

Compiler Support for Ferroelectric Compute-in-Memory Solutions (and beyond)

Jeronimo Castrillon

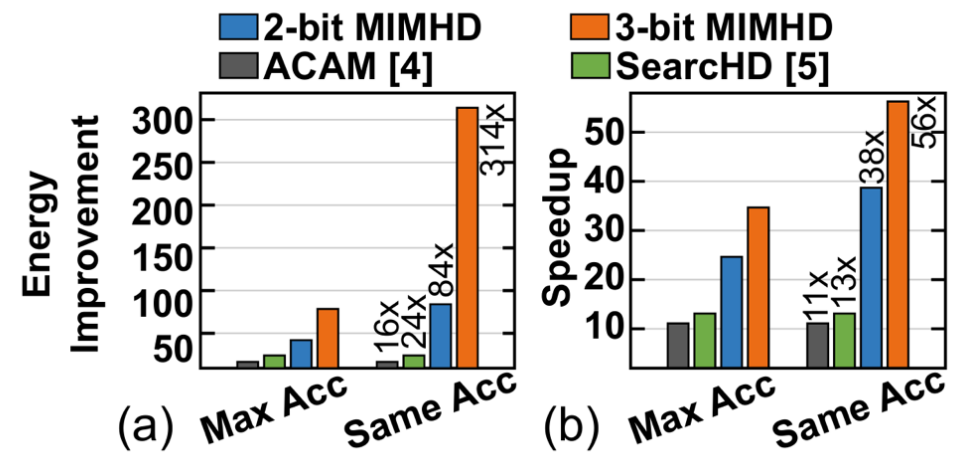
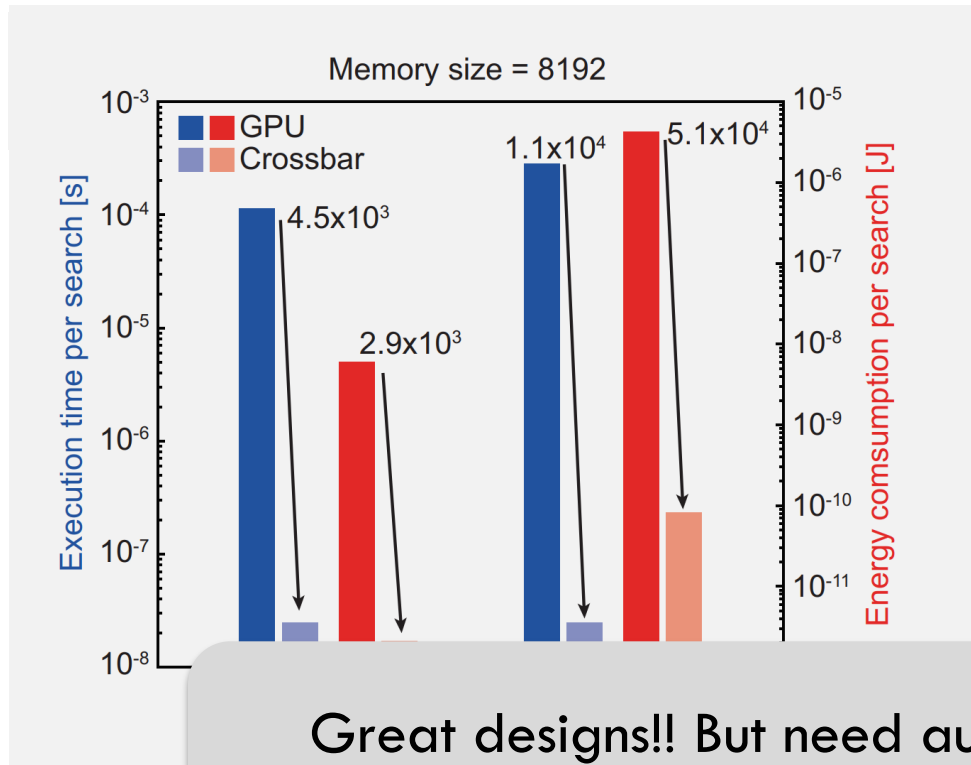
Chair for Compiler Construction (CCC), TU Dresden,
SCADS.AI Dresden/Leipzig & Center for Advancing Electronics (cfaed) Dresden

Design, Automation and Test in Europe Conference (DATE)

W06: Cross-stack Explorations of Ferroelectric-based Logic and Memory Solutions for At-Scale Compute Workloads

Lyon, France. April 1, 2025

Great potential in CIM systems!



A. Kazemi, "Cross-Layer Design with Emerging Devices for Machine

Great designs!! But need automation to **generalize** to other patterns and **optimize around kernels**

The need for abstractions and compiler support

Current practice

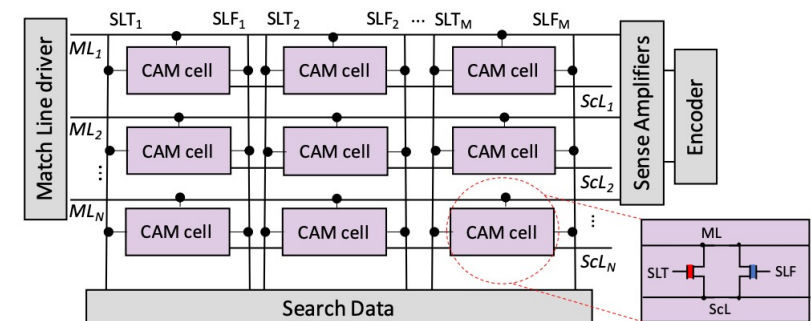
- Low-level code: Hard to write, no formalization/generalization
- Manual **app-by-app** optimization: Data mapping, synchronization, ...

