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# InfiniGen

## Efficient Generative Inference of Large Language Models with Dynamic KV Cache Management

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Seoul National University

<sup>†</sup>Co-first Authors

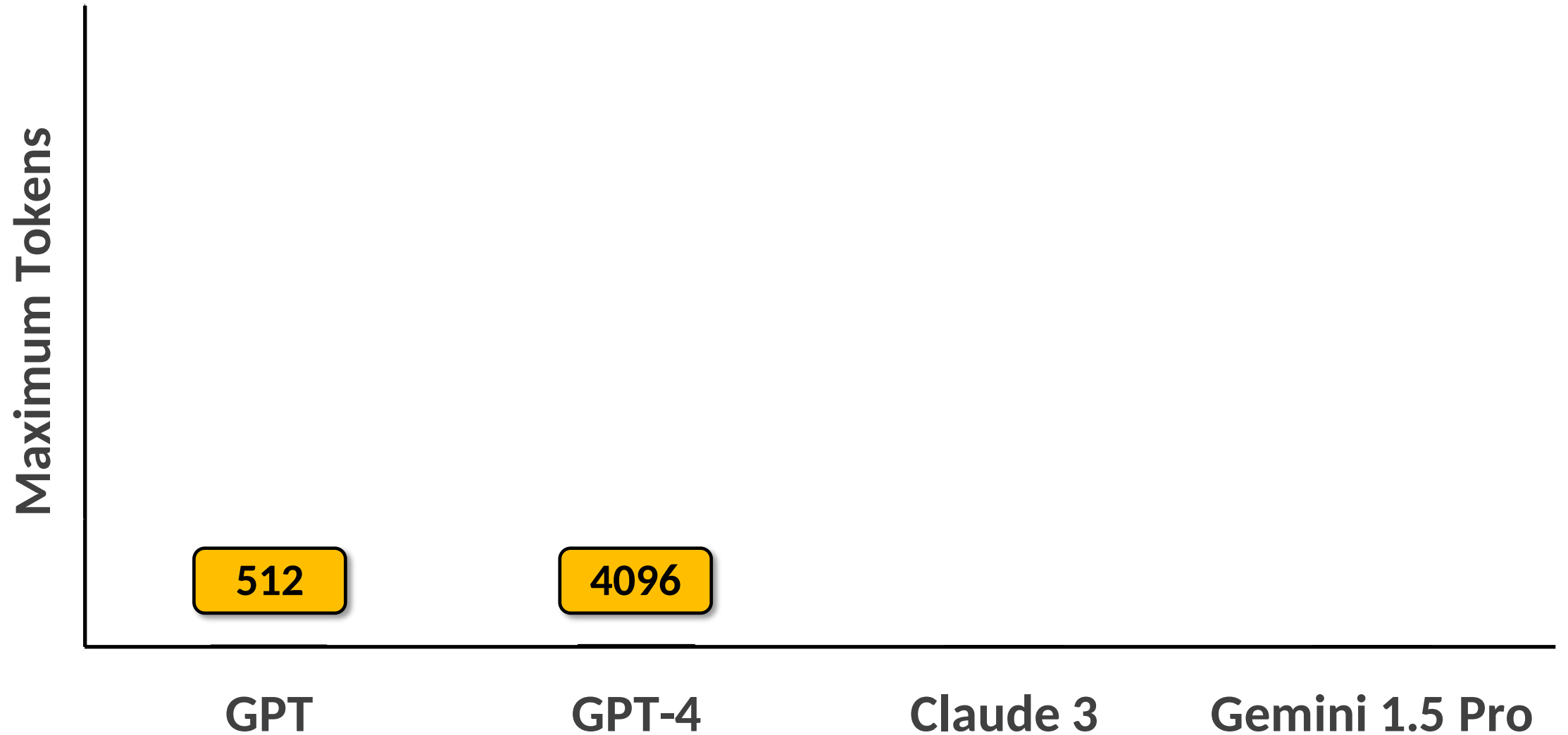
OSDI'24 | July 2024



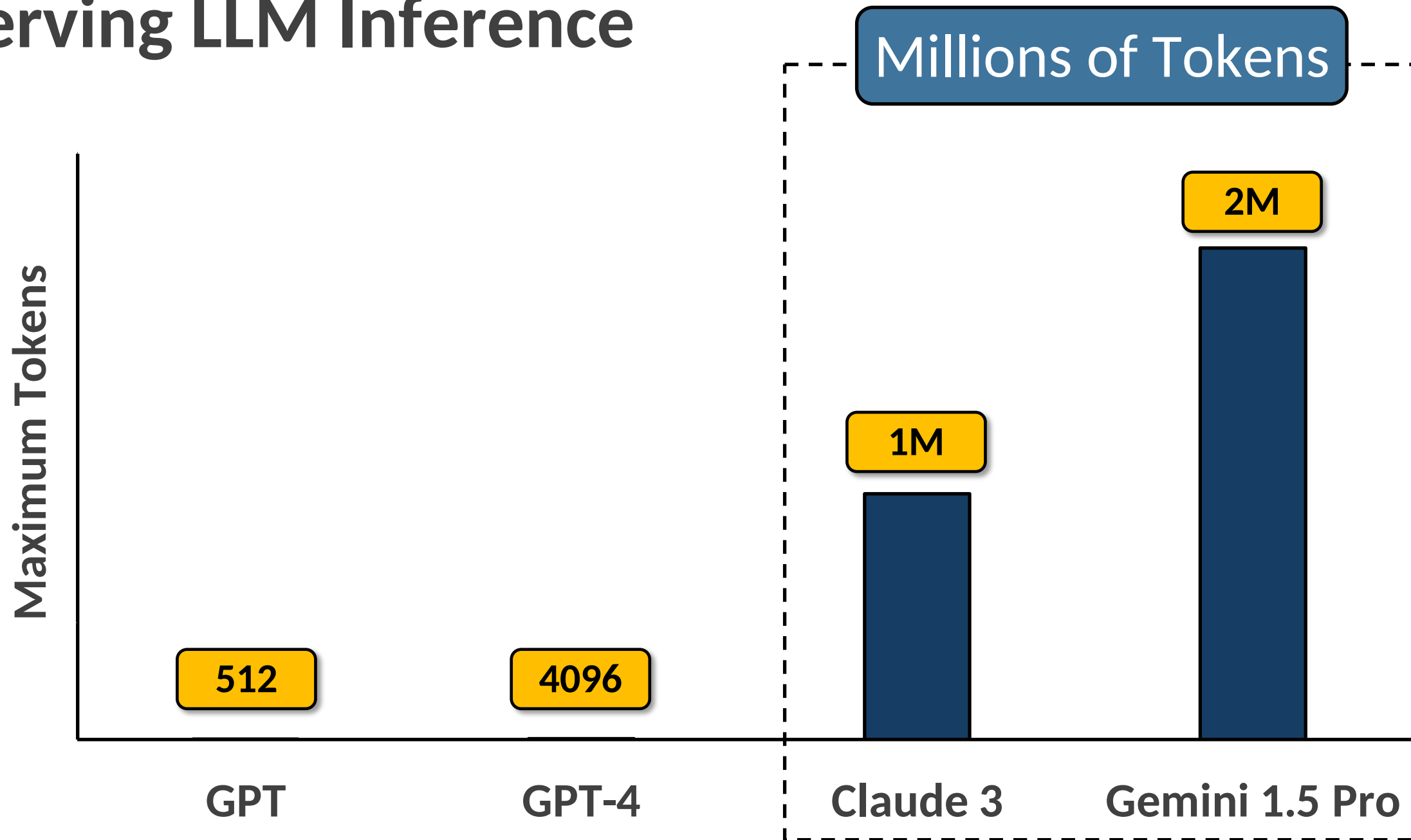
# Outline

- LLM Inference & KV Cache
- Prior Approaches & Limitations
- **InfiniGen: Dynamic KV Cache Management**
  - Speculative KV Prefetching
  - Key/Query Skewing
- Evaluation
- Conclusion

