Q^1, Q^2 \ldots, Q^{n_H}] = \text{Partition}_{-1}(Q)$	$Q \in \mathbb{R}^{L\times D}$	$Q^h \in \mathbb{R}^{L\times H}, h = 1, \ldots n_H$
$\text{score}^\text{h} = \text{softmax}(\frac{Q^h K^T}{\sqrt{D}}), \text{h} = 1, \ldots n_H$	$Q^h, K \in \mathbb{R}^{L\times H}$	$\text{score}^\text{h} \in \mathbb{R}^{L\times L}$
$Z^h = \text{score}^\text{h} V, h = 1, \ldots n_H$	$\text{score}^\text{h} \in \mathbb{R}^{L\times L}, V \in \mathbb{R}^{L\times H}$	$Z^h \in \mathbb{R}^{L\times H}$



Group-Query Attention (GQA)

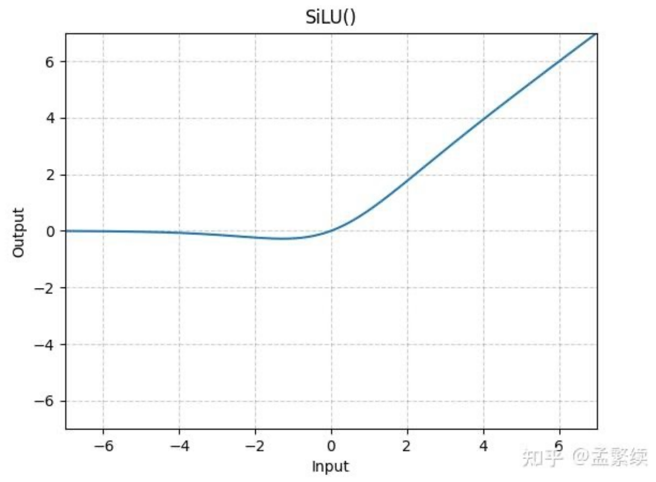
- The trade-off between MHA and MQA:
  - Divide query heads into g groups, each sharing a single key head and value head;
  - MHA: $g = n_H$; MQG: $g = 1$.