Towards high-level pythonic programming

```

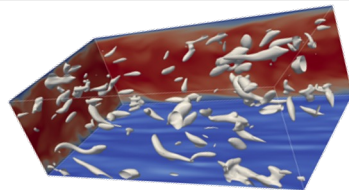
1 i_flav = spectra.bnd_to_flav[i_strato][:,i_bnd]
2 i_eta = j_eta[i_lay,i_flav,...]
3 i_eta = np.stack((i_eta,i_eta+1), -1)[:,None,:,:]
4 a = n_prime_mix[None,i_lay,i_flav,None,:,None]
5 b = f_major[None,i_lay,i_flav,:,:,:]
6 c = spectra.k_major[gptS:gptE,i_p,i_T,i_eta]
7 result[gptS:gptE,:] = np.sum(a * b * c, (2,3,4))

```



Existence proof: Tensor expressions (Physics, ML)

CFDlang



$$v_{ijk,e} = \sum_{i'=0}^p \sum_{j'=0}^p \sum_{k'=0}^p A_{kk'} A_{jj'} A_{ii'} u_{i'j'k'e}$$

```

source = ...
var input A : matrix &
var input u : tensorIN &
var input output v : tensorOUT &
var input alpha : [] &
var input beta : [] &
v = alpha * (A # A # A # u .
  [[5 8] [3 7] [1 6]]) + beta * v

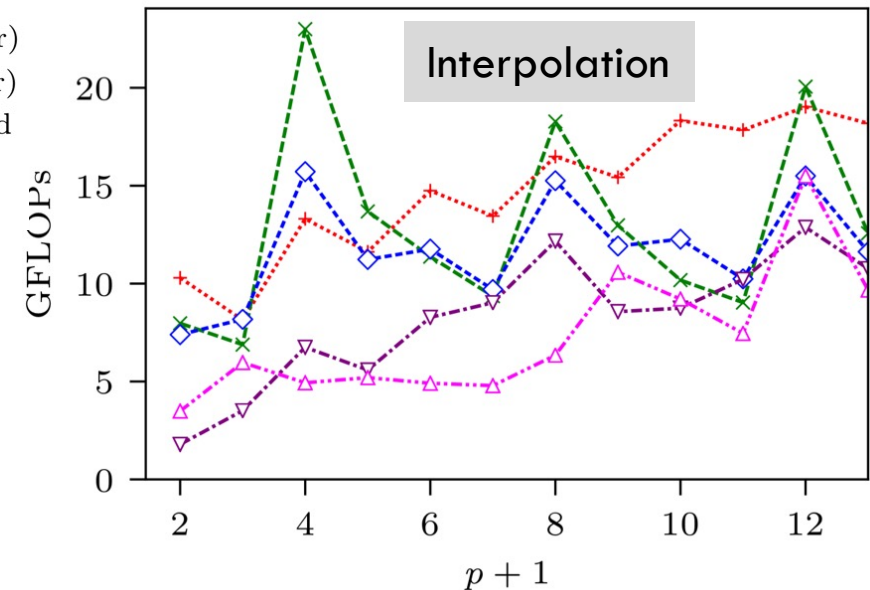
```

```

auto A = Matrix(m, n), B = Matrix(m, n),
      C = Matrix(m, n);
auto u = Tensor<3>(n, n, n);
auto v = (A*B*C)(u);

```

- +...+ CFDlang(outer)
- x--x CFDlang(inner)
- ◇--◇ hand-optimized
- ▽--▽ DGEMM
- △--△ specialized



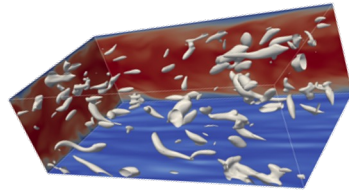
N. A. Rink, et al. "CFDlang: High-level code generation for high-order methods in fluid dynamics". RWDSL'18.

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Existence proof: Tensor expressions (Physics, ML)

