HDF5 FastQuery

Accelerating Complex Queries on HDF Datasets using Fast Bitmap Indices

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QuickTime™ and a
TIFF (Uncompressed) decompressor
are needed to see this picture.

Motivation and Problem Statement

- Too much data.
- Visualization “meat grinders” not especially responsive to needs of scientific research community.
- What scientific users want:
  - Scientific Insight
  - Quantitative results
  - Feature detection, tracking, characterization
  - (lots of bullets here omitted)
- See:
  - http://vis.lbl.gov/Publications/2002/VisGreenFindings-LBNL-51699.pdf
  - http://www-user.slac.stanford.edu/rmount/dm-workshop-04/Final-report.pdf

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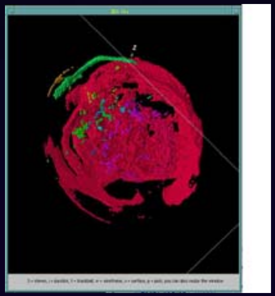
What is FastBit?

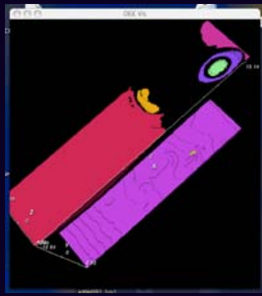
(what is it's role in data analysis?)

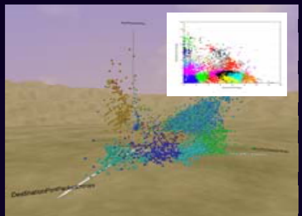
Using Indexing Technology to Accelerate Data Analysis

- Use cases for indexed datasets
  - Support Compound Range Queries: eg. *Get me all cells where Temperature > 300k AND Pressure is < 200 millibars*
  - Subsetting: Only load data that corresponds to the query.
    - Get rid of visual “clutter”
    - Reduce load on data analysis pipeline
  - Quickly find and label connected regions
  - Do it really fast!

- Applications
  - Astrophysics:
    - Remove clutter from messy supernova explosions
  - Combustion:
    - Locate and track ignition kernels
  - Particle Accelerator Modeling:
    - identify and select errant electrons
  - Network Security Data:
    - Pose queries against enormous packet logs
    - Identify candidate security events

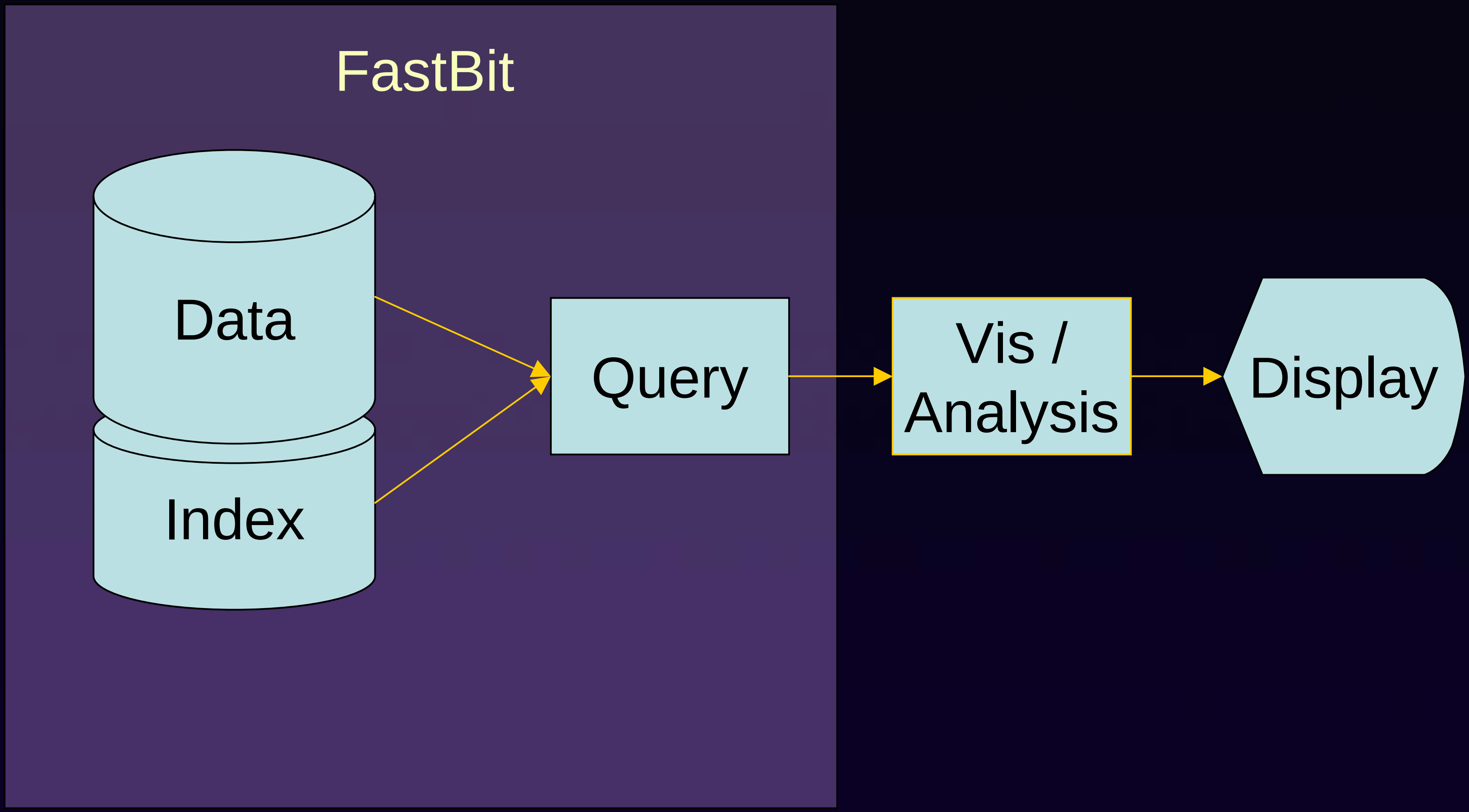






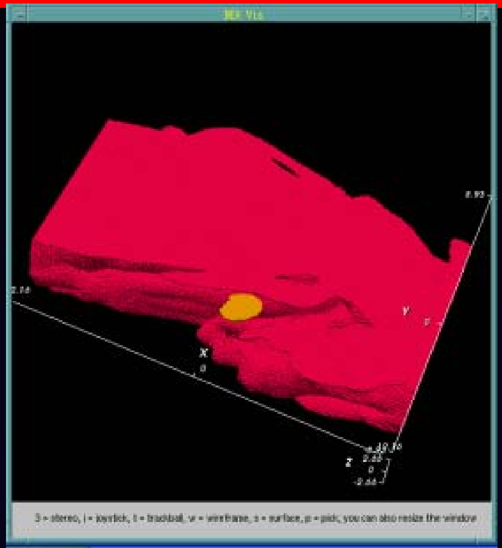
Architecture Overview: Generic Visualization Pipeline

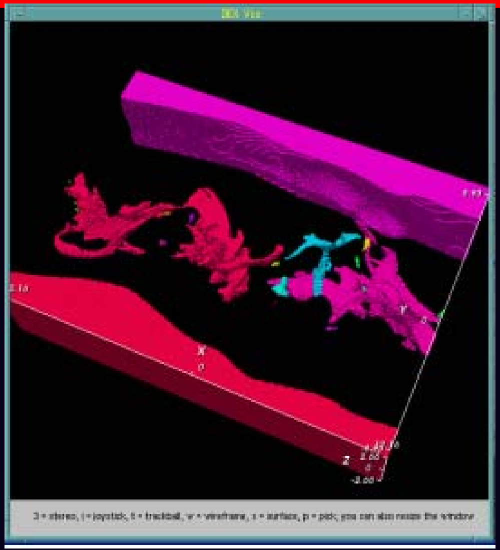
Architecture Overview: Query-Driven Vis. Pipeline



