



CS 412 Intro. to Data Mining

Chapter 4. Data Warehousing and On-line Analytical Processing

Jiawei Han, Computer Science, Univ. Illinois at Urbana-Champaign, 2017



Chapter 4: Data Warehousing and On-line Analytical Processing

- Data Warehouse: Basic Concepts
- Data Warehouse Modeling: Data Cube and OLAP
- Data Warehouse Design and Usage
- Data Warehouse Implementation
- Summary



What is a 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
- “A data warehouse is a subject-oriented, integrated, time-variant, and nonvolatile collection of data in support of management’s decision-making process.”—W. H. Inmon
- Data warehousing:
 - The process of constructing and using data warehouses

Data Warehouse—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**

Data Warehouse—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
 - When data is moved to the warehouse, it is converted

Data Warehouse—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”

Data Warehouse—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.

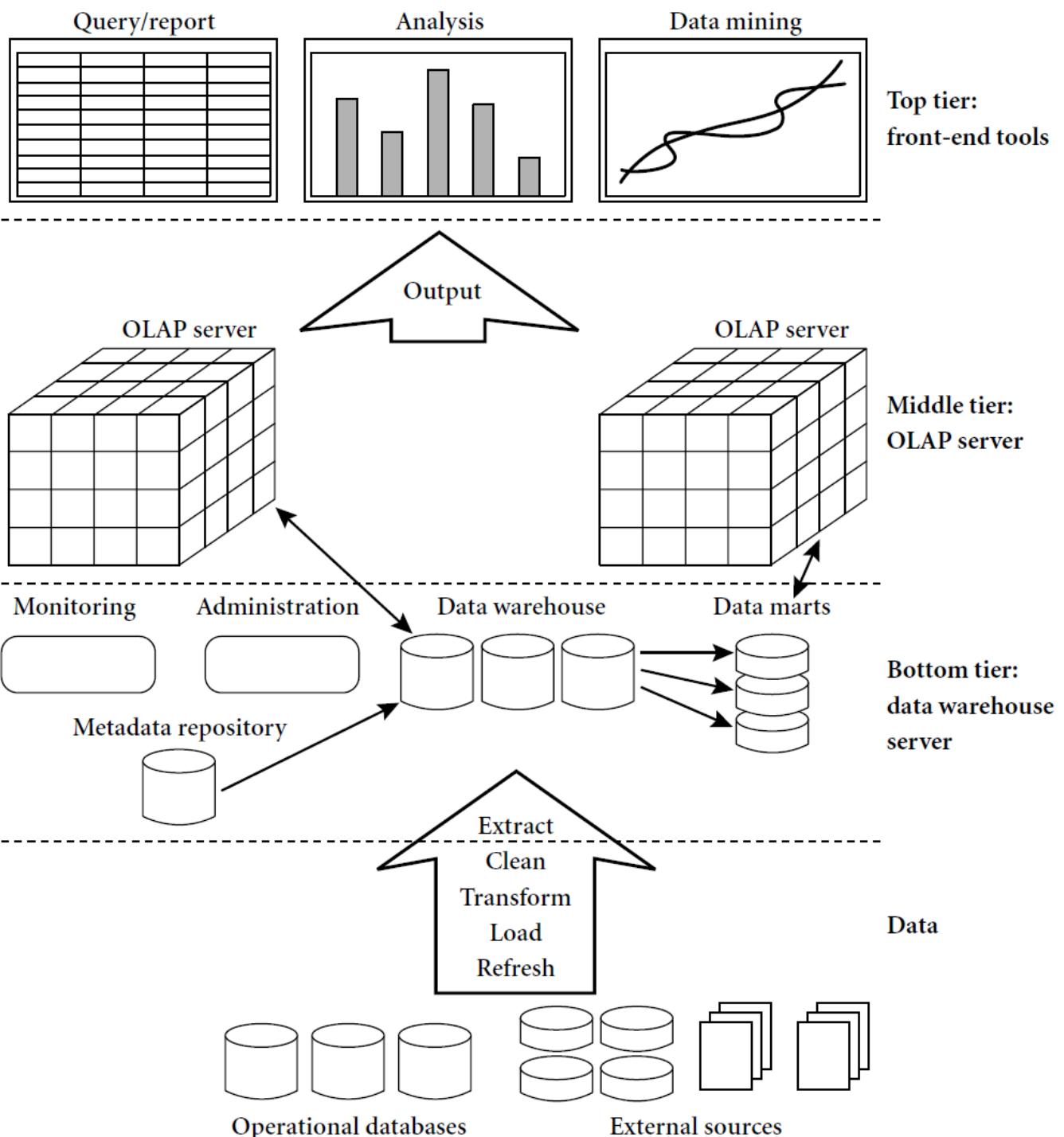
	OLTP	OLAP
users	clerk, IT professional	knowledge worker
function	day-to-day operations	decision support
DB design	application-oriented	subject-oriented
data	current, up-to-date detailed, flat relational isolated	historical, summarized, multidimensional integrated, consolidated
usage	repetitive	ad-hoc
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

Why a Separate Data Warehouse?

- ❑ High performance for both systems
 - ❑ DBMS— tuned for OLTP: access methods, indexing, concurrency control, recovery
 - ❑ Warehouse—tuned for OLAP: complex OLAP queries, multidimensional view, consolidation
- ❑ Different functions and different data:
 - ❑ missing data: Decision support requires historical data which operational DBs do not typically maintain
 - ❑ data consolidation: DS requires consolidation (aggregation, summarization) of data from heterogeneous sources
 - ❑ data quality: different sources typically use inconsistent data representations, codes and formats which have to be reconciled
- ❑ Note: There are more and more systems which perform OLAP analysis directly on relational databases

Data Warehouse: A Multi-Tiered Architecture

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



Three Data Warehouse Models

- **Enterprise warehouse**
 - Collects all of the information about subjects spanning the entire organization
- **Data Mart**
 - A subset of corporate-wide data that is of value to a specific groups of users
 - Its scope is confined to specific, selected groups, such as marketing data mart
 - Independent vs. dependent (directly from warehouse) data mart
- **Virtual warehouse**
 - A set of views over operational databases
 - Only some of the possible summary views may be materialized

Extraction, Transformation, and Loading (ETL)

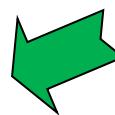
- Data extraction**
 - get data from multiple, heterogeneous, and external sources
- Data cleaning**
 - detect errors in the data and rectify them when possible
- Data transformation**
 - convert data from legacy or host format to warehouse format
- Load**
 - sort, summarize, consolidate, compute views,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

Metadata Repository

- ❑ **Meta data** is the data defining warehouse objects. It stores:
 - ❑ Description of the structure of the data warehouse
 - ❑ schema, view, dimensions, hierarchies, derived data defn, data mart locations and contents
 - ❑ Operational meta-data
 - ❑ data lineage (history of migrated data and transformation path), currency of data (active, archived, or purged), monitoring information (warehouse usage statistics, error reports, audit trails)
 - ❑ The algorithms used for summarization
 - ❑ The mapping from operational environment to the data warehouse
 - ❑ Data related to system performance
 - ❑ warehouse schema, view and derived data definitions
 - ❑ Business data
 - ❑ business terms and definitions, ownership of data, charging policies