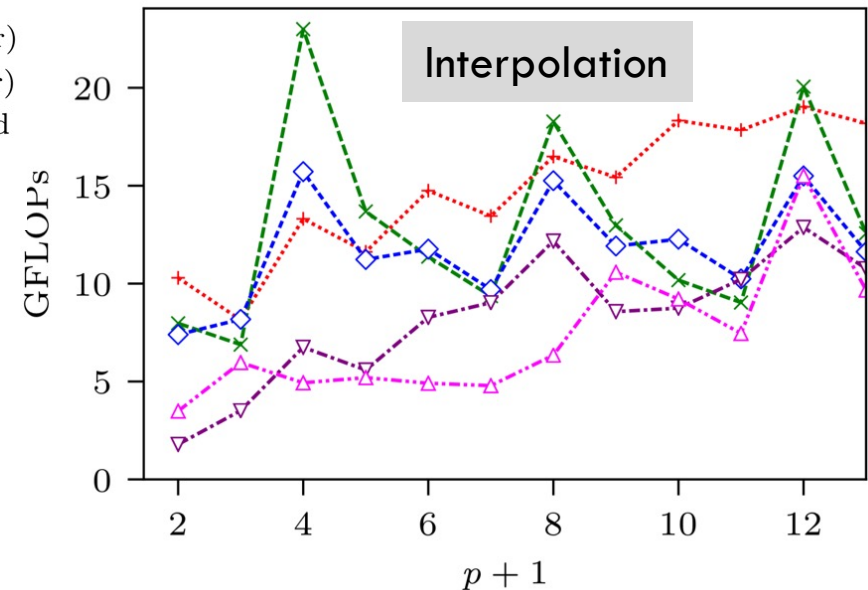
CFDlang



$$v_{ijk,e} = \sum_{i'=0}^p \sum_{j'=0}^p \sum_{k'=0}^p A_{kk'} A_{jj'} A_{ii'} u_{i'j'k'e}$$

```
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```

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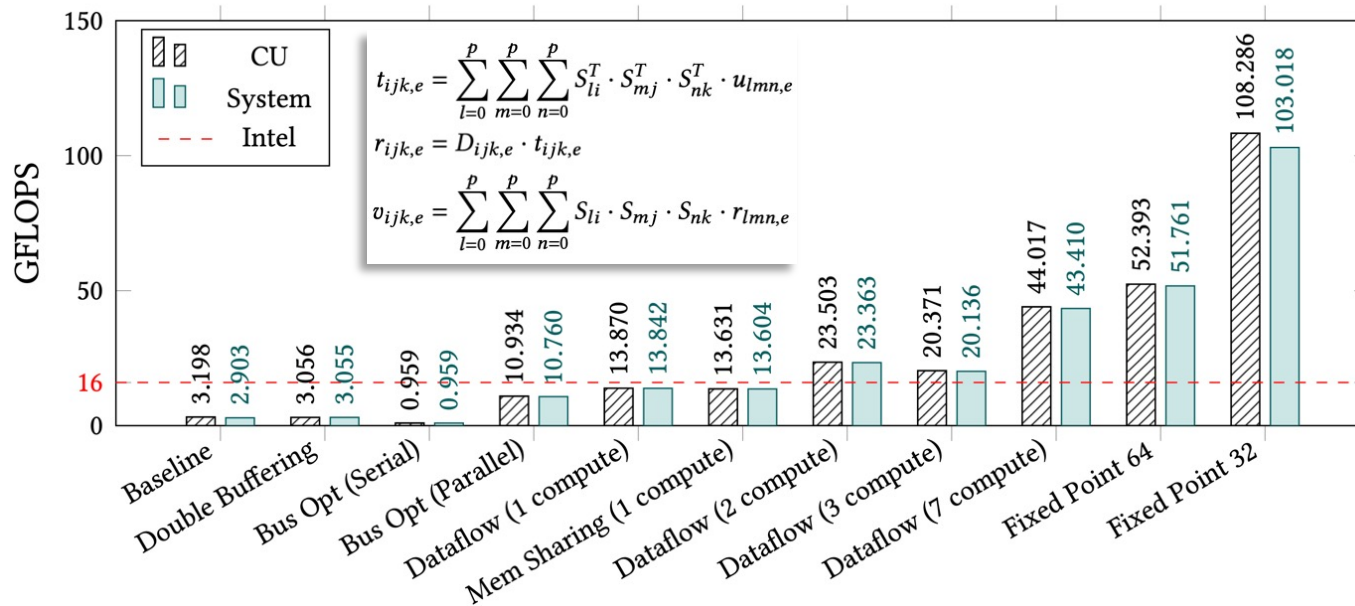
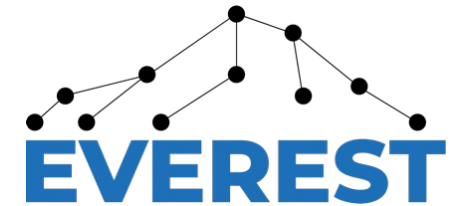


Plenty of other great DSL examples, e.g., Spiral, TACO, Halide, Lift, Firedrake, ML frameworks, ... for CPUs, GPUs and TPUs.

