S.K.P INSTITUTE OF TECHNOLOGY

Tiruvannamalai– 606 611

CS2032 DATA WAREHOUSING AND DATA MINING

LECTURE NOTES FOR ALL 5 UINTS

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Unit 1

Data Warehouse Introduction

A data warehouse is a collection of data marts representing historical data from different operations in the company. This data is stored in a structure optimized for querying and data analysis as a data warehouse. Table design, dimensions and organization should be consistent throughout a data warehouse so that reports or queries across the data warehouse are consistent.

A data warehouse can also be viewed as a database for historical data from different functions within a company. The term Data Warehouse was coined by Bill Inmon in 1990, which he defined in the following way: "A warehouse is a subject-oriented, integrated, time-variant and non-volatile collection of data in support of management's decision making process". He defined the terms in the sentence as follows:

- *Subject Oriented:* Data that gives information about a particular subject instead of about a company's ongoing operations.
- *Integrated:* Data that is gathered into the data warehouse from a variety of sources and merged into a coherent whole.
- *Time-variant:* All data in the data warehouse is identified with a particular time period.
- *Non-volatile:* Data is stable in a data warehouse. More data is added but data is never removed. This enables management to gain a consistent picture of the business. It is a single, complete and consistent store of data obtained from a variety of different sources made available to end users in what they can understand and use in a business context. It can be Used for decision Support, Used to manage and control business, Used by managers and end-users to understand the business and make judgments.

Data Warehousing is an architectural construct of information systems that provides users with current and historical decision support information that is hard to access or present in traditional operational data stores

Other important terminology

- *Enterprise Data warehouse:* It collects all information about subjects (*customers, products, sales, assets, personnel*) that span the entire organization
- Data Mart: Departmental subsets that focus on selected subjects. A data mart is a segment of a data warehouse that can provide data for reporting and analysis on a section, unit, department or operation in the company, e.g. sales, payroll, production. Data marts are sometimes complete individual data warehouses which are usually smaller than the corporate data warehouse.
- *Decision Support System (DSS):* Information technology to help the knowledge worker (executive, manager, and analyst) makes faster & better decisions
- *Drill-down:* Traversing the summarization levels from highly summarized data to the underlying current or old detail
- *Metadata:* Data about data. Containing location and description of warehouse system components: names, definition, structure…

Benefits of data warehousing

• Data warehouses are designed to perform well with aggregate queries running on large amounts of data.

• The structure of data warehouses is easier for end users to navigate, understand and query against unlike the relational databases primarily designed to handle lots of transactions.

• Data warehouses enable queries that cut across different segments of a company's operation. E.g. production data could be compared against inventory data even if they were originally stored in different databases with different structures.

• Queries that would be complex in very normalized databases could be easier to build and maintain in data warehouses, decreasing the workload on transaction systems.

• Data warehousing is an efficient way to manage and report on data that is from a variety of sources, non uniform and scattered throughout a company.

• Data warehousing is an efficient way to manage demand for lots of information from lots of users.

• Data warehousing provides the capability to analyze large amounts of historical data for nuggets of wisdom that can provide an organization with competitive advantage.

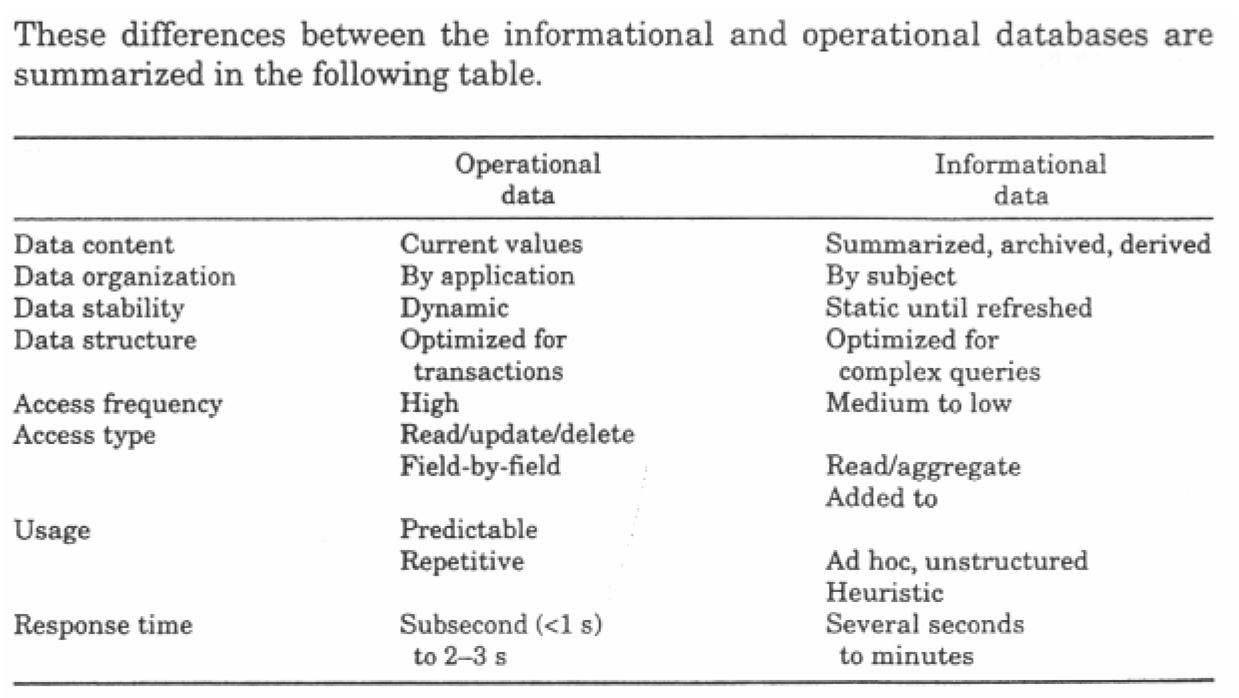
Operational and informational Data

Operational Data:

- Focusing on transactional function such as bank card withdrawals and deposits
- Detailed
- Updateable
- Reflects current data

Informational Data:

- Focusing on providing answers to problems posed by decision makers
- Summarized
- Non updateable



These differences between the informational and operational databases are summarized in the following table.

	Operational data	Informational data
Data content	Current values	Summarized, archived, derived
Data organization	By application	By subject
Data stability	Dynamic	Static until refreshed
Data structure	Optimized for transactions	Optimized for complex queries
Access frequency	High	Medium to low
Access type	Read/update/delete Field-by-field	Read/aggregate Added to
Usage	Predictable Repetitive	Ad hoc, unstructured Heuristic
Response time	Subsecond (<1 s) to 2–3 s	Several seconds to minutes

Data Warehouse Characteristics

• A data warehouse can be viewed as an information system with the following attributes:

– It is a database designed for analytical tasks

– It's content is periodically updated

– It contains current and historical data to provide a historical perspective of information

Operational data store (ODS)

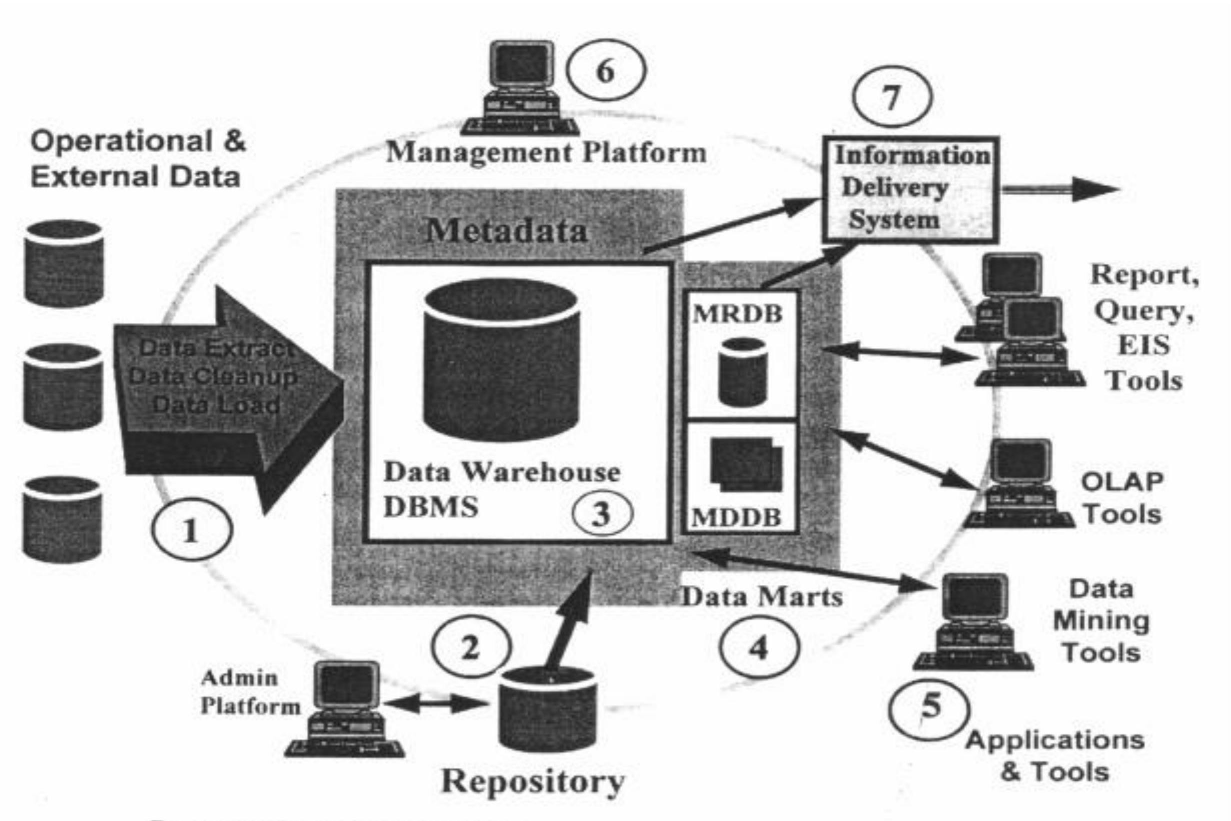
• ODS is an architecture concept to support day-to-day operational decision support and contains current value data propagated from operational applications

• ODS is subject-oriented, similar to a classic definition of a Data warehouse

• ODS is integrated

Data warehouse Architecture and its seven components

1. Data sourcing, cleanup, transformation, and migration tools
2. Metadata repository
3. Warehouse/database technology
4. Data marts
5. Data query, reporting, analysis, and mining tools
6. Data warehouse administration and management
7. Information delivery system



Data warehouse environment.

Data warehouse is an environment, not a product which is based on relational database management system that functions as the central repository for informational data. The central repository information is surrounded by number of key components designed to make the environment is functional, manageable and accessible.

The data source for data warehouse is coming from operational applications. The data entered into the data warehouse transformed into an integrated structure and format. The transformation process involves conversion, summarization, filtering and condensation. The data warehouse must be capable of holding and managing large volumes of data as well as different structure of data structures over the time.

1 Data warehouse database

This is the central part of the data warehousing environment. This is the item number 2 in the above arch. diagram. This is implemented based on RDBMS technology.

2 Sourcing, Acquisition, Clean up, and Transformation Tools

This is item number 1 in the above arch diagram. They perform conversions, summarization, key changes, structural changes and condensation. The data transformation is required so that the information can by used by decision support tools. The transformation produces programs, control statements, JCL code, COBOL code, UNIX scripts, and SQL DDL code etc., to move the data into data warehouse from multiple operational systems.

The functionalities of these tools are listed below:

- To remove unwanted data from operational db
- Converting to common data names and attributes
- Calculating summaries and derived data
- Establishing defaults for missing data
- Accommodating source data definition change.

Issues to be considered while data sourcing, cleanup, extract and transformation:

Data heterogeneity: It refers to DBMS different nature such as it may be in different data modules, it may have different access languages, it may have data navigation methods, operations, concurrency, integrity and recovery processes etc.,

Data heterogeneity: It refers to the different way the data is defined and used in different modules.

Some experts involved in the development of such tools:

Prism Solutions, Evolutionary Technology Inc., Vality, Praxis and Carleton

3 Meta data

It is data about data. It is used for maintaining, managing and using the data warehouse. It is classified into two:

1.Technical Meta data: It contains information about data warehouse data used by warehouse designer, administrator to carry out development and management tasks. It includes,

- Info about data stores
- Transformation descriptions. That is mapping methods from operational db to warehousedb
- Warehouse Object and data structure definitions for target data
- The rules used to perform clean up, and data enhancement
- Data mapping operations
- Access authorization, backup history, archive history, info delivery history, data acquisition history, data access etc.,

2.Business Meta data: It contains info that gives info stored in data warehouse to users. It includes,

- Subject areas, and info object type including queries, reports, images, video, audio clips etc.
- Internet home pages
- Info related to info delivery system
- Data warehouse operational info such as ownerships, audit trails etc.,

Meta data helps the users to understand content and find the data. Meta data are stored in a separate data stores which is known as informational directory or Meta data repository which helps to integrate, maintain and view the contents of the data warehouse.

The following lists the characteristics of info directory/ Meta data:

- It is the gateway to the data warehouse environment
- It supports easy distribution and replication of content for high performance and availability
- It should be searchable by business oriented key words
- It should act as a launch platform for end user to access data and analysis tools
- It should support the sharing of info
- It should support scheduling options for request
- IT should support and provide interface to other applications

• It should support end user monitoring of the status of the data warehouse environment

4 Access tools

Its purpose is to provide info to business users for decision making. There are five categories:

• Data query and reporting tools

• Application development tools

• Executive info system tools (EIS)

• OLAP tools

• Data mining tools

Query and reporting tools are used to generate query and report. There are two types of reporting tools. They are:

• Production reporting tool used to generate regular operational reports

• Desktop report writer are inexpensive desktop tools designed for end users.

Managed Query tools: used to generate SQL query. It uses Meta layer software in between users and databases which offers a point-and-click creation of SQL statement. This tool is a preferred choice of users to perform segment identification, demographic analysis, territory management and preparation of customer mailing lists etc.

Application development tools: This is a graphical data access environment which integrates
OLAP tools with data warehouse and can be used to access all db systems

OLAP Tools: are used to analyze the data in multi dimensional and complex views. To enable multidimensional properties it uses MDDB and MRDB where MDDB refers multi dimensional data base and MRDB refers multi relational data bases.

Data mining tools: are used to discover knowledge from the data warehouse data also can be
used for data visualization and data correction purposes.

5 Data marts

Departmental subsets that focus on selected subjects. They are independent used by dedicated user group. They are used for rapid delivery of enhanced decision support functionality to end users. Data mart is used in the following situation:

• Extremely urgent user requirement

• The absence of a budget for a full scale data warehouse strategy

• The decentralization of business needs

• The attraction of easy to use tools and mind sized project

Data mart presents two problems:

1. Scalability: A small data mart can grow quickly in multi dimensions. So that while designing it, the organization has to pay more attention on system scalability, consistency and manageability issues
2. Data integration

6. Data warehouse admin and management

The management of data warehouse includes,

- Security and priority management
- Monitoring updates from multiple sources
- Data quality checks
- Managing and updating meta data
- Auditing and reporting data warehouse usage and status
- Purging data
- Replicating, sub setting and distributing data
- Backup and recovery
- Data warehouse storage management which includes capacity planning, hierarchical storage management and purging of aged data etc.,

7. Information delivery system

- It is used to enable the process of subscribing for data warehouse info.
- Delivery to one or more destinations according to specified scheduling algorithm

Building a Data warehouse

There are two reasons why organizations consider data warehousing a critical need. In other words, there are two factors that drive you to build and use data warehouse. They are:

Business factors:

- Business users want to make decision quickly and correctly using all available data.

Technological factors:

- To address the incompatibility of operational data stores
- IT infrastructure is changing rapidly. Its capacity is increasing and cost is decreasing so that building a data warehouse is easy

There are several things to be considered while building a successful data warehouse

Business considerations:

Organizations interested in development of a data warehouse can choose one of the following two approaches:

• Top - Down Approach (Suggested by Bill Inmon)

• Bottom - Up Approach (Suggested by Ralph Kimball)

Top - Down Approach

In the top down approach suggested by Bill Inmon, we build a centralized repository to house corporate wide business data. This repository is called Enterprise Data Warehouse (EDW). The data in the EDW is stored in a normalized form in order to avoid redundancy.

The central repository for corporate wide data helps us maintain one version of truth of the data. The data in the EDW is stored at the most detail level. The reason to build the EDW on the most detail level is to leverage

1. Flexibility to be used by multiple departments.
2. Flexibility to cater for future requirements.

The disadvantages of storing data at the detail level are

1. The complexity of design increases with increasing level of detail.
2. It takes large amount of space to store data at detail level, hence increased cost.

Once the EDW is implemented we start building subject area specific data marts which contain data in a de normalized form also called star schema. The data in the marts are usually summarized based on the end users analytical requirements.

The reason to de normalize the data in the mart is to provide faster access to the data for the end users analytics. If we were to have queried a normalized schema for the same analytics, we would end up in a complex multiple level joins that would be much slower as compared to the one on the de normalized schema.

We should implement the top-down approach when

1. The business has complete clarity on all or multiple subject areas data warehosue requirements.
2. The business is ready to invest considerable time and money.

The advantage of using the Top Down approach is that we build a centralized repository to cater for one version of truth for business data. This is very important for the data to be reliable, consistent across subject areas and for reconciliation in case of data related contention between subject areas.

The disadvantage of using the Top Down approach is that it requires more time and initial investment. The business has to wait for the EDW to be implemented followed by building the data marts before which they can access their reports.

Bottom Up Approach

The bottom up approach suggested by Ralph Kimball is an incremental approach to build a data warehouse. Here we build the data marts separately at different points of time as and when the specific subject area requirements are clear. The data marts are integrated or combined together to form a data warehouse. Separate data marts are combined through the use of conformed dimensions and conformed facts. A conformed dimension and a conformed fact is one that can be shared across data marts.

A Conformed dimension has consistent dimension keys, consistent attribute names and consistent values across separate data marts. The conformed dimension means exact same thing with every fact table it is joined.

A Conformed fact has the same definition of measures, same dimensions joined to it and at the same granularity across data marts.

The bottom up approach helps us incrementally build the warehouse by developing and integrating data marts as and when the requirements are clear. We don't have to wait for knowing the overall requirements of the warehouse.

We should implement the bottom up approach when

1. We have initial cost and time constraints.
2. The complete warehouse requirements are not clear. We have clarity to only one data mart.

The advantage of using the Bottom Up approach is that they do not require high initial costs and have a faster implementation time; hence the business can start using the marts much earlier as compared to the top-down approach.

The disadvantages of using the Bottom Up approach are that it stores data in the de normalized format, hence there would be high space usage for detailed data. We have a tendency of not keeping detailed data in this approach hence losing out on advantage of having detail data .i.e. flexibility to easily cater to future requirements.

Bottom up approach is more realistic but the complexity of the integration may become a serious obstacle.

Design considerations

To be a successful data warehouse designer must adopt a holistic approach that is considering all data warehouse components as parts of a single complex system, and take into account all possible data sources and all known usage requirements.

Most successful data warehouses that meet these requirements have these common characteristics:

- Are based on a dimensional model
- Contain historical and current data
- Include both detailed and summarized data
- Consolidate disparate data from multiple sources while retaining consistency

Data warehouse is difficult to build due to the following reason:

- Heterogeneity of data sources
- Use of historical data
- Growing nature of data base

Data warehouse design approach muse be business driven, continuous and iterative engineering approach. In addition to the general considerations there are following specific points relevant to the data warehouse design:

Data content

The content and structure of the data warehouse are reflected in its data model. The data model is the template that describes how information will be organized within the integrated warehouse framework. The data warehouse data must be a detailed data. It must be formatted, cleaned up and transformed to fit the warehouse data model.

Meta data

It defines the location and contents of data in the warehouse. Meta data is searchable by users to find definitions or subject areas. In other words, it must provide decision support oriented pointers to warehouse data and thus provides a logical link between warehouse data and decision support applications.

Data distribution

One of the biggest challenges when designing a data warehouse is the data placement and distribution strategy. Data volumes continue to grow in nature. Therefore, it becomes necessary to know how the data should be divided across multiple servers and which users should get access to which types of data. The data can be distributed based on the subject area, location (geographical region), or time (current, month, year).

Tools

A number of tools are available that are specifically designed to help in the implementation of the data warehouse. All selected tools must be compatible with the given data warehouse environment and with each other. All tools must be able to use a common Meta data repository.

Design steps

The following nine-step method is followed in the design of a data warehouse:

1. Choosing the subject matter
2. Deciding what a fact table represents
3. Identifying and conforming the dimensions
4. Choosing the facts
5. Storing pre calculations in the fact table
6. Rounding out the dimension table
7. Choosing the duration of the db
8. The need to track slowly changing dimensions
9. Deciding the query priorities and query models

Technical considerations

A number of technical issues are to be considered when designing a data warehouse environment. These issues include:

- The hardware platform that would house the data warehouse
- The dbms that supports the warehouse data
- The communication infrastructure that connects data marts, operational systems and end users
- The hardware and software to support meta data repository
- The systems management framework that enables admin of the entire environment

Implementation considerations

The following logical steps needed to implement a data warehouse:

- Collect and analyze business requirements
- Create a data model and a physical design
- Define data sources
- Choose the db tech and platform
- Extract the data from operational db, transform it, clean it up and load it into the warehouse
- Choose db access and reporting tools
- Choose db connectivity software
- Choose data analysis and presentation s/w
- Update the data warehouse

Access tools

Data warehouse implementation relies on selecting suitable data access tools. The best way to choose this is based on the type of data can be selected using this tool and the kind of access it permits for a particular user. The following lists the various type of data that can be accessed:

- Simple tabular form data
- Ranking data
- Multivariable data
- Time series data
- Graphing, charting and pivoting data
- Complex textual search data
- Statistical analysis data
- Data for testing of hypothesis, trends and patterns
- Predefined repeatable queries
- Ad hoc user specified queries
- Reporting and analysis data
- Complex queries with multiple joins, multi level sub queries and sophisticated search criteria

Data extraction, clean up, transformation and migration

A proper attention must be paid to data extraction which represents a success factor for a data warehouse architecture. When implementing data warehouse several the following selection criteria that affect the ability to transform, consolidate, integrate and repair the data should be considered:

- Timeliness of data delivery to the warehouse
- The tool must have the ability to identify the particular data and that can be read by conversion tool
- The tool must support flat files, indexed files since corporate data is still in this type
- The tool must have the capability to merge data from multiple data stores
- The tool should have specification interface to indicate the data to be extracted
- The tool should have the ability to read data from data dictionary
- The code generated by the tool should be completely maintainable
- The tool should permit the user to extract the required data
- The tool must have the facility to perform data type and character set translation
- The tool must have the capability to create summarization, aggregation and derivation of records
- The data warehouse database system must be able to perform loading data directly from these tools

Data placement strategies

– As a data warehouse grows, there are at least two options for data placement. One is to put some of the data in the data warehouse into another storage media.

– The second option is to distribute the data in the data warehouse across multiple servers.

User levels

The users of data warehouse data can be classified on the basis of their skill level in accessing the warehouse.

There are three classes of users:

Casual users: are most comfortable in retrieving info from warehouse in pre defined formats and running pre existing queries and reports. These users do not need tools that allow for building standard and ad hoc reports

Power Users: can use pre defined as well as user defined queries to create simple and ad hoc reports. These users can engage in drill down operations. These users may have the experience of using reporting and query tools.

Expert users: These users tend to create their own complex queries and perform standard analysis on the info they retrieve. These users have the knowledge about the use of query and report tools

Benefits of data warehousing

Data warehouse usage includes,

– Locating the right info

– Presentation of info

– Testing of hypothesis

– Discovery of info

– Sharing the analysis

The benefits can be classified into two:

• Tangible benefits (quantified / measureable): It includes,

– Improvement in product inventory

– Decrement in production cost

– Improvement in selection of target markets

– Enhancement in asset and liability management

• Intangible benefits (not easy to quantified): It includes,

– Improvement in productivity by keeping all data in single location and eliminating rekeying of data

– Reduced redundant processing

– Enhanced customer relation

Mapping the data warehouse architecture to Multiprocessor architecture

The functions of data warehouse are based on the relational data base technology. The relational data base technology is implemented in parallel manner. There are two advantages of having parallel relational data base technology for data warehouse:

- ***Linear Speed up***: refers the ability to increase the number of processor to reduce response time
- ***Linear Scale up***: refers the ability to provide same performance on the same requests as the

database size increases

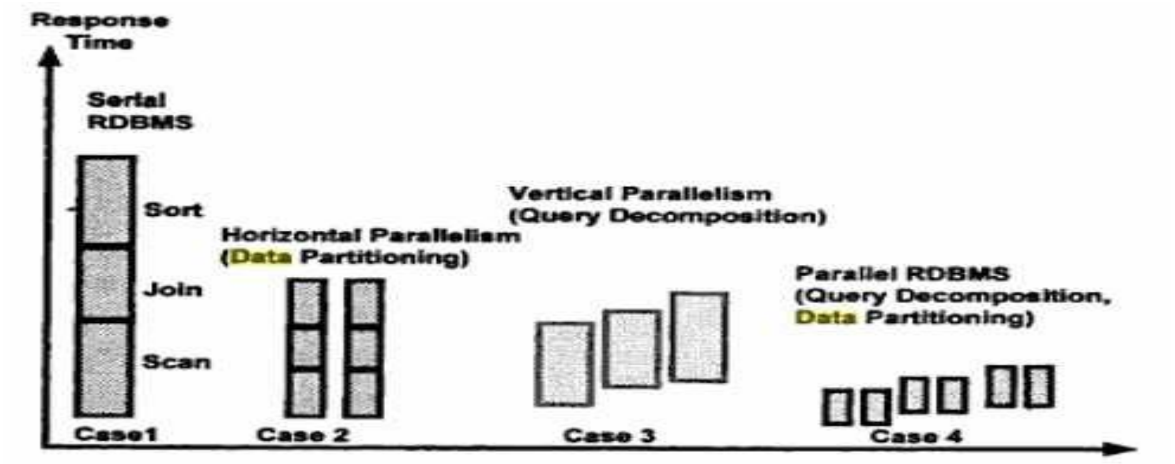
Types of parallelism

There are two types of parallelism:

- *Inter query Parallelism:* In which different server threads or processes handle multiple requests at the same time.
- *Intra query Parallelism:* This form of parallelism decomposes the serial SQL query into lower level operations such as scan, join, sort etc. Then these lower level operations are executed concurrently in parallel.

Intra query parallelism can be done in either of two ways:

- *Horizontal parallelism:* which means that the data base is partitioned across multiple disks and parallel processing occurs within a specific task that is performed concurrently on different processors against different set of data
- *Vertical parallelism:* This occurs among different tasks. All query components such as scan, join, sort etc are executed in parallel in a pipelined fashion. In other words, an output from one task becomes an input into another task.


Response Time
Serial RDBMS
Sort
Join
Scan
Horizontal Parallelism (Data Partitioning)
Vertical Parallelism (Query Decomposition)
Parallel RDBMS (Query Decomposition, Data Partitioning)
Case1
Case 2
Case 3
Case 4

Types of DBMS parallelism.

Data partitioning:

Data partitioning is the key component for effective parallel execution of data base operations. Partition can be done randomly or intelligently.

Random portioning includes random data striping across multiple disks on a single server.

Another option for random portioning is round robin fashion partitioning in which each record is placed on the next disk assigned to the data base.

Intelligent partitioning assumes that DBMS knows where a specific record is located and does not waste time searching for it across all disks. The various intelligent partitioning include:

Hash partitioning: A hash algorithm is used to calculate the partition number based on the value of the partitioning key for each row

Key range partitioning: Rows are placed and located in the partitions according to the value of the partitioning key. That is all the rows with the key value from A to K are in partition 1, L to T are in partition 2 and so on.

Schema portioning: an entire table is placed on one disk; another table is placed on different disk etc. This is useful for small reference tables.

User defined portioning: It allows a table to be partitioned on the basis of a user defined expression.

Data base architectures of parallel processing

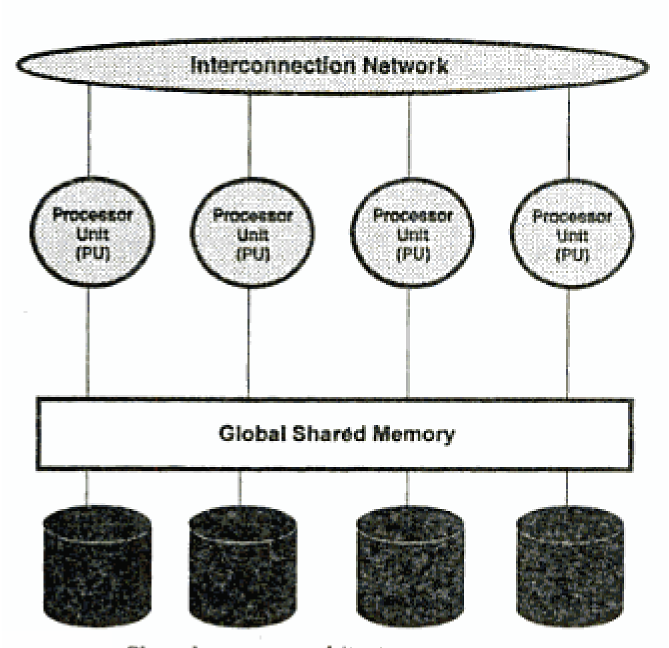
There are three DBMS software architecture styles for parallel processing:

1. Shared memory or shared everything Architecture
2. Shared disk architecture
3. Shred nothing architecture

Shared Memory Architecture

Tightly coupled shared memory systems, illustrated in following figure have the following characteristics:

- Multiple PUs share memory.
- Each PU has full access to all shared memory through a common bus.
- Communication between nodes occurs via shared memory.
- Performance is limited by the bandwidth of the memory bus.



Shared-memory architecture.

Symmetric multiprocessor (SMP) machines are often nodes in a cluster. Multiple SMP nodes can be used with Oracle Parallel Server in a tightly coupled system, where memory is shared among the multiple PUs, and is accessible by all the PUs through a memory bus. Examples of tightly coupled systems include the Pyramid, Sequent, and Sun SparcServer.

Performance is potentially limited in a tightly coupled system by a number of factors. These include various system components such as the memory bandwidth, PU to PU communication bandwidth, the memory available on the system, the I/O bandwidth, and the bandwidth of the common bus.

Parallel processing advantages of shared memory systems are these:

- Memory access is cheaper than inter-node communication. This means that internal synchronization is faster than using the Lock Manager.
- Shared memory systems are easier to administer than a cluster.

A disadvantage of shared memory systems for parallel processing is as follows:

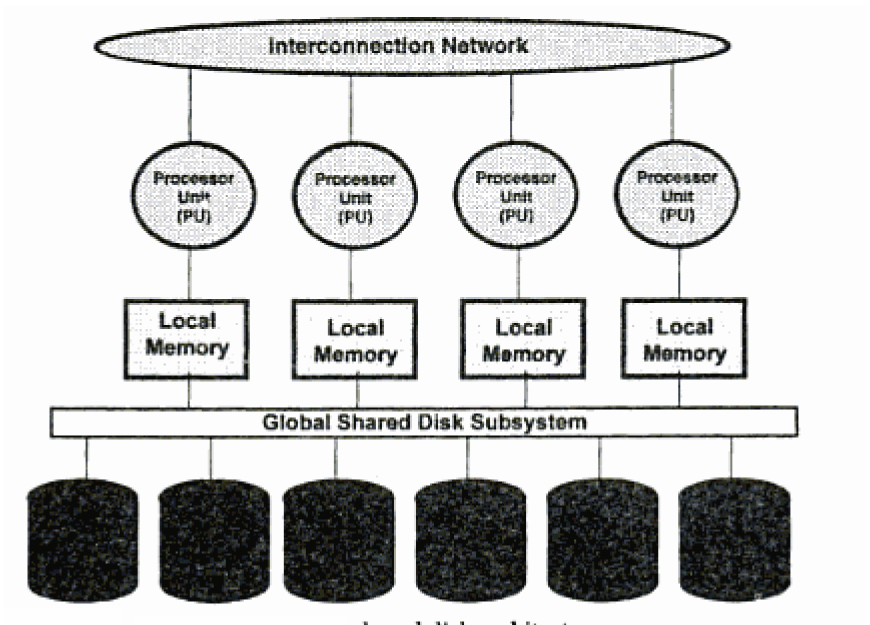
- Scalability is limited by bus bandwidth and latency, and by available memory.

Shared Disk Architecture

Shared disk systems are typically loosely coupled. Such systems, illustrated in following figure, have the following characteristics:

- Each node consists of one or more PUs and associated memory.

- Memory is not shared between nodes.
- Communication occurs over a common high-speed bus.
- Each node has access to the same disks and other resources.
- A node can be an SMP if the hardware supports it.
- Bandwidth of the high-speed bus limits the number of nodes (scalability) of the system.



shared-disk architecture.

The cluster illustrated in figure is composed of multiple tightly coupled nodes. The Distributed Lock Manager (DLM) is required. Examples of loosely coupled systems are VAX clusters or Sun clusters.

Since the memory is not shared among the nodes, each node has its own data cache. Cache consistency must be maintained across the nodes and a lock manager is needed to maintain the consistency. Additionally, instance locks using the DLM on the Oracle level must be maintained to ensure that all nodes in the cluster see identical data.

There is additional overhead in maintaining the locks and ensuring that the data caches are consistent. The performance impact is dependent on the hardware and software components, such as the bandwidth of the high-speed bus through which the nodes communicate, and DLM performance.

<u>Parallel processing advantages of shared disk systems are as follows:</u>

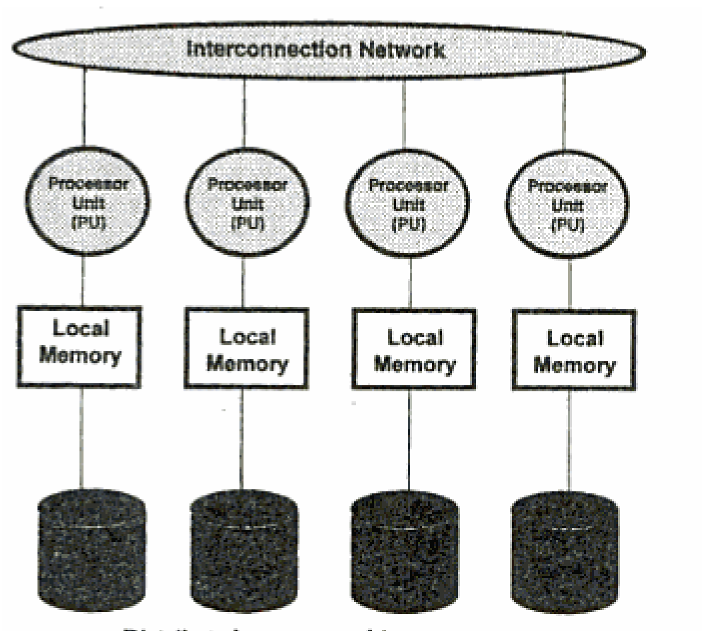
- Shared disk systems permit high availability. All data is accessible even if one node dies.
- These systems have the concept of one database, which is an advantage over shared nothing systems.
- Shared disk systems provide for incremental growth.

Parallel processing disadvantages of shared disk systems are these:

- Inter-node synchronization is required, involving DLM overhead and greater dependency on high-speed interconnect.
- If the workload is not partitioned well, there may be high synchronization overhead.
- There is operating system overhead of running shared disk software.

Shared Nothing Architecture

Shared nothing systems are typically loosely coupled. In shared nothing systems only one CPU is connected to a given disk. If a table or database is located on that disk, access depends entirely on the PU which owns it. Shared nothing systems can be represented as follows:



Distributed memory architecture.

Shared nothing systems are concerned with access to disks, not access to memory. Nonetheless, adding more PUs and disks can improve scale up. Oracle Parallel Server can access the disks on a shared nothing system as long as the operating system provides transparent disk access, but this access is expensive in terms of latency.

Shared nothing systems have advantages and disadvantages for parallel processing:

Advantages

- Shared nothing systems provide for incremental growth.
- System growth is practically unlimited.
- MPPs are good for read-only databases and decision support applications.

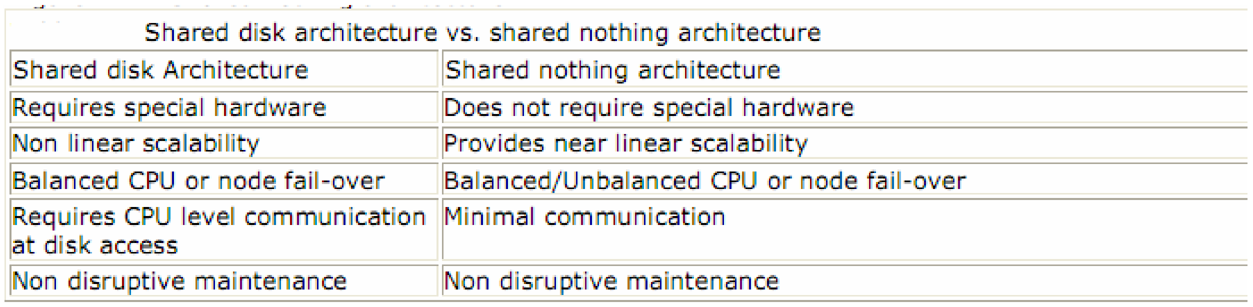
• Failure is local: if one node fails, the others stay up.

Disadvantages

• More coordination is required.

• More overhead is required for a process working on a disk belonging to another node.

• If there is a heavy workload of updates or inserts, as in an online transaction processing system, it may be worthwhile to consider data-dependent routing to alleviate contention.



Shared disk architecture vs. shared nothing architecture

Shared disk Architecture	Shared nothing architecture
Requires special hardware	Does not require special hardware
Non linear scalability	Provides near linear scalability
Balanced CPU or node fail-over	Balanced/Unbalanced CPU or node fail-over
Requires CPU level communication at disk access	Minimal communication
Non disruptive maintenance	Non disruptive maintenance

Parallel DBMS features

• Scope and techniques of parallel DBMS operations

• Optimizer implementation

• Application transparency

• Parallel environment which allows the DBMS server to take full advantage of the existing facilities on a very low level

• DBMS management tools help to configure, tune, admin and monitor a parallel RDBMS as effectively as if it were a serial RDBMS

• Price / Performance: The parallel RDBMS can demonstrate a non linear speed up and scale up at reasonable costs.

Parallel DBMS vendors

1. Oracle: Parallel Query Option (PQO)

Architecture: shared disk arch

Data partition: Key range, hash, round robin

Parallel operations: hash joins, scan and sort

2. Informix: eXtended Parallel Server (XPS)

Architecture: Shared memory, shared disk and shared nothing models

Data partition: round robin, hash, schema, key range and user defined

Parallel operations: INSERT, UPDATE, DELELTE

3. IBM: DB2 Parallel Edition (DB2 PE)

Architecture: Shared nothing models

Data partition: hash

Parallel operations: INSERT, UPDATE, DELELTE, load, recovery, index creation, backup, table reorganization

4. SYBASE: SYBASE MPP

Architecture: Shared nothing models

Data partition: hash, key range, Schema

Parallel operations: Horizontal and vertical parallelism

DBMS schemas for decision support

The basic concepts of dimensional modeling are: facts, dimensions and measures. A fact is a collection of related data items, consisting of measures and context data. It typically represents business items or business transactions. A dimension is a collection of data that describe one business dimension. Dimensions determine the contextual background for the facts; they are the parameters over which we want to perform OLAP. A measure is a numeric attribute of a fact, representing the performance or behavior of the business relative to the dimensions.

