Operating Systems (Honor Track)

Memory 5: Memory Management in Modern Computer Systems

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Acknowledgments: Ion Stoica, Berkeley CS 162

Memory Management in Modern Computer Systems

- Memory Abstraction
  - NSDI’14 FaRM
- Demand paging: remote memory over RDMA
  - NSDI’17 InfiniSwap
  - OSDI’20 AIFM
- Demand paging: memory swapping between GPU memory and host memory
  - OSDI’20 PipeSwitch
  - NSDI’23 TGS

Microsoft Research

Microsoft

FaRM: Fast Remote Memory

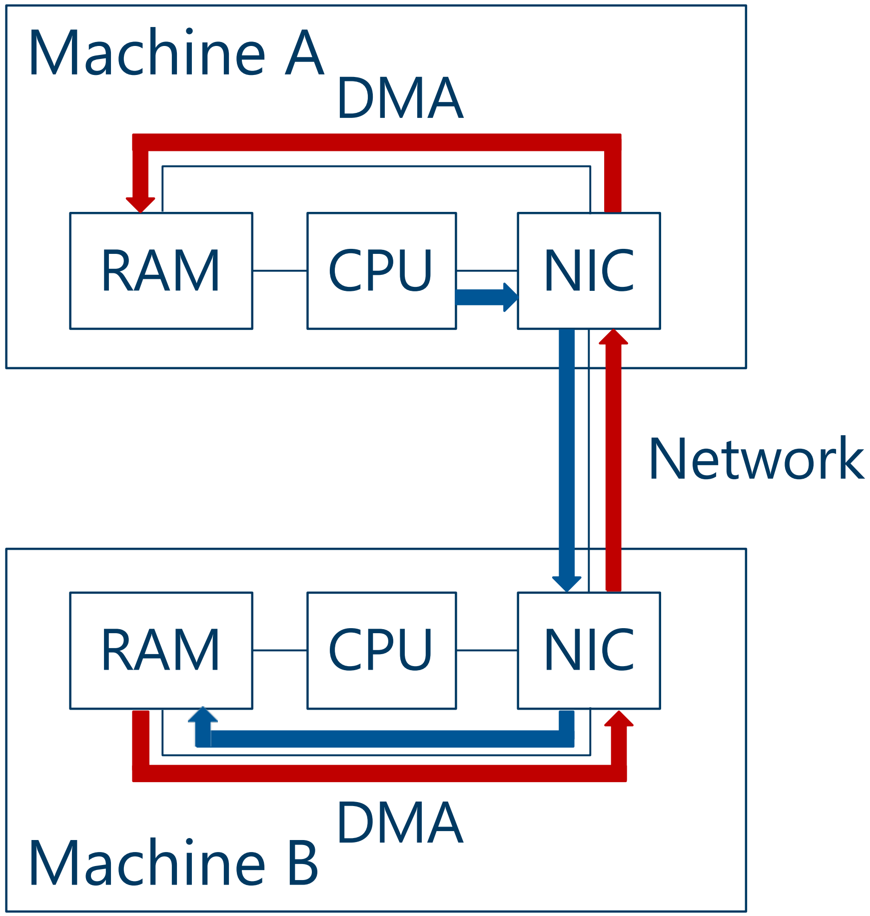
Aleksandar Dragojević, Dushyanth Narayanan,
Orion Hodson, Miguel Castro

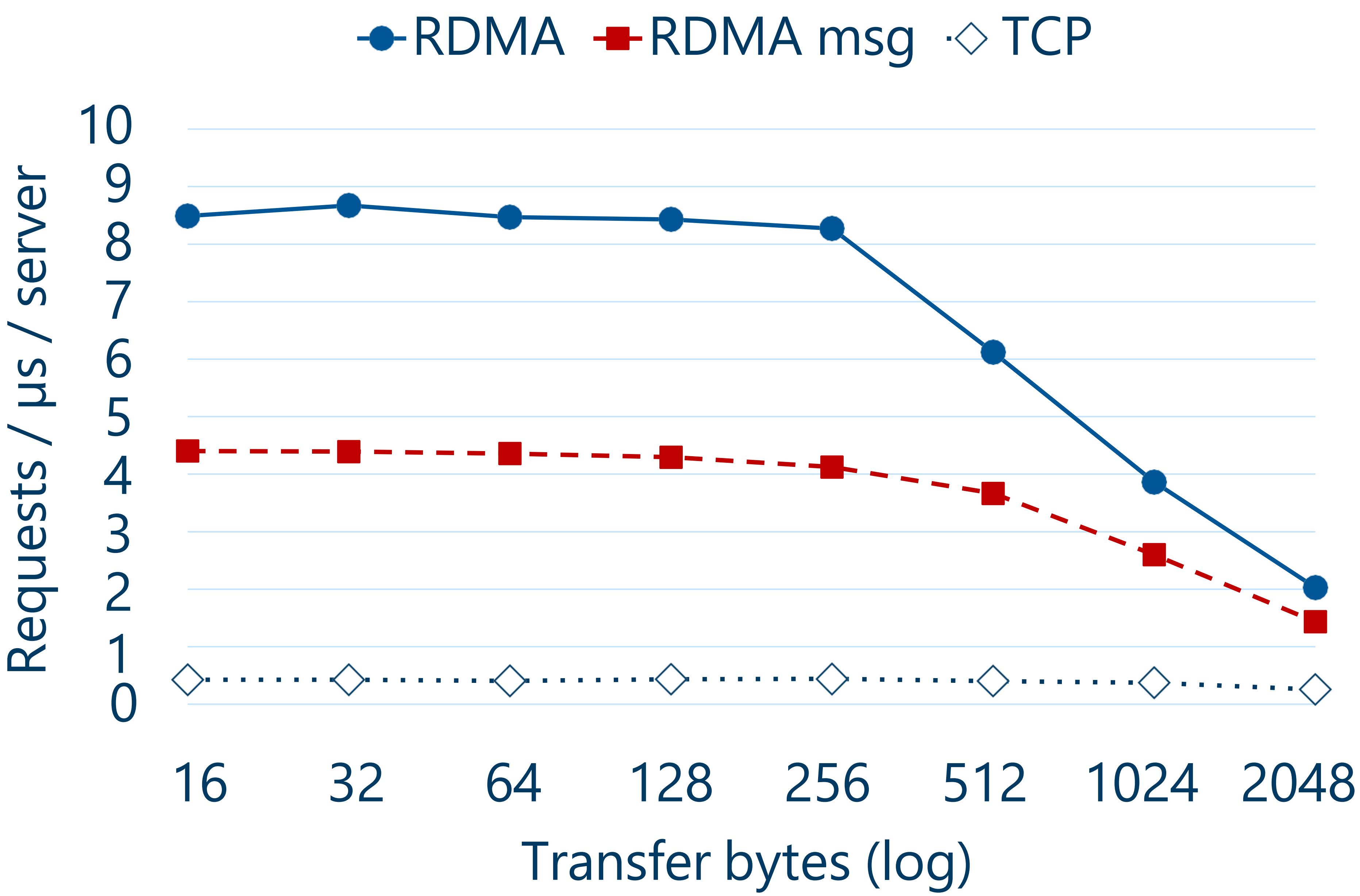
Hardware trends

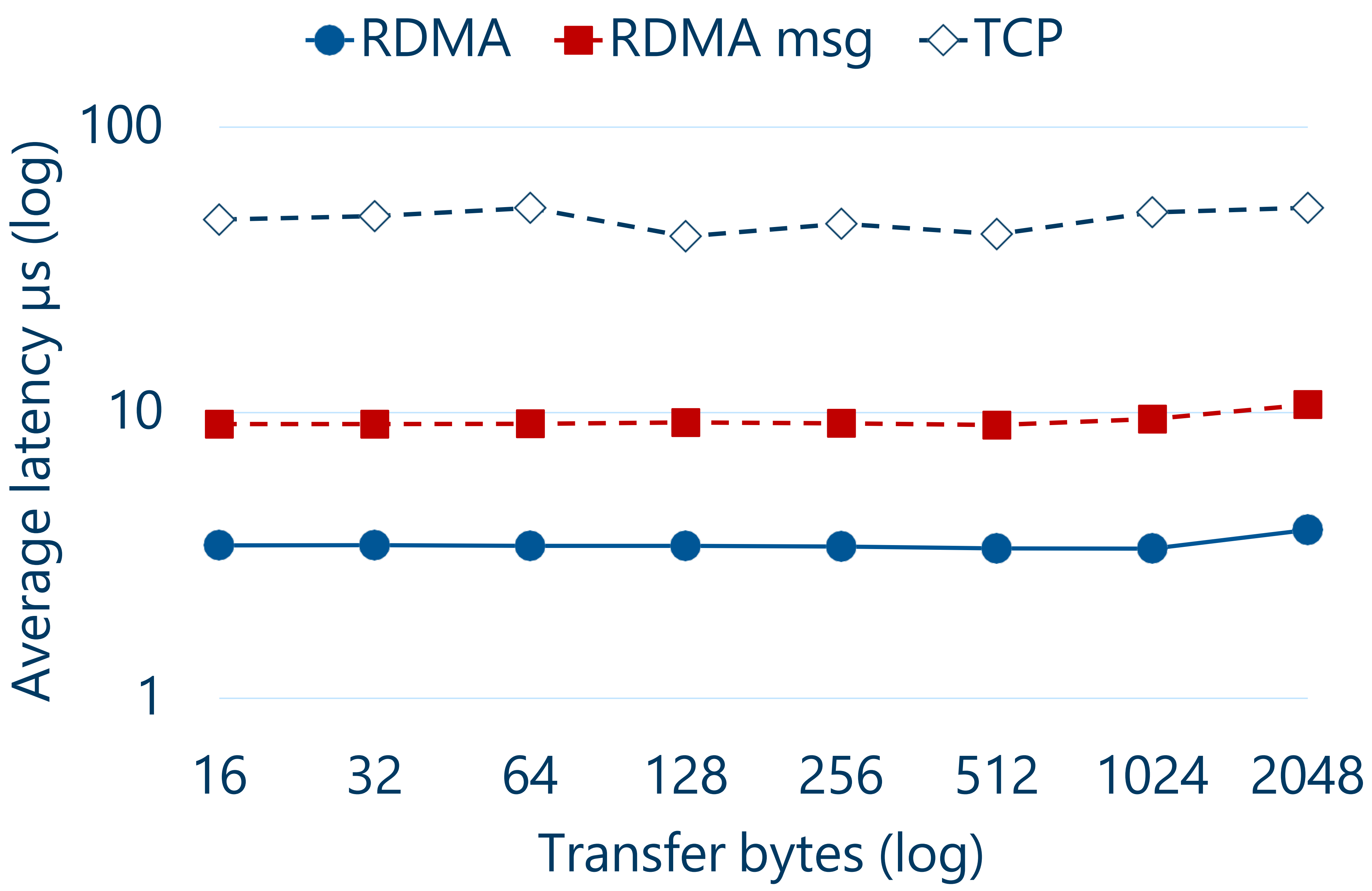
- Main memory is cheap
  - 100 GB – 1 TB per server
  - 10 – 100 TBs in a small cluster
- New data centre networks
  - 40 Gbps throughput (100 this year)
  - 1-3 μs latency
  - RDMA primitives

Remote direct memory access

- Read / write remote memory
  - NIC performs DMA requests
- FaRM uses RDMA extensively
  - Reads to directly read data
  - Writes into remote buffers for messaging
- Great performance
  - Bypasses the kernel
  - Bypasses the remote CPU




RDMA
RDMA msg
TCP
Requests / µs / server
10
9
8
7
6
5
4
3
2
1
0
16
32
64
128
256
512
1024
2048
Transfer bytes (log)



RDMA
RDMA msg
TCP
100
10
1
Average latency µs (log)
16
32
64
128
256
512
1024
2048
Transfer bytes (log)

Applications

- Data centre applications
  - Irregular access patterns
  - Latency sensitive
- Data serving
  - Key-value store
  - Graph store
- Enabling new applications

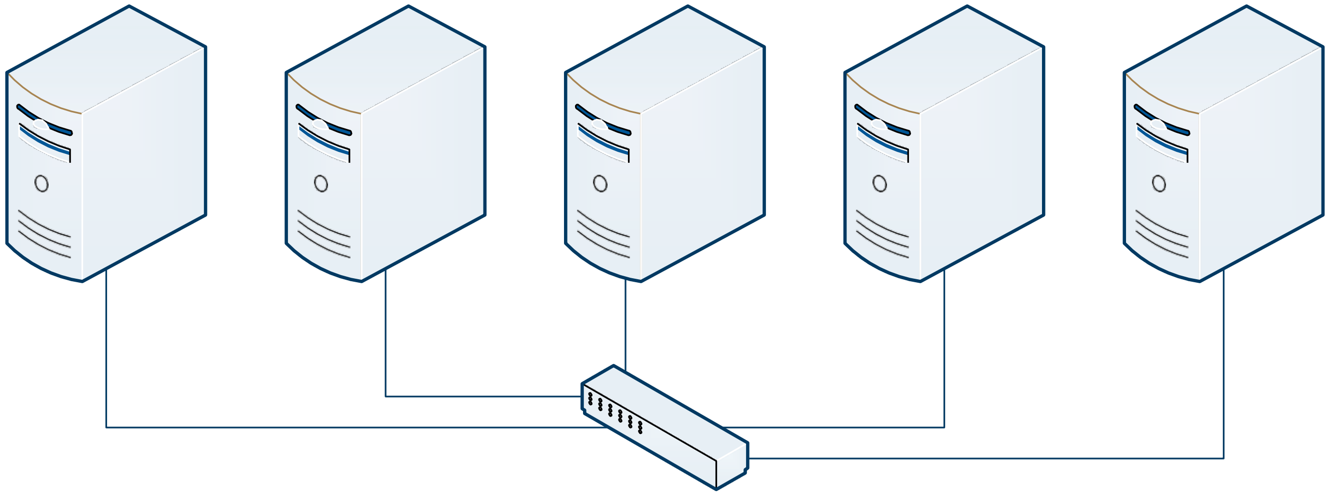
How to program a modern cluster?

We have:

- TBs of DRAM
- 100s of CPU cores
- RDMA network

Desirable:

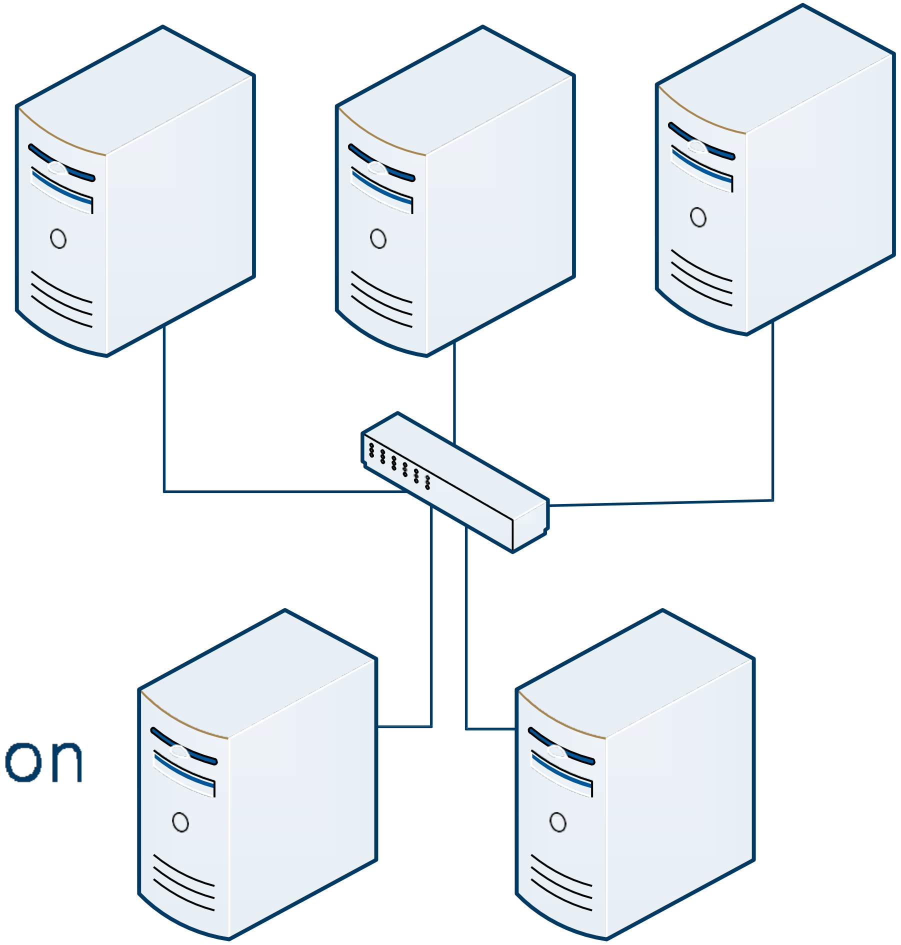
- Keep data in memory
- Access data using RDMA
- Collocate data and computation



Traditional model

Servers: store data

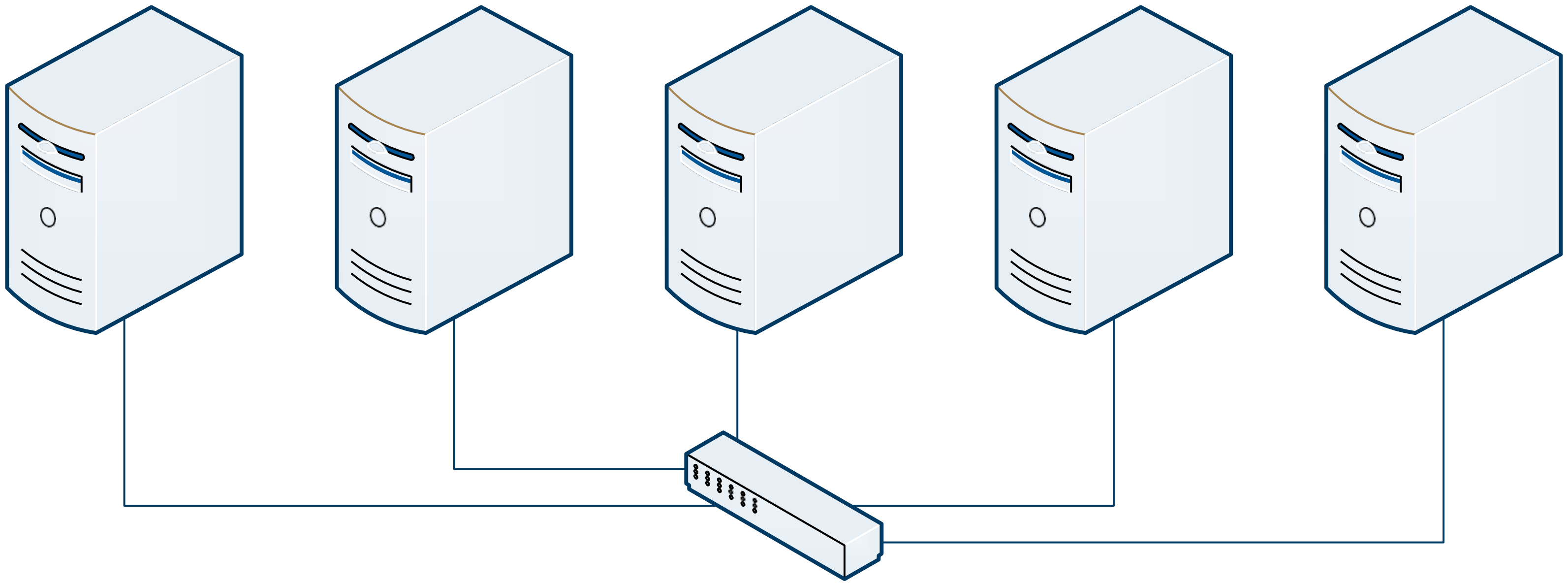
Clients: execute application



Symmetric model

Access to local memory is much faster

Server CPUs are mostly idle with RDMA

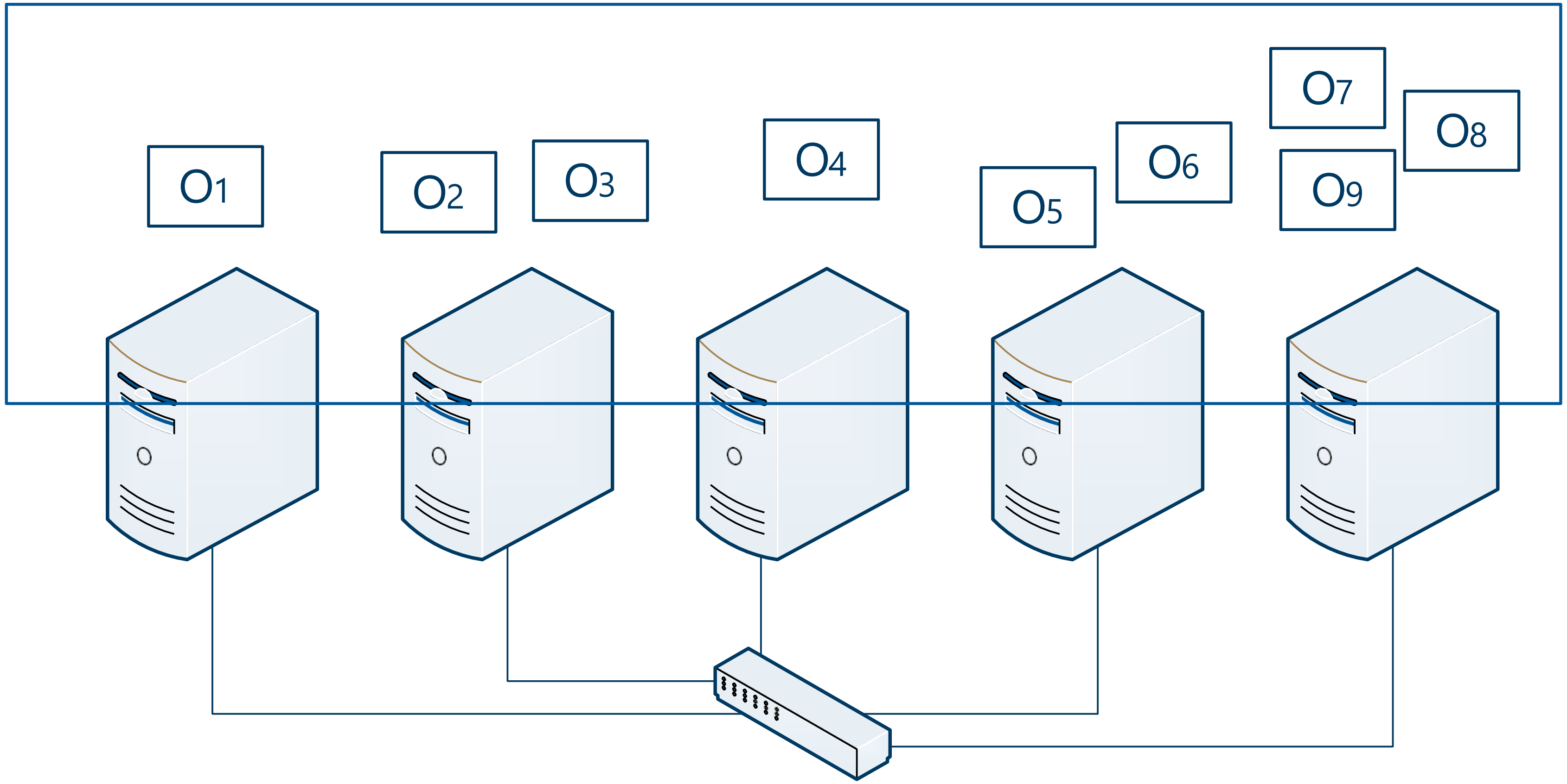


Machines store data and execute application

Shared address space

Supports direct RDMA of objects

Programmability a welcome bonus

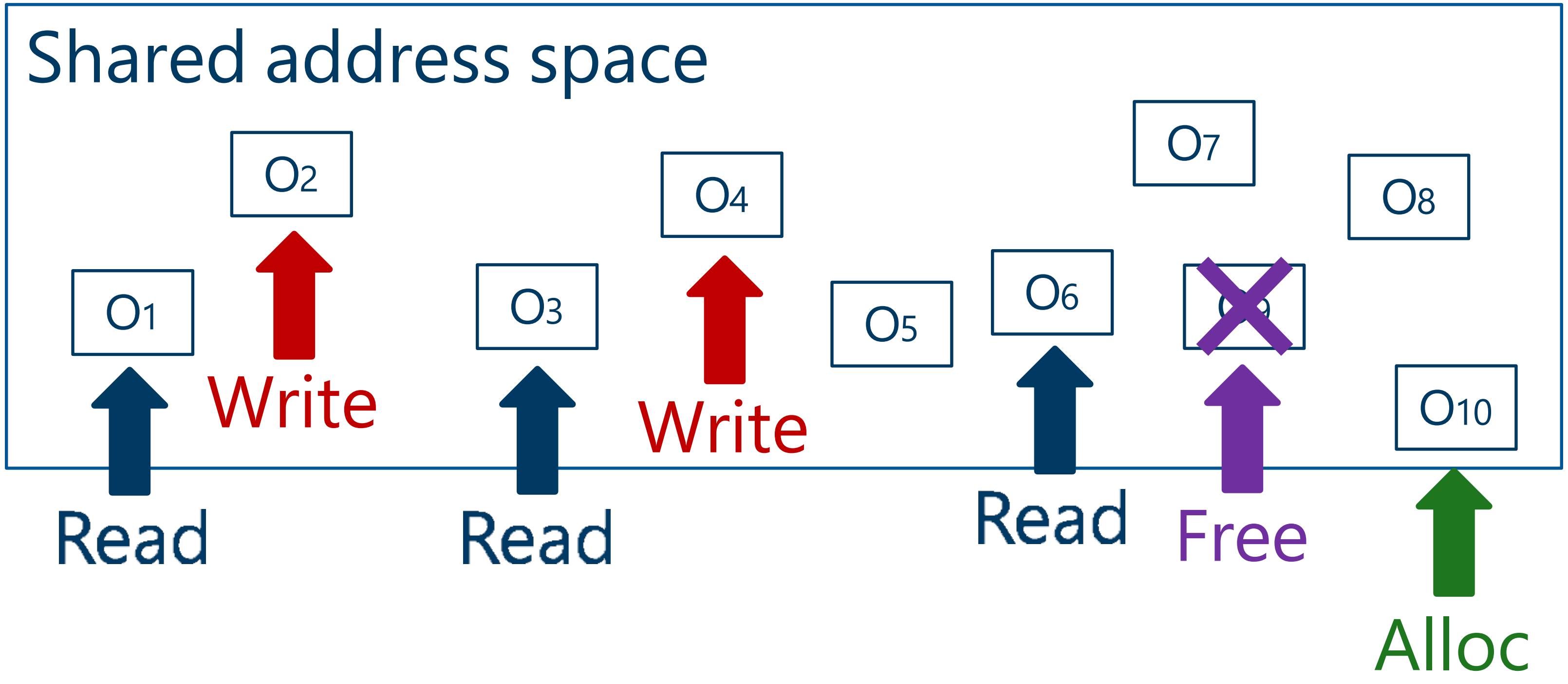


Shared address space

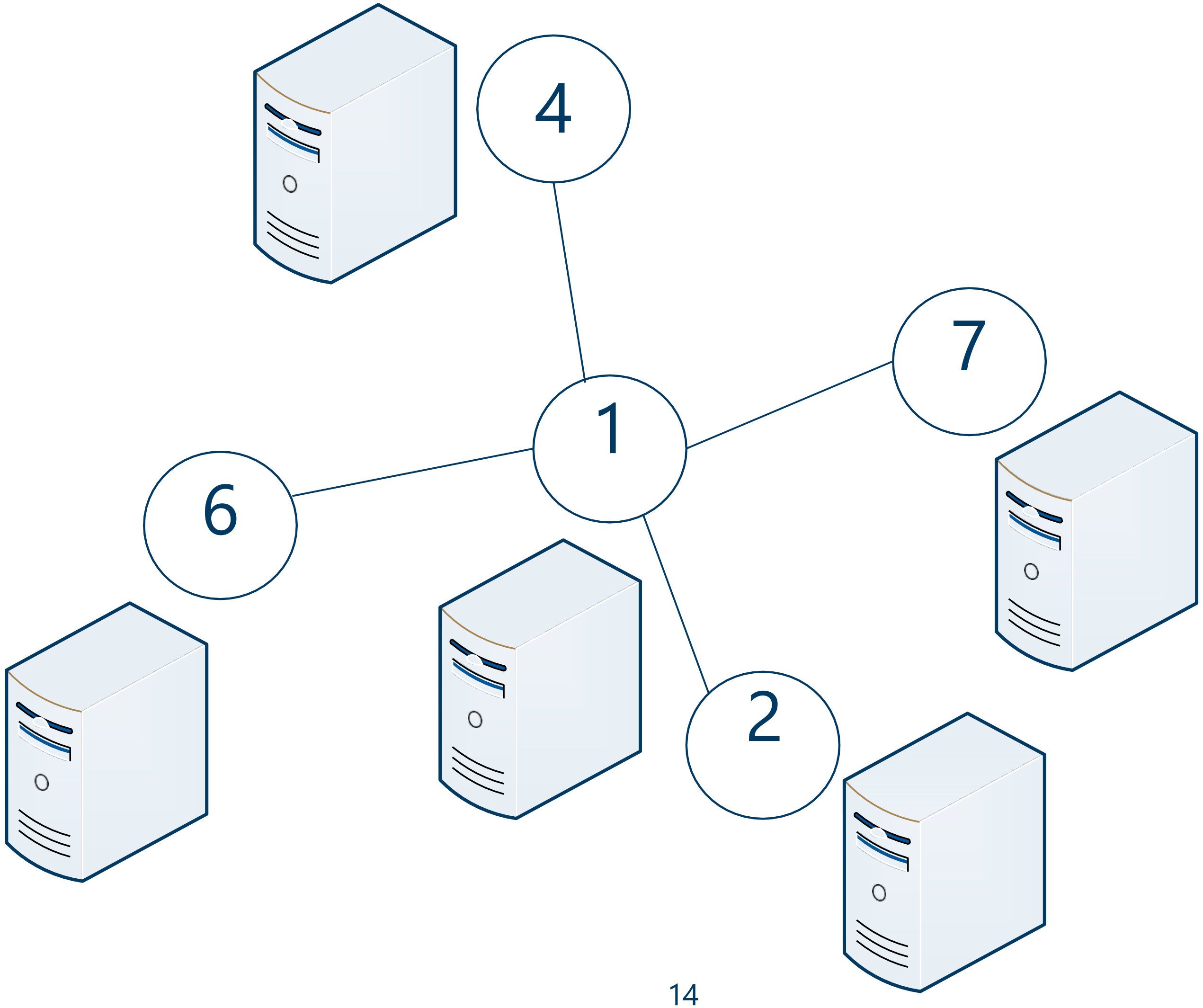
General primitive

Strong consistency: serializability

Transparent:
- location
- concurrency
- failures



Optimizations: locality awareness

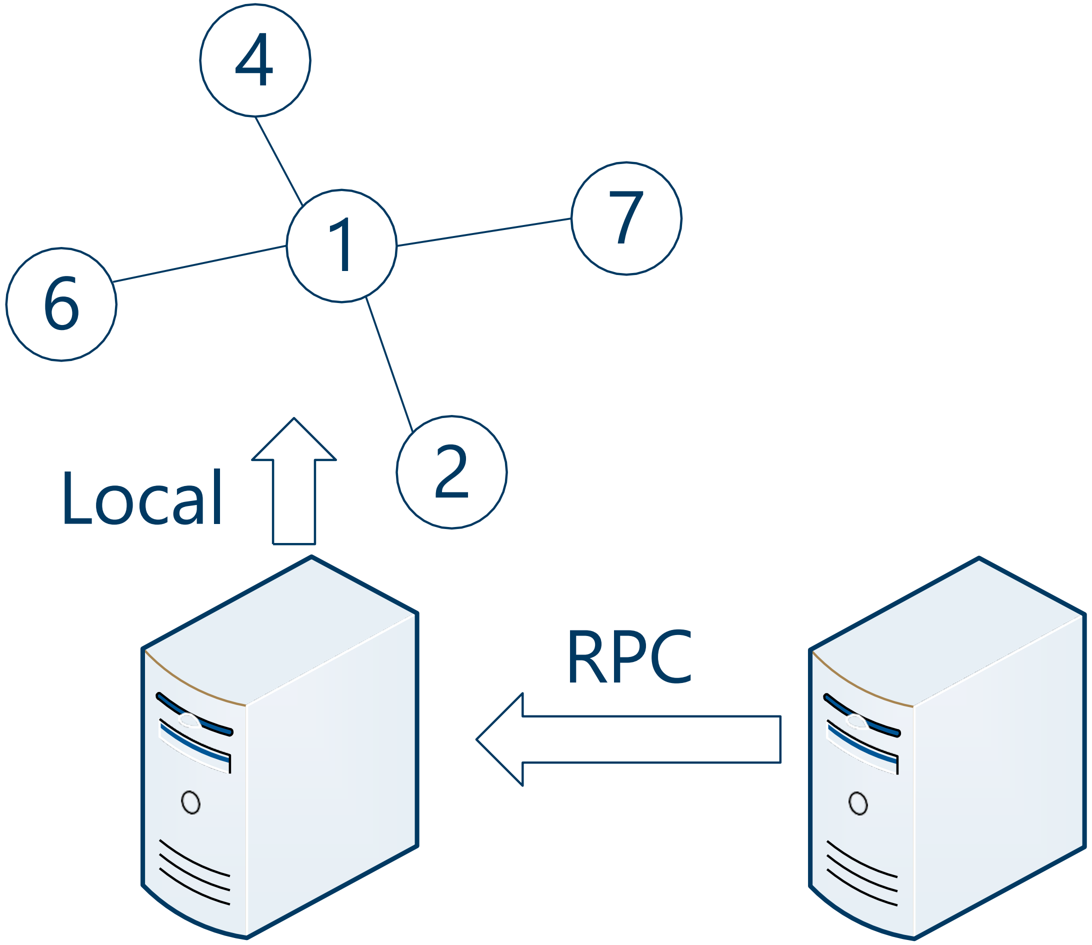


Optimizations: locality awareness

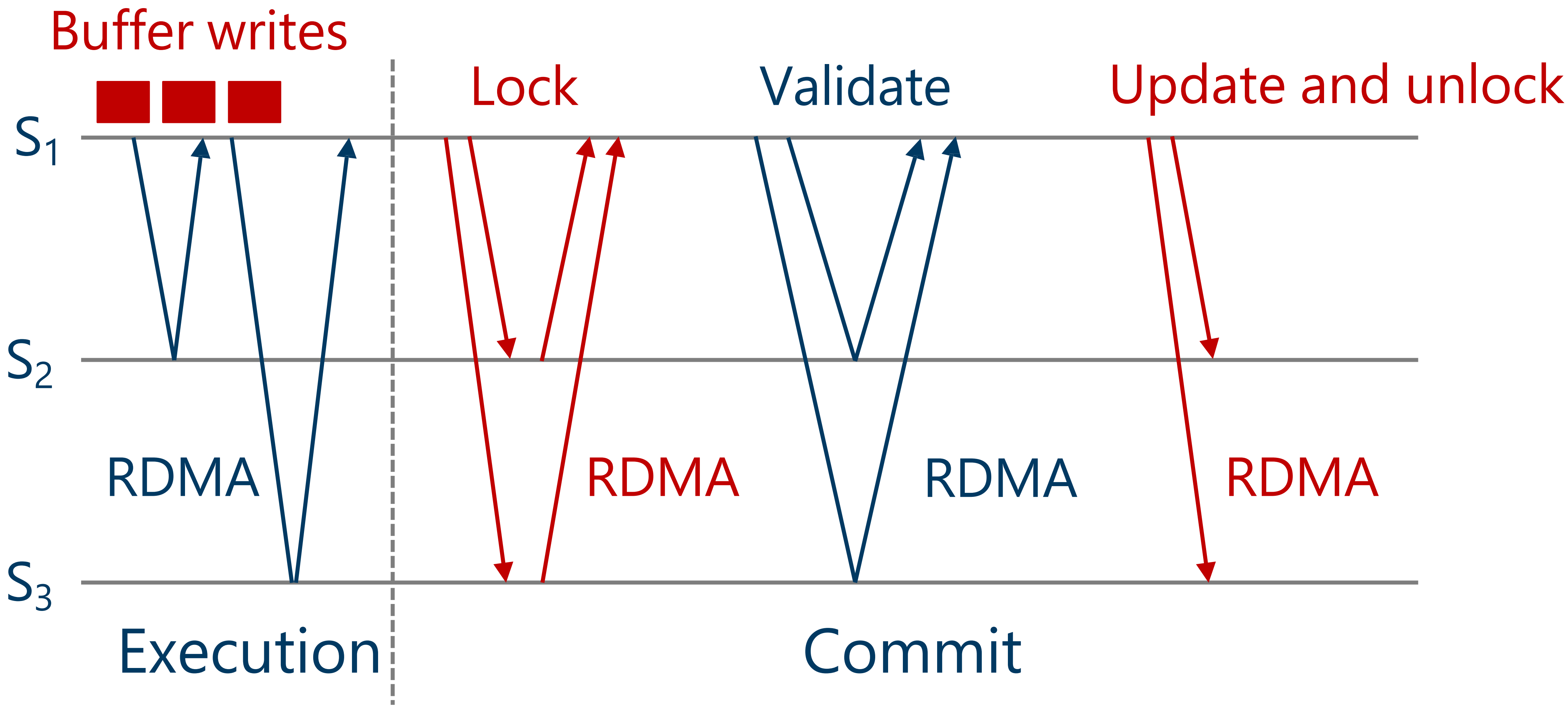
Collocate data accessed together

Ship computation to target data

Optimized single server transactions



Transactions



TAO [Bronson '13, Armstrong '13]

