DéjàVu: KV-cache Streaming for Fast, Fault-tolerant Generative LLM Serving

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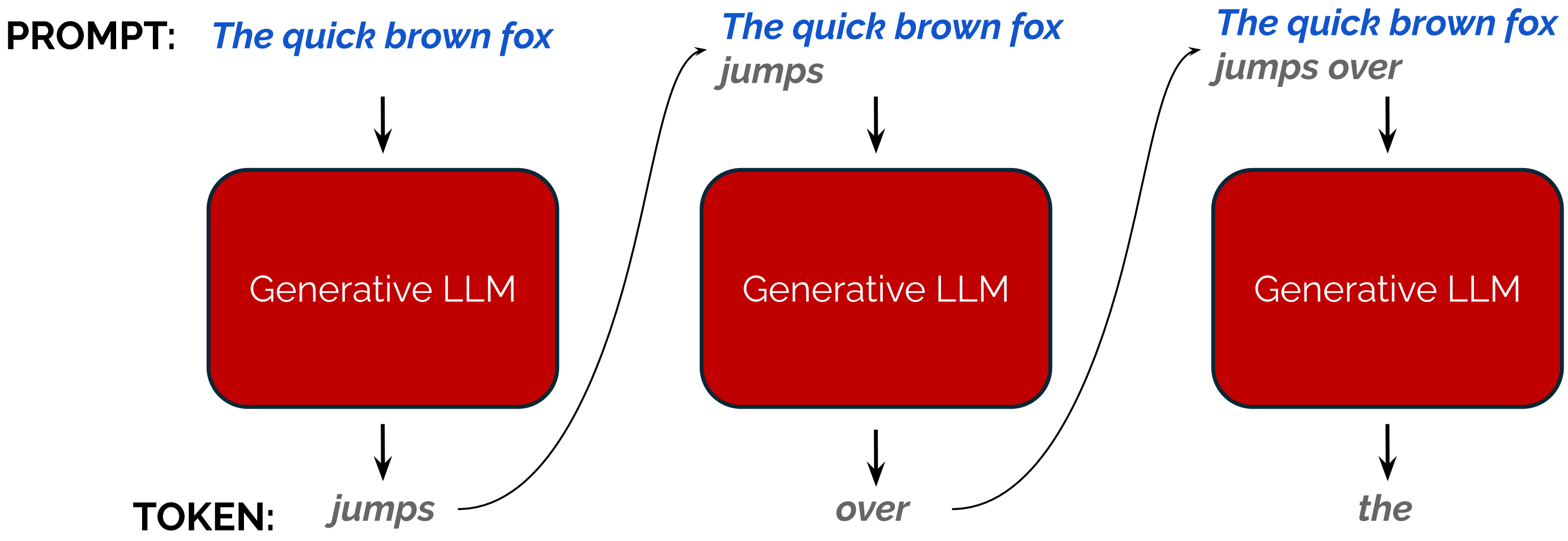
ICML
International Conference
On Machine Learning

Generative LLM Serving



Generative LLM Serving characteristics

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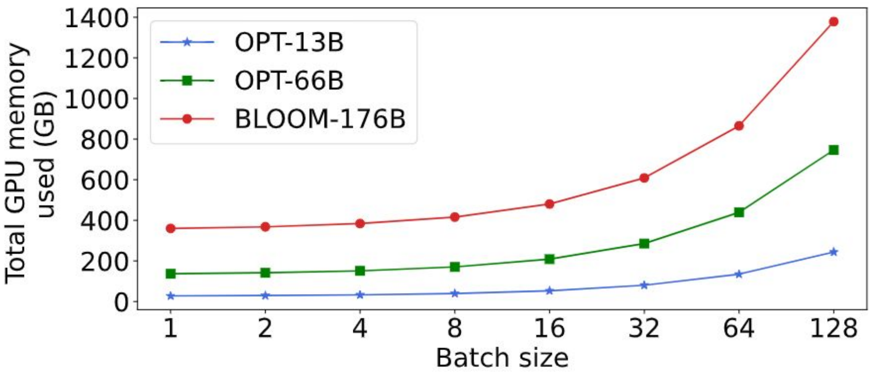
1. **Is stateful:**
- Generation at position *i* depends on tokens at positions *[0, i-1]*
- Results saved at a ***Key-Value cache*** to speed up computation

Generative LLM Serving characteristics

1. Is stateful
2. **Has large memory footprint:**
    - Model parameters
    - KV cache and other intermediate states



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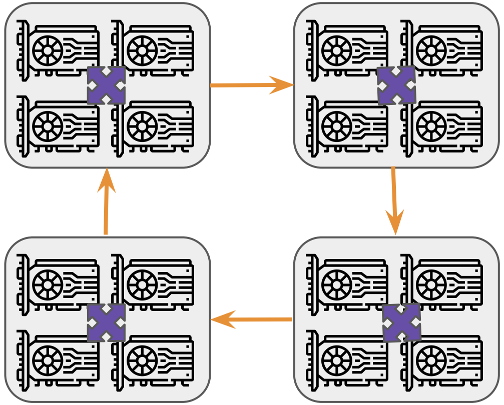
Inference is distributed across multiple GPUs with tensor and pipeline parallelism



Challenges of distributed LLM serving

1. Difference in prompt and per-token generation latency leads to pipeline bubbles
2. Inefficient usage of GPU memory
3. No failure handling

