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Analyzing data movement through storage, network, and memory

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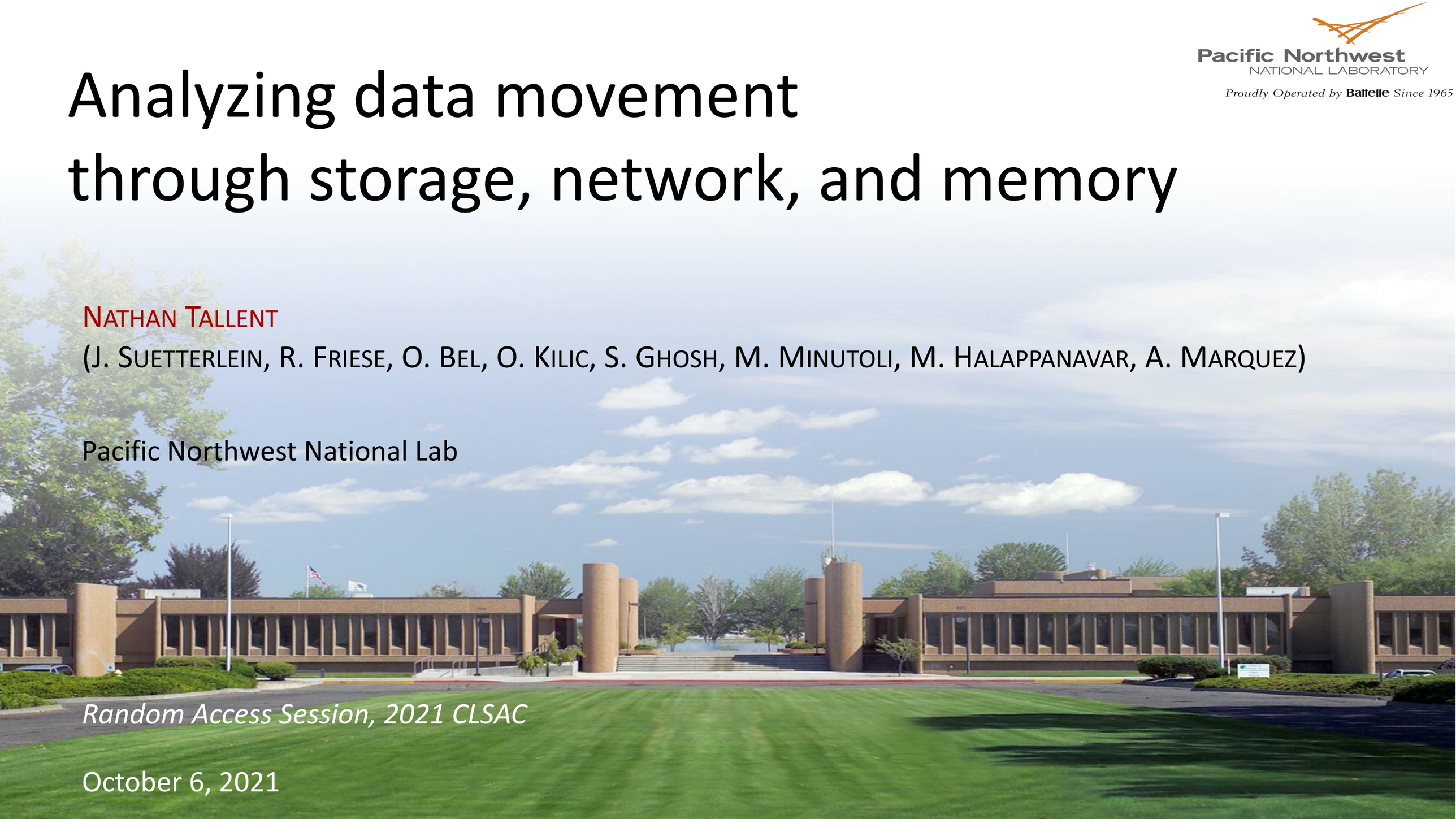
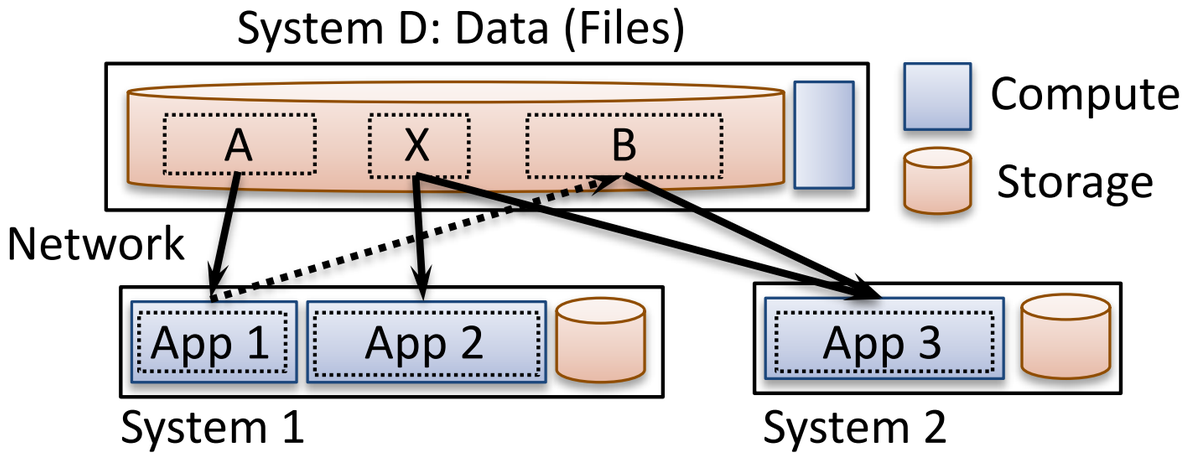