- Facebook's in-memory graph store
- Workload
  - Read-dominated (99.8%)
  - 10 operation types
- FaRM implementation
  - Nodes and edges are FaRM objects
  - Lock-free reads for lookups
  - Transactions for updates

6 Mops/s/srv
(10x improvement)

42 μs average latency
(40 – 50x improvement)

FaRM

- Platform for distributed computing
  - Data is in memory
  - RDMA
- Shared memory abstraction
  - Transactions
  - Lock-free reads
- Order-of-magnitude performance improvements
  - Enables new applications

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Efficient Memory Disaggregation with Infiniswap

Juncheng Gu, Youngmoon Lee, Yiwen Zhang,

Mosharaf Chowdhury, Kang G. Shin

UNIVERSITY OF
MICHIGAN

Agenda

- **Motivation and related work**
- Design and system overview
- Implementation and evaluation
- Future work and conclusion

Memory-intensive applications

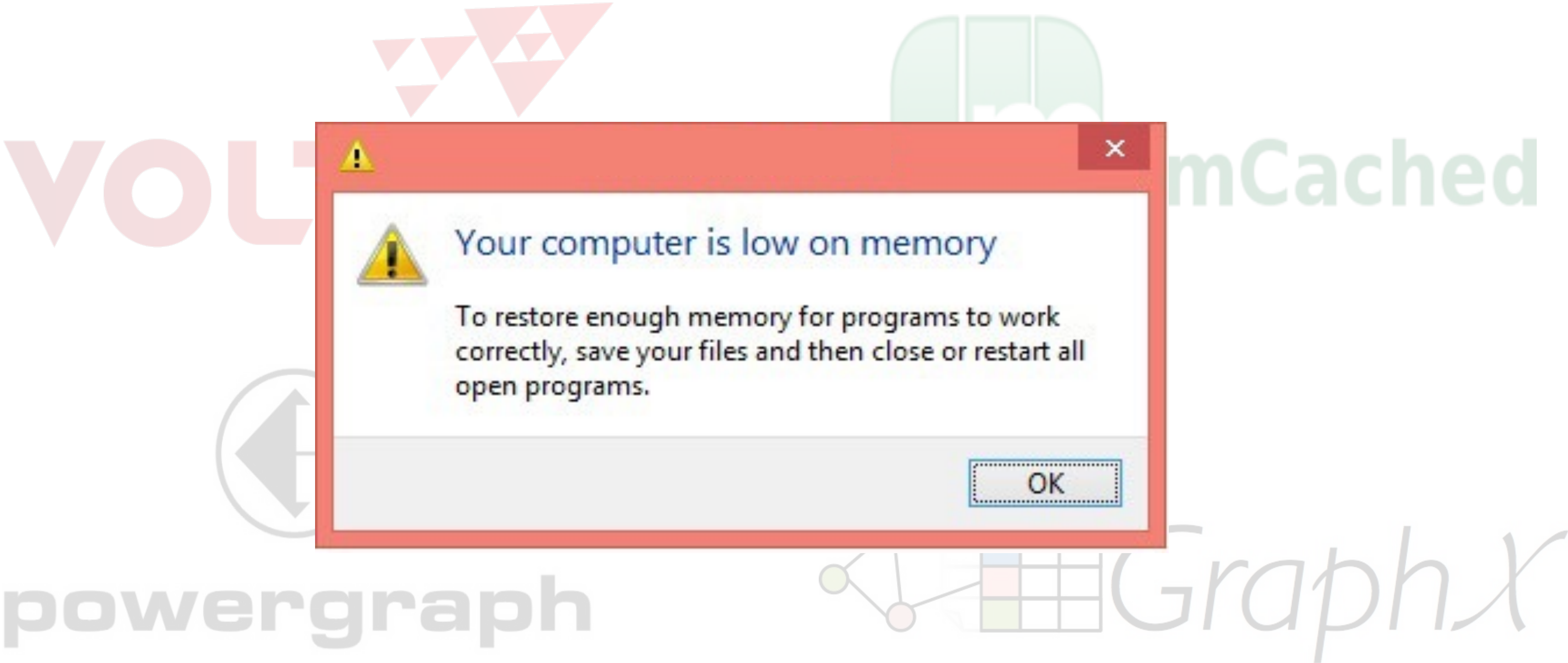
VOLTDB

memCached

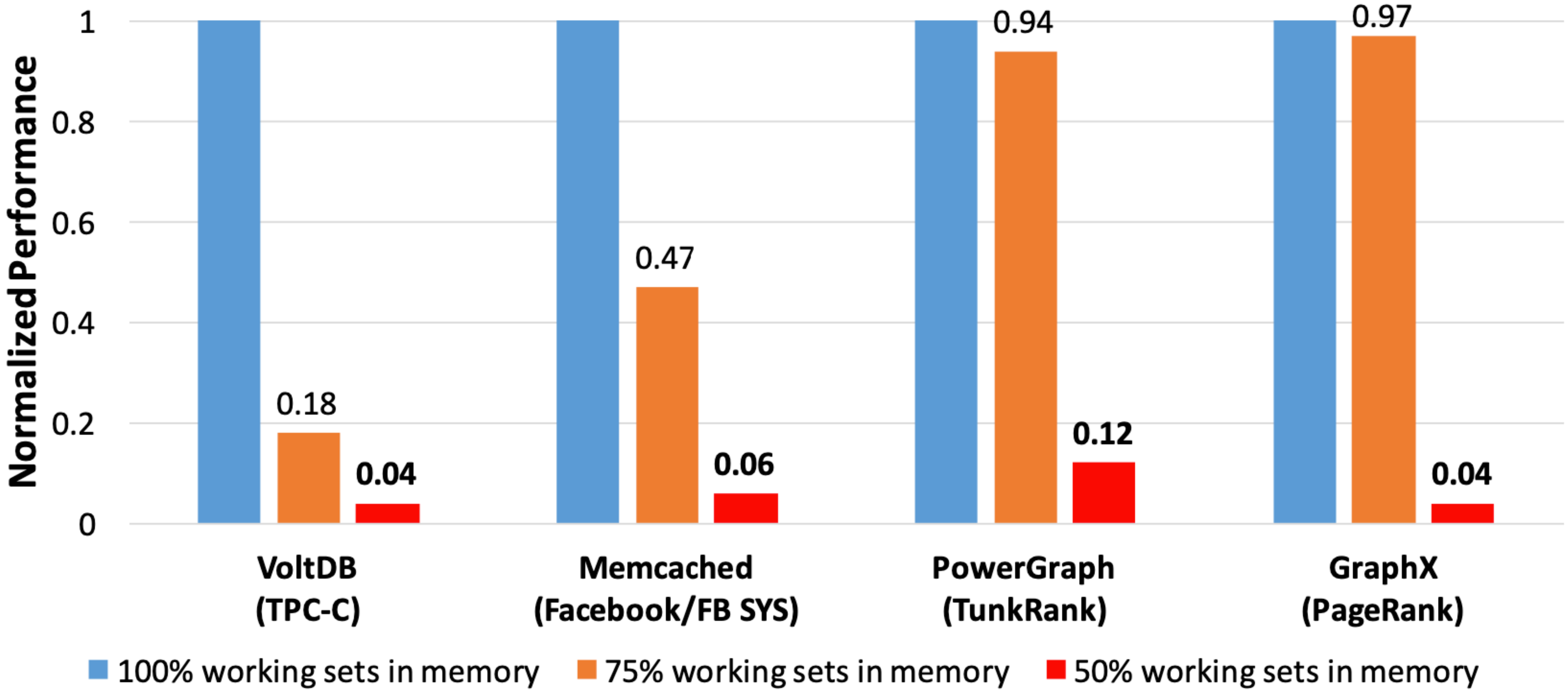
powergraph

GraphX

Memory-intensive applications

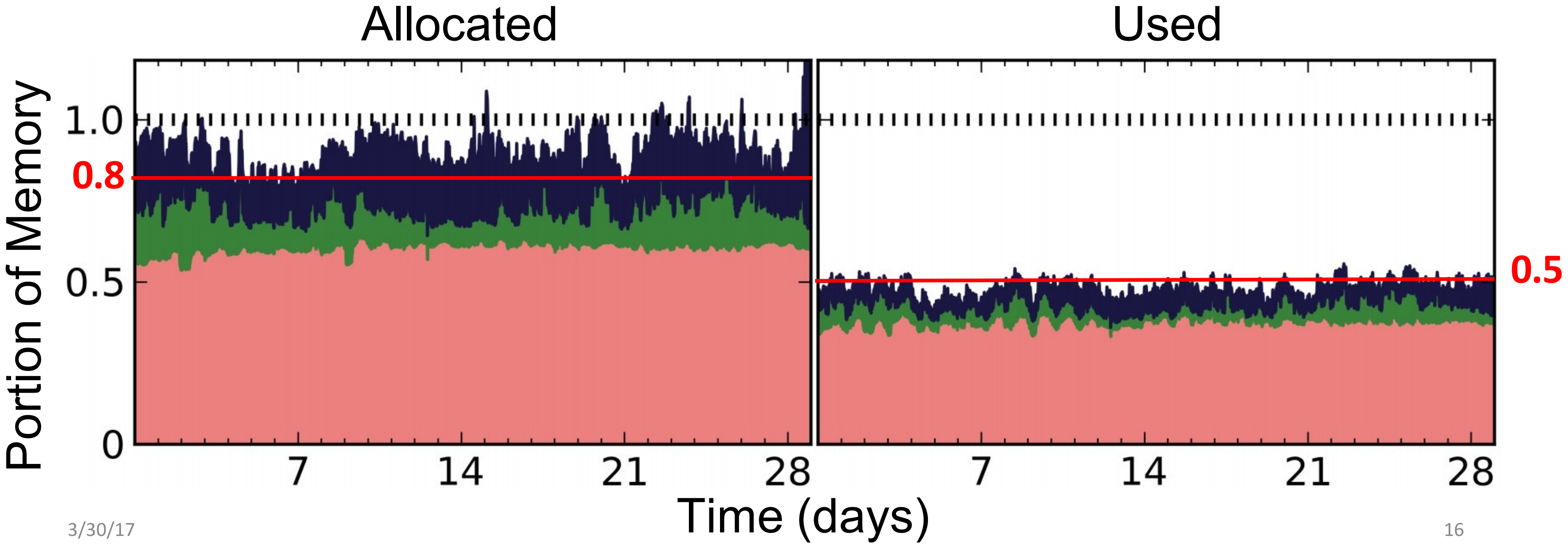


Performance degradation



Memory underutilization

- Google Cluster Analysis[1]



[1] Reiss, Charles, et al. "Heterogeneity and dynamicity of clouds at scale: Google trace analysis." *SoCC'12*.

Memory underutilization

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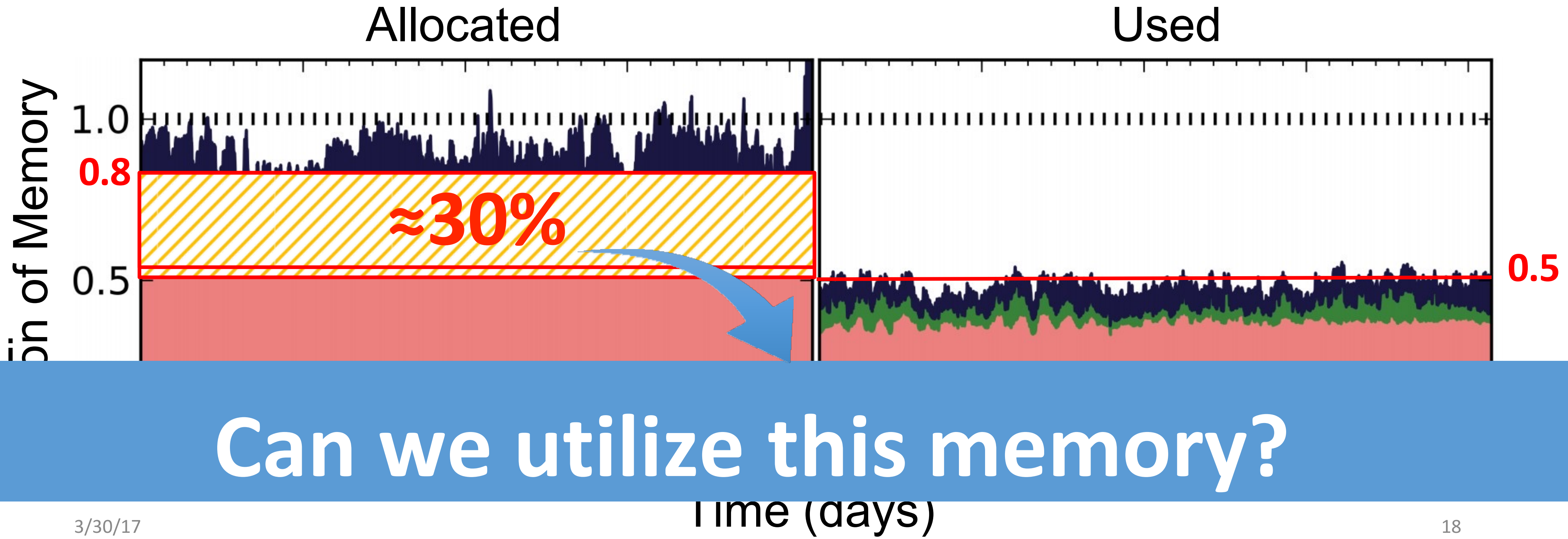
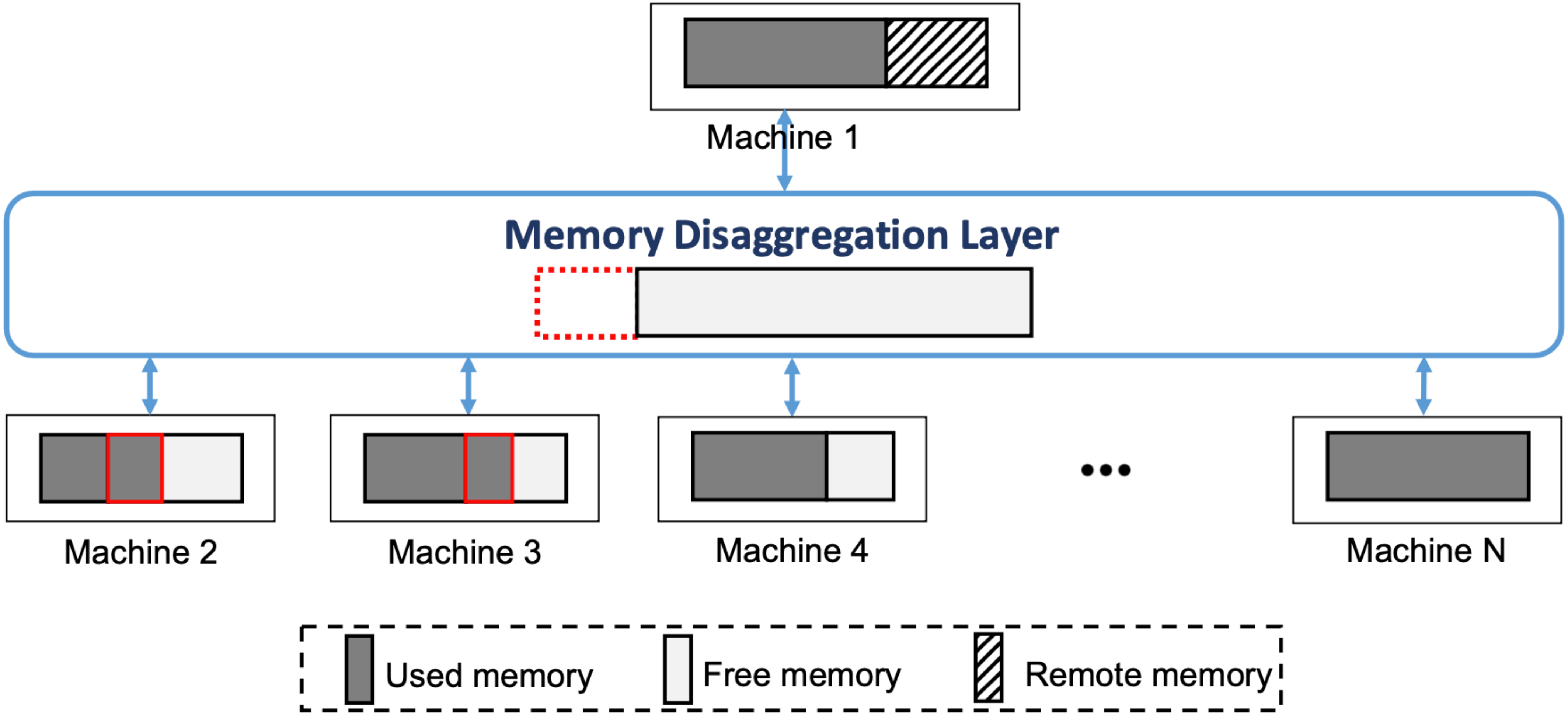


Can we utilize this memory?

[1] Reiss, Charles, et al. "Heterogeneity and dynamicity of clouds at scale: Google trace analysis." *SoCC'12*.

Disaggregate free memory



What are the challenges?

- **Minimize deployment overhead**
  - **No hardware design**
  - **No application modification**

- **Tolerate failures**
  - e.g. network disconnection, machine crash

- **Manage remote memory at scale**

Recent work on memory disaggregation

	No HW design	No app modification	Fault-tolerance	Scalability
Memory Blade[ISCA'09]	✗	✓	✓	✓
HPBD[CLUSTER'05] / **NBDX**[1]	✓	✓	✗	✗
RDMA key-value service (e.g. HERD[SIGCOMM'14], FaRM[NSDI'14])	✓	✗	✓	✓
Intel Rack Scale Architecture (RSA)[2]	✗	✓	✓	✓
Infiniswap	✓	✓	✓	✓

1 https://github.com/accelio/NBDX
2 http://www.intel.com/content/www/us/en/architecture-and-technology/rack-scale-design-overview.html

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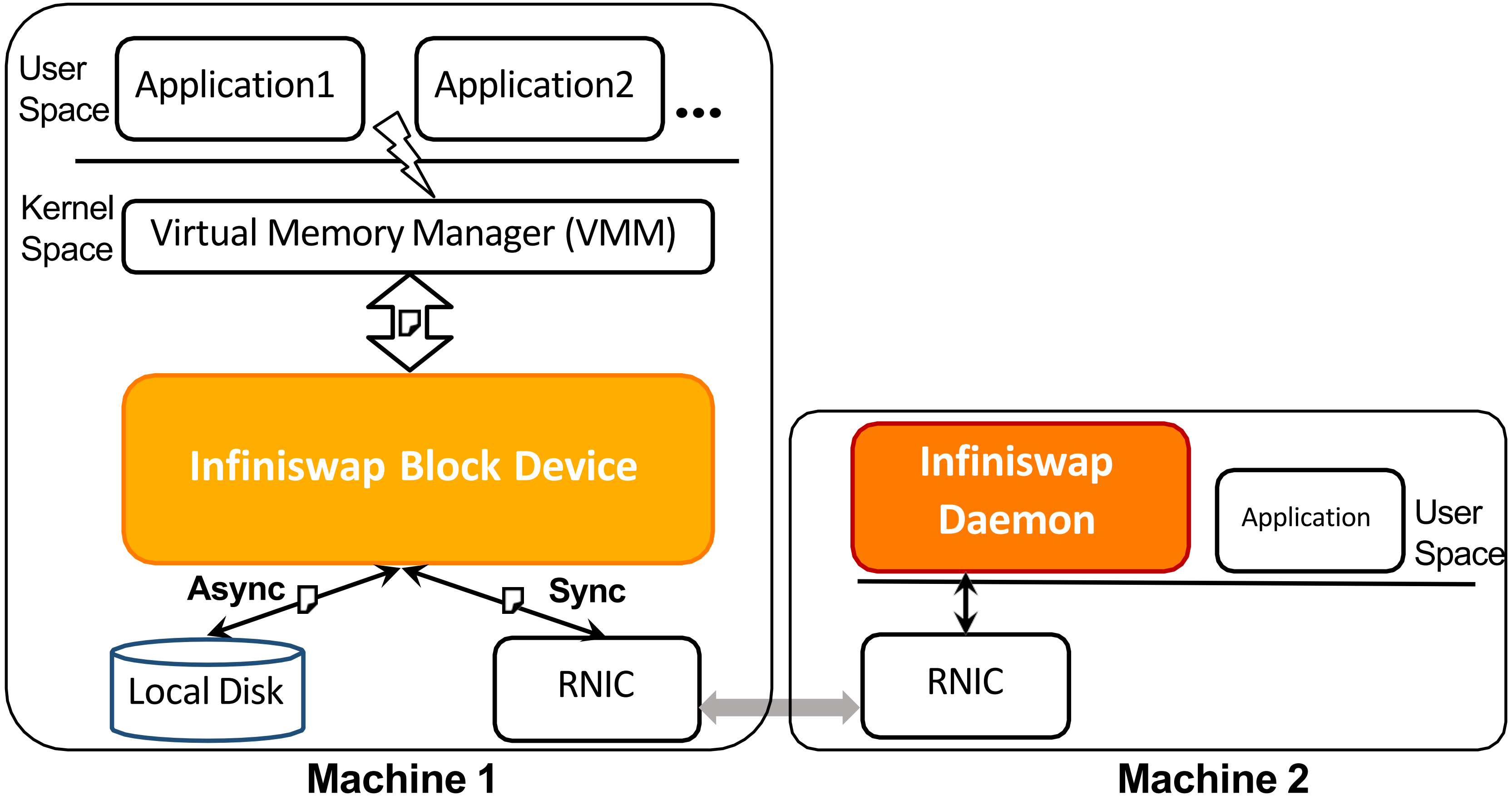
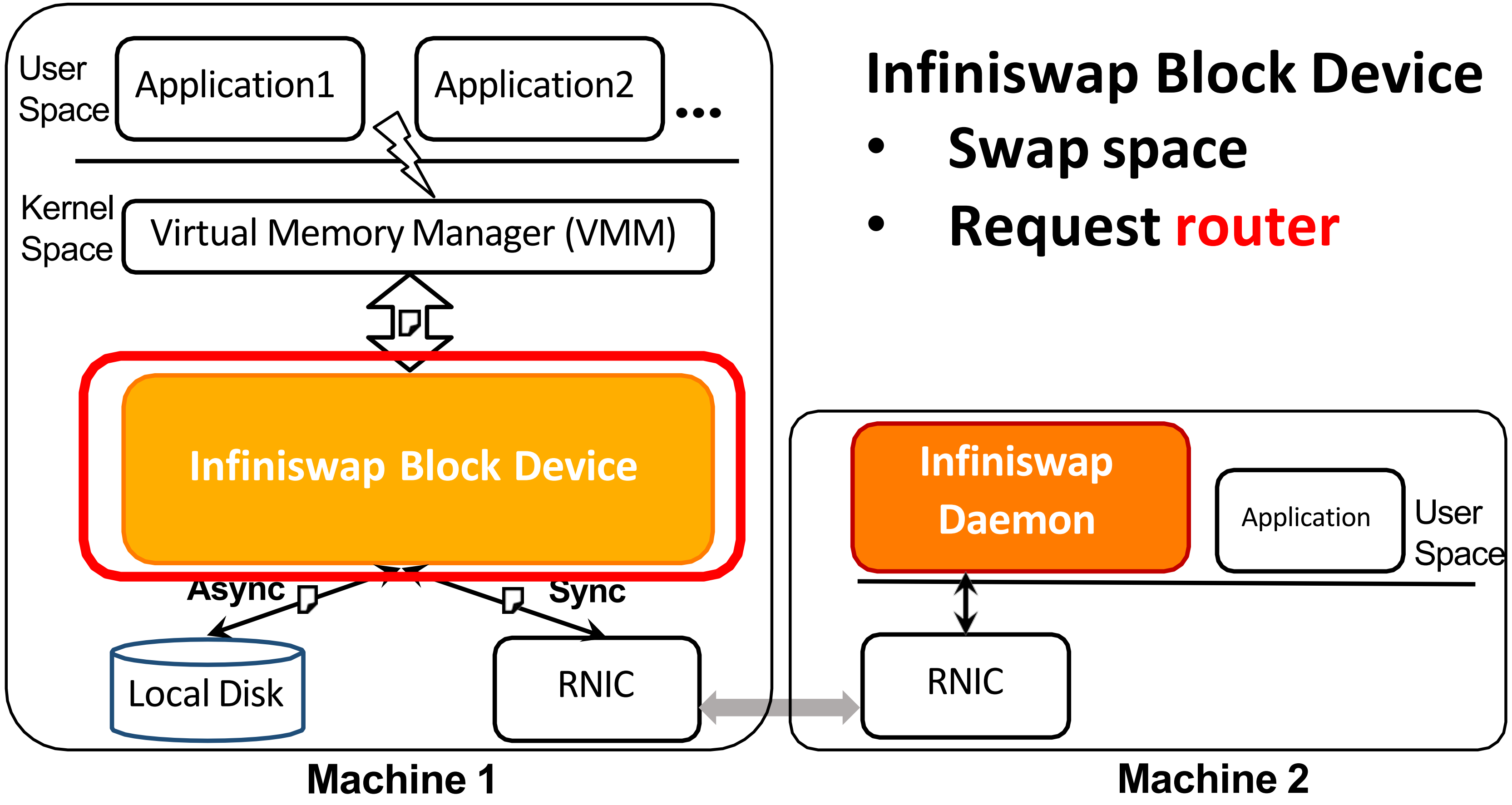
- Design and system overview
- Implementation and evaluation
- Future work and conclusion