```
auto v = (A*B*C)(u);
```

Own example for complex designs on HBM FPGA

- Transformations for a **17x speedup** (same precision)
- Variants with up to **24x better energy efficiency**



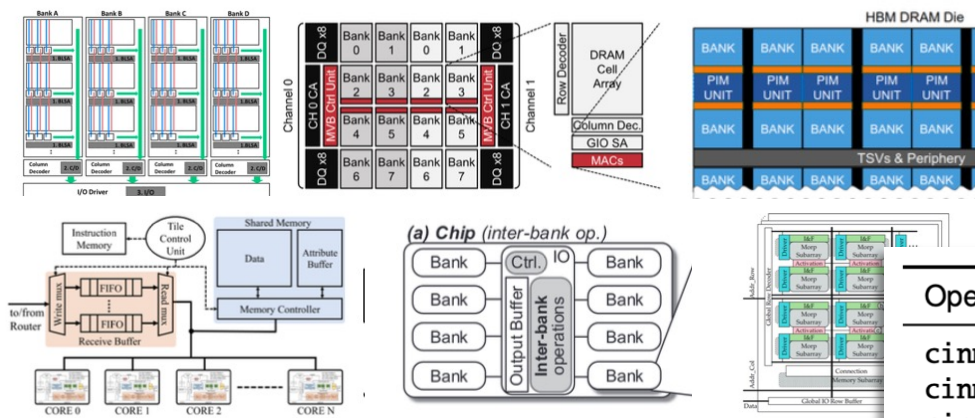
HBM+FPGA

C. Pilato, et al. "EVEREST: A design environment for extreme-scale big data analytics on heterogeneous platforms", DATE 2021

S. Soldavini, K. F. A. Friebel, et al. "Automatic Creation of High-Bandwidth Memory Architectures from Domain-Specific Languages: The Case of Computational Fluid Dynamics". In: ACM TRET, 2023.

Colorful landscape

□ Lots in and near memory systems!



□ Commonalities

- Hierarchical HW
- Common high-level operations

A. Khan et al, "CINM (Cinnamon): A Compilation Infrastructure for Heterogeneous Compute In-Memory and Compute Near-Memory Paradigms", ASPLOS'25

The Landscape of Compute-near-memory and Compute-in-memory: A Research and Commercial Overview

ASIF ALI KHAN, TU Dresden, Germany
 JOÃO PAULO C. DE LIMA, TU Dresden and ScADS.AI, Germany
 HAMID FARZANEH, TU Dresden, Germany
 JERONIMO CASTRILLON, TU Dresden and ScADS.AI, Germany

In today's data-centric world, where data fuels numerous application domains, with machine learning at the

2024

A. Khan, et al "The Landscape of Compute-near-memory and Compute-in-memory: A Research and Commercial Overview." arXiv:2401.1442 (2024)

