Data Warehouse and Data Mining

CSL608

Unit-2

Data Preprocessing in Data Mining

Data preprocessing is an important step in the data mining process. It refers to the cleaning, transforming, and integrating of data in order to make it ready for analysis. The goal of data preprocessing is to improve the quality of the data and to make it more suitable for the specific data mining task.

Some common steps in data preprocessing include:

Data preprocessing is an important step in the data mining process that involves cleaning and transforming raw data to make it suitable for analysis. Some common steps in data preprocessing include:

Data Cleaning: This involves identifying and correcting errors or inconsistencies in the data, such as missing values, outliers, and duplicates. Various techniques can be used for data cleaning, such as imputation, removal, and transformation.

Data Integration: This involves combining data from multiple sources to create a unified dataset. Data integration can be challenging as it requires handling data with different formats, structures, and semantics. Techniques such as record linkage and data fusion can be used for data integration.

Data Transformation: This involves converting the data into a suitable format for analysis. Common techniques used in data transformation include normalization, standardization, and discretization. Normalization is used to scale the data to a common range, while standardization is used to transform the data to have zero mean and unit variance. Discretization is used to convert continuous data into discrete categories.

Data Reduction: This involves reducing the size of the dataset while preserving the important information. Data reduction can be achieved through techniques such as feature selection and feature extraction. Feature selection involves selecting a subset of relevant features from the dataset, while feature extraction involves transforming the data into a lower-dimensional space while preserving the important information.

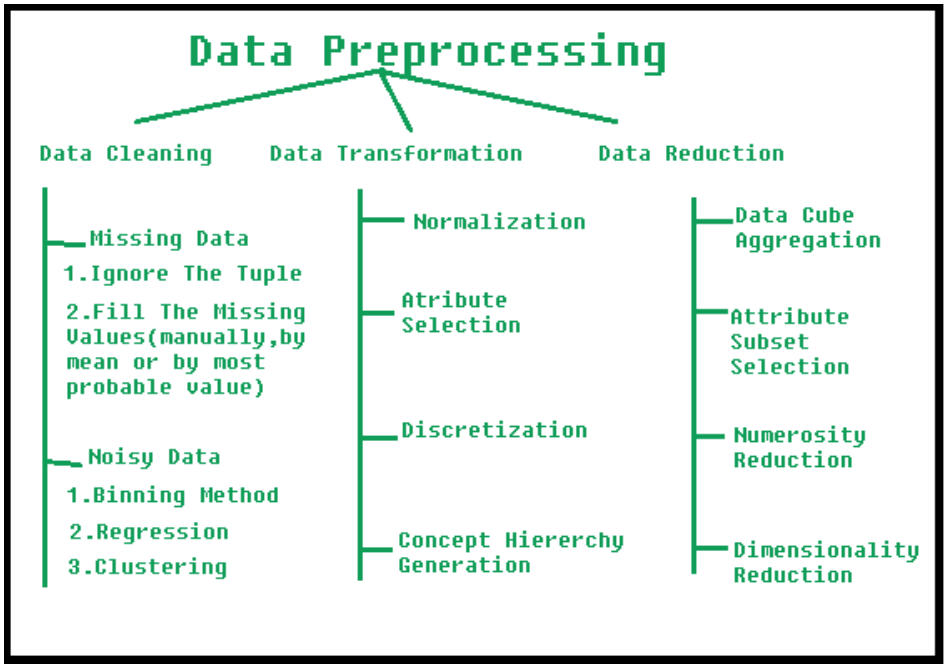
Data Discretization: This involves dividing continuous data into discrete categories or intervals. Discretization is often used in data mining and machine learning algorithms that require categorical data. Discretization can be achieved through techniques such as equal width binning, equal frequency binning, and clustering.

Data Normalization: This involves scaling the data to a common range, such as between 0 and 1 or -1 and 1. Normalization is often used to handle data with different units and scales. Common normalization techniques include min-max normalization, z-score normalization, and decimal scaling.

Data preprocessing plays a crucial role in ensuring the quality of data and the accuracy of the analysis results. The specific steps involved in data preprocessing may vary depending on the nature of the data and the analysis goals.

By performing these steps, the data mining process becomes more efficient and the results become more accurate.

Preprocessing in Data Mining:
Data preprocessing is a data mining technique which is used to transform the raw data in a useful and efficient format.



Steps Involved in Data Preprocessing:

1. Data Cleaning:

The data can have many irrelevant and missing parts. To handle this part, data cleaning is done. It involves handling of missing data, noisy data etc.

(a). Missing Data:

This situation arises when some data is missing in the data. It can be handled in various ways. Some of them are:

1. **Ignore the tuples:**
   This approach is suitable only when the dataset we have is quite large and multiple values are missing within a tuple.
2. **Fill the Missing values:**
   There are various ways to do this task. You can choose to fill the missing values manually, by attribute mean or the most probable value.

(b). Noisy Data:

Noisy data is a meaningless data that can't be interpreted by machines.It can be generated due to faulty data collection, data entry errors etc. It can be handled in following ways :

1. Binning Method:

This method works on sorted data in order to smooth it. The whole data is divided into segments of equal size and then various methods are performed to complete the task. Each segmented is handled separately. One can replace all data in a segment by its mean or boundary values can be used to complete the task.

2. Regression:

Here data can be made smooth by fitting it to a regression function.The regression used may be linear (having one independent variable) or multiple (having multiple independent variables).

3. Clustering:

This approach groups the similar data in a cluster. The outliers may be undetected or it will fall outside the clusters.

2. Data Transformation:
This step is taken in order to transform the data in appropriate forms suitable for mining process. This involves following ways:

1. **Normalization:**
   It is done in order to scale the data values in a specified range (-1.0 to 1.0 or 0.0 to 1.0)
2. **Attribute Selection:**
   In this strategy, new attributes are constructed from the given set of attributes to help the mining process.
3. **Discretization:**
   This is done to replace the raw values of numeric attribute by interval levels or conceptual levels.
4. **Concept Hierarchy Generation:**
   Here attributes are converted from lower level to higher level in hierarchy. For Example-The attribute “city” can be converted to “country”.