Query-Driven Subsetting of Combustion Data Set

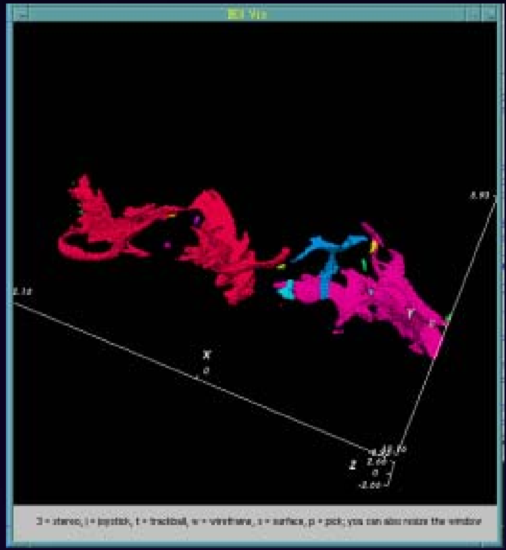
a) Query: CH4 > 0.3

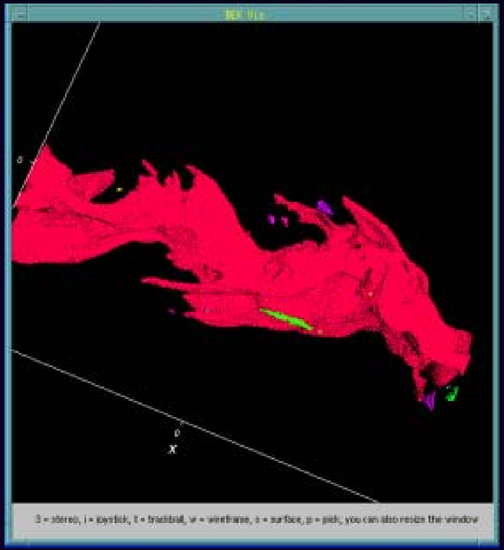




b) Q: temp < 3

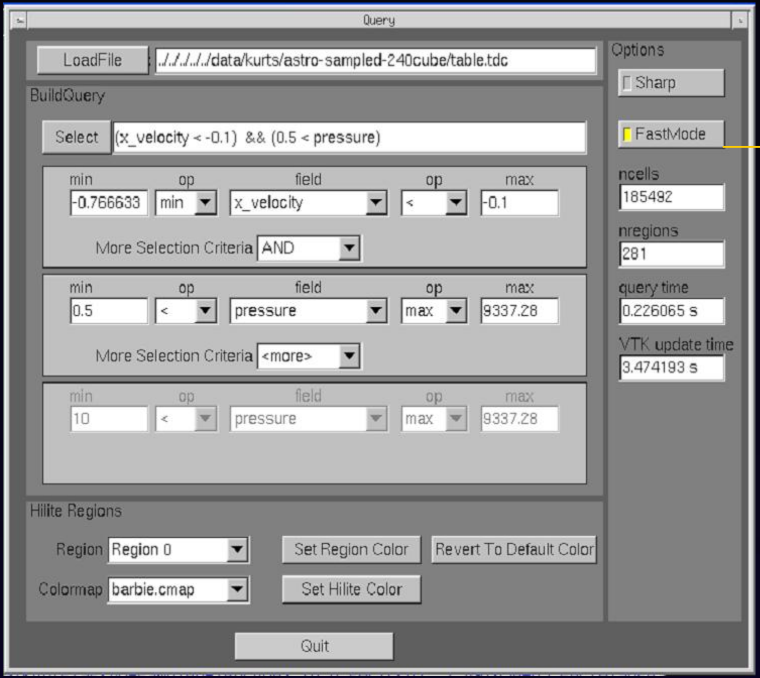
c) Q: CH4 > 0.3 AND temp < 3

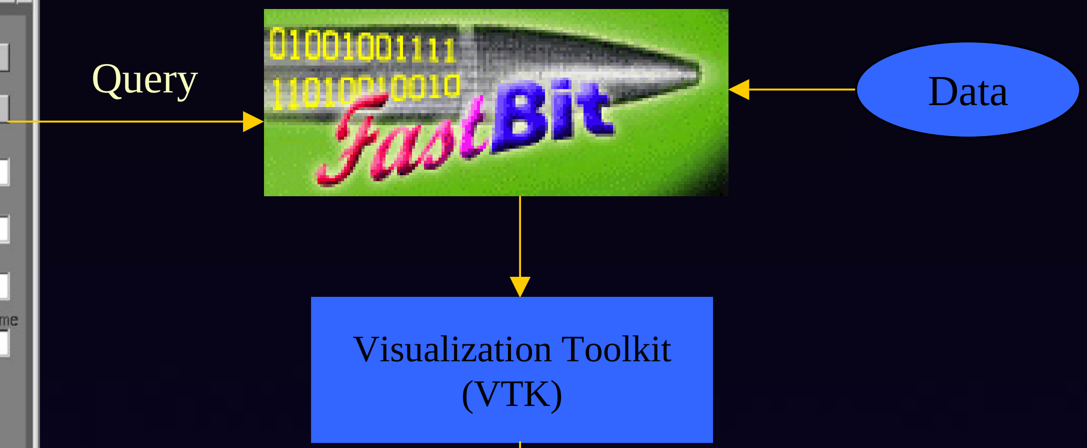


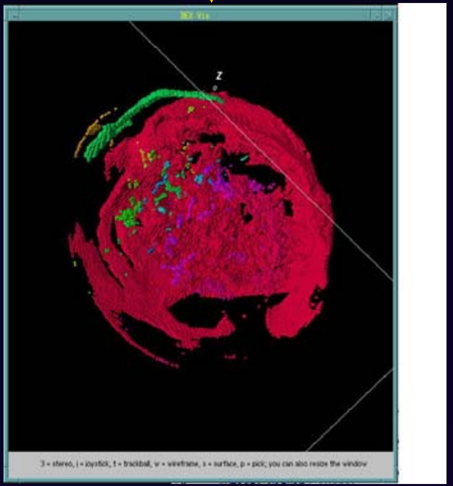


d) Q: CH4 > 0.3 AND temp < 4

DEX Visualization Pipeline

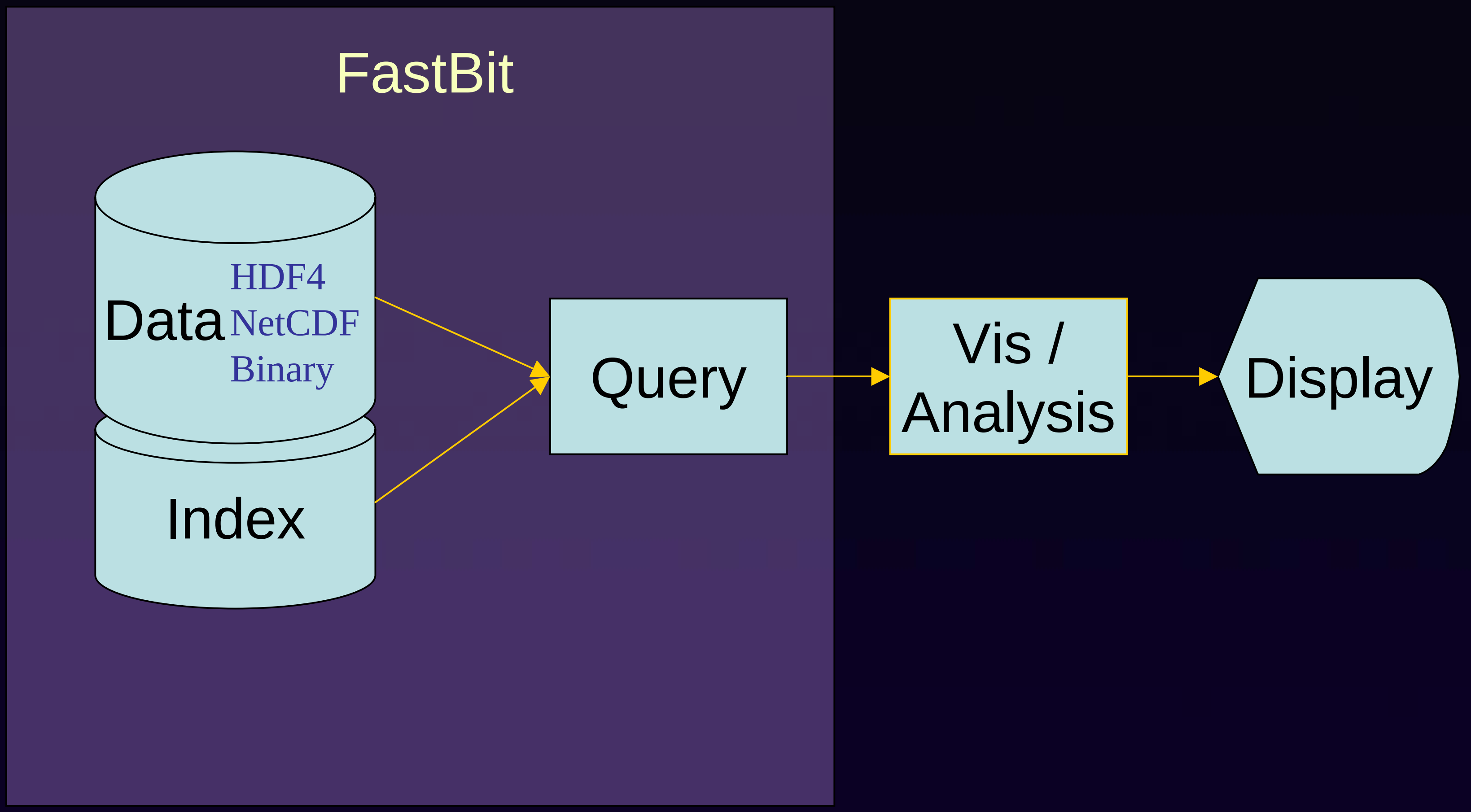






3D visualization of a Supernova explosion

Architecture Overview: Query-Driven Analysis Pipeline



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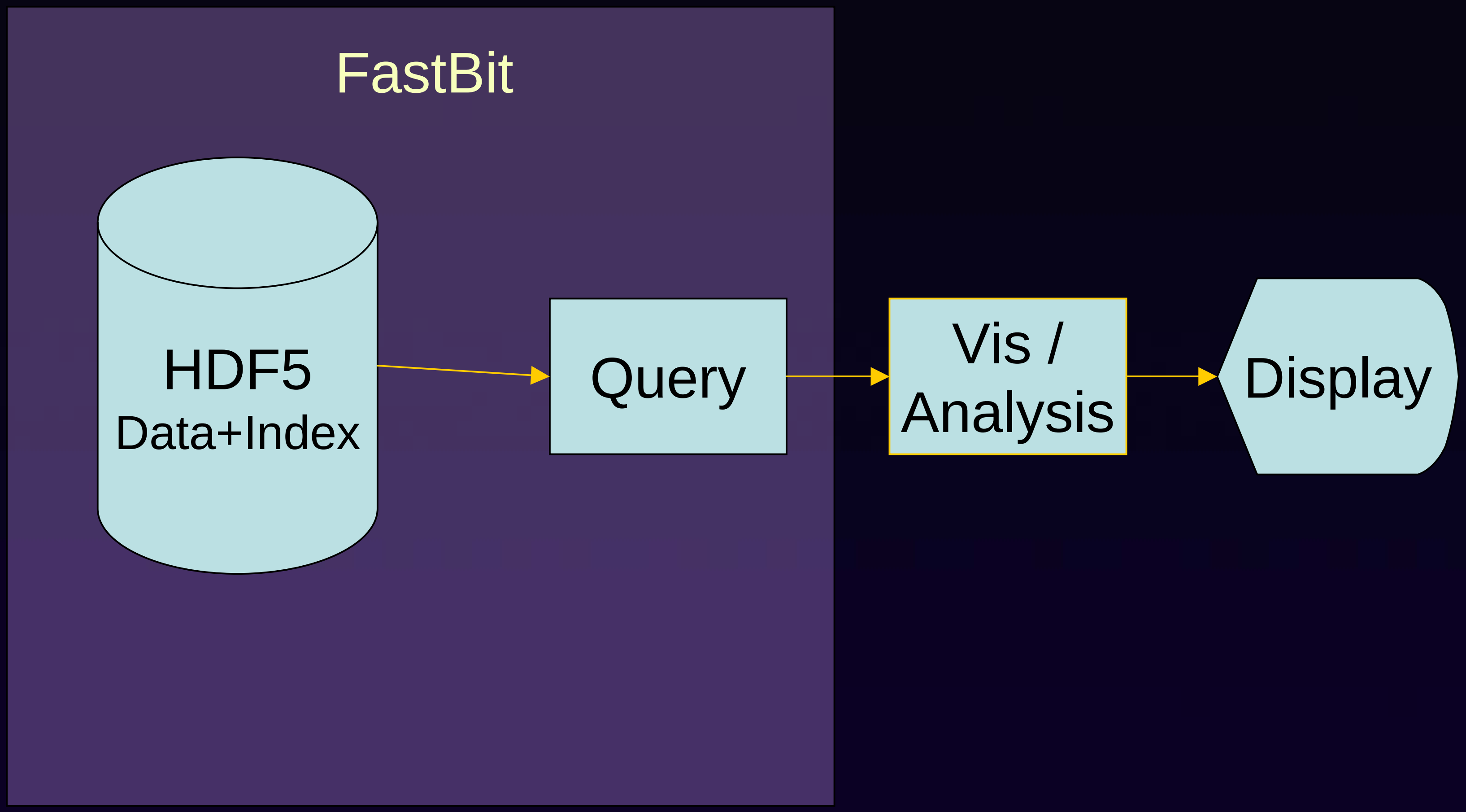


How do Fast Bitmap Indices Work?

Why Bitmap Indices?

- Goal: efficient search of *multi-dimensional* read-only (append-only) data:
  - E.g. temp < 104.5 AND velocity > 10^7 AND density < 45.6

- Commonly-used indices are designed to be updated quickly
  - E.g. family of B-Trees
  - Sacrifice search efficiency to permit dynamic update

- Most multi-dimensional indices suffer *curse of dimensionality*
  - E.g. R-tree, Quad-trees, KD-trees, …
  - Don't scale to large number of dimensions (< 10)
  - Are efficient only if all dimensions are queried

- Bitmap indices
  - Sacrifice update efficiency to gain more search efficiency
  - Are efficient for multi-dimensional queries
  - Query response time scales linearly in the actual number of dimensions in the query

What is a Bitmap Index?

Data values	b_0	b_1	b_2	b_3	b_4	b_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

- Compact: one bit per distinct value per object.
