Trading More Storage for Less Computation – A KVCache-centric Architecture for Serving LLM Chatbot

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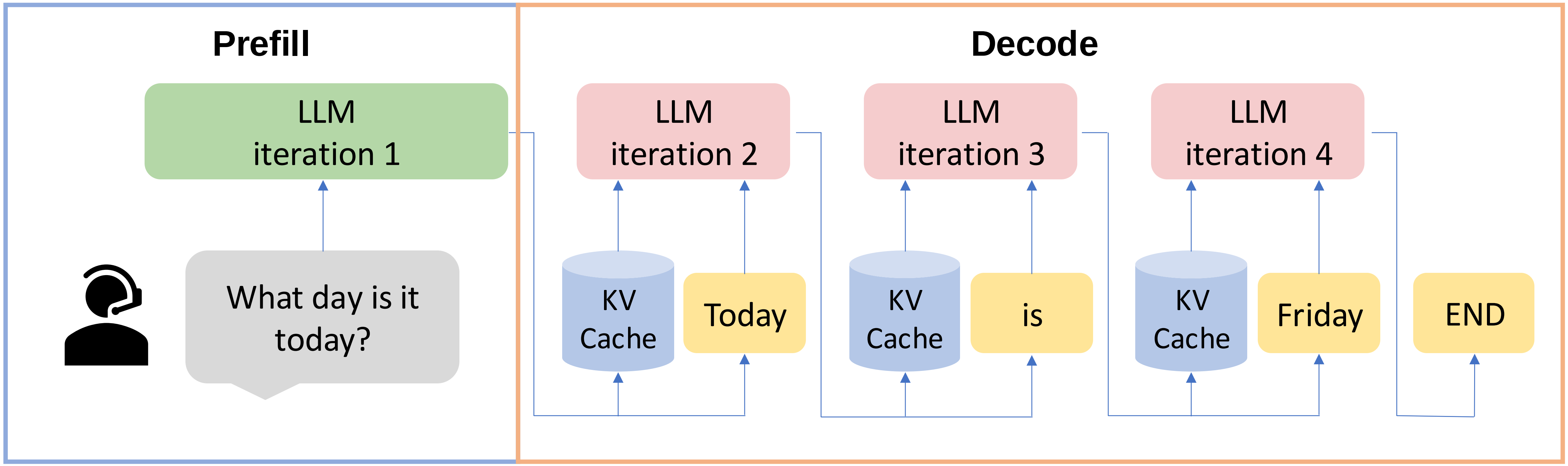
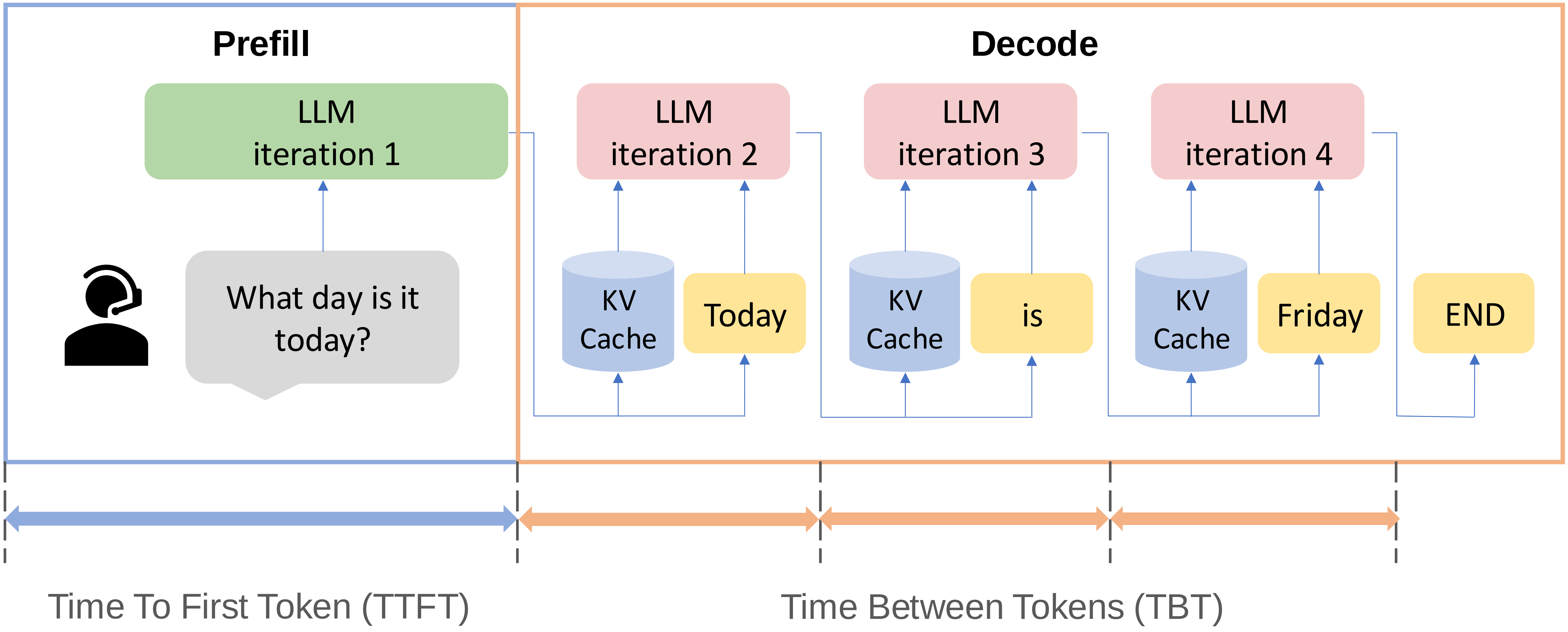
LLM Inference



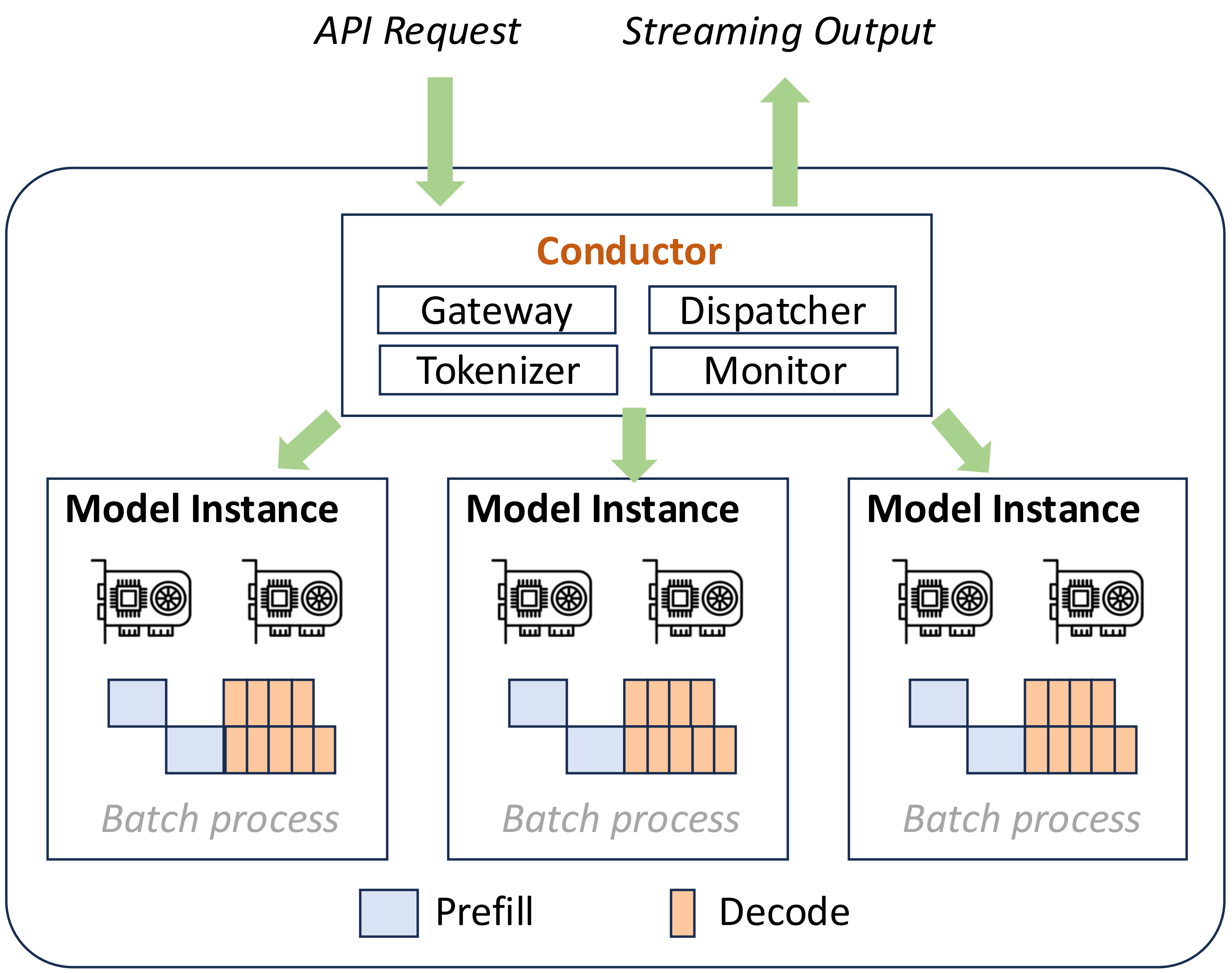
LLM Inference



LLM Inference: Latency

	TTFT	TBT
Program (~1k tokens)	Low (~100ms)	Very low (~50ms)
Web search (~8k tokens)	High (~1s)	Match read speed (~100ms)
Multi-document summary (~128k tokens)	Very high (> 5s)	Match read speed (~100ms)

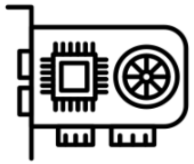
Online LLM Serving System



Online LLM Serving System

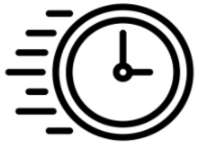
More Data + Larger Model + Longer Context = ☺ ***Higher Intelligence***

BUT ☹



Lack of GPU Supply

Higer Inference Cost



Longer Response Time

Online LLM Serving System

*More Data + Larger Model + Longer Context = ☺ **Higher Intelligence***

Reduce the cost for large-scale long-context LLM inference!

