Tally: Non-Intrusive Performance Isolation for Concurrent Deep Learning Workloads

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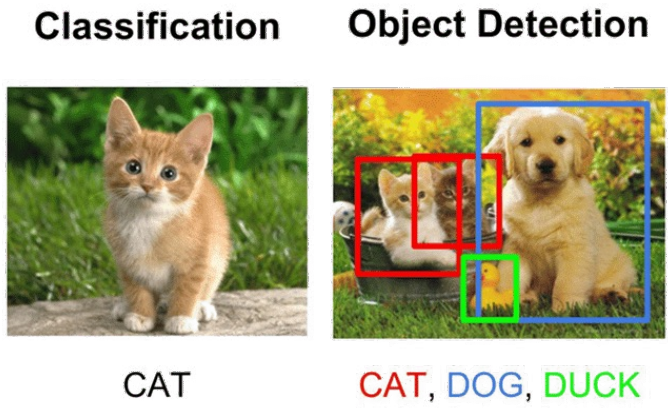
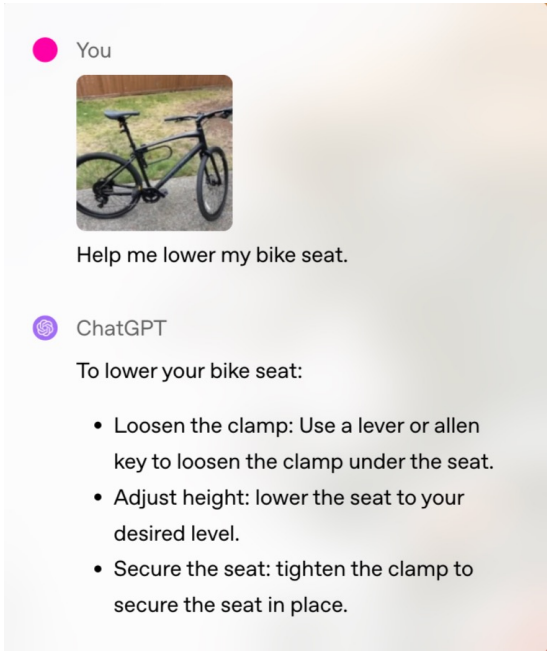
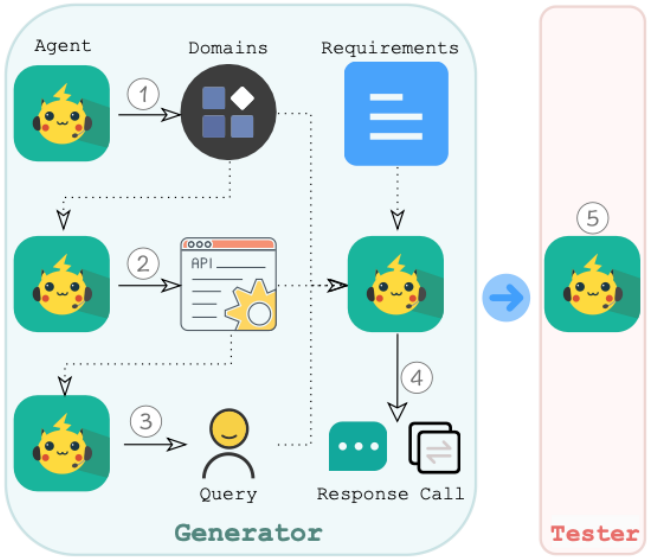
DL is Gaining Unprecedented Popularity







Soaring Investments in GPU Clusters

NVIDIA H100 GPU Units By Company

Company/Entity	H100 GPU Count
Meta	350,000
XAI/X	100,000
Tesla	
Lambda	
Google A3	
Oracle Cloud	

Ensuring high GPU utilization is crucial for cost-efficiency!

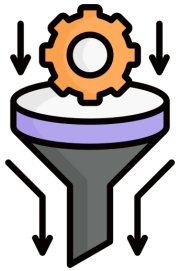
While we don't know the precise mix of GPUs sold, each Nvidia H100 80GB HBM2E compute GPU add-in-card (14,592 CUDA cores, 26 FP64 TFLOPS, 1,513 FP16 TFLOPS) retails for around $30,000 in the U.S. However, this is not the company's highest-performing Hopper architecture-based part. In fact, this is the cheapest one, at least for now. Meanwhile in China, one such card can cost as much as $70,000.

350,000 * 30,000 ≈ $10 billion

https://www.visualcapitalist.com/which-companies-own-the-most-nvidia-h100-gpus/
https://www.tomshardware.com/news/nvidia-to-sell-550000-h100-compute-gpus-in-2023-report

Meanwhile - GPUs are Severely Underutilized

- 2022 Alibaba Study:
  - median GPU utilization in 6000-GPU cluster is only **4.2%**.
- Sources of Inefficiency:

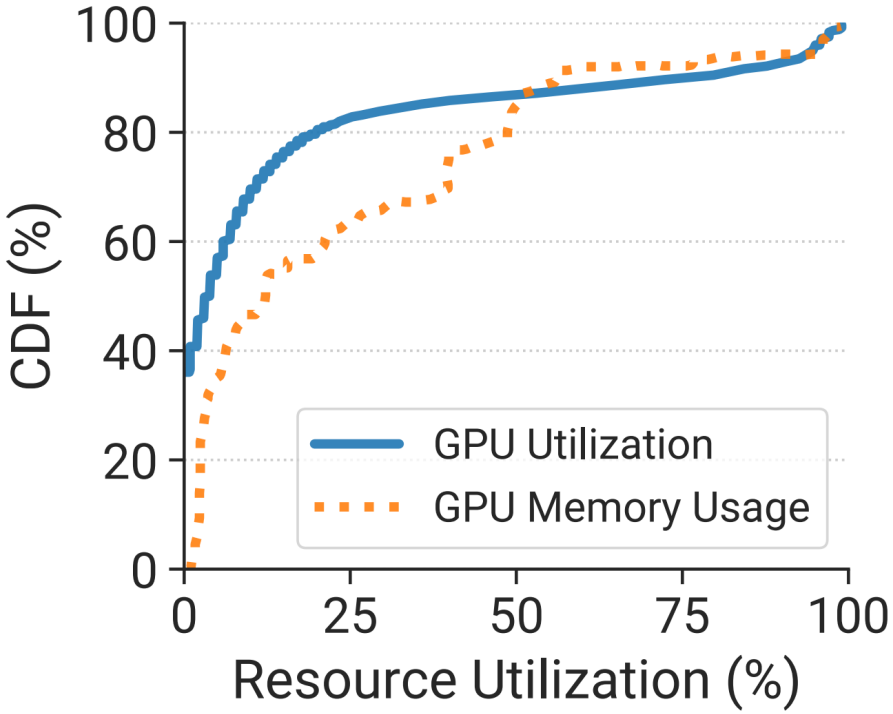


Training:

bottlenecks in CPU execution

Inference:

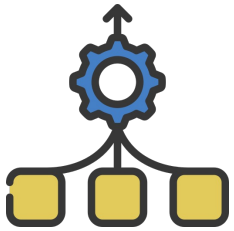
fluctuating user traffic



GPU utilization distribution in an Alibaba cluster

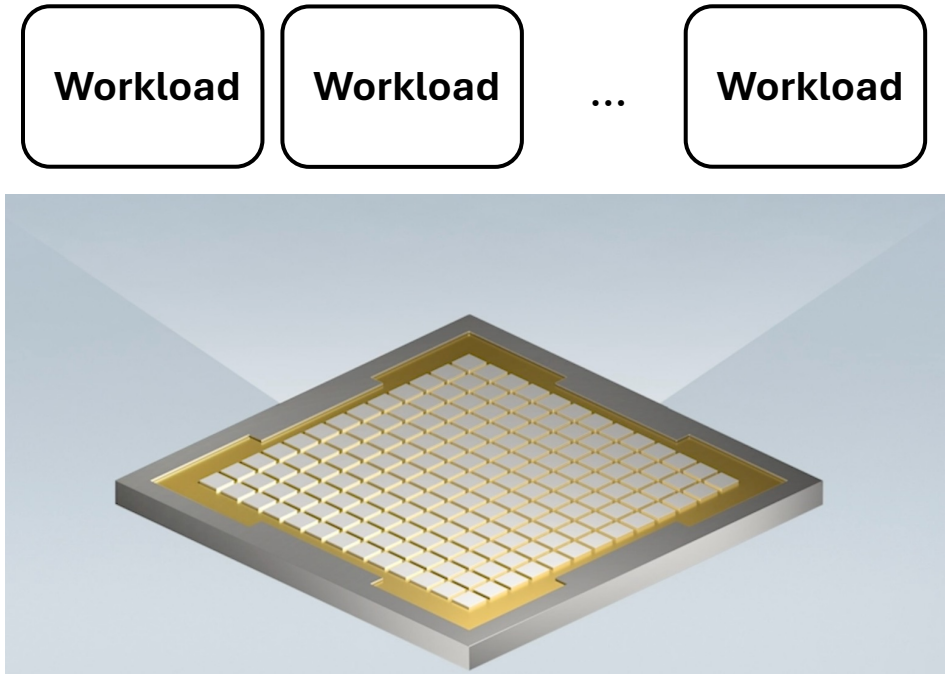
Weng et al., "MLaaS in the Wild: Workload Analysis and Scheduling in Large-Scale Heterogeneous GPU Clusters," NSDI 2022.

GPU Sharing to the Rescue



Consolidating multiple workloads to share a single GPU's resources.

The same Alibaba study shows GPU sharing can cut resource requirements by up to **73%**.



https://developer.nvidia.com/techdemos/video/disc03

Weng et al., " MLaaS in the Wild: Workload Analysis and Scheduling in Large-Scale Heterogeneous GPU Clusters," NSDI 2022.

Yet, GPU Sharing is Rarely Used in Clusters

Limitations of Current GPU Sharing Solutions:

High integration and maintenance cost due to intrusive code modifications

Lack of performance isolation guarantees leads to violations of task SLAs

Limited application compatibility due to reliance on workload-specific characteristics

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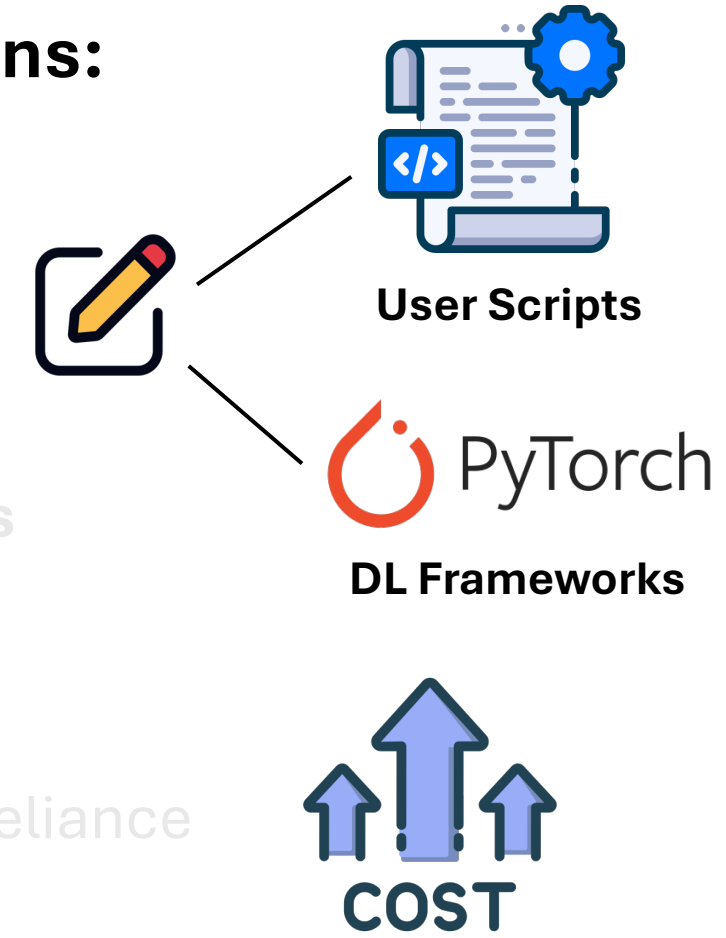

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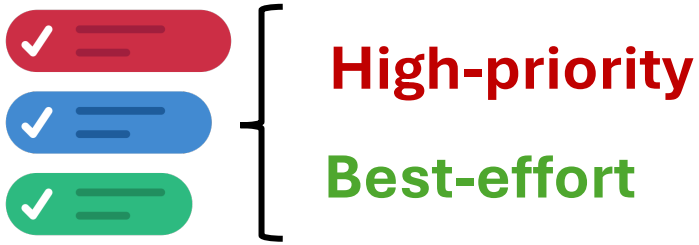
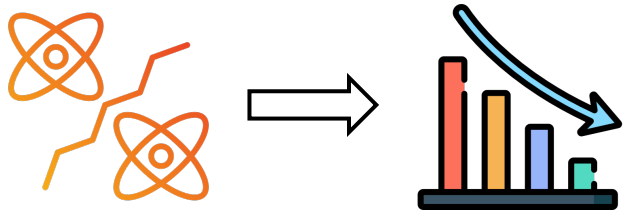


