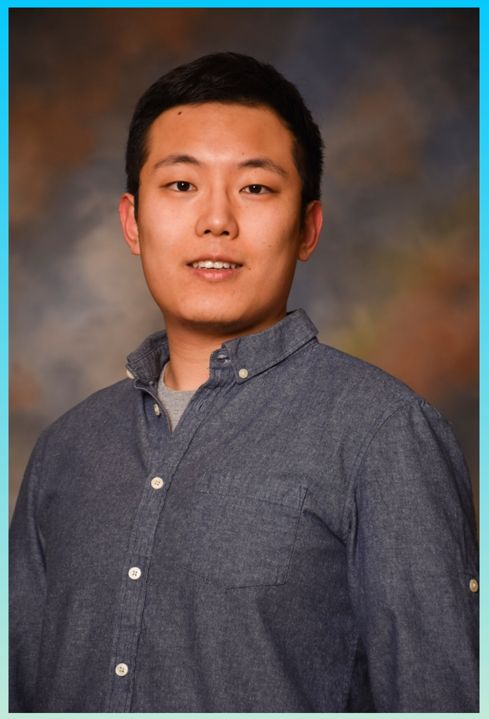
Serving DNNs like Clockwork

Performance Predictability from the Bottom Up


Arpan Gujarati


Safya Alzayat


Wei Hao


Antoine Kaufman


Jonathan Mace


Reza Karimi


Ymir Vigfusson

MAX PLANCK INSTITUTE FOR SOFTWARE SYSTEMS

EMORY UNIVERSITY

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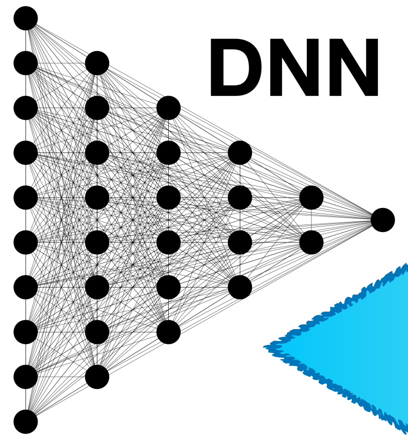
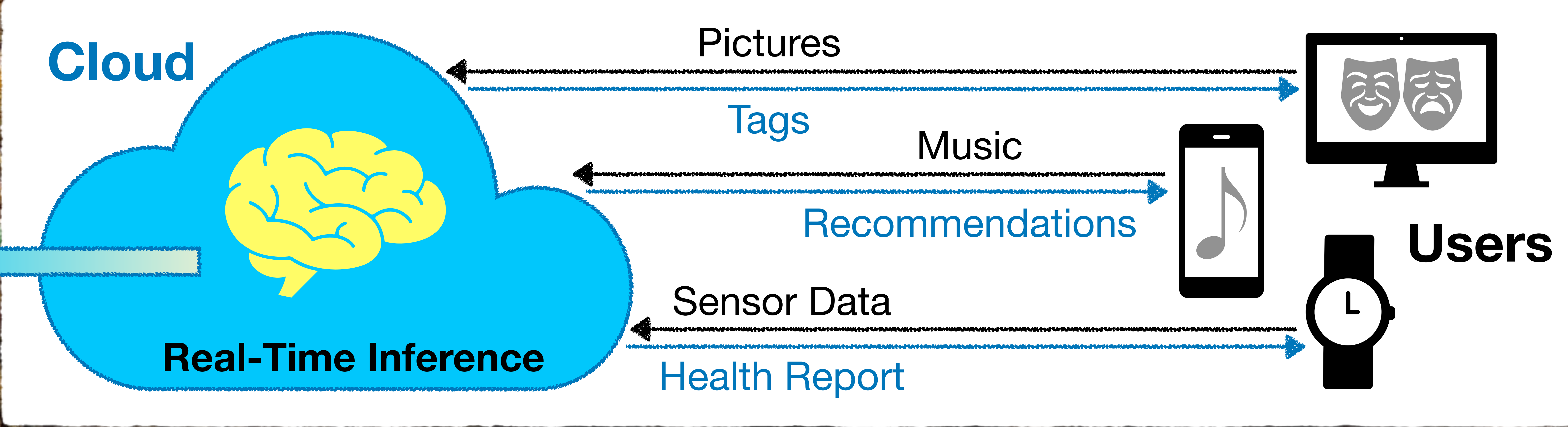
DNN inference has a very predictable execution time!





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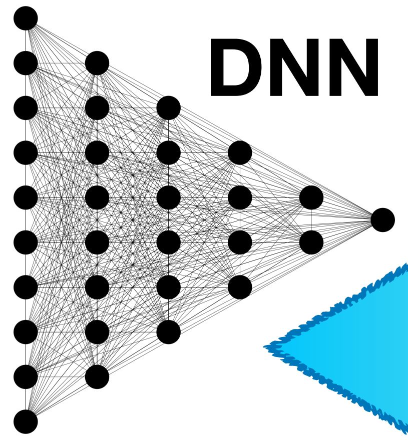

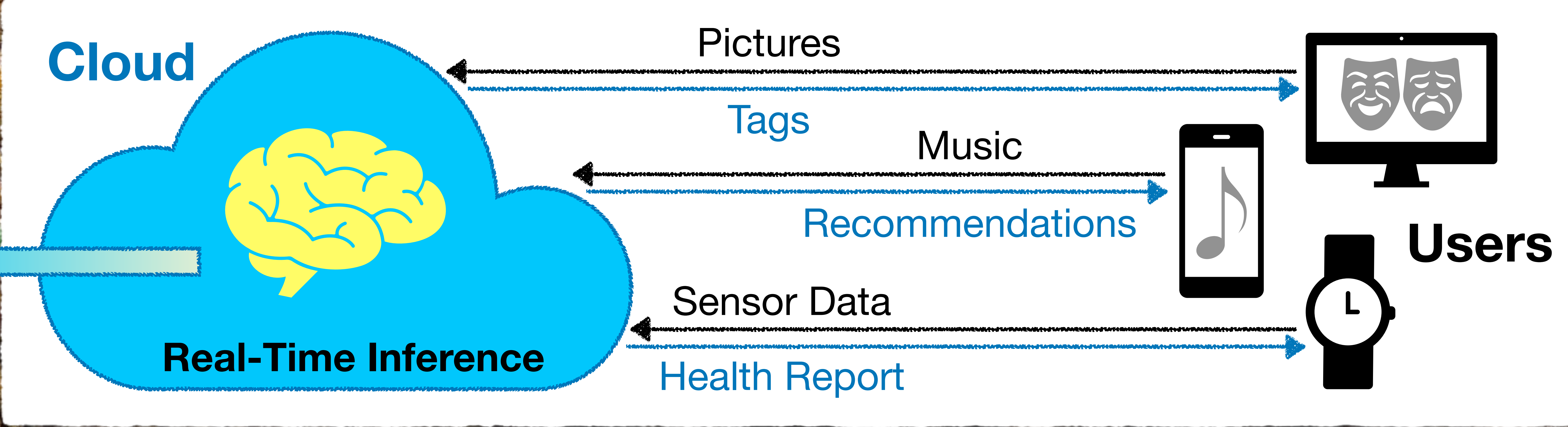

Clockwork

End-to-end predictable DNN serving platform for the Cloud

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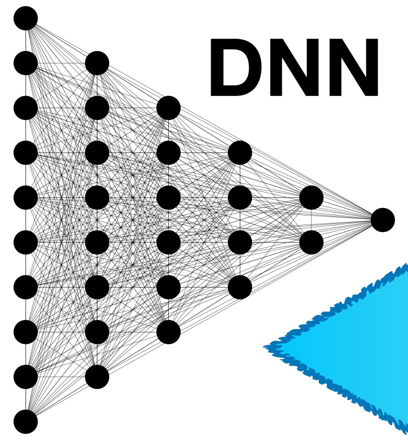

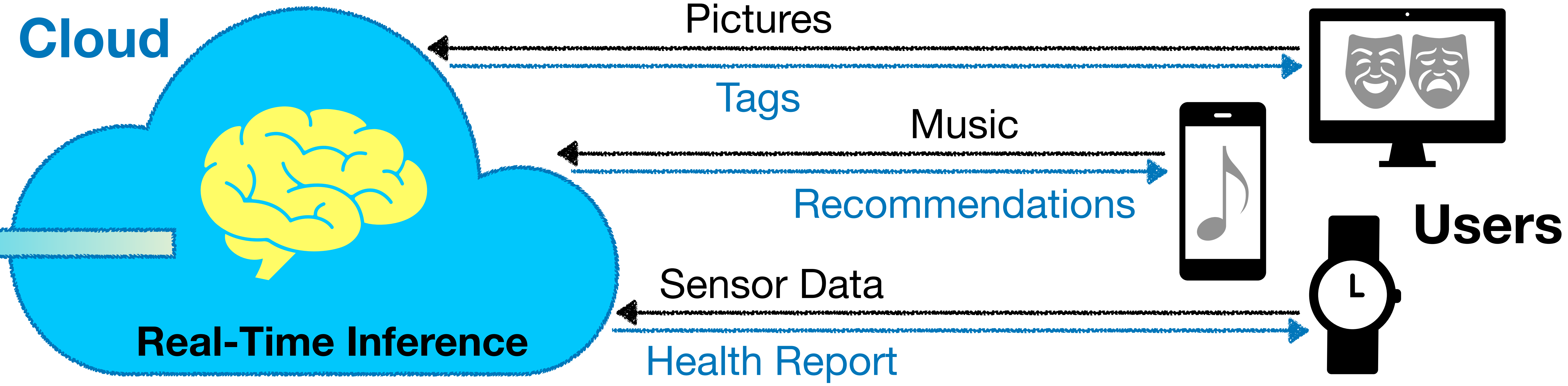

Clockwork

End-to-end predictable DNN serving platform for the Cloud

- ✓ Supports 1000s of models concurrently per GPU
- ✓ Mitigates tail latency, supporting tight latency SLOs (10—100 ms)
- ✓ Close to ideal goodput under overload, contention, and bursts

Background

Inference Serving at the Cloud Scale is Difficult

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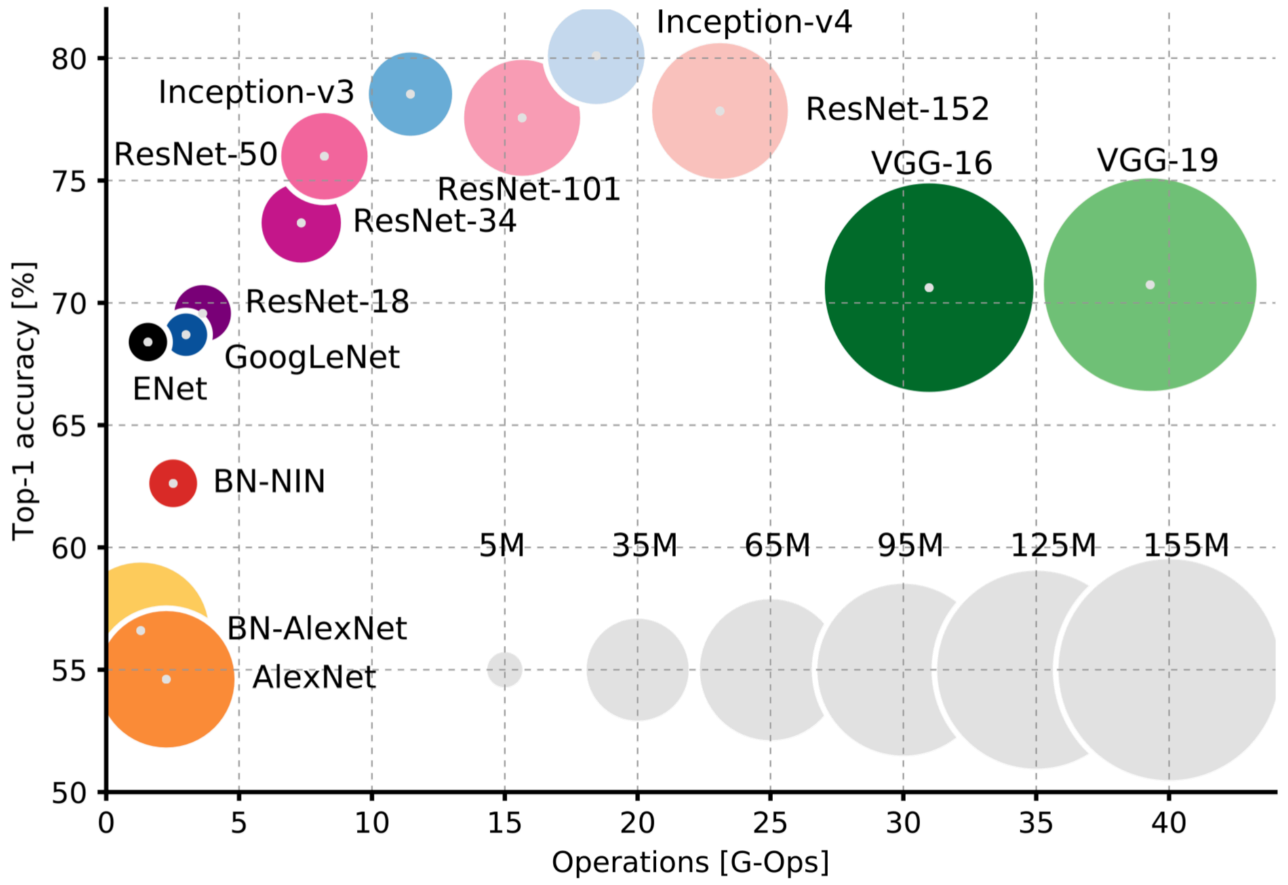
1000s of trained models of different types and resource requirements



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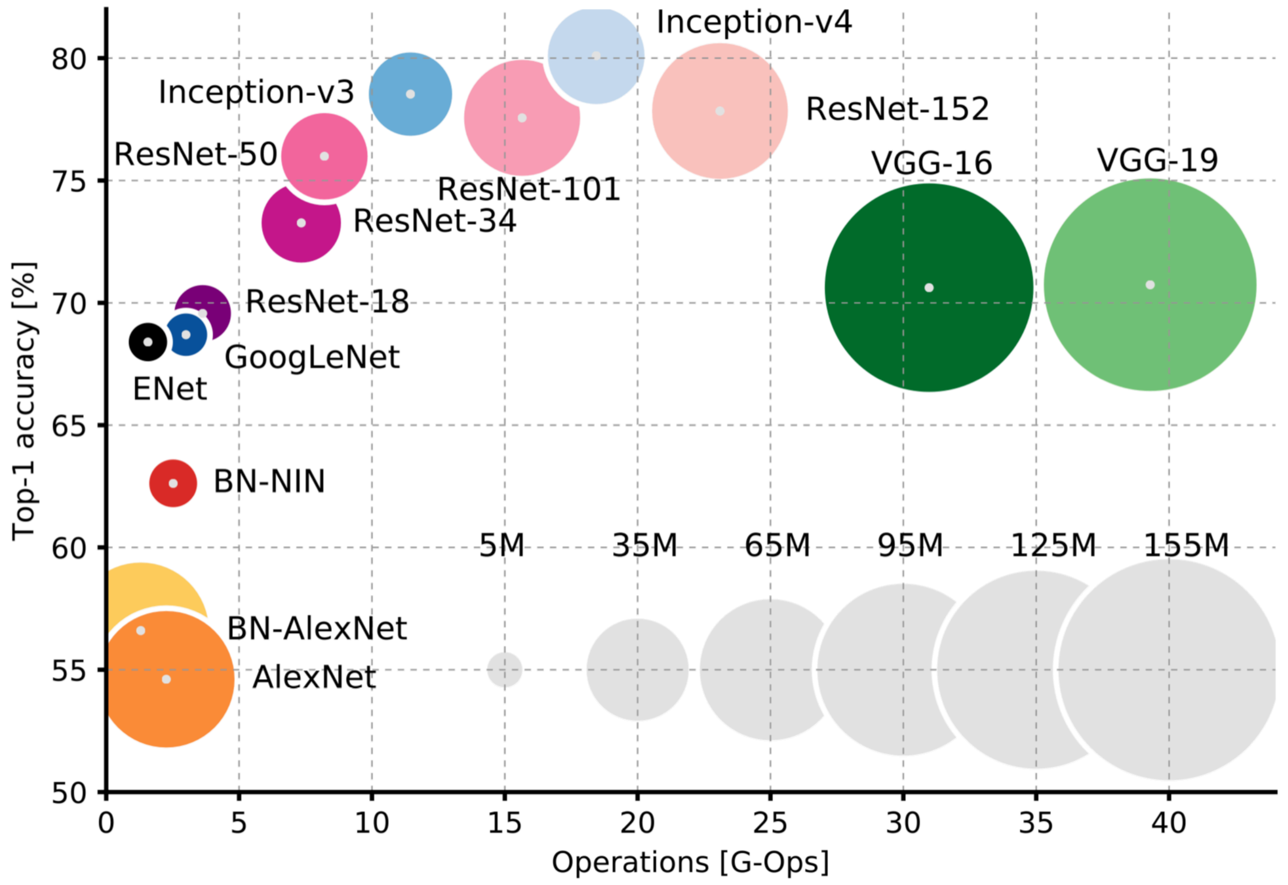
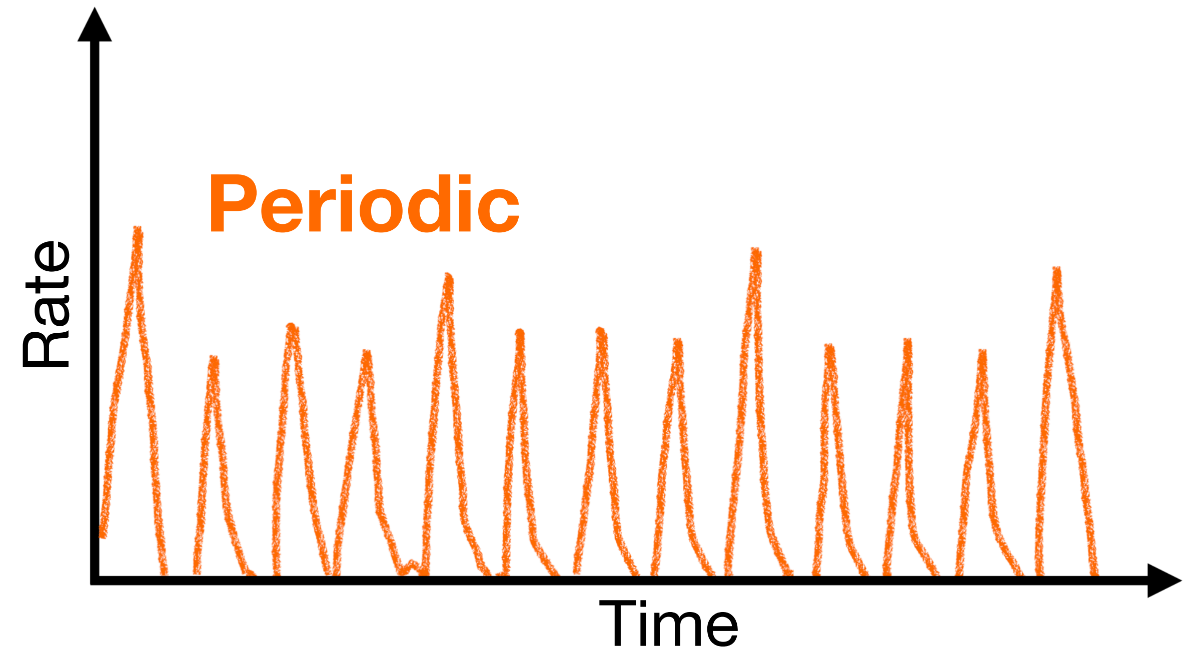


Requests arrive at different rates and regularity



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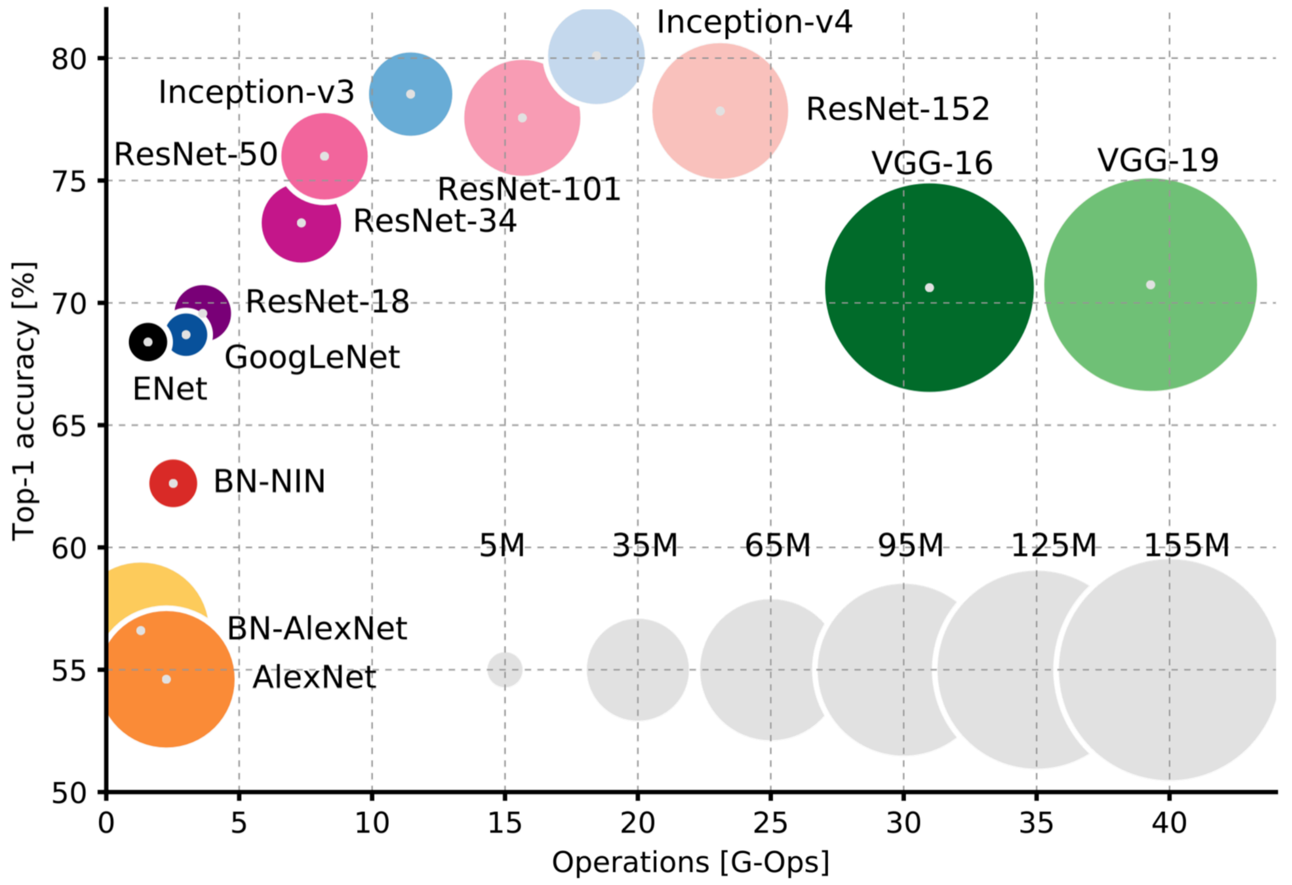

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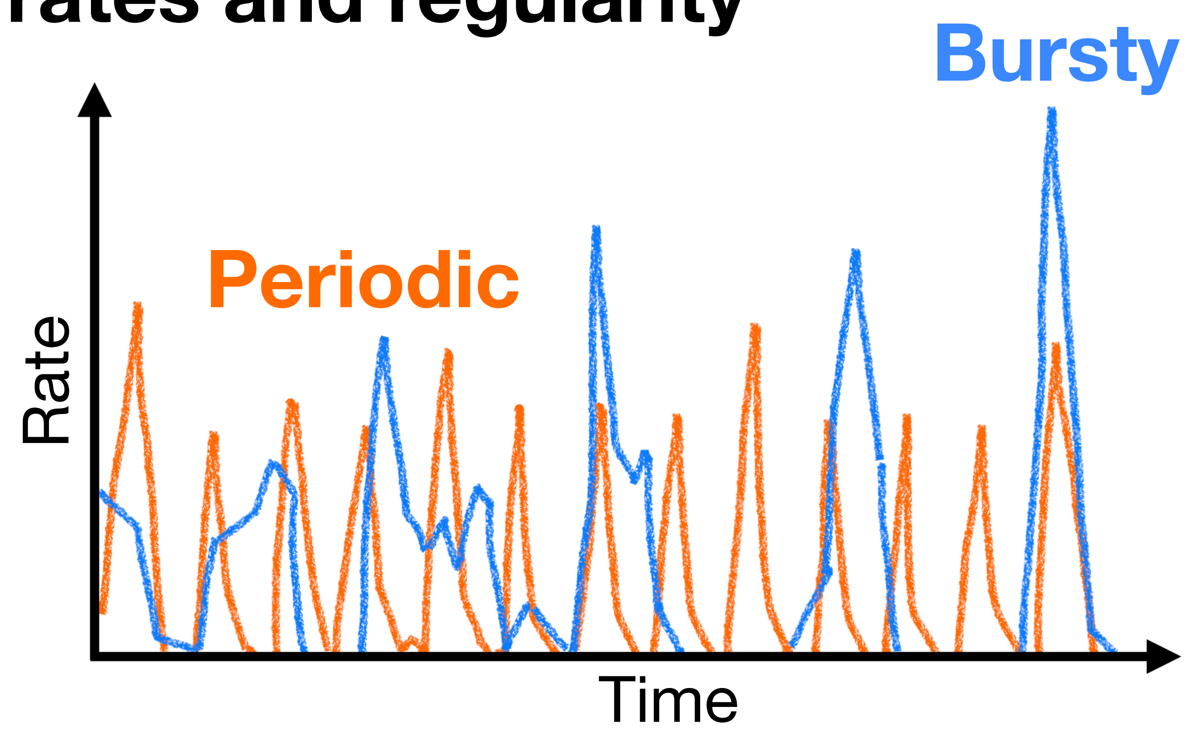

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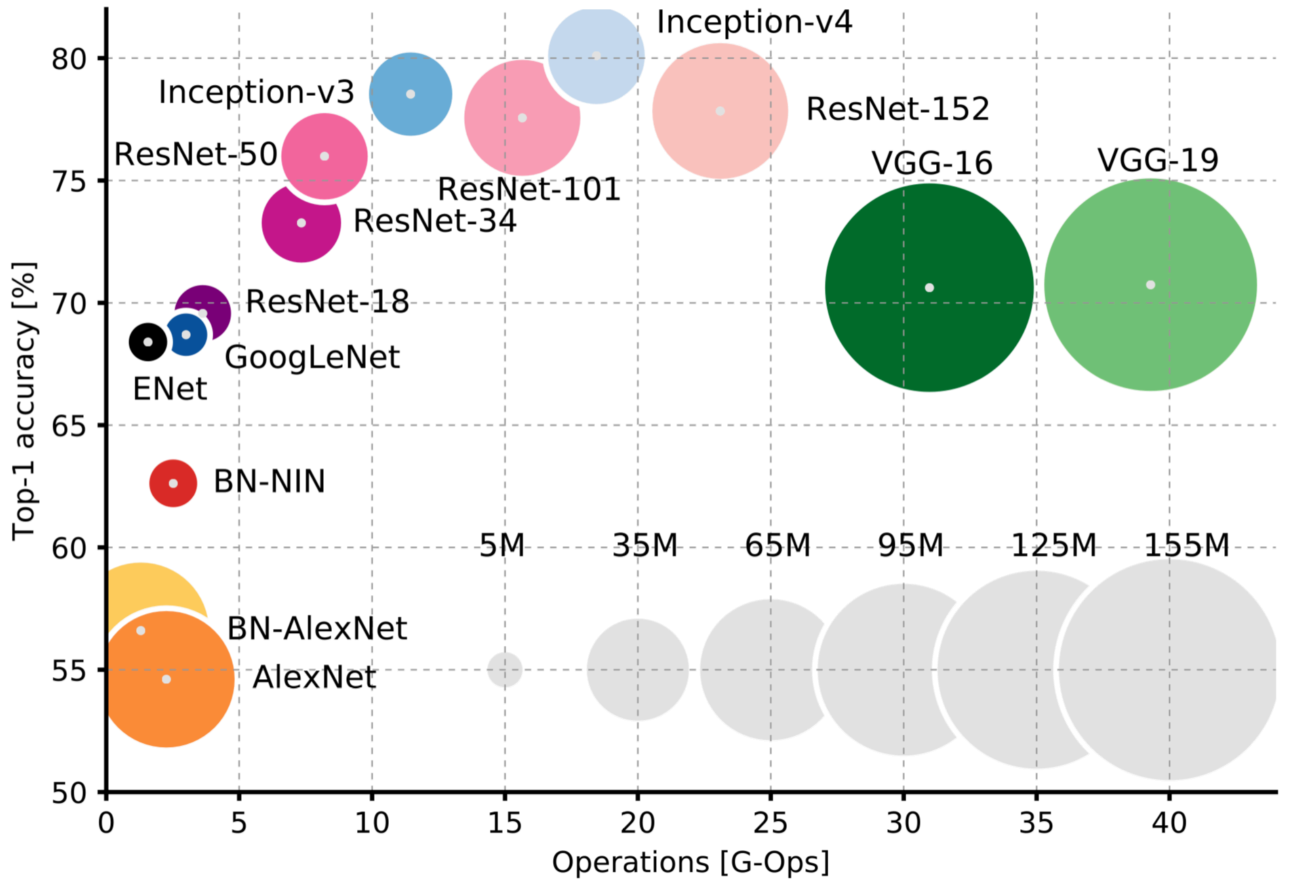

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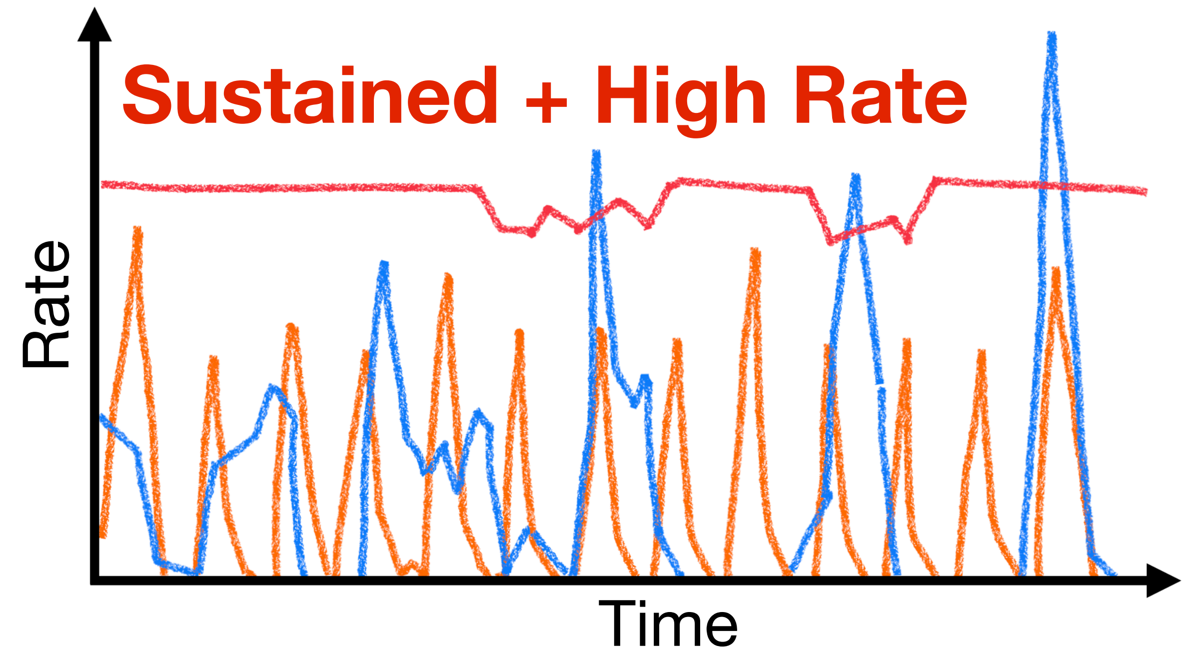

