

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

Ruoyu Qin[†], Zheming Li[†], Weiran He, Jialei Cui, Feng Ren, Mingxing Zhang, Yongwei Wu, Weimin Zheng, Xinran Xu

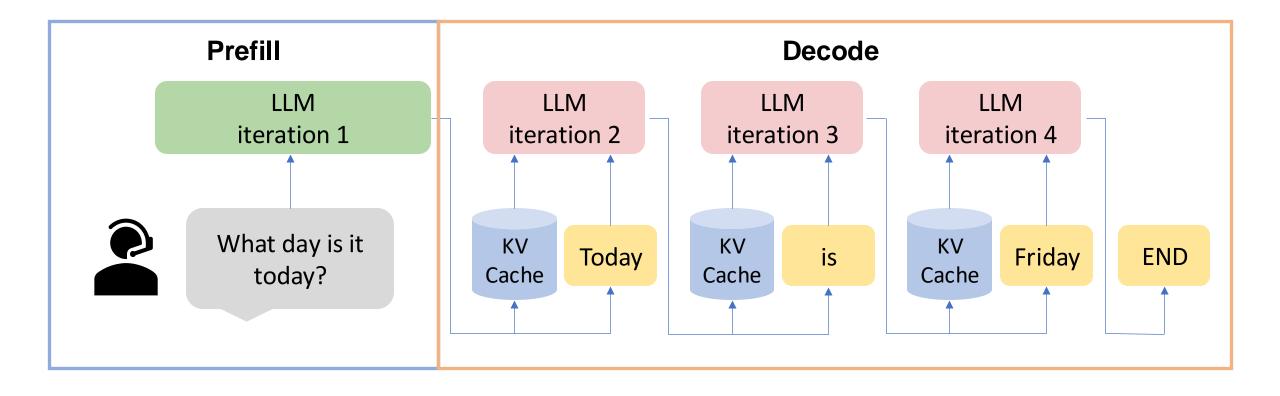




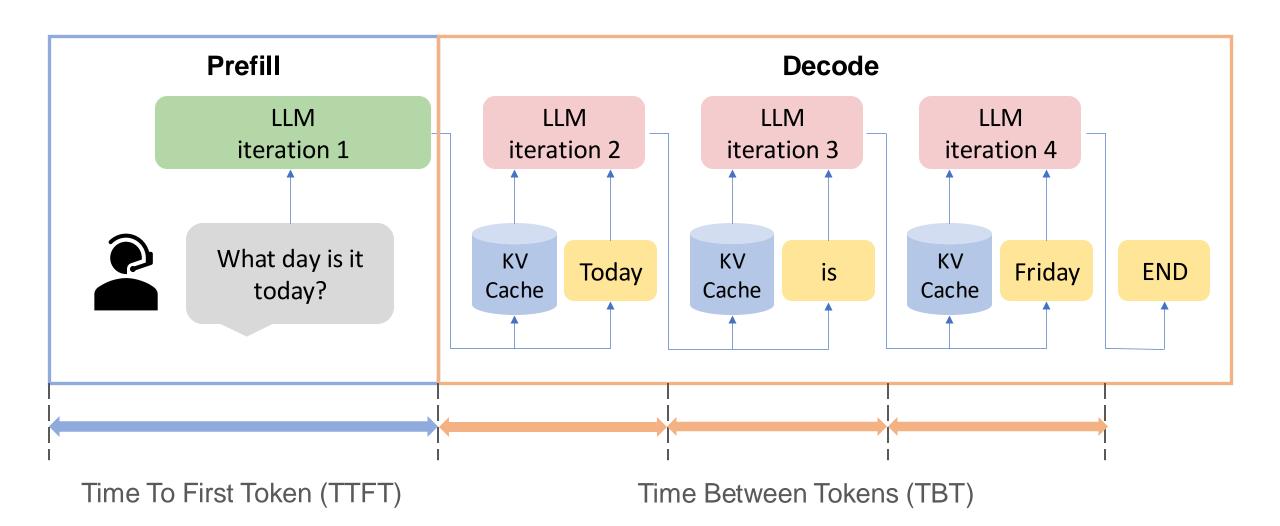
†Co-first Authors

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LLM Inference



LLM Inference



LLM Inference: Latency

Program (~1k tokens)

