Module 1

Outline of Module 1

Introduction

Data Warehousing

Multidimensional Data Model

OLAP Operations

Introduction to KDD process

Data mining

Data mining -On What kinds of Data

Data mining Functionalities

Classification of Data Mining Systems.

What is Data Warehouse?

Defined in many different ways

- The process of **centralizing an organization's historical data** from various sources into a single, comprehensive database.
- *allows for advanced analytics, reporting, and informed decision-making across the enterprise.*
- Provides architectures and tools for business executives **to systematically organize, understand, and use their data to make strategic decisions**.
- **A data repository that is maintained separately** from an organization’s operational database.

Outline of Module 1

Data Pre-processing

Data Cleaning

Data Integration and Transformation

Data Reduction

Data discretization

Concept hierarchy generation

What is 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. Inmon

Data warehousing: The process of constructing and using data warehouses

Requires data cleaning, data integration, and data consolidation

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

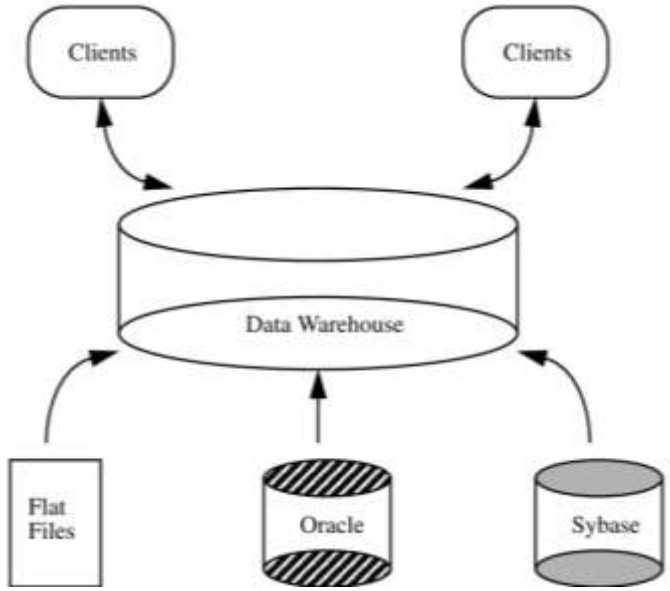
  relational databases, flat files, on-line transaction records

- **Data cleaning and data integration techniques** are applied

  Ensure consistency in naming conventions, encoding structures, attribute measures, etc. among different data sources

  E.g., Hotel price: 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"*

Data Warehouse—Nonvolatile

- A physically separate store of data transformed from the application data found in the operational environment.
- 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*

How are organizations using the information from data warehouses?

To support business decision-making activities

(1) increasing customer focus

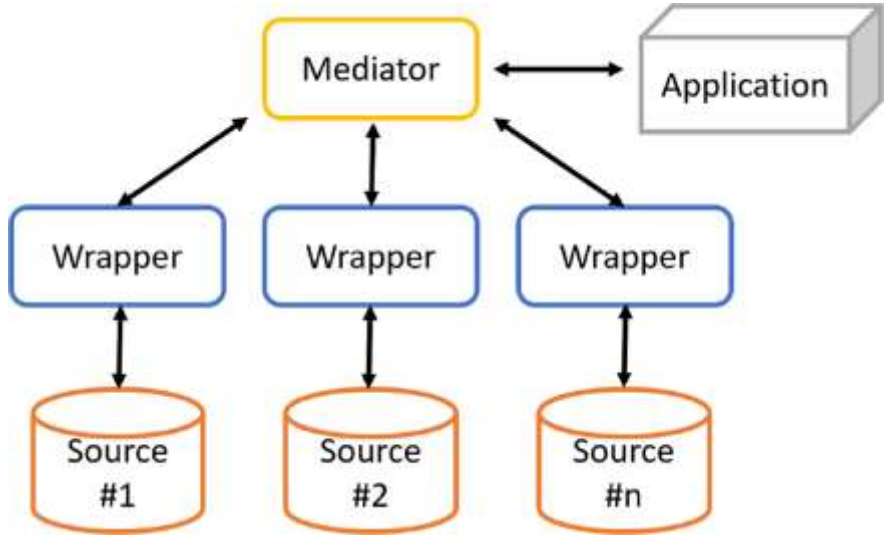
(2)Repositioning products and managing product portfolios by comparing the performance of sales

(3) analyzing operations and looking for sources of profit

- (4) managing customer relationships,
- making environmental corrections
- managing the cost of corporate assets.

