HES-SO - University of Applied Sciences of western Switzerland - MSE

Data management / Data mining

Resume of the MSE lecture

by

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Largeley inspired from

"Data management - MSE lecture 2010 - Laura Elena Raileanu / HES-SO"

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Resume of the Data management lecture

Abstract:

TODO

Keywords: Data management, Data mining, Market Basket Analysis

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CHAPTER 1

Data Warehouse and OLAP

Contents

1.1 Motivation

The traditional database approach to heterogeneous database integration is to build wrappers and integrators (or mediators), on top of multiple, heterogeneous databases. When a query is posed to a client site, a metadata dictionary is used to translate the query into queries appropriate for the individual heterogeneous sites involved. These queries are then mapped and sent to local query processors. The results returned from the different sites are integrated into a global answer set. This query-driven approach requires complex information filtering and integration processes, and competes for resources with processing at local sources. It is inefficient and potentially expensive for frequent queries, especially for queries requiring aggregations.

Data warehousing provides an interesting alternative to the traditional approach of heterogeneous database integration described above. Rather than using a query-driven approach, data warehousing employs an update-driven approach in which information from multiple, heterogeneous sources is integrated in advance and stored in a warehouse for direct querying and analysis. Unlike on-line transaction processing databases, data warehouses do not contain the most current information. However, a data warehouse brings high performance to the integrated heterogeneous database system because data are copied, preprocessed, integrated, annotated, summarized, and restructured into one semantic data store.
Furthermore, query processing in data warehouses does not interfere with the processing at local sources. Moreover, data warehouses can store and integrate historical information and support complex multidimensional queries. As a result, data warehousing has become popular in industry.

For decision-making queries and frequently-asked queries, the update-driven approach is more preferable. This is because expensive data integration and aggregate computation are done before query processing time. For the data collected in multiple heterogeneous databases to be used in decision-making processes, any semantic heterogeneity problem among multiple databases must be analyzed and solved so that the data can be integrated and summarized. If the query-driven approach is employed, these queries will be translated into multiple (often complex) queries for each individual database. The translated queries will compete for resources with the activities at the local sites, thus degrading their performance. In addition, these queries will generate a complex answer set, which will require further filtering and integration. Thus, the query-driven approach is, in general, inefficient and expensive. The update-driven approach employed in data warehousing is faster and more efficient since most of the queries needed could be done on-line.

Note

For queries that either are used rarely, reference the most current data, and/or do not require aggregations, the query-driven approach is preferable over the update-driven approach. In this case, it may not be justifiable for an organization to pay the heavy expenses of building and maintaining a data warehouse if only a small number and/or relatively small-sized databases are used. This is also the case if the queries rely on the current data because data warehouses do not contain the most current information.

Data Warehouses (DW) generalize and consolidate data in multidimensional space

The construction of DW is an important preprocessing step for data mining involving :

- data cleaning;
- data integration;
- data reduction;
- data transformation.

As opposed in usual databse design, data mining requires at all cost a very effective performance. This often involves duplicating the data on multidimensional spaces in order to avoid joins.

1.1.1 OLAP

DW provides **O**n-**L**ine **A**nalytical **P**rocessing (OLAP) tools for the interactive analysis of multidimensional data of varied granularities.
$\rightarrow$ OLAP facilitates effective data generalization and data mining

Data mining functions can be integrated with OLAP operations. Data mining **functions** are:

- association
- classification
- prediction
- clustering
- market basket analysis

$\rightarrow$ to enhance interactive mining of knowledge at multiple levels of abstraction

1.1.2 DW

The *Data Warhouse* is a platform for :

- data analysis;
- online analytical processing (OLAP);
- and data mining

Data warehousing and OLAP form an essential step in the **Knowledge Discovery Process (KDD)**.

1.2 Basic concepts

1.2.1 What is a Data Warehouse?

What is a DW is defined in many different ways, but not rigorously :

- A decision support database that is maintained separately from the organization's operational database
- Support information processing by providing a solid platform of consolidated, historical data for analysis.

"A data warehouse is a subject-oriented, integrated, timevariant, and nonvolatile collection of data in support of management's decision-making process."

Data warehousing is the process of constructing and using data warehouses

1.2.1.1 Subject Oriented

- Organized around major subjects, such as for e.g., customer, product, sales
- Focusing on the modeling and analysis of data for decision makers, not on daily operations or transaction processing
- Provide a *simple and concise* view around particular subject issues by *excluding data that are not useful in the decision support process*

1.2.1.2 Integrated

- Constructed by integrating multiple, heterogeneous data sources : Relational databases, flat files, on-line transaction records
- Data cleaning and data integration techniques are applied to Ensure consistency in naming conventions, encoding structures, attribute measures, etc. among different data sources (E.g., Hotel price: currency, tax, breakfast covered, etc.)
- When data is moved to the warehouse, it is converted.

1.2.1.3 Time variant

- The time horizon for the data warehouse is significantly longer than that of operational systems
    - Operational database: current value data
    - Data warehouse data: provide information from a historical perspective (e.g., past 5-10 years)
- Every key structure in the data warehouse contains an element of time, explicitly or implicitly
- On the other side, the key of operational data may or may not contain "time element"

1.2.1.4 Nonvolatile

- A physically separate store of data transformed from the operational environment
- Operational update of data does not occur in the data warehouse environment
    - Does not require transaction processing, recovery, and concurrency control mechanisms

- Requires only two operations in data accessing: *initial loading* of data and *access of data*

1.2.2 Differences between OLTP and OLAP (DW)

Usual production transactional systems databases are called OLTP:

The on-line operational database systems perform on-line transaction and query processing: **O**n-**L**ine **T**ransaction **P**rocessing (OLTP) systems.
The OLTP systems cover most of the day-to-day operations of an organization (purchasing, inventory, manufacturing, banking, payroll, registration, and accounting).

On the other hand, DW systems serve users or knowledge workers in the role of data analysis and decision making.
They can organize and present data in various formats in order to accommodate the diverse needs of the different users. These systems are known as **O**n-**L**ine **A**nalytical **P**rocessing (OLAP) systems.

	OLTP	**OLAP**
users clerk	IT professional	knowledge worker
function	day to day	operations decision support
DB design	application-oriented	subject-oriented
data	current, up-to-date detailed, flat relational isolated	historical, summarized, multi-dimensional, integrated, consolidated
usage	repetitive	ad-hoc
access	read/write, index/hash on prim. key	lots of scans
unit of work	short, simple transaction	complex query
#records accessed	tens	millions
#users	thousands	hundreds
DB size	100MB-GB	100GB-TB
metric	transaction throughput	query throughput, response

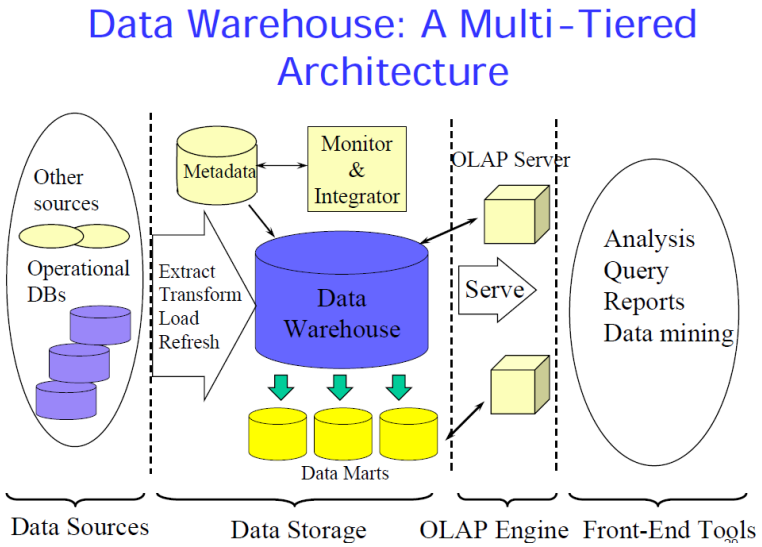
1.2.3 Why a separate Data Warehouse ?

- High performance for both systems
  - DBMS - tuned for OLTP: access methods, indexing, concurrency control, recovery
  - Warehouse - tuned for OLAP: complex OLAP queries, multidimensional view, consolidation
- Different functions and different data:
  - missing data: Decision support requires historical data which operational DBs do not typically maintain

- data consolidation: DS requires consolidation (aggregation, summarization) of data from heterogeneous sources
- data quality: different sources typically use inconsistent data representations, codes and formats which have to be reconciled

- Note: There are more and more systems which perform OLAP analysis directly on relational databases

1.2.4 DW : A multi-tiers architecture



The Bottom Tier : a warehouse database server (almost always a relational database system but $\neq$ to the transaction production transactional DB system).

- feeded with data from operational databases or external sources by back-end tools and utilities (data extraction, cleaning, transformation, load and refresh functions)
- the data are extracted using *APIs - Application Programming Interfaces* known as gateways. A gateway is supported by the underlying DBMS and allows client programs to generate SQL code to be executed at a server.
  (ODBC (Open Database Connection), OLEDB (Object Linking and Embedding Database) by Microsoft and JDBC (Java Database Connection).
- it also contains a metadata repository, which stores information about the data warehouse and its contents.

The Middle Tier : an OLAP server that is typically implemented using either

- a relational OLAP (ROLAP) model: an extended relational DBMS that maps operations on multidimensional data to standard relational operations;
- a multidimensional OLAP (MOLAP) model: a special-purpose server that directly implements multidimensional data and operations.

The Top Tier : a front-end client layer

- query and reporting tools, analysis tools, and/or data mining tools (e.g., trend analysis, prediction)

1.2.5 Three Data Warehouse Models

Enterprise warehouse :

- collects all of the information about subjects spanning the entire organization
- provides corporate-wide data integration
- contains detailed and summarized data

Data Mart :

- a subset of corporate-wide data that is of value to a specific groups of users
- its scope is confined to specific, selected groups, such as marketing data mart
- data contained inside tend to be summarized
- $\rightarrow$ Independent vs. dependent (directly from warehouse) data mart

Virtual warehouse :

- a set of views over operational databases
- only some of the possible summary views may be materialized
- easy to build but requires excess capacity on operational database server

1.2.6 Data warehouse development approaches

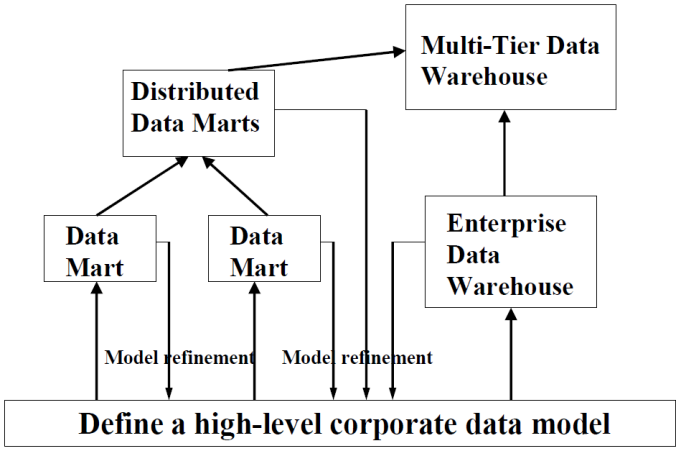
The *top-down* development :

- a systematic solution, minimizes integration problems
- expensive, takes a long time to develop, and lacks flexibility due to the difficulty in achieving consistency and consensus for a common data model for the entire organization

The *bottom-up* approach to the design, development, and deployment of independent data marts:

- provides flexibility, low cost, and rapid return of investment
- problems when integrating various disparate data marts into a consistent enterprise data warehouse

A recommended method for the development of data warehouse systems is to implement the warehouse in an incremental and evolutionary manner by using both of these two approaches :



1.2.7 ETL : (Data) Extraction, Transform and Loading

Extraction :	get data from multiple, heterogeneous, and external sources
Cleaning :	detect errors in the data and rectify them when possible
Transformation :	convert data from legacy or host format to warehouse format
Load :	sort, summarize, consolidate, compute views, check integrity, and build indicies and partitions
Refresh :	propagate the updates from the data sources to the warehouse

1.2.8 Metadata repository

Meta data is the data defining warehouse objects. It stores:

- Description of the structure of the data warehouse (schema, view, dimensions, hierarchies, derived data defn, data mart locations and contents)
- Operational meta-data $\rightarrow$ data lineage (history of migrated data and transformation path), currency of data (active, archived, or purged), monitoring information (warehouse usage statistics, error reports, audit trails)
- The *algorithms* used for summarization
- The *mapping* from operational environment to the data warehouse
- Data related to *system performance* (warehouse schema, view and derived data definitions)
- *Business data* (business terms and definitions, ownership of data, charging policies)

1.3 DW modeling : Data Cube and OLAP

1.3.1 From table and spreadseets to datacube

A data warehouse is based on a *multidimensional data model* which views data in the form of a data cube.

A data cube, such as sales, allows data to be modeled and viewed in multiple dimensions :

- **Dimension tables**, such as item (item_name, brand, type), or time (day, week, month, quarter, year)
- The **fact table** contains **measures** (such as dollars_sold) and keys to each of the related dimension tables

1.3.2 Examples

1.3.2.1 A 2-D cube representation (time, item)

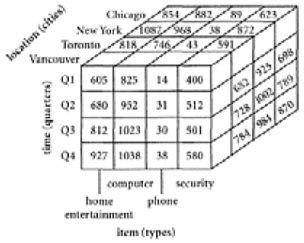
A 2-D view of sales data for *AllElectronics* according to the dimensions *time* and *item*, where the sales are from branches located in the city of Vancouver. The measure displayed is *dollars_sold* (in thousands) :

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

1.3.2.2 A 3-D cube representation (time, item, location)

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

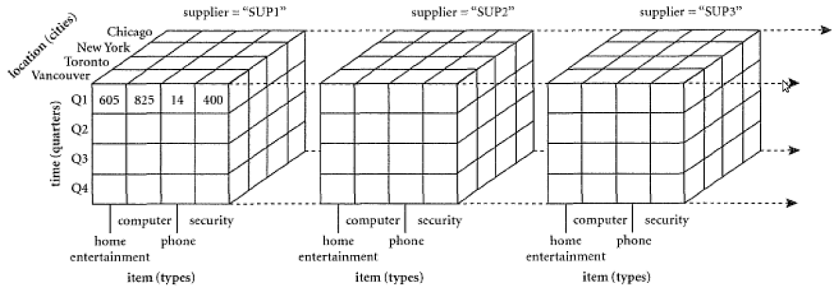
	location = "Chicago"				location = "New York"				location = "Toronto"				location = "Vancouver"			
	item				item				item				item			
time	home ent.	comp.	phone	sec.	home ent.	comp.	phone	sec.	home ent.	comp.	phone	sec.	home ent.	comp.	phone	sec.
Q1	854	882	89	623	1087	968	38	872	818	746	43	591	605	825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



1.3.2.3 A 4-D cube representation (time, item, location, supplier)

We can imagine a 4-D cube as being a serires of 3-D cubes.

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

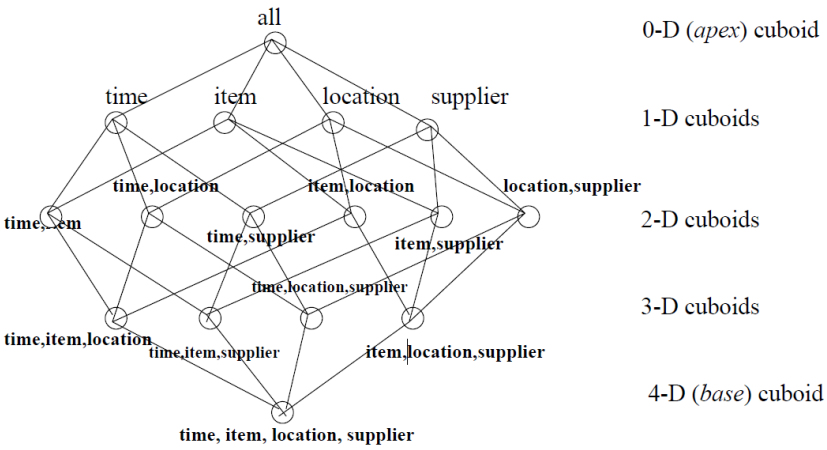


A possible implementation for such cubes is a big table containing all the measures and as many columns than the various dimensions. Each of these columns containing a reference to the corresponding dimension table.

1.3.3 Data cubes

- In data warehousing literature, an n-D base cube is called a base cuboid. (i.e. the base DB table containing every single dimension)
- The top most 0-D cuboid, which holds the highest-level of summarization, is called the apex cuboid. (i.e. there is only one row matching *all* values for all dimensions)
- The lattice of cuboids forms a data cube. (i.e all these different "views" together form the data cube)

The Data Cube is a lattice of cuboids :



The whole idea is to really have all this indexing and values redundance stored in the database in order to be able to serve data queries very fast and efficiently.

1.3.4 Conceptual modeling of Data warehouses

Modeling data warehouses: dimensions & measures :

Star schema: A fact table in the middle connected to a set of dimension tables

Snowflake schema:
A refinement of star schema where some dimensional hierarchy is normalized into a set of smaller dimension tables, forming a shape similar to snowflake

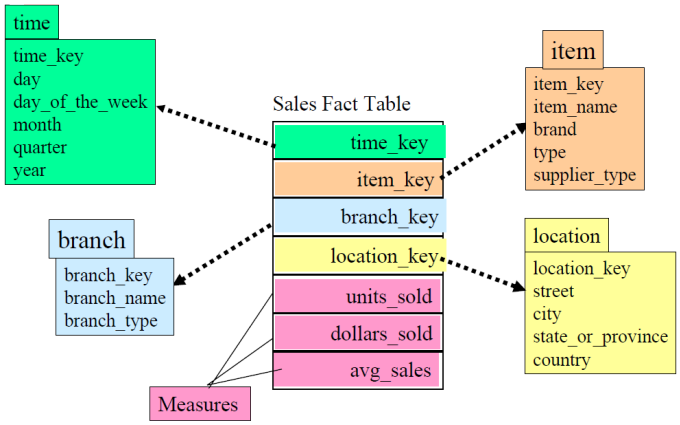
Fact constellations:
Multiple fact tables share dimension tables, viewed as a collection of stars, therefore called galaxy schema or fact constellation

1.3.4.1 Star schema

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

- a large central table (fact table) containing the bulk of the data, with no redundancy
- a set of smaller attendant tables (dimension tables), one for each dimension

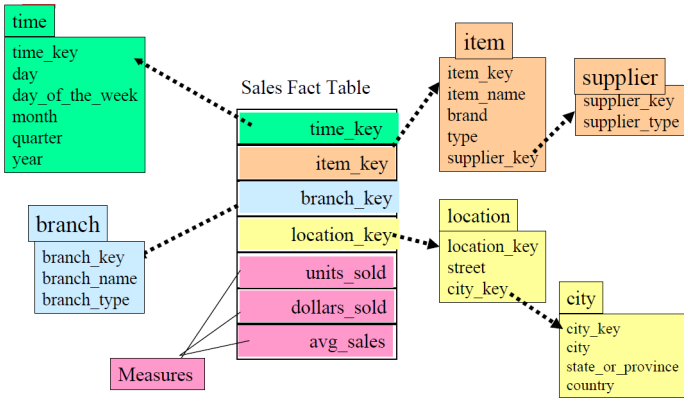
The schema graph resembles a starburst, with the dimension tables displayed in a radial pattern around the central fact table. Example :



1.3.4.2 Snowflake schema

- A variant of the star schema model, where some dimension tables are normalized, thereby further splitting the data into additional tables
- The resulting schema graph forms a shape similar to a snowflake.
- The dimension tables of the snowflake model may be kept in normalized form to reduce redundancies.
- But, the snowflake structure can reduce the effectiveness of browsing, since more joins will be needed to execute a query.
- Although the snowflake schema reduces redundancy, it is not as popular as the star schema in data warehouse design. (performance concerns)

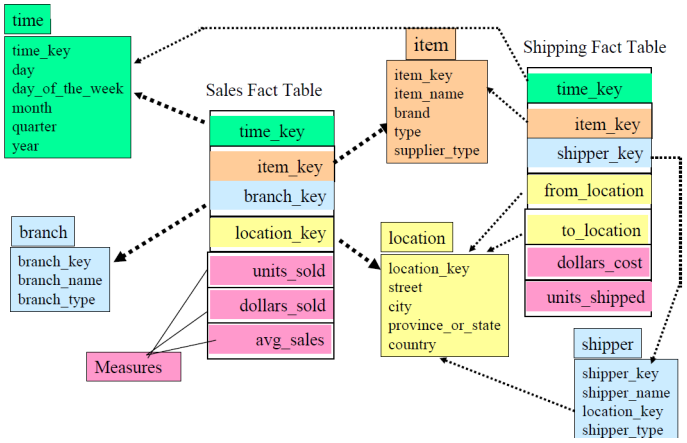
Example :



1.3.4.3 Fact constellation schema

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

Example :



1.3.4.4 Use of the schemas

- A data warehouse collects information about subjects that span the entire organization, such as customers, items, sales, assets, and personnel, and thus its scope is enterprise-wide.
  → For data warehouses, the fact constellation schema is commonly used, since it can model multiple, interrelated subjects.
- A data mart, on the other hand, is a department subset of the data warehouse that focuses on selected subjects, and thus its scope is department-wide.
  → For data marts, the star or snowflake schema are commonly used, since both are geared toward modeling single subjects, although the star schema is more popular and efficient.

