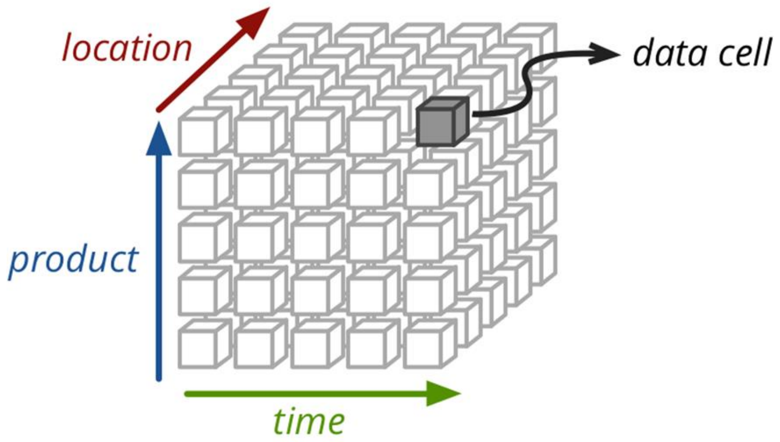
CS 412 Intro. to Data Mining

Chapter 5. Data Cube Technology

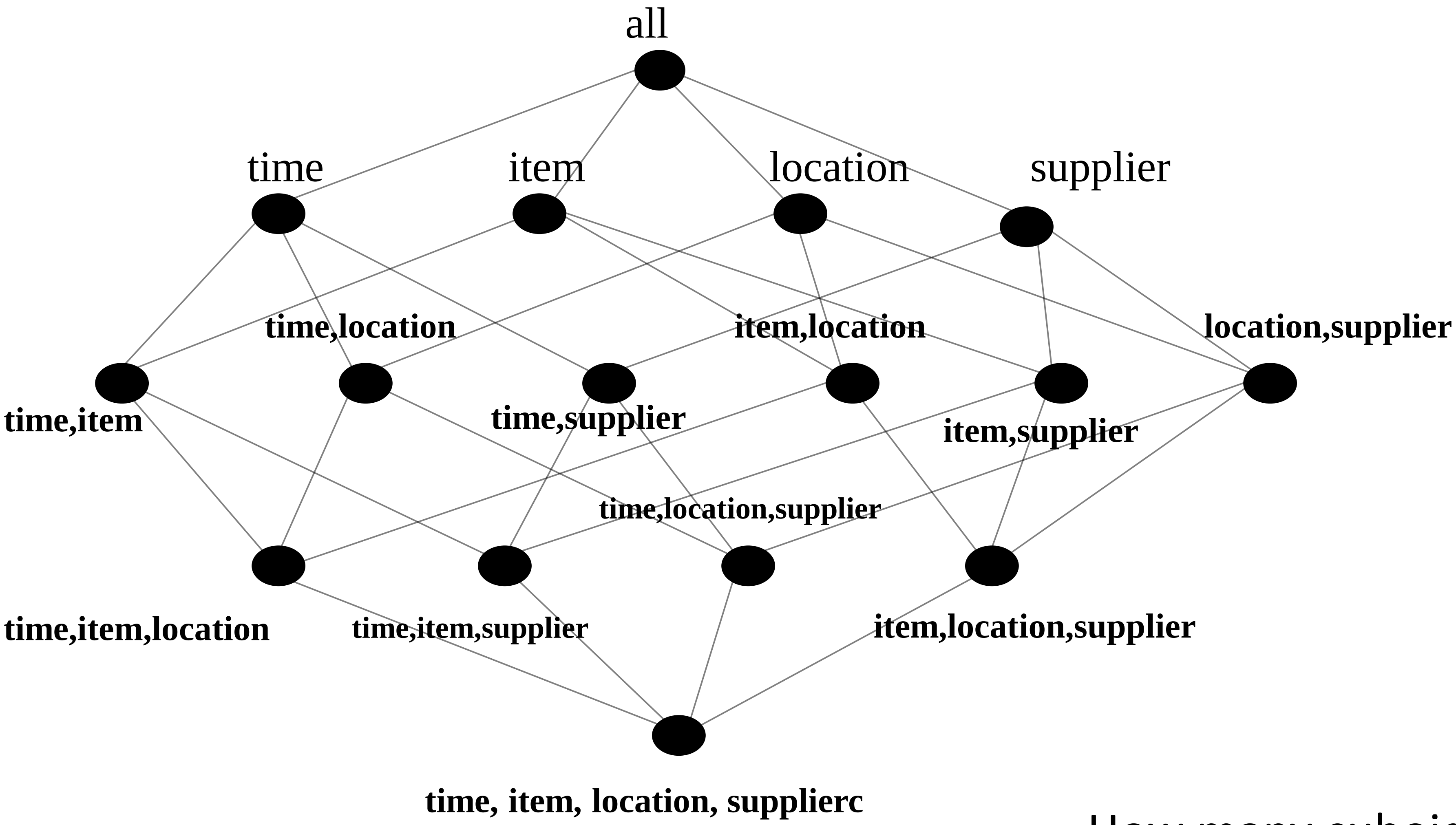
Qi Li, Computer Science, Univ. Illinois at Urbana-Champaign, 2018

Chapter 5: Data Cube Technology



- ❑ Data Cube Computation: Basic Concepts
- ❑ Data Cube Computation Methods
- ❑ Processing Advanced Queries with Data Cube Technology
- ❑ Multidimensional Data Analysis in Cube Space
- ❑ Summary

Data Cube: A Lattice of Cuboids



0-D (apex) cuboid

1-D cuboids

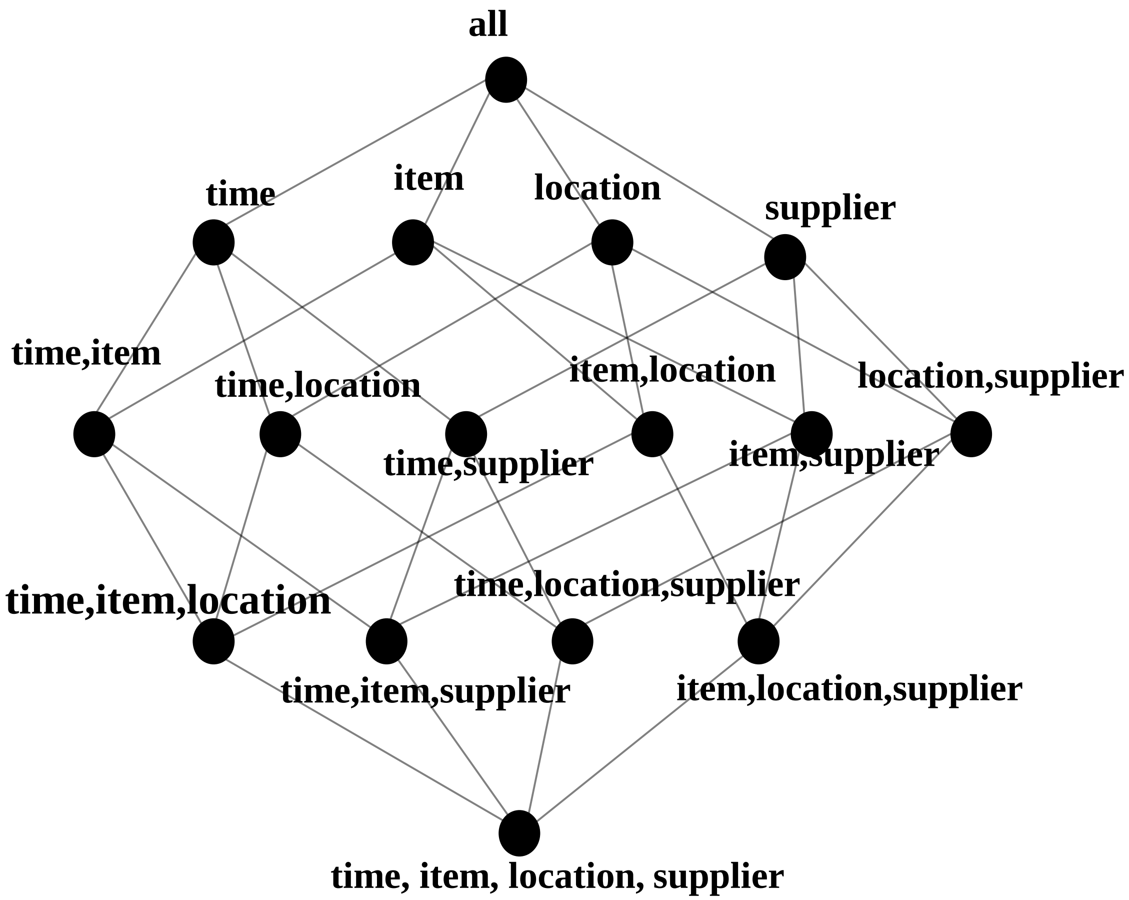
2-D cuboids

3-D cuboids

4-D (base) cuboid

How many cuboids are there at each level?

