Data Mining:
Concepts and Techniques

— Slides slightly adapted from—
— Chapter 3 —

Original slides by: Jiawei Han
Department of Computer Science
University of Illinois at Urbana-Champaign
www.cs.uiuc.edu/~hanj

Chapter 3: Data Warehousing and OLAP Technology: An Overview

- What is a data warehouse?
- A multi-dimensional data model
- Data warehouse architecture
- Data warehouse implementation
- From data warehousing to data mining

What is 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; or
  - patient, disease, gene, protein-class, etc.
- 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
    - E.g., Hotel prices at different international locations: currency, tax, breakfast covered, etc.
  - 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" => time derived

Data Warehouse—Nonvolatile

- A physically separate store of data transformed from the operational environment
- Operational update of data does not occur in the data warehouse environment but in the operational data sources themselves
  - 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*

Data Warehouse vs. Heterogeneous DBMS

- **Traditional heterogeneous DB integration**: A query driven approach
  - Build wrappers/mediators on top of heterogeneous databases
  - When a query is posed to a client site, a meta-dictionary is used to translate the query into queries appropriate for individual heterogeneous sites involved, and the results are integrated into a global answer set
  - => Complex information filtering, compete for resources
- **Data warehouse:** update-driven, high performance
  - Information from heterogeneous sources is integrated in advance and stored in warehouses for direct query and analysis

Data Warehouse vs. Operational DBMS

- OLTP (on-line transaction processing)
  - Major task of traditional relational DBMS
  - Day-to-day operations: purchasing, inventory, banking, manufacturing, payroll, registration, accounting, etc.
- OLAP (on-line analytical processing)
  - Major task of data warehouse system
  - Data analysis and decision making
- Distinct features (OLTP vs. OLAP):
  - User and system orientation: *customer* vs. *market*
  - Data contents: *current, detailed* vs. *historical, consolidated*
  - Database design: *ER + application* vs. *star + subject*
  - View: *current, local* vs. *evolutionary, integrated*
  - Access patterns: *updates* vs. *read-only but complex queries*

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

Why 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 (DS) 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 (… one size fits all?)

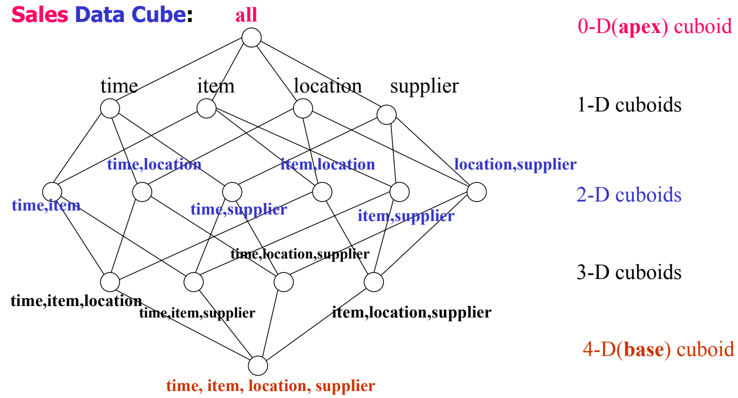
Chapter 3: Data Warehousing and OLAP Technology: An Overview

- What is a data warehouse?
- A multi-dimensional data model
- Data warehouse architecture
- Data warehouse implementation
- From data warehousing to data mining

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), **location** (…), etc.
  - *Fact table* contains *measures* (such as dollars_sold) and *keys* to each of the related dimension tables
- In data warehousing literature, an ***n****-dimensional base cube* is called a base cuboid. The top most ***0****-dimensional cuboid*, which holds the highest-level of summarization, is called the apex cuboid. The lattice of cuboids forms a data cube.

