Infinite-LLM: Efficient LLM Service for Long Context with DistAttention and Distributed KVCache

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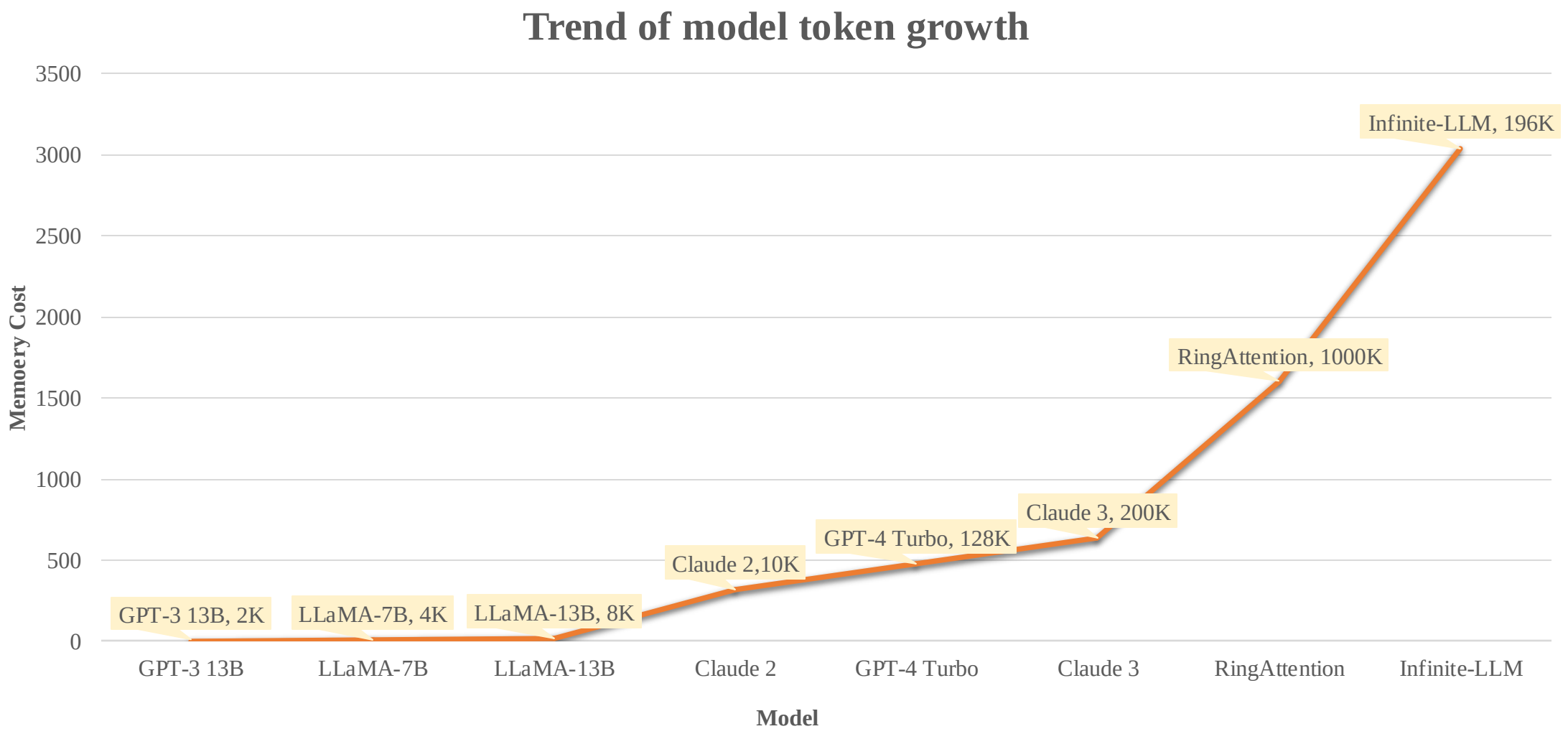
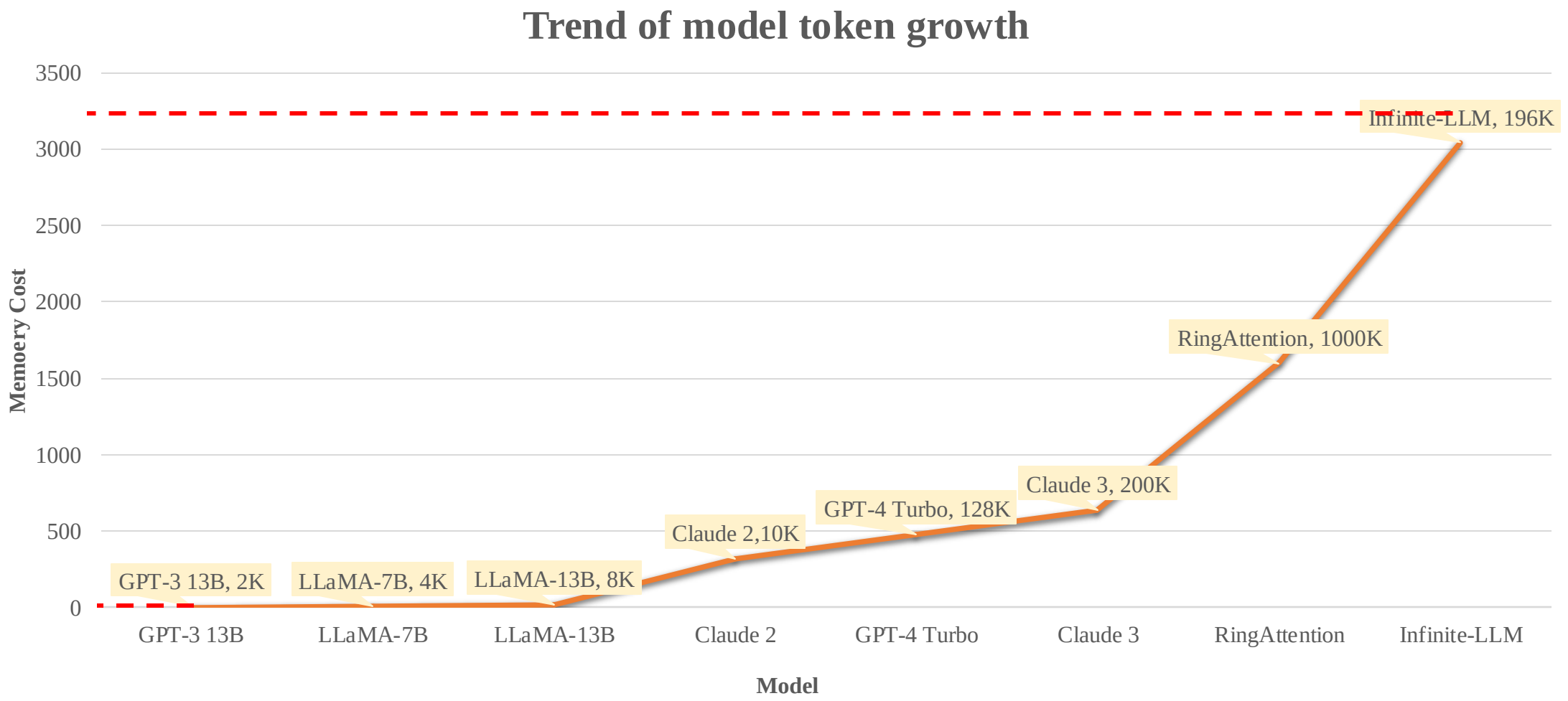
Trend of model token growth



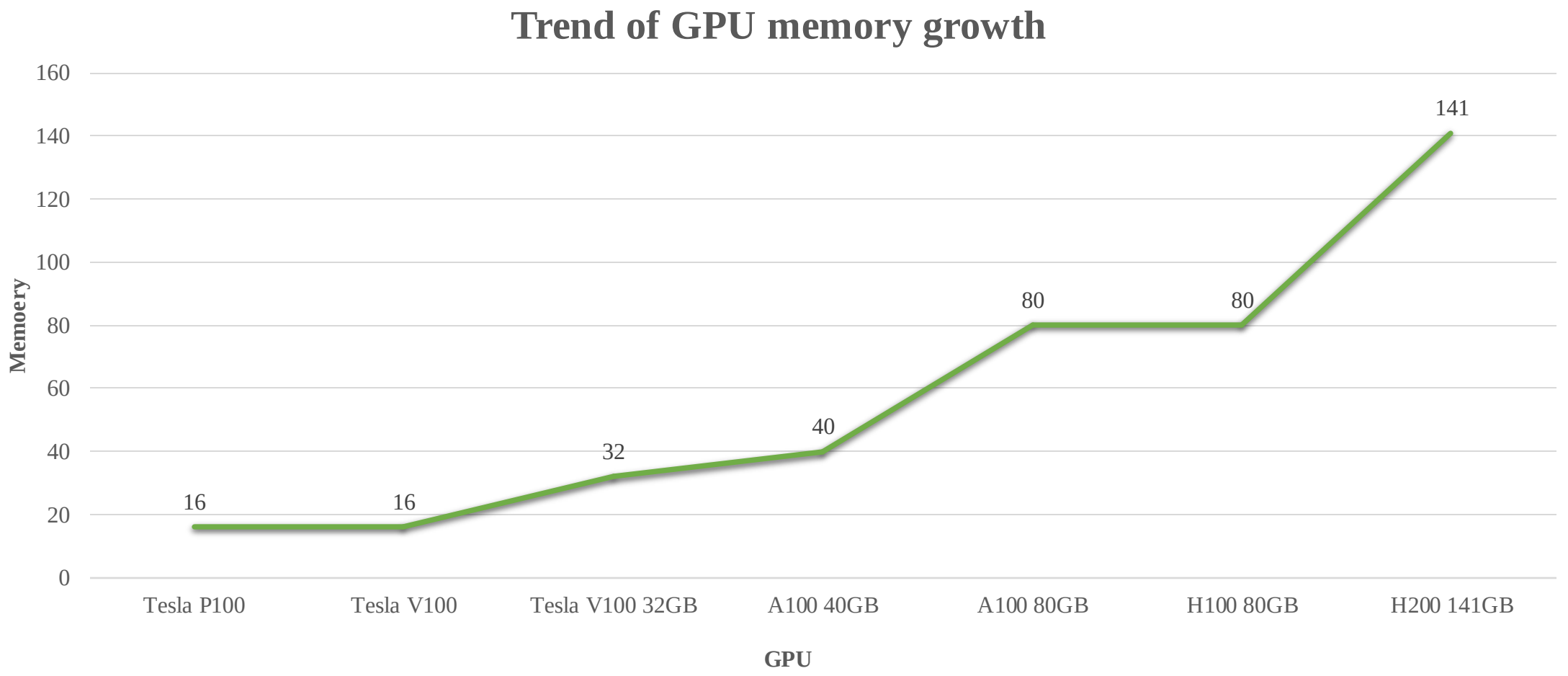
Trend of model token growth

- Use BF16, Layer=50, Heads=64, Dimension=128



Trend of GPU memory growth

- Maximum VRAM of a single GPU card is **141 GB**



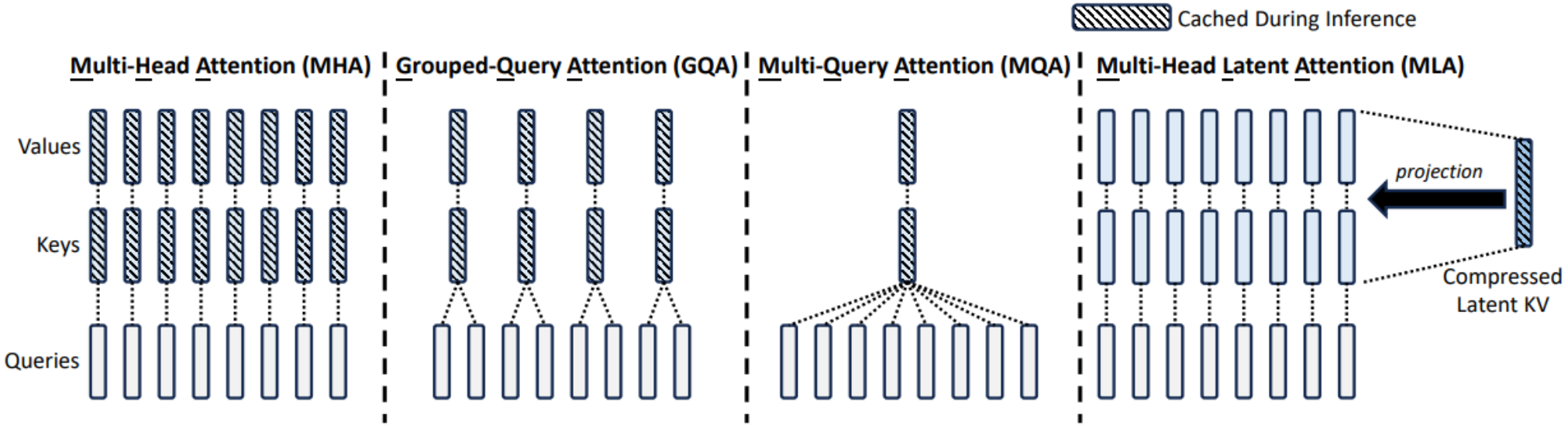
How to cut LLM cloud service costs?

- ❑ **Optimizations of Attention**
- ❑ **Parallelism Method**

Optimizations of Attention

❑ MHA vs GQA vs MQA vs MLA

n_h:heads number of each head　　d_h:vector dimension of each head　　l :layers　　n_g:number of groups

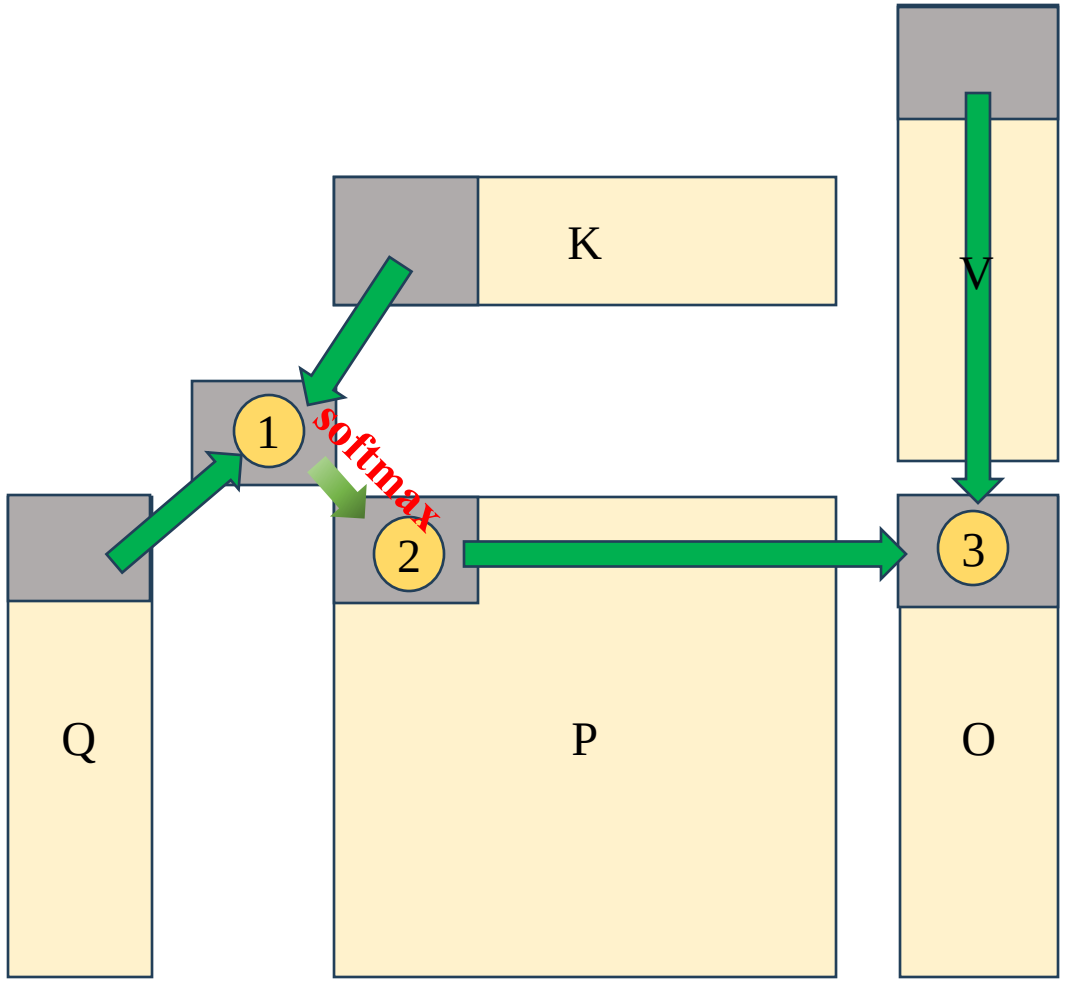


	Multi-Head Attention (MHA)	Grouped-Query Attention (GQA)	Multi-Query Attention (MQA)	Multi-Head Latent Attention (MLA)
KV-cache per Token	$2n_h d_h l$	$2n_g d_h l$	$2d_h l$	$\frac{9}{2} d_h l$
Performance	**Strong**	**Moderate**	**Weak**	**Stronger**

Flash Attention & Paged Attention

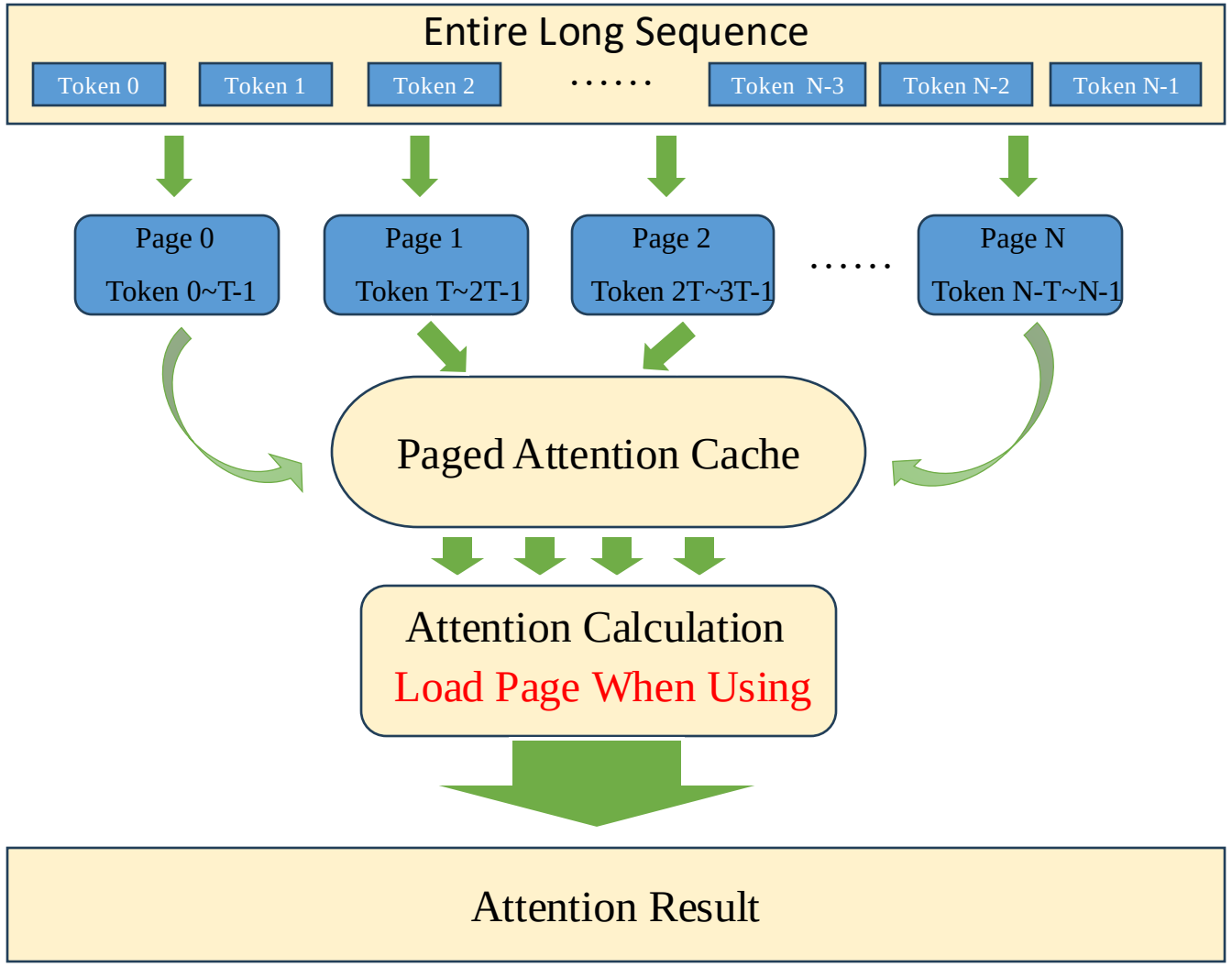
❑ Flash Attention: Block-by-Block Sequential Computation