Data Cube: A Lattice of Cuboids



- Base vs. aggregate cells
- Ancestor vs. descendant cells
- Parent vs. child cells

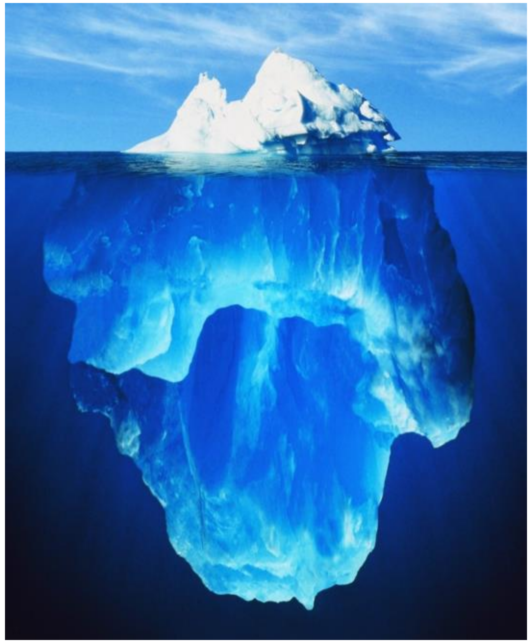
0-D (agg)	(*,*,*,*)
1-D (agg)	(*, milk, *, *)
2-D (agg)	(*, milk, Urbana, *)
2-D (agg)	(*, milk, Chicago, *)
3-D (agg)	(9/15, milk, Urbana, *)
4-D (base)	(9/15, milk, Urbana, Dairy_land)

Cube Materialization: Full Cube vs. Iceberg Cube

- Full cube vs. iceberg cube

  compute cube *sales_iceberg* **as**
  SELECT *month, city, customer_group*, **COUNT(*)**
  FROM *salesInfo*
  CUBE BY *month, city, customer_group*
  HAVING count(*) >= min support

  iceberg condition



- Compute *only* the cells whose measure satisfies the iceberg condition
  - Ex.: Show only those cells whose count is at least 100
- Only a small portion of cells may be "above the water'' in a sparse cube

Why Iceberg Cube?

- No need to save nor show those cells whose value is below the threshold (iceberg condition)
- Efficient methods may even avoid computing the un-needed, intermediate cells
- Avoid explosive growth

Example

- Example: A cube with 100 dimensions
  - Suppose it contains only 2 base cells: $\{(a_1, a_2, a_3, ..., a_{100}), (a_1, a_2, b_3, ..., b_{100})\}$
  - How many aggregate cells if “having count >= 1”?
    - Answer: $(2^{101} – 2) – 4$ (Why?!)

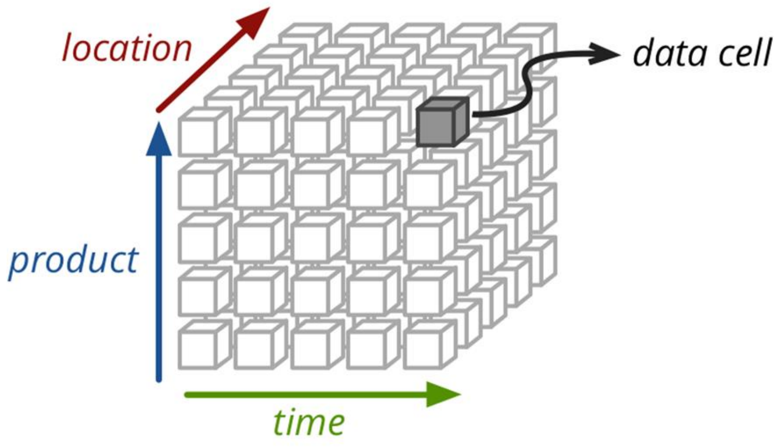
Example

- Example: A cube with 100 dimensions
  - Suppose it contains only 2 base cells: $\{(a_1, a_2, a_3, \ldots., a_{100}), (a_1, a_2, b_3, \ldots, b_{100})\}$
  - What about the iceberg cells, (i,e., with condition: “having count >= 2”)?
    - Answer: 4 (Why?!)

Is Iceberg Cube Good Enough? Closed Cube & Cube Shell

- Let cube P have only 2 base cells: $\{(a_1, a_2, a_3 \ldots, a_{100}):10, (a_1, a_2, b_3, \ldots, b_{100}):10\}$
  - How many cells will the iceberg cube contain if "having count(*) ≥ 10"?
    - Answer: $2^{101} - 4$ (still too big!)
- **Closed cube:**
  - A cell c is ***closed*** if there exists no cell *d*, such that *d* is a descendant of *c*, and *d* has the same measure value as *c*
    - Ex. The same cube P has only 3 closed cells:
      - $\{(a_1, a_2, *, \ldots, *): 20, (a_1, a_2, a_3 \ldots, a_{100}): 10, (a_1, a_2, b_3, \ldots, b_{100}): 10\}$
  - A ***closed cube*** is a cube consisting of only closed cells
- **Cube Shell:** The cuboids involving only a small # of dimensions, e.g., 2
  - Idea: Only compute cube shells, other dimension combinations can be computed on the fly

Chapter 5: Data Cube Technology



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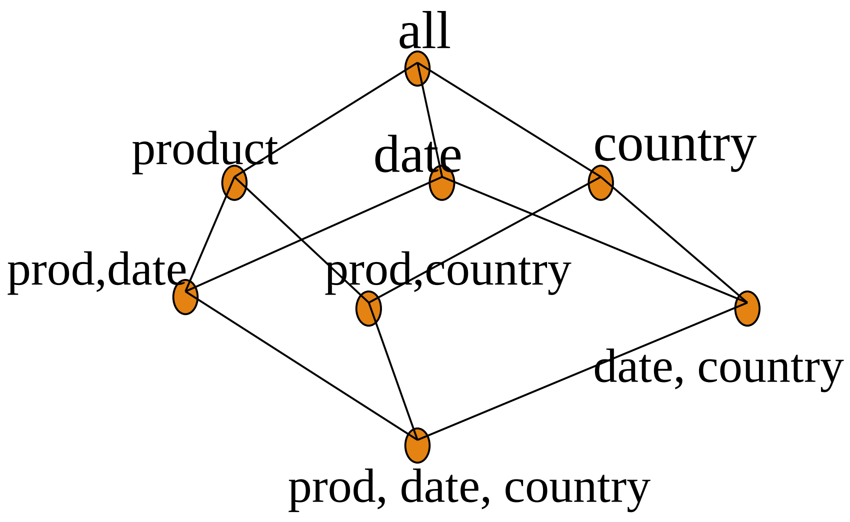
Roadmap for Efficient Computation

- General computation heuristics [1]
- Computing full/iceberg cubes: 3 methodologies
  - Bottom-Up:
    - Multi-Way array aggregation [2]
  - Top-down:
    - BUC [3]
- High-dimensional OLAP:
  - A Shell-Fragment Approach [4]
- Computing alternative kinds of cubes:
  - Partial cube, closed cube, approximate cube, ……

1. (Agarwal et al.'96)
2. (Zhao, Deshpande & Naughton, SIGMOD'97)
3. (Beyer & Ramarkrishnan, SIGMOD'99)
4. (Li, et al. VLDB'04)

Efficient Data Cube Computation: General Heuristics

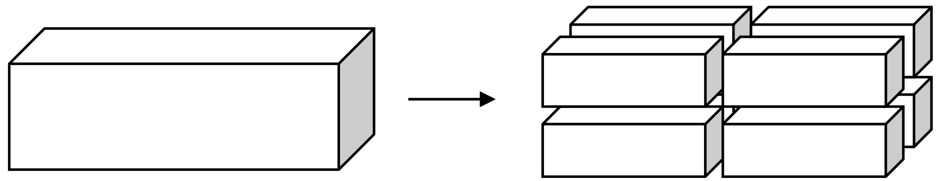
- Sorting, hashing, and grouping operations are applied
  - **Share-sorts**
  - **Share-partitions**
- **Reuse**
  - **Smallest-child:** computing a cuboid from the smallest, previously computed cuboid
  - **Cache-results:** caching results of a cuboid from which other cuboids are computed to reduce disk I/Os
  - **Amortize-scans:** computing as many as possible cuboids at the same time to amortize disk reads



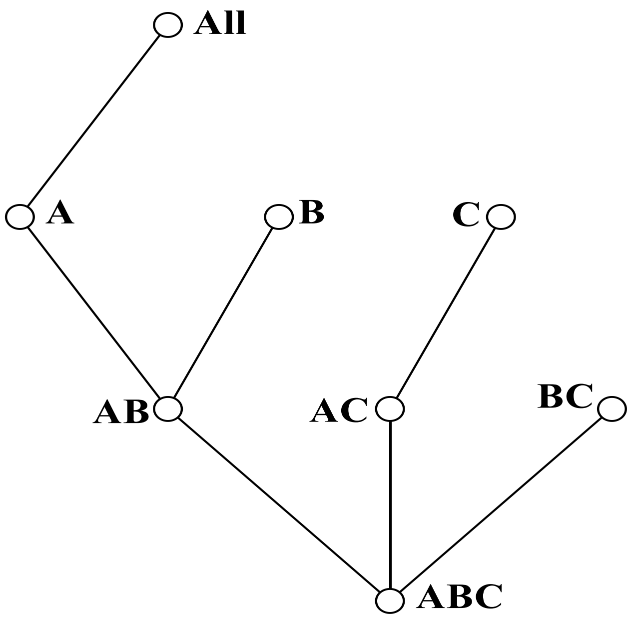
S. Agarwal, R. Agrawal, P. M. Deshpande, A. Gupta, J. F. Naughton, R. Ramakrishnan, S. Sarawagi. On the computation of multidimensional aggregates. VLDB'96

Multi-Way Array Aggregation (MOLAP)

- How can I efficiently calculate all group-by cell aggregations? Full cube computation
- *Fundamental Concept*: AB, AC, and BC can be computed from ABC.   A, B, and C can be computed from AB/AC/BC.
- *Common Practice with limited memory: Do not* load the entire dimension (in array form) into memory at once. Use Chunks:



