Mistral explained (7B and 8x7B)

Rajesh Thakur

Prerequisites

- Structure of the Transformer model and how the attention mechanism works.

Topics not covered

The following topics will not be covered in the current video, as they have already been explained in my previous video on LLaMA.

- RMS Normalization
- Rotary Positional Encoding
- Grouped Query Attention

Topics

- Architectural differences between the vanilla Transformer and Mistral
- Sliding Window Attention
  - Review of self-attention
  - Receptive field
- KV-Cache
  - Motivation
  - How it works
  - Rolling Buffer Cache
  - Pre-fill and chunking
- Sparse Mixture of Experts
- Model Sharding
  - Pipeline Parallelism
- Understanding the Mistral model's code
  - Block attention in xformers

https://github.com/RajeshThakur1/Mistral

Topics

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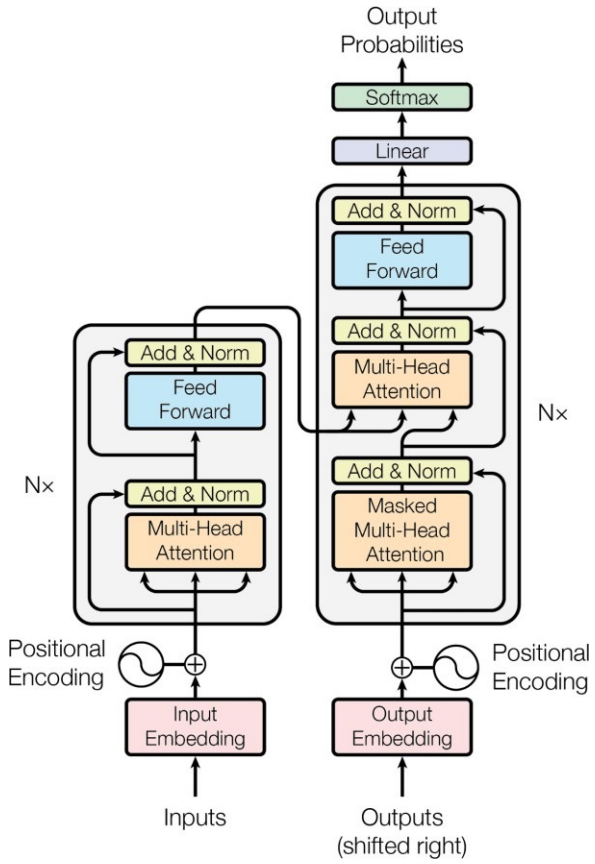
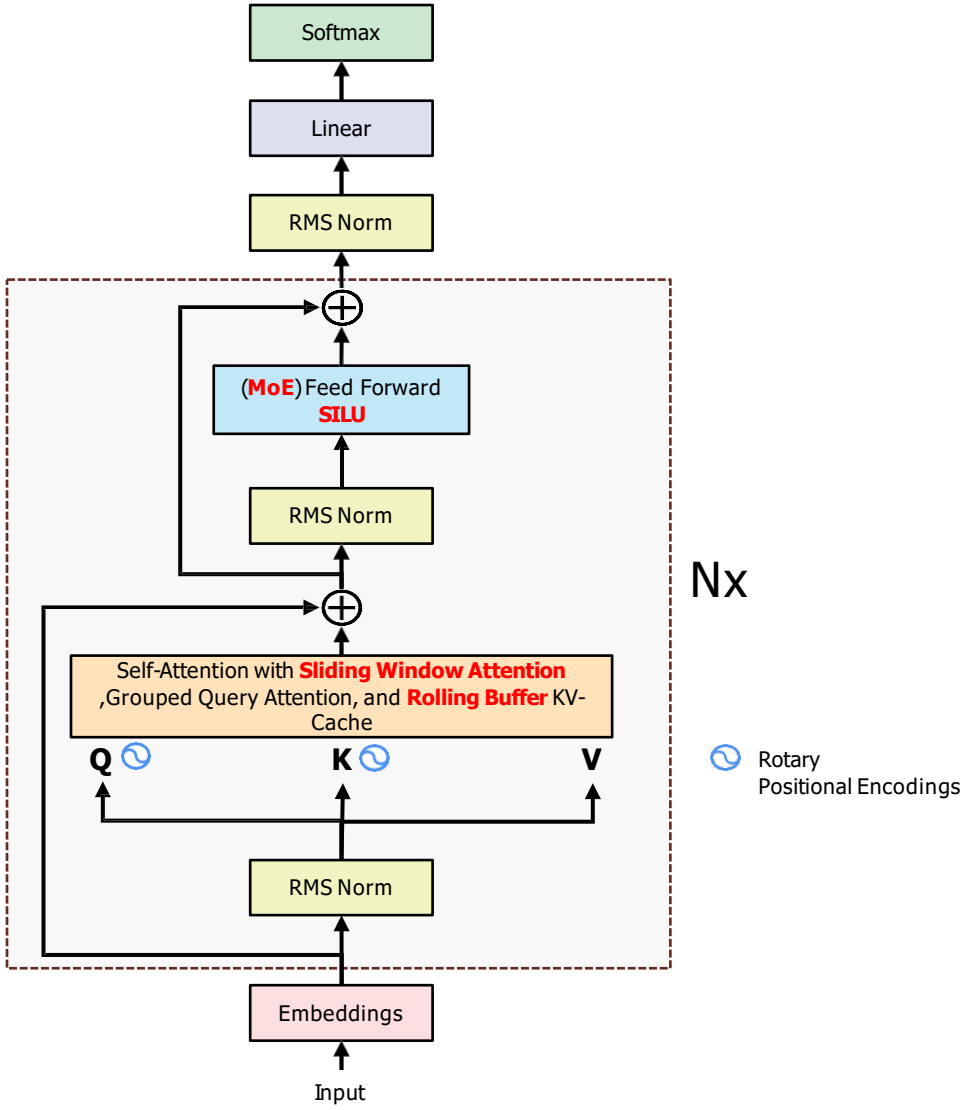
Transformer vs Mistral



Transformer
("Attention is all you need")



Mistral

Models

Parameter	Description	Value (7B)	Value (8x7B)	Notes
dim	Size of the embedding vector	4096	4096	
n_layers	Number of encoder layers	32	32	
head_dim	dim / n_heads	128	128	
hidden_dim	Hidden dimension in the feedforward layer	14336	14336	
n_heads	Number of attention heads (Q)	32	32	Different numbers because of Grouped Query Attention
n_kv_heads	Number of attention heads (K, V)	8	8	
windows_size	Size of the sliding window for attention calculation and Rolling Cache	4096	N / A	window_size is not set in the params.json of the 8x7B model
context_len	Context on which model was trained upon	8192	32000	For 8x7B, values are from the official announcement page
vocab_size	Number of tokens in the vocabulary	32000	32000	The tokenizer is the SentencePiece tokenizer
num_experts_per_tok	Number of expert models for each token	N / A	2	Sparse Mixture of Experts only available for 8x7B
num_experts	Number of exper models	N / A	8	

Topics

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What is Self-Attention?

Self-Attention allows the model to relate words to each other. Imagine we have the following sentence: "**The cat is on a chair**"

Here I show the product of the Q and the K matrix **before** we apply the softmax.

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

Q (6, 4096) X **K**^{T} (4096, 6) $= \frac{}{\sqrt{4096}}$

	THE	CAT	IS	ON	A	CHAIR
THE	0.268	0.119	0.134	0.148	0.179	0.152
CAT	0.124	0.278	0.201	0.128	0.154	0.115
IS	0.147	0.132	0.262	0.097	0.218	0.145
ON	0.210	0.128	0.206	0.212	0.119	0.125
A	0.146	0.158	0.152	0.143	0.227	0.174
CHAIR	0.195	0.114	0.203	0.103	0.157	0.229

(6, 6)

*all values are random.

Let's apply a causal mask

After applying the causal mask we apply the softmax, which makes the remaining values on the row in such a way that the row sums up to 1.

Now, let's look at the **sliding window attention**.

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

Q (6, 4096) X **K**^{T} (4096, 6) / $\sqrt{4096}$ =

	THE	CAT	IS	ON	A	CHAIR
THE	0.268	$-\infty$	$-\infty$	$-\infty$	$-\infty$	$-\infty$
CAT	0.124	0.278	$-\infty$	$-\infty$	$-\infty$	$-\infty$
IS	0.147	0.132	0.262	$-\infty$	$-\infty$	$-\infty$
ON	0.210	0.128	0.206	0.212	$-\infty$	$-\infty$
A	0.146	0.158	0.152	0.143	0.227	$-\infty$
CHAIR	0.195	0.114	0.203	0.103	0.157	0.229

(6, 6)

*all values are random.

Let's apply sliding window attention

The sliding window size is 3

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

Q

(6, 4096)

X

K^T

(4096, 6)

$\sqrt{4096}$

=

	THE	CAT	IS	ON	A	CHAIR
THE	0.268	$-\infty$	$-\infty$	$-\infty$	$-\infty$	$-\infty$
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IS	0.147	0.132	0.262	$-\infty$	$-\infty$	$-\infty$
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(6, 6)

*all values are random.

Sliding Window Attention: details

- Reduces the number of dot-products to perform, and thus, performance during training and inference.
- Sliding window attention may lead to degradation in the performance of the model, as some "interactions" between tokens will not be captured.
  The model mostly focuses on the **local context**, which depending on the size of the window, is enough for most cases.
  This makes sense if you think about a book: the words in a paragraph on chapter number 5 depend on the paragraphs in the same chapter but may be totally unrelated to the words used in chapter 1.
- Sliding window attention can still allow one token to watch tokens outside the window, using a reasoning similar to the **receptive field** in convolutional neural networks.

Receptive field in CNNs

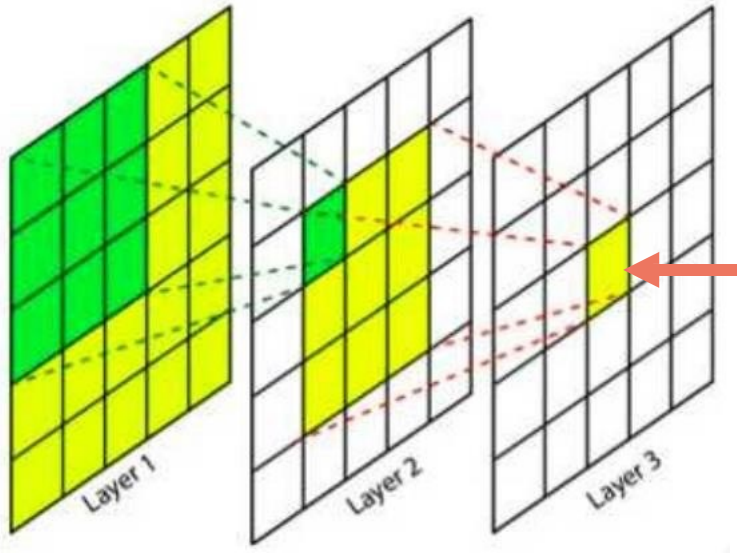


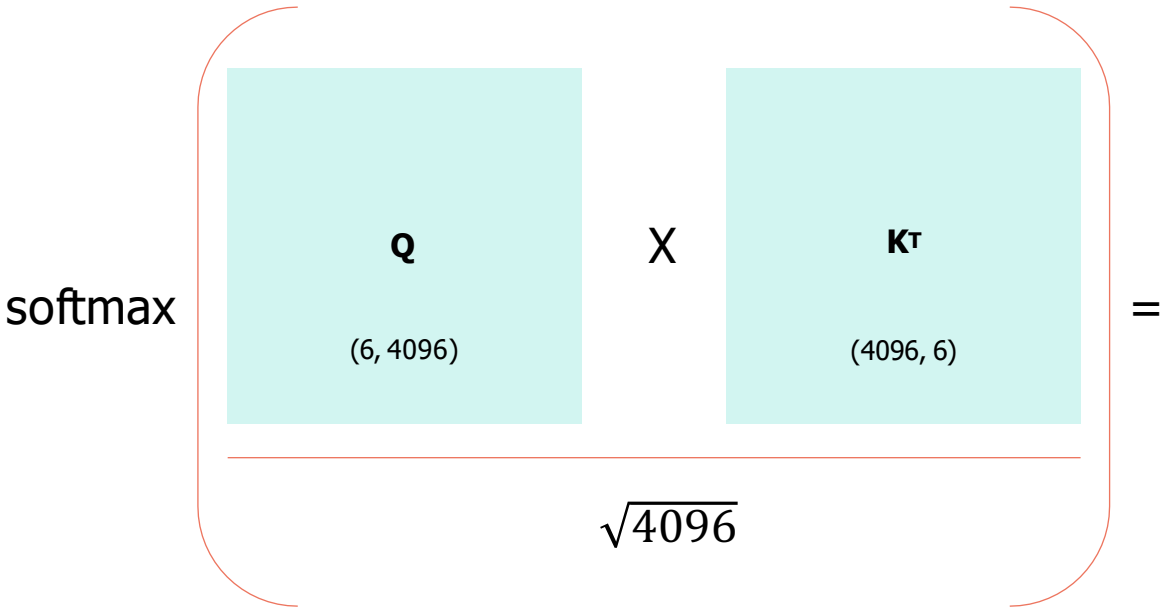
Image source: https://theaisummer.com/receptive-field/

This feature depends **directly** on 9 features of the previous layers, but **indirectly** on all the features of the initial layers, since each feature of the intermediate layer depends on 9 features of the previous layer. This means that a change in any of the features of the layer 1 will influence this features as well.

Sliding Window Attention: information flow (1)

After applying the softmax, all the –Infinity have become 0, while the other values in the row are changed in such a way that they sum up to one. The output of the softmax can be thought of as a probability distribution.