Lack of performance isolation guarantees leads to violations of task SLAs



Interference causes performance degradation

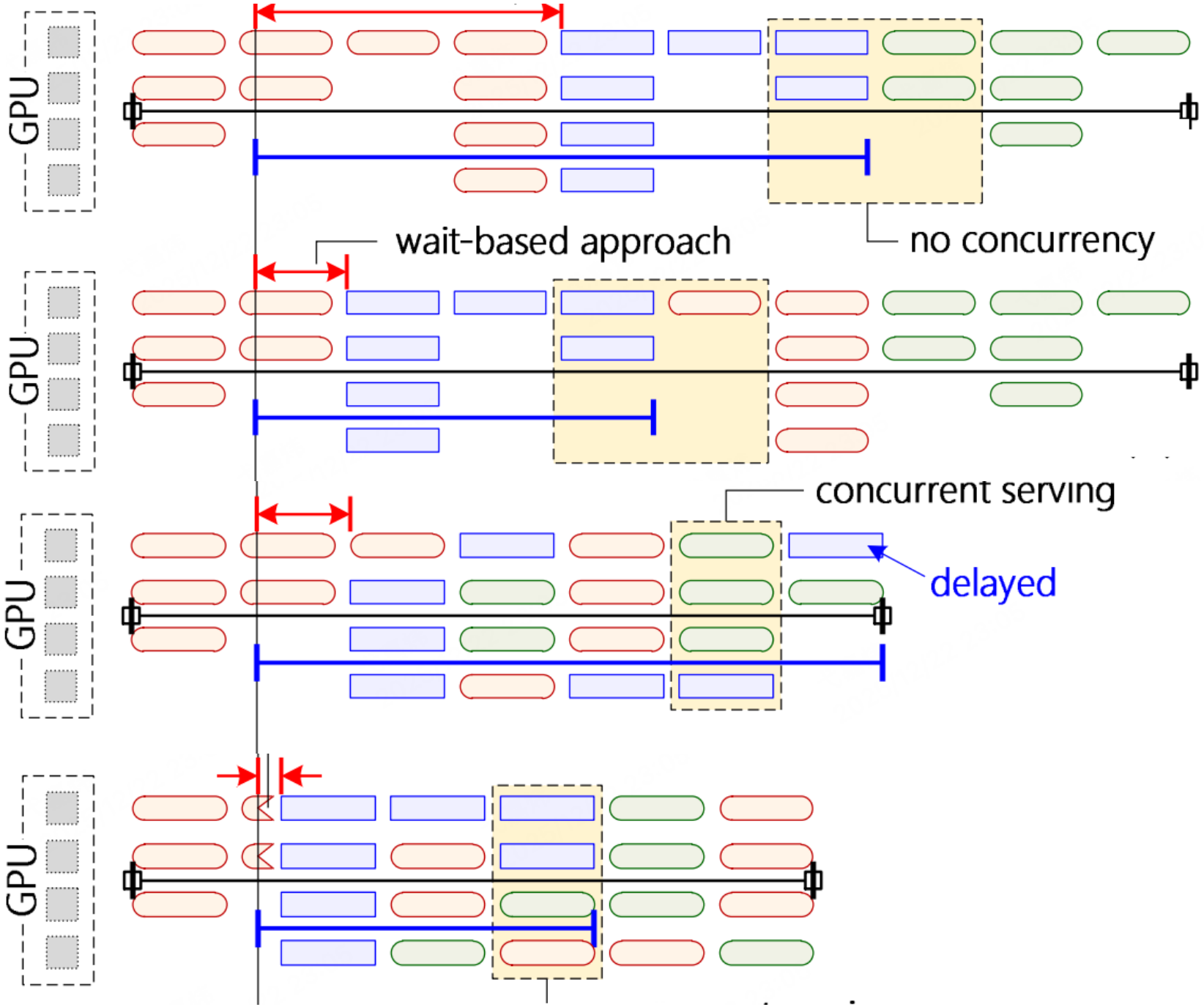
Limited application compatibility due to reliance on workload-specific characteristics

Iteration

Kernel

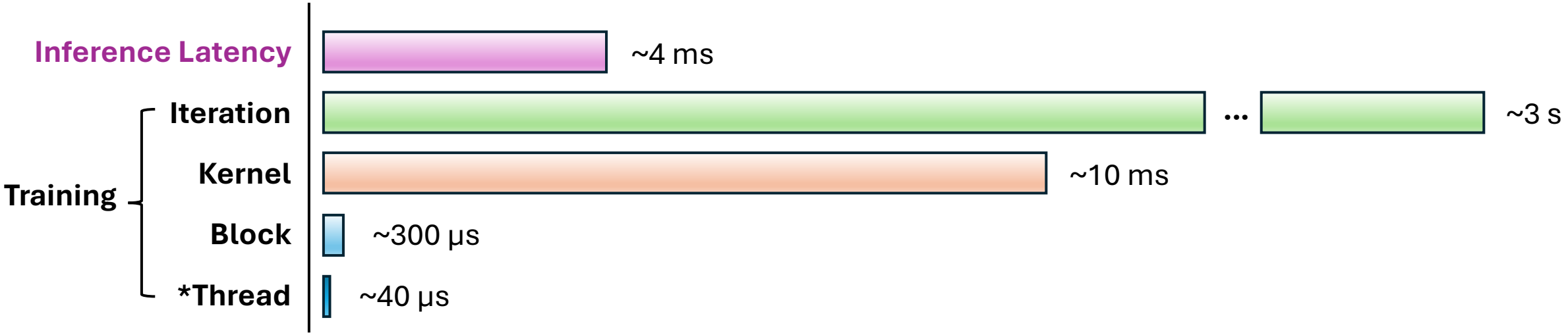
Stream

Block



Scheduling Granularity for DL Workloads

- High-priority: **BERT Inference**
- Best-effort: **Whisper Training**
- Co-executed on a NVIDIA A100 GPU



*: the thread-level latency is taken from the REEF paper as it is not supported in NVIDIA GPUs.

Yet, GPU Sharing is Rarely Used in Clusters

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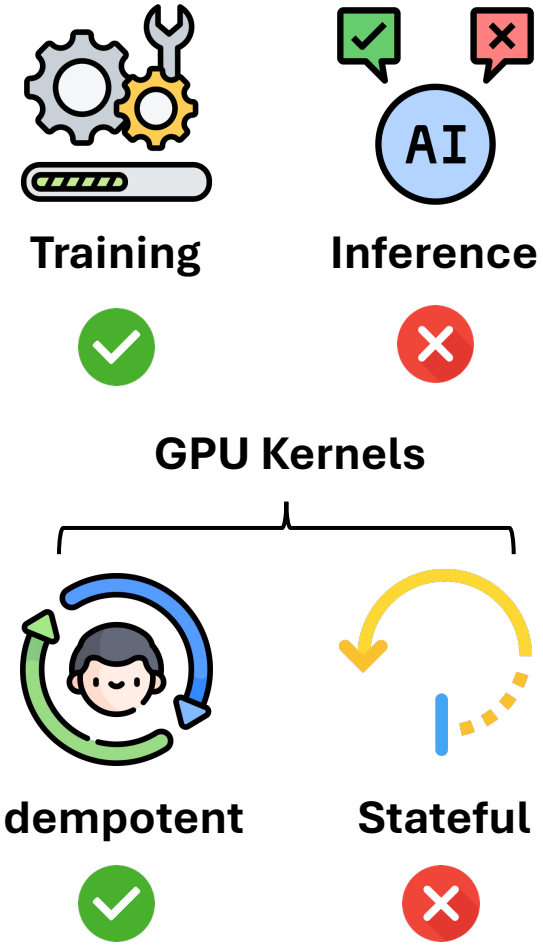

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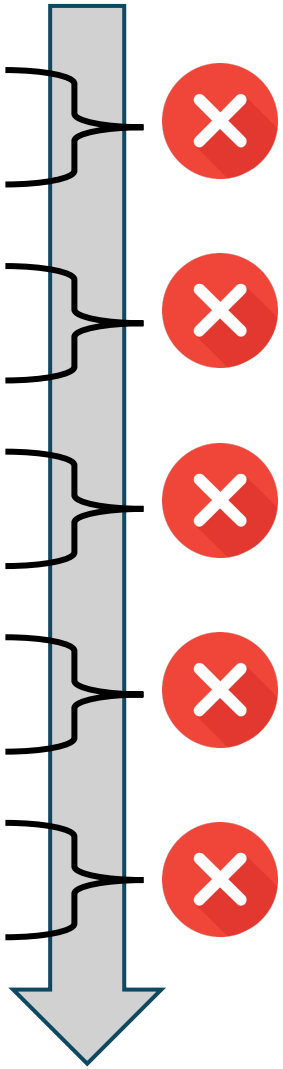


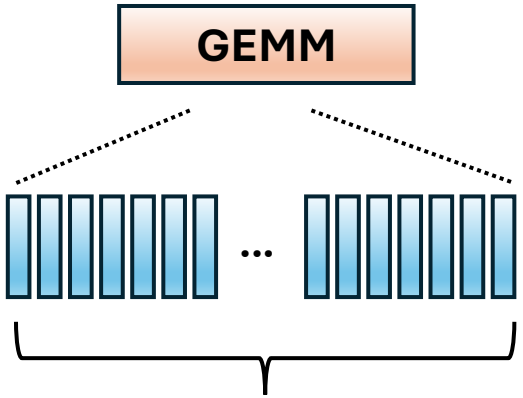
		Intrusiveness	Granularity	Generality
2017	EffiSha [PPoPP'17]	Intrusive code	Block level	All
2020	Salus [MLSys'20]	Non-Intrusive	Iteration level	All
2022	REEF [OSDI'22]	Non-Intrusive	thread level	Indempotent
2023	TGS [NSDI'23]	Non-Intrusive	kernel level	Static
2024	Orion [EuroSys'24]	Intrusive code	stream level	All

Choosing the Right Scheduling Granularity

Adopted by Tally

	Block-level	*Thread-level*
Latency	~100s μs 	~10s μs 
Generality	Universally applicable 	Limited to idempotent kernels 

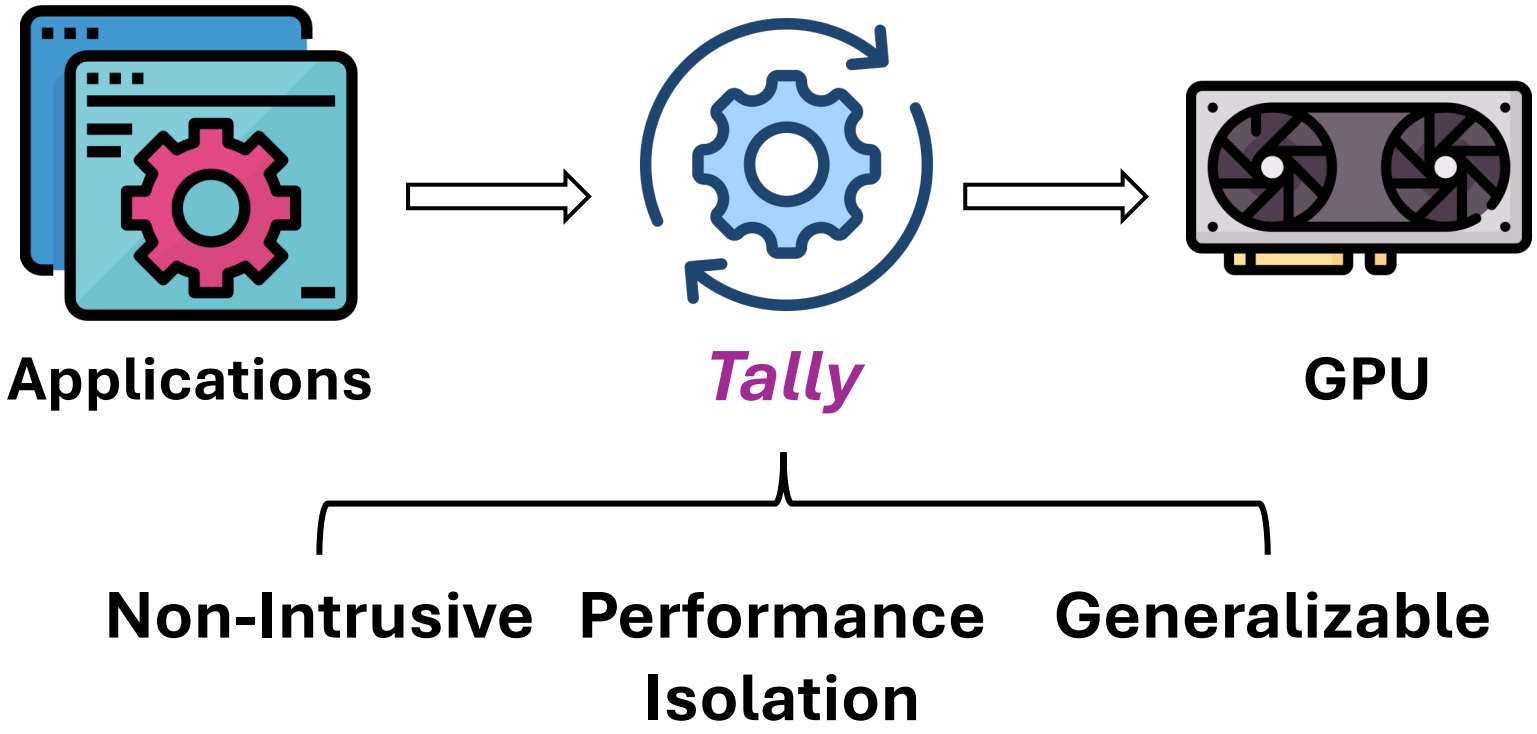
Block-level:



