Memory Systems and Memory-Centric Computing

Lecture 4.1: Memory-Centric Computing III

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HiPEAC ACACES Summer School 2024





Agenda For Today

- Memory Systems and Memory-Centric Computing
 - July 15-19, 2024
- Topic 1: Memory Trends, Challenges, Opportunities, Basics
- Topic 2: Memory-Centric Computing
- Topic 3: Memory Robustness: RowHammer, RowPress & Beyond
- Topic 4: Machine Learning Driven Memory Systems
- Topic 5 (another course): Architectures for Genomics and ML
- Topic 6 (unlikely): Non-Volatile Memories and Storage
- Topic 7 (unlikely): Memory Latency, Predictability & QoS
- Major Overview Reading:
 - Mutlu et al., "A Modern Primer on Processing in Memory," Book Chapter on Emerging Computing and Devices, 2022.

Processing in Memory: Two Approaches

- 1. Processing using Memory
- 2. Processing **near** Memory

Processing in Memory: Two Approaches

- 1. Processing using Memory
- 2. Processing near Memory

PIM Review and Open Problems

A Modern Primer on Processing in Memory

Onur Mutlu^{a,b}, Saugata Ghose^{b,c}, Juan Gómez-Luna^a, Rachata Ausavarungnirun^d

SAFARI Research Group

^aETH Zürich

^bCarnegie Mellon University

^cUniversity of Illinois at Urbana-Champaign

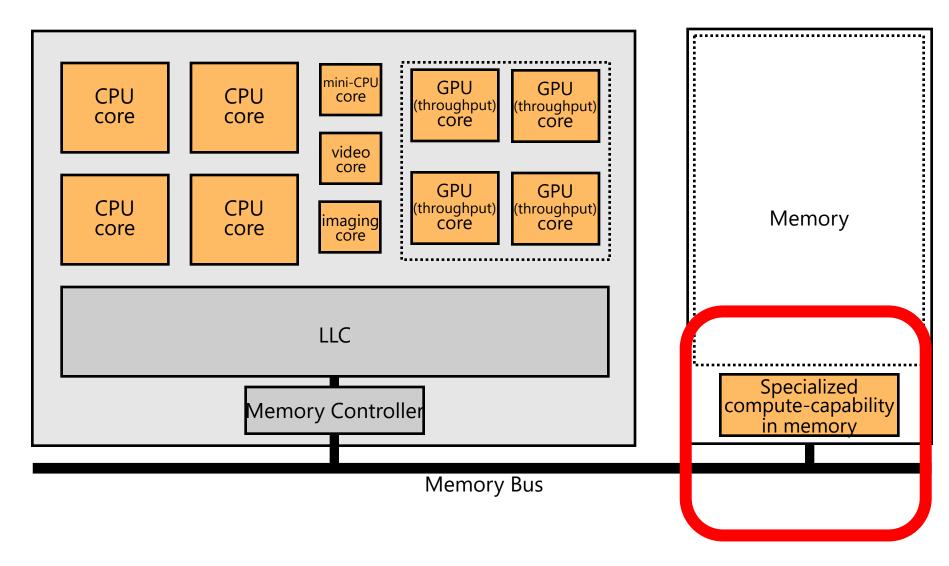
^dKing Mongkut's University of Technology North Bangkok

Onur Mutlu, Saugata Ghose, Juan Gomez-Luna, and Rachata Ausavarungnirun,

"A Modern Primer on Processing in Memory"

Invited Book Chapter in Emerging Computing: From Devices to Systems
Looking Beyond Moore and Von Neumann, Springer, to be published in 2021.

Mindset: Memory as an Accelerator



Memory similar to a "conventional" accelerator

In-Storage Acceleration of Genome Analytics

In-Storage Genomic Data Filtering [ASPLOS 2022]

Nika Mansouri Ghiasi, Jisung Park, Harun Mustafa, Jeremie Kim, Ataberk Olgun, Arvid Gollwitzer, Damla Senol Cali, Can Firtina, Haiyu Mao, Nour Almadhoun Alserr, Rachata Ausavarungnirun, Nandita Vijaykumar, Mohammed Alser, and Onur Mutlu, "GenStore: A High-Performance and Energy-Efficient In-Storage Computing

<u>"GenStore: A High-Performance and Energy-Efficient In-Storage Computing System for Genome Sequence Analysis"</u>

Proceedings of the <u>27th International Conference on Architectural Support for</u>
<u>Programming Languages and Operating Systems</u> (**ASPLOS**), Virtual, February-March 2022.

[<u>Lightning Talk Slides (pptx) (pdf)</u>] [<u>Lightning Talk Video</u> (90 seconds)]

GenStore: A High-Performance In-Storage Processing System for Genome Sequence Analysis

Nika Mansouri Ghiasi¹ Jisung Park¹ Harun Mustafa¹ Jeremie Kim¹ Ataberk Olgun¹ Arvid Gollwitzer¹ Damla Senol Cali² Can Firtina¹ Haiyu Mao¹ Nour Almadhoun Alserr¹ Rachata Ausavarungnirun³ Nandita Vijaykumar⁴ Mohammed Alser¹ Onur Mutlu¹

¹ETH Zürich ²Bionano Genomics ³KMUTNB ⁴University of Toronto

In-Storage Metagenomics [ISCA 2024]

 Nika Mansouri Ghiasi, Mohammad Sadrosadati, Harun Mustafa, Arvid Gollwitzer, Can Firtina, Julien Eudine, Haiyu Mao, Joel Lindegger, Meryem Banu Cavlak, Mohammed Alser, Jisung Park, and Onur Mutlu,

"MegIS: High-Performance and Low-Cost Metagenomic Analysis with In-Storage Processing"

Proceedings of the <u>51st Annual International Symposium on Computer</u> <u>Architecture</u> (**ISCA**), Buenos Aires, Argentina, July 2024.
[Slides (pptx) (pdf)]

arXiv version

MegIS: High-Performance, Energy-Efficient, and Low-Cost Metagenomic Analysis with In-Storage Processing

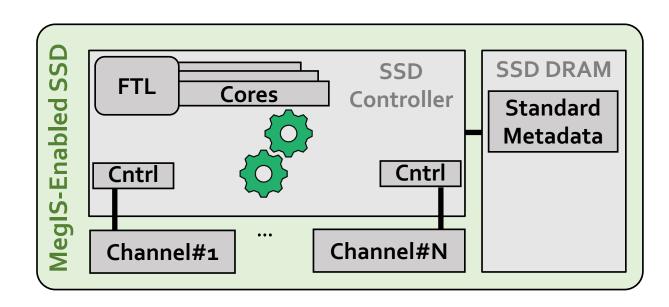
Nika Mansouri Ghiasi¹ Mohammad Sadrosadati¹ Harun Mustafa¹ Arvid Gollwitzer¹ Can Firtina¹ Julien Eudine¹ Haiyu Mao¹ Joël Lindegger¹ Meryem Banu Cavlak¹ Mohammed Alser¹ Jisung Park² Onur Mutlu¹

¹ETH Zürich ²POSTECH

MegIS: Metagenomics In-Storage

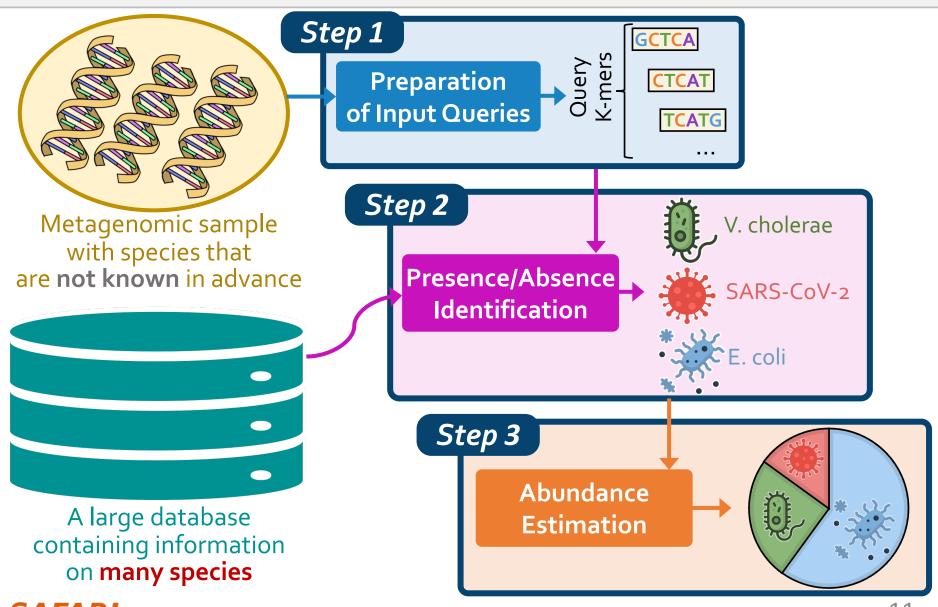
- First in-storage system for end-to-end metagenomic analysis
- Idea: Cooperative in-storage processing for metagenomic analysis
 - Hardware/software co-design between





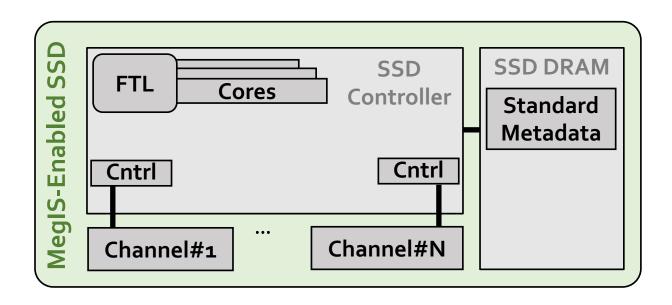


MegIS's Steps



SAFARI

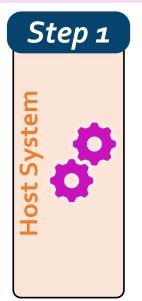
Host System

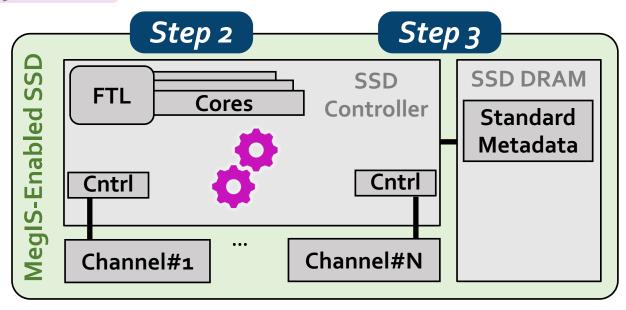




Task partitioning and mapping

• Each step executes in its most suitable system



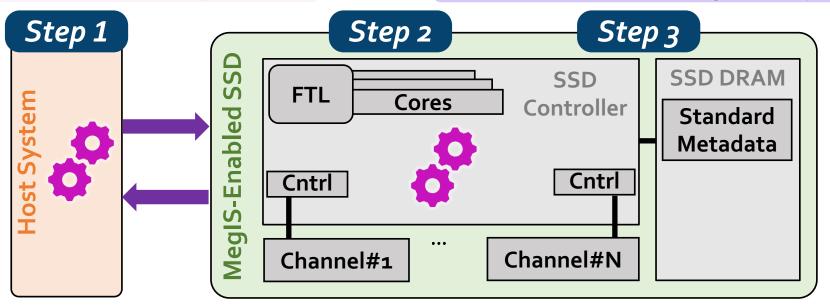


Task partitioning and mapping

• Each step executes in its most suitable system

Data/computation flow coordination

- Reduce communication overhead
 - Reduce #writes to flash chips

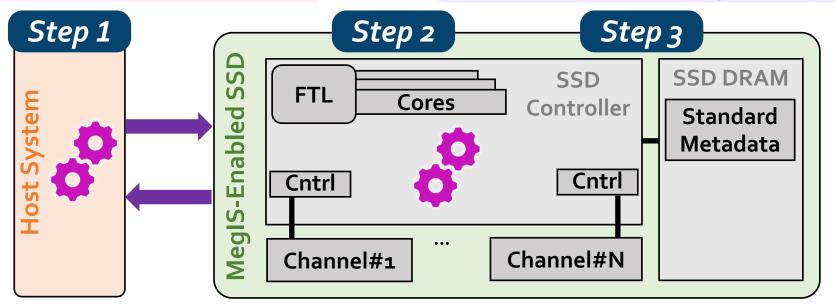


Task partitioning and mapping

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Data/computation flow coordination

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Storage-aware algorithms

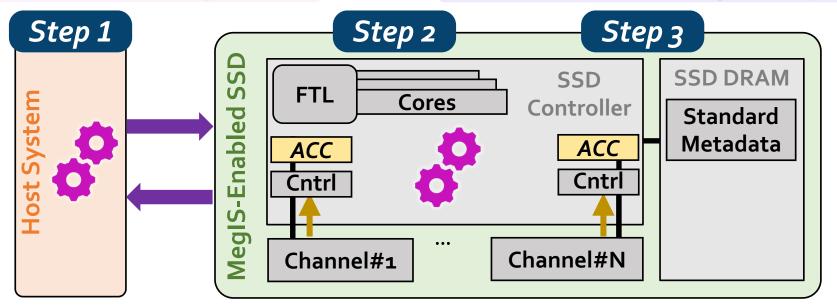
• Enable efficient access patterns to the SSD

Task partitioning and mapping

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Storage-aware algorithms

• Enable efficient access patterns to the SSD

Lightweight in-storage accelerators

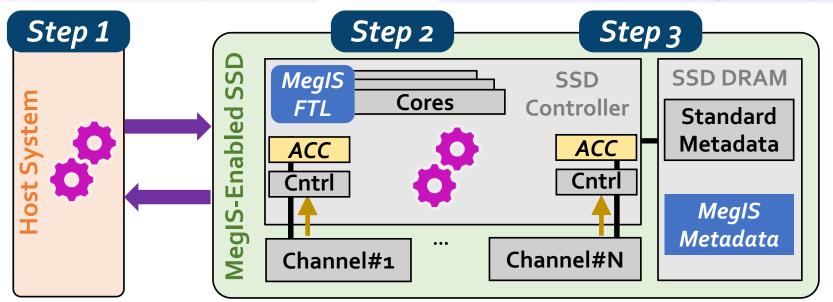
 Minimize SRAM/DRAM buffer spaces needed inside the SSD

Task partitioning and mapping

• Each step executes in its most suitable system

Data/computation flow coordination

- Reduce communication overhead
 - Reduce #writes to flash chips



Storage-aware algorithms

• Enable efficient access patterns to the SSD

Lightweight in-storage accelerators

 Minimize SRAM/DRAM buffer spaces needed inside the SSD

Data mapping scheme and Flash Translation Layer (FTL)

- Specialize to the characteristics of metagenomic analysis
 - Leverage the SSD's full internal bandwidth

Evaluation: Methodology Overview

Performance, Energy, and Power Analysis

Hardware Components

- Synthesized Verilog model for the in-storage accelerators
- MQSim [Tavakkol+, FAST'18] for SSD's internal operations
- Ramulator [Kim+, CAL'15] for SSD's internal DRAM

Software Components

Measure on a real system:

- AMD® EPYC® CPU with 128 physical cores
- 1-TB DRAM

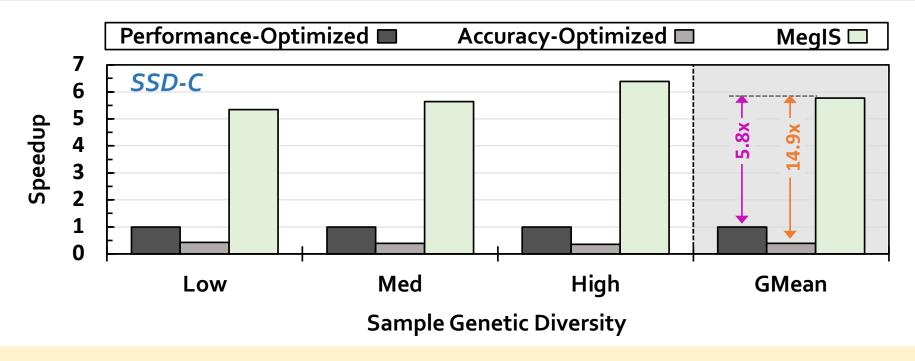
Baseline Comparison Points

- Performance-optimized software, Kraken2 [Genome Biology'19]
- Accuracy-optimized software, Metalign [Genome Biology'20]
- PIM hardware-accelerated tool (using processing-in-memory), Sieve [ISCA'21]

SSD Configurations

- SSD-C: with SATA3 interface (0.5 GB/s sequential read bandwidth)
- SSD-P: with PCle Gen4 interface (7 GB/s sequential read bandwidth)

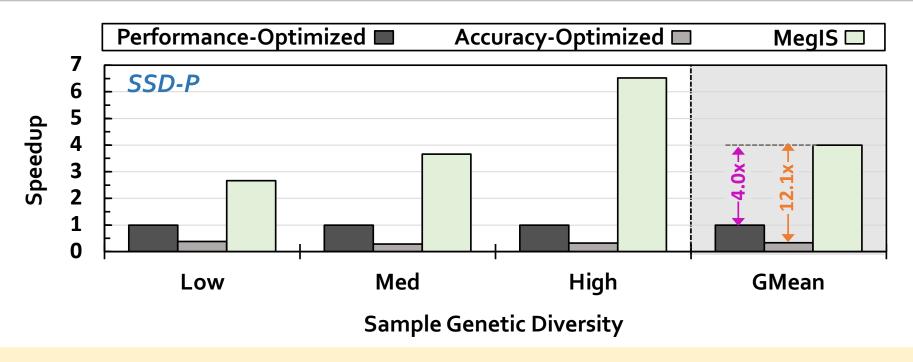
Evaluation: Speedup over the Software Baselines



MegIS provides significant speedup over both

Performance-Optimized and Accuracy-Optimized baselines

Evaluation: Speedup over the Software Baselines

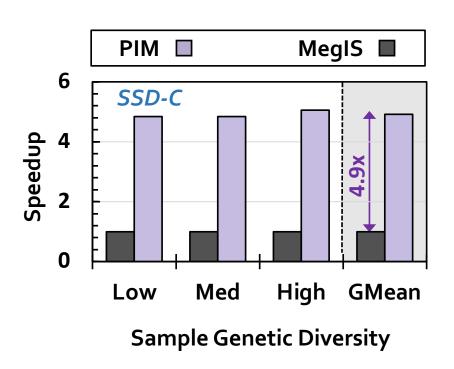


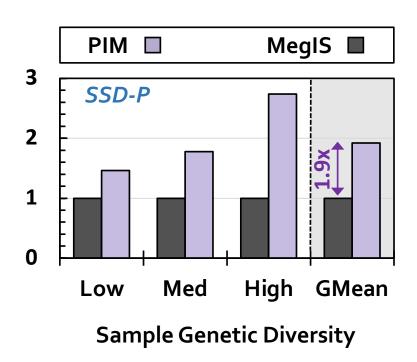
MegIS provides significant speedup over both

Performance-Optimized and Accuracy-Optimized baselines

MegIS improves performance on both cost-optimized and performance-optimized SSDs

Evaluation: Speedup over the PIM Baseline

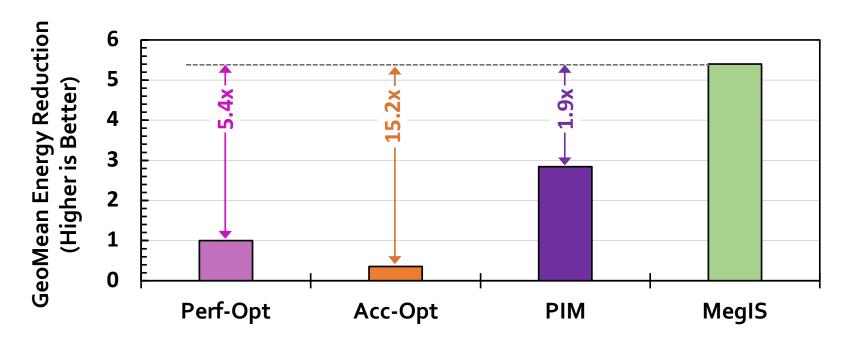




MegIS provides significant speedup over the PIM baseline

Evaluation: Reduction in Energy Consumption

• On average across different input sets and SSDs



MegIS provides significant energy reduction over

the Performance-Optimized, Accuracy-Optimized, and PIM baselines

Evaluation: Accuracy, Area, and Power

Accuracy

- Same accuracy as the accuracy-optimized baseline
- Significantly higher accuracy than the performance-optimized and PIM baselines
 - $4.6 5.2 \times$ higher F1 scores
 - 3 24% lower L1 norm error

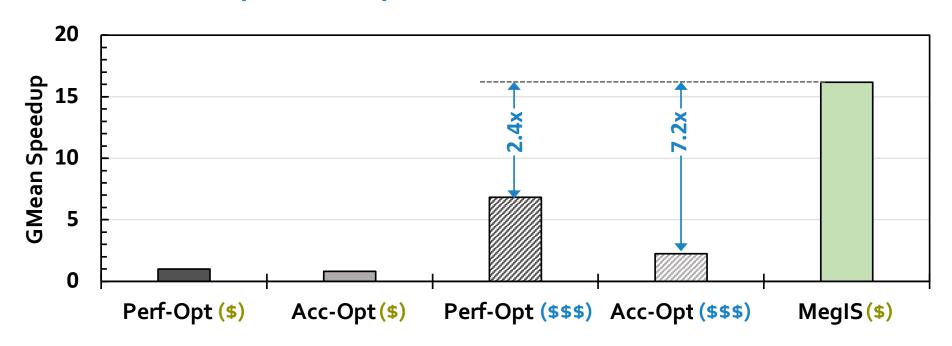
Area and Power

Total for an 8-channel SSD:

- Area: 0.04 mm² (Only 1.7% of the area of three ARM Cortex R4 cores in an SSD controller)
- **Power:** 7.658 mW

Evaluation: System Cost-Efficiency

- Cost-optimized system (\$): With SSD-C and 64-GB DRAM
- Performance-optimized system (\$\$\$): With SSD-P and 1-TB DRAM



MegIS outperforms the baselines even when running on a much less costly system

Evaluation: System Cost-Efficiency

- Cost-optimized system (\$): With SSD-C and 64-GB DRAM
- Performance-optimized system (\$\$\$): With SSD-P and 1-TB DRAM

20

MegIS improves system cost-efficiency and makes metagenomics more accessible for wider adoption

Perf-Opt (\$) Acc-Opt (\$) Perf-Opt (\$\$\$) Acc-Opt (\$\$\$) MegIS (\$

MegIS outperforms the baselines even when running on a much less costly system

More in the Paper

- MegIS's performance when running in-storage processing operations on the cores existing in the SSD controller
- MegIS's performance when using the same accelerators outside SSD
- Sensitivity analysis with varying
 - Database sizes
 - Memory capacities
 - #SSDs
 - #Channels
 - #Samples
- MegIS's performance for abundance estimation

More in the Paper

MegIS: High-Performance, Energy-Efficient, and Low-Cost Metagenomic Analysis with In-Storage Processing

Nika Mansouri Ghiasi¹ Mohammad Sadrosadati¹ Harun Mustafa¹ Arvid Gollwitzer¹ Can Firtina¹ Julien Eudine¹ Haiyu Mao¹ Joël Lindegger¹ Meryem Banu Cavlak¹ Mohammed Alser¹ Jisung Park² Onur Mutlu¹

1ETH Zürich ²POSTECH

- Database sizes
- Memory capacities
- #SSDs
- #Channels
- #Samples



MegIS's performance for abundance estimation

https://arxiv.org/abs/2406.19113

MegIS: Summary

Metagenomic analysis suffers from significant storage I/O data movement overhead

MegIS

The *first* **in-storage processing** system for *end-to-end* metagenomic analysis Leverages and orchestrates **processing inside** and **outside** the storage system



Improves performance

2.7×-37.2× over performance-optimized software 6.9×-100.2× over accuracy-optimized software 1.5×-5.1× over hardware-accelerated PIM baseline



High accuracy

Same as accuracy-optimized

4.8× higher F1 scores

over performance-optimized/PIM



Reduces energy consumption

5.4× over performance-optimized software
 15.2× over accuracy-optimized software
 1.9× over hardware-accelerated PIM baseline



Low area overhead

1.7% of the three cores in an SSD controller



MQSim: Simulating Storage [FAST 2018]

 Arash Tavakkol, Juan Gomez-Luna, Mohammad Sadrosadati, Saugata Ghose, and Onur Mutlu,

"MQSim: A Framework for Enabling Realistic Studies of Modern Multi-Queue SSD Devices"

Proceedings of the <u>16th USENIX Conference on File and Storage</u> <u>Technologies</u> (**FAST**), Oakland, CA, USA, February 2018.

