SNIA DEVELOPER CONFERENCE

SDC 24

BY Developers FOR Developers

September 16-18, 2024
Santa Clara, CA

Optimized Resource Allocation for CXL Tiered-Memory Systems

Heiner Litz & Andrew Quinn
UC Santa Cruz

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The Center:

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- 15 Ph.D. & MS
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Research Topics:

- CXL
- AI Systems
- Sustainability
- Data centers
- Storage Devices
- Operating Systems
- Networking

Output:

- High-impact research

ceph

- Publications

(ASPLOS, MICRO, SoCC, OSDI, ISCA, PLDI, HotOS, FAST)

- Excellently-trained graduates

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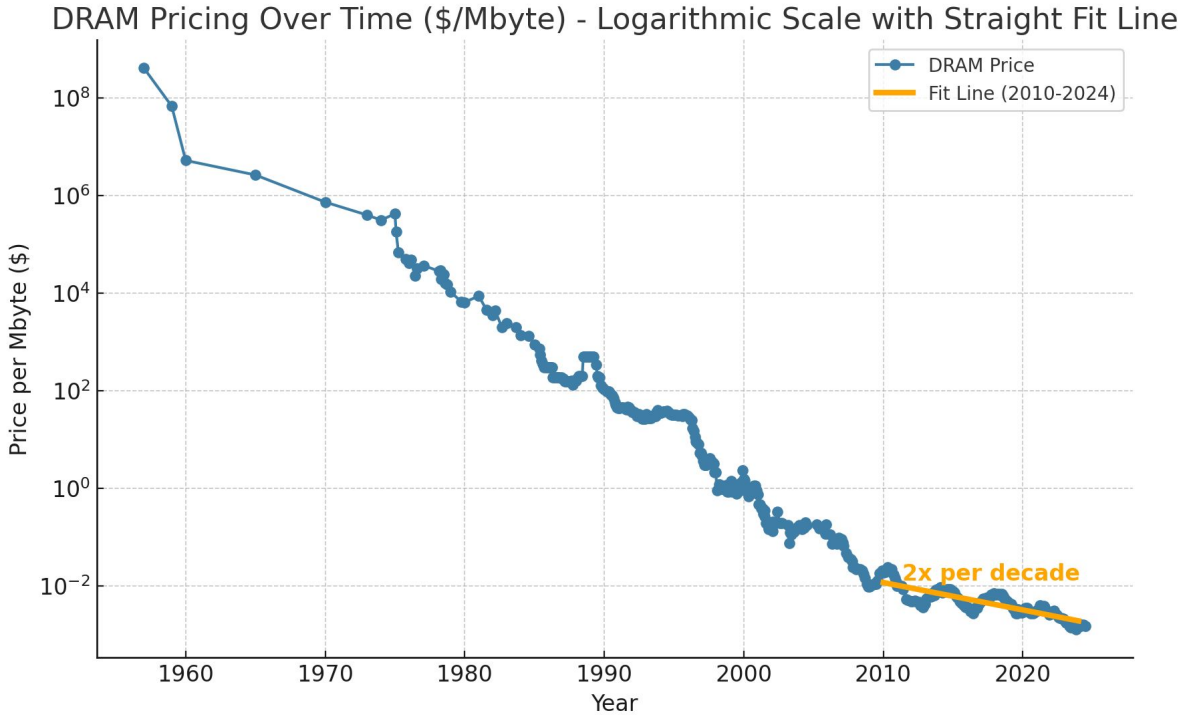
Today's Problem



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CXL: Opportunities & Challenges

- Opportunities
  - Addresses scaling issue by reducing memory cost
  - Open standard enables “small players” to innovate
  - Computational memory enables TCO & perf improvements
- Challenges
  - Performance overhead
  - Heterogeneity increases complexity
  - Requires cross-layer (SW/HW) optimizations

Today's Talk

- Part 1: How can we exploit CXL memory to improve TCO (TMC)?
  - Delivered by Dr. Heiner Litz
- Part 2: How can we exploit CXL memory to improve cluster job performance (Bede)?
  - Delivered by Dr. Andrew Quinn

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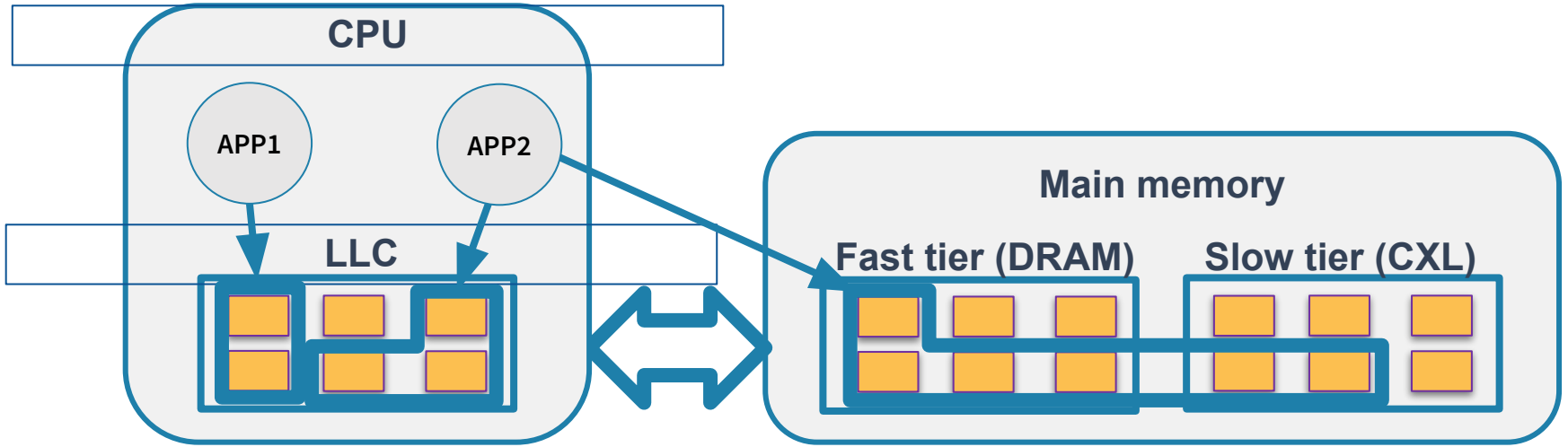
Memory Tiering



Tiered memory seeks to maintain similar performance at a lower cost

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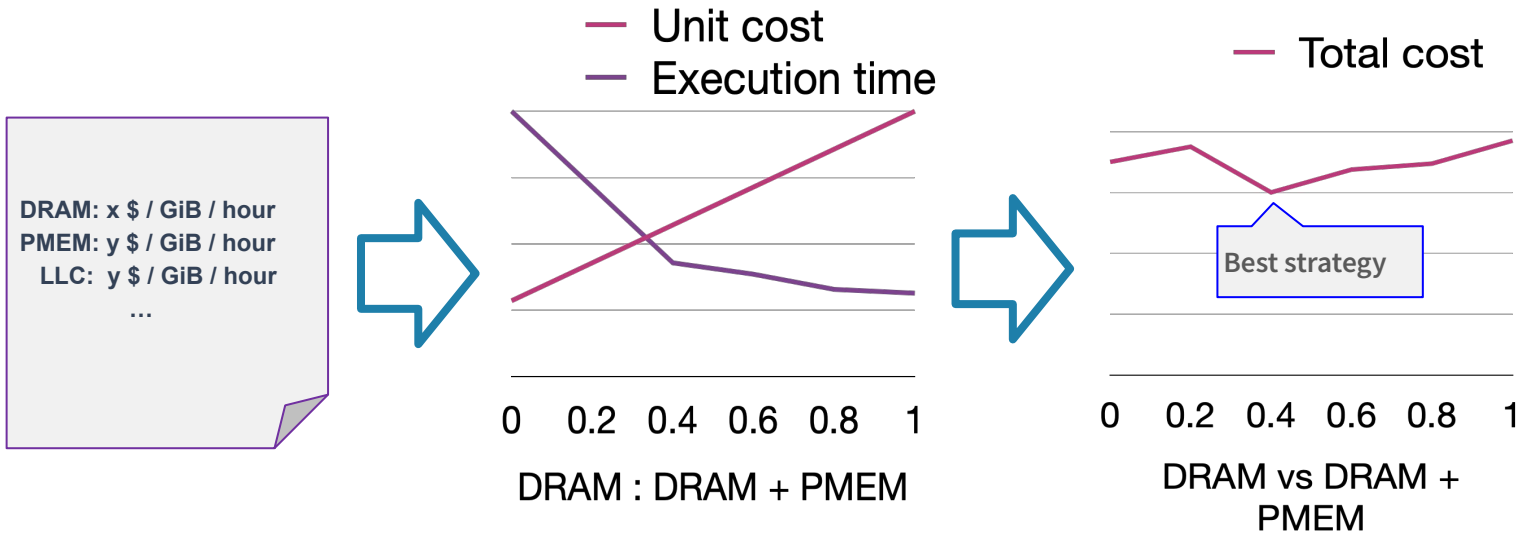
Determining Optimal Memory Ratio is Hard



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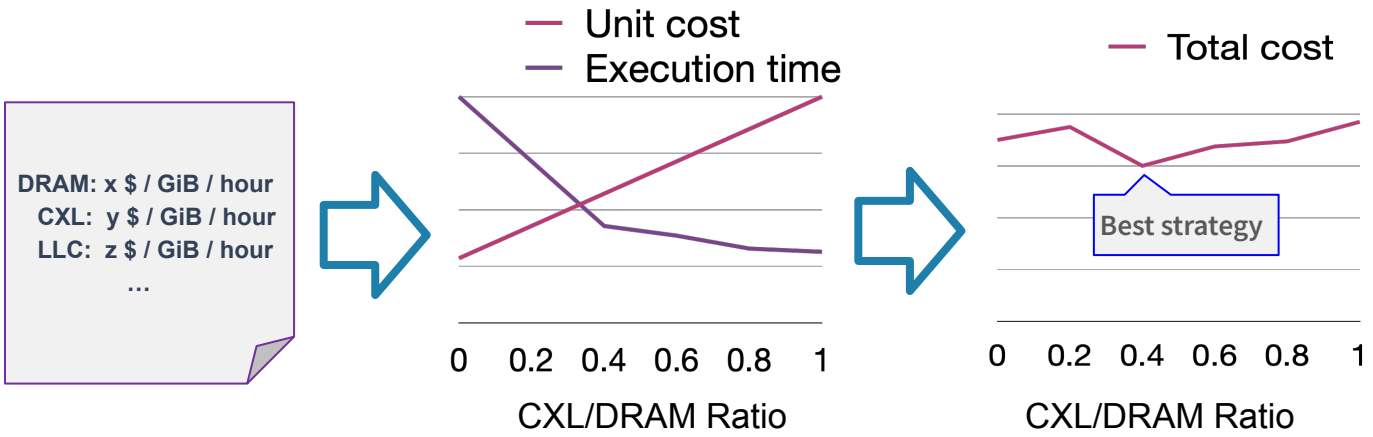