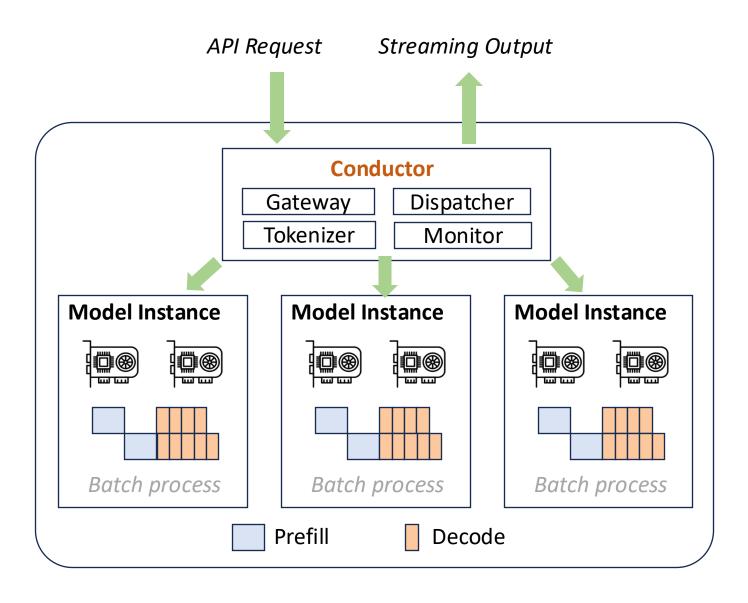
Web search (~8k tokens)

Multi-document summary (~128k tokens) TTFT TBT

Low (~100ms)	Very low (~50ms)
High (~1s)	Match read speed (~100ms)
Very high (> 5s)	Match read speed (~100ms)

LLM Inference: Latency







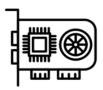
Kimi: a Leading AI service provided by Moonshot AI

- Process over 100 billion tokens daily
- Real-time response
- Up to 1M tokens context

More Data + Larger Model + Longer Context = Higher Intelligence

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Lack of GPU Supply



Higer Inference Cost



Longer Response Time

More Data + Larger Model + Longer Context = (∵) Higher Intelligence

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

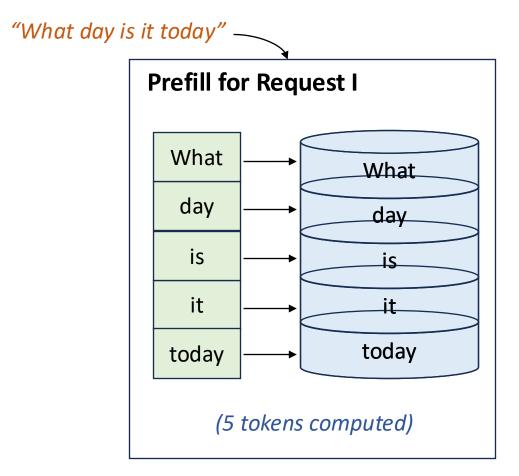
Lack of

Higer **GPU Supply** Inference Cost

Longer **Response Time**

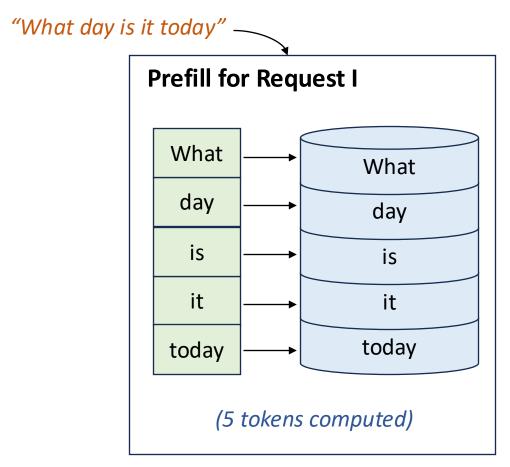
LLM Inference: Prefix Caching

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



LLM Inference: Prefix Caching

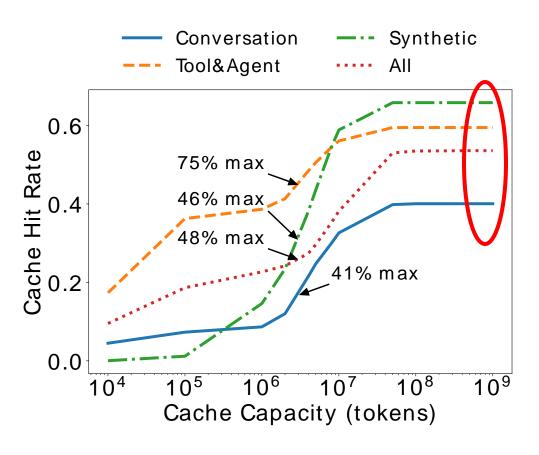
 KVCache can be shared across requests with the same prefix, reducing computation during prefill



"What day is it tomorrow" -**Prefill for Request II** What What day day KVCache Reuse is is it it tomor tomorrow row

(1 token computed)

Trace Analysis: Is Prefix Caching a Simple Solution?



