Parallel, In Situ Indexing for Data-intensive Computing

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Introduction

- Many scientific applications produce large outputs
  - For example, GTC generates 260 GB data per 120 sec
  - But, a relatively small fraction of the data is interesting, e.g., blobs and clumps in fusion, magnetic nulls in magnetohydrodynamic models
- Challenge:
  - Accessing data on disk is slow
  - Disk is getting slower relative to computing power
- We explore performance impact on parallelism and in situ indexing for large data

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ADIOS

- Adaptable IO Systems developed by ORNL
  - Proven read/write performance
  - Widely adopted as a middleware for data-intensive scientific computing
- Provides good architectural merits for "in situ" processing
  - By decoupling compute nodes with staging nodes
  - Staging nodes take full charges of writing data
- Examples
  - Statistics computation when data is generated
    - Min, max, average, standard deviation

http://www.olcf.ornl.gov/center-projects/adios/

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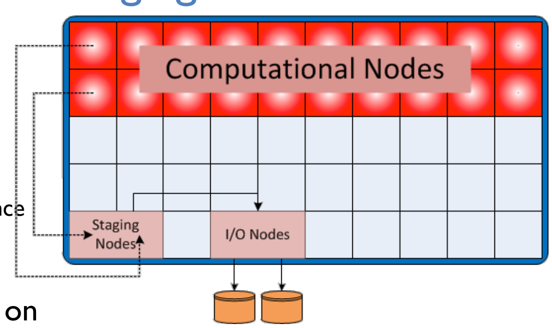
Data Staging

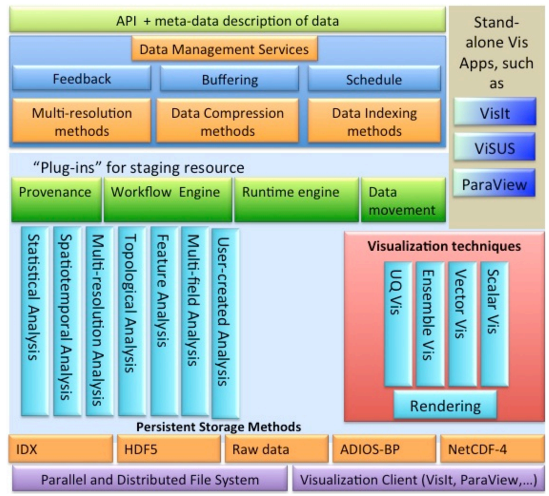
- Why asynchronous I/O?
  - Eliminates performance linkage between I/O subsystem and application
  - Decouples file system performance variations and limitations from application run time



- Enables optimizations based on dynamic number of writers
- High bandwidth data extraction from application
- Scalable data movement with shared resources requires us to manage the transfers
- Scheduling properly can greatly reduce the impact of I/O

In Situ Processing

- The cost of data movement, both from the application to storage and from storage to analysis or visualization, is a deterrent to effective use of the data
- The output costs increase the overall application running time and often forces the user to reduce the total volume of data being produced by outputting data less frequently
- Input costs, especially to visualization, can make up to 80% of the total run time
- Solution: perform analysis operations *in situ* or in place



FastQuery Challenges & Approaches

(1) Mismatch between the array model used by scientific data and the relational model when applying database indexing technology
- Map array data to relational table structure on-the-fly

(2) Arbitrary hierarchical data layout
- Deploy a flexible yet simple variable naming scheme based on regular expression

(3) Diverse scientific data format
- Define a unified array I/O interface

(4) High index building cost
- Parallel I/O strategy and system design to reduce the index building time

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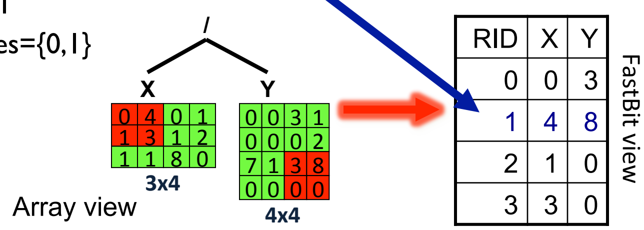
Mapping between FastBit & Array Data