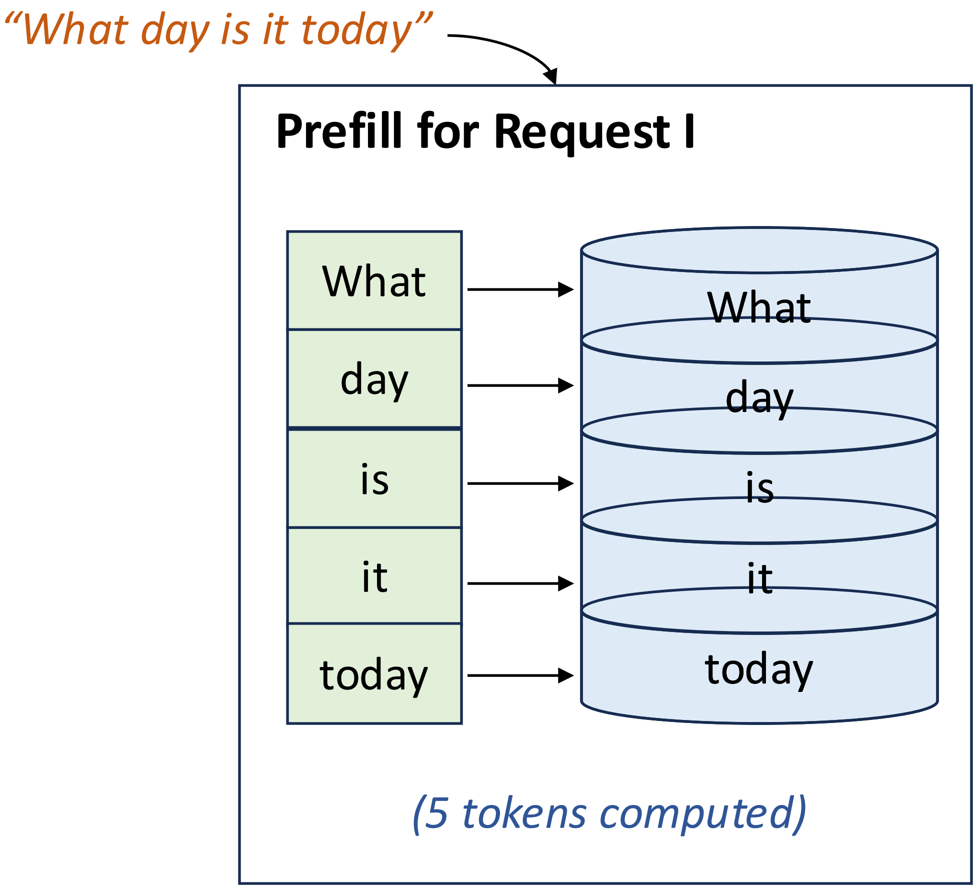
Lack of GPU Supply

Higer Inference Cost

Longer Response Time

LLM Inference: Prefix Caching

- KVCache can be shared across requests with the same prefix, reducing computation during prefill



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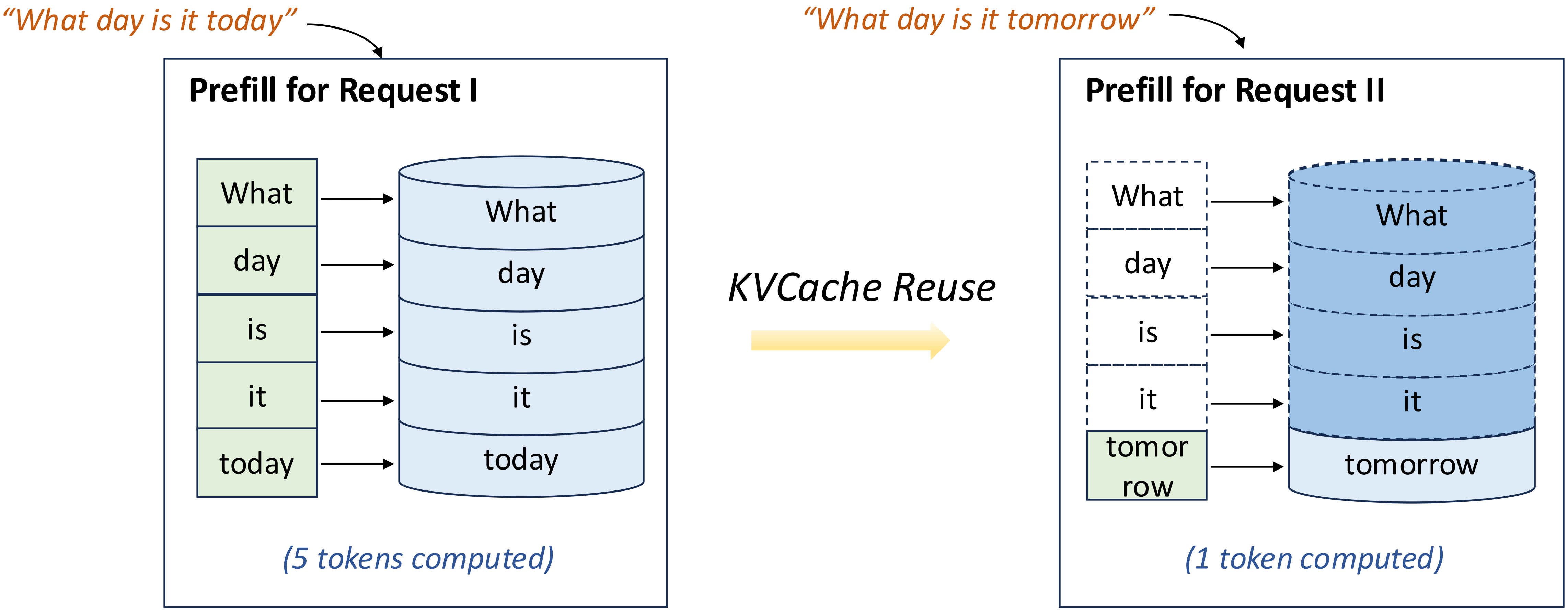
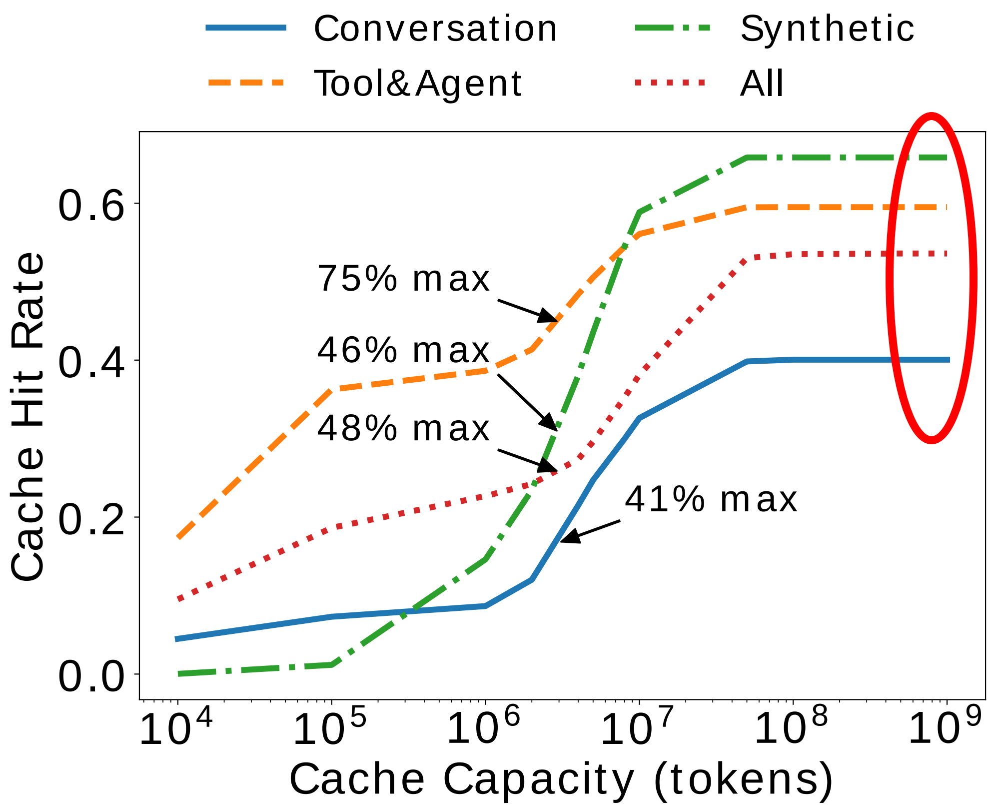


Trace Analysis: Is Prefix Caching a Simple Solution?



Traces in our paper
(open-sourced in https://github.com/kvcache-ai/Mooncake)

Conversation: collected from real-world online conversation requests

Tool&Agent: collected from real-world online requests that include tool use

Synthetic: synthesized from publicly available long context datasets

- Around **50%** of the tokens' KVCache in the real-world workloads can be reused

