

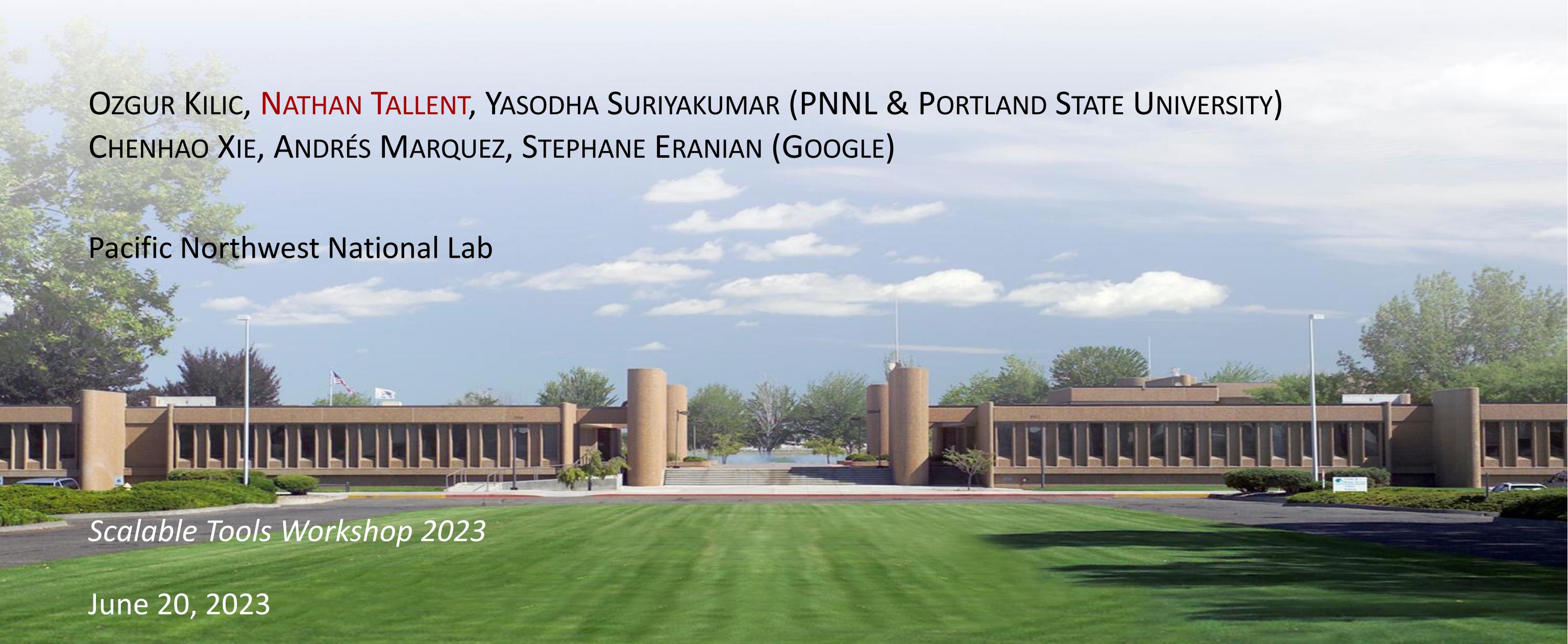


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MemGaze: Rapid and Effective Load-Level Memory Trace Analysis

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Scalable Tools Workshop 2023

June 20, 2023

MemGaze: low-overhead, high-resolution memory trace analysis

O. Kilic et al. "MemGaze: Rapid and effective load-level memory and data analysis" CLUSTER '22



▪ MemGaze: low-overhead, high-resolution, access sequences

- Uses Processor Tracing to collect sampled, compressed memory address traces

- Supported on x86 and ARM

- Focus: x86 ptwrite

- Emerging x86 support

- Server: from Sapphire Rapids
 - Desktop: from Alder Lake; Atom

- Multi-resolution analysis for

- accesses vs. memory locations

- reuse (distance, rate, volume) vs. access patterns

- spatio-temporal correlations for time vs. location

- Both trace size and trace resolution are controllable

Space savings:
1% of full trace

Accuracy:
Within 25% for sequences;
5% for hotspots

Optional: Code hotspot (PT guards)

1. Instrument
(ptwrite)

2. Lightweight
memory
tracing

3. Memory & data analysis:

- Data reuse v. movement
- Reuse locations v. distances
- Temporal & spatial locality
- Patterns: regular, irregular

Time overhead, good
implementation:
10–35%

Highlights of Processor Tracing



- Control flow packets
- Per-core state/buffer
- Write arbitrary packet (64-bits)
- Mask instructions/packets on/off in hardware
 - Enables sampling
- New: Cycle-Accurate Mode
 - Cycle accurate timing
- New: Power events
 - P-states and C-states

Binary instrumentation and Trace compression



- Ensure all instrumentation can be masked by hardware

- single inline instruction
 - no change of CPU state (e.g., no spilling)

- Static analysis to classify loads

- Classification:
 - constant: e.g., stack frame, static data
 - strided: affine
 - irregular: not strided or constant
 - Benefit 1: Compression
 - Indirectly capture Constant loads (often uninteresting) with ptwrite proxy
 - Average of 1.2x (O3) and 2x (O0) space savings
 - For correctness, ensure basic block has at one ptwrite proxy

basic block	for (i = 0; i < N; i+=2) // a[idx[i]] load N load a load idx[i] load a[idx[i]]	trace annotation
	class	Constant
	Constant	{ }
	Strided	{strided, 2}
	Irregular	{irregular}

ptwrite s1
ptwrite s2
load d $\leftarrow [s] + o$
load d $\leftarrow [s1] + k [s2] + o$