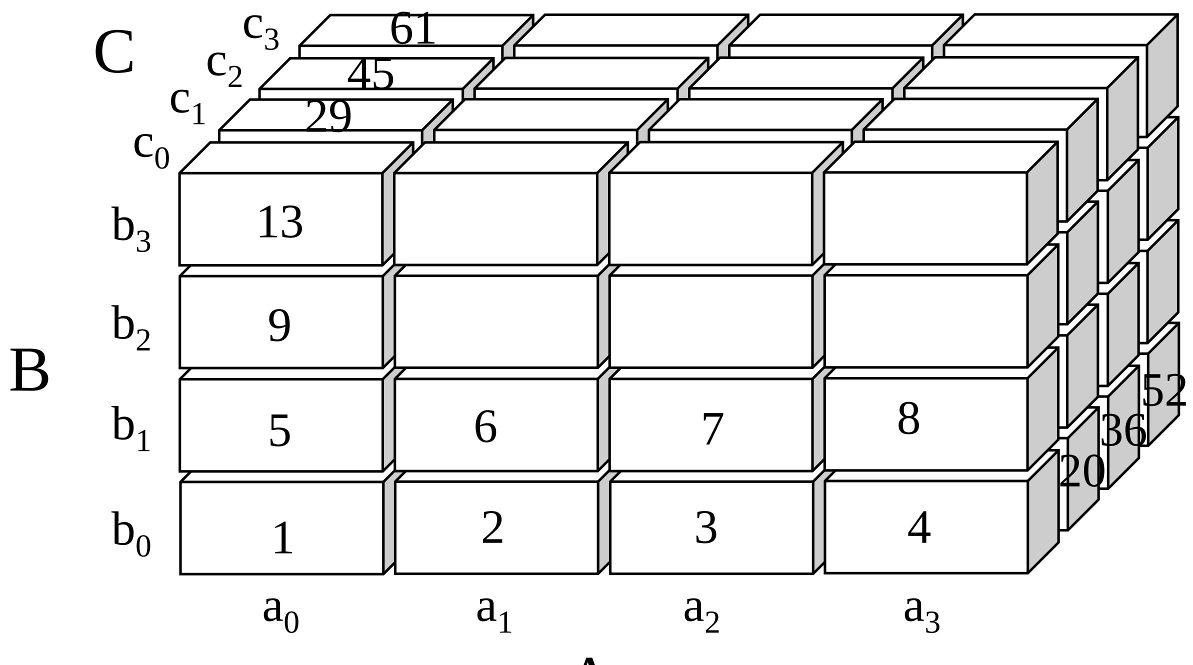
- http://pages.cs.wisc.edu/~nil/764/DADS/38_zhao97arraybased.pdf - Zhao et al. '97



Multi-Way Array Aggregation (MOLAP)

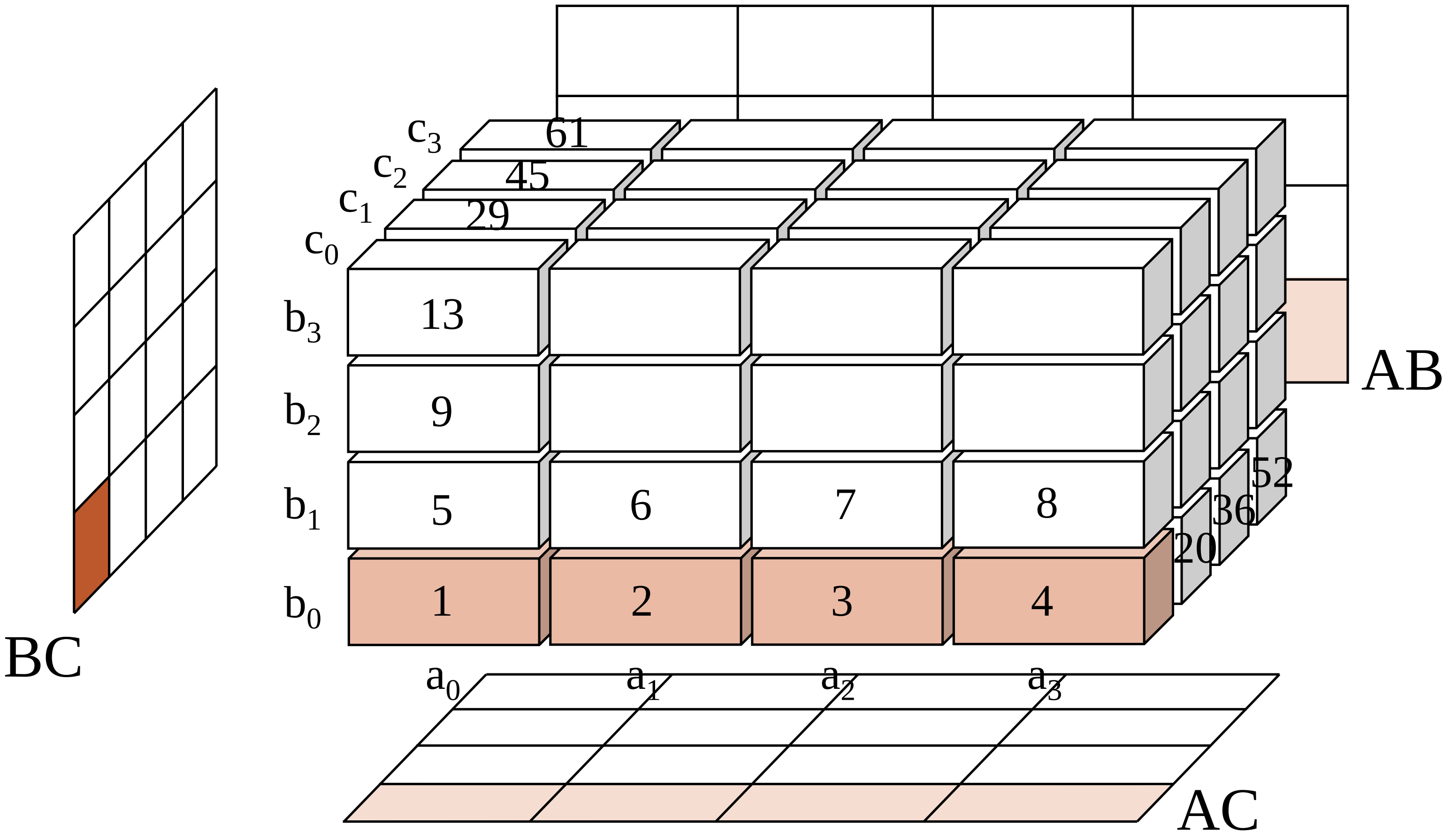
- Chunk and store as(chunk_id, offset)
  - Tells which cells in the chunk have data
- *Goal:* Read chunk only once in memory
  - BC /AB only once
- Example: Student Record Data Warehouse
- *count*(A) > *count* (B) > *count(C*)
- What is best order to put the chunks in order to calculate the aggregation?

Example:
A: 4000, B: 400, C: 40
Chunk:
1000 x 100 x 10



Cube Computation: Multi-Way Array Aggregation (MOLAP)

- **Scan Order**: 1 – 2 – 3 – 4 – 5 – 6 – …
- ***Goal***: Fully compute chunk only once



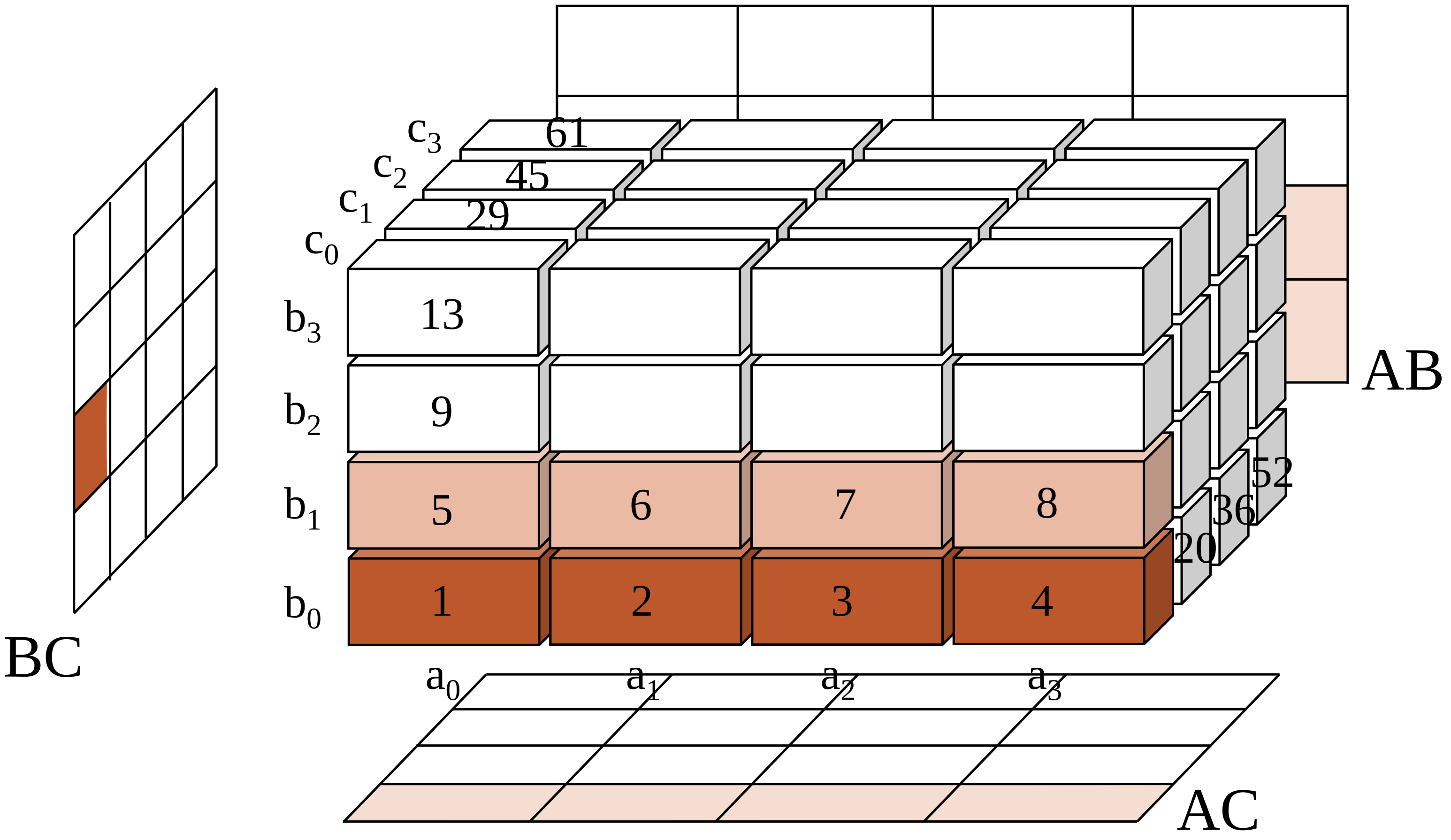
Example:
A: 4000, B: 400, C: 40
Chunk:
1000 x 100 x 10