Large search space, scales with memory tiers

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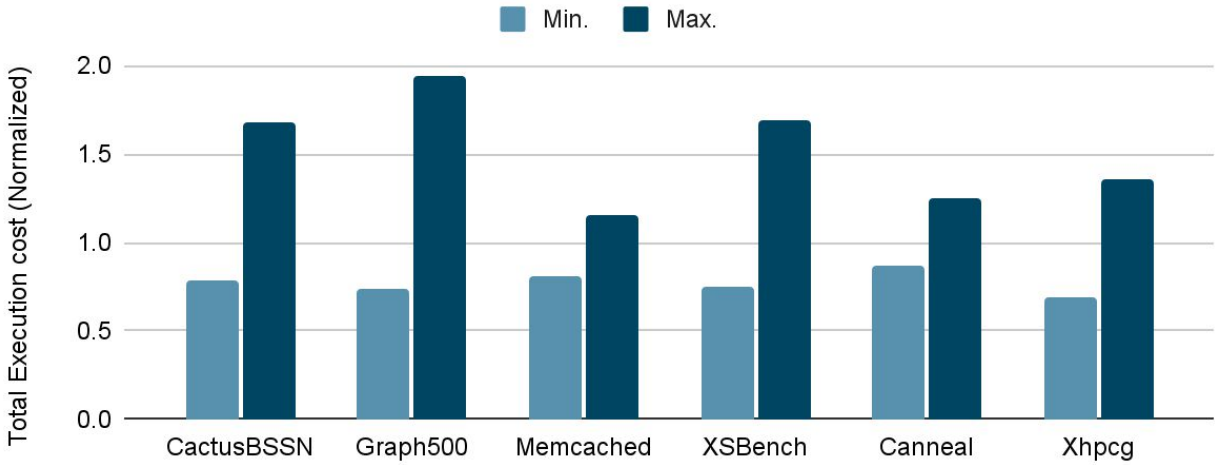
User: Lowest $ at certain performance level



Wrong configurations increases users' cost significantly

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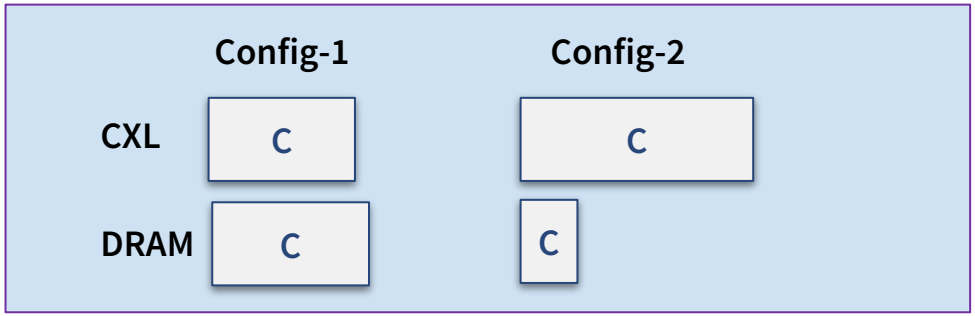
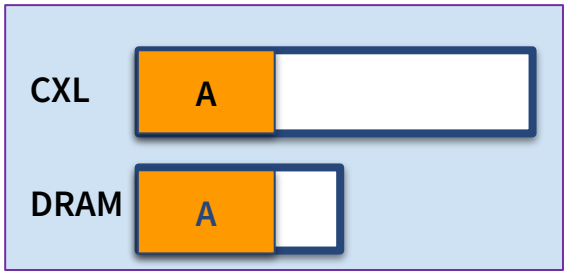
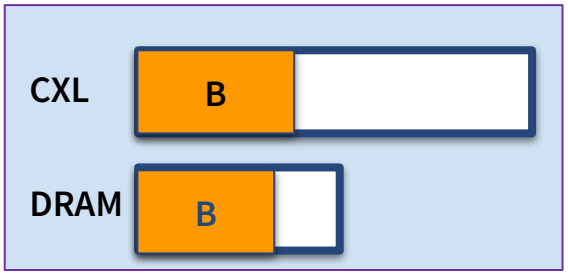
Cloud Provider: Highest Packing Density





Server 1



Server 2

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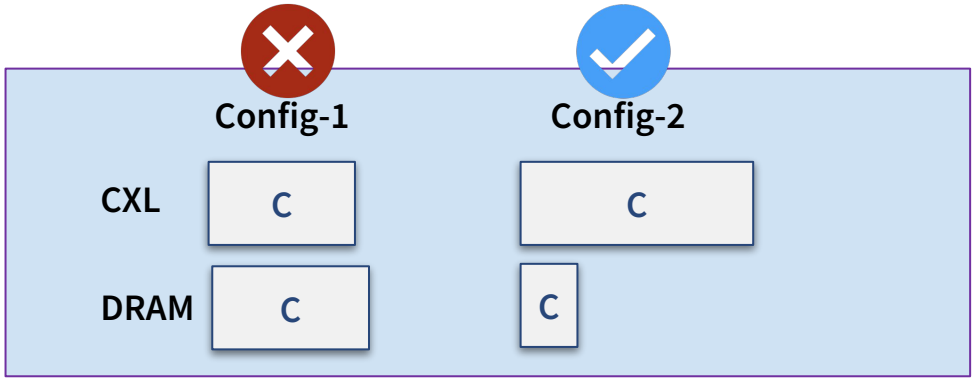

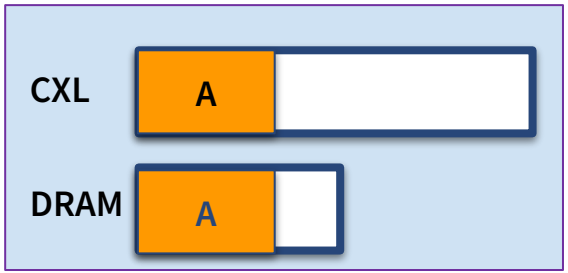

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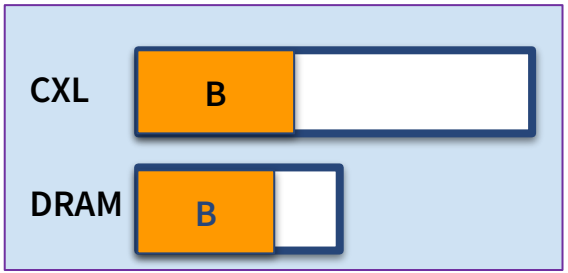

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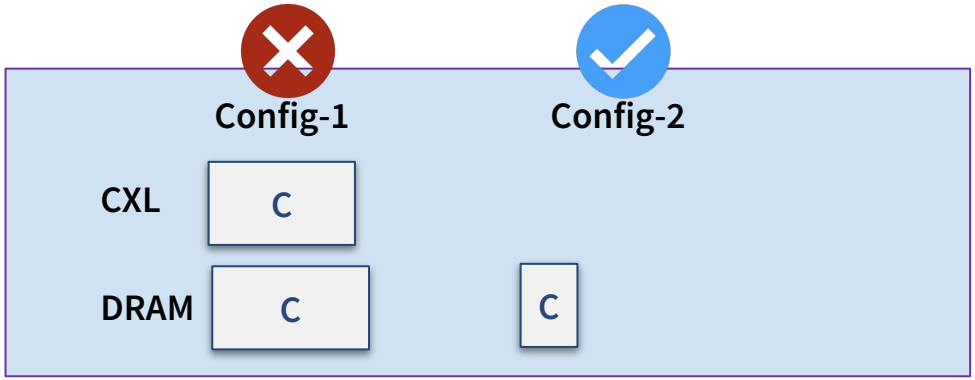

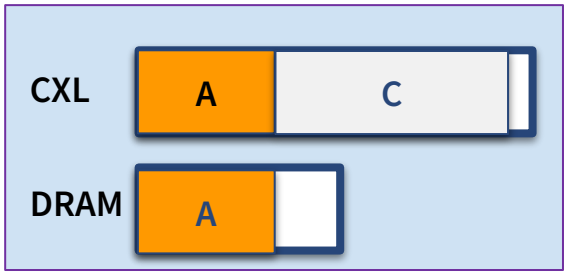

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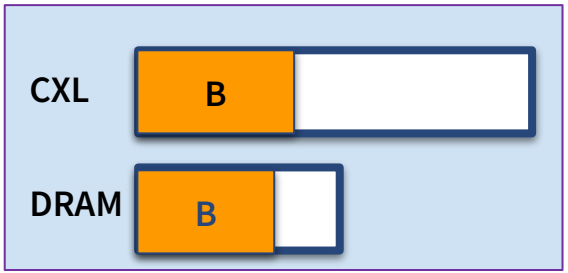

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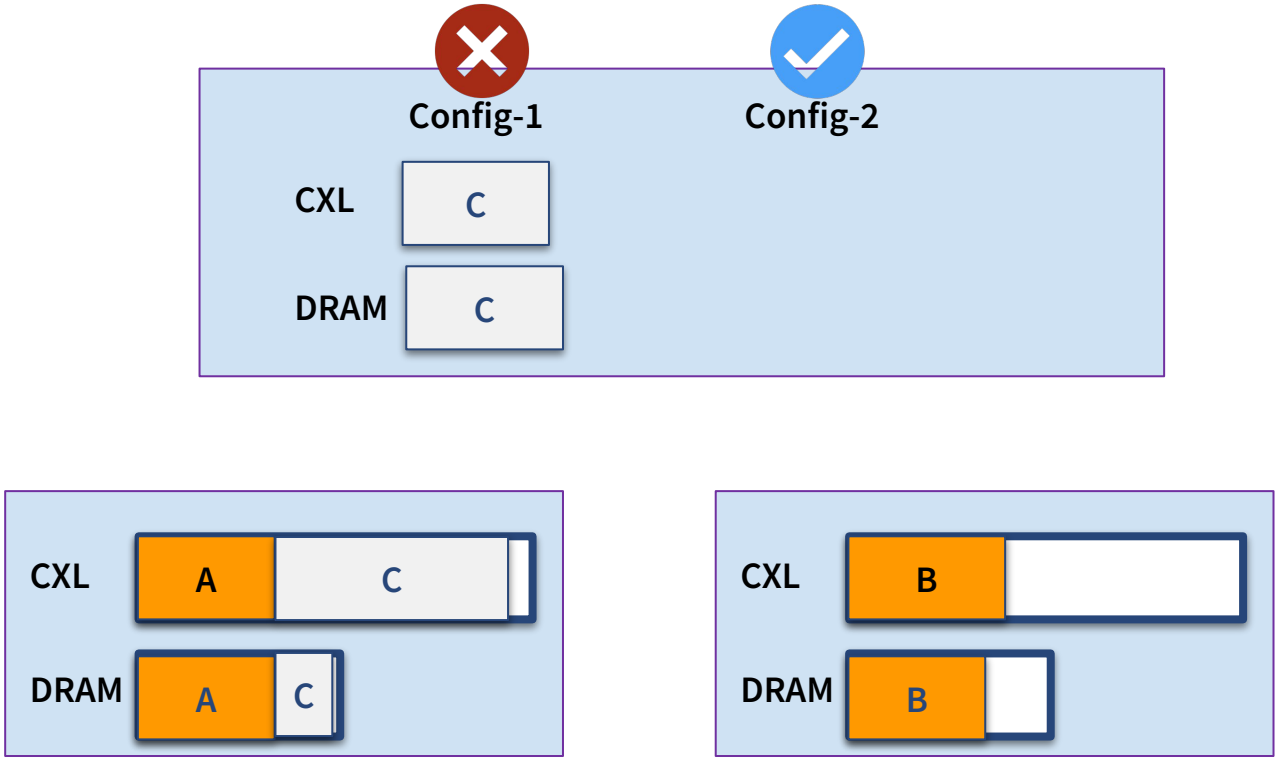

