Data Mining 2 – Advanced Aspects and Applications

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http://kdd.isti.cnr.it

- **DIPARTIMENTO DI INFORMATICA - Università di Pisa**

•anno accademico 2012/2013

Data Mining

- Monday 9-11 aula N1, Wednesday 9-11 aula L1
- Teachers:
  - Fosca Giannotti, ISTI-CNR, fosca.giannotti@isti.cnr.it
  - Mirco Nanni, ISTI-CNR, mirco.nanni@isti.cnr.it
- Question time: Wednesday 15-17, ISTI, Area Ricerca CNR, località San Cataldo, Pisa (send a request by e-mail)

Data Mining

- Reference
  - **Pang-Ning Tan, Michael Steinbach, Vipin Kumar, Introduction to DATA MINING, Addison Wesley, ISBN 0-321-32136-7, 2006**
  - Barry Linoff Data Mining Techniques for Marketing Sales and Customer Support, John Wiles & Sons, 2002
- Slides available at: http://didawiki.cli.di.unipi.it
- Blog on privacy & DM
  - anna.monreale@isti.cnr.it
  - http://hd.media.mit.edu/wef_globalit.pdf

Data Mining

- Riferimenti bibliografici
  - **Pang-Ning Tan, Michael Steinbach, Vipin Kumar, Introduction to DATA MINING, Addison Wesley, ISBN 0-321-32136-7, 2006**
  - Barry Linoff Data Mining Techniques for Marketing Sales and Customer Support, John Wiles & Sons, 2002
- I lucidi utilizzati nelle lezioni saranno resi disponibili attraverso il sito web del corso: http://didawiki.cli.di.unipi.it

Data Mining- Theory

- KDD process: CRISP standard.
- Frequent Pattern Mining
- Sequential Pattern Mining,
- Mining of Time Series, spactial and spatio-temporal data
- Mining di grandi grafi e reti
- Ethical issues of data mining - Data mining and personal data privacy
- Opinion Mining

Data Mining – Applications

- Fraude Detection: Sogei1, DIVA (progetto 1)
- CRM: data set COOP, TargetMarketing, ChurnAnalysis: coop (progetto 2)
- E-health and Mining Official Data
- ICT digital traces: analysing GSM data: ORANGE, and WIND – visitor profile and .
- Mobility and Transportation: understanding human mobility. Progetto3

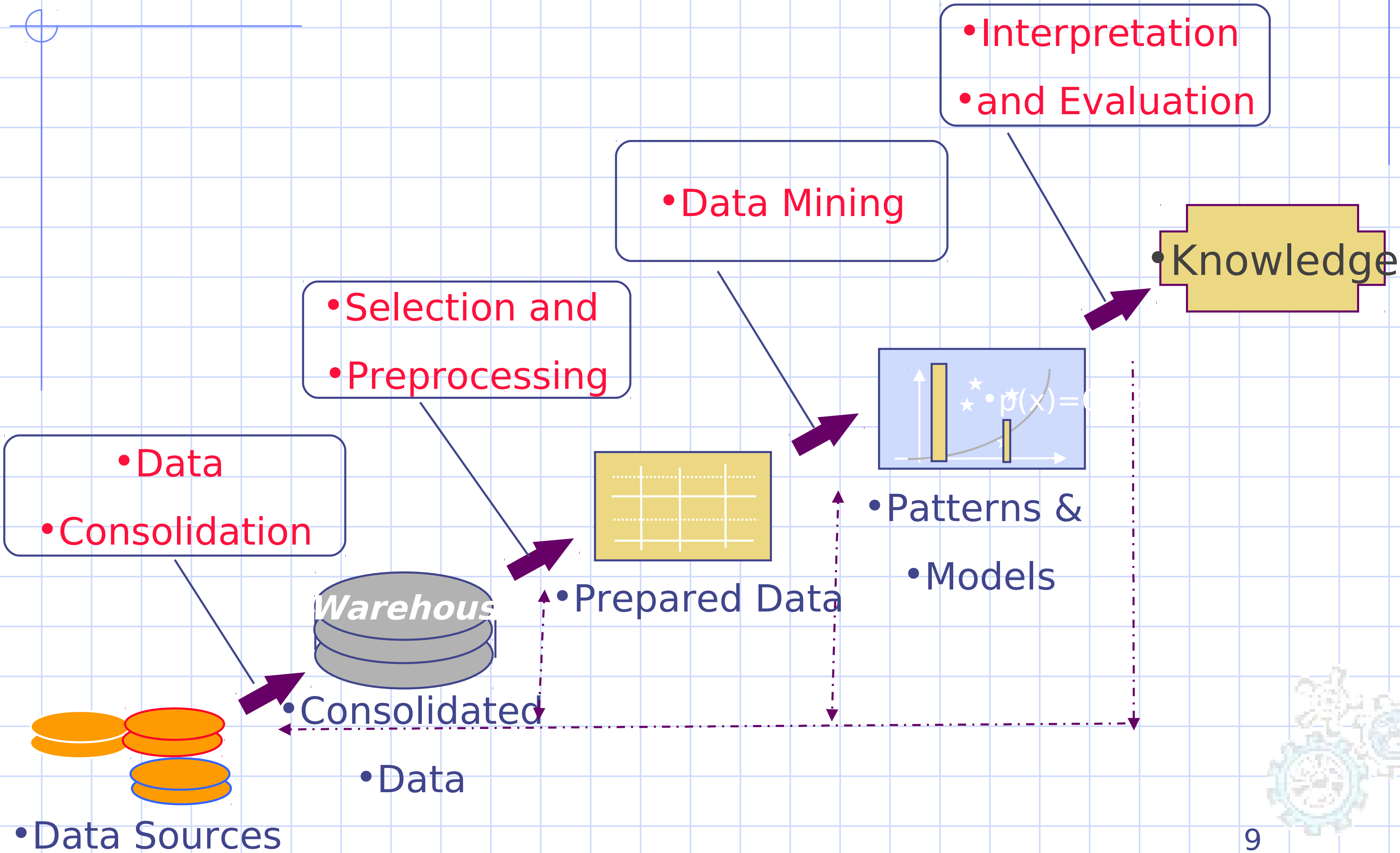
Evaluation

- Ongoing projects (on small datasets) with presentation to the class
- Team Project
  - Team of 2-3 person.
  - Unique grade.
  - Projects consist into the realization of some complete analytical processes on a given problem and a given dataset.
  - A final report followign the CRISP standard describing all steps: esploration, preparation and anaysis and final evaluation.
- Individual Project Discussion

Outline this lesson

- KDD Process
- The KDD steps in short
- CRM and Data Mining - AirMiles
- Health and Data Mining – Stulong
- Fraude detection and DataMining
- CRISP model for developing Data Mining based services

The KDD process



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 B.I. platform

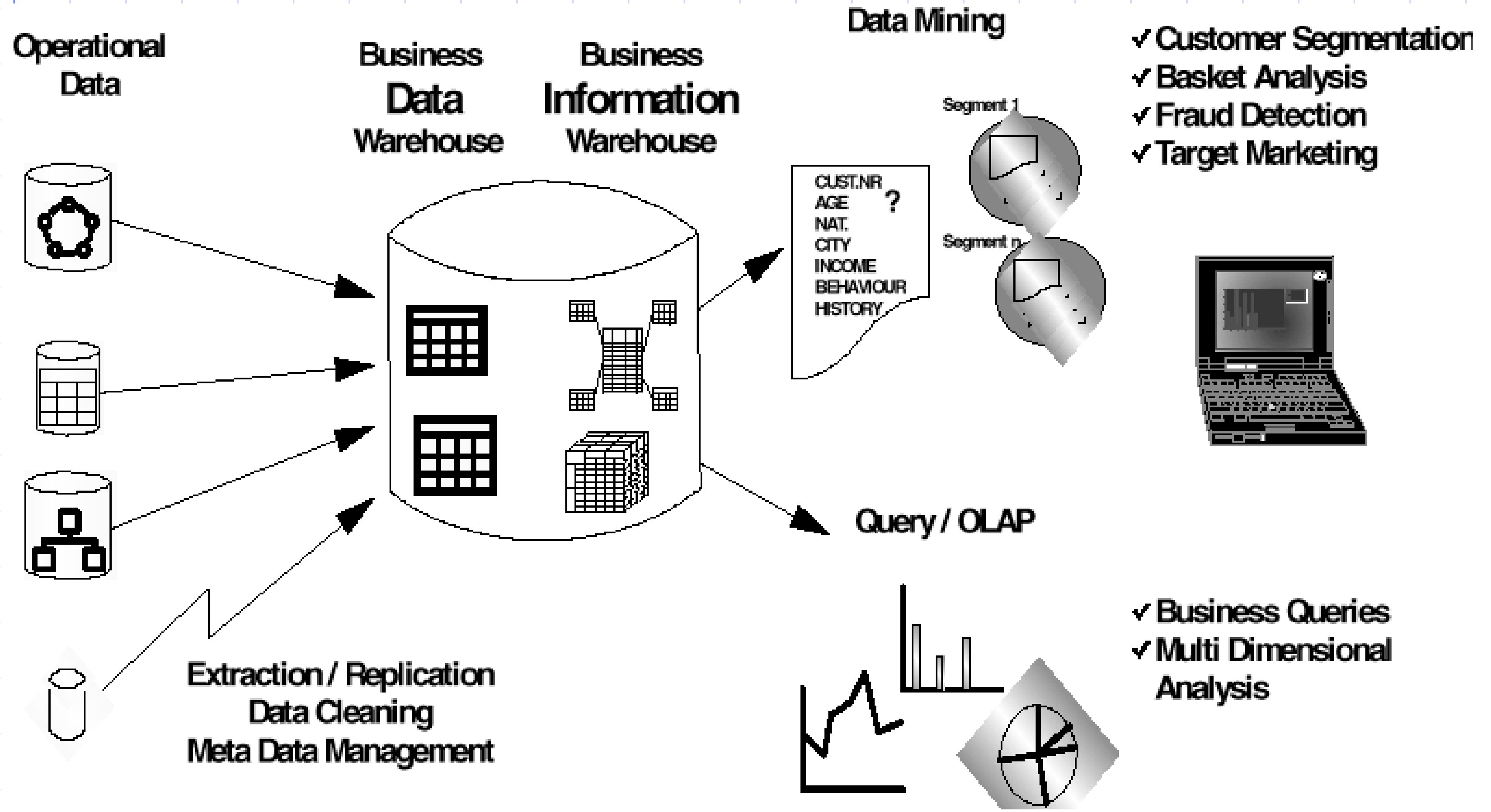


Figure per la B.I.

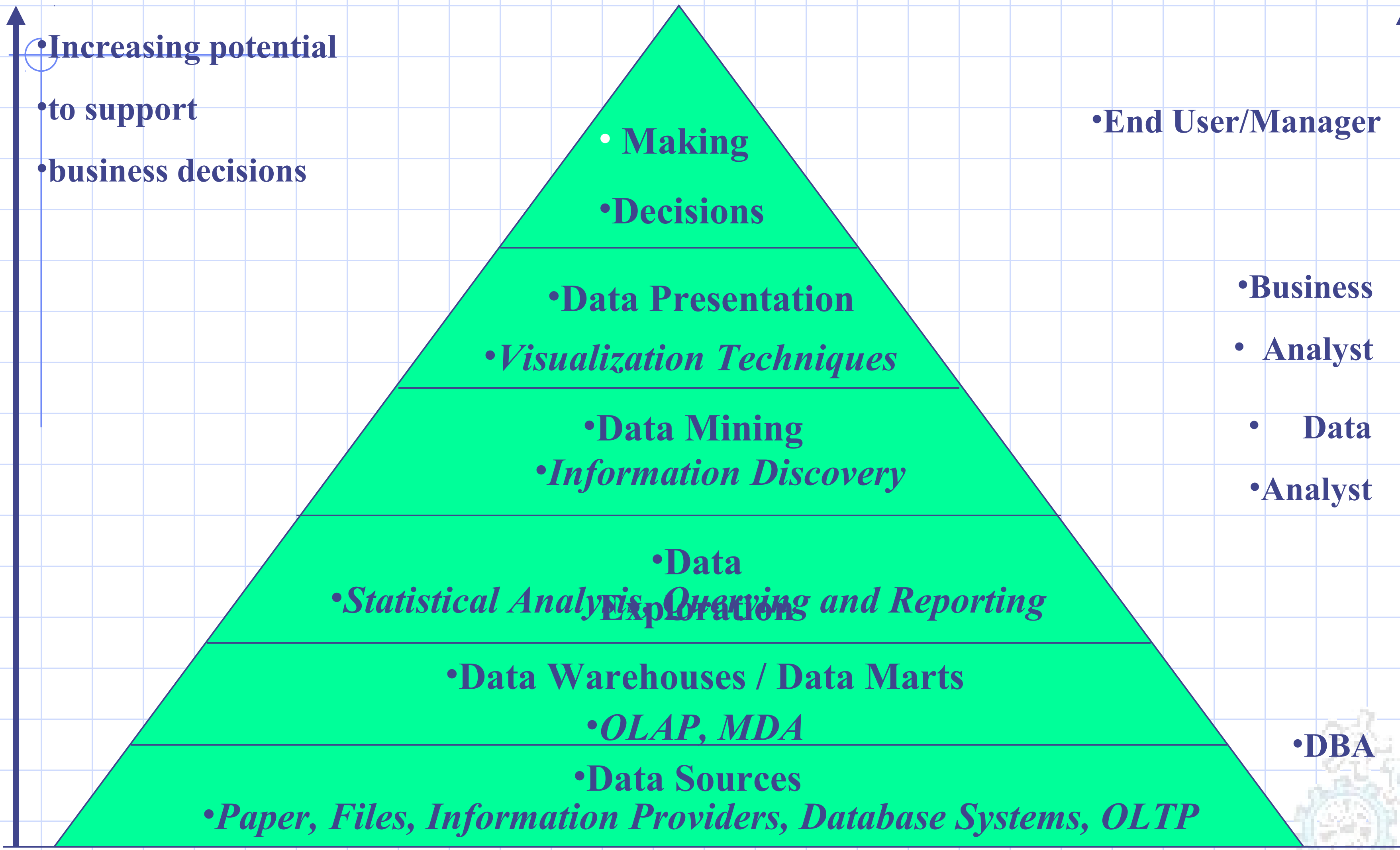
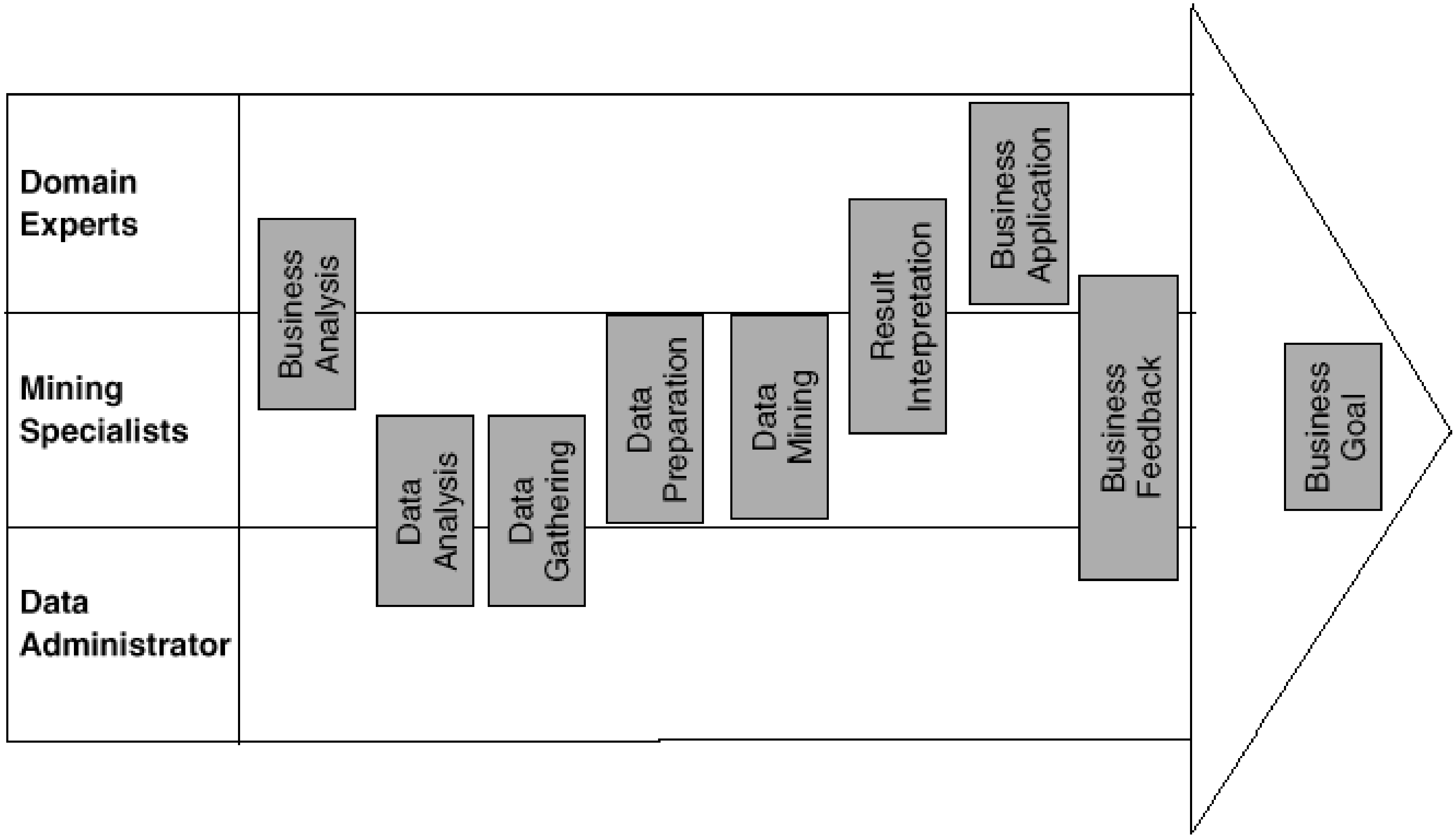