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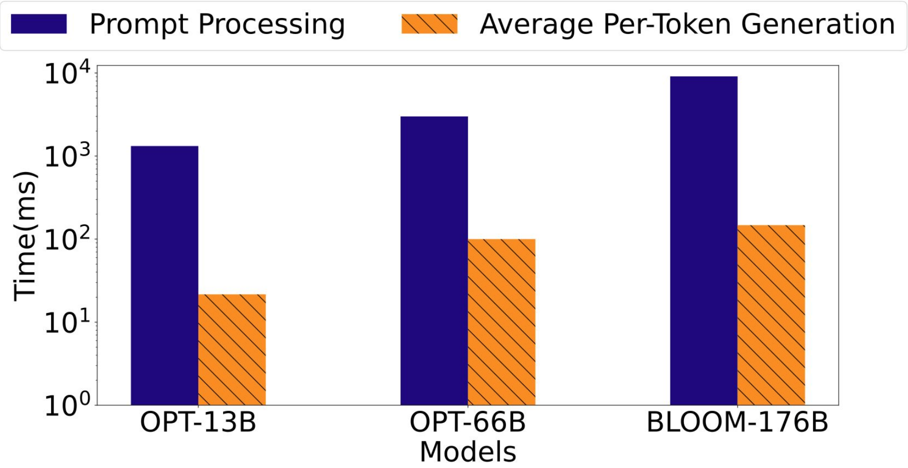
Prompt processing vs per-token generation latency

Due to the usage of KV cache, the time for prompt processing can be much higher than per-token generation time



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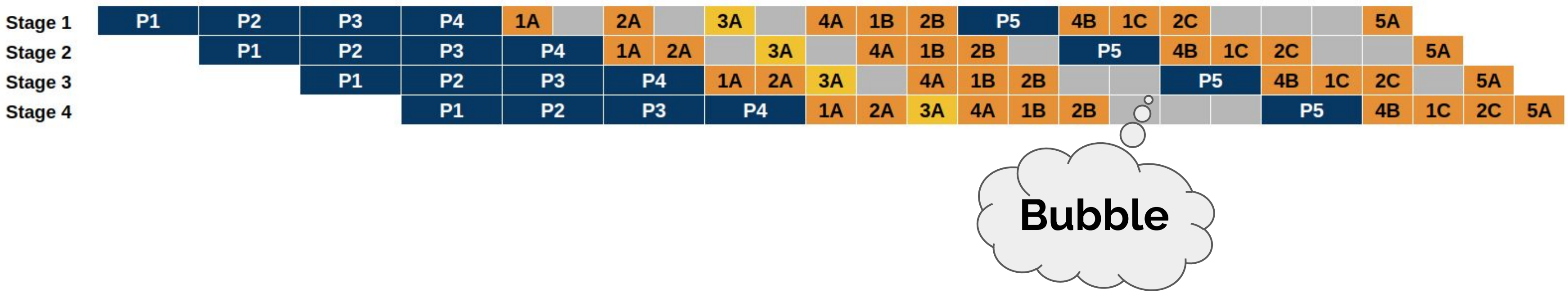
Bubbles and resource underutilization in pipeline parallel setups



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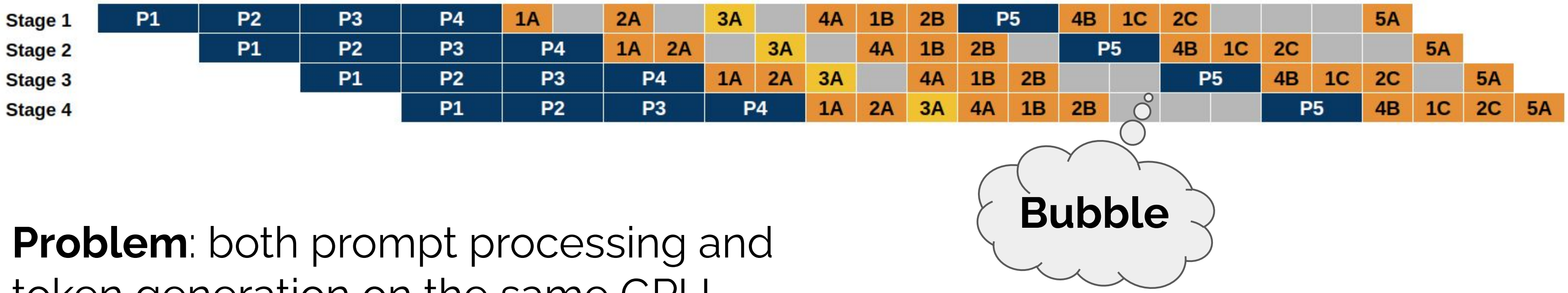
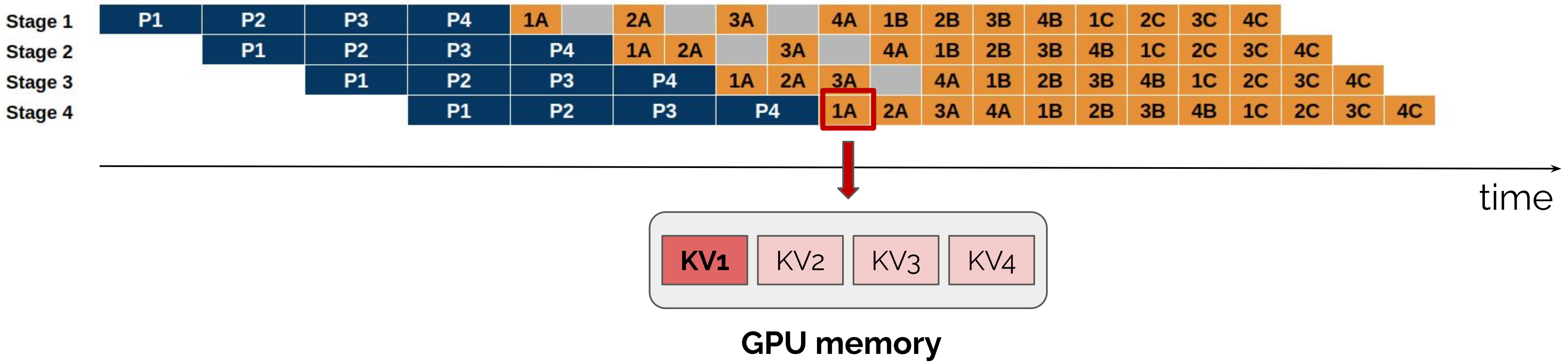


