Carnegie Mellon University

Efficient Inference Methods

Large Language Models: Methods and Applications

Daphne Ippolito and Chenyan Xiong

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Audience Q&A

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Learning Objectives

Learn the general concepts of efficient inference methods for LLM serving

Learn to build speculative decoding systems and potentially conduct research on model-based efficiency

Learn the basics of paged attention and flash attention

Outline

Overview

Model level efficiency: Speculative Decoding

Memory management efficiency: Paged Attention

System level optimization: Flash Attention

Serving LLMs

Serving large models live was costly and slow.

- Lots of OpenAI's cost are on serving
- E.g. if one model instance require 8 A100 then it's $10+ per hour

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- Missing the economies of scale
- Even losing money per token sometimes
- Restricting to cloud-backed scenarios

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Are we on a bubble bursting trajectory?

Model gets larger →Cost per user more expensive → No one makes money (except Nvidia) →VC gets inpatient (or broke) → bubble burst

Serving LLMs

Guido Appenzeller • 2nd

Investing in Infra & AI at a16z. Previously CTO @ Intel & VMwar...

2mo •

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Generative AI is becoming crazy cheap. The cost of LLM inference has come down by 100x over 2 years (~$50 to $0.50 per 1M tokens) and having an LLM listen to everything you say for the entire year costs about $3.50.

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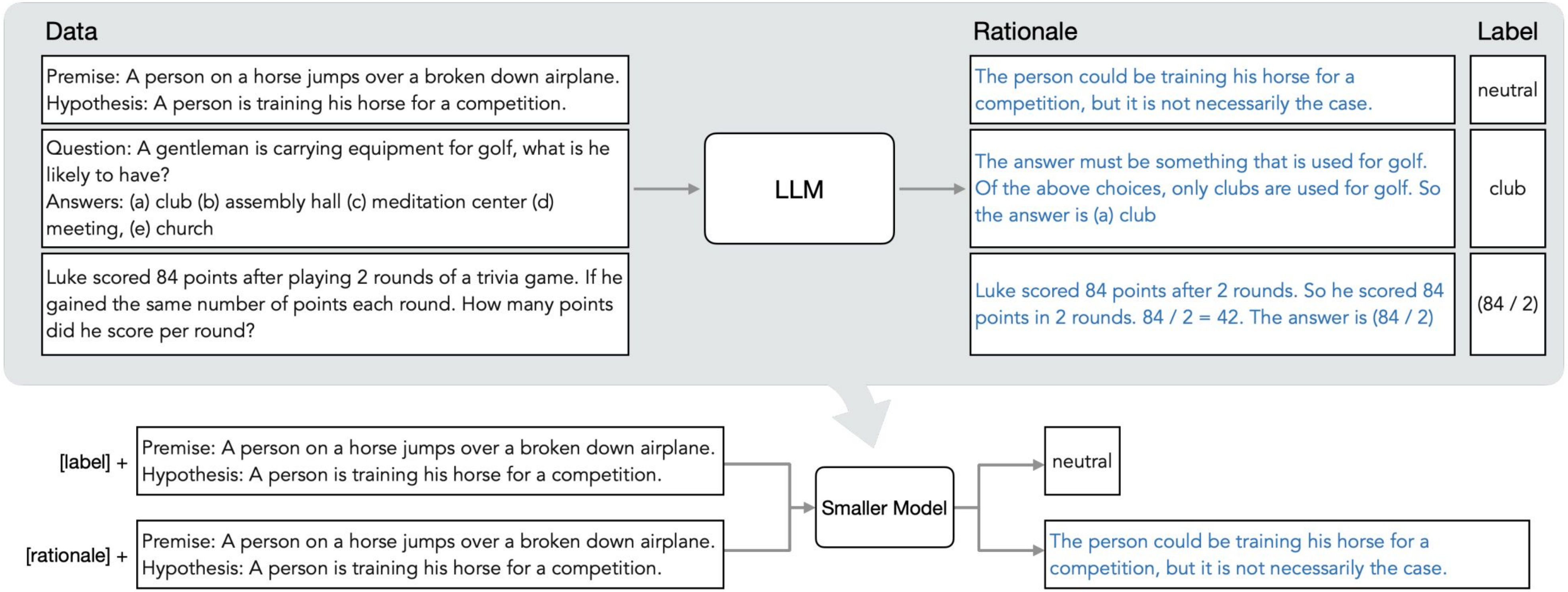
What got us here?

Trading Capability for Efficiency

Distillation: train smaller student models from the big teacher

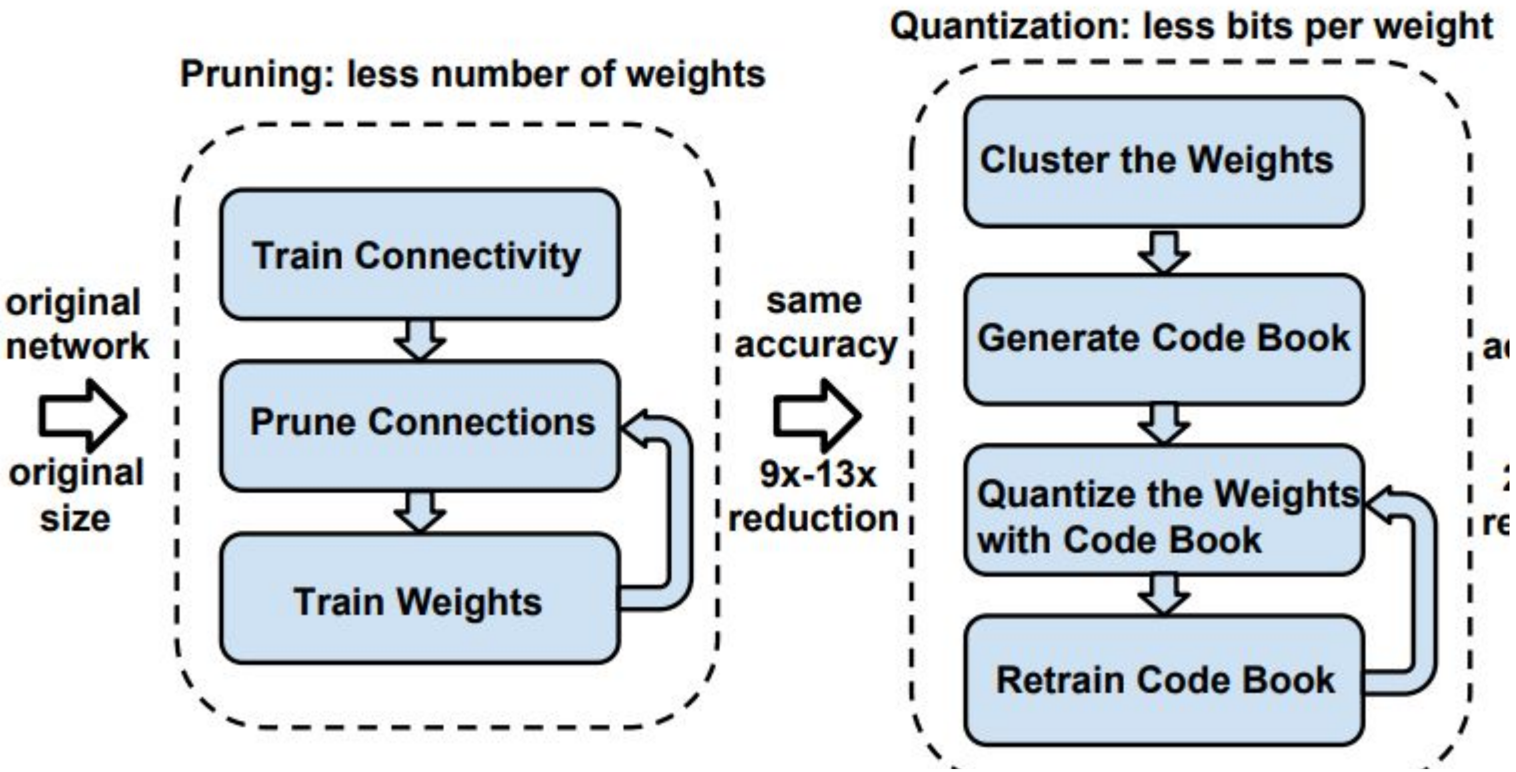


Distillation Step-by-Step [1]

[1] Hsieh et al. 2023. Distilling Step-by-Step! Outperforming Larger Language Models with Less Training Data and Smaller Model Sizes

Trading Capability for Efficiency

Pruning and Quantization: Delete and shrink parameters to cheaper formats

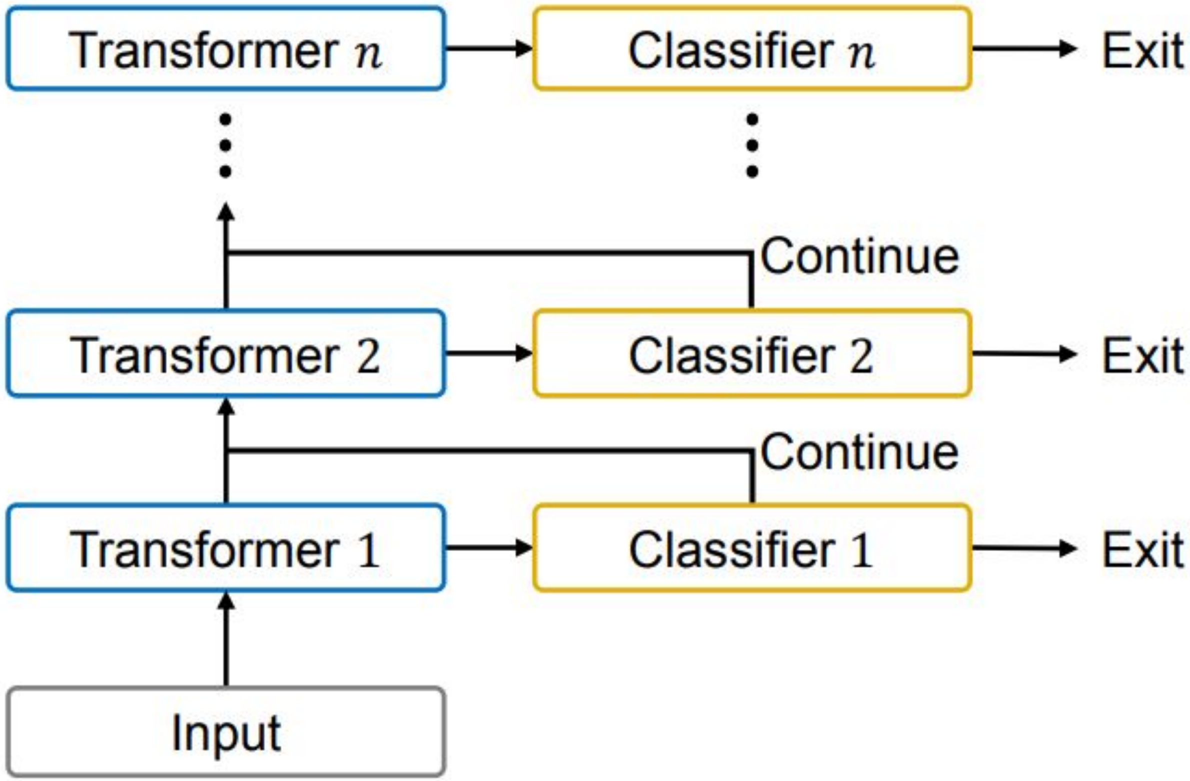


Pruning and Quantization of Neural Networks [2]

[2] Han et al. 2016. Deep compression: Compressing deep neural network with pruning, trained quantization and huffman coding