Random Access Session, 2021 CLSAC

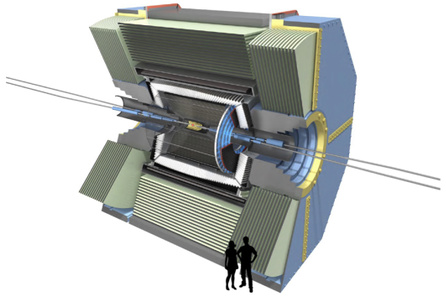
October 6, 2021

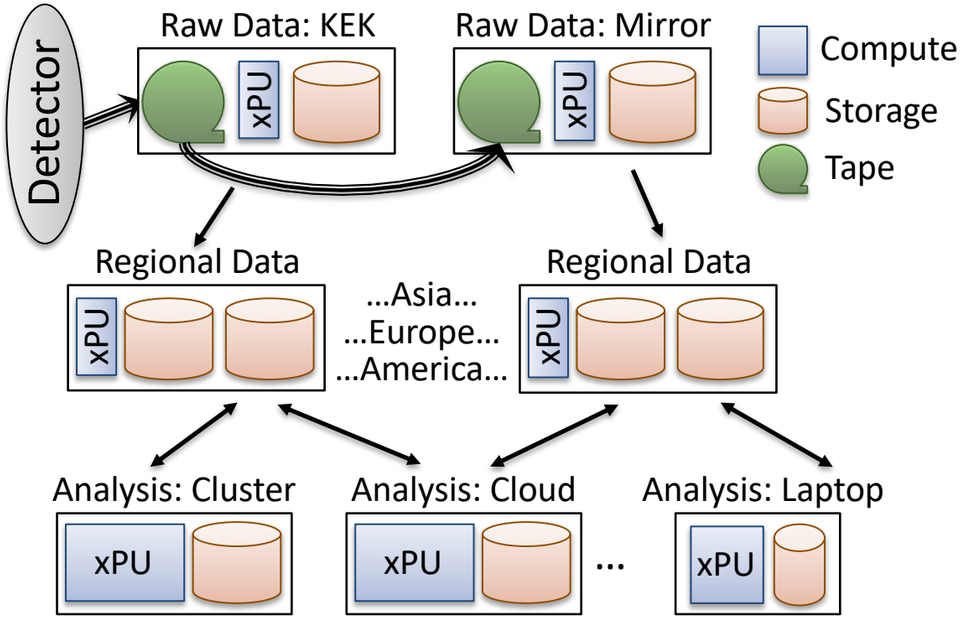
Scientific Exploration Is Increasingly Distributed & Data-intensive

- Domain science uses *workflows*:
  - Loose composition of different apps/tasks
  - Potentially different programming models
  - Data sources are distributed
  - Distributed I/O: productive method for task composition/communication