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
  - It is inefficient and potentially expensive for frequent queries.



Data Warehouse vs. Heterogeneous DBMS

- Data warehouse: update-driven, high performance
- Information from heterogeneous sources is integrated in advance and stored in warehouses for direct query and analysis.
- DW does not contain current information.
- Reason for high performance of DW –
  - *data are copied, preprocessed, integrated, annotated, summarized, and restructured into one semantic data store.*
  - *does not interfere with the processing at local sources.*
  - *can store and integrate historic information and support complex multidimensional queries.*

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 oriented vs. market-oriented

Data contents: current, detailed vs. historical, consolidated

Database design: ER + application oriented DB Design vs. star or snowflake + subject oriented DB Design

View: current, local vs. evolutionary nature of organization, data from various sources, various orgzns, huge volume , stored on multiple media

Access patterns: up-to-date data, short, atomic transactions vs. read-only but complex queries

Module 1

Multidimensional Data Model

Multidimensional Data Model

Data warehouses and OLAP tools are based on a multidimensional data model.

This model views data in the form of a *data cube.*

"What is a data cube?"

- A **data cube** allows data to be modeled and viewed in multiple dimensions.
- It is defined by **dimensions and facts.**
- In DW, the data cube is *n*-dimensional.

From Tables and Spreadsheets to Data Cubes

- Dimensions are perspectives or entities with respect to which an organization wants to keep records. Eg. Sales with respect to time, item, branch, location.
- Each dimension may have a table associated with it, called a **dimension table**, which further describes the dimension.
- For example, a dimension table for **item** (may contain the attributes item name, brand, and type) or **time** (day, week, month, quarter, year)
- Dimension tables can be specified by users or experts, or automatically generated and adjusted based on data distributions
- Facts are numerical measures.
- Fact table contains measures (such as dollars_sold, units_sold, amount_budgeted) and keys to each of the related dimension tables

From Tables and Spreadsheets to Data Cubes

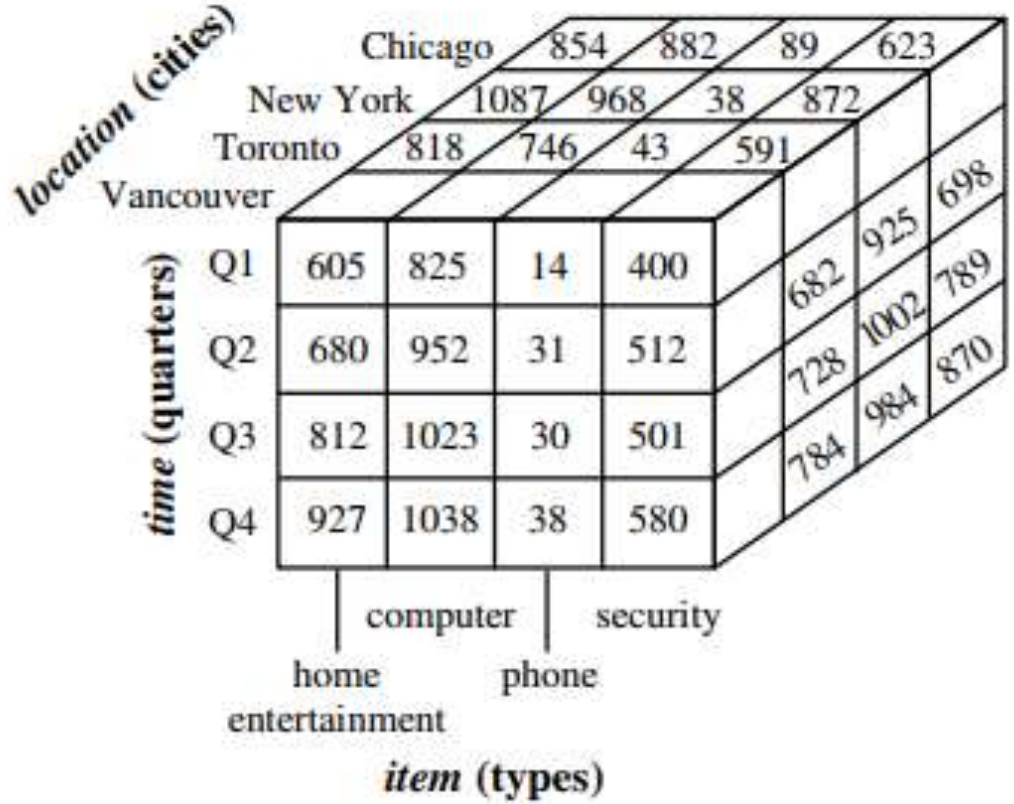
- A multidimensional data model is organized around a central **theme**, eg: sales.
- Theme is represented by a **fact table.**
- **Facts** are numeric measures.
- Facts are quantities by which we analyze relationships between dimensions.
- Examples: facts for a sales data warehouse include dollars_sold (sales amount in dollars),units_sold (number of units sold), and amount_budgeted.
- The fact table contains the names of the facts, or measures, as well as keys to each of the related dimension tables.