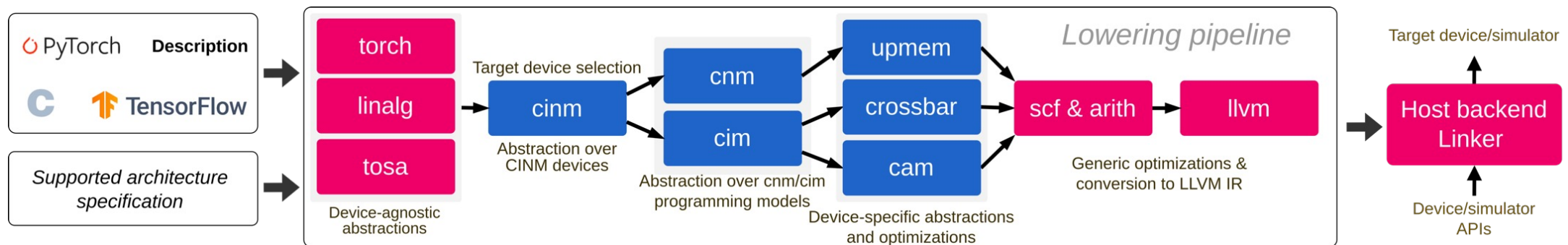
Operation

Type

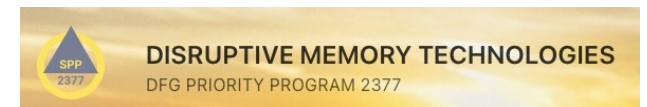
<code>cinm.{add,sub,mul,div,min,max}(%lhs, %rhs)</code>	$T \times T \rightarrow T$
<code>cinm.{and,or,xor,not}(%lhs, %rhs)</code>	$T \times T \rightarrow T$
<code>cinm.gemv(%lhs, %rhs)</code>	$S^{m \times n} \times S^n \rightarrow S^m$
<code>cinm.gemm(%lhs, %rhs)</code>	$S^{m \times k} \times S^{k \times n} \rightarrow S^{m \times n}$
<code>cinm.transpose(%in, %perms)</code>	$S^n \times N^n \rightarrow S'$
<code>cinm.{histogram,majority}(%in)</code>	$S^n \rightarrow S^k$
<code>cinm.topk(%in, %k)</code>	$S^n \times N \rightarrow S^k \times N^k$
<code>cinm.simSearch #E, #k (%in1, %in2)</code>	$E \times N^k \times S^n \times S^n \times N \rightarrow S^k$
<code>cinm.mergePartial #op #dir (%lhs, %rhs)</code>	$E \times D \times T \times T \rightarrow T$
<code>cinm.popCount(%in)</code>	$T \rightarrow N$
<code>cinm.reduce #op (%in)</code>	$E \times S^n \rightarrow S$
<code>cinm.scan #op (%in)</code>	$E \times S^n \rightarrow S^n$

CINM: Generalized MLIR infrastructure

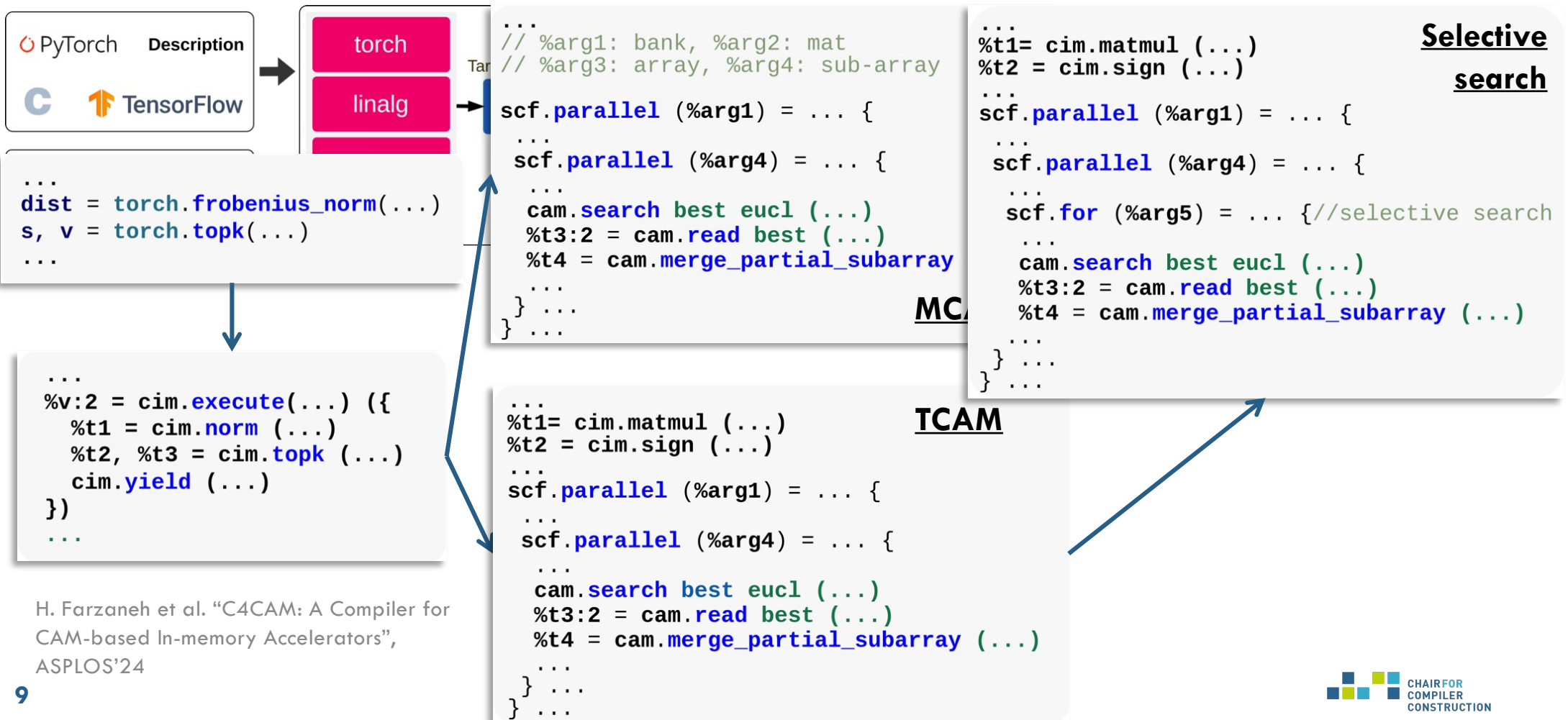
- ❑ From linear algebra abstractions (common to ML frameworks and beyond)
- ❑ Intermediate languages for **in and near memory computing**
- ❑ **Pattern recognition, target-specific models and optimizations**
- ❑ Targets: memristive crossbars, CAMs, logic in memory, UPMEM, ...



