



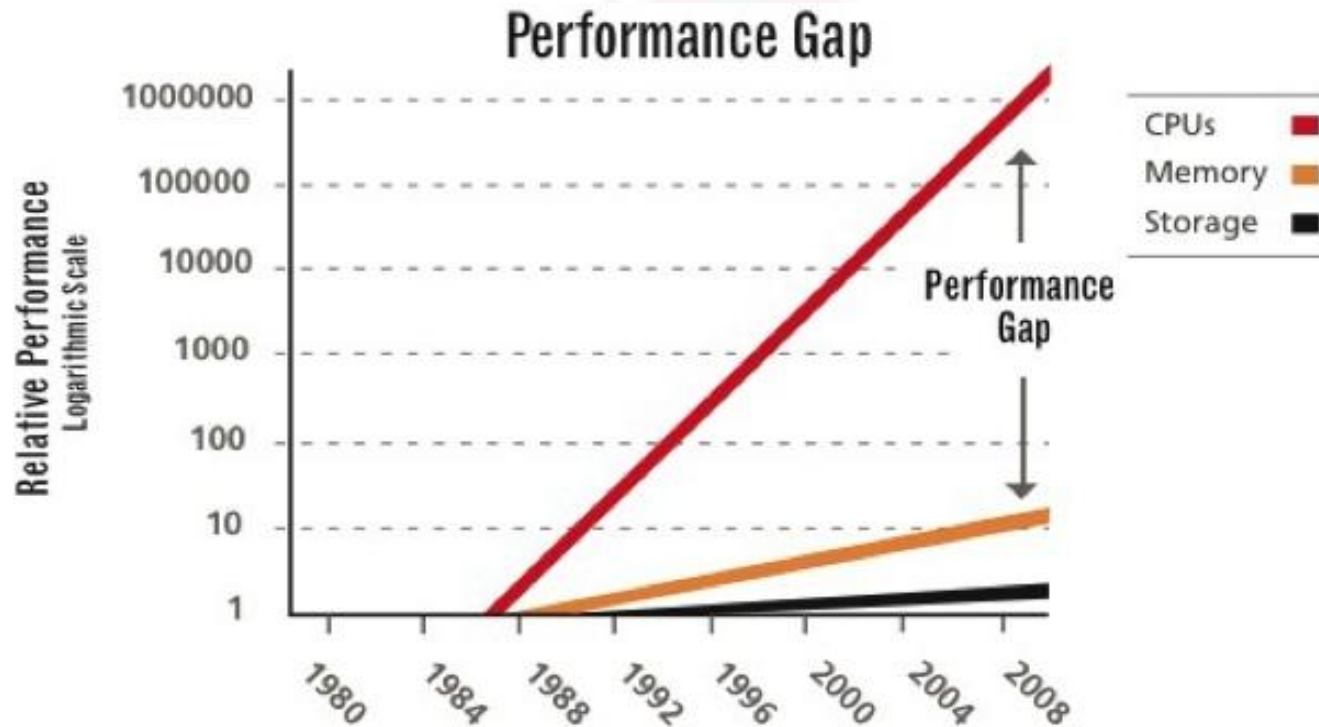
In-Situ Bitmaps Generation and Efficient Data Analysis based on Bitmaps

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Motivation – HPC Trends

- Huge performance gap
 - ✓ CPU: extremely fast for generating data
 - ✓ Disk, Network: very slow to store or transfer data
 - ✓ Memory: not large enough to hold data





In-Situ Analysis – What and Why

- **Process of transforming data at run time**
 - Analysis
 - Classification
 - Reduction
 - Visualization
- In-Situ has the promise of
 - Saving more information dense data
 - Saving I/O or network transfer time
 - Saving disk space
 - Saving time in analysis



Key Questions

- **How do we decide what data to save?**
 - This analysis cannot take too much time/memory
 - Simulations already consume most available memory
 - Scientists cannot accept much slowdown for analytics
- **How insights can be obtained in-situ?**
 - Must be memory and time efficient
- **What representation to use for data stored in disks?**
 - Effective analysis/visualization
 - Disk/Network Efficient



Quick Answers

- How do we decide what data to save?
 - Use Bitmaps!
- How insights can be obtained in-situ?
 - Use Bitmaps!!
- What representation to use for data stored on disks?
 - Bitmaps!!!



Specific Issues

- Bitmaps as data summarization
 - Utilize extra computer power for data reduction
 - Save memory usage, disk I/O and network transfer time
- In-Situ Data Reduction
 - In-Situ generate bitmaps
 - ✓ Bitmaps generation is time-consuming
 - ✓ Bitmaps before compression has big memory cost
- In-Situ Data Analysis
 - Time steps selection
 - ✓ Can bitmaps support time step selection?
 - ✓ Efficiency of time step selection using bitmaps
- Offline Analysis:
 - Only keep bitmaps instead of data
 - Types of analysis supported by bitmaps