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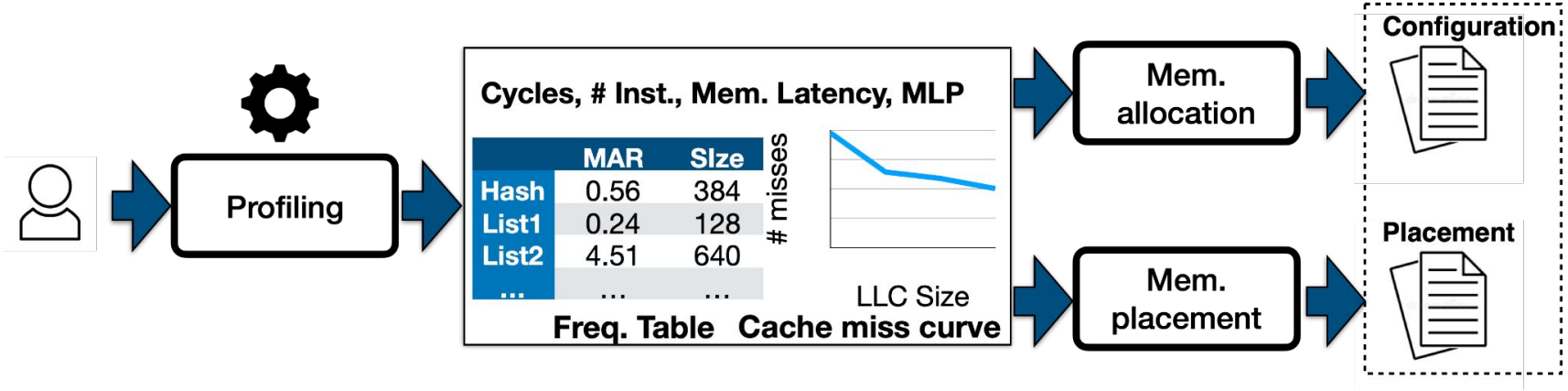
Contributions
Contributions

- Prior Work
  - Blackbox ML-based techniques Bayes[1], Collaborative Filtering [2]
  - Trained on N workloads and M configurations, predict a configuration
- Our Work (TMC)
  - White-box performance model
  - Data-layout hints (what data into CXL/DRAM?)
  - *Why* is a configuration best?
  - Predicts performance of a workload (instead of suggesting a configuration)
  - What-if analysis

[1] Alipourfard et al.: CherryPick: Adaptively Unearthing the Best Cloud Configurations for Big Data Analytics (NSDI'17).

[2] Klimovic et al.: Selecta: Heterogeneous cloud storage configuration for data analytics (ATC'18).

TMC Overview



TMC devises a performance model based on the understanding of hardware performance characteristics

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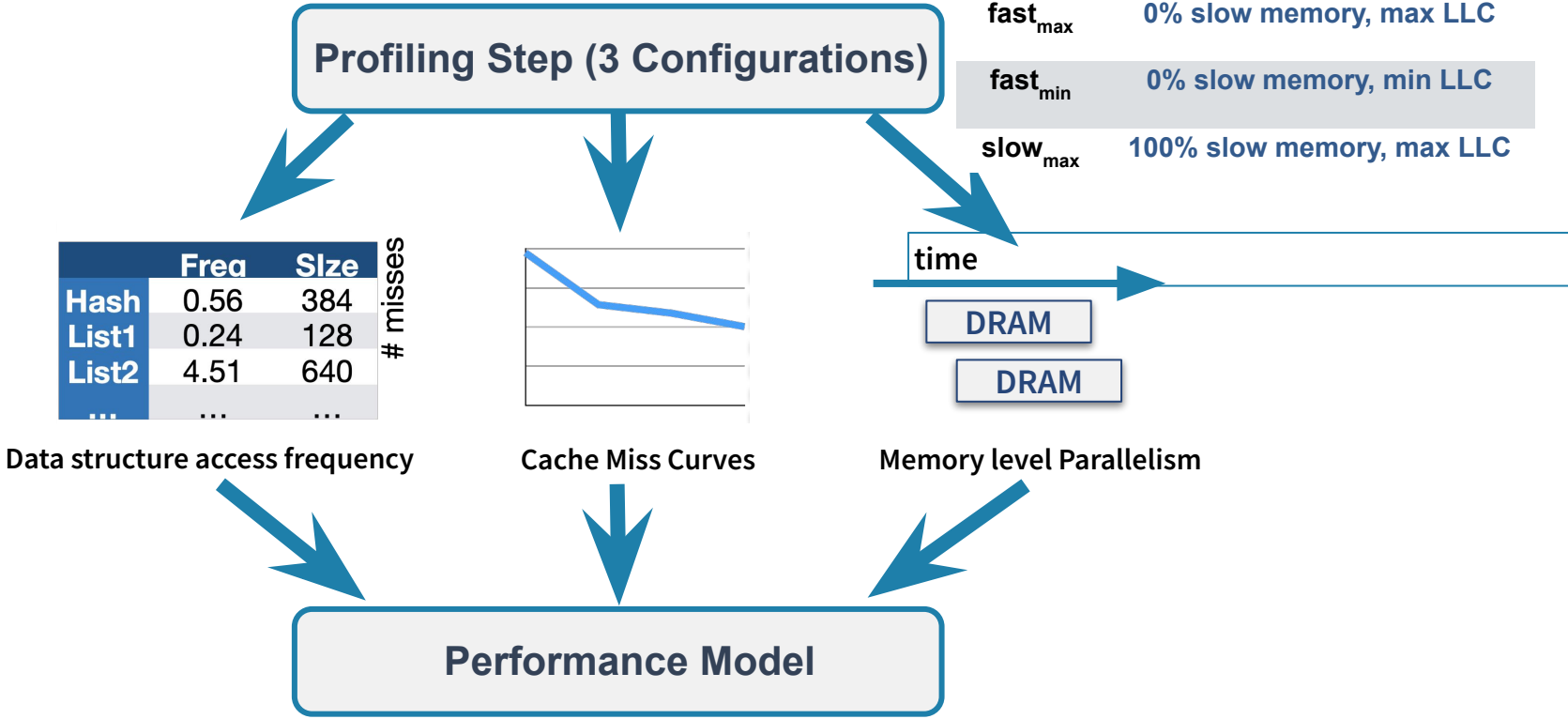
Model Generation



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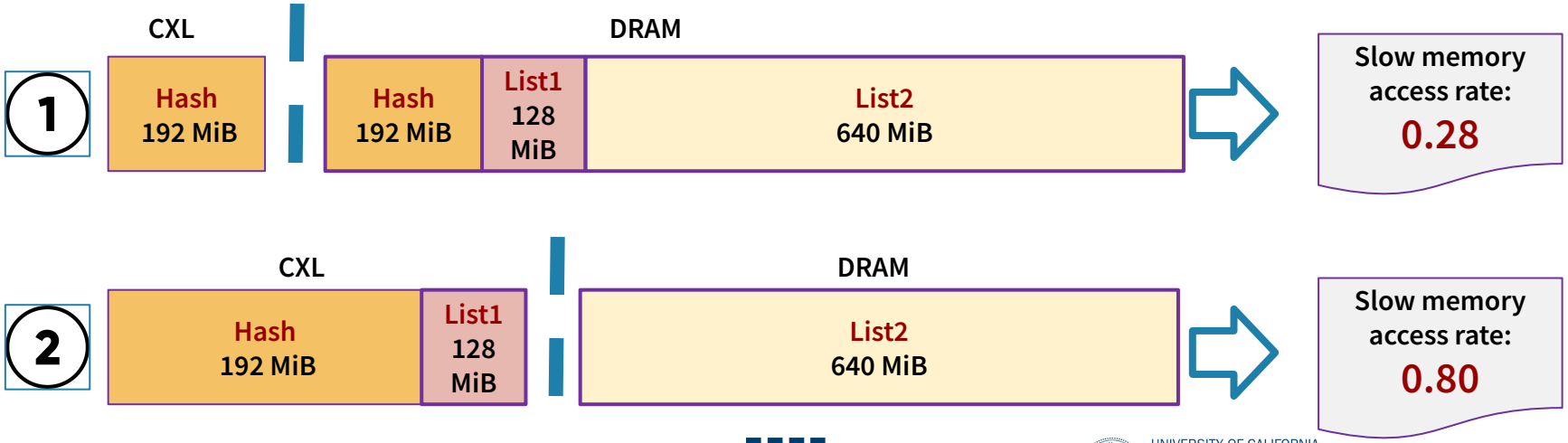
Model Prediction