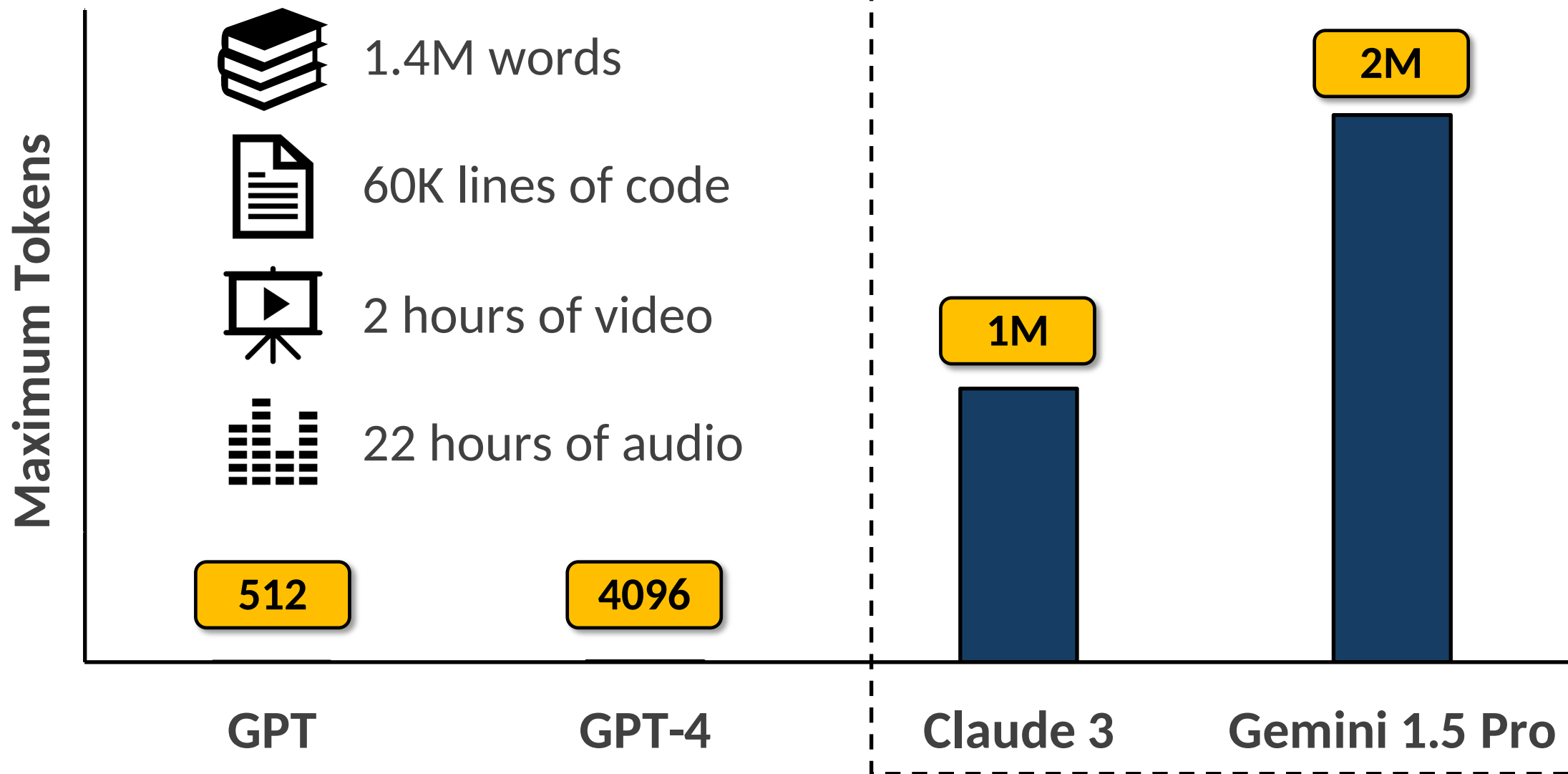
# Serving LLM Inference



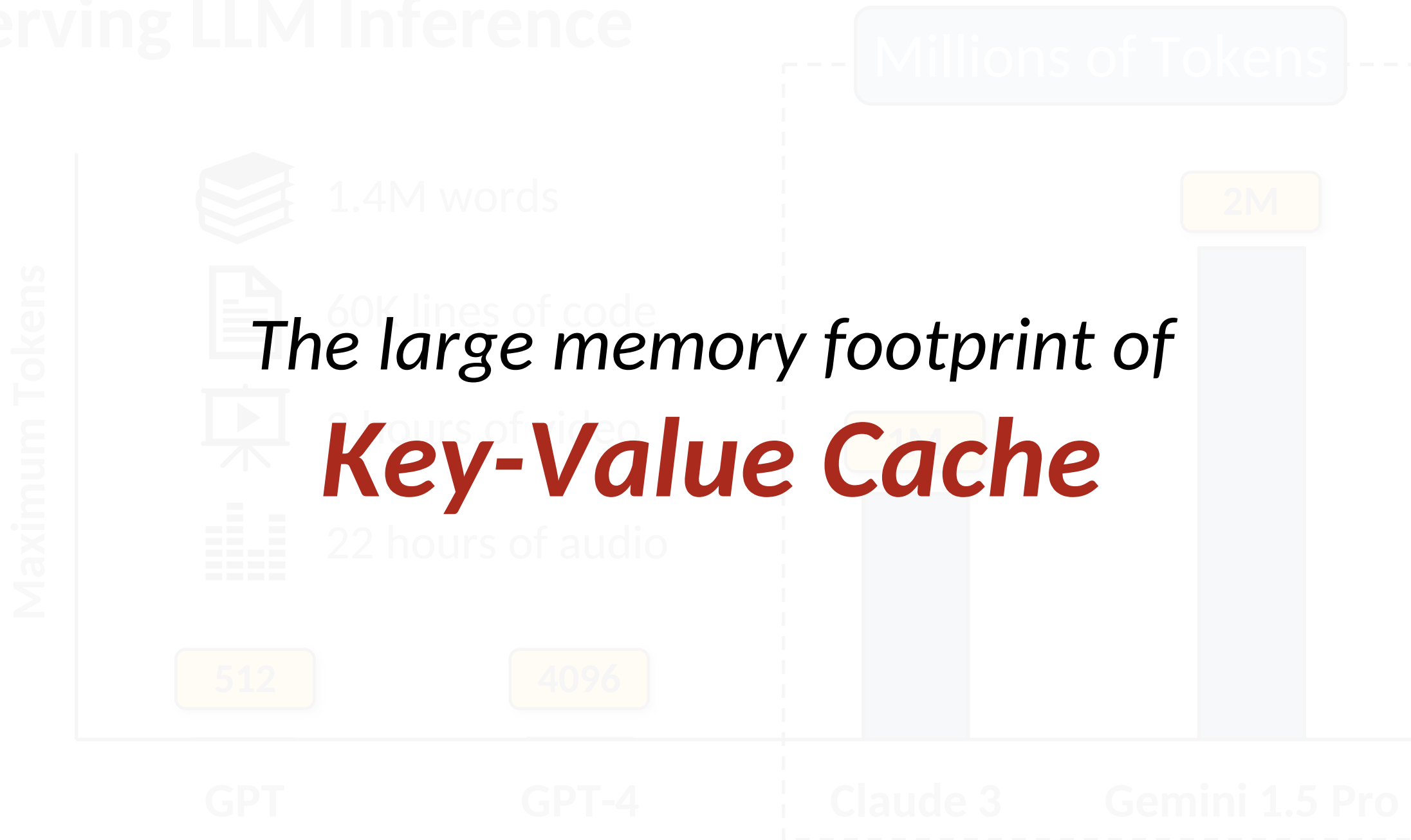
# Serving LLM Inference



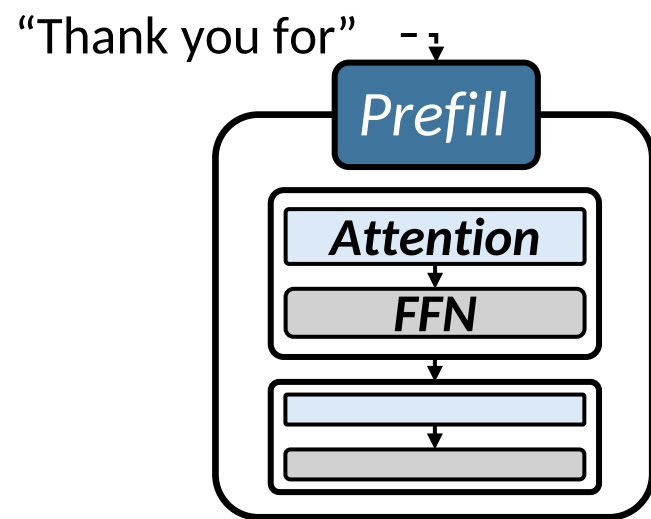
# Serving LLM Inference



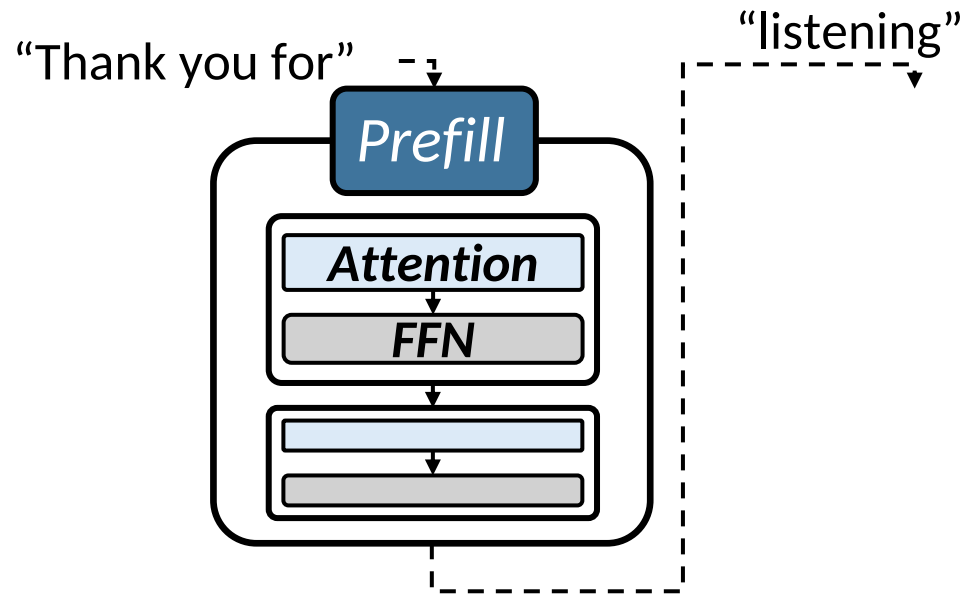
# Serving LLM Inference



# KV Cache in LLM Inference

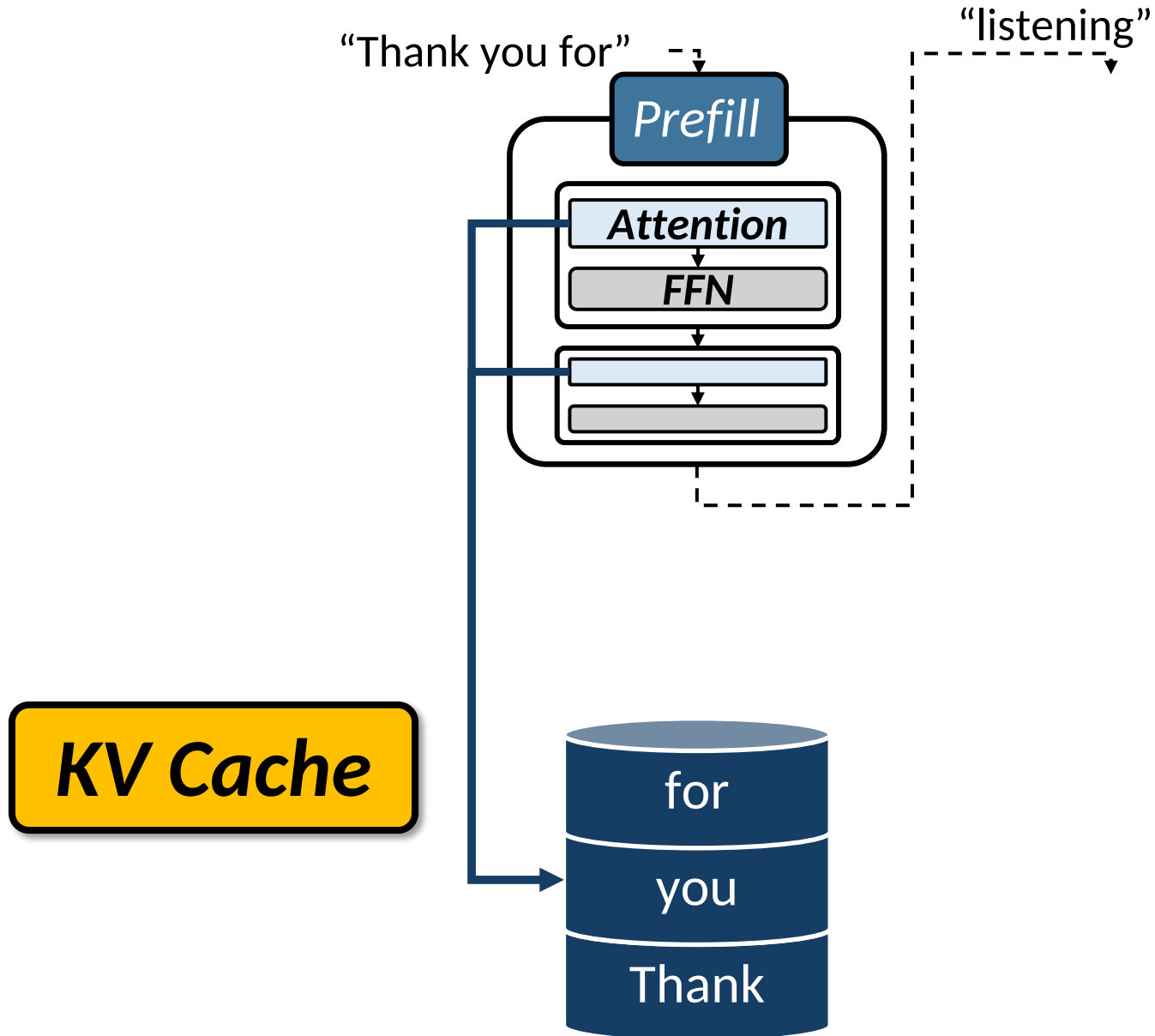


# KV Cache in LLM Inference

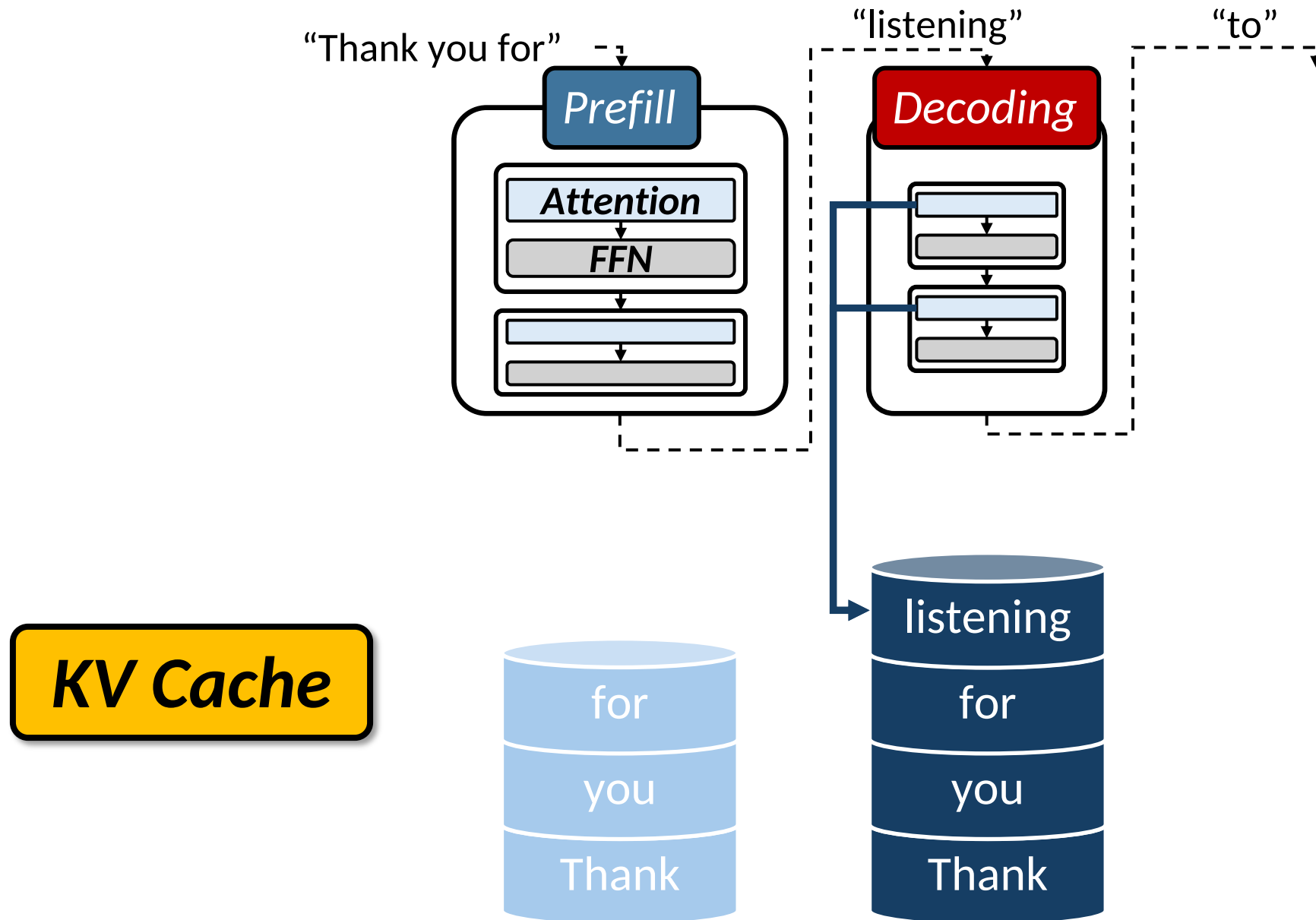




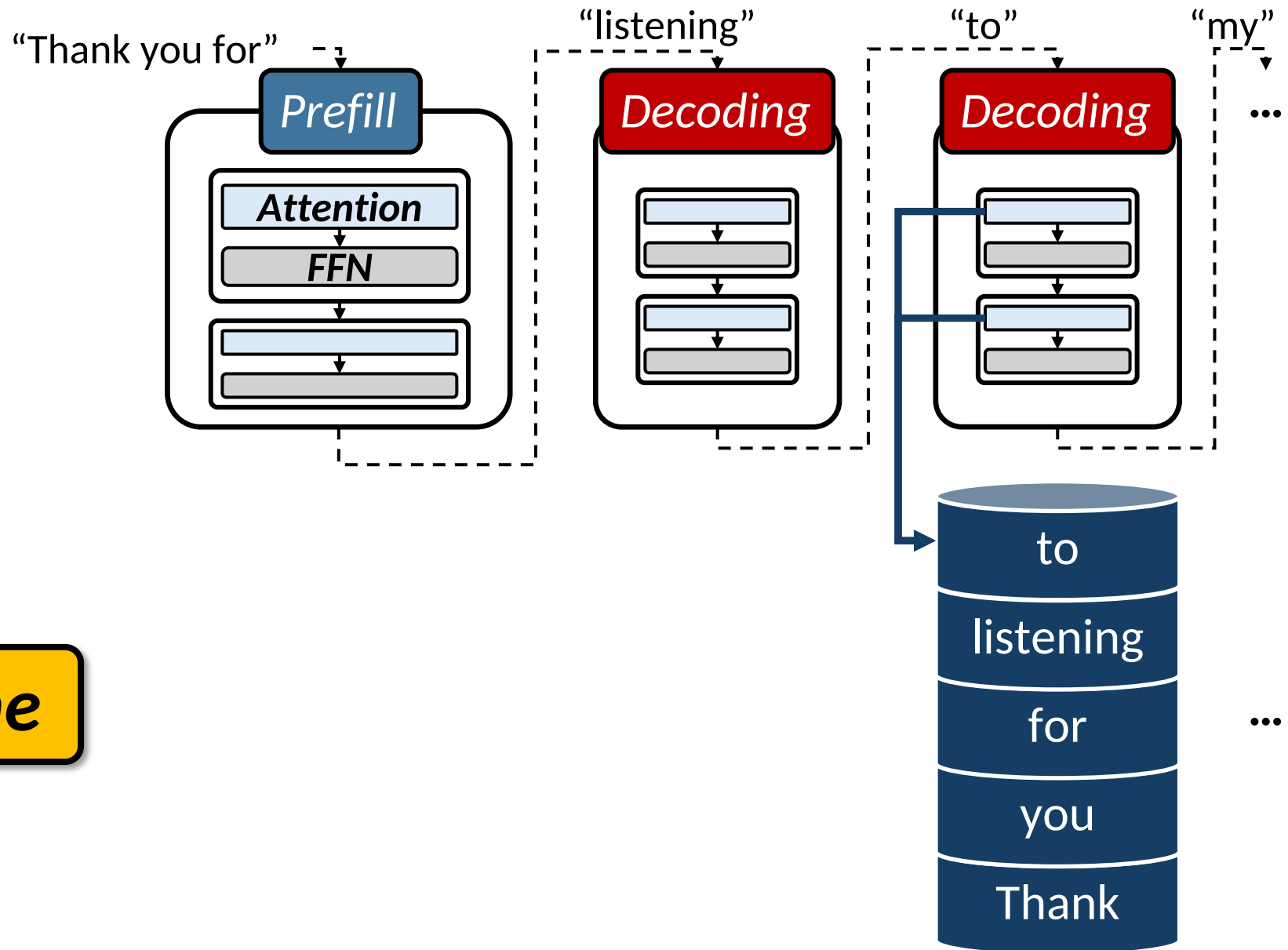
# KV Cache in LLM Inference



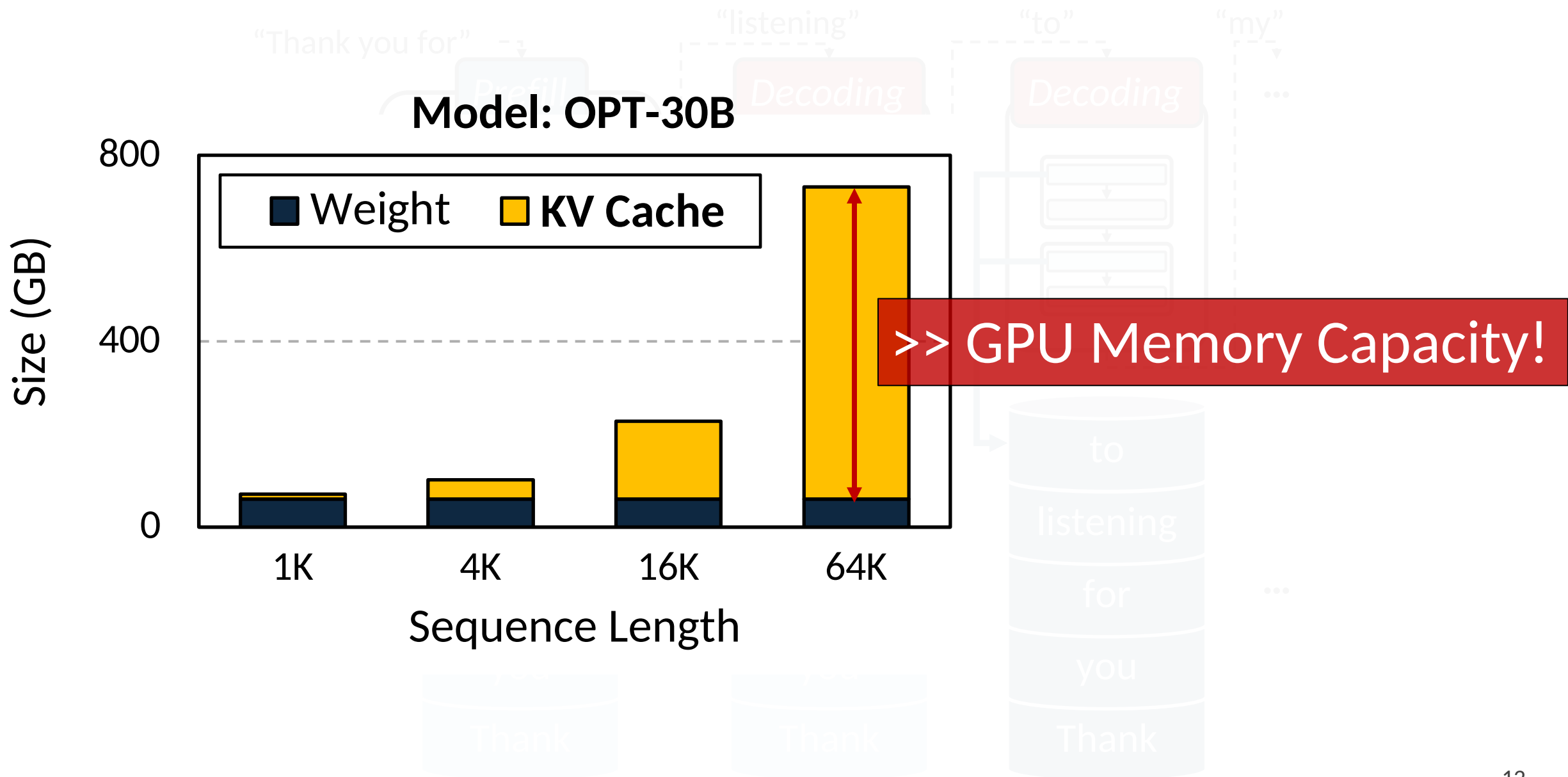
# KV Cache in LLM Inference



# KV Cache in LLM Inference

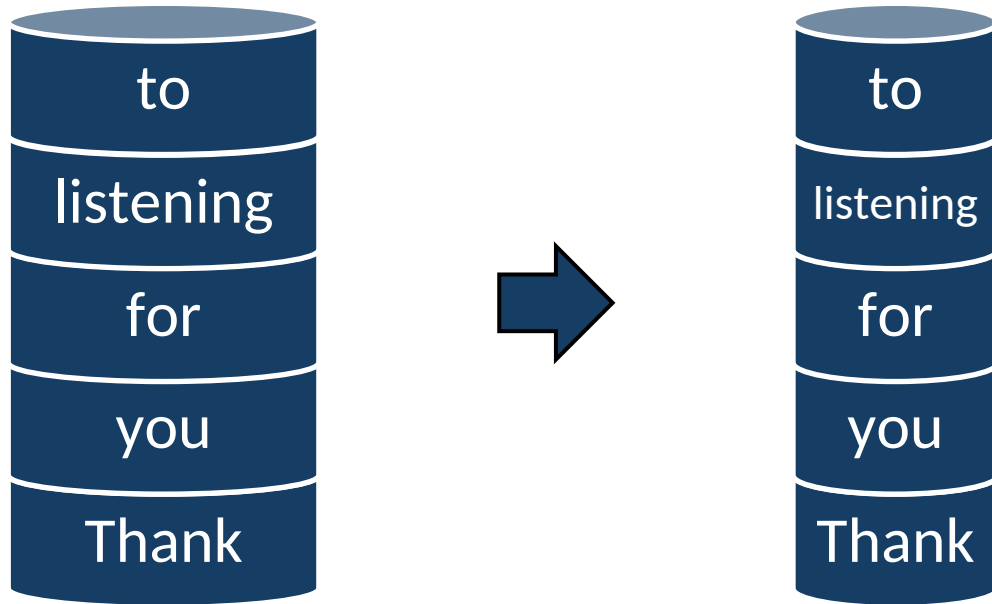


# KV Cache in LLM Inference



# Prior Approaches for KV Cache Problem

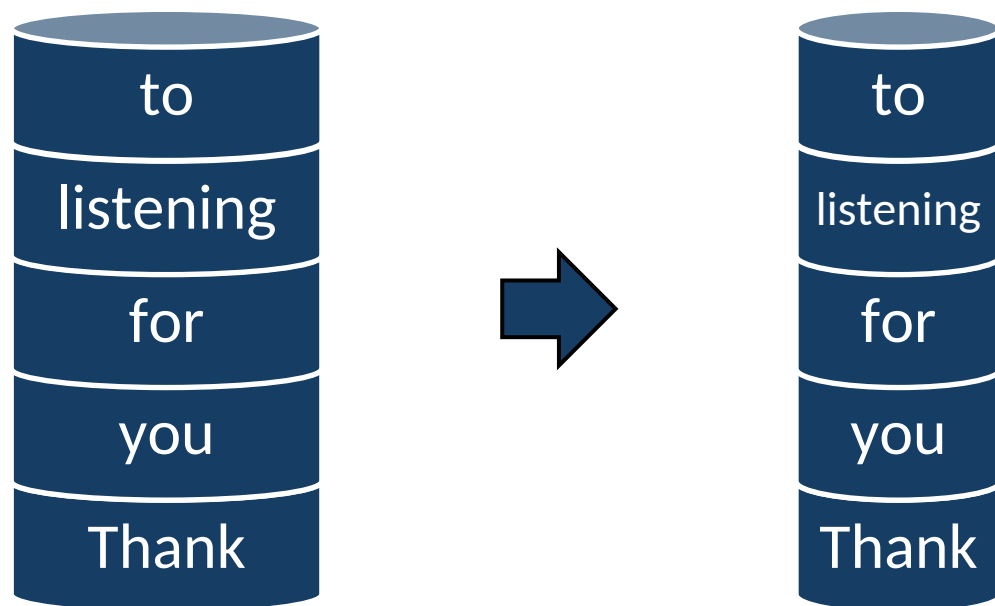
## 1. Quantization



Compress the **KV cache**  
by converting it into **a low-bit data format**

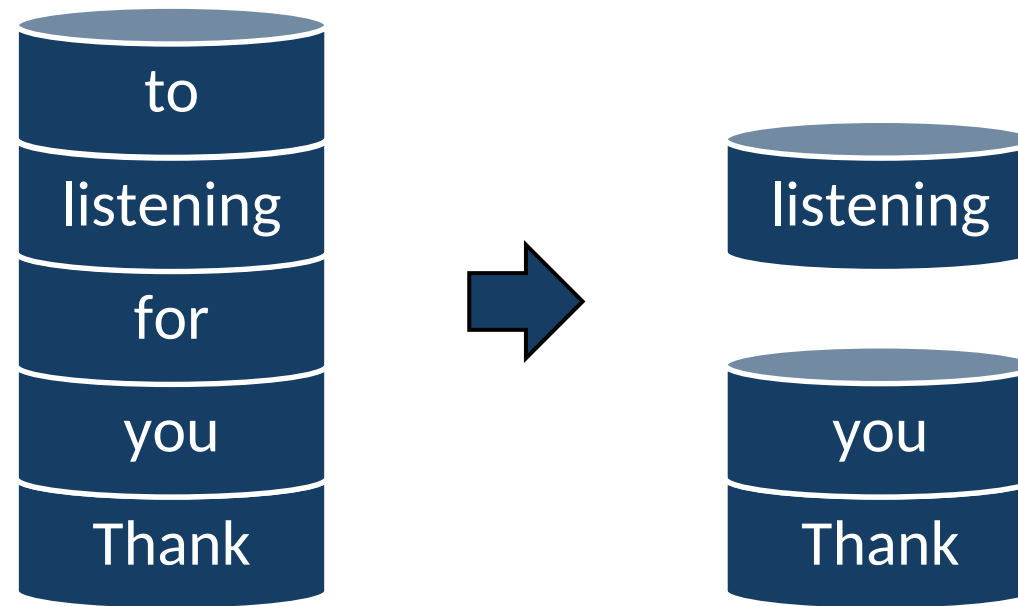
# Prior Approaches for KV Cache Problem

## 1. Quantization



Compress the **KV cache** by converting it into **a low-bit data format**

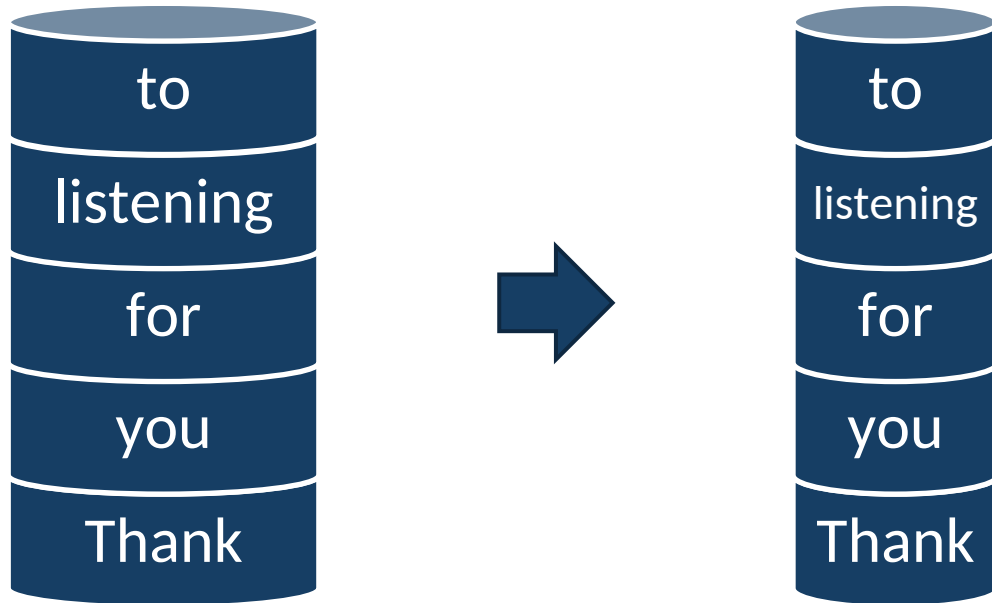
## 2. Eviction



**Permanently eliminate** unimportant tokens to keep the KV cache size in check

# Limitations of Prior Approaches

## 1. Quantization



Compress the **KV cache**  
by converting it into **a low-bit data format**

## 2. Eviction

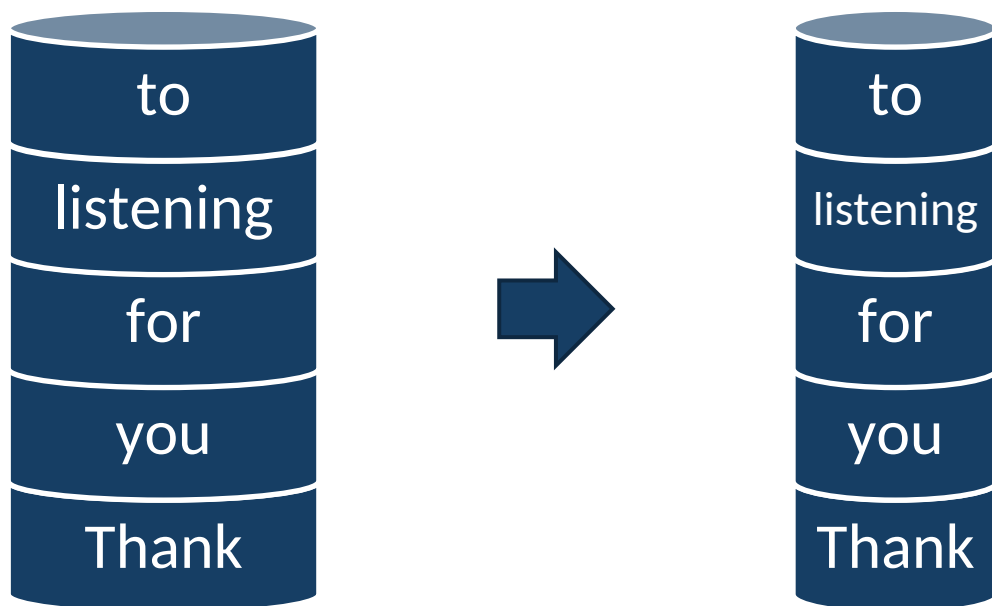


### *Problem 1*

KV cache access still  
**linearly increases** with the sequence length

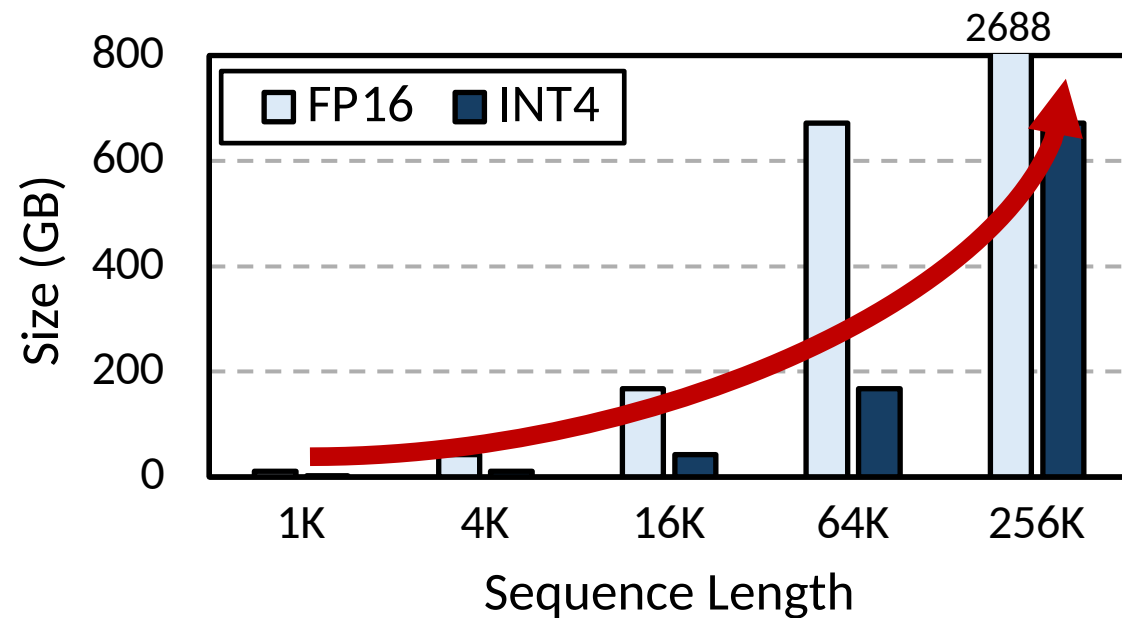
# Limitations of Prior Approaches

## 1. Quantization



Compress the **KV cache**  
by converting it into **a low-bit data format**

## 2. Eviction



### *Problem 1*

KV cache access still  
**linearly increases** with the sequence length

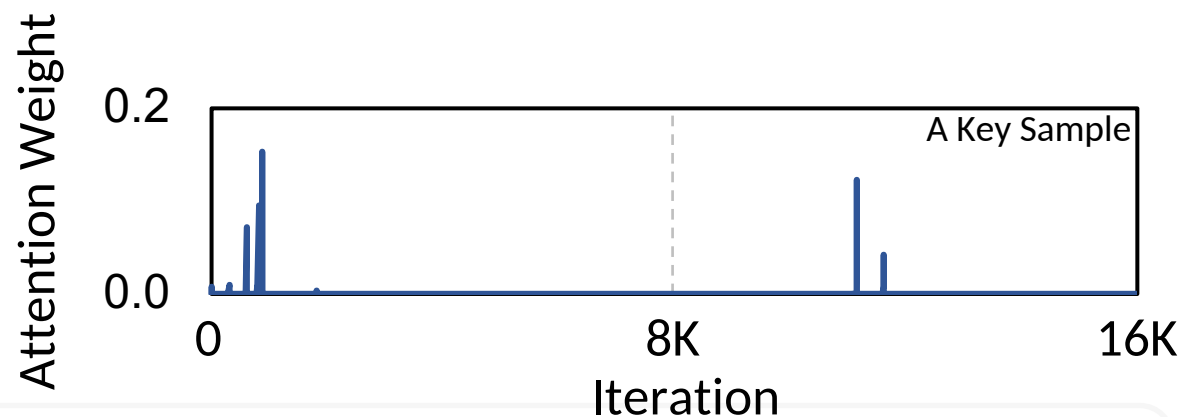


# Limitations of Prior Approaches

## 1. Quantization

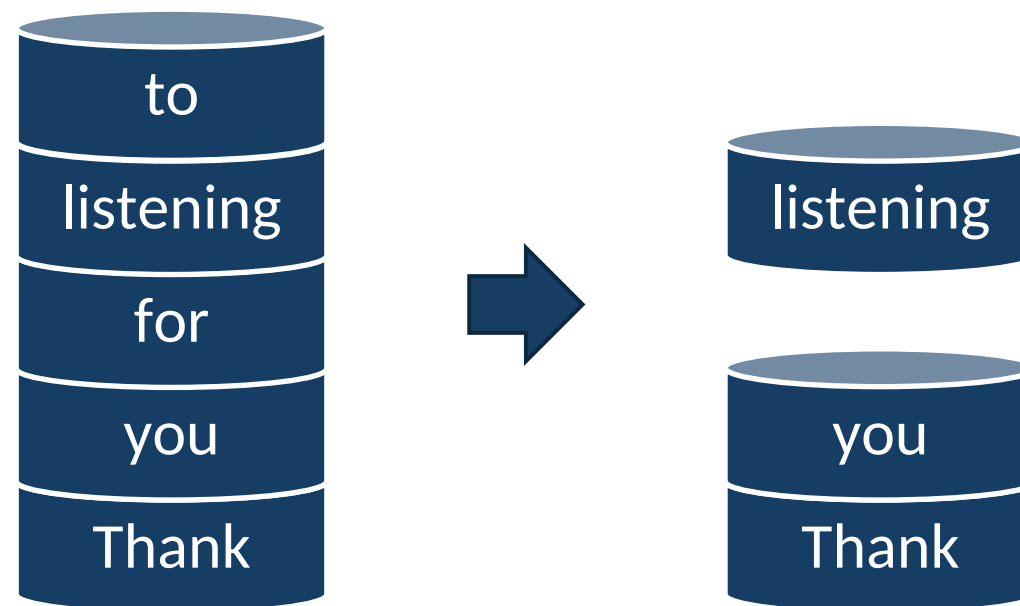
### Problem 2

Permanent elimination of tokens can lead to an **accuracy drop**



Compress the KV Cache by quantizing into Low-bit Data Format

## 2. Eviction



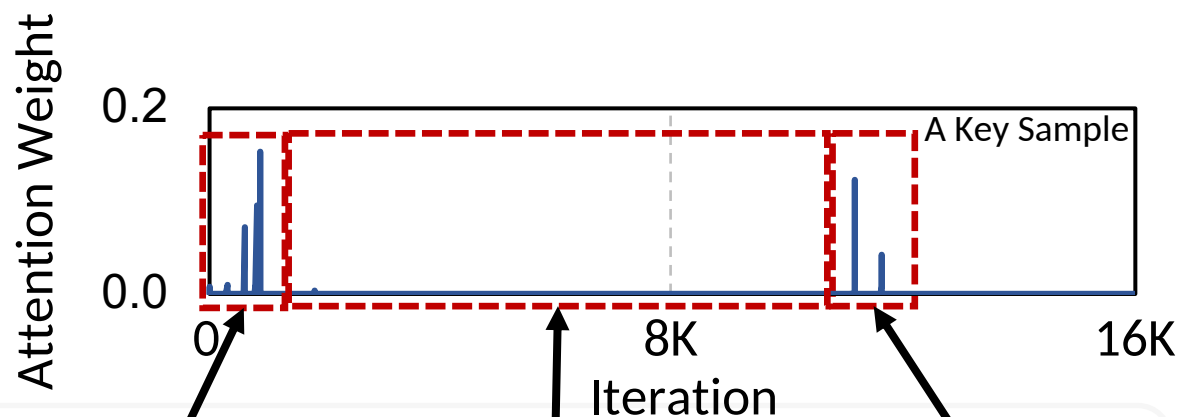
