Heterogeneous Memory Management in Servers with fitd

Chun Deng, Anna Eaton, Evan Laufer, Philip Levis

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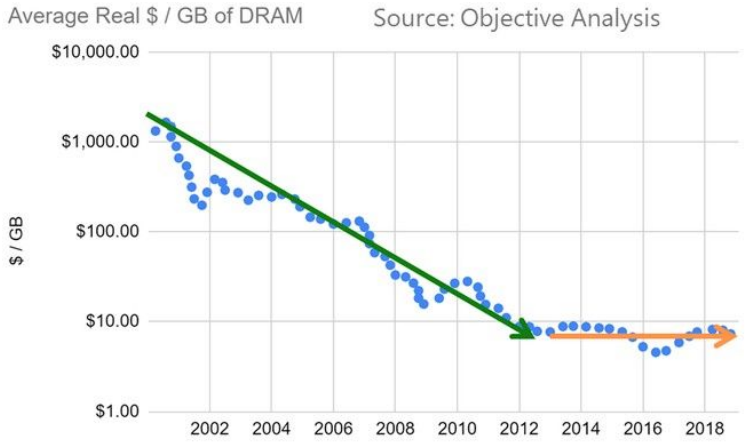
DRAM costs are driving new memory approaches



- DRAM costs dominate in servers
  - Microsoft claims that 50% of their server costs are from memory, Meta claims 40%[1]
- New memory types
  - 3D crosspoint
- New interconnects
  - CXL
- Software approaches
  - zswap

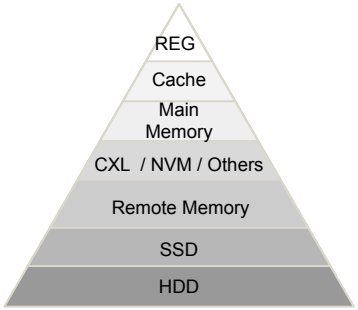
[1] Maruf et al. TPP: Transparent Page Placement for CXL-Enabled Tiered-Memory

Systems today assume a hierarchy

- Research into adding a new “tier” of memory
  - HeMem (SOSP 21’)
  - Memtis (SOSP 23’)
  - TPP (ASPLOS 23’)
  - Colloid (SOSP 24’)
  - Nomad, Memstrata (OSDI 24’)
- Use “temperature” (hot/cold) to decide where to place data
- Placing data in tiers based on temperature implies a hierarchy
  - Faster to slower (latency, bandwidth, etc.)
  - Expensive to cheap

Memory is not always a strict hierarchy

Memory	Read Latency	Read Bandwidth	Write Bandwidth
DDR5 DRAM	114ns	38 GB/s	38 GB/s
Optane DC	172ns	32 GB/s	11 GB/s
CXL	239ns	52 GB/s	52 GB/s



- Optane read bandwidth similar to DRAM, write bandwidth is ⅓ of DRAM
- DDR5 over CXL is higher bandwidth *and* higher latency than Optane
- CXL and Optane don’t have a strict ordering

[1] Liu et al. Dissecting CXL Memory Performance at Scale: Analysis, Modeling, and Optimization
[2] Raybuck et al. HeMem: Scalable Tiered Memory Management for Big Data Applications and Real NVM

Deciding where to put data

- Suppose we have a server with multiple types of memory, each with different tradeoffs (not a hierarchy)
  - Capacity/cost
  - Latency
  - Read bandwidth
  - Write bandwidth
- How can an operating system decide which pages to put in what memory type?
  - Needs to understand all of the tradeoffs
  - Needs to observe access patterns at extremely high speed

Proposal: fitd, the memory fitness daemon

Add a small amount of hardware support in the MMU to score memory access patterns for different memories (“fitness”)

> Challenge: how can we very inexpensively score access patterns across a diverse set of tradeoffs?

Operating system decides when to move pages between memory types based on fitness scores

> Challenge: how can we scale to a large amount of pages, while maintaining the quality of assignments?

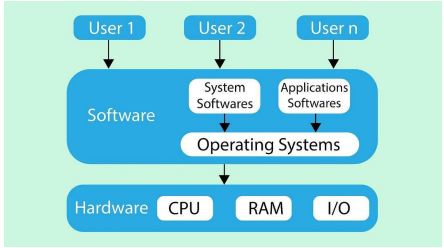
Outline of this talk

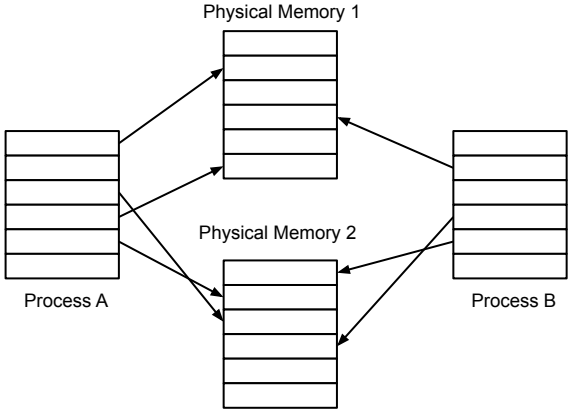
1. Background
    a. Operating systems and memory management
    b. OS page placement
    c. OS-Level system example