- Easy and fast to build: O(*n*) vs. O(*n* log *n*) for trees.
- Efficient to query: use bitwise logical operations.
  - (0.0 < H_2O < 0.1) AND (1000 < temp < 2000)
- Efficient for multidimensional queries.
  - No "curse of dimensionality"
- What about floating-point data?
  - Binning strategies.

Bitmap Index Encoding

List of Attributes | Equality Encoding | Range Encoding

	$\pi_A(R)$	E^9	E^8	E^7	E^6	E^5	E^4	E^3	E^2	E^1	E^0	R^8	R^7	R^6	R^5	R^4	R^3	R^2	R^1	R^0
1	3	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	1	0	0	0
2	2	0	0	0	0	0	0	0	1	0	0	1	1	1	1	1	1	1	0	0
3	1	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	0
4	2	0	0	0	0	0	0	0	1	0	0	1	1	1	1	1	1	1	0	0
5	8	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
6	2	0	0	0	0	0	0	0	1	0	0	1	1	1	1	1	1	1	0	0
7	9	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
9	7	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
10	5	0	0	0	0	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0
11	6	0	0	0	1	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0
12	4	0	0	0	0	0	1	0	0	0	0	1	1	1	1	1	0	0	0	0

(a) (b) (c)

- Equality encoding compresses very well
- Range encoding optimized for one-sided range queries, e.g. temp < 3

Performance

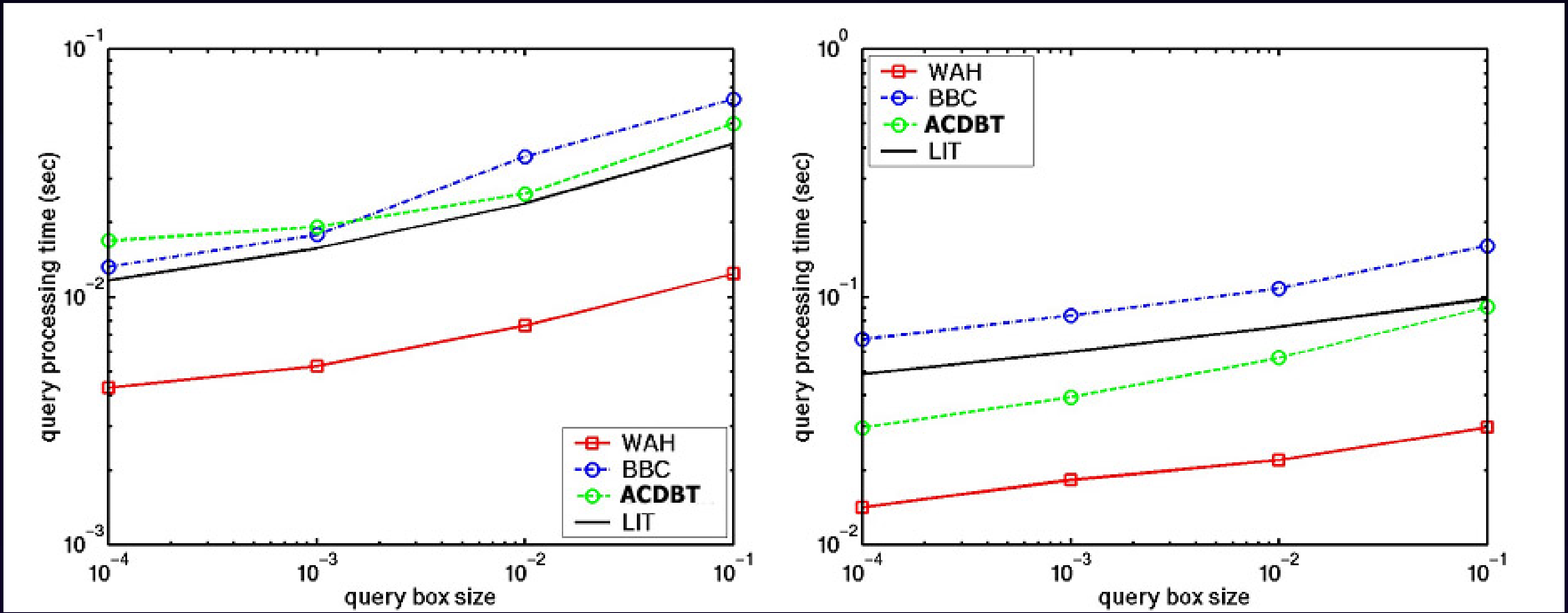
Bitmap Index Query Complexity and Space Requirements

- How Fast are Queries Answered?
  - Let N denote the number of objects and H denote the number of hits of a condition.
  - Using uncompressed bitmap indices, search time is O(N)
  - With a good compression scheme, the search time is O(H) – the theoretical optimum

