



Near-Memory Processing: It's the SW *and* HW, stupid!

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The End is Mar Here!



Where do we go from here?





An **exponential** is ending...

10%, 20%, .. improvement in performance of component X won't get you far

- No new transistors
- Fixed power ceiling

Emerging technologies are either incremental (e.g., Intel's Xpoint Memory) or cover niche areas (e.g., quantum)







The Way Forward: Vertical Integration

Software/hardware co-design for high efficiency and programmability

Is this **always** a good idea? **No!**

Need high volume for cost-efficiency Need large perf/Watt gains to be worth the effort







hedooo

APACHE STORM

MESOS

neo4

redis

Spai

mongoDP

♥Sphinx

Institute for Computing Systems Architecture

mriak

ariaD

This Talk

Vertical integration for in-memory data analytics









Data Analytics Takes Center Stage

User data grows exponentially

Need to monetize data

In-memory data operators

- Poor locality
- Low computational requirement
- Highly parallel



ICSO



iCSO

Data Analytics Takes Center Stage

- User data grows exponentially
 - Need to monetize data
- In-memory data operators
 - Poor locality
 - Low computational requirement
 - Highly parallel

Data movement

- High energy cost
- High BW requirement









Cost of Moving Data



Data access much more expensive than arithmetic operation





DRAM BW Bottleneck



Internal DRAM BW presents big opportunity





Logic inside DRAM? Not a Good Idea

Fabrication processes not compatible

- DRAM is optimized for density
- Logic is irregular, wire-intensive

In-memory logic failed in the 90s – DRAM is cost-sensitive



Must exploit DRAM in a non-disruptive manner





Near-Memory Processing (NMP)

3D logic/DRAM stack

- Exposes internal BW to processing elements
- But constrains logic layer's area/power envelope



Exploit the bandwidth without data movement





How to Best Exploit DRAM BW?

DRAM internals optimized for density

DRAM accesses must activate rows

- Single access activates KBs of data
- Activations dominate access latency & energy



Can't utilize internal BW with random access

- Need to maintain many open rows
- Complex bookkeeping logic

Need sequential access to utilize DRAM BW





NMP HW-Algorithm Co-Design

Algorithms: Must have sequential access – Even if we perform more work

Hardware: Must leverage data parallelism – On a tight area/power budget

HW-algorithm co-design necessary to make best use of NMP





Example data operator: Join

Iterates over a pair of tables to find matching keys

Major operation in data analytics

Q: SELECT ... FROM A, B WHERE A.Key = B.Key

A B Result







Baseline: CPU Hash Join

Best performing algorithm in CPU-centric systems

Performed in two phases: Partition & Probe

- 1. Partition generates cache sized partitions
- 2. Probe builds and queries cache resident hash tables

Partition



Probe



Optimized for random accesses to cached data











NMP Hash Join







NMP Hash Join



Random accesses are inefficient and under-utilize internal BW





Eliminate Random Access?

Insight: use Sort Join

- Performs mostly sequential accesses
- But has higher algorithmic complexity

Trade algorithmic complexity for desirable access pattern



Utilizing internal DRAM BW compensates for increased cost































Sequential access moves bottleneck to compute





NMP Sort Join: Compute



General purpose SIMD keeps up with memory BW





Partitioning Phase

Partitioning basics:

- Each partition contains buckets of objects
- For a given object, target bucket determined using a hash
- The order of objects within each bucket is irrelevant → buckets are unordered



Partitioning phase: tuples are permutable





Partitioning Phase

Leverage tuple's permutability property

Turn partition's random accesses sequential – Enable use of SIMD during partition





Mondrian

Algorithm + hardware co-design for near-memory processing of data analytics

NMP Algorithms

- Use sequential memory accesses
- Avoid random memory accesses
- Target partitioning and compute phases

NMP Harware

- High memory parallelism using simple SIMD hardware
- Exploit sequential memory accesses





Methodology

Flexus cycle accurate simulator [Wenisch'06]

Big data operators:

- Scan
- Join
- Group By
- Sort

Memory subsystem:

- 4 HMC stacks
 - 20 GB/s external BW
 - 128 GB/s internal BW

Simulated systems:

- CPU-centric: ARM Cortex-A57
 - 16 cores
 - 3-wide,128-entry ROB @ 2GHz
- NMP: Mobile ARM core
 - 16 cores per stack
 - 3-wide, 48-entry ROB @ 1GHz
- Mondrian: SIMD in-order
 - 16 cores per stack
 - 1024-bit SIMD @ 1GHz













Mondrian achieves superior BW utilization







NMP can't utilize memory BW with random accesses







Mondrian BW utilization compensates for extra log(n) work





Summary

- End of technology scaling \rightarrow must think vertical
 - Software + hardware co-design
- Big data analytics are a critical workload
 - Large datasets, little locality \rightarrow memory bottleneck!
- Moving compute near memory improves performance
 - But need to conform to DRAM constraints

Mondrian is algorithm-hardware NMP for analytics

- Adapt algorithms/HW to DRAM constraints
- Sequential rather than random memory access
- Simple hardware to exploit memory bandwidth





Thank you!

Questions?

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Mondrian Energy Efficiency