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



	THE	CAT	IS	ON	A	CHAIR
THE	1.0	0	0	0	0	0
CAT	0.461	0.538	0	0	0	0
IS	0.3219	0.317	0.361	0	0	0
ON	0	0.316	0.341	0.343	0	0
A	0	0	0.326	0.323	0.351	0
CHAIR	0	0	0	0.313	0.331	0.356

Sliding Window Attention: information flow (2)

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

	THE	CAT	IS	ON	A	CHAIR
THE	1.0	0	0	0	0	0
CAT	0.461	0.538	0	0	0	0
IS	0.3219	0.317	0.361	0	0	0
ON	0	0.316	0.341	0.343	0	0
A	0	0	0.326	0.323	0.351	0
CHAIR	0	0	0	0.313	0.331	0.356

(6, 6)

X

V

(6, 4096)

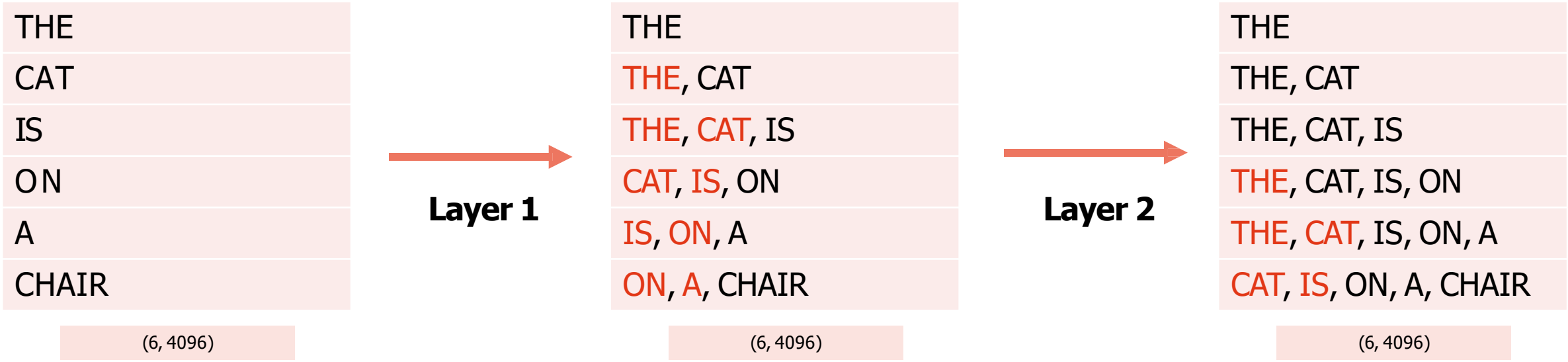
=

Output

(6, 4096)

The output of the Self-Attention is a matrix of the same shape as the input sequence, but where each token now captures information about other tokens according to the mask applied. In our case, the last token of the output captures information about itself and the two preceding tokens.

Sliding Window Attention: information flow (3)



With a sliding window size $W = 3$, every layer adds information about $(W - 1) = 2$ tokens.
This means that after N layers, we will have an information flow in the order of $W \times N$.
You can test all the future configurations using the Python Notebook provided in the GitHub repository.

Sliding Window Attention: information flow (4)

	THE	THE/CAT	THE/CAT /IS	CAT/IS/ ON	IS/ON/A	ON/A/C HAIR
THE	1.0	0	0	0	0	0
THE/C A T	0.461	0.538	0	0	0	0
THE/C A T/IS	0.3219	0.317	0.361	0	0	0
CAT/IS / ON	0	0.316	0.341	0.343	0	0
IS/ON/ A	0	0	0.326	0.323	0.351	0
ON/A/ C HAIR	0	0	0	0.313	0.331	0.356

(6, 6)

X

V

(6, 4096)

=

Output

(6, 4096)

Sliding Window Attention: information flow (5)

As you can see, the information flow is very similar to the receptive field of a CNN.

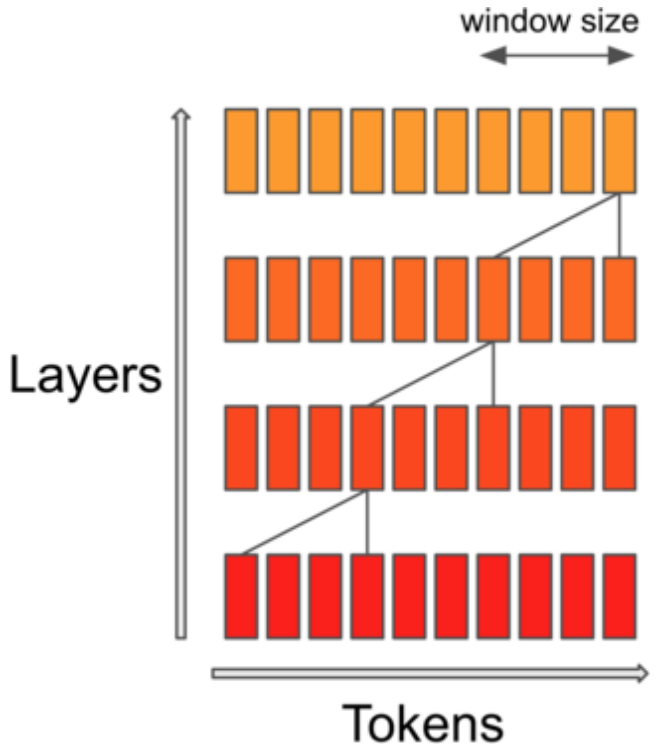


Image source: Mistral 7B paper

Topics

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Next Token Prediction Task

- Imagine we want to train a model to write Dante Alighieri's Divine Comedy's 5th Canto from the Inferno.

Amor, ch'al cor gentil ratto s'apprende,
prese costui de la bella persona
che mi fu tolta; e 'l modo ancor m'offende.

Amor, ch'a nullo amato amar perdona,
mi prese del costui piacer sì forte,
che, come vedi, ancor non m'abbandona.

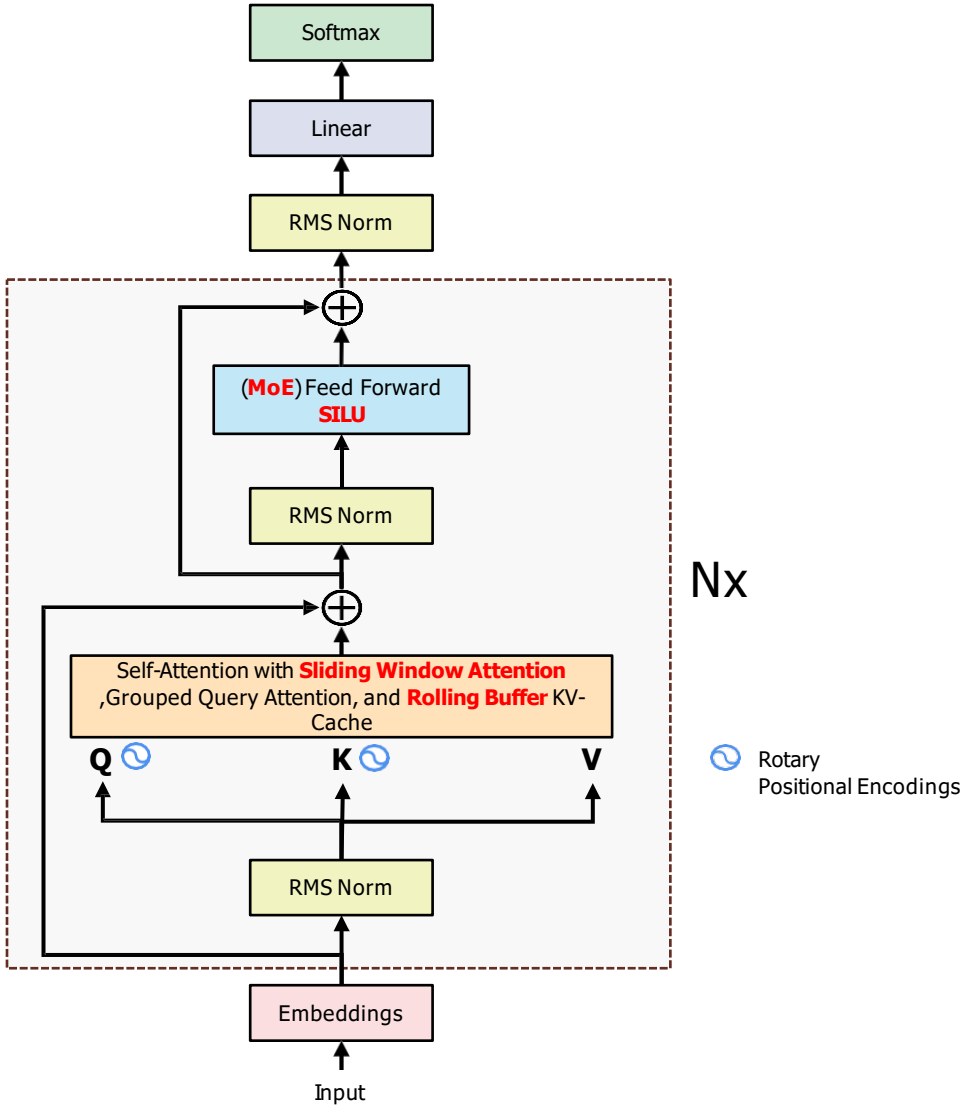
Amor condusse noi ad una morte.
Caina attende chi a vita ci spense.

Love, that can quickly seize the gentle heart,
took hold of him because of the fair body
taken from me—how that was done still wounds me.

Love, that releases no beloved from loving,
took hold of me so strongly through his beauty
that, as you see, it has not left me yet.

Love led the two of us unto one death.
Caina waits for him who took our life."

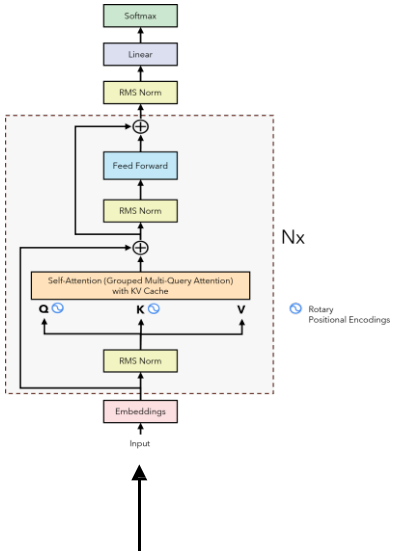
Source: https://digitaldante.columbia.edu/dante/divine-comedy/inferno/inferno-5/



Next Token Prediction Task

Target Love that can quickly seize the gentle heart [EOS]

Training

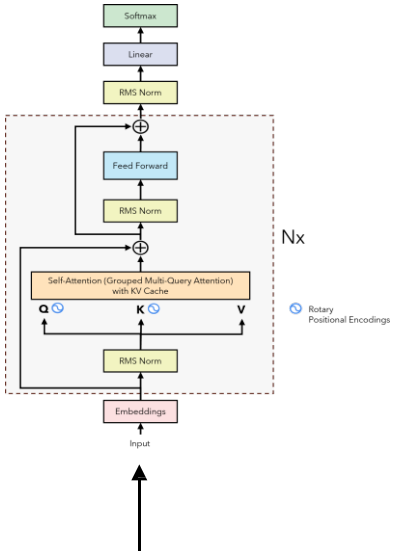


Input [SOS] Love that can quickly seize the gentle heart

Next Token Prediction Task: Inference

Output Love

Inference
T = 1

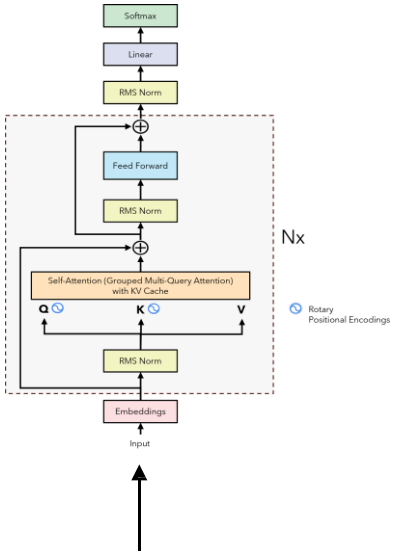


Input [SOS]