Background: Bitmaps

- Widely used in scientific data management

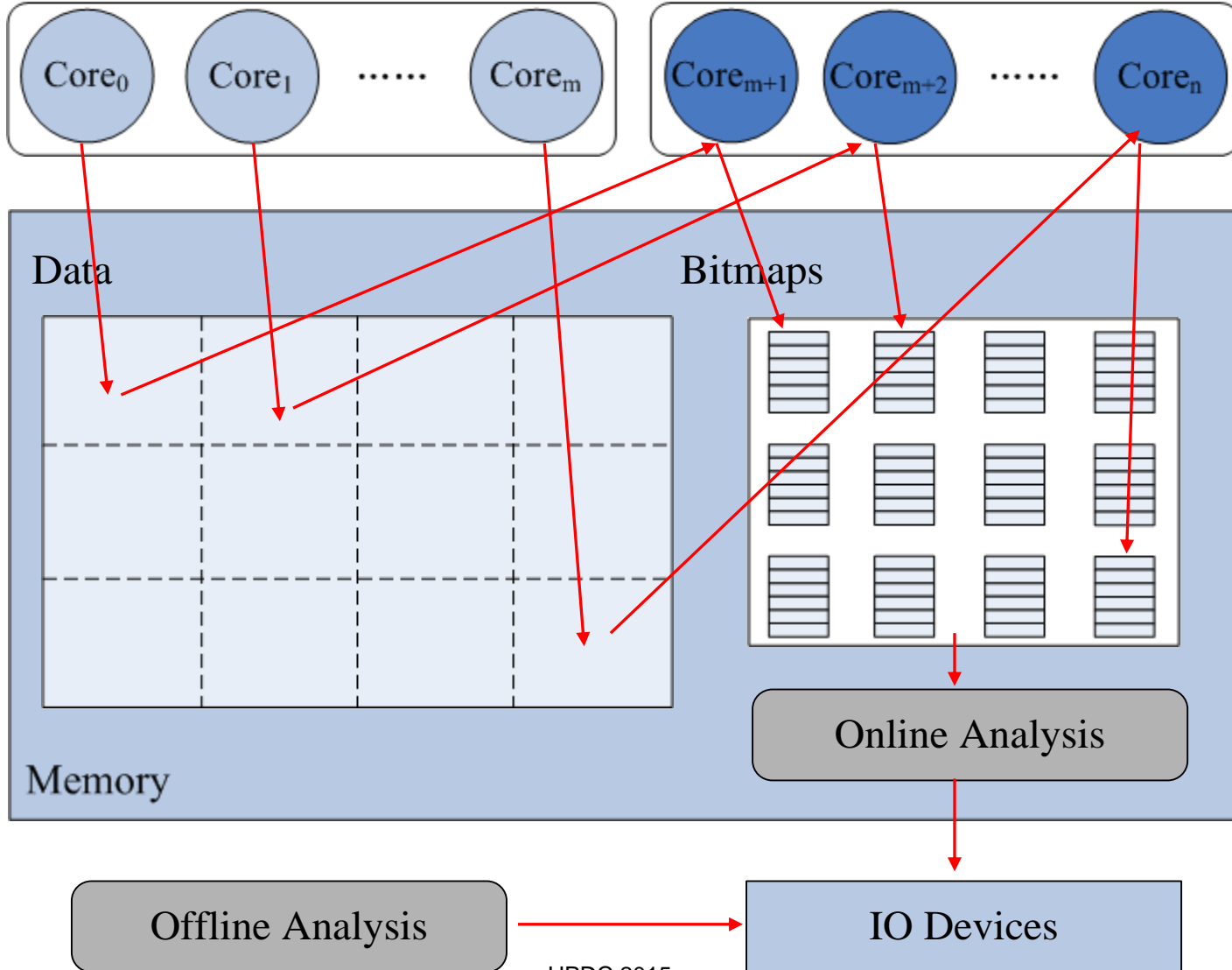
ID	Dimension		Value	v0	v1	v0	v1	v2	v3
	D0	D1		[1, 2]	[3, 4]	= 1	= 2	= 3	= 4
0	0	0	4	0	1	0	0	0	1
1	0	1	1	1	0	1	0	0	0
2	0	2	2	1	0	0	1	0	0
3	0	3	2	1	0	0	1	0	0
4	1	0	3	0	1	0	0	1	0
5	1	1	4	0	1	0	0	0	1
6	1	2	3	0	1	0	0	1	0
7	1	3	1	1	0	1	0	0	0
Dataset				1st Level Indices		2nd Level Indices			

- Suitable for floating value by binning small ranges
- Run Length Compression (WAH, BBC)
- Bitmaps can be treated as a small profile of the data