1. Heterogeneous memory management with fitd
    b. Estimating fit
    c. Score-based decision-making
    d. Implementation
    e. Preliminary results

Background: Operating System and Memory

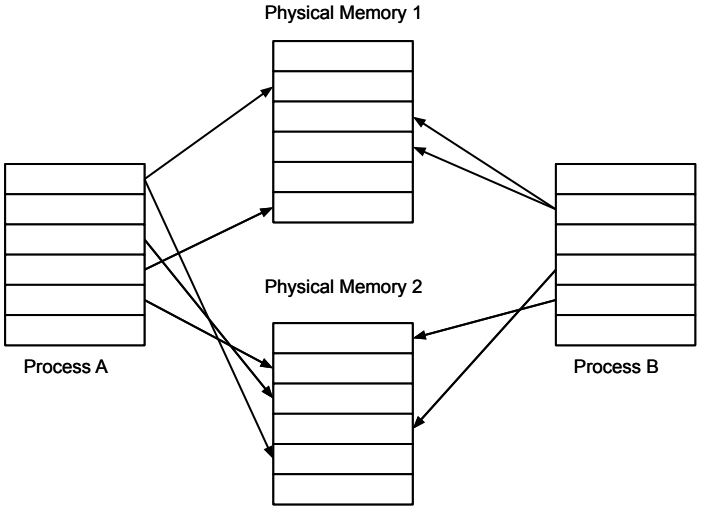
- Operating system is the lowest software layer, it can directly access all of the hardware
- Provides useful abstractions to applications (e.g., files instead of disk blocks)
- Virtualizes memory, mapping application addresses to actual physical memory
- Operating system gets to decide which physical memory a given part of an application's data lives in





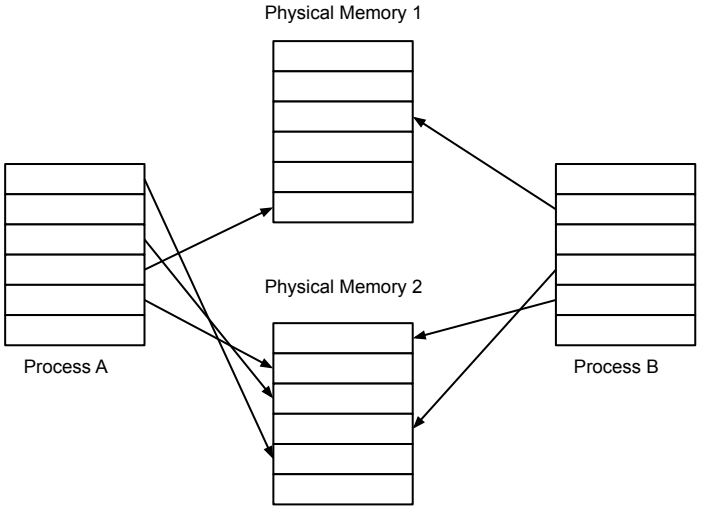
Background: OS-Level Page Placement Policies

- The OS decides where a page should reside in physical memory



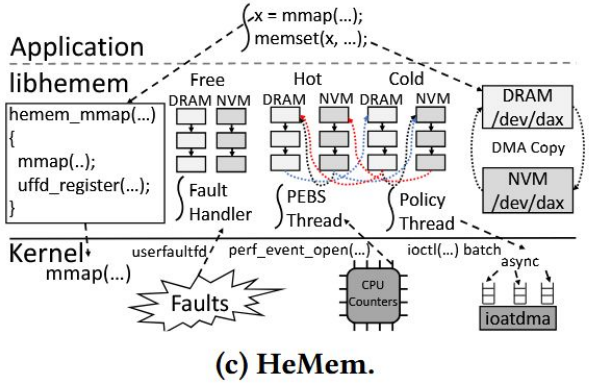
Background: OS-Level Page Placement Policies

- The OS decides where a page should reside in physical memory
- It can change this decision and *migrate* a page from one memory to another, updating the virtual memory pointers
- Migration hidden from application



Example Prior Work: HeMem *[1]

- HeMem is a system that chooses between DRAM and Optane
- The OS tracks the number of access counts to pages
- Once the counter hits 8 reads or 4 writes, it is considered “hot” and HeMem promotes it to DRAM
- Periodically halve access counts to “cool” pages, demote pages with low counter values
- Every few seconds, decide on promotions and demotions, move pages



(c) HeMem.