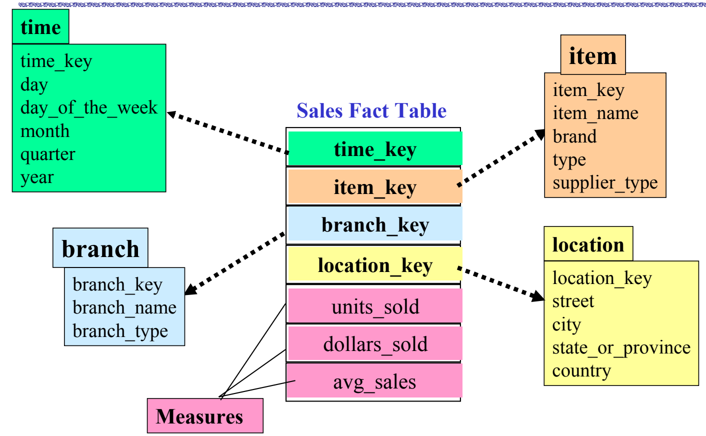
Cube: A Lattice of Cuboids



Conceptual Modeling of Data Warehouses

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

Example of Star Schema



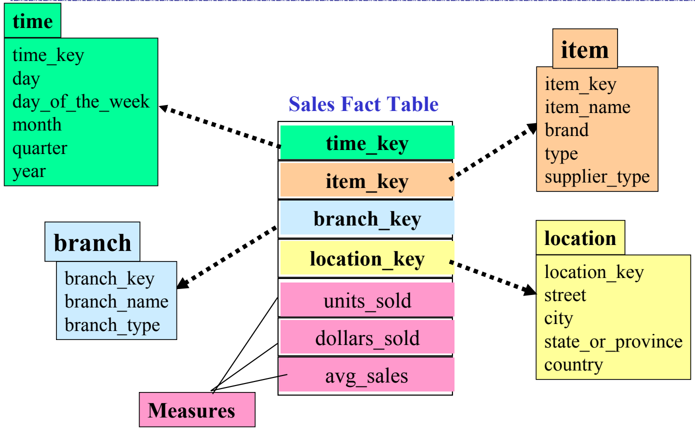
Cube Definition Syntax (BNF) in DMQL

- Cube Definition (Fact Table)

  define cube <cube_name> [<dimension_list>]: <measure_list>
- Dimension Definition (Dimension Table)

  define dimension <dimension_name> as (<attribute_or_subdimension_list>)
- Special Case (Shared Dimension Tables)
  - First time as "cube definition"
  - define dimension <dimension_name> as <dimension_name_first_time> in cube <cube_name_first_time>

Example of Star Schema



Example 1: Defining *Star Schema* in DMQL

define cube sales_star [time, item, branch, location]:

dollars_sold = sum(sales_in_dollars), avg_sales = avg(sales_in_dollars), units_sold = count(*)

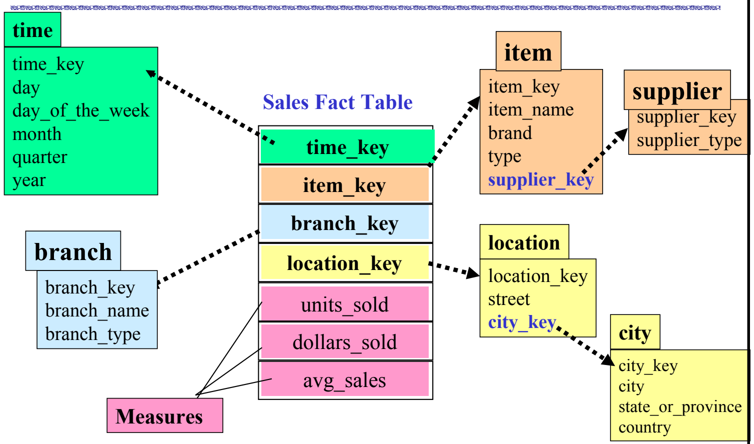
define dimension time as (time_key, day, day_of_week, month, quarter, year)

define dimension item as (item_key, item_name, brand, type, supplier_type)

define dimension branch as (branch_key, branch_name, branch_type)

define dimension location as (location_key, street, city, province_or_state, country)

Example of Snowflake Schema



Example 2: Defining ***Snowflake Schema*** in DMQL

define cube sales_snowflake [time, item, branch, location]:

dollars_sold = sum(sales_in_dollars), avg_sales = avg(sales_in_dollars), units_sold = count(*)