Figure nel processo di KDD



Intelligence/Value

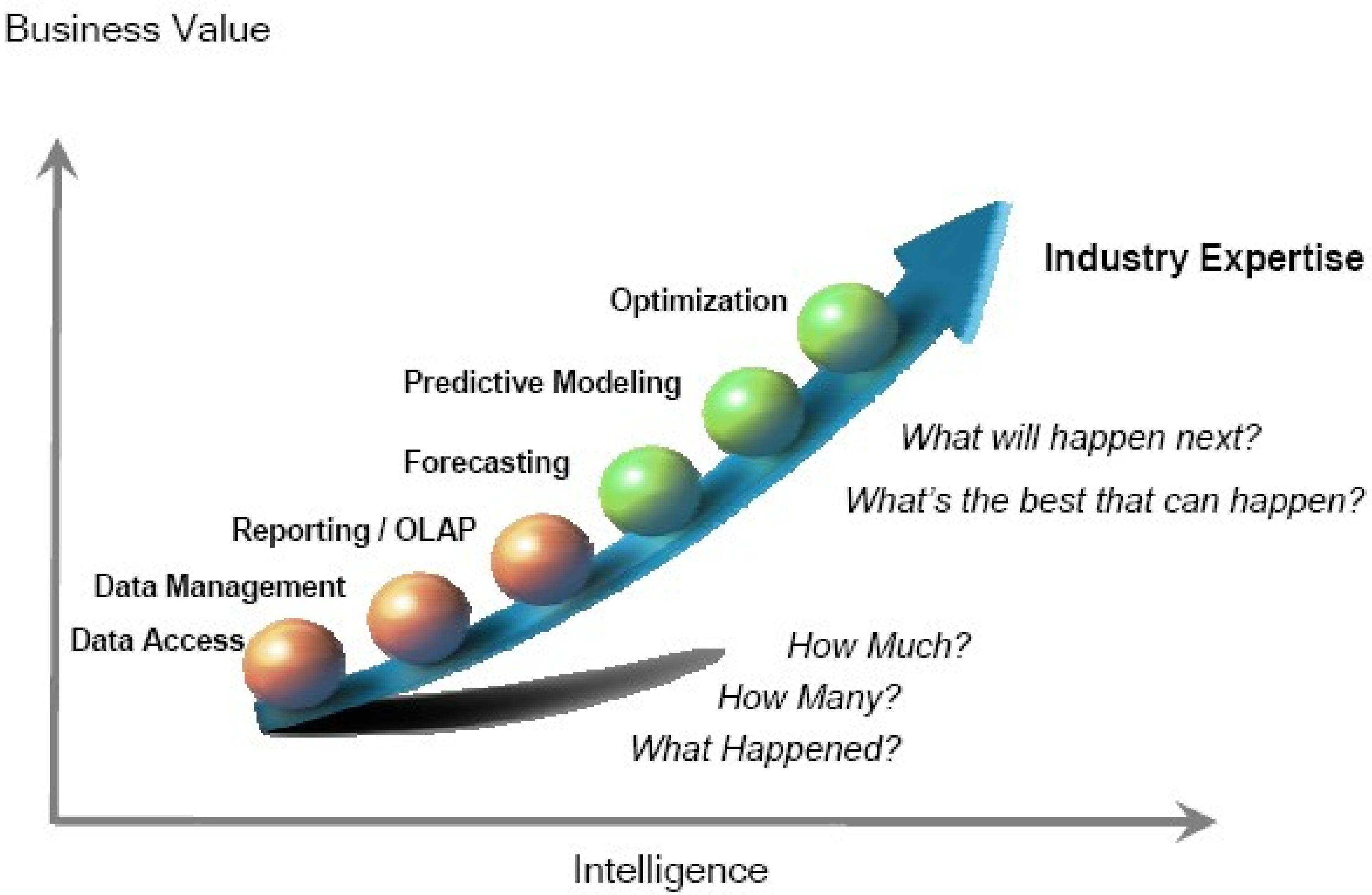


Figure 1: Business value increases exponentially with intelligence.

AIR MILES

a case-study on customer segmentation

From: G. Saarenvirta, “Mining customer data”, DB2 magazine on line, 1998

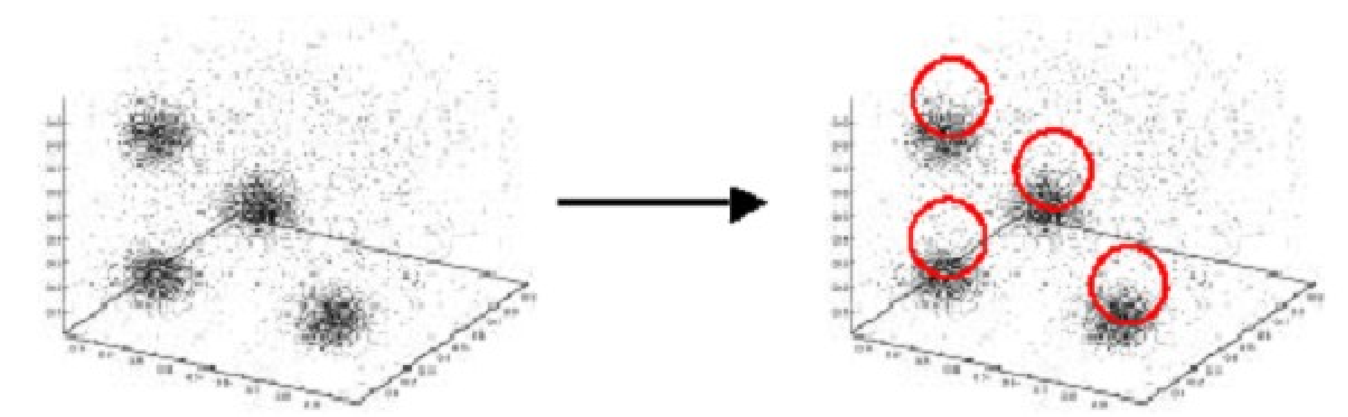
http://www.db2mag.com/98fsaar.html

Application: customer segmentation

- Given:
  - Large data base of customer data containing their properties and past buying records
- Goal:
  - Find groups of customers with similar behavior

clustering in 3D

- Data: points in the 3D space
- Similarity: based on (Euclidean) distance



Customer clustering & segmentation

- two of the most important data mining methodologies used in marketing
- use customer-purchase transaction data to
  - track buying behavior
  - create strategic business initiatives.
  - divide customers into segments based on "shareholder value" variables:
    - customer profitability,
    - measure of risk,
    - measure of the lifetime value of a customer,
    - retention probability.

Customer segments

- Example: high-profit, high-value, and low-risk customers
  - typically 10% to 20% of customers who create 50% to 80% of a company's profits
  - strategic initiative for the segment is retention
- A low-profit, high-value, and low-risk customer segment may be also attractive
  - strategic initiative for the segment is to increase profitability
  - cross-selling (selling new products)
  - up-selling (selling more of what customers currently buy)

Behavioral vs. demographic segments

- Within behavioral segments, a business may create demographic subsegments.
- Customer demographic data are not typically used together with behavioral data to create segments.
- Demographic (sub)segmenting is used to select appropriate tactics (advertising, marketing channels, and campaigns) to satisfy the strategic behavioral segment initiatives.

The Loyalty Group in Canada

- runs an AIR MILES Reward Program (AMRP) for a coalition of more than 125 companies in all industry sectors - finance, credit card, retail, grocery, gas, telecom.
- 60% of Canadian households enrolled
- AMRP is a frequent-shopper program:
  - the consumer collects bonuses that can then redeem for rewards (air travel, hotel accommodation, rental cars, theatre tickets, tickets for sporting events, …)

Data capture

- The coalition partners capture consumer transactions and transmit them to The Loyalty Group, which
- stores these transactions and uses the data for database marketing initiatives on behalf of the coalition partners.
- The Loyalty Group data warehouse currently contains
  - more than 6.3 million household records
  - 1 billion transaction records.

Before data mining

- The Loyalty Group has employed standard analytical techniques
  - Recency, Frequency, Monetary value (RFM) analysis
  - online analytic processing tools
  - linear statistical methods
- to analyze the success of the various marketing initiatives undertaken by the coalition and its partners.

Data mining project at AMRP

- Goal: create a customer segmentation using a data mining tool and compare the results to an existing segmentation developed using RFM analysis.
- data mining platform
  - DB2 Universal Database Enterprise parallelized over a five-node RS/6000 SP parallel system.
  - Intelligent Miner for Data (reason: has categorical clustering and product association algorithms which are not available in most other tools)

Data model

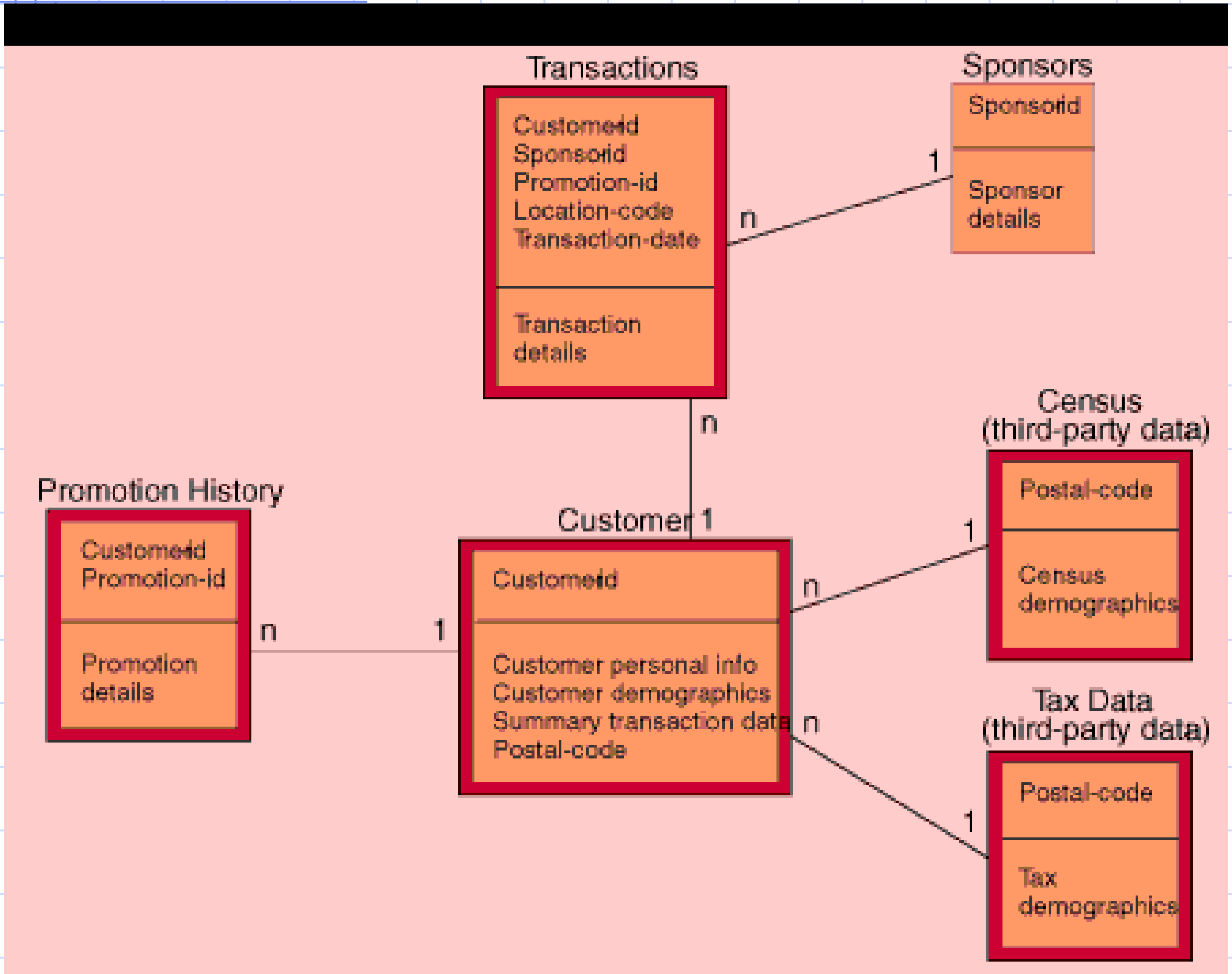


Figure 2. *AIR MILES case study data model.*

- ~ 50,000 customers and their associated transactions for a 12-month period.