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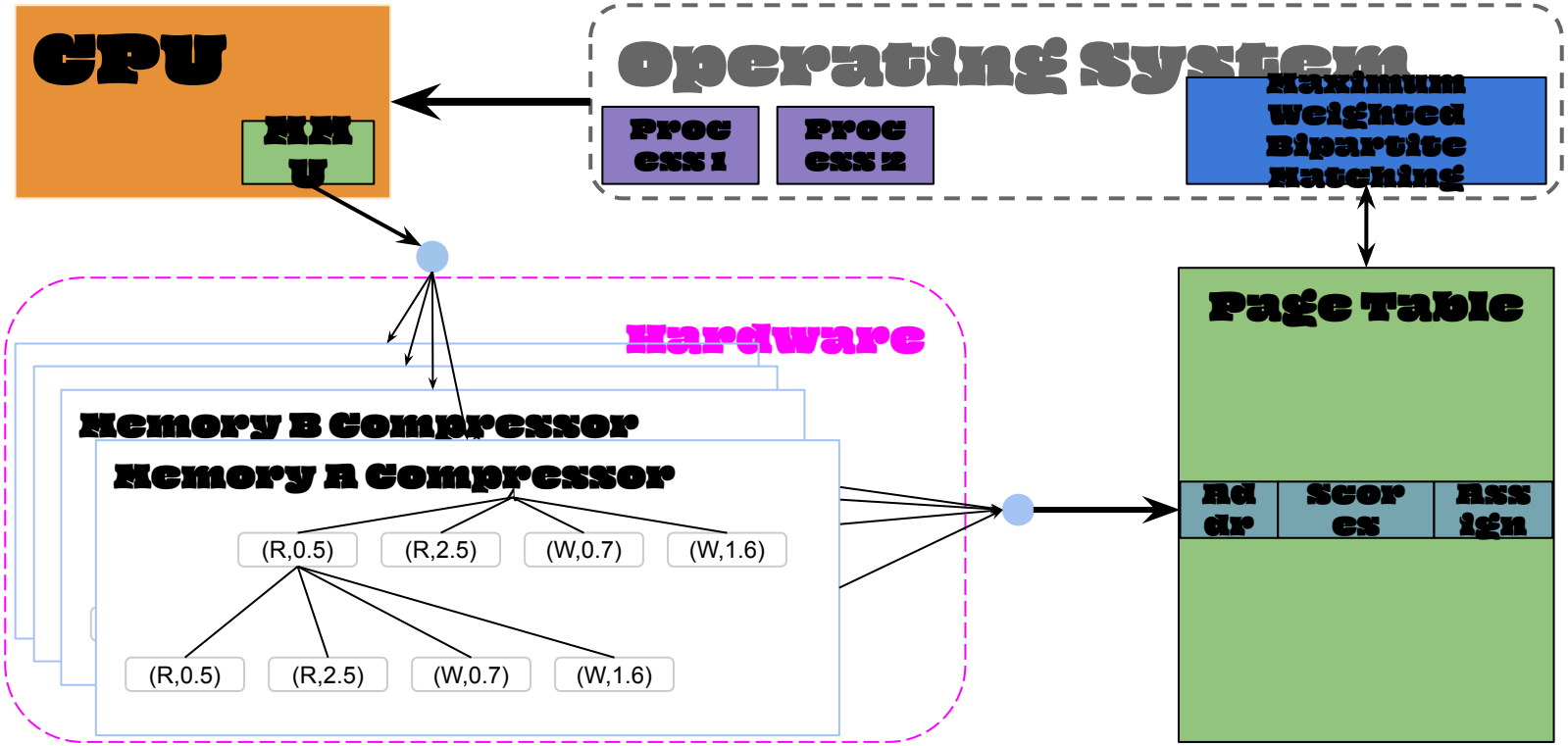
fitd: System for Heterogeneous Memory Management

1. fitd is composed of two parts - a hardware scoring component, and an operating system daemon.