❖ Calculation in HBM: $\mathbf{S} = \mathbf{QK}^{\top} \in \mathbb{R}^{N \times N}$, $\mathbf{P} = \mathrm{softmax}(\mathbf{S}) \in \mathbb{R}^{N \times N}$, $\mathbf{O} = \mathbf{PV} \in \mathbb{R}^{N \times d}$



Flash Attention & Paged Attention

❑ Paged Attention: Paged Dynamic Loading

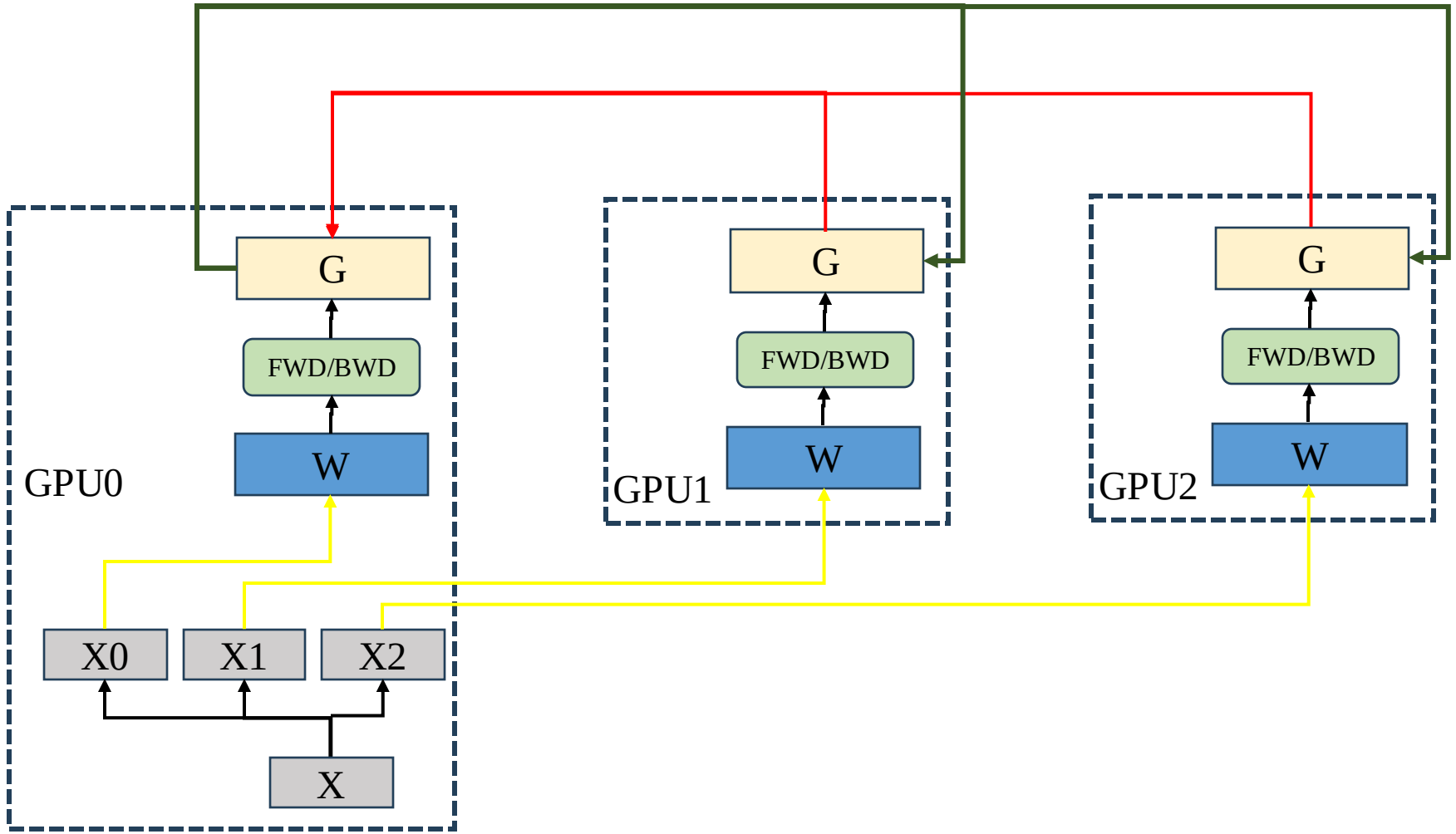


How to cut LLM cloud service costs?

- ❑ Optimizations of Attention
- ❑ **Parallelism Method**
  - ❖ Data Parallelism
    - ➢ Data Parallelism
    - ➢ Distributed Data Parallelism
  - ❖ Model Parallelism

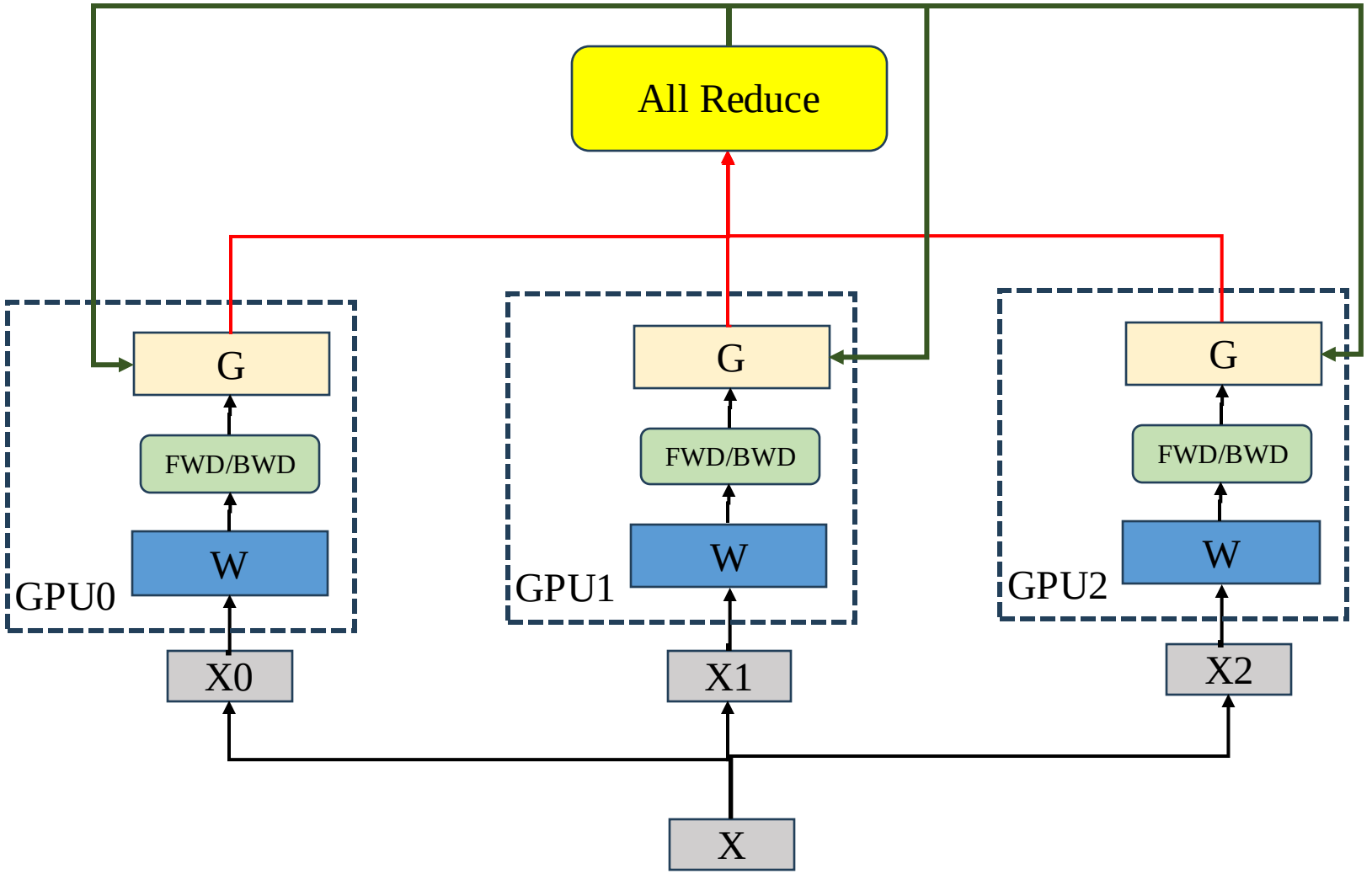
Parallelism Method

❑ Data Parallelism



Parallelism Method

❑ Distributed Data Parallelism



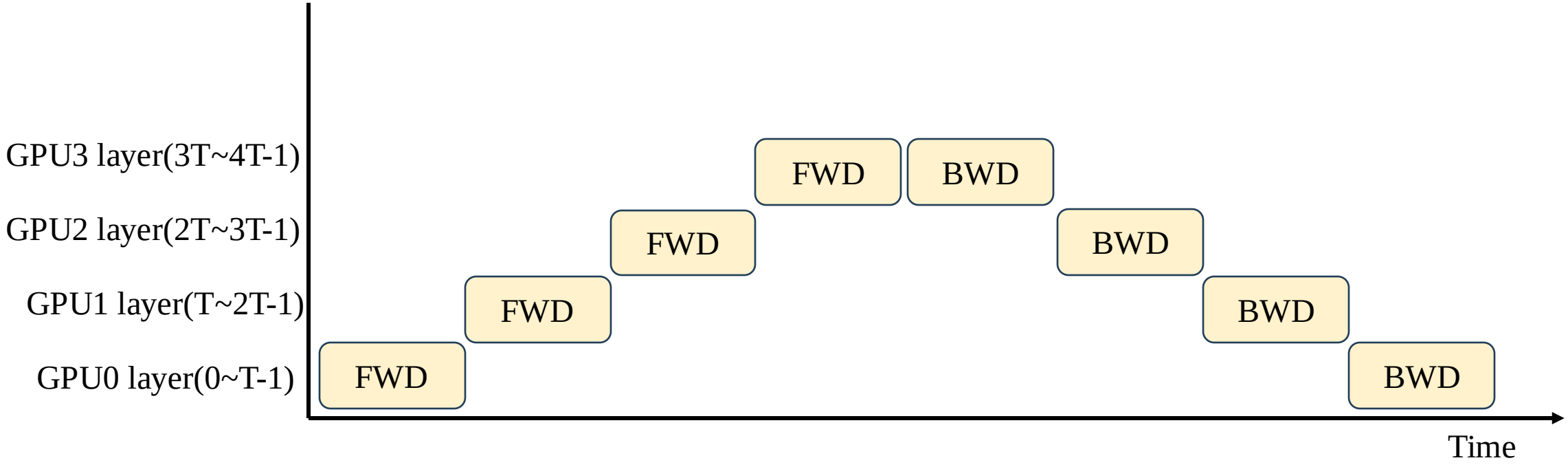
How to cut LLM cloud service costs?

- ❑ Optimizations of Attention
- ❑ **Parallelism Method**
  - ❖ Data Parallelism
  - ❖ Model Parallelism
    - ➢ Pipeline Parallelism
    - ➢ Tensor Parallelism

Parallelism Method

❑ Pipeline Parallelism

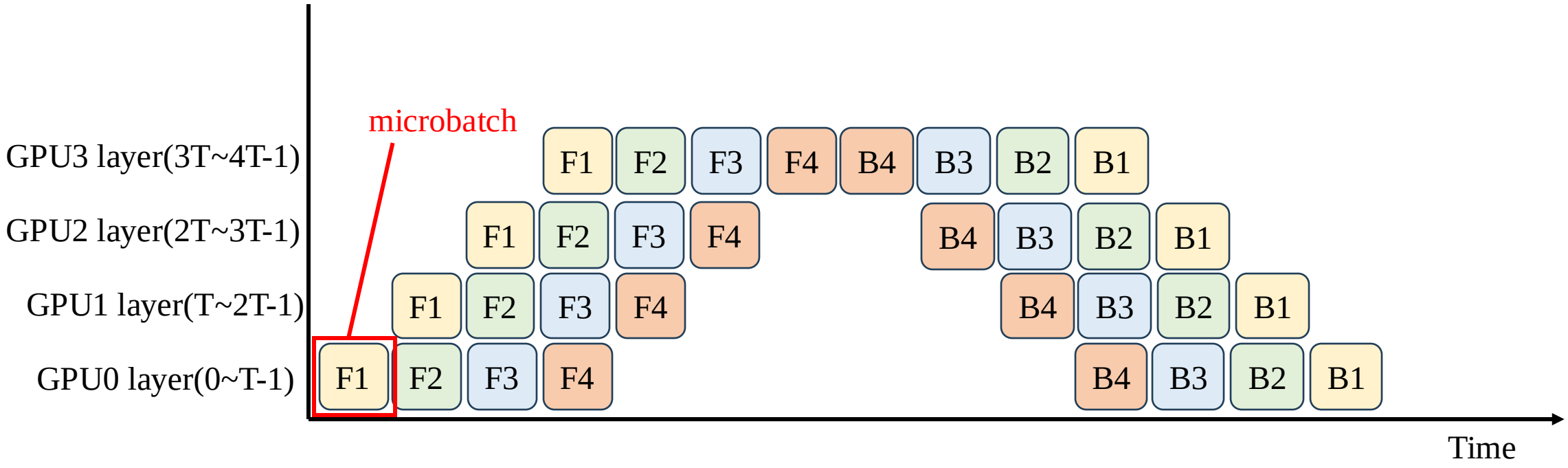
- ❖ Pipeline Parallelism in 4 GPUS, use model with 4T layers



Parallelism Method

❑ Pipeline Parallelism

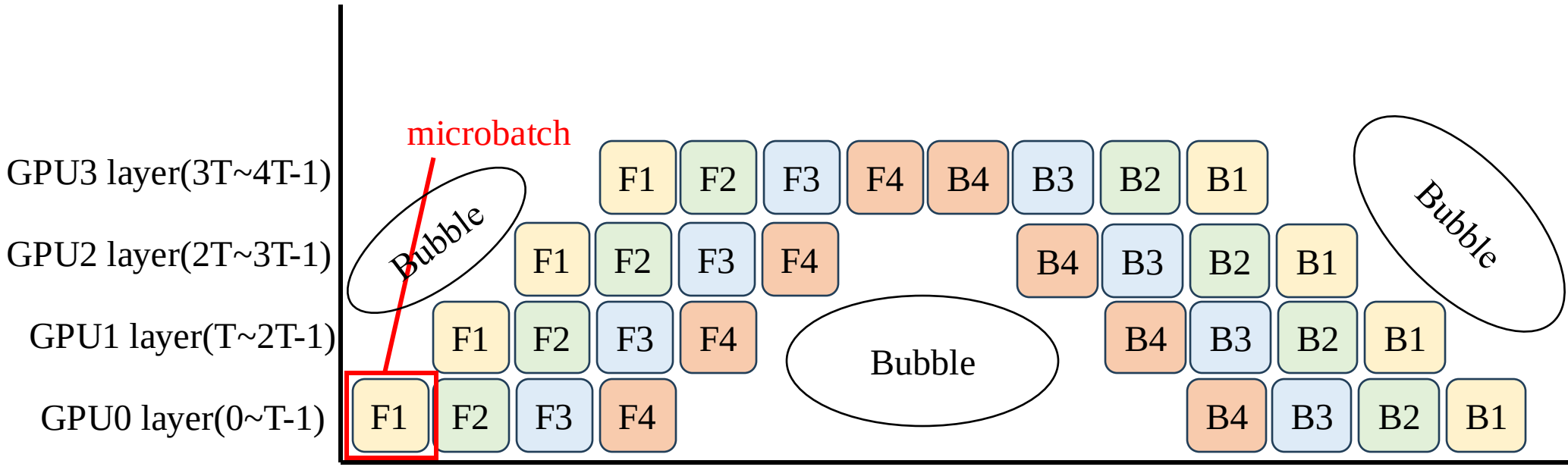
❖ Gpipe: use smaller, equally-sized microbatches to improve efficiency



Parallelism Method

❑ Pipeline Parallelism

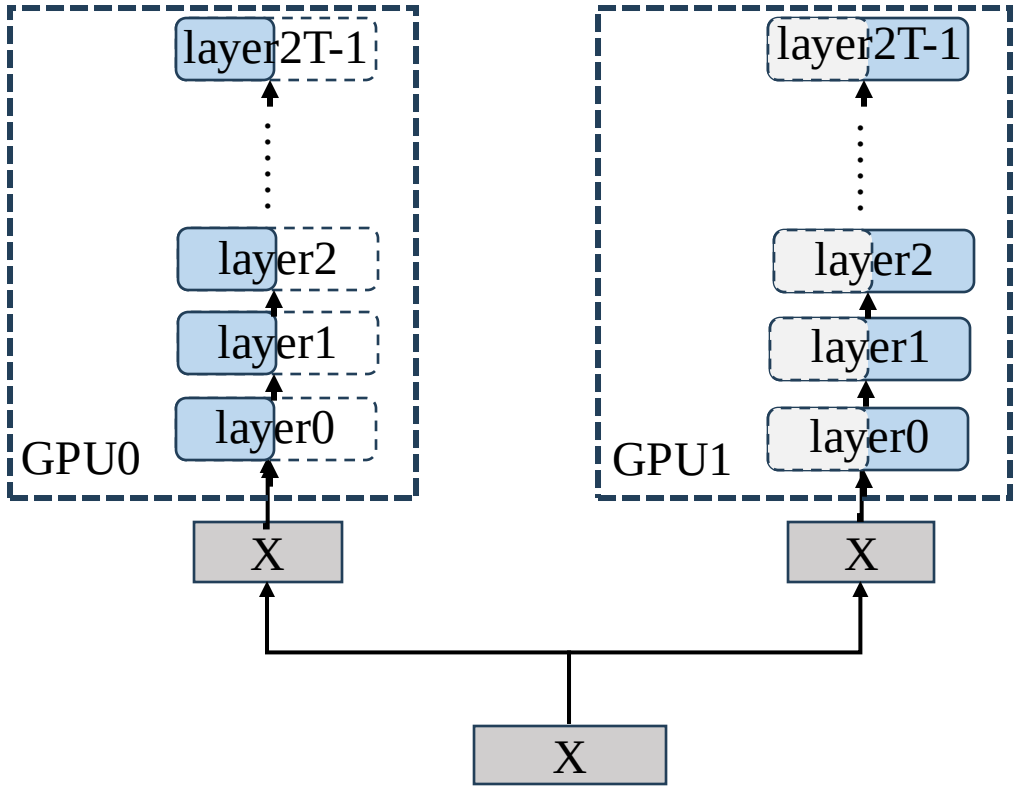
- ❖ Gpipe: use smaller, equally-sized microbatches to improve efficiency
- ❖ Bubble: idle time slots caused by dependencies
- ❖ PipeDream: BWD begins when a microbatch completes its FWD