- While we scan through 1..4
  - One **row** of AC plane is partially computed
  - One **chunk** of BC plane is fully computed (write to file)
  - One row in AB plane is partially computed
- now scan through 5…8

Cube Computation: Multi-Way Array Aggregation (MOLAP)

- **Scan Order**: 1 – 2 – 3 – 4 – 5 – 6 – …
- ***Goal***: Fully compute chunk only once

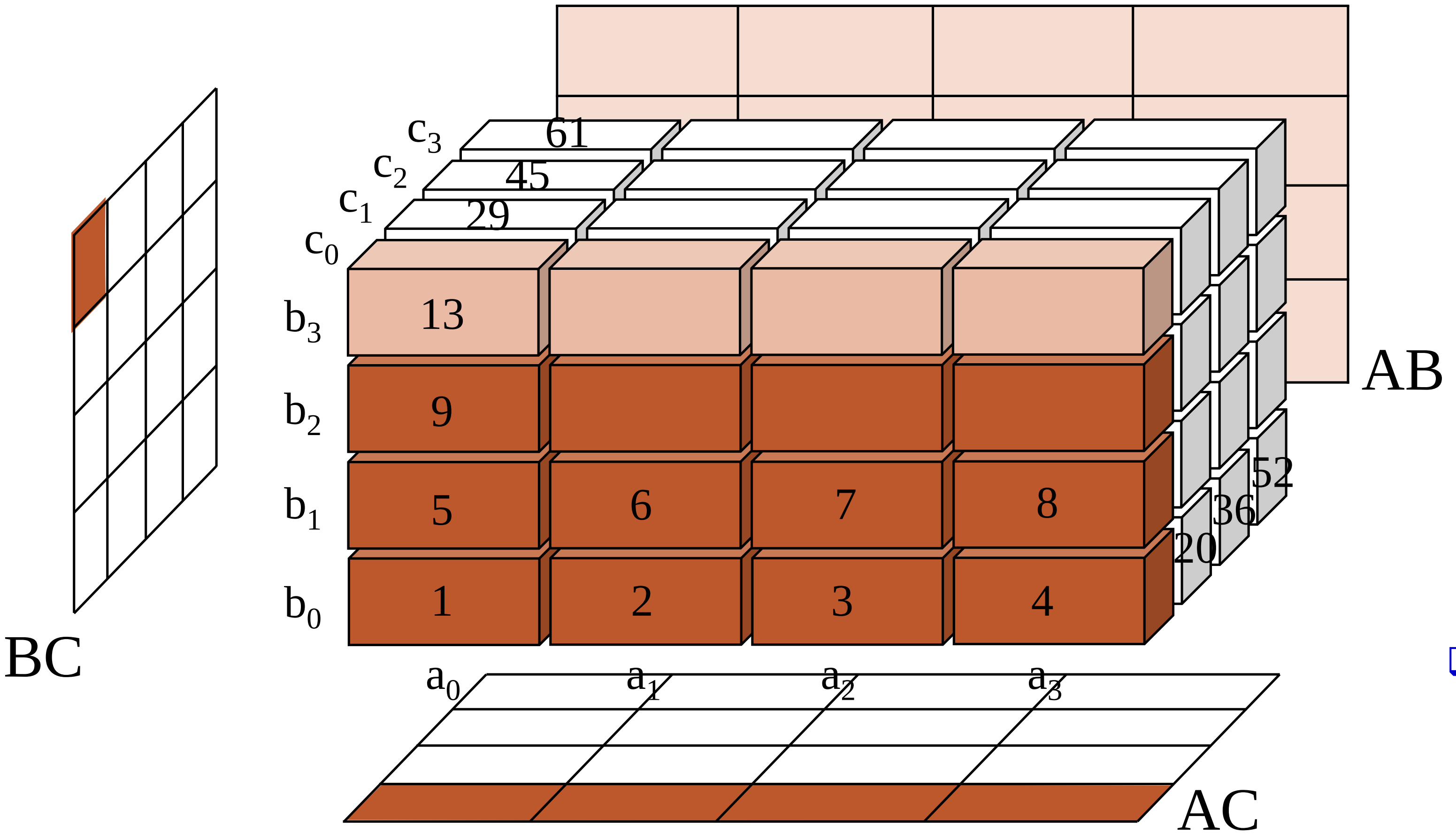
Example:
A: 4000, B: 400, C: 40
Chunk:
1000 x 100 x 10



- While we scan through 5…8
  - Same **row** of AC plane is updated
  - Another **chunk** of BC plane is fully computed (reuse the same place in memory)
  - another row in AB plane is partially computed
- Continue on 9…12
- Continue on 13…16

Cube Computation: Multi-Way Array Aggregation (MOLAP)

- **Scan Order**: 1 – 2 – 3 – 4 – 5 – 6 – …
- ***Goal***: Fully compute chunk only once



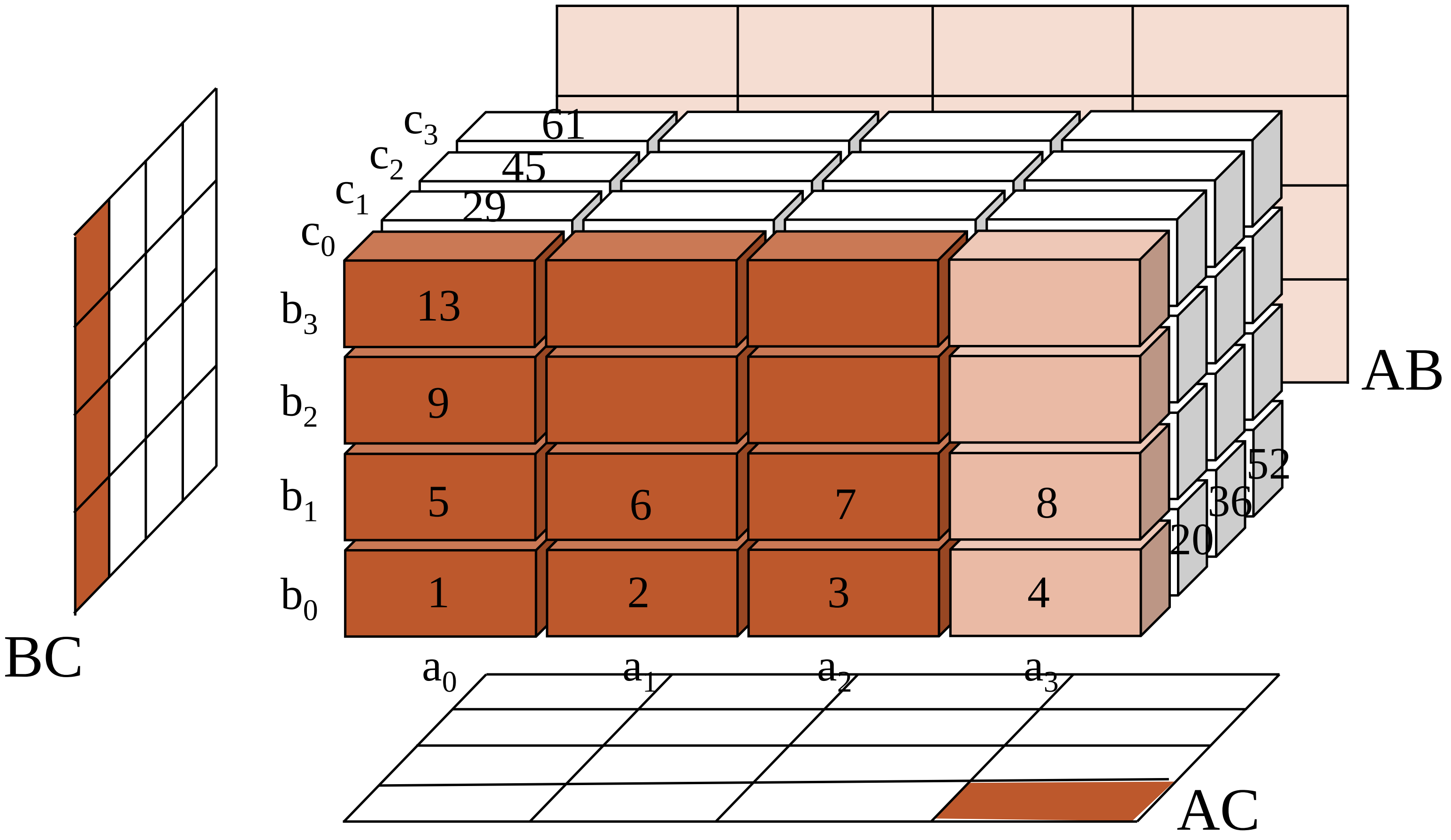
Example:
A: 4000, B: 400, C: 40
Chunk:
1000 x 100 x 10

- While we scan through 13…16
  - One **row** of AC plane is fully computed (write to file)
  - Another **chunk** of BC plane is fully computed (reuse the same place in memory)
  - Whole AB plane is partially computed
- Memory requirement:
  - 4000 x 10 (AC) + 100 x 10 (BC) + 4000 x 400 (AB) = **1,641,000 units**

Cube Computation: Multi-Way Array Aggregation (MOLAP)