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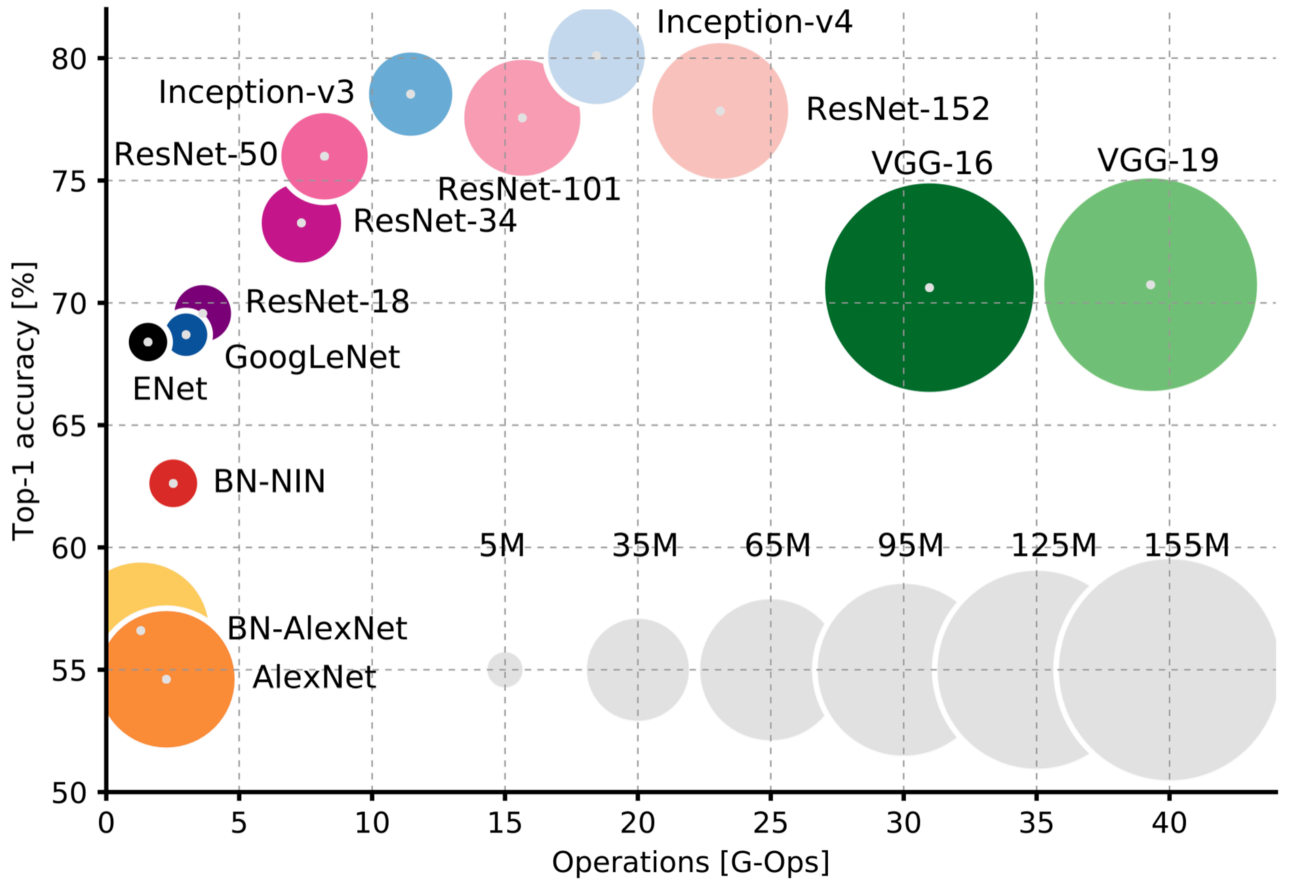

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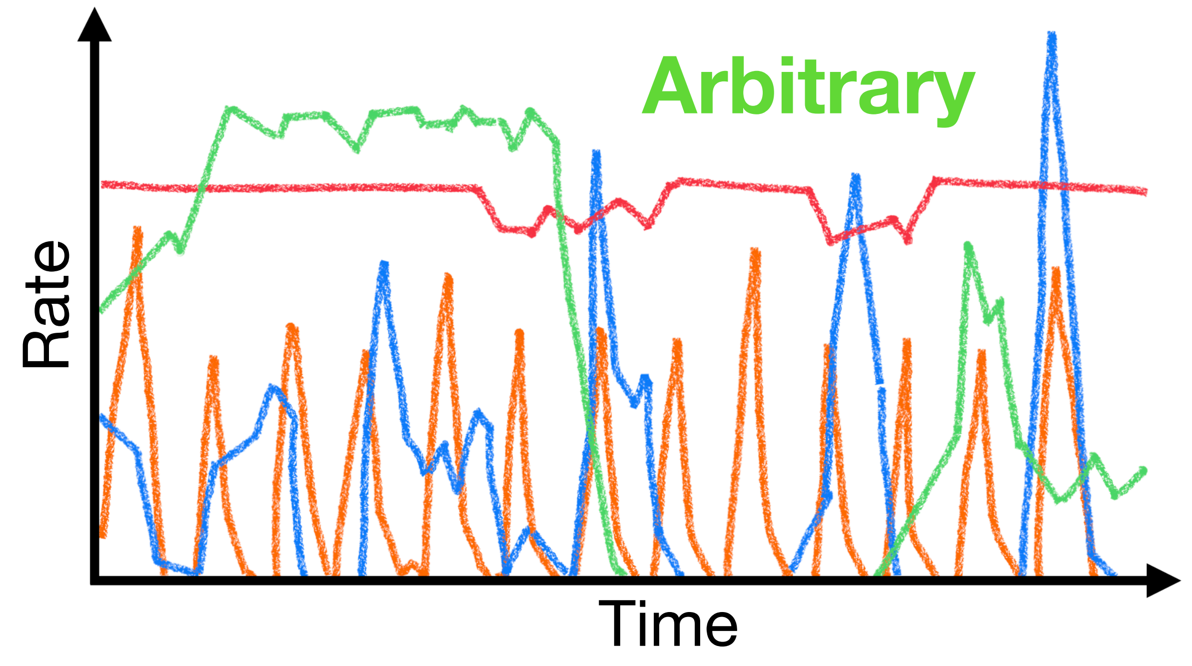

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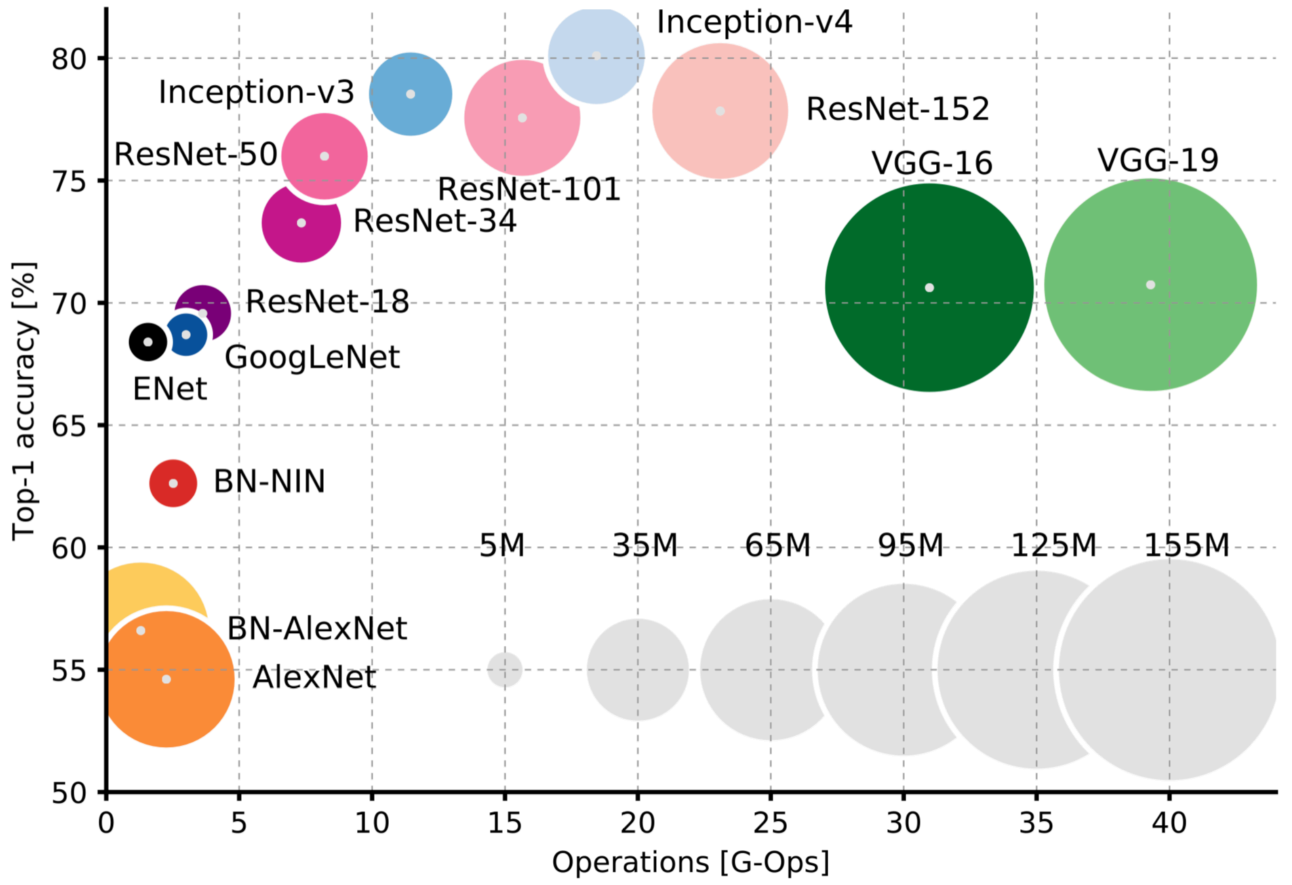

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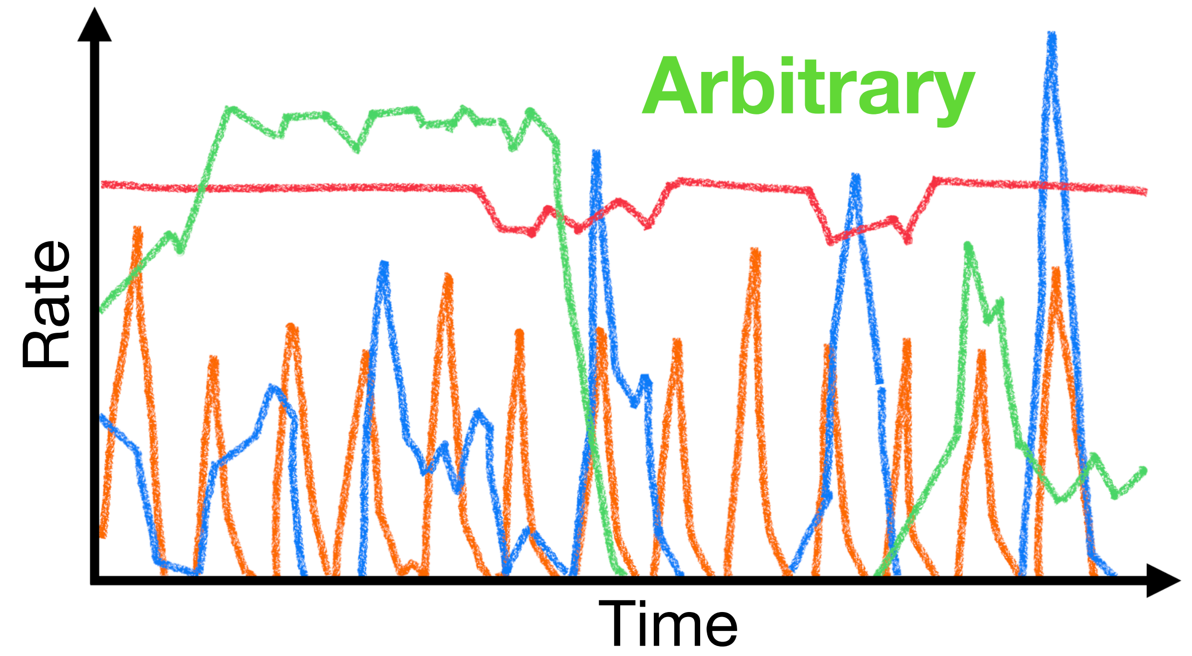

Each request has an inherent deadline

Latency SLOs

(e.g., 100ms)

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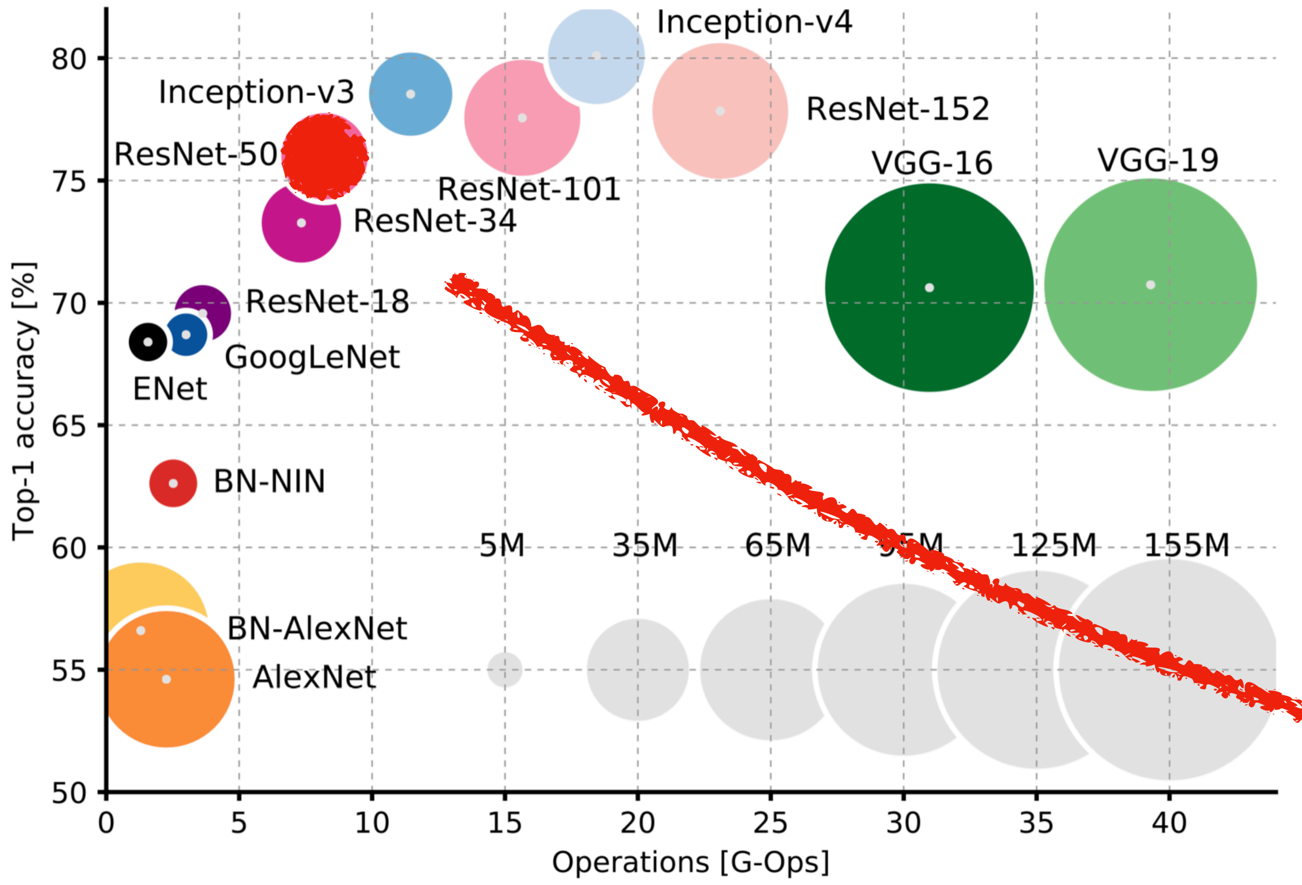

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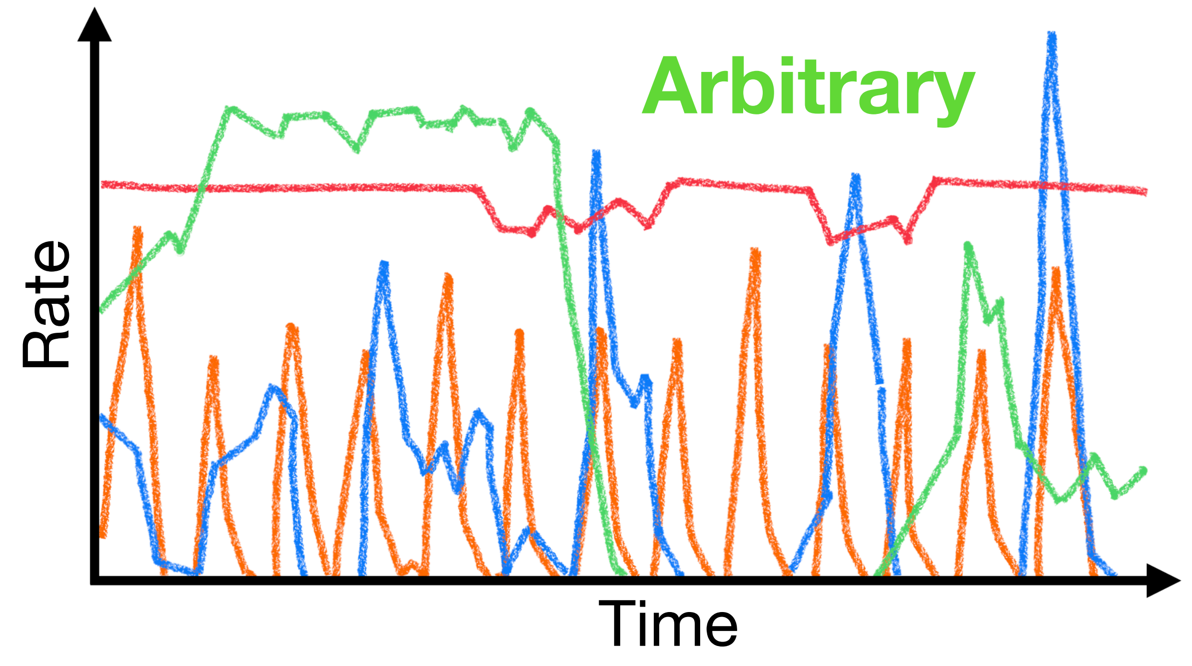

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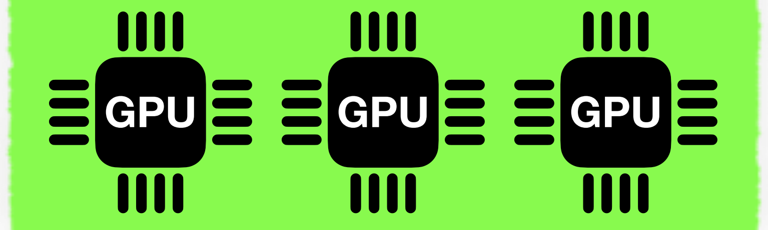
HW accelerators are necessary!



ResNet-50	Latency	Throughput
CPU	175 ms	6 req/s
GPU	2.8 ms	350 req/s

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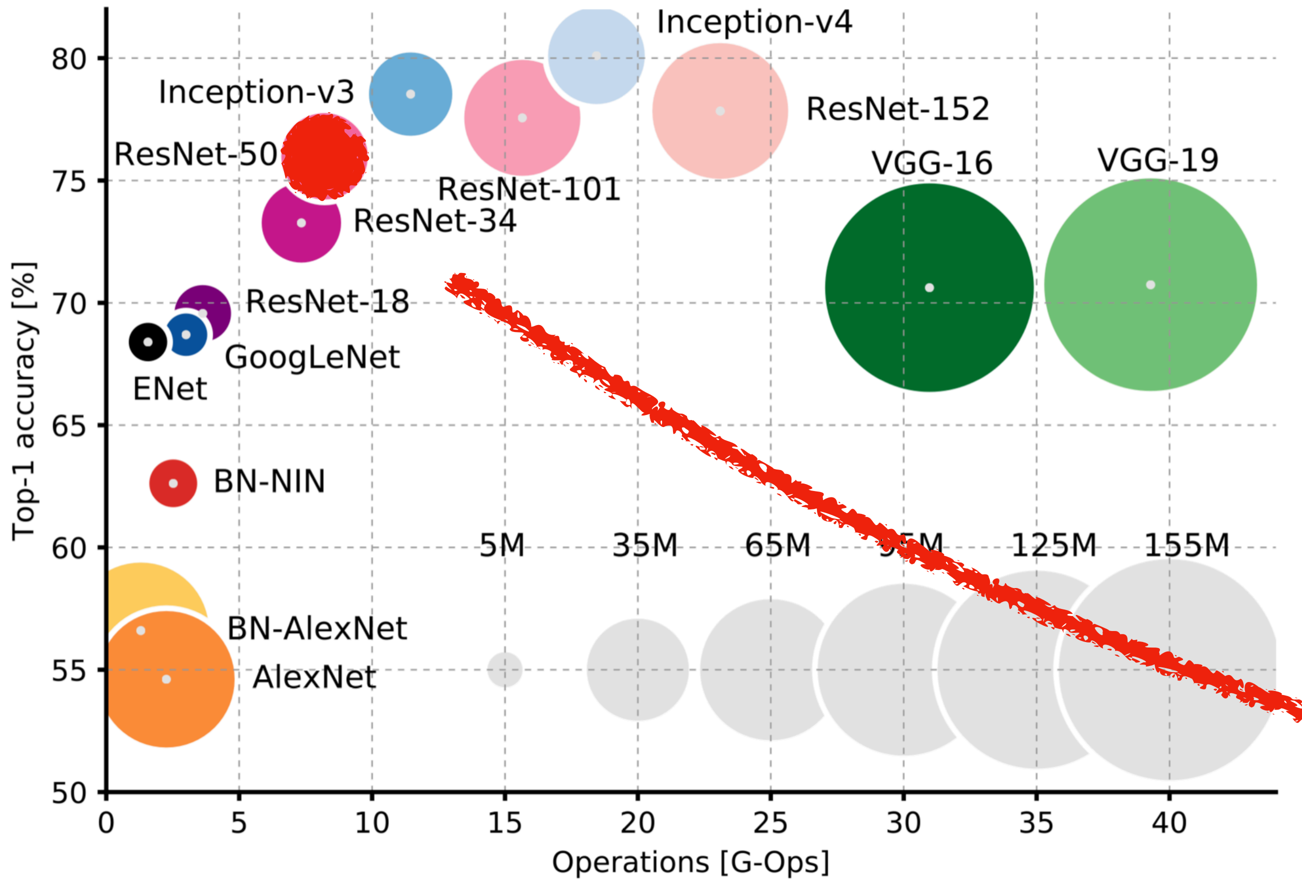

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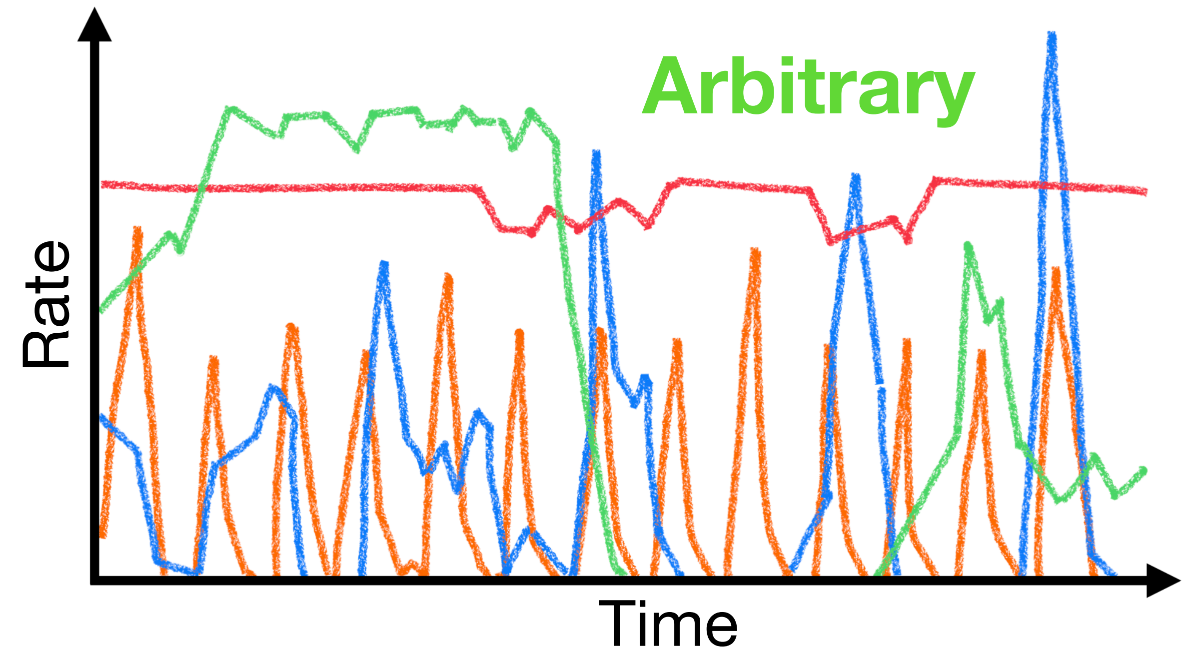

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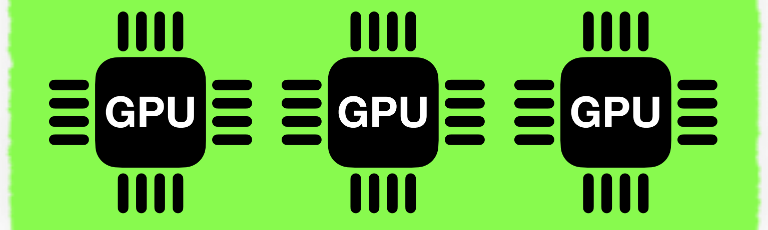

ResNet-50	Latency	Throughput	Cost
CPU	175 ms	6 req/s	$
GPU	2.8 ms	350 req/s	$$$

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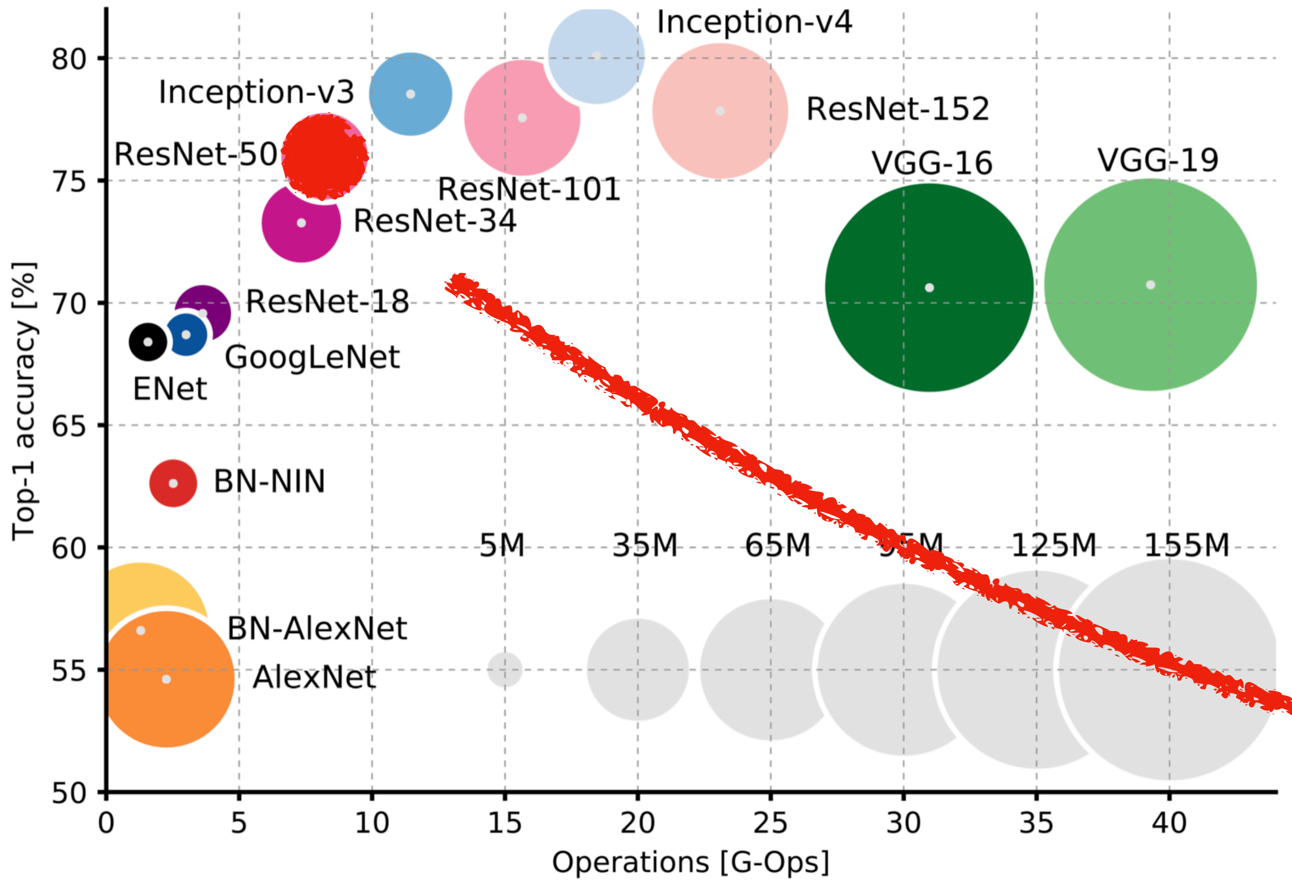

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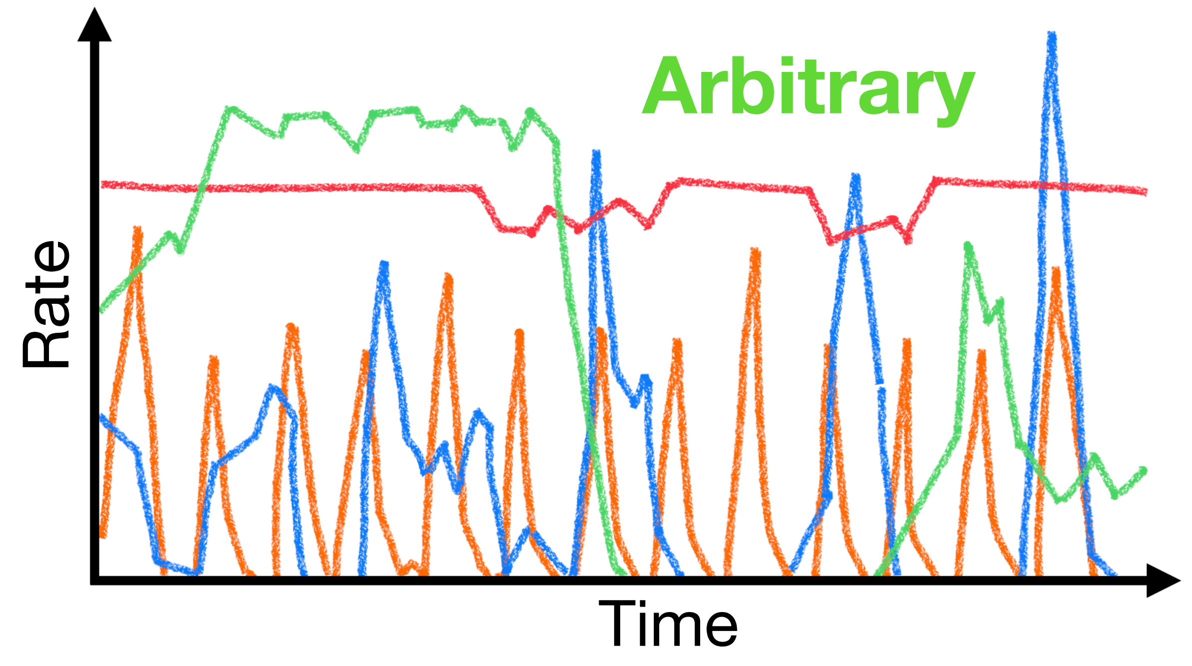

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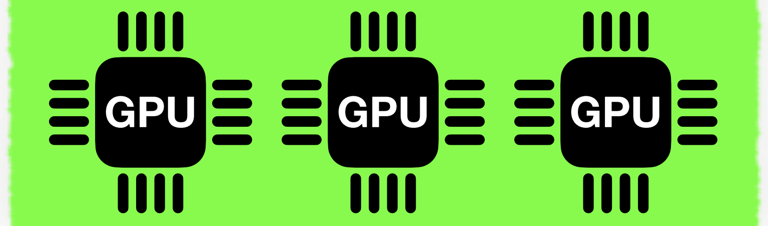

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Problem

How can cloud providers efficiently share resources while meeting SLOs?