	Memory access rate	Size
List1	0.24	128 MiB
List2	4.51	640 MiB
Hash	0.56	384 MIB



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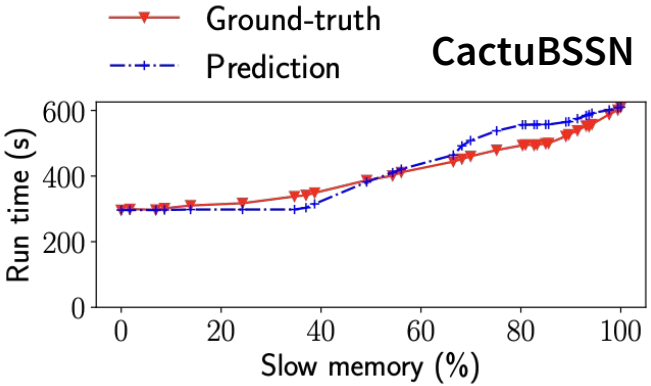
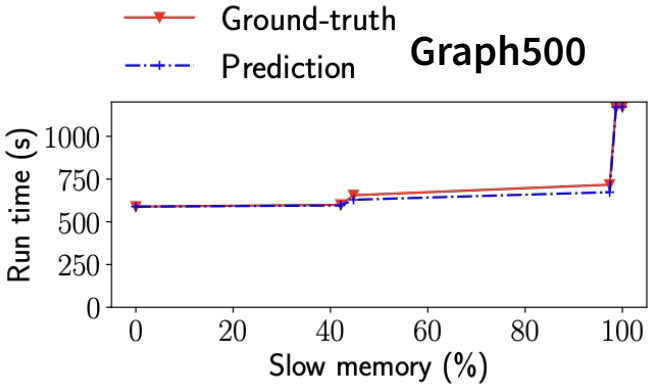
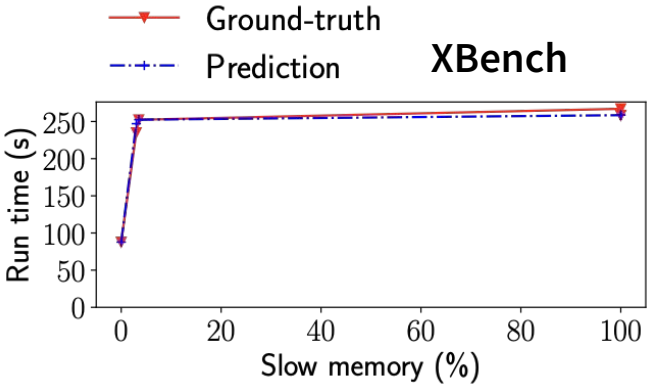
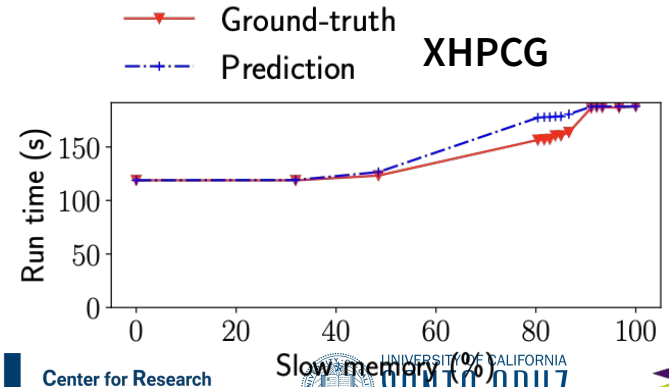
Evaluation

Evaluation Performance Prediction









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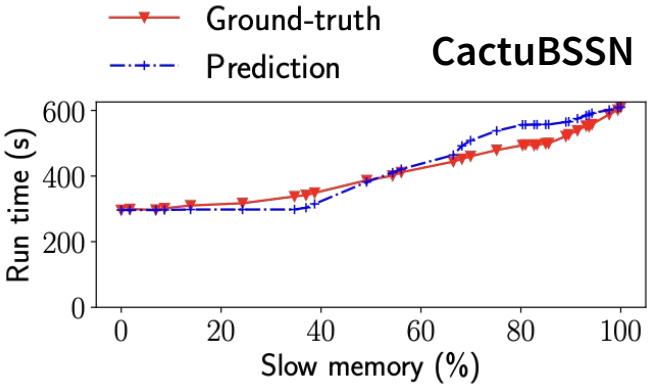
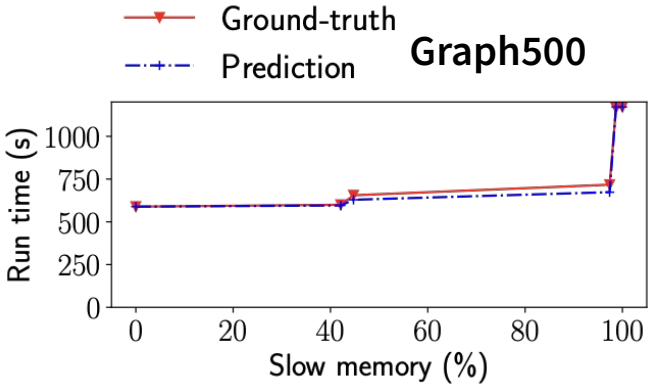
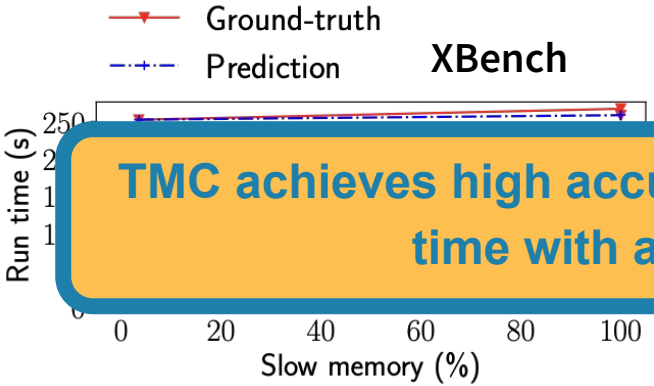
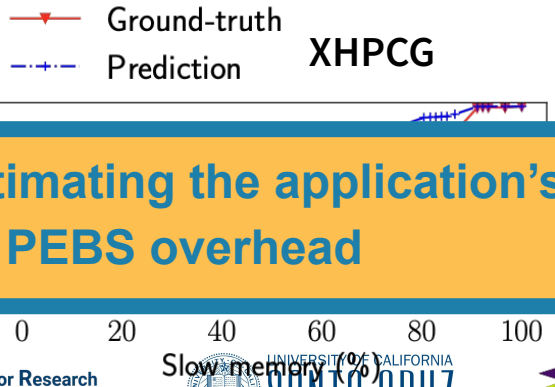
Evaluation Performance Prediction









TMC achieves high accuracy in estimating the application's run time with almost zero PEBS overhead

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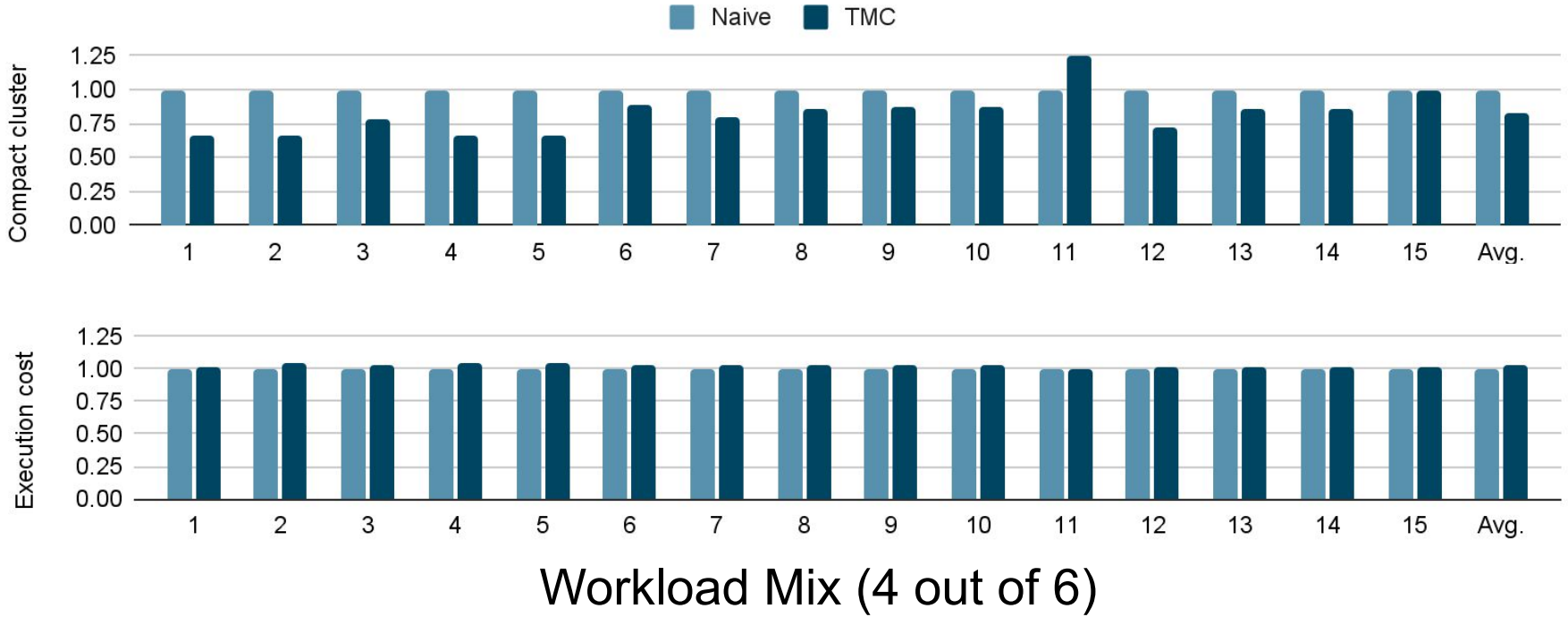
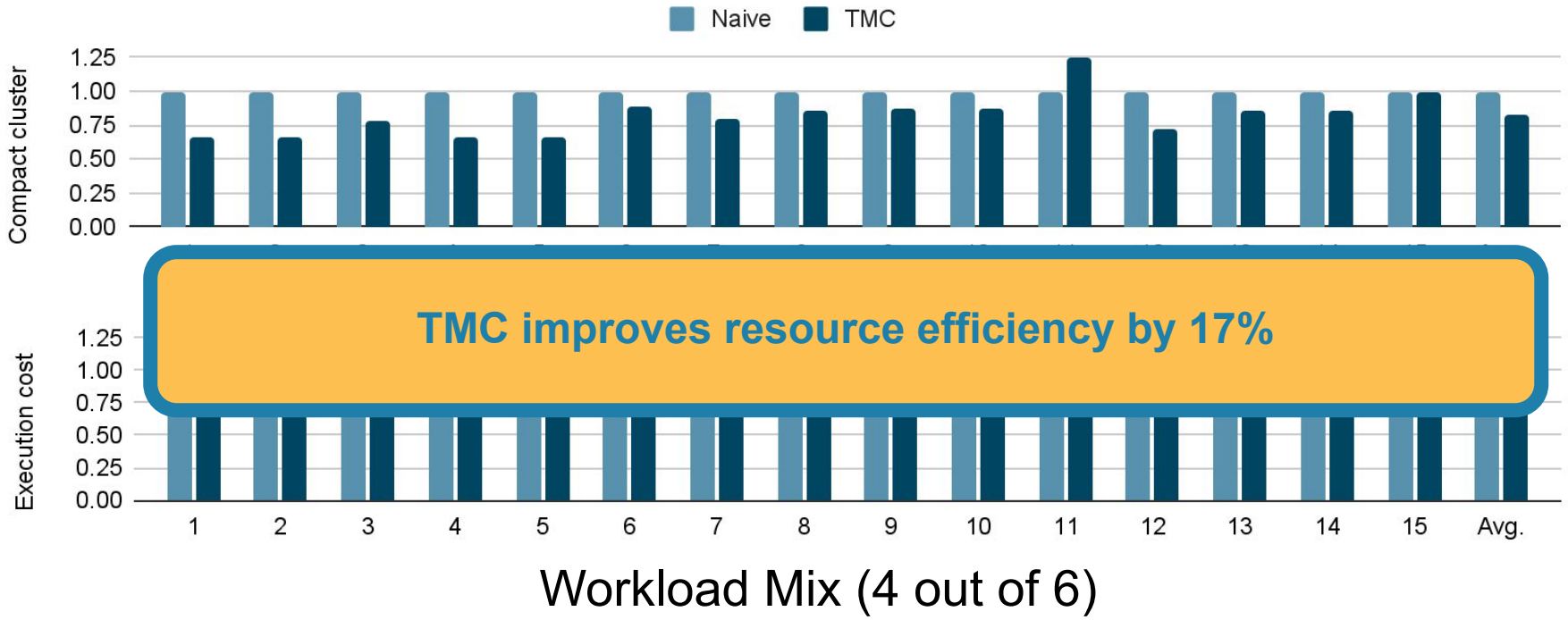
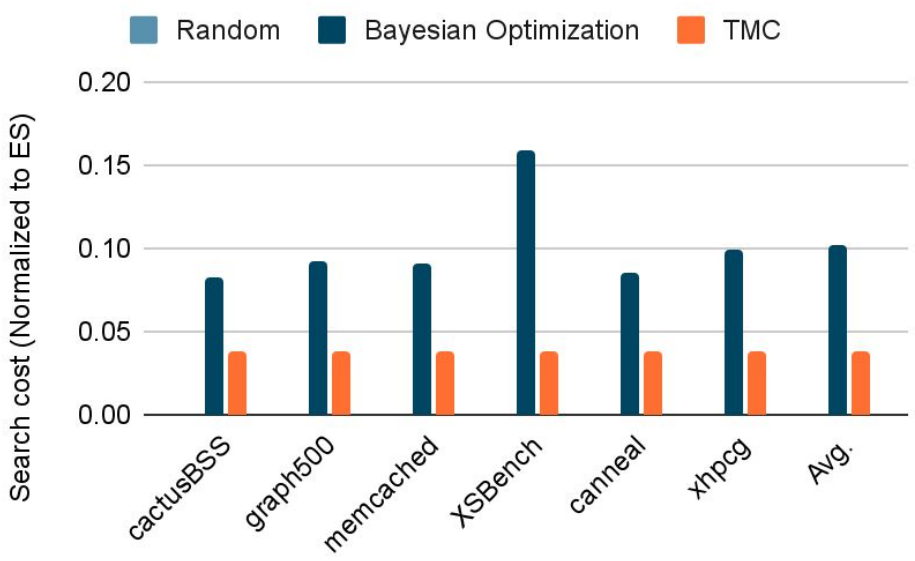
Operator Resource efficiency