[Slides (pptx) (pdf)]

Source Code

MQSim: A Framework for Enabling Realistic Studies of Modern Multi-Queue SSD Devices

Arash Tavakkol[†], Juan Gómez-Luna[†], Mohammad Sadrosadati[†], Saugata Ghose[‡], Onur Mutlu^{†‡}

†ETH Zürich [‡]Carnegie Mellon University

https://github.com/CMU-SAFARI/MQSim

Tools to Decide What to Execute Where

DAMOV Analysis Methodology & Workloads

DAMOV: A New Methodology and Benchmark Suite for Evaluating Data Movement Bottlenecks

GERALDO F. OLIVEIRA, ETH Zürich, Switzerland
JUAN GÓMEZ-LUNA, ETH Zürich, Switzerland
LOIS OROSA, ETH Zürich, Switzerland
SAUGATA GHOSE, University of Illinois at Urbana-Champaign, USA
NANDITA VIJAYKUMAR, University of Toronto, Canada
IVAN FERNANDEZ, University of Malaga, Spain & ETH Zürich, Switzerland
MOHAMMAD SADROSADATI, Institute for Research in Fundamental Sciences (IPM), Iran & ETH
Zürich, Switzerland
ONUR MUTLU, ETH Zürich, Switzerland

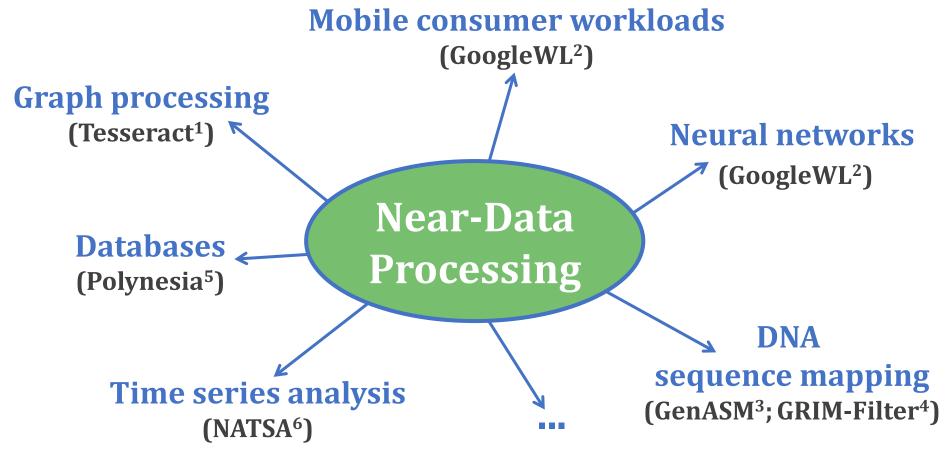
Data movement between the CPU and main memory is a first-order obstacle against improving performance, scalability, and energy efficiency in modern systems. Computer systems employ a range of techniques to reduce overheads tied to data movement, spanning from traditional mechanisms (e.g., deep multi-level cache hierarchies, aggressive hardware prefetchers) to emerging techniques such as Near-Data Processing (NDP), where some computation is moved close to memory. Prior NDP works investigate the root causes of data movement bottlenecks using different profiling methodologies and tools. However, there is still a lack of understanding about the key metrics that can identify different data movement bottlenecks and their relation to traditional and emerging data movement mitigation mechanisms. Our goal is to methodically identify potential sources of data movement over a broad set of applications and to comprehensively compare traditional compute-centric data movement mitigation techniques (e.g., caching and prefetching) to more memory-centric techniques (e.g., NDP), thereby developing a rigorous understanding of the best techniques to mitigate each source of data movement.

With this goal in mind, we perform the first large-scale characterization of a wide variety of applications, across a wide range of application domains, to identify fundamental program properties that lead to data movement to/from main memory. We develop the first systematic methodology to classify applications based on the sources contributing to data movement bottlenecks. From our large-scale characterization of 77K functions across 345 applications, we select 144 functions to form the first open-source benchmark suite (DAMOV) for main memory data movement studies. We select a diverse range of functions that (1) represent different types of data movement bottlenecks, and (2) come from a wide range of application domains. Using NDP as a case study, we identify new insights about the different data movement bottlenecks and use these insights to determine the most suitable data movement mitigation mechanism for a particular application. We open-source DAMOV and the complete source code for our new characterization methodology at https://github.com/CMU-SAFARI/DAMOV.

SAFARI

https://arxiv.org/pdf/2105.03725.pdf

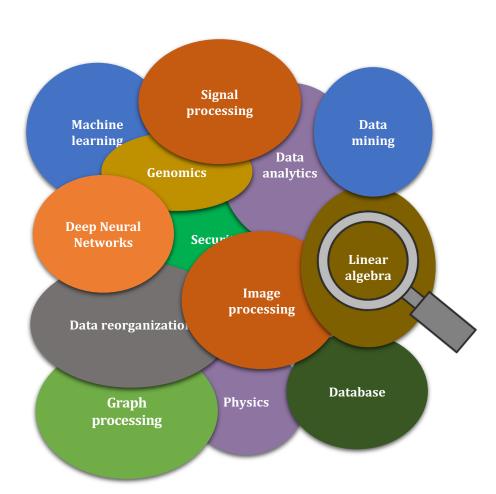
When to Employ Near-Data Processing?



- [1] Ahn+, "A Scalable Processing-in-Memory Accelerator for Parallel Graph Processing," ISCA, 2015
- [2] Boroumand+, "Google Workloads for Consumer Devices: Mitigating Data Movement Bottlenecks," ASPLOS, 2018
- [3] Cali+, "GenASM: A High-Performance, Low-Power Approximate String Matching Acceleration Framework for Genome Sequence Analysis," MICRO, 2020
- [4] Kim+, "GRIM-Filter: Fast Seed Location Filtering in DNA Read Mapping Using Processing-in-Memory Technologies," BMC Genomics, 2018
- [5] Boroumand+, "Polynesia: Enabling Effective Hybrid Transactional/Analytical Databases with Specialized Hardware/Software Co-Design," arXiv:2103.00798 [cs.AR], 2021
- [6] Fernandez+, "NATSA: A Near-Data Processing Accelerator for Time Series Analysis," ICCD, 2020

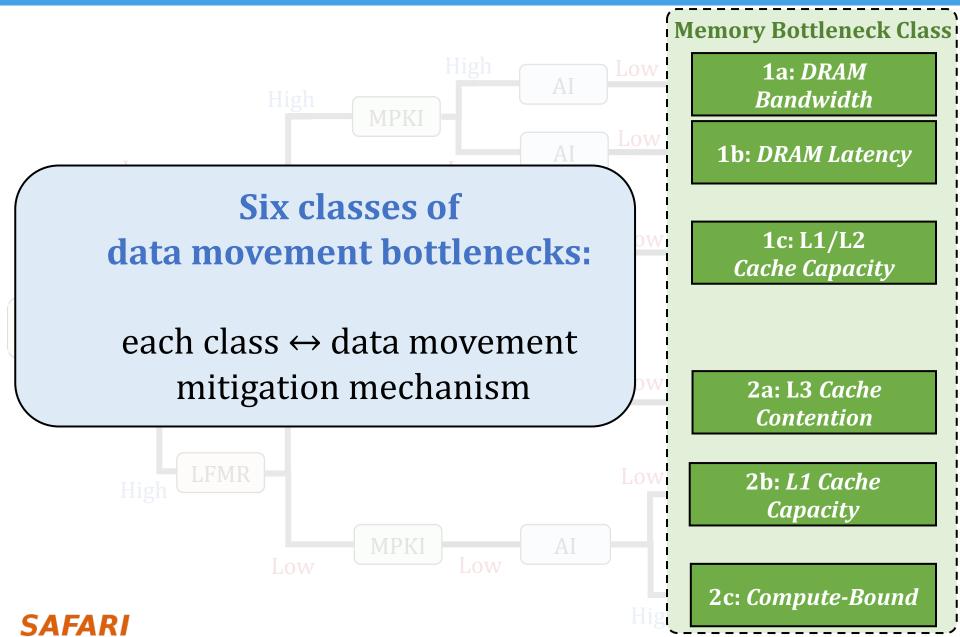
Step 1: Application Profiling

- We analyze 345 applications from distinct domains:
- Graph Processing
- Deep Neural Networks
- Physics
- High-Performance Computing
- Genomics
- Machine Learning
- Databases
- Data Reorganization
- Image Processing
- Map-Reduce
- Benchmarking
- Linear Algebra



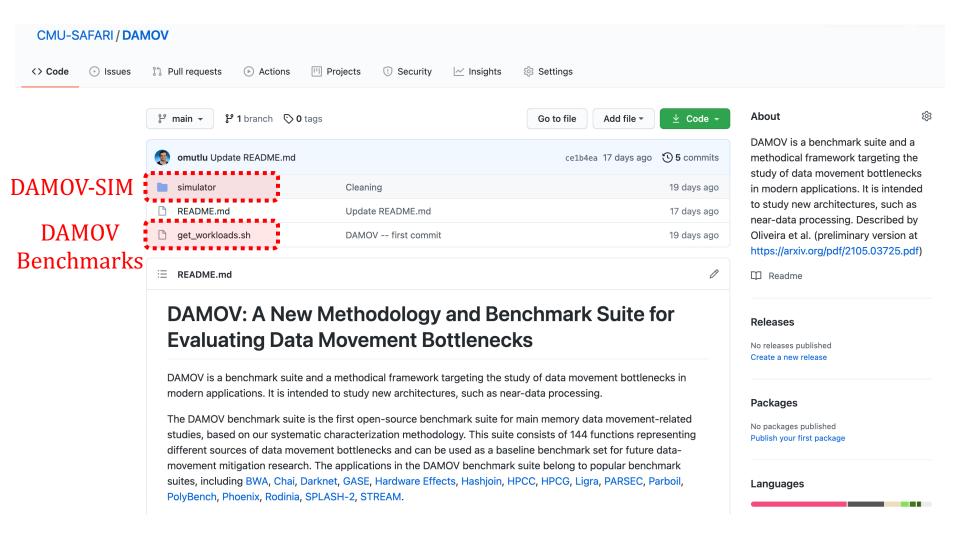


Step 3: Memory Bottleneck Analysis



DAMOV is Open Source

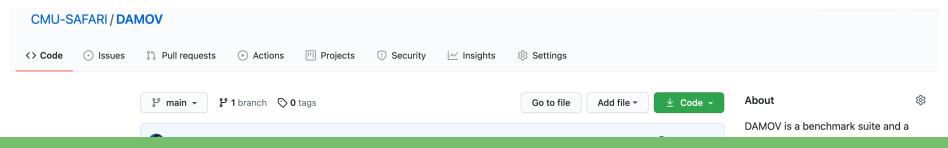
We open-source our benchmark suite and our toolchain





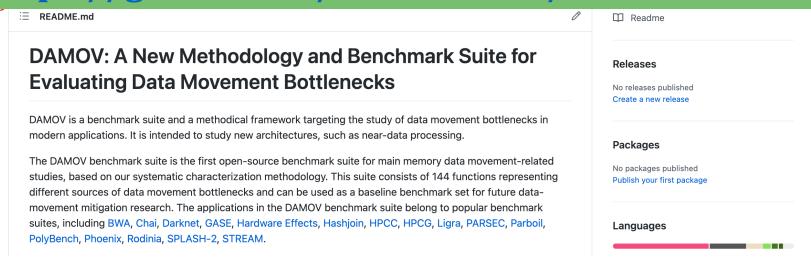
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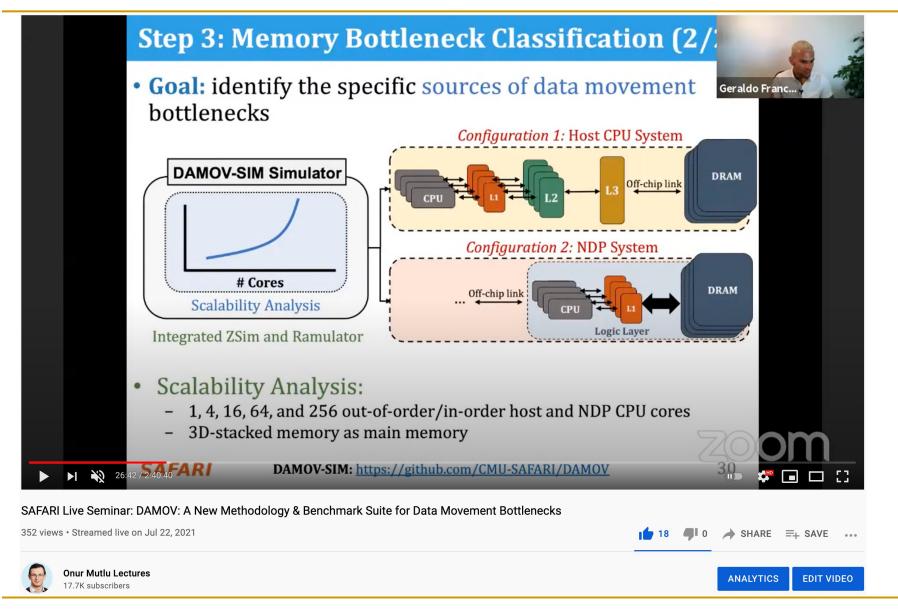
Get DAMOV at:

https://github.com/CMU-SAFARI/DAMOV





More on DAMOV Analysis Methodology & Workloads



More on DAMOV Methods & Benchmarks

 Geraldo F. Oliveira, Juan Gomez-Luna, Lois Orosa, Saugata Ghose, Nandita Vijaykumar, Ivan fernandez, Mohammad Sadrosadati, and Onur Mutlu,
 "DAMOV: A New Methodology and Benchmark Suite for Evaluating Data Movement Bottlenecks"

IEEE Access, 8 September 2021. Preprint in <u>arXiv</u>, 8 May 2021.

[arXiv preprint]

[IEEE Access version]

[DAMOV Suite and Simulator Source Code]

[SAFARI Live Seminar Video (2 hrs 40 mins)]

ONUR MUTLU, ETH Zürich, Switzerland

[Short Talk Video (21 minutes)]

DAMOV: A New Methodology and Benchmark Suite for Evaluating Data Movement Bottlenecks

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MOHAMMAD SADROSADATI, ETH Zürich, Switzerland

Ramulator 2.0 for PIM Systems

 Haocong Luo, Yahya Can Tugrul, F. Nisa Bostanci, Ataberk Olgun, A. Giray Yaglikci, and Onur Mutlu,

"Ramulator 2.0: A Modern, Modular, and Extensible DRAM Simulator" Preprint on arxiv, August 2023.

[arXiv version]

[Ramulator 2.0 Source Code]

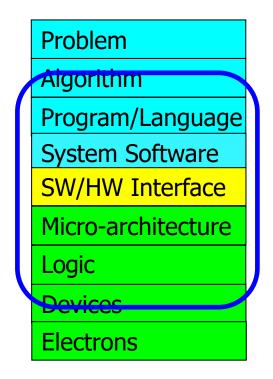
Ramulator 2.0: A Modern, Modular, and Extensible DRAM Simulator

Haocong Luo, Yahya Can Tuğrul, F. Nisa Bostancı, Ataberk Olgun, A. Giray Yağlıkçı, and Onur Mutlu

https://arxiv.org/pdf/2308.11030.pdf

We Need to Revisit the Entire Stack

With a memory-centric mindset



We can get there step by step

PIM Review and Open Problems

A Modern Primer on Processing in Memory

Onur Mutlu^{a,b}, Saugata Ghose^{b,c}, Juan Gómez-Luna^a, Rachata Ausavarungnirun^d

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Onur Mutlu, Saugata Ghose, Juan Gomez-Luna, and Rachata Ausavarungnirun,

"A Modern Primer on Processing in Memory"

Invited Book Chapter in Emerging Computing: From Devices to Systems
Looking Beyond Moore and Von Neumann, Springer, to be published in 2021.

PIM Review and Open Problems (II)

A Workload and Programming Ease Driven Perspective of Processing-in-Memory

Saugata Ghose[†] Amirali Boroumand[†] Jeremie S. Kim[†]§ Juan Gómez-Luna[§] Onur Mutlu^{§†}

†Carnegie Mellon University §ETH Zürich

Saugata Ghose, Amirali Boroumand, Jeremie S. Kim, Juan Gomez-Luna, and Onur Mutlu, "Processing-in-Memory: A Workload-Driven Perspective"

Invited Article in IBM Journal of Research & Development, Special Issue on Hardware for Artificial Intelligence, to appear in November 2019.

[Preliminary arXiv version]

Processing in Memory: Adoption Challenges

- 1. Processing using Memory
- 2. Processing **near** Memory

Eliminating the Adoption Barriers

How to Enable Adoption of Processing in Memory

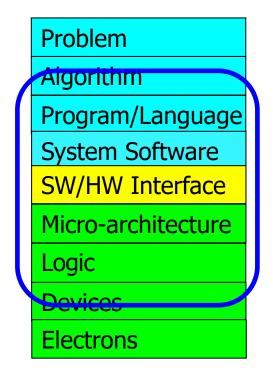
Potential Barriers to Adoption of PIM

- 1. **Applications** & **software** for PIM
- 2. Ease of **programming** (interfaces and compiler/HW support)
- 3. **System** and **security** support: coherence, synchronization, virtual memory, isolation, communication interfaces, ...
- 4. **Runtime** and **compilation** systems for adaptive scheduling, data mapping, access/sharing control, ...
- 5. **Infrastructures** to assess benefits and feasibility

All can be solved with change of mindset

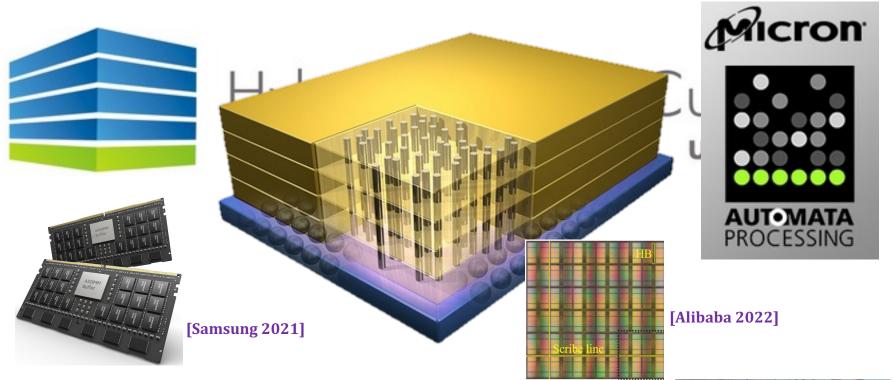
We Need to Revisit the Entire Stack

With a memory-centric mindset



We can get there step by step

Processing-in-Memory Landscape Today









[Samsung 2021]



[UPMEM 2019]



Adoption: How to Keep It Simple?

Junwhan Ahn, Sungjoo Yoo, Onur Mutlu, and Kiyoung Choi,
 "PIM-Enabled Instructions: A Low-Overhead,
 Locality-Aware Processing-in-Memory Architecture"
 Proceedings of the <u>42nd International Symposium on</u>
 Computer Architecture (ISCA), Portland, OR, June 2015.
 [Slides (pdf)] [Lightning Session Slides (pdf)]

PIM-Enabled Instructions: A Low-Overhead, Locality-Aware Processing-in-Memory Architecture

Junwhan Ahn Sungjoo Yoo Onur Mutlu[†] Kiyoung Choi junwhan@snu.ac.kr, sungjoo.yoo@gmail.com, onur@cmu.edu, kchoi@snu.ac.kr

Seoul National University †Carnegie Mellon University

SAFARI

PEI: PIM-Enabled Instructions (Ideas)

- Goal: Develop mechanisms to get the most out of near-data processing with minimal cost, minimal changes to the system, no changes to the programming model
- Key Idea 1: Expose each PIM operation as a cache-coherent, virtually-addressed host processor instruction (called PEI) that operates on only a single cache block
 - \circ e.g., __pim_add(&w.next_rank, value) \rightarrow pim.add r1, (r2)
 - No changes sequential execution/programming model
 - No changes to virtual memory
 - Minimal changes to cache coherence
 - No need for data mapping: Each PEI restricted to a single memory module
- Key Idea 2: Dynamically decide where to execute a PEI (i.e., the host processor or PIM accelerator) based on simple locality characteristics and simple hardware predictors
 - Execute each operation at the location that provides the best performance

Simple PIM Operations as ISA Extensions (II)

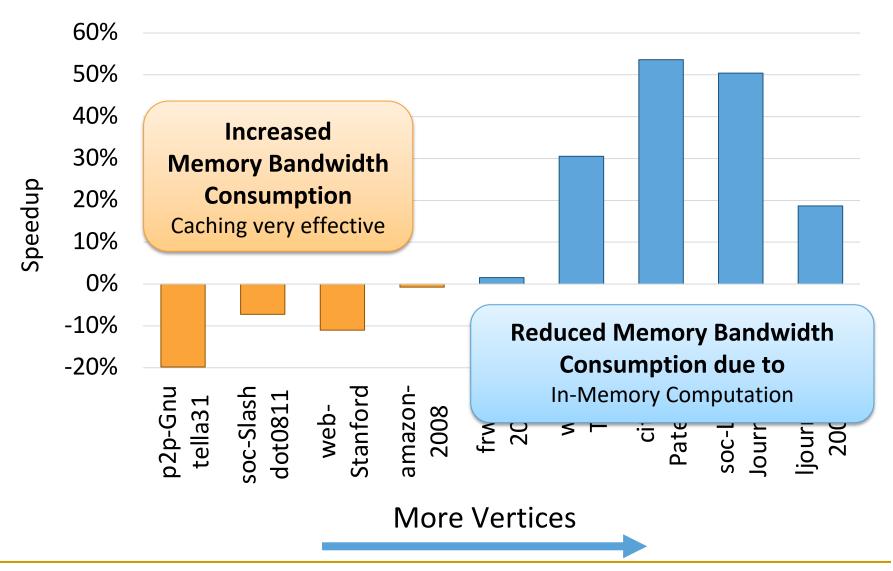
```
for (v: graph.vertices) {
  value = weight * v.rank;
  for (w: v.successors) {
    w.next rank += value;
                                             Main Memory
      Host Processor
        w.next rank
                                              w.next rank
                           64 bytes in
                          64 bytes out
```

Conventional Architecture

Simple PIM Operations as ISA Extensions (III)

```
for (v: graph.vertices) {
  value = weight * v.rank;
                                                   pim.add r1, (r2)
  for (w: v.successors) {
       pim_add(&w.next_rank, value);
                                             Main Memory
      Host Processor
                                               w.next rank
           value
                            8 bytes in
                           0 bytes out
```