In-Situ Bitmaps Generation

Core Allocation Strategy



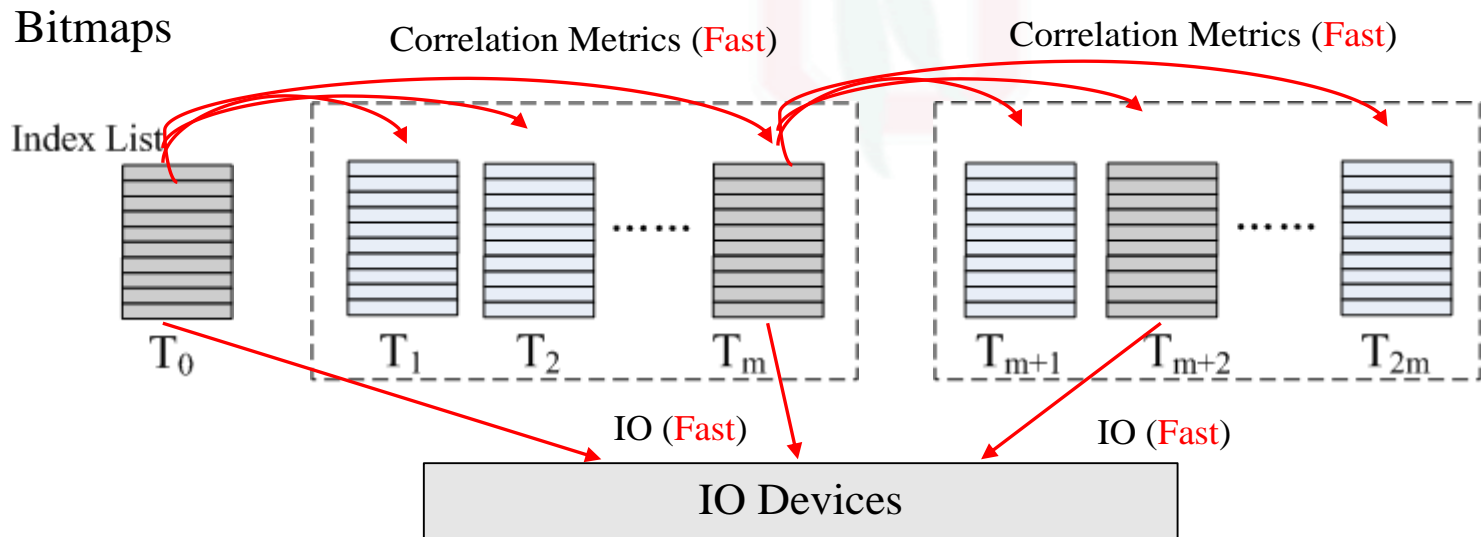
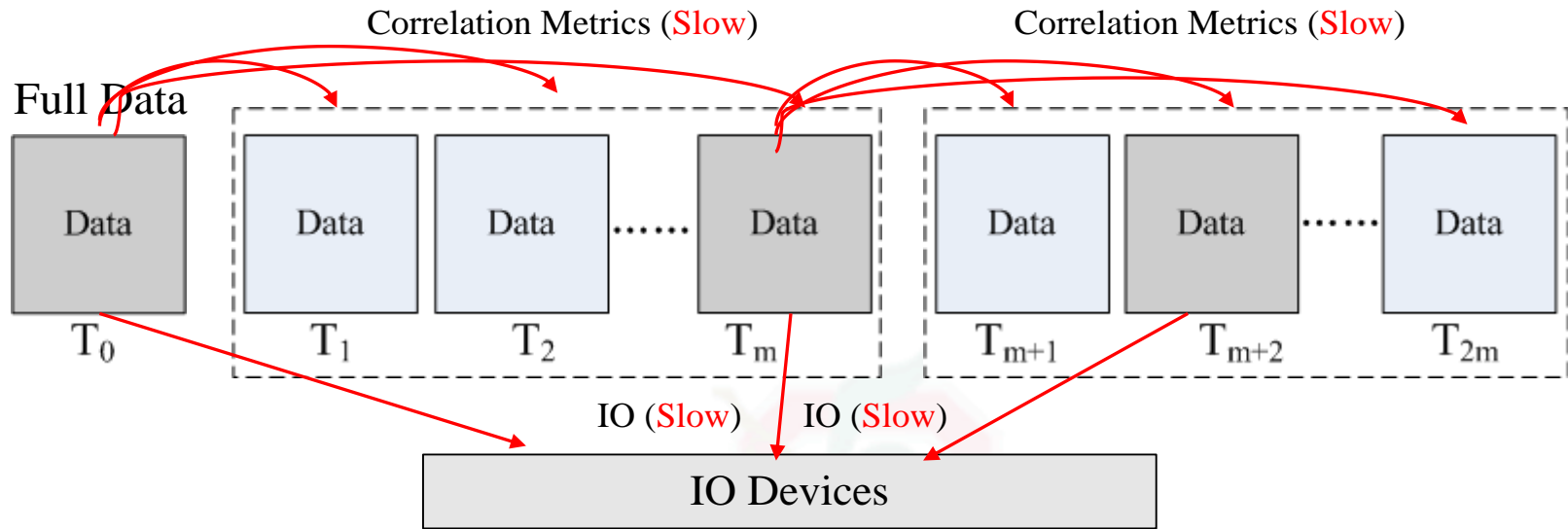


In-Situ Bitmaps Generation

- Parallel index generation
 - Save the data loading cost
 - Multi-Core based index generation
- Core allocation strategies
 - Shared Cores
 - ✓ Allocate all cores to simulation and bitmaps generation
 - ✓ Executed in sequence
 - Separate Cores
 - ✓ Allocate different core sets to simulation and bitmaps generation
 - ✓ A data queue is shared between simulation and bitmaps generation
 - ✓ Executed in parallel
- In-place bitvector compression
 - Scan data by segments
 - Merge segment into compressed bitvectors



Time-Steps Selection





Correlation Metrics

- **Earth Mover's Distance:**
 - Indicate distance between two probability distributions over a region
 - Cost of changing value distributions of data
- ***Shannon's Entropy:***
 - A metric to show the variability of the dataset
 - High entropy => more random distributed data
- **Mutual Information:**
 - A metric for computing the dependence between two variables
 - Low M => two variables are relatively independent
- **Conditional Entropy:**
 - Self-contained information
 - Information with respect to others



