Data Mining

Knowledge Discovery in Databases

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LM MAINS
A.A. 2011-2012

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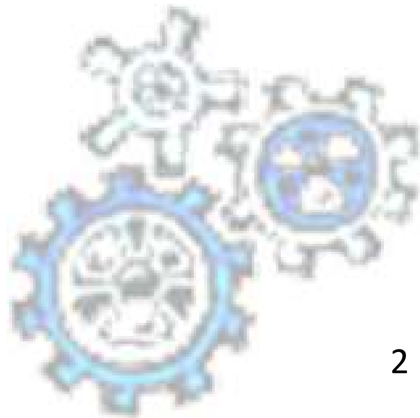
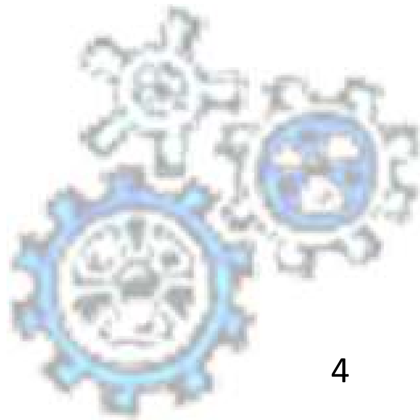


DM textbooks

- Pang-Ning Tan, Michael Steinbach, Vipin Kumar, Introduction to DATA MINING, Pearson - Addison Wesley, ISBN 0-321-32136-7, 2006
  - http://www-users.cs.umn.edu/~kumar/dmbook/index.php (slides e capitoli 4, 6 e 8 scaricabili liberamente)
- Jiawei Han, Micheline Kamber, Data Mining: Concepts and Techniques, Morgan Kaufmann Publishers, 2000
- Micheael J. A. Berry, Gordon S. Linoff, Mastering Data Mining, Wiley, 2000

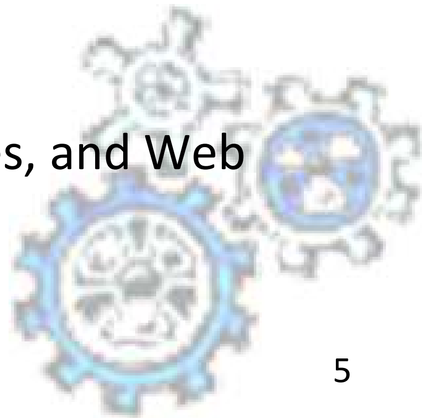
Outline

- Motivations
- Application Areas
- KDD Decisional Context
- KDD Process
- Architecture of a KDD system
- The KDD steps in short
- Some examples in short



Evolution of Database Technology: from data management to data analysis

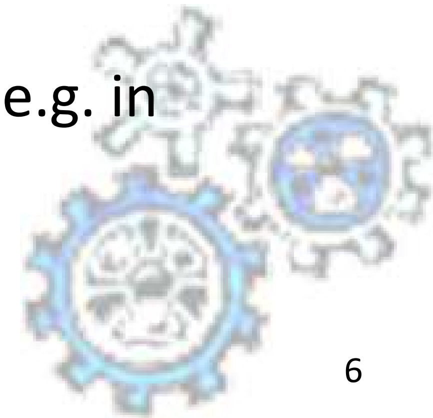
- 1960s:
  - Data collection, database creation, IMS and network DBMS.
- 1970s:
  - Relational data model, relational DBMS implementation.
- 1980s:
  - RDBMS, advanced data models (extended-relational, OO, deductive, etc.) and application-oriented DBMS (spatial, scientific, engineering, etc.).
- 1990s:
  - Data mining and data warehousing, multimedia databases, and Web technology.



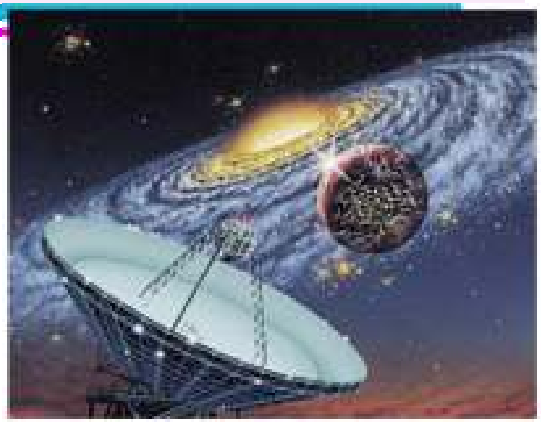
Why Mine Data? Commercial Viewpoint

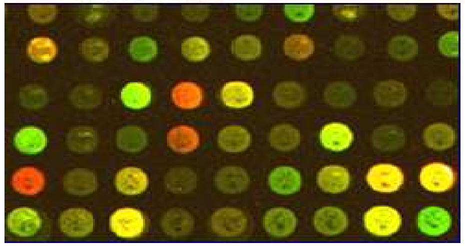
- Lots of data is being collected and warehoused
  - Web data, e-commerce
  - purchases at department/ grocery stores
  - Bank/Credit Card transactions

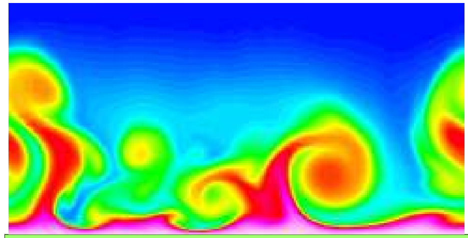
- Computers have become cheaper and more powerful
- Competitive Pressure is Strong
  - Provide better, customized services for an *edge* (e.g. in Customer Relationship Management)

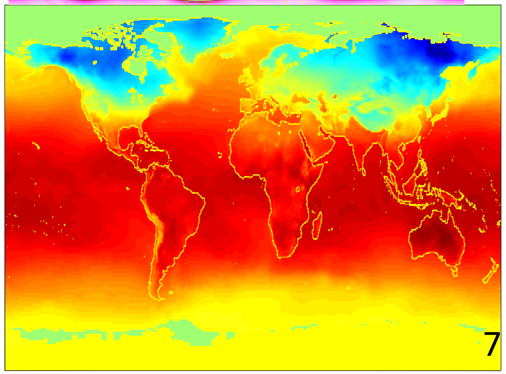


Why Mine Data? Scientific Viewpoint





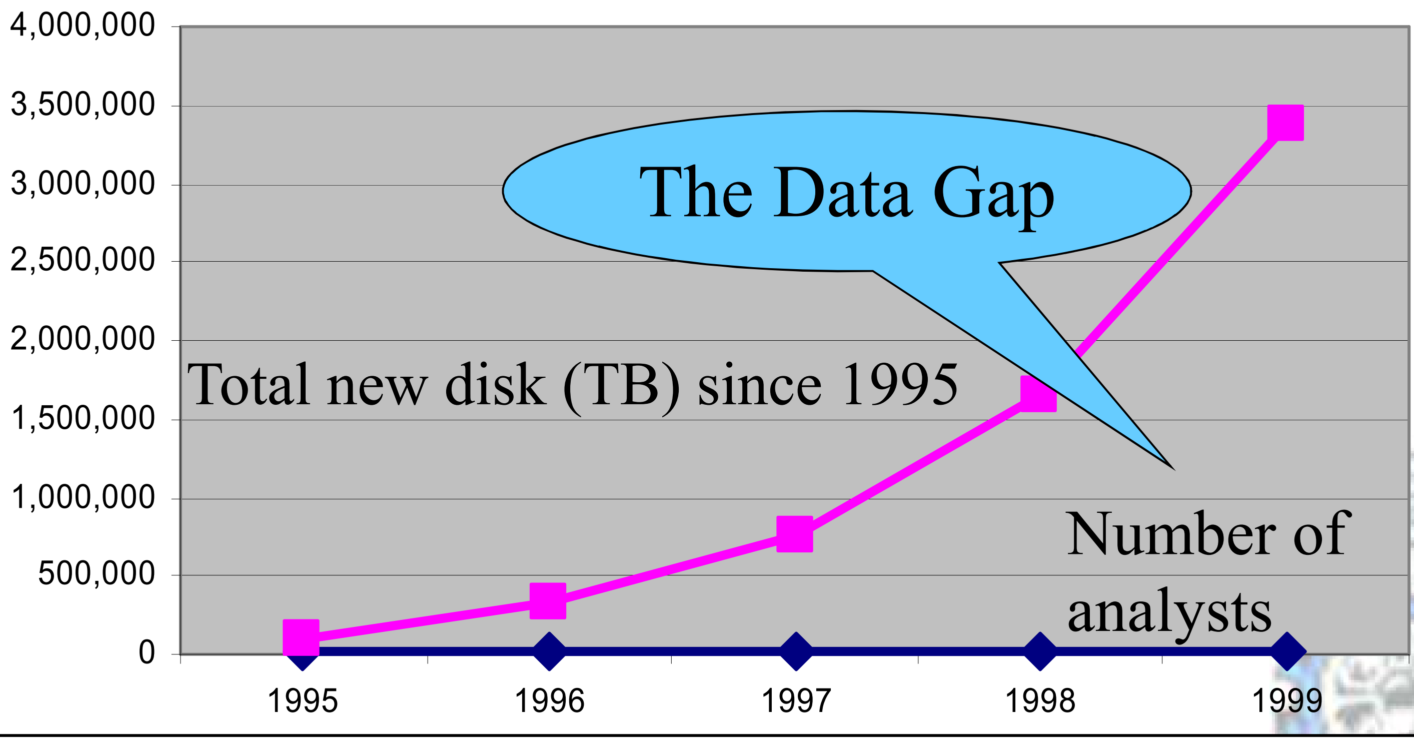




- Data collected and stored at enormous speeds (GB/hour)
  - remote sensors on a satellite
  - telescopes scanning the skies
  - microarrays generating gene expression data
  - scientific simulations generating terabytes of data
- Traditional techniques infeasible
- Data mining may help scientists
  - in classifying and segmenting data
  - in Hypothesis Formation

Mining Large Data Sets - Motivation

- There is often information "hidden" in the data that is not readily evident
- Human analysts may take weeks to discover useful information
- Much of the data is never analyzed at all

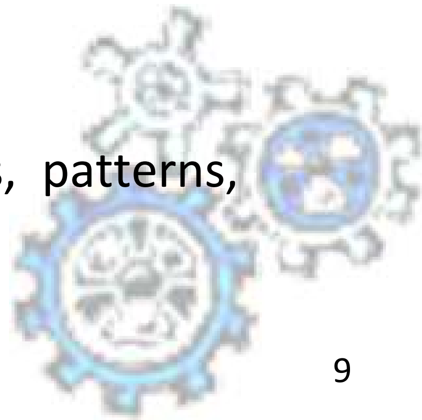


From: R. Grossman, C. Kamath, V. Kumar, "Data Mining for Scientific and Engineering Applications"

Motivations
"Necessity is the Mother of Invention"

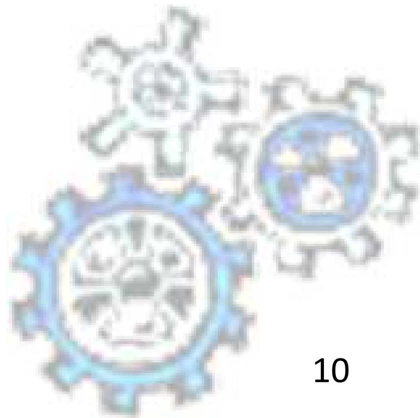
- *Data explosion problem*:
  - Automated data collection tools, mature database technology and internet lead to tremendous amounts of data stored in databases, data warehouses and other information repositories.
- *We are drowning in information, but starving for knowledge!* (John Naisbett)

- *Data warehousing and data mining :*
  - On-line analytical processing
  - Extraction of interesting knowledge (rules, regularities, patterns, constraints) from data in large databases.



Why Data Mining

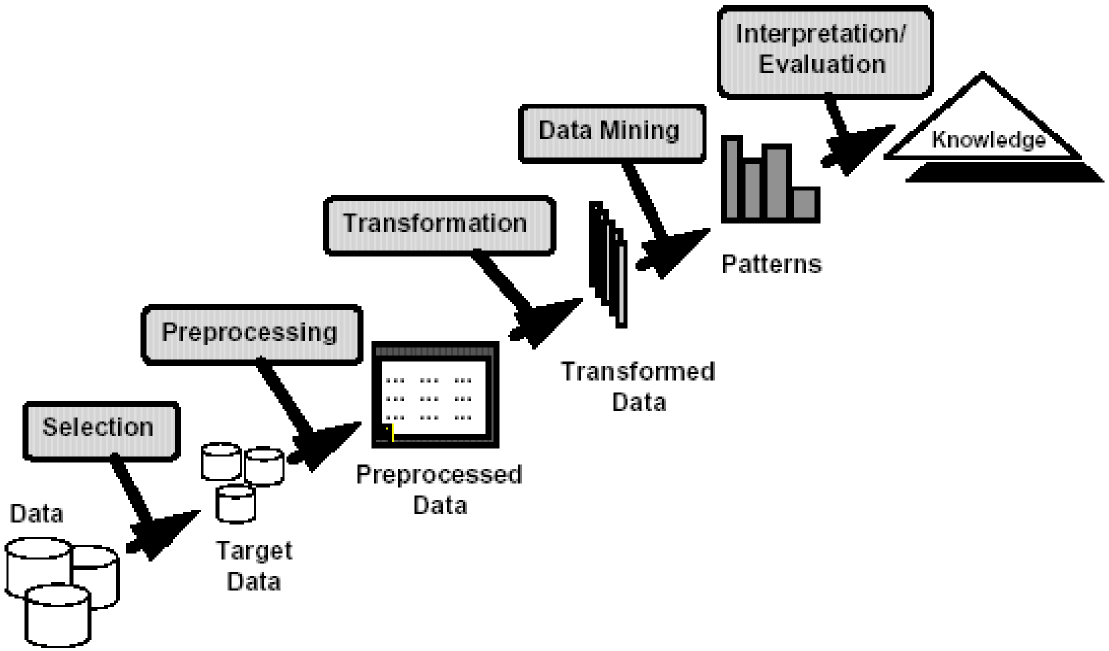
- **Increased Availability of Huge Amounts of Data**
  - point-of-sale customer data
  - digitization of text, images, video, voice, etc.
  - World Wide Web and Online collections
- **Data Too Large or Complex for Classical or Manual Analysis**
  - number of records in millions or billions
  - high dimensional data (too many fields/features/attributes)
  - often too sparse for rudimentary observations
  - high rate of growth (e.g., through logging or automatic data collection)
  - heterogeneous data sources
- **Business Necessity**
  - e-commerce
  - high degree of competition
  - personalization, customer loyalty, market segmentation



What is Data Mining?

⌘Many Definitions

- Non-trivial extraction of implicit, previously unknown and potentially useful information from data
- Exploration & analysis, by automatic or semi-automatic means, of large quantities of data in order to discover meaningful patterns

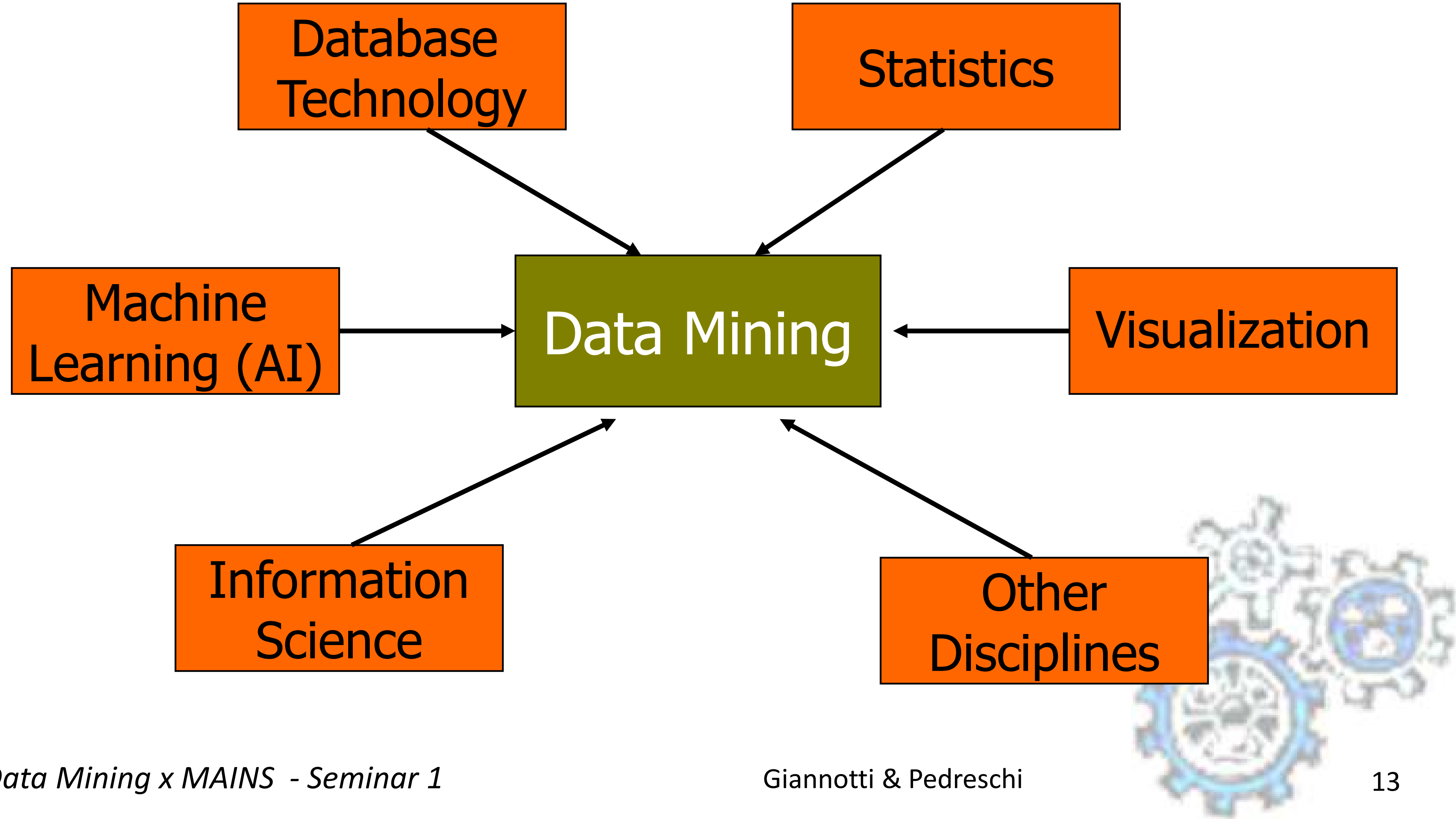


What is (not) Data Mining?

