Chapter-1

1.1 What Is Data Mining?

Data mining refers to extracting or mining knowledge from large amountsof data. The term is actually a misnomer. Thus, data miningshould have been more appropriately named as knowledge mining which emphasis on mining from large amounts of data.

It is the computational process of discovering patterns in large data sets involving methods at the intersection of artificial intelligence, machine learning, statistics, and database systems.
The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use.

The key properties of data mining are

- Automatic discovery of patterns
- Prediction of likely outcomes
- Creation of actionable information
- Focus on large datasets and databases

1.2 The Scope of Data Mining

Data mining derives its name from the similarities between searching for valuable business information in a large database — for example, finding linked products in gigabytes of store scanner data — and mining a mountain for a vein of valuable ore. Both processes require either sifting through an immense amount of material, or intelligently probing it to find exactly where the value resides. Given databases of sufficient size and quality, data mining technology can generate new business opportunities by providing these capabilities:

Automated prediction of trends and behaviors. Data mining automates the process of finding predictive information in large databases. Questions that traditionally required extensive hands-on analysis can now be answered directly from the data — quickly. A typical example of a predictive problem is targeted marketing. Data mining uses data on past promotional mailings to identify the targets most likely to maximize return on investment in future mailings. Other predictive problems include forecasting bankruptcy and other forms of default, and identifying segments of a population likely to respond similarly to given events.

Automated discovery of previously unknown patterns. Data mining tools sweep through databases and identify previously hidden patterns in one step. An example of pattern discovery is the analysis of retail sales data to identify seemingly unrelated products that are often purchased together. Other pattern discovery problems include detecting fraudulent credit card transactions and identifying anomalous data that could represent data entry keying errors.

1.3 Tasks of Data Mining

Data mining involves six common classes of tasks:

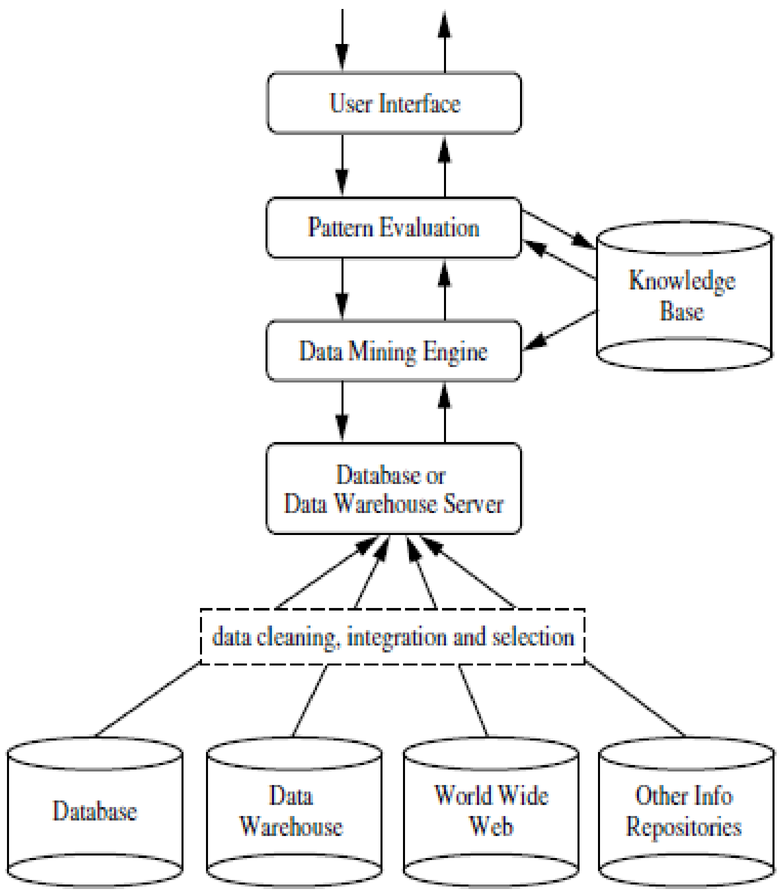
- **Anomaly detection (Outlier/change/deviation detection)** – The identification of unusual data records, that might be interesting or data errors that require further investigation.
- **Association rule learning (Dependency modelling)** – Searches for relationships between variables. For example a supermarket might gather data on customer purchasing habits. Using association rule learning, the supermarket can determine which products are frequently bought together and use this information for marketing purposes. This is sometimes referred to as market basket analysis.
- **Clustering** – is the task of discovering groups and structures in the data that are in some way or another "similar", without using known structures in the data.

- **Classification** – is the task of generalizing known structure to apply to new data. For example, an e-mail program might attempt to classify an e-mail as "legitimate" or as "spam".
- **Regression** – attempts to find a function which models the data with the least error.

- **Summarization** – providing a more compact representation of the data set, including visualization and report generation.

1.4 Architecture of Data Mining

A typical data mining system may have the following major components.



1. **Knowledge Base:**

   This is the domain knowledge that is used to guide the search orevaluate the interestingness of resulting patterns. Such knowledge can include concepthierarchies, used to organize attributes or attribute values into different levels of abstraction. Knowledge such as user beliefs, which can be used to assess a pattern's interestingness based on its unexpectedness, may also be included. Other examples of domain knowledge are additional interestingness constraints or thresholds, and metadata (e.g., describing data from multiple heterogeneous sources).

2. **Data Mining Engine:**

This is essential to the data mining systemand ideally consists ofa set of functional modules for tasks such as characterization, association and correlationanalysis, classification, prediction, cluster analysis, outlier analysis, and evolutionanalysis.

3. **Pattern Evaluation Module:**

This component typically employs interestingness measures interacts with the data mining modules so as to focus thesearch toward interesting patterns. It may use interestingness thresholds to filterout discovered patterns. Alternatively, the pattern evaluation module may be integratedwith the mining module, depending on the implementation of the datamining method used. For efficient data mining, it is highly recommended to pushthe evaluation of pattern interestingness as deep as possible into the mining processso as to confine the search to only the interesting patterns.

4. **User interface:**

Thismodule communicates between users and the data mining system,allowing the user to interact with the system by specifying a data mining query ortask, providing information to help focus the search, and performing exploratory datamining based on the intermediate data mining results. In addition, this componentallows the user to browse database and data warehouse schemas or data structures,evaluate mined patterns, and visualize the patterns in different forms.

1.5 Data Mining Process:

Data Mining is a process of discovering various models, summaries, and derived values from a given collection of data.

The general experimental procedure adapted to data-mining problems involves the following steps:

1. State the problem and formulate the hypothesis

Most data-based modeling studies are performed in a particular application domain. Hence, domain-specific knowledge and experience are usually necessary in order to come up with a meaningful problem statement. Unfortunately, many application studies tend to focus on the data-mining technique at the expense of a clear problem statement. In this step, a modeler usually specifies a set of variables for the unknown dependency and, if possible, a general form of this dependency as an initial hypothesis. There may be several hypotheses formulated for a single problem at this stage. The first step requires the combined expertise of an application domain and a data-mining model. In practice, it usually means a close interaction between the data-mining expert and the application expert. In successful data-mining applications, this cooperation does not stop in the initial phase; it continues during the entire data-mining process.

2. Collect the data

This step is concerned with how the data are generated and collected. In general, there are two distinct possibilities. The first is when the data-generation process is under the control of an expert (modeler): this approach is known as a designed experiment. The second possibility is when the expert cannot influence the data- generation process: this is known as the observational approach. An observational setting, namely, random data generation, is assumed in most data-mining applications. Typically, the sampling distribution is completely unknown after data are collected, or it is partially and implicitly given in the data-collection procedure. It is very important, however, to understand how data collection affects its theoretical distribution, since such a priori knowledge can be very useful for modeling and, later, for the final interpretation of results. Also, it is important to make sure that the data used for estimating a model and the data used later for testing and applying a model come from the same, unknown, sampling distribution. If this is not the case, the estimated model cannot be successfully used in a final application of the results.

3. Preprocessing the data

In the observational setting, data are usually "collected" from the existing databses, data warehouses, and data marts. Data preprocessing usually includes at least two common tasks:

1. **Outlier detection (and removal)** – Outliers are unusual data values that are not consistent with most observations. Commonly, outliers result from measurement errors, coding and recording errors, and, sometimes, are natural, abnormal values. Such nonrepresentative samples can seriously affect the model produced later. There are two strategies for dealing with outliers:

a. Detect and eventually remove outliers as a part of the preprocessing phase, or
b. Develop robust modeling methods that are insensitive to outliers.