Chapter 4: Data Warehousing and On-line Analytical Processing

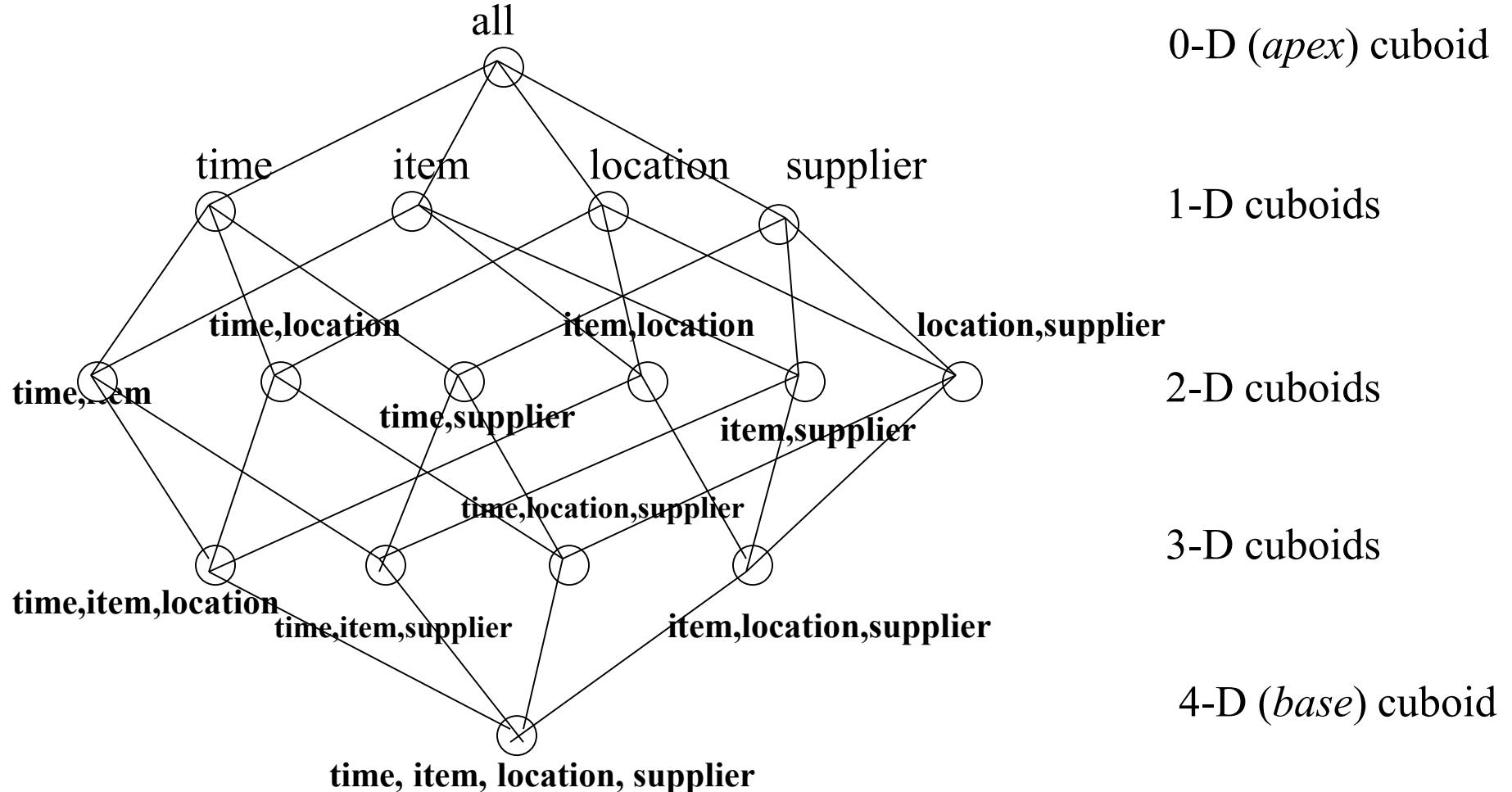
- Data Warehouse: Basic Concepts
- Data Warehouse Modeling: Data Cube and OLAP
- Data Warehouse Design and Usage
- Data Warehouse Implementation
- Summary



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) *ទីតាំងទិន្នន័យ*
- **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 Cube: A Lattice of Cuboids



3D

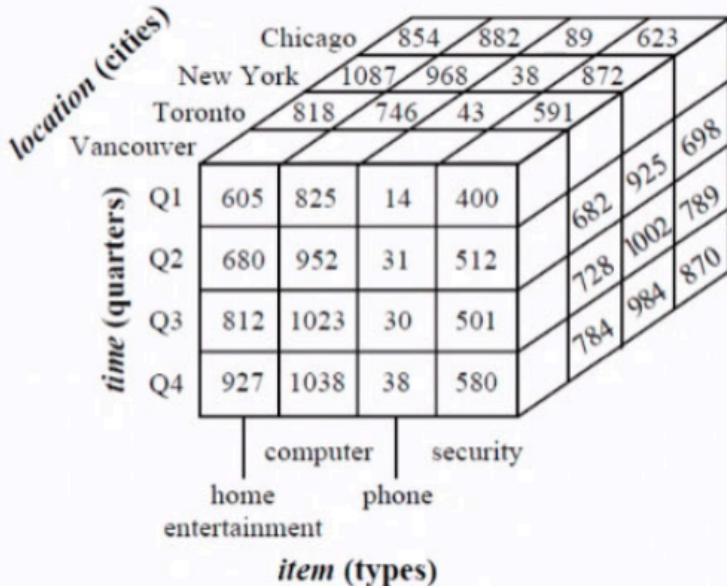


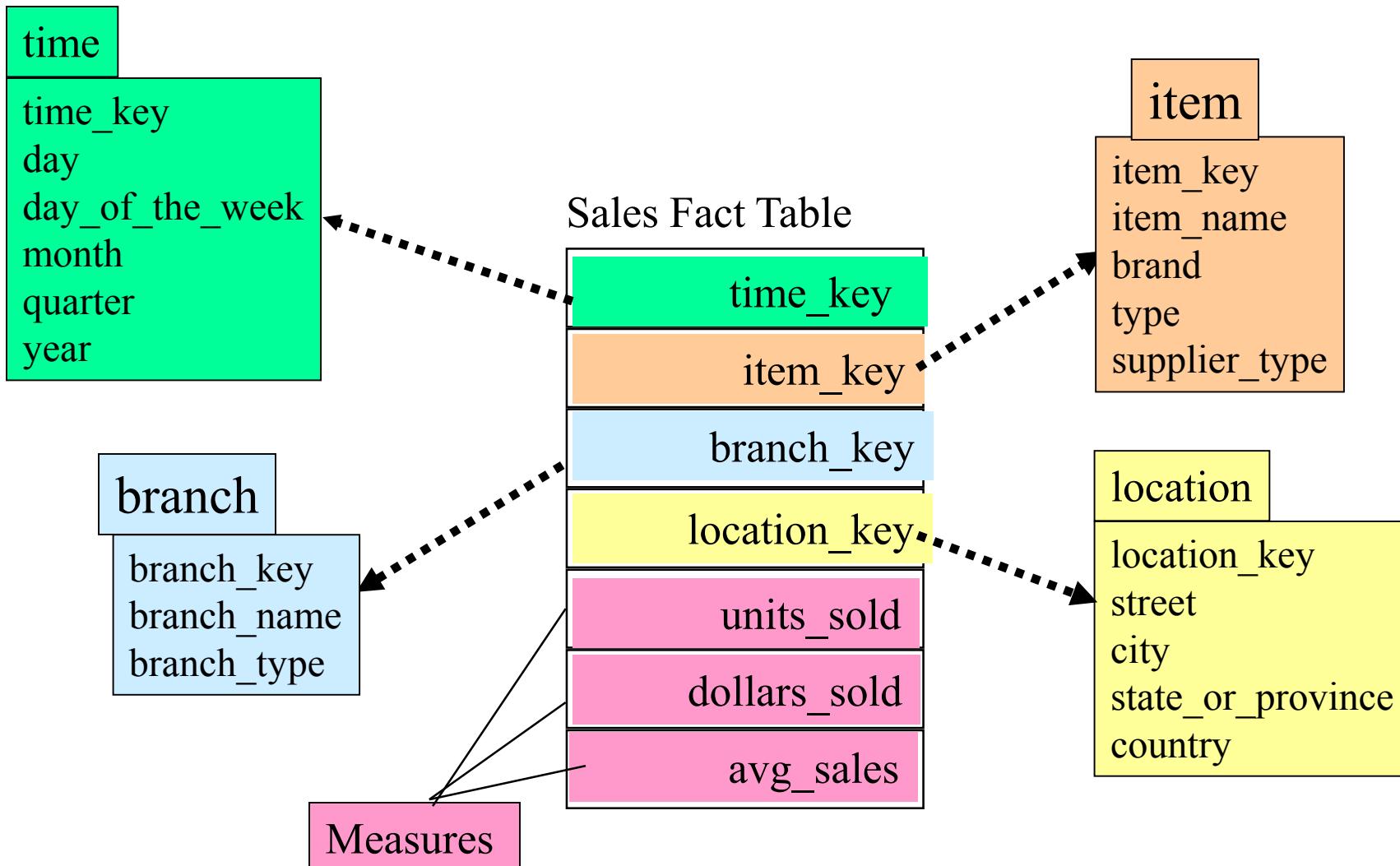
Figure 4.3: A 3-D data cube representation of the data in Table 4.3, according to the dimensions *time*, *item*, and *location*. The measure displayed is *dollars_sold* (in thousands).

