Chapter 4&5. Data Cube: Data Warehousing and OLAP

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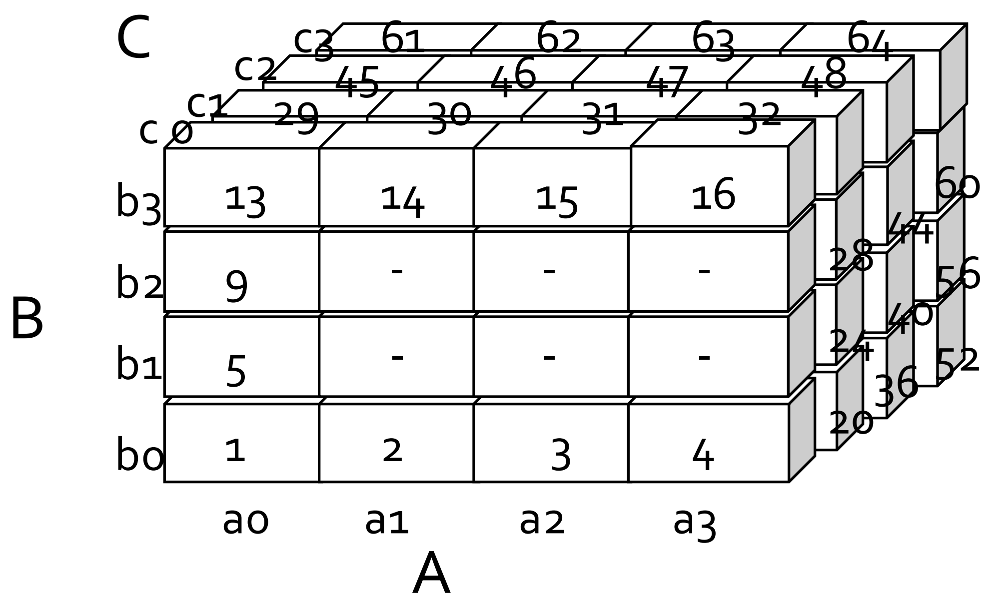
Introduction to Data Mining

Efficient Computation

- General computation heuristics (Agarwal et al.'96)
- Computing full/iceberg cubes: 3 methodologies
  - Bottom-Up:
    - **Multi-way array aggregation** (Zhao, Deshpande & Naughton, SIGMOD'97)
  - Top-down:
    - **BUC** (Beyer & Ramarkrishnan, SIGMOD'99)
  - Integrating Top-Down and Bottom-Up:
    - Star-cubing algorithm (Xin, Han, Li & Wah: VLDB'03)
- High-dimensional OLAP:
  - A shell-fragment approach (Li, et al. VLDB'04)
- Computing alternative kinds of cubes:
  - Partial cube, closed cube, approximate cube, ...

Multi-Way Array Aggregation

- Bottom-up: Partition a huge *sparse* array into *chunks* (a small subcube which fits in memory) and aggregation.
- Data addressing: Compressed *sparse array addressing* (chunk_id, offset)
- Compute **aggregates in “multiway”** by visiting cube cells in the order which **minimizes** the # of times to visit each cell, and **reduces** memory access and storage cost



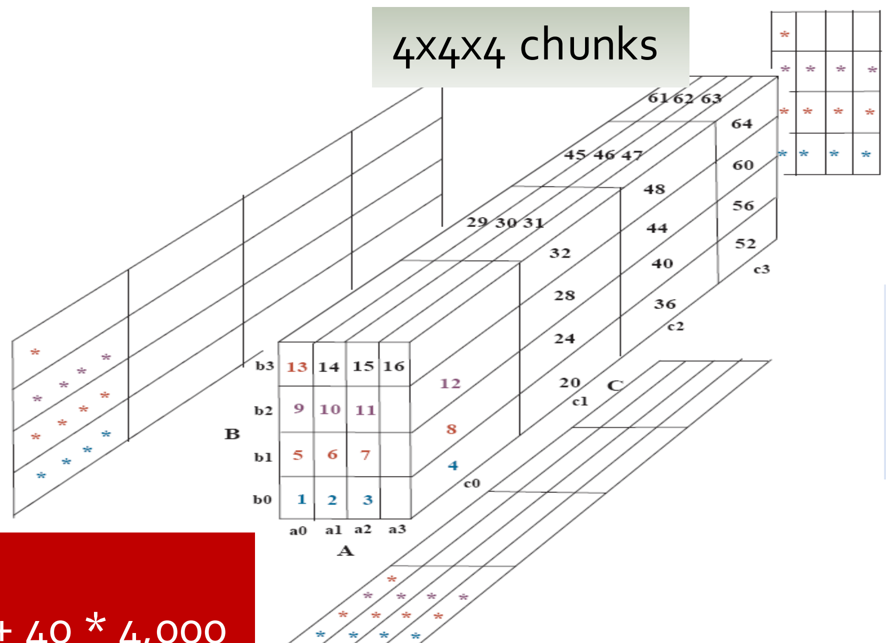
What is the best traversing order to do multi-way aggregation?