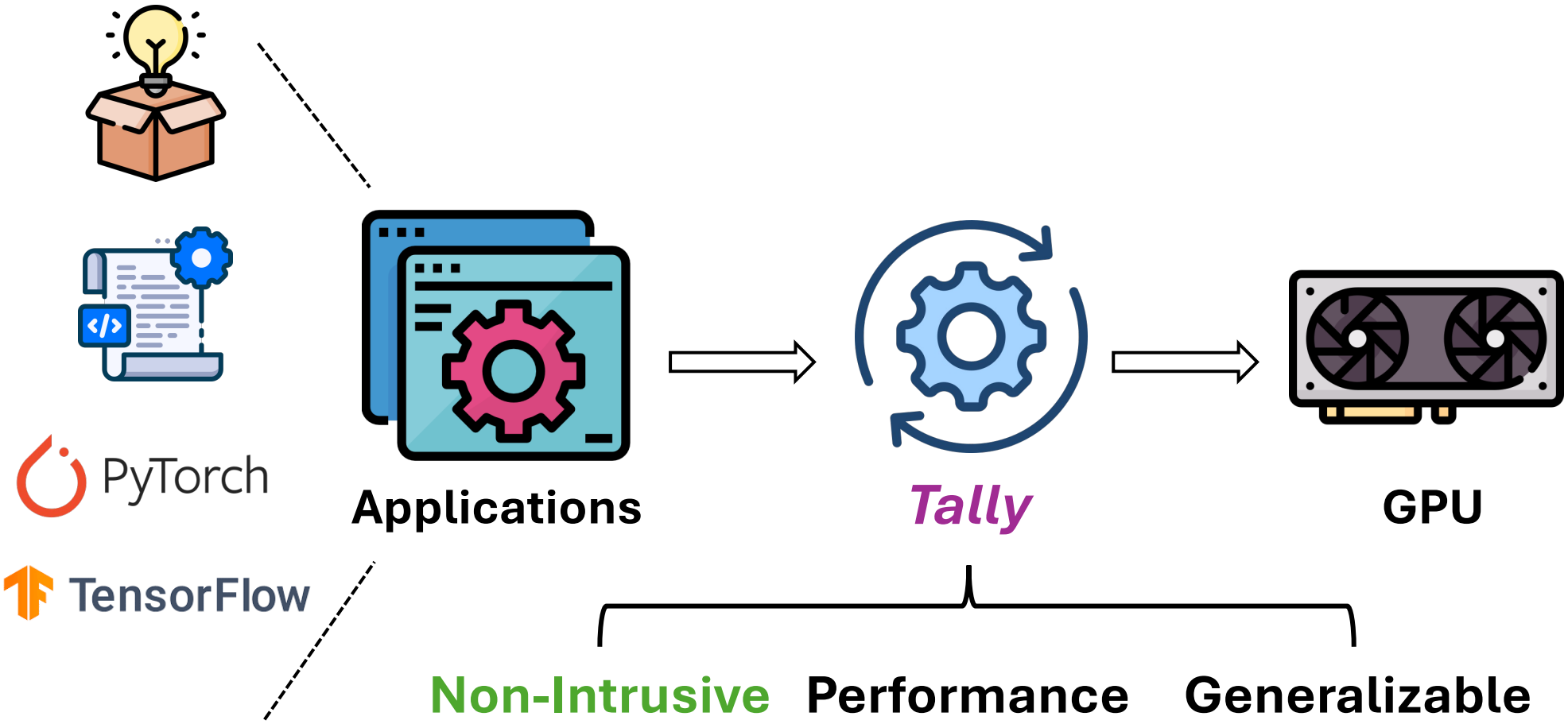
Thread-level:

Disruptive abort and restart of a block require idempotency

Tally: Enabling Practical GPU Sharing



Tally: Enabling Practical GPU Sharing



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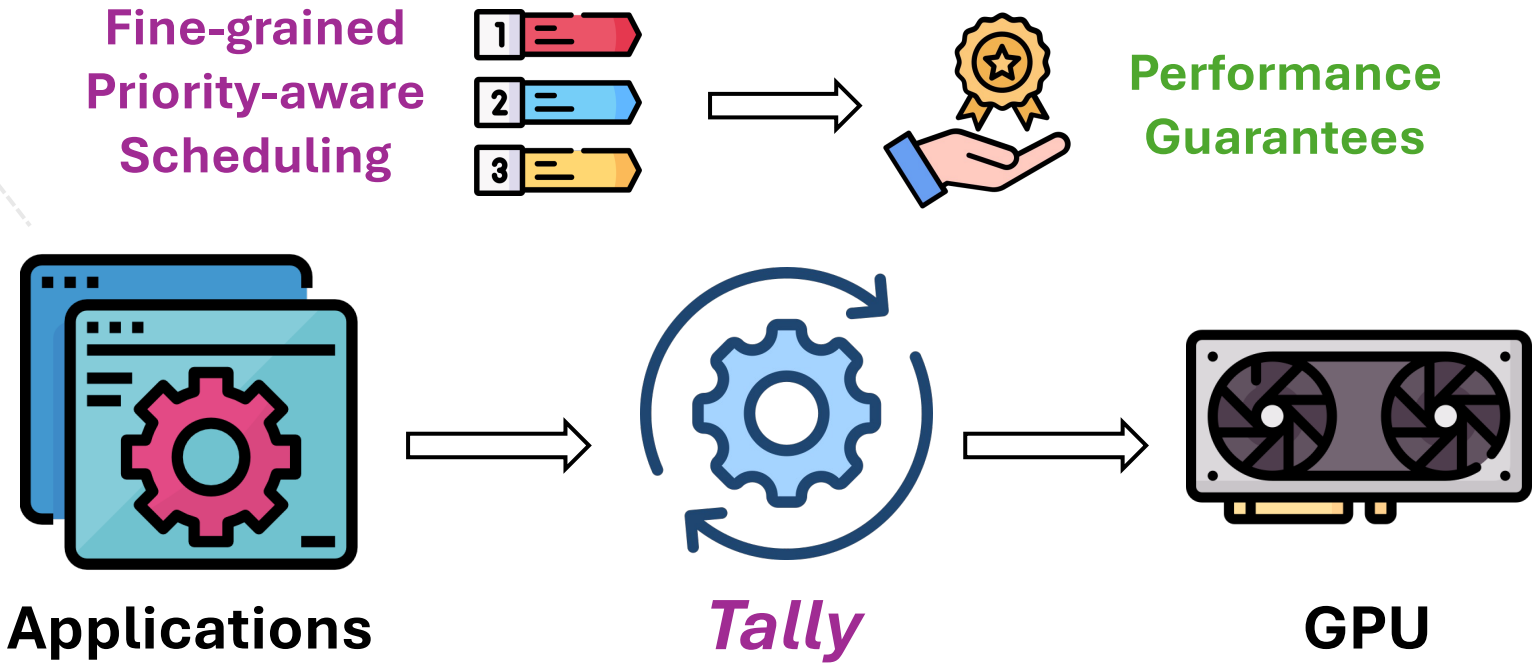

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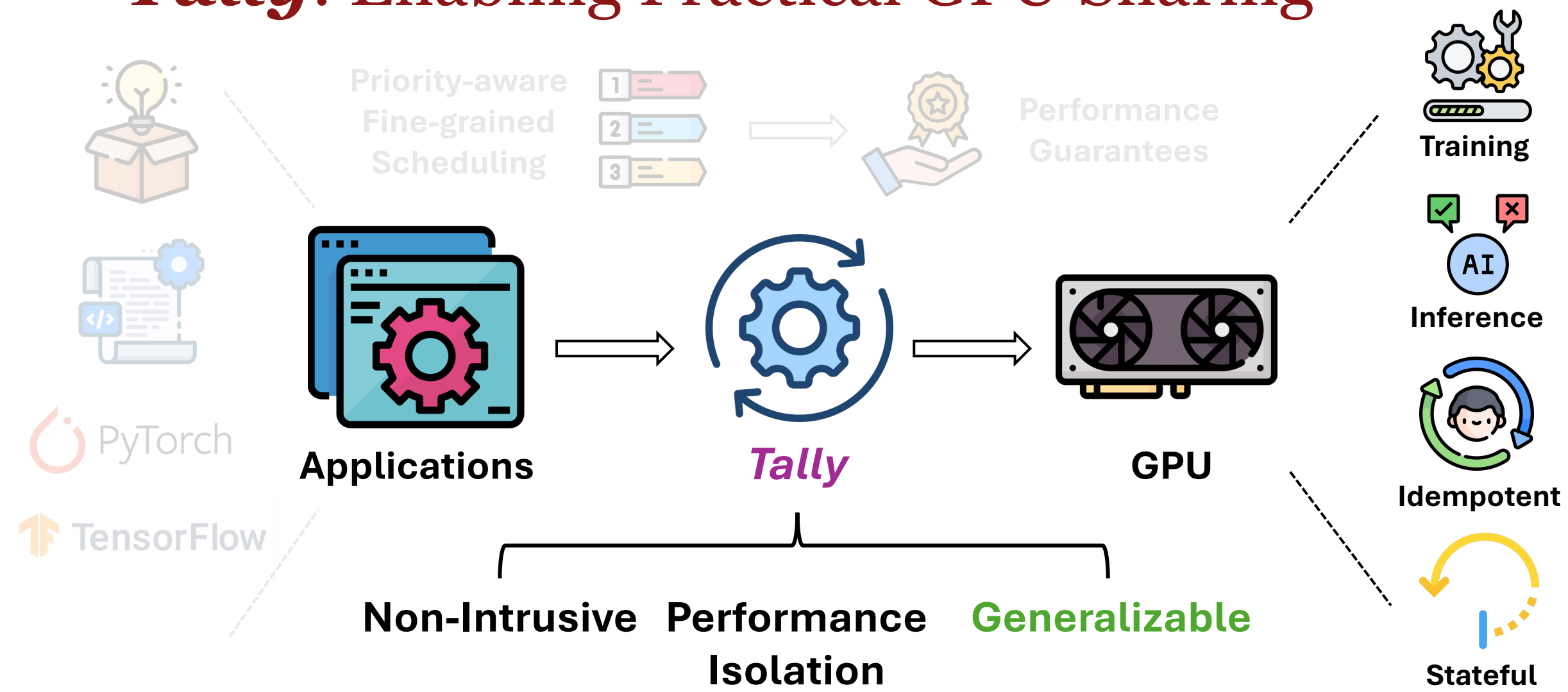

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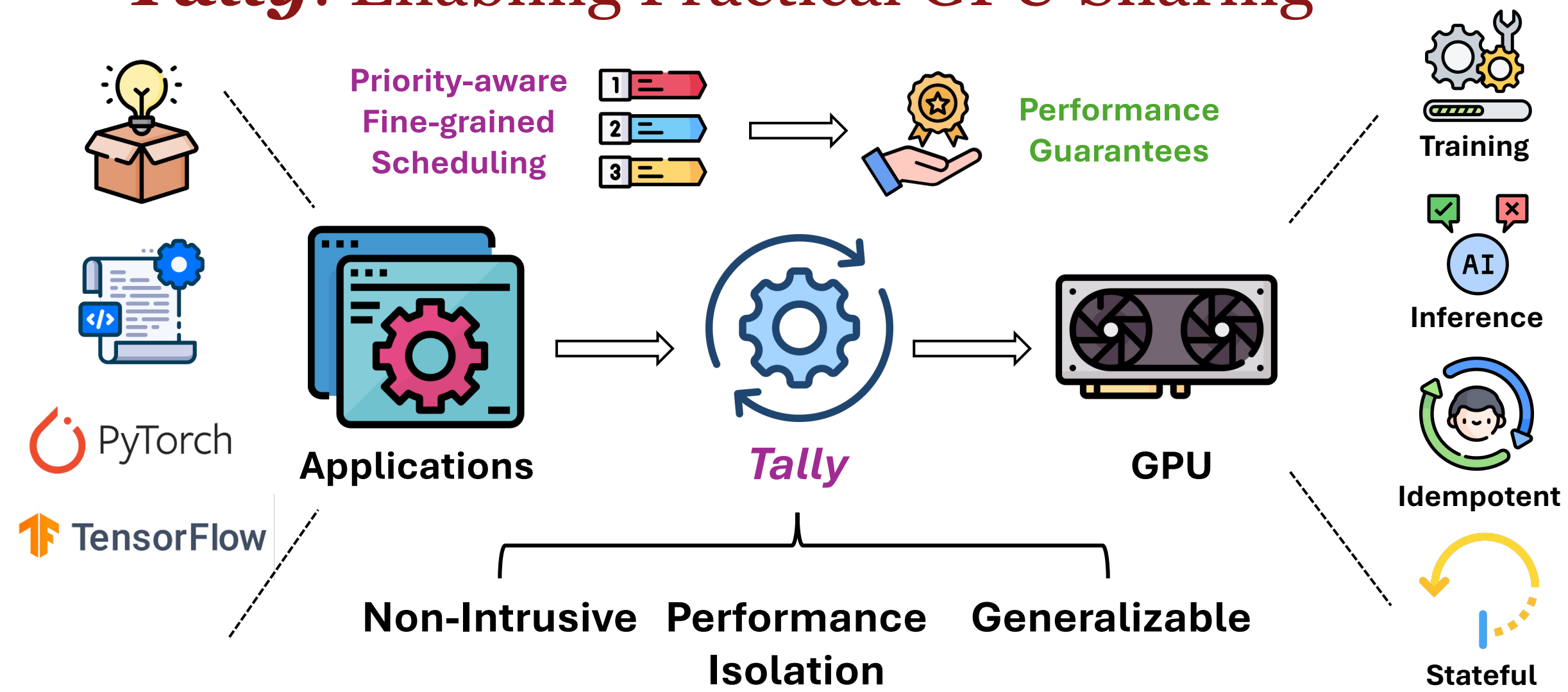
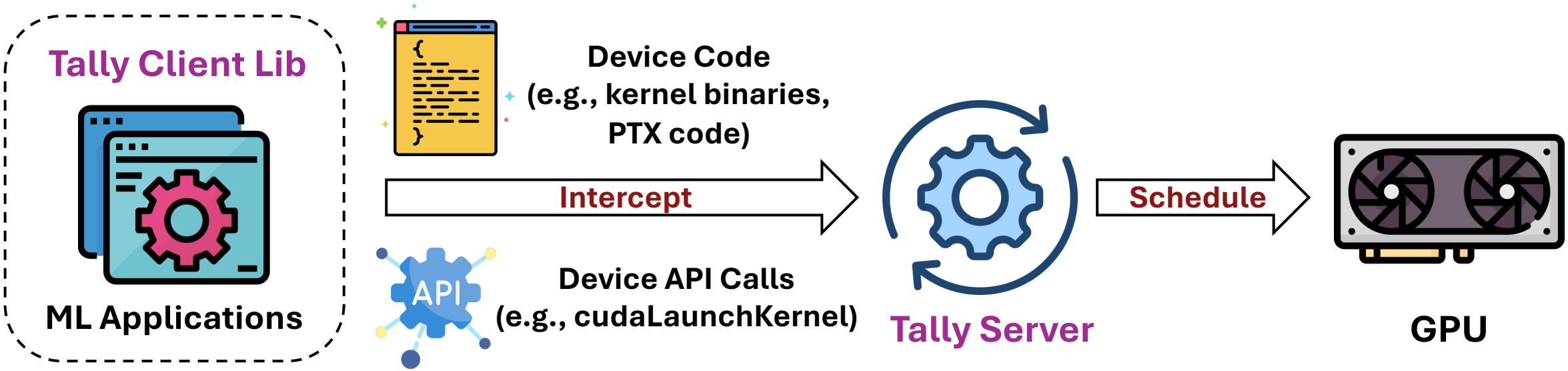
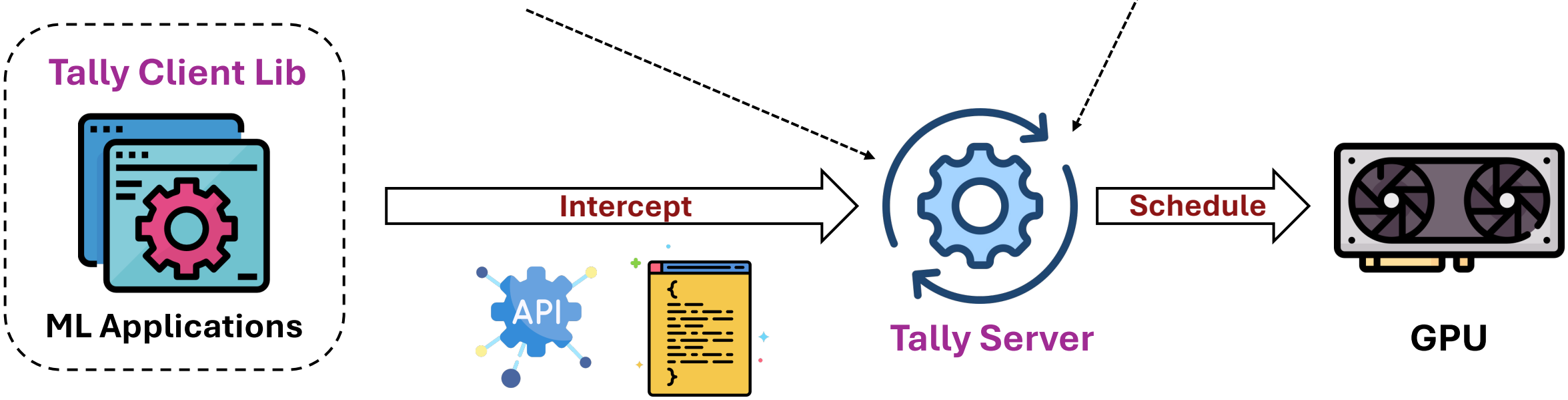