Problem: both prompt processing and token generation on the same GPU

Challenges of distributed LLM serving

1. Difference in prompt and per-token generation latency leads to pipeline bubbles
2. **Inefficient usage of GPU memory**
3. No failure handling

Inefficient usage of GPU memory



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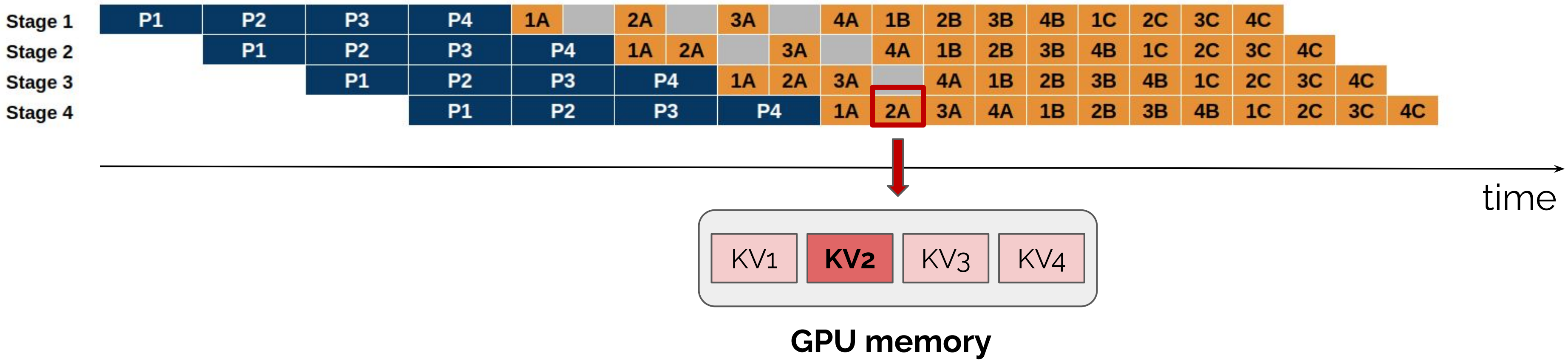

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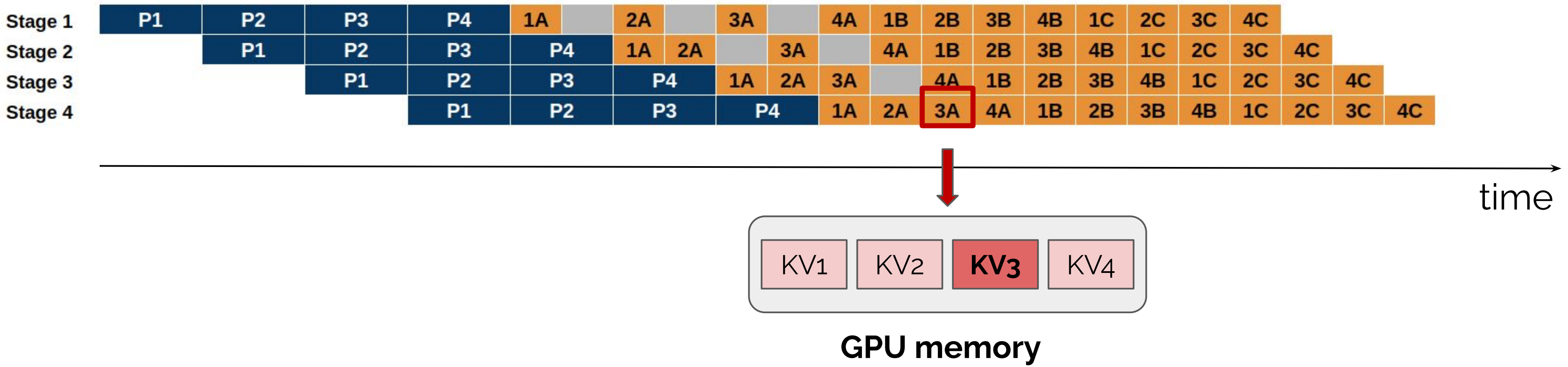

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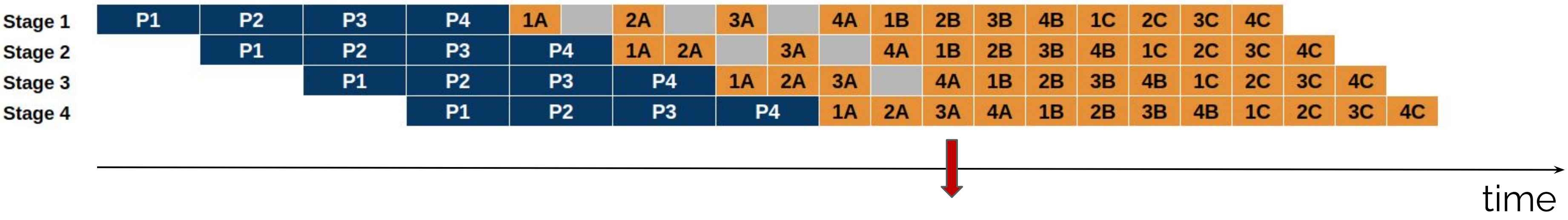

One microbatch is processed at a time.