Trading Capability for Efficiency

Early Exit: Skip some transformer layers or use earlier layer's predictions

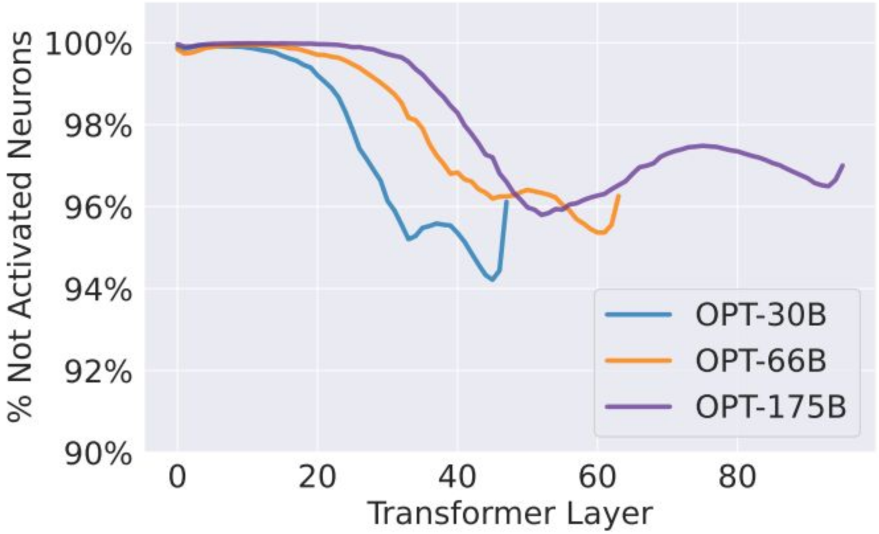


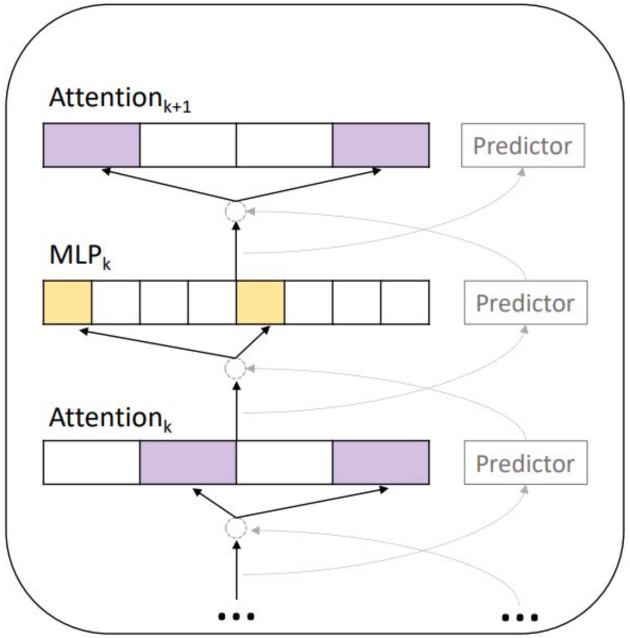
Early Exit in Classification [3]

[3] Xin et al. 2020. Early Exiting BERT for Efficient Document Ranking

Trading Capability for Efficiency

Sparsity: Skip certain neurons/blocks if predicted sparse likely





Early Exit in Classification [4]

Trading Capability for Efficiency

All above methods make the LLM "smaller"

- Inevitably lose some model "capability"

Though on benchmarks the loss is small, but there is no guarantee in real world scenarios

- Zero-shot
- New usage
- Edge cases
- Complicated cases
- Etc….

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Are there any "free" lunch?

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Speculative Decoding

- Observations:
- We have a lot of decent smaller models
- They likely mimic the large model's behavior
  - Same model family, Distilled, or sub model from the large model
- Though generation of a sequence is sequential, scoring the sequence is O(1)

$$O\big(p(x_{n:n+k}|x_{<n})\big) \approx O(p(x_n|x_{<n}))$$

[5] Xia et al. 2024. Unlocking Efficiency in Large Language Model Inference: A Comprehensive Survey of Speculative Decoding

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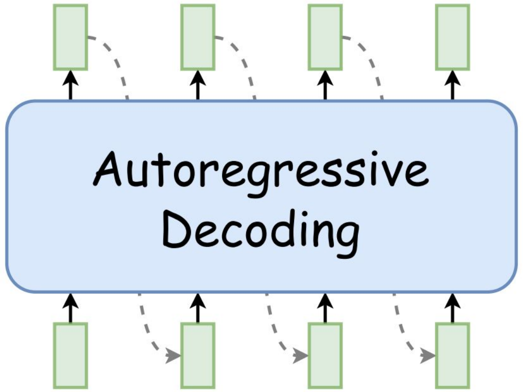

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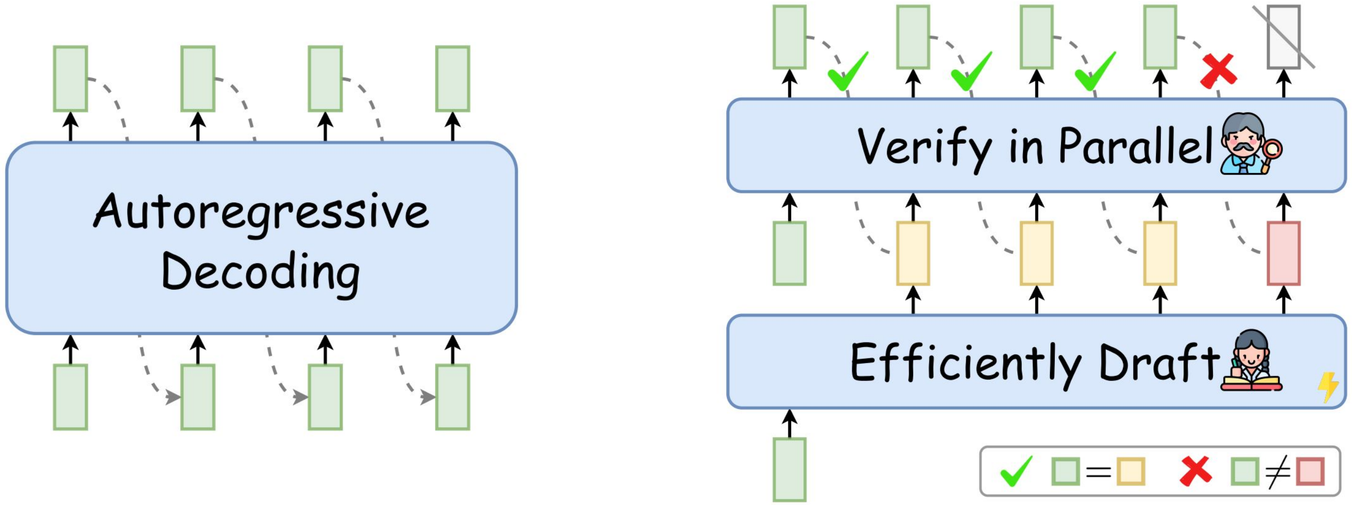

Speculative Decoding with Smaller Models to Propose and Large Model to verify [5]

[5] Xia et al. 2024. Unlocking Efficiency in Large Language Model Inference: A Comprehensive Survey of Speculative Decoding

Speculative Decoding

- Rejection Sampling to Recover the Large Model's Distribution p(x) Using a Small Model q(x) [6]

1. Sample $x \sim q(x)$
2. If $q(x) < p(x)$, keep x, finish
3. else reject x and
4. resample $x \sim norm(\max(0, p(x) - q(x)))$

[6] Leviathan et al. 2023. Fast Inference from Transformers via Speculative Decoding

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To speed up need to speculate

Algorithm 1 SpeculativeDecodingStep

Inputs: $M_p, M_q, prefix$.
▷ Sample γ guesses $x_{1,\ldots,\gamma}$ from M_q autoregressively.
for $i = 1$ **to** γ **do**
  $q_i(x) \leftarrow M_q(prefix + [x_1, \ldots, x_{i-1}])$
  $x_i \sim q_i(x)$
end for
▷ Run M_p in parallel.
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▷ Adjust the distribution from M_p if needed.
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Worse case still breaks even

- Sampled one x with one run of p()

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Speculative Decoding

[START] japan ' s benchmark ~~bond~~ n

[START] japan ' s benchmark nikkei 22 ~~,~~5

[START] japan ' s benchmark nikkei 225 index rose 22 ~~,~~6

[START] japan ' s benchmark nikkei 225 index rose 226 . 69 ~~,~~ points

[START] japan ' s benchmark nikkei 225 index rose 226 . 69 points , or 0 1

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[START] japan ' s benchmark nikkei 225 index rose 226 . 69 points , or 1 . 5 percent , to 10 , 989 . 79 in late morning trading . [END]

Speculative Decoding with accepted drafts, rejected, and resampled tokens [6]

[6] Leviathan et al. 2023. Fast Inference from Transformers via Speculative Decoding

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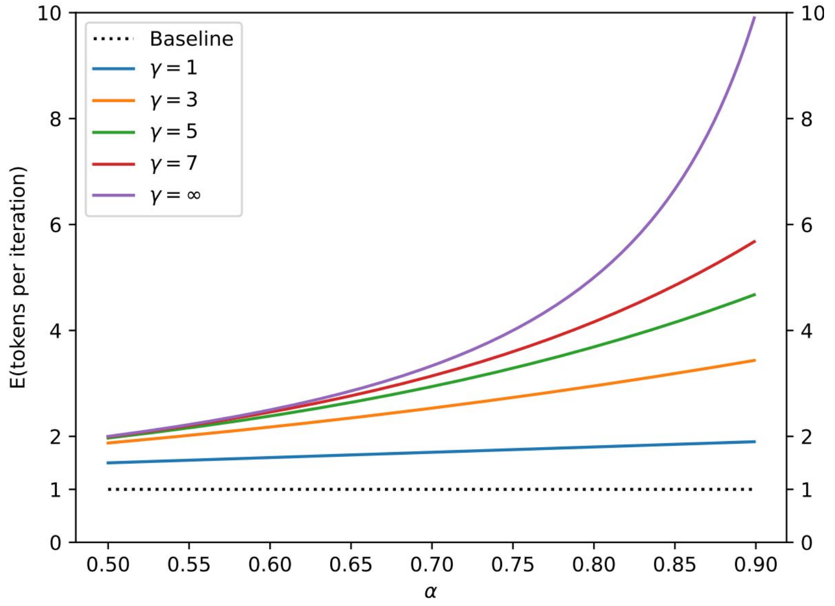
Speculative Decoding: Speed Up

- Two factors determining the speed up:
- Acceptance rate α: the expectation of a drafted token $q(x_t|x_{<t})$ being accepted
  - Stronger and closer q → better α

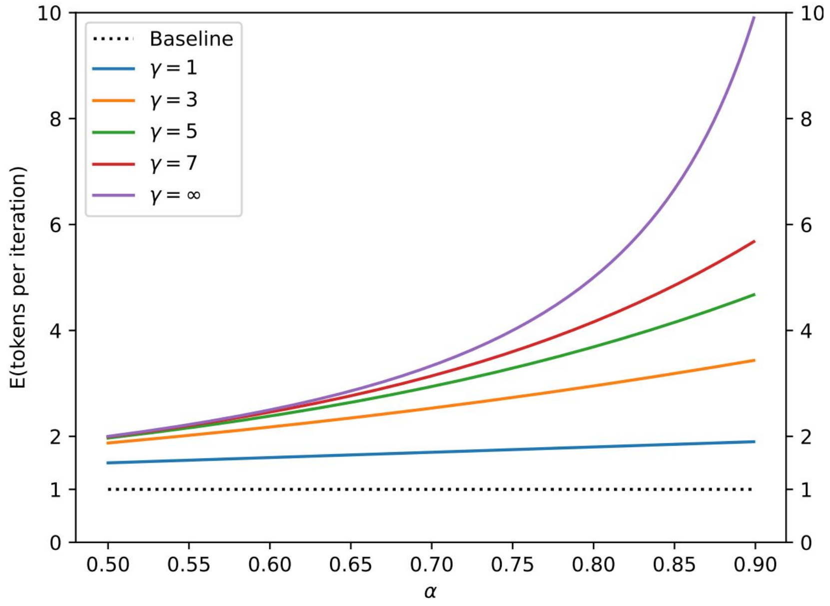


Expected Accepted Token Count with Different α [6]

[6] Leviathan et al. 2023. Fast Inference from Transformers via Speculative Decoding

Speculative Decoding: Speed Up

- Two factors determining the speed up:
- Acceptance rate α: the expectation of a drafted token $q(x_t|x_{<t})$ being accepted
  - Stronger and closer q → better α
- Cost coefficient c: time required to run q over to run p $\frac{cost(q)}{cost(p)}$
  - Smaller q leads to better c