Overview of Tally — Act as Virtualization Layer



Overview of Tally

- Core mechanisms
  - Block-level scheduling primitives for best-effort kernels
  - Transparent profiler
  - Priority-aware scheduler



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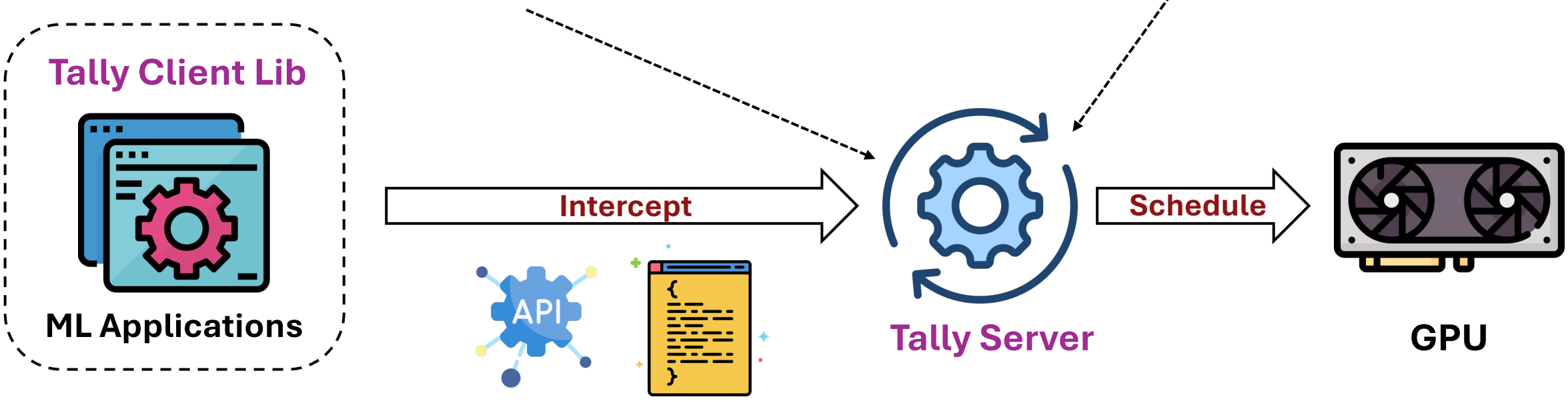
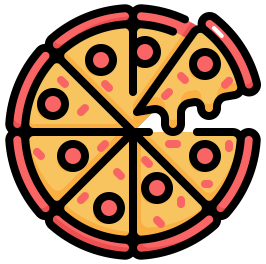


Tally's Block-level Scheduling

- Key Insights:
  - Block-level scheduling is **non-intrusive** and **generalizable** for all ML tasks
  - Previous results are **kept** instead of simply discarding
  - Turnaround latency (~100us) is **tolerable**

- Tally's Scheduling Strategy towards Different Tasks
  - High-priority: keep it **as-is**
  - Best-effort: **transform** and schedule kernels at block-level **via two primitives**



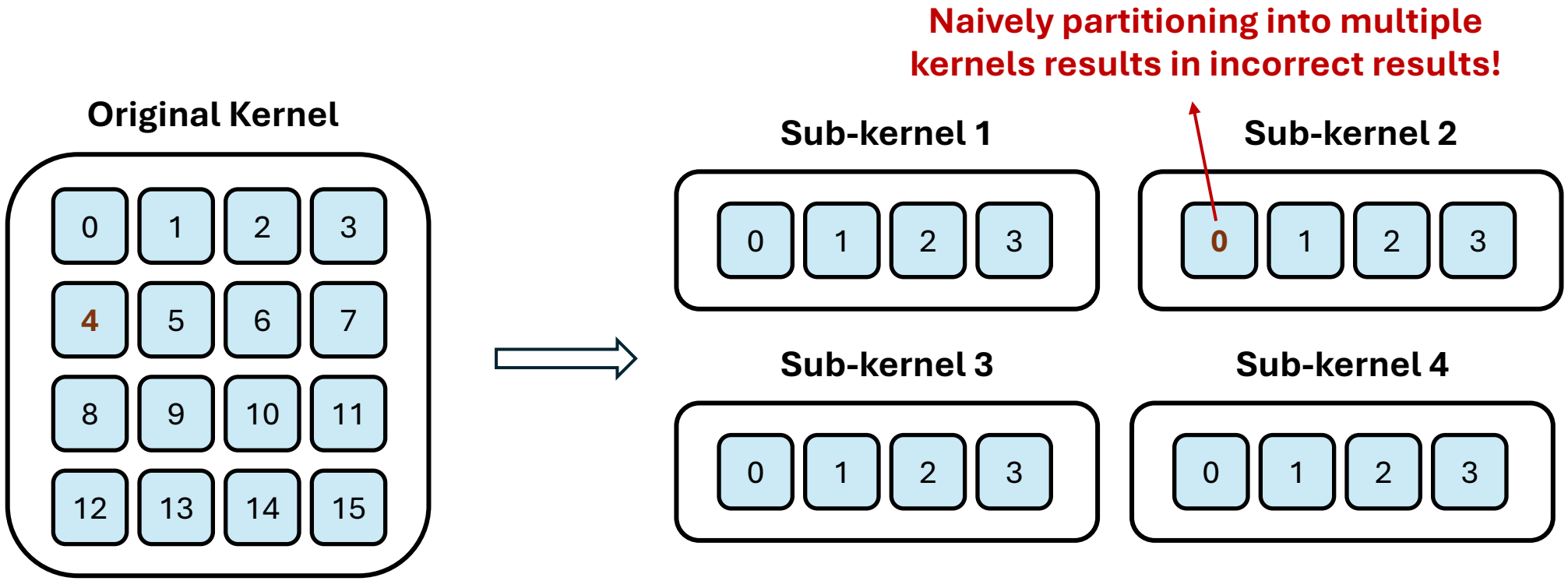
Slicing

or

Preemption

Slicing Transformation

- Divide a kernel into multiple sub-kernels to allow for more fine-grained scheduling



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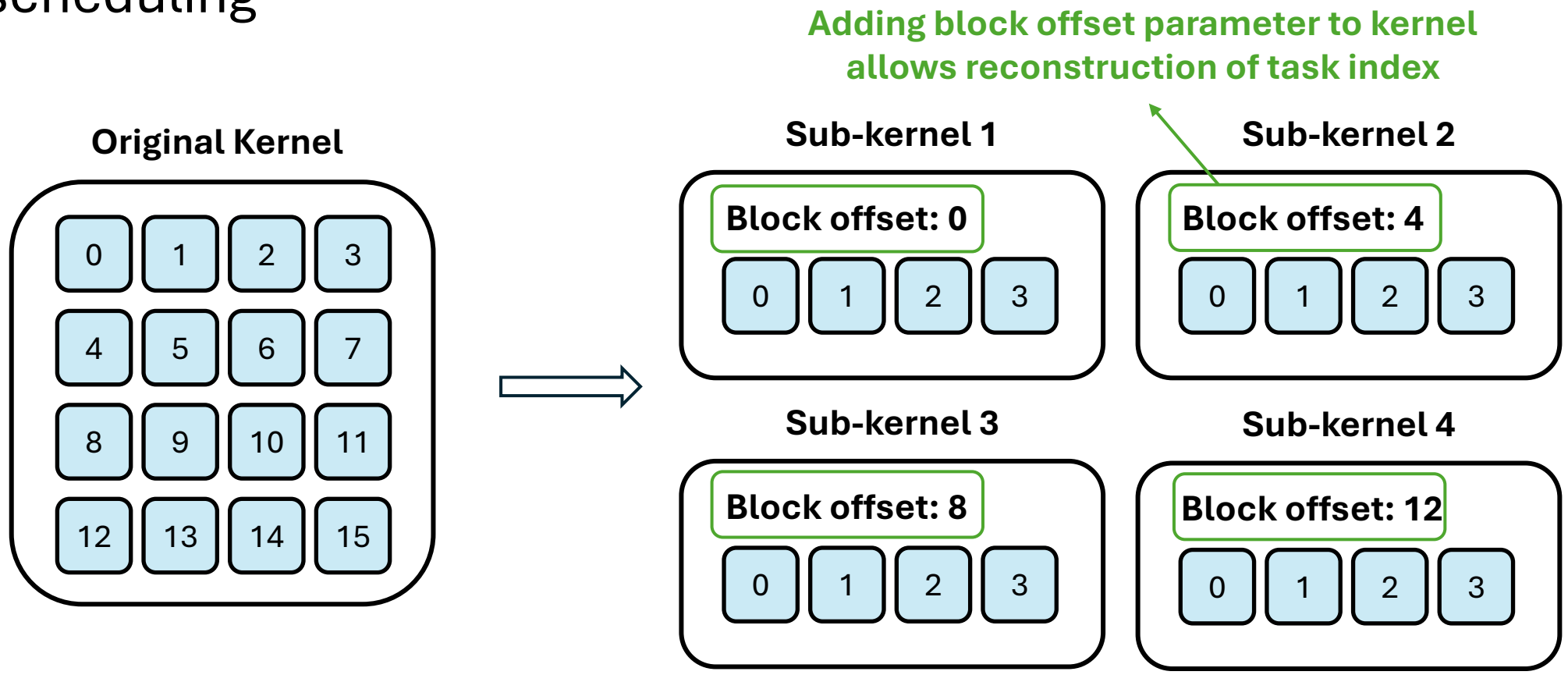
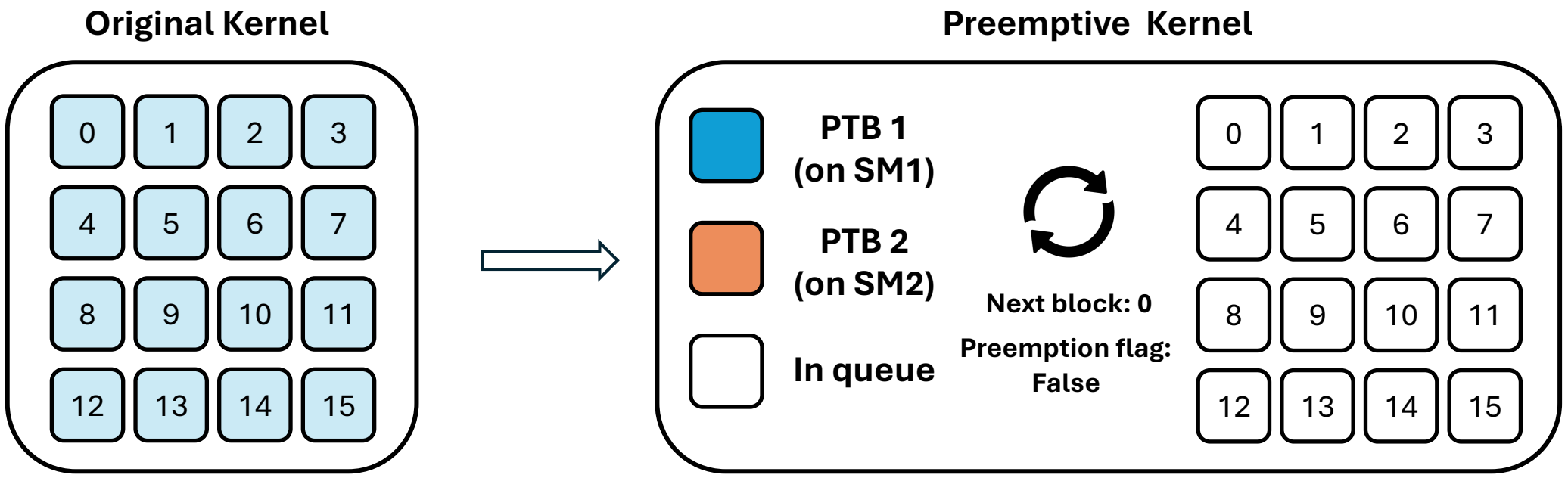


Preemption Transformation

- Modify the kernel execution mode to **Persistent Thread Block** (PTB)



