OSNABRÜCK UNIVERSITY

Embedded Software Systems

Project Report and Outlook: SMAUG

System-Level Modelling and Optimized Use of Disruptive Memory Technologies

Birte Friesel, Michael Müller, Olaf Spinczyk

birte.friesel@uos.de

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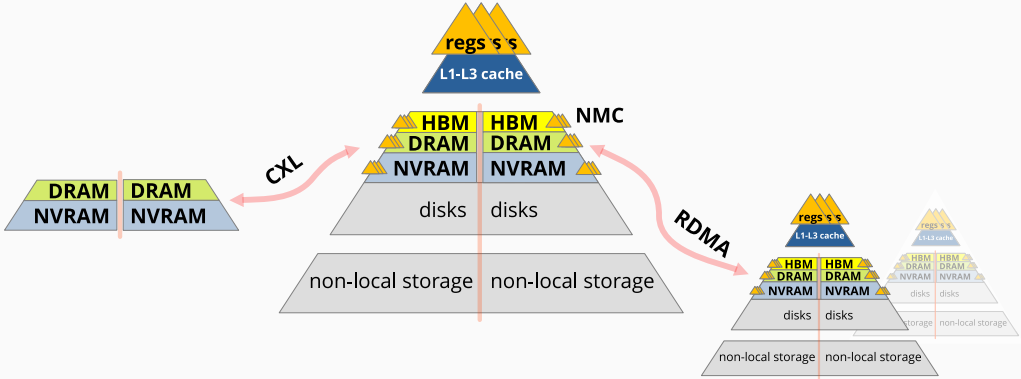
Universität Osnabrück

Motivation



Memory hierarchies are becoming increasingly complex

System software needs HW/SW models for resource management

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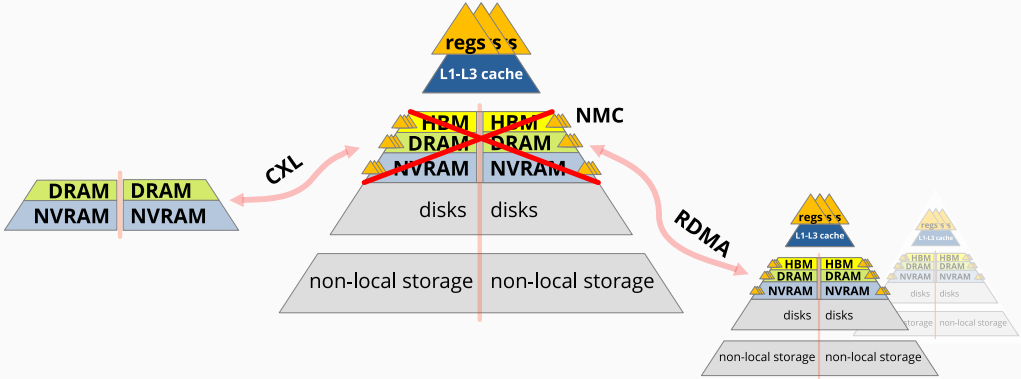

Disruptive memory technologies break out of the hierarchy:
Setup/transfer costs and access patterns must be considered

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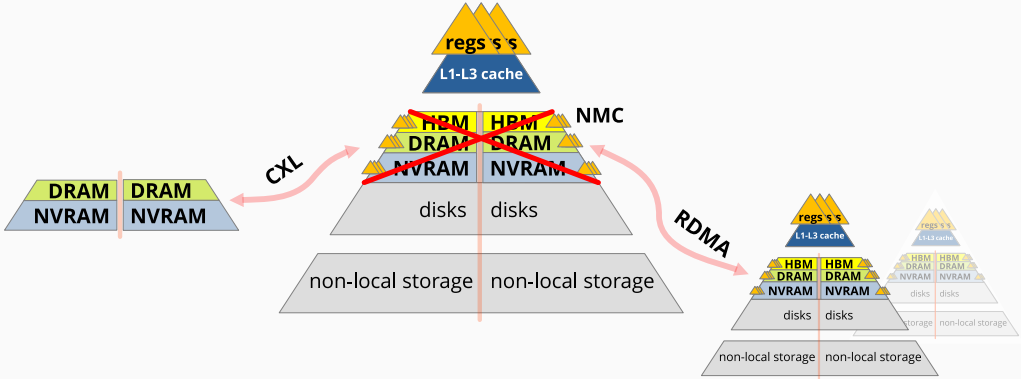

System-Level Modelling and Optimized Use of DMTs

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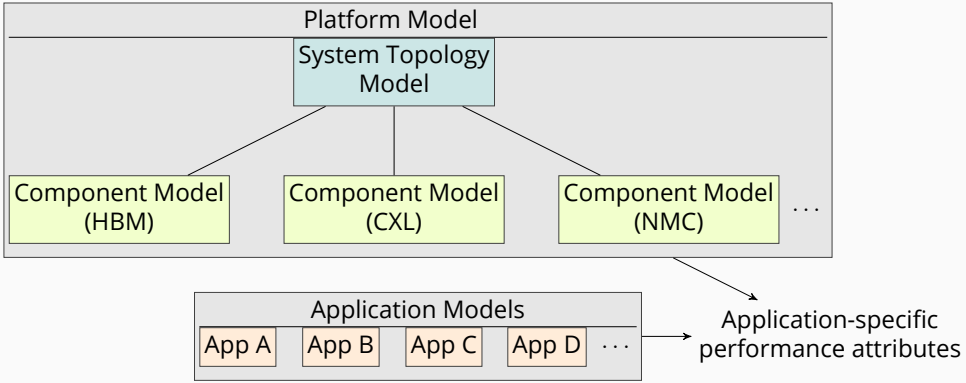
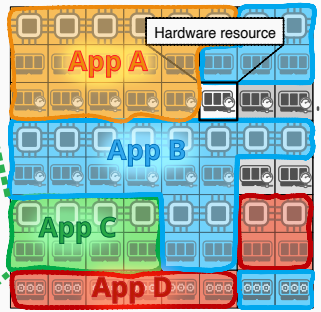


First funding period (Mar 2023 – Feb 2026):
System-Level Modelling and Optimized Use of DMTs

Motivation

Cells

- **Elastic** resource domain **for a single process**
- **Managed** by **MxVisor, directly**
- Use **task annotations** and resource metrics (e.g.,performance counters)
- To enable **fast reaction** to **load**



Second funding period (Mar 2026 – Feb 2029):
System-Level Modelling and Optimized Use of DMTs

Contents

Component Model: NMC (UPMEM PIM)

- UPMEM PIM: Near-Memory Computing ≙ offloading engine [Góm+22]
  - Up to 2560 cores: ideal for “embarrassingly parallel” problems