2. Scaling, encoding, and selecting features – Data preprocessing includes several steps such as variable scaling and different types of encoding. For example, one feature with the range [0, 1] and the other with the range [−100, 1000] will not have the same weights in the applied technique; they will also influence the final data-mining results differently. Therefore, it is recommended to scale them and bring both features to the same weight for further analysis. Also, application-specific encoding methods usually achieve dimensionality reduction by providing a smaller number of informative features for subsequent data modeling.

These two classes of preprocessing tasks are only illustrative examples of a large spectrum of preprocessing activities in a data-mining process.

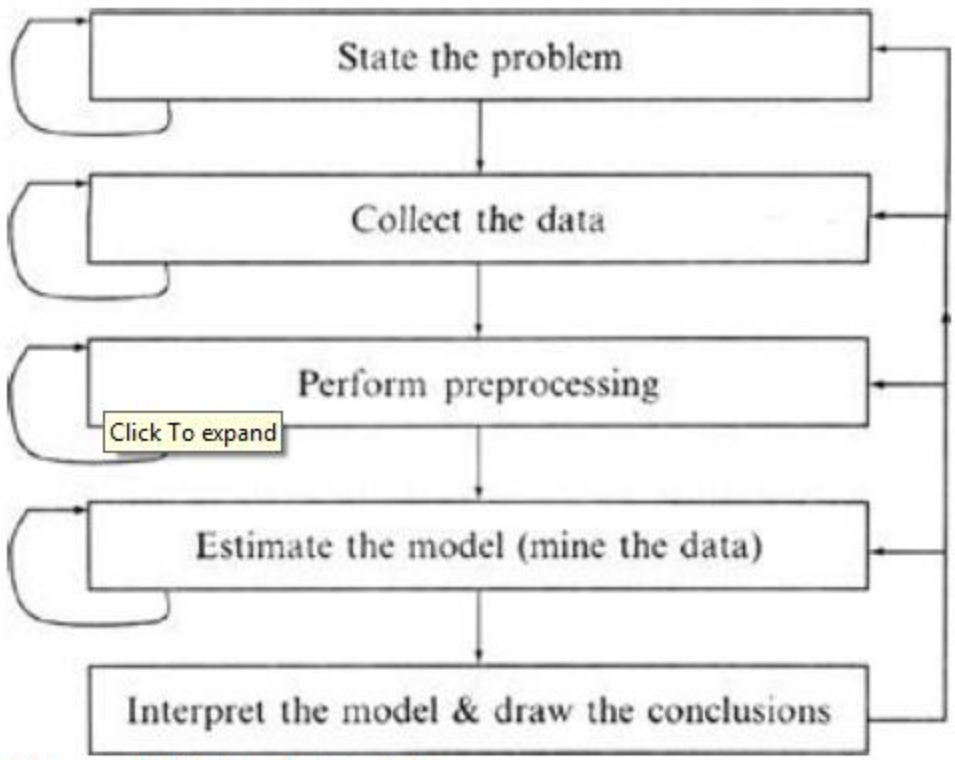
Data-preprocessing steps should not be considered completely independent from other data-mining phases. In every iteration of the data-mining process, all activities, together, could define new and improved data sets for subsequent iterations. Generally, a good preprocessing method provides an optimal representation for a data-mining technique by incorporating a priori knowledge in the form of application-specific scaling and encoding.

4. Estimate the model

The selection and implementation of the appropriate data-mining technique is the main task in this phase. This process is not straightforward; usually, in practice, the implementation is based on several models, and selecting the best one is an additional task. The basic principles of learning and discovery from data are given in Chapter 4 of this book. Later, Chapter 5 through 13 explain and analyze specific techniques that are applied to perform a successful learning process from data and to develop an appropriate model.

5. Interpret the model and draw conclusions

In most cases, data-mining models should help in decision making. Hence, such models need to be interpretable in order to be useful because humans are not likely to base their decisions on complex "black-box" models. Note that the goals of accuracy of the model and accuracy of its interpretation are somewhat contradictory. Usually, simple models are more interpretable, but they are also less accurate. Modern data-mining methods are expected to yield highly accurate results using highdimensional models. The problem of interpreting these models, also very important, is considered a separate task, with specific techniques to validate the results. A user does not want hundreds of pages of numeric results. He does not understand them; he cannot summarize, interpret, and use them for successful decision making.



The Data mining Process

1.6 Classification of Data mining Systems:

The data mining system can be classified according to the following criteria:

- Database Technology
- Statistics
- Machine Learning
- Information Science
- Visualization
- Other Disciplines

Some Other Classification Criteria:

- Classification according to kind of databases mined
- Classification according to kind of knowledge mined
- Classification according to kinds of techniques utilized
- Classification according to applications adapted

Classification according to kind of databases mined

We can classify the data mining system according to kind of databases mined. Database system can be classified according to different criteria such as data models, types of data etc. And the data mining system can be classified accordingly. For example if we classify the database according to data model then we may have a relational, transactional, object- relational, or data warehouse mining system.

Classification according to kind of knowledge mined

We can classify the data mining system according to kind of knowledge mined. It is means data mining system are classified on the basis of functionalities such as:

- Characterization
- Discrimination
- Association and Correlation Analysis
- Classification
- Prediction
- Clustering
- Outlier Analysis
- Evolution Analysis

Classification according to kinds of techniques utilized

We can classify the data mining system according to kind of techniques used. We can describes these techniques according to degree of user interaction involved or the methods of analysis employed.

Classification according to applications adapted

We can classify the data mining system according to application adapted. These applications are as follows:

- Finance
- Telecommunications
- DNA
- Stock Markets
- E-mail

1.7 Major Issues In Data Mining:

•**Mining different kinds of knowledge in databases.** - The need of different users is not the same. And Different user may be in interested in different kind of knowledge. Therefore it is necessary for data mining to cover broad range of knowledge discovery task.

•**Interactive mining of knowledge at multiple levels of abstraction.** - The data mining process needs to be interactive because it allows users to focus the search for patterns, providing and refining data mining requests based on returned results.

•**Incorporation of background knowledge.** - To guide discovery process and to express the discovered patterns, the background knowledge can be used. Background knowledge may be used to express the discovered patterns not only in concise terms but at multiple level of abstraction.

- **Data mining query languages and ad hoc data mining.** - Data Mining Query language that allows the user to describe ad hoc mining tasks, should be integrated with a data warehouse query language and optimized for efficient and flexible data mining.

- **Presentation and visualization of data mining results.** - Once the patterns are discovered it needs to be expressed in high level languages, visual representations. This representations should be easily understandable by the users.

- **Handling noisy or incomplete data.** - The data cleaning methods are required that can handle the noise, incomplete objects while mining the data regularities. If data cleaning methods are not there then the accuracy of the discovered patterns will be poor.

- **Pattern evaluation.** - It refers to interestingness of the problem. The patterns discovered should be interesting because either they represent common knowledge or lack novelty.

- **Efficiency and scalability of data mining algorithms.** - In order to effectively extract the information from huge amount of data in databases, data mining algorithm must be efficient and scalable.