Traces in our paper

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

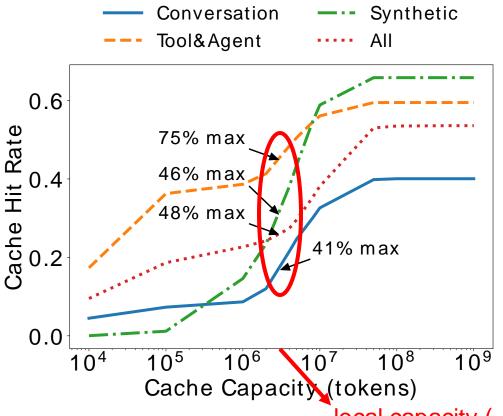
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Tool&Agent: collected from real-world online requests that include tool use

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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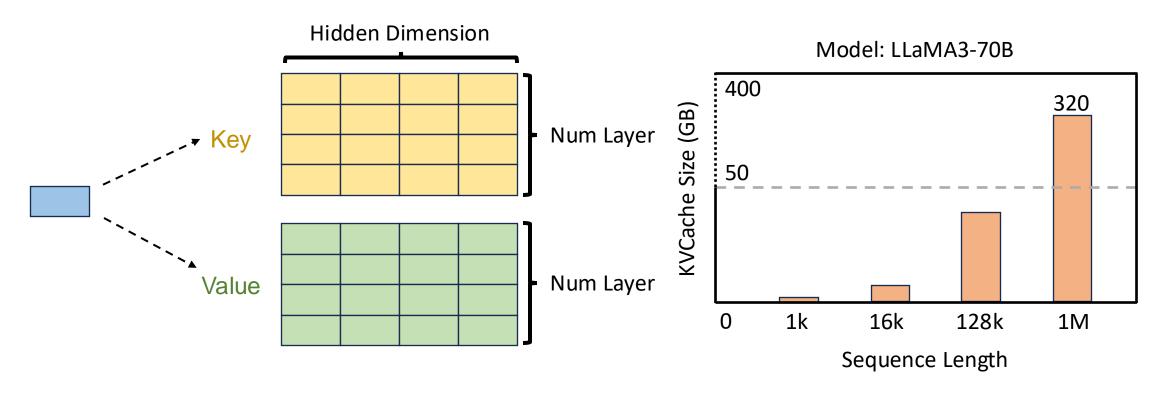
local capacity (~3M tokens)

- 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

Over 100 billion tokens per day

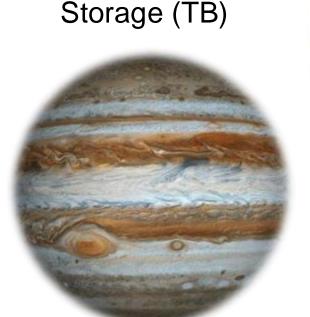
One Token's GPU VRAM

KVCache (Hundreds of GB)

(Tens of KB)







DRAM or Other

Reusable KVCache (Hundreds of TB ~ PB)

One Token (Bytes)



KVCache: Huge Challenge to Storage System

- High transfer bandwidth required to avoid stall of GPU (see Section 2.2)
 - 6 GB/s for A800 GPUs
 - 19 GB/s for H800 GPUs

DRAM or Other Storage (TB)

Reusable KVCache (Hundreds of TB ~ PB)

One Token (Bytes)

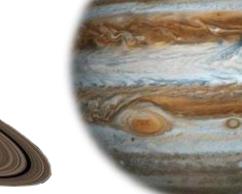


One Token's KVCache (Tens of KB)



GPU VRAM (Hundreds of GB)





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

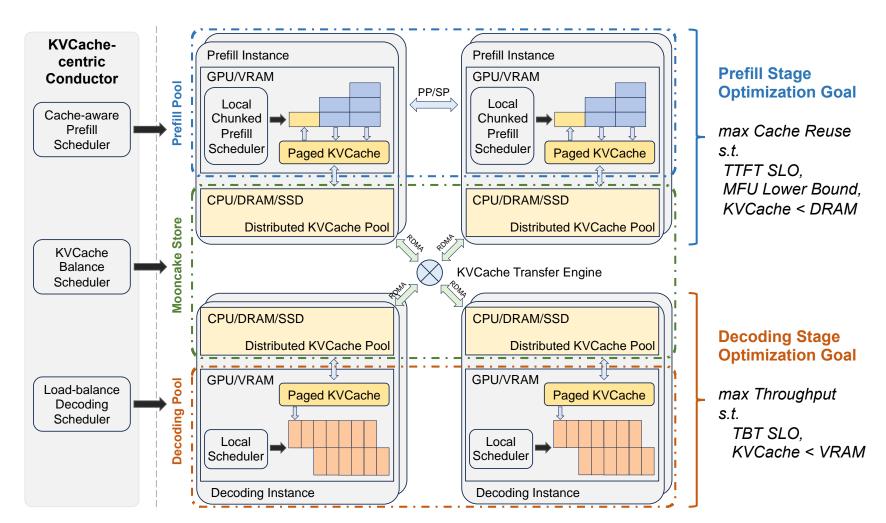
KVCache-centric Architecture is All You Need!