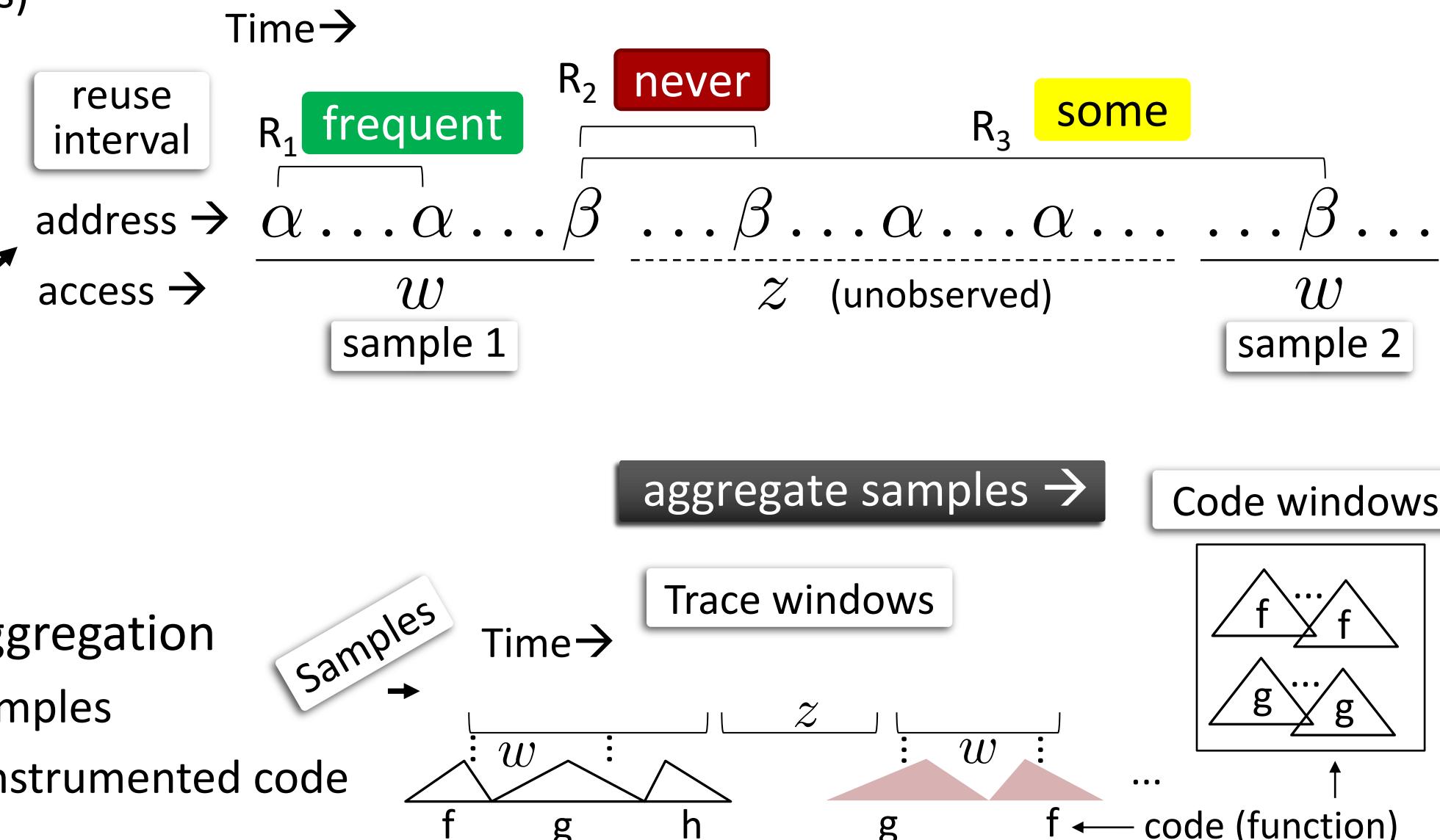
- Benefit 2: Rapid trace analysis

- Load classes → automatic access patterns, reduces time and overhead of subsequent analysis

Sampled memory traces with Processor Tracing



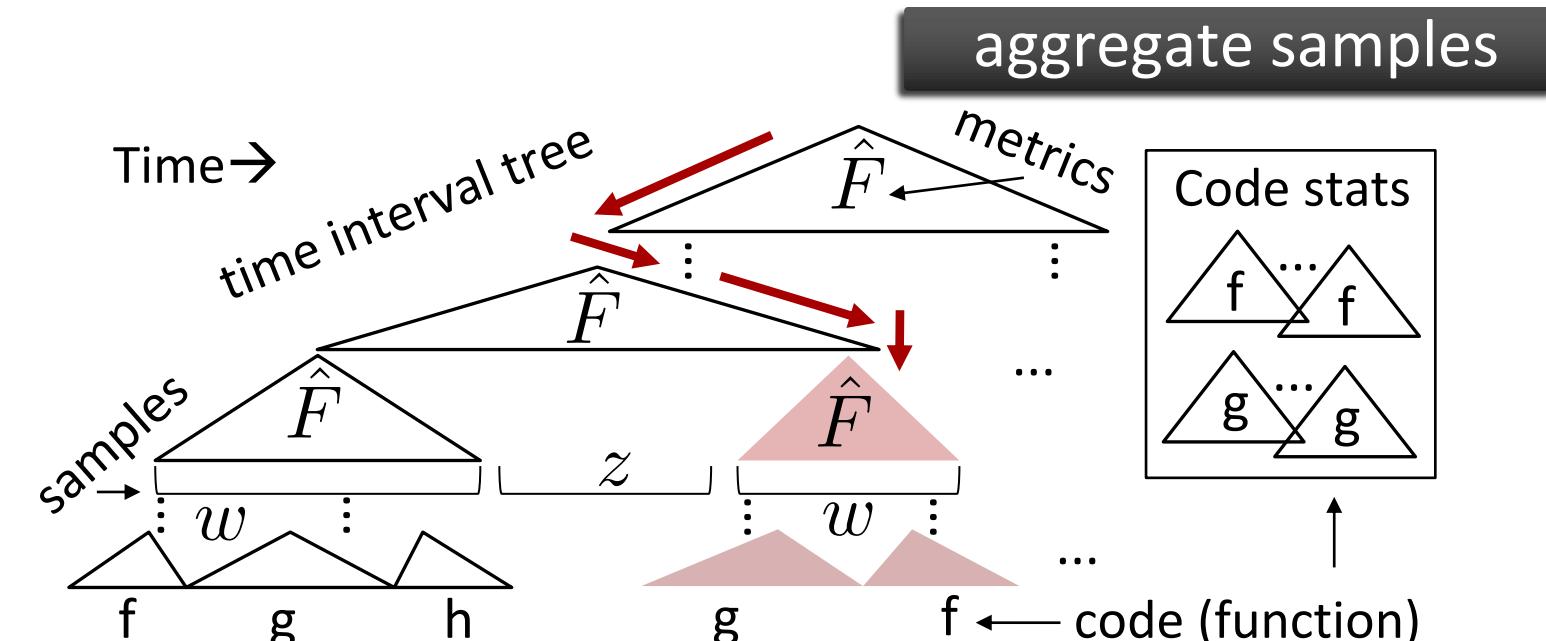
- Processor Tracing cannot collect exhaustive traces
 - Unpredictable data drops when buffers fill (e.g., kernel to user)
 - Unmanageably large, $O(\text{GB}/\text{s})$
- Sampled trace: sequence of w seen & z unseen accesses
 - Control buffer size and period between samples
- Question: Blind spots?
 - R1 *frequently* observed
 - R2 *never* observed
 - R3 *sometimes* observed
- Reduce error with sample aggregation
 - Code windows aggregate samples
 - Source code attribution of instrumented code



