Chapter 3

Data Warehouse Logical and Physical Design

Data Warehouse Logical Design:

Logical design is the phase of a database design concerned with identifying the relationships among the data elements. A logical design is conceptual and abstract. Logical design deals with concepts related to a certain kind of DBMS (e.g. relational, object oriented,) but are understandable by end users. The logical design should result in

(1) A set of entities and attributes corresponding to fact tables and dimension tables.

(2) A model of operational data from your source into subject-oriented information in your target data warehouse schema.

The steps of the logical data model include identification of all entities and relationships among them. All attributes for each entity are identified and then the primary key and foreign key is identified. Normally normalization occurs at this level.

In data warehousing, it is common to combine the conceptual data model and the logical data model to a single step. The steps for logical data model are indicated below:

1. Identify all entities.
2. Identify primary keys for all entities.
3. Find the relationships between different entities.
4. Find all attributes for each entity.
5. Resolve all entity relationships that is many-to-many relationships.
6. Normalization if required.

The process of logical design involves arranging data into a series of logical relationships called **entities** and **attributes**. An **entity** represents a chunk of information. In relational databases, an entity often maps to a table. An **attribute** is a component of an entity that helps define the uniqueness of the entity. In relational databases, an attribute maps to a column.

An **entity** is a person, place, event, or thing for which we intend to collect data.

- **University** - Students, Faculty Members, Courses
- **Airlines** - Pilots, Aircraft, Routes, Suppliers

Each entity has certain characteristics known as **attributes**.

- **Student** – Student_Number, Name, GPA, Date of Enrollment, Data of Birth, Home Address, Phone Number, Major
- **Aircraft**– Aircraft_Number, Date of Last Maintenance, Total Hours Flown, Hours Flown since Last Maintenance

A grouping of related entities becomes an **entity set.**

- The STUDENT entity set contains all student entities.
- The FACULTY entity set contains all faculty entities.
- The AIRCRAFT entity set contains all aircraft entities

A table contains a group of related entities -- i.e. an entity set. The terms entity set and table are often used interchangeably. A table is also called a relation.

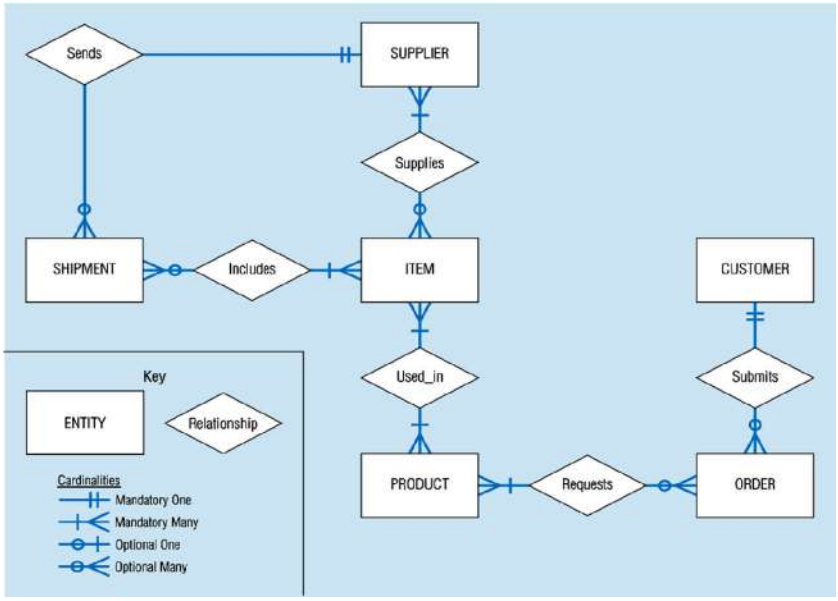


Figure: Sample E-R Diagram

Multi-dimensional data model

- The multidimensional data model is an integral part of On-Line Analytical Processing, or OLAP.
- Because OLAP is on-line, it must provide answers quickly; analysts pose iterative queries during interactive sessions, not in batch jobs that run overnight.
- Because OLAP is also analytic, the queries are complex. The multidimensional data model is designed to solve complex queries in real time.
- The multidimensional data model is important because it enforces simplicity.
- The multidimensional data model is composed of logical cubes, measures, dimensions, hierarchies, levels, and attributes.
- The simplicity of the model is inherent because it defines objects that represent real-world business entities.
- 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
- The lattice of cuboids forms a data cube.