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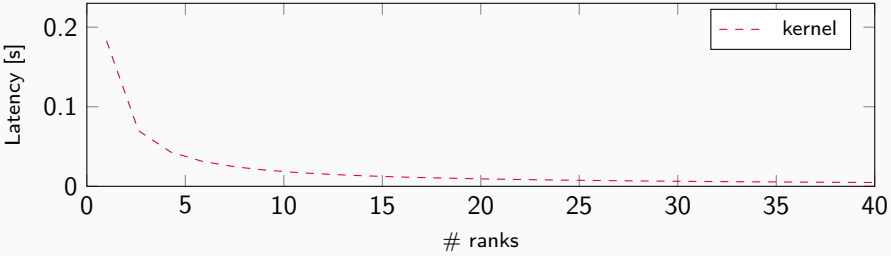

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DBMS SELECT kernel latency: $237\,\mu s + 0.68\,ns \cdot \frac{\#rows}{\#ranks}$

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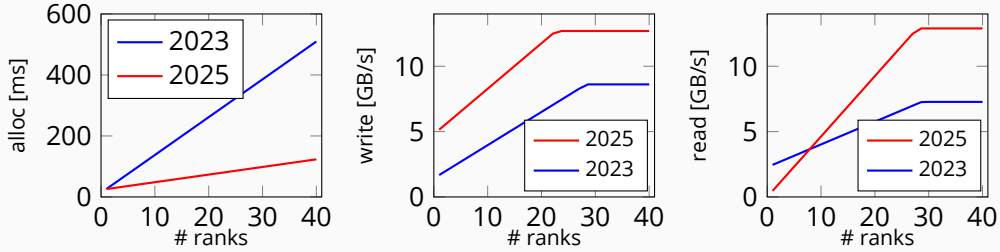

- UPMEM PIM: Near-Memory Computing ≙ offloading engine [Góm+22]
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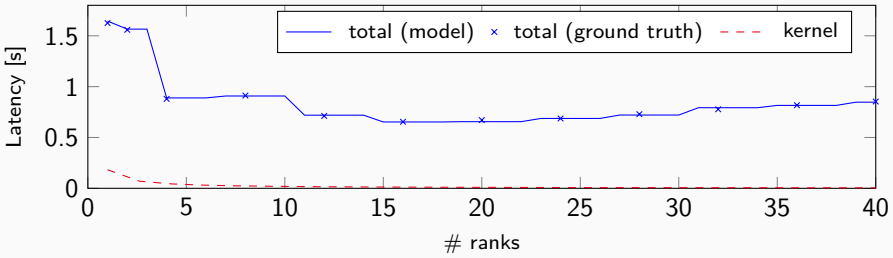

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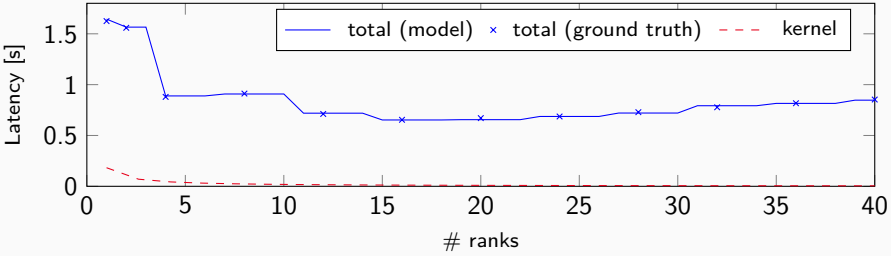

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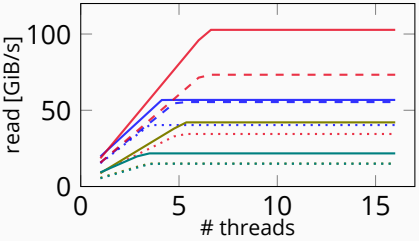
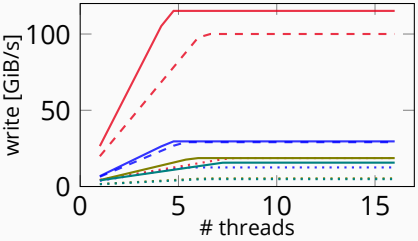
→ System-level models enable optimal resource utilization [FLS24; FLS25]

Platform Model: HBM, CXL



HBM
DRAM
CXL x16
CXL x8

local
intra -
cross -
pkg



- HBM: bandwidth ↑, but capacity ↓
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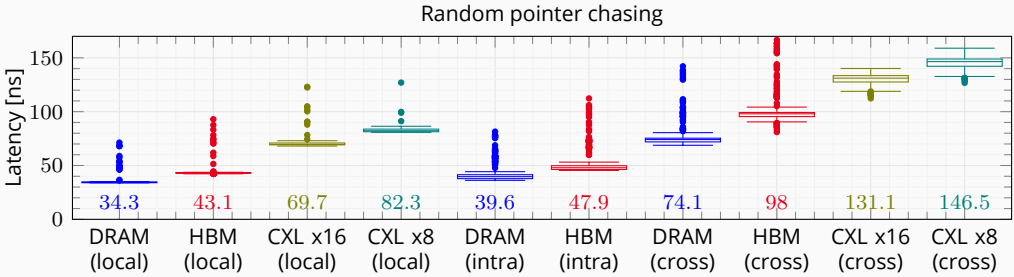

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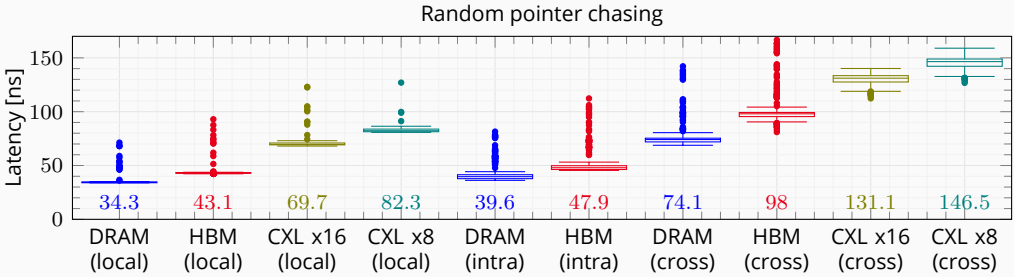

- HBM: bandwidth ↑, but capacity ↓, latency ↑

→ HBM can slow down applications; depends on access patterns [FLS24]