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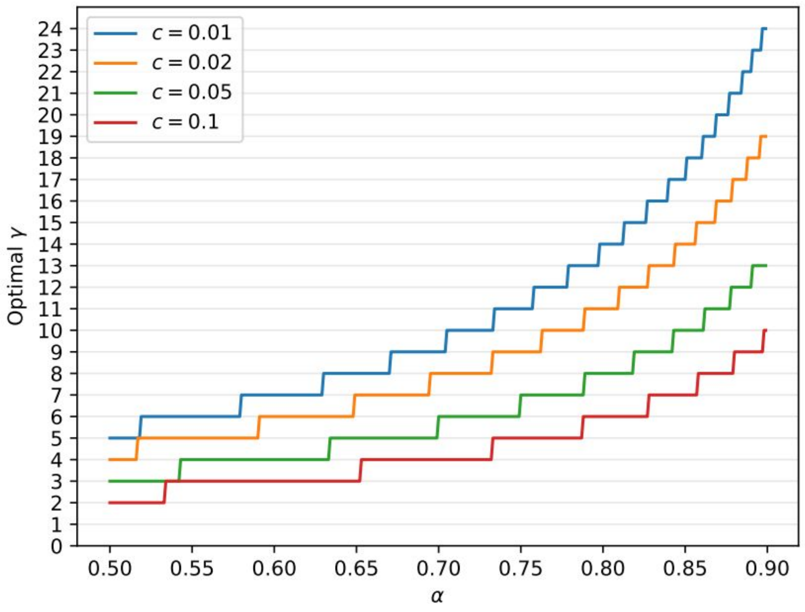
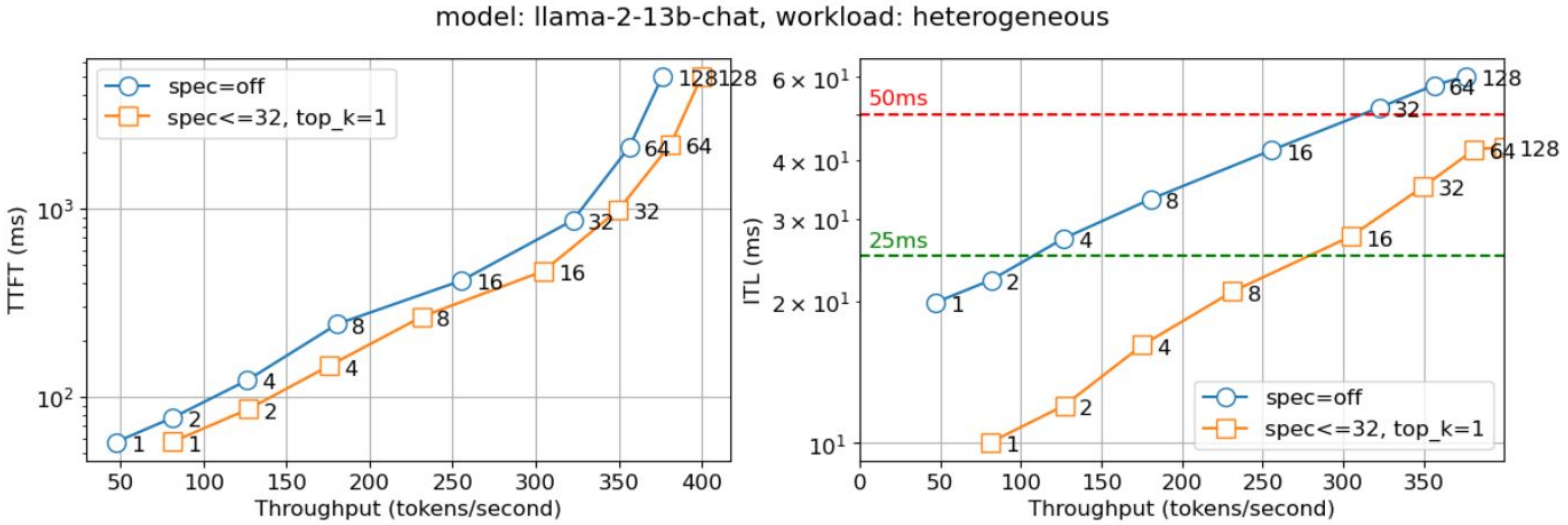


Optimal Configuration for Different α and c [6]

Speculative Decoding: Performance

Performance gains while guaranteed exactness with rejection sampling



Speed improvement in time to first token (TTFT), inter token latency (ITL) and throughput [7]

Speculative Decoding: Remarks

A commonly deployed technology in various industry systems.

- Makes the system more complicated
- But gains of efficiency (huge $$$) without trading effectiveness

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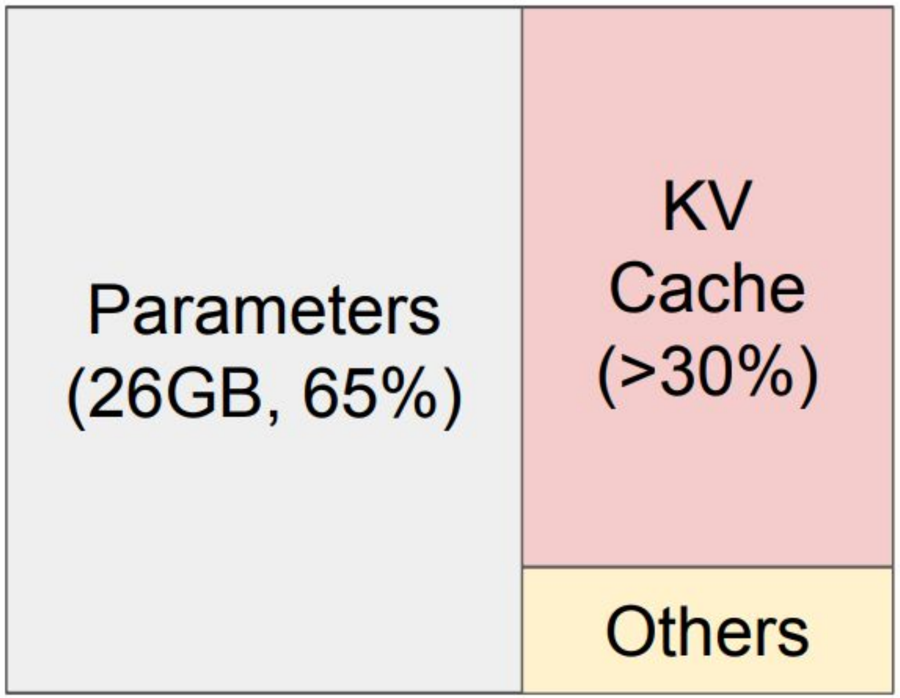
Further ways to improve:

- Better acceptance rate while cheaper drafting model
  - Align drafting model better with target model
- Better infrastructure support
  - MLSys developments

What is the bottleneck in LLM serving?

One GPU serving batched inferences of multiple requests

Model Parameter Storage that is constant, and shared by all inference requests



NVIDIA A100 40GB

Key-Value Activations, unique to every request and dynamically grows during inference

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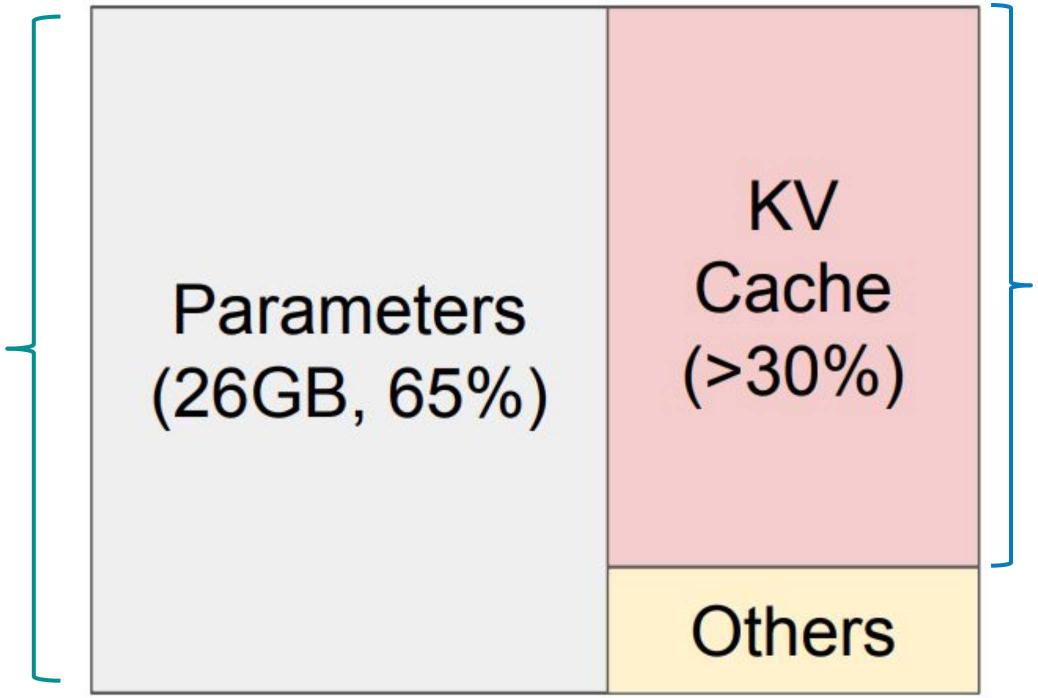


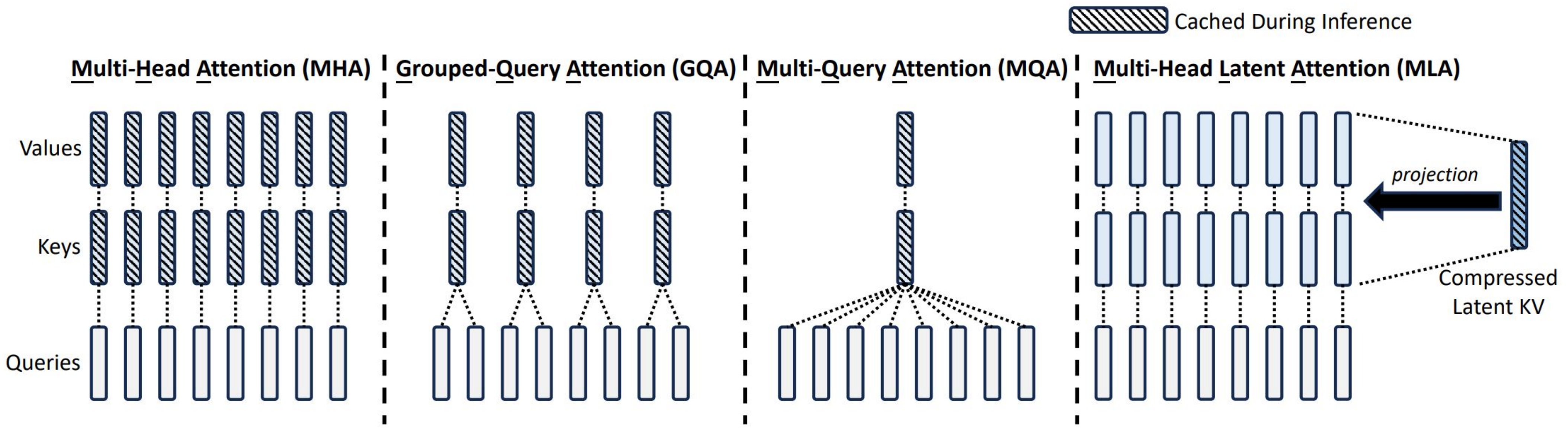
Key-Value Activations, unique to every request and dynamically grows during inference

NVIDIA A100 40GB

Typical LLM service is KV cache memory bound:
GPU memory becomes bottleneck first than other factors like FLOPs

Lossy KV Cache Reduction

Various attention versions with reduced KV cache memory footprint



KV Cache Management is Challenging

- Super dynamic: Grows token by token in our autoregressive generation
- From K,V of $\boldsymbol{x}_{<n}$ to $\boldsymbol{x}_{<n+1}$ after we generated $\boldsymbol{x}_n$