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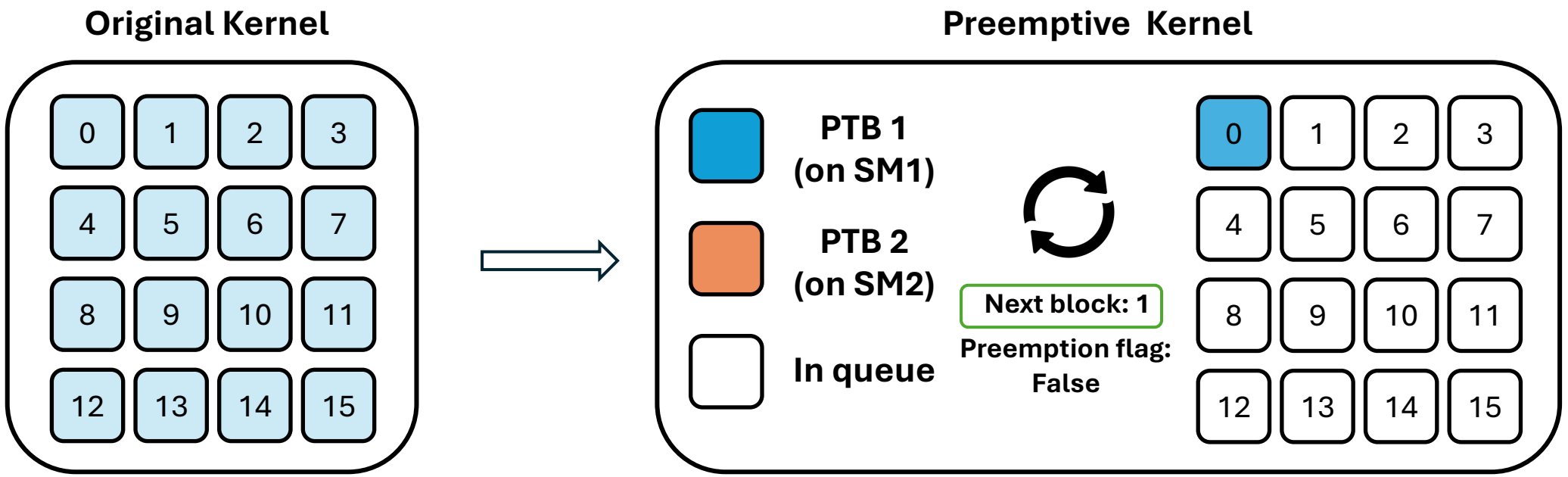

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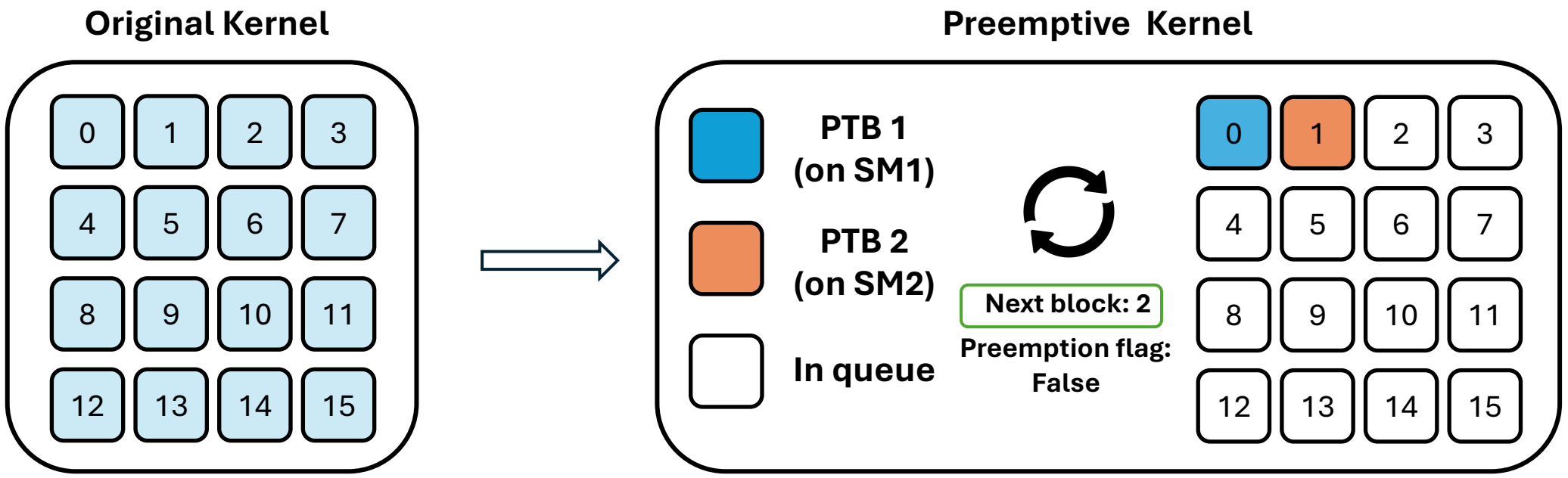

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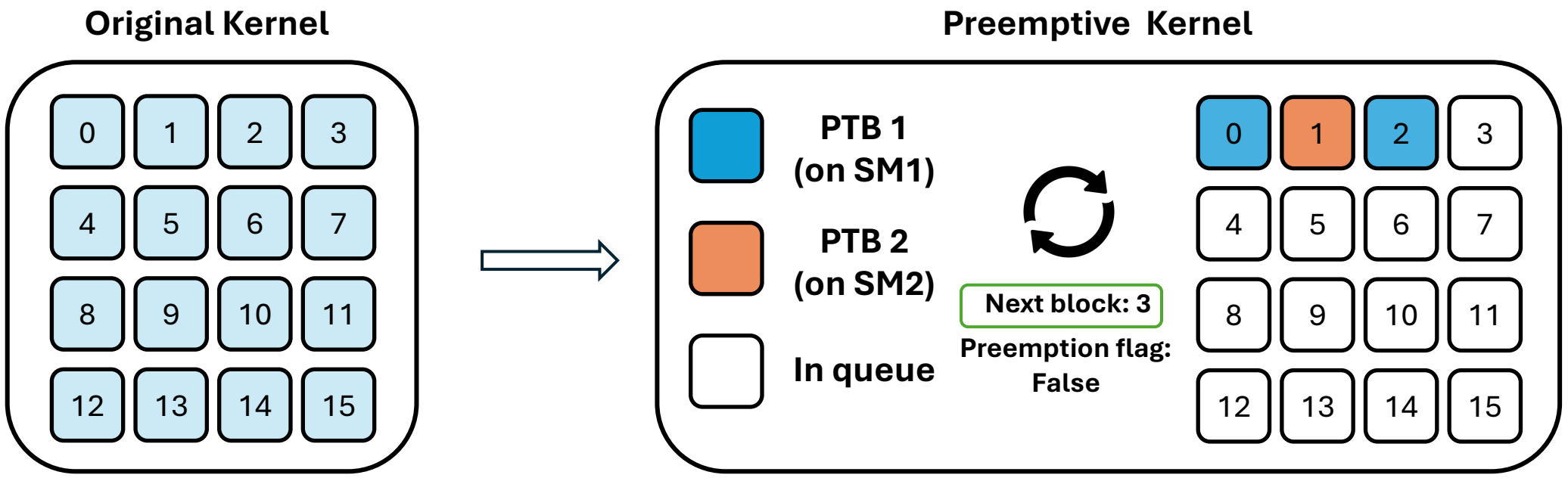
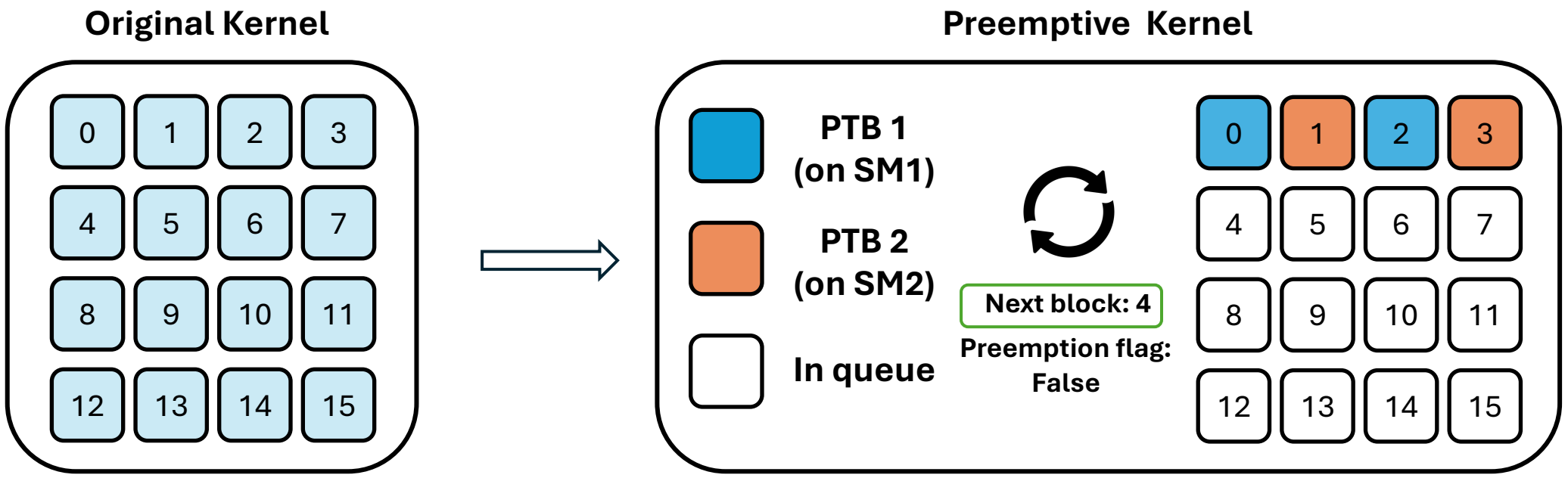


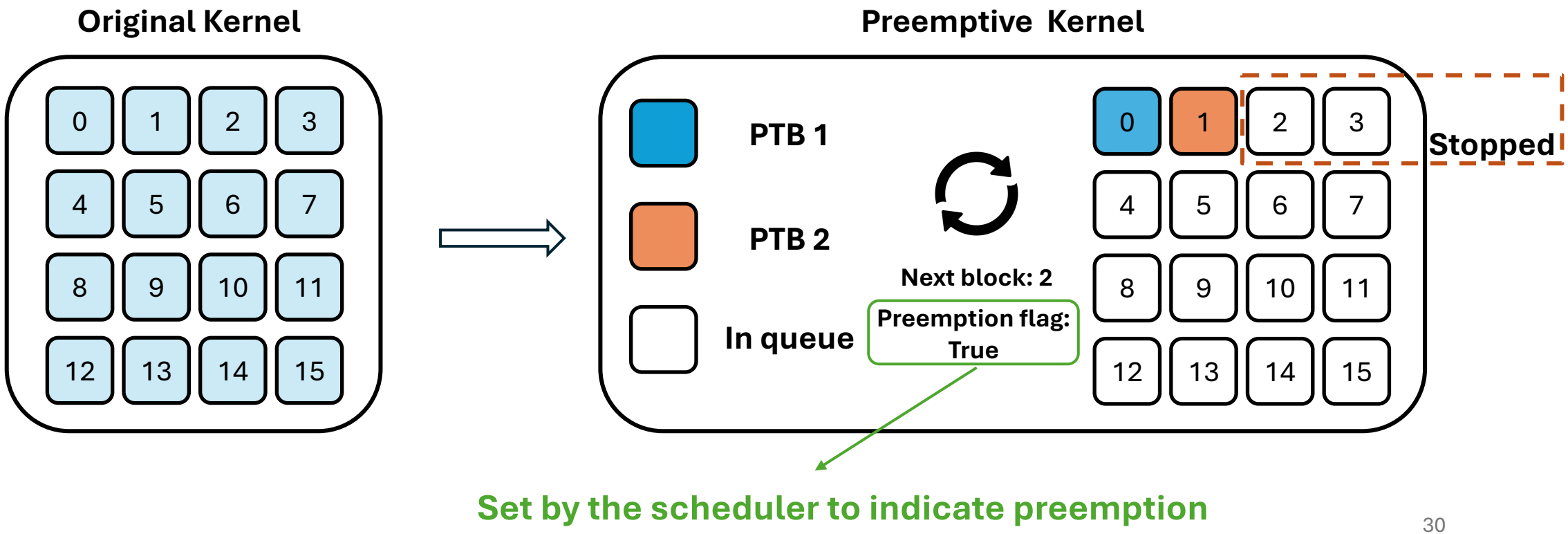
Preemption Transformation

- Modify the kernel execution mode to Persistent Thread Block (PTB)
  - **DeepGEMM also uses PTB to control SM number**