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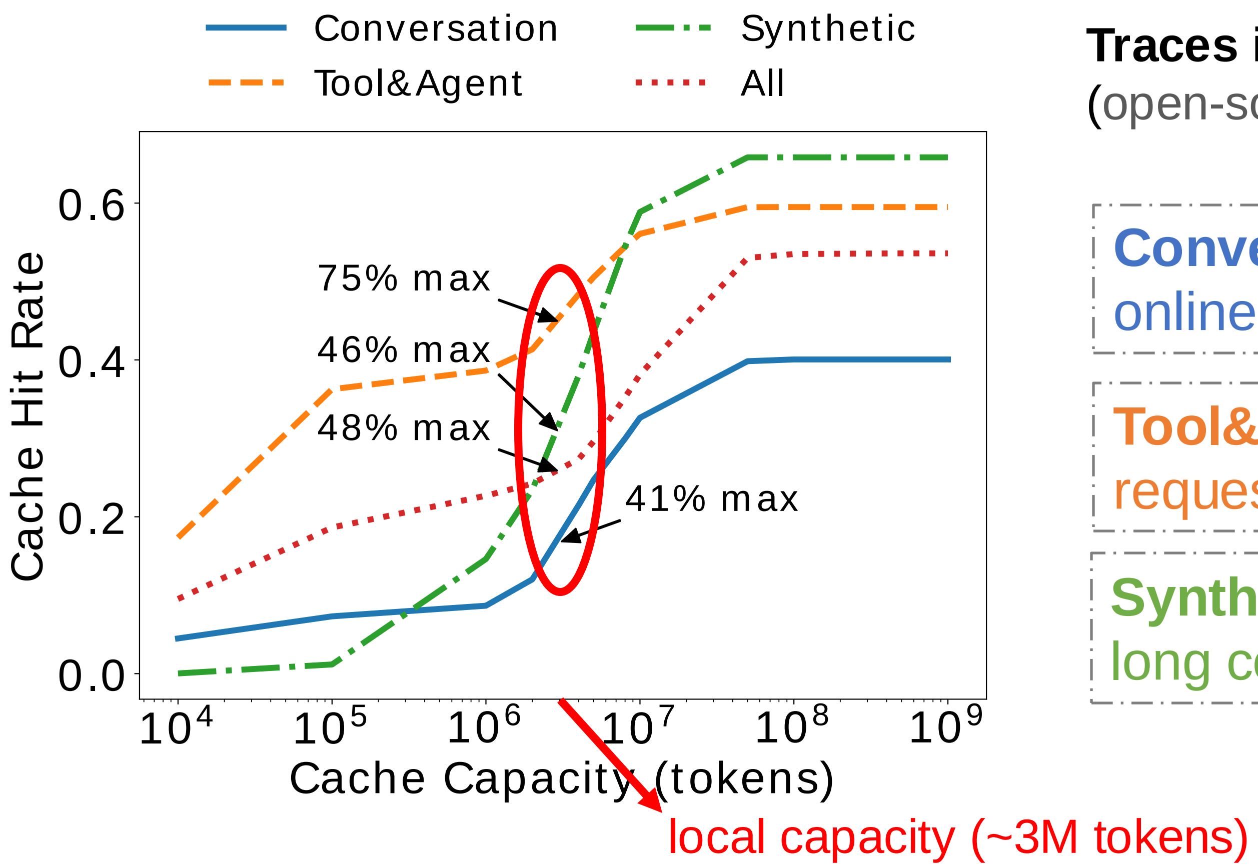

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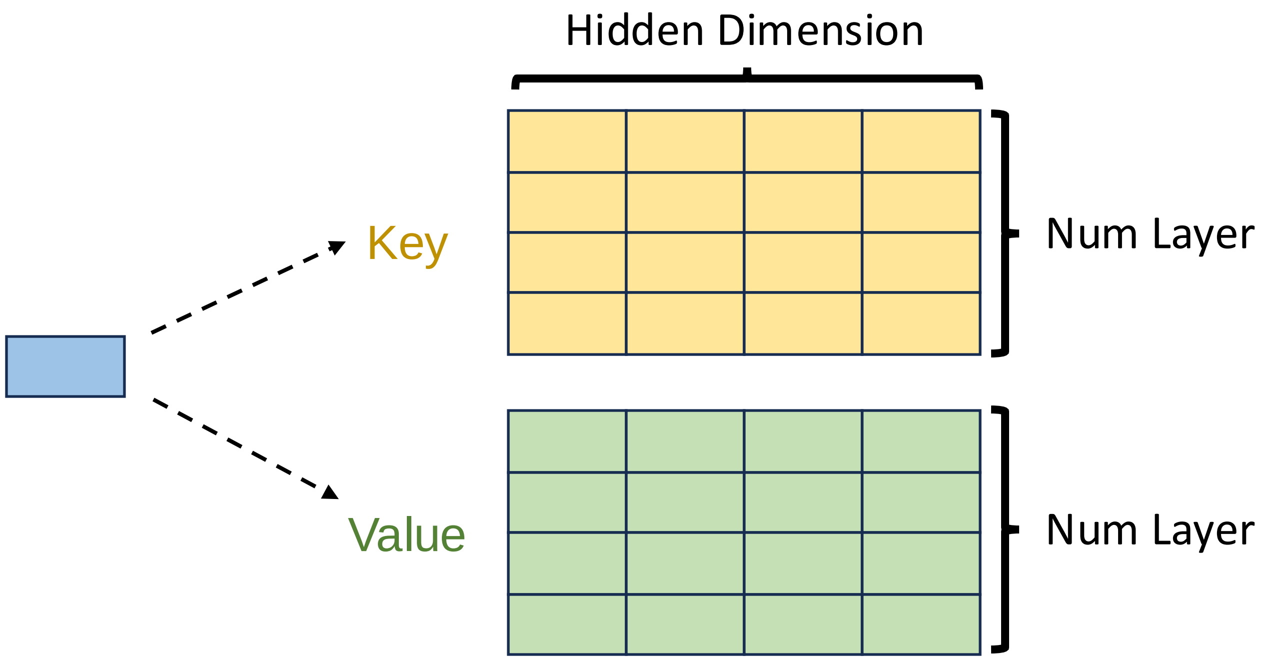
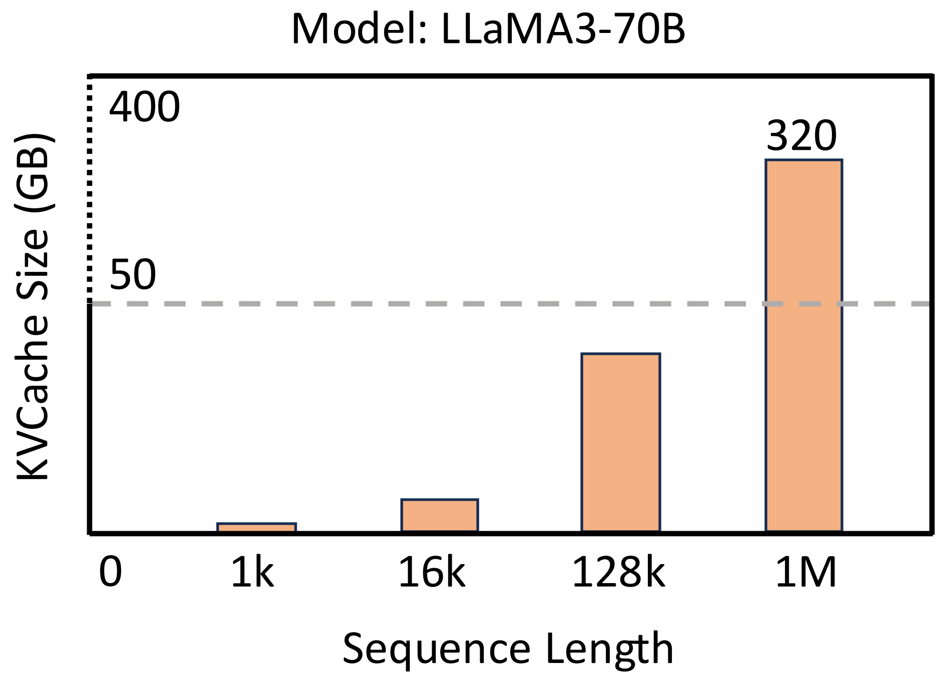
- Around **50%** of the tokens' KVCache in the real-world workloads can be reused
- **However**, the cache hit rate will significantly drop if only using the local cache

KVCache: Huge Challenge to Storage System

- One token's KVCache size is quite large
- KVCache linearly increases with the sequence length

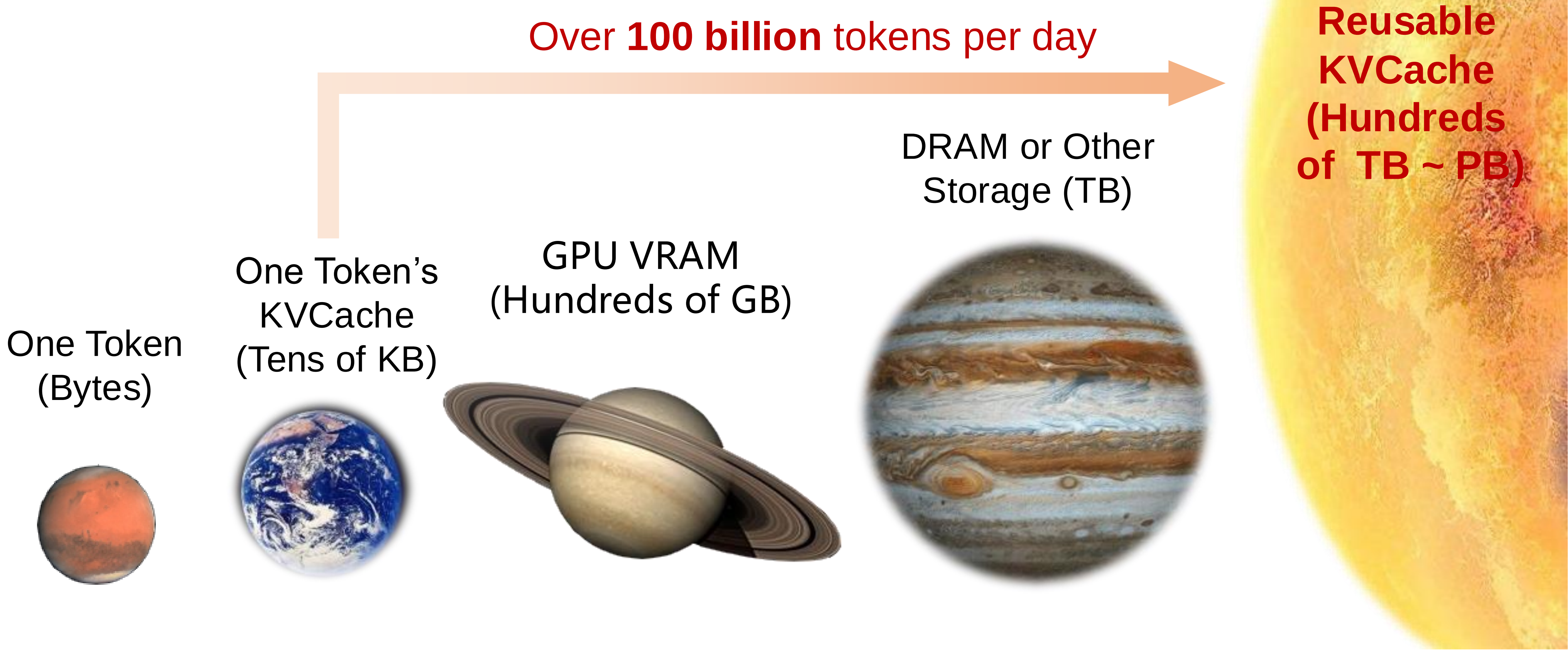
One token (Bytes) *One token’s KVCache (Tens of KB)*