Existing Systems Incur Very High Tail Latency

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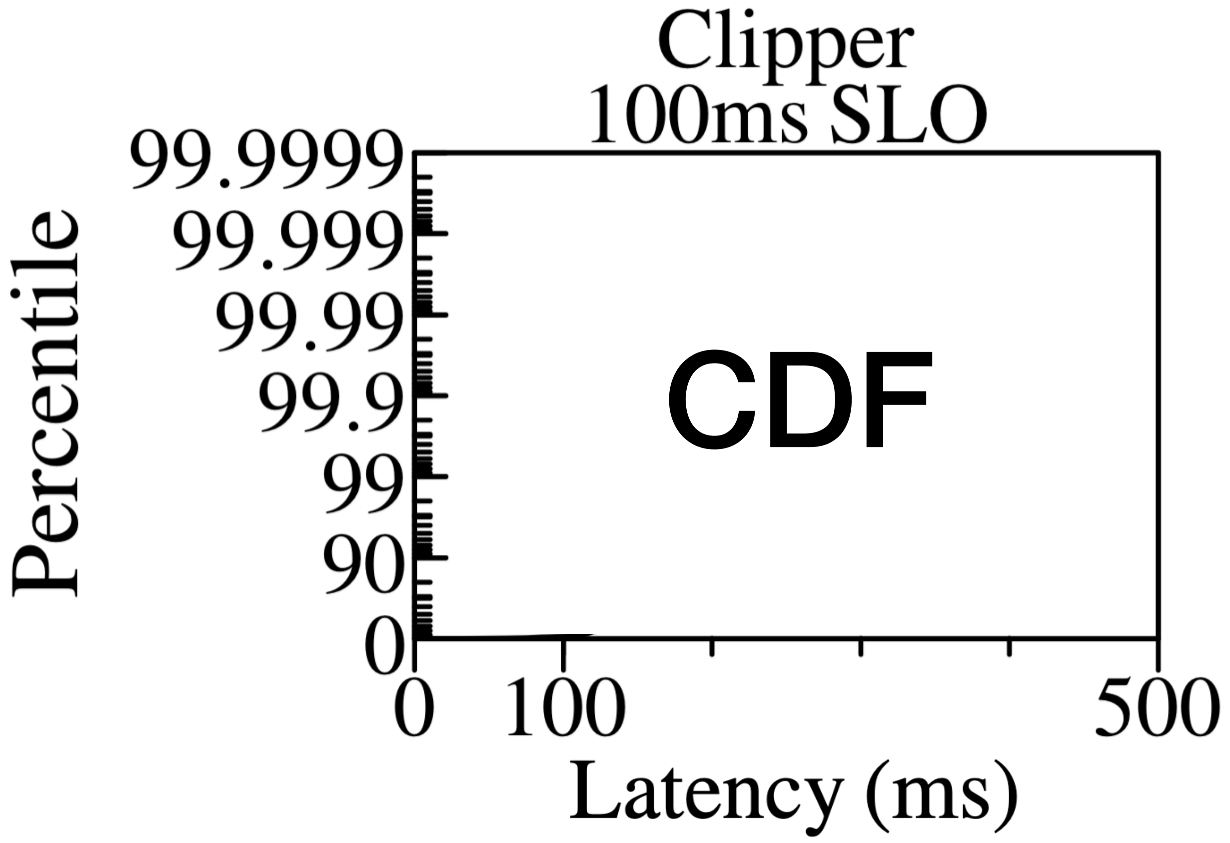
Inference latency

- **15 trained ResNet50**
- **Single GPU worker**
- **16 concurrent requests per model**



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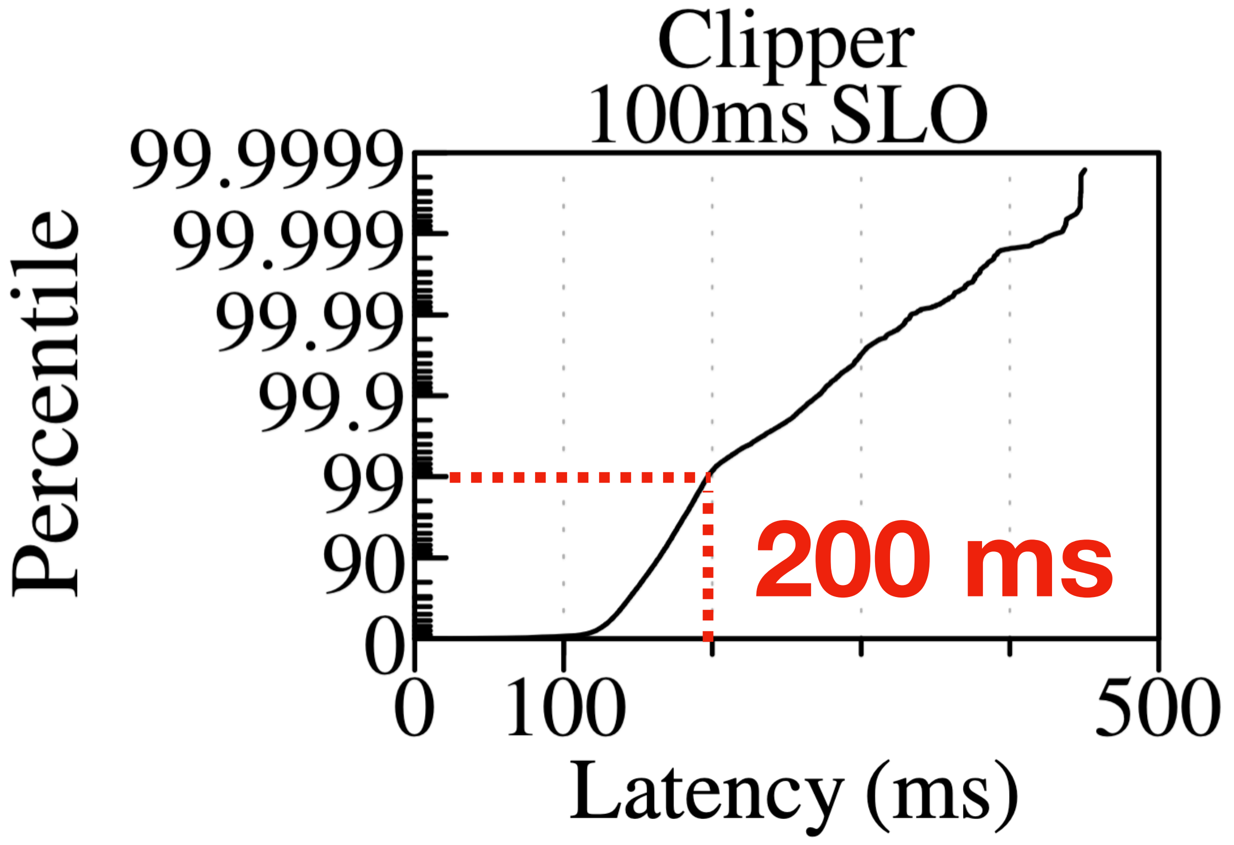
Tail latency >> SLO



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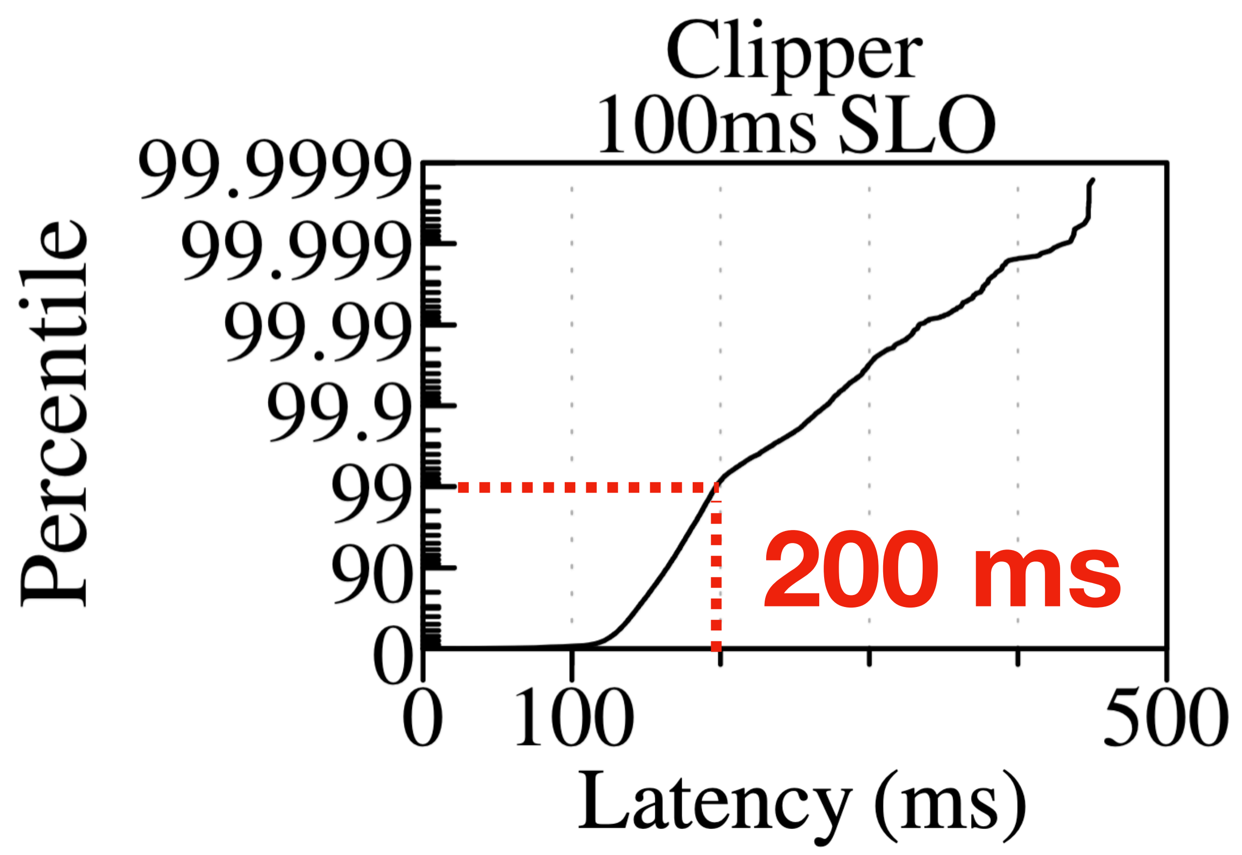

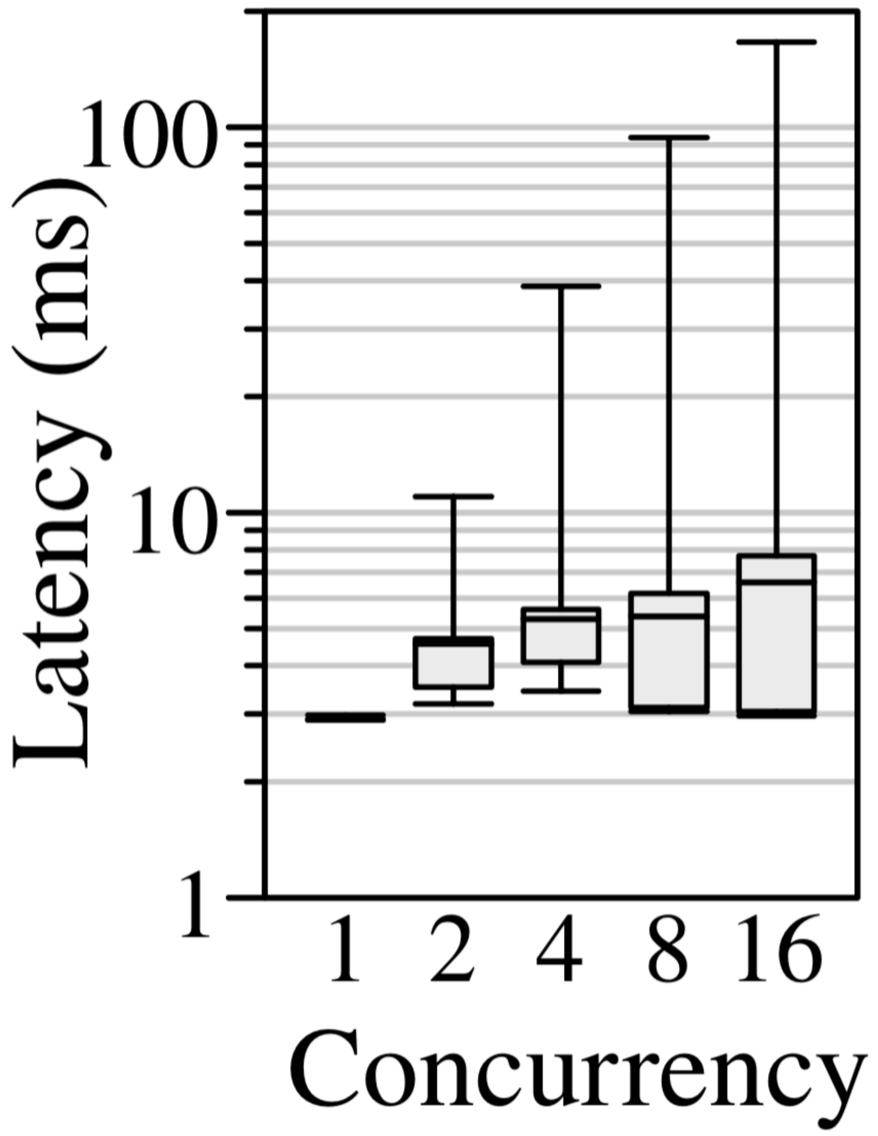

Concurrent DNN inference over GPU

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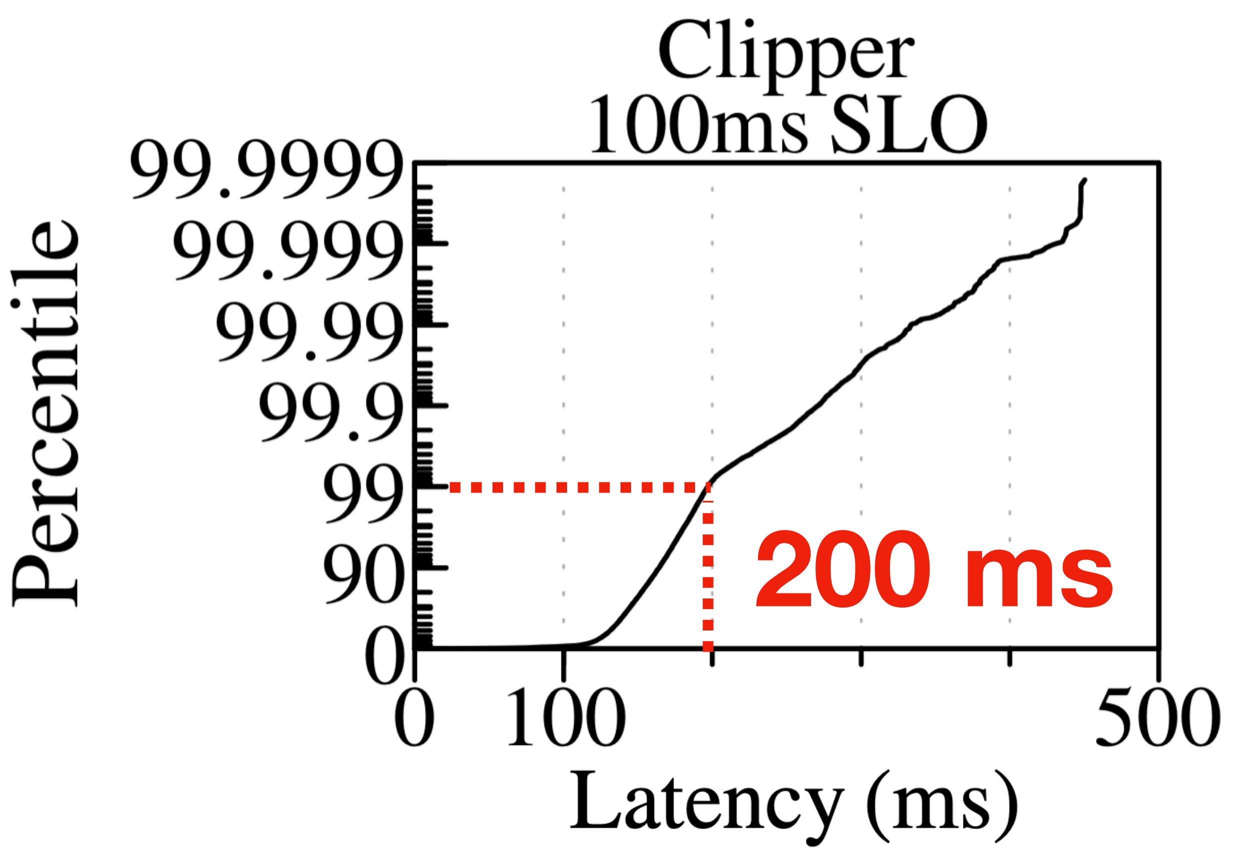

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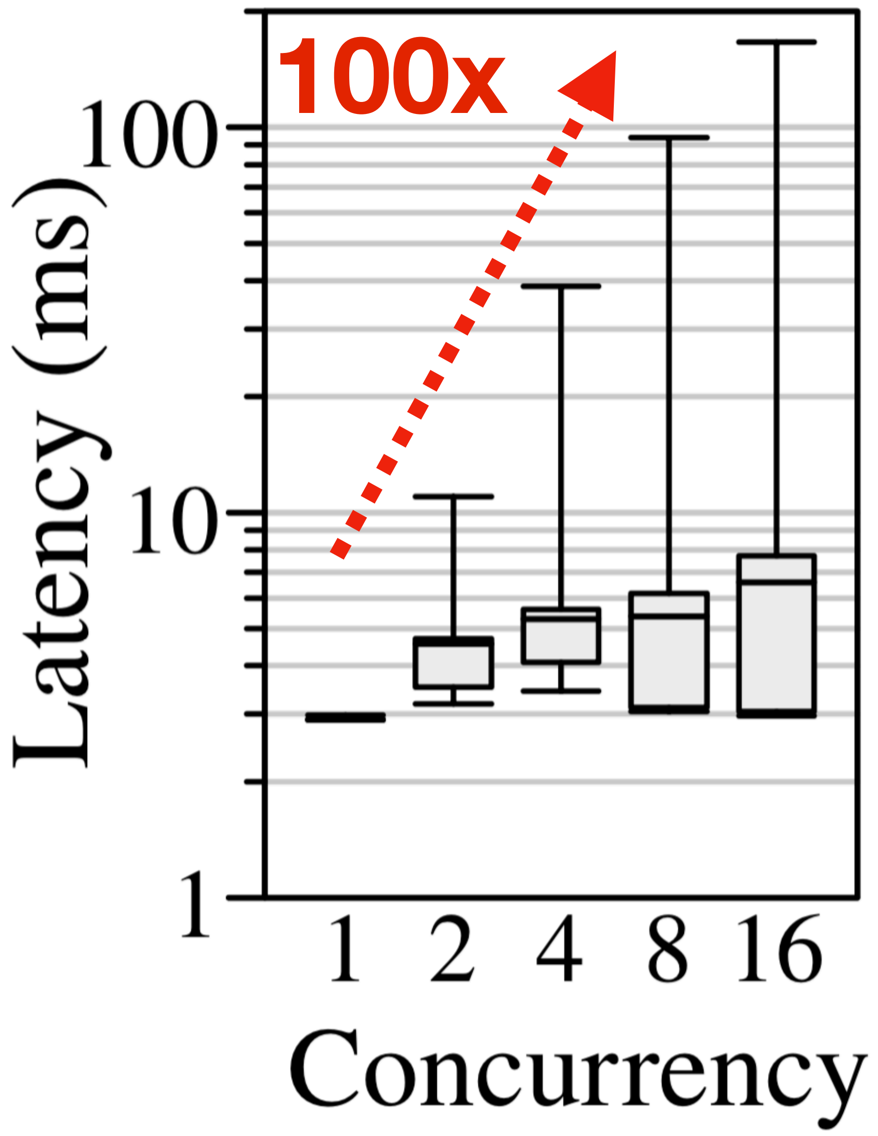

Concurrent DNN inference over GPU

High variance in latency

Throughput gains only 25%

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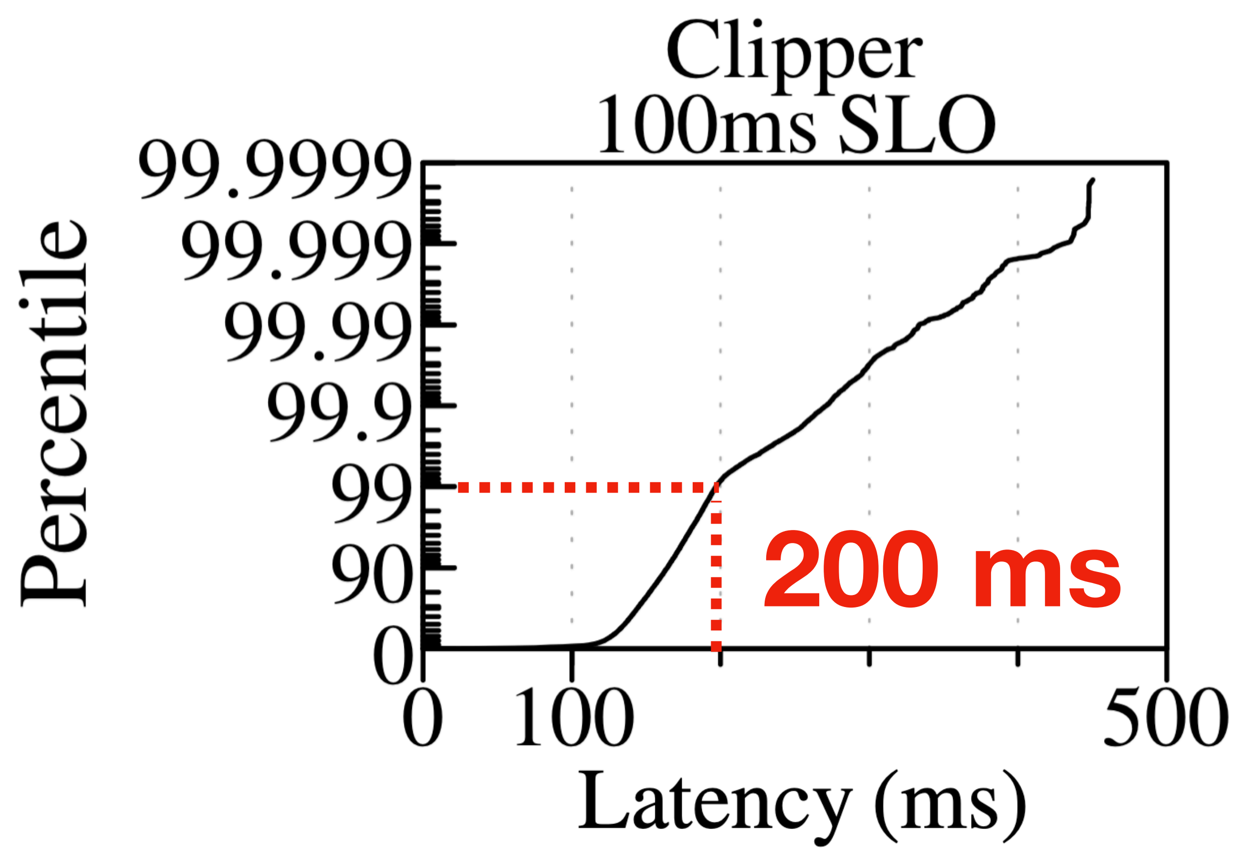

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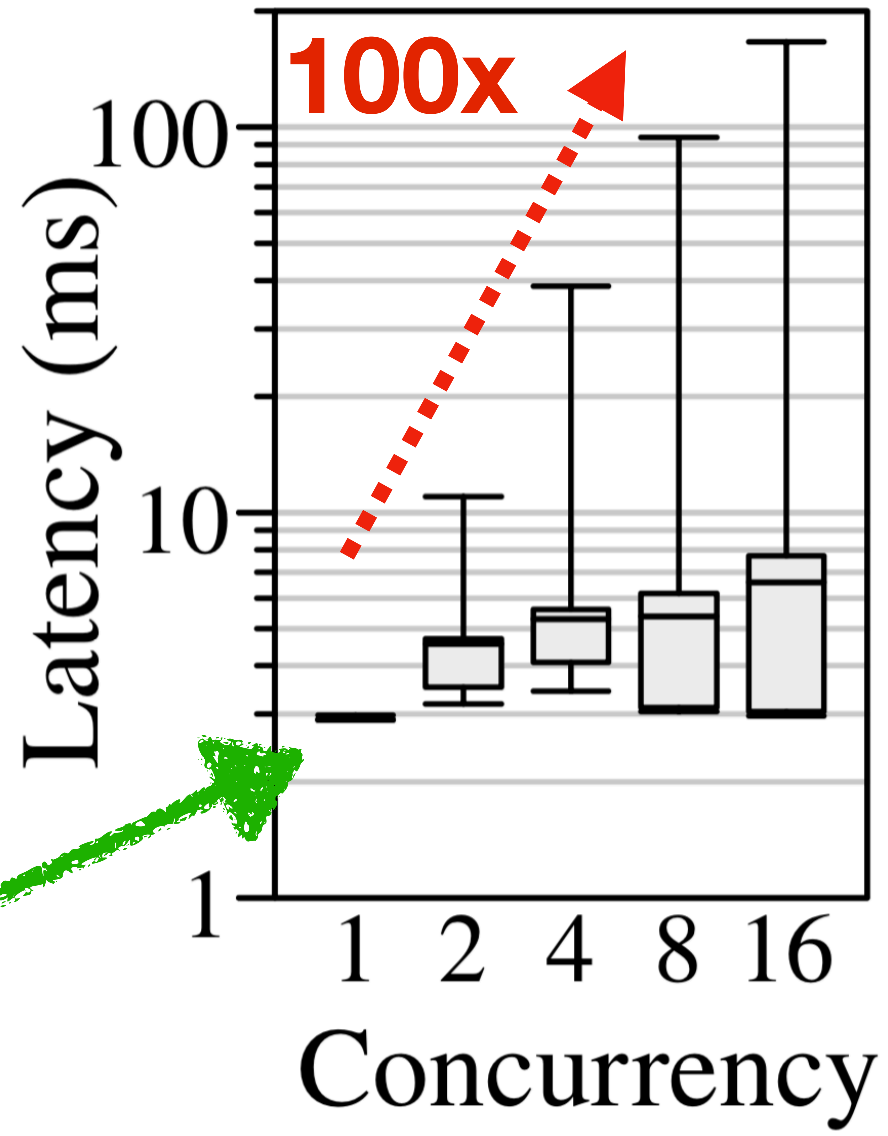

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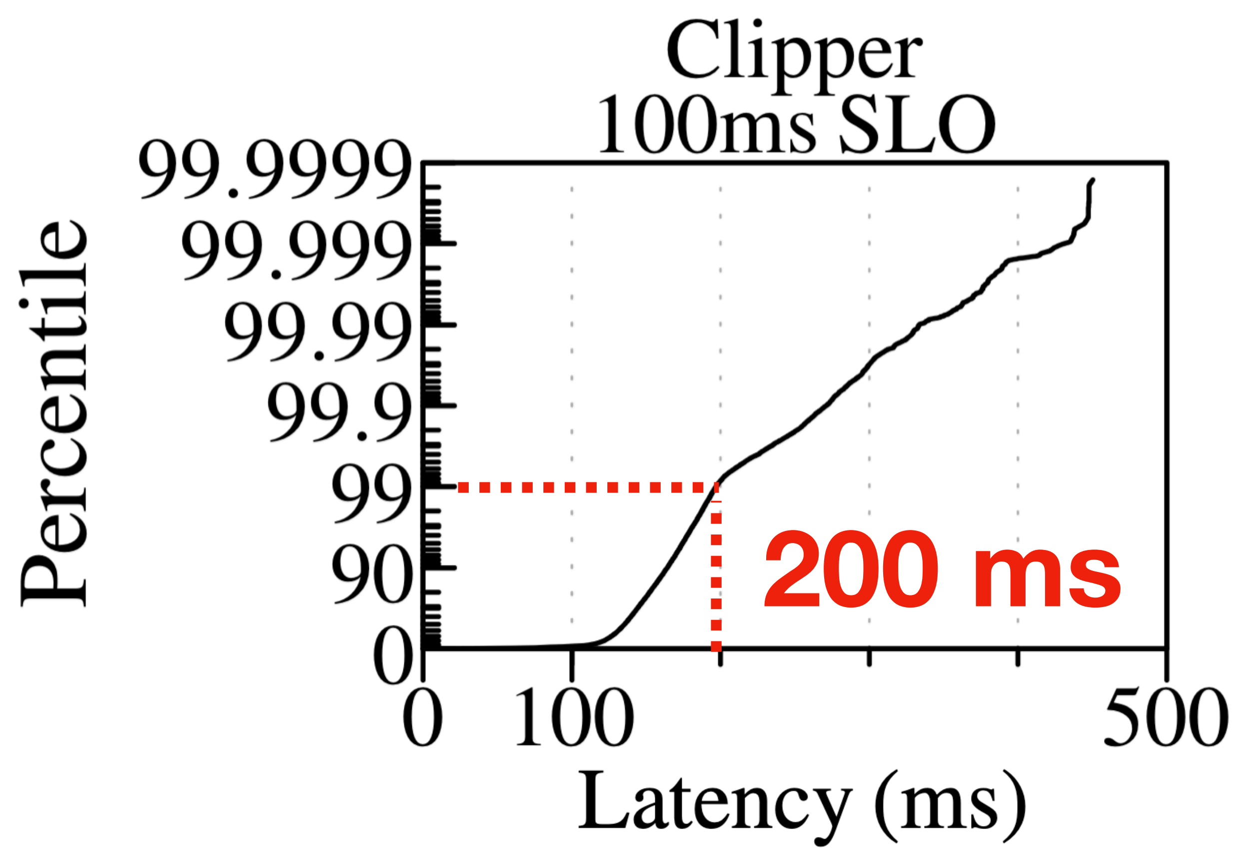
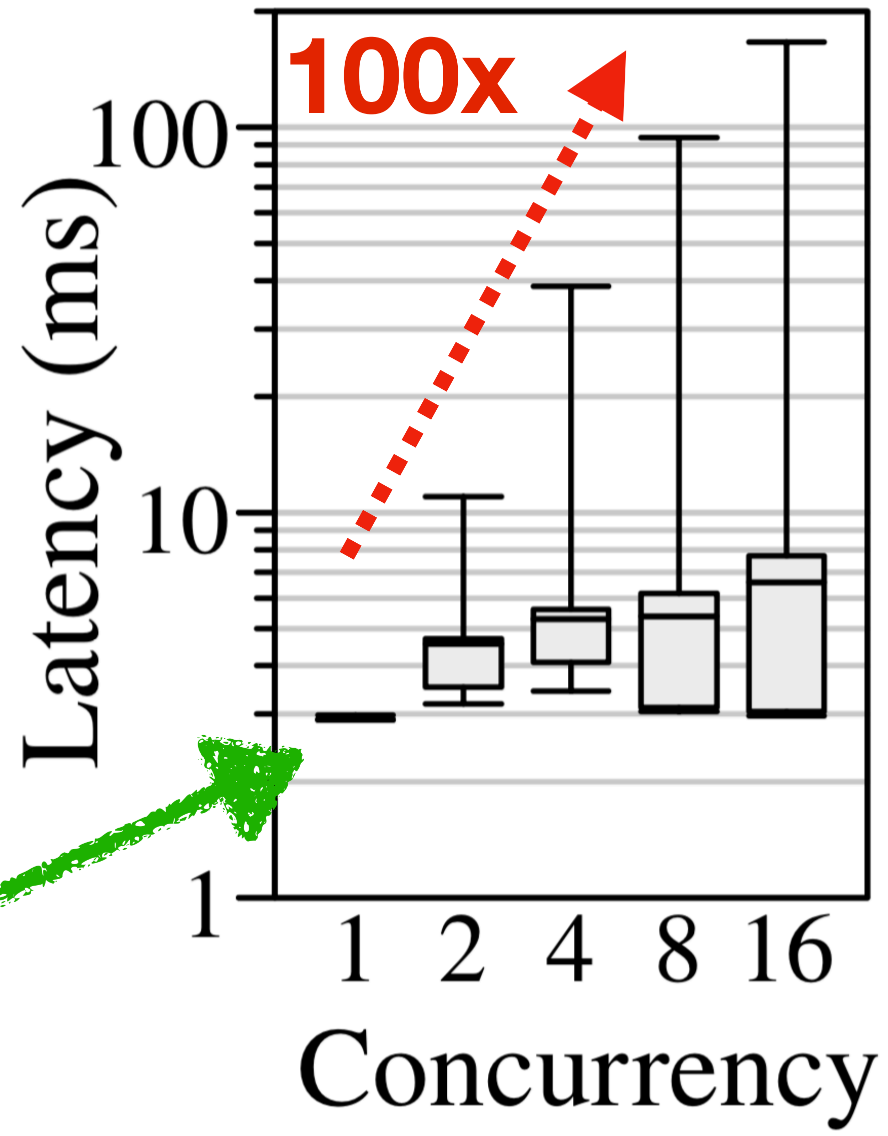


Tail latency >> SLO

Preserves DNN predictability at every stage of model serving

Clockwork adopts a contrasting approach!