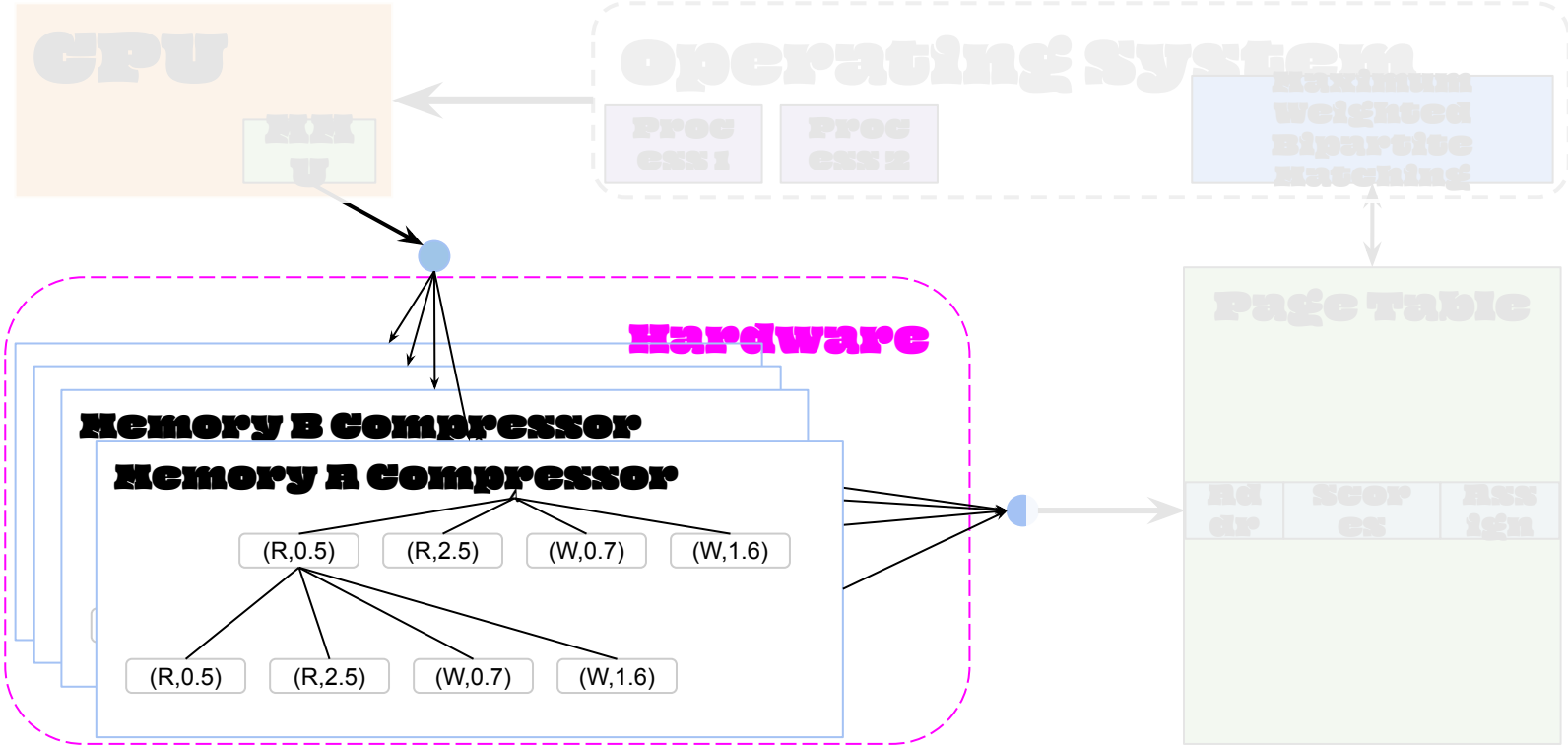
1. The hardware component creates “fit” scores indicating how much a memory prefers a particular page’s access patterns
   a. Key insight: Instead of counting patterns, treat the problem as matching the two distributions.
   b. Use a novel lightweight compression algorithm to estimate match

1. The operating system daemon uses these “fit” scores to determine placement.

fitd design: Overview



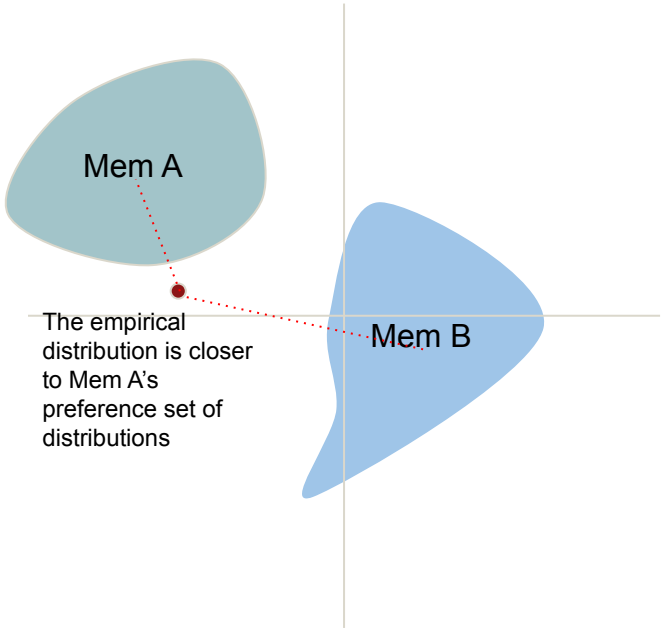
fitd Design: Hardware Component



Compression as a distribution learner

- We want to be able to estimate how well a pattern “fits” a memory.
- First step: model what “good” patterns are for each memory