- Dimension Order: 1 – 5 – 9 – 13 – 2 – 6 – …

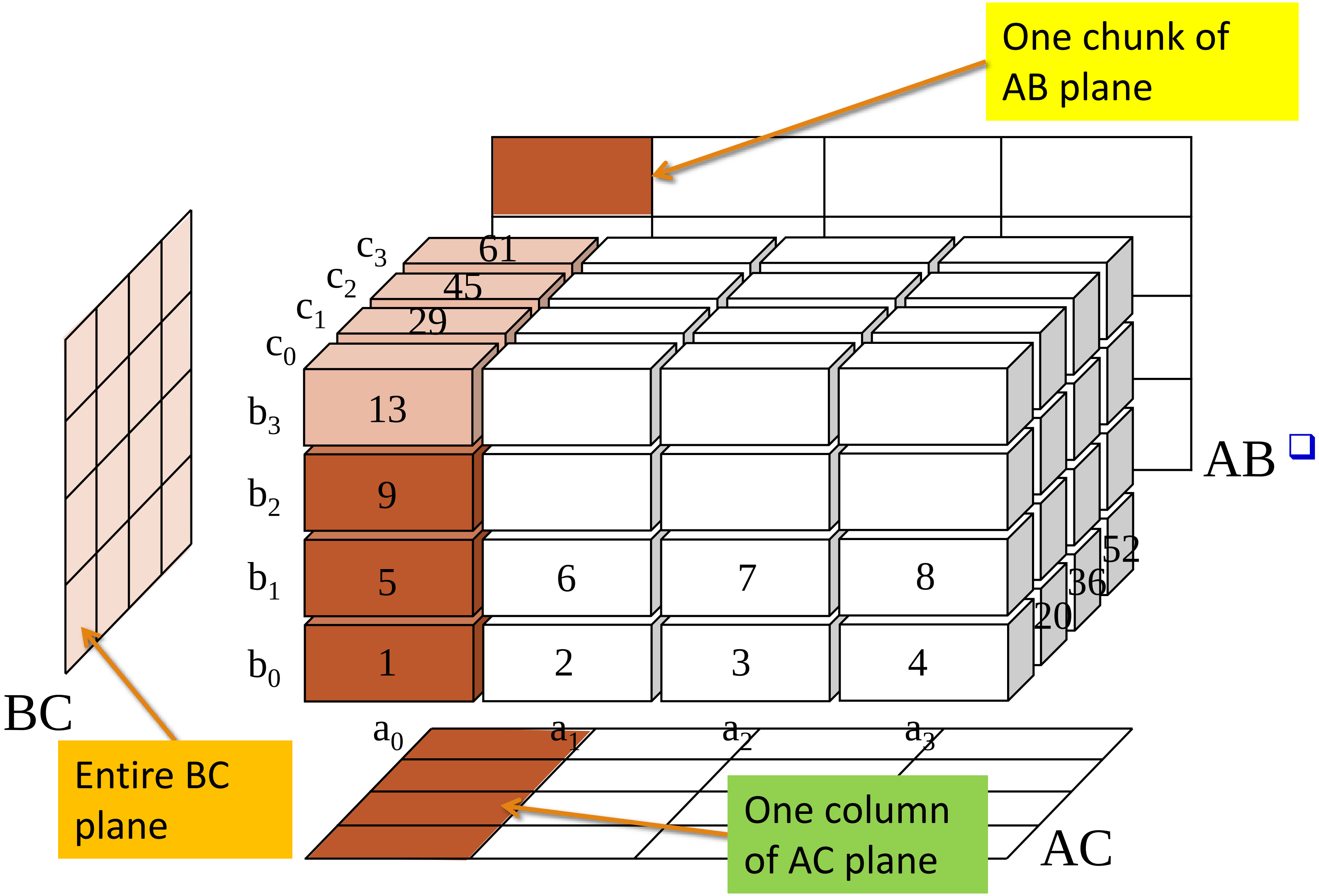
Example:
A: 4000, B: 400, C: 40
Chunk:
1000 x 100 x 10



- One **column** of BC plane is fully computed (write to file)
- Another **chunk** of AC plane is fully computed (reuse the same place in memory)
- Whole AB plane is partially computed
- Memory:
  - 400 x 10 (BC) + 100 x 10 (BC) + + 4000 x 400 (AB)
- **1,605,000 units**

Cube Computation: Multi-Way Array Aggregation (MOLAP)

- Dimension Order: 1 – 17 – … – 13 – 29 – 45 – 61 …



Example:
A: 4000, B: 400, C: 40
Chunk:
1000 x 100 x 10

- One **row** of AC plane
- One **chunk** of AB plane
- All chunks in BC plane
- Memory:
  - 1000 x 40 (AC) + 1000 x 100 (AB) + 400 x 40 (AB)
  - 156,000 units
  - The best order

Cube Computation: Multi-Way Array Aggregation (MOLAP)

- Main Goal of Multi-Way: Reducing memory and I/O
  - How?
    - Keep the smallest plane in main memory
    - Fetch and compute only one chunk at a time for the largest plane
  - The planes should be sorted and computed according to their size in ascending order
  - Suppose A>B>C>…

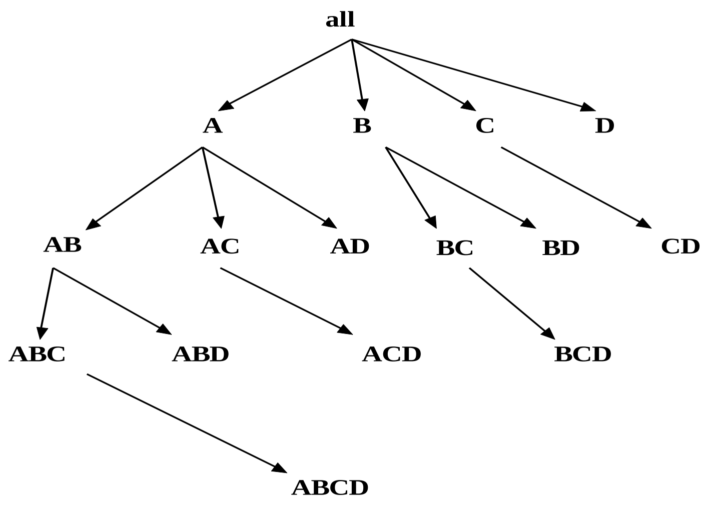
```
for a in A:
    for b in B:
        for c in C: …
```

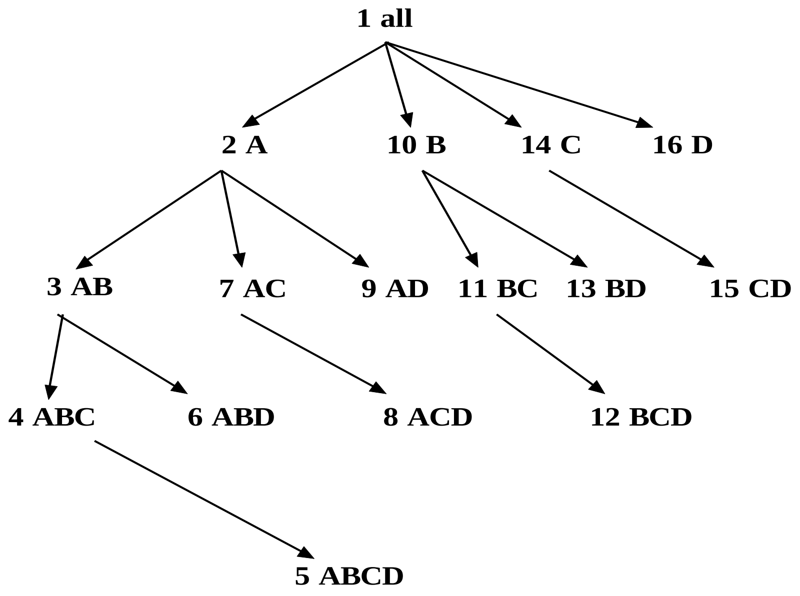
Cube Computation: Multi-Way Array Aggregation (MOLAP)

- Pros and Cons of Multi-Way
  - **Pro:** Efficient for computing the **full cube** for a small number of dimensions
  - **Con:** Can not calculate iceberg cube.
    - i.e: If there are a large number of dimensions, “top-down” computation and iceberg cube computation methods (e.g., BUC) should be used

Cube Computation: Computing in Reverse Order

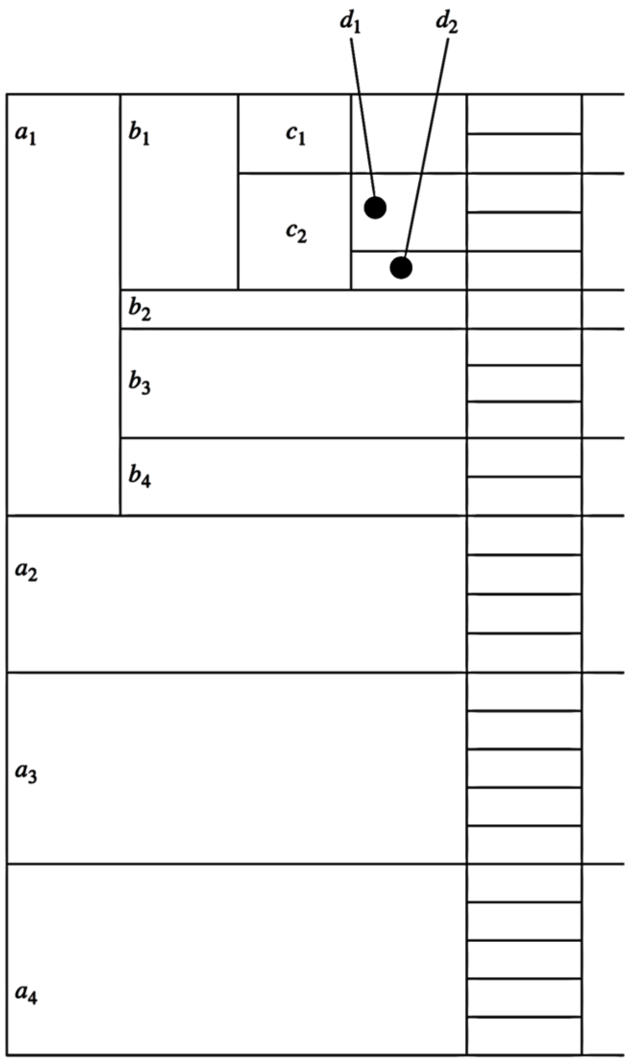
- Iceberg cube computation
- BUC (Beyer & Ramakrishnan, SIGMOD'99)
  - Bottom-Up (cube) Computation
  - "top-down" in our view since we put Apex cuboid on the top!
- Divides dimensions into partitions and facilitates iceberg pruning
  - Prune if not satisfy min_sup
  - If *minsup* = 1 Þ compute full CUBE!
- No simultaneous aggregation



