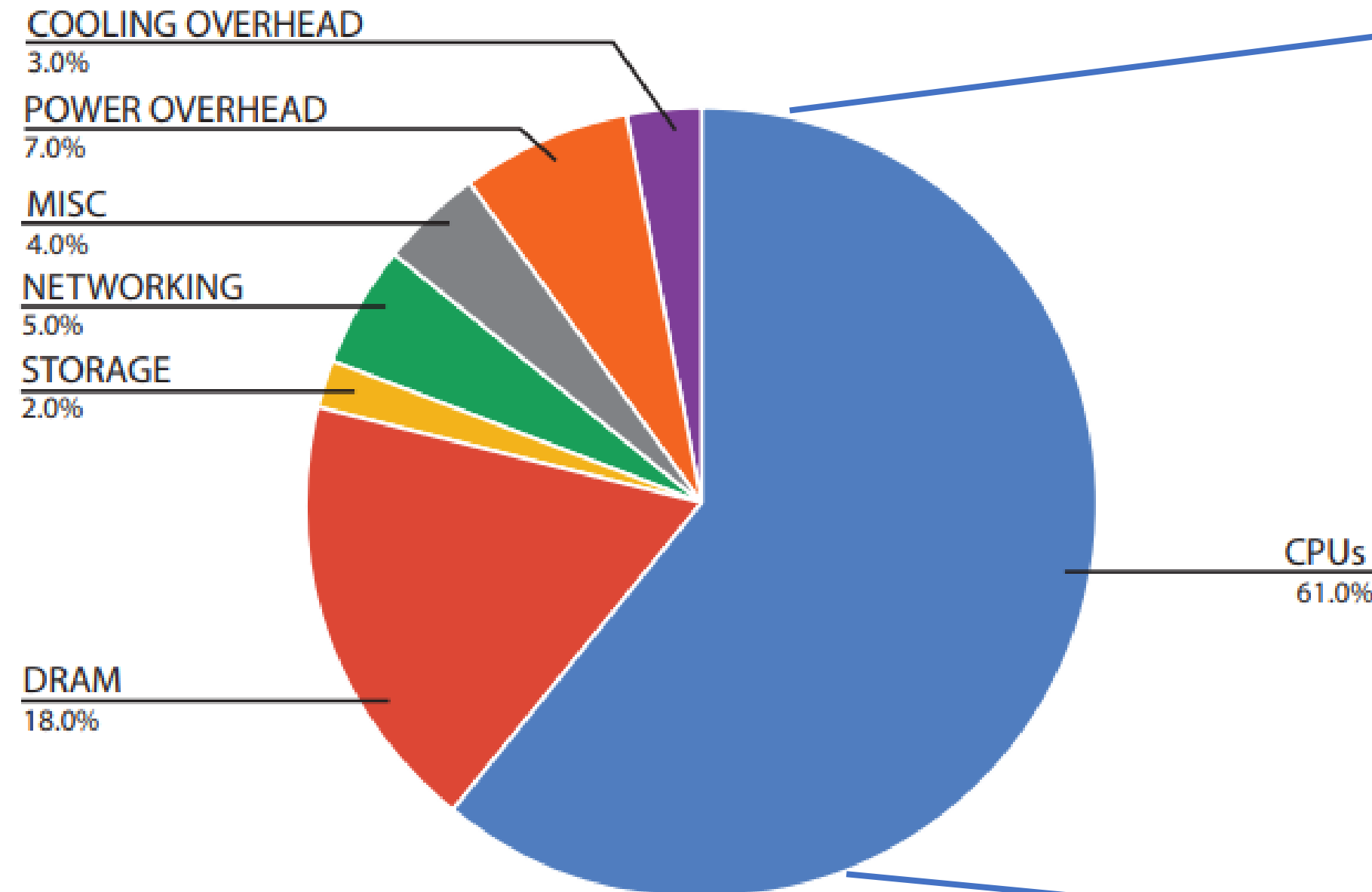


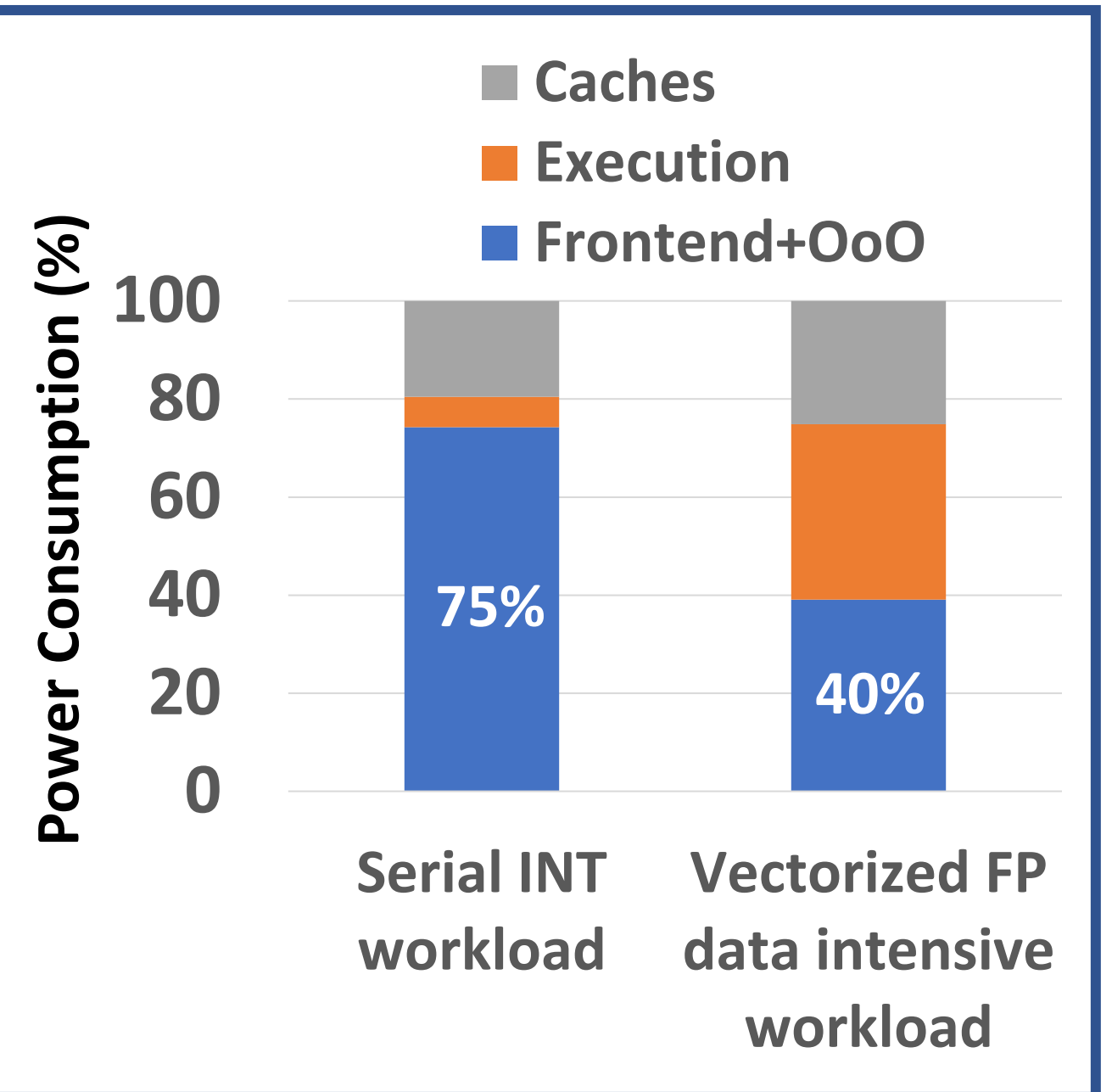
SIMR: Single Instruction Multiple Request Processing for Energy-Efficient Data Center Microservices