Considering Relational context, there are three basic schemas that are used in dimensional
modeling:

1. Star schema
2. Snowflake schema
3. Fact constellation schema

Star schema

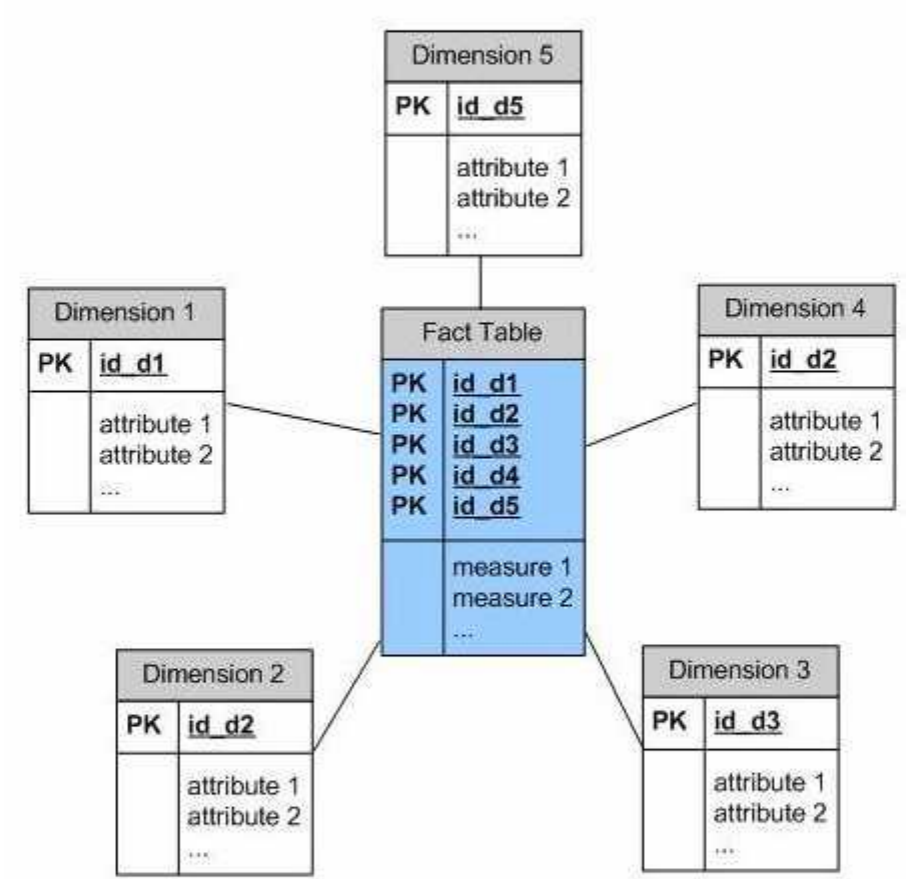
The multidimensional view of data that is expressed using relational data base semantics is provided by the data base schema design called star schema. The basic of stat schema is that information can be classified into two groups:

• Facts

• Dimension

Star schema has one large central table (fact table) and a set of smaller tables (dimensions) arranged in a radial pattern around the central table.

Facts are core data element being analyzed while dimensions are attributes about the facts. The determination of which schema model should be used for a data warehouse should be based upon the analysis of project requirements, accessible tools and project team preferences.



What is star schema? The star schema architecture is the simplest data warehouse schema. It is called a star schema because the diagram resembles a star, with points radiating from a center. The center of the star consists of fact table and the points of the star are the dimension tables. Usually the fact tables in a star schema are in third normal form(3NF) whereas dimensional tables are de-normalized. Despite the fact that the star schema is the simplest architecture, it is most commonly used nowadays and is recommended by Oracle.

Fact Tables

A fact table is a table that contains summarized numerical and historical data (facts) and a multipart index composed of foreign keys from the primary keys of related dimension tables.

A fact table typically has two types of columns: foreign keys to dimension tables and measures those that contain numeric facts. A fact table can contain fact's data on detail or aggregated level.

Dimension Tables

Dimensions are categories by which summarized data can be viewed. E.g. a profit summary in a fact table can be viewed by a Time dimension (profit by month, quarter, year), Region dimension (profit by country, state, city), Product dimension (profit for product1, product2). A dimension is a structure usually composed of one or more hierarchies that categorizes data. If a dimension hasn't got a hierarchies and levels it is called flat dimension or list. The primary keys of each of the dimension tables are part of the composite primary key of the fact table.

Dimensional attributes help to describe the dimensional value. They are normally descriptive, textual values. Dimension tables are generally small in size then fact table. Typical fact tables store data about sales while dimension tables data about geographic region (markets, cities), clients, products, times, channels.

Measures

Measures are numeric data based on columns in a fact table. They are the primary data which end users are interested in. E.g. a sales fact table may contain a profit measure which represents profit on each sale.

Aggregations are pre calculated numeric data. By calculating and storing the answers to a query before users ask for it, the query processing time can be reduced. This is key in providing fast query performance in OLAP.

Cubes are data processing units composed of fact tables and dimensions from the data warehouse. They provide multidimensional views of data, querying and analytical capabilities to clients.

The main characteristics of star schema:

- Simple structure -> easy to understand schema
- Great query effectives -> small number of tables to join
- Relatively long time of loading data into dimension tables -> de-normalization, redundancy data caused that size of the table could be large.
- The most commonly used in the data warehouse implementations -> widely supported by a large number of business intelligence tools

Snowflake schema: is the result of decomposing one or more of the dimensions. The many-to one relationship among sets of attributes of a dimension can separate new dimension tables, forming a hierarchy. The decomposed snowflake structure visualizes the hierarchical structure of dimensions very well.

Fact constellation schema: For each star schema it is possible to construct fact constellation schema (for example by splitting the original star schema into more star schemes each of them describes facts on another level of dimension hierarchies). The fact constellation architecture contains multiple fact tables that share many dimension tables.

The main shortcoming of the fact constellation schema is a more complicated design because many variants for particular kinds of aggregation must be considered and selected. Moreover, dimension tables are still large.

Multi relational Database:

The relational implementation of multidimensional data base systems is referred to as multi relational database systems.

Data Extraction, Cleanup and Transformation Tools:

- The task of capturing data from a source data system, cleaning and transforming it and then loading the results into a target data system can be carried out either by separate products, or by a single integrated solution. More contemporary integrated solutions can fall into one of the categories described below:
  - Code Generators
  - Database data Replications
  - Rule-driven Dynamic Transformation Engines (Data Mart Builders)

Code Generator:

- It creates 3GL/4GL transformation programs based on source and target data definitions, and data transformation and enhancement rules defined by the developer.
- This approach reduces the need for an organization to write its own data capture, transformation, and load programs. These products employ DML Statements to capture a set of the data from source system.
- These are used for data conversion projects, and for building an enterprise-wide data warehouse, when there is a significant amount of data transformation to be done involving a variety of different flat files, non-relational, and relational data sources.

Database Data Replication Tools:

- These tools employ database triggers or a recovery log to capture changes to a single data source on one system and apply the changes to a copy of the data source data located on a different system.

- Most replication products do not support the capture of changes to non-relational files and databases, and often do not provide facilities for significant data transformation and enhancement.
- These point-to-point tools are used for disaster recovery and to build an operational data store, a data warehouse, or a data mart when the number of data sources involved are small and a limited amount of data transformation and enhancement is required.

Rule-driven Dynamic Transformation Engines (Data Mart Builders):

- They are also known as Data Mart Builders and capture data from a source system at User-defined intervals, transform data, and then send and load the results into a target environment, typically a data mart.
- To date most of the products of this category support only relational data sources, though now this trend have started changing.
- Data to be captured from source system is usually defined using query language statements, and data transformation and enhancement is done on a script or a function logic defined to the tool.
- With most tools in this category, data flows from source systems to target systems through one or more servers, which perform the data transformation and enhancement. These transformation servers can usually be controlled from a single location, making the job of such environment much easier.

Meta Data:

Meta Data Definitions:

- Metadata – additional data warehouse used to understand what information is in the warehouse, and what it means
- Metadata Repository – specialized database designed to maintain metadata, together with the tools and interfaces that allow a company to collect and distribute its metadata.
- Operational Data – elements from operation systems, external data (or other sources) mapped to the warehouse structures.

Industry trend:

Why were early Data Warehouses that did not include significant amounts of metadata collection able to succeed?

- Usually a subset of data was targeted, making it easier to understand content, organization, ownership.
- Usually targeted a subset of (technically inclined) end users

Early choices were made to ensure the success of initial data warehouse efforts.

Meta Data Transitions:

- Usually, metadata repositories are already in existence. Traditionally, metadata was aimed at overall systems management, such as aiding in the maintenance of legacy systems through impact analysis, and determining the appropriate reuse of legacy data structures.
- Repositories can now aide in tracking metadata to help all data warehouse users understand what information is in the warehouse and what it means. Tools are now being positioned to help manage and maintain metadata.

Meta Data Lifecycle:

1. **Collection**: Identify metadata and capture it in a central repository.
2. **Maintenance**: Put in place processes to synchronize metadata automatically with the changing data architecture.
3. **Deployment**: Provide metadata to users in the right form and with the right tools.

The key to ensuring a high level of collection and maintenance accuracy is to incorporate as much automation as possible. The key to a successful metadata deployment is to correctly match the metadata offered to the specific needs of each audience.

Meta Data Collection:

- Collecting the right metadata at the right time is the basis for a success. If the user does not already have an idea about what information would answer a question, the user will not find anything helpful in the warehouse.
- Metadata spans many domains from physical structure data, to logical model data, to business usage and rules.
- Typically the metadata that should be collected is already generated and processed by the development team anyway. Metadata collection preserves the analysis performed by the team.

Meta Data Categories:

Warehouse Data Sources:

- Information about the potential sources of data for a data warehouse (existing operational systems, external data, manually maintained information). The intent is to understand both the physical structure of the data and the meaning of the data. Typically the physical structure is easier to collect as it may exist in a repository that can be parsed automatically.

Data Models:

Correlate the enterprise model to the warehouse model.

- Map entities in the enterprise model to their representation in the warehouse model. This will provide the basis for further change impact analysis and end user content analysis.
- Ensure the entity, element definition, business rules, valid values, and usage guidelines are transposed properly from the enterprise model to the warehouse model.

Warehouse Mappings:

Map the operational data into the warehouse data structures

- Each time a data element is mapped to the warehouse, the logical connection between the data elements, as well as any transformations should be recorded.
- Along with being able to determine that an element in the warehouse is populated from specific sources of data, the metadata should also discern exactly what happens to those elements as they are extracted from the data sources, moved, transformed, and loaded into the warehouse.

Warehouse Usage Information:

Usage information can be used to:

- Understand what tables are being accessed, by whom, and how often. This can be used to fine tune the physical structure of the data warehouse.
- Improve query reuse by identifying existing queries (catalog queries, identify query authors, descriptions).
- Understand how data is being used to solve business problems.

This information is captured after the warehouse has been deployed. Typically, this information is not easy to collect.

Maintaining Meta Data:

- As with any maintenance process, automation is key to maintaining current high-quality information. The data warehouse tools can play an important role in how the metadata is maintained.

- Most proposed database changes already go through appropriate verification and authorization, so adding a metadata maintenance requirement should not be significant.
- Capturing incremental changes is encouraged since metadata (particularly structure information) is usually very large.

Maintaining the Warehouse:

The warehouse team must have comprehensive impact analysis capabilities to respond to change that may affect:

- Data extraction\movement\transformation routines
- Table structures
- Data marts and summary data structures
- Stored user queries
- Users who require new training (due to query or other changes)

What business problems are addressed in part using the element that is changing (help understand the significance of the change, and how it may impact decision making).

Meta Data Deployment:

Supply the right metadata to the right audience

- Warehouse developers will primarily need the physical structure information for data sources. Further analysis on that metadata leads to the development of more metadata (mappings).
- Warehouse maintainers typically require direct access to the metadata as well.
- End Users require an easy-to-access format. They should not be burdened with technical names or cryptic commands. Training, documentation and other forms of help, should be readily available.

End Users:

Users of the warehouse are primarily concerned with two types of metadata.

1. A high-level topic inventory of the warehouse (what is in the warehouse and where it came from).
2. Existing queries that are pertinent to their search (reuse).

The important goal is that the user is easily able to correctly find and interpret the data they need.

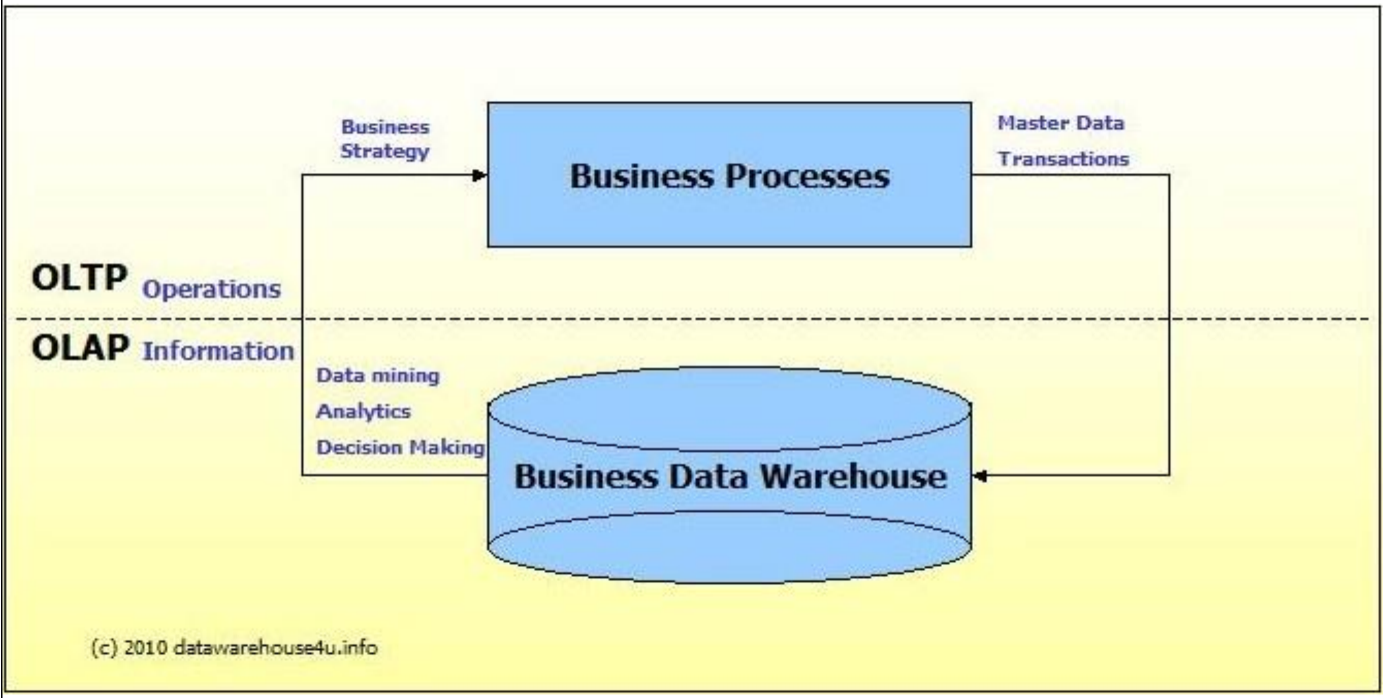
Integration with Data Access Tools:

1. Side by Side access to metadata and to real data. The user can browse metadata and write queries against the real data.

2. Populate query tool help text with metadata exported from the repository. The tool can now provide the user with context sensitive help at the expense of needing updating whenever metadata changes and the user may be using outdated metadata.
3. Provide query tools that access the metadata directly to provide context sensitive help. This eliminates the refresh issue, and ensures the user always sees current metadata.
4. Full interconnectivity between query tool and metadata tool (transparent transactions between tools).

OLTP vs. OLAP

We can divide IT systems into transactional (OLTP) and analytical (OLAP). In general we can assume that OLTP systems provide source data to data warehouses, whereas OLAP systems help to analyze it.



- **OLTP (On-line Transaction Processing)** is characterized by a large number of short on-line transactions (INSERT, UPDATE, DELETE). The main emphasis for OLTP systems is put on very fast query processing, maintaining data integrity in multi-access environments and an effectiveness measured by number of transactions per second. In OLTP database there is detailed and current data, and schema used to store transactional databases is the entity model (usually 3NF).

- **OLAP (On-line Analytical Processing)** is characterized by relatively low volume of transactions. Queries are often very complex and involve aggregations. For OLAP systems a response time is an effectiveness measure. OLAP applications are widely used by Data Mining techniques. In OLAP database there is aggregated, historical data, stored in multi-dimensional schemas (usually star schema).

The following table summarizes the major differences between OLTP and OLAP system design.

	OLTP System **Online Transaction Processing** **(Operational System)**	**OLAP System** **Online Analytical Processing** **(Data Warehouse)**
Source of data	Operational data; OLTPs are the original source of the data.	Consolidation data; OLAP data comes from the various OLTP Databases
Purpose of data	To control and run fundamental business tasks	To help with planning, problem solving, and decisionsupport
What the data	Reveals a snapshot of ongoing business processes	Multi-dimensional views of various kinds of business activities
Inserts and Updates	Short and fast inserts and updates initiated by end users	Periodic long-running batch jobs refresh the data
Queries	Relatively standardized and simple queries Returning relatively few records	Often complex queries involving aggregations
Processing Speed	Typically very fast	Depends on the amount of data involved; batch datarefreshes and complex queries may take many hours; query speed can be improved by creating indexes
Space Requirements	Can be relatively small if historical data is archived	Larger due to the existence of aggregation structures and history data; requires more indexes than OLTP
DatabaseDesign	Highly normalized with many tables	Typically de-normalized with fewer tables; use of star and/or snowflake schemas
Backup and Recovery	Backup religiously; operational data is critical to run the business, data loss is likely to entail significant monetary loss and legal liability	Instead of regular backups, some environments may consider simply reloading the OLTP data as a recovery method

Unit 2

Reporting and Query Tools and Applications:

Tool Categories:

- There are 5 categories of Decision support tools, They are;

a) Reporting
b) Managed Query
c) Executive Information Systems
d) OLAP
e) Data Mining

a. Reporting:

- Reporting tools can be divided into two types.

1. Production reporting tools
2. Desktop report writers.

1. Production Reporting Tools:

- It will let companies to generate regular operational reports or support high volume batch jobs, such as calculating and printing paychecks.
- This tool includes third generation languages such as COBOL, specialized fourth generation languages and high end client/server tools.

2. Report writers:

- Inexpensive desktop tools designed for End users.
- Generally they have graphical interfaces and built in charting functions.
- They can pull a group of data from a variety of data sources and integrating them in a single report.
- Vendors are trying to increase the scalability of report writers by supporting 3-tired architecture in Windows NT and Unix server.
- At the beginning they are offered for Object oriented interfaces for designing and manipulating reports and modules for performing ad hoc queries and OLAP Analysis.

b. Managed Query Tools:

- It shields end users from the complexities of SQL and Data base structures by inserting a meta layer between Users and the Data base.
- Meta layer is the software that provides subject oriented views of a data base and supports point –and –click creation of SQL.
- They have embraced three tiered architecture to improve scalability
- They support asynchronous Query execution and integrate with web servers.
- These vendors are racing to embed support for OLAP and data mining features.

c. Executive Information System:

- An **executive information system** (EIS) is a type of management information system intended to facilitate and support the information and decision-making needs of senior executives by providing easy access to both internal and external information relevant to meeting the strategic goals of the organization.
- It is commonly considered as a specialized form of decision support system (DSS).
- The emphasis of EIS is on graphical displays and easy-to-use user interfaces.
- They offer strong reporting and drill-down capabilities.
- In general, EIS are enterprise-wide DSS that help top-level executives analyze, compare, and highlight trends in important variables so that they can monitor performance and identify opportunities and problems.

Advantages of EIS

- Easy for upper-level executives to use, extensive computer experience is not required in operations
- Provides timely delivery of company summary information
- Information that is provided is better understood

Disadvantages of EIS

- System dependent
- Limited functionality, by design
- Information overload for some managers

d. <u>OLAP Tools:</u>

- In computing, online analytical processing, or OLAP is an approach to swiftly answer multi-dimensional analytical (MDA) queries.
- OLAP is part of the broader category of business intelligence, which also encompasses relational reporting and data mining.
- Typical applications of OLAP include business reporting for sales, marketing, management reporting, business process management (BPM),budgeting and forecasting, financial reporting and similar areas, with new applications coming up, such as agriculture.
- The term *OLAP* was created as a slight modification of the traditional database term OLTP (Online Transaction Processing).
- OLAP tools enable users to interactively analyze multidimensional data from multiple perspectives.
- OLAP consists of three basic analytical operations: consolidation (roll-up), drill-down, and slicing and dicing.
- Consolidation involves the aggregation of data that can be accumulated and computed in one or more dimensions.
- Slicing and dicing is a feature whereby users can take out (slicing) a specific set of data of the cube and view (dicing) the slices from different viewpoints.

e. <u>Data Mining Tools:</u>

- Data mining tools are software components and theories that allow users to extract information from data.
- The tools provide individuals and companies with the ability to gather large amounts of data and use it to make determinations about a particular user or groups of users.
- Data mining tools can be classified into one of three categories:

1. traditional data mining tools
2. dashboards, and
3. text-mining tools.

1.Traditional Data Mining Tools:

- Help companies establish data patterns and trends by using a number of complex algorithms and techniques.
- Some of these tools are installed on the desktop to monitor the data and highlight trends and others capture information residing outside a database.
- The majority are available in both Windows and UNIX versions, although some specialize in one operating system only.
- While some may concentrate on one database type, most will be able to handle any data using online analytical processing or a similar technology.

2. Dash boards:

- Installed in computers to monitor information in a database.
- Dashboards reflect data changes and updates onscreen — often in the form of a chart or table — enabling the user to see how the business is performing.
- Historical data also can be referenced, enabling the user to see where things have changed (e.g., increase in sales from the same period last year).
- This functionality makes dashboards easy to use and particularly appealing to managers who wish to have an overview of the company's performance.

3. Text Mining Tools:

- Its ability to mine data from different kinds of text — for example from Microsoft Word and Acrobat PDF documents to simple text files.
- These tools scan content and convert the selected data into a format that is compatible with the tool's database, thus providing users with an easy and convenient way of accessing data without the need to open different applications.
- Scanned content can be unstructured (i.e., information is scattered almost randomly across the document, including e-mails, Internet pages, audio and video data) or structured (i.e., the data's form and purpose is known, such as content found in a database).

The Need for Applications:

- The discussion is focus on the tools and applications that fit into the managed Query and EIS categories.
- It is already mentioned that these are easy to use, point-and-click tools that either accept SQL or generate SQL statements to query relational data stored in the warehouse.
- Some of these tools and applications can format the retrieved data into easy-to-read report, while others concentrate on the on-screen presentation.
- These tools are the preferred choice of the users of business applications such as segment identification, demographic analysis, territory management and customer mailing list.
- As the complexity of the question grows, these tools may rapidly become inefficient.
- The reporting can be identified into 3 distinct types. They are:
    1. Creation and viewing of standard reports.
    2. Definition and creation of ad hoc reports.
    3. Data exploration.

Creation and viewing of standard reports:

- This is today's main reporting activity.
- The routine delivery of reports based on predetermined measures.

Definition and creation of ad hoc reports:

- These can be quite complex, and the trend is to off-load this time consuming activity to the users.
- As a result, reporting tools that allow mangers and business users to quickly create their own report and get quick answers to business questions are becoming increasingly popular.

Data Exploration:

- With the newest wave of business intelligence tools, users can easily "surf" through data without a preset path to quickly uncover business trends or problems.
- This is the domain of OLAP tool.

Cognos Impromptu:

What is impromptu?

- Impromptu is an interactive database reporting tool.
- It allows Power Users to query data without programming knowledge.
- When using the Impromptu tool, no data is written or changed in the database.
- It is only capable of reading the data.

Impromptu's main features

- Interactive reporting capability
- Enterprise-wide scalability
- Superior user interface
- Fastest time to result
- Lowest cost of ownership

Catalogs

- Impromptu stores metadata in subject related folders.
- This metadata is what will be used to develop a query for a report.
- The metadata set is stored in a file called a 'catalog'.
- The catalog does not contain any data.
- It just contains information about connecting to the database and the fields that will be accessible for reports.

A catalog contains:

- Folders—meaningful groups of information representing columns from one or more tables
- Columns—individual data elements that can appear in one or more folders
- Calculations—expressions used to compute required values from existing data
- Conditions—used to filter information so that only a certain type of information is displayed
- Prompts—pre-defined selection criteria prompts that users can include in reports they create
  Other components, such as metadata, a logical database name, join information, and user classes

We can use catalogs to

- view, run, and print reports
- export reports to other applications
- disconnect from and connect to the database
- create reports
- change the contents of the catalog
- add user classes

Prompts

We can use prompts to

- filter reports
- calculate data items
- format data

Pick list Prompts

- A pick list prompt presents you with a list of data items from which you select one or more values, so you need not be familiar with the database.
- The values listed in pick list prompts can be retrieved from
    a. a database via a catalog when you want to select information that often changes.
    b. a column in another saved Impromptu report, a snapshot, or a Hot File
- A report can include a prompt that asks you to select a product type from a list of those available in the database.
- Only the products belonging to the product type you select are retrieved and displayed in your report.

Reports

- Reports are created by choosing fields from the catalog folders.
- This process will build a SQL (Structured Query Language) statement behind the scene.
- No SQL knowledge is required to use Impromptu.
- The data in the report may be formatted, sorted and/or grouped as needed. Titles, dates, headers and footers and other standard text formatting features (italics, bolding, and font size) are also available.
- Once the desired layout is obtained, the report can be saved to a report file.
- This report can then be run at a different time, and the query will be sent to the database.

- It is also possible to save a report as a snapshot.
- This will provide a local copy of the data.
- This data will not be updated when the report is opened.

Frame-Based Reporting

Frames are the building blocks of all Impromptu reports and templates. They may contain report objects, such as data, text, pictures, and charts. There are no limits to the number of frames that you can place within an individual report or template. You can nest frames within other frames to group report objects within a report.

Different types of frames and its purpose for creating frame based reporting

- Form frame: An empty form frame appears.
- List frame: An empty list frame appears.
- Text frame: The flashing I-beam appears where you can begin inserting text.
- Picture frame: The Source tab (Picture Properties dialog box) appears. You can use this tab to select the image to include in the frame.
- Chart frame: The Data tab (Chart Properties dialog box) appears. You can use this tab to select the data item to include in the chart.
- OLE Object: The Insert Object dialog box appears where you can locate and select the file you want to insert, or you can create a new object using the software listed in the Object Type box.

Impromptu features

- **Unified query and reporting interface**: It unifies both query and reporting interface in a single user interface
- **Object oriented architecture**: It enables an inheritance based administration so that more than 1000 users can be accommodated as easily as single user
- **Complete integration with Power Play**: It provides an integrated solution for exploring trends and patterns
- **Scalability**: Its scalability ranges from single user to 1000 user
- **Security and Control**: Security is based on user profiles and their classes.
- **Data presented in a business context**: It presents information using the terminology of the business.

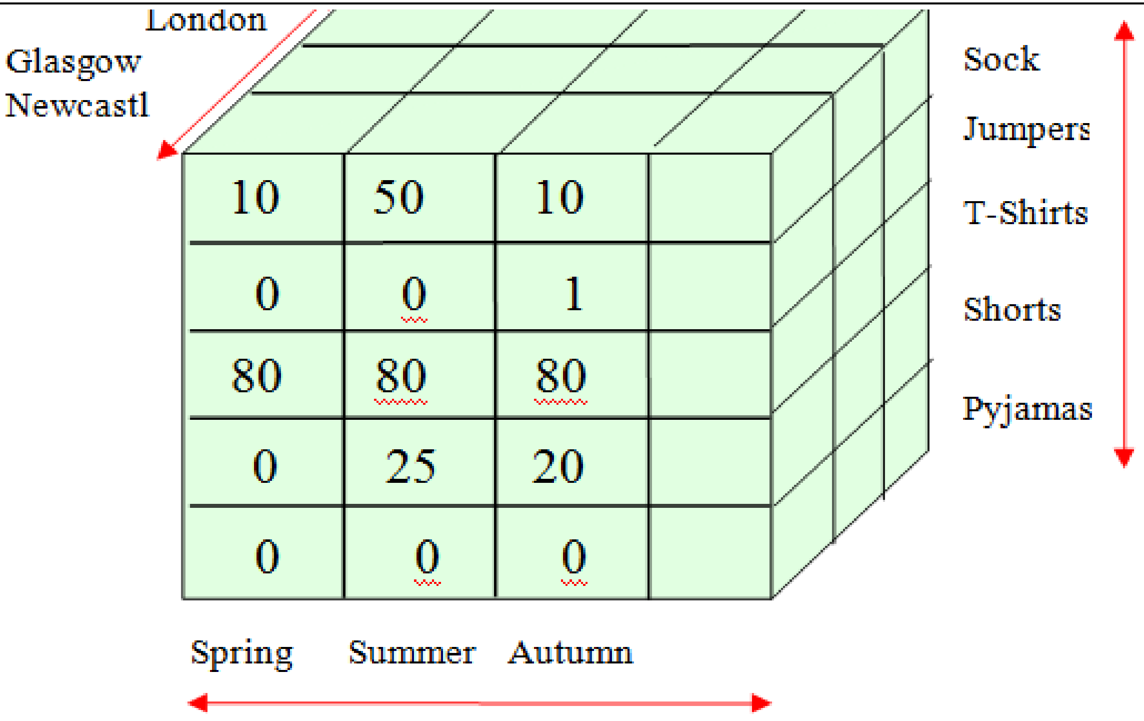
- **Over 70 pre defined report templates**: It allows users can simply supply the data to create an interactive report
- **Frame based reporting**: It offers number of objects to create a user designed report
- **Business relevant reporting**: It can be used to generate a business relevant report through filters, pre conditions and calculations
- **Database independent catalogs**: Since catalogs are in independent nature they require minimum maintenance

OLAP – On Line Analytical Processing:

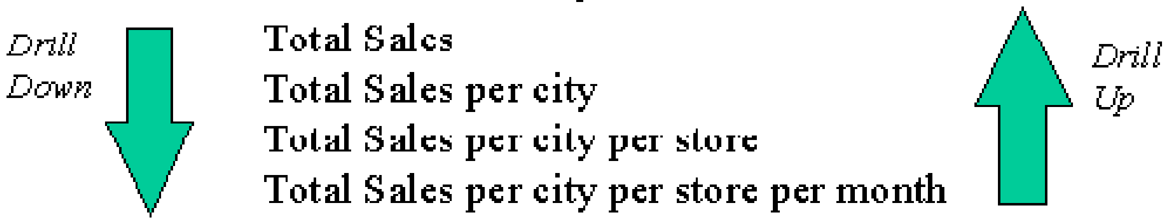
- **Basic idea**: converting data into information that decision makers need
- Concept to analyze data by multiple dimension in a structure called data cube.
- The key driver of OLAP is the multidimensional nature of the business problem.
- These problems are characterized by retrieving a very large number of records that can reach gigabytes and terabytes and summarizing this data into a form information that can be used by business analysts.
- One of the limitations that SQL has, it cannot represent these complex problems.
- A query will be translated in to several SQL statements.
- These SQL statements will involve multiple joints, intermediate tables, sorting, aggregations and a huge temporary memory to store these tables.
- Therefore the use of OLAP is preferable to solve this kind of problem.

The Multi Dimensional Data Model:

- As have been stated before, Business questions aren't as simple as before.
- The questions become more complex and multi dimensional.
- Let's take the question proposed before as our example.
- The question is as follows, how much profit from selling our products at our different centers per month. In order to look at this question we can imagine a 3 dimensional cube.



- In this cube we can observe, that each side of the cube represents one of the elements of the question.
- The x-axis represents the tome, the y-axis represents the products and the z-axis represents different centers.
- The cells of in the cube represents the number of product sold or can represent the price of the items.
- It can be observed that as the size of the dimension increase, the size of the cube will also increase exponentially.
- The time response of the cube depends on the size of the cube.
- That's why pre-aggregation is valuable because the dimensions of the cube can be hierarchal.
- For example time can be divided into half years, quarters, months and days.
- Predefining such hierarchal relations allows for smooth drilling down and pre-aggregation.


Drill Down
Total Sales
Total Sales per city
Total Sales per city per store
Total Sales per city per store per month
Drill Up

- This Figure also gives a different understanding to the drilling down operations.
- The relations defined must not be directly related, they related directly, what counts is defining the relations
- The size of the cube can be controlled by handling the sparse data.
- Not necessarily, that all the data in the cube must have a meaning.
- In marketing databases 95 % of the cells are empty or contain Zero.
- Also, in handling involves handling duplicate data of the cells.
- Let's assume that the cost of the product is one value for all markets the company is dealing with, therefore it is not necessary to have a cube with a multiple data item.
- Dimensional Hierarchy, sparse management and pre-aggregation are the main tools that speed up the execution of multi dimensional queries and reduce the size of the database.

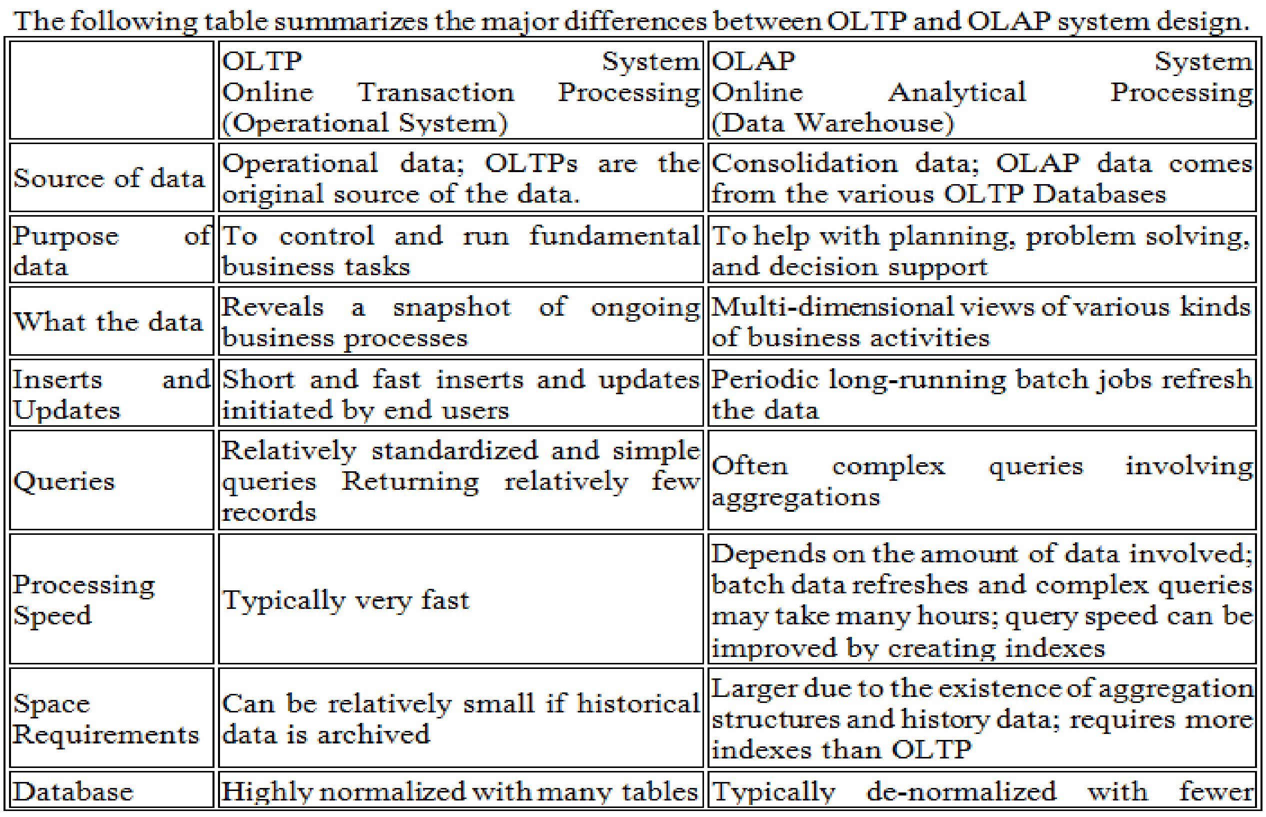
OLAP Guidelines:

- The rules are:
- Multidimensional conceptual view: The OLAP should provide an appropriate multidimensional Business model that suits the Business problems and Requirements.
- Transparency: The OLAP tool should provide transparency to the input data for the users.
- Accessibility: The OLAP tool should only access the data required only to the analysis needed.
- Consistent reporting performance: The Size of the database should not affect in any way the performance.
- Client/server architecture: The OLAP tool should use the client server architecture to ensure better performance and flexibility.
- Generic dimensionality: Data entered should be equivalent to the structure and operation requirements.
- Dynamic sparse matrix handling: The OLAP too should be able to manage the sparse matrix and so maintain the level of performance.
- Multi-user support: The OLAP should allow several users working concurrently to work together.
- Unrestricted cross-dimensional operations: The OLAP tool should be able to perform operations across the dimensions of the cube.
- Flexible reporting: It is the ability of the tool to present the rows and column in a manner suitable to be analyzed.

- Unlimited dimensions and aggregation levels: This depends on the kind of Business, where multiple dimensions and defining hierarchies can be made.

OLTP vs OLAP:

- OLTP stands for On Line Transaction Processing
- It is a data modeling approach typically used to facilitate and manage usual business applications.
- Most of applications you see and use are OLTP based.
- OLTP technology used to perform updates on operational or transactional systems (e.g., point of sale systems)
- OLAP stands for On Line Analytic Processing
- It is an approach to answer multi-dimensional queries.
- OLAP was conceived for Management Information Systems and Decision Support Systems.
- OLAP technology used to perform complex analysis of the data in a data warehouse.


The following table summarizes the major differences between OLTP and OLAP system design.

	OLTP System Online Transaction Processing (Operational System)	OLAP System Online Analytical Processing (Data Warehouse)
Source of data	Operational data; OLTPs are the original source of the data.	Consolidation data; OLAP data comes from the various OLTP Databases
Purpose of data	To control and run fundamental business tasks	To help with planning, problem solving, and decision support
What the data	Reveals a snapshot of ongoing business processes	Multi-dimensional views of various kinds of business activities
Inserts and Updates	Short and fast inserts and updates initiated by end users	Periodic long-running batch jobs refresh the data
Queries	Relatively standardized and simple queries Returning relatively few records	Often complex queries involving aggregations
Processing Speed	Typically very fast	Depends on the amount of data involved; batch data refreshes and complex queries may take many hours; query speed can be improved by creating indexes
Space Requirements	Can be relatively small if historical data is archived	Larger due to the existence of aggregation structures and history data; requires more indexes than OLTP
Database	Highly normalized with many tables	Typically de-normalized with fewer

Categorization of OLAP Tools:

The OLAP tools can be categorized into 3 major types. They are:

- Multidimensional OLAP (MOLAP)
- Relational OLAP (ROLAP)
- Hybrid OLAP (HOLAP)

MOLAP

- This is the more traditional way of OLAP analysis.
- In MOLAP, data is stored in a multidimensional cube.
- The storage is not in the relational database, but in proprietary formats.
- That is, data stored in array-based structures.