Data preparation

- “shareholder value” variables
  - revenue
  - customer tenure
  - number of sponsor companies shopped at over the customer tenure
  - number of sponsor companies shopped at over the last 12 months,
  - recency (in months) of the last transaction
- calculated by aggregating the transaction data and then adding then to each customer record

Data preparation (2)

- Dataset obtained by joining the transaction data to the customer file to create the input for clustering algorithms
- 84 variables =
  - 14 categories of sponsor companies ×
  - 3 variables per category ×
  - 2 quarters (first two quarters of 1997)

Data cleansing - missing values

- demographic data
  - is usually categorical
  - has a high % of missing values
  - the missing values can be set to either unknown or unanswered (if result of unanswered questions)
- if a large portion of the field is missing, it may be discarded.
- In the case study, missing numeric values set to 0

Data transformation

- Ratio variables.
  - E.g.: profitability = profit / tenure
- Time-derivative variables.
  - E.g.: profit 2nd quarter - profit 1st quarter
- Discretization using quantiles.
  - E.g., break points at 10, 25, 50, 75, and 90.
- Discretization using predefined ranges.
  - E.g., those used in census
- Log transforms.
  - E.g., for very skewed distributions

Distribution of original data

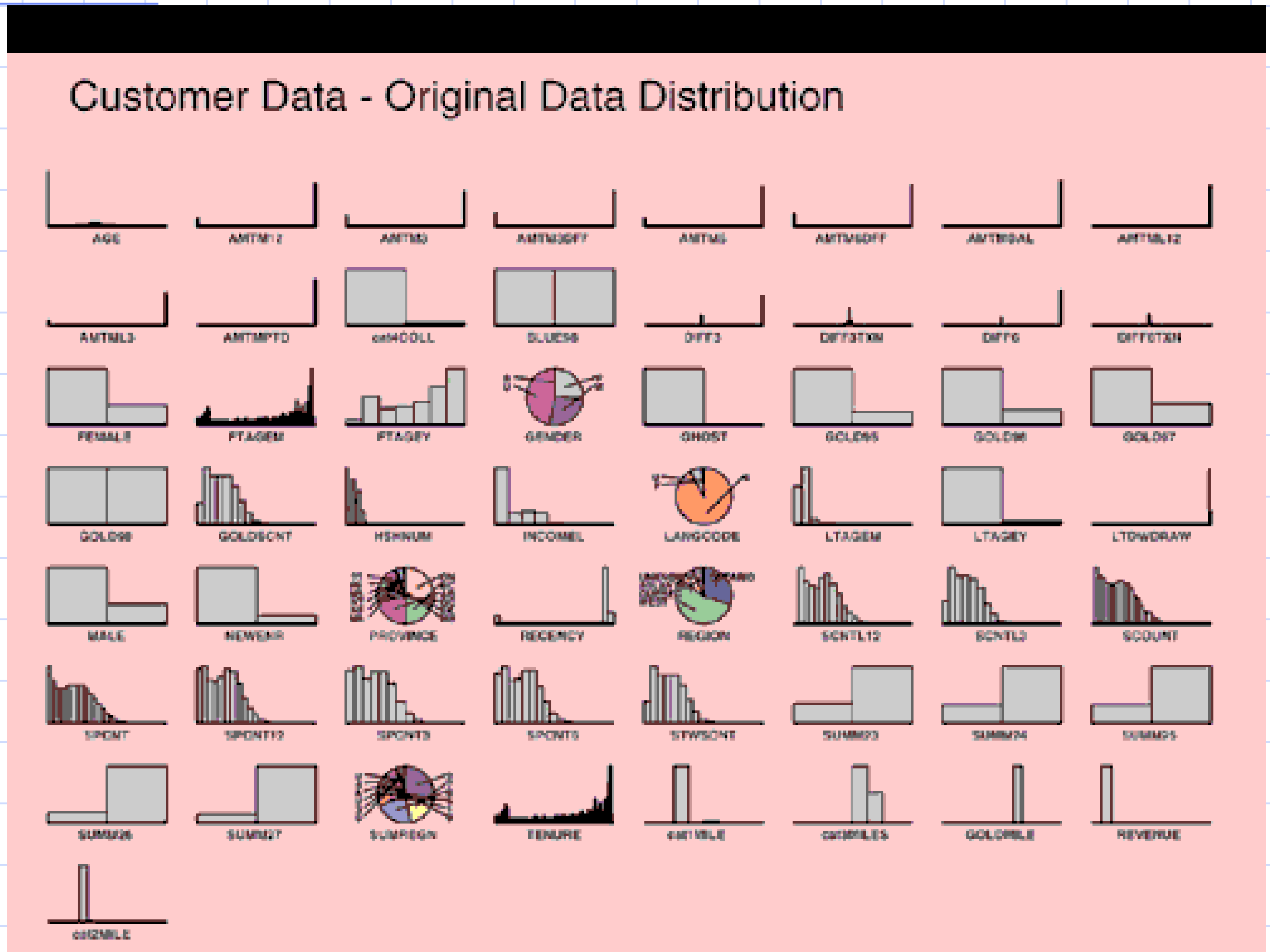


Figure3. *Original data.*

Distribution of discretized data

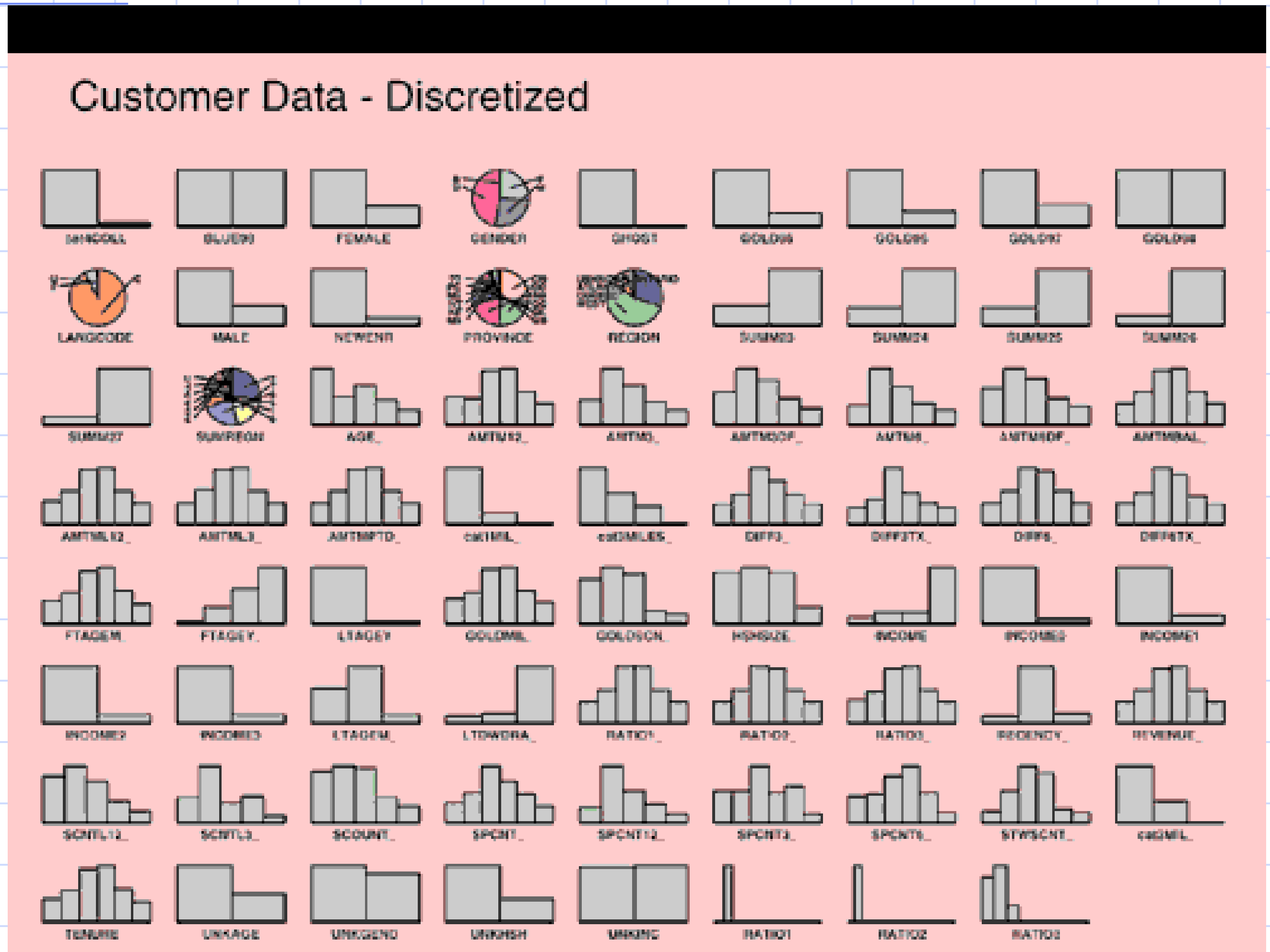


Figure 4. *Discretized data.*

Before/after discretization

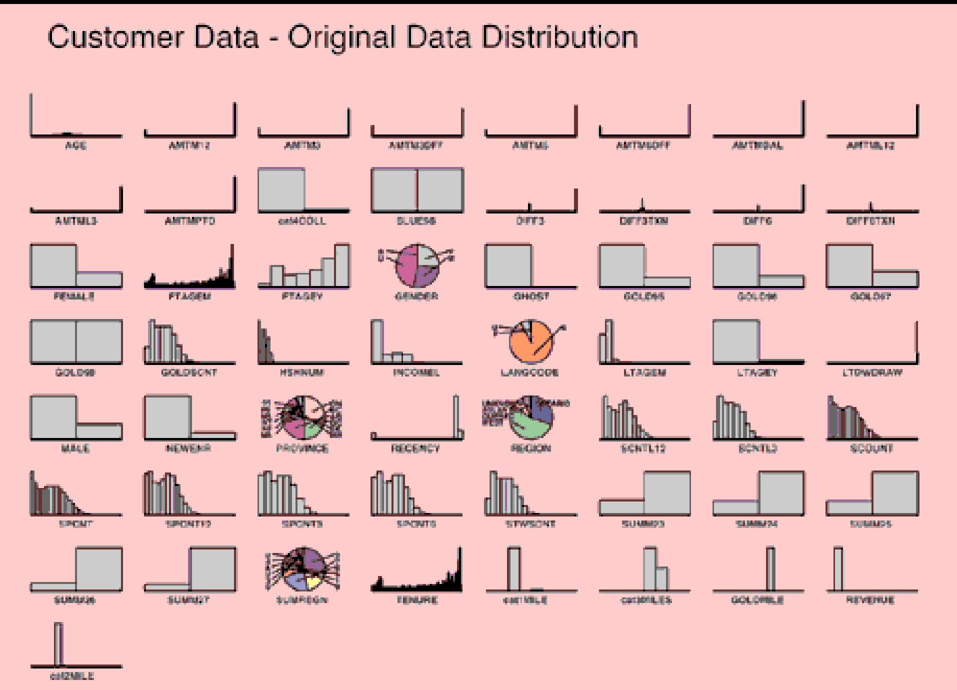


Figure3. *Original data.*

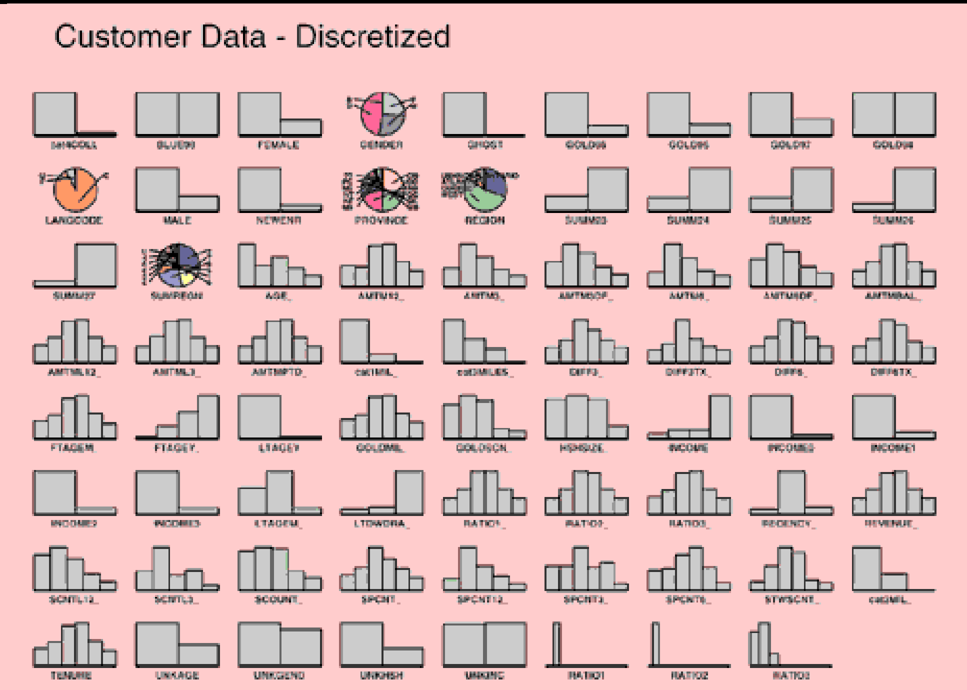
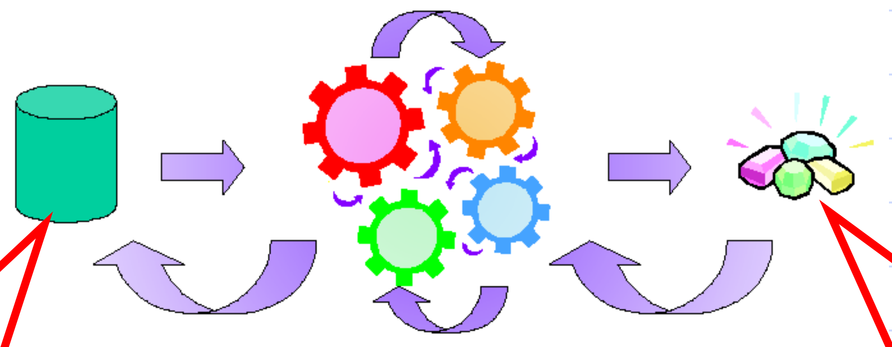