**Permanently eliminate** unimportant tokens to keep the KV cache size in check

# Limitations of Prior Approaches

## 1. Quantization

### Problem 2

Permanent elimination of tokens can lead to an **accuracy drop**

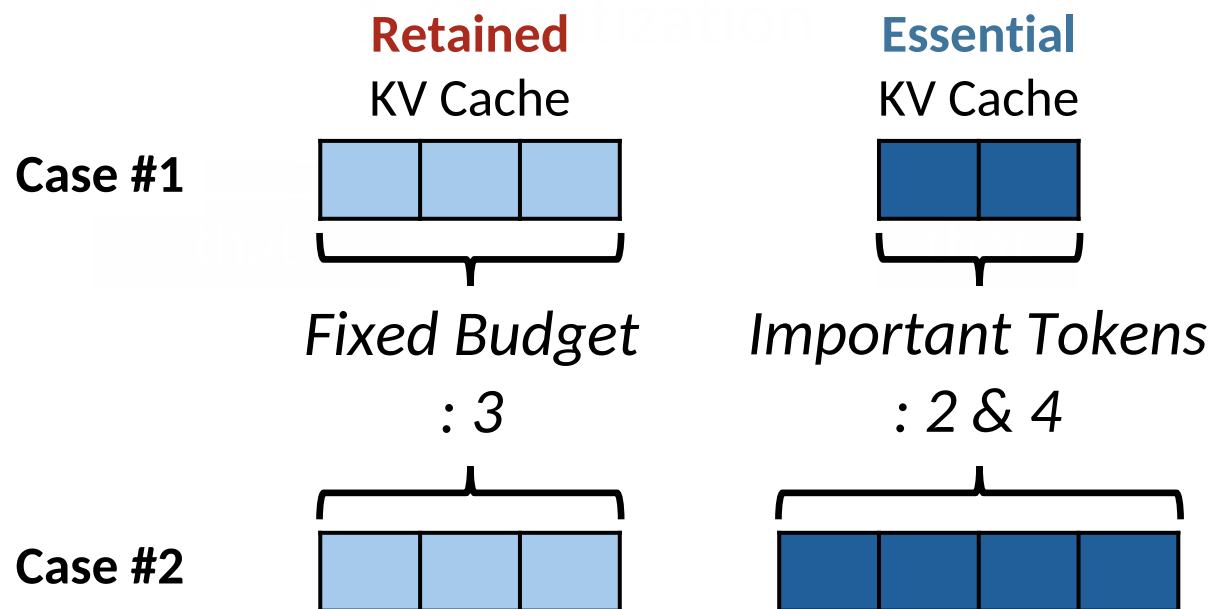


## 2. Eviction



**Permanently eliminate** unimportant tokens to keep the KV cache size in check

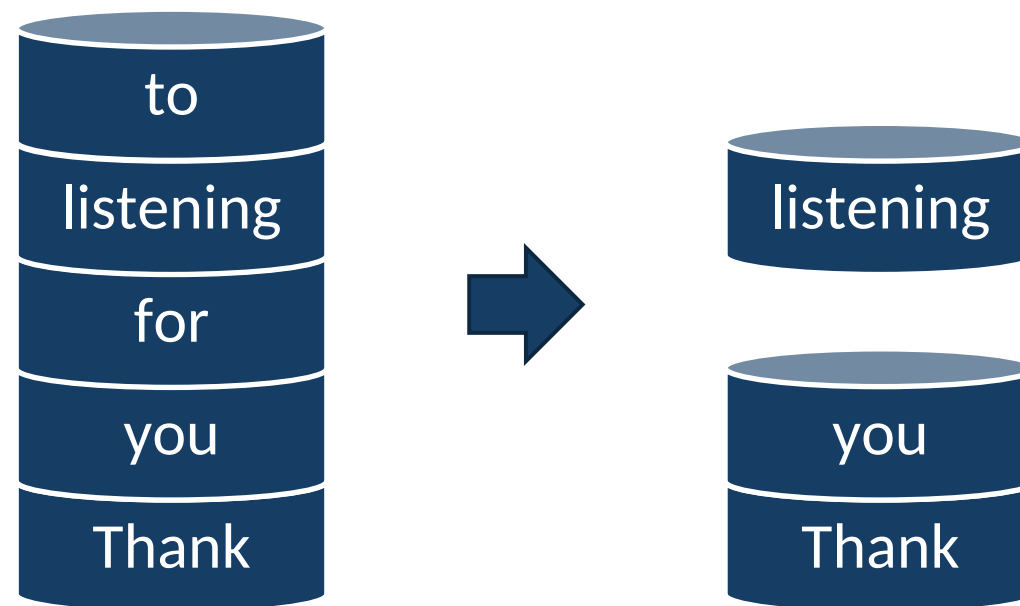
# Limitations of Prior Approaches



## Problem 3

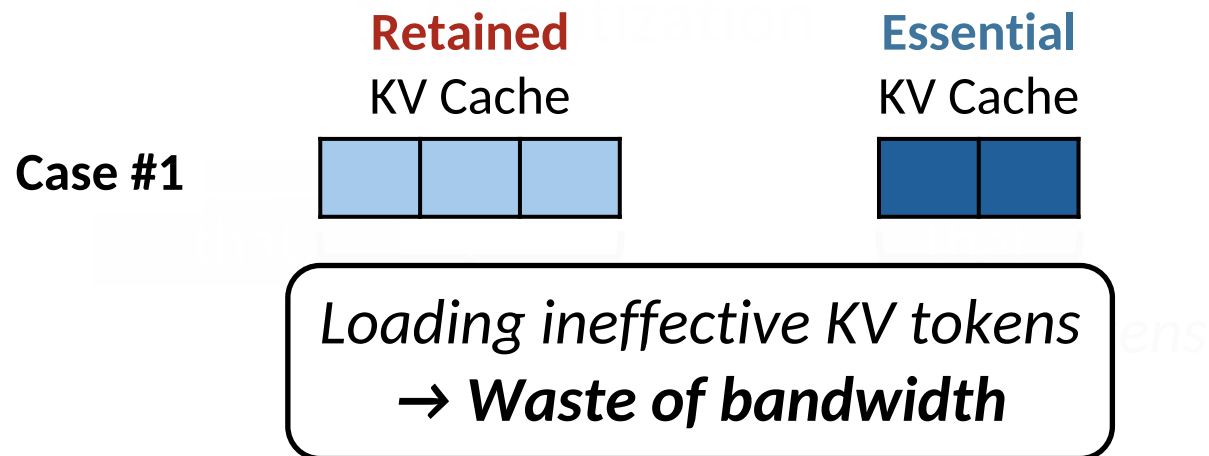
Fixed KV cache budget can lead to **subpar performance**

## 2. Eviction



**Permanently eliminate** unimportant tokens to keep the KV cache size in check

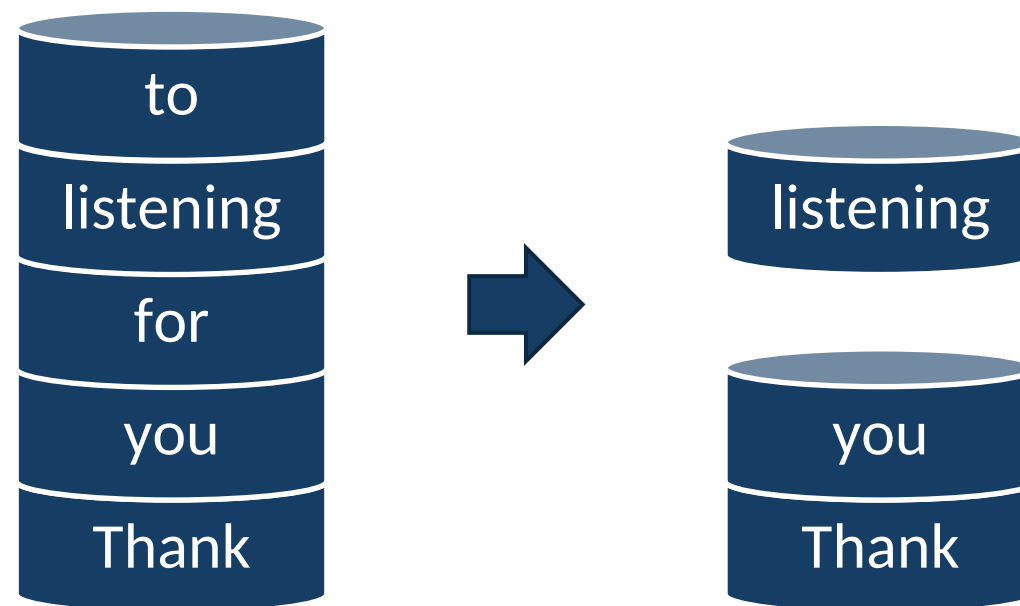
# Limitations of Prior Approaches



## Problem 3

Fixed KV cache budget  
can lead to **subpar performance**

## 2. Eviction



**Permanently eliminate** unimportant tokens  
to keep the KV cache size in check

# Limitations of Prior Approaches

Retained  
KV Cache

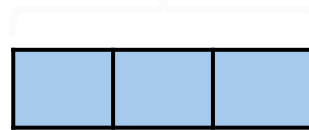
Essential  
KV Cache

Case #1



Missing essential KV tokens  
→ Accuracy drop

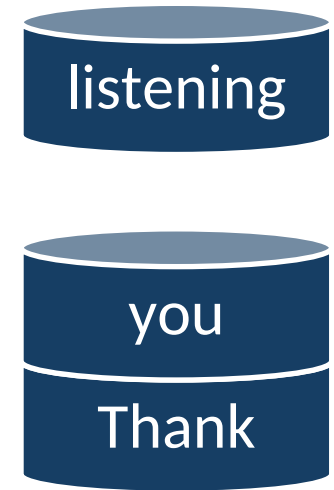
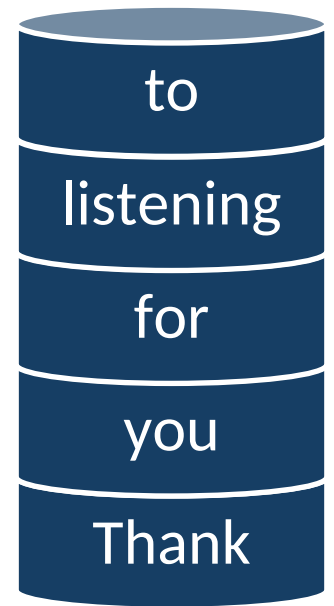
Case #2



**Problem 3**

Fixed KV cache budget  
can lead to **subpar performance**

## 2. Eviction



**Permanently eliminate** unimportant tokens  
to keep the KV cache size in check

# Prior Approaches

## *Problem 1*

KV cache access still linearly increases with the sequence length

## *Problem 2*

Permanent elimination of tokens can lead to an accuracy drop

## *Problem 3*

Fixed KV cache budget can lead to subpar performance

# Prior Approaches

## *Problem 1*

KV cache access still linearly increases  
with the sequence length

**Not a scalable nor effective solution  
in an era of millions of tokens!**

## *Problem 3*

Fixed KV cache budget  
can lead to subpar performance

# Outline

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  - Speculative KV Prefetching
  - Key/Query Skewing
- Evaluation
- Conclusion



# InfiniGen: Key Direction

## *Problem 1*

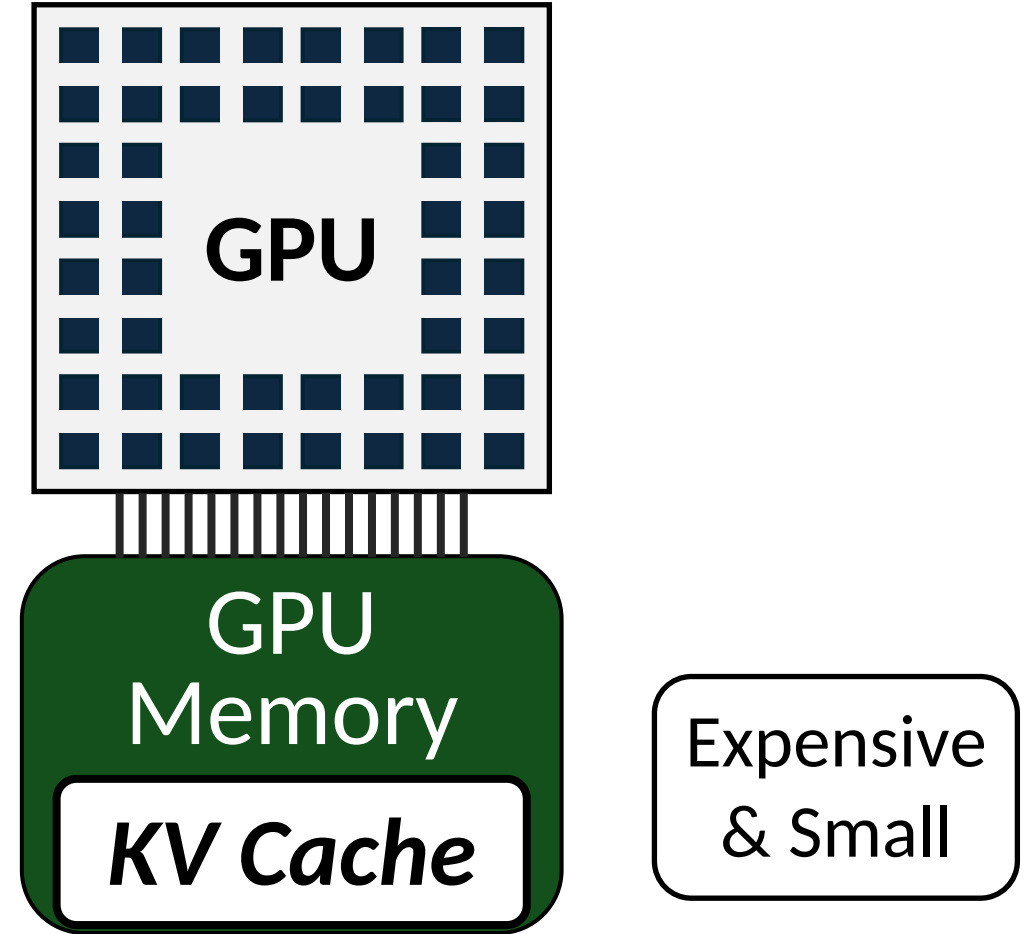
Memory access overhead still linearly scales with the sequence length