- **This can be framed as a compression task**
  - Compressors learn an expected distribution of values (patterns)
  - If it can compress an access pattern well, the accesses are closer to the “good” patterns



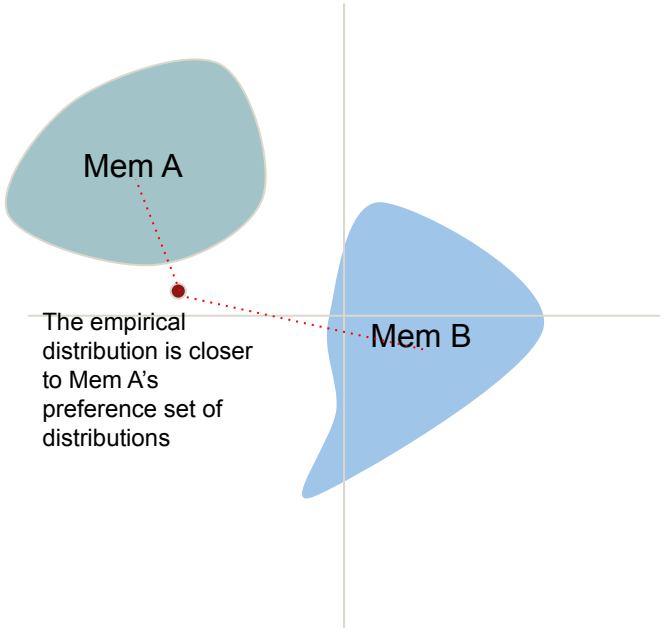
distribution “simplex” - each point is a distribution

Compression as a distribution learner

Offline: Build a compressor, trained on “good” patterns for that memory, incorporated into MMU

Hardware: Compress the access pattern of each page with each compressor

Software: See which compressor works best! High compression means good fit.



distribution “simplex” - each point is a distribution

Need a new lossy compression algorithm

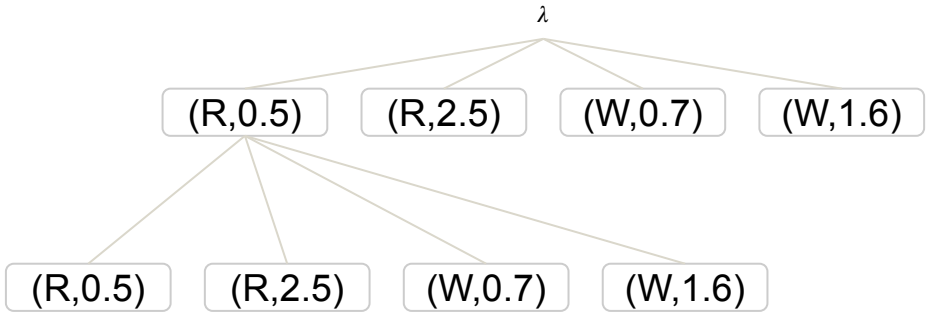
- Standard lossless compressors (LZ77, LZ78) are poor for memory traces

- Use exact phrase matching
  - Encode “nop nop write” separately from “nop nop nop write”
  - Dictionary sizes grows rapidly

- Limiting dictionary/window sizes performs poorly
  - Around 60-70% in a binary classification setting, over simple traces
  - Compressor A trained on 7 0’s followed by a 1
  - Compressor B trained on 14 0’s followed by a 1
  - Evaluated on 9 0’s followed by a 1, Compressor B compressed better (this isn’t what we want)