Figure 4. *Discretized data.*

Estrazione del modello di clustering

ustering = raggruppamento di oggetti simili in gruppi omoge



- Dati in input: variabili economiche di ciascun cliente

- Modello in output: segmentazione dei clienti simili in clusters

Clustering/segmentation methodology

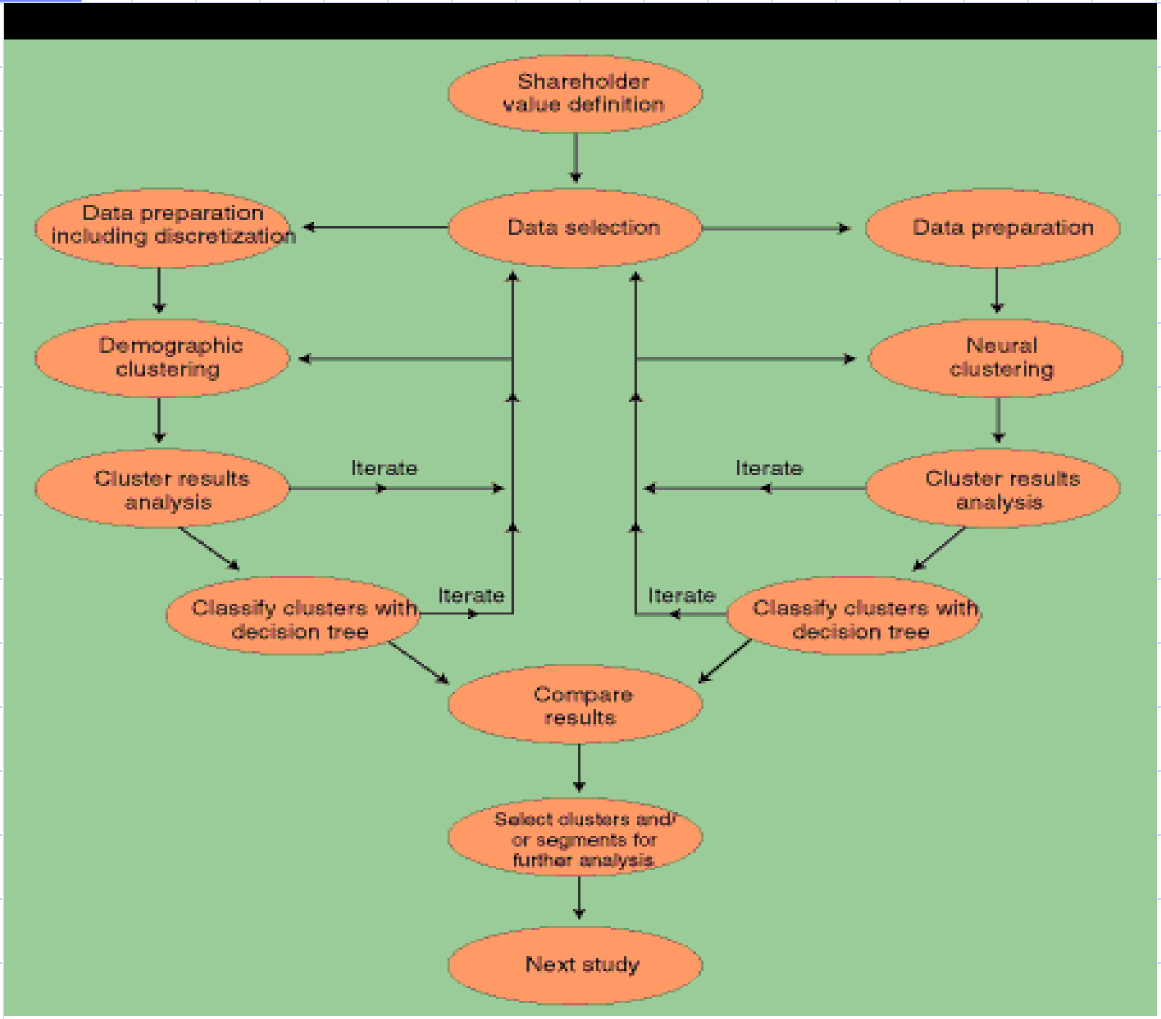
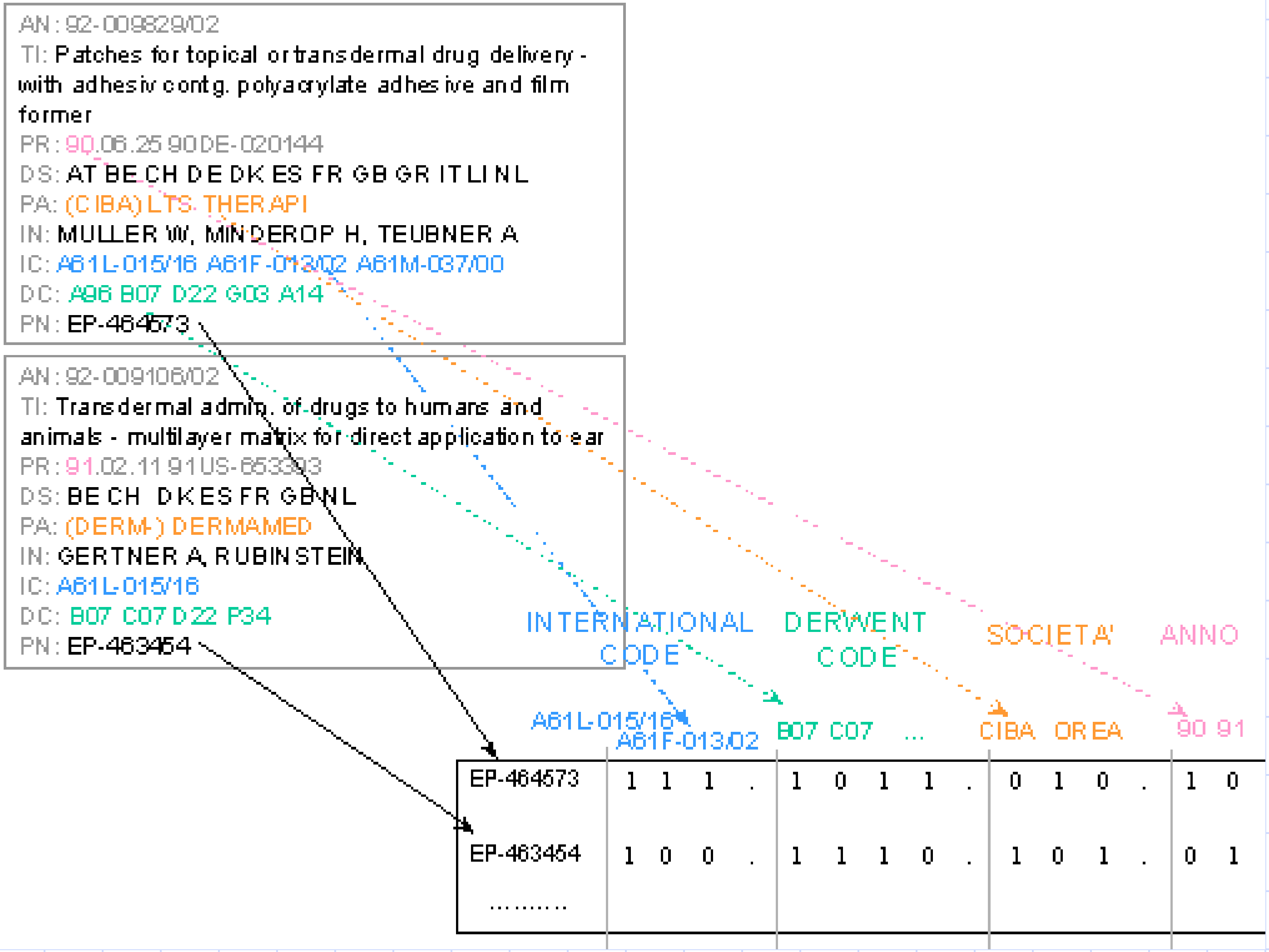


Figure 6. *Clustering workflow.*

IBM-IM demographic clustering

- Designed for categorical variables
- Similarity index:
  - increases with number of common values on same attribute
  - decreases with number of different values on same attribute
- # of clusters is not fixed a priori
  - only upper bound set

Demographic clustering: data structure



Demographic clustering: parameters

	W_1	W_2	...									W_n
Doc i	1	1	1	1	0	1	1	0	1	0	1	0
Doc j	1	0	0	1	1	1	0	1	0	0	0	1

$$N_{11} = \sum_{k=1}^{m} x_{ik} x_{jk}$$

$$N_{10} = \sum_{k=1}^{m} x_{ik} (1 - x_{jk})$$

$$N_{01} = \sum_{k=1}^{m} (1 - x_{ik}) x_{jk}$$

$$N_{00} = \sum_{k=1}^{m} (1 - x_{ik}) (1 - x_{jk})$$

- Indice di Somiglianza

$$s(i,j) = \frac{a N_{11}}{b N_{11} + c (N_{10} + N_{01})} \Rightarrow$$

  - **Condorcet** $a = b = 1$ $c = 1/2$
  - **Dice** $a = b = 1$ $c = 1/4$

- Soglia di Somiglianza

se $s(i,j) > \alpha$ ⇒ **Doc_i e Doc_j sono simili** α in $[0,1]$

  - default: $\alpha = 0.5$

- Sistema di ponderazione

$$N_{11} = \sum_{k=1}^{m} x_{ik} x_{jk} w_k \quad (N_{10} = \ldots N_{01} = \ldots) \Rightarrow$$

  - $w_k = 1 / x_{.k}$
  - $w_k = \log(N / x_{.k})$

Demographic clustering: similarity index

- proportional to 1-1
- inversely proportional to 0-1 and 1-0
- unaffected by 0-0
- Condorcet index=
  - $N_{11} / (N_{11} + {}^{1}/_{2}(N_{01} + N_{10}))$
- Dice index=
  - $N_{11} / (N_{11} + {}^{1}/_{4}(N_{01} + N_{10}))$
- Dice looser then Condorcet
  - appropriate with highly different objects

Demographic clustering: similarity index

- Similarity threshold α
  - i,j assumed similar if $s(i,j)>\alpha$
  - low values (<0.5) appropriate with highly different objects

- Weights for attributes
  - importance of attributes in the similarity index may be varied with different weights
  - default weight = 1

IM Demographic clustering

- basic parameters:
  - Maximum number of clusters.
  - Maximum number of passes through the data.
  - Accuracy: a stopping criterion for the algorithm. If the change in the Condorcet criterion between data passes is smaller than the accuracy (as %), the algorithm will terminate.
  - The Condorcet criterion is a value in [0,1], where 1 indicates a perfect clustering -- all clusters are homogeneous and entirely different from all other clusters

… more parameters

- Similarity threshold.
  - defines the similarity threshold between two values in distance units.
  - If the similarity threshold is 0.5, then two values are considered equal if their absolute difference is less than or equal to 0.5.
- In the case study:
  - maximum # of clusters: 9
  - maximum # of passes: 5
  - accuracy: 0.1

Input dataset

- dataset: all continuous variables discretized.
- input variables :
  - # of products purchased over customer’s lifetime
  - # of products purchased in the last 12 months
  - Customer's revenue contribution over lifetime
  - Customer tenure in months
  - Ratio of revenue to tenure
  - Ratio of number of products to tenure
  - Region
  - Recency
  - Tenure (# of months since customer first enrolled in the program).

Input dataset

- Other discrete and categorical variables and some interesting continuous variables were input as supplementary variables:
- variables used to profile the clusters but not to define them.
- easier interpretation of clusters using data other than the input variables.