Analyzing memory operations over time



- Top-down analysis with tree structure
 - root: entire execution
 - interior: decreasing time intervals
 - leaves: samples
- Guidance with data locality metrics
- Code structure within sample
 - support line mapping for PT instrumentation



DarkNet (CNN) Inference (gemm): Data locality over time, hot access intervals

Access Interval	AlexNet			ResNet152			Δ
	F	footprint rate	\mathcal{A}	reuse distance	\mathcal{A}		
0	28M	0.475	0.01	30K	639M	0.747	0.47
1	55M	0.675	0.02	30K	772M	0.799	0.57
2	89M	0.983	0.02	25K	640M	0.617	2.71
3	64M	0.794	0.14	26K	620M	0.599	2.62
4	39M	0.489	1.64	29K	591M	0.574	2.69
5	55M	0.627	1.66	26K	638M	0.618	2.65
6	41M	0.493	1.66	29K	648M	0.625	2.63
7	38M	0.644	1.49	17K	549M	0.514	2.66

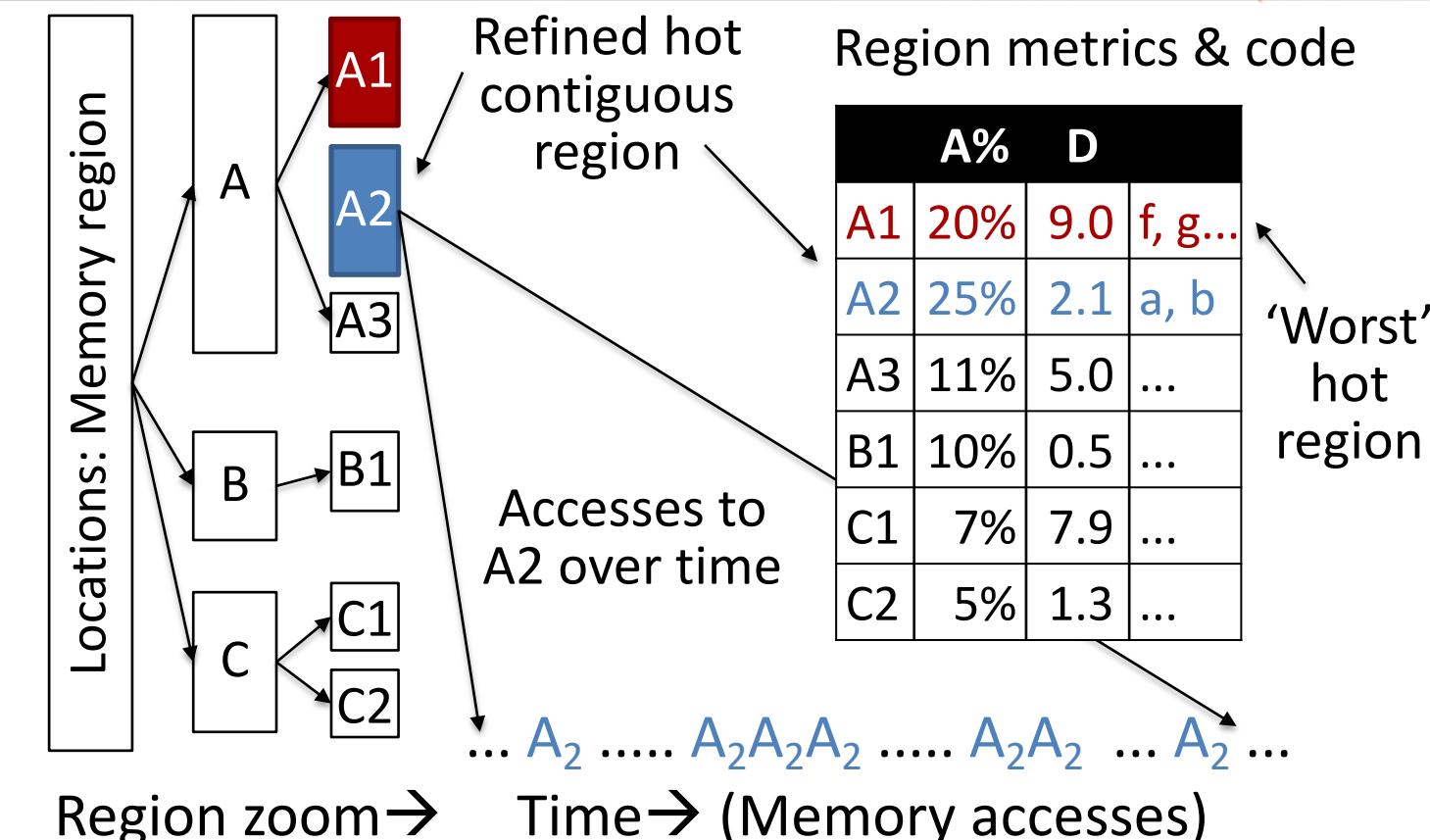
- AlexNet: ΔF changes with layer (conv., fully, pooling) vs. ResNet's consistency
- ResNet: $\Delta F \approx$ decreases: matrix dims change (N , decreases; K , small increase)
- $D \approx$ increases time: matrix dim N decreases with higher level CNN filters

Analyzing memory *locations* over time



- Top-down analysis with tree structure
 - root: all memory locations
 - leaves: refined, hot contiguous regions
- Guidance with data locality metrics
 - Spatio-temporal analysis
- Associate region with code and object

Darknet: Spatio-temporal reuse of hot memory (64 B)



Region zoom →

Time → (Memory accesses)