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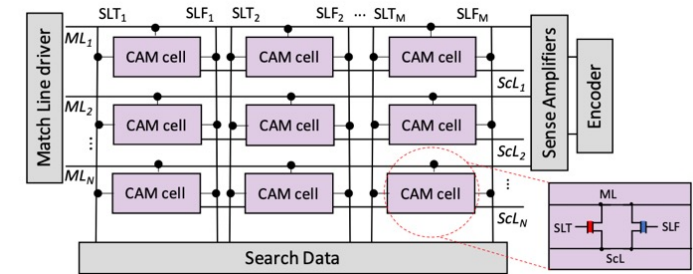
Lowering for different CAM-based accelerators



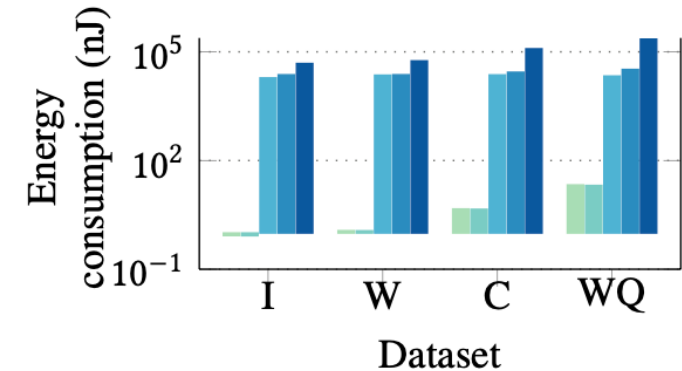
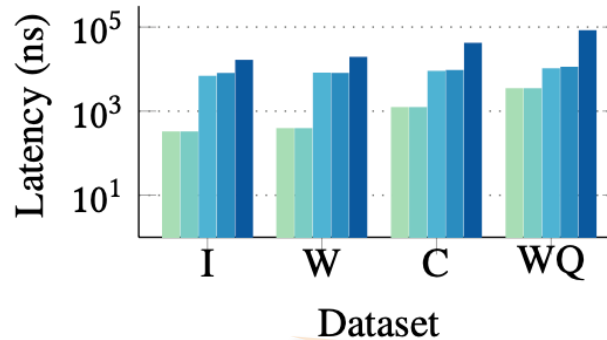
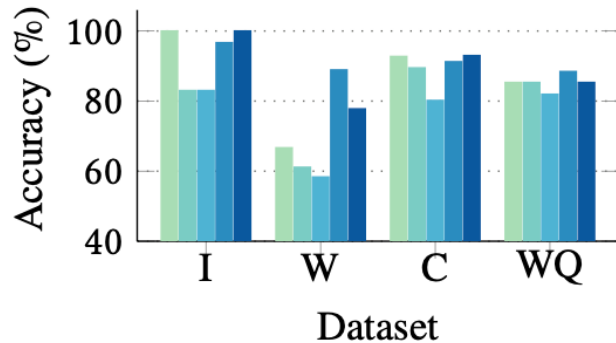
H. Farzaneh et al. "C4CAM: A Compiler for CAM-based In-memory Accelerators", ASPLOS'24

C4CAM: Programming and Design

- ❑ Pattern matching in high-level TorchScript code
- ❑ Automatic flow **matches manual designs**



■ C4CAM-3b ■ C4CAM-2b ■ C4CAM-1b+LSH ■ Cosine-GPU ■ Euclidean-GPU

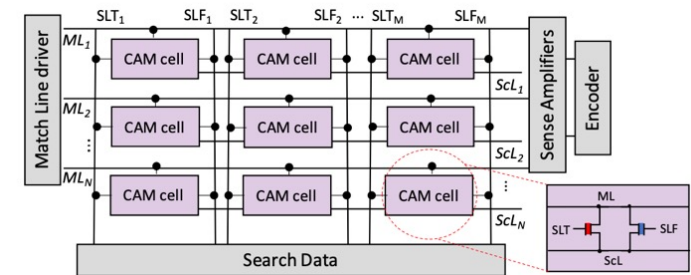


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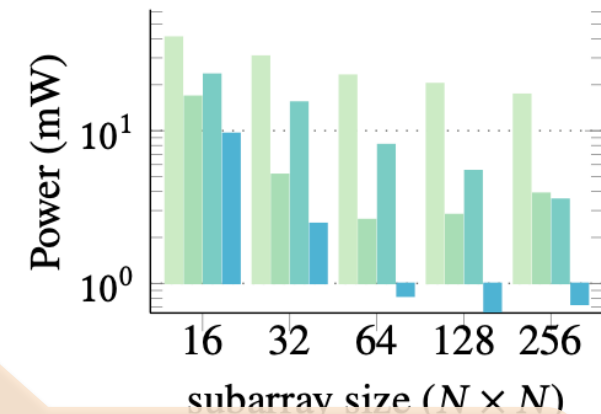
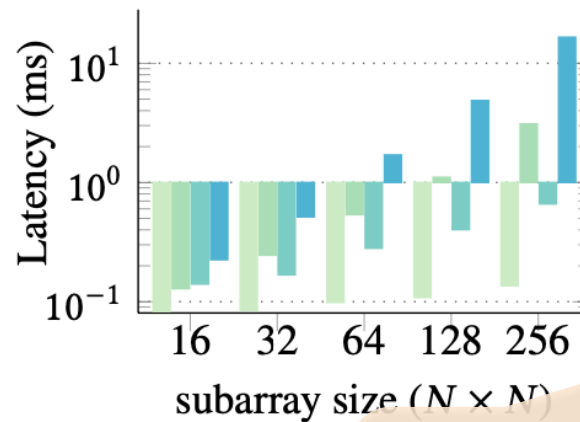
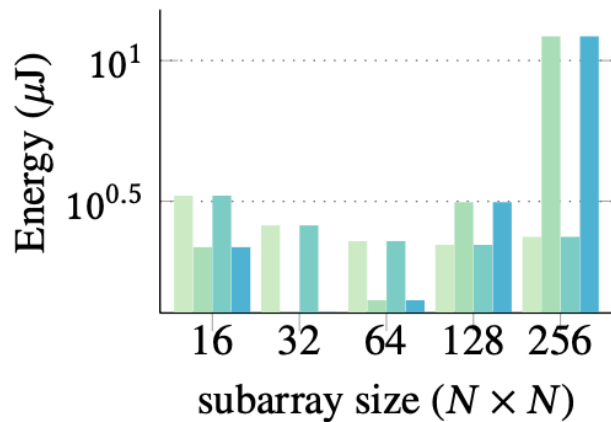
KNN results (128x128 CAM): 14x faster and ~10⁴ less energy compared to GPU

C4CAM: Programming and Design (2)

- Retargetable compiler for CAM exploration: Sizes and features
- Compiler flags for optimization target



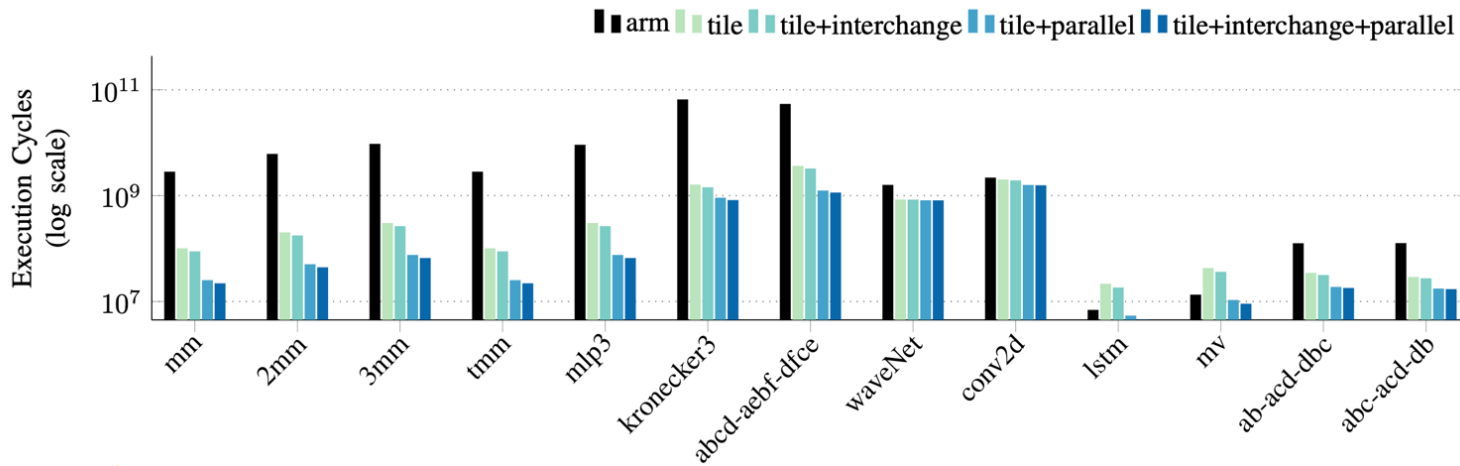
■ cam-base
 ■ cam-density
 ■ cam-power
 ■ cam-density+power



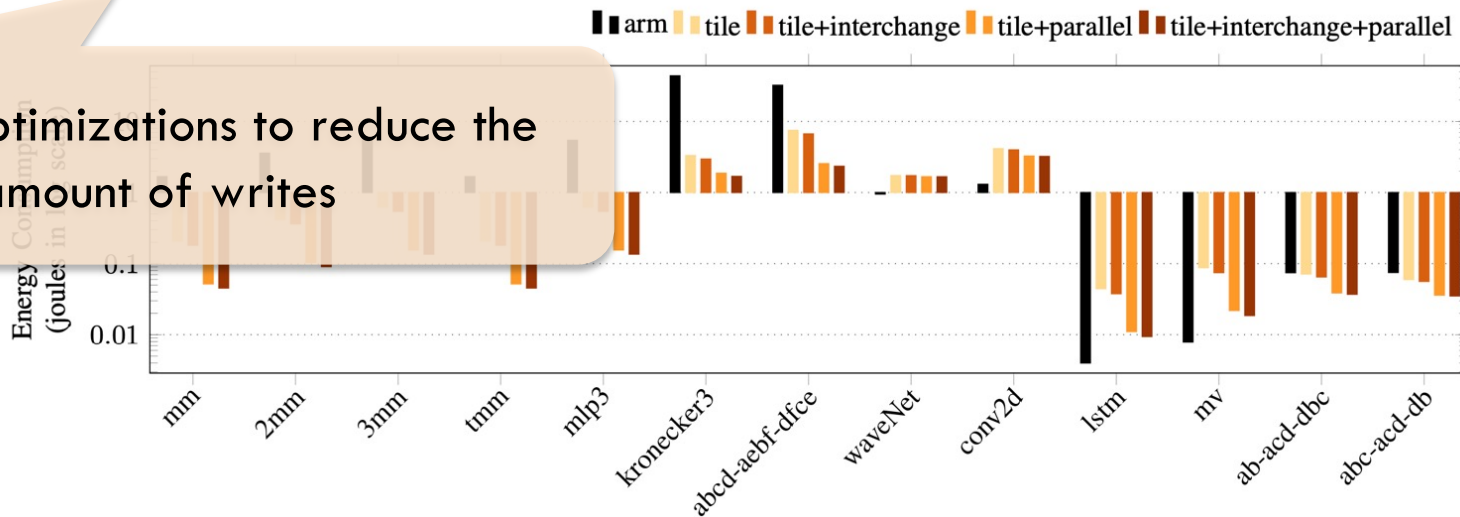
H. Farzaneh, et al. "C4CAM: A Compiler for CAM-based In-memory Accelerators", ASPLOS, 2024

Different flags expose trade-offs w/o manual re-coding.

Optimization results: Crossbars beyond matmult



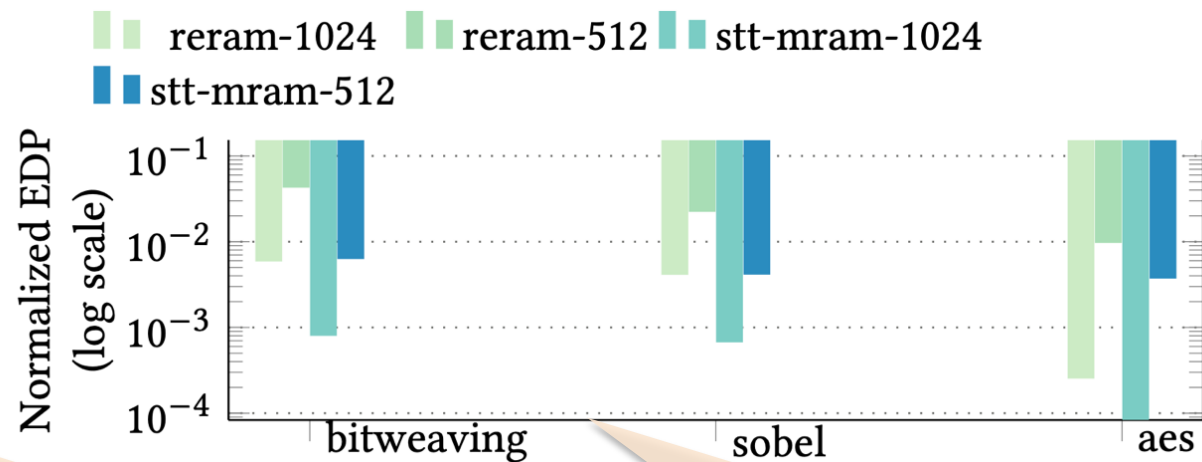