Output of demographic clustering

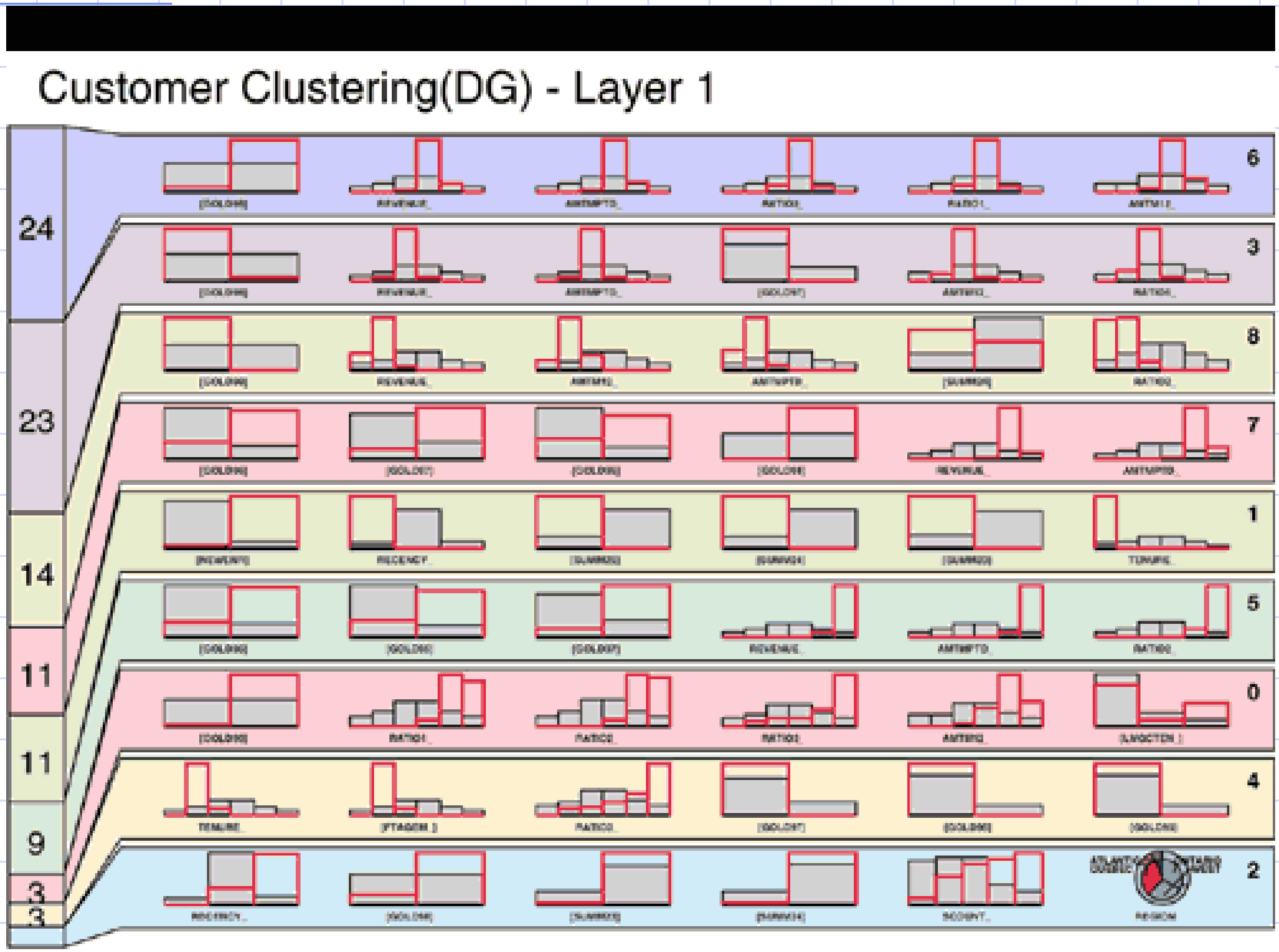


Figure 7. *Demographic clustering output.*

Visualization of clusters

- horizontal strip = a cluster
- clusters are ordered from top to bottom in order of size
- variables are ordered from left to right in order of importance to the cluster, based on a chi-square test between variable and cluster ID.
- other metrics include entropy, Condorcet criterion, and database order.

Visualization of clusters

- variables used to define clusters are without brackets, while the supplementary variables appear within brackets.
- numeric (integer), discrete numeric (small integer), binary, and continuous variables have their frequency distribution shown as a bar graph.

- red bars = distribution of the variable within the current cluster.
- gray solid bars = distribution of the variable in the whole universe.

Visualization of clusters

- Categorical variables are shown as pie charts.
- inner pie = distribution of the categories for the current cluster
- outer ring = distribution of the variable for the entire universe.

- The more different the cluster distribution is from the average, the more interesting or distinct the cluster.

Output of demographic clustering

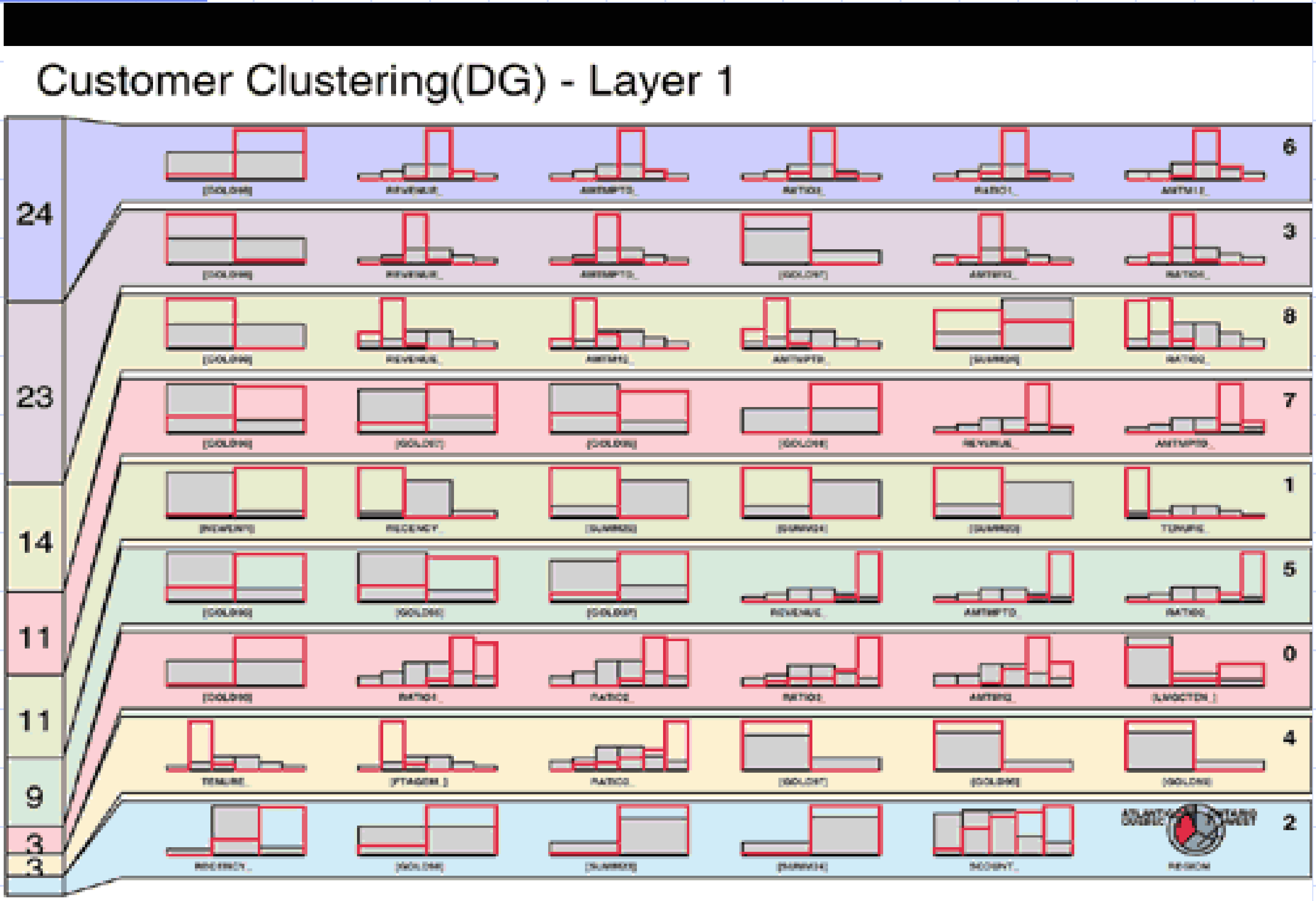


Figure 7. *Demographic clustering output.*

characterization of clusters

- Gold98 is a binary variable that indicates the best customers in the database, created previously by the business using RFM analysis.
- The clustering model agrees very well with this existing definition: Most of the clusters seem to have almost all Gold or no Gold customers.
- Confirmed the current Gold segment!

characterization of clusters

- Our clustering results
  - not only validate the existing concept of Gold customers,
  - they extend the idea of the Gold customers by creating clusters within the Gold98 customer category.
  - A platinum customer group
- Cluster 5
  - almost all Gold98 customers, whose revenue, bonus collected lifetime to date, revenue per month, and lifetime to date per month are all in the 50th to 75th percentile.

characterization of clusters

- Cluster 3:
  - no Gold98 customers. Its customer revenue, bonus collected, revenue per month, are all in the 25th to 50th percentile.
- Cluster 5:
  - 9 %of the population.
  - revenue, bonus collected are all in the 75th percentile and above, skewed to almost all greater than the 90th percentile.
  - looks like a very profitable cluster

Detailed view of cluster 5

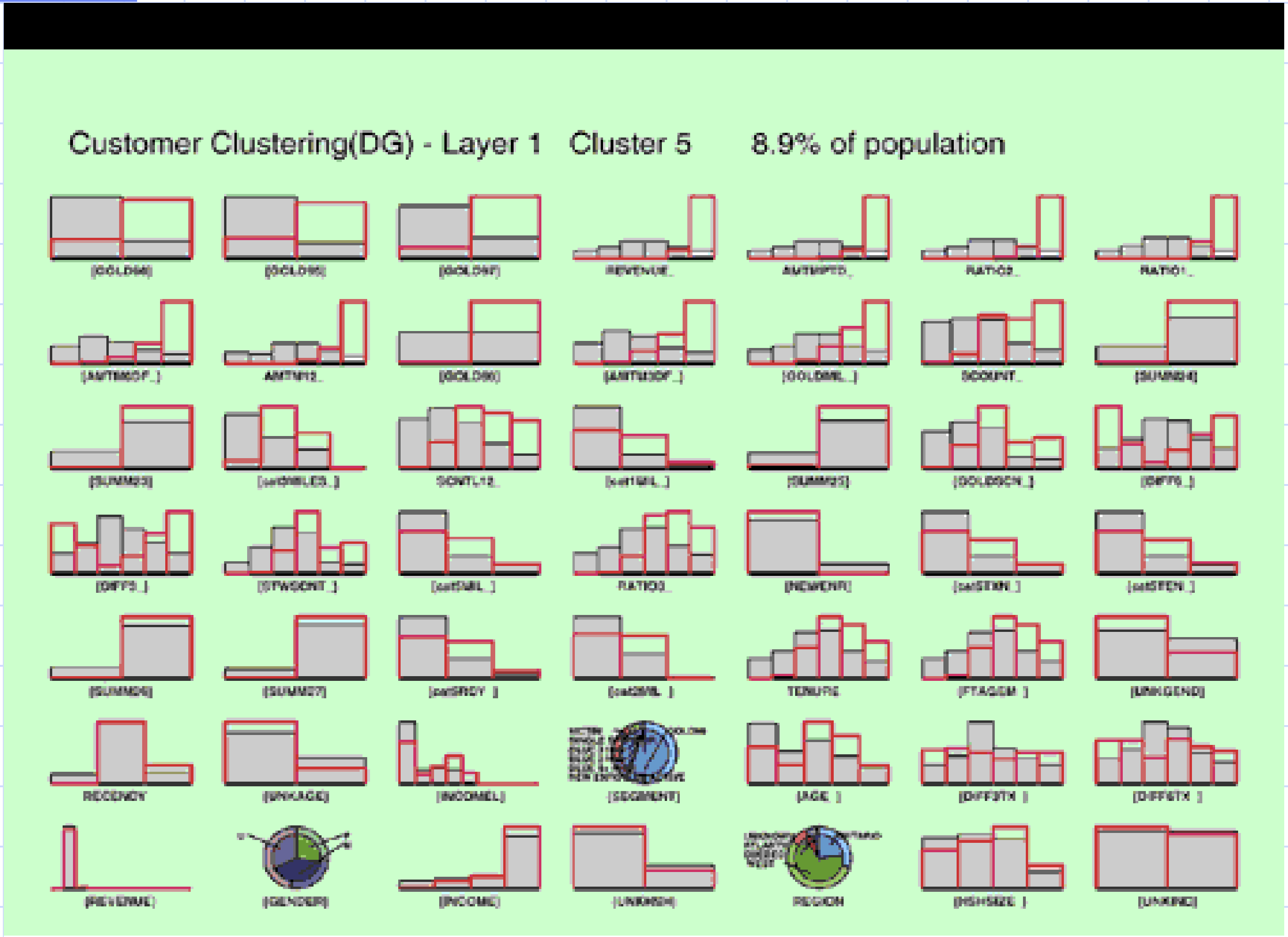


Figure 8. *Cluster 5 output.*

Profiling clusters

- Goal: assess the potential business value of each cluster quantitatively by profiling the aggregate values of the shareholder value variables by cluster.

CLUSTERID	REVENUE	CUSTOMERS	PRODUCT INDEX	LEVERAGE	TENURE
5	34.74%	8.82%	1.77	3.94	60.92
6	26.13%	23.47%	1.41	1.11	57.87
7	21.25%	10.71%	1.64	1.98	63.52
3	6.62%	23.32%	.73	.28	47.23
0	4.78%	3.43%	1.45	1.40	31.34
2	4.40%	2.51%	1.46	1.75	61.38
4	1.41%	2.96%	.99	.48	20.10
8	.45%	14.14%	.36	.03	30.01
1	.22%	10.64%	.00	.02	4.66

Table 1. *Profiling a cluster.*

Profiling clusters

- leverage = ratio of revenue to customer.
- cluster 5 is the most profitable cluster.
  - as profitability increases, so does the average number of products purchased.
  - product index = ratio of the average number of products purchased by the customers in the cluster divided by the average number of products purchased overall.
  - customer profitability increases as tenure increases.

Business opportunities

- Best customers in clusters 2, 5, and 7. :
  - indication: retention
- clusters 2, 6, and 0
  - indication: cross-selling by contrasting with clusters 5 and 7.
  - Clusters 2, 6, and 0 have a product index close to those of clusters 5 and 7, which have the highest number of products purchased.
  - Try to convert customers from clusters 2, 6, and 0 to clusters 5 and 7. By comparing which products are bought we can find products that are candidates for cross-

Business opportunities

- Clusters 3 and 4
  - indication: cross-selling to clusters 2, 6, and 0 •
- Cluster 1
  - indication: wait and see. It appears to be a group of new customers
- Cluster 8
  - indication: no waste of marketing dollars

Follow-up

- Reactions from The Loyalty Group
  - visualization of results allowed for meaningful and actionable analysis.
  - original segmentation methodology validated, but that refinements to the original segmentation could prove valuable.
  - decision to undertake further data mining projects, including
    - predictive models for direct mail targeting,
    - further work on segmentation using more detailed behavioral data,
    - opportunity identification using association algorithms within the segments discovered.