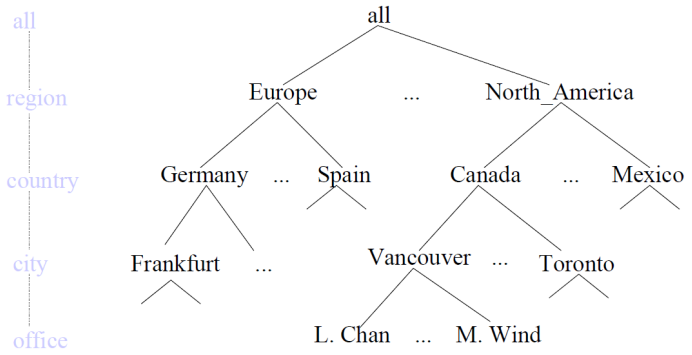
1.3.5 A concept hierarchy

A concept hierarchy defines a sequence of mappings from a set of low-level concepts to higher-level, more general concepts.

Exemple: location :

- City values for location : Vancouver, Toronto, NewYork, and Chicago
- Each city, can be mapped to the province or state to which it belongs: Vancouver can be mapped to British Columbia, and Chicago to Illinois
- The provinces and states can in turn be mapped to the country to which they belong, such as Canada or the USA

These mappings form a concept hierarchy for the dimension location, mapping a set of low-level concepts (i.e., cities) to higher-level,more general concepts (i.e., countries).



1.3.6 Data Cube measures

*A data cube measure is a **numerical function** that can be evaluated at each point in the data cube space.*
→ E.g., a multidimensional point in the data cube space :time = "Q1", location = "Vancouver", item = "computer"

A measure value is computed for a given point by aggregating the data corresponding to the respective dimension-value pairs defining the given point.

1.3.6.1 Three categories

Distributive: if the result can be derived by applying the function to *n* aggregate values, i.e. it is the same as that derived by applying the function on all the data without partitioning
→ Distributive measures can be computed efficiently because of the way the computation can be partitioned
E.g., count(), sum(), min(), max()

Algebraic: if it can be computed by an algebraic function with *M* arguments (where M is a bounded integer), each of which is obtained by applying a distributive aggregate function.
E.g., avg(), min_N(), standard_deviation()
See practice

Holistic: if there is no constant bound on the storage size needed to describe a sub-aggregate. → It is difficult to compute holistic measures efficiently. Efficient techniques to approximate. The computation of some holistic measures, however, do exist.
E.g., median(), mode(), rank()

1.3.7 DMQL : Data Mining Query Language

DMQL is a language for creating cubes. There are other specific languages supported by some RDBMS or environment, but here we will focus in DMQL :

Cube Definition (Fact Table) :

```
define cube <cube_name> [<dimension_list>]:  <measure_list>
```

Dimension Definition (Dimension Table) :

```
define dimension <dimension_name> as (<attribute_or_subdimension_list>)
```

Special Case (Shared Dimension Tables) :
(First time as "cube definition" above)

```
define dimension <dimension_name> as <dimension_name_first<_time> in cube
<cube_name_first_time>
```

1.3.7.1 Example of a star schema definition in DMQL

```
define cube sales star [time, item, branch, location]:
   dollars sold = sum(sales in dollars), units sold = count(*)
define dimension time as    (time key, day, day of week, month, quarter, year)
define dimension item as
   (item key, item name, brand, type, supplier type)
define dimension branch as
   (branch key, branch name, branch type)
define dimension location as
   (location key, street, city, province or state, country)
```

1.3.7.2 Example of a snowflake schema definition in DMQL

```
define cube sales snowflake [time, item, branch, location]:
   dollars sold = sum(sales in dollars), units sold = count(*)
define dimension time as
   (time key, day, day of week, month, quarter, year)
define dimension item as
   (item key, item name, brand, type, supplier (supplier key, supplier type))
define dimension branch as
   (branch key, branch name, branch type)
define dimension location as
   (location key, street, city (city key, city, province or state, country))
```

- The item and location dimension tables are normalized
- Defining supplier in this way implicitly creates a supplier key in the item dimension table definition
- A city key is implicitly created as well.

1.3.7.3 Example of a fact constellation schema definition in DMQL

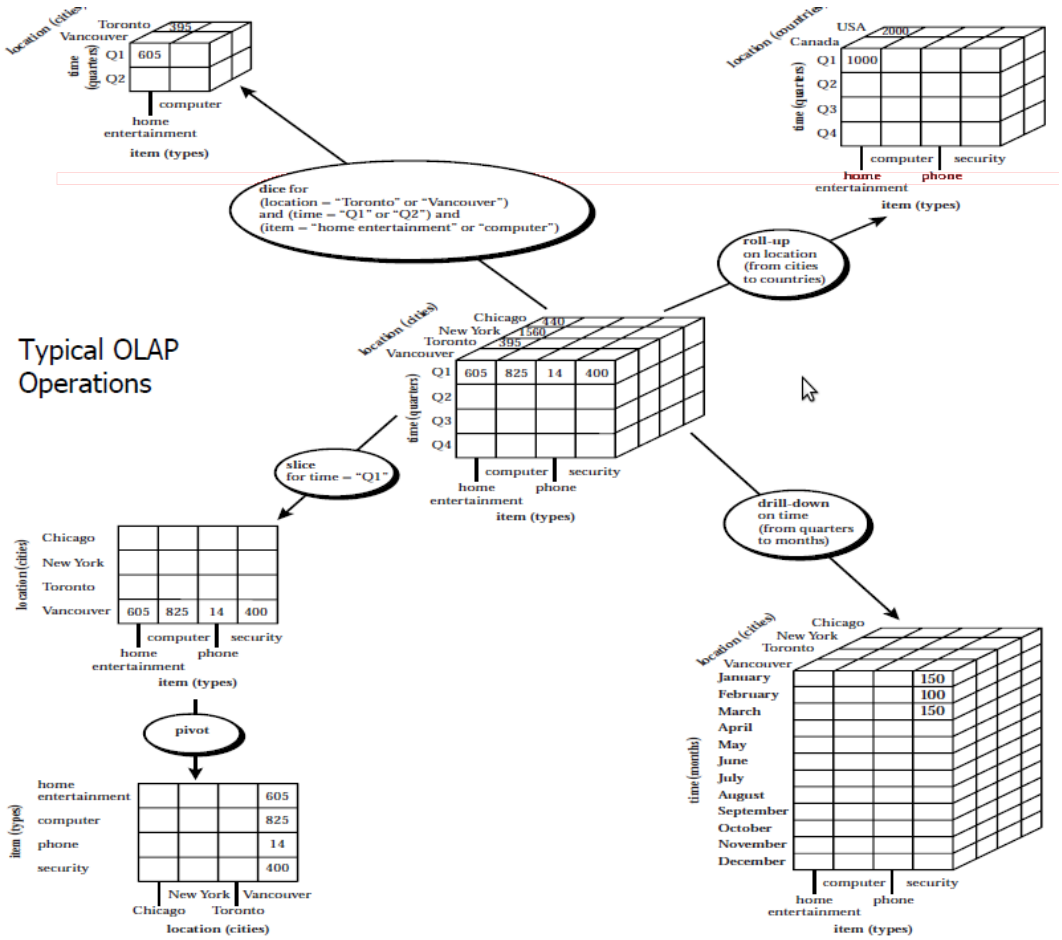
```
define cube sales [time, item, branch, location]:
   dollars sold = sum(sales in dollars), units sold = count(*)
define dimension time as
   (time key, day, day of week, month, quarter, year)
define dimension item as
   (item key, item name, brand, type, supplier type)
define dimension branch as
   (branch key, branch name, branch type)
define dimension location as
   (location key, street, city, province or state, country)
define cube shipping [time, item, shipper, from location, to location]:
   dollars cost = sum(cost in dollars), units shipped = count(*)
define dimension time as time in cube sales
define dimension item as item in cube sales
define dimension shipper as
   (shipper key, shipper name, location as location in cube sales, shipper type)
define dimension from location as location in cube sales
```

1.3.8 Typical OLAP Operations

Roll up:	(drill-up) summarize data by climbing up hierarchy or by dimension reduction
Drill down:	(roll down) reverse of roll-up, from higher level summary to lower level summary or detailed data, or introducing new dimensions
Slice and dice:	project and select
Pivot:	(rotate) reorient the cube, visualization, 3D to series of 2D planes

Other operations :

drill across:	involving (across) more than one fact table
drill through:	through the bottom level of the cube to its backend relational tables (using SQL)



1.3.8.1 Slice and Dice examples

Example 1

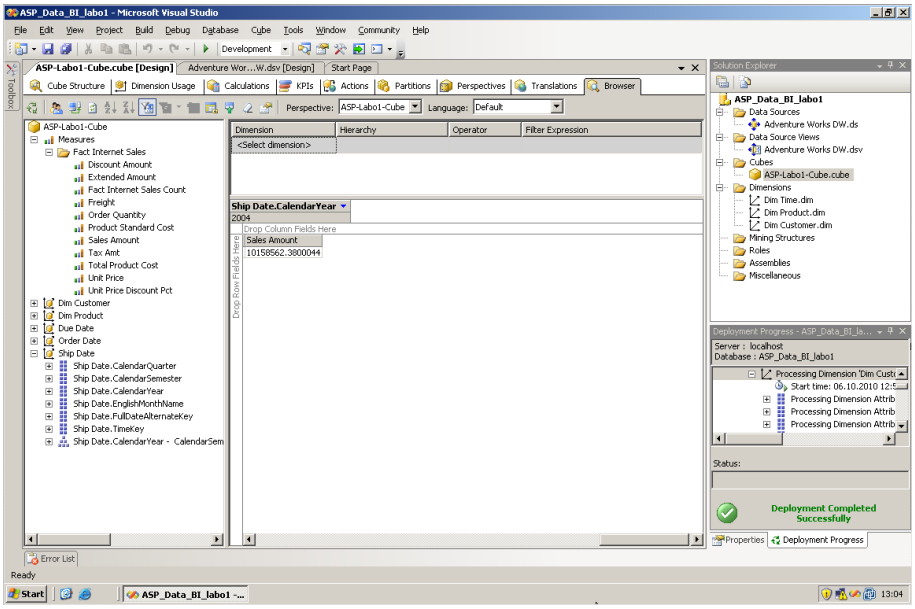
The slice operation performs a selection on one dimension of the given cube, resulting in a subcube.
→ The sales data are selected from the central cube for the dimension time using the criterion time = "Q1"

The dice operation defines a subcube by performing a selection on two or more dimensions.
→ The selection criteria involve three dimensions: (location = "Toronto" or "Vancouver") and (time = "Q1" or "Q2") and (item = "home entertainment" or "computer").

Example 2 : Taken from lab 1

Here we run a simple request aimed at computing the sales amount for year 2004 (ship date).

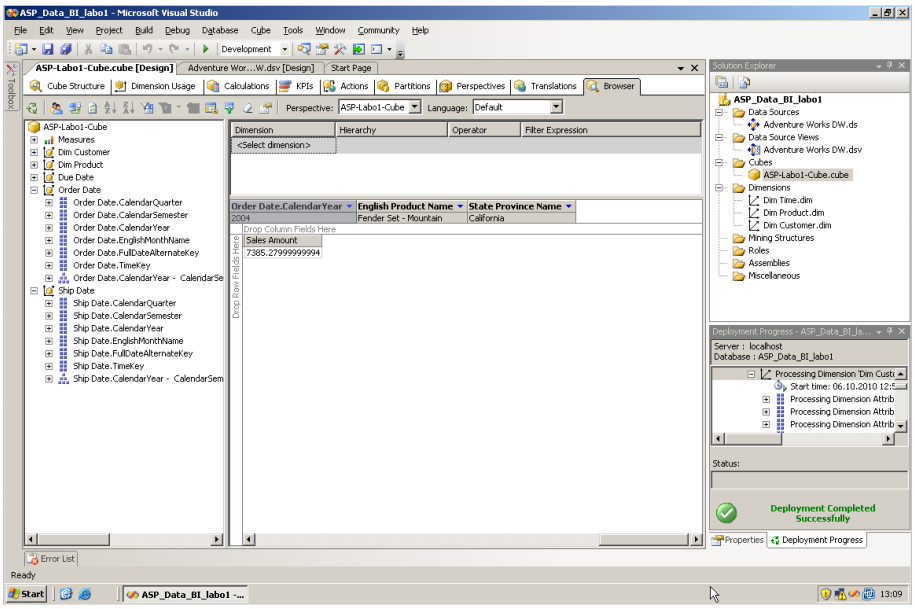
We run this simple request by dropping the desired filtering field right in the filtering fields location. Then one simply needs to select the filtering value in order to actually perform the data selection.
The colum wich we one wants to compute as a result is dropped in the column fields :



And the result is **10'158'562.38 USD**.

Then we should compute the total sales amount for a specific article - "Fender Set-Mountain" - for year 2004 (order date) but only in the California (state province name).

This is actually quite simply performed as one only needs to add the additional filtering fields and values in the same filtering fields location.



And the result is **7'385.28 USD**.

1.3.8.2 Roll-Up examples

Example 1

A roll-up operation performed on the central cube by climbing up the concept hierarchy for location from the level of city to the level of country.

Hierarchy definition (total order) : "street < city < province or state < country."

The roll-up operation aggregates the data by ascending the location hierarchy, the resulting cube groups the data by country.

Example 2

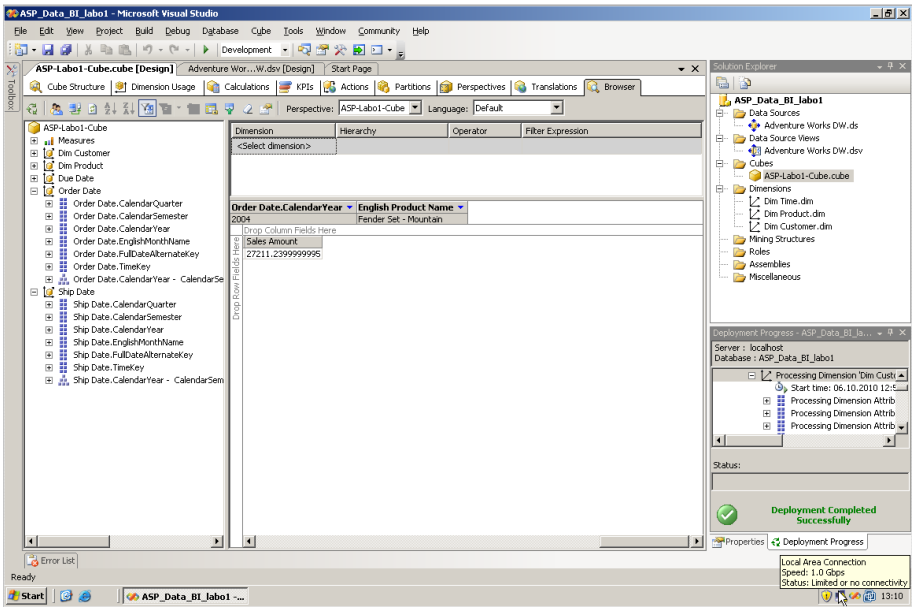
A roll-up performed by dimension reduction, is considered on a sales data cube (with two dimensions location and time) by removing, the time dimension, resulting in an aggregation of the total sales by location, rather than by location and by time.

Example 3 : Taken from lab 1

Now we should emphasize the *roll-up* principle by getting rid of the filtering on the state value (California).

Based on this principle we should answer the very same question related to the amount of sales for article "Fender Set-Mountain" for year 2004 but this time for every known states all together.

Again this is quite simply executed as one only needs to get rid of the related filtering field from the filtering fields location :



And the result is **27'211.24 USD**.

1.3.8.3 Drill-Down examples

Example 1

A drill-down operation performed on the central cube by stepping down a concept hierarchy for time defined as "day < month < quarter < year." , by descending the time hierarchy from the level of quarter to the more detailed level of month.

The resulting data cube details the total sales per month rather than summarizing them by quarter.

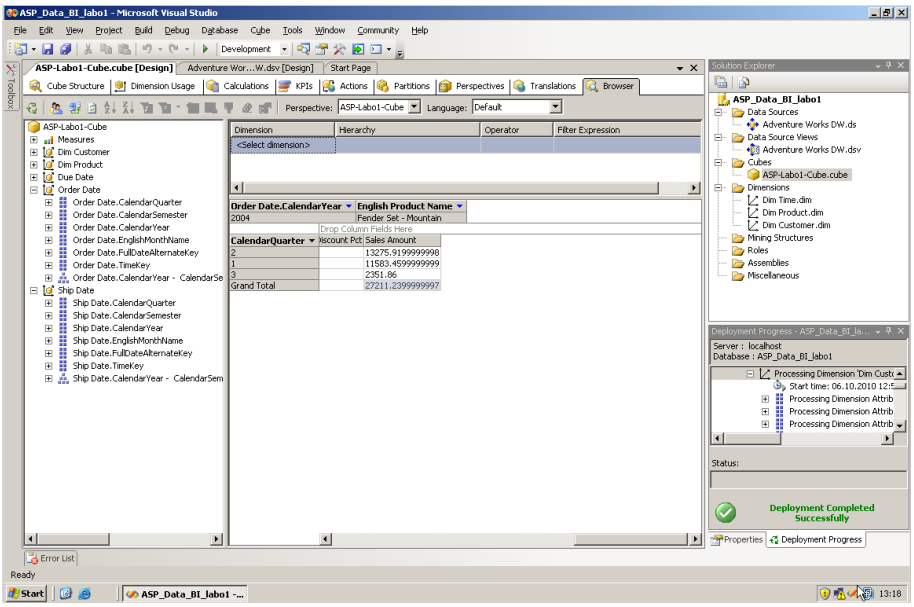
Example 2

A drill-down performed by adding new dimensions to a cube is done on the central cube by introducing an additional dimension, such as customer group.

Example 3 : Taken from lab 1

Here we should emphasize the *drill-down* principle by attempting to find out which quarter of year 2004 has been the most profitable regarding the sales of the very same article.

The easiest way to achieve this consists of using the various quarters for year 2004 as row fields. This way we can order the sales values in a descending way and easily spot the most profitable quarter :



And the result is **the second quarter**.

1.3.8.4 Pivot (Rotate) examples

A visualization operation that rotates the data axes in view in order to provide an alternative presentation of the data.

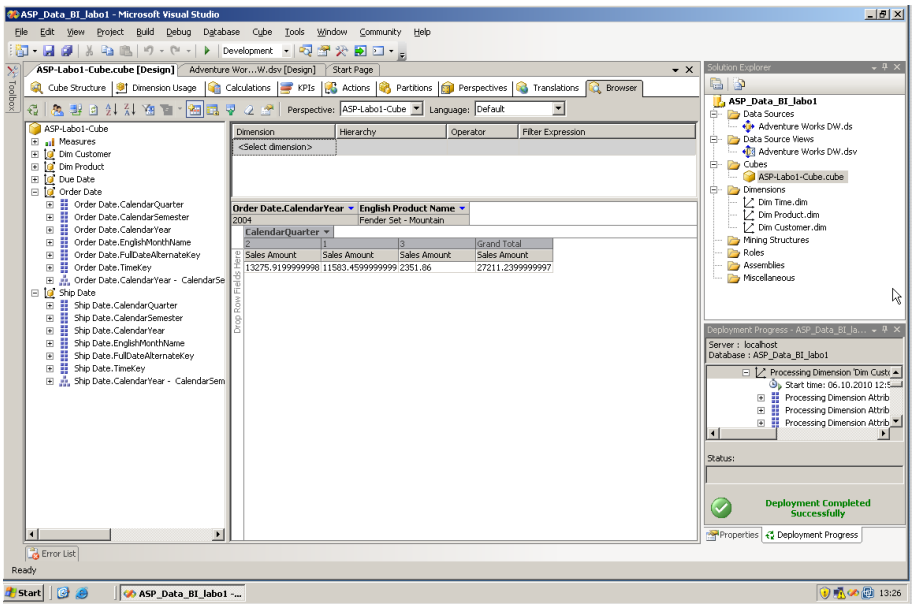
Example 1

- A pivot operation where the item and location axes in a 2-D slice are rotated.
- Rotating the axes in a 3-D cube, or transforming a 3-D cube into a series of 2-D planes.

Example 2 : Taken from lab 1

Finally we will illustrate how a *pivot* operation is typically achieved by switching the fields from both axis.

Happily this is easily done with Microsoft Visual Studio as a specific menu item is provided in this intent :

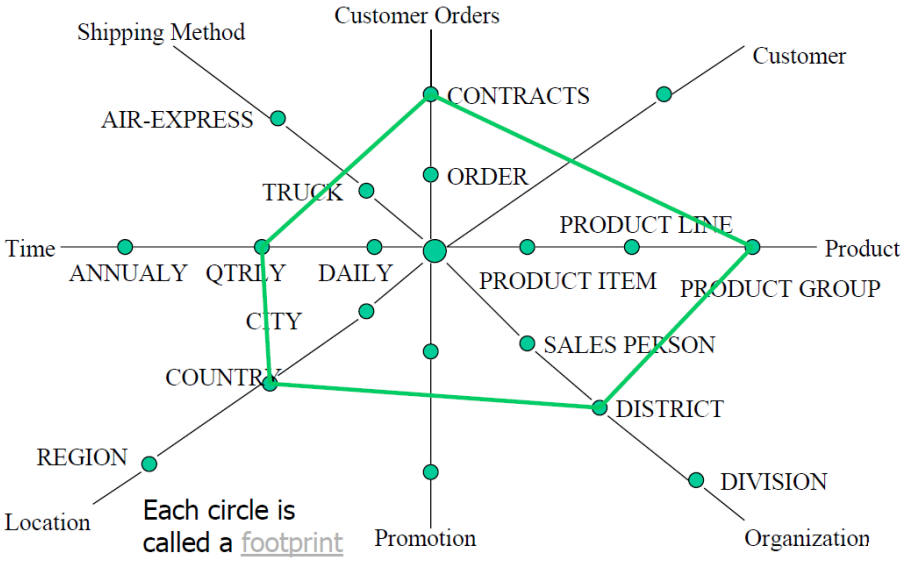


As a matter of fact we get the same result.