KVCache: Huge Challenge to Storage System

- The volume of reusable KVCache is much larger than the available storage capacity of a single inference node



Trading More Storage for Less Computation

Requirement 1

Large-capacity KVCache storage

Requirement 2

Low-latency and high-bandwidth KVCache transfer

Requirement 3

KVCache-aware scheduling

Trading More Storage for Less Computation

Requirement 1

High-capacity KVCache storage

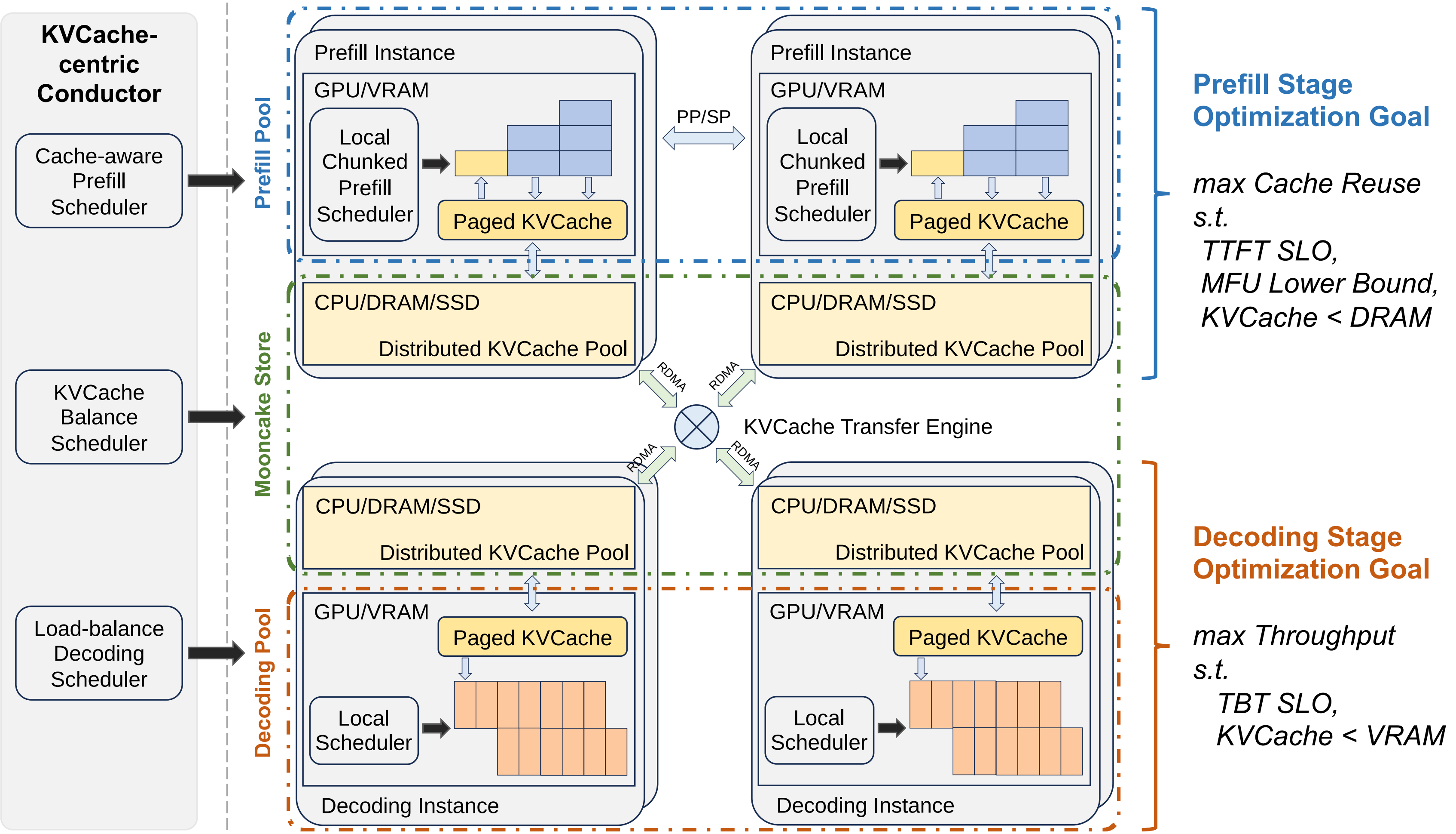
KVCache-centric Architecture is All You Need!

Requirement 3

KVCache-aware scheduling

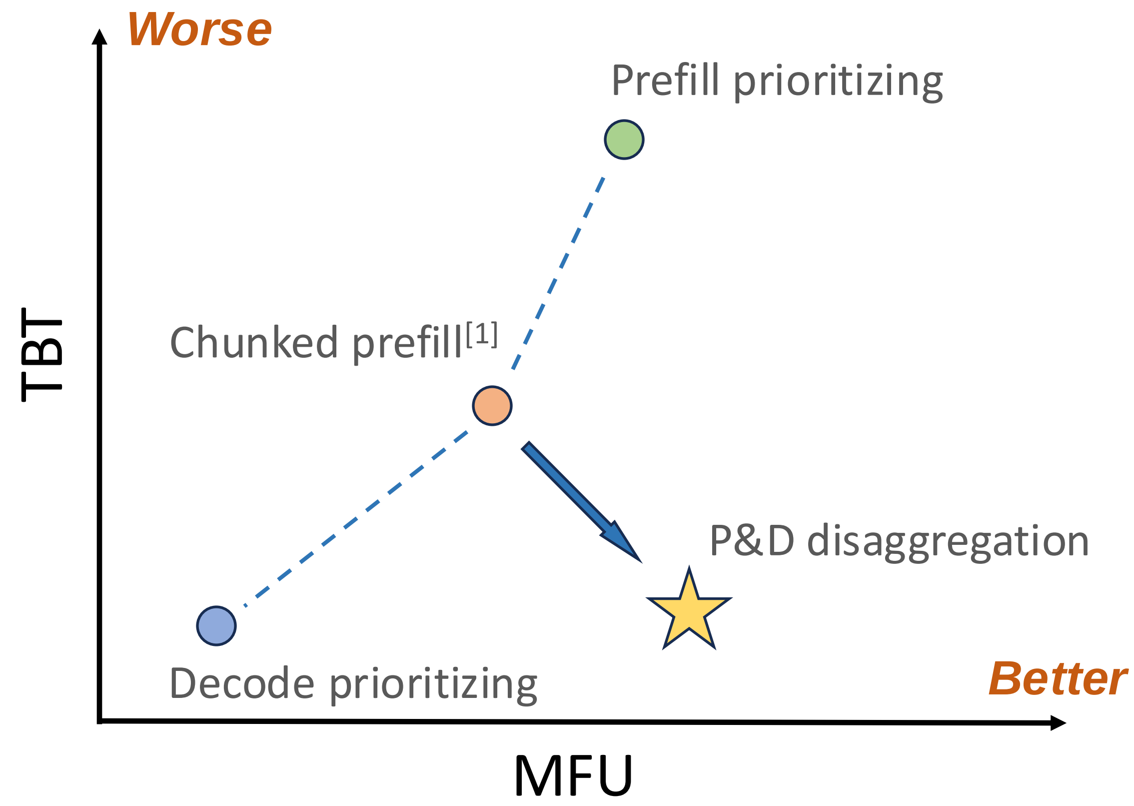
Mooncake: A KVCache-centric Disaggregated Architecture

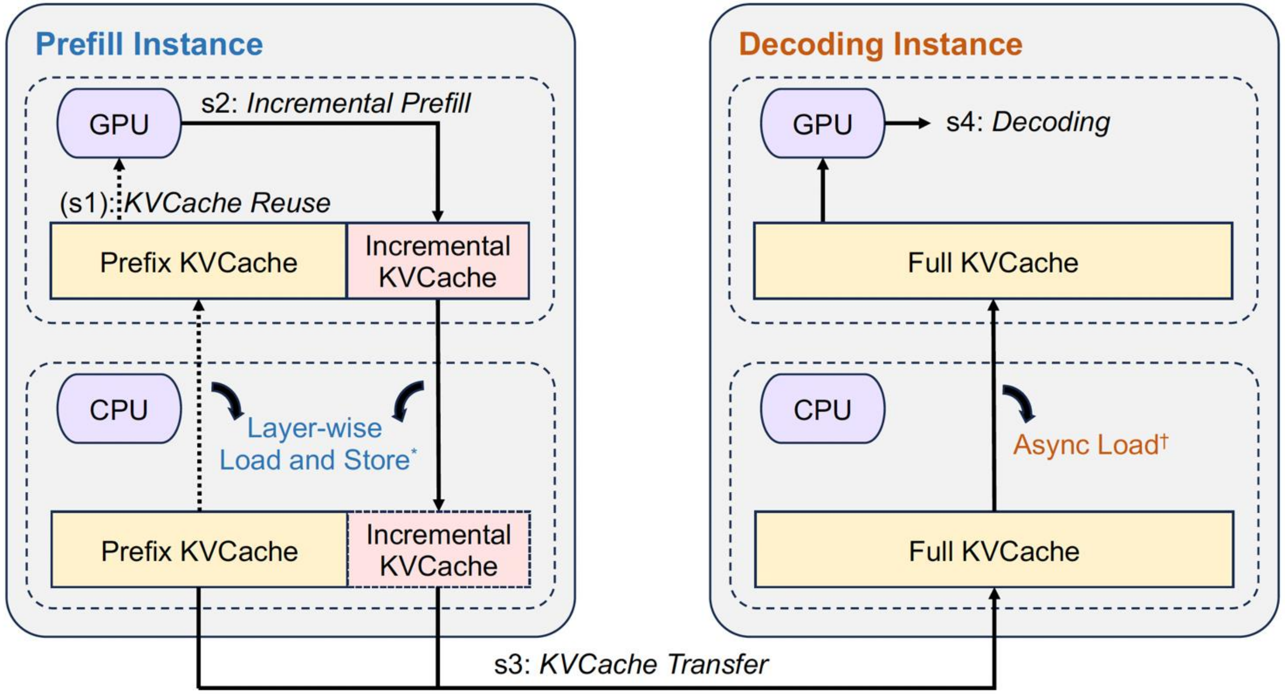
- P&D disaggregation architecture centered around the distributed KVCache pool – Mooncake Store