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

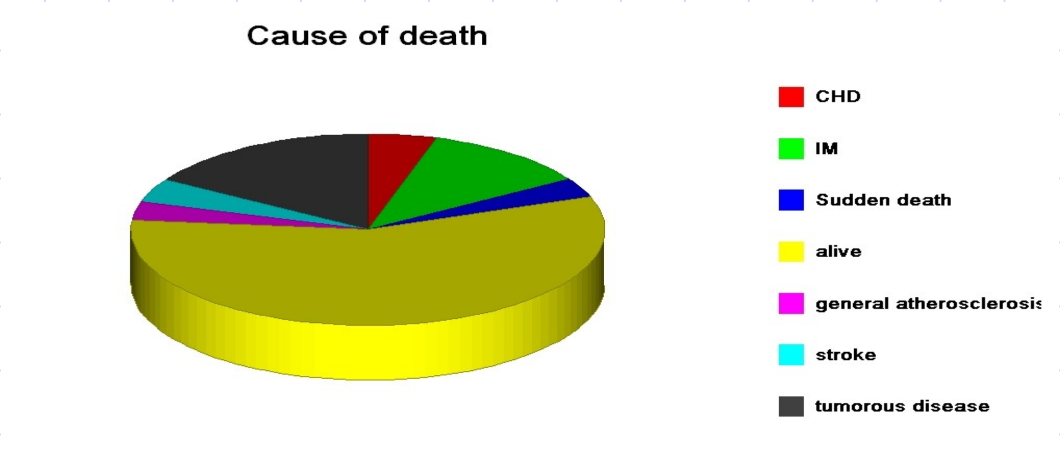
General characteristics	Examinations	habits
Marital status	Chest pain	Alcohol
Transport to a job	Breathlesness	Liquors
Physical activity in a job	Cholesterol	Beer 10
Activity after a job	Urine	Beer 12
Education	Subscapular	Wine
Responsibility	Triceps	Smoking
Age		Former smoker
Weight		Duration of smoking
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	
	Activity after work	**Education**	**Chest pain**	…	**Alcohol**	…..
1	moderate activity	university	not present		no	
2	great activity		not ischaemic		occasionally	
3	he mainly		other pains		regularly	

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.

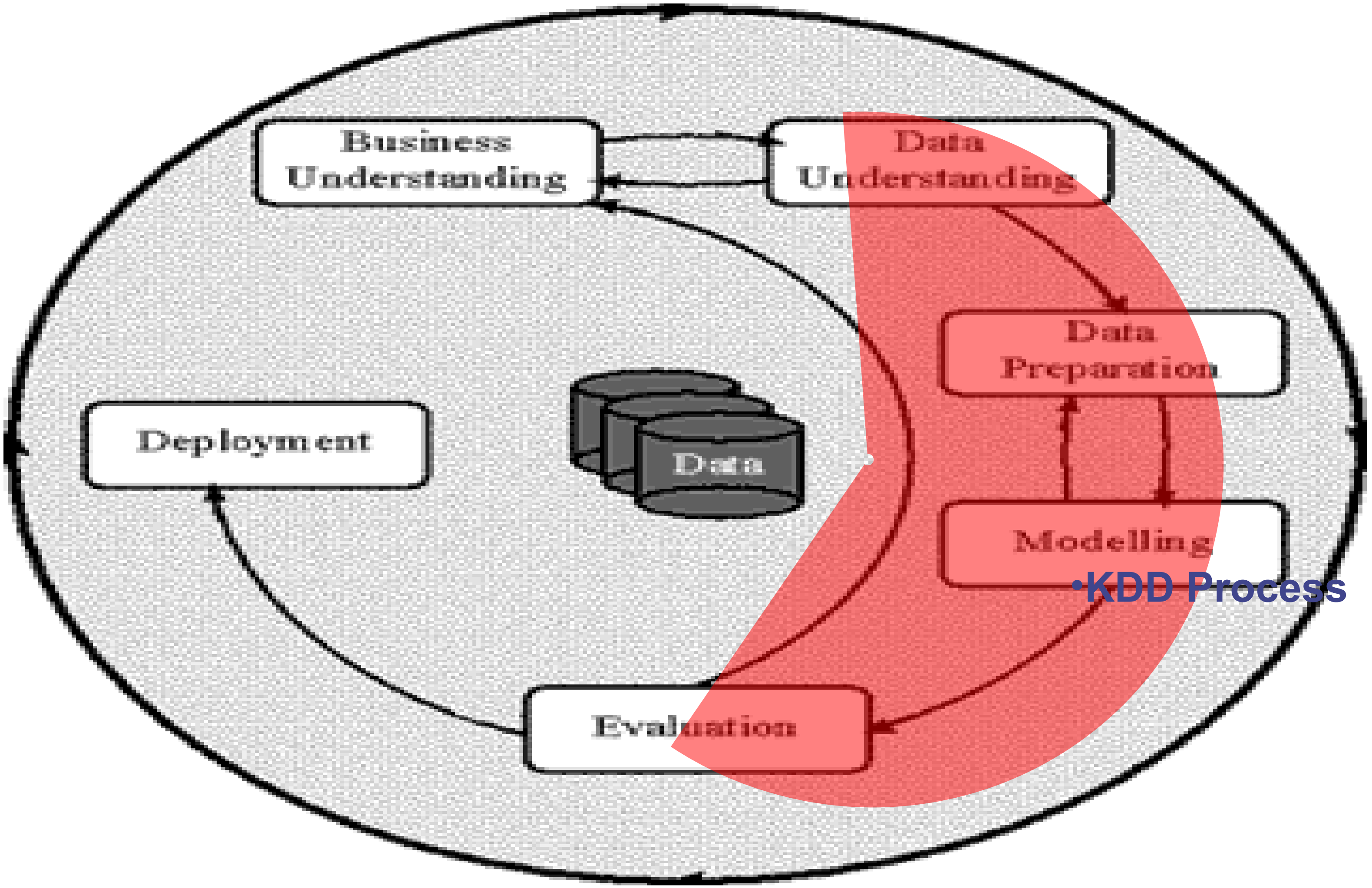
Example of extracted rules

- 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

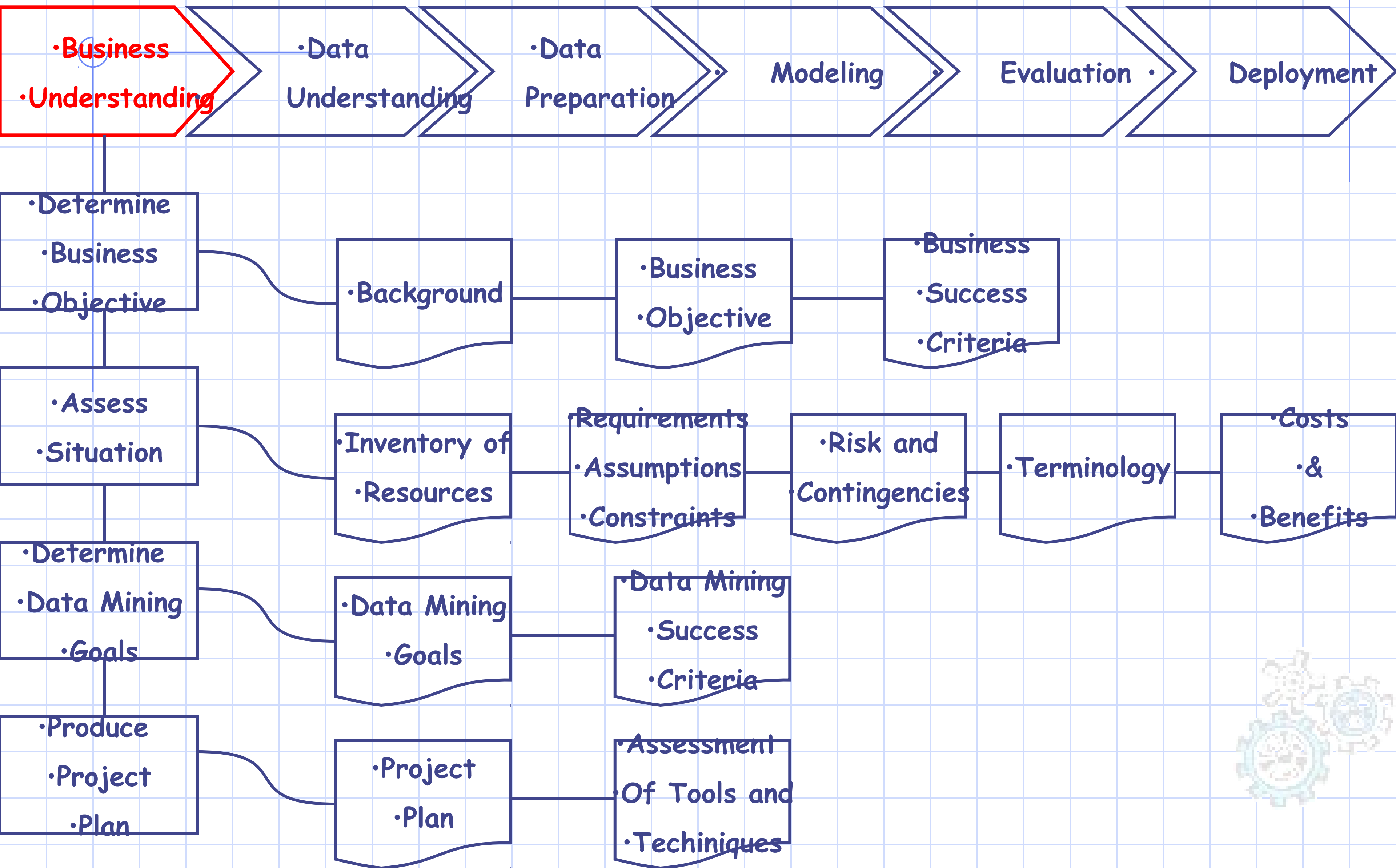
- Education(university) & Height<176-180>
  $\Rightarrow$Death cause (tumouros disease),
  16; 0.62; +1.1;
- the relative frequency of patients who died on tumorous disease among patients with university education and with height 176-180 cm is 110 per cent higher than the relative frequency of patients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