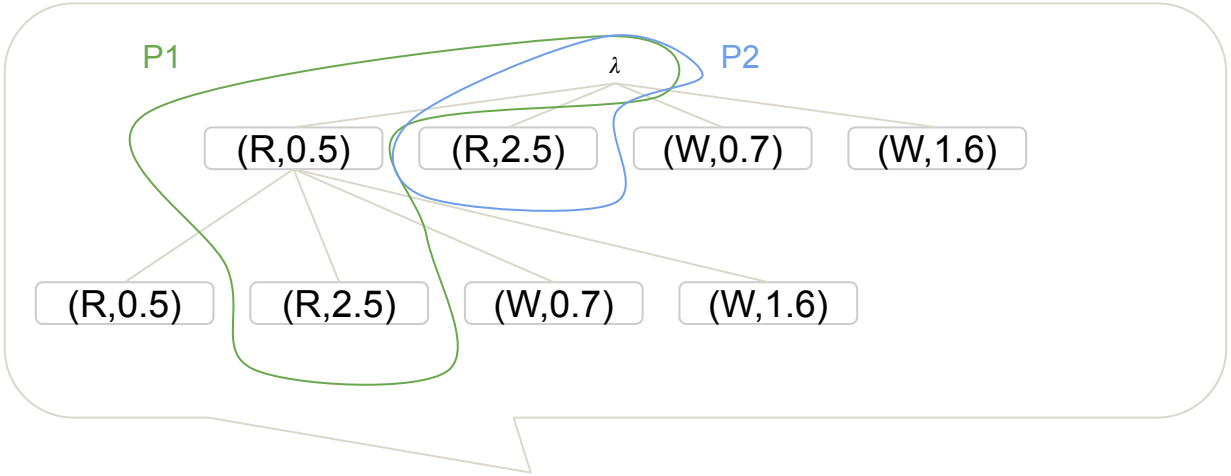
Soft Context Tree Weighting

- Adapt Context Tree Weighting (CTW) algorithm to work with run-length encoded data
- Cluster branches of the context tree based on access type (read/write) and sparsity of access (high = sparse)
- Use KDE estimation to blend probabilities from the KT-estimator



$$P(i) = \frac{\sum_i \omega_i * KT(i)}{\sum_i w_i}$$

A Running Example



Access Trace: (R, 1), (R, 2.5), (R, 0.9), (W, 1.4), (R, 0.5)

Cost: C1 + C2

Where C2 = log(blending of P1 & P2)

Picking out traces to train our compressor model

- What traces are considered “good” for each memory?
  - Depends on the objective function that is being optimized. Is it average read latency, endurance, cost? or a mixture?
  - Can also be manually defined
  - Ideally, these traces pulls the preference distributions apart. But are still in-distribution of real workloads

- We use a memory simulator to evaluate traces for each memory, currently optimizing for total simulation time

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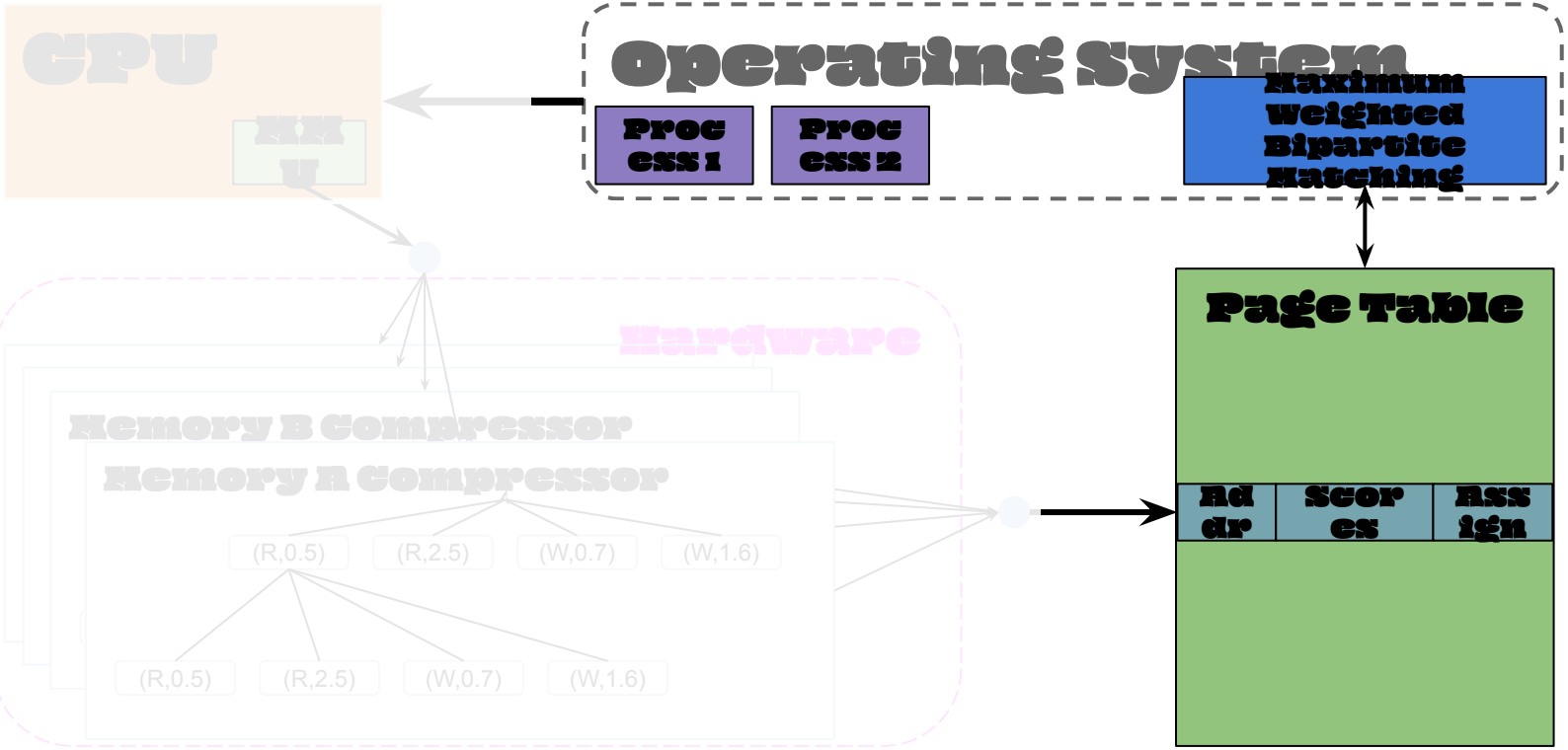
fitd design: Software Component