P&D Disaggregated Inference

- Avoid interference between prefill and decoding in a mixed batch
- Decouple resources and parallelism to improve MFU (Model Flops Utilization)

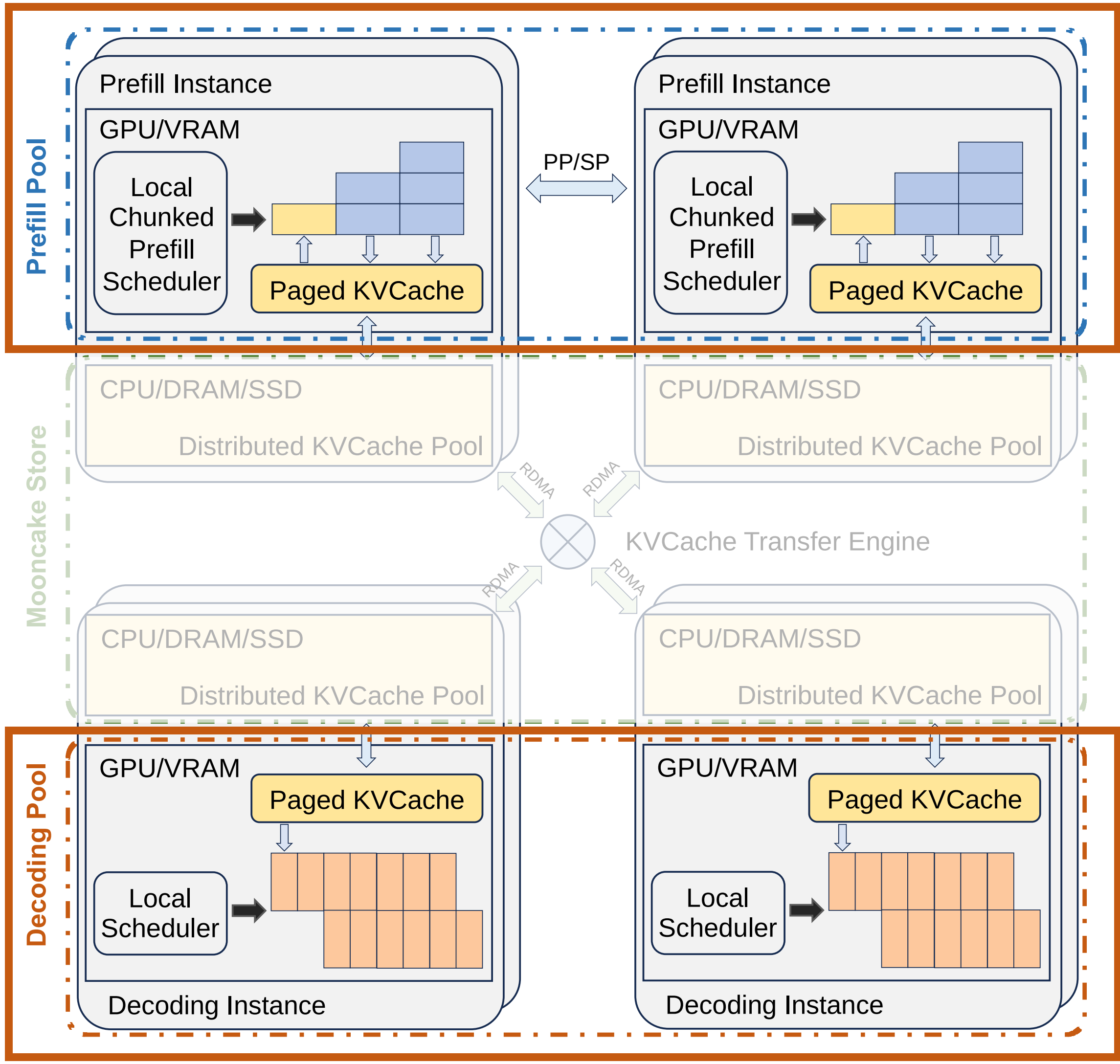




[1] Agrawal et al. Taming Throughput-Latency Tradeoff in LLM Inference with Sarathi-Serve (OSDI'24)

Mooncake Store – Distributed Multi-layer KVCache Pool

- Large size and bandwidth (**Key of KVCache Storage**)
  - Distributed KVCache pool across all inference nodes
  - Utilize high performance connection like (GPUDirect) RDMA/Storage
  - Optimized for multi-NIC scenarios
- Design features
  - High scalability and fault tolerance
  - Independent to specific inference engine
  - Flexible API (adopted by vLLM [1])



[1] https://github.com/vllm-project/vllm

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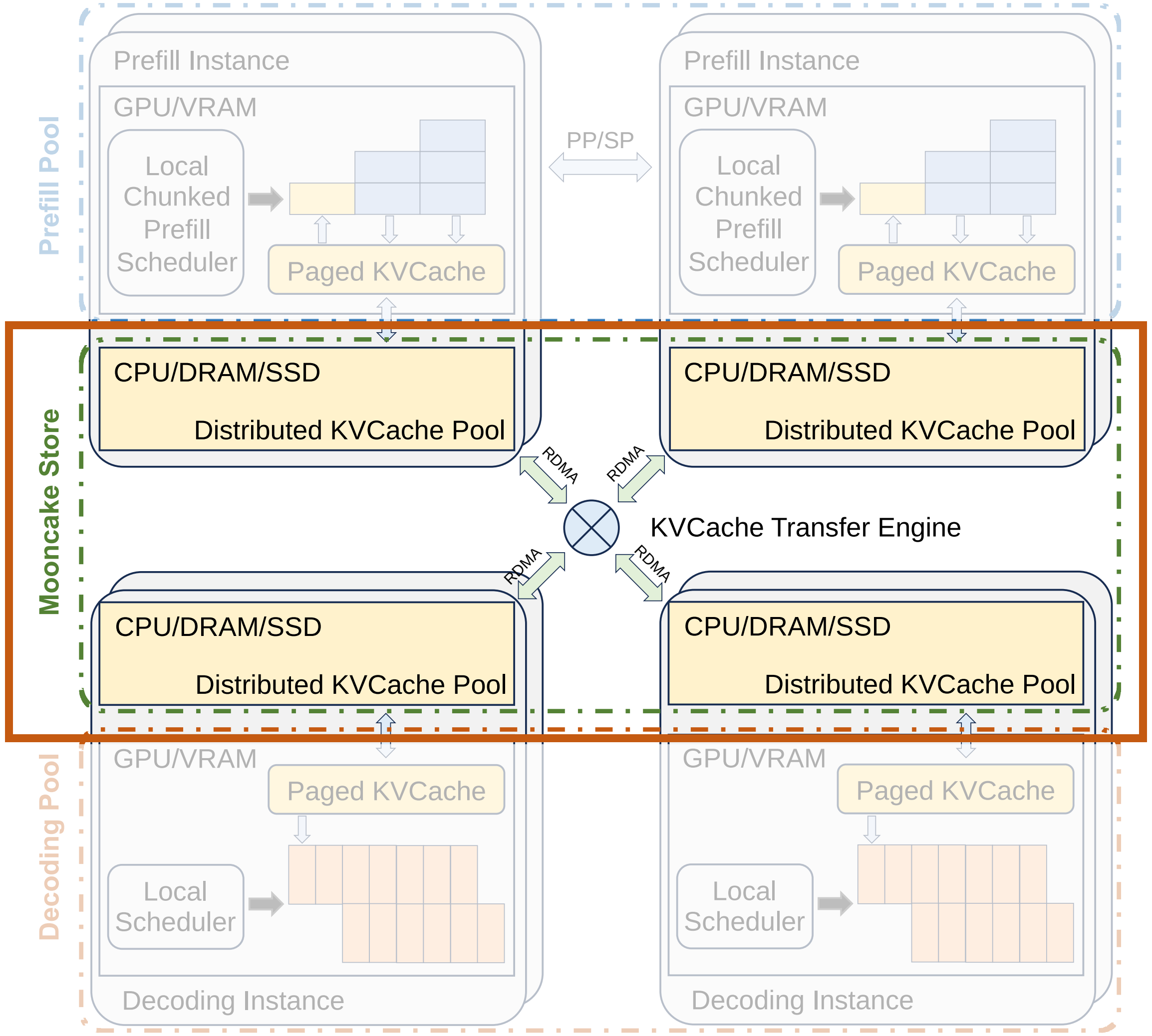