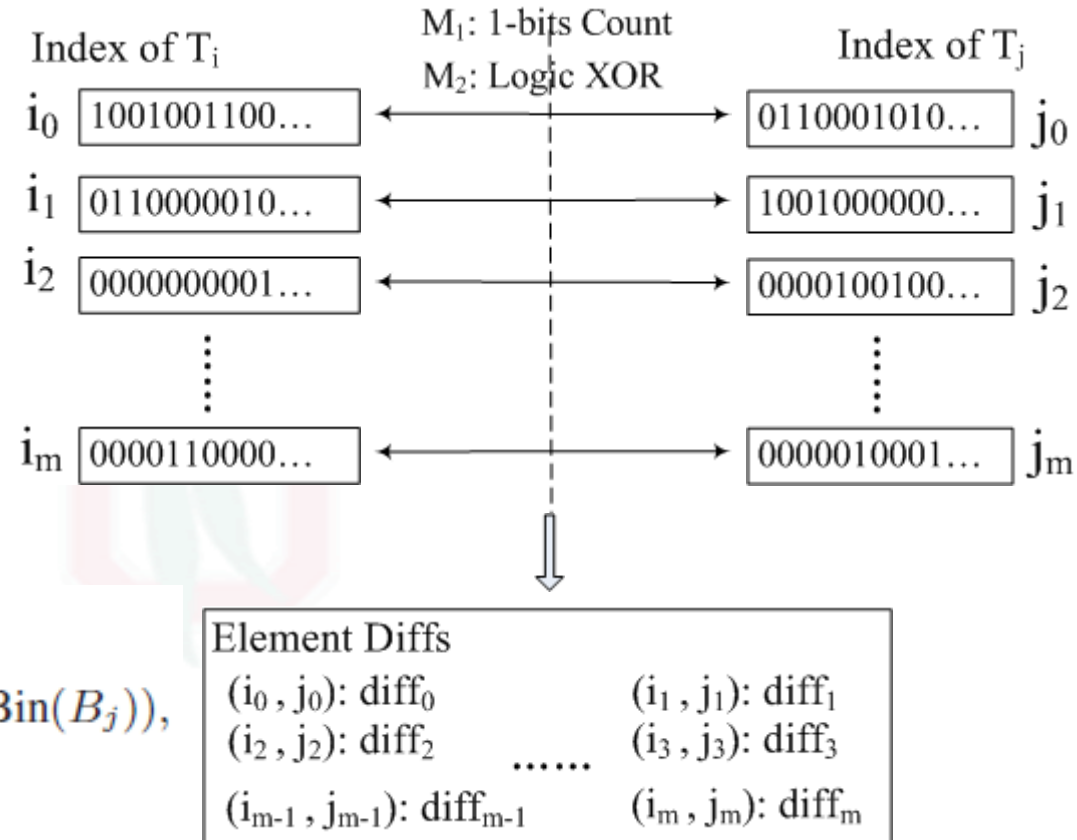
Calculate Earth Mover's Distance Using Bitmaps

- Divide T_i and T_j into bins over value subsets
- Generate a CFP based on value differences between bins of T_i and T_j
- Accumulate results

$$EMD = \sum_{j=1}^N CFP(j),$$

$$CFP(j) = CFP(j - 1) + Diff(\text{Bin}(A_j), \text{Bin}(B_j)),$$

$$CFP(0) = 0.$$





Correlation Mining Using Bitmaps

- Correlation mining
 - Automatically suggest data subsets with high correlations
 - Correlation Analysis: keep submitting queries
 - Traditional Method
 - ✓ Exhaustive calculation over data subsets (spatial and value)
 - ✓ Huge time and memory cost
- Correlation mining using bitmap
 - Mutual Information
 - ✓ Calculated by probability distribution (value subsets)
 - A top-down method for value subsets
 - ✓ Multi-level bitmap indexing
 - ✓ Go to low-level index only if high-level has high mutual info
 - A bottom-up method for spatial subsets
 - ✓ Divide bitvectors (with high correlations) into basic strides
 - ✓ Perform 1-bits count operation over strides



Correlation Mining

Bitvectors of Variable A

a_0 1111011100..... 0001111000
 a_1 0000000010..... 0010000000
 a_2 0000000001..... 0000000001

 a_i 0000100000..... 1100000110

Logic AND

Bitvectors of Variable B

b_0 0011001100..... 0001100000
 b_1 1100010000..... 0000011001
 b_2 0000100001..... 0000000000

 b_j 0000000000..... 1100000110

Joint Bitvectors

a_0b_0	0011001100..... 0001100000	Minfo > 0.001
a_0b_1	1100010000..... 0000011000	Minfo > 0.001
a_0b_2	0000000000..... 0000000000	Minfo < 0.001
a_0b_3	0000000000..... 0000000000	Minfo < 0.001
.....		
a_ib_j	0000000000..... 1100000110	Minfo > 0.001

Filtered Joint Bitvectors

a_0b_0	0011001100	0001100000
	Minfo > 0.01		
a_0b_1	1100010000	0000011000
	Minfo > 0.01	
a_ib_j	0000000000	1100000110
			Minfo > 0.01