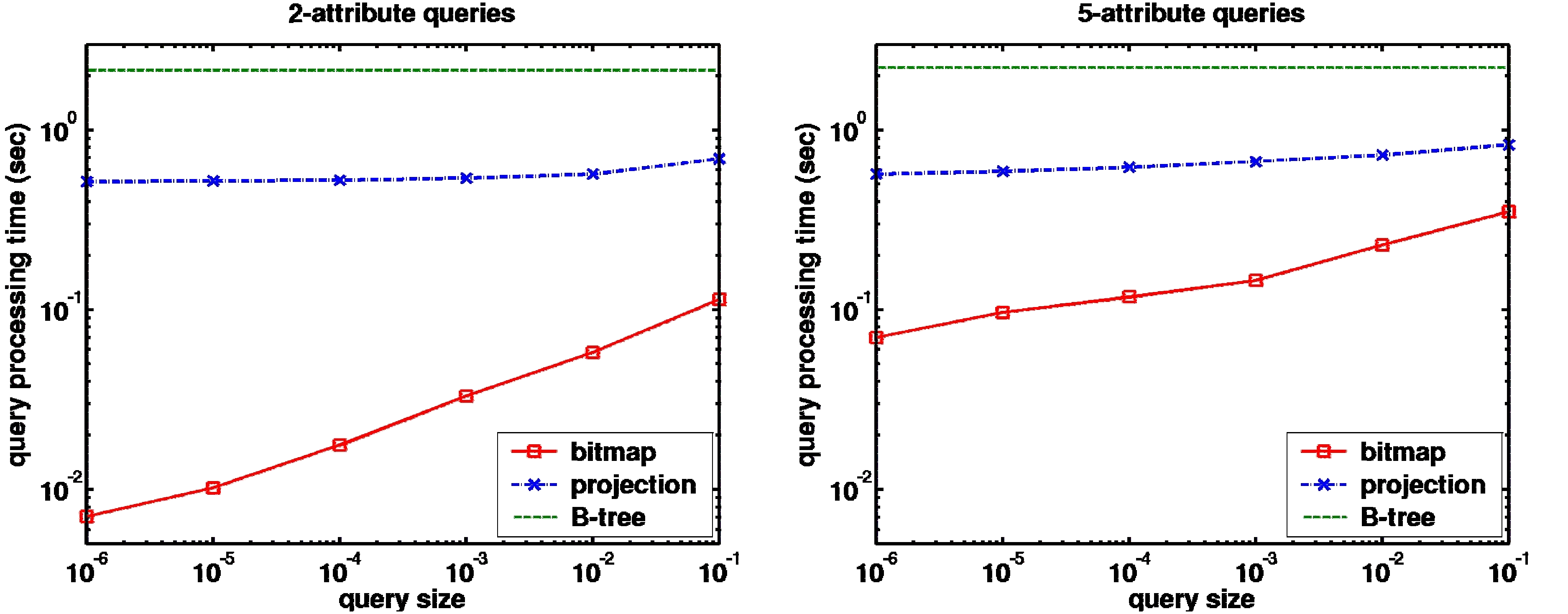
- How Big are the Indices?
  - In the worst case (completely random data), the bitmap index requires about 2x in data size for one variable (typically 0.3x).
  - In contrast, 4x space requirement not uncommon for tree-based methods for one variable.
  - Curse of dimensionality: for N points in D dimensions:
    - Bitmap index size: O(D*N)
    - Tree-based method: O(N**D)!!!

Compressed Bitmap Index Query Performance

- FastBit Word-Aligned Hybrid (WAH) compression performance better than commercial systems.
- Different bitmap compression technologies have different performance characteristics.

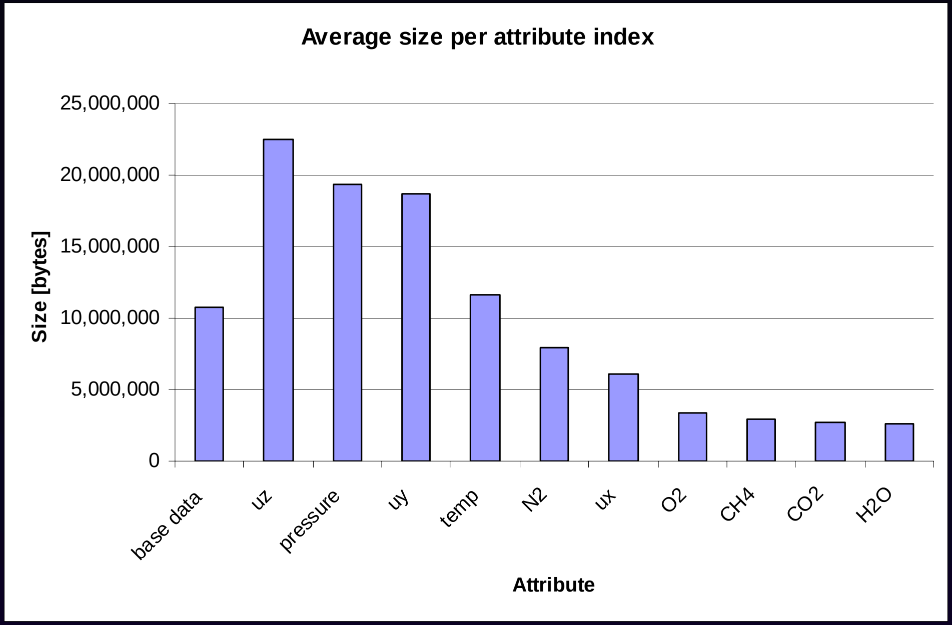


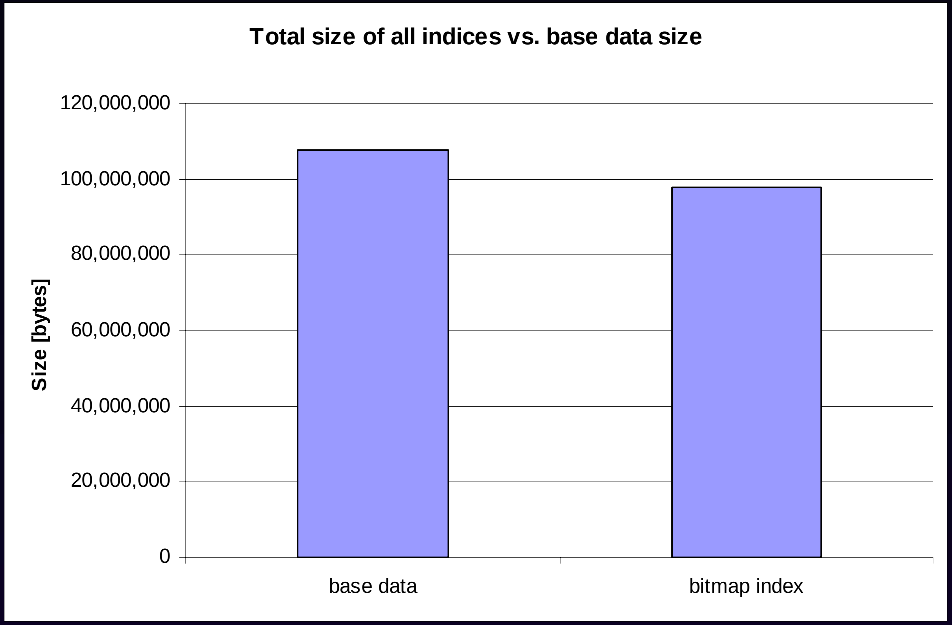
Queries Using Bitmap Indices are Fast



- Log-log plot of query processing time for different size queries
- The compressed bitmap index is at least 10X faster than B-tree and 3X faster than the projection index

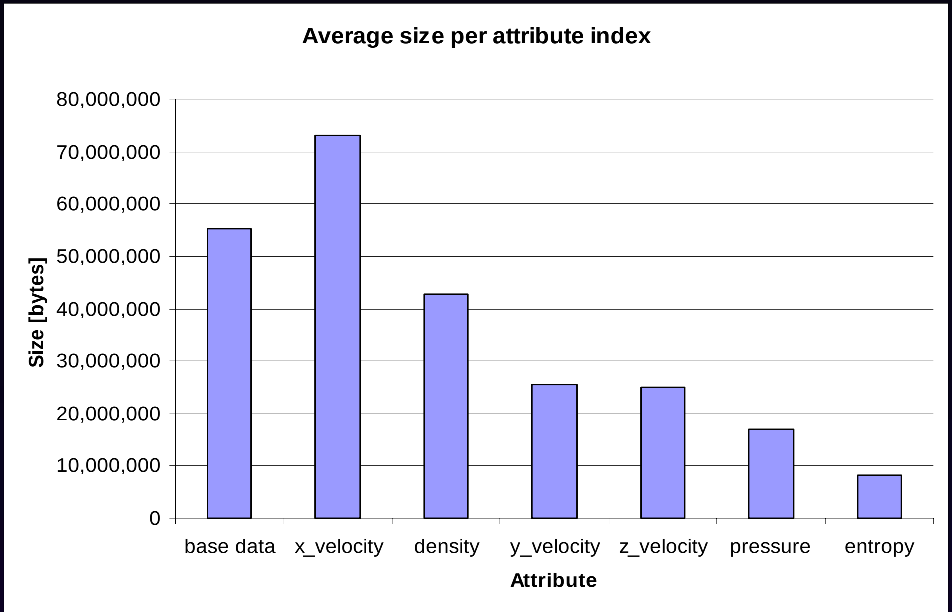
Size of Bitmap Index vs. Base Data *(Combustion)*

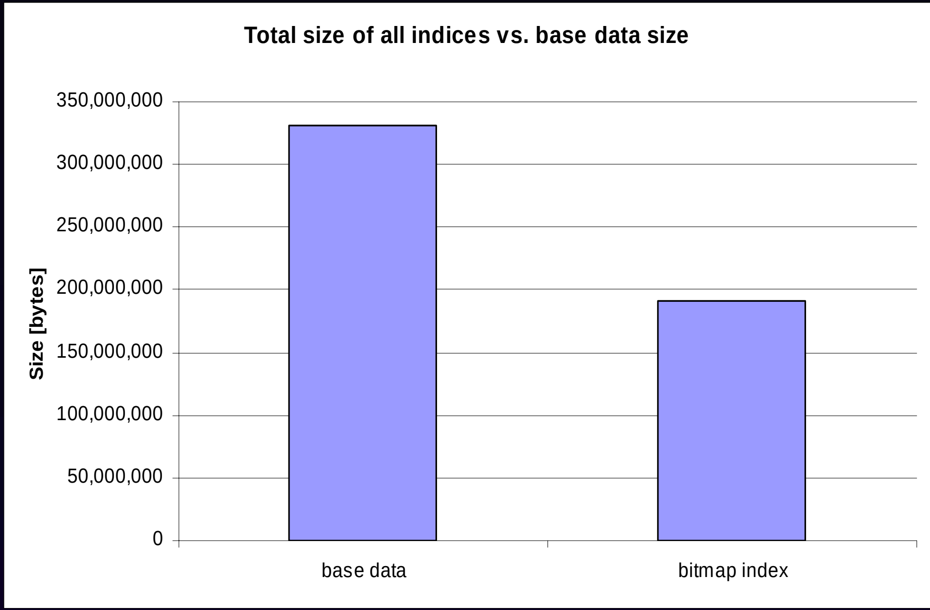




- Compressed bitmap index with 100 range-encoded bins is about same size as base data.
- Note: B-tree index is about 3 times the size of the base data.
- Building the index takes ~5 seconds for 100Megs on P4 2.4GHz workstation