[8] Kwon, et al. 2023. Efficient Memory Management for Large Language Model Serving with PagedAttention

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[8] Kwon, et al. 2023. Efficient Memory Management for Large Language Model Serving with PagedAttention

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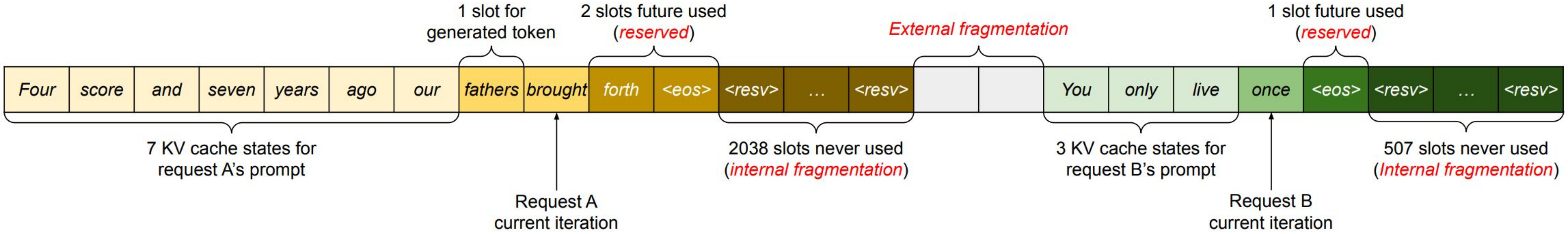
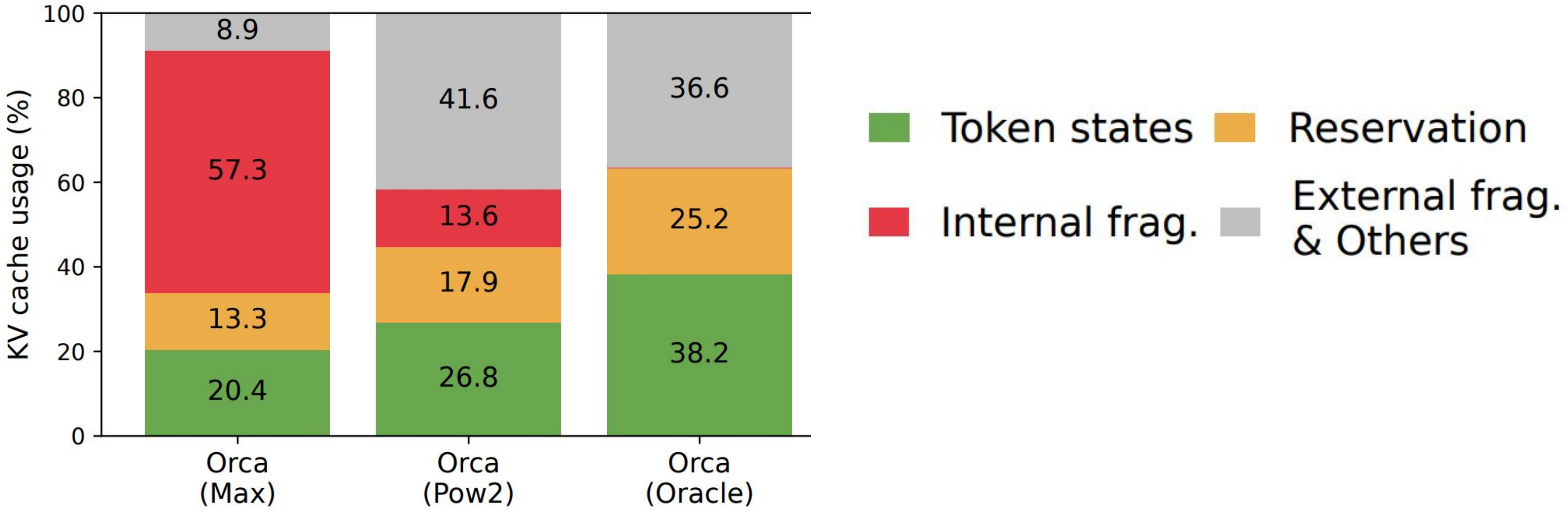


KV Cache Management in Vanilla LLM Serving Systems [8]

[8] Kwon, et al. 2023. Efficient Memory Management for Large Language Model Serving with PagedAttention

KV Cache Management is Challenging

Resulted in Huge waste of GPU memory $$$



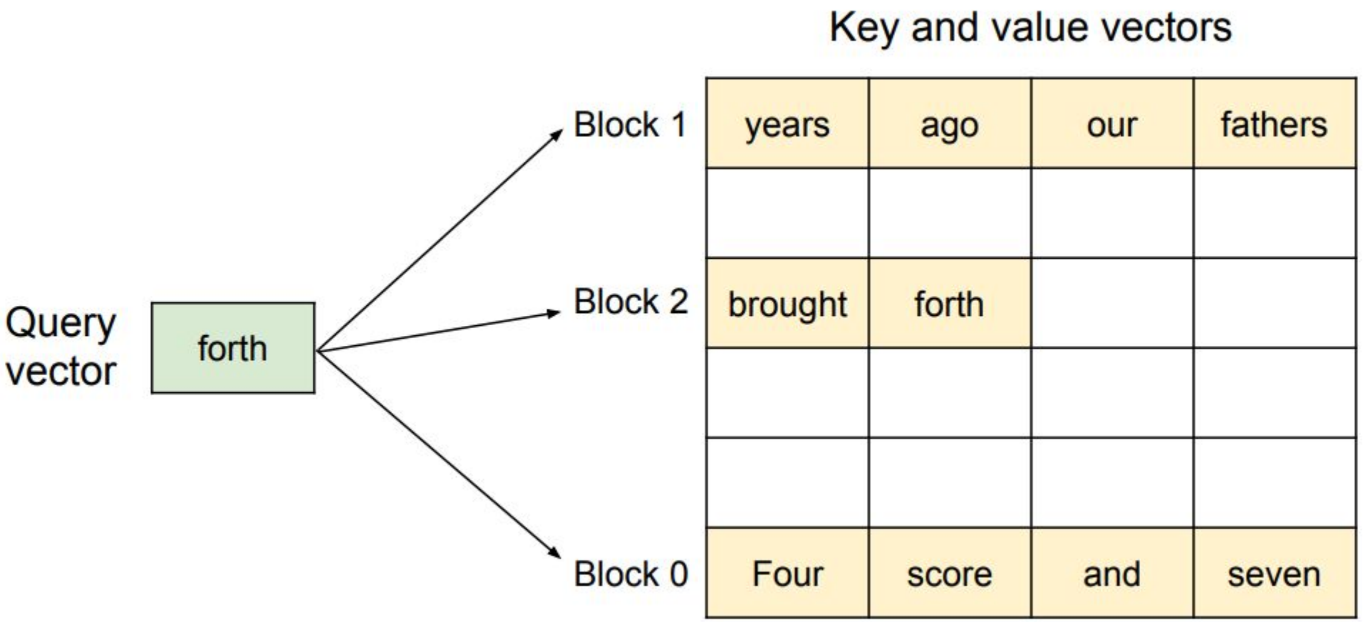
GPU Memory Fragmentations and Wastes in LLM Serving [8]

[8] Kwon, et al. 2023. Efficient Memory Management for Large Language Model Serving with PagedAttention

KV Cache Management in vLLM

Splitting KV cache of a sequence into blocks for more flexible allocations [8]

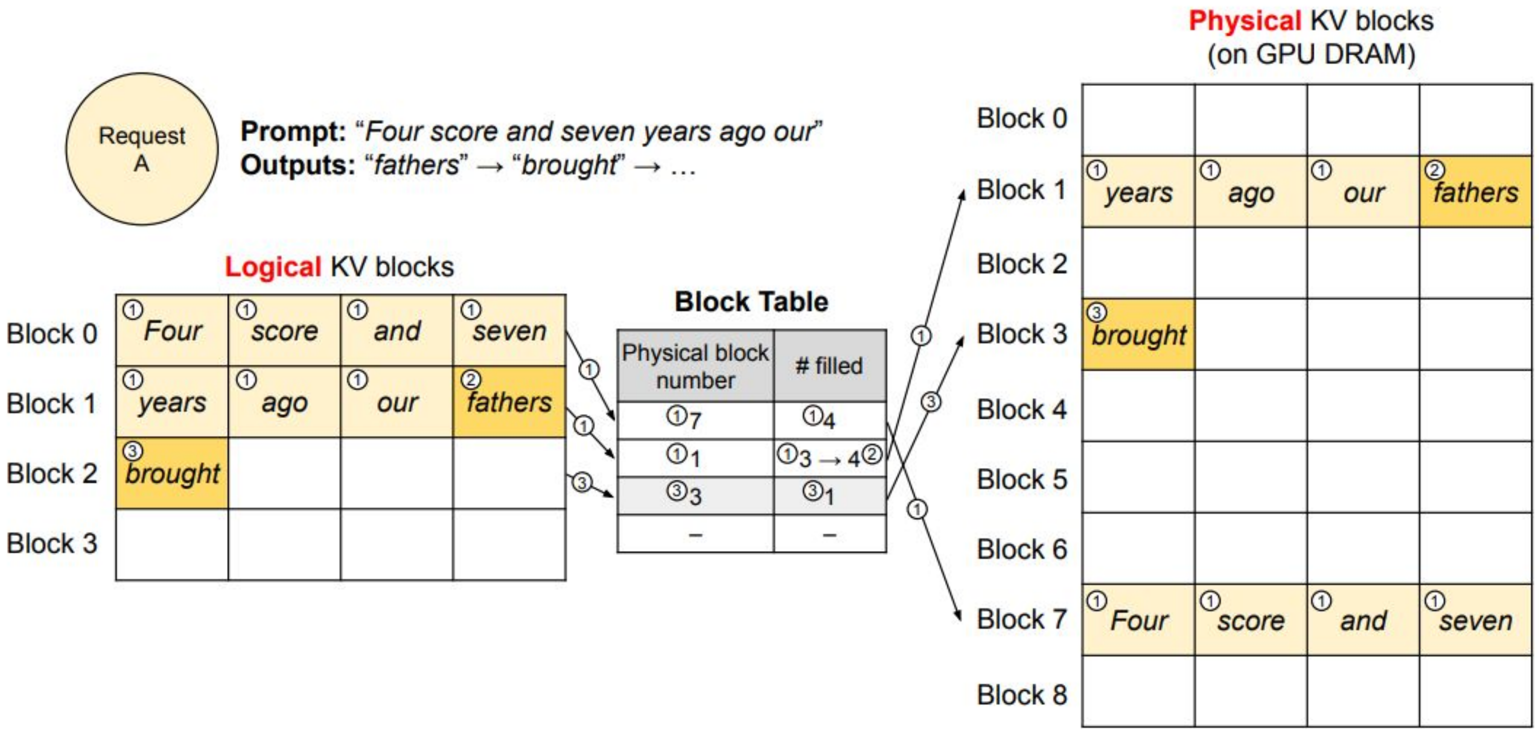
- Classic paging idea in CPU memory management



Splitting Sequence's KV into sub blocks for flexibility [8]