Parallelism Method

❑ Tensor Parallelism

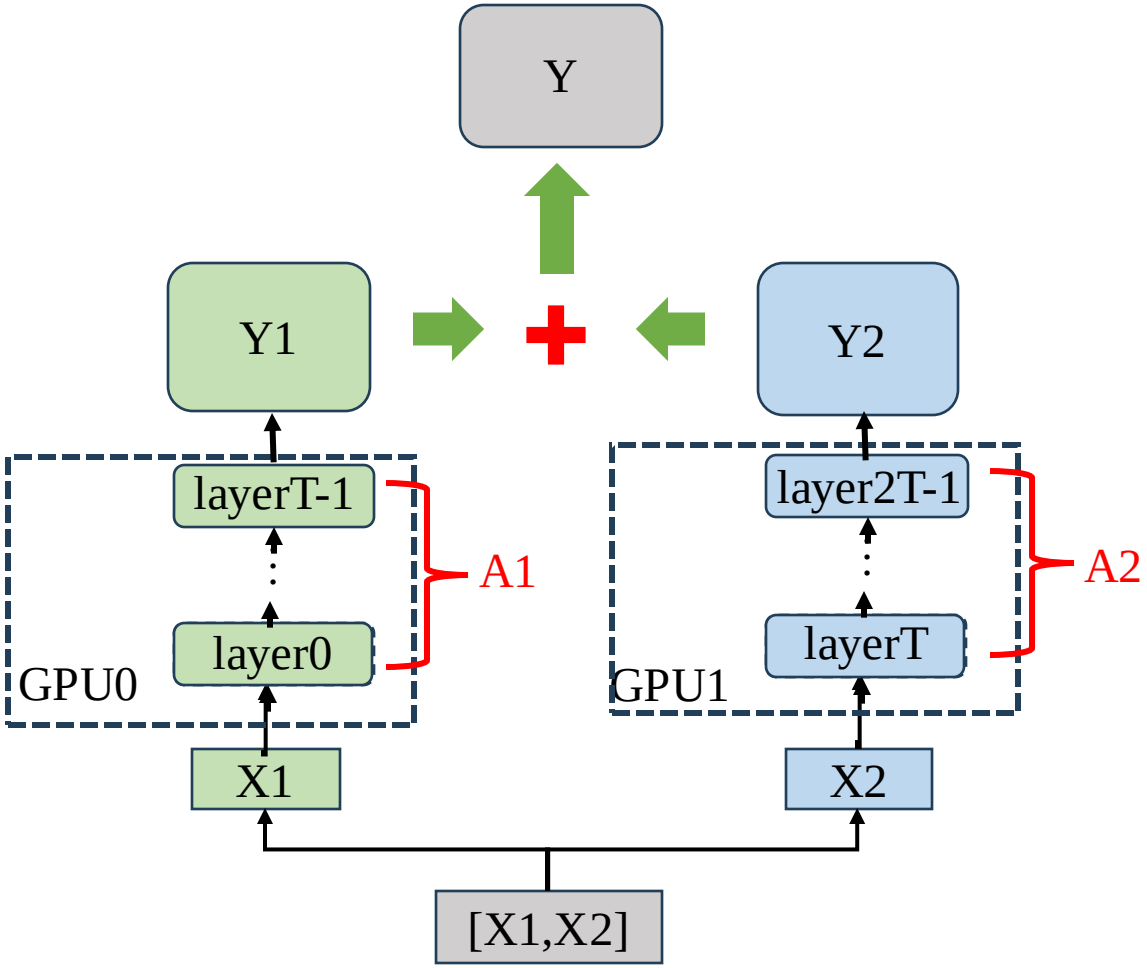
❖ Parameters (tensors) within a layer are split across different devices



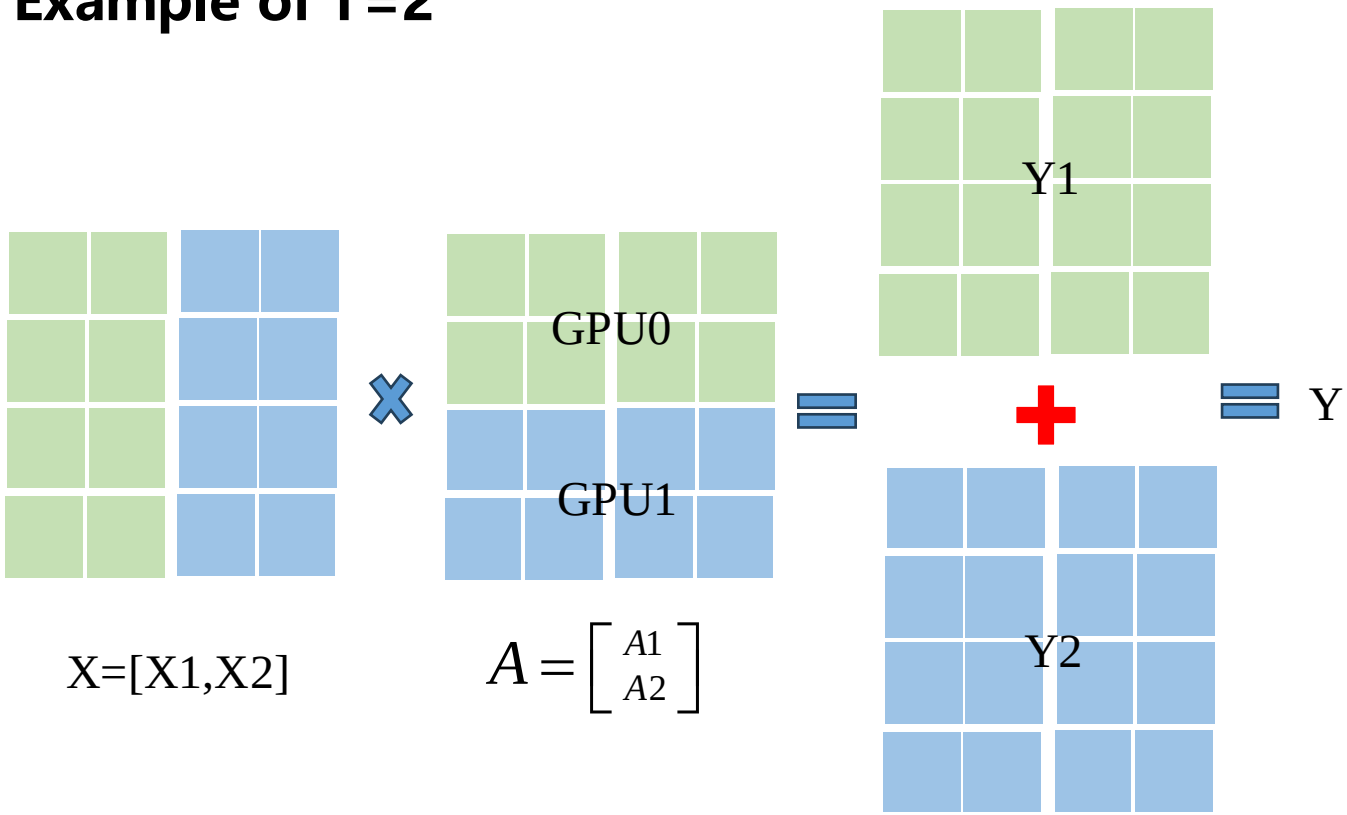
Parallelism Method

❑ Tensor Parallelism

❖ Row Parallelism : $XA = [X1, X2]\begin{bmatrix} A1 \\ A2 \end{bmatrix} = X1A1 + X2A2 = Y1 + Y2 = Y$



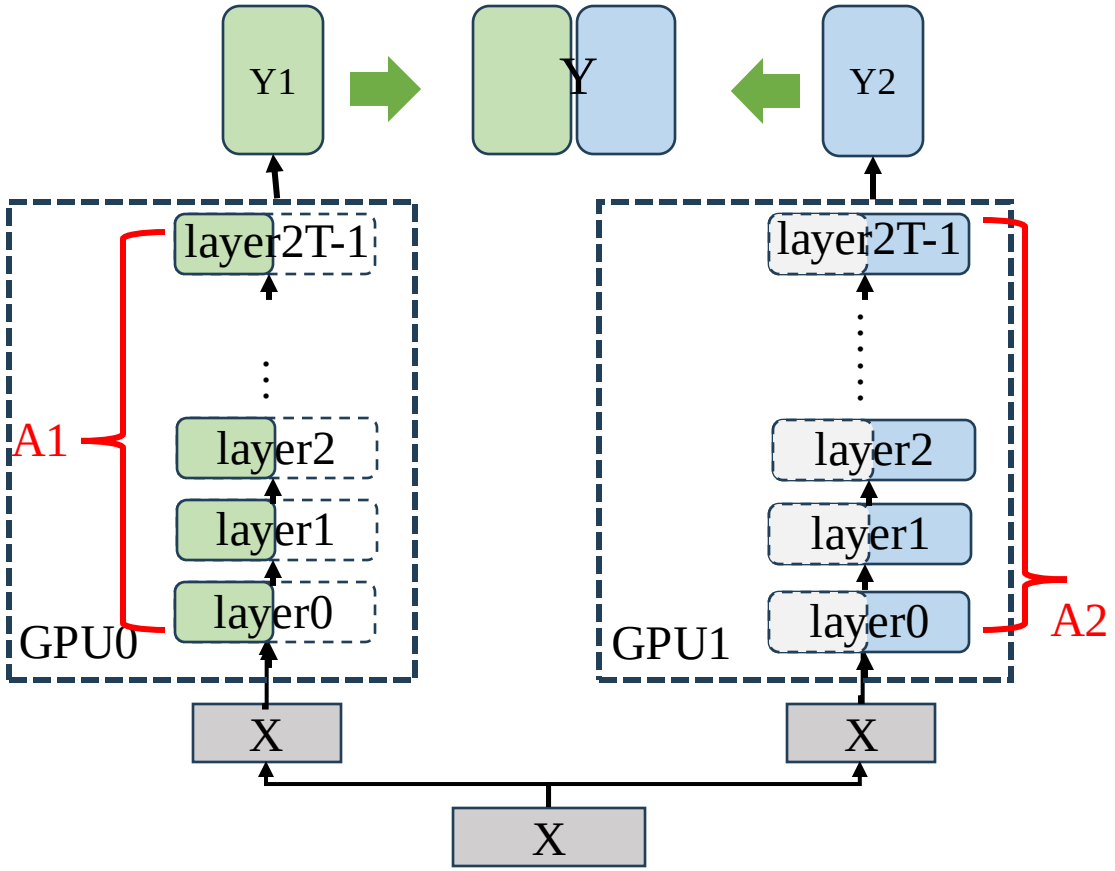
Example of T=2



Parallelism Method

❑ Tensor Parallelism

❖ Column Parallelism: $XA = [X][A1, A2] = [XA1, XA2] = [Y1, Y2] = Y$



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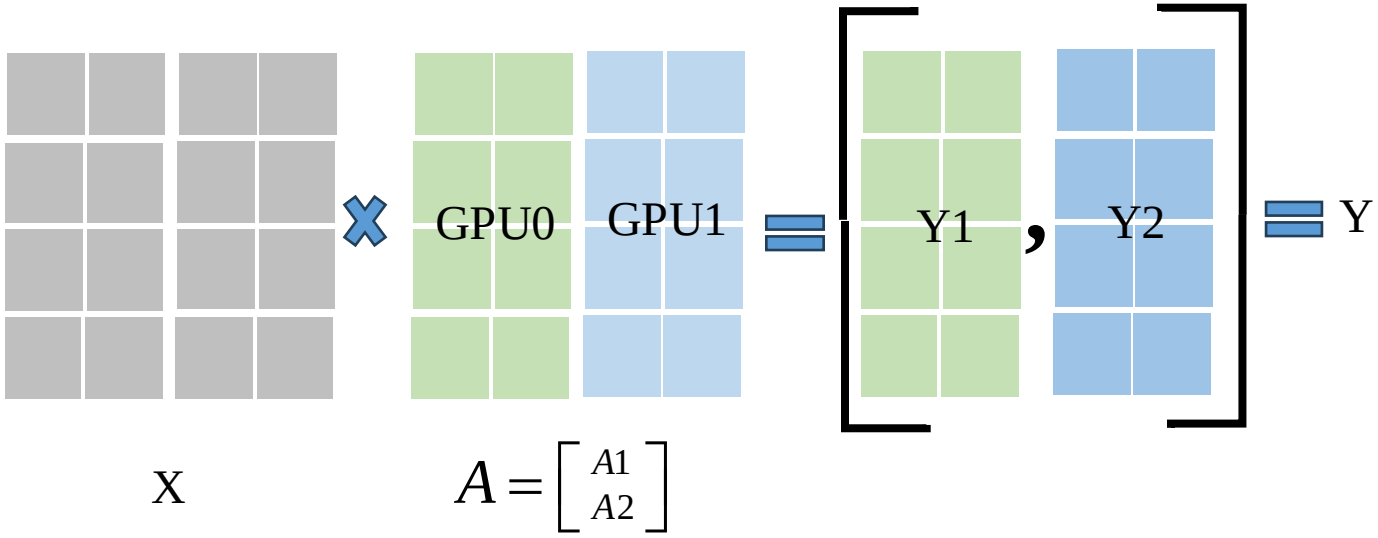
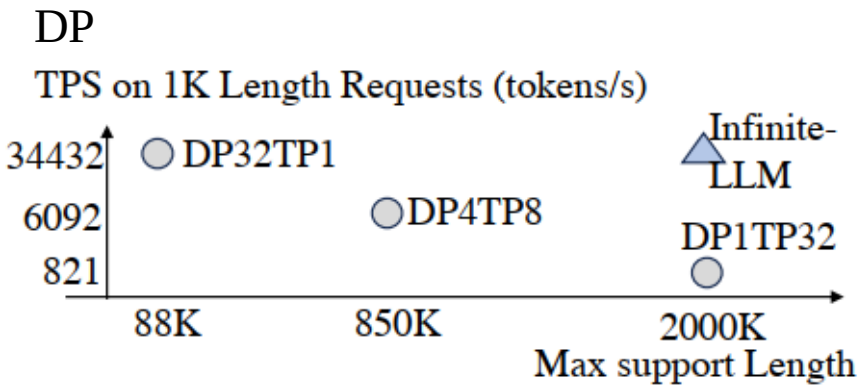


Challenges of deploying LLM services

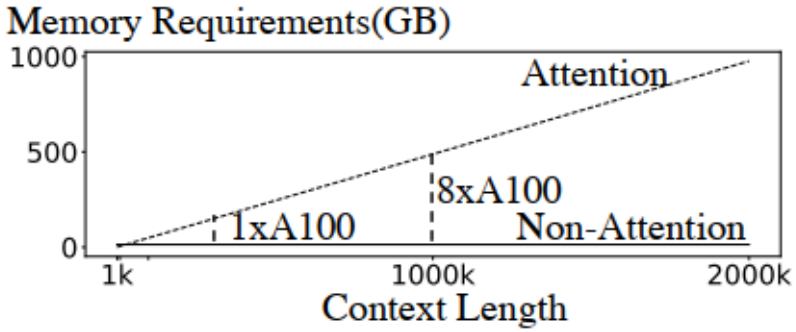
- ❑ More GPUs support long-text but perform poorly
- ❑ Dynamic KV Cache Complicates Resource Management

More GPUs support long-text but perform poorly

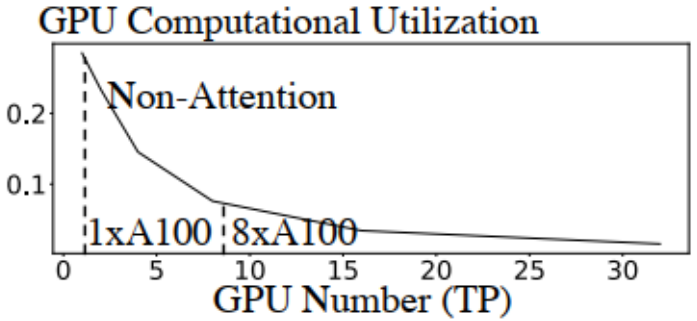
- Traditional parallel methods do not differentiate between attention and non-attention layers, causing performance degradation due to over-segmentation.