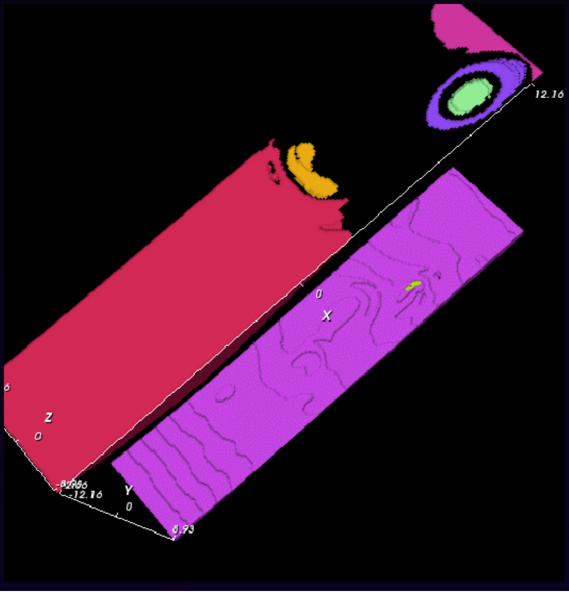
Size of Bitmap Index vs. Base Data (Astrophysics)

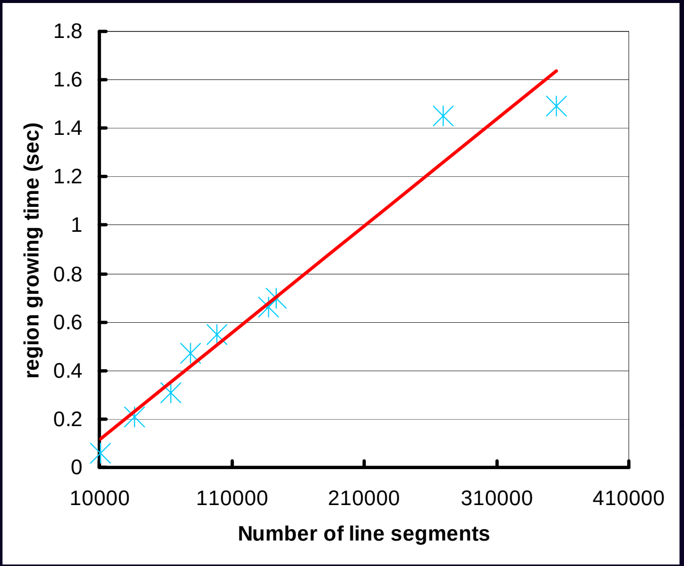




- Size of compressed bitmap index is only 57% of base data.
- Building an index for all attributes takes ~17 seconds for 340 Megs.

Region Growing and Connected Component Labeling





- The result of the bitmap index query is a set of blocks.
- Given a set of blocks, find connected regions and label them.

- Region growing scales linearly with the number of cells selected.

HDF5 - FastQuery File Organization

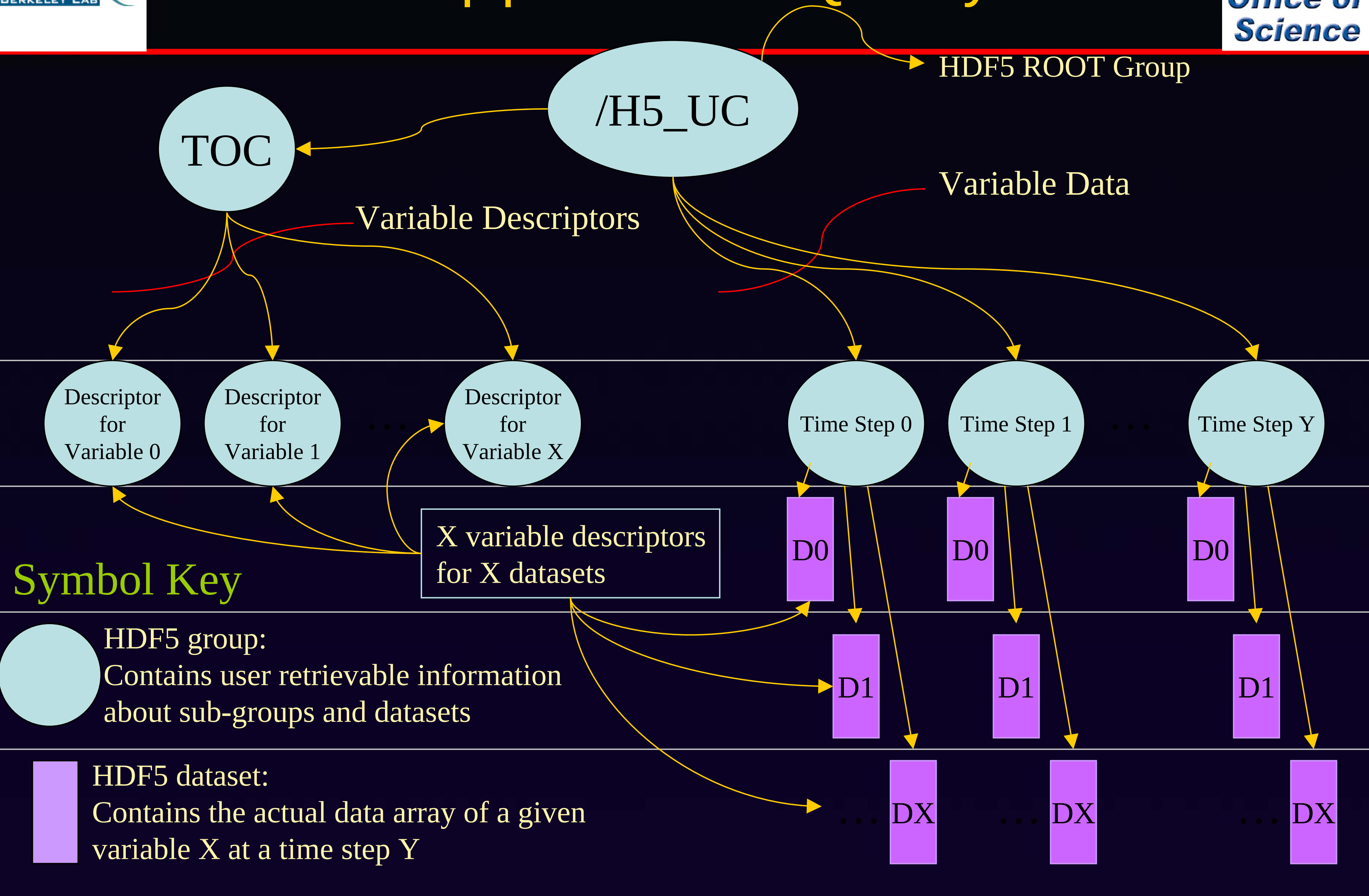
File Organization

- Current
  - Data in HDF4, NetCDF converted to raw binary
  - One file per species + one file per index
  - ASCII file for metadata
  - One directory per timestep
  - Non-portable binary (must byte-swap data)
- HDF5 FastQuery
  - Indices + data all in same file
  - Machine independent binary representation
  - Multiple time-steps per file
  - Pose queries against data stored in “indexed” HDF5 file

Some Simplifying Assumptions

- Block structured data
  - 0-3 Dimensional topology (arbitrary geometry)
  - Limited Datatypes: *float, double, int32, int64, byte*
  - Vectors and Tensors identified via metadata
- Two Level hierarchical organization
  - TimeStep
  - VariableName
  - Queries can be posed implicitly across time dimension
- Future
  - Arbitrary nesting
    - AMR "Level"
    - CalibrationSet
  - More Data Schemas
    - Unstructured
    - AMR
    - NetLogs