Requirement 3

KVCache-aware scheduling

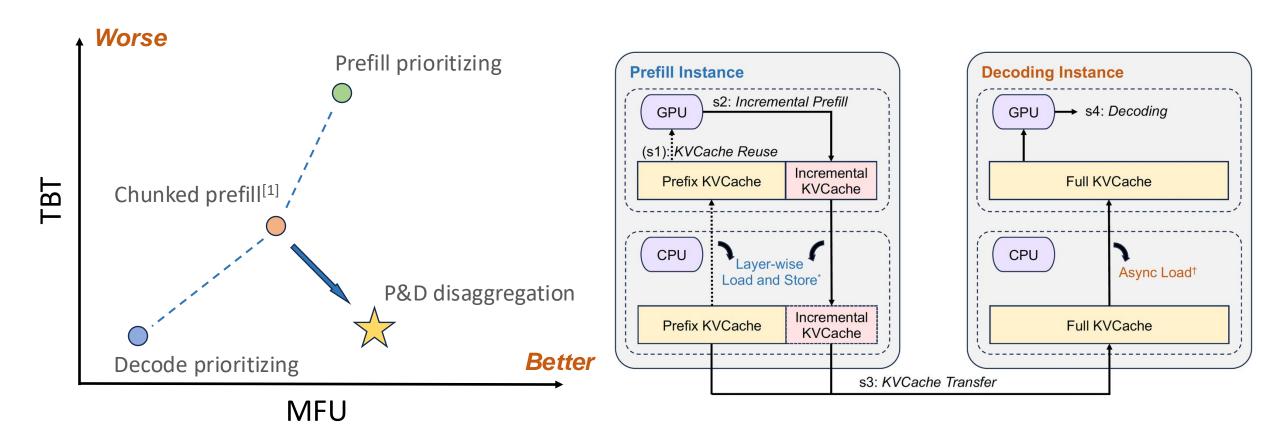
Mooncake: A KVCache-centric Disaggregated Architecture

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



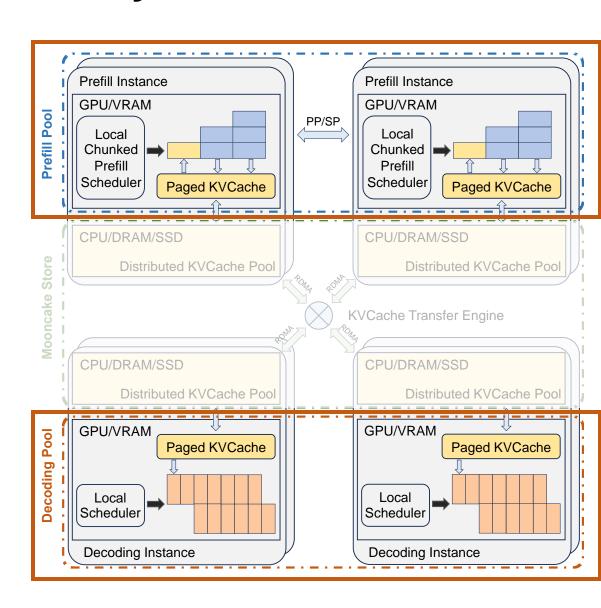
P&D Disaggregated Inference

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



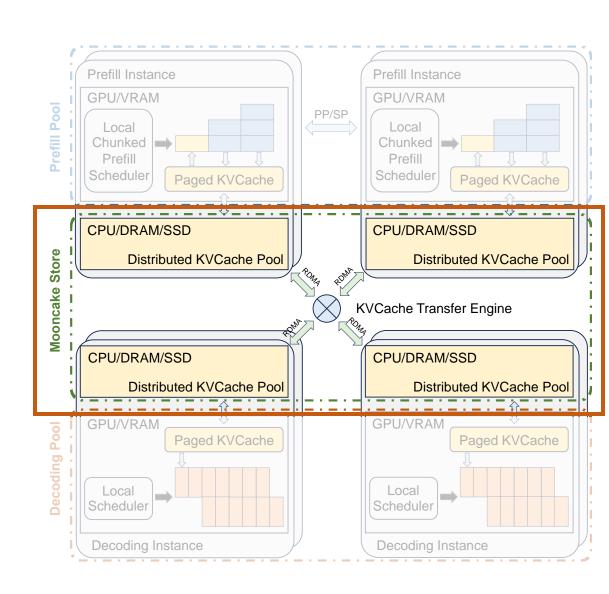
Mooncake Store - Distributed Multi-layer KVCache Pool