(a) Efficiency and max support length



(b) Memory requirement with context length



(c) Computational util with different DOP

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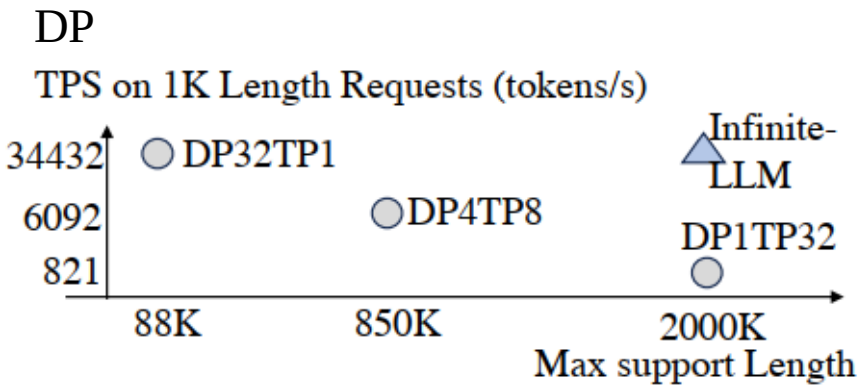

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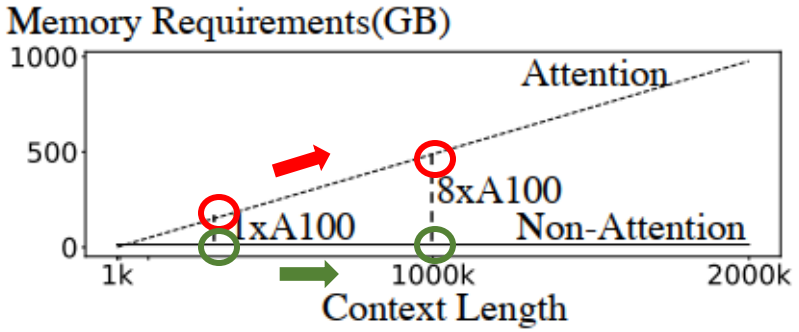

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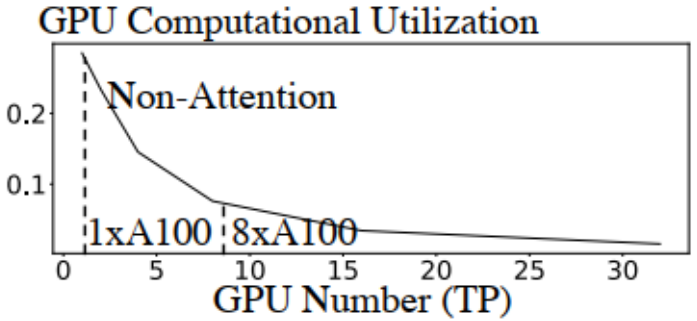

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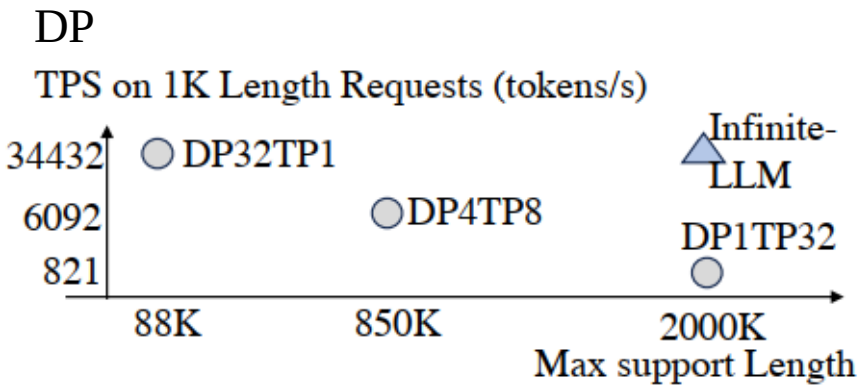

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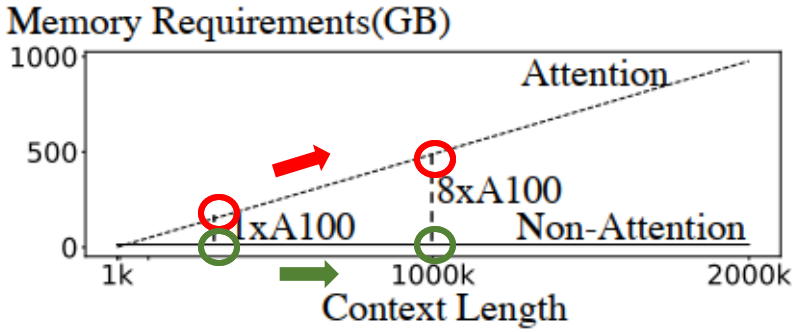

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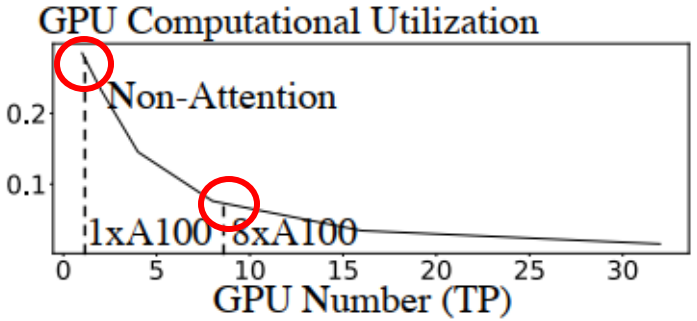


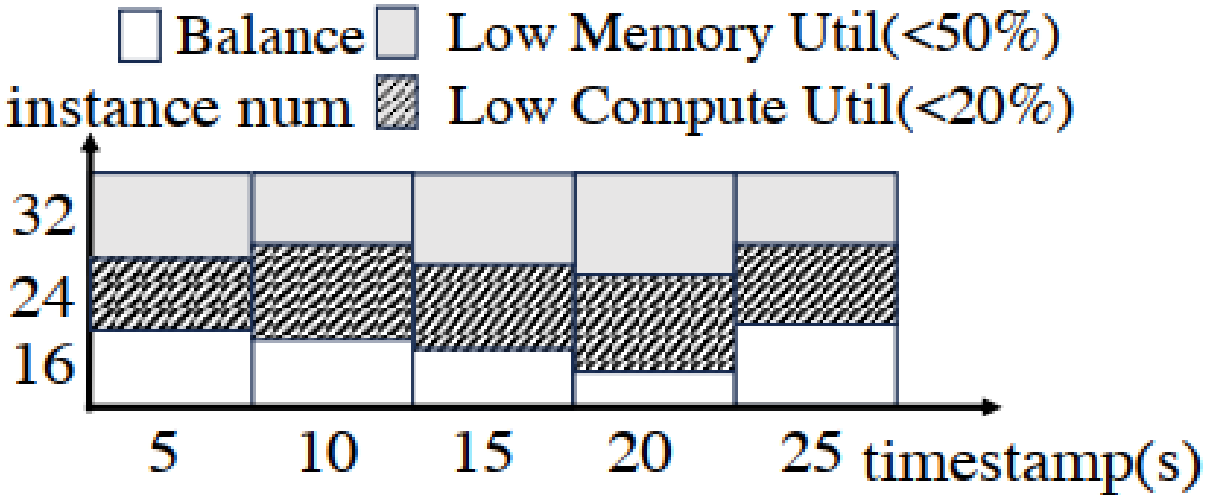
(c) Computational util with different DOP

Challenges of deploying LLM services

- More GPUs support long-text but perform poorly
- **Dynamic KV Cache Complicates Resource Management**

Dynamic KV Cache Complicates Resource Management

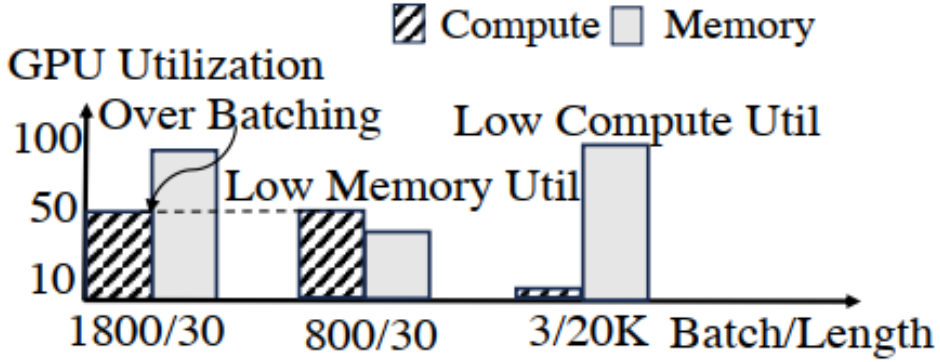
- Final context length of inference tasks is unknown and highly variable



(a) Many instances are in a state of low computational/memory utilization.

Dynamic KV Cache Complicates Resource Management

- Final context length of inference tasks is unknown and highly variable
  - Large memory causes waste, while small memory leads to a reduced batch size



(b) Long request competes with short requests, resulting in low batch size and low GPU util.

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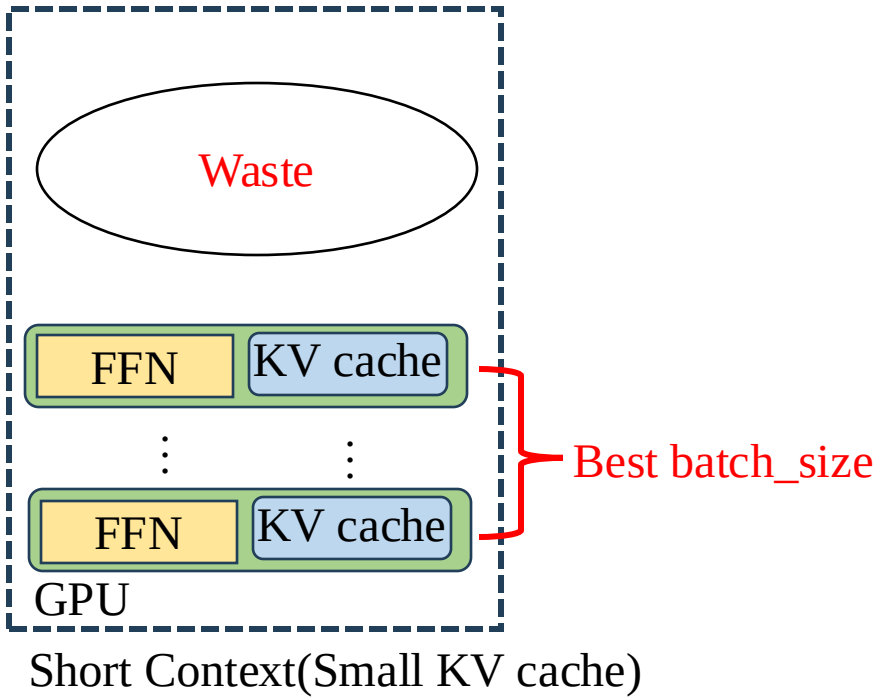
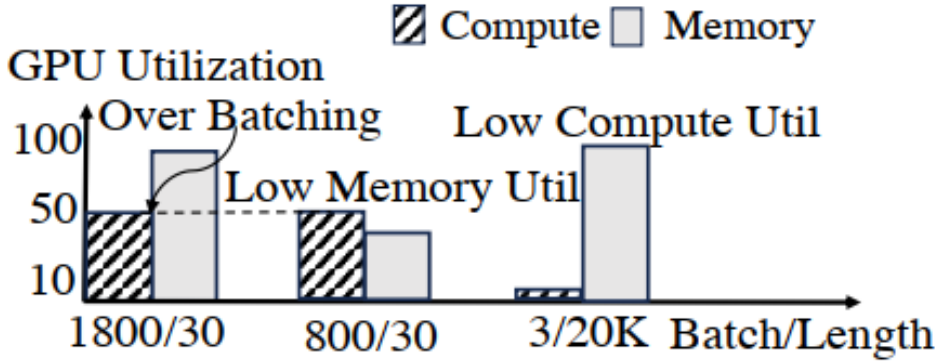


Short Context(Small KV cache)



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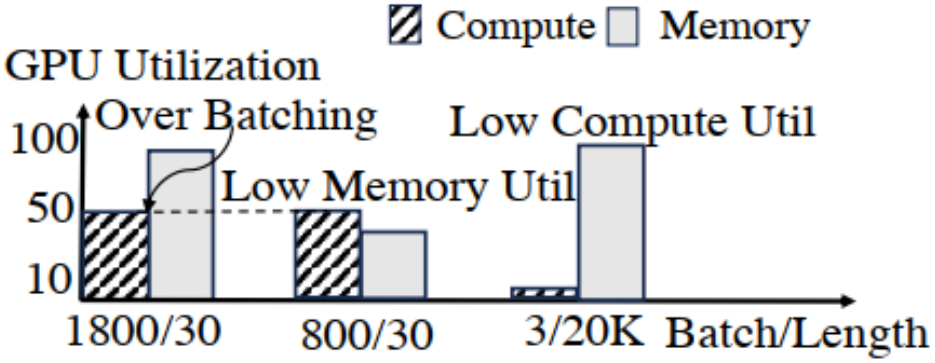
Dynamic KV Cache Complicates Resource Management

- Final context length of inference tasks is unknown and highly variable
  - Small memory leads to a reduced batch size, lowering GPU computational utilization



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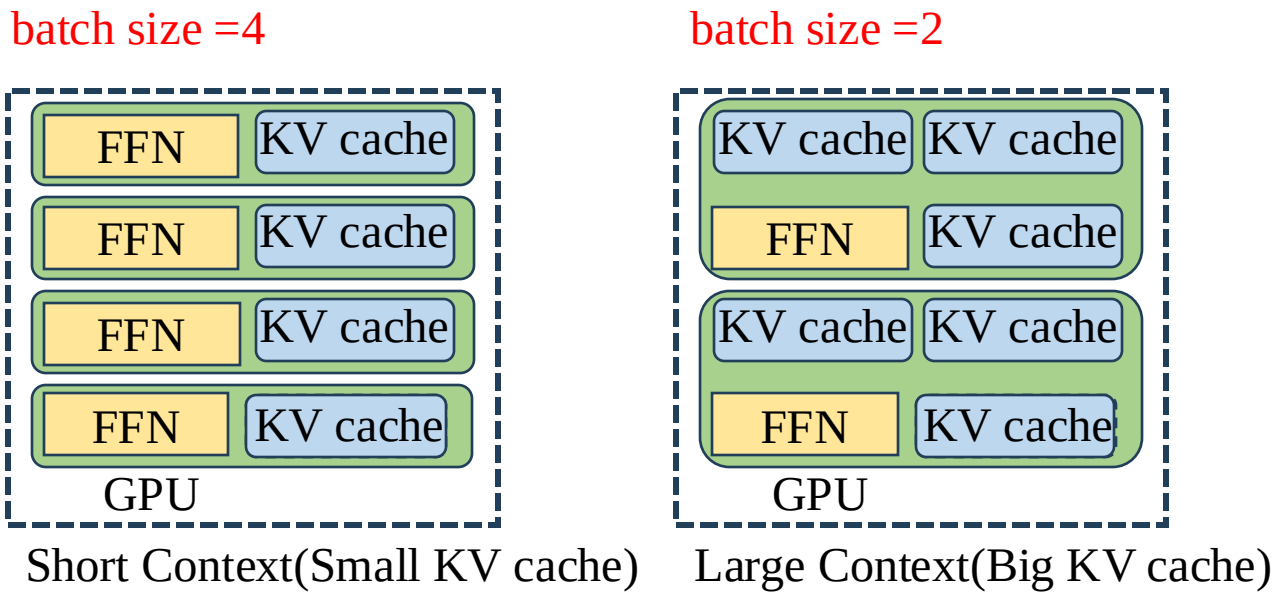
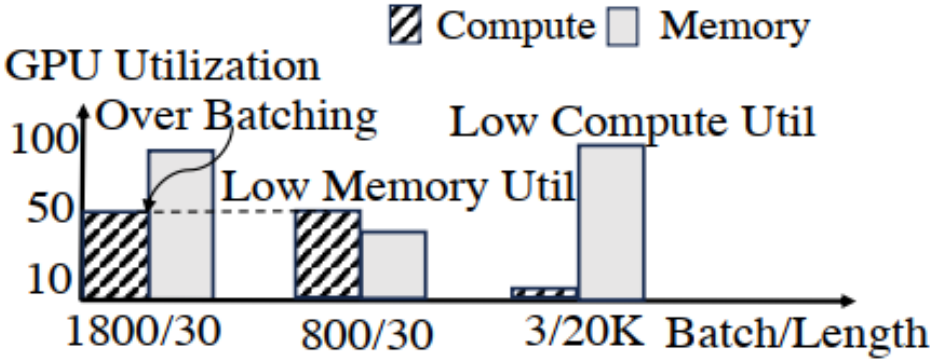


Short Context(Small KV cache)

Large Context(Big KV cache)



(b) Long request competes with short requests, resulting in low batch size and low GPU util.

Dynamic KV Cache Complicates Resource Management

- Dynamically allocating appropriate video memory for each task becomes crucial！
  - Large memory causes waste, while small memory leads to a reduced batch size