- **What is not Data Mining?**
  - Look up phone number in phone directory
  - Query a Web search engine for information about "Amazon"

- **What is Data Mining?**
  - Certain names are more prevalent in certain US locations (O'Brien, O'Rurke, O'Reilly… in Boston area)
  - Group together similar documents returned by search engine according to their context (e.g. Amazon rainforest, Amazon.com,)

Data Mining: Confluence of Multiple Disciplines



Sources of Data

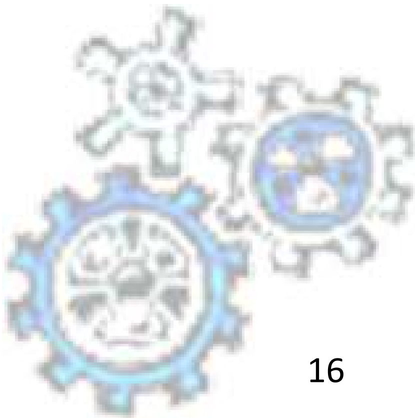
- **Business Transactions**
  - widespread use of bar codes => storage of millions of transactions daily (e.g., Walmart: 2000 stores => 20M transactions per day)
  - most important problem: effective use of the data in a reasonable time frame for competitive decision-making
  - e-commerce data
- **Scientific Data**
  - data generated through multitude of experiments and observations
  - examples, geological data, satellite imaging data, NASA earth observations
  - rate of data collection far exceeds the speed by which we analyze the data

Sources of Data

- Financial Data
  - company information
  - economic data (GNP, price indexes, etc.)
  - stock markets
- Personal / Statistical Data
  - government census
  - medical histories
  - customer profiles
  - demographic data
  - data and statistics about sports and athletes

Sources of Data

- **World Wide Web and Online Repositories**
  - email, news, messages
  - Web documents, images, video, etc.
  - link structure of of the hypertext from millions of Web sites
  - Web usage data (from server logs, network traffic, and user registrations)
  - online databases, and digital libraries
- Mobility and location data
  - GSM phones, GPS devices



Classes of applications

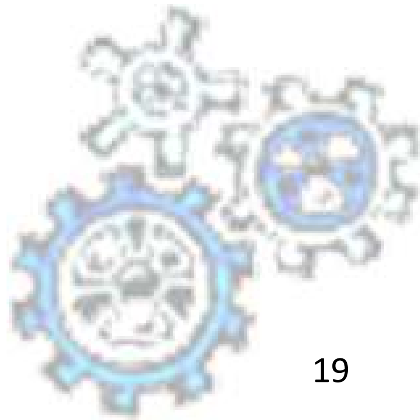
- **Database analysis and decision support**
  - **Market analysis**
    - target marketing, customer relation management, market basket analysis, cross selling, market segmentation.
  - **Risk analysis**
    - Forecasting, customer retention, improved underwriting, quality control, competitive analysis.
  - **Fraud detection**
- **New Applications from New sources of data**
  - **Text (news group, email, documents)**
  - **Web analysis and intelligent search**
  - **Mobility analysis**

Market Analysis

- Where are the data sources for analysis?
  - Credit card transactions, loyalty cards, discount coupons, customer complaint calls, plus (public) lifestyle studies.
- Target marketing
  - Find clusters of “model” customers who share the same characteristics: interest, income level, spending habits, etc.
- Determine customer purchasing patterns over time
  - Conversion of single to a joint bank account: marriage, etc.
- Cross-market analysis
  - Associations/co-relations between product sales
  - Prediction based on the association information.

Market Analysis (2)

- Customer profiling
  - data mining can tell you what types of customers buy what products (clustering or classification).
- Identifying customer requirements
  - identifying the best products for different customers
  - use prediction to find what factors will attract new customers
- Summary information
  - various multidimensional summary reports;
  - statistical summary information (data central tendency and variation)



Risk Analysis

- Finance planning and asset evaluation:
  - cash flow analysis and prediction
  - contingent claim analysis to evaluate assets
  - trend analysis
- Resource planning:
  - summarize and compare the resources and spending
- Competition:
  - monitor competitors and market directions (CI: *competitive intelligence*).
  - group customers into classes and class-based pricing procedures
  - set pricing strategy in a highly competitive market

Fraud Detection

- Applications:
  - widely used in health care, retail, credit card services, telecommunications (phone card fraud), etc.
- Approach:
  - use historical data to build models of fraudulent behavior and use data mining to help identify similar instances.
- Examples:
  - auto insurance: detect a group of people who stage accidents to collect on insurance
  - money laundering: detect suspicious money transactions (US Treasury's Financial Crimes Enforcement Network)
  - medical insurance: detect professional patients and ring of doctors and ring of references

Fraud Detection (2)

- **More examples:**
  - ***Detecting inappropriate medical treatment***:
    - Australian Health Insurance Commission identifies that in many cases blanket screening tests were requested (save Australian $1m/yr).
  - ***Detecting telephone fraud***:
    - Telephone call model: destination of the call, duration, time of day or week. Analyze patterns that deviate from an expected norm.
  - **Retail:** Analysts estimate that 38% of retail shrink is due to dishonest employees**.**

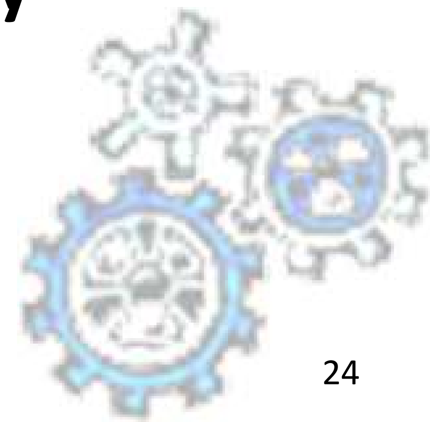
Other applications

- **Sports**
  - IBM Advanced Scout analyzed NBA game statistics (shots blocked, assists, and fouls) to gain competitive advantage for New York Knicks and Miami Heat.
- **Astronomy**
  - JPL and the Palomar Observatory discovered 22 quasars with the help of data mining
- **Internet Web Surf-Aid**
  - IBM Surf-Aid applies data mining algorithms to Web access logs for market-related pages to discover customer preference and behavior pages, analyzing effectiveness of Web marketing, improving Web site organization, etc.

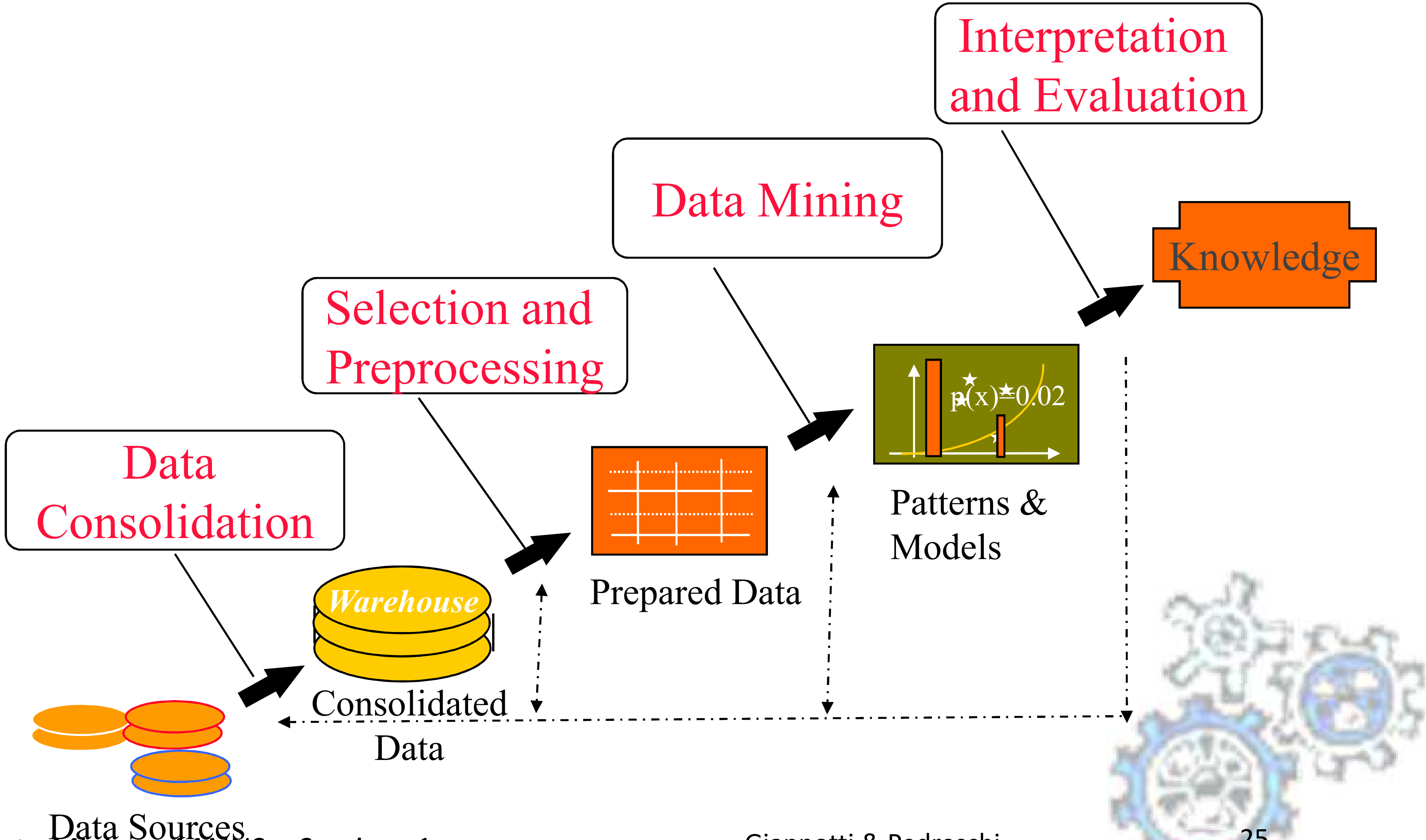
What is Knowledge Discovery in Databases (KDD)? A process!

- **The selection and processing of data for:**
  - **the identification of novel, accurate, and useful patterns, and**
  - **the modeling of real-world phenomena.**

- **Data mining is a major component of the KDD process - automated discovery of patterns and the development of predictive and explanatory models.**