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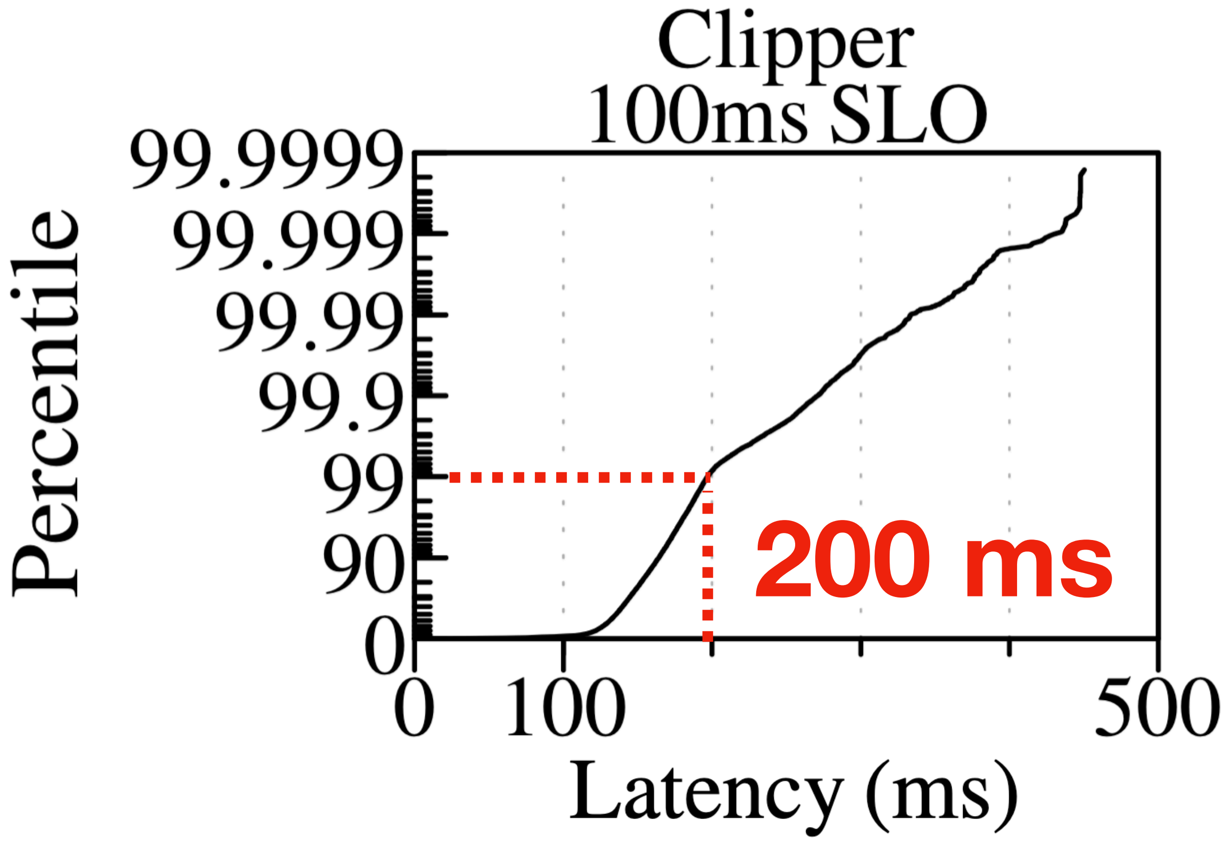

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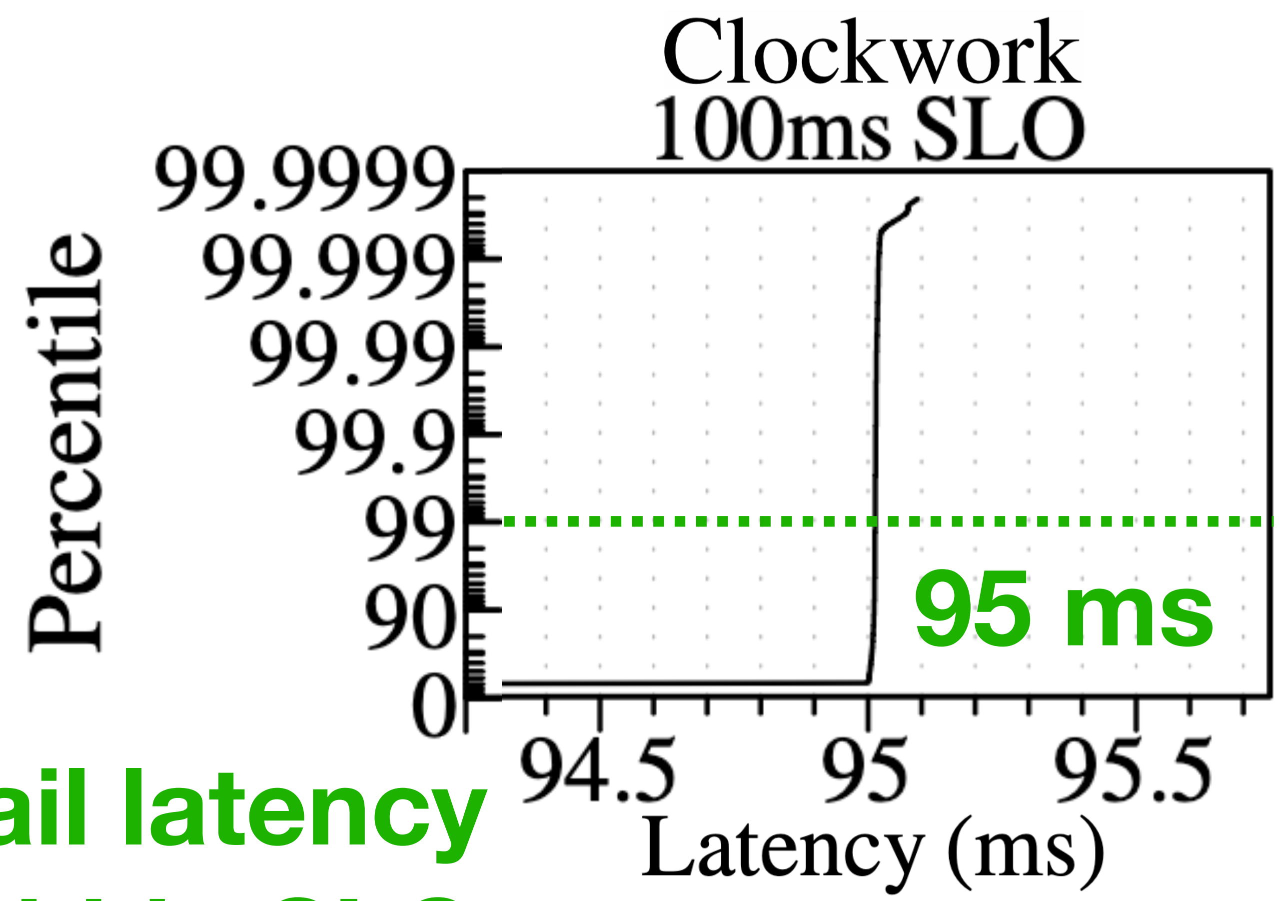
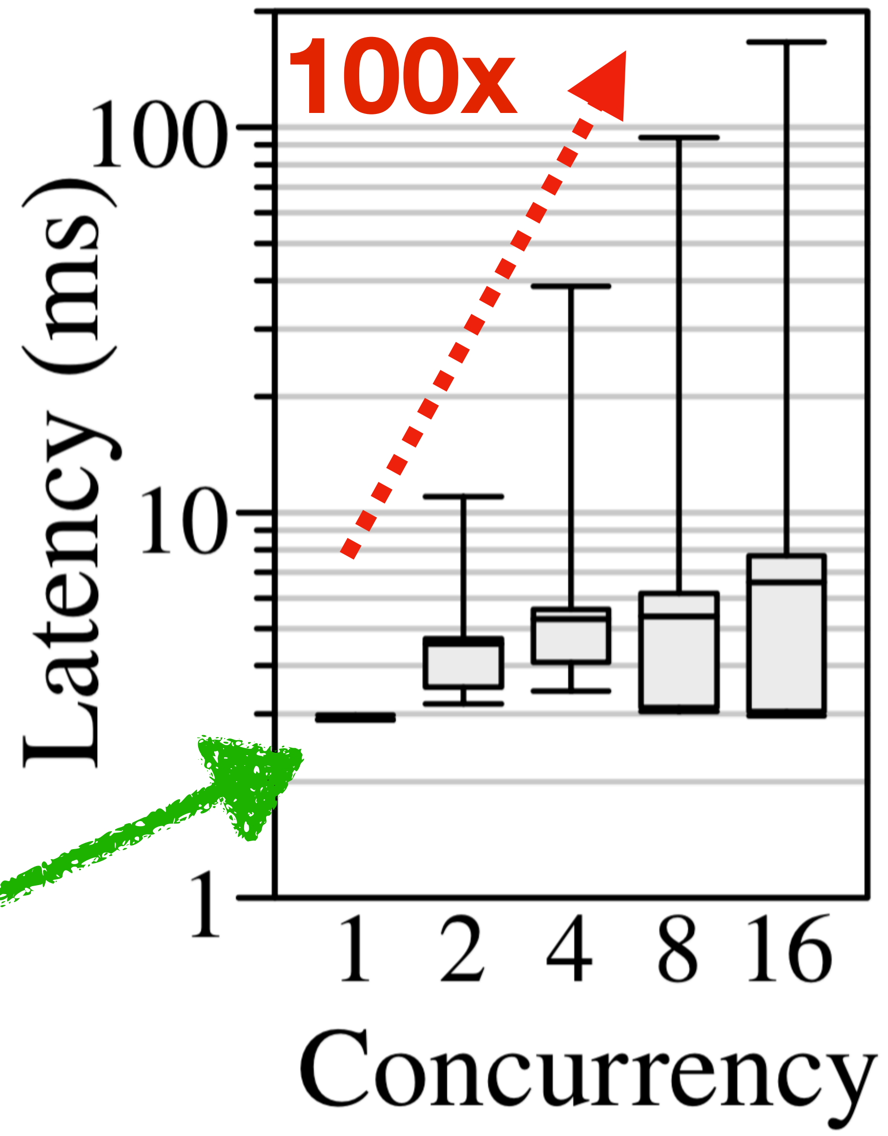


Tail latency within SLO



Concurrent DNN inference over GPU

High variance in latency

Throughput gains only 25%

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Single-thread latency is extremely predictable

How does Clockwork Achieve End-to-End Predictability?

Design Principles

Goal: 1000s of models, many users, limited resources

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Maximize sharing

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1. Predictable worker with no choices

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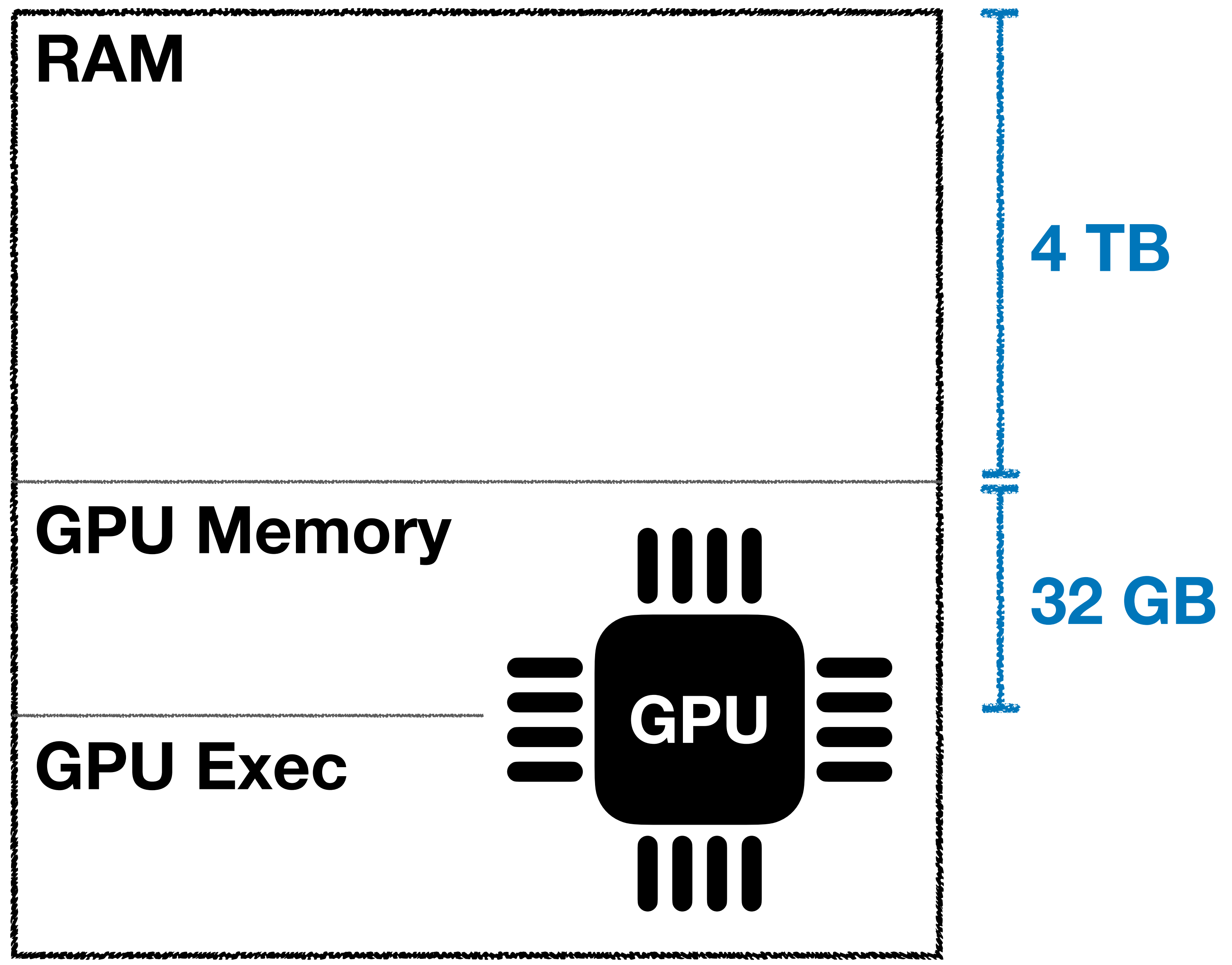
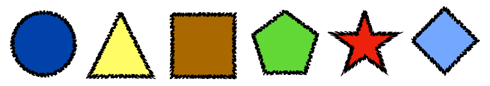
3. Deadline-aware scheduling for SLO compliance

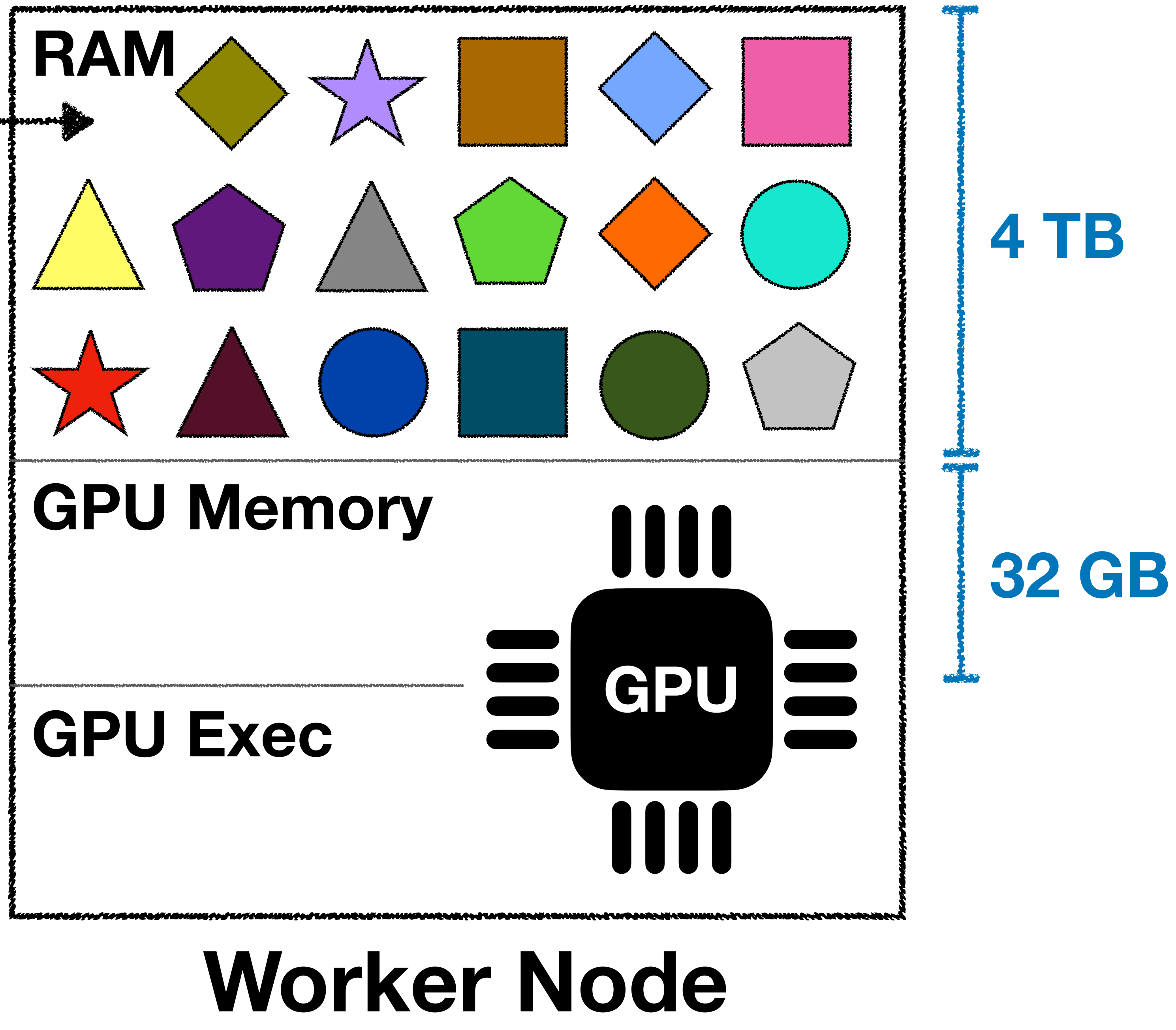
Designing a Predictable Worker (1/2)



Worker Node

Designing a Predictable Worker (1/2)

Users upload pre-trained models in advance:  **...**



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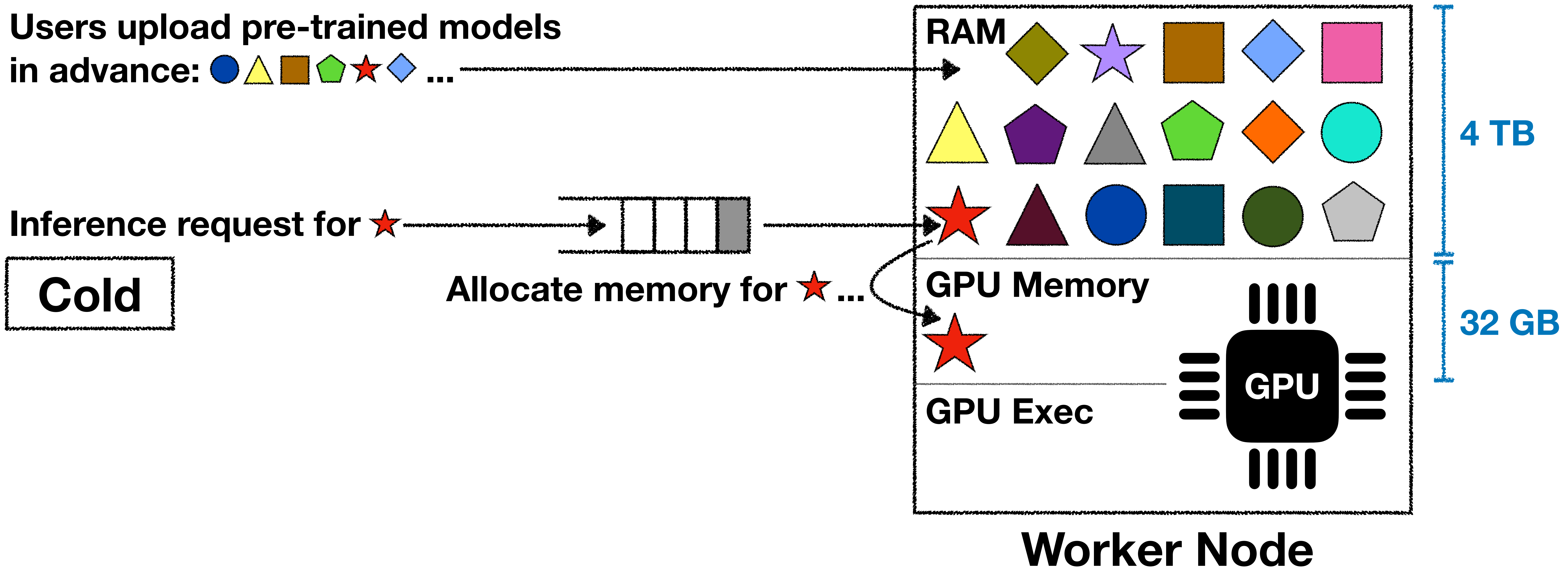

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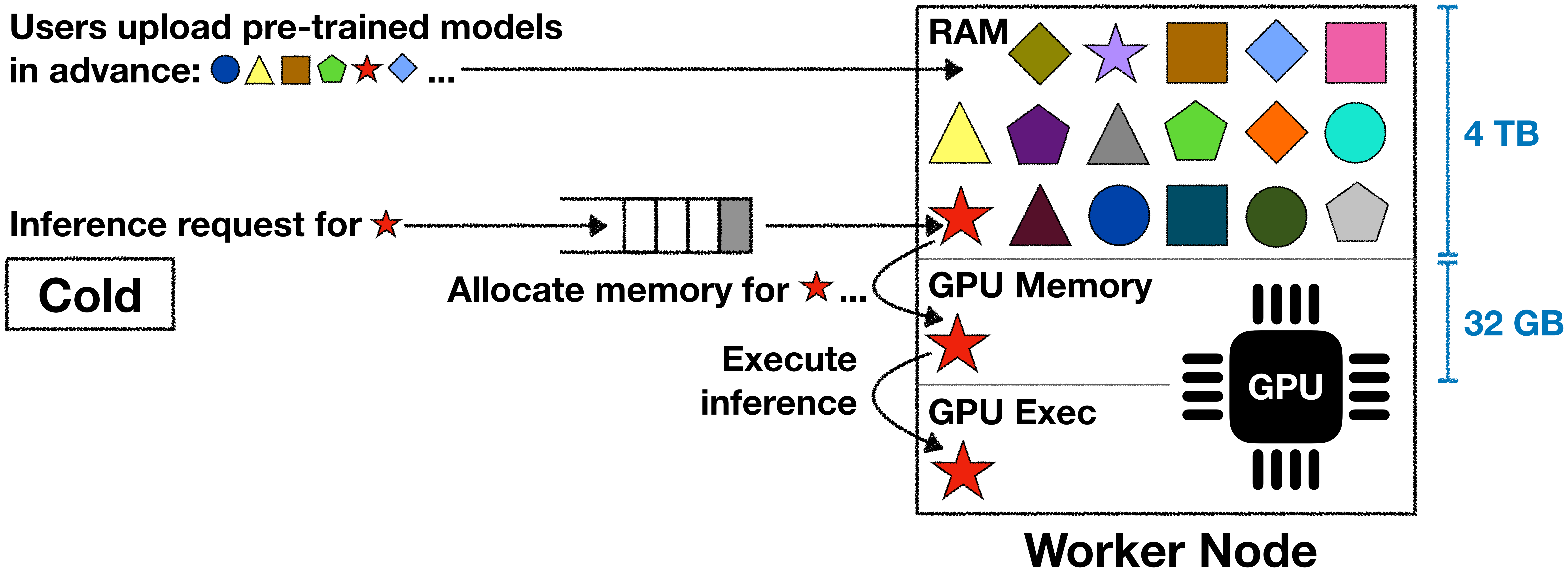

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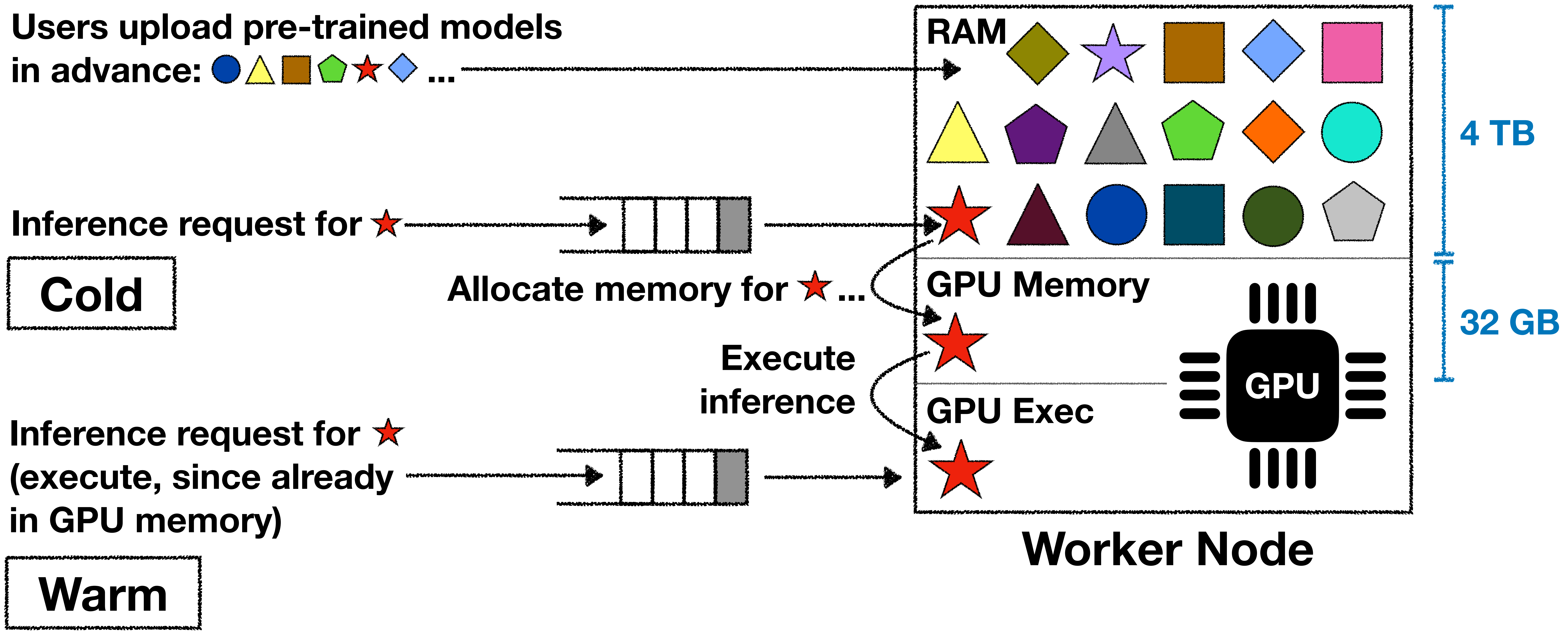

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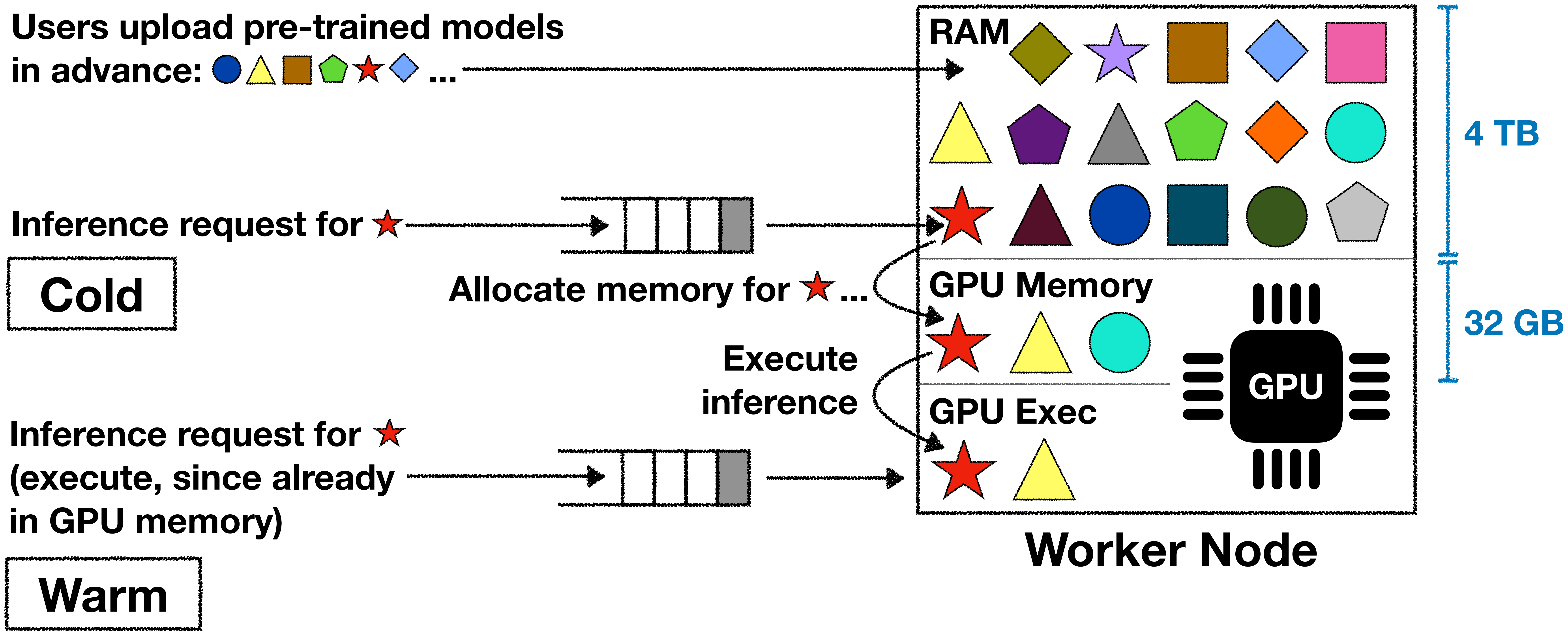