KV Cache Management in vLLM

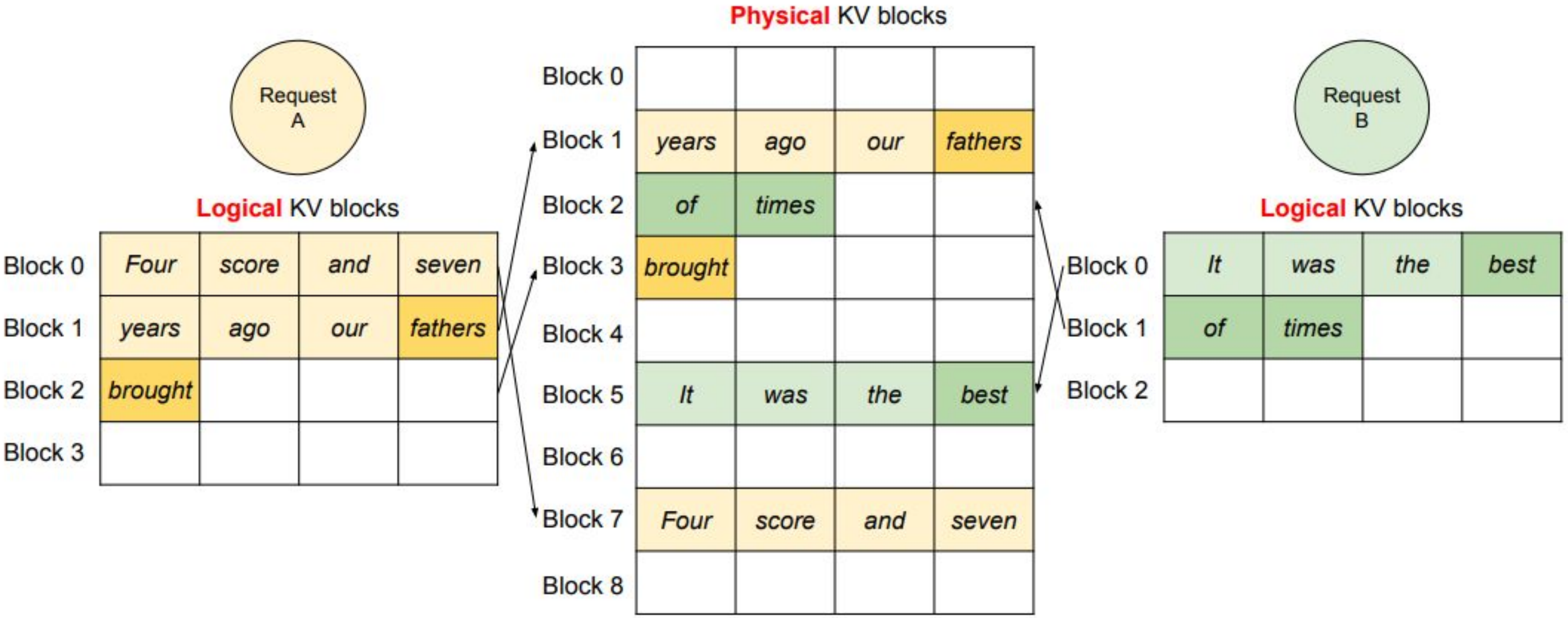
Managing the KV blocks with virtual block tables



Splitting Sequence's KV into sub blocks for flexibility [8]

KV Cache Management in vLLM

More efficient KV cache management at block level

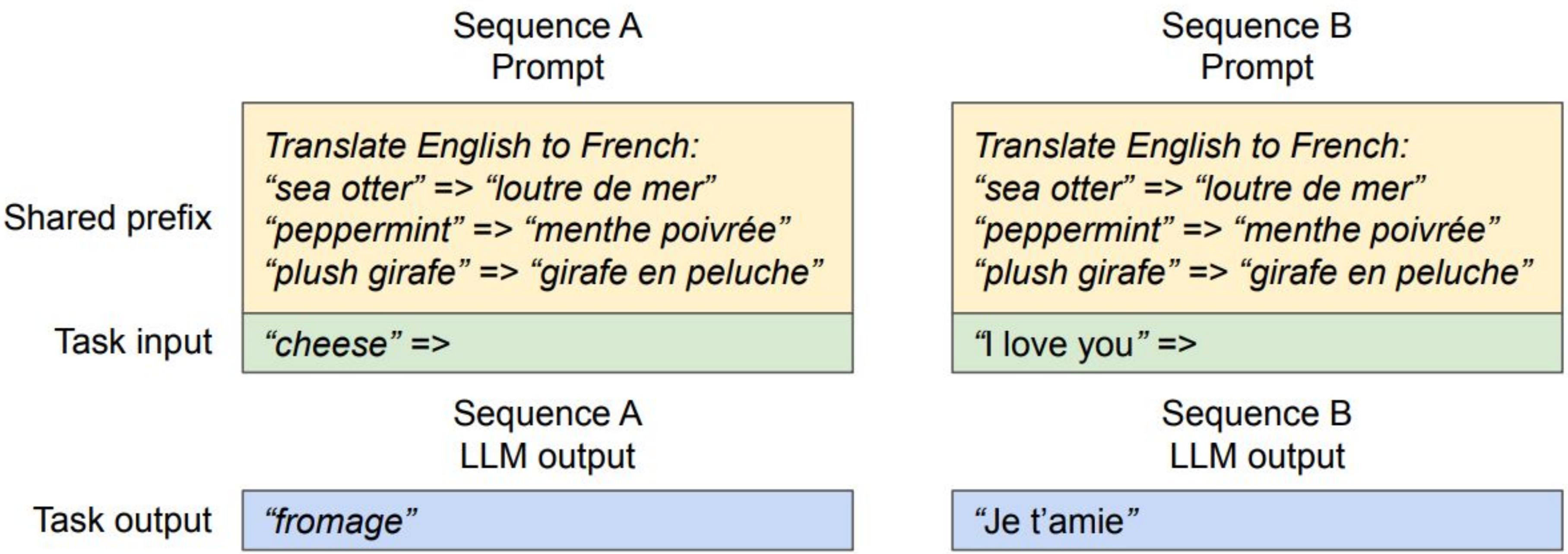


Mixing KV blocks of two requests [8]

[8] Kwon, et al. 2023. Efficient Memory Management for Large Language Model Serving with PagedAttention

KV Cache Management in vLLM

Design KV cache block management algorithms for common LLM serving scenarios



Shared Prompts Using Shared KV Blocks [8]

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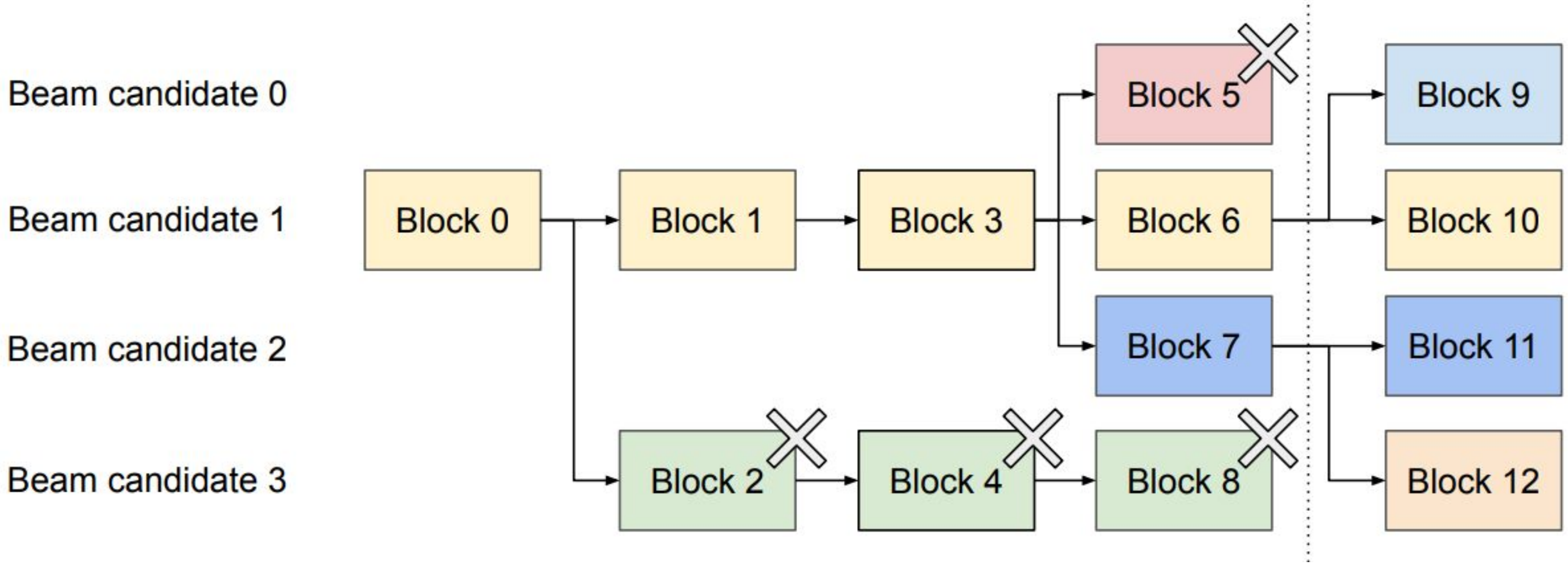
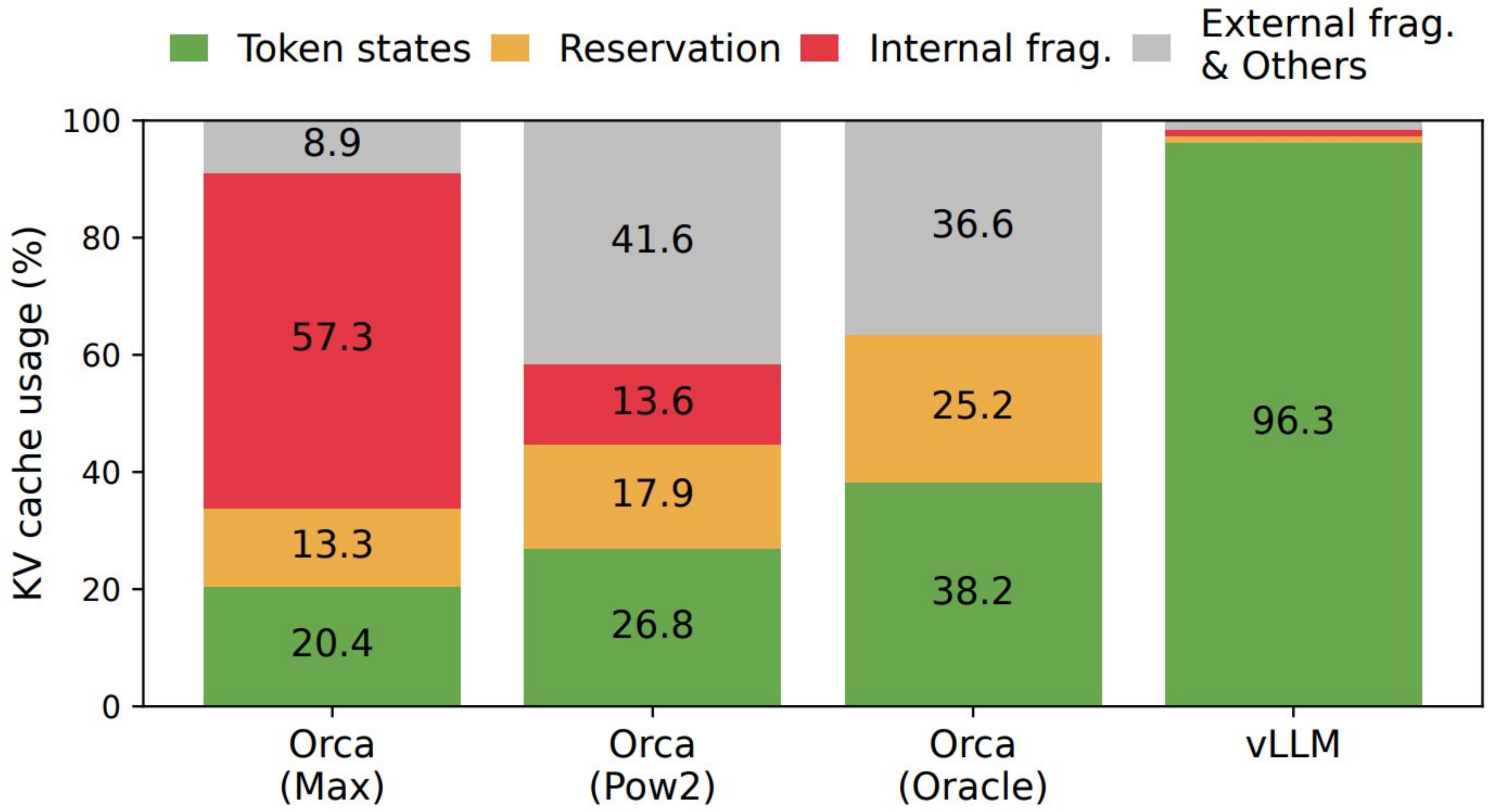


Shared KV Blocks in Beam Search [8]