Preemption Transformation

- Allow the interruption of active kernels to accelerate resource reallocation



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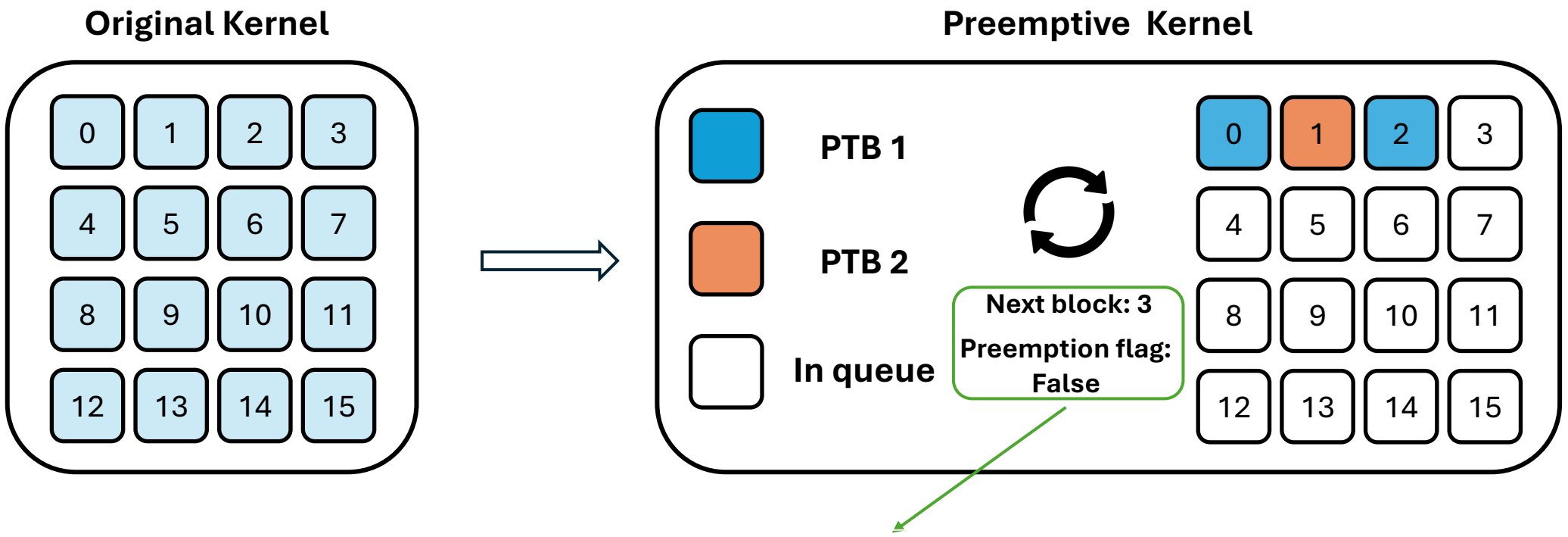
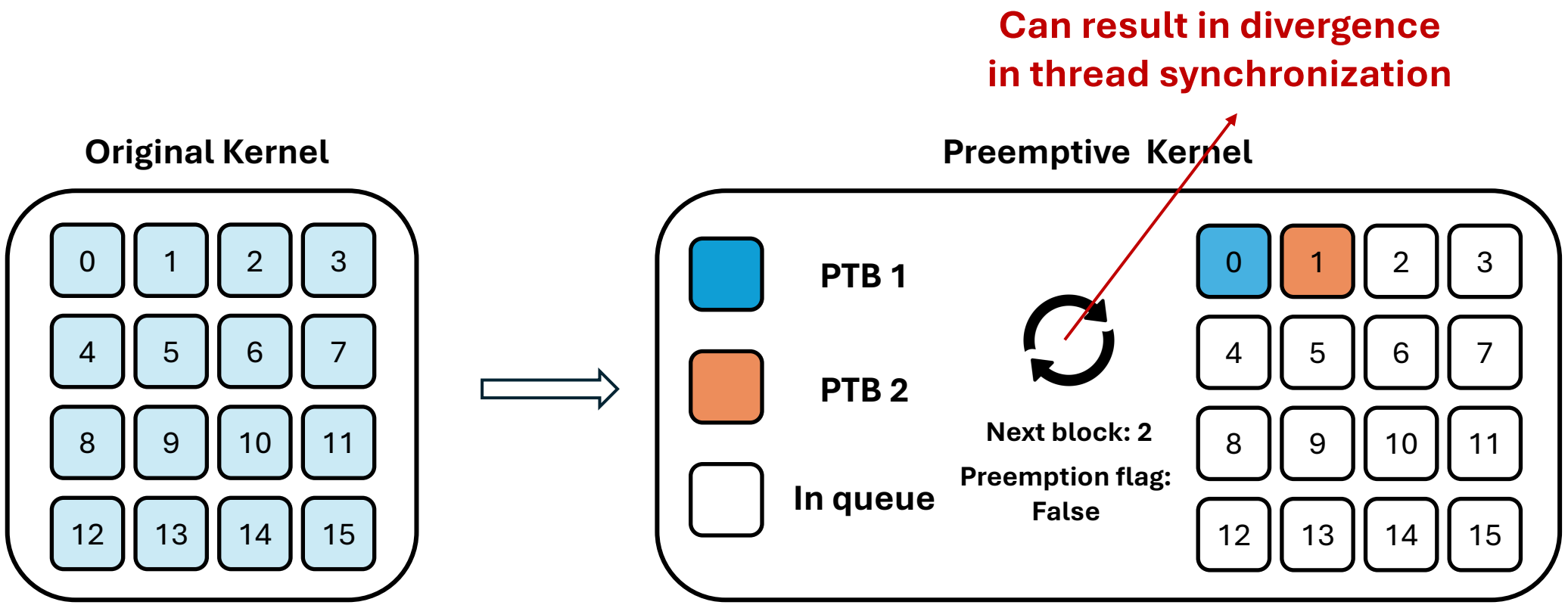


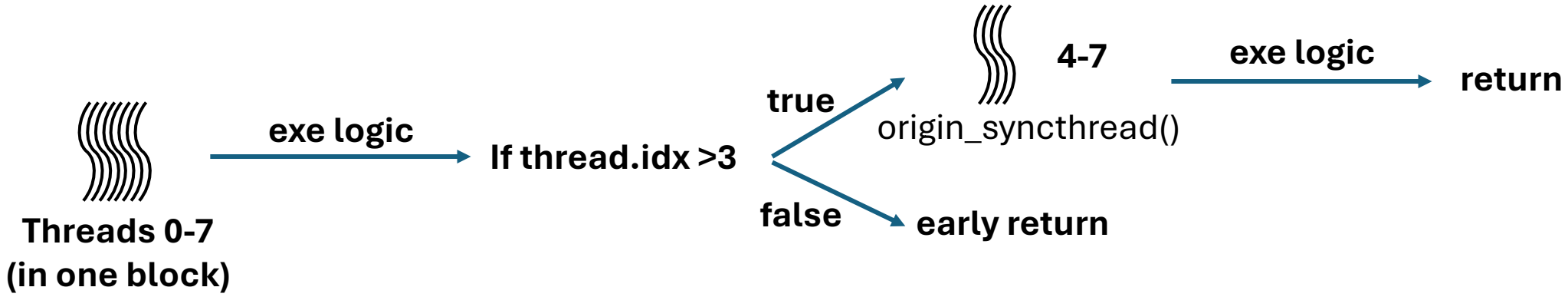
Preemption Transformation

- Transform kernels to PTB by wrapping it with an **outer control loop**



Unified Synchronization Transformation (UST)

- Original code before preemption transformation



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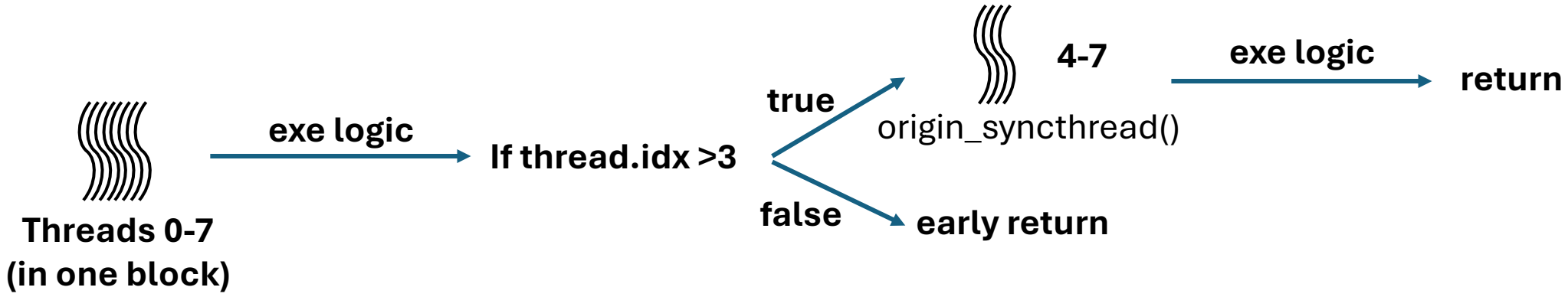
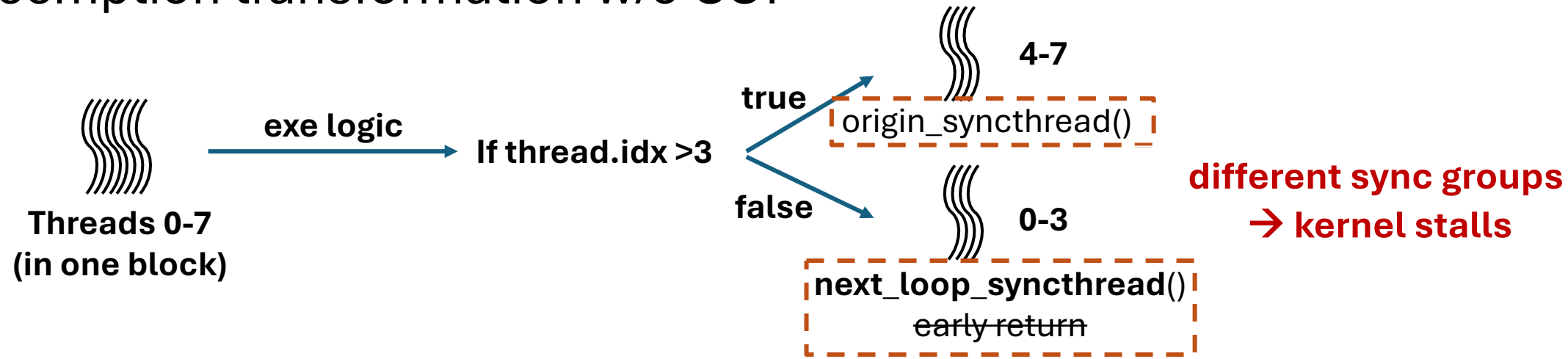


- Preemption transformation w/o UST



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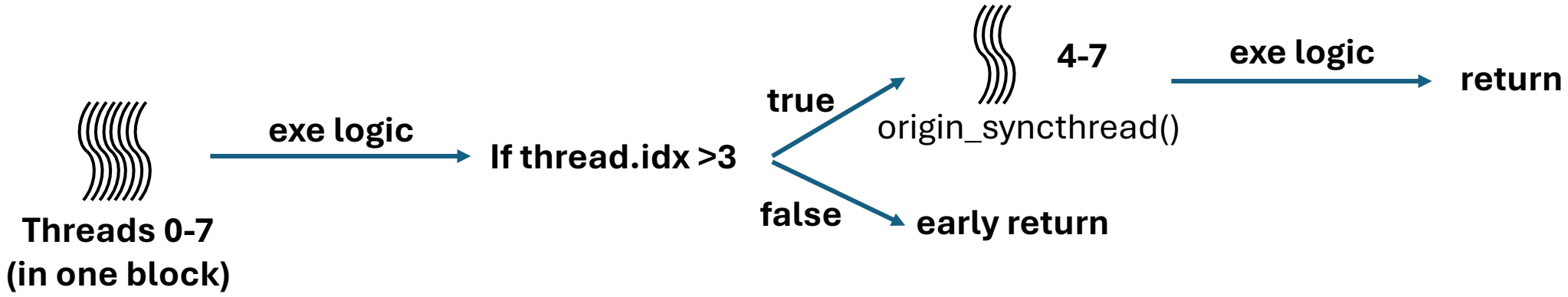
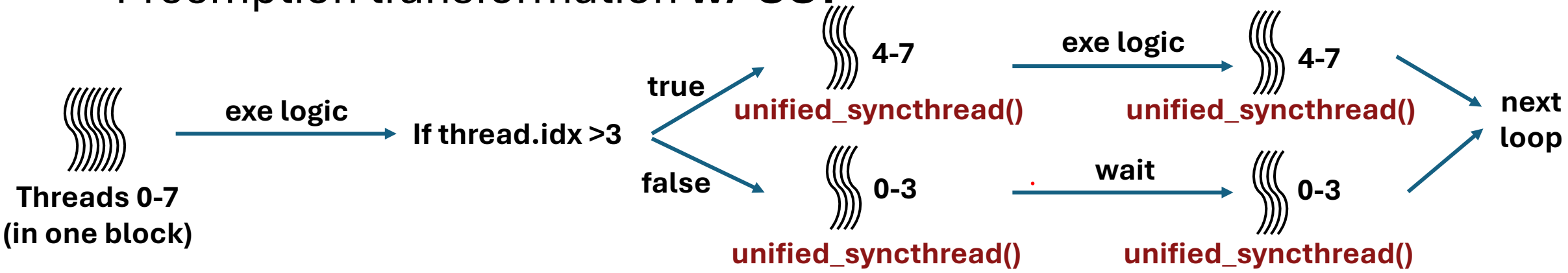