Advantages:

- Excellent performance: MOLAP cubes are built for fast data retrieval, and are optimal for slicing and dicing operations.
- Can perform complex calculations: All calculations have been pre-generated when the cube is created. Hence, complex calculations are not only doable, but they return quickly.

Disadvantages:

- Limited in the amount of data it can handle: Because all calculations are performed when the cube is built, it is not possible to include a large amount of data in the cube itself. This is not to say that the data in the cube cannot be derived from a large amount of data. Indeed, this is possible. But in this case, only summary-level information will be included in the cube itself.
- Requires additional investment: Cube technology are often proprietary and do not already exist in the organization. Therefore, to adopt MOLAP technology, chances are additional investments in human and capital resources are needed.

ROLAP

- 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.
- Data stored in relational tables

Advantages:

- Can handle large amounts of data: The data size limitation of ROLAP technology is the limitation on data size of the underlying relational database. In other words, ROLAP itself places no limitation on data amount.
- Can leverage functionalities inherent in the relational database: Often, relational database already comes with a host of functionalities. ROLAP technologies, since they sit on top of the relational database, can therefore leverage these functionalities.

Disadvantages:

- Performance can be slow: Because each ROLAP report is essentially a SQL query (or multiple SQL queries) in the relational database, the query time can be long if the underlying data size is large.
- Limited by SQL functionalities: Because ROLAP technology mainly relies on generating SQL statements to query the relational database, and SQL statements do not fit all needs (for example, it is difficult to perform complex calculations using SQL), ROLAP technologies are therefore traditionally limited by what SQL can do. ROLAP vendors have mitigated this risk by building into the tool out-of-the-box complex functions as well as the ability to allow users to define their own functions.

HOLAP (MQE: Managed Query Environment)

- HOLAP technologies attempt to combine the advantages of MOLAP and ROLAP.
- For summary-type information, HOLAP leverages cube technology for faster performance.
- It stores only the indexes and aggregations in the multidimensional form while the rest of the data is stored in the relational database.

OLAP and the Internet Tools:

- The mainly comprehensive premises in computing have been the internet and data warehousing thus the integration of these two giant technologies is a necessity.
- The advantages of using the Web for access are inevitable.

These advantages are:

- The internet provides connectivity between countries acting as a free resource.
- The web eases administrative tasks of managing scattered locations.

- The Web allows users to store and manage data and applications on servers that can be managed, maintained and updated centrally.

Conclusion:

- OLAP is a significant improvement over query systems
- OLAP is an interactive system to show different summaries of multidimensional data by interactively selecting the attributes in a multidimensional data cube

OLAP Tools and the internet:

The mainly comprehensive premises in computing have been the internet and data warehousing thus the integration of these two giant technologies is a necessity. The advantages of using the Web for access are inevitable.(Reference 3) These advantages are:

- The internet provides connectivity between countries acting as a free resource.
- The web eases administrative tasks of managing scattered locations.

The Web allows users to store and manage data and applications on servers that can be managed, maintained and updated centrally.

These reasons indicate the importance of the Web in data storage and manipulation. The Web-enabled data access has many significant features, such as:

- **The first**
- **The second**
- **The emerging third HTML publishing**
- **Helper applications**
- **Plug-ins**
- **Server-centric components**
- **Java and active-x applications**

Products for OLAP

Microsoft Analysis Services (previously called OLAP Services, part of SQL Server), IBM's DB2 OLAP Server, SAP BW and products from Brio, Business Objects, Cognos, Micro Strategy and others. **Companies using OLAP**

MIS AG Overview

MIS AG is the leading European provider of business intelligence solutions and services, providing development, implementation, and service of systems for budgeting, reporting, consolidation, and analysis. MIS AG products include industry and platform independent software for efficient corporate controlling. **Poet Overview**

With FastObjects™, German Poet Software GmbH (Poet) provides developers with a flexible Object-oriented Database Management System (ODBMS) solution optimized for managing complexity in high-performance applications using Java technology, C++ and .NET.

Unit 3

Data Mining:

What is Data Mining?

Simply stated, data mining refers to *extracting or "mining" knowledge from large amounts of data*. The term is actually a misnomer. Remember that the mining of gold from rocks or sand is referred to as *gold* mining rather than rock or sand mining. Thus, data mining should have been more appropriately named "knowledge mining from data," which is unfortunately somewhat long. "Knowledge mining," a shorter term may not reflect the emphasis on mining from large amounts of data. Nevertheless, mining is a vivid term characterizing the process that finds a small set of precious nuggets from a great deal of raw material (Figure 1.3). Thus, such a misnomer that carries both "data" and "mining" became a popular choice. Many other terms carry a similar or slightly different meaning to data mining, such as knowledge mining from data, knowledge extraction, data/pattern analysis, data archaeology, and data dredging.

Many people treat data mining as a synonym for another popularly used term, Knowledge Discovery from Data, or KDD. Alternatively, others view data mining as simply an essential step in the process of knowledge discovery. Knowledge discovery as a process is depicted in Figure 1.4 and consists of an iterative sequence of the following steps:

1. **Data cleaning** (to remove noise and inconsistent data)
2. **Data integration** (where multiple data sources may be combined)1
3. **Data selection** (where data relevant to the analysis task are retrieved from the database)
4. **Data transformation** (where data are transformed or consolidated into forms appropriate for mining by performing summary or aggregation operations, for instance)2
5. **Data mining** (an essential process where intelligent methods are applied in order to extract data patterns)
6. **Pattern evaluation** (to identify the truly interesting patterns representing knowledge based on some interestingness measures; Section 1.5)
7. **Knowledge presentation** (where visualization and knowledge representation techniques are used to present the mined knowledge to the user)

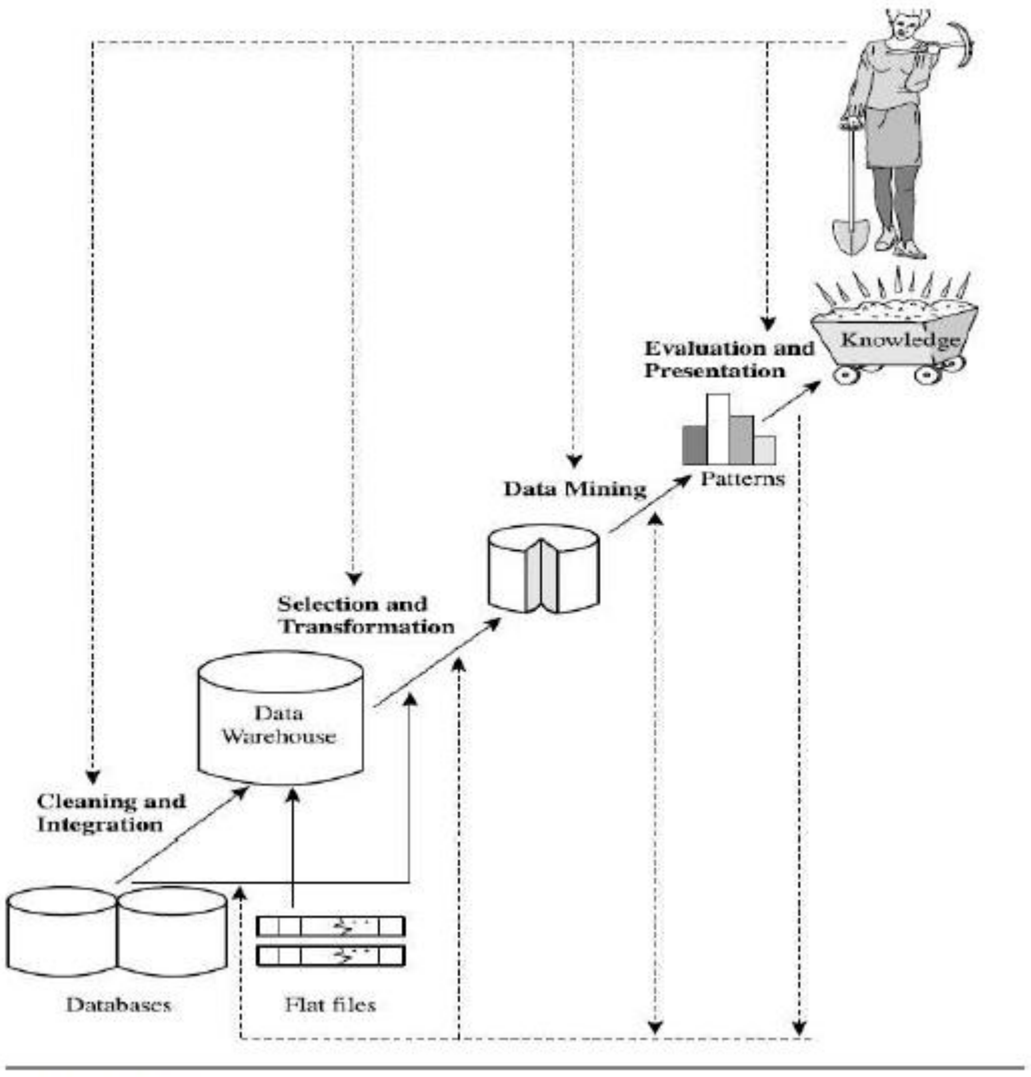


Figure 1.4 Data mining as a step in the process of knowledge discovery.

Steps 1 to 4 are different forms of data preprocessing, where the data are prepared for mining. The data mining step may interact with the user or a knowledge base. The interesting patterns are presented to the user and may be stored as new knowledge in the knowledge base. Note that according to this view, data mining is only one step in the entire process, albeit an essential one because it uncovers hidden patterns for evaluation. We agree that data mining is a step in the knowledge discovery process. However, in industry, in media, and in the database research milieu, the term data mining is becoming more popular than the longer term of knowledge discovery from data. Therefore, here, we choose to use the term data mining. We adopt a broad view of data mining functionality: data mining is the process of discovering interesting knowledge from large amounts of data stored in databases, data warehouses, or other information repositories.

Based on this view, the architecture of a typical data mining system may have the following major components (Figure 1.5):

- Database, data warehouse, World Wide Web, or other information repository: This is one or a set of databases, data warehouses, spreadsheets, or other kinds of information repositories. Data cleaning and data integration techniques may be performed on the data.
- Database or data warehouse server: The database or data warehouse server is responsible for fetching the relevant data, based on the user's data mining request.

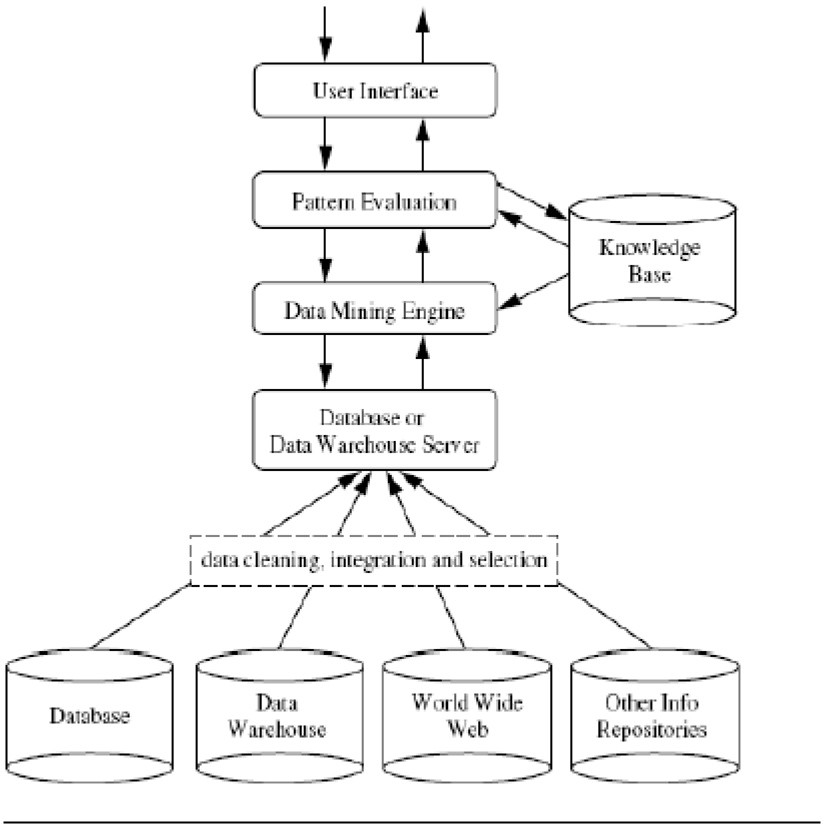


Figure 1.5 Architecture of a typical data mining system.

Knowledge base:

This is the domain knowledge that is used to guide the search or evaluate the interestingness of resulting patterns. Such knowledge can include concept hierarchies, 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).

Data mining engine:

This is essential to the data mining system and ideally consists of a set of functional modules for tasks such as characterization, association and correlation analysis, classification, prediction, cluster analysis, outlier analysis, and evolution analysis.

Pattern evaluation module:

This component typically employs interestingness measures (Section 1.5) and interacts with the data mining modules so as to *focus* the search toward interesting patterns. It may use interestingness thresholds to filter out discovered patterns. Alternatively, the pattern evaluation module may be integrated with the mining module, depending on the implementation of the data mining method used. For efficient data mining, it is highly recommended to push the evaluation of pattern interestingness as deep as possible into the mining process so as to confine the search to only the interesting patterns.

User interface:

This module communicates between users and the data mining system, allowing the user to interact with the system by specifying a data mining query or task, providing information to help focus the search, and performing exploratory data mining based on the intermediate data mining results.

In addition, this component allows the user to browse database and data warehouse schemas or data structures, evaluate mined patterns, and visualize the patterns in different forms.

From a data warehouse perspective, data mining can be viewed as an advanced stage of on-line analytical processing (OLAP). However, data mining goes far beyond the narrow scope of summarization style analytical processing of data warehouse systems by incorporating more advanced techniques for data analysis.

Data mining involves an integration of techniques from multiple disciplines such as database and data warehouse technology, statistics, machine learning, high-performance computing, pattern recognition, neural networks, data visualization, information retrieval, image and signal processing, and spatial or temporal data analysis. We adopt a database perspective in our presentation of data mining in this note. That is, emphasis is placed on *efficient* and *scalable* data mining techniques. For an algorithm to be scalable, its running time should grow approximately linearly in proportion to the size of the data, given the available system resources such as main memory and disk space. By performing data mining, interesting knowledge, regularities, or high-level information can be extracted from databases and viewed or browsed from different angles. The discovered knowledge can be applied to decision making, process control, information management, and query processing. Therefore, data mining is considered one of the most important frontiers in database and information systems and one of the most promising interdisciplinary developments in the information technology.

<u>Data Mining—On What Kind of Data? (Types of Data)</u>

Relational Databases

A database system, also called a database management system (DBMS), consists of a collection of interrelated data, known as a database, and a set of software programs to manage and access the data.

A relational database is a collection of tables, each ofwhich is assigned a unique name Each table consists of a set of attributes (*columns* or *fields*) and usually stores a large set of tuples (*records* or *rows*). Each tuple in a relational table represents an object identified by a unique *key* and described by a set of attribute values. A semantic data model, such as an entity-relationship (ER) data model, is often constructed for relational databases. An ER data model represents the database as a set of entities and their relationships.

Relational databases are one of the most commonly available and rich information repositories, and thus they are a major data form in our study of data mining.

Data Warehouses

Suppose that *All Electronics* is a successful international company, with branches around the world. Each branch has its own set of databases. The president of *All Electronics* has asked you to provide an analysis of the company's sales per item type per branch for the third quarter. This is a difficult task, particularly since the relevant data are spread out over several databases, physically located at numerous sites.

If *All Electronics* had a data warehouse, this task would be easy. A data warehouse is a repository of information collected from multiple sources, stored under a unified schema, and that usually resides at a single site. Data warehouses are constructed via a process of data cleaning, data integration, data transformation, data loading, and periodic data refreshing.

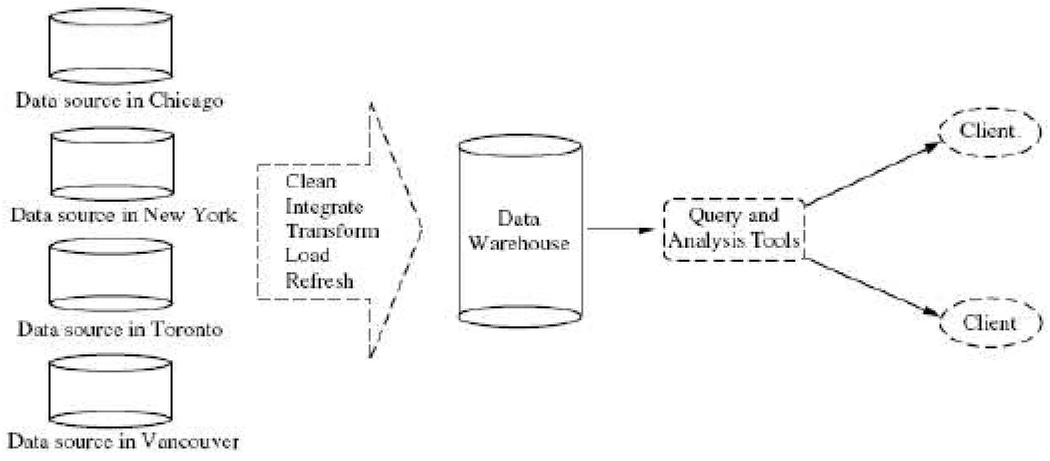


Figure 1.7 shows the typical framework for construction and use of a data warehouse for *AllElectronics*

To facilitate decision making, the data in a data warehouse are *organized around major subjects*, such as customer, item, supplier, and activity. The data are stored to provide information from a *historical perspective* (such as from the past 5–10 years) and are typically *summarized*. For example, rather than storing the details of each sales transaction, the data warehouse may store a summary of the transactions per item type for each store or, summarized to a higher level, for each sales region.

A data warehouse is usually modeled by a multidimensional database structure, where each dimension corresponds to an attribute or a set of attributes in the schema, and each cell stores the value of some aggregate measure, such as *count* or *sales amount*. The actual physical structure of a data warehouse may be a relational data store or a multidimensional data cube. A data cube provides a multidimensional view of data and allows the pre computation and fast accessing of summarized data.

Example A data cube for *All Electronics*. A data cube for summarized sales data of *All Electronics* is presented in Figure 1.8(a). The cube has three dimensions: *address* (with city values *Chicago, New York,* *Toronto*, *Vancouver*), *time* (with quarter values *Q1*, *Q2*, *Q3*, *Q4*), and *item*(with item type values *home entertainment*, *computer*, *phone*, *security*). The aggregate value stored in each cell of the cube is *sales amount* (in thousands). For example, the total sales forthefirstquarter,*Q1*, for items relating to security systems in Vancouver is$400,000, as stored in cell (*Vancouver*, *Q1*, *security)*. Additional cubes may be used to store aggregate sums over each dimension, corresponding to the aggregate values obtained using different SQL group-bys (e.g., the total sales amount per city and quarter, or per city and item, or per quarter and item, or per each individual dimension).

What is the difference between a data warehouse and a data mart?

A data warehouse collects information about subjects that span an *entire organization*, and thus its scope is *enterprise-wide*.

A data mart, on the other hand, is a department subset of a data warehouse. It focuses on selected subjects, and thus its scope is *department-wide*.

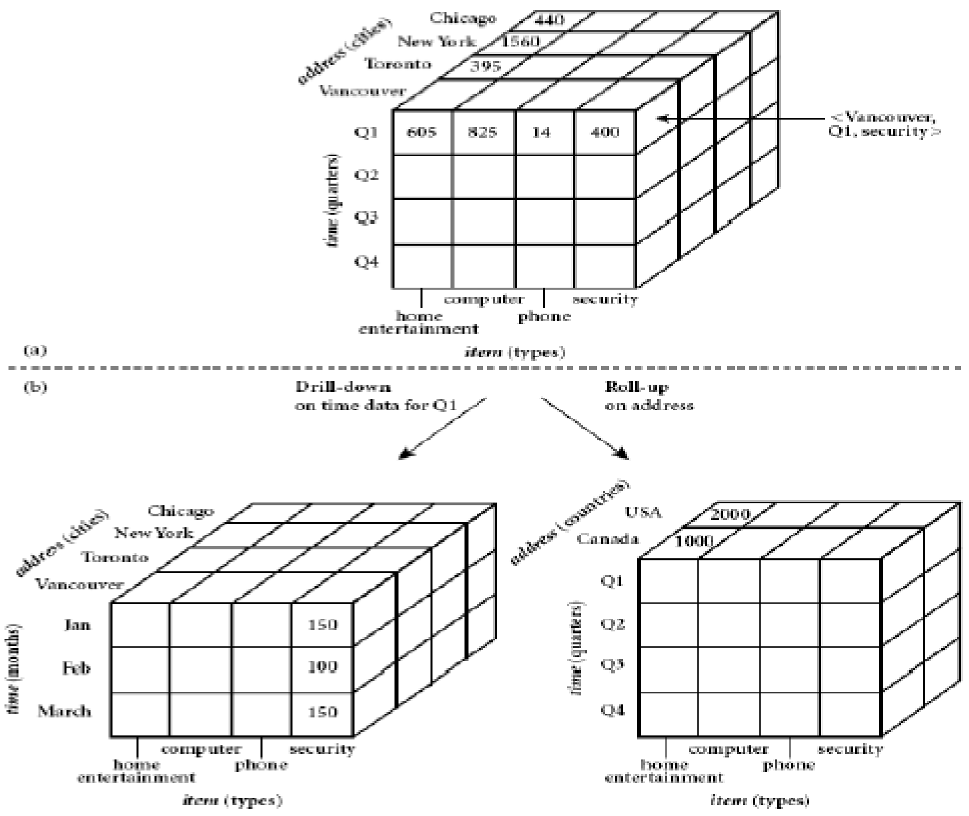


Figure 1.8 A multidimensional data cube, commonly used for data warehousing, (a) showing summarized data for *AllElectronics* and (b) showing summarized data resulting fromdrill-down and roll-up operations on the cube in (a). For improved readability, only some of the cube cell values are shown.

By providing multidimensional data views and the pre computation of summarized data, data warehouse systems are well suited for on-line analytical processing, or OLAP. OLAP operations use background knowledge regarding the domain of the data being studied in order to allow the presentation of data at *different levels of abstraction*. Such operations accommodate different user viewpoints.

Examples of OLAP operations include drill-down and roll-up, which allow the user to view the data at differing degrees of summarization, as illustrated in Figure 1.8(b). For instance, we can drill down on sales data summarized by *quarter* to see the data summarized by *month*. Similarly, we can roll up on sales data summarized by *city* to view the data summarized by *country*.

Transactional Databases

In general, a transactional database consists of a file where each record represents a transaction. A transaction typically includes a unique transaction identity number (*trans ID*) and a list of the items making up the transaction (such as items purchased in a store).

The transactional database may have additional tables associated with it, which contain other information regarding the sale, such as the date of the transaction, the customer ID number, the ID number of the salesperson and of the branch at which the sale occurred, and so on.

trans_ID	*list of item_IDs*
T100	I1, I3, I8, I16
T200	I2, I8
...	...

Figure 1.9 Fragment of a transactional database for sales at *AllElectronics*.

Example: A transactional database for *All Electronics*. Transactions can be stored in a table, with one record per transaction. From the relational database point of view, the *sales* table in Figure 1.9 is a nested relation because the attribute *list of item IDs* contains a set of *items*. Because most relational database systems do not support nested relational structures, the transactional database is usually either stored in a flat file in a format similar to that of the table in Figure 1.9 or unfolded into a standard relation in a format similar to that of the *items sold* table in Figure 1.6.

Advanced Data and Information Systems and Advanced Applications

Relational database systems have been widely used in business applications. With the progress of database technology, various kinds of advanced data and information systems have emerged and are undergoing development to address the requirements of new applications.

The new database applications include handling spatial data (such as maps), engineering design data (such as the design of buildings, system components, or integrated circuits), hypertext and multimedia data (including text, image, video, and audio data), time-related data (such as historical records or stock exchange data), stream data (such as video surveillance and sensor data, where data flow in and out like streams), and the World Wide Web (a huge, widely distributed information repository made available by the Internet). These applications require efficient data structures and scalable methods for handling complex object structures; variable-length records; semi structured or unstructured data; text, spatiotemporal, and multimedia data; and database schemas with complex structures and dynamic changes.

Object-Relational Databases

Object-relational databases are constructed based on an object-relational data model. This model extends the relational model by providing a rich data type for handling complex objects and object orientation. Because most sophisticated database applications need to handle complex objects and structures, object-relational databases are becoming increasingly popular in industry and applications.

Conceptually, the object-relational data model inherits the essential concepts of object-oriented databases, where, in general terms, each entity is considered as an object. Following the *All Electronics* example, objects can be individual employees, customers, or items. Data and code relating to an object are *encapsulated* into a single unit. Each object has associated with it the following:

- **A set of variables** that describe the objects. These correspond to attributes in the entity relationship and relational models.
- **A set of messages** that the object can use to communicate with other objects, or with the rest of the database system.
- **A set of methods**, where each method holds the code to implement a message. Upon receiving a message, the method returns a value in response. For instance, the method for the message *get photo*(*employee*) will retrieve and return a photo of the given employee object.

Objects that share a common set of properties can be grouped into an object class. Each object is an instance of its class. Object classes can be organized into class/subclass hierarchies so that each class represents properties that are common to objects in that class. For instance, an *employee* class can contain variables like *name*, *address*, and *birth date*. Suppose that the class, *sales person*, is a subclass of the class, *employee*. A *sales person* object would inherit all of the variables pertaining to its super class of *employee*. In addition, it has all of the variables that pertain specifically to being a salesperson (e.g., *commission*). Such a class inheritance feature benefits information sharing.

For data mining in object-relational systems, techniques need to be developed for handling complex object structures, complex data types, class and subclass hierarchies, property inheritance, and methods and procedures.

Temporal Databases, Sequence Databases, and Time-Series Databases

A temporal database typically stores relational data that include time-related attributes. These attributes may involve several timestamps, each having different semantics.

A sequence database stores sequences of ordered events, with or without a concrete notion of time. Examples include customer shopping sequences, Web click streams, and biological sequences. A time series database stores sequences of values or events obtained over repeated measurements of time (e.g., hourly, daily, weekly). Examples include data collected from the stock exchange, inventory control, and the observation of natural phenomena (like temperature and wind).

Data mining techniques can be used to find the characteristics of object evolution or the trend of changes for objects in the database. Such information can be useful in decision making and strategy planning. For instance, the mining of banking data may aid in the scheduling of bank tellers according to the volume of customer traffic. Stock exchange data can be mined to uncover trends that could help you plan investment strategies (e.g., when is the best time to purchase *All Electronics* stock?). Such analyses typically require defining multiple granularity of time. For example, time may be decomposed according to fiscal years, academic years, or calendar years. Years may be further decomposed into quarters or months.

Spatial Databases and Spatiotemporal Databases

Spatial databases contain spatial-related information. Examples include geographic (map) databases, very large-scale integration (VLSI) or computer-aided design databases, and medical and satellite image databases. Spatial data may be represented in raster format, consisting of *n*-dimensional bit maps or pixel maps. For example, a 2-D satellite image may be represented as raster data, where each pixel registers the rainfall in a given area. Maps can be represented in vector format, where roads, bridges, buildings, and lakes are represented as unions or overlays of basic geometric constructs, such as points, lines, polygons, and the partitions and networks formed by these components.

Geographic databases have numerous applications, ranging from forestry and ecology planning to providing public service information regarding the location of telephone and electric cables, pipes, and sewage systems. In addition, geographic databases are commonly used in vehicle navigation and dispatching systems. An example of such a system for taxis would store a city map with information regarding one-way streets, suggested routes for moving from region A to region B during rush hour, and the location of restaurants and hospitals, as well as the current location of each driver.

"What kind of data mining can be performed on spatial databases?" you may ask. Data mining may uncover patterns describing the characteristics of houses located near a specified kind of location, such as a park, for instance.

A spatial database that stores spatial objects that change with time is called a spatiotemporal database, from which interesting information can be mined. For example, we may be able to group the trends of moving objects and identify some strangely moving vehicles, or distinguish a bioterrorist attack from a normal outbreak of the flu based on the geographic spread of a disease with time.

Text Databases and Multimedia Databases

Text databases are databases that contain word descriptions for objects. These word descriptions are usually not simple keywords but rather long sentences or paragraphs, such as product specifications, error or bug reports, warning messages, summary reports, notes, or other documents. Text databases may be highly unstructured (such as some Web pages on the World Wide Web). Some text databases may be somewhat structured, that is, *semi structured* (such as e-mail messages and many HTML/XML Web pages), whereas others are relatively well structured (such as library catalogue databases). Text databases with highly regular structures typically can be implemented using relational database systems.

"What can data mining on text databases uncover?" By mining text data, one may uncover general and concise descriptions of the text documents, keyword or content associations, as well as the clustering behavior of text objects. To do this, standard data mining methods need to be integrated with information retrieval techniques and the construction or use of hierarchies specifically for text data (such as dictionaries and thesauruses), as well as discipline-oriented term classification systems (such as in biochemistry, medicine, law, or economics).

Multimedia databases

Store image, audio, and video data. They are used in applications such as picture content-based retrieval, voice-mail systems, video-on-demand systems, the World Wide Web, and speech-based user interfaces that recognize spoken commands. Multimedia databases must support large objects, because data objects such as video can require gigabytes of storage. Specialized storage and search techniques are also required. Because video and audio data require real-time retrieval at a steady and predetermined rate in order to avoid picture or sound gaps and system buffer overflows, such data are referred to as continuous-media data.

Heterogeneous Databases and Legacy Databases

A heterogeneous database consists of a set of interconnected, autonomous component databases. The components communicate in order to exchange information and answer queries. Objects in one component database may differ greatly from objects in other component databases, making it difficult to assimilate their semantics into the overall heterogeneous database.

A legacy database is a group of *heterogeneous databases* that combines different kinds of data systems, such as relational or object-oriented databases, hierarchical databases, network databases, spreadsheets, multimedia databases, or file systems. The heterogeneous databases in a legacy database may be connected by intra or inter-computer networks. Information exchange across such databases is difficult because it would require precise transformation rules from one representation to another, considering diverse semantics.

Data Streams

Many applications involve the generation and analysis of a new kind of data, called stream data, where data flow in and out of an observation platform (or window) dynamically. Such data streams have the following unique features: *huge or possibly infinite volume, dynamically changing, flowing in and out in a fixed order, allowing only one or a small number of scans, and demanding fast (often real-time) response time*. Typical examples of data streams include various kinds of scientific and engineering data, time-series data, and data produced in other dynamic environments, such as power supply, network traffic, stock exchange, telecommunications, Web click streams, video surveillance, and weather or environment monitoring.

Because data streams are normally not stored in any kind of data repository, effective and efficient management and analysis of stream data poses great challenges to researchers. Currently, many researchers are investigating various issues relating to the development of data stream management systems. Atypical query model in such a system is the *continuous query model*, where predefined queries constantly evaluate incoming streams, collect aggregate data, report the current status of data streams, and respond to their changes.

Mining data streams involves the efficient discovery of general patterns and dynamic changes within stream data.

The World Wide Web

The World Wide Web and its associated distributed information services, such as Yahoo!, Google, America Online, and AltaVista, provide rich, worldwide, on-line information services, where data objects are linked together to facilitate interactive access. Users seeking information of interest traverse from one object via links to another. Such systems provide ample opportunities and challenges for data mining. For example, understanding user access patterns will not only help improve system design (by providing efficient access between highly correlated objects), but also leads to better marketing decisions (e.g., by placing advertisements in frequently visited documents, or by providing better customer/user classification and behavior analysis). Capturing user access patterns in such distributed information environments is called Web usage mining (or Weblog mining).

Although Web pages may appear fancy and informative to human readers, they can be highly unstructured and lack a predefined schema, type, or pattern. Thus it is difficult for computers to understand the semantic meaning of diverse Web pages and structure them in an organized way for systematic information retrieval and data mining. Web services that provide keyword-based searches without understanding the context behind the Web pages can only offer limited help to users. For example, a Web search based on a single keyword may return hundreds of Web page pointers containing the keyword, but most of the pointers will be very weakly related to what the user wants to find. Data mining can often provide additional help here than Web search services. For example, authoritative Web page analysis based on linkages among Web pages can help rank Web pages based on their importance, influence, and topics. Automated Web page clustering and classification help group and arrange Web pages in a multidimensional manner based on their contents. Web community analysis helps identify hidden Web social networks and communities and observe their evolution.

Web mining is the development of scalable and effective Web data analysis and mining methods. It may help us learn about the distribution of information on the Web in general, characterize and classify Web pages, and uncover Web dynamics and the association and other relationships among different Web pages, users, communities, and Web-based activities.

Data Mining Functionalities—What Kinds of Patterns Can Be Mined?

Data mining functionalities are used to specify the kind of patterns to be found in data mining tasks. In general, data mining tasks can be classified into two categories: descriptive and predictive.

Descriptive mining tasks characterize the general properties of the data in the database. Predictive mining tasks perform inference on the current data in order to make predictions.

In some cases, users may have no idea regarding what kinds of patterns in their data may be interesting, and hence may like to search for several different kinds of patterns in parallel. Thus it is important to have a data mining system that can mine multiple kinds of patterns to accommodate different user expectations or applications.

Concept/Class Description: Characterization and Discrimination

Data can be associated with classes or concepts. For example, in the *All Electronics* store, classes of items for sale include *computers* and *printers*, and concepts of customers include ***Big Spenders*** and ***budget Spenders*****.** It can be useful to describe individual classes and concepts in summarized, concise, and yet precise terms. Such descriptions of a class or a concept are called class/concept descriptions. These descriptions can be derived via (1) *data characterization*, by summarizing the data of the class under study (often called the target class) in general terms, or (2) *data discrimination*, by comparison of the target class with one or a set of comparative classes (often called the contrasting classes), or (3) both data characterization and discrimination.

Data characterization is a summarization of the general characteristics or features of a target class of data. The data corresponding to the user-specified class are typically collected by a database query. For example, to study the characteristics of software products whose sales increased by 10% in the last year, the data related to such products can be collected by executing an SQL query.

The output of data characterization can be presented in various forms. Examples include pie charts, bar charts, curves, multidimensional data cubes, and multidimensional tables, including crosstabs. The resulting descriptions can also be presented as generalized relations or in rule form (called characteristic rules).

Example: Data characterization. A data mining system should be able to produce a description summarizing the characteristics of customers who spend more than $1,000 a year at *All Electronics*.

Data discrimination is a comparison of the general features of target class data objects with the general features of objects from one or a set of contrasting classes. The target and contrasting classes can be specified by the user, and the corresponding data objects retrieved through database queries. For example, the user may like to compare the general features of software products whose sales increased by 10% in the last year with those whose sales decreased by at least 30% during the same period. The methods used for data discrimination are similar to those used for data characterization.

"How are discrimination descriptions output?" The forms of output presentation are similar to those for characteristic descriptions, although discrimination descriptions should include comparative measures that help distinguish between the target and contrasting classes. Discrimination descriptions expressed in rule form are referred to as discriminate rules.

Example: Data discrimination. A data mining system should be able to compare two groups of *All Electronics* customers, such as those who shop for computer products regularly (more than two times a month) versus those who rarely shop for such products (i.e., less than three times a year).

The resulting description provides a general comparative profile of the customers, such as 80% of the customers who frequently purchase computer products are between 20 and 40 years old. Whereas 60% of the customers who infrequently buy such products are either seniors. Drilling down on a dimension, such as *occupation*, or adding new dimensions, such as *income level*, may help in finding even more discriminative features between the two classes.

Mining Frequent Patterns, Associations, and Correlations

Frequent patterns, as the name suggests, are patterns that occur frequently in data. There are many kinds of frequent patterns, including item sets, subsequences, and substructures.

A *frequent item set* typically refers to a set of items that frequently appear together in a transactional data set, such as Computer and Software. A frequently occurring subsequence, such as the pattern that customers tend to purchase first a PC, followed by a digital camera, and then a memory card, is a (*frequent*) *sequential pattern*.

A substructure can refer to different structural forms, such as graphs, trees, or lattices, which may be combined with item sets or subsequences. If a substructure occurs frequently, it is called a (*frequent*) *structured pattern*. Mining frequent patterns leads to the discovery of interesting associations and correlations within data.

Example: Association analysis. Suppose, as a marketing manager of *All Electronics*, you would like to determine which items are frequently purchased together within the same transactions. An example of such a rule, mined from the *All Electronics* transactional database, is

***buys*(*X*; "*computer*") *buys*(*X*; "*software*") [*support* = 1%, *confidence* = 50%]**

Where *X* is a variable representing a customer. A confidence, or certainty, of 50% means that if a customer buys a computer, there is a 50% chance that she will buy software as well. A 1% support means that 1% of all of the transactions under analysis showed that computer and software were purchased together. This association rule involves a single attribute or predicate (i.e., *buys*) that repeats.

Association rules that contain a single predicate are referred to as single-dimensional association rules. Dropping the predicate notation, the above rule can be written simply as "*compute software* [1%, 50%]". Suppose, instead, that we are given the *All Electronics* relational database relating to purchases. A data mining system may find association rules like

***age*(*X*, "20…29")^*income*(*X*, "20K…29K") *buys*(*X*, "*CD player*") [*support* = 2%, *confidence* =60%]**

The rule indicates that of the *All Electronics* customers under study, 2% are 20 to 29 years of age with an income of 20,000 to 29,000 and have purchased a CD player at *All Electronics*. There is a 60% probability that a customer in this age and income group will purchase a CD player. Note that this is an association between more than one attribute, or predicate (i.e., *age*, *income*, and *buys*). Adopting the terminology used in multidimensional databases, where each attribute is referred to as a dimension, the above rule can be referred to as a multidimensional association rule.

Typically, association rules are discarded as uninteresting if they do not satisfy both a minimum support threshold and a minimum confidence threshold. Additional analysis can be performed to uncover interesting statistical correlations between associated attribute-value pairs.

Classification and Prediction

Classification is the process of finding a model (or function) that describes and distinguishes data classes or concepts, for the purpose of being able to use the model to predict the class of objects whose class label is unknown. The derived model is based on the analysis of a set of training data (i.e., data objects whose class label is known).