Next Token Prediction Task: Inference

Output Love that

Inference
T = 2

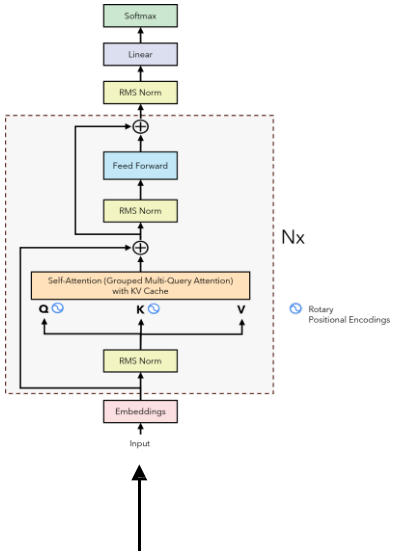


Input [SOS] Love

Next Token Prediction Task: Inference

Output Love that can

Inference
T = 3

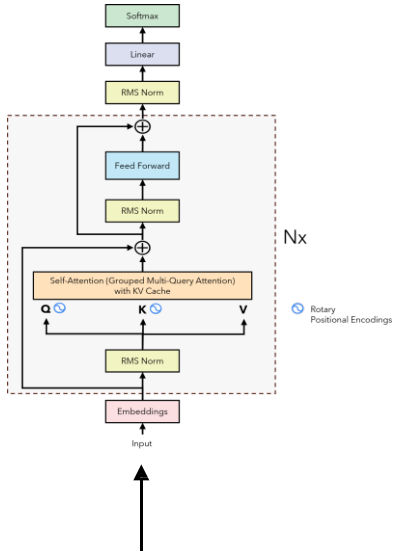


Input [SOS] Love that

Next Token Prediction Task: Inference

Output Love that can quickly

Inference
T = 4



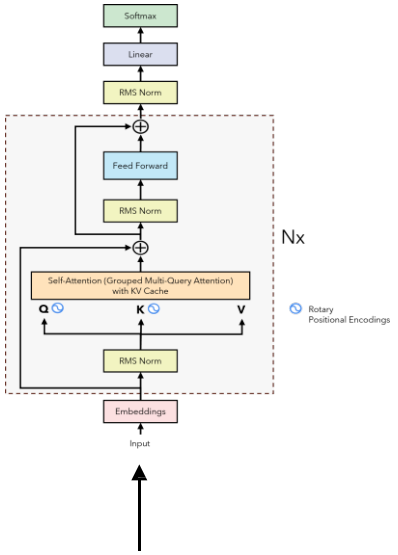
Input [SOS] Love that can

Umar Jamil – https://github.com/hkproj/mistral-llm-notes

Next Token Prediction Task: Inference

Output Love that can quickly seize

Inference
T = 5

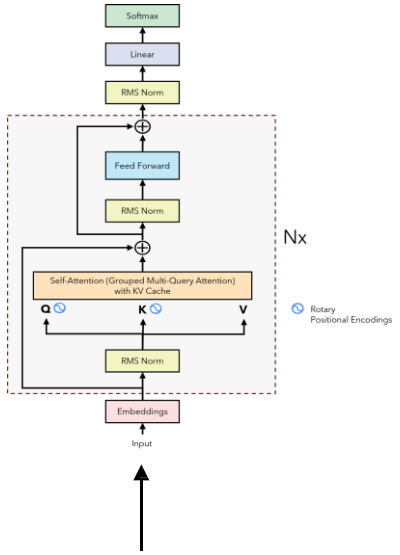


Input [SOS] Love that can quickly

Next Token Prediction Task: Inference

Output Love that can quickly seize the

Inference
T = 6

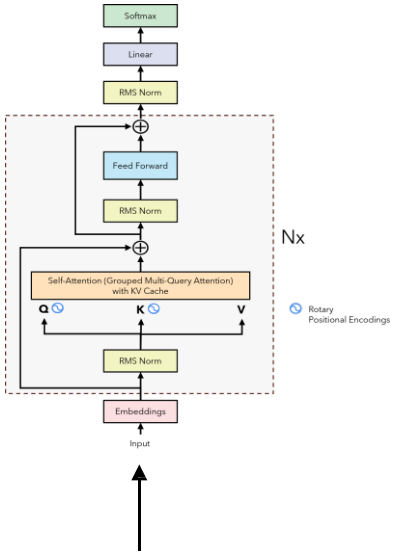


Input [SOS] Love that can quickly seize

Next Token Prediction Task: Inference

Output Love that can quickly seize the gentle

Inference
T = 7

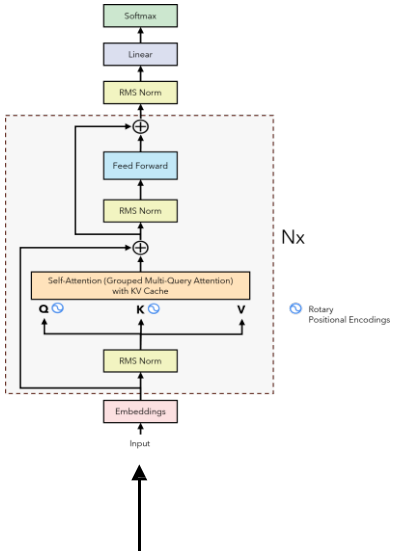


Input [SOS] Love that can quickly seize the

Next Token Prediction Task: Inference

Output Love that can quickly seize the gentle heart

Inference
T = 8

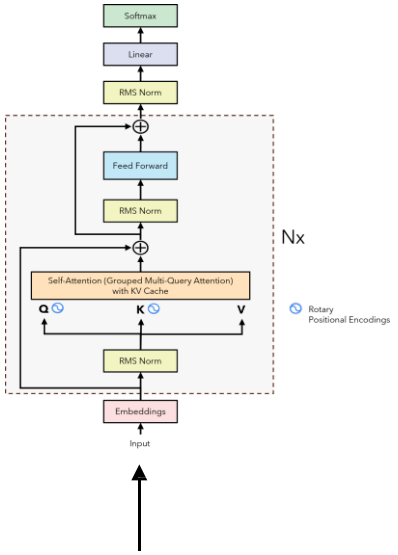


Input [SOS] Love that can quickly seize the gentle

Next Token Prediction Task: Inference

Output Love that can quickly seize the gentle heart [EOS]

Inference
T = 9

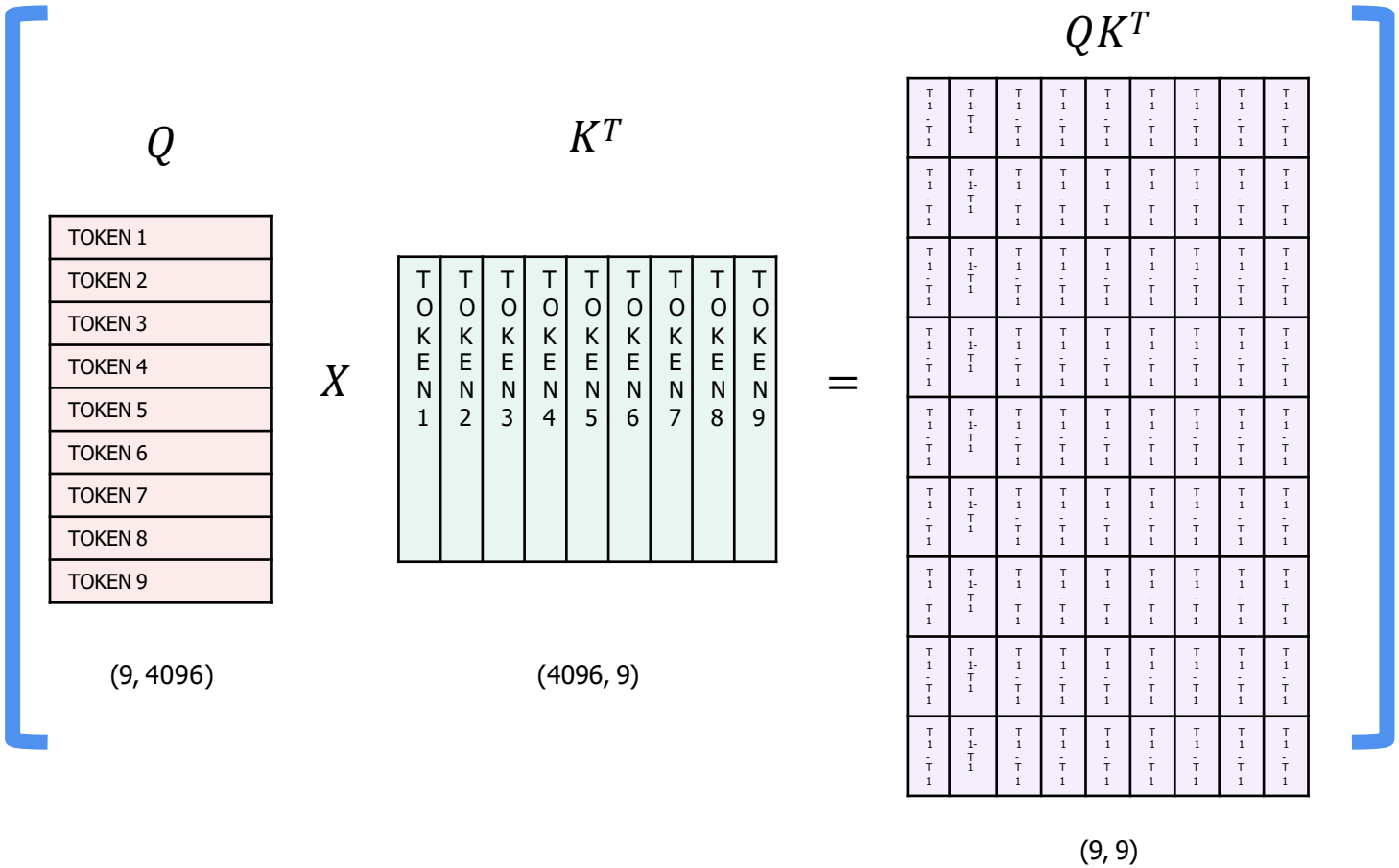


Input [SOS] Love that can quickly seize the gentle heart

Next Token Prediction Task: the motivation behind the KV cache

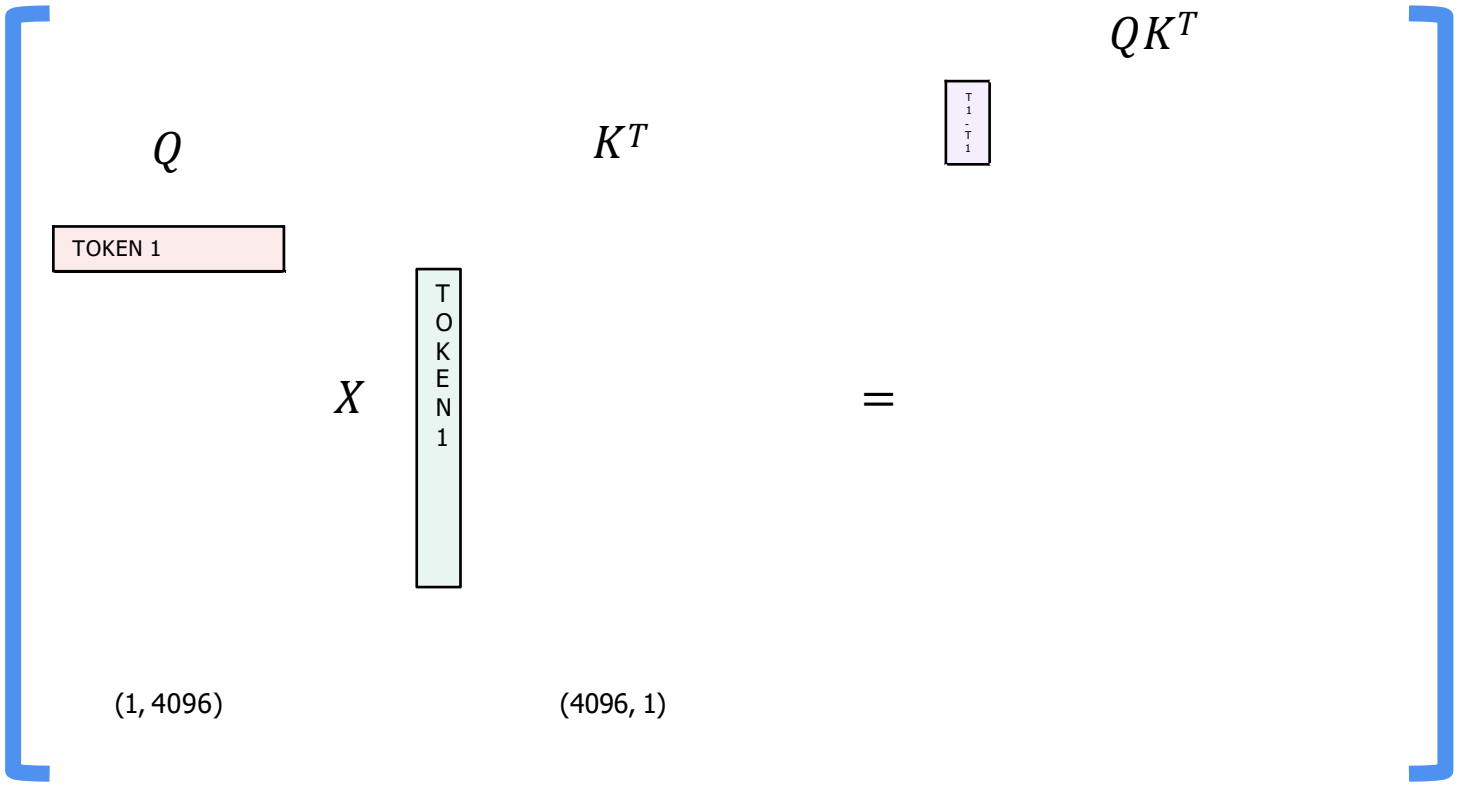
- At every step of the inference, we are only interested in the **last token** output by the model, because we already have the previous ones. However, the model needs access to all the previous tokens to decide on which token to output, since they constitute its context (or the "prompt").
- Is there a way to make the model do less computation on the token it has already seen **during inference**?
  YES! The solution is the **KV cache**!

Self-Attention during Next Token Prediction Task



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

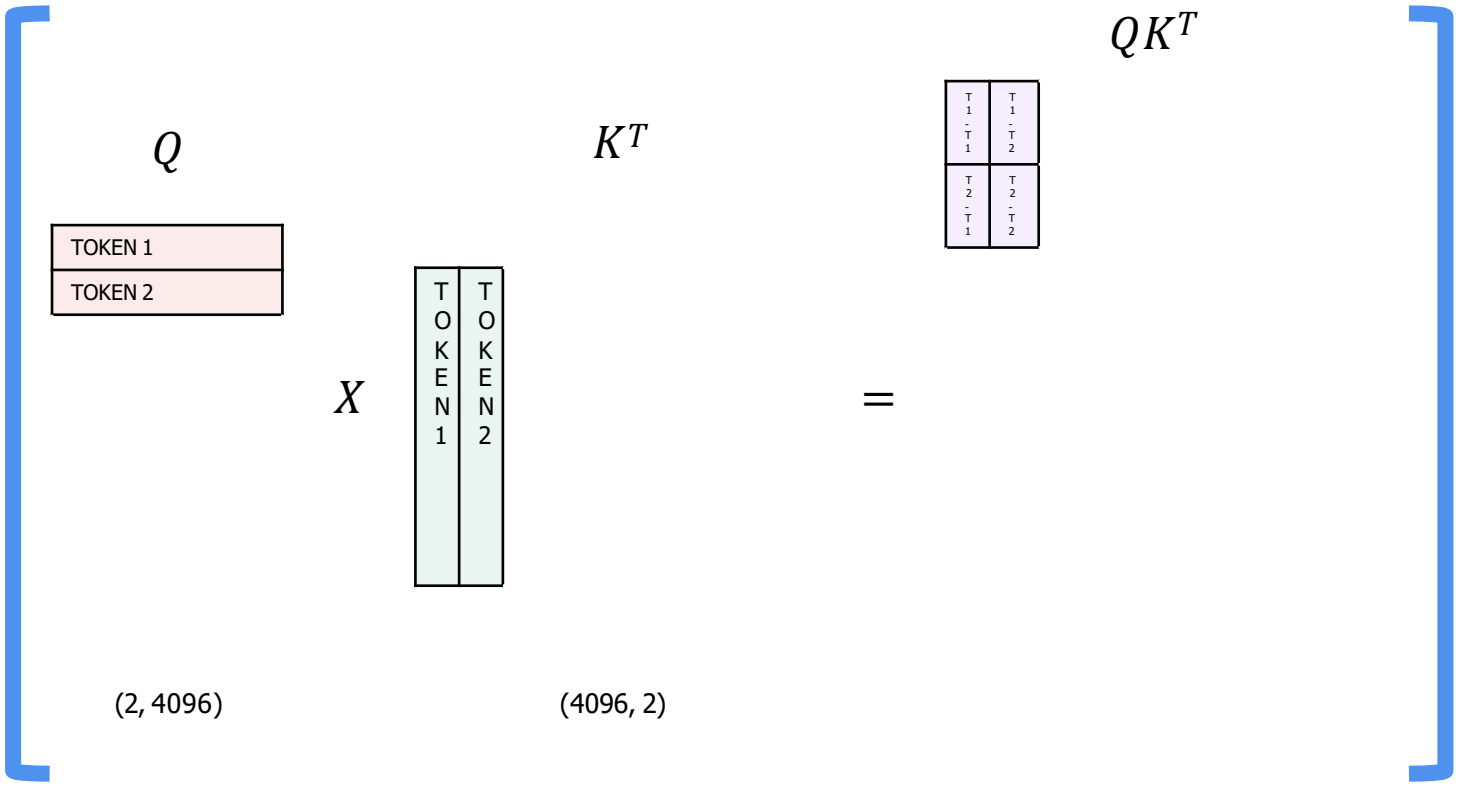
Self-Attention during Next Token Prediction Task