System Overview



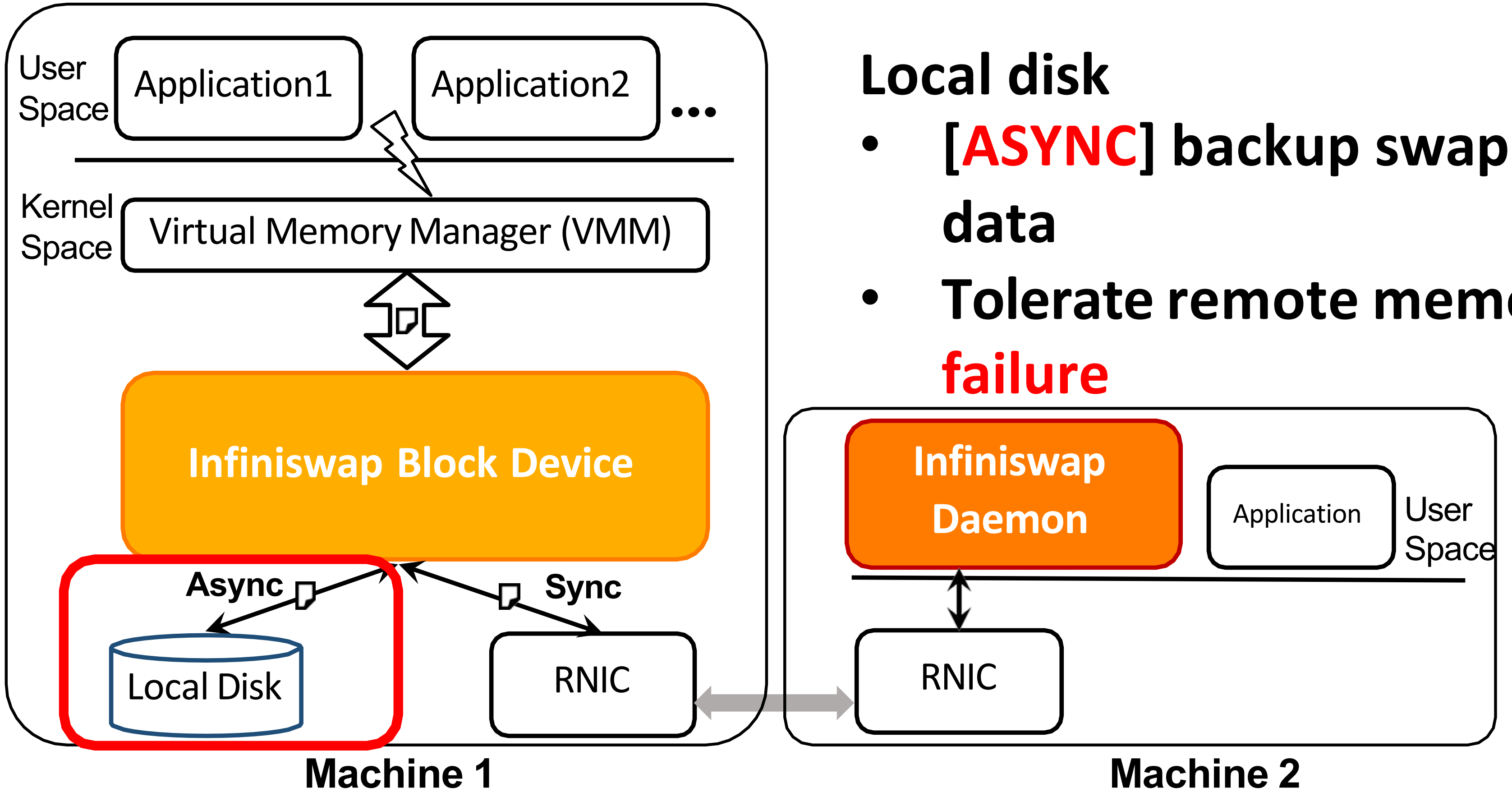
System Overview



Infiniswap Block Device

- **Swap space**
- **Request router**

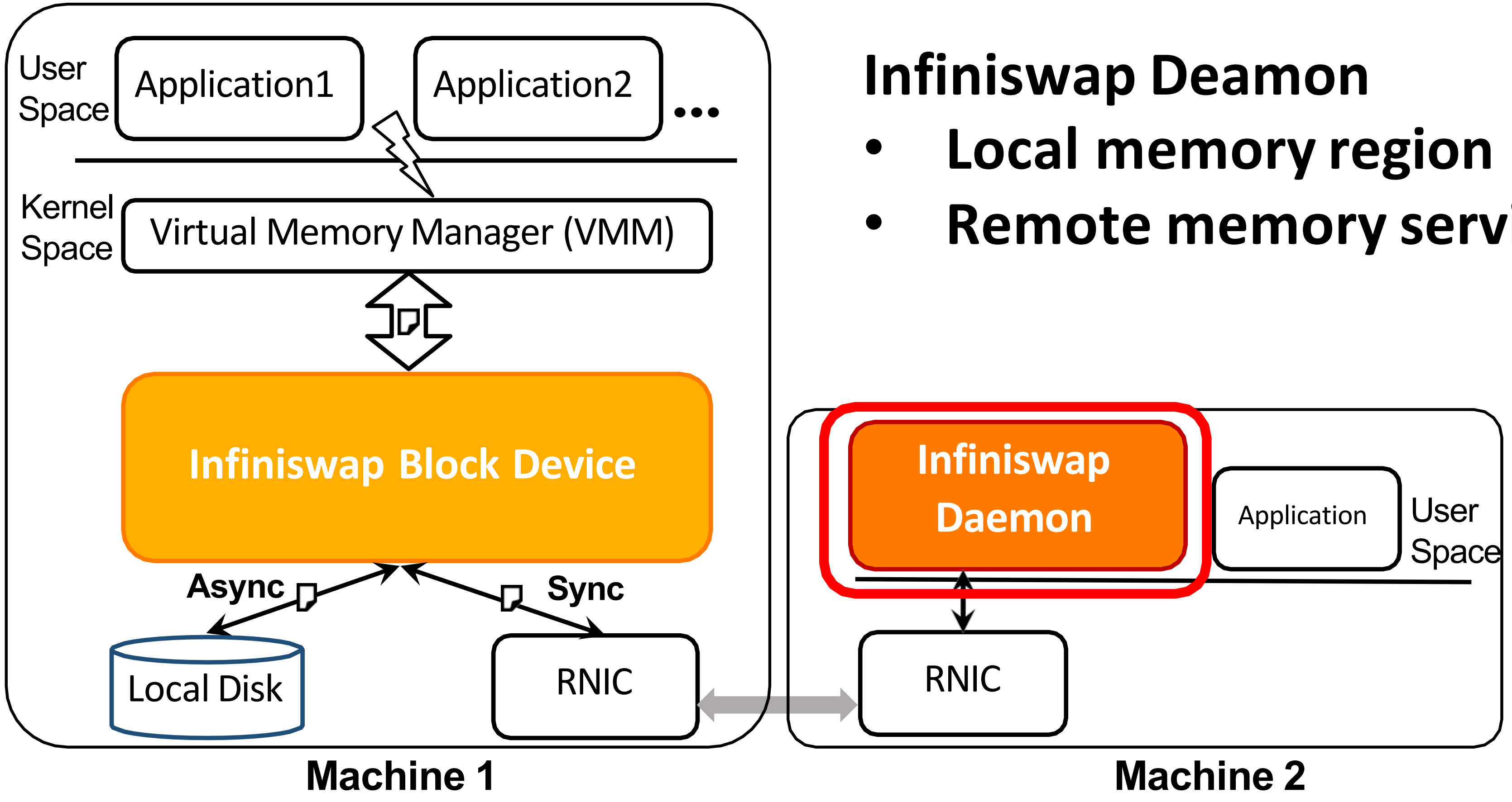
System Overview



Local disk

- **[ASYNC] backup swapped-out data**
- **Tolerate remote memory failure**

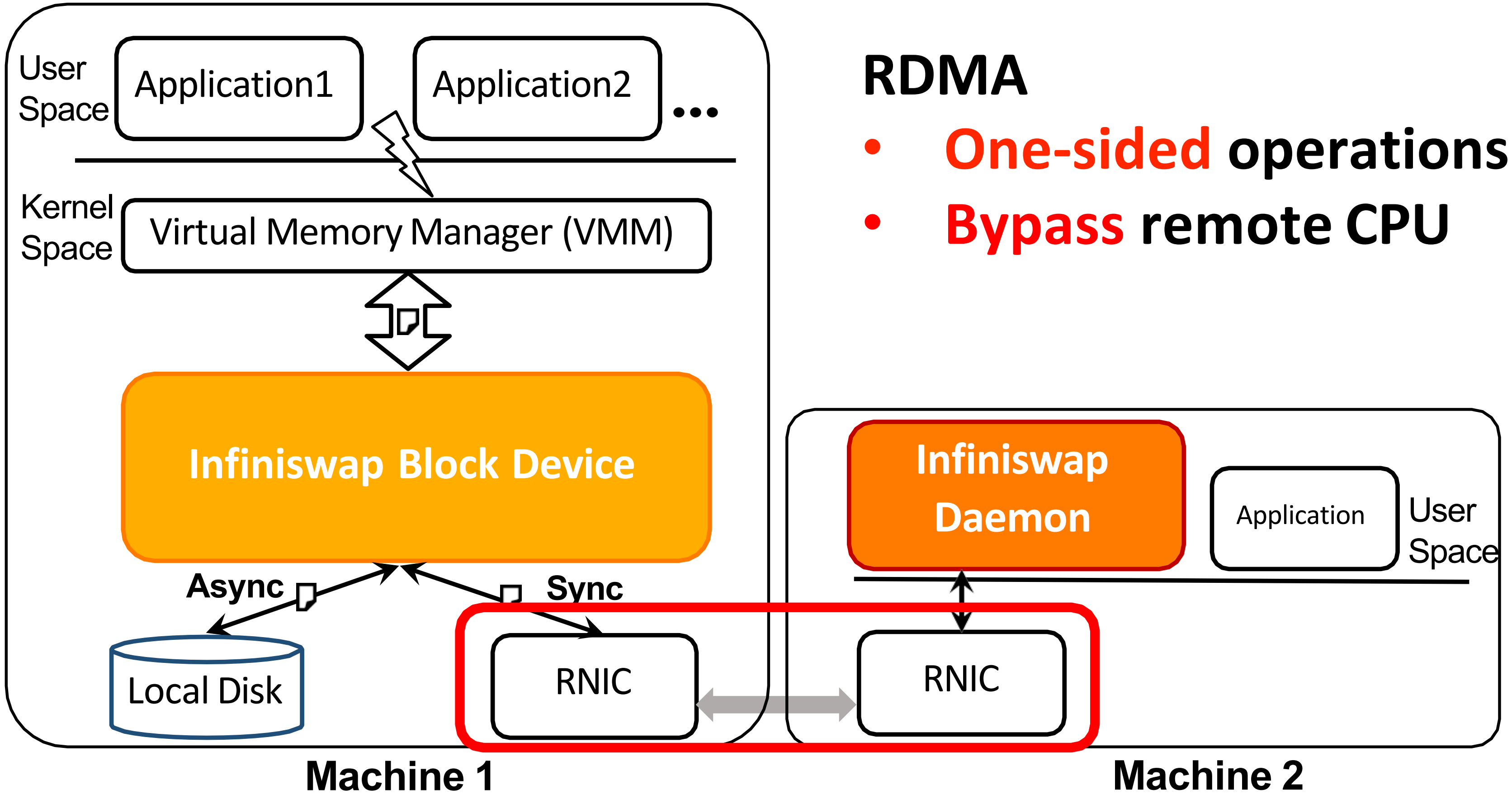
System Overview



Infiniswap Deamon

- **Local memory region**
- **Remote memory service**

System Overview



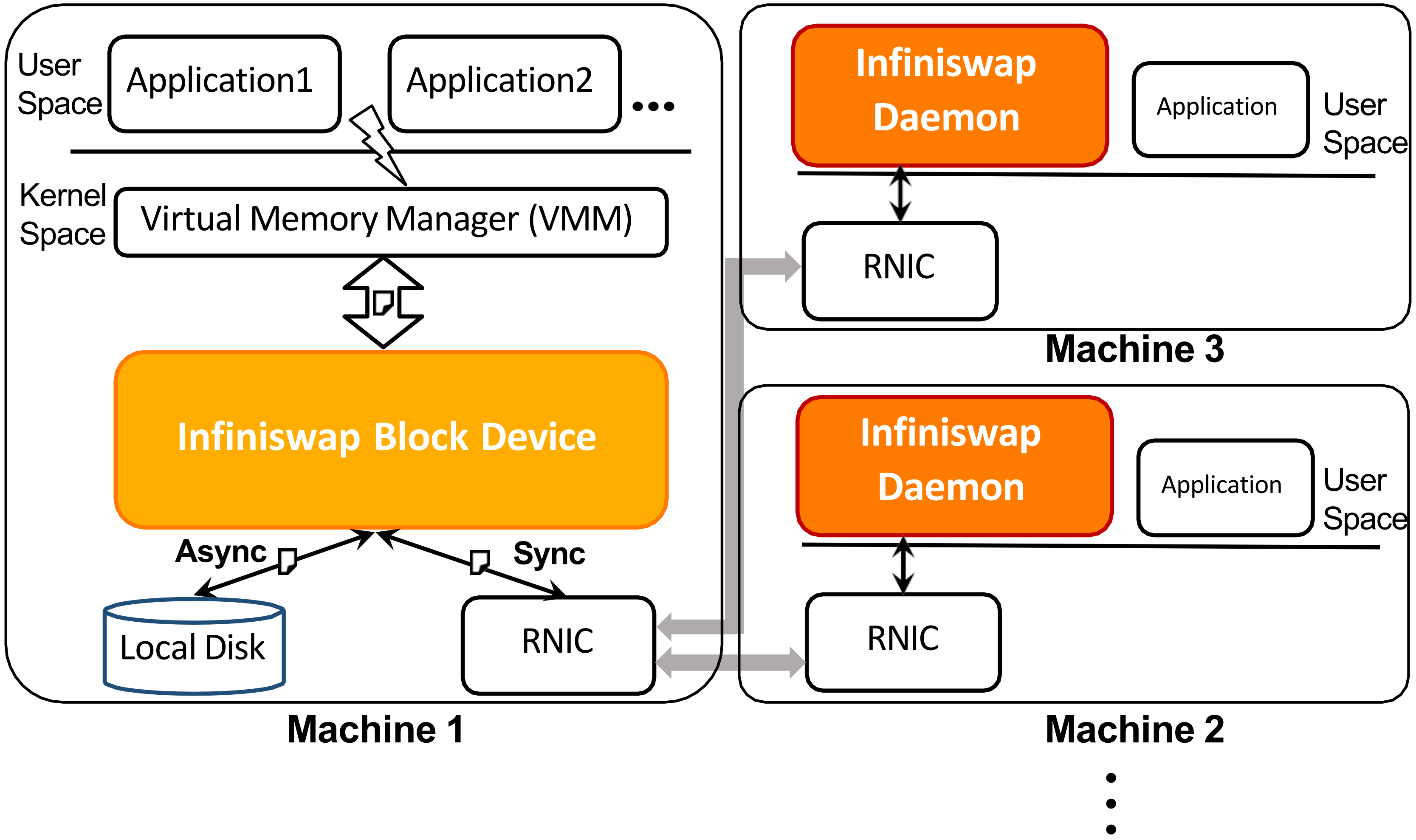
RDMA

- **One-sided operations**
- **Bypass remote CPU**

How to meet the design objectives?

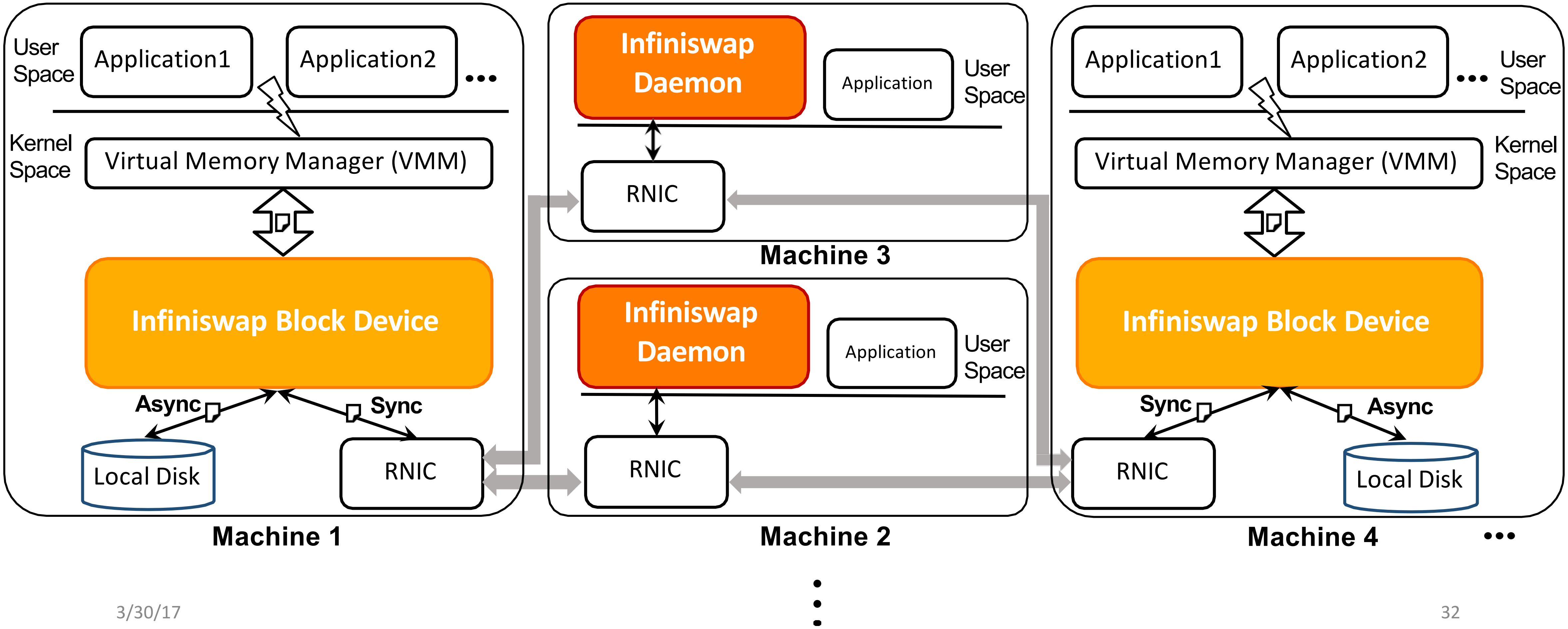
Objectives	Ideas
No hardware design	Remote paging
No application modification	
Fault-tolerance	Local backup disk

One-to-many



User Space
Application1
Application2
...
Kernel Space
Virtual Memory Manager (VMM)
Infiniswap Block Device
Async
Sync
Local Disk
RNIC
Machine 1
Infiniswap Daemon
Application
User Space
RNIC
Machine 3
Infiniswap Daemon
Application
User Space
RNIC
Machine 2

Many-to-many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Local Disk
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Application
User Space
RNIC
Machine 3
Infiniswap Daemon
Application
User Space
RNIC
Machine 2
Application1
Application2
...
User Space
Virtual Memory Manager (VMM)
Kernel Space
Infiniswap Block Device
Sync
Async
RNIC
Local Disk
Machine 4
...

Many-to-many

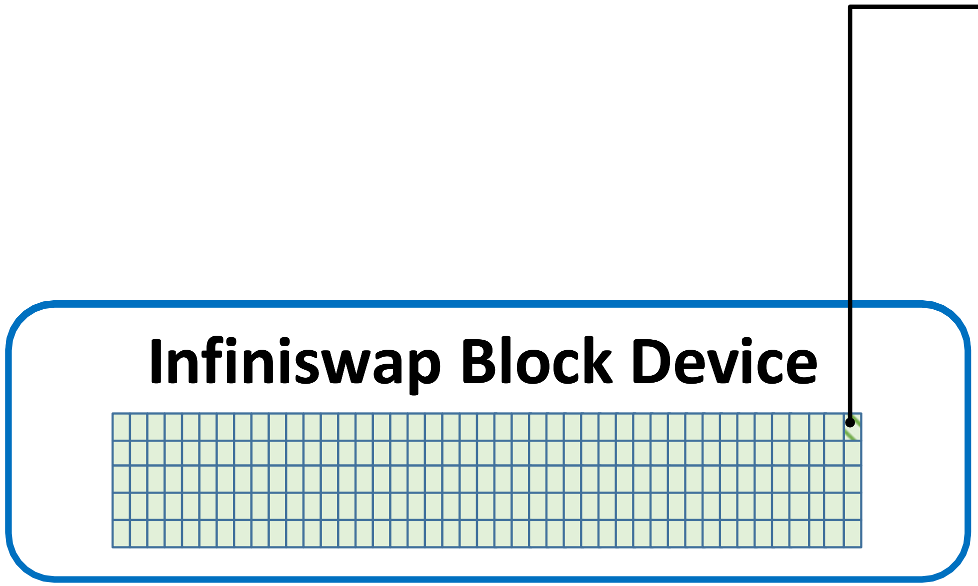
How to scale remote memory?

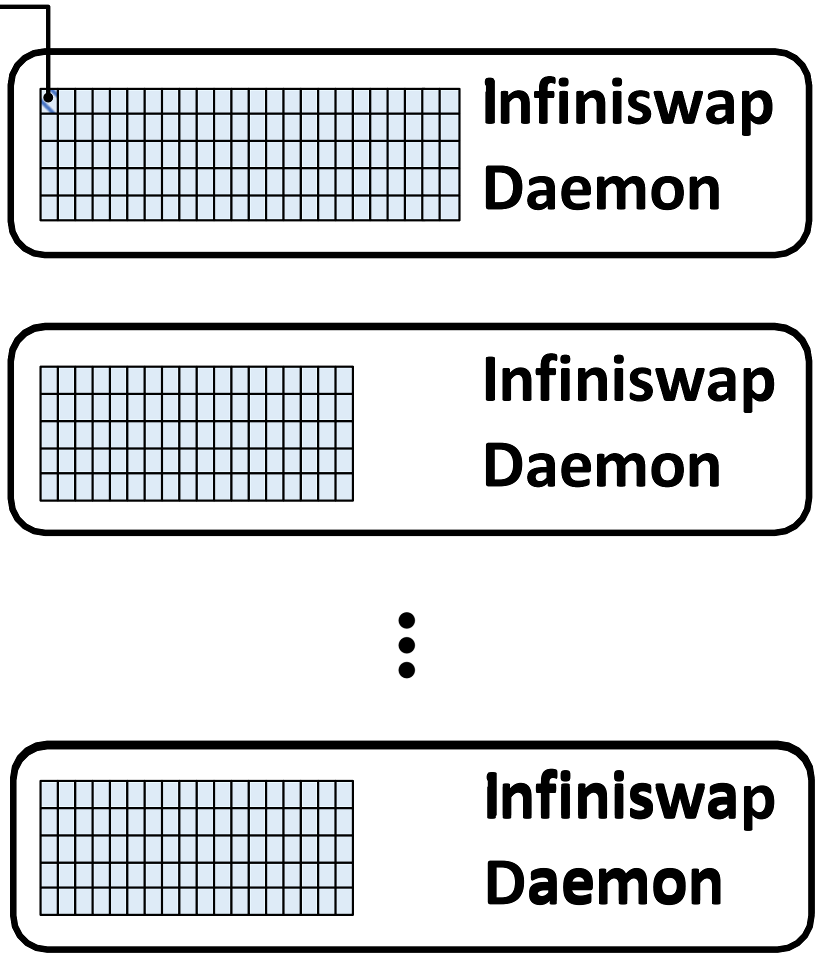
- How to **find** remote memory in the cluster?
- Which remote mapping should be **evicted**?

How to meet the design objectives?

Objectives	Ideas
No hardware design	Remote paging
No application modification	
Fault-tolerance	Local backup disk
Scalability	**Decentralized** remote memory management

Management unit: memory page?





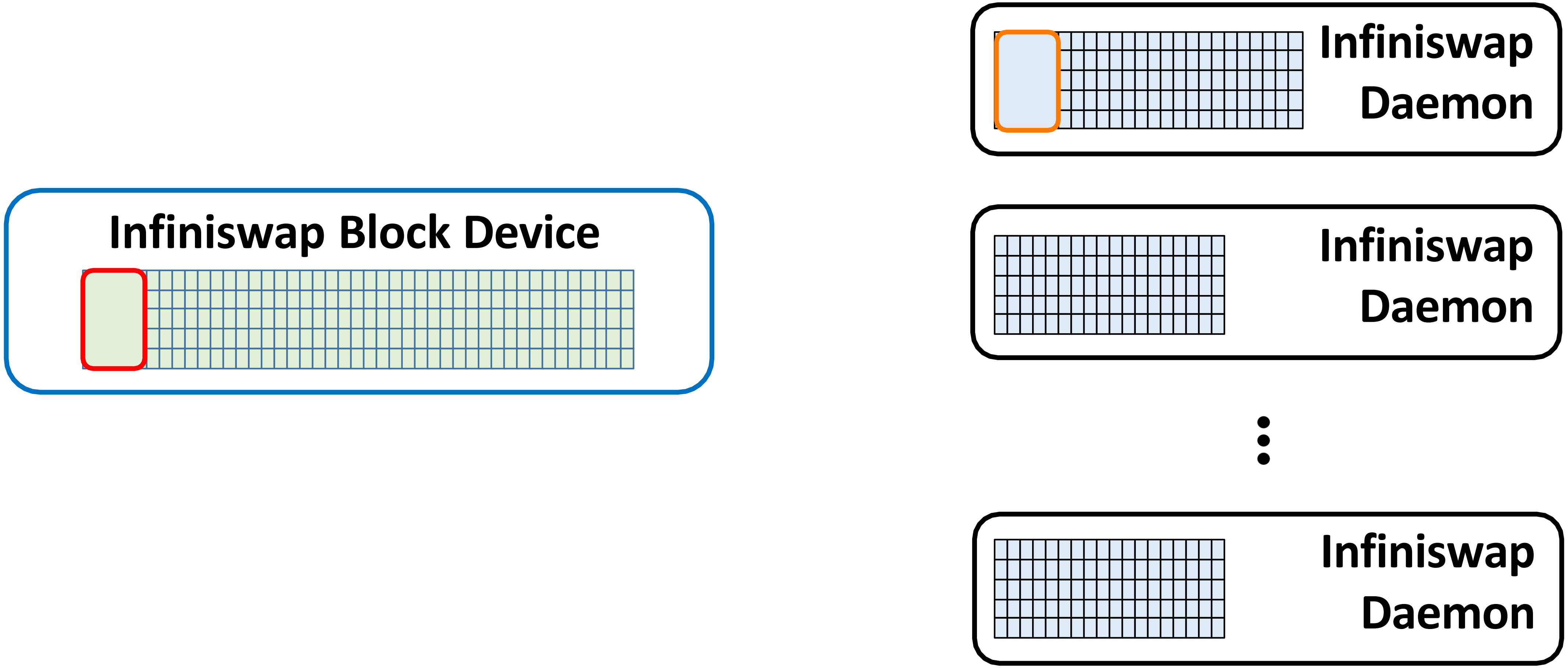
Local Page	Remote Page
p100	<s1, p1>

⋮

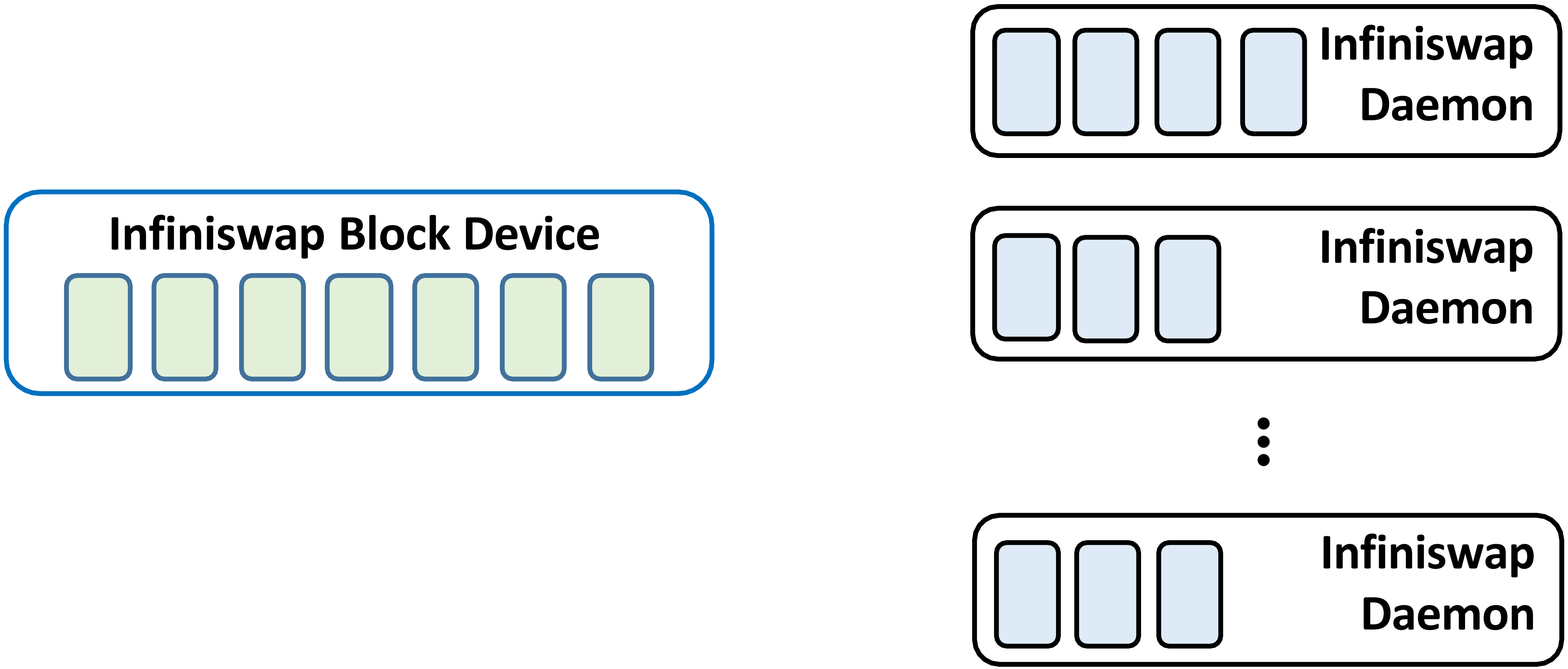
1GB = 256K entries

1GB = 256K RTTs

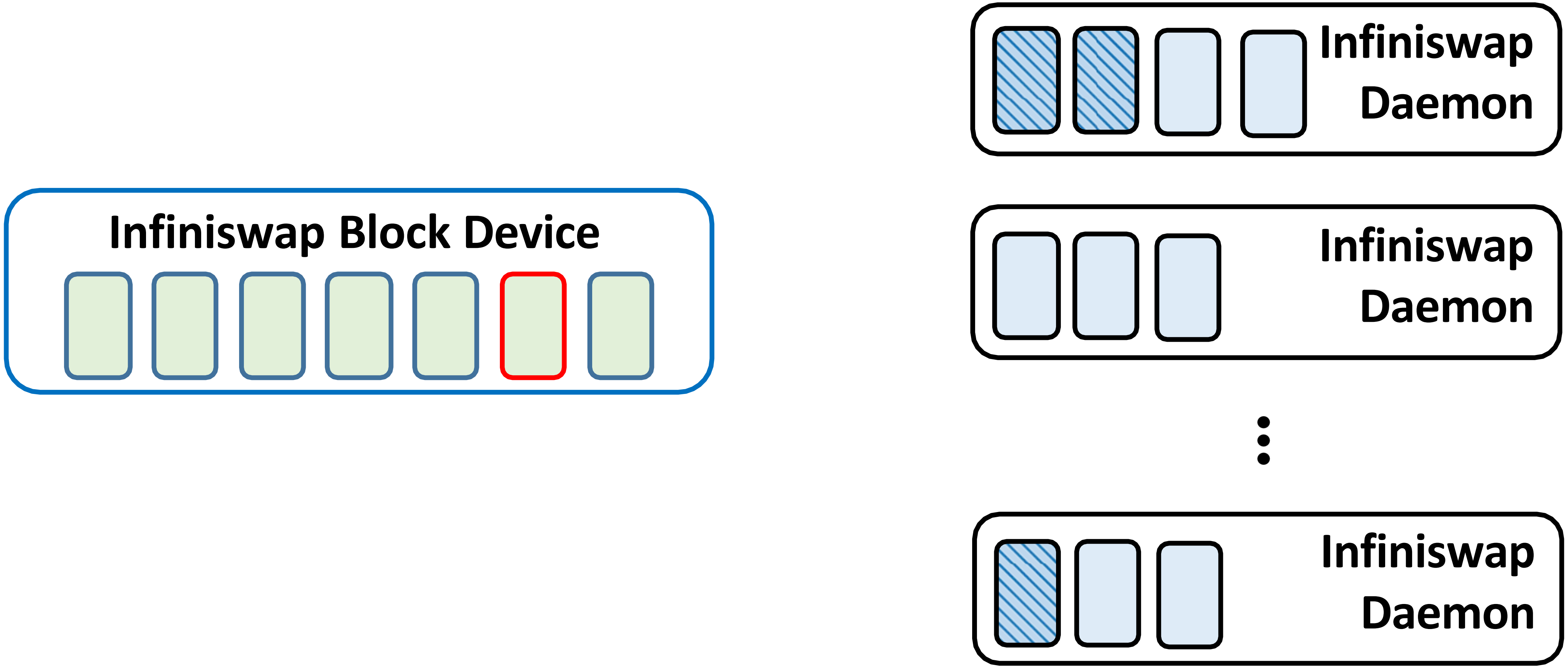
Management unit: memory slab!



Management unit: memory slab!



Which remote machine should be selected?



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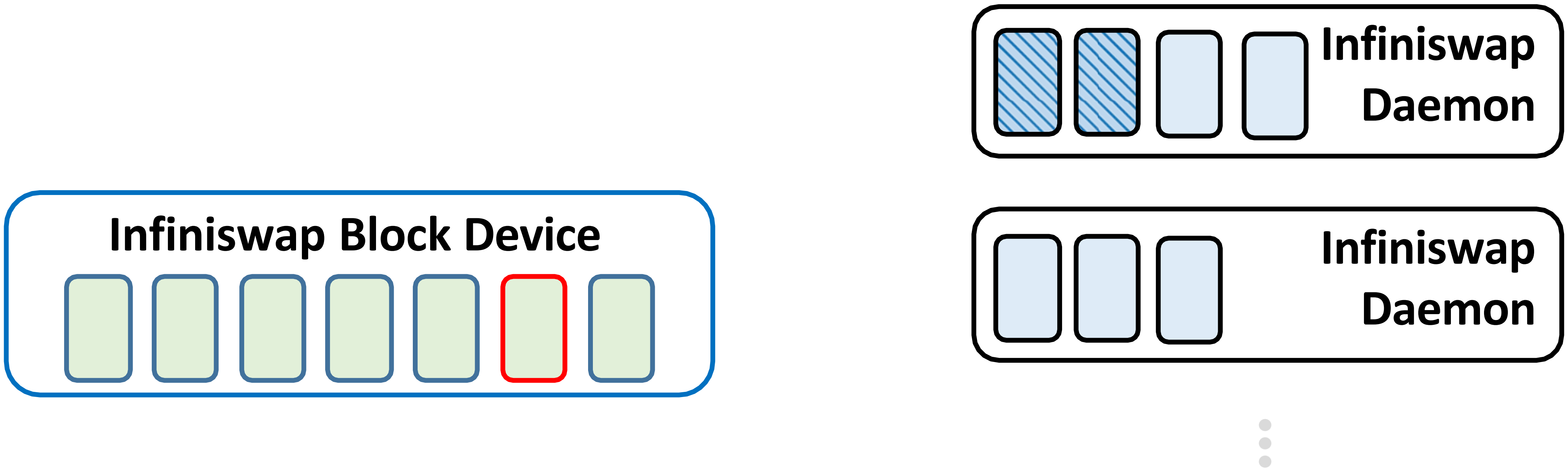
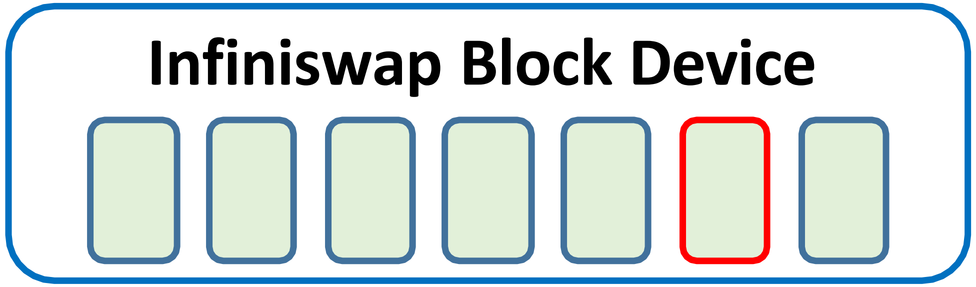
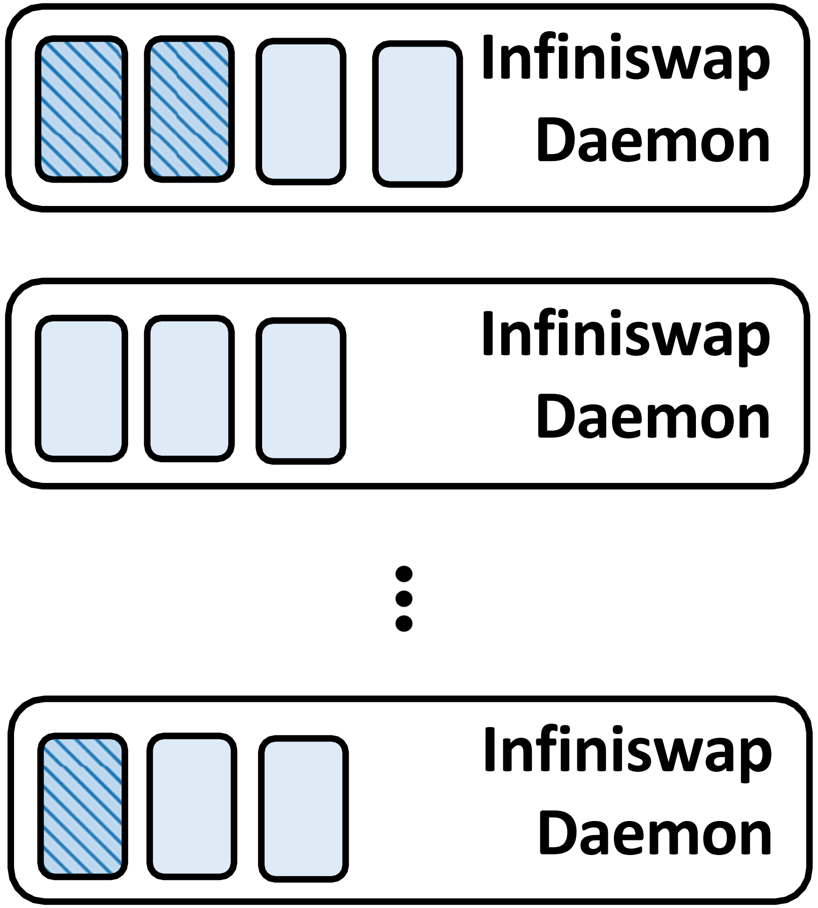


Goal: balance memory utilization

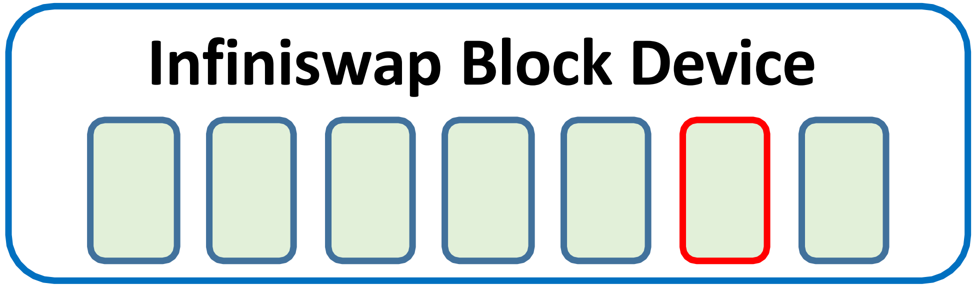
Which remote machine should be selected?