Object	Model	Reuse distance	# blocks	A	A / block
		Reuse (D)			
gemm's A,B,C	AlexNet	0.76	66048	977K	14.8
gemm's B	ResNet152	0.01		598K	15.6
hot region in im2_col	AlexNet	1.87	8192	167K	20.4
	ResNet152	2.54		7K	1.9

gemm matrices → hottest data

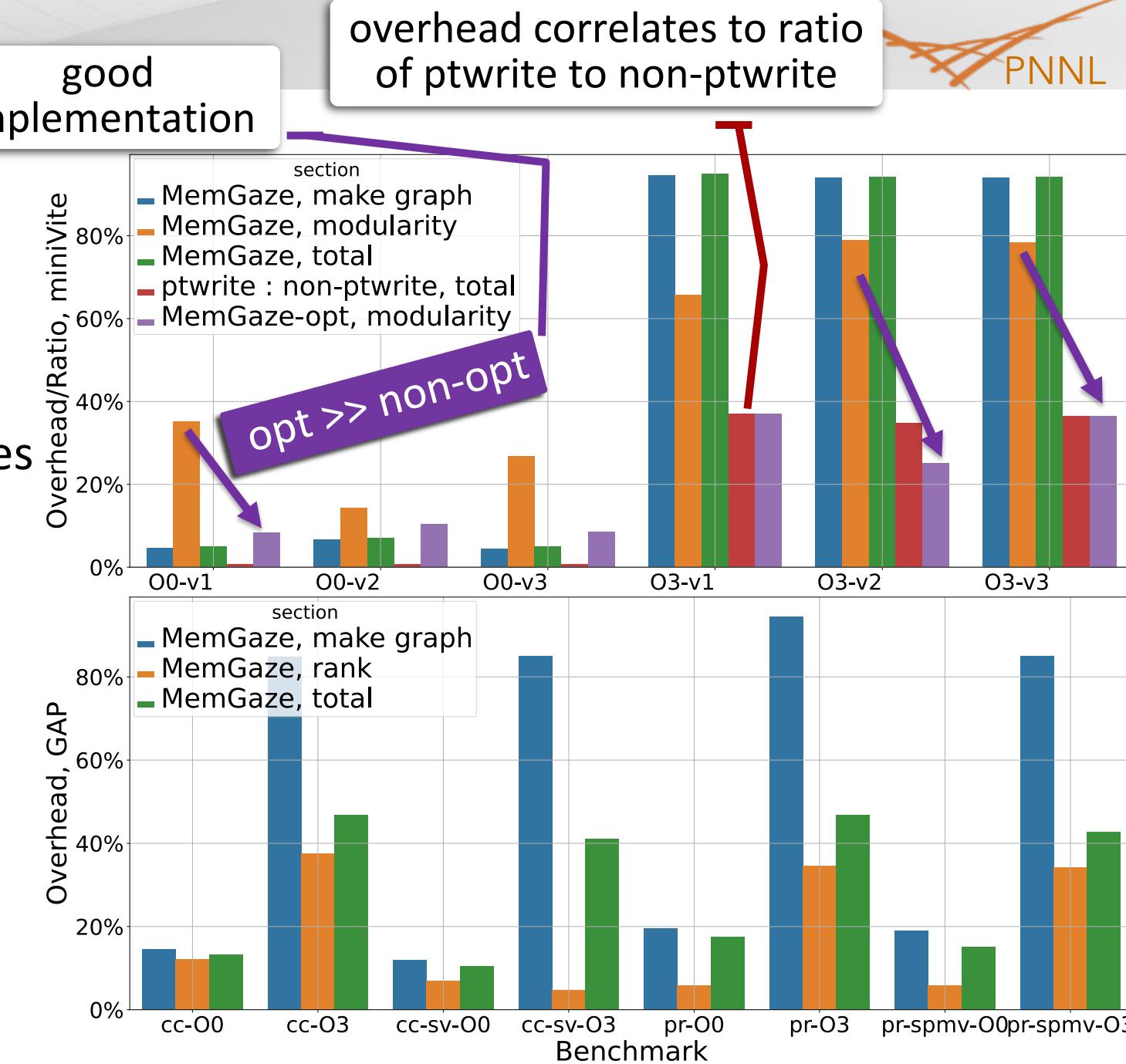
Reuse distance depends on data & neural network

Time overhead for tracing

- Overhead proportional to ptwrites
 - depends on code generation, application/phase
- MemGaze: 5-7x, 10-95%
 - suboptimal implementation (current)
 - PT runs *continuously*; retains data during samples
- MemGaze-opt: 7x → <10%, 80% → 35%
 - PT enabled only during sample
 - user space implementation (proof-of-concept)
- Times for instrumentation & post-mortem analysis in paper
 - suboptimal implementations
 - reasonable times b/c of reduced trace size

For a good implementation (PT only during samples), overhead is 10-35% on memory intensive regions

Early eval
(Atom)



Space reduction for traces



- Full trace – not exhaustive due to drops!

- Rec: recorded, with throttling and drops
- All: adjusted with drop information
- All⁺: full size (includes ‘Constant’ loads)

- MemGaze trace: $\approx 1\%$ of full (All⁺ vs All)

- sampled and compressed

- Trace compression saves...

- High compiler opt (O3): 1.2 \times
- No compiler opt (O0): 2 \times

MemGaze trace is $\approx 1\%$ of full

Benchmark	Full (GB)			(MB)	Ratio (%)		
	Rec	All	All ⁺		Rec	All	All ⁺
all μ bench-O0 (1 \times)	1.9	1.9	3.5	63	3.3	3.3	1.8
all μ bench-O3 (1 \times)	1.9	1.9	1.91	20	1.1	1.1	1
all μ bench-O3	112	112	113	865	0.8	0.8	0.7
miniVite-O0-v1	77	163	316.5	1620	2.1	0.9	0.5
miniVite-O0-v2	71	198	387.9	1697	2.4	0.9	0.4
miniVite-O0-v3	79	150	292.7	1660	2.1	1.1	0.6
miniVite-O3-v1	19	41	41.1	310	1.6	0.8	0.7
miniVite-O3-v2	22	43	54.9	310	1.4	0.7	0.6
miniVite-O3-v3	13	23	29.4	341	2.6	1.5	1.1
GAP-cc-O0	2.3	3.4	6.6	355	15.4	10.4	5.3
GAP-cc-O3	4.9	7.9	9.5	31	0.6	0.4	0.3
GAP-cc-sv-O0	4.4	6.4	12.5	377	8.6	5.9	3
GAP-cc-sv-O3	6.7	10.8	13	35	0.5	0.3	0.3
GAP-pr-O0	5.1	7.5	14.6	377	7.4	5.0	2.5
GAP-pr-O3	5.4	7.9	9.5	35	0.7	0.4	0.4
GAP-pr-spmv-O0	6.3	8.9	17.4	385	6.1	4.3	2.2
GAP-pr-spmv-O3	6.5	10.1	12.1	36	0.6	0.4	0.3
Darknet-AlexNet	4.6	11.2	16.9	71	1.6	0.6	0.4
Darknet-ResNet	29	59	66	748	2.6	1.3	1.2