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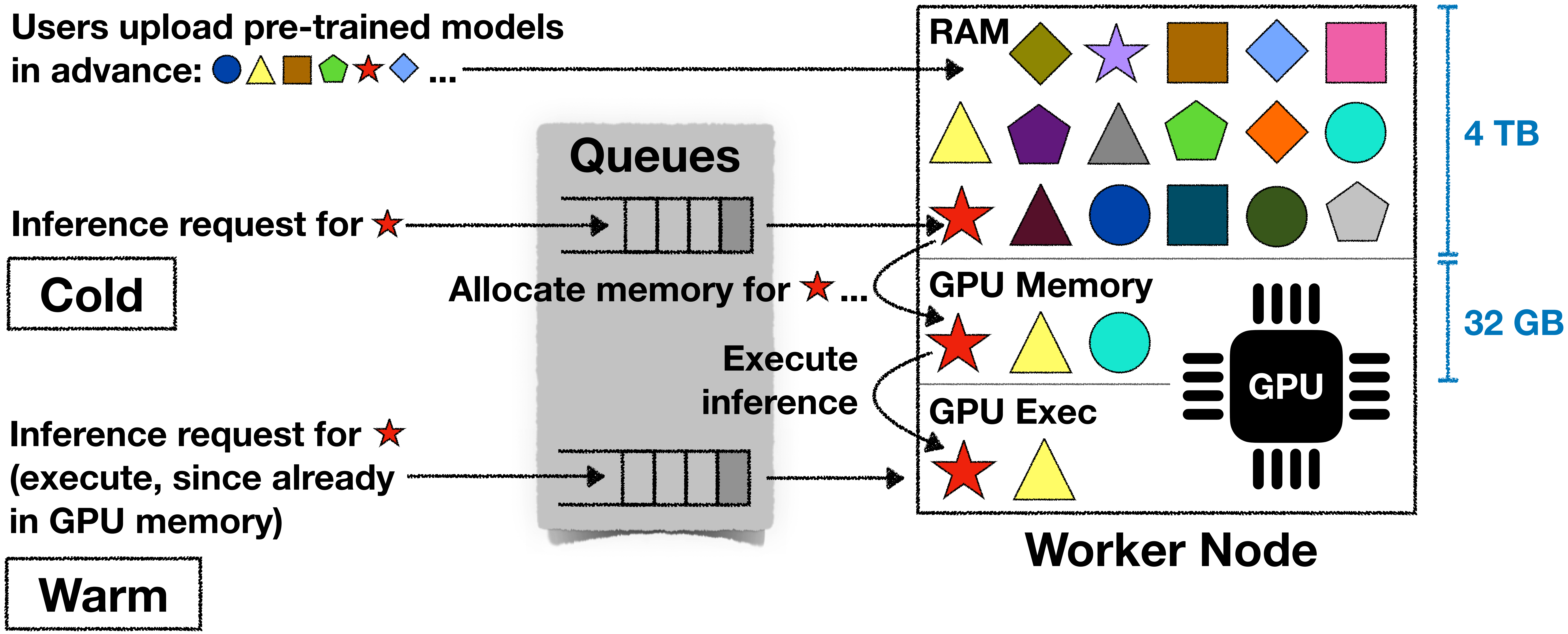

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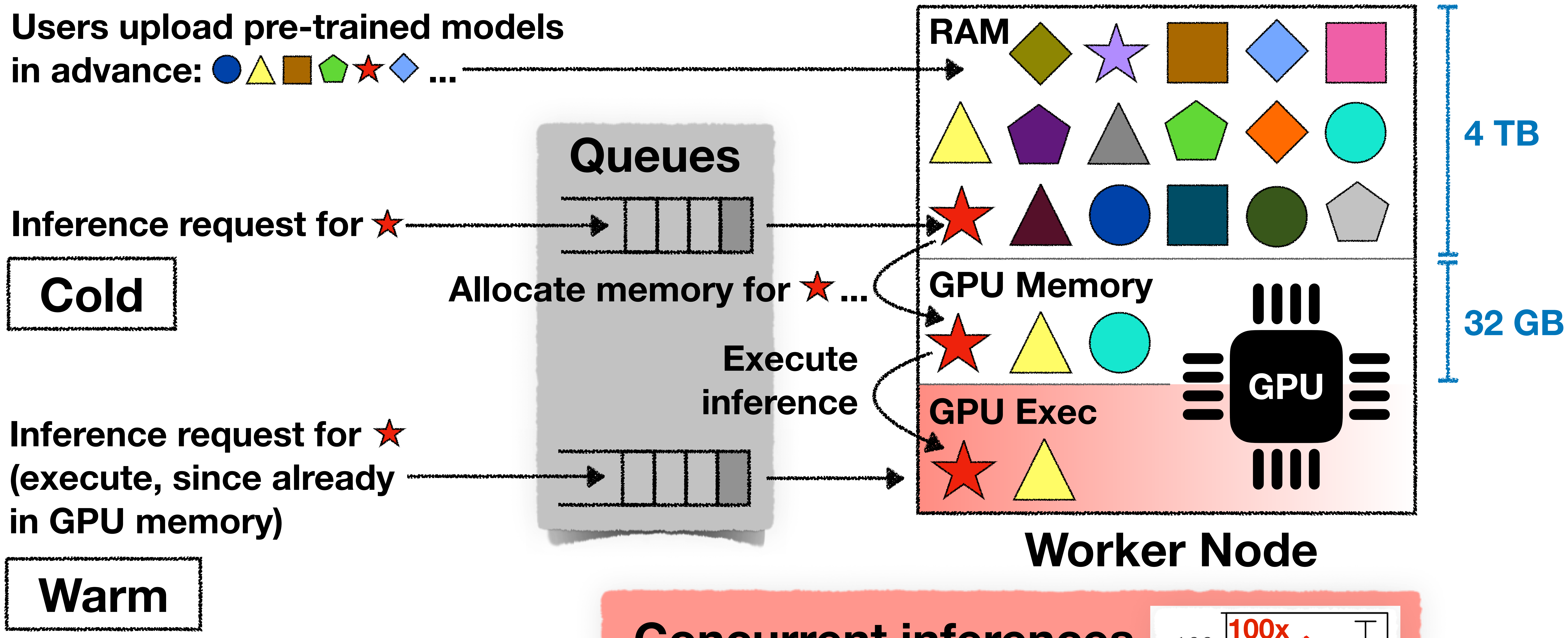
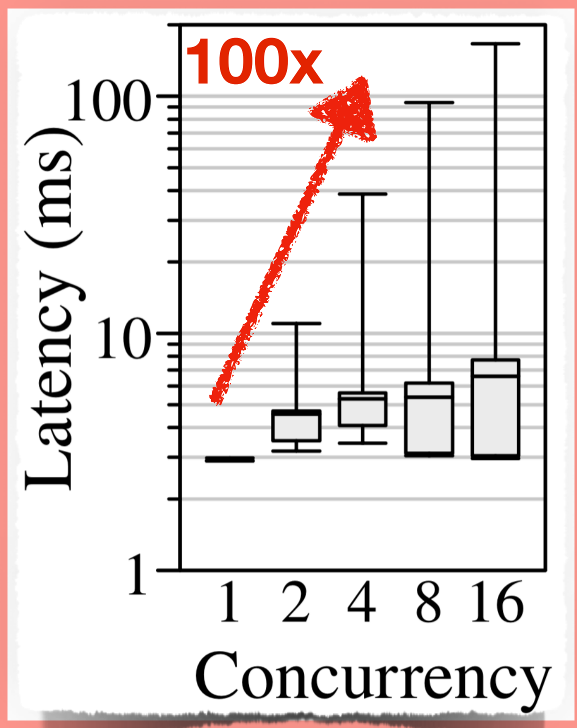


Concurrent inferences

+ Proprietary & undocumented policies

→ Unpredictable response times



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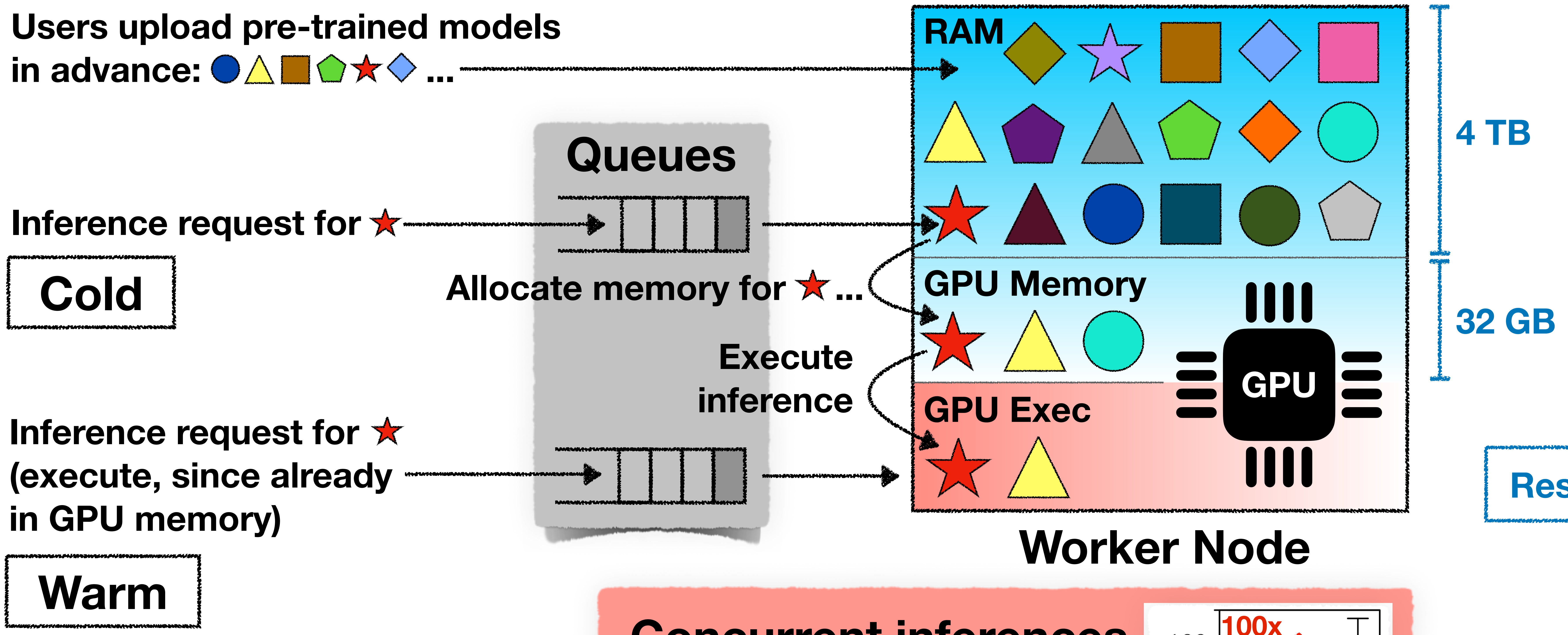

Managed memory can be unpredictable

- GPU memory (cache) hits & misses

ResNet-50 — Hit: 2.3 ms | Miss: 10.6 ms

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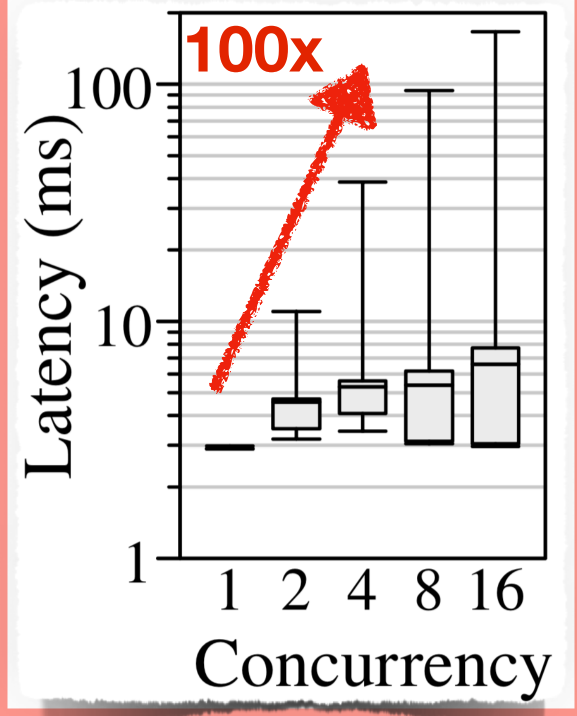

Designing a Predictable Worker (2/2)

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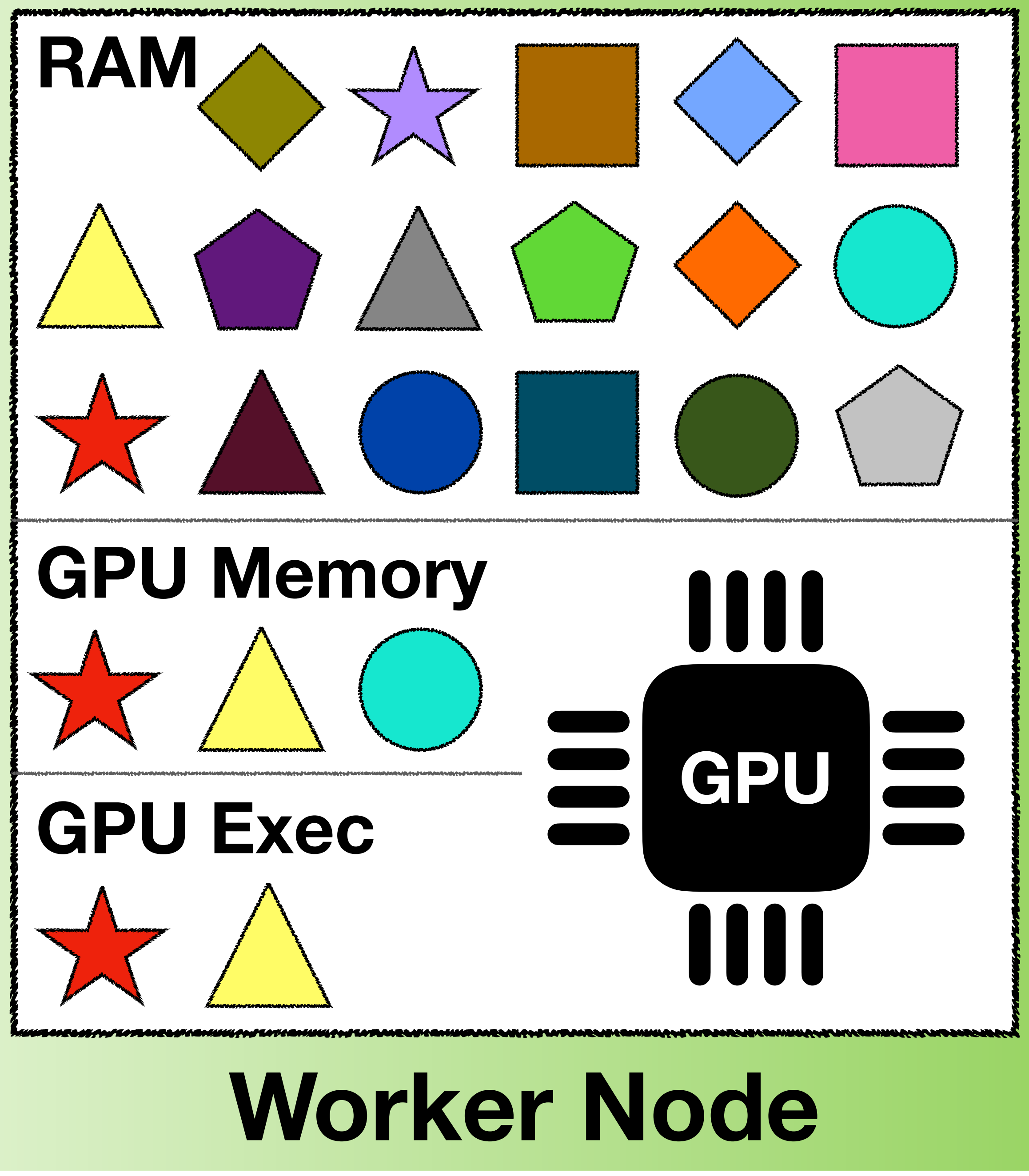
Predictable Clockwork worker process



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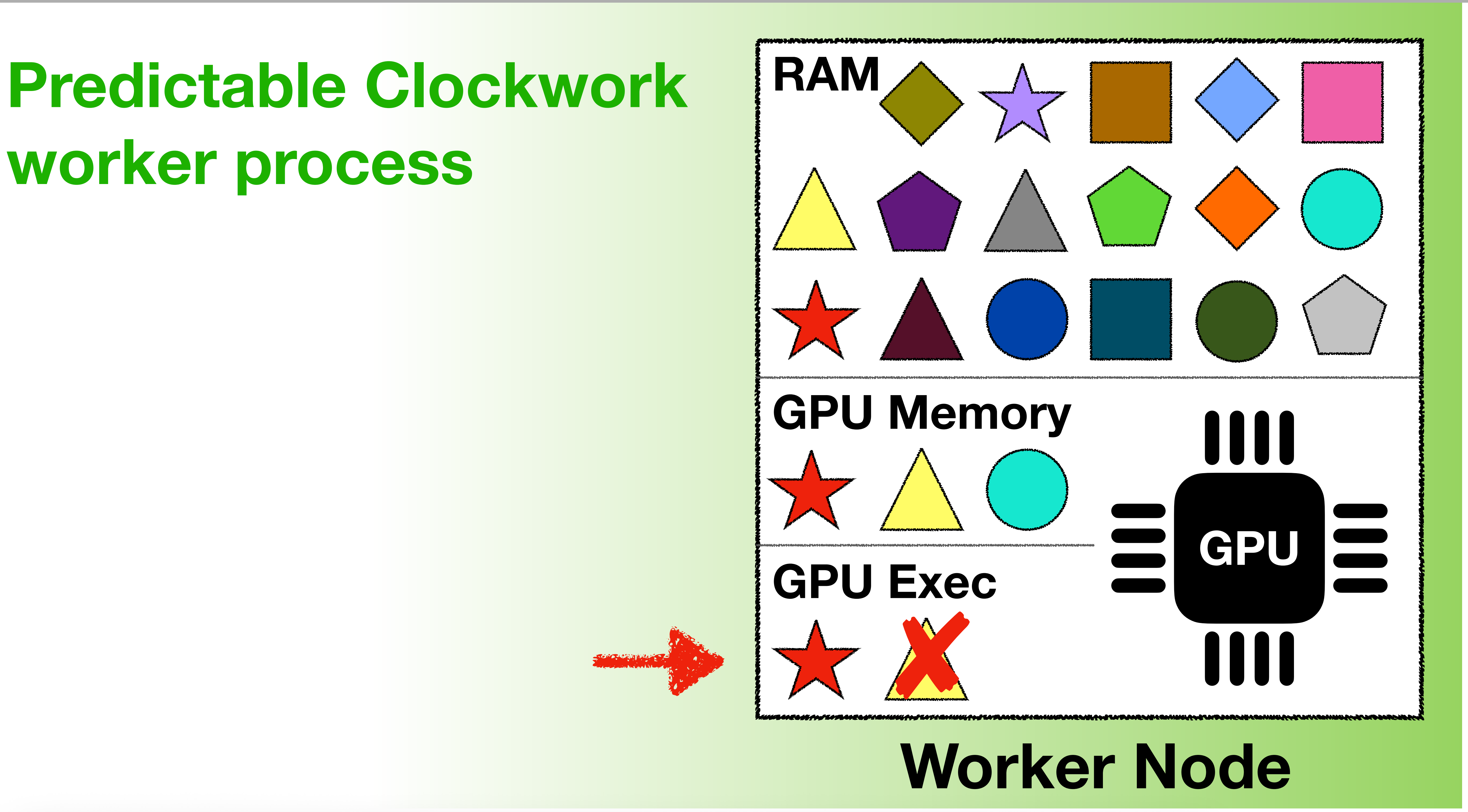

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Execute inference one at a time

Designing a Predictable Worker (2/2)

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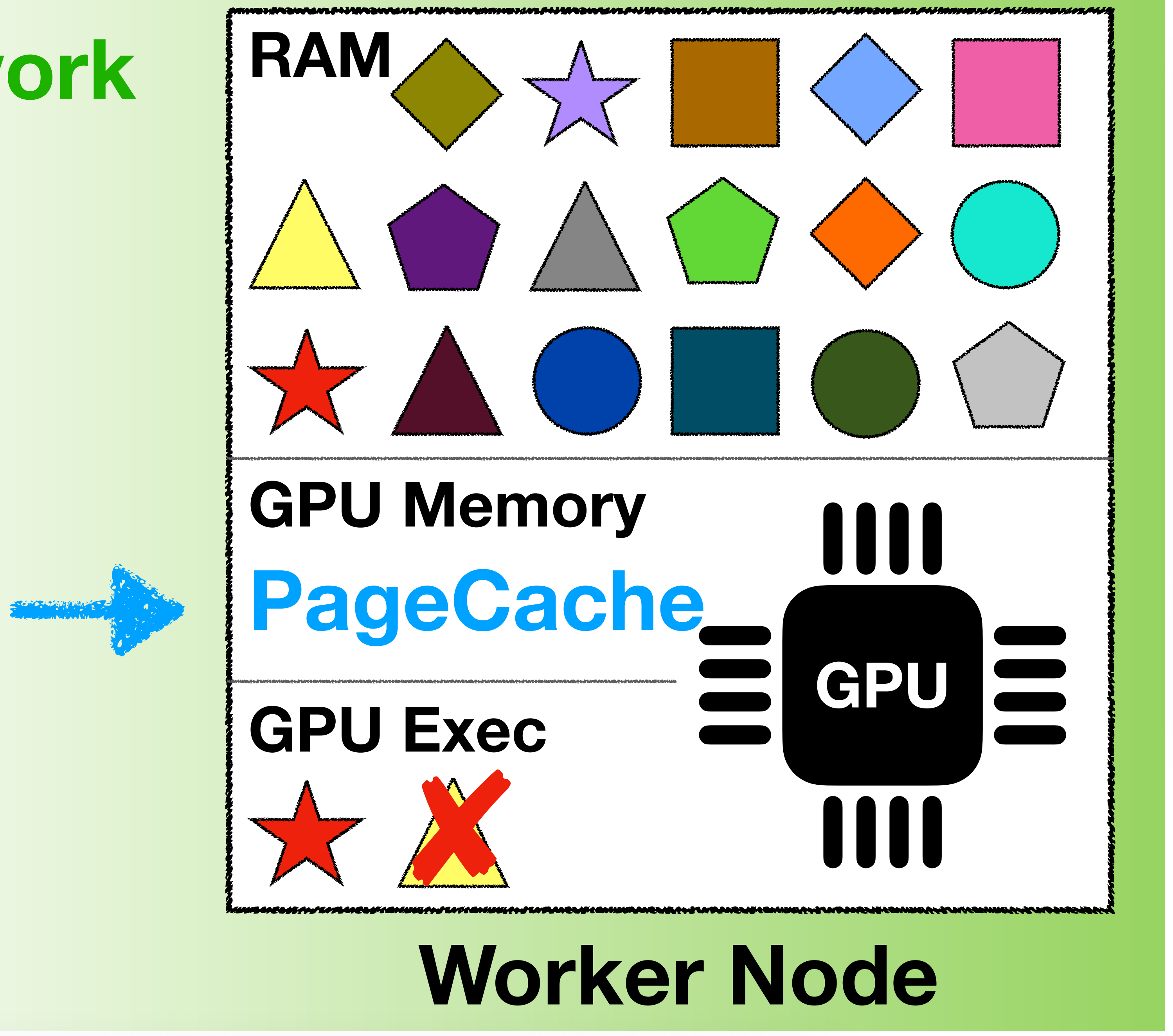

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Preallocate GPU memory & manage it explicitly using LOAD/UNLOAD actions

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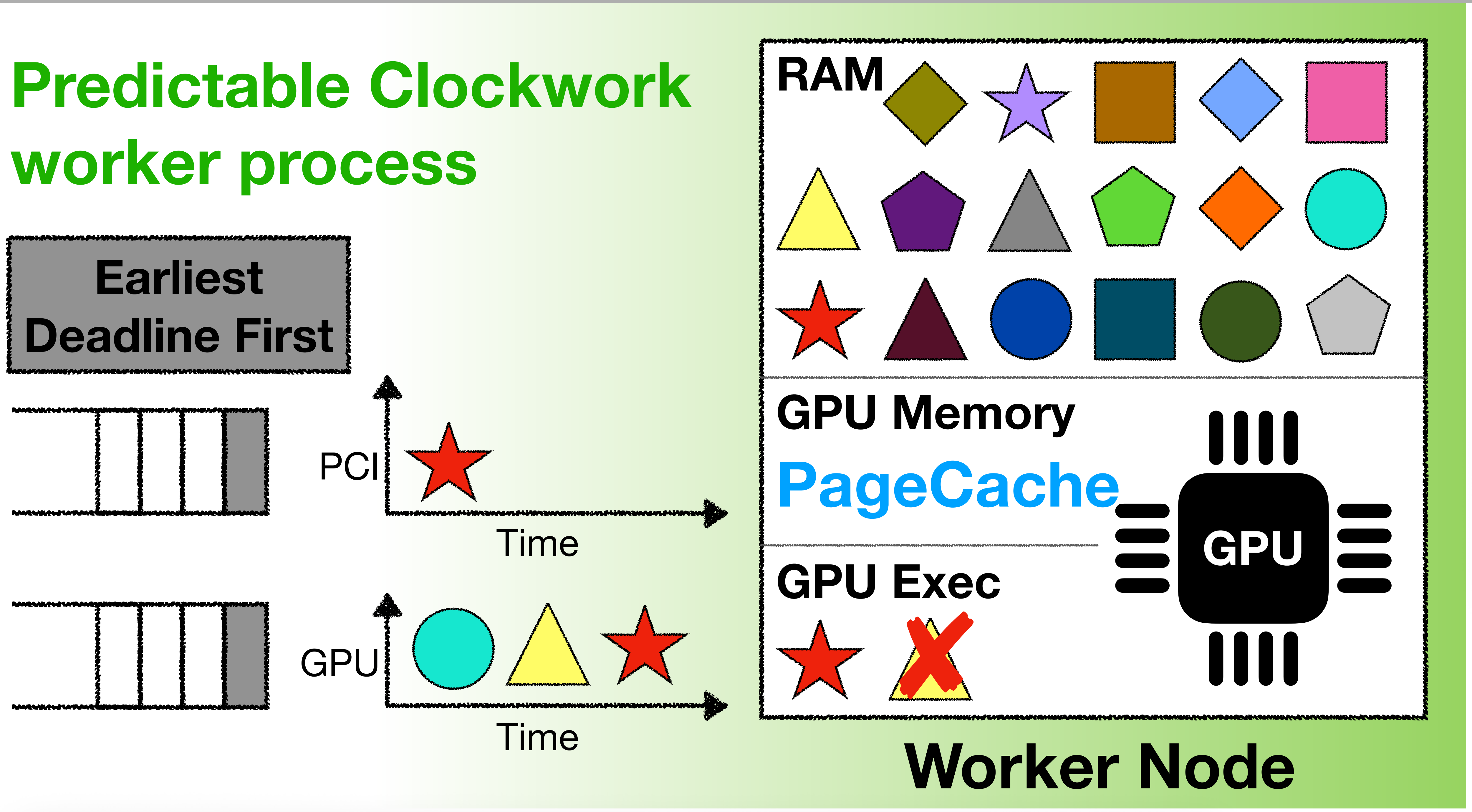

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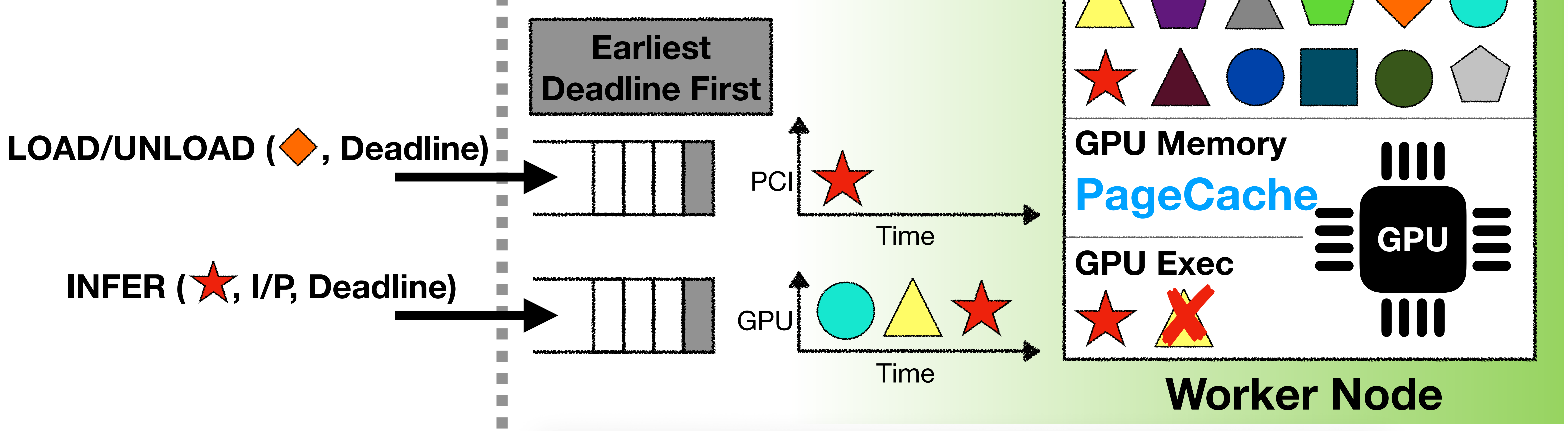
Designing a Predictable Worker (2/2)

Choices outsourced via action APIs

Predictable Clockwork worker process



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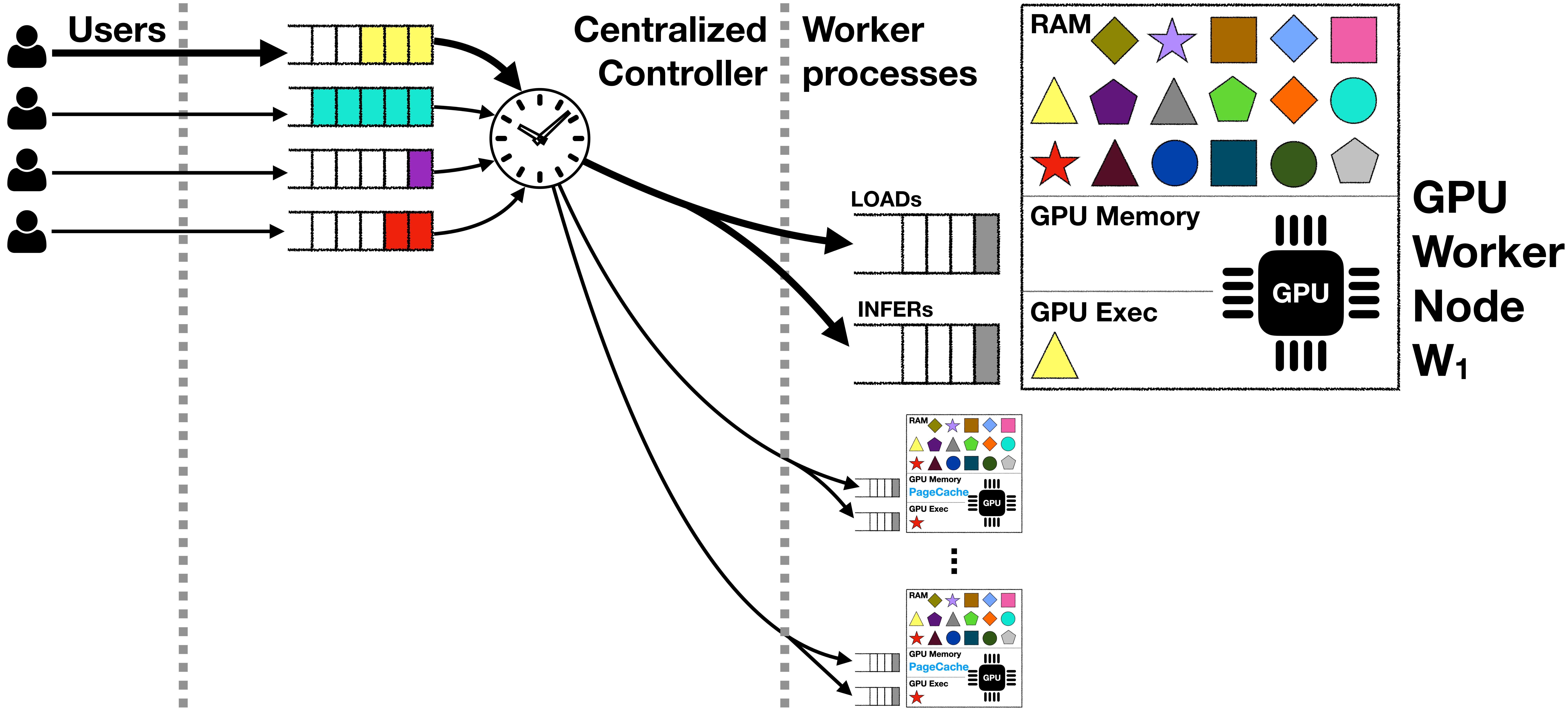
Execute inference one at a time