Always Executing in Memory? Not A Good Idea



PEI: PIM-Enabled Instructions (Example)

```
for (v: graph.vertices) {
   value = weight * v.rank;
   for (w: v.successors) {
        __pim_add(&w.next_rank, value);
   }
}
pfence();
```

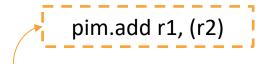


Table 1: Summary of Supported PIM Operations

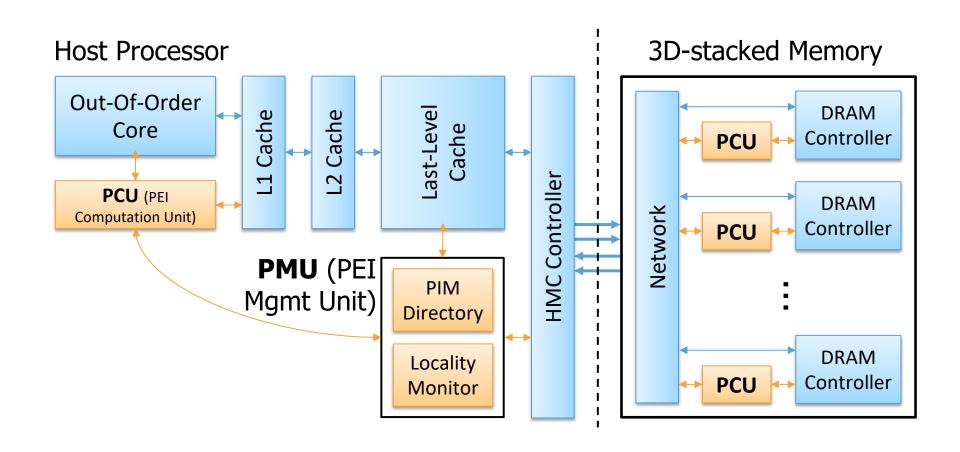
Operation	R	W	Input	Output	Applications
8-byte integer increment	О	O	0 bytes	0 bytes	AT
8-byte integer min	O	O	8 bytes	0 bytes	BFS, SP, WCC
Floating-point add	O	O	8 bytes	0 bytes	PR
Hash table probing	O	X	8 bytes	9 bytes	HJ
Histogram bin index	O	X	1 byte	16 bytes	HG, RP
Euclidean distance	O	X	64 bytes	4 bytes	SC
Dot product	O	X	32 bytes	8 bytes	SVM

- Executed either in memory or in the processor: dynamic decision
 - Low-cost locality monitoring for a single instruction
- Cache-coherent, virtually-addressed, single cache block only
- Atomic between different PEIs
- Not atomic with normal instructions (use pfence for ordering)

PIM-Enabled Instructions

- Key to practicality: single-cache-block restriction
 - Each PEI can access at most one last-level cache block
 - Similar restrictions exist in atomic instructions
- Benefits
 - Localization: each PEI is bounded to one memory module
 - Interoperability: easier support for cache coherence and virtual memory
 - Simplified locality monitoring: data locality of PEIs can be identified simply by the cache control logic

Example (Abstract) PEI uArchitecture



Example PEI uArchitecture

PEI: Initial Evaluation Results

- Initial evaluations with 10 emerging data-intensive workloads
 - Large-scale graph processing
 - In-memory data analytics
 - Machine learning and data mining
 - Three input sets (small, medium, large)
 for each workload to analyze the impact of data locality

Table 2: Baseline Simulation Configuration

Component	Configuration
Core	16 out-of-order cores, 4 GHz, 4-issue
L1 I/D-Cache	Private, 32 KB, 4/8-way, 64 B blocks, 16 MSHRs
L2 Cache	Private, 256 KB, 8-way, 64 B blocks, 16 MSHRs
L3 Cache	Shared, 16 MB, 16-way, 64 B blocks, 64 MSHRs
On-Chip Network	Crossbar, 2 GHz, 144-bit links
Main Memory	32 GB, 8 HMCs, daisy-chain (80 GB/s full-duplex)
HMC	4 GB, 16 vaults, 256 DRAM banks [20]
- DRAM	FR-FCFS, $tCL = tRCD = tRP = 13.75 \text{ ns}$ [27]
 Vertical Links 	64 TSVs per vault with 2 Gb/s signaling rate [23]

Pin-based cycle-level x86-64 simulation

Performance Improvement and Energy Reduction:

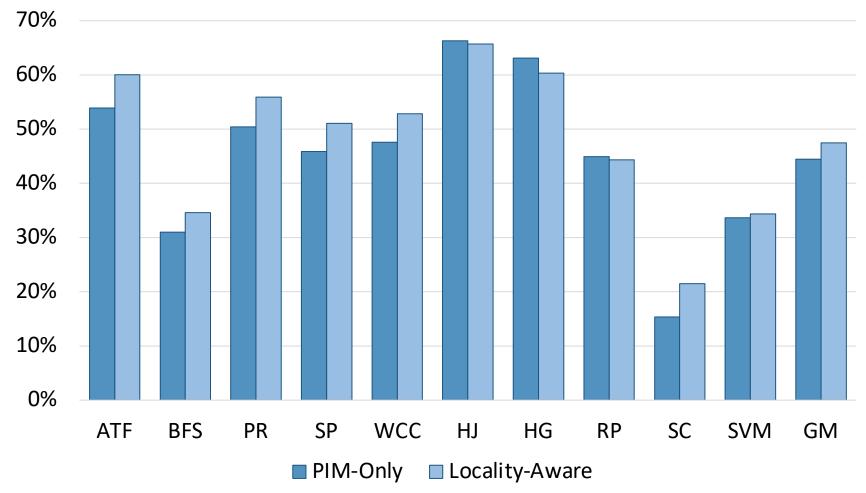
- 47% average speedup with large input data sets
- 32% speedup with small input data sets
- 25% avg. energy reduction in a single node with large input data sets

Evaluated Data-Intensive Applications

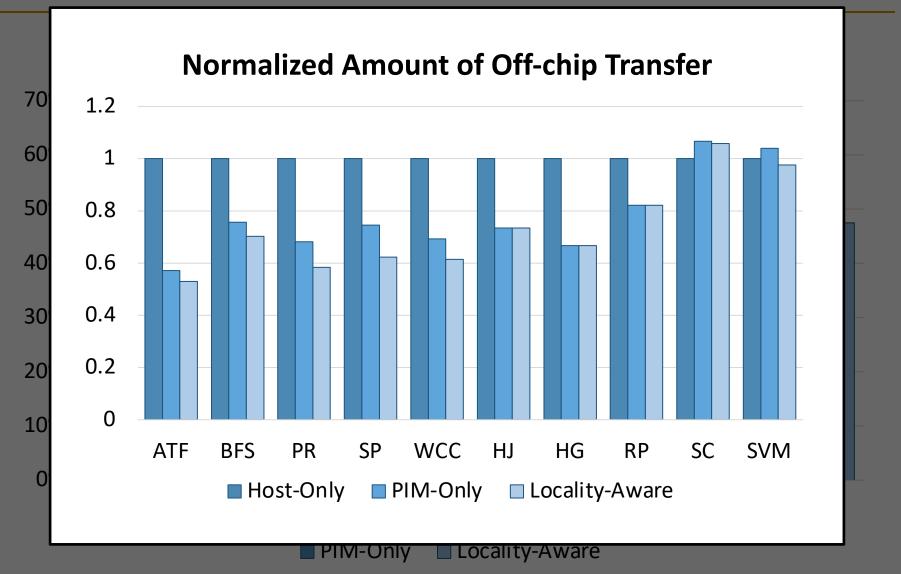
- Ten emerging data-intensive workloads
 - Large-scale graph processing
 - Average teenage follower, BFS, PageRank, single-source shortest path, weakly connected components
 - In-memory data analytics
 - Hash join, histogram, radix partitioning
 - Machine learning and data mining
 - Streamcluster, SVM-RFE
- Three input sets (small, medium, large) for each workload to show the impact of data locality

PEI Performance Delta: Large Data Sets

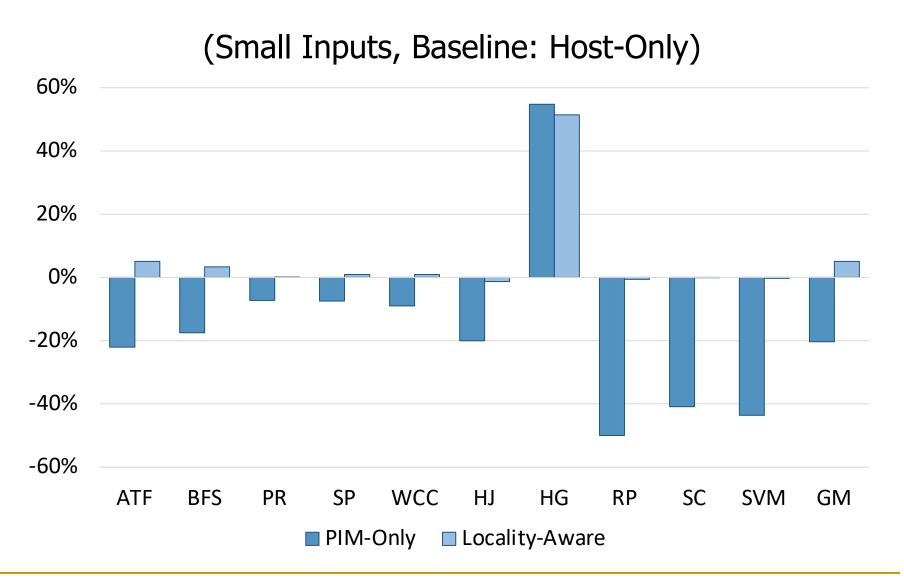




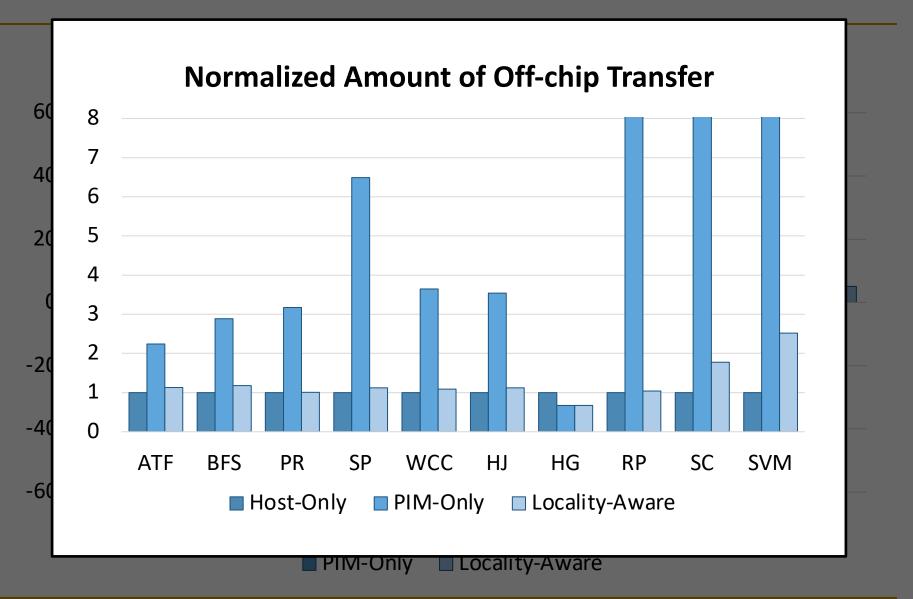
PEI Performance: Large Data Sets



PEI Performance Delta: Small Data Sets

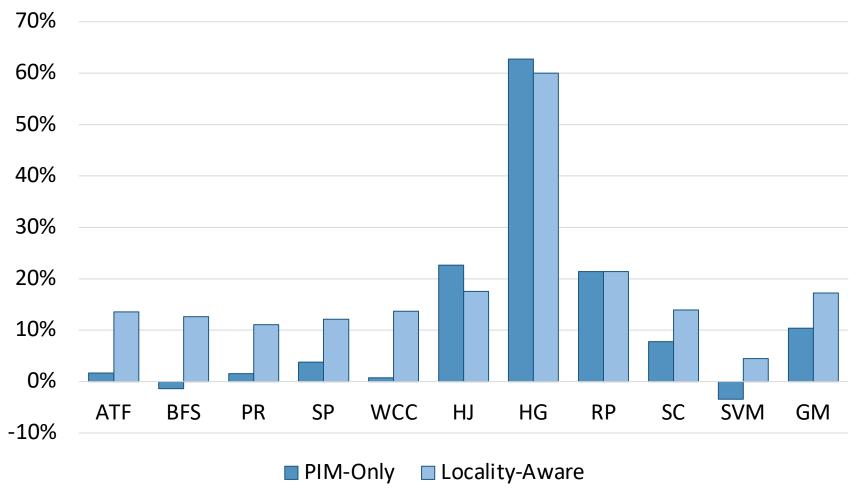


PEI Performance: Small Data Sets



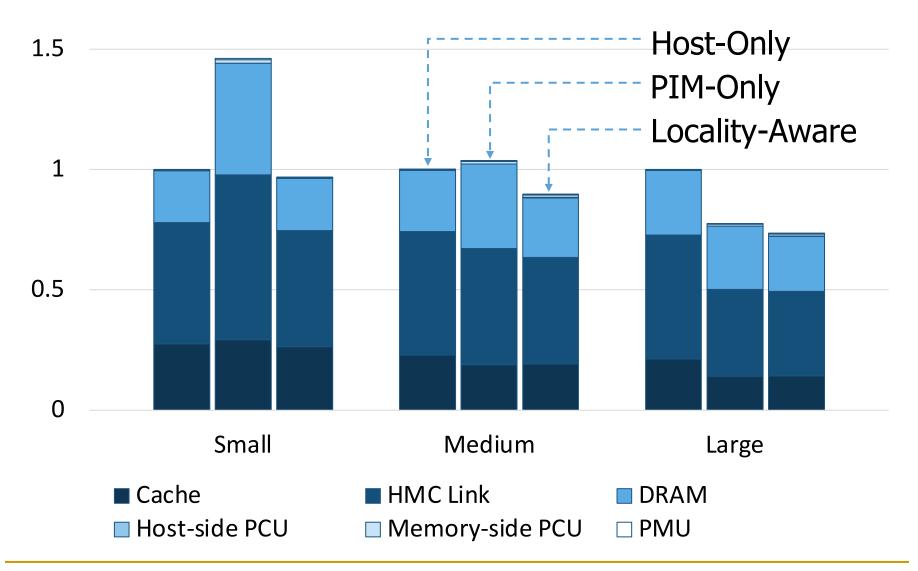
PEI Performance Delta: Medium Data Sets







PEI Energy Consumption



PEI: Advantages & Disadvantages

Advantages

- + Simple and low-cost approach to PIM
- + No changes to programming model, virtual memory
- + Dynamically decides where to execute an instruction

Disadvantages

- Does not take full advantage of PIM potential
 - Single cache block restriction is limiting

Adoption: How to Keep It Simple?

Junwhan Ahn, Sungjoo Yoo, Onur Mutlu, and Kiyoung Choi,
 "PIM-Enabled Instructions: A Low-Overhead,
 Locality-Aware Processing-in-Memory Architecture"
 Proceedings of the <u>42nd International Symposium on</u>
 Computer Architecture (ISCA), Portland, OR, June 2015.
 [Slides (pdf)] [Lightning Session Slides (pdf)]

PIM-Enabled Instructions: A Low-Overhead, Locality-Aware Processing-in-Memory Architecture

Junwhan Ahn Sungjoo Yoo Onur Mutlu[†] Kiyoung Choi junwhan@snu.ac.kr, sungjoo.yoo@gmail.com, onur@cmu.edu, kchoi@snu.ac.kr

Seoul National University †Carnegie Mellon University

SAFARI

Adoption: How to Ease **Programmability?** (I)

Kevin Hsieh, Eiman Ebrahimi, Gwangsun Kim, Niladrish Chatterjee, Mike O'Connor, Nandita Vijaykumar, Onur Mutlu, and Stephen W. Keckler, "Transparent Offloading and Mapping (TOM): Enabling Programmer-Transparent Near-Data Processing in GPU Systems"

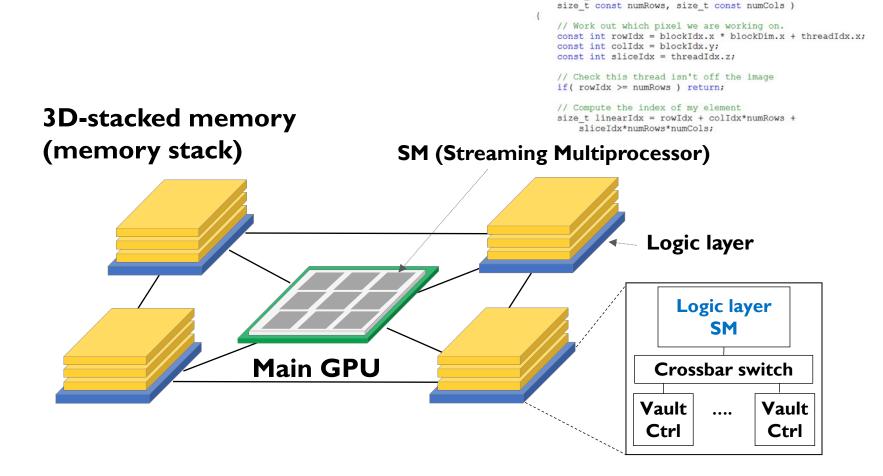
Proceedings of the <u>43rd International Symposium on Computer</u> <u>Architecture</u> (**ISCA**), Seoul, South Korea, June 2016. [<u>Slides (pptx) (pdf)</u>]

[Lightning Session Slides (pptx) (pdf)]

Transparent Offloading and Mapping (TOM): Enabling Programmer-Transparent Near-Data Processing in GPU Systems

Kevin Hsieh[‡] Eiman Ebrahimi[†] Gwangsun Kim^{*} Niladrish Chatterjee[†] Mike O'Connor[†] Nandita Vijaykumar[‡] Onur Mutlu^{§‡} Stephen W. Keckler[†] [‡]Carnegie Mellon University [†]NVIDIA *KAIST [§]ETH Zürich

Truly Distributed GPU Processing with PIM



void applyScaleFactorsKernel(uint8_T * const out, uint8_T const * const in, const double *factor,

Adoption: How to Ease Programmability? (II)

Geraldo F. Oliveira, Alain Kohli, David Novo,
Juan Gómez-Luna, Onur Mutlu,
 "DaPPA: A Data-Parallel Framework for Processing-in-Memory Architectures,"
 in PACT SRC Student Competition, Vienna, Austria, October 2023.

DaPPA: A Data-Parallel Framework for Processing-in-Memory Architectures

Geraldo F. Oliveira* Alain Kohli* David Novo[‡] Juan Gómez-Luna* Onur Mutlu*

*ETH Zürich [‡]LIRMM, Univ. Montpellier, CNRS

Adoption: How to Ease Programmability? (III)

 Jinfan Chen, Juan Gómez-Luna, Izzat El Hajj, YuXin Guo, and Onur Mutlu,

"SimplePIM: A Software Framework for Productive and Efficient Processing in Memory"

Proceedings of the <u>32nd International Conference on</u>
<u>Parallel Architectures and Compilation Techniques</u> (**PACT**),
Vienna, Austria, October 2023.

SimplePIM: A Software Framework for Productive and Efficient Processing-in-Memory

Jinfan Chen 1 Juan Gómez-Luna 1 Izzat El Hajj 2 Yuxin Guo 1 Onur Mutlu 1 ETH Zürich 2 American University of Beirut

Adoption: How to Ease **Programmability?** (IV)

 Geraldo F. Oliveira, Juan Gomez-Luna, Lois Orosa, Saugata Ghose, Nandita Vijaykumar, Ivan fernandez, Mohammad Sadrosadati, and Onur Mutlu, "DAMOV: A New Methodology and Benchmark Suite for Evaluating Data Movement Bottlenecks"

IEEE Access, 8 September 2021. Preprint in **arXiv**, 8 May 2021.

[arXiv preprint]

[IEEE Access version]

[DAMOV Suite and Simulator Source Code]

[SAFARI Live Seminar Video (2 hrs 40 mins)]

[Short Talk Video (21 minutes)]

DAMOV: A New Methodology and Benchmark Suite for Evaluating Data Movement Bottlenecks

GERALDO F. OLIVEIRA, ETH Zürich, Switzerland
JUAN GÓMEZ-LUNA, ETH Zürich, Switzerland
LOIS OROSA, ETH Zürich, Switzerland
SAUGATA GHOSE, University of Illinois at Urbana-Champaign, USA
NANDITA VIJAYKUMAR, University of Toronto, Canada
IVAN FERNANDEZ, University of Malaga, Spain & ETH Zürich, Switzerland
MOHAMMAD SADROSADATI, ETH Zürich, Switzerland
ONUR MUTLU, ETH Zürich, Switzerland

Adoption: How to Ease **Programmability?** (V)

Appears in IEEE TETC 2023

ALP: Alleviating CPU-Memory Data Movement Overheads in Memory-Centric Systems

Nika Mansouri Ghiasi, Nandita Vijaykumar, Geraldo F. Oliveira, Lois Orosa, Ivan Fernandez, Mohammad Sadrosadati, Konstantinos Kanellopoulos, Nastaran Hajinazar, Juan Gómez Luna, Onur Mutlu

Abstract—Recent advances in memory technology have enabled near-data processing (NDP) to tackle main memory bottlenecks in modern systems. Prior works partition applications into segments (e.g., instructions, loops, functions) and execute memory-bound segments of the applications on NDP computation units, while mapping the cache-friendly application segments to host CPU cores that access a deeper cache hierarchy. Partitioning applications between NDP and host cores causes inter-segment data movement overhead, which is the overhead from moving data generated from one segment and used in the consecutive segments. This overhead can be large if the segments map to cores in different parts of the system (i.e., host and NDP). Prior works take two approaches to the inter-segment data movement overhead when partitioning applications between NDP and host cores. The first class of works maps segments to NDP or host cores based on the properties of each segment, neglecting the performance impact of the inter-segment data movement. Such partitioning techniques suffer from inter-segment data movement overhead. The second class of works maps segments to host or NDP cores based on the overall memory bandwidth savings of each segment (which depends on the memory bandwidth savings within each segment and the inter-segment data movement overhead between other segments). These works do not offload each segment to the best-fitting core if they incur high inter-segment data movement overhead. Therefore these works miss some of the potential NDP performance benefits. We show that mapping each segment (here basic block) to its best-fitting core based on the properties of each segment, assuming no inter-segment data movement, can provide substantial performance benefits. However, we show that the inter-segment data movement reduces this benefit significantly.

To this end, we introduce ALP, a new programmer-transparent technique to leverage the performance benefits of NDP by *alleviating* the performance impact of inter-segment data movement between host and memory and enabling efficient partitioning of applications between host and NDP cores. ALP alleviates the inter-segment data movement overhead by *proactively and accurately* transferring the required data between the segments mapped on host and NDP cores. This is based on the key observation that the instructions that generate the inter-segment data stay the same across different executions of a program on different input sets. ALP uses a compiler pass to identify these instructions and uses specialized hardware support to transfer data between the host and NDP cores at runtime. Using both the compiler and runtime information, ALP efficiently maps application segments to either host or NDP cores considering 1) the properties of each segment, 2) the inter-segment data movement overhead between different segments, and 3) whether this inter-segment data movement overhead can be alleviated proactively and in a timely manner. We evaluate ALP across a wide range of workloads and show on average 54.3% and 45.4% speedup compared to executing the application only on the host CPU or only the NDP cores, respectively.