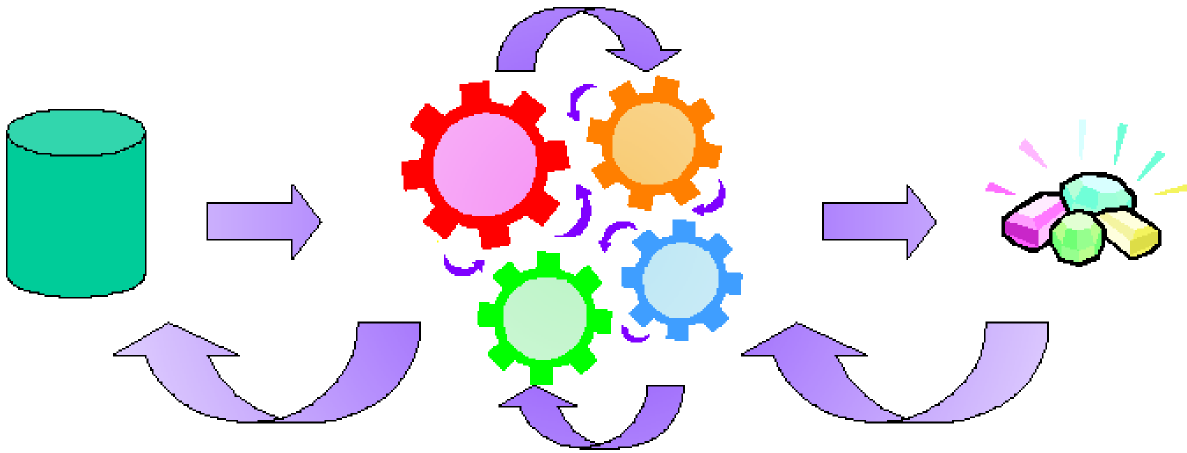


The KDD process



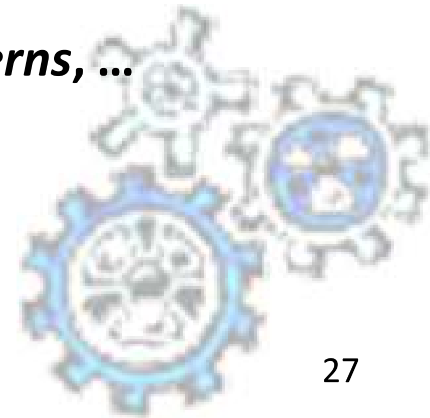
The KDD Process in Practice

- KDD is an Iterative Process
  - art + engineering rather than science

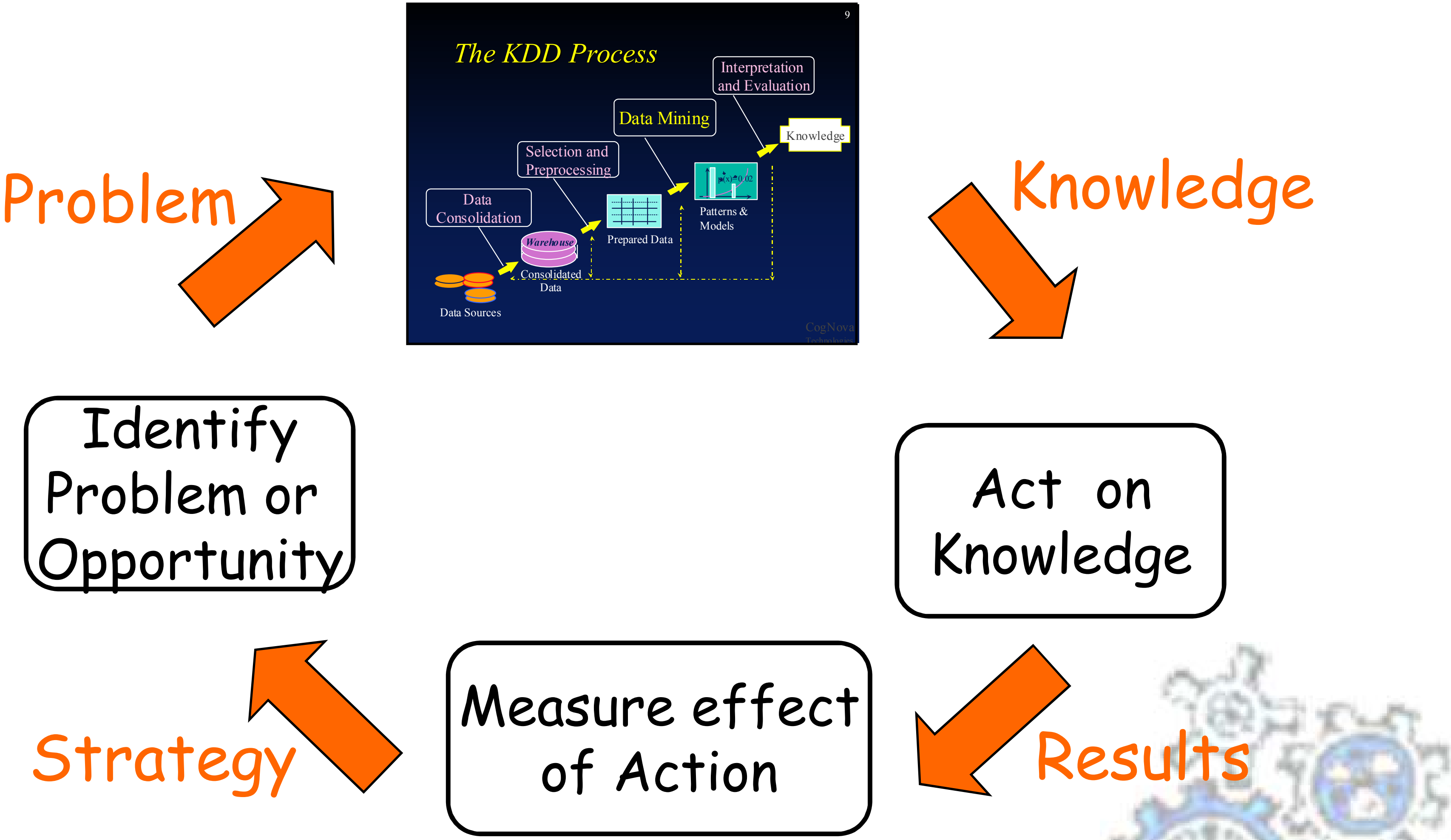


The steps of the KDD process

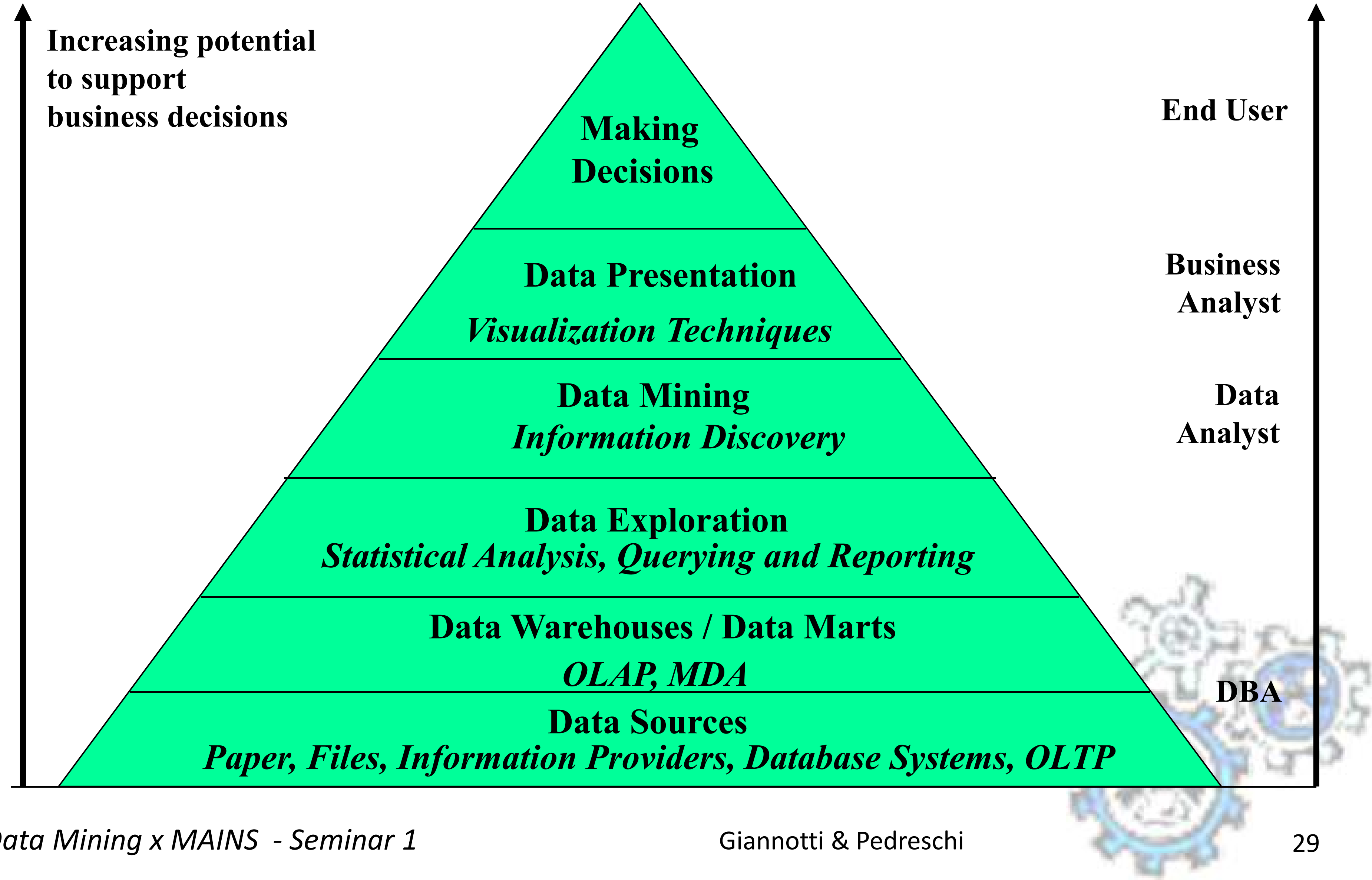
- **Learning the application domain:**
  - **relevant prior knowledge and goals of application**
- **Data consolidation: Creating a target data set**
- **Selection and Preprocessing**
  - ***Data cleaning* : (may take 60% of effort!)**
  - ***Data reduction and projection*:**
    - find useful features, dimensionality/variable reduction, invariant representation.
- **Choosing functions of data mining**
  - **summarization, classification, regression, association, clustering.**
- **Choosing the mining algorithm(s)**
- **Data mining: search for patterns of interest**
- **Interpretation and evaluation: analysis of results.**
  - ***visualization, transformation, removing redundant patterns, …***
- **Use of discovered knowledge**