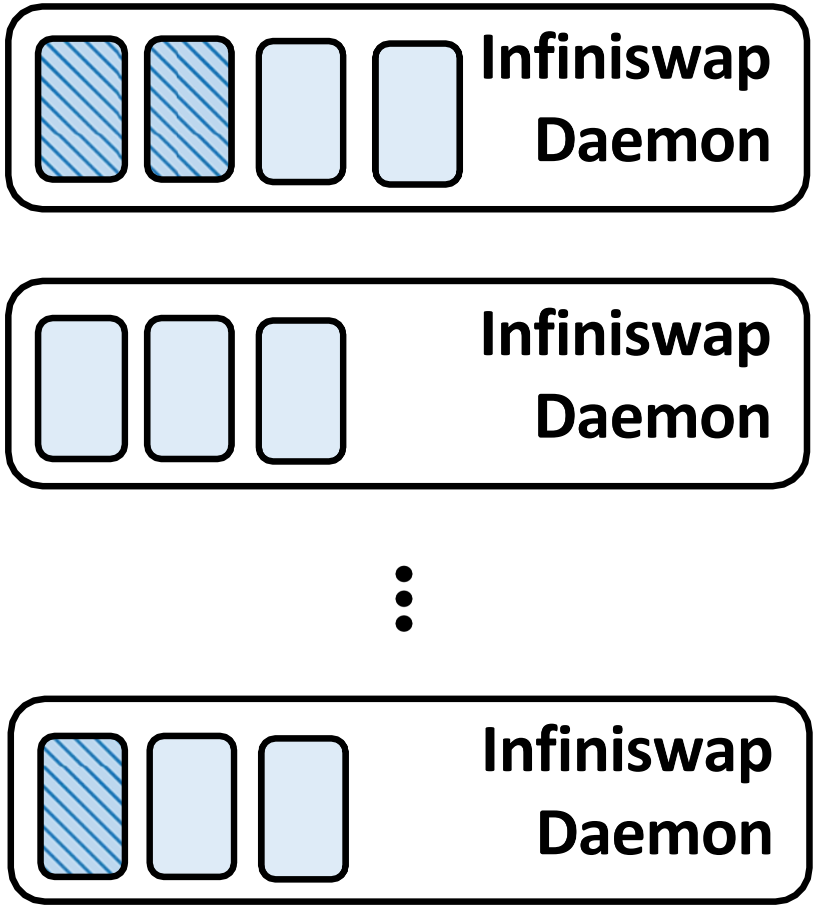


- Central controller



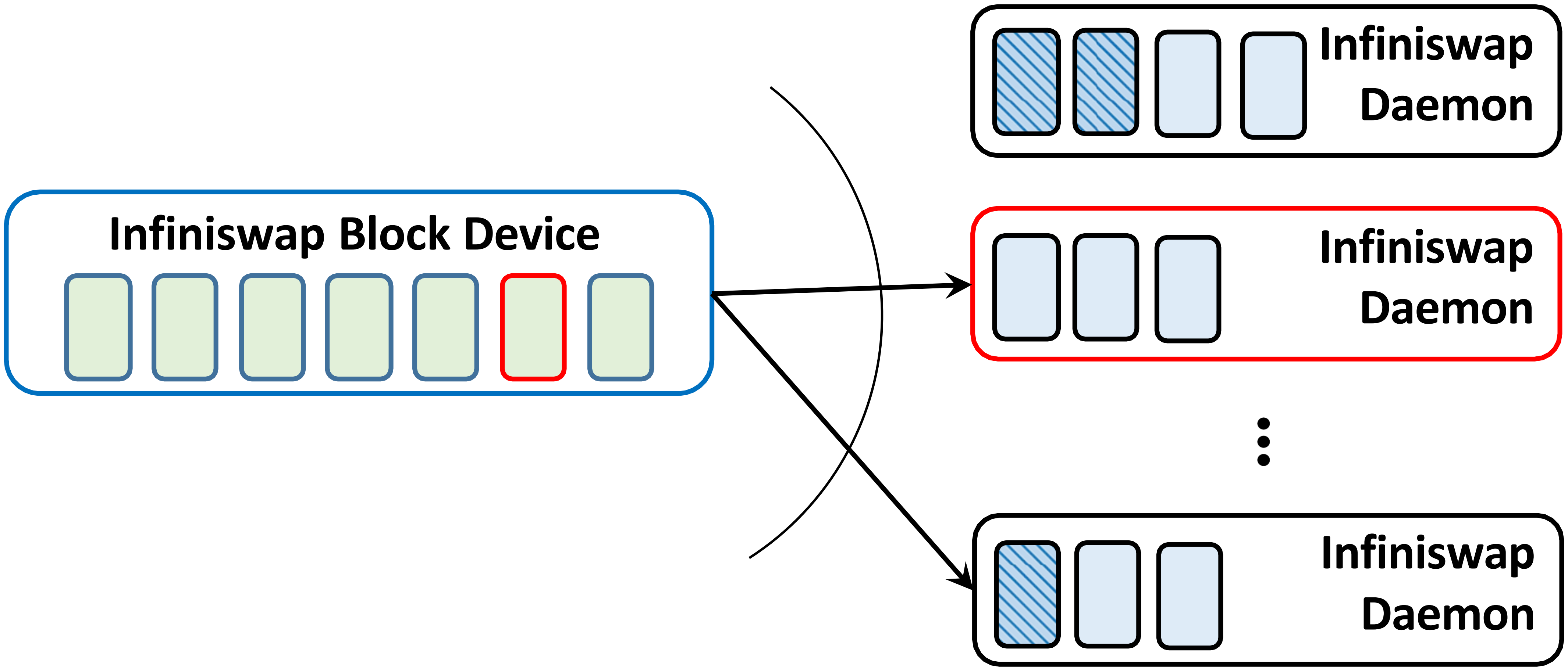
Which remote machine should be selected?





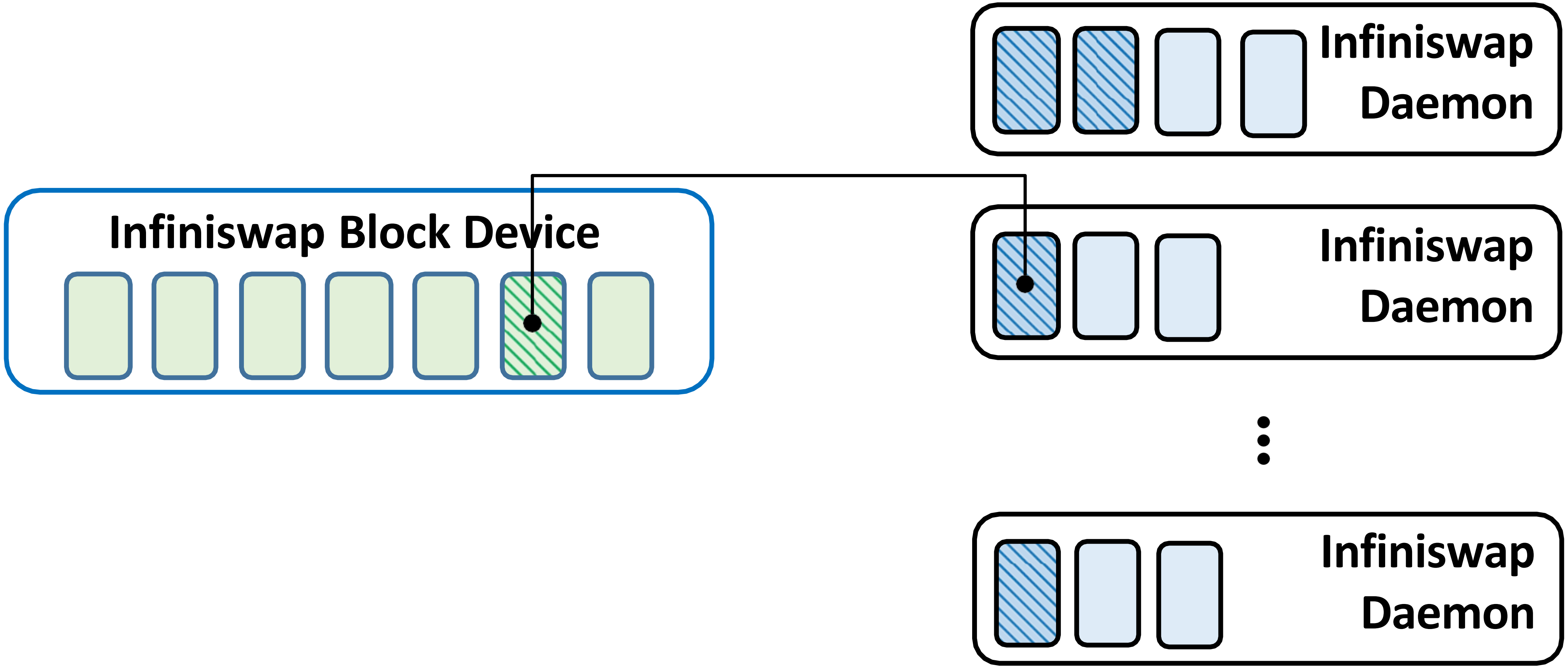
- ~~Central controller~~
- Decentralized approach

Power of two choices[1]



[1] Mitzenmacher, Michael. "The power of two choices in randomized load balancing.", Ph.D. thesis, U.C. Berkeley, 1996

Power of two choices[1]



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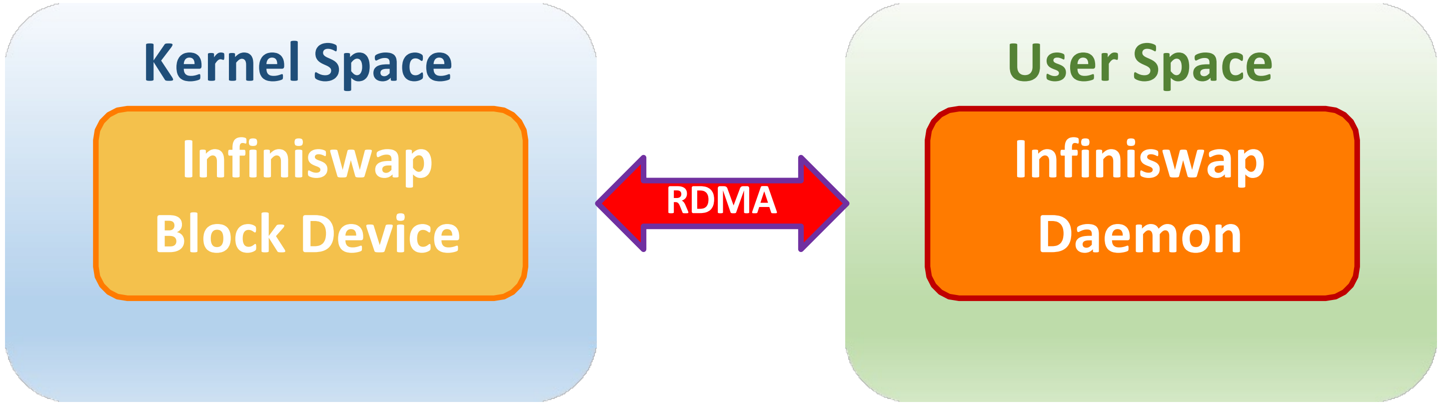
Implementation



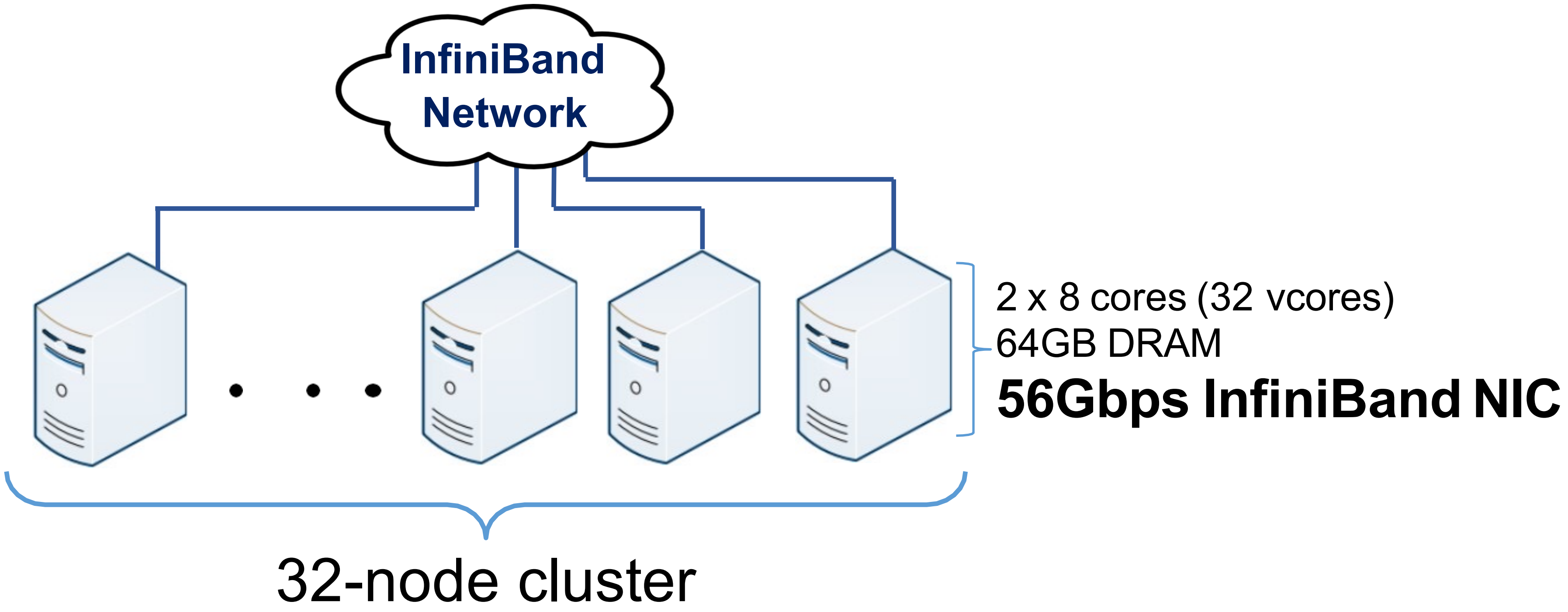
- **Connection Management**
  - **One** RDMA connection per active block device - daemon pair
- **Control Plane**
  - **SEND, RECV**
- **Data Plane**
  - **One-sided RDMA READ, WRITE**

What are we expecting from Infiniswap?

- **Application performance**
- **Cluster memory utilization**
- Network usage
- Eviction overhead
- Fault-tolerance overhead
- Performance as a block device

⋮

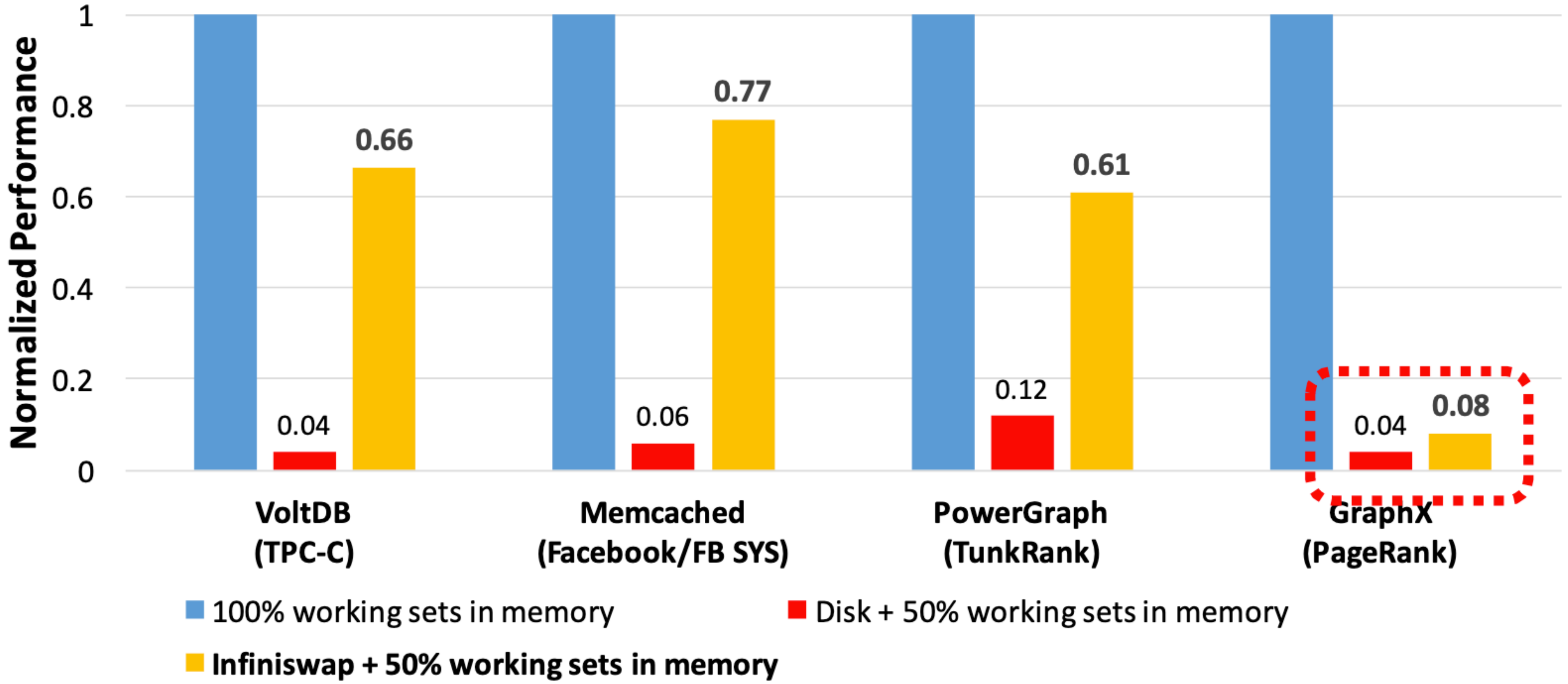
Evaluation



VOLTDB memCached powergraph GraphX

Application performance

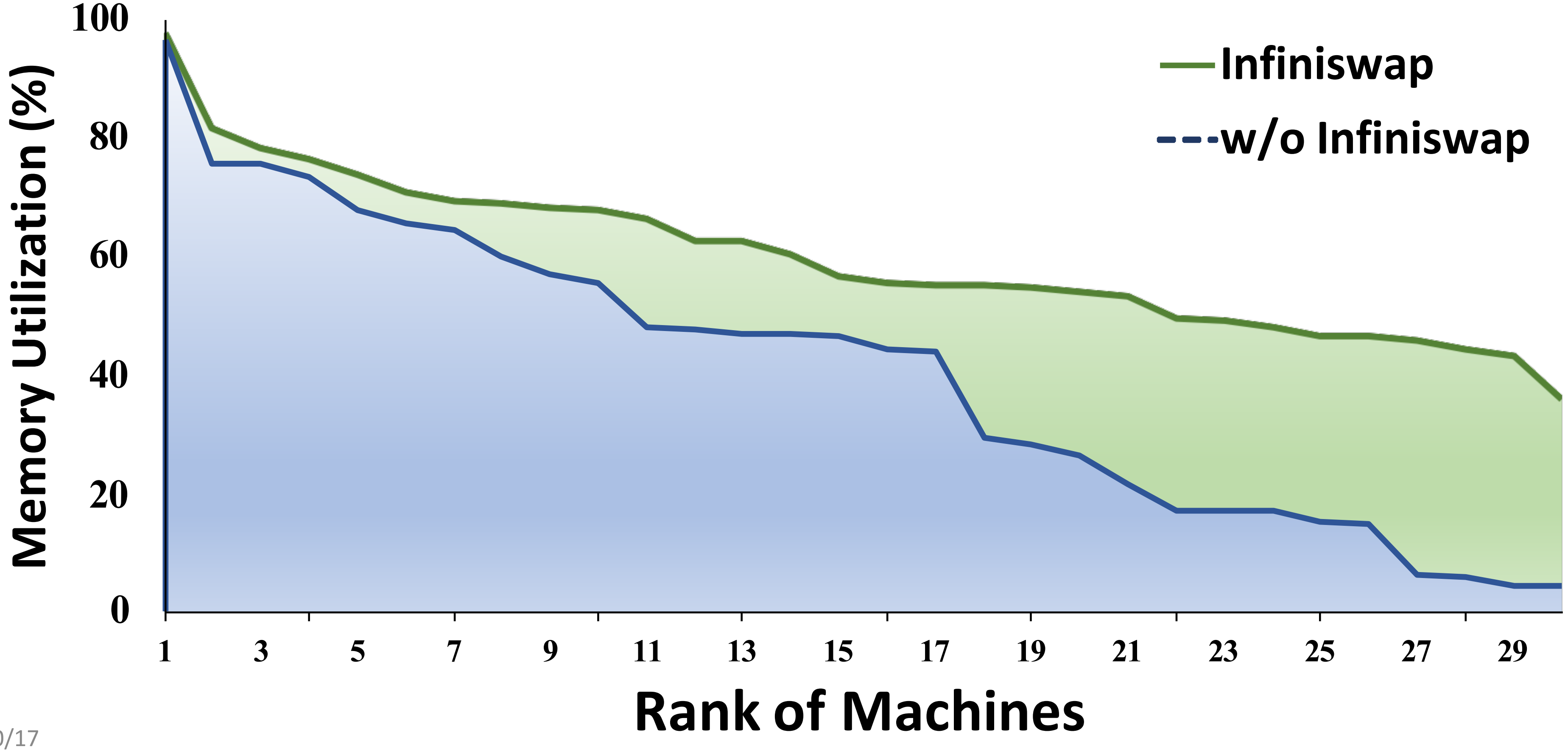
- 50% working sets in memory



- Application performance is improved by 2-16x

Cluster memory utilization

- 90 containers (applications), mixing all applications and memory constraints.



- Cluster memory utilization is improved from **40.8%** to **60%** (1.47x)

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Limitations and future work

- **Trade-off in fault-tolerance**
  - Local disk is the bottleneck
  - Multiple remote replicas
    - Fault-tolerance vs. space-efficiency

- **Performance isolation among applications**

Conclusion

- **Infiniswap: remote paging over RDMA**
  - Application performance
  - Cluster memory utilization
- **Efficient, practical memory disaggregation**
  - No hardware design
  - No application modification
  - **Fault-tolerance**
  - **Scalability**

https://github.com/Infiniswap/infiniswap.git

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AIFM: High-Performance, Application-Integrated Far Memory

Zain (Zhenyuan) Ruan[*] Malte Schwarzkopf[†] Marcos K. Aguilera[‡] Adam Belay[*]

[*]MIT CSAIL [†]Brown University [‡]VMware Research

In-Memory Applications

Data Analytics

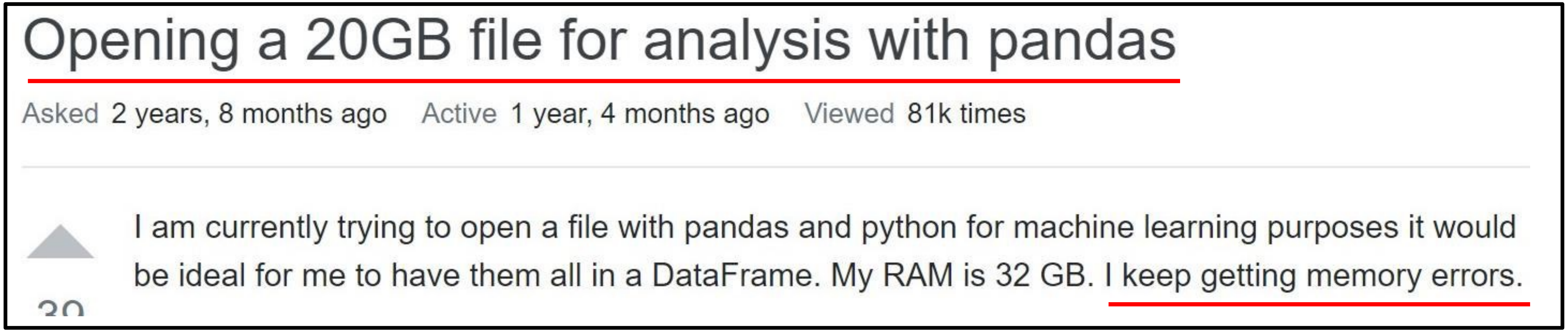
Web Caching

Database

Graph Processing

Memory Is Inelastic

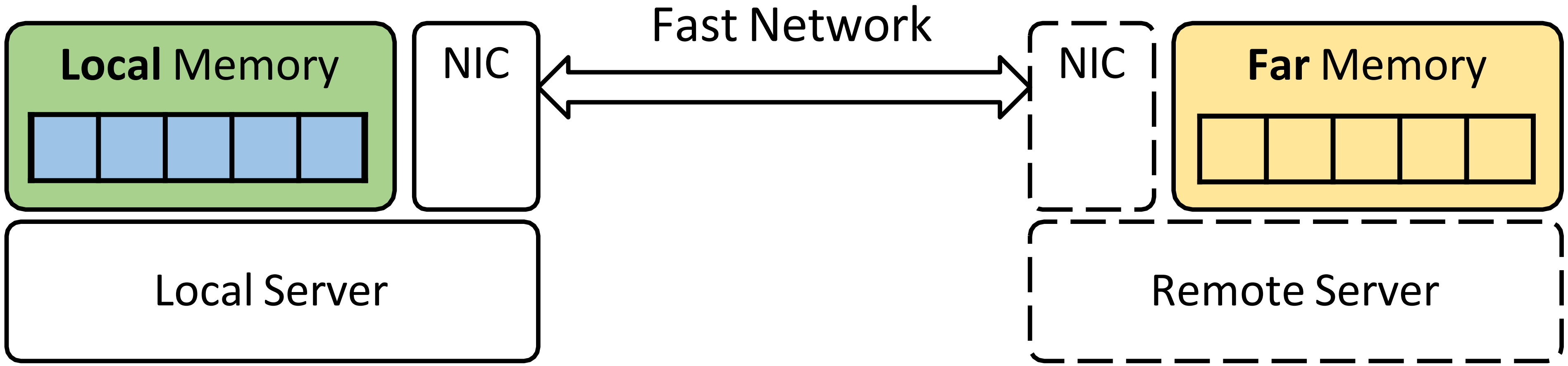
- Limited by the server physical boundary.
- Applications cannot overcommit memory.



➢ Expensive solution: overprovision memory for peak usage.

Trending Solution: Far Memory

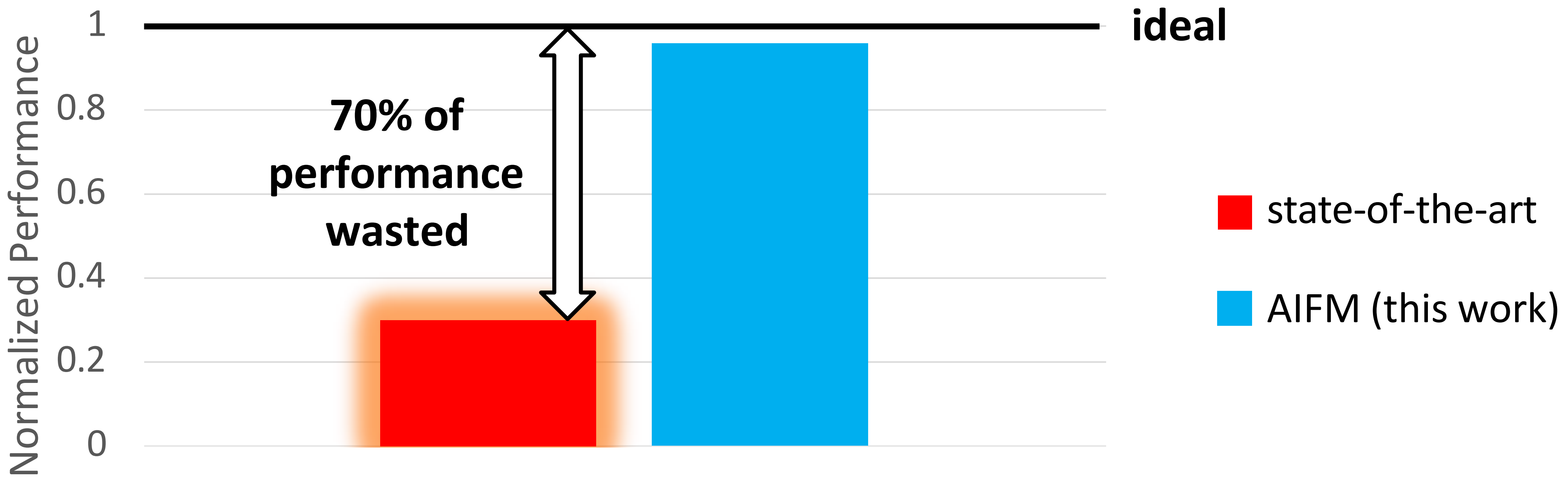
- Leverage the idle memory of remote servers (with fast network).



Existing Far-Memory Systems Perform Poorly

- Real-world Data Analytics from Kaggle.
  - Provision **25%** of working set in local mem.

➢Goal: reclaim the wasted performance.

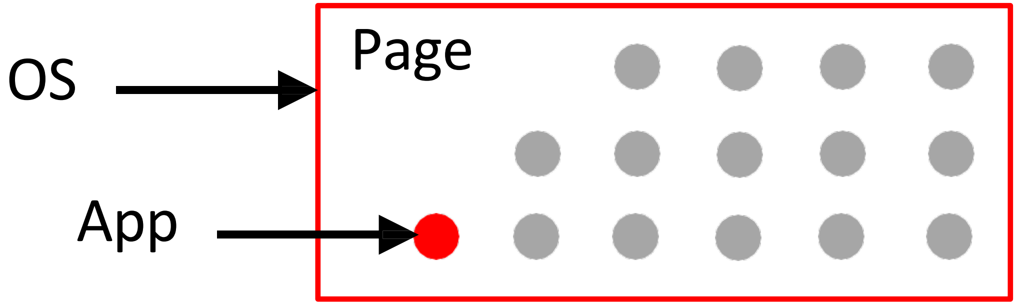


Why Do Existing Systems Waste Performance?

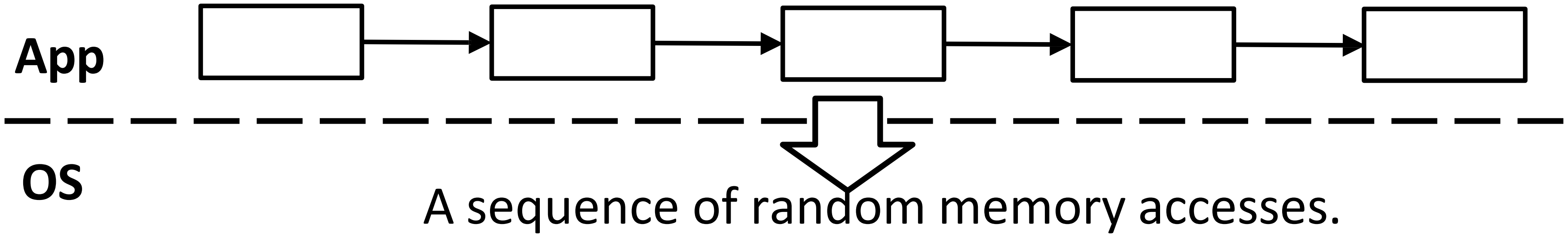
- Problem: based on **OS paging**.
  - Semantic gap.
  - High kernel overheads.