ABC → AB, BC and AC

A: 40 (location),
B: 400 (item),
C: 4,000 (time)

Multi-way Array Aggregation (3-D to 2-D)

- How much **memory cost of computation (aggregation for AB, AC, BC planes)** can we save?



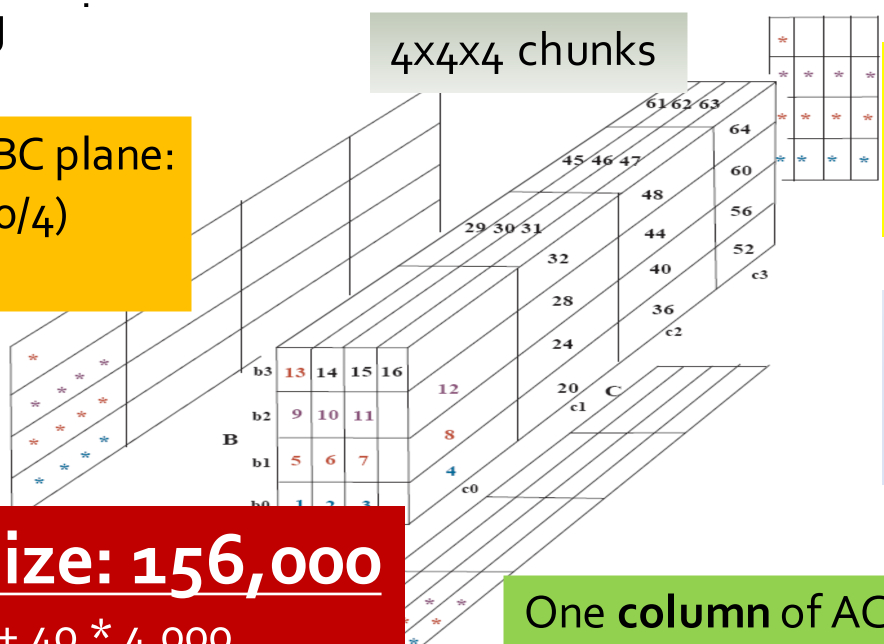
A: 40 (location),
B: 400 (item),
C: 4,000 (time)

Min memory size: ?
< 40*400 + 400*4,000 + 40 * 4,000
= 1,776,000

Multi-way Array Aggregation (3-D to 2-D)

- How to minimizes the memory requirement and reduced I/Os?
  - 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

4x4x4 chunks



One **chunk** of BC plane:
(400/4) * (4,000/4)
= 100,000

Entire AB plane:
40 * 400
= 16,000

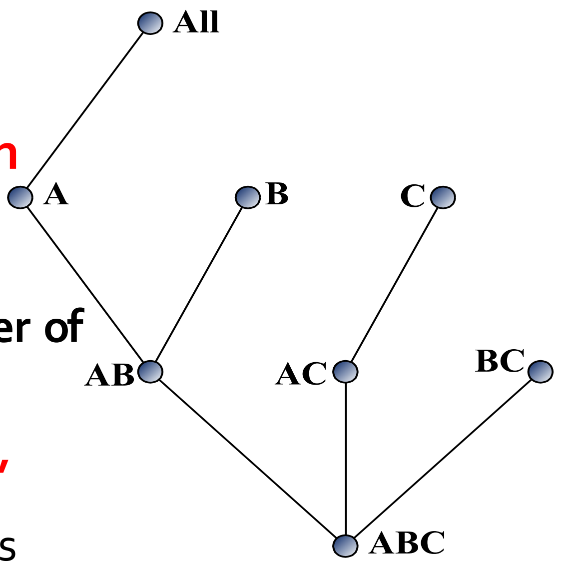
A: 40 (location),
B: 400 (item),
C: 4,000 (time)