Conceptual Modeling of Data Warehouses

- Modeling data warehouses: dimensions & measures
 - Star schema: A fact table in the middle connected to a set of dimension tables
 - Snowflake schema: A refinement of star schema where some dimensional hierarchy is normalized into a set of smaller dimension tables, forming a shape similar to snowflake
 - Fact constellations: Multiple fact tables share dimension tables, viewed as a collection of stars, therefore called **galaxy schema** or fact constellation

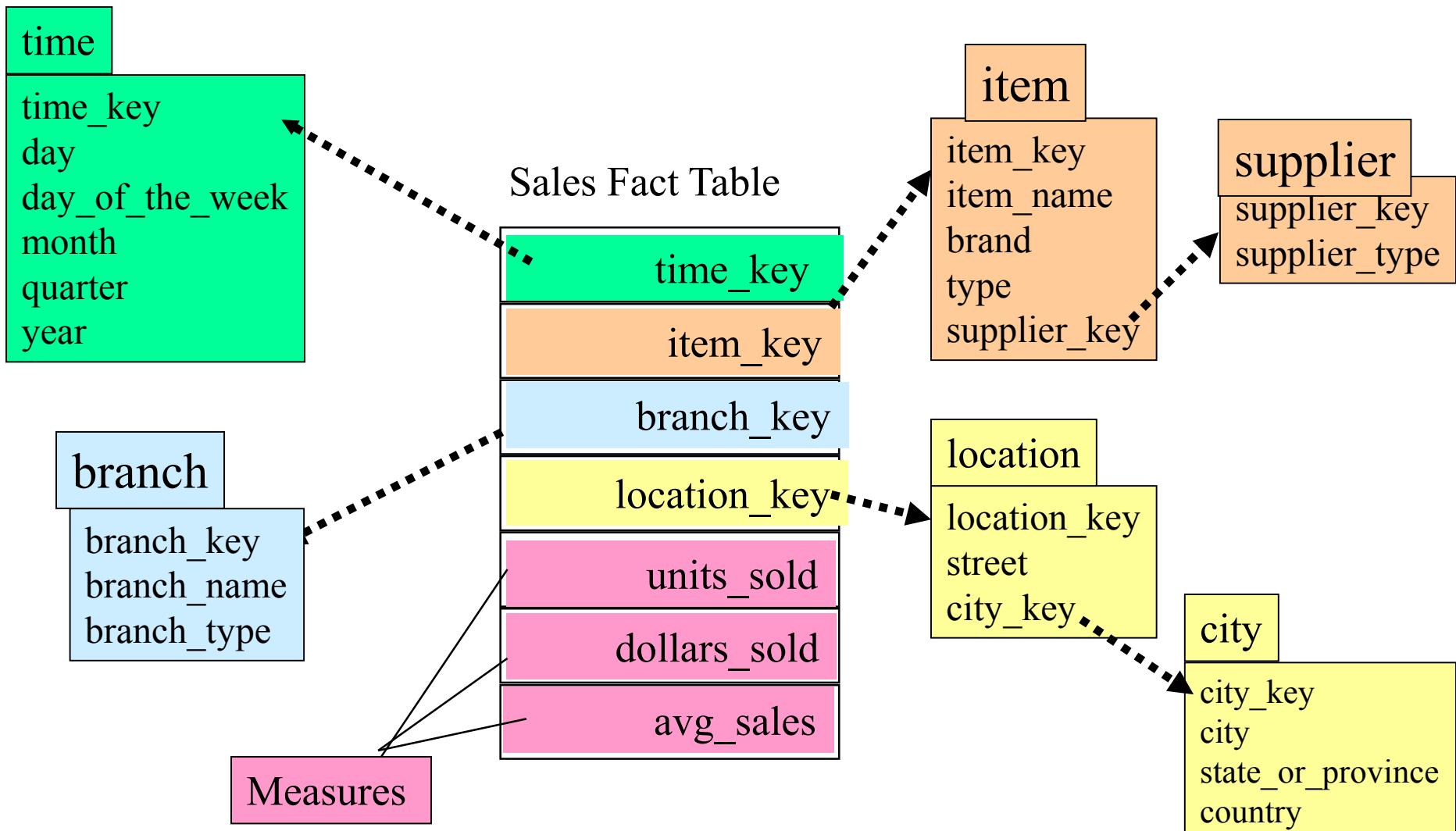
Star Schema: An Example

ស៊ត្រុកអាមេរិកណ៍ភោជនការបែងចែក

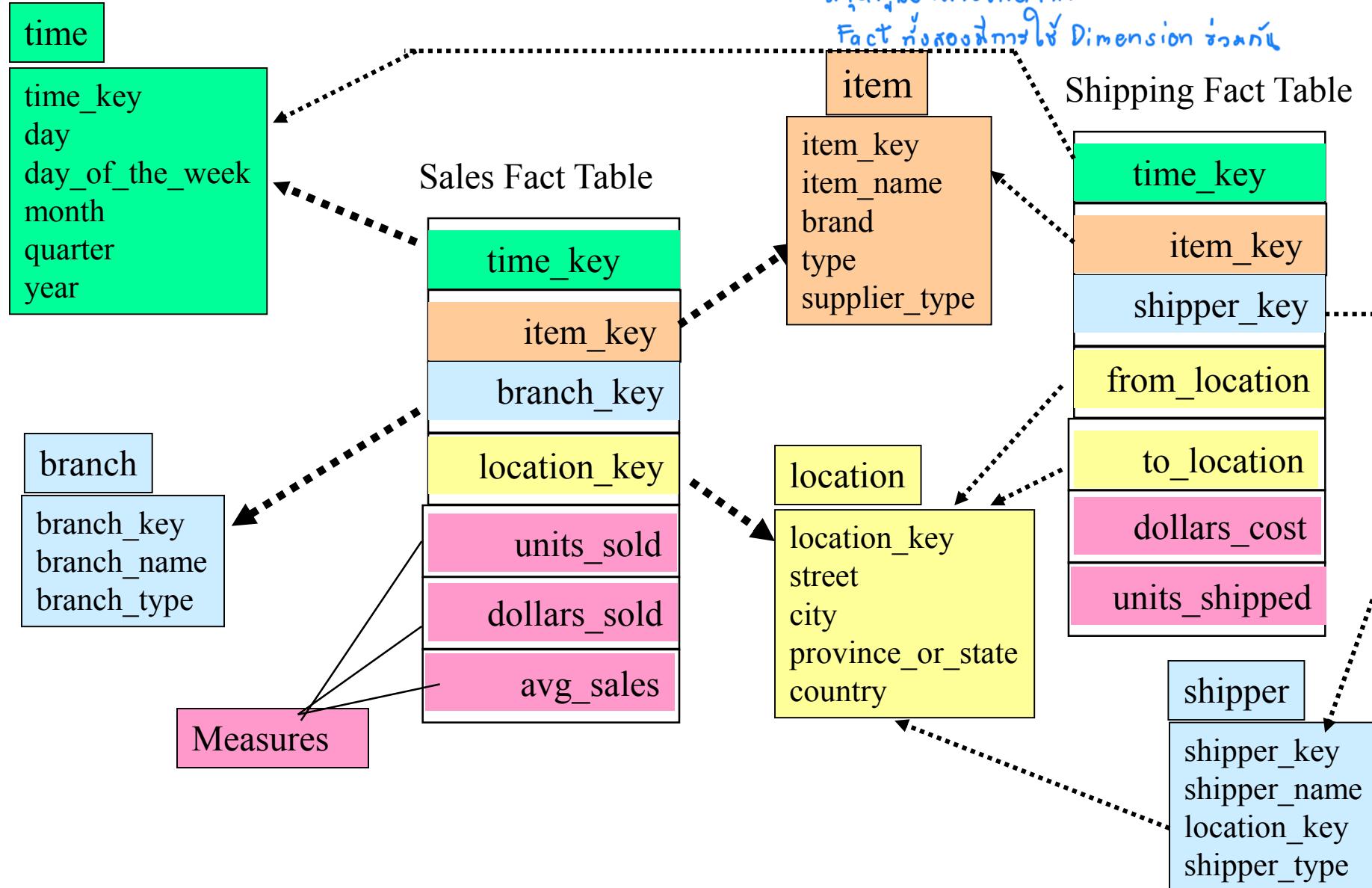


Snowflake Schema: An Example

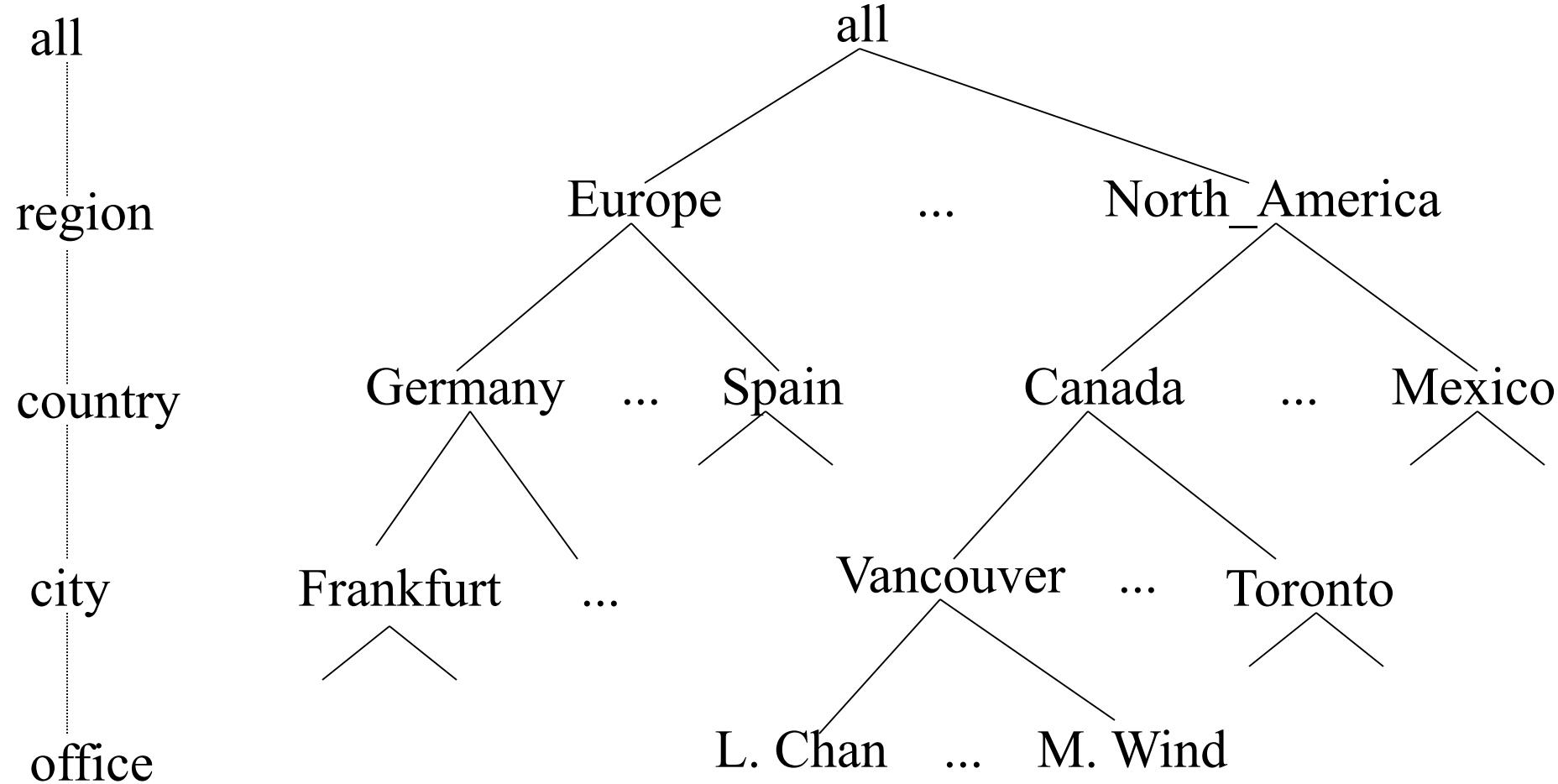
เกล็ดหินปืน



Fact Constellation: An Example



A Concept Hierarchy for a Dimension (location)

