

Practical Near-Data Processing for In-Memory Analytics Frameworks

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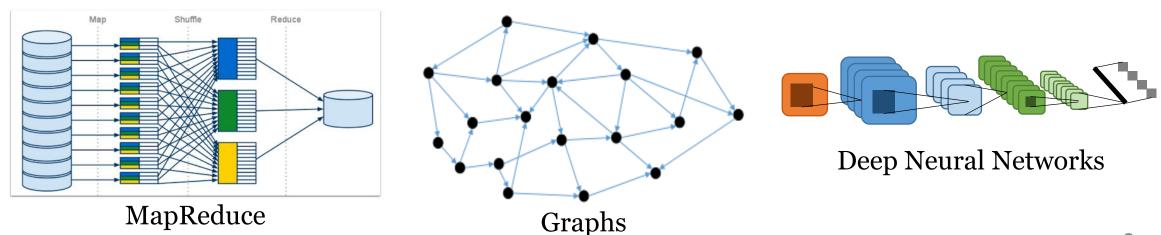
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Motivating Trends



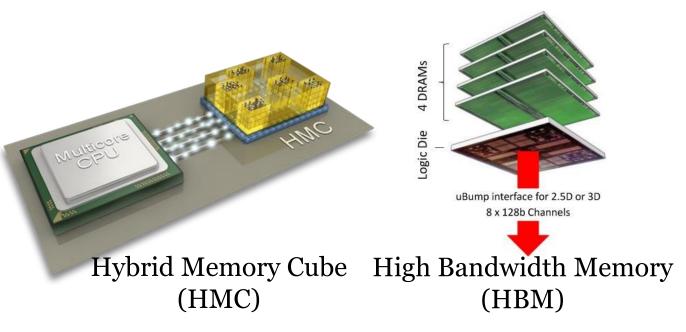
- End of Dennard scaling → systems are energy limited
- Emerging big data workloads
 - Massive datasets, limited temporal locality, irregular access patterns
 - They perform poorly on conventional cache hierarchies
- Need alternatives to improve energy efficiency



PIM & NDP

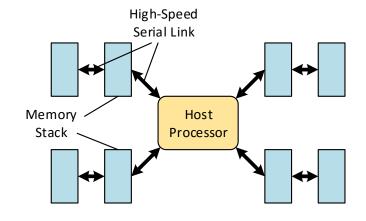


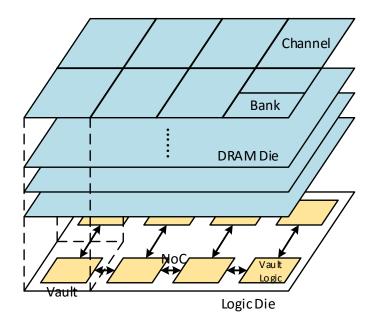
- Improve performance & energy by avoiding data movement
- □ Processing-In-Memory (1990's 2000's)
 - Same-die integration is too expensive
- Near-Data Processing
 - Enabled by 3D integration
 - Practical technology solution
 - Processing on the logic die



Base NDP Hardware







- Stacks linked to host multi-core processor
 - Code with temporal locality: runs on host
 - Code without temporal locality: runs on NDP
- 3D memory stack
 - x10 bandwidth, x3-5 power improvement
 - 8-16 vaults per stack
 - Vertical channel
 - Dedicated vault controller
 - NDP cores
 - General-purpose, in-order cores
 - FPU, L1 caches I/D, no L2
 - Multithreaded for latency tolerance