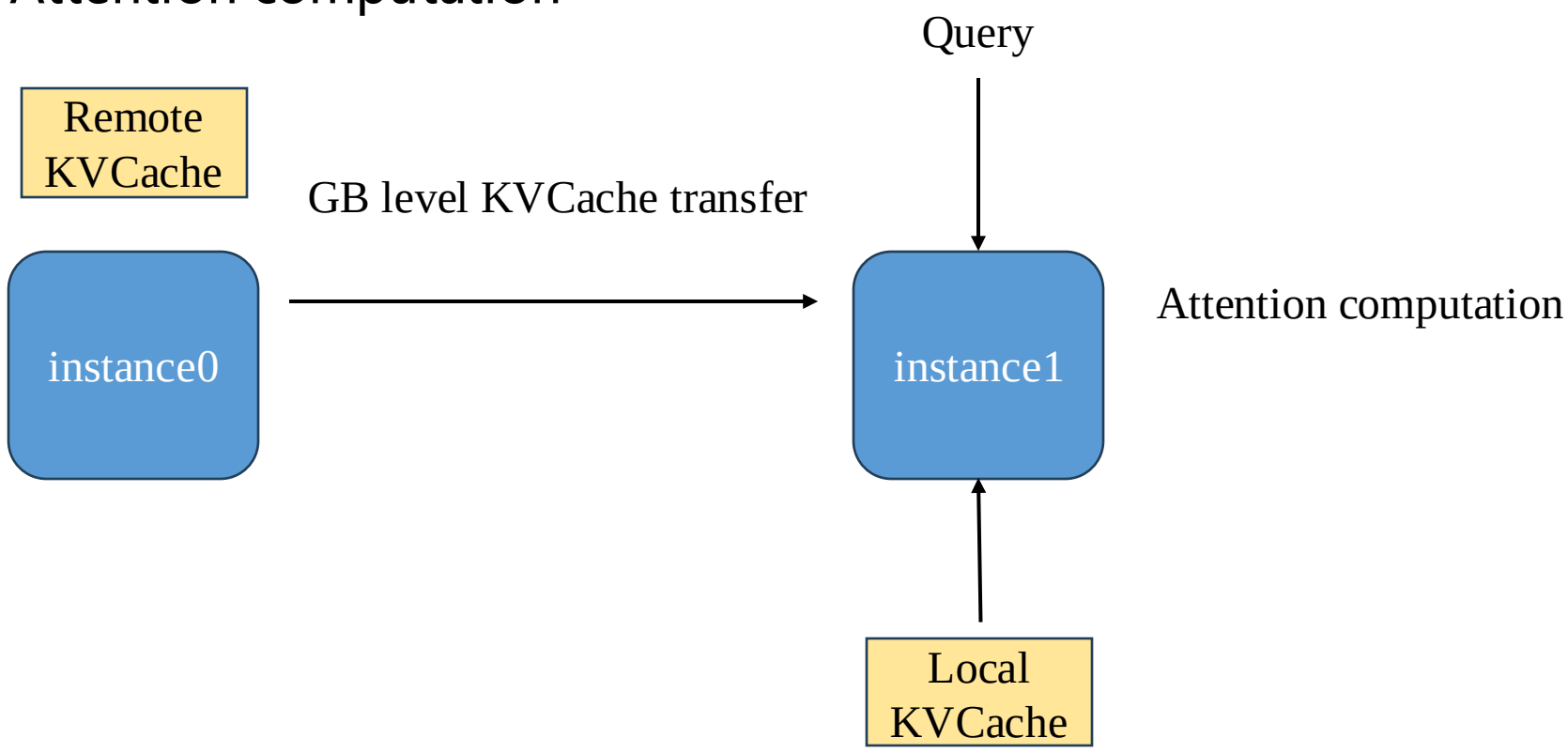
Design

- ❑ DistAttention
- ❑ Cluster-scale Throughput Optimization

Design

❑ DistAttention

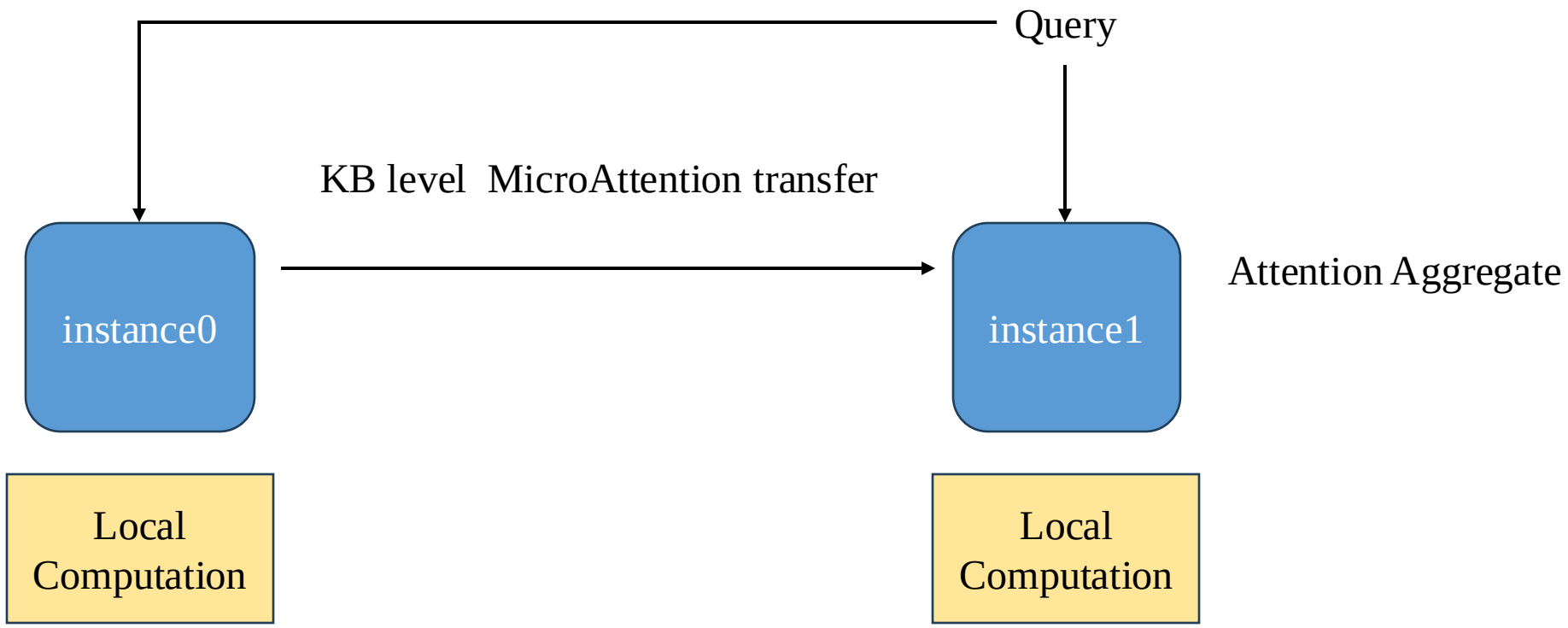
❖ Normal Attention computation



Design

❑ DistAttention

❖ Distributed Attention computation



Cluster-scale Throughput Optimization

- ❑ Debtors and Creditors
- ❑ Greedy Algorithm based on Performance model

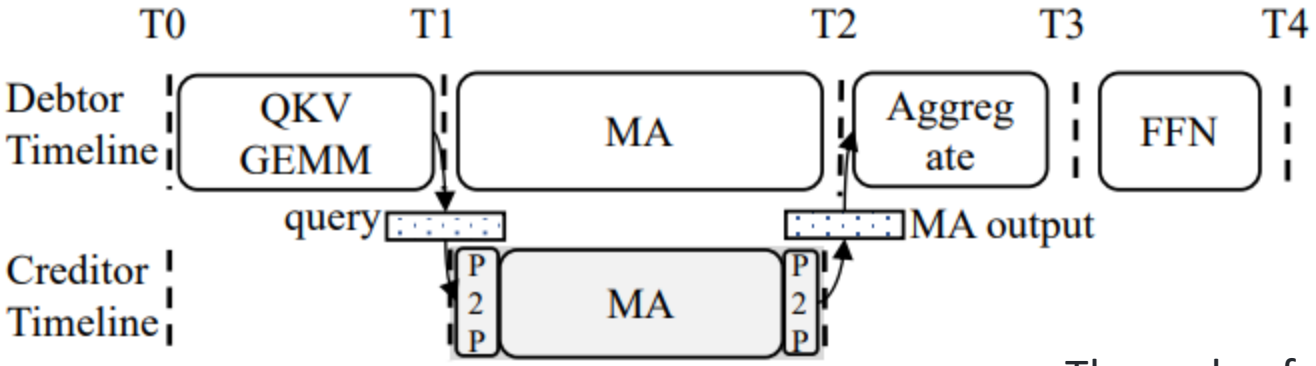
Cluster-scale Throughput Optimization

- **Debtors and Creditors**
  - Local First
  - Limited Offload

Cluster-scale Throughput Optimization

❑ Debtors and Creditors

- ❖ Local First
- ❖ Limited Offload



The scale of offloaded KVCache not exceed the local's, for overlapping the local computation with data transfers and remote computation

Cluster-scale Throughput Optimization

- **Greedy Algorithm based on Performance model**
  - Performance model
  - Greedy Algorithm

Cluster-scale Throughput Optimization

❑ Greedy Algorithm based on Performance model

❖ Performance model

$$T^{lyr}(\beta, S) = T^{natn}(\beta) + T^{atn}(S) = \frac{W(\beta)}{f(\beta)} + \sum_{r=1}^{\beta} \frac{S^r}{g(S)}$$

One Transformer layer's Throughput
β is batch size
S is length of Sequence

Cluster-scale Throughput Optimization

❑ Greedy Algorithm based on Performance model

❖ Performance model

$$T^{lyr}(\beta, S) = T^{natn}(\beta) + T^{atn}(S) = \frac{W(\beta)}{f(\beta)} + \sum_{r=1}^{\beta} \frac{S^r}{g(S)}$$

Non Attention Layer is dictated by batch size
Attention Layer is dictated by the requests' length S.

Cluster-scale Throughput Optimization

❑ Greedy Algorithm based on Performance model

❖ Performance model

$$T^{lyr}(\beta, S) = T^{natn}(\beta) + T^{atn}(S) = \frac{W(\beta)}{f(\beta)} + \sum_{r=1}^{\beta} \frac{S^r}{g(S)}$$

$W(\beta)$: Workload of non-Attention layer
S^r: rth Sequence of batch
$f(\beta), g(S)$: The GPU's real performance

Cluster-scale Throughput Optimization

❑ Greedy Algorithm based on Performance model

❖ Performance model

$$T_{dbt}^{lyr}(\beta', K^d) = T^{lyr} - \frac{K^d}{g(S)}$$

$$T_{cdt}^{lyr}(\beta, K^c) = T^{lyr} + \frac{K^c}{g(S)}$$

Affect of KVCache's computation performance

Cluster-scale Throughput Optimization

❑ Greedy Algorithm based on Performance model

❖ Performance model

$$T_{dbt}^{lyr}(\beta', K^d) = T^{lyr} - \frac{K^d}{g(S)}$$

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Affect of KVCache's computation performance

$$TPS = \frac{\beta}{n \cdot T^{layer}}$$

A LLM instance's Throughput with n layer, batch β

$$TPS_{cluster} = \sum_{i=1}^{M} TPS_i$$

A cluster deployed with M instances'TPS

Cluster-scale Throughput Optimization

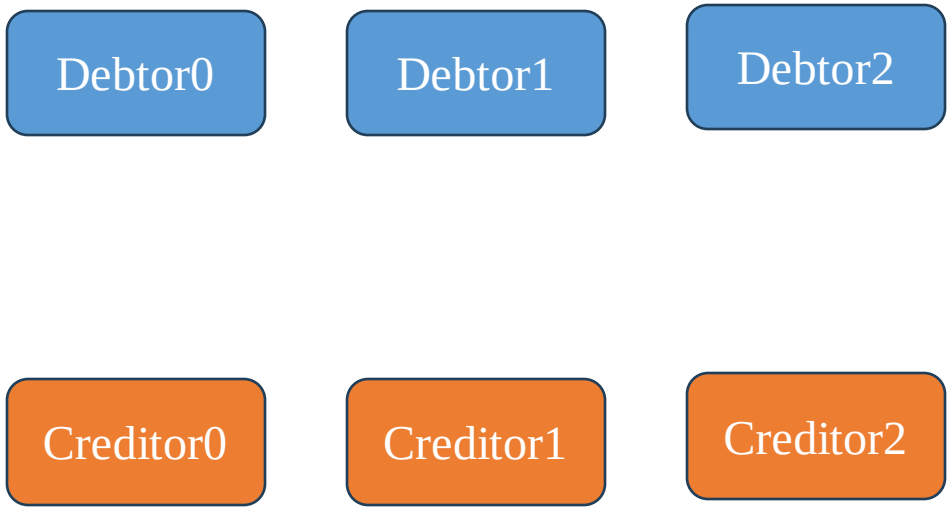
❑ Greedy Algorithm based on Performance model

- ❖ Greedy Algorithm
  - ➢ maximize the cluster throughput with DistAttention approximately
  - ➢ pairing overloaded debtor instances with the free creditor

Cluster-scale Throughput Optimization

❑ Greedy Algorithm based on Performance model

❖ Greedy Algorithm



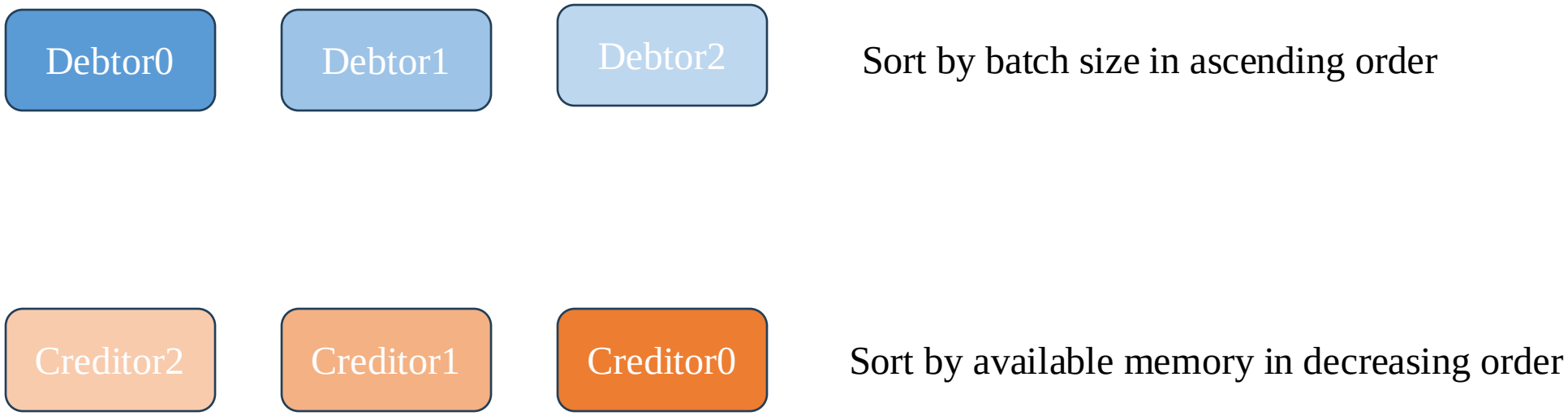
Debtors: Instance of batch size lower than β^{thres}

Creditors: Instance of memory usage lower than U^{thres}

Cluster-scale Throughput Optimization

❑ Greedy Algorithm based on Performance model

❖ Greedy Algorithm



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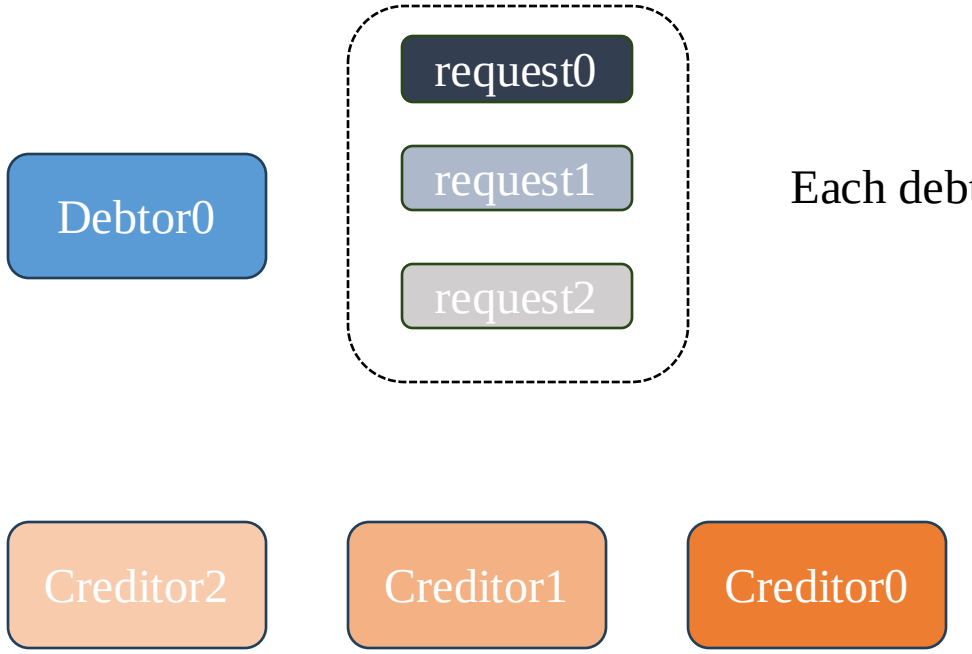

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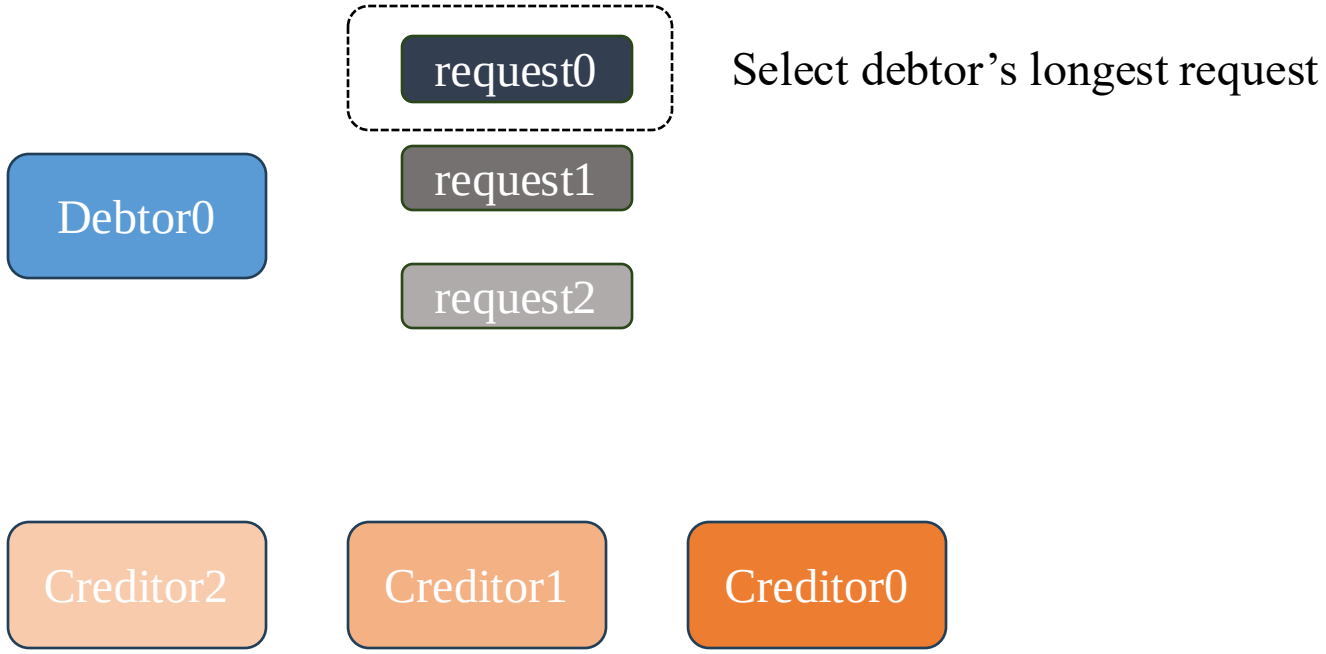

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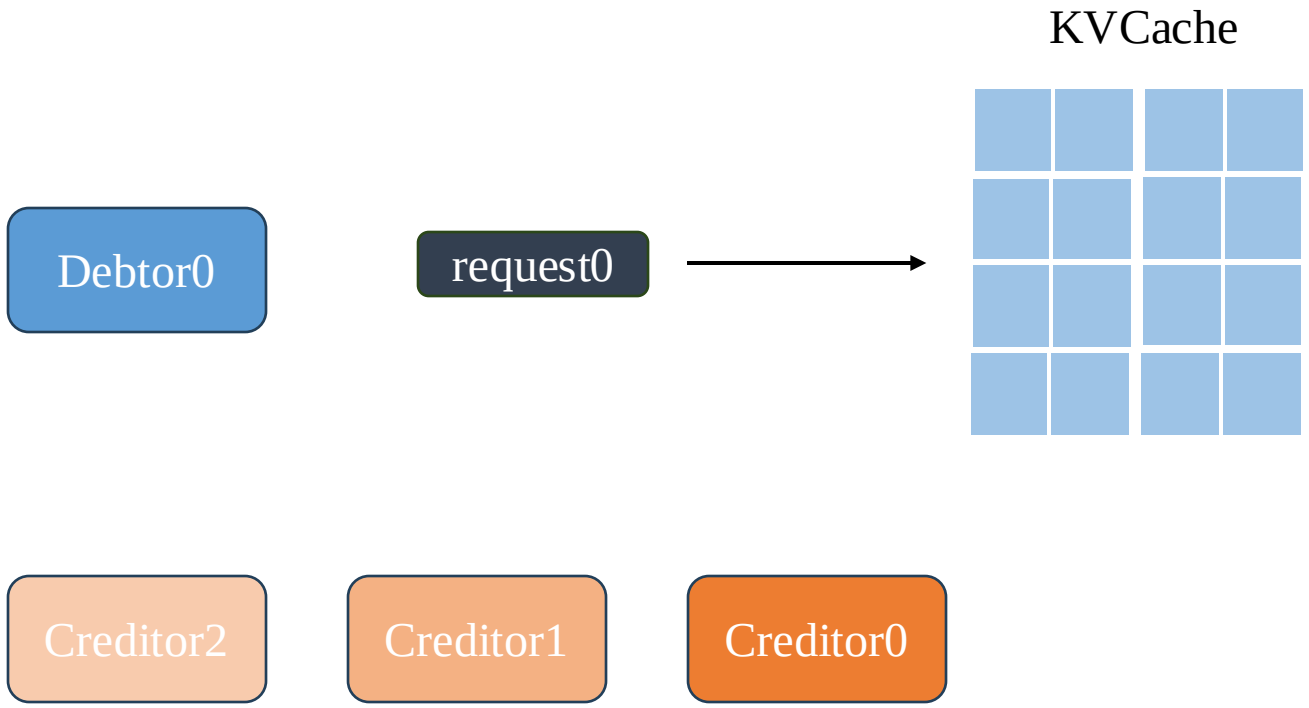