- Each variable associated with a query is mapped to a column of a relational table *on-the-fly*
- Elements of a multidimensional array are linearized
- An arbitrary number of arrays or subarrays can be placed into a logical table as long as they have the same array dimensions
- Ex: getNumHits("x[0:2,0:2] > 3 && y[2:4,2:4]>3")
  - NumHits=1
  - Coordinates={0,1}



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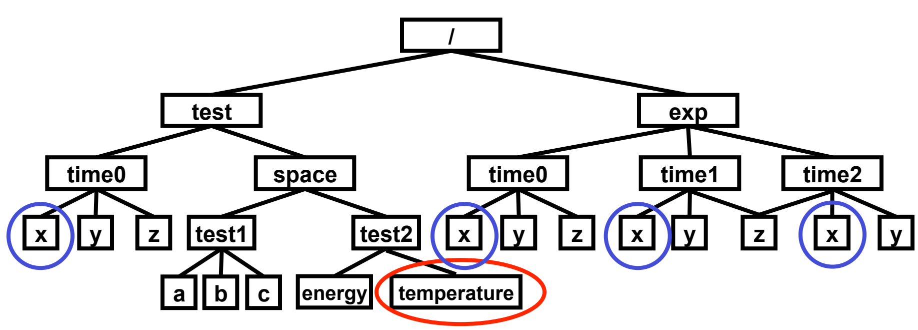
Flexible Naming Schema

- Naïve option: use the full path
  - getNumHits("/test/space/test2/temperature > 100")
- Can we do better?
  - getNumHits("x > 3")



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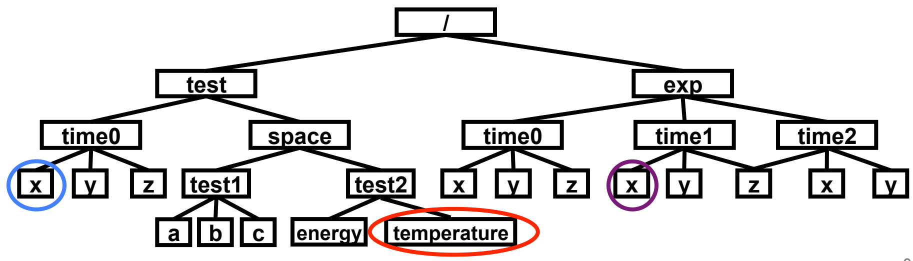
Flexible Naming Schema

- Separate variable name and path
  - Implemented with a tuple (varName, varPath)
  - Variable is identified by the rule "*/varPath/*/varName"
- Example:
  - ("temperature > 100","") ➔ "/test/space/test2/temperature > 100"
  - ("x > 3", test) ➔ "/test/time0/x > 3"
  - ("x > 3", time1) ➔ "/exp/time1/x > 3"
- Advantage:
  - Simplify query string
  - Decouple user specification from file layout



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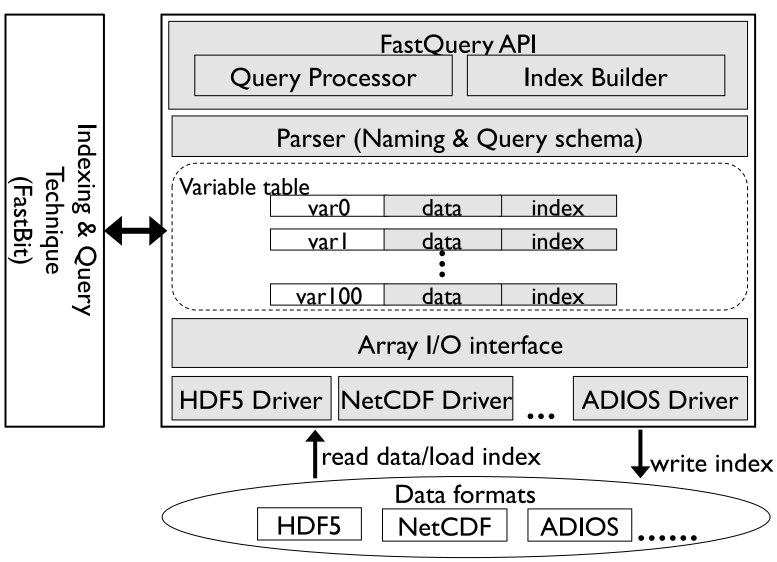
FastQuery System Architecture