- Preemption transformation **w/ UST**



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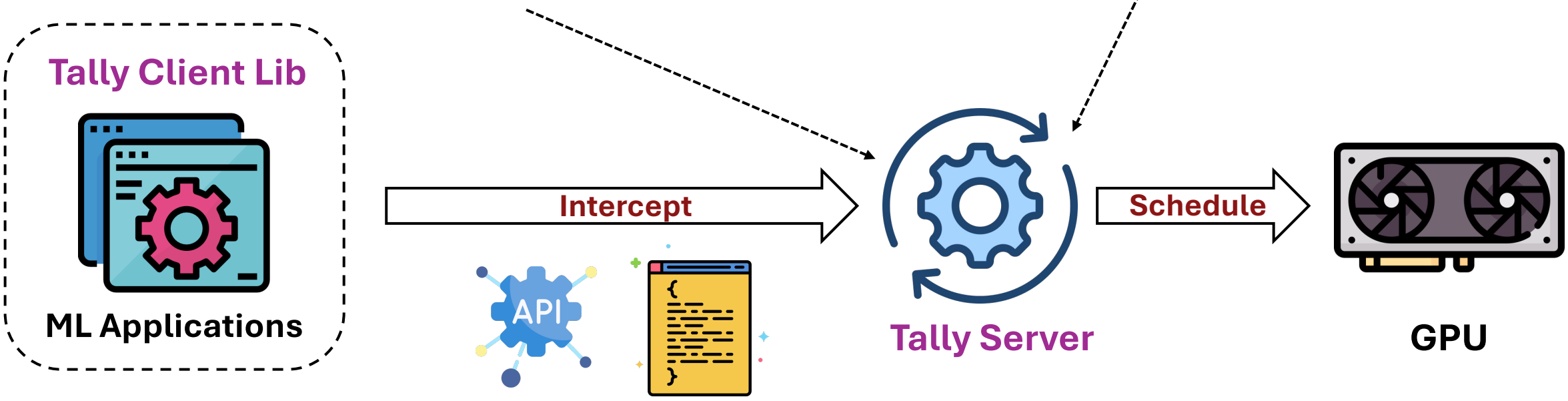
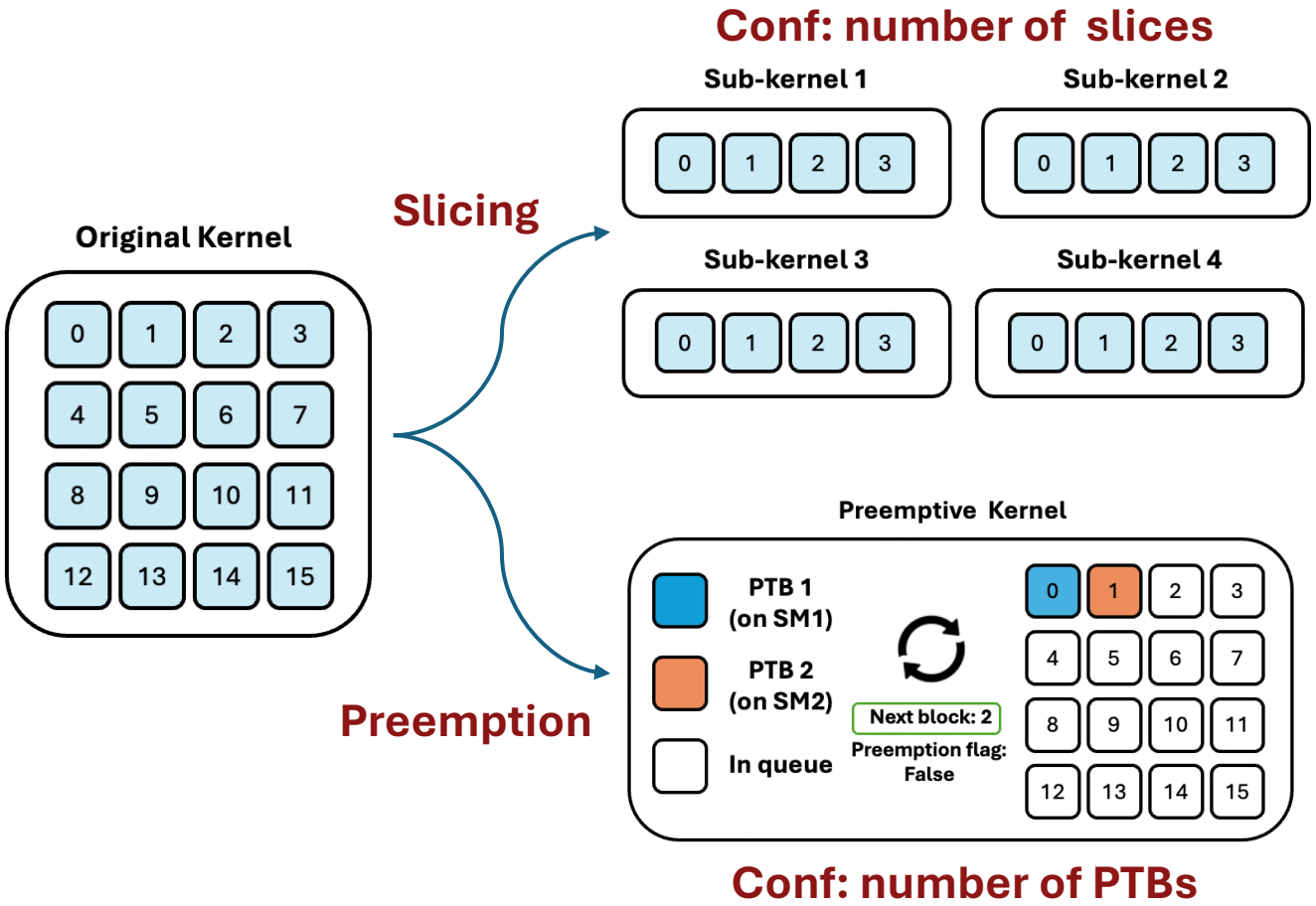
  - Block-level scheduling primitives for best-effort kernels
  - **Transparent profiler**
  - Priority-aware scheduler



Pros and Cons of Different Primitives

- **Turnaround latency** and **throughput** vary when using different block-level primitives and their launch configurations



Pros: lightweight, no sync overhead
Cons: launch overhead of sub-kernels

Pros: one-time kernel launch
Cons: sync overhead by UST

Transparent Profiler

- Profile and estimate the performance of transformed kernels in **best-effort** tasks **at runtime**
  - Generate candidate configurations encompassing both slicing and preemption
  - Estimates **turnaround latency** of different configurations
    - Slicing: execution time of one sub-kernel
    - Preemption: heuristic approximation → $$turnaround\_latency = \frac{kernel\_latency \times PTB\_blocks}{total\_blocks}$$

- **Scheduler** selects the one that achieves the optimal performance while complying with a predefined turnaround latency threshold

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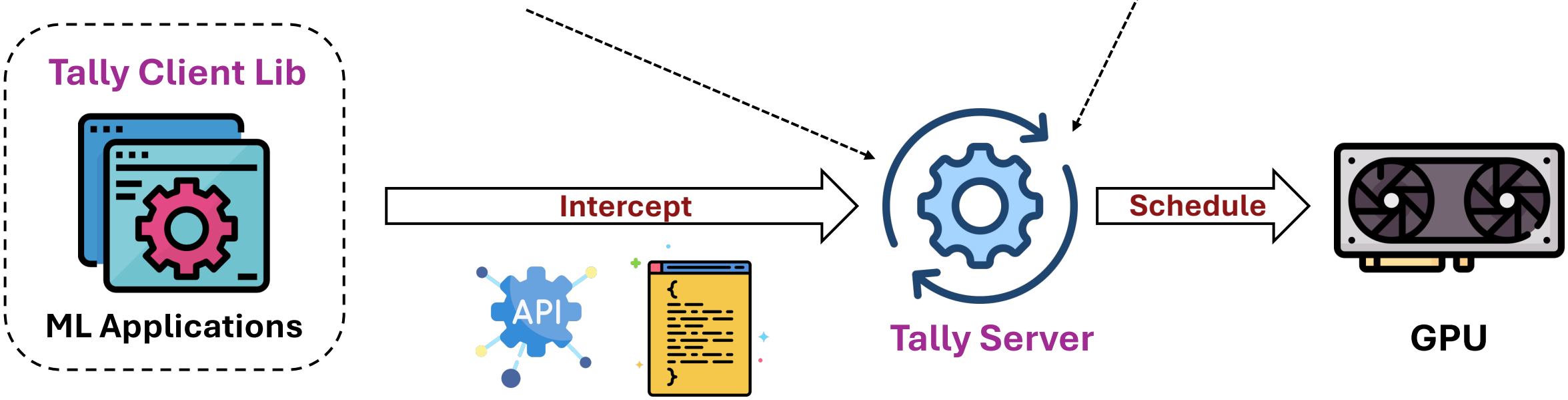

Priority-aware Scheduler

- Wisely schedules kernel to guarantee **SLA** and improve **throughput** based on block-level primitives and transparent profiler

- Scheduling strategy **in a nutshell**
  - If meets high-priority kernel
    1. **Preempt** block-level best-effort kernels (slicing/preemption)
    2. Schedule high-priority kernel instantly
  - If doesn't have high-priority kernel
    1. Choose best-effort kernels to schedule
    2. If kernel doesn't have block-level launch configuration, use **transparent profiler** to find optimal configuration **on-the-fly**

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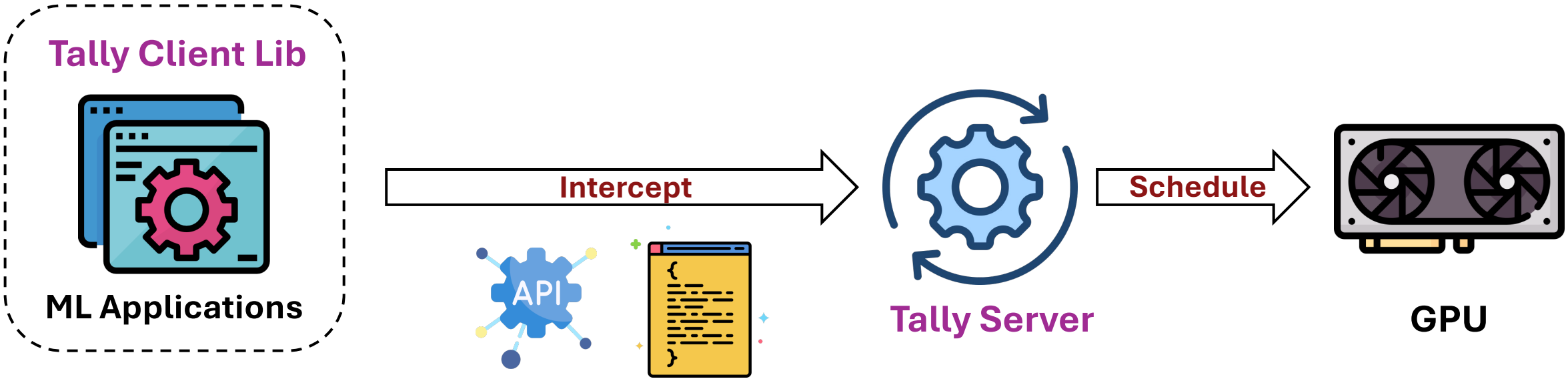
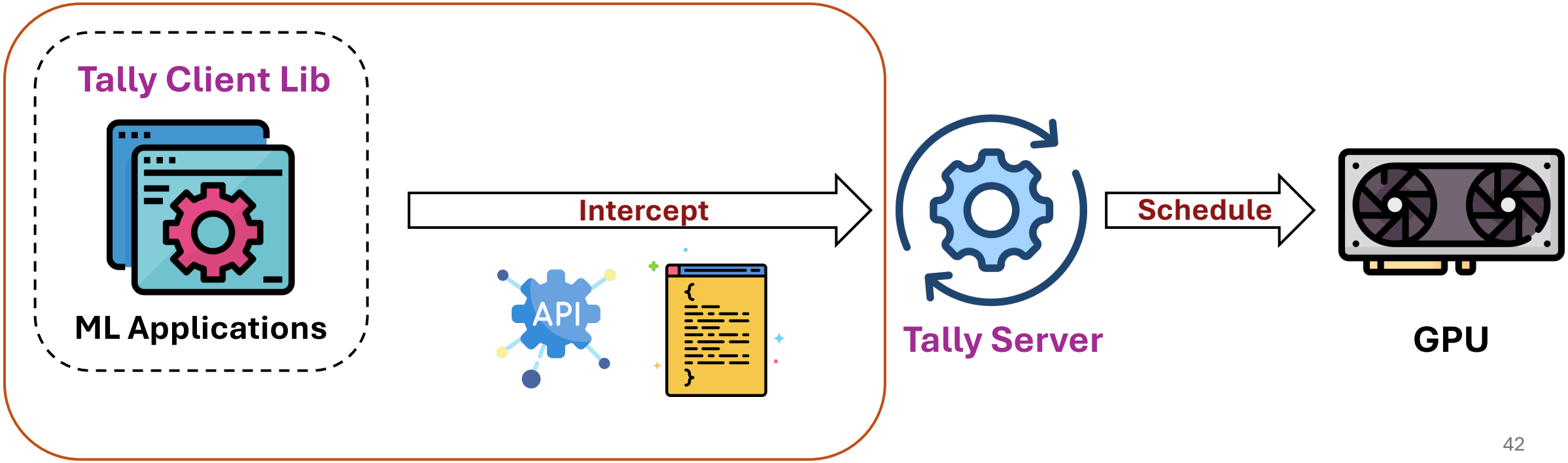
Non-Intrusive
Generalizable

Performance
Isolation



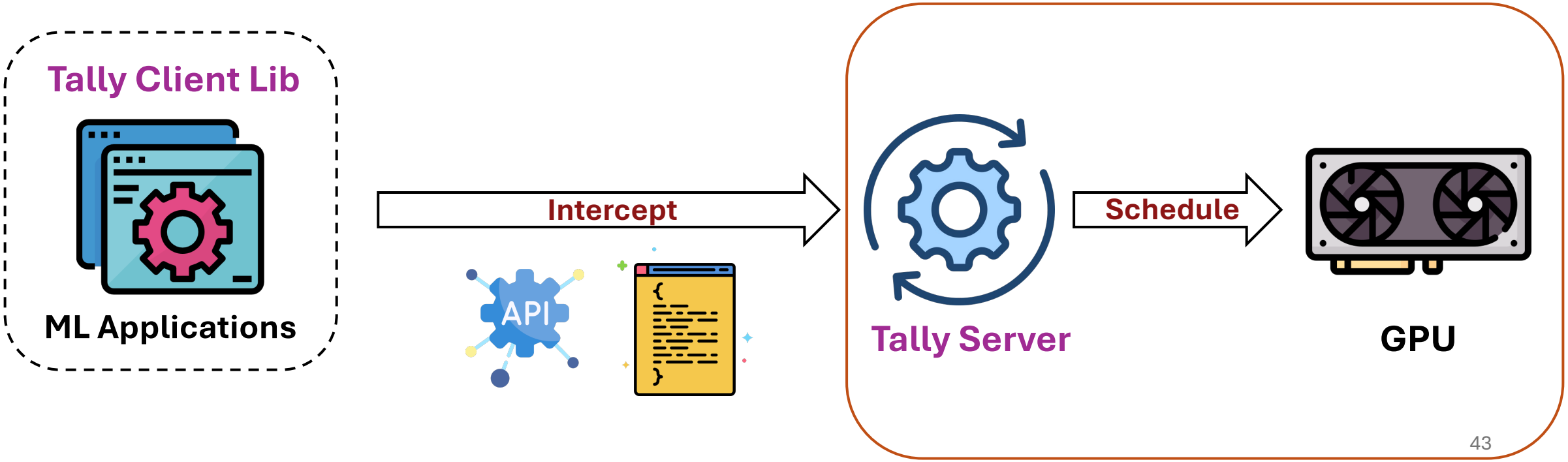
Implementation Details

- Tally's client-side
  1. Use LD_PRELOAD in Linux to **intercept** API calls
  2. Intercepted API calls are **sent** to the server for actual execution
     - **Shared memory** and **local state caching** are used to reduce communication overhead



Implementation Details

- Tally's server-side
  1. Apply kernel transformations for best-effort kernels at **PTX level**, then **recompile** to executable GPU kernels
  2. Schedule kernels based on priority-aware scheduler