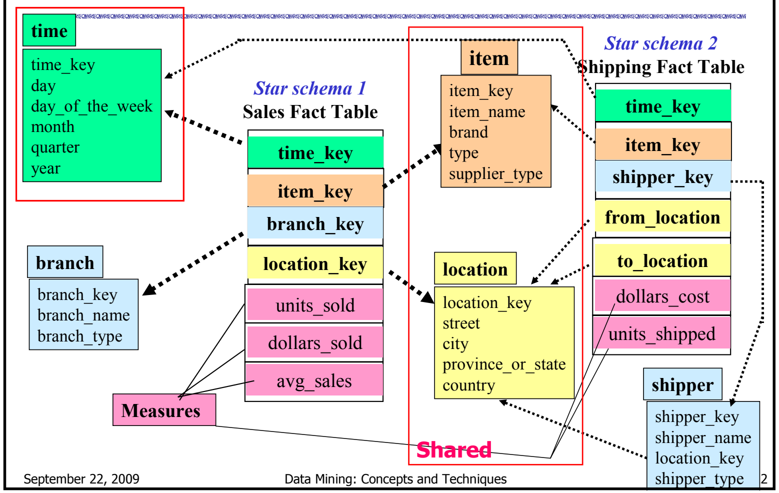
define dimension time as (time_key, day, day_of_week, month, quarter, year)

define dimension item as (item_key, item_name, brand, type, supplier(supplier_key, supplier_type))

define dimension branch as (branch_key, branch_name, branch_type)

define dimension location as (location_key, street, city(city_key, province_or_state, country))

Example of Fact Constellation



Example 3: Defining ***Fact Constellation*** in DMQL

define cube sales [time, item, branch, location]:

dollars_sold = sum(sales_in_dollars), avg_sales = avg(sales_in_dollars), units_sold = count(*)

define dimension time as (time_key, day, day_of_week, month, quarter, year)

define dimension item as (item_key, item_name, brand, type, supplier_type)

define dimension branch as (branch_key, branch_name, branch_type)

define dimension location as (location_key, street, city, province_or_state, country)

define cube shipping [time, item, shipper, from_location, to_location]:

dollar_cost = sum(cost_in_dollars), unit_shipped = count(*)

define dimension time as time in cube sales

define dimension item as item in cube sales

define dimension shipper as (shipper_key, shipper_name, location as location in cube sales, shipper_type)

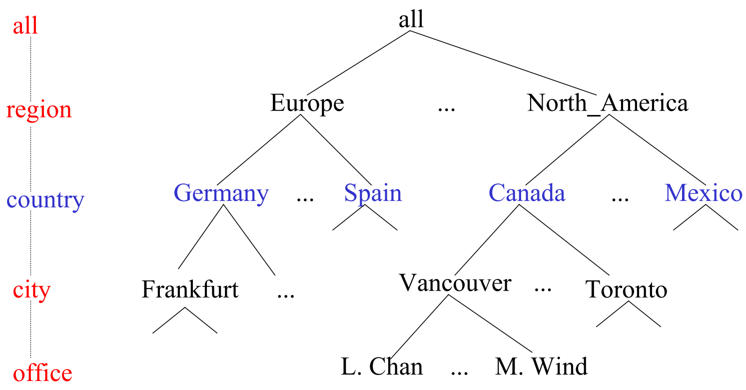
define dimension from_location as location in cube sales

define dimension to_location as location in cube sales

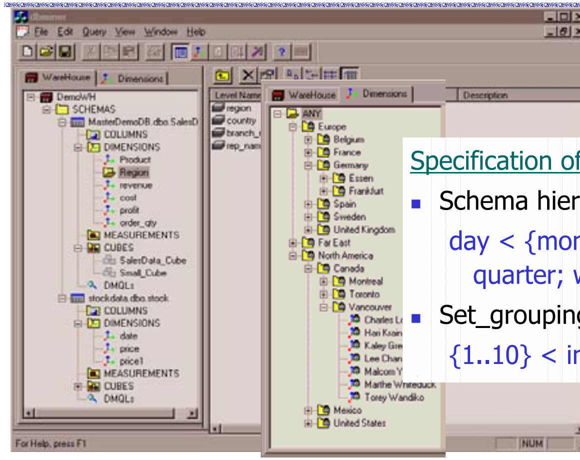
Measures of Data Cube: Three Categories

- 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()
  - sum(all) = sum(europe) + sum(america) + sum(asia) + …
- 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
  - E.g., avg(), min_N(), standard_deviation()
  - Avg(all) = sum(all) / #items (arguments: sum(all), and #items)
- Holistic: if there is no constant bound on the storage size needed to describe a subaggregate.
  - E.g., median(), mode(), rank()
  - Median(all) = … no constant sized subaggregates for computing median

A Concept Hierarchy: Dimension (location)