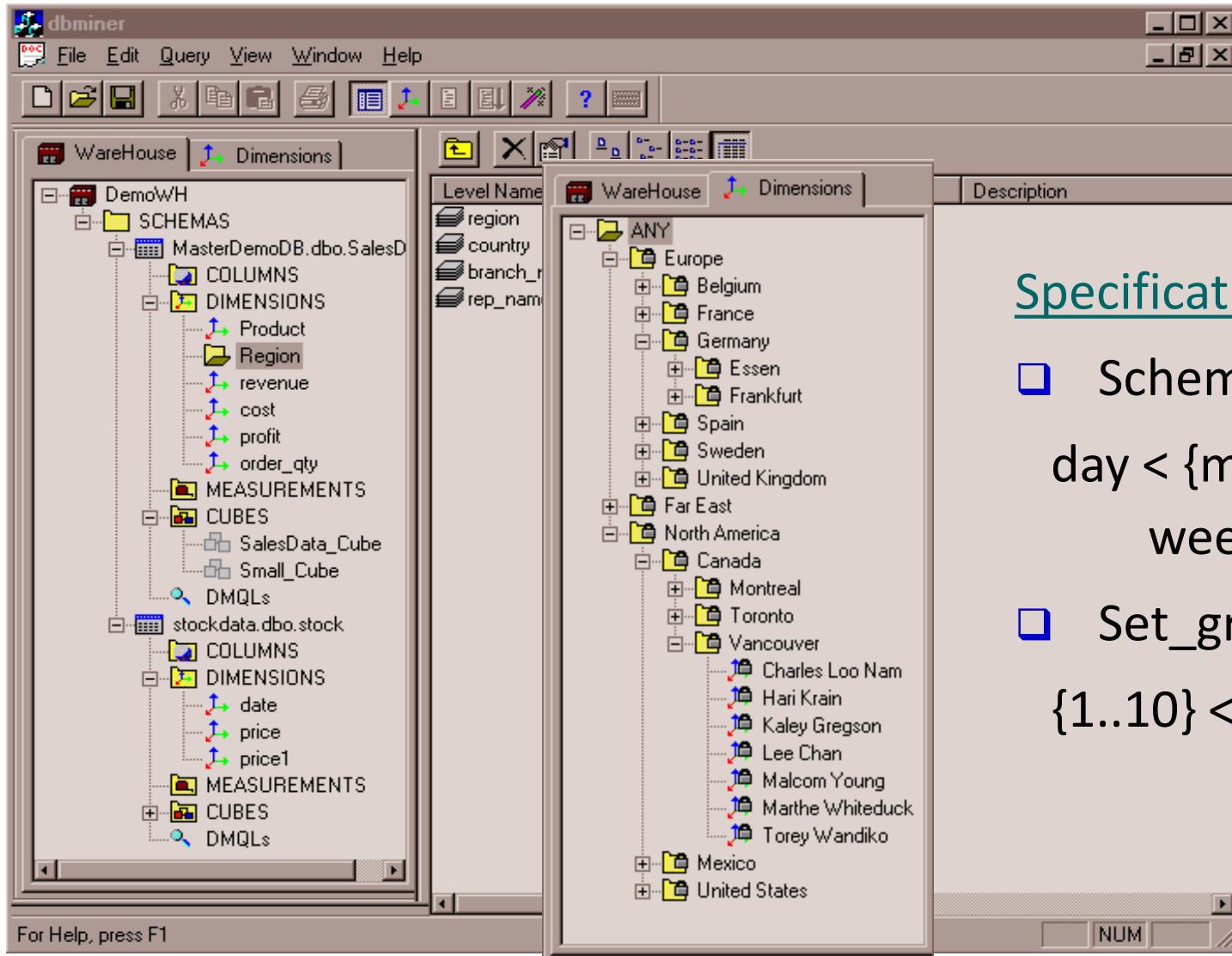


மாண்பும் மூலம்

Data Cube Measures: Three Categories

- **Distributive**: if the result derived by applying the function to n aggregate values is the same as that derived by applying the function on all the data without partitioning
 - E.g., `count()`, `sum()`, `min()`, `max()`
- **Algebraic**: if it can be computed by an algebraic function with M arguments (where M is a bounded integer), each of which is obtained by applying a distributive aggregate function
 - $\text{avg}(x) = \text{sum}(x) / \text{count}(x)$
 - Is `min_N()` an algebraic measure? How about `standard_deviation()`?
- **Holistic**: if there is no constant bound on the storage size needed to describe a subaggregate.
 - E.g., `median()`, `mode()`, `rank()`

