CompSci 590.6

Understanding Data:

Theory and Applications

Lecture 5

Index for ROLAP Cube
and
An Algorithm for MOLAP Cube

Instructor: Sudeepa Roy
Email: *sudeepa@cs.duke.edu*

Today's Paper(s)

Paper 1

Index Selection for OLAP

Gupta-Harinarayan-Rajaraman-Ullman

ICDE 1997

Paper 2

An Array-Based Algorithm for Simultaneous Multidimensional Aggregates

Zhao-Deshpande-Naughton

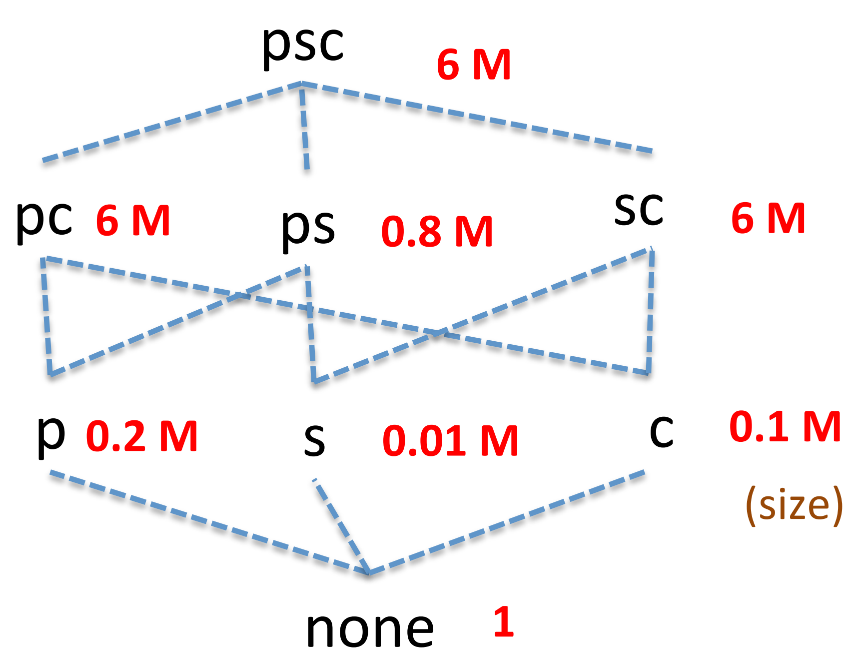
SIGMOD 1997

Paper#1

- Recall Lecture 3 (selective materialization)
- Materialized views for cubes
  - Greedy algorithm
  - By a subset of the authors
- This paper
  - Data cubes with indexes on the materialized views

Running Example

- From TPC-D (again)
- part (p), supplier (s), customer (c), sales
  - The business buys a part from a supplier and sells it to a customer
- p, s, c: Dimensions or attributes
- sub-cube on 1 or 2 out of 3 dimensions



Queries Considered

- Each dimension (p, s, c)
  - as a selection attribute (in WHERE, σ),
  - or as an output attribute (in GROUP-BY, ϒ)

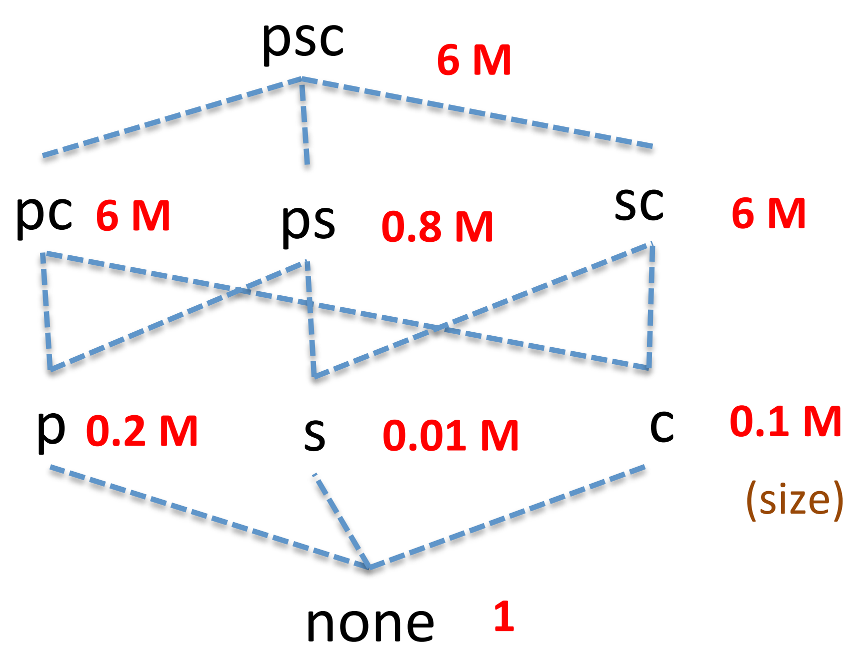
- Example
  - Find the "sales" to each customer of a given "part" = `widget' bought from a given "supplier" = 'widgets-r-us'
  - Denoted by $Q = \Upsilon_{c}\ \sigma_{ps}$
  - The order of dimensions in ϒ, σ is assumed to be non-important
  - Any subcube that has all the output and selection attributes can answer such queries

Indexes

- B-tree indexes or variants
- For subcube ps, we can construct
  - I_{ps}: search key is a concatenation of p and s
  - I_{sp}: search key is a concatenation of s and p
- Order matters
  - Given a value of p, I_{ps} can efficiently retrieve those rows in subcube ps that have this value
  - Cannot do so "efficiently" given a value of s
- $I_{X1, X2, \ldots, Xk}$ can efficiently answer a query that has some prefix of $X_1, X_2, \ldots, X_k$ in its σ

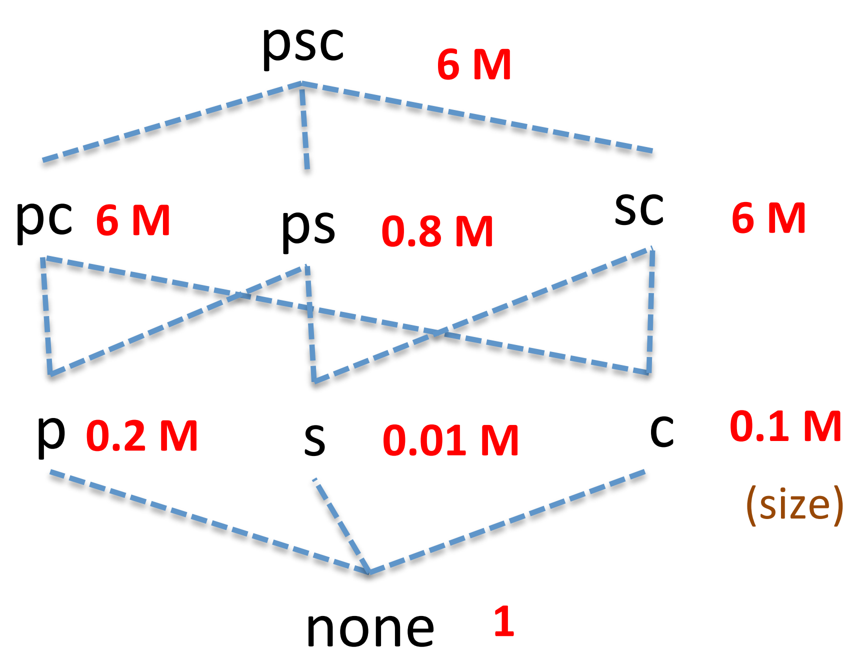
Cost Model

- Cost of answering a query = #rows processed
- Consider $Q_1 = \Upsilon_p \sigma_s$
- How can we answer Q_1 ?
- using ps
  - = 0.8M
- using psc
  - = 6M
- using ps and index I_{sp}
  - The avg. no. of rows per s value = |ps|/|s| = 0.8/0.01 = 80