Challenge 1: Semantic Gap

- Page granularity ➔ **R/W amplification.**



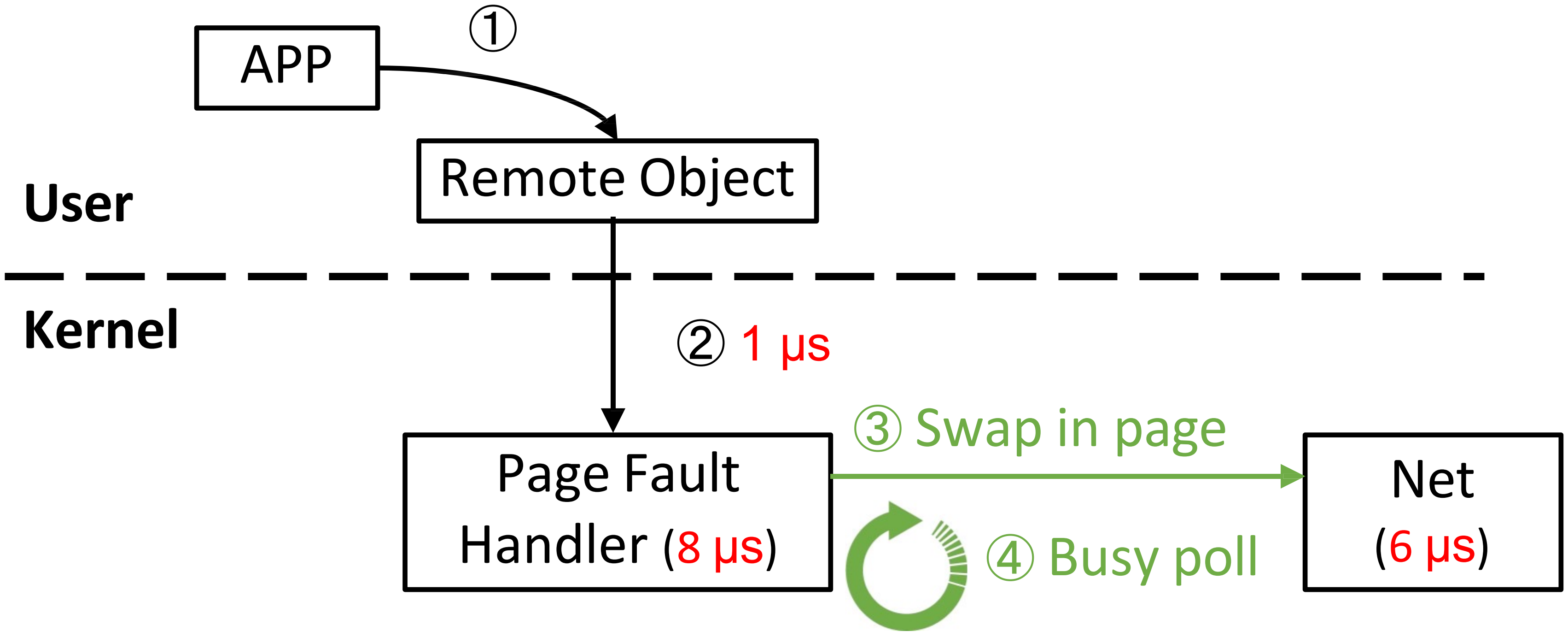
➢ OS lacks app knowledge ➔ **hard to prefetch, etc.**



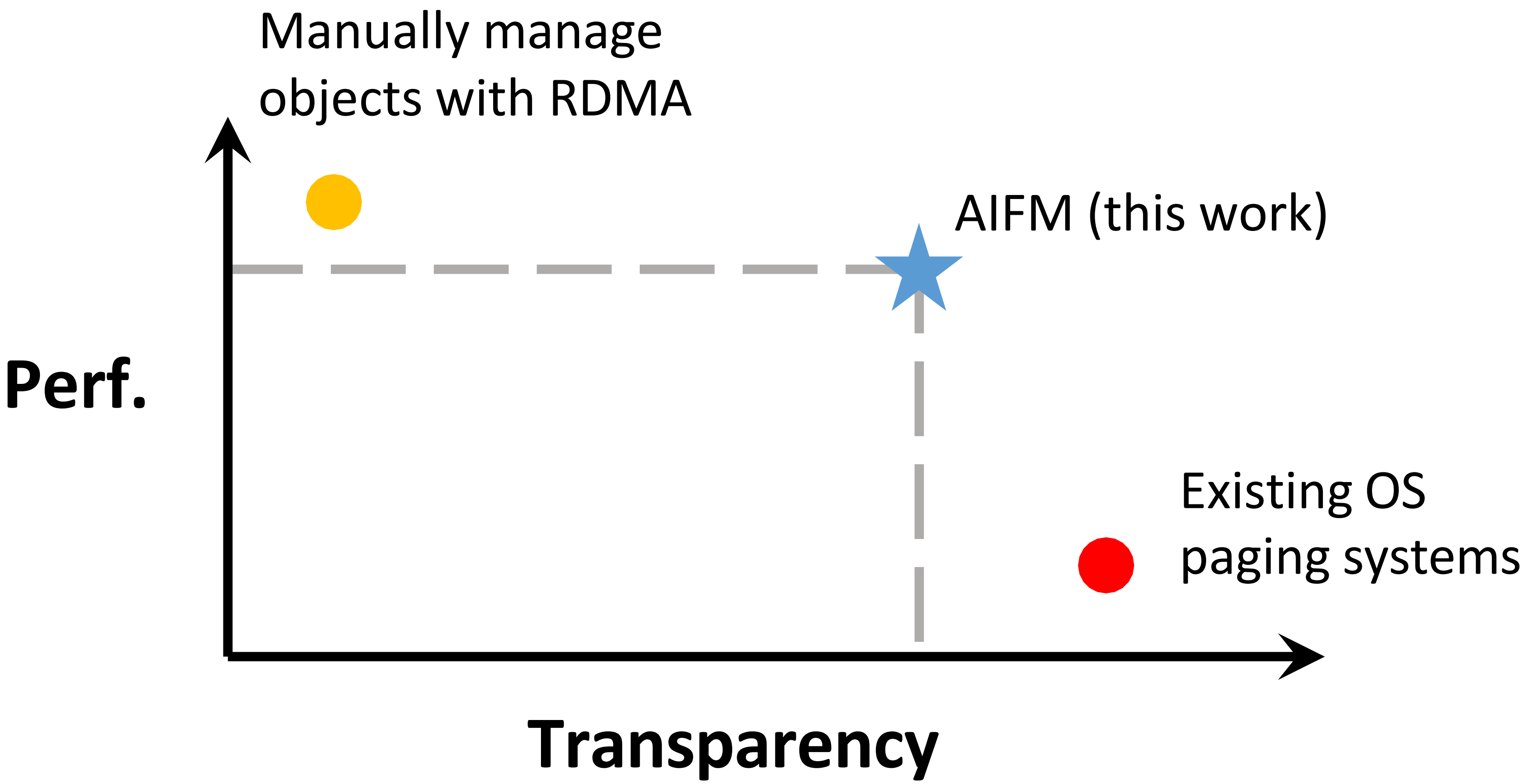
Challenge 2: High Kernel Overheads

- **Expensive page faults.**

➢ Busy Polling for in-kernel net I/O ➔ **burn CPU cycles**.



Design Space



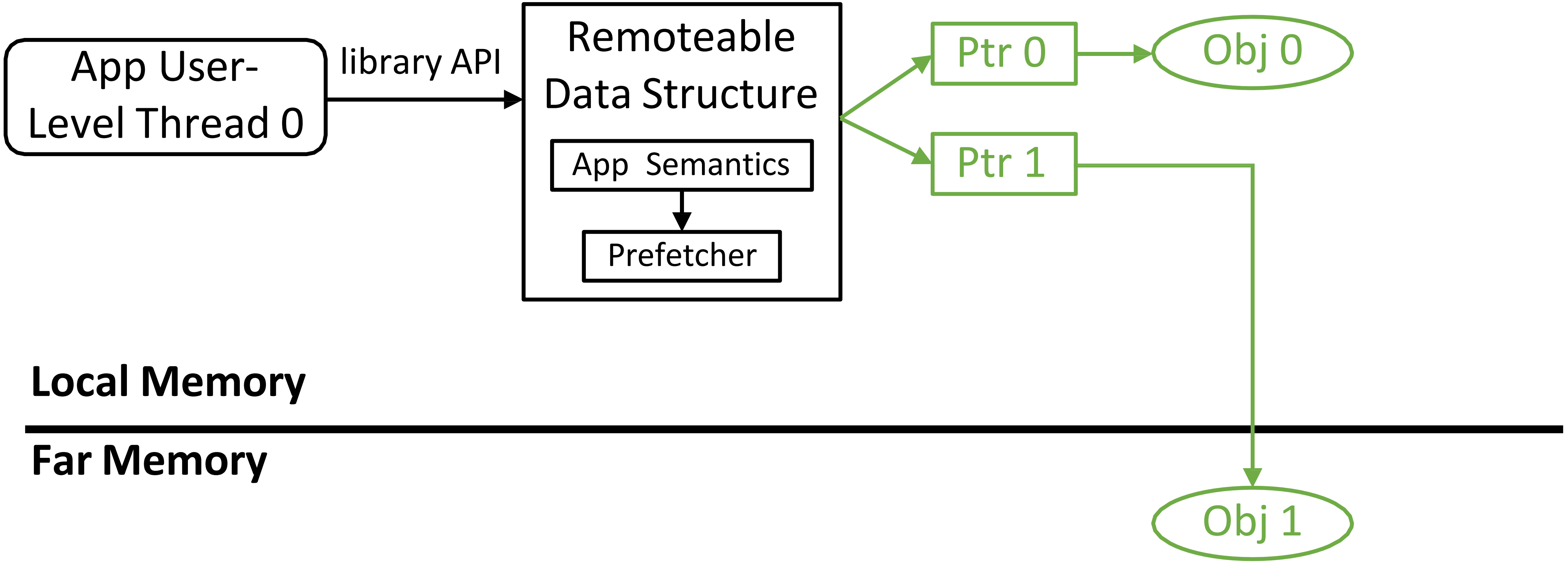
AIFM's Design Overview

- Key idea: swap memory using a userspace runtime.

Challenge	Solution
1. Semantic gap (Amplification, Hard to prefetch)	Remoteable Data structure library
2. Kernel overheads (page faults, busy poll for net I/O)	Userspace runtime
3. Impact of Memory Reclamation (pause app threads)	Pauseless evacuator
4. network BW < DRAM BW	Remote Agent

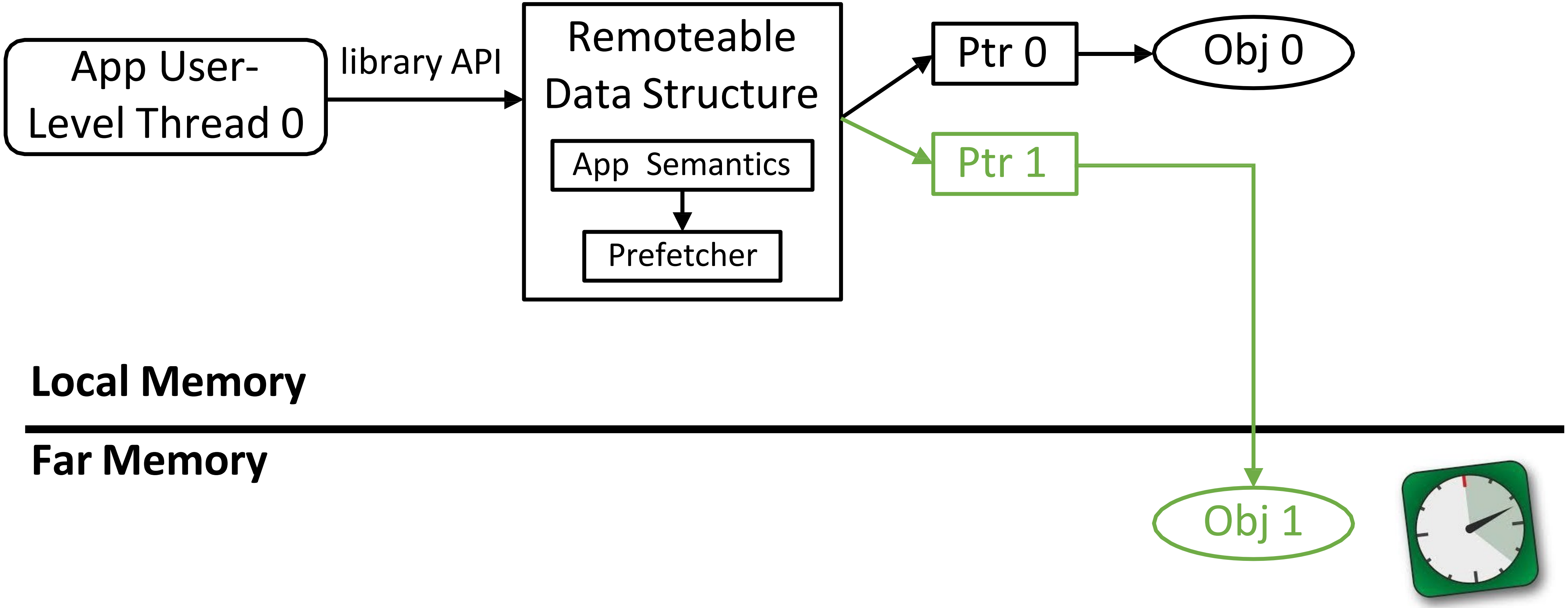
1. Remoteable Data Structure Library

- Solved challenge: semantic gap.



2. Userspace Runtime

➢ Solved challenge: kernel overheads.



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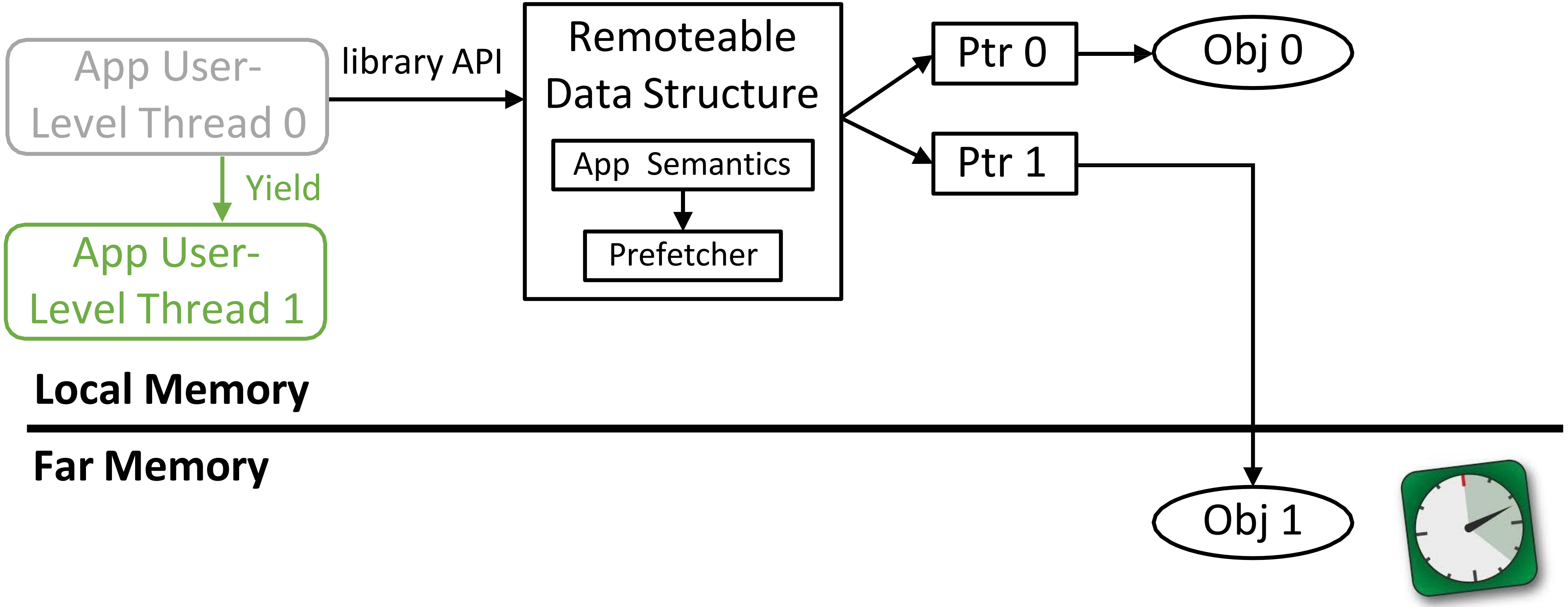

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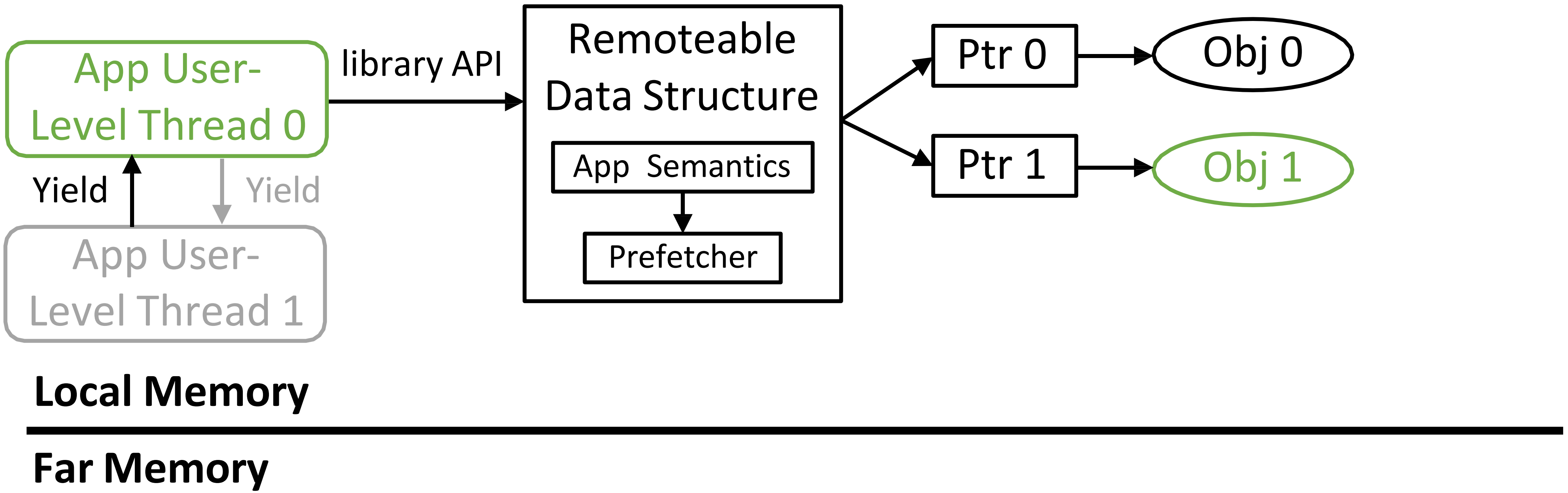
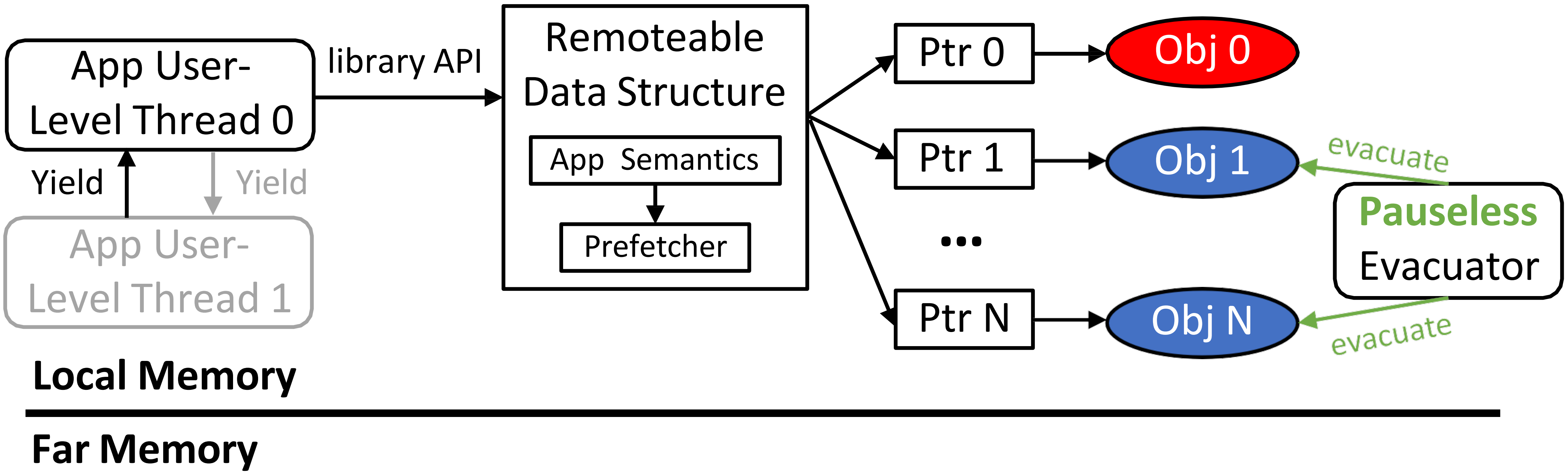


3. Pauseless Evacuator

- Solved challenge: impact of memory reclamation.



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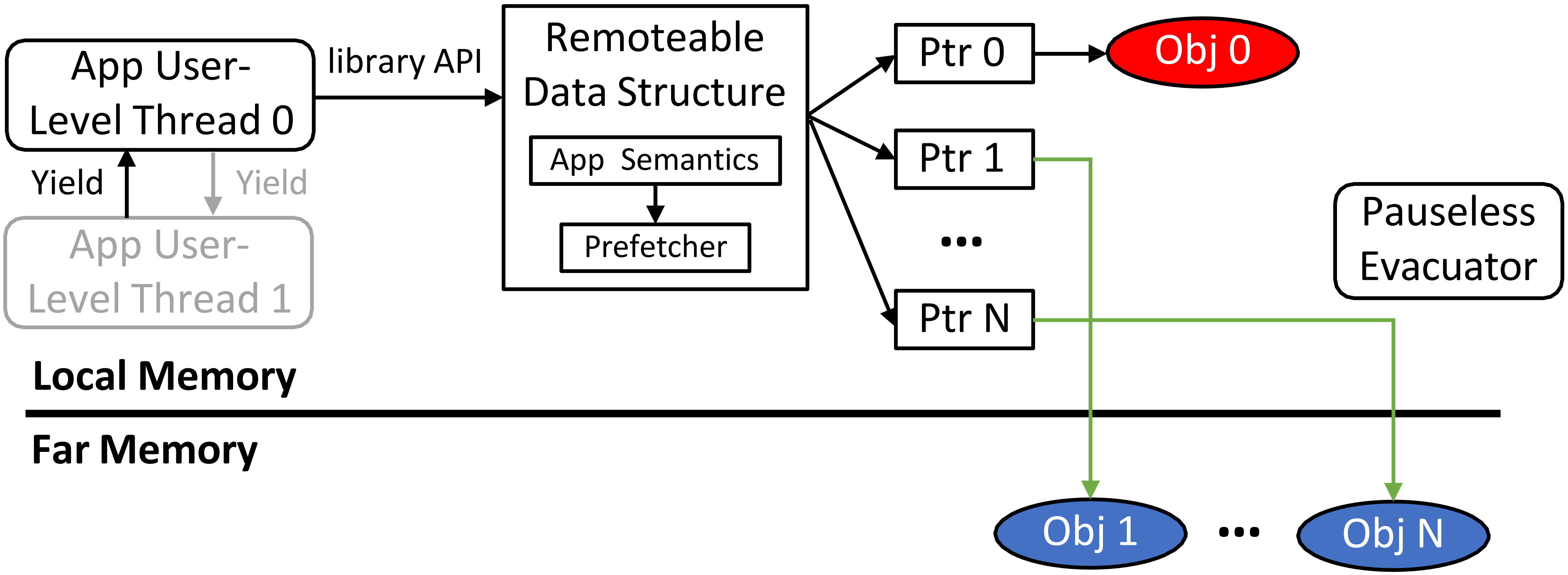
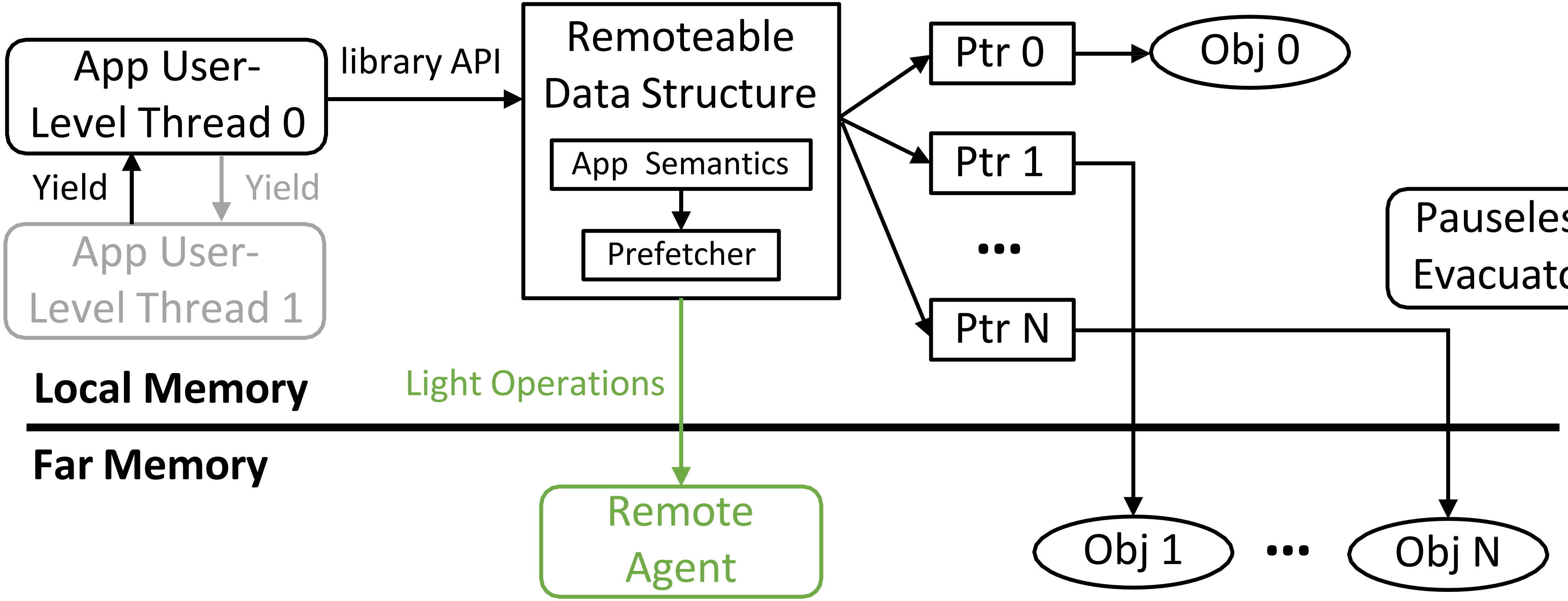


4. Remote Agent

➢Solved challenge: network BW < DRAM BW.



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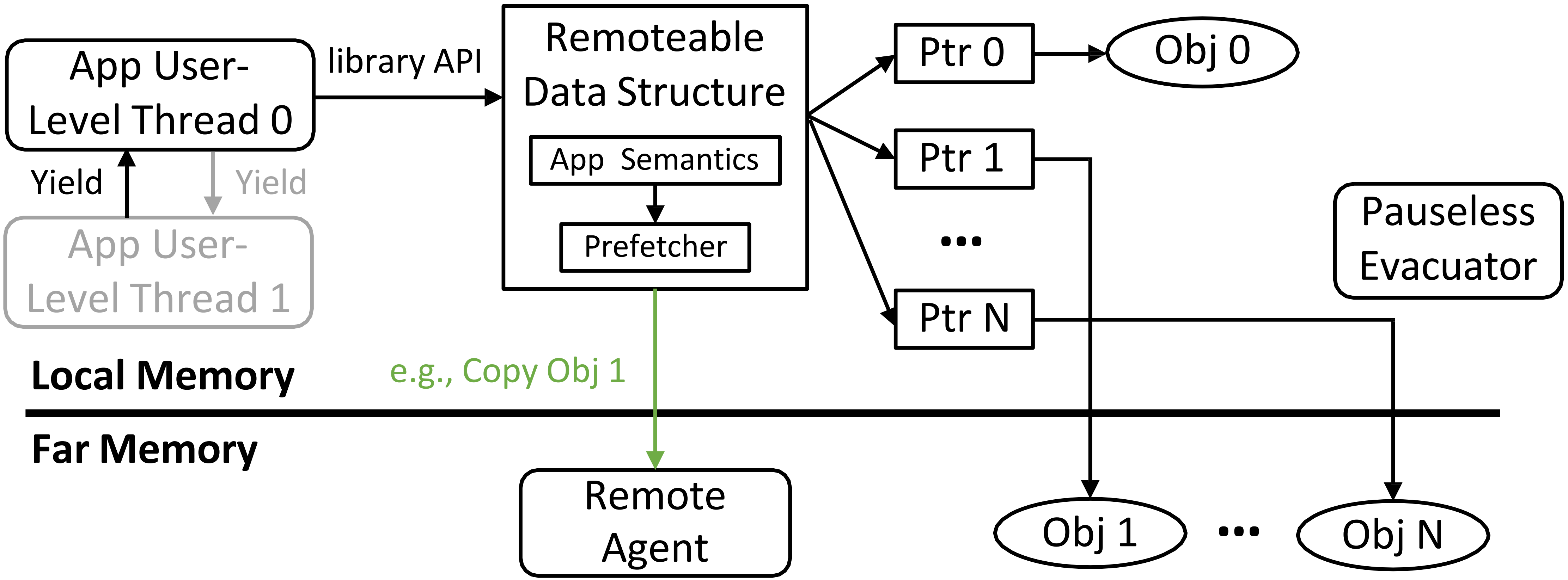

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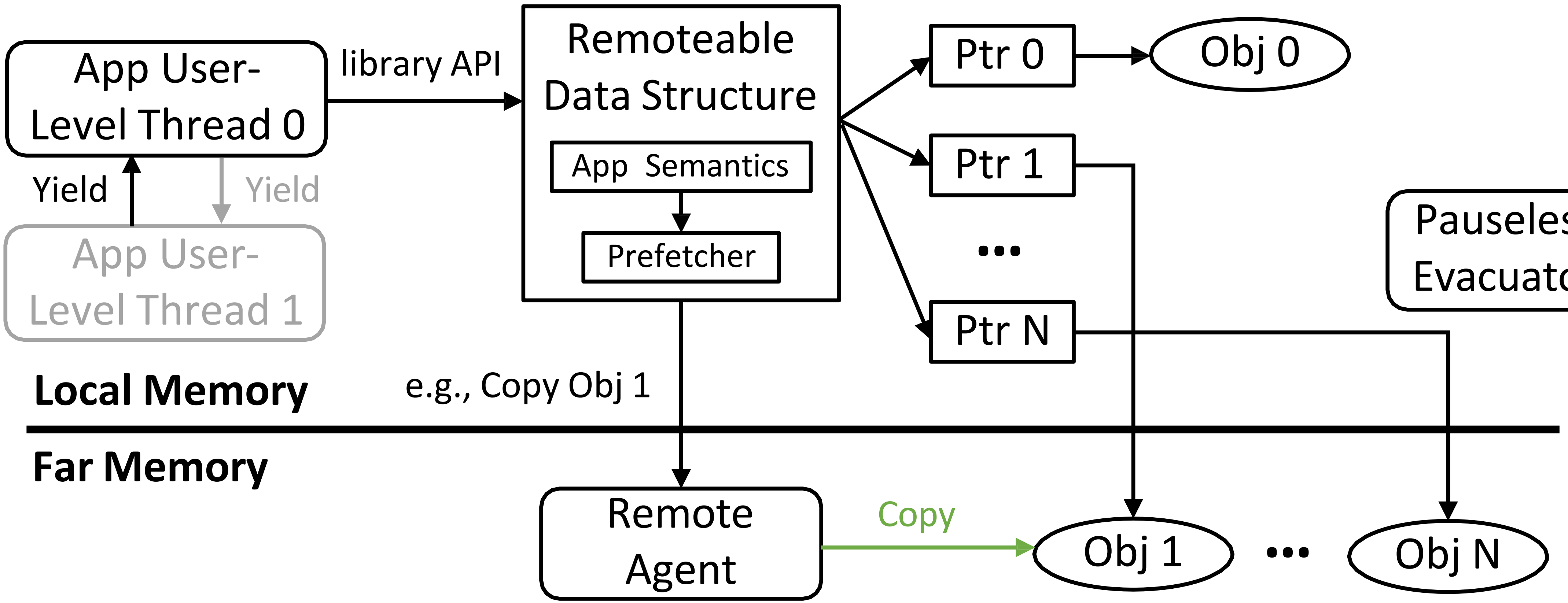


Sample Code

```
std::unordered_map<key_t, int> hashtable;
std::array<LargeData> arr;

LargeData foo(std::list<key_t> &keys_list) {
    int sum = 0;
    for (auto key : keys_list) {

        sum += hashtable.at(key);
    }

    LargeData ret = arr.at(sum);
    return ret;
}
```

Sample Code

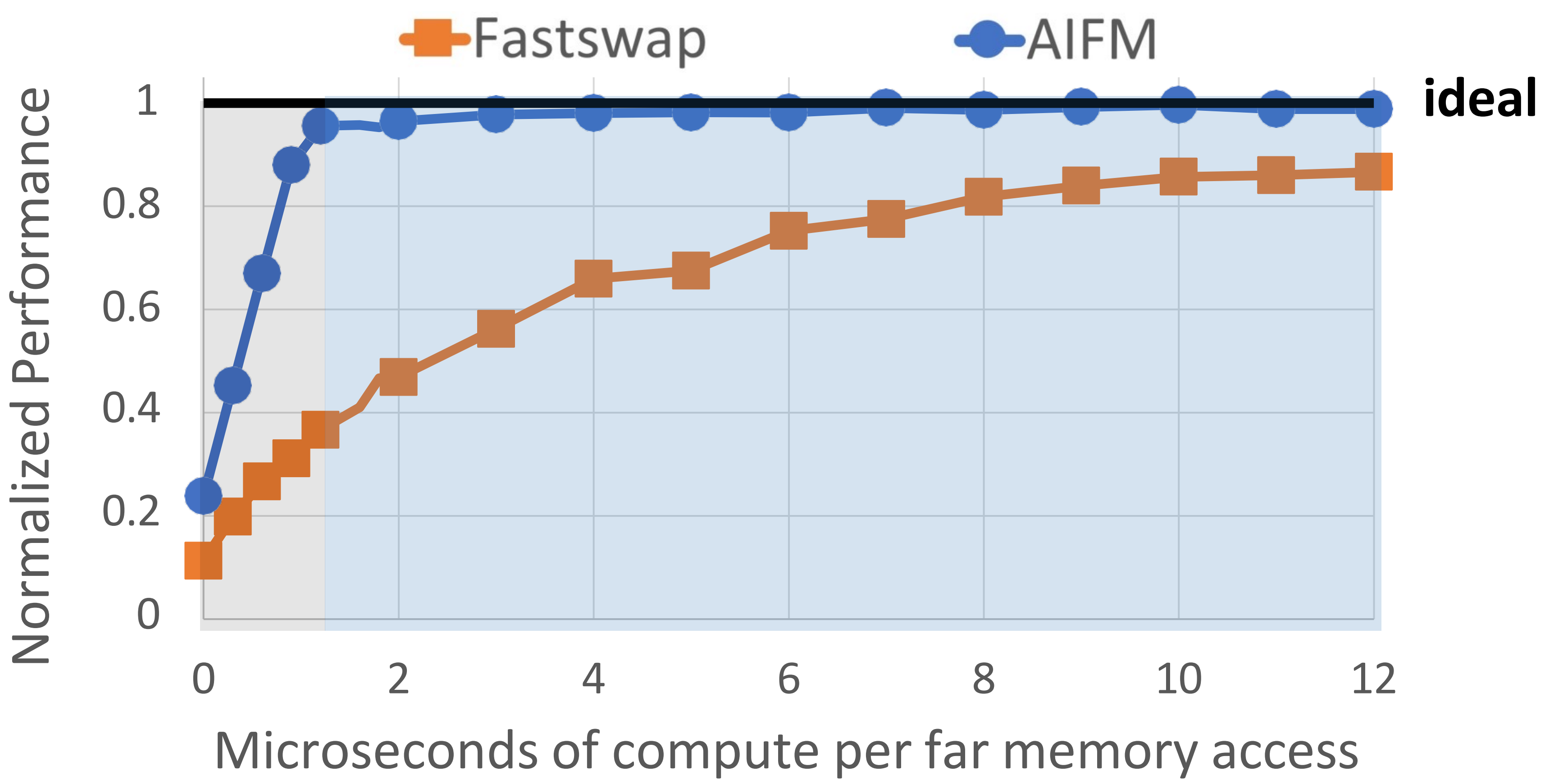
```
RemHashTable<key_t, int> hashtable;
RemArray<LargeData> arr;

LargeData foo(RemList<key_t> &keys_list) {
  int sum = 0;
  for (auto key : keys_list) {                                    Prefetch list data.
    DerefScope scope;
    sum += hashtable.at(key, scope);                              Cache hot objects.
  }
  DerefScope scope;
  LargeData ret = arr.at</*don't cache*/ true>(sum, scope);       Avoid polluting local mem.
  return ret;
}
```

Implementation

- Implemented 6 data structures.
  - Array, List, Hashtable, Vector, Stack, and Queue.
- Runtime is built on top of Shenango [NSDI' 19].
- TCP far-memory backend.