- 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])

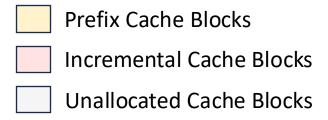


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Prefix-hashed KVCache object storage



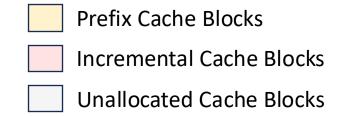
Token Blocks (16~512 tokens)

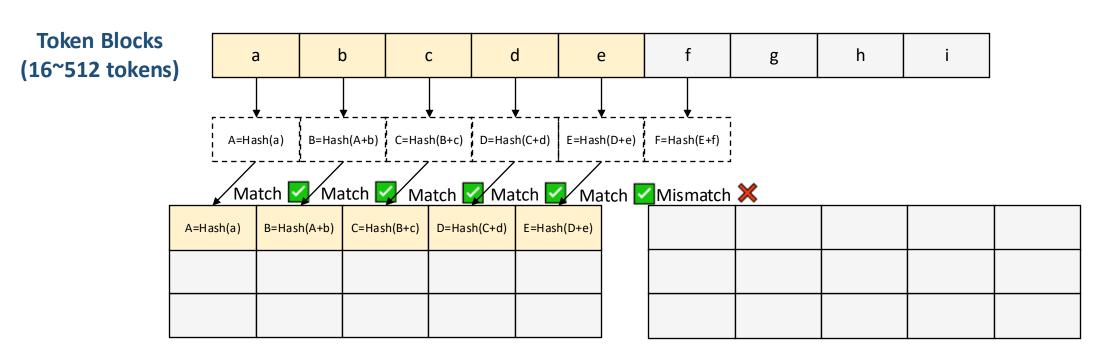
a b c d e f g h

A=Hash(a)	B=Hash(A+b)	C=Hash(B+c)	D=Hash(C+d)	E=Hash(D+e)