1.3.9 Starnet Query Model

The querying of multidimensional databases can be based on a starnet model. A starnet model consists of radial lines emanating from a central point, where each line represents a concept hierarchy for a dimension.

Each abstraction level in the hierarchy is called a footprint. These represent the granularities available for use by OLAP operations such as drill-down and rollup.



1.4 Design and Usage

A Data Warehouse (DW) is a business analysis framework. Why should one bother implementing a DW ?

- **Provide competitive advantage**
  → measure performance and make critical adjustments
- **Enhance business productivity**
  → information that accurately describes the organization
- **Facilitate customer relationship management**
  → consistent view of customers and items across all lines of business, all departments, and all market
- **Bring about cost reduction**
  → by tracking trends, patterns, and exceptions over

1.4.1 Four views

The design of a data warehouse can be seen from four distinct views :

- **Top-down view**
  → allows selection of the relevant information necessary for the data warehouse (current and future business needs)
- **Data source view**
  → exposes the information being captured, stored, and managed by operational systems
- **Data warehouse view**
  → consists of fact tables and dimension tables
- **Business query view**
  → sees the perspectives

1.4.2 Skills to build and use a DW

Business Skills

- To know systems storage and management data
- To build extractors, warehouse, to refresh software
- To understand the significance of the data
- To translate the business requirements into queries

Technology skills

- To understand how to make assessments from quantitative information
- To discover patterns and trends, to extrapolate them based on history and look for anomalies
- To present coherent managerial recommendations

Program management skills

- To interface with technologies, vendors, and end users, to deliver results in a timely and cost-effective manner

1.4.3 Data Warehouse Design Process

1.4.3.1 What approach ?

What approach is to be used ? Top-down, bottom-up approaches or a combination of both ?

Top-down: Starts with overall design and planning, useful when the technology is mature and well known, and where the business problems that must be solved are clear and well understood.

Bottom-up: Starts with experiments and prototypes (rapid), useful in the early stage of business modeling and technology development. It is less expensive and evaluate the benefits of the technology before making significant commitments.

1.4.3.2 From software engineering point of view

The steps are : planning, requirements study, problem analysis, warehouse design, data integration and testing, and the deployment of the DW

Waterfall: structured and systematic analysis at each step before proceeding to the next

Spiral: rapid generation of increasingly functional systems, short turn around time, quick turn around
$\rightarrow$ a good choice for DW development, especially for data marts, because the turnaround

1.4.3.3 Typical data warehouse design process

1. Choose a business process to model
   e.g., orders, invoices

2. Choose the grain (atomic level of data) of the business process
   e.g., individual transactions, individual daily snapshots

3. Choose the dimensions that will apply to each fact table record,
   e.g., time, item, customer, supplier, warehouse, transaction, type, and status.

4. Choose the measure that will populate each fact table record
   e.g, dollars sold and units sold.

1.4.4 Data Warehouse Deployment

- Initial installation, planning, training
- DW administration: data refreshment, data source synchronization, planning for disaster recovery, managing access control and security, managing data growth, managing database performance, and DW enhancement and extension
- Scope management: controlling the number and range of queries, dimensions, and reports; limiting the size of the DW
- DW development tools: functions to define and edit metadata repository contents (such as schemas, scripts, or rules), answer queries, output reports, and ship metadata to and from relational database system catalogue

1.4.5 Data Warehouse Usage

Three kinds of data warehouse applications :

Information processing :

- supports querying, basic statistical analysis, and reporting using crosstabs, tables, charts and graphs

Analytical processing :

- multidimensional analysis of data warehouse data
- supports basic OLAP operations, slice-dice, drilling, pivoting

Data mining :

- knowledge discovery from hidden patterns
- supports associations, constructing analytical models, performing classification and prediction, and presenting the mining results using visualization tools

1.4.6 OLAM : Online Analytical Mining

From On-Line Analytical Processing (OLAP) to On Line Analytical Mining (OLAM) - Why online analytical mining?

- High quality of data in data warehouses.
  → DW contains integrated, consistent, cleaned data
- Available information processing structure surrounding data warehouses
  → ODBC, OLEDB, Web accessing, service facilities, reporting and OLAP tools
- OLAP-based exploratory data analysis
  → Mining with drilling, dicing, pivoting, etc.
- On-line selection of data mining functions
  →Integration and swapping of multiple mining functions, algorithms, and tasks

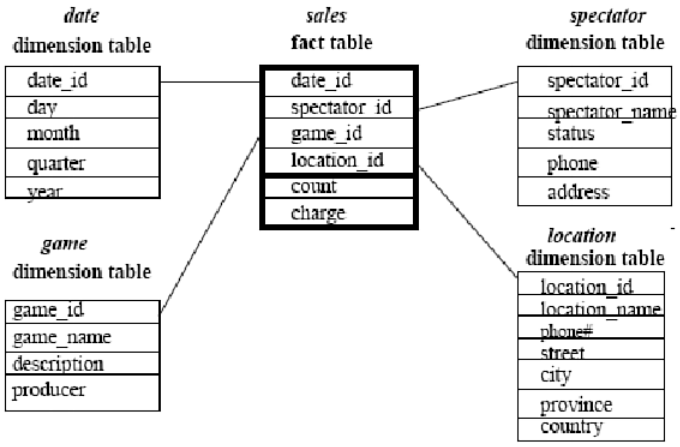
1.5 Practice

1.5.1 OLAP operations

Suppose that a data warehouse consists of the four dimensions, date, spectator, location, and game, and the two measures, count and charge, where charge is the fare that a spectator pays when watching a game on a given date. Spectators may be students, adults, or seniors, with each category having its own charge rate.

1.5.1.1 Star schema

Draw a star schema diagram for the data warehouse :



1.5.1.2 OLAP operations

Starting with the base cuboid [date; spectator; location; game], what specific OLAP operations should one perform in order to list the total charge paid by student spectators at GM_Place in 2004?

- Roll-up on date from date id to year.
- Roll-up on game from game id to all.
- Roll-up on location from location id to location name.
- Roll-up on spectator from spectator id to status.
- Dice with status="students", location name="GM Place", and year="2004"

1.5.2 Data Warhouse And Data Mart

What are the difference and similarities between a Data Mart and a Data warehouse ?

Similarities :

- Both are a storage of data i n a subject-oriented, integrated, time-variant and non-volatile way.

Differences :

- A Data Mart is oriented on a single business-domain or a single subject (for instance marketing) while a Data Warehouse is global to the enterprise and covers the whole enterprise domain.
- A Data Mart is expected to be much simplier than a Data Warehouse and sometimes even summarized while a Data Warehouse contains detailed and summarized data.
- A Data Mart is usually cheaper to implement.
- A Data warehouse can be implemented bottom-up by aggregating Data Marts while a Data Mart is usually designed top-down.

1.5.3 OLAP operations, another example

Suppose a data warehouse consosts of the three dimensions *time*, *doctor* and *patient* and two measures of count and charge, where charged is the fee that a doctor charges a patient for a visit.
Starting with the base cuboid [day, doctor, patient[, what specific OLAP operations should be performed in order to list the total fee collected by each doctor in 2010 ?

- roll up on time from day to year
- roll up on patient from patient_id to all
- slice with year = "2010"

1.5.4 Data Warhouse modeling

A data warehouse can be modelled by either a star schema or a snowflake schema. Briefly describe the similarities and the differences of the two models, and then analyze their advantages and disadvantages with regard to one another. Give your opinion of which might be more empirically useful and state the reasons behind your answer.

They are similar in the sense that they all have a fact table, as well as some dimensional tables. The major difference is that some dimension tables in the snowflake schema are normalized, thereby further splitting the data into additional tables. The advantage of the star schema is its simplicity, which will enable efficiency, but it requires more space. For the snowflake schema, it reduces some redundancy by sharing common tables: the tables are easy to maintain and save some space. However, it is less efficient and the saving of space is negligible in comparison with the typical magnitude of the fact table. Therefore, empirically, the star schema is better simply because efficiency typically has higher priority over space as long as the space requirement is not too huge. In industry, sometimes the data from a snowflake schema may be denormalized into a star schema to speed up processing.

1.5.5 Computation of measures

1.5.5.1 Categories of measures

Enumerate three categories of measures, based on the kind of aggregate functions used in computing a data cube.

The three categories of measures are distributive, algebraic, and holistic.

1.5.5.2 variance

For a data cube with the three dimensions time, location, and item, which category does the function variance belong to? Describe how to compute it if the cube is partitioned into many chunks.

The variance belongs to the *algebraic* category.

Recall :

The **sample mean** $\bar{x}$ of observations x_1,x_2,...,x_n is given by

$$\bar{x} = \frac{x_1 + x_2 + ... + x_n}{n} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

The numerator of $\bar{x}$ can be written more informally as $\sum x_i$, where the summation is over all sample observations.

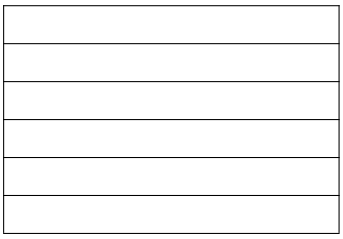
The **variance** can be obtained as

$$\sigma_X = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2$$

One can write

$$\begin{aligned}
\sigma_X &= \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2 \\
&= \frac{1}{n}\sum_{i=1}^{n}(x_i^2 - 2x_i\bar{x} + \bar{x}^2) \\
&= \frac{1}{n}\sum_{i=1}^{n}x_i^2 - \frac{2}{n}\bar{x}\sum_{i=1}^{n}x_i + \frac{1}{n}\sum_{i=1}^{n}\bar{x}^2 \\
&= \frac{1}{n}\sum_{i=1}^{n}x_i^2 - \frac{2}{n}\bar{x}n\bar{x} + \frac{1}{n}n\bar{x}^2 \\
&= \frac{1}{n}\sum_{i=1}^{n}x_i^2 - 2\bar{x}^2 + \bar{x}^2 \\
&= \frac{1}{n}\sum_{i=1}^{n}x_i^2 - \bar{x}^2 (\Rightarrow \ alternate\ variance\ formula)
\end{aligned}$$

So now we end up with various different k little cubes :



The values are computed this way :

$$\sigma_X = \frac{1}{n}\sum_{i=1}^{n}x_i^2 - (\frac{\sum_{i=1}^{n}x_i}{n})^2$$

where

- $\frac{1}{n}$ is easily computed : n is the total amount of rows in all cubes
- $\sum_{i=1}^{n}x_i^2$ is easy : one only need to sum the partial sums.
- $(\frac{\sum_{i=1}^{n}x_i}{n})^2$ is easy as well : simply keep track of the partial $\sum_{i=1}^{n}x_i$ and compute n = $(n_1 + n_2 + ... + n_k)$

This way we don't need to recompute everything each time a new chunk of data is added. One only needs to compute the partial results for the new chunk and then integrate these results in the totals.

The very same principle can be applied to the function computing the 10 top values (the 10 top values are mandatorily in the 10 top values for each chunk) and other functions as well.

This is called **Distributive aggregate functions**

CHAPTER 2

Data Preprocessing

Contents

2.1 Overview

2.1.1 Why preprocess the data ?

Data usually has to respect these principles : Accuracy, Completeness, Consistency, Timeliness, Believability, Interpretability.

2.1.1.1 Accuracy, completeness, consistency

Introducing Example

- You are a manager at AllElectronics and have been charged with analyzing the company's data with respect to the sales at your branch.
- You identify and select the attributes to be included in your analysis (item, price, and units sold).
- You notice that several of the attributes for various tuples have no recorded value.
- For your analysis, you would like to include information as to whether each item purchased was advertised as on sale, yet you discover that this information has not been recorded.
- Users of your database system have reported errors, unusual values, and inconsistencies in the data recorded for some transactions.

→ This underscores the kind of issues one can have with the data.

Preprocessing helps avoiding situations where the data one wish to analyze by data mining techniques are:

incomplete:	lacking attribute values or certain attributes of interest, or containing only aggregate data
inaccurate:	(or noisy) containing errors, or outlier values that deviate from the expected
inconsistent:	e.g., containing discrepancies in the department codes used to categorize items

2.1.1.2 Timeliness

Introducing Example

- Suppose that you are overseeing the distribution of monthly sales bonuses to the top sales representatives at AllElectronics.
- Several sales representatives, however, fail to submit their sales records on time at the end of the month.
  There are also a number of corrections and adjustments that flow in after the month's end.
- For a period of time following each month, the data stored in the database is incomplete.
- However, once all of the data is received, it is correct.
- The fact that the month-end data is not updated in a timely fashion has a negative impact on the data quality.

→ *Timeliness issues can be managed by having a preprocessing step which postpones the update of the data in the warehouse until the input data set is complete*

2.1.1.3 Believability

Introducing Example

- A few years back, a programming error miscalculated the sales commissions for its sales representatives so that these employees received 20% less than was due.
- The software bug was quickly fixed and the data corrected.
- Even though the database is now accurate, complete, consistent, and timely, it is still not trusted because of the memory users have of the past error.
- Sales managers prefer to compute the expected commissions by hand based on their employees handsubmitted reports rather than believe the data stored in the database.

→ People losing faith in the data is a severe issue. Data need to be believable / reliable.

2.1.1.4 Interpretability

Introducing Example

- Consider a sales database, where it is common to create "adjustment" orders to handle complaints and returns.
- This procedure assigns new order numbers to the adjustment and replacement orders.
- The accounting department knows how to interpret the resulting data.
- A business analyst may have a hard time understanding the data, thinking that each order number represents a distinct order.
- Thus, to the business analyst, the data is of low quality due to poor interpretability.

2.1.2 Major Tasks in Data Preprocessing

Data cleaning: - see 2.2

- Fill in missing values. - see 2.2.2
- Smooth noisy data, identify or remove outliers, and resolve inconsistencies - see 2.2.4

Data integration: - see 2.3

- Integration of multiple databases, data cubes, or files

Data reduction: (a reduced representation of data set, smaller in volume, producing the same (almost) analytical results)

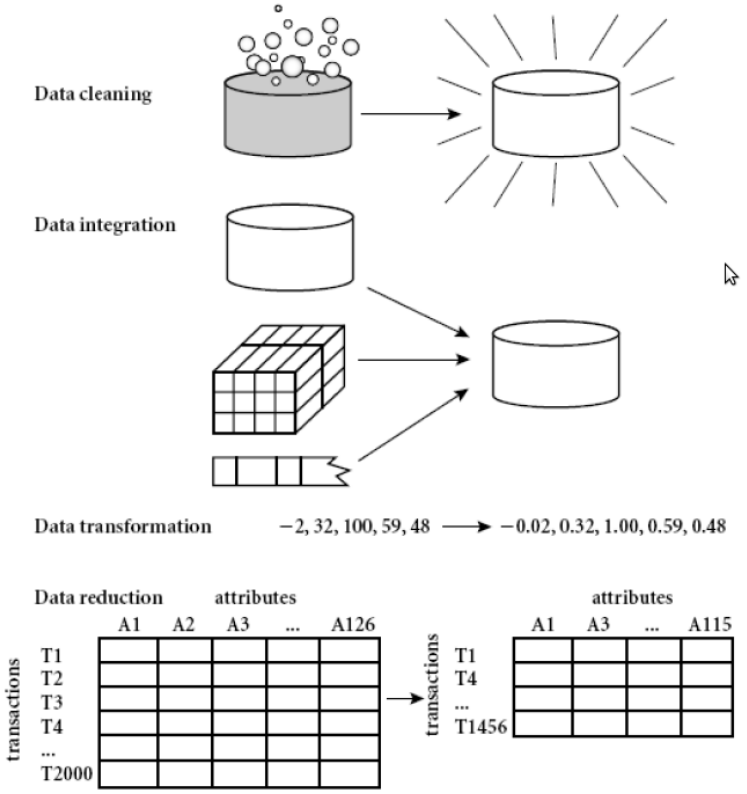
- Dimensionality reduction (by applying data encoding schemes)
- Numerosity reduction (replace data by alternative, smaller representations using parametric or non parametric models

- Data compression

Data transformation and data discretization

- Normalization (scale data to ranges)
- Concept hierarchy generation

TODO list all techniques here with references



2.2 Data Cleaning

Data in the real world is dirty:

incomplete:	lacking attribute values, lacking certain attributes of interest, or containing only aggregate data → e.g., Occupation=" " (missing data)
noisy:	containing noise, errors, or outliers → e.g., Salary="-10" (an error)
inconsistent:	containing discrepancies in codes or names, e.g., → e.g. Age="42" Birthday="03/07/1997" → e.g. was rating "1,2,3", now rating "A, B, C" → e.g. discrepancy between duplicate records

2.2.1 Incomplete (Missing) Data

Data is not always available.

- E.g., many tuples have no recorded value for several attributes, such as customer income in sales data

Missing data may be due to

- equipment malfunction
- inconsistent with other recorded data and thus deleted
- data not entered due to misunderstanding
- certain data may not be considered important at the time of entry
- not register history or changes of the data

Missing data may need to be inferred.

2.2.2 How to Handle Missing Data?

- **Ignore the tuple**: usually done when class label is missing (when doing classification); not effective when the % of missing values per attribute varies considerably
  $\rightarrow$ This method is not very effective unless the tuple contains several attributes with missing values. It is especially poor when the percentage of missing values per attribute varies considerably.

- **Fill in the missing value manually**: tedious + infeasible?
  $\rightarrow$ In general, this approach is time-consuming and may not be a reasonable task for large data sets with many missing values, especially when the value to be filled in is not easily determined.

- **Fill in it automatically with**
  - **a global constant** : e.g., "unknown", a new class?!
    $\rightarrow$ If missing values are replaced by, say, "Unknown", then the mining program may mistakenly think that they form an interesting concept, since they all have a value in common, that of "Unknown." Hence, although this method is simple, it is not recommended.
  - **the attribute mean** : (Using the attribute mean for quantitative (numeric) values or attribute mode for categorical (nominal) values.)
  - **the attribute mean for all samples belonging to the same class** : smarter (Using the attribute mean for quantitative (numeric) values or attribute mode for categorical (nominal) values, for all samples belonging to the same class as the given tuple.) $\rightarrow$ For example, if classifying customers according to credit risk, replace the missing value with the average income value for customers in the same credit risk category as that of the given tuple.

- **the most probable value** : inference-based such as Bayesian formula or decision tree (Using the most probable value to fill in the missing value: This may be determined with regression, inference-based tools using Bayesian formalism, or decision tree induction.)
  → For example, using the other customer attributes in the data set, we can construct a decision tree to predict the missing values for income.

2.2.3 Noisy Data

- Noise: random error or variance in a measured variable
- Incorrect attribute values may be due to
  - faulty data collection instruments
  - data entry problems
  - data transmission problems
  - technology limitation
  - inconsistency in naming convention
- Other data problems which require data cleaning
  - duplicate records
  - incomplete data
  - inconsistent data

2.2.4 How to Handle Noisy Data?

Binning: (lissage)

- first sort data and partition into (equal-frequency) bins
- then one can smooth by *bin means*, smooth by *bin median*, smooth by *bin boundaries*, etc.

Regression:

- smooth by fitting the data into regression functions

Clustering:

- detect and remove outliers

Combined computer and human inspection:

- detect suspicious values and check by human (e.g., deal with possible outliers)

2.2.4.1 Regression

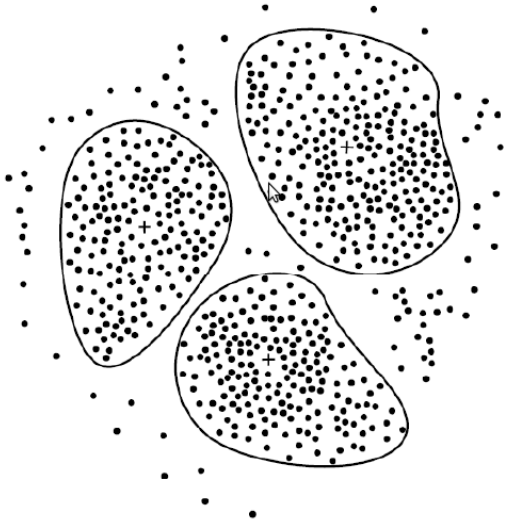
- **Linear regression** involves finding the "best" line to fit two attributes (or variables), so that one attribute can be used to predict the other.

- **Multiple linear regression** is an extension of linear regression, where more than two attributes are involved and the data are fit to a multidimensional surface.

The principle : Let's imagine a line in the cloud of points on a plan. We look for the line minimizing the sum of the distance between every point and the line. Then we get rid of the points that have a distance to the line above the average (mean) distance (or we fix them).

2.2.4.2 Clustering

The principle : First, the points on the plan are grouped together according to some distance calculation. Then the points which could not be grouped to any other are discarded (or fixed).