Min memory size: 156,000
< 40*400 + 400*4,000 + 40 * 4,000
= 1,776,000

One **column** of AC plane:
40 * (4,000/4) = 40,000

Multi-Way Array Aggregation

- Array-based "**bottom-up**" algorithm (from ABC to AB,...)
- Using multi-dimensional **chunks**
- Simultaneous aggregation on multiple dimensions
- **Cannot do *Apriori* pruning: No iceberg optimization**
- Comments on the method
  - Efficient for computing the full cube for **a small number of dimensions**
  - If there are a large number of dimensions, **"top-down" computation** and **iceberg cube computation** methods should be used



Zhao, Deshpande & Naughton. An Array-Based Algorithm for Simultaneous Multidimensional Aggregates. SIGMOD'97

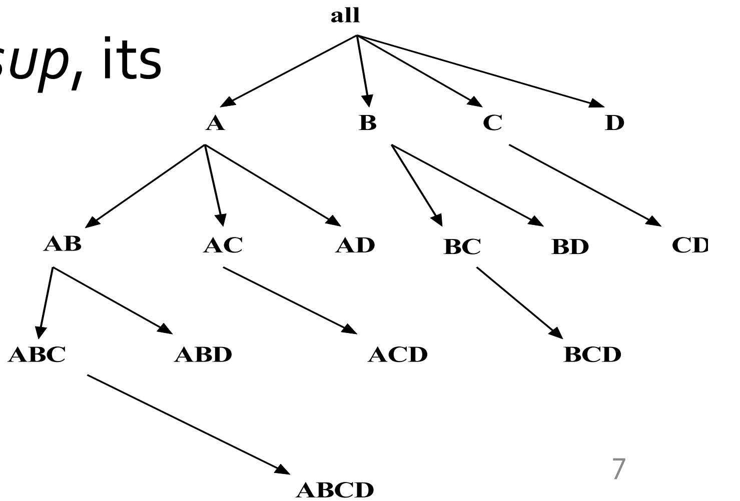
BUC (Top Down: From AB to ABC)

- BUC (Beyer & Ramakrishnan, SIGMOD'99)

  BUC: acronym of Bottom-Up (cube) Computation

  (Note: It is "**top-down**" in our view since we put Apex cuboid on the top!)

- Divides dimensions into partitions and facilitates **iceberg pruning (it works now!)**
  - If a partition does not satisfy *min_sup*, its **descendants** can be pruned



K. Beyer and R. Ramakrishnan. *Bottom-Up Computation of Sparse and Iceberg CUBEs.* SIGMOD'99

Data Warehouse: From Tables and Spreadsheets to Data Cubes

- A **data warehouse** is based on a multidimensional data model which views data in the form of a **data cube**
- A data cube, such as sales, allows data to be modeled and viewed in multiple dimensions
  - **Dimension tables**, such as item (item_name, brand, type), or time (day, week, month, quarter, year)
  - **Fact table** contains **measures** (such as dollars_sold) and keys to each of the related dimension tables
- **Data cube**: A lattice of cuboids
  - In data warehousing literature, an **n-D base cube** is called a **base cuboid**
  - The top most **0-D cuboid**, which holds the highest-level of summarization, is called the **apex cuboid**
  - The lattice of cuboids forms a **data cube**