Mahmoud Khairy*, Ahmad Alawneh, Aaron Barnes, and Timothy G. Rogers
Purdue University

Datacenter Power Breakdown



**Datacenter Power Breakdown
(from Google)**



CPU Power Breakdown

25-45% of datacenter power is consumed in CPU's instruction supply (frontend & OoO)

1 Application, Million of Users

Google

facebook

Private Datacenter

Uber



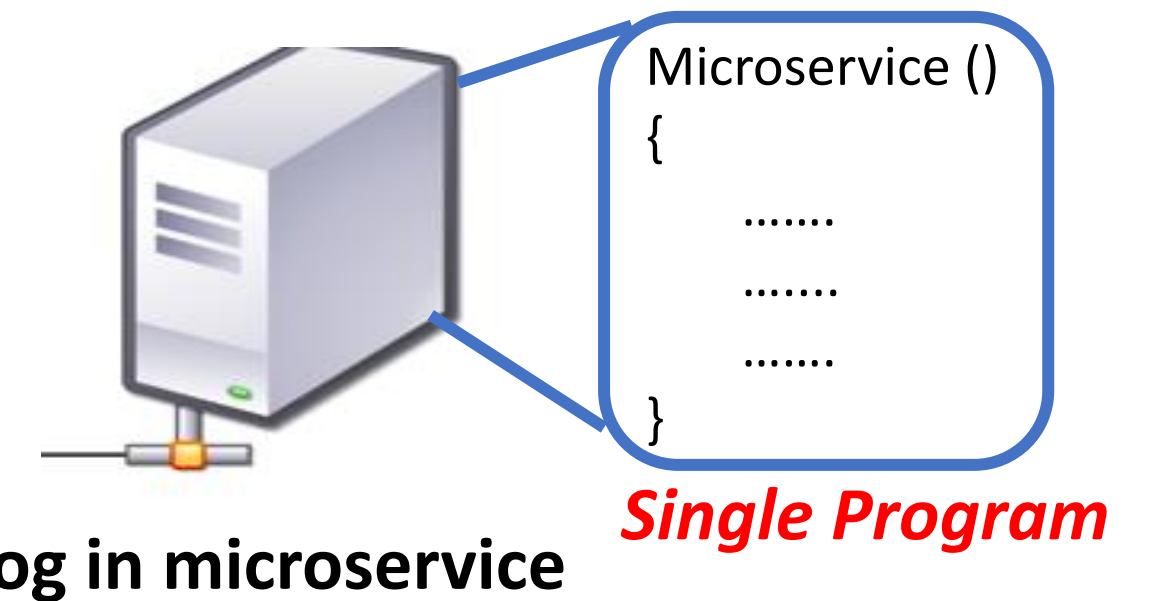
Public Datacenter

“Similar” Request-Level Parallelism

1000s of independent requests are all running the same code

Log-in reqs
("xyz", "1234")
("john", "5678")
("ma98", "4444")
("mah", "ko56")

Multiple Data



search reqs
("purdue univ")
("arsenal fc")
("elections 2024")
("stock today")



Key Observation #1: Single Program Multiple Data (SPMD) are abundant in the datacenters

Server Workloads on GPU's

- **Key Idea:** Exploit SPMD by batching requests and run them on GPU's Single Instruction Multiple Thread (SIMT) or CPU's SIMD
- **Advantage:** Significant energy efficiency (throughput/watts) vs multi-threaded CPU
- **Drawbacks:**
 - (1) Hindering programmability (C++/PHP vs CUDA/OpenCL)
 - (2) Limited system calls support
 - (3) High service latency (10-6000x)
 - GPUs tradeoff single threaded optimizations (OoO, speculative execution, etc.) in favor of excessive multithreading
 - In SIMD, relying on branch predicates & fine grain context

Rhythm: Harnessing Data Parallel Hardware for Server Workloads

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Rhythm, ASPLOS 2014

MemcachedGPU: Scaling-up Scale-out Key-value Stores

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MemcachedGPU, SoCC 2015

ispc: A SPMD Compiler for High-Performance CPU Programming

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William R. Mark
Intel Corporation
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ispc, InPar 2012