Prefill Instance Decoding Instance

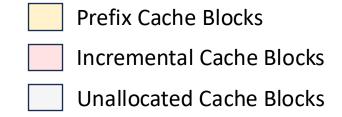
Prefix-hashed KVCache object storage

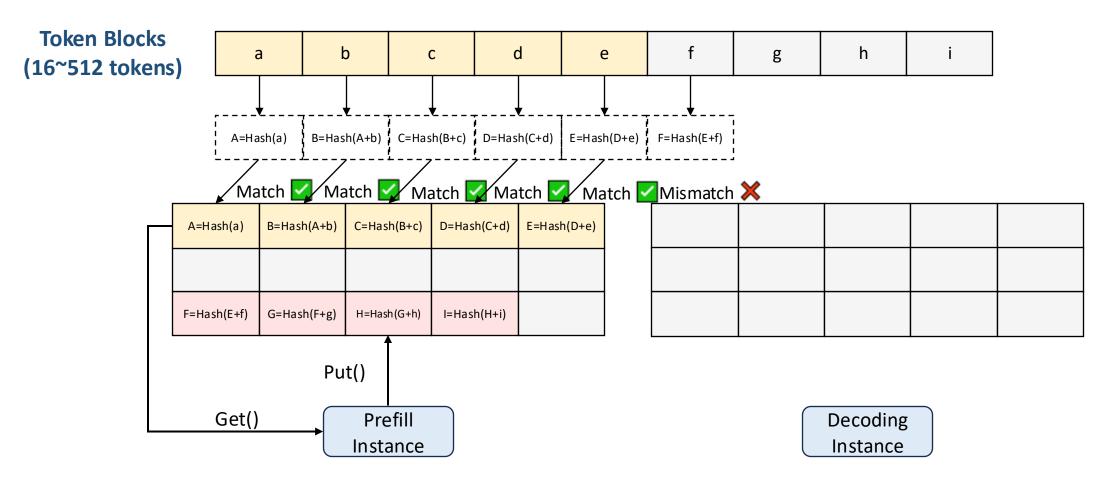




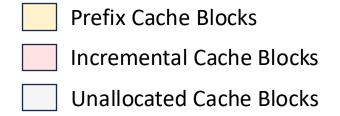
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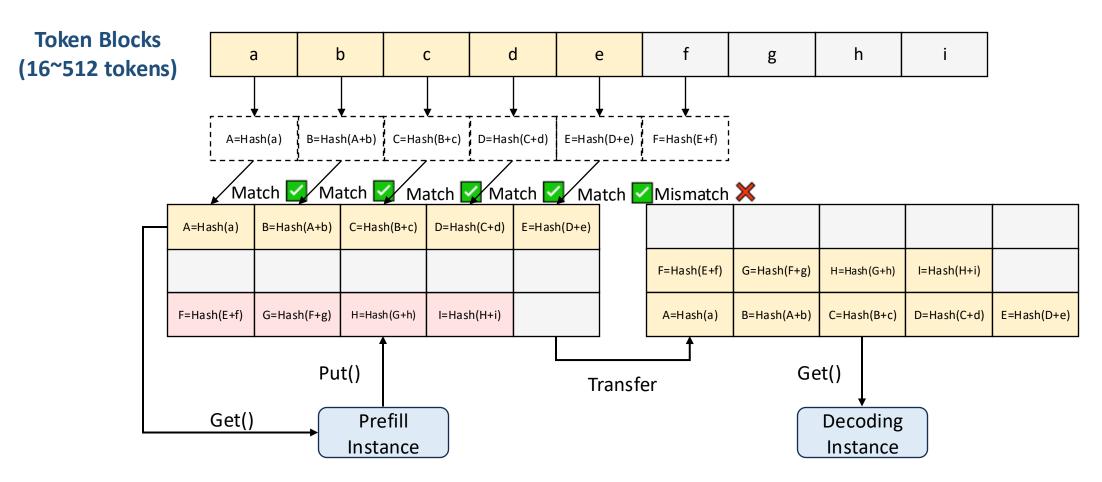
Prefix-hashed KVCache object storage



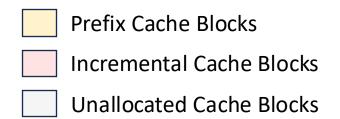


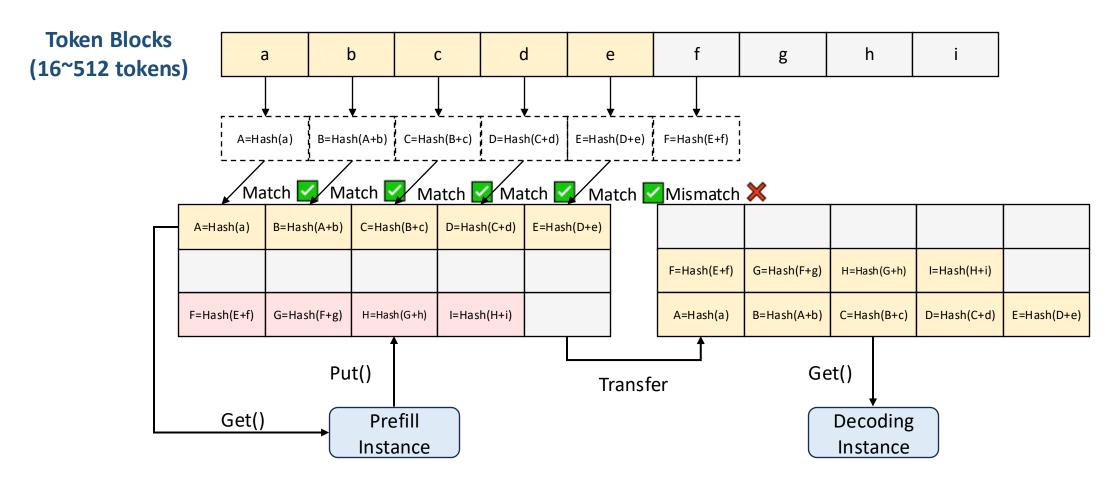
Prefix-hashed KVCache object storage





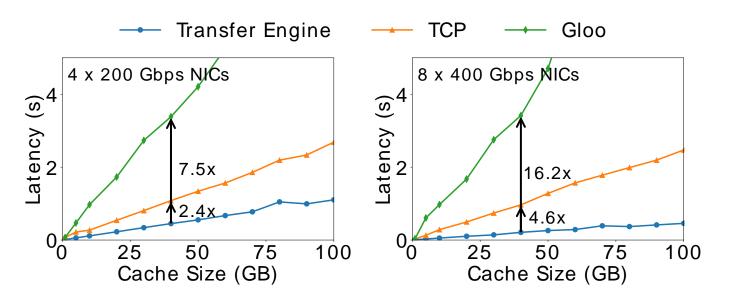
- Prefix-hashed KVCache object storage
- LRU (Least Recently Used) eviction policy