Validation of data locality metrics

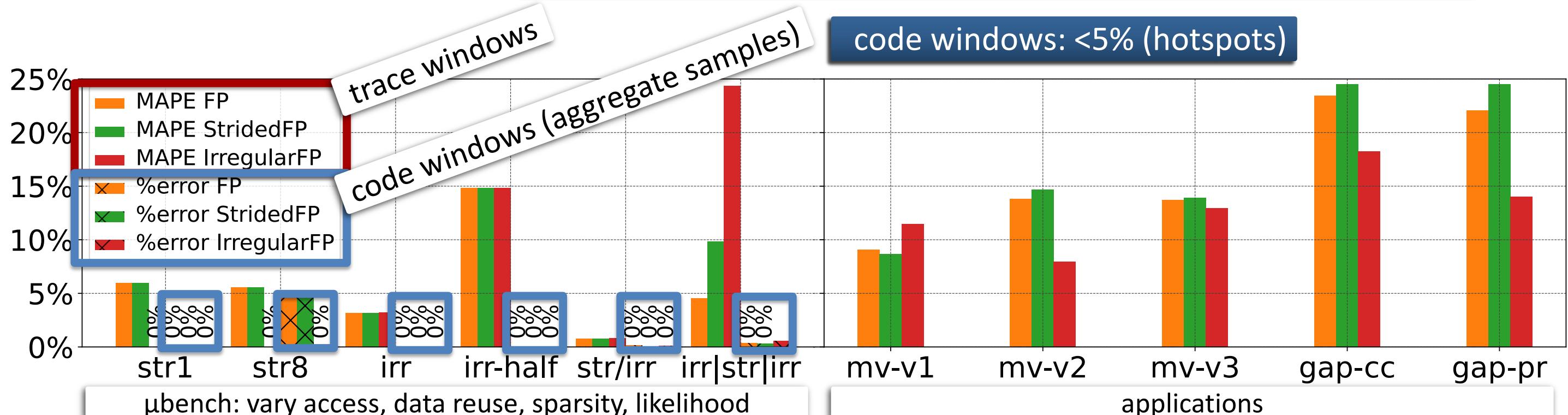
- Compare against full traces for microbenchmarks and applications
 - μ bench: no drops by inserting OS sleep after each load
 - apps: 10 \times more samples (full not feasible due to space)

▪ Trace and Code windows

For sampled, compressed trace (\approx 1% of full)...

- Trace: mean absolute % error (MAPE) for histograms of trace windows: 1-25%
- Code: % error: <5%

trace windows: 1-25% MAPE (varying dynamic sequence lengths)



Case studies (Details in paper)



- Graph clustering (Louvain Community Detection, miniVite): vary data structures
 - Vary hash table implementations, “open” (array + lists) vs. “closed” (array)
 - Vary compiler optimization levels
- Deep N. Net Inference (DarkNet): vary models
 - AlexNet vs. ResNet
- Graph analytics (GAP): vary algorithms
 - PageRank: Gauss-Seidel vs. Jacobi-style
 - Connected Component:
Afforest vs. Shiloach-Vishkin
- Observations:
 - Need time-based & location-based analysis
 - Need complementary metrics and views

All use OpenMP threading

Several analyses w.r.t. time and location

access...	Symbol	Analysis
hotness	A	Accesses (memory)
distance	D	Spatio-temporal block reuse distance
volume	F	Footprint
	$F_{\text{str}}, F_{\text{irr}}$	Footprint with strided/irregular access
	$F_{\text{str}\%}, F_{\text{irr}\%}$	Fraction of strided/irregular footprint
	$A_{\text{const}\%}$	Fraction of accesses to ‘constant’ data
pattern	ΔF	Footprint growth rate; footprint per access
rate	$\Delta F_{\text{str}\%}, \Delta F_{\text{irr}\%}$	Fraction of strided/irregular footprint growth

Graph Clustering (miniVite): Vary hash table implementations

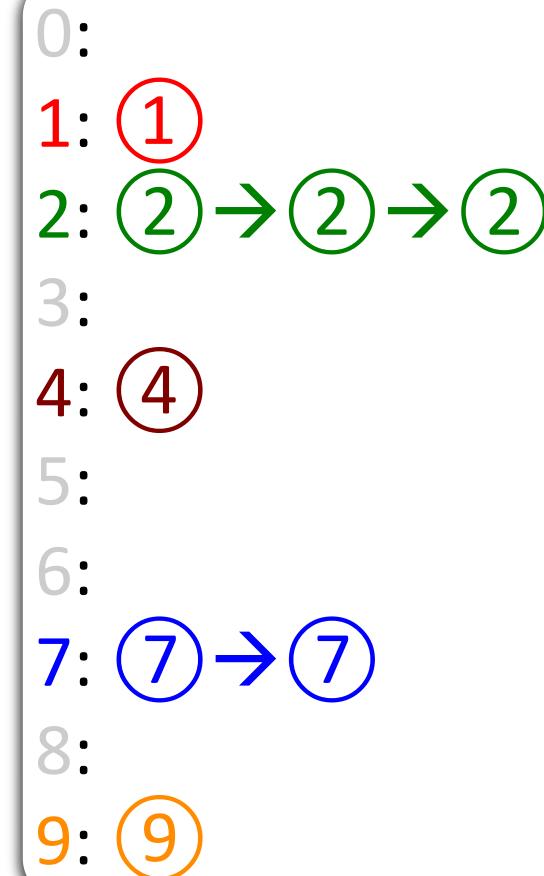


V1: C++ map
(unordered)