3. Data Reduction:
Data reduction is a crucial step in the data mining process that involves reducing the size of the dataset while preserving the important information. This is done to improve the efficiency of data analysis and to avoid overfitting of the model. Some common steps involved in data reduction are:

1. Feature Selection: This involves selecting a subset of relevant features from the dataset. Feature selection is often performed to remove irrelevant or redundant features from the dataset. It can be done using various techniques such as correlation analysis, mutual information, and principal component analysis (PCA).

2. Feature Extraction: This involves transforming the data into a lower-dimensional space while preserving the important information. Feature extraction is often used when the original features are high-dimensional and complex. It can be done using techniques such as PCA, linear discriminant analysis (LDA), and non-negative matrix factorization (NMF).

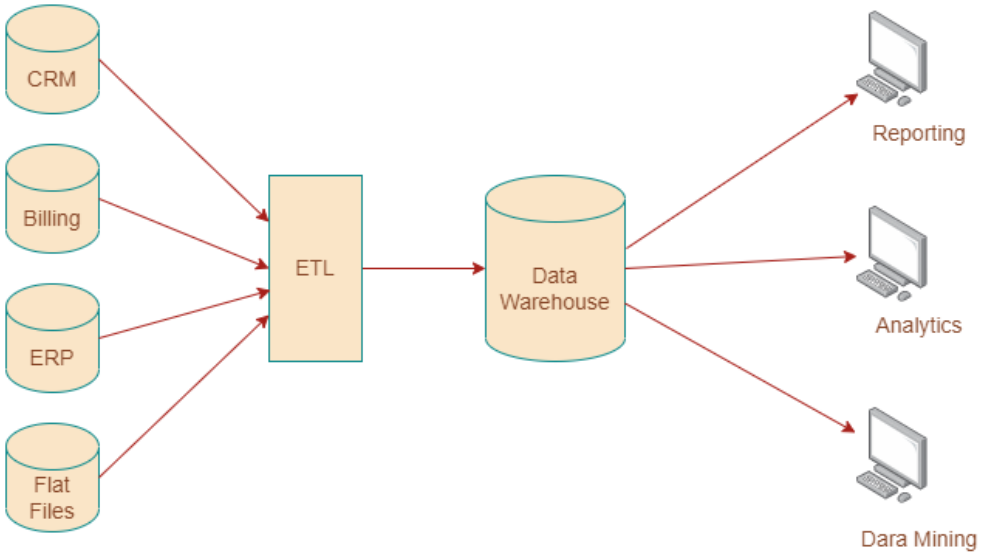
3. Sampling: This involves selecting a subset of data points from the dataset. Sampling is often used to reduce the size of the dataset while preserving the important information. It can be done using techniques such as random sampling, stratified sampling, and systematic sampling.

4. Clustering: This involves grouping similar data points together into clusters. Clustering is often used to reduce the size of the dataset by replacing similar data points with a representative centroid. It can be done using techniques such as k-means, hierarchical clustering, and density-based clustering.

5. Compression: This involves compressing the dataset while preserving the important information. Compression is often used to reduce the size of the dataset for storage and transmission purposes. It can be done using techniques such as wavelet compression, JPEG compression, and gzip compression.

What is data warehouse

A data warehouse is like a big library where we keep a lot of information from different places. It analyzes and understands the information easily. So you can make good decisions based on these facts. You have all the required information that you need in one place. We organize the information so it's easy to find and use. It takes information from different places and put it all together in one place, hence it is easier to understand.



Characteristics of Data Warehouse

Data Warehouse has the following characteristics.

Subject-oriented

A data warehouse focuses on a specific topic like sales, marketing, or distribution. It is designed to provide information about a particular theme rather than the day-to-day operations of an organization.

Integrated

A data warehouse combines data from different sources. These sources are mainframes and relational databases, into a single, reliable format. The data must be organized and structured in a way that allows for effective analysis.

Time-variant

Data in a data warehouse is maintained over time, in weekly/monthly/annual intervals. So you can do historical analysis and the ability to track changes over time.

Non-volatile

Data in a data warehouse is permanent. Data cannot be deleted or modified once it's stored. So you can do historical analysis and ensure that the data is always available in its original state.

By understanding these characteristics, organizations can use data warehouses to make better decisions by analyzing large amounts of data from different sources in a consistent and reliable way.

Data warehousing has some advantages and disadvantages.

Advantages

- Makes data easier to understand
- Continuous updating
- Accessibility

Disadvantages

- Accumulation of irrelevant data
- Data loss and erasure
- Data cleansing and transformation

Functions of Data warehouse

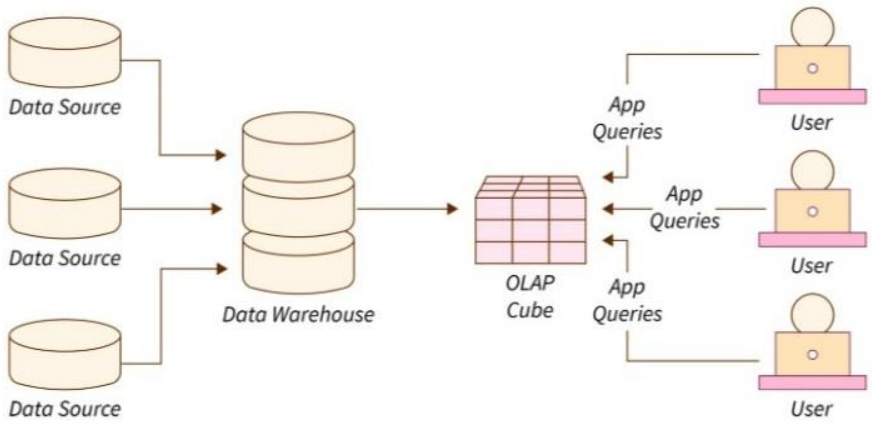
A data warehouse is a collection of data that is organized to provide various functions for managing and analyzing data. Some of the important functions of a data warehouse are −

- Data Consolidation
- Data Cleaning
- Data Integration
- Data Storage
- Data Transformation
- Data Analysis
- Data Reporting
- Data Mining
- Performance Optimization

These functions enable organizations to manage and analyze large amounts of data from different sources, and make informed decisions based on reliable and accurate information.

Online Analytical Processing Server (OLAP)

Online Analytical Processing Server (OLAP) is a software. Users can analyze information from many different databases all at once. It uses a multidimensional data model where users can ask questions based on multiple dimensions at the same time. For example, a user could ask for sales data from Delhi in the year 2018. OLAP databases are split up into cubes, which are also called hyper-cubes.