However, the KV cache of *all* microbatches is kept in GPU memory!

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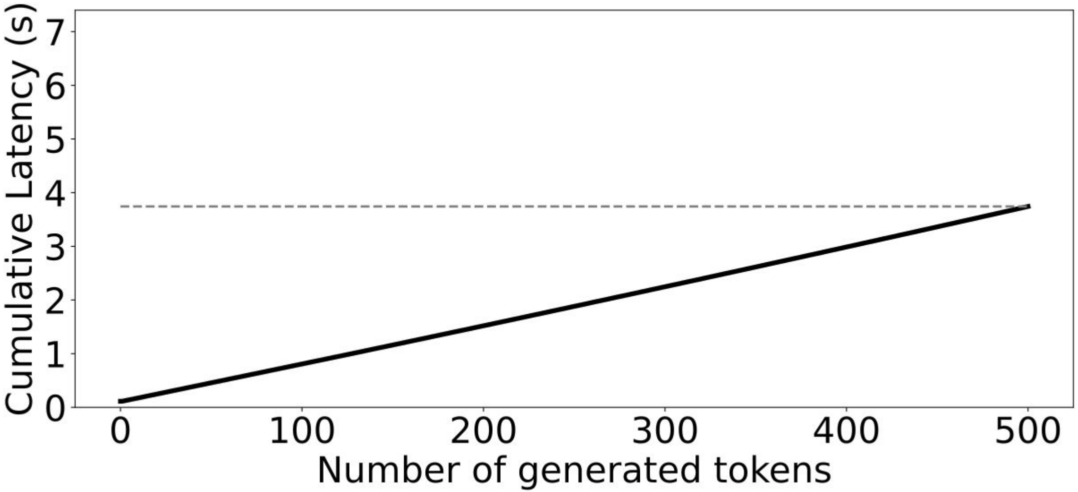
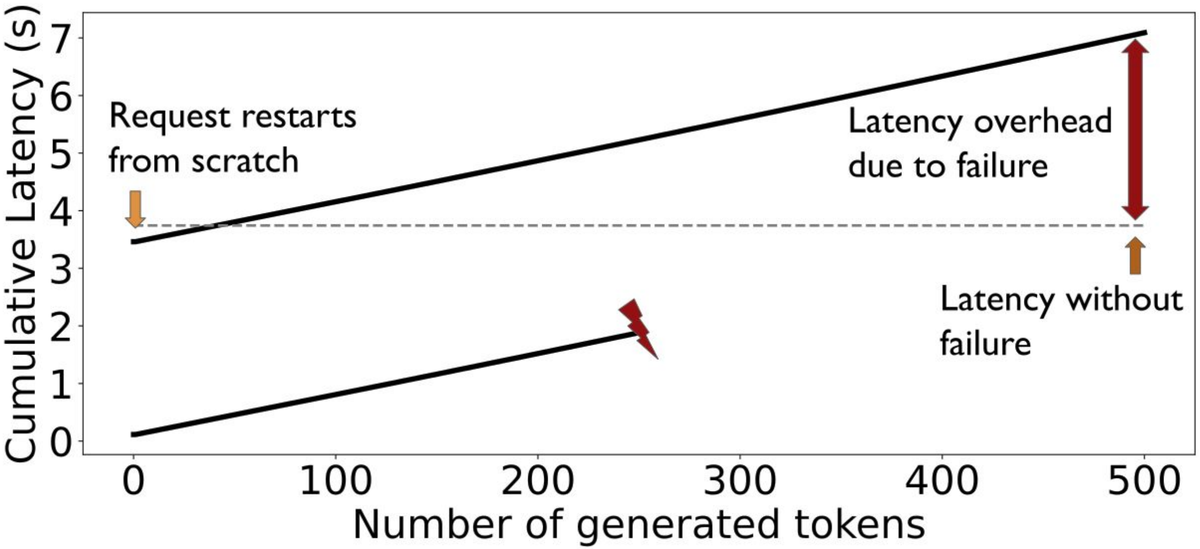
Latency without failures



Latency with a failure



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Challenges and our proposed solutions

1. Difference in prompt and per-token generation latency leads to pipeline bubbles

   Prompt-token disaggregation

2. Inefficient usage of GPU memory
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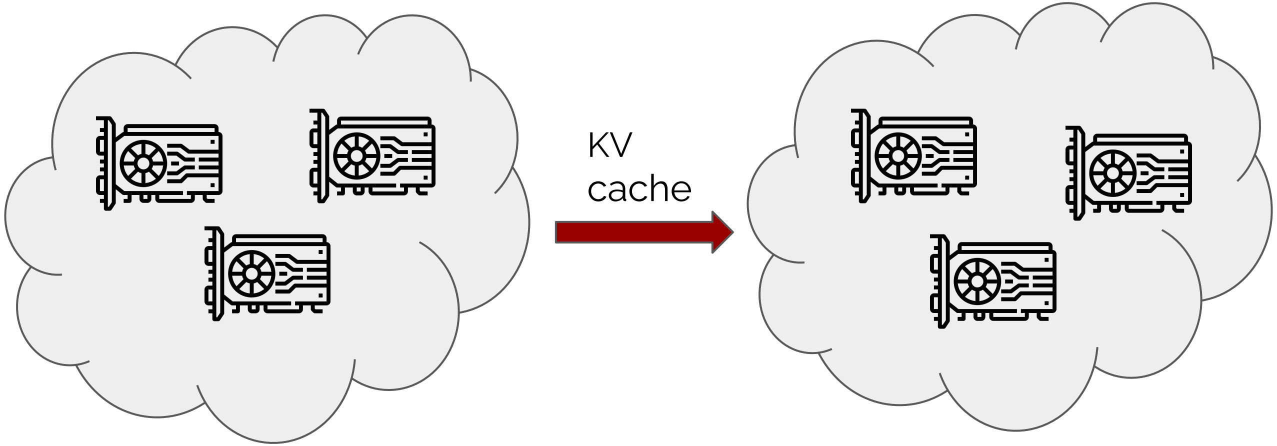
DéjàVu Key Idea 1: Prompt-Token disaggregation