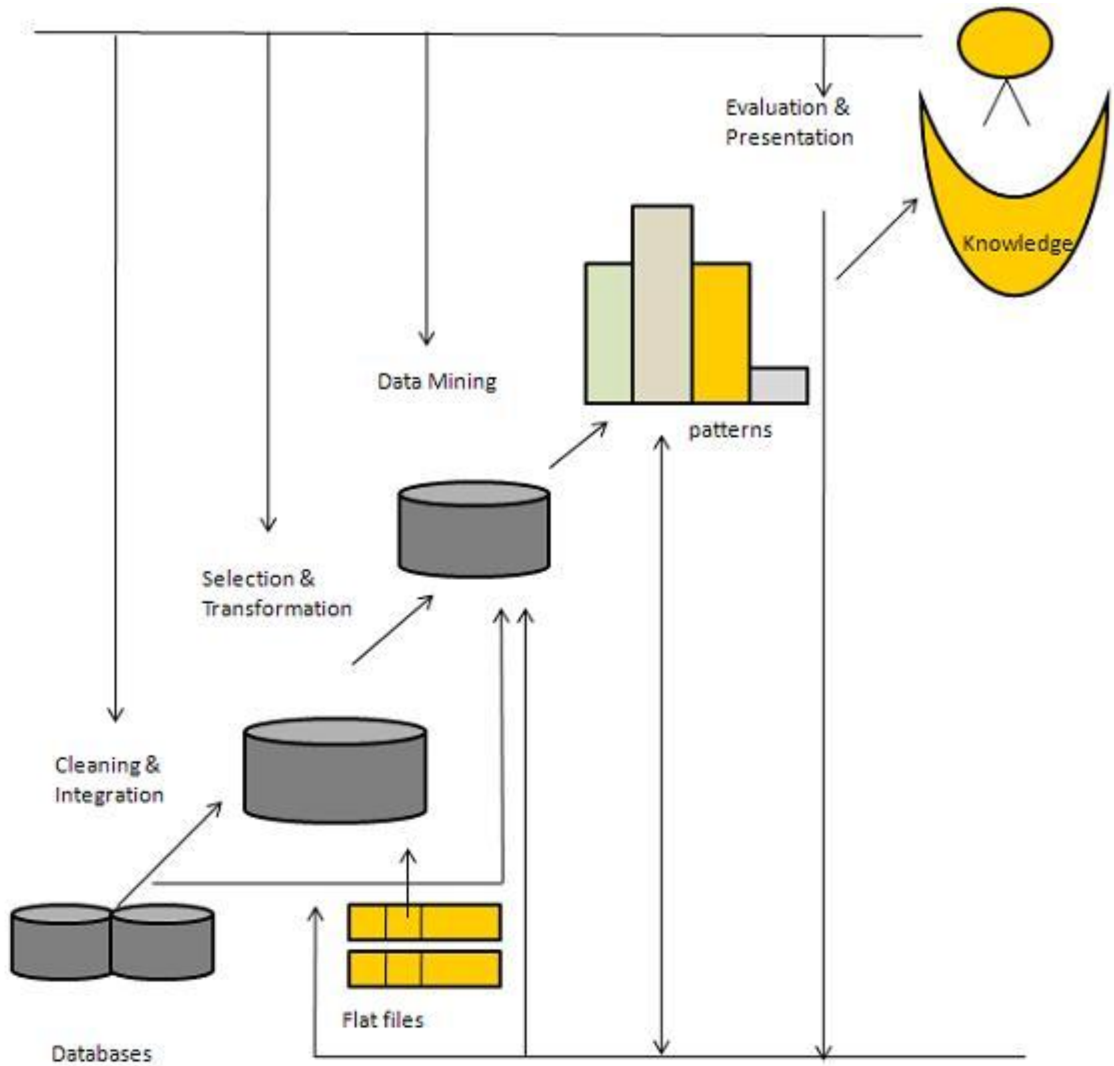
- **Parallel, distributed, and incremental mining algorithms.** - The factors such as huge size of databases, wide distribution of data,and complexity of data mining methods motivate the development of parallel and distributed data mining algorithms. These algorithm divide the data into partitions which is further processed parallel. Then the results from the partitions is merged. The incremental algorithms, updates databases without having mine the data again from scratch.

1.8 Knowledge Discovery in Databases(KDD)

Some people treat data mining same as Knowledge discovery while some people view data mining essential step in process of knowledge discovery. Here is the list of steps involved in knowledge discovery process:

- **Data Cleaning** - In this step the noise and inconsistent data is removed.
- **Data Integration** - In this step multiple data sources are combined.
- **Data Selection** - In this step relevant to the analysis task are retrieved from the database.
- **Data Transformation** - In this step data are transformed or consolidated into forms appropriate for mining by performing summary or aggregation operations.
- **Data Mining** - In this step intelligent methods are applied in order to extract data patterns.
- **Pattern Evaluation** - In this step, data patterns are evaluated.
- **Knowledge Presentation** - In this step,knowledge is represented.

The following diagram shows the process of knowledge discovery process:



Architecture of KDD

1.9 Data Warehouse:

A data warehouse is a subject-oriented, integrated, time-variant and non-volatile collection of data in support of management's decision making process.

Subject-Oriented: A data warehouse can be used to analyze a particular subject area. For example, "sales" can be a particular subject.

Integrated: A data warehouse integrates data from multiple data sources. For example, source A and source B may have different ways of identifying a product, but in a data warehouse, there will be only a single way of identifying a product.

Time-Variant: Historical data is kept in a data warehouse. For example, one can retrieve data from 3 months, 6 months, 12 months, or even older data from a data warehouse. This contrasts with a transactions system, where often only the most recent data is kept. For example, a transaction system may hold the most recent address of a customer, where a data warehouse can hold all addresses associated with a customer.

Non-volatile: Once data is in the data warehouse, it will not change. So, historical data in a data warehouse should never be altered.

1.9.1 Data Warehouse Design Process:

A data warehouse can be built using a *top-down approach*, a *bottom-up approach*, or a *combination of both*.

- The top-down approach starts with the overall design and planning. It is useful in cases where the technology is mature and well known, and where the business problems that must be solved are clear and well understood.

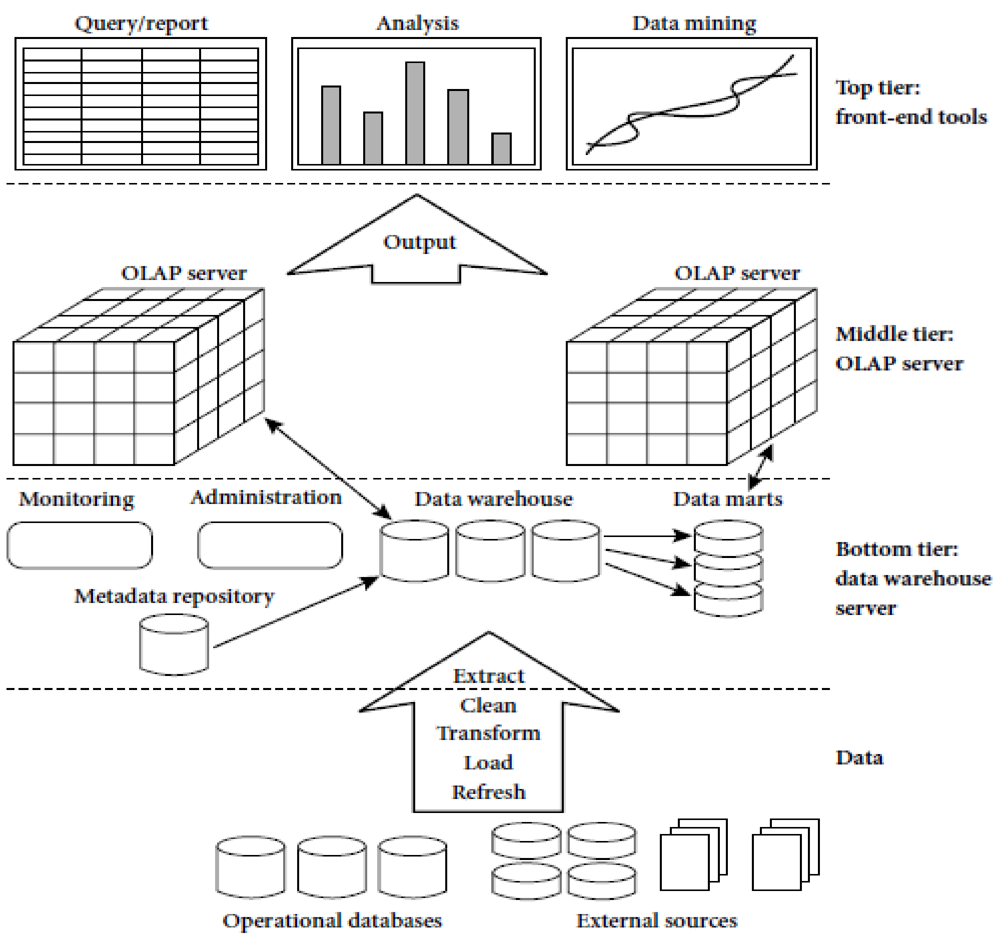
- The bottom-up approach starts with experiments and prototypes. This is useful in the early stage of business modeling and technology development. It allows an organization to move forward at considerably less expense and to evaluate the benefits of the technology before making significant commitments.

- In the combined approach, an organization can exploit the planned and strategic nature of the top-down approach while retaining the rapid implementation and opportunistic application of the bottom-up approach.