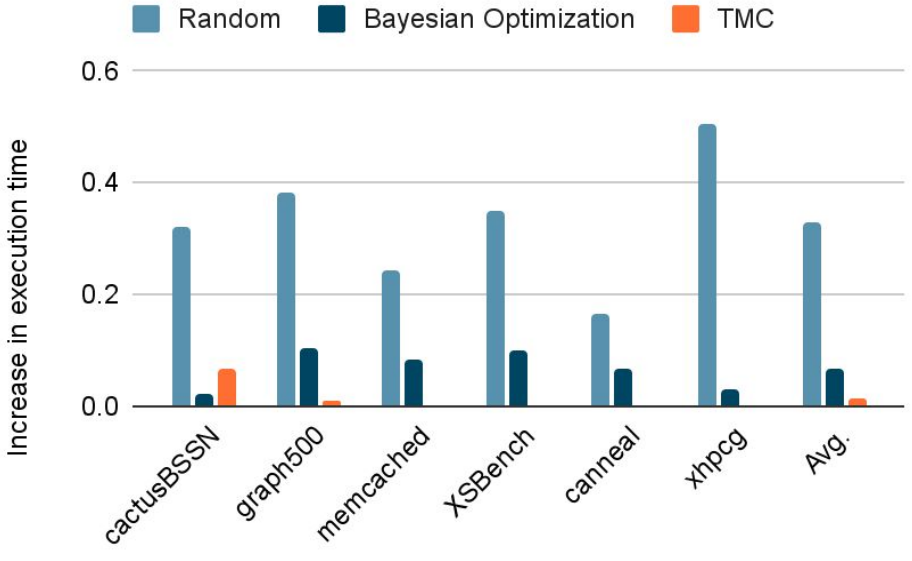


Resource efficiency



Search cost





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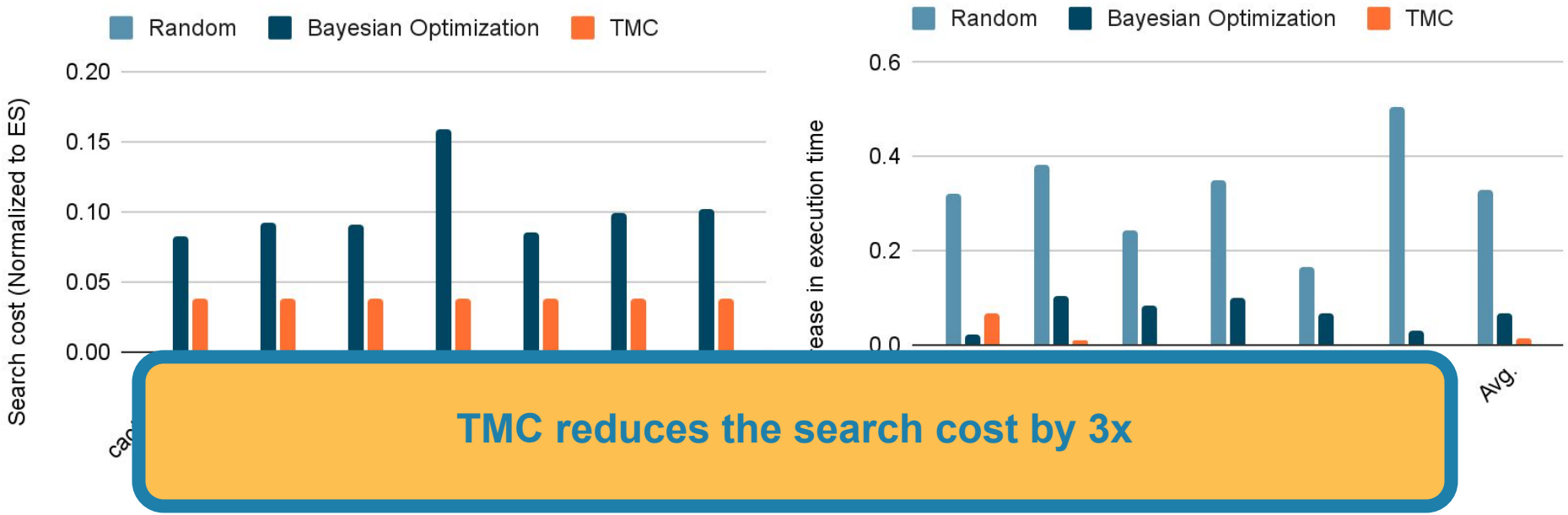
Search cost



TMC reduces the search cost by 3x

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Conclusion

- TMC provides a performance model over prior work
  - Selects optimal performance/TCO for the client
  - Optimizes resource allocation for the data center operator
  - Enables what-if analysis
- TMC reduces the search cost by 3x over prior work
- TMC increases resource efficiency by 17%

Scheduling

- Job Scheduling is key across many computer systems
  - Cluster management (e.g., Kubernetes, Mesos, Borg)
  - Data Analytics (e.g., Spark, Hadoop)
  - Machine Learning (e.g., PyTorch, TensorFlow)
- Efficient scheduling is crucial for large data centers
  - Even small improvements can save millions at scale

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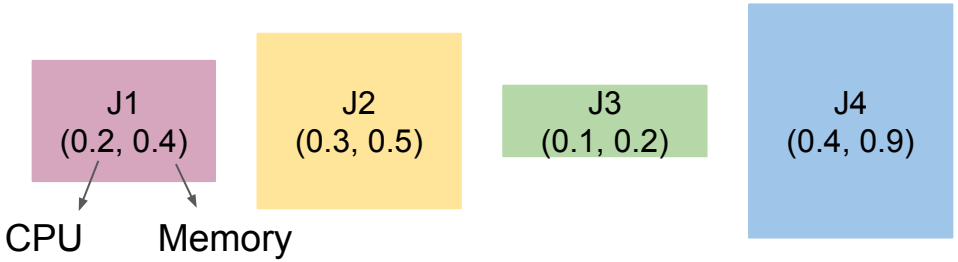
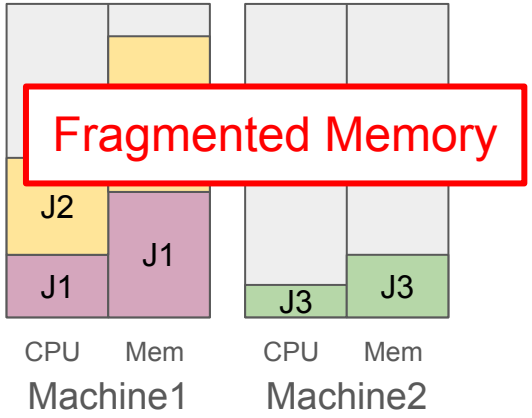
Scheduling Example

- Allocate data-center resources for compute jobs
- Jobs require resources, schedule assigns idle resources