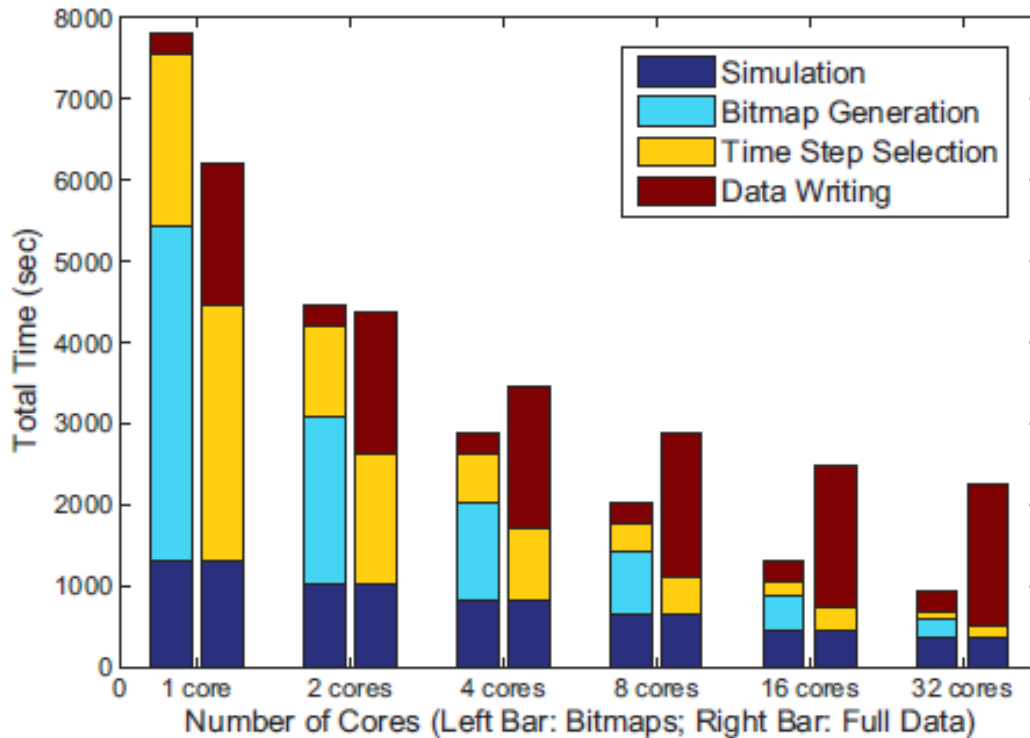


Experiment Results

- Goals:
 - Efficiency and storage improvement using bitmaps
 - Scalability in parallel in-situ environment
 - Efficiency improvement for correlation mining
 - Efficiency and accuracy comparison with sampling
- Simulations: Heat3D, Lulesh
- Datasets: Parallel Ocean Program
- Environment:
 - 32 Intel Xeon x5650 CPUs and 1TB memory
 - MIC: 60 Intel Xeon Phi coprocessors and 8GB memory
 - OSC Oakley Cluster: 32 nodes with 12 Intel Xeon x5650 CPUs and 48 GB memory



Efficiency Comparison for In-Situ Analysis - CPU

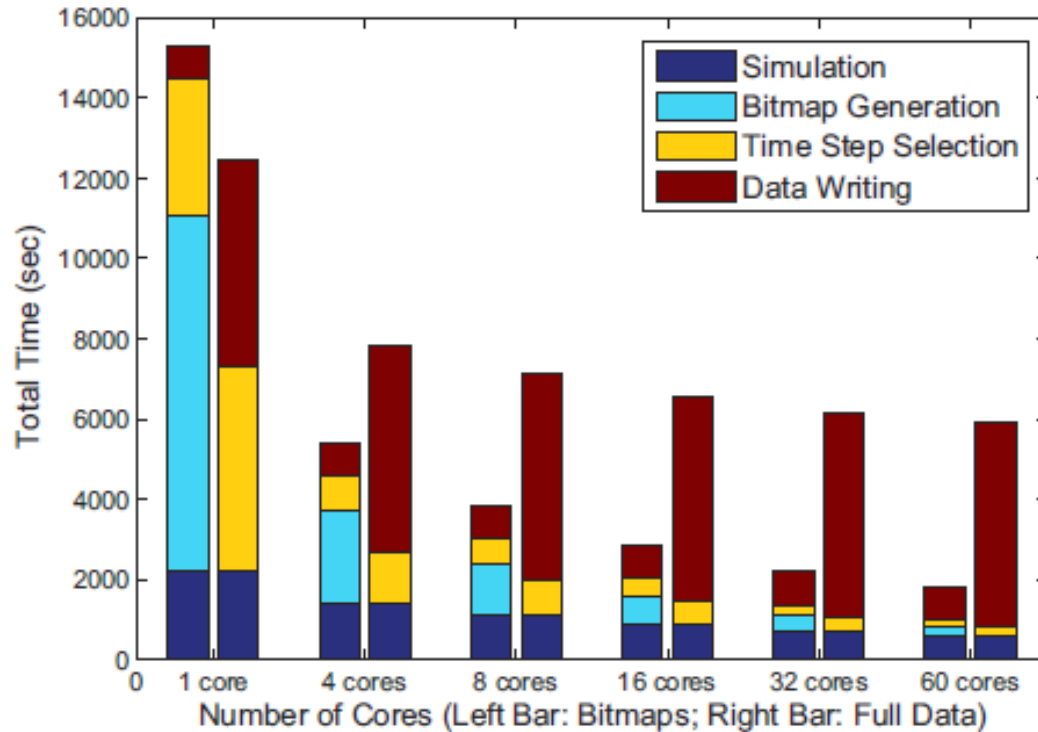


- Simulation: Heat3D; Processor: CPU
- Time steps: select 25 over 100 time steps
- 6.4 GB per time step (800*1000*1000)
- Metrics: Conditional Entropy