The warehouse design process consists of the following steps:

- Choose a business process to model, for example, orders, invoices, shipments, inventory, account administration, sales, or the general ledger. If the business process is organizational and involves multiple complex object collections, a data warehouse model should be followed. However, if the process is departmental and focuses on the analysis of one kind of business process, a data mart model should be chosen.
- Choose the grain of the business process. The grain is the fundamental, atomic level of data to be represented in the fact table for this process, for example, individual transactions, individual daily snapshots, and so on.
- Choose the dimensions that will apply to each fact table record. Typical dimensions are time, item, customer, supplier, warehouse, transaction type, and status.
- Choose the measures that will populate each fact table record. Typical measures are numeric additive quantities like dollars sold and units sold.

1.9.2 A Three Tier Data Warehouse Architecture:



Tier-1:

The bottom tier is a warehouse database server that is almost always a relationaldatabase system. Back-end tools and utilities are used to feed data into the bottomtier from operational databases or other external sources (such as customer profileinformation provided by external consultants). These tools and utilities performdataextraction, cleaning, and transformation (e.g., to merge similar data from differentsources into a unified format), as well as load and refresh functions to update thedata warehouse . The data are extracted using application programinterfaces known as gateways. A gateway is supported by the underlying DBMS andallows client programs to generate SQL code to be executed at a server.

Examplesof gateways include ODBC (Open Database Connection) and OLEDB (Open Linkingand Embedding for Databases) by Microsoft and JDBC (Java Database Connection).

This tier also contains a metadata repository, which stores information aboutthe data warehouse and its contents.

Tier-2:

The middle tier is an OLAP server that is typically implemented using either a relational OLAP (ROLAP) model or a multidimensional OLAP.

- OLAP model is an extended relational DBMS thatmaps operations on multidimensional data to standard relational operations.
- A multidimensional OLAP (MOLAP) model, that is, a special-purpose server that directly implements multidimensional data and operations.

Tier-3:

The top tier is a front-end client layer, which contains query and reporting tools, analysis tools, and/or data mining tools (e.g., trend analysis, prediction, and so on).

1.9.3 Data Warehouse Models:

There are three data warehouse models.

1. Enterprise warehouse:

- An enterprise warehouse collects all of the information about subjects spanning the entire organization.
- It provides corporate-wide data integration, usually from one or more operational systems or external information providers, and is cross-functional in scope.
- It typically contains detailed data aswell as summarized data, and can range in size from a few gigabytes to hundreds of gigabytes, terabytes, or beyond.
- An enterprise data warehouse may be implemented on traditional mainframes, computer superservers, or parallel architecture platforms. It requires extensive business modeling and may take years to design and build.

2. Data mart:

- A data mart contains a subset of corporate-wide data that is of value to aspecific group of users. The scope is confined to specific selected subjects. For example,a marketing data mart may confine its subjects to customer, item, and sales. Thedata contained in data marts tend to be summarized.

- Data marts are usually implemented on low-cost departmental servers that areUNIX/LINUX- or Windows-based. The implementation cycle of a data mart ismore likely to be measured in weeks rather than months or years. However, itmay involve complex integration in the long run if its design and planning werenot enterprise-wide.

- Depending on the source of data, data marts can be categorized as independent ordependent. Independent data marts are sourced fromdata captured fromone or moreoperational systems or external information providers, or fromdata generated locallywithin a particular department or geographic area. Dependent data marts are sourceddirectly from enterprise data warehouses.

3. Virtual warehouse:

- A virtual warehouse is a set of views over operational databases. Forefficient query processing, only some of the possible summary views may be materialized.
- A virtual warehouse is easy to build but requires excess capacity on operational database servers.

1.9.4 Meta Data Repository:

Metadata are data about data.When used in a data warehouse, metadata are the data thatdefine warehouse objects. Metadata are created for the data names anddefinitions of the given warehouse. Additional metadata are created and captured fortimestamping any extracted data, the source of the extracted data, and missing fieldsthat have been added by data cleaning or integration processes.

A metadata repository should contain the following:

- A description of the structure of the data warehouse, which includes the warehouse schema, view, dimensions, hierarchies, and derived data definitions, as well as data mart locations and contents.

- Operational metadata, which include data lineage (history of migrated data and the sequence of transformations applied to it), currency of data (active, archived, or purged), and monitoring information (warehouse usage statistics, error reports, and audit trails).

- The algorithms used for summarization, which include measure and dimension definitionalgorithms, data on granularity, partitions, subject areas, aggregation, summarization,and predefined queries and reports.

- The mapping from the operational environment to the data warehouse, which includessource databases and their contents, gateway descriptions, data partitions, data extraction, cleaning, transformation rules and defaults, data refresh and purging rules, andsecurity (user authorization and access control).

- Data related to system performance, which include indices and profiles that improvedata access and retrieval performance, in addition to rules for the timing and scheduling of refresh, update, and replication cycles.

- Business metadata, which include business terms and definitions, data ownershipinformation, and charging policies.

1.10 OLAP(Online analytical Processing):

- OLAP is an approach to answering multi-dimensional analytical (MDA) queries swiftly.
- OLAP is part of the broader category of business intelligence, which also encompasses relational database, report writing and data mining.
- OLAP tools enable users to analyze multidimensional data interactively from multiple perspectives.

OLAP consists of three basic analytical operations:

- Consolidation (Roll-Up)
- Drill-Down

- Slicing And Dicing

- Consolidation involves the aggregation of data that can be accumulated and computed in one or more dimensions. For example, all sales offices are rolled up to the sales department or sales division to anticipate sales trends.

- The drill-down is a technique that allows users to navigate through the details. For instance, users can view the sales by individual products that make up a region's sales.

- Slicing and dicing is a feature whereby users can take out (slicing) a specific set of data of the OLAP cube and view (dicing) the slices from different viewpoints.

1.10.1 Types of OLAP:

1. Relational OLAP (ROLAP):

- ROLAP works directly with relational databases. The base data and the dimension tables are stored as relational tables and new tables are created to hold the aggregated information. It depends on a specialized schema design.
- This methodology relies on manipulating the data stored in the relational database to give the appearance of traditional OLAP's slicing and dicing functionality. In essence, each action of slicing and dicing is equivalent to adding a "WHERE" clause in the SQL statement.
- ROLAP tools do not use pre-calculated data cubes but instead pose the query to the standard relational database and its tables in order to bring back the data required to answer the question.
- ROLAP tools feature the ability to ask any question because the methodology does not limit to the contents of a cube. ROLAP also has the ability to drill down to the lowest level of detail in the database.

2. Multidimensional OLAP (MOLAP):

- MOLAP is the 'classic' form of OLAP and is sometimes referred to as just OLAP.

- MOLAP stores this data in an optimized multi-dimensional array storage, rather than in a relational database. Therefore it requires the pre-computation and storage of information in the cube - the operation known as processing.

- MOLAP tools generally utilize a pre-calculated data set referred to as a data cube. The data cube contains all the possible answers to a given range of questions.

- MOLAP tools have a very fast response time and the ability to quickly write back data into the data set.

3. Hybrid OLAP (HOLAP):

- There is no clear agreement across the industry as to what constitutes Hybrid OLAP, except that a database will divide data between relational and specialized storage.
- For example, for some vendors, a HOLAP database will use relational tables to hold the larger quantities of detailed data, and use specialized storage for at least some aspects of the smaller quantities of more-aggregate or less-detailed data.
- HOLAP addresses the shortcomings of MOLAP and ROLAP by combining the capabilities of both approaches.
- HOLAP tools can utilize both pre-calculated cubes and relational data sources.