**Exploit the abundant CPU memory capacity to manage the KV cache!**

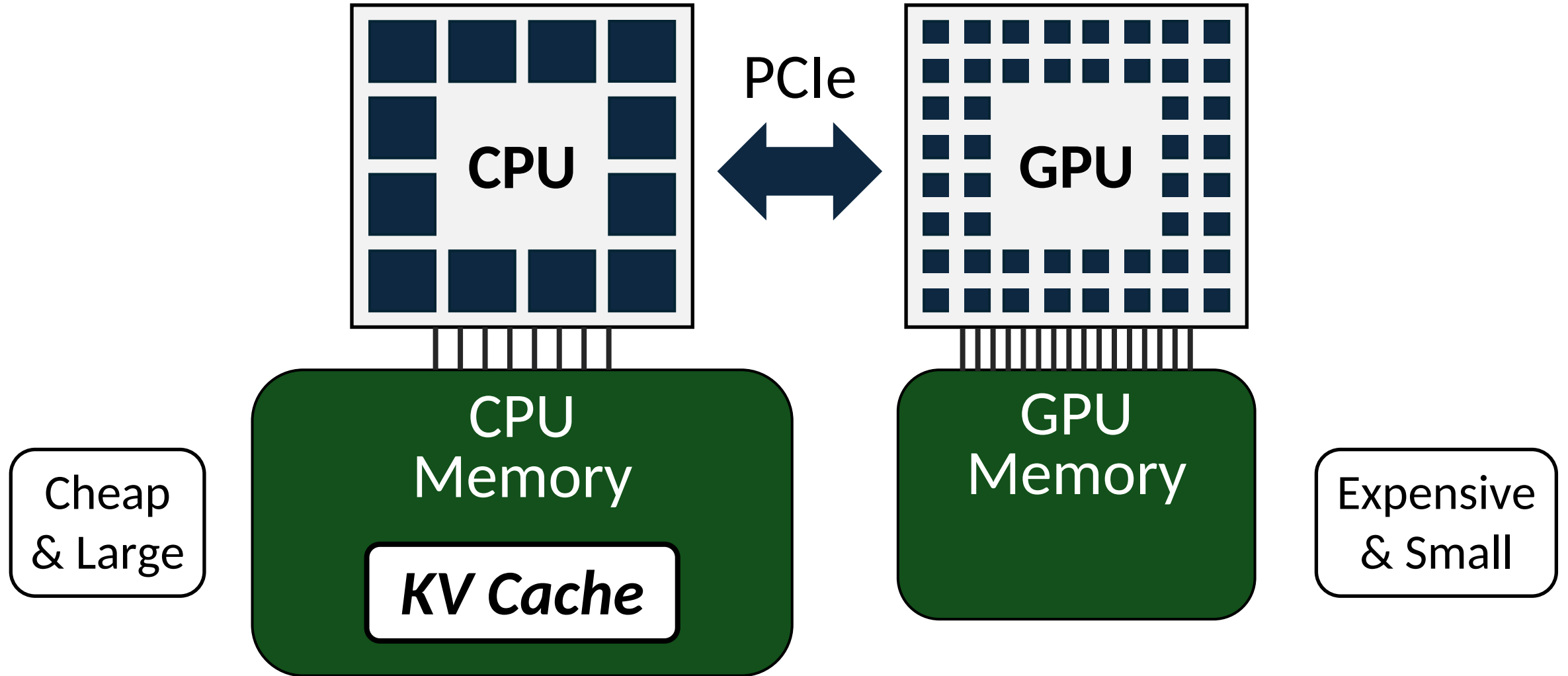
## *Problem 3*

Fixed KV cache budget can lead to subpar performance

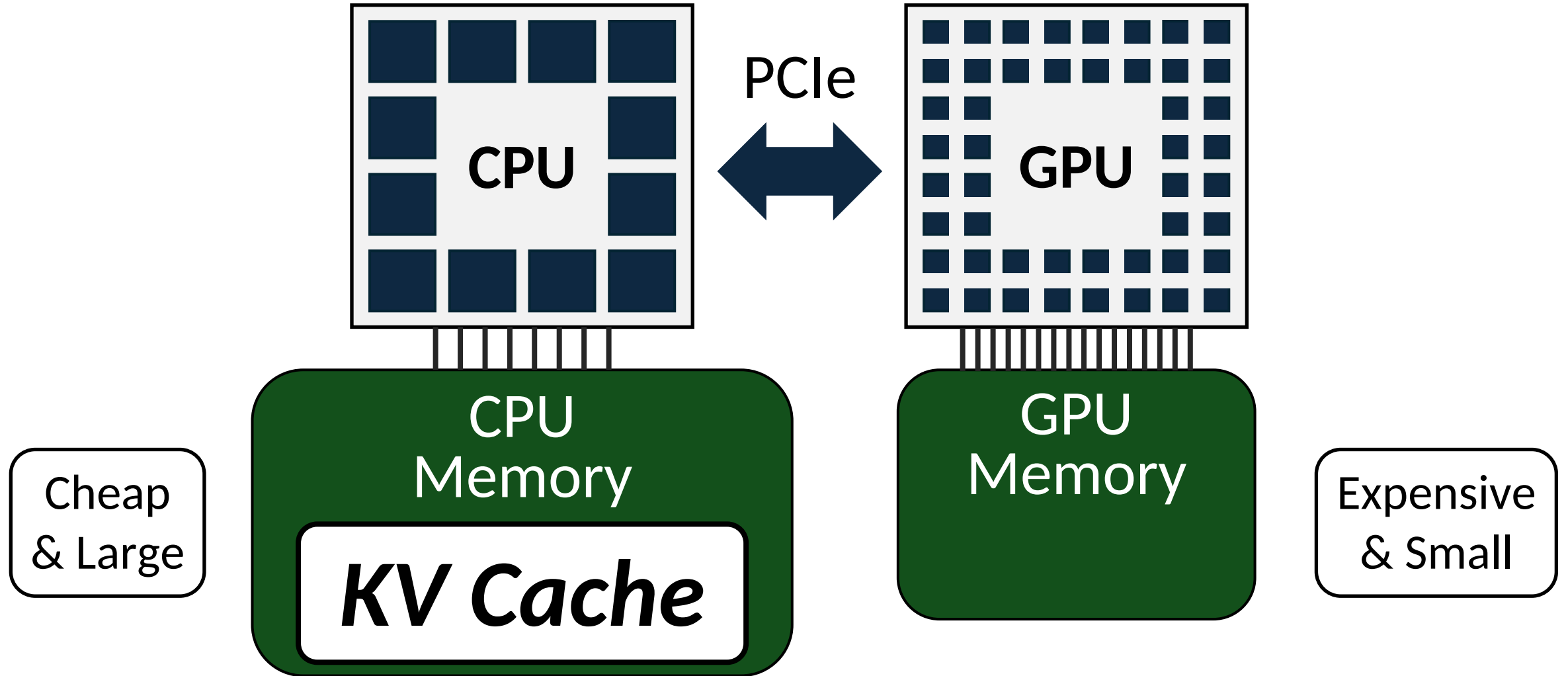
# KV Cache Offloading



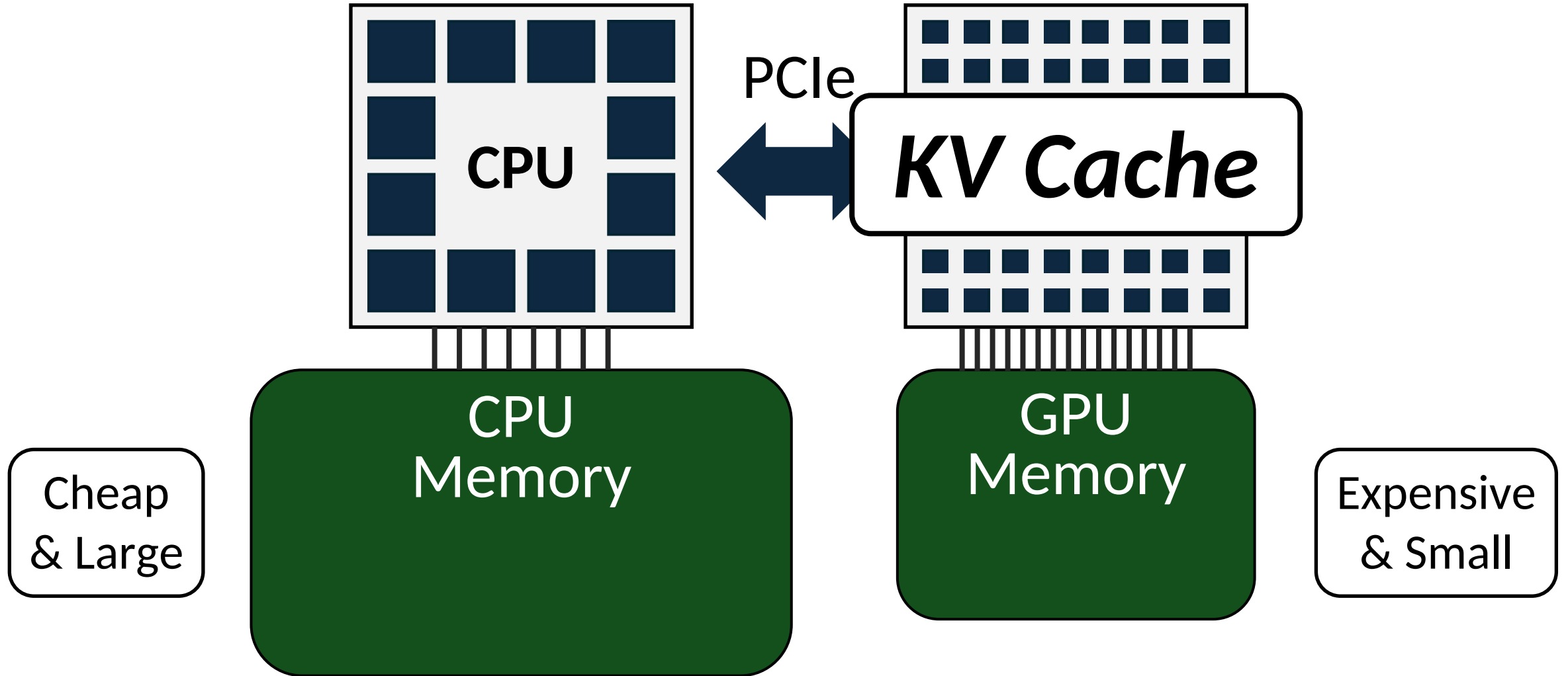
# KV Cache Offloading



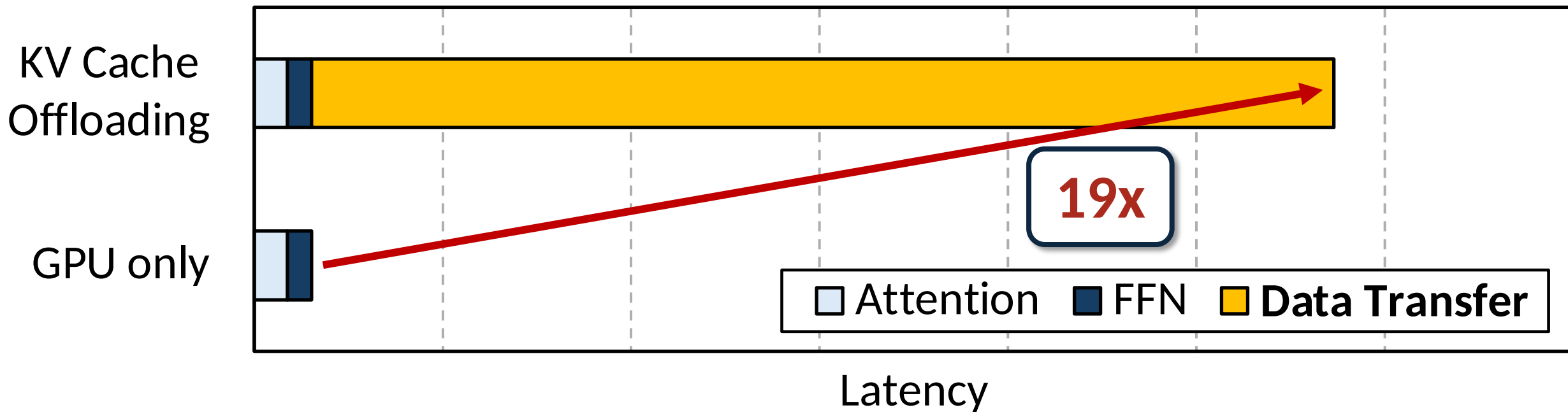
# KV Cache Offloading



# KV Cache Offloading



# KV Cache Offloading



***Significant slowdown  
due to the limited PCIe bandwidth***

# KV Cache Offloading

Transfer Less

Transfer Early

*due to the limited PCIe bandwidth*

# KV Cache Offloading

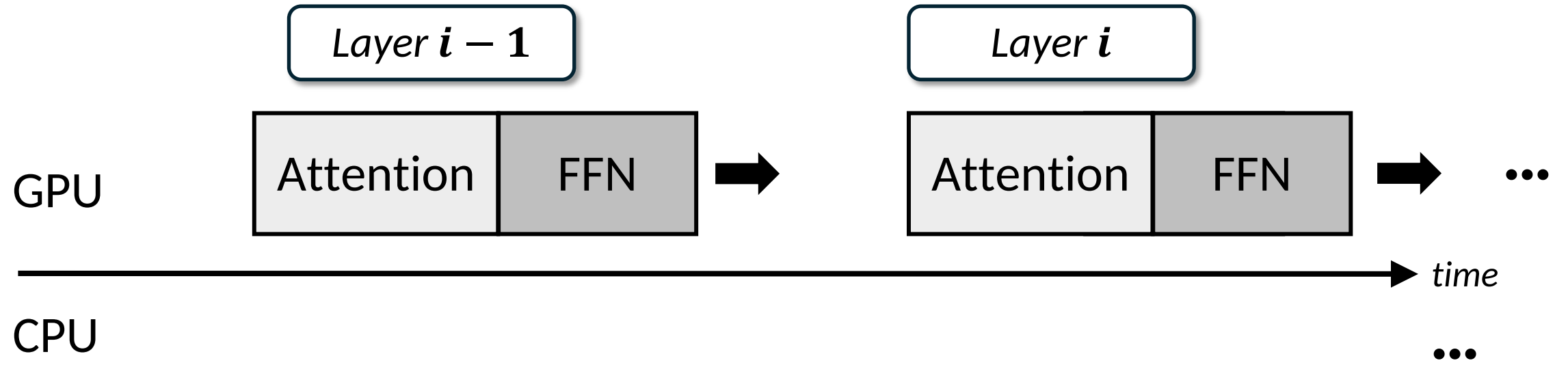
*Load and compute only with a few important tokens*

*Prefetch essential KV entries in the preceding layer*

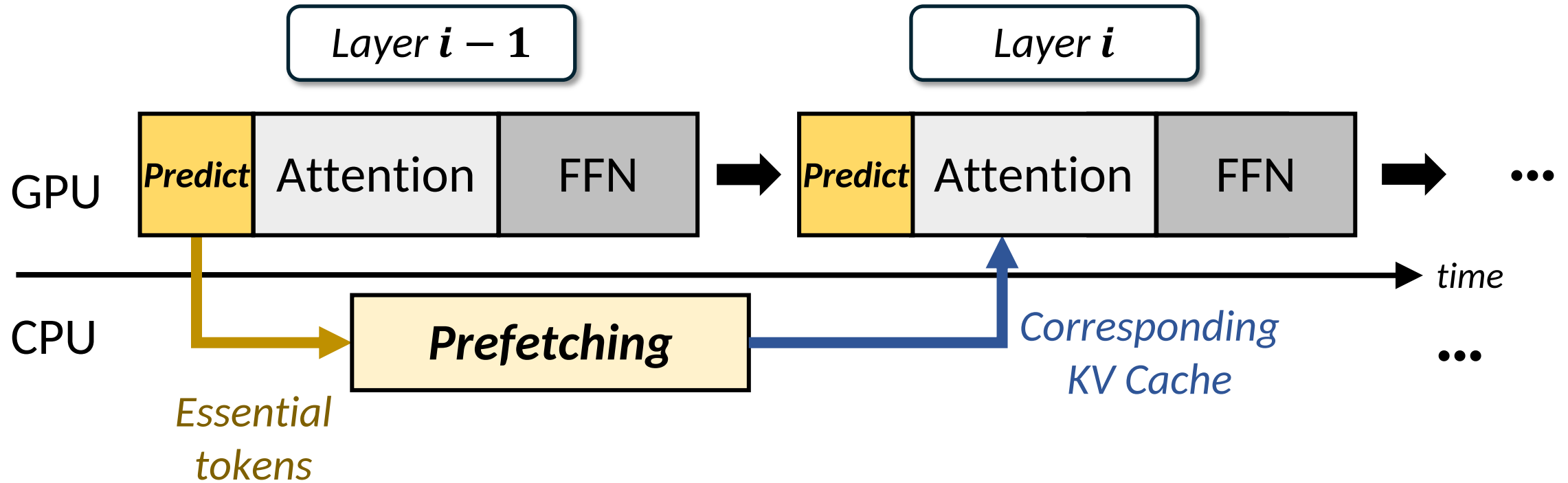
*due to the limited PCIe bandwidth*



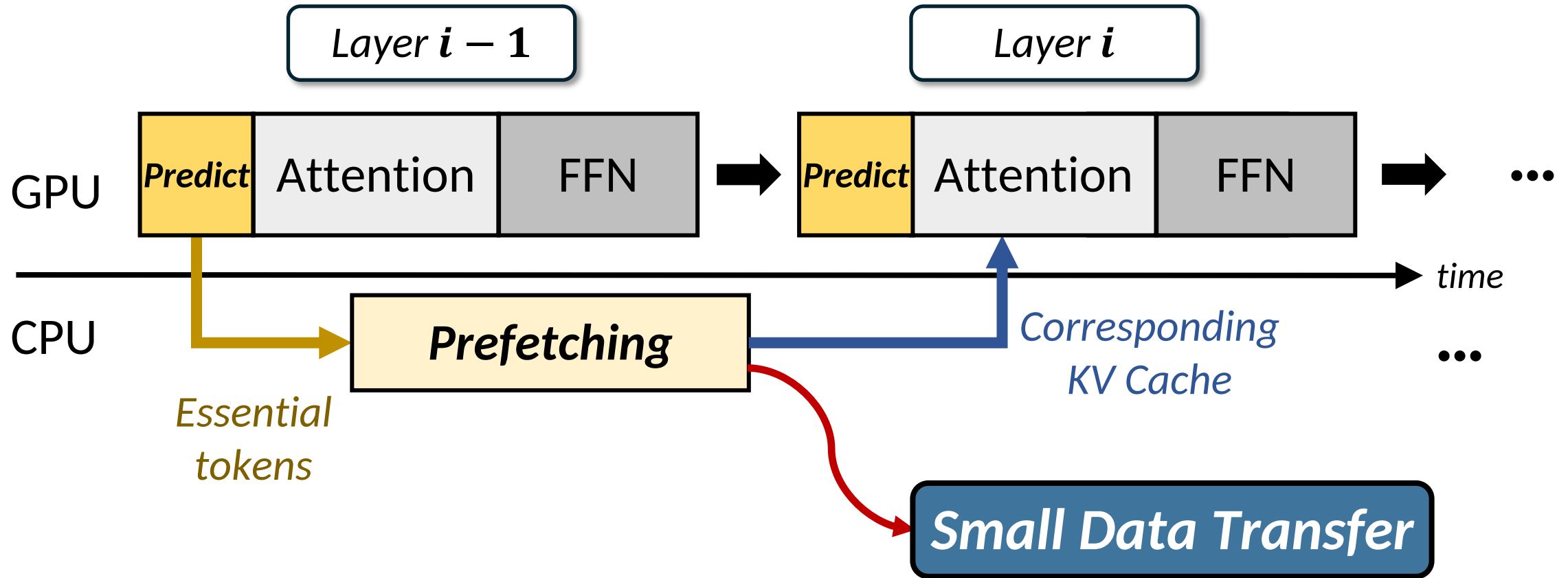
# Speculative KV Prefetching



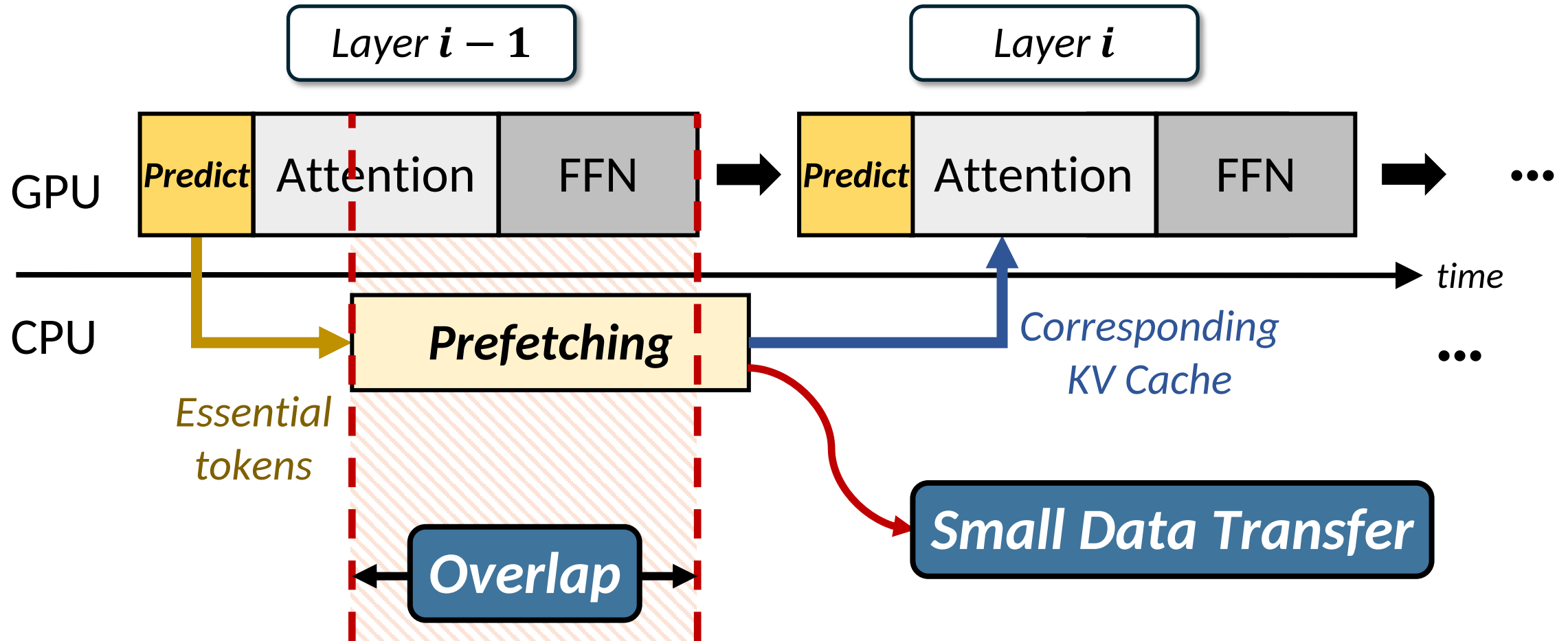
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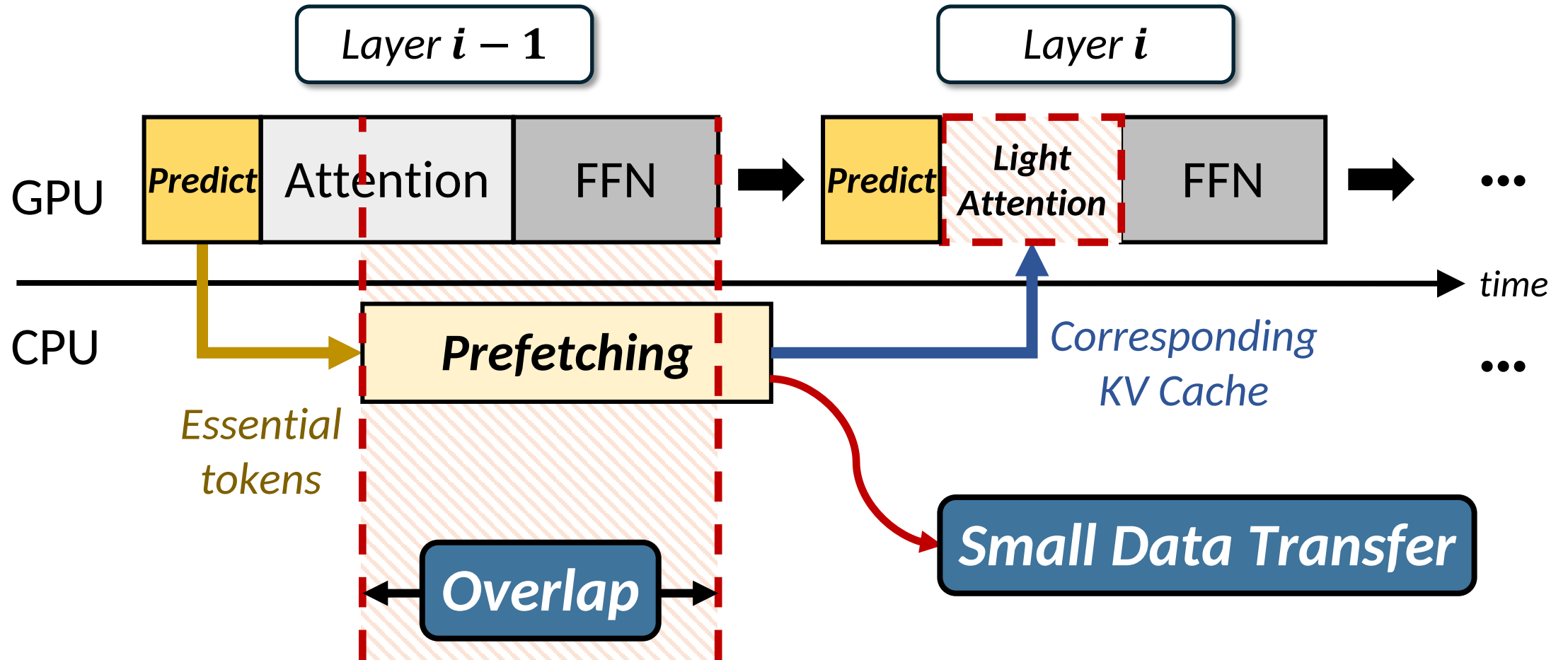
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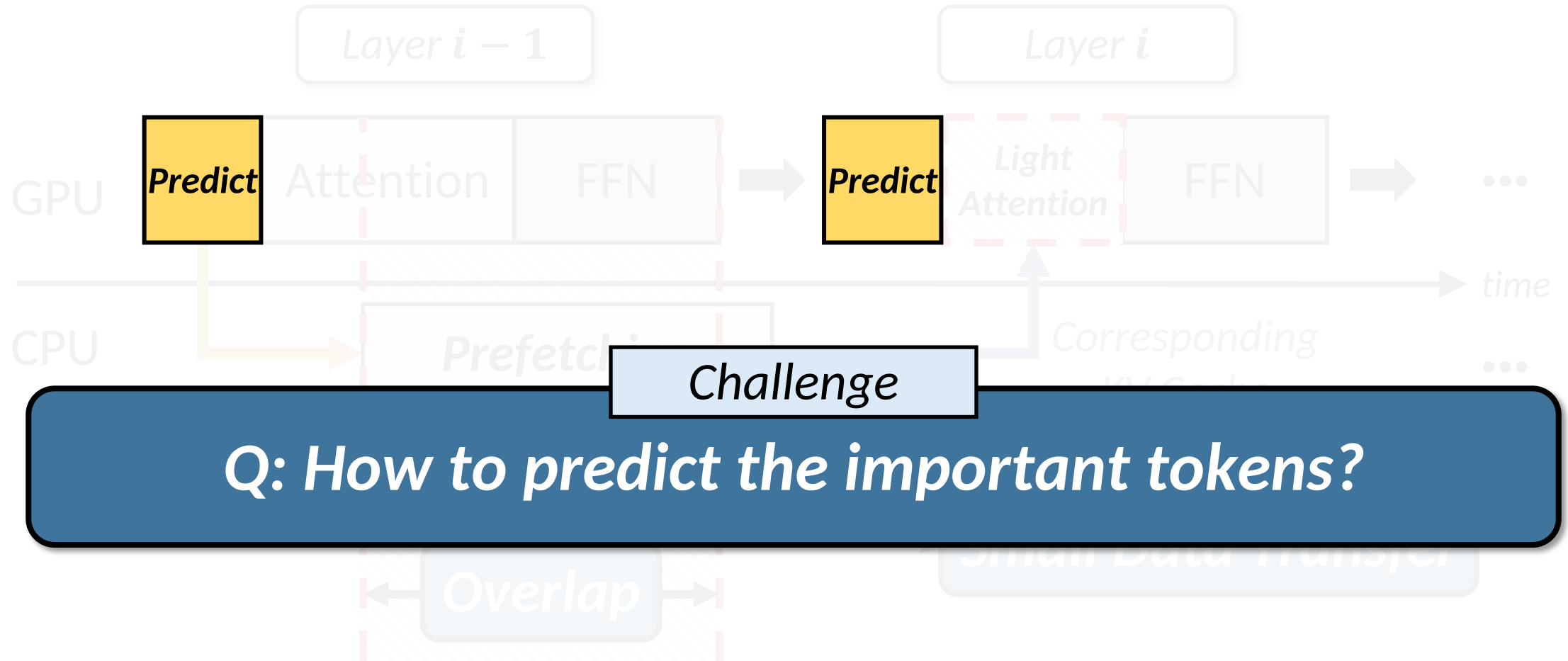
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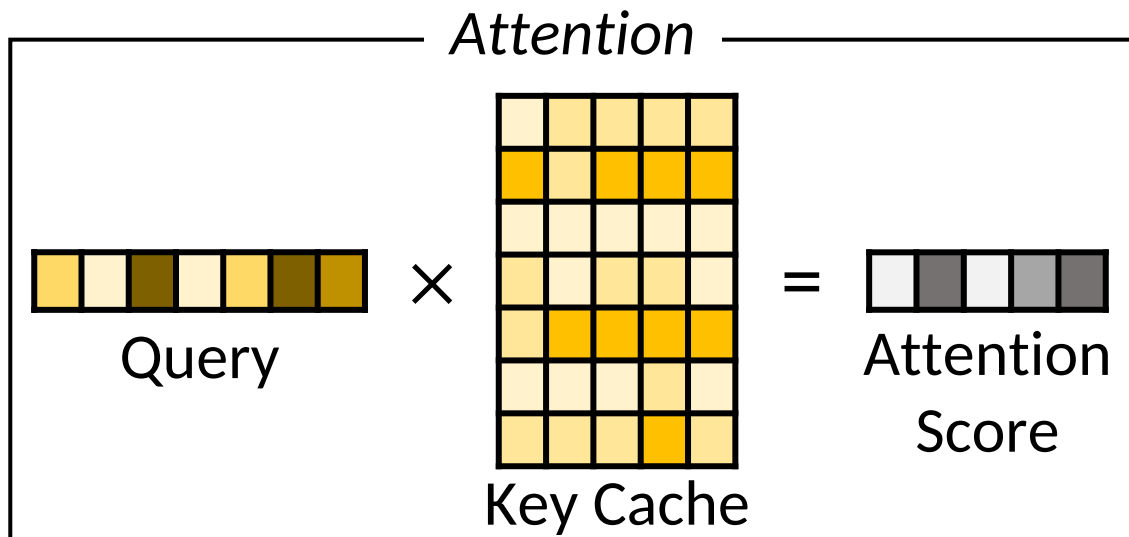
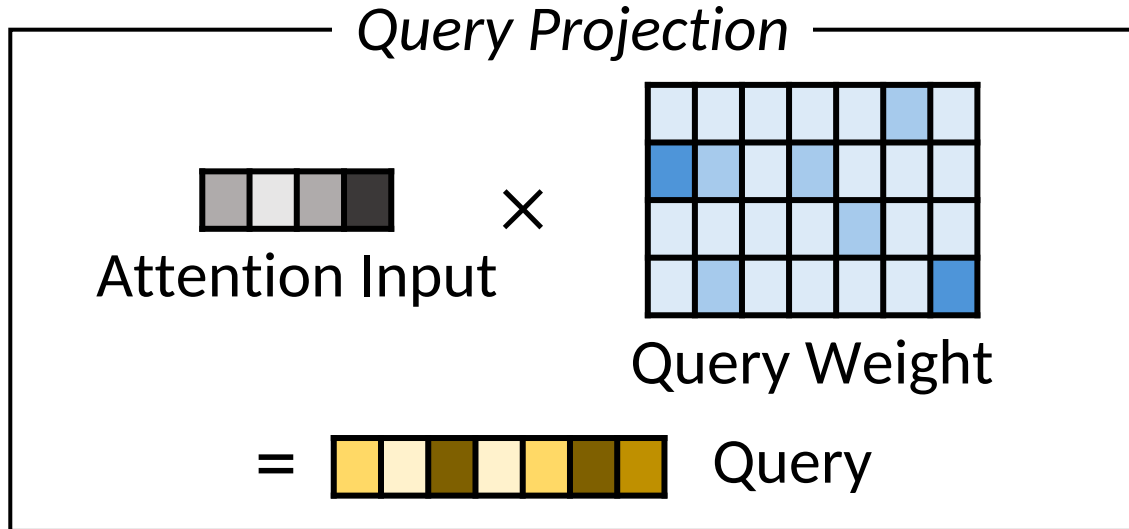