- Belle II Monte Carlo Sim: Big Data + Big Compute
  - Many logically independent tasks
  - Read intensive: inputs >> outputs
  - Simple data consistency: no files in read/write mode
  - Non-streaming accesses
  - Some inputs may be common





TAZeR: Transparent Asynchronous Zero-copy Remote I/O

Suetterlein, Friese, Tallent, and Schram, "TAZeR: Hiding the cost of remote I/O in distributed scientific workflows" BigData 2019

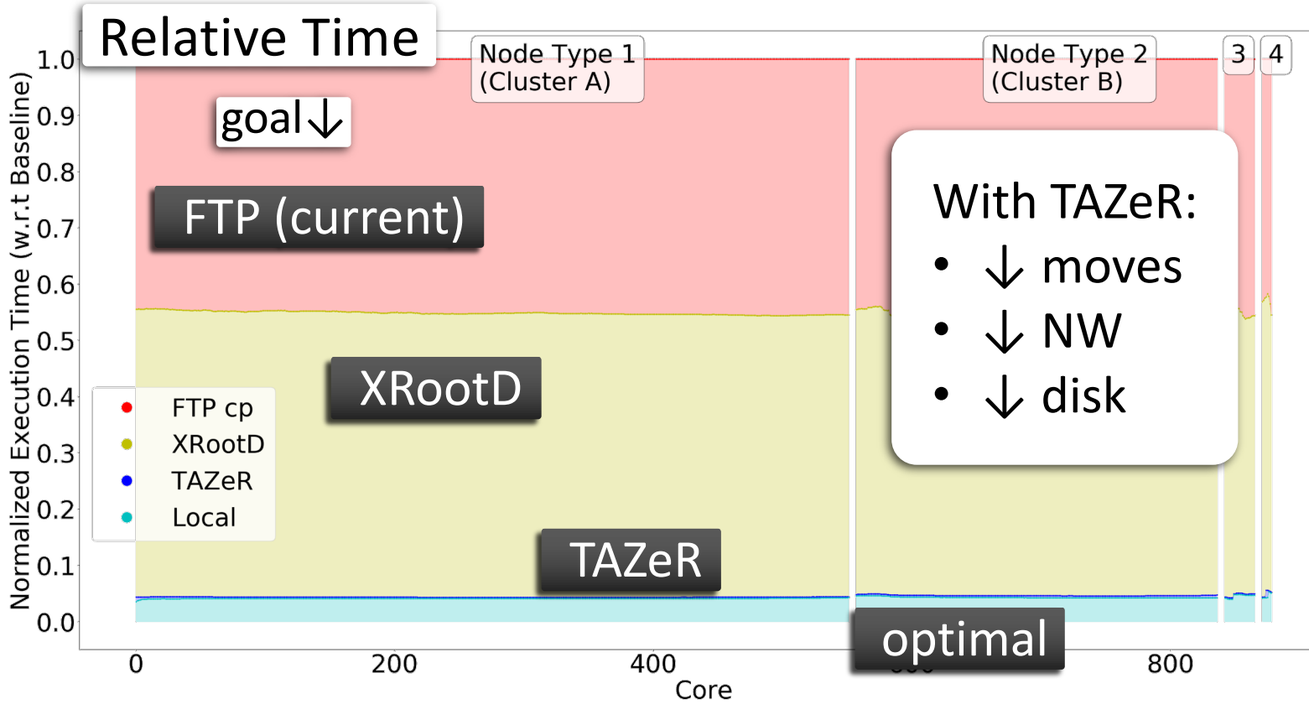
PNNL

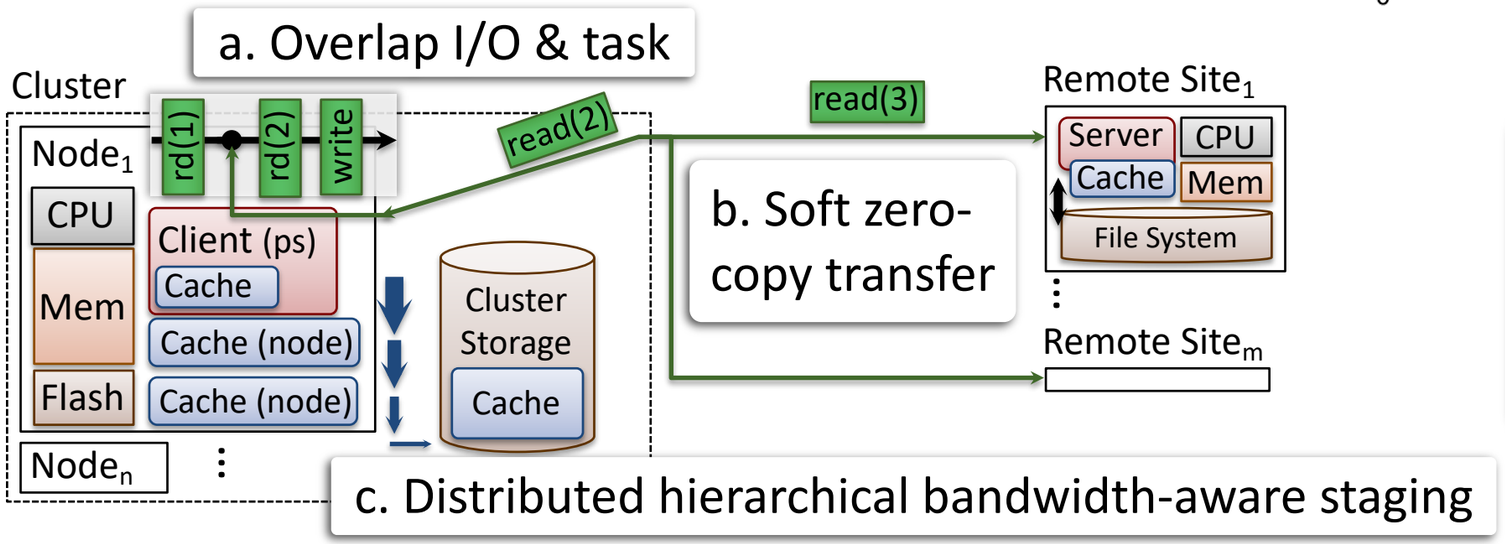
How to reuse/move data among tasks?

Belle II Monte Carlo (HEP)
- majority of Belle II compute
- 48 Gb/s over 2x 1 Gb/s WAN
- complex access pattern

TAZeR: intelligent data runtime

- Capture dynamic reuse
- ↓ access times
- ↓ data movement
- ↓ random access cost





- TAZeR: 22×/12× faster than FTP/XRootD
  - within 7% of optimal
- Workload with high reuse (4K tasks, 5 BG sets, 100 events)

BigFlowSim: Predict performance impact of I/O parameters

Friese, Mutlu, Tallent, Suetterlein, Strube. “Effectively using remote I/O for work composition in distributed workflows” BigData ’20

PNNL

- Workload Generator/Simulator for distributed workflows and remote I/O
- Study effects of data optimizations
  - (1) Reduce total data transferred over network
  - (2) Hide cost of network transfers
  - (3) Reduce inter-task footprints
  - (4) Reduce intra-task footprints

Parameters

Runtime
- Baseline: copy in/out
- Optimal: pre-staged

Data Intensity

Change I/O per work
- Data reducers
- Work aggregation

Data (re)Uses

Tasks reuse data for write-once read-many

Models & measurements order parameter impact by effects of footprints & movement

1 I/O intensity ≈ I/O Aware Locality (task ensembles) 1 3 ≥ Data (re)use 1 4

Code ≈ Access Pattern (density) 1 2

Scheduling & TAZeR

2 3 Access Pattern (ordered) ≈ Access Pattern (random)

I/O Aware Locality (no chunking) ≈ I/O Aware Locality (chunking) 3

With TAZeR

Capture reuse
↓ access time & moves
↓ random access cost

I/O Locality

Task ensembles, I/O chunking for temporal locality
- I/O-aware access/schedules
- In-situ computation

Access Pattern
- Data layout for I/O spatial locality
- Regular accesses for prefetching