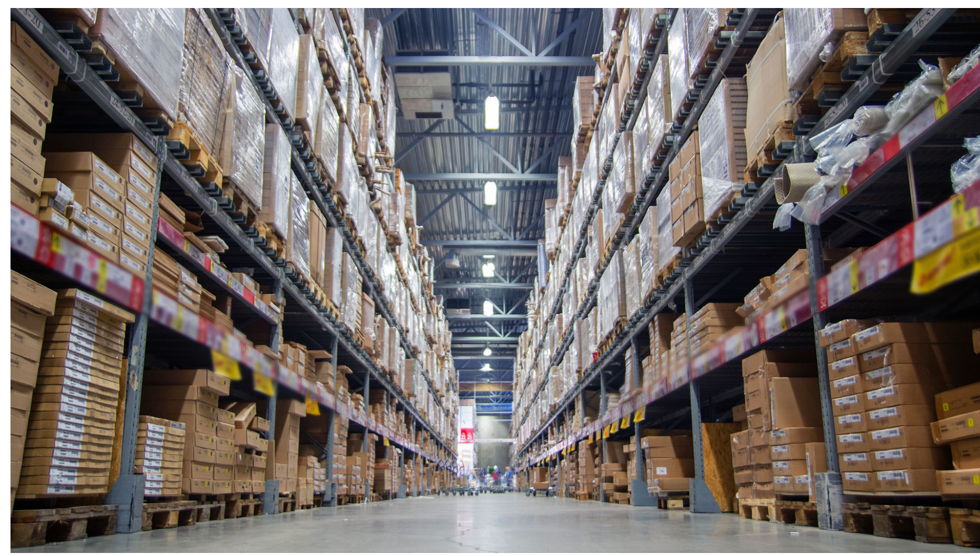
Data Warehouse

- Defined in many different ways, but not rigorously
  - A decision support database that is maintained separately from the organization's operational database

Operational Databases

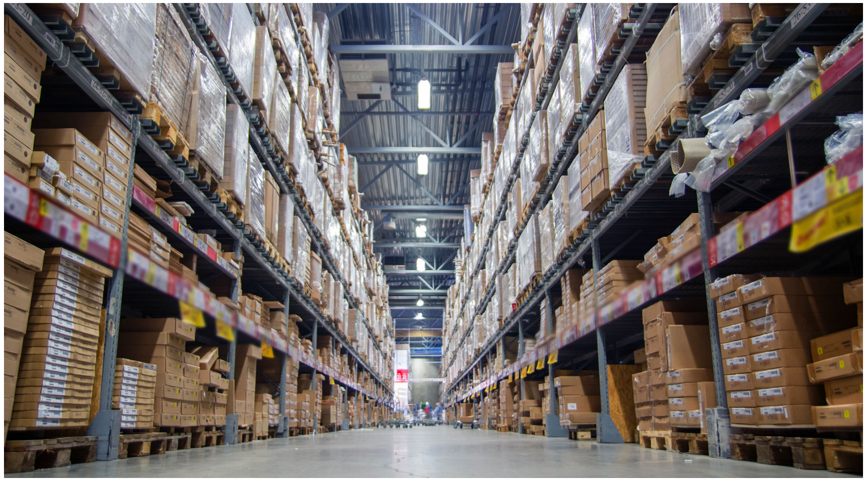
(Data) Marts

(Data) Warehouse



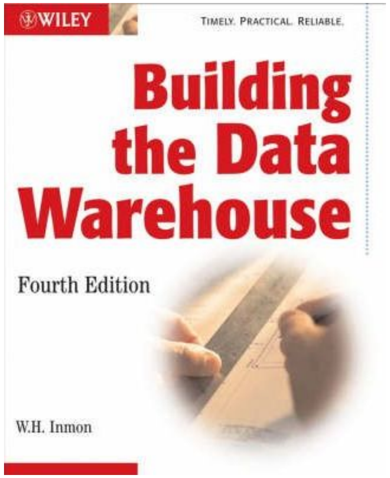
Data Warehouse

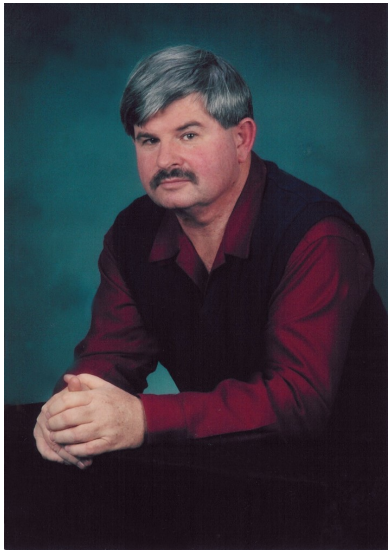
- Defined in many different ways, but not rigorously
  - A decision support database that is maintained separately from the organization's operational database
  - Support information processing by providing a solid platform of consolidated, historical data for analysis