OLAP operations

These are used to analyze data in an OLAP cube. There are five basic operations:

Drill down

This makes the data more detailed by moving down the concept hierarchy or adding a new dimension. For example, in a cube showing sales data by Quarter, drilling down would show sales data by Month.

Roll up

This makes the data less detailed by climbing up the concept hierarchy or reducing dimensions. For example, in a cube showing sales data by City, rolling up would show sales data by Country.

Dice

This selects a sub-cube by choosing two or more dimensions and criteria. For example, in a cube showing sales data by Location, Time, and Item, dicing could select sales data for Delhi or Kolkata, in Q1 or Q2, for Cars or Buses.

Slice

This selects a single dimension and creates a new sub-cube. For example, in a cube showing sales data by Location, Time, and Item, slicing by Time would create a new sub-cube showing sales data for Q1.

Pivot

This rotates the current view to get a new representation. For example, after slicing by Time, pivoting could show the same data but with Location and Item as rows instead of columns

Comparison between Data Warehousing and OLAP

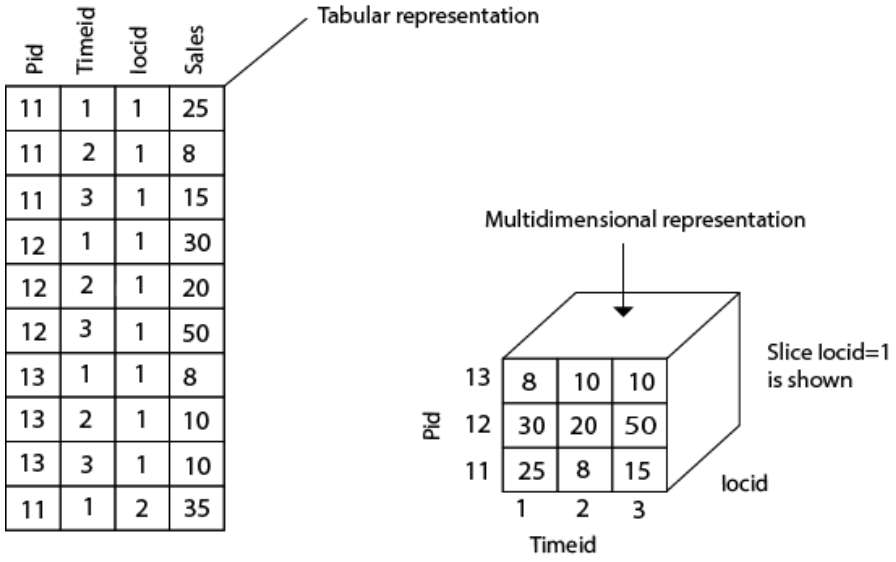
Feature	**Data Warehousing**	**OLAP**
Definition	A process of collecting, storing, and managing data from various sources to provide meaningful business insights	A technology that allows users to analyze information from multiple database systems at the same time based on the multi-dimensional data model
Purpose	To make data accessible and understandable for business users	To provide quick and interactive analysis of data from multiple sources
Data structure	Relational database	Multidimensional data model
Data source	Multiple data sources	Multiple data sources
Data type	Historical data	Current and historical data
Data processing	Batch processing	Real-time processing
Operations	Data cleaning, consolidation, integration, transformation, analysis, and reporting	Drill-down, roll-up, slice, dice, and pivot
Cube creation	Not applicable	Cubes are created to support fast and efficient analysis
Query performance	Slower query performance due to complex querying and data processing	Faster query performance due to pre-aggregation and indexing
User type	Business users and data analysts	Business users and data analysts
Use case	Decision-making and strategic planning	Real-time analysis and interactive reporting

Multi-Dimensional Data Model

A multidimensional model views data in the form of a data-cube. A data cube enables data to be modeled and viewed in multiple dimensions. It is defined by dimensions and facts.

The dimensions are the perspectives or entities concerning which an organization keeps records. For example, a shop may create a sales data warehouse to keep records of the store's sales for the dimension time, item, and location. These dimensions allow the save to keep track of things, for example, monthly sales of items and the locations at which the items were sold. Each dimension has a table related to it, called a dimensional table, which describes the dimension further. For example, a dimensional table for an item may contain the attributes item_name, brand, and type.

A multidimensional data model is organized around a central theme, for example, sales. This theme is represented by a fact table. Facts are numerical measures. The fact table contains the names of the facts or measures of the related dimensional tables.



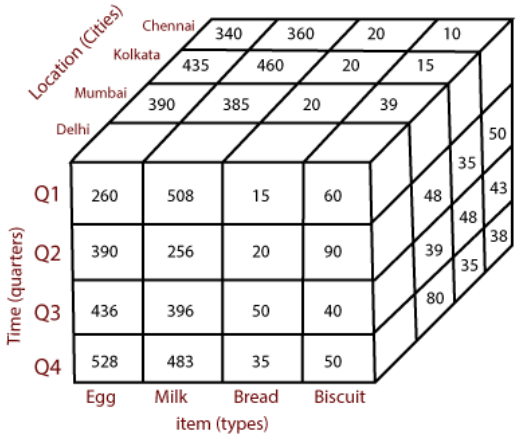
Consider the data of a shop for items sold per quarter in the city of Delhi. The data is shown in the table. In this 2D representation, the sales for Delhi are shown for the time dimension (organized in quarters) and the item dimension (classified according to the types of an item sold). The fact or measure displayed in rupee_sold (in thousands).

Location="Delhi"				
	item (type)			
Time (quarter)	Egg	Milk	Bread	Biscuit
Q1	260	508	15	60
Q2	390	256	20	90
Q3	436	396	50	40
Q4	528	483	35	50

Now, if we want to view the sales data with a third dimension, For example, suppose the data according to time and item, as well as the location is considered for the cities Chennai, Kolkata, Mumbai, and Delhi. These 3D data are shown in the table. The 3D data of the table are represented as a series of 2D tables.