[8] Kwon, et al. 2023. Efficient Memory Management for Large Language Model Serving with PagedAttention

KV Cache Management in vLLM: Performance

No wastes with PagedAttention block management

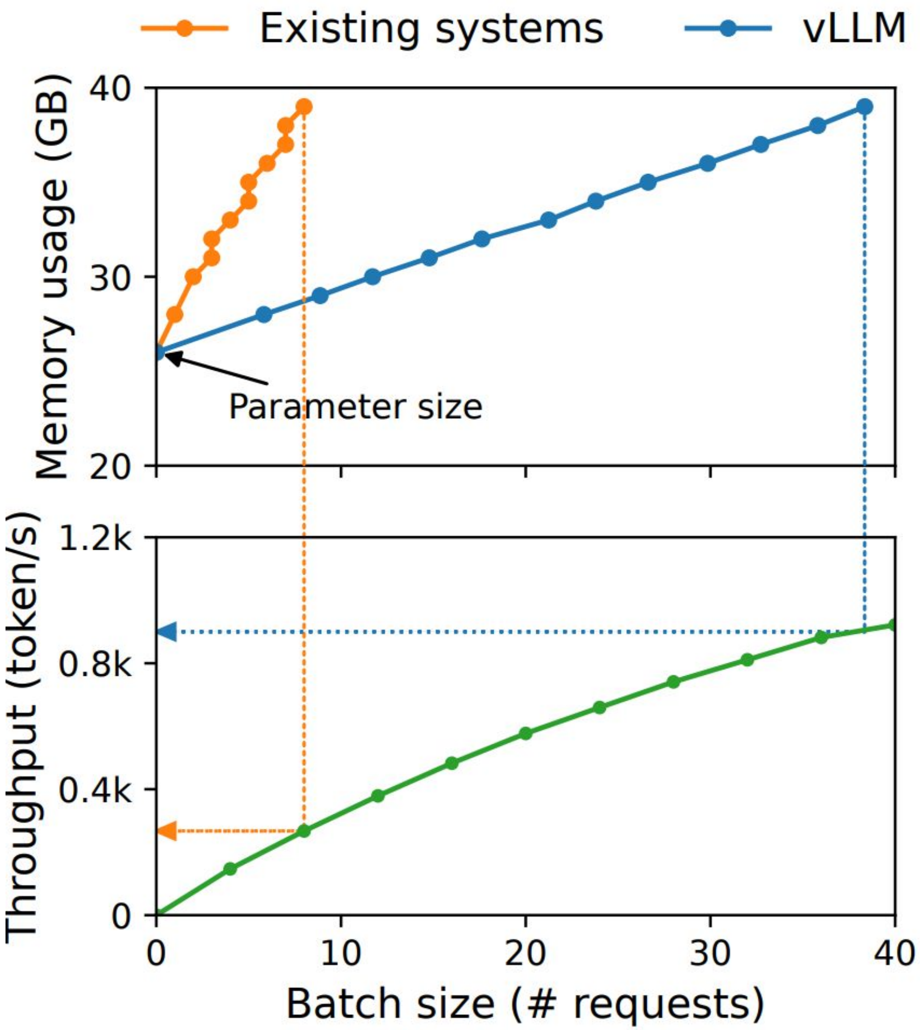


Fragmentation of GPU Memory [8]

[8] Kwon, et al. 2023. Efficient Memory Management for Large Language Model Serving with PagedAttention

KV Cache Management in vLLM: Performance

Fits significantly more requests per batch with efficient usage of GPU memory



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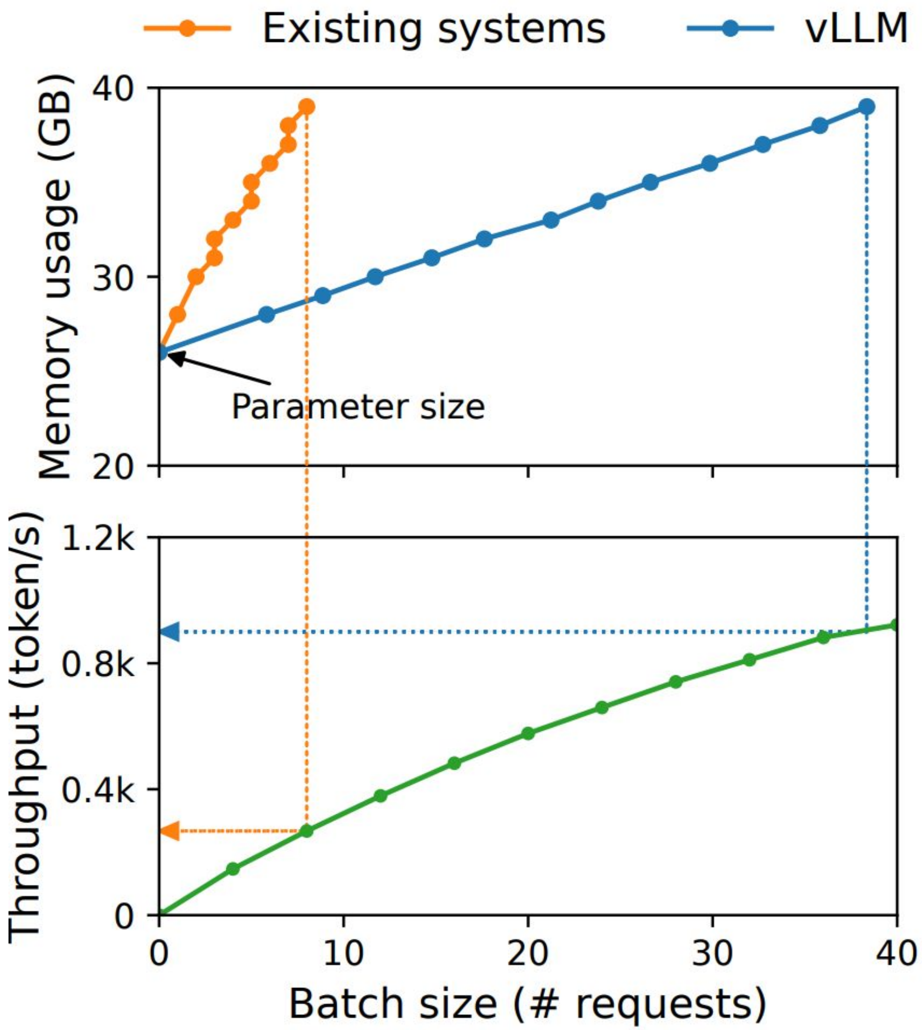

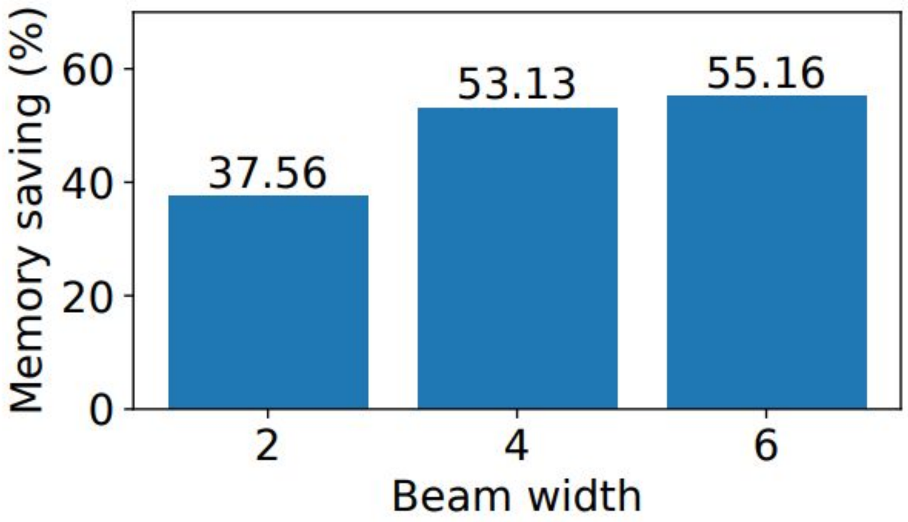

vLLM Community Outreach

vLLM x Snowflake Meetup (Wednesday, November 13th, 5:30-8PM PT) at Snowflake HQ, San Mateo

We are excited to announce the last in-person vLLM meetup of the year! Join the vLLM developers and engineers from Snowflake AI Research to chat about the latest LLM inference optimizations and your 2025 vLLM wishlist! Register here and be a part of the event!

Latest News 🔥

- [2024/10] We have just created a developer slack (slack.vllm.ai) focusing on coordinating contributions and discussing features. Please feel free to join us there!
- [2024/10] Ray Summit 2024 held a special track for vLLM! Please find the opening talk slides from the vLLM team here. Learn more from the talks from other vLLM contributors and users!
- [2024/09] We hosted the sixth vLLM meetup with NVIDIA! Please find the meetup slides here.
- [2024/07] We hosted the fifth vLLM meetup with AWS! Please find the meetup slides here.
- [2024/07] In partnership with Meta, vLLM officially supports Llama 3.1 with FP8 quantization and pipeline parallelism! Please check out our blog post here.
- [2024/06] We hosted the fourth vLLM meetup with Cloudflare and BentoML! Please find the meetup slides here.
- [2024/04] We hosted the third vLLM meetup with Roblox! Please find the meetup slides here.
- [2024/01] We hosted the second vLLM meetup with IBM! Please find the meetup slides here.
- [2023/10] We hosted the first vLLM meetup with a16z! Please find the meetup slides here.
- [2023/08] We would like to express our sincere gratitude to Andreessen Horowitz (a16z) for providing a generous grant to support the open-source development and research of vLLM.
- [2023/06] We officially released vLLM! FastChat-vLLM integration has powered LMSYS Vicuna and Chatbot Arena since mid-April. Check out our blog post.

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Audience Q&A

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Outline

Overview

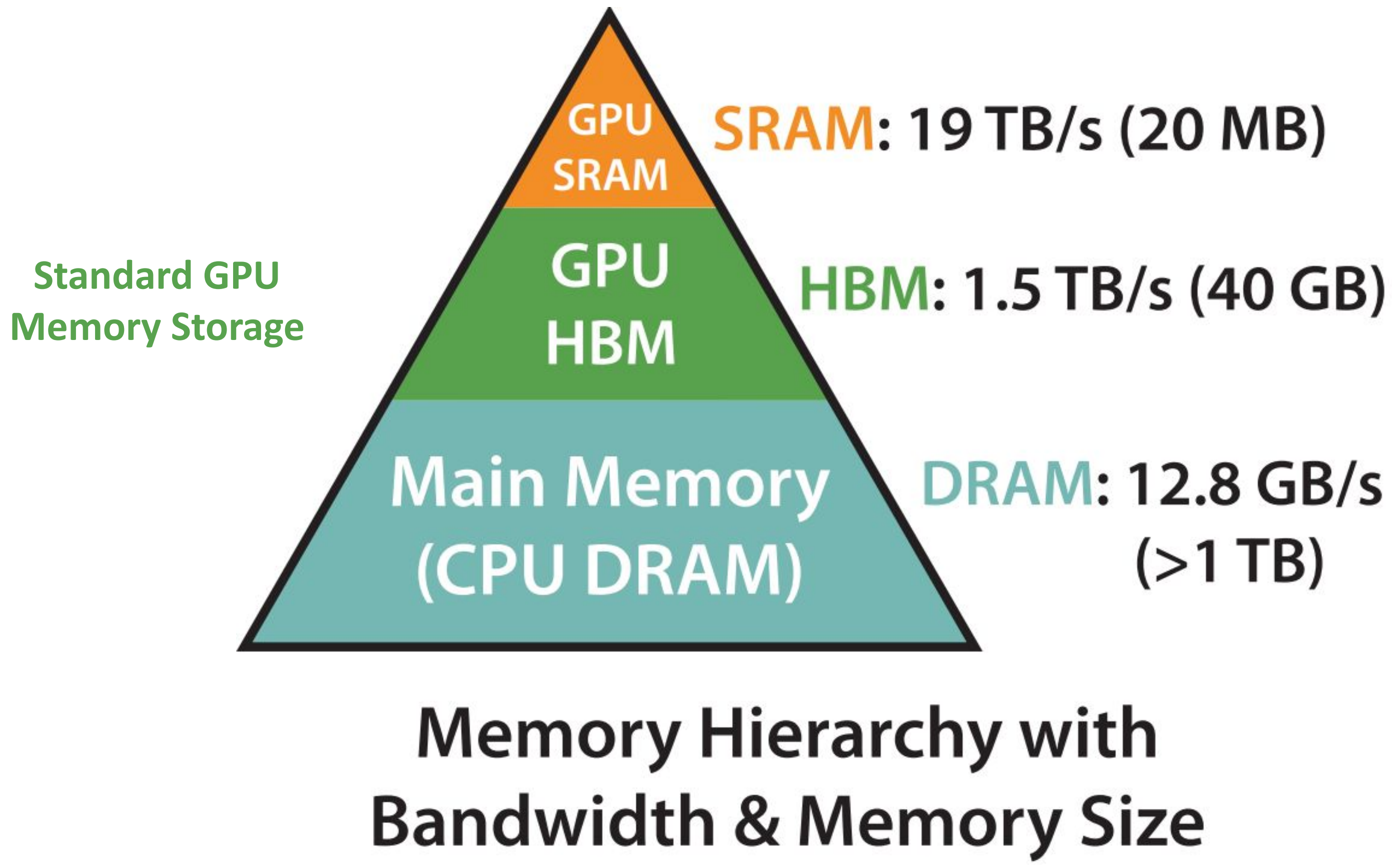
Model level efficiency: Speculative Decoding