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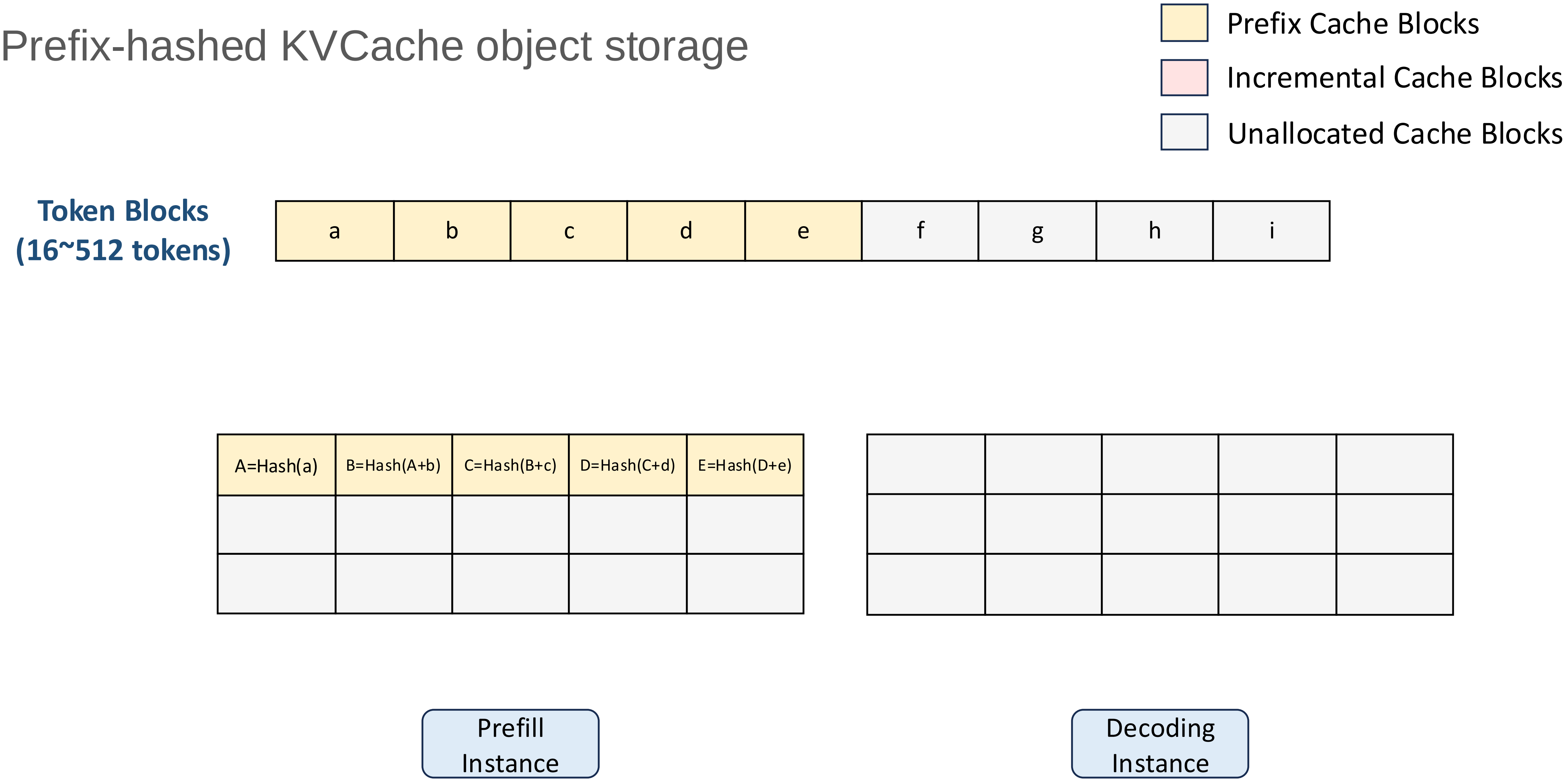
Mooncake Store: KVCache Management

- Prefix-hashed KVCache object storage



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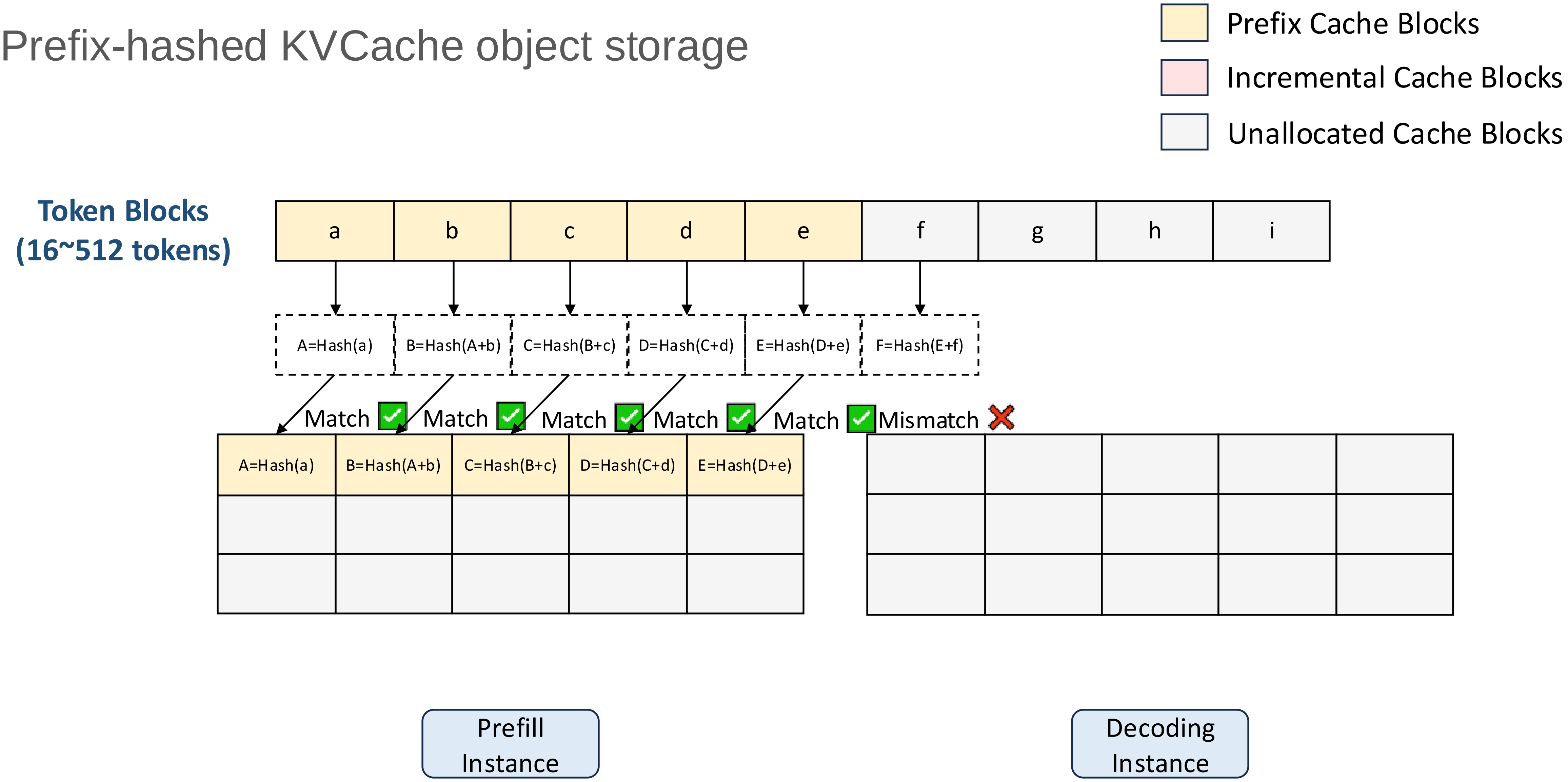

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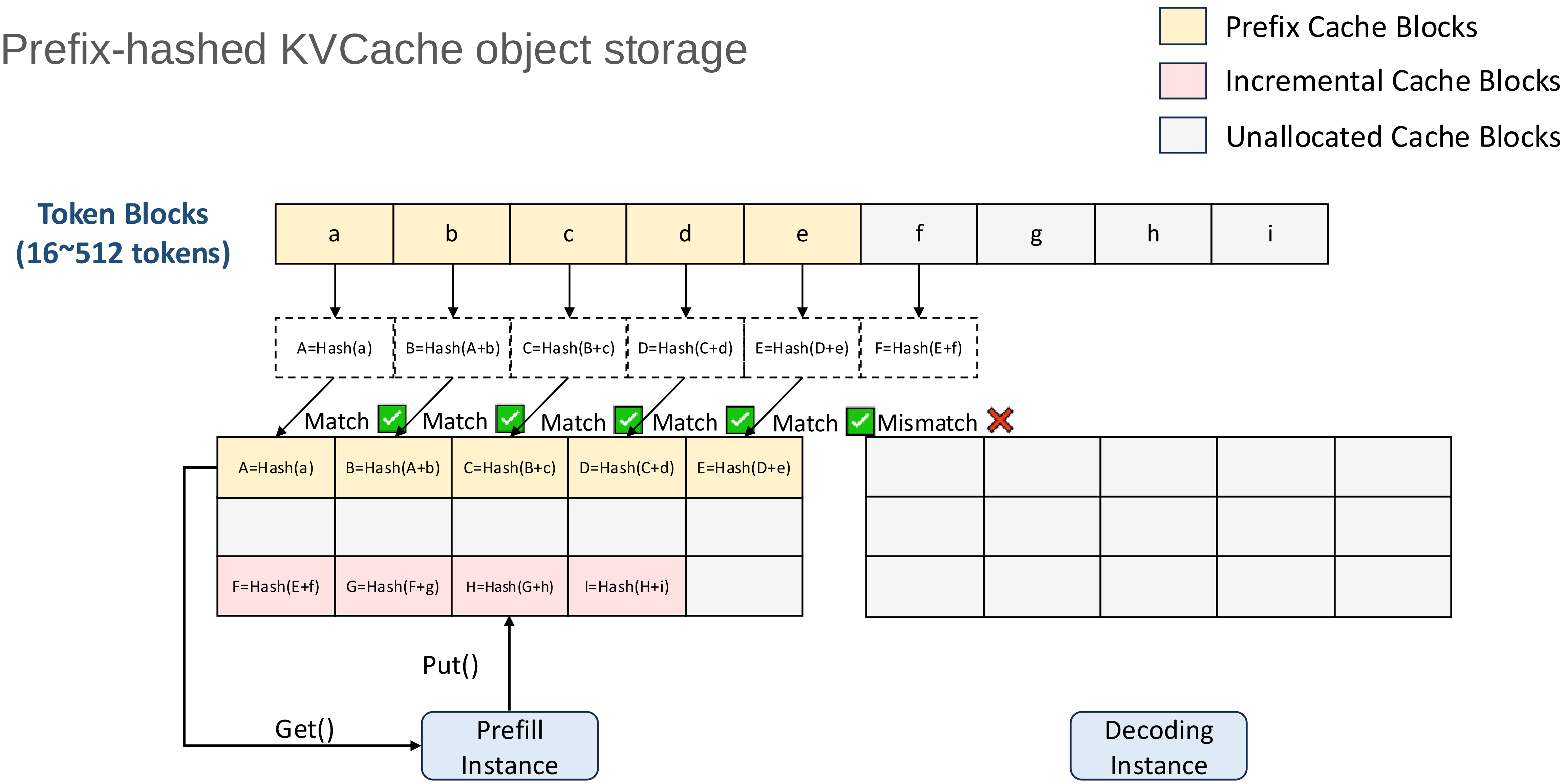