1.11 Data Preprocessing:

1.11.1 Data Integration:

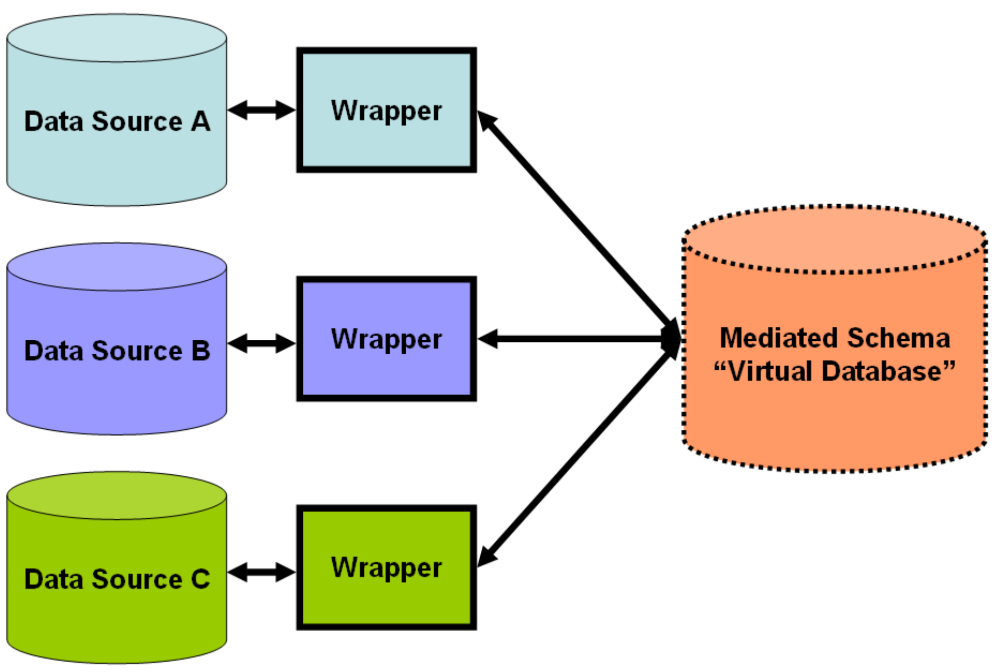
It combines datafrom multiple sources into a coherent data store, as in data warehousing. These sourcesmay include multiple databases, data cubes, or flat files.

The data integration systems are formally defined as triple<G,S,M>

Where G: The global schema

S:Heterogeneous source of schemas

M: Mapping between the queries of source and global schema



1.11.2 Issues in Data integration:

1. **Schema integration and object matching:**

   How can the data analyst or the computer be sure that customer id in one database and customer number in another reference to the same attribute.

2. **Redundancy:**

   An attribute (such as annual revenue, forinstance) may be redundant if it can be derived from another attribute or set ofattributes. Inconsistencies in attribute or dimension naming can also cause redundanciesin the resulting data set.

3. **detection and resolution of datavalue conflicts:**

   For the same real-world entity, attribute values fromdifferent sources may differ.

1.11.3 Data Transformation:

In data transformation, the data are transformed or consolidated into forms appropriatefor mining.

Data transformation can involve the following:

- **Smoothing**, which works to remove noise from the data. Such techniques includebinning, regression, and clustering.
- **Aggregation**, where summary or aggregation operations are applied to the data. For example, the daily sales data may be aggregated so as to compute monthly and annualtotal amounts. This step is typically used in constructing a data cube for analysis of the data at multiple granularities.

- **Generalization of the data**, where low-level or “primitive” (raw) data are replaced byhigher-level concepts through the use of concept hierarchies. For example, categoricalattributes, like street, can be generalized to higher-level concepts, like city or country.
- **Normalization**, where the attribute data are scaled so as to fall within a small specifiedrange, such as 1:0 to 1:0, or 0:0 to 1:0.
- **Attribute construction** (or feature construction),wherenewattributes are constructedand added from the given set of attributes to help the mining process.

1.11.4 Data Reduction:

Data reduction techniques can be applied to obtain a reduced representation of thedata set that ismuch smaller in volume, yet closely maintains the integrity of the originaldata. That is, mining on the reduced data set should be more efficient yet produce thesame (or almost the same) analytical results.

Strategies for data reduction include the following:

- **Data cube aggregation**, where aggregation operations are applied to the data in theconstruction of a data cube.
- **Attribute subset selection**, where irrelevant, weakly relevant, or redundant attributesor dimensions may be detected and removed.
- **Dimensionality reduction**, where encoding mechanisms are used to reduce the dataset size.
- **Numerosityreduction**,where the data are replaced or estimated by alternative, smallerdata representations such as parametric models (which need store only the modelparameters instead of the actual data) or nonparametric methods such as clustering,sampling, and the use of histograms.
- **Discretization and concept hierarchy generation**,where rawdata values for attributesare replaced by ranges or higher conceptual levels. Data discretization is a form ofnumerosity reduction that is very useful for the automatic generation of concept hierarchies.Discretization and concept hierarchy generation are powerful tools for datamining, in that they allow the mining of data at multiple levels of abstraction.

Chapter-2

2.1 Association Rule Mining:

- Association rule mining is a popular and well researched method for discovering interesting relations between variables in large databases.
- It is intended to identify strong rules discovered in databases using different measures of interestingness.
- Based on the concept of strong rules, RakeshAgrawal et al. introduced association rules.

Problem Definition:

The problem of association rule mining is defined as:

Let $I = \{i_1, i_2, \ldots, i_n\}$ be a set of n binary attributes called *items*.

Let $D = \{t_1, t_2, \ldots, t_m\}$ be a set of transactions called the *database*.

Each transaction in D has a unique transaction ID and contains a subset of the items in I.

A *rule* is defined as an implication of the form $X \Rightarrow Y$

where $X, Y \subseteq I$ and $X \cap Y = \emptyset$.

The sets of items (for short *itemsets*) X and Y are called *antecedent* (left-hand-side or LHS) and *consequent* (right-hand-side or RHS) of the rule respectively.

Example:

To illustrate the concepts, we use a small example from the supermarket domain. The set of items is $I = \{\mathrm{milk}, \mathrm{bread}, \mathrm{butter}, \mathrm{beer}\}$ and a small database containing the items (1 codes presence and 0 absence of an item in a transaction) is shown in the table.

An example rule for the supermarket could be $\{\mathrm{butter}, \mathrm{bread}\} \Rightarrow \{\mathrm{milk}\}$ meaning that if butter and bread are bought, customers also buy milk.

Example database with 4 items and 5 transactions

Transaction ID	milk	bread	butter	beer
1	1	1	0	0
2	0	0	1	0
3	0	0	0	1
4	1	1	1	0
5	0	1	0	0

2.1.1 Important concepts of Association Rule Mining:

- The **support** $\mathrm{supp}(X)$ of an itemset X is defined as the proportion of transactions in the data set which contain the itemset. In the example database, the itemset $\{\mathrm{milk}, \mathrm{bread}, \mathrm{butter}\}$ has a support of $1/5 = 0.2$ since it occurs in 20% of all transactions (1 out of 5 transactions).

- The **confidence** of a rule is defined

  $$\mathrm{conf}(X \Rightarrow Y) = \mathrm{supp}(X \cup Y)/\mathrm{supp}(X).$$

  For example, the rule $\{\mathrm{butter}, \mathrm{bread}\} \Rightarrow \{\mathrm{milk}\}$ has a confidence of $0.2/0.2 = 1.0$ in the database, which means that for 100% of the transactions containing butter and bread the rule is correct (100% of the times a customer buys butter and bread, milk is bought as well). Confidence can be interpreted as an estimate of the probability $P(Y|X)$, the probability of finding the RHS of the rule in transactions under the condition that these transactions also contain the LHS.

- The ***lift*** of a rule is defined as

$$\mathrm{lift}(X \Rightarrow Y) = \frac{\mathrm{supp}(X \cup Y)}{\mathrm{supp}(X) \times \mathrm{supp}(Y)}$$

or the ratio of the observed support to that expected if X and Y were independent. The rule $\{\mathrm{milk, bread}\} \Rightarrow \{\mathrm{butter}\}$ has a lift of $\frac{0.2}{0.4 \times 0.4} = 1.25$.