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Basic Bitmap Index

Data values	b_0 =0	b_1 =1	b_2 =2	b_3 =3	b_4 =4	b_5 =5
0	1	0	0	0	0	0
1	0	1	0	0	0	0
5	0	0	0	0	0	1
3	0	0	0	1	0	0
1	0	1	0	0	0	0
2	0	0	1	0	0	0
0	1	0	0	0	0	0
4	0	0	0	0	1	0
1	0	1	0	0	0	0

A < 2 (b_0, b_1)   2 < A (b_3, b_4, b_5)

- First commercial version
  - Model 204, P. O'Neil, 1987
- Easy to build: faster than building B-trees
- Efficient for querying: only bitwise logical operations
  - $A < 2 \rightarrow b_0$ OR b_1
  - $A > 2 \rightarrow b_3$ OR b_4 OR b_5
- Efficient for multi-dimensional queries
  - Use bitwise operations to combine the partial results
- Size: one bit per distinct value per row
  - Definition: Cardinality == number of distinct values
  - Compact for low cardinality attributes, say, cardinality < 100
  - Worst case: cardinality = N, number of rows; index size: N*N bits

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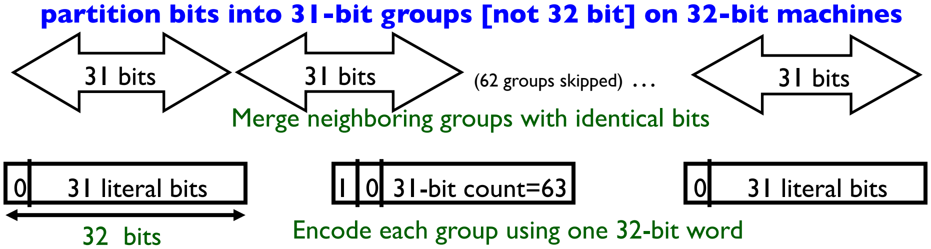
FastBit Compression

Example: 2015 bits

100000000000000000000111000000000000000000000000000000000……………..00000000000000000000000000000000111111111111111111111111

Main Idea: Use run-length-encoding, but…
partition bits into 31-bit groups [not 32 bit] on 32-bit machines



- Name: Word-Aligned Hybrid (WAH) code (US patent)
- Key features: WAH is compute-efficient [Wu, Otoo, and Shoshani 2006]
  - ➢ Uses the run-length encoding (simple)
  - ➢ Allows operations directly on compressed bitmaps
  - ➢ Never breaks any words into smaller pieces during operations
  - ➢ Worst case index size 4N words, not N*N (without compression)

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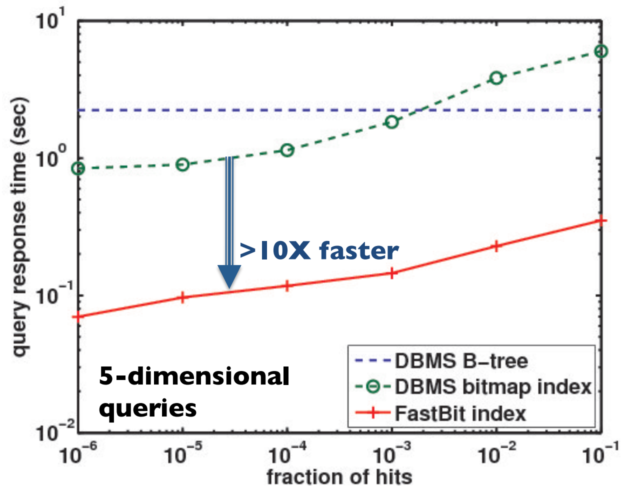
Multi-Dimensional Query Performance