A 2-D view of sales data for *AllElectronics* according to the dimensions *time* and *item*, where the sales are from branches located in the city of Vancouver. The measure displayed is *dollars_sold* (in thousands).

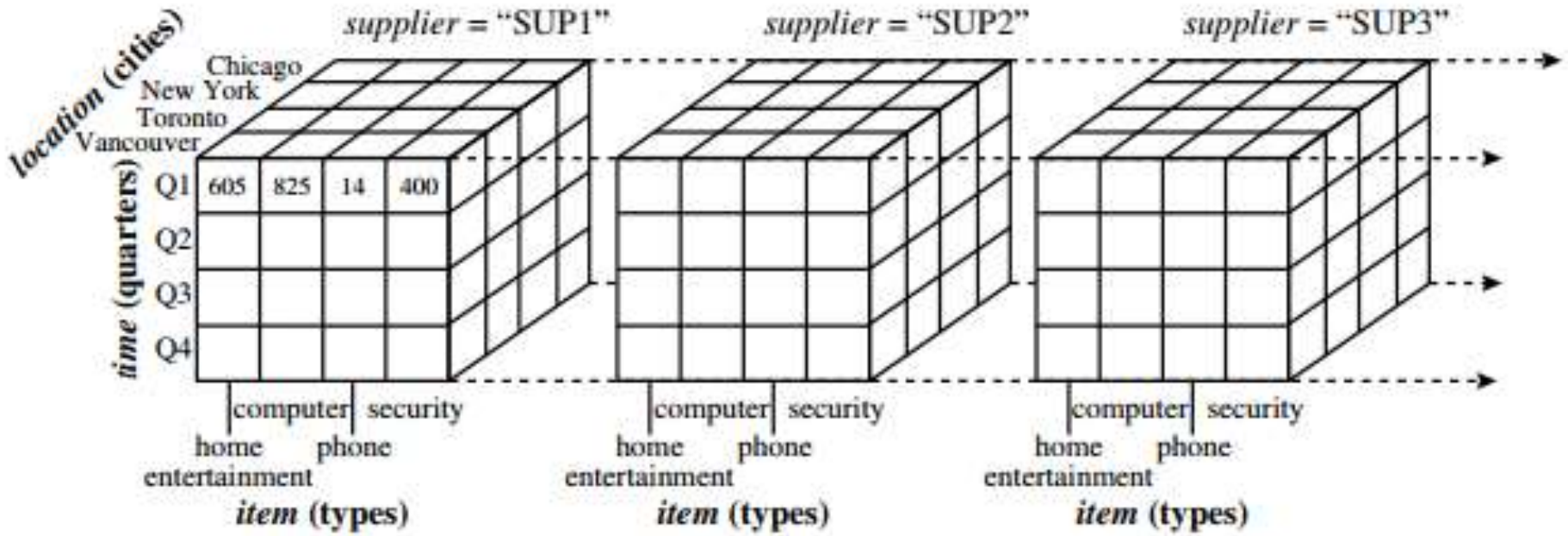
	location = "Vancouver"			
	item (type)			
time (quarter)	home entertainment	computer	phone	security
Q1	605	825	14	400
Q2	680	952	31	512
Q3	812	1023	30	501
Q4	927	1038	38	580