Challenges and Contributions



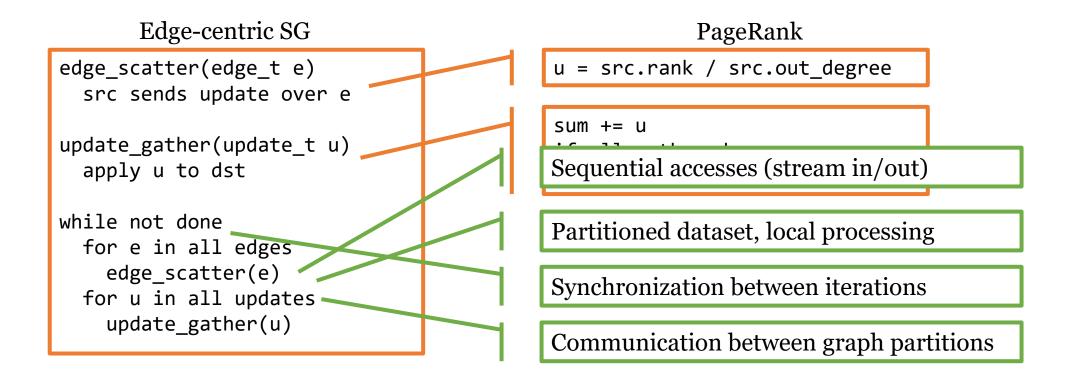
- NDP for large-scale highly distributed analytics frameworks
 - ? General coherence maintaining is expensive
 - ✓ Scalable and adaptive software-assisted coherence
 - ? Inefficient communication and synchronization through host processor
 - ✓ Pull-based model to directly communicate, remote atomic operations
 - ? Hardware/software interface
 - ✓ A lightweight runtime to hide low-level details to make program easier
 - ? Processing capability and energy efficiency
 - ✓ Balanced and efficient hardware

A general, efficient, balanced, practical-to-use NDP architecture

Example App: PageRank



- Edge-centric, scatter-gather, graph processing framework
- Other analytics frameworks have similar behaviors



Architecture Design

Memory model, communication, coherence, ...
Lightweight hardware structures and software runtime



Shared Memory Model



- Unified physical address space across stacks
 - Direct access from any NDP/host core to memory in any vault/stack

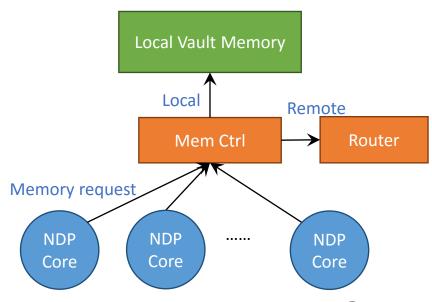
In PageRank

One thread to access data in a remote graph partition

For edges across two partitions

Implementation

- Memory ctrl forwards local/remote accesses
- Shared router in each vault



Virtual Memory Support



- NDP threads access virtual address space
 - Small TLB per core (32 entries)
 - Large pages to minimize TLB misses (2 MB)
 - Sufficient to cover local memory & remote buffers

In PageRank

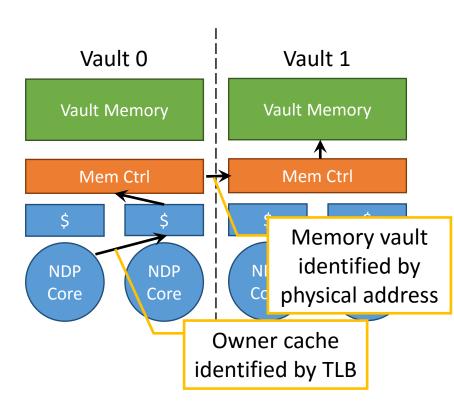
- Each core works on local data, much smaller than the entire dataset
- o.25% miss rate for PageRank
- TLB misses served by OS in host
 - Similar to IOMMU misses in conventional systems

Software-Assisted Coherence



- Maintaining general coherence is expensive in NDP systems
 - Highly distributed, multiple stacks
- Analytics frameworks
 - Little data sharing except for communication
 - Data partitioning is coarse-grained

- Only allow data to be cached in one cache
 - Owner cache
 - No need to check other caches
- Page-level coarse-grained
 - Owner cache configurable through PTE



Software-Assisted Coherence



- Scalable
 - Avoids directory lookup and storage
- Adaptive
 - Data may overflow to other vault
 - Able to cache data from any vault in local cache
- Vault 0