- Full Data (original):
 - Simulation: **bad scalability**
 - Time Step Selection: **big**
 - Data Writing: **big and bad scalability**
- Bitmaps:
 - Simulation: utilize extra computing power for bitmaps generation
 - Extra bitmaps generation time but good scalability
 - Time Step Selection Using Bitmaps: **1.38x to 1.5x**
 - Bitmaps Writing: **6.78x**
 - Overall: **0.79x to 2.38x**
 - More number of cores, better speedup we can achieve



Efficiency Comparison for In-Situ Analysis - MIC

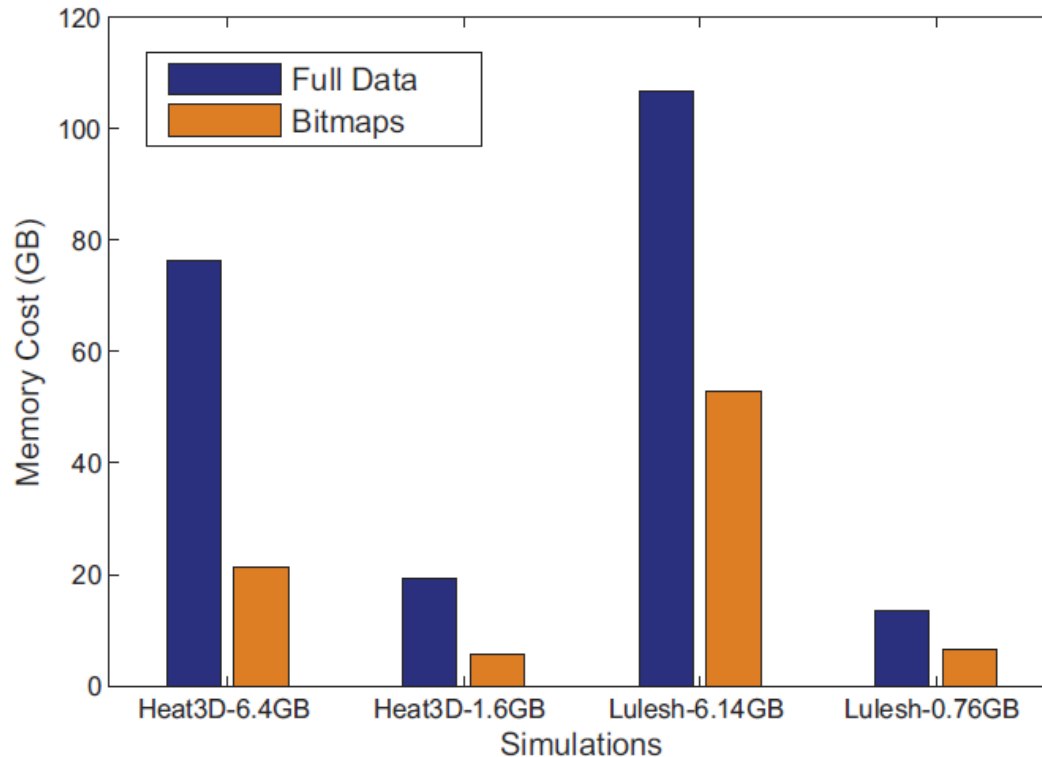


- Simulation: Heat3D; Processor: MIC
- Time steps: select 25 over 100 time steps
- 1.6 GB per time step (200*1000*1000)
- Metrics: Conditional Entropy

- MIC:
 - More cores
 - Lower bandwidth
- Full Data (original):
 - Huge data writing time
- Bitmaps:
 - Good scalability of both bitmaps generation and time step selection using bitmaps
 - Much smaller data writing time
 - Overall: **0.81x to 3.28x**