Table 3.3 A 3-D view of sales data for *AllElectronics*, according to the dimensions *time*, *item*, and *location*. The measure displayed is *dollars_sold* (in thousands).

	location = *"Chicago"*				***location*** = *"New York"*				***location*** = *"Toronto"*				***location*** = *"Vancouver"*			
	item				***item***				***item***				***item***			
	home				*home*				*home*				*home*			
time	*ent.*	*comp.*	*phone*	*sec.*	*ent.*	*comp.*	*phone*	*sec.*	*ent.*	*comp.*	*phone*	*sec.*	*ent.*	*comp.*	*phone*	*sec.*
Q1	854	882	89	623	1087	968	38	872	818	746	43	591	605	825	14	400
Q2	943	890	64	698	1130	1024	41	925	894	769	52	682	680	952	31	512
Q3	1032	924	59	789	1034	1048	45	1002	940	795	58	728	812	1023	30	501
Q4	1129	992	63	870	1142	1091	54	984	978	864	59	784	927	1038	38	580



A 3-D data cube representation of the data in Table 3.3, according to the dimensions *time*, *item*, and *location*. The measure displayed is *dollars_sold* (in thousands).



A 4-D data cube representation of sales data, according to the dimensions *time*, *item*, *location*, and *supplier*. The measure displayed is *dollars_sold* (in thousands). For improved readability, only some of the cube values are shown.

In data warehousing literature, a data cube is often referred to as a **cuboid**.

Given a set of dimensions, we can generate a cuboid for each of the possible subsets of the given dimensions.

The result would form a ***lattice* of cuboids**, each showing the data at a different level of summarization, or group-by.

The lattice of cuboids is then referred to as a **data cube.**

A base cuboid -The cuboid that holds the lowest level of summarization.

The 0-D cuboid, which holds the highest level of summarization, is called the **apex cuboid**.