Data Warehouse

- "A data warehouse is a subject-oriented, integrated, time-variant, and nonvolatile collection of data in support of management's decision-making process."—William H. (Bill) Inmon





- Data warehousing:
  - The process of constructing and using data warehouses

(1) Subject-Oriented

- Organized around major subjects, such as customer, product, sales
- Focusing on the modeling and analysis of data for decision makers, NOT on daily operations or transaction processing
- Provide a simple and concise view around particular subject issues by excluding data that are not useful in the decision support process

(2) Integrated

- Constructed by integrating multiple, heterogeneous data sources
  - relational databases, flat files, on-line transaction records
- Data cleaning and data integration techniques are applied
  - Ensure **consistency** in naming conventions, encoding structures, attribute measures, etc. among different data sources
    - Ex. Hotel price: differences on currency, tax, breakfast covered, and parking

(3) Time-Variant

- The time horizon for the data warehouse is significantly **longer** than that of operational systems
  - Operational database: current value data
  - Data warehouse data: provide information from a **historical** perspective (e.g., past 5-10 years)
- **Every key** structure in the data warehouse
  - Contains an element of **time**, explicitly or implicitly
  - But the key of operational data may or may not contain "time element"

(4) Nonvolatile

- Independence
  - A physically separate store of data transformed from the operational environment
- Static: Operational update of data does NOT occur in the data warehouse environment
  - Does not require transaction processing, recovery, and concurrency control mechanisms
  - Requires only two operations in data accessing:
    - initial loading of data and access of data

OLTP vs OLAP

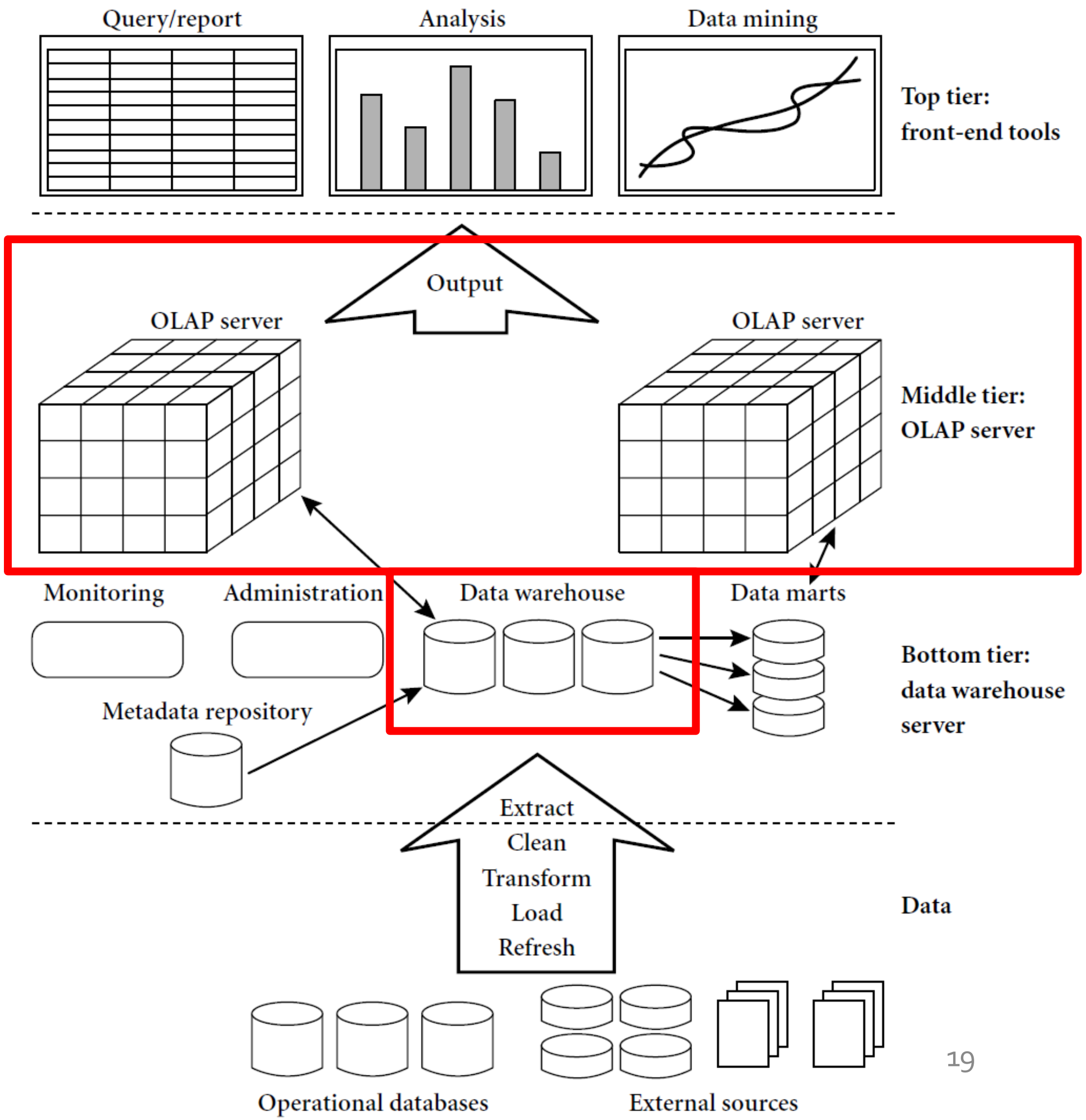
- OLTP: **Online** transactional processing
  - DBMS operations
  - Query and transactional processing
- OLAP: **Online** analytical processing
  - Data warehouse operations (drilling, slicing, dicing, etc.)
  - Data analysis to support decision making