Data Cube:

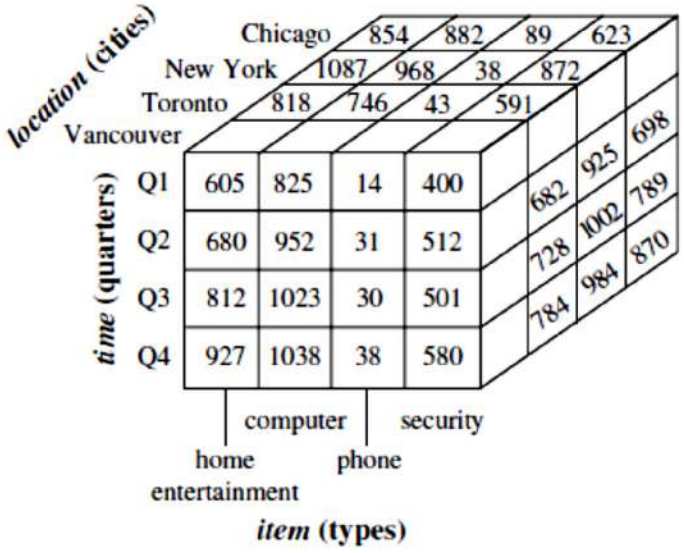
A **data cube** provides a multidimensional view of data and allows the pre-computation and fast accessing of summarized data. A data cube allows data to be modeled and viewed in multiple dimensions. It is defined by dimensions and facts. A **data cube** is a three- (or higher) dimensional array of value.

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).

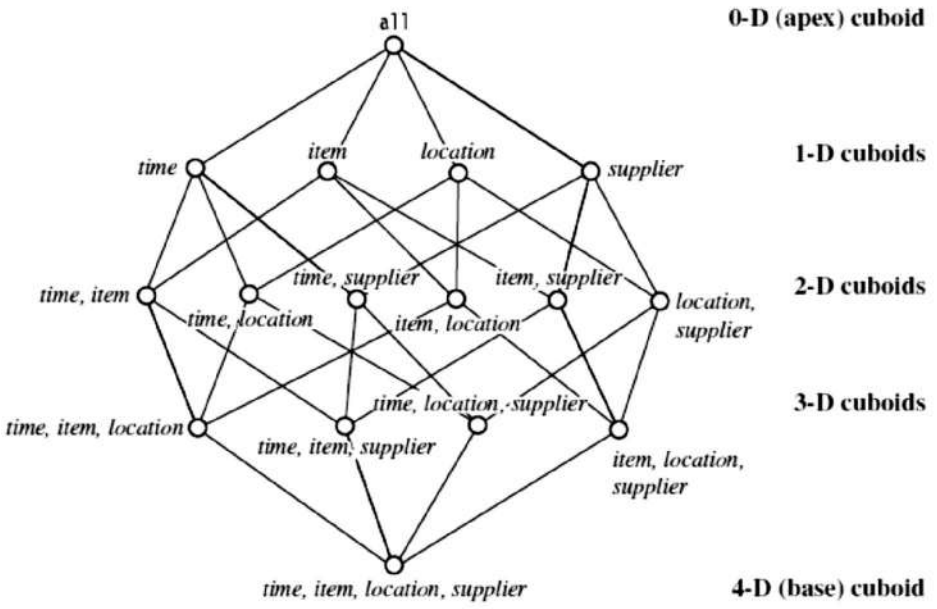
location = "Vancouver"				
	item (type)			
time (quarter)	home entertainment	computer	phone	security
Q1	605	825	14	400
Q2	680	952	31	512
Q3	812	1023	30	501
Q4	927	1038	38	580

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).



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

Dimensions and Measures:

The database component of a data warehouse is described using a technique called dimensionality modelling. Every dimensional model (DM) is composed of one table with a composite primary key, called the fact table, and a set of smaller tables called dimension tables. Each dimension table has a simple (non-composite) primary key that corresponds exactly to one of the components of the composite key in the fact table.

In general terms, dimensions are the perspectives or entities with respect to which an organization wants to keep records. For example, *AllElectronics* may create a *sales* data warehouse in order to keep records of the store's sales with respect to the dimensions *time, item, branch,* and *location*. These dimensions allow the store to keep track of things like monthly sales of items and the branches and locations at which the items were sold. 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. Dimension tables can be specified by users or experts, or automatically generated and adjusted based on data distributions.