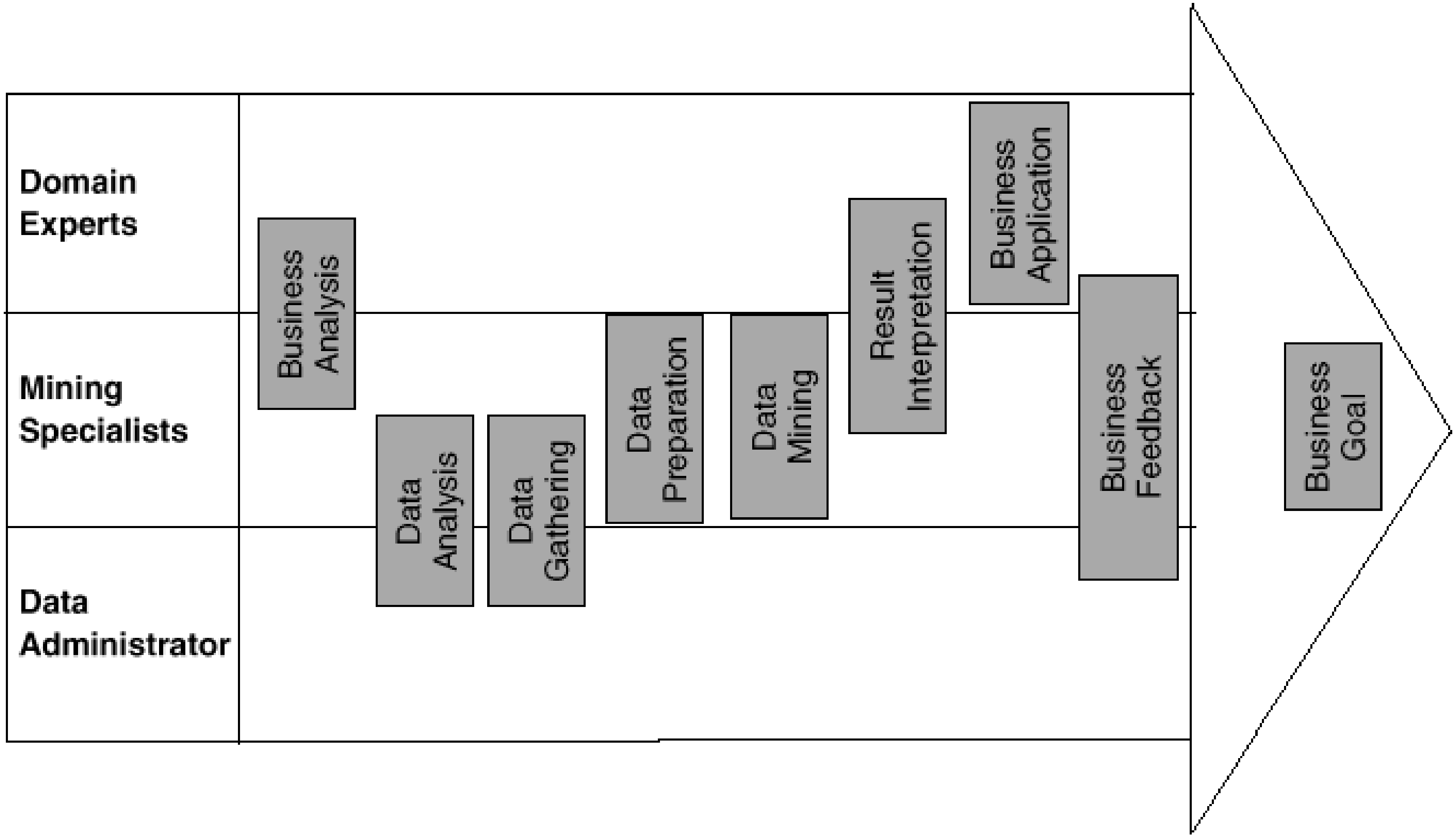
The *virtuous cycle*



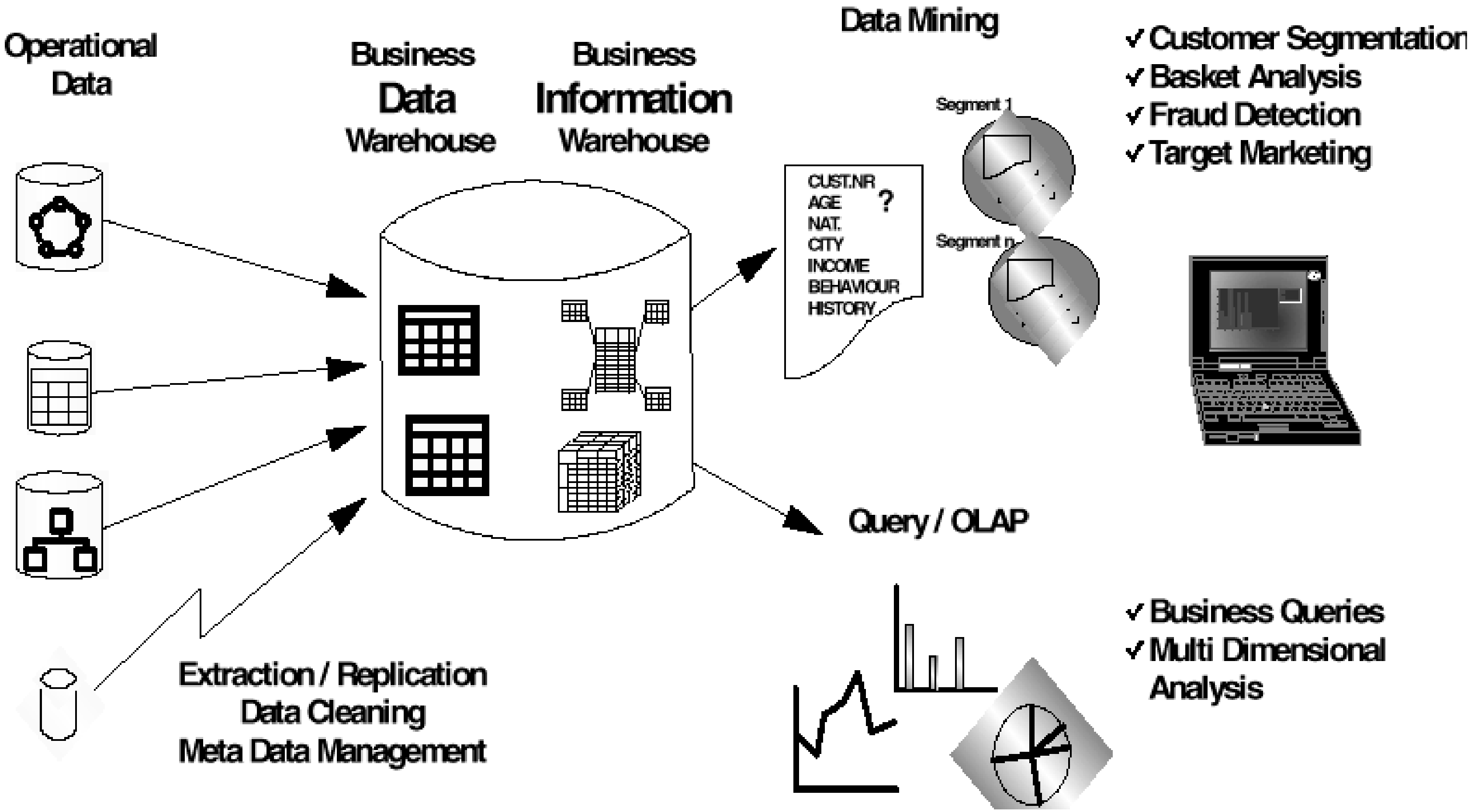
Data mining and business intelligence



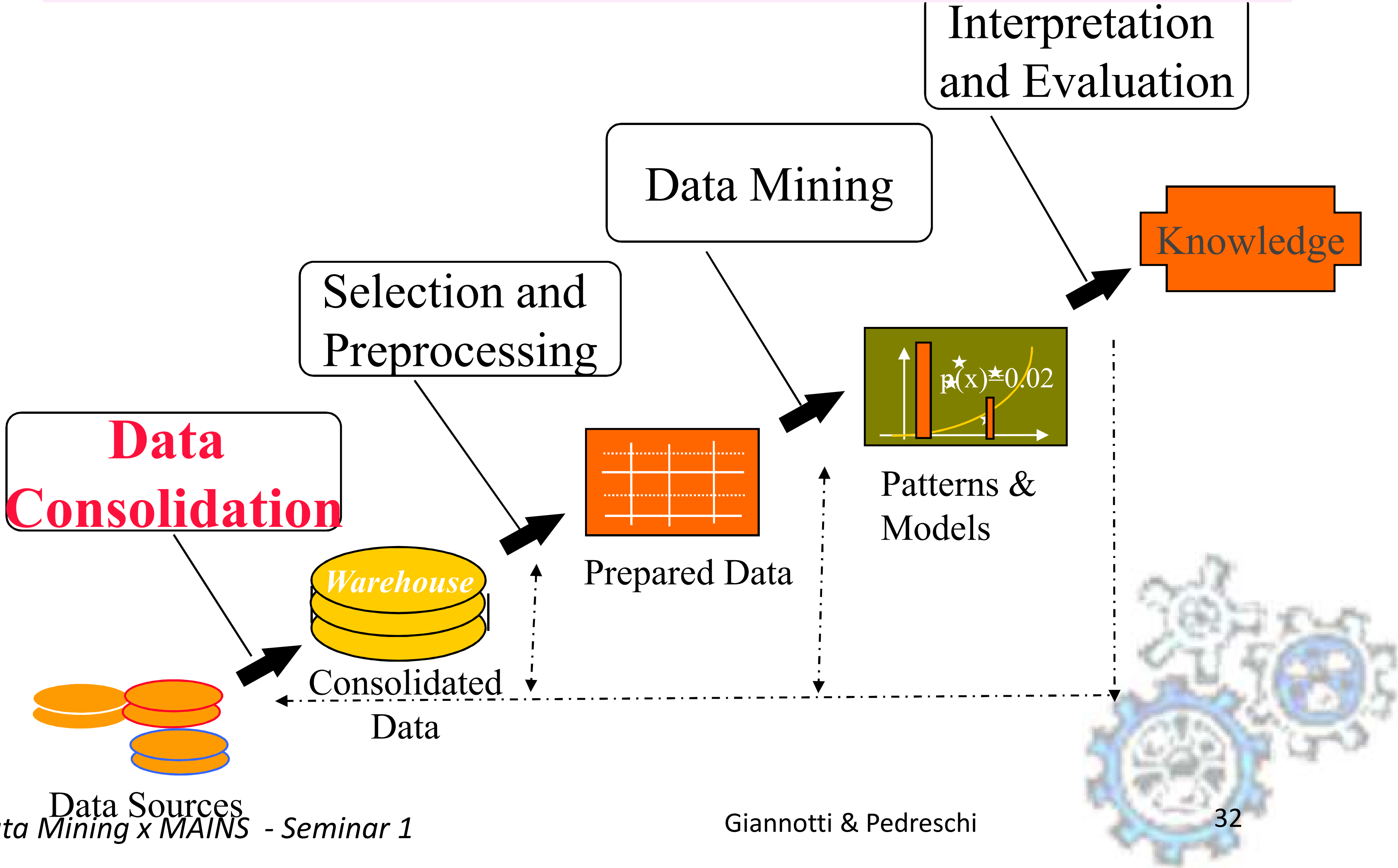
Roles in the KDD process



A business intelligence environment



The KDD process



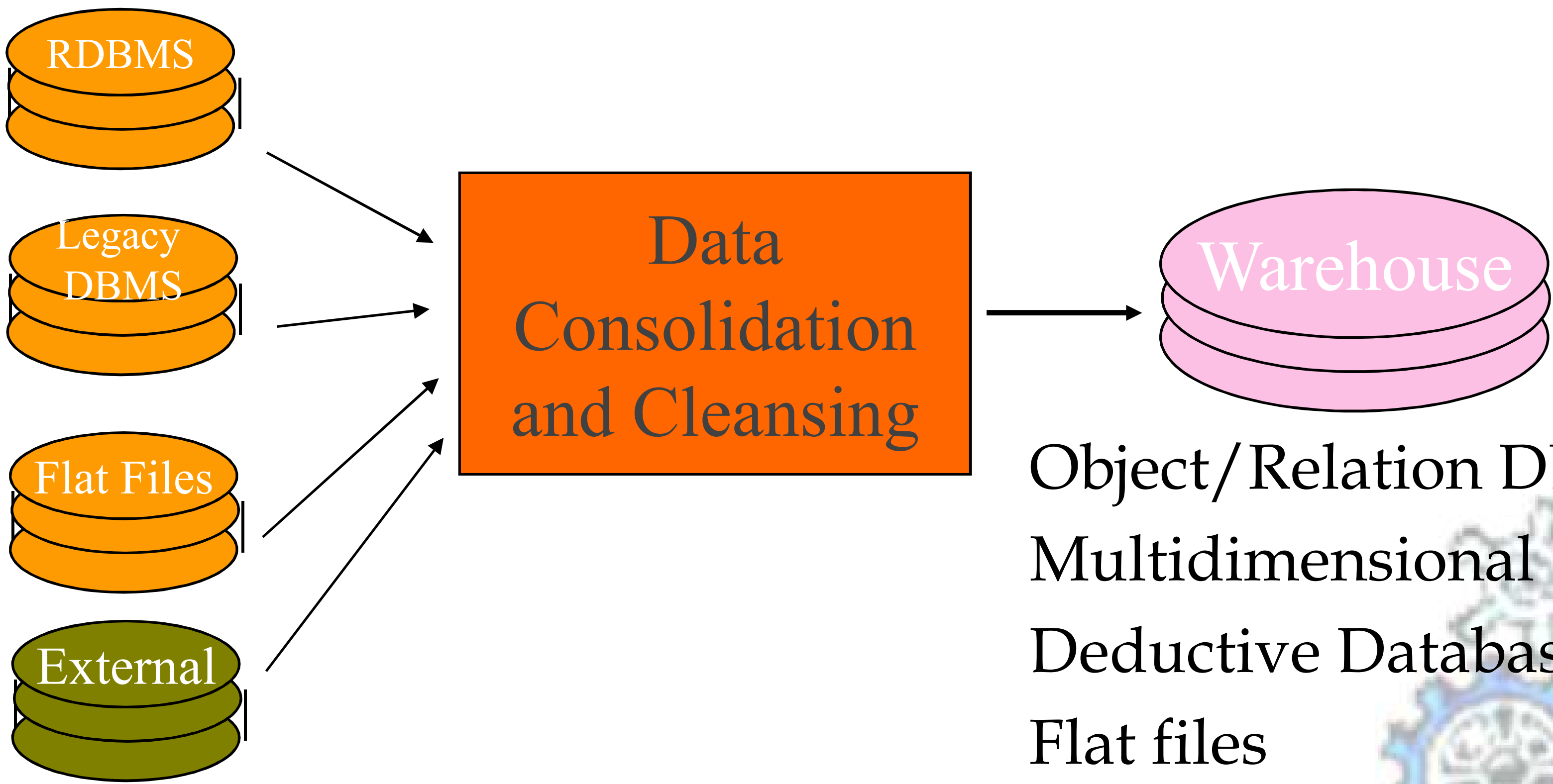
Data consolidation and preparation

Garbage in ➪ Garbage out

- **The quality of results relates directly to quality of the data**
- **50%-70% of KDD process effort is spent on data consolidation and preparation**
- **Major justification for a corporate data warehouse**

Data consolidation

From data sources to consolidated data repository

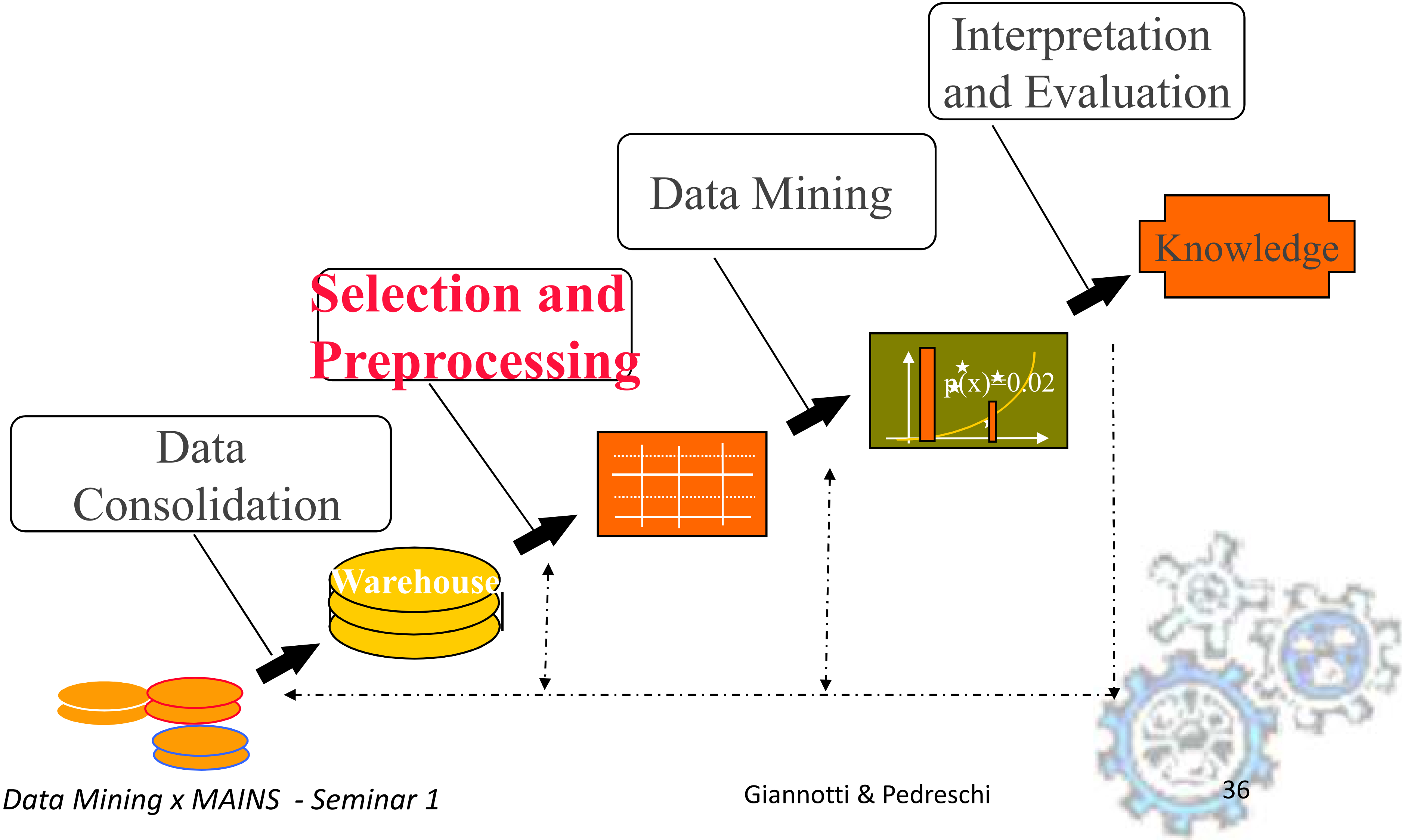


Object/Relation DBMS
Multidimensional DBMS
Deductive Database
Flat files

Data consolidation

- **Determine preliminary list of attributes**
- **Consolidate data into working database**
  - **Internal and External sources**
- **Eliminate or estimate missing values**
- **Remove *outliers* (obvious exceptions)**
- **Determine prior probabilities of categories and deal with *volume bias***

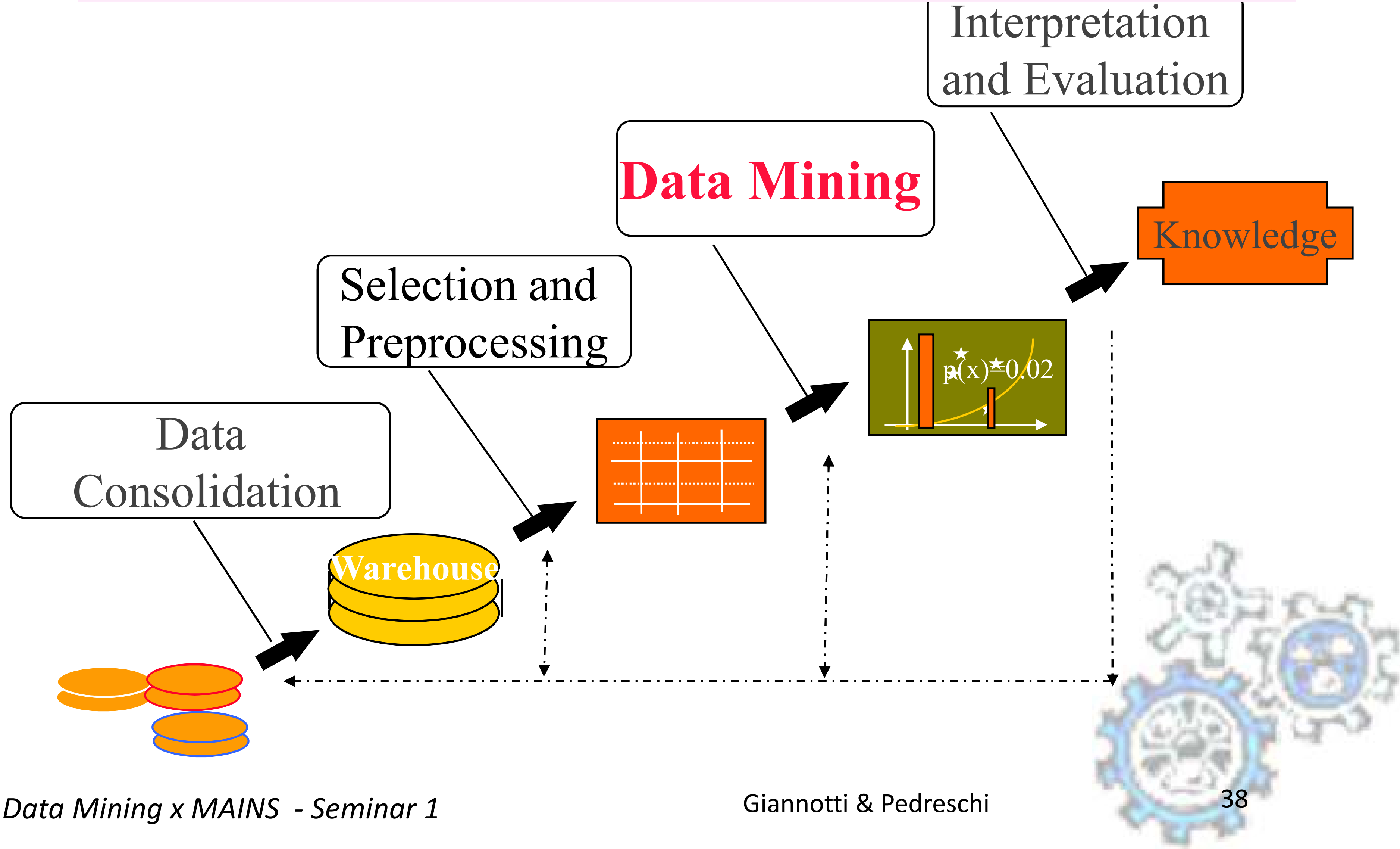
The KDD process



Data selection and preprocessing

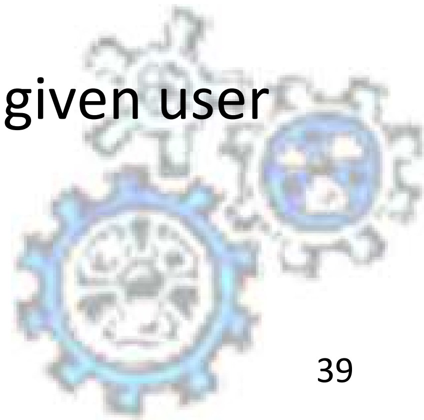
- Generate a set of examples
  - choose sampling method
  - consider sample complexity
  - deal with volume bias issues
- Reduce attribute dimensionality
  - remove redundant and/or correlating attributes
  - combine attributes (sum, multiply, difference)
- Reduce attribute value ranges
  - group symbolic discrete values
  - quantify continuous numeric values
- Transform data
  - de-correlate and normalize values
  - map time-series data to static representation
- OLAP and visualization tools play key role

The KDD process



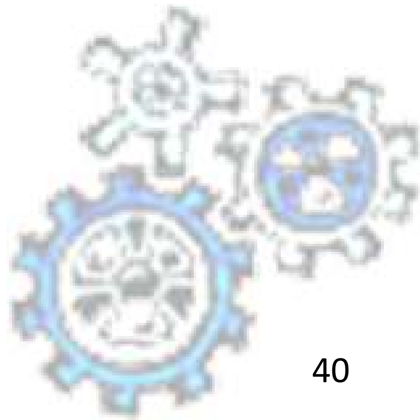
Data mining tasks and methods

- **Directed Knowledge Discovery**
  - **Purpose: Explain value of some field in terms of all the others (goal-oriented)**
  - **Method: select the target field based on some hypothesis about the data; ask the algorithm to tell us how to predict or classify new instances**
  - **Examples:**
    - what products show increased sale when cream cheese is discounted
    - which banner ad to use on a web page for a given user coming to the site



Data mining tasks and methods

- **Undirected Knowledge Discovery (Explorative Methods)**
  - **Purpose: Find patterns in the data that may be interesting (no target specified)**
  - **Method: clustering, association rules (affinity grouping)**
  - **Examples:**
    - which products in the catalog often sell together
    - market segmentation (groups of customers/users with similar characteristics)



Data Mining Tasks

- **Prediction Methods**
  - **Use some variables to predict unknown or future values of other variables.**

- **Description Methods**
  - **Find human-interpretable patterns that describe the data.**

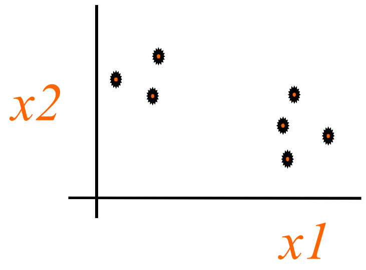
From [Fayyad, et.al.] Advances in Knowledge Discovery and Data Mining, 1996

Data Mining Tasks...

- **Classification** **[Predictive]**
- **Clustering** **[Descriptive]**
- **Association Rule Discovery** **[Descriptive]**
- **Sequential Pattern Discovery** **[Descriptive]**
- **Regression** **[Predictive]**
- **Deviation Detection** **[Predictive]**

Data Mining Models

- **Automated Exploration/Discovery**
  - ***e.g..*** **discovering new market segments**
  - **clustering analysis**



- **Prediction/Classification**
  - ***e.g..*** **forecasting gross sales given current factors**
  - **regression, neural networks, genetic algorithms, decision trees**

- **Explanation/Description**
  - ***e.g..*** **characterizing customers by demographics and purchase history**
  - **decision trees, association rules**

if age > 35
  and income < $35k
    then ...

Prediction and classification

- **Learning** a predictive model
- **Classification** of a new case/sample
- **Many methods:**
  - **Artificial neural networks**
  - **Inductive decision tree and rule systems**
  - **Genetic algorithms**
  - **Nearest neighbor clustering algorithms**
  - **Statistical (parametric, and non-parametric)**

Classification: Definition

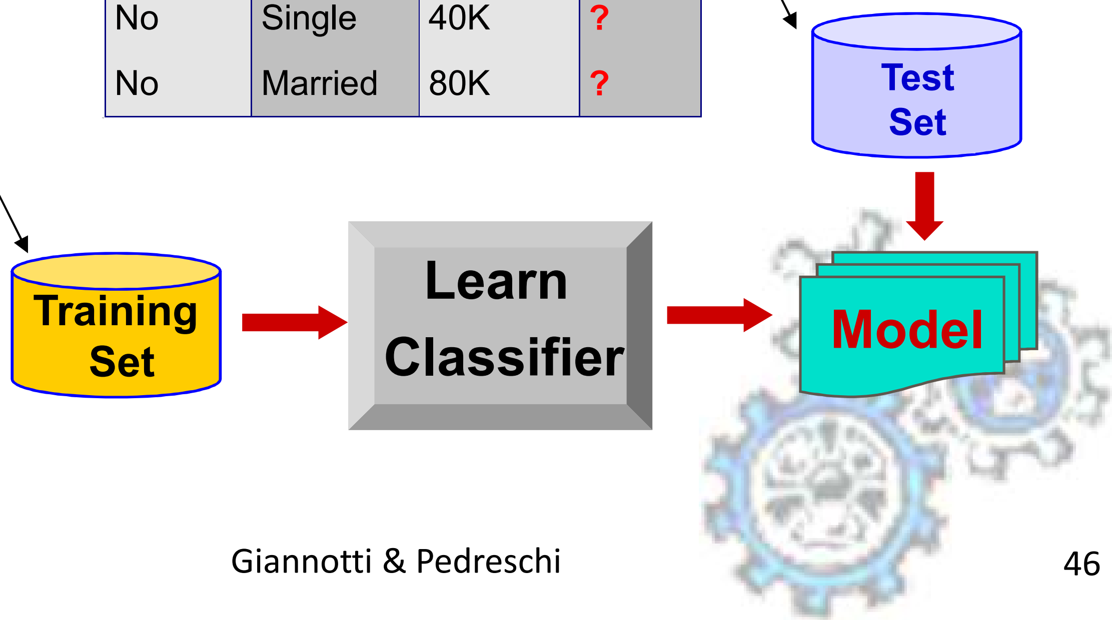
- **Given a collection of records (*training set*)**
  - **Each record contains a set of *attributes*, one of the attributes is the *class*.**
- **Find a *model* for class attribute as a function of the values of other attributes.**
- **Goal: <u>previously unseen</u> records should be assigned a class as accurately as possible.**
  - **A *test set* is used to determine the accuracy of the model. Usually, the given data set is divided into training and test sets, with training set used to build the model and test set used to validate it.**

Classification Example

categorical categorical continuous class

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

Refund	Marital Status	Taxable Income	Cheat
No	Single	75K	?
Yes	Married	50K	?
No	Married	150K	?
Yes	Divorced	90K	?
No	Single	40K	?
No	Married	80K	?