	Location="Chennai"				Location="Kolkata"				Location="Mumbai"				Location="Delhi"			
	item				item				item				item			
Time	Egg	Milk	Bread	Biscuit	Egg	Milk	Bread	Biscuit	Egg	Milk	Bread	Biscuit	Egg	Milk	Bread	Biscuit
Q1	340	360	20	10	435	460	20	15	390	385	20	39	260	508	15	60
Q2	490	490	16	50	389	385	45	35	463	366	25	48	390	256	20	90
Q3	680	583	46	43	684	490	39	48	568	594	36	39	436	396	50	40
Q4	535	694	39	38	335	365	83	35	338	484	48	80	528	483	35	50

Conceptually, it may also be represented by the same data in the form of a 3D data cube, as shown in fig:



Data Warehouse Architecture

A data warehouse architecture is a method of defining the overall architecture of data communication processing and presentation that exist for end-clients computing within the enterprise. Each data warehouse is different, but all are characterized by standard vital components.

Production applications such as payroll accounts payable product purchasing and inventory control are designed for online transaction processing **(OLTP)**. Such applications gather detailed data from day to day operations.

Data Warehouse applications are designed to support the user ad-hoc data requirements, an activity recently dubbed online analytical processing (OLAP). These include applications such as forecasting, profiling, summary reporting, and trend analysis.

Production databases are updated continuously by either by hand or via OLTP applications. In contrast, a warehouse database is updated from operational systems periodically, usually during off-hours. As OLTP data accumulates in production databases, it is regularly extracted, filtered, and then loaded into a dedicated warehouse server that is accessible to users. As the warehouse is populated, it must be restructured tables de-normalized, data cleansed of errors and redundancies and new fields and keys added to reflect the needs to the user for sorting, combining, and summarizing data.

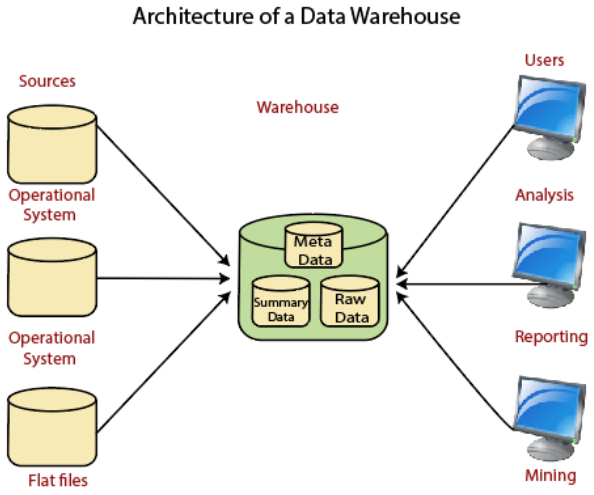
Backward Skip 10sPlay VideoForward Skip 10s

Data warehouses and their architectures very depending upon the elements of an organization's situation.

Three common architectures are:

- Data Warehouse Architecture: Basic
- Data Warehouse Architecture: With Staging Area
- Data Warehouse Architecture: With Staging Area and Data Marts

Data Warehouse Architecture: Basic



Operational System

An **operational system** is a method used in data warehousing to refer to a **system** that is used to process the day-to-day transactions of an organization.

Flat Files

A **Flat file** system is a system of files in which transactional data is stored, and every file in the system must have a different name.

Meta Data

A set of data that defines and gives information about other data.

Meta Data used in Data Warehouse for a variety of purpose, including:

Meta Data summarizes necessary information about data, which can make finding and work with particular instances of data more accessible. For example, author, data build, and data changed, and file size are examples of very basic document metadata.

Metadata is used to direct a query to the most appropriate data source.

Lightly and highly summarized data

The area of the data warehouse saves all the predefined lightly and highly summarized (aggregated) data generated by the warehouse manager.

The goals of the summarized information are to speed up query performance. The summarized record is updated continuously as new information is loaded into the warehouse.

End-User access Tools

The principal purpose of a data warehouse is to provide information to the business managers for strategic decision-making. These customers interact with the warehouse using end-client access tools.

The examples of some of the end-user access tools can be:

- Reporting and Query Tools
- Application Development Tools
- Executive Information Systems Tools

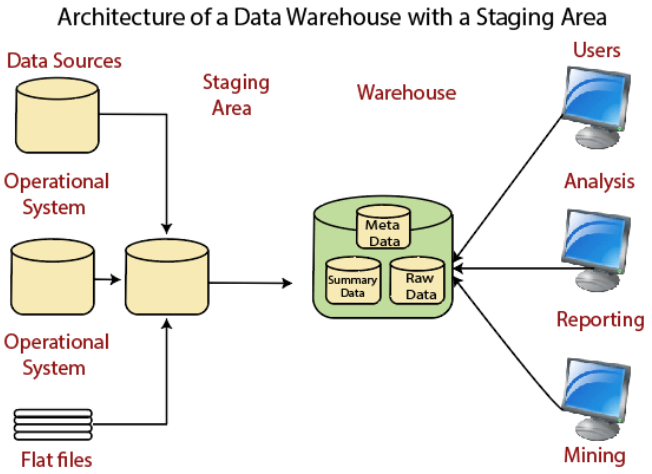
- Online Analytical Processing Tools
- Data Mining Tools

Data Warehouse Architecture: With Staging Area

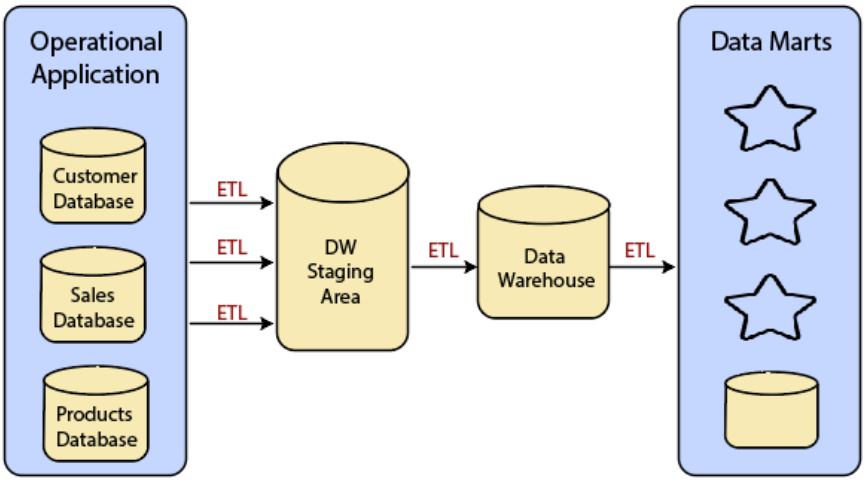
We must clean and process your operational information before put it into the warehouse.