Fact Table:

A multidimensional data model is typically organized around a central theme, like *sales*, for instance. This theme is represented by a fact table. Facts are numerical measures. Think of them as the quantities by which we want to analyze relationships between dimensions. Examples of 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 fact table is the central table in a star schema of a data warehouse. A fact table stores quantitative information for analysis and is often de-normalized. A fact table works with dimension tables. The fact table contains business facts (or measures), and foreign keys which refer to candidate keys (normally primary keys) in the dimension tables.

A fact table is composed of two or more primary keys and usually also contains numeric data. Because it always contains at least two primary keys it is always a M-M relationship. Fact tables contain business event details for summarization. Because dimension tables contain records that describe facts, the fact table can be reduced to columns for dimension foreign keys and numeric fact values. Text and de-normalized data are typically not stored in the fact table.

The logical model for a fact table contains a foreign key column for the primary keys of each dimension. The combination of these foreign keys defines the primary key for the fact table. Fact tables are often very large, containing hundreds of millions of rows and consuming hundreds of gigabytes or multiple terabytes of storage.

Dimension table:

Dimension tables encapsulate the attributes associated with facts and separate these attributes into logically distinct groupings, such as time, geography, products, customers, and so forth. A dimension table stores data about the ways in which the data in the fact table can be analyzed. Contrary to fact tables, dimension tables contain descriptive attributes (or fields) that are typically textual fields. These attributes are designed to serve two critical purposes: query constraining and/or filtering, and query result set labeling.

A dimension table may be used in multiple places if the data warehouse contains multiple fact tables or contributes data to data marts. The data in a dimension is usually hierarchical in nature. Hierarchies are determined by the business need to group and summarize data into usable information.

For example, a time dimension often contains the hierarchy elements: (all time), Year, Quarter, Month, Day, or (all time), Year Quarter, Week, Day.

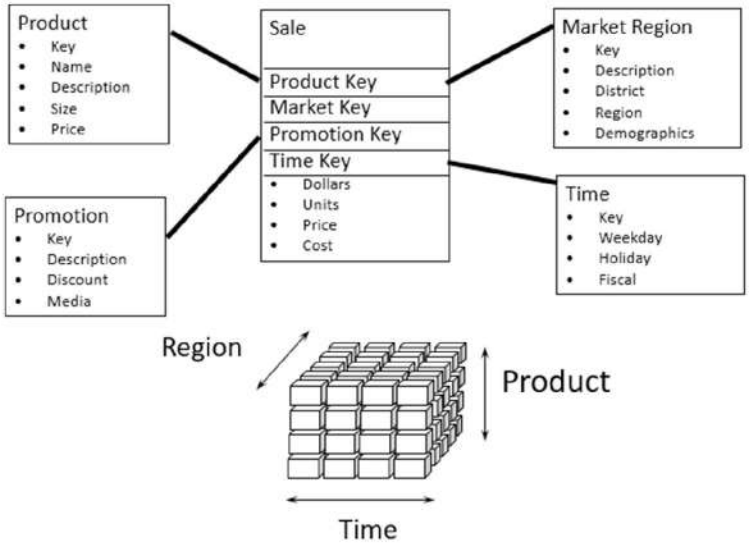


Figure: Dimensional Model

A Data Warehouse Schema

The schema is a logical description of the entire database. The schema includes the name and description of records of all record types including all associated data-items and aggregates. Likewise, the database, the data warehouse also requires the schema. The database uses the relational model on the other hand the data warehouse uses the Stars, snowflake and fact constellation schema.

A data warehouse, however, requires a concise, subject-oriented schema that facilitates on-line data processing (OLAP). The most popular data model for a data warehouse is **a multidimensional model.** Such a model can exist in the following forms

- a star schema
- a snowflake schema
- a fact constellation schema.

The major focus will be on the star schema which is commonly used in the design of many data warehouse.

Star Schema

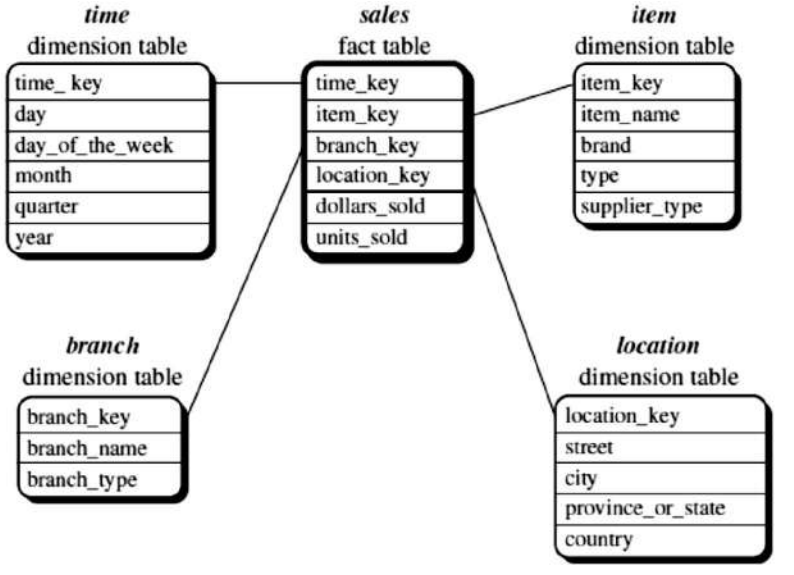
The star schema is a data modeling technique used to map multidimensional decision support into a relational database. Star schemas yield an easily implemented model for multidimensional data analysis while still preserving the relational structure of the operational database. Others name: star-join schema, data cube, data list, grid file and multi-dimension schema.

The most common modeling paradigm is the star schema, in which the data warehouse contains

1. a large central table (fact table) containing the bulk of the data, with no redundancy, and
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. In star schema, there is a fact table at the center. This fact table contains the keys to each of the dimensions. The fact table also contains the attributes. Each dimension is represented with only one dimension table. This dimension table contains the set of attributes.

In the following diagram, a star schema of sales data of a company is shown along with four dimensions, namely, *time, item, branch,* and *location*. The schema contains a central fact table for sales that contains keys to each of the four dimensions, along with two measures: *dollars_sold* and *units_sold*. To minimize the size of the fact table, dimension identifiers (such as time key and item key) are system-generated identifiers.



Star schema of a data warehouse for sales.

Key Points About Star Schema

- The most popular schema design for data warehouses is the Star Schema.
- Each dimension is stored in a dimension table and each entry is given its own unique identifier.

- The dimension tables are related to one or more fact tables.
- The fact table contains a composite key made up of the identifiers (primary keys) from dimension tables.
- The fact table also contains facts about the given combination of dimensions. For example, a combination of store_key, date_key and product_key giving the amount of a certain product sold on a given day at a given store.
- Fact table has foreign keys to all dimension tables in a star schema. In the example, there are three foreign keys (date key, product key, and store key).
- Fact tables are normalized, whereas dimension tables are not.
- Fact tables are very large as compared to dimension tables.

The facts in a star schema are of the following three types

- Fully-additive
- Semi-additive
- Non-additive

Advantages of Star Schema

- The star schema is a way to implement multi-dimensional database (MDDB) functionality using a mainstream relational database
- A star schema is very simple from the users' point of view.
- Queries are never complex because the only joins and conditions involve a fact table and a single level of dimension tables, without the indirect dependencies to other tables.
- Provide a direct mapping between the business entities being analyzed by end users and the schema design.
- Provide highly optimized performance for typical star queries.
- Are widely supported by a large number of business intelligence tools, which may anticipate or even require that the data-warehouse schema contain dimension tables.,
- Star schemas are used for both simple data marts and very large data warehouses.
- Star Schema is very easy to understand, even for non-technical business manager.
- Star Schema provides better performance and smaller query times
- Star Schema is easily extensible and will handle future changes easily

Issues Regarding Star Schema

- Dimension table keys must be *surrogate* (non-intelligent and non-business related), because:
  - Keys may change over time
  - Length/format consistency
- Granularity of Fact Table – what level of detail do you want?
  - Transactional grain – finest level
  - Aggregated grain – more summarized
  - Finer grains ➔ better *market basket analysis* capability
  - Finer grain ➔ more dimension tables, more rows in fact table
- Duration of the database – how much history should be kept?
  - Natural duration – 13 months or 5 quarters
  - Financial institutions may need longer duration
  - Older data is more difficult to source and cleanse

Snowflake Schema

The snowflake schema is a variant of the star schema model, where some dimension tables are normalized, thereby further splitting the data into additional tables. The resulting schema graph forms a shape similar to a snowflake.

A schema is called a *snowflake schema* if one or more dimension tables do not join directly to the fact table but must join through other dimension tables. It is a variant of star schema model. It has a single, large and central fact table and one or more tables for each dimension.

The major difference between the snowflake and star schema models is that the dimension tables of the snowflake model may be kept in normalized form to reduce redundancies. Such a table is easy to maintain and saves storage space. However, this saving of space is negligible in comparison to the typical magnitude of the fact table. Furthermore, the 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. Hence, although the snowflake schema reduces redundancy, it is not as popular as the star schema in data warehouse design.

Characteristics:

- Normalization of dimension tables
- Each hierarchical level has its own table
- less memory space is required
- a lot of joins can be required if they involve attributes in secondary dimension tables

A snowflake schema for sales of a company is given in figure below. Here, the *sales* fact table is identical to that of the star schema in Figure above. The main difference between the two schemas is in the definition of dimension tables. The single dimension table for *item* in the star schema is normalized in the snowflake schema, resulting in new *item* and *supplier* tables. For example, the *item* dimension table now contains the attributes *item_key, item_name, brand, type*, and *supplier_key*, where *supplier_key* is linked to the *supplier* dimension table, containing *supplier_key* and *supplier_type* information. Similarly, the single dimension table for *location* in the star schema can be normalized into two new tables: *location* and *city*. The *city key* in the new *location* table links to the *city* dimension. Notice that further normalization can be performed on *province or state* and *country* in the snowflake schema shown in above, when desirable.

Advantages of Snowflake Schema

- If a dimension is very sparse (i.e., most of the possible values for the dimension have no data) and/or a dimension has a very long list of attributes which may be used in a query, the dimension table may occupy a significant proportion of the database and snowflake schema is good.
- A multidimensional view is sometimes added to an existing transactional database to aid reporting. In this case, the tables which describe the dimensions will already exist and will typically be normalized. A snowflake schema will hence be easier to implement.
- A snowflake schema can sometimes reflect the way in which users think about data. Users may prefer to generate queries using a star schema in some cases, although this may or may not be reflected in the underlying organization of the database.
- Some users may wish to submit queries to the database which, using conventional multidimensional reporting tools, cannot be expressed within a simple star schema. This is particularly common in data mining of customer databases, where a common requirement is to locate common factors between customers who bought products meeting complex criteria.

Disadvantages of Snowflake Schema

Normalization splits up data to avoid redundancy (duplication) by moving commonly repeating groups of data into a new table. Normalization therefore tends to increase the number of tables that need to be joined in order to perform a given query, but reduces the space required to hold the data and the number of places where it needs to be updated if the data changes.

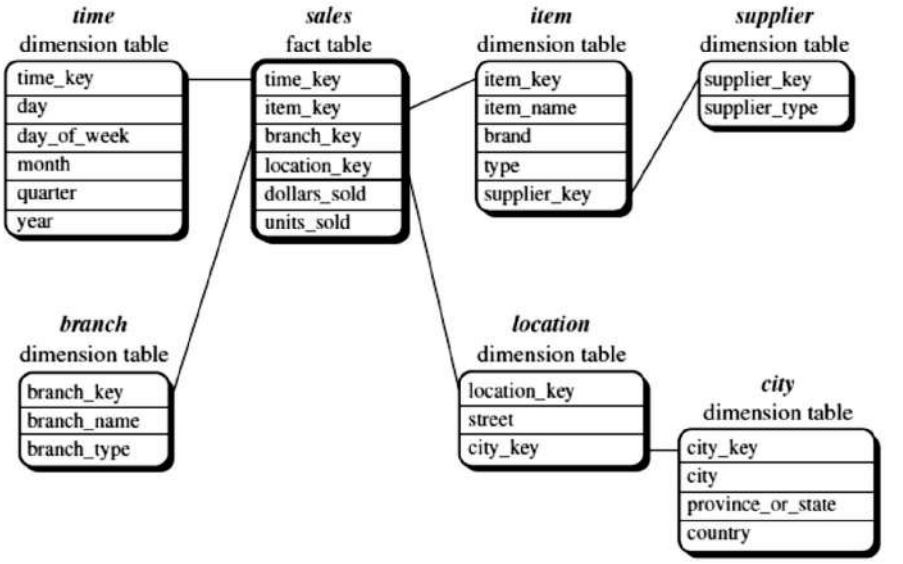
In a data warehouse, the fact table in which data values and their associated indexes are stored is typically responsible for 90% or more of the storage requirements, so the benefit here is normally insignificant.

However, normalization of the dimension tables in snowflake schema can impair the performance of a data warehouse. Snow flaking will increase the time taken to perform a query, and the design goals of many data warehouse projects are to minimize these response times.

Also, many data warehouses are designed to be used by business users, and without appropriate views, the added complexity of the snowflake schema will often preclude non-specialist users from forming their own queries.

Difference between Star Schema and Snow-flake Schema

- Star Schema is a multi-dimension model where each of its disjoint dimension is represented in single table.
- Snow-flake is normalized multi-dimension schema when each of disjoint dimension is represent in multiple tables.
- Star schema can become a snow-flake
- Both star and snowflake schemas are dimensional models; the difference is in their physical implementations.
- Snowflake schemas support ease of dimension maintenance because they are more normalized.
- Star schemas are easier for direct user access and often support simpler and more efficient queries.
- It may be better to create a star version of the snowflake dimension for presentation to the users.

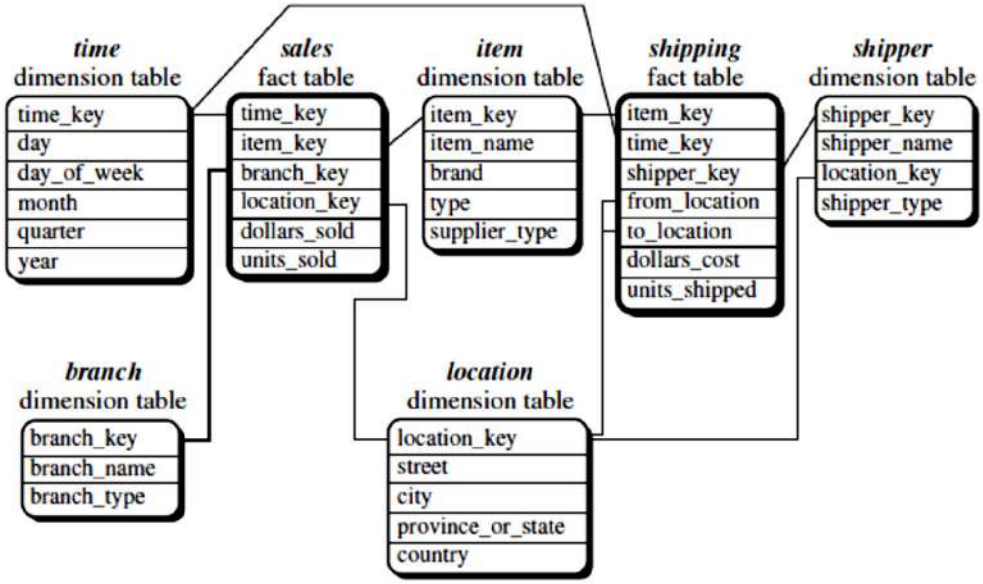


Snowflake schema of a data warehouse for sales.

Fact Constellation Schema

Sophisticated applications may require 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. In a fact constellation, there are multiple fact tables. In the Fact Constellations, aggregate tables are created separately from the detail, therefore, it is impossible to pick up other queries from different tables. Fact Constellation is a good alternative to the Star, but when dimensions have very high cardinality, the sub-selects in the dimension tables can be a source of delay.

A fact constellation schema is shown in Figure below. This schema specifies two fact tables, *sales* and *shipping*. The *sales* table definition is identical to that of the star schema (Figure above). The *shipping* table has five dimensions, or keys: *item_key, time_key, shipper_key, from_location*, and *to_location*, and two measures: *dollars_cost* and *units_shipped*. A fact constellation schema allows dimension tables to be shared between fact tables. For example, the dimensions tables for *time, item*, and *location* are shared between both the *sales* and *shipping* fact tables.



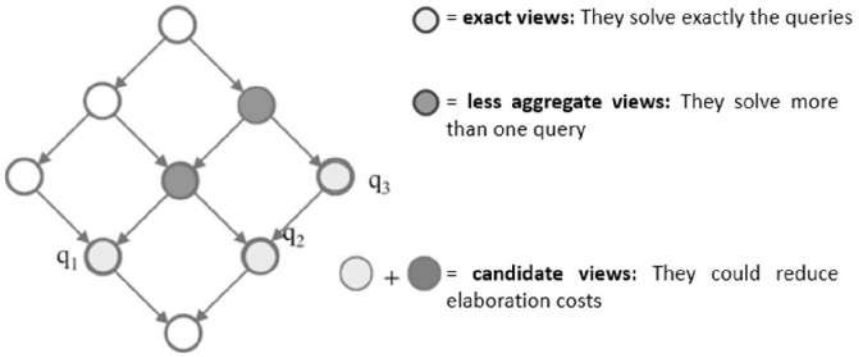
Fact constellation schema of a data warehouse for sales and shipping.

Starflake Schema

A starflake schema is a combination of a star schema and a snowflake schema. Starflake schemas are snowflake schemas where only some of the dimension tables have been de-normalized.

Materialized View

Materialized views are query results that have been stored in advance so long-running calculations are not necessary when you actually execute your SQL statements. Materialized views can be best explained by Multidimensional lattice.



It is useful to materialize a view when:

- It directly solves a frequent query
- It reduces the costs of some queries

It is not useful to materialize a view when:

- Its aggregation pattern is the same as another materialized view
- Its materialization does not reduce the cost

Data Warehouse Physical Design

Physical design is the phase of a database design following the logical design that identifies the actual database tables and index structures used to implement the logical design. In the physical design, you look at the most effective way of storing and retrieving the objects as well as handling them from a transportation and backup/recovery perspective. Physical design decisions are mainly driven by query performance and database maintenance aspects. During the logical design phase, you defined a model for your data warehouse consisting of entities, attributes, and relationships. The entities are linked together using relationships. Attributes are used to describe the entities. The unique identifier (UID) distinguishes between one instance of an entity and another.

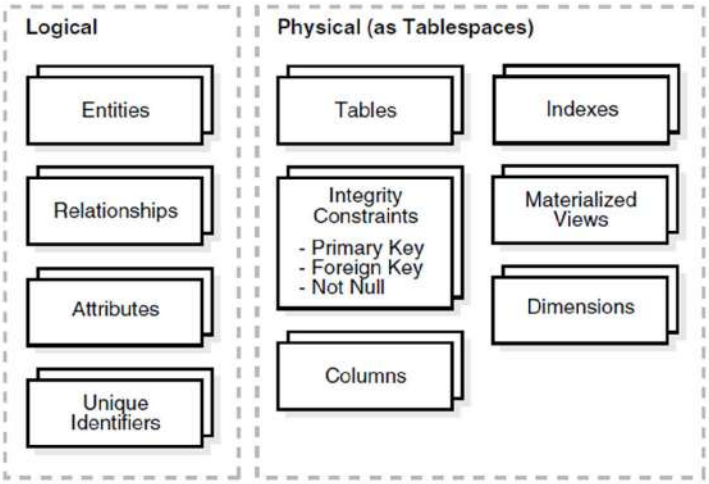


Figure: Logical Design Compared with Physical Design

During the physical design process, you translate the expected schemas into actual database structures. At this time, you have to map:

- Entities to tables
- Relationships to foreign key constraints
- Attributes to columns
- Primary unique identifiers to primary key constraints
- Unique identifiers to unique key constraints

Features of physical data model include:

- ❖ Specification all tables and columns.
- ❖ Specification of Foreign keys.
- ❖ De-normalization may be performed if necessary.
- ❖ At this level, specification of logical data model is realized in the database.

The steps for physical data model design involves:

- ❖ Conversion of entities into tables,
- ❖ Conversion of relationships into foreign keys, Conversion of attributes into columns, and
- ❖ Changes to the physical data model based on the physical constraints.

LOGICAL MODEL

PHYSICAL MODEL

Name	Type	Comments
PRODUCT		Product dimension table including all of
		company's products
product_key	integer	Primary key
product_name	char(25)	Name of product as used by marketing
product_sku	char(20)	Stock Keeping Unit in source systems
product_brand	char(25)	Name of brand as used by marketing
SALESPERSON		Sales Person dimension table includes all
		sales persons from all regions
salpers_key	integer	Primary key
salpers_name	char(30)	Name of sales person as used officially
territory	char(20)	Territory covered by the sales person
region	char(20)	Region containing the territory
ORDER FACT		Fact table containing metrics about all
		the orders received by the company
product_ref	integer	Partial primary key, also foreign key
		referencing product dimension table
salpers_ref	integer	Partial primary key, also foreign key
		referencing salesperson dimension table
order_amount	num(8,2)	Sales amount of order in dollars
order_cost	num(8,2)	Cost amount for the order in dollars