View of Warehouses and Hierarchies



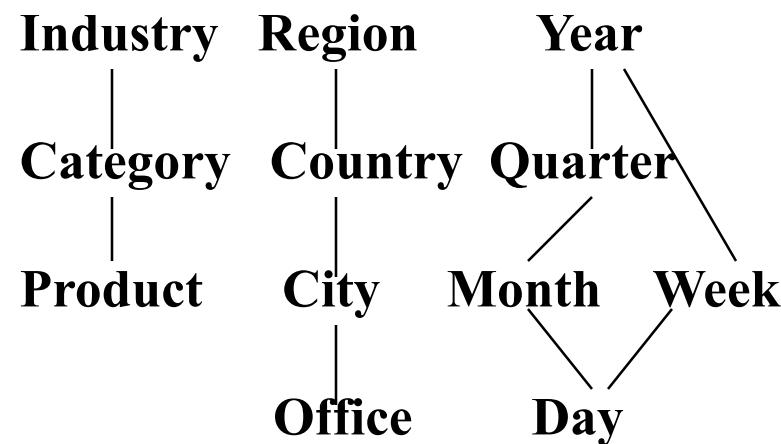
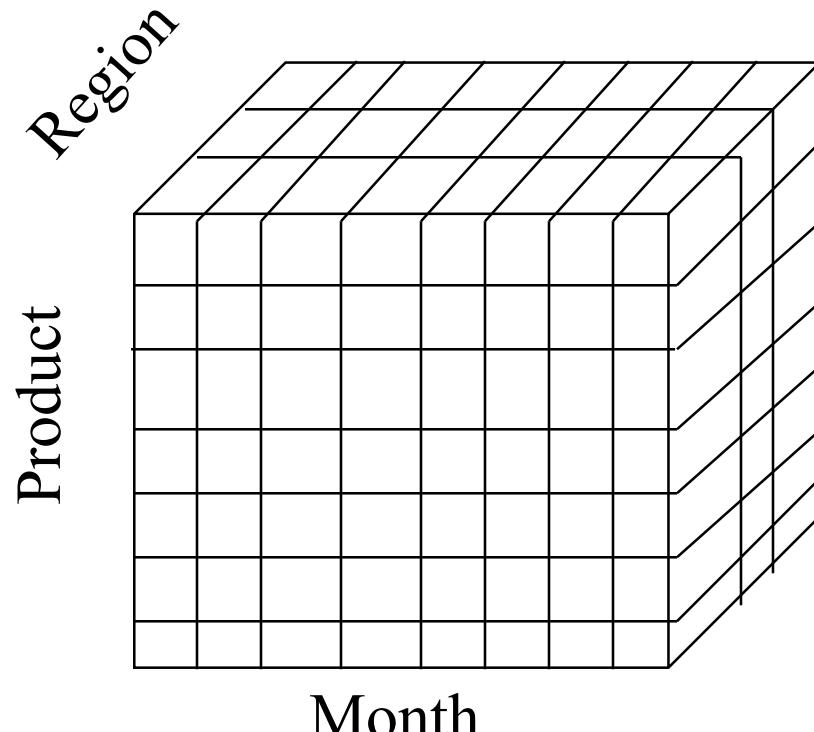
Specification of hierarchies

- Schema hierarchy
day < {month < quarter;
week} < year
- Set_grouping hierarchy
{1..10} < inexpensive

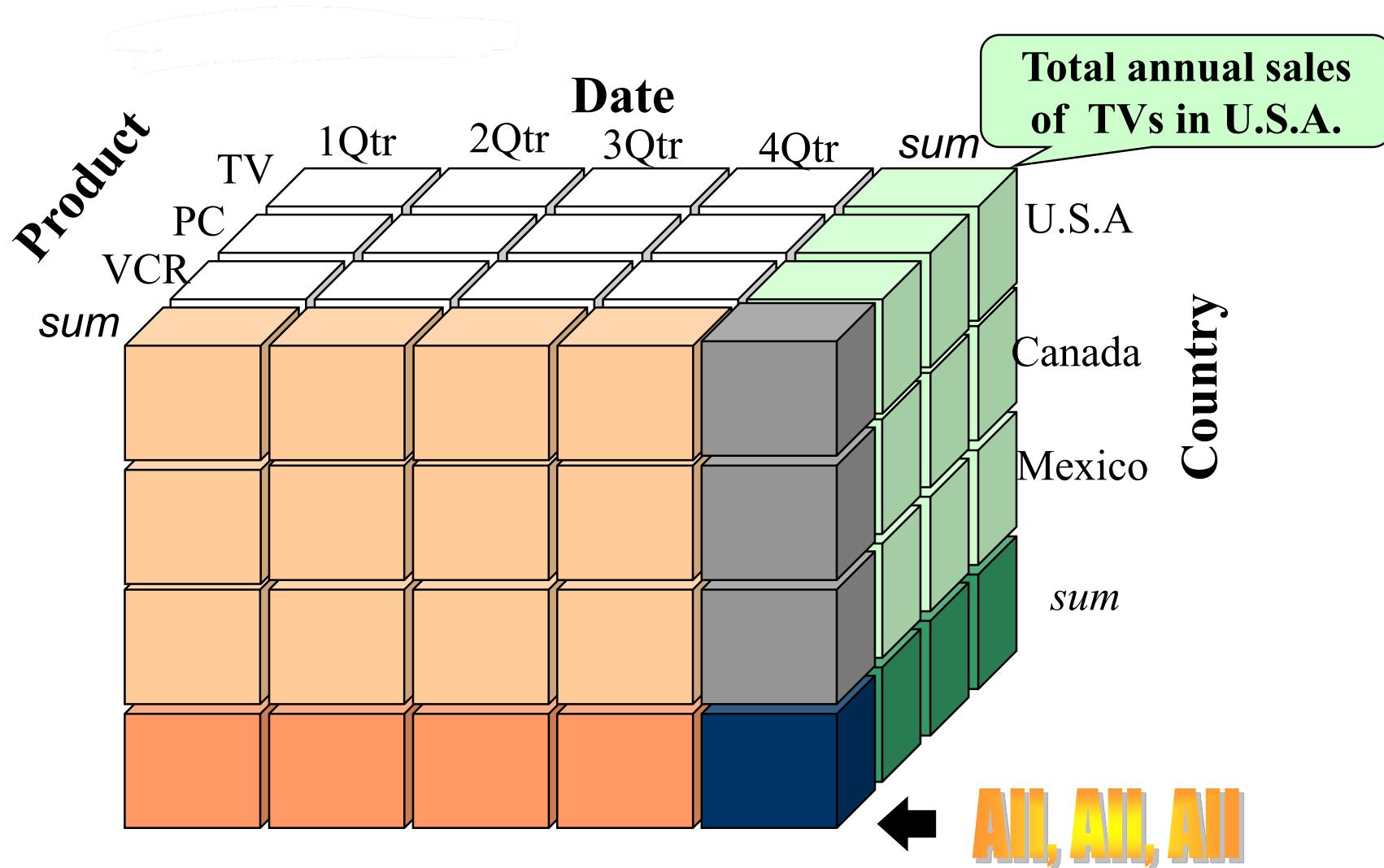
Multidimensional Data

- Sales volume as a function of product, month, and region

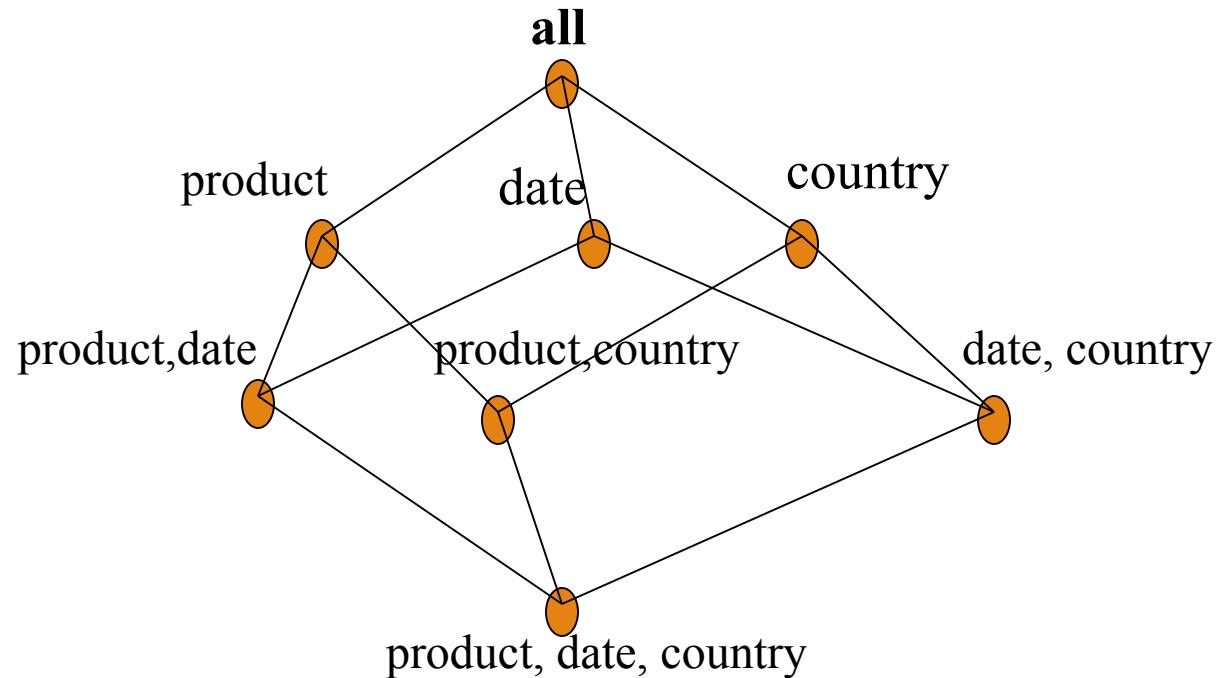
Dimensions: *Product, Location, Time*
Hierarchical summarization paths