Memory Cost of In-Situ Analysis

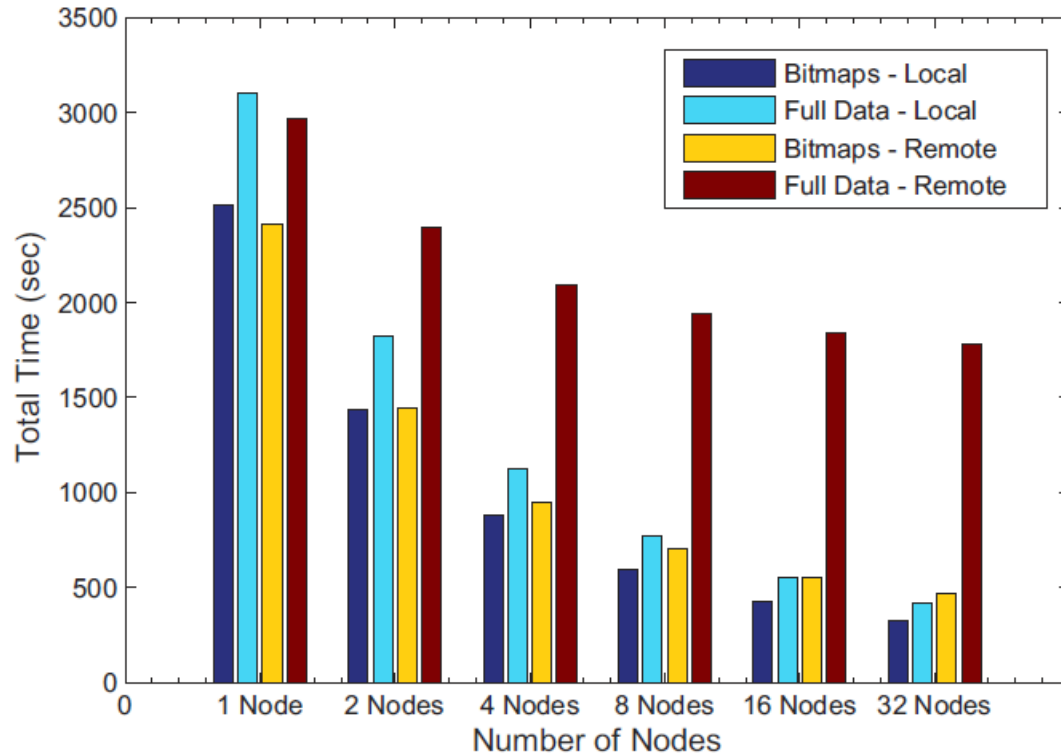


- Simulation: Heat3D, Lulesh
- Processor: CPU, MIC
- Keep 10 time steps in memory

- Heat3D - No Indexing:
 - 12 time steps (pre, temp, cur)
- Heat3D - Bitmap Indexing:
 - 2 time steps (pre, temp)
 - 1 previous selected indices
 - 10 current indices
- Lulesh – No Indexing:
 - 11 time steps (pre, cur)
 - Huge extra memory for edges
- Lulesh – Bitmap Indexing:
 - 1 time step (pre)
 - 1 previous selected indices
 - 10 current indices
 - Huge extra memory for edges
- **2.0x to 3.59x smaller memory**
- Better as **bigger data** simulated and **more time steps** to hold



Scalability in Parallel Environment

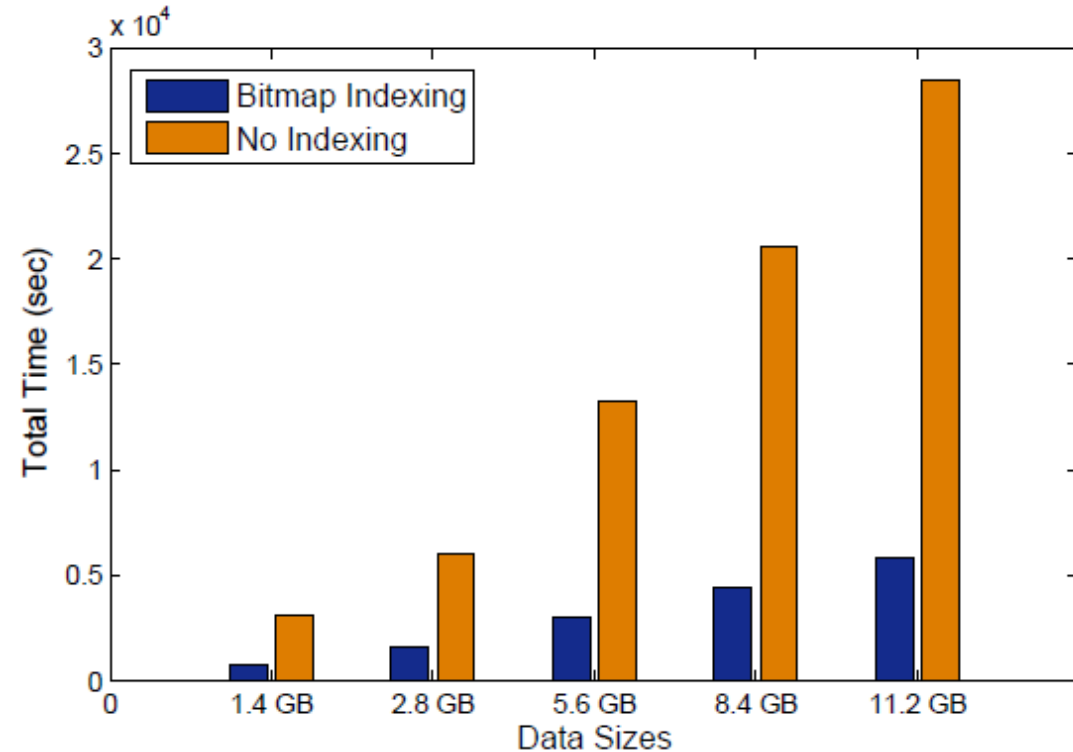


- Select 25 time steps out of 100
- TEMP Variable: 6.4 GB per time step
- Number of nodes: 1 to 32
- Number of cores: 8

- Simulation: Heat3D
- Full Data– Local:
 - Each node write its data subblock into its own disk
- Bitmaps– Local:
 - Each node writes its bitmaps subblock into its own disk
 - Fast time step selection and local writing
 - **1.24x – 1.29x speedup**
- Full Data– Remote:
 - Different nodes send data sub-blocks to a master node
- Bitmaps – Remote:
 - Greatly alleviate data transfer burden of master node
 - **1.24x – 3.79x speedup**