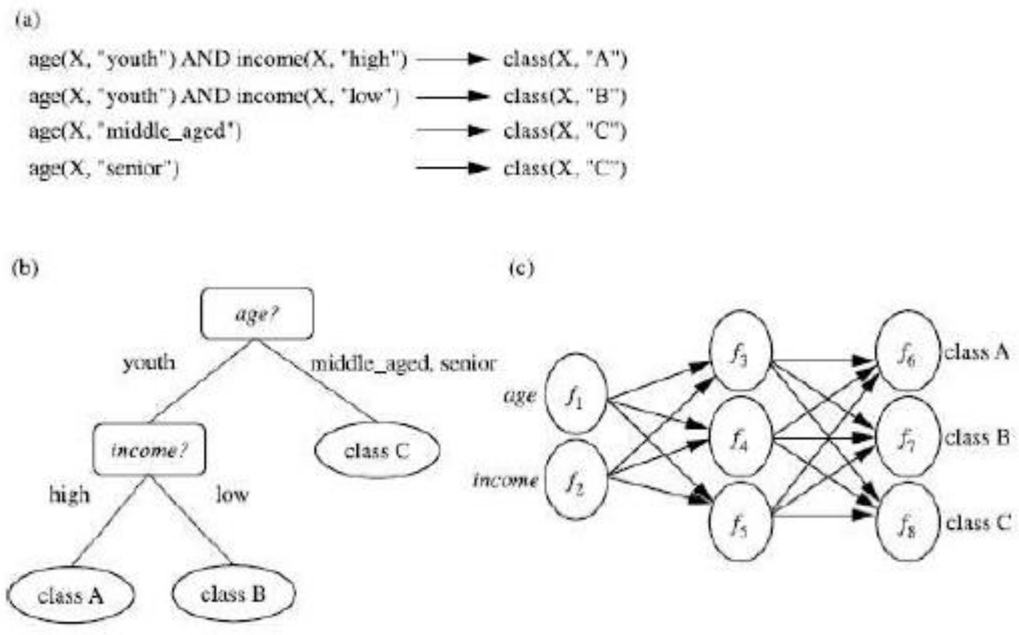
"How is the derived model presented?" The derived model may be represented in various forms, such as ***classification (IF-THEN) rules***, *decision trees*, *mathematical formulae*, or *neural networks* (Figure 1.10).

A decision tree is a flow-chart-like tree structure, where each node denotes a test on an attribute value, each branch represents an outcome of the test, and tree leaves represent classes or class distributions. Decision trees can easily be converted to classification rules.

A neural network, when used for classification, is typically a collection of neuron-like processing units with weighted connections between the units. There are many other methods for constructing classification models, such as naïve Bayesian classification, support vector machines, and *k*-nearest neighbor classification. Whereas classification predicts categorical (discrete, unordered) labels, prediction models continuous-valued functions. That is, it is used to predict missing or unavailable *numerical data values* rather than class labels. Although the term *prediction* may refer to both numeric prediction and class label prediction,

Example: Classification and prediction. Suppose, as sales manager of *All Electronics*, you would like to classify a large set of items in the store, based on three kinds of responses to a sales campaign: *good response*, *mild response*, and *no response*. You would like to derive a model for each of these three classes based on the descriptive features of the items, such as *price*, *brand*, *place made*, *type*, and *category*. The resulting classification should maximally distinguish each class from the others, presenting an organized picture of the data set. Suppose that the resulting classification is expressed in the form of a decision tree.

The decision tree, for instance, may identify *price* as being the single factor that best distinguishes the three classes. The tree may reveal that, after *price*, other features that help further distinguish objects of each class from another include *brand* and *place made*. Such a decision tree may help you understand the impact of the given sales campaign and design a more effective campaign for the future.



(a)

age(X, "youth") AND income(X, "high") ⟶ class(X, "A")
age(X, "youth") AND income(X, "low") ⟶ class(X, "B")
age(X, "middle_aged") ⟶ class(X, "C")
age(X, "senior") ⟶ class(X, "C")

Figure 1.10 A classification model can be represented in various forms, such as (a) IF-THEN rules, (b) a decision tree, or a (c) neural network.

Cluster Analysis

Classification and prediction analyze class-labeled data objects, where as **clustering** analyzes data objects without consulting a known class label.

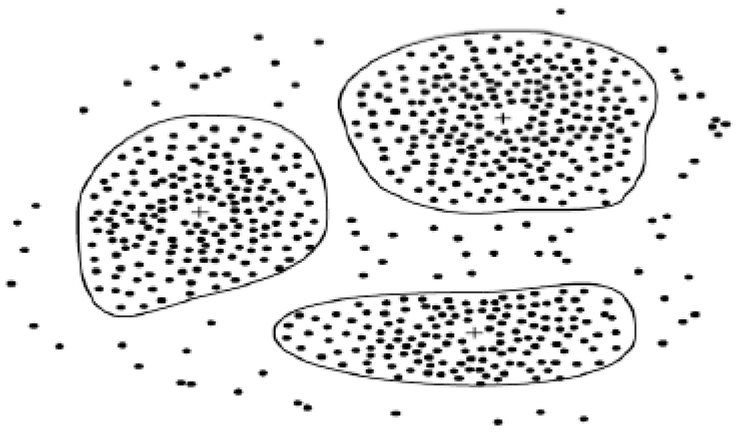


Figure 1.11 A 2-D plot of customer data with respect to customer locations in a city, showing three data clusters. Each cluster "center" is marked with a "+".

In general, the class labels are not present in the training data simply because they are not known to begin with. Clustering can be used to generate such labels. The objects are clustered or grouped based on the principle of *maximizing the intra class similarity and minimizing the interclass similarity*. That is, clusters of objects are formed so that objects within a cluster have high similarity in comparison to one another, but are very dissimilar to objects in other clusters. Each cluster that is formed can be viewed as a class of objects, from which rules can be derived.

Example: Cluster analysis can be performed on *All Electronics* customer data in order to identify homogeneous subpopulations of customers. These clusters may represent individual target groups for marketing. Figure 1.11 shows a 2-D plot of customers with respect to customer locations in a city. Three clusters of data points are evident.

Outlier Analysis

A database may contain data objects that do not comply with the general behavior or model of the data. These data objects are outliers. Most data mining methods discard outliers as noise or exceptions. However, in some applications such as fraud detection, the rare events can be more interesting than the more regularly occurring ones. The analysis of outlier data is referred to as outlier mining.

Outliers may be detected using statistical tests that assume a distribution or probability model for the data, or using distance measures where objects that are a substantial distance from any other cluster are considered outliers. Rather than using statistical or distance measures, deviation-based methods identify outliers by examining differences in the main characteristics of objects in a group.

Example: Outlier analysis. Outlier analysis may uncover fraudulent usage of credit cards by detecting purchases of extremely large amounts for a given account number in comparison to regular charges incurred by the same account. Outlier values may also be detected with respect to the location and type of purchase, or the purchase frequency.

Evolution Analysis

Data evolution analysis describes and models regularities or trends for objects whose behavior changes over time. Although this may include characterization, discrimination, association and correlation analysis, classification, prediction, or clustering of *time related* data, distinct features of such an analysis include time-series data analysis, sequence or periodicity pattern matching, and similarity-based data analysis.

Example: Evolution analysis. Suppose that you have the major stock market (time-series) data of the last several years available from the New York Stock Exchange and you would like to invest in shares of high tech industrial companies. A data mining study of stock exchange data may identify stock evolution regularities for overall stocks and for the stocks of particular companies. Such regularities may help predict future trends in stock market prices, contributing to your decision making regarding stock investments.

Are All of the Patterns Interesting?

A data mining system has the potential to generate thousands or even millions of patterns, or rules. Then *"are all of the patterns interesting?"* Typically not—only a small fraction of the patterns potentially generated would actually be of interest to any given user.

This raises some serious questions for data mining. You may wonder, *“**What makes a pattern interesting? Can a data mining system generate all of the interesting patterns? Can a data mining system generate only interesting patterns?”***

To answer the first question, a pattern is interesting if it is (1) *easily understood* by humans, (2) *valid* on new or test data with some degree of *certainty*, (3) potentially *useful*, and (4) *novel*. A pattern is also interesting if it validates a hypothesis that the user *sought to confirm*. An interesting pattern represents **knowledge.**

Several objective measures of pattern interestingness exist. These are based on the structure of discovered patterns and the statistics underlying them. An objective measure for association rules of the form *X Y* is rule support, representing the percentage of transactions from a transaction database that the given rule satisfies. This is taken to be the probability *P*(XU*Y*),where *XUY* indicates that a transaction contains both *X* and *Y*, that is, the union of item sets *X* and *Y*. Another objective measure for association rules is confidence, which assesses the degree of certainty of the detected association. This is taken to be the conditional probability *P*(Y | *X*), that is, the probability that a transaction containing *X* also contains *Y*. More formally, support and confidence are defined as

Support(X Y) = P(XUY)
Confidence(X Y) = P(Y | X)

In general, each interestingness measure is associated with a threshold, which may be controlled by the user. For example, rules that do not satisfy a confidence threshold of, say, 50% can be considered uninteresting. Rules below the threshold likely reflect noise, exceptions, or minority cases and are probably of less value.

The second question—“***Can a data mining system generate all of the interesting patterns***?” refers to the completeness of a data mining algorithm. It is often unrealistic and inefficient for data mining systems to generate all of the possible patterns. Instead, user-provided constraints and interestingness measures should be used to focus the search.

Finally, the third question—*“**Can a data mining system generate only interesting patterns**?”*— is an optimization problem in data mining. It is highly desirable for data mining systems to generate only interesting patterns. This would be much more efficient for users and data mining systems, because neither would have to search through the patterns generated in order to identify the truly interesting ones. Progress has been made in this direction; however, such optimization remains a challenging issue in data mining.

Classification of Data Mining Systems

Data mining is an interdisciplinary field, the confluence of a set of disciplines, including database systems, statistics, machine learning, visualization, and information science (Figure 1.12).Moreover, depending on the data mining approach used, techniques from other disciplines may be applied, such as neural networks, fuzzy and/or rough set theory, knowledge representation, inductive logic programming, or high-performance computing. Depending on the kinds of data to be mined or on the given data mining application, the data mining system may also integrate techniques from spatial data analysis, information retrieval, pattern recognition, image analysis, signal processing, computer graphics, Web technology, economics, business, bioinformatics, or psychology.

Data mining systems can be categorized according to various criteria, as follows:

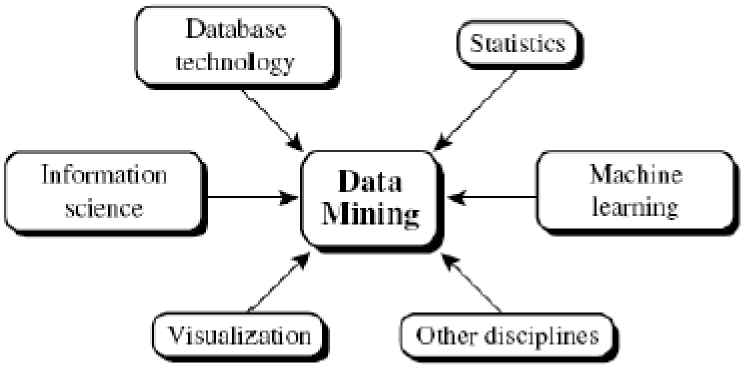


Figure 1.12 Data mining as a confluence of multiple disciplines.

Classification according to the *kinds of databases* mined: A data mining system can be classified according to the kinds of databases mined. Database systems can be classified according to different criteria (such as data models, or the types of data or applications involved), each of which may require its own data mining technique. Data mining systems can therefore be classified accordingly.

Classification according to the *kinds of knowledge* mined: Data mining systems can be categorized according to the kinds of knowledge they mine, that is, based on data mining functionalities, such as characterization, discrimination, association and correlation analysis, classification, prediction, clustering, outlier analysis, and evolution analysis. A comprehensive data mining system usually provides multiple and/or integrated data mining functionalities.

Classification according to the *kinds of techniques* utilized: Data mining systems can be categorized according to the underlying data mining techniques employed. These techniques can be described according to the degree of user interaction involved (e.g., autonomous systems, interactive exploratory systems, query-driven systems) or the methods of data analysis employed (e.g., database-oriented or data warehouse– oriented techniques, machine learning, statistics, visualization, pattern recognition, neural networks, and so on). A sophisticated data mining system will often adopt multiple data mining techniques or work out an effective, integrated technique that combines the merits of a few individual approaches.

Classification according to the *applications adapted*: Data mining systems can also be categorized according to the applications they adapt. For example, data mining systems may be tailored specifically for finance, telecommunications, DNA, stock markets, e-mail, and so on. Different applications often require the integration of application-specific methods. Therefore, a generic, all-purpose data mining system may not fit domain-specific mining tasks.

Data Mining Task Primitives

Each user will have a data mining task in mind, that is, some form of data analysis that he or she would like to have performed. A data mining task can be specified in the form of a data mining query, which is input to the data mining system. A data mining query is defined in terms of data mining task primitives. These primitives allow the user to *interactively* communicate with the data mining system during discovery in order to direct the mining process, or examine the findings from different angles or depths. The data mining primitives specify the following, as illustrated in Figure 1.13.

- The set of ***task-relevant data*** to be mined: This specifies the portions of the database or the set of data in which the user is interested. This includes the database attributes or data warehouse dimensions of interest (referred to as the *relevant attributes or dimensions*).
- The ***kind of knowledge*** to be mined: This specifies the *data mining functions* to be performed, such as characterization, discrimination, association or correlation analysis, classification, prediction, clustering, outlier analysis, or evolution analysis.
- The ***background knowledge*** to be used in the discovery process: This knowledge about the domain to be mined is useful for guiding the knowledge discovery process and for evaluating the patterns found. *Concept hierarchies* are a popular form of background knowledge, which allow data to be mined at multiple levels of abstraction. An example of a concept hierarchy for the attribute (or dimension) *age* is shown in Figure 1.14. User beliefs regarding relationships in the data are another form of background knowledge.
- The ***interestingness measures*** *and thresholds* for pattern evaluation: They may be used to guide the mining process or, after discovery, to evaluate the discovered patterns. Different kinds of knowledge may have different interestingness measures. For example, interestingness measures for association rules include *support* and *confidence*. Rules whose support and confidence values are below user-specified thresholds are considered uninteresting.
- The expected ***representation for visualizing*** the discovered patterns: This refers to the form in which discovered patterns are to be displayed, which may include rules, tables, charts, graphs, decision trees, and cubes.

A data mining query language can be designed to incorporate these primitives, allowing users to flexibly interact with data mining systems. Having a data mining query language provides a foundation on which user-friendly graphical interfaces can be built.

Designing a comprehensive data mining language is challenging because data mining covers a wide spectrum of tasks, from data characterization to evolution analysis. Each task has different requirements. The design of an effective data mining query language requires a deep understanding of the power, limitation, and underlying mechanisms of the various kinds of data mining tasks.

Integration of a Data Mining System with a Database or Data Warehouse System

A good system architecture will facilitate the data mining system to make best use of the software environment, accomplish data mining tasks in an efficient and timely manner, interoperate and exchange information with other information systems, be adaptable to users' diverse requirements, and evolve with time.

A critical question in the design of a data mining (DM) system is how to integrate or *couple* the DM system with a database (DB) system and/or a data warehouse (DW) system. If a DM system works as a stand-alone system or is embedded in an application program, there are no DB or DW systems with which it has to communicate. This simple scheme is called *no coupling*, where the main focus of the DM design rests on developing effective and efficient algorithms for mining the available data sets. However, when a DM system works in an environment that requires it to communicate with other information system components, such as DB and DW systems, possible integration schemes include *no coupling*, *loose coupling*, *semi tight coupling*, and *tight coupling*. We examine each of these schemes, as follows:

- **No coupling:** *No coupling* means that a DM system will not utilize any function of a DB or DW system. It may fetch data from a particular source (such as a file system), process data using some data mining algorithms, and then store the mining results in another file. Such a system, though simple, suffers from several drawbacks. First, a DB system provides a great deal of flexibility and efficiency at storing, organizing, accessing, and processing data. Without using a DB/DW system, a DM system may spend a substantial amount of time finding, collecting, cleaning, and transforming data. In DB and/or DW systems, data tend to be well organized, indexed, cleaned, integrated, or consolidated, so that finding the task-relevant, high-quality data becomes an easy task. Second, there are many tested, scalable algorithms and data structures implemented in DB and DW systems. It is feasible to realize efficient, scalable implementations using such systems. Moreover, most data have been or will be stored in DB/DW systems. Without any coupling of such systems, a DM system will need to use other tools to extract data, making it difficult to integrate such a system into an information processing environment. Thus, no coupling represents a poor design.
- **Loose coupling:** *Loose coupling* means that a DM system will use some facilities of a DB or DW system, fetching data from a data repository managed by these systems, performing data mining, and then storing the mining results either in a file or in a designated place in a database or data warehouse. Loose coupling is better than no coupling because it can fetch any portion of data stored in databases or data warehouses by using query processing, indexing, and other system facilities. It incurs some advantages of the flexibility, efficiency, and other features provided by such systems. However, many loosely coupled mining systems are main memory-based. Because mining does not explore data structures and query optimization methods provided by DB or DW systems, it is difficult for loose coupling to achieve high scalability and good performance with large data sets.
- **Semi tight coupling:** *Semi tight coupling* means that besides linking a DM system to a DB/DW system, efficient implementations of a few essential data mining primitives (identified by the analysis of frequently encountered data mining functions) can be provided in the DB/DW system. These primitives can include sorting, indexing, aggregation, histogram analysis, multi way join, and pre computation of some essential statistical measures, such as sum, count, max, min, standard deviation, and so on. Moreover, some frequently used intermediate mining results can be pre computed and stored in the DB/DW system. Because these intermediate mining results are either pre computed or can be computed efficiently, this design will enhance the performance of a DM system.
- **Tight coupling:** *Tight coupling* means that a DM system is smoothly integrated into the DB/DW system. The data mining subsystem is treated as one functional component of an information system. Data mining queries and functions are optimized based on mining query analysis, data structures, indexing schemes, and query processing methods of a DB or DW system. With further technology advances, DM, DB, and DW systems will evolve and integrate together as one information system with multiple

functionalities. This will provide a uniform information processing environment. This approach is highly desirable because it facilitates efficient implementations of data mining functions, high system performance, and an integrated information processing environment.

With this analysis, it is easy to see that a data mining system should be coupled with a DB/DW system. Loose coupling, though not efficient, is better than no coupling because it uses both data and system facilities of a DB/DW system. Tight coupling is highly desirable, but its implementation is nontrivial and more research is needed in this area. Semi tight coupling is a compromise between loose and tight coupling. It is important to identify commonly used data mining primitives and provide efficient implementations of such primitives in DB or DW systems.

Major Issues in Data Mining

Major issues in data mining regarding mining methodology, user interaction, performance, and diverse data types. These issues are introduced below:

- **Mining methodology and user interaction issues:** These reflect the kinds of knowledge mined, the ability to mine knowledge at multiple granularities, the use of domain knowledge, ad hoc mining, and knowledge visualization.
- ***Mining different kinds of knowledge in databases****:* Because different users can be interested in different kinds of knowledge, data mining should cover a wide spectrum of data analysis and knowledge discovery tasks, including data characterization, discrimination, association and correlation analysis, classification, prediction, clustering, outlier analysis, and evolution analysis (which includes trend and similarity analysis). These tasks may use the same database in different ways and require the development of numerous data mining techniques.
- ***Interactive mining of knowledge at multiple levels of abstraction****:* Because it is difficult to know exactly what can be discovered within a database, the data mining process should be *interactive*. For databases containing a huge amount of data, appropriate sampling techniques can first be applied to facilitate interactive data exploration. Interactive mining allows users to focus the search for patterns, providing and refining data mining requests based on returned results. Specifically, knowledge should be mined by drilling down, rolling up, and pivoting through the data space and knowledge space interactively, similar to what OLAP can do on data cubes. In this way, the user can interact with the data mining system to view data and discovered patterns at multiple granularities and from different angles.
- ***Incorporation of background knowledge****:* Background knowledge, or information regarding the domain under study, may be used to guide the discovery process and allow discovered patterns to be expressed in concise terms and at different levels of abstraction. Domain knowledge related to databases, such as integrity constraints and deduction rules, can help focus and speed up a data mining process, or judge the interestingness of discovered patterns.
- ***Data mining query languages and ad hoc data mining****:* Relational query languages (such as SQL) allow users to pose ad hoc queries for data retrieval. In a similar vein, high-level data mining query languages need to be developed to allow users to describe ad hoc data mining tasks by facilitating the specification of the relevant sets of data for analysis, the domain knowledge, the kinds of knowledge to be mined, and the conditions and constraints to be enforced on the discovered patterns. Such a language should be integrated with a database or data warehouse query language and optimized for efficient and flexible data mining.

- ***Presentation and visualization of data mining results****:* Discovered knowledge should be expressed in high-level languages, visual representations, or other expressive forms so that the knowledge can be easily understood and directly usable by humans. This is especially crucial if the data mining system is to be interactive. This requires the system to adopt expressive knowledge representation techniques, such as trees, tables, rules, graphs, charts, crosstabs, matrices, or curves.
- ***Handling noisy or incomplete data****:* The data stored in a database may reflect noise, exceptional cases, or incomplete data objects. When mining data regularities, these objects may confuse the process, causing the knowledge model constructed to over fit the data. As a result, the accuracy of the discovered patterns can be poor. Data cleaning methods and data analysis methods that can handle noise are required, as well as outlier mining methods for the discovery and analysis of exceptional cases.
- ***Pattern evaluation****—the interestingness problem:* A data mining system can uncover thousands of patterns. Many of the patterns discovered may be uninteresting to the given user, either because they represent common knowledge or lack novelty. Several challenges remain regarding the development of techniques to assess the interestingness of discovered patterns, particularly with regard to subjective measures that estimate the value of patterns with respect to a given user class, based on user beliefs or expectations. The use of interestingness measures or user specified constraints to guide the discovery process and reduce the search space is another active area of research.

Performance issues: These include efficiency, scalability, and parallelization of data mining algorithms.

- ***Efficiency and scalability of data mining algorithms****:* To effectively extract information from a huge amount of data in databases, data mining algorithms must be efficient and scalable. In other words, the running time of a data mining algorithm must be predictable and acceptable in large databases. From a database perspective on knowledge discovery, efficiency and scalability are key issues in the implementation of data mining systems. Many of the issues discussed above under *mining methodology and user interaction* must also consider efficiency and scalability.
- ***Parallel, distributed, and incremental mining algorithms****:* The huge size of many databases, the wide distribution of data, and the computational complexity of some data mining methods are factors motivating the development of parallel and distributed data mining algorithms. Such algorithms divide the data into partitions, which are processed in parallel. The results from the partitions are then merged. Moreover, the high cost of some data mining processes promotes the need for incremental data mining algorithms that incorporate database updates without having to mine the entire data again "from scratch." Such algorithms perform knowledge modification incrementally to amend and strengthen what was previously discovered.

Issues relating to the diversity of database types:

- ***Handling of relational and complex types of data****:* Because relational databases and data warehouses are widely used, the development of efficient and effective data mining systems for such data is important. However, other databases may contain complex data objects, hypertext and multimedia data, spatial data, temporal data, or transaction data. It is unrealistic to expect one system to mine all kinds of data, given the diversity of data types and different goals of data mining. Specific data mining systems should be constructed for mining specific kinds of data. Therefore, one may expect to have different data mining systems for different kinds of data.

- ***Mining information from heterogeneous databases and global information systems***: Local and wide-area computer networks (such as the Internet) connect many sources of data, forming huge, distributed, and heterogeneous databases. The discovery of knowledge from different sources of structured, semi structured, or unstructured data with diverse data semantics poses great challenges to data mining. Data mining may help disclose high-level data regularities in multiple heterogeneous databases that are unlikely to be discovered by simple query systems and may improve information exchange and interoperability in heterogeneous databases. Web mining, which uncovers interesting knowledge about Web contents, Web structures, Web usage, and Web dynamics, becomes a very challenging and fast-evolving field in data mining.

Data Preprocessing

The data you wish to analyze by data mining techniques are **incomplete** (lacking attribute values or certain attributes of interest, or containing only aggregate data), **noisy** (containing errors, or *outlier* values that deviate from the expected), and **inconsistent** (e.g., containing discrepancies in the department codes used to categorize items)

Incomplete, noisy, and inconsistent data are commonplace properties of large real world databases and data warehouses. Incomplete data can occur for a number of reasons. Attributes of interest may not always be available, such as customer information for sales transaction data. Other data may not be included simply because it was not considered important at the time of entry. Relevant data may not be recorded due to a misunderstanding, or because of equipment malfunctions. Data that were inconsistent with other recorded data may have been deleted. Furthermore, the recording of the history or modifications to the data may have been overlooked. Missing data, particularly for tuples with missing values for some attributes, may need to be inferred.

Data cleaning routines work to “clean” the data by filling in missing values, smoothing noisy data, identifying or removing outliers, and resolving inconsistencies. If users believe the data are dirty, they are unlikely to trust the results of any data mining that has been applied to it.

Data transformation operations, such as normalization and aggregation, are additional data preprocessing procedures that would contribute toward the success of the mining process. Data reduction obtains a reduced representation of the data set that is much smaller in volume, yet produces the same (or almost the same) analytical results. There are a number of strategies for data reduction. These include *data aggregation* (e.g., building a data cube), *attribute subset selection* (e.g., removing irrelevant attributes through correlation analysis), *dimensionality reduction* (e.g., using encoding schemes such as minimum length encoding or wavelets), and *numerosity reduction* (e.g., “replacing” the data by alternative, smaller representations such as clusters or parametric models).

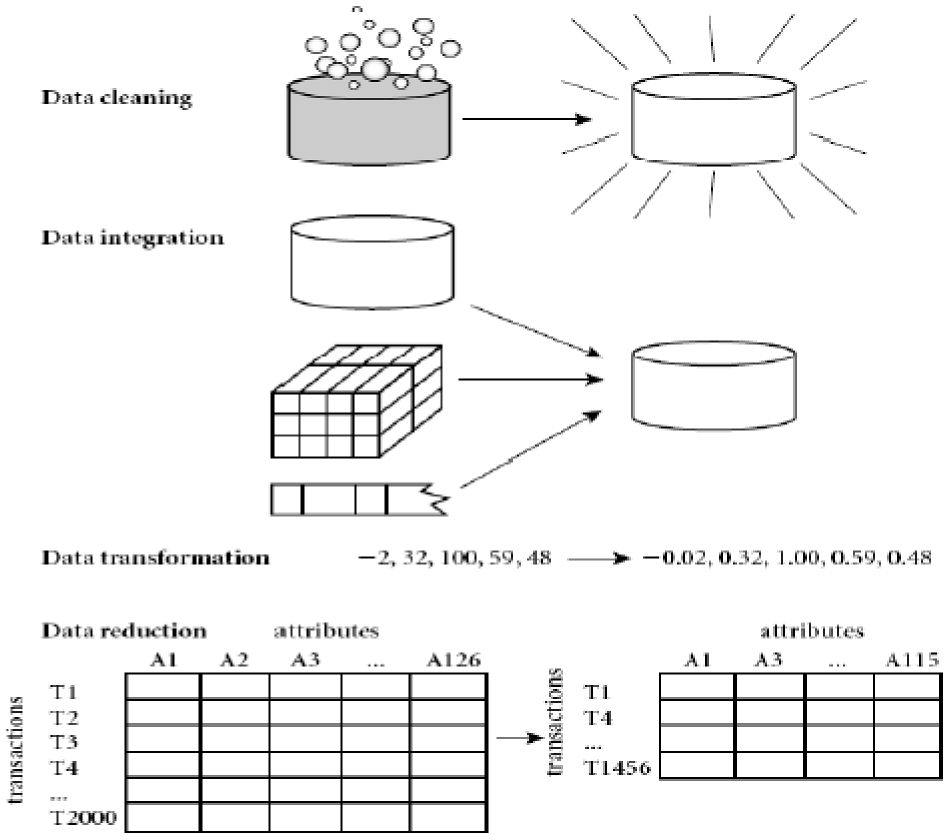


Figure 2.1 Forms of data preprocessing.

Descriptive Data Summarization

For data preprocessing to be successful, it is essential to have an overall picture of your data. Descriptive data summarization techniques can be used to identify the typical properties of your data and highlight which data values should be treated as noise or outliers.

a) Measuring the Central Tendency

In this section, we look at various ways to measure the central tendency of data. The most common and most effective numerical measure of the "center" of a set of data is the *(arithmetic) mean*.

Let *x*1,*x*2,….*xN* be a set of *N* values or observations, such as for some attribute, like *salary*. The mean of this set of values is

$$\bar{x} = \frac{\sum_{i=1}^{N} x_i}{N} = \frac{x_1 + x_2 + \cdots + x_N}{N}.$$

This corresponds to the built-in aggregate function, *average* (avg() in SQL), provided in relational database systems.

A distributive measure is a measure (i.e., function) that can be computed for a given data set by partitioning the data into smaller subsets, computing the measure for each subset, and then merging the results in order to arrive at the measure's value for the original (entire) data set. Both sum() and count() are distributive measures because they can be computed in this manner. Other examples include max() and min(). An algebraic measure is a measure that can be computed by applying an algebraic function to one or more distributive measures. Hence, *average* (or mean()) is an algebraic measure because it can be computed by sum()/count().When computing data cubes, sum() and count() are typically saved in pre computation. Thus, the derivation of *average* for data cubes is straightforward.

Sometimes, each value *xi* in a set may be associated with a weight *wi*, for *i* = 1…..*N*. The weights reflect the significance, importance, or occurrence frequency attached to their respective values. In this case, we can compute

$$\bar{x} = \frac{\sum_{i=1}^{N} w_i x_i}{\sum_{i=1}^{N} w_i} = \frac{w_1x_1 + w_2x_2 + \cdots + w_Nx_N}{w_1 + w_2 + \cdots + w_N}.$$

This is called the weighted arithmetic mean or the weighted average. Note that the weighted average is another example of an algebraic measure.

A holistic measure is a measure that must be computed on the entire data set as a whole. It cannot be computed by partitioning the given data into subsets and merging the values obtained for the measure in each subset. The median is an example of a holistic measure.

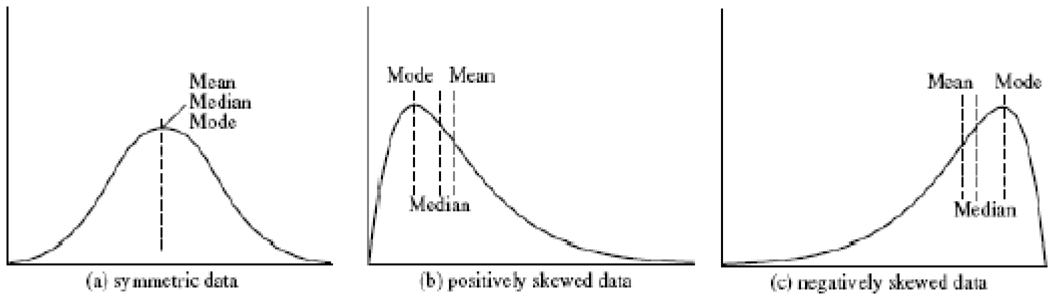


Figure 2.2 Mean, median, and mode of symmetric versus positively and negatively skewed data.

b) Measuring the Dispersion of Data

The degree to which numerical data tend to spread is called the dispersion, or variance of the data. The most common measures of data dispersion are *range*, the *five-number summary* (based on *quartiles*), the *inter quartile range*, and the *standard deviation*. Box plots can be plotted based on the five number summary and are a useful tool for identifying outliers.

Range, Quartiles, Outliers, and Box plots

Let *x*1;*x*2; : : : ;*xN* be a set of observations for some attribute. The range of the set is the difference between the largest (max()) and smallest (min()) values. For the remainder of this section, let's assume that the data are sorted in increasing numerical order.

The most commonly used percentiles other than the median are quartiles. The first quartile, denoted by *Q*1, is the 25th percentile; the third quartile, denoted by *Q*3, is the 75th percentile. The quartiles, including the median, give some indication of the center, spread, and shape of a distribution. The distance between the first and third quartiles is a simple measure of spread that gives the range covered by the middle half of the data. This distance is called the **inter quartile range** (*IQR*) and is defined as *IQR= Q3-Q1*

The five-number summary of a distribution consists of the median, the quartiles *Q*1 and *Q*3, and the smallest and largest individual observations, written in the order ***Minimum, Q1, Median, Q3, Maximum***:

Box plots are a popular way of visualizing a distribution. A box plot incorporates the five-number summary
as follows:

- Typically, the ends of the box are at the quartiles, so that the box length is the inter quartile range, *IQR*.
- The median is marked by a line within the box.
- Two lines (called *whiskers*) outside the box extend to the smallest (*Minimum*) and largest (*Maximum*) observations.

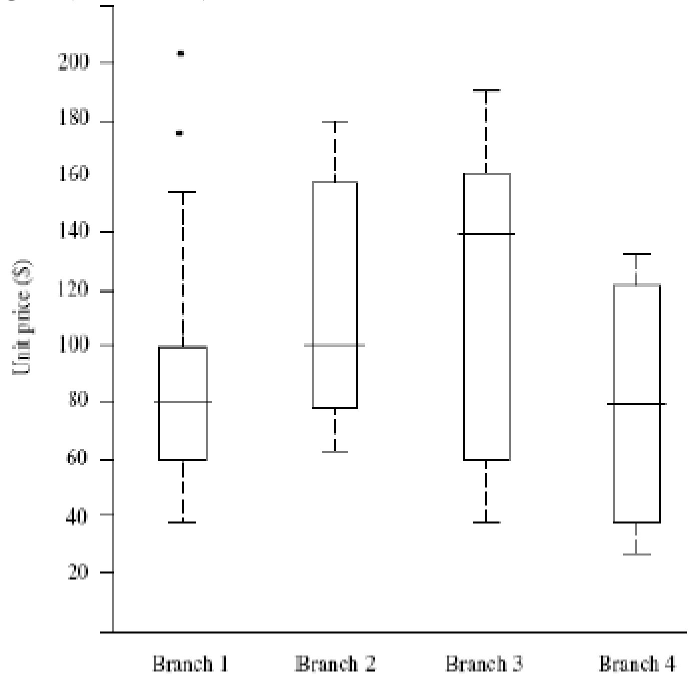


Figure 2.3 Boxplot for the unit price data for items sold at four branches of *AllElectronics* during a given time period.

Variance and Standard Deviation

The variance of *N* observations, *x*1;*x*2; : : : ;*xN*, is

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})^2 = \frac{1}{N}\left[\sum x_i^2 - \frac{1}{N}\left(\sum x_i\right)^2\right],$$

Where *x* is the mean value of the observations, as defined in Equation (2.1). The standard deviation, s, of the observations is the square root of the variance, s2.

The basic properties of the standard deviation, s, as a measure of spread are

- s measures spread about the mean and should be used only when the mean is chosen as the measure of center.
- s=0 only when there is no spread, that is, when all observations have the same value. Otherwise s > 0.

The variance and standard deviation are algebraic measures because they can be computed from distributive measures.

Unit 4

Association Rule Mining and Classification:

Basic Concepts

Frequent pattern mining searches for recurring relationships in a given data set. It introduces the basic concepts of frequent pattern mining for the discovery of interesting associations and correlations between item sets in transactional and relational databases.

Market Basket Analysis: A Motivating Example

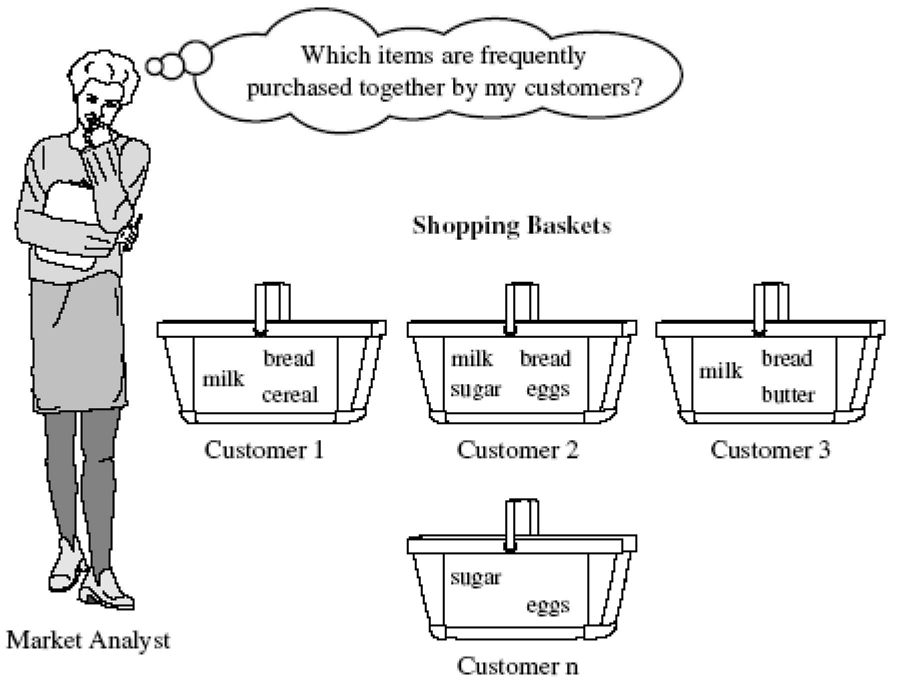


Figure 5.1 Market basket analysis.

A typical example of frequent item set mining is market basket analysis. This process analyzes customer buying habits by finding associations between the different items that customers place in their “shopping baskets” (Figure 5.1). The discovery of such associations can help retailers develop marketing strategies by gaining insight into which items are frequently purchased together by customers. For instance, if customers are buying milk, 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 do selective marketing and plan their shelf space.

If we think of the universe as the set of items available at the store, then each item has a Boolean variable representing the presence or absence of that item. Each basket can then be represented by a Boolean vector of values assigned to these variables. The Boolean vectors can be analyzed for buying patterns that reflect items that are frequently *associated* or purchased together. These patterns can be represented in the form of association rules. For example, the information that customers who purchase computers also tend to buy antivirus software at the same time is represented in Association Rule (5.1) below:

Computer =>*antivirus software* [*support* = 2%; *confidence* = 60%] (5.1)

Rule support and confidence are two measures of rule interestingness. They respectively reflect the usefulness and certainty of discovered rules. A support of 2% for Association Rule (5.1) means that 2% of all the transactions under analysis show that computer and antivirus software are purchased together. A confidence of 60% means that 60% of the customers who purchased a computer also bought the software. Typically, association rules are considered interesting if they satisfy both a minimum support threshold and a minimum confidence threshold. Such thresholds can be set by users or domain experts. Additional analysis can be performed to uncover interesting statistical correlations between associated items.

Frequent Item sets, Closed Item sets, and Association Rules

- A set of items is referred to as an **item set.**
- An item set that contains *k* items is a ***k*-item set**.
- The set {*computer, antivirus software}* is a **2-itemset**.
- The occurrence frequency of an item set is the number of transactions that contain the item set. This is also known, simply, as the **frequency, support count,** or **count** of the item set.

$$\begin{aligned} support(A \Rightarrow B) &= P(A \cup B) \\ confidence(A \Rightarrow B) &= P(B|A). \end{aligned}$$

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

- Rules that satisfy both a minimum support threshold (*min sup*) and a minimum confidence threshold (*min conf*) are called **Strong Association Rules.**

In general, association rule mining can be viewed as a **two-step process**:

1. Find all frequent item sets: By definition, each of these item sets will occur at least as frequently as a predetermined minimum support count, *min_sup*.

2. Generate strong association rules from the frequent itemsets: By definition, these rules must satisfy minimum support and minimum confidence.

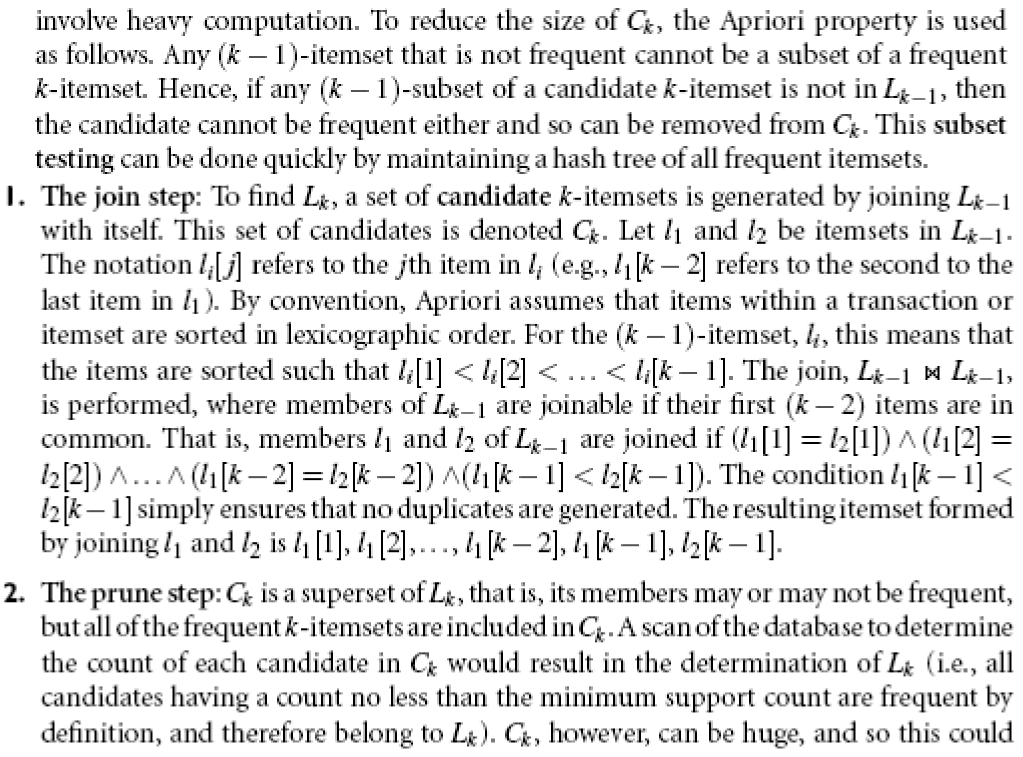
The Apriori Algorithm: Finding Frequent Item sets Using Candidate Generation

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 item set properties, as we shall see following. Apriori employs an iterative approach known as a *level-wise* search, where *k*-item sets are used to explore (*k*+1)-item sets. 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 *Lk* requires one full scan of the database.

To improve the efficiency of the level-wise generation of frequent itemsets, an important property called the Apriori property, presented below, is used to reduce the search space. We will first describe this property, and then show an example illustrating its use.

Apriori property: *All nonempty subsets of a frequent itemset must also be frequent.*

A two-step process is followed, consisting of join and prune actions



involve heavy computation. To reduce the size of C_k, the Apriori property is used as follows. Any $(k-1)$-itemset that is not frequent cannot be a subset of a frequent k-itemset. Hence, if any $(k-1)$-subset of a candidate k-itemset is not in L_{k-1}, then the candidate cannot be frequent either and so can be removed from C_k. This **subset testing** can be done quickly by maintaining a hash tree of all frequent itemsets.

1. **The join step**: To find L_k, a set of **candidate** k-itemsets is generated by joining L_{k-1} with itself. This set of candidates is denoted C_k. Let l_1 and l_2 be itemsets in L_{k-1}. The notation $l_i[j]$ refers to the jth item in l_i (e.g., $l_1[k-2]$ refers to the second to the last item in l_1). By convention, Apriori assumes that items within a transaction or itemset are sorted in lexicographic order. For the $(k-1)$-itemset, l_i, this means that the items are sorted such that $l_i[1] < l_i[2] < \ldots < l_i[k-1]$. The join, $L_{k-1} \bowtie L_{k-1}$, is performed, where members of L_{k-1} are joinable if their first $(k-2)$ items are in common. That is, members l_1 and l_2 of L_{k-1} are joined if $(l_1[1] = l_2[1]) \wedge (l_1[2] = l_2[2]) \wedge \ldots \wedge (l_1[k-2] = l_2[k-2]) \wedge (l_1[k-1] < l_2[k-1])$. The condition $l_1[k-1] < l_2[k-1]$ simply ensures that no duplicates are generated. The resulting itemset formed by joining l_1 and l_2 is $l_1[1], l_1[2], \ldots, l_1[k-2], l_1[k-1], l_2[k-1]$.
2. **The prune step:** C_k is a superset of L_k, that is, its members may or may not be frequent, but all of the frequent k-itemsets are included in C_k. A scan of the database to determine the count of each candidate in C_k would result in the determination of L_k (i.e., all candidates having a count no less than the minimum support count are frequent by definition, and therefore belong to L_k). C_k, however, can be huge, and so this could

Table 5.1 Transactional data for an *AllElectronics* branch.

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

Example 5.3 **Apriori.** Let's look at a concrete example, based on the *AllElectronics* transaction database, D, of Table 5.1. There are nine transactions in this database, that is, $|D| = 9$. We use Figure 5.2 to illustrate the Apriori algorithm for finding frequent itemsets in D.

1. In the first iteration of the algorithm, each item is a member of the set of candidate 1-itemsets, C_1. The algorithm simply scans all of the transactions in order to count the number of occurrences of each item.
2. Suppose that the minimum support count required is 2, that is, $min\_sup = 2$. (Here, we are referring to *absolute* support because we are using a support count. The corresponding relative support is $2/9 = 22\%$). The set of frequent 1-itemsets, L_1, can then be determined. It consists of the candidate 1-itemsets satisfying minimum support. In our example, all of the candidates in C_1 satisfy minimum support.
3. To discover the set of frequent 2-itemsets, L_2, the algorithm uses the join $L_1 \bowtie L_1$ to generate a candidate set of 2-itemsets, C_2.[8] C_2 consists of $\binom{|L_1|}{2}$ 2-itemsets. Note that no candidates are removed from C_2 during the prune step because each subset of the candidates is also frequent.

4. Next, the transactions in D are scanned and the support count of each candidate itemset in C_2 is accumulated, as shown in the middle table of the second row in Figure 5.2.
5. The set of frequent 2-itemsets, L_2, is then determined, consisting of those candidate 2-itemsets in C_2 having minimum support.
6. The generation of the set of candidate 3-itemsets, C_3, is detailed in Figure 5.3. From the join step, we first get $C_3 = L_2 \bowtie L_2 = \{\{I1, I2, I3\}, \{I1, I2, I5\}, \{I1, I3, I5\}, \{I2, I3, I4\}, \{I2, I3, I5\}, \{I2, I4, I5\}\}$. Based on the Apriori property that all subsets of a frequent itemset must also be frequent, we can determine that the four latter candidates cannot possibly be frequent. We therefore remove them from C_3, thereby saving the effort of unnecessarily obtaining their counts during the subsequent scan of D to determine L_3. Note that when given a candidate k-itemset, we only need to check if its $(k-1)$-subsets are frequent since the Apriori algorithm uses a level-wise search strategy. The resulting pruned version of C_3 is shown in the first table of the bottom row of Figure 5.2.
7. The transactions in D are scanned in order to determine L_3, consisting of those candidate 3-itemsets in C_3 having minimum support (Figure 5.2).

8. The algorithm uses $L_3 \bowtie L_3$ to generate a candidate set of 4-itemsets, C_4. Although the join results in {{I1, I2, I3, I5}}, this itemset is pruned because its subset {{I2, I3, I5}} is not frequent. Thus, $C_4 = \phi$, and the algorithm terminates, having found all of the frequent itemsets. ■

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 (where *strong* association rules satisfy both minimum support and minimum confidence). This can be done using Equation (5.4) for confidence, which we show again here for completeness:

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

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:

```
(1)   $L_1$ = find_frequent_1-itemsets(D);
(2)   for ($k = 2; L_{k-1} \neq \phi; k{+}{+}$) {
(3)       $C_k$ = apriori_gen($L_{k-1}$);
(4)       for each transaction $t \in D$ { // scan $D$ for counts
(5)           $C_t$ = subset($C_k, t$); // get the subsets of $t$ that are candidates
(6)           for each candidate $c \in C_t$
(7)               c.count++;
(8)       }
(9)       $L_k = \{c \in C_k | c.count \geq min\_sup\}$
(10)  }
(11)  return $L = \cup_k L_k$;

procedure apriori_gen($L_{k-1}$:frequent $(k-1)$-itemsets)
(1)   for each itemset $l_1 \in L_{k-1}$
(2)       for each itemset $l_2 \in L_{k-1}$
(3)           if $(l_1[1] = l_2[1]) \wedge (l_1[2] = l_2[2]) \wedge ... \wedge (l_1[k-2] = l_2[k-2]) \wedge (l_1[k-1] < l_2[k-1])$ then {
(4)               $c = l_1 \bowtie l_2$; // join step: generate candidates
(5)               if has_infrequent_subset($c, L_{k-1}$) then
(6)                   delete $c$; // prune step: remove unfruitful candidate
(7)               else add $c$ to $C_k$;
(8)           }
(9)   return $C_k$;

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

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.

Because the rules are generated from frequent itemsets, each one automatically satisfies minimum support. Frequent itemsets can be stored ahead of time in hash tables along with their counts so that they can be accessed quickly.

Example 5.4 **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:

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

If the minimum confidence threshold is, say, 70%, then only the second, third, and last rules above are output, because these are the only ones generated that are strong. Note that, unlike conventional classification rules, association rules can contain more than one conjunct in the right-hand side of the rule. ■

FP-Growth Method: Mining Frequent Itemsets without Candidate Generation

As we have seen, in many cases the Apriori candidate generate-and-test method significantly reduces the size of candidate sets, leading to good performance gain.

An interesting method in this attempt is called frequent-pattern growth, or simply FP-growth, which adopts a *divide-and-conquer* strategy as follows. First, it compresses the database representing frequent items into a frequent-pattern tree, or FP-tree, which retains the itemset association information. It then divides the compressed database into a set of *conditional databases* (a special kind of projected database), each associated with one frequent item or "pattern fragment," and mines each such database separately. You'll see how it works with the following example.

Example 5.5 FP-growth (finding frequent itemsets without candidate generation). We re-examine the mining of transaction database, *D*, of Table 5.1 in Example 5.3 using the frequent pattern growth approach.

The first scan of the database is the same as Apriori, which derives the set of frequent items (1-itemsets) and their support counts (frequencies). Let the minimum support count be 2. The set of frequent items is sorted in the order of descending support count. This resulting set or *list* is denoted *L*. Thus, we have *L* ={{I2: 7}, {I1: 6}, {I3: 6}, {I4: 2}, {I5: 2}}.

An FP-tree is then constructed as follows. First, create the root of the tree, labeled with "null." Scan database *D* a second time. The items in each transaction are processed in *L* order (i.e., sorted according to descending support count), and a branch is created for each transaction. For example, the scan of the first transaction, "T100: I1, I2, I5," which contains three items (I2, I1, I5 in *L* order), leads to the construction of the first branch of the tree with three nodes, ⟨I2: 1⟩, ⟨I1:1⟩, and ⟨I5: 1⟩, where I2 is linked as a child of the root, I1 is linked to I2, and I5 is linked to I1. The second transaction, T200, contains the items I2 and I4 in *L* order, which would result in a branch where I2 is linked to the root and I4 is linked to I2. However, this branch would share a common **prefix**, I2, with the existing path for T100. Therefore, we instead increment the count of the I2 node by 1, and create a new node, ⟨I4: 1⟩, which is linked as a child of ⟨I2: 2⟩. In general, when considering the branch to be added for a transaction, the count of each node along a common prefix is incremented by 1, and nodes for the items following the prefix are created and linked accordingly.

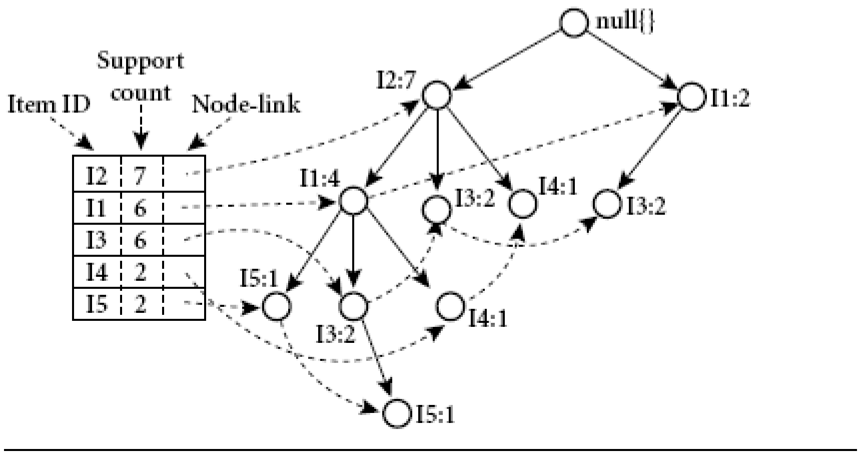


Figure 5.7 An FP-tree registers compressed, frequent pattern information.

Mining the FP-tree by creating conditional (sub-)pattern bases.

Item	*Conditional Pattern Base*	*Conditional FP-tree*	*Frequent Patterns Generated*
I5	{{I2, I1: 1}, {I2, I1, I3: 1}}	⟨I2: 2, I1: 2⟩	{I2, I5: 2}, {I1, I5: 2}, {I2, I1, I5: 2}
I4	{{I2, I1: 1}, {I2: 1}}	⟨I2: 2⟩	{I2, I4: 2}
I3	{{I2, I1: 2}, {I2: 2}, {I1: 2}}	⟨I2: 4, I1: 2⟩, ⟨I1: 2⟩	{I2, I3: 4}, {I1, I3: 4}, {I2, I1, I3: 2}
I1	{{I2: 4}}	⟨I2: 4⟩	{I2, I1: 4}

Mining of the FP-tree is summarized in Table 5.2 and detailed as follows. We first consider I5, which is the last item in L, rather than the first. The reason for starting at the end of the list will become apparent as we explain the FP-tree mining process. I5 occurs in two branches of the FP-tree of Figure 5.7. (The occurrences of I5 can easily be found by following its chain of node-links.) The paths formed by these branches are ⟨I2, I1, I5: 1⟩ and ⟨I2, I1, I3, I5: 1⟩. Therefore, considering I5 as a suffix, its corresponding two prefix paths are ⟨I2, I1: 1⟩ and ⟨I2, I1, I3: 1⟩, which form its conditional pattern base. Its conditional FP-tree contains only a single path, ⟨I2: 2, I1: 2⟩; I3 is not included because its support count of 1 is less than the minimum support count. The single path generates all the combinations of frequent patterns: {I2, I5: 2}, {I1, I5: 2}, {I2, I1, I5: 2}.

For I4, its two prefix paths form the conditional pattern base, {{I2 I1: 1}, {I2: 1}}, which generates a single-node conditional FP-tree, ⟨I2: 2⟩, and derives one frequent pattern, {I2, I1: 2}. Notice that although I5 follows I4 in the first branch, there is no need to include I5 in the analysis here because any frequent pattern involving I5 is analyzed in the examination of I5.

Similar to the above analysis, I3's conditional pattern base is {{I2, I1: 2}, {I2: 2}, {I1: 2}}. Its conditional FP-tree has two branches, ⟨I2: 4, I1: 2⟩ and ⟨I1: 2⟩, as shown in Figure 5.8, which generates the set of patterns, {{I2, I3: 4}, {I1, I3: 4}, {I2, I1, I3: 2}}. Finally, I1's conditional pattern base is {{I2: 4}}, whose FP-tree contains only one node, ⟨I2: 4⟩, which generates one frequent pattern, {I2, I1: 4}. This mining process is summarized in Figure 5.9. ■

Algorithm: FP_growth. Mine frequent itemsets using an FP-tree by pattern fragment growth.

Input:

- D, a transaction database;
- *min_sup*, the minimum support count threshold.

Output: The complete set of frequent patterns.

Method:

1. The FP-tree is constructed in the following steps:

   (a) Scan the transaction database D once. Collect F, the set of frequent items, and their support counts. Sort F in support count descending order as L, the *list* of frequent items.

   (b) Create the root of an FP-tree, and label it as "null." For each transaction *Trans* in D do the following.
   Select and sort the frequent items in *Trans* according to the order of L. Let the sorted frequent item list in *Trans* be $[p|P]$, where p is the first element and P is the remaining list. Call insert_tree($[p|P]$, T), which is performed as follows. If T has a child N such that N.*item-name* = p.*item-name*, then increment N's count by 1; else create a new node N, and let its count be 1, its parent link be linked to T, and its node-link to the nodes with the same *item-name* via the node-link structure. If P is nonempty, call insert_tree(P, N) recursively.

2. The FP-tree is mined by calling FP_growth(*FP_tree*, *null*), which is implemented as follows.

```
procedure FP_growth(Tree, $\alpha$)
(1)  if Tree contains a single path P then
(2)     for each combination (denoted as $\beta$) of the nodes in the path P
(3)        generate pattern $\beta \cup \alpha$ with support_count = minimum support count of nodes in $\beta$;
(4)  else for each $a_i$ in the header of Tree {
(5)     generate pattern $\beta = a_i \cup \alpha$ with support_count = $a_i$.support_count;
(6)     construct $\beta$'s conditional pattern base and then $\beta$'s conditional FP_tree $Tree_\beta$;
(7)     if $Tree_\beta \neq \emptyset$ then
(8)        call FP_growth($Tree_\beta$, $\beta$); }
```

Figure 5.9 The FP-growth algorithm for discovering frequent itemsets without candidate generation.

Mining Various Kinds of Association Rules

1) 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. Moreover, what may represent common sense to one user may seem novel to another. Therefore, data mining systems should provide capabilities for mining association rules at multiple levels of abstraction, with sufficient flexibility for easy traversal among different abstraction spaces.

Let's examine the following example.

Mining multilevel association rules. Suppose we are given the task-relevant set of transactional data in Table for sales in an *AllElectronics* store, showing the items purchased for each transaction. The concept hierarchy for the items is shown in Figure 5.10. A concept hierarchy defines a sequence of mappings from a set of low-level concepts to higher level, more general concepts. Data can be generalized by replacing low-level concepts
within 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
...	...

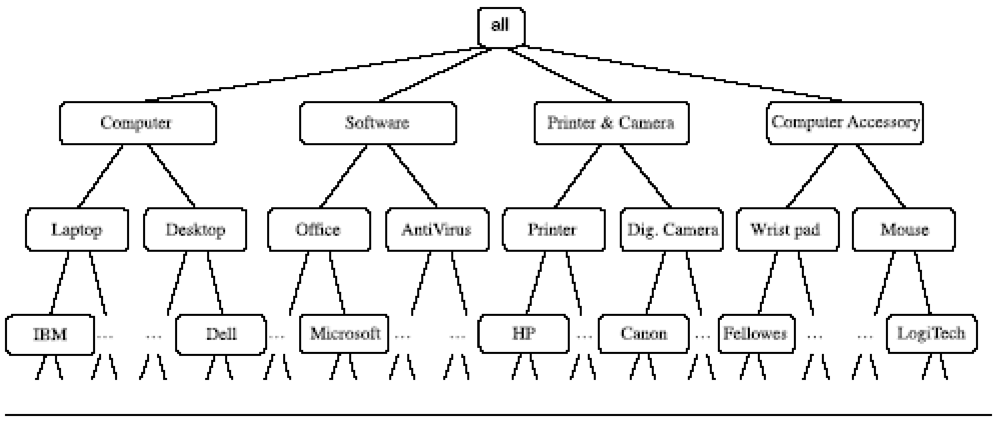
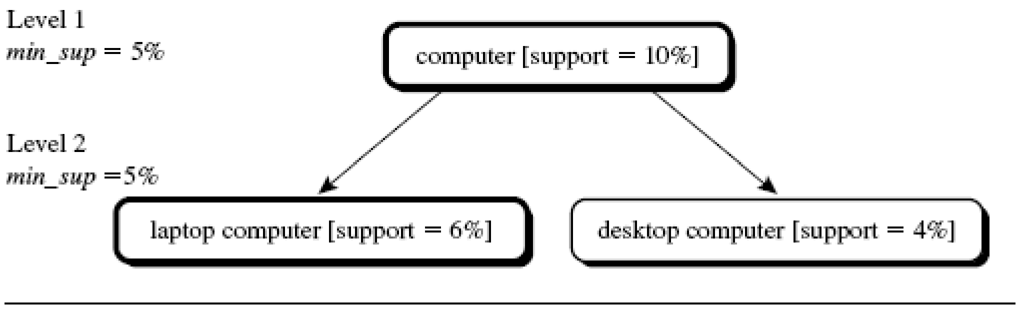


Figure 5.10 A concept hierarchy for *AllElectronics* computer items.

Association rules generated from mining data at multiple levels of abstraction are called 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. For each level, any algorithm for discovering frequent itemsets may be used, such as Apriori or its variations.

- **Using uniform minimum support for all levels (referred to as uniform support):** The same minimum support threshold is used when mining at each level of abstraction. For example, in Figure 5.11, a minimum support threshold of 5% is used throughout (e.g., for mining from *"computer"* down to *"laptop computer"*). Both *"computer"* and *"laptop computer"* are found to be frequent, while *"desktop computer"* is not.

  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. An Apriori-like optimization technique can be adopted, based on the knowledge that an ancestor is a superset of its descendants: The search avoids examining itemsets containing any item whose ancestors do not have minimum support.



Multilevel mining with uniform support.

- **Using reduced minimum support at lower levels (referred to as reduced 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, in Figure, the minimum support thresholds for levels 1 and 2 are 5% and 3%, respectively. In this way, *"computer," "laptop computer,"* and *"desktop computer"* are all considered frequent.

- **Using item or group-based minimum support (referred to as group-based 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 computers* and *flash drives* in order to pay particular attention to the association patterns containing items in these categories.

2) Mining Multidimensional Association Rules from Relational Databases and DataWarehouses

We have studied association rules that imply a single predicate, that is, the predicate *buys*. For instance, in mining our *AllElectronics* database, we may discover the Boolean association rule

$$buys(X, \text{"digital camera"}) \Rightarrow buys(X, \text{"HP printer"}).$$

Following the terminology used in multidimensional databases, we refer to each distinct predicate in a rule as a dimension. Hence, we can refer to Rule above as a single dimensional or intra dimensional association rule because it contains a single distinct predicate (e.g., *buys*)with multiple occurrences (i.e., the predicate occurs more than once within the rule). As we have seen in the previous sections of this chapter, such rules are commonly mined from transactional data.

Considering each database attribute or warehouse dimension as a predicate, we can therefore mine association rules containing *multiple* predicates, such as

$$age(X, \text{"20...29"}) \wedge occupation(X, \text{"student"}) \Rightarrow buys(X, \text{"laptop"}).$$

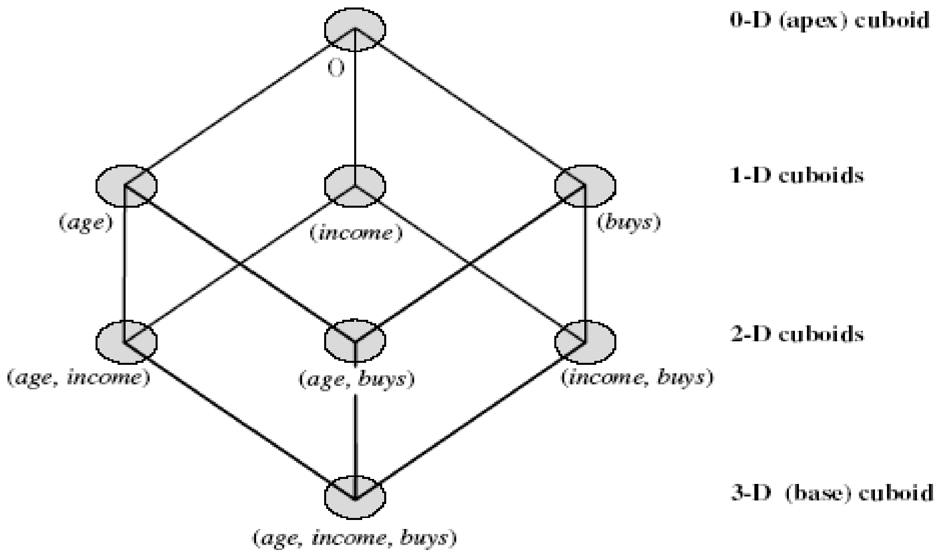
Association rules that involve two or more dimensions or predicates can be referred to as multidimensional association rules. Rule above contains three predicates (*age, occupation*, and *buys*), each of which occurs *only once* in the rule. Hence, we say that it has no repeated predicates. Multidimensional association rules with no repeated predicates are called inter dimensional association rules. We can also mine multidimensional association rules with repeated predicates, which contain multiple occurrences of some predicates. These rules are called hybrid-dimensional association rules. An example of such a rule is the following, where the predicate *buys* is repeated:

$$age(X, \text{"20...29"}) \wedge buys(X, \text{"laptop"}) \Rightarrow buys(X, \text{"HP printer"})$$

Note that database attributes can be categorical or quantitative. Categorical attributes have a finite number of possible values, with no ordering among the values (e.g., *occupation*, *brand*, *color*). Categorical attributes are also called nominal attributes, because their values are "names of things." Quantitative attributes are numeric and have an implicit ordering among values (e.g., *age, income*, *price*). Techniques for mining multidimensional association rules can be categorized into two basic approaches regarding the treatment of quantitative attributes.

Mining Multidimensional Association Rules Using Static Discretization of Quantitative Attributes

Quantitative attributes, in this case, are discretized before mining using predefined concept hierarchies or data discretization techniques, where numeric values are replaced by interval labels. Categorical attributes may also be generalized to higher conceptual levels if desired. If the resulting task-relevant data are stored in a relational table, then any of the frequent itemset mining algorithms we have discussed can be modified easily so as to find all frequent predicate sets rather than frequent itemsets. In particular, instead of searching on only one attribute like *buys*, we need to search through all of the relevant attributes, treating each attribute-value pair as an itemset.



Lattice of cuboids, making up a 3-D data cube. Each cuboid represents a different group-by. The base cuboid contains the three predicates *age*, *income*, and *buys*.

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,

$$A_{quan1} \wedge A_{quan2} \Rightarrow A_{cat}$$

where *Aquan*1 and *Aquan*2 are tests on quantitative attribute intervals (where the intervals are dynamically determined), and *Acat* tests a categorical attribute from the task-relevant data. 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

$$age(X, \text{"30...39"}) \wedge income(X, \text{"42K...48K"}) \Rightarrow buys(X, \text{"HDTV"})$$

Binning: Quantitative attributes can have a very wide range of values defining their domain. Just think about how big a 2-D grid would be if we plotted *age* and *income* as axes, where each possible value of *age* was assigned a unique position on one axis, and similarly, each possible value of *income* was assigned a unique position on the other axis! To keep grids down to a manageable size, we instead partition the ranges of quantitative attributes into intervals. These intervals are dynamic in that they may later be further combined during the mining process. The partitioning process is referred to as binning, that is, where the intervals are considered "bins." Three common binning strategies area as follows:

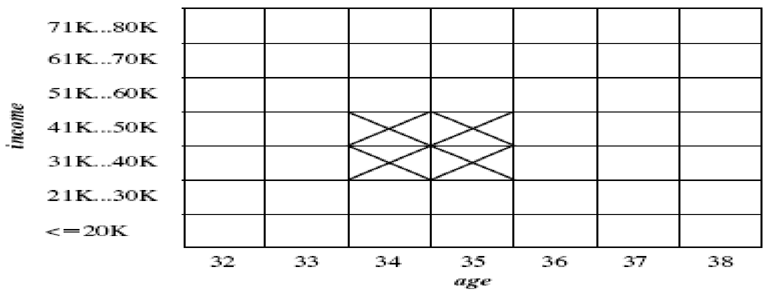
- **Equal-width binning**, where the interval size of each bin is the same
- **Equal-frequency binning**, where each bin has approximately the same number of tuples assigned to it,
- **Clustering-based binning**, where clustering is performed on the quantitative attribute to group *neighboring points* (judged based on various distance measures) into the same bin

Finding frequent predicate sets: Once the 2-D array containing the count distribution for each category is set up, it can be scanned to find the frequent predicate sets (those satisfying minimum support) that also satisfy minimum confidence. Strong association rules can then be generated from these predicate sets, using a rule generation algorithm.

Clustering the association rules: The strong association rules obtained in the previous step are then mapped to a 2-D grid. Figure 5.14 shows a 2-D grid for 2-D quantitative association rules predicting the condition *buys*(*X*, "*HDTV*") on the rule right-hand side, given the quantitative attributes *age* and *income*. The four Xs correspond to the rules

$$age(X, 34) \wedge income(X, \text{“}31K...40K\text{”}) \Rightarrow buys(X, \text{“}HDTV\text{”}) \quad (5.16)$$
$$age(X, 35) \wedge income(X, \text{“}31K...40K\text{”}) \Rightarrow buys(X, \text{“}HDTV\text{”}) \quad (5.17)$$
$$age(X, 34) \wedge income(X, \text{“}41K...50K\text{”}) \Rightarrow buys(X, \text{“}HDTV\text{”}) \quad (5.18)$$
$$age(X, 35) \wedge income(X, \text{“}41K...50K\text{”}) \Rightarrow buys(X, \text{“}HDTV\text{”}). \quad (5.19)$$

"Can we find a simpler rule to replace the above four rules?" Notice that these rules are quite "close" to one another, forming a rule cluster on the grid. Indeed, the four rules can be combined or "clustered" together to form the following simpler rule, which subsumes and replaces the above four rules:



A 2-D grid for tuples representing customers who purchase high-definition TVs.

From Association Mining to Correlation Analysis

Most association rule mining algorithms employ a support-confidence framework. Often, many interesting rules can be found using low support thresholds. Although minimum support and confidence thresholds *help* weed out or exclude the exploration of a good number of uninteresting rules, many rules so generated are still not interesting to the users. Unfortunately, this is especially true *when mining at low support thresholds or mining for long patterns*. This has been one of the major bottlenecks for successful application of association rule mining.

1)Strong Rules Are Not Necessarily Interesting: An Example

Whether or not a rule is interesting can be assessed either subjectively or objectively. Ultimately, only the user can judge if a given rule is interesting, and this judgment, being subjective, may differ from one user to another. However, objective interestingness measures, based on the statistics "behind" the data, can be used as one step toward the goal of weeding out uninteresting rules from presentation to the user.

The support and confidence measures are insufficient at filtering out uninteresting association rules. To tackle this weakness, a correlation measure can be used to augment the support-confidence framework for association rules. This leads to *correlation rules* of the form

$$A \Rightarrow B\ [support, confidence. correlation].$$

That is, a correlation rule is measured not only by its support and confidence but also by the correlation between itemsets *A* and *B*. There are many different correlation measures from which to choose. In this section, we study various correlation measures to determine which would be good for mining large data sets.

Constraint-Based Association Mining

A data mining process may uncover thousands of rules from a given set of data, most of which end up being unrelated or uninteresting to the users. Often, users have a good sense of which "direction" of mining may lead to interesting patterns and the "form" of the patterns or rules they would like to find. Thus, a good heuristic is to have the users specify such intuition or expectations as *constraints* to confine the search space. This strategy is known as constraint-based mining. The constraints can include the following:

- **Knowledge type constraints:** These specify the type of knowledge to be mined, such as association or correlation.
- **Data constraints:** These specify the set of task-relevant data.
- **Dimension/level constraints:** These specify the desired dimensions (or attributes) of the data, or levels of the concept hierarchies, to be used in mining.
- **Interestingness constraints:** These specify thresholds on statistical measures of rule interestingness, such as support, confidence, and correlation.
- **Rule constraints:** These specify the form of rules to be mined. Such constraints may be expressed as metarules (rule templates), as the maximum or minimum number of predicates that can occur in the rule antecedent or consequent, or as relationships among attributes, attribute values, and/or aggregates.

1) Metarule-Guided Mining of Association Rules

"How are metarules useful?" Metarules allow users to specify the syntactic form of rules that they are interested in mining. The rule forms can be used as constraints to help improve the efficiency of the mining process. Metarules may be based on the analyst's experience, expectations, or intuition regarding the data or may be automatically generated based on the database schema.

Metarule-guided mining:- Suppose that as a market analyst for *AllElectronics*, you have access to the data describing customers (such as customer age, address, and credit rating) as well as the list of customer transactions. You are interested in finding associations between customer traits and the items that customers buy. However, rather than finding *all* of the association rules reflecting these relationships, you are particularly interested only in determining which pairs of customer traits promote the sale of office software.A metarule can be used to specify this information describing the form of rules you are interested in finding. An example of such a metarule is

$$P_1(X, Y) \wedge P_2(X, W) \Rightarrow buys(X, \text{"office software"}),$$

where $P1$ and $P2$ are predicate variables that are instantiated to attributes from the given database during the mining process, X is a variable representing a customer, and Y and W take on values of the attributes assigned to $P1$ and $P2$, respectively. Typically, a user will specify a list of attributes to be considered for instantiation with $P1$ and $P2$. Otherwise, a default set may be used.

2) Constraint Pushing: Mining Guided by Rule Constraints

Rule constraints specify expected set/subset relationships of the variables in the mined rules, constant initiation of variables, and aggregate functions. Users typically employ their knowledge of the application or data to specify rule constraints for the mining task. These rule constraints may be used together with, or as an alternative to, metarule-guided mining. In this section, we examine rule constraints as to how they can be used to make the mining process more efficient. Let's study an example where rule constraints are used to mine hybrid-dimensional association rules.

Our association mining query is to *"Find the sales of which cheap items (where the sum of the prices is less than $100) may promote the sales of which expensive items (where the minimum price is $500) of the same group for Chicago customers in 2004."* This can be expressed in the DMQL data mining query language as follows,

(1) mine associations as
(2) $lives\_in(C, \_, \text{"Chicago"}) \wedge sales^{+}(C, ?\{I\}, \{S\}) \Rightarrow sales^{+}(C, ?\{J\}, \{T\})$
(3) from sales
(4) where S.year = 2004 and T.year = 2004 and I.group = J.group
(5) group by C, I.group
(6) having sum(I.price) $<$ 100 and min(J.price) $\geq$ 500
(7) with support threshold = 1%
(8) with confidence threshold = 50%

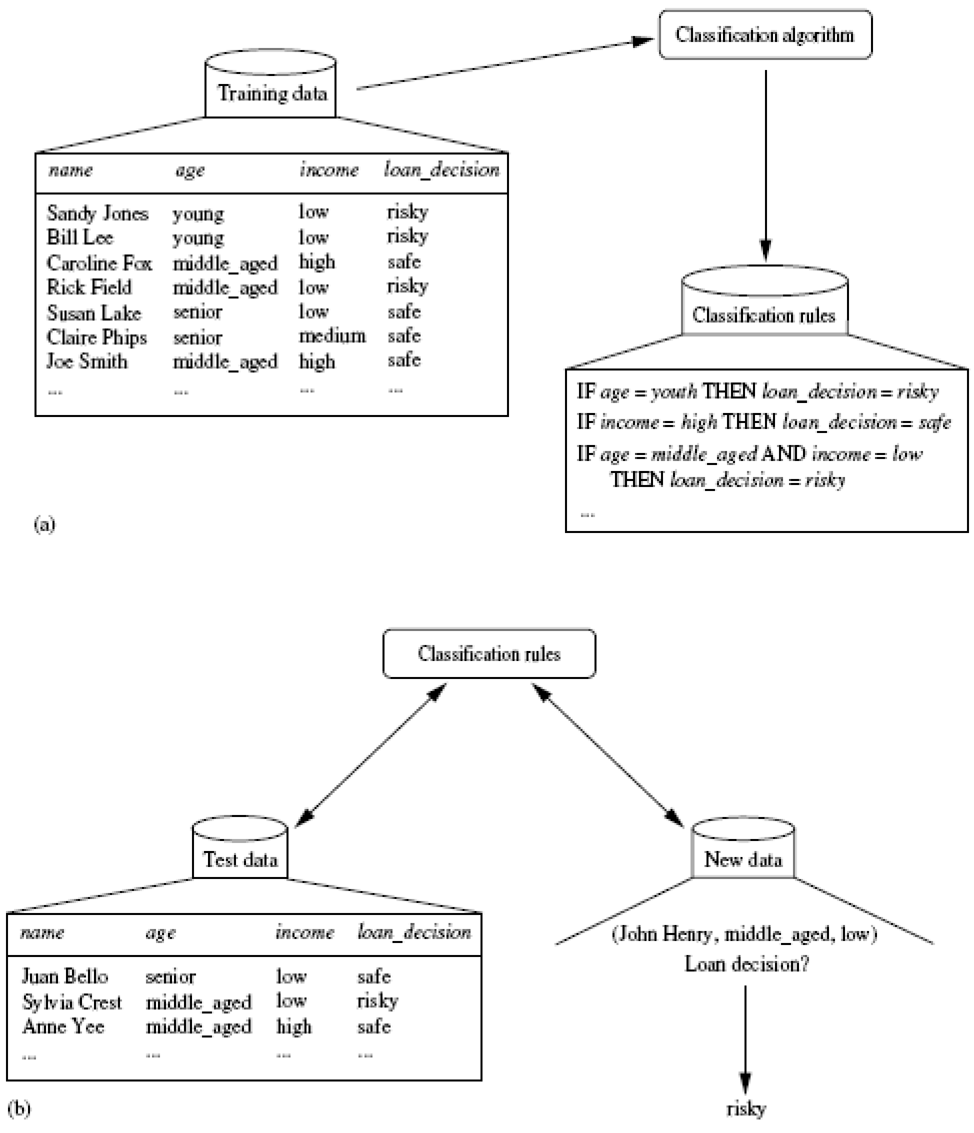
Classification and Prediction

What Is Classification? What Is Prediction?

A bank loans officer needs analysis of her data in order to learn which loan applicants are "safe" and which are "risky" for the bank. A marketing manager at *AllElectronics* needs data analysis to help guess whether a customer with a given profile will buy a new computer. A medical researcher wants to analyze breast cancer data in order to predict which one of three specific treatments a patient should receive. In each of these examples, the data analysis task is classification, where a model or classifier is constructed to predict *categorical labels*, such as "safe" or "risky" for the loan application data; "yes" or "no" for the marketing data; or "treatment A," "treatment B," or "treatment C" for the medical data. These categories can be represented by discrete values, where the ordering among values has no meaning. For example, the values 1, 2, and 3 may be used to represent treatments A, B, and C, where there is no ordering implied among this group of treatment regimes.

Suppose that the marketing manager would like to predict how much a given customer will spend during a sale at *AllElectronics*. This data analysis task is an example of numeric prediction, where the model constructed predicts a *continuous-valued function*, or *ordered value*, as opposed to a categorical label. This model is a predictor

"How does classification work?" Data classification is a two-step process, as shown for the loan application data of Figure 6.1. (The data are simplified for illustrative purposes. In reality, we may expect many more attributes to be considered.) In the first step, a classifier is built describing a predetermined set of data classes or concepts. This is the learning step (or training phase), where a classification algorithm builds the classifier by analyzing or "learning from" a training set made up of database tuples and their associated class labels.



name	*age*	*income*	*loan_decision*
Sandy Jones	young	low	risky
Bill Lee	young	low	risky
Caroline Fox	middle_aged	high	safe
Rick Field	middle_aged	low	risky
Susan Lake	senior	low	safe
Claire Phips	senior	medium	safe
Joe Smith	middle_aged	high	safe
...	...	...	...

IF *age* = *youth* THEN *loan_decision* = *risky*
IF *income* = *high* THEN *loan_decision* = *safe*
IF *age* = *middle_aged* AND *income* = *low*
THEN *loan_decision* = *risky*
...

name	*age*	*income*	*loan_decision*
Juan Bello	senior	low	safe
Sylvia Crest	middle_aged	low	risky
Anne Yee	middle_aged	high	safe
...	...	...	...

The data classification process: (a) *Learning*: Training data are analyzed by a classification algorithm. Here, the class label attribute is *loan_decision*, and the learned model or classifier is represented in the form of classification rules. (b) *Classification*: Test data are used to estimate the accuracy of the classification rules. If the accuracy is considered acceptable, the rules can be applied to the classification of new data tuples.

Issues Regarding Classification and Prediction

- **Data cleaning**: This refers to the preprocessing of data in order to remove or reduce *noise* (by applying smoothing techniques, for example) and the treatment of *missing values* (e.g., by replacing a missing value with the most commonly occurring value for that attribute, or with the most probable value based on statistics). Although most classification algorithms have some mechanisms for handling noisy or missing data, this step can help reduce confusion during learning.

- **Relevance analysis**: Many of the attributes in the data may be *redundant*. Correlation analysis can be used to identify whether any two given attributes are statistically related. For example, a strong correlation between attributes *A*1 and *A*2 would suggest that one of the two could be removed from further analysis. A database may also contain *irrelevant* attributes. Attribute subset selection4 can be used in these cases to find a reduced set of attributes such that the resulting probability distribution of the data classes is as close as possible to the original distribution obtained using all attributes. Hence, relevance analysis, in the form of correlation analysis and attribute subset selection, can be used to detect attributes that do not contribute to the classification or prediction task. Including such attributes may otherwise slow down, and possibly mislead, the learning step. Ideally, the time spent on relevance analysis, when added to the time spent on learning from the resulting "reduced" attribute (or feature) subset, should be less than the time that would have been spent on learning from the original set of attributes. Hence, such analysis can help improve classification efficiency and scalability.

- **Data transformation and reduction:** The data may be transformed by normalization, particularly when neural networks or methods involving distance measurements are used in the learning step. Normalization involves scaling all values for a given attribute so that they fall within a small specified range, such as -1.0 to 1.0, or 0.0 to 1.0. In methods that use distance measurements, for example, this would prevent attributes with initially large ranges (like, say, *income*) from out weighing attributes with initially smaller ranges (such as binary attributes).

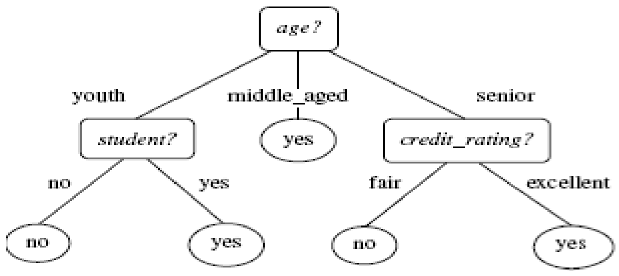
Comparing Classification and Prediction Methods

Classification and prediction methods can be compared and evaluated according to the following criteria:

- **Accuracy**
- **Speed**
- **Robustness**
- **Scalability**
- **Interpretability**
-

Classification by Decision Tree Induction (16 Mark Question)

Decision tree induction is the learning of decision trees from class-labeled training tuples. A decision tree is a flowchart-like tree structure, where each internal node (nonleaf node) denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (or *terminal node*) holds a class label. The topmost node in a tree is the root node.



A decision tree for the concept *buys_computer*, indicating whether a customer at *AllElectronics* is likely to purchase a computer. Each internal (nonleaf) node represents a test on an attribute. Each leaf node represents a class (either *buys_computer = yes* or *buys_computer = no*).

A typical decision tree is shown in Figure. It represents the concept *buys computer*, that is, it predicts whether a customer at *AllElectronics* is likely to purchase a computer. Internal nodes are denoted by rectangles, and leaf nodes are denoted by ovals. Some decision tree algorithms produce only *binary* trees (where each internal node branches to exactly two other nodes), whereas others can produce non binary trees.

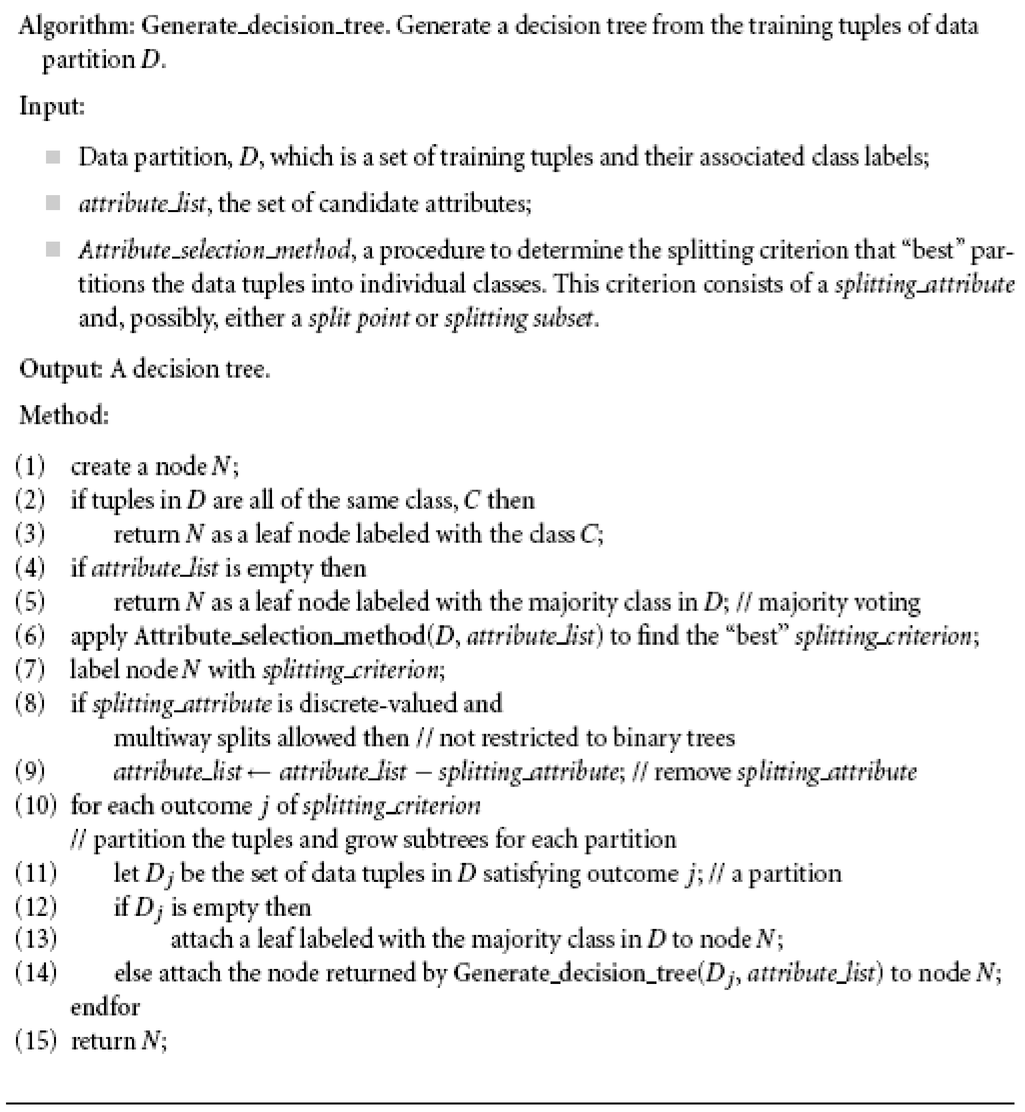
"How are decision trees used for classification?" Given a tuple, ***X***, for which the associated class label is unknown, the attribute values of the tuple are tested against the decision tree. A path is traced from the root to a leaf node, which holds the class prediction for that tuple. Decision trees can easily be converted to classification rules.

Decision Tree Induction

The algorithm is called with three parameters: *D*, *attribute list*, and *Attribute selection method*. We refer to *D* as a data partition. Initially, it is the complete set of training tuples and their associated class labels. The parameter *attribute list* is a list of attributes describing the tuples. *Attribute selection method* specifies a heuristic procedure for selecting the attribute that "best" discriminates the given tuples accordingto class. This procedure employs an attribute selection measure, such as information gain or the gini index. Whether the tree is strictly binary is generally driven by the attribute selection measure. Some attribute selection measures, such as the gini index, enforce the resulting tree to be binary. Others, like information gain, do not, therein allowing multiway splits (i.e., two or more branches to be grown from a node).

- The tree starts as a single node, *N*, representing the training tuples in *D* (step 1)
- If the tuples in *D* are all of the same class, then node *N* becomes a leaf and is labeled with that class (steps 2 and 3). Note that steps 4 and 5 are terminating conditions. All of the terminating conditions are explained at the end of the algorithm.
- Otherwise, the algorithm calls *Attribute selection method* to determine the splitting criterion. The splitting criterion tells us which attribute to test at node *N* by determining the "best" way to separate or partition the tuples in *D* into individual classes(step 6). The splitting criterion also tells us which branches to grow from node *N* with respect to the outcomes of the chosen test. More specifically, the splitting criterion indicates the splitting attribute and may also indicate either a split-point or a splitting subset. The splitting criterion is determined so that, ideally, the resulting partitions at each branch are as "pure" as possible. A partition is pure if all of the tuples in it belong to the same class. In other words, if

we were to split up the tuples in *D* according to the mutually exclusive outcomes of the splitting criterion, we hope for the resulting partitions to be as pure as possible.



Algorithm: Generate_decision_tree. Generate a decision tree from the training tuples of data partition *D*.

Input:

- Data partition, *D*, which is a set of training tuples and their associated class labels;
- *attribute_list*, the set of candidate attributes;
- *Attribute_selection_method*, a procedure to determine the splitting criterion that "best" partitions the data tuples into individual classes. This criterion consists of a *splitting_attribute* and, possibly, either a *split point* or *splitting subset*.

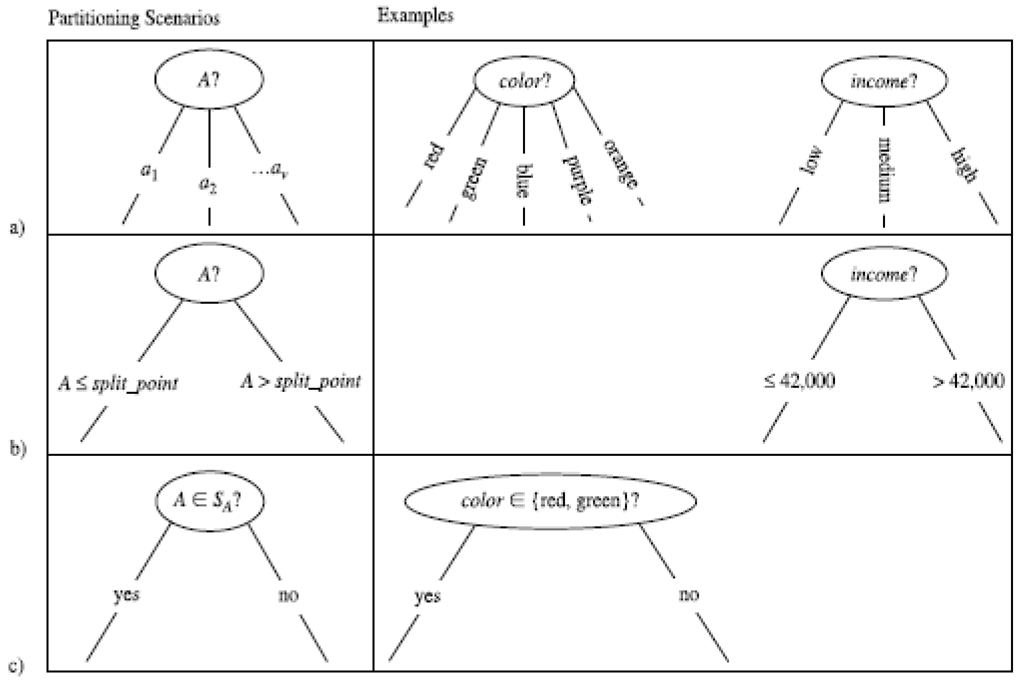
Output: A decision tree.

Method:

```
(1)  create a node $N$;
(2)  if tuples in $D$ are all of the same class, $C$ then
(3)      return $N$ as a leaf node labeled with the class $C$;
(4)  if attribute_list is empty then
(5)      return $N$ as a leaf node labeled with the majority class in $D$; // majority voting
(6)  apply Attribute_selection_method($D$, attribute_list) to find the "best" splitting_criterion;
(7)  label node $N$ with splitting_criterion;
(8)  if splitting_attribute is discrete-valued and
         multiway splits allowed then // not restricted to binary trees
(9)      attribute_list $\leftarrow$ attribute_list $-$ splitting_attribute; // remove splitting_attribute
(10) for each outcome $j$ of splitting_criterion
     // partition the tuples and grow subtrees for each partition
(11)     let $D_j$ be the set of data tuples in $D$ satisfying outcome $j$; // a partition
(12)     if $D_j$ is empty then
(13)         attach a leaf labeled with the majority class in $D$ to node $N$;
(14)     else attach the node returned by Generate_decision_tree($D_j$, attribute_list) to node $N$;
     endfor
(15) return $N$;
```

Basic algorithm for inducing a decision tree from training tuples.

- The node *N* is labeled with the splitting criterion, which serves as a test at the node (step 7). A branch is grown from node *N* for each of the outcomes of the splitting criterion. The tuples in *D* are partitioned accordingly (steps 10 to 11). There are three possible scenarios, as illustrated in Figure. Let *A* be the splitting attribute. *A* has *v* distinct values, {a_1, a_2, : : : , a_v}, based on the training data.



Three possibilities for partitioning tuples based on the splitting criterion, shown with examples. Let A be the splitting attribute. (a) If A is discrete-valued, then one branch is grown for each known value of A. (b) If A is continuous-valued, then two branches are grown, corresponding to $A \leq split\_point$ and $A > split\_point$. (c) If A is discrete-valued and a binary tree must be produced, then the test is of the form $A \in S_A$, where S_A is the splitting subset for A.

Attribute Selection Measures

An attribute selection measure is a heuristic for selecting the splitting criterion that "best" separates a given data partition, *D*, of class-labeled training tuples into individual classes. If we were to split *D* into smaller partitions according to the outcomes of the splitting criterion, ideally each partition would be pure (i.e., all of the tuples that fall into a given partition would belong to the same class). Conceptually, the "best" splitting criterion is the one that most closely results in such a scenario. Attribute selection measures are also known as splitting rules because they determine how the tuples at a given node are to be split. The attribute selection measure provides a ranking for each attribute describing the given training tuples. The attribute having the best score for the measure6 is chosen as the *splitting attribute* for the given tuples. If the splitting attribute is continuous-valued or if we are restricted to binary trees then, respectively, either a *split point* or a *splitting subset* must also be determined as part of the splitting criterion. The tree node created for partition *D* is labeled with the splitting criterion, branches are grown for each outcome of the criterion, and the tuples are partitioned accordingly. This section describes three popular attribute selection measures—*information gain, gain ratio,* and *gini inde*

Information gain

ID3 uses information gain as its attribute selection measure.

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i),$$

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j).$$

Information gain is defined as the difference between the original information requirement (i.e., based on just the proportion of classes) and the new requirement (i.e., obtained after partitioning on *A*). That is,

$$Gain(A) = Info(D) - Info_A(D).$$

In other words, *Gain(A)* tells us how much would be gained by branching on *A*. It is the expected reduction in the information requirement caused by knowing the value of *A*. The attribute *A* with the highest information gain, (*Gain*(*A*)), is chosen as the splitting attribute at node *N*.

Example 6.1 Induction of a decision tree using information gain.

Table 6.1 presents a training set, *D*, of class-labeled tuples randomly selected from the *AllElectronics* customer database. (The data are adapted from [Qui86]. In this example, each attribute is discrete-valued. Continuous-valued attributes have been generalized.) The class label attribute, *buys computer*, has two distinct values (namely, {*yes*, *no*}); therefore, there are two distinct classes (that is, *m* = 2). Let class *C*1 correspond to *yes* and class *C*2 correspond to *no*. There are nine tuples of class *yes* and five tuples of class *no*. A (root) node *N* is created for the tuples in *D*. To find the splitting criterion for these tuples, we must compute the information gain of each attribute. We first use Equation (6.1) to compute the expected information needed to classify a tuple in *D*:

$$Info(D) = -\frac{9}{14}\log_2\left(\frac{9}{14}\right) - \frac{5}{14}\log_2\left(\frac{5}{14}\right) = 0.940 \text{ bits.}$$

Table 6.1 Class-labeled training tuples from the *AllElectronics* customer database.

RID	*age*	*income*	*student*	*credit_rating*	*Class: buys_computer*
1	youth	high	no	fair	no
2	youth	high	no	excellent	no
3	middle_aged	high	no	fair	yes
4	senior	medium	no	fair	yes
5	senior	low	yes	fair	yes
6	senior	low	yes	excellent	no
7	middle_aged	low	yes	excellent	yes
8	youth	medium	no	fair	no
9	youth	low	yes	fair	yes
10	senior	medium	yes	fair	yes
11	youth	medium	yes	excellent	yes
12	middle_aged	medium	no	excellent	yes
13	middle_aged	high	yes	fair	yes
14	senior	medium	no	excellent	no

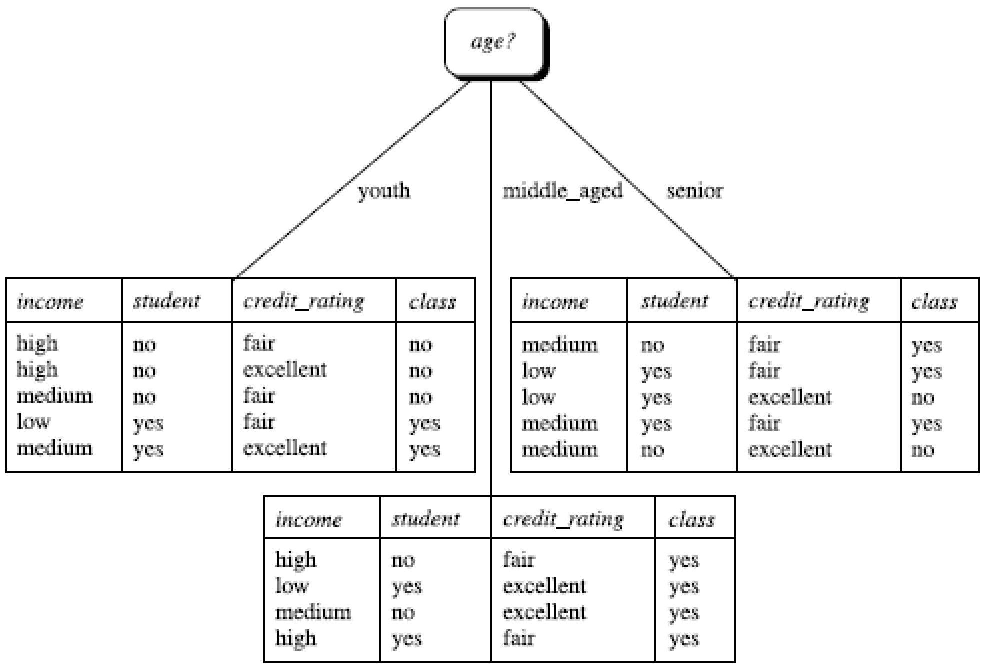
The expected information needed to classify a tuple in *D* if the tuples are partitioned according to *age* is

$$\begin{aligned} Info_{age}(D) &= \frac{5}{14} \times \left(-\frac{2}{5}\log_2\frac{2}{5} - \frac{3}{5}\log_2\frac{3}{5}\right) \\ &+ \frac{4}{14} \times \left(-\frac{4}{4}\log_2\frac{4}{4} - \frac{0}{4}\log_2\frac{0}{4}\right) \\ &+ \frac{5}{14} \times \left(-\frac{3}{5}\log_2\frac{3}{5} - \frac{2}{5}\log_2\frac{2}{5}\right) \\ &= 0.694 \text{ bits.} \end{aligned}$$

Hence, the gain in information from such a partitioning would be

$$Gain(age) = Info(D) - Info_{age}(D) = 0.940 - 0.694 = 0.246 \text{ bits.}$$

Similarly, we can compute *Gain*(*income*) = 0.029 bits, *Gain*(*student*) = 0.151 bits, and *Gain*(*credit rating*) = 0.048 bits. Because *age* has the highest information gain among the attributes, it is selected as the splitting attribute. Node *N* is labeled with *age*, and branches are grown for each of the attribute's values. The tuples are then partitioned accordingly, as shown in Figure 6.5. Notice that the tuples falling into the partition for *age* = *middle aged* all belong to the same class. Because they all belong to class *"yes,"* a leaf should therefore be created at the end of this branch and labeled with *"yes."* The final decision tree returned by the algorithm is shown in Figure 6.5.



income	*student*	*credit_rating*	*class*
high	no	fair	no
high	no	excellent	no
medium	no	fair	no
low	yes	fair	yes
medium	yes	excellent	yes

income	*student*	*credit_rating*	*class*
high	no	fair	yes
low	yes	excellent	yes
medium	no	excellent	yes
high	yes	fair	yes

income	*student*	*credit_rating*	*class*
medium	no	fair	yes
low	yes	fair	yes
low	yes	excellent	no
medium	yes	fair	yes
medium	no	excellent	no

Figure 6.5 The attribute *age* has the highest information gain and therefore becomes the splitting attribute at the root node of the decision tree. Branches are grown for each outcome of *age*. The tuples are shown partitioned accordingly.

Bayesian Classification (16 mark Question)

“What are Bayesian classifiers?” Bayesian classifiers are statistical classifiers. They can predict class membership probabilities, such as the probability that a given tuple belongs to a particular class.

Bayesian classification is based on Bayes’ theorem, described below. Studies comparing classification algorithms have found a simple Bayesian classifier known as the *naïve Bayesian classifier* to be comparable in performance with decision tree and selected neural network classifiers. Bayesian classifiers have also exhibited high accuracy and speed when applied to large databases.

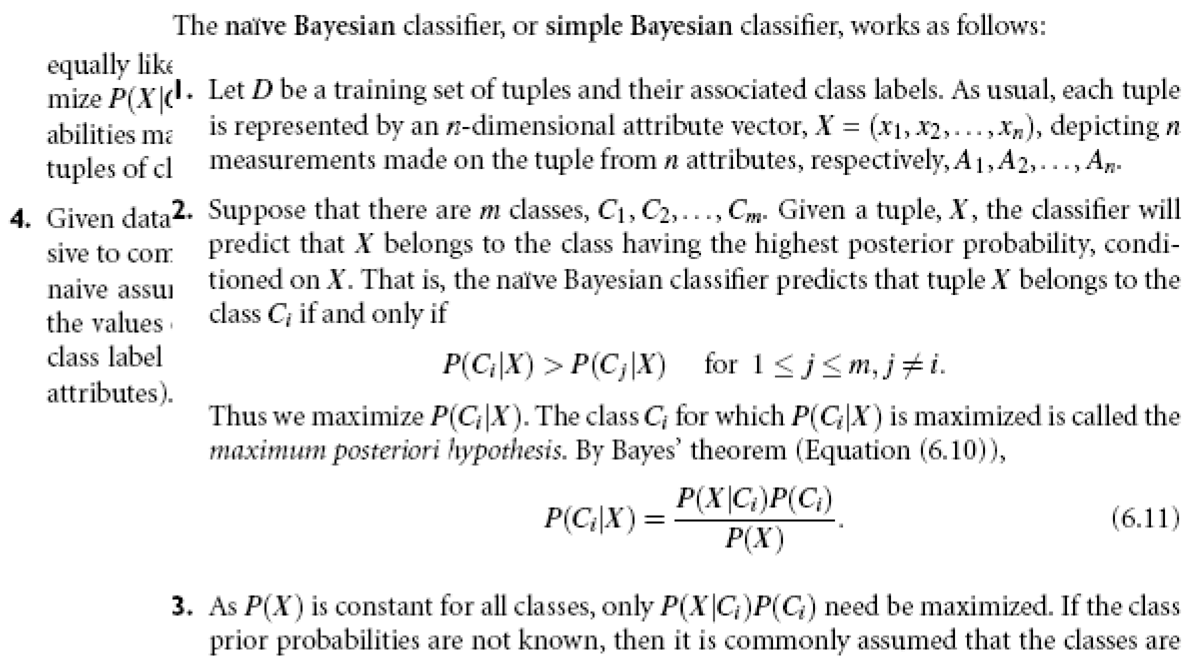
1) Bayes’ Theorem

Bayes’ theorem is named after Thomas Bayes, a nonconformist English clergyman who did early work in probability and decision theory during the 18th century. Let ***X*** be a data tuple. In Bayesian terms, ***X*** is considered “evidence.” As usual, it is described by measurements made on a set of *n* attributes. Let *H* be some hypothesis, such as that the data tuple ***X*** belongs to a specified class *C*. For classification problems, we want to determine *P*(*H*j***X***), the probability that the hypothesis *H* holds given the “evidence” or observed data tuple ***X***. In other words, we are looking for the probability that tuple ***X*** belongs to class *C*, given that we know the attribute description of ***X***.

“How are these probabilities estimated?” *P*(*H*), *P*(***X***j*H*), and *P*(***X***) may be estimated from the given data, as we shall see below. Bayes’ theorem is useful in that it provides a way of calculating the posterior probability, *P*(*H*j***X***), from *P*(*H*), *P*(***X***j*H*), and *P*(***X***). Bayes’ theorem is

$$P(H|X) = \frac{P(X|H)P(H)}{P(X)}.$$

2) Naïve Bayesian Classification


The naïve Bayesian classifier, or simple Bayesian classifier, works as follows:

equally lik
mize $P(X|C$
abilities ma
tuples of cl

4. Given data
sive to com
naive assu
the values
class label
attributes).

1. Let D be a training set of tuples and their associated class labels. As usual, each tuple is represented by an n-dimensional attribute vector, $X = (x_1, x_2, \ldots, x_n)$, depicting n measurements made on the tuple from n attributes, respectively, $A_1, A_2, \ldots, A_n$.
2. Suppose that there are m classes, $C_1, C_2, \ldots, C_m$. Given a tuple, X, the classifier will predict that X belongs to the class having the highest posterior probability, conditioned on X. That is, the naïve Bayesian classifier predicts that tuple X belongs to the class C_i if and only if
$$P(C_i|X) > P(C_j|X) \quad \text{for } 1 \le j \le m, j \ne i.$$
Thus we maximize $P(C_i|X)$. The class C_i for which $P(C_i|X)$ is maximized is called the *maximum posteriori hypothesis*. By Bayes’ theorem (Equation (6.10)),
$$P(C_i|X) = \frac{P(X|C_i)P(C_i)}{P(X)}. \qquad (6.11)$$
3. As $P(X)$ is constant for all classes, only $P(X|C_i)P(C_i)$ need be maximized. If the class prior probabilities are not known, then it is commonly assumed that the classes are

$$P(X|C_i) = \prod_{k=1}^{n} P(x_k|C_i) = P(x_1|C_i) \times P(x_2|C_i) \times \cdots \times P(x_n|C_i).$$

5. In order to predict the class label of X, $P(X|C_i)P(C_i)$ is evaluated for each class C_i. The classifier predicts that the class label of tuple X is the class C_i if and only if

$$P(X|C_i)P(C_i) > P(X|C_j)P(C_j) \quad \text{for } 1 \le j \le m, j \ne i. \tag{6.15}$$

In other words, the predicted class label is the class C_i for which $P(X|C_i)P(C_i)$ is the maximum.

Example 6.4 Predicting a class label using naïve Bayesian classification. We wish to predict the class label of a tuple using naïve Bayesian classification, given the same training data as in Example 6.3 for decision tree induction. The training data are in Table 6.1. The data tuples are described by the attributes *age*, *income*, *student*, and *credit_rating*. The class label attribute, *buys_computer*, has two distinct values (namely, {*yes, no*}). Let C_1 correspond to the class *buys_computer = yes* and C_2 correspond to *buys_computer = no*. The tuple we wish to classify is

$$X = (age = youth, income = medium, student = yes, credit\_rating = fair)$$

We need to maximize $P(X|C_i)P(C_i)$, for $i = 1, 2$. $P(C_i)$, the prior probability of each class, can be computed based on the training tuples:

$$P(buys\_computer = yes) = 9/14 = 0.643$$
$$P(buys\_computer = no) = 5/14 = 0.357$$

To compute $PX|C_i)$, for $i = 1, 2$, we compute the following conditional probabilities:

$$P(age = youth \mid buys\_computer = yes) = 2/9 = 0.222$$
$$P(age = youth \mid buys\_computer = no) = 3/5 = 0.600$$
$$P(income = medium \mid buys\_computer = yes) = 4/9 = 0.444$$
$$P(income = medium \mid buys\_computer = no) = 2/5 = 0.400$$
$$P(student = yes \mid buys\_computer = yes) = 6/9 = 0.667$$
$$P(student = yes \mid buys\_computer = no) = 1/5 = 0.200$$
$$P(credit\_rating = fair \mid buys\_computer = yes) = 6/9 = 0.667$$
$$P(credit\_rating = fair \mid buys\_computer = no) = 2/5 = 0.400$$

Using the above probabilities, we obtain

$$\begin{aligned} P(X|buys\_computer = yes) = {} & P(age = youth \mid buys\_computer = yes) \times \\ & P(income = medium \mid buys\_computer = yes) \times \\ & P(student = yes \mid buys\_computer = yes) \times \\ & P(credit\_rating = fair \mid buys\_computer = yes) \\ = {} & 0.222 \times 0.444 \times 0.667 \times 0.667 = 0.044. \end{aligned}$$

Similarly,

$P(X|buys\_computer = no) = 0.600 \times 0.400 \times 0.200 \times 0.400 = 0.019.$

To find the class, C_i, that maximizes $P(X|C_i)P(C_i)$, we compute

$$P(X|buys\_computer = yes)P(buys\_computer = yes) = 0.044 \times 0.643 = 0.028$$

$$P(X|buys\_computer = no)P(buys\_computer = no) = 0.019 \times 0.357 = 0.007$$

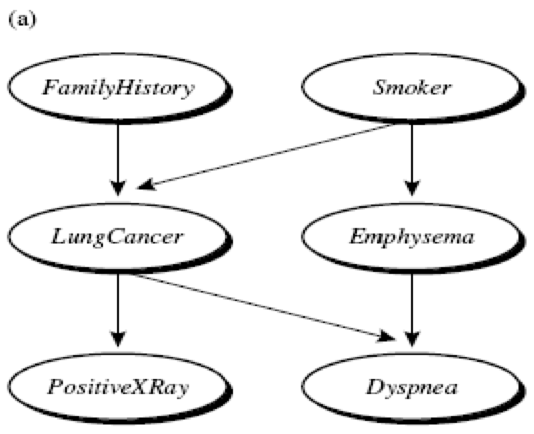
Therefore, the naïve Bayesian classifier predicts $buys\_computer = yes$ for tuple X. ■

3) Bayesian Belief Networks

The naïve Bayesian classifier makes the assumption of class conditional independence, that is, given the class label of a tuple, the values of the attributes are assumed to be conditionally independent of one another. This simplifies computation. When the assumption holds true, then the naïve Bayesian classifier is the most accurate in comparison with all other classifiers. In practice, however, dependencies can exist between variables. Bayesian belief networks specify joint conditional probability distributions. They allow class conditional independencies to be defined between subsets of variables. They provide a graphical model of causal relationships, on which learning can be performed. Trained Bayesian belief networks can be used for classification. Bayesian belief networks are also known as belief networks, Bayesian networks, and probabilistic networks. For brevity, we will refer to them as belief networks.

A belief network is defined by two components—a *directed acyclic graph* and a set of *conditional probability tables* (Figure 6.11). Each node in the directed acyclic graph represents a random variable. The variables may be discrete or continuous-valued. They may correspond to actual attributes given in the data or to "hidden variables" believed to form a relationship (e.g., in the case of medical data, a hidden variable may indicate a syndrome, representing a number of symptoms that, together, characterize a specific disease). Each arc represents a probabilistic dependence. If an arc is drawn from a node *Y* to a node *Z*, then *Y* is a parent or immediate predecessor of *Z*, and *Z* is a descendant of *Y*. *Each variable is conditionally independent of its non descendants in the graph, given its parents.*

(a)



(b)

	FH, S	*FH, ~S*	*~FH, S*	*~FH, ~S*
LC	0.8	0.5	0.7	0.1
~LC	0.2	0.5	0.3	0.9

A simple Bayesian belief network: (a) A proposed causal model, represented by a directed acyclic graph. (b) The conditional probability table for the values of the variable *LungCancer* *(LC)* showing each possible combination of the values of its parent nodes, *FamilyHistory (FH)* and *Smoker (S)*. Figure is adapted from [RBKK95].

A belief network has one conditional probability table (CPT) for each variable. The CPT for a variable *Y* specifies the conditional distribution *P*(*Y*j*Parents*(*Y*)), where *Parents*(*Y*) are the parents of *Y*. Figure(b) shows a CPT for the variable *LungCancer*. The conditional probability for each known value of *LungCancer* is given for each possible combination of values of its parents. For instance, from the upper leftmost and bottom rightmost entries, respectively, we see that

$$P(LungCancer = yes \mid FamilyHistory = yes, Smoker = yes) = 0.8$$

$$P(LungCancer = no \mid FamilyHistory = no, Smoker = no) = 0.9$$

Let ***X*** = (*x*1, : : : , *xn*) be a data tuple described by the variables or attributes *Y*1, : : : , *Yn*, respectively. Recall that each variable is conditionally independent of its non descendants in the network graph, given its parents. This allows the network to provide a complete representation of the existing joint probability distribution with the
following equation:

$$P(x_1,\ldots,x_n) = \prod_{i=1}^{n} P(x_i|Parents(Y_i)),$$

Rule-Based Classification

We look at rule-based classifiers, where the learned model is represented as a set of IF-THEN rules. We first examine how such rules are used for classification. We then study ways in which they can be generated, either from a decision tree or directly from the training data using a *sequential covering algorithm.*

1) **Using IF-THEN Rules for Classification**

Rules are a good way of representing information or bits of knowledge. A rule-based classifier uses a set of IF-THEN rules for classification. An IF-THEN rule is an expression of the form

IF *condition* THEN *conclusion*.

An example is rule *R*1,

R1: IF *age* = *youth* AND *student* = *yes* THEN *buys computer* = *yes*.

The "IF"-part (or left-hand side)of a rule is known as the rule antecedent or precondition. The "THEN"-part (or right-hand side) is the rule consequent. In the rule antecedent, the condition consists of one or more *attribute tests* (such as *age* = *youth*, and *student* = *yes*) that are logically ANDed. The rule's consequent contains a class prediction (in this case, we are predicting whether a customer will buy a computer). *R*1 can also be written as

$$\text{R1: } (age = youth) \wedge (student = yes) \Rightarrow (buys\_computer = yes).$$

If the condition (that is, all of the attribute tests) in a rule antecedent holds true for a given tuple, we say that the rule antecedent is satisfied (or simply, that the rule is satisfied) and that the rule covers the tuple.

A rule *R* can be assessed by its coverage and accuracy. Given a tuple, ***X***, from a class labeled data set *D*, let *ncovers* be the number of tuples covered by *R*; *ncorrect* be the number of tuples correctly classified by *R*; and |*D*| be the number of tuples in *D*. We can define the coverage and accuracy of *R* as

$$coverage(R) = \frac{n_{covers}}{|D|}$$

$$accuracy(R) = \frac{n_{correct}}{n_{covers}}.$$

That is, a rule's coverage is the percentage of tuples that are covered by the rule (i.e. whose attribute values hold true for the rule's antecedent). For a rule's accuracy, we look at the tuples that it covers and see what percentage of them the rule can correctly classify.

2) Rule Extraction from a Decision Tree

We learned how to build a decision tree classifier from a set of training data. Decision tree classifiers are a popular method of classification—it is easy to understand how decision trees work and they are known for their accuracy. Decision trees can become large and difficult to interpret. In this subsection, we look at how to build a rule based classifier by extracting IF-THEN rules from a decision tree. In comparison with a decision tree, the IF-THEN rules may be easier for humans to understand, particularly if the decision tree is very large.

To extract rules from a decision tree, one rule is created for each path from the root to a leaf node. Each splitting criterion along a given path is logically ANDed to form the rule antecedent ("IF" part). The leaf node holds the class prediction, forming the rule consequent ("THEN" part).

Extracting classification rules from a decision tree. The decision tree of Figure 6.2 can be converted to classification IF-THEN rules by tracing the path from the root node to each leaf node in the tree. The rules extracted from Figure 6.2 are

*R*1: IF *age* = *youth*	AND *student* = *no*	THEN *buys_computer* = *no*
*R*2: IF *age* = *youth*	AND *student* = *yes*	THEN *buys_computer* = *yes*
*R*3: IF *age* = *middle_aged*		THEN *buys_computer* = *yes*
*R*4: IF *age* = *senior*	AND *credit_rating* = *excellent*	THEN *buys_computer* = *yes*
*R*5: IF *age* = *senior*	AND *credit_rating* = *fair*	THEN *buys_computer* = *no*

■

Classification by Backpropagation

"What is backpropagation?" Backpropagation is a neural network learning algorithm. The field of neural networks was originally kindled by psychologists and neurobiologists who sought to develop and test computational analogues of neurons. Roughly speaking, a neural network is a set of connected input/output units in which each connection has a weight associated with it. During the learning phase, the

network learns by adjusting the weights so as to be able to predict the correct class label of the input tuples. Neural network learning is also referred to as connectionist learning due to the connections between units.

Neural networks involve long training times and are therefore more suitable for applications where this is feasible. They require a number of parameters that are typically best determined empirically, such as the network topology or "structure." Neural networks have been criticized for their poor interpretability. For example, it is difficult for humans to interpret the symbolic meaning behind the learned weights and of "hidden units" in the network. These features initially made neural networks less desirable for data mining.

1) A Multilayer Feed-Forward Neural Network

The backpropagation algorithm performs learning on a *multilayer feed-forward* neural network. It iteratively learns a set of weights for prediction of the class label of tuples. A multilayer feed-forward neural network consists of an *input layer*, one or more *hidden layers*, and an *output layer*. An example of a multilayer feed-forward network is shown in Figure 6.15.

Each layer is made up of units. The inputs to the network correspond to the attributes measured for each training tuple. The inputs are fed simultaneously into the units making up the input layer. These inputs pass through the input layer and are then weighted and fed simultaneously to a second layer of "neuron like" units, known as a hidden layer. The outputs of the hidden layer units can be input to another hidden layer, and so on. The number of hidden layers is arbitrary, although in practice, usually only one is used. The weighted outputs of the last hidden layer are input to units making up the output layer, which emits the network's prediction for given tuples.

The units in the input layer are called input units. The units in the hidden layers and output layer are sometimes referred to as neurodes, due to their symbolic biological basis, or as output units. The multilayer neural network shown in Figure 6.15 has two layers

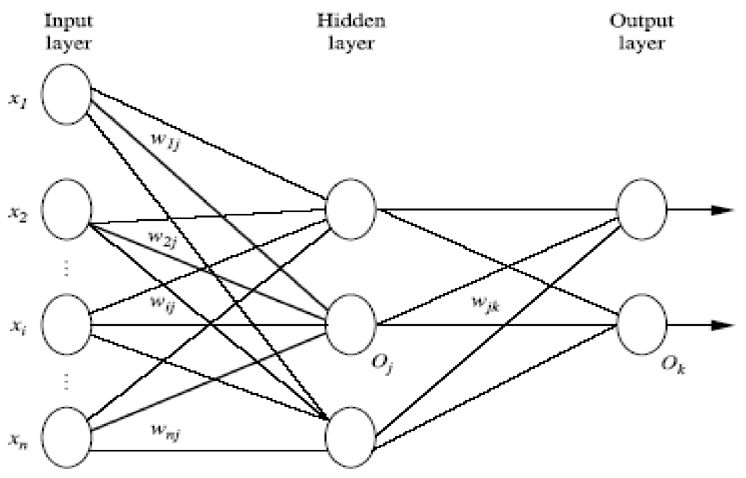


Figure 6.15 A multilayer feed-forward neural network.

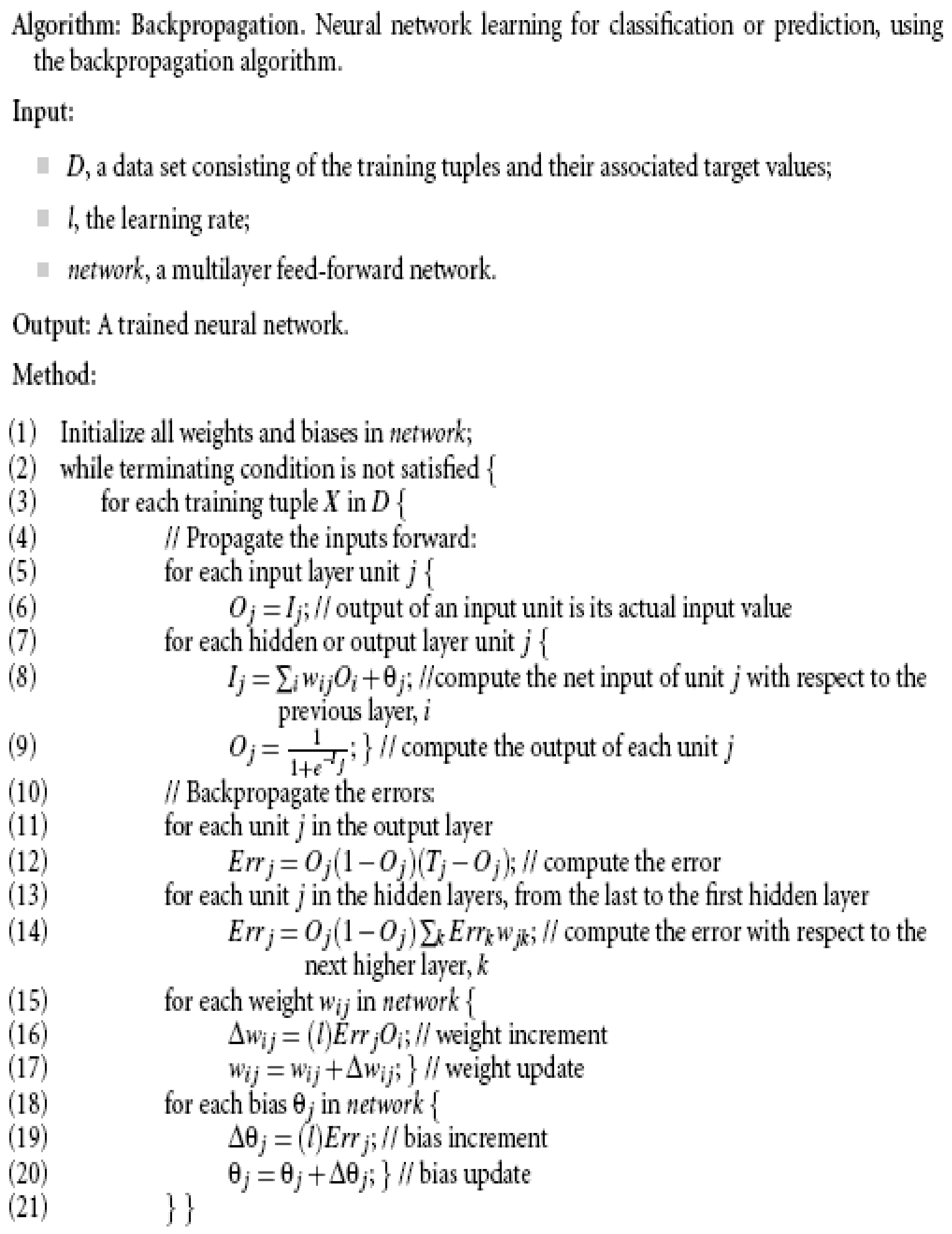
2) Defining a Network Topology

"How can I design the topology of the neural network?" Before training can begin, the user must decide on the network topology by specifying the number of units in the input layer, the number of hidden layers (if more than one), the number of units in each hidden layer, and the number of units in the output layer.

Normalizing the input values for each attribute measured in the training tuples will help speed up the learning phase. Typically, input values are normalized so as to fall between 0:0 and 1:0. Discrete-valued attributes may be encoded such that there is one input unit per domain value. For example, if an attribute *A* has three possible or known values, namely f*a*0, *a*1, *a*2g, then we may assign three input units to represent *A*. That is, we may have, say, *I*0, *I*1, *I*2 as input units. Each unit is initialized to 0. If *A*=*a0*, then I0 is set to 1. If *A* = *a*1, *I*1 is set to 1, and so on. Neural networks can be used for both classification (to predict the class label of a given tuple) or prediction (to predict a continuous-valued output). For classification, one output unit may be used to represent two classes (where the value 1 represents one class, and the value 0 represents the other). If there are more than two classes, then one output unit per class is used.

3) Backpropagation

"How does backpropagation work?" Backpropagation learns by iteratively processing a data set of training tuples, comparing the network's prediction for each tuple with the actual known *target* value. The target value may be the known class label of the training tuple (for classification problems) or a continuous value (for prediction). For each training tuple, the weights are modified so as to minimize the mean squared error between the network's prediction and the actual target value. These modifications are made in the "backwards" direction, that is, from the output layer, through each hidden layer down to the first hidden layer (hence the name *backpropagation*). Although it is not guaranteed, in general the weights will eventually converge, and the learning process stops. The algorithm is summarized in Figure 6.16. The steps involved are expressed in terms of inputs, outputs, and errors, and may seem awkward if this is your first look at neural network learning. However, once you become familiar with the process, you will see that each step is inherently simple. The steps are described below.



Algorithm: Backpropagation. Neural network learning for classification or prediction, using the backpropagation algorithm.

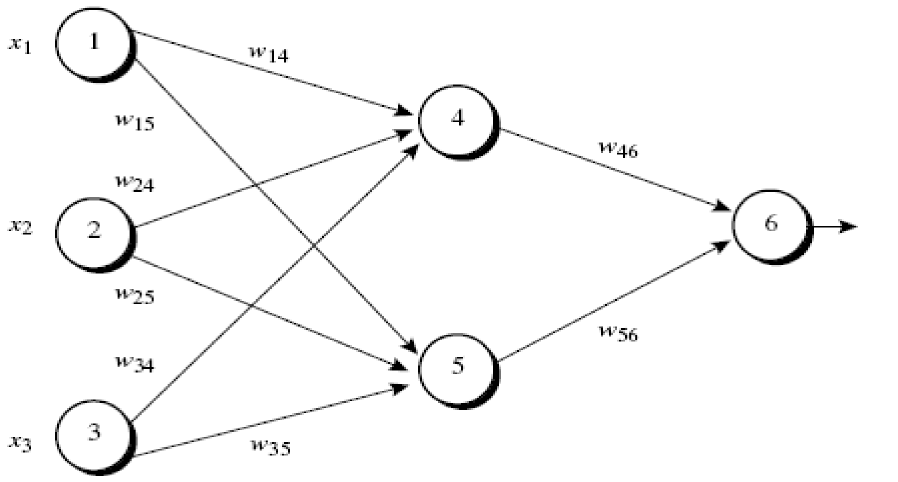
Input:

- D, a data set consisting of the training tuples and their associated target values;
- l, the learning rate;
- *network*, a multilayer feed-forward network.

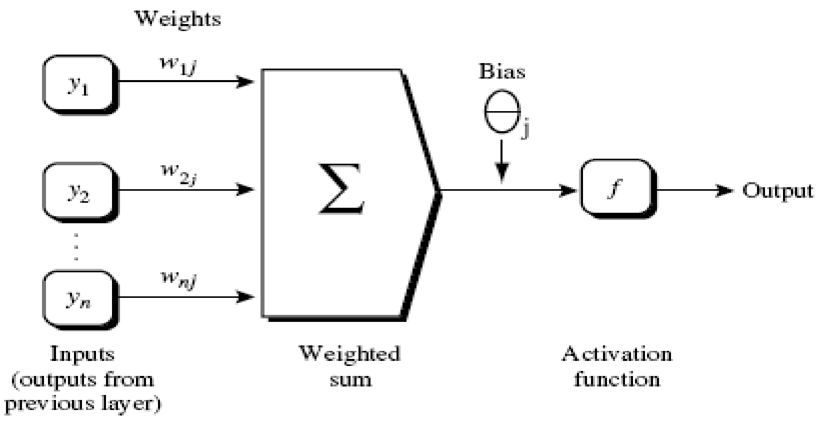
Output: A trained neural network.

Method:

```
(1)  Initialize all weights and biases in network;
(2)  while terminating condition is not satisfied {
(3)      for each training tuple X in D {
(4)          // Propagate the inputs forward:
(5)          for each input layer unit j {
(6)              $O_j = I_j$; // output of an input unit is its actual input value
(7)          for each hidden or output layer unit j {
(8)              $I_j = \sum_i w_{ij}O_i + \theta_j$; //compute the net input of unit j with respect to the
                     previous layer, i
(9)              $O_j = \frac{1}{1+e^{-I_j}}$; } // compute the output of each unit j
(10)         // Backpropagate the errors:
(11)         for each unit j in the output layer
(12)             $Err_j = O_j(1-O_j)(T_j-O_j)$; // compute the error
(13)         for each unit j in the hidden layers, from the last to the first hidden layer
(14)             $Err_j = O_j(1-O_j)\sum_k Err_k w_{jk}$; // compute the error with respect to the
                     next higher layer, k
(15)         for each weight $w_{ij}$ in network {
(16)             $\Delta w_{ij} = (l)Err_j O_i$; // weight increment
(17)             $w_{ij} = w_{ij} + \Delta w_{ij}$; } // weight update
(18)         for each bias $\theta_j$ in network {
(19)             $\Delta\theta_j = (l)Err_j$; // bias increment
(20)             $\theta_j = \theta_j + \Delta\theta_j$; } // bias update
(21)         } }
```



An example of a multilayer feed-forward neural network.



A hidden or output layer unit j: The inputs to unit j are outputs from the previous layer. These are multiplied by their corresponding weights in order to form a weighted sum, which is added to the bias associated with unit j. A nonlinear activation function is applied to the net input. (For ease of explanation, the inputs to unit j are labeled $y_1, y_2, \ldots, y_n$. If unit j were in the first hidden layer, then these inputs would correspond to the input tuple $(x_1, x_2, \ldots, x_n)$.)

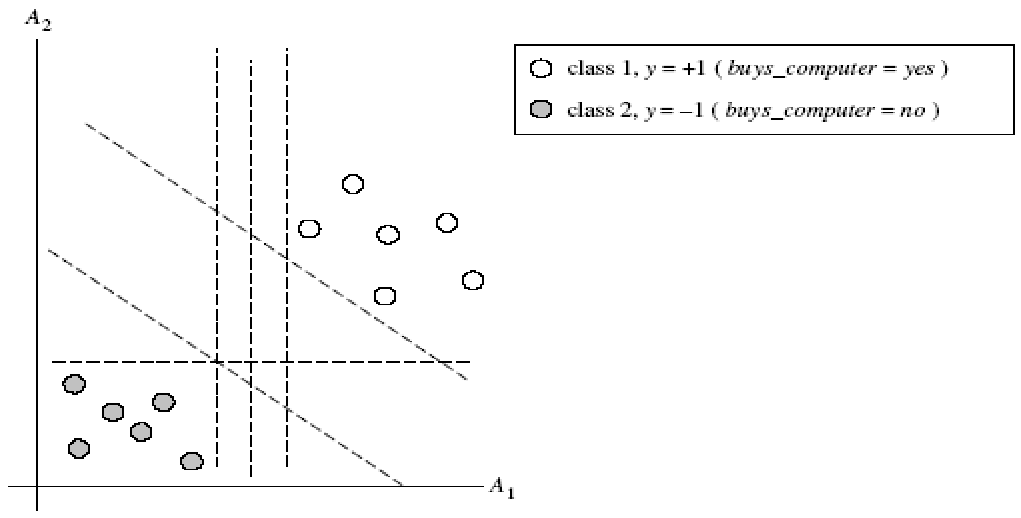
Support Vector Machines

We study Support Vector Machines, a promising new method for the classification of both linear and nonlinear data. In a nutshell, a support vector machine (or SVM) is an algorithm that works as follows. It uses a nonlinear mapping to transform the original training data into a higher dimension. Within this new dimension, it searches for the linear optimal separating hyperplane (that is, a "decision boundary" separating the tuples of one class from another). With an appropriate nonlinear mapping to a sufficiently high dimension, data from two classes can always be separated by a hyperplane. The SVM finds this hyperplane using *support vectors* ("essential" training tuples) and *margins* (defined by the support vectors).We will delve more into these new concepts further below.

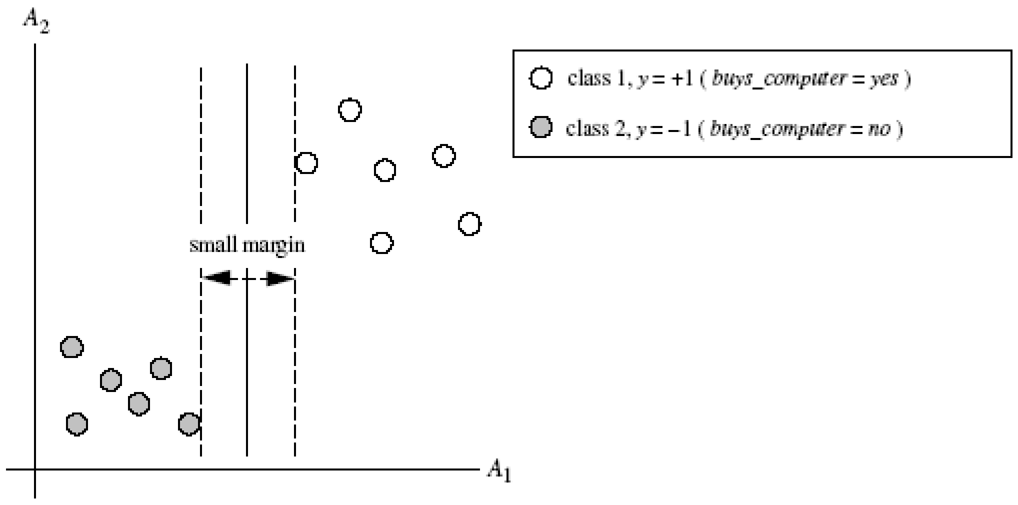
"I've heard that SVMs have attracted a great deal of attention lately. Why?" The first paper on support vector machines was presented in 1992 by Vladimir Vapnik and colleagues Bernhard Boser and Isabelle Guyon, although the groundwork for SVMs has been around since the 1960s (including early work by Vapnik and Alexei Chervonenkis on statistical learning theory). Although the training time of even the fastest SVMs can be extremely slow, they are highly accurate, owing to their ability to model complex nonlinear decision boundaries. They aremuch less prone to overfitting than othermethods. The support vectors found also provide a compact description of the learned model. SVMs can be used for prediction as well as classification. They have been applied to a number of areas, including handwritten digit recognition, object recognition, and speaker identification, as well as benchmark time-series prediction tests.

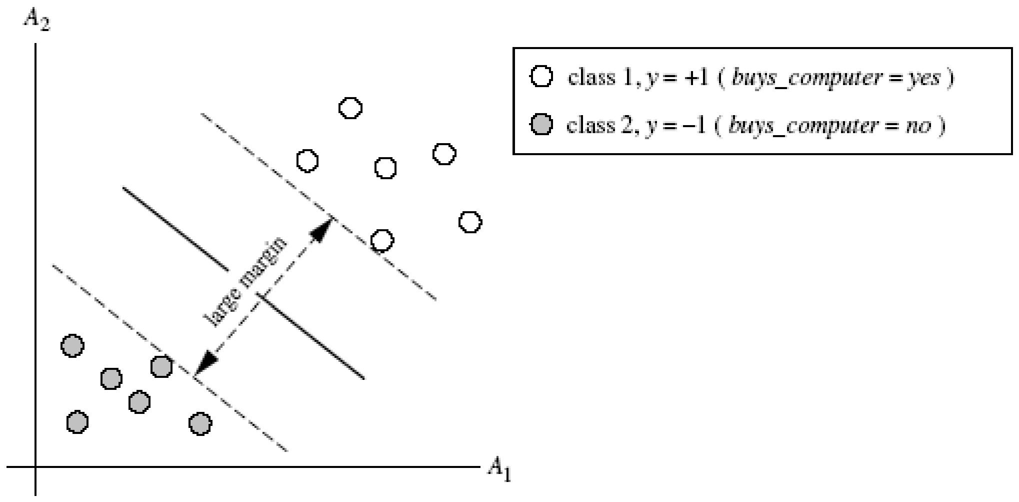
1) The Case When the Data Are Linearly Separable

An SVM approaches this problem by searching for the maximum marginal hyperplane. Consider the below Figure , which shows two possible separating hyperplanes and their associated margins. Before we get into the definition of margins, let's take an intuitive look at this figure. Both hyperplanes can correctly classify all of the given data tuples. Intuitively, however, we expect the hyperplane with the larger margin to be more accurate at classifying future data tuples than the hyperplane with the smaller margin. This is why (during the learning or training phase), the SVM searches for the hyperplane with the largest margin, that is, the *maximum marginal hyperplane* (MMH). The associated margin gives the largest separation between classes. Getting to an informal definition of margin, we can say that the shortest distance from a hyperplane to one side of its margin is equal to the shortest distance from the hyperplane to the other side of its margin, where the "sides" of the margin are parallel to the hyperplane. When dealing with the MMH, this distance is, in fact, the shortest distance from the MMH to the closest training tuple of either class.


A_2
A_1
class 1, $y = +1$ (*buys_computer = yes*)
class 2, $y = -1$ (*buys_computer = no*)

The 2-D training data are linearly separable. There are an infinite number of (possible) separating hyperplanes or "decision boundaries." Which one is best?


A_2
A_1
small margin
○ class 1, $y = +1$ (*buys_computer = yes*)
● class 2, $y = -1$ (*buys_computer = no*)


A_2
A_1
large margin
○ class 1, $y = +1$ (*buys_computer = yes*)
● class 2, $y = -1$ (*buys_computer = no*)

Here we see just two possible separating hyperplanes and their associated margins. Which one is better? The one with the larger margin should have greater generalization accuracy.

2) The Case When the Data Are Linearly Inseparable

We learned about linear SVMs for classifying linearly separable data, but what if the data are not linearly separable no straight line cajn be found that would separate the classes. The linear SVMs we studied would not be able to find a feasible solution here. Now what?

The good news is that the approach described for linear SVMs can be extended to create *nonlinear SVMs* for the classification of *linearly inseparable data* (also called *nonlinearly separable data*, or *nonlinear data*, for short). Such SVMs are capable of finding nonlinear decision boundaries (i.e., nonlinear hypersurfaces) in input space.

"So," you may ask, *"how can we extend the linear approach?"* We obtain a nonlinear SVM by extending the approach for linear SVMs as follows. There are two main steps. In the first step, we transform the original input data into a higher dimensional space using a nonlinear mapping. Several common nonlinear mappings can be used in this step, as we will describe further below. Once the data have been transformed into the new higher space, the second step searches for a linear separating hyperplane in the new space.We again end up with a quadratic optimization problem that can be solved using the linear SVM formulation. The maximal marginal hyperplane found in the new space corresponds to a nonlinear separating hypersurface in the original space.

Associative Classification: Classification by Association Rule Analysis

Frequent patterns and their corresponding association or correlation rules characterize interesting relationships between attribute conditions and class labels, and thus have been recently used for effective classification. Association rules show strong associations between attribute-value pairs (or *items*) that occur frequently in a given data set. Association rules are commonly used to analyze the purchasing patterns of customers in a store. Such analysis is useful in many decision-making processes, such as product placement, catalog design, and cross-marketing.

The discovery of association rules is based on *frequent itemset mining*. Many methods for frequent itemset mining and the generation of association rules were described in Chapter 5. In this section, we look at associative classification, where association rules are generated and analyzed for use in classification. The general idea is that we can search for strong associations between frequent patterns (conjunctions of attribute-value pairs) and class labels. Because association rules explore highly confident associations among multiple attributes, this approach may overcome some constraints introduced by decision-tree induction, which considers only one attribute at a time. In many studies, associative classification has been found to be more accurate than some traditional classification methods, such as C4.5. In particular, we study three main methods: CBA, CMAR, and CPAR.

Lazy Learners (or Learning from Your Neighbors)

The classification methods discussed so far in this chapter—decision tree induction, Bayesian classification, rule-based classification, classification by backpropagation, support vector machines, and classification based on association rule mining—are all examples of *eager learners.* Eager learners, when given a set of training tuples, will construct a generalization (i.e., classification) model before receiving new (e.g., test) tuples to classify. We can think of the learned model as being ready and eager to classify previously unseen tuples.

1) ***k*-Nearest-Neighbor Classifiers**

The *k*-nearest-neighbor method was first described in the early 1950s. The method is labor intensive when given large training sets, and did not gain popularity until the 1960s when increased computing power became available. It has since been widely used in the area of pattern recognition.

Nearest-neighbor classifiers are based on learning by analogy, that is, by comparing a given test tuple with training tuples that are similar to it. The training tuples are described by *n* attributes. Each tuple represents a point in an *n*-dimensional space. In this way, all of the training tuples are stored in an *n*-dimensional pattern space. When given an unknown tuple, a ***k***-nearest-neighbor classifier searches the pattern space for the *k* training tuples that are closest to the unknown tuple. These *k* training tuples are the *k* "nearest neighbors" of the unknown tuple.

"Closeness" is defined in terms of a distance metric, such as Euclidean distance. The Euclidean distance between two points or tuples, say, ***X***1 = (*x*11, *x*12, : : : , *x*1*n*) and ***X***2 = (*x*21, *x*22, : : : , *x*2*n*), is

$$dist(X_1, X_2) = \sqrt{\sum_{i=1}^{n} (x_{1i} - x_{2i})^2}.$$

2) **Case-Based Reasoning**

Case-based reasoning (CBR) classifiers use a database of problem solutions to solve new problems. Unlike nearest-neighbor classifiers, which store training tuples as points in Euclidean space, CBR stores the tuples or "cases" for problem solving as complex symbolic descriptions. Business applications of CBR include problem resolution for customer service help desks, where cases describe product-related diagnostic problems. CBR has also been applied to areas such as engineering and law, where cases are either technical designs or legal rulings, respectively. Medical education is another area for CBR, where patient case histories and treatments are used to help diagnose and treat new patients.

When given a new case to classify, a case-based reasoner will first check if an identical training case exists. If one is found, then the accompanying solution to that case is returned. If no identical case is found, then the case-based reasoner will search for training cases having components that are similar to those of the new case. Conceptually, these training cases may be considered as neighbors of the new case. If cases are represented as graphs, this involves searching for subgraphs that are similar to subgraphs within the new case. The case-based reasoner tries to combine the solutions of the neighboring training cases in order to propose a solution for the new case. If incompatibilities arise with the individual solutions, then backtracking to search for other solutions may be necessary. The case-based reasoner may employ background knowledge and problem-solving strategies in order to propose a feasible combined solution.

Other Classification Methods

1) **Genetic Algorithms**

Genetic algorithms attempt to incorporate ideas of natural evolution. In general, genetic learning starts as follows. An initial population is created consisting of randomly generated rules. Each rule can be represented by a string of bits. As a simple example, suppose that samples in a given training set are described by two Boolean attributes, *A*1 and *A*2, and that there are two classes,*C*1 and*C*2. The rule "*IF A*1 *AND NOT A*2 *THEN C*2" can be encoded as the bit string "100," where the two leftmost bits represent attributes *A*1 and *A*2, respectively, and the rightmost bit represents the class. Similarly, the rule "*IF NOT*

*A*1 *AND NOT A*2 *THEN C*1" can be encoded as "001." If an attribute has *k* values, where *k* > 2, then *k* bits may be used to encode the attribute's values. Classes can be encoded in a similar fashion.

Based on the notion of survival of the fittest, a new population is formed to consist of the *fittest* rules in the current population, as well as *offspring* of these rules. Typically, the fitness of a rule is assessed by its classification accuracy on a set of training samples.

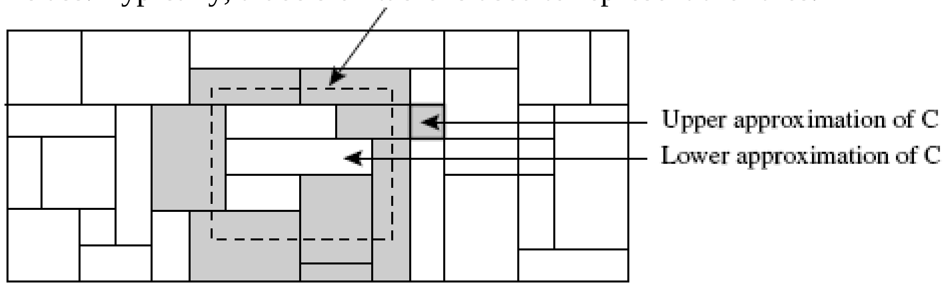
Offspring are created by applying genetic operators such as crossover and mutation. In crossover, substrings from pairs of rules are swapped to form new pairs of rules. In mutation, randomly selected bits in a rule's string are inverted. The process of generating new populations based on prior populations of rules continues until a population, *P*, evolves where each rule in *P* satisfies a prespecified fitness threshold.

Genetic algorithms are easily parallelizable and have been used for classification as well as other optimization problems. In data mining, they may be used to evaluate the fitness of other algorithms.

2) Rough Set Approach

Rough set theory can be used for classification to discover structural relationships within imprecise or noisy data. It applies to discrete-valued attributes. Continuous-valued attributes must therefore be discretized before its use.

Rough set theory is based on the establishment of equivalence classes within the given training data. All of the data tuples forming an equivalence class are indiscernible, that is, the samples are identical with respect to the attributes describing the data. Given real world data, it is common that some classes cannot be distinguished in terms of the available attributes. Rough sets can be used to approximately or "roughly" define such classes. A rough set definition for a given class, *C*, is approximated by two sets—a lower approximation of *C* and an upper approximation of *C*. The lower approximation of *C* consists of all of the data tuples that, based on the knowledge of the attributes, are certain to belong to *C* without ambiguity. The upper approximation of *C* consists of all of the tuples that, based on the knowledge of the attributes, cannot be described as not belonging to *C*. The lower and upper approximations for a class *C* are shown in Figure, where each rectangular region represents an equivalence class. Decision rules can be generated for each class. Typically, a decision table is used to represent the rules.



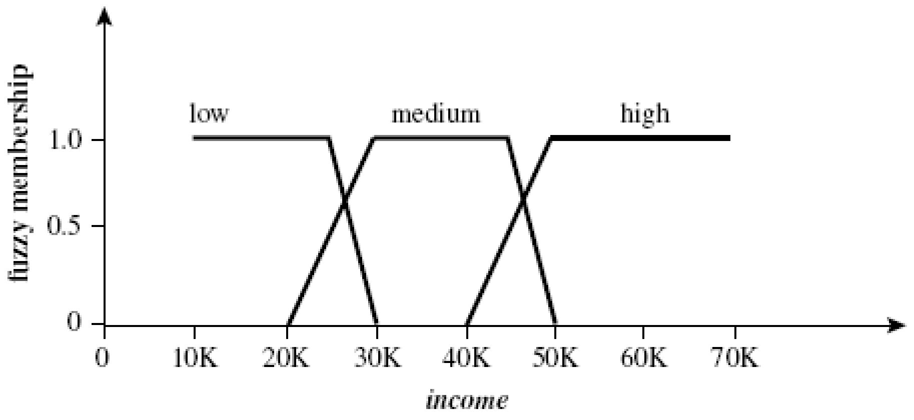
A rough set approximation of the set of tuples of the class *C* using lower and upper approximation sets of *C*. The rectangular regions represent equivalence classes.

3) Fuzzy Set Approaches

Rule-based systems for classification have the disadvantage that they involve sharp cutoffs for continuous attributes. For example, consider the following rule for customer credit application approval. The rule essentially says that applications for customers who have had a job for two or more years and who have a high income (i.e., of at least $50,000) are approved:

$$IF\ (years\_employed \geq 2)\ AND\ (income \geq 50K)\ THEN\ credit = approved.$$

By above Rule, a customer who has had a job for at least two years will receive credit if her income is, say, $50,000, but not if it is $49,000. Such harsh thresholding may seem unfair. Instead, we can discretize *income* into categories such as {*low income, medium income, high income*}, and then apply fuzzy logic to allow "fuzzy" thresholds or boundaries to be defined for each category (Figure 6.25). Rather than having a precise cutoff between
categories, fuzzy logic uses truth values between 0:0 and 1:0 to represent the degree of membership that a certain value has in a given category. Each category then represents a fuzzy set. Hence, with fuzzy logic, we can capture the notion that an income of $49,000 is, more or less, high, although not as high as an income of $50,000. Fuzzy logic systems typically provide graphical tools to assist users in converting attribute values to fuzzy truth
values.



Fuzzy truth values for *income*, representing the degree of membership of *income* values with respect to the categories {*low, medium, high*}. Each category represents a fuzzy set. Note that a given income value, *x*, can have membership in more than one fuzzy set. The membership values of *x* in each fuzzy set do not have to total to 1.

Prediction

"What if we would like to predict a continuous value, rather than a categorical label?" Numeric prediction is the task of predicting continuous (or ordered) values for given input. For example, we may wish to predict the salary of college graduates with 10 years of work experience, or the potential sales of a new product given its price. By far, the most widely used approach for numeric prediction (hereafter referred to as prediction) is regression, a statistical methodology that was developed by Sir Frances Galton

(1822–1911), a mathematician who was also a cousin of Charles Darwin. In fact, many texts use the terms "regression" and "numeric prediction" synonymously. However, as we have seen, some classification techniques (such as backpropagation, support vector machines, and *k*-nearest-neighbor classifiers) can be adapted for prediction. In this section, we discuss the use of regression techniques for prediction

.

1) Linear Regression

Straight-line regression analysis involves a response variable, y, and a single predictor variable, x. It is the simplest form of regression, and models y as a linear function of x. That is,

$$y = b + wx, \tag{6.48}$$

where the variance of y is assumed to be constant, and b and w are **regression coefficients** specifying the Y-intercept and slope of the line, respectively. The regression coefficients, w and b, can also be thought of as weights, so that we can equivalently write,

$$y = w_0 + w_1 x. \tag{6.49}$$

These coefficients can be solved for by the **method of least squares**, which estimates the best-fitting straight line as the one that minimizes the error between the actual data and the estimate of the line. Let D be a training set consisting of values of predictor variable, x, for some population and their associated values for response variable, y. The training set contains $|D|$ data points of the form $(x_1, y_1), (x_2, y_2), \ldots, (x_{|D|}, y_{|D|})$.[12] The regression coefficients can be estimated using this method with the following equations:

$$w_1 = \frac{\sum_{i=1}^{|D|}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{|D|}(x_i - \bar{x})^2} \tag{6.50}$$

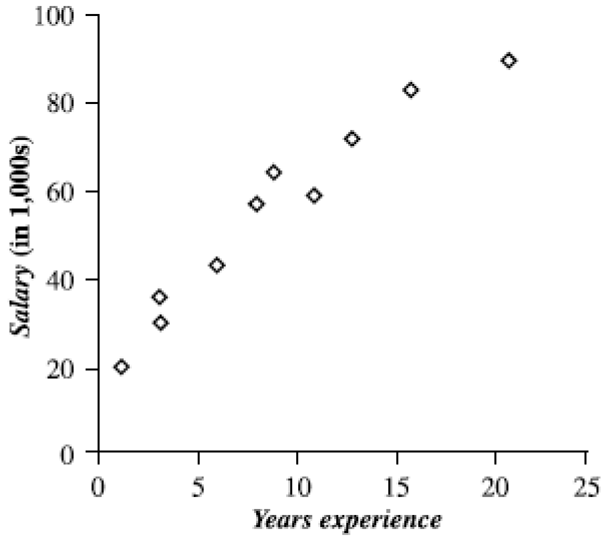
$$w_0 = \bar{y} - w_1 \bar{x} \tag{6.51}$$

where $\bar{x}$ is the mean value of $x_1, x_2, \ldots, x_{|D|}$, and $\bar{y}$ is the mean value of $y_1, y_2, \ldots, y_{|D|}$. The coefficients w_0 and w_1 often provide good approximations to otherwise complicated regression equations.

Straight-line regression using the method of least squares. Table 6.7 shows a set of paired data where x is the number of years of work experience of a college graduate and y is the

Salary data.

x years experience	*y salary (in \$1000s)*
3	30
8	57
9	64
13	72
3	36
6	43
11	59
21	90
1	20
16	83



Plot of the data in Table 6.7 for Example 6.11. Although the points do not fall on a straight line, the overall pattern suggests a linear relationship between x (*years experience*) and y (*salary*).

corresponding salary of the graduate. The 2-D data can be graphed on a *scatter plot*, as in Figure 6.26. The plot suggests a linear relationship between the two variables, x and y. We model the relationship that salary may be related to the number of years of work experience with the equation $y = w_0 + w_1 x$.

Given the above data, we compute $\bar{x} = 9.1$ and $\bar{y} = 55.4$. Substituting these values into Equations (6.50) and (6.51), we get

$$w_1 = \frac{(3-9.1)(30-55.4)+(8-9.1)(57-55.4)+\cdots+(16-9.1)(83-55.4)}{(3-9.1)^2+(8-9.1)^2+\cdots+(16-9.1)^2} = 3.5$$

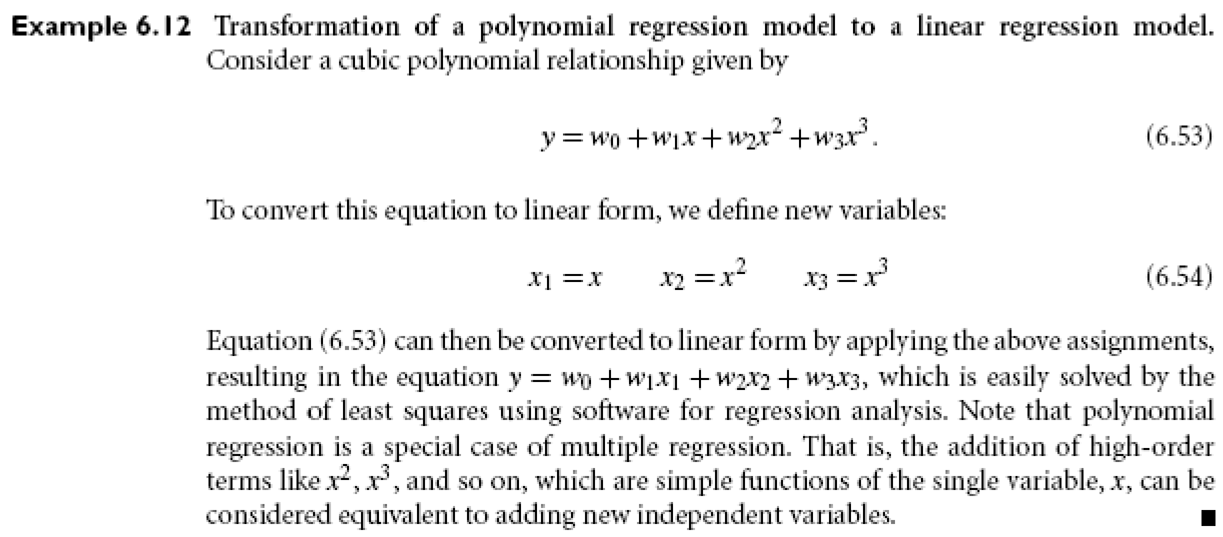
$$w_0 = 55.4-(3.5)(9.1) = 23.6$$

Thus, the equation of the least squares line is estimated by $y = 23.6 + 3.5x$. Using this equation, we can predict that the salary of a college graduate with, say, 10 years of experience is \$58,600. ■

2) Nonlinear Regression

"How can we model data that does not show a linear dependence? For example, what if a given response variable and predictor variable have a relationship that may be modeled by a polynomial function?" Think back to the straight-line linear regression case above where dependent response variable, y, is modeled as a linear function of a single independent predictor variable, x. What if we can get a more accurate model using a nonlinear model, such as a parabola or some other higher-order polynomial? Polynomial regression is often of interest when there is just one predictor variable. It can be modeled by

adding polynomial terms to the basic linear model. By applying transformations to the variables, we can convert the nonlinear model into a linear one that can then be solved by the method of least squares.



Example 6.12 **Transformation of a polynomial regression model to a linear regression model.** Consider a cubic polynomial relationship given by

$$y = w_0 + w_1 x + w_2 x^2 + w_3 x^3. \qquad (6.53)$$

To convert this equation to linear form, we define new variables:

$$x_1 = x \qquad x_2 = x^2 \qquad x_3 = x^3 \qquad (6.54)$$

Equation (6.53) can then be converted to linear form by applying the above assignments, resulting in the equation $y = w_0 + w_1x_1 + w_2x_2 + w_3x_3$, which is easily solved by the method of least squares using software for regression analysis. Note that polynomial regression is a special case of multiple regression. That is, the addition of high-order terms like x^2, x^3, and so on, which are simple functions of the single variable, x, can be considered equivalent to adding new independent variables. ■

Unit 5

Clustering and Applications and Trends in Data Mining:

What is Cluster Analysis?

- Cluster: a collection of data objects
- Similar to one another within the same cluster
- Dissimilar to the objects in other clusters
- Cluster analysis
- Grouping a set of data objects into clusters
- Clustering is unsupervised classification: no predefined classes
- Typical applications
- As a stand-alone tool to get insight into data distribution
- As a preprocessing step for other algorithms

General Applications of Clustering:

- Pattern Recognition
- Spatial Data Analysis
- create thematic maps in GIS by clustering feature spaces
- detect spatial clusters and explain them in spatial data mining
- Image Processing
- Economic Science (especially market research)
- WWW
- Document classification

- Cluster Weblog data to discover groups of similar access patterns

Examples of Clustering Applications:

- Marketing: Help marketers discover distinct groups in their customer bases, and then use this knowledge to develop targeted marketing programs
- Land use: Identification of areas of similar land use in an earth observation database
- Insurance: Identifying groups of motor insurance policy holders with a high average claim cost
- City-planning: Identifying groups of houses according to their house type, value, and geographical location
- Earth-quake studies: Observed earth quake epicenters should be clustered along continent faults

What Is Good Clustering?

- A good clustering method will produce high quality clusters with
- high intra-class similarity
- low inter-class similarity
- The quality of a clustering result depends on both the similarity measure used by the method and its implementation.
- The quality of a clustering method is also measured by its ability to discover some or all of the hidden patterns.

Requirements of Clustering in Data Mining:

- Scalability
- Ability to deal with different types of attributes
- Discovery of clusters with arbitrary shape
- Minimal requirements for domain knowledge to determine input parameters
- Able to deal with noise and outliers

- Insensitive to order of input records
- High dimensionality
- Incorporation of user-specified constraints
- Interpretability and usability

What is Cluster Analysis?

The process of grouping a set of physical or abstract objects into classes of similar objects is called clustering. A cluster is a collection of data objects that are similar to one another within the same cluster and are dissimilar to the objects in other clusters. A cluster of data objects can be treated collectively as one group and so may be considered as a form of data compression. Although classification is an effective means for distinguishing groups or classes of objects, it requires the often costly collection and labeling of a large set of training tuples or patterns, which the classifier uses to model each group. It is often more desirable to proceed in the reverse direction: First partition the set of data into groups based on data similarity (e.g., using clustering), and then assign labels to the relatively small number of groups. Additional advantages of such a clustering-based process are that it is adaptable to changes and helps single out useful features that distinguish different groups.

Clustering is a challenging field of research in which its potential applications pose their own special requirements. The following are typical requirements of clustering in data mining: **Scalability:** Many clustering algorithms work well on small data sets containing fewer than several hundred data objects; however, a large database may contain millions of objects. Clustering on a sample of a given large data set may lead to biased results. Highly scalable clustering algorithms are needed.

Ability to deal with different types of attributes: Many algorithms are designed to cluster interval-based (numerical) data. However, applications may require clustering other types of data, such as binary, categorical (nominal), and ordinal data, or mixtures of these data types.

Discovery of clusters with arbitrary shape: Many clustering algorithms determine clusters based on Euclidean or Manhattan distance measures. Algorithms based on such distance measures tend to find spherical clusters with similar size and density. However, a cluster could be of any shape. It is important to develop algorithms that can detect clusters of arbitrary shape. Minimal requirements for domain knowledge to determine input parameters: Many clustering algorithms require users to input certain parameters in cluster analysis (such as the number of desired clusters). The clustering results can be quite sensitive to input parameters. Parameters are often difficult to determine, especially for data sets containing high-dimensional objects. This not only burdens users, but it also makes the quality of clustering difficult to control.

Ability to deal with noisy data: Most real-world databases contain outliers or missing, unknown, or erroneous data. Some clustering algorithms are sensitive to such data and may lead to clusters of poor quality. Incremental clustering and insensitivity to the order of input records: Some clustering algorithms cannot incorporate newly inserted data (i.e., database updates) into existing clustering structures and, instead, must determine a new clustering from scratch. Some clustering algorithms are sensitive to the order of input data. That is, given a set of data objects, such an algorithm may return dramatically different clustering's depending on the order of presentation of the input objects. It is important to develop incremental clustering algorithms and algorithms that are insensitive to the order of input.

High dimensionality: A database or a data warehouse can contain several dimensions or attributes. Many clustering algorithms are good at handling low-dimensional data, involving only two to three dimensions. Human eyes are good at judging the quality of clustering for up to three dimensions. Finding clusters of data objects in high dimensional space is challenging, especially considering that such data can be sparse and highly skewed. Constraint-based clustering: Real-world applications may need to perform clustering under various kinds of constraints. Suppose that your job is to choose the locations for a given number of new automatic banking machines (ATMs) in a city. To decide upon this, you may cluster households while considering constraints such as the city's rivers and highway networks, and the type and number of customers per cluster. A challenging task is to find groups of data with good clustering behavior that satisfy specified constraints.

Interpretability and usability: Users expect clustering results to be interpretable, comprehensible, and usable. That is, clustering may need to be tied to specific semantic interpretations and applications. It is important to study how an application goal may influence the selection of clustering features and methods.

Type of data in clustering analysis:

Data Structures:

- **Data matrix**
  - **(two modes)**

$$\begin{bmatrix} x_{11} & \cdots & x_{1f} & \cdots & x_{1p} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i1} & \cdots & x_{if} & \cdots & x_{ip} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{n1} & \cdots & x_{nf} & \cdots & x_{np} \end{bmatrix}$$

- **Dissimilarity matrix**
  - **(one mode)**

$$\begin{bmatrix} 0 & & & & \\ d(2,1) & 0 & & & \\ d(3,1) & d(3,2) & 0 & & \\ \vdots & \vdots & \vdots & & \\ d(n,1) & d(n,2) & \cdots & \cdots & 0 \end{bmatrix}$$

Measure the Quality of Clustering:

- Dissimilarity/Similarity metric: Similarity is expressed in terms of a distance function, which is typically metric: $d(i, j)$
- There is a separate "quality" function that measures the "goodness" of a cluster.
- The definitions of distance functions are usually very different for interval-scaled, boolean, categorical, ordinal and ratio variables.
- Weights should be associated with different variables based on applications and data semantics.
- It is hard to define "similar enough" or "good enough"
  - The answer is typically highly subjective.

Type of data in clustering analysis:

- Interval-scaled variables:
- Binary variables:
- Nominal, ordinal, and ratio variables:
- Variables of mixed types:

Interval-valued variables:

- Standardize data
  - Calculate the mean absolute deviation:

$$s_f = \frac{1}{n}(|x_{1f} - m_f| + |x_{2f} - m_f| + \ldots + |x_{nf} - m_f|)$$

Where

$$m_f = \frac{1}{n}(x_{1f} + x_{2f} + \ldots + x_{nf})$$

- Calculate the standardized measurement (*z-score*)

$$z_{if} = \frac{x_{if} - m_f}{s_f}$$

- Using mean absolute deviation is more robust than using standard deviation

Similarity and Dissimilarity between Objects:

- Distances are normally used to measure the similarity or dissimilarity between two data objects
- Some popular ones include: *Minkowski distance*:

$$d(i,j) = \sqrt[q]{(|x_{i1} - x_{j1}|^q + |x_{i2} - x_{j2}|^q + \ldots + |x_{ip} - x_{jp}|^q)}$$

where $i = (x_{i1}, x_{i2}, \ldots, x_{ip})$ and $j = (x_{j1}, x_{j2}, \ldots, x_{jp})$ are two p-dimensional data objects, and q is a positive integer

- If $q = 1$, d is Manhattan distance

$$d(i,j) = |x_{i1} - x_{j1}| + |x_{i2} - x_{j2}| + \ldots + |x_{ip} - x_{jp}|$$

- *If* $q = 2$, d is Euclidean distance:

$$d(i,j) = \sqrt{(|x_{i1} - x_{j1}|^2 + |x_{i2} - x_{j2}|^2 + \ldots + |x_{ip} - x_{jp}|^2)}$$

  - Properties
    - $d(i,j) \geq 0$
    - $d(i,i) = 0$
    - $d(i,j) = d(j,i)$
    - $d(i,j) \leq d(i,k) + d(k,j)$
- Also one can use weighted distance, parametric Pearson product moment correlation, or other dissimilarity measures.

Nominal Variables:

- A generalization of the binary variable in that it can take more than 2 states, e.g., red, yellow, blue, green
- Method 1: Simple matching
  - m: # of matches, p: total # of variables

$$d(i,j) = \frac{p - m}{p}$$

- Method 2: use a large number of binary variables
  - creating a new binary variable for each of the M nominal states

Ordinal Variables:

- An ordinal variable can be discrete or continuous
- order is important, e.g., rank
- Can be treated like interval-scaled
  - replacing x_{if} by their rank $r_{if} \in \{1, \ldots, M_f\}$
  - map the range of each variable onto [0, 1] by replacing *i*-th object in the *f*-th variable by

$$z_{if} = \frac{r_{if} - 1}{M_f - 1}$$

  - compute the dissimilarity using methods for interval-scaled variables

Major Clustering Approaches:

- **Partitioning algorithms**: Construct various partitions and then evaluate them by some criterion
- **Hierarchy algorithms**: Create a hierarchical decomposition of the set of data (or objects) using some criterion
- **Density-based**: based on connectivity and density functions
- **Grid-based**: based on a multiple-level granularity structure
- **Model-based**: A model is hypothesized for each of the clusters and the idea is to find the best fit of that model to each other.

A Categorization of Major Clustering Methods:

- Partitioning approach:
  - Construct various partitions and then evaluate them by some criterion, e.g., minimizing the sum of square errors
  - Typical methods: k-means, k-medoids, CLARANS
- Hierarchical approach:
  - Create a hierarchical decomposition of the set of data (or objects) using some criterion
  - Typical methods: Diana, Agnes, BIRCH, ROCK, CHAMELEON
- Density-based approach:
  - Based on connectivity and density functions
  - Typical methods: DBSCAN, OPTICS, DenClue

- Grid-based approach:
  - based on a multiple-level granularity structure
  - Typical methods: STING, WaveCluster, CLIQUE
- Model-based:
  - A model is hypothesized for each of the clusters and tries to find the best fit of that model to each other
  - Typical methods: EM, SOM, COBWEB
- Frequent pattern-based:
  - Based on the analysis of frequent patterns
  - Typical methods: pCluster
- User-guided or constraint-based:
  - Clustering by considering user-specified or application-specific constraints
  - Typical methods: COD (obstacles), constrained clustering

Typical Alternatives to Calculate the Distance between Clusters:

- Single link: smallest distance between an element in one cluster and an element in the other, i.e., $dis(K_i, K_j) = min(t_{ip}, t_{jq})$
- Complete link: largest distance between an element in one cluster and an element in the other, i.e., $dis(K_i, K_j) = max(t_{ip}, t_{jq})$
- Average: avg distance between an element in one cluster and an element in the other, i.e., $dis(K_i, K_j) = avg(t_{ip}, t_{jq})$
- Centroid: distance between the centroids of two clusters, i.e., $dis(K_i, K_j) = dis(C_i, C_j)$
- Medoid: distance between the medoids of two clusters, i.e., $dis(K_i, K_j) = dis(M_i, M_j)$
  - Medoid: one chosen, centrally located object in the cluster

Centroid, Radius and Diameter of a Cluster (for numerical data sets):

- Centroid: the "middle" of a cluster

$$C_m = \frac{\Sigma_{i=1}^{N}(t_{ip})}{N}$$

- Radius: square root of average distance from any point of the cluster to its centroid

$$R_m = \sqrt{\frac{\Sigma_{i=1}^{N}(t_{ip} - c_m)^2}{N}}$$

- Diameter: square root of average mean squared distance between all pairs of points in the cluster

$$D_m = \sqrt{\frac{\Sigma_{i=1}^{N}\Sigma_{i=1}^{N}(t_{ip} - t_{iq})^2}{N(N-1)}}$$

Partitioning Methods:

- Partitioning method: Construct a partition of a database *D* of *n* objects into a set of *k* clusters, s.t., some objective is minimized. E.g., min sum of squared distance in k-means

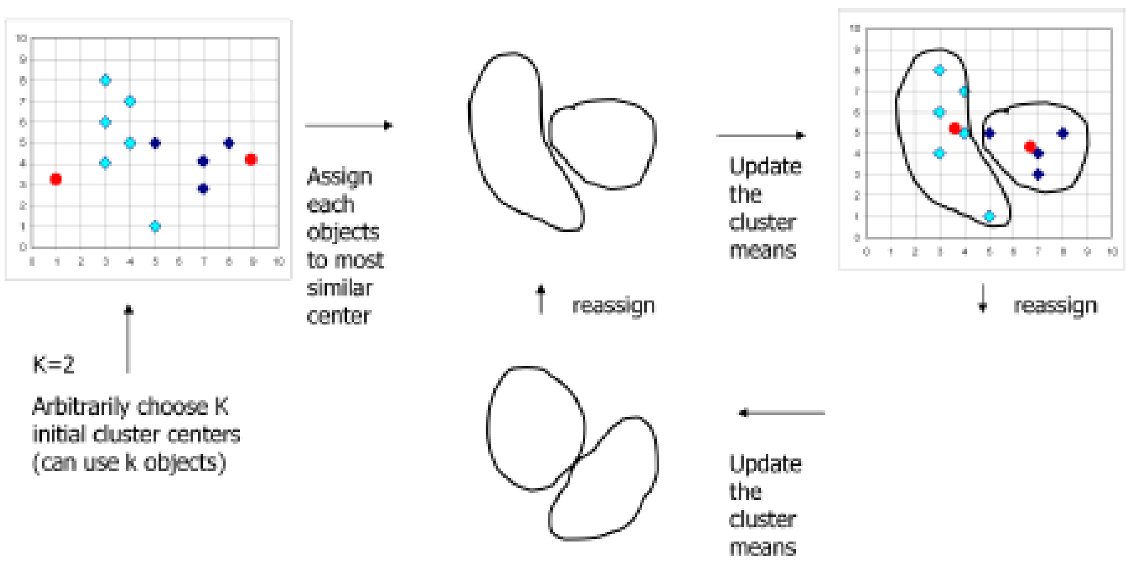
$$\Sigma_{m=1}^{k}\Sigma_{t_{mi}\in Km}(C_m - t_{mi})^2$$

- **Given a *k*, find a partition of *k clusters* that optimizes the chosen partitioning criterion**
  - Global optimal: exhaustively enumerate all partitions
  - Heuristic methods: *k-means* and *k-medoids* algorithms
  - *k-means* (MacQueen'67): Each cluster is represented by the center of the cluster
  - *k-medoids* or PAM (Partition around medoids) (Kaufman & Rousseeuw'87): Each cluster is represented by one of the objects in the cluster

The *K-Means* Clustering Method:

- Given *k*, the *k-means* algorithm is implemented in four steps:
  - Partition objects into *k* nonempty subsets
  - Compute seed points as the centroids of the clusters of the current partition (the centroid is the center, i.e., *mean point*, of the cluster)
  - Assign each object to the cluster with the nearest seed point
  - Go back to Step 2, stop when no more new assignment

The *K-Means* Clustering Method:



Comments on the *K-Means* Method:

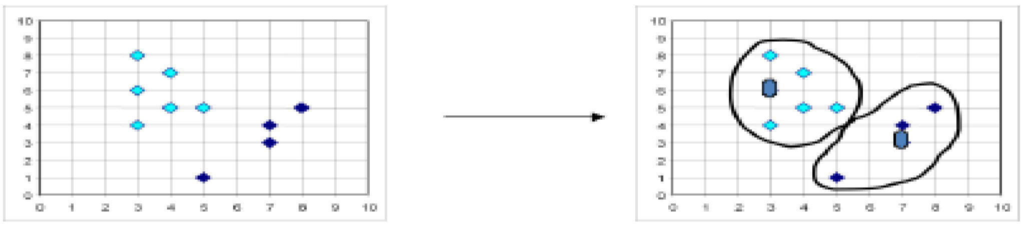
- Strength: *Relatively efficient*: *O*(*tkn*), where *n* is # objects, *k* is # clusters, and *t* is # iterations. Normally, *k*, *t* << *n*.
  - **Comparing: PAM: O(k(n-k)^2), CLARA: O(ks^2 + k(n-k))**
- **Comment:** Often terminates at a *local optimum*. The *global optimum* may be found using techniques such as: *deterministic annealing* and *genetic algorithms*
- Weakness
  - Applicable only when *mean* is defined, then what about categorical data?
  - Need to specify *k,* the *number* of clusters, in advance
  - Unable to handle noisy data and *outliers*
  - Not suitable to discover clusters with *non-convex shapes*

Variations of the *K-Means* Method:

- A few variants of the *k-means* which differ in
  - Selection of the initial *k* means
  - Dissimilarity calculations
  - Strategies to calculate cluster means
- Handling categorical data: *k-modes* (Huang'98)
  - Replacing means of clusters with modes
  - Using new dissimilarity measures to deal with categorical objects
  - Using a frequency-based method to update modes of clusters
  - A mixture of categorical and numerical data: *k-prototype* method

What Is the Problem of the K-Means Method?:

- The k-means algorithm is sensitive to outliers !
  - Since an object with an extremely large value may substantially distort the distribution of the data.
- K-Medoids: Instead of taking the mean value of the object in a cluster as a reference point, medoids can be used, which is the most centrally located object in a cluster.



Prepared by: N.Gopinath

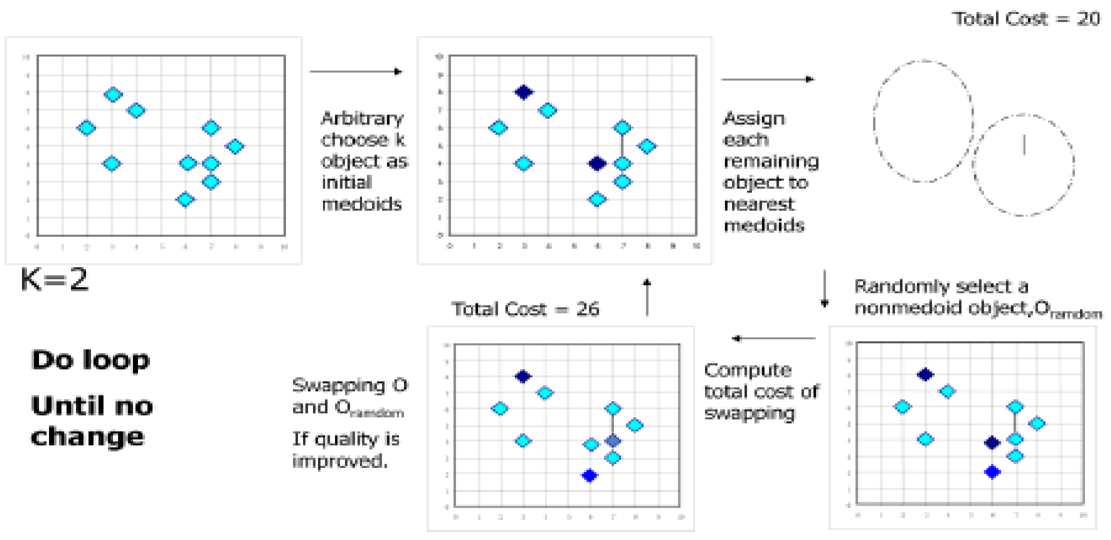
Verified by : HOD

Approved by:PRINCIPAL

The *K-Medoids* Clustering Method:

- Find *representative* objects, called medoids, in clusters
- *PAM* (Partitioning Around Medoids, 1987)
    - starts from an initial set of medoids and iteratively replaces one of the medoids by one of the non-medoids if it improves the total distance of the resulting clustering
    - *PAM* works effectively for small data sets, but does not scale well for large data sets
- *CLARA* (Kaufmann & Rousseeuw, 1990)
- *CLARANS* (Ng & Han, 1994): Randomized sampling
- Focusing + spatial data structure (Ester et al., 1995)

A Typical K-Medoids Algorithm (PAM):


Total Cost = 20
Arbitrary choose k object as initial medoids
Assign each remaining object to nearest medoids
K=2
Randomly select a nonmedoid object,O_random
Total Cost = 26
Do loop
Until no change
Swapping O and O_random
If quality is improved.
Compute total cost of swapping

What Is the Problem with PAM?

- PAM is more robust than k-means in the presence of noise and outliers because a medoid is less influenced by outliers or other extreme values than a mean
- Pam works efficiently for small data sets but does not scale well for large data sets.
    - O(k(n-k)^2) for each iteration

      where n is # of data, k is # of clusters

➔ Sampling based method,

CLARA(Clustering LARge Applications)

***CLARA* (Clustering Large Applications) (1990):**

- *CLARA* (Kaufmann and Rousseeuw in 1990)
    - Built in statistical analysis packages, such as S+
- It draws *multiple samples* of the data set, applies *PAM* on each sample, and gives the best clustering as the output
- Strength: deals with larger data sets than *PAM*
- Weakness:

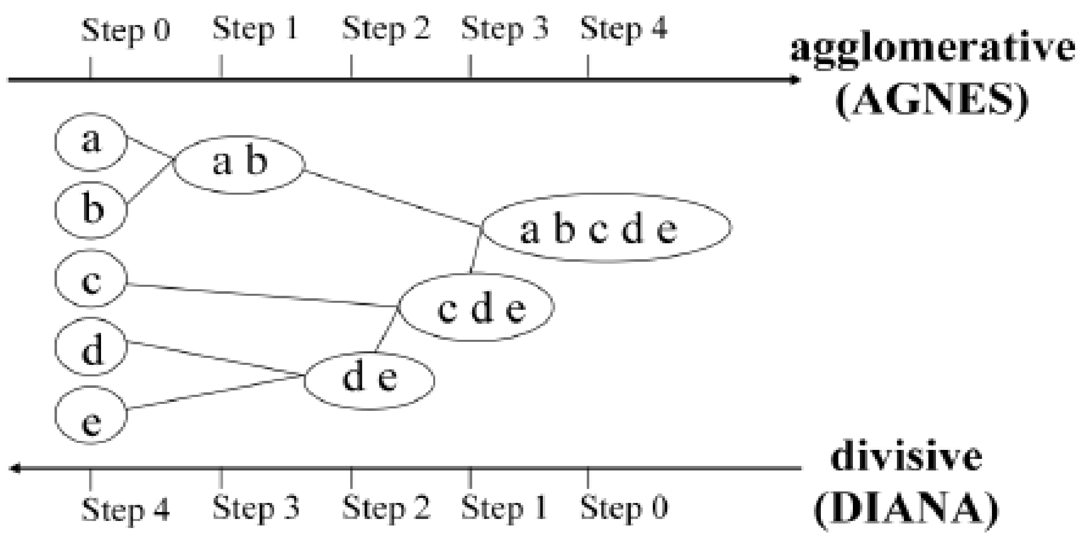
- Efficiency depends on the sample size
- A good clustering based on samples will not necessarily represent a good clustering of the whole data set if the sample is biased

CLARANS* ("Randomized" CLARA) *(1994):

- *CLARANS* (A Clustering Algorithm based on Randomized Search) (Ng and Han'94)
- CLARANS draws sample of neighbors dynamically
- The clustering process can be presented as searching a graph where every node is a potential solution, that is, a set of *k* medoids
- If the local optimum is found, *CLARANS* starts with new randomly selected node in search for a new local optimum
- It is more efficient and scalable than both *PAM* and *CLARA*
- Focusing techniques and spatial access structures may further improve its performance (Ester et al.'95)

Hierarchical Clustering:

- Use distance matrix. This method does not require the number of clusters *k* as an input, but needs a termination condition



AGNES (Agglomerative Nesting):

- Introduced in Kaufmann and Rousseeuw (1990)
- Implemented in statistical analysis packages, e.g., Splus

- Use the Single-Link method and the dissimilarity matrix.
- Merge nodes that have the least dissimilarity
- Go on in a non-descending fashion
- Eventually all nodes belong to the same cluster

***Dendrogram:* Shows How the Clusters are Merged :**

Decompose data objects into a several levels of nested partitioning (tree of clusters), called a *dendrogram*.

A clustering of the data objects is obtained by cutting the dendrogram at the desired level, then each connected component forms a cluster.

DIANA (Divisive Analysis):

- Introduced in Kaufmann and Rousseeuw (1990)
- Implemented in statistical analysis packages, e.g., Splus
- Inverse order of AGNES
- Eventually each node forms a cluster on its own

Recent Hierarchical Clustering Methods:

- Major weakness of agglomerative clustering methods
  - do not scale well: time complexity of at least $O(n^2)$, where n is the number of total objects
  - can never undo what was done previously
- Integration of hierarchical with distance-based clustering
  - BIRCH (1996): uses CF-tree and incrementally adjusts the quality of sub-clusters
  - ROCK (1999): clustering categorical data by neighbor and link analysis
  - CHAMELEON (1999): hierarchical clustering using dynamic modeling

BIRCH (1996):

- Birch: Balanced Iterative Reducing and Clustering using Hierarchies (Zhang, Ramakrishnan & Livny, SIGMOD'96)
- Incrementally construct a CF (Clustering Feature) tree, a hierarchical data structure for multiphase clustering
  - Phase 1: scan DB to build an initial in-memory CF tree (a multi-level compression of the data that tries to preserve the inherent clustering structure of the data)
  - Phase 2: use an arbitrary clustering algorithm to cluster the leaf nodes of the CF-tree

- *Scales linearly*: finds a good clustering with a single scan and improves the quality with a few additional scans
- *Weakness:* handles only numeric data, and sensitive to the order of the data record.

Clustering Feature Vector in BIRCH :

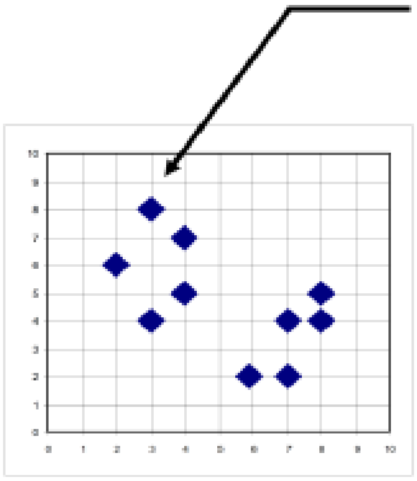
Clustering Feature: *CF = (N, LS, SS)*

N: **Number of data points**

LS (linear sum): $\Sigma^{N}_{i=1} X_i$

SS (square sum): $\Sigma^{N}_{i=1} X_i^2$

CF = (5, (16,30),(54,190))



(3,4)
(2,6)
(4,5)
(4,7)
(3,8)

CF-Tree in BIRCH:

- Clustering feature:
    - summary of the statistics for a given subcluster: the 0-th, 1st and 2nd moments of the subcluster from the statistical point of view.
    - registers crucial measurements for computing cluster and utilizes storage efficiently
- A CF tree is a height-balanced tree that stores the clustering features for a hierarchical clustering
    - A nonleaf node in a tree has descendants or "children"
    - The nonleaf nodes store sums of the CFs of their children
- A CF tree has two parameters
    - Branching factor: specify the maximum number of children.
    - threshold: max diameter of sub-clusters stored at the leaf nodes

- If memory not enough, rebuild the tree from leaf node by adjusting threshold

<u>Clustering Categorical Data: The ROCK Algorithm:</u>

- ROCK: RObust Clustering using linKs
    - S. Guha, R. Rastogi & K. Shim, ICDE'99
- Major ideas
    - Use links to measure similarity/proximity
    - Not distance-based
    - Computational complexity:
- Algorithm: sampling-based clustering
    - Draw random sample
    - Cluster with links
    - Label data in disk
- Experiments
    - Congressional voting, mushroom data

<u>Similarity Measure in ROCK:</u>

- **Traditional measures for categorical data may not work well, e.g., Jaccard coefficient**
- **Example: Two groups (clusters) of transactions**
    - **C_1. <a, b, c, d, e>: {a, b, c}, {a, b, d}, {a, b, e}, {a, c, d}, {a, c, e}, {a, d, e}, {b, c, d}, {b, c, e}, {b, d, e}, {c, d, e}**
    - **C_2. <a, b, f, g>: {a, b, f}, {a, b, g}, {a, f, g}, {b, f, g}**
- **Jaccard co-efficient may lead to wrong clustering result**
    - **C_1: 0.2 ({a, b, c}, {b, d, e}} to 0.5 ({a, b, c}, {a, b, d})**
    - **C_1 & C_2: could be as high as 0.5 ({a, b, c}, {a, b, f})**

$$Sim(T_1, T_2) = \frac{|T_1 \cap T_2|}{|T_1 \cup T_2|}$$

- **Jaccard co-efficient-based similarity function:**
    - **Ex. Let T_1 = {a, b, c}, T_2 = {c, d, e}**

$$Sim(T_1, T_2) = \frac{|\{c\}|}{|\{a,b,c,d,e\}|} = \frac{1}{5} = 0.2$$

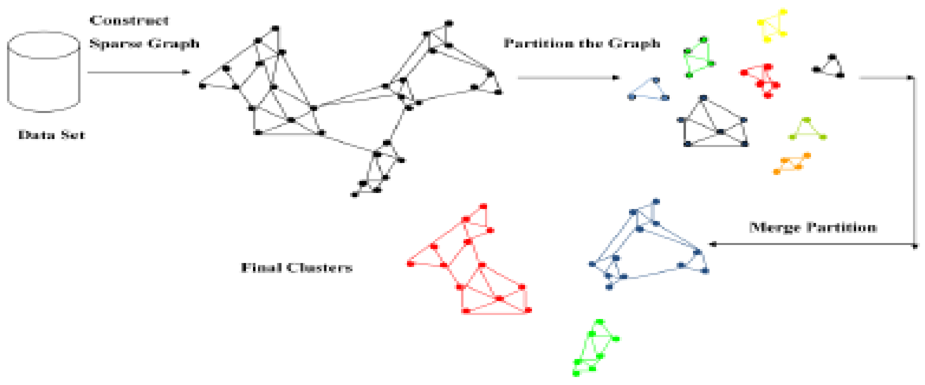
Link Measure in ROCK:

- Links: # of common neighbors
  - C_1 <a, b, c, d, e>: {a, b, c}, {a, b, d}, {a, b, e}, {a, c, d}, {a, c, e}, {a, d, e}, {b, c, d}, {b, c, e}, {b, d, e}, {c, d, e}
  - C_2 <a, b, f, g>: {a, b, f}, {a, b, g}, {a, f, g}, {b, f, g}
- Let T_1 = {a, b, c}, T_2 = {c, d, e}, T_3 = {a, b, f}
  - link(T_1, T_2) = 4, *since they have 4 common neighbors*
    - {a, c, d}, {a, c, e}, {b, c, d}, {b, c, e}
  - link(T_1, T_3) = 3, *since they have 3 common neighbors*
    - {a, b, d}, {a, b, e}, {a, b, g}
- Thus link is a better measure than Jaccard coefficient

CHAMELEON: Hierarchical Clustering Using Dynamic Modeling (1999):

- **CHAMELEON: by G. Karypis, E.H. Han, and V. Kumar'99**
- Measures the similarity based on a dynamic model
  - Two clusters are merged only if the *interconnectivity* and *closeness (proximity)* between two clusters are high *relative to* the internal interconnectivity of the clusters and closeness of items within the clusters
  - Cure ignores information about interconnectivity of the objects, Rock ignores information about the closeness of two clusters
- A two-phase algorithm
  - Use a graph partitioning algorithm: cluster objects into a large number of relatively small sub-clusters
  - Use an agglomerative hierarchical clustering algorithm: find the genuine clusters by repeatedly combining these sub-clusters

Overall Framework of CHAMELEON:



Density-Based Clustering Methods:

- Clustering based on density (local cluster criterion), such as density-connected points
- Major features:
  - Discover clusters of arbitrary shape
  - Handle noise
  - One scan
  - Need density parameters as termination condition
- Several interesting studies:
  - DBSCAN: Ester, et al. (KDD'96)
  - OPTICS: Ankerst, et al (SIGMOD'99).
  - DENCLUE: Hinneburg & D. Keim (KDD'98)
  - CLIQUE: Agrawal, et al. (SIGMOD'98) (more grid-based)

DBSCAN: The Algorithm:

- Arbitrary select a point *p*
- Retrieve all points density-reachable from *p* w.r.t. *Eps* and *MinPts*.
- If *p* is a core point, a cluster is formed.
- If *p* is a border point, no points are density-reachable from *p* and DBSCAN visits the next point of the database.
- Continue the process until all of the points have been processed.

Grid-Based Clustering Method:

- Using multi-resolution grid data structure
- Several interesting methods
  - STING (a STatistical INformation Grid approach) by Wang, Yang and Muntz (1997)
  - WaveCluster by Sheikholeslami, Chatterjee, and Zhang (VLDB'98)
    - A multi-resolution clustering approach using wavelet method
  - CLIQUE: Agrawal, et al. (SIGMOD'98)
    - On high-dimensional data (thus put in the section of clustering high-dimensional data

STING: A Statistical Information Grid Approach:

- Wang, Yang and Muntz (VLDB'97)
- The spatial area area is divided into rectangular cells
- There are several levels of cells corresponding to different levels of resolution

The STING Clustering Method:

- Each cell at a high level is partitioned into a number of smaller cells in the next lower level
- Statistical info of each cell is calculated and stored beforehand and is used to answer queries
- Parameters of higher level cells can be easily calculated from parameters of lower level cell
  - *count, mean, s, min, max*
  - type of distribution—normal, *uniform*, etc.
- Use a top-down approach to answer spatial data queries
  - Start from a pre-selected layer—typically with a small number of cells
  - For each cell in the current level compute the confidence interval

Comments on STING:

- Remove the irrelevant cells from further consideration
- When finish examining the current layer, proceed to the next lower level
- Repeat this process until the bottom layer is reached
- Advantages:
  - Query-independent, easy to parallelize, incremental update
  - *O(K),* where *K* is the number of grid cells at the lowest level
- Disadvantages:
  - All the cluster boundaries are either horizontal or vertical, and no diagonal boundary is detected

Model-Based Clustering?:

- What is model-based clustering?
  - Attempt to optimize the fit between the given data and some mathematical model
  - Based on the assumption: Data are generated by a mixture of underlying probability distribution

- Typical methods
  - Statistical approach
    - EM (Expectation maximization), AutoClass
  - Machine learning approach
    - COBWEB, CLASSIT
  - Neural network approach
    - SOM (Self-Organizing Feature Map)

<u>Conceptual Clustering:</u>

- <u>Conceptual clustering</u>
  - A form of clustering in machine learning
  - Produces a classification scheme for a set of unlabeled objects
  - Finds characteristic description for each concept (class)
- COBWEB (Fisher'87)
  - A popular a simple method of incremental conceptual learning
  - Creates a hierarchical clustering in the form of a classification tree
  - Each node refers to a concept and contains a probabilistic description of that concept

<u>Neural Network Approach:</u>

- Neural network approaches
  - Represent each cluster as an exemplar, acting as a "prototype" of the cluster
  - New objects are distributed to the cluster whose exemplar is the most similar according to some distance measure
- Typical methods
  - SOM (Soft-Organizing feature Map)
  - Competitive learning
    - Involves a hierarchical architecture of several units (neurons)
    - Neurons compete in a "winner-takes-all" fashion for the object currently being presented

CLIQUE: The Major Steps:

- Partition the data space and find the number of points that lie inside each cell of the partition.
- Identify the subspaces that contain clusters using the Apriori principle
- Identify clusters
  - Determine dense units in all subspaces of interests
  - Determine connected dense units in all subspaces of interests.
- Generate minimal description for the clusters
  - Determine maximal regions that cover a cluster of connected dense units for each cluster
  - Determination of minimal cover for each cluster

Frequent Pattern-Based Approach:

- Clustering high-dimensional space (e.g., clustering text documents, microarray data)
  - Projected subspace-clustering: which dimensions to be projected on?
    - CLIQUE, ProClus
  - Feature extraction: costly and may not be effective?
  - Using frequent patterns as "features"
    - "Frequent" are inherent features
    - Mining freq. patterns may not be so expensive
- Typical methods
  - Frequent-term-based document clustering
  - Clustering by pattern similarity in micro-array data (pClustering)

Why Constraint-Based Cluster Analysis?:

- Need user feedback: Users know their applications the best
- Less parameters but more user-desired constraints, e.g., an ATM allocation problem: obstacle & desired clusters

A Classification of Constraints in Cluster Analysis:

- Clustering in applications: desirable to have user-guided (i.e., constrained) cluster analysis
- Different constraints in cluster analysis:
  - Constraints on individual objects (do selection first)
    - Cluster on houses worth over $300K
  - Constraints on distance or similarity functions
    - Weighted functions, obstacles (e.g., rivers, lakes)
  - Constraints on the selection of clustering parameters
    - # of clusters, MinPts, etc.
  - User-specified constraints
    - Contain at least 500 valued customers and 5000 ordinary ones
  - Semi-supervised: giving small training sets as "constraints" or hints

Clustering with User-Specified Constraints:

- Example: Locating k delivery centers, each serving at least m valued customers and n ordinary ones
- Proposed approach
  - Find an initial "solution" by partitioning the data set into k groups and satisfying user-constraints
  - Iteratively refine the solution by micro-clustering relocation (e.g., moving δ μ-clusters from cluster C_i to C_j) and "deadlock" handling (break the microclusters when necessary)
  - Efficiency is improved by micro-clustering
- How to handle more complicated constraints?
  - E.g., having approximately same number of valued customers in each cluster?! — Can you solve it?

What Is Outlier Discovery?:

- **What are outliers?**
  - The set of objects are considerably dissimilar from the remainder of the data
  - Example: Sports: Michael Jordon, Wayne Gretzky, ...
- **Problem: Define and find outliers in large data sets**
- **Applications:**
  - Credit card fraud detection
  - Telecom fraud detection
  - Customer segmentation
  - Medical analysis

Outlier Discovery: Statistical Approaches

- Assume a model underlying distribution that generates data set (e.g. normal distribution)
- Use discordancy tests depending on
  - data distribution
  - distribution parameter (e.g., mean, variance)
  - number of expected outliers
- Drawbacks
  - most tests are for single attribute
  - In many cases, data distribution may not be known

Outlier Discovery: Distance-Based Approach:

- Introduced to counter the main limitations imposed by statistical methods
  - We need multi-dimensional analysis without knowing data distribution
- Distance-based outlier: A DB(p, D)-outlier is an object O in a dataset T such that at least a fraction p of the objects in T lies at a distance greater than D from O
- Algorithms for mining distance-based outliers
  - Index-based algorithm
  - Nested-loop algorithm
  - Cell-based algorithm

Density-Based Local Outlier Detection:

- Distance-based outlier detection is based on global distance distribution
- It encounters difficulties to identify outliers if data is not uniformly distributed
- Ex. C_1 contains 400 loosely distributed points, C_2 has 100 tightly condensed points, 2 outlier points o_1, o_2
- Distance-based method cannot identify o_2 as an outlier
- Need the concept of local outlier

Outlier Discovery: Deviation-Based Approach:

- Identifies outliers by examining the main characteristics of objects in a group
- Objects that "deviate" from this description are considered outliers
- Sequential exception technique
  - simulates the way in which humans can distinguish unusual objects from among a series of supposedly like objects
- OLAP data cube technique
  - uses data cubes to identify regions of anomalies in large multidimensional data

Summary:

- Cluster analysis groups objects based on their similarity and has wide applications
- Measure of similarity can be computed for various types of data
- Clustering algorithms can be categorized into partitioning methods, hierarchical methods, density-based methods, grid-based methods, and model-based methods
- Outlier detection and analysis are very useful for fraud detection, etc. and can be performed by statistical, distance-based or deviation-based approaches
- There are still lots of research issues on cluster analysis

Problems and Challenges:

- **Considerable progress has been made in scalable clustering methods**
  - Partitioning: k-means, k-medoids, CLARANS
  - Hierarchical: BIRCH, ROCK, CHAMELEON
  - Density-based: DBSCAN, OPTICS, DenClue
  - Grid-based: STING, WaveCluster, CLIQUE
  - Model-based: EM, Cobweb, SOM
  - Frequent pattern-based: pCluster
  - Constraint-based: COD, constrained-clustering
- Current clustering techniques do not address all the requirements adequately, still an active area of research