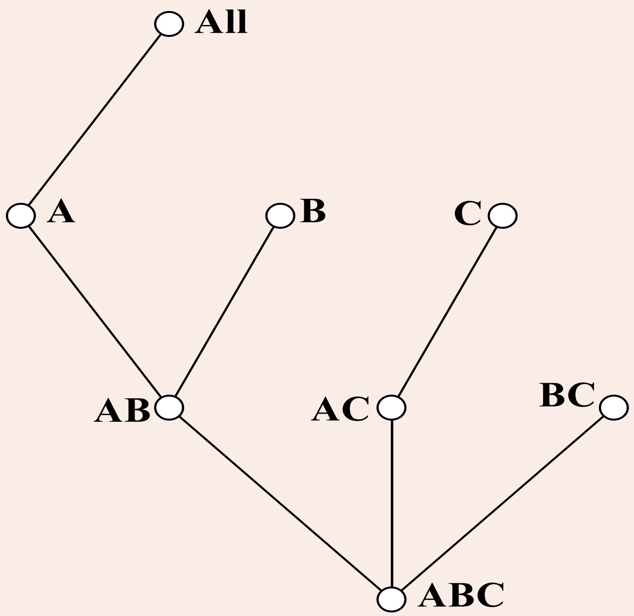
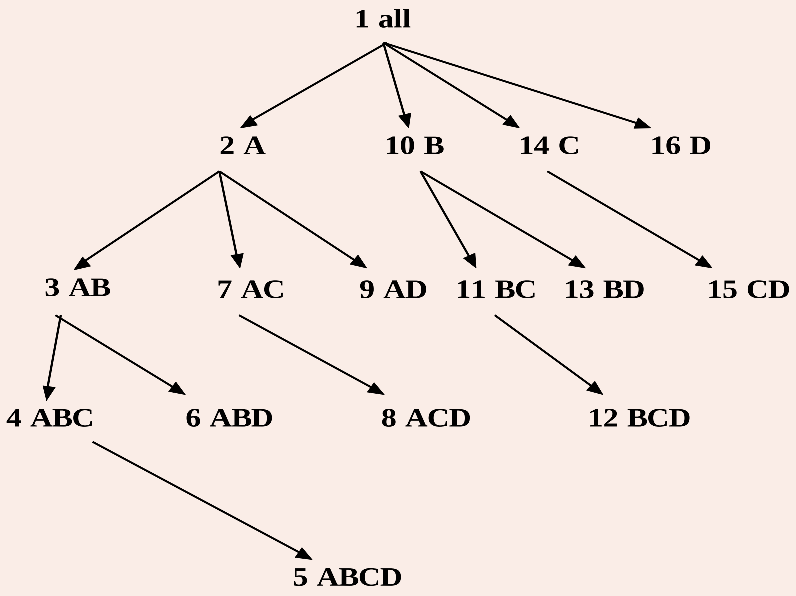


BUC: Partitioning and Aggregating

- Cannot fit in main memory
  - Sort *distinct* values and partition to fit
  - Aggregation when sorting
  - Continue processing
- Iceberg cube
  - If count of (a1, b1, *, *, *) < min_support
  - No need to sort on C

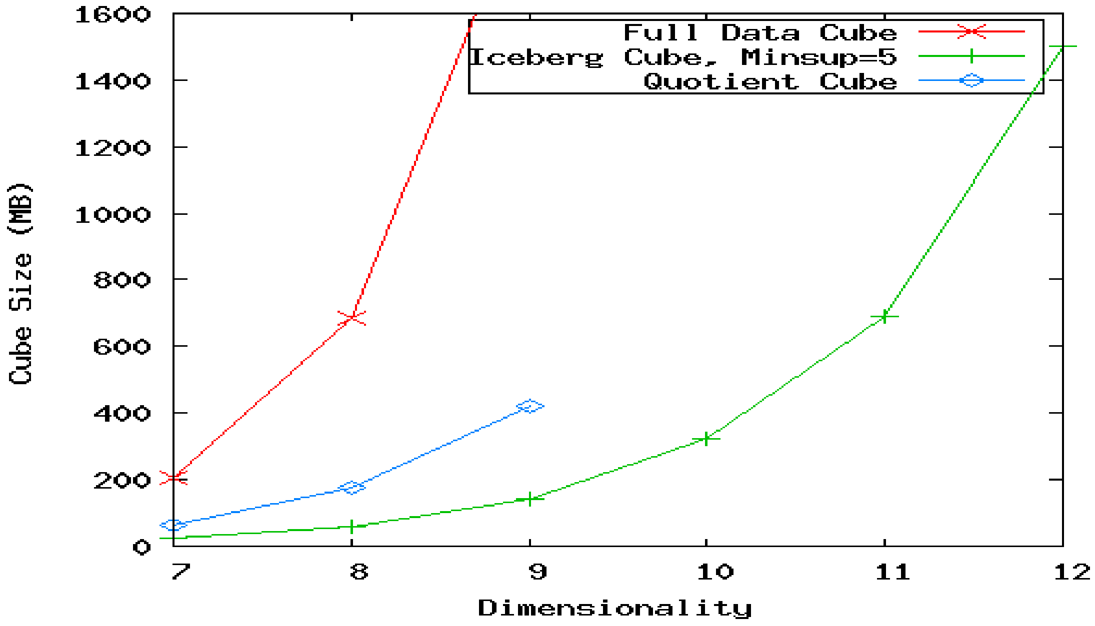


MultiWay VS BUC

	multiway	BUC
Input format	Multi-dimensional array	Relational database
Good for	Full cube	Iceberg cube
Key idea	Simultaneously Aggregation	Partition and sort
Calculation direction		

High-Dimensional OLAP?—The Curse of Dimensionality

- High-D OLAP Applications:
  - E.g. bio-data analysis, statistical surveys
- **None** of the previous cubing method can handle high dimensionality!
  - Iceberg cube and compressed cubes: only delay the inevitable explosion
  - Full materialization: still significant overhead in accessing results on disk
- **A shell-fragment approach**: X. Li, J. Han, and H. Gonzalez, High-Dimensional OLAP: A Minimal Cubing Approach, VLDB'04

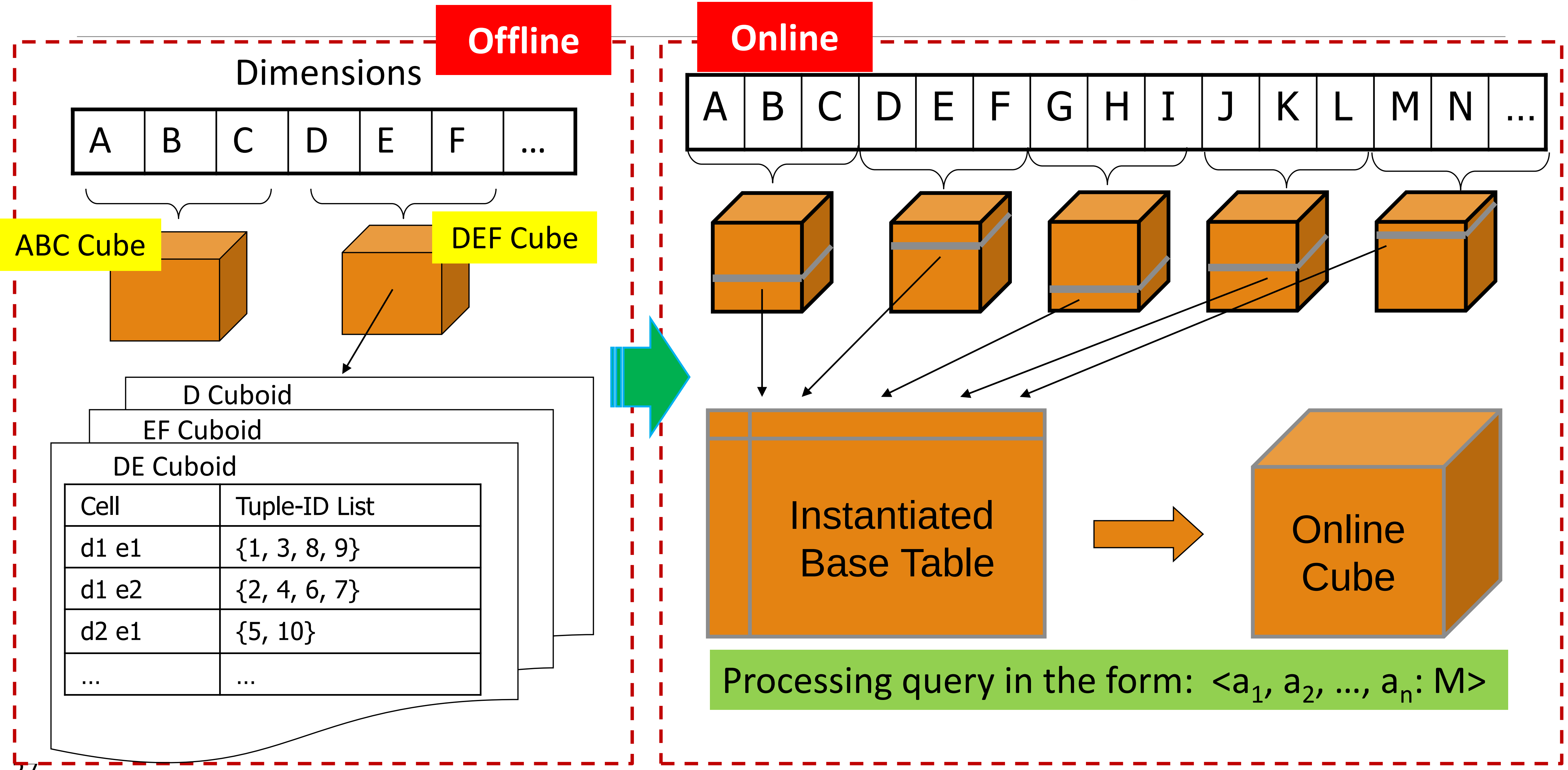


A curse of dimensionality: A database of 600k tuples. Each dimension has cardinality of 100 and *zipf* of 2.