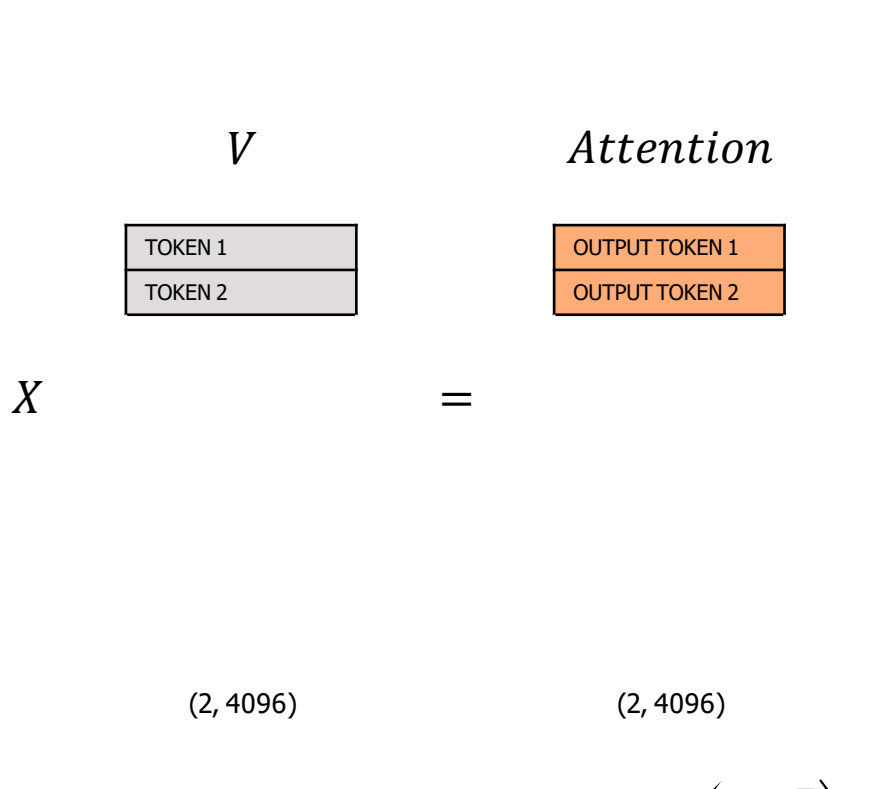


Inference
T = 1

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

Self-Attention during Next Token Prediction Task

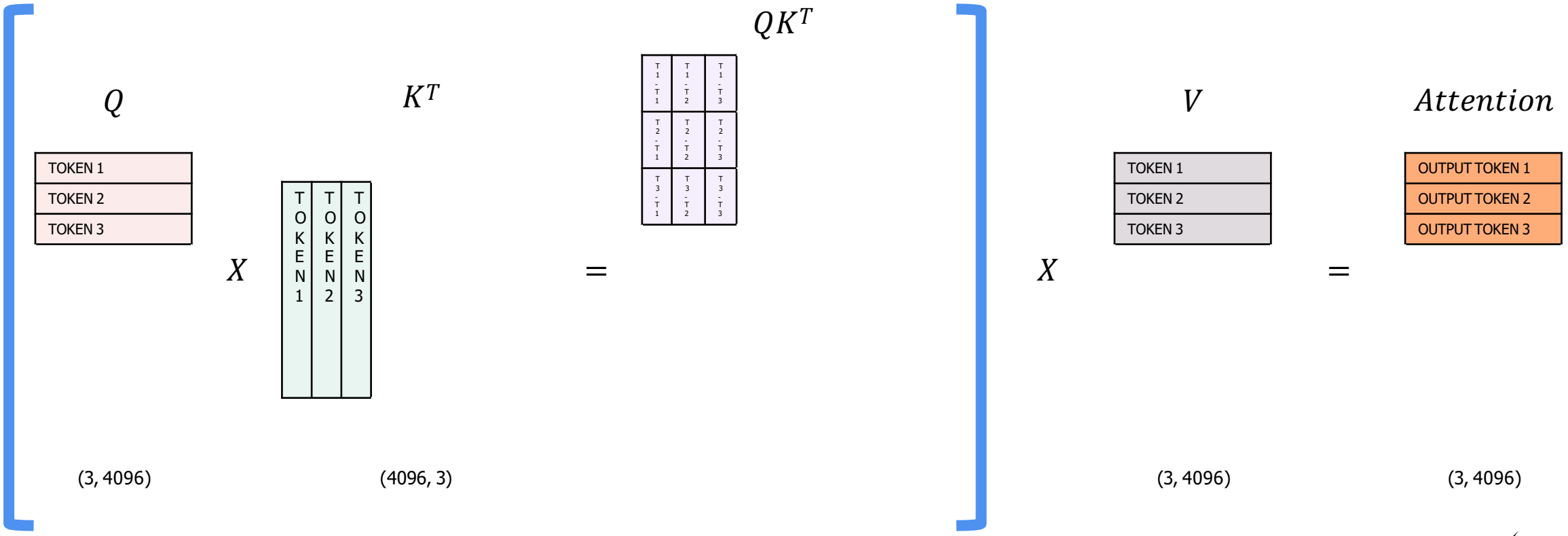




Inference
T = 2

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

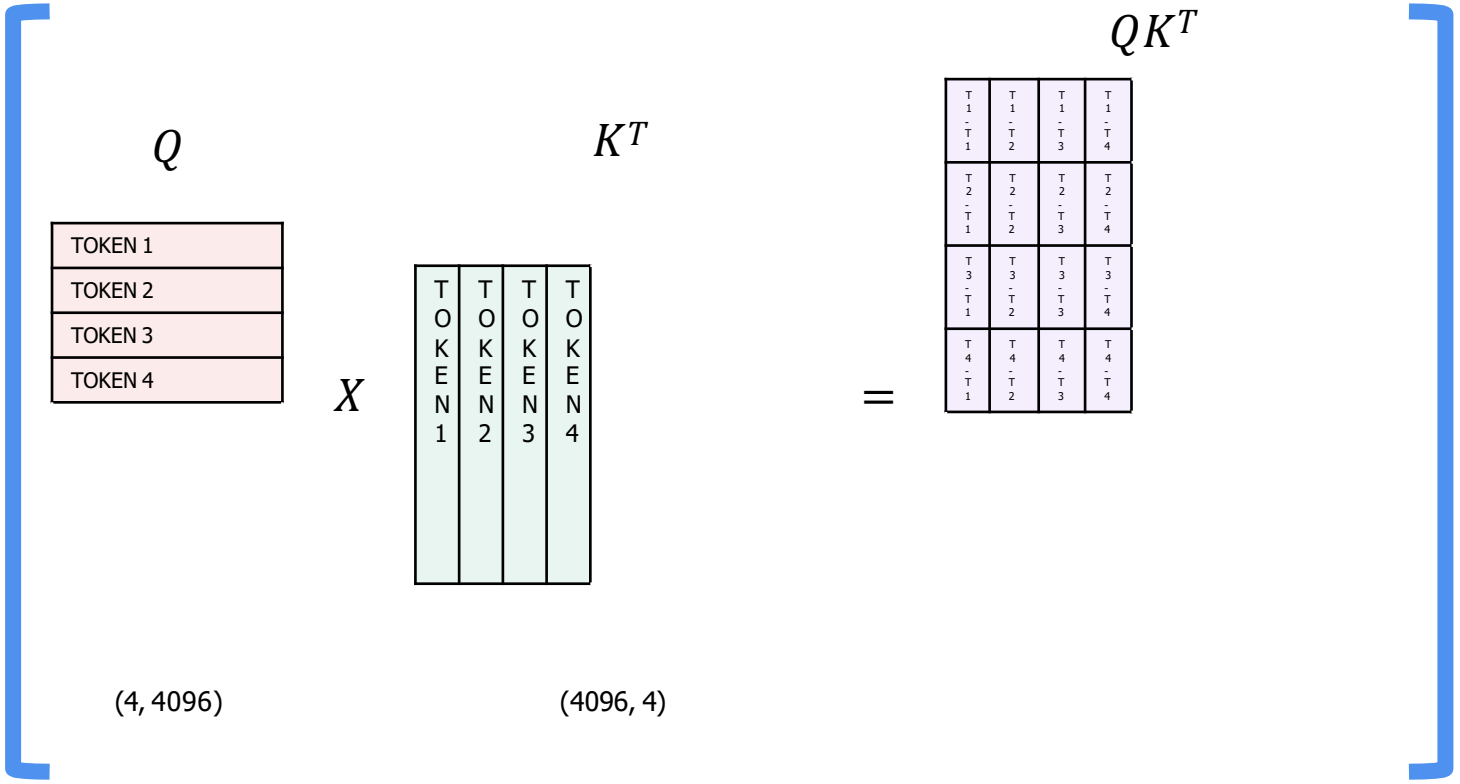
Self-Attention during Next Token Prediction Task



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

Inference
T = 3

Self-Attention during Next Token Prediction Task



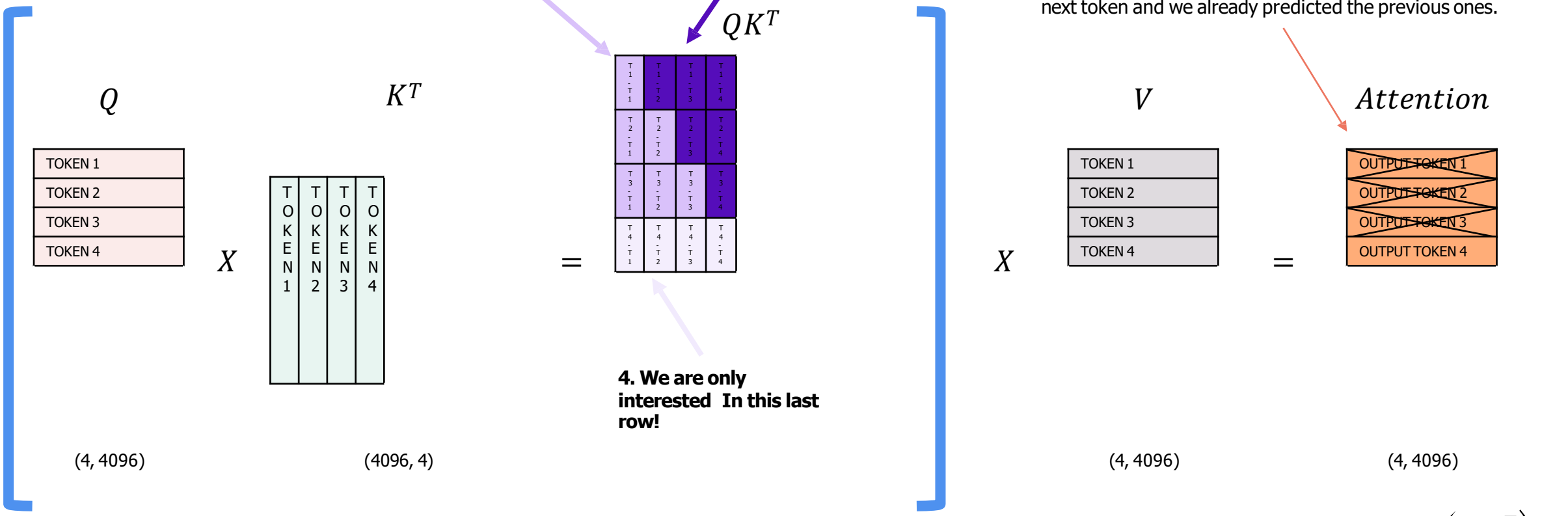
$$Attention(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Inference
T = 4

1. We already computed these dot products In the previous steps. **Can we cache them**?

2. Since the model is causal, **we don't care about the attention of a token with its successors**, but only with the tokens before it.