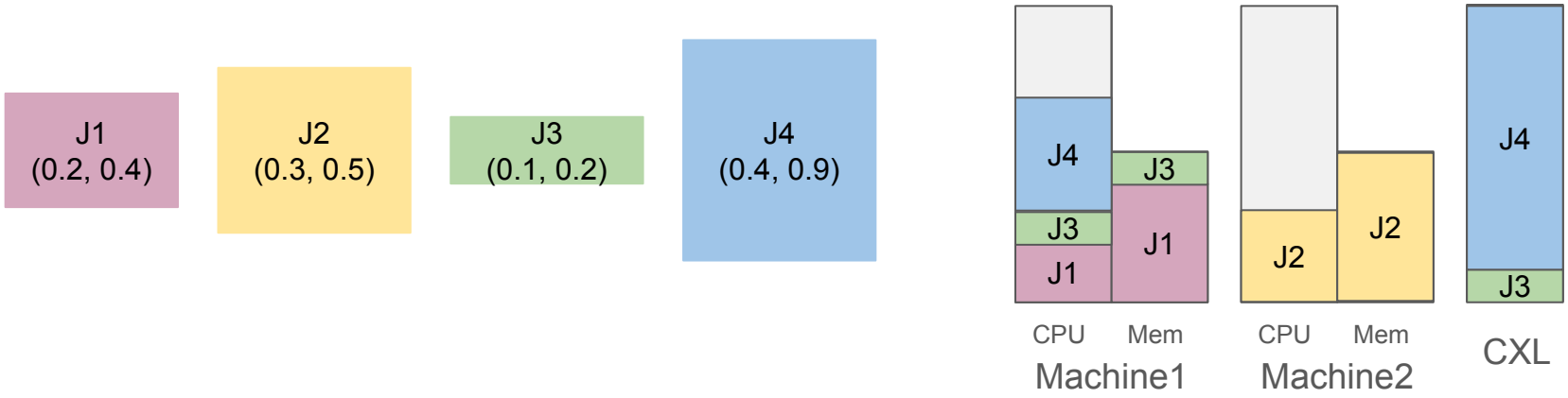


Up to 50% of Jobs face scheduling delays[1]!

[1] Tirmazi et al. Eurosys 20.

CXL to the Rescue?

- Split memory across machines and a CXL memory Pool



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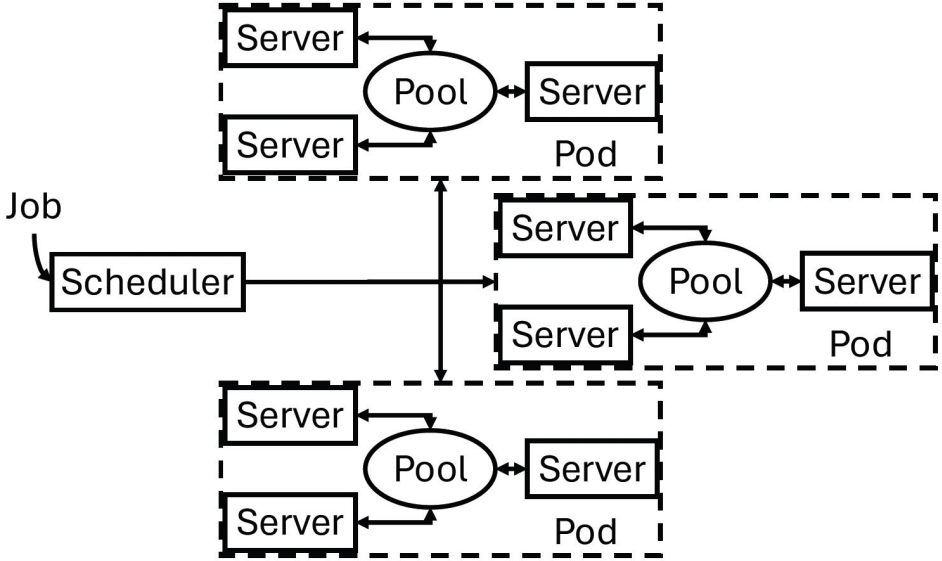
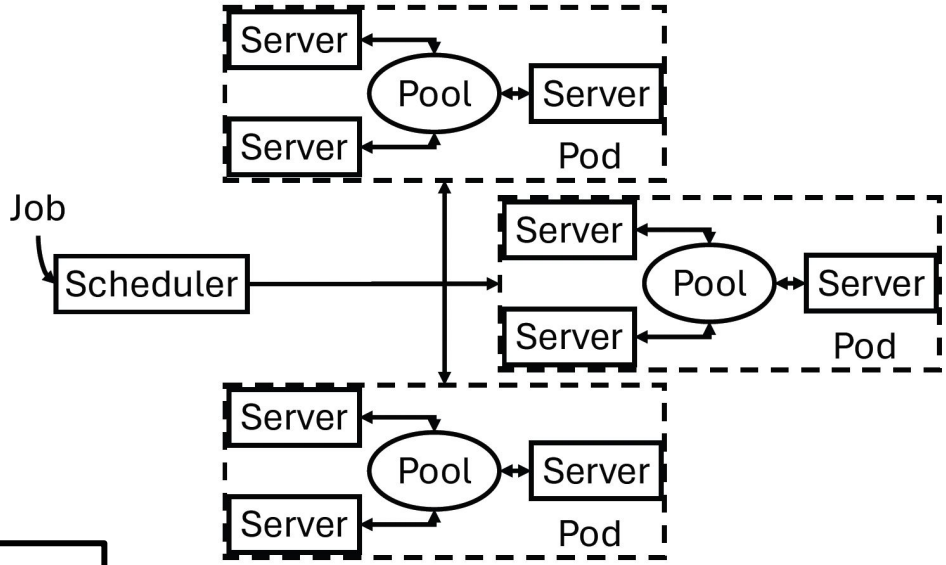
Bede

- Advantages:
  - Less scheduling delay
  - Lower cost
- Disadvantages:
  - Jobs execute more slowly



Bede Research Questions

- Bede Configuration?
  - Built cluster simulator!
- Bede Scheduler?
  - Two new schedulers!



Up to 30x faster than State-of-the-art!

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Bede Cluster Simulator

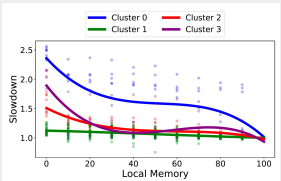
Workload Trace:

Job_id,Start,End,Cores,Memory
1,0,658200,8,16
2,0,2591400,2,4
3,0,2796400,4,32

Configuration:

- Number of servers
- Server shape
- Servers per pool
- Pool size
- Scheduling Policy

Slowdown Models:



Cluster Simulator

Job, machine, local memory, Start, Finish
1,M1,20,0,658200
2,M2,100,1500,2592900
…

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Bede Cluster Simulator–Workloads

- Azure Cluster Traces (2017, 2019)
  - Cortez et al. SOSP 2017

- Google Borg Traces (Clusters B, D)
  - Tirmazi et al. Eurosys 2020

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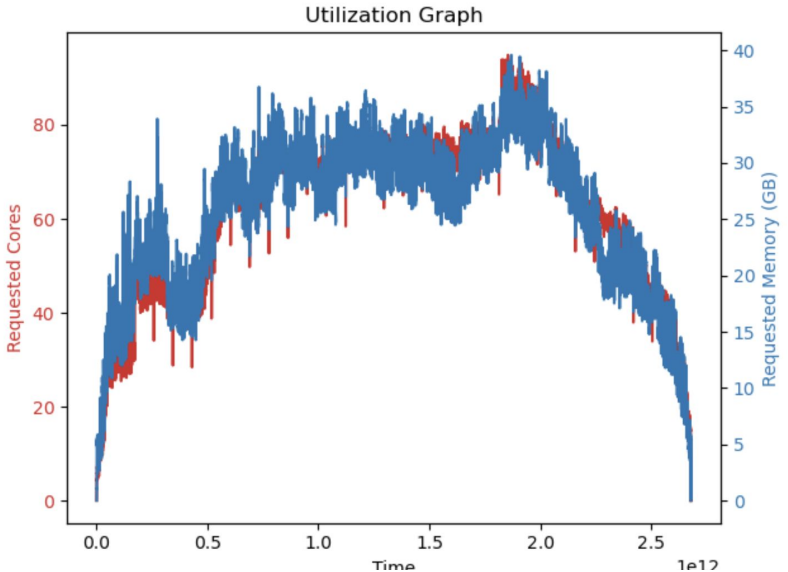
Bede Cluster Simulator–Configuration Methodology

- Server Shapes
  - 100th percentile of requested CPU
  - 192 cores (large cloud instance)
  - Memory at 50th, 75th, 85th, 95th percentile
- #Servers-per-pool of 2,4,...,32
- Pools of 0,10,...,100% of memory
- SOTA scheduling policies



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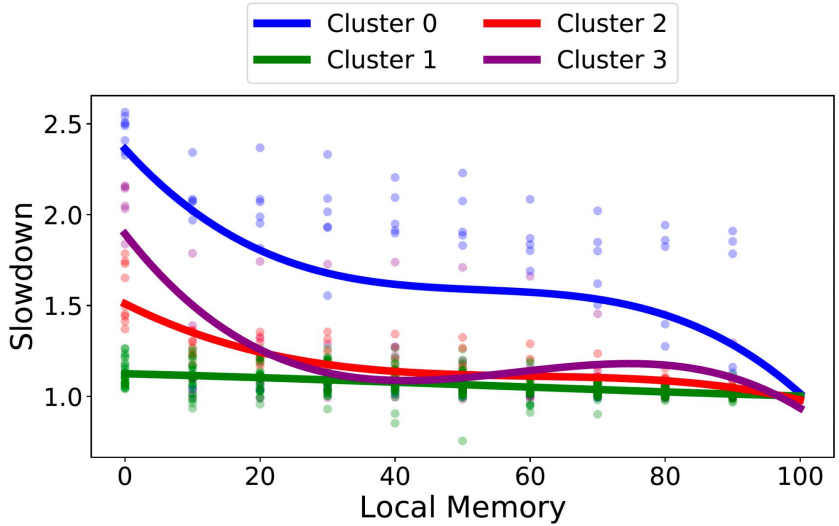
Bede Cluster Simulator–Slowdown Models

- Methodology:
  - Use Dual-socket NUMA
  - All compute on node 1
  - Vary memory [0–100%] across nodes
- Scale Factor (SF)
  - Account for uncertainty
  - Multiplies NUMA models by constant factor
  - SF 2 means CXL twice as slow as NUMA.