2.2.5 Data cleaning as a process

We'll now focus on the usual process for data cleaning.

2.2.5.1 Data discrepancy detection

What are the ways for detecting data discrepency ?

- Use metadata: the data type and domain of each attribute, the acceptable values for each attribute
- Basic statistical data descriptions to grasp data trends and identify anomalies (values that are more than two standard deviations away from the mean for a given attribute may be flagged as potential outliers)
- Write your own scripts

What are typically the kind of descrepencies detected ?

- Inconsistent use of codes
  $\rightarrow$ e.g., "2010/12/25" and "25/12/2010" for date
- Field overloading, when developers squeeze few attribute definitions into unused (bit) portions of already defined attributes
  $\rightarrow$ e.g., using an unused bit of an attribute whose value range uses only, say, 31 out of 32 bits

Data should be examined regarding :

- **unique rules:** each value of the given attribute must be different from all other values for that attribute
- **consecutive rules:** there can be no missing values between the lowest and highest values for the attribute and that all values must also be unique
  (e.g., as in check numbers)
- **null rules:** specify the use of blanks, question marks, special characters, or other strings that may indicate the null condition (e.g., where a value for a given attribute is not available), and how such values should be handled

A possibility: use commercial tools to detect discrepencies :

- **Data scrubbing:** use simple domain knowledge (e.g., postal code, spellcheck) to detect errors and make corrections
- **Data auditing:** by analyzing data to discover rules and relationship to detect violators (e.g., correlation and clustering to find outliers)

A possibility: use commercial tools for data transformation step :

- Data migration tools: allow simple transformations to be specified (e.g., replace the string “gender" by "sex")
- ETL (Extraction/Transformation/Loading) tools: allow users to specify transformations through a graphical user interface
- They support only a restricted set of transforms: write custom scripts

2.3 Data Integration

Goal : Combines data from multiple sources into a coherent store

Schema integration :

- Integrate metadata from different sources
- e.g., A.cust-id $\equiv$ B.cust-#

Entity identification problem:

- Identify real world entities from multiple data sources
- e.g., Bill Clinton = William Clinton

Detecting and resolving data value conflicts:

- For the same real world entity, attribute values from different sources are different
- Possible reasons: different representations,

2.3.1 Handling Redundancy in Data Integration

- Redundant data occur often when integration of multiple databases
  - Object identification: The same attribute or object may have different names in different databases
  - Derivable data: One attribute may be a "derived" attribute in another table, e.g., annual revenue
- Redundant attributes may be able to be detected by correlation analysis and covariance analysis
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

2.3.2 Correlation Analysis (Nominal Data)

We use the χ^2 **(chi-square) test**

$$\chi^2 = \sum \frac{(Observerd - Expected)^2}{Expected}$$

- The larger the χ^2 value, the more likely the variables are related
- The cells that contribute the most to the χ^2 value are those whose actual count is very different from the expected count
- Correlation does not imply causality
  - # of hospitals and # of car-theft in a city are correlated
  - Both are causally linked to the third variable: population

2.3.2.1 χ^2 test : an example

	Play Chess	**Not Play Chess**	**Sum (row)**
Like Sci-Fi	250(90)	200(360)	450
Not Like Sci-Fi	50(210)	1000(840)	1050
Sum(col)	300	1200	1500

- *The values in parenthesis are expected values. To compute them one should just do as if the individual results were missing and compute the expected values out of the partial sums. For instance : Cell "Play Chess & Likes Sci-Fi2 is (Sum for Play Chess * Sum for Likes Sci-Fi / Global Sum)*
- The χ^2 (chi-square) calculation (numbers in parenthesis are expected counts calculated based on the data distribution in the two categories)

$$\chi^2 = \frac{(250-90)^2}{90} + \frac{(50-210)^2}{210} + \frac{(200-360)^2}{360} + \frac{(1000-840)^2}{840} = 507.93$$

- The χ^2 statistic tests the hyp that A and B are independent. The test is based on a significance level , with (r-1)x(c-1)= (2-1)x(2-1)=1 degrees of freedom. For 1 degree of freedom, the χ^2 value needed to reject the hypothesis at 0.001 significance level is 10.828. Since 507.93>10.828, we can reject the hypothesis that like_science_fiction and play_chess are independent and conclude that they are strongly correlated for the given group of people.

Note : The values in parenthesis are computed this way :

$$90 = (300 * 450)/1500$$
$$210 = (300 * 1050)/1500$$
$$etc.$$

2.3.3 Correlation Analysis (Numerical Data)

In this case we use the **Correlation coefficient** also called the Pearson's product moment coefficient :

Let's assume p and q are the values taken for two distinct attributes by a population.

$$r_{p,q} = \frac{\sum(p-\bar{p})(q-\bar{q})}{(n-1)\sigma_p\sigma_q} = \frac{\sum(pq) - n\bar{p}\bar{q}}{(n-1)\sigma_p\sigma_q}$$

where

- *n* is the number of tuples,
- $\bar{p}$ and $\bar{q}$ are the respective means of p and q,
- σ_p and σ_q are the respective standard deviation of p and q,
- $\sum pq$ is the sum of the pq cross-product.

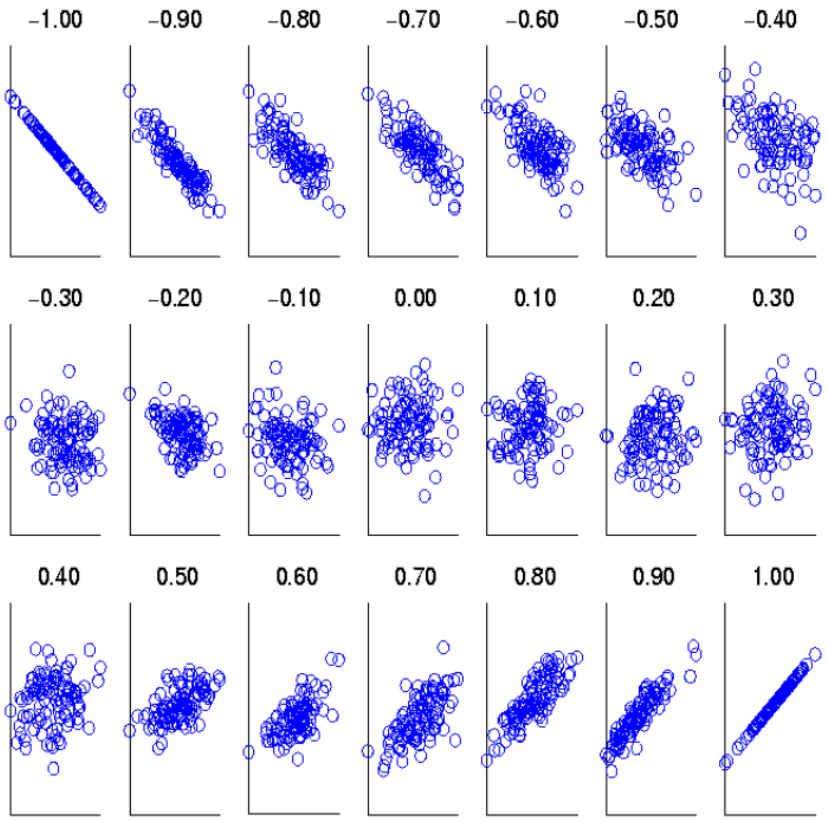
Principle :

- $r_{p,q} > 0 \rightarrow$ p and q are positively correlated (p's values increase as q's).
- $r_{p,q} = 0 \rightarrow$ independent;
- $r_{p,q} < 0 \rightarrow$ negatively correlated

Note : $1 \leq 1r_{p,q} \leq 1$

2.3.3.1 Visually Evaluating Correlation

This figures displays a scatter plots showing similarities from -1 to +1 :



2.3.3.2 Correlation viewed as a linear relationship

Correlation measures the linear relationship between objects. So to compute correlation, we can standardize data objects, p and q, and then take their dot product :

$$p'_k = (p_k - mean(p))/std(p)$$
$$q'_k = (q_k - mean(q))/std(q)$$
$$correlation(p, q) = p' \cdot q'$$

2.3.4 Covariance (Numeric Data)

Covariance is similar to correlation :

$$Cov(p, q) = E((p - \bar{p})(q - \bar{q})) = \frac{\sum_{i=1}^{n}(p_i - \bar{p})(q_i - \bar{q})}{n}$$
$$r_{p,q} = \frac{Cov(p, q)}{\sigma_p \sigma_q}$$

where

- *n* is the number of tuples,
- $\bar{p}$ and $\bar{q}$ are the respective means of p and q,
- σ_p and σ_q are the respective standard deviation of p and q,

Positive covariance:
if $Cov_{p,q} > 0$ then p and q both tend to be larger than their expected values

Negative covariance:
if $Cov_{p,q} < 0$ then if p is larger than its expected valuem q is likely to be small than its expected value

Independence: if p and q are independent then $Cov_{p,q} = 0$ (but the inverse is not necessarily true)

Some pairs of random variables may have a covariance of 0 but are not independent. Only under some additional assumptions (e.g., the data follow multivariate normal distributions) does a covariance of 0 imply independence

2.3.4.1 An example

$$Cov(A, B) = E((A - \bar{A})(B - \bar{B})) = \frac{\sum_{i=1}^{n}(a_i - \bar{A})(b_i - \bar{B})}{n}$$

This can be simplified in computation as

$$Cov(A, B) = E(A \cdot B) - \bar{A}\bar{B}$$

Suppose two stocks A and B have the following values in one week: (2, 5), (3, 8), (5, 10), (4, 11), (6, 14).

Question: If the stocks are affected by the same industry trends, will their prices rise or fall together?

- E(A) = (2 + 3 + 5 + 4 + 6)/ 5 = 20/5 = 4
- E(B) = (5 + 8 + 10 + 11 + 14) /5 = 48/5 = 9.6
- Cov(A,B) = (2x5 + 3x8 + 5x10 + 4x11 + 6x14)/5 - 4 x 9.6 = 4

Thus, A and B rise together since Cov(A, B) > 0.

2.4 Data Reduction

2.4.1 Data Reduction Strategies

Data reduction: Obtain a reduced representation of the data set that is much smaller in volume but yet produces the same (or almost the same) analytical results

Why data reduction? A database/data warehouse may store terabytes of data. Complex data analysis may take a very long time to run on the complete data set.

Data reduction strategies :

- Dimensionality reduction, e.g., remove unimportant attributes
  - Wavelet transforms
  - Principal Components Analysis (PCA)
  - Feature subset selection, feature creation
- Numerosity reduction (some simply call it: Data Reduction)
  - Regression and Log-Linear Models
  - Histograms, clustering, sampling
  - Data cube aggregation
- Data compression

2.4.2 Dimensionality Reduction

= Smoothing

Consists either of :

- reducing the amount of attributes or
- reducing the amount of values per attribute

Curse of dimensionality:

- When dimensionality increases, data becomes increasingly sparse
- Density and distance between points, which is critical to clustering, outlier analysis, becomes less meaningful
- The possible combinations of subspaces will grow exponentially

Dimensionality reduction:

- Avoid the curse of dimensionality
- Help eliminate irrelevant features and reduce noise
- Reduce time and space required in data mining
- Allow easier visualization

Dimensionality reduction techniques:

- Wavelet transforms
- Principal Component Analysis (PCA)
- Supervised and nonlinear techniques (e.g., feature selection)

2.4.2.1 What Is Wavelet Transform?

$\rightarrow$ Reduction of the amount of different values per attribute

Wavelet Transform decomposes a signal into different frequency subbands
→ Applicable to n-dimensional signals

- Data are transformed to preserve relative distance between objects at different levels of resolution
- Allow natural clusters to become more distinguishable
- Used for image compression

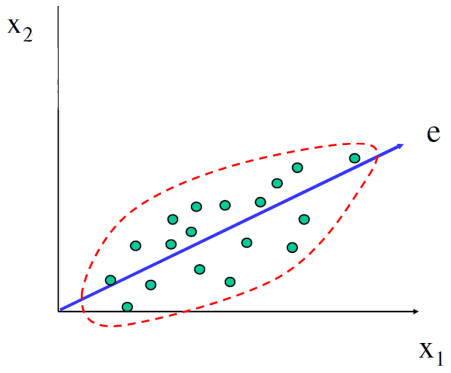
→ Only keep the most important values for a set of attributes (other values are changed to the closest most important value kept)

2.4.2.2 Principal Component Analysis (PCA)

→ Reduction of the amount of attributes

- Find a projection that captures the largest amount of variation in data
- The original data are projected onto a much smaller space, resulting in dimensionality reduction. We find the eigenvectors of the covariance matrix, and these eigenvectors define the new space.

→ Only the attributes that have the highest variance are kept ≡ the attributes that bring the most information.



2.4.2.3 Attribute Subset Selection

→ Reduction of the amount of attributes

Once we got a grasp on the main attributes, we might want to reduce them even further.

- Another way to reduce dimensionality of data

1. Redundant attributes
    - duplicate much or all of the information contained in one or more other attributes
    - E.g., purchase price of a product and the amount of sales tax paid

2. Irrelevant attributes
    - contain no information that is useful for the data mining task at hand
    - E.g., students' ID is often irrelevant to the task of predicting students' GPA

Heuristic search in Attribute Selection

There are 2^d possible attribute combinations of d attributes $\Rightarrow$ we can't take into consideration every possible combination $\Rightarrow$ We need an heuristic approach

Typical heuristic attribute selection methods:

- Best single attribute under the attribute independence assumption: choose by significance tests. Iterate :
- *Either* Best step-wise feature selection:
    - The best single-attribute is picked first
    - Then next best attribute condition to the first, ...
- *Or* Step-wise attribute elimination:
    - Repeatedly eliminate the worst attribute
- Best combined attribute selection and elimination

2.4.2.4 Attribute Creation (Feature generation)

$\rightarrow$ Create new attributes (features) that can capture the important information in a data set more effectively than the original ones

Three general methodologies :

- Attribute extraction $\rightarrow$ domain-specific
- Mapping data to new space (see: data reduction). E.g., Fourier transformation, wavelet transformation
- Attribute construction : Combining features / Data discretization.

2.4.3 Numerosity Reduction

Reduce data volume by choosing alternative, *smaller forms* of data representation.

Parametric methods (e.g., regression) :

- Assume the data fits some model, estimate model parameters, store only the parameters, and discard the data (except possible outliers)
- Example: Log-linear models—obtain value at a point in m-D space as the product on appropriate marginal subspaces

Non-parametric methods :

- Do not assume models

- Major families:
  - histograms,
  - clustering,
  - sampling

2.4.3.1 Parametric Data Reduction: Regression and Log-Linear Models

Linear regression: data modeled to fit a straight line

- Often uses the least-square method to fit the line

Multiple regression: allows a response variable Y to be modeled as a linear function of multi-dimensional feature vector

Log-linear model: approximates discrete multidimensional probability distributions

2.4.3.2 Regression analysis

Regression analysis: A collective name for techniques for the modeling and analysis of numerical data consisting of values of a dependent variable (also called response variable or measurement) and of one or more independent variables (explanatory variables or predictors)

The parameters are estimated so as to give a "best fit" of the data. Most commonly the best fit is evaluated by using the least squares method, but other criteria have also been used

$\rightarrow$ Used for prediction (including forecasting of time-series data), inference, hypothesis testing, and modeling of causal relationships

Log-linear models

Linear regression: $Y = wX + b$

- Two regression coefficients, w and b, specify the line and are to be estimated by using the data at hand
- Using the least squares criterion to the known values of Y1, Y2, ..., X1, X2, ...

Multiple regression: $Y = b0 + b1X1 + b2X2.$

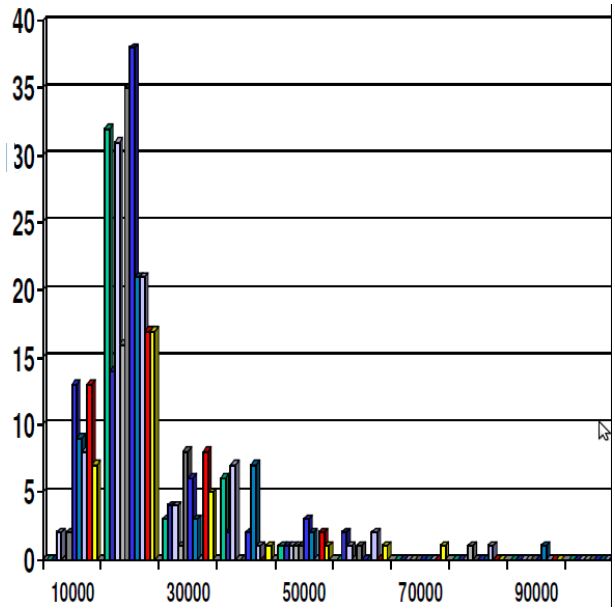
- Many nonlinear functions can be transformed into the above

2.4.3.3 Histogram analysis

$\rightarrow$ Divide data into buckets and store average (sum) for each bucket

Partitioning rules:

- Equal-width: equal bucket range
- Equal-frequency (or equal-depth)



→ See practice 2.6.4.1

2.4.3.4 Clustering

- Partition data set into clusters based on similarity, and store cluster representation (e.g., centroid and diameter) only
- Can have hierarchical clustering and be stored in multi-dimensional index tree structures
- There are many choices of clustering definitions and clustering algorithms

2.4.3.5 Sampling

- Sampling: obtaining a small sample s to represent the whole data set N
- Allow a mining algorithm to run in complexity that is potentially sub-linear to the size of the data
- Key principle: Choose a *representative* subset of the data
    - Simple random sampling may have very poor performance in the presence of skew
    - Develop adaptive sampling methods, e.g., stratified sampling.
- Note: Sampling may not reduce database I/Os

Note : What is skewed data?

In terms of SQL, Skewness is an asymmetry in the distribution of the data values or how the value is distributed accross.

Consider a table employees where you have millions of employee records and a column in that table which have either a value as 0 or 1 (F or T). Now consider out of one million records, the 1 value is applicable for only 2000 employees and the rest are having value as 0.

Types of Sampling

Simple random sampling

- There is an equal probability of selecting any particular item

Sampling without replacement

- Once an object is selected, it is removed from the population

Sampling with replacement

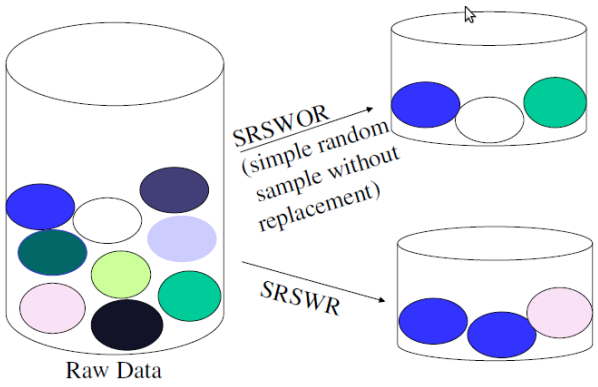
- A selected object is not removed from the population

Stratified sampling:

- Partition the data set, and draw samples from each partition (proportionally, i.e., approximately the same percentage of the data)
- Used in conjunction with skewed data

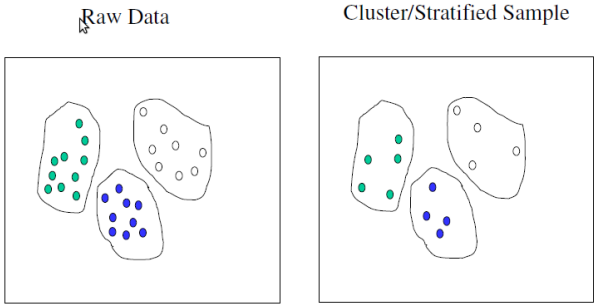
Sampling with or without Replacement

SRSWOR Sampling with or without Replacement
SRSWR Sampling with Replacement



Cluster or stratified Sampling

⇒ Try to pick same number of samples in each cluster-



2.4.3.6 Data Cube agregation

- The lowest level of a data cube (base cuboid)
  - The aggregated data for an individual entity of interest
  - E.g., a customer in a phone calling data warehouse
- Multiple levels of aggregation in data cubes
  - Further reduce the size of data to deal with
- Reference appropriate levels
  - Use the smallest representation which is enough to solve the task
- Queries regarding aggregated information should be answered using data cube, when possible

2.4.4 Data Compression

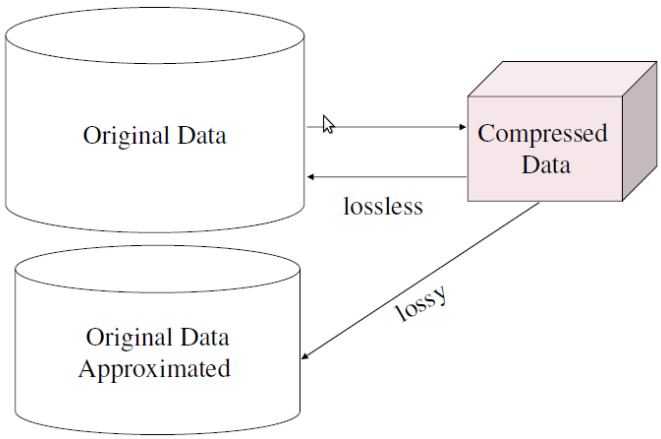
String compression:

- There are extensive theories and well-tuned algorithms
- Typically lossless
- But only limited manipulation is possible without expansion

Audio/video compression

- Typically lossy compression, with progressive refinement
- Sometimes small fragments of signal can be reconstructed without reconstructing the whole