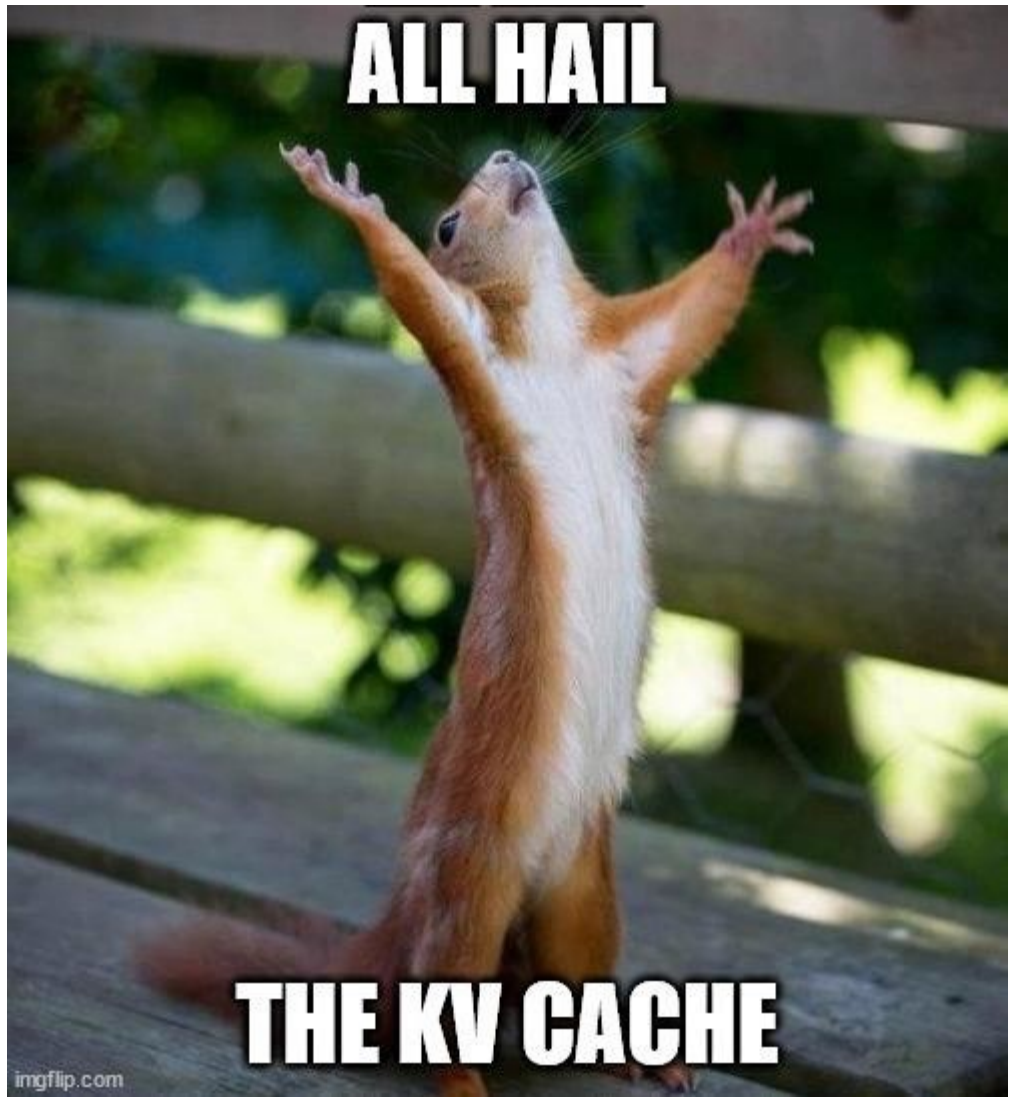
3. We don't care about these, as we want to predict the next token and we already predicted the previous ones.



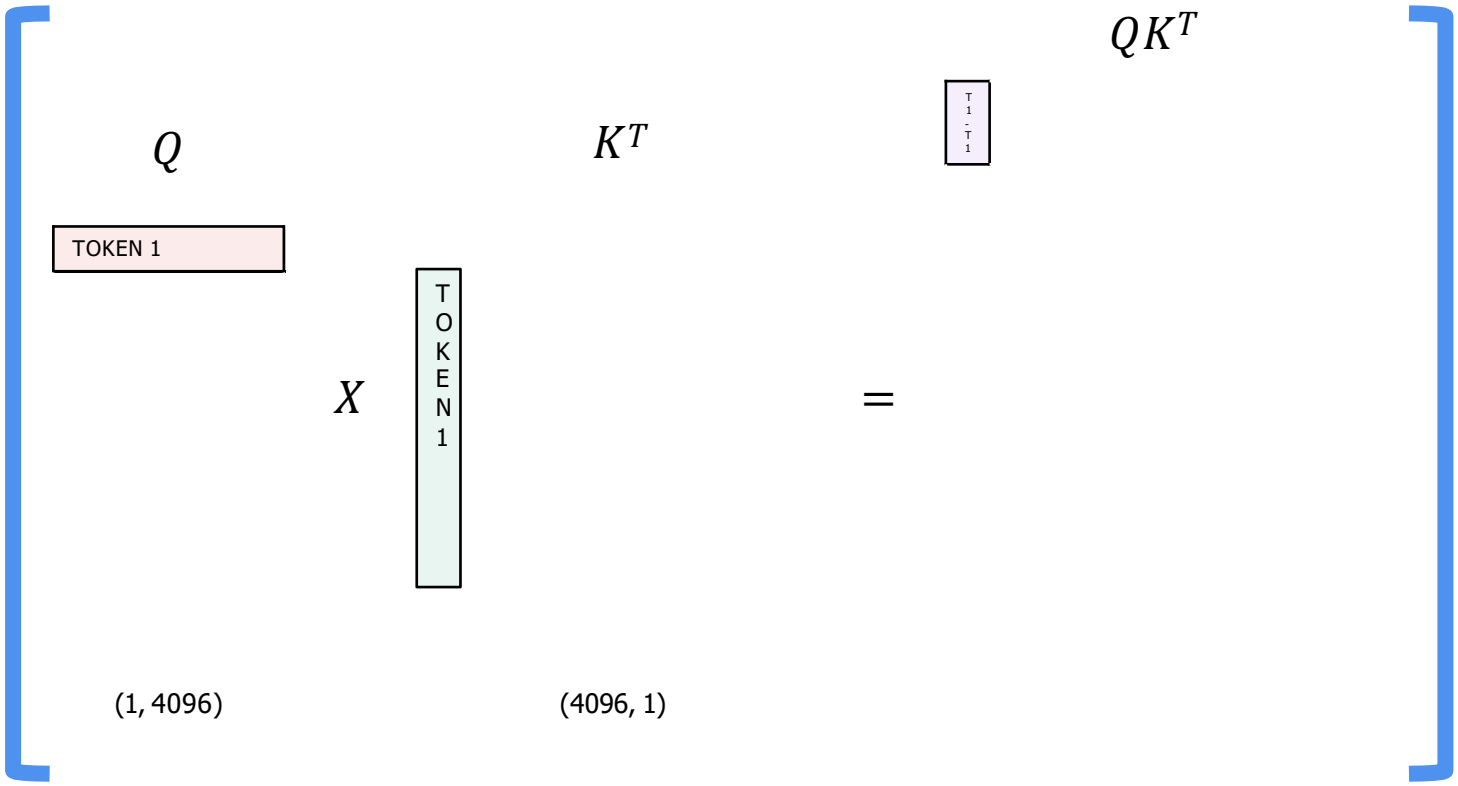
4. We are only interested In this last row!