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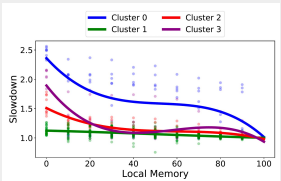

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Job, machine, local memory, Start, Finish
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2,M2,100,1500,2592900
…

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Bede Scheduling Policies

- Existing State-of-the-art
  - Generic: FIFO, SJF
  - Far-memory specific: CFM, Pond

- Novel alignment-based policies
  - EVPM-Far: FIFO with alignment
  - T(etris)-Far: SJF with alignment

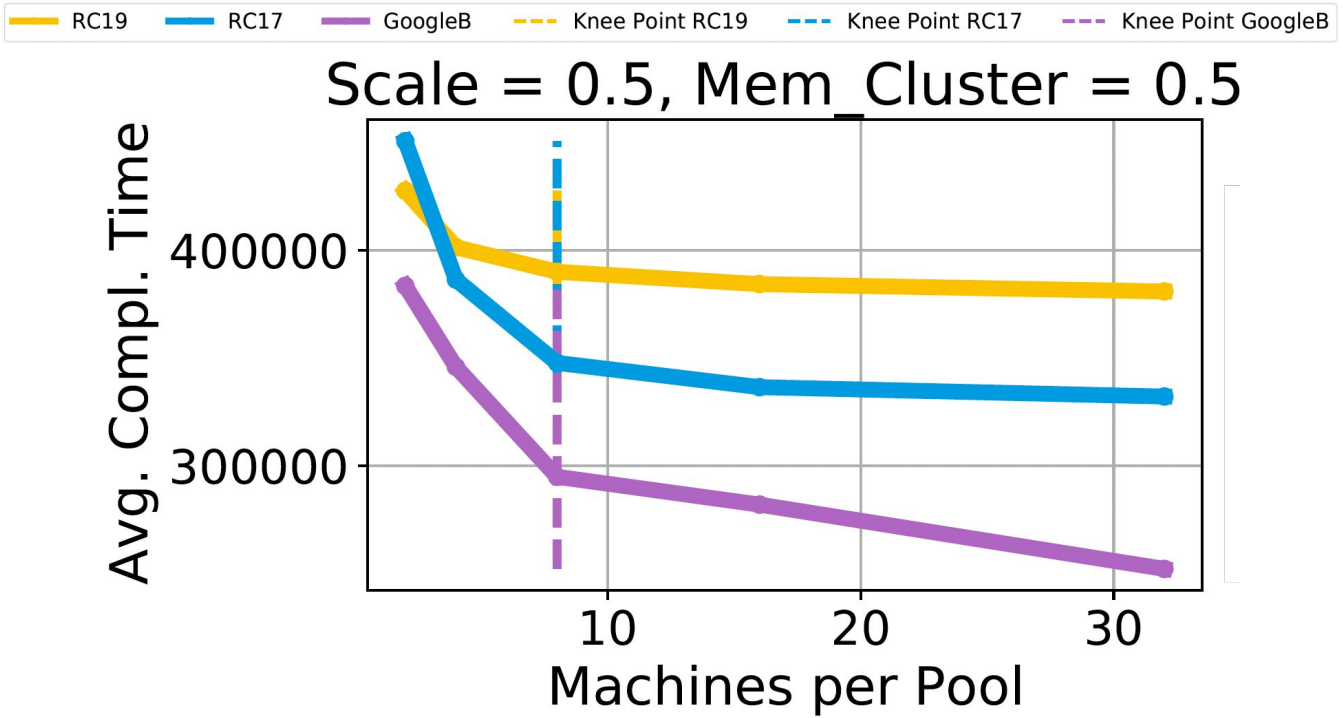
$$L = \min(mem_{Server}, mem_{Job})$$
$$A = \langle core_{Server}, mem_{Server}, mem_{pool} \rangle$$
$$R = \langle core_{Job}, L, 1 - L \rangle$$

$$Alignment = A \cdot R$$

Evaluation

- How many servers should be attached to each pool?
- How should memory be split between servers and pools?
- How does job performance vary by scheduling policy?

Servers Per Pool



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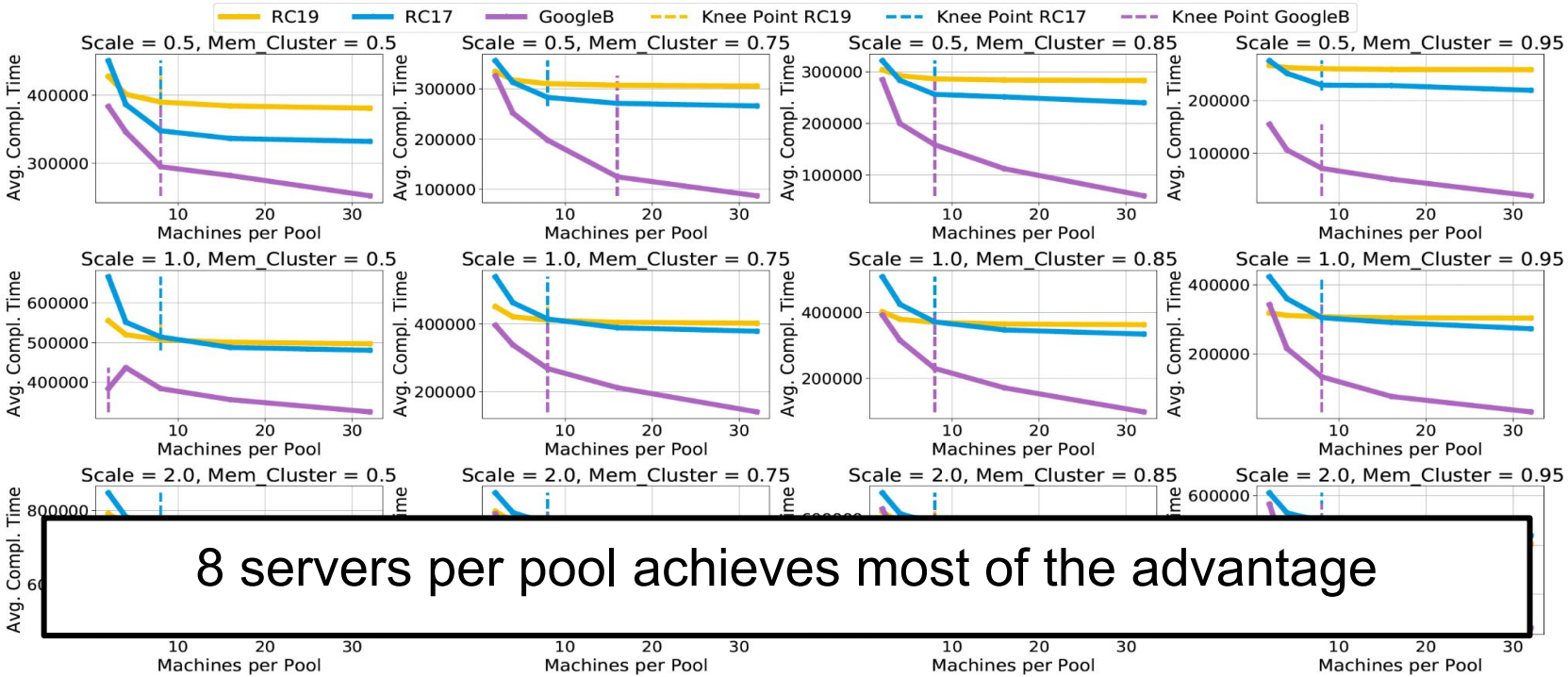
Servers Per Pool



8 servers per pool achieves most of the advantage

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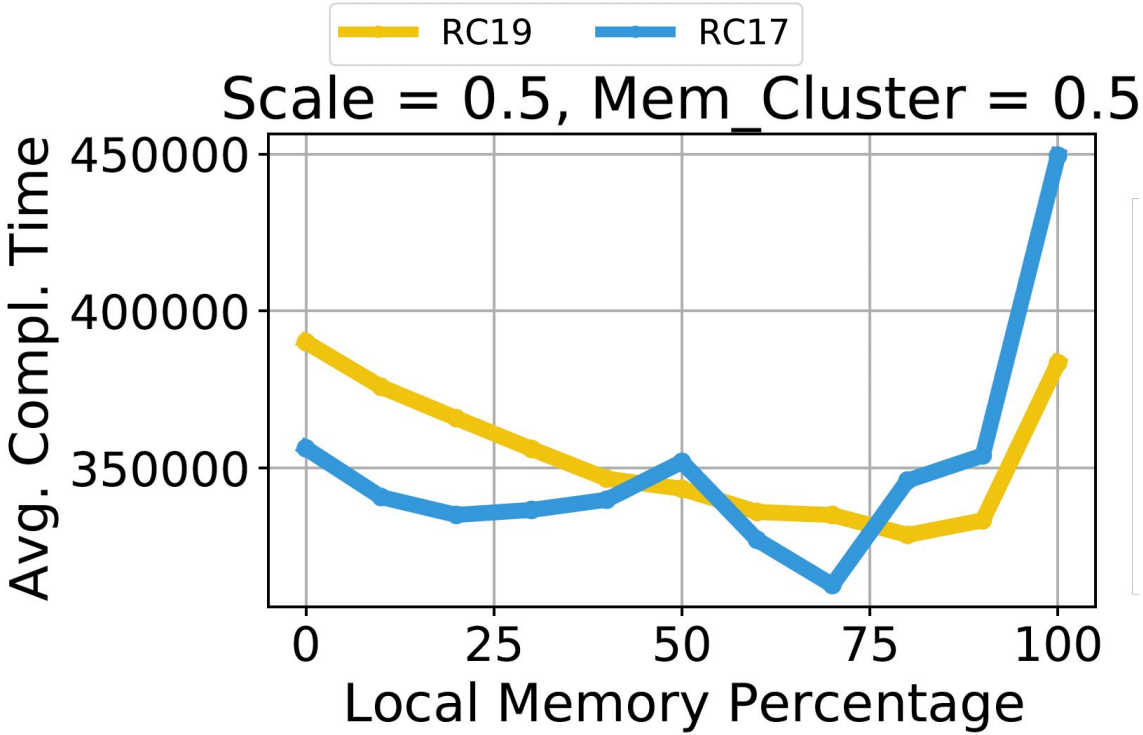
Pool server memory split