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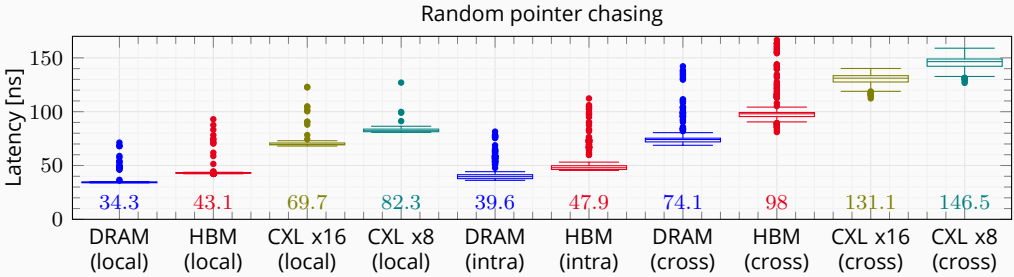

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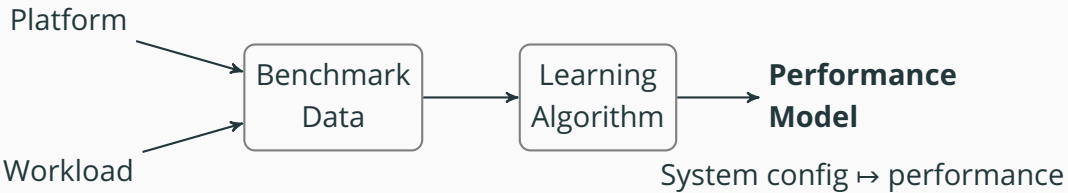
- CXL: capacity ↑, but bandwidth ↓, latency ↑ (worse than DRAM)
- Local CXL.mem ≋ remote DRAM → caching; contention avoidance

Application Models

- Existing approaches mix platform and application attributes



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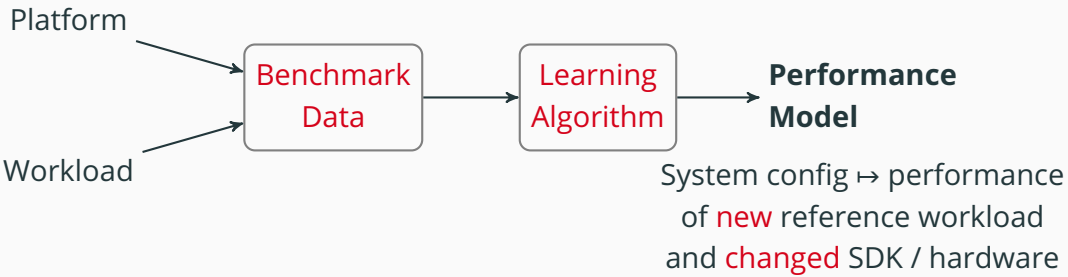
  - New hardware, new SDK version, different workloads, . . .



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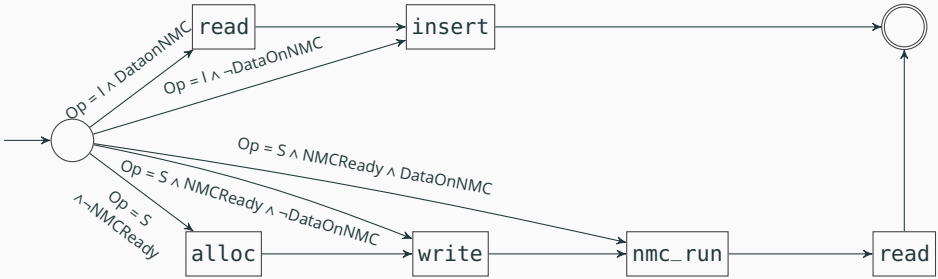
  - Changes in either → re-build model from scratch
  - New hardware, new SDK version, different workloads, . . .
- Thus: incapable of dealing with workload changes;
  useless for compute/data placement decisions
- SMAUG: application model is independent of platform model
  - Decoupled from hardware or SDK performance
  - Can be learnt on simulated hardware
- Contribution: state-machine based behaviour models

Performance-Aware Behaviour Models

Simplified example: NMC-enabled DBMS, **I**NSERT on CPU, **S**ELECT on NMC



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- Transitions guarded with workload-dependent runtime parameters

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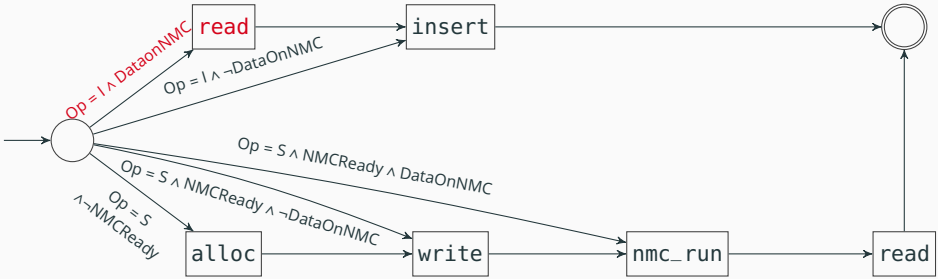

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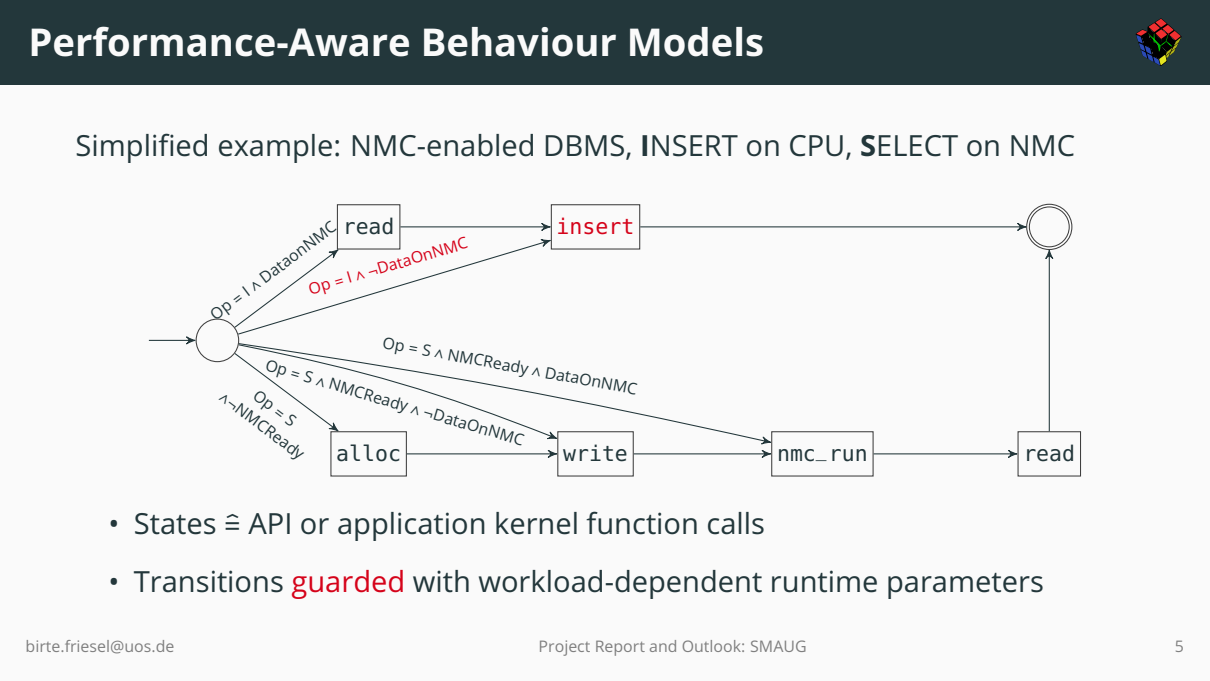