View of Warehouses and Hierarchies



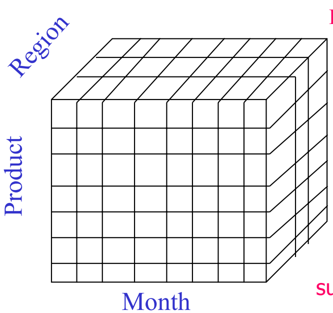
Specification of hierarchies

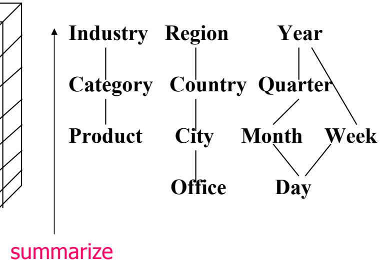
- Schema hierarchy
  day < {month < quarter; week} < year
- Set_grouping hierarchy
  {1..10} < inexpensive

Multidimensional Data

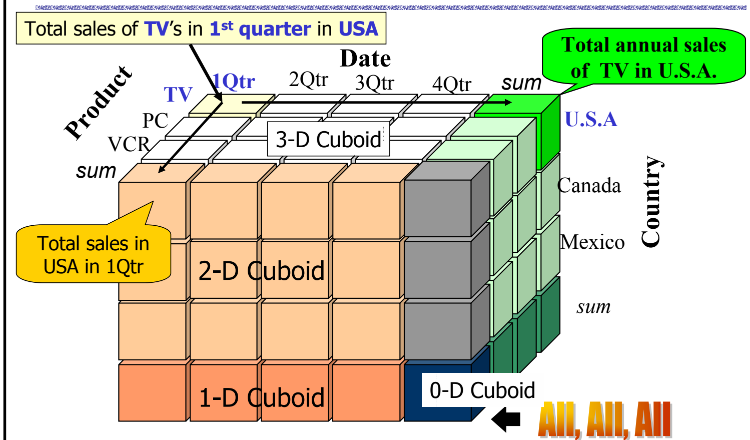
- Sales volume as a function of product, month, and region