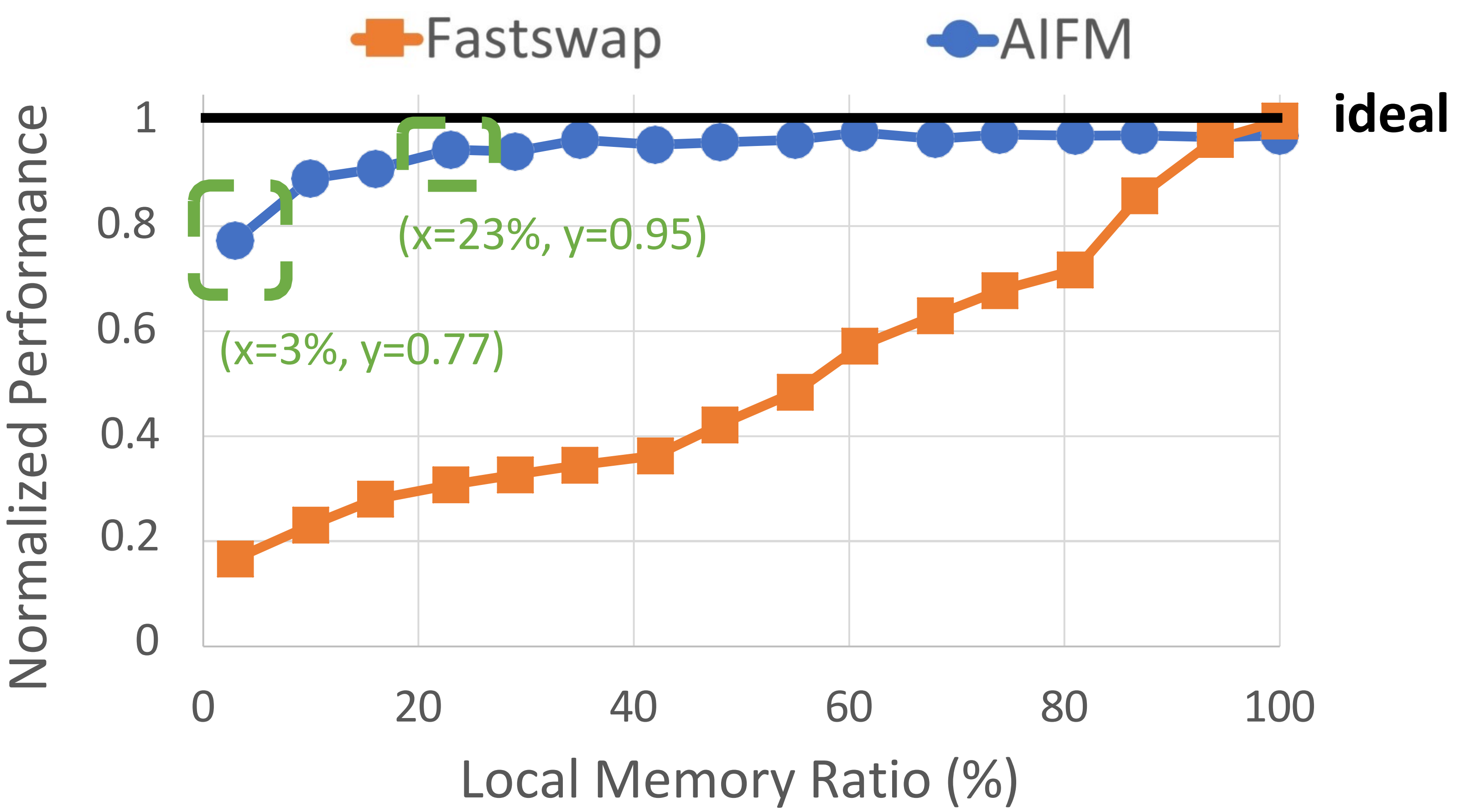
➢ LoC: 6.5K (runtime) + 5.5K (data structures) + 0.8K (Shenango)

Performance on Different Compute Intensities



AIFM hides far memory latency with moderate compute.

NYC Taxi Analysis (C++ DataFrame)



AIFM achieves near-ideal performance with small local memory.

Other Experiments

- Synthetic web frontend: up to **13X end-to-end** speedup.
- Data structures microbenchmarks: up to **61X** speedup.
- Design Drill-Down.

Read our paper for details.

Related Work

- OS-paging systems.
  - Fastswap [EuroSys’ 20], Leap [ATC’ 20]
- Distributed shared memory.
  - Treadmarks [IEEE Computer’ 96]
- Garbage collection (GC).

Conclusion

- AIFM: Application-Integrated Far Memory.
- Key idea: swap memory using a userspace runtime.
  - Data Structure Library: captures application semantics.
  - Userspace Runtime: efficiently manages objects and memory.
- Achieves 13X end-to-end speedup over Fastswap.

➢Code released at https://github.com/AIFM-sys/AIFM

Please send your questions to us

zainruan@csail.mit.edu

Memory Management in Modern Computer Systems

- Memory Abstraction
  - NSDI'14 FaRM

- Demand paging: remote memory over RDMA
  - NSDI'17 InfiniSwap
  - OSDI'20 AIFM

- Demand paging: memory swapping between GPU memory and host memory
  - OSDI'20 PipeSwitch
  - NSDI'23 TGS

PipeSwitch: Fast Pipelined Context Switching for Deep Learning Applications

Zhihao Bai, Zhen Zhang, Yibo Zhu, Xin Jin

Johns Hopkins University

ByteDance

Deep learning powers intelligent applications in many domains

Google

amazon

Uber

Microsoft

IBM

PayPal

Training and inference

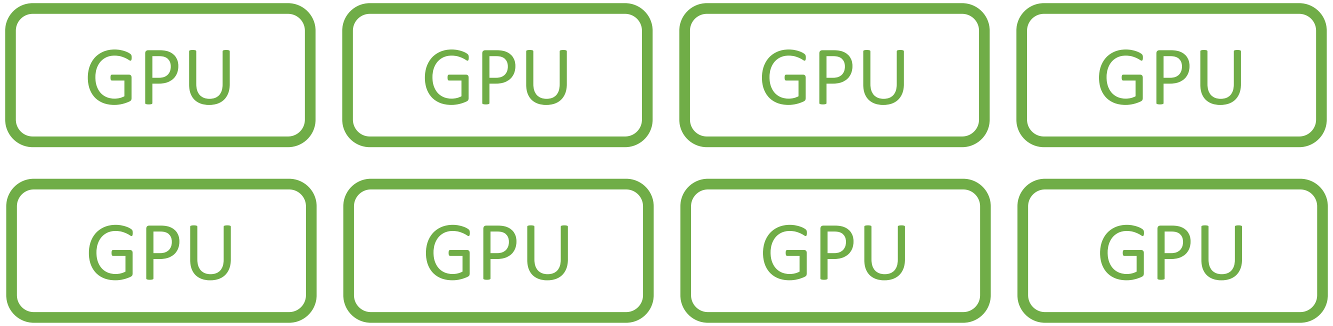
Training

High throughput

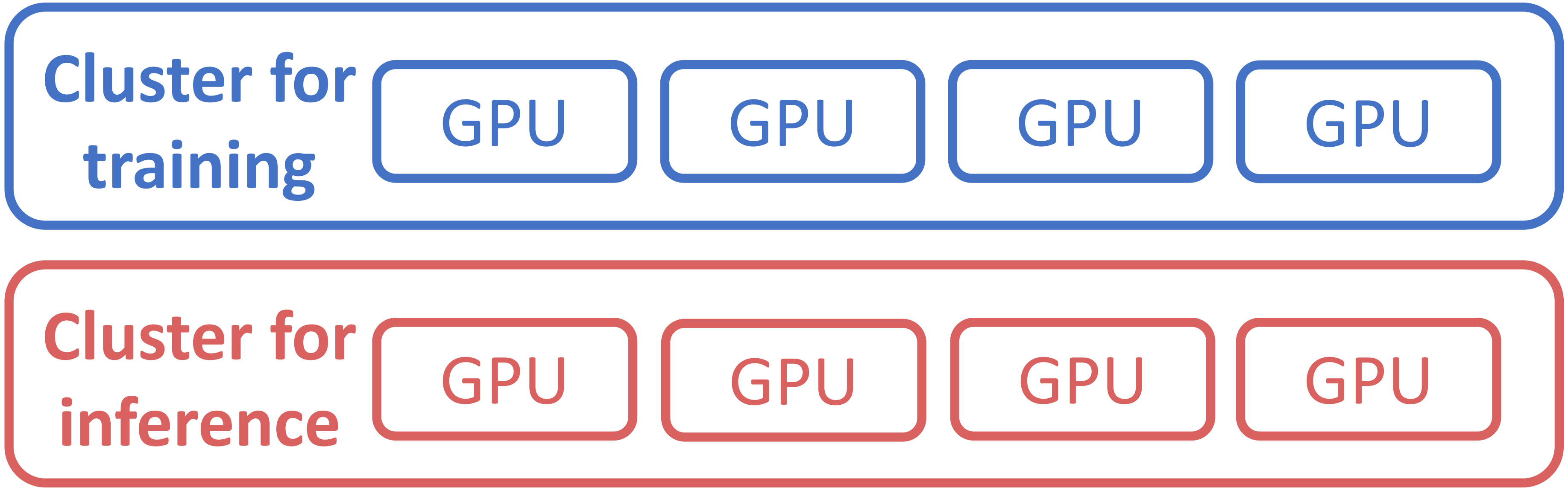
Inference

Low latency

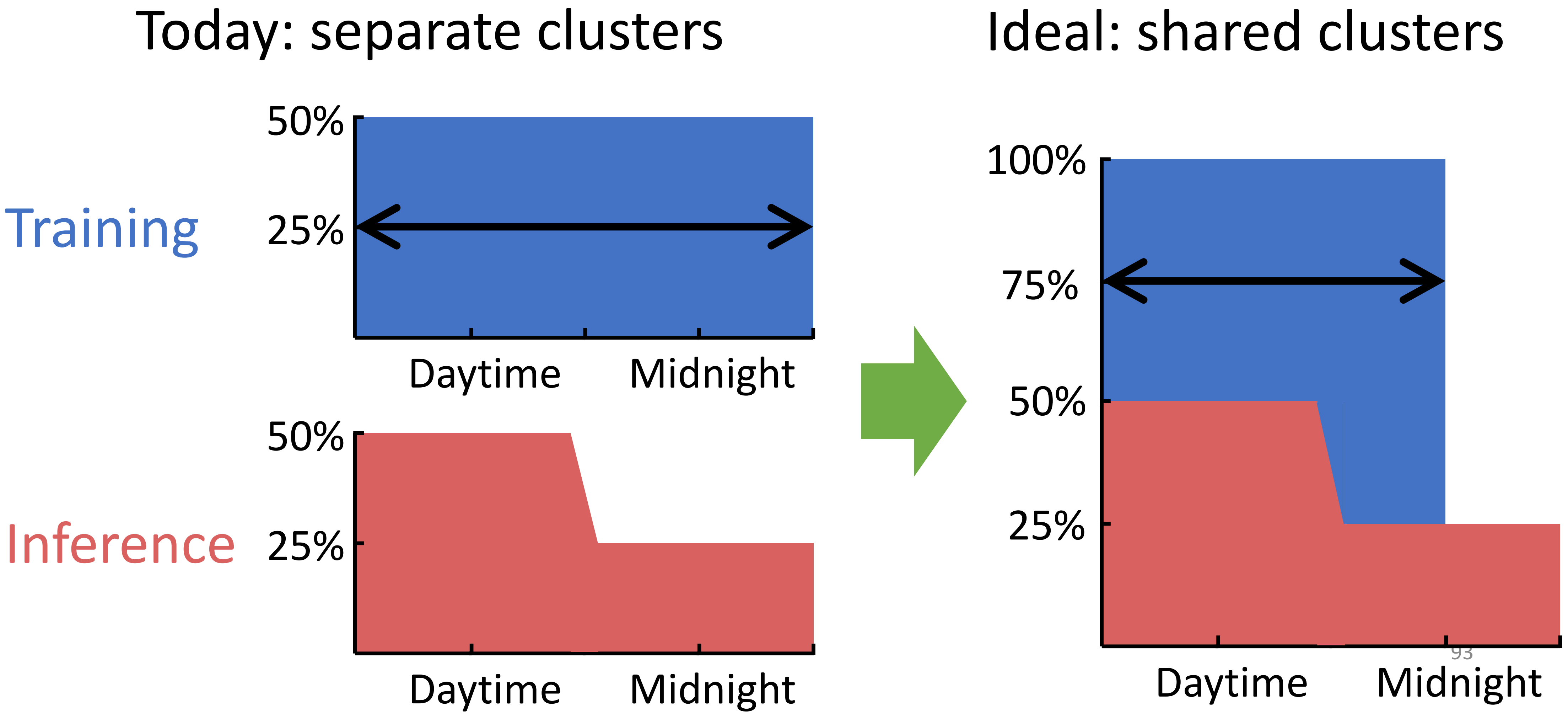
GPUs clusters for DL workloads



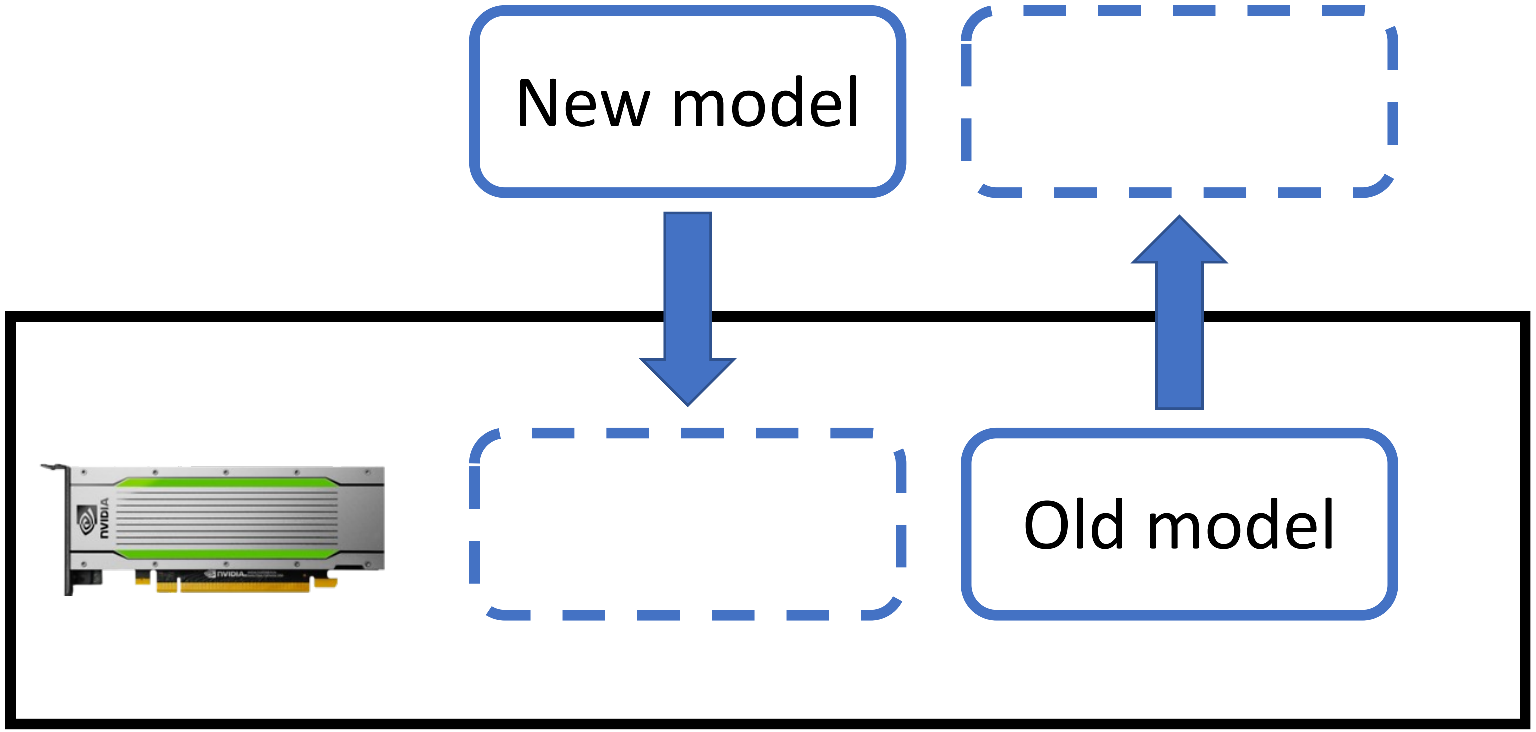
Separate clusters for training and inference



Utilization of GPU clusters is low



Context switching overhead is high



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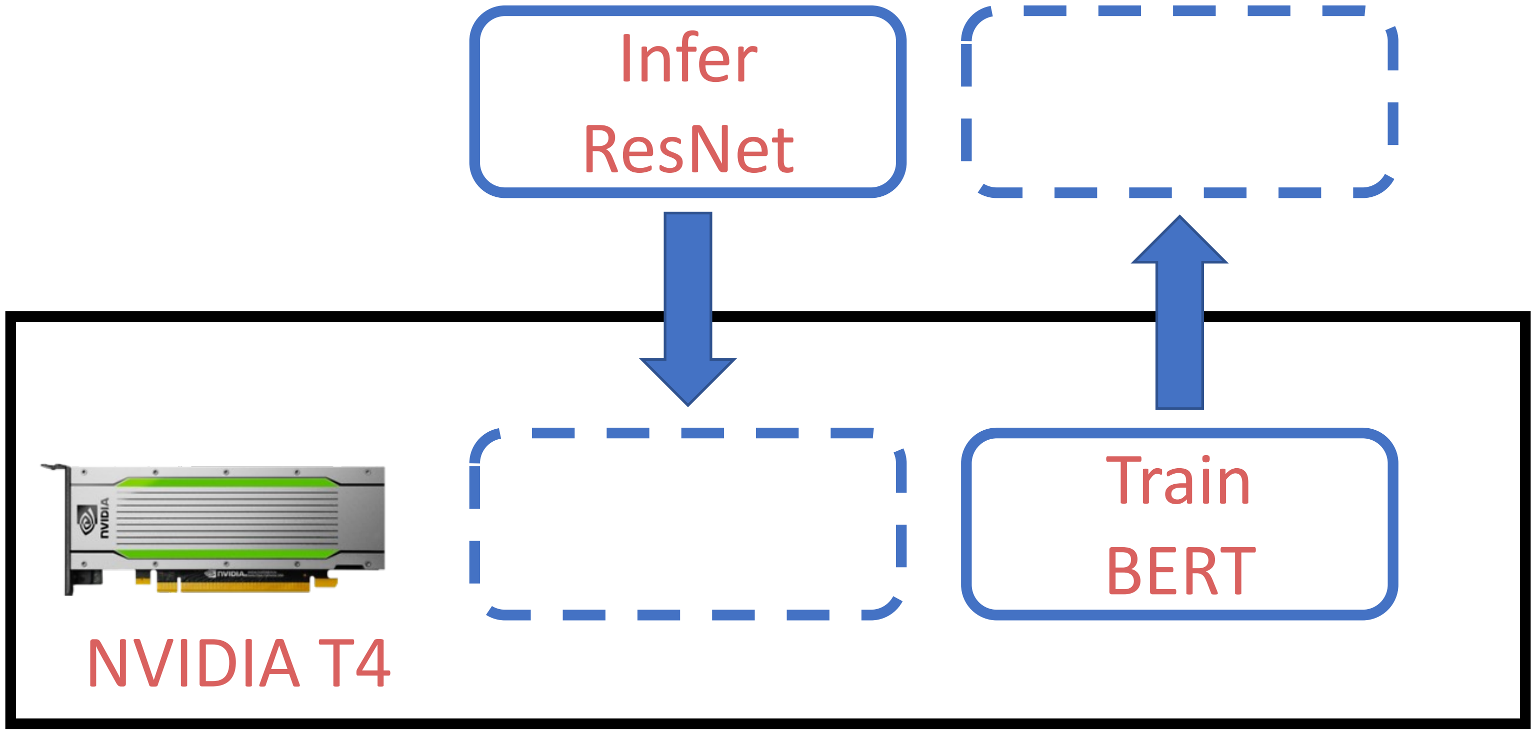


Latency: 6s

Drawbacks of existing solutions

- NVIDIA MPS
  - High overhead due to contention
- Salus[MLSys'20]
  - Requires all the models to be preloaded into the GPU memory

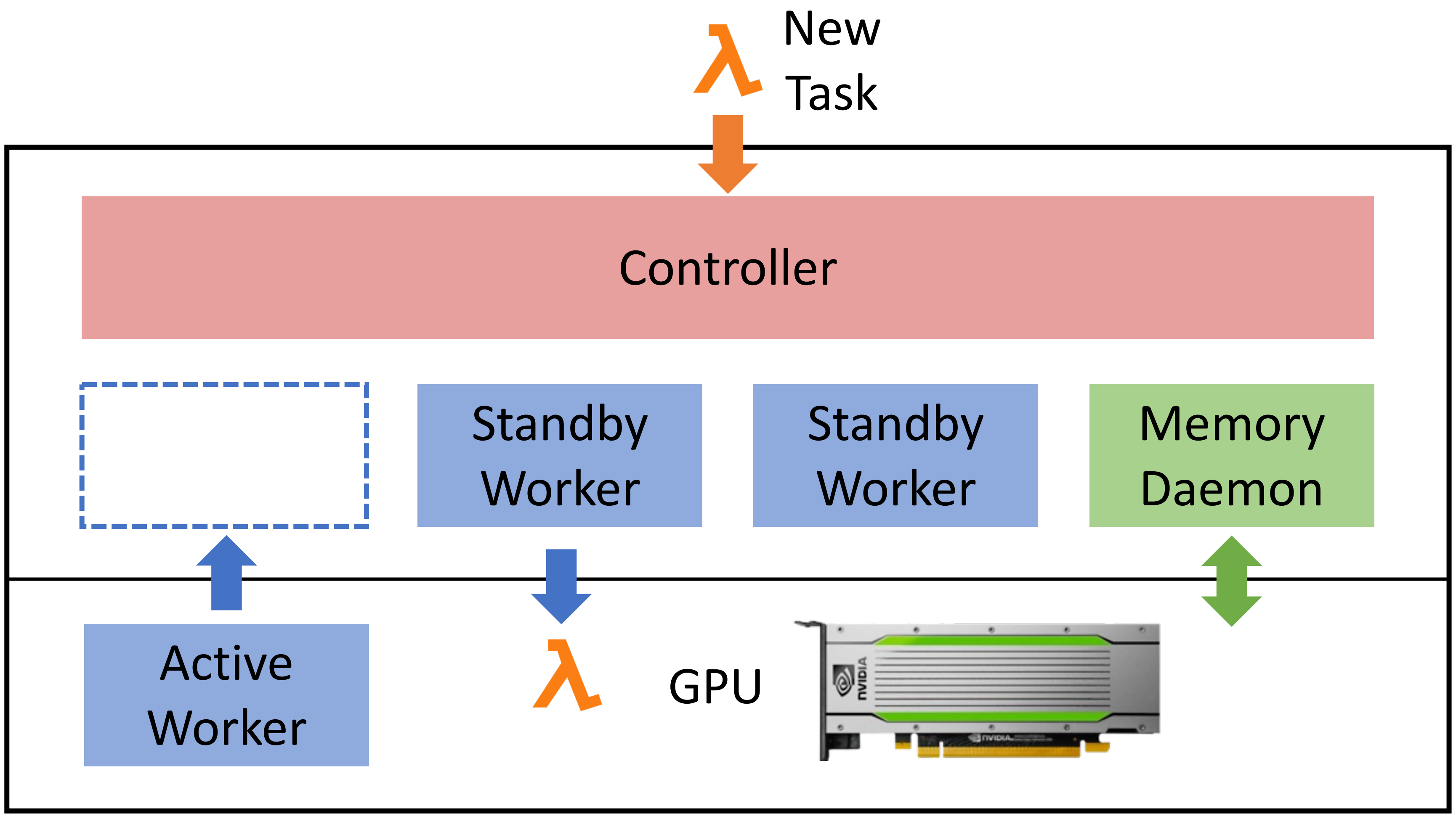
Latency: 6s

Goal: fast context switching

- Enable GPU-efficient **multiplexing** of multiple DL apps with **fine-grained time-sharing**
- Achieve **millisecond-scale** context switching latencies and high throughput

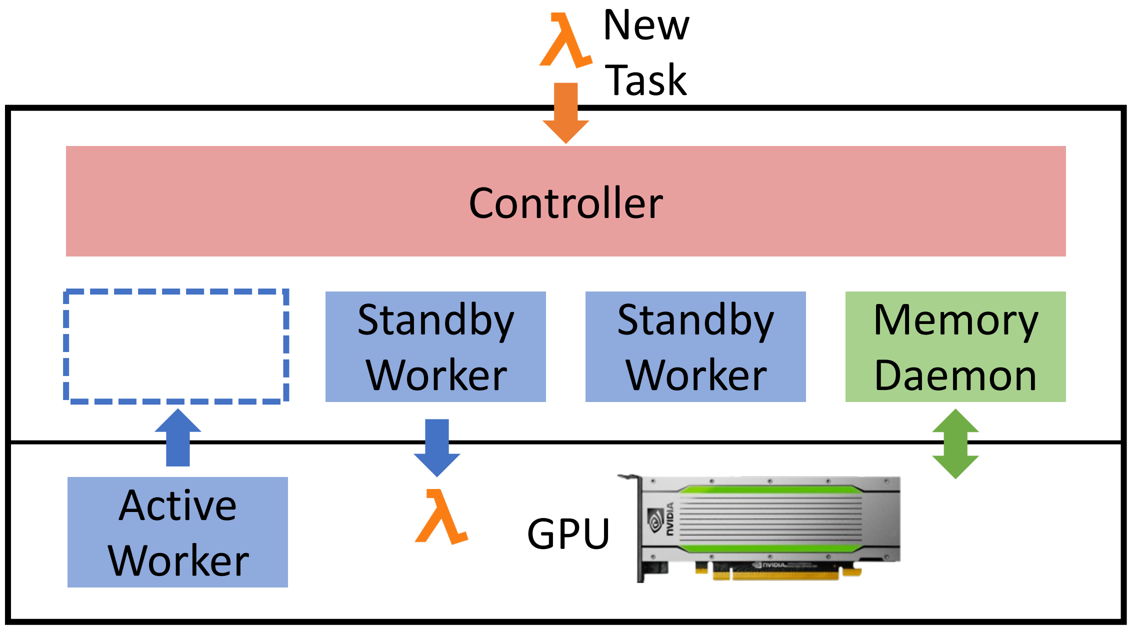
Latency: 6s

PipeSwitch overview: architecture



PipeSwitch overview: execution

- Stop the current task and prepare for the next task.
- Execute the task with pipelined model transmission.
- Clean the environment for the previous task.



Sources of context switching overhead

Model transmission

Memory allocation

Task initialization

Task cleaning

How to reduce the overhead?

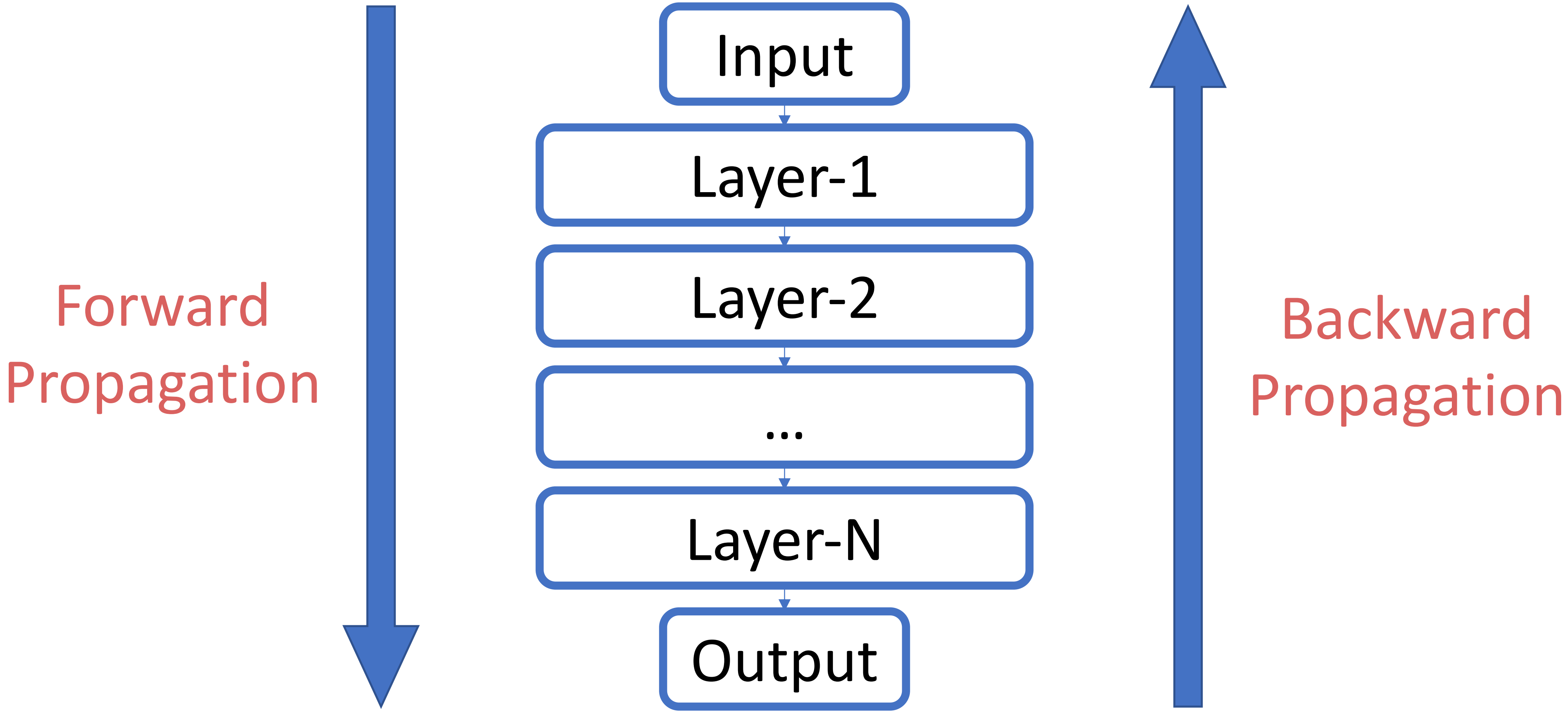
Model transmission → Pipelined model transmission

Memory allocation

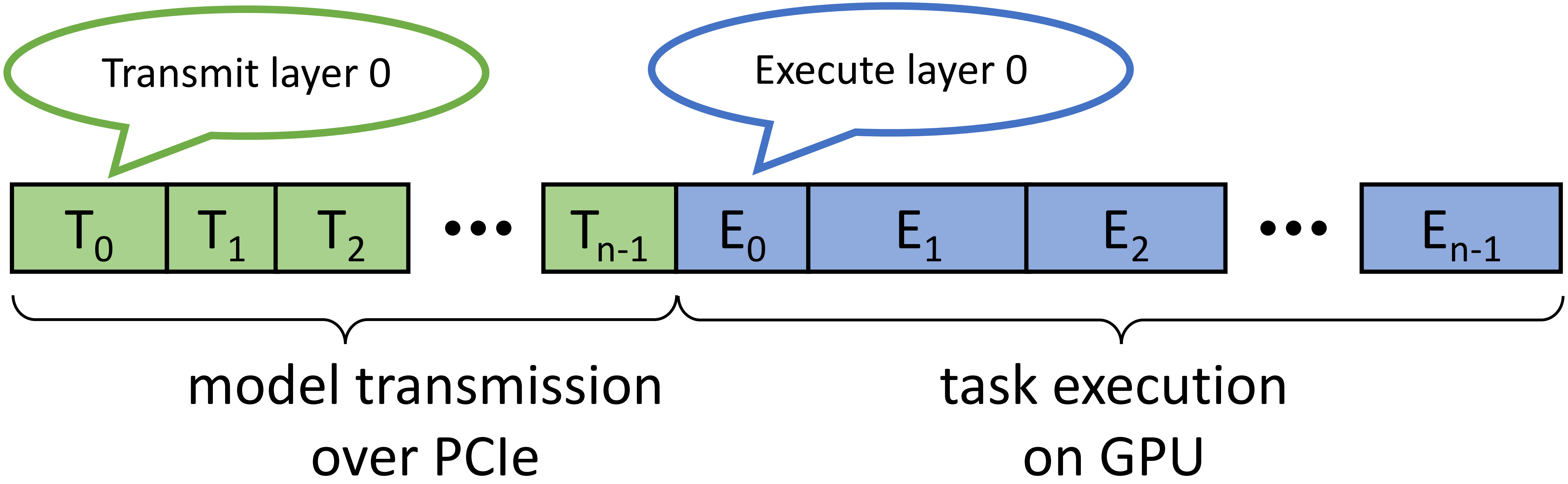
Task initialization

Task cleaning

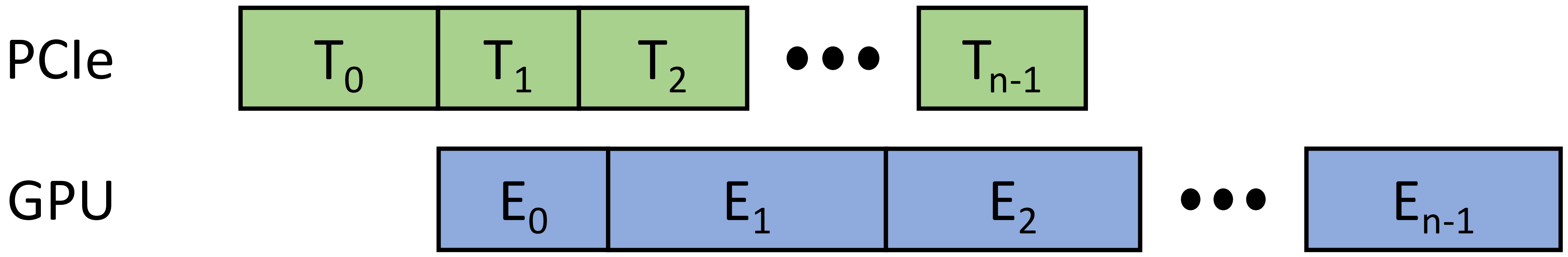
DL models have layered structures



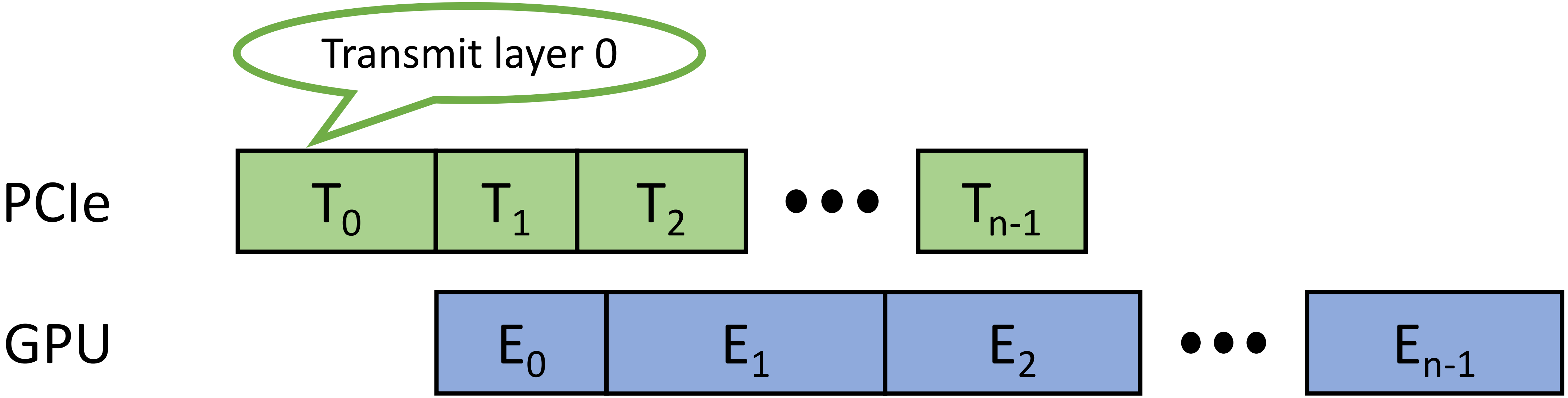
Sequential model transmission and execution