 Vault 1

 Vault Memor Dataset

 Vault Memory

 Mem Ctrl

 \$ \$ \$ \$

 NDP Core

 NDP Core

 NDP Core

 NDP Core

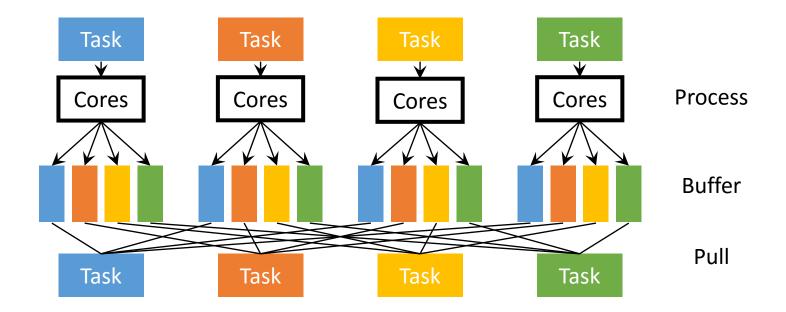
- Flush only when owner cache changes
 - Rarely happen as dataset partitioning is fixed

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Communication

Pull-based model

- Producer buffers intermediate/result data locally and separately
- Post small message (address, size) to consumer
- Consumer pulls data when it needs with load instructions



Communication



- Pull-based model is efficient and scalable
 - Sequential accesses to data
 - Asynchronous and highly parallel
 - Avoids the overheads of extra copies
 - Eliminates host processor bottleneck

In PageRank

Used to communicate the update lists across partitions

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Communication

- HW optimization: remote load buffer (RLBs)
 - A small buffer per NDP core (a few cachelines)
 - Prefetch and cache remote (sequential) load accesses
 - Remote data are not cache-able in the local cache
 - Do not want owner cache change as it results in cache flush
- Coherence guarantee with RLBs
 - Remote stores bypass RLB
 - All writes go to the owner cache
 - Owner cache always has the most up-to-date data
 - Flush RLBs at synchronization point
 - ... at which time new data are guaranteed to be visible to others
 - Cheap as each iteration is long and RLB is small

Synchronization

- Remote atomic operations
 - Fetch-and-add, compare-and-swap, etc.
 - HW support at memory controllers [Ahn et al. HPCA'05]
- Higher-level synchronization primitives
 - Build by remote atomic operations
 - E.g., hierarchical, tree-style barrier implementation
 - Core → vault → stack → global
- In PageRank
 - Build barrier between iterations

Software Runtime



- Hide low-level coherence/communication features
 - Expose simple set of API
- Data partitioning and program launch
 - Optionally specify running core and owner cache close to dataset
 - No need to be perfect, correctness is guaranteed by remote access
- Hybrid workloads
 - Coarsely divide work between host and NDP by programmers
 - Based on temporal locality and parallelism
 - Guarantee no concurrent accesses from host and NDP cores

Evaluation

Three analytics framework: MapReduce, Graph, DNN



Methodology

- Infrastructure
 - o zsim
 - McPAT + CACTI + Micron's DRAM power calculator
- Calibrate with public HMC literatures
- Applications
 - o MapReduce: Hist, LinReg, grep
 - o Graph: PageRank, SSSP, ALS
 - o DNN: ConvNet, MLP, dA

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Porting Frameworks

MapReduce

- In map phase, input data streamed in
- Shuffle phase handled by pull-based communication

Graph

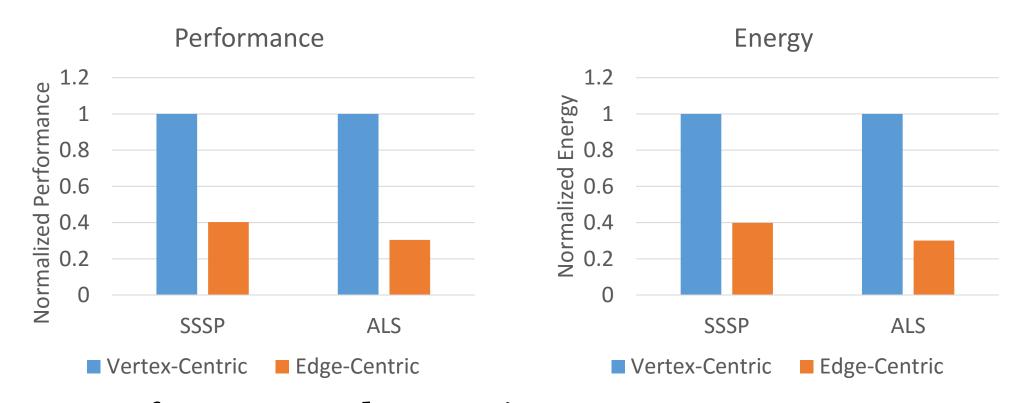
- Edge-centric
- Pull remote update lists when gathering