Figure: Logical model and physical model

Physical Design Structures

Once you have converted your logical design to a physical one, you will need to create some or all of the following structures:

- Tablespaces
- Tables and Partitioned Tables
- Views
- Integrity Constraints
- Dimensions

Some of these structures require disk space. Others exist only in the data dictionary. Additionally, the following structures may be created for performance improvement:

- Indexes and Partitioned Indexes
- Materialized Views

Tablespaces

A tablespace consists of one or more datafiles, which are physical structures within the operating system you are using. A datafile is associated with only one tablespace. From a design perspective, tablespaces are containers for physical design structures.

Tables and Partitioned Tables

Tables are the basic unit of data storage. They are the container for the expected amount of raw data in your data warehouse. Using partitioned tables instead of non-partitioned ones addresses the key

problem of supporting very large data volumes by allowing you to divide them into smaller and more manageable pieces. Partitioning large tables improves performance because each partitioned piece is more manageable.

Views

A view is a tailored presentation of the data contained in one or more tables or other views. A view takes the output of a query and treats it as a table. Views do not require any space in the database.

Integrity Constraints

Integrity constraints are used to enforce business rules associated with your database and to prevent having invalid information in the tables. In data warehousing environments, constraints are only used for query rewrite. NOT NULL constraints are particularly common in data warehouses.

Indexes and Partitioned Indexes

Indexes are optional structures associated with tables. Indexes are just like tables in that you can partition them (but the partitioning strategy is not dependent upon the table structure). Partitioning indexes makes it easier to manage the data warehouse during refresh and improves query performance.

Materialized Views

Materialized views are query results that have been stored in advance so long-running calculations are not necessary when you actually execute your SQL statements. From a physical design point of view, materialized views resemble tables or partitioned tables and behave like indexes in that they are used transparently and improve performance.

Hardware and I/O Considerations

I/O performance should always be a key consideration for data warehouse designers and administrators. The typical workload in a data warehouse is especially I/O intensive, with operations such as large data loads and index builds, creation of materialized views, and queries over large volumes of data. The underlying I/O system for a data warehouse should be designed to meet these heavy requirements. In fact, one of the leading causes of performance issues in a data warehouse is poor I/O configuration. Database administrators who have previously managed other systems will likely need to pay more careful attention to the I/O configuration for a data warehouse than they may have previously done for other environments. The I/O configuration used by a data warehouse will depend on the characteristics of the specific storage and server capabilities

There are following five high-level guidelines for data-warehouse I/O configurations:

- Configure I/O for Bandwidth not Capacity
- Stripe Far and Wide
- Use Redundancy
- Test the I/O System Before Building the Database
- Plan for Growth

Parallelism

Parallelism is the idea of breaking down a task so that, instead of one process doing all of the work in a query, many processes do part of the work at the same time. Parallel execution is sometimes called parallelism. Parallel execution dramatically reduces response time for data-intensive operations on large databases typically associated with decision support systems (DSS) and data warehouses. An

example of this is when four processes handle four different quarters in a year instead of one process handling all four quarters by itself.

Parallelism improves processing for:

- Queries requiring large table scans, joins, or partitioned index scans
- Creation of large indexes
- Creation of large tables (including materialized views)
- Bulk inserts, updates, merges, and deletes

Parallelism benefits systems with all of the following characteristics:

- Symmetric multiprocessors (SMPs), clusters, or massively parallel systems
- Sufficient I/O bandwidth
- Underutilized or intermittently used CPUs (for example, systems where CPU usage is typically less than 30%)
- Sufficient memory to support additional memory-intensive processes, such as sorts, hashing, and I/O buffers

Indexes

Indexes are optional structures associated with tables and clusters. Indexes are structures actually stored in the database, which users create, alter, and drop using SQL statements. You can create indexes on one or more columns of a table to speed SQL statement execution on that table. In a query-centric system like the data warehouse environment, the need to process queries faster dominates. Among the various methods to improve performance, indexing ranks very high. Indexes are typically used to speed up the retrieval of records in response to search conditions. **Indexes** can be unique or non-unique. Unique indexes guarantee that no two rows of a table have duplicate values in the key column (or columns). Non-unique indexes do not impose this restriction on the column values.

Index structures applied in warehouses are:

- Inverted lists
- Bitmap indexes
- Join indexes
- Text indexes
- B-Tree Index