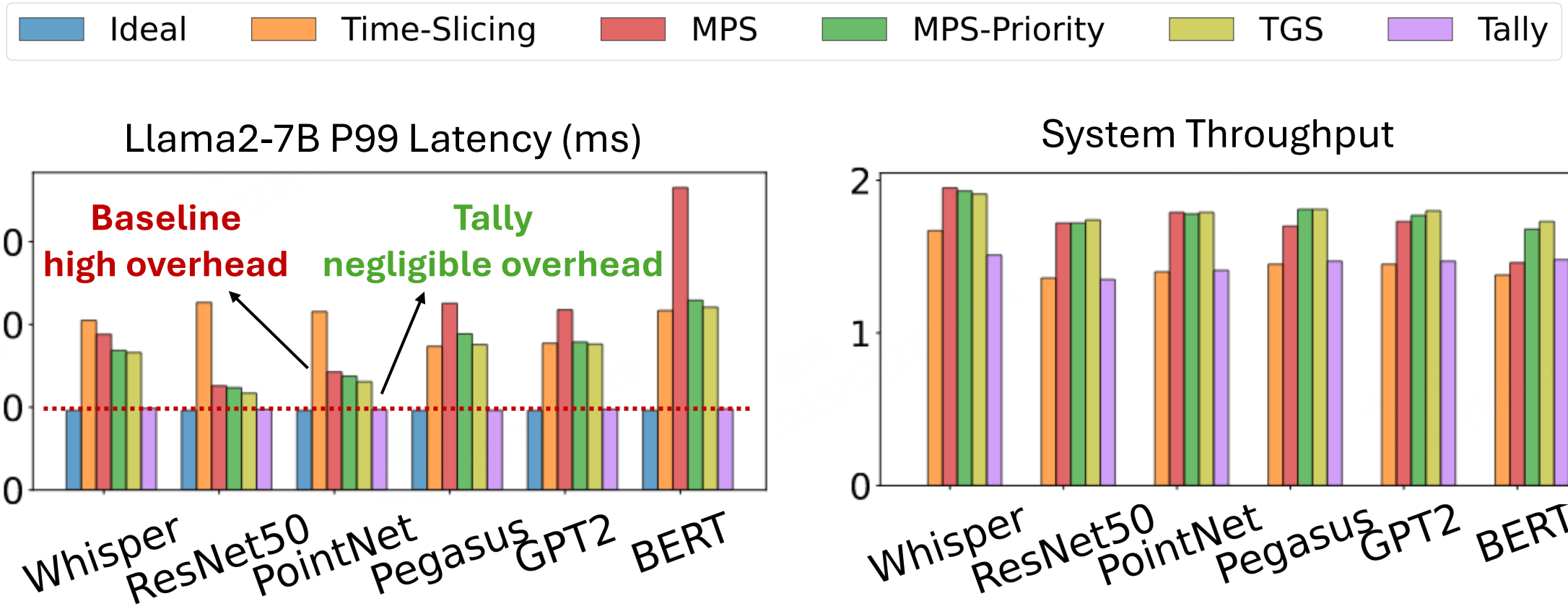


Evaluation

- Hardware:
  - NVIDIA A100 GPU
- Workloads:
  - High-priority Inference + Best-effort Training
- Metrics:
  - 99th Percentile Latency
  - System Throughput
- Baselines:
  - Ideal (no sharing, evaluate **latency**)
  - Time-Slicing (default sharing mechanism)
  - NVIDIA MPS (with and w/o priority mode)
  - TGS (state-of-the-art GPU sharing)

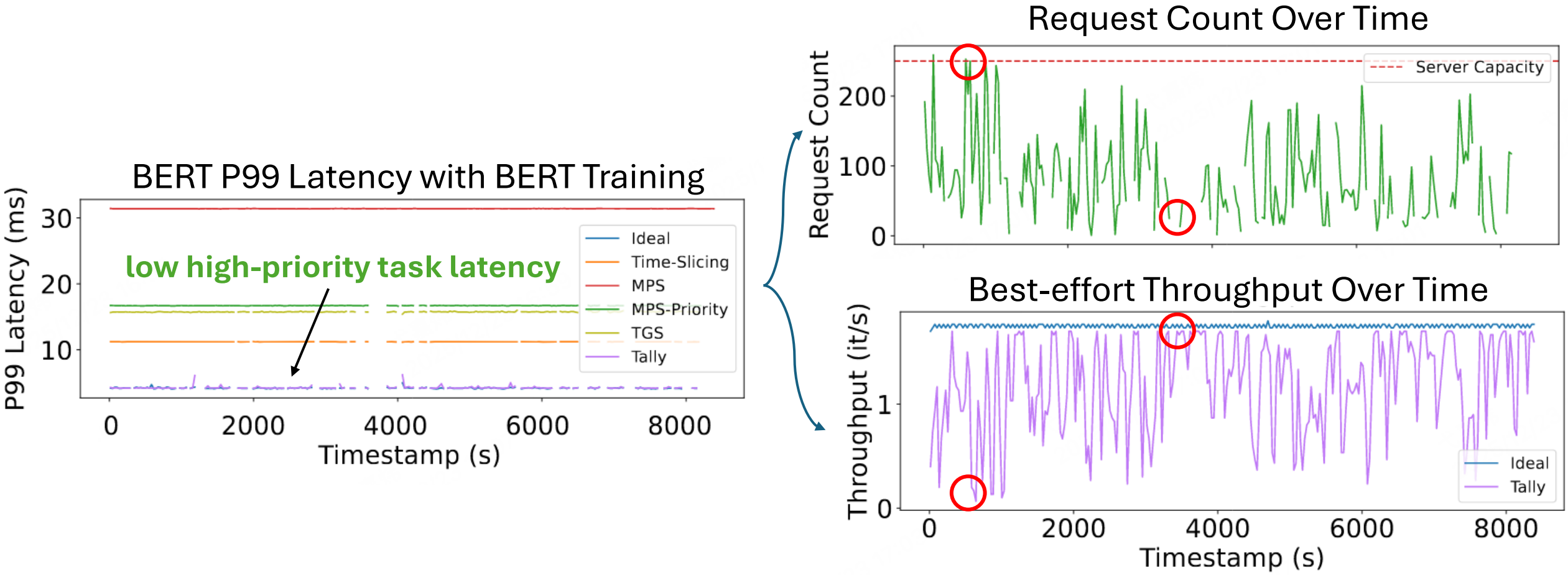
Inference	Training
ResNet50	ResNet50
BERT	PointNet
YOLOv6m	BERT
Llama2-7b	GPT2-Large
Stable Diffusion	PEGASUS
GPT-Neo	Whisper-v3

End-to-end Results



On average, Tally incurs only a **7% overhead** on the P99 latency of high-priority inference tasks, compared to **188% overhead** of the best baseline, while attaining more than **80% throughput**.

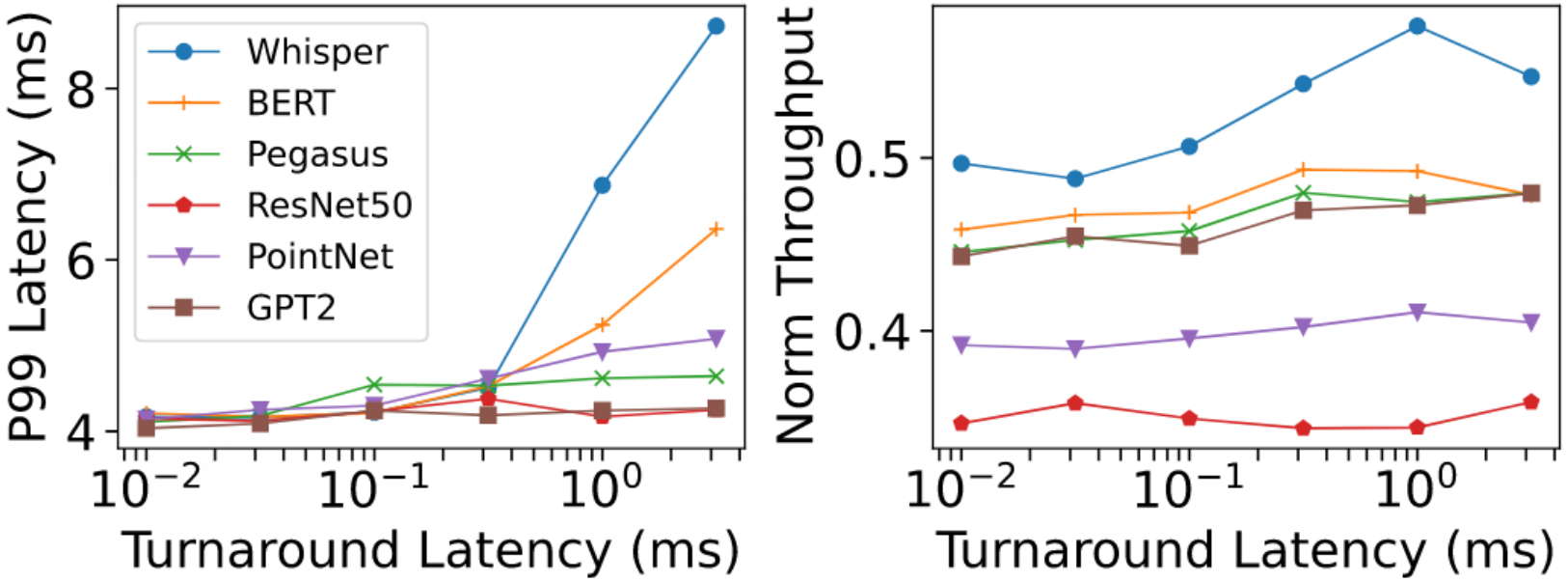
Responsiveness of Tally



Tally can **adaptively adjust the throughput** of the best-effort task in correspondence with the fluctuating traffic load to the high-priority inference task.

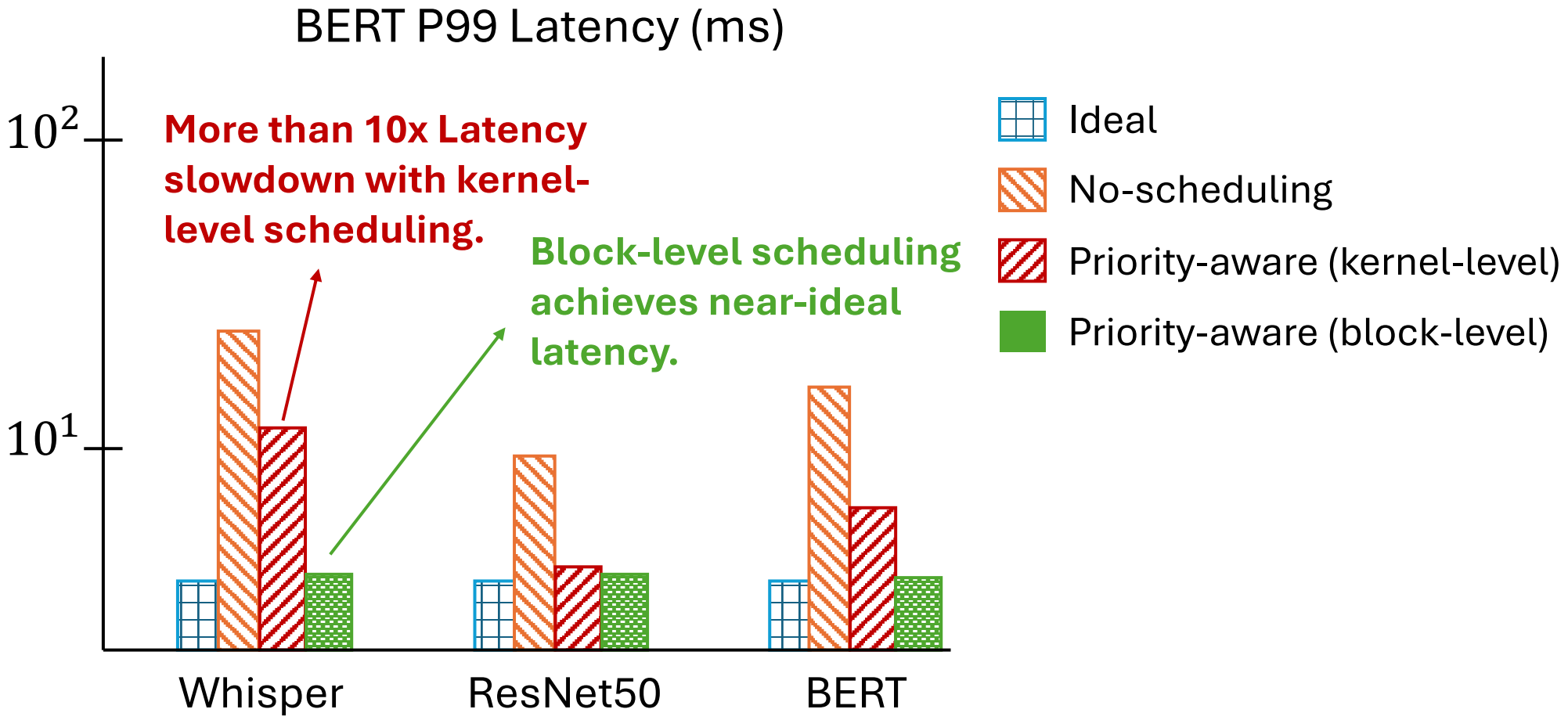
Selection of Turnaround Latency Threshold

P99 Latency and Throughput during BERT Inference Varying Turnaround Latency



Based on **empirical results**, Tally chooses threshold of **0.0316 ms** that provides the best balance between latency and throughput.

Importance of Block-level Scheduling (Ablation)



Overhead Analysis

- Virtualization (client-server)
  - Incurs an average overhead pf only **1%**, proving minimal performance impact
- Transformed kernel execution
  - Execution of block-level best-effort kernels causes **25%** average overhead
- Profiling
  - One-time online profiling for each kernel in one best-effort task complete within **minutes**, negligible given training workloads often run for hours/days

Summary

- Challenges of current GPU sharing solutions:
  - **High Integration costs** due to intrusive code modifications (**Intrusive**)
  - **Performance degradation** leading to SLA violations (**Bad Performance Isolation**)
  - **Limited workload compatibility** across applications (**Non-generalizable**)
- Method:
  - Implements **block-level scheduling primitives** for GPU virtualization
  - Ensures **effective performance isolation** in a **non-intrusive, task-agnostic** manner
- Results:
  - **7% overhead** vs **188%** in state-of-the-art GPU sharing
  - Maintains over **80% throughput** of the best-performing baseline

Remaining Problems

- Selection of **turnaround latency threshold** at block-level launch configuration is very **ad-hoc**
- Doesn’t compare with **REEF**
- Fundamentally **incompatible** with **CUDA Graph**, may encounter launch bubble issues on high-end GPUs (e.g., NVIDIA H100)