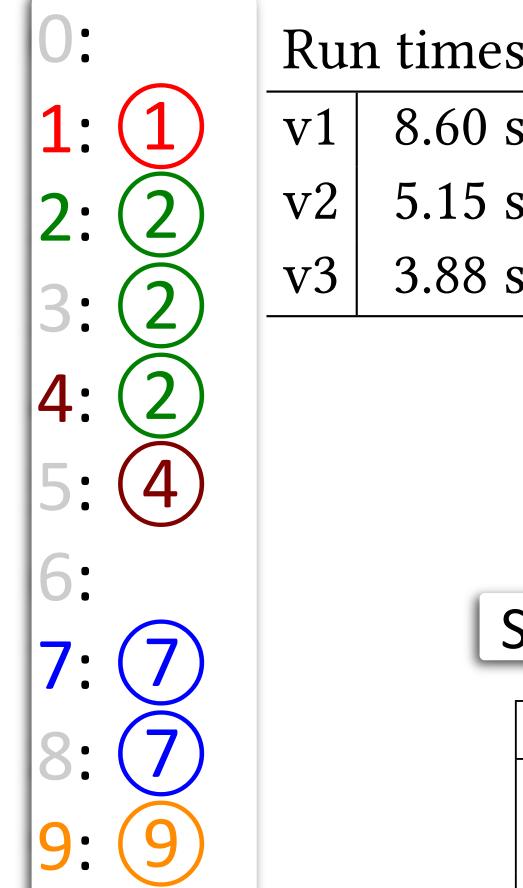
V2: hopscotch
default size

V3: hopscotch
'right' size
(vertex degree)

Open (C++ map)



Closed
(Hopscotch)



Data locality of hot function accesses

Function	Variant	F	ΔF	$F_{str\%}$	\mathcal{A}
buildMap (make <i>map</i>)	v1	2.3G	0.156	66.4	291K
	v2	2.1G	0.151	66.9	273K
	v3	2.1G	0.160	66.8	270K
<i>map.insert</i>	v1	>0.7G	0.011	73.3	106K
	v2	2.4G	0.003	93.7	318K
	v3	0.5G	0.009	92.8	67.8K
getMax (use <i>map</i>)	v1	0.4G	0.150	0.5	44.7K
	v2	1.3G	0.040	98.4	182K
	v3	1.5G	0.040	97.8	194K

better pattern

hopscotch must manage size!

Location analysis clearer than time

Spatio-temporal reuse, hot memory (64 B block)

Object	Variant	Reuse (D)	# blocks	A	A / block
<i>map</i> (hash table)	v1	2.65	768	55K	71.9
	v2	2.79	768	119K	155.2
	v3	1.97	768	85K	111.3
remote edges of local vertices	v1	8.71	4864	24K	4.9
	v2	4.90	4864	19K	3.9
	v3	3.32	4864	19K	3.9
other objs in <i>buildMap</i> (from caller)	v1	0.37	104K	19235	0.2
	v2	0.15	101K	21362	0.2
	v3	0.24	110K	22306	0.2

Sparse structures → smaller footprint, more irregular

Dense structures → larger footprint, more regular, but...

GAP PageRank and Connect Components (CC): Vary algorithms



Spatio-temporal reuse of hot memory (64 B block)

Heatmaps!

Distribution of spatio-temporal metrics

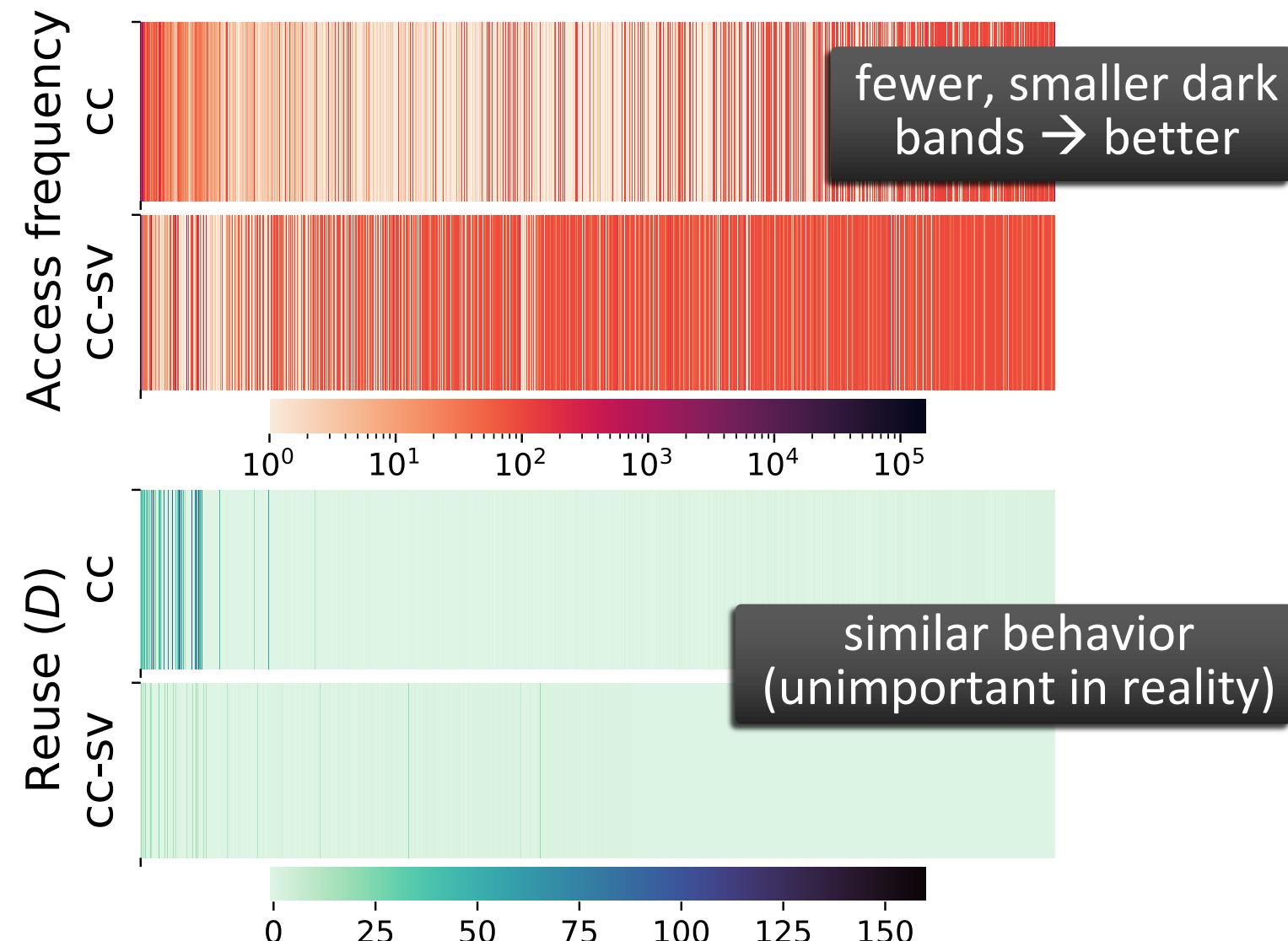
Object	Algorithm	Accesses			Time
		Avg	Max	A	
<i>o-score</i>	pr	1.13	152	64K	0.76 57.2 s
<i>o-score</i>	pr-spmv	2.41	132	82K	1.14 80.1 s
cc	cc	5.21	154	581K	8.87 2.7 s
cc	cc-sv	0.83	36	476K	8.65 45.5 s

For PageRank, spatio-temporal shows difference

- pr (optimized) vs. pr-spmv
 - pr updates o-score ‘now’ vs. next iteration
- Reuse and ΔF (not shown) are better
- Accesses are better → fewer iterations

For CC, averages are misleading → heatmaps

- cc (optimized) vs. cc-sv
 - cc → more accesses; can improve locality
- Metrics (D , ΔF , $F_{\text{irr}\%}$) for cc are worse...