Deep Neural Networks

- Convolution/pooling layers handled similar to Graph
- Fully-connected layers use local combiner before communication
- Once the framework is ported, no changes to the user-level apps

Graph: Edge- vs. Vertex-Centric

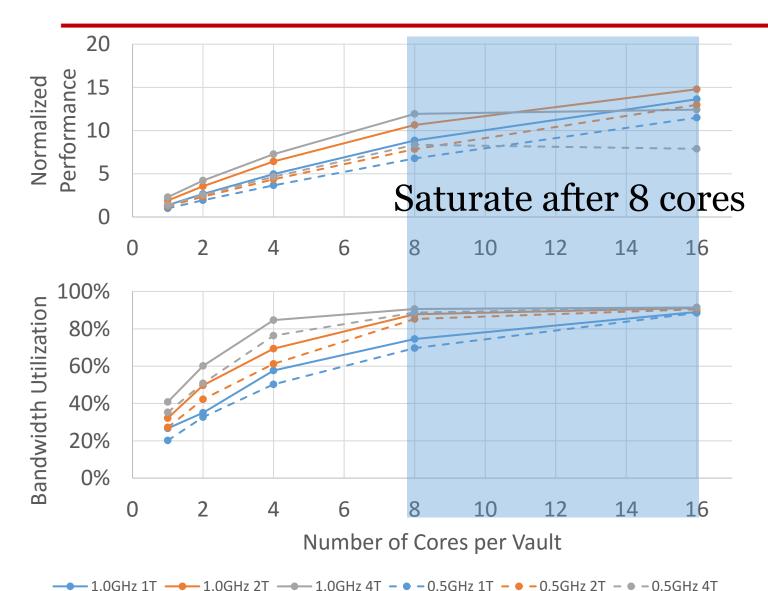




- 2.9x performance and energy improvement
 - Edge-centric version optimize for spatial locality
 - Higher utilization for cachelines and DRAM rows

Balance: PageRank



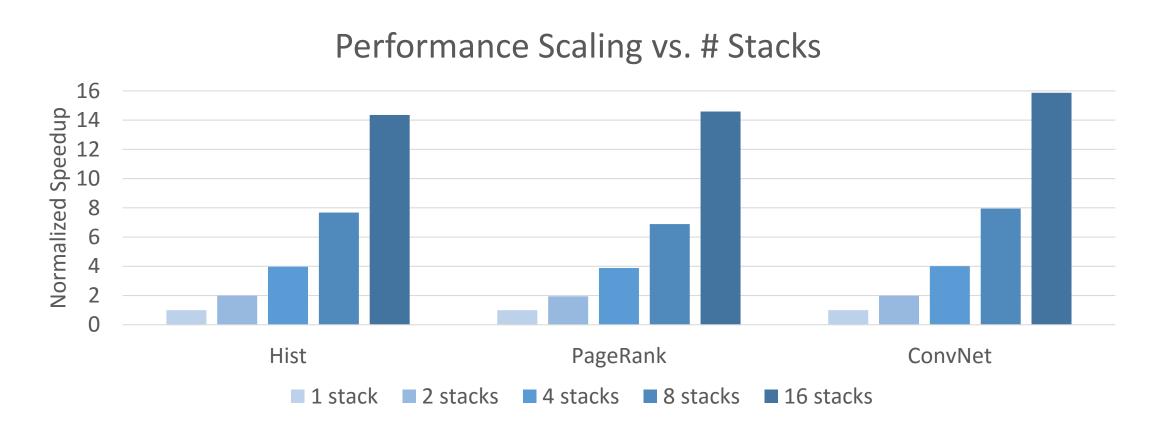


- Performance scales to 4-8 cores per vault
 - Bandwidth saturates

- Final design
 - 4 cores per vault
 - 1.0 GHz
 - 2-threaded
 - Area constrained

Scalability





- Performance scales well up to 16 stacks (256 vaults, 1024 threads)
- Inter-stack links are not heavily used