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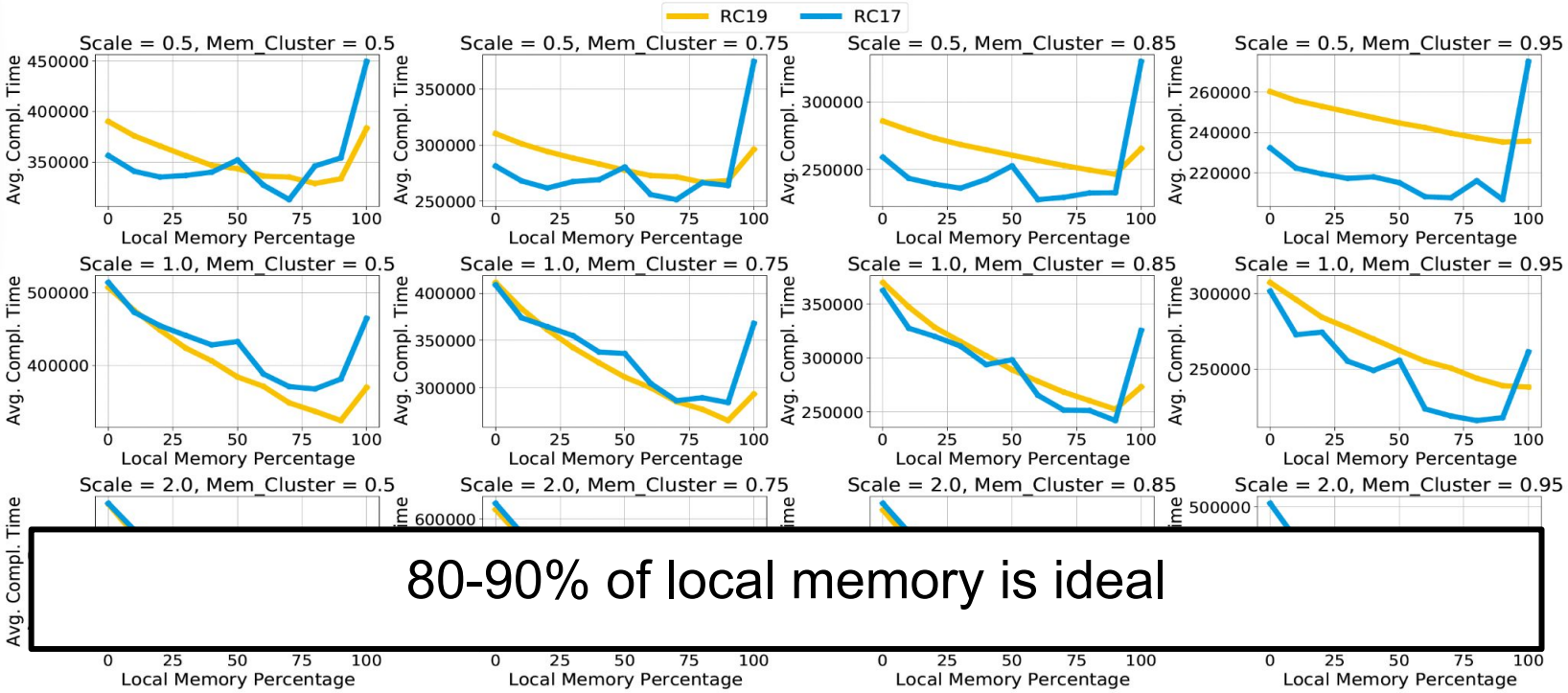
Pool server memory split



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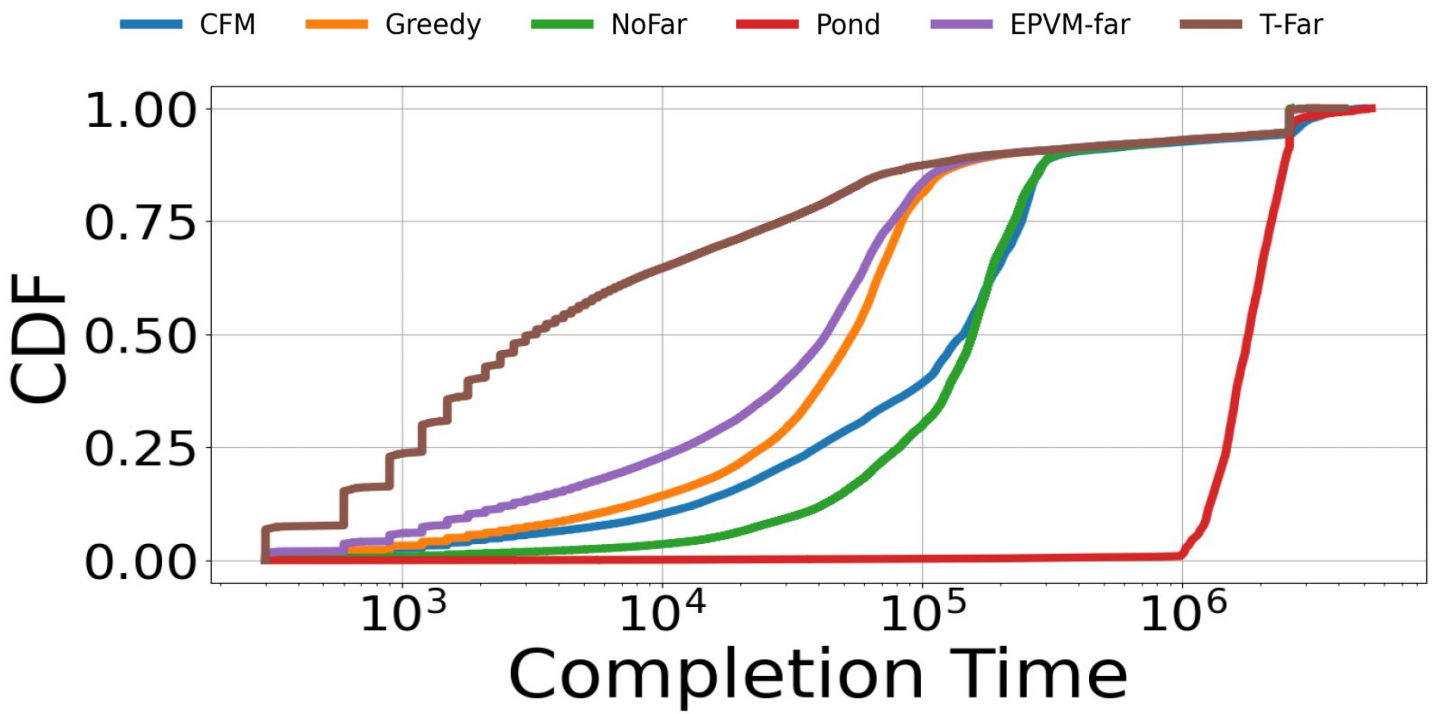
Scheduling Policies



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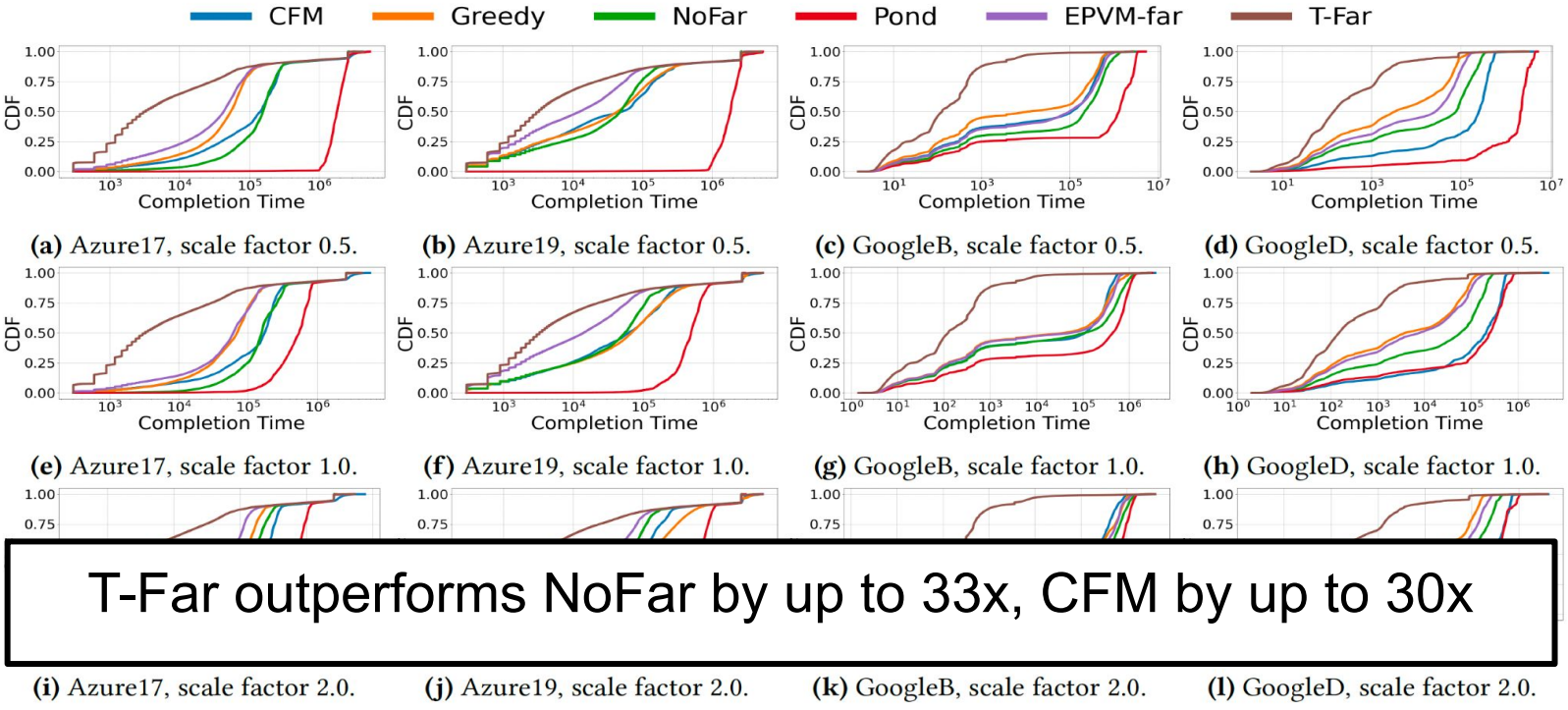
Scheduling Policies



T-Far outperforms NoFar by up to 33x, CFM by up to 30x

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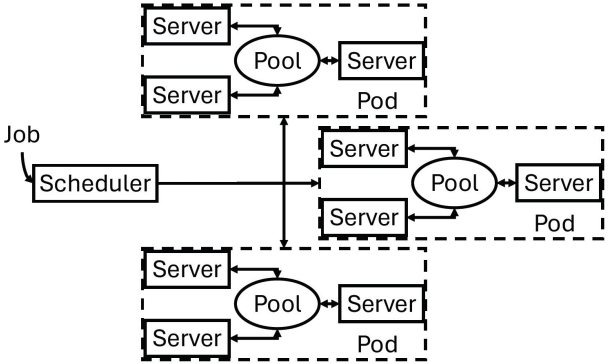
Bede Conclusion

- Built simulator to explore configurations
  - Small pools work well
- Two novel scheduling algorithms
  - Up to 30x improvement over state of the art



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Contributions

- CXL is a promising technique to address memory cost
- Not a plug-in replacement, many deployment challenges
- Our work enables modeling of CXL performance & TCO
- Automation can address the complexity challenges of CXL

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Please reach out if you want to collaborate with us: www.crss.us

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