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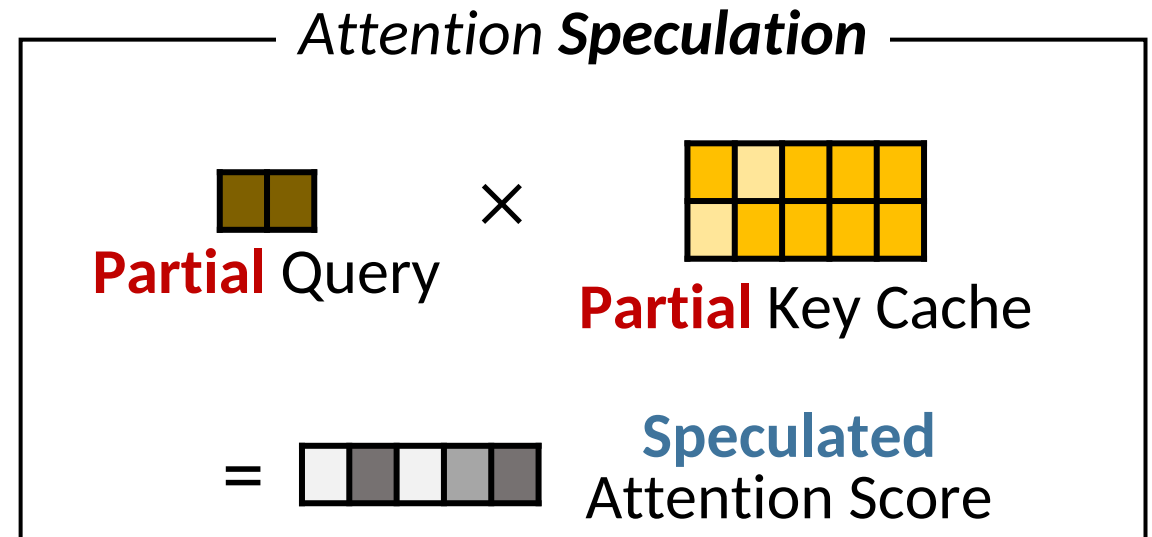
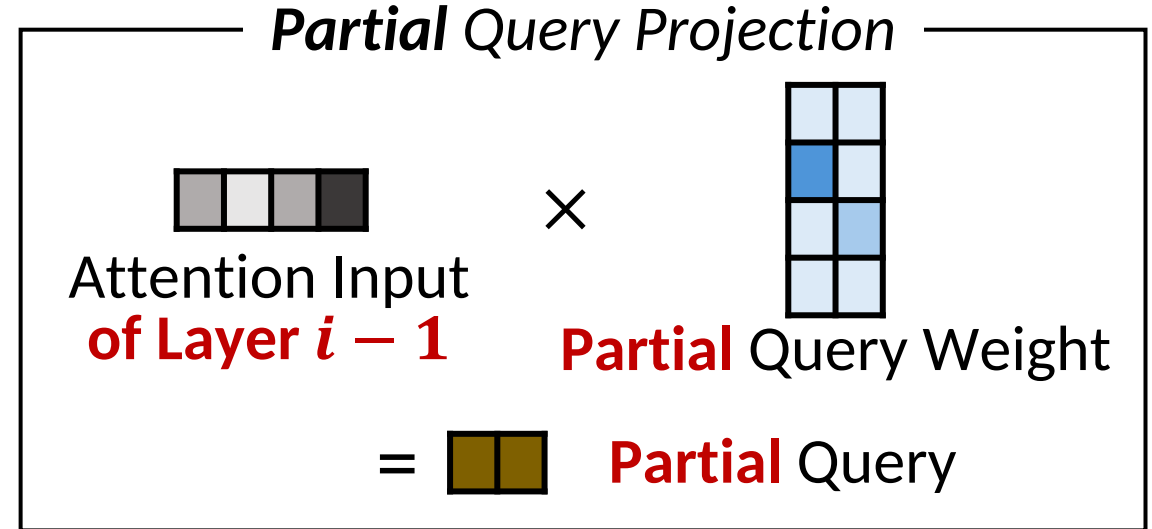


# Speculative KV Prefetching

**Original Attention: Layer  $i$**

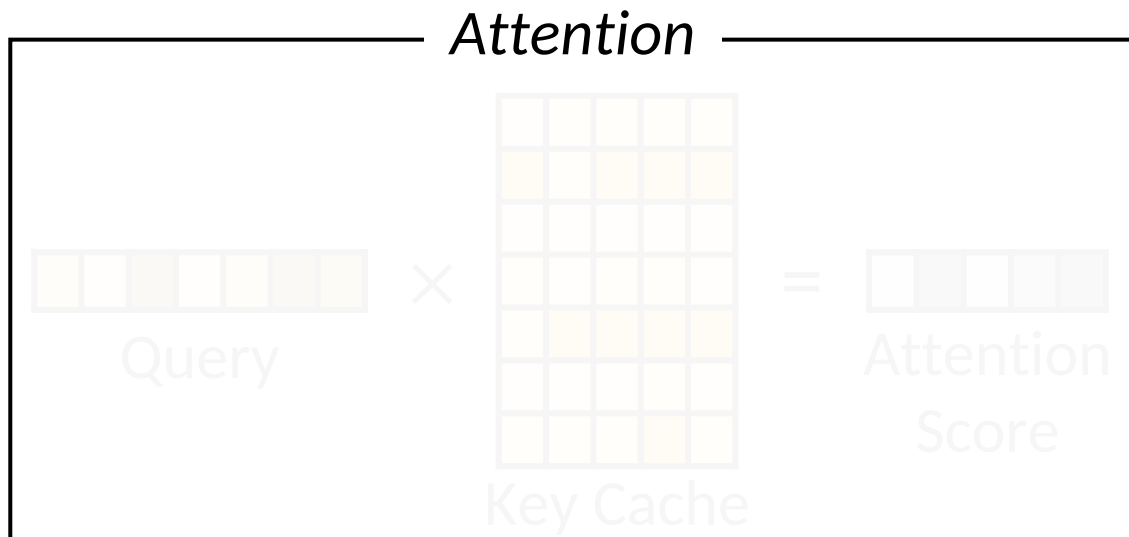
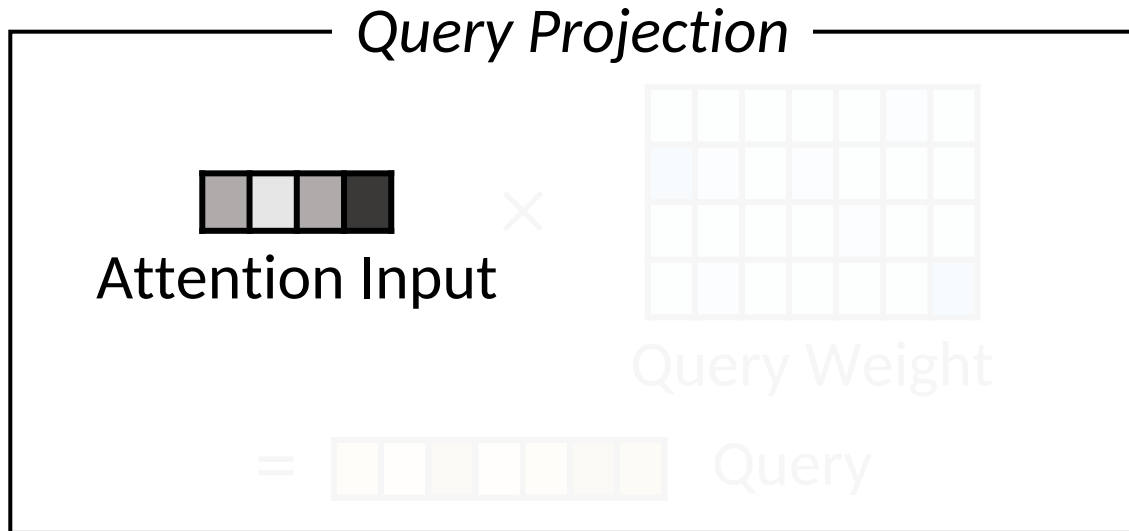


**Minimal Rehearsal: Layer  $i - 1$**

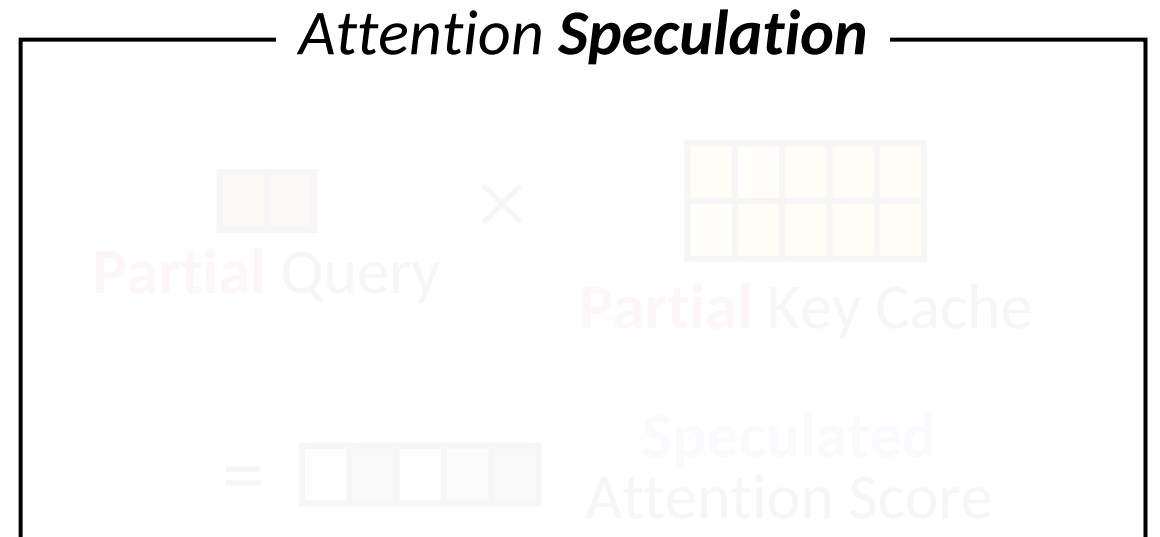
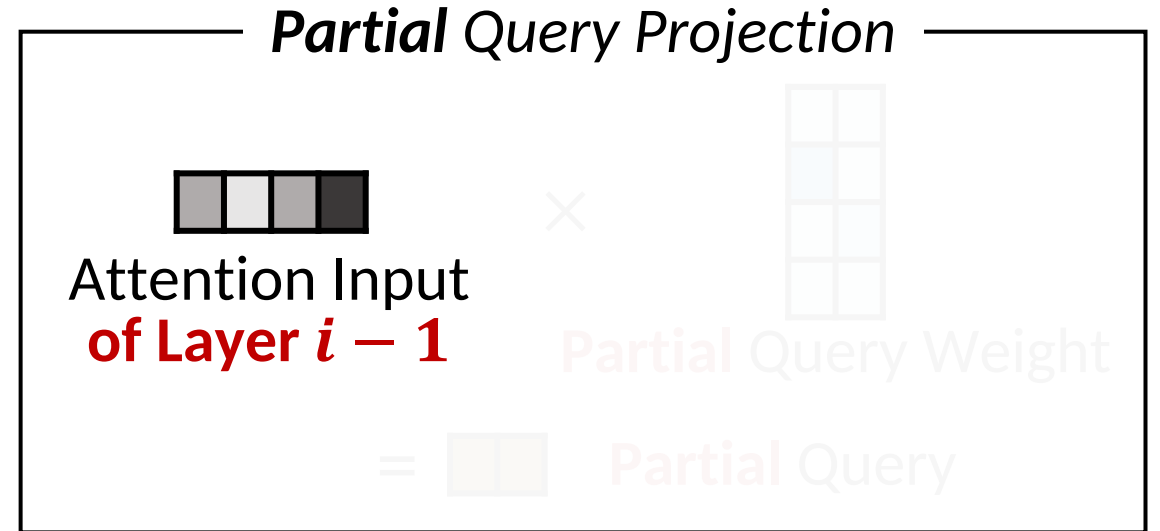


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**Original Attention: Layer  $i$**



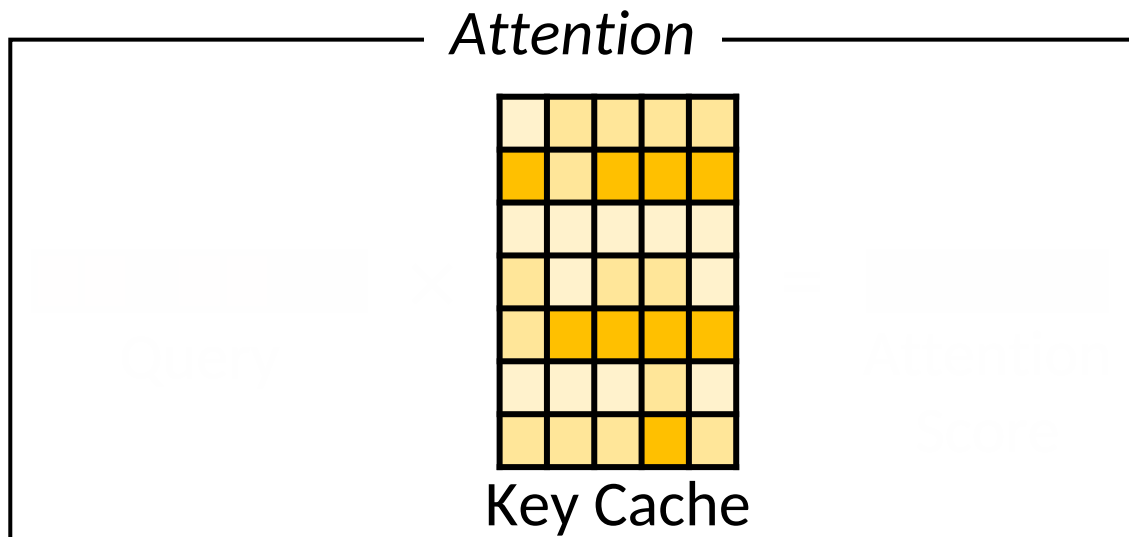
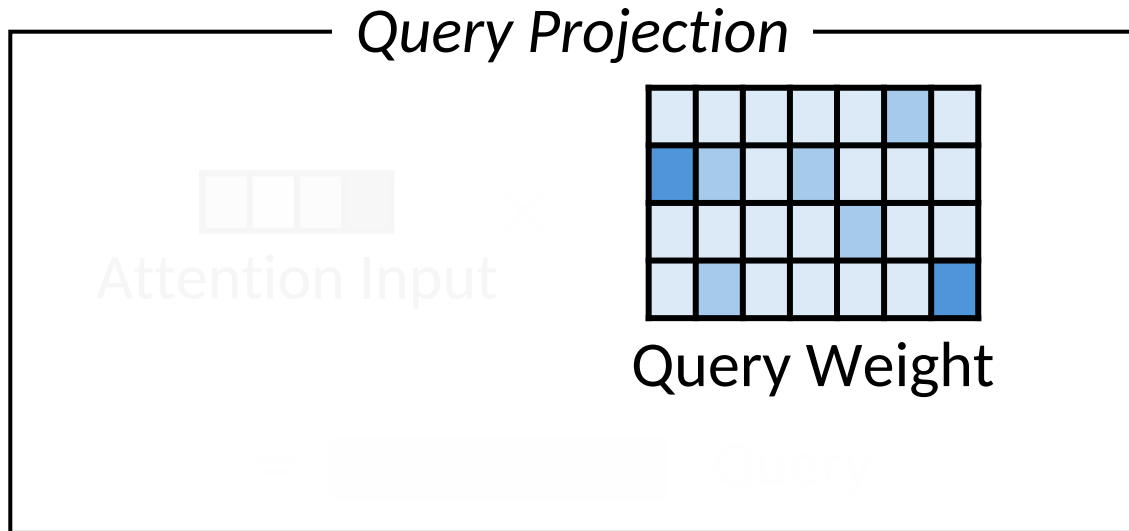
**Minimal Rehearsal: Layer  $i - 1$**



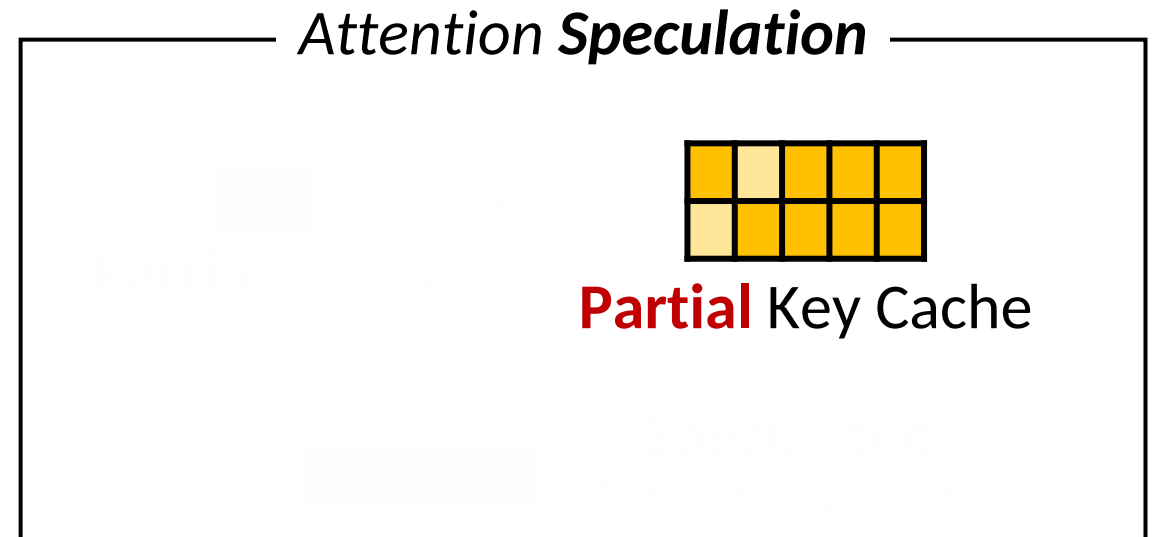
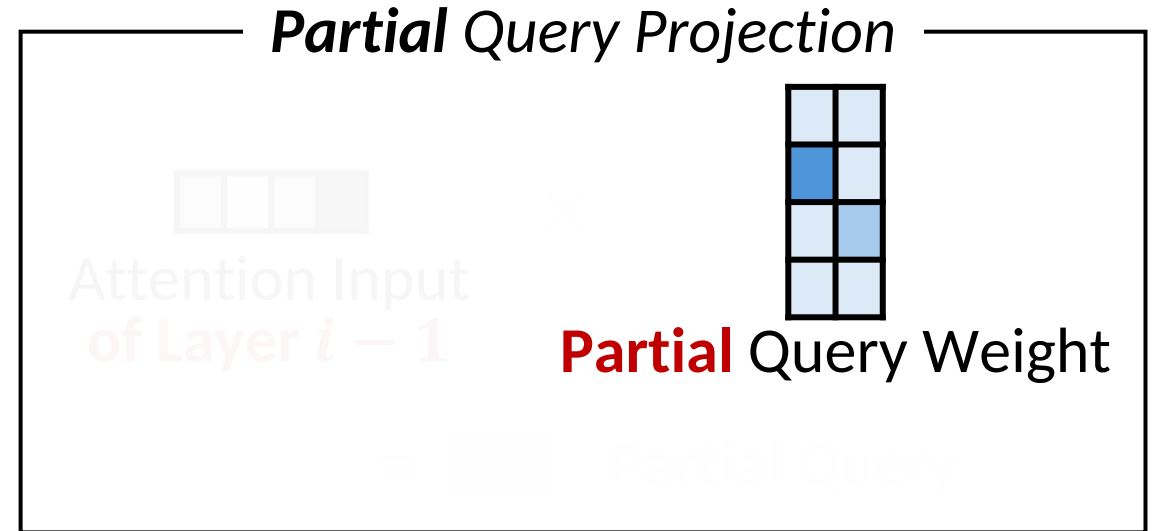