Lattice of Cuboids

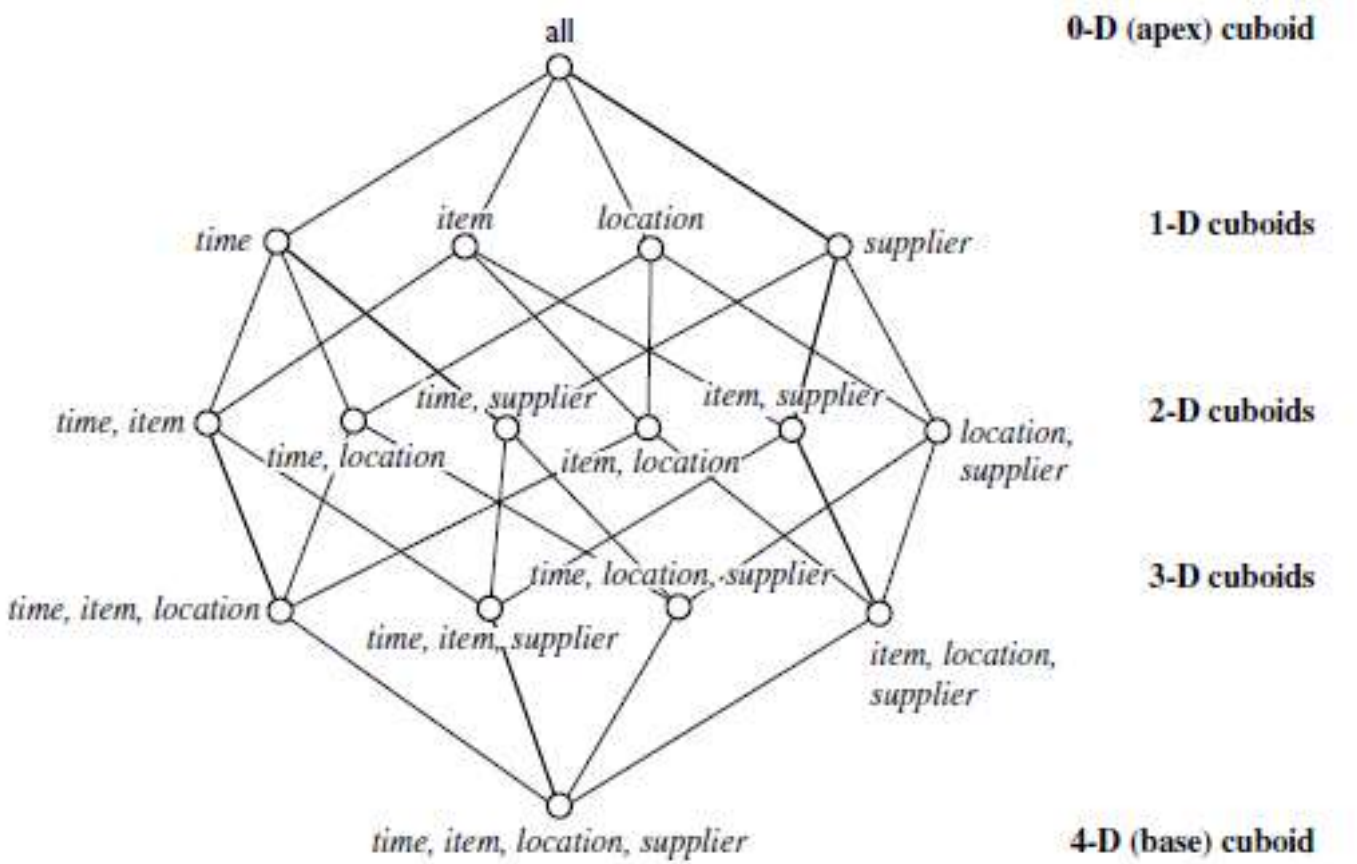


Figure 4.5 Lattice of cuboids, making up a 4-D data cube for *time*, *item*, *location*, and *supplier*. Each cuboid represents a different degree of summarization.

Schemas for Multidimensional Databases

The ER model is used for relational database design. For data warehouse design we need a concise, subject-oriented schema that facilitates data analysis.

Multidimensional model exist in the form of :

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

The most common modeling paradigm is the star schema.

The data warehouse contains

(1) a large central table (**fact table**) containing the bulk of the data, with no redundancy

(2) a set of smaller attendant tables (**dimension tables**), one for each dimension.

The schema graph resembles a starburst, with the dimension tables displayed in a radial pattern around the central fact table.

Limitation:

Each dimension is represented by only one table, and each table contains a set of attributes.

This constraint may introduce some redundancy.

For example, the *location* dimension table contains the attribute set {*location key, street, city, province or state, country}*. (Eg:Urbana, Chicago are cities in Illinois, USA).