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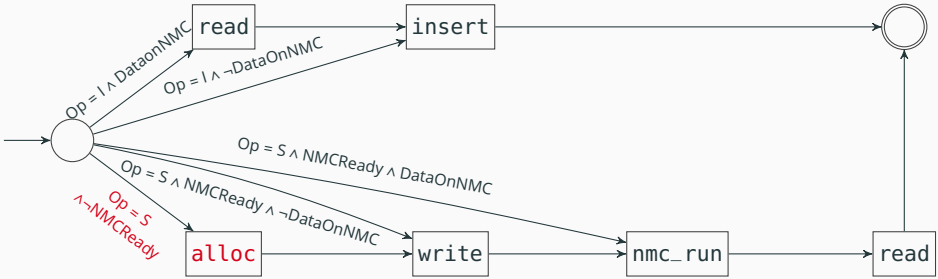

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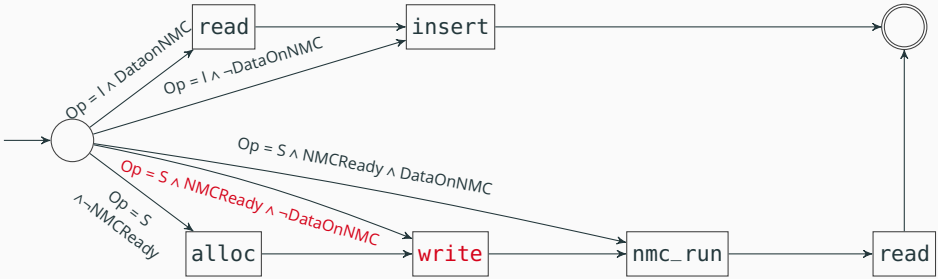

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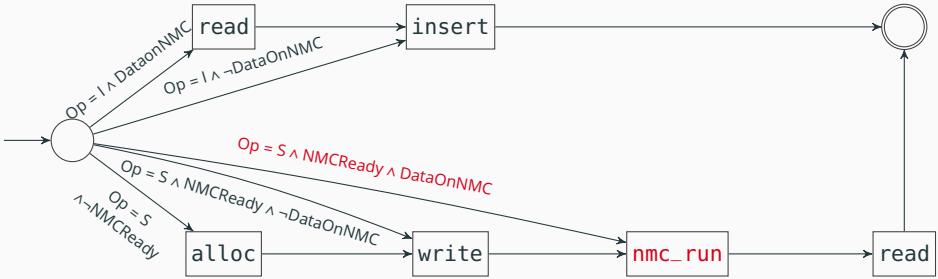

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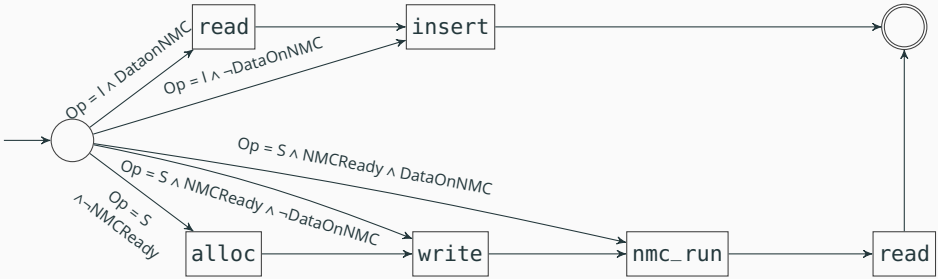

- States annotated with performance models
- Foundation: regression model trees (RMTs)

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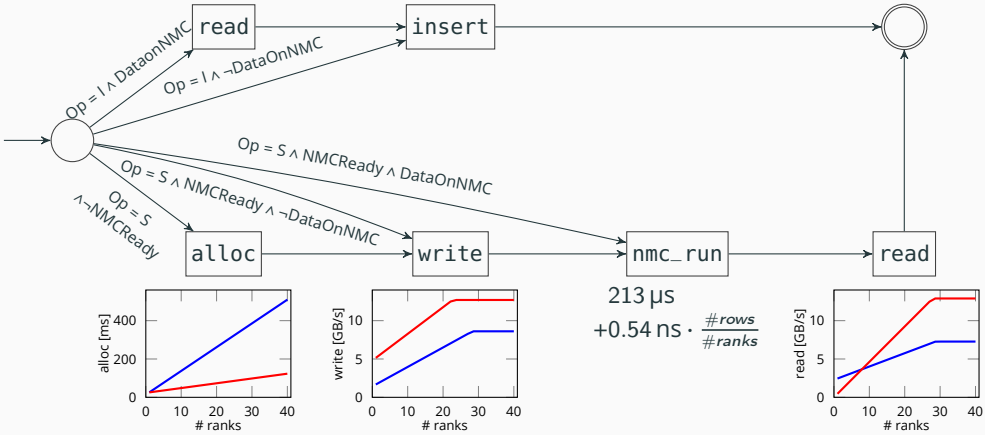
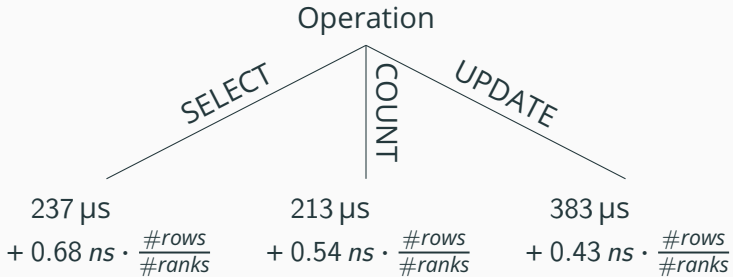


Regression Model Trees (RMTs)



Regression model trees [FS22]

= regression trees [Bre+84]

\+ unsupervised least-squares [FBS18]