# Speculative KV Prefetching

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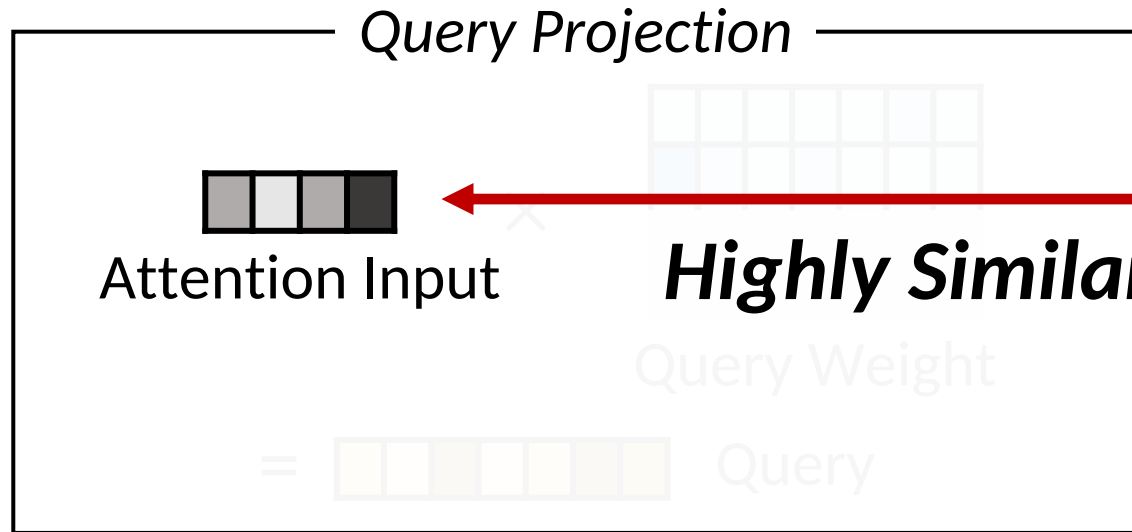


**Minimal Rehearsal: Layer  $i - 1$**

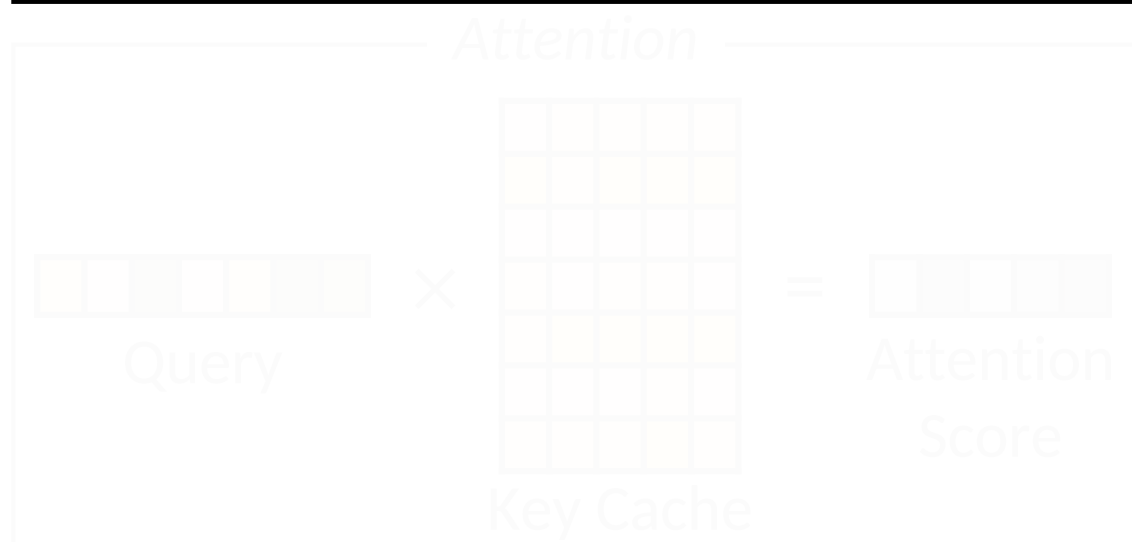
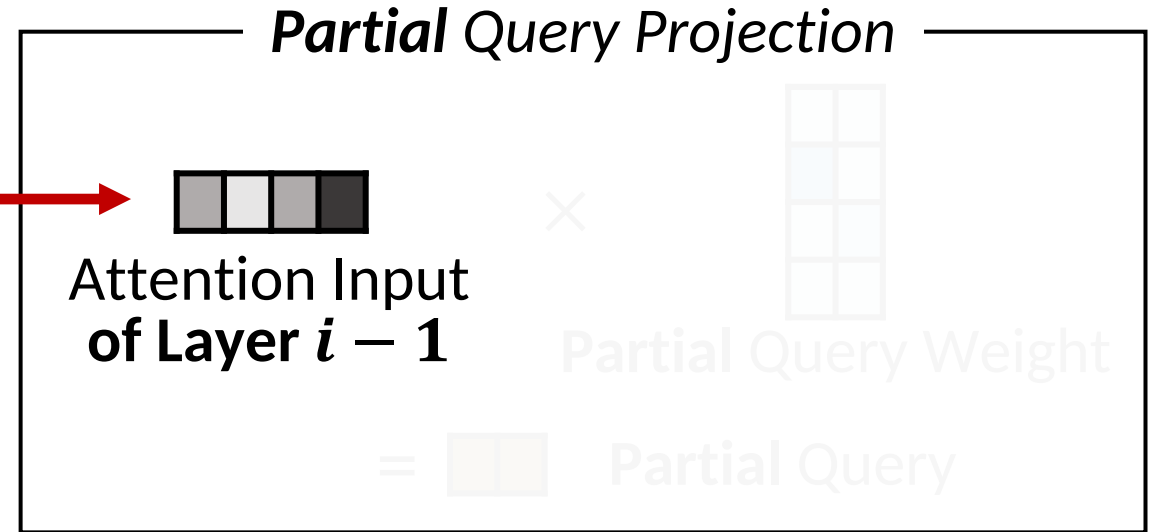


# Speculative KV Prefetching

**Original Attention: Layer  $i$**



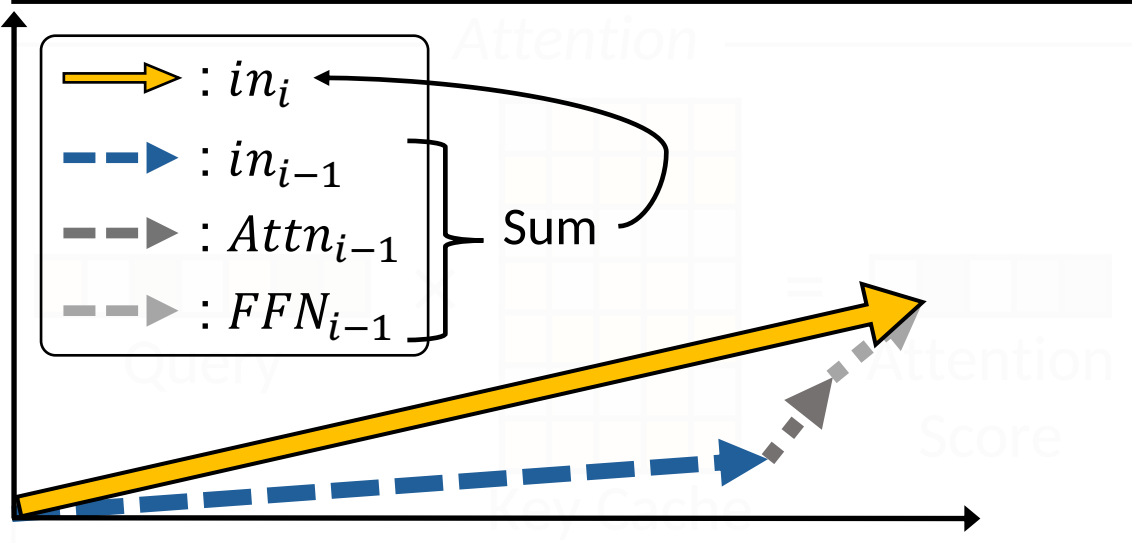
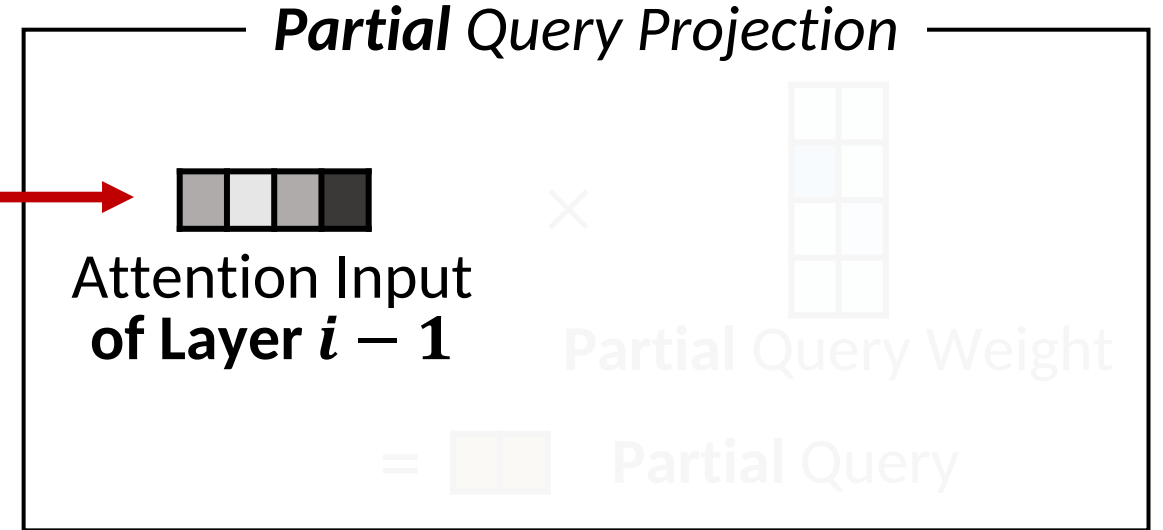
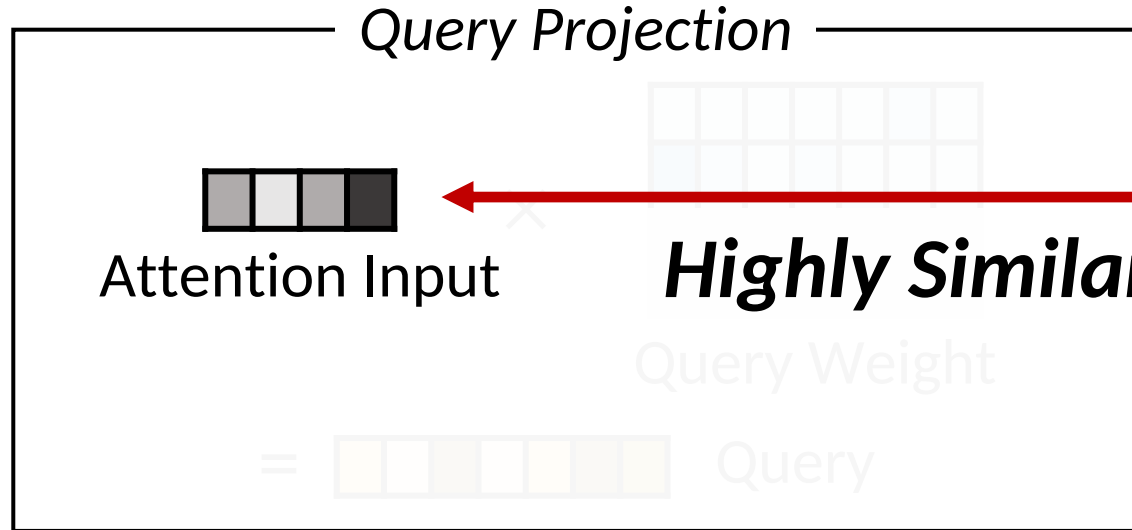
**Minimal Rehearsal: Layer  $i - 1$**



# Speculative KV Prefetching

Original Attention: Layer  $i$

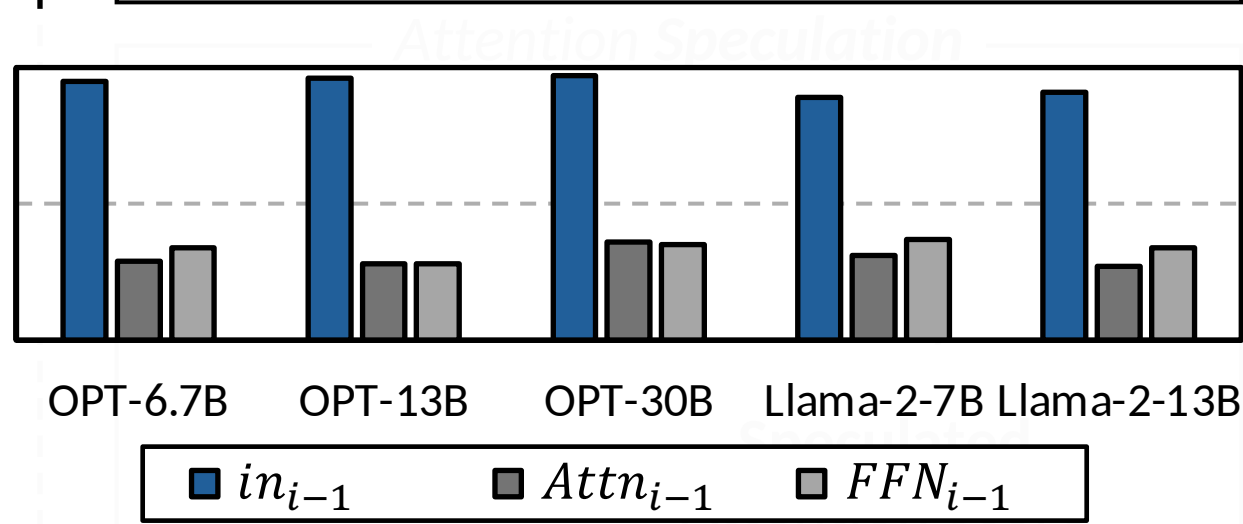
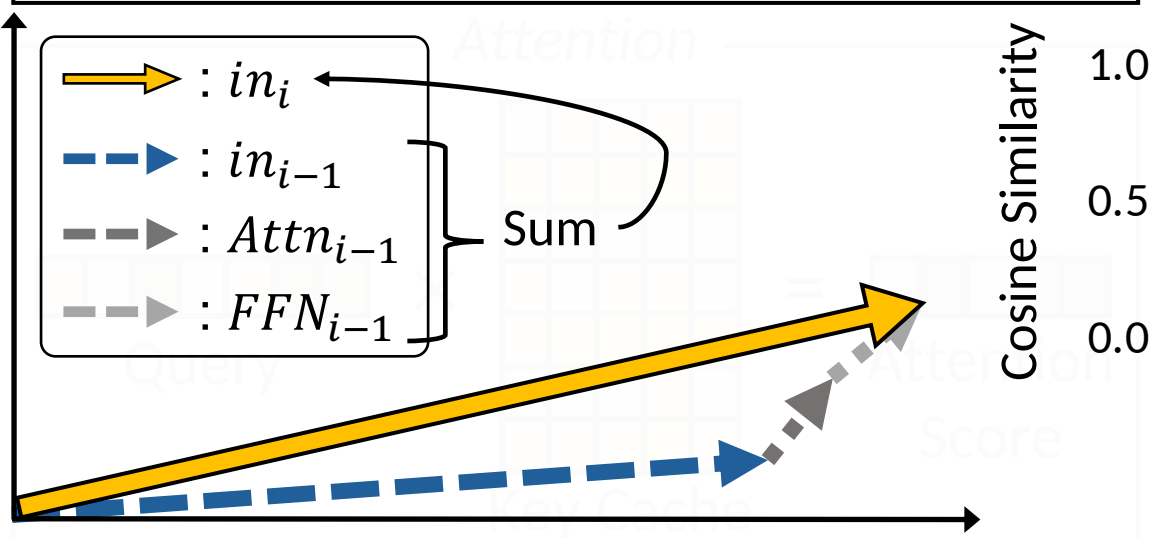
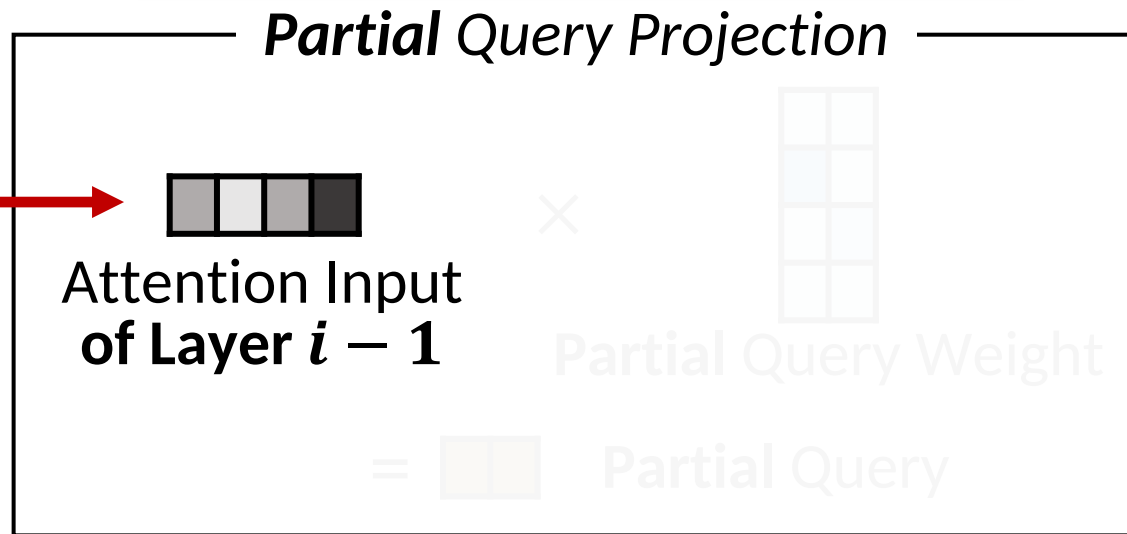
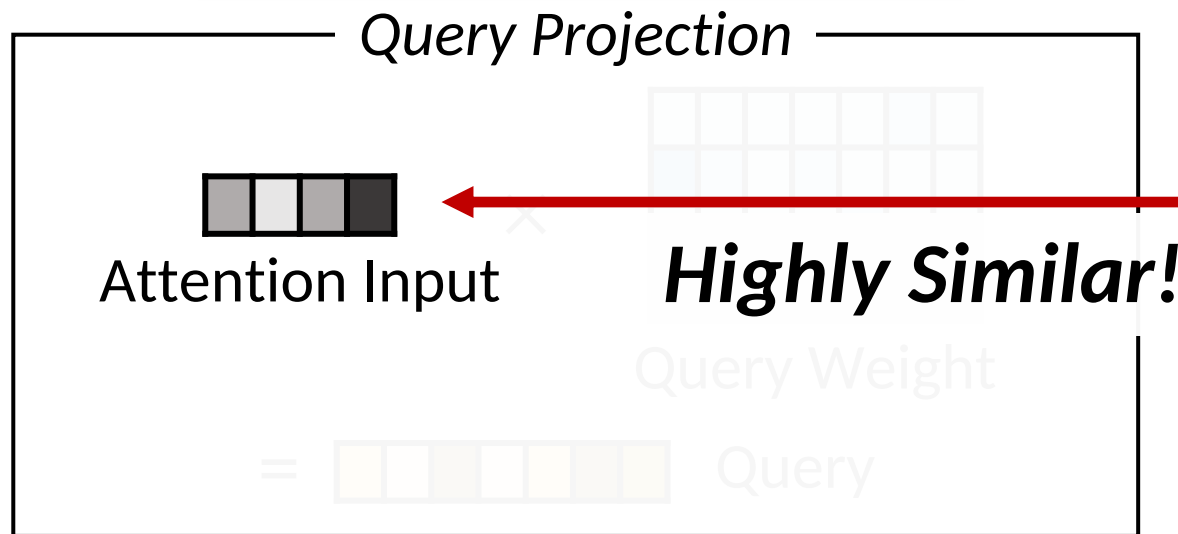
Minimal Rehearsal: Layer  $i - 1$