- Queries 5 out of 12 most popular variables from STAR (2.2 million records)
- Average attribute cardinality (distinct values): 222,000
- FastBit uses WAH compression
- DBMS uses BBC compression
- FastBit >10X faster than DBMS
- FastBit indexes are 30% of raw data sizes



Wu, Otoo andShoshani 2002

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Experimental Evaluation

- Impact of indexing
- Parallel index building
- In situ index building

- Measurements collected on Franklin at NERSC
  - ~10000 nodes
  - 8 cores
  - 8 GB memory
  - Lustre file system
- Test problem sizes
  - Small: 3.6GB
  - Medium: 27GB
  - Large: 208GB
  - Large2: 173GB

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Why Indexing?

Hits (%)	Method	Small (3.6GB)	Medium (27GB)	Large (208GB)	Huge (1.7TB)
99%	Scanning	38.2s	321.3s	3176.7s	19534
	Indexing	9.6s	32.8s	55.5s	111.8s
	Speed-up	4x	10x	57x	175x
20%	Scanning	37.9s	327.3s	3132.4s	19705
	Indexing	11.7s	61.8s	153.6s	1195.4s
	Speed-up	3x	5x	20x	16x
1%	Scanning	48.0s	348.7s	3301.3s	19756s
	Indexing	7.8s	28.1s	41.0s	99.1s
	Speed-up	6x	12x	81x	199x

- Speed-up with indexing: 3x – 199x

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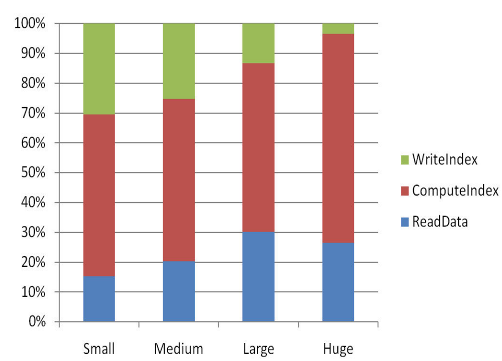
But challenges remain…

- Index construction time
  - 3 min/3.6GB
  - 23 min/27GB
  - 3 hr/208GB
  - > 12hr/1.7TB



❑Solution:

– Building indexes in parallel!

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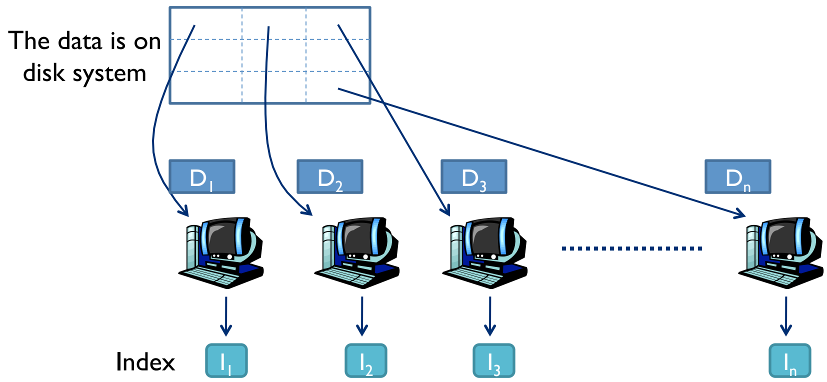
Parallel Index Construction



- Split and assign data blocks to multiple processors

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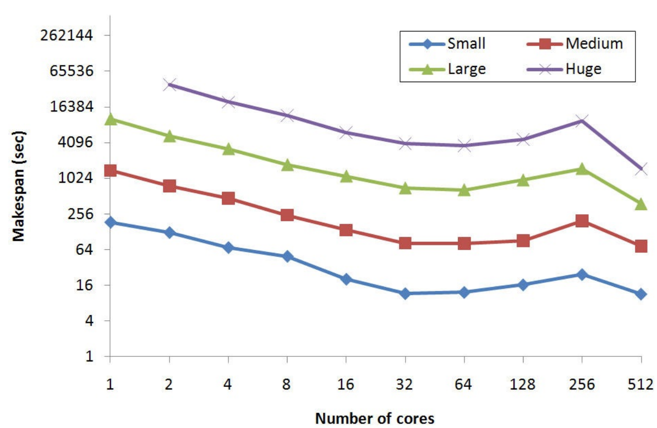
Performance with Parallelism