Recall: GPUs and SIMDs were designed to execute data parallel portion (i.e., loops) not the entire application

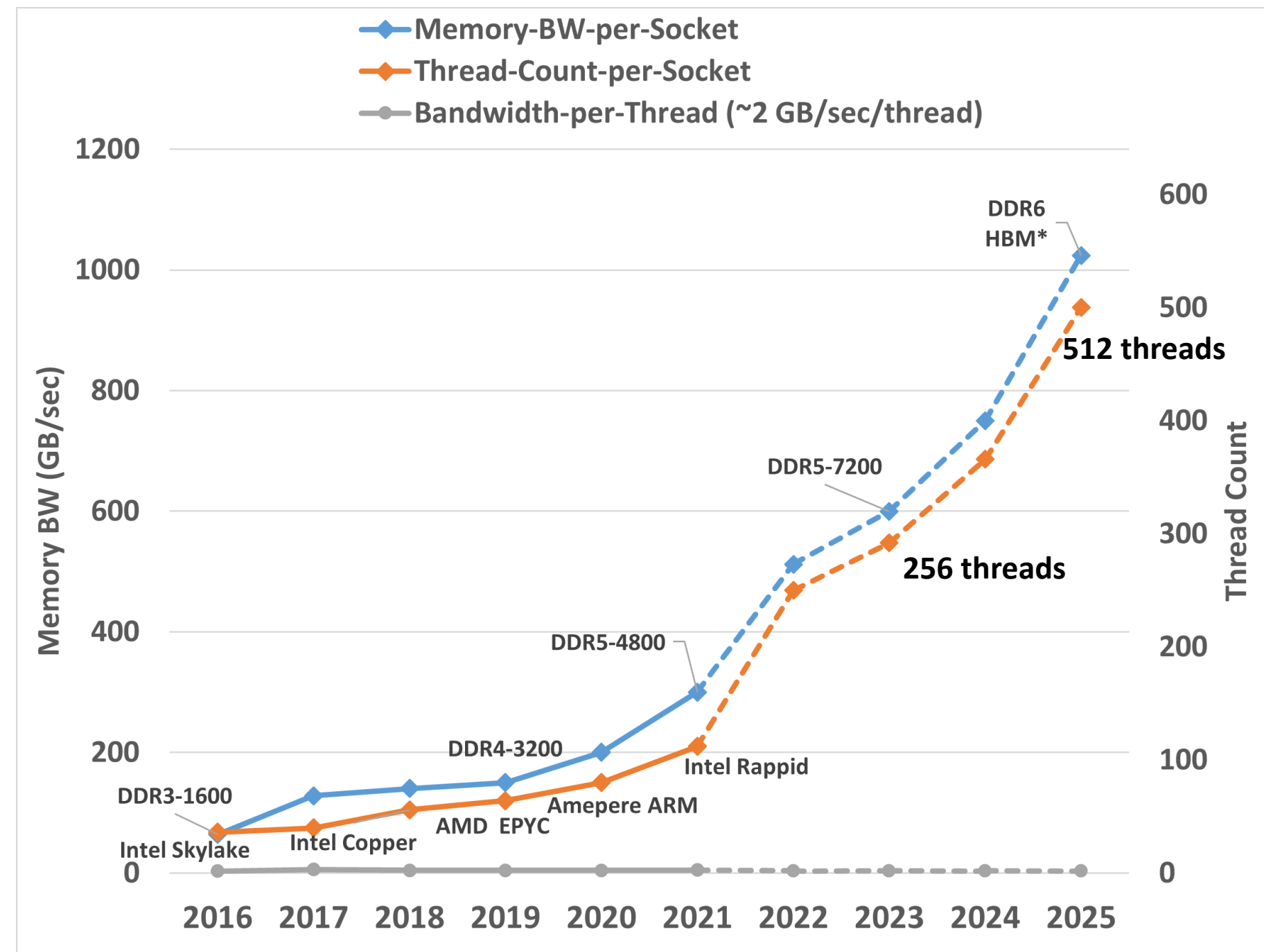
“Slower but energy-efficient wimpy cores only win for general data center workloads if their single-core speed is reasonably close to that of mid-range brawny cores”

Up to 2x slower latency should be tolerated by data center providers





Urs Hölzle
Google SVP

Off-Chip BW Scaling



Key Observation #2: There is available headroom to increase on-chip throughput (thread count) in the foreseeable future.