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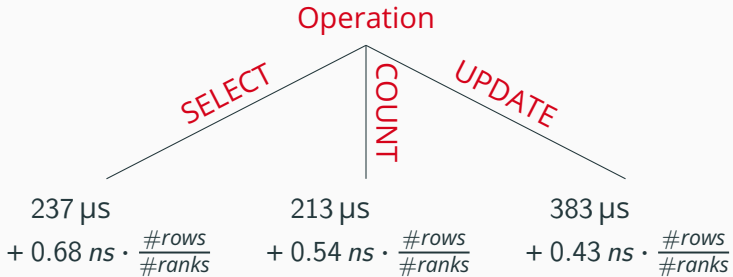

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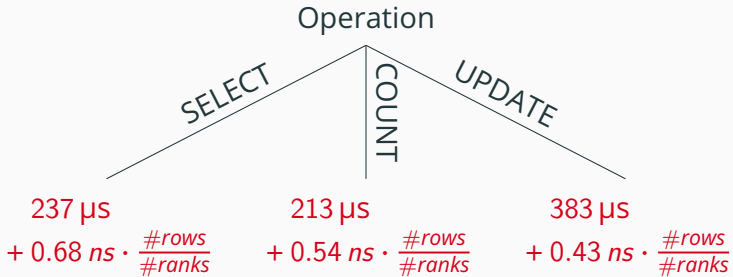

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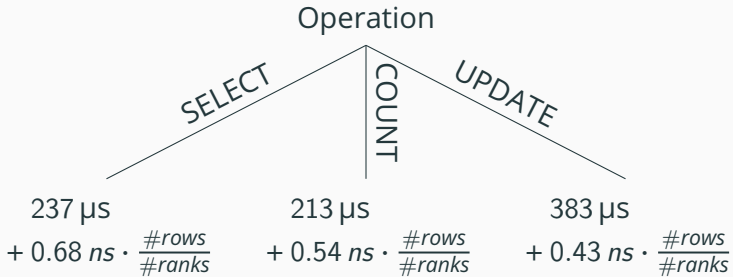

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- Accurate and interpretable
- Input domain: arbitrary
- Output domain: $\mathbb{R}$

Application Models: Learning and Usage

- Performance prediction and model learning in two steps:
  1. Workload definition $\mapsto$ function call sequence (with function arguments)
     Example: Op = I, #rows = 2^{30}, DataOnNMC = $\top \mapsto$ `read`(8 GiB) $\cdot$ `insert`()
  2. For each function call: arguments $\mapsto$ latency/throughput
     Example: `read`(8 GiB) with #ranks = 40 $\mapsto$ 12.5 GiB/s

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- Performance prediction and model learning in two steps:
  1. Workload definition ↦ function call sequence (with function arguments)
     (state machine learnt from application traces; simulator is sufficient)
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→ Predict latency/throughput of arbitrary workloads [FS25b; FS25a]

→ Understand bottlenecks and changes, e.g., between SDK releases [FS25c]

→ Simulation-based optimization of placement decisions [FLS25]

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- Compatible with HetSim (DMT-aware scheduling simulator) [LFS24]
- Both prediction steps use regression model trees (RMTs) [FS22]

Summary of First Funding Period

- 30/36 months elapsed (started in March, 2023)

(✓) Platform model: NMC (UPMEM PIM), HBM, CXL.mem (legacy mode)

† NVRAM (Intel Optane)

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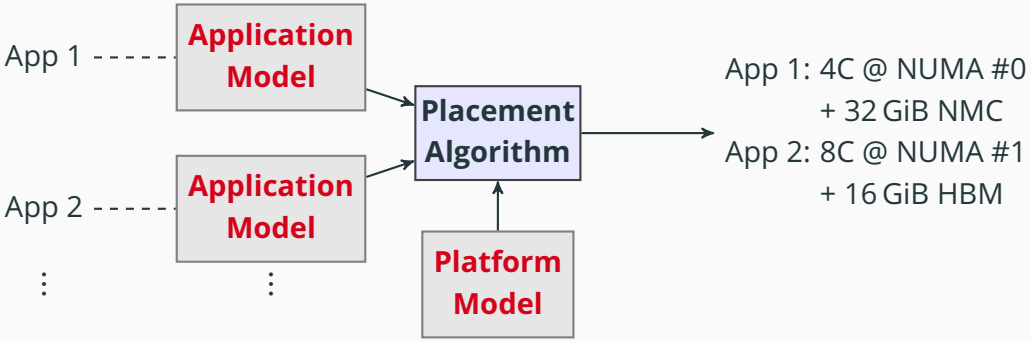
- Findings published at DIMES (2×), WOSP-C, VaMoS, NoDMC, SPLC, CCMCC
  [FLS23; LFS24; FLS24; FS25b; FLS25; FS25c; FS25a]
  - Artifacts for all publications available at `ess.cs.uos.de/git/artifacts`
  - SPLC: artifacts evaluated: available and functional

Contents

Second Funding Period: Optimized Use of DMTs

Goal: Use models from first period for holistic, model-guided strategies



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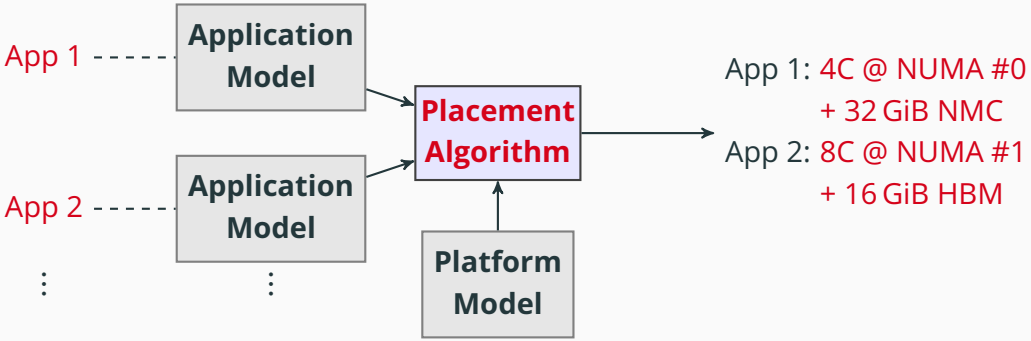