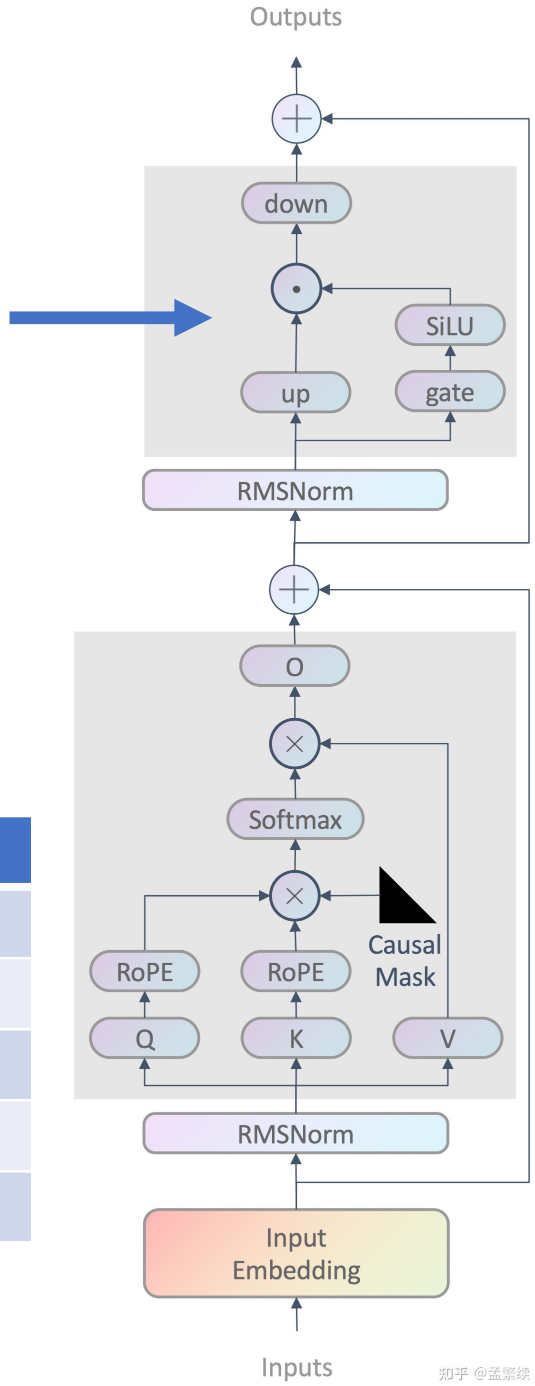
Computation	Input	Output
$Q = XW^Q$	$X \in \mathbb{R}^{L\times D}$, $\mathrm{W}^Q \in \mathbb{R}^{D\times D}$	$Q \in \mathbb{R}^{L\times D}$
$K = XW^K$	$X \in \mathbb{R}^{L\times D}$, $\mathrm{W}^K \in \mathbb{R}^{D\times gH}$	$K \in \mathbb{R}^{L\times gH}$
$V = XW^V$	$X \in \mathbb{R}^{L\times D}$, $\mathrm{W}^V \in \mathbb{R}^{D\times gH}$	$V \in \mathbb{R}^{L\times gH}$
$[Q^1, Q^2 \ldots, Q^{n_H}] = \mathrm{Partition}_{-1}(Q)$	$Q \in \mathbb{R}^{L\times D}$	$Q^h \in \mathbb{R}^{L\times H}, h = 1, \ldots n_\mathrm{H}$
$[K^1, K^2 \ \ldots, K^g] = \mathrm{Partition}_{-1}(K)$	$K \in \mathbb{R}^{L\times gH}$	$K^h \in \mathbb{R}^{L\times H}, h = 1, \ldots g$
$[V^1, V^2 \ \ldots, V^g] = \mathrm{Partition}_{-1}(V)$	$V \in \mathbb{R}^{L\times gH}$	$V^h \in \mathbb{R}^{L\times H}, h = 1, \ldots g$
$\mathrm{score}^\mathrm{h} = \mathrm{softmax}(\frac{Q^h {K^{\lfloor \mathrm{h}/g \rfloor}}^T}{\sqrt{D}}), \mathrm{h} = 1, \ldots n_H$	$Q^h, K^{\lfloor h/g \rfloor} \in \mathbb{R}^{L\times H}$	$\mathrm{score}^\mathrm{h} \in \mathbb{R}^{L\times L}$
$Z^h = \mathrm{score}^\mathrm{h} V^{\lfloor \mathrm{h}/g \rfloor}, h = 1, \ldots n_H$	$\mathrm{score}^\mathrm{h} \in \mathbb{R}^{L\times L}, V^{\lfloor \mathrm{h}/g \rfloor} \in \mathbb{R}^{L\times H}$	$Z^h \in \mathbb{R}^{L\times H}$



Llama-3 SiLU MLP

- Empirically shown to enhance model quality in various tasks.





Computation	Input	Output
$A = \text{Out}\, W^1$	$\text{Out} \in \mathbb{R}^{L\times D}$, $\text{W}^1 \in \mathbb{R}^{D\times 4D}$	$A \in \mathbb{R}^{L\times 4D}$
$B = \text{Out}W^2$	$\text{Out} \in \mathbb{R}^{L\times D}$, $\text{W}^2 \in \mathbb{R}^{D\times 4D}$	$B \in \mathbb{R}^{L\times 4D}$
$B' = SiLU(B)$	$B \in \mathbb{R}^{L\times 4D}$	$B' \in \mathbb{R}^{L\times 4D}$
$B'' = A \otimes B'$	$A \in \mathbb{R}^{L\times 4D}$, $B' \in \mathbb{R}^{L\times 4D}$	$B'' \in \mathbb{R}^{L\times 4D}$
$X' = B''W^2$	$B'' \in \mathbb{R}^{L\times 4D}$, $\text{W}^3 \in \mathbb{R}^{4D\times D}$	$X' \in \mathbb{R}^{L\times D}$

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References

- https://scholar.harvard.edu/sites/scholar.harvard.edu/files/binxuw/files/mlfs_tutorial_nlp_transformer_ssl_updated.pdf
- https://jalammar.github.io/illustrated-transformer/
- https://stanford-cs324.github.io/winter2022/lectures/introduction/
- https://stanford-cs324.github.io/winter2022/lectures/modeling/
- https://stanford-cs324.github.io/winter2022/lectures/training/
- https://zhuanlan.zhihu.com/p/636784644
- https://arxiv.org/pdf/2104.09864
- https://medium.com/@parulsharmmaa/understanding-rotary-positional-embedding-and-implementation-9f4ad8b03e32