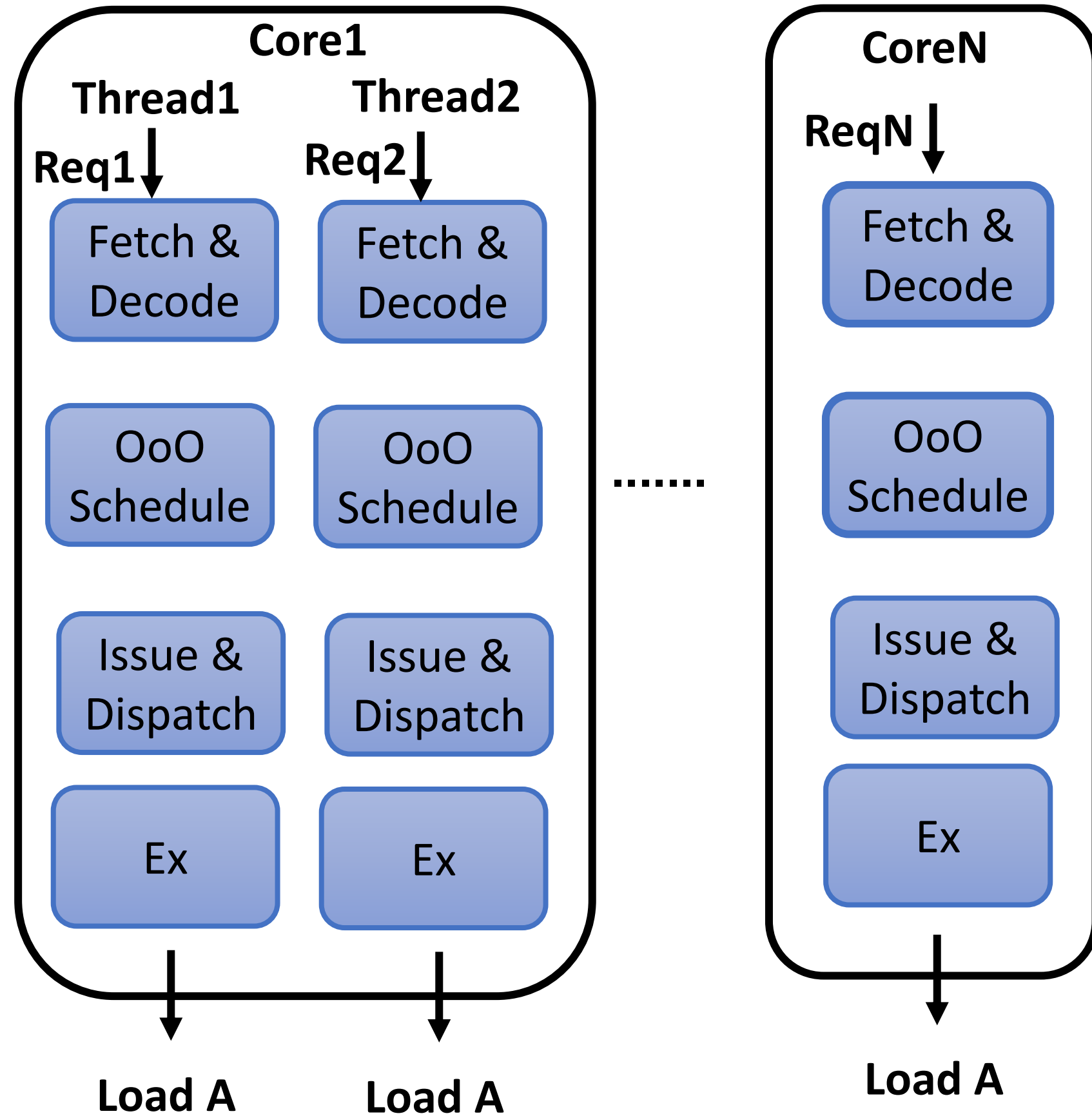
How to increase on-chip throughput of CPU?

- Direction#1 (industry standard): Add more Chiplets + Cores + SMT 
- Direction#2 (this work): Move to *SIMT* 
 - More energy efficient (throughput/watts)
 - Cost-effective (throughput/area)
 - Better scalability

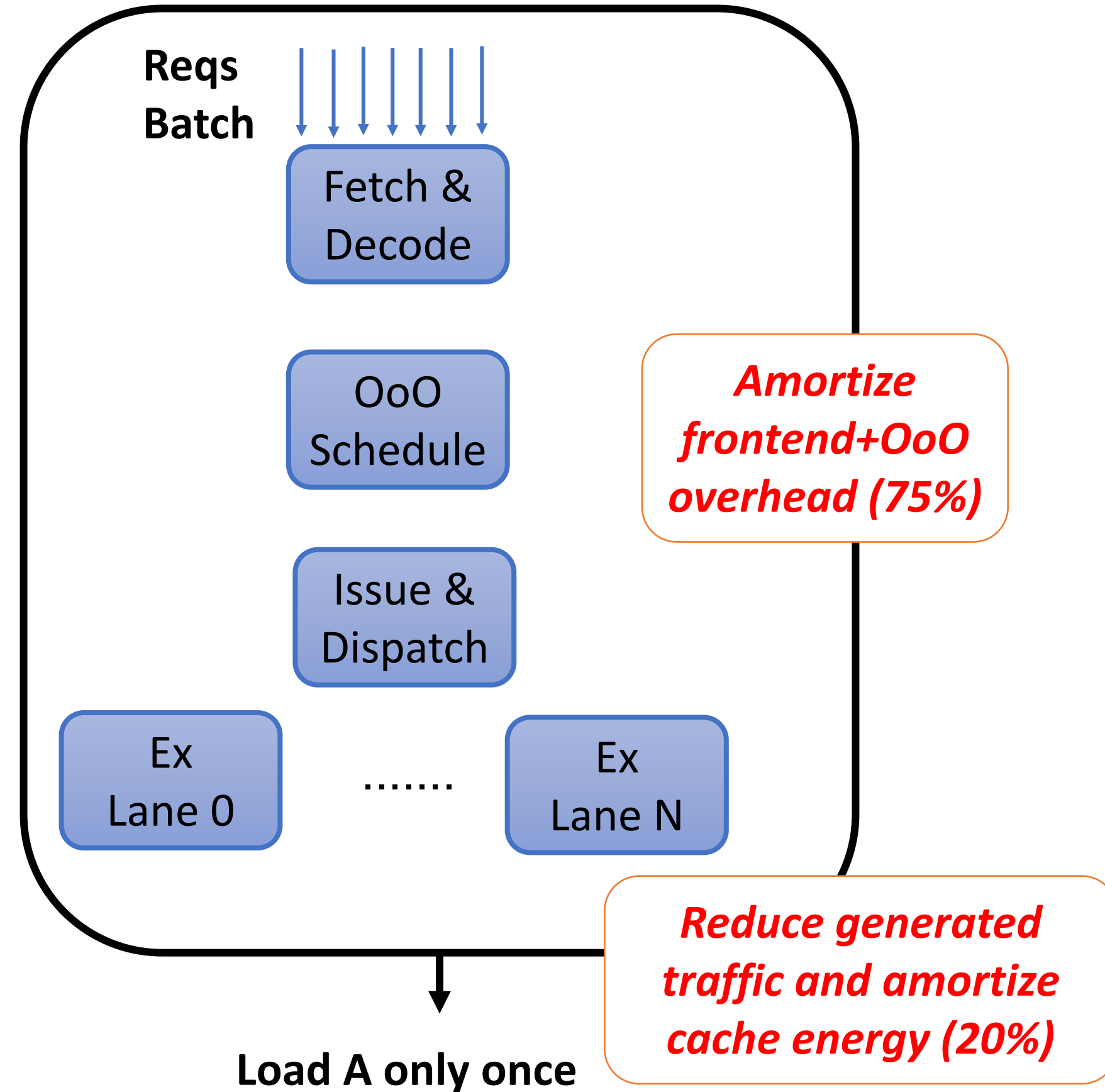
“Let’s bring SIMD efficiency to the CPU world!”