A Sample Data Cube



Cuboids Corresponding to the Cube



0-D (*apex*) cuboid

1-D cuboids

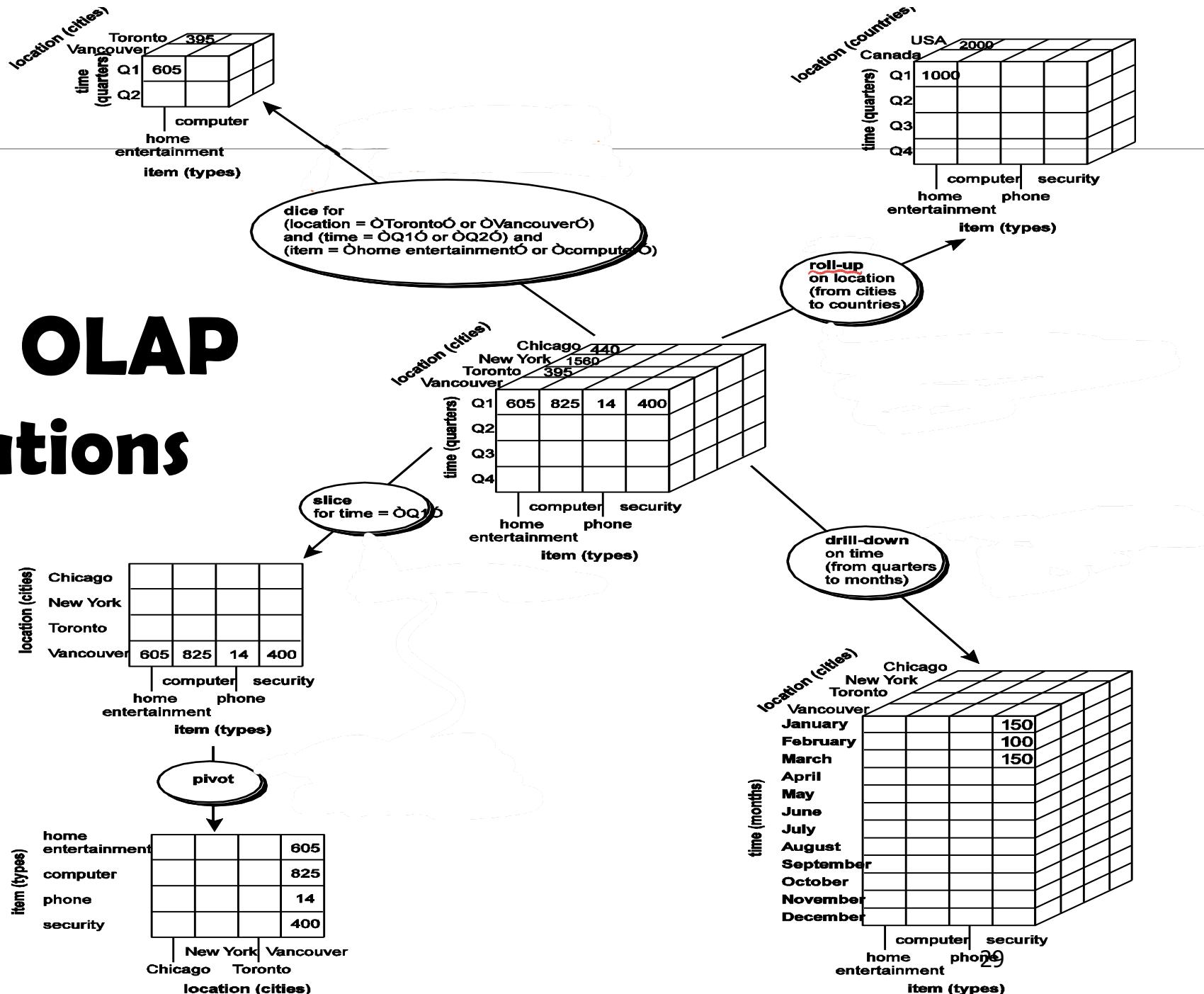
2-D cuboids

3-D (*base*) cuboid

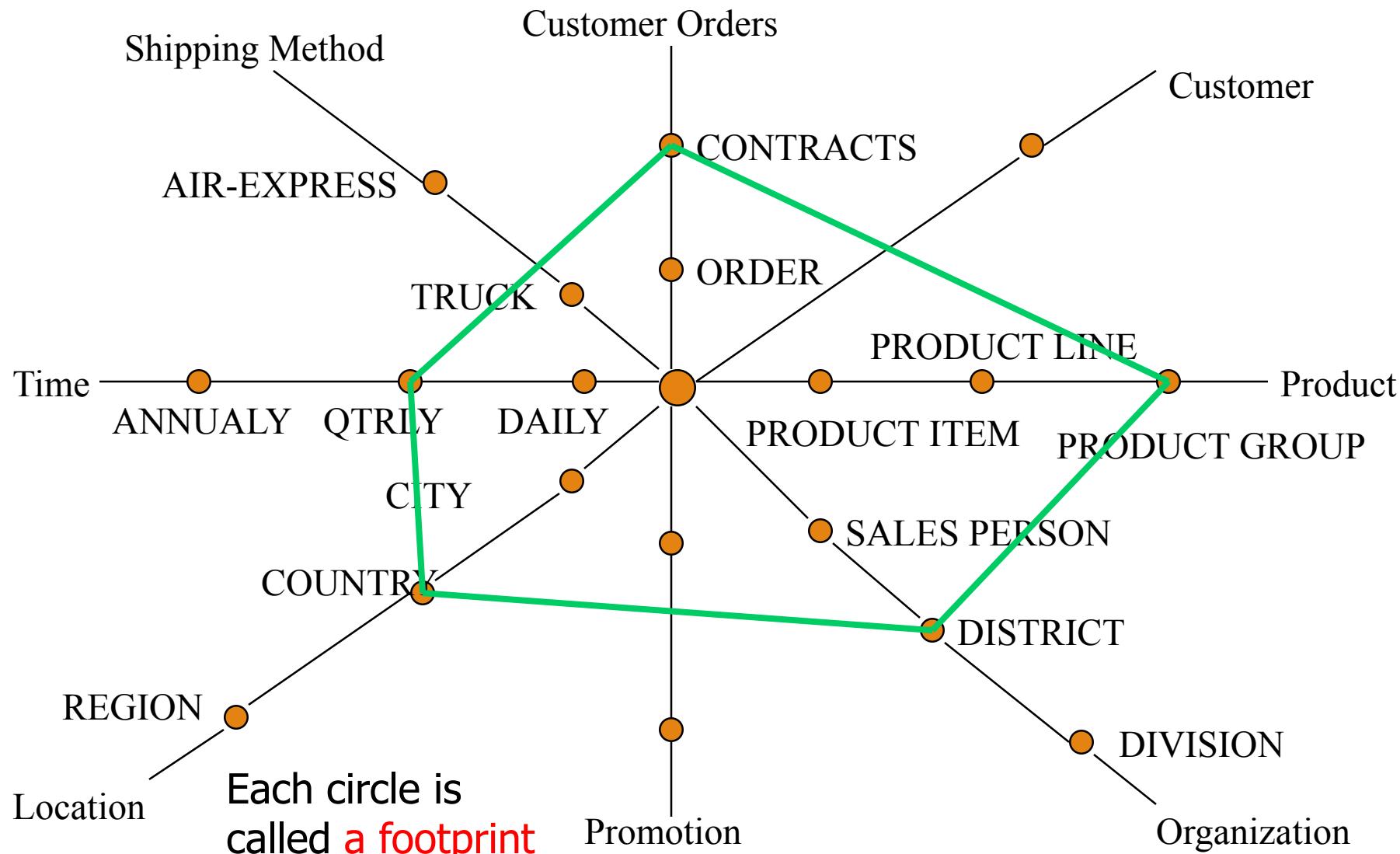
Typical OLAP Operations

- Roll up (drill-up): summarize data
 - *by climbing up hierarchy or by dimension reduction*
- Drill down (roll down): reverse of roll-up
 - *from higher level summary to lower level summary or detailed data, or introducing new dimensions*
- Slice and dice: *project and select*
- Pivot (rotate):
 - *reorient the cube, visualization, 3D to series of 2D planes*
- Other operations
 - *Drill across: involving (across) more than one fact table*
 - *Drill through: through the bottom level of the cube to its back-end relational tables (using SQL)*