Memory management efficiency: Paged Attention

System level optimization: Flash Attention

Full System Optimization

Many other resources available in the computing system



[10] Dao, et al. 2022. Fast and Memory-Efficient Exact Attention with IO-Awareness

Full System Optimization

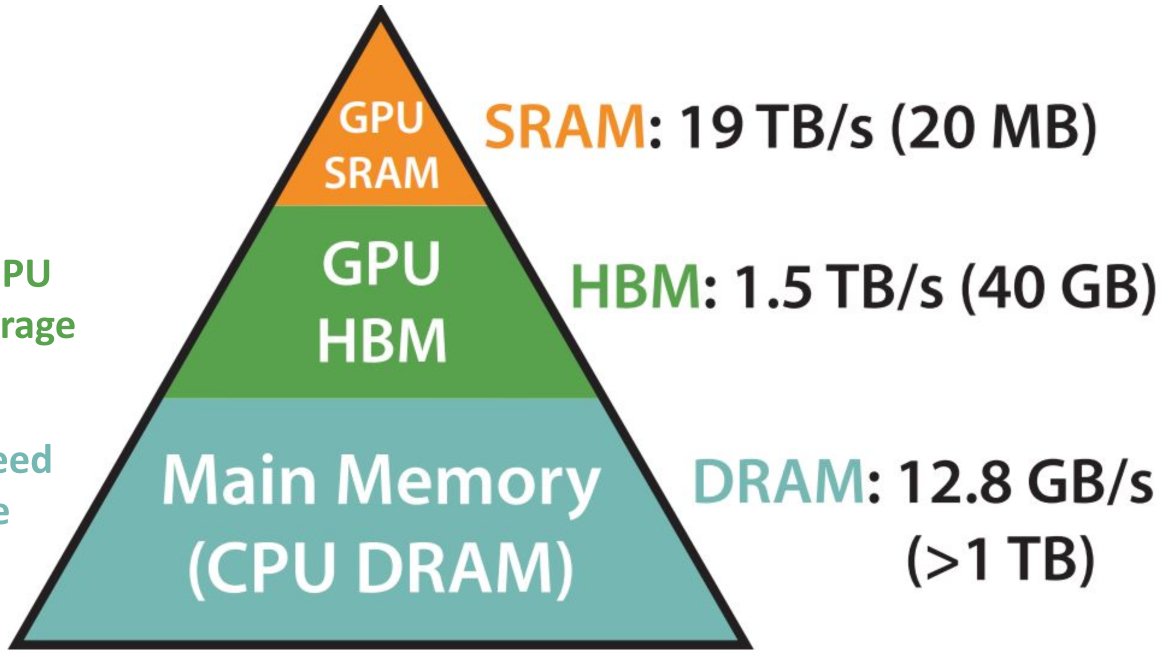
Many other resources available in the computing system

E.g., Gradient Checkpointing

Standard GPU Memory Storage

↓

Trading Speed for Space



Memory Hierarchy with Bandwidth & Memory Size

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Next: Flash Attention

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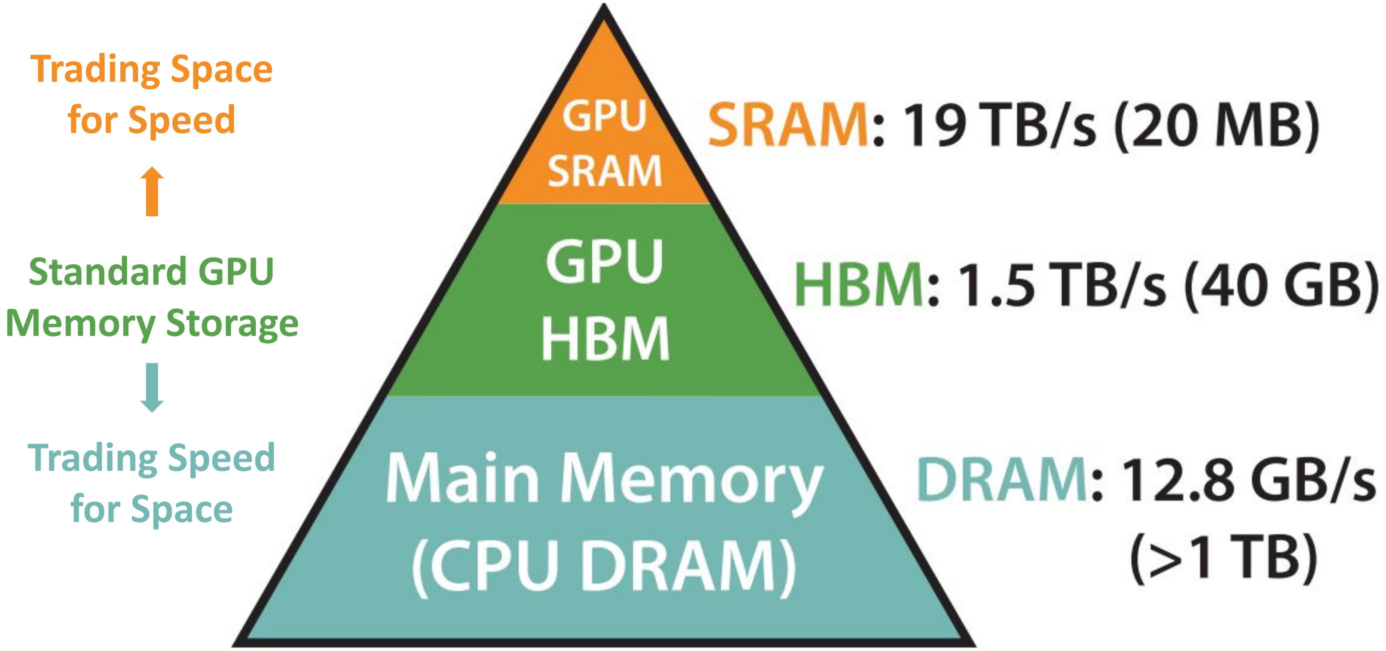

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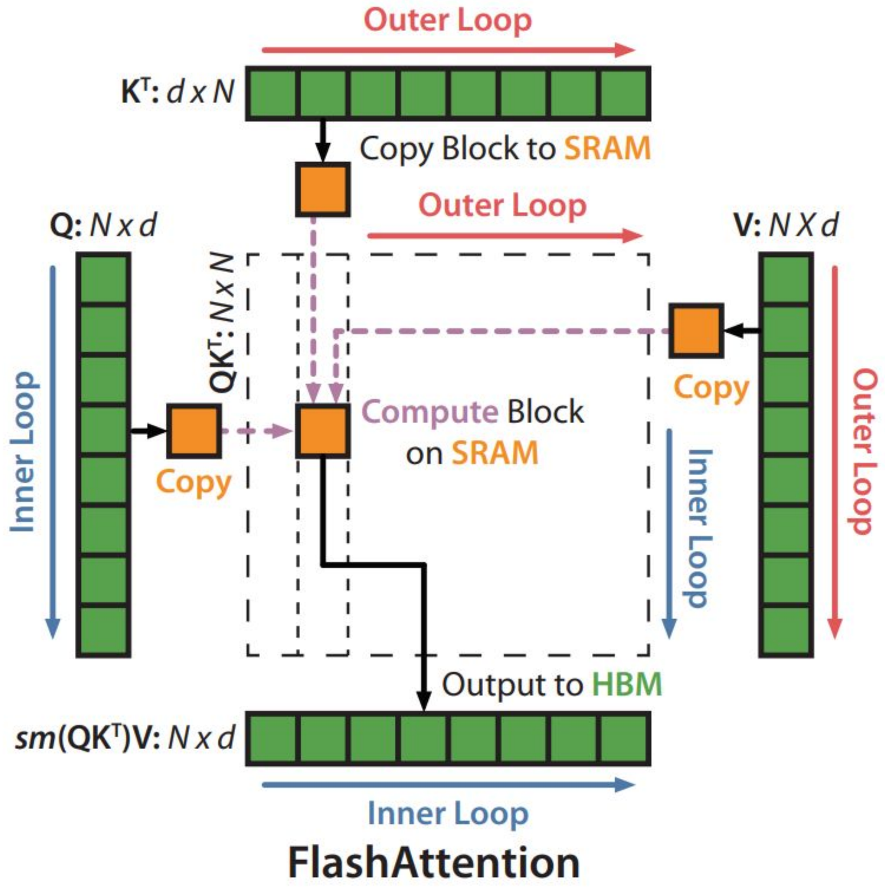
Flash Attention: Managing SRAM IO Efficiently

Compute Attention as small blocks in fast SRAM

Load K blocks in SRAM and work with all Q



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Compute Attention as small blocks in fast SRAM

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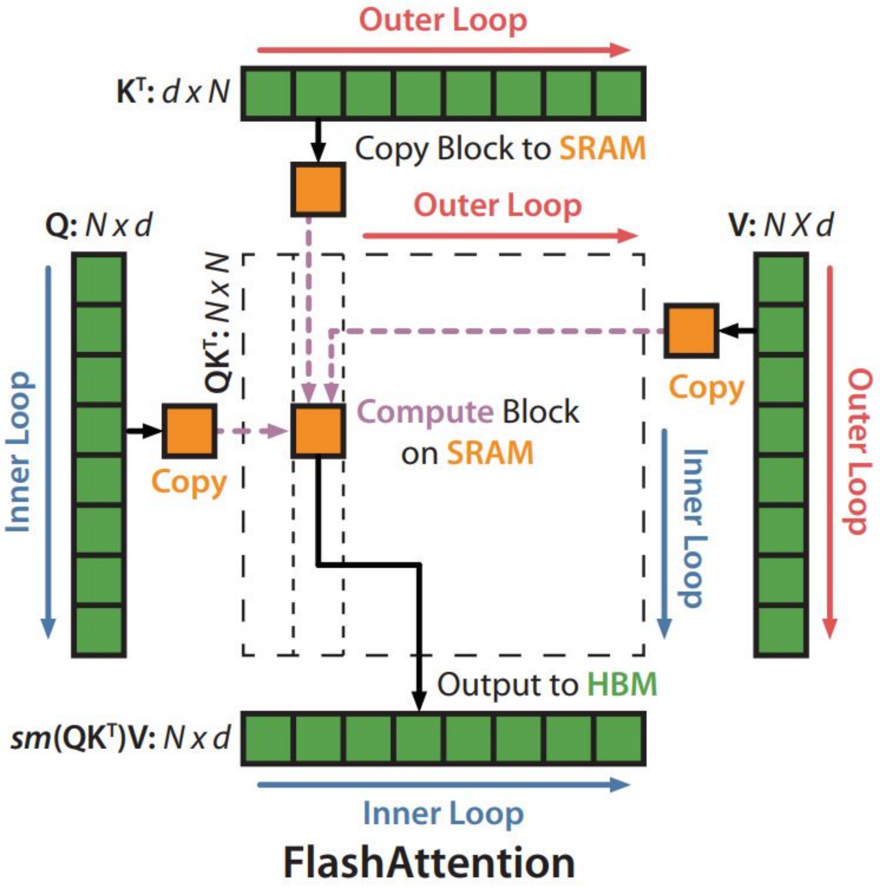
Moving Q block by block to SRAM