Consolidating Choices



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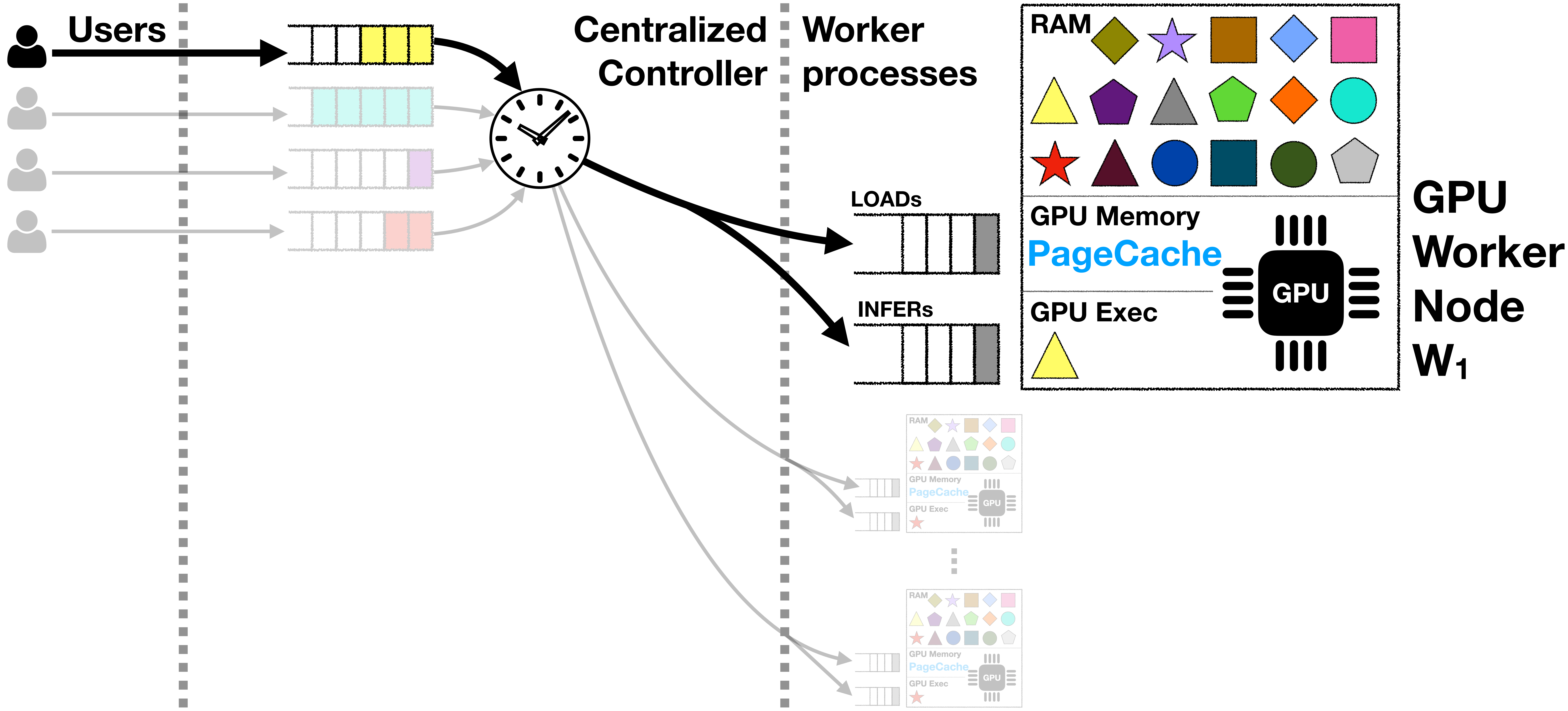

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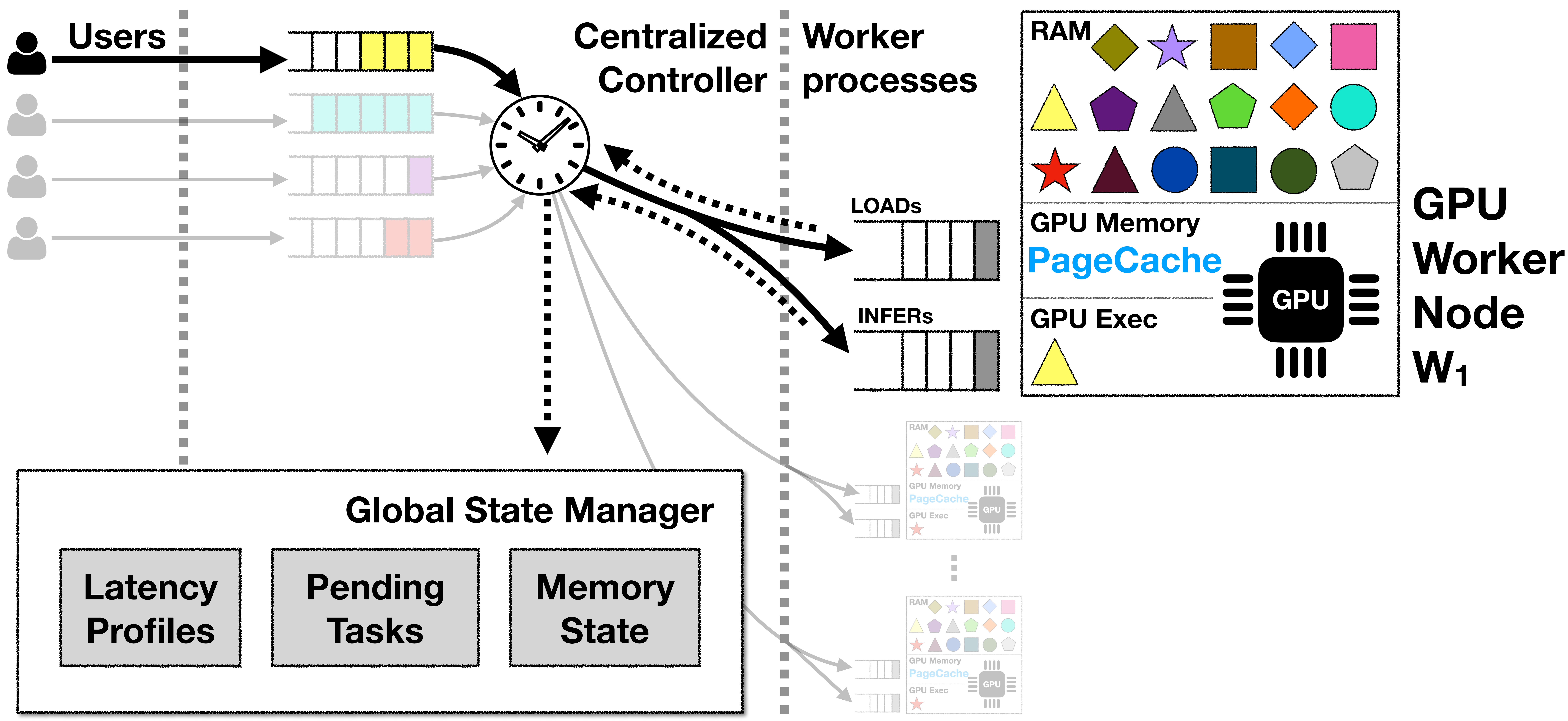

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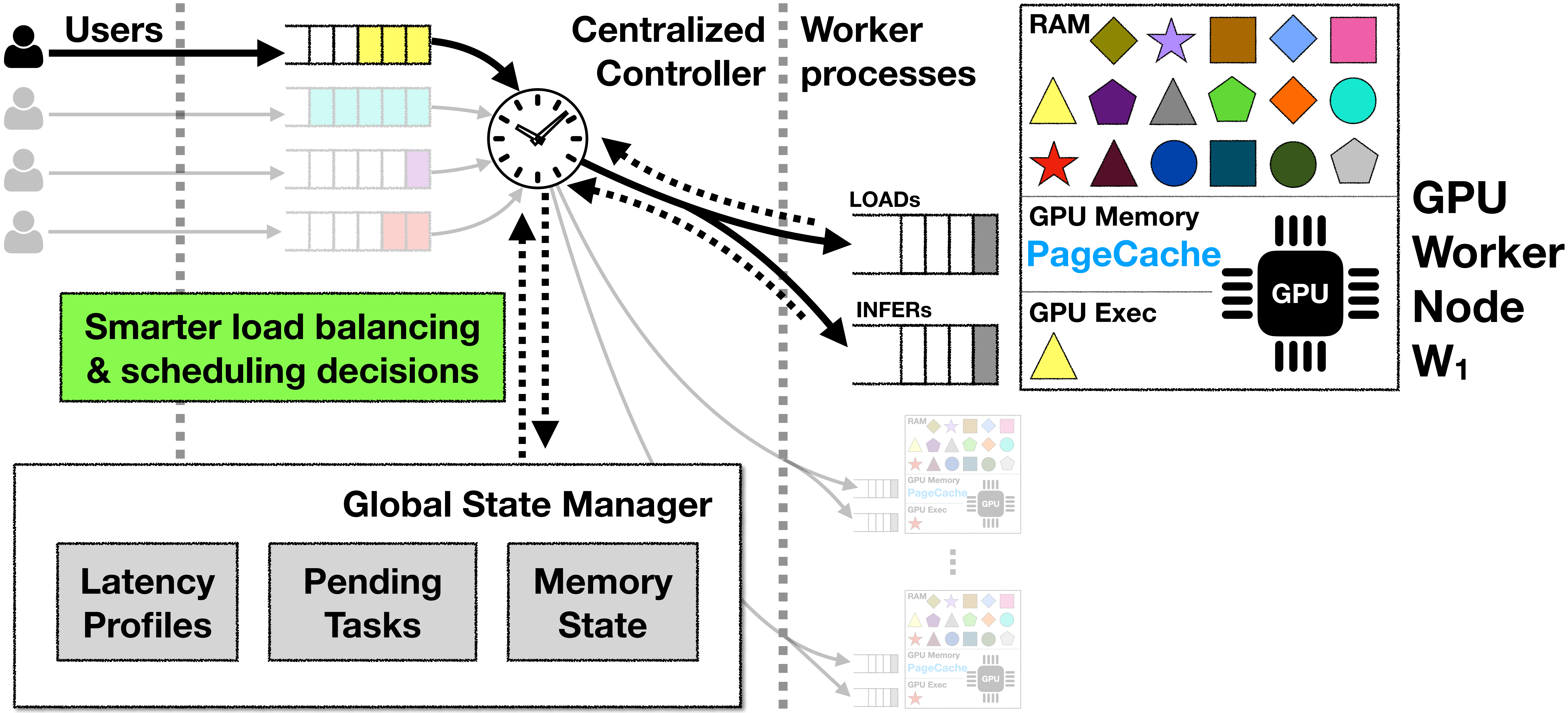

SLO-aware Scheduling

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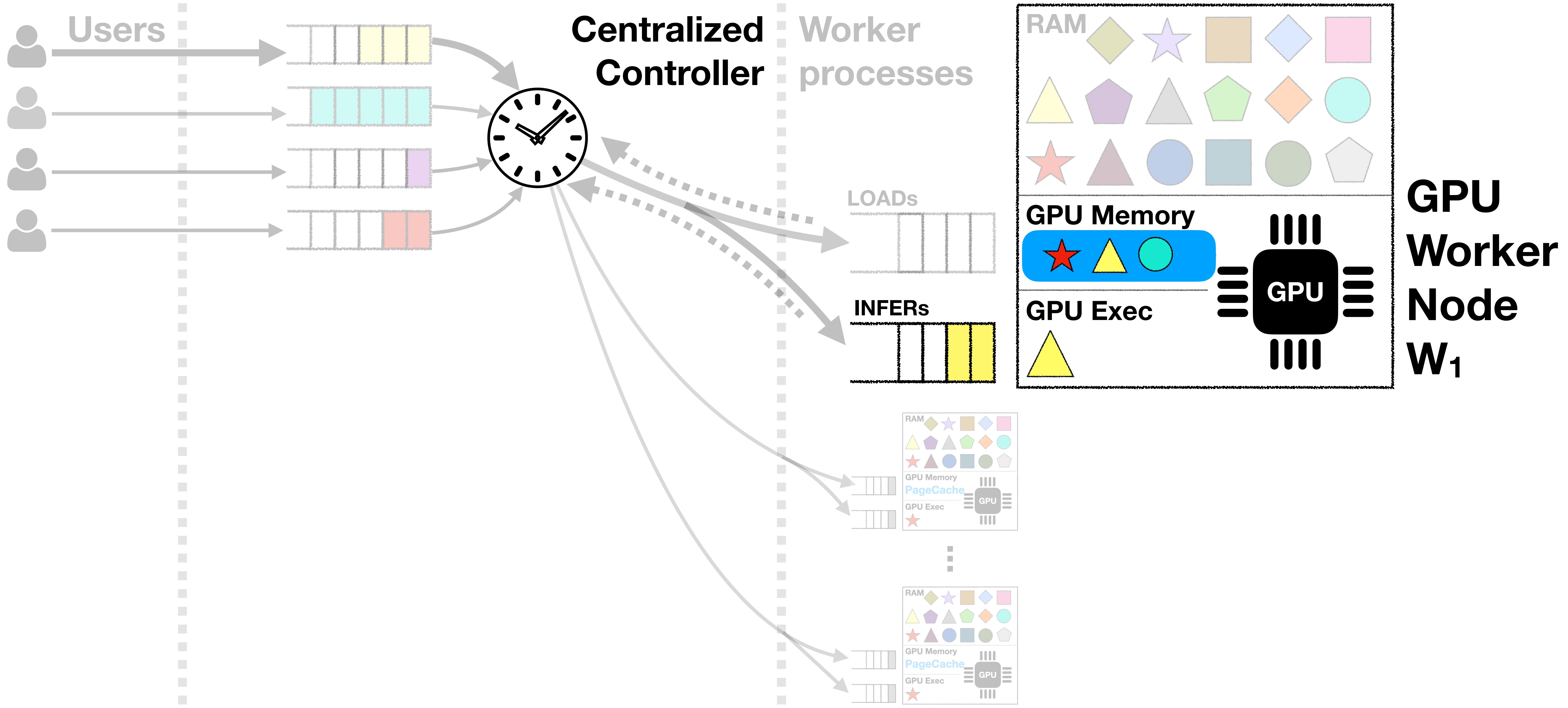

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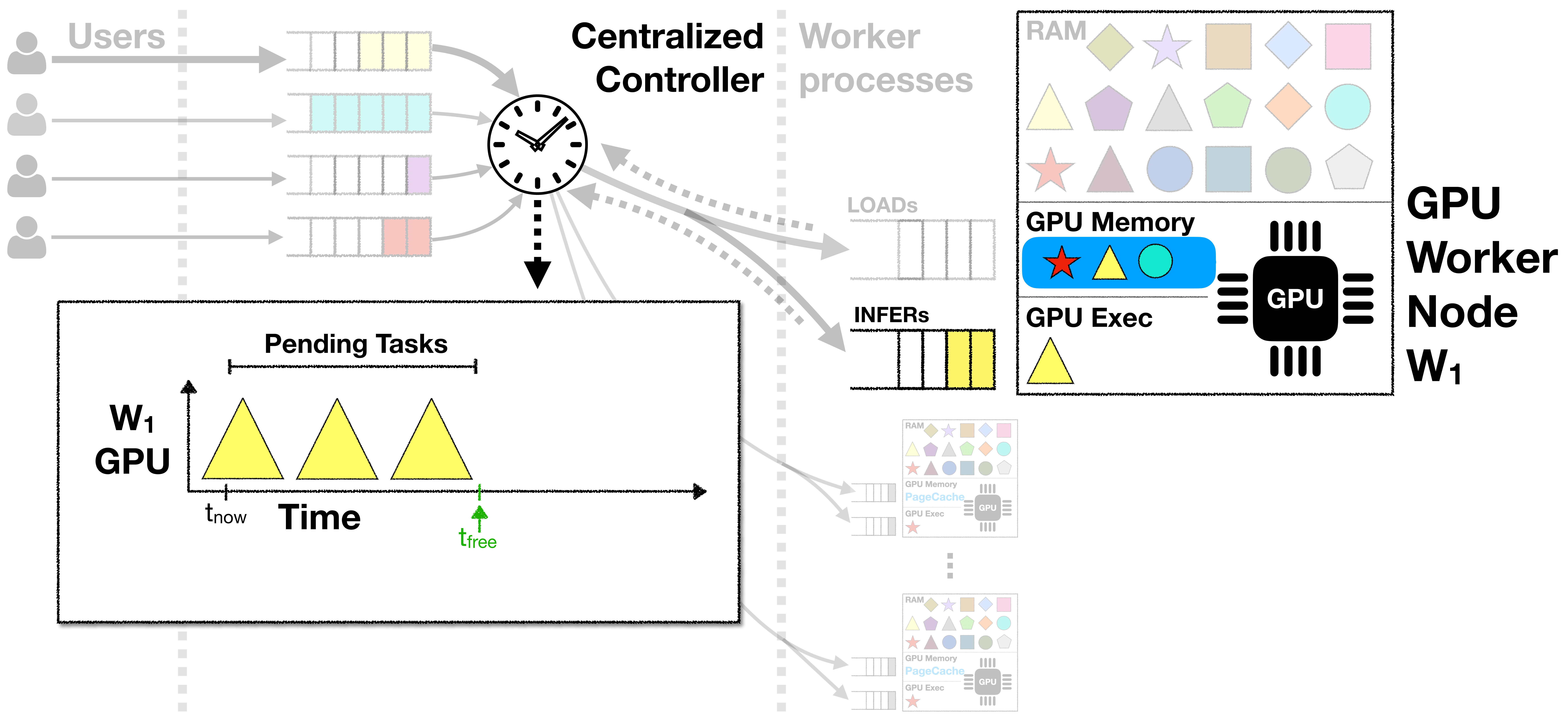

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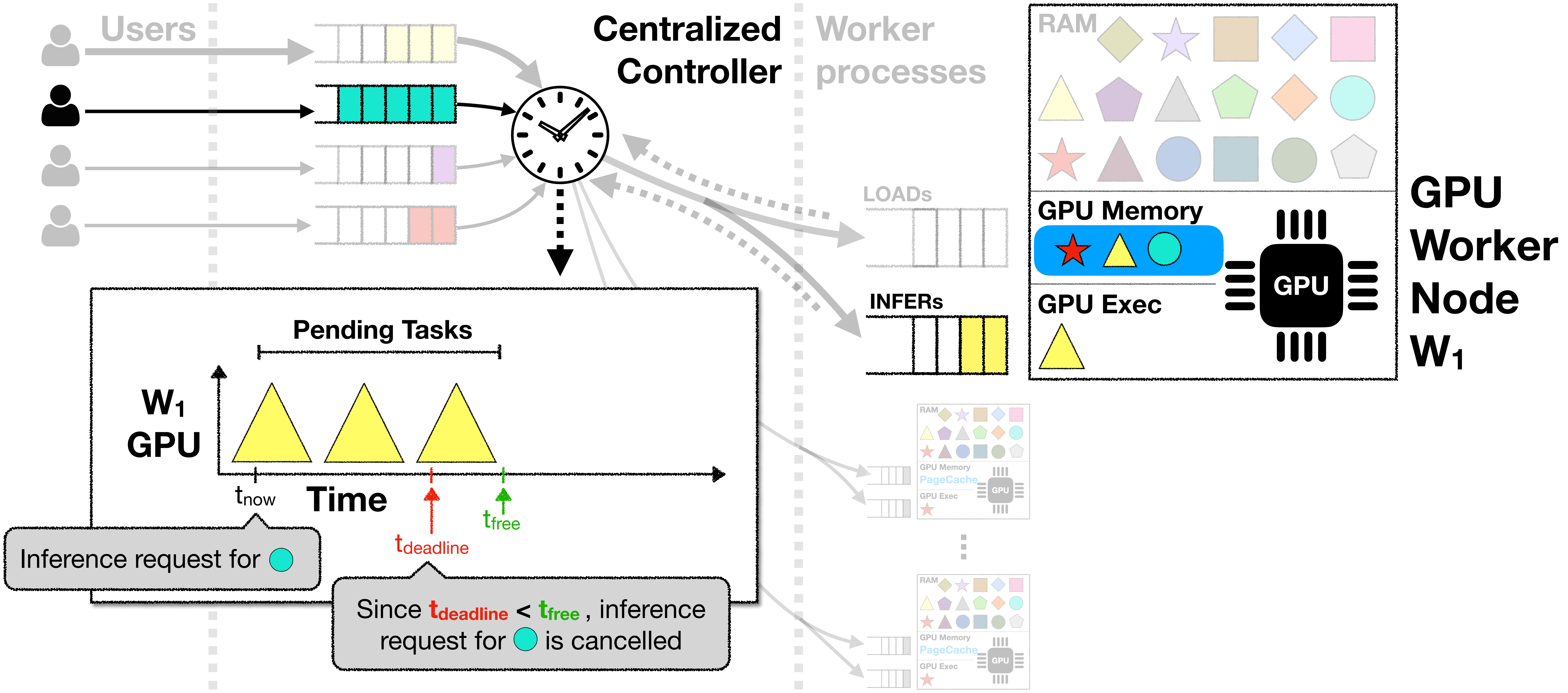

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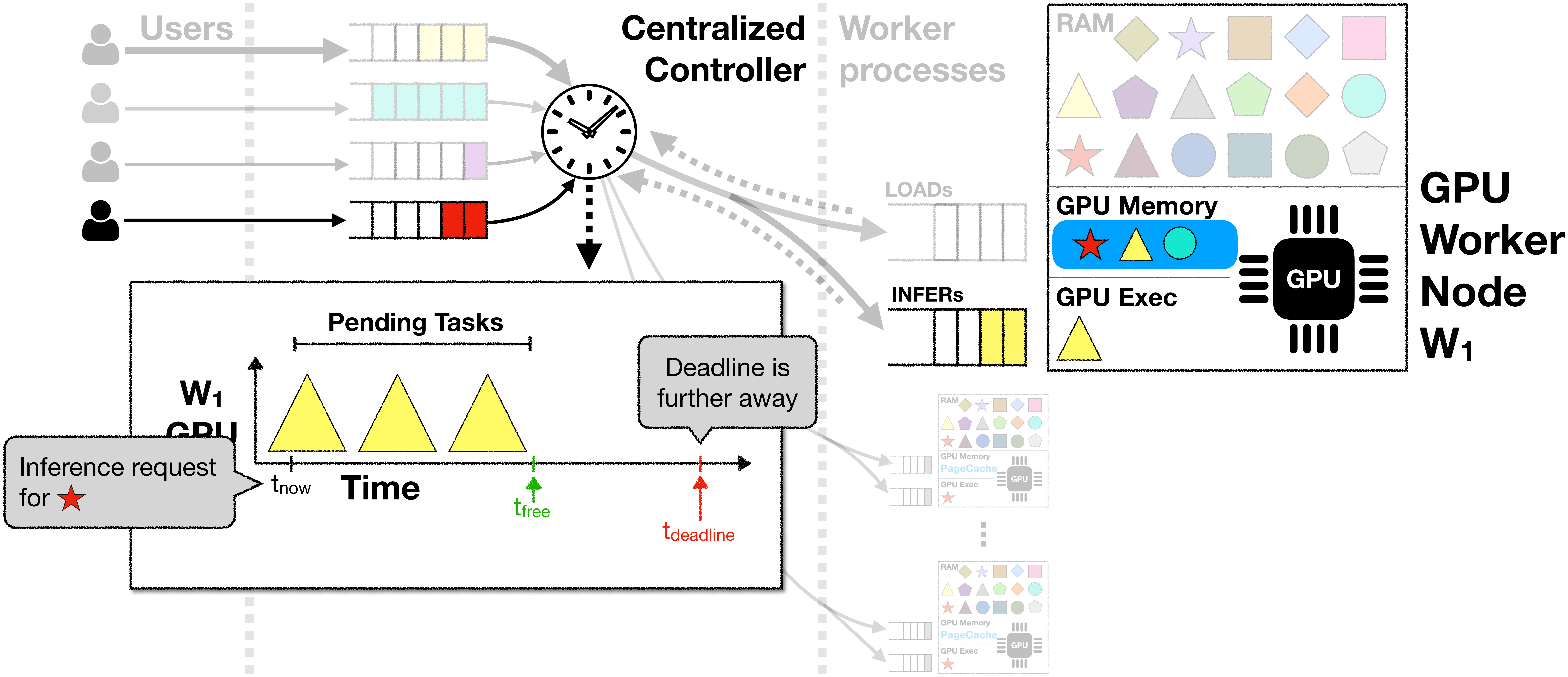

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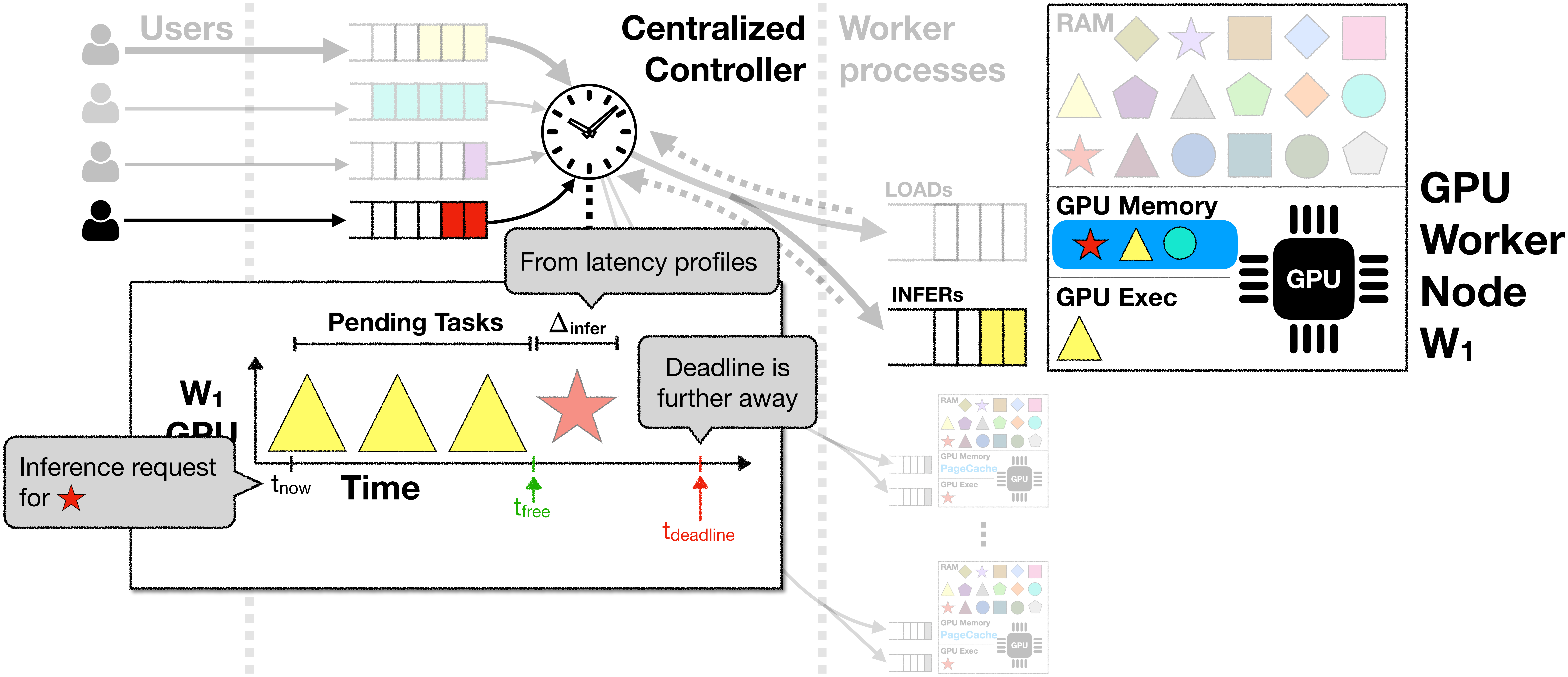

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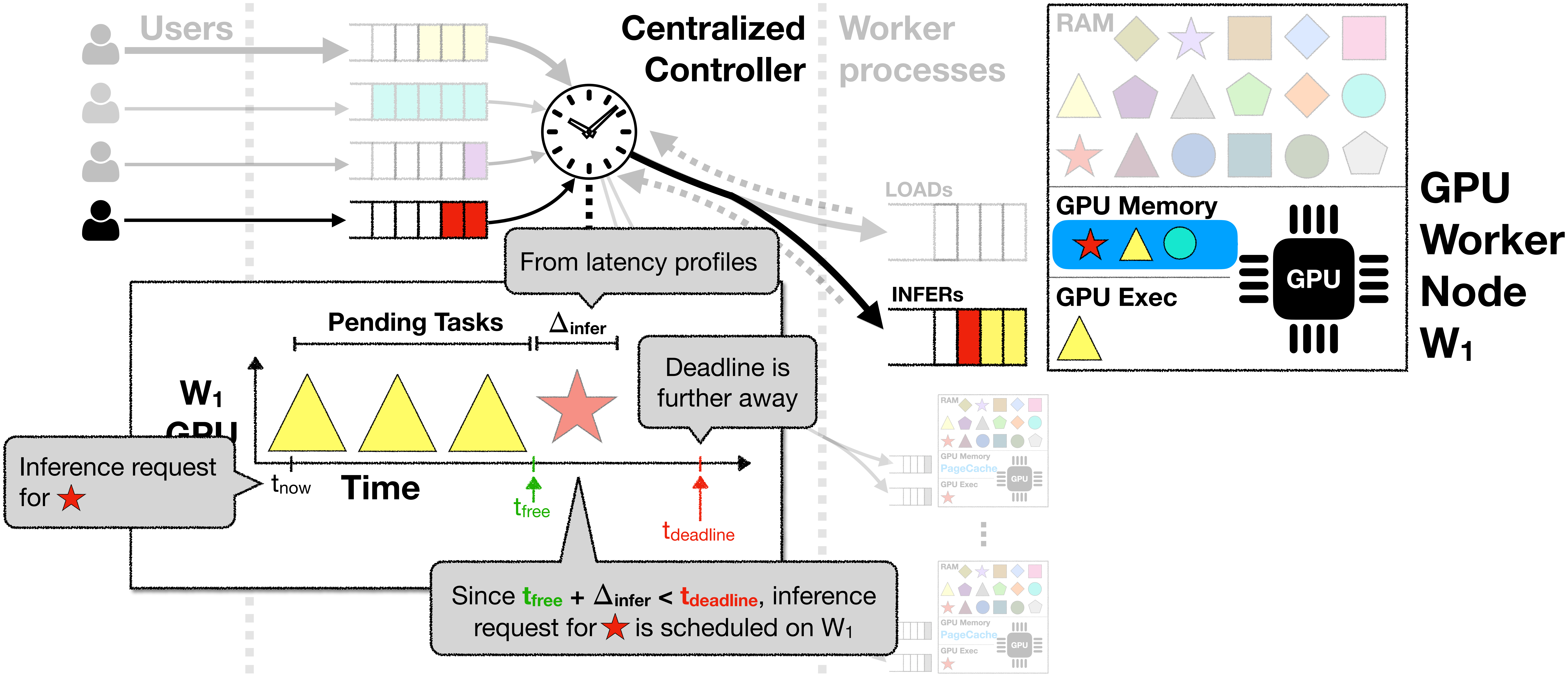