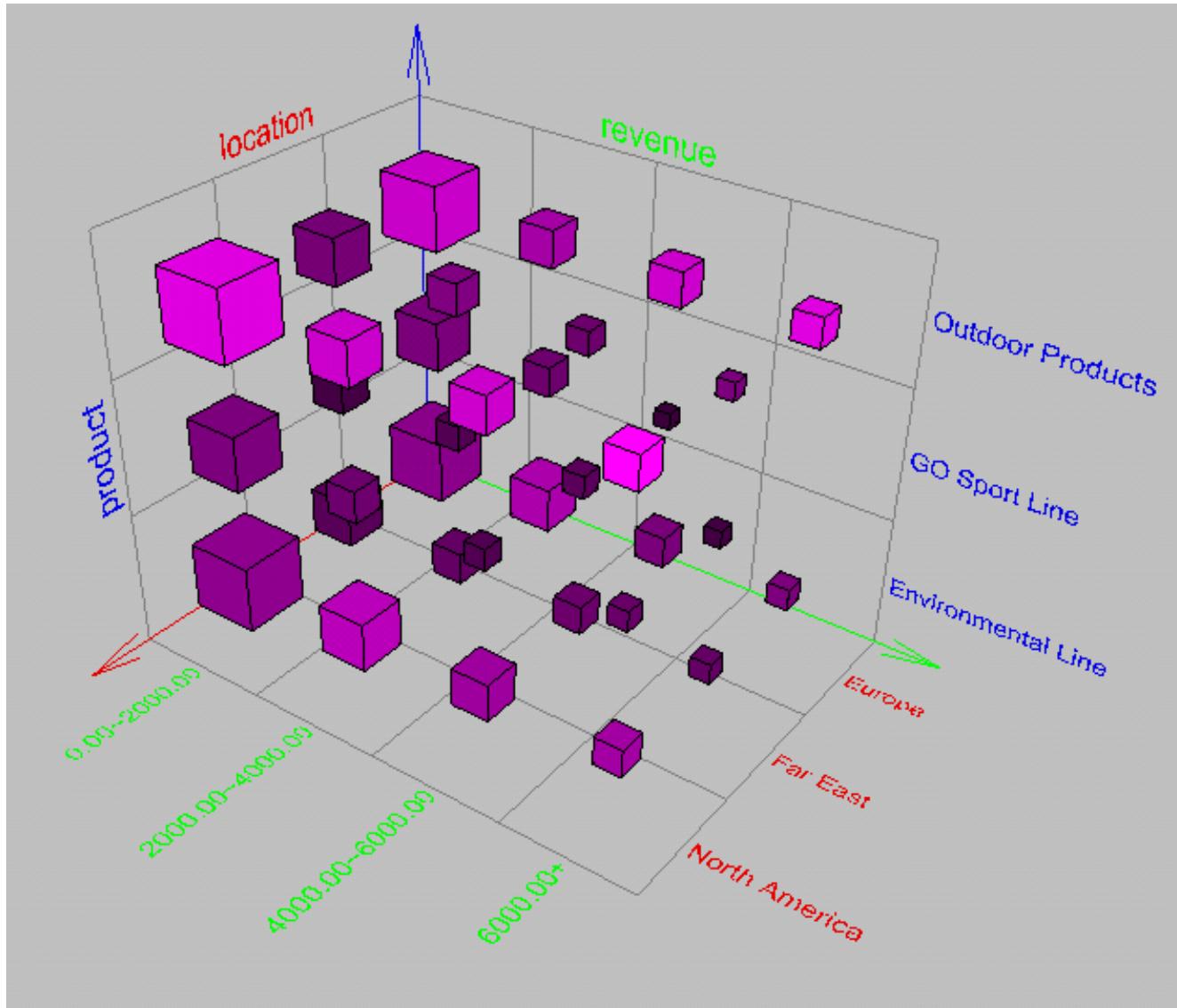
Typical OLAP Operations



A Star-Net Query Model



Browsing a Data Cube



- Visualization
- OLAP capabilities
- Interactive manipulation

Chapter 4: Data Warehousing and On-line Analytical Processing

- Data Warehouse: Basic Concepts
- Data Warehouse Modeling: Data Cube and OLAP
- Data Warehouse Design and Usage
- Data Warehouse Implementation
- Summary



Design of Data Warehouse: A Business Analysis Framework

- Four views regarding the design of a data warehouse
 - Top-down view
 - allows selection of the relevant information necessary for the data warehouse
 - Data source view
 - exposes the information being captured, stored, and managed by operational systems
 - Data warehouse view
 - consists of fact tables and dimension tables
 - Business query view
 - sees the perspectives of data in the warehouse from the view of end-user

Data Warehouse Design Process

- ❑ **Top-down, bottom-up approaches or a combination of both**
 - ❑ Top-down: Starts with overall design and planning (mature)
 - ❑ Bottom-up: Starts with experiments and prototypes (rapid)
- ❑ **From software engineering point of view**
 - ❑ Waterfall: structured and systematic analysis at each step before proceeding to the next
 - ❑ Spiral: rapid generation of increasingly functional systems, short turn around time, quick turn around
- ❑ **Typical data warehouse design process**
 - ❑ Choose a business process to model, e.g., orders, invoices, etc.
 - ❑ Choose the grain (*atomic level of data*) of the business process
 - ❑ Choose the dimensions that will apply to each fact table record
 - ❑ Choose the measure that will populate each fact table record

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

From On-Line Analytical Processing (OLAP) to On Line Analytical Mining (OLAM)

- Why online analytical mining?
 - High quality of data in data warehouses
 - DW contains integrated, consistent, cleaned data
 - Available information processing structure surrounding data warehouses
 - ODBC, OLEDB, Web accessing, service facilities, reporting and OLAP tools
 - OLAP-based exploratory data analysis
 - Mining with drilling, dicing, pivoting, etc.
 - On-line selection of data mining functions
 - Integration and swapping of multiple mining functions, algorithms, and tasks

Chapter 4: Data Warehousing and On-line Analytical Processing

- Data Warehouse: Basic Concepts
- Data Warehouse Modeling: Data Cube and OLAP
- Data Warehouse Design and Usage
- Data Warehouse Implementation
- Summary

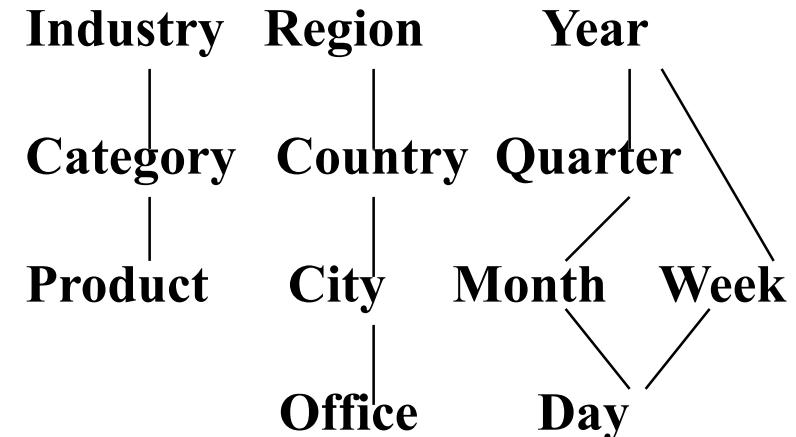


Efficient Data Cube Computation

- ❑ Data cube can be viewed as a lattice of cuboids
 - ❑ The bottom-most cuboid is the base cuboid
 - ❑ The top-most cuboid (apex) contains only one cell
 - ❑ How many cuboids in an n-dimensional cube with L levels?
- ❑ Materialization of data cube
 - ❑ **Full materialization:** Materialize every (cuboid)
 - ❑ **No materialization:** Materialize none (cuboid)
 - ❑ **Partial materialization:** Materialize some cuboids
 - ❑ Which cuboids to materialize?
 - ❑ Selection based on size, sharing, access frequency, etc.

Why this formula?

$$T = \prod_{i=1}^n (L_i + 1)$$



The “Compute Cube” Operator

- Cube definition and computation in DMQL

```
define cube sales [item, city, year]: sum (sales_in_dollars)  
compute cube sales
```

- Transform it into a SQL-like language (with a new operator `cube by`, introduced by Gray et al.'96)

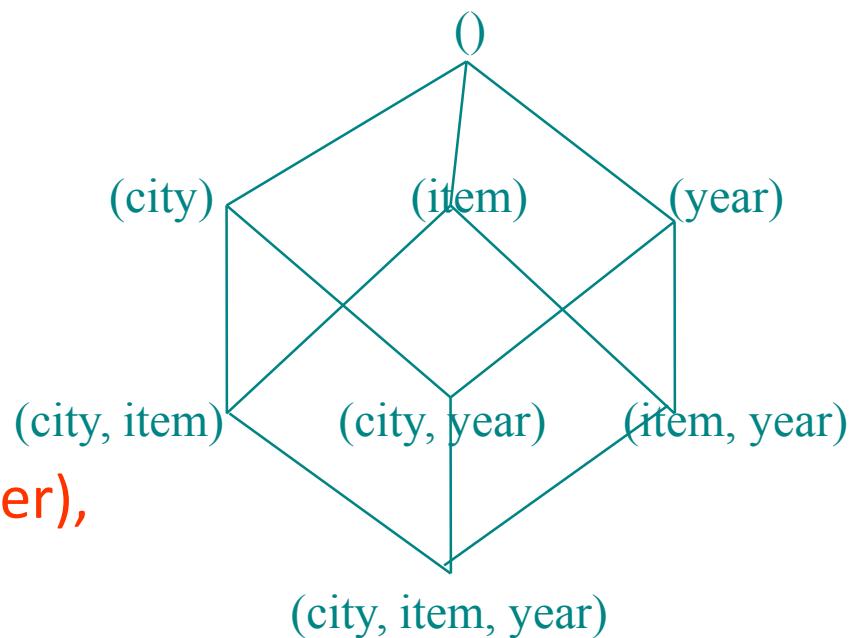
```
SELECT item, city, year, SUM (amount)  
FROM SALES  
CUBE BY item, city, year
```