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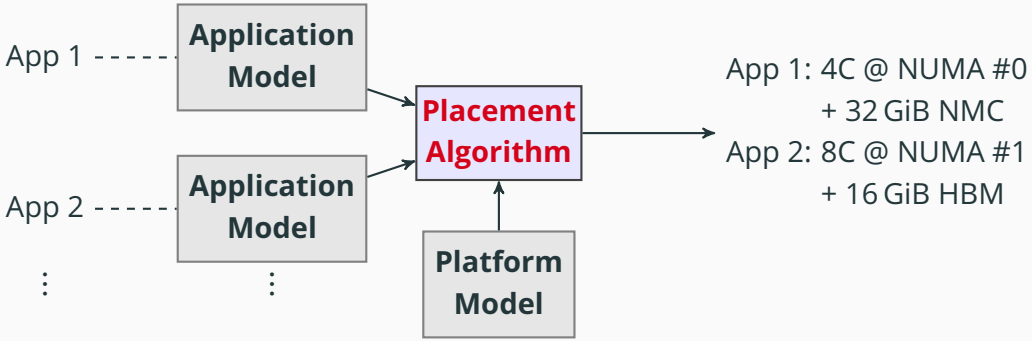
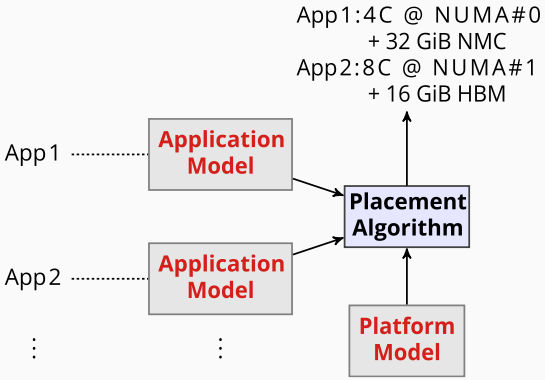


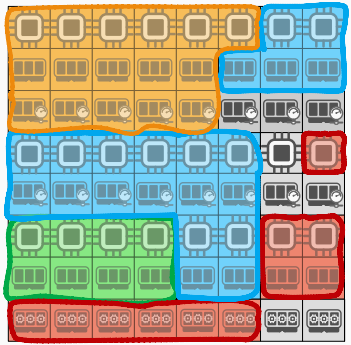
⇒ Benefit of resource management strategies for systems with DMTs?

Research Objectives

① Coarse-grained (system-wide) resource partitioning strategies

→ Avoid interference for latency-critical applications





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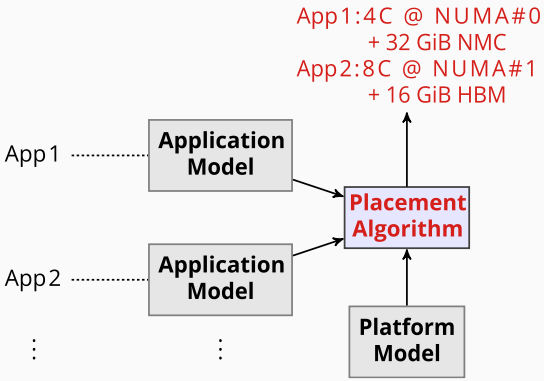

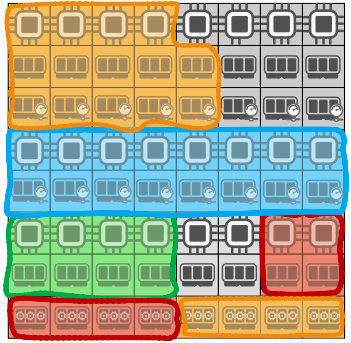

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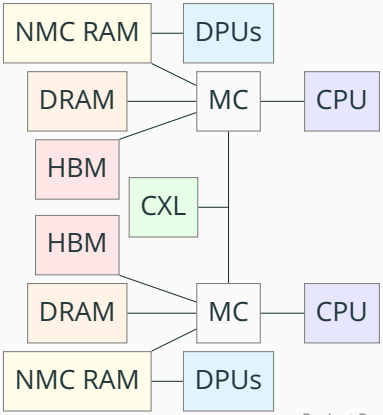
② Fine-grained resource usage optimization

→ Place compute and data of given application on appropriate DMTs



Application
Bandwidth-bound
Latency-bound
Background
Parallel

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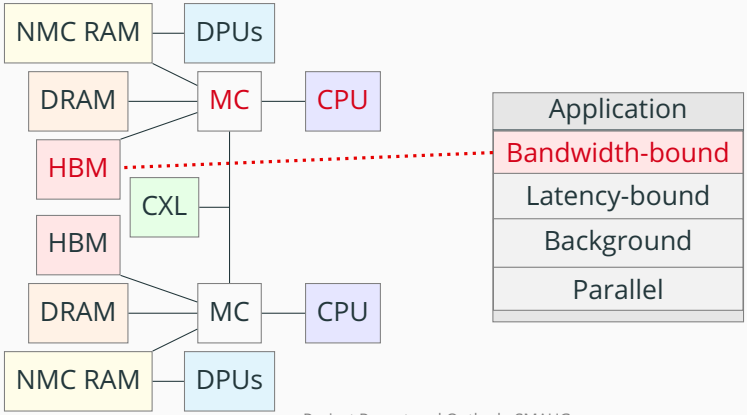

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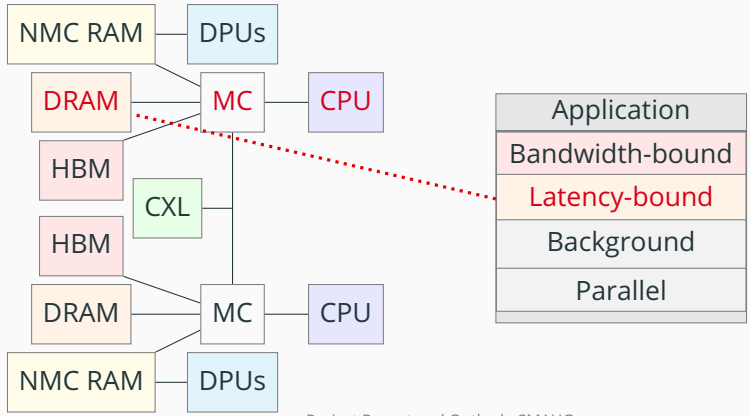

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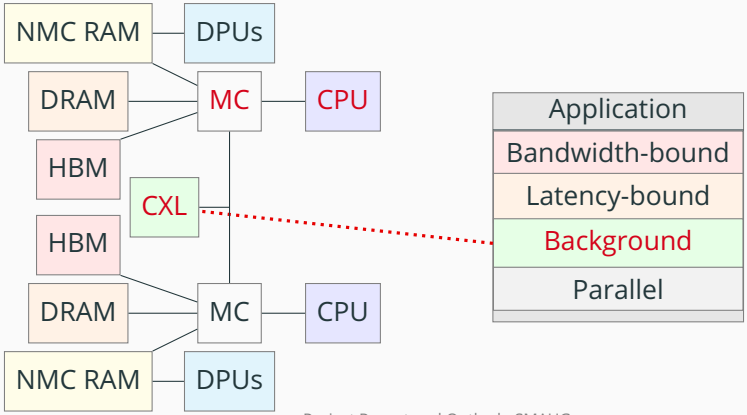