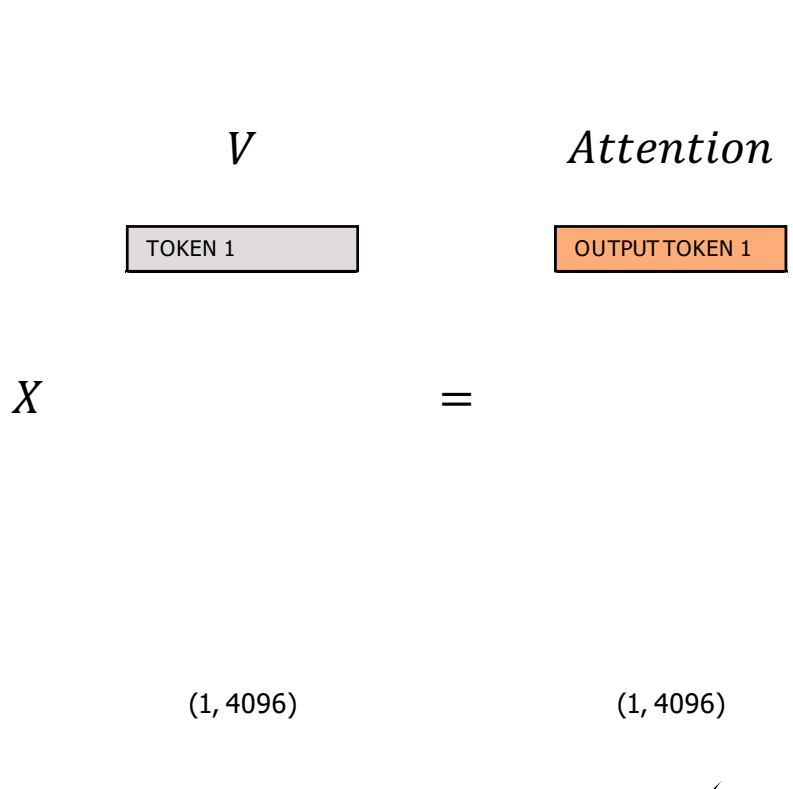
Inference
T = 4

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


ALL HAIL
THE KV CACHE
imgflip.com

Self-Attention with KV-Cache

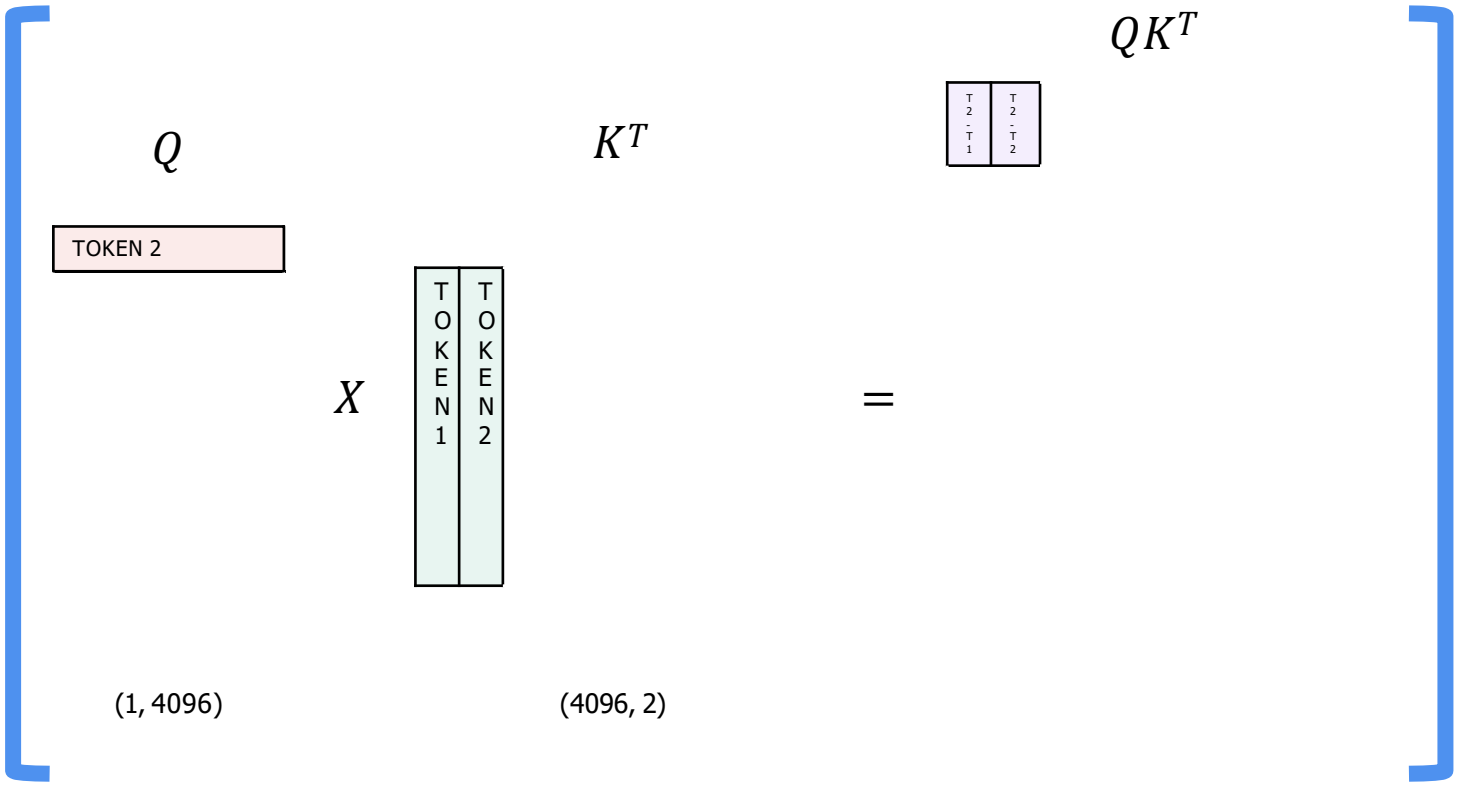


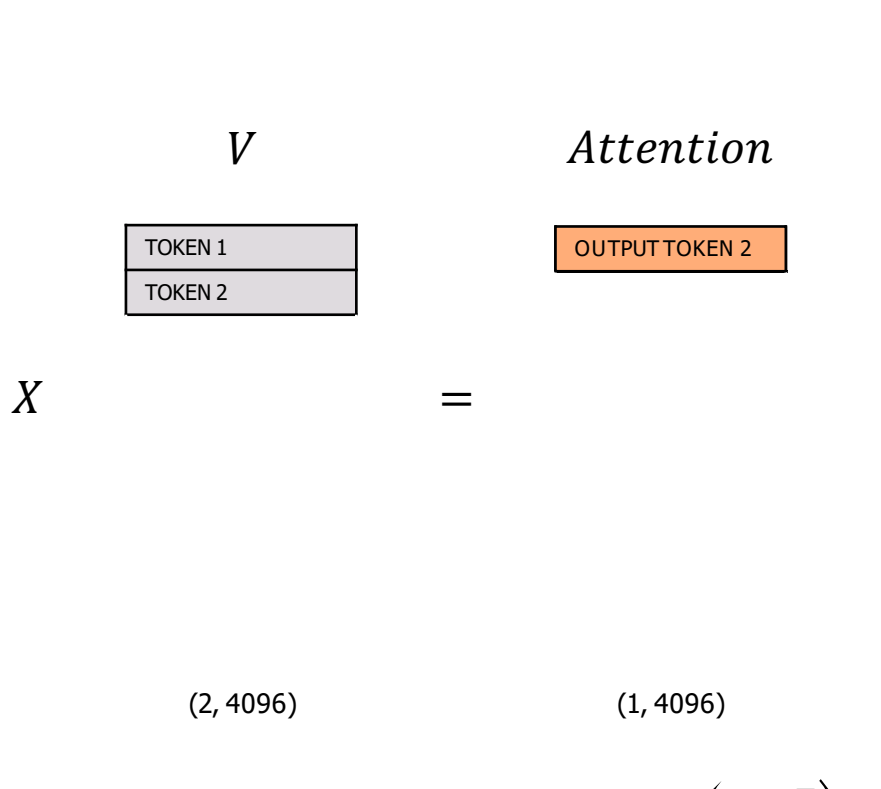


Inference
T = 1

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

Self-Attention with KV-Cache

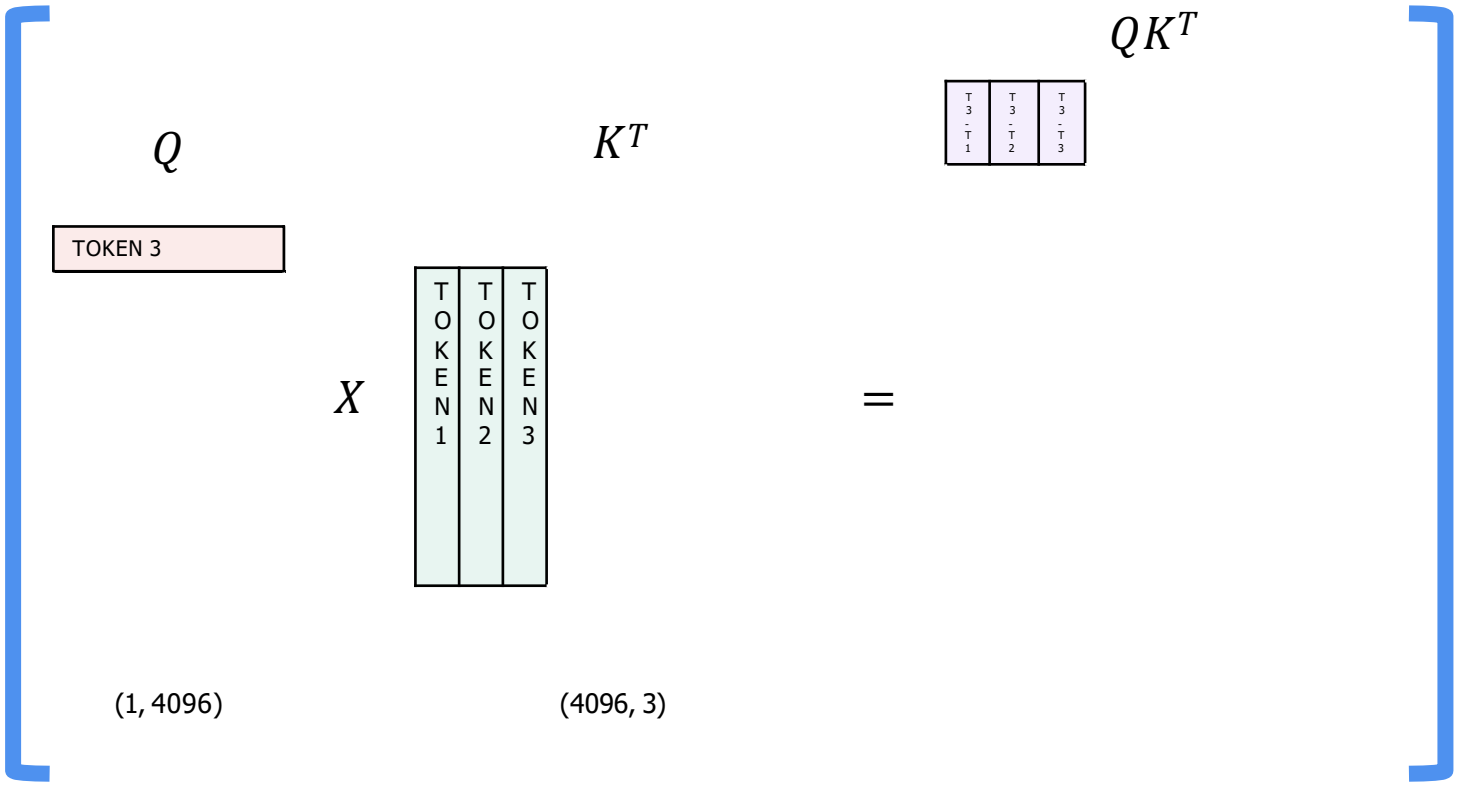


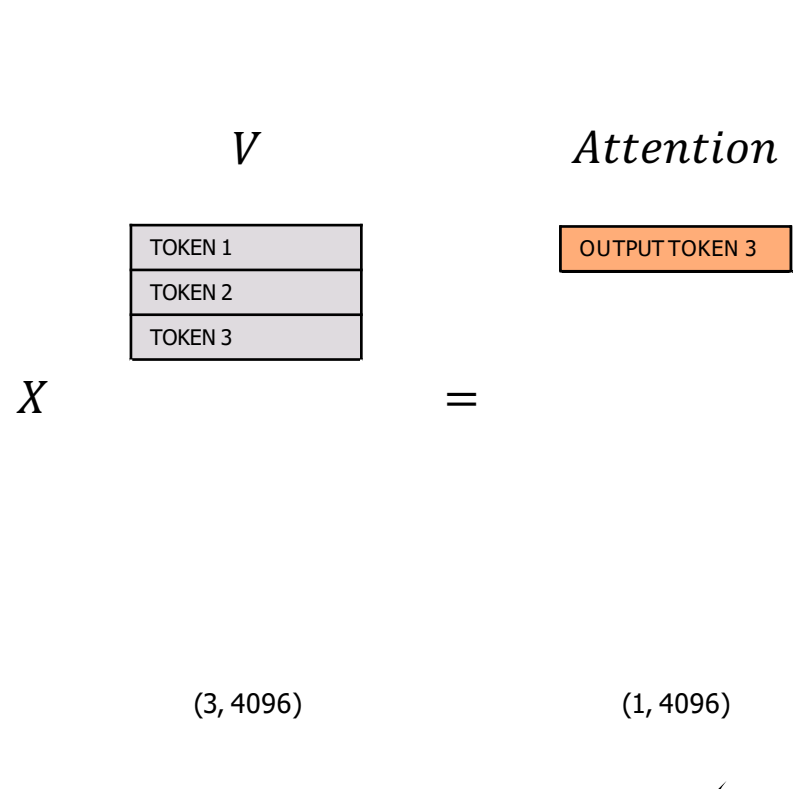


$$Attention(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Inference
T = 2

Self-Attention with KV-Cache

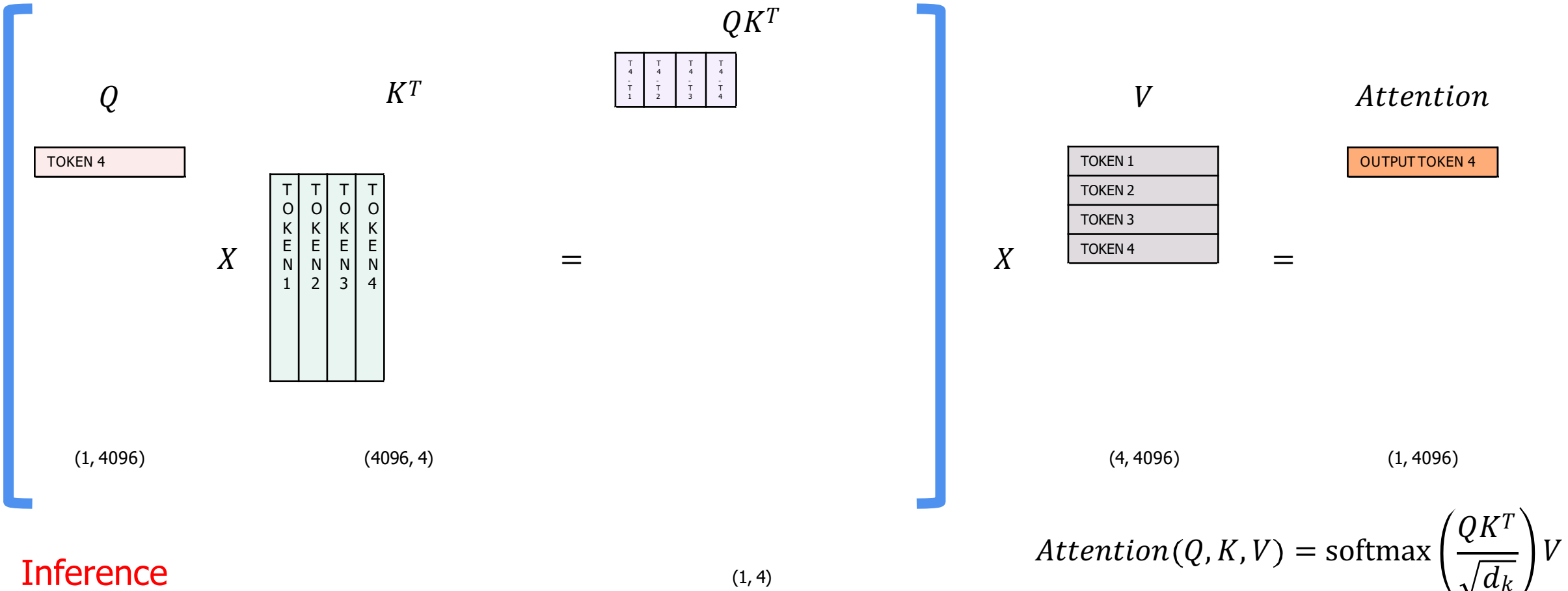




Inference
T = 3

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

Self-Attention with KV-Cache



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

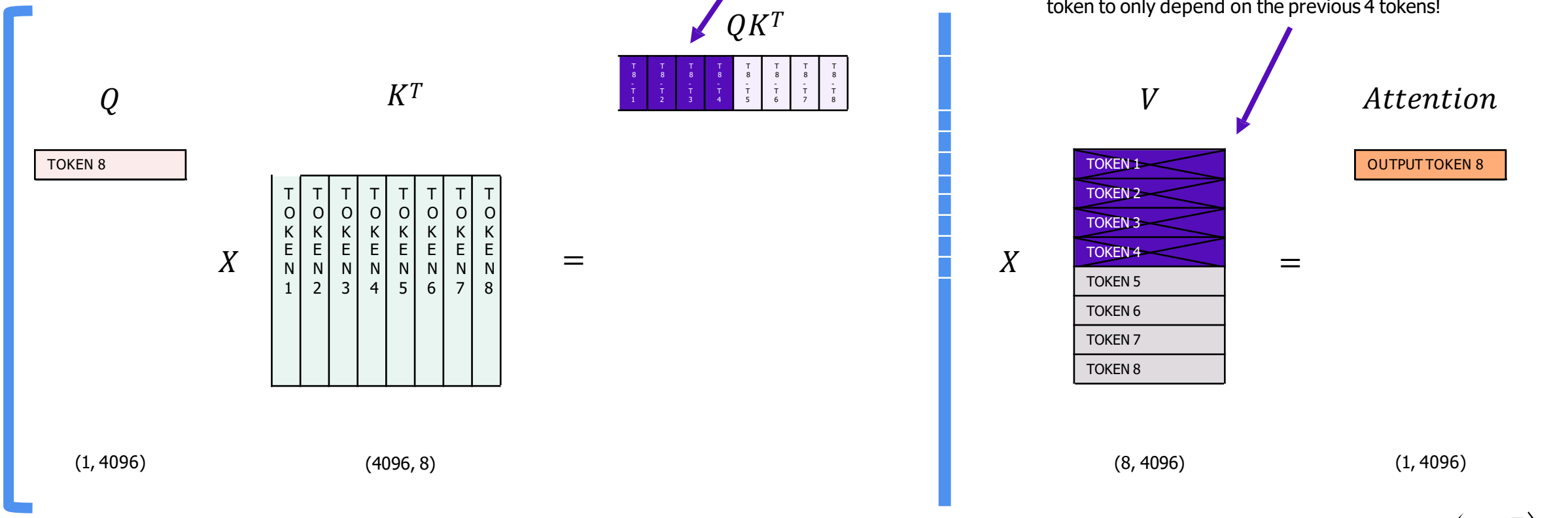
Inference
T = 4

Rolling Buffer Cache

- Since we are using Sliding Window Attention (with size **W**), we don’t need to keep all the previous tokens in the KV-Cache, but we can limit it to the latest **W** tokens.

The motivation

Since our sliding window size is 4, we only want the dot-product of the current token with the previous 4 (including the token itself)



We don't care about these either, as we want the output token to only depend on the previous 4 tokens!

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

Inference
T = 4

Rolling Buffer Cache: how it works

We keep track of write pointer that tells us where we added the last token in the rolling buffer cache.