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



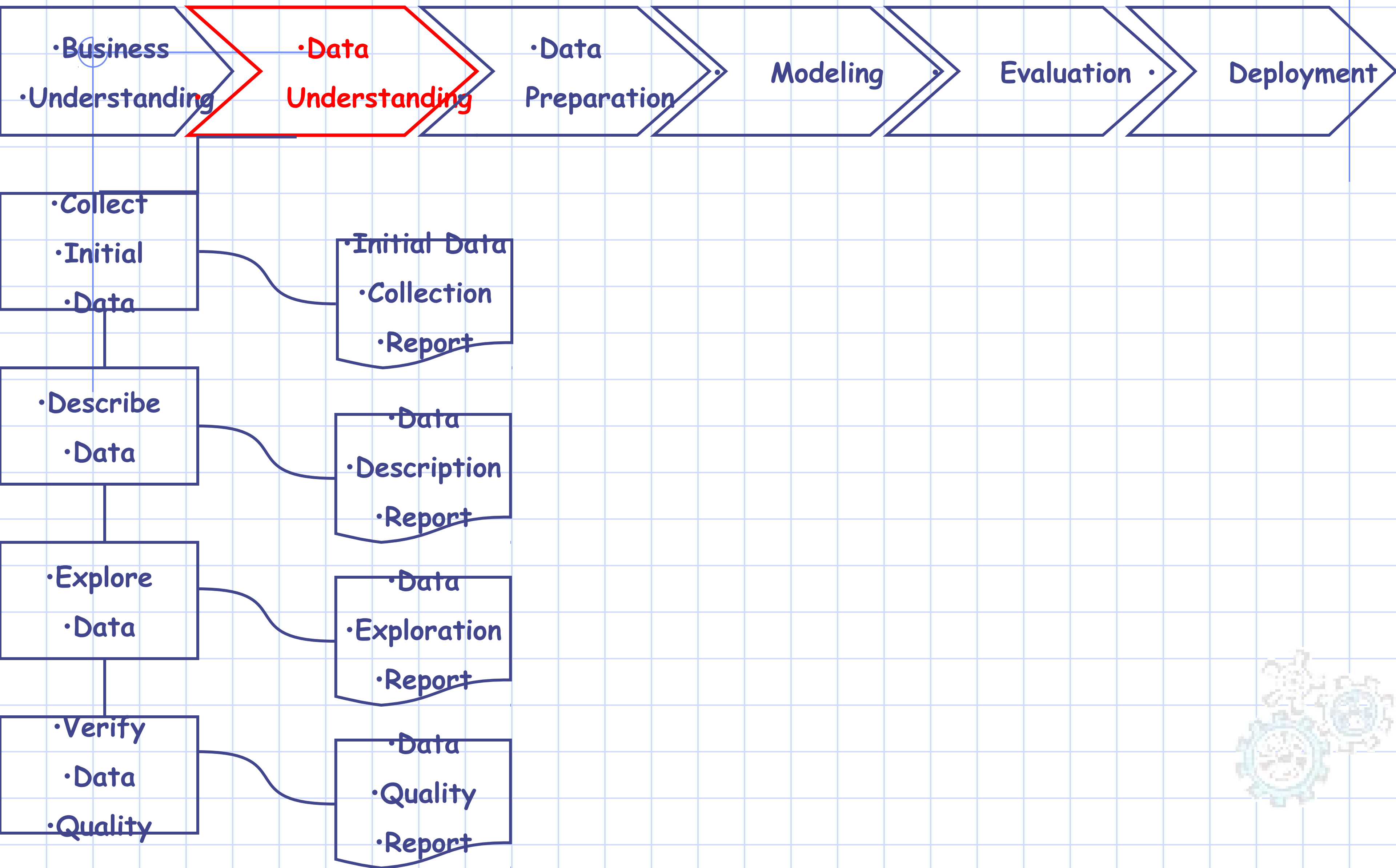
Business understanding

- 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**

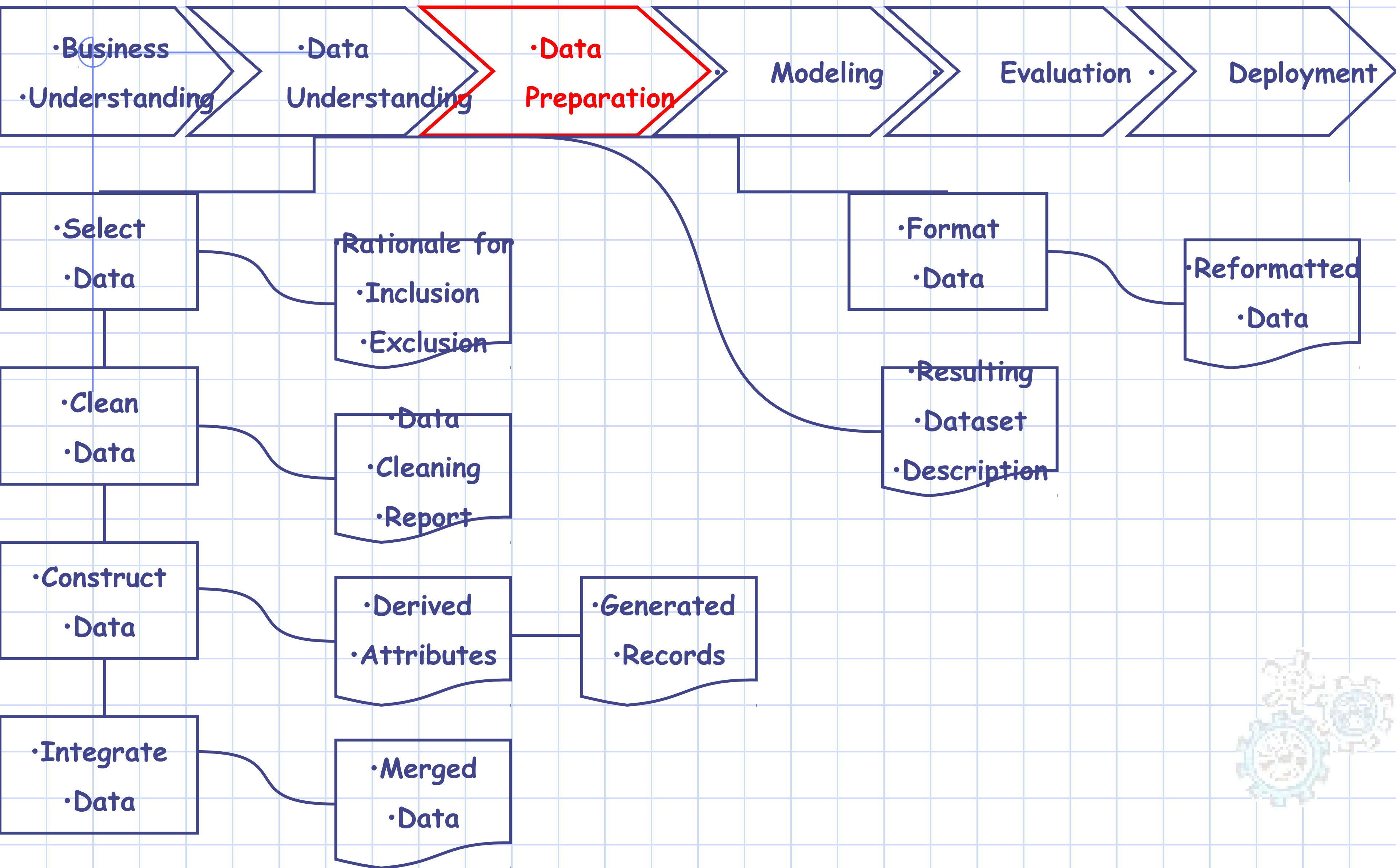

Business Understanding
Data Understanding
Data Preparation
Modeling
Evaluation
Deployment
Determine Business Objective
Background
Business Objective
Business Success Criteria
Assess Situation
Inventory of Resources
Requirements Assumptions Constraints
Risk and Contingencies
Terminology
Costs & Benefits
Determine Data Mining Goals
Data Mining Goals
Data Mining Success Criteria
Produce Project Plan
Project Plan
Assessment Of Tools and Techiniques

Data understanding

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

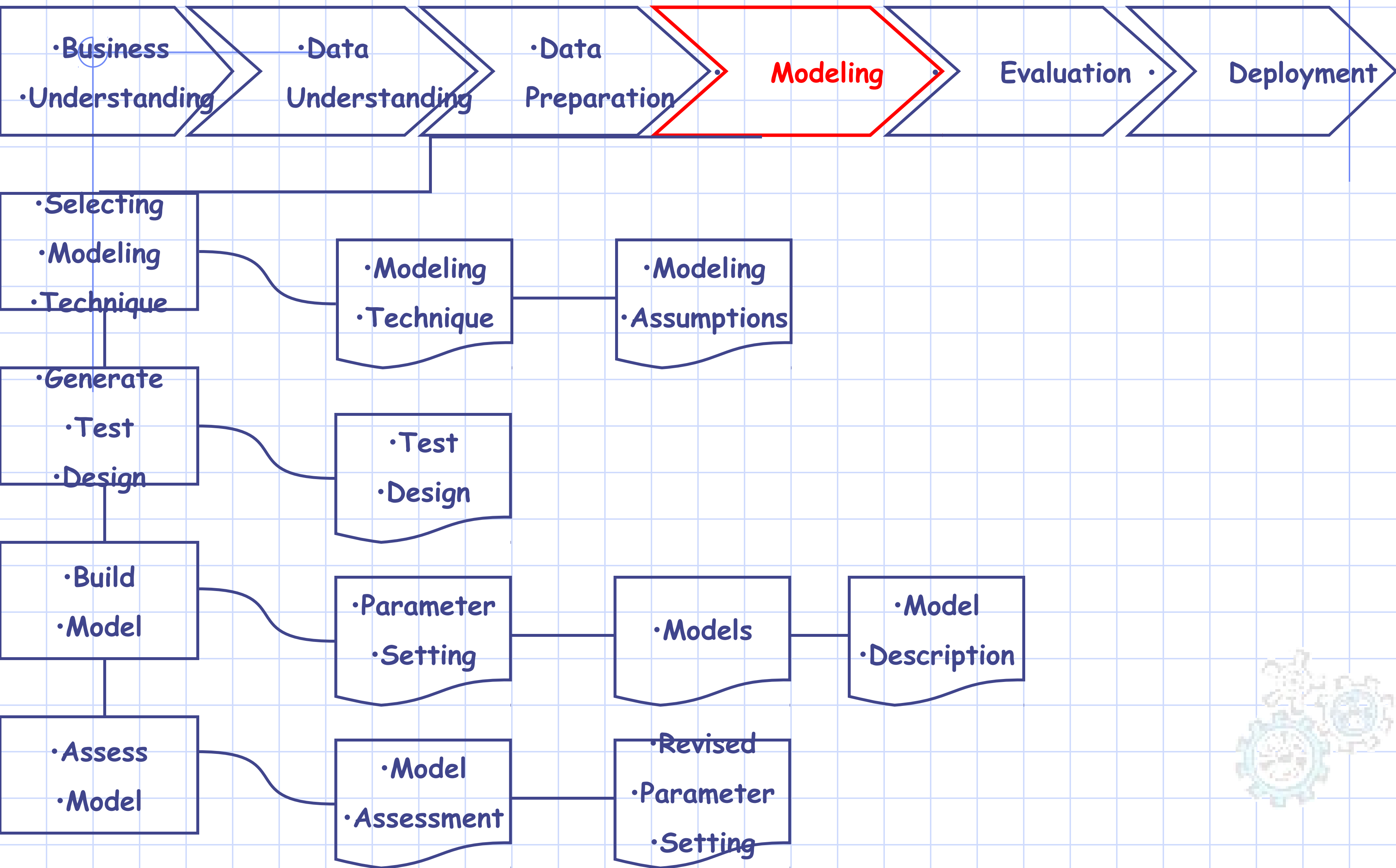


·Business ·Understanding
·Data Understanding
·Data Preparation
Modeling
Evaluation
Deployment
·Collect ·Initial ·Data
·Initial Data ·Collection ·Report
·Describe ·Data
·Data ·Description ·Report
·Explore ·Data
·Data ·Exploration ·Report
·Verify ·Data ·Quality
·Data ·Quality ·Report


Business Understanding
Data Understanding
Data Preparation
Modeling
Evaluation
Deployment
Select Data
Rationale for Inclusion / Exclusion
Clean Data
Data Cleaning Report
Construct Data
Derived Attributes
Generated Records
Integrate Data
Merged Data
Format Data
Reformatted Data
Resulting Dataset Description

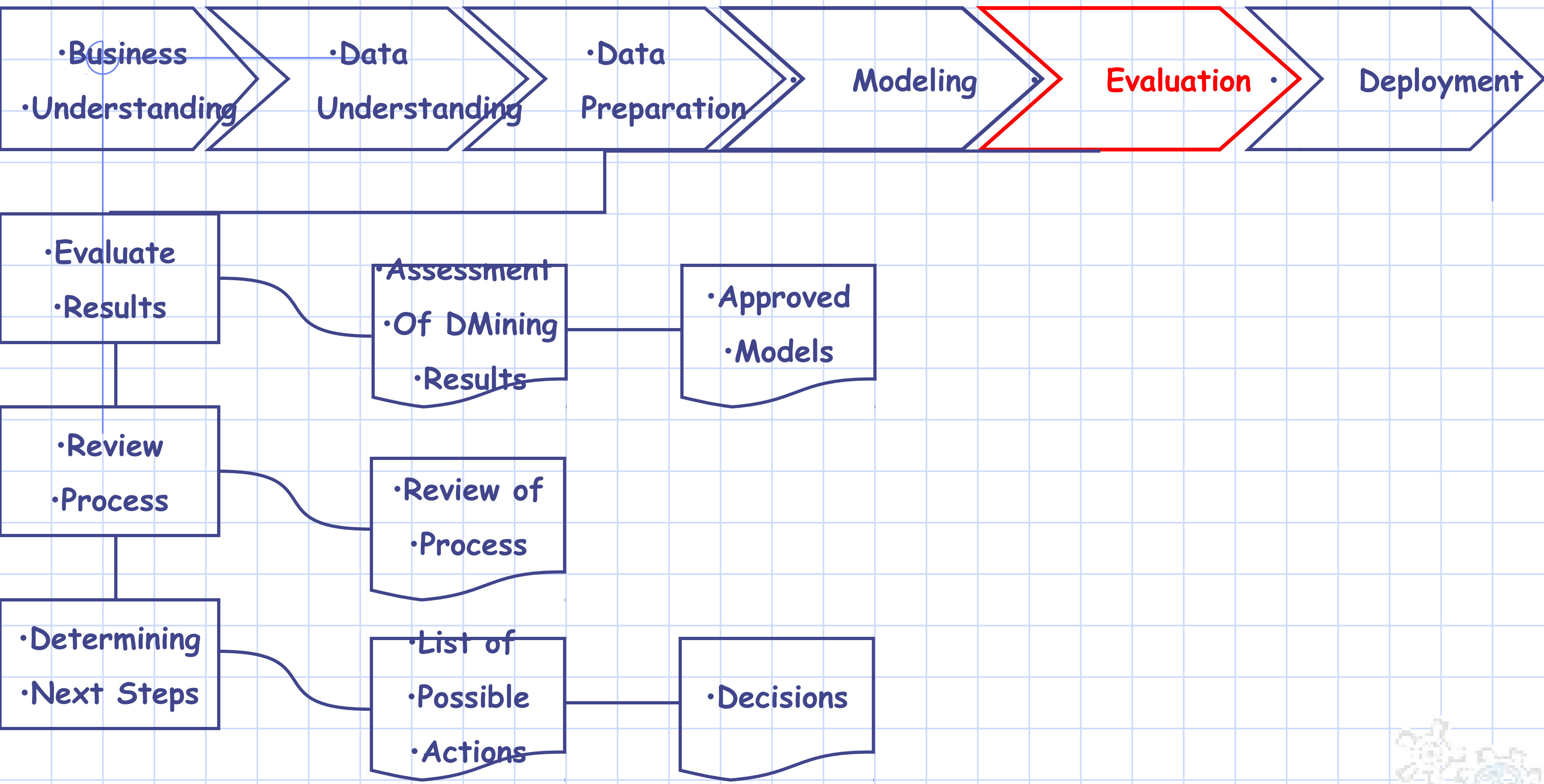
Modeling:

- 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.


Business Understanding
Data Understanding
Data Preparation
Modeling
Evaluation
Deployment
Selecting Modeling Technique
Modeling Technique
Modeling Assumptions
Generate Test Design
Test Design
Build Model
Parameter Setting
Models
Model Description
Assess Model
Model Assessment
Revised Parameter Setting

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.