- Need compute the following Group-Bys

(date, product, customer),

(date, product), (date, customer), (product, customer),

(date), (product), (customer)



Indexing OLAP Data: Bitmap Index

- Index on a particular column
 - Each value in the column has a bit vector: bit-op is fast
 - The length of the bit vector: # of records in the base table
 - The i -th bit is set if the i -th row of the base table has the value for the indexed column
 - not suitable for high cardinality domains
- A recent bit compression technique, Word-Aligned Hybrid (WAH), makes it work for high cardinality domain as well [Wu, et al. TODS'06]

Base table

Cust	Region	Type
C1	Asia	Retail
C2	Europe	Dealer
C3	Asia	Dealer
C4	America	Retail
C5	Europe	Dealer

Index on Region

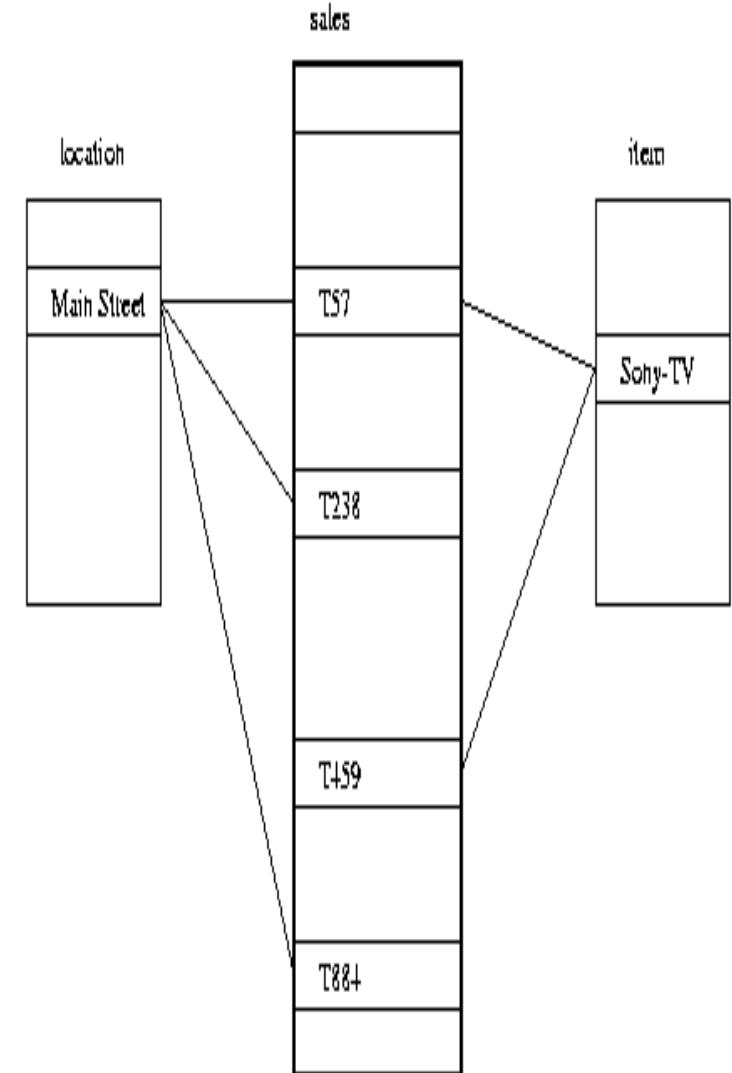
RecID	Asia	Europe	America
1	1	0	0
2	0	1	0
3	1	0	0
4	0	0	1
5	0	1	0

Index on Type

RecID	Retail	Dealer
1	1	0
2	0	1
3	0	1
4	1	0
5	0	1

Indexing OLAP Data: Join Indices

- ❑ Join index: $JI(R\text{-id}, S\text{-id})$ where $R (R\text{-id}, \dots) \bowtie S (S\text{-id}, \dots)$
- ❑ Traditional indices map the values to a list of record ids
 - ❑ It materializes relational join in JI file and speeds up relational join
- ❑ In data warehouses, join index relates the values of the dimensions of a start schema to rows in the fact table.
- ❑ E.g., fact table: *Sales* and two dimensions *city* and *product*
 - ❑ A join index on *city* maintains for each distinct city a list of R-IDs of the tuples recording the Sales in the city
 - ❑ Join indices can span multiple dimensions



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 $\{brand, \text{province_or_state}\}$ with the condition “ $year = 2004$ ”, and there are 4 materialized cuboids available:
 - 1) $\{year, item_name, city\}$
 - 2) $\{year, brand, country\}$
 - 3) $\{year, brand, \text{province_or_state}\}$
 - 4) $\{item_name, \text{province_or_state}\}$ where $year = 2004$Which should be selected to process the query?
- ❑ Explore indexing structures and compressed vs. dense array structs in MOLAP

OLAP Server Architectures

- **Relational OLAP (ROLAP)**

- Use relational or extended-relational DBMS to store and manage warehouse data and OLAP middle ware
- Include optimization of DBMS backend, implementation of aggregation navigation logic, and additional tools and services
- Greater scalability

- **Multidimensional OLAP (MOLAP)**

- Sparse array-based multidimensional storage engine
- Fast indexing to pre-computed summarized data

- **Hybrid OLAP (HOLAP)** (e.g., Microsoft SQLServer)

- Flexibility, e.g., low level: relational, high-level: array
- Specialized SQL servers (e.g., Redbricks)
- Specialized support for SQL queries over star/snowflake schemas

Chapter 4: Data Warehousing and On-line Analytical Processing

- Data Warehouse: Basic Concepts
- Data Warehouse Modeling: Data Cube and OLAP
- Data Warehouse Design and Usage
- Data Warehouse Implementation
- Summary



Summary

- Data warehousing: A multi-dimensional model of a data warehouse
 - A data cube consists of *dimensions & measures*
 - Star schema, snowflake schema, fact constellations
 - OLAP operations: drilling, rolling, slicing, dicing and pivoting
- Data Warehouse Architecture, Design, and Usage
 - Multi-tiered architecture
 - Business analysis design framework
 - Information processing, analytical processing, data mining, OLAM
- Implementation: Efficient computation of data cubes
 - Partial vs. full vs. no materialization
 - Indexing OLAP data: Bitmap index and join index
 - OLAP query processing
 - OLAP servers: ROLAP, MOLAP, HOLAP

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
- D. Agrawal, A. E. Abbadi, A. Singh, and T. Yurek. Efficient view maintenance in data warehouses. SIGMOD'97
- R. Agrawal, A. Gupta, and S. Sarawagi. Modeling multidimensional databases. ICDE'97
- **S. Chaudhuri and U. Dayal. An overview of data warehousing and OLAP technology. ACM SIGMOD Record, 26:65-74, 1997**
- J. Gray, et al. Data cube: A relational aggregation operator generalizing group-by, cross-tab and sub-totals. Data Mining and Knowledge Discovery, 1:29-54, 1997.
- A. Gupta and I. S. Mumick. Materialized Views: Techniques, Implementations, and Applications. MIT Press, 1999
- J. Han. Towards on-line analytical mining in large databases. *SIGMOD Record*, 1998
- V. Harinarayan, A. Rajaraman, and J. D. Ullman. Implementing data cubes efficiently. SIGMOD'96

References (II)

- ❑ C. Imhoff, N. Galemmo, and J. G. Geiger. Mastering Data Warehouse Design: Relational and Dimensional Techniques. John Wiley, 2003
- ❑ W. H. Inmon. Building the Data Warehouse. John Wiley, 1996
- ❑ R. Kimball and M. Ross. The Data Warehouse Toolkit: The Complete Guide to Dimensional Modeling. 2ed. John Wiley, 2002
- ❑ P. O'Neil and D. Quass. Improved query performance with variant indexes. SIGMOD'97
- ❑ S. Sarawagi and M. Stonebraker. Efficient organization of large multidimensional arrays. ICDE'94
- ❑ P. Valduriez. Join indices. ACM Trans. Database Systems, 12:218-246, 1987.
- ❑ J. Widom. Research problems in data warehousing. CIKM'95.
- ❑ K. Wu, E. Otoo, and A. Shoshani, Optimal Bitmap Indices with Efficient Compression, ACM Trans. on Database Systems (TODS), 31(1), 2006, pp. 1-38.