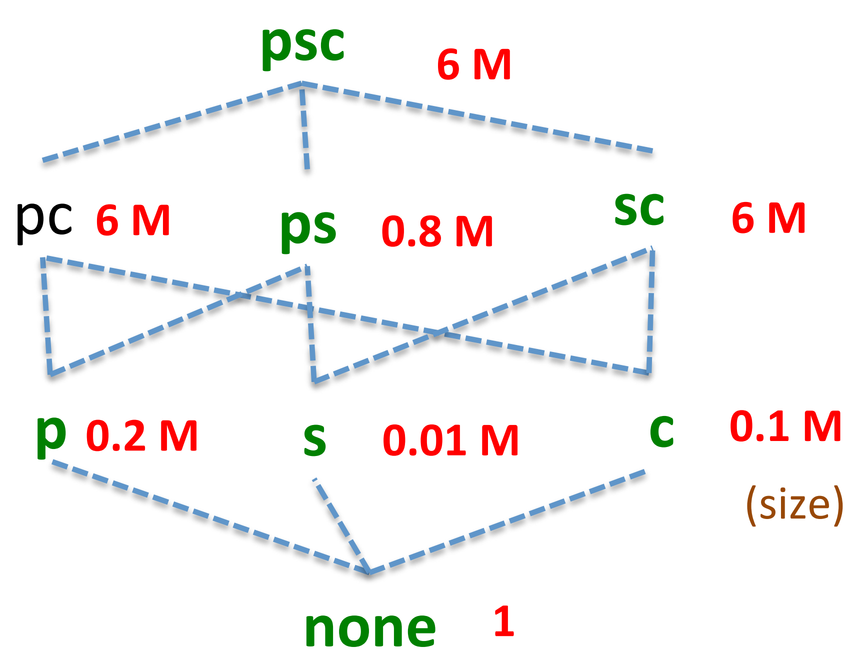
What to materialize?

- Which subcube and indexes?
- Assume all queries are equi-probable
  - Queries associated with ps are
  - $\Upsilon_p \, \sigma_s$
  - $\Upsilon_{ps} \, \sigma_{\{\}}$
  - $\Upsilon_{\{\}} \, \sigma_{ps}$
  - $\Upsilon_s \, \sigma_p$
- Cannot materialize everything
- Suppose
  - all subcubes and indexes require 80M rows
  - You can store only 25M rows



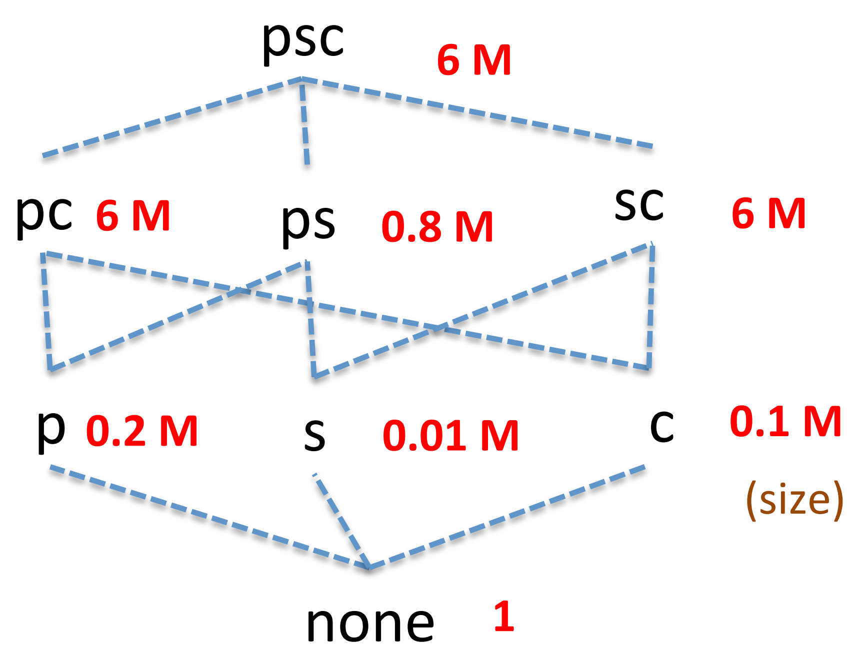
Simple Two-step Approach

- Divide available space for cubes and indexes
  - say equally
- Use greedy algo to select views (Lecture 3)
  - say psc, ps, sc, c, s, p, none
- Then select indexes
  - say I_{csp}, I_{pcs}
- 1.18M rows per query on average



1-Greedy Approach

- One step
- Greedily choose
  - subcube
  - or the index on a subcube (if the subcube is already chosen)
- psc – I_{csp} – ps – I_{pcs} – I_{spc} – c – s – p – none
- average query cost = 0.74M rows
  - 40% savings
  - ¾ to index ¼ to cube
  - hard to decide a priori
- But still can be improved



Slice Queries

- $\Upsilon_c\ \sigma_{p=\text{'widget'}}\ R$
  - slice through the subcube pc
- $\Upsilon_{G1,\dots GK}\ \sigma_{S1,\dots,Sl}$ associated with the subcube G1..GkS1…Sl
  - smallest cube that can answer this query
- An r-dimensional subcube has 2^r slice queries
  - each dimension can go to either Υ or σ
- every query is a slice query
- An n-dimensional cube has ${}^{n}C_{r}$ r-dimensional subcubes
- Total slice queries for a data cube = 3^n
  - summing over all r = 0 to n

How many indexes per cube?

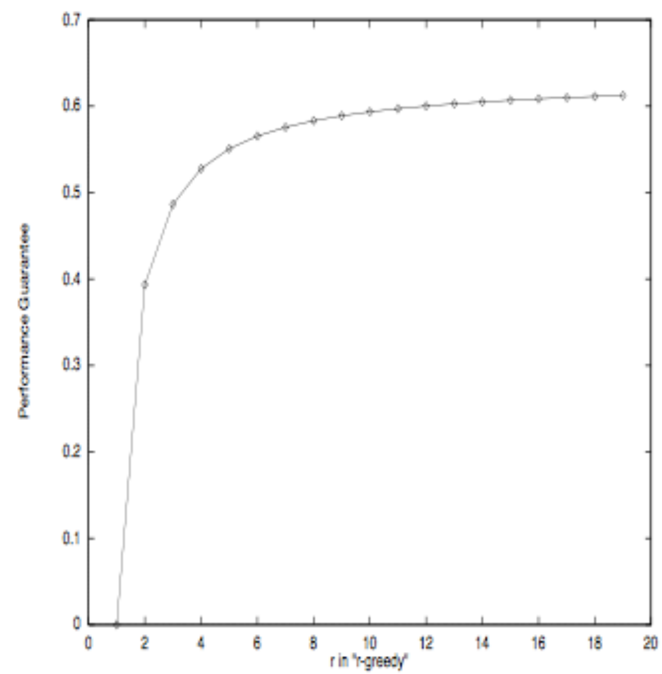
- e.g. 4 with subcube ps
  – $I_p(ps)$, $I_s(ps)$, $I_{ps}(ps)$, $I_{sp}(ps)$
- order matters in an index
- #Index for a view with m attr
  – $= \Sigma_{r=0}^{m} \; {}^{m}C_{r} \; r!$ ---> $(e-1)m!$
- Total #indexes for a n-dimensional cube
  – about 3n!
- Total #fat indexes (same attr in view and index)
  – about 2n!
  – where index attributes are permutations of cube attributes