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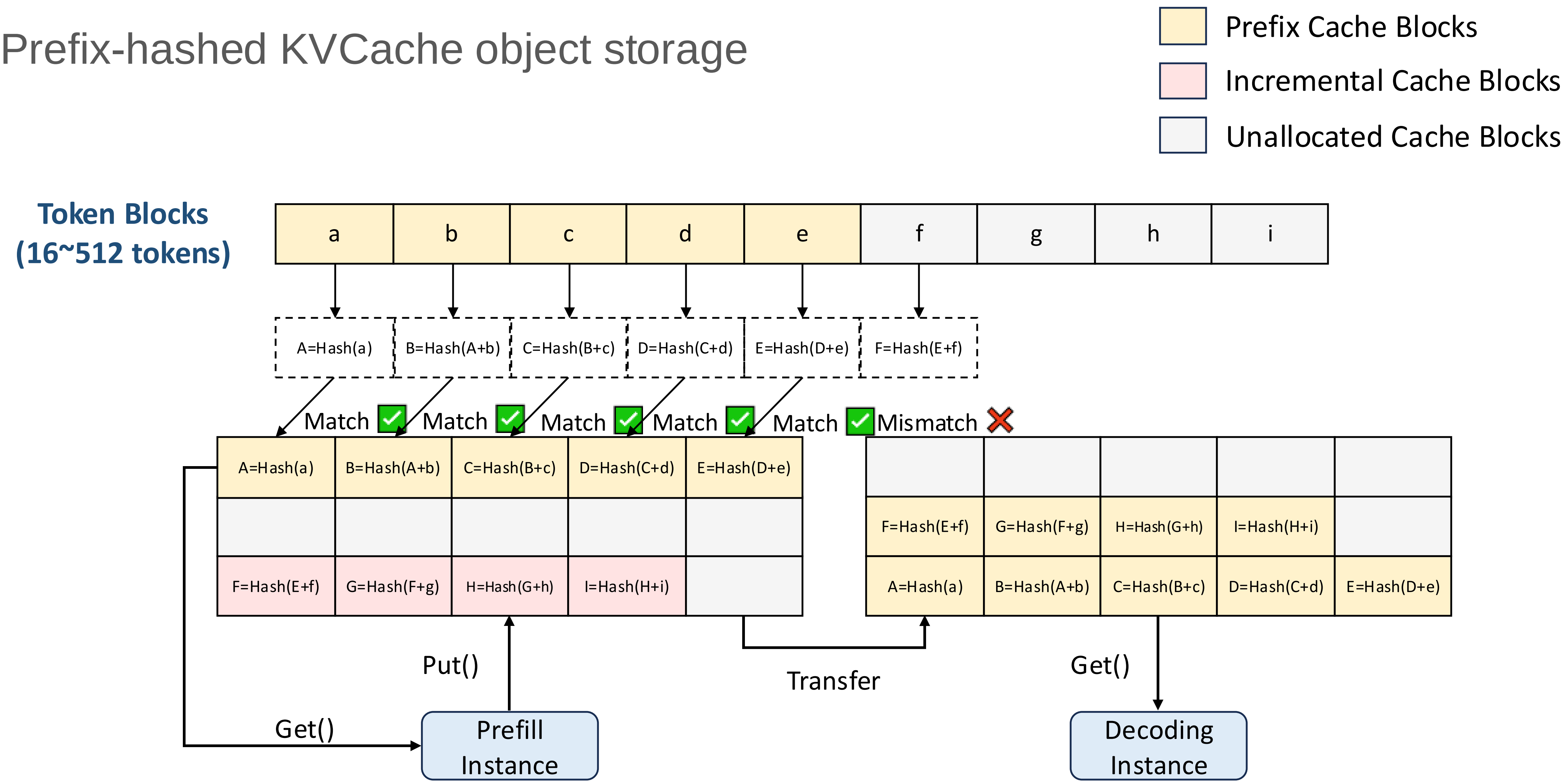
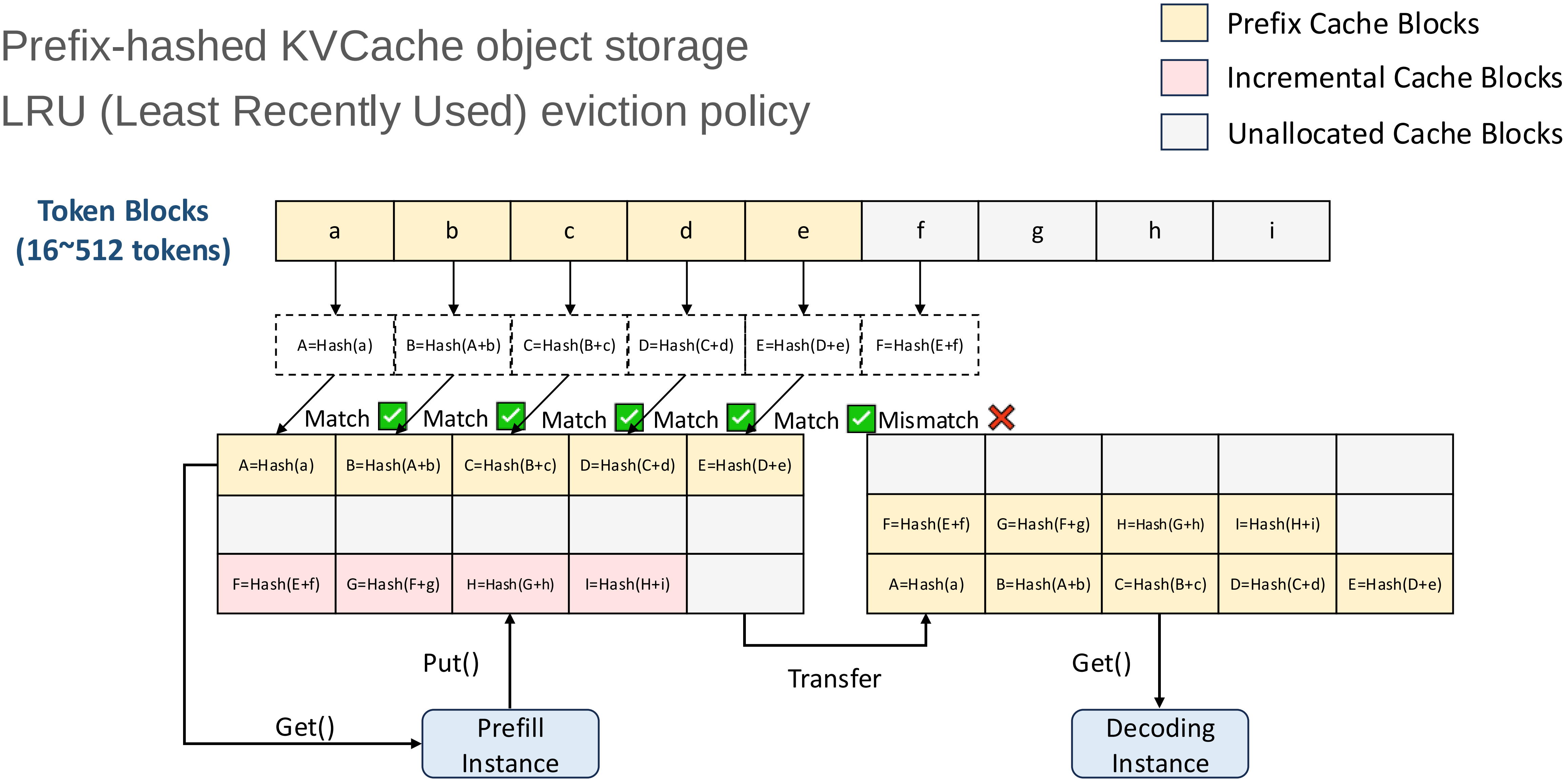