# Speculative KV Prefetching

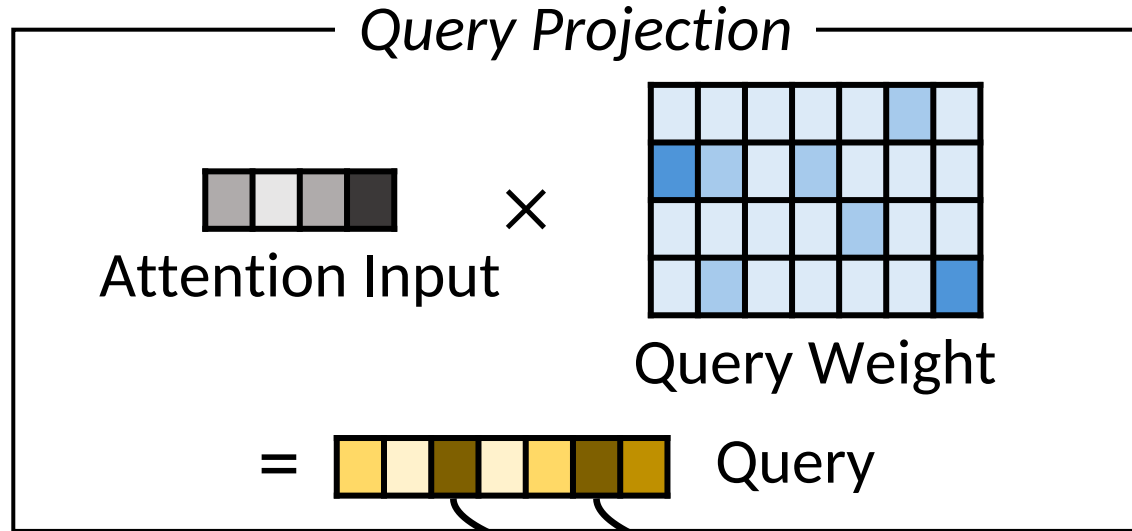
Original Attention: Layer  $i$

Minimal Rehearsal: Layer  $i - 1$

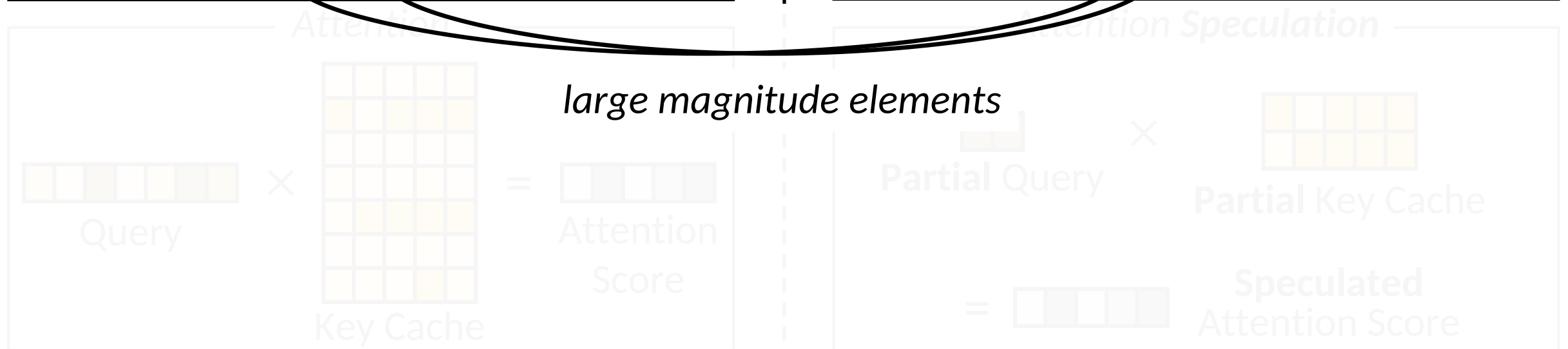
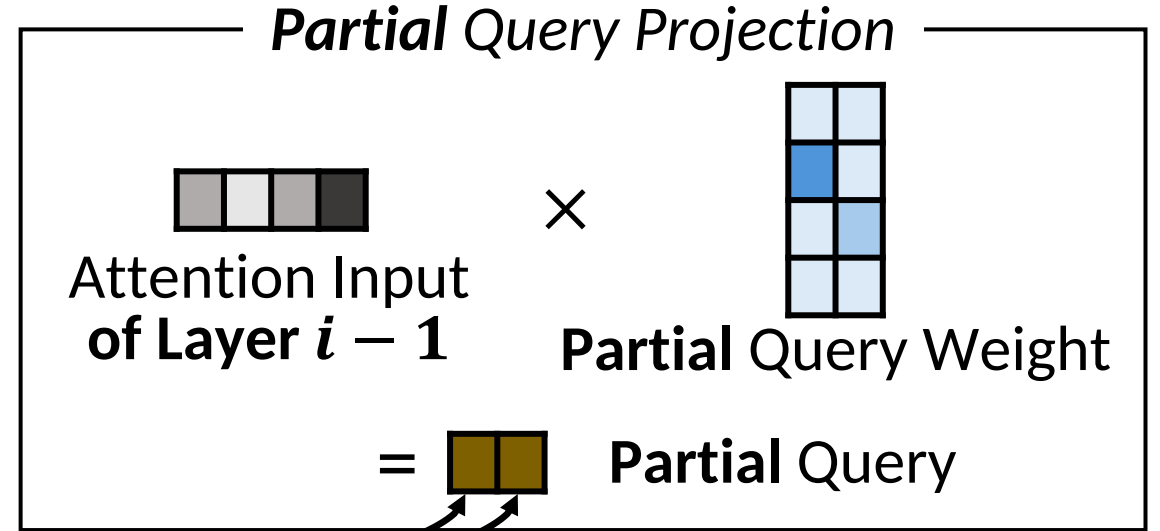


# Speculative KV Prefetching

**Original Attention: Layer  $i$**



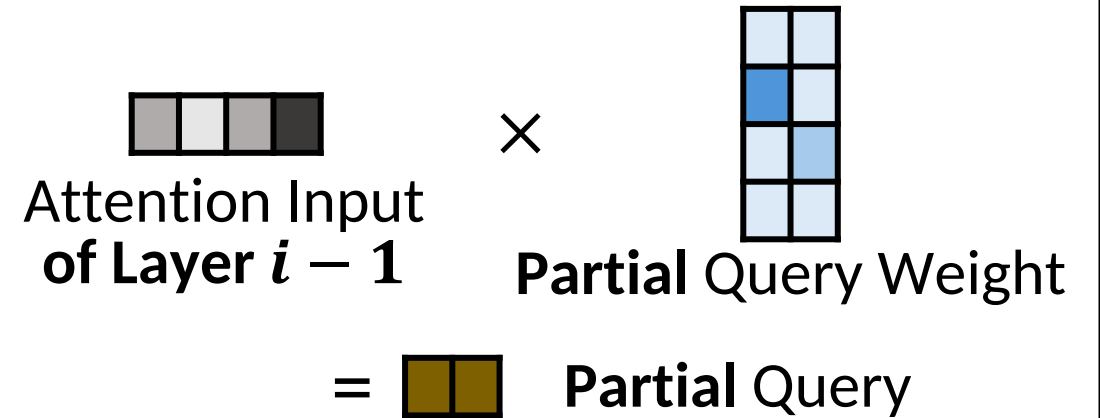
**Minimal Rehearsal: Layer  $i - 1$**



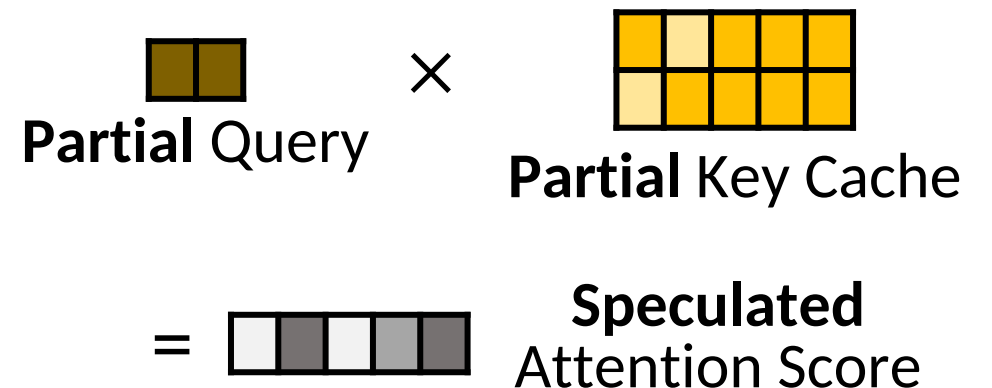
# Speculative KV Prefetching

*Minimal Rehearsal: Layer  $i - 1$*

*Partial Query Projection*

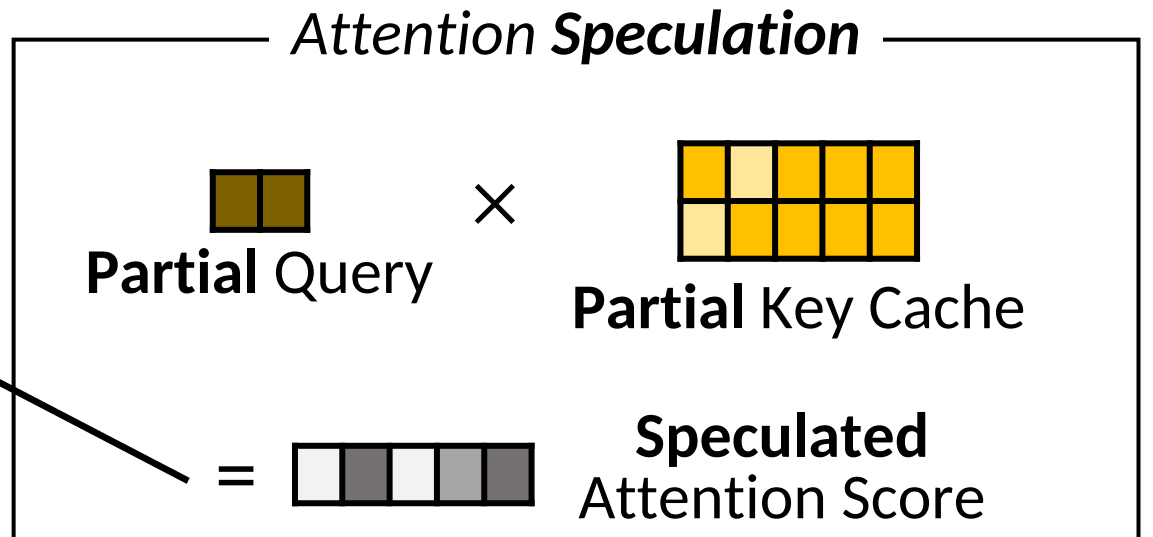
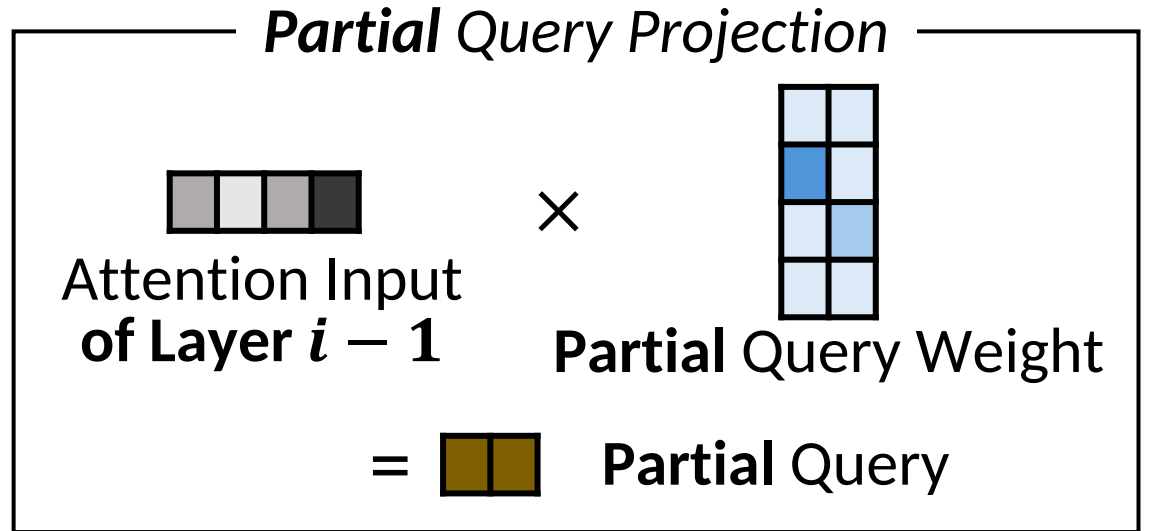
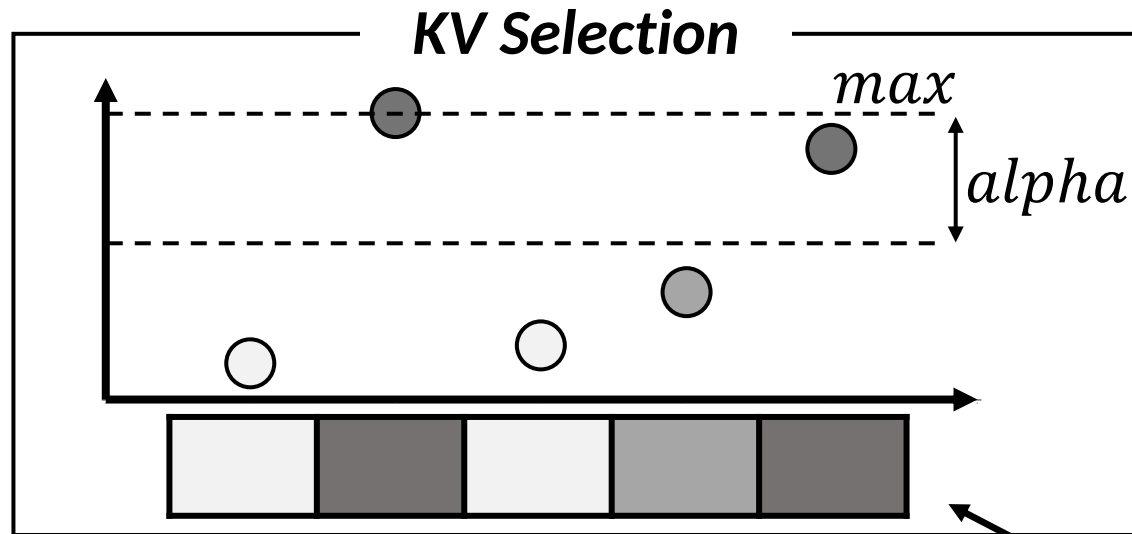


*Attention Speculation*

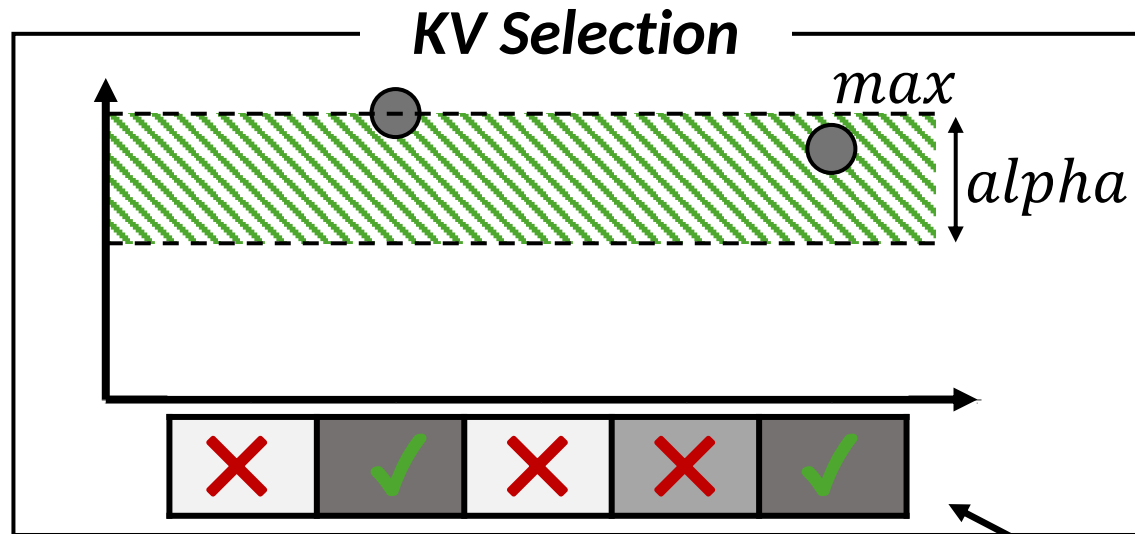


# Speculative KV Prefetching

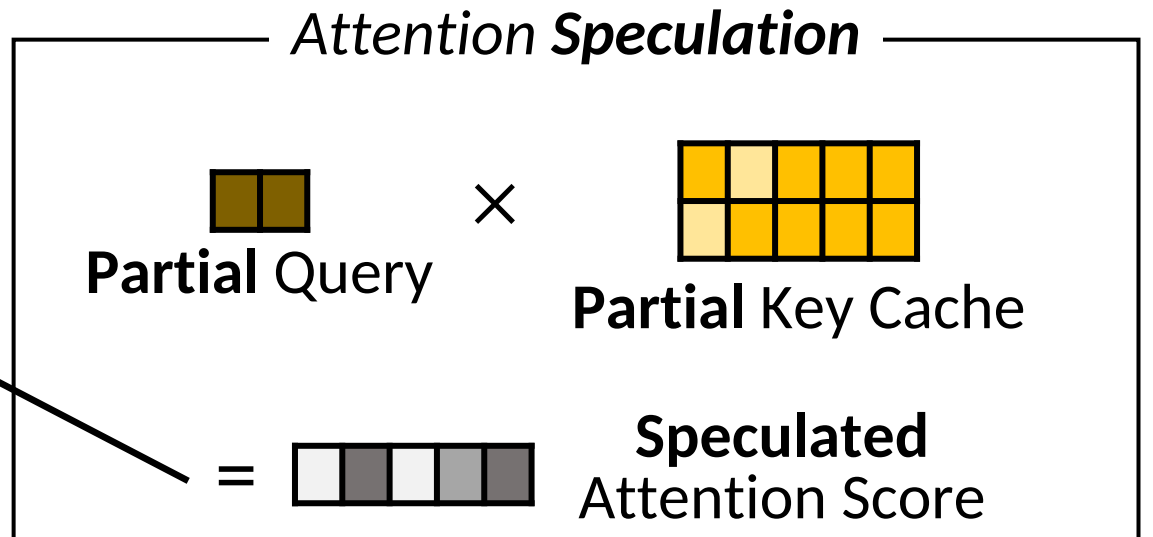
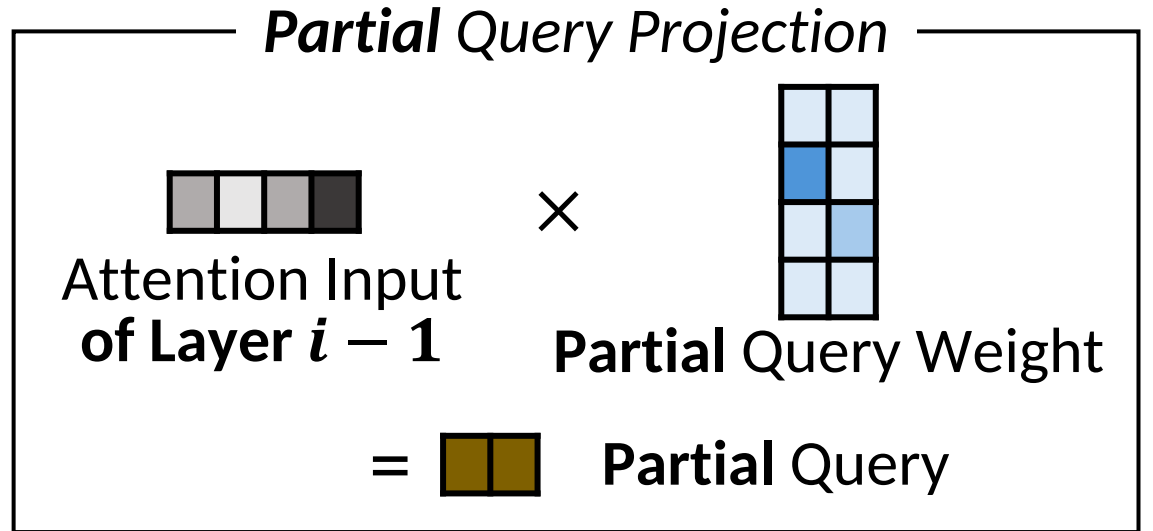
Minimal Rehearsal: Layer  $i - 1$



# Speculative KV Prefetching

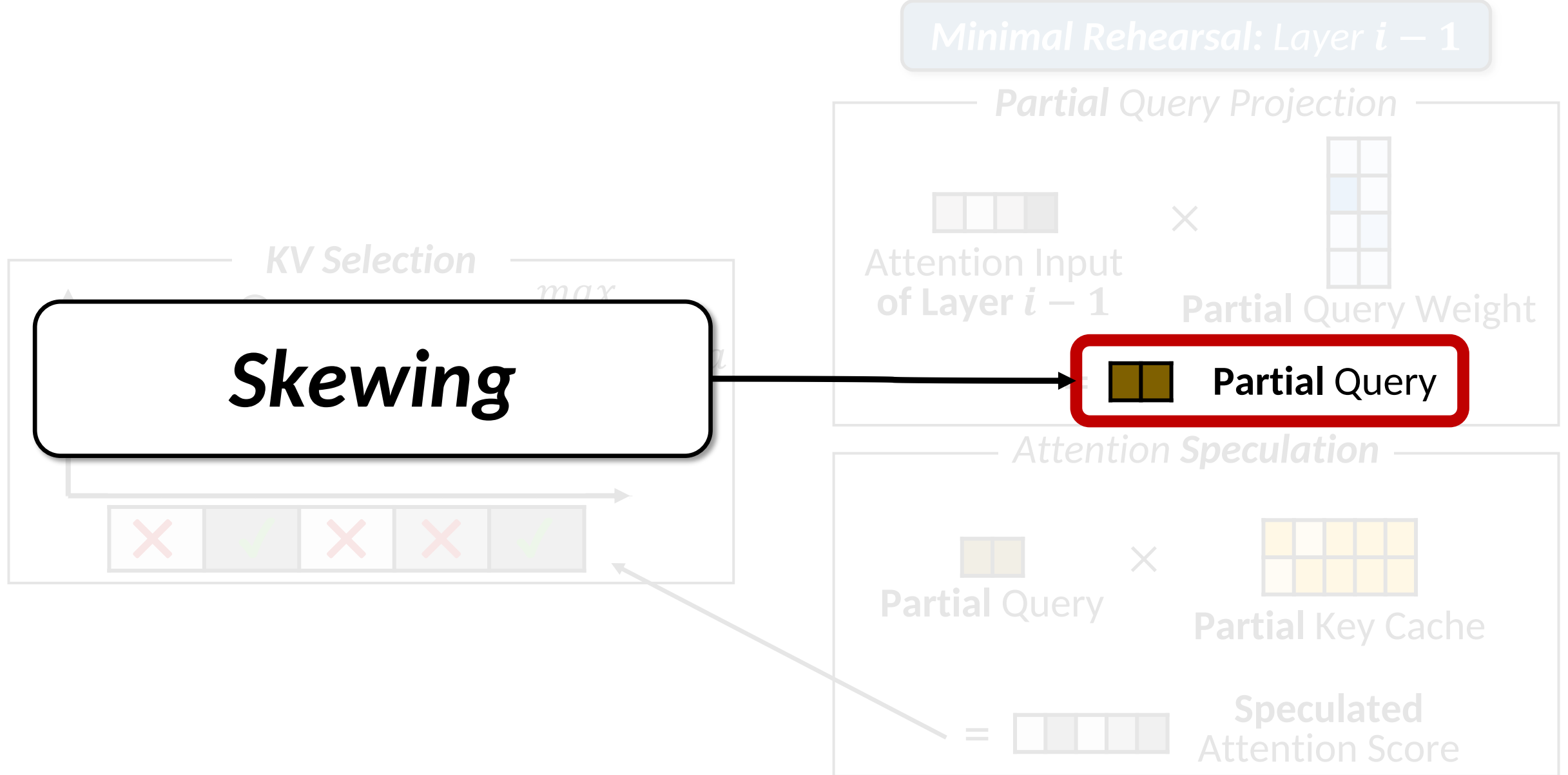


## Minimal Rehearsal: Layer $i - 1$



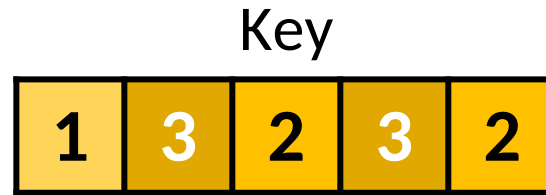


# Speculative KV Prefetching



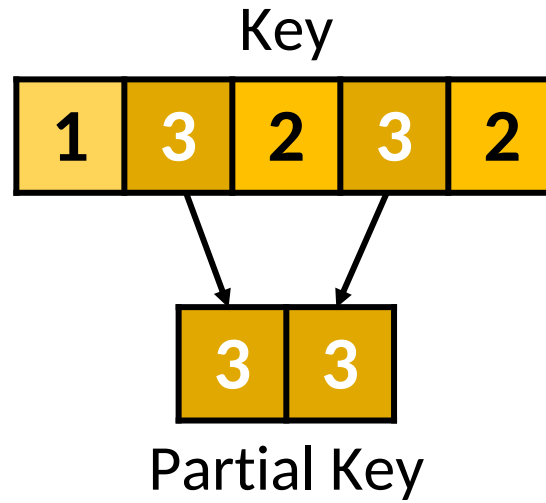
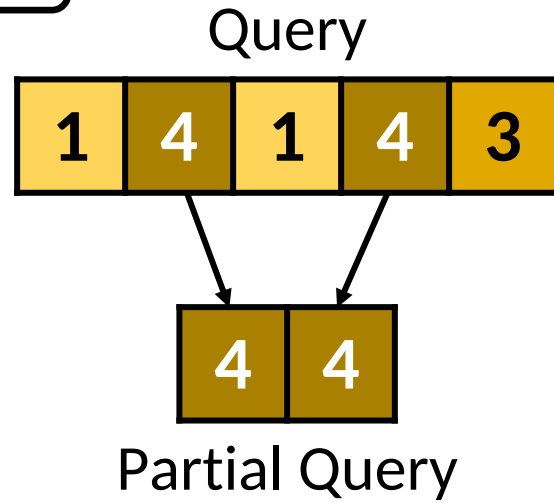
# Key/Query Skewing