Fast High-D OLAP with Minimal Cubing

- Observation: OLAP occurs only on a small subset of dimensions at a time
- Semi-Online Computational Model
  - Partition the set of dimensions into **shell fragments**
  - Compute data cubes for each shell fragment while retaining **inverted indices** or **value-list indices**
  - Given the pre-computed **fragment cubes**, dynamically compute cube cells of the high-dimensional data cube *online*
- Major idea: Tradeoff between the amount of pre-computation and the speed of online computation
  - Reducing computing high-dimensional cube into precomputing a set of lower dimensional cubes
  - Online re-construction of original high-dimensional space
  - Lossless reduction

Use Frag-Shells for Online OLAP Query Computation



Computing a 5-D Cube with 2-Shell Fragments

- Example: Let the cube aggregation function be **count**

TID	**A**	**B**	**C**	**D**	**E**
1	a1	b1	c1	d1	e1
2	a1	b2	c1	d2	e1
3	a1	b2	c1	d1	e2
4	a2	b1	c1	d1	e2
5	a2	b1	c1	d1	e3

- Divide the 5-D table into 2 shell fragments:
  - (A, B, C) and (D, E)
- Build traditional invert index or RID list (**1-D**)

Attribute Value	TID List	List Size
a1	1 2 3	3
a2	4 5	2
b1	1 4 5	3
b2	2 3	2
c1	1 2 3 4 5	5
d1	1 3 4 5	4
d2	2	1
e1	1 2	2
e2	3 4	2
e3	5	1

Shell Fragment Cubes: Ideas

- Generalize the **1-D** inverted indices to **multi-dimensional** ones in the data cube sense
- Compute all cuboids for data cubes ABC and DE while retaining the inverted indices
  - Ex. shell fragment cube ABC contains 7 cuboids:
    - A, B, C; AB, AC, BC; ABC
- This completes the offline computation

Attribute Value	TID List	List Size
a1	1 2 3	3
a2	4 5	2
b1	1 4 5	3
b2	2 3	2
c1	1 2 3 4 5	5
d1	1 3 4 5	4
d2	2	1
e1	1 2	2
e2	3 4	2
e3	5	1

Shell-fragment AB

Cell	Intersection	TID List	List Size
a1 b1	1 2 3 ∩ 1 4 5	1	1
a1 b2	1 2 3 ∩ 2 3	2 3	2
a2 b1	4 5 ∩ 1 4 5	4 5	2
a2 b2	4 5 ∩ 2 3	ϕ	0

- ID_Measure Table
  - If measures other than count are present, store in *ID_measure* table separate from the shell fragments

tid	count	sum
1	5	70
2	3	10
3	8	20
4	5	40
5	2	30

Shell Fragment Cubes: Size and Design

- Given a database of T tuples, D dimensions, and F shell fragment size, the fragment cubes' space requirement is: $O\left(T\left\lceil\frac{D}{F}\right\rceil(2^F-1)\right)$
  - For F < 5, the growth is sub-linear
- Fragment groupings can be arbitrary to allow for maximum online performance
  - Known common combinations (e.g.,<city, state>) should be grouped together
- Shell fragment sizes can be adjusted for optimal balance between offline and online computation

Attribute Value	TID List	List Size
a1	1 2 3	3
a2	4 5	2
b1	1 4 5	3
b2	2 3	2
c1	1 2 3 4 5	5
d1	1 3 4 5	4
d2	2	1
e1	1 2	2
e2	3 4	2
e3	5	1

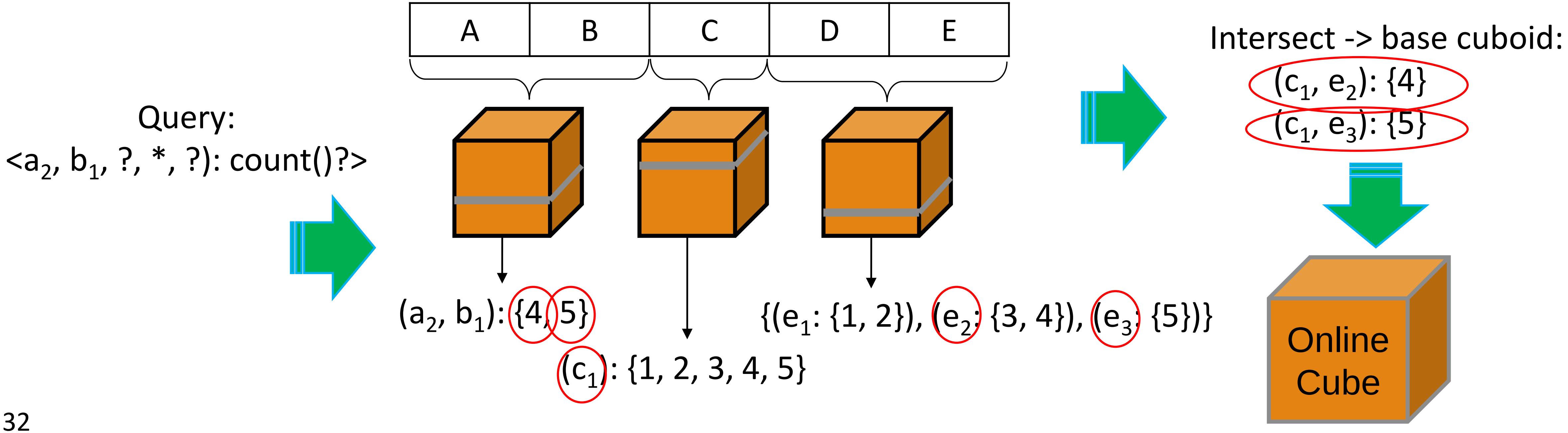
Cell	Intersection	TID List	List Size
a1 b1	1 2 3 ∩ 1 4 5	1	1
a1 b2	1 2 3 ∩ 2 3	2 3	2
a2 b1	4 5 ∩ 1 4 5	4 5	2
a2 b2	4 5 ∩ 2 3	ϕ	0

Online Query Computation with Shell-Fragments

- A query has the general form: $<a_1, a_2, \ldots, a_n: M>$
- Each a_i has 3 possible values
  - Instantiated value– this is what we want to look at
  - Inquire ? Function – want to analyze these dimensions
  - Aggregate * function – don’t care about these dimensions
- Ex: Suppose we want to query student data for junior (year 3) students and want to compare scores for different genders and ages, but don’t care about what high school they attended.
  - <3, ?, ?, *, 1: count>

Online Query Computation with Shell-Fragments

- Method: Given the materialized fragment cubes, process a query as follows
  - Divide the query into fragments, same as the shell-fragment
  - Fetch the corresponding TID list for each fragment from the fragment cube
  - Intersect the TID lists from each fragment to construct **instantiated base table**
  - Compute the data cube using the base table with any cubing algorithm



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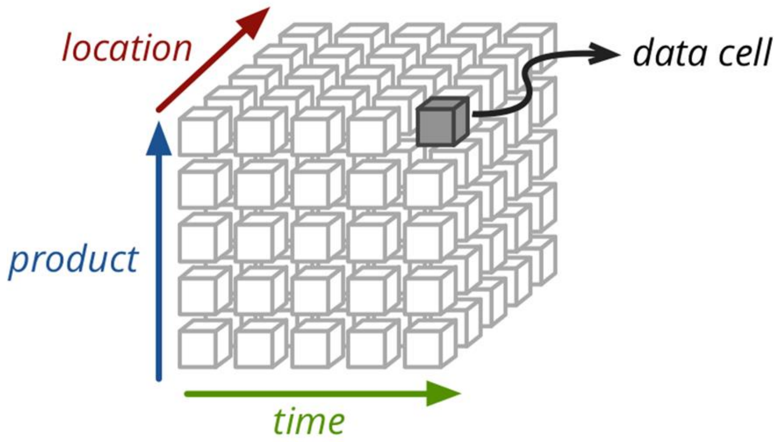

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Data Mining in Cube Space

- Data cube is already aggregated
- Reports generated from a Data Cube can easily by drilled into through query in a drill-down fashion.