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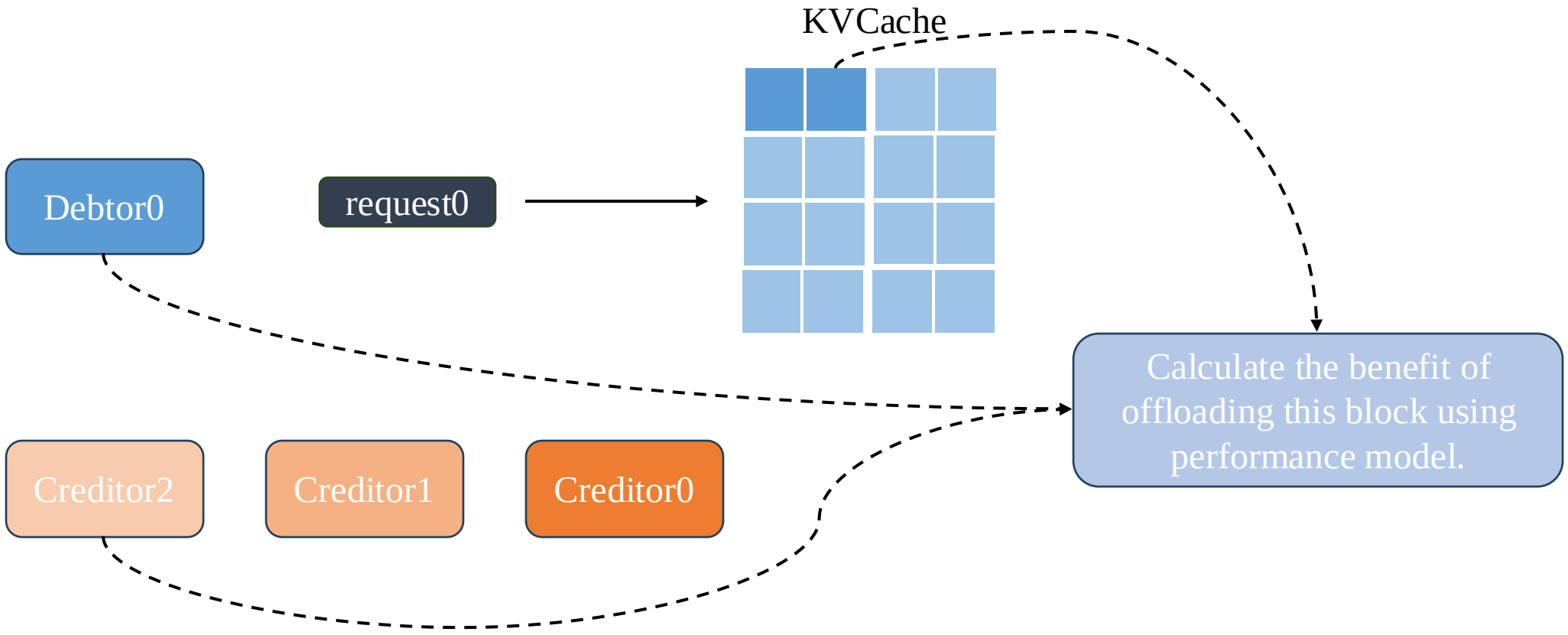
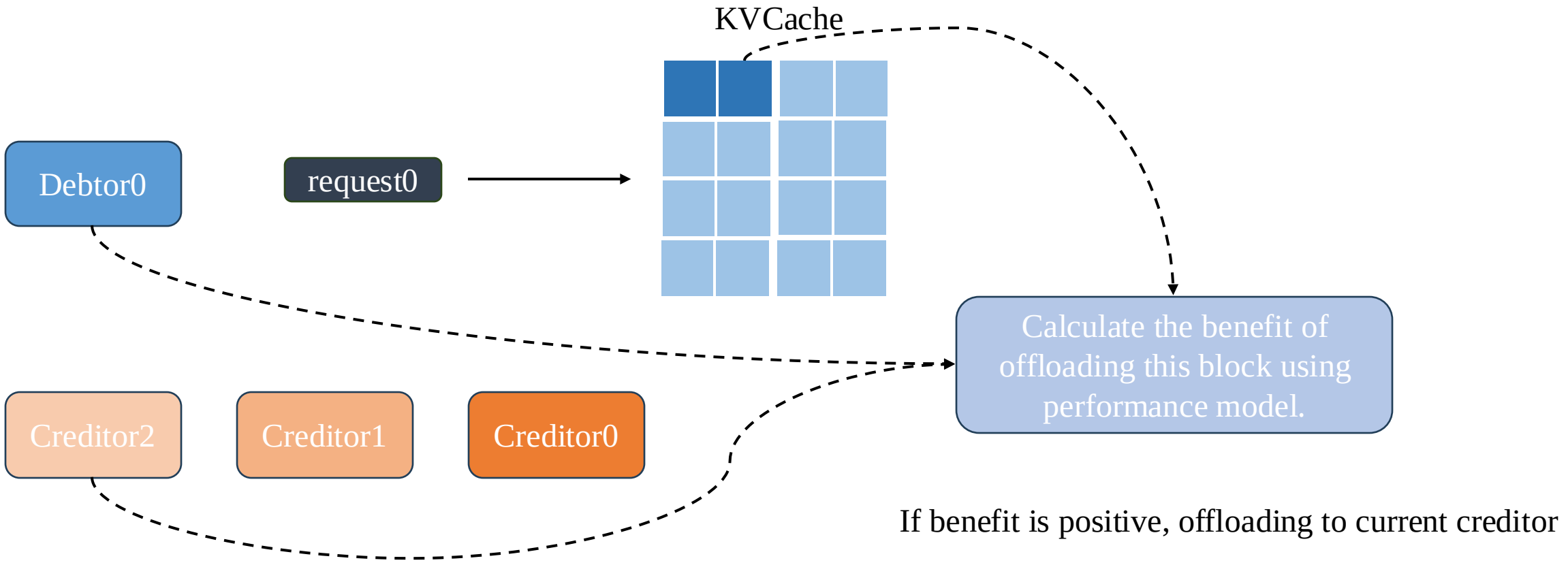
❖ Greedy Algorithm



Cluster-scale Throughput Optimization

❑ Greedy Algorithm based on Performance model

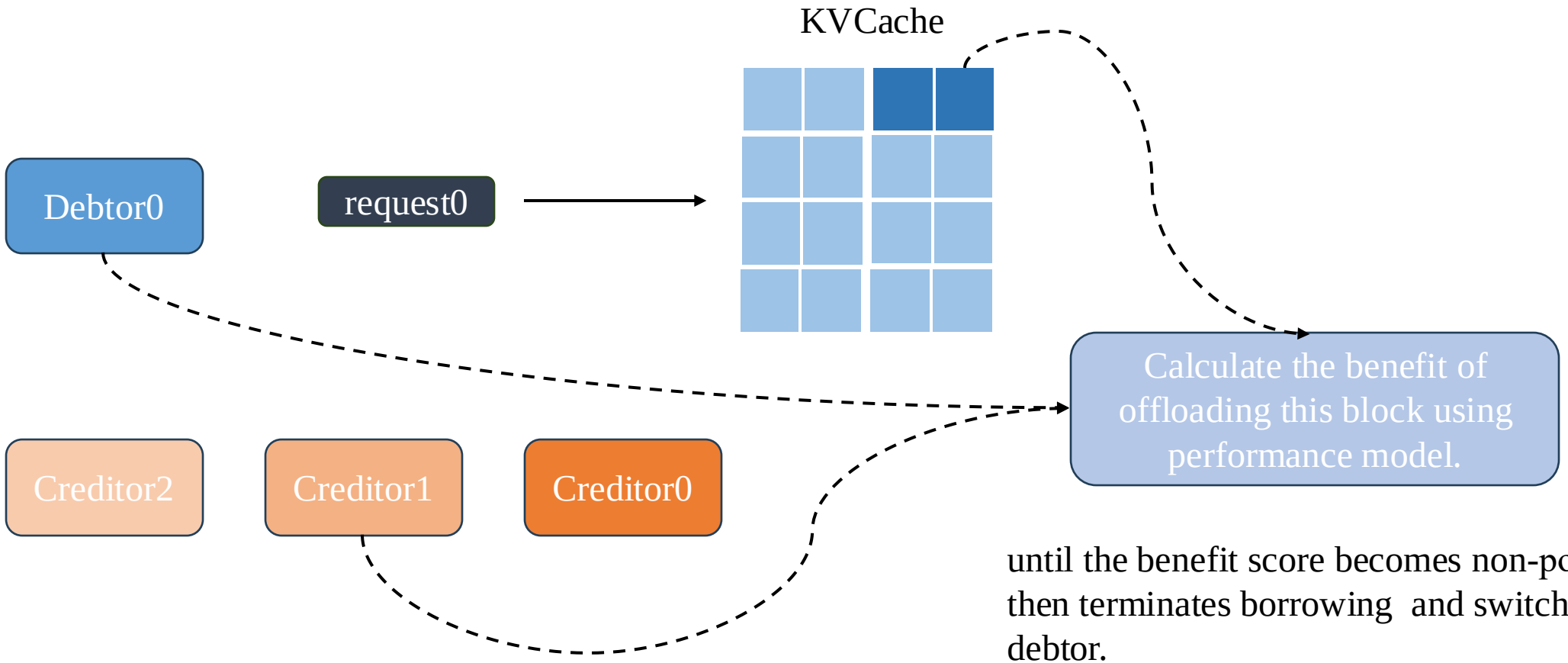
❖ Greedy Algorithm



Cluster-scale Throughput Optimization

❑ Greedy Algorithm based on Performance model

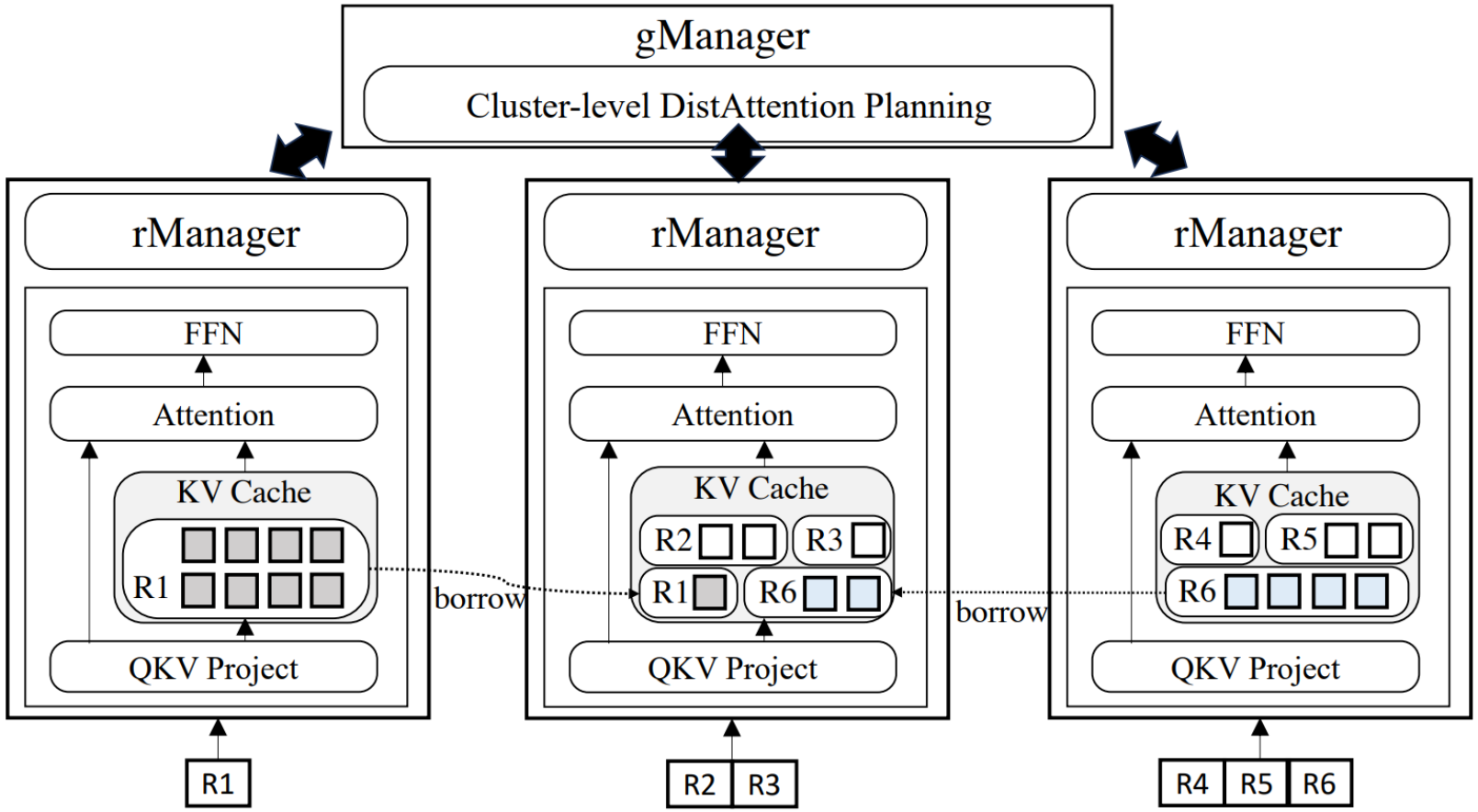
❖ Greedy Algorithm



until the benefit score becomes non-positive (≤0), then terminates borrowing and switches to next debtor.

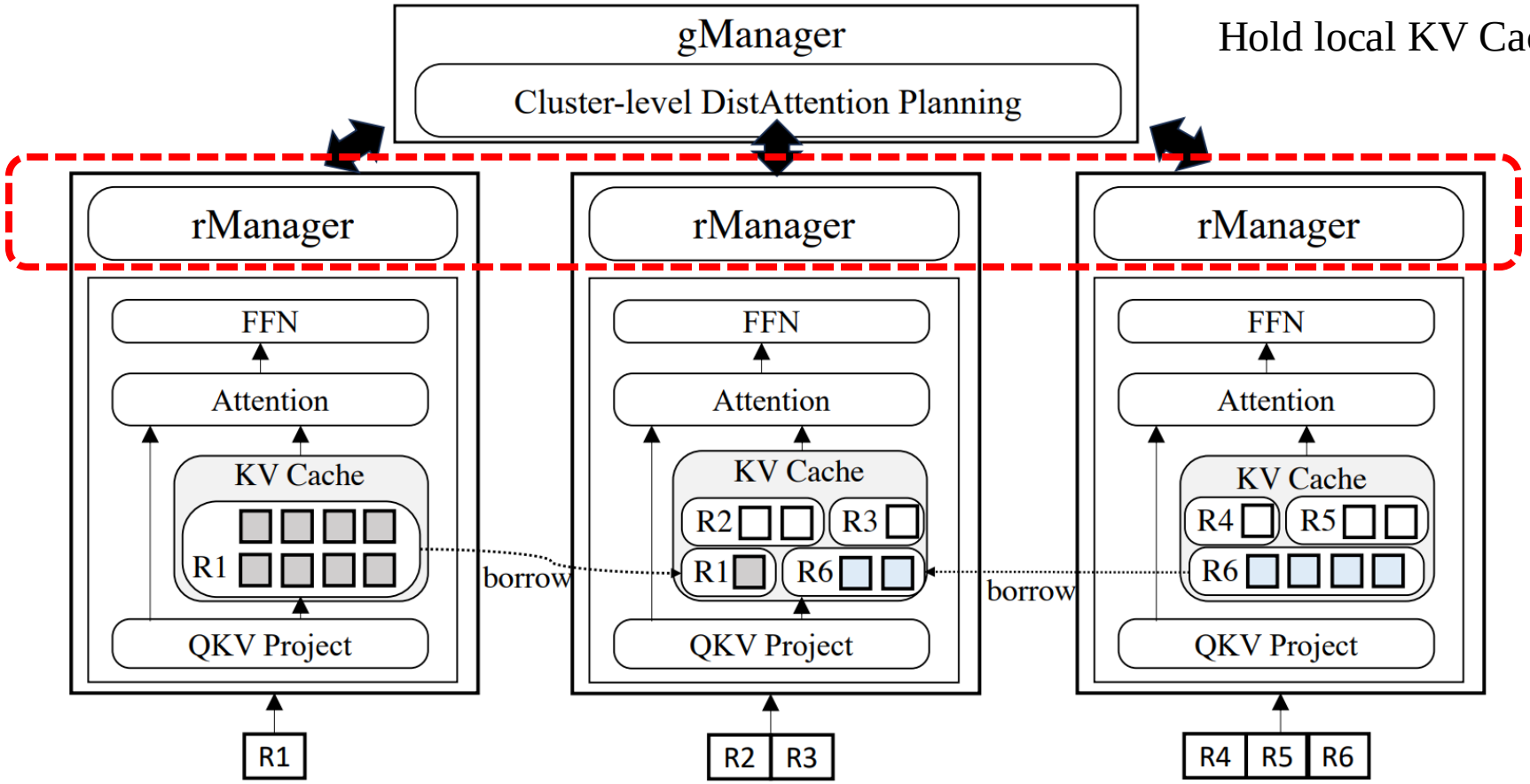
Implement

❑ gManager & rManager



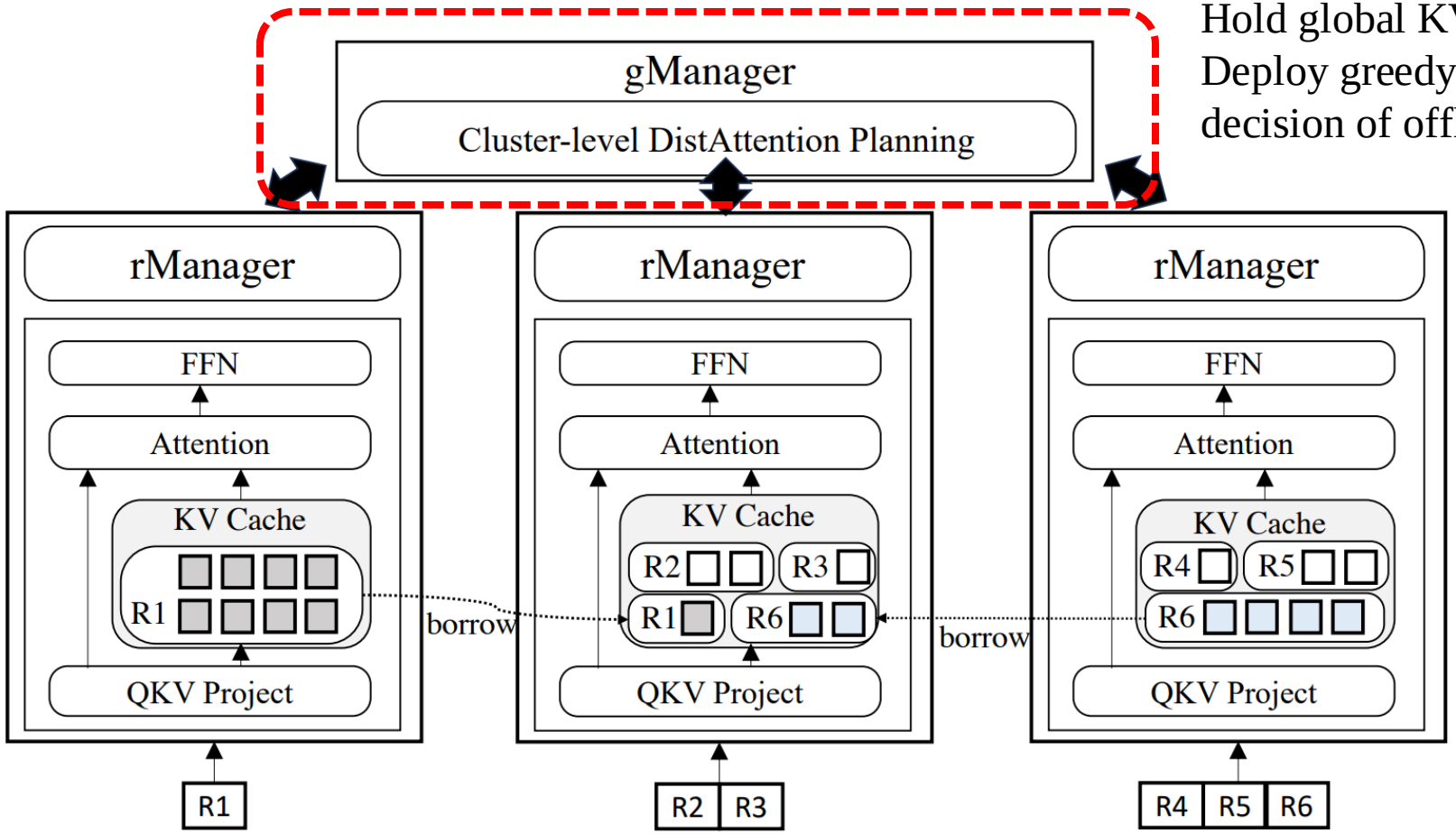
Implement

❑ gManager & rManager



Implement

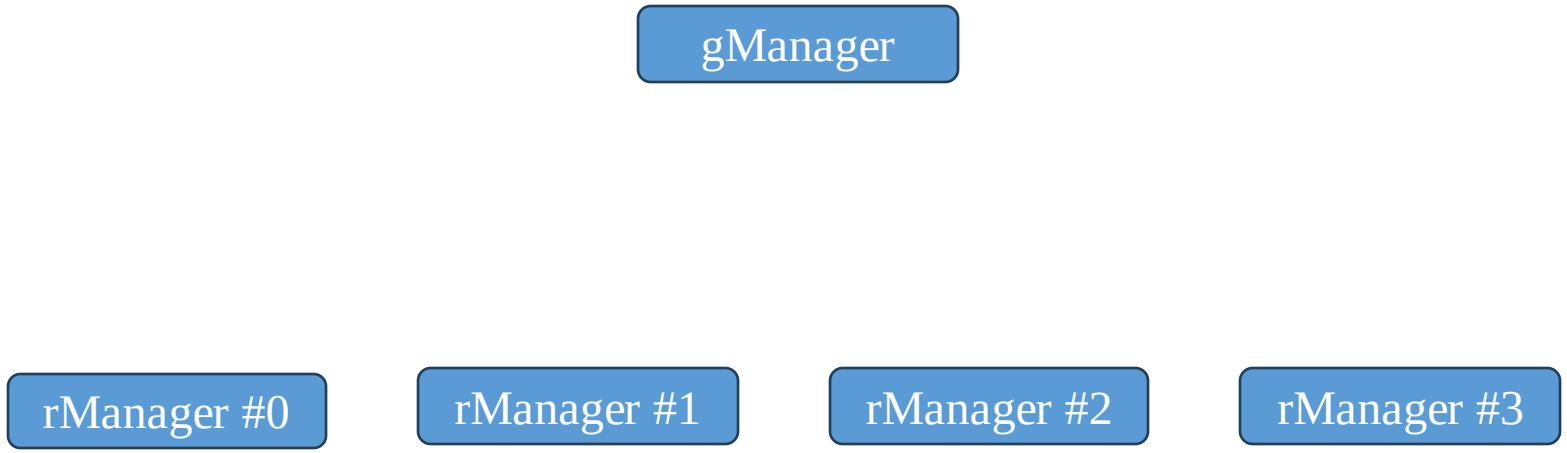
❑ gManager & rManager



Hold global KV Cache distribution
Deploy greedy Algorithm, make decision of offload KVCache