HDF5 Data Organization to Support FastQuery



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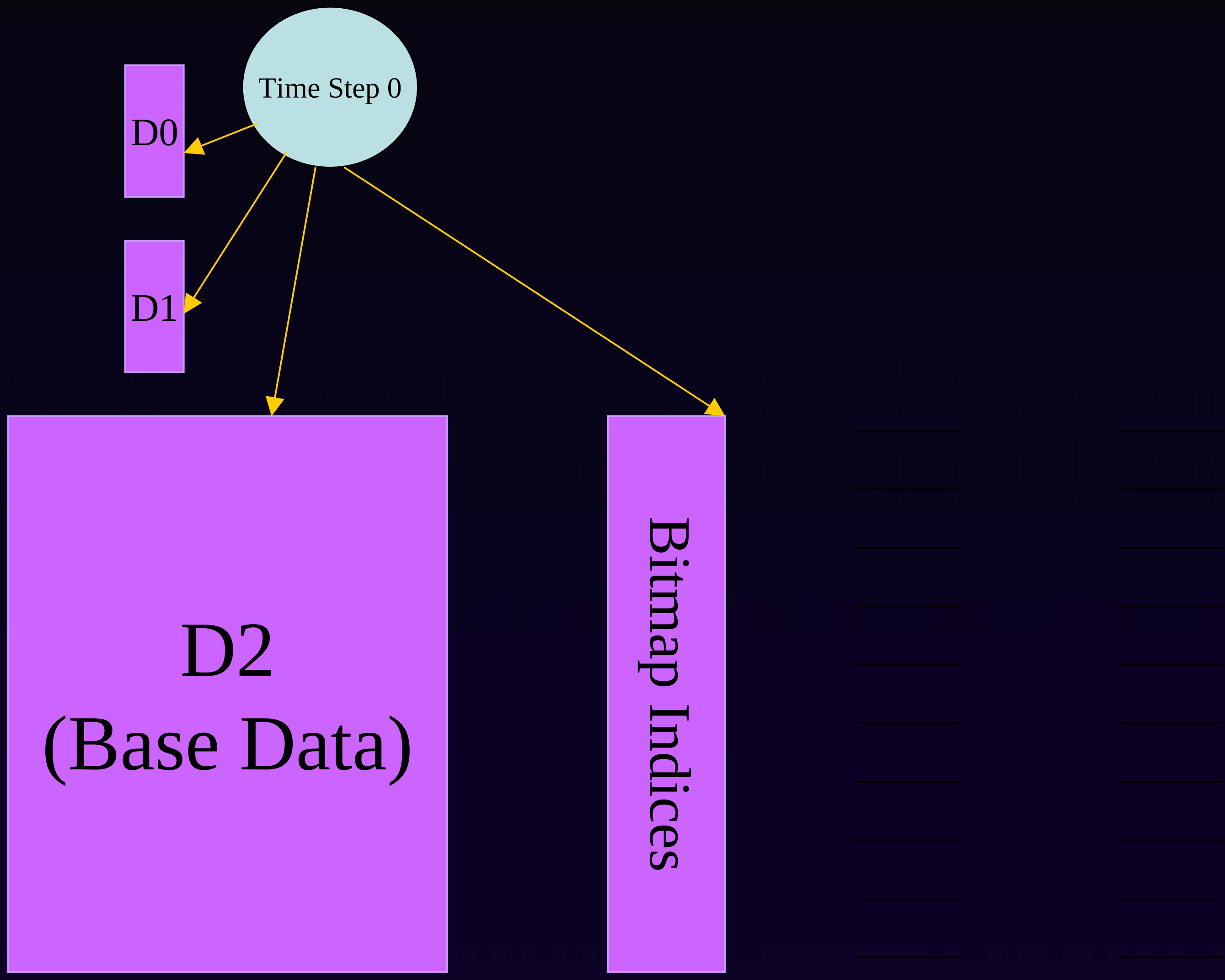

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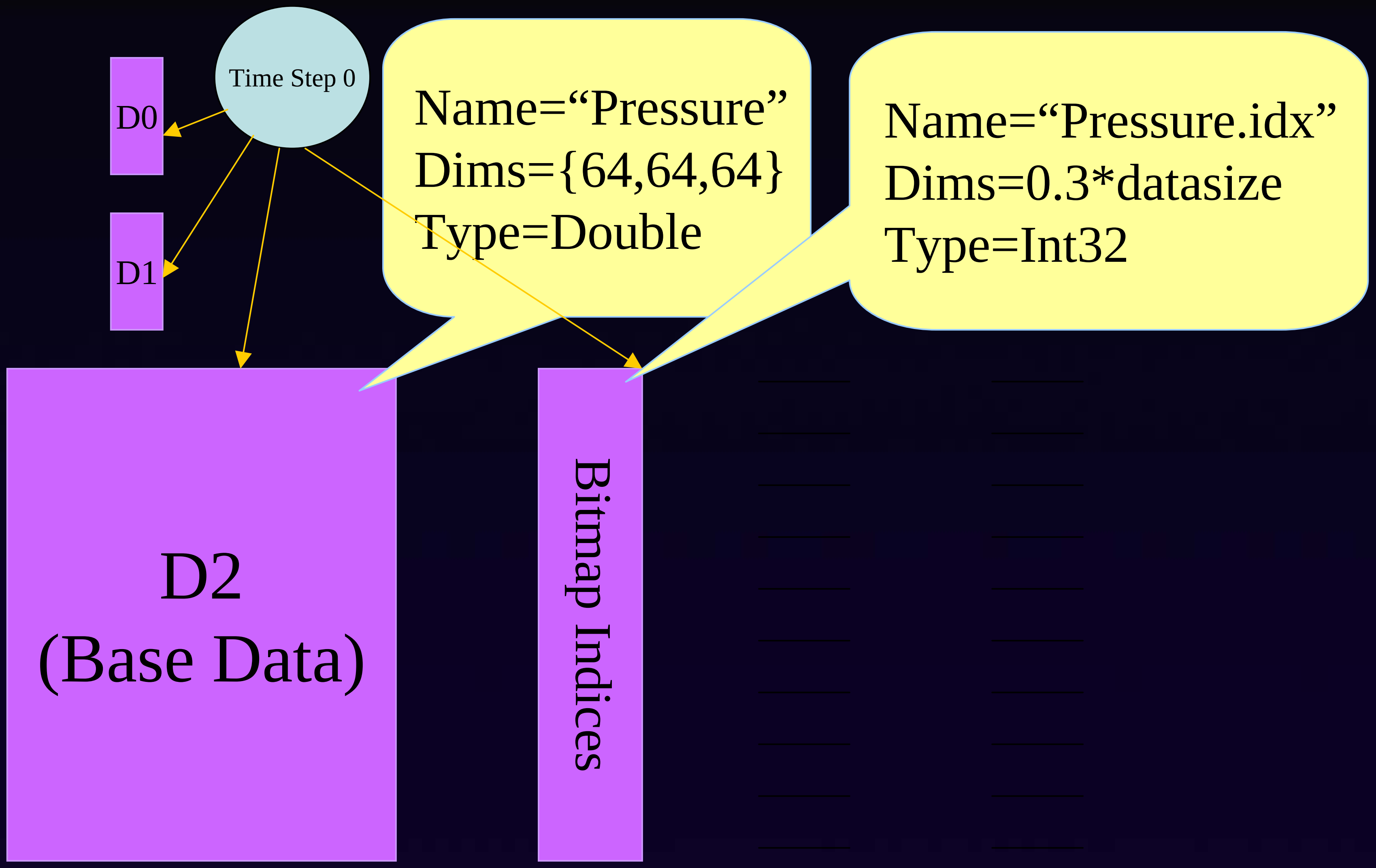

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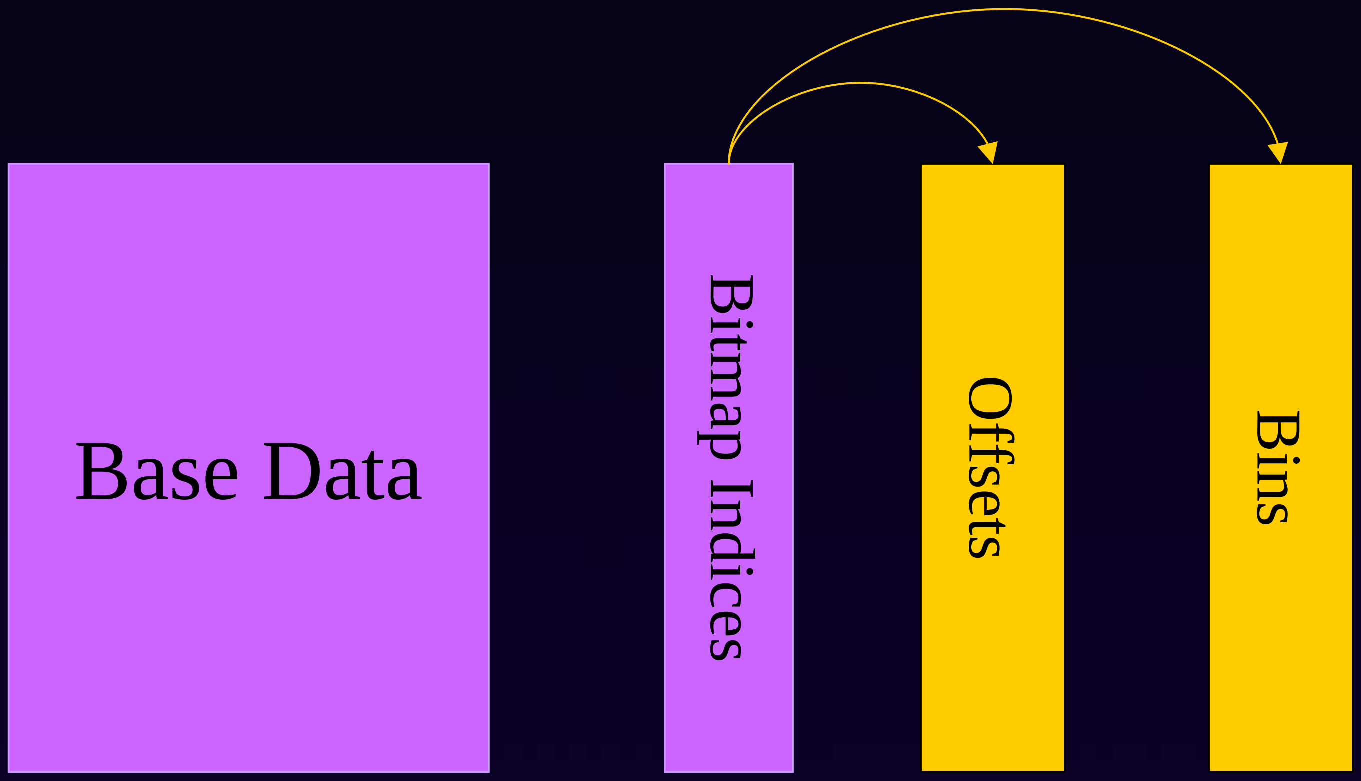

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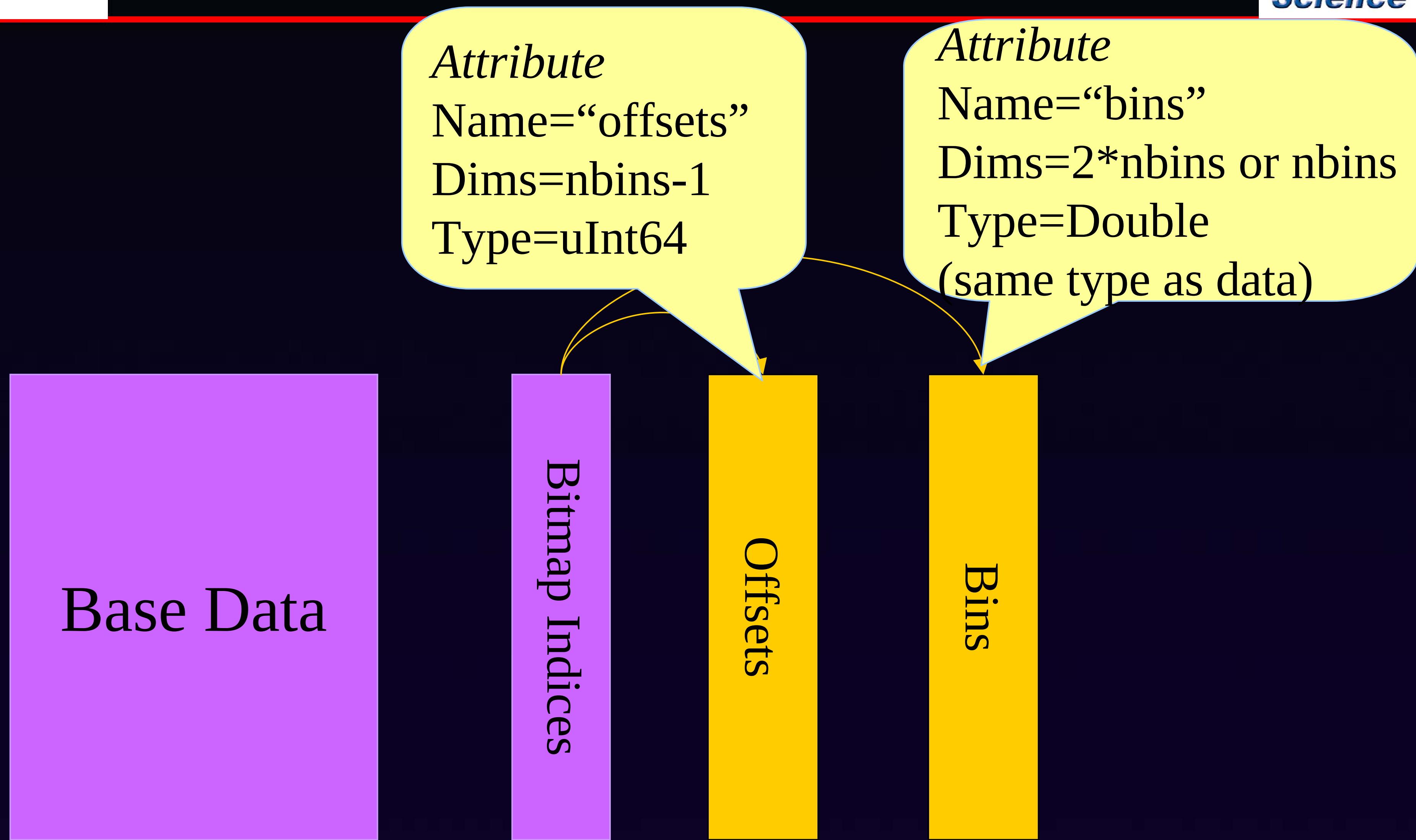
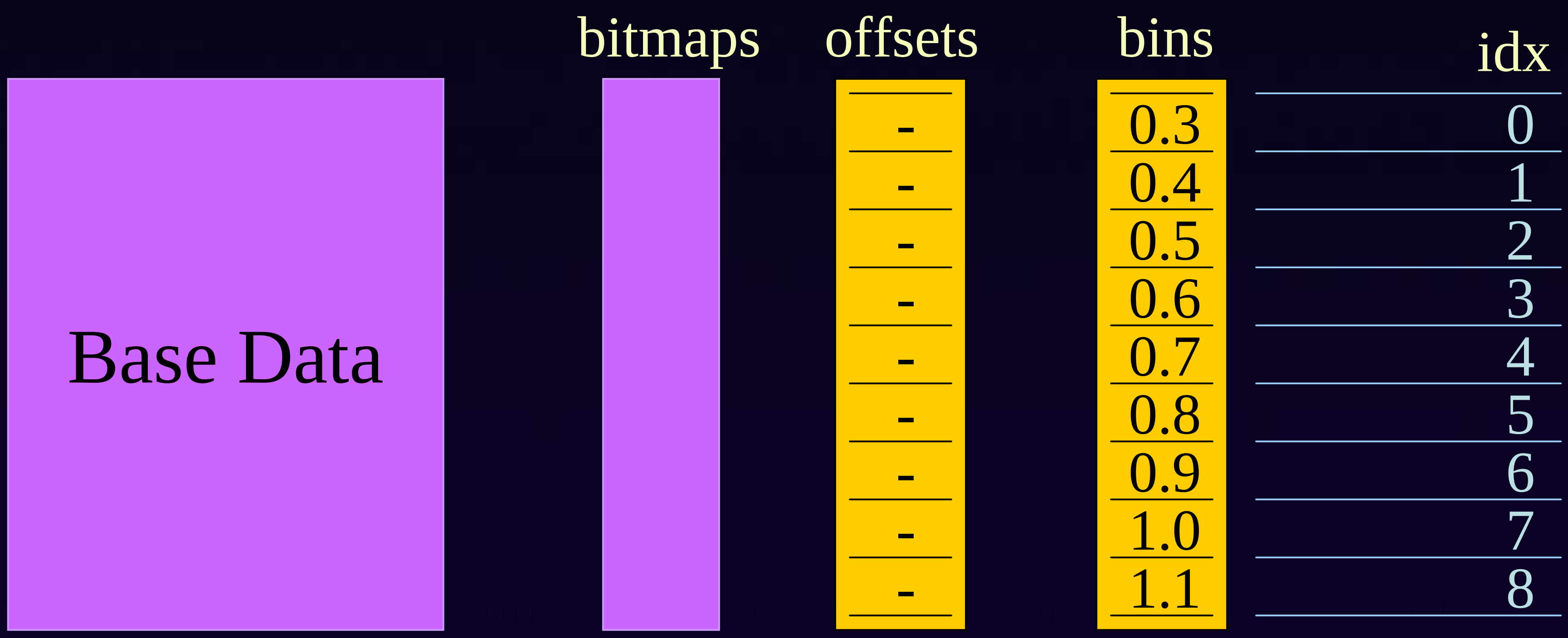


File Organization

Query: Pressure < 0.5



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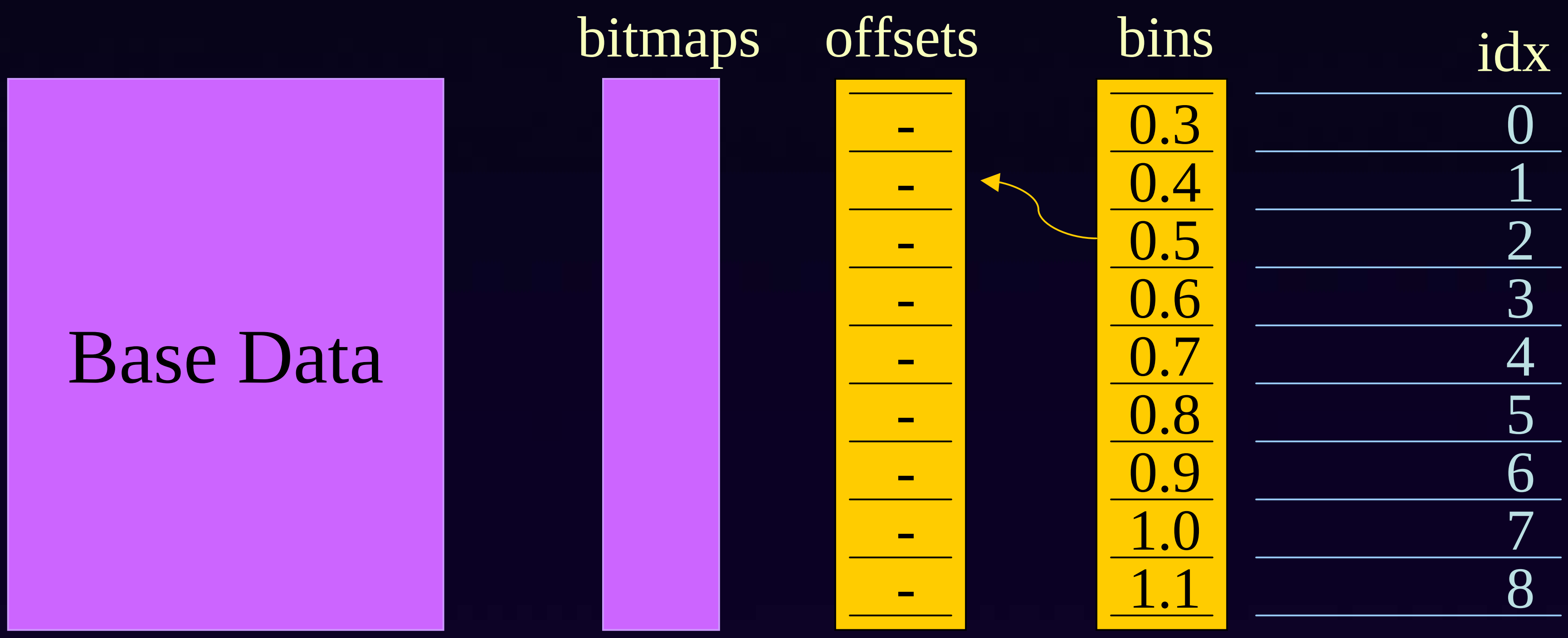