SIMT Efficiency

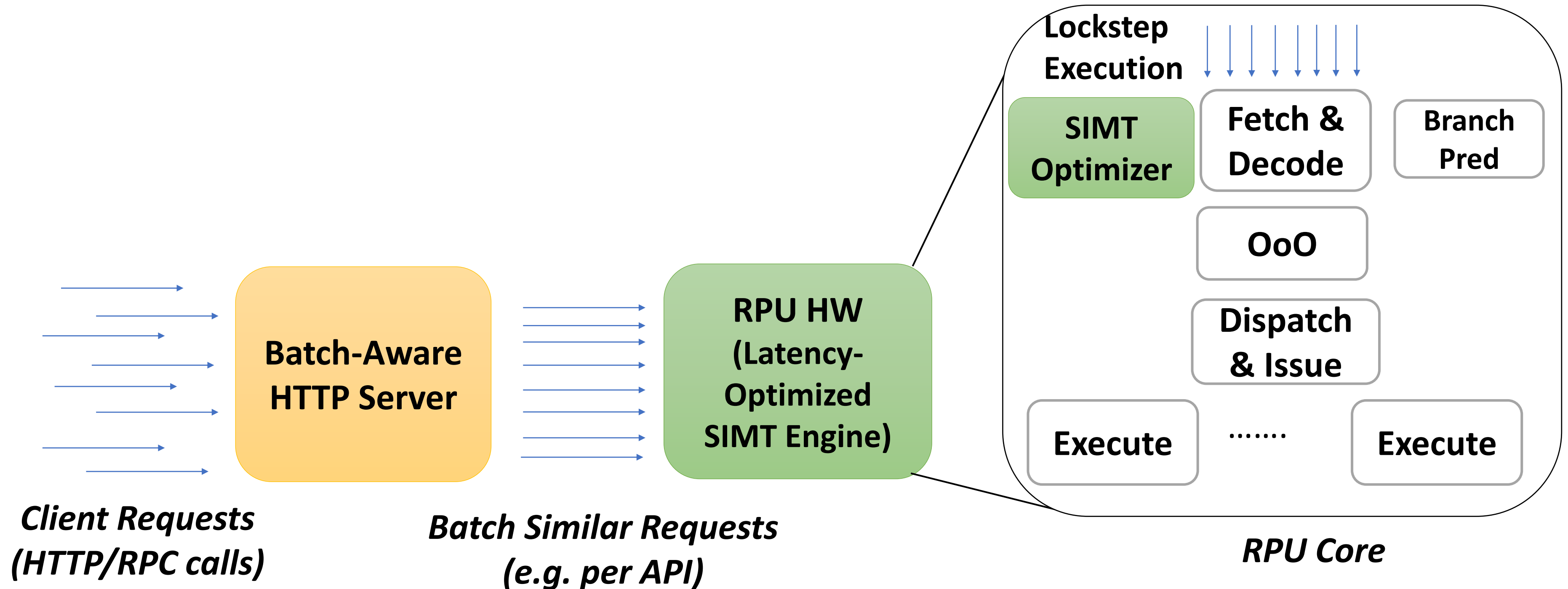
CPU Multi-Core with Simultaneous Multi-Threading



Request Processing Unit (RPU)
SIMT+OoO Architecture



SIMR System Overview



CPU vs GPU vs RPU

Metric	CPU	GPU	RPU
Core model	OoO	In-Order	OoO
Programming	General-Purpose	CUDA/OpenCL	General-Purpose
ISA	x86/ARM	HSAIL/PTX	x86/ARM
System Calls Support	Yes	No	Yes
Thread grain	Coarse grain	Fine grain	Coarse grain
Threads per core	Low (1-8)	Massive (2K)	Moderate (8-32)
Thread model	SMT	SIMT	SIMT
Consistency	Variant	Weak+NMCA*	Weak+NMCA*
Interconnect	Mesh/Ring	Crossbar	Crossbar