Dedicated GPUs for
Prompt processing

Dedicated GPUs for
Token generation



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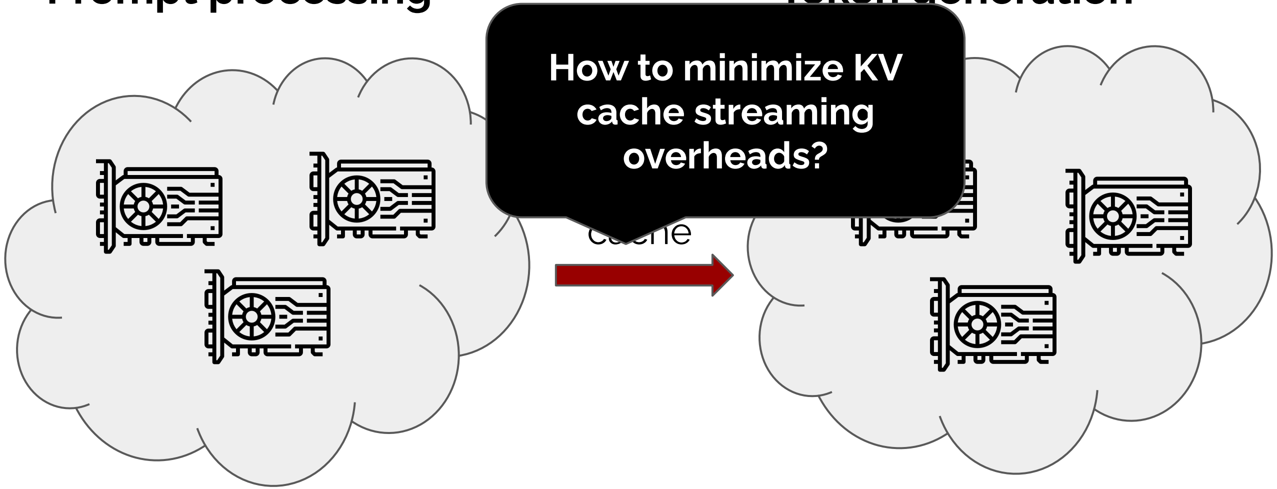


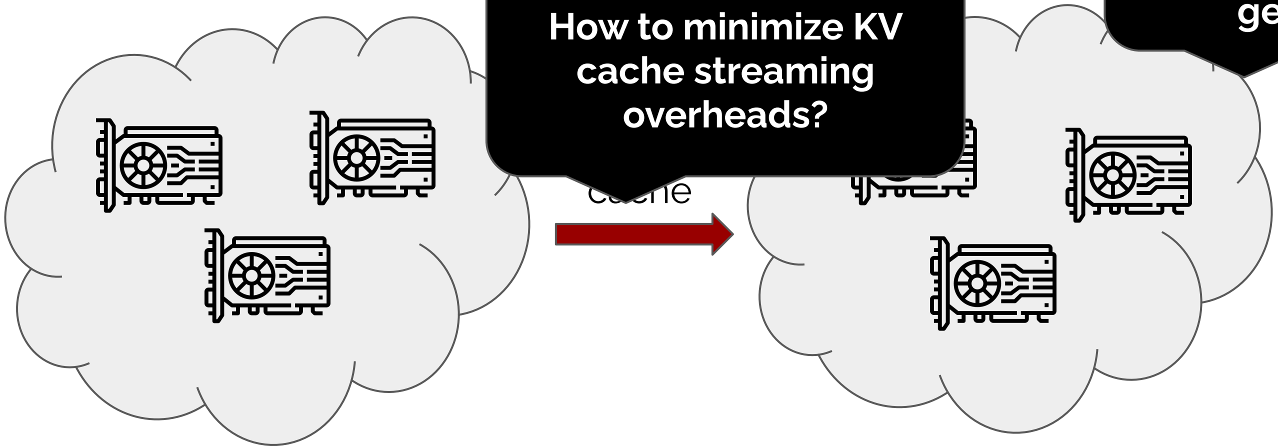
DéjàVu Key Idea 1: Prompt-Token disaggregation

Dedicated GPUs for
Prompt processing

Dedicated GPUs
Token generatio

How to minimize KV cache streaming overheads?

How to allocate resources for prompt processing and token generation?