Adoption: How to Maintain Coherence? (I)

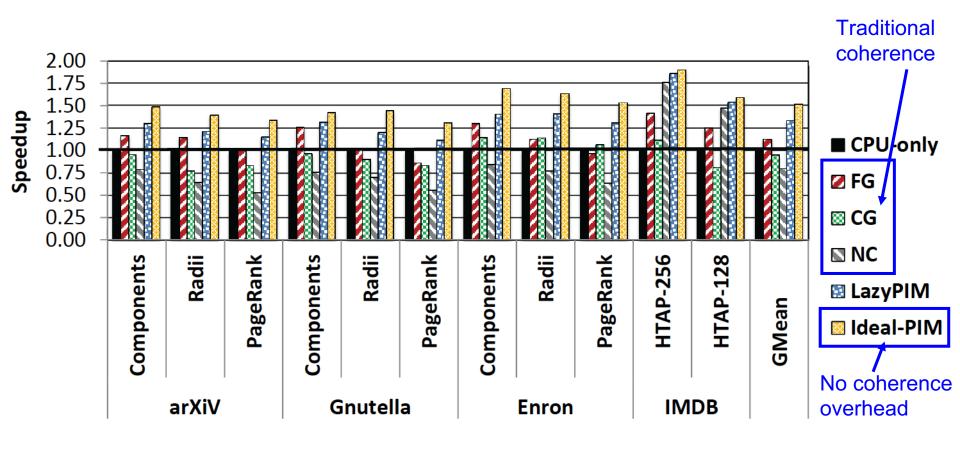
Amirali Boroumand, Saugata Ghose, Minesh Patel, Hasan Hassan, Brandon Lucia, Kevin Hsieh, Krishna T. Malladi, Hongzhong Zheng, and Onur Mutlu, "LazyPIM: An Efficient Cache Coherence Mechanism for Processing-in-Memory" IEEE Computer Architecture Letters (CAL), June 2016.

LazyPIM: An Efficient Cache Coherence Mechanism for Processing-in-Memory

Amirali Boroumand[†], Saugata Ghose[†], Minesh Patel[†], Hasan Hassan[†], Brandon Lucia[†], Kevin Hsieh[†], Krishna T. Malladi^{*}, Hongzhong Zheng^{*}, and Onur Mutlu^{‡†}

† Carnegie Mellon University * Samsung Semiconductor, Inc. § TOBB ETÜ [‡] ETH Zürich

Challenge: Coherence for Hybrid CPU-PIM Apps



Adoption: How to Maintain Coherence? (II)

Amirali Boroumand, Saugata Ghose, Minesh Patel, Hasan Hassan, Brandon Lucia, Kevin Hsieh, Krishna T. Malladi, Hongzhong Zheng, and Onur Mutlu, "CoNDA: Efficient Cache Coherence Support for Near-**Data Accelerators**"

Proceedings of the <u>46th International Symposium on Computer</u> Architecture (ISCA), Phoenix, AZ, USA, June 2019.

CoNDA: Efficient Cache Coherence Support for Near-Data Accelerators

Amirali Boroumand[†] Saugata Ghose[†] Minesh Patel* Hasan Hassan* Brandon Lucia[†] Rachata Ausavarungnirun^{†‡} Kevin Hsieh[†] Nastaran Hajinazar^{⋄†} Krishna T. Malladi[§] Hongzhong Zheng[§] Onur Mutlu^{⋆†}

> [†]Carnegie Mellon University *ETH Zürich *Simon Fraser University

‡KMUTNB §Samsung Semiconductor, Inc.

Adoption: How to Support Synchronization?

 Christina Giannoula, Nandita Vijaykumar, Nikela Papadopoulou, Vasileios Karakostas, Ivan Fernandez, Juan Gómez-Luna, Lois Orosa, Nectarios Koziris, Georgios Goumas, Onur Mutlu, "SynCron: Efficient Synchronization Support for Near-Data-Processing Architectures"

Proceedings of the <u>27th International Symposium on High-Performance Computer</u> <u>Architecture</u> (**HPCA**), Virtual, February-March 2021.

[Slides (pptx) (pdf)]

[Short Talk Slides (pptx) (pdf)]

[Talk Video (21 minutes)]

[Short Talk Video (7 minutes)]

SynCron: Efficient Synchronization Support for Near-Data-Processing Architectures

```
Christina Giannoula<sup>†‡</sup> Nandita Vijaykumar<sup>*‡</sup> Nikela Papadopoulou<sup>†</sup> Vasileios Karakostas<sup>†</sup> Ivan Fernandez<sup>§‡</sup>
Juan Gómez-Luna<sup>‡</sup> Lois Orosa<sup>‡</sup> Nectarios Koziris<sup>†</sup> Georgios Goumas<sup>†</sup> Onur Mutlu<sup>‡</sup>

<sup>†</sup>National Technical University of Athens <sup>‡</sup>ETH Zürich <sup>*</sup>University of Toronto <sup>§</sup>University of Malaga
```

Adoption: How to Support Virtual Memory?

Kevin Hsieh, Samira Khan, Nandita Vijaykumar, Kevin K. Chang, Amirali Boroumand, Saugata Ghose, and Onur Mutlu, "Accelerating Pointer Chasing in 3D-Stacked Memory: Challenges, Mechanisms, Evaluation" Proceedings of the 34th IEEE International Conference on Computer Design (ICCD), Phoenix, AZ, USA, October 2016.

Accelerating Pointer Chasing in 3D-Stacked Memory: Challenges, Mechanisms, Evaluation

Kevin Hsieh[†] Samira Khan[‡] Nandita Vijaykumar[†] Kevin K. Chang[†] Amirali Boroumand[†] Saugata Ghose[†] Onur Mutlu^{§†} [†] Carnegie Mellon University [‡] University of Virginia [§] ETH Zürich

Adoption: Evaluation Infrastructures

 Haocong Luo, Yahya Can Tugrul, F. Nisa Bostanci, Ataberk Olgun, A. Giray Yaglikci, and Onur Mutlu,

"Ramulator 2.0: A Modern, Modular, and Extensible DRAM Simulator" Preprint on arxiv, August 2023.

[arXiv version]

[Ramulator 2.0 Source Code]

Ramulator 2.0: A Modern, Modular, and Extensible DRAM Simulator

Haocong Luo, Yahya Can Tuğrul, F. Nisa Bostancı, Ataberk Olgun, A. Giray Yağlıkçı, and Onur Mutlu

https://arxiv.org/pdf/2308.11030.pdf

Methodologies, Workloads, and Tools for Processing-in-Memory: Enabling the Adoption of Data-Centric Architectures

Geraldo F. Oliveira and Onur Mutlu

geraldofojunior@gmail.com

https://geraldofojunior.github.io/





Processing-in-Memory: Challenges

To fully support PIM systems, we need to develop:

- 1 Workload characterization methodologies and benchmark suites targeting PIM architectures
- 2 Frameworks that can facilitate the implementation of complex operations and algorithms using PIM primitives
- 3 Compiler support and compiler optimizations targeting PIM architectures
- Operating system support for PIM-aware virtual memory, memory management, data allocation and mapping
- 5 End-to-End System-on-Chip Design Beyond DRAM

The <u>lack of tools</u> and <u>system support</u> for PIM architectures limit the <u>adoption</u> of PIM systems

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An Example: SimplePIM Framework

 Jinfan Chen, Juan Gómez-Luna, Izzat El Hajj, YuXin Guo, and Onur Mutlu,

"SimplePIM: A Software Framework for Productive and Efficient Processing in Memory"

Proceedings of the <u>32nd International Conference on</u>

<u>Parallel Architectures and Compilation Techniques</u> (**PACT**),

Vienna, Austria, October 2023.

SimplePIM: A Software Framework for Productive and Efficient Processing-in-Memory

Jinfan Chen 1 Juan Gómez-Luna 1 Izzat El Hajj 2 Yuxin Guo 1 Onur Mutlu 1 ETH Zürich 2 American University of Beirut

Executive Summary

- Real PIM hardware is now available, e.g., UPMEM PIM
- However, programming real PIM hardware is challenging, e.g., need to:
 - Distribute data across PIM memory banks,
 - Manage data transfers between host cores and PIM cores, between PIM cores, and between DRAM bank and PIM scratchpad
 - Launch PIM kernels on the PIM cores, etc.
 - Synchronize properly between threads
- SimplePIM is a high-level programming framework for real PIM hardware
 - Iterators such as map, reduce, and zip
 - Collective communication with broadcast, scatter, and gather
- Implementation on UPMEM and evaluation with six different workloads
 - Reduction, vector add, histogram, linear/logistic regression, K-means
 - 4.4x fewer lines of code compared to hand-optimized code
 - Between 15% and 43% faster than hand-optimized code for three workloads
- Source code: https://github.com/CMU-SAFARI/SimplePIM

The SimplePIM Programming Framework

Our Goal

Design a high-level programming framework that abstracts hardware-specific complexities and provides a clean yet powerful interface for ease of use and high program performance

- SimplePIM provides standard abstractions to build and deploy applications on PIM systems
 - Management interface
 - Metadata management for PIM-resident arrays
 - Communication interface
 - Abstractions for host-PIM and PIM-PIM communication
 - Collective communication with broadcast, scatter, and gather
 - Processing interface
 - Iterators (map, reduce, zip) to implement workloads

SimpePIM: General Code Optimizations

- Strength reduction
- Loop unrolling
- Avoiding boundary checks
- Function inlining

Adjustment of data transfer sizes

More in the Paper

SimplePIM: A Software Framework for Productive and Efficient Processing-in-Memory

```
Jinfan Chen<sup>1</sup> Juan Gómez-Luna<sup>1</sup> Izzat El Hajj<sup>2</sup> Yuxin Guo<sup>1</sup> Onur Mutlu<sup>1</sup>

<sup>1</sup>ETH Zürich <sup>2</sup>American University of Beirut
```

https://arxiv.org/pdf/2310.01893.pdf

Productivity Improvement (I)

• Example: Hand-optimized histogram with UPMEM SDK

```
... // Initialize global variables and functions for histogram
int main kernel() {
  if (tasklet id == 0)
    mem reset(); // Reset the heap
  ... // Initialize variables and the histogram
  T *input buff A = (T^*) mem alloc(2048); // Allocate buffer in scratchpad memory
  for (unsigned int byte index = base tasklet; byte index < input size; byte index += stride) {</pre>
    // Boundary checking
    uint32 t l size bytes = (byte index + 2048 >= input size) ? (input size - byte index) : 2048;
    // Load scratchpad with a DRAM block
    mram read((const mram ptr void*)(mram base addr A + byte index), input buff A, 1 size bytes);
    // Histogram calculation
    histogram(hist, bins, input buff A, 1 size bytes/sizeof(uint32 t));
  barrier wait(&my barrier); // Barrier to synchronize PIM threads
  ... // Merging histograms from different tasklets into one histo dpu
  // Write result from scratchpad to DRAM
  if (tasklet id == 0)
    if (bins * sizeof(uint32 t) <= 2048)</pre>
      mram write(histo dpu, ( mram ptr void*)mram base addr histo, bins * sizeof(uint32 t));
    else
      for (unsigned int offset = 0; offset < ((bins * sizeof(uint32 t)) >> 11); offset++) {
        mram write(histo dpu + (offset << 9), ( mram ptr void*) (mram base addr histo +</pre>
                  (offset << 11)), 2048);
  return 0;
```

Productivity Improvement (II)

• Example: SimplePIM histogram

```
// Programmer-defined functions in the file "histo filepath"
void init func (uint32 t size, void* ptr) {
  char* casted value ptr = (char*) ptr;
  for (int i = 0; i < size; i++)</pre>
    casted value ptr[i] = 0;
void acc func (void* dest, void* src) {
  *(uint32 t*)dest += *(uint32 t*)src;
void map to val func (void* input, void* output, uint32 t* key) {
 uint32 t d = *((uint32 t*)input);
 *(uint32 t*)output = 1;
  *key = d * bins >> 12;
// Host side handle creation and iterator call
handle t* handle = simple pim create handle("histo filepath", REDUCE, NULL, 0);
// Transfer (scatter) data to PIM, register as "t1"
simple pim array scatter("t1", src, bins, sizeof(T), management);
// Run histogram on "t1" and produce "t2"
simple pim array red("t1", "t2", sizeof(T), bins, handle, management);
```

Productivity Improvement (III)

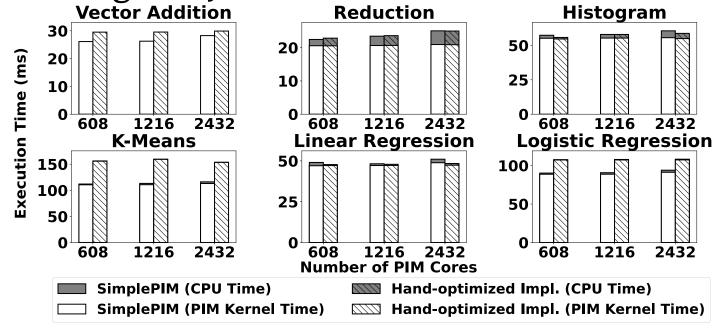
Lines of code (LoC) reduction

	SimplePIM	Hand-optimized	LoC Reduction
Reduction	14	83	5.93×
Vector Addition	14	82	5.86×
Histogram	21	114	5•43×
Linear Regression	48	157	3.27×
Logistic Regression	59	176	2.98×
K-Means	68	206	3.03×

SimplePIM reduces the number of lines of effective code by a factor of 2.98× to 5.93×

Performance Evaluation

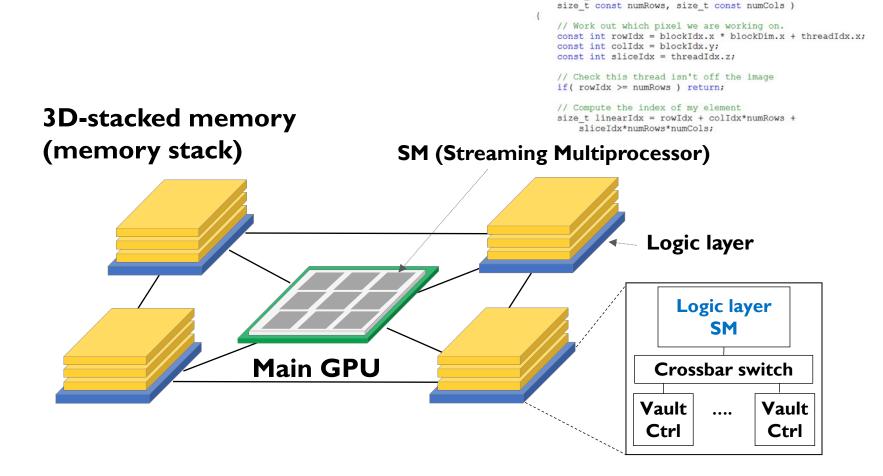
Weak scaling analysis



SimplePIM achieves comparable performance for reduction, histogram, and linear regression

SimplePIM outperforms hand-optimized implementations for vector addition, logistic regression, and k-means by 10%-37%

Truly Distributed GPU Processing with PIM



void applyScaleFactorsKernel(uint8_T * const out, uint8_T const * const in, const double *factor,

Accelerating GPU Execution with PIM (I)

Kevin Hsieh, Eiman Ebrahimi, Gwangsun Kim, Niladrish Chatterjee, Mike O'Connor, Nandita Vijaykumar, Onur Mutlu, and Stephen W. Keckler, "Transparent Offloading and Mapping (TOM): Enabling Programmer-Transparent Near-Data Processing in GPU Systems"

Proceedings of the <u>43rd International Symposium on Computer</u> <u>Architecture</u> (**ISCA**), Seoul, South Korea, June 2016. [Slides (pptx) (pdf)]

[Lightning Session Slides (pptx) (pdf)]

Transparent Offloading and Mapping (TOM): Enabling Programmer-Transparent Near-Data Processing in GPU Systems

Kevin Hsieh[‡] Eiman Ebrahimi[†] Gwangsun Kim^{*} Niladrish Chatterjee[†] Mike O'Connor[†] Nandita Vijaykumar[‡] Onur Mutlu^{§‡} Stephen W. Keckler[†] [‡]Carnegie Mellon University [†]NVIDIA *KAIST [§]ETH Zürich

Accelerating GPU Execution with PIM (II)

Ashutosh Pattnaik, Xulong Tang, Adwait Jog, Onur Kayiran, Asit K.
 Mishra, Mahmut T. Kandemir, Onur Mutlu, and Chita R. Das,
 "Scheduling Techniques for GPU Architectures with Processing-In-Memory Capabilities"

Proceedings of the <u>25th International Conference on Parallel</u>
<u>Architectures and Compilation Techniques</u> (**PACT**), Haifa, Israel,
September 2016.

Scheduling Techniques for GPU Architectures with Processing-In-Memory Capabilities

Ashutosh Pattnaik¹ Xulong Tang¹ Adwait Jog² Onur Kayıran³
Asit K. Mishra⁴ Mahmut T. Kandemir¹ Onur Mutlu^{5,6} Chita R. Das¹

¹Pennsylvania State University ²College of William and Mary

³Advanced Micro Devices, Inc. ⁴Intel Labs ⁵ETH Zürich ⁶Carnegie Mellon University

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Accelerating Linked Data Structures

Kevin Hsieh, Samira Khan, Nandita Vijaykumar, Kevin K. Chang, Amirali Boroumand, Saugata Ghose, and Onur Mutlu,
 "Accelerating Pointer Chasing in 3D-Stacked Memory:
 Challenges, Mechanisms, Evaluation"
 Proceedings of the 34th IEEE International Conference on Computer
 Design (ICCD), Phoenix, AZ, USA, October 2016.

Accelerating Pointer Chasing in 3D-Stacked Memory: Challenges, Mechanisms, Evaluation

Kevin Hsieh[†] Samira Khan[‡] Nandita Vijaykumar[†] Kevin K. Chang[†] Amirali Boroumand[†] Saugata Ghose[†] Onur Mutlu^{§†} [†] Carnegie Mellon University [‡] University of Virginia [§] ETH Zürich

Accelerating Dependent Cache Misses

Milad Hashemi, Khubaib, Eiman Ebrahimi, Onur Mutlu, and Yale N. Patt,
 "Accelerating Dependent Cache Misses with an Enhanced Memory Controller"

Proceedings of the <u>43rd International Symposium on Computer</u> <u>Architecture</u> (**ISCA**), Seoul, South Korea, June 2016. [Slides (pptx) (pdf)]

[Lightning Session Slides (pptx) (pdf)]

Accelerating Dependent Cache Misses with an Enhanced Memory Controller

Milad Hashemi*, Khubaib[†], Eiman Ebrahimi[‡], Onur Mutlu[§], Yale N. Patt*

*The University of Texas at Austin †Apple ‡NVIDIA §ETH Zürich & Carnegie Mellon University

Accelerating Runahead Execution

Milad Hashemi, Onur Mutlu, and Yale N. Patt,
 "Continuous Runahead: Transparent Hardware Acceleration for Memory Intensive Workloads"
 Proceedings of the 49th International Symposium on

Microarchitecture (MICRO), Taipei, Taiwan, October 2016.

[Slides (pptx) (pdf)] [Lightning Session Slides (pdf)] [Poster (pptx) (pdf)]

Best paper session.

Continuous Runahead: Transparent Hardware Acceleration for Memory Intensive Workloads

Milad Hashemi*, Onur Mutlu§, Yale N. Patt*

*The University of Texas at Austin §ETH Zürich

Accelerating Climate Modeling

 Gagandeep Singh, Dionysios Diamantopoulos, Christoph Hagleitner, Juan Gómez-Luna, Sander Stuijk, Onur Mutlu, and Henk Corporaal, "NERO: A Near High-Bandwidth Memory Stencil Accelerator for Weather Prediction Modeling"

Proceedings of the <u>30th International Conference on Field-Programmable Logic</u> <u>and Applications</u> (**FPL**), Gothenburg, Sweden, September 2020.

[Slides (pptx) (pdf)]

[Lightning Talk Slides (pptx) (pdf)]

[Talk Video (23 minutes)]

Nominated for the Stamatis Vassiliadis Memorial Award.

NERO: A Near High-Bandwidth Memory Stencil Accelerator for Weather Prediction Modeling

Gagandeep Singh a,b,c Dionysios Diamantopoulos c Christoph Hagleitner c Juan Gómez-Luna b Sander Stuijk a Onur Mutlu b Henk Corporaal a Eindhoven University of Technology b ETH Zürich c IBM Research Europe, Zurich

Accelerating DNA Read Mapping

 Jeremie S. Kim, Damla Senol Cali, Hongyi Xin, Donghyuk Lee, Saugata Ghose, Mohammed Alser, Hasan Hassan, Oguz Ergin, Can Alkan, and Onur Mutlu,

"GRIM-Filter: Fast Seed Location Filtering in DNA Read Mapping Using Processing-in-Memory Technologies"

BMC Genomics, 2018.

Proceedings of the <u>16th Asia Pacific Bioinformatics Conference</u> (**APBC**), Yokohama, Japan, January 2018.

[Slides (pptx) (pdf)]

[Source Code]

[arxiv.org Version (pdf)]

[Talk Video at AACBB 2019]

GRIM-Filter: Fast seed location filtering in DNA read mapping using processing-in-memory technologies

Jeremie S. Kim^{1,6*}, Damla Senol Cali¹, Hongyi Xin², Donghyuk Lee³, Saugata Ghose¹, Mohammed Alser⁴, Hasan Hassan⁶, Oguz Ergin⁵, Can Alkan^{4*} and Onur Mutlu^{6,1*}



Accelerating Approximate String Matching

Damla Senol Cali, Gurpreet S. Kalsi, Zulal Bingol, Can Firtina, Lavanya Subramanian, Jeremie S. Kim, Rachata Ausavarungnirun, Mohammed Alser, Juan Gomez-Luna, Amirali Boroumand, Anant Nori, Allison Scibisz, Sreenivas Subramoney, Can Alkan, Saugata Ghose, and Onur Mutlu, "GenASM: A High-Performance, Low-Power Approximate String Matching Acceleration Framework for Genome Sequence Analysis"
Proceedings of the 53rd International Symposium on Microarchitecture (MICRO), Virtual, October 2020.