Hopper2 @ LBNL

- **~6000 nodes**
- **24 cores**
- **32-64 GB memory**
- **Lustre file system**

- Parallelism improves performance, but
- Why the benefit disappears after a certain parallelism factor?

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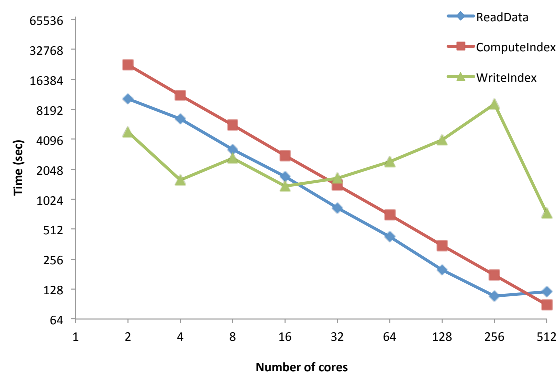
Index Construction Time Breakdown



- Write performance shows little improvement!
- Why? Collective writes → Sync overhead

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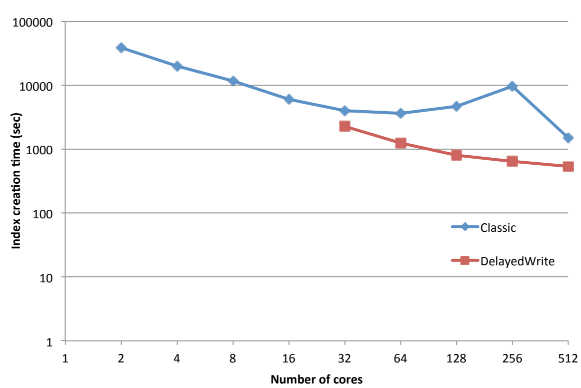
Optimization: Delayed Writes

- Reduce number of synchronizations!
  - Delaying writing index whenever possible
  - Retain created indexes in memory, then write them together



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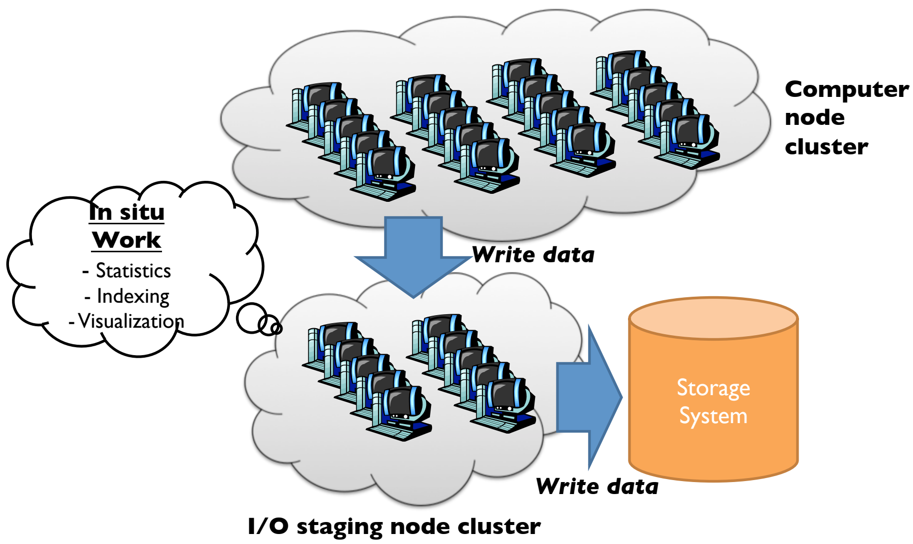
Cluster with Dedicated Staging Nodes