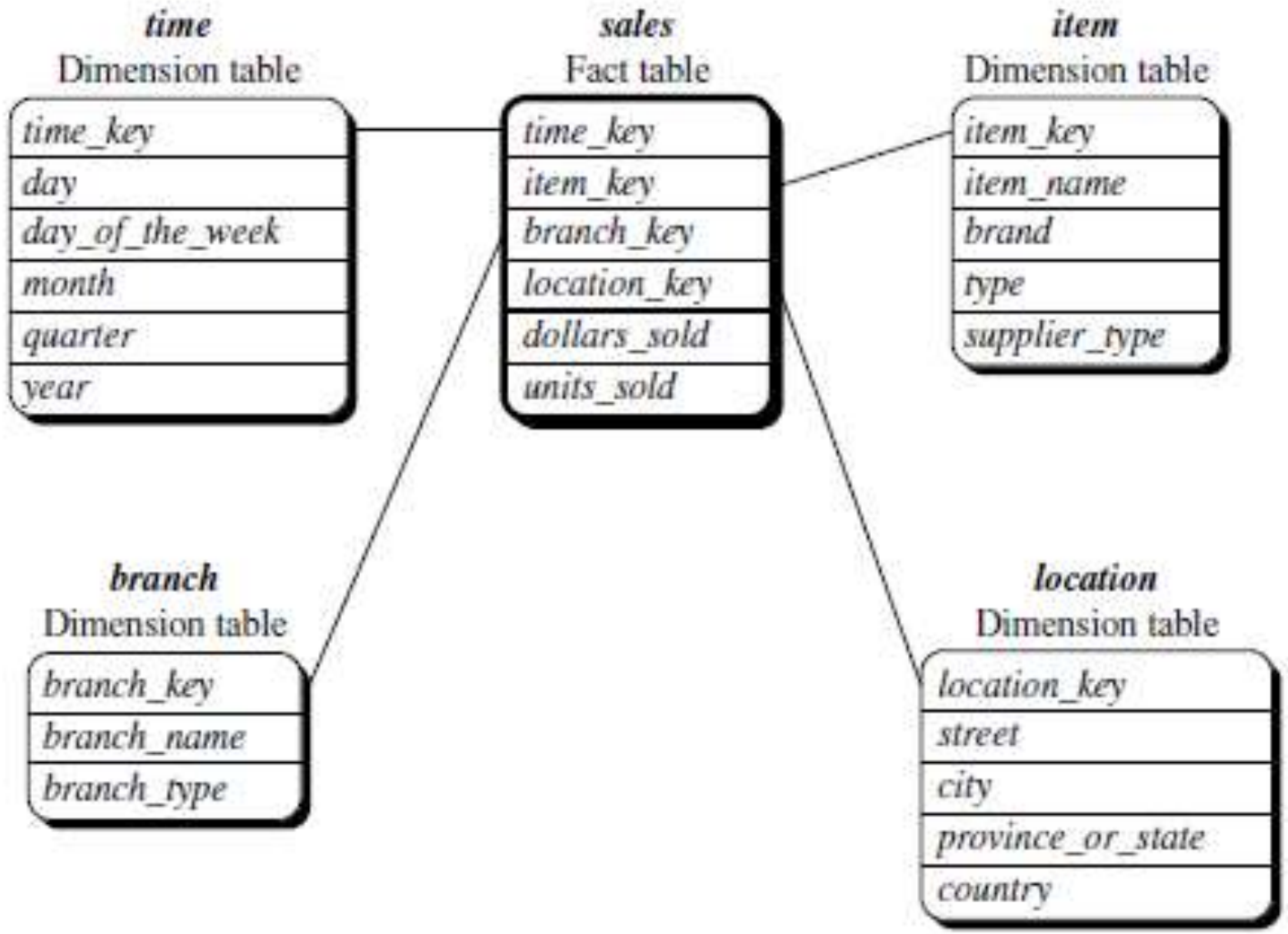


Figure 4.6 Star schema of *sales* data warehouse.

Snowflake schema

- The snowflake schema is a variant of the star schema model.
- Some dimension tables are *normalized*, thereby further splitting the data into additional tables.
- The resulting schema graph forms a shape similar to a snowflake.
- The dimension tables of the snowflake model may be kept in normalized form to reduce redundancies.
- Tables - Easy to maintain and saves storage space.
- However, this space savings is negligible.
- Snowflake structure can reduce the effectiveness of browsing, since more joins will be needed to execute a query.
- Consequently, the system performance may be adversely impacted.