[<u>Lighting Talk Video</u> (1.5 minutes)] [<u>Lightning Talk Slides (pptx) (pdf)</u>] [<u>Talk Video</u> (18 minutes)] [<u>Slides (pptx) (pdf)</u>]

GenASM: A High-Performance, Low-Power Approximate String Matching Acceleration Framework for Genome Sequence Analysis

Damla Senol Cali^{†™} Gurpreet S. Kalsi[™] Zülal Bingöl[▽] Can Firtina[⋄] Lavanya Subramanian[‡] Jeremie S. Kim^{⋄†} Rachata Ausavarungnirun[⊙] Mohammed Alser[⋄] Juan Gomez-Luna[⋄] Amirali Boroumand[†] Anant Nori[™] Allison Scibisz[†] Sreenivas Subramoney[™] Can Alkan[▽] Saugata Ghose^{*†} Onur Mutlu^{⋄†▽}

† Carnegie Mellon University [™] Processor Architecture Research Lab, Intel Labs [▽] Bilkent University [⋄] ETH Zürich

‡ Facebook [⊙] King Mongkut's University of Technology North Bangkok ^{*} University of Illinois at Urbana–Champaign

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SAFARI

Accelerating Sequence-to-Graph Mapping

Damla Senol Cali, Konstantinos Kanellopoulos, Joel Lindegger, Zulal Bingol, Gurpreet S. Kalsi, Ziyi Zuo, Can Firtina, Meryem Banu Cavlak, Jeremie Kim, Nika MansouriGhiasi, Gagandeep Singh, Juan Gomez-Luna, Nour Almadhoun Alserr, Mohammed Alser, Sreenivas Subramoney, Can Alkan, Saugata Ghose, and Onur Mutlu, "SeGraM: A Universal Hardware Accelerator for Genomic Sequence-to-Graph and Sequence-to-Sequence Mapping"

Proceedings of the <u>49th International Symposium on Computer Architecture</u> (**ISCA**), New York, June 2022.

arXiv version

SeGraM: A Universal Hardware Accelerator for Genomic Sequence-to-Graph and Sequence-to-Sequence Mapping

Damla Senol Cali¹ Konstantinos Kanellopoulos² Joël Lindegger² Zülal Bingöl³ Gurpreet S. Kalsi⁴ Ziyi Zuo⁵ Can Firtina² Meryem Banu Cavlak² Jeremie Kim² Nika Mansouri Ghiasi² Gagandeep Singh² Juan Gómez-Luna² Nour Almadhoun Alserr² Mohammed Alser² Sreenivas Subramoney⁴ Can Alkan³ Saugata Ghose⁶ Onur Mutlu²

¹Bionano Genomics ²ETH Zürich ³Bilkent University ⁴Intel Labs ⁵Carnegie Mellon University ⁶University of Illinois Urbana-Champaign

Accelerating Basecalling + Read Mapping

 Haiyu Mao, Mohammed Alser, Mohammad Sadrosadati, Can Firtina, Akanksha Baranwal, Damla Senol Cali, Aditya Manglik, Nour Almadhoun Alserr, and Onur Mutlu,
 "GenPIP: In-Memory Acceleration of Genome Analysis via Tight Integration of Basecalling and Read Mapping"

Proceedings of the <u>55th International Symposium on Microarchitecture</u> (**MICRO**), Chicago, IL, USA, October 2022.

[Slides (pptx) (pdf)]

[Longer Lecture Slides (pptx) (pdf)]

[<u>Lecture Video</u> (25 minutes)]

[arXiv version]

GenPIP: In-Memory Acceleration of Genome Analysis via Tight Integration of Basecalling and Read Mapping

Haiyu Mao¹ Mohammed Alser¹ Mohammad Sadrosadati¹ Can Firtina¹ Akanksha Baranwal¹ Damla Senol Cali² Aditya Manglik¹ Nour Almadhoun Alserr¹ Onur Mutlu¹

IETH Zürich* **Pionano Genomics**

Accelerating Basecalling

 Taha Shahroodi, Gagandeep Singh, Mahdi Zahedi, Haiyu Mao, Joel Lindegger, Can Firtina, Stephan Wong, Onur Mutlu, and Said Hamdioui, "Swordfish: A Framework for Evaluating Deep Neural Network-based Basecalling using Computation-In-Memory with Non-Ideal Memristors"

Proceedings of the <u>56th International Symposium on</u>

<u>Microarchitecture</u> (**MICRO**), Toronto, ON, Canada, November 2023.

[<u>Slides (pptx) (pdf)</u>]

[<u>arXiv version</u>]

Swordfish: A Framework for Evaluating Deep Neural Network-based Basecalling using Computation-In-Memory with Non-Ideal Memristors

Taha Shahroodi¹ Gagandeep Singh^{2,3} Mahdi Zahedi¹ Haiyu Mao³ Joel Lindegger³ Can Firtina³ Stephan Wong¹ Onur Mutlu³ Said Hamdioui¹

¹TU Delft ²AMD Research ³ETH Zürich

Accelerating Time Series Analysis (I)

Ivan Fernandez, Ricardo Quislant, Christina Giannoula, Mohammed Alser, Juan Gómez-Luna, Eladio Gutiérrez, Oscar Plata, and Onur Mutlu, "NATSA: A Near-Data Processing Accelerator for Time Series Analysis" Proceedings of the 38th IEEE International Conference on Computer Design (ICCD), Virtual, October 2020.

[Slides (pptx) (pdf)]

[Talk Video (10 minutes)]

Source Code

NATSA: A Near-Data Processing Accelerator for Time Series Analysis

Ivan Fernandez§ Ricardo Quislant§ Christina Giannoula† Mohammed Alser‡ Juan Gómez-Luna‡ Eladio Gutiérrez§ Oscar Plata§ Onur Mutlu‡ §University of Malaga †National Technical University of Athens ‡ETH Zürich

Accelerating Time Series Analysis (II)

 Ivan Fernandez, Christina Giannoula, Aditya Manglik, Ricardo Quislant, Nika Mansouri Ghiasi, Juan Gomez Luna, Eladio Gutierrez, Oscar Plata and Onur Mutlu,

"MATSA: An MRAM-Based Energy-Efficient Accelerator for Time Series Analysis"

IEEE Access, March 2024.

[arXiv version]

[IEEE Access version]

Accelerating Time Series Analysis via Processing using Non-Volatile Memories

Ivan Fernandez^{§†¶} *Christina Giannoula^{†‡} *Aditya Manglik[†] Ricardo Quislant[§] Nika Mansouri Ghiasi[†] Juan Gómez-Luna[†] Eladio Gutierrez[§] Oscar Plata[§] Onur Mutlu[†]

 § University of Malaga † ETH Zürich § Barcelona Supercomputing

[¶]Barcelona Supercomputing Center [‡]National Technical University of Athens

Accelerating Graph Pattern Mining

 Maciej Besta, Raghavendra Kanakagiri, Grzegorz Kwasniewski, Rachata Ausavarungnirun, Jakub Beránek, Konstantinos Kanellopoulos, Kacper Janda, Zur Vonarburg-Shmaria, Lukas Gianinazzi, Ioana Stefan, Juan Gómez-Luna, Marcin Copik, Lukas Kapp-Schwoerer, Salvatore Di Girolamo, Nils Blach, Marek Konieczny, Onur Mutlu, and Torsten Hoefler,

<u>"SISA: Set-Centric Instruction Set Architecture for Graph Mining on Processing-in-Memory Systems"</u>

Proceedings of the <u>54th International Symposium on Microarchitecture</u> (**MICRO**), Virtual, October 2021.

[Slides (pdf)]

[Talk Video (22 minutes)]

[<u>Lightning Talk Video</u> (1.5 minutes)]

[Full arXiv version]

SISA: Set-Centric Instruction Set Architecture for Graph Mining on Processing-in-Memory Systems

Maciej Besta¹, Raghavendra Kanakagiri², Grzegorz Kwasniewski¹, Rachata Ausavarungnirun³, Jakub Beránek⁴, Konstantinos Kanellopoulos¹, Kacper Janda⁵, Zur Vonarburg-Shmaria¹, Lukas Gianinazzi¹, Ioana Stefan¹, Juan Gómez-Luna¹, Marcin Copik¹, Lukas Kapp-Schwoerer¹, Salvatore Di Girolamo¹, Nils Blach¹, Marek Konieczny⁵, Onur Mutlu¹, Torsten Hoefler¹

¹ETH Zurich, Switzerland ²IIT Tirupati, India ³King Mongkut's University of Technology North Bangkok, Thailand ⁴Technical University of Ostrava, Czech Republic ⁵AGH-UST, Poland

Accelerating HTAP Database Systems

Amirali Boroumand, Saugata Ghose, Geraldo F. Oliveira, and Onur Mutlu,
 "Polynesia: Enabling High-Performance and Energy-Efficient Hybrid
 <u>Transactional/Analytical Databases with Hardware/Software Co-Design"</u>
 *Proceedings of the <u>38th International Conference on Data Engineering</u> (ICDE),
 Virtual, May 2022.*

[arXiv version]
[Slides (pptx) (pdf)]
[Short Talk Slides (pptx) (pdf)]

Polynesia: Enabling High-Performance and Energy-Efficient Hybrid Transactional/Analytical Databases with Hardware/Software Co-Design

Amirali Boroumand[†] Saugata Ghose[†] Geraldo F. Oliveira[‡] Onur Mutlu[‡]

†Google [†]Univ. of Illinois Urbana-Champaign [‡]ETH Zürich

Accelerating ML Inference

Amirali Boroumand, Saugata Ghose, Berkin Akin, Ravi Narayanaswami, Geraldo F. Oliveira, Xiaoyu Ma, Eric Shiu, and Onur Mutlu, "Google Neural Network Models for Edge Devices: Analyzing and Mitigating Machine Learning Inference Bottlenecks"

Proceedings of the 30th International Conference on Parallel Architectures and Compilation Techniques (PACT), Virtual, September 2021.

[Slides (pptx) (pdf)]

[Talk Video (14 minutes)]

Google Neural Network Models for Edge Devices: Analyzing and Mitigating Machine Learning Inference Bottlenecks

Amirali Boroumand[†] Saugata Ghose[‡] Berkin Akin[§] Ravi Narayanaswami[§] Geraldo F. Oliveira^{*} Xiaoyu Ma[§] Eric Shiu[§] Onur Mutlu^{*†}

 $^\dagger C$ arnegie Mellon Univ. $^\diamond S$ tanford Univ. $^\ddagger U$ niv. of Illinois Urbana-Champaign $^\S G$ oogle $^\star ETH$ Zürich

Accelerating Data-Intensive Workloads

Junwhan Ahn, Sungjoo Yoo, Onur Mutlu, and Kiyoung Choi,
 "PIM-Enabled Instructions: A Low-Overhead,
 Locality-Aware Processing-in-Memory Architecture"
 Proceedings of the <u>42nd International Symposium on</u>
 Computer Architecture (ISCA), Portland, OR, June 2015.
 [Slides (pdf)] [Lightning Session Slides (pdf)]

PIM-Enabled Instructions: A Low-Overhead, Locality-Aware Processing-in-Memory Architecture

Junwhan Ahn Sungjoo Yoo Onur Mutlu[†] Kiyoung Choi junwhan@snu.ac.kr, sungjoo.yoo@gmail.com, onur@cmu.edu, kchoi@snu.ac.kr

Seoul National University [†]Carnegie Mellon University

SAFARI

FPGA-based Processing Near Memory

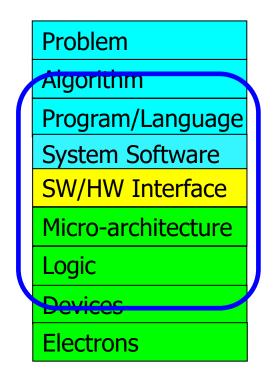
Gagandeep Singh, Mohammed Alser, Damla Senol Cali, Dionysios
 Diamantopoulos, Juan Gómez-Luna, Henk Corporaal, and Onur Mutlu,
 "FPGA-based Near-Memory Acceleration of Modern Data-Intensive
 Applications"
 IFFE Micro (IEEE MICRO), 2021.

FPGA-based Near-Memory Acceleration of Modern Data-Intensive Applications

Gagandeep Singh[⋄] Mohammed Alser[⋄] Damla Senol Cali[⋈]
Dionysios Diamantopoulos[▽] Juan Gómez-Luna[⋄]
Henk Corporaal[⋆] Onur Mutlu^{⋄⋈}

[⋄]ETH Zürich [⋈] Carnegie Mellon University *Eindhoven University of Technology [▽]IBM Research Europe

We Need to Revisit the Entire Stack



We can get there step by step

Security Issues in Processing in Memory

- Does PIM make security better or easier?
- Does PIM make security worse?
- Many interesting questions here
- Some recent papers:
 - Evaluating Homomorphic Operations on a Real-World Processing-In-Memory System [IISWC 2023]
 - Amplifying Main Memory-Based Timing Covert and Side Channels using Processing-in-Memory Operations [arxiv 2024]

Homomorphic Operations on Real PIM Systems

 Harshita Gupta, Mayank Kabra, Juan Gómez-Luna, Konstantinos Kanellopoulos, and Onur Mutlu,

"Evaluating Homomorphic Operations on a Real-World Processing-In-Memory System"

<u>Proceedings of the 2023 IEEE International Symposium on Workload</u> <u>Characterization</u> Poster Session (**IISWC**), Ghent, Belgium, October 2023.

arXiv version

[Lightning Talk Slides (pptx) (pdf)]

[Poster (pptx) (pdf)]

Evaluating Homomorphic Operations on a Real-World Processing-In-Memory System

Harshita Gupta* Mayank Kabra* Juan Gómez-Luna Konstantinos Kanellopoulos Onur Mutlu

ETH Zürich

PIM Amplifies Covert & Side Channels

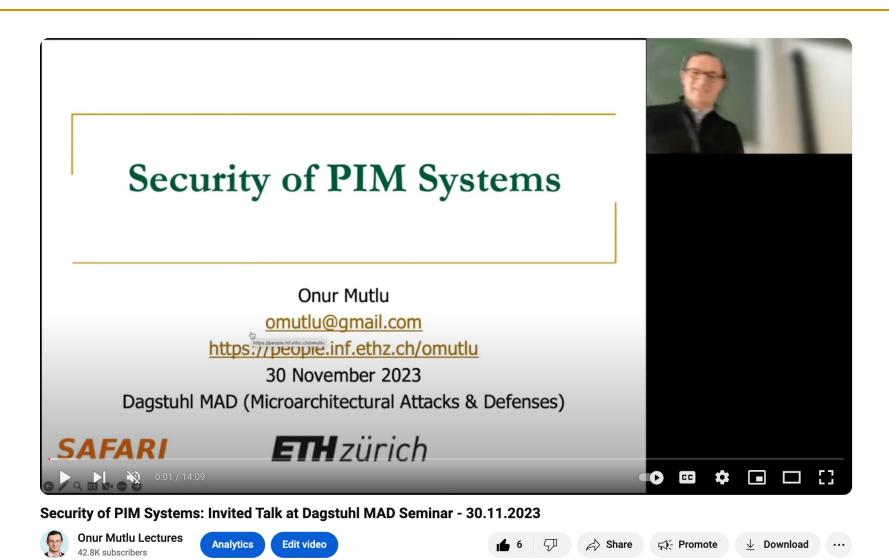
Amplifying Main Memory-Based Timing Covert and Side Channels using Processing-in-Memory Operations

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Konstantinos Kanellopoulos<sup>†*</sup> F. Nisa Bostancı<sup>†*</sup> Ataberk Olgun<sup>†</sup>
A. Giray Yağlıkçı<sup>†</sup> İsmail Emir Yüksel<sup>†</sup> Nika Mansouri Ghiasi<sup>†</sup>
Zülal Bingöl<sup>†‡</sup> Mohammad Sadrosadati<sup>†</sup> Onur Mutlu<sup>†</sup>

<sup>†</sup>ETH Zürich <sup>‡</sup>Bilkent University
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https://arxiv.org/pdf/2404.11284

A Talk on Security of PIM Systems



Eliminating the Adoption Barriers

Processing-in-Memory in the Real World

PIM Tutorial at ISCA 2024

ISCA 2024 Memory-Centric Computing Systems Tutorial

Saturday, June 29, Buenos Aires, Argentina

Organizers: Geraldo F. Oliveira, Dr. Mohammad Sadrosadati,

Ataberk Olgun, Professor Onur Mutlu

Program: https://events.safari.ethz.ch/isca24-memorycentric-tutorial/

Overview of PIM | PIM taxonomy
PIM in memory & storage
Real-world PNM systems
PUM for bulk bitwise operations
Programming techniques & tools
Infrastructures for PIM Research
Research challenges &
opportunities

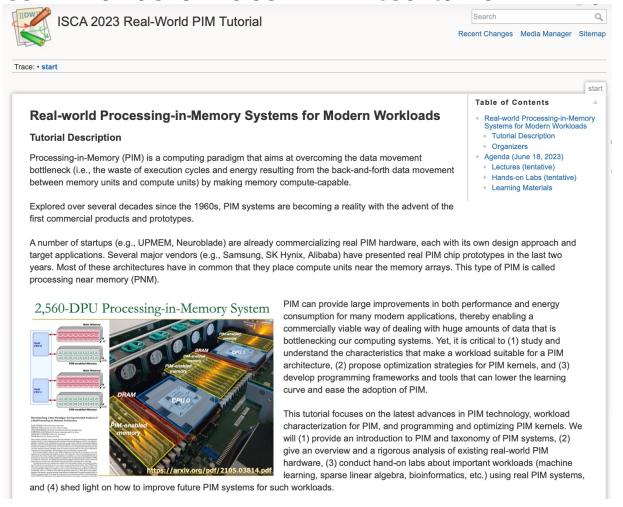




https://www.youtube.com/watch?v=KV2MXvcBgb0

PIM Tutorials [micro'23, isca'23, asplos'23, hpca'23, isca'24]

Lectures + Hands-on labs + Invited talks



https://www.youtube.com/live/GIb5EqSrWk0

https://events.safari.ethz.ch/isca-pim-tutorial/

Real PIM Tutorial [ISCA 2023]

June 18: Lectures + Hands-on labs + Invited talks



Tutorial Materials

Time	Speaker	Title	Materials
8:55am- 9:00am	Dr. Juan Gómez Luna	Welcome & Agenda	▶(PDF) P (PPT)
9:00am- 10:20am	Prof. Onur Mutlu	Memory-Centric Computing	▶(PDF) P (PPT)
10:20am- 11:00am	Dr. Juan Gómez Luna	Processing-Near-Memory: Real PNM Architectures / Programming General-purpose PIM	▶(PDF) P (PPT)
11:20am- 11:50am	Prof. Izzat El Hajj	High-throughput Sequence Alignment using Real Processing-in-Memory Systems	▶(PDF) P (PPT)
11:50am- 12:30pm	Dr. Christina Giannoula	SparseP: Towards Efficient Sparse Matrix Vector Multiplication for Real Processing-In-Memory Systems	▶(PDF) P (PPT)
2:00pm- 2:45pm	Dr. Sukhan Lee	Introducing Real-world HBM-PIM Powered System for Memory-bound Applications	(PDF) (PPT)
2:45pm- 3:30pm	Dr. Juan Gómez Luna / Ataberk Olgun	Processing-Using-Memory: Exploiting the Analog Operational Properties of Memory Components / PUM Prototypes: PiDRAM	→ (PDF) P (PPT) → (PDF) P (PPT)
4:00pm- 4:40pm	Dr. Juan Gómez Luna	Accelerating Modern Workloads on a General-purpose PIM System	▶(PDF) P (PPT)
4:40pm- 5:20pm	Dr. Juan Gómez Luna	Adoption Issues: How to Enable PIM?	▶(PDF) P (PPT)
5:20pm- 5:30pm	Dr. Juan Gómez Luna	Hands-on Lab: Programming and Understanding a Real Processing-in- Memory Architecture	→ (Handout) → (PDF) P (PPT)

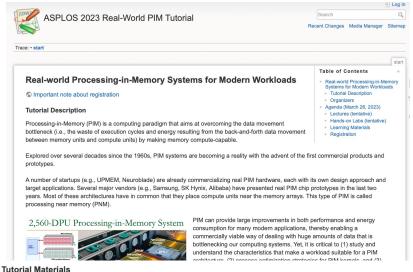


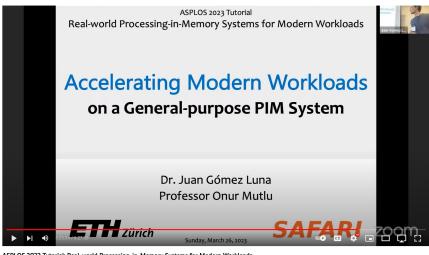
https://www.youtube.com/ live/GIb5EgSrWk0

https://events.safari.ethz.ch/ isca-pim-tutorial/

Real PIM Tutorial [ASPLOS 2023]

March 26: Lectures + Hands-on labs + Invited talks





ASPLOS 2023 Tutorial: Real-world Processing-in-Memory Systems for Modern Workloads

P (PPT)

Onur Mutlu Lectures 32.1K subscribers

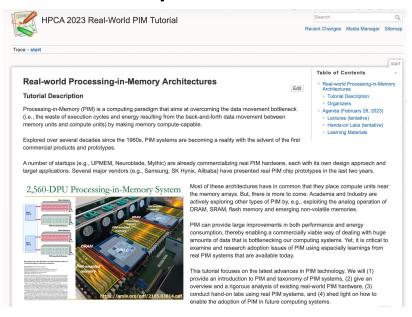


https://www.youtube.com/ watch?v=oYCaLcT0Kmo

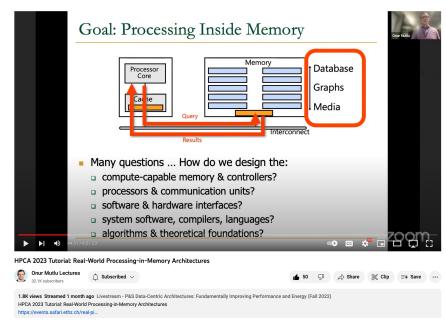
https://events.safari.ethz.ch/ asplos-pim-tutorial/

Real PIM Tutorial [HPCA 2023]

February 26: Lectures + Hands-on labs + Invited Talks



Time	Speaker	Title	Materials		
8:00am- 8:40am	Prof. Onur Mutlu	Memory-Centric Computing			
8:40am- 10:00am	Dr. Juan Gómez Luna	Processing-Near-Memory: Real PNM Architectures Programming General-purpose PIM			
10:20am- 11:00am	Dr. Dimin Niu	A 3D Logic-to-DRAM Hybrid Bonding Process-Near-Memory Chip for Recommendation	on System		
11:00am- 11:40am	Dr. Christina Giannoula	SparseP: Towards Efficient Sparse Matrix Vector Multiplication on Real Processing- In-Memory Architectures	P (PDF)		
1:30pm- 2:10pm	Dr. Juan Gómez Luna	Processing-Using-Memory: Exploiting the Analog Operational Properties of Memory Components	P (PDF)		
2:10pm- 2:50pm	Dr. Manuel Le Gallo	Deep Learning Inference Using Computational Phase-Change Memory			
2:50pm- 3:30pm	Dr. Juan Gómez Luna	PIM Adoption Issues: How to Enable PIM Adoption?			
3:40pm- 5:40pm	Dr. Juan Gómez Luna	Hands-on Lab: Programming and Understanding a Real Processing-in-Memory Architecture			

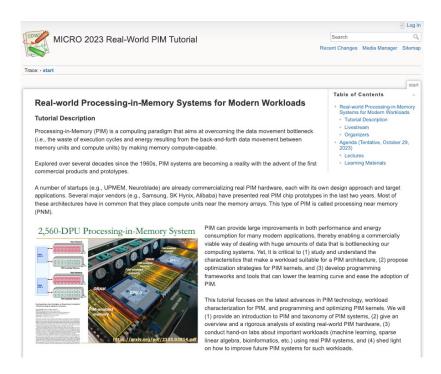


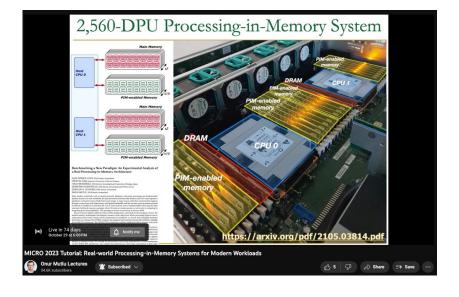
https://www.youtube.com/watch?v=f5-nT1tbz5w

https://events.safari.ethz.ch/ real-pim-tutorial/

Real PIM Tutorial [MICRO 2023]

October 29: Lectures + Hands-on labs + Invited talks





https://www.youtube.com/watch ?v=ohUooNSIxOI

https://events.safari.ethz.ch/micro -pim-tutorial

Agenda (Tentative, October 29, 2023)

Lectures

- 1. Introduction: PIM as a paradigm to overcome the data movement bottleneck.
- 2. PIM taxonomy: PNM (processing near memory) and PUM (processing using memory).
- 3. General-purpose PNM: UPMEM PIM.
- 4. PNM for neural networks: Samsung HBM-PIM, SK Hynix AiM.
- 5. PNM for recommender systems: Samsung AxDIMM, Alibaba PNM.
- 6. PUM prototypes: PiDRAM, SRAM-based PUM, Flash-based PUM.
- 7. Other approaches: Neuroblade, Mythic.
- 8. Adoption issues: How to enable PIM?
- Hands-on labs: Programming a real PIM system.