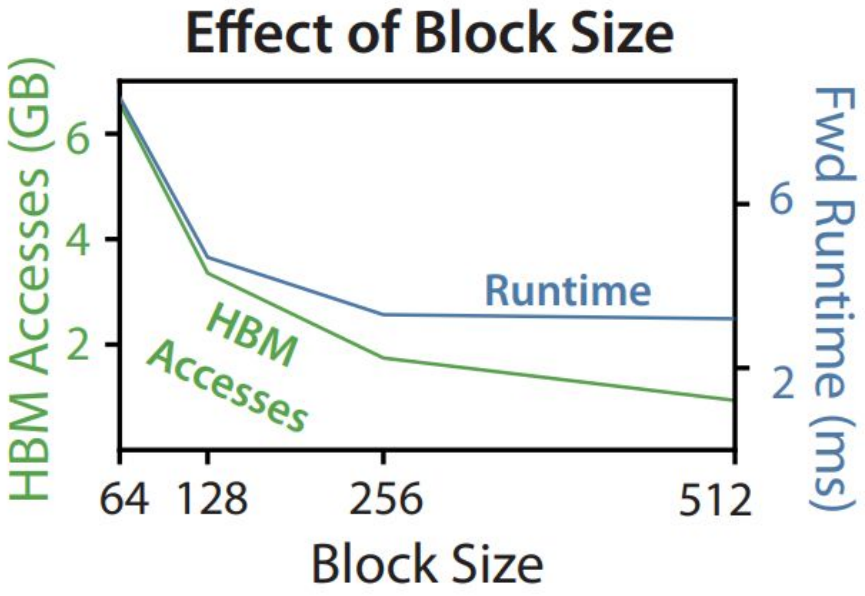
Load V blocks in SRAM for all Q



Flash Attention: Managing SRAM IO Efficiently

Fewer HBM (GPU Memory) IO, faster performance

Attention	Standard	FLASHATTENTION
GFLOPs	66.6	75.2
HBM R/W (GB)	40.3	4.4
Runtime (ms)	41.7	7.3



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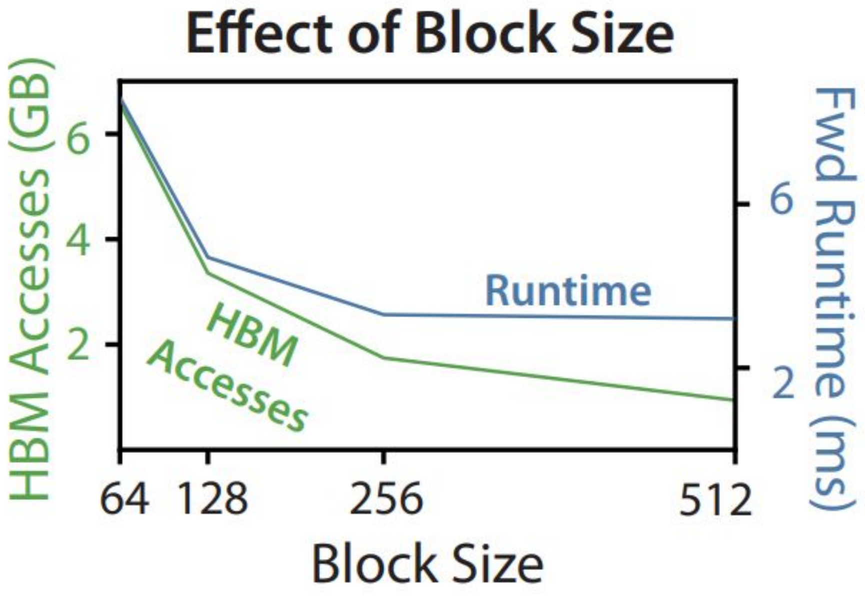

BERT Implementation	Training time (minutes)
Nvidia MLPerf 1.1 [58]	20.0 ± 1.5
FlashAttention (ours)	**17.4** ± 1.4

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Remarks

Trading Effectiveness for Efficiency

- Some scenarios do not need too large a model

Model level efficiency: Speculative Decoding

- Utilization the strong agreement of small LM and large LM

Memory management efficiency: Paged Attention

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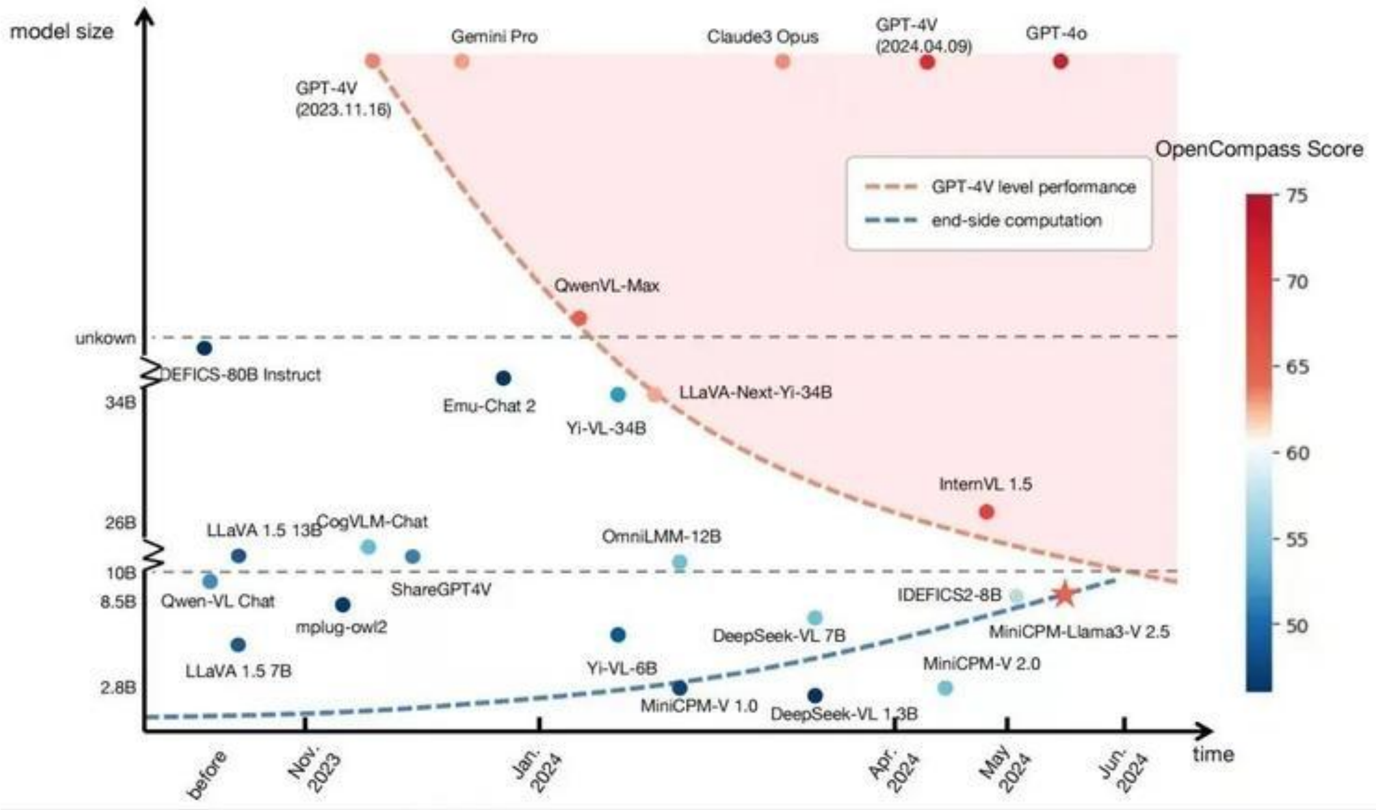
Are these sustainable?

Where is the next 100x speed up?

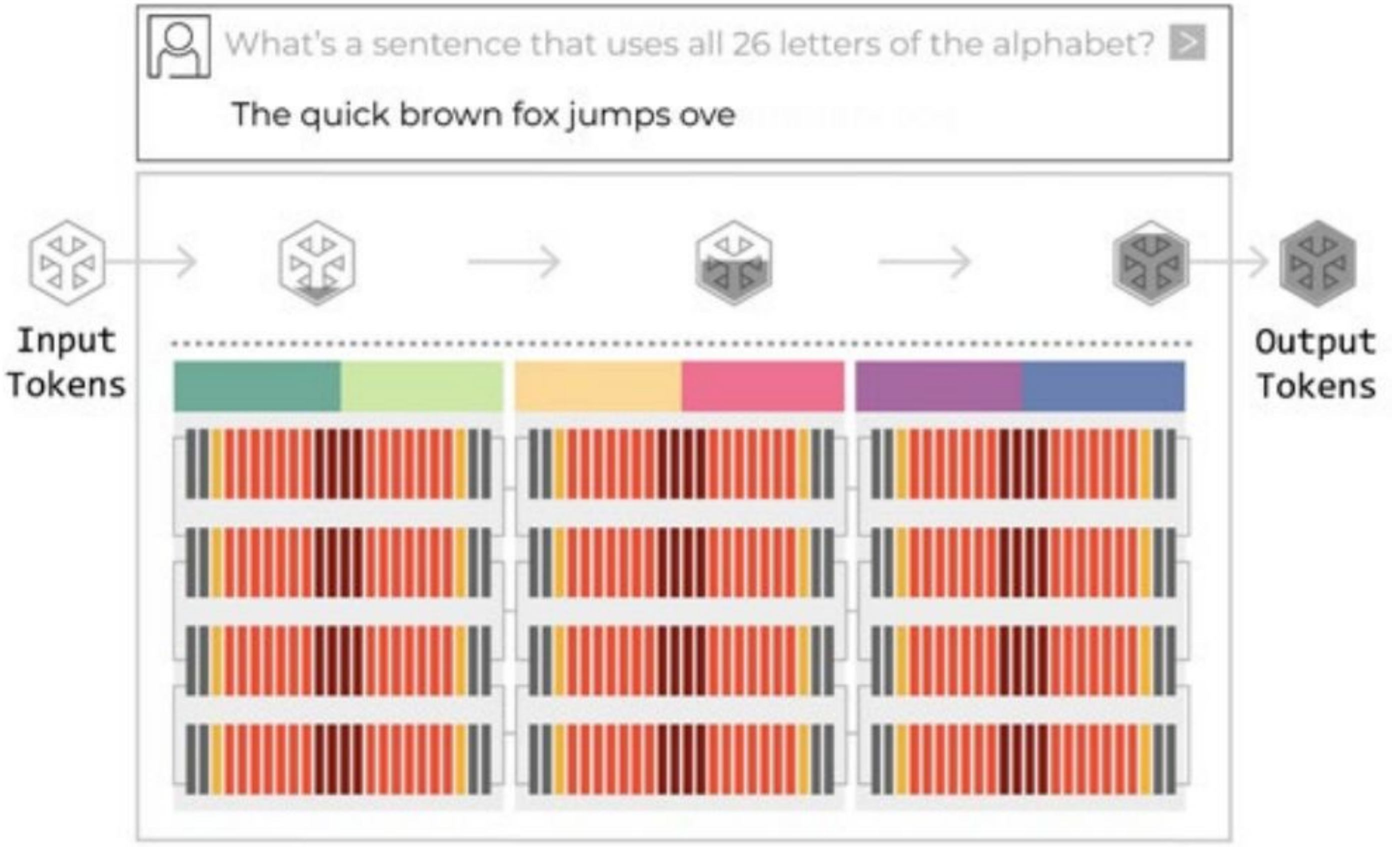
Moore's law of model knowledge density (capability/inference cost)



Model performance at different scale and time [11]

Where is the next 100x speed up?

Hardware super specialized for Transformer LLMs



[12] Grop https://groq.com/docs/

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