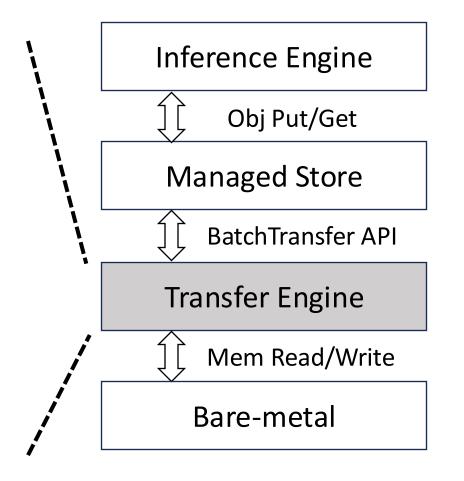


Mooncake Store: Transfer Engine

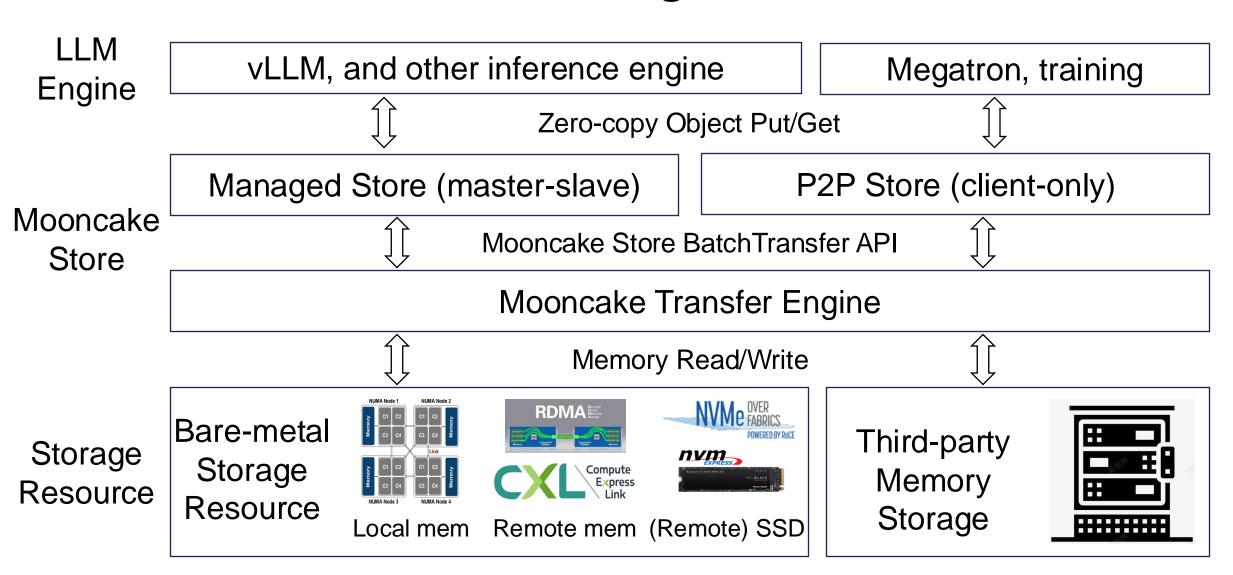
• **Key technologies**: Zero-copy, multi-NIC up to 8*400Gbps aggregated bandwidth, topology aware, failure recovery, load balance, multi-transport support, etc