Challenges and our proposed solutions

1. Difference in prompt and per-token generation latency leads to pipeline bubbles

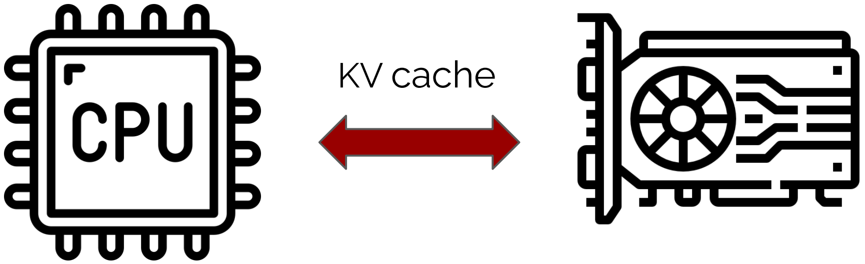
   Prompt-token disaggregation

2. Inefficient usage of GPU memory

   Microbatch swapping

3. No failure handling

DéjàVu Key Idea 2: Microbatch swapping



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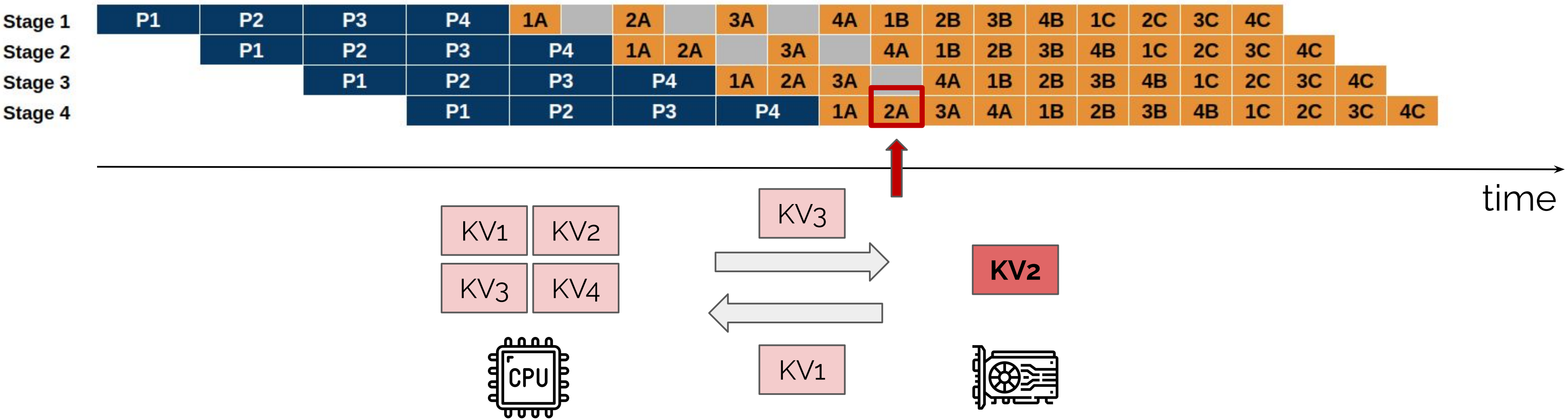

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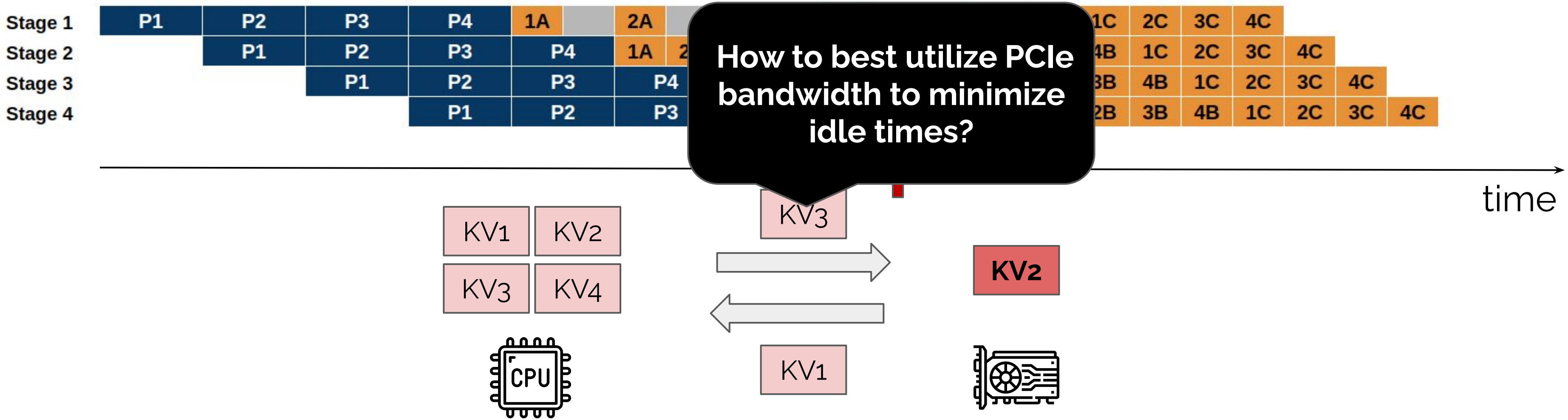

Challenges and our proposed solutions

1. Difference in prompt and per-token generation latency leads to pipeline bubbles

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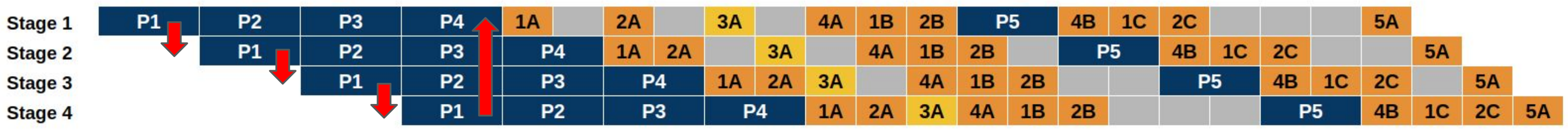
   KV cache replication and fault-handling mechanism

DéjàVu Key Idea 3: KV cache replication

KV cache replication to CPU memory



- efficient fault detection and recovery

Proposed solutions

3. Statefulness and inefficient failure handling

Idea: Replicate the KV cache to persistent storage or remote CPU memory

How to minimize KV cache streaming overheads?