Dimensionality and numerosity reduction may also be considered as forms of data



2.5 Data Transformation and data Discretization

2.5.1 Data Transformation

A function that maps the entire set of values of a given attribute to a new set of replacement values s.t. each old value can be identified with one of the new values

Methods :

Data Cleaning

- Smoothing: Remove noise from data

→ Seen in previous section 2.4.2

Data Reduction

- Attribute/feature construction → New attributes constructed from the given ones
- Aggregation: Summarization, data cube construction

→ Seen in previous section 2.4

Other transformations

- Normalization: Scaled to fall within a smaller, specified range
  - min-max normalization
  - z-score normalization
  - normalization by decimal scaling
- Discretization: Concept hierarchy climbing

2.5.1.1 Normalization

Min-max normalization: to $[new\_min_A, new\_max_A]$

$$\nu' = \frac{\nu - min_A}{max_A - min_A}(new\_max_A - new\_min_A) + new\_min_A$$

Ex. Let income range \$12,000 to \$98,000 normalized to [0.0, 1.0]. Then \$73,000 is mapped to

$$\frac{73600 - 12000}{98000 - 12000}(1.0 - 0.0) + 0.0)0.716$$

New range runs from new_min_A to new_max_A

Z-score normalization (μ: mean, σ: standard deviation):

$$\nu' = \frac{\nu - \mu_A}{\sigma_A}$$

Ex. Let μ = 54,000, σ = 16,000. Then

$$\frac{73600 - 54000}{16000} = 1.225$$

New range runs from $-\infty$ to ∞

Normalization by decimal scaling

$$\nu' = \frac{\nu}{10^j}$$

where j is the smallest integer such that $Max(|\nu'|) < 1$

Ex. Suppose that the recorded values of A range from -986 to 917. The maximum absolute value of A is 986. To normalize by decimal scaling, we therefore divide each value by 1,000 (i.e., j = 3) so that -986 normalizes to -0.986 and 917 normalizes to 0.917

New range runs from -1 to $+1$

2.5.2 Data Discretization

Three types of attributes :

- **Nominal - values** from an unordered set, e.g., color, profession
- **Ordinal - values** from an ordered set, e.g., military or academic rank
- **Numeric - values**: real numbers, e.g., integer or real numbers

Discretization: Divide the range of a continuous attribute into intervals

- Interval labels can then be used to replace actual data values
- Reduce data size by discretization
- Supervised vs. unsupervised
- Split (top-down) vs. merge (bottom-up)
- Discretization can be performed recursively on an attribute
- Prepare for further analysis, e.g., classification

2.5.2.1 Data Discretization Methods

Typical methods: All the methods can be applied recursively

- Binning : Top-down split, unsupervised (*Closed to what is done in data reduction but this time applied to attributes*)
- Histogram analysis : Top-down split, unsupervised
- Other Methods :
  - Clustering analysis (unsupervised, top-down split or bottom-up merge)
  - Decision-tree analysis (supervised, top-down split)
  - Correlation (e.g. χ^2) analysis (unsupervised, bottom-up merge)

2.5.2.2 Simple Discretization : Binning

Equal-width (distance) partitioning :

- Divides the range into N intervals of equal width (equals range size, uniform grid)
- if A and B are the lowest and highest values of the attribute, the width of intervals will be: $W = (B - A)/N$.
- The most straightforward, but outliers may dominate presentation
- Skewed data is not handled well

Equal-depth (frequency) partitioning

- Divides the range into N intervals, each containing approximately same number of samples
- Good data scaling
- Managing categorical attributes can be tricky

Examples :

Sorted data for price (in dollars): 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34

→ Partition into equal-frequency (equi-depth) bins:

- Bin 1: 4, 8, 9, 15
- Bin 2: 21, 21, 24, 25
- Bin 3: 26, 28, 29, 34

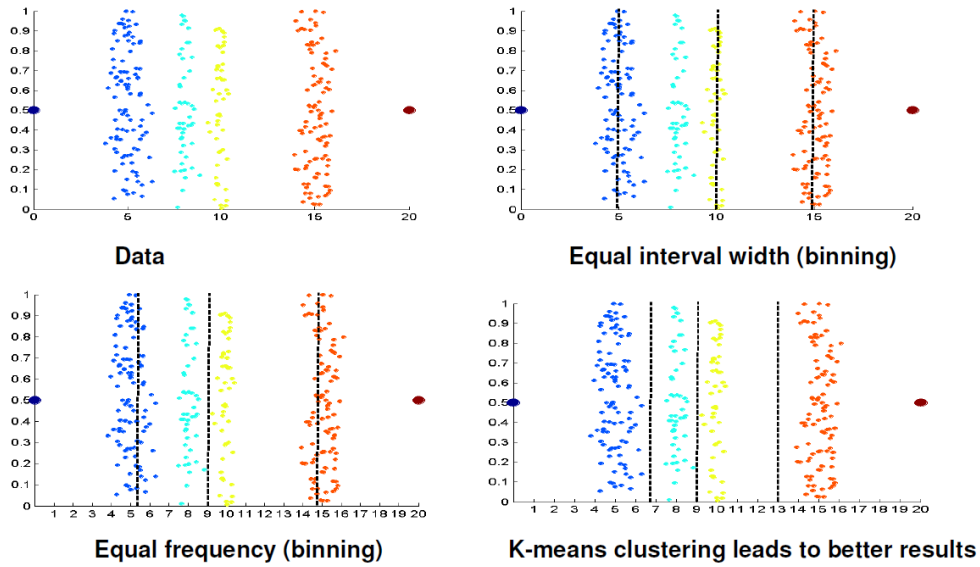
→ Smoothing by bin means:

- Bin 1: 9, 9, 9, 9
- Bin 2: 23, 23, 23, 23
- Bin 3: 29, 29, 29, 29

→ Smoothing by bin boundaries:

- Bin 1: 4, 4, 4, 15
- Bin 2: 21, 21, 25, 25
- Bin 3: 26, 26, 26, 34

2.5.2.3 Discretization without using Class Labels - Binning vs. Clustering



Here we see that the best is clearly the last image, i.e clustering is way better than binning in this case.

2.5.3 Concept Hierarchy Generation

- Concept hierarchy organizes concepts (i.e., attribute values) hierarchically and is usually associated with each dimension in a data warehouse
- Concept hierarchies facilitate drilling and rolling in data warehouses to view data in multiple granularity
- Concept hierarchy formation: Recursively reduce the data by collecting and replacing low level concepts (such as numeric values for age) by higher level concepts (such as youth, adult, or senior)
- Concept hierarchies can be explicitly specified by domain experts and/or data warehouse designers
- Concept hierarchy can be automatically formed for both numeric and nominal

2.5.3.1 Concept Hierarchy Generation for Nominal Data

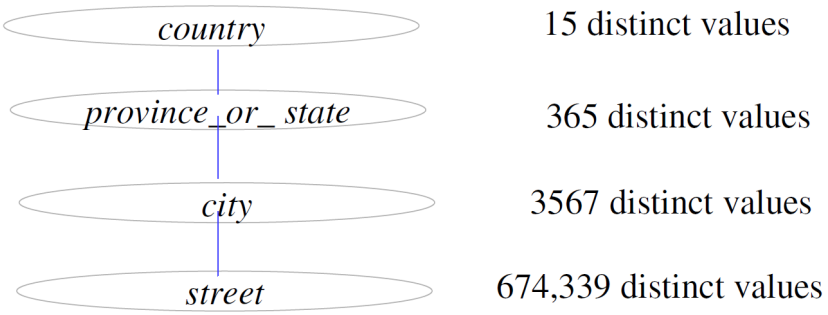
- Specification of a partial/total ordering of attributes explicitly at the schema level by users or experts
  $\rightarrow$ street < city < state < country
- Specification of a hierarchy for a set of values by explicit data grouping
  $\rightarrow$ Urbana, Champaign, Chicago < Illinois
- Specification of only a partial set of attributes
  $\rightarrow$ E.g., only street < city, not others

- Automatic generation of hierarchies (or attribute levels) by the analysis of the number of distinct values
  → E.g., for a set of attributes: street, city, state, country

2.5.3.2 Automatic Concept Hierarchy Generation

Some hierarchies can be automatically generated based on the analysis of the number of distinct values per attribute in the data set

- The attribute with the most distinct values is placed at the lowest level of the hierarchy
- Exceptions, e.g., weekday, month, quarter, year



2.6 Practice

2.6.1 Computation on Data

Suppose that the data for analysis includes the attribute age. The age values for the data tuples are (in increasing order) 13, 15, 16, 16, 19, 20, 20, 21, 22, 22, 25, 25, 25, 25, 30, 33, 33, 35, 35, 35, 35, 36, 40, 45, 46, 52, 70.

2.6.1.1 mean / median

What is the mean of the data ? What is the median?

Remainder :

- odd number of values : take middle values
- even number of values : take mean of both middle values

The (arithmetic) mean of the data is approx 30.
The median (middle value of the ordered set, as the number of values in the set is odd) of the data is: 25.

2.6.1.2 mode

What is the mode of the data? Comment on the data's modality (i.e., bimodal, trimodal, etc.).

Remainder :

1. find the value occuring at the highest frequency, count the very highest frequency
2. count the number of different values occuring at this very highest frequency

This data set has two values that occur with the same highest frequency and is, therefore, bimodal.
The modes (values occurring with the greatest frequency) of the data are 25 and 35.

2.6.1.3 midrange

What is the midrange of the data?

Remainder :

- The midrange is the average of the largest and smallest values in the data set

The midrange of the data is: $(70 + 13)/2 = 41.5$

2.6.1.4 quartile

Can you find (roughly) the first quartile (Q1) and the third quartile (Q3) of the data?

The first quartile (corresponding to the 25th percentile) of the data is: 20. The third quartile (corresponding to the 75th percentile) of the data is: 35.

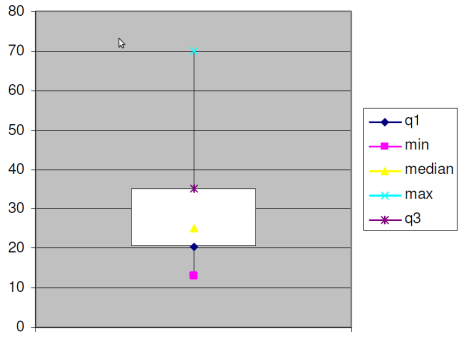
2.6.1.5 5-numbers summary

Give the five-number summary of the data (the minimum value, first quartile, median value, third quartile, and maximum value)

The five number summary of a distribution consists of the minimum value, first quartile, median value, third quartile, and maximum value. It provides a good summary of the shape of the distribution and for this data is: 13, 20, 25, 35, 70.

2.6.1.6 boxplot

Show a boxplot of the data.



2.6.2 Smoothing

Suppose that the data for analysis includes the attribute age. The age values for the data tuples are (in increasing order) 13, 15, 16, 16, 19, 20, 20, 21, 22, 22, 25, 25, 25, 25, 30, 33, 33, 35, 35, 35, 35, 36, 40, 45, 46, 52, 70.

2.6.2.1 Smoothing by bin means

Use smoothing by bin means to smooth the above data, using a bin depth of 3. Illustrate your steps.

The following steps are required to smooth the above data using smoothing by bin means with a bin depth of 3.

Step 1: Sort the data. (This step is not required here as the data are already sorted.)

Step 2: Partition the data into equal-frequency bins of size 3.

```
Bin 1: 13, 15, 16
Bin 2: 16, 19, 20
Bin 3: 20, 21, 22
Bin 4: 22, 25, 25
Bin 5: 25, 25, 30
Bin 6: 33, 33, 35
Bin 7: 35, 35, 35
Bin 8: 36, 40, 45
Bin 9: 46, 52, 70
```

Step 3: Calculate the arithmetic mean of each bin.

Replace each of the values in each bin by the arithmetic mean calculated for the bin.

```
Bin 1: 14.7 14.7 14.7
Bin 2: 18.33 18.33 18.33
```

```
Bin 3: 21, 21, 21
Bin 4: 24, 24, 24
Bin 5: 26.7 26.7 26.7
Bin 6: 33.7 33.7 33.7
Bin 7: 35, 35, 35
Bin 8: 40.3 40.3 40.3
Bin 9: 56, 56, 56
```

2.6.2.2 Outliers

How might you determine outliers in the data?

Outliers in the data may be detected by clustering, where similar values are organized into groups, or "clusters". Values that fall outside of the set of clusters may be considered outliers. Alternatively, a combination of computer and human inspection can be used where a predetermined data distribution is implemented to allow the computer to identify possible outliers. These possible outliers can then be verified by human inspection with much less effort than would be required to verify the entire initial data set.

2.6.2.3 Data smoothing

What other methods are there for data smoothing?

Other methods that can be used for data smoothing include alternate forms of binning such as smoothing by bin medians or smoothing by bin boundaries. Alternatively, equal-width bins can be used to implement any of the forms of binning, where the interval range of values in each bin is constant. Methods other than binning include using regression techniques to smooth the data by fitting it to a function such as through linear or multiple regression. Classification techniques can be used to implement concept hierarchies that can smooth the data by rolling-up lower level concepts to higher-level concepts.

2.6.3 Data Reduction and tranformation

Suppose a hospital tested the age and body fat data for 18 randomly selected adults with the following result:

age	23	23	27	27	39	41	47	49	50
%fat	9.5	26.5	7.8	17.8	31.4	25.9	27.4	27.2	31.2
age	52	54	54	56	57	58	58	60	61
%fat	34.6	42.5	28.8	33.4	30.2	34.1	32.9	41.2	35.7

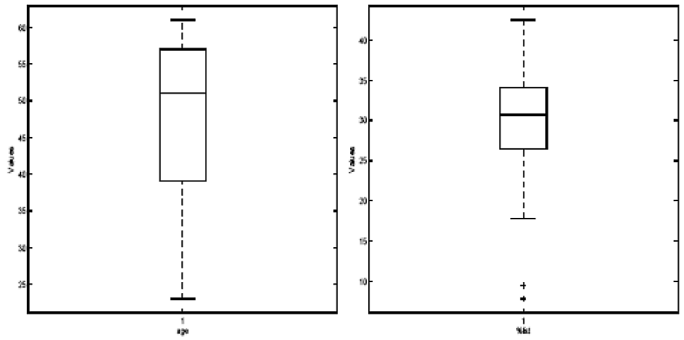
2.6.3.1 Computation on data

Calculate the mean, median and standard deviation of age and %fat.

For the variable age the mean is 46.44, the median is 51, and the standard deviation is 12.85. For the variable %fat the mean is 28.78, the median is 30.7, and the standard deviation is 8.99.

2.6.3.2 Boxplot

Draw the boxplots for age and %fat.



2.6.3.3 z-scores normalization

Normalize the two variables based on z-score normalization.

Remainder $Z_A = \frac{v_A - \mu_A}{\sigma_A}$

age	23	23	27	27	39	41	47	49	50
z-age	-1.83	-1.83	-1.51	-1.51	-0.58	-0.42	-0.04	0.20	0.28
%fat	9.5	26.5	7.8	17.8	31.4	25.9	27.4	27.2	31.2
z-fat	-2.14	-0.25	-2.33	-1.22	-0.29	-0.32	-0.15	-0.18	0.27
age	52	54	54	56	57	58	58	60	61
z-age	0.43	0.59	0.59	0.74	0.82	0.90	0.90	1.06	1.13
%fat	34.6	42.5	28.8	33.4	30.2	34.1	32.9	41.2	35.7
z-fat	0.65	1.53	0.0	0.51	0.16	0.59	0.56	1.38	0.77

2.6.3.4 Correlation coefficient

Calculate the correlation coefficient (Pearson's product moment coefficient). Are these two variables positively or negatively correlated?

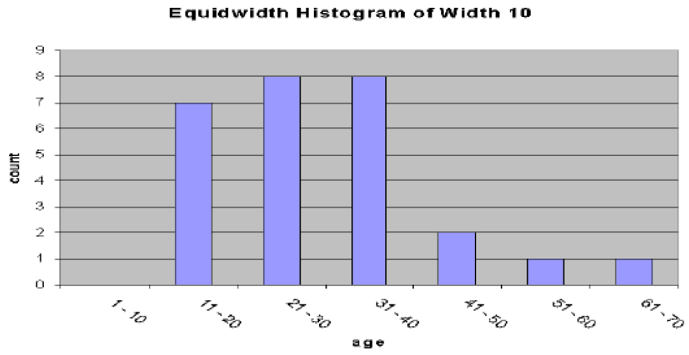
The correlation coefficient is 0.82. The variables are positively correlated.

2.6.4 Sampling

Suppose that the data for analysis includes the attribute age. The age values for the data tuples are (in increasing order) 13, 15, 16, 16, 19, 20, 20, 21, 22, 22, 25, 25, 25, 25, 30, 33, 33, 35, 35, 35, 35, 36, 40, 45, 46, 52, 70.

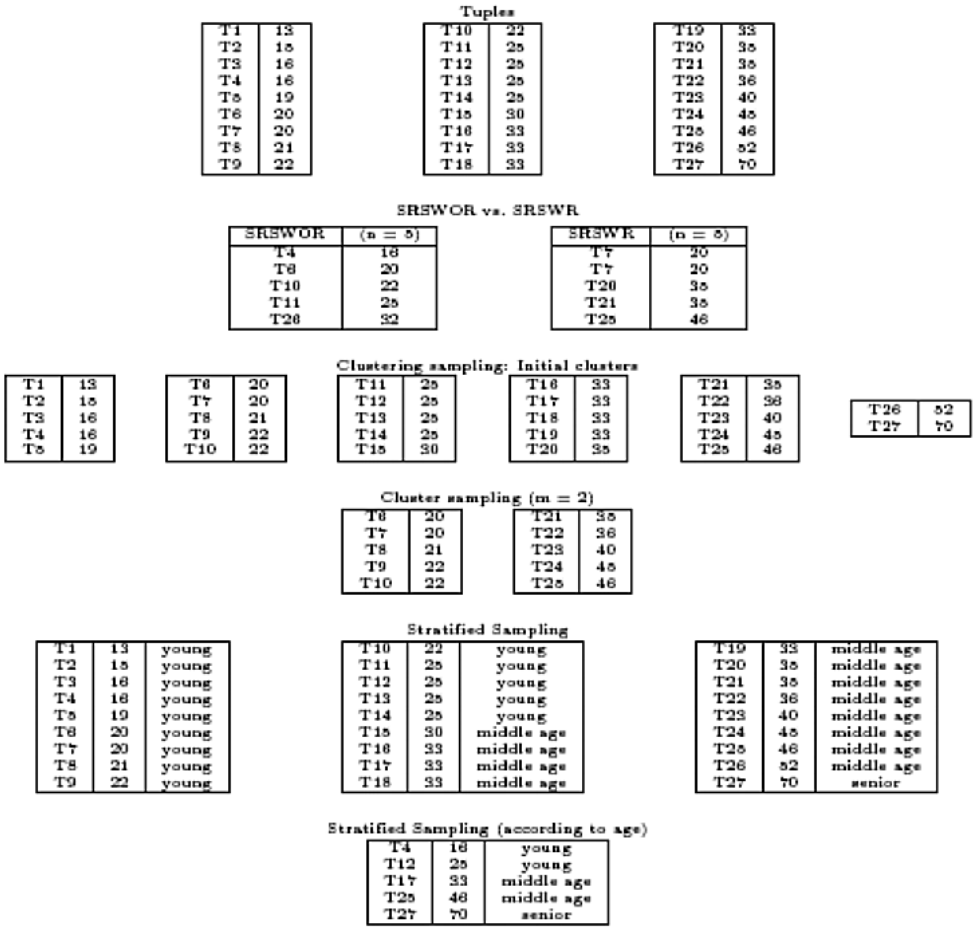
2.6.4.1 Equal-width histogram

Plot an equal-width histogram of width 10.



2.6.4.2 Sampling

Sketch examples of each of the following sampling techniques: SRSWOR, SRSWR, cluster sampling, stratified sampling.
Use samples of size 5 and the strata “young", “middle-age", and ”senior".


Tuples
T1 13
T2 15
T3 16
T4 16
T5 19
T6 20
T7 20
T8 21
T9 22
T10 22
T11 25
T12 25
T13 25
T14 25
T15 30
T16 33
T17 33
T18 33
T19 35
T20 35
T21 36
T22 36
T23 40
T24 45
T25 46
T26 52
T27 70
SRSWOR vs. SRSWR
SRSWOR (n = 5)
T4 16
T8 20
T10 22
T11 25
T26 32
SRSWR (n = 5)
T7 20
T7 20
T20 35
T21 36
T25 46
Clustering sampling: Initial clusters
T1 13
T2 15
T3 16
T4 16
T5 19
T6 20
T7 20
T8 21
T9 22
T10 22
T11 25
T12 25
T13 25
T14 25
T15 30
T16 33
T17 33
T18 33
T19 33
T20 35
T21 35
T22 36
T23 40
T24 45
T25 46
T26 52
T27 70
Cluster sampling (m = 2)
T6 20
T7 20
T8 21
T9 22
T10 22
T21 35
T22 36
T23 40
T24 45
T25 46
Stratified Sampling
T1 13 young
T2 15 young
T3 16 young
T4 16 young
T5 19 young
T8 20 young
T7 20 young
T8 21 young
T9 22 young
T10 22 young
T11 25 young
T12 25 young
T13 25 young
T14 25 young
T15 30 middle age
T16 33 middle age
T17 33 middle age
T18 33 middle age
T19 33 middle age
T20 35 middle age
T21 35 middle age
T22 36 middle age
T23 40 middle age
T24 45 middle age
T25 46 middle age
T26 52 middle age
T27 70 senior
Stratified Sampling (according to age)
T4 16 young
T12 25 young
T17 33 middle age
T25 46 middle age
T27 70 senior

CHAPTER 3

An introduction to Data Mining

Contents

3.1 Why Data Mining ?

The Explosive Growth of Data: from terabytes to petabytes

→ Data collection and availability :

- Automated data collection tools, database systems, Web, computerized society

→ Major sources of abundant data

- Business: Web, e-commerce, transactions, stocks, ...
- Science: Remote sensing, bioinformatics, scientific simulation, ...
- Society and everyone: news, digital cameras, YouTube

→ We are drowning in data, but starving for knowledge!

→ "Necessity is the mother of invention" → Data mining → Automated analysis of massive data sets

Raw data is useless: need techniques to automatically extract information from it

- Data: recorded facts
- Information: patterns underlying the data

3.1.1 Information is crucial

Example 1: in vitro fertilization

- Given: embryos described by 60 features
- Problem: selection of embryos that will survive
- Data: historical records of embryos and outcome

Example 2: cow culling

- Given: cows described by 700 features
- Problem: selection of cows that should be culled
- Data: historical records and farmer's decisions

3.2 What is Mining ?

Data mining (knowledge discovery from data) :

- Extraction of interesting (non-trivial, implicit, previously unknown and potentially useful) patterns or knowledge from huge amount of data
- Data mining: a misnomer?

Alternative names :

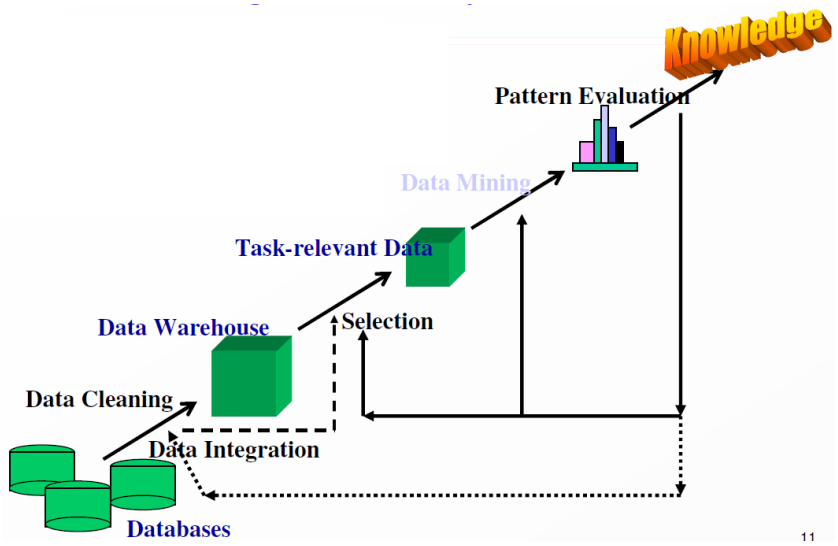
- Knowledge discovery (mining) in databases (KDD), knowledge extraction, data/pattern analysis, data archeology, data dredging, information harvesting, business intelligence, etc.

Watch out: Is everything "data mining"?

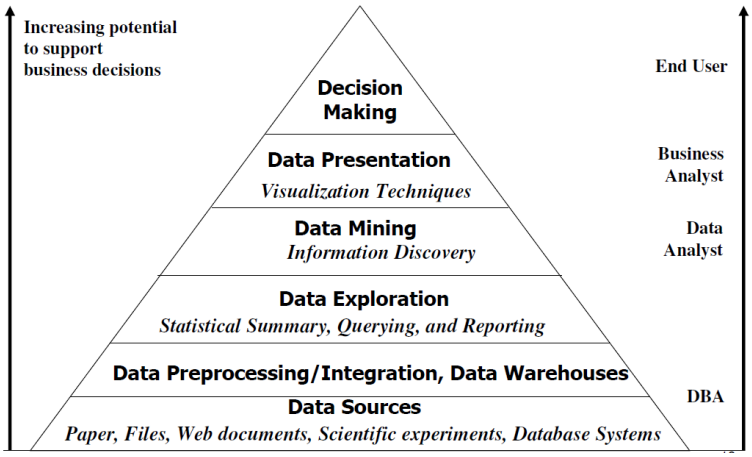
- Simple search and query processing
- (Deductive) expert systems

3.2.1 Knowledge Discovery (KDD) Process

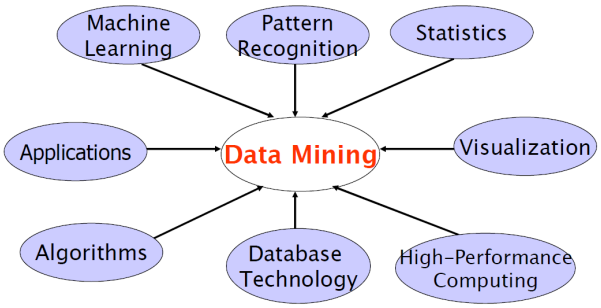
Below is a view from typical database systems and data warehousing communities.Data mining plays an essential role in the knowledge discovery process :



3.2.2 Data mining in Business Intelligence



3.2.3 Data mining : confluence of multiple disciplines



→ Tremendous amount of data :

- Algorithms must be highly scalable to handle such as terabytes of data

→ High-dimensionality of data :

- Micro-array may have tens of thousands of dimensions

→ High complexity of data :

- Data streams and sensor data
- Time-series data, temporal data, sequence data
- Structure data, graphs, social networks and multi-linked data
- Heterogeneous databases and legacy databases
- Spatial, spatiotemporal, multimedia, text and Web data
- Software programs, scientific simulations

→ New and sophisticated applications

3.3 Data mining functions

3.3.1 Generalization

→ Information integration and data warehouse construction :

- Data cleaning, transformation, integration, and multidimensional data model

→ Data cube technology :

- Scalable methods for computing (i.e., materializing) multidimensional aggregates
- OLAP (online analytical processing)

→ Multidimensional concept description: Characterization and discrimination :

- Generalize, summarize, and contrast data characteristics, e.g., dry vs. wet region

3.3.2 Association and Correlation Analysis

→ Frequent patterns (or frequent itemsets)

- What items are frequently purchased together in your Walmart?

→ Association, correlation vs. causality

- A typical association rule : Diaper → Beer [0.5%, 75%] (support, confidence)
- Are strongly associated items also strongly correlated?

→ How to mine such patterns and rules efficiently in large datasets?

→ How to use such patterns for classification, clustering, and other applications?

3.3.3 Classification

→ Classification and label prediction

- Construct models (functions) based on some training examples
- Describe and distinguish classes or concepts for future prediction. E.g., classify countries based on (climate), or classify cars based on (gas mileage)
- Predict some unknown class labels

→ Typical methods

- Decision trees, naïve Bayesian classification, support vector machines, neural networks, rule-based classification, pattern-based classification, logistic regression, ...

→ Typical applications:

- Credit card fraud detection, direct marketing, classifying stars, diseases, web-pages, ...

3.3.4 Cluster Analysis

- Unsupervised learning (i.e., Class label is unknown)
- Group data to form new categories (i.e., clusters), e.g., cluster houses to find distribution patterns
- Principle: Maximizing intra-class similarity & minimizing interclass similarity
- Many methods and applications

3.3.5 Outlier analysis

- Outlier: A data object that does not comply with the general behavior of the data
- Noise or exception? - One person's garbage could be another person's treasure
- Methods: by product of clustering or regression analysis, ...
- Useful in fraud detection, rare events analysis

3.4 Evaluation of Knowledge

Are all mined knowledge interesting?

- One can mine tremendous amount of "patterns" and knowledge
- Some may fit only certain dimension space (time, location, ...)
- Some may not be representative, may be transient, ...

Evaluation of mined knowledge → directly mine only interesting knowledge?

- Descriptive vs. predictive
- Coverage
- Typicality vs. novelty

- Accuracy
- Timeliness

3.5 Practice

Define the data mining tasks and give an example for each of them:

Generalization:

Generalization consists of data cleaning, transformation, integration, aggregation and/or summarization.

For instance one might want to replace the age attribute of some data by a category such as young, middle aged or old.

Association and Correlation Analysis:

This is typically finding association between data enabling one to deduce rules such as "if one buys beer then he watches footbal on TV" or find closely related attributes sur as *play_chess* and *read_books*.

Classification:

Classification is about constructing models or distinguishing classes or concepts for future prediction.

For instance one might want to classify countries based on (climate), or classify cars based on (gas mileage)

Cluster Analysis:

Cluster analysis is about building clusters to form categories or for data reduction.

For instance one might want to cluster houses to find distribution patterns.

Outlier analysis:

Outlier analysis is about finding objects that does not comply with the general behavior of the data. It is for instance used in fraud detection or rare event analysis.

CHAPTER 4

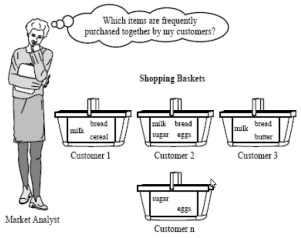
Market Basket Analysis

Contents

4.1 Motivation

Example :

- Where to place laundry products in order to optimize sales?
- Does one also buy butter when on buys milk?
- Is sugar likely to be also sold when one buys bread and milk at the same time?



→ Sales information : who ? what ? why ?

- Most sales organisms encounter decision-making tool.
- Bar code technologies enables sales organisms to collect huge and massive amount of sales data "market basket data".
- Those organisms are interested in analyzing those data to extract informations aimed at helping marketing to develop and apply commercial programs and strategies adapted to the client needs.

4.2 Market Basket Analysis : MBA

MBA is a technic enabling to find the list of articles having a tendency to be sold together upon a client transaction.

- The transaction data is available
- The groups of articles we are looking for are unknown before the analysis
- → Undirected Data-Mining

We try to build a model built on conditional rules :

- **If** condition **then** result
- Several conditions can be combined to obtain the result : **If** A **and** B **then** C
- Several logical operators can be combined : **If** A **and not** B **then** C

4.2.1 Usefulness of MBA

MBA's result is a set of association rules :

useful and clear rules :

- Association rule : simple rules : " **If** condition **then** result "
  Ex : if a client buys butter, the he buys milk too.
  Ex : if a client buys milk and salt, the he buys cheese too.

useful rules lead to actions, practice

- Ex. Useful rule " If today is thursday, then I should buy disposable diapers and beer "

Useless rules :

- Ex: trivial rule « If one buys a car, then he signs up a car insurance. "
- Ex: ununderstandable rule « If one opens a shop, the he buys paper. "

MBA applies to sales, banks, insurances, telecoms, medical, etc. MBA is an ideal starting point to test hypothesis.

MBA is often used to compare shops :

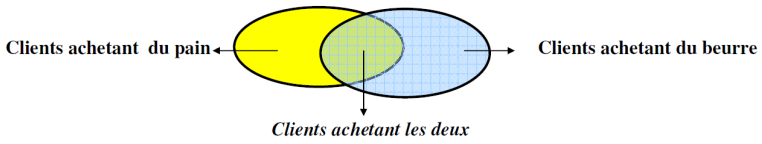
- management efficiency
- sales tendencies by region, cities, periods, etc.
- demographic rules

By extending the data with *virtual articles*, many Data mining taks can be achieved through market basket analysis.

4.3 Association rule

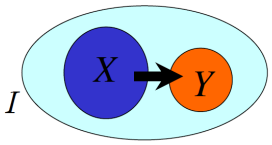
4.3.1 Formalisation of the problem

- Input data :
  - A set of articles I = { i_1, i_2, ..-, i_m }
  - A set of transactions D, each transaction T_j from D is a subset of I.
  - Simple example :
    - I = { Bread, Milk, Butter, Sugar } = {i_1, i_2, i_3, i_4}
    - D = { T_1, T_2, T_3, T_4, T_5 }
    - T_1 = { Bread, Milk, Butter }
    - T_2 = { Bread, Milk, Sugar }
    - T_3 = { Bread }
    - T_4 = { Bread, Milk }
    - T_5 = { Bread, Milk, Butter, Sugar }
- Searched patterns
  - Interesting association rules in the form $X \Rightarrow Y$ where X and Y are subsets of I
    - Butter $\Rightarrow$ Milk
    - Milk$\Rightarrow$ Butter
    - Bread, Milk $\Rightarrow$ Butter
- The whole question now is : what is an *interesting* association rule ?



4.3.2 Association rule - definition

- Let I be a a set of articles
- Let D be a set of transactions, each transaction T_j is a set of articles from I
- An association rule is an implication of the form $X \Rightarrow Y$ where $X \subset I$ and $Y \subset I$ and $X \cap Y = \emptyset$



4.3.3 Example

This is the example we will be focusing on in the rest of this document

I = { Bread, Milk, Butter, Sugar }

Tran. ID	Articles list
T_1	Bread, Milk, Butter
T_2	Bread, Milk, Sugar
T_3	Bread
T_4	Bread, Milk
T_5	Bread, Milk, Butter, Sugar

4.3.4 Measure of the *Support*

Definition : The support of the association rule $X \Rightarrow Y$ in the base D represents the ratio between the number of transactions in the base D where both X and Y appear and the total number of number transactions.

$Sup(X \Rightarrow Y, D) = |\{T \in D, T \supset X \cup Y\}|/|D| = P(X \cup Y)$

Notation issue : Sup($X \Rightarrow Y$) is sometimes noted Sup(X,Y) and Sup ($X, Y \Rightarrow Z$) is sometimes noted Sup(X,Y,Z) in the rest of this document.

Example (using example 4.3.3) :

- Sup(Bread, Milk) = 4 / 5 = 0.8 = 80%

- Sup(Bread, Milk, Sugar) = 2 / 5 = 0.4 = 40%

Note: We also speak of support when considerating a single article: Sup(Milk) = 4 / 5 = 0.8 = 80%

4.3.5 Measure of the *Confidence*

Definition : The confidence of the association rule $X \Rightarrow Y$ in the base D represents the ratio between the number of transactions in the base D where both X and Y appear and the number of number transactions where only X appear.

$Conf(X \Rightarrow Y, D) = Sup(X \Rightarrow Y, D)/Sup(X, D) = P(Y|X)$
(where D is the set of transactions)

Other notation (without any mention to D the set of transactions)

$Conf(X, Y \Rightarrow Z) = Sup(X, Y, Z)/Sup(X, Y) = P(Z|(XandY))$

Example (using example 4.3.3) :

- Conf(Bread $\Rightarrow$ Milk) = 4 / 5 = 0.8 = 80%
- Conf(Bread, Milk $\Rightarrow$ Suggar) = 2 / 4 = 0.5 = 50%

4.3.6 Support and confidence

- support (X $\Rightarrow$ Y) = P (X and Y) = support (Y $\Rightarrow$ X)
  - Note : however we will always consider lexicographical order. Hence we have to sort the article set, transactions, etc.
- confidence (X $\Rightarrow$ Y) = P (Y | X) = P (X and Y) / P (X)
- support and confidence represent propabilities
- sup, conf $\in$ [0, 1]

4.3.7 *Interesting* rules

Definition : Given two threshold values fixed a priori by some user :

- a minimal *support* threshold value *"minsup"* and
- a minimal *confidence* threshold value *"minconf"* and

A rule $X \Rightarrow Y$ is **interesting** within D if *and only if*

- Sup(X $\Rightarrow$ Y, D) $\geq$ minsup
- Conf(X $\Rightarrow$ Y, D) $\geq$ minconf

The whole purpose of *Market Basket Analysis* is to spot out every interesting rule given the two threshold values "minsup" and "minconf".

Example (using example 4.3.3) :

Let's assume minsup = 2/5 and minconf = 3/4.

- {Milk, Butter, Sugar ⇒ Bread}: not interesting
  → Conf = 1 / 1 ≥ minconf but Sup = 1 / 5 < minsup
- {Bread, Milk ⇒ Butter}: not interesting → Sup = 2 / 5 ≥ minsup but Conf = 2 / 4 < minconf
- {Milk, Butter ⇒ Bread}: interesting → Sup = 2 / 5 ≥ minsup and Conf = 2 / 2 ≥ minconf

4.3.8 Lift

Definition : The lift (interest, amelioration, correlation) of the rule { condition ⇒ result } is defined by the ratio between the confidence of the rule and the support of the result.

$Lift(condition \Rightarrow result) = Conf(condition\ and\ result)/Sup(result)$
$Lift(condition \Rightarrow result) = P(condition\ and\ result)/(P(condition) * P(result))$

- If the the *lift* is > 1, then the rule *"condition ⇒ result"* is better for the prediction than simply guessing the result.
- If the the *lift* is ≤ 1, then guessing the result is simply better.
- Note: *If* P(condition and result) = P(condition) * P(result) *Then* (⇒) condition and result are independent.

Example :

Let A, B, C be three articles :

- P(A)=45% =Sup(A)
- P(B)=42.5% =Sup(B)
- P(C)=40 =Sup(C)
- P(A and B)=25% =Sup(A and B)
- P(A and C)=20% =Sup(A and C)
- P(B and C)=15% =Sup(B and C)
- P(A and B and C)=5% =Sup(A and B and C)

Rule	**P(cond.)**	**P(cond. and res.)**	**P(res.)**	**Confidence**	**lift**
Computat.	*(given)*	*P(A and B and C)*	*(given)*	*P(cond. and res.) / P(cond)*	*P(cond. and res.) /(P(cnd.)*P(res))*
A,B ⇒ C	0.25	0.05	0.4	0.05 / 0.25 = 0.2	0.05 / (0.25 * 0.4)
A,C ⇒ B	0.2	0.05	0.425	0.05 / 0.2 = 0.25	0.05 / (0.2 * 0.425)
B,C ⇒ A	0.15	0.05	0.45	0.05 / 0.15 = 0.33	0.05 / (0.15 * 0.44)

4.3.9 Dissociation rules

A dissociation rule is quite similar to an association rule except it can contain the *not* operator :

If A and not B then C

They are generated using exactly the same algorithm. For this to work, a new set of articles is added to the article set.

A, B, C $\rightarrow$ *not-A, not-B, not-C*

Problems :

- The number of article doubles, so the performance decreases
- the frequency of the *not-X* tends to be much higher than the frequency of the usual articles $\rightarrow$ If not-A and not-B then not-C (pretty much useless)

4.3.10 The co-events table

It is sometimes useful to put events in a table in order to compute in one singe place the support and / or confidence for ever possible rule

2D table : column gives X , row gives X - type in each cell conf(X$\Rightarrow$Y) and use the array in conjuction with a minimum confidence to decide which rules are worth investigating.

Can be generalized in the very same principle to nD tables (n dimensions).

4.4 MBA : The base process

1. Choose the right set of article
2. Create rules by using the co-events table
3. Lower complexity by using tresholds values (i.e. everything below is not taken into account).

4.4.1 Choose the right set of article

We have the details of transaction and hierarchies. So we can :

agregate : { red apple, green apple, yellow apple } = {apple}

generalize :

- for instance by using *taxonomies*
- Caution: choose the "right" level of generalization.

4.4.2 Anonymity $\leftrightarrow$ nominated

Client transaction are anonym in general.

However the usage of credit cards or fidelity cards enables the sales departement to know about clients, their habits, etc. This enables the tracking ot the various kinds of behaviours across time.

4.4.3 Notation / Vocabulary

- A set of articles is called an itemset
- a set of k articles is called a k-itemset
- a k-itemset which satisfies the minsup (minimal support) criteria is called a frequent k-itemset

4.5 Rule extraction algorithm

The rule extraction algorithm is called Apriori. It consists of two principal phases :

1. Computation of all frequent article sub-sets X
   $\rightarrow$ Search of all the frequent sub-sets X of I, i.e those respecting Sup (X , D) $\geq$ minsup
2. Computation of all the interesting association rules (X - Y $\Rightarrow$ Y)
   Note : X and Y are article sets. Hence a rule of the form (X - Y $\Rightarrow$ Y), if X = {A, B, C} and Y = {C} is a well know association rule form : (A,B $\Rightarrow$ C)
   $\rightarrow$ A partir des sous-ensembles X fréquents déterminés lors de la première phase, calculer toutes les règles de confiances suffisantes, c.a.d. les règles d'association telles que Conf(X -Y $\Rightarrow$ Y / D) $\geq$ minconf

Note :

X - Y $\Rightarrow$ Y can be noted X / Y $\Rightarrow$ Y, it's exactly the same. The two notations are equivalent.