- The **conviction** of a rule is defined as

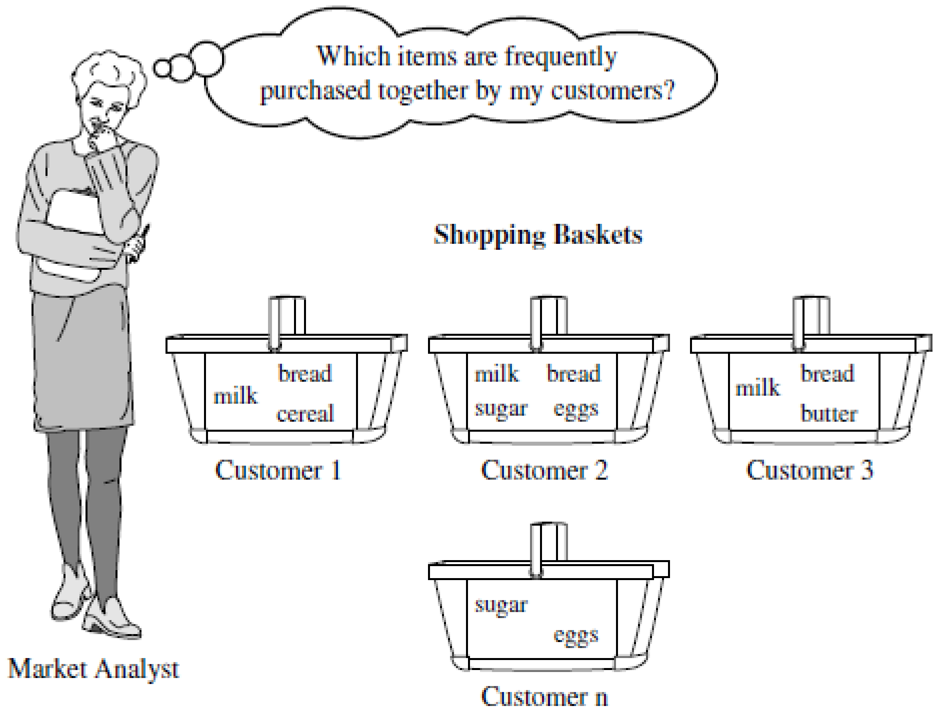
$$\mathrm{conv}(X \Rightarrow Y) = \frac{1 - \mathrm{supp}(Y)}{1 - \mathrm{conf}(X \Rightarrow Y)}.$$

The rule $\{\mathrm{milk, bread}\} \Rightarrow \{\mathrm{butter}\}$ has a conviction of $\frac{1 - 0.4}{1 - .5} = 1.2$,

and can be interpreted as the ratio of the expected frequency that X occurs without Y (that is to say, the frequency that the rule makes an incorrect prediction) if X and Y were independent divided by the observed frequency of incorrect predictions.

2.2 Market basket analysis:

This processanalyzes customer buying habits by finding associations between the different items thatcustomers place in their shopping baskets. The discovery of such associationscan help retailers develop marketing strategies by gaining insight into which itemsare frequently purchased together by customers. For instance, if customers are buyingmilk, how likely are they to also buy bread (and what kind of bread) on the same trip to the supermarket. Such information can lead to increased sales by helping retailers doselective marketing and plan their shelf space.



Example:

If customers who purchase computers also tend to buy antivirussoftware at the same time, then placing the hardware display close to the software displaymay help increase the sales of both items. In an alternative strategy, placing hardware andsoftware at opposite ends of the store may entice customers who purchase such items topick up other items along the way. For instance, after deciding on an expensive computer,a customer may observe security systems for sale while heading toward the software displayto purchase antivirus software and may decide to purchase a home security systemas well. Market basket analysis can also help retailers plan which items to put on saleat reduced prices. If customers tend to purchase computers and printers together, thenhaving a sale on printers may encourage the sale of printers *as well as* computers.

2.3 Frequent Pattern Mining:

Frequent patternmining can be classified in various ways, based on the following criteria:

1. **Based on the completeness of patterns to be mined:**

- We can mine the complete set of frequent itemsets, the closed frequent itemsets, and the maximal frequent itemsets, given a minimum support threshold.
- We can also mine constrained frequent itemsets, approximate frequent itemsets,near-match frequent itemsets, top-k frequent itemsets and so on.

2. **Based on the levels of abstraction involved in the rule set:**

Some methods for associationrule mining can find rules at differing levels of abstraction.

For example, supposethat a set of association rules mined includes the following rules where X is a variablerepresenting a customer:

buys(X, “computer”))=>buys(X, “HP printer”) (1)

buys(*X*, “*laptop computer*”)) =>*buys*(*X*, “*HP printer*”) (2)

In rule (1) and (2), the items bought are referenced at different levels ofabstraction (e.g., “*computer*” is a higher-level abstraction of “*laptop computer*”).

3. **Based on the number of data dimensions involved in the rule:**

- If the items or attributes in an association rule reference only one dimension, then it is a single-dimensional association rule.
  buys(X, “computer”))=>buys(X, “antivirus software”)

- If a rule references two or more dimensions, such as the dimensions age, income, and buys, then it is amultidimensional association rule. The following rule is an exampleof a multidimensional rule:
  age(X, “30,31…39”) ^ income(X, “42K,…48K”))=>buys(X, “high resolution TV”)

4. **Based on the types of values handled in the rule:**
   - If a rule involves associations between the presence or absence of items, it is a Boolean association rule.
   - If a rule describes associations between quantitative items or attributes, then it is a quantitative association rule.

5. **Based on the kinds of rules to be mined:**
   - Frequent pattern analysis can generate various kinds of rules and other interesting relationships.
   - Association rule mining cangenerate a large number of rules, many of which are redundant or do not indicatea correlation relationship among itemsets.
   - The discovered associations can be further analyzed to uncover statistical correlations, leading to correlation rules.

6. **Based on the kinds of patterns to be mined:**
   - Many kinds of frequent patterns can be mined from different kinds of data sets.
   - Sequential pattern mining searches for frequent subsequences in a sequence data set, where a sequence records an ordering of events.
   - For example, with sequential pattern mining, we can study the order in which items are frequently purchased. For instance, customers may tend to first buy a PC, followed by a digitalcamera,and then a memory card.
   - Structuredpatternminingsearches for frequent substructuresin a structured data set.
   - Single items are the simplest form of structure.
   - Each element of an itemsetmay contain a subsequence, a subtree, and so on.
   - Therefore, structuredpattern mining can be considered as the most general formof frequent pattern mining.

2.4 Efficient Frequent Itemset Mining Methods:

2.4.1 Finding Frequent Itemsets Using Candidate Generation:The Apriori Algorithm

- Apriori is a seminal algorithm proposed by R. Agrawal and R. Srikant in 1994 for mining frequent itemsets for Boolean association rules.
- The name of the algorithm is based on the fact that the algorithm uses *prior knowledge* of frequent itemset properties.
- Apriori employs an iterative approach known as a *level-wise* search, where *k*-itemsets are used to explore (*k*+1)-itemsets.
- First, the set of frequent 1-itemsets is found by scanning the database to accumulate the count for each item, and collecting those items that satisfy minimum support. The resulting set is denoted *L*1.Next, *L*1 is used to find *L*2, the set of frequent 2-itemsets, which is used to find *L*3, and so on, until no more frequent *k*-itemsets can be found.
- The finding of each $L_k$requires one full scan of the database.
- A two-step process is followed in Aprioriconsisting of joinand prune action.

Algorithm: Apriori. Find frequent itemsets using an iterative level-wise approach based on candidate generation.

Input:

- D, a database of transactions;
- min_sup, the minimum support count threshold.

Output: L, frequent itemsets in D.

Method:

L_1 = find_frequent_1-itemsets(D);
for ($k = 2; L_{k-1} \neq \phi; k{+}{+}$) {
    C_k = apriori_gen(L_{k-1});
    for each transaction $t \in D$ { // scan D for counts
        C_t = subset(C_k, t); // get the subsets of t that are candidates
        for each candidate $c \in C_t$
            c.count++;
    }
    $L_k = \{c \in C_k | c.count \geq min\_sup\}$
}
return $L = \cup_k L_k$;

procedure apriori_gen(L_{k-1}:frequent ($k-1$)-itemsets)
for each itemset $l_1 \in L_{k-1}$
    for each itemset $l_2 \in L_{k-1}$
        if $(l_1[1] = l_2[1]) \wedge (l_1[2] = l_2[2]) \wedge \ldots \wedge (l_1[k-2] = l_2[k-2]) \wedge (l_1[k-1] < l_2[k-1])$ **then** {
            $c = l_1 \bowtie l_2$; // join step: generate candidates
            if has_infrequent_subset(c, L_{k-1}) **then**
                delete c; // prune step: remove unfruitful candidate
            else add c **to** C_k;
        }
return C_k;

procedure has_infrequent_subset(c: candidate k-itemset;
    L_{k-1}: frequent ($k-1$)-itemsets); // use prior knowledge
for each ($k-1$)-subset s **of** c
    if $s \notin L_{k-1}$ **then**
        return TRUE;
return FALSE;

Example:

TID	List of item IDs
T100	I1, I2, I5
T200	I2, I4
T300	I2, I3
T400	I1, I2, I4
T500	I1, I3
T600	I2, I3
T700	I1, I3
T800	I1, I2, I3, I5
T900	I1, I2, I3

There are nine transactions in this database, that is, |D| = 9.

Steps:

1. In the first iteration of the algorithm, each item is a member of the set of candidate1-itemsets, C1. The algorithm simply scans all of the transactions in order to countthe number of occurrences of each item.