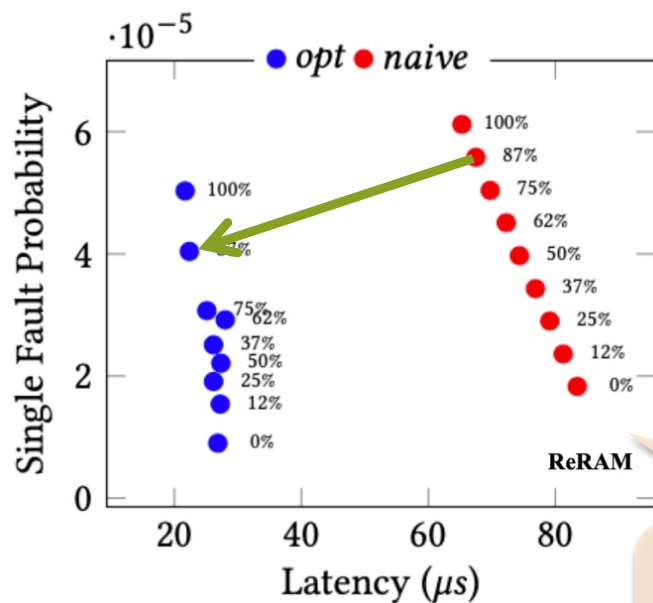
Studied optimizations to reduce the amount of writes



A. Siemieniuk, L. Learning Optim

Logic-in-memory in NVMs

- ❑ Massively parallel multi-operand bit-wise operations in-memory
- ❑ Complex mapping of operands, operations and temporaries to columns



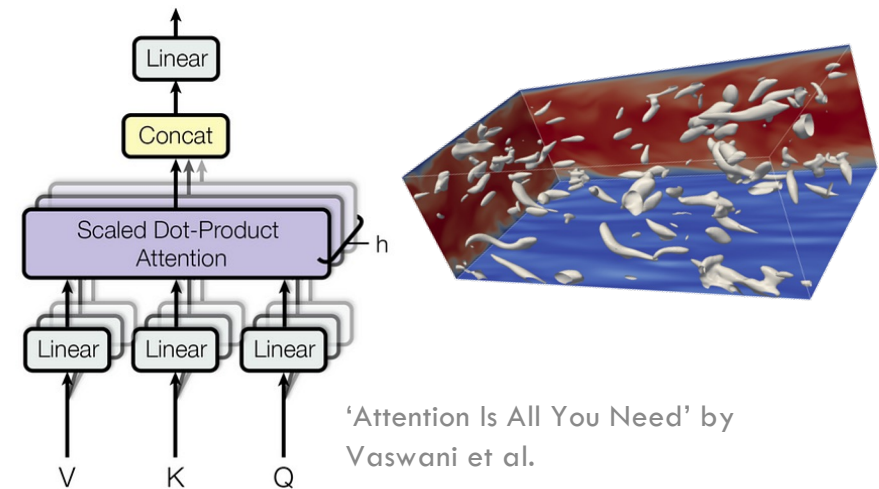
Optimized mapping: **Less latency (3x), better reliability (~1.4x)**

Orders of magnitude better EDP vs CPU baseline

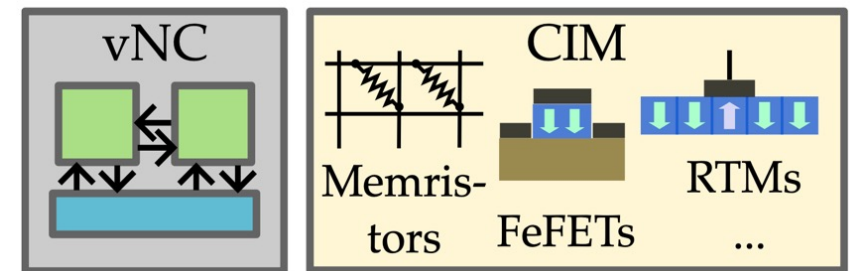
H. Farzaneh, et al. "SHERLOCK: Scheduling Efficient and Reliable Bulk Bitwise Operations in NVMs", DAC 2024

Summary: Scratching the surface

- ❑ Abstraction and compilation infrastructure
 - ❑ Capture "HW semantics" for execution
 - ❑ Single flows: Crossbars, FeFET CAMs, Logic
 - ❑ Leverage domain-specific abstractions
 - ❑ Automated practices from manual designs



- ❑ Upcoming and challenges
 - ❑ End-to-end mapping on heterogeneous CIM
 - ❑ Models (time, energy, endurance, resilience)
 - ❑ Truly cross layer down to device parameters
 - ❑ Runtime reconfigurability of mem arrays



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Nesrine Khouzami



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Christian Menard



Julian Robledo



Lars Schütze



Felix Wittwer

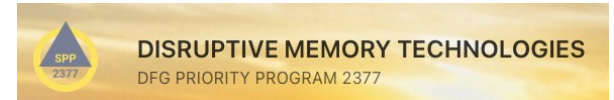


Dr. Fazal Hameed

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BMBF (01IS18026A-D)