Speedup for Correlation Mining

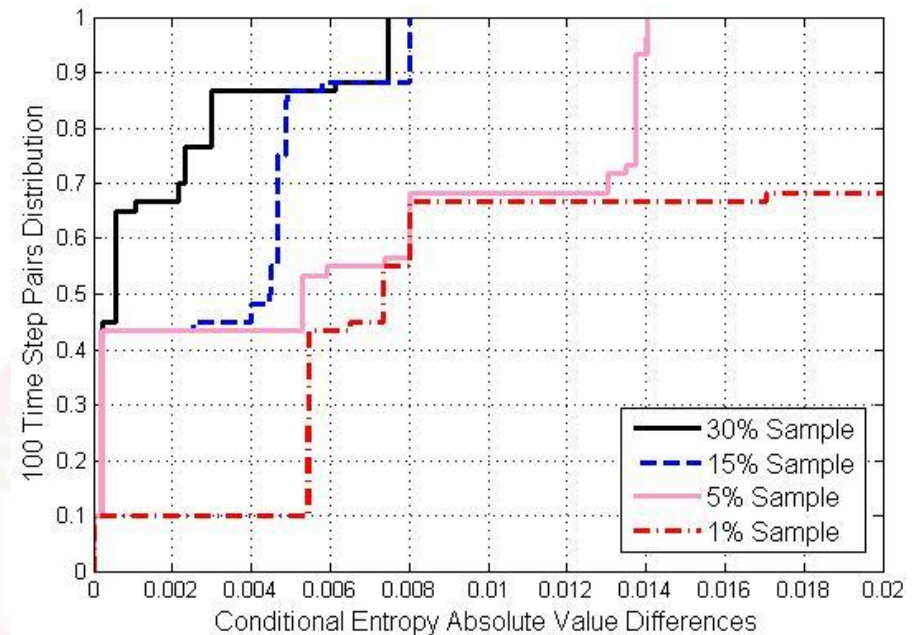
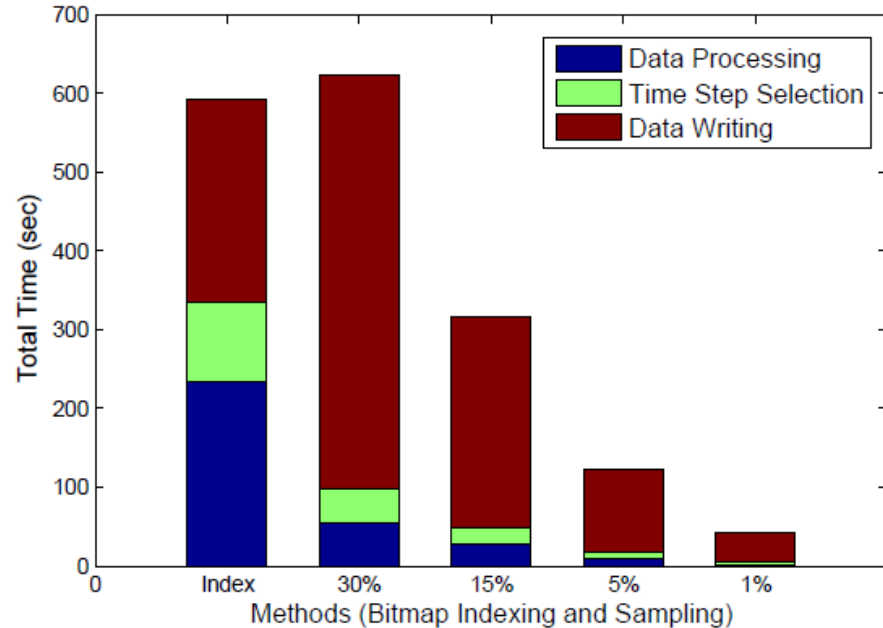


- Variables: TEMP, SALT
- Data size per variable: 1.4 GB to 11.2 GB
- Number of cores: 1

- Simulation: POP
- Full Data:
 - Big data loading cost
 - Exhaustive calculations over data subsets
 - Each calculation is time consuming
- Bitmaps:
 - Smaller data loading
 - Multi-level bitmaps to improve the mining process
 - Bitwise AND and 1-bits count operations to improve the calculation efficiency
 - **3.81x – 4.92x speedup**



In-Situ Sampling vs. Bitmaps



- Heat3D ,100 time steps (6.4 GB), 32 cores
- Bitmaps generation (binning, compression) has more time cost then down-sampling
- Sampling can effectively improve the time step selection cost
- Bitmaps generation can still achieve better efficiency if the index size is smaller than sample size

- Bitmaps: using the same binning scale, does not have any information loss
- Sampling: information loss is unavoidable no matter what sample%
- **30% - 21.03% loss**
- **15% - 37.56% loss**
- **5% - 58.37% loss**



Conclusion

- 'Big Data' issue brings challenges for scientific data management
- Efficient in-situ bitmaps generation
- Efficient online data analysis (time step selection) using only bitmaps
- Efficient offline data analysis (correlation mining) using only bitmaps
- Compare in-situ data sampling with in-situ bitmaps