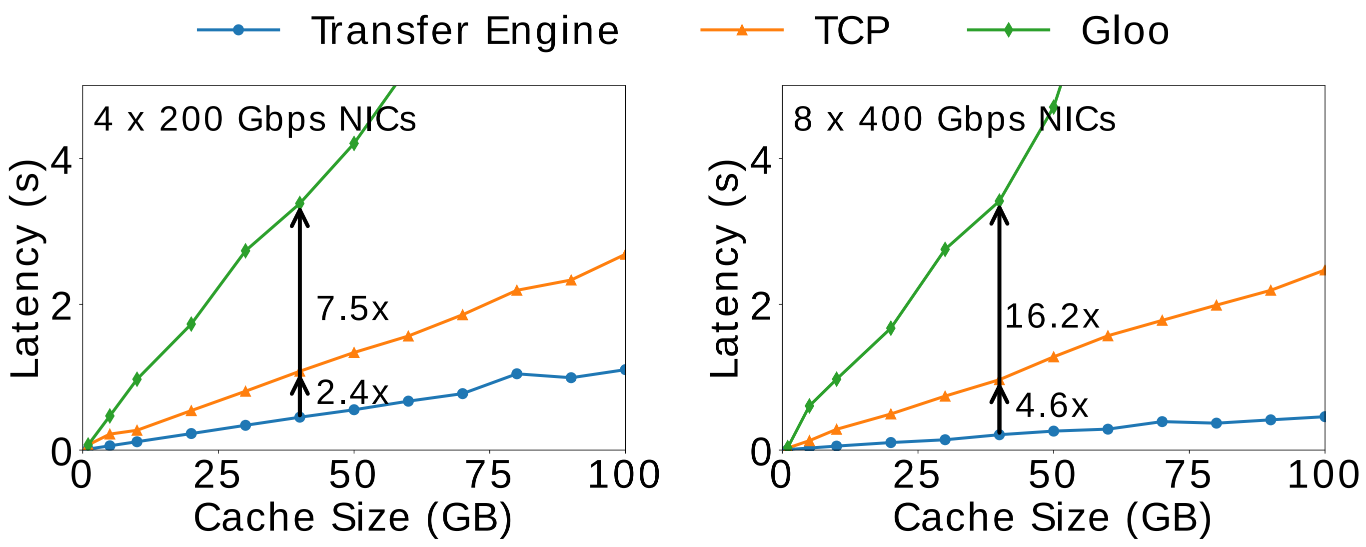
Mooncake Store: KVCache Management

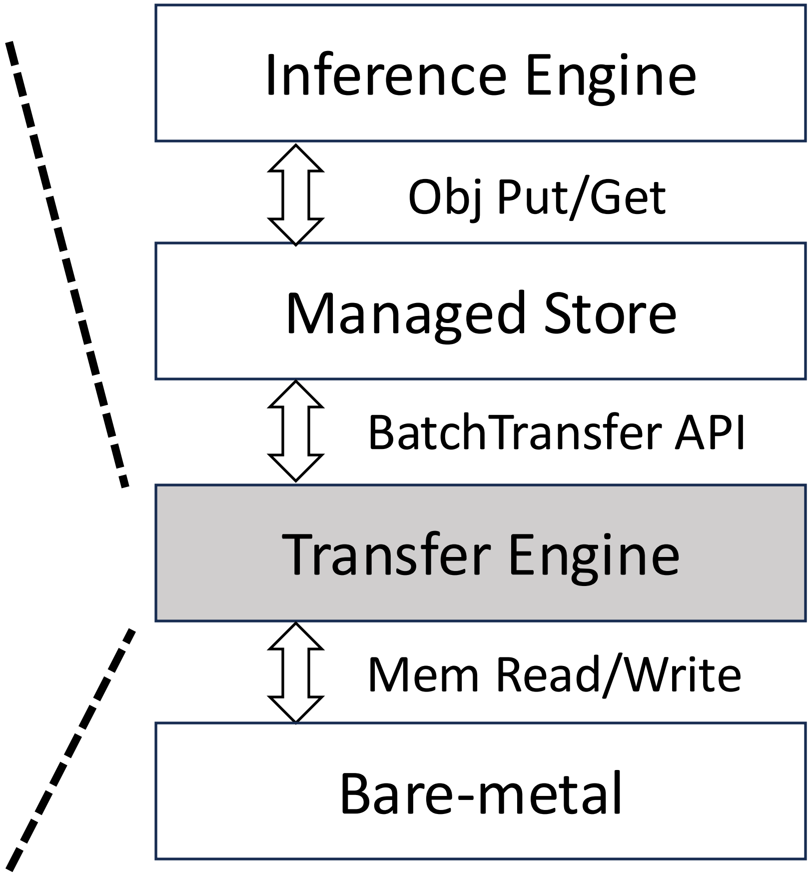
- Prefix-hashed KVCache object storage
- LRU (Least Recently Used) eviction policy



Mooncake Store: Transfer Engine

- **Key technologies**： Zero-copy, multi-NIC up to 8*400Gbps aggregated bandwidth, topology aware, failure recovery, load balance, multi-transport support, etc





- Better leverage multiple high-performance NICs
- More flexible without building process groups

Evaluation

1) Does **Mooncake** outperform existing LLM inference systems in real-world scenarios?

2) Compared to conventional prefix caching methods, does the design of **Mooncake Store** significantly improve Mooncake performance?

Online statistics of Kimi

- Mooncake enables Kimi to handle **115%** and **107%** more requests on the A800 and H800 clusters, respectively, compared to our previous systems based on vLLM.

Evaluation

1) Does **Mooncake** outperform existing LLM inference systems in real-world scenarios?

2) Compared to conventional prefix caching methods, does the design of **Mooncake Store** significantly improve Mooncake's performance?

Evaluation environment

- **Model**: Dummy LLaMA3-70B
- **Testbed**: 16 nodes configured with eight A800 GPUs and four 200 Gbps RDMA NICs
- **Baseline**: vLLM[1], vLLM with prefix caching and with chunked prefill
- **Workload**: Three real or synthetic traces that resemble the online distribution
- **Metric**: Effective request capacity and GPU cost

[1] Kwon et al. Efficient Memory Management for Large Language Model Serving with PagedAttention (SOSP'23)

Evaluation

- Traces in our paper (open-sourced in https://github.com/kvcache-ai/Mooncake)

	Conversation	**Tool&Agent**	**Synthetic**
Avg Input Len	12035	8596	15325
Avg Output Len	343	182	149
Cache Ratio	40%	59%	66%
Arrival Pattern	Timestamp	Timestamp	Poisson
Num Requests	12031	23608	3993

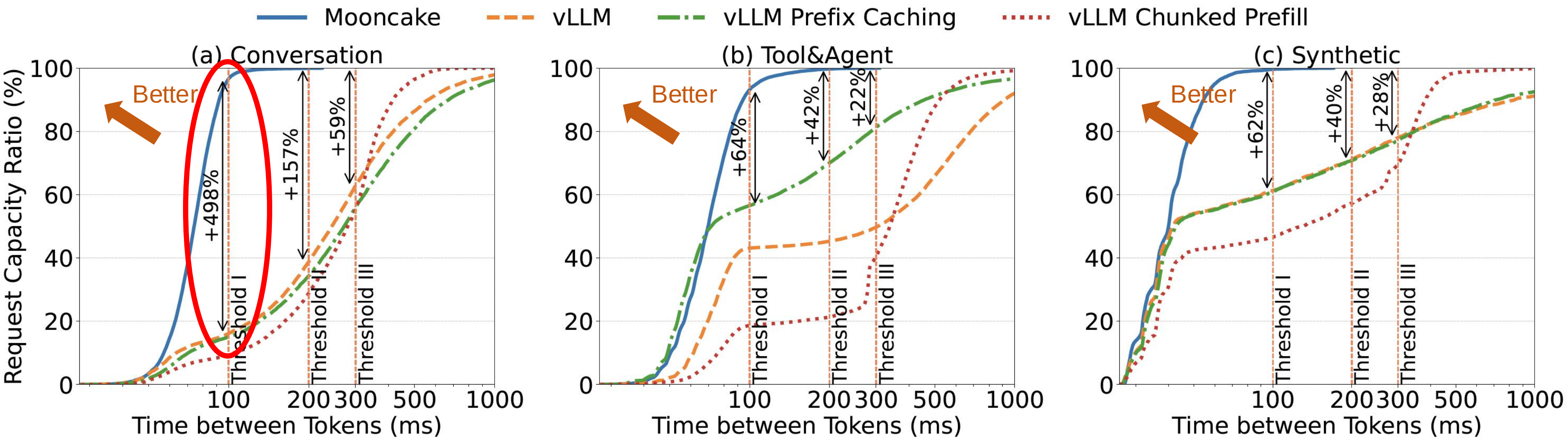
Conversation: collected from real-world online conversation requests

Tool&Agent: collected from real-world online requests that include tool use

Synthetic: synthesized from publicly available long context datasets

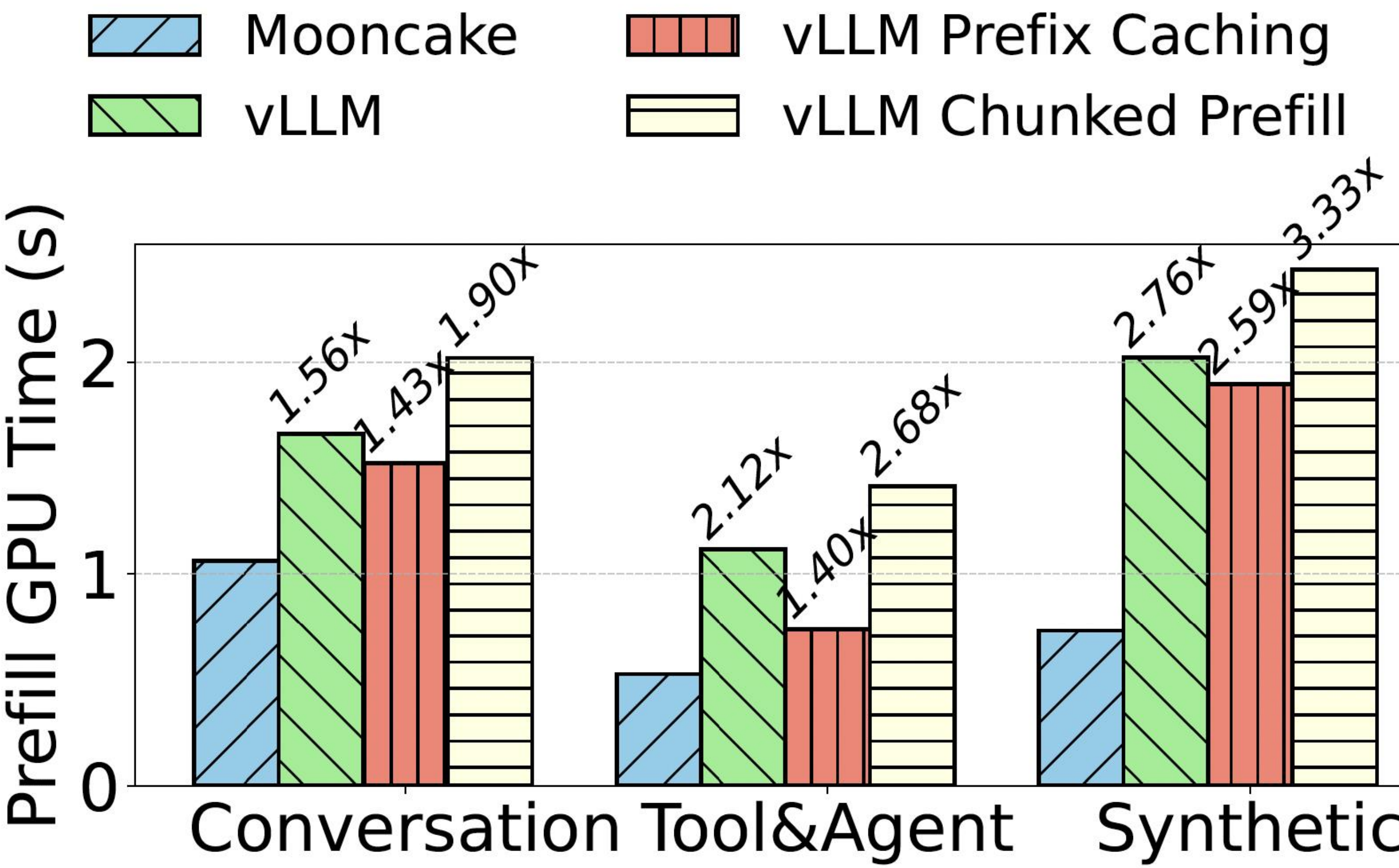
Evaluation: Effective Request Capacity

- Effective request capacity: Number of requests that meet the latency requirements
- Achieve up to a **498%** increase in effective request capacity compared to vLLM, vLLM with prefix caching and with chunked prefill



Evaluation: GPU Computation Cost

- Cache hit rate: global cache > local cache
- Save **29% - 61%** on GPU computation costs



Summary

Mooncake

Deployed System: Mooncake

- Trading more storage for less computation
- A KVCache-centric LLM serving architecture for higher throughput

Infrastructure: Mooncake Store

- Fast, scalable and fault-tolerant KVCache storage and transfer engine

Benefits of Mooncake Store

- Efficient P&D disaggregation
- More KVCache reuse
- Flexible KVCache scheduling

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Paper

Github

Use in vLLM