Let's add the sentence "**The cat is on a chair**"

Rolling Buffer Cache: how it works

We add a new token and move the pointer forward

Let's add the sentence "**The cat is on a chair**"

Rolling Buffer Cache: how it works

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Rolling Buffer Cache: how it works

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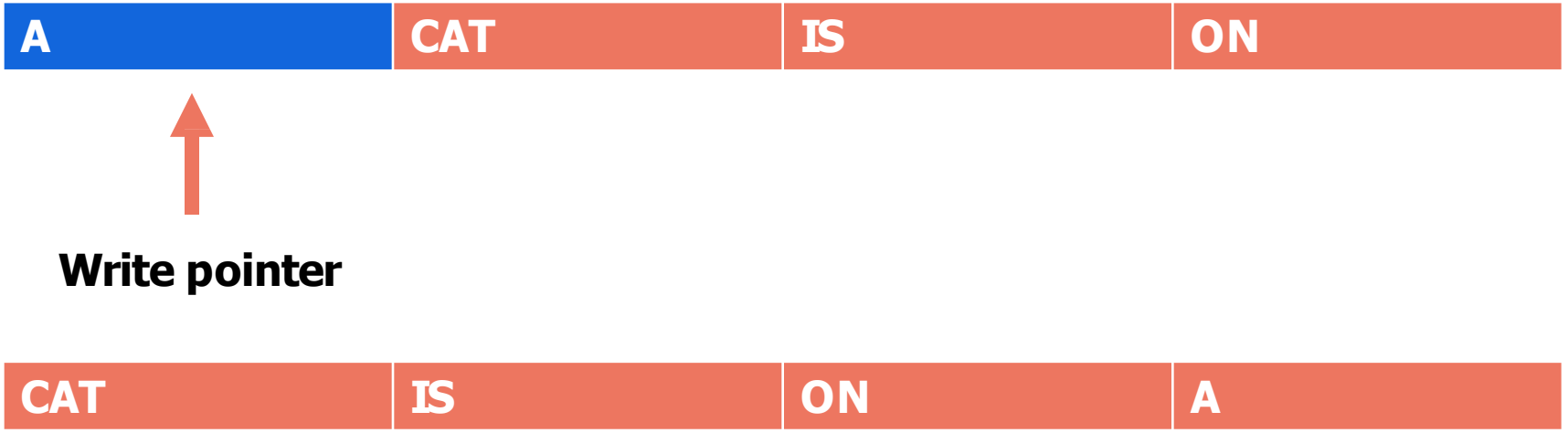
Rolling Buffer Cache: how it works

We add a new token and move the pointer forward

Let's add the sentence "**The cat is on a chair**"

Rolling Buffer Cache: unrolling

Imagine we want to "unroll" the cache because we want to calculate the attention of the incoming token. It's very easy! We just need to use the write pointer to understand how to order the items: we first take all the items AFTER the write pointer, and then all the items from the 0th index to the position of the write pointer.




```python
def unrotate(cache: torch.Tensor, seqlen: int) -> torch.Tensor:
    assert cache.ndim == 3  # (W, H, D)
    position = seqlen % cache.shape[0]
    if seqlen < cache.shape[0]:
        return cache[:seqlen]
    elif position == 0:
        return cache
    else:
        return torch.cat([cache[position:], cache[:position]], dim=0)
```

Since the cache is not full yet, ignore unfilled items.

Since the cache is not full yet, ignore unfilled items.

Rotate the cache around the write pointer

Pre-fill and chunking

When generating text using a Language Model, we use a prompt and then generate tokens one by one using the previous tokens. When dealing with a KV-Cache, we first need to add all the prompt tokens to the KV-Cache so that we can then exploit it to generate the next tokens.

Since the prompt is known in advance (we don't need to generate it), we can prefill the KV-Cache using the tokens of the prompt. But what if the prompt is very big? We can either add one token at a time, but this can be time-consuming, otherwise we can add all the tokens of the prompt at once, but in that case the attention matrix (which is $N \times N$) may be very big and not fit in the memory.

The solution is to use pre-filling and chunking. Basically, we divide the prompt into chunks of a fixed size set to **W** (except the last one), where **W** is the size of the sliding window of the attention.

Imagine we have a large prompt, with a sliding window size of $W = 4$.

For simplicity, let's pretend that each word is a token.

Prompt: "Can you tell me who is the richest man in history"

Pre-fill and chunking: first chunk

Prompt: "Can you tell me who is the richest man in history"

The KV-Cache

The attention mask

	CAN	YOU	TELL	ME
CAN	0.268	$-\infty$	$-\infty$	$-\infty$
YOU	0.124	0.278	$-\infty$	$-\infty$
TELL	0.147	0.132	0.262	$-\infty$
ME	0.132	0.128	0.206	0.212

At every step, we calculate the attention using the tokens of the KV-Cache + the tokens of the current chunk as **Keys** and **Values**, while only the tokens of the incoming chunk as **Query**.
During the first step of pre-fill, the KV-Cache is initially empty.

After calculating the attention, we add the tokens of the current chunk to the KV-Cache. This is different from token generation in which we first add the previously-generated token to the KV-Cache and then calculate the attention**. We will see layer why.**

Pre-fill and chunking: second chunk

Prompt: "Can you tell me who is the richest man in history"

The KV-Cache

CAN	YOU	TELL	ME

The attention mask

	CAN	YOU	TELL	ME	WHO	IS	THE	RICHEST
WHO	−∞	0.132	0.262	0.132	0.951	−∞	−∞	−∞
IS	−∞	−∞	0.956	0.874	0.148	0.253	−∞	−∞
THE	−∞	−∞	−∞	0.132	0.262	0.259	0.456	−∞
RICHEST	−∞	−∞	−∞	−∞	0.132	0.687	0.159	0.357

You may have noticed that the size of the attention mask is bigger than the size of the KV-Cache. This is done on purpose, otherwise the newly added tokens will not have their dot products calculated with items that were previously in the cache (for example the word "*Who*" will not have its attention calculated with the previous tokens). **This mechanism is only used during pre-fill of the prompt. Why do we do like this?** Because the KV-Cache has a fixed size, but at the same time we need all these attentions computed.

Let's review how this is implemented in code

Pre-fill and chunking: code reference

Only during prefill the attention is calculated using an attention mask that is bigger than the KV-Cache.

As you can see, during the prefill of the first chunk and the subsequent chunks, we use the size of the KV-Cache and the number of tokens in the current chunk to generate the attention mask.

During pre-fill, the attention mask is calculated using the KV-Cache + the tokens in the current chunk, **so the size of the attention mask can be bigger than that of the KV-Cache (W)**.

During generation, we first add the previous token to the KV-Cache and then use the contents of the KV-Cache to generate the attention mask. **During generation, the size of the attention mask is the size of the KV-Cache (W).**

First chunk (KV-Cache is empty)

Subsequent chunks (KV-Cache is not empty)

Token generation

```
if first_prefill:
    assert all([pos == 0 for pos in seqpos]), (seqpos)
    mask = BlockDiagonalCausalMask.from_seqlens(seqlens).make_local_attention(self.sliding_window)
elif subsequent_prefill:
    mask = BlockDiagonalMask.from_seqlens(
        q_seqlen=seqlens,
        kv_seqlen=[s + cached_s.clamp(max=self.sliding_window).item() for (s, cached_s) in zip(seqlens, self.kv_seqlens)]
    ).make_local_attention_from_bottomright(self.sliding_window)
else:
    mask = BlockDiagonalCausalWithOffsetPaddedKeysMask.from_seqlens(
        q_seqlen=seqlens,
        kv_padding=self.sliding_window,
        kv_seqlen=(self.kv_seqlens + cached_elements).clamp(max=self.sliding_window).tolist()
    )
```

Pre-fill and chunking: last chunk

Prompt: "Can you tell me who is the richest man in history"

The KV-Cache

WHO	IS	THE	RICHEST

The attention mask

	WHO	IS	THE	RICHEST	MAN	IN	HISTORY
MAN	$-\infty$	0.132	0.262	0.132	0.951	$-\infty$	$-\infty$
IN	$-\infty$	$-\infty$	0.956	0.874	0.148	0.253	$-\infty$
HISTORY	$-\infty$	$-\infty$	$-\infty$	0.132	0.262	0.259	0.456

The last chunk may be smaller, that's why we have less rows.

Topics

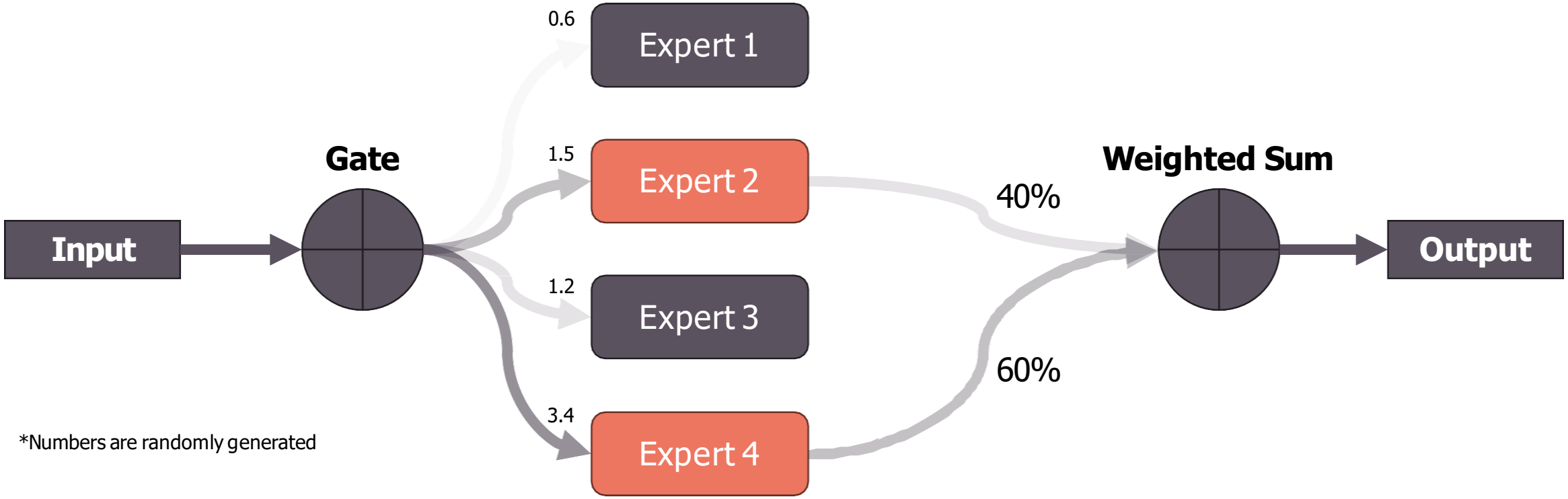
- Architectural differences between the vanilla Transformer and Mistral
- Sliding Window Attention
  - Review of self-attention
  - Receptive field
- KV-Cache
  - Motivation
  - How it works
  - Rolling Buffer Cache
  - Pre-fill and chunking
- Sparse Mixture of Experts
- Model Sharding
  - Pipeline Parallelism
- Understanding the Mistral model's code
  - Block attention in xformers

Mixture of Experts: an introduction

Mixture of Experts is an ensemble technique, in which we have multiple "expert" models, each trained on a subset of the data, such that each model specializes on it and then the output of the experts are combined (usually a weighted sum or by averaging) to produce one single output.

In the case of **Mistral 8x7B**, we talk about **Sparse Mixture of Experts (SMoE)**, because only 2 out of 8 experts are used for every token.

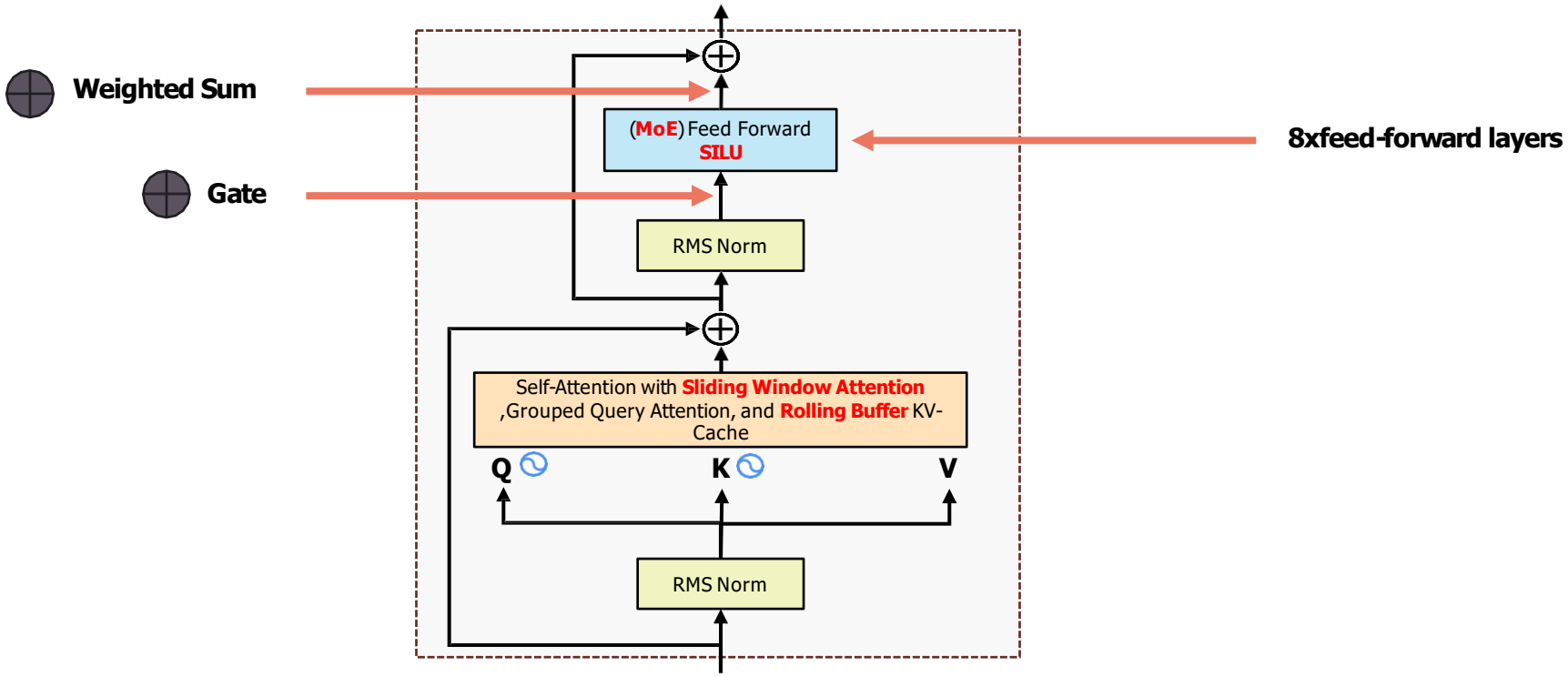
The gate produces **logits** which are used to select the top-k experts. The top-k logits are then run through a **softmax** to produce weights.