Assignment and Placement

	Mem A	Mem B	Mem C
Page 1	**1.4**	2.7	3.9
Page 2	2.3	3.1	**1.2**
Page 3	5.1	**0.5**	1.3

fitness scores from each page to each memory

- Standard algorithms can find the global optimum, but are too slow ($O(N^3)$, N is # of pages)
- Solution: use an incremental algorithm that converges to a local optimum
- Swap operator incrementally swaps pages that improve fitness

The swap operator

- Each memory keeps k - 1 ordered lists on the willingness of it's assigned pages to go to a memory elsewhere, where k is the number of memories

- To check for swap candidates, we check the most willing to leave element from each memory to other memory
  - At most there are k(k-1) / 2 checks

- If there are no swap candidates, by definition we are at a local optima

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SCTW Hardware Implementation Optimization

- KT-probabilities are retrieved from a lookup table

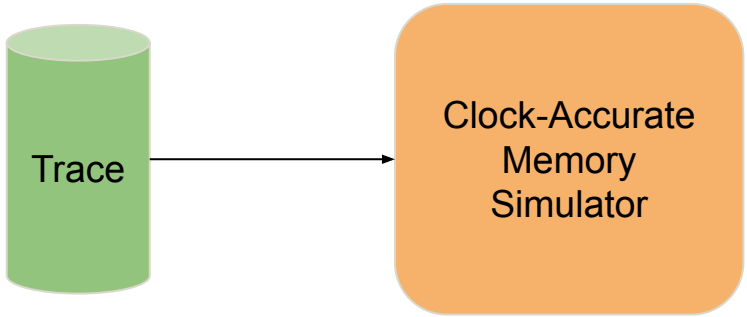
- Blending KT-probabilities at specific depth d involves a linear combination of these looked-up probabilities.
  - since addition operators are associative, we can do them in parallel

$$P(i) = \frac{\sum_i \omega_i * KT(i)}{\sum_i w_i}$$

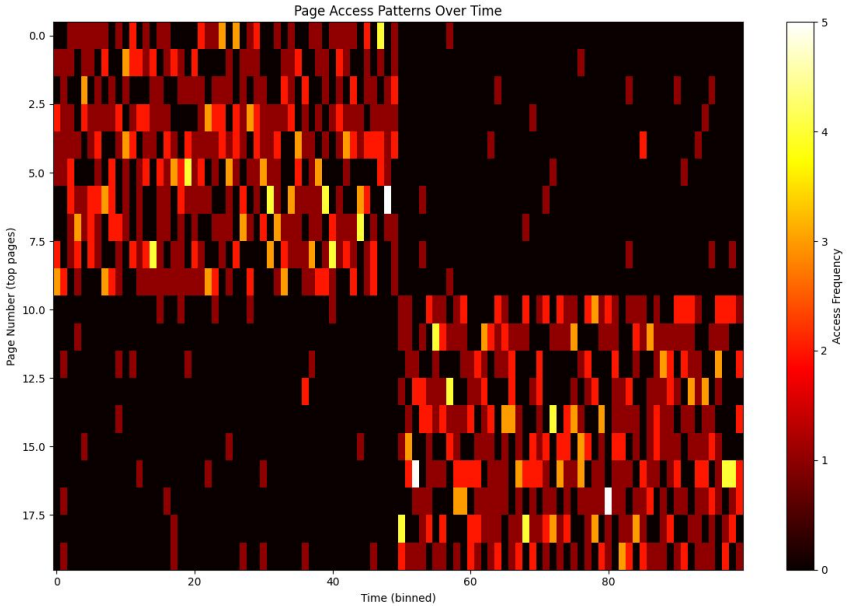
- Blending probabilities across depths also involves a linear combination, which we can also do in parallel if needed.
  - In practice, a model of depth 2 is sufficient to capture first order read write dependencies