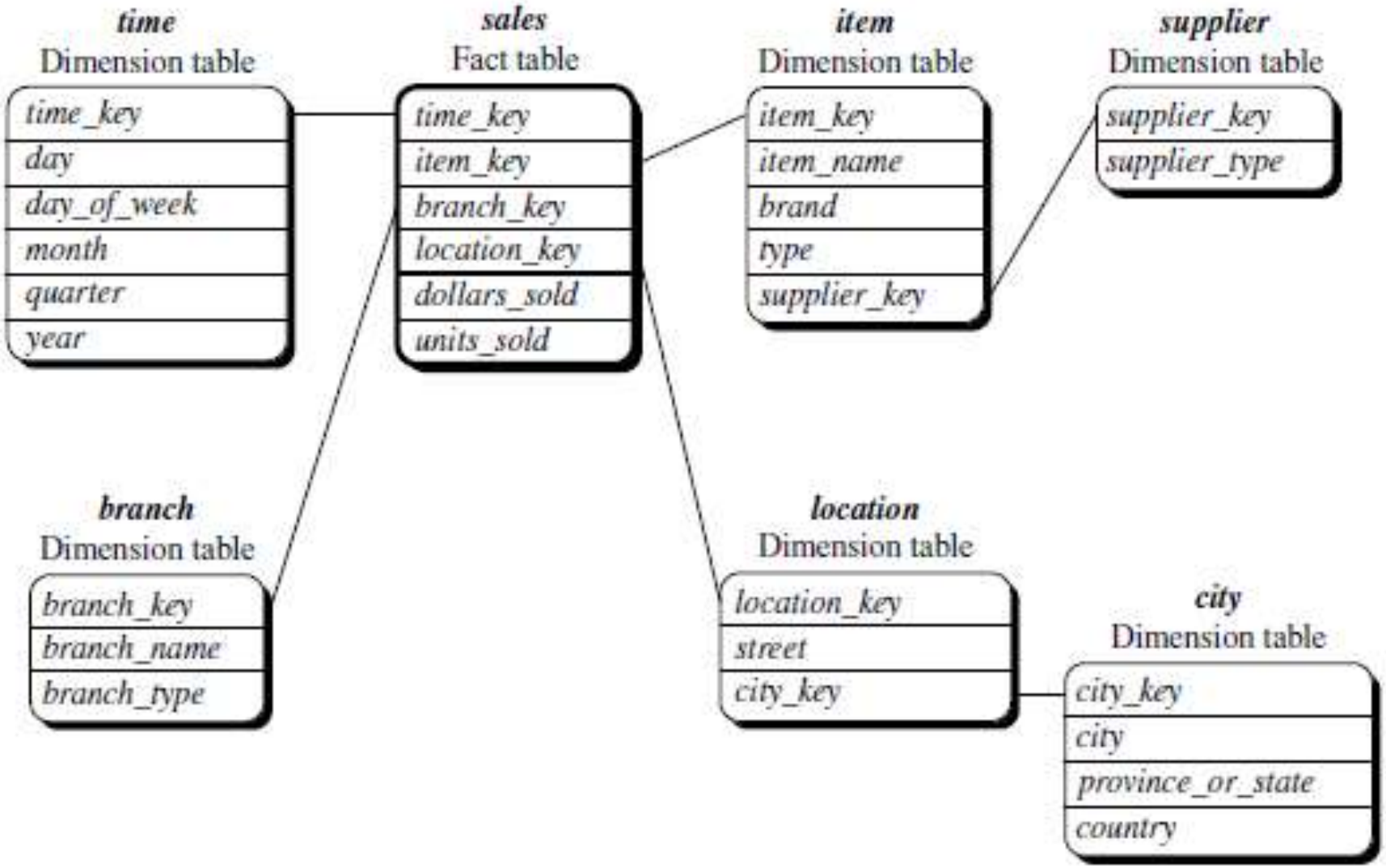


Figure 4.7 Snowflake schema of a *sales* data warehouse.

Fact constellation

- Sophisticated applications.
- Multiple fact tables to *share* dimension tables.
- This kind of schema can be viewed as a collection of stars, and hence is called a galaxy schema or a fact constellation.

A fact constellation schema allows dimension tables to be shared between fact tables.