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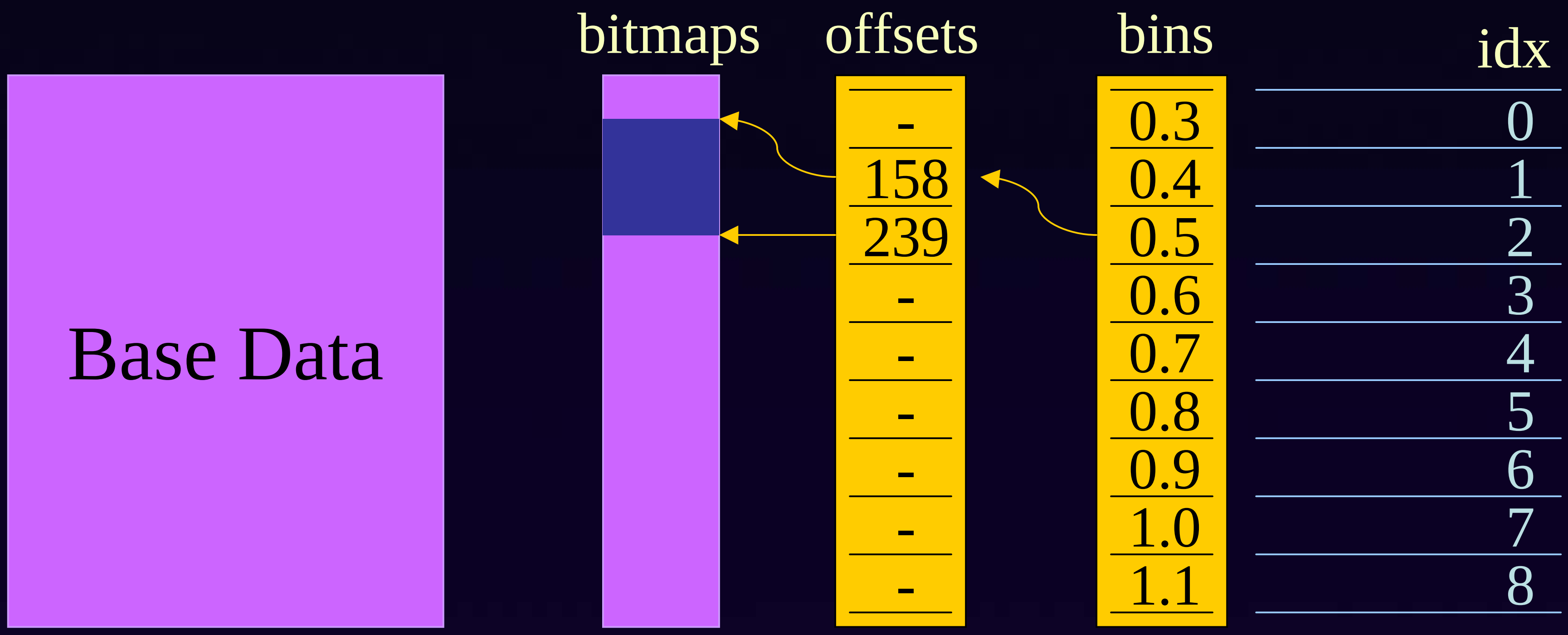

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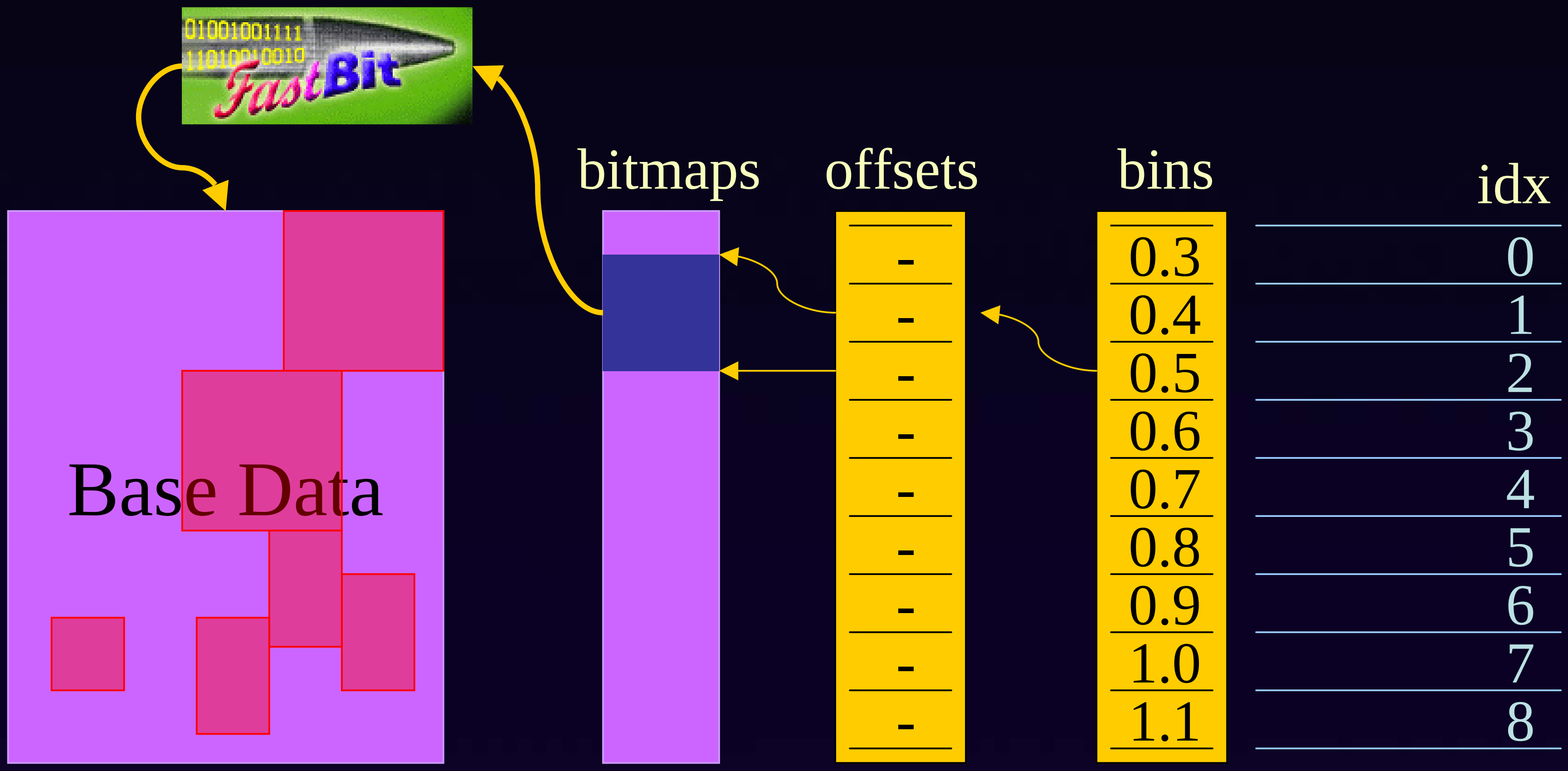

Final Notes

- Need for Higher level data organization
  - Demonstrated simple convention for index storage
  - Require higher level data organization to support more complex queries demanded by our scientific applications
  - Adoption of higher-level schema is a sociological problem rather than a technical problem
- Top Down (the Grand Unified Data Model)
  - DMF: Describe everything in the known universe
- Bottom up (community building)
  - Research Group: *Store data fro Cactus*
  - Scientific Community: *eg. HDF-EOS, NetCDF, FITS*
  - *?*

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  - World Domination

Questions?

Performance of Event Catalog

- The Event Catalog uses compressed bitmap indices
  - The most commonly used index is B-tree
  - The most efficient one is often the projection index
- The following table reports the size and the average query processing time
  - 1-attribute, 2-attribute, and 5-attribute refer to the number of attributes in a query
- Compressed bitmap indices are about half the size of B-trees, and are 10 times faster
- Compressed bitmap indices are larger than projection indices, but are 3 times faster

2.2 Million Events 12 common attributes		B-tree	Projection index	Bitmap index
Size (MB)		408	113	186
Query processing (seconds)	1-attribute	0.95	0.51	0.02
	2-attribute	2.15	0.56	0.04
	5-attribute	2.23	0.67	0.17