Classification: Application 1

- **Direct Marketing**
  - **Goal: Reduce cost of mailing by *targeting* a set of consumers likely to buy a new cell-phone product.**
  - **Approach:**
    - Use the data for a similar product introduced before.
    - We know which customers decided to buy and which decided otherwise. This *{buy, don't buy}* decision forms the *class attribute*.
    - Collect various demographic, lifestyle, and company-interaction related information about all such customers.
      - Type of business, where they stay, how much they earn, etc.
    - Use this information as input attributes to learn a classifier model.

From [Berry & Linoff] Data Mining Techniques, 1997

Classification: Application 2

- **Fraud Detection**
  - **Goal: Predict fraudulent cases in credit card transactions.**
  - **Approach:**
    - Use credit card transactions and the information on its account-holder as attributes.
      - When does a customer buy, what does he buy, how often he pays on time, etc
    - Label past transactions as fraud or fair transactions. This forms the class attribute.
    - Learn a model for the class of the transactions.
    - Use this model to detect fraud by observing credit card transactions on an account.

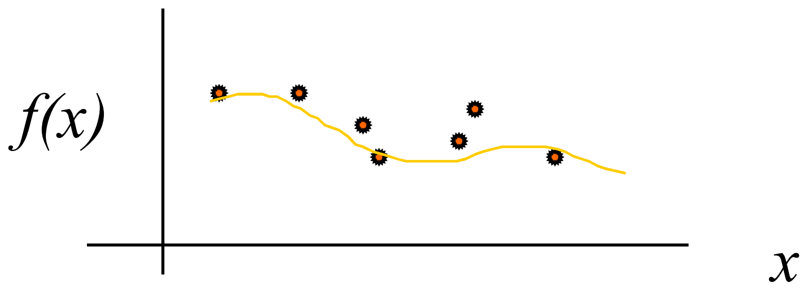
Classification: Application 3

- **Customer Attrition/Churn:**
  - **Goal: To predict whether a customer is likely to be lost to a competitor.**
  - **Approach:**
    - Use detailed record of transactions with each of the past and present customers, to find attributes.
      - How often the customer calls, where he calls, what time-of-the day he calls most, his financial status, marital status, etc.
    - Label the customers as loyal or disloyal.
    - Find a model for loyalty.

From [Berry & Linoff] Data Mining Techniques, 1997

Generalization and regression

- The objective of learning is to achieve good *generalization* to new unseen cases.
- Generalization can be defined as a mathematical *interpolation* or *regression* over a set of training points
- Models can be validated with a previously unseen test set or using cross-validation methods



Regression

- Predict a value of a given continuous valued variable based on the values of other variables, assuming a linear or nonlinear model of dependency.
- Greatly studied in statistics, neural network fields.
- Examples:
  - Predicting sales amounts of new product based on advetising expenditure.
  - Predicting wind velocities as a function of temperature, humidity, air pressure, etc.
  - Time series prediction of stock market indices.

Automated exploration and discovery

- **Clustering: partitioning a set of data into a set of classes, called *clusters*, whose members share some interesting common properties.**
- **Distance-based numerical clustering**
  - **metric grouping of examples (K-NN)**
  - **graphical visualization can be used**
- **Bayesian clustering**
  - **search for the number of classes which result in best fit of a probability distribution to the data**
  - **AutoClass (NASA) one of best examples**

Clustering Definition

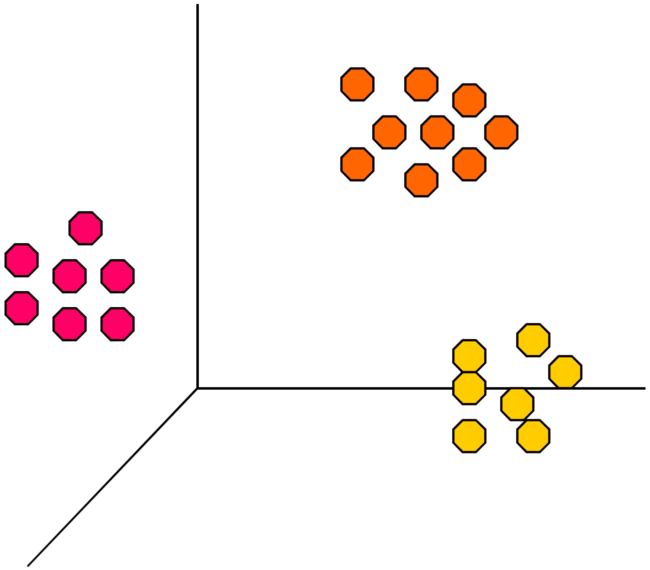
- Given a set of data points, each having a set of attributes, and a similarity measure among them, find clusters such that
  - Data points in one cluster are more similar to one another.
  - Data points in separate clusters are less similar to one another.
- Similarity Measures:
  - Euclidean Distance if attributes are continuous.
  - Other Problem-specific Measures.

Illustrating Clustering

☒Euclidean Distance Based Clustering in 3-D space.

Intracluster distances are minimized

Intercluster distances are maximized



Clustering: Application 1

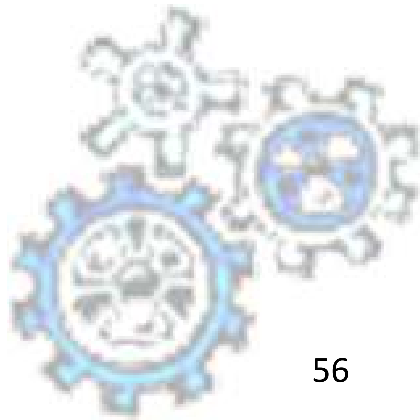
- **Market Segmentation:**
  - **Goal: subdivide a market into distinct subsets of customers where any subset may conceivably be selected as a market target to be reached with a distinct marketing mix.**
  - **Approach:**
    - Collect different attributes of customers based on their geographical and lifestyle related information.
    - Find clusters of similar customers.
    - Measure the clustering quality by observing buying patterns of customers in same cluster vs. those from different clusters.

Association Rule Discovery: Definition

- **Given a set of records each of which contain some number of items from a given collection;**
  - **Produce dependency rules which will predict occurrence of an item based on occurrences of other items.**

TID	***Items***
1	**Bread, Coke, Milk**
2	**Beer, Bread**
3	**Beer, Coke, Diaper, Milk**
4	**Beer, Bread, Diaper, Milk**
5	**Coke, Diaper, Milk**

Rules Discovered:
{Milk} --> {Coke}
{Diaper, Milk} --> {Beer}



Association Rule Discovery: Application 1

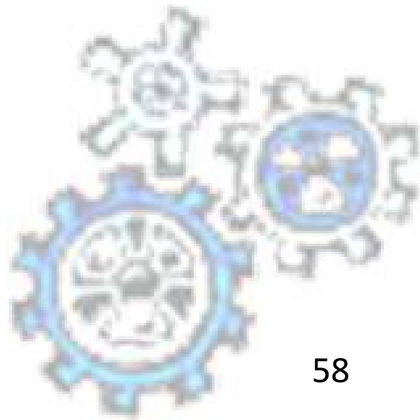
- **Marketing and Sales Promotion:**
  - **Let the rule discovered be**

    {Bagels, … } --> {Potato Chips}

  - **Potato Chips as consequent => Can be used to determine what should be done to boost its sales.**
  - **Bagels in the antecedent => Can be used to see which products would be affected if the store discontinues selling bagels.**
  - **Bagels in antecedent *and* Potato chips in consequent => Can be used to see what products should be sold with Bagels to promote sale of Potato chips!**

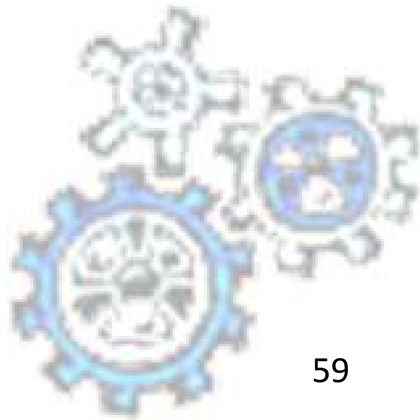
Association Rule Discovery: Application 2

- **Supermarket shelf management.**
  - **Goal: To identify items that are bought together by sufficiently many customers.**
  - **Approach: Process the point-of-sale data collected with barcode scanners to find dependencies among items.**
  - **A classic rule --**
    - If a customer buys diaper and milk, then he is very likely to buy beer.
    - So, don’t be surprised if you find six-packs stacked next to diapers!



Association Rule Discovery: Application 3

- **Inventory Management:**
  - **Goal: A consumer appliance repair company wants to anticipate the nature of repairs on its consumer products and keep the service vehicles equipped with right parts to reduce on number of visits to consumer households.**
  - **Approach: Process the data on tools and parts required in previous repairs at different consumer locations and discover the co-occurrence patterns.**

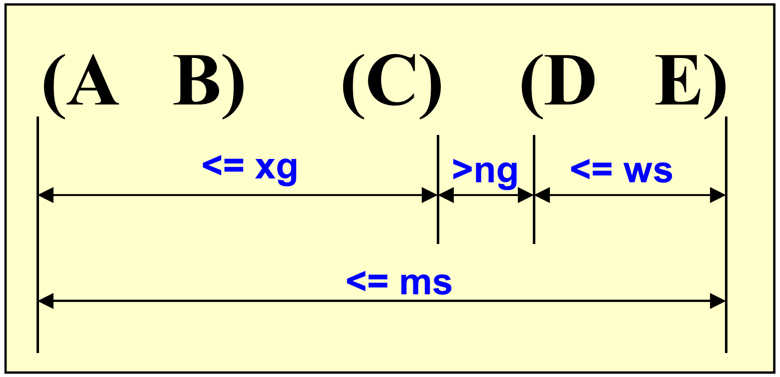


Sequential Pattern Discovery: Definition

- **Given is a set of *objects*, with each object associated with its own *timeline of events*, find rules that predict strong sequential dependencies among different events.**

$$(A\quad B)\quad (C) \longrightarrow (D\quad E)$$

- **Rules are formed by first disovering patterns. Event occurrences in the patterns are governed by timing constraints.**



Sequential Pattern Discovery: Examples

- **In telecommunications alarm logs,**
  - **(Inverter_Problem Excessive_Line_Current)**
    (Rectifier_Alarm) --> (Fire_Alarm)
- **In point-of-sale transaction sequences,**
  - **Computer Bookstore:**
    (Intro_To_Visual_C) (C++_Primer) -->
    (Perl_for_dummies,Tcl_Tk)
  - **Athletic Apparel Store:**
    (Shoes) (Racket, Racketball) --> (Sports_Jacket)

Deviation/Anomaly Detection

- Detect significant deviations from normal behavior
- Applications:
  - Credit Card Fraud Detection

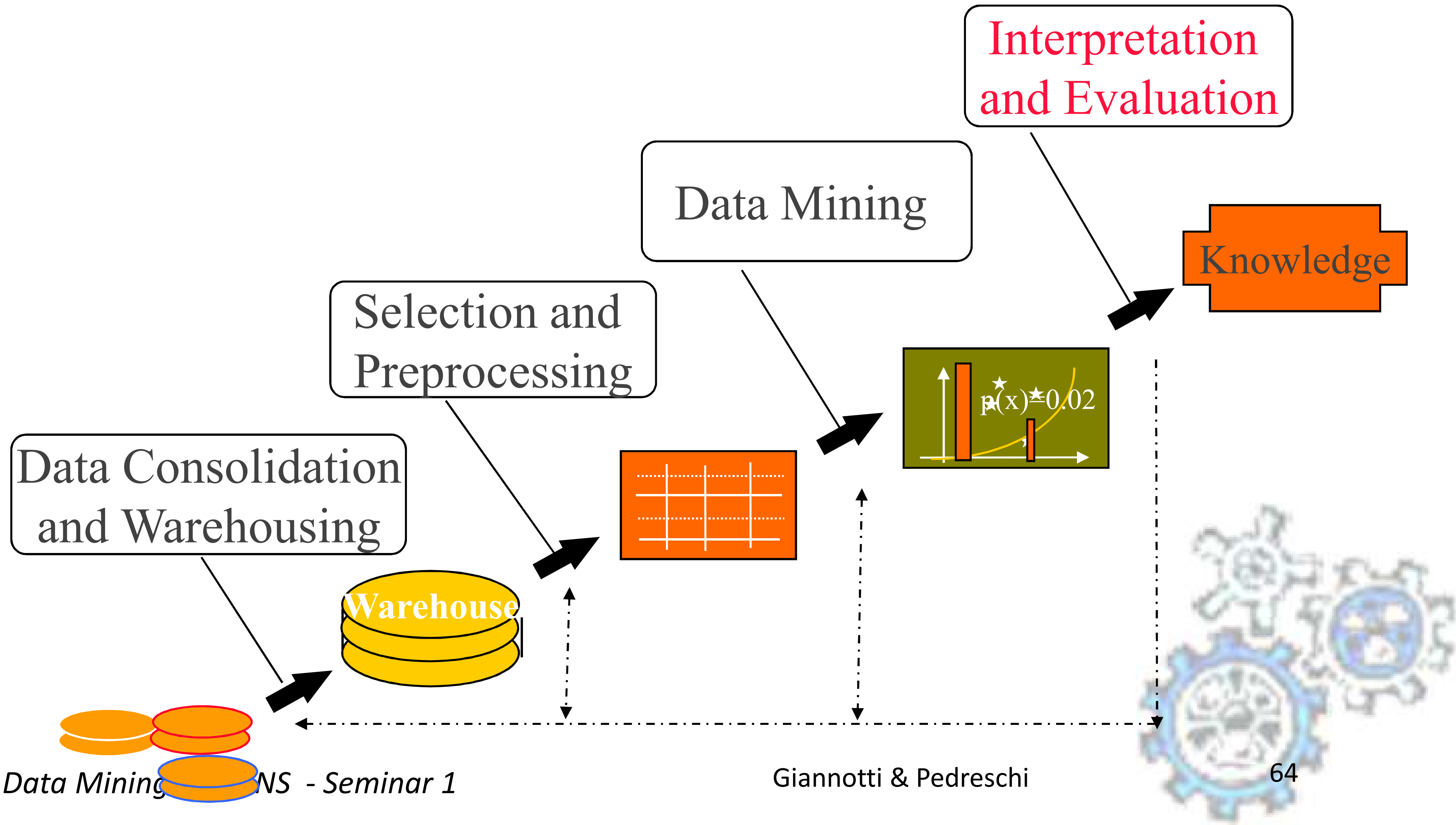
  - Network Intrusion Detection

Typical network traffic at University level may reach over 100 million connections per day

Challenges of Data Mining

- Scalability
- Dimensionality
- Complex and Heterogeneous Data
- Data Quality
- Data Ownership and Distribution
- Privacy Preservation
- Streaming Data

The KDD process



Are all the discovered pattern interesting?

- A data mining system/query may generate thousands of patterns, not all of them are interesting.
- Interestingness measures:
  - easily understood by humans
  - valid on new or test data with some degree of certainty.
  - potentially useful
  - novel, or validates some hypothesis that a user seeks to confirm
- Objective vs. subjective interestingness measures
  - Objective: based on statistics and structures of patterns, e.g., support, confidence, etc.
  - Subjective: based on user's beliefs in the data, e.g., unexpectedness, novelty, etc.