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



Mooncake Store: External Integration



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

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

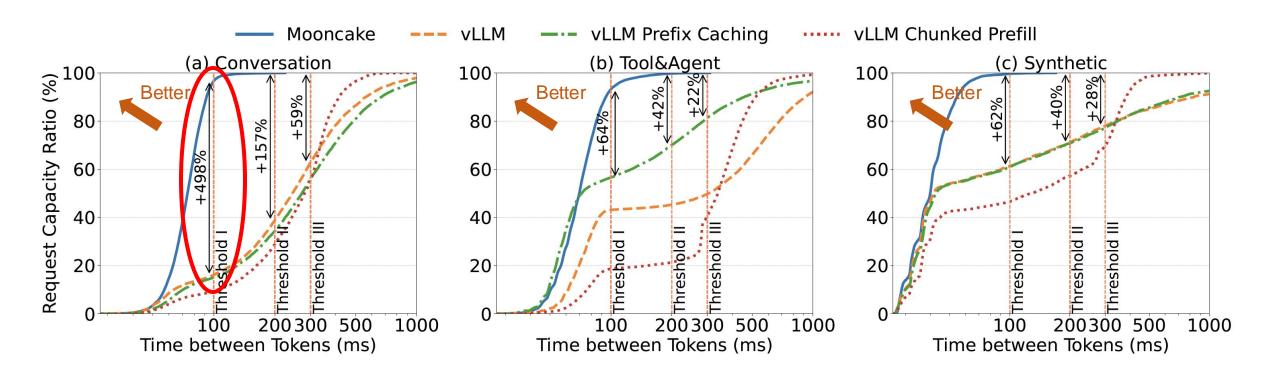
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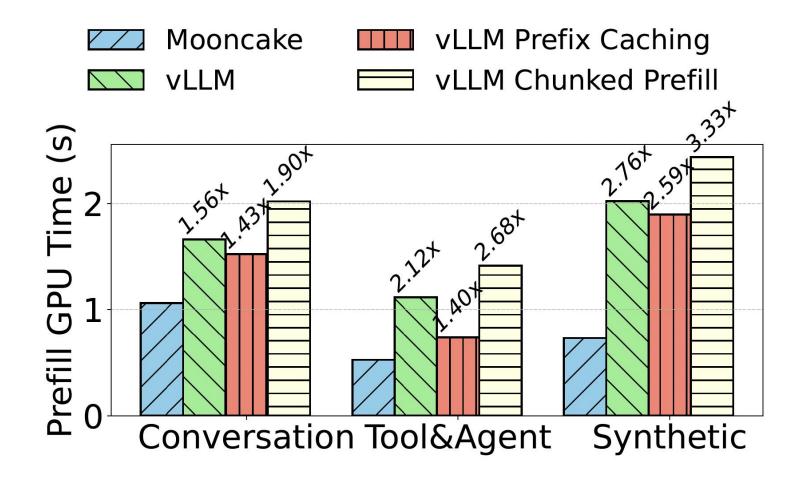
Evaluation: Effective Request Capacity

- 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



More Details in Our Paper

Inference Engine

Chunked pipeline prefill (Section 3.3)

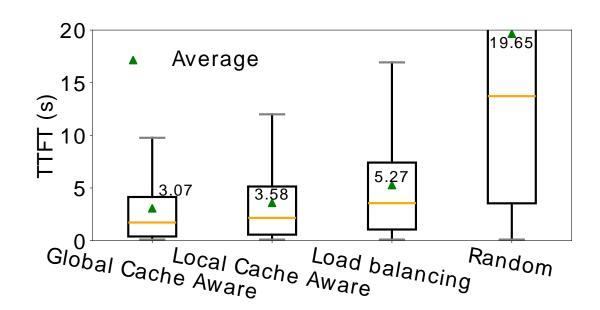
Scheduling

- KVCache-aware scheduling (Section 4.1)
- Cache load balancing (Section 4.2)

Ablation Experiments

- Distribution of hot caches (Section 5.3.3)
- Bandwidth demand by Mooncake (Section 5.4.2)
- Latency breakdown (Section 5.4.3)
- Impact of P/D ratio (Section 5.5)

<u>Ablation Study:</u> Impact of Scheduling Algorithms on TTFT



Mooncake Store: Roadmap of Integration with vLLM

Phase 1: 1P1D Support (Merged)

- Support disaggregated inference of one prefill and one decoding instance
- [Core] Support disaggregated prefill with Mooncake Transfer Engine #10884

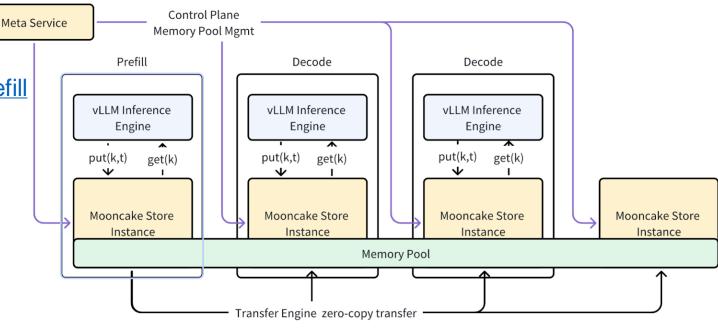
The integration part are contributed by our collaborators from — Alibaba Cloud

Phase 2: xPyD Support (WIP)

• Support disaggregated inference of an arbitrary number of prefill and decoding instances, based on Mooncake's distributed KVCache pool Control Plane

- ➤ Initial PR: [Feature][Frontend] Add

 KVTransferParams for disaggregated prefill
 feature by ShangmingCai · Pull Request
 #12957 · vllm-project/vllm
- ➤ Discussed in #feat-prefill-disaggregation channel on vLLM's Slack



Summary



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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