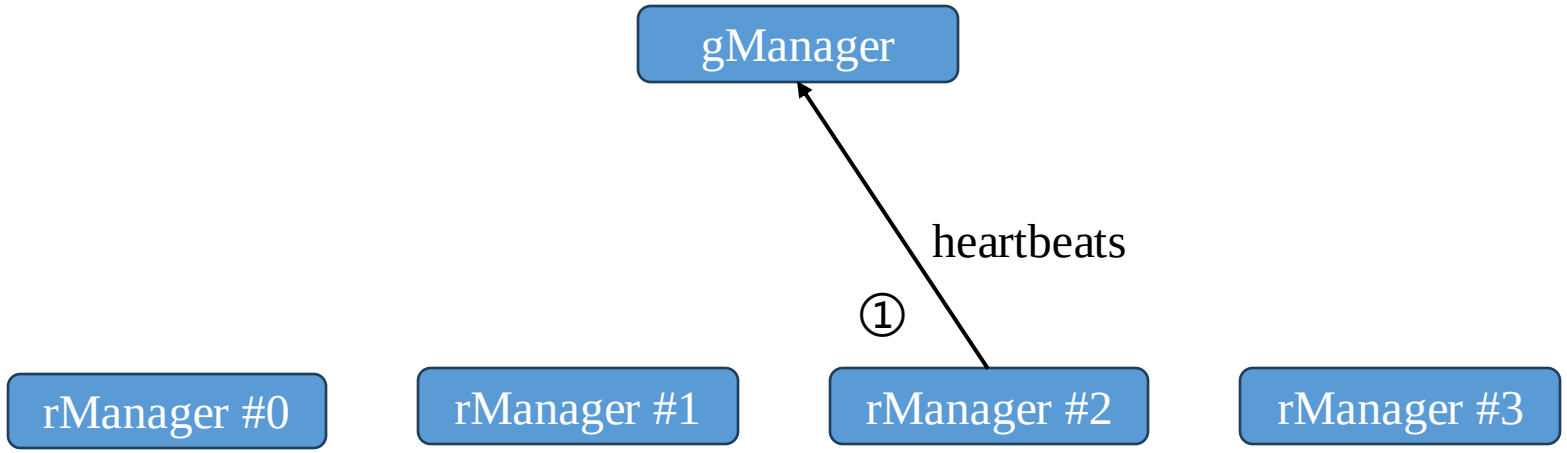
gManager & rManager

❑ workflow



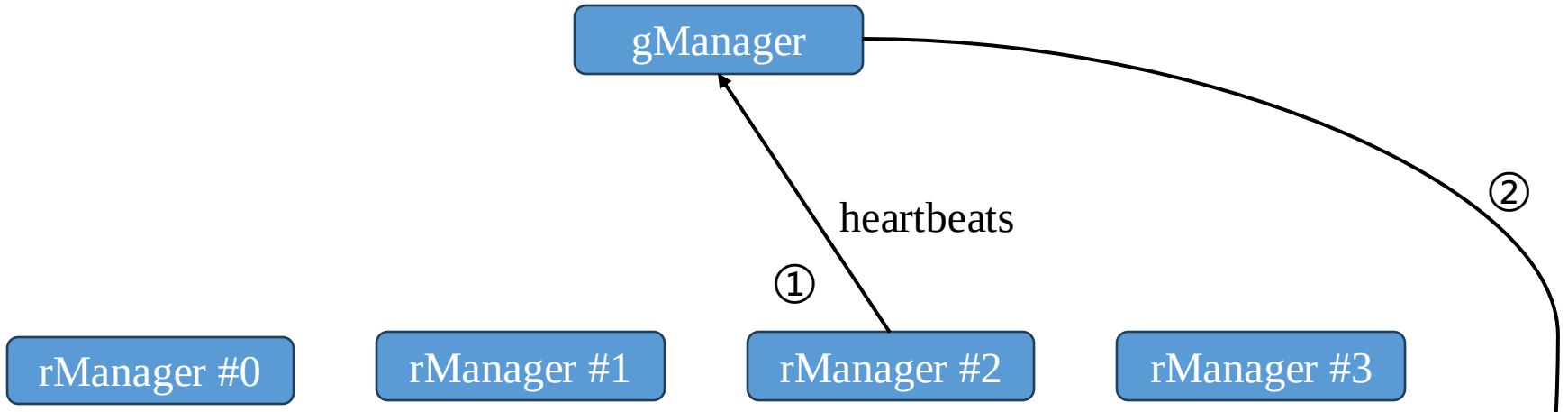
gManager & rManager

❑ workflow



gManager & rManager

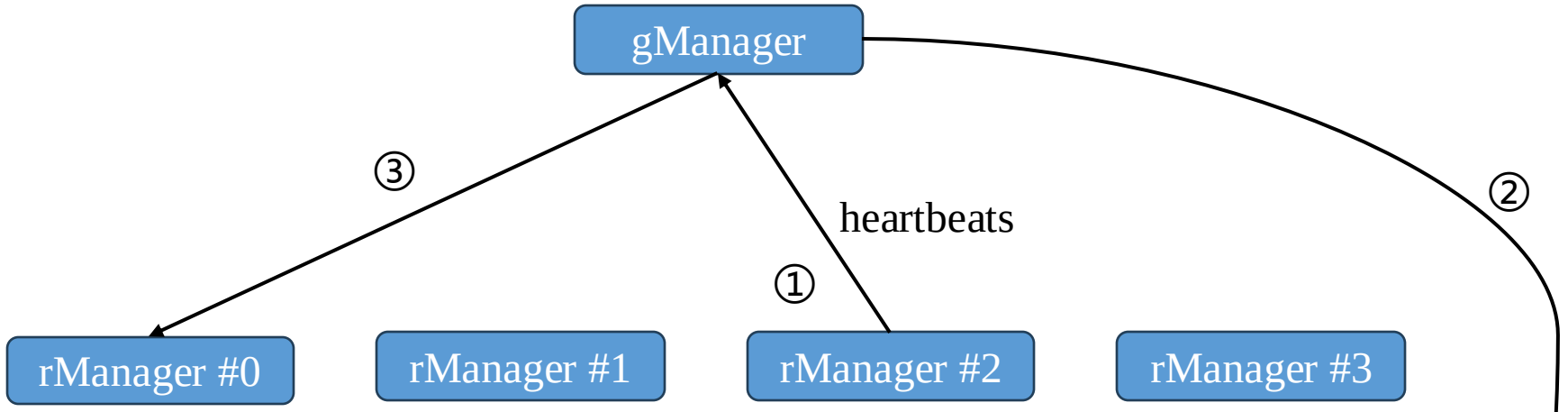
❑ workflow



Req ID	Length	Instance0		Instance1	
		Block num	Is local	Block num	Is local
0	100k	1562	False	4688	False
…	…	…	…	…	…

gManager & rManager

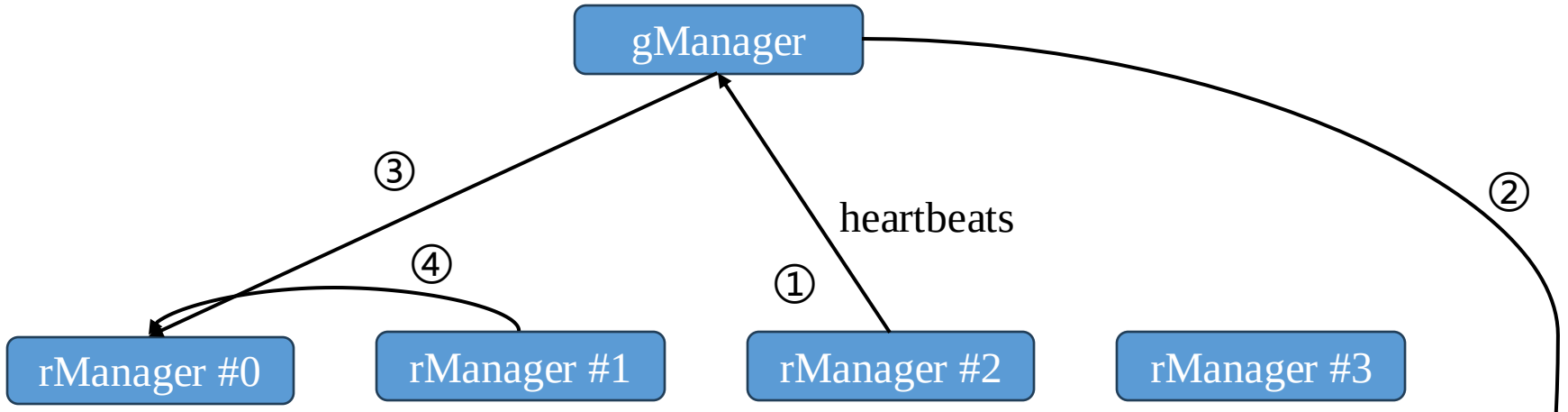
❑ workflow



Req ID	Length	Instance0		Instance1	
		Block num	Is local	Block num	Is local
0	100k	1562	False	4688	False
…	…	…	…	…	…

gManager & rManager

❑ workflow



Req ID	Length	Instance0		Instance1	
		Block num	Is local	Block num	Is local
0	100k	1562	False	4688	False
…	…	…	…	…	…

Evaluation

❑ Experimental Setup

- ❖ 4 nodes and 32 GPUs. (each node 8 A100, 80G)
- ❖ GPUs are connected via NVLink (600GB/s) within each node
- ❖ Ethernet (125MB/s) across nodes
- ❖ Model: LLaMA2(7B, 13B, 70B)

Evaluation

❑ Traces

- ❖ 9 traces with different context length ranges and length distributions
- ❖ Trace 0
  - ➢ open-source dataset ShareGPT4
  - ➢ contains GPT-4 conversation records.
- ❖ Trace 1-2
  - ➢ subsets of ShareGPT4
  - ➢ assess performance on different length distribution
- ❖ Trace 3-8
  - ➢ opensource dataset L-Eval and these online service
  - ➢ assess performance on longer contexts

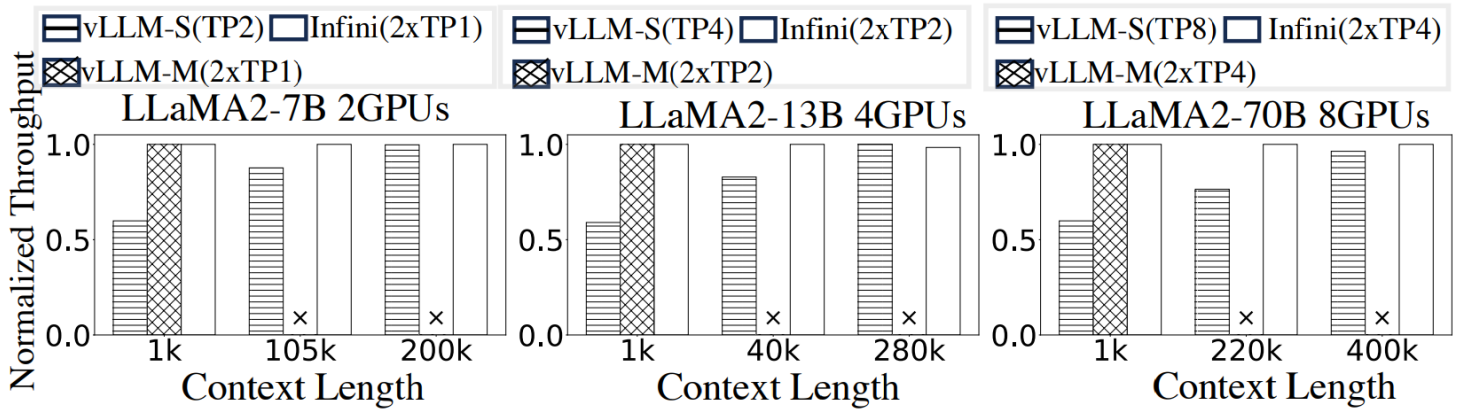
Evaluation

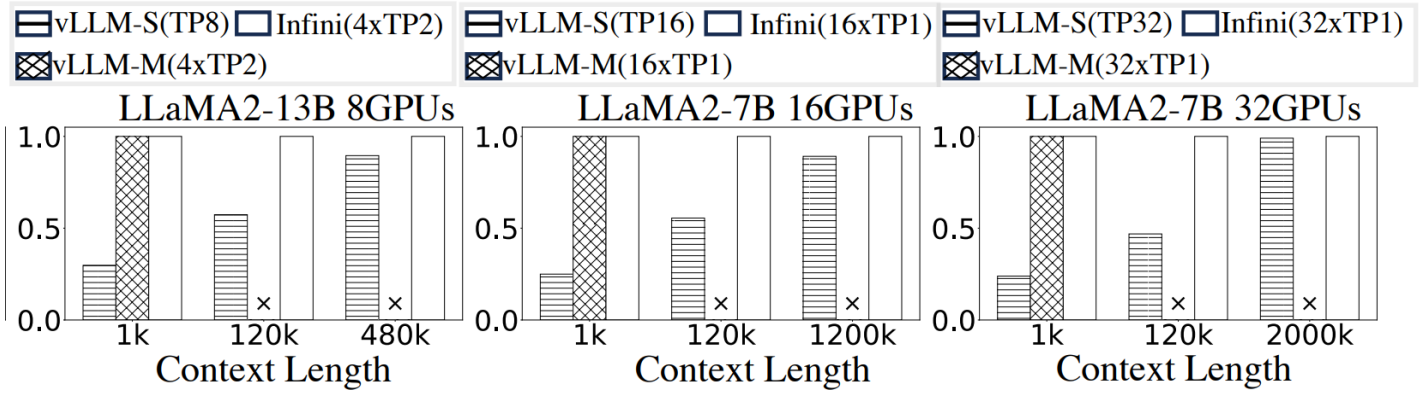
❑ Comparison

- ❖ focuses on comparing Infinite-LLM with static model parallelism and resource planning (vLLM signal worker & multi workers).
- ❖ infinite-LLM & vLLM multi wokers support multiple instances

Evaluation

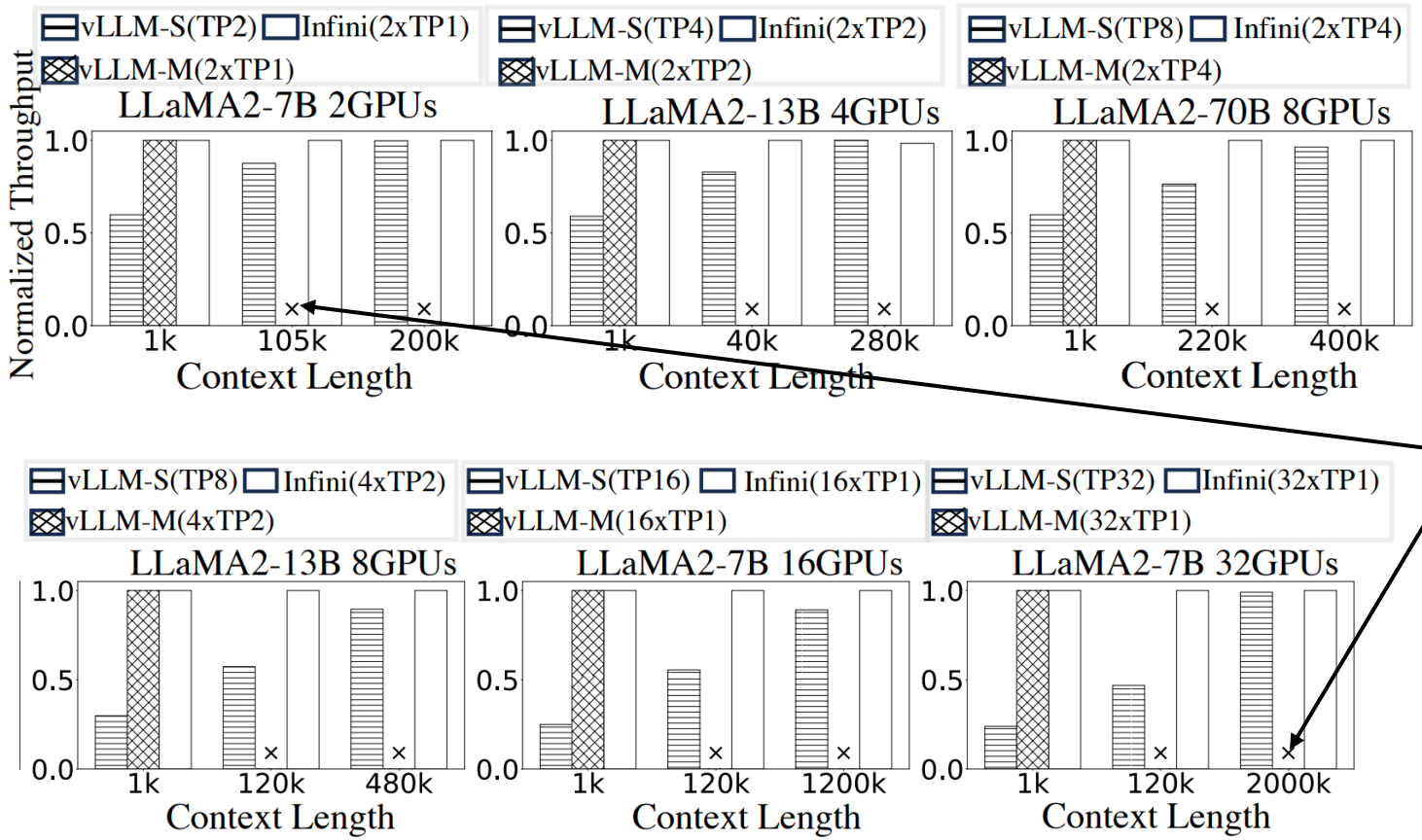
❑ Comparison(context length)