FPGA-based Processing Near Memory

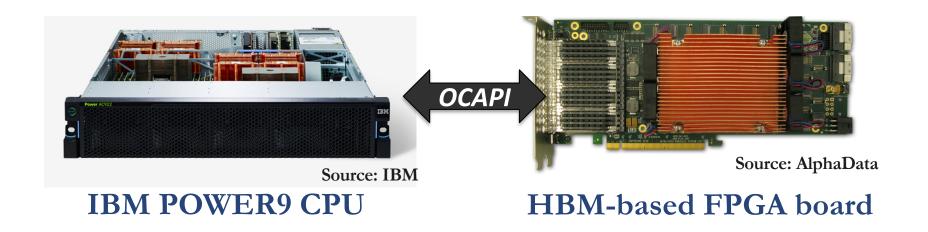
Gagandeep Singh, Mohammed Alser, Damla Senol Cali, Dionysios
 Diamantopoulos, Juan Gómez-Luna, Henk Corporaal, and Onur Mutlu,
 "FPGA-based Near-Memory Acceleration of Modern Data-Intensive
 Applications"
 IFFE Micro (IEEE MICRO), 2021.

FPGA-based Near-Memory Acceleration of Modern Data-Intensive Applications

Gagandeep Singh[⋄] Mohammed Alser[⋄] Damla Senol Cali[⋈]
Dionysios Diamantopoulos[▽] Juan Gómez-Luna[⋄]
Henk Corporaal[⋆] Onur Mutlu^{⋄⋈}

[⋄]ETH Zürich [⋈] Carnegie Mellon University *Eindhoven University of Technology [▽]IBM Research Europe

Near-Memory Acceleration using FPGAs



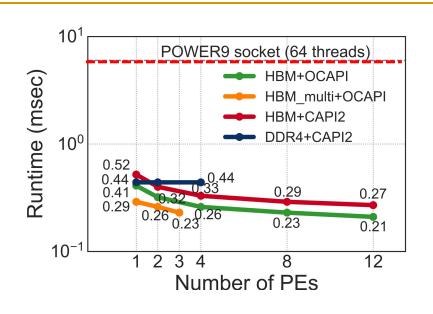
Near-HBM FPGA-based accelerator

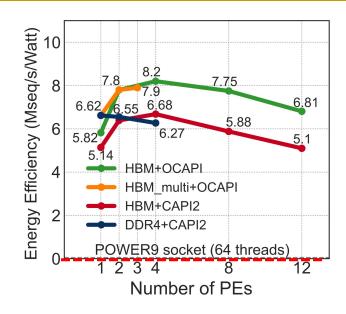
Two communication technologies: CAPI2 and OCAPI

Two memory technologies: DDR4 and HBM

Two workloads: Weather Modeling and Genome Analysis

Performance & Energy Greatly Improve





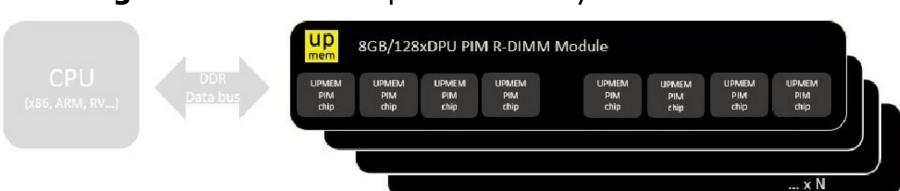
5-27× performance vs. a 16-core (64-thread) IBM POWER9 CPU

12-133× energy efficiency vs. a 16-core (64-thread) IBM POWER9 CPU

HBM alleviates memory bandwidth contention vs. DDR4

UPMEM Processing-in-DRAM Engine (2019)

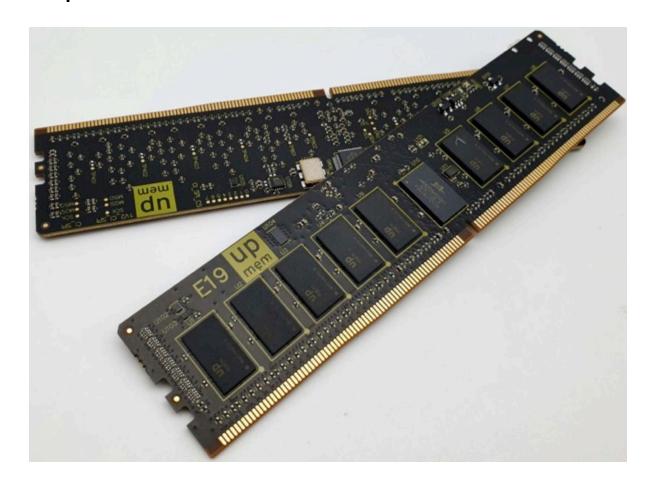
- Processing in DRAM Engine
- Includes standard DIMM modules, with a large number of DPU processors combined with DRAM chips.
- Replaces standard DIMMs
 - DDR4 R-DIMM modules
 - 8GB+128 DPUs (16 PIM chips)
 - Standard 2x-nm DRAM process
 - Large amounts of compute & memory bandwidth





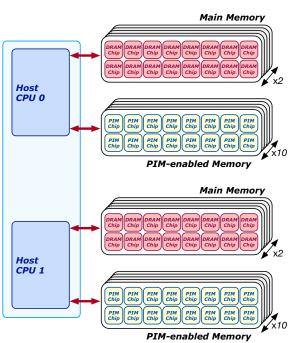
UPMEM Memory Modules

- E19: 8 chips DIMM (1 rank). DPUs @ 267 MHz
- P21: 16 chips DIMM (2 ranks). DPUs @ 350 MHz





2,560-DPU Processing-in-Memory System



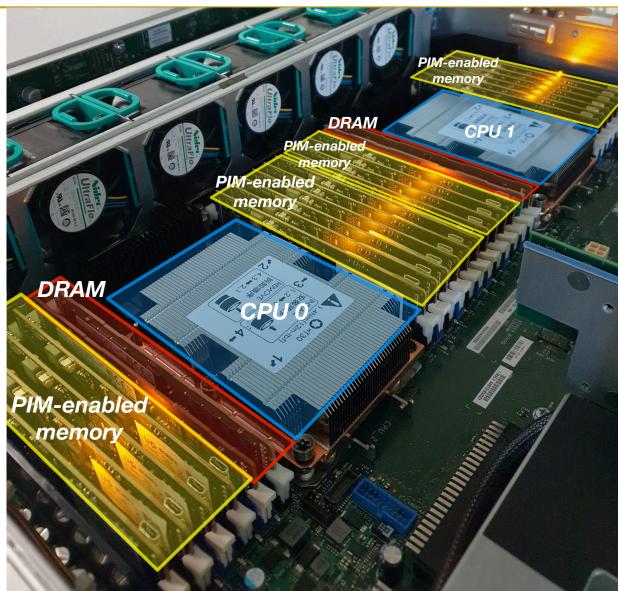
Benchmarking a New Paradigm: An Experimental Analysis of a Real Processing-in-Memory Architecture

JUAN GÓMEZ-LUNA, ETH Zürich, Switzerland
IZZAT EL HAJJ, American University of Beirut, Lebanon
IVAN FERNANDEZ, ETH Zürich, Switzerland and University of Malaga, Spain
CHRISTINA GIANNOULA, ETH Zürich, Switzerland and NTUA, Greece
GERALDO F. OLIVEIRA, ETH Zürich, Switzerland
ONUR MUTLU, ETH Zürich, Switzerland

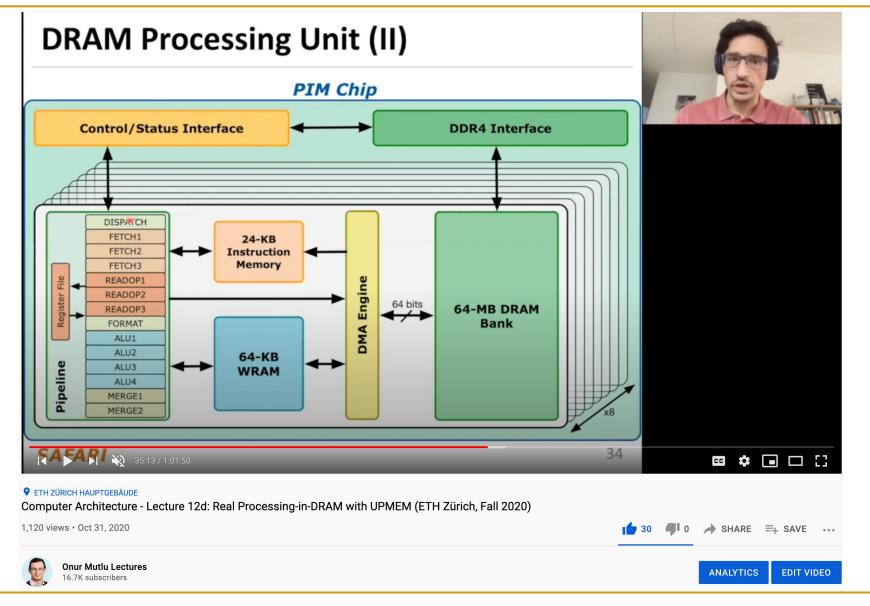
Many modern workloads, such as neural networks, databases, and graph processing, are fundamentally memory-bound for such workloads, the data nowment between main memory and CPU core simpose a significant overhead in terms of both latency and energy. A major reason is that this communication happens through a narrow bus with high latency and limited bandwidth, and the low data reuse in memory-bound workloads is insufficient to amortize the cost of main memory access. Fundamentally addressing this data movement bottleneck requires a paradigm where the memory system assumes an active role in computing by integrating processing capabilities. This paradigm is known as processing—in-memory (PRI).

Recent research explores different forms of PIM architectures, motivated by the emergence of new 3Dstacked memory technologies that integrate memory with a logic layer where processing elements can be easily placed. Past works evaluate these architectures in simulation or, at best, with simplified hardware prototypes. In contrast, the UPMEM company has designed and manufactured the first publicly-available real-world PIM architecture. The UPMEM PIM architecture combines traditional DRAM memory arrays with general-purpose in-order cores, called DRAM Processing Units (DPUs), integrated in the same chip.

This paper provides the first comprehensive analysis of the first publicly-available real-world PIM architecture. We make two key contributions. First, we conduct an experimental characterization of the UPIMEM-based to PIM system using microbenchmarks to assess various architecture limits such as compute throughput and memory bandwidth, yielding new insights. Second, we present PPIM (Processing, in-Pigmory) benchmarks) as a benchmark suite of 16 workfoads from different application domains (e.g., dense/sparse linear algebra, databases, data naphytics, graph processing, which we identify as memory-bound. We evaluate the performance and scaling characteristics of PIM benchmarks on the UPIMEM PIM architecture, and compare their performance and energy consumption to their state-of-the-art CPU and CPU counterparts. Our extensive evaluation conducted on two real UPIMEM-based PIM systems with 640 and 2550 PDIS provides new insights about satiability of different workloads to the PIM systems with 640 was not software designers, and suggestions and hints for hardware and architecture designers of future PIM systems.



More on the UPMEM PIM System



Experimental Analysis of the UPMEM PIM Engine

Benchmarking a New Paradigm: An Experimental Analysis of a Real Processing-in-Memory Architecture

JUAN GÓMEZ-LUNA, ETH Zürich, Switzerland IZZAT EL HAJJ, American University of Beirut, Lebanon IVAN FERNANDEZ, ETH Zürich, Switzerland and University of Malaga, Spain CHRISTINA GIANNOULA, ETH Zürich, Switzerland and NTUA, Greece GERALDO F. OLIVEIRA, ETH Zürich, Switzerland ONUR MUTLU, ETH Zürich, Switzerland

Many modern workloads, such as neural networks, databases, and graph processing, are fundamentally memory-bound. For such workloads, the data movement between main memory and CPU cores imposes a significant overhead in terms of both latency and energy. A major reason is that this communication happens through a narrow bus with high latency and limited bandwidth, and the low data reuse in memory-bound workloads is insufficient to amortize the cost of main memory access. Fundamentally addressing this *data movement bottleneck* requires a paradigm where the memory system assumes an active role in computing by integrating processing capabilities. This paradigm is known as *processing-in-memory (PIM)*.

Recent research explores different forms of PIM architectures, motivated by the emergence of new 3D-stacked memory technologies that integrate memory with a logic layer where processing elements can be easily placed. Past works evaluate these architectures in simulation or, at best, with simplified hardware prototypes. In contrast, the UPMEM company has designed and manufactured the first publicly-available real-world PIM architecture. The UPMEM PIM architecture combines traditional DRAM memory arrays with general-purpose in-order cores, called *DRAM Processing Units* (*DPUs*), integrated in the same chip.

This paper provides the first comprehensive analysis of the first publicly-available real-world PIM architecture. We make two key contributions. First, we conduct an experimental characterization of the UPMEM-based PIM system using microbenchmarks to assess various architecture limits such as compute throughput and memory bandwidth, yielding new insights. Second, we present *PrIM* (*Processing-In-Memory benchmarks*), a benchmark suite of 16 workloads from different application domains (e.g., dense/sparse linear algebra, databases, data analytics, graph processing, neural networks, bioinformatics, image processing), which we identify as memory-bound. We evaluate the performance and scaling characteristics of PrIM benchmarks on the UPMEM PIM architecture, and compare their performance and energy consumption to their state-of-the-art CPU and GPU counterparts. Our extensive evaluation conducted on two real UPMEM-based PIM systems with 640 and 2,556 DPUs provides new insights about suitability of different workloads to the PIM system, programming recommendations for software designers, and suggestions and hints for hardware and architecture designers of future PIM systems.

https://arxiv.org/pdf/2105.03814.pdf

Recent SRC TECHCON Presentation

- Dr. Juan Gomez-Luna
 - Benchmarking Memory-Centric Computing Systems: Analysis of Real Processing-in-Memory Hardware
 - Based on two major works
 - https://arxiv.org/pdf/2105.03814.pdf
 - https://arxiv.org/pdf/2207.07886.pdf

Benchmarking Memory-Centric Computing Systems: Analysis of Real Processing-In-

Memory Hardware

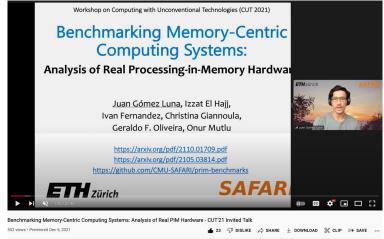
Year: 2021, Pages: 1-7

DOI Bookmark: 10.1109/IGSC54211.2021.9651614

Authors

Juan Gómez-Luna, ETH Zürich Izzat El Hajj, American University of Beirut Ivan Fernandez, University of Malaga Christina Giannoula, National Technical University of Athens

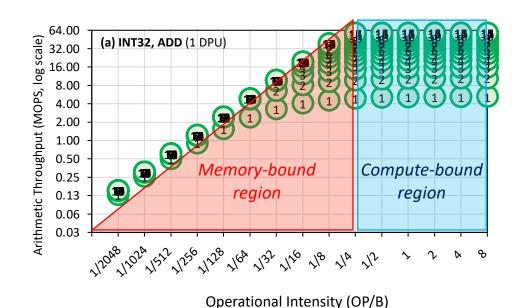
Geraldo F. Oliveira, ETH Zürich Onur Mutlu, ETH Zürich







Key Takeaway 1



The throughput saturation point is as low as ¼ OP/B, i.e., 1 integer addition per every 32-bit element fetched

KEY TAKEAWAY 1

The UPMEM PIM architecture is fundamentally compute bound. As a result, the most suitable workloads are memory-bound.

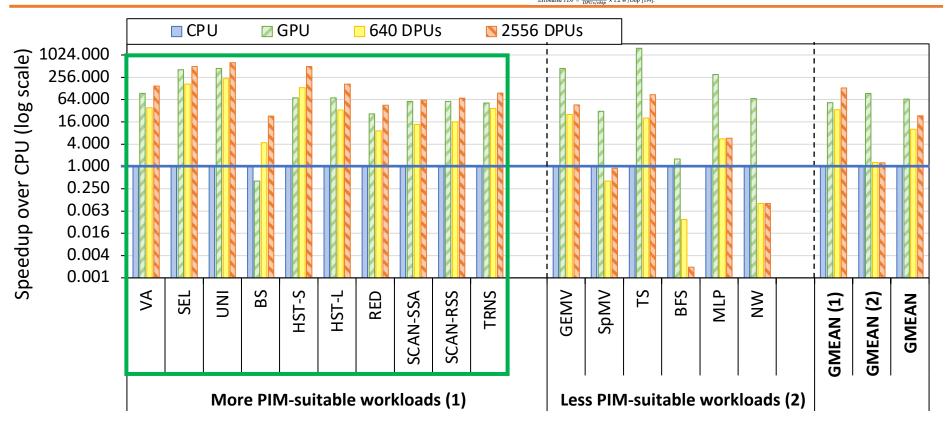
${\bf Table~4: Evaluated~CPU, GPU, and~UPMEM-based~PIM~Systems.}$

Key Takeaway 2

System	Process	Processor Cores			Memory		TDP
System	Node	Total Cores	Frequency	Peak Performance	Capacity	Total Bandwidth	IDF
Intel Xeon E3-1225 v6 CPU [241]	14 nm	4 (8 threads)	3.3 GHz	26.4 GFLOPS*	32 GB	37.5 GB/s	73 W
NVIDIA Titan V GPU [277]	14 nm	80 (5,120 SIMD lanes)	1.2 GHz	12,288.0 GFLOPS	12 GB	652.8 GB/s	250 W
2,556-DPU PIM System	2x nm	2,556 ⁹	350 MHz	894.6 GOPS	159.75 GB	1.7 TB/s	383 W [†]
640-DPU PIM System	2x nm	640	267 MHz	170.9 GOPS	40 GB	333.75 GB/s	96 W [†]

^{*}Estimated GFLOPS = 3.3 GHz × 4 cores × 2 instructions per cycle.

†Estimated TDP = Total DPUs / DPII / LAis × 1.2 W / chip [199].



KEY TAKEAWAY 2

The most well-suited workloads for the UPMEM PIM architecture use no arithmetic operations or use only simple operations (e.g., bitwise operations and integer addition/subtraction).

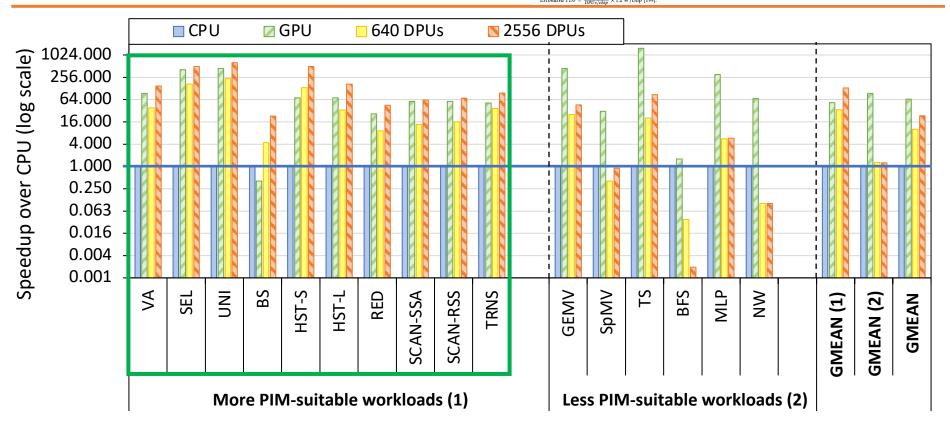
Table 4: Evaluated CPU, GPU, and UPMEM-based PIM Systems.

Key Takeaway 3

System	Process	Processor Cores			Memory		TDP
system	Node	Total Cores	Frequency	Peak Performance	Capacity	Total Bandwidth	IDF
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^{*}Estimated GFLOPS = 3.3 GHz × 4 cores × 2 instructions per cycle.

†Estimated TDP = Total DPUs / DPU



KEY TAKEAWAY 3

The most well-suited workloads for the UPMEM PIM architecture require little or no communication across DPUs (inter-DPU communication).

UPMEM PIM System Summary & Analysis

Juan Gomez-Luna, Izzat El Hajj, Ivan Fernandez, Christina Giannoula, Geraldo F. Oliveira, and Onur Mutlu,

"Benchmarking Memory-Centric Computing Systems: Analysis of Real **Processing-in-Memory Hardware**"

Invited Paper at Workshop on Computing with Unconventional *Technologies (CUT)*, Virtual, October 2021.