Need many angles & many resolutions!

Conclusions



- Processor Tracing effective for low-overhead, high-resolution memory analysis
 - accesses (operations) vs. memory locations
 - accesses vs. spatio-temporal reuse
 - reuse (distance, rate, volume) vs. access patterns
- Sampled traces are 1% of full ones → MB vs. GB-TB
- With a straightforward optimization, time overhead is 10-35% vs. 100× or more
 - PT generalizes much performance and state telemetry (without interrupts)
- Analyses explain effects of...
 - different data structures, algorithms, and data sets
 - different access patterns (strided, irregular), that both have ‘good’ spatio-temporal locality
- Future work: hardware/software co-design, automated diagnostics, ...

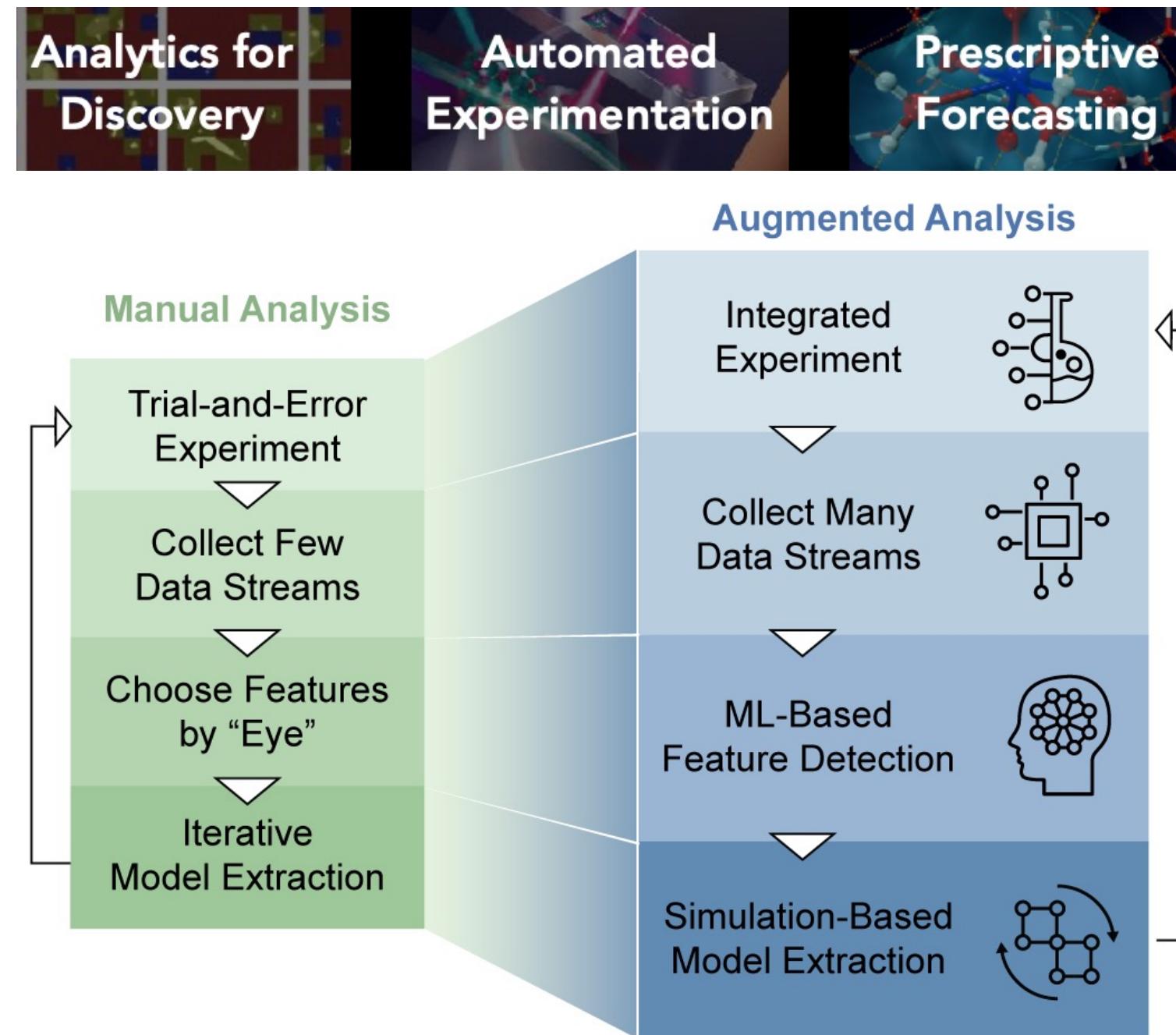
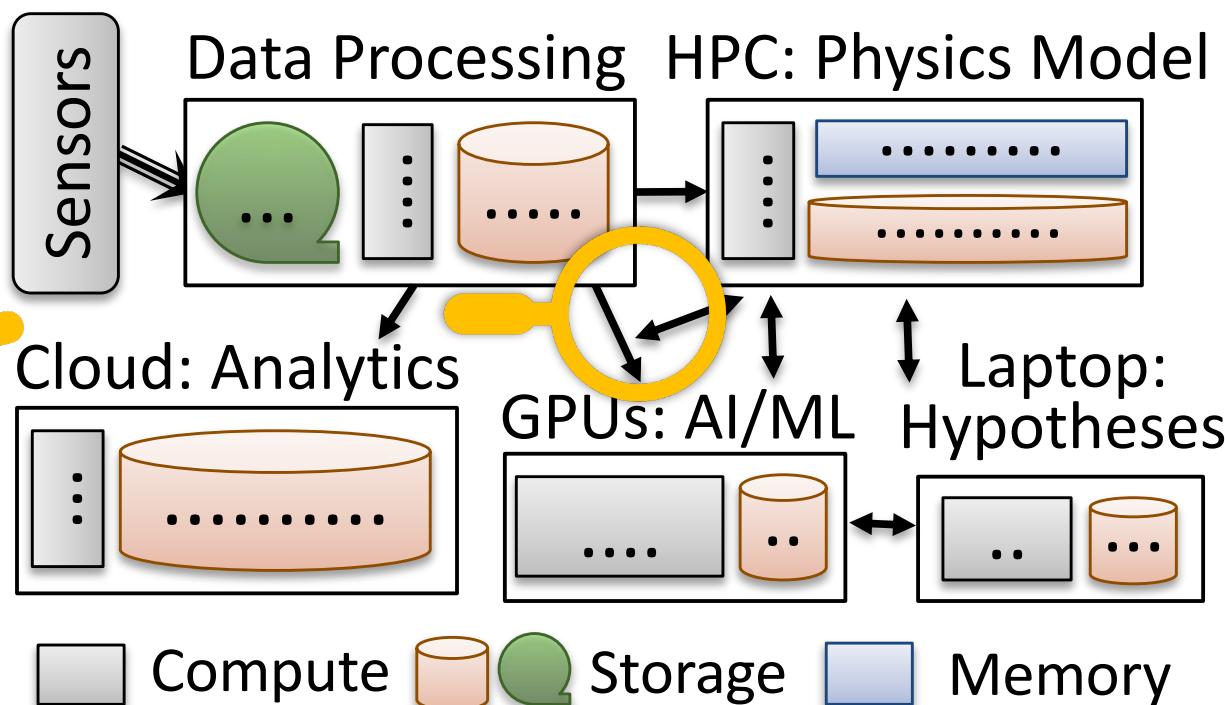
github.com/pnnl/memgaze