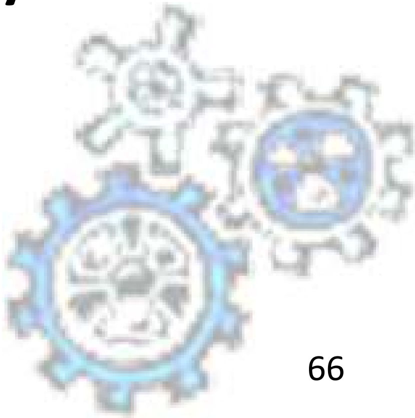
Interpretation and evaluation

Evaluation

- ⌘ **Statistical validation and significance testing**
- ⌘ **Qualitative review by experts in the field**
- ⌘ **Pilot surveys to evaluate model accuracy**

Interpretation

- ⌘ **Inductive tree and rule models can be read directly**
- ⌘ **Clustering results can be graphed and tabled**
- ⌘ **Code can be automatically generated by some systems**
  (IDTs, Regression models)



DM textbooks

- Pang-Ning Tan, Michael Steinbach, Vipin Kumar, **Introduction to DATA MINING**, Pearson - Addison Wesley, ISBN 0-321-32136-7, 2006
  - http://www-users.cs.umn.edu/~kumar/dmbook/index.php (slides e capitoli 4, 6 e 8 scaricabili liberamente)
- Jiawei Han, Micheline Kamber, **Data Mining: Concepts and Techniques**, Morgan Kaufmann Publishers, 2000
- Micheael J. A. Berry, Gordon S. Linoff, **Mastering Data Mining**, Wiley, 2000

Seminar 1 - Bibliography

Jiawei Han, Micheline Kamber, Data Mining: Concepts and Techniques, Morgan Kaufmann Publishers, 2000 http://www.mkp.com/books_catalog/catalog.asp?ISBN=1-55860-489-8

- U. Fayyad, G. Piatetsky-Shapiro, P. Smyth, R. Uthurusamy (editors). Advances in Knowledge discovery and data mining, MIT Press, 1996.
- David J. Hand, Heikki Mannila, Padhraic Smyth, Principles of Data Mining, MIT Press, 2001.
- S. Chakrabarti, Mining the Web: Discovering Knowledge from Hypertext Data, Morgan Kaufmann, ISBN 1-55860-754-4, 2002

Examples of DM projects

Competitive Intelligence

Fraud Detection

Health care

Traffic Accident Analysis

Moviegoers database

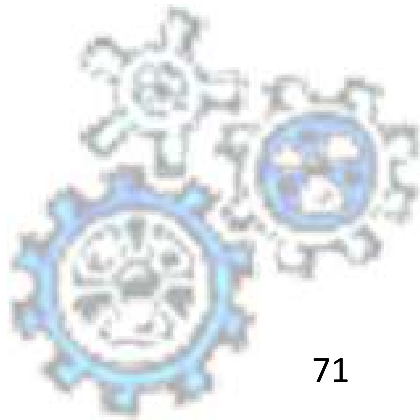
L’Oreal, a case-study on competitive intelligence:

Source: DM@CINECA

http://open.cineca.it/datamining/dmCineca/

A small example

- Domain: technology watch - a.k.a. competitive intelligence
  - Which are the emergent technologies?
  - Which competitors are investing on them?
  - In which area are my competitors active?
  - Which area will my competitor drop in the near future?
- Source of data:
  - public (on-line) databases



The Derwent database

- **Contains all patents filed worldwide in last 10 years**
- **Searching this database by keywords may yield thousands of documents**
- **Derwent document are semi-structured: many long text fields**

- **Goal: analyze Derwent document to build a model of competitors' strategy**

Structure of Derwent documents

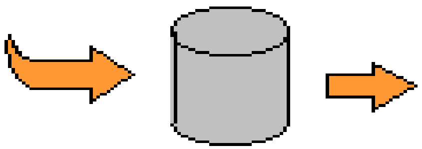
Raccolta dei Documenti

<u>**esempio di documento brevettuale**</u>

1/3881 - (C) Derwent Info 1994

AN: 94-364398 [45]

TI: Television with function for enlarging picture by variation of deflection frequency - has microprocessor for controlling system synchronous signal output, horizontal and vertical frequency drive circuit, sync. signal counter, signal detector.



DC: W03

PA: (GLDS) GOLDSTAR CO LTD

IN: O.KEITH

NP: 1

PR: 88KR-011143 880831

IC: H04N-005/262;C08J-005/18;G11B-005/704

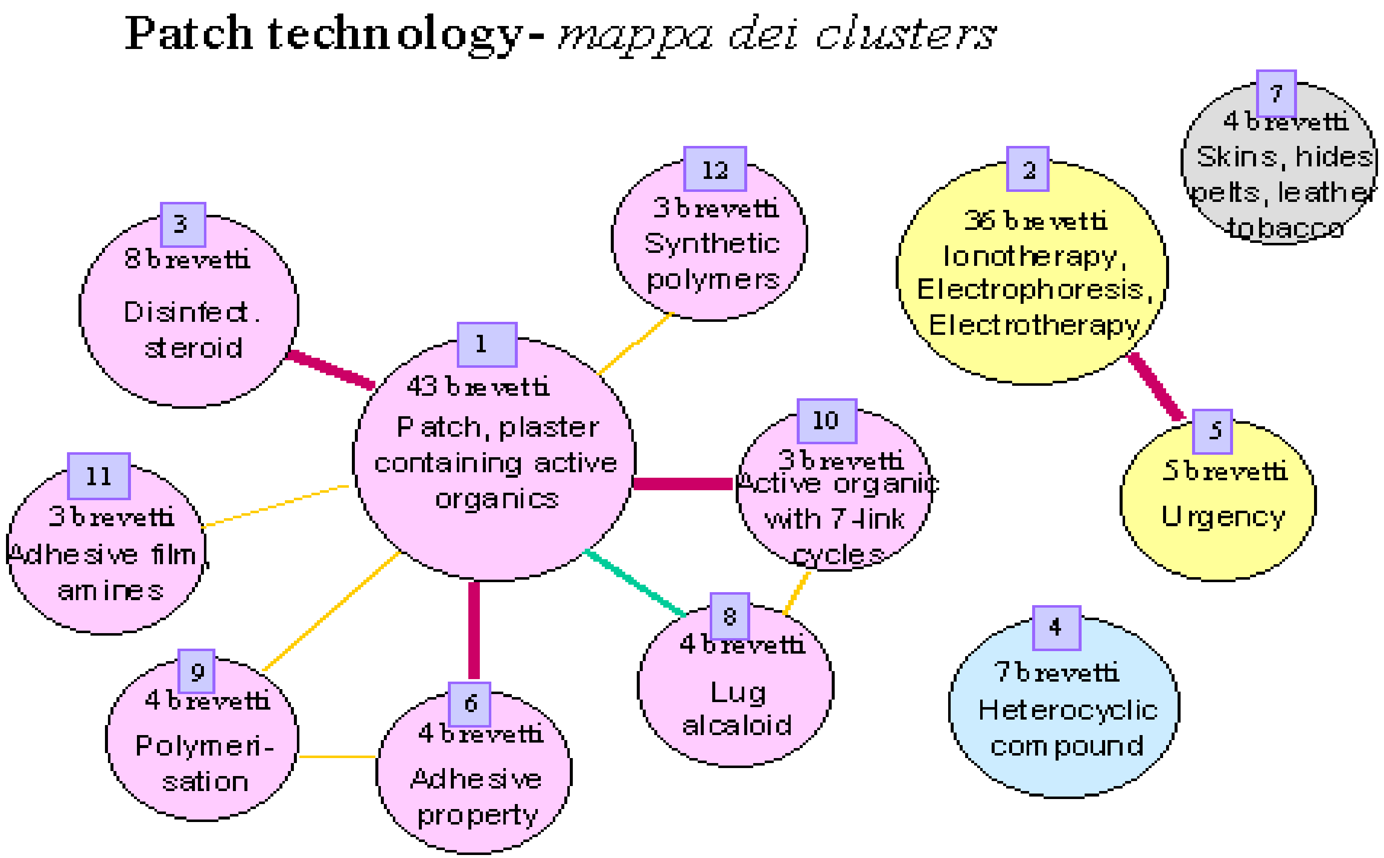
PN: KR940043 B1 940120 DW9445

AB: .... abstract ....

Example dataset

- Patents in the area: patch technology (cerotto medicale)
  - 105 companies from 12 countries
  - 94 classification codes
  - 52 Derwent codes

Clustering output



Zoom on cluster 2

Patch technology- *descrizione del cluster n.2*

Classificazione Internazionale:

A61N-001/30 Electrotherapy; Appliances of electrical power by contact electrodes; Ionotherapy or electrophorese devices
A61M-037/00 Therapeutic patch

Classificazione Derwent:

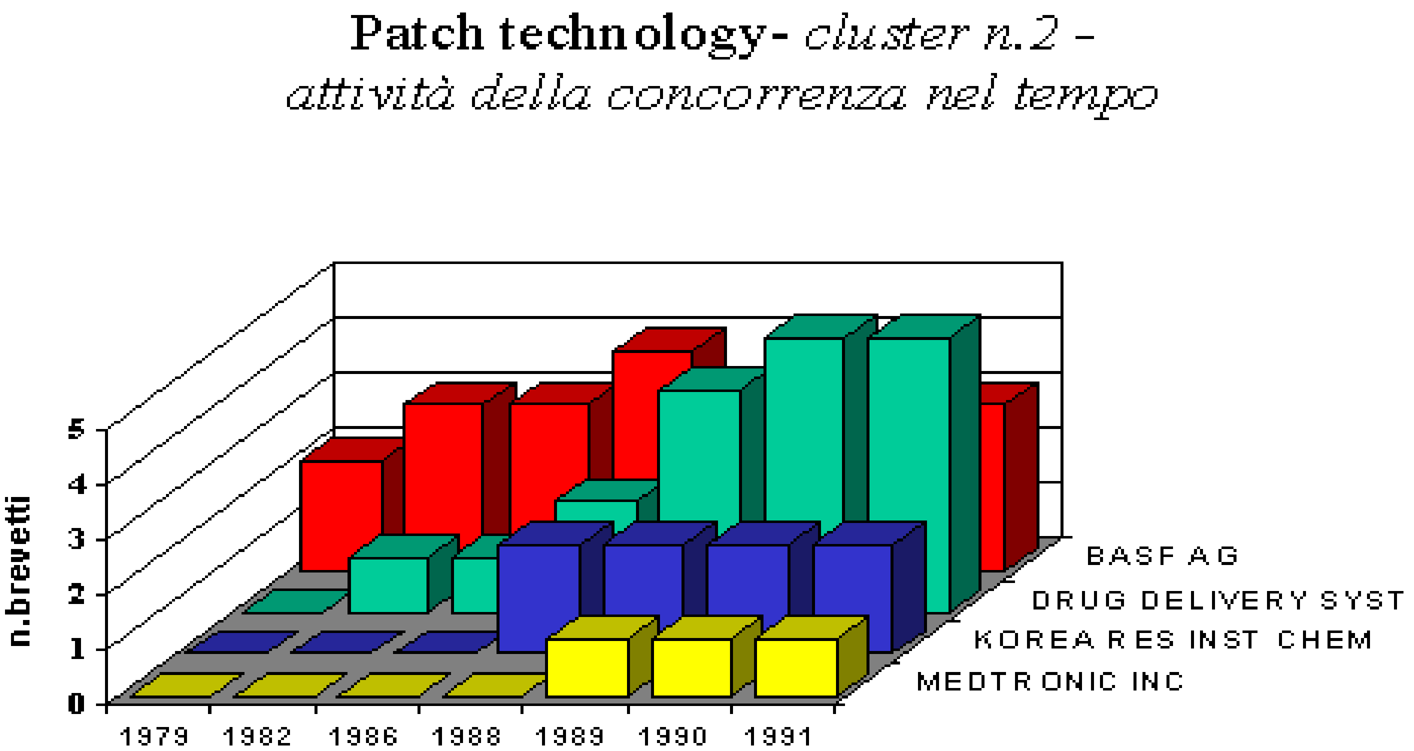
S05 Electromedical
P34 Health, Electrotherapy

Società proprietarie:

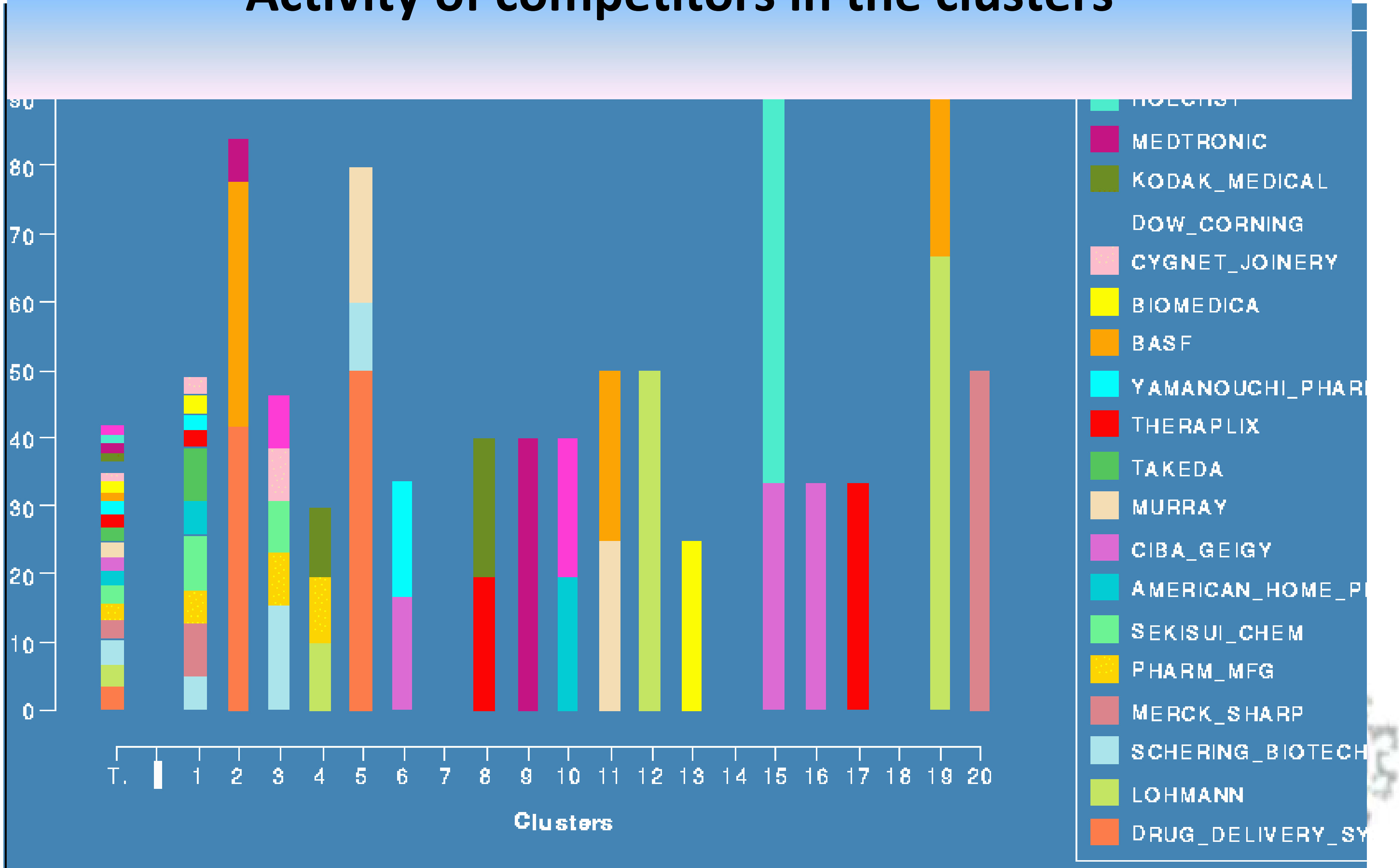
DRUG DELIVERY SYST	42%
BASF AG	36%
KOREA RES INST CHEM	16%
MEDTRONIC INC	6%

Anno	n. brevetti
1979	2
1982	4
1986	4
1988	8
1989	10
1990	11
1991	11

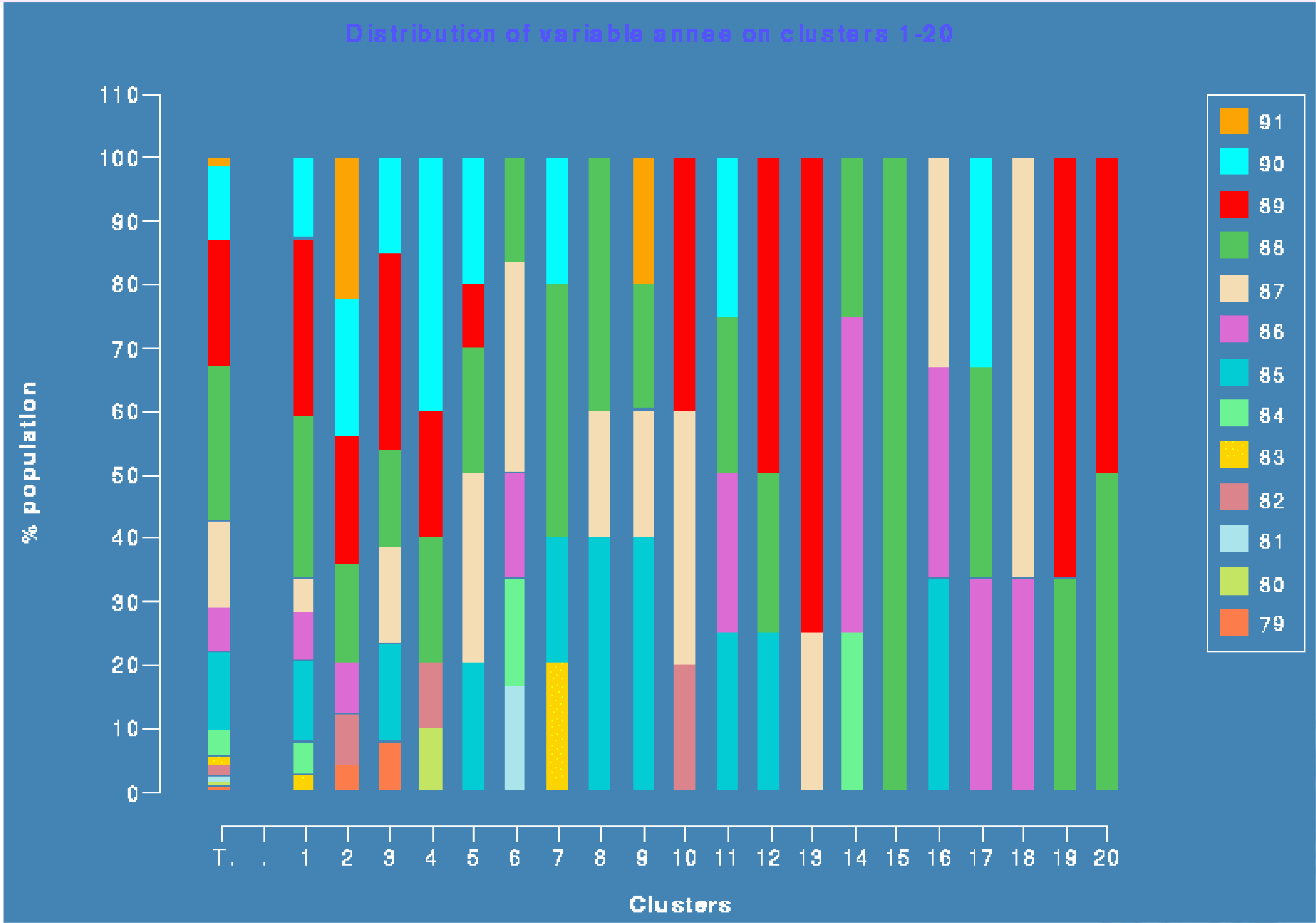
Zoom on cluster 2 - profiling competitors