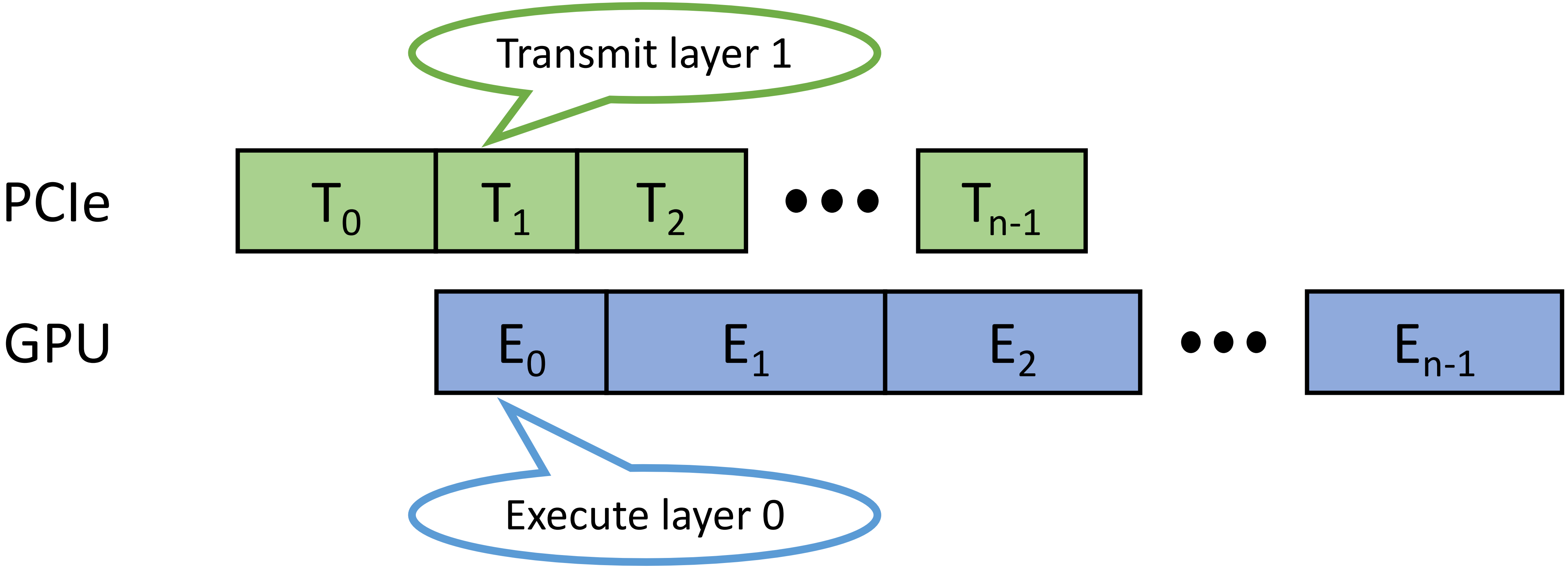
Pipelined model transmission and execution



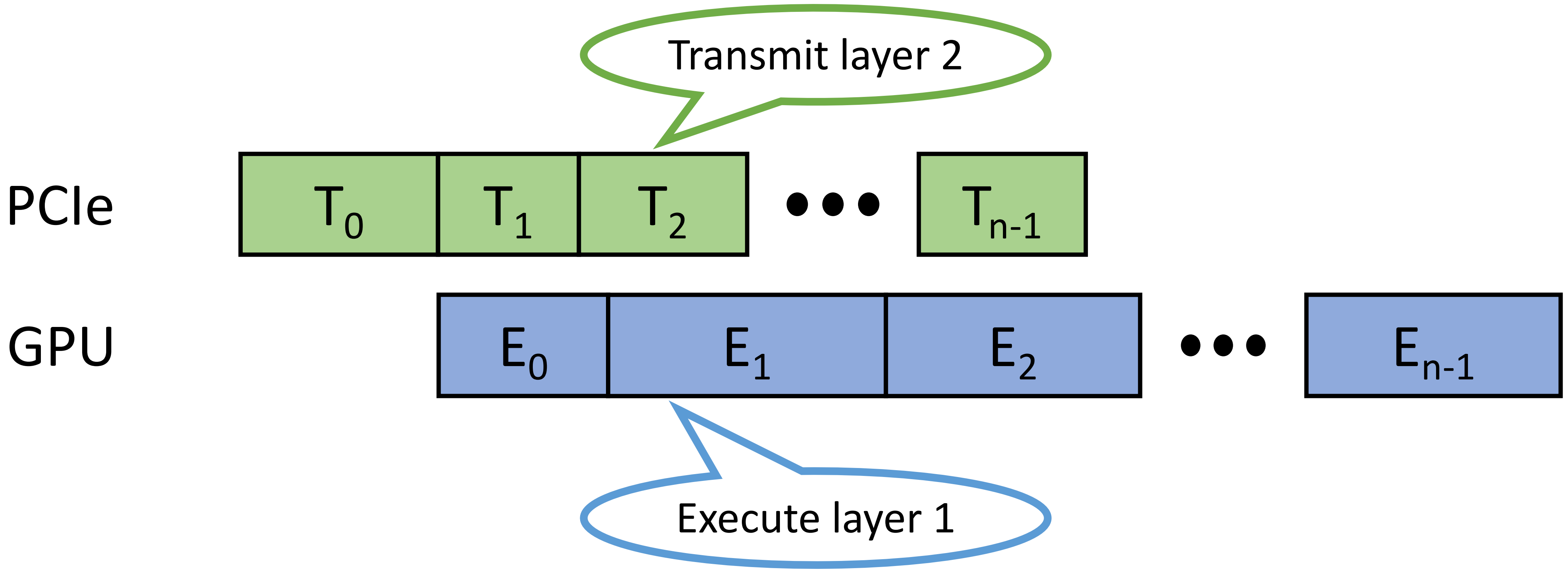
Pipelined model transmission and execution



Pipelined model transmission and execution



Pipelined model transmission and execution



Pipelined model transmission and execution

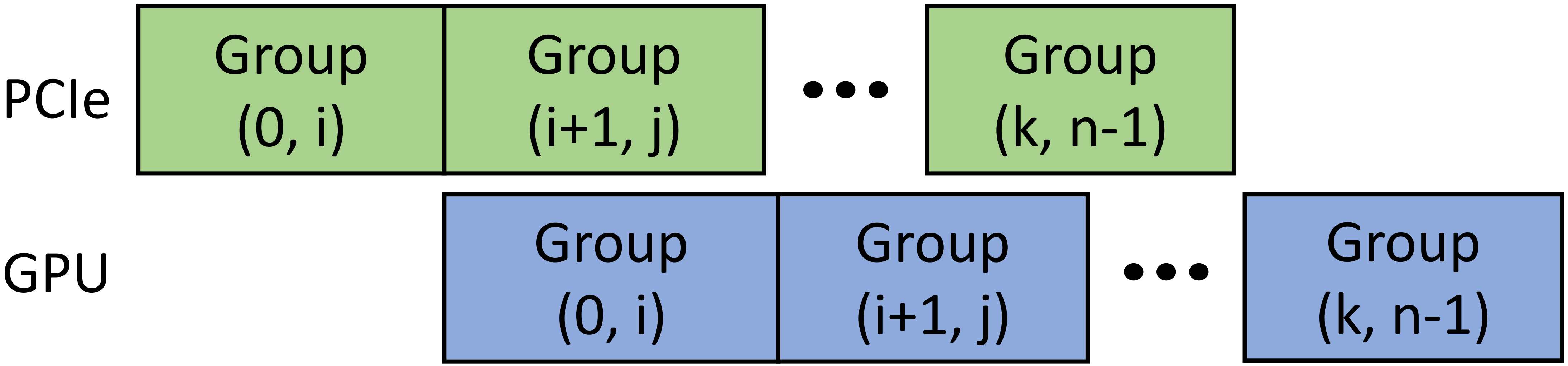
PCIe

GPU

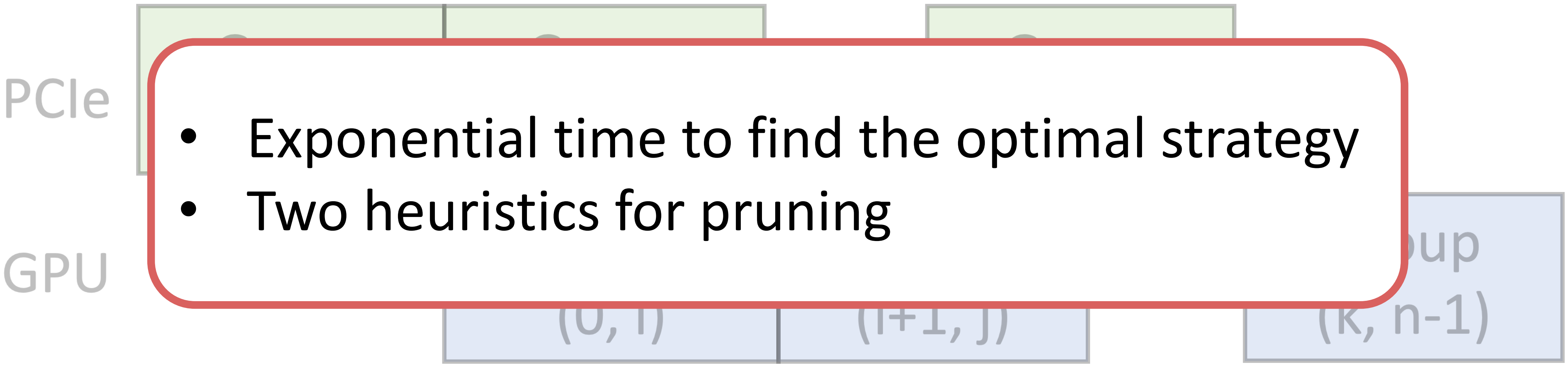
1. Multiple calls to PCIe;
2. Synchronize transmission and execution.

E_{n-1}

Pipelined model transmission and execution



Pipelined model transmission and execution



- Exponential time to find the optimal strategy
- Two heuristics for pruning

How to reduce the overhead?

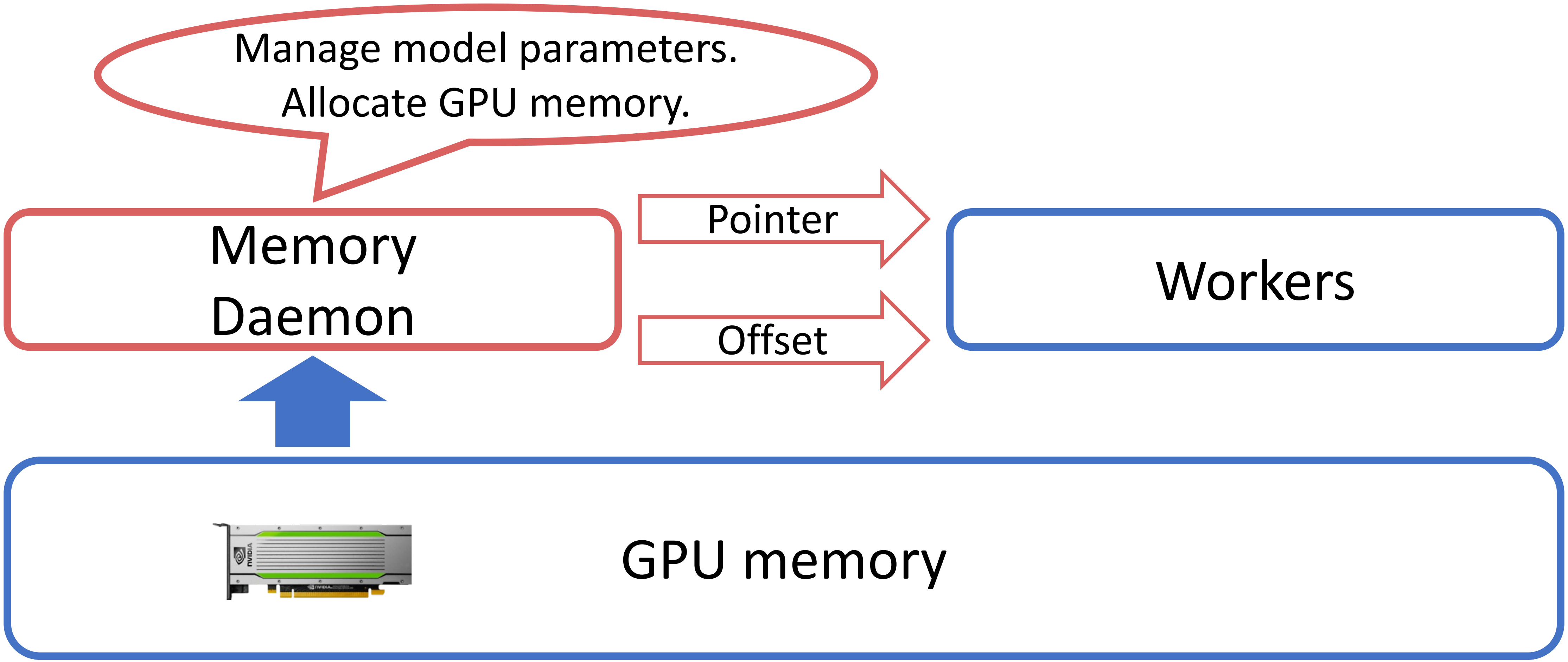
Model transmission → Pipelined model transmission

Memory allocation → Unified memory management

Task initialization

Task cleaning

Unified memory management



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Model transmission → Pipelined model transmission

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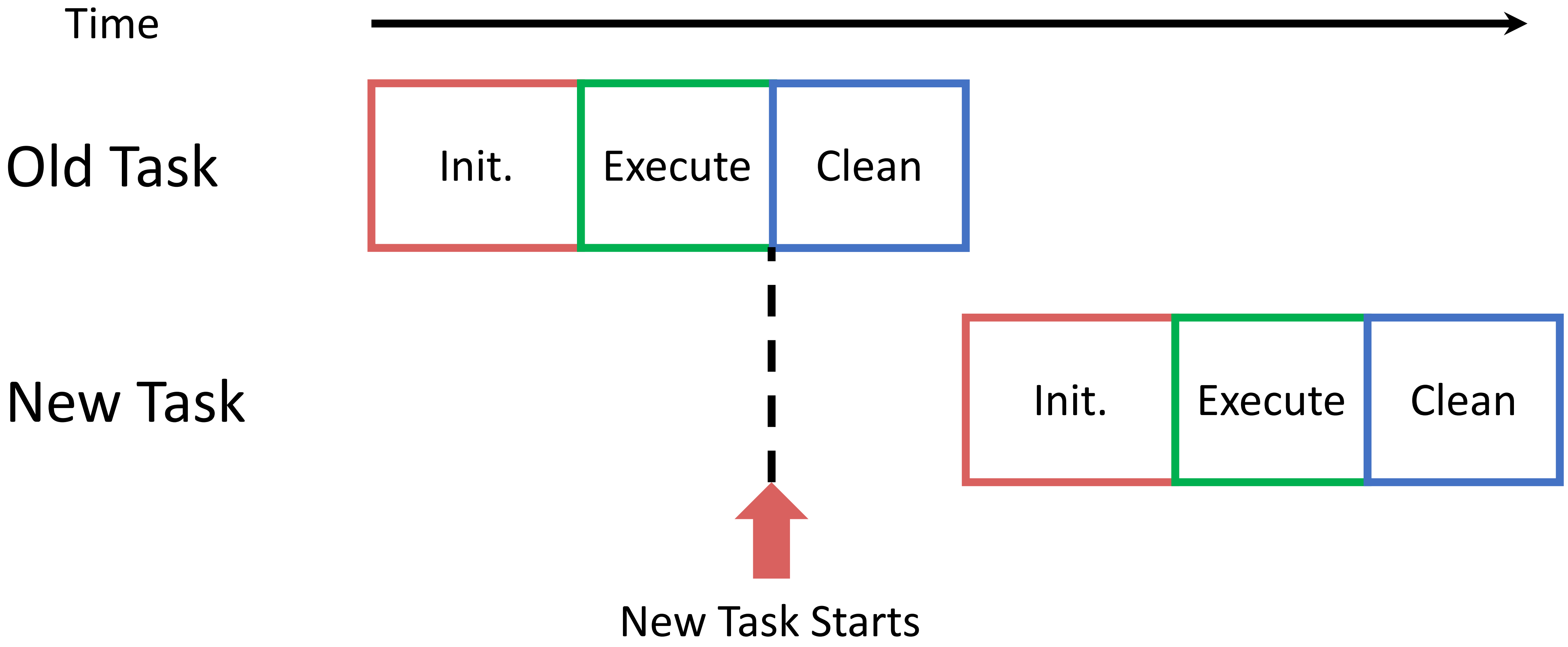
Task initialization

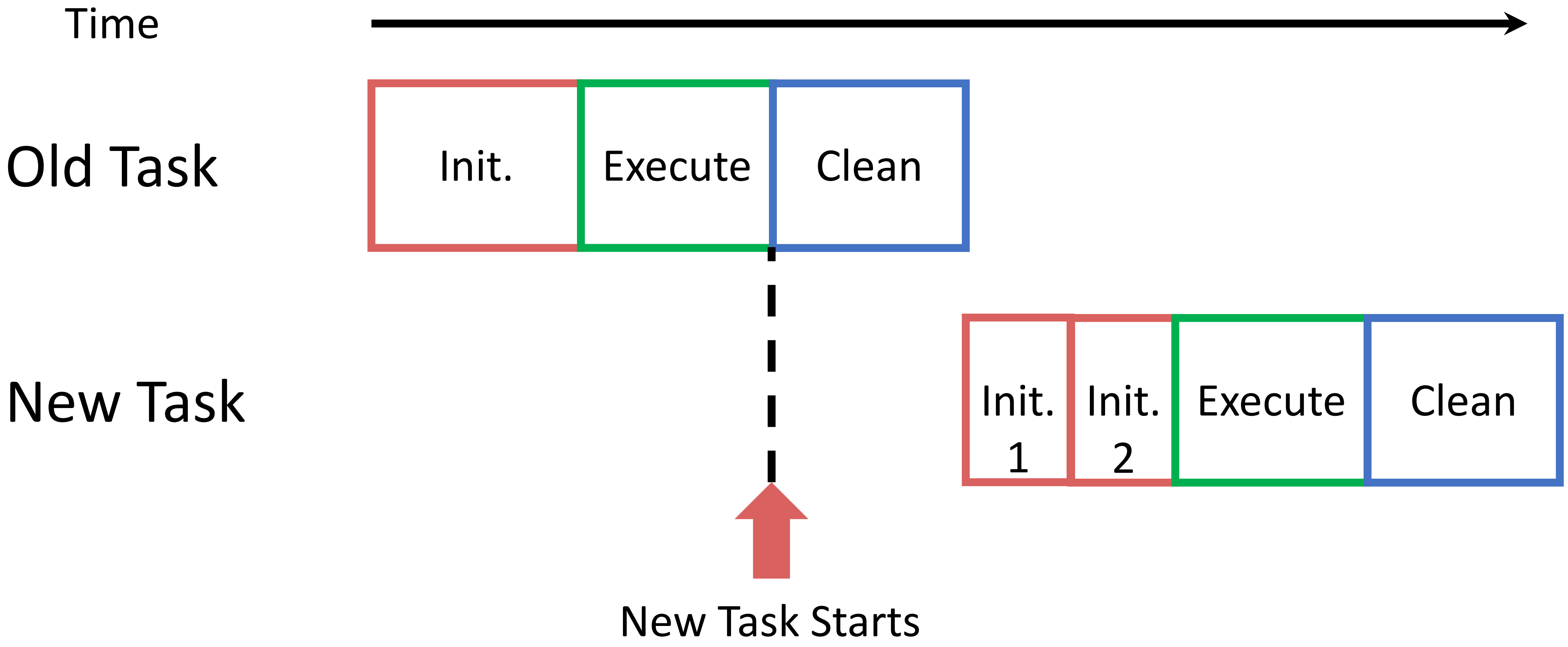
Task cleaning

Active-standby worker switching

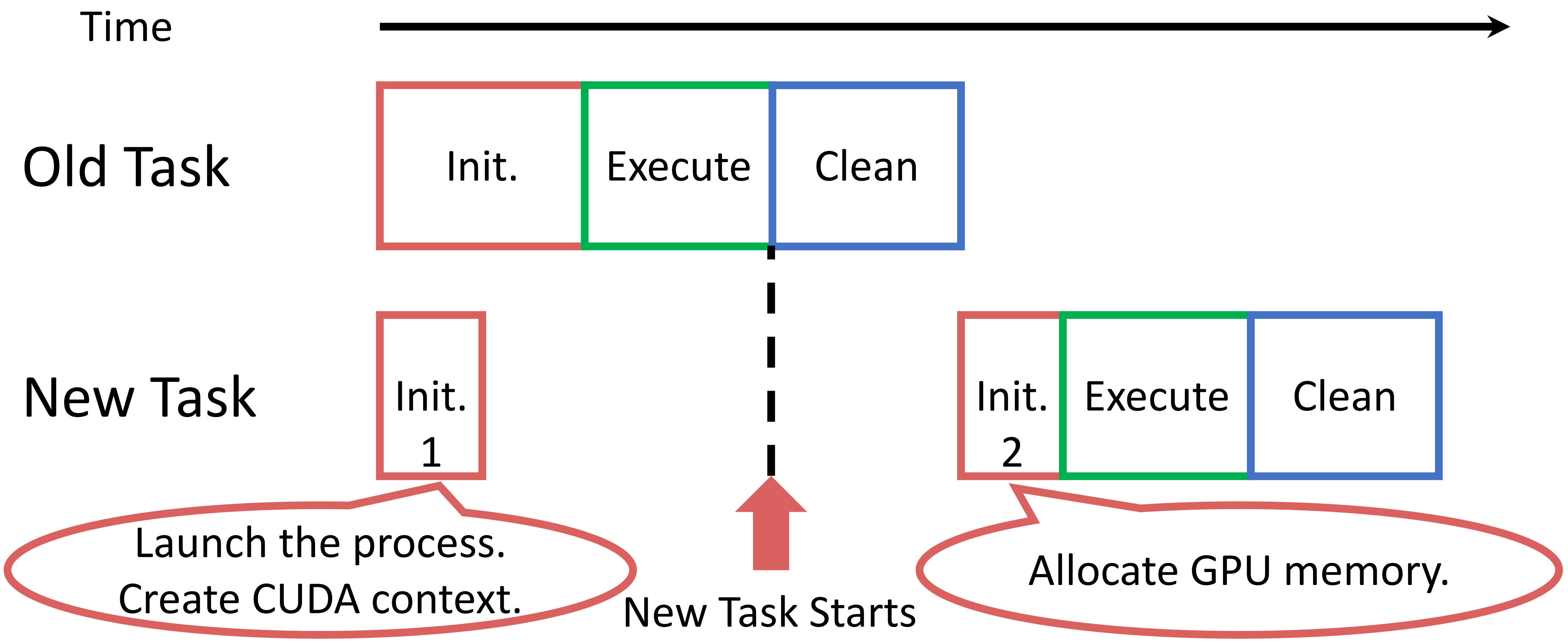
Active-standby worker switching



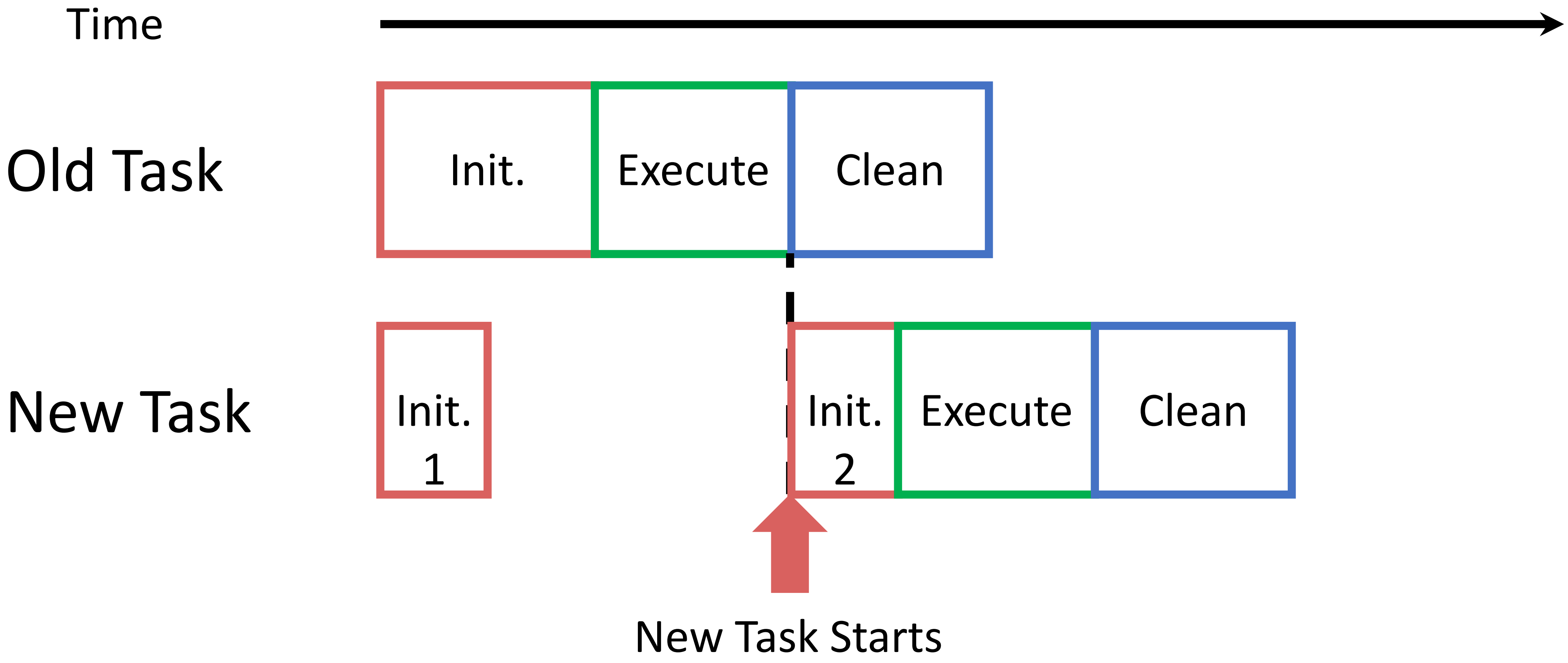
Active-standby worker switching



Active-standby worker switching



Active-standby worker switching



Implementation

- Testbed: AWS EC2
  - p3.2xlarge: **PCIe 3.0x16**, NVIDIA Tesla **V100** GPU
  - g4dn.2xlarge: **PCIe 3.0x8**, NVIDIA Tesla **T4** GPU
- Software
  - CUDA 10.1
  - PyTorch 1.3.0
- Models
  - ResNet-152
  - Inception-v3
  - BERT-base

Evaluation

- Can PipeSwitch satisfy SLOs?

- Can PipeSwitch provide high utilization?

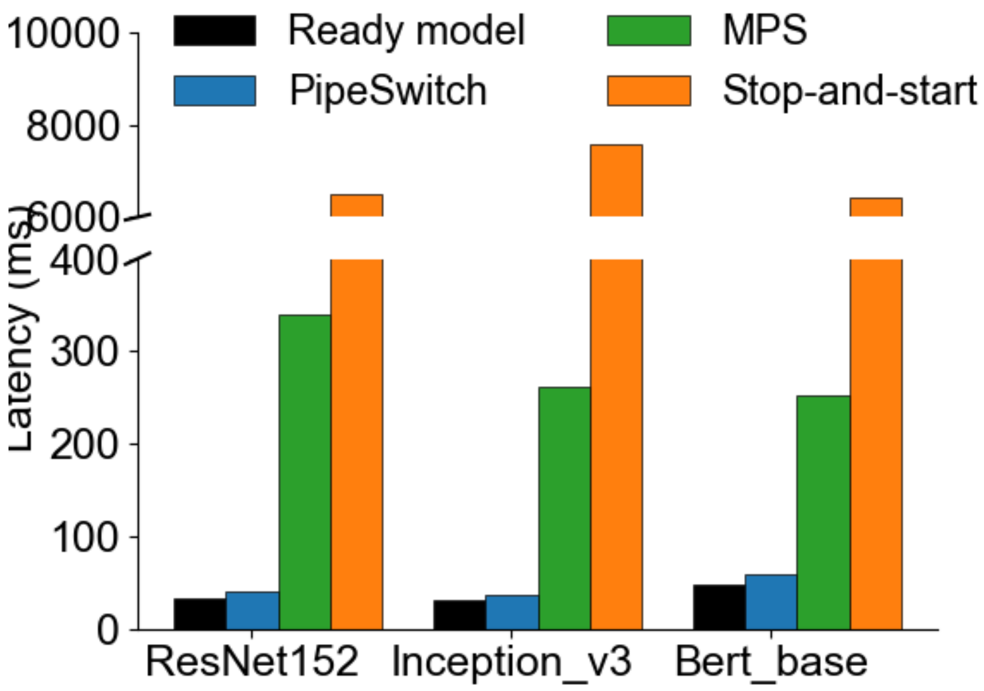
- How well do the design choices of PipeSwitch work?

Evaluation

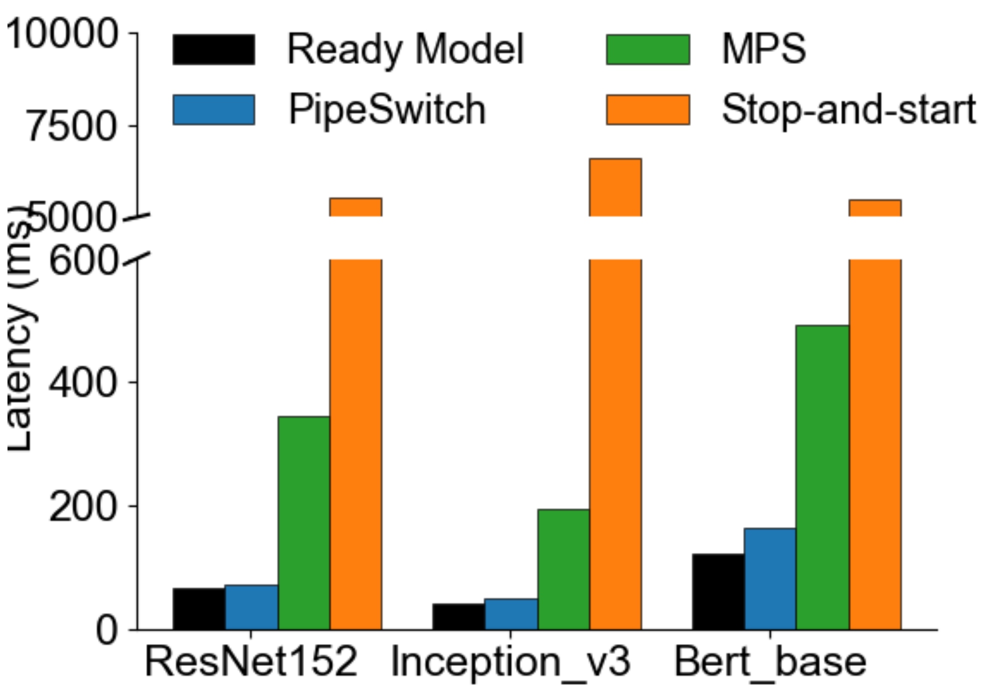
- Can PipeSwitch satisfy SLOs?
- Can PipeSwitch provide high utilization?
- How well do the design choices of PipeSwitch work?