Complex Aggregation at Multiple Granularities: Multi-Feature Cubes

- Multi-feature cubes (Ross, et al. 1998): Compute complex queries involving multiple dependent aggregates at multiple granularities
- Ex. Grouping by all subsets of {item, region, month}, find the maximum price in 2019 for each group, and the total sales among all maximum price tuples

```
select item, region, month, max(price), sum(R.sales)
from purchases
where year = 2010
cube by item, region, month: R
such that R.price = max(price)
```

Discovery-Driven Exploration of Data Cubes

- Discovery-driven exploration of huge cube space (Sarawagi, et al.'98), suggested way to highlight data:
  - Pre-compute measures indicating **exceptions.**
    - i.e: significantly different from the value anticipated
  - Visual cues such as background color can be used to show the degree of exception of each cell

Examples: Discovery-Driven Data Cubes

item	all
region	all

Sum of sales	month										
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Total		1%	-1%	0%	1%	3%	-1	-9%	-1%	2%	-4%	3%

Avg sales	month										
item	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Sony b/w printer		9%	-8%	2%	-5%	14%	-4%	0%	41%	-13%	-15%	-11%
Sony color printer		0%	0%	3%	2%	4%	-10%	-13%	0%	4%	-6%	4%
HP b/w printer		-2%	1%	2%	3%	8%	0%	-12%	-9%	3%	-3%	6%
HP color printer		0%	0%	-2%	1%	0%	-1%	-7%	-2%	1%	-5%	1%
IBM home computer		1%	-2%	-1%	-1%	3%	3%	-10%	4%	1%	-4%	-1%
IBM laptop computer		0%	0%	-1%	3%	4%	2%	-10%	-2%	0%	-9%	3%
Toshiba home computer		-2%	-5%	1%	1%	-1%	1%	5%	-3%	-5%	-1%	-1%
Toshiba laptop computer		1%	0%	3%	0%	-2%	-2%	-5%	3%	2%	-1%	0%
Logitech mouse		3%	-2%	-1%	0%	4%	6%	-11%	2%	1%	-4%	0%
Ergo-way mouse		0%	0%	2%	3%	1%	-2%	-2%	-5%	0%	-5%	8%

item	IBM home computer

Avg sales	month										
region	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
North		-1%	-3%	-1%	0%	3%	4%	-7%	1%	0%	-3%	-3%
South		-1%	1%	-9%	6%	-1%	-39%	9%	-34%	4%	1%	7%
East		-1%	-2%	2%	-3%	1%	18%	-2%	11%	-3%	-2%	-1%
West		4%	0%	-1%	-3%	5%	1%	-18%	8%	5%	-8%	1%

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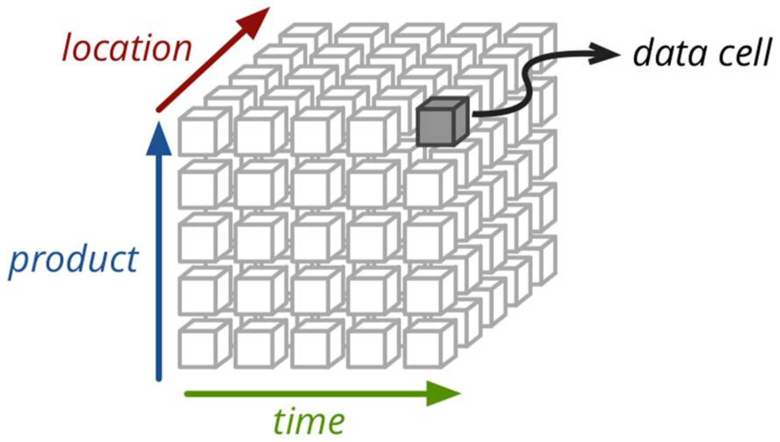
Chapter 5: Data Cube Technology

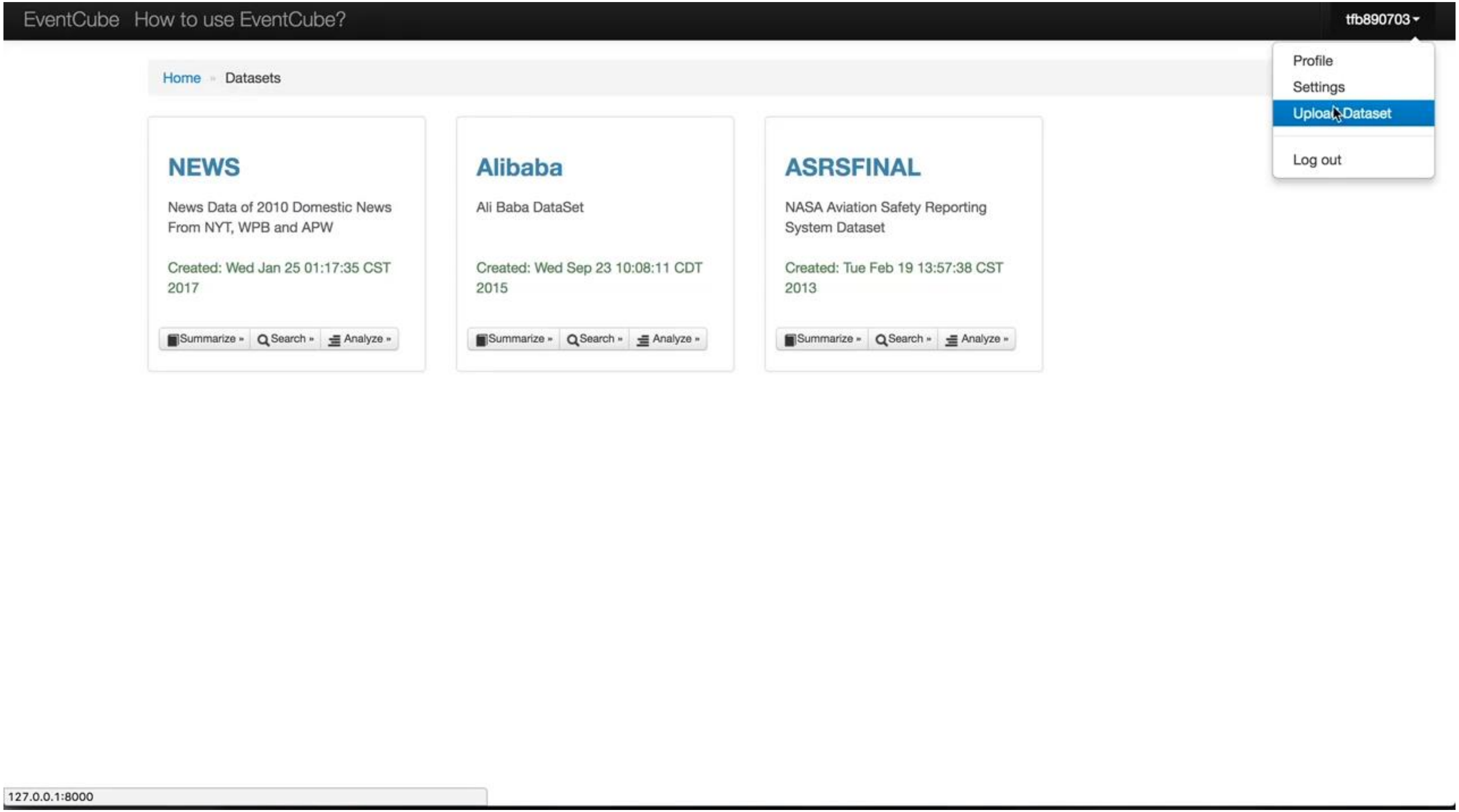


- Data Cube Computation: Basic Concepts
- Data Cube Computation Methods
- Multidimensional Data Analysis in Cube Space
- Summary

Data Cube Technology: Summary

- Data Cube Computation: Cuboids; iceberg cube; closed cube and cube shell
- Data Cube Computation Methods
  - MultiWay Array Aggregation
  - BUC
  - High-Dimensional OLAP with Shell-Fragments
- Multidimensional Data Analysis in Cube Space
  - Multi-feature Cubes
  - Discovery-Driven Exploration of Data Cubes

Text Cube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News Data of 2010 Domestic News From NYT, WPB and APW
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Ali Baba DataSet
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ASRSFINAL
NASA Aviation Safety Reporting System Dataset
Created: Tue Feb 19 13:57:38 CST 2013
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Data Cube Technology: References (I)

- S. Agarwal, R. Agrawal, P. M. Deshpande, A. Gupta, J. F. Naughton, R. Ramakrishnan, and S. Sarawagi. On the computation of multidimensional aggregates. VLDB'96
- K. Beyer and R. Ramakrishnan. Bottom-Up Computation of Sparse and Iceberg CUBEs.. SIGMOD'99
- J. Han, J. Pei, G. Dong, K. Wang. Efficient Computation of Iceberg Cubes With Complex Measures. SIGMOD'01
- L. V. S. Lakshmanan, J. Pei, and J. Han, Quotient Cube: How to Summarize the Semantics of a Data Cube, VLDB'02
- X. Li, J. Han, and H. Gonzalez, High-Dimensional OLAP: A Minimal Cubing Approach, VLDB'04
- X. Li, J. Han, Z. Yin, J.-G. Lee, Y. Sun, "Sampling Cube: A Framework for Statistical OLAP over Sampling Data", SIGMOD'08
- K. Ross and D. Srivastava. Fast computation of sparse datacubes. VLDB'97
- D. Xin, J. Han, X. Li, B. W. Wah, Star-Cubing: Computing Iceberg Cubes by Top-Down and Bottom-Up Integration, VLDB'03
- Y. Zhao, P. M. Deshpande, and J. F. Naughton. An array-based algorithm for simultaneous multidimensional aggregates. SIGMOD'97
- D. Burdick, P. Deshpande, T. S. Jayram, R. Ramakrishnan, and S. Vaithyanathan. OLAP over uncertain and imprecise data. VLDB'05

Data Cube Technology: References (II)

- R. Agrawal, A. Gupta, and S. Sarawagi. Modeling multidimensional databases. ICDE'97
- B.-C. Chen, L. Chen, Y. Lin, and R. Ramakrishnan. Prediction cubes. VLDB'05
- B.-C. Chen, R. Ramakrishnan, J.W. Shavlik, and P. Tamma. Bellwether analysis: Predicting global aggregates from local regions. VLDB'06
- Y. Chen, G. Dong, J. Han, B. W. Wah, and J. Wang, Multi-Dimensional Regression Analysis of Time-Series Data Streams, VLDB'02
- R. Fagin, R. V. Guha, R. Kumar, J. Novak, D. Sivakumar, and A. Tomkins. Multi-structural databases. PODS'05
- J. Han. Towards on-line analytical mining in large databases. SIGMOD Record, 27:97–107, 1998
- T. Imielinski, L. Khachiyan, and A. Abdulghani. Cubegrades: Generalizing association rules. Data Mining & Knowledge Discovery, 6:219–258, 2002.
- R. Ramakrishnan and B.-C. Chen. Exploratory mining in cube space. Data Mining and Knowledge Discovery, 15:29–54, 2007.
- K. A. Ross, D. Srivastava, and D. Chatziantoniou. Complex aggregation at multiple granularities. EDBT'98
- S. Sarawagi, R. Agrawal, and N. Megiddo. Discovery-driven exploration of OLAP data cubes. EDBT'98
- G. Sathe and S. Sarawagi. Intelligent Rollups in Multidimensional OLAP Data. *VLDB'01*