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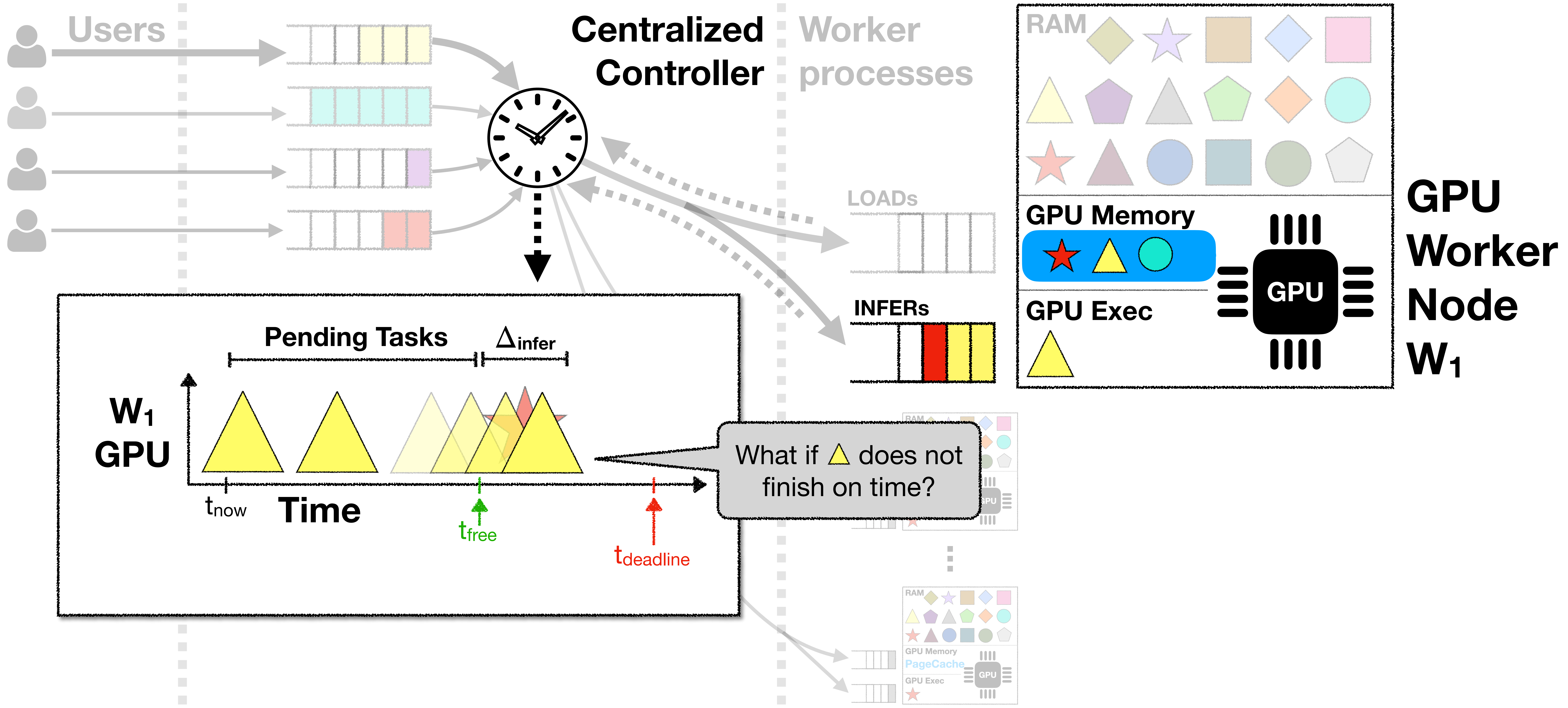

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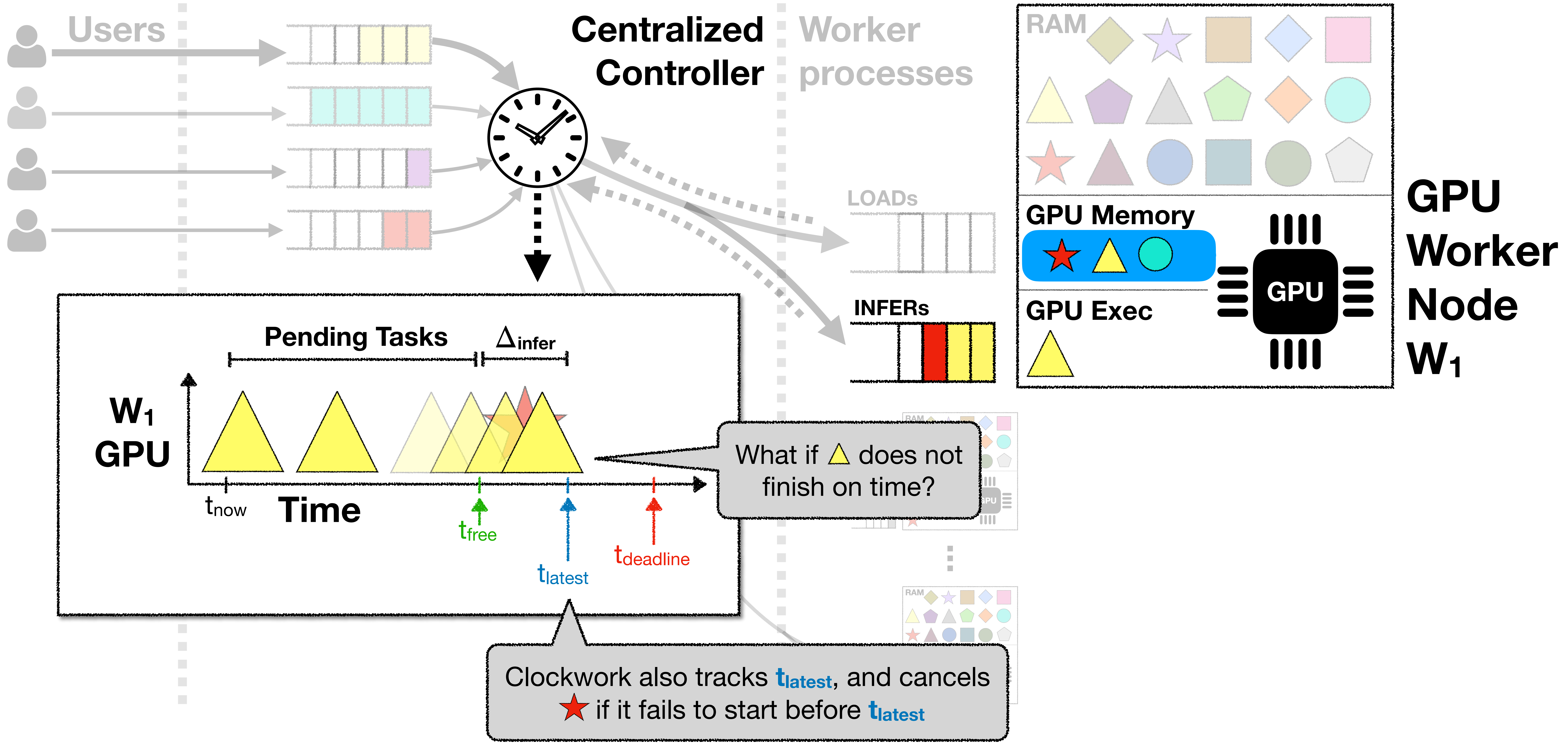

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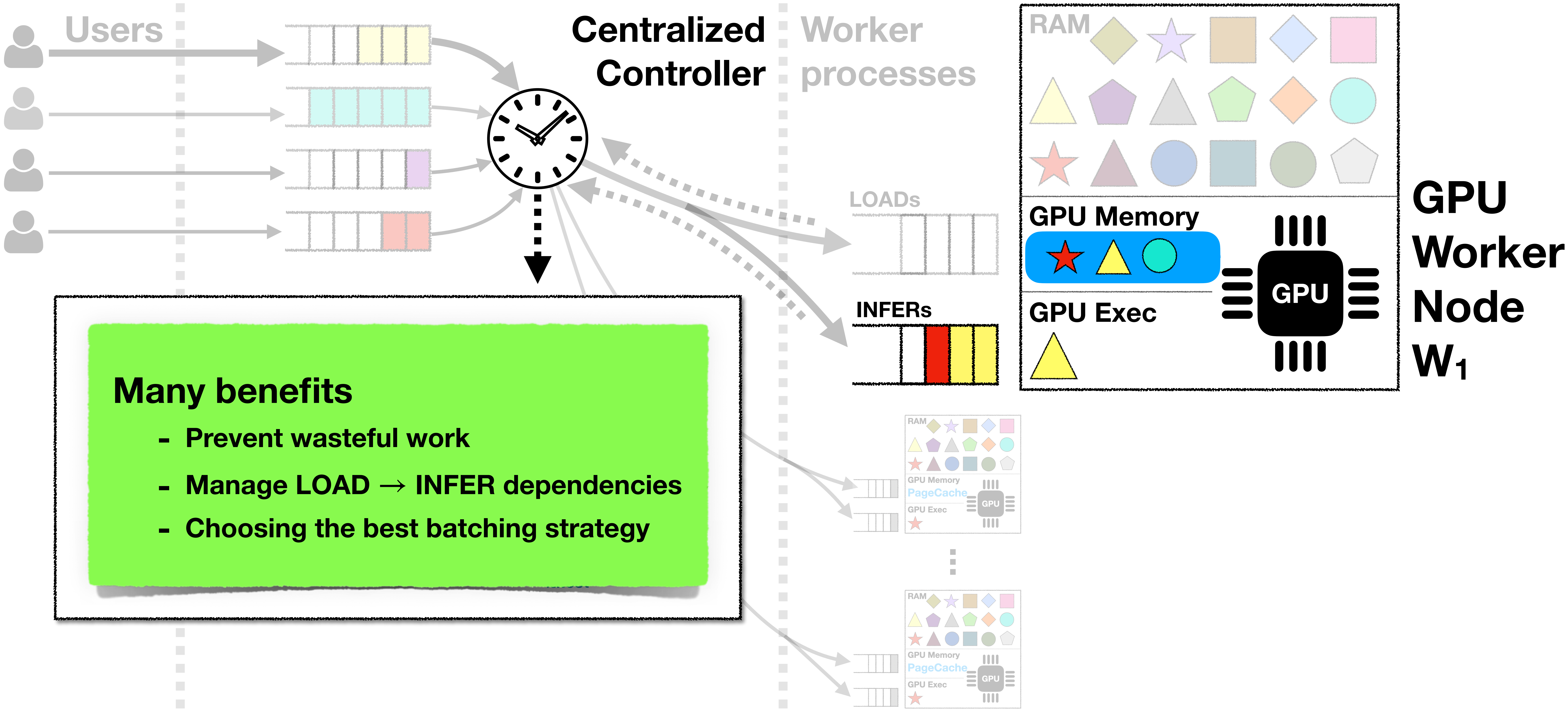

Many benefits

- Prevent wasteful work
- Manage LOAD → INFER dependencies
- Choosing the best batching strategy

Evaluation

Questions

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12 Workers: NVIDIA Tesla v100 GPU | 32 GB GPU Memory + 1 Controller + 1 Client

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Microsoft's Azure Functions →

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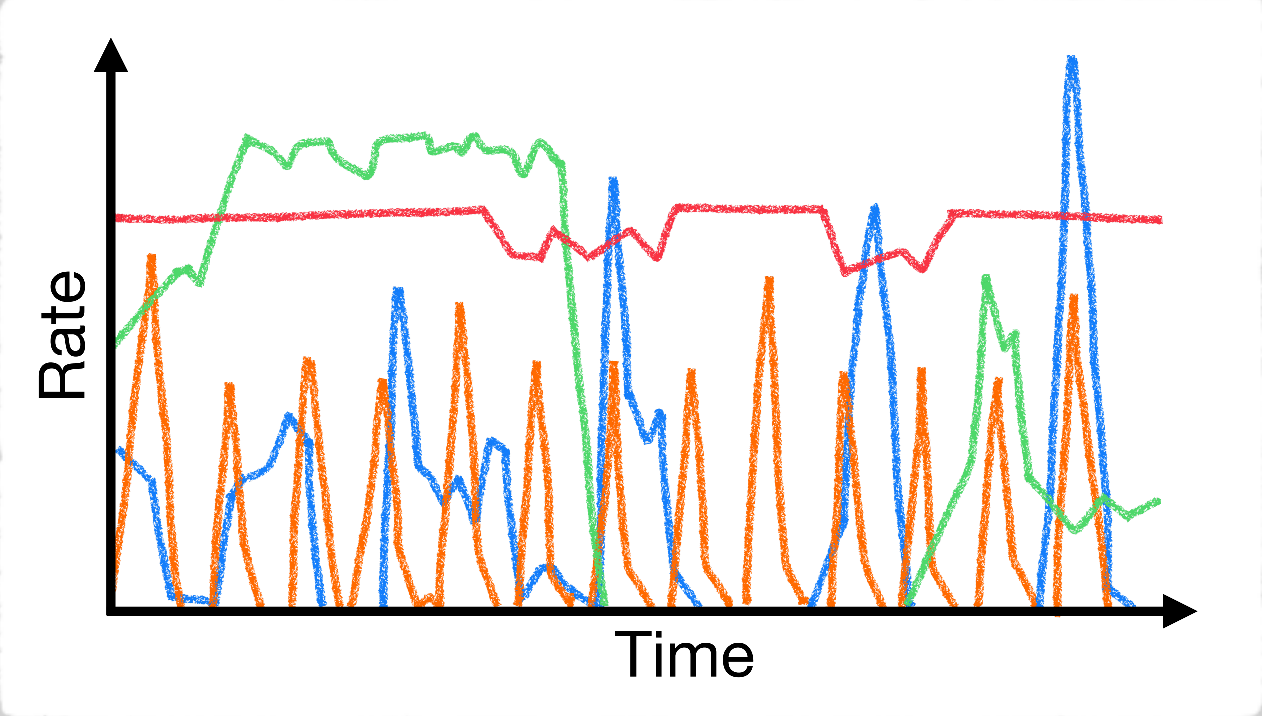
46,000 functions, 2 weeks
- Heavy sustained workloads
- Low utilization cold workloads
- Workloads with periodic spikes
- Bursty workloads



Workload

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12 Workers: NVIDIA Tesla v100 GPU | 32 GB GPU Memory **+** **1 Controller** **+** **1 Client**

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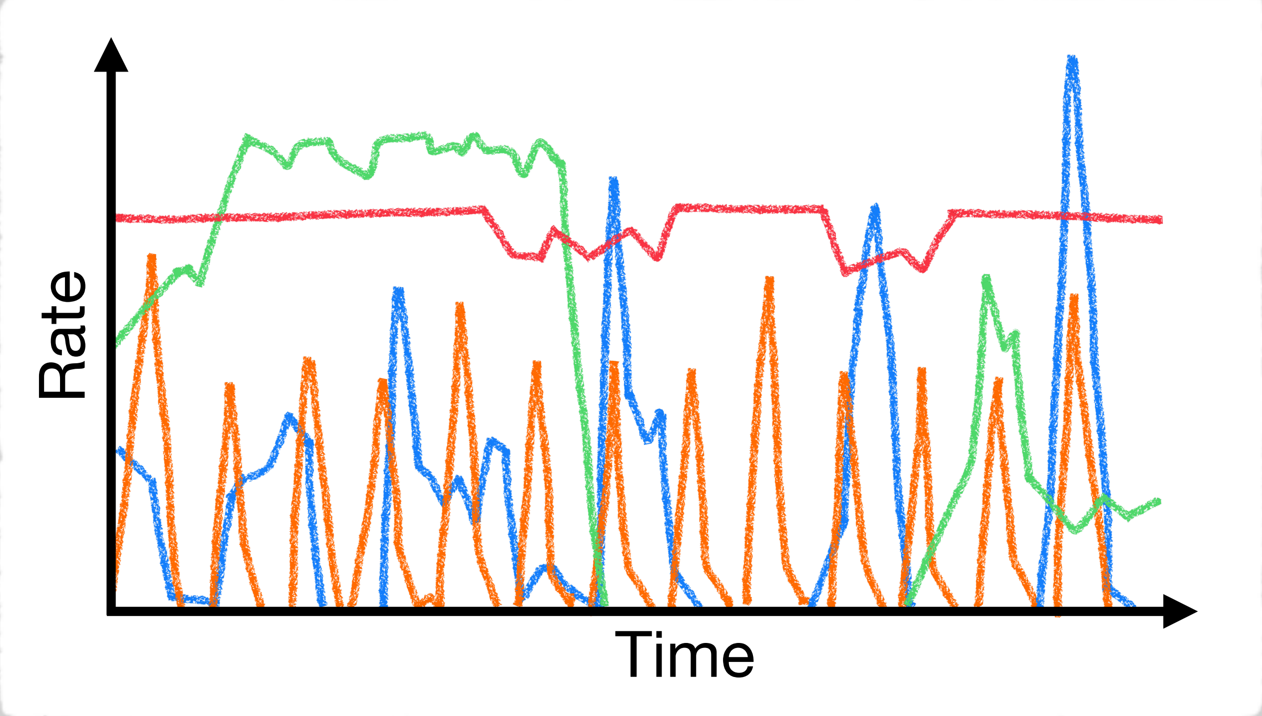

4026 model instances
- Saturates 768 GB RAM
- 61 different model architectures
- ResNet, DenseNet, Inception, etc.

Workload

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Overpredictions → Idle resources

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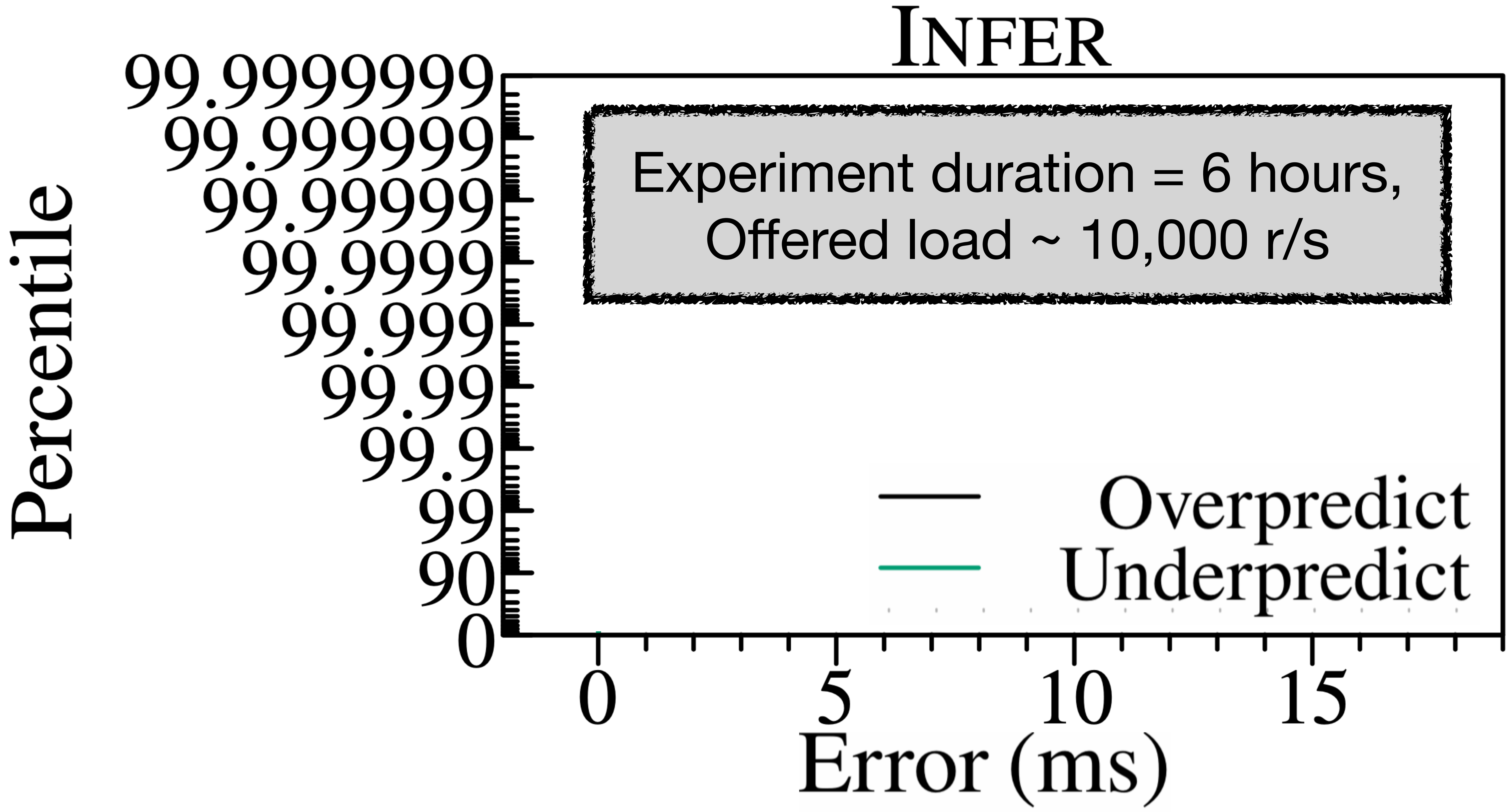

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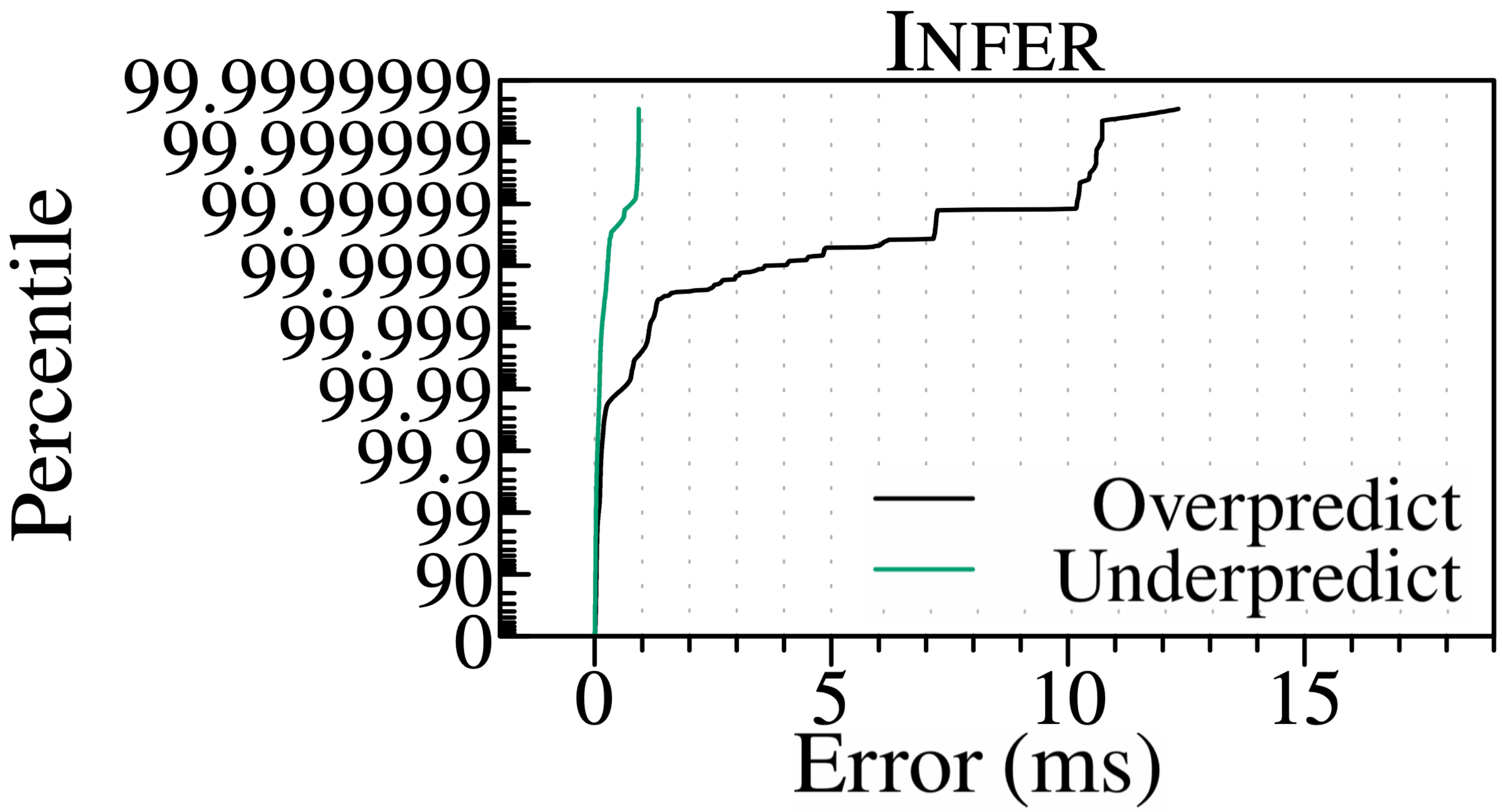

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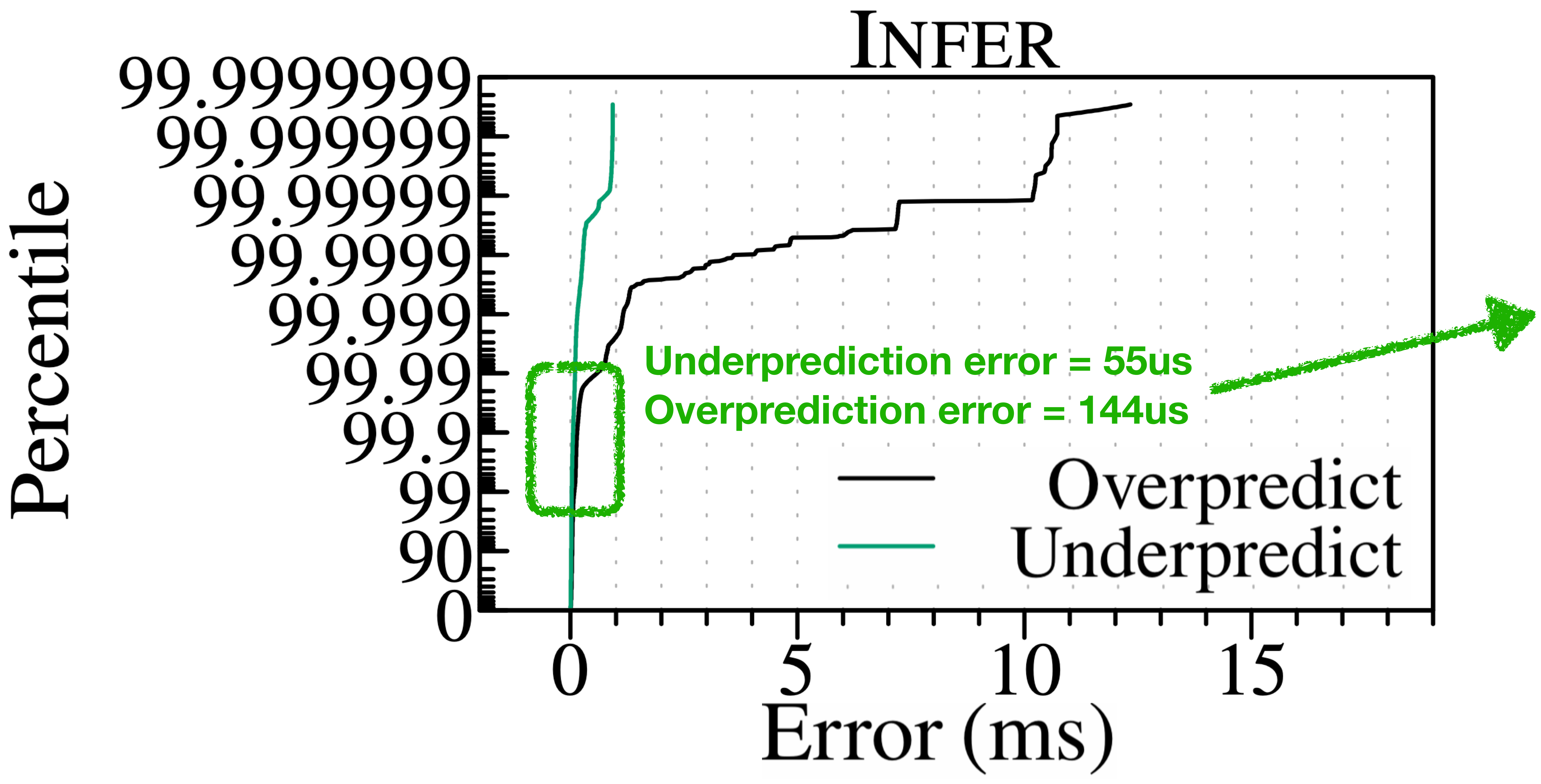

Clockwork consistently overpredicts more than its underpredicts

Errors are significant only in extremely rare cases

Does Consolidating Choice Help?