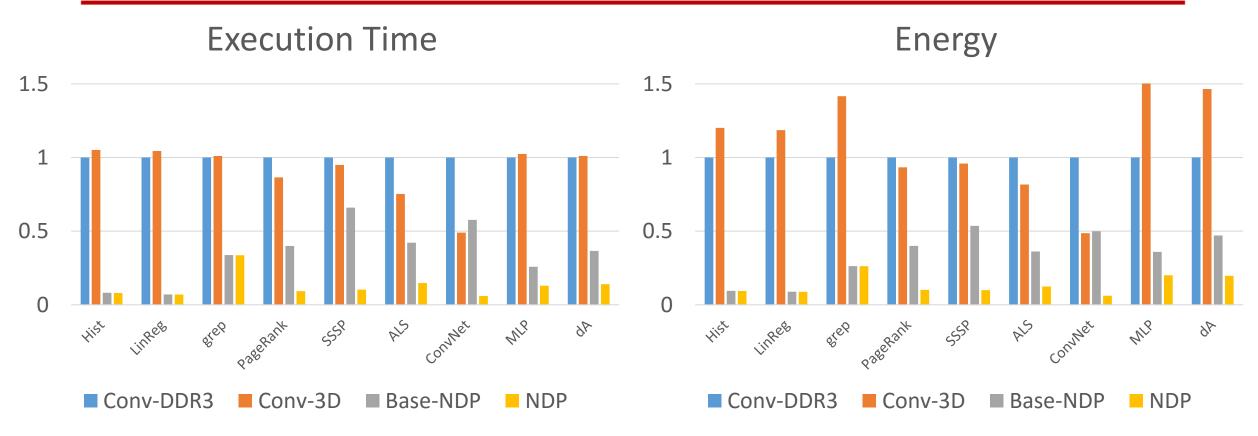
Final Comparison

Four systems

- o Conv-DDR3
 - Host processor + 4 DDR3 channels
- o Conv-3D
 - Host processor + 8 HMC stacks
- Base-NDP
 - Host processor + 8 HMC stacks with NDP cores
 - Communication coordinated by host
- NDP
 - Similar to Base-NDP
 - With our coherence and communication

Final Comparison

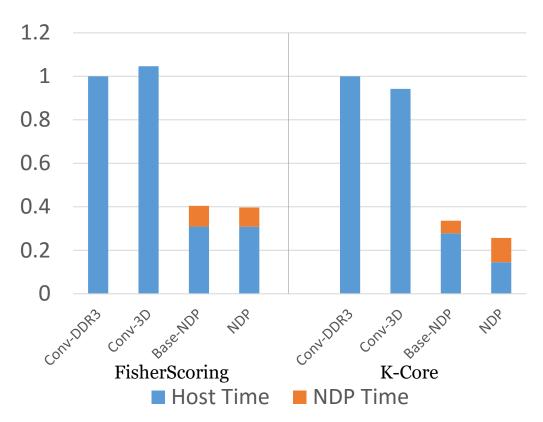




- Conv-3D: improve 20% for Graph (bandwidth-bound), more energy
- Base-NDP: 3.5x faster and 3.4x less energy than Conv-DDR3
- □ NDP: up to 16x improvement than Conv-DDR3, 2.5x over Base-NDP₂₄

Hybrid Workloads

Execution Time Breakdown



 Use both host processor and NDP cores for processing

NDP portion: similar speedup

- Host portion: slight slowdown
 - Due to coarse-grained address interleaving

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Conclusion

- Lightweight hardware structures and software runtime
 - Hides hardware details
 - Scalable and adaptive software-assisted coherence model
 - Efficient communication and synchronization
- Balanced and efficient hardware
- Up to 16x improvement over DDR3 baseline
 - 2.5x improvement over previous NDP systems
- Software optimization
 - 3x improvement from spatial locality

Thanks!

Questions?