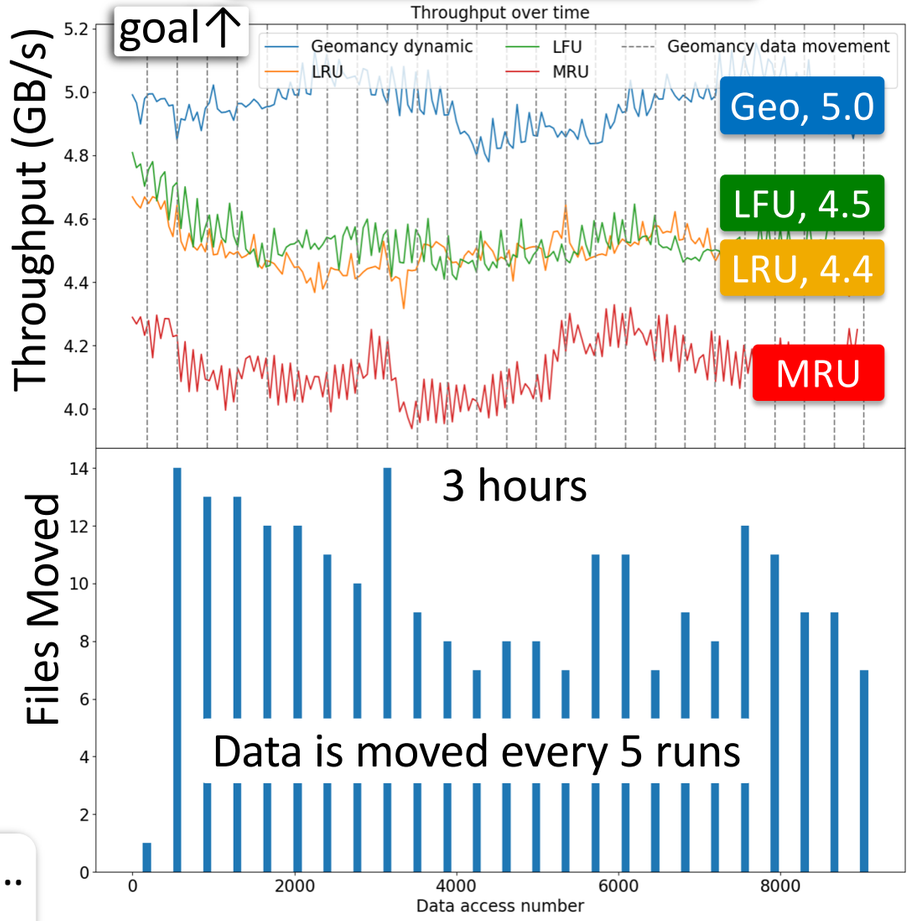
Geomancy: Adjust Data Layout To Improve Throughput

O. Bel, et al. “Geomancy: Automated Performance Enhancement through Data Layout Optimization” MSST ’20

- Data layout (storage) significantly affects performance
  - layout = map of files to storage system/devices
- Adjusting data layout can
  - tailor mapping for varying workloads
  - avoid congestion from other workloads
  - avoid failures (storage) & misconfigurations (nw link)
- Geomancy uses online learning:
  - monitor I/O activity and data layout
  - model performance (throughput)
  - predict performance during next window
  - select and realize new layout

Geomancy: 11% over LFU

Geomancy *v.* Heuristics



On Belle II MC, Geomancy learns:
- indicators of read contention
- RAID-5 has different read/write speeds

LFU: Least frequently used…
LRU: Least recently used…
MRU: Most recently used…
file to slowest

Adjusting layouts dynamically: more consistent and higher performance

Footprint Access Diagnostics Improve Distributed Graph Clustering

Kilic, Tallent, Friese. "Rapid memory footprint access diagnostics" ISPASS '20

PNNL

Analyze dynamic data locality.
Runtime overhead of 5-10%.

miniVite
(Intel SkyLake)

3 Hash Tables

0: unorder map
open hash tbl
(array + list)

1: hopscotch,
default size
closed hash tbl
(array)

2: hopscotch,
dynamic size
(vertex degree)