Evaluation

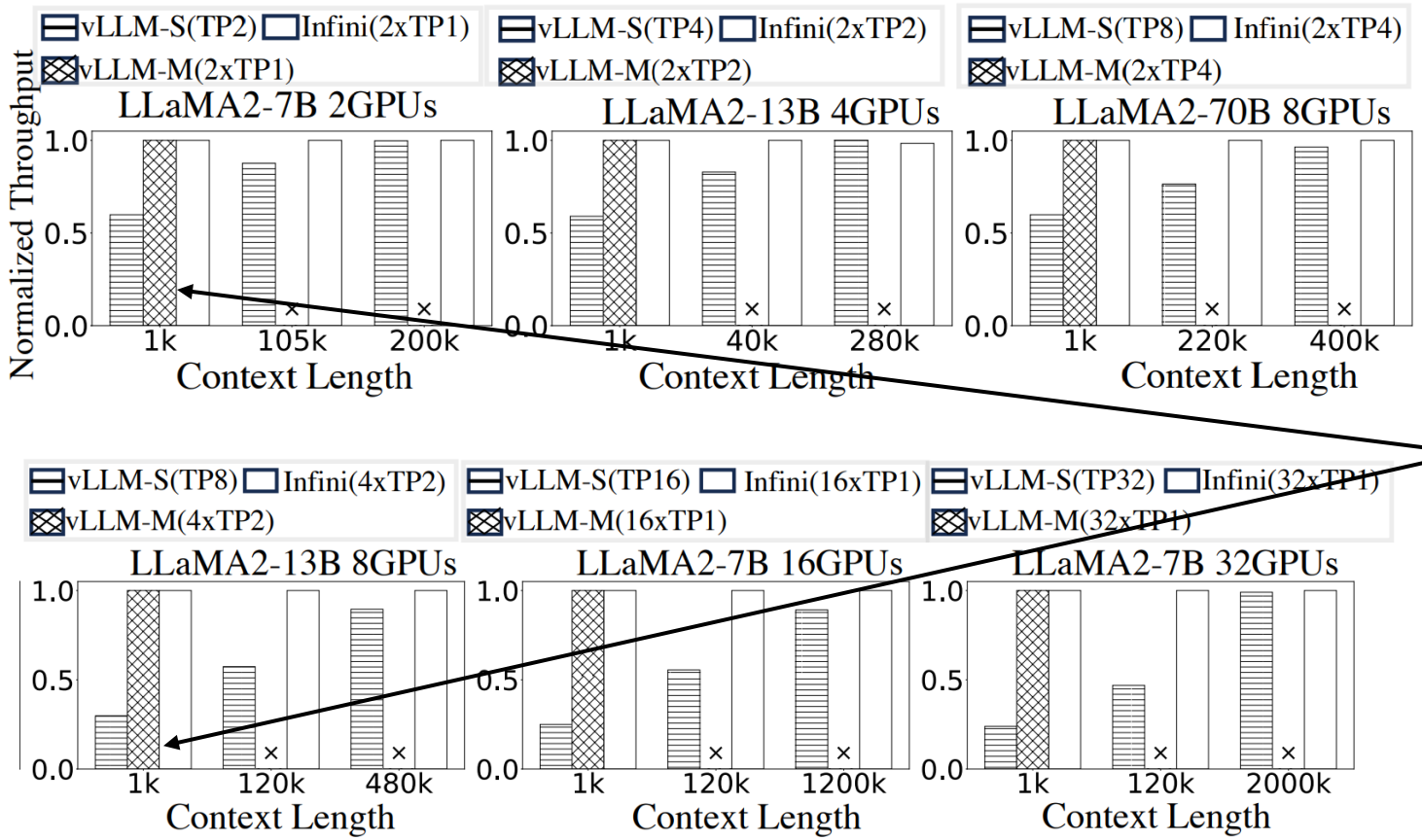
❑ Comparison(context length)



Support long context requirement
Compared with vLLM-M

Evaluation

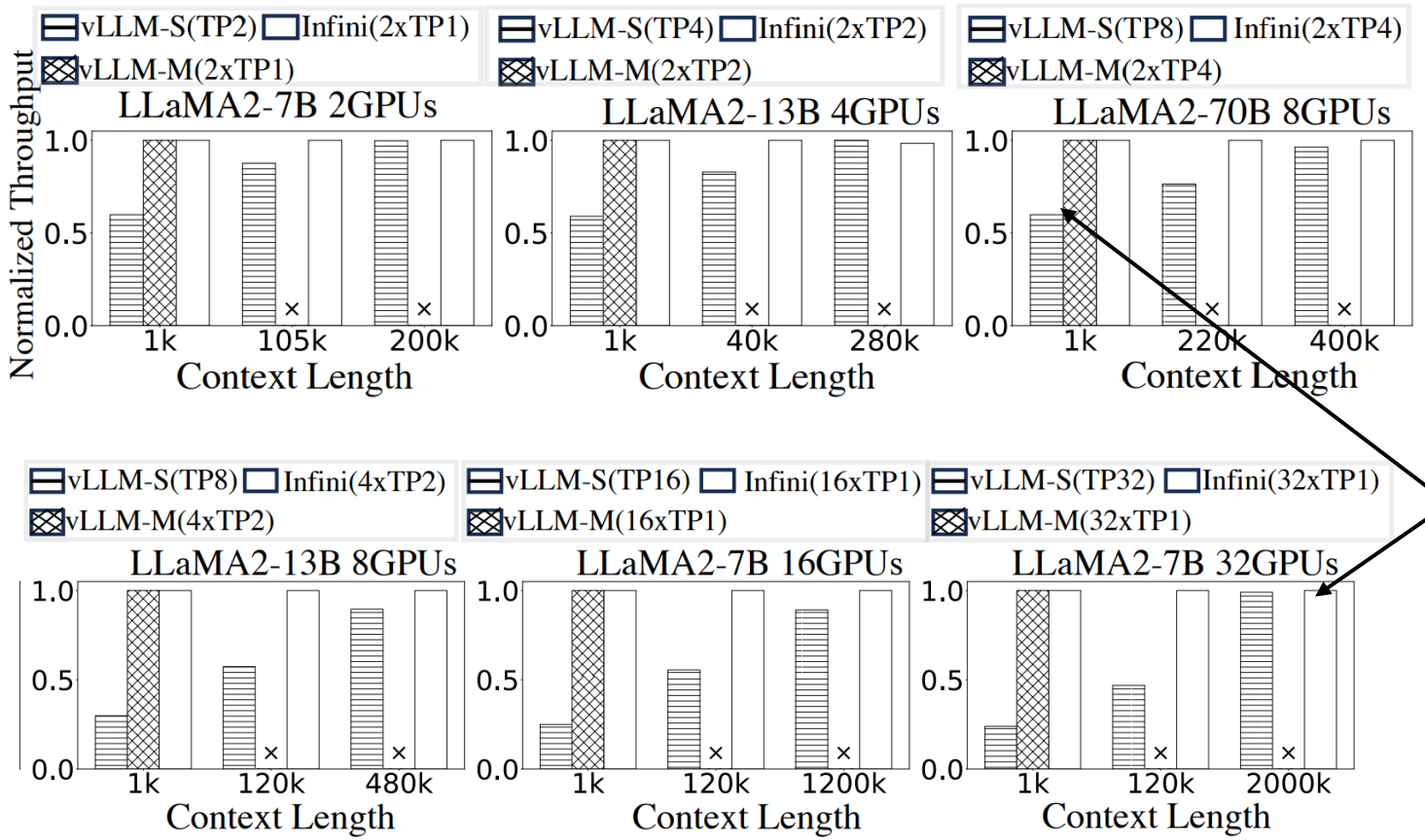
❑ Comparison(context length)



Under short sequences, the throughput is comparable to vLLM-M.

Evaluation

❑ Comparison(context length)

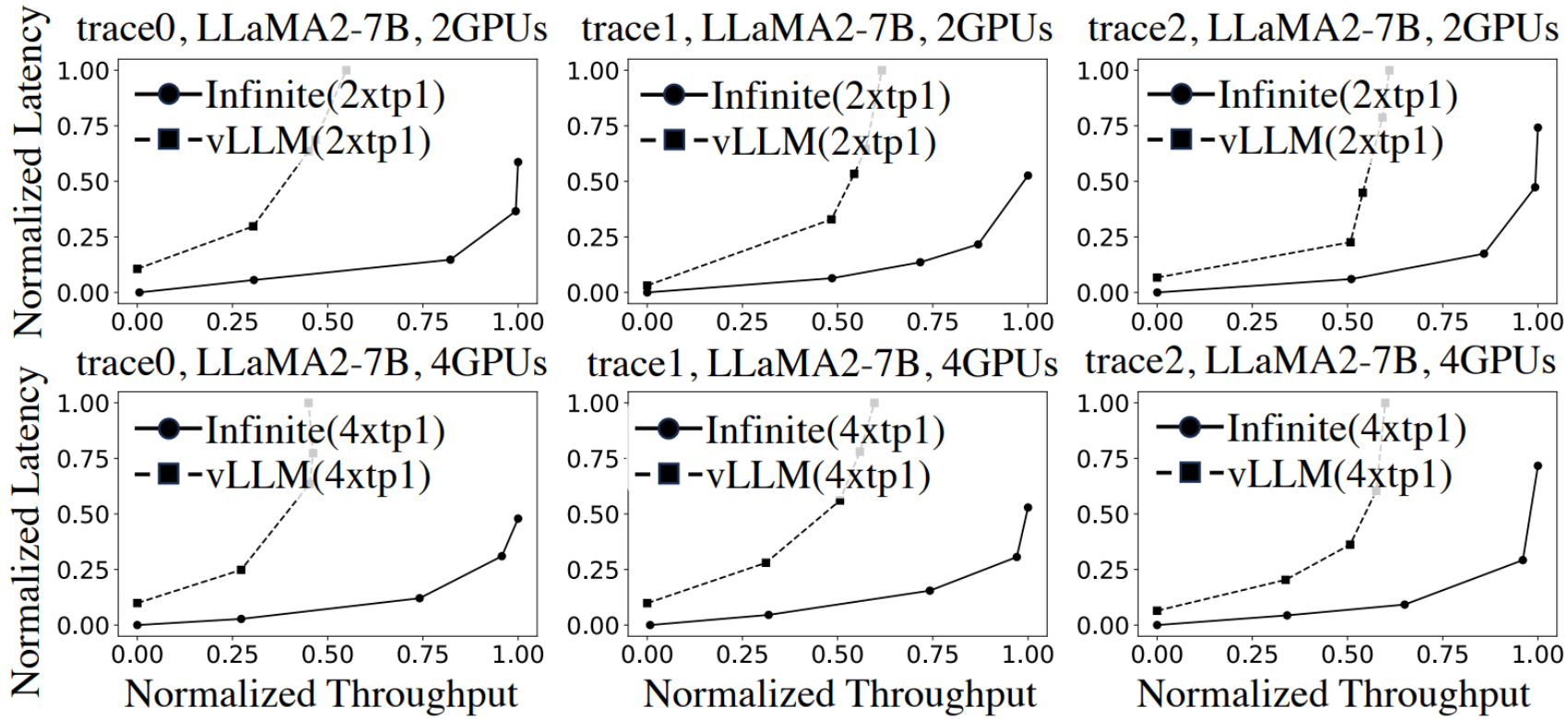


For short sequences
Infinite-LLM achieves **1.4x to 5.3x throughput improvement.**

For long sequences
both frameworks support **similar maximum context lengths**, but Infinite-LLM reduces **OOM risks.**

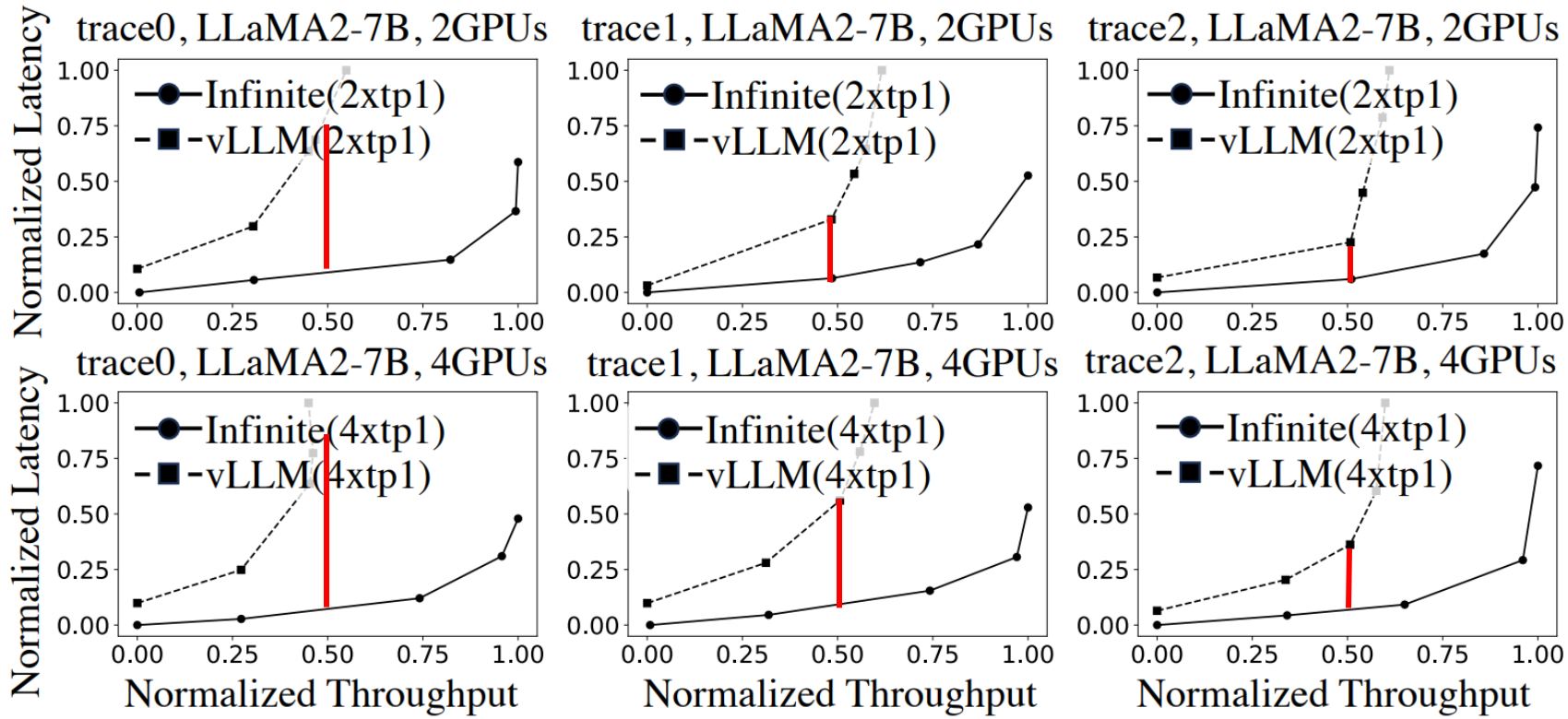
Evaluation

❑ Comparison(end-to-end performance)



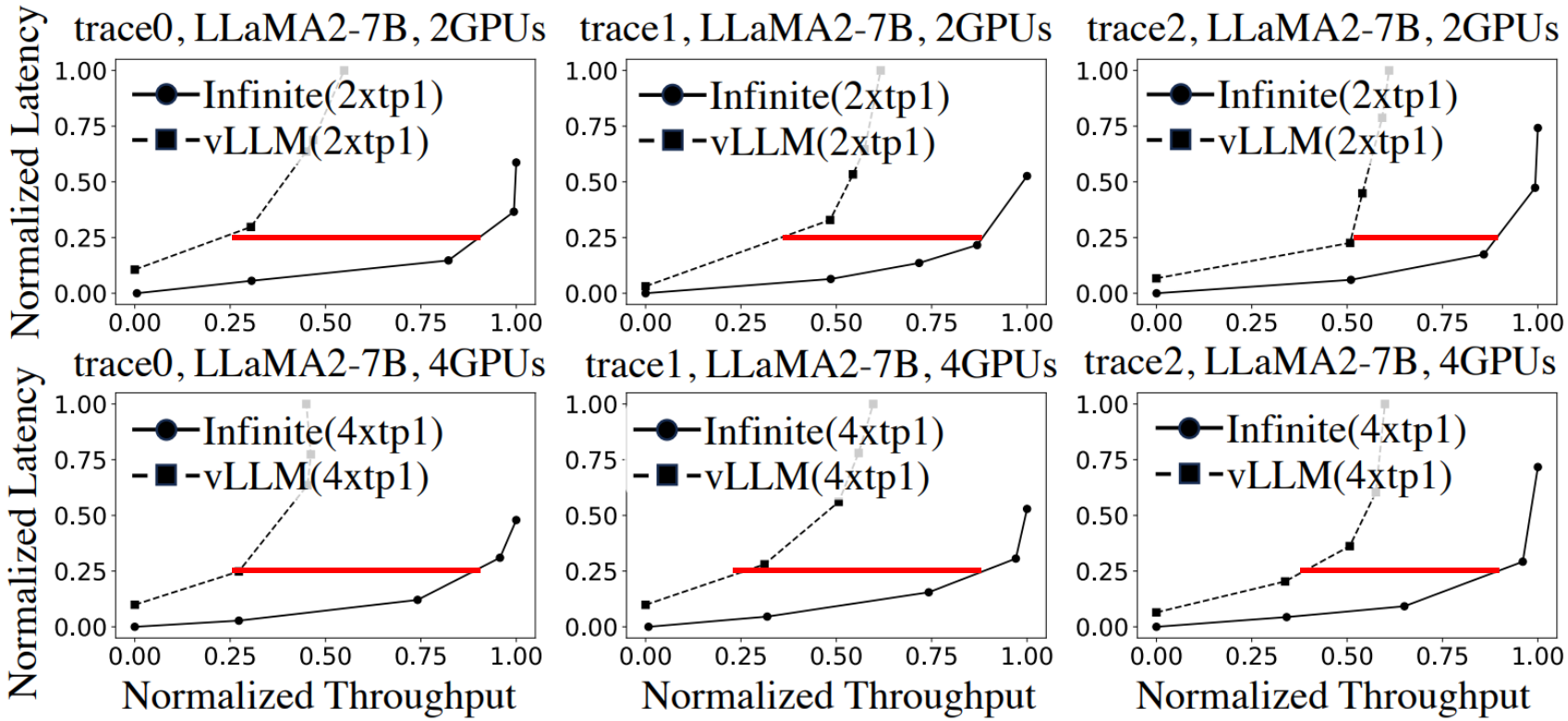
Evaluation

❑ Comparison(end-to-end performance)



Evaluation

❑ Comparison(end-to-end performance)



Summary

- **Background**
  - Different Context length
  - waste of memory and computation resources
- **Infinite-LLM**
  - DistAttention
  - Greedy Algorithm
- **thinking**