[arXiv version]

[PrIM Benchmarks Source Code]

[Slides (pptx) (pdf)]

[Talk Video (37 minutes)]

[Lightning Talk Video (3 minutes)]

Benchmarking Memory-Centric Computing Systems: Analysis of Real Processing-in-Memory Hardware

Juan Gómez-Luna ETH Zürich

Izzat El Haji American University of Beirut

University of Malaga

National Technical University of Athens

Ivan Fernandez Christina Giannoula Geraldo F. Oliveira Onur Mutlu ETH Zürich

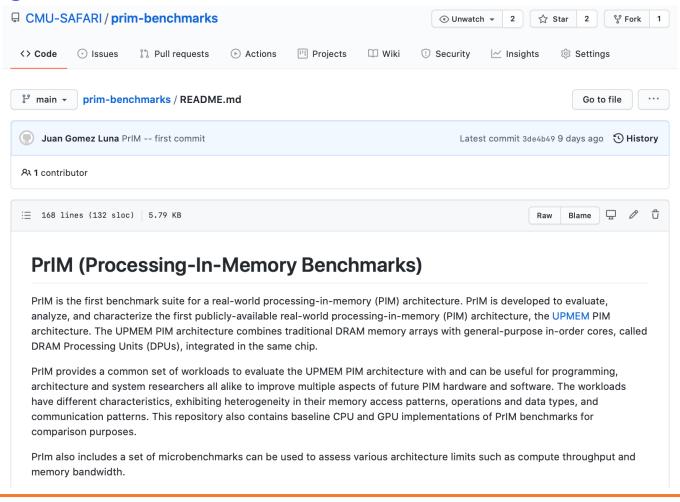
ETH Zürich

PrIM Benchmarks: Application Domains

Domain	Benchmark	Short name
Dance linear algebra	Vector Addition	VA
Dense linear algebra		GEMV
Sparse linear algebra	Sparse Matrix-Vector Multiply	SpMV
Databasas	Select	SEL
Databases	Vector Addition Matrix-Vector Multiply Sparse Matrix-Vector Multiply Select Unique Binary Search Time Series Analysis Breadth-First Search Multilayer Perceptron Needleman-Wunsch Image histogram (short) Image histogram (large) Reduction Prefix sum (scan-scan-add)	UNI
Data analytica	Binary Search	BS
Data analytics	Matrix-Vector Multiply Sparse Matrix-Vector Multiply Select Unique Binary Search Time Series Analysis Breadth-First Search Multilayer Perceptron Needleman-Wunsch Image histogram (short) Image histogram (large) Reduction Prefix sum (scan-scan-add)	TS
Graph processing	Breadth-First Search	BFS
Neural networks	Multilayer Perceptron	MLP
Bioinformatics	Needleman-Wunsch	NW
lung of a pure species of	Image histogram (short)	HST-S
Image processing	Image histogram (large)	HST-L
	Reduction	RED
Devellel maioritives	Prefix sum (scan-scan-add)	SCAN-SSA
Parallel primitives	Prefix sum (reduce-scan-scan)	SCAN-RSS
	Matrix transposition	TRNS

PrIM Benchmarks are Open Source

- All microbenchmarks, benchmarks, and scripts
- https://github.com/CMU-SAFARI/prim-benchmarks



Understanding a Modern PIM Architecture

Benchmarking a New Paradigm: Experimental Analysis and Characterization of a Real Processing-in-Memory System

JUAN GÓMEZ-LUNA¹, IZZAT EL HAJJ², IVAN FERNANDEZ^{1,3}, CHRISTINA GIANNOULA^{1,4}, GERALDO F. OLIVEIRA¹, AND ONUR MUTLU¹

Corresponding author: Juan Gómez-Luna (e-mail: juang@ethz.ch).

https://arxiv.org/pdf/2105.03814.pdf

https://github.com/CMU-SAFARI/prim-benchmarks

¹ETH Zürich

²American University of Beirut

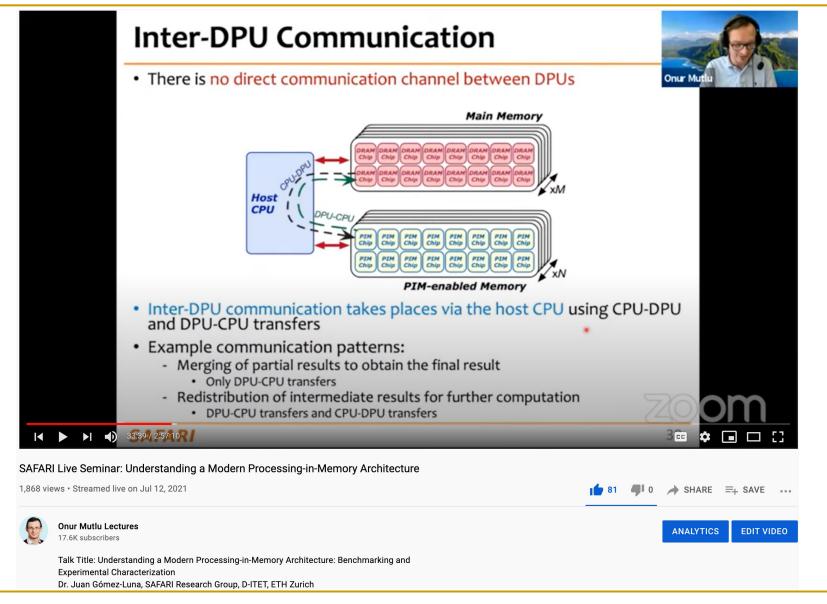
³University of Malaga

⁴National Technical University of Athens

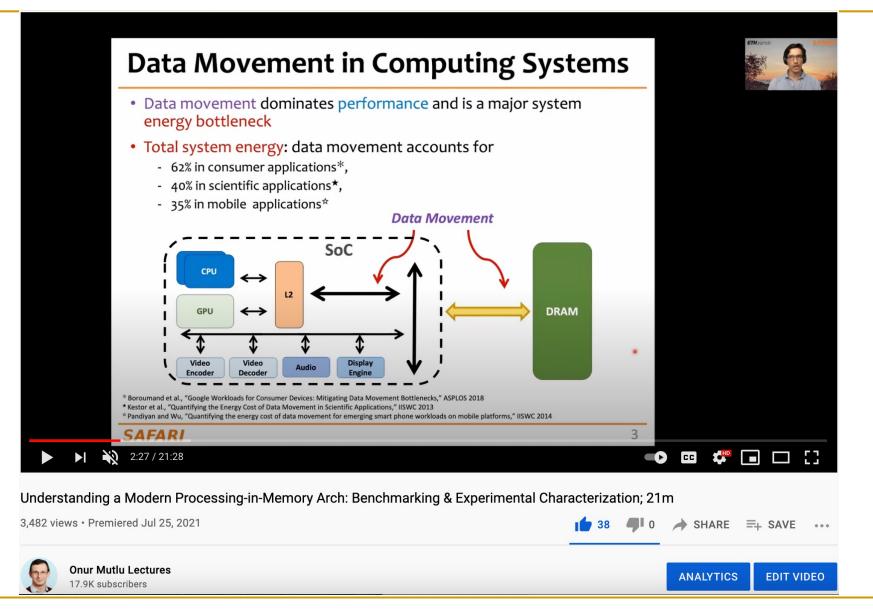
Understanding a Modern PIM Architecture



More on Analysis of the UPMEM PIM Engine



More on Analysis of the UPMEM PIM Engine



ML Training on a Real PIM System

Machine Learning Training on a Real Processing-in-Memory System

Juan Gómez-Luna¹ Yuxin Guo¹ Sylvan Brocard² Julien Legriel² Remy Cimadomo² Geraldo F. Oliveira¹ Gagandeep Singh¹ Onur Mutlu¹

¹ETH Zürich ²UPMEM

An Experimental Evaluation of Machine Learning Training on a Real Processing-in-Memory System

Juan Gómez-Luna¹ Yuxin Guo¹ Sylvan Brocard² Julien Legriel² Remy Cimadomo² Geraldo F. Oliveira¹ Gagandeep Singh¹ Onur Mutlu¹

¹ETH Zürich ²UPMEM

Short version: https://arxiv.org/pdf/2206.06022.pdf

Long version: https://arxiv.org/pdf/2207.07886.pdf

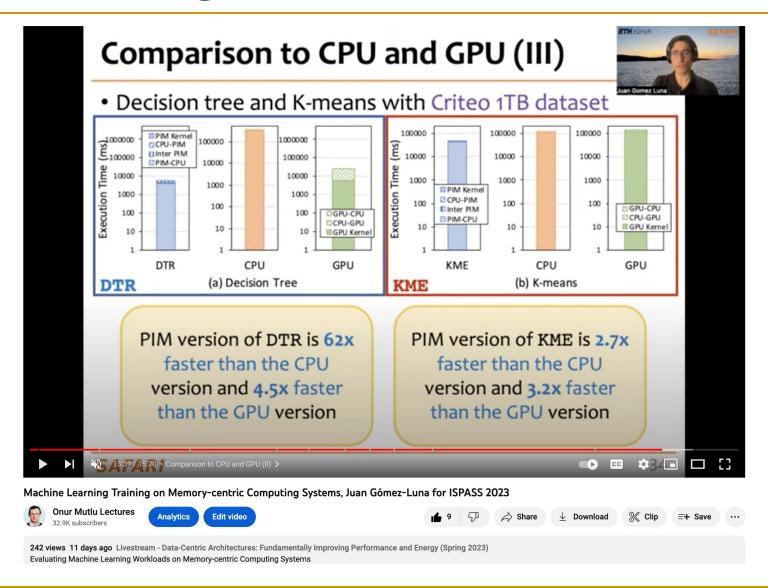
https://www.youtube.com/watch?v=qeukNs5XI3g&t=11226s

ML Training on a Real PIM System

- Need to optimize data representation
 - (1) fixed-point
 - (2) quantization
 - (3) hybrid precision
- Use lookup tables (LUTs) to implement complex functions (e.g., sigmoid)
- Optimize data placement & layout for streaming

• Large speedups: 2.8X/27X vs. CPU, 1.3x/3.2x vs. GPU

ML Training on Real PIM Talk Video



ML Training on Real PIM Systems

 Juan Gómez Luna, Yuxin Guo, Sylvan Brocard, Julien Legriel, Remy Cimadomo, Geraldo F. Oliveira, Gagandeep Singh, and Onur Mutlu, "Evaluating Machine Learning Workloads on Memory-Centric Computing Systems"

Proceedings of the <u>2023 IEEE International Symposium on Performance</u>

<u>Analysis of Systems and Software</u> (**ISPASS**), Raleigh, North Carolina, USA,
April 2023.

[arXiv version, 16 July 2022.]

[PIM-ML Source Code]

Best paper session.

An Experimental Evaluation of Machine Learning Training on a Real Processing-in-Memory System

Juan Gómez-Luna¹ Yuxin Guo¹ Sylvan Brocard² Julien Legriel² Remy Cimadomo² Geraldo F. Oliveira¹ Gagandeep Singh¹ Onur Mutlu¹

¹ETH Zürich ²UPMEM

https://github.com/CMU-SAFARI/pim-ml

SpMV Multiplication on Real PIM Systems

Appears at SIGMETRICS 2022

SparseP: Towards Efficient Sparse Matrix Vector Multiplication on Real Processing-In-Memory Systems

CHRISTINA GIANNOULA, ETH Zürich, Switzerland and National Technical University of Athens, Greece

IVAN FERNANDEZ, ETH Zürich, Switzerland and University of Malaga, Spain

JUAN GÓMEZ-LUNA, ETH Zürich, Switzerland

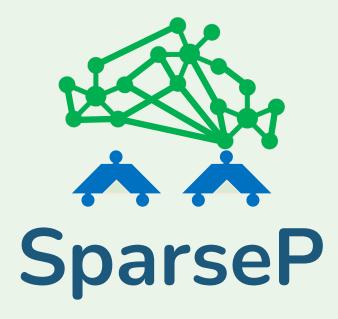
NECTARIOS KOZIRIS, National Technical University of Athens, Greece

GEORGIOS GOUMAS, National Technical University of Athens, Greece

ONUR MUTLU, ETH Zürich, Switzerland

https://arxiv.org/pdf/2201.05072.pdf https://github.com/CMU-SAFARI/SparseP

SAFARI



Towards Efficient Sparse Matrix Vector Multiplication on Real Processing-In-Memory Architectures

Christina Giannoula

Ivan Fernandez, Juan Gomez-Luna, Nectarios Koziris, Georgios Goumas, Onur Mutlu









SparseP: Key Contributions

- 1. Efficient SpMV kernels for current & future PIM systems
 - SparseP library = 25 SpMV kernels
 - Compression, data types, data partitioning, synchronization, load balancing

SparseP is Open-Source

SparseP: https://github.com/CMU-SAFARI/SparseP

2. Comprehensive analysis of SpMV on the first commercially-available real PIM system



- 26 sparse matrices
- Comparisons to state-of-the-art CPU and GPU systems
- Recommendations for software, system and hardware designers

Recommendations for Architects and Programmers

Full Paper: https://arxiv.org/pdf/2201.05072.pdf

SparseP Talk Video



More on SparseP

Christina Giannoula, Ivan Fernandez, Juan Gomez-Luna, Nectarios Koziris, Georgios Goumas, and Onur Mutlu,

<u>"SparseP: Towards Efficient Sparse Matrix Vector Multiplication on Real Processing-In-Memory Architectures"</u>

Proceedings of the <u>ACM International Conference on Measurement and Modeling of Computer</u>
<u>Systems</u> (**SIGMETRICS**), Mumbai, India, June 2022.

Extended arXiv Version

[Abstract]

[Slides (pptx) (pdf)]

[Long Talk Slides (pptx) (pdf)]

SparseP Source Code

Talk Video (16 minutes)

[Long Talk Video (55 minutes)]

SparseP: Towards Efficient Sparse Matrix Vector Multiplication on Real Processing-In-Memory Systems

CHRISTINA GIANNOULA, ETH Zürich, Switzerland and National Technical University of Athens, Greece

 ${\bf IVAN\ FERNANDEZ, ETH\ Z\"{u}rich,\ Switzerland\ and\ University\ of\ Malaga,\ Spain}$

JUAN GÓMEZ-LUNA, ETH Zürich, Switzerland

NECTARIOS KOZIRIS, National Technical University of Athens, Greece

GEORGIOS GOUMAS, National Technical University of Athens, Greece

ONUR MUTLU, ETH Zürich, Switzerland

https://github.com/CMU-SAFARI/SparseP

Transcendental Functions on Real PIM Systems

 Maurus Item, Juan Gómez Luna, Yuxin Guo, Geraldo F. Oliveira, Mohammad Sadrosadati, and Onur Mutlu,

<u>"TransPimLib: Efficient Transcendental Functions for Processing-in-Memory Systems"</u>

Proceedings of the <u>2023 IEEE International Symposium on Performance</u>

<u>Analysis of Systems and Software</u> (**ISPASS**), Raleigh, North Carolina, USA,
April 2023.

[arXiv version]

[Slides (pptx) (pdf)]

TransPimLib Source Code

[Talk Video (17 minutes)]

TransPimLib: Efficient Transcendental Functions for Processing-in-Memory Systems

Maurus Item Geraldo F. Oliveira Juan Gómez-Luna

Yuxin Guo

Mohammad Sadrosadati

Onur Mutlu

ETH Zürich

https://github.com/CMU-SAFARI/transpimlib

Sequence Alignment on Real PIM Systems

 Safaa Diab, Amir Nassereldine, Mohammed Alser, Juan Gómez Luna, Onur Mutlu, and Izzat El Hajj,

"A Framework for High-throughput Sequence Alignment using Real Processing-in-Memory Systems"

Bioinformatics, [published online on] 27 March 2023.

[Online link at Bioinformatics Journal]

[arXiv preprint]

[AiM Source Code]

A Framework for High-throughput Sequence Alignment using Real Processing-in-Memory Systems

```
Safaa Diab <sup>1</sup> Amir Nassereldine <sup>1</sup> Mohammed Alser <sup>2</sup> Juan Gómez Luna <sup>2</sup> Onur Mutlu <sup>2</sup> Izzat El Hajj <sup>1</sup>
```

¹American University of Beirut ²ETH Zürich

https://github.com/CMU-SAFARI/alignment-in-memory







Summary

- Sequence alignment on traditional systems is limited by the memory bandwidth bottleneck
- Processing-in-memory (PIM) overcomes this bottleneck by placing cores near the memory
- Our framework, Alignment-in-Memory (AIM), is a PIM framework that supports multiple alignment algorithms (NW, SWG, GenASM, WFA)
 - □ Implemented on UPMEM, the first real PIM system
- Results show substantial speedups over both CPUs (1.8X-28X) and GPUs (1.2X-2.7X)
- AIM is available at:
 - https://github.com/CMU-SAFARI/alignment-in-memory

Homomorphic Operations on Real PIM Systems

 Harshita Gupta, Mayank Kabra, Juan Gómez-Luna, Konstantinos Kanellopoulos, and Onur Mutlu,

"Evaluating Homomorphic Operations on a Real-World Processing-In-Memory System"

<u>Proceedings of the 2023 IEEE International Symposium on Workload</u> <u>Characterization</u> Poster Session (**IISWC**), Ghent, Belgium, October 2023.

[arXiv version]

[Lightning Talk Slides (pptx) (pdf)]

[Poster (pptx) (pdf)]

Evaluating Homomorphic Operations on a Real-World Processing-In-Memory System

Harshita Gupta* Mayank Kabra* Juan Gómez-Luna Konstantinos Kanellopoulos Onur Mutlu

ETH Zürich

Accelerating Reinforcement Learning

Kailash Gogineni, Sai Santosh Dayapule, Juan Gomez-Luna, Karthikeya Gogineni, Peng Wei, Tian Lan, Mohammad Sadrosadati, Onur Mutlu, Guru Venkataramani,
 "SwiftRL: Towards Efficient Reinforcement Learning on Real Processing-In-Memory Systems"

Proceedings of the <u>2024 IEEE International Symposium on Performance Analysis of Systems and Software</u> (**ISPASS**), Indianapolis, Indiana, May 2024.

[Slides (pptx) (pdf)]

arXiv version

SwiftRL: Towards Efficient Reinforcement Learning on Real Processing-In-Memory Systems

Kailash Gogineni¹ Sai Santosh Dayapule¹ Juan Gómez-Luna² Karthikeya Gogineni³ Peng Wei¹ Tian Lan¹ Mohammad Sadrosadati² Onur Mutlu² Guru Venkataramani¹ George Washington University, USA ²ETH Zürich, Switzerland ³Independent

Accelerating ML Training on Real PIM Systems

https://arxiv.org/pdf/2404.07164

Analysis of Distributed Optimization Algorithms on a Real Processing-In-Memory System

```
Steve Rhyner<sup>1</sup> Haocong Luo<sup>1</sup> Juan Gómez-Luna<sup>2</sup> Mohammad Sadrosadati<sup>1</sup> Jiawei Jiang<sup>3</sup> Ataberk Olgun<sup>1</sup> Harshita Gupta<sup>1</sup> Ce Zhang<sup>4</sup> Onur Mutlu<sup>1</sup>

<sup>1</sup>ETH Zurich <sup>2</sup>NVIDIA <sup>3</sup>Wuhan University <sup>4</sup>University of Chicago
```

Accelerating ML Training on Real PIM Systems

https://arxiv.org/pdf/2404.07164

8. Conclusion

We evaluate and train ML models on large-scale datasets with centralized parallel optimization algorithms on a real-world PIM architecture. We show the importance of carefully choosing the distributed optimization algorithm that fits PIM and analyze tradeoffs. We demonstrate that commercial generalpurpose PIM systems can be a viable alternative for many ML training workloads on large-scale datasets to processor-centric architectures. Our results demonstrate the necessity of adapting PIM architectures to enable inter-DPU communication to overcome scalability challenges for many ML training workloads and discuss decentralized parallel SGD optimization algorithms as a potential solution.

Accelerating GNNs on Real PIM Systems

https://arxiv.org/pdf/2402.16731

Accelerating Graph Neural Networks on Real Processing-In-Memory Systems

```
Christina Giannoula*†, Peiming Yang*, Ivan Fernandez Vega§†, Jiacheng Yang*, Yu Xin Li*, Juan Gomez Luna¶†, Mohammad Sadrosadati†, Onur Mutlu†‡, Gennady Pekhimenko*||
*University of Toronto †ETH Zürich §Barcelona Supercomputing Center
¶NVIDIA ‡Stanford ||CentML
```

Accelerating GNNs on Real PIM Systems

https://arxiv.org/pdf/2402.16731

Abstract—Graph Neural Networks (GNNs) are emerging ML models to analyze graph-structure data. Graph Neural Network (GNN) execution involves both compute-intensive and memoryintensive kernels, the latter dominates the total time, being significantly bottlenecked by data movement between memory and processors. Processing-In-Memory (PIM) systems can alleviate this data movement bottleneck by placing simple processors near or inside to memory arrays. In this work, we introduce PyGim, an efficient ML framework that accelerates GNNs on real PIM systems. We propose intelligent parallelization techniques for memory-intensive kernels of GNNs tailored for real PIM systems, and develop handy Python API for them. We provide hybrid GNN execution, in which the compute-intensive and memory-intensive kernels are executed in processor-centric and memory-centric computing systems, respectively, to match their algorithmic nature. We extensively evaluate PyGim on a real-world PIM system with 1992 PIM cores using emerging GNN models, and demonstrate that it outperforms its state-of-the-art CPU counterpart on Intel Xeon by on average 3.04×, and achieves higher resource utilization than CPU and GPU systems. Our work provides useful recommendations for software, system and hardware designers. PyGim will be open-sourced to enable the widespread use of PIM systems in GNNs.

Samsung Newsroom

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ABOUT US

Q

Samsung Develops Industry's First High Bandwidth Memory with Al Processing Power

Korea on February 17, 2021

Audio



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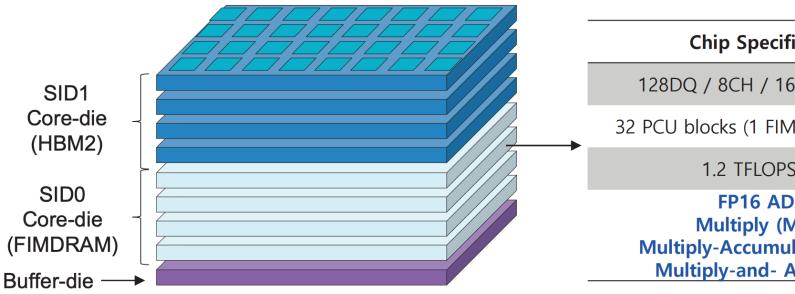


The new architecture will deliver over twice the system performance and reduce energy consumption by more than 70%

Samsung Electronics, the world leader in advanced memory technology, today announced that it has developed the industry's first High Bandwidth Memory (HBM) integrated with artificial intelligence (AI) processing power – the HBM-PIM The new processing-in-memory (PIM) architecture brings powerful AI computing capabilities inside high-performance memory, to accelerate large-scale processing in data centers, high performance computing (HPC) systems and AI-enabled mobile applications.

Kwangil Park, senior vice president of Memory Product Planning at Samsung Electronics stated, "Our groundbreaking HBM-PIM is the industry's first programmable PIM solution tailored for diverse Al-driven workloads such as HPC, training and inference. We plan to build upon this breakthrough by further collaborating with Al solution providers for even more advanced PIM-powered applications."