Offered load ~10,000 r/s, periodic spikes ~12,000 r/s

Latency SLO = 100 ms deadline for each request

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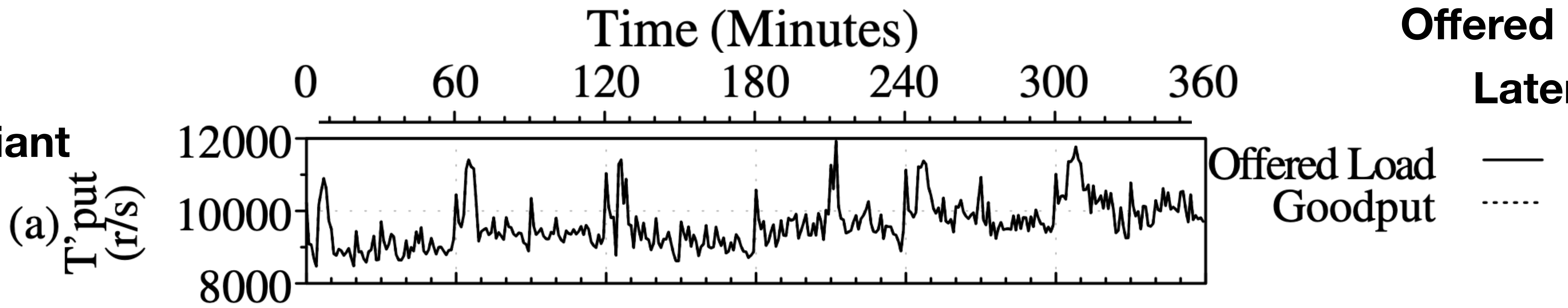

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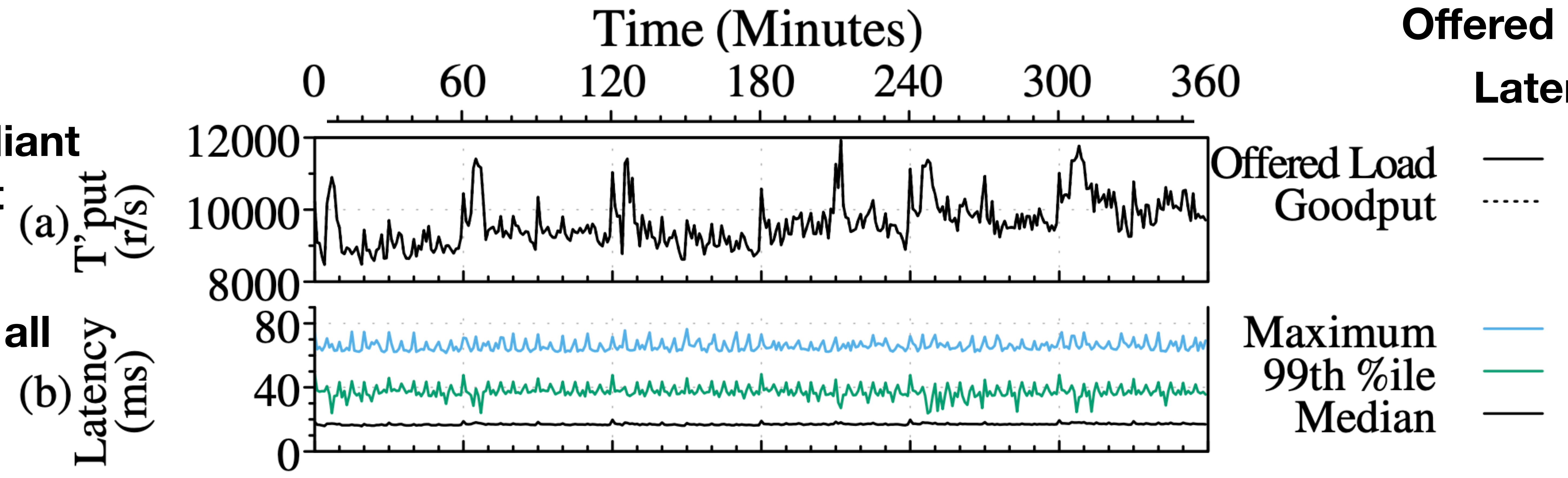

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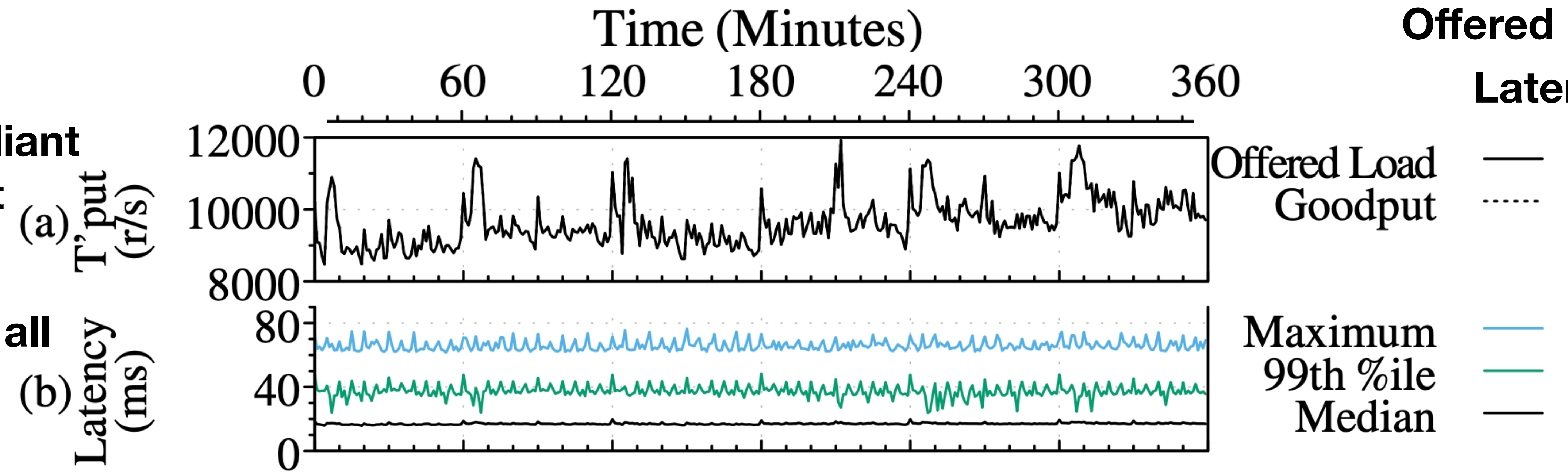

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- Goodput ≈ offered load
- Out of 208 million requests, only 58 failed due to mispredictions
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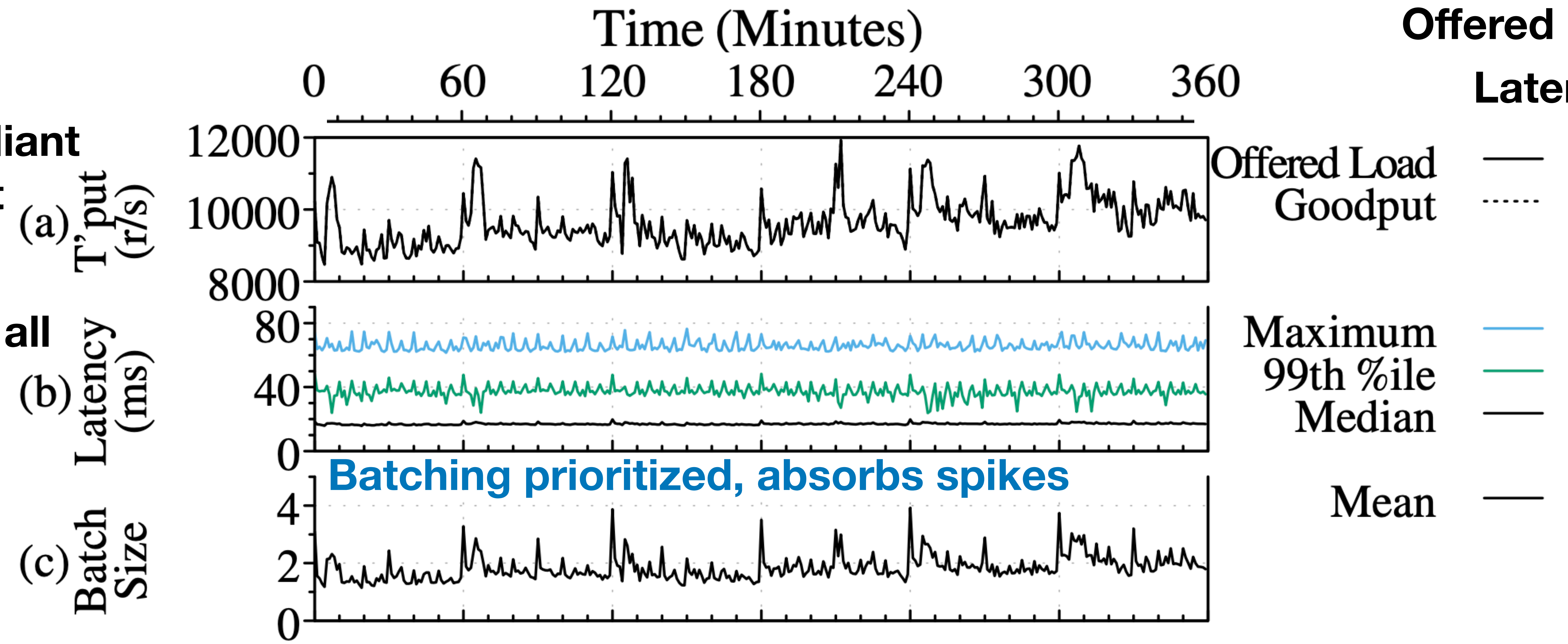

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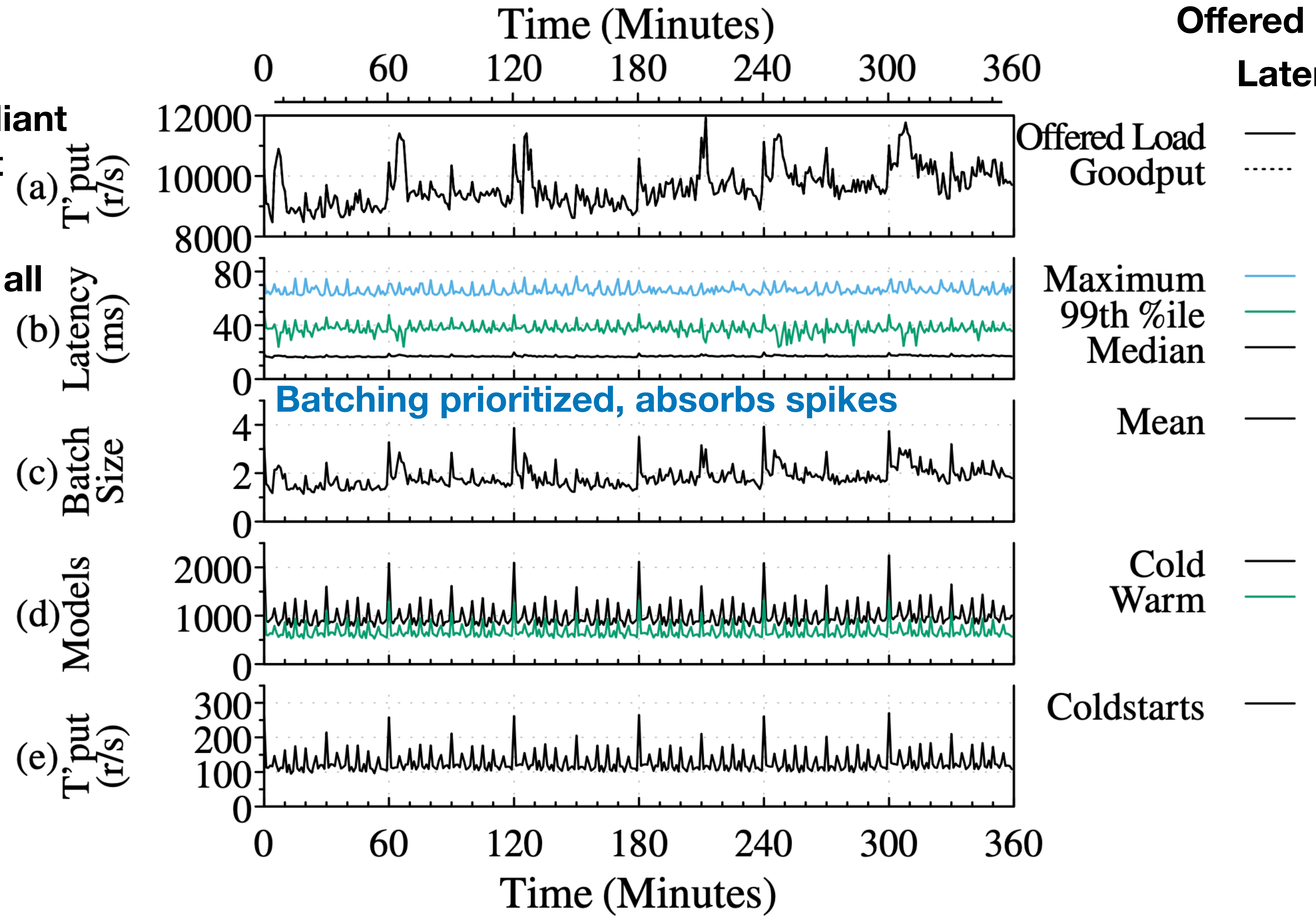

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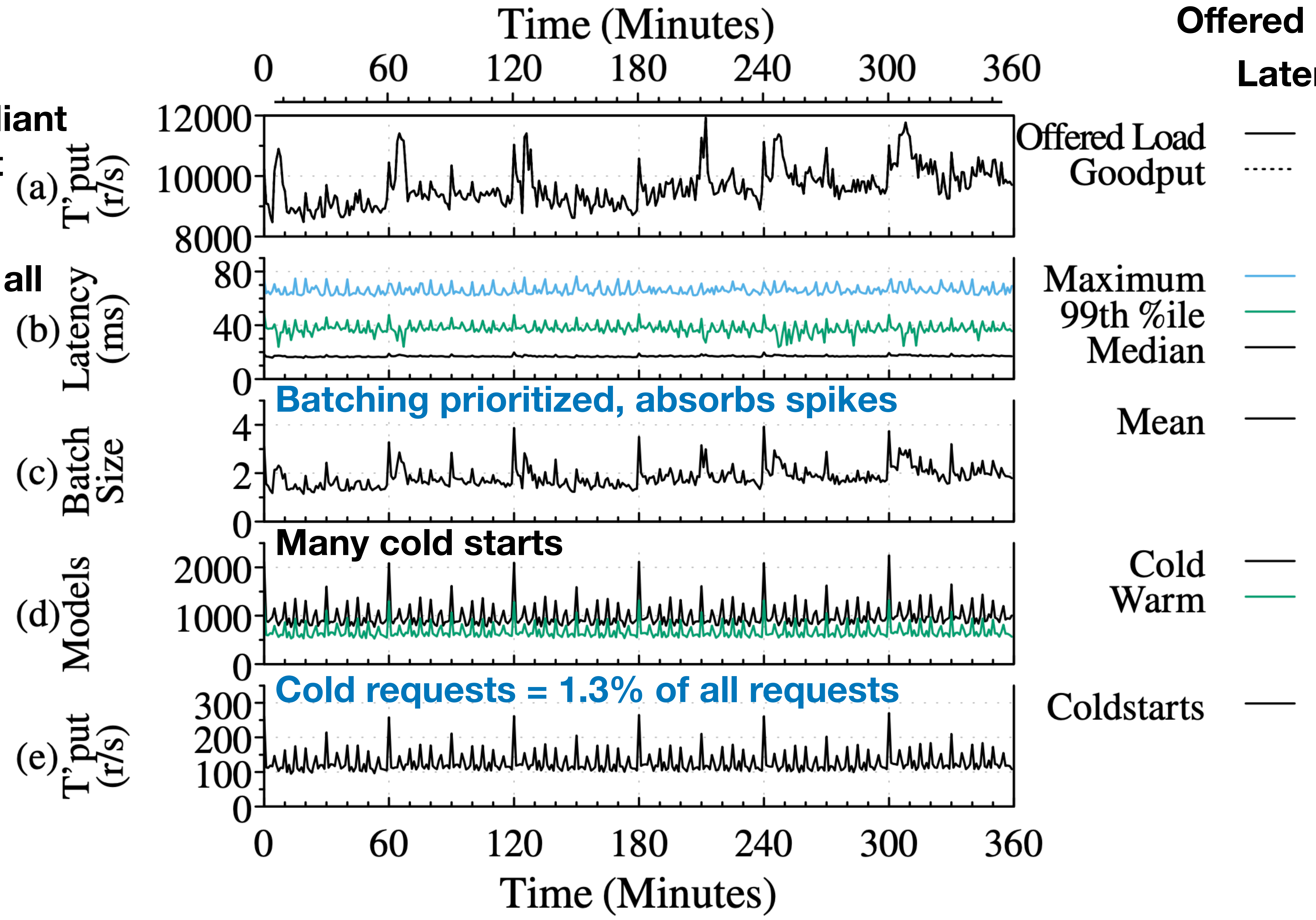

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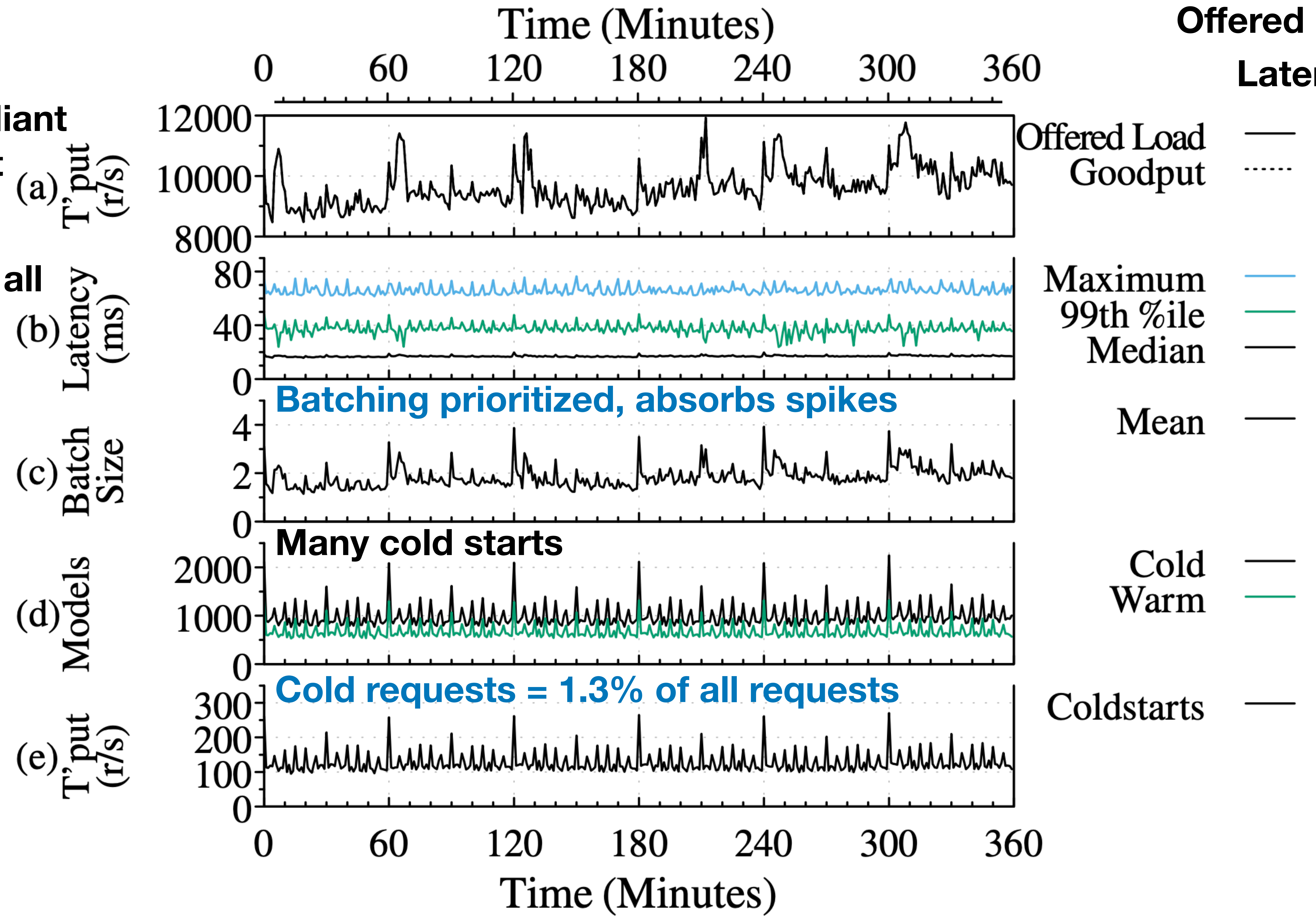

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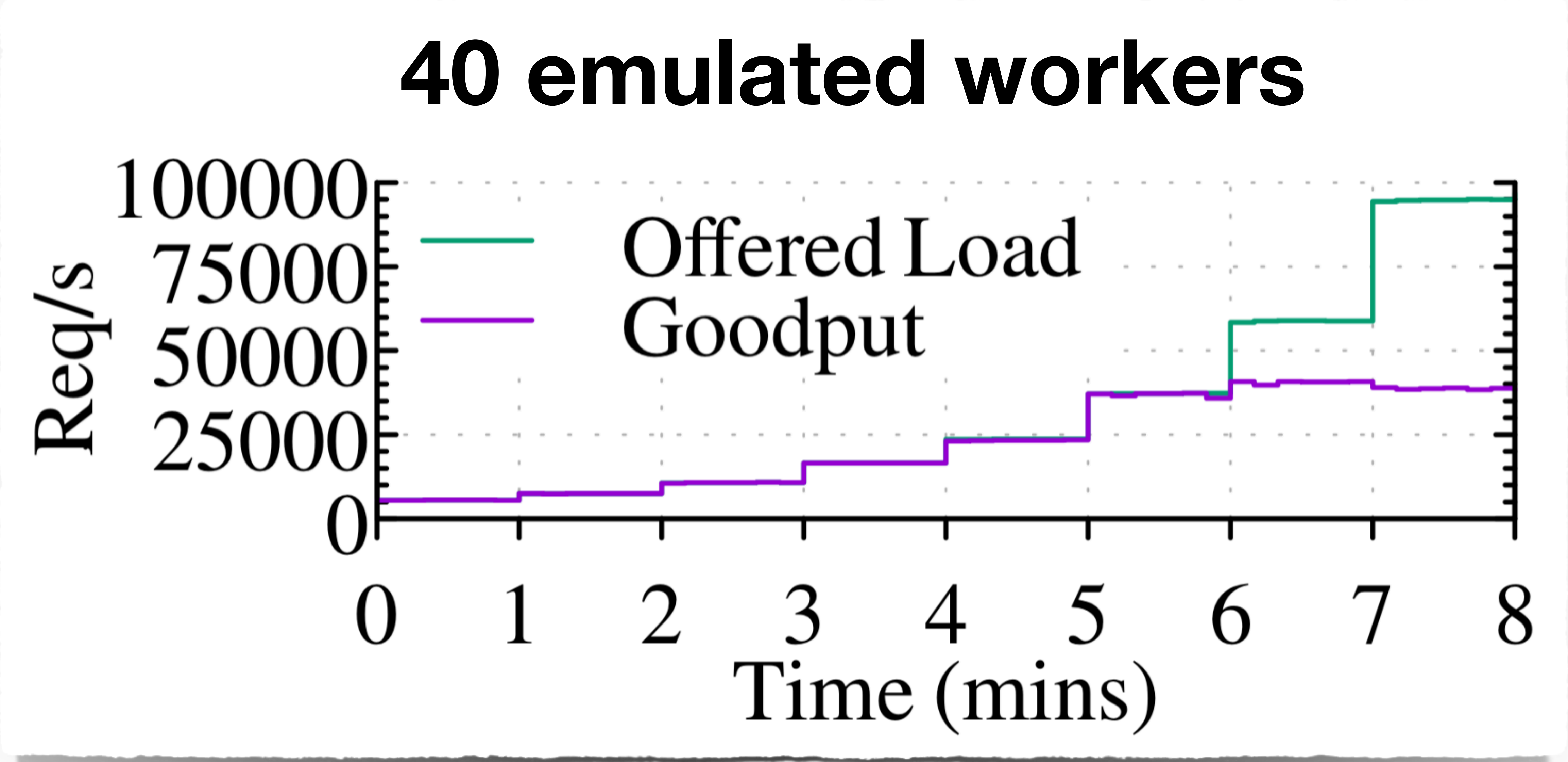

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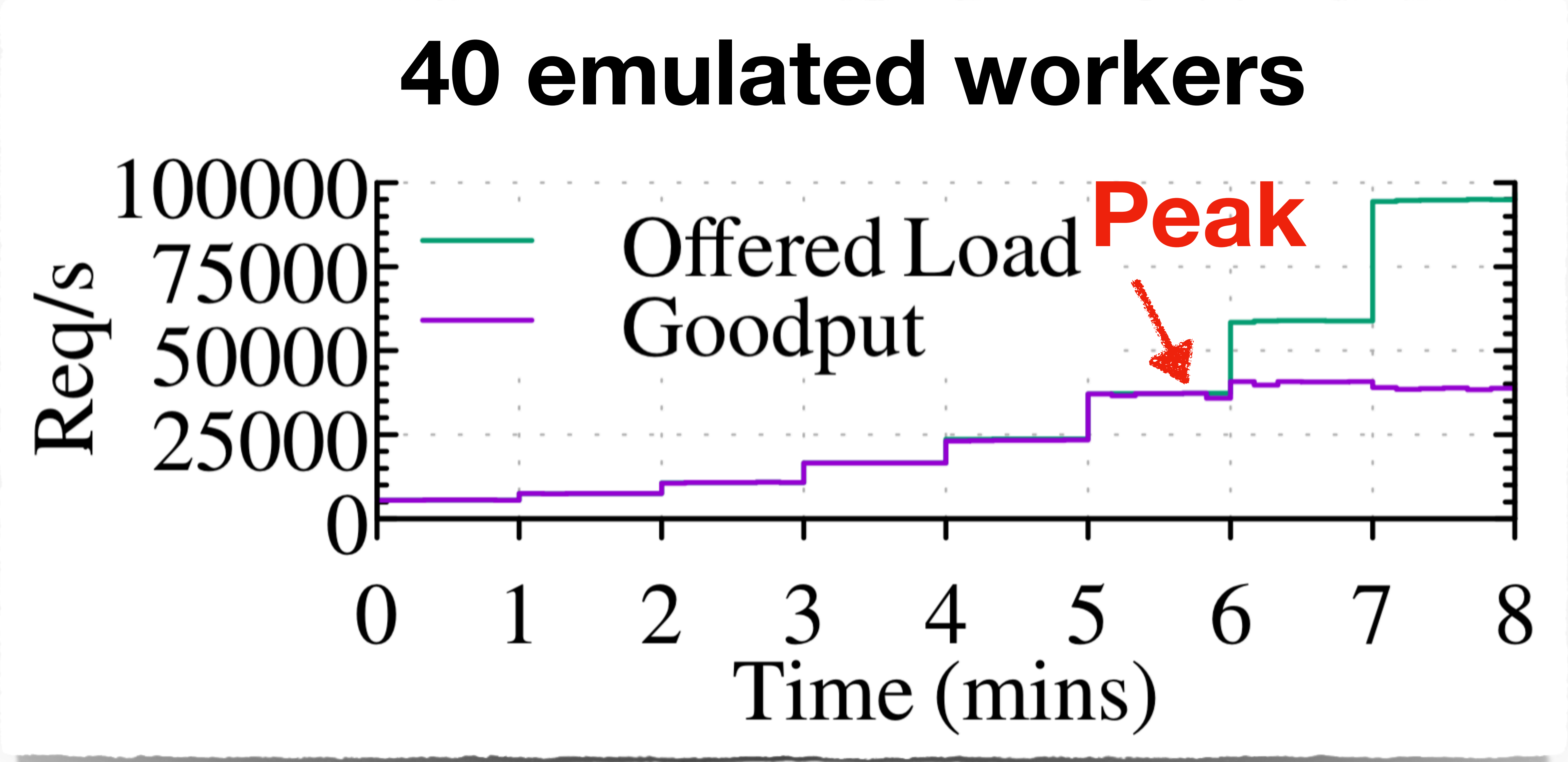

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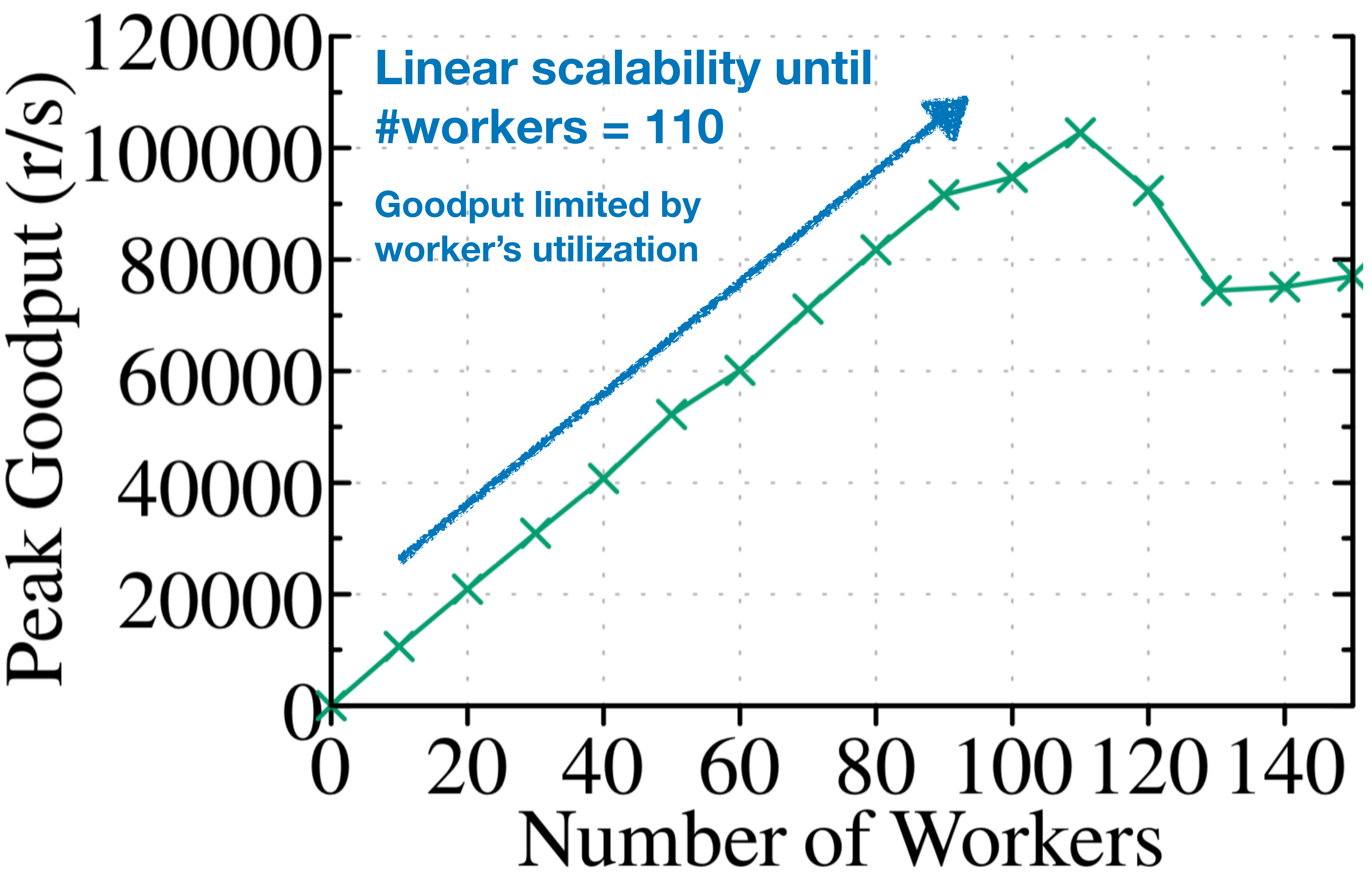

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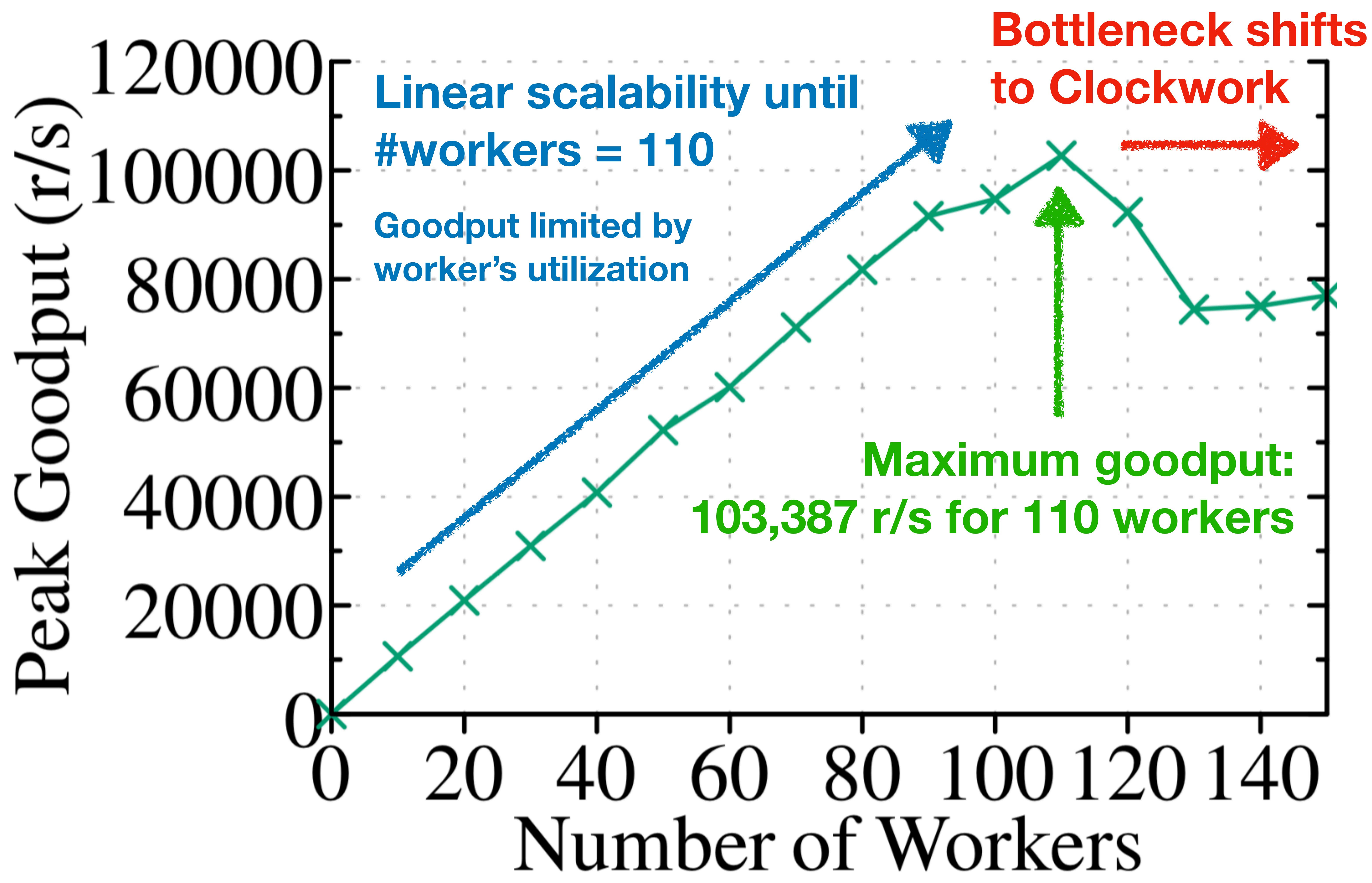

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https://gitlab.mpi-sws.org/cld/ml/clockwork

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