Call path →

Metrics:	time(usec)	fp-$\overline{pf}$	footprint	fp-$\overline{pf}$%	fpΔ	fpΔ-$\overline{pf}$
171: distLouvainMethod	4.83e+07	2.50e+09	1.59e+10		4.01e-01	6.30e-02
loop at dspl.hpp-v1: 1353			0		3.98e-01	6.29e-02
loop at dspl.hpp-v1: 1353			0		3.98e-01	6.29e-02
1353: distExecuteLouvainIteration			0	1.56e+01	3.97e-01	6.18e-02
331: distBuildLocalMapCounter			0	9.07e+00	3.99e-01	3.62e-02
loop at dspl.hpp-v1: 254	3.30e+07	9.69e+08	1.11e+10	8.78e+00	3.99e-01	3.50e-02
map.insert() 281: [I] std::pair<std::__deta	2.59e+07	1.20e+09	6.93e+09	1.74e+01	3.87e-01	6.73e-02
map.find() 276: [I] std::unordered_map	3.11e+06	4.28e+07	1.82e+09	2.39e+00	3.53e-01	8.42e-03
1353: distExecuteLouvainIteration	2.76e+07	3.23e			.47e-01	6.80e-02
331: distBuildLocalMapCounter	2.29e+07	2.35e			.79e-01	5.64e-02
loop at dspl.hpp-v1: 254	2.28e+07	2.28e+09	1.99e+10	1.14e+01	4.78e-01	5.47e-02
map.insert() 281: [I] tsl::hopscotch_map<	1.71e+07	6.84e+07	1.42e+10	4.82e-01	4.82e-01	2.32e-03
map.find() 276: [I] tsl::hopscotch_map<	2.02e+06	1.78e+08	1.95e+09	9.19e+00	4.07e-01	3.74e-02
331: distBuildLocalMapCounter	1.09e+07	1.86e+09	1.69e+10	1.10e+01	7.04e-01	7.77e-02
loop at dspl.hpp-v1: 254	1.09e+07	1.85e+09	1.69e+10	1.09e+01	7.05e-01	7.72e-02
map.insert() 281: [I] tsl::hopscotch_map	6.36e+06	3.79e+08	1.18e+10	3.23e+00	8.80e-01	2.84e-02
map.find() 276: [I] tsl::hopscotch_map	1.13e+06	4.66e+06	1.24e+09	3.76e-01	3.54e-01	1.33e-03

- Hot call path by time
- Solution: new hash table
- V0→V2: high fp, low fp-$\overline{pf}$%
- V1: extra copies!