We can do this programmatically, although data warehouses uses a **staging area** (A place where data is processed before entering the warehouse).

A staging area simplifies data cleansing and consolidation for operational method coming from multiple source systems, especially for enterprise data warehouses where all relevant data of an enterprise is consolidated.



Data Warehouse Staging Area is a temporary location where a record from source systems is copied.

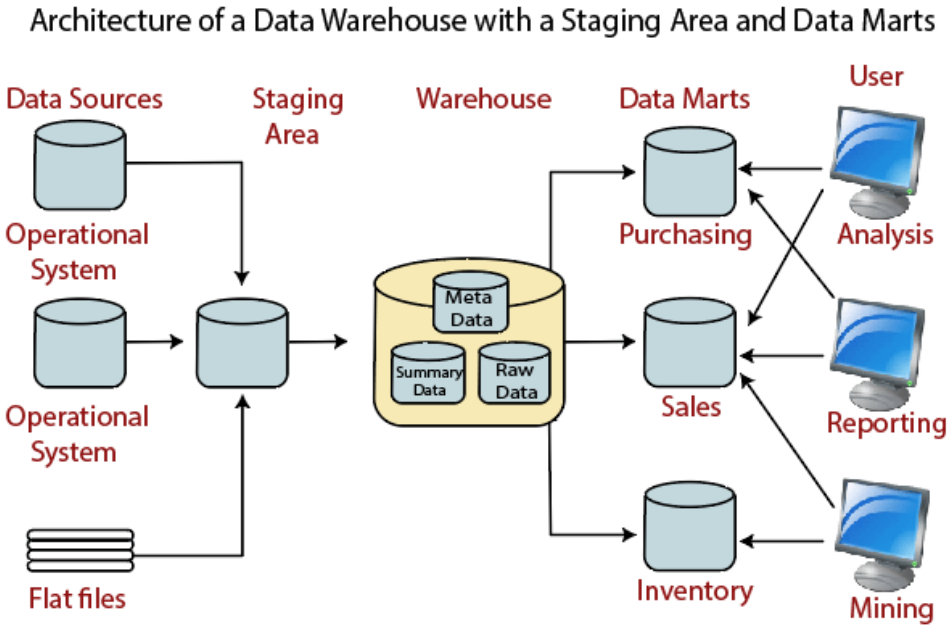


Data Warehouse Architecture: With Staging Area and Data Marts

We may want to customize our warehouse's architecture for multiple groups within our organization.

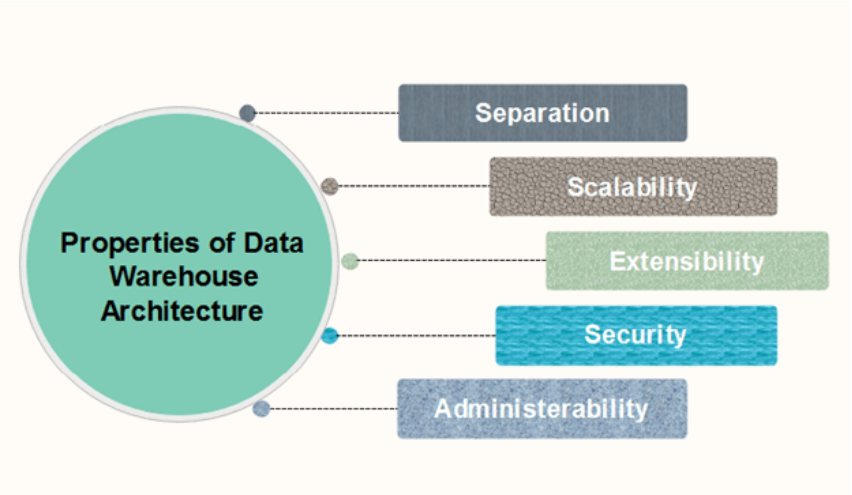
We can do this by adding **data marts**. A data mart is a segment of a data warehouses that can provided information for reporting and analysis on a section, unit, department or operation in the company, e.g., sales, payroll, production, etc.

The figure illustrates an example where purchasing, sales, and stocks are separated. In this example, a financial analyst wants to analyze historical data for purchases and sales or mine historical information to make predictions about customer behavior.



Properties of Data Warehouse Architectures

The following architecture properties are necessary for a data warehouse system:



1. Separation: Analytical and transactional processing should be keep apart as much as possible.

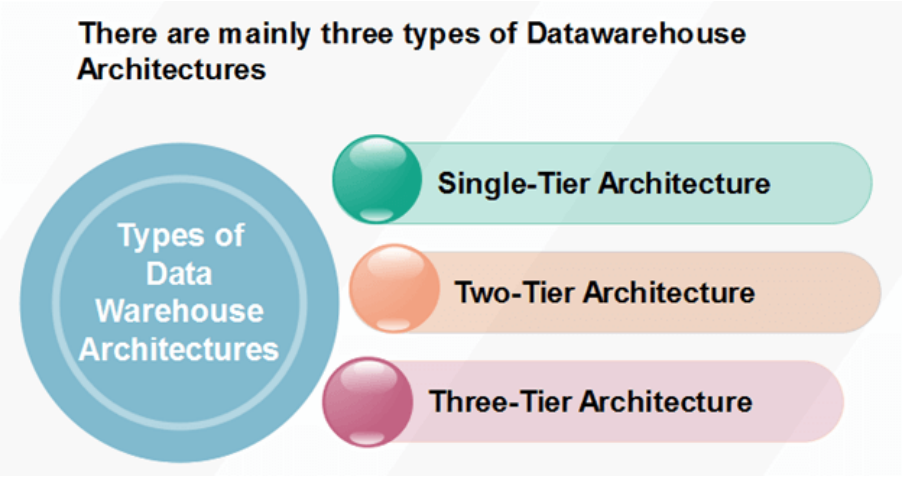
2. Scalability: Hardware and software architectures should be simple to upgrade the data volume, which has to be managed and processed, and the number of user's requirements, which have to be met, progressively increase.

3. Extensibility: The architecture should be able to perform new operations and technologies without redesigning the whole system.