Activity of competitors in the clusters



Temporal analysis of clusters



Fraud detection and audit planning

Source: Ministero delle Finanze

Progetto Sogei, KDD Lab. Pisa

Fraud detection

- **A major task in fraud detection is constructing *models* of fraudulent behavior, for:**
  - **preventing future frauds (*on-line* fraud detection)**
  - **discovering past frauds (*a posteriori* fraud detection)**
- **analyze historical audit data to plan effective future audits**

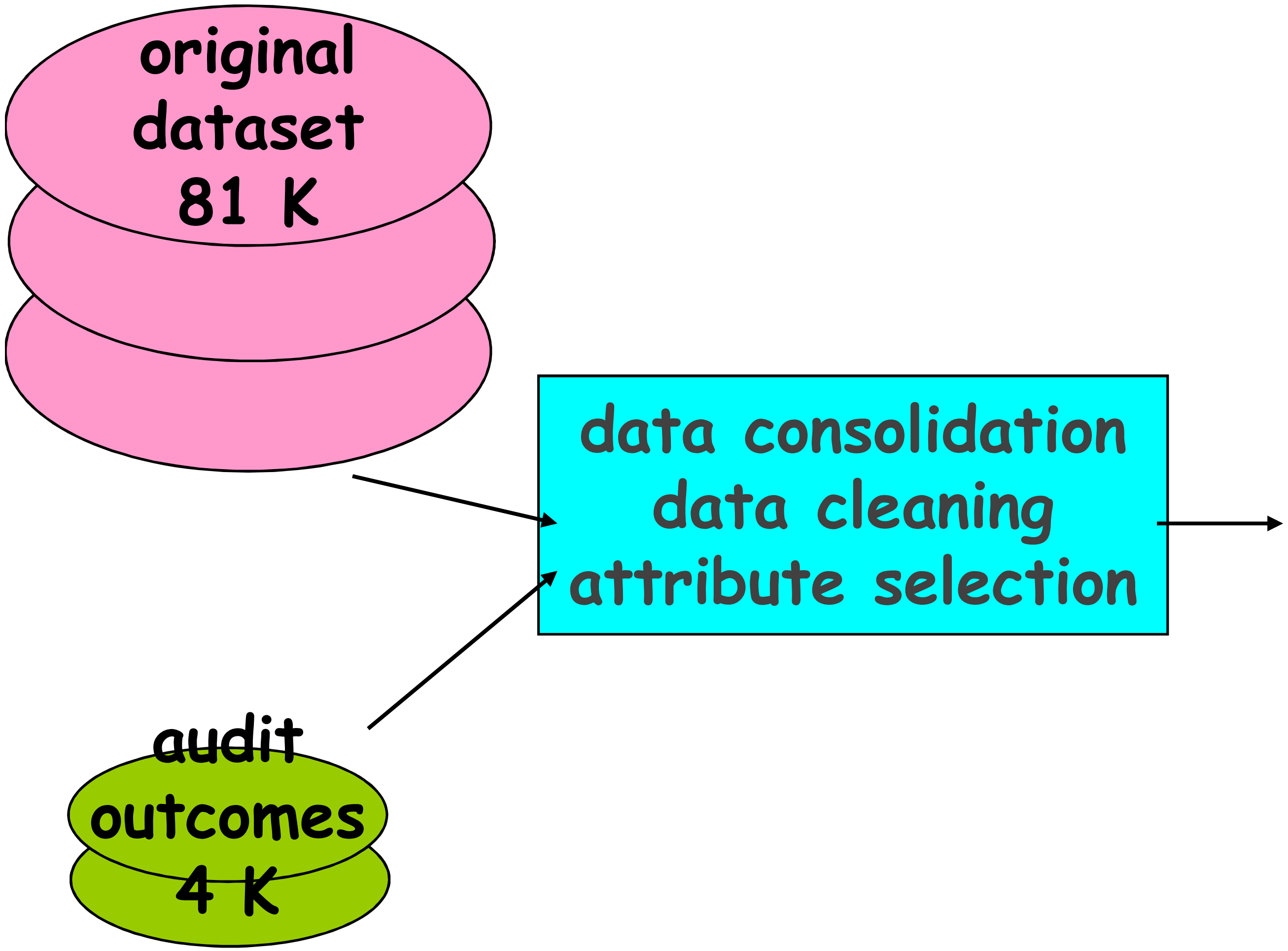
Audit planning

- **Need to face a trade-off between conflicting issues:**
  - ***maximize audit benefits*: select subjects to be audited to maximize the recovery of evaded tax**
  - ***minimize audit costs*: select subjects to be audited to minimize the resources needed to carry out the audits.**

Available data sources

- **Dataset: tax declarations, concerning a targeted class of Italian companies, integrated with other sources:**
  - **social benefits to employees, official budget documents, electricity and telephone bills.**
- **Size: 80 K tuples, 175 numeric attributes.**
- **A subset of 4 K tuples corresponds to the *audited* companies:**
  - **outcome of audits recorded as the *recovery* attribute (= *amount of evaded tax ascertained*)**

Data preparation



TAX DECLARATION
- Codice Attivita'
- Debiti Vs banche
- Totale Attivita'
- Totale Passivita'
- Esistenze Iniziali
- Rimanenze Finali
- Profitti
- Ricavi
- Costi Funzionamento
- Oneri Personale
- Costi Totali
- Utile o Perdita
- Reddito IRPEG

SOCIAL BENEFITS
- Numero Dipendenti'
- Contributi Totali
- Retribuzione Totale

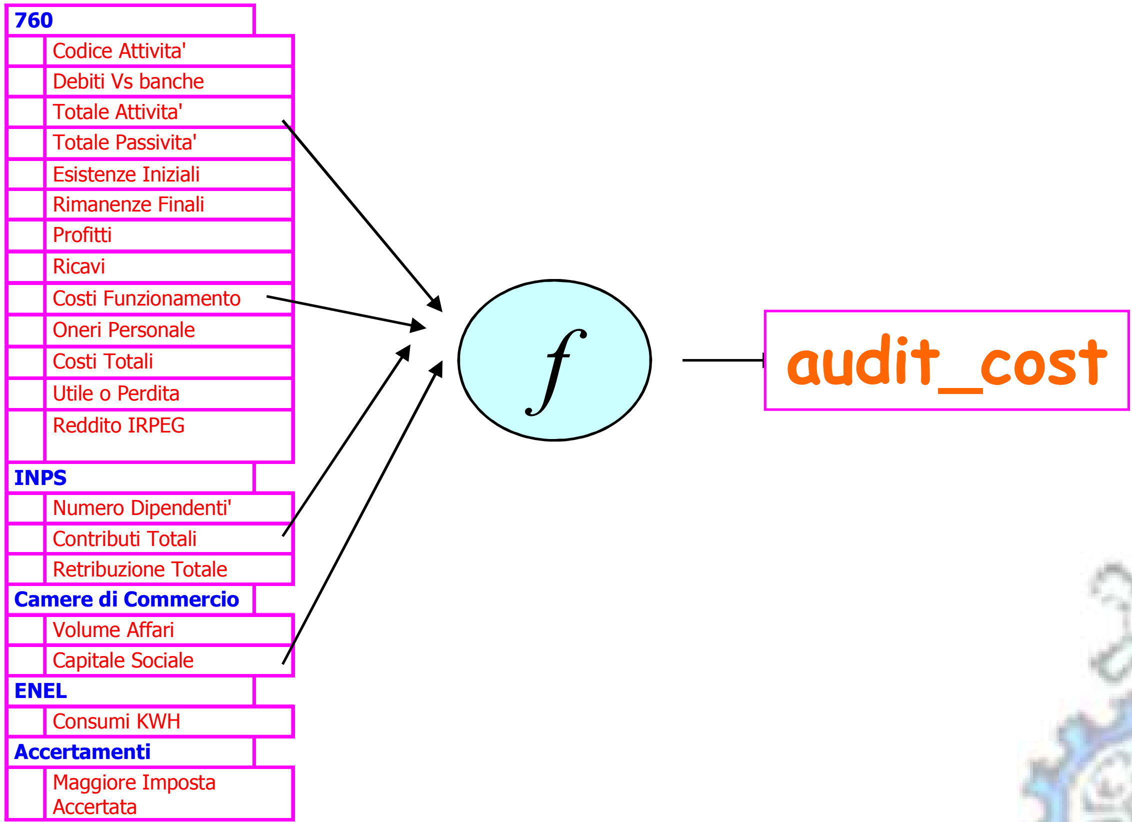
OFFICIAL BUDGET
- Volume Affari
- Capitale Sociale

ELECTRICITY BILLS
- Consumi KWH

AUDIT
- Recovery

Cost model

⌘ A derived attribute audit_cost is defined as a function of other attributes



Cost model and the target variable

- **recovery of an audit after the audit cost actual_recovery = recovery - audit_cost**

- **target variable (class label) of our analysis is set as the Class of Actual Recovery (c.a.r.):**

- ***c.a.r.* =**

$$\text{c.a.r.} = \begin{cases} \textit{negative} & \textbf{\textit{if}} \ \ \textit{actual\_recovery} \le 0 \\ \textit{positive} & \textbf{\textit{if}} \ \ \textit{actual\_recovery} > 0. \end{cases}$$

Quality assessment indicators

- The obtained classifiers are evaluated according to several indicators, or metrics
- Domain-independent indicators
  - confusion matrix
  - misclassification rate
- Domain-dependent indicators
  - audit #
  - actual recovery
  - profitability
  - relevance

Domain-dependent quality indicators

- **audit #** (of a given classifier): number of tuples classified as positive =

  $$\#\,(FP \cup TP)$$

- **actual recovery**: total amount of actual recovery for all tuples classified as positive
- **profitability**: average actual recovery per audit
- **relevance**: ratio between profitability and misclassification rate

The REAL case

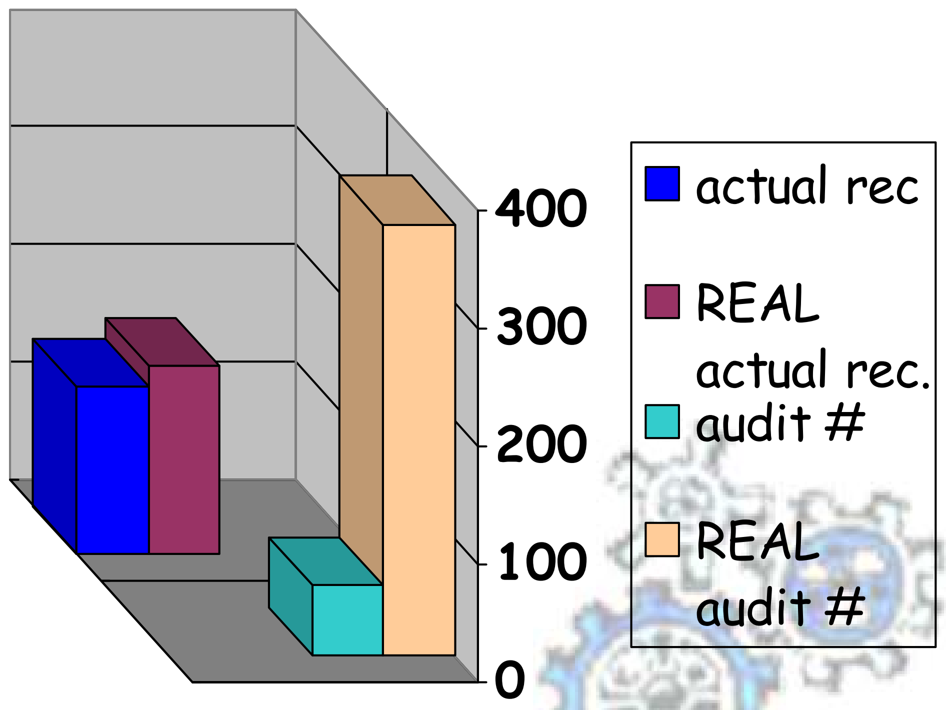
- **Classifiers can be compared with the REAL case, consisting of the whole test-set:**

- **audit # (REAL) = 366**
- **actual recovery(REAL) = 159.6 M euro**

Model evaluation: classifier 1 (min FP)

- no replication in training-set (unbalance towards negative)
- 10-trees adaptive boosting

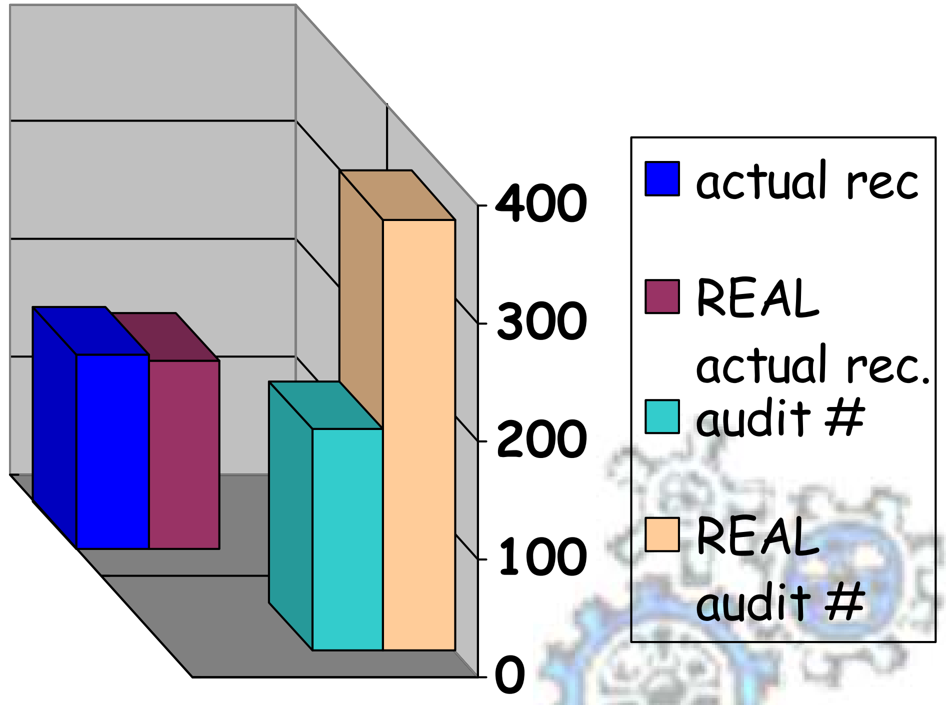
- *misc. rate* = 22%
- *audit #* = 59 (11 FP)
- *actual rec.*= 141.7 Meuro
- *profitability* = 2.401



Model evaluation: classifier 2 (min FN)

- replication in training-set (balanced neg/pos)
- misc. weights (trade 3 FP for 1 FN)
- 3-trees adaptive boosting

- *misc. rate* = 34%
- *audit #* = 188 (98 FP)
- *actual rec.*= 165.2 Meuro
- *profitability* = 0.878



Atherosclerosis prevention study

**2nd Department of Medicine,
1st Faculty of Medicine of Charles
University and Charles University Hospital,
U nemocnice 2, Prague 2
(head. Prof. M. Aschermann, MD, SDr, FESC)**

Atherosclerosis prevention study:

- **The STULONG 1 data set is a real database that keeps information about the study of the development of atherosclerosis risk factors in a population of middle aged men.**
- **Used for Discovery Challenge at PKDD 00-02-03-04**

Atherosclerosis prevention study:

- **Study on 1400 middle-aged men at Czech hospitals**
  - **Measurements concern development of cardiovascular disease and other health data in a series of exams**
- **The aim of this analysis is to look for associations between medical characteristics of patients and death causes.**
- **Four tables**
  - **Entry and subsequent exams, questionnaire responses, deaths**

The input data

Data from Entry and Exams		
General characteristics	**Examinations**	**habits**
Marital status	**Chest pain**	**Alcohol**
Transport to a job	**Breathlesness**	**Liquors**
Physical activity in a job	**Cholesterol**	**Beer 10**
Activity after a job	**Urine**	**Beer 12**
Education	**Subscapular**	**Wine**
Responsibility	**Triceps**	**Smoking**
Age		**Former smoker**
Weight		**Duration of smoking**
Height		**Tea**
		Sugar
		Coffee

The input data

DEATH CAUSE	PATIENTS	%
myocardial infarction	80	20.6
coronary heart disease	33	8.5
stroke	30	7.7
other causes	79	20.3
sudden death	23	5.9
unknown	8	2.0
tumorous disease	114	29.3
general atherosclerosis	22	5.7
TOTAL	389	100.0

Data selection

- When joining “Entry” and “Death” tables we implicitely create a new attribute “Cause of death”, which is set to “alive” for subjects present in the “Entry” table but not in the “Death” table.
- We have only 389 subjects in death table.