How to efficiently detect failures and recover?

Common requirement

1. Prompt-token disaggregation
2. Microbatch swapping
3. KV cache replication and fault-handling mechanism

They all require a fast and versatile KV cache streaming mechanism

DéjàVuLib

- An **efficient** and **modular** KV cache streaming library, with **optimizations for fast streaming**

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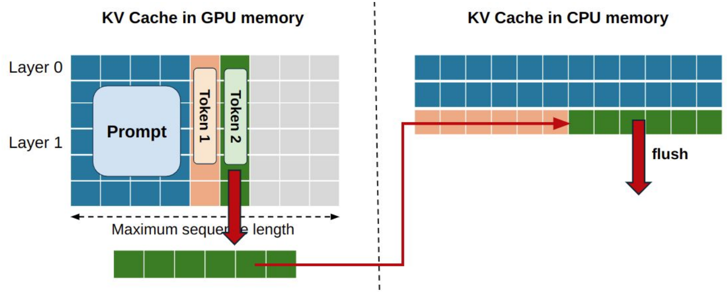
1. **Buffered Transfers**



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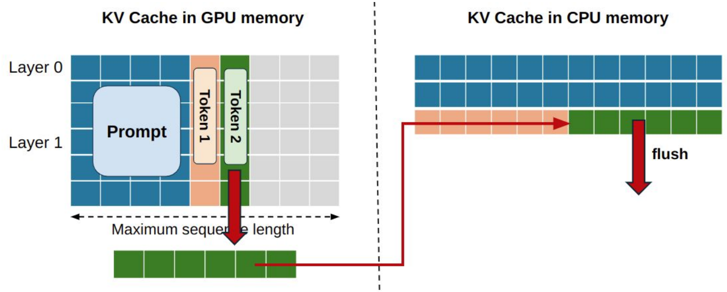
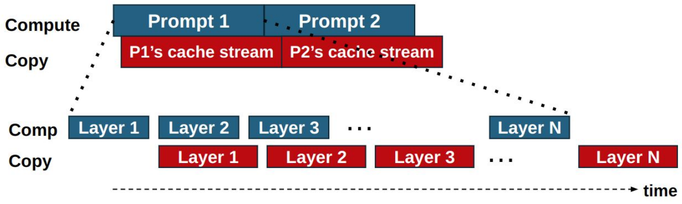


2. **Layer-by-layer prompt cache streaming**



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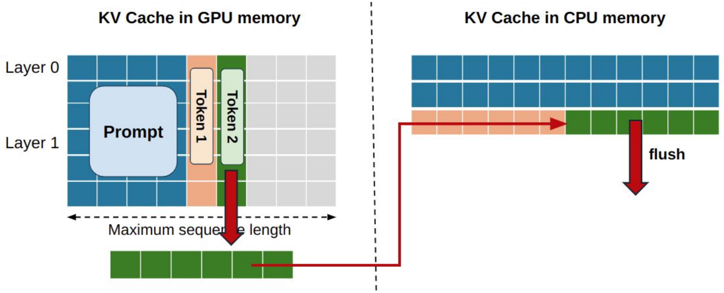

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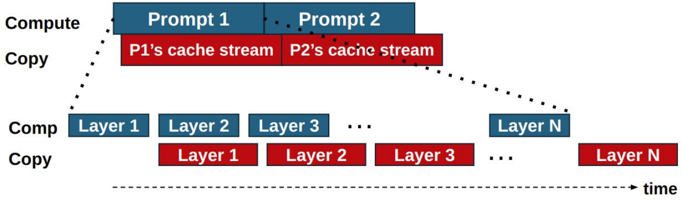
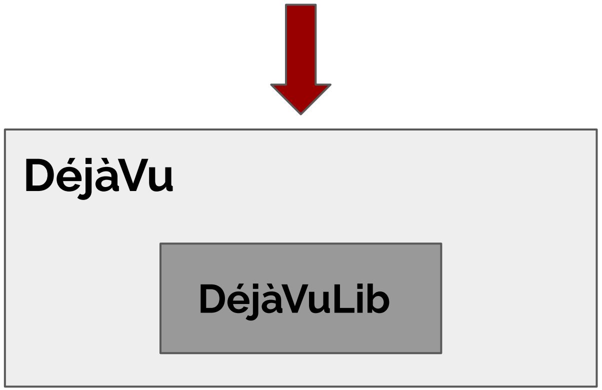