4. Security: Monitoring accesses are necessary because of the strategic data stored in the data warehouses.

5. Administerability: Data Warehouse management should not be complicated.

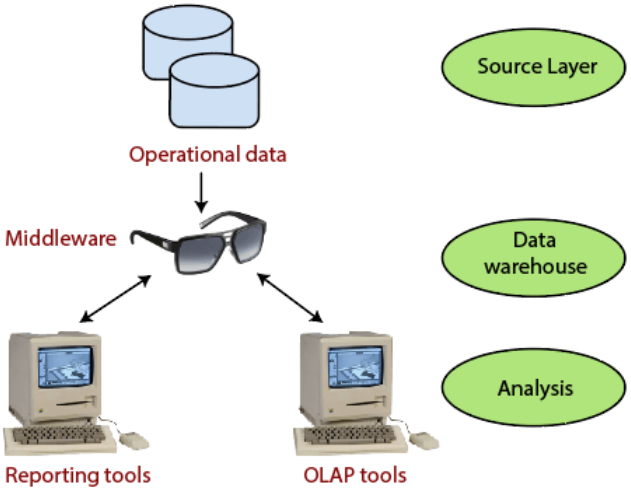
Types of Data Warehouse Architectures



Single-Tier Architecture

Single-Tier architecture is not periodically used in practice. Its purpose is to minimize the amount of data stored to reach this goal; it removes data redundancies.

The figure shows the only layer physically available is the source layer. In this method, data warehouses are virtual. This means that the data warehouse is implemented as a multidimensional view of operational data created by specific middleware, or an intermediate processing layer.

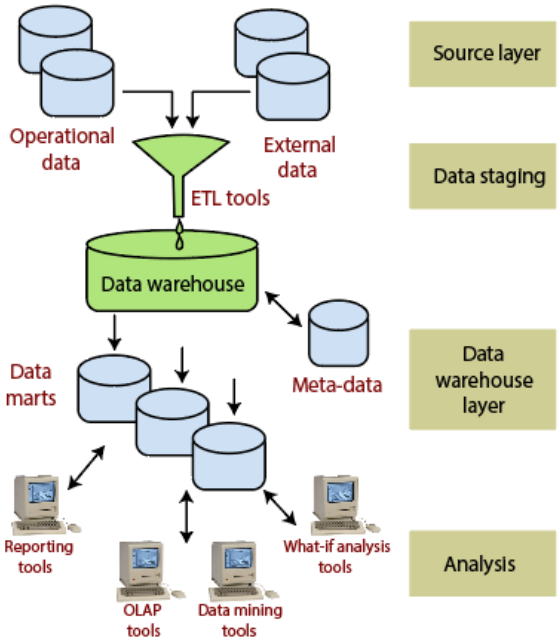


Single-Tier Data Warehouse Architecture

The vulnerability of this architecture lies in its failure to meet the requirement for separation between analytical and transactional processing. Analysis queries are agreed to operational data after the middleware interprets them. In this way, queries affect transactional workloads.

Two-Tier Architecture

The requirement for separation plays an essential role in defining the two-tier architecture for a data warehouse system, as shown in fig:



Two-Tier Data Warehouse Architecture

Although it is typically called two-layer architecture to highlight a separation between physically available sources and data warehouses, in fact, consists of four subsequent data flow stages:

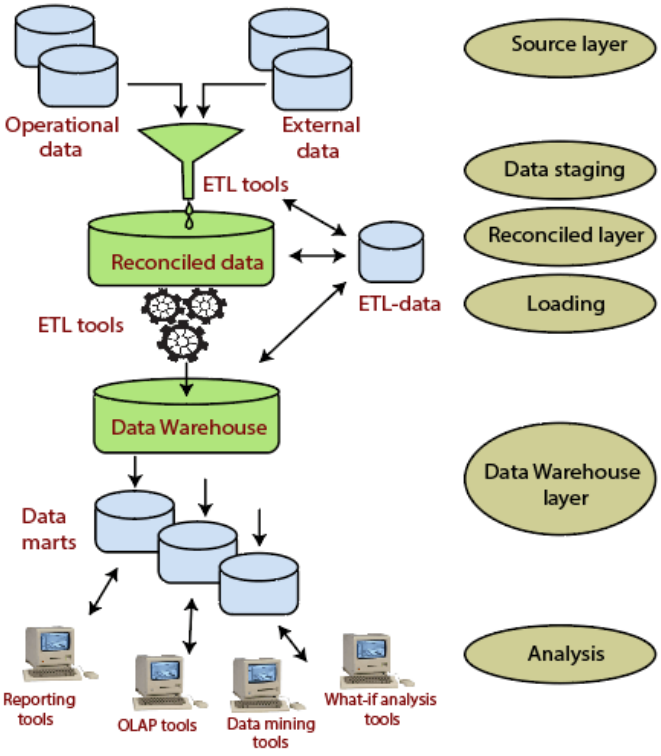
1. **Source layer:** A data warehouse system uses a heterogeneous source of data. That data is stored initially to corporate relational databases or legacy databases, or it may come from an information system outside the corporate walls.
2. **Data Staging:** The data stored to the source should be extracted, cleansed to remove inconsistencies and fill gaps, and integrated to merge heterogeneous sources into one standard schema. The so-named **Extraction**, **Transformation**, and **Loading Tools (ETL)** can combine heterogeneous schemata, extract, transform, cleanse, validate, filter, and load source data into a data warehouse.
3. **Data Warehouse layer:** Information is saved to one logically centralized individual repository: a data warehouse. The data warehouses can be directly accessed, but it can also be used as a source for creating data marts, which partially replicate data warehouse contents and are designed for specific enterprise departments. Meta-data repositories store information on sources, access procedures, data staging, users, data mart schema, and so on.
4. **Analysis:** In this layer, integrated data is efficiently, and flexible accessed to issue reports, dynamically analyze information, and simulate hypothetical business scenarios. It should feature aggregate information navigators, complex query optimizers, and customer-friendly GUIs.

Three-Tier Architecture

The three-tier architecture consists of the source layer (containing multiple source system), the reconciled layer and the data warehouse layer (containing both data warehouses and data marts). The reconciled layer sits between the source data and data warehouse.

The main advantage of the **reconciled layer** is that it creates a standard reference data model for a whole enterprise. At the same time, it separates the problems of source data extraction and integration from those of data warehouse population. In some cases, the **reconciled layer** is also directly used to accomplish better some operational tasks, such as producing daily reports that cannot be satisfactorily prepared using the corporate applications or generating data flows to feed external processes periodically to benefit from cleaning and integration.

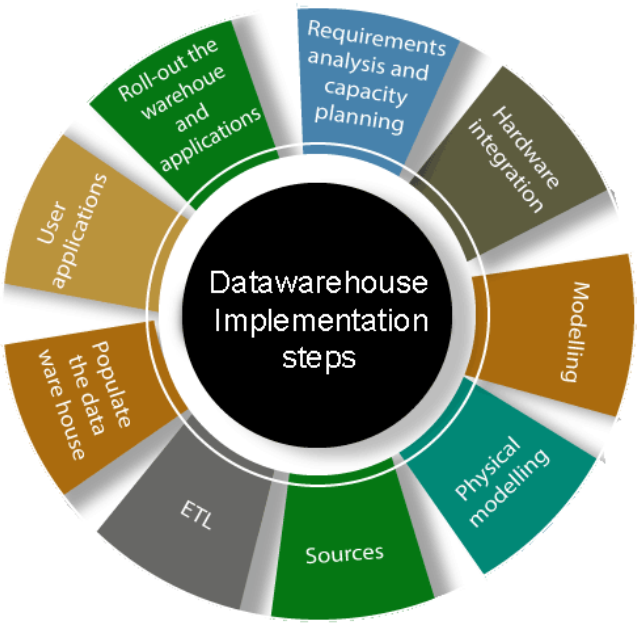
This architecture is especially useful for the extensive, enterprise-wide systems. A disadvantage of this structure is the extra file storage space used through the extra redundant reconciled layer. It also makes the analytical tools a little further away from being real-time.



Three-Tier Architecture for a data warehouse system

Data Warehouse Implementation

There are various implementation in data warehouses which are as follows



1. Requirements analysis and capacity planning: The first process in data warehousing involves defining enterprise needs, defining architectures, carrying out capacity planning, and selecting the hardware and software tools. This step will contain be consulting senior management as well as the different stakeholder.

2. Hardware integration: Once the hardware and software has been selected, they require to be put by integrating the servers, the storage methods, and the user software tools.

3. Modeling: Modelling is a significant stage that involves designing the warehouse schema and views. This may contain using a modeling tool if the data warehouses are sophisticated.

4. Physical modeling: For the data warehouses to perform efficiently, physical modeling is needed. This contains designing the physical data warehouse organization, data placement, data partitioning, deciding on access techniques, and indexing.

5. Sources: The information for the data warehouse is likely to come from several data sources. This step contains identifying and connecting the sources using the gateway, ODBC drives, or another wrapper.

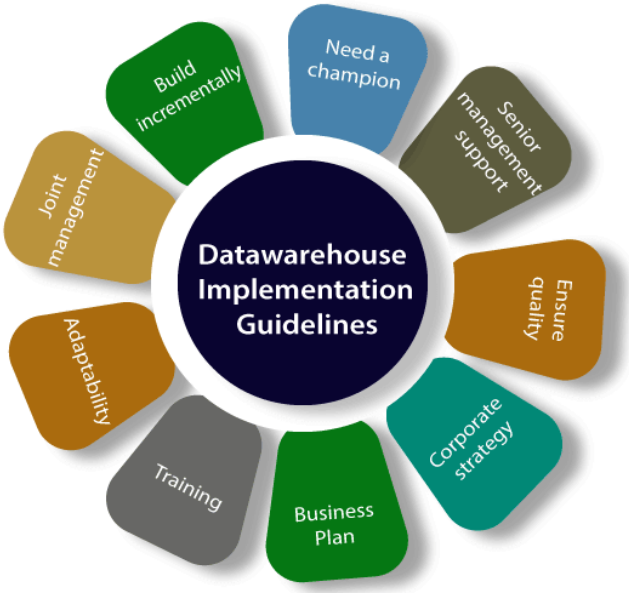
6. ETL: The data from the source system will require to go through an ETL phase. The process of designing and implementing the ETL phase may contain defining a suitable ETL tool vendors and purchasing and implementing the tools. This may contains customize the tool to suit the need of the enterprises.

7. Populate the data warehouses: Once the ETL tools have been agreed upon, testing the tools will be needed, perhaps using a staging area. Once everything is working adequately, the ETL tools may be used in populating the warehouses given the schema and view definition.

8. User applications: For the data warehouses to be helpful, there must be end-user applications. This step contains designing and implementing applications required by the end-users.

9. Roll-out the warehouses and applications: Once the data warehouse has been populated and the end-client applications tested, the warehouse system and the operations may be rolled out for the user's community to use.

Implementation Guidelines



1. Build incrementally: Data warehouses must be built incrementally. Generally, it is recommended that a data marts may be created with one particular project in mind, and once it is implemented, several other sections of the enterprise may also want to implement similar systems. An enterprise data warehouses can then be implemented in an iterative manner allowing all data marts to extract information from the data warehouse.

2. Need a champion: A data warehouses project must have a champion who is active to carry out considerable researches into expected price and benefit of the project. Data warehousing projects requires inputs from many units in an enterprise and therefore needs to be driven by someone who is needed for interacting with people in the enterprises and can actively persuade colleagues.

3. Senior management support: A data warehouses project must be fully supported by senior management. Given the resource-intensive feature of such project and the time they can take to implement, a warehouse project signal for a sustained commitment from senior management.

4. Ensure quality: The only record that has been cleaned and is of a quality that is implicit by the organizations should be loaded in the data warehouses.

5. Corporate strategy: A data warehouse project must be suitable for corporate strategies and business goals. The purpose of the project must be defined before the beginning of the projects.

6. Business plan: The financial costs (hardware, software, and peopleware), expected advantage, and a project plan for a data warehouses project must be clearly outlined and understood by all stakeholders. Without such understanding, rumors about expenditure and benefits can become the only sources of data, subversion the projects.

7. Training: Data warehouses projects must not overlook data warehouses training requirements. For a data warehouses project to be successful, the customers must be trained to use the warehouses and to understand its capabilities.

8. Adaptability: The project should build in flexibility so that changes may be made to the data warehouses if and when required. Like any system, a data warehouse will require to change, as the needs of an enterprise change.

9. Joint management: The project must be handled by both IT and business professionals in the enterprise. To ensure that proper communication with the stakeholder and which the project is the target for assisting the enterprise's business, the business professional must be involved in the project along with technical professionals.