Materializing Views with Indexes

- Input
  - a set of views
  - each view has a set of indexes
  - a set of queries to be supported
  - cost c(Q, V, J) of answering query Q using view V and index J
    - estimated
  - amount of space available S
- Goal:
  - select a set of views and indexes that will minimize the total cost to answer the queries not exceeding the space S
- NP-hard
  - Lecture 3
  - even if no index and unit cost

r-Greedy

- Use greedy algorithms
- r-Greedy
  - Generalization of 1-greedy
  - Instead of choosing at most one index/view with max benefit per unit space…
  - …choose “at most r views” or index (for chosen views) every step with max benefit per unit space as a set
  - Runtime: $O(km^r)$
    - m: Number of structures (views/ index) in query graph
    - k: Number of structures selected
    - Max size (assuming unit size): S +r-1 units
  - Only practical for r ≤ 4



Paper#2

An Array-Based Algorithm for Simultaneous Multidimensional Aggregates

Zhao-Deshpande-Naughton

SIGMOD'97

Acknowledgement:

The following slides have been prepared using the slides by Manuel Calimlim, in CS632-Advanced Database Systems, Spring 2000, Cornell University

ROLAP vs MOLAP cube

- ROLAP = Relational OLAP
  - All algorithms so far were for ROLAP
  - A cell in the space is a tuple
  - e.g. (shoes, WestTown, 3-July-96, $34)
- MOLAP = Multi-dimensional OLAP
  - Data in sparse arrays
  - just stores the data value $34
  - The position in the array encodes (shoes, WestTown, 3-July-96)

- This paper: MOLAP algorithm for cube

- Similar example
  - Dimensions = product, store, time
  - Measure = sales

ROLAP Cube

In ROLAP systems, 3 main ideas for efficiently computing the CUBE

1. Group related tuples together (using sorting or hashing)
2. Use grouping performed on sub-aggregates to speed computation
3. Compute an aggregate from another aggregate rather than the base table

MOLAP cube

- No “bring together related values”
  - Data values are stored in their own fixed location
  - Rather, visit those values in the right order so that the computation is efficient
- Simultaneously compute spatially-delimited partial aggregates
  - so that a cell is not visited for each sub-aggregate
- Store arrays efficiently on disk
  - “chunk” them into pieces
  - do compression to avoid wasting space on cells with no data

Multidimensional Array Storage

Data is stored in large, sparse arrays, which leads to certain problems:

1. The array may be too big for memory
2. Many of the cells may be empty and the array will be too sparse

Chunking Arrays

Sarawagi-Stonebraker, ICDE'94: Efficient Organization of Large Multidimensional Arrays

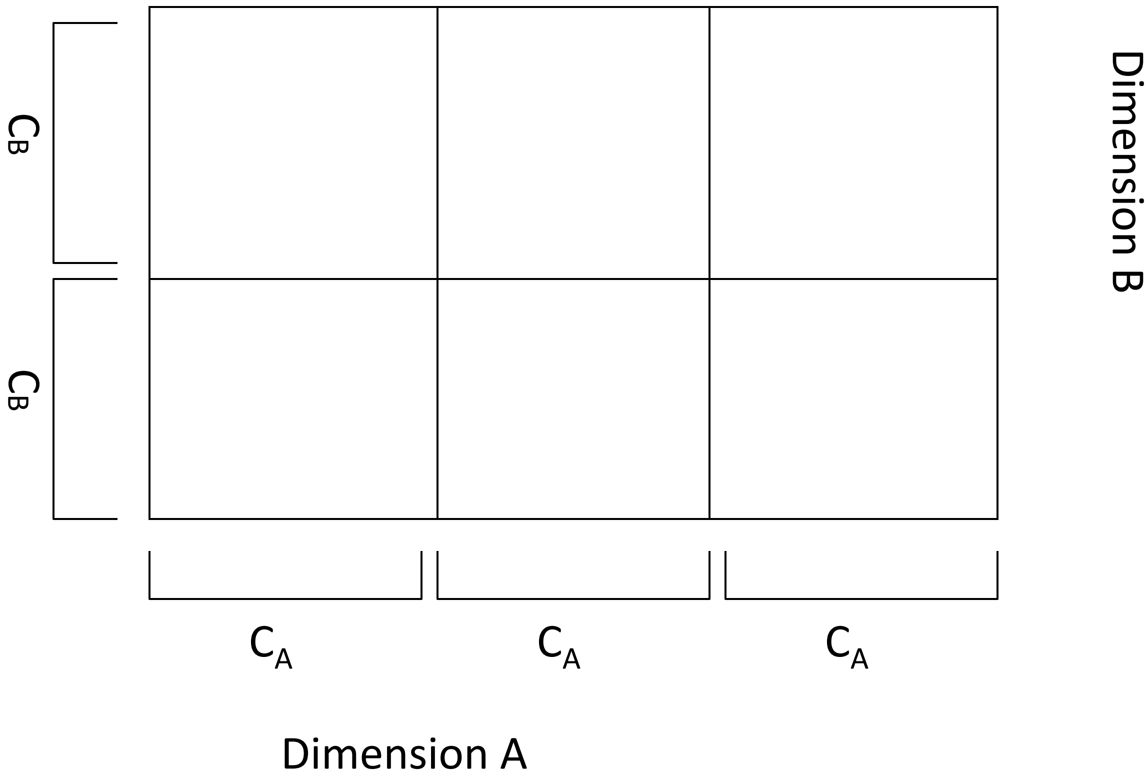
Why chunk?

- A simple row major or column major layout (partitioning by dimension) will favor certain dimensions over others
- e.g. assume (store, day) – row major
  - to access a day may need multiple block read from disk

What is chunking?

- Divide an n-dimensional array into smaller n-dimensional chunks and store each chunk as one object on disk

Chunks



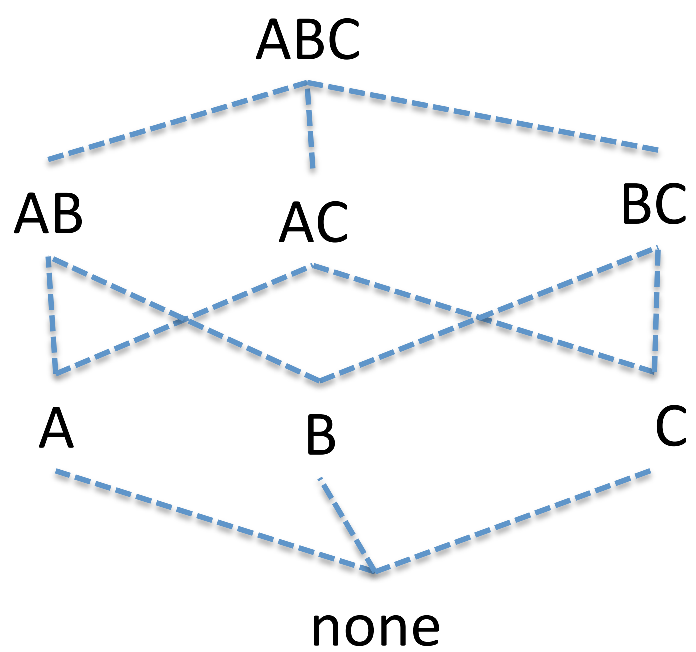
Array Compression

- No compression for dense arrays
  - more than 40% filled with data
  - fixed length chunks
  - assign a null value to invalid cells
  - Still compression since none of the dimension values are stored

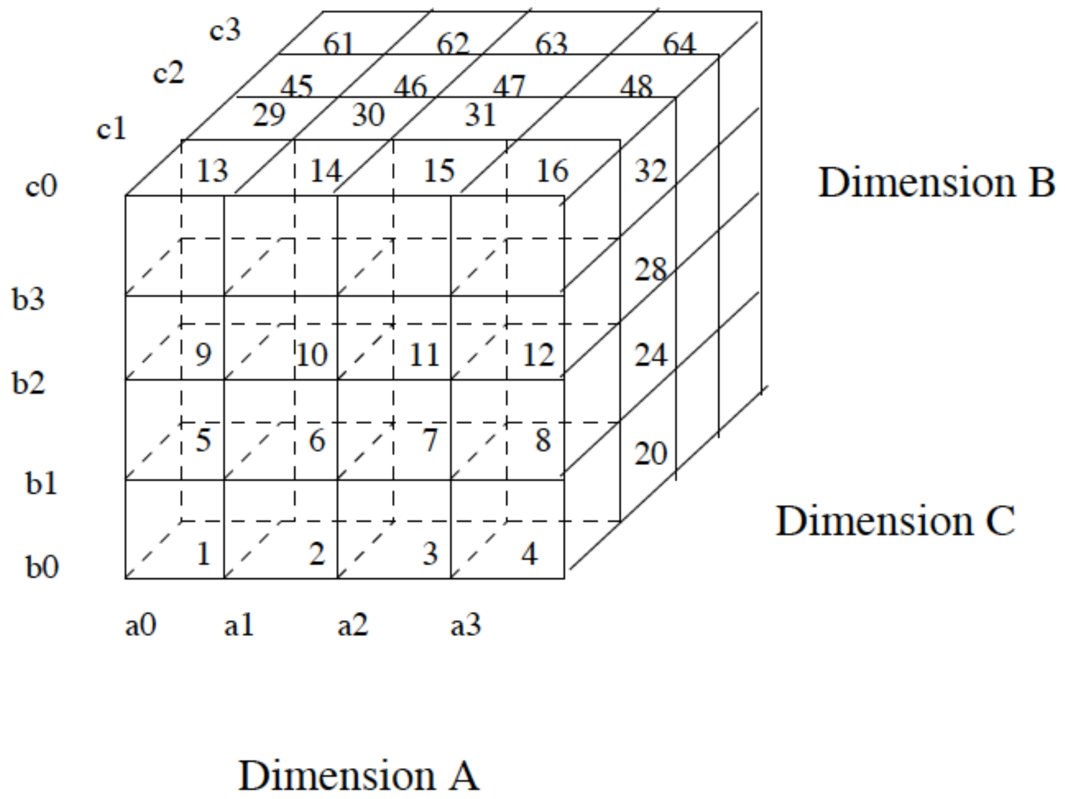
- Compression for sparse array
  - less than 40% filled, most cells invalid
  - use “Chunk-offset compression”
  - for each valid entry, store (offsetInChunk, data) where offsetInChunk is the offset from the start of the chunk
  - e.g. for 3-D array, convert address (I, j, k) into an offset
  - chunks will be of variable length – needs metadata for each chunk and data file

Naïve Array Cubing Algorithm

- Multiple passes
- compute each group-by in a separate pass with min memory
- No overlap of computation and minimizing I/O cost
- Similar to ROLAP, each aggregation is computed from its parent in the lattice.
- Each chunk is aggregated completely and then written to disk before moving on the next chunk.



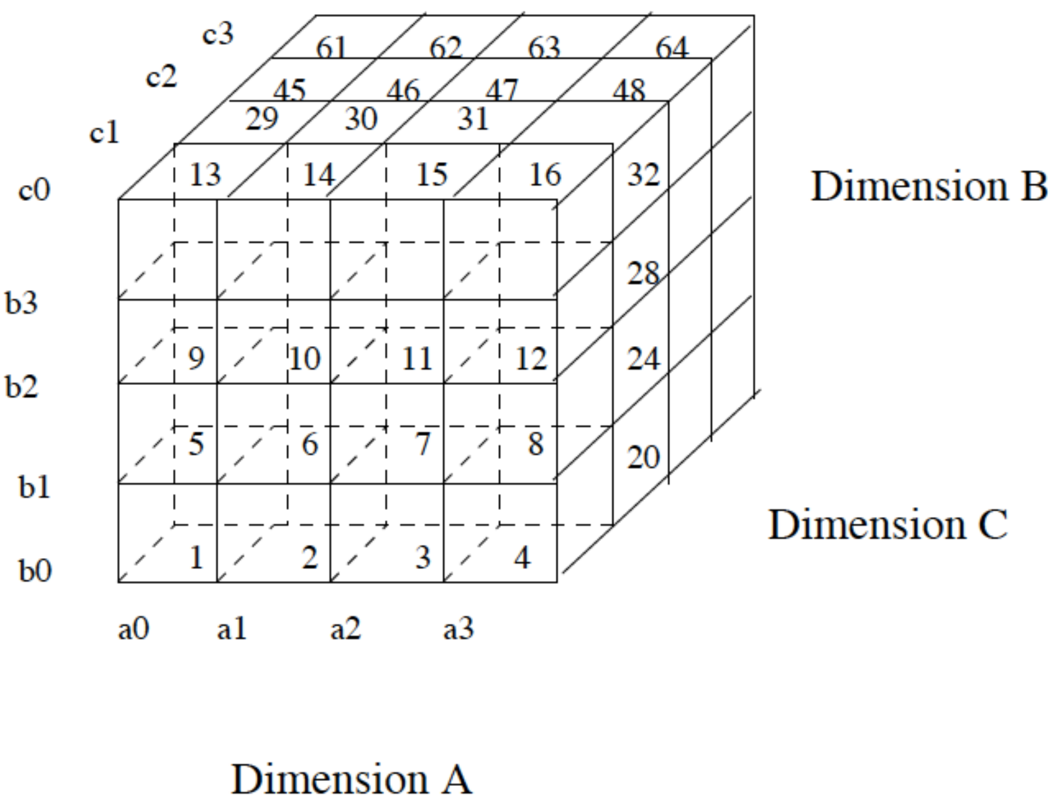
Naïve Array Cubing Algorithm

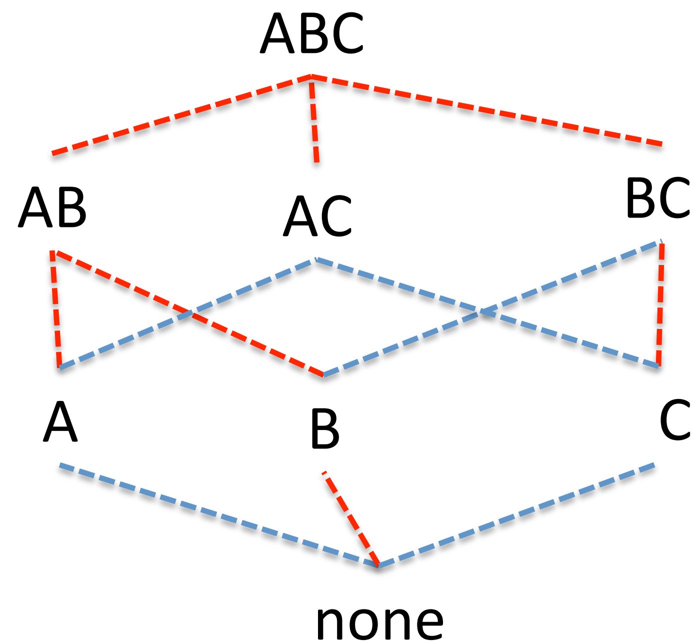


- Compute AB
  - sweep through the C-plane if no chunks
- Suppose ABC is stored in a no. of chunks
  - they are numbered in dimension order (ABC)
  - need to sweep chunk by chunk
  - To compute group by for a_0b_0, need to sum over 4 chunks for c_0, c_1, c_2, c_3

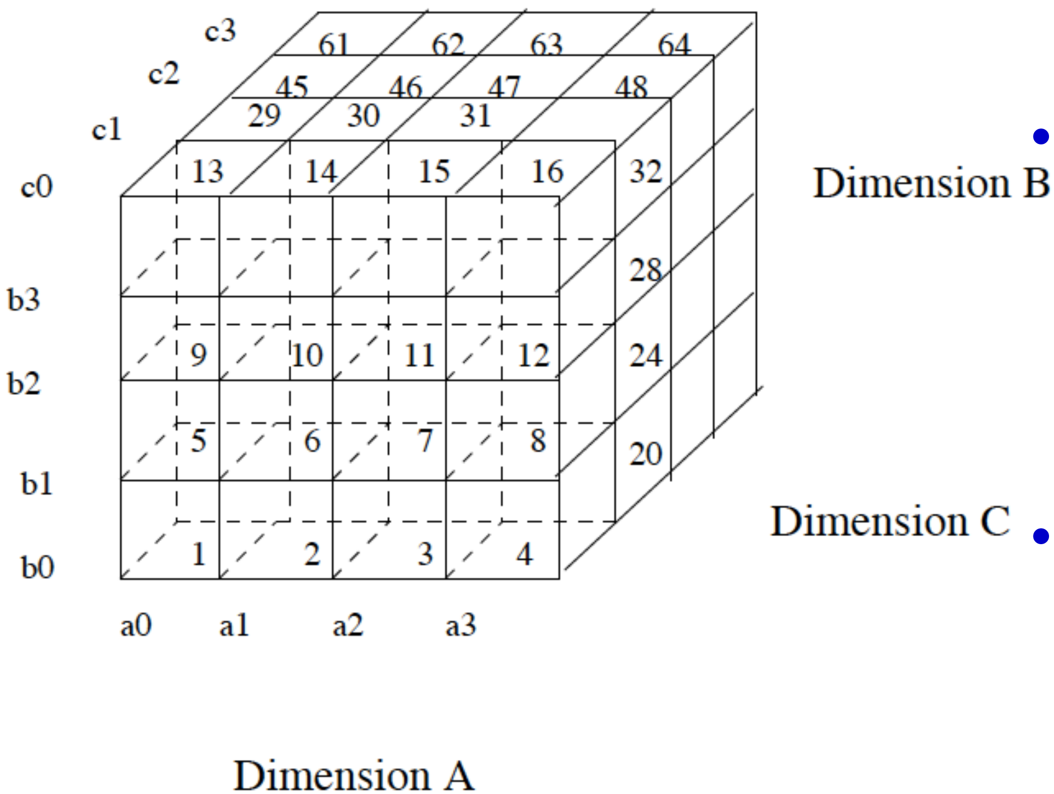
Naïve Array Cubing Algorithm

- Multiple aggregates in cube
- Compute A from AB or AC, not from ABC
- Embed a “minimum spanning tree” to the lattice – min size parent





Problems with Naïve approach

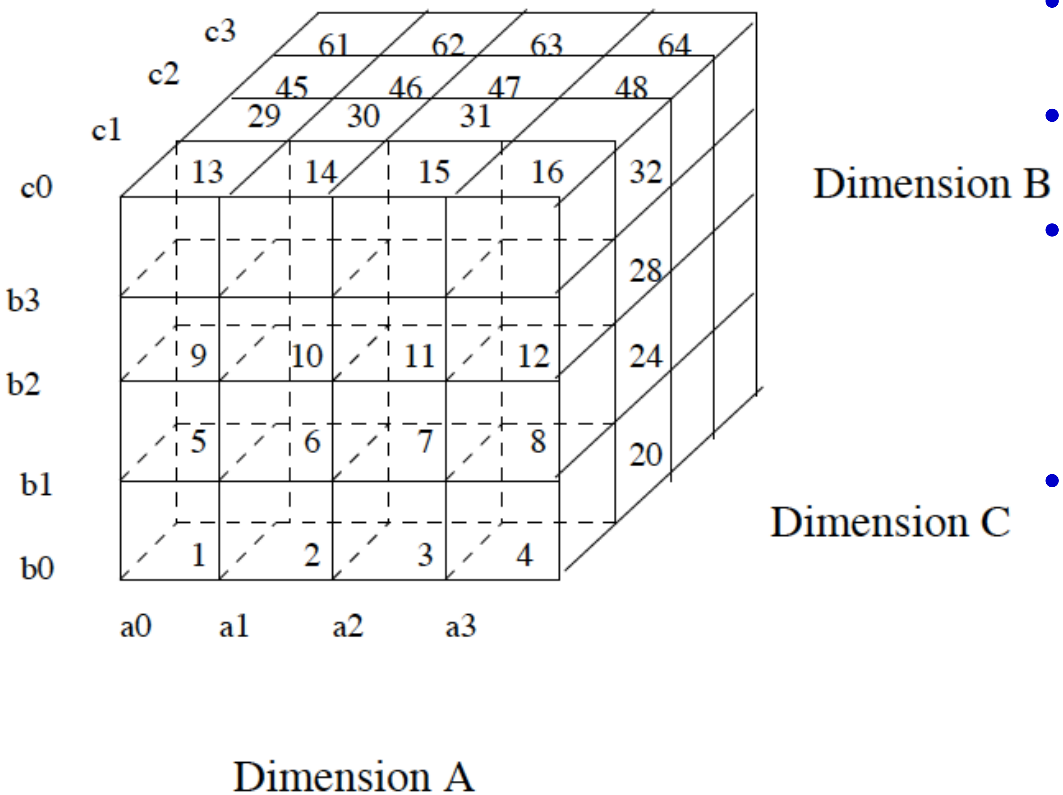


- Each sub aggregate is calculated independently
- E.g. this algorithm will compute AB from ABC, then rescan ABC to calculate AC, then rescan ABC to calculate BC
- We need a method to simultaneously compute all children of a parent in a single pass over the parent

Single-Pass Multi-Way Array Cubing Algorithm

- The order of scanning is vitally important in determining how much memory is needed to compute the aggregates.
- A dimension order $O = (D_{j1}, D_{j2}, \ldots D_{jn})$ defines the order in which dimensions are scanned
  - Logical order, independent of physical layout on disk
- $|D_i|$ = size of dimension i
- $|C_i|$ = size of the chunk for dimension i
- $|C_i| \ll |D_i|$ in general

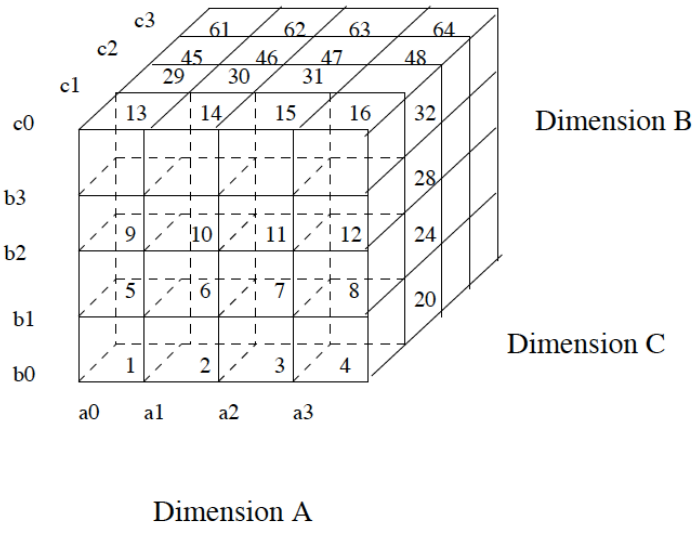
Order determines memory requirement



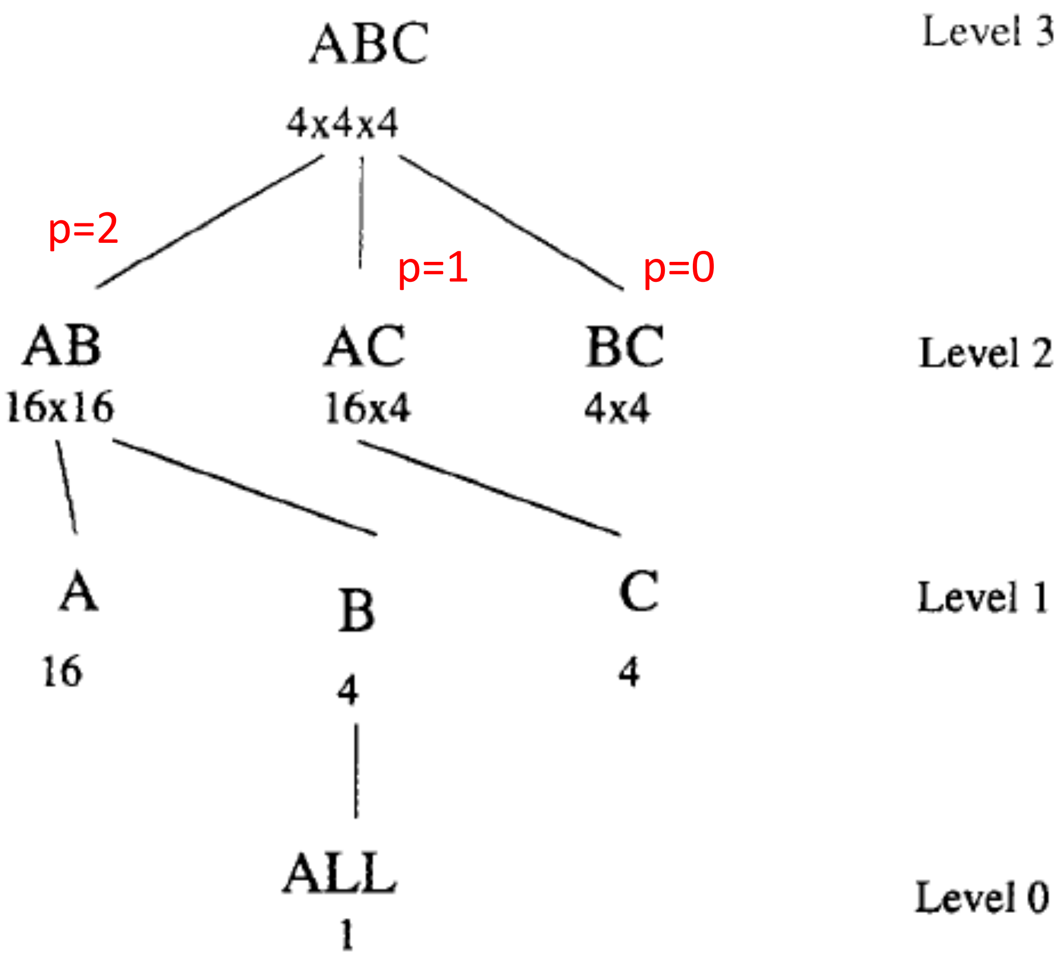
- $|C_i| = 4$, $|D_i| = 16$ for all i
- Dimension order (ABC)
- For BC, we need 4 chunks
  - 1-4 computes one chunk b_0c_0 of BC
  - give the memory to b_1c_0
- For AC, we need 16 chunks
  - allocate space to 4 chunks a_0c_0, a_1c_0, a_2c_0, a_3c_0
  - after reading 16 chunks (a plane) give the memory to a_0c_1, a_1c_1, a_2c_1, a_3c_1
- For AB, we need all 64 chunks
  - allocate memory to all 16 chunks of AB as we read chunks of the cube
  - after aggregation is complete, output those chunks in AB order

Concrete Example

- For BC group-bys, we need 1 chunk (4x4)
- For AC, we need 4 chunks (16x4)
- For AB, we need to keep track of whole slice of the AB plane, so (16x16)



Minimum Memory Spanning Trees (MMST)



MMST for a given dimension order

p = size of the largest common prefix between the current group-by (size n-1) and its parent

$\Pi_{i = 1 \text{ to } p} |Di| \times \Pi_{i = p+1 \text{ to } n-1} |Ci|$

$D_i = 16$, $C_i = 4$

order = (A B C)

Q. What is the optimal dimension order in general?

Effects of Dimension Order

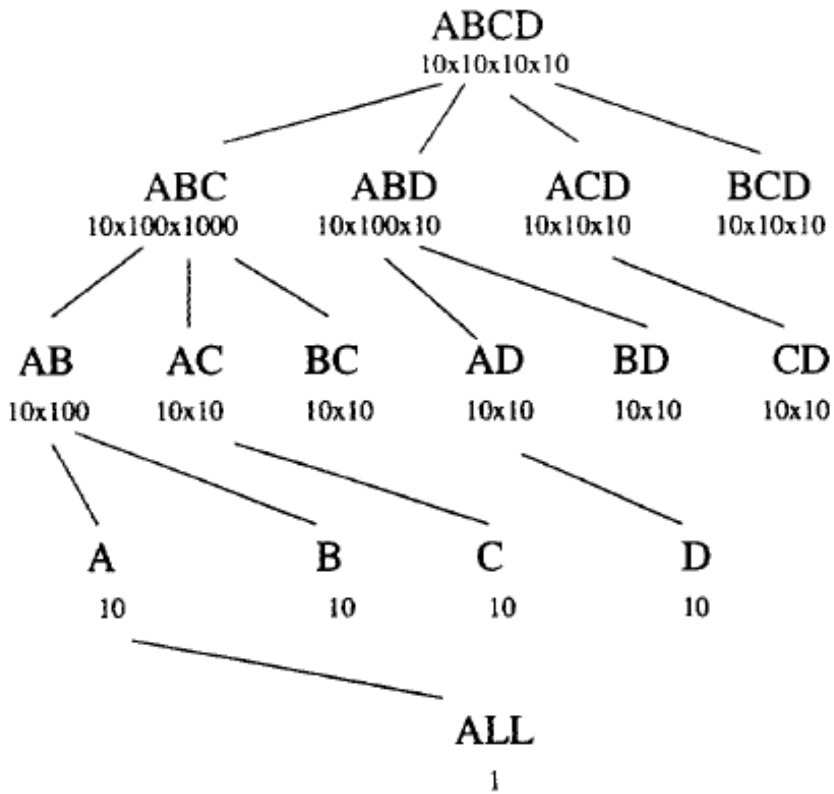


Figure 3: MMST for Dimension Order ABCD (Total Memory Required 4 MB)

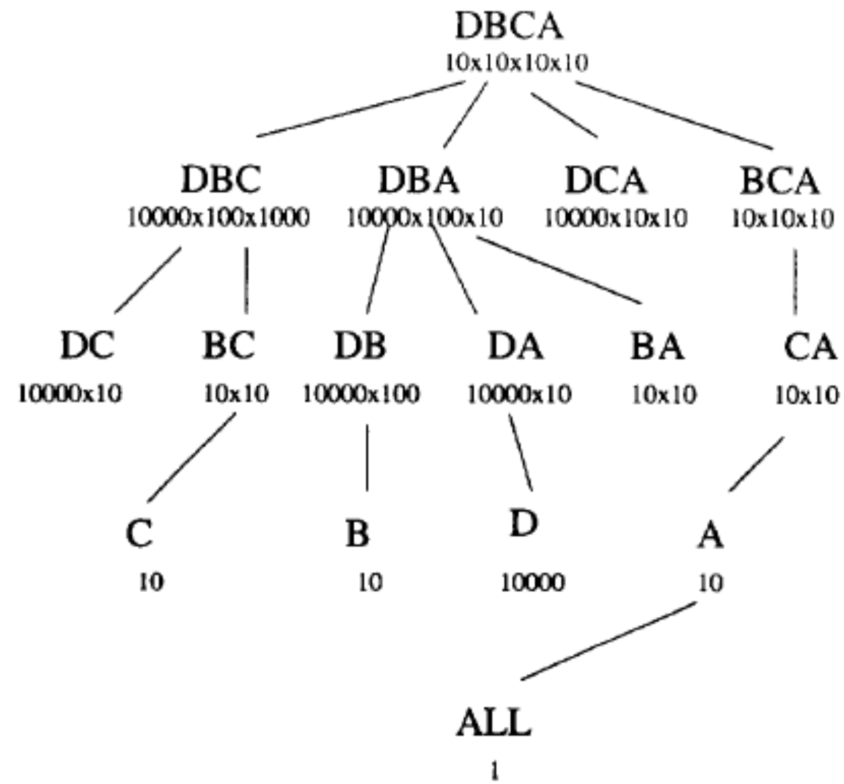


Figure 4: MMST for Dimension Order DBCA (Total Memory Required 4 GB)

$|D_A| = 10$, $|D_B| = 100$, $|D_C| = 1000$, $|D_D| = 10000$

$|C_A| = |C_B| = |C_C| = |C_D| = 10$

Effects of Dimension Order

- The early elements in O (particularly the first one) appear in the most prefixes
  - contribute their dimension sizes to the memory requirements

- The last element in O can never appear in any prefix
  - The total memory requirement for computing the CUBE is independent of the size of the last dimension

Optimal Dimension Order

- Sort them on increasing dimension size
  - order is $(D_{i1}, D_{i2}, \ldots, D_{in})$
  - where $|D_{i1}| <= |D_{i2}| <= |D_{i3}| <= \ldots. <= |D_{in}|$

- The total memory requirement will be minimized
  - a formal proof in the paper

- The total memory requirement is Independent of the size of the largest dimension
  - huge benefit if the largest dimension is big

- Extension to multiple passes
  - limited memory, suppose required memory is not
  - Right to left scan – first compute BC so that it is not divided into multiple passes

Results

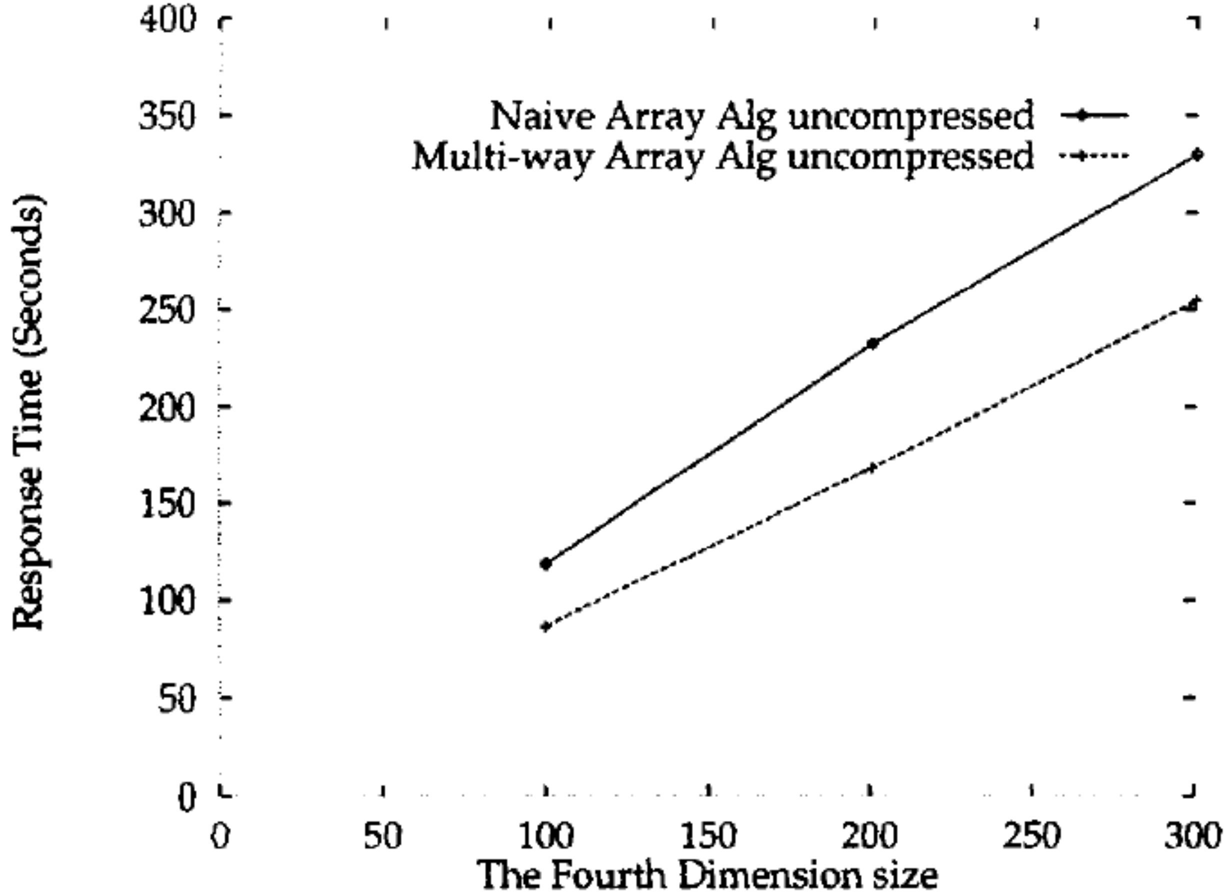
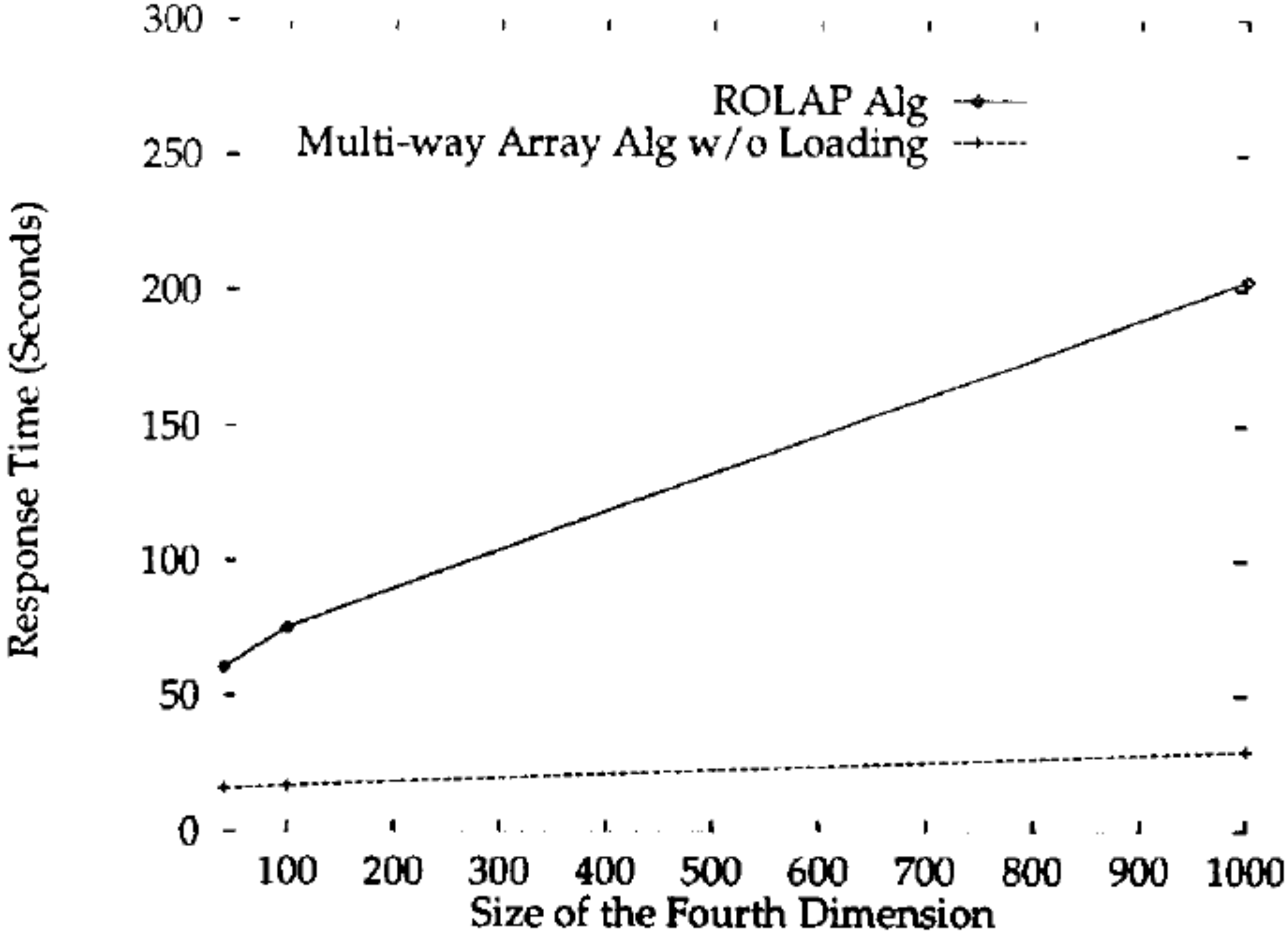


Figure 5: Naive vs. Multi-way Array Alg.

ROLAP vs. MOLAP



ROLAP vs. MOLAP

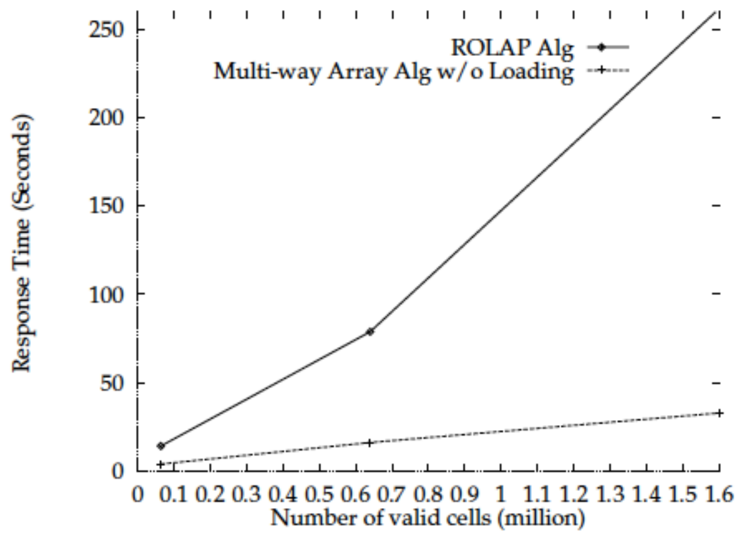


Figure 8: ROLAP vs. Multi-way Array for Data Set 2

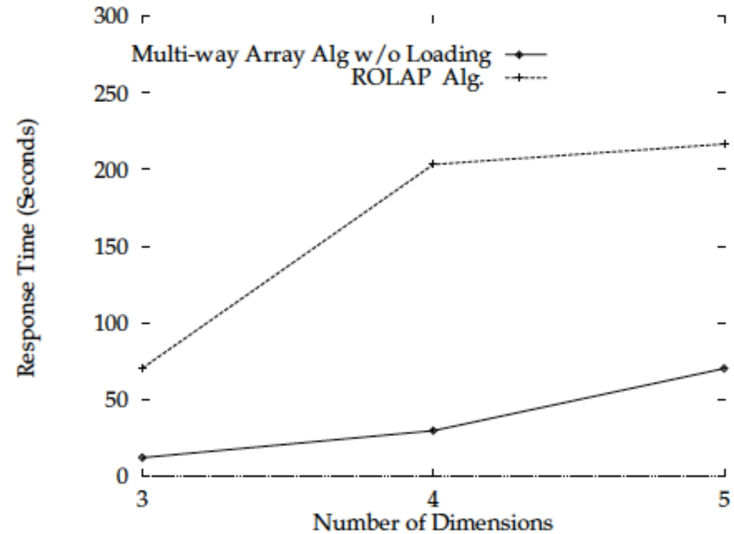


Figure 9: ROLAP vs. Multi-way Array for Data Set 3

- Memory constant, ROLAP does multiple passes
- Array dimension size not changing with density
- Largest dimension has no effect

MOLAP for ROLAP system

We can use the MOLAP algorithm with ROLAP systems:

1. Scan the table and load into an array.
2. Compute the CUBE on the array.
3. Convert results into tables

- Even with the additional cost of conversion between data structures, the MOLAP algorithm
  - runs faster than directly computing the CUBE on the ROLAP tables
  - scales much better
- the multidimensional-array can be used as a query evaluation data structure rather than a persistent storage structure.

Summary

- The multidimensional array of MOLAP should be chunked and compressed
- The Single-Pass Multi-Way Array method simultaneously updates all GROUP-Bys in the CUBE with a single pass over the data
  - assumes required memory is available
  - Multiple passes are needed otherwise
- By minimizing the overlap in prefixes and sorting dimensions in order of increasing size, we can build a MMST that gives a plan for computing the CUBE
- On MOLAP systems, the CUBE is calculated much faster than on ROLAP systems
  - can be used even for cube for ROLAP