FIMDRAM based on HBM2



[3D Chip Structure of HBM with FIMDRAM]

Chip Specification

128DQ / 8CH / 16 banks / BL4

32 PCU blocks (1 FIM block/2 banks)

1.2 TFLOPS (4H)

FP16 ADD / Multiply (MUL) / Multiply-Accumulate (MAC) / Multiply-and- Add (MAD)

ISSCC 2021 / SESSION 25 / DRAM / 25.4

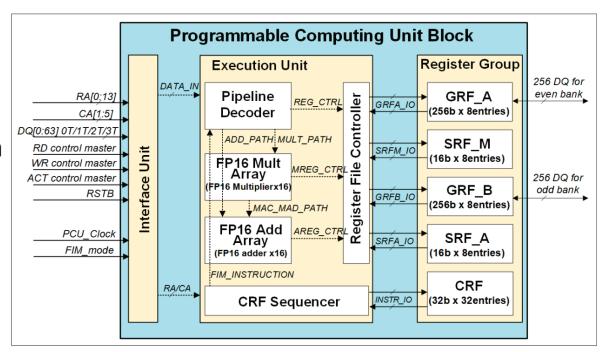
25.4 A 20nm 6GB Function-In-Memory DRAM, Based on HBM2 with a 1.2TFLOPS Programmable Computing Unit Using Bank-Level Parallelism, for Machine Learning Applications

Young-Cheon Kwon1, Suk Han Lee1, Jaehoon Lee1, Sang-Hyuk Kwon1, Je Min Ryu1, Jong-Pil Son1, Seongil O1, Hak-Soo Yu1, Haesuk Lee1, Soo Young Kim¹, Youngmin Cho¹, Jin Guk Kim¹, Jongyoon Choi¹, Hyun-Sung Shin¹, Jin Kim¹, BengSeng Phuah¹, HyoungMin Kim¹. Myeong Jun Song¹, Ahn Choi¹, Daeho Kim¹, SooYoung Kim¹, Eun-Bong Kim¹, David Wang², Shinhaeng Kang¹, Yuhwan Ro³, Seungwoo Seo³, JoonHo Song³, Jaeyoun Youn1, Kyomin Sohn1, Nam Sung Kim1

¹Samsung Electronics, Hwaseong, Korea ²Samsung Electronics, San Jose, CA 3Samsung Electronics, Suwon, Korea

Programmable Computing Unit

- Configuration of PCU block
 - Interface unit to control data flow
 - Execution unit to perform operations
 - Register group
 - 32 entries of CRF for instruction memory
 - 16 GRF for weight and accumulation
 - 16 SRF to store constants for MAC operations



[Block diagram of PCU in FIMDRAM]

ISSCC 2021 / SESSION 25 / DRAM / 25.4

25.4 A 20nm 6GB Function-In-Memory DRAM, Based on HBM2 with a 1.2TFLOPS Programmable Computing Unit Using Bank-Level Parallelism, for Machine Learning Applications

Young-Cheon Kwon', Suk Han Ler', Jaehoon Lee', Sang-Hruk Kwon', Je Min Ryu', Jong-Pil Son', Seongil O', Hak-Soo Yu', Haesuk Lee', Soo Young Kim', Youngmin Cho', Jin Guk Kim', Jongyoon Choi', Hyun-Sung Shin', Jin Kim', BengSeng Phuah', HyoungMin Kim', Hyeong Jun Song', Aln Choi', Deach Kim', Soo'Oung Kim', Eun-Bong Kim', David Wang', Shinhaeng Kang', Yuhwan Ro', Seungwoo Seo', JoonHo Song', Jaeyoun Youn', Kyomin Sonh', Man Sung Kim'

[Available instruction list for FIM operation]

Туре	CMD	Description	
Floating Point	ADD	FP16 addition	
	MUL	FP16 multiplication	
	MAC	FP16 multiply-accumulate	
	MAD	FP16 multiply and add	
Data Path	MOVE	Load or store data	
	FILL	Copy data from bank to GRFs	
	NOP	Do nothing	
Control Path	JUMP	Jump instruction	
	EXIT	Exit instruction	

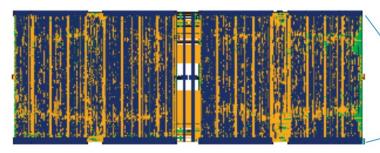
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Chip Implementation

- Mixed design methodology to implement FIMDRAM
 - Full-custom + Digital RTL



[Digital RTL design for PCU block]

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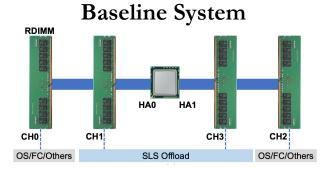
Young-Cheon Kwon', Suk Han Let', Jaehoon Let', Sang-Hvuk Kwon', Je Min Ryu', Jong-Pil Son', Seongil O', Hak-Soo Yu', Haesuk Lee', Soo Young Kim', Youngmin Cho', Jin Guk Kim', Jongyoon Choi', Hyun-Sung Shin', Jin Kim', BengSeng Phuah', HyoungMin Kim', Hyeeng Juan Song', Ahn Choi', Jeacho Kim', Soo'Oung Kim', Eun-Bong Kim', David Wang', Shinhaeng Kang', Yuhwan Ro', Seungwoo Seo', JoonHo Song', Jaeyoun Youn', Kyomin Sohn', Man Sung Kim'

Cell array for bank0	Cell array for bank4	Cell array for bank0	Cell array for bank4	Pseudo	Pseudo
PCU block for bank0 & 1	PCU block for bank4 & 5	PCU block for bank0 & 1	PCU block for bank4 & 5	channel-0	channel-1
Cell array for bank1 Cell array for bank2	Cell array for bank5 Cell array for bank6	Cell array for bank1 Cell array for bank2	Cell array for bank5 Cell array for bank6		
PCU block for bank2 & 3	PCU block for bank6 & 7	PCU block for bank2 & 3	PCU block for bank6 & 7		and a major part of a major
Cell array for bank3	Cell array for bank7	Cell array for bank3	Cell array for bank7		
		TSV &	Peri C	ontrol Block	
Cell array for bank11	Cell array for bank15	Cell array for bank11	Cell array for bank15		
PCU block for bank10 & 11	PCU block for bank14 & 15	PCU block for bank10 & 11	PCU block for bank14 & 15		
Cell array for bank10 Cell array for bank9	Cell array for bank14 Cell array for bank13	Cell array for bank10 Cell array for bank9	Cell array for bank14 Cell array for bank13		
PCU block for bank8 & 9	PCU block for bank12 & 13	PCU block for bank8 & 9	PCU block for bank12 & 13	Pseudo	Pseudo
Cell array for bank8	Cell array for bank12	Cell array for bank8	Cell array for bank12	channel-0	channel-1

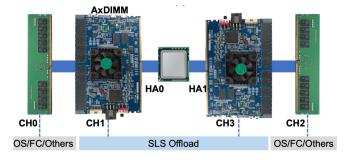
Samsung AxDIMM (2021)

- DDRx-PIM
 - DLRM recommendation system





AxDIMM System





SK Hynix Accelerator-in-Memory (2022)

SKhynix NEWSROOM

⊕ ENG ∨

SK hvnix STORY INSIGHT

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SK hynix Develops PIM, Next-Generation AI Accelerator

February 16, 2022







Seoul, February 16, 2022

SK hynix (or "the Company", www.skhynix.com) announced on February 16 that it has developed PIM*, a nextgeneration memory chip with computing capabilities.

*PIM(Processing In Memory): A next-generation technology that provides a solution for data congestion issues for AI and big data by adding computational functions to semiconductor memory

It has been generally accepted that memory chips store data and CPU or GPU, like human brain, process data. SK hynix, following its challenge to such notion and efforts to pursue innovation in the next-generation smart memory, has found a breakthrough solution with the development of the latest technology.

SK hynix plans to showcase its PIM development at the world's most prestigious semiconductor conference, 2022 ISSCC*, in San Francisco at the end of this month. The company expects continued efforts for innovation of this technology to bring the memory-centric computing, in which semiconductor memory plays a central role, a step closer in Paper 11.1. SK Hynix describes an Tynm, GDDR6-based accelerator-in-memory with a command set for deep-learning operation. The to the reality in devices such as smartphones.

*ISSCC: The International Solid-State Circuits Conference will be held virtually from Feb. 20 to Feb. 24 this year with a theme of "Intelligent Silicon for a Sustainable World'

For the first product that adopts the PIM technology, SK hynix has developed a sample of GDDR6-AiM (Accelerator* in memory). The GDDR6-AiM adds computational functions to GDDR6* memory chips, which process data at 16Gbps. A combination of GDDR6-AiM with CPU or GPU instead of a typical DRAM makes certain computation speed 16 times faster. GDDR6-AiM is widely expected to be adopted for machine learning, high-performance computing, and big data computation and storage.

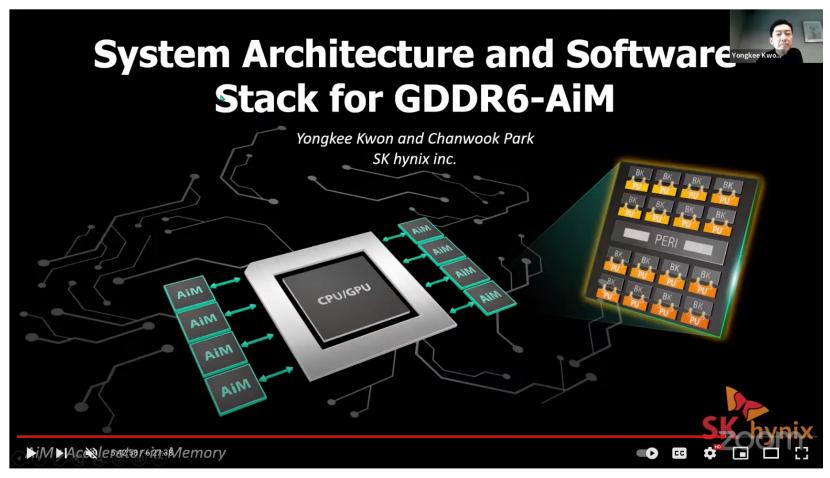


11.1 A 1ynm 1.25V 8Gb, 16Gb/s/pin GDDR6-based Accelerator-in-Memory supporting 1TFLOPS MAC Operation and Various Activation Functions for Deep-Learning Applications

Seongiu Lee, SK hynix, Icheon, Korea

8Gb design achieves a peak throughput of 1TFLOPS with 1GHz MAC operations and supports major activation functions to improve

SK Hynix Accelerator-in-Memory (2022)

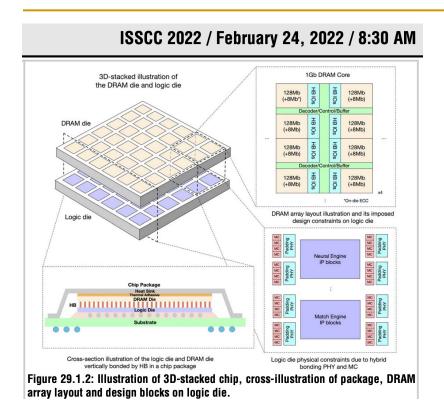


ASPLOS 2023 Tutorial: Real-world Processing-in-Memory Systems for Modern Workloads



1,146 views Streamed live on Mar 26, 2023 Livestream - Data-Centric Architectures: Fundamentally Improving Performance and Energy (Spring 2023)
ASPLOS 2023 Tutorial: Real-world Processing-in-Memory Systems for Modern Workloads
https://events.safari.ethz.ch/asplos-...

AliBaba PIM Recommendation System (2022)



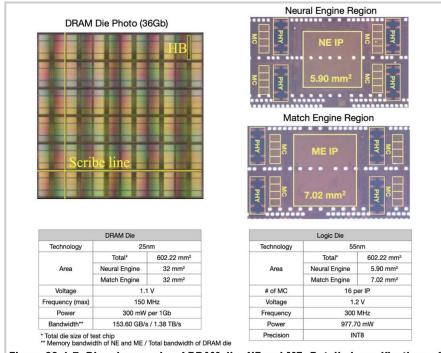


Figure 29.1.7: Die micrographs of DRAM die, NE and ME. Detailed specifications of DRAM die and logic die.

29.1 184QPS/W 64Mb/mm² 3D Logic-to-DRAM Hybrid Bonding with Process-Near-Memory Engine for Recommendation System

Dimin Niu¹, Shuangchen Li¹, Yuhao Wang¹, Wei Han¹, Zhe Zhang², Yijin Guan², Tianchan Guan³, Fei Sun¹, Fei Xue¹, Lide Duan¹, Yuanwei Fang¹, Hongzhong Zheng¹, Xiping Jiang⁴, Song Wang⁴, Fengguo Zuo⁴, Yubing Wang⁴, Bing Yu⁴, Qiwei Ren⁴, Yuan Xie¹

SK Hynix CXL Processing Near Memory (2023)

IEEE COMPUTER ARCHITECTURE LETTERS, VOL. 22, NO. 1, JANUARY-JUNE

Computational CXL-Memory Solution for Accelerating Memory-Intensive Applications

Joonseop Sim[®], Soohong Ahn[®], Taeyoung Ahn[®], Seungyong Lee[®], Myunghyun Rhee, Jooyoung Kim[®], Kwangsik Shin, Donguk Moon[®], Euiseok Kim, and Kyoung Park[®]

Abstract—CXL interface is the up-to-date technology that enables effective memory expansion by providing a memory-sharing protocol in configuring heterogeneous devices. However, its limited physical bandwidth can be a significant bottleneck for emerging data-intensive applications. In this work, we propose a novel CXL-based memory disaggregation architecture with a real-world prototype demonstration, which overcomes the bandwidth limitation of the CXL interface using near-data processing. The experimental results demonstrate that our design achieves up to 1.9× better performance/power efficiency than the existing CPU system.

Index Terms—Compute express link (CXL), near-data-processing (NDP)

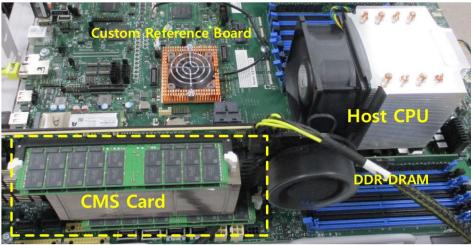




Fig. 6. FPGA prototype of proposed CMS card.

Samsung CXL Processing Near Memory (2023)

Samsung Processing in Memory Technology at Hot Chips 2023

By Patrick Kennedy - August 28, 2023

















Samsung PIM PNM For Transformer Based AI HC35_Page_24

Concluding Remarks

Challenge and Opportunity for Future

Fundamentally **Energy-Efficient** (Data-Centric) Computing Architectures

Challenge and Opportunity for Future

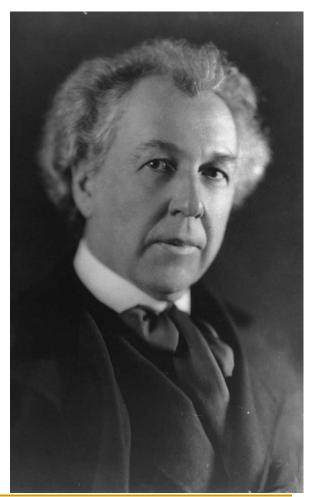
Fundamentally High-Performance (Data-Centric) Computing Architectures

Challenge and Opportunity for Future

Computing Architectures with Minimal Data Movement

A Quote from A Famous Architect

"architecture [...] based upon principle, and not upon precedent"



Precedent-Based Design?

"architecture [...] based upon principle, and not upon precedent"

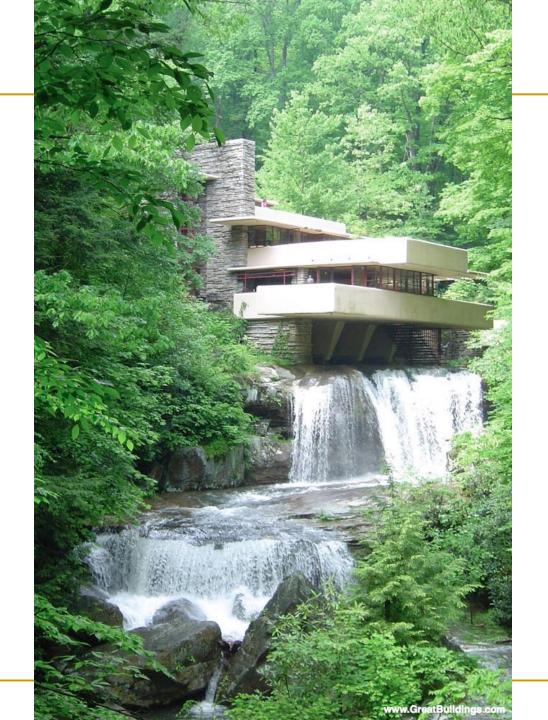


Principled Design

"architecture [...] based upon principle, and not upon precedent"



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The Overarching Principle

Organic architecture

From Wikipedia, the free encyclopedia

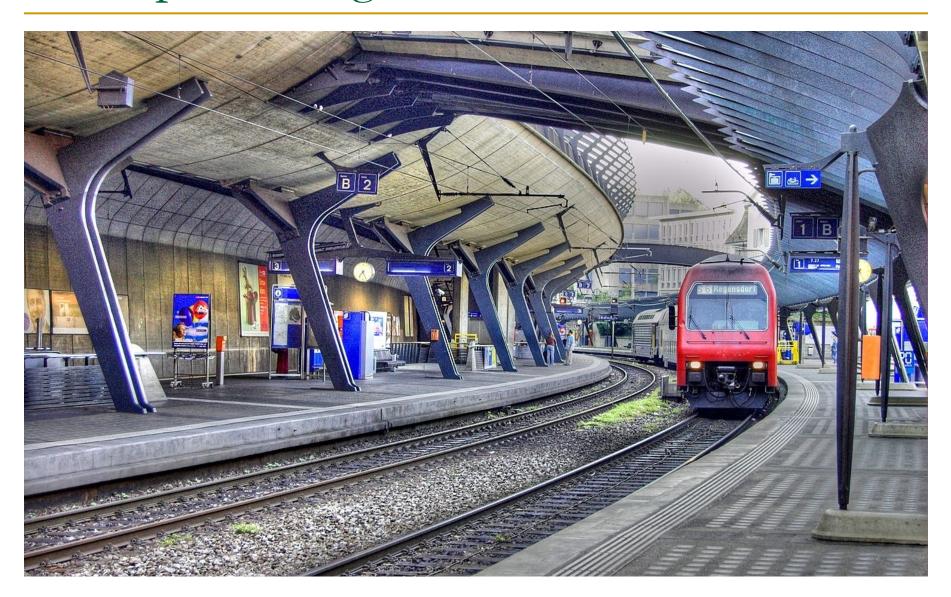
Organic architecture is a philosophy of architecture which promotes harmony between human habitation and the natural world through design approaches so sympathetic and well integrated with its site, that buildings, furnishings, and surroundings become part of a unified, interrelated composition.

A well-known example of organic architecture is Fallingwater, the residence Frank Lloyd Wright designed for the Kaufmann family in rural Pennsylvania. Wright had many choices to locate a home on this large site, but chose to place the home directly over the waterfall and creek creating a close, yet noisy dialog with the rushing water and the steep site. The horizontal striations of stone masonry with daring cantilevers of colored beige concrete blend with native rock outcroppings and the wooded environment.

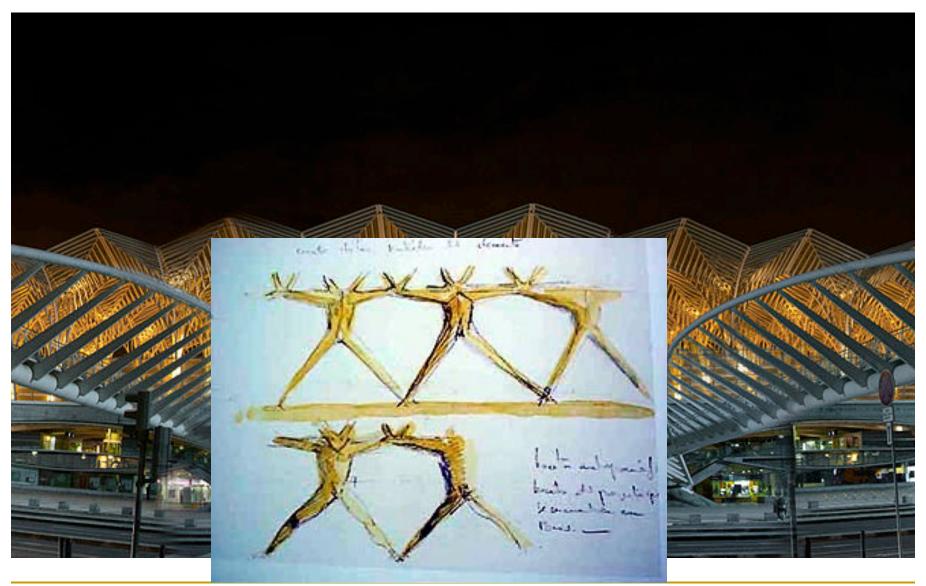
Another Example: Precedent-Based Design



Principled Design



Another Principled Design



Another Principled Design



Principle Applied to Another Structure





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Source: By 準建築人手札網站 Forgemind ArchiMedia - Flickr: IMG_2489.JPG, CC BY 2.0, FOR SOURCE: A SOURC

The Overarching Principle

Zoomorphic architecture

From Wikipedia, the free encyclopedia

Zoomorphic architecture is the practice of using animal forms as the inspirational basis and blueprint for architectural design. "While animal forms have always played a role adding some of the deepest layers of meaning in architecture, it is now becoming evident that a new strand of biomorphism is emerging where the meaning derives not from any specific representation but from a more general allusion to biological processes."^[1]

Some well-known examples of Zoomorphic architecture can be found in the TWA Flight Center building in New York City, by Eero Saarinen, or the Milwaukee Art Museum by Santiago Calatrava, both inspired by the form of a bird's wings.^[3]

Overarching Principles for Computing?



Concluding Remarks

- It is time to design principled system architectures to solve the memory problem
- We must design systems to be balanced, high-performance, and energy-efficient → memory-centric
 - Enable computation capabilities in memory
- This can
 - Lead to orders-of-magnitude improvements
 - Enable new applications & computing platforms
 - Enable better understanding of nature
 - **...**
- Future of truly memory-centric computing is bright
 - We need to do research & design across the computing stack

Fundamentally Better Architectures

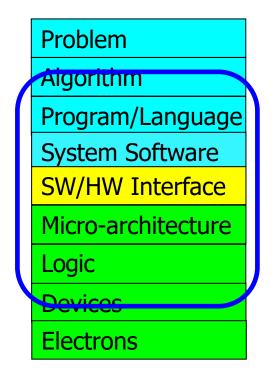
Data-centric

Data-driven

Data-aware

We Need to Revisit the Entire Stack

With a memory-centric mindset



We can get there step by step

PIM Review and Open Problems

A Modern Primer on Processing in Memory

Onur Mutlu^{a,b}, Saugata Ghose^{b,c}, Juan Gómez-Luna^a, Rachata Ausavarungnirun^d

SAFARI Research Group

^aETH Zürich

^bCarnegie Mellon University

^cUniversity of Illinois at Urbana-Champaign

^dKing Mongkut's University of Technology North Bangkok

Onur Mutlu, Saugata Ghose, Juan Gomez-Luna, and Rachata Ausavarungnirun,

"A Modern Primer on Processing in Memory"

Invited Book Chapter in Emerging Computing: From Devices to Systems
Looking Beyond Moore and Von Neumann, Springer, to be published in 2021.

Open Source Tools: SAFARI GitHub



SAFARI Research Group at ETH Zurich and Carnegie Mellon University

Site for source code and tools distribution from SAFARI Research Group at ETH Zurich and Carnegie Mellon University.

● ETH Zurich and Carnegie Mellon U... Anttps://safari.ethz.ch/ omutlu@gmail.com

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Repositories 98

Packages

8 People 13

ramulator Public

A Fast and Extensible DRAM Simulator, with built-in support for modeling many different DRAM technologies including DDRx, LPDDRx, GDDRx, WIOx, HBMx, and various academic proposals. Described in the...

● C++ ☆ 532 ¥ 206

prim-benchmarks Public

PrIM (Processing-In-Memory benchmarks) is the first benchmark suite for a real-world processing-in-memory (PIM) architecture. PrIM is developed to evaluate, analyze, and characterize the first publ...

● C ☆ 126 ¥ 47

MQSim Public

MQSim is a fast and accurate simulator modeling the performance of modern multi-queue (MQ) SSDs as well as traditional SATA based SSDs. MQSim faithfully models new high-bandwidth protocol implement...

● C++ ☆ 268 ¥ 143

rowhammer (Public

Source code for testing the Row Hammer error mechanism in DRAM devices. Described in the ISCA 2014 paper by Kim et al. at http://users.ece.cmu.edu/~omutlu/pub/dram-row-hammer_isca14.pdf.

● C ☆ 211 ♀ 42

SoftMC Public ::

SoftMC is an experimental FPGA-based memory controller design that can be used to develop tests for DDR3 SODIMMs using a C++ based API. The design, the interface, and its capabilities and limitatio...

● Verilog ☆ 120 ♀ 27

Pythia Public

A customizable hardware prefetching framework using online reinforcement learning as described in the MICRO 2021 paper by Bera et al. (https://arxiv.org/pdf/2109.12021.pdf).

● C++ ☆ 109 🖁 34

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Referenced Papers, Talks, Artifacts

All are available at

https://people.inf.ethz.ch/omutlu/projects.htm

https://www.youtube.com/onurmutlulectures

https://github.com/CMU-SAFARI/

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- Alibaba, AMD, ASML, Google, Facebook, Hi-Silicon, HP Labs, Huawei, IBM, Intel, Microsoft, Nvidia, Oracle, Qualcomm, Rambus, Samsung, Seagate, VMware, Xilinx
- NSF
- NIH
- GSRC
- SRC
- CyLab
- EFCL
- SNSF
- ACCESS

Thank you!

Memory Systems and Memory-Centric Computing

Lecture 4.1: Memory-Centric Computing III

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18 July 2024

HiPEAC ACACES Summer School 2024