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References

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[**Array'19**] N.A. Rink, N. A. and J. Castrillon. "TelL: a type-safe imperative Tensor Intermediate Language", ARRAY'19, pp. 57-68

[**DATE'21**] C. Pilato, et al. "EVEREST: A design environment for extreme-scale big data analytics on heterogeneous platforms", DATE 2021

[**TRETS'23**] S. Soldavini, K. F. A. Friebel, M. Tibaldi, G. Hempel, J. Castrillon, and C. Pilato. "Automatic Creation of High-Bandwidth Memory Architectures from Domain-Specific Languages: The Case of Computational Fluid Dynamics". In: ACM TRETS, March 2023.

[**ASPLOS'25**] A. Khan et al, "CINM (Cinnamon): A Compilation Infrastructure for Heterogeneous Compute In-Memory and Compute Near-Memory Paradigms", arXiv, Aug 2023

[**ArXiv'24**] A. Khan, et al "The Landscape of Compute-near-memory and Compute-in-memory: A Research and Commercial Overview." arXiv:2401.1442 (2024)

[**TCAD'21**] A. Siemieniuk, et al. "OCC: An Automated End-to-End Machine Learning Optimizing Compiler for Computing-In-Memory", IEEE TCAD, 2021

[**ASPLOS'24**] H. Farzaneh, et al. "C4CAM: A Compiler for CAM-based In-memory Accelerators", ASPLOS 2024

[**DAC'24**] H. Farzaneh, et al. "SHERLOCK: Scheduling Efficient and Reliable Bulk Bitwise Operations in NVMs", DAC'24