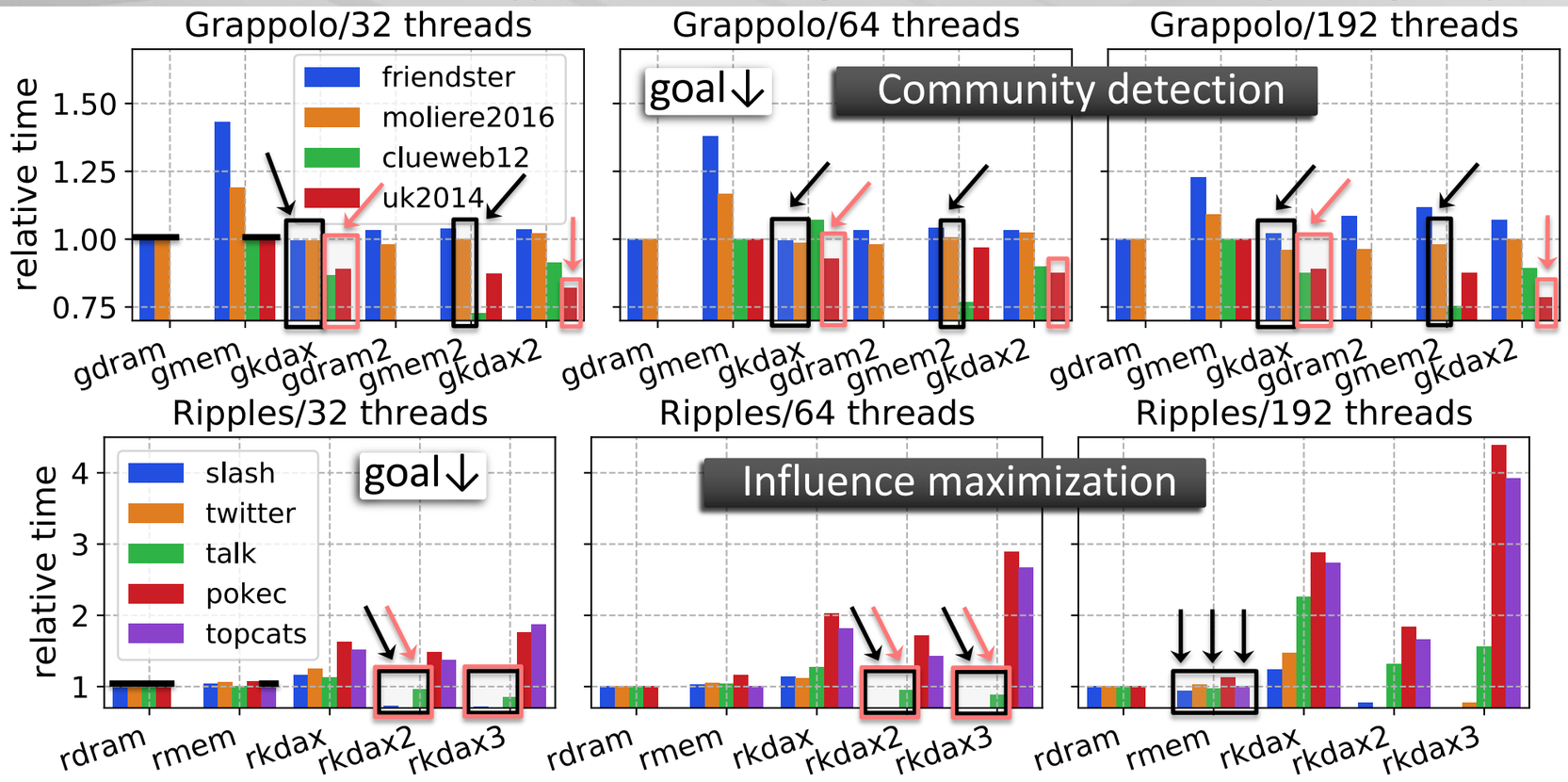
% footprint, irregular accesses

Reduce time by 67%
(26 s → 17 s → 6.4 s)

Single-Node Partitioned-Memory Graph Analytics (DRAM + Optane)

Ghosh, Tallent, Minutoli, Halappanavar, et al. “Single-Node Partitioned-Memory for Huge Graph Analytics: Cost & Performance...” SC ’21

PNNL



Apps: Different working set, partitioning, access patterns, synchronization.
Vary parallelism, variants, Optane modes.

AppDirect/Memory can equal DRAM...

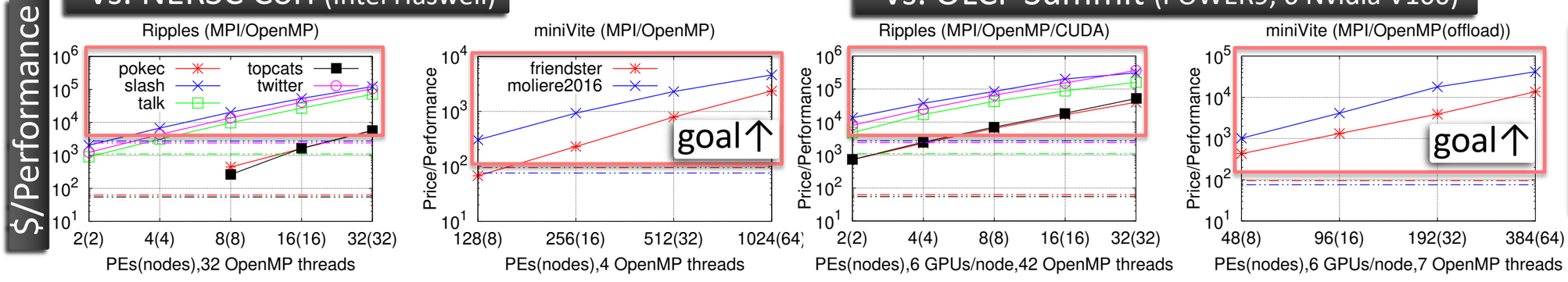
AppDirect can beat Memory...

...even with irregular access patterns, *if* most accesses are NUMA-local and Optane accesses are frequently reads

Memory v. AppDirect: L3 cache invalidations can change!
Fix with non-temporal hints.

Vs. NERSC Cori (Intel Haswell)

Vs. OLCF Summit (POWER9, 6 Nvidia V100)



Big-node often >4-10× vs. supercomputers
(Key: memory & comm for ghost vertices)