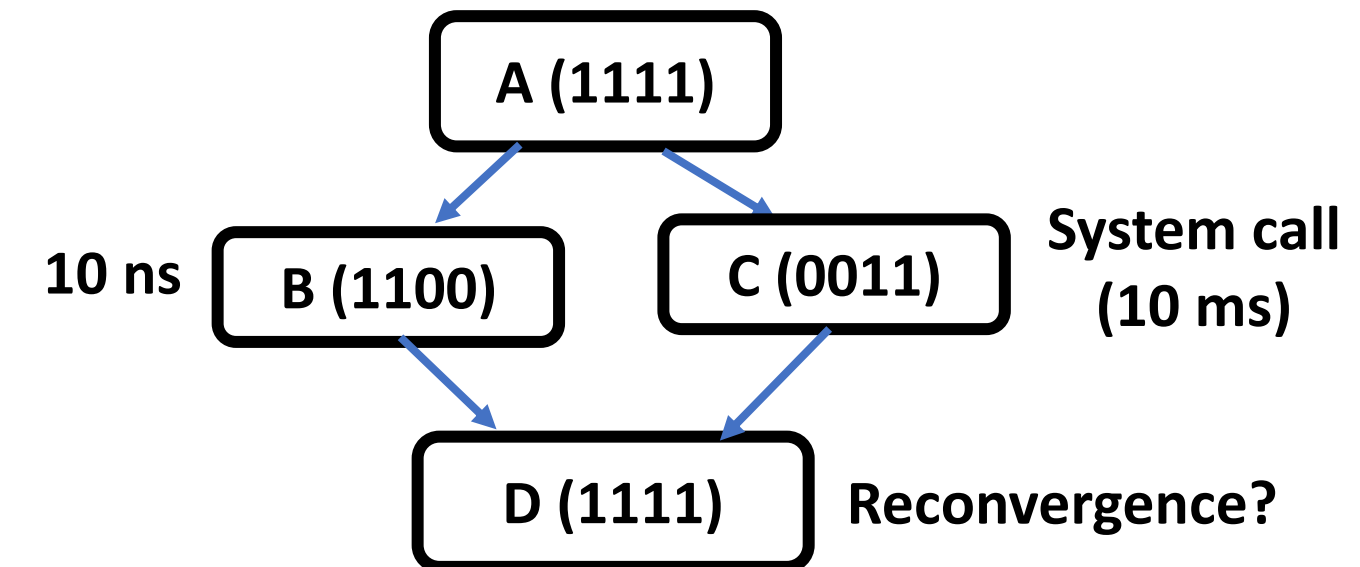
The RPU takes advantage of the latency optimizations and programmability of the CPU

& SIMT efficiency and memory model scalability of the GPU

*NMCA: non-multi copy atomicity

RPU's Challenges

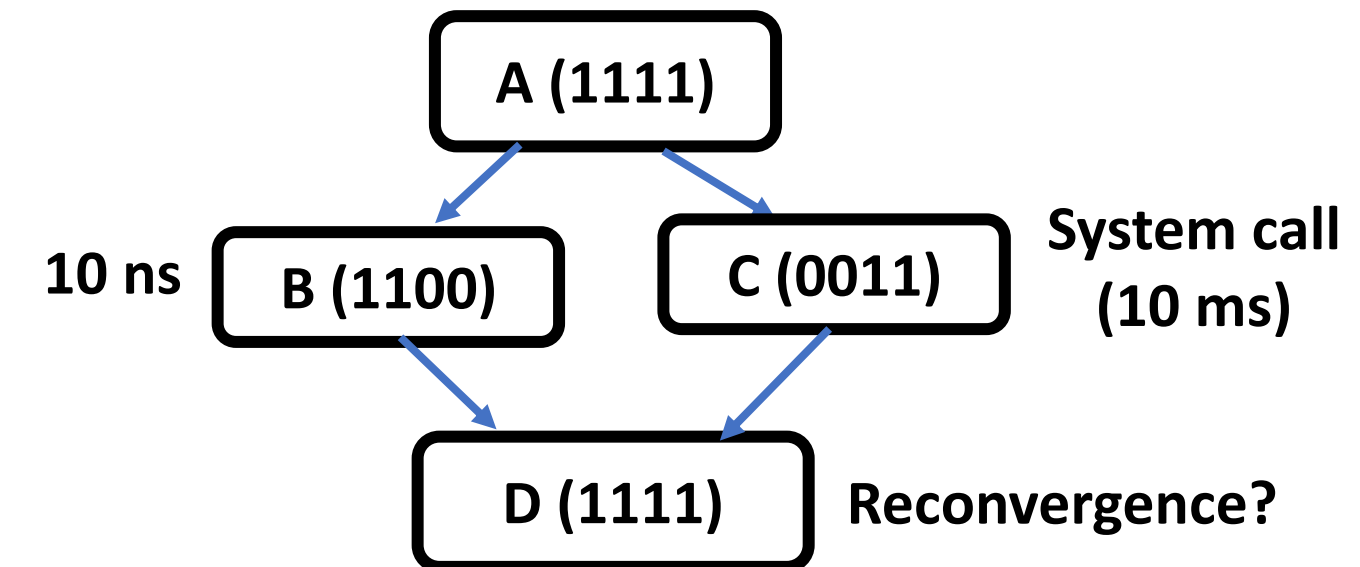
- Control Divergence
 - Challenge: Control divergence with high latency path
 - Solution: System-level batch split
- Memory Divergence
 - Challenge: Cache contention & bank conflicts
 - Solution: Batch tuning, stack/memory coalescing and SIMR-aware memory allocation
- Larger execution units & cache resources
 - Challenge: Higher instruction execution & L1 hit latency
 - Solution: Exploit low IPC and less generated traffic



RPU's Challenges

- Control Divergence

- Challenge: Control divergence with high latency path
- Solution: System-level batch split



- Memory

- Challenge: Control divergence with high latency path
- Solution: Batch splitting, stack coalescing and SIMR-aware memory allocation