PipeSwitch satisfies SLOs

NVIDIA Tesla V100

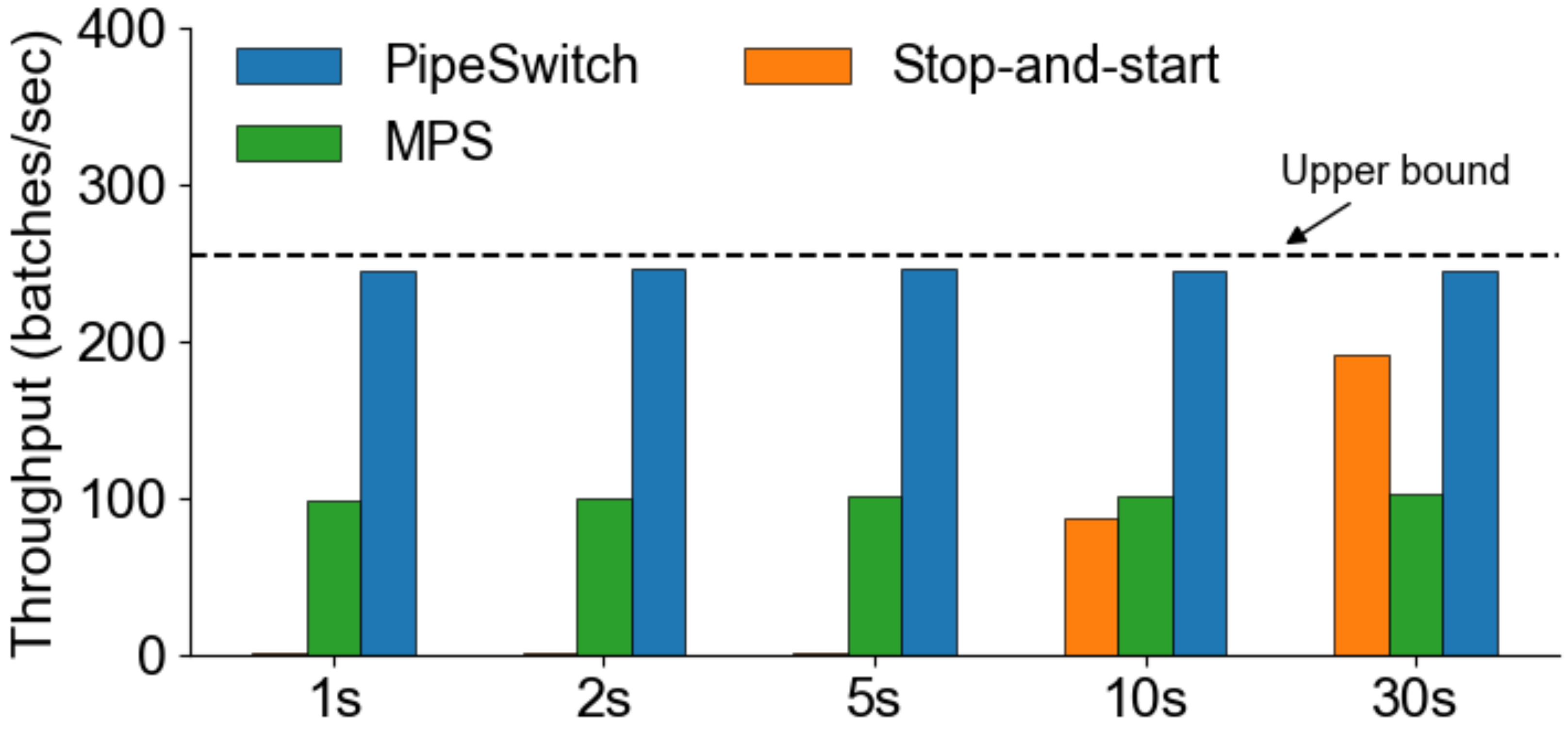


NVIDIA Tesla T4



PipeSwitch achieves low context switching latency.

PipeSwitch provide high utilization



Scheduling cycles

PipeSwitch achieves near 100% utilization.

Summary

- GPU clusters for DL applications suffer from low utilization
  - Limited share between training and inference workloads
- PipeSwitch introduces pipelined context switching
  - Enable GPU-efficient multiplexing of DL apps with fine-grained time-sharing
  - Achieve millisecond-scale context switching latencies and high throughput

Memory Management in Modern Computer Systems

- Memory Abstraction
  - NSDI’14 FaRM

- Demand paging: remote memory over RDMA
  - NSDI’17 InfiniSwap
  - OSDI’20 AIFM

- Demand paging: memory swapping between GPU memory and host memory
  - OSDI’20 PipeSwitch
  - NSDI’23 TGS

Transparent GPU Sharing in Container Clouds for Deep Learning Workloads

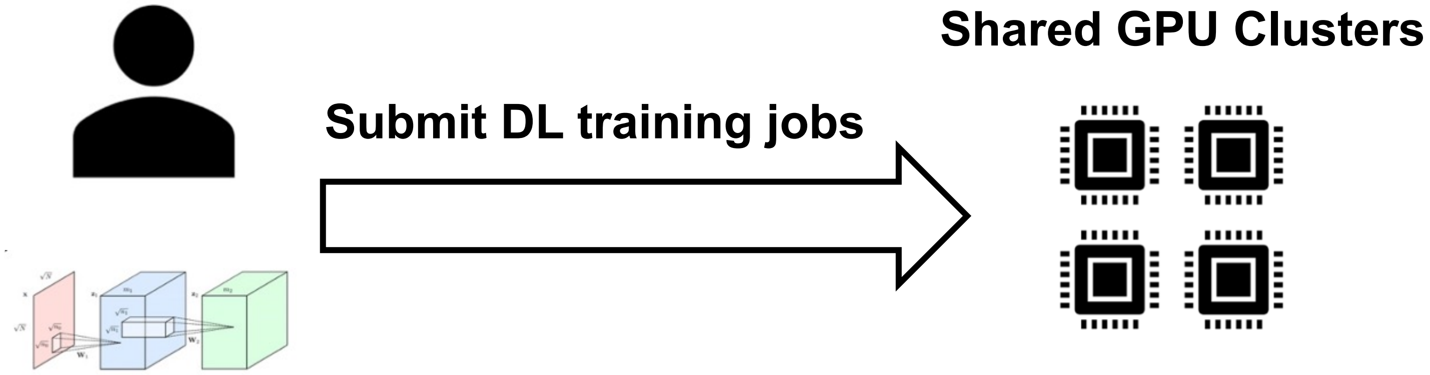
Bingyang Wu, Zili Zhang, Zhihao Bai, Xuanzhe Liu, Xin Jin

PEKING UNIVERSITY

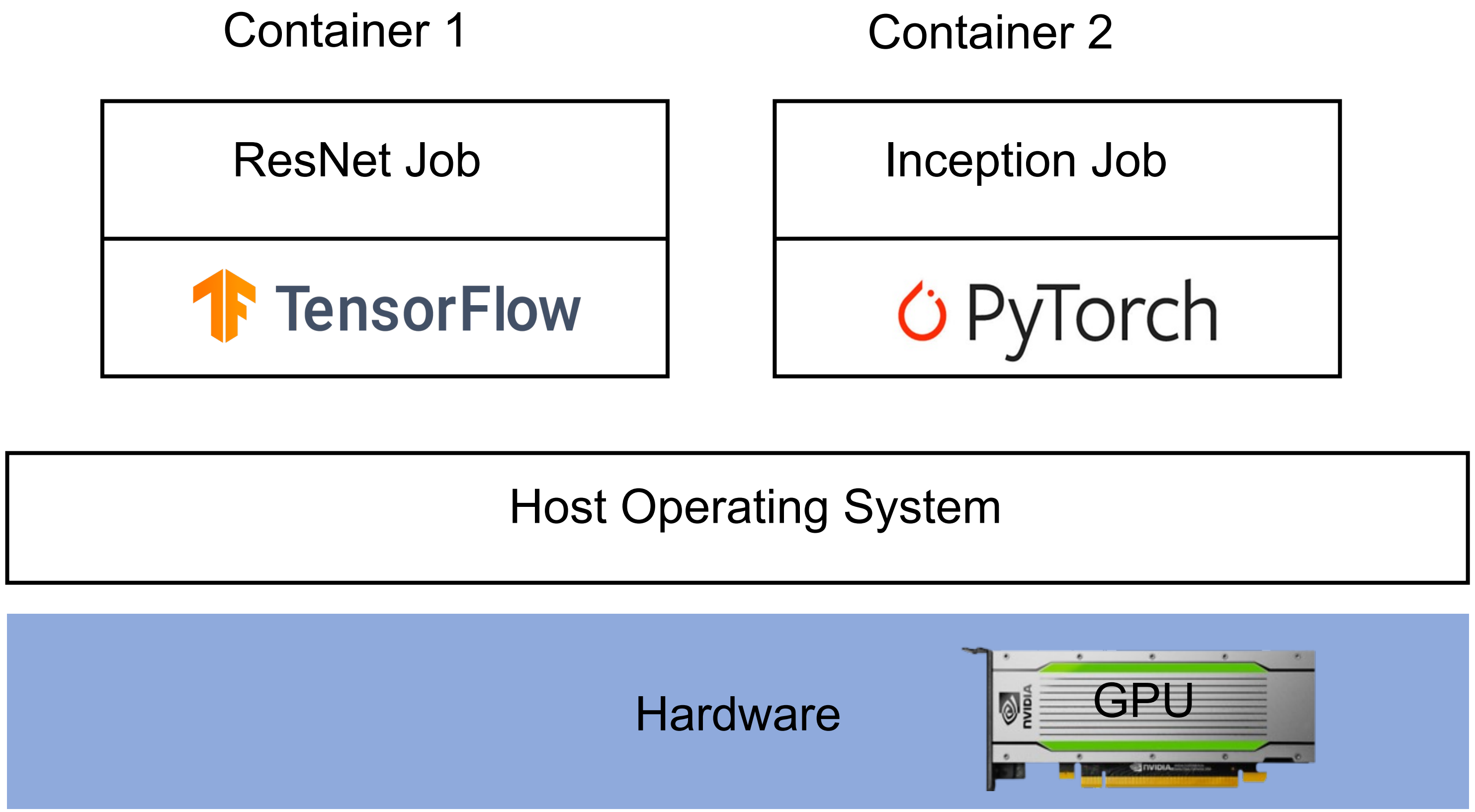
JOHNS HOPKINS UNIVERSITY

Deep learning training jobs: important workloads in datacenters

- Deep learning is widely used in many applications
  - Recommendation
  - Machine Translation
  - Voice Assistant
  - ……
- Deep learning models are often trained in shared GPU clusters



Deep learning training jobs in container clouds



Low GPU utilization in production

- Microsoft [1]: the average GPU utilization is only 52%
- Alibaba [2]: the median GPU utilization is no more than 10%
- Low GPU utilization is bad
  - Container clouds: idle GPUs are a huge waste
  - Users: longer queueing delay, longer job completion time

- **Root cause:** Each GPU is statically assigned to a single container

[1] M. Jeon, et al., “Analysis of large-scale multitenant GPU clusters for DNN training workloads,” in *USENIX ATC 2019*.
[2] W. Xiao, et al., “Antman: Dynamic scaling on GPU clusters for deep learning,” in *USENIX OSDI 2020*.

Existing GPU sharing solutions

- **Key idea:** Share GPUs to improve GPU utilization
- Classify DLT jobs into two classes
  - Production job: Run without performance degradation
  - Opportunistic job: Utilize spare GPU resources to execute
- SOTA solutions:
  - Application-layer solution：AntMan [OSDI' 20]
  - OS-layer solution: NVIDIA MPS, NVIDIA MIG

Application-layer solution: AntMan

- Custom DL framework
  - Modify TensorFlow (~4000 LoC) or PyTorch (~2000 LoC)
- Support GPU compute sharing and GPU memory oversubscription

- **Limitations:** Lack of Transparency
  - **Limited use cases:** restricts users to use particular frameworks
  - **Huge operation overhead:** need to maintain custom frameworks

OS-layer solution: NVIDIA MPS

- A software solution for GPU sharing provided by NVIDIA
- Limitations:
  - Low GPU utilization
    - Does not support GPU memory oversubscription
    - Requires application knowledge to properly set the resource limit
  - Weak fault isolation
    - When a job fails, other jobs may be affected and even fails

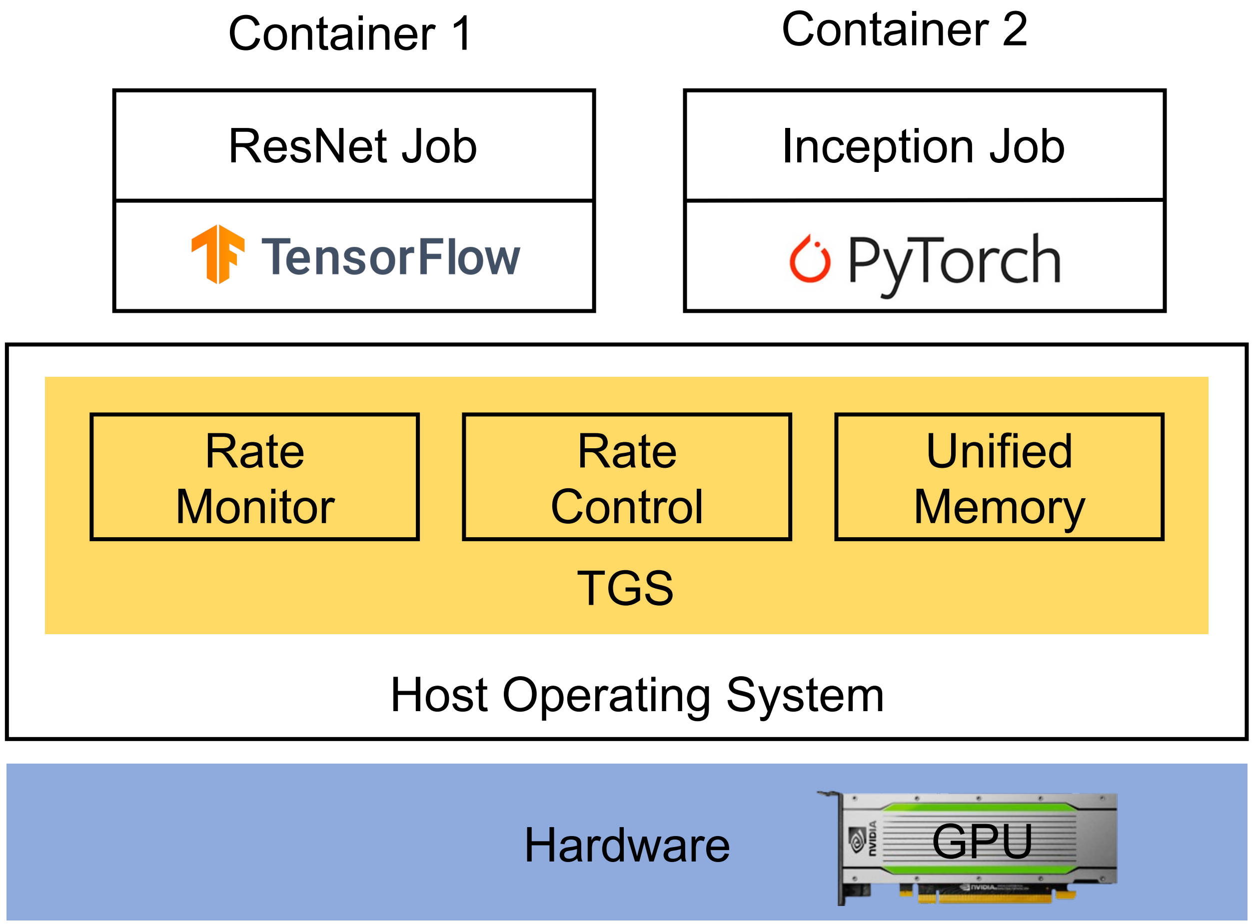
OS-layer solution: NVIDIA MIG

- A recent hardware solution for GPU sharing provided by NVIDIA
- Limitations:
    - Performance isolation
        - Cannot arbitrarily partition a GPU
        - Cannot dynamically change GPU resources
    - Compatibility
        - Only available on a few high-end GPUs
        - Does not support GPU sharing for the multi-GPU instance

A more practical solution: TGS

	AntMan	MPS	MIG	TGS
Transparency		✓	✓	✓
High utilization	✓			✓
Performance isolation	✓	✓	✓	✓
Fault isolation	✓		✓	✓

TGS architecture

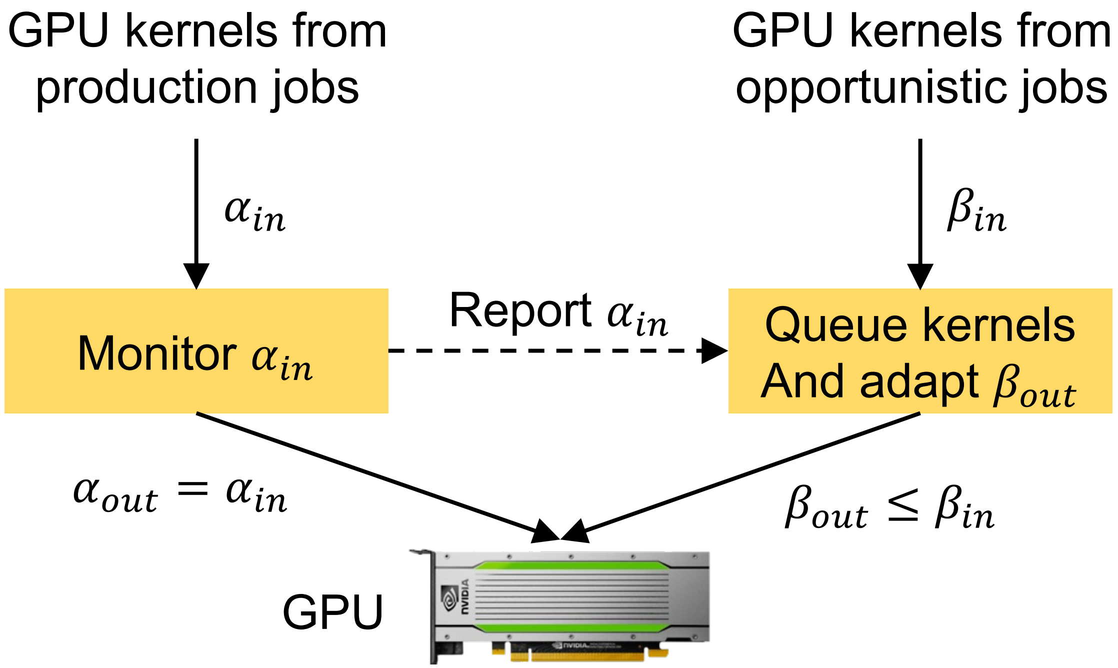


Sharing GPU compute resources

- Strawman solution: priority scheduling
  - Control the opportunistic job based on the GPU kernel queues

- Low GPU utilization:
  - The state of queues do not reflect the remaining GPU resources

Adaptive rate control of TGS



Sharing GPU memory resources

- Weak Fault isolation: total GPU memory consumption may exceed GPU memory capacity and cause OOM
- Low GPU utilization: some jobs always claim all GPU memory

- Application-layer technique cannot be used in the OS layer
  - Cannot directly ask DL framework to release unused GPU memory
  - Cannot directly change pointer address from GPU memory to host memory

Transparent unified memory of TGS

- **Key ideas:** leverage CUDA unified memory to transparently unify GPU memory and host memory

- High GPU utilization: The actual physical GPU memory is allocated when jobs first access to them
- Fault isolation: When GPU memory is oversubscribed, TGS changes virtual memory mapping to evict GPU memory of opportunistic job to host memory

Evaluation setup

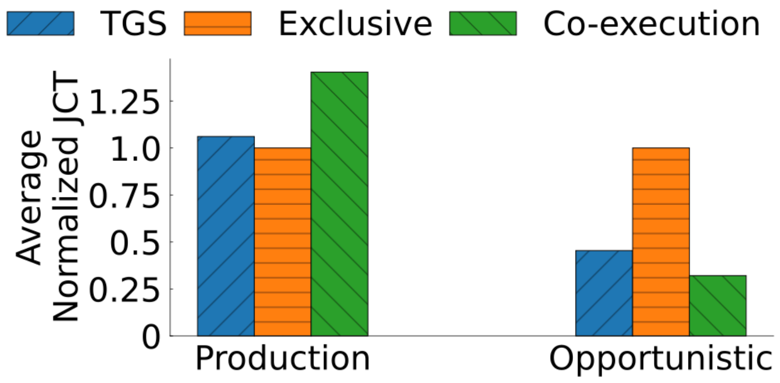
- Implementation: ~3000 LoC C++ & Python
  - Integration with Docker and Kubernetes
- Testbed: NVIDIA A100 GPUs and NVIDIA V100 GPUS
- Trace: Philly Trace from Microsoft [Jeon et al. 2019]
- Models
  - CV: ResNet, ShuffleNet, MobileNet
  - Graph: GCN
  - NLP: Bert, GPT-2
  - Recommendation: DLRM

Evaluation baselines

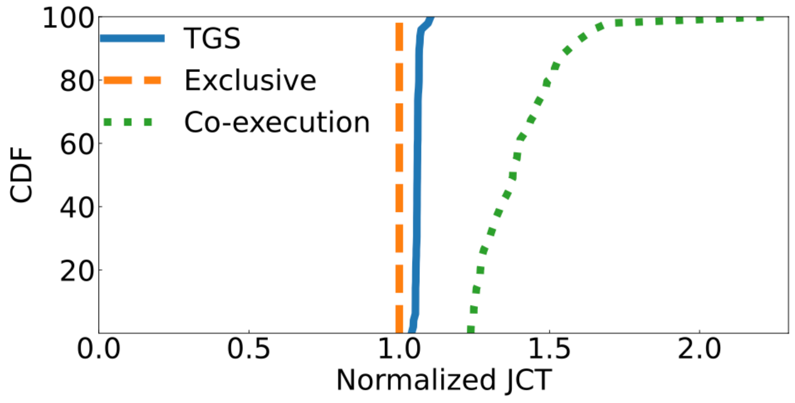
- TGS: our work
- AntMan: the state-of-the-art application-layer solution
- MPS: manually set appropriate limit
- MIG: manually set best configuration
- Exclusive: give exclusive access to a GPU
- Co-execution: share a GPU without any control

Mixed workload job stream

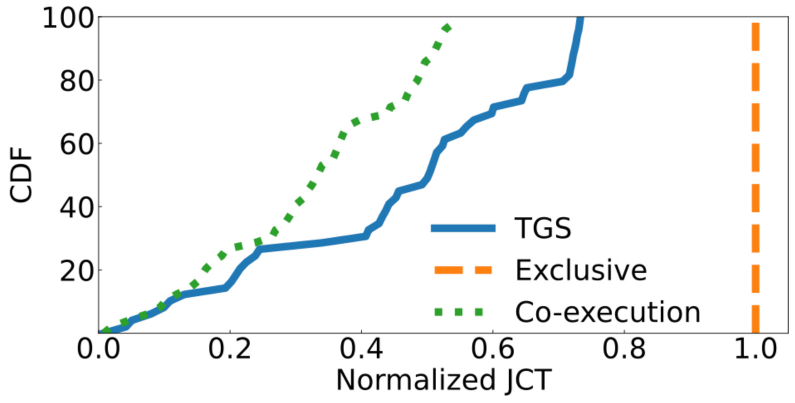
- A job stream contains 50 production jobs and 50 opportunistic jobs
- Opportunistic jobs: 52% JCT reduction compared to Exclusive
- Production jobs: 21% JCT reduction compared to Co-execution



(a) Average JCT.



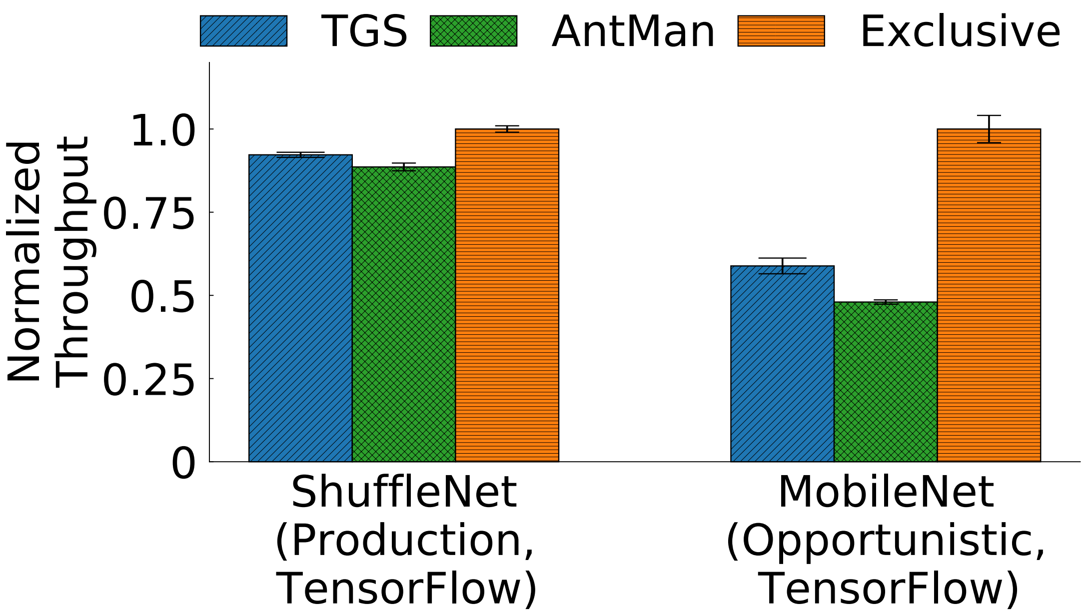
(b) CDF of production jobs.



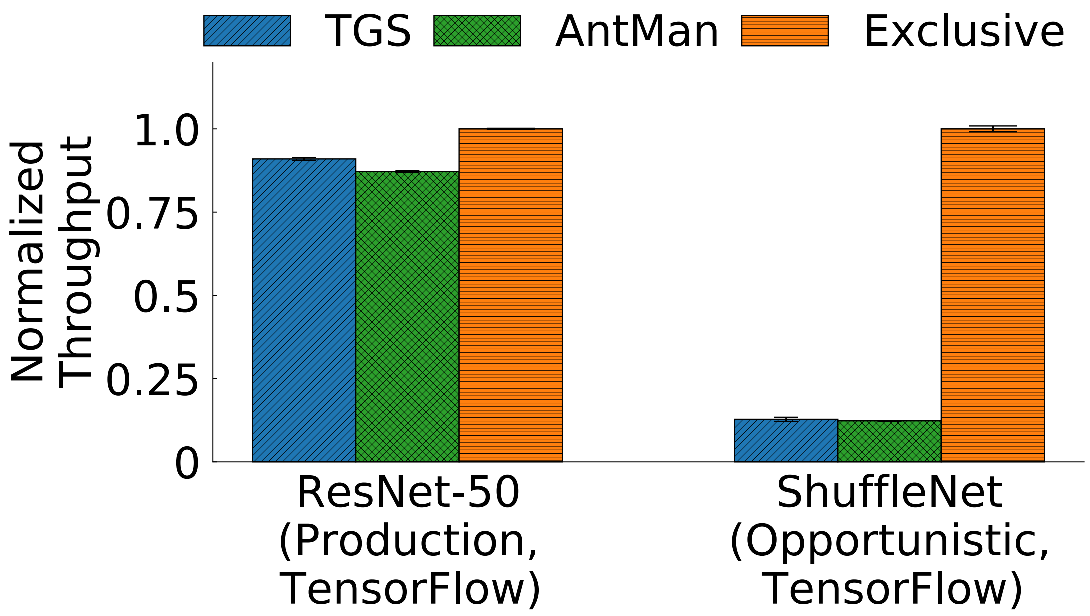
(c) CDF of opportunistic jobs.

Comparison with AntMan

- Achieve comparable performance in different contention scenarios
- Provide transparency without sacrificing performance



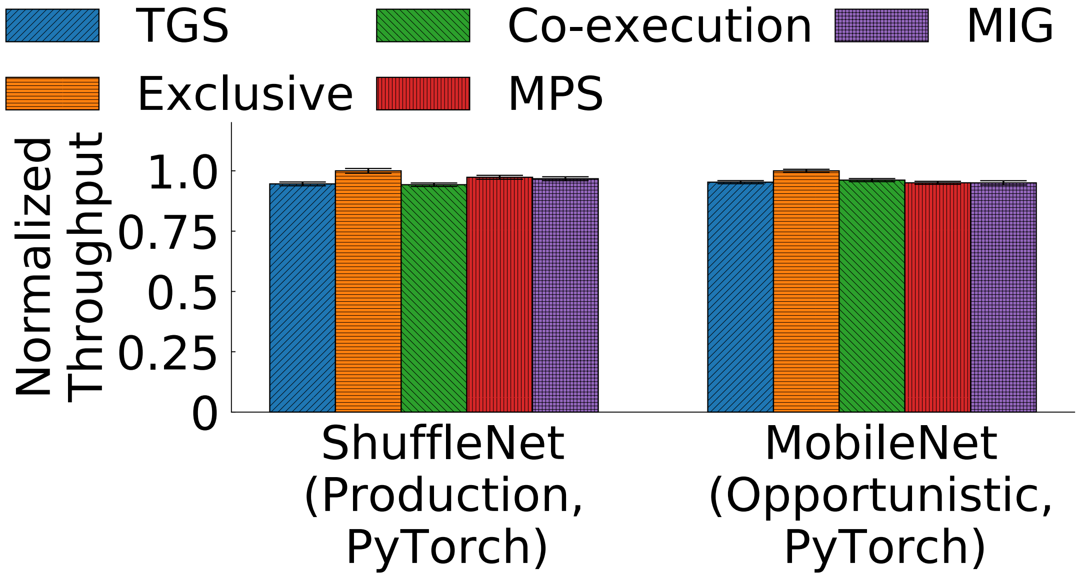
(a). Low-contention scenario



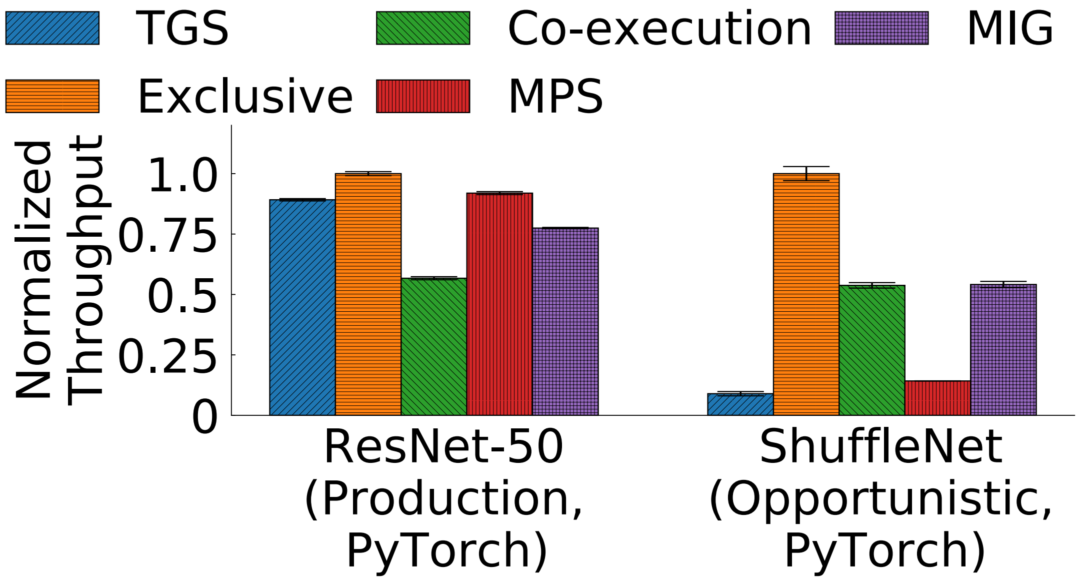
(b).High-contention scenario

Adaptive rate control of TGS

- TGS protects productions job with little overhead, while providing remaining GPU resources to opportunistic jobs



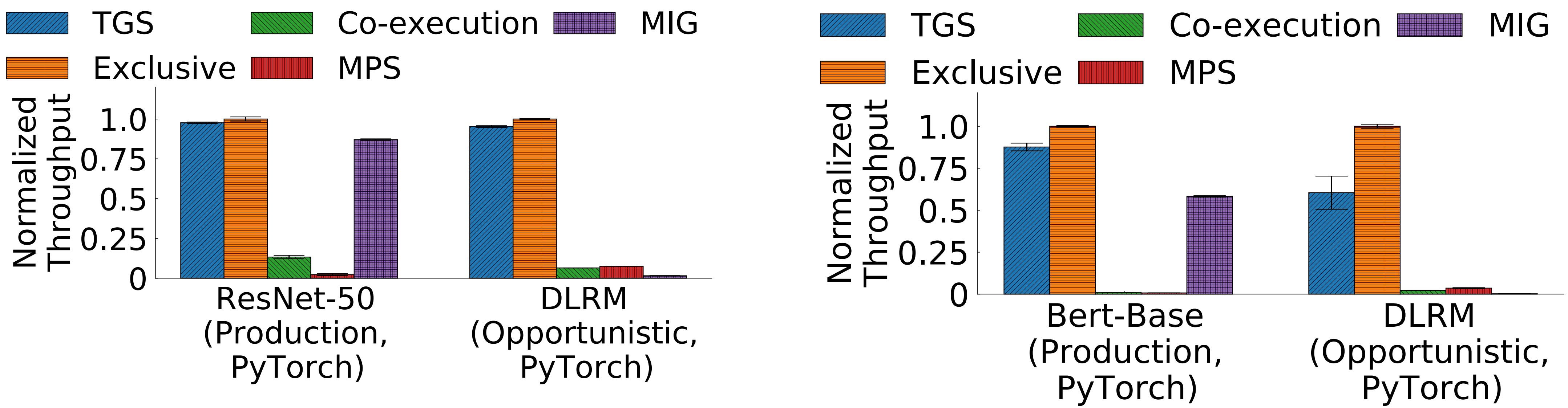
(a). Low-contention scenario



(b).High-contention scenario

Transparent unified memory of TGS

- TGS protects production jobs under GPU memory oversubscription
- 15× throughput improvement compared to MPS



(a). Low-contention scenario

(b).High-contention scenario

More experiments in our paper

- System overhead
- Convergence of TGS in different scenarios
  - Convergence of the rate control under dynamic job arrival
  - Convergence of the rate control under dynamic resource usage
- Supporting different DL frameworks
- GPU sharing for large model training

Conclusion

- TGS provides transparent GPU sharing to DL training in container clouds with four important properties:
  - Transparency
  - Performance isolation
  - High GPU utilization
  - Fault isolation
- TGS improves the throughput of the opportunistic job by up to 15× compared to the existing OS-layer solution MPS

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Thanks!