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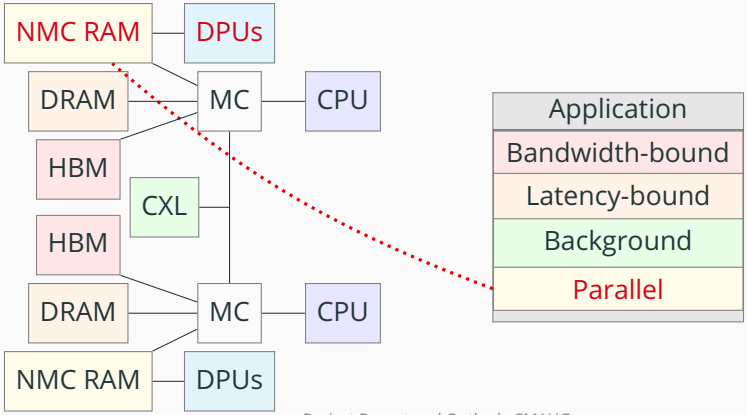
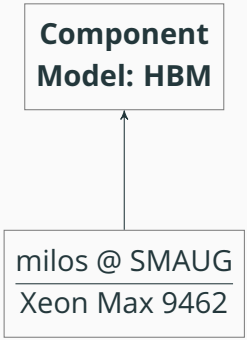


Research Objectives

③ Model maintenance

→ Avoid re-learning models from scratch after system changes



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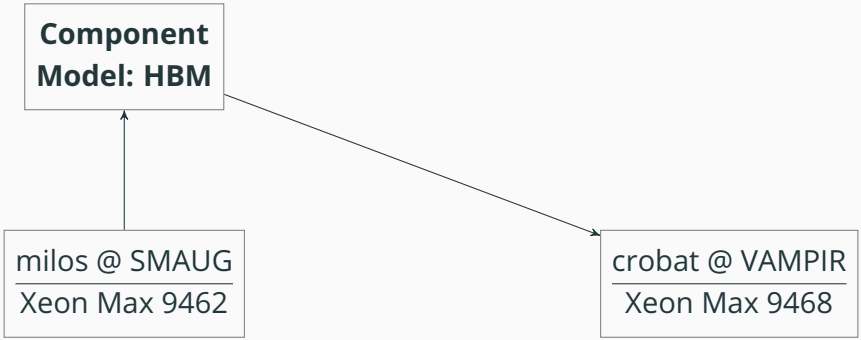

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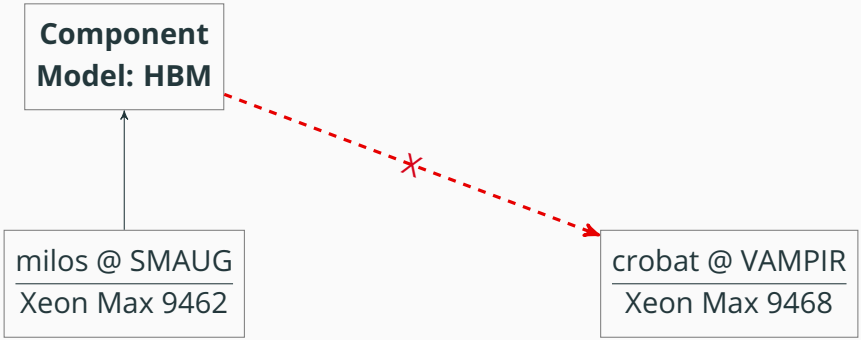

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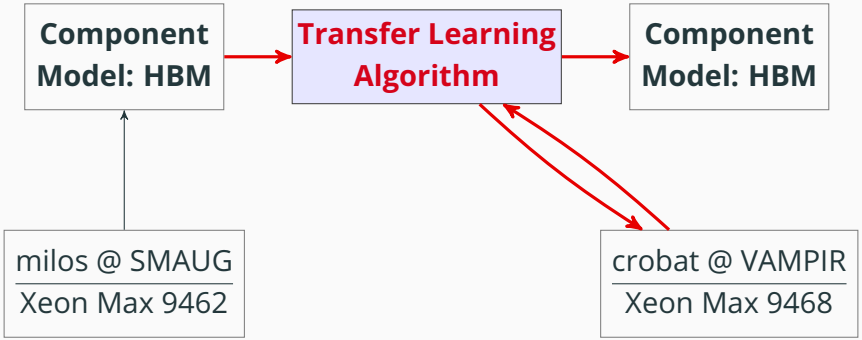

Research Objectives

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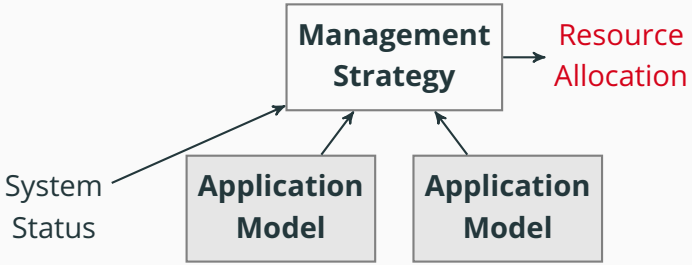
→ Microsecond-scale decisions to minimize tail latency



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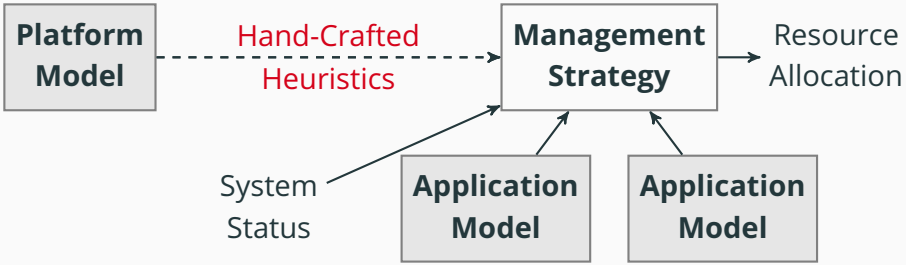

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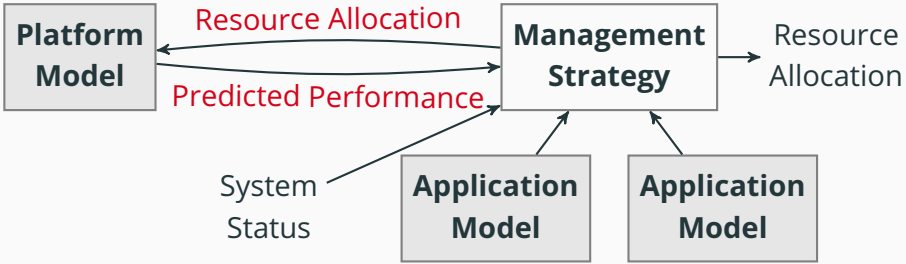