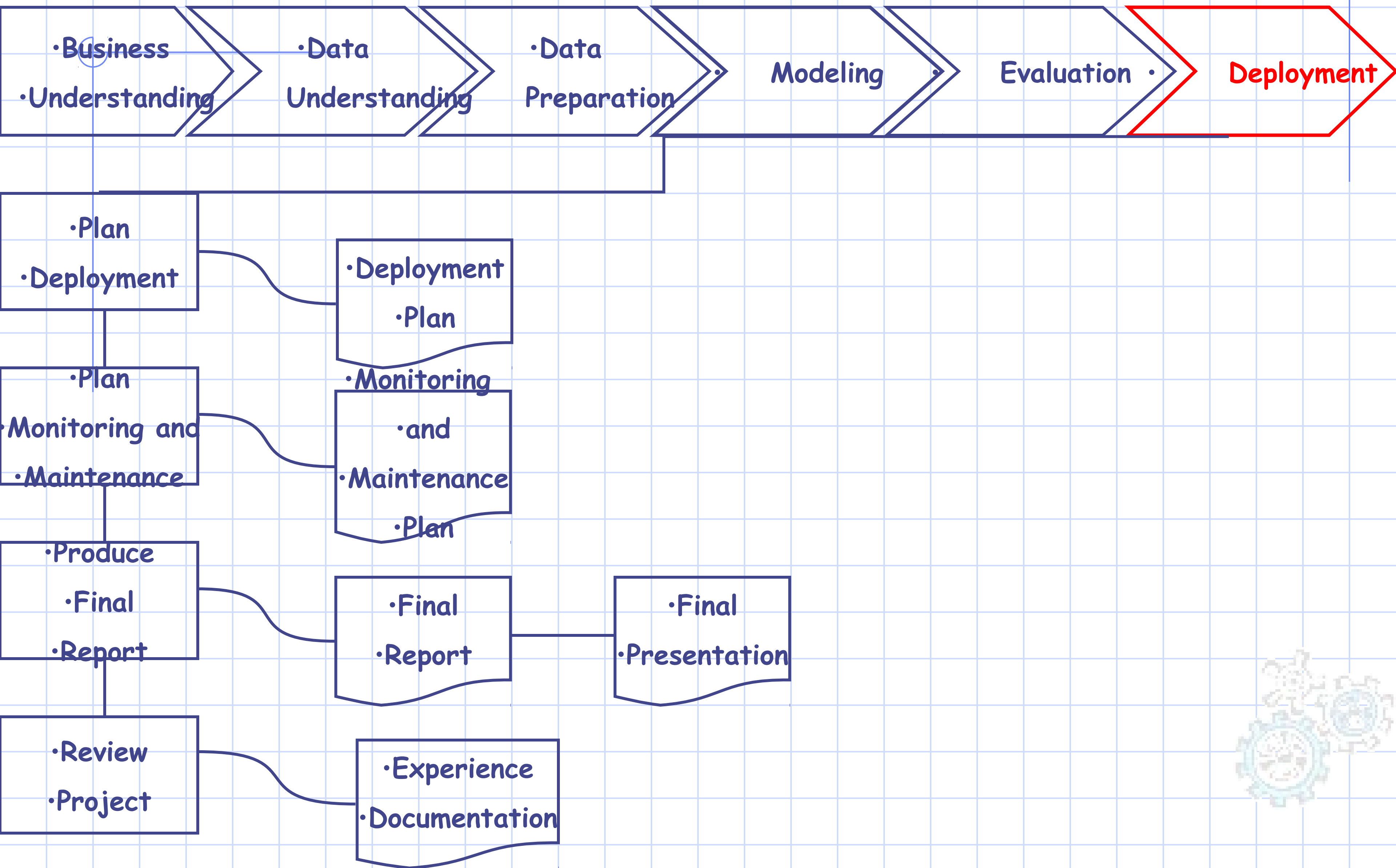
•Business
•Understanding
•Data
Understanding
•Data
Preparation
Modeling
Evaluation
Deployment
•Evaluate
•Results
•Assessment
•Of DMining
•Results
•Approved
•Models
•Review
•Process
•Review of
•Process
•Determining
•Next Steps
•List of
•Possible
•Actions
•Decisions

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.

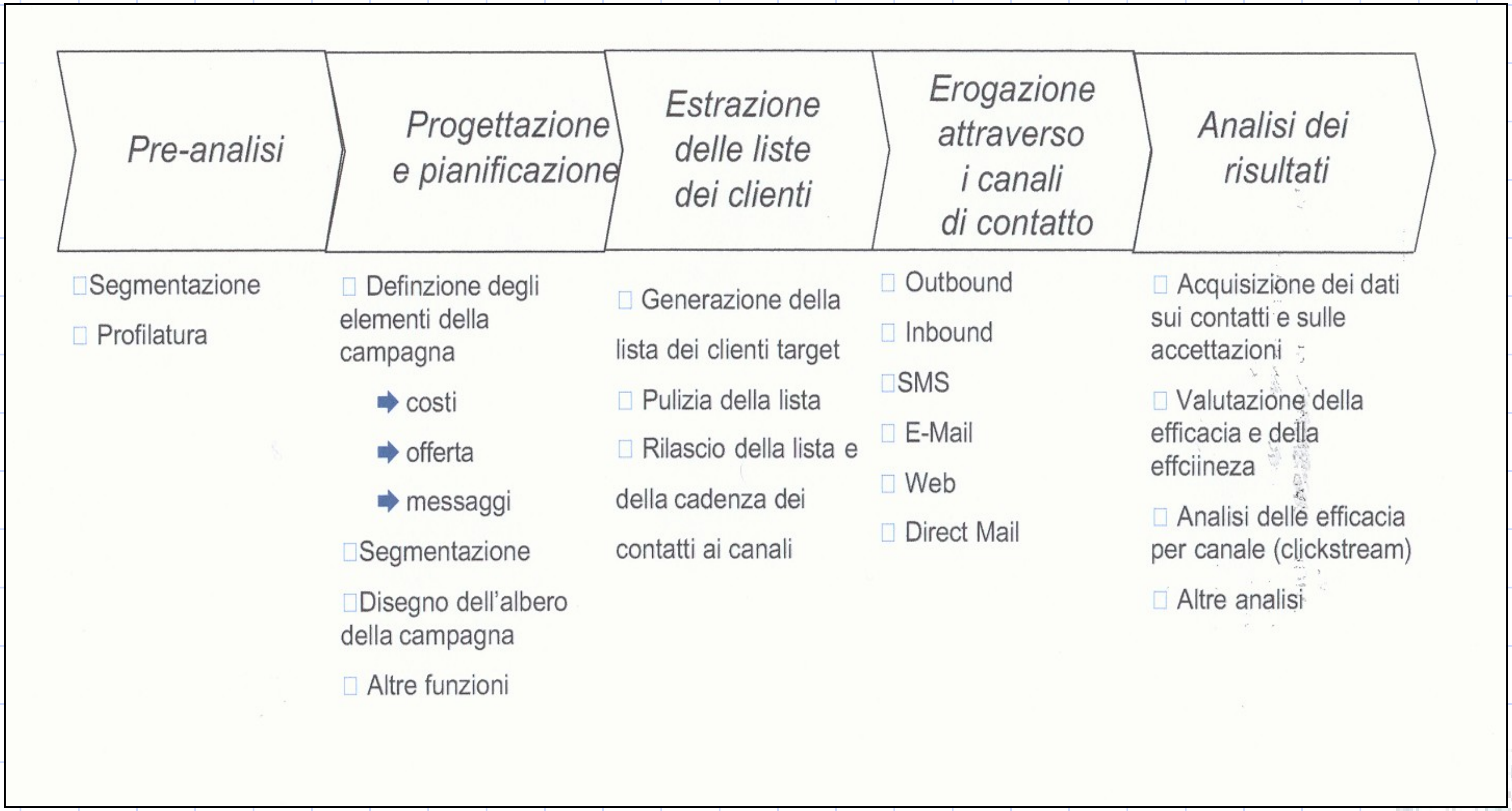
Deployment:

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

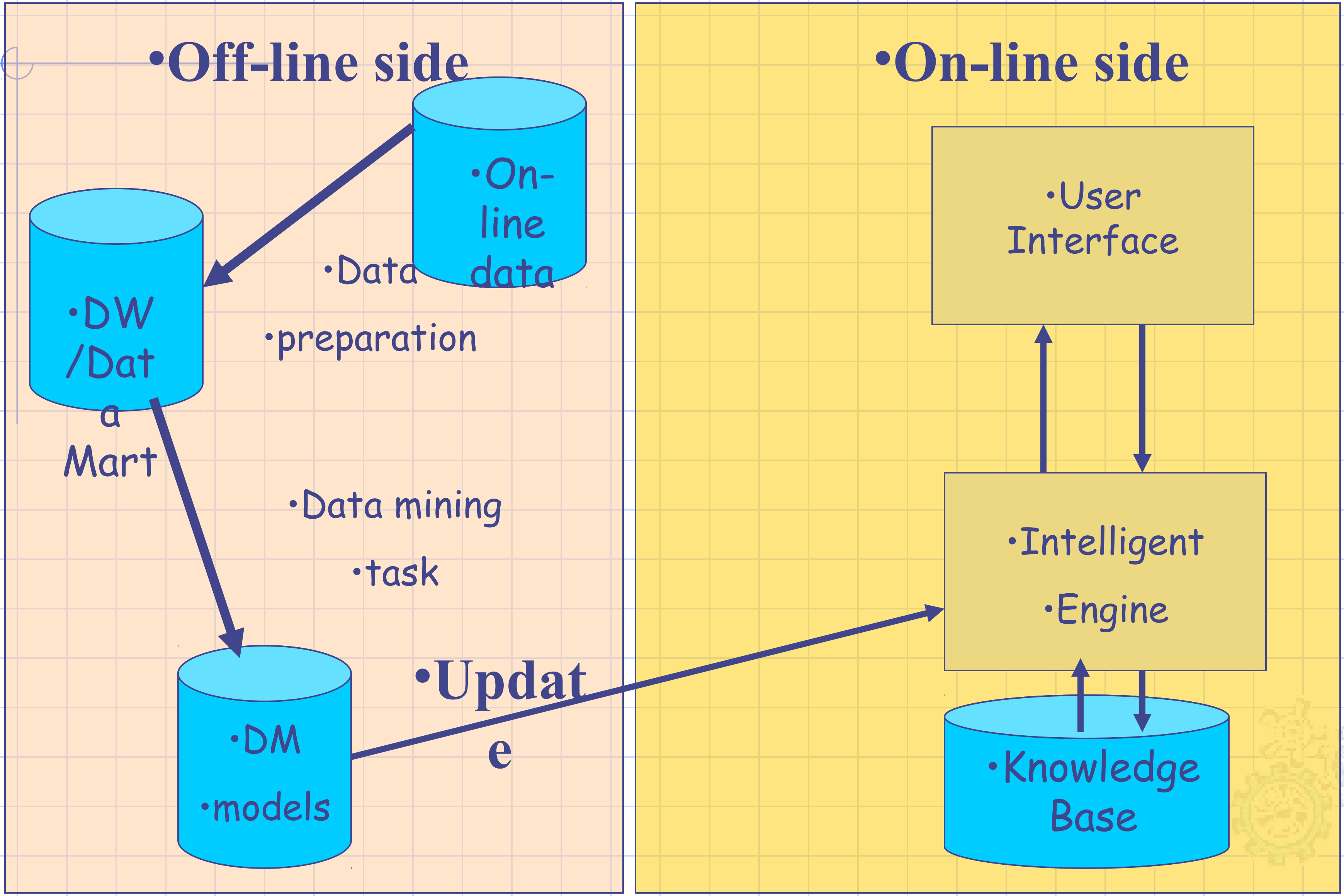


•Business •Understanding
•Data Understanding
•Data Preparation
Modeling
Evaluation
Deployment
•Plan •Deployment
•Deployment •Plan
•Plan •Monitoring and •Maintenance
•Monitoring •and •Maintenance •Plan
•Produce •Final •Report
•Final •Report
•Final •Presentation
•Review •Project
•Experience •Documentation

Es: Automatic Target Marketing



•Mining Based Decision Support System: Adaptive Architecture



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

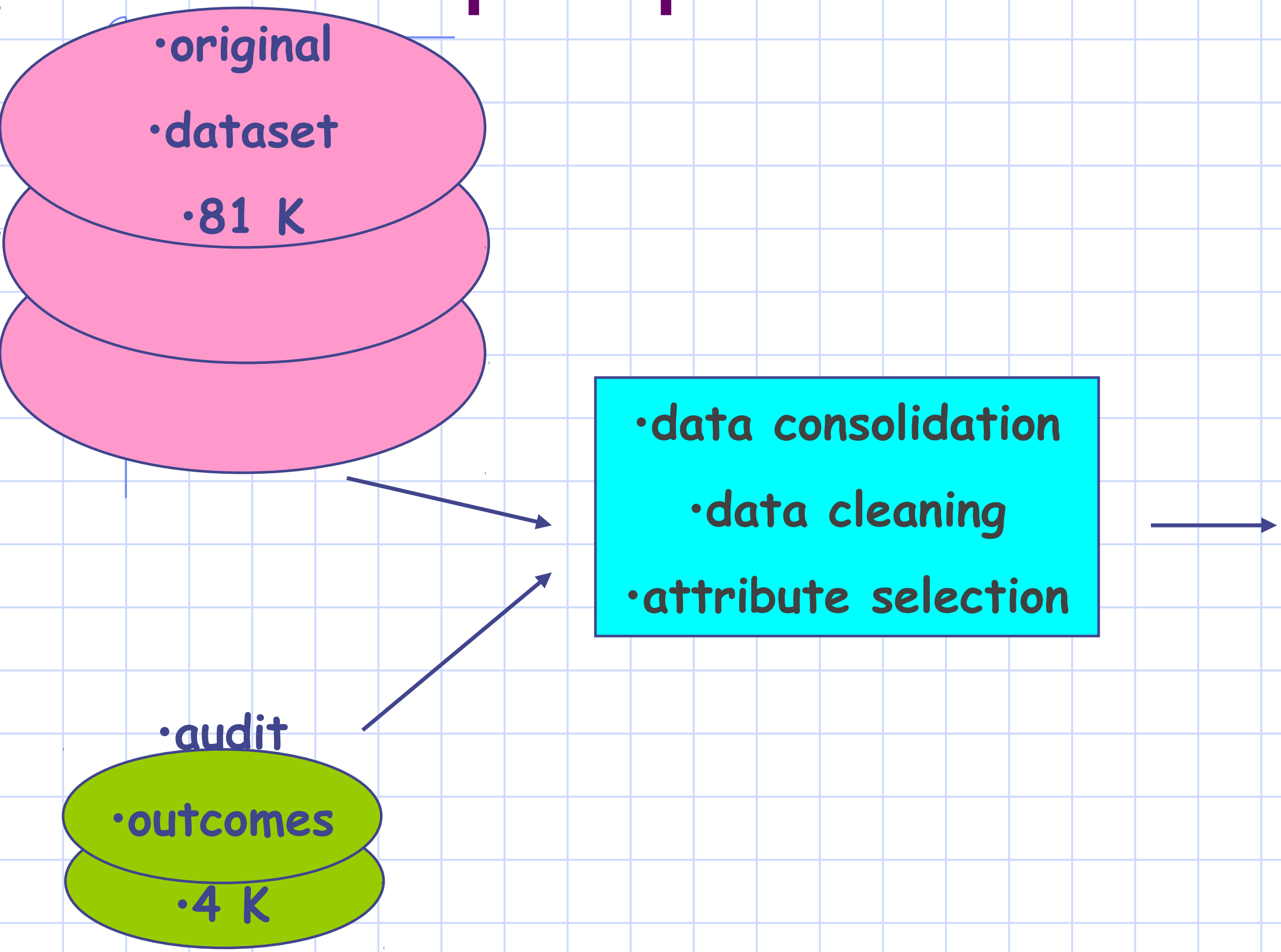
Audit planning

- 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*)