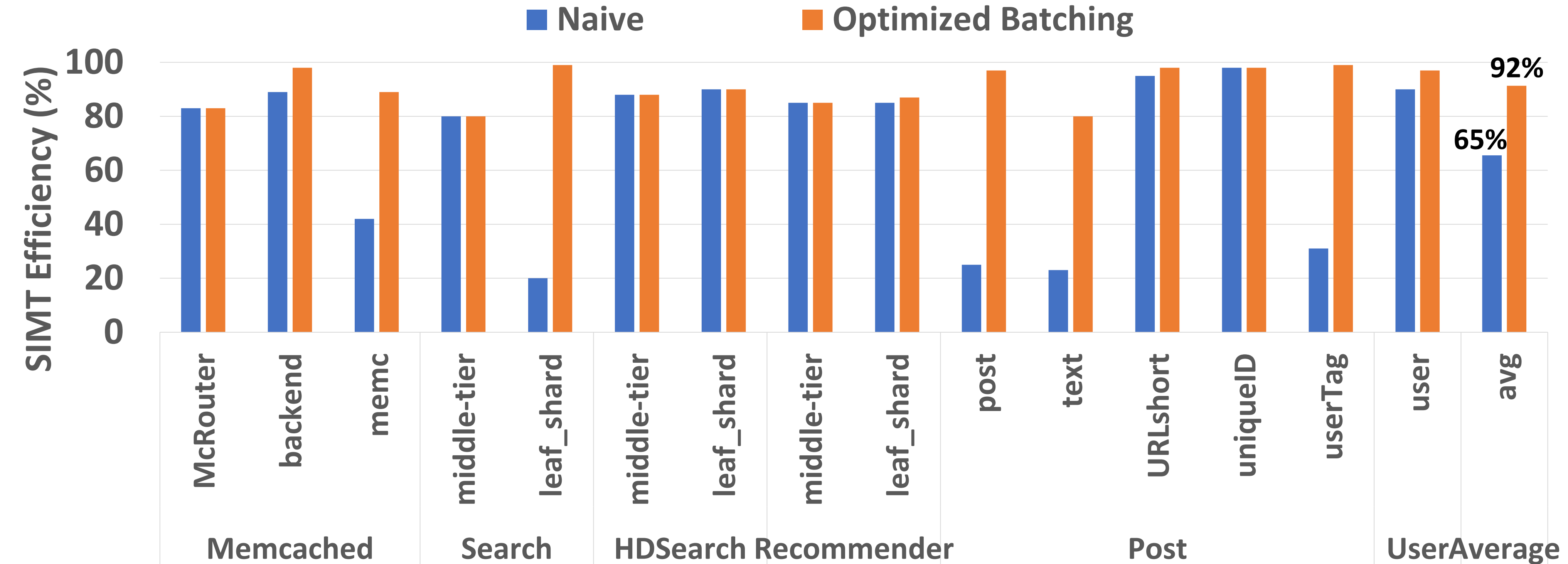
Read more details in the paper on how we address these challenges



- Larger execution units & cache resources

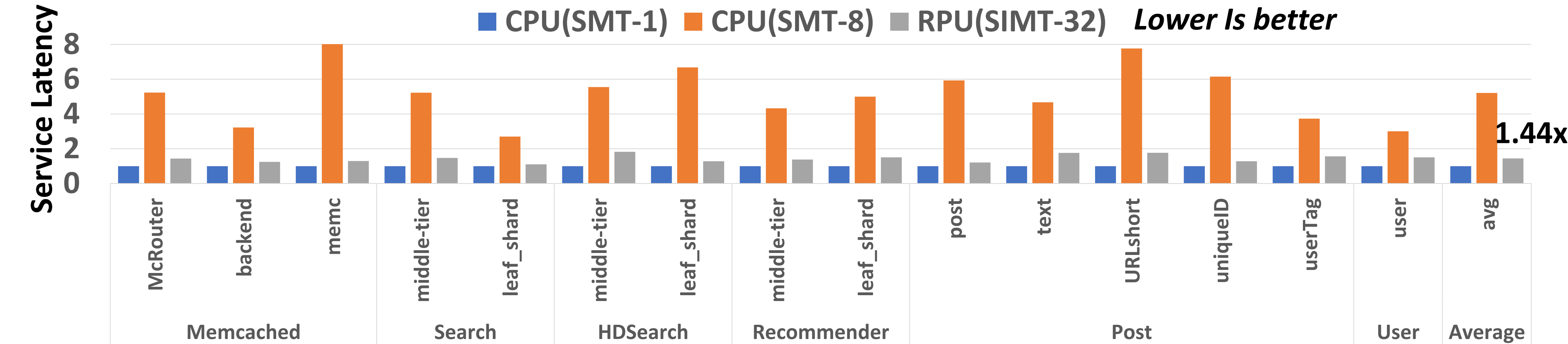
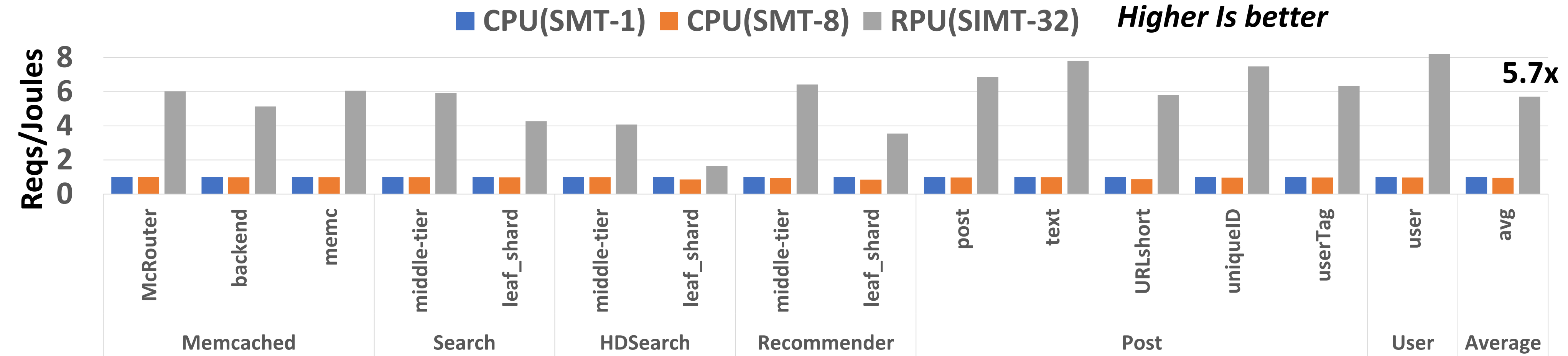
- Challenge: Higher instruction execution & L1 hit latency
- Solution: Exploit low IPC and less generated traffic