Opportunities: Job, intern, and collaboration

Scientific exploration is increasingly distributed & data-intensive



- Domain science uses *workflows*:
 - Loose composition of different apps/tasks
 - motivated by productivity
 - Potentially different programming models
 - Data sources are distributed
 - Intensive use of memory, storage, networks
 - storage the means for task composition



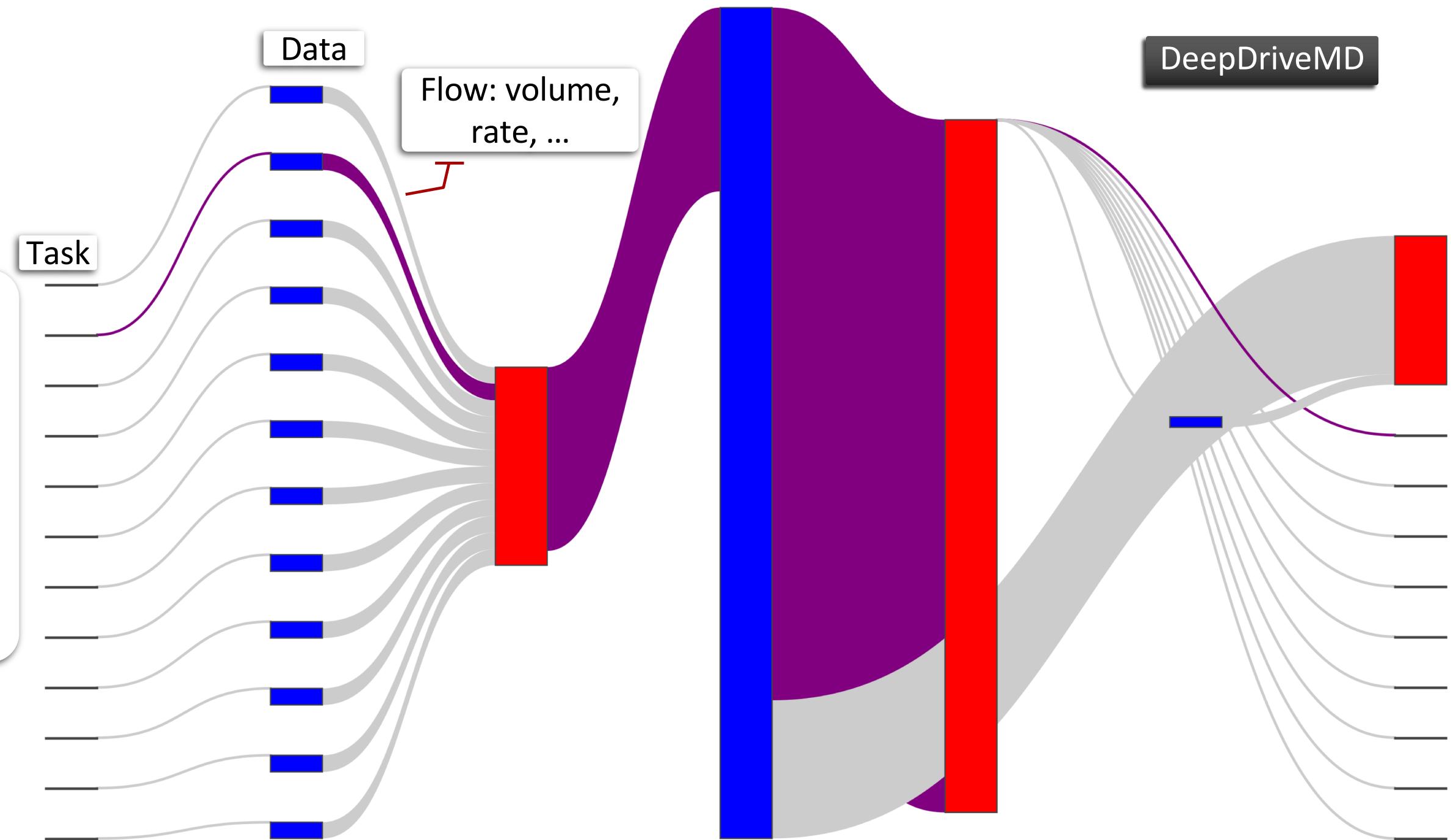
Data Flow Lifecycles: Runtime data & flow lifecycles



Flow: left → right

Data Task

- Sankey diagrams: represent *flow*
- Vertices: Data & Task
- Flow: Edges
- Vertices and edges associated with many dynamic properties (affects rendering)



Data Flow Lifecycles: Runtime data & flow lifecycles



Flow: left→right

Data Task

- Entities & Patterns (many more)
- Opportunity analysis... (not shown)