2. Suppose that the minimum support count required is 2, that is, min sup = 2. The set of frequent 1-itemsets, L1, can thenbe determined. It consists of the candidate 1-itemsets satisfying minimum support.In our example, all of the candidates in C1 satisfy minimum support.

3. To discover the set of frequent 2-itemsets, L2, the algorithm uses the join L1 on L1 togenerate a candidate set of 2-itemsets, C2.No candidates are removed fromC2 during the prune step because each subset of thecandidates is also frequent.

4.Next, the transactions inDare scanned and the support count of each candidate itemsetInC2 is accumulated.

5. The set of frequent 2-itemsets, L2, is then determined, consisting of those candidate2-itemsets in C2 having minimum support.

6. The generation of the set of candidate 3-itemsets,C3, Fromthejoin step, we first getC3 =L2x L2 = ({I1, I2, I3}, {I1, I2, I5}, {I1, I3, I5}, {I2, I3, I4},{I2, I3, I5}, {I2, I4, I5}. Based on the Apriori property that all subsets of a frequentitemsetmust also be frequent, we can determine that the four latter candidates cannotpossibly be frequent.

7.The transactions in D are scanned in order to determine L3, consisting of those candidate 3-itemsets in C3 having minimum support.

8.The algorithm uses L3x L3 to generate a candidate set of 4-itemsets, C4.

Scan D for count of each candidate →

C_1

Itemset	Sup. count
{I1}	6
{I2}	7
{I3}	6
{I4}	2
{I5}	2

Compare candidate support count with minimum support count →

L_1

Itemset	Sup. count
{I1}	6
{I2}	7
{I3}	6
{I4}	2
{I5}	2

Generate C_2 candidates from L_1 →

C_2

Itemset
{I1, I2}
{I1, I3}
{I1, I4}
{I1, I5}
{I2, I3}
{I2, I4}
{I2, I5}
{I3, I4}
{I3, I5}
{I4, I5}

Scan D for count of each candidate →

C_2

Itemset	Sup. count
{I1, I2}	4
{I1, I3}	4
{I1, I4}	1
{I1, I5}	2
{I2, I3}	4
{I2, I4}	2
{I2, I5}	2
{I3, I4}	0
{I3, I5}	1
{I4, I5}	0

Compare candidate support count with minimum support count →

L_2

Itemset	Sup. count
{I1, I2}	4
{I1, I3}	4
{I1, I5}	2
{I2, I3}	4
{I2, I4}	2
{I2, I5}	2

Generate C_3 candidates from L_2 →

C_3

Itemset
{I1, I2, I3}
{I1, I2, I5}

Scan D for count of each candidate →

C_3

Itemset	Sup. count
{I1, I2, I3}	2
{I1, I2, I5}	2

Compare candidate support count with minimum support count →

L_3

Itemset	Sup. count
{I1, I2, I3}	2
{I1, I2, I5}	2

Generation of candidate itemsets and frequent itemsets, where the minimum support count is 2.

(a) Join: $C_3 = L_2 \bowtie L_2$ = {{I1, I2}, {I1, I3}, {I1, I5}, {I2, I3}, {I2, I4}, {I2, I5}} $\bowtie$ {{I1, I2}, {I1, I3}, {I1, I5}, {I2, I3}, {I2, I4}, {I2, I5}} = {{I1, I2, I3}, {I1, I2, I5}, {I1, I3, I5}, {I2, I3, I4}, {I2, I3, I5}, {I2, I4, I5}}.

(b) Prune using the Apriori property: All nonempty subsets of a frequent itemset must also be frequent. Do any of the candidates have a subset that is not frequent?

- The 2-item subsets of {I1, I2, I3} are {I1, I2}, {I1, I3}, and {I2, I3}. All 2-item subsets of {I1, I2, I3} are members of L_2. Therefore, keep {I1, I2, I3} in C_3.
- The 2-item subsets of {I1, I2, I5} are {I1, I2}, {I1, I5}, and {I2, I5}. All 2-item subsets of {I1, I2, I5} are members of L_2. Therefore, keep {I1, I2, I5} in C_3.
- The 2-item subsets of {I1, I3, I5} are {I1, I3}, {I1, I5}, and {I3, I5}. {I3, I5} is not a member of L_2, and so it is not frequent. Therefore, remove {I1, I3, I5} from C_3.
- The 2-item subsets of {I2, I3, I4} are {I2, I3}, {I2, I4}, and {I3, I4}. {I3, I4} is not a member of L_2, and so it is not frequent. Therefore, remove {I2, I3, I4} from C_3.
- The 2-item subsets of {I2, I3, I5} are {I2, I3}, {I2, I5}, and {I3, I5}. {I3, I5} is not a member of L_2, and so it is not frequent. Therefore, remove {I2, I3, I5} from C_3.
- The 2-item subsets of {I2, I4, I5} are {I2, I4}, {I2, I5}, and {I4, I5}. {I4, I5} is not a member of L_2, and so it is not frequent. Therefore, remove {I2, I4, I5} from C_3.

(c) Therefore, C_3 = {{I1, I2, I3}, {I1, I2, I5}} after pruning.

Generation and pruning of candidate 3-itemsets, C_3, from L_2 using the Apriori property.

2.4.2 Generating Association Rules from Frequent Itemsets:

Once the frequent itemsets from transactions in a database *D* have been found, it is straightforward to generate strong association rules from them.

$$confidence(A \Rightarrow B) = P(B|A) = \frac{support\_count(A \cup B)}{support\_count(A)}.$$

The conditional probability is expressed in terms of itemset support count, where $support\_count(A \cup B)$ is the number of transactions containing the itemsets $A \cup B$, and $support\_count(A)$ is the number of transactions containing the itemset A. Based on this equation, association rules can be generated as follows:

- For each frequent itemset l, generate all nonempty subsets of l.
- For every nonempty subset s of l, output the rule "$s \Rightarrow (l - s)$" if $\frac{support\_count(l)}{support\_count(s)} \geq min\_conf$, where min_conf is the minimum confidence threshold.

Example:

Generating association rules. Let's try an example based on the transactional data for *AllElectronics* shown in Table 5.1. Suppose the data contain the frequent itemset l = {I1, I2, I5}. What are the association rules that can be generated from l? The nonempty subsets of l are {I1, I2}, {I1, I5}, {I2, I5}, {I1}, {I2}, and {I5}. The resulting association rules are as shown below, each listed with its confidence:

$$\begin{array}{ll}
I1 \wedge I2 \Rightarrow I5, & confidence = 2/4 = 50\% \\
I1 \wedge I5 \Rightarrow I2, & confidence = 2/2 = 100\% \\
I2 \wedge I5 \Rightarrow I1, & confidence = 2/2 = 100\% \\
I1 \Rightarrow I2 \wedge I5, & confidence = 2/6 = 33\% \\
I2 \Rightarrow I1 \wedge I5, & confidence = 2/7 = 29\% \\
I5 \Rightarrow I1 \wedge I2, & confidence = 2/2 = 100\%
\end{array}$$

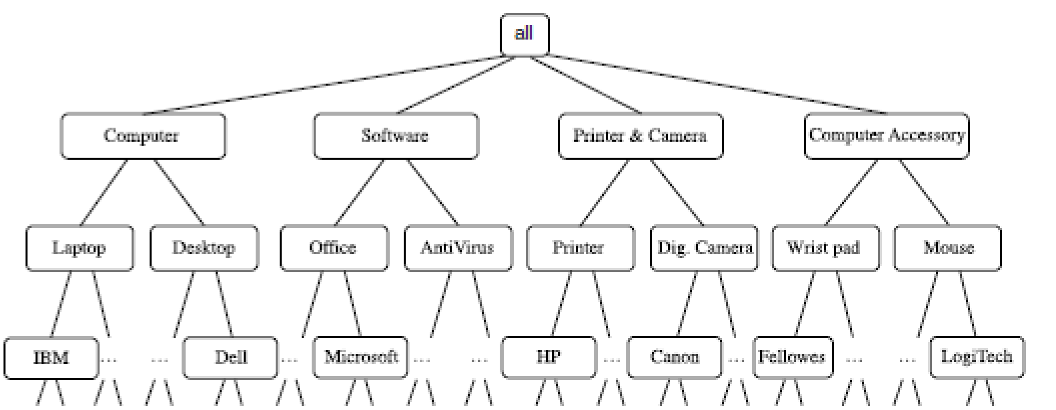
2.5 Mining Multilevel Association Rules:

- For many applications, it is difficult to find strong associations among data items at low or primitive levels of abstraction due to the sparsity of data at those levels.
- Strong associations discovered at high levels of abstraction may represent commonsense knowledge.
- Therefore, data mining systems should provide capabilities for mining association rules at multiple levels of abstraction, with sufficient flexibility for easy traversal amongdifferentabstraction spaces.

- Association rules generated from mining data at multiple levels of abstraction arecalled multiple-level or multilevel association rules.
- Multilevel association rules can be mined efficiently using concept hierarchies under a support-confidence framework.
- In general, a top-down strategy is employed, where counts are accumulated for the calculation of frequent itemsets at each concept level, starting at the concept level 1 and working downward in the hierarchy toward the more specific concept levels,until no more frequent itemsets can be found.

A concepthierarchy defines a sequence of mappings froma set of low-level concepts to higherlevel,more general concepts. Data can be generalized by replacing low-level conceptswithin the data by their higher-level concepts, or ancestors, from a concept hierarchy.

TID	*Items Purchased*
T100	IBM-ThinkPad-T40/2373, HP-Photosmart-7660
T200	Microsoft-Office-Professional-2003, Microsoft-Plus!-Digital-Media
T300	Logitech-MX700-Cordless-Mouse, Fellowes-Wrist-Rest
T400	Dell-Dimension-XPS, Canon-PowerShot-S400
T500	IBM-ThinkPad-R40/P4M, Symantec-Norton-Antivirus-2003
...	...



A concept hierarchy for *AllElectronics* computer items.

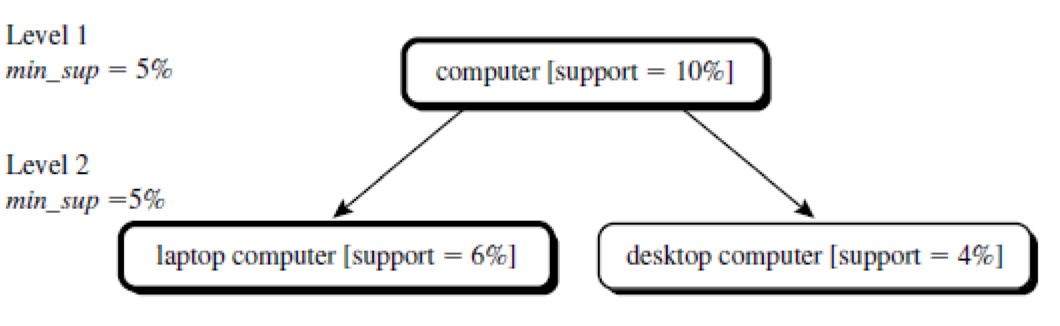
The concept hierarchy has five levels, respectively referred to as levels 0to 4, starting with level 0 at the root node for all.

- Here, Level 1 includes computer, software, printer&camera, and computer accessory.
- Level 2 includes laptop computer, desktop computer, office software, antivirus software
- Level 3 includes IBM desktop computer, . . . , Microsoft office software, and so on.
- Level 4 is the most specific abstraction level of this hierarchy.

2.5.1 Approaches ForMining Multilevel Association Rules:

1.UniformMinimum Support:

- The same minimum support threshold is used when mining at each level of abstraction.
- When a uniform minimum support threshold is used, the search procedure is simplified.
- The method is also simple in that users are required to specify only one minimum support threshold.
- The uniform support approach, however, has some difficulties. It is unlikely thatitems at lower levels of abstraction will occur as frequently as those at higher levelsof abstraction.
- If the minimum support threshold is set too high, it could miss somemeaningful associations occurring at low abstraction levels. If the threshold is set too low, it may generate many uninteresting associations occurring at high abstractionlevels.

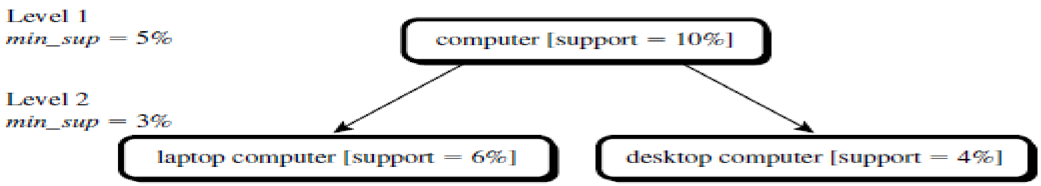


Multilevel mining with uniform support.

2.Reduced Minimum Support:

- Each level of abstraction has its own minimum support threshold.

- The deeper the level of abstraction, the smaller the corresponding threshold is.
- For example,the minimum support thresholds for levels 1 and 2 are 5% and 3%,respectively. In this way, “computer,” “laptop computer,” and “desktop computer” areall considered frequent.



3.Group-Based Minimum Support:

- Because users or experts often have insight as to which groups are more important than others, it is sometimes more desirable to set up user-specific, item, or group based minimal support thresholds when mining multilevel rules.
- For example, a user could set up the minimum support thresholds based on product price, or on items of interest, such as by setting particularly low support thresholds for laptop computersand flash drives in order to pay particular attention to the association patterns containing items in these categories.

2.6 Mining Multidimensional Association Rules from Relational Databases and Data Warehouses:

- Single dimensional or intradimensional association rule contains a single distinct predicate (e.g., buys)with multiple occurrences i.e., the predicate occurs more than once within the rule.

  buys(*X*, “*digital camera*”)=>*buys*(*X*, “*HP printer*”)

- Association rules that involve two or more dimensions or predicates can be referred to as multidimensional association rules.

age(X, “20…29”)^occupation(X, “student”)=>buys(X, “laptop”)

- Above Rule contains three predicates (age, occupation,and buys), each of which occurs only once in the rule. Hence, we say that it has norepeated predicates.
- Multidimensional association rules with no repeated predicates arecalled interdimensional association rules.
- We can also mine multidimensional associationrules with repeated predicates, which contain multiple occurrences of some predicates.These rules are called hybrid-dimensional association rules. An example of sucha rule is the following, where the predicate buys is repeated:

  age(X, “20…29”)^buys(X, “laptop”)=>buys(X, “HP printer”)

2.7 Mining Quantitative Association Rules:

- Quantitative association rules are multidimensional association rules in which the numeric attributes are *dynamically* discretized during the mining process so as to satisfy some mining criteria, such as maximizing the confidence or compactness of the rules mined.
- In this section, we focus specifically on how to mine quantitative association rules having two quantitative attributes on the left-hand side of the rule and one categorical attribute on the right-hand side of the rule. That is

*Aquan*1 ^*Aquan*2 =>*Acat*

where*Aquan*1 and *Aquan*2 are tests on quantitative attribute interval

*Acat*tests a categorical attribute fromthe task-relevantdata.

- Such rules have been referred to as two-dimensional quantitative association rules,

because they contain two quantitative dimensions.

- For instance, suppose you are curious about the association relationship between pairs of quantitative attributes, like customer age and income, and the type of television (such as *high-definition TV*, i.e., *HDTV*) that customers like to buy.

An example of such a 2-D quantitative association rule is

age(*X*, “30…39”)^*income*(*X*, “42*K*…48*K*”)=>*buys*(*X*, “*HDTV*”)

2.8 From Association Mining to Correlation Analysis:

- A correlation measure can be used to augment the support-confidence framework for association rules. This leads to *correlation rules* of the form
  A=>*B* [*support*, *confidence*, *correlation*]
- That is, a correlation rule is measured not only by its support and confidence but alsoby the correlation between itemsets*A* and *B*. There are many different correlation measuresfrom which to choose. In this section, we study various correlation measures todetermine which would be good for mining large data sets.

- Lift is a simple correlation measure that is given as follows. The occurrence of itemset *A* is independent of the occurrence of itemset*B* if $P(A \cup B)$ = *P*(*A*)*P*(*B*); otherwise, itemsets*A* and *B* are dependent and correlated as events. This definition can easily be extended to more than two itemsets.

The lift between the occurrence of *A* and *B* can bemeasured by computing

$$lift(A, B) = \frac{P(A \cup B)}{P(A)P(B)}.$$

- If the lift(A,B) is less than 1, then the occurrence of A is negativelycorrelated with the occurrence of B.
- If the resulting value is greater than 1, then A and B are positively correlated, meaning that the occurrence of one implies the occurrence of the other.
- If the resulting value is equal to 1, then A and B are independent and there is no correlation between them.