4.5.1 First phase : Compute frequent article subsets

Base principle :

- Base on the support computation fundamental property : If X $\subseteq$ Y, then Sup(X , D) $\geq$ Sup(Y , D) for all D
- Any subset of a frequent itsemset is frequent
- any sur-set of a non-frequent itemset is not frequent

Ascending search of frequent itsemsets :

- Stage 1 : compute frequent 1-itemsets = frequent subsets of I containing only 1 article
- Stage k : compute frequent k-itemsets from the (k-1)-itemsets = frequent subsets of I containing only k articles

4.5.1.1 The *Apriori* algorithm (1st phase)

- **Input** :
  - A set D of transactions T_i
  - minsup
- **Output** :
  - A set L of all frequent itemsets
- **Method** :
  - Compute the set L(1) of frequent 1-itemsets
  - Let K = 2
  - While L(K-1) is not empty (L(K-1) = result from the previous iteration)
    - // Stage 1.a : candidates generation
      Compute the set C(K) of the K-itemsets candidate from L(K-1) (see below)
    - // Stage 1.b : candidates evaluation
      $\rightarrow$ Compute the support for each candidate C in C(K)
      $\rightarrow$ Let L(K) be the set of candidates C from C(K) such that Sup(C,D) $\geq$ minsup. L(K) is the set of all frequent K-itemsets.
    - K = K + 1

candidates generation :

- **Input** :
  - A set L(K-1) of the frequent (K-1)-itemsets
- **Output** :
  - A set C(K) of the K-itemsets candidates
- **Method** :
  - (join or composition phase)
    Built C(K) the set of K-itemsets C :
    - C = F1 $\cup$ F2 where F1 and F2 are elements of L(K-1)
    - F1 $\cap$ F2 contains K-2 elements
  - (pruning phase [FR : élagage])
    Remove from C(K) any candidate C if there is
    - a subset of C of (K-1) elements not present in L(K-1)
  - Return C(K)

Note : the candidate generation occurs in memory without accessing the data.

candidates evaluation :

- **Input** :
  - A set C(K) of the candidates K-itemsets
  - The set of transactions D
  - minsup
- **Output** :

- A set L(K) of the frequent K-itemsets

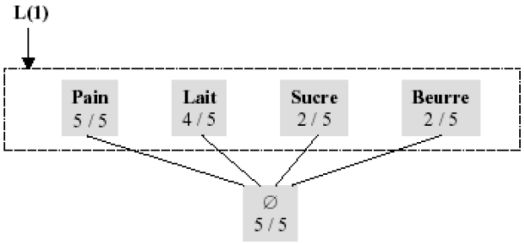
- **Method** :
  - Initialize L(K) to the empty set
  - Count the number of occurence of every candidate of C(K) in D
    For every candidate of C(K),
    - For every transaction T_i of D : if C is included in T_i, then C.Sup += 1
    - id C.Sup $\geq$ minsup, then add C to L(K)
  - Return L(K)

Note : the evaluation of the candidates occurs in one single pass on the data.

4.5.1.2 Example

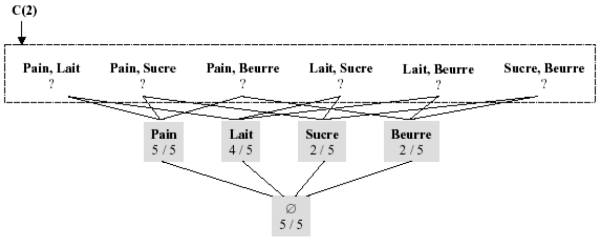
Computation of L(1)

- T1 = { Pain, Lait, Beurre },
- T2 = { Pain, Lait, Sucre },
- T3 = { Pain },
- T4 = { Pain, Lait }
- T5 = { Pain, Lait, Beurre, Sucre }
- Minsup = 2/5



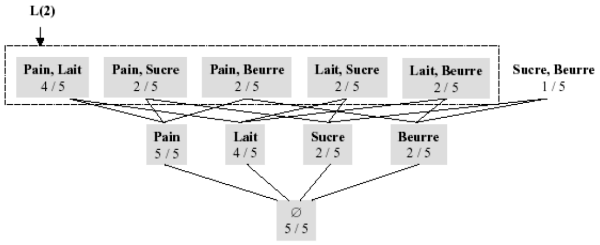
Generation of C(2)

- Composition of the L(1) elements : two-by-two union
- Pruning of the candidates : none at this level



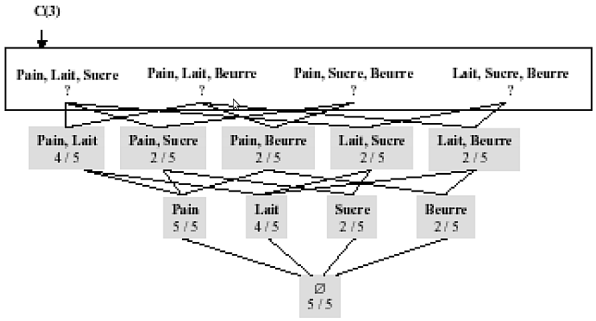
Evaluation of C(2)

The computation of L(2) occurs in one single pass on the data.

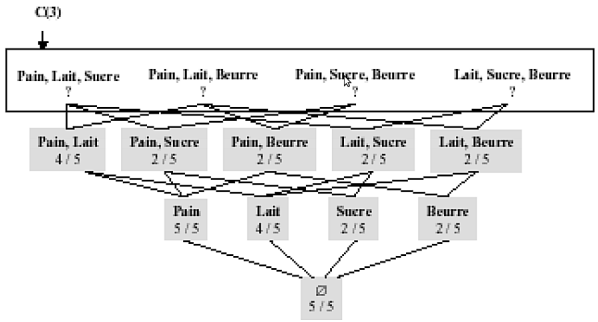


Generation of C(3)

The composition of the elements from C(3) happens by composing withthe elements from L(2). Only the itemsets having the same *first elements* are combined



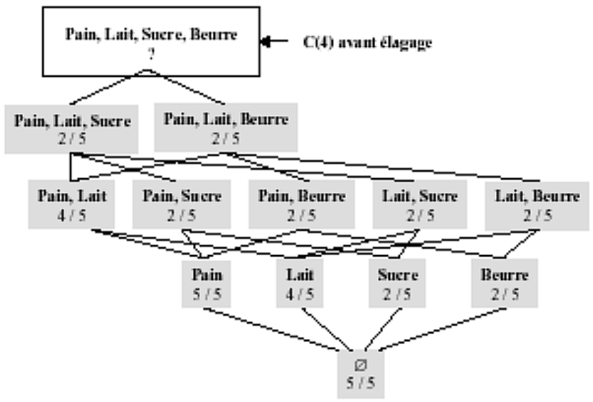
Pruning the elements from C(3) : The candidates {Bread, Sugar, Butter} and {Milk, Sugar, Butter } are removed from C3 as {Sugar, Butter} is not present in L(2) :



Evaluation of C(3) : straightforward

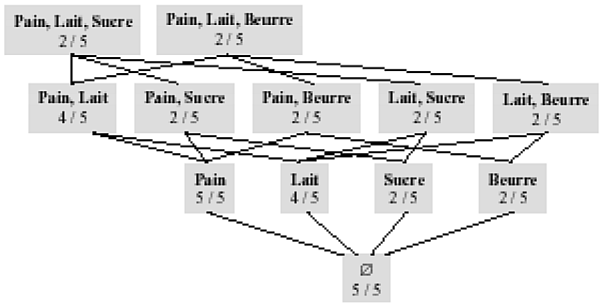
Generation of C(4)

Composition des éléments de L(3) :



Pruning the elements from C(4) : {Bread, Milk, Sugar, Butter} is removed as {Milk, Sugar, Butter} is not present in L(3). C(4) is hence empty and so is L(4)

End of the frequent itemset calculation :



4.5.2 Constraints

- Every transaction T should be sorted by ascending order (lexicographical order or anything else)
- Every set L(k) should be sorted in ascending order.
- Every frequentr k-itsemset should be sorted in ascending order.

4.5.2.1 Another exemple - starting from level 3

- Let L(3) = { {1, 2, 3}, {1, 2, 4}, {1, 3, 4}, {1, 3, 5}, {2, 3, 4} }
- The join phase for C(4) :
  - {1, 2, 3} is joined to {1, 2, 4} to produce {1, 2, 3, 4}
  - {1, 3, 4} is joined to {1, 3, 5} to produce {1, 3, 4, 5}
  - After the join, C4 ={{1, 2, 3, 4}, {1, 3, 4, 5}}
- In the pruning stage :
  - For {1, 2, 3, 4} one should test the existence within L(3) of every 3-itemset, so {1, 2,3}; {1, 2, 4}; {1, 3, 4}; {2, 3, 4} $\Rightarrow$ OK

    - For {1, 3, 4, 5} one tests {1, 3, 4}; {1, 3, 5}; {1, 4, 5}; {3, 4, 5}; As {1, 4, 5} is not found in L3, {1, 3, 4, 5} is pruned
- Only {1, 2, 3, 4} stays in C4
- The one still needs to compute the support and get rid of the 4-itemsets with a support below *minsup* to build L(4)

4.5.3 Second phase : Compute interesting rules

4.5.3.1 The principle (naive method)

- For every k-itemset X frequent (with K > 1)
    - For every possible Y $\subset$ X
        - Compute the confidence in the rule X - Y $\Rightarrow$ Y
        - If that confidence is greater than minconf, then the generated association rule is interesting.

In other words :

- For every frequent itemset l, we find every subset of l different from the empty set.
- For each of these subsets *a*, we generate the rule *a* $\Rightarrow$ (*l* - *a*) if the ratio between the support of *l* and the support of *a* is at least as big as minconf.

Note this phase doesn't require any access to the data.

4.5.3.2 Example

Looking back at the 4.5.1.2 for the stage 1 of apriori shown before, when using minconf = 3 / 4 and X = {Bread, Milk, Butter} is frequent :

- { Bread, Milk => Butter } not interesting because Conf = 2 / 4
- { Bread, Butter => Milk } interesting because Conf = 2 / 2
- { Milk, Butter => Bread } interesting because Conf = 2 / 2
- { Bread => Milk, Butter } not interesting because Conf = 2 / 5
- { Milk => Bread, Butter } not interesting because Conf = 2 / 4
- { Butter => Bread, Milk } not interesting because Conf = 2 / 4

4.5.3.3 Optimize-it

- We can quite effectively optimize the procedure by generating the subsets of a frequent itemset in a recursive fashion.
- For instance, for a given itemset {A,B,C,D}, we will first consider the subset {A,B,C}, then {A,B}, etc.
- Whenever a subset *a* of a frequent itemset l doesn't generate any valable rule, the subsets of *a* are not considered to generate rule from *l*.

- For instance if {A,B,C} $\Rightarrow$ D doesn't have a sufficient confidence, one doesn't need to control whether {A,B} $\Rightarrow$ {C,D} is valable

A typical implementation for this consists of using a HashTree. The lecture support provides an extended discussion on this implementation but this resume won't dig it any further.

4.6 Partitionning

The principle :

- Divide the set of transactions in a list of subsets : D_1, D_2, ...,D_p
- Apply apriori to each subset of the transactions
- Every frequent itemset must be frequent in at least *one* subset of the transactions

4.6.1 Algorithm

- Divide D in D_1, D_2, ..., D_p;
- For i = 1 to p do
    - L_i = Apriori (D_i);
- C = $L_1 \cup ... \cup L_p$;
- To Generate L, evaludate candidates on D;

Advantages :

- Adapts to the available amount of memory
- easily parallelizable
- the amount of scans of D is 2

Drawbacks :

- Might have a lof of condidates to analyze in phase 2

4.7 Conclusion

Perspectives:

- One might want to use other measures of interest that support and confidence $\rightarrow$ Conviction, implication strength, etc.

Generalization of the association rules

- Taking numerical data into consideration
- Taking hierarchies of attribute into consideration
- Taking several tables into consideration
- etc.

4.8 Practice

4.8.1 support and confidence

The Apriori algorithm uses prior knowledge of subset support properties.

4.8.1.1 support

Prove that all nonempty subsets of a frequent itemset must also be frequent:

- Let *s* be a frequent itemset
- Let *s'* be a subset of s
- Let *minsup* be the minimum support
- Let D be the set of database transaction (relevant data) and $|D|$ the number of transactions in D

Let's assume that it's not the case :

$$s\ is\ frequent \Rightarrow sup(s) \geq minsup$$
$$where\ sup(s) = \frac{count(s)\ in\ D}{|D|}$$
$$s\ is\ frequent \Rightarrow count(s)\ in\ D \geq minsup * |D|$$

But :

$$s'\ is\ NOT\ frequent \Rightarrow sup(s') < minsup$$
$$where\ sup(s') = \frac{count(s')\ in\ D}{|D|}$$
$$s'\ is\ NOT\ frequent \Rightarrow count(s')\ in\ D < minsup * |D|$$

Which implies :

$$count(s')\ in\ D < count(s)\ in\ D$$

which is impossible because s' is a subset of s (set theory).

Which confirms the initial statement.

Prove that the support of any nonempty subset s' of itemset s must be at least as great as the support of s:

- Let *s* be a frequent itemset
- Let *s'* be a subset of s
- Let *minsup* be the minimum support
- Let D be the set of database transaction (relevant data) and $|D|$ the number of transactions in D

Let's assume that it's not the case :

$$\begin{aligned} & sup(s') < sup(s) \\ \Rightarrow & \frac{count(s') \ in \ D}{|D|} < \frac{count(s) \ in \ D}{|D|} \\ \Rightarrow & count(s') \ in \ D < count(s) \ in \ D \end{aligned}$$

which is impossible because s' is a subset of s (set theory).

Which confirms the initial statement.

4.8.1.2 confidence

Given frequent itemset l and subset s of l, prove that the confidence of the rule " s' $\Rightarrow$ l - s' " cannot be more than the confidence of " s $\Rightarrow$ l - s ", where s' is a subset of s.

- Let *s* be a subset of l. then $conf(s \Rightarrow (l - s) = \frac{sup(l)}{sup(s)}$
- Let *s'* be a non-empty subset of s. then $conf(s' \Rightarrow (l - s') = \frac{sup(l)}{sup(s')}$

We know from the prevous exercise that

$$s' \subset s \Rightarrow sup(s') \geq sup(s)$$

From this we can derive :

$$\begin{aligned} & sup(s') \geq sup(s) \\ \Rightarrow & \frac{1}{sup(s')} \leq \frac{1}{sup(s)} \\ \Rightarrow & \frac{sup(l)}{sup(s')} \leq \frac{sup(l)}{sup(s)} \\ \Rightarrow & conf(s') \leq conf(s) \end{aligned}$$

Which confirms the initial statement.

This property is essential as it is at the very root of the optimisation we can bring on the phase 2 of the a priori algoruthm (genRules): we do not need to follow the recursion on a rule that is not interesting.

4.8.1.3 Partitioning

A partitioning variation of Apriori subdivides the transactions of a database D into n nonoverlapping partitions. Prove that any itemset that is frequent in D must be frequent in at least one partition of D.

Proof by contradiction : Let's assume that the itemset is not frequent in any of the partition of D.

- Let F be any frequent itemset
- Let D be the task relevant data - the set of transactions
- Let C=|D| be the total number of transactions in D
- Let A be the number of transactions in D containing the itemset F
- Let minsup be the minimum support

$$F\ frequent \Rightarrow A > C * minsup$$

Let us partition D into *n* non overlapping partitions d_1, d_2, ..., d_n such that D = d_1 + d_2 + ... + d_n.

Let us define c_i as the total number of partition in d_i and a_i the number of partition in d_i containing F.

We can write

$$A > C * minsup$$
$$as\ (a_1 + a_2 + ... + a_n) > (c_1 + c_2 + ... + c_n) * minsup$$

if F is not frequent in any of the subpartition, we can assume :

$$a_1 < c_1 * minsup$$
$$a_2 < c_2 * minsup$$
$$...$$
$$a_3 < c_3 * minsup$$

summing it up, we get :

$$(a_1 + a_2 + ... + a_n) < (c_1 + c_2 + ... + c_n) * minsup$$
$$or\ simply\ A < C * minsup$$

which gives us our contradiction.

This property is essential as it enables one to build a distributed algorithm to compute the frequent itemsets for the apriori algorithm.

4.8.2 apriori

A database has five transactions. Let min sup = 60% and min conf = 80%.

TID	items bought
T100	{M,O,N,K,E,Y}
T200	{D,O,N,K,E,Y}
T300	{M,A,K,E}
T400	{M,U,C,K,Y}
T500	{C,O,O,K,I,E}

Find all frequent itemsets using Apriori and apply after the GenRules algorithm:

4.8.2.1 Step 0 : sort transactions

We first have to sort transactions in a lexicographically correct order :

TID	items bought
T100	{E,K,M,N,O,Y}
T200	{D,E,K,N,O,Y}
T300	{A,E,K,M}
T400	{C,K,M,U,Y}
T500	{C,E,I,K,O}

4.8.2.2 Step 1 : apriori - generate frequent itemsets

Let's first compute the support of the 1-itemsets

{A}	$\rightarrow \frac{1}{5} = 0.2 < 0.6 \Rightarrow$ NOK	{M}	$\rightarrow \frac{3}{5} = 0.6 >= 0.6 \Rightarrow$ OK
{C}	$\rightarrow \frac{2}{5} = 0.4 < 0.6 \Rightarrow$ NOK	{N}	$\rightarrow \frac{2}{5} = 0.4 < 0.6 \Rightarrow$ NOK
{D}	$\rightarrow \frac{1}{5} = 0.2 < 0.6 \Rightarrow$ NOK	{O}	$\rightarrow \frac{3}{5} = 0.6 >= 0.6 \Rightarrow$ OK
{E}	$\rightarrow \frac{4}{5} = 0.8 >= 0.6 \Rightarrow$ OK	{U}	$\rightarrow \frac{1}{5} = 0.2 < 0.6 \Rightarrow$ NOK
{I}	$\rightarrow \frac{1}{5} = 0.2 < 0.6 \Rightarrow$ NOK	{Y}	$\rightarrow \frac{3}{5} = 0.6 >= 0.6 \Rightarrow$ OK
{K}	$\rightarrow \frac{5}{5} = 1.0 >= 0.6 \Rightarrow$ OK		

So we get the L_1 set :

L_1 = {	{E},	{K},	{M},	{O},	{Y}	}
	0.8	1	0.6	0.6	0.6	

We compute C_2 out if L_1 *(compose and compute support)*:

C_2 = {	{E,K},	{E,M},	{E,O},	{E,Y},	{K,M}	{K,O}	{K,Y}	{M,O}	{M,Y}	{O,Y}	}
	0.8	0.4	0.6	0.4	0.6	0.6	0.6	0.2	0.4	0.4	

Getting rid of those not respecting the *minsup* limit, we end up with L_2 :

$$L_2 = \{ \underset{0.8}{\{E,K\}}, \underset{0.6}{\{E,O\}}, \underset{0.6}{\{K,M\}} \underset{0.6}{\{K,O\}} \underset{0.6}{\{K,Y\}} \}$$

We build C_3 by joining L_2 with itself. We only join the itemsets where the k - 1 = 1 items are the same :

$$C_2 = \{ \{E,K,O\}, \{K,M,O\}, \{K,M,Y\} \{K,O,Y\} \}$$

This time we perform pruning before computing the support. Pruning consists of getting rid of the itemsets where at least one subset isn't part of the previous L_l sets.

Here we keep : {C,K,O} : OK
{K,M,O} : {M,O} is not in $L_2 \Rightarrow$ NOK
{K,M,Y} : {M,Y} is not in $L_2 \Rightarrow$ NOK
{K,O,Y} : {O,Y} is not in $L_2 \Rightarrow$ NOK

We end up with :

$$L_3 = \{ \underset{0.6}{\{E,K,O\}} \}$$

which stay in L_3. (L_3 being single, there is not need to go any further in this stage.

Finally we can constitue $L = L_1 \cup L_2 \cup L_3$

4.8.2.3 Step 2 : genRules - compute interesting rules

genrules works by making the following calls in the first recursion :

- *genRules({E,K},{E,K})* $\rightarrow$ 1 single rule : {E} $\Rightarrow$ {K}
  | conf({E} $\Rightarrow$ {K}) = $\frac{sup(\{E,K\})}{sup(\{E\})}$ = $\frac{0.8}{0.8}$ = 1.0 $\geq$ 0.8 $\rightarrow$ {E} $\Rightarrow$ {K} is kept !
- *genRules({E,O},{E,O})* $\rightarrow$ 1 single rule : {E} $\Rightarrow$ {O}
  | conf({E} $\Rightarrow$ {O}) = $\frac{sup(\{E,O\})}{sup(\{E\})}$ = $\frac{0.6}{0.8}$ = 0.75 < 0.8 $\rightarrow$ {E} $\Rightarrow$ {O} is not kept.
- *genRules({K,M},{K,M})* $\rightarrow$ 1 single rule : {K} $\Rightarrow$ {M}
  | conf({K} $\Rightarrow$ {M}) = $\frac{sup(\{K,M\})}{sup(\{K\})}$ = $\frac{0.6}{1}$ = 0.6 < 0.8 $\rightarrow$ {K} $\Rightarrow$ {M} is not kept.
- *genRules({K,O},{K,O})* $\rightarrow$ 1 single rule : {K} $\Rightarrow$ {O}
  | conf({K} $\Rightarrow$ {O}) = $\frac{sup(\{K,O\})}{sup(\{K\})}$ = $\frac{0.6}{1}$ = 0.6 < 0.8 $\rightarrow$ {K} $\Rightarrow$ {O} is not kept.
- *genRules({K,Y},{K,Y})* $\rightarrow$ 1 single rule : {K} $\Rightarrow$ {Y}
  | conf({K} $\Rightarrow$ {Y}) = $\frac{sup(\{K,Y\})}{sup(\{K\})}$ = $\frac{0.6}{1}$ = 0.6 < 0.8 $\rightarrow$ {K} $\Rightarrow$ {Y} is not kept.

- *genRules({E,K,O},{E,K,O})* $\rightarrow$ *(now this is the interesting part ...)*

  1. Generate all subsets : *(only K - 1 subsets !)*
     A = {{E,K},{E,O},{K,O}}
  2. $\forall a \in A$:
     - {E,K} $\rightarrow$ rule : {E,K} $\Rightarrow$ {E,K,O} - {E,K} $\rightarrow$ {E,K} $\Rightarrow$ {O}
       | conf({E,K} $\Rightarrow$ {O}) = $\frac{sup(\{E,K,O\})}{sup(\{E,K\})}$ = $\frac{0.6}{0.8}$ = 0.75 < 0.8
       $\rightarrow$ {E,K} $\Rightarrow$ {O} is not kept.
     - {E,O} $\rightarrow$ rule : {E,O} $\Rightarrow$ {K}
       | conf({E,O} $\Rightarrow$ {K}) = $\frac{sup(\{E,K,O\})}{sup(\{E,O\})}$ = $\frac{0.6}{0.6}$ = 1.0 $\geq$ 0.8
       $\rightarrow$ {E,O} $\Rightarrow$ {K} is kept!
       $\rightarrow$ *recursive call :*
       - genRules({E,K,O},{E,O}) $\rightarrow$ ...
         (a) Generate all subsets : *(only K - 1 subsets !)*
         A = {{E},{O}}
         (b) $\forall a \in A$:
         - {E} $\rightarrow$ rule : {E} $\Rightarrow$ {E,K,O} - {E} $\rightarrow$ {E} $\Rightarrow$ {K,O}
           | conf({E} $\Rightarrow$ {K,O}) = $\frac{sup(\{E,K,O\})}{sup(\{E\})}$ = $\frac{0.6}{0.8}$ = 0.75 < 0.8
           $\rightarrow$ {E} $\Rightarrow$ {K,O} is not kept.
         - {O} $\rightarrow$ rule : {O} $\Rightarrow$ {E,K}
           | conf({O} $\Rightarrow$ {E,K}) = $\frac{sup(\{E,K,O\})}{sup(\{O\})}$ = $\frac{0.6}{0.6}$ = 1.0 $\geq$ 0.8
           $\rightarrow$ {E} $\Rightarrow$ {K,O} is kept !
           no recursive call as there is no subset for {O}
     - {K,O} $\rightarrow$ rule : {K,O} $\Rightarrow$ {E}
       | conf({K,O} $\Rightarrow$ {E}) = $\frac{sup(\{E,K,O\})}{sup(\{K,O\})}$ = $\frac{0.6}{0.6}$ = 1.0 $\geq$ 0.8
       $\rightarrow$ {K,O} $\Rightarrow$ {E} is kept!
       $\rightarrow$ *recursive call :*
       - genRules({E,K,O},{K,O}) $\rightarrow$ ...
         (a) Generate all subsets : *(only K - 1 subsets !)*
         A = {{K},{O}}
         (b) $\forall a \in A$:
         - {K} $\rightarrow$ rule : {K} $\Rightarrow$ {E,K,O} - {K} $\rightarrow$ {K} $\Rightarrow$ {E,O}
           | conf({K} $\Rightarrow$ {E,O}) = $\frac{sup(\{E,K,O\})}{sup(\{K\})}$ = $\frac{0.6}{1.0}$ = 0.6 < 0.8
           $\rightarrow$ {K} $\Rightarrow$ {E,O} is not kept.
         - {O} $\rightarrow$ rule : {O} $\Rightarrow$ {E,K} *(already analyzed above)*

After the *genRules* algorithm, we end up with the following set of interesting rules :

{ (E $\Rightarrow$ K), (E,O $\Rightarrow$ K), (E $\Rightarrow$ K,O), (K,O $\Rightarrow$ E) }

CHAPTER 5

Classification

Contents

5.1 Basic concepts

5.1.1 Supervised vs. Unsupervised Learning

Supervised learning (classification):

- Supervision: The training data (observations, measurements, etc.) are accompanied by labels indicating the class of the observations
- New data is classified based on the training set

Unsupervised learning (clustering):

- The class labels of training data is unknown
- Given a set of measurements, observations, etc. with the aim of establishing the existence of classes or clusters in the data

5.1.2 Classification vs. Estimation

Classification:

- predicts categorical class labels (discrete or nominal)
- classifies data (constructs a model) based on the training set and the values (class labels) in a classifying attribute and uses it in classifying new data

Estimation:

- models continuous-valued functions, i.e., predicts unknown or missing values

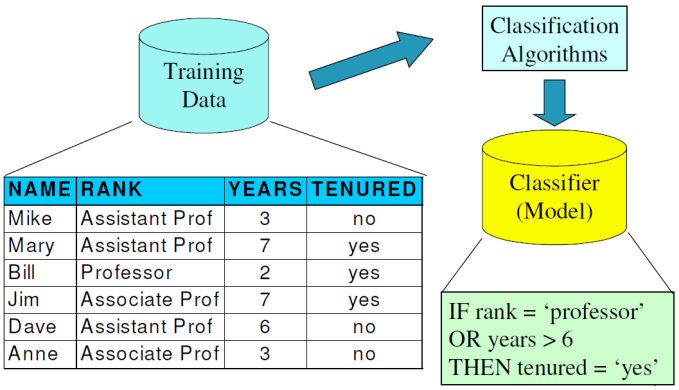
Typical applications:

- Credit/loan approval
- Medical diagnosis: if a tumor is cancerous or benign
- Fraud detection: if a transaction is fraudulent
- Web page categorization: which category it is

5.1.3 Classification - A Two-Step Process

Model construction: describing a set of predetermined classes:

- Each tuple/sample is assumed to belong to a predefined class, as determined by the **class label attribute**
- The set of tuples used for model construction is **training set**
- The model is represented as classification rules, decision trees, or mathematical formulae



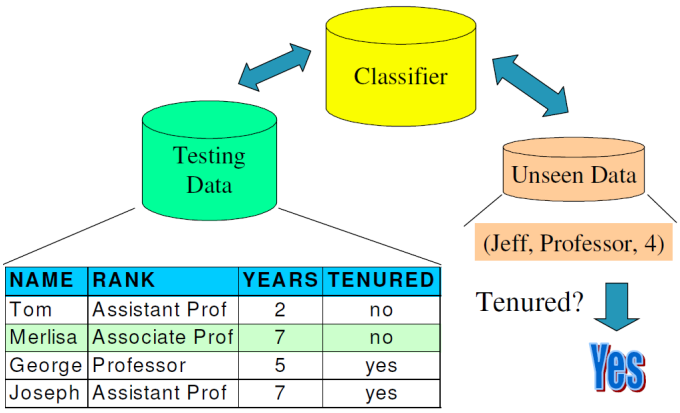
NAME	RANK	YEARS	TENURED
Mike	Assistant Prof	3	no
Mary	Assistant Prof	7	yes
Bill	Professor	2	yes
Jim	Associate Prof	7	yes
Dave	Assistant Prof	6	no
Anne	Associate Prof	3	no

Model usage: for classifying future or unknown objects:

- **Estimate accuracy** of the model
  - The known label of test sample is compared with the classified result from the model
  - Accuracy rate is the percentage of test set samples that are correctly classified by the model

- Test set is independent of training set, otherwise over-fitting will occur

- If the accuracy is acceptable, use the model to classify data tuples whose class labels are not known



NAME	RANK	YEARS	TENURED
Tom	Assistant Prof	2	no
Merlisa	Associate Prof	7	no
George	Professor	5	yes
Joseph	Assistant Prof	7	yes

5.1.4 Issues

5.1.4.1 Data Preparation

- Data cleaning: Preprocess data in order to reduce noise and handle missing values
- Relevance analysis (feature selection) : Remove the irrelevant or redundant attributes
- Data transformation : Generalize and/or normalize data

5.1.4.2 Evaluating Classification Methods

- Accuracy
  - classifier accuracy: predicting class label
  - predictor accuracy: guessing value of predicted attributes
- Speed
  - time to construct the model (training time)
  - time to use the model (classification/prediction time)
- Robustness: handling noise and missing values
- Scalability: efficiency in disk-resident databases
- Interpretability : understanding and insight provided by the model
- Other measures, e.g., goodness of rules, such as decision tree size or compactness of classification rules

5.2 Decision tree induction

5.2.1 Introductory example

5.2.1.1 Training dataset

Let's consider this training datasets:

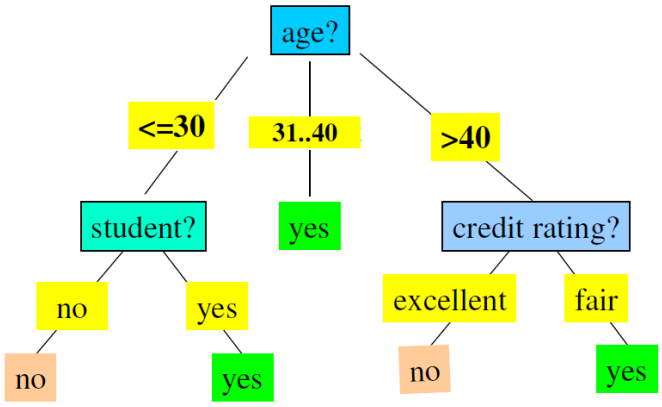
This follows an example of Quinlan's ID3 (Playing Tennis)

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31…40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31…40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31…40	medium	no	excellent	yes
31…40	high	yes	fair	yes
>40	medium	no	excellent	no

- What attribute to take in consideration and in what order ?
- Problem: one cannnot generate every possible tree to answer this question...

5.2.1.2 Sample expected decision tree

We are looking for the attributes which provide the best *split* of the data, for instance:



5.2.2 Algorithm for Decision Tree Induction

Basic algorithm (a greedy algorithm)

- Tree is constructed in a top-down recursive divide-and-conquer manner

- At start, all the training examples are at the root
- Attributes are categorical (if continuous-valued, they are discretized in advance)
- Examples are partitioned recursively based on selected attributes
- Test attributes are selected on the basis of a heuristic or statistical measure (e.g., information gain)

Conditions for stopping partitioning

- All samples for a given node belong to the same class
- There are no remaining attributes for further partitioning - majority voting is employed for classifying the leaf
- There are no samples left

5.2.2.1 Algorithm

Notation:

- Let D be set of tuples with their attributes.
- Let C be the target classification which we want to achieve, and C_i (i=1..m) a class in C (C contains m classes)
- Let A be whatever attribute providing a classification of the elements in D. A contains v classes.

Definition:

- The Expected Information (entropy) needed to classify a tuple in D:
  $Info(D) = -\sum_{i=1}^{m} p_i log_2(p_i)$
  - where p_i be the probability that an arbitrary tuple in D belongs to class C_i
    p_i can be estimated as $p_i = \frac{|C_{i,D}|}{|D|}$

- The Information needed (still needed) after using A to split D into v partitions to classify D:
  $Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info_A(D_j)$
  - where $Info_A(D_j)$ is the expected information (entropy) needed to classify a tuple (according to the target attribute) in D_j : $Info_A(D_j) = -\sum_{i=1}^{m} p_{(i \to D_j)} log_2(p_{(i \to D_j)})$
    - where $p_{(i \to D_j)}$ be the probability that an arbitrary tuple in D_j belongs to class $C_{(i \to D_j)}$
      $p_{(i \to D_j)}$ can be estimated as $p_{(i \to D_j)} = \frac{|C_{i,D_j}|}{|D_j|}$

- The Information gained by branching on attribute A is $Gain(A) = Info(D) - Info_A(D)$

Algo:

1. Compute the expected information (entropy) neeed to classify a tuple in D as

   (a) The expected information $Info(D)$ is computed by
   $Info(D) = -\sum_{i=1}^{m} \frac{|C_{i,D}|}{|D|} log_2(\frac{|C_{i,D}|}{|D|})$

2. Compute information gain (entropy) for each attribute A (except C - the target attribute):
   For each attribute A, compute Information Gained by branching on A
   $Gain(A)$
   (a) Compute each $Info_A(D_j)$ where j=1.."number of classes of A"
   $Info_A(D_j) = -\sum_{i=1}^{m} \frac{|C_{i,D_j}|}{|D_j|} log_2(\frac{|C_{i,D_j}|}{|D_j|})$
   (b) Compute Information needed after using A to split D into v partitions to classify D:
   $Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info_A(D_j)$
   (c) The Information gained by branching on attribute A is $Gain(A) = Info(D) - Info_A(D)$
3. Select the attribute with the highest information gain (highest entropy):
   $\rightarrow$ use the values computed above and select the attribute with the highest one.
4. The first level of classifications becomes this attribute. From the current node (which might be the root node one the first iteration), create branches for each value oif this attibute.
5. Then for each of these new branches, apply this algorithm recursively starting with point 2, as if the root node has become the current branch and the new set D has become the subset of D thus computed.
   (The split might well be a different attribute for each branch.)
6. **The recursion stops when every element of the specific branch have the same results!**

5.2.2.2 Example

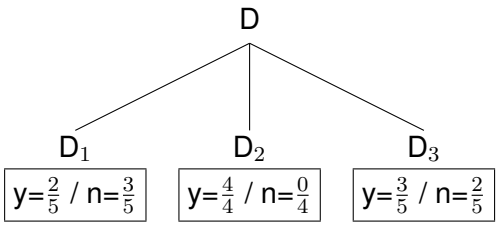
$\rightarrow$ Using the example provided in 5.2.1.

Compute expected information:

- First let's count the elements in each group:
  - $|c = yes| = 9$
  - $|c = no| = 5$
- Thus $Info(D) = -\frac{9}{14} log_2(\frac{9}{14}) - \frac{5}{14} log_2(\frac{5}{14})$

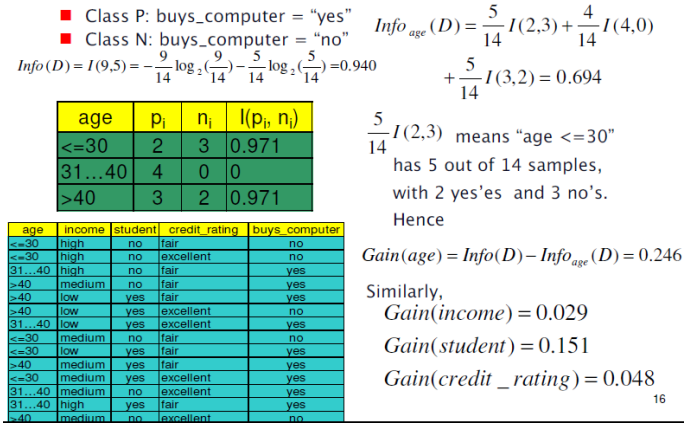
Compute $Gain(age)$

- Age is splitted in three classes: $below = age <= 30 \rightarrow j = 1$, $middle = 31 >= age < 40 \rightarrow j = 2$ and $above = age >= 40 \rightarrow j = 3$:



- Compute each individual $Info_age(D_j)$:
  - $Info_{age}(D_1) = -\frac{2}{5}log_2(\frac{2}{5}) - \frac{3}{5}log_2(\frac{3}{5}) = 0.971$
  - $Info_{age}(D_2) = -\frac{4}{4}log_2(\frac{4}{4}) - \frac{0}{4}log_2(\frac{0}{4}) = 0$
  - $Info_{age}(D_3) = -\frac{3}{5}log_2(\frac{3}{5}) - \frac{2}{5}log_2(\frac{2}{5}) = 0.971$
- Compute *Information needed* when using *age* for the split:
  $Info_{age}(d) = \frac{5}{14} \times Info_{age}(D_1) + \frac{4}{14} \times Info_{age}(D_2) + \frac{5}{14} \times Info_{age}(D_3) = 0.694$
- Compute *Information gained* when using *age* for the split:
  $Gain(age) = Info(D) - Info_{age}(D) = 0.246$

Then one needs to compute $Gain(income)$, $Gain(student)$ and $Gain(credit\_rating)$ the same way:



age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31…40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31…40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31…40	medium	no	excellent	yes
31…40	high	yes	fair	yes
>40	medium	no	excellent	no

Then, we take the one having the littlest value for $Info_x(D)$, i.e. the highest value for $Gain(x)$ as the next split value.

Then, for each branch, we start all over again as described in the algorithm above.

5.2.3 Note about the *Information* or *entropy* formula ...

The *info* funtion gives the *amount of information* or *entropy*:

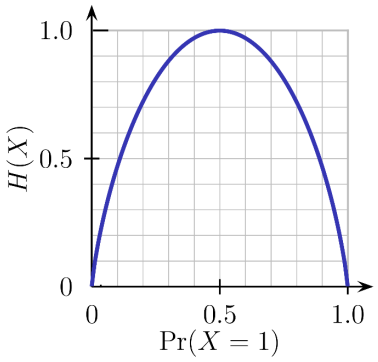
$$f(x) = -\sum_{i=1}^{n} p(x_i) log_b(p(x_i))$$

or in our case :

$$f(x) = -xlog_b(x) - (1-x)log_b(1-x)$$

The usage of the *info* formula is a trick. What we want is a formula which returns the minimum value 0 when every single element are within the same class and the maximum possible value when the values are well mixed amongst the two classes.
And we get exactly that with the *info* forumla.

This is how the *info* curve looks like:



The function returns 0 when all elements are 1 or 0 (in the same class) and 1 when elements are the most spread amonst the two classes.

This function is also called *degree of disorder*.

5.2.4 Computing information gain for continuous-value attributes

Whenever A is a continuous value, it must be *discretized*.

Determine the best split point for A:

- Sort the value A in increasing order
- Typically, the midpoint between each pair of adjacent values is considered as a possible split point :
  (a_i + a_{i+1}) / 2 is the midpoint between the values of a_i and a_{i+1}
- The point with the minimum expected information requirement for A is selected as the split-point for A

Split:

- D_1 is the set of tuples in D satisfying $A \leq$ "$split - point$", and D_2 is the set of tuples in D satisfying $A >$ "$split - point$"

5.2.5 Gini Index

The *Gini Index* method consists in using a differenign formula than the *Information Quantity* or *Entropy* we have been using before.

The *Gini Index* is used by the *CART* or *IBM IntelligentMiner* products.

Instead of the formulas we have been using before, we use the following below. And we always built a binary tree, i.e. split the set of values for an attribute in two groups

- If a data set D contains examples from n classes, gini index, $gini(D)$ is defined as $gini(D) = 1 - \sum_{i=1}^{n} p_i^2$
    - where p_j is the relative frequency of class j in D
- If a data set D is split on A into two subsets D_1 and D_2, the gini index $gini(D)$ is defined as
  $gini_A(D) = \frac{|D_1|}{D} \times gini(D_1) + \frac{|D_2|}{D} \times gini(D_2)$
- Reduction in Impurity:
  $\Delta gini(A) = gini(D) - gini_A(D)$
- The attribute provides the smallest $gini_{split}(D)$ (or the largest reduction in impurity) is chosen to split the node (need to enumerate all the possible splitting points for each attribute)
- All attributes are assumed continuous-valued
- May need other tools, e.g., clustering, to get the possible split values
- Can be modified for categorical attributes

The *gini* function has exactly the same shape than the *entropy* function seen above

5.2.5.1 Gini Index - example

- Ex. D has 9 tuples in buys_computer = “yes” and 5 in “no”
  $gini(D) = 1 - (\frac{9}{14})^2 - (\frac{5}{14})^2) = 0.459$
- Suppose the attribute *income* partitions D into 10 in D1: low, medium and 4 in D2: high:
  $gini_{income \in \{l,m\} \cup \{h\}}(D) = \frac{10}{14} \times gini(D_1) + \frac{4}{14} \times gini(D_2))$
  where:
    - $gini(D_1) = (1 - (\frac{6}{10})^2 - (\frac{4}{10})^2)$
    - $gini(D_2) = (1 - (\frac{1}{4})^2 - (\frac{3}{4})^2)$
- Hence $gini_{income \in \{l,m\} \cup \{h\}}(D) = 0.450$
- But $gini_{income \in \{l\} \cup \{m,h\}}(D) = 0.30$ and thus is the best value since it is the lowest

5.2.6 Comparing attribute selection measures

The two measures, in general, return good results, but:

- Information gain: biased towards multivalued attributes
- Gini index:

- biased to multivalued attribute
- has difficulty when number of classes is large
- tends to favor tests that result in equal-sized partitions and purity in both partitions

5.2.7 Overfitting and Tree Pruning

Overfitting: An induced tree may overfit the training data

- Too many branches, some may reflect anomalies due to noise or outliers
- Poor accuracy for unseen samples

Two approaches to avoid overfitting

- Prepruning: Halt tree construction early—do not split a node if this would result in the goodness measure falling below a threshold.
  $\rightarrow$ Difficult to choose an appropriate threshold
- Postpruning: Remove branches from a "fully grown" tree—get a sequence of progressively pruned trees.
  $\rightarrow$ Use a set of data different from the training data to decide which is the "best pruned tree"

5.2.8 Classification in Large Databases

- Classification: a classical problem extensively studied by statisticians and machine learning researchers
- Scalability: Classifying data sets with millions of examples and hundreds of attributes with reasonable speed
- Why decision tree induction in data mining?
  - relatively faster learning speed (than other classification methods)
  - convertible to simple and easy to understand classification rules
  - can use SQL queries for accessing databases
  - comparable classification accuracy with other methods

5.3 Model evaluation and selection

(Globaly outside the scope of the lecture, except the few details below)

Accuracy - definition:

Accuracy of a classifier M, acc(M): percentage of test set tuples that are correctly classified by the model M

The holdout method:

- Training set (e.g., 2/3) for model construction

- Test set (e.g., 1/3) for accuracy estimation

A variation of the holdout method: random sampling:

- Repeat holdout k times, accuracy = avg. of the accuracies obtained