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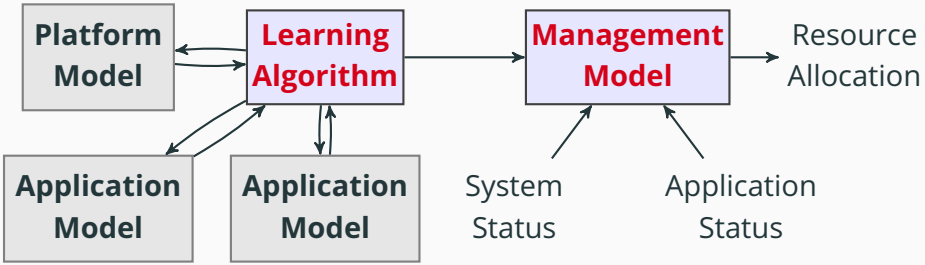

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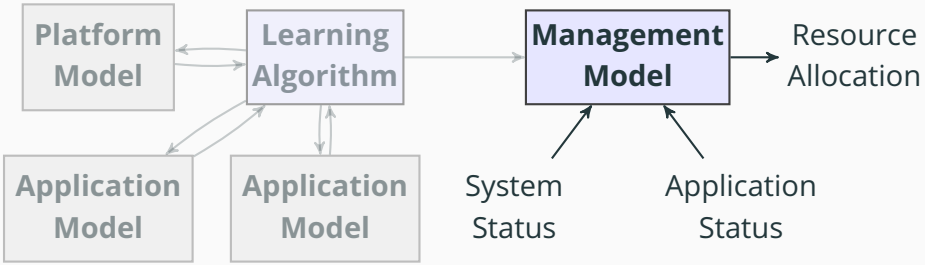

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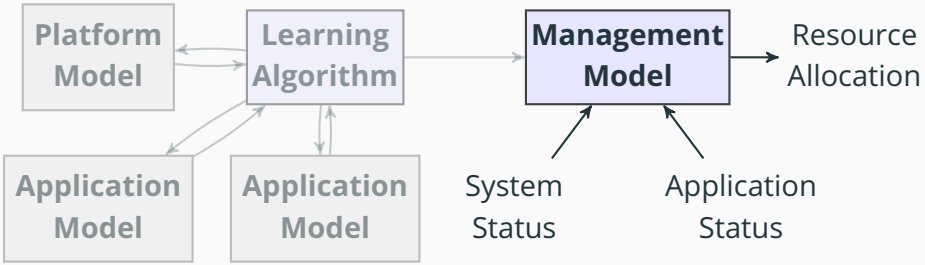


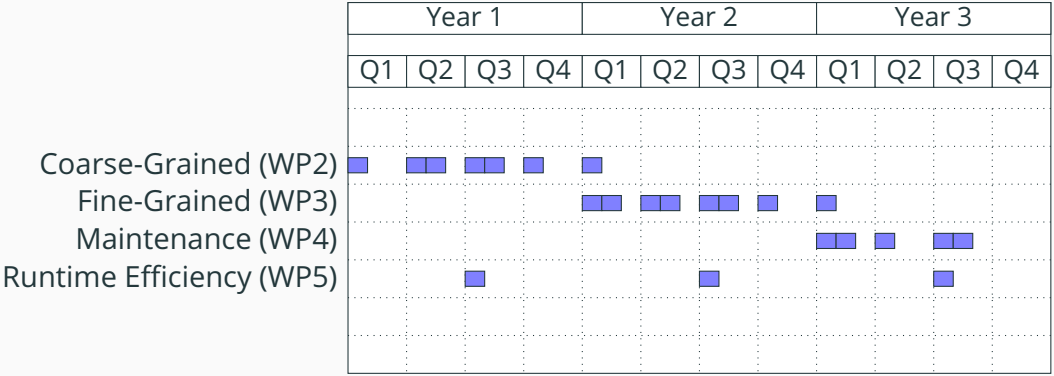
Idea: Adjust RMTs for multi-dimensional output

→ fast and interpretable management decisions

Evaluation Platforms

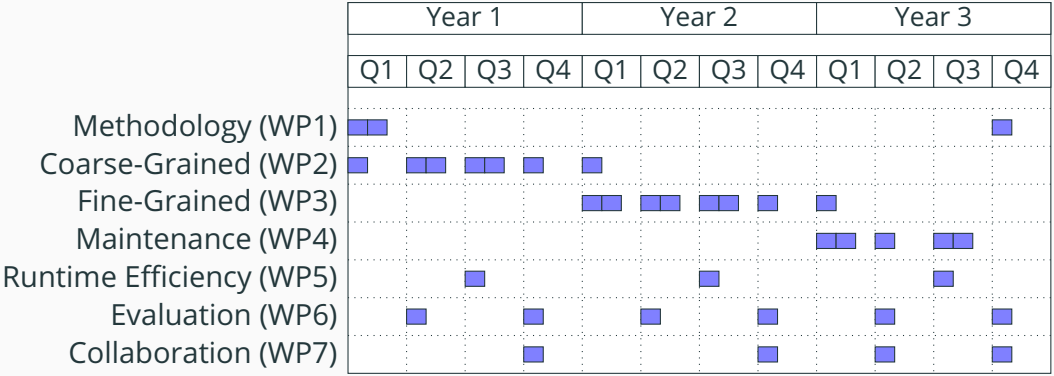
- HetSim: heterogeneous scheduling simulator [LFS24]
  - Supports CPU, GPU, FPGA, UPMEM NMC, (DRAM / HBM / CXL)
  - Already used and verified in first phase [FLS24]
- EalánOS / MxKernel: bare-metal OS for heterogeneous servers [MS19]
  - Supports CPU, GPU, and NMC execution
  - Evaluation of coarse- and fine-grained management strategies

Work Packages



WP2 . . . WP5 ≙ research objectives ① . . . ④

Work Packages



WP2 . . . WP5 ≙ research objectives ① . . . ④

Collaboration Opportunities

- HetCIM: behaviour models + kernel performance prediction [Sil+25]
- HetCIM, Memento, PIMPDM: performance-aware placement algorithms
- PIMPDM, VAMPIR: evaluation of results in DBMS context
- VAMPIR: model maintenance (slightly different HBM servers)

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- VAMPIR: model maintenance (slightly different HBM servers)
- *Your Project Here*
  - SMAUG: Evaluation on HetSim and EalánOS
  - We are always interested in more use cases and evaluation targets

Conclusion

- Goal: examine benefits of
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- Research objectives:
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  - Model maintenance / transfer after software / hardware changes
  - Efficient (microsecond-scale) runtime decisions
- Implementation and evaluation: HetSim, EalánOS
- Lots of potential for collaboration – please reach out

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