Dimensions: Product, Location, Time
Hierarchical summarization paths

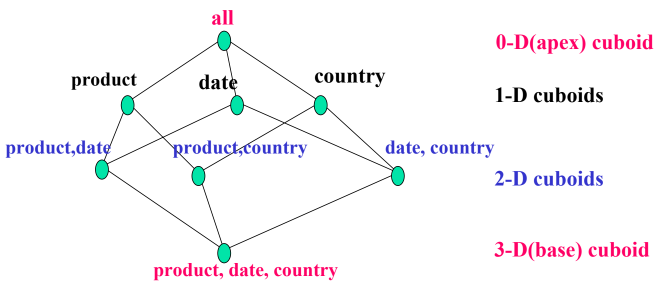




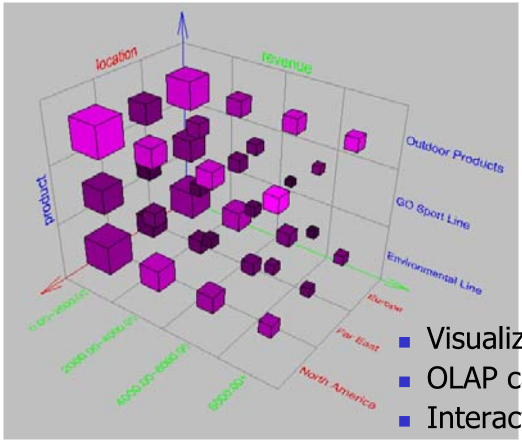
A Sample Data Cube



Cuboids Corresponding to the Cube



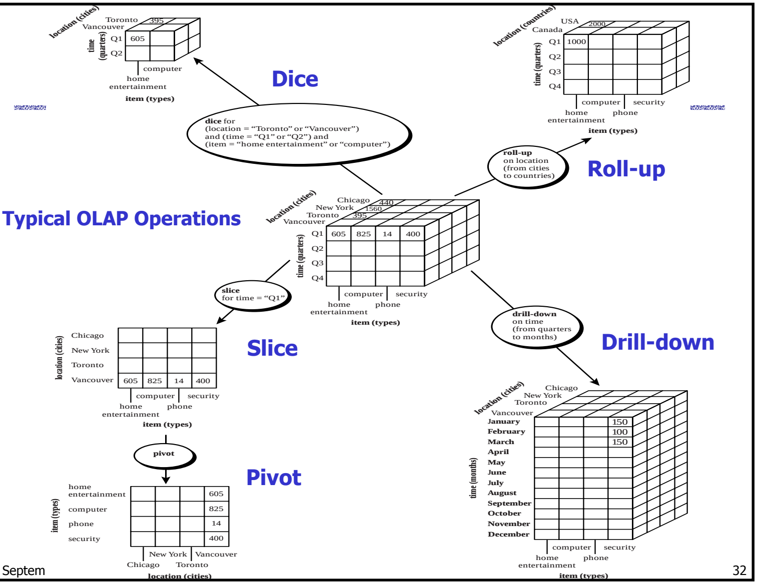
Browsing a Data Cube

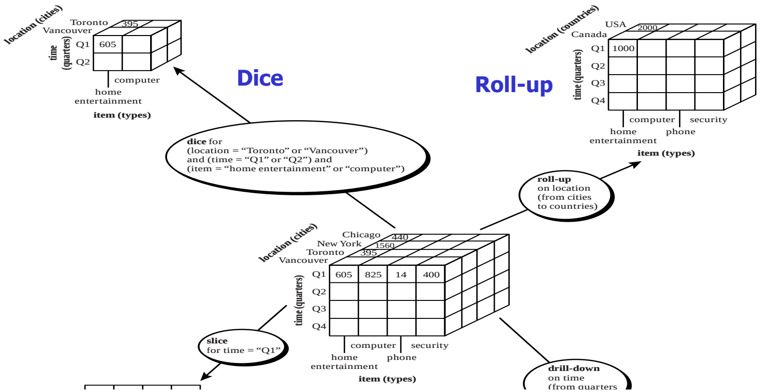


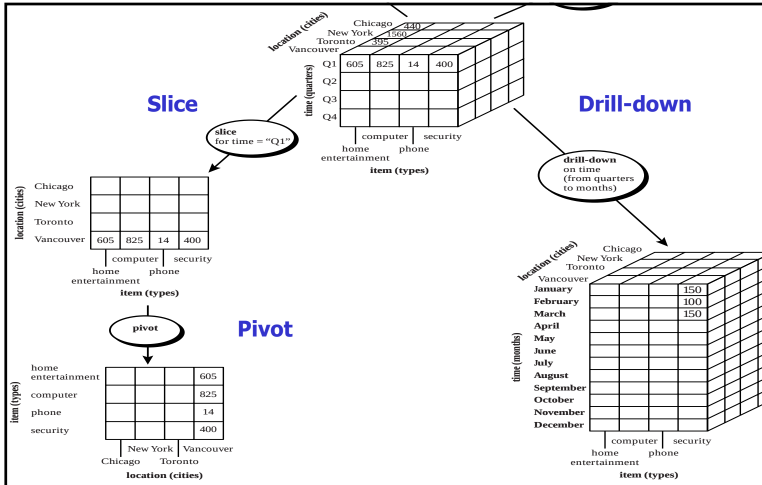
- Visualization
- OLAP capabilities
- Interactive manipulation

Typical **OLAP** Operations

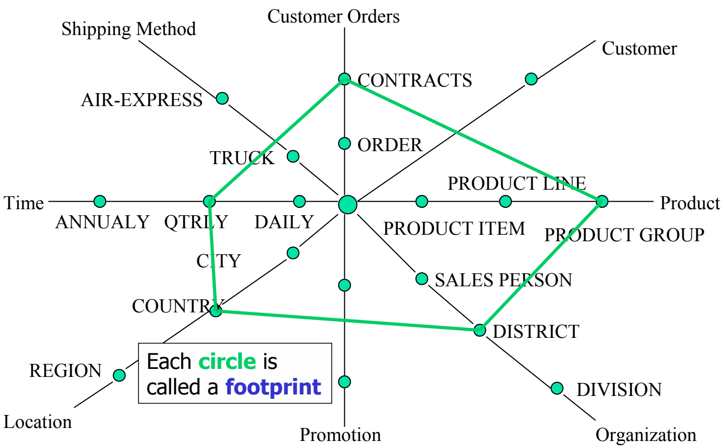
- **Roll up (drill-up): summarize data**
  - by climbing up hierarchy or by dimension reduction
- **Drill down (roll down): reverse of roll-up**
  - from higher level summary to lower level summary or detailed data, or introducing new dimensions
- **Slice and dice: project and select**
- **Pivot (rotate):**
  - 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)