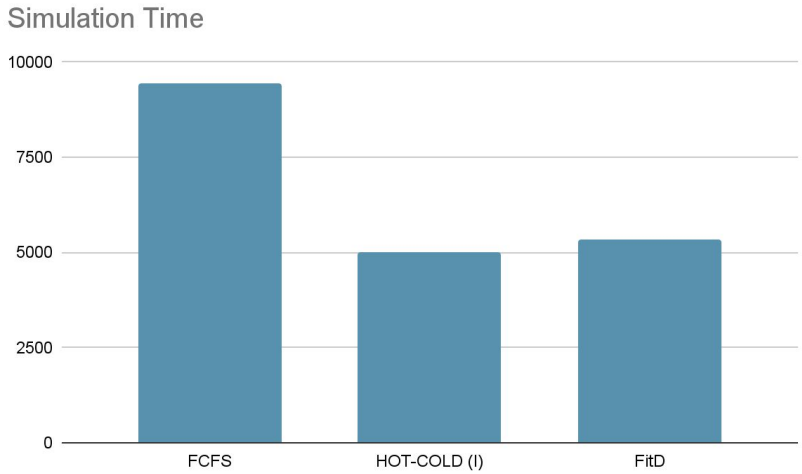
Simulator

- Trained two context trees with a generated set of microbenchmark traces
  - Optane DC and DRAM
- Evaluate fitd with those two trained context trees on microbenchmarks
  - regenerated traces for validation



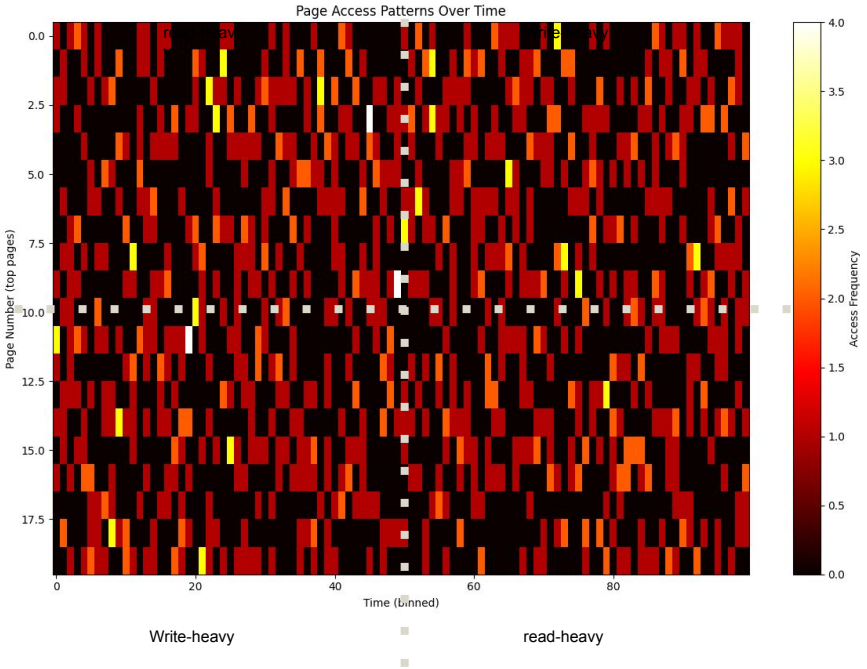
Results - Hot-cold workloads (GUPS)

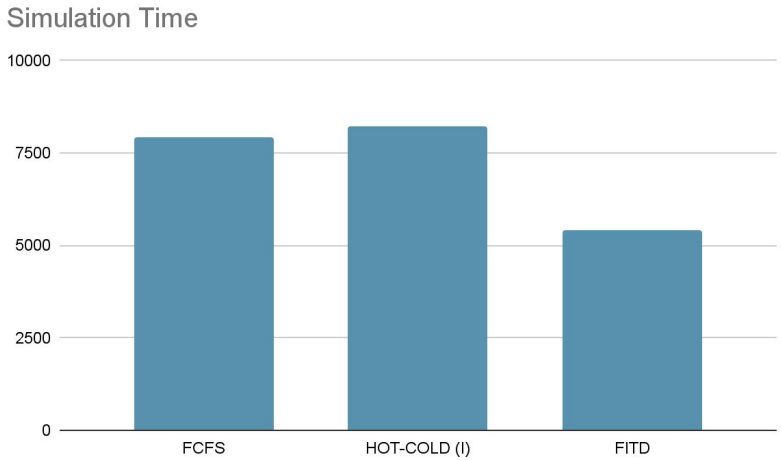




fitd can effectively represent hot-cold policies when facing hot-cold workloads

Results - Read heavy vs Write Heavy workloads





fitd significantly outperforms by exploiting patterns beyond hot-cold
i.e. read-heavy vs write-heavy patterns

Thanks