SIMT Control Efficiency

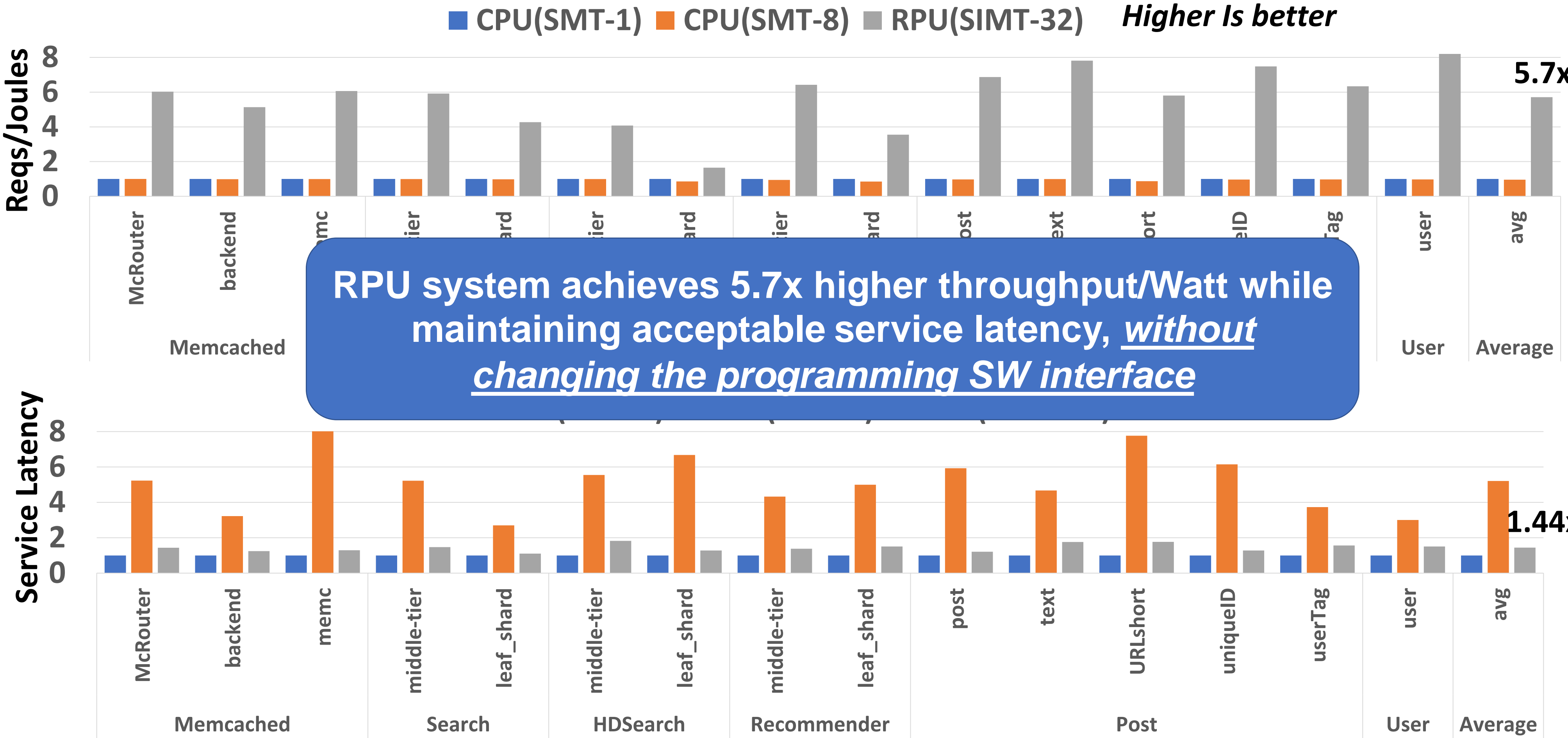


Notes: (1) Batch Size = 32 & #batches=75, (2) System Calls are not traced, (3) $\text{SIMT Eff} = \text{scalar-instructions} / (\text{batch-instructions} * \text{batch-size})$, (4) fine-grain locking are assumed. Other assumptions are included in the paper.

Efficiency and Service Latency Results (Simulation)



Efficiency and Service Latency Results (Simulation)



Summary

- Request Similarity is abundant in the data center.
- We start with OoO CPU design and augment it with SIMT execution to maximize chip utilization and exploit the similarity.
- We co-design the software stack to support batching and awareness of SIMT execution.

SIMT efficiency is high in the open-source microservices we study.



DeathStarBench

μ Suite: A Benchmark Suite for Microservices

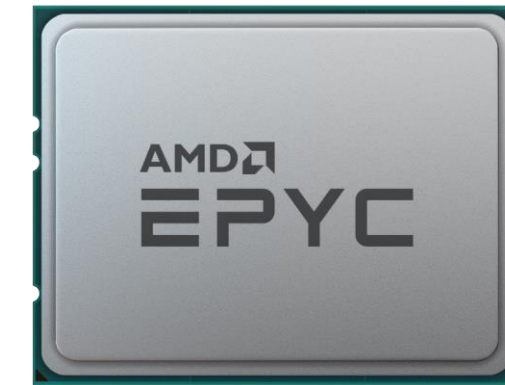
We are very interested in evaluating SIMT control efficiency in proprietary production microservices.

Google
facebook

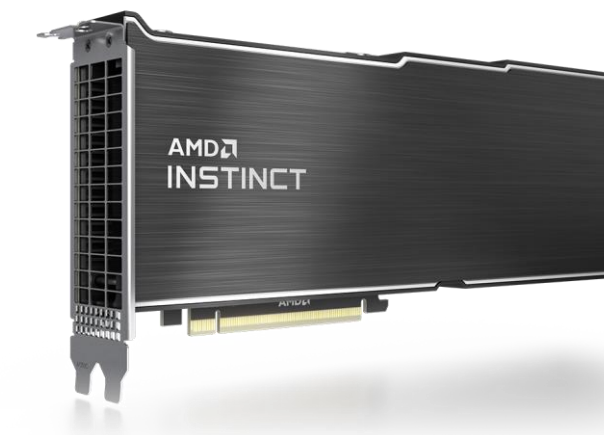
Thank You!

Q&A?

Instruction level parallelism (ILP) &
Thread level parallelism (TLP)



Data level parallelism (DLP)



Request level parallelism (RLP)