A Star-Net Query Model



Chapter 3: Data Warehousing and OLAP Technology: An Overview

- What is a data warehouse?
- A multi-dimensional data model
- Data warehouse architecture
- Data warehouse implementation
- From data warehousing to data mining

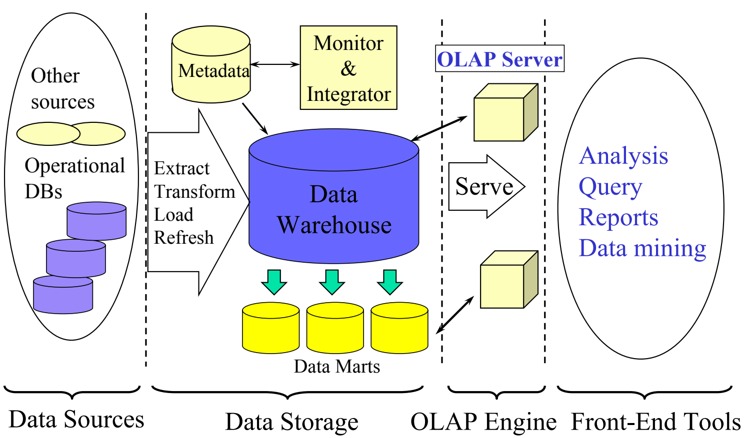
Design of Data Warehouse: A Business Analysis Framework

- 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

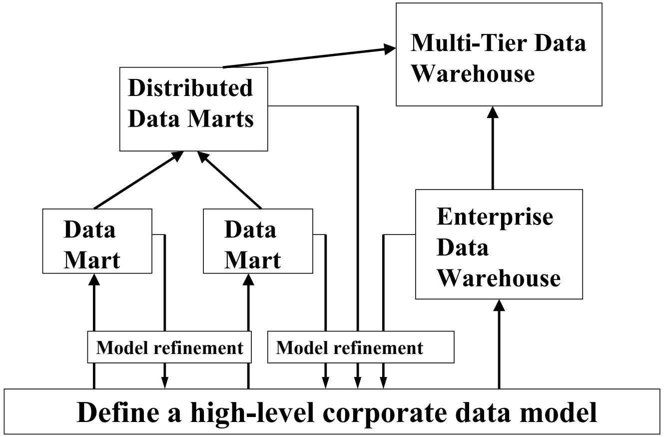
Data Warehouse: A Multi-Tiered Architecture



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 a 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

Data Warehouse Development: A Recommended Approach



Data Warehouse Back-End Tools and Utilities

- **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 definition, 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**
- **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

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 3: Data Warehousing and OLAP Technology: An Overview

- What is a data warehouse?
- A multi-dimensional data model
- Data warehouse architecture
- Data warehouse implementation
- From data warehousing to data mining

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?

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

where L_i is the number of conceptual levels associated with dimension i.

- Materialization of data cube
  - Materialize every cuboid (full materialization), none (no materialization), or some (partial materialization)
  - Selection of which cuboids to materialize
    - Based on size, sharing, access frequency, etc.

Cube Operation

- 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

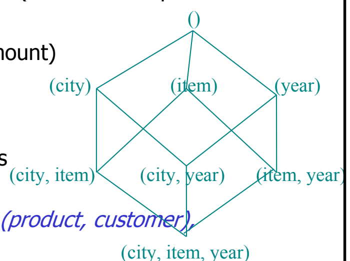
- Need compute the following Group-Bys

  (date, product, customer),

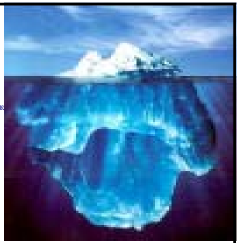
  (date,product),(date, customer), (product, customer),

  (date), (product), (customer)

  ()



Iceberg Cube



- Computing only the cuboid cells whose count or other aggregates satisfying the condition like

  HAVING COUNT(*) >= *minsup*

- Motivation
  - Only a small portion of cube cells may be "above the water" in a sparse cube
  - Only calculate "interesting" cells—data above certain threshold
  - Avoid explosive growth of the cube
    - Suppose 100 dimensions, only 1 base cell. How many aggregate cells if count >= 1? What about count >= 2?