OLAP (Online Analytical Processing)

OLAP stands for **On-Line Analytical Processing**. OLAP is a classification of software technology which authorizes analysts, managers, and executives to gain insight into information through fast, consistent, interactive access in a wide variety of possible views of data that has been transformed from raw information to reflect the real dimensionality of the enterprise as understood by the clients.

OLAP implement the multidimensional analysis of business information and support the capability for complex estimations, trend analysis, and sophisticated data modeling. It is rapidly enhancing the essential foundation for Intelligent Solutions containing Business Performance Management, Planning, Budgeting, Forecasting, Financial Documenting, Analysis, Simulation-Models, Knowledge Discovery, and Data Warehouses Reporting. OLAP enables end-clients to perform ad hoc analysis of record in multiple dimensions, providing the insight and understanding they require for better decision making.

Who uses OLAP and Why?

OLAP applications are used by a variety of the functions of an organization.

Finance and accounting:

- Budgeting
- Activity-based costing
- Financial performance analysis
- And financial modeling

Sales and Marketing

- Sales analysis and forecasting
- Market research analysis
- Promotion analysis
- Customer analysis
- Market and customer segmentation

Production

- Production planning
- Defect analysis

OLAP cubes have two main purposes. The first is to provide business users with a data model more intuitive to them than a tabular model. This model is called a Dimensional Model.

The second purpose is to enable fast query response that is usually difficult to achieve using tabular models.

How OLAP Works?

Fundamentally, OLAP has a very simple concept. It pre-calculates most of the queries that are typically very hard to execute over tabular databases, namely aggregation, joining, and grouping. These queries are calculated during a process that is usually called 'building' or 'processing' of the OLAP cube. This process happens overnight, and by the time end users get to work - data will have been updated.

OLAP Guidelines (Dr.E.F.Codd Rule)

Dr E.F. Codd, the "father" of the relational model, has formulated a list of 12 guidelines and requirements as the basis for selecting OLAP systems:

1) Multidimensional Conceptual View: This is the central features of an OLAP system. By needing a multidimensional view, it is possible to carry out methods like slice and dice.

2) Transparency: Make the technology, underlying information repository, computing operations, and the dissimilar nature of source data totally transparent to users. Such transparency helps to improve the efficiency and productivity of the users.

3) Accessibility: It provides access only to the data that is actually required to perform the particular analysis, present a single, coherent, and consistent view to the clients. The OLAP system must map its own logical schema to the heterogeneous physical data stores and perform any necessary transformations. The OLAP operations should be sitting between data sources (e.g., data warehouses) and an OLAP front-end.

4) Consistent Reporting Performance: To make sure that the users do not feel any significant degradation in documenting performance as the number of dimensions or the size of the database increases. That is, the performance of OLAP should not suffer as the number of dimensions is increased. Users must observe consistent run time, response time, or machine utilization every time a given query is run.

5) Client/Server Architecture: Make the server component of OLAP tools sufficiently intelligent that the various clients to be attached with a minimum of effort and integration programming. The server should be capable of mapping and consolidating data between dissimilar databases.

6) Generic Dimensionality: An OLAP method should treat each dimension as equivalent in both is structure and operational capabilities. Additional operational capabilities may be allowed to selected dimensions, but such additional tasks should be grantable to any dimension.

7) Dynamic Sparse Matrix Handling: To adapt the physical schema to the specific analytical model being created and loaded that optimizes sparse matrix handling. When encountering the sparse matrix, the system must be easy to dynamically assume the distribution of the information and adjust the storage and access to obtain and maintain a consistent level of performance.

8) Multiuser Support: OLAP tools must provide concurrent data access, data integrity, and access security.

9) Unrestricted cross-dimensional Operations: It provides the ability for the methods to identify dimensional order and necessarily functions roll-up and drill-down methods within a dimension or across the dimension.

10) Intuitive Data Manipulation: Data Manipulation fundamental the consolidation direction like as reorientation (pivoting), drill-down and roll-up, and another manipulation to be accomplished naturally and precisely via point-and-click and drag and drop methods on the cells of the scientific model. It avoids the use of a menu or multiple trips to a user interface.

11) Flexible Reporting: It implements efficiency to the business clients to organize columns, rows, and cells in a manner that facilitates simple manipulation, analysis, and synthesis of data.

12) Unlimited Dimensions and Aggregation Levels: The number of data dimensions should be unlimited. Each of these common dimensions must allow a practically unlimited number of customer-defined aggregation levels within any given consolidation path.

OLAM

OLAM stands for Online analytical mining. It is also known as OLAP Mining. It integrates online analytical processing with data mining and mining knowledge in multi-dimensional databases. There are several paradigms and structures of data mining systems.

Various data mining tools must work on integrated, consistent, and cleaned data. This requires costly pre-processing for data cleaning, data transformation, and data integration. Thus, a data warehouse constructed by such pre-processing is a valuable source of high-quality information for both OLAP and data mining. Data mining can serve as a valuable tool for data cleaning and data integration.

OLAM is particularly important for the following reasons which are as follows −

High quality of data in data warehouses − Most data mining tools are required to work on integrated, consistent, and cleaned information, which needs costly data cleaning, data integration, and data transformation as a pre-processing phase. A data warehouse constructed by such pre-processing serves as a valuable source of high-quality data for OLAP and data mining. Data mining can also serve as a valuable tool for data cleaning and data integration.

Available information processing infrastructure surrounding data warehouses − Comprehensive data processing and data analysis infrastructures have been or will be orderly constructed surrounding data warehouses, which contains accessing, integration, consolidation, and transformation of various heterogeneous databases, ODBC/OLE DB connections, Web-accessing and service facilities, and documenting and OLAP analysis tools. It is careful to create the best use of the available infrastructures instead of constructing everything from scratch.

OLAP-based exploratory data analysis − Effective data mining required exploratory data analysis. A user will be required to traverse through a database, select areas of relevant information, analyze them at multiple granularities, and display knowledge/results in multiple forms.

Online analytical mining supports facilities for data mining on multiple subsets of data and at several levels of abstraction, by drilling, pivoting, filtering, dicing, and slicing on a data cube and some intermediate data mining outcomes.

On-line selection of data mining functions − It supports a user who cannot understand what type of knowledge they would like to mine. By integrating OLAP with various data mining functions, online analytical mining provides users with the flexibility to choose desired data mining functions and swap data mining tasks dynamically.