The prepared data

Patient	General characteristics		Examinations		Habits		Cause of death
	Activity after work	Education	Chest pain	…	Alcohol	…..	
1	moderate activity	university	not present		no		Stroke
2	great activity		not ischaemic		occasionally		myocardial infarction
3	he mainly sits		other pains		regularly		tumorous disease
……	……..	……..	……….	..	…	……	alive
389	he mainly sits		other pains		regularly		tumorous disease

Descriptive Analysis/ Subgroup Discovery /Association Rules

Are there strong relations concerning death cause?

General characteristics (?) $\Rightarrow$ Death cause (?)

Examinations (?) $\Rightarrow$ Death cause (?)

Habits (?) $\Rightarrow$ Death cause (?)

Combinations (?) $\Rightarrow$ Death cause (?)

Example of extracted rules

- **Education(university) & Height<176-180> ⇒Death cause (tumouros disease),** ***16 ; 0.62***
- **It means that on tumorous disease have died 16, i.e. 62% of patients with university education and with height 176-180 cm.**

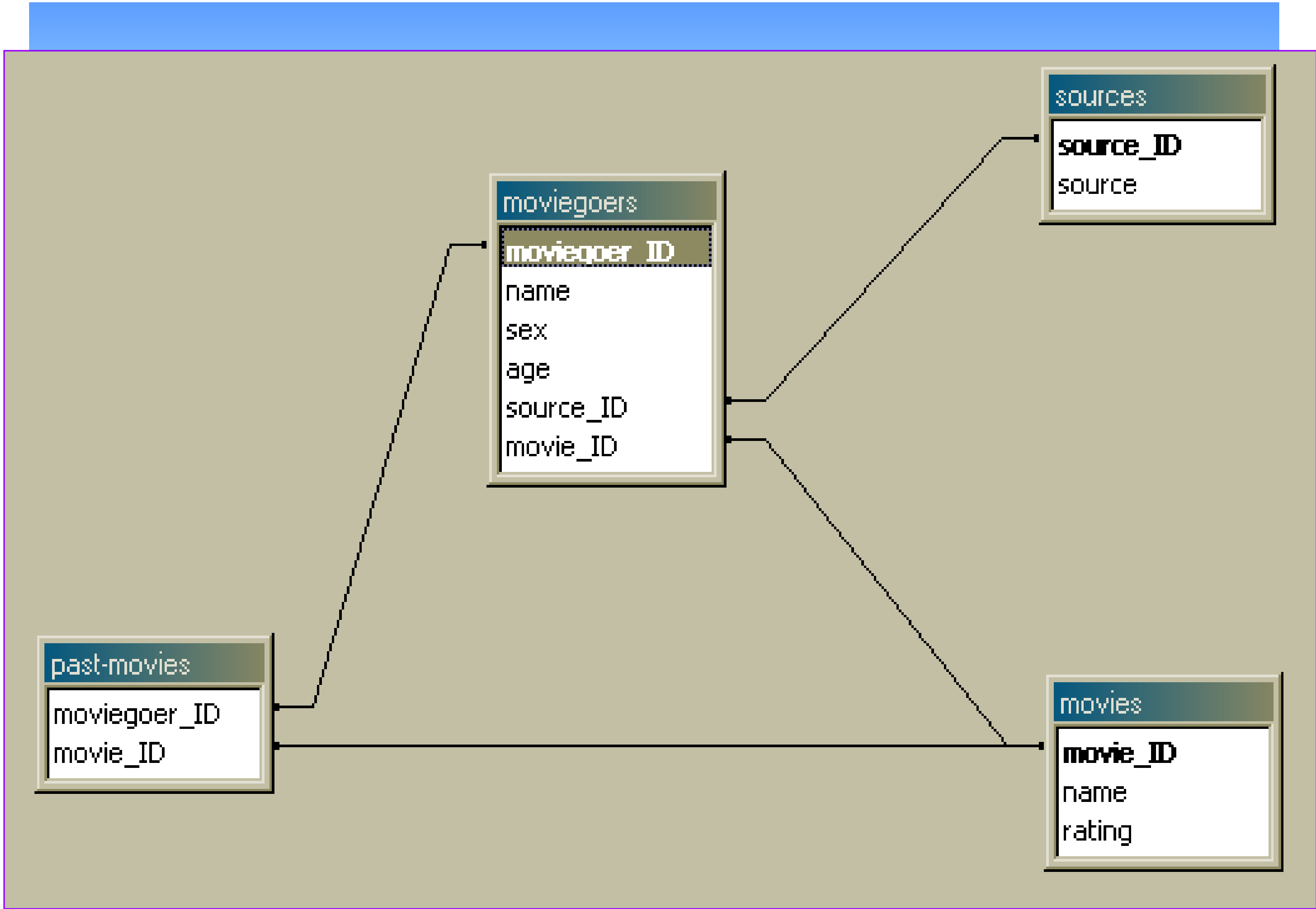
Example of extracted rules

- **Physical activity in work(he mainly sits) & Height<176-180> $\Rightarrow$ Death cause (tumouros disease),** ***24; 0.52***
- **It means that on tumorous disease have died 24 i.e. 52% of patients that mainly sit in the work and whose height is 176-180 cm.**

Example of extracted rules

- **Education(university) & Height<176-180> ⇒Death cause (tumouros disease),**
  16; 0.62; +1.1;
- **the** relative frequency **of patients who died on tumorous disease among patients with university education and with height 176-180 cm is 110 per cent higher than the relative frequency of patients who died on tumorous disease among all the 389 observed patients**

Moviegoer Database :


sources
source_ID
source
moviegoers
moviegoer_ID
name
sex
age
source_ID
movie_ID
past-movies
moviegoer_ID
movie_ID
movies
movie_ID
name
rating

```sql
SELECT moviegoers.name, moviegoers.sex, moviegoers.age,
sources.source, movies.name
FROM movies, sources, moviegoers
WHERE sources.source_ID = moviegoers.source_ID AND
movies.movie_ID = moviegoers.movie_ID
ORDER BY moviegoers.name;
```

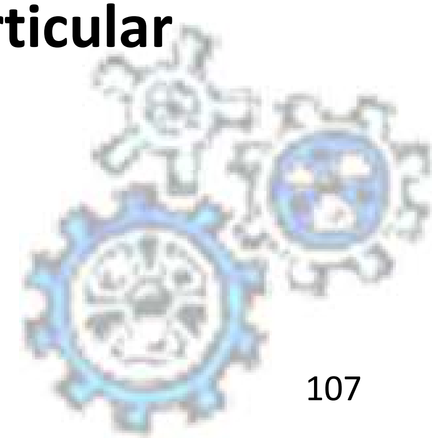
moviegoers.name	sex	age	source	movies.name
Amy	f	27	Oberlin	Independence Day
Andrew	m	25	Oberlin	12 Monkeys
Andy	m	34	Oberlin	The Birdcage
Anne	f	30	Oberlin	Trainspotting
Ansje	f	25	Oberlin	I Shot Andy Warhol
Beth	f	30	Oberlin	Chain Reaction
Bob	m	51	Pinewoods	Schindler's List
Brian	m	23	Oberlin	Super Cop
Candy	f	29	Oberlin	Eddie
Cara	f	25	Oberlin	Phenomenon
Cathy	f	39	Mt. Auburn	The Birdcage
Charles	m	25	Oberlin	Kingpin
Curt	m	30	MRJ	T2 Judgment Day
David	m	40	MRJ	Independence Day
Erica	f	23	Mt. Auburn	Trainspotting

Example: Moviegoer Database

- **Classification**
  - **determine** sex **based on age, source, and movies seen**
  - **determine** source **based on sex, age, and movies seen**
  - **determine** most recent movie **based on past movies, age, sex, and source**
- **Estimation**
  - **for predict, need a continuous variable (e.g., “age”)**
  - **predict** age **as a function of source, sex, and past movies**
  - **if we had a “rating” field for each moviegoer, we could predict the** rating a new moviegoer **gives to a movie based on age, sex, past movies, etc.**

Example: Moviegoer Database

- **Clustering**
  - **find groupings of movies that are often seen by the same people**
  - **find groupings of people that tend to see the same movies**
  - **clustering might reveal relationships that are not necessarily recorded in the data (e.g., we may find a cluster that is dominated by people with young children; or a cluster of movies that correspond to a particular genre)**



Example: Moviegoer Database

⌘ Association Rules

- market basket analysis (MBA): "which movies go together?"
- need to create "transactions" for each moviegoer containing movies seen by that moviegoer:

name	TID	Transaction
Amy	001	{Independence Day, Trainspotting}
Andrew	002	{12 Monkeys, The Birdcage, Trainspotting, Phenomenon}
Andy	003	{Super Cop, Independence Day, Kingpin}
Anne	004	{Trainspotting, Schindler's List}
...	...	...

- may result in association rules such as:

```
{"Phenomenon", "The Birdcage"} ==> {"Trainspotting"}
{"Trainspotting", "The Birdcage"} ==> {sex = "f"}
```

Example: Moviegoer Database

- **Sequence Analysis**
  - **similar to MBA, but order in which items appear in the pattern is important**
  - **e.g., people who rent “The Birdcage” during a visit tend to rent “Trainspotting” in the next visit.**

On the road to knowledge:
mining 21 years of UK traffic accident reports

Peter Flach et al.
Silnet Network of Excellence

Mining traffic accident reports

- The Hampshire County Council (UK) wanted to obtain a better insight into how the characteristics of traffic accidents may have changed over the past 20 years as a result of improvements in highway design and in vehicle design.
- The database, contained police traffic accident reports for all UK accidents that happened in the period 1979-1999.

Business Understanding

- Understanding of road safety in order to reduce the occurrences and severity of accidents.
  - influence of road surface condition;
  - influence of skidding;
  - influence of location (for example: junction approach);
  - and influence of street lighting.
- trend analysis: long-term overall trends, regional trends, urban trends, and rural trends.
- the comparison of different kinds of locations is interesting: for example, rural versus metropolitan versus suburban.

Data understanding

- **Low data quality. Many attribute values were missing or recorded as unknown.**
- **Different maps were created to investigate the effect of several parameters like accident severity and accident date.**

Modelling

- The aim of this effort was to find interesting associations between road number, conditions (e.g., weather, and light) and serious or fatal accidents.
- Certain localities had been selected and performed the analysis only over the years 1998 and 1999.

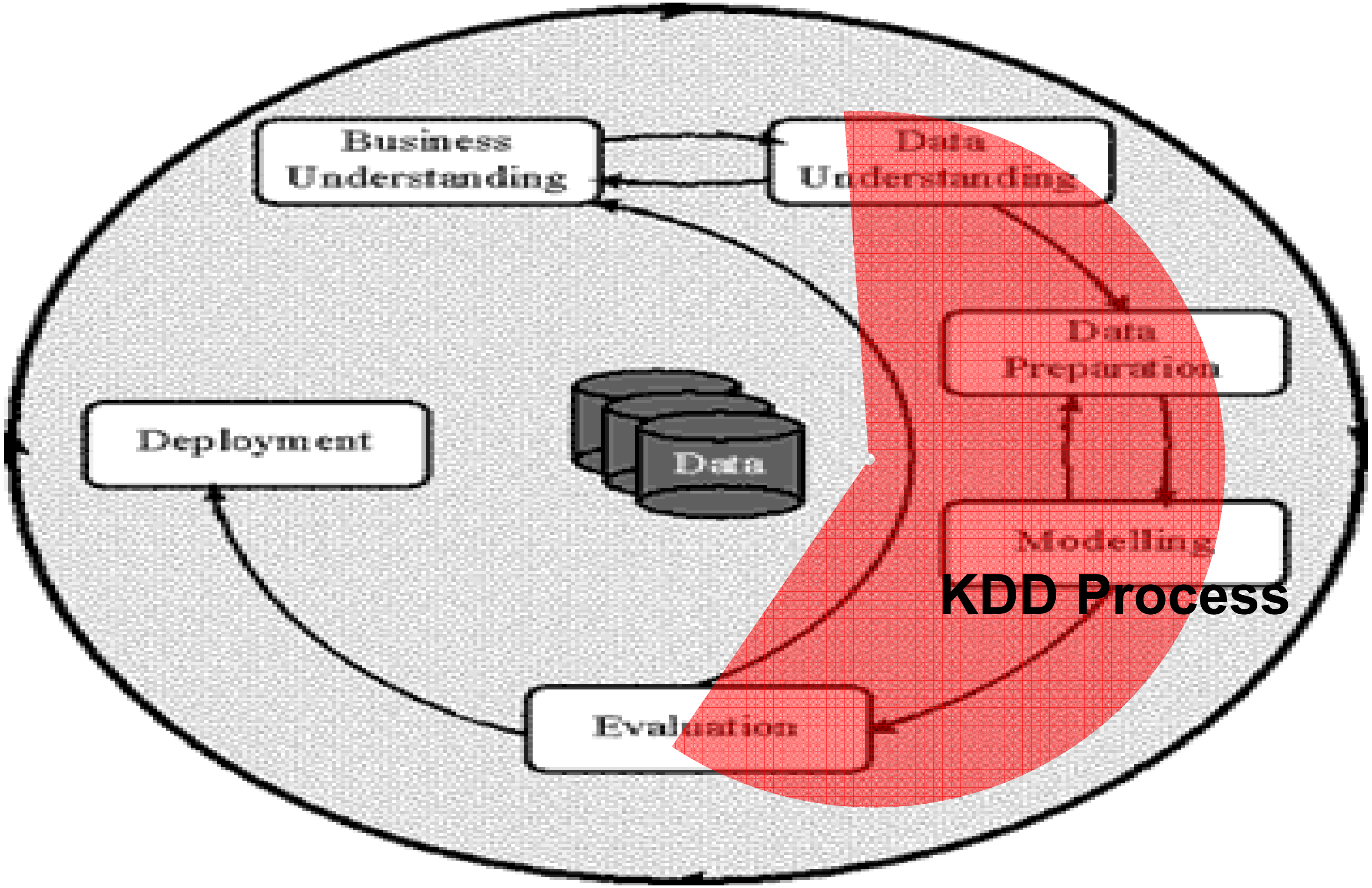
Extracted rule

	FATAL	Non FATAL	TOTAL
Road=V61 AND Weather=1	15	141	156
NOT(Road=V61 AND Weather=1)	147	5056	5203

- The relative frequency of fatal accidents among all accidents in the locality was 3%.
- The relative frequency of fatal accidents on the road (V61) under fine weather with no winds was 9.6% — more than 3 times greater.

How to develop a Data Mining Project?

CRISP-DM: **The life cicle of a data mining project**



Business understanding

- **Understanding the project objectives and requirements from a business perspective.**

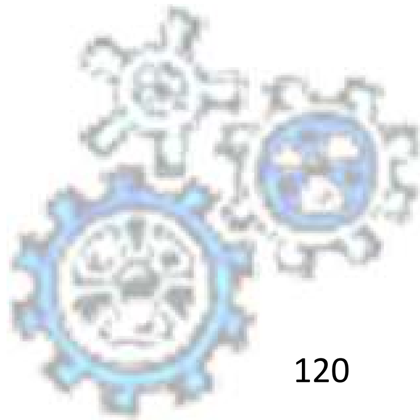
- **then converting this knowledge into a data mining problem definition and a preliminary plan.**
  - **Determine the Business Objectives**
  - **Determine Data requirements for Business Objectives**
  - **Translate Business questions into Data Mining Objective**

Data understanding

- **Data understanding: characterize data available for modelling. Provide assessment and verification for data.**

Modeling

- In this phase, various modeling techniques are selected and applied and their parameters are calibrated to optimal values.
- Typically, there are several techniques for the same data mining problem type. Some techniques have specific requirements on the form of data.
- Therefore, stepping back to the data preparation phase is often necessary.



Evaluation

- At this stage in the project you have built a model (or models) that appears to have high quality from a data analysis perspective.
- Evaluate the model and review the steps executed to construct the model to be certain it properly achieves the business objectives.
- A key objective is to determine if there is some important business issue that has not been sufficiently considered.

Deployment

- The knowledge gained will need to be organized and presented in a way that the customer can use it.
- It often involves applying “live” models within an organization’s decision making processes, for example in real-time personalization of Web pages or repeated scoring of marketing databases.

Deployment

- It can be as simple as generating a report or as complex as implementing a repeatable data mining process across the enterprise.
- In many cases it is the customer, not the data analyst, who carries out the deployment steps.