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 attributes in the domain
- 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

Base table

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

Index on Region

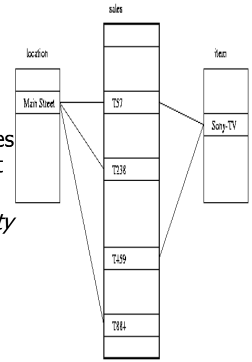
RecID	Asia	Europe	America
1	1	0	0
2	0	1	0
3	1	0	0
4	0	0	1
5	0	1	0

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-id, S-id) where R (R-id, …) ⊳⊲ S (S-id, …)
- Traditional indices map the values to a list of record ids
  - It materializes relational join in a JI file and speeds up the relational join
- In data warehouses, join index relates the values of the dimensions (*e.g. location, item*) of a start schema to rows (*e.g. sales*) 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, 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?
- Explore indexing structures and compressed vs. dense array structs in MOLAP

Chapter 3: Data Warehousing and OLAP Technology: An Overview

- What is a data warehouse?
- A multi-dimensional data model
- Data warehouse architecture
- Data warehouse implementation
- From data warehousing to data mining

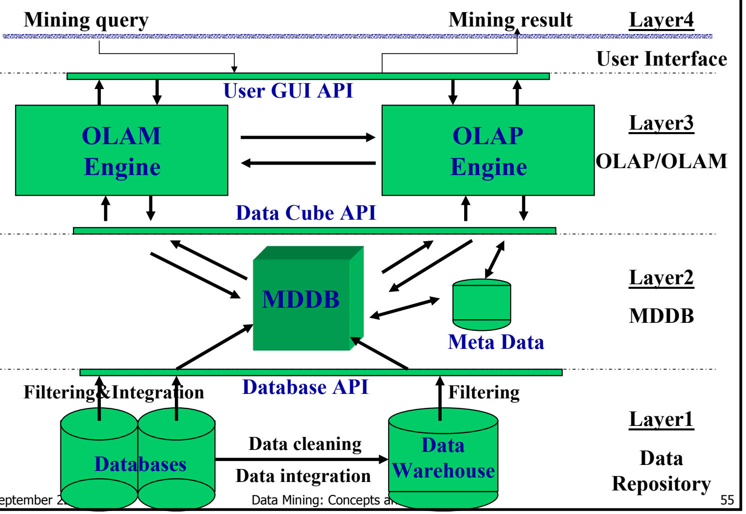
Data Warehouse Usage

- 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

An OLAM System Architecture



Chapter 3: Data Warehousing and OLAP Technology: An Overview

- What is a data warehouse?
- A multi-dimensional data model
- Data warehouse architecture
- Data warehouse implementation
- From data warehousing to data mining
- Summary

Summary: Data Warehouse and OLAP Technology

- Why data warehousing?
- A multi-dimensional model of a data warehouse
  - Star schema, snowflake schema, fact constellations
  - A data cube consists of dimensions & measures
- OLAP operations: drilling, rolling, slicing, dicing and pivoting
- Data warehouse architecture
- OLAP servers: ROLAP, MOLAP, HOLAP
- Efficient computation of data cubes
  - Partial vs. full vs. no materialization
  - Indexing OALP data: Bitmap index and join index
  - OLAP query processing
- From OLAP to OLAM (on-line analytical mining)

Data Mining Tools and Links

See the website on knowledge discovery:

http://www.kdnuggets.com

Commercial and free data mining tools:

http://www.kdnuggets.com/software/suites.html

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
- E. F. Codd, S. B. Codd, and C. T. Salley. Beyond decision support. Computer World, 27, July 1993.
- 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. *ACM SIGMOD Record*, 27:97-107, 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
- Microsoft. OLEDB for OLAP programmer's reference version 1.0. In http://www.microsoft.com/data/oledb/olap, 1998
- A. Shoshani. OLAP and statistical databases: Similarities and differences. PODS'00.
- S. Sarawagi and M. Stonebraker. Efficient organization of large multidimensional arrays. ICDE'94
- OLAP council. MDAPI specification version 2.0. In http://www.olapcouncil.org/research/apily.htm, 1998
- E. Thomsen. OLAP Solutions: Building Multidimensional Information Systems. John Wiley, 1997
- P. Valduriez. Join indices. ACM Trans. Database Systems, 12:218-246, 1987.
- J. Widom. Research problems in data warehousing. CIKM'95.