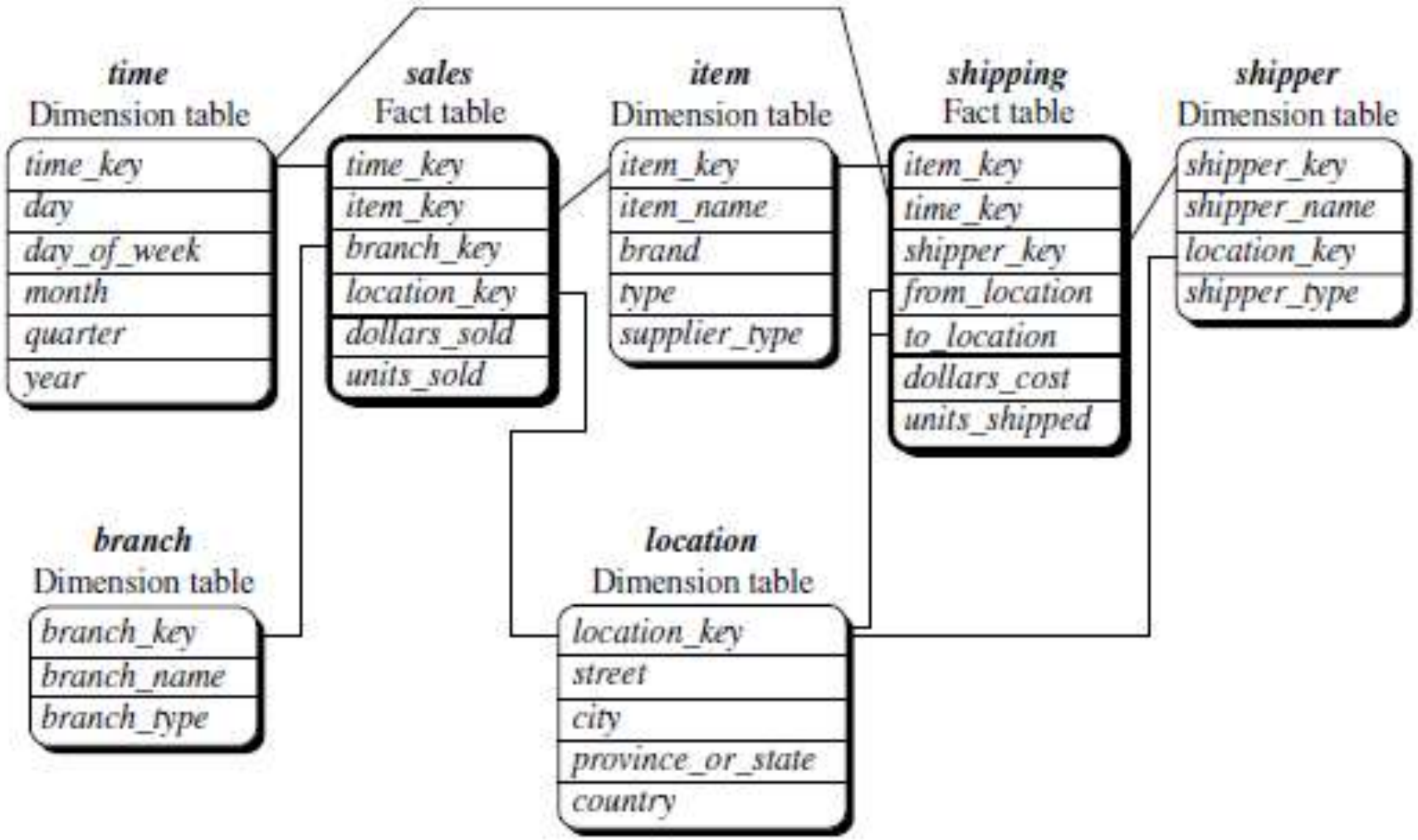


Figure 4.8 Fact constellation schema of a sales and shipping data warehouse.

Data Warehouse and Data Mart

DATA WAREHOUSE

- Collects information about subjects that span the *entire organization*, such as *customers, items, sales, assets*, and *personnel*
- Its scope is *enterprise-wide*.
- The fact constellation schema is commonly used, since it can model multiple, interrelated subjects.

DATA MART

- A department subset of the data warehouse that focuses on selected subjects((e.g., sales, marketing, finance).
- Its scope is *departmentwide*.
- The *star* or *snowflake* schema is commonly used, since both are geared toward modeling single subjects, although the star schema is more popular and efficient.