*Before*



# Key/Query Skewing

Before

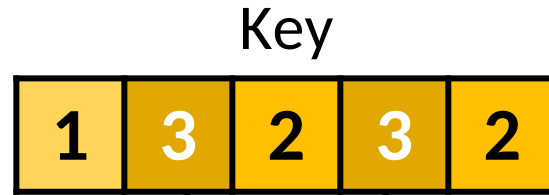


# Key/Query Skewing

Before



×



×



Partial Query



Partial Key

Attention Score

$$= \begin{matrix} 33 \\ 24 \end{matrix}$$

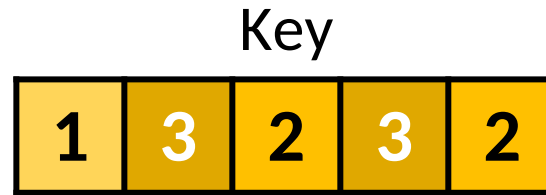
$\rightarrow$  9 ☹️

# Key/Query Skewing

Before



×



=

Attention Score

33



×



=

24

9 ☹️

Partial Query

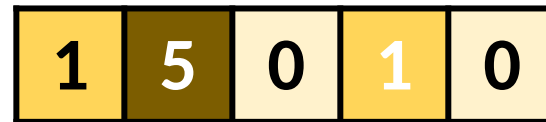
Partial Key

After

Skewed Query

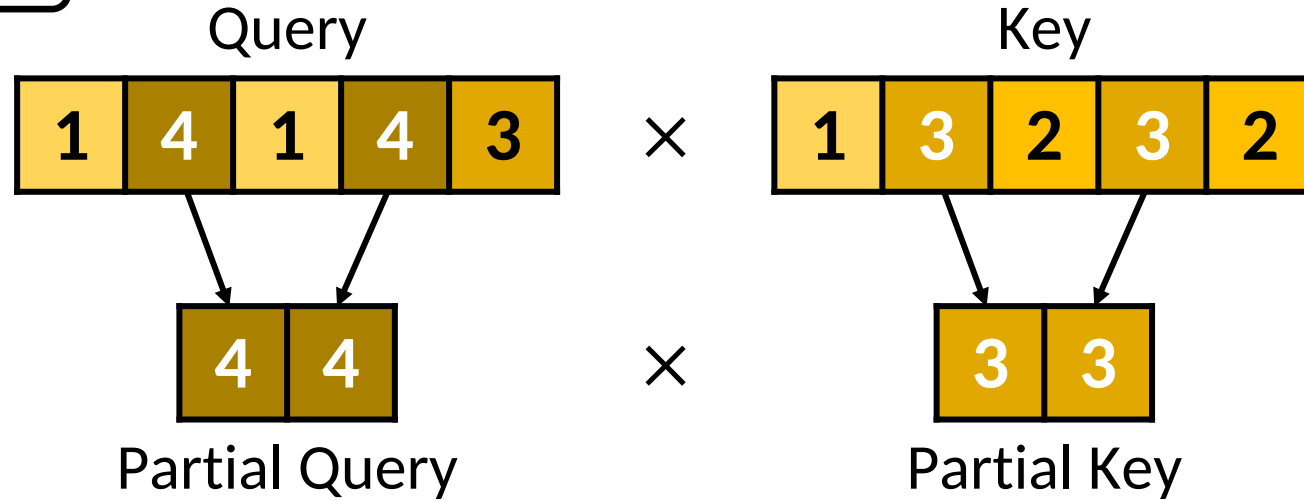


Skewed Key



# Key/Query Skewing

Before



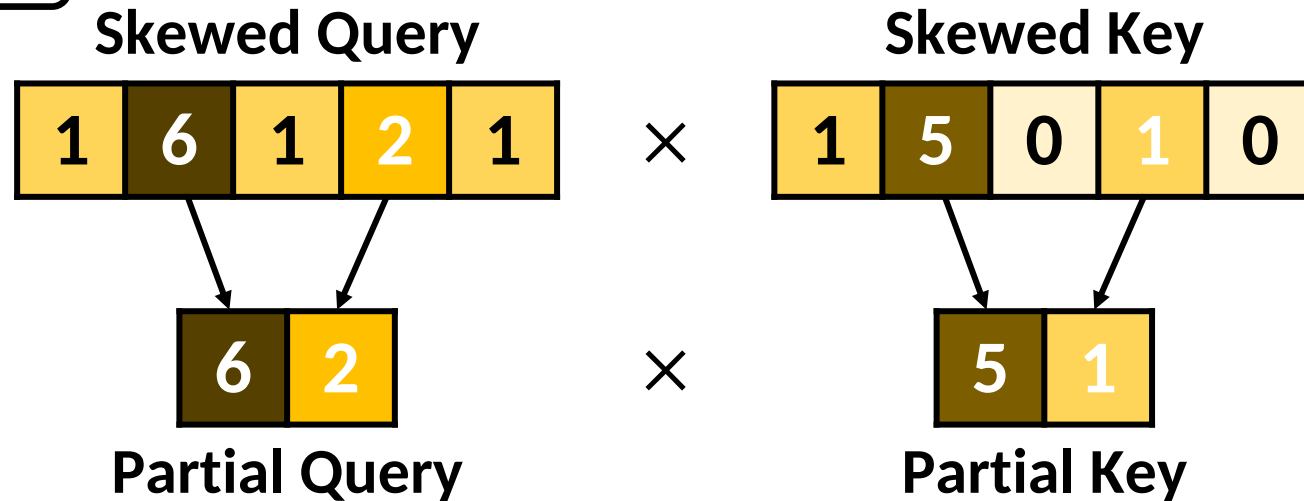
Attention Score

$$= \begin{matrix} 33 \\ 24 \end{matrix}$$

9 ☹️

Diagram illustrating the Attention Score calculation. The scores 33 and 24 are shown, with a red bracket indicating a difference of 9, which is associated with a sad face emoji.

After



Attention Score

$$= \begin{matrix} 33 \\ 32 \end{matrix}$$

1 😊

Diagram illustrating the Attention Score calculation. The scores 33 and 32 are shown, with a green bracket indicating a difference of 1, which is associated with a happy face emoji.

# Key/Query Skewing

Before

**Offline modification** of the query and key weights using **singular value decomposition**

Partial Query

Partial Key



After

The **identical** computation result

$$(Q \times A) \times (A^T \times K^T) = Q \times K^T$$

Partial Query

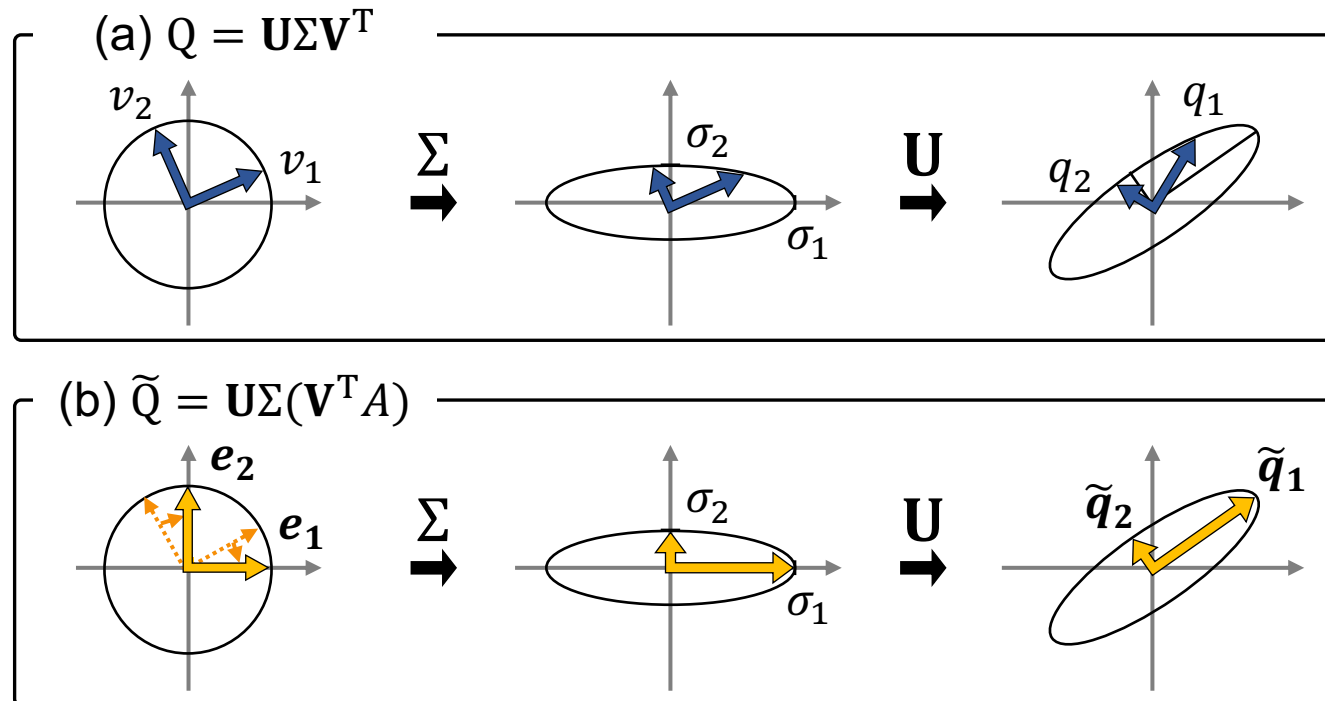
Partial Key



# Key/Query Skewing

Before

**Offline modification** of the query and key weights using **singular value decomposition**



After



# Outline

- LLM Inference & KV Cache
- Prior Approaches & Limitations
- InfiniGen: Dynamic KV Cache Management
  - Speculative KV Prefetching
  - Key/Query Skewing
- **Evaluation**
- Conclusion

# Experimental Setup

## Model

- Open Pre-trained Transformer (OPT)  
: 6.7B, 13B, 30B
- Llama-2  
: 7B, 13B

## Baseline

- KV Cache Offloading
  - CUDA Unified Virtual Memory (UVM)
  - **FlexGen**
- KV Cache Management Methods
  - **H<sub>2</sub>O: Eviction-based**
  - Quantization

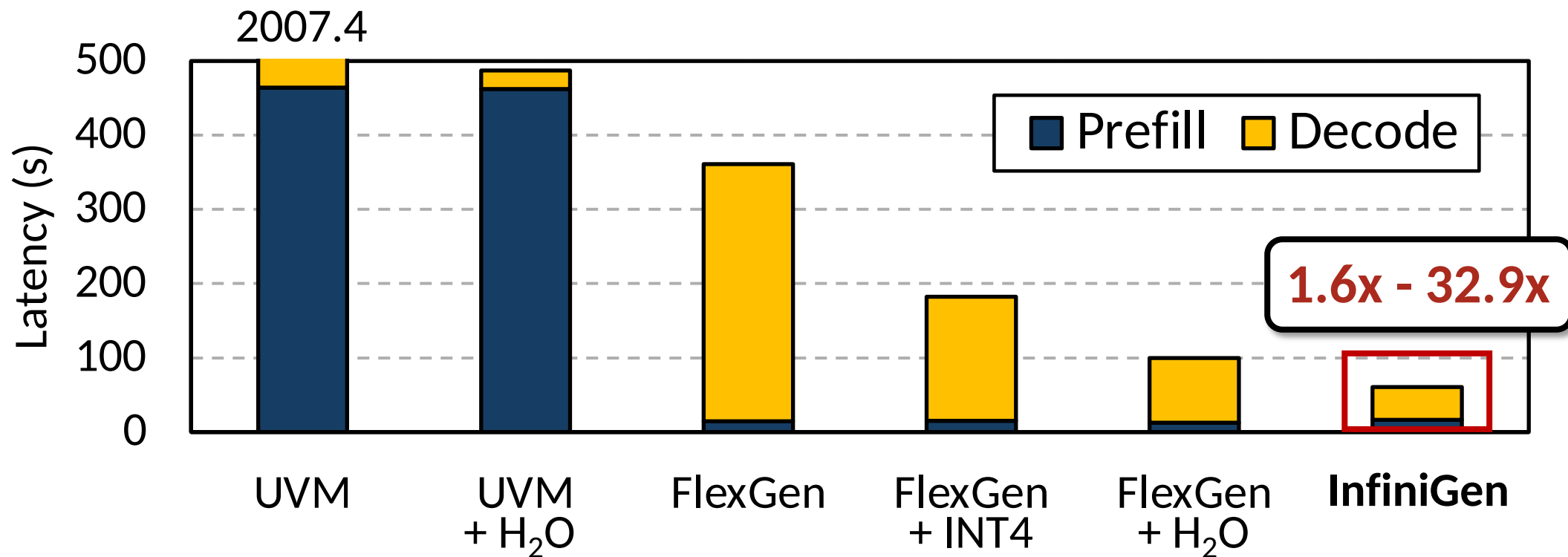
## Workload

- Im-evaluation-harness
- PG-19

## System Configuration

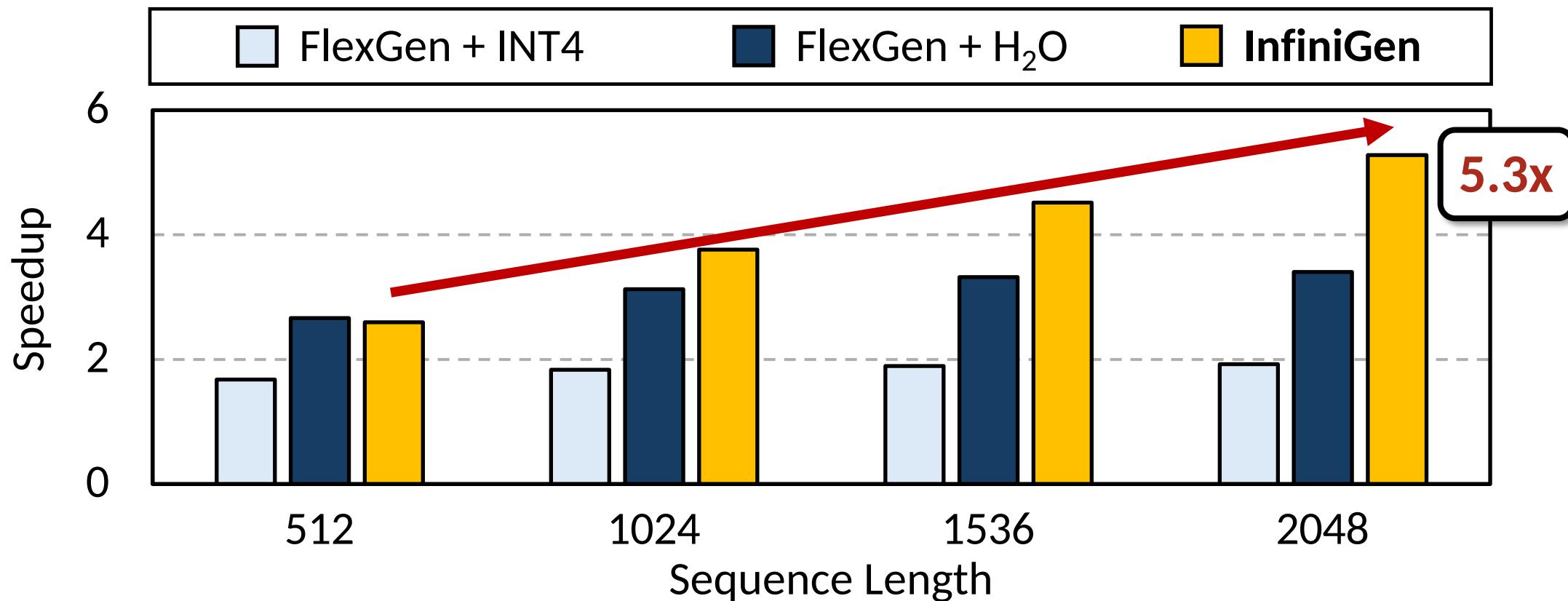
GPU	
GPU	NVIDIA RTX A6000
GPU Memory Size	48 GB
CPU	
CPU	Intel Xeon Gold 6136
CPU Memory Size	96GB
Interconnect	
PCIe Generation	3.0
Lane	16

# Performance



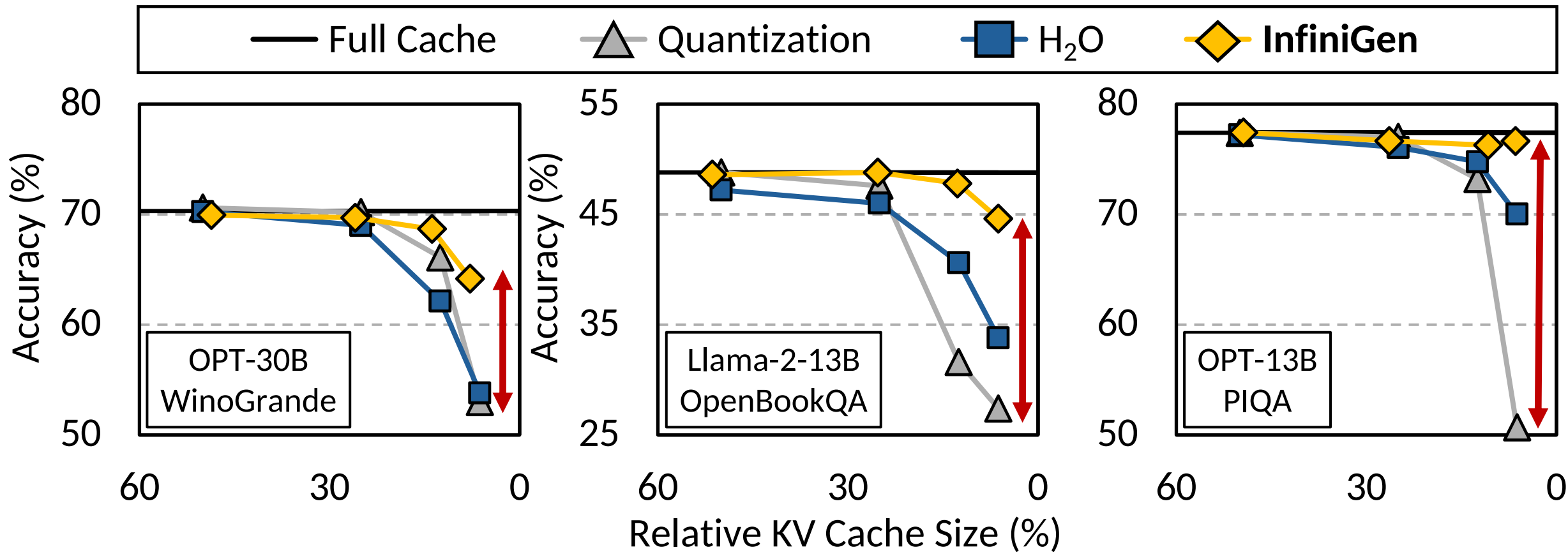
**InfiniGen greatly improves the overall performance**  
of a modern offloading-based inference system

# Performance



**InfiniGen improves performance with longer sequences**  
while others lead to saturating speedups

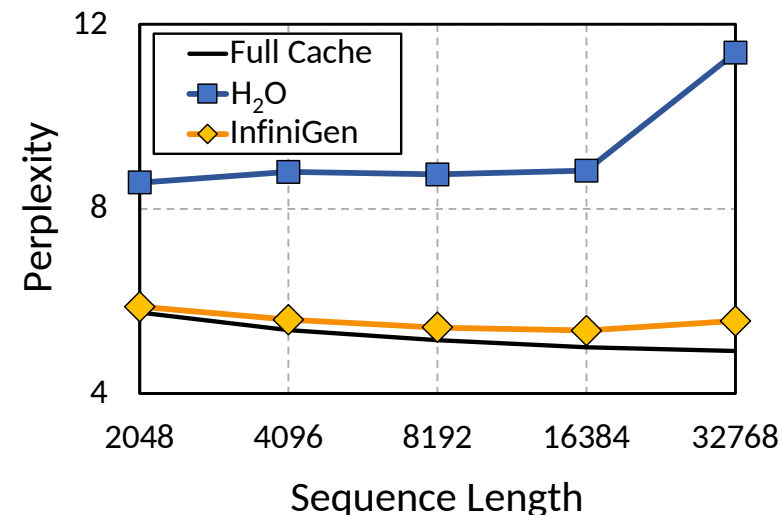
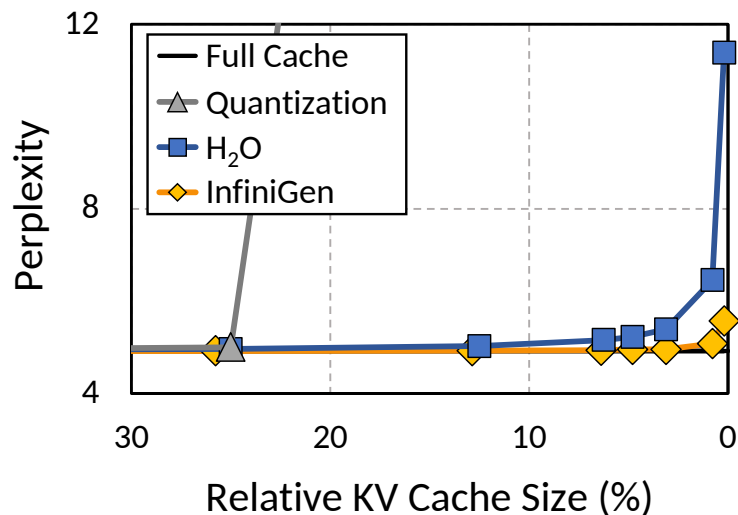
# Accuracy



**InfiniGen offers substantially better model accuracy than other KV cache management methods**

# More Details in Our Paper

- Long Sequences



- Key/Query Skewing
- Sensitivity Study and Overhead Analysis
- Latency across batch sizes and model sizes
- Accuracy with Other Combinations
- Others ...

# Conclusion

## Problem

- The large memory footprint of **the KV cache size** in LLM inference
- Existing methods show subpar performance

**Solution: InfiniGen**, a dynamic KV cache management framework

- **Speculative prefetching** of the essential KV cache
- **Skewing** query and key for efficient speculation

## Result

- **InfiniGen** shows **3x faster** performance while **preserving model accuracy**
- It also shows **better scalability** than prior solutions! 😊

# Thank You!



Github Repo

## InfiniGen

Efficient Generative Inference  
of Large Language Models  
with Dynamic KV Cache Management

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