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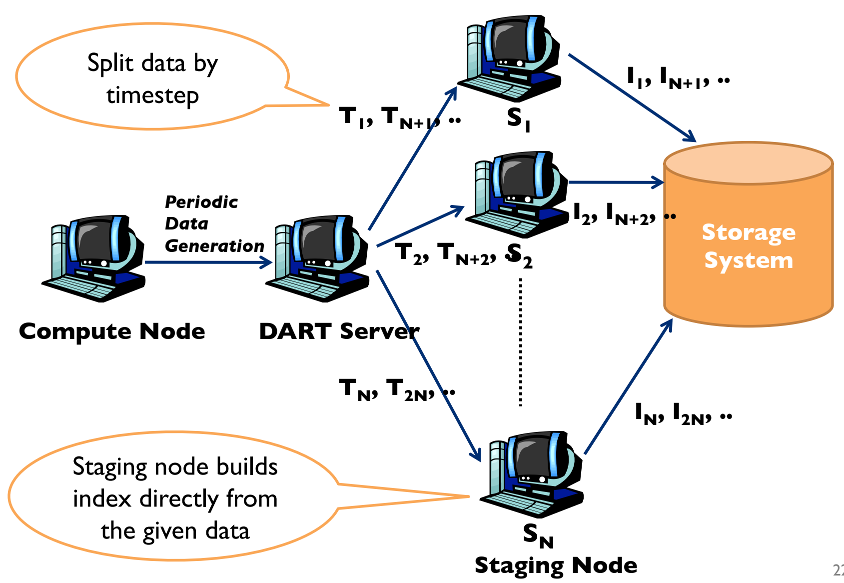
Experiments for In Situ Indexing



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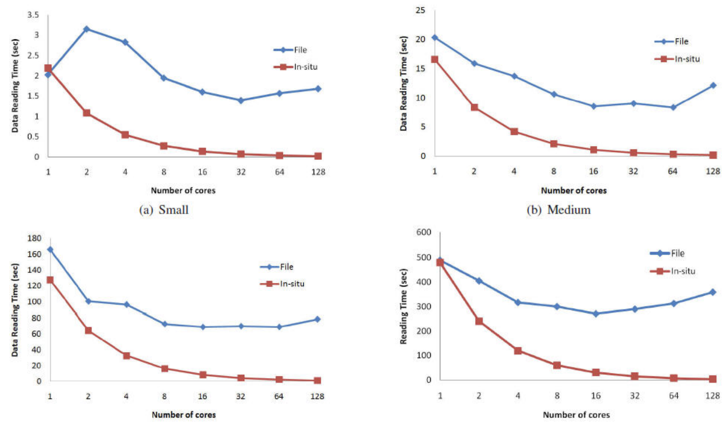
Reading Time



(a) Small (b) Medium (c) Large (d) Large2

Franklin @ LBNL

- ~10000 nodes
- 8 cores
- 8 GB memory
- Lustre file system

Small: 3.6GB
Medium: 27GB
Large: 208GB
Large2: 173GB

- Getting data from another processor (in situ) is faster than getting data from disk

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Summary

- Indexing dramatically reduces query time
  - But expensive with 12+ hours for 1 TB data
- Parallelism offers performance improvement for building index
  - But collective writes causes random delay
  - Delayed write optimization can mitigate the delay
- In situ indexing improves performance by significantly reducing data read time

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Lessons Learned

- Avoiding synchronization
  – One delayed processor causes severe delay in writing
  – It is fine to delay writing index blocks if the base data is safely stored already
- Choosing a moderate number of processors
  – Performance benefits are not linear!
  – Finding sweet spot may be interesting (maybe GLEAN could help)
- Tuning file system parameters
  – For example, striping count has direct performance impact to some extent

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FastBit http://sdm.lbl.gov/fastbit/
FastQuery http://portal.nersc.gov/svn/fq/
ADIOS http://www.olcf.ornl.gov/center-projects/adios/

QUESTIONS?

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