*Numbers are randomly generated

Mistral 8x7B: expert feed-forward layers

- In the case of Mistral 8x7B, the experts are the Feed-Forward layers present at every Encoder layer. Each Encoder layer is comprised of a single Self-Attention mechanism, followed by a mixture of experts of 8 FFN. The gate function selects the top 2 experts for each incoming token. The output is combined with a weighted sum.
- This allows to increase the parameters of the model, but without impacting the computation time, since the input will only pass through the top 2 experts, so the intermediate matrix multiplications will be performed only on the selected experts.



Mistral 8x7B : the gating function

- The gating function is just a linear layer **(in_features=4096, out_feature=8, bias=False)** that's trained along with the rest of the model. For each token embedding, it produces 8 logits, which indicate which expert to select.

Mistral 8x7B →

Mistral 7B →

```
self.feed_forward: nn.Module
if args.moe is not None:
    self.feed_forward = MoeLayer(
        experts=[FeedForward(args=args) for _ in range(args.moe.num_experts)],
        gate=nn.Linear(args.dim, args.moe.num_experts, bias=False),
        moe_args=args.moe,
    )
else:
    self.feed_forward = FeedForward(args=args)
```

Mixture of Experts: why we apply the softmax after selecting the top-k experts?

- If we apply the softmax directly to the output of the gate function, this will result in a "probability distribution" (weights that sum up to 1) over all the experts. But since we are only going to use the top-k of them, we want a "probability distribution" over only the selected experts.
- This also makes it easier to compare two models trained on different number of experts, since the sum of the weights applied to the output will always be 1 independently on the number of experts chosen by the gate function.

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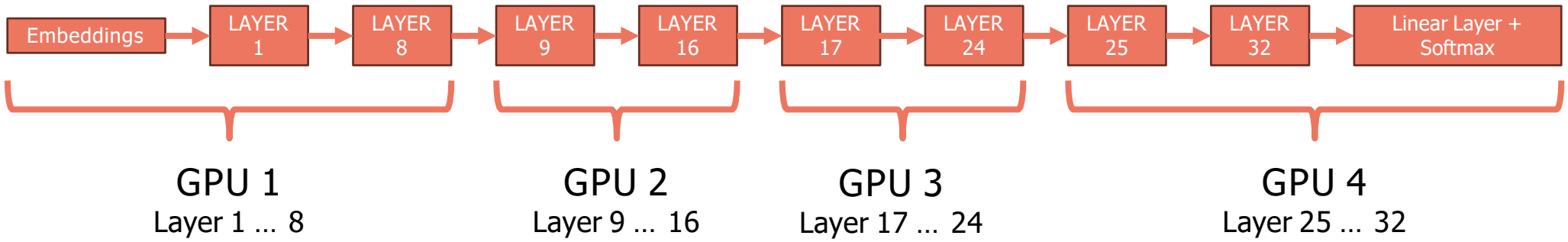
Model sharding

When we have a model that is too big to fit in a single GPU, we can divide the model into "groups of layers" and place each group of layers in a GPU. When we inference iteratively: **the output of each GPU is fed as input to the next GPU, and so on…**

This technique is known as model sharding.

In the case of Mistral, since we have 32 Encoder layers, if we have 4 GPUs, we can store 8 of them in each GPU.



A pipeline like this one works fine, but **it is not very efficient, because at any time only one GPU is working**. A better approach (**not** implemented in the open-source release of Mistral), used especially during training, is to work on multiple batches at the same time, but shift them on the time scale. This approach is known as **Pipeline Parallelism**. Let's see how it works.

Pipeline Parallelism

GPipe: Easy Scaling with Micro-Batch Pipeline Parallelism

Pipeline Parallelism: the problem

Imagine we want to train our sharded model on a single batch: it will take 8 timesteps to do it, and at each time step, only one GPU is working while the others are waiting idle.

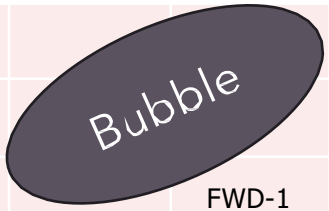
Timestep	0	1	2	3	4	5	6	7
GPU 4				FORWARD	BACKWARD			
GPU 3			FORWARD			BACKWARD		
GPU 2		FORWARD					BACKWARD	
GPU 1	FORWARD							BACKWARD

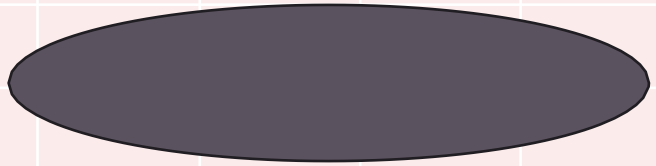
Pipeline Parallelism: the solution

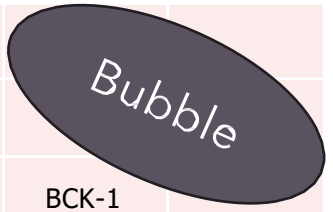
We divide our batch into smaller microbatches, and shift each microbatch's forward and backward step on the timeline.

Each timestep in this case takes less, since we are working on a small microbatch. The gradients for each microbatch is accumulated (**gradient accumulation**) and then we can run the optimizer to update the weights.

Timestep	0	1	2	3	4	5	6	7	8	9	10	11	12	13
GPU 4				FW-1	FW-2	FW-3	FW-4	BCW-4	BCK-3	BCK-2	BCK-1			
GPU 3			FW-1	FW-2	FW-3	FW-4			BCW-4	BCK-3	BCK-2	BCK-1		
GPU 2		FWD-1	FW-2	FW-3	FW-4					BCW-4	BCK-3	BCK-2	BCK-1	
GPU 1	FWD-1	FW-2	FW-3	FW-4							BCW-4	BCK-3	BCK-2	BCK-1







We still have timesteps in which not all GPUs are working (called "bubbles"). To avoid bubbling, we can increase the size of the batch

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Optimizing inference with multiple prompts

Imagine you are running an AI company providing LLM inference service: you have many customers that send their prompts and want to run inference on your models. Each prompt may have a different lengths. For simplicity, suppose that each word is a token.

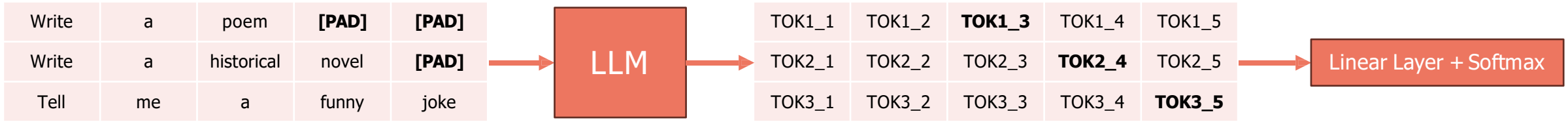
Consider the following prompts:

Prompt 1: "Write a poem" (3 tokens)

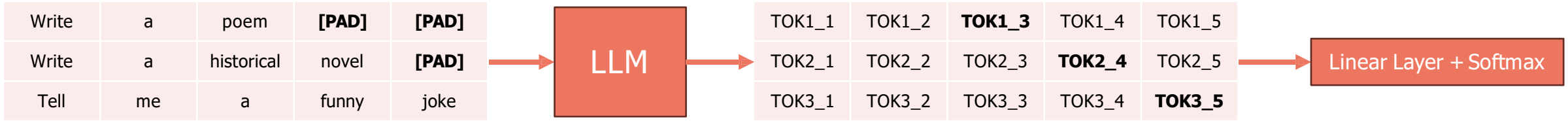
Prompt 2: "Write a historical novel" (4 tokens)

Prompt 3: "Tell me a funny joke" (5 tokens)

If we want to fully exploit our GPU, we should put all the prompts in a batch, but since they have different lengths, we have to pad them with a [PAD] token, and when the model produces the output, we should only look at the output corresponding to the last non-padding token, discarding any future tokens.



Optimizing inference with multiple prompts



To select the next token to generate, we will check the embedding corresponding to the last non-padding token, which are highlighted in the output above. Because our modal is an LLM, we will apply a causal mask. This mask works fine for all the three sequences.

0	$-\infty$	$-\infty$	$-\infty$	$-\infty$
0	0	$-\infty$	$-\infty$	$-\infty$
0	0	0	$-\infty$	$-\infty$
0	0	0	0	$-\infty$
0	0	0	0	0

We **cannot** use a different mask for each prompt, because all the prompts are of the same length, so the mask must be 5x5 for each prompt!

The problem here is that we are calculating a lot of dot products, especially for the first and the second prompt that will not be used! Let's see with an example.

Optimizing inference with multiple prompts

All the useless dot-products are highlighted in red.

	WRITE	A	POEM	[PAD]	[PAD]
WRITE	0.268	−∞	−∞	−∞	−∞
A	0.124	0.278	−∞	−∞	−∞
POEM	0.147	0.132	0.262	−∞	−∞
[PAD]	**0.210**	**0.128**	**0.206**	**0.212**	−∞
[PAD]	**0.146**	**0.158**	**0.152**	**0.143**	**0.227**

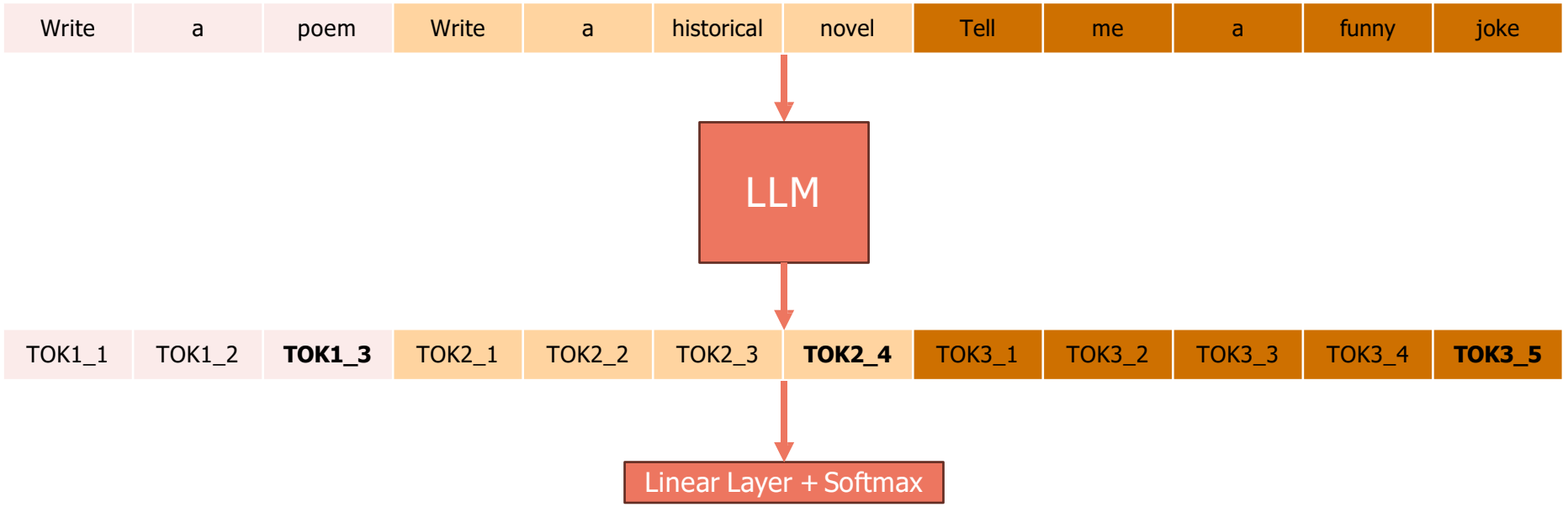
	WRITE	A	HISTOR I CAL	NOVEL	[PAD]
WRITE	0.268	−∞	−∞	−∞	−∞
A	0.124	0.278	−∞	−∞	−∞
HISTOR I CAL	0.147	0.132	0.262	−∞	−∞
NOVEL	0.210	0.128	0.206	0.212	−∞
[PAD]	**0.146**	**0.158**	**0.152**	**0.143**	**0.227**

	TELL	ME	A	FUNNY	JOKE
TELL	0.268	−∞	−∞	−∞	−∞
ME	0.124	0.278	−∞	−∞	−∞
A	0.147	0.132	0.262	−∞	−∞
FUNNY	0.210	0.128	0.206	0.212	−∞
JOKE	0.146	0.158	0.152	0.143	0.227

There is also the problem of the KV-Cache: each prompt may have a different KV-Cache size (imagine one prompt with only 10 tokens and another one with 500 tokens!). **We must find a better solution!**

Combining multiple prompts into a single sequence

The solution is to combine all the tokens of all the prompts into a single sequence and keep track of the length of each prompt when we calculate the output.



You may be wondering: how do we build an attention mask for such a sequence? Simple! We use **xformers BlockDiagonalCausalMask**!

xformers BlockDiagonalCausalMask

	Write	a	poem	Write	a	histor i cal	novel	Tell	me	a	funny	joke
Write	0	−∞	−∞	−∞	−∞	−∞	−∞	−∞	−∞	−∞	−∞	−∞
a	0	0	−∞	−∞	−∞	−∞	−∞	−∞	−∞	−∞	−∞	−∞
poem	0	0	0	−∞	−∞	−∞	−∞	−∞	−∞	−∞	−∞	−∞
Write	−∞	−∞	−∞	0	−∞	−∞	−∞	−∞	−∞	−∞	−∞	−∞
a	−∞	−∞	−∞	0	0	−∞	−∞	−∞	−∞	−∞	−∞	−∞
histo r ical	−∞	−∞	−∞	0	0	0	−∞	−∞	−∞	−∞	−∞	−∞
novel	−∞	−∞	−∞	0	0	0	0	−∞	−∞	−∞	−∞	−∞
Tell	−∞	−∞	−∞	−∞	−∞	−∞	−∞	0	−∞	−∞	−∞	−∞
me	−∞	−∞	−∞	−∞	−∞	−∞	−∞	0	0	−∞	−∞	−∞
a	−∞	−∞	−∞	−∞	−∞	−∞	−∞	0	0	0	−∞	−∞
funny	−∞	−∞	−∞	−∞	−∞	−∞	−∞	0	0	0	0	−∞
joke	−∞	−∞	−∞	−∞	−∞	−∞	−∞	0	0	0	0	0

The mask may be different in case we use Sliding Window Attention.

Let's have a look at the code!

Thanks for watching!
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