OLTP vs OLAP

	OLTP	OLAP
users	clerk, IT professional	knowledge worker
function	day to day operations	decision support
DB design	application-oriented	subject-oriented
data	current, up-to-date detailed, flat relational isolated	historical, summarized, multidimensional integrated, consolidated
usage	repetitive	ad-hoc
access	read/write index/hash on prim. key	lots of scans
unit of work	short, simple transaction	complex query
# records accessed	tens	millions
#users	thousands	hundreds
DB size	100MB-GB	100GB-TB
metric	transaction throughput	query throughput, response

Data Warehouse: A Multi-Tiered Architecture

- Top Tier: Front-End Tools
- **Middle Tier: OLAP Server**
- **Bottom Tier: Data Warehouse Server**
- Data



From Data to Data Warehouse: Extraction, Transformation, and Loading (ETL)

- **Data extraction**
  - get data from multiple, heterogeneous, and external sources
- **Data cleaning**
  - detect errors in the data and rectify them when possible
- **Data transformation**
  - convert data from legacy or host format to warehouse format
- **Load**
  - sort, summarize, consolidate, compute views, check integrity, and build indices and partitions
- **Refresh**
  - propagate the updates from the data sources to the warehouse

Data Warehouse Usage

- Three kinds of data warehouse applications
  - Information processing
    - supports querying, basic statistical analysis, and reporting using crosstabs, tables, charts and graphs
  - Analytical processing
    - multidimensional analysis of data warehouse data
    - supports basic OLAP operations, slice-dice, drilling, pivoting
  - Data mining
    - knowledge discovery from hidden patterns
    - supports associations, constructing analytical models, performing classification and prediction, and presenting the mining results using visualization tools

Efficient Processing OLAP Queries

- **Determine which operations** should be performed on the available cuboids
  - Transform drill, roll, etc. into corresponding SQL and/or OLAP operations, e.g., dice = selection + projection
- **Determine which materialized cuboid(s)** should be selected for OLAP op.
  - Let the query to be processed be on {*brand*, *province_or_state*} with the condition "*year = 2004*", and there are 4 materialized cuboids available:

    1) {*year*, *item_name*, *city*}

    2) {*year*, *brand*, *country*}

    3) {*year*, *brand*, *province_or_state*} √

    4) {*item_name*, *province_or_state*} where *year = 2004*

    Which should be selected to process the query?

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