3. **Token computation and streaming overlap**

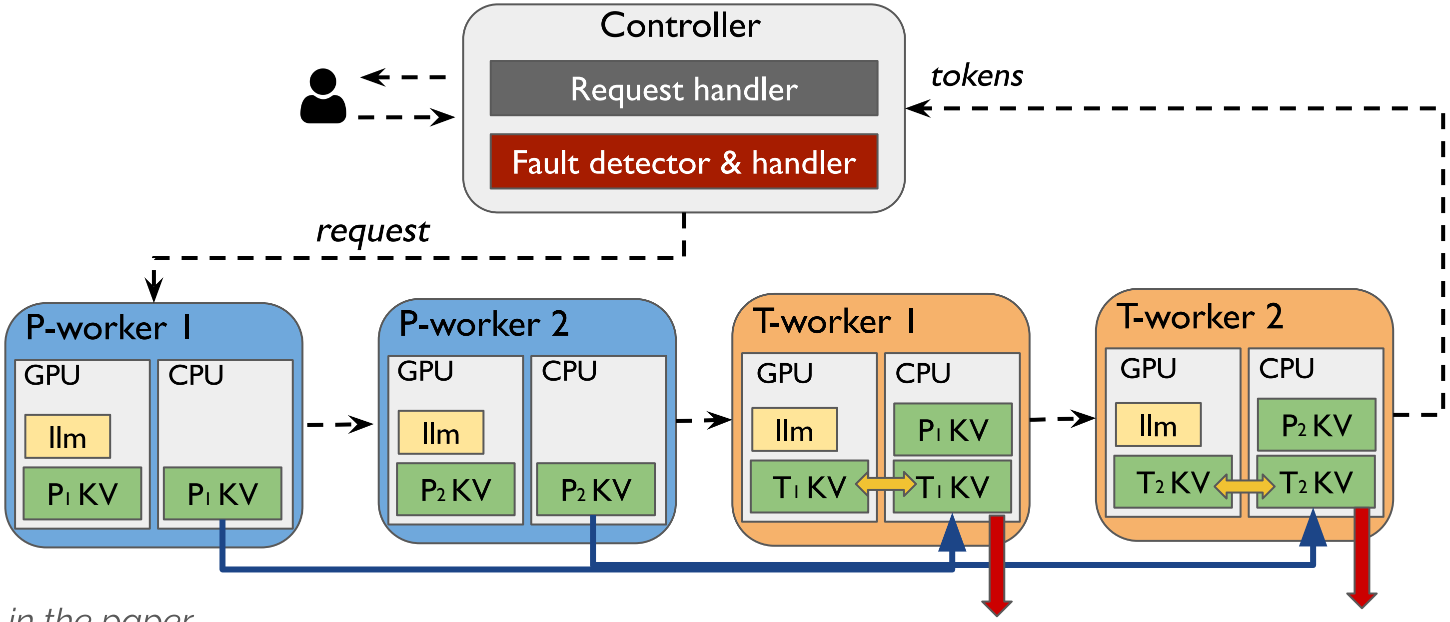
Common requirement

1. Prompt-token disaggregation
2. Microbatch swapping
3. KV cache replication and fault-handling mechanism



The DéjàVu system

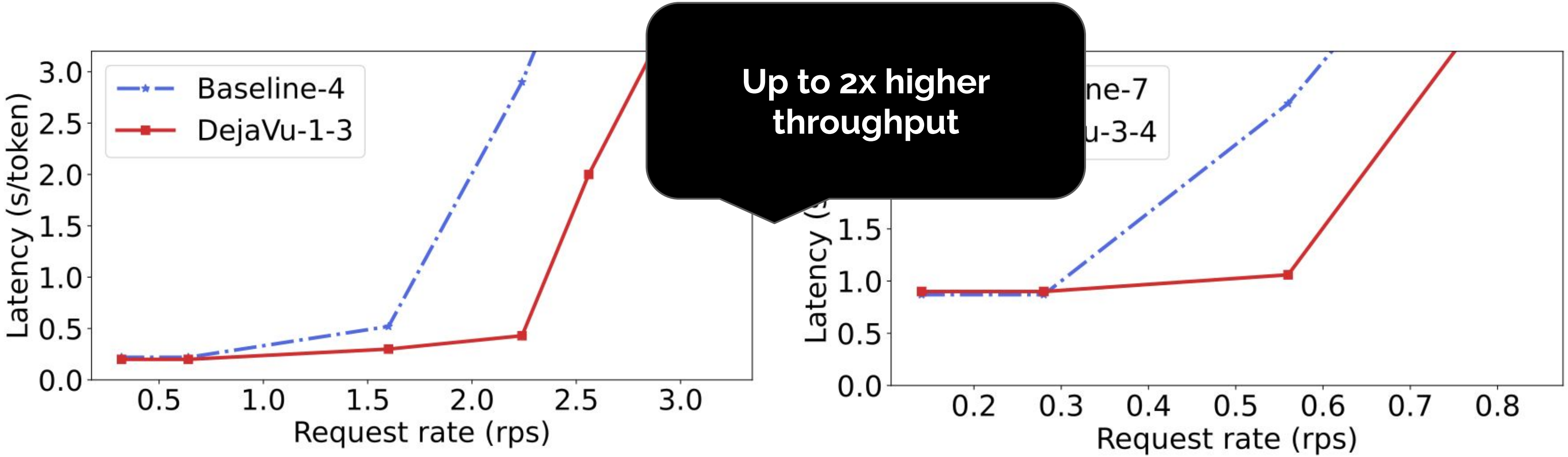
Supports: **disaggregation, KV cache swapping, fault-tolerance**



More details in the paper

Evaluation

DéjàVu disaggregation



OPT-66B **BLOOM-176B**

- Baseline-X: FasterTransformer with X machines
- DejaVu-X-Y: Disaggregation with X machines for prompt, Y for token

lmsys dataset

Conclusion

Challenges	DéjàVu Solutions
Bimodal prompt vs per-token generation latency	**Prompt-token disaggregation**
Inefficient usage of GPU memory	**Microbatch swapping**
Statefulness and inefficient failure handling	**KV cache replication and fault-handling mechanism**

Conclusion

Challenges		DéjàVu Solutions
Bimodal prompt vs per-token generation latency	→	**Prompt-token disaggregation**
Inefficient usage of GPU memory	→	**Microbatch swapping**
Statefulness and inefficient failure handling	→	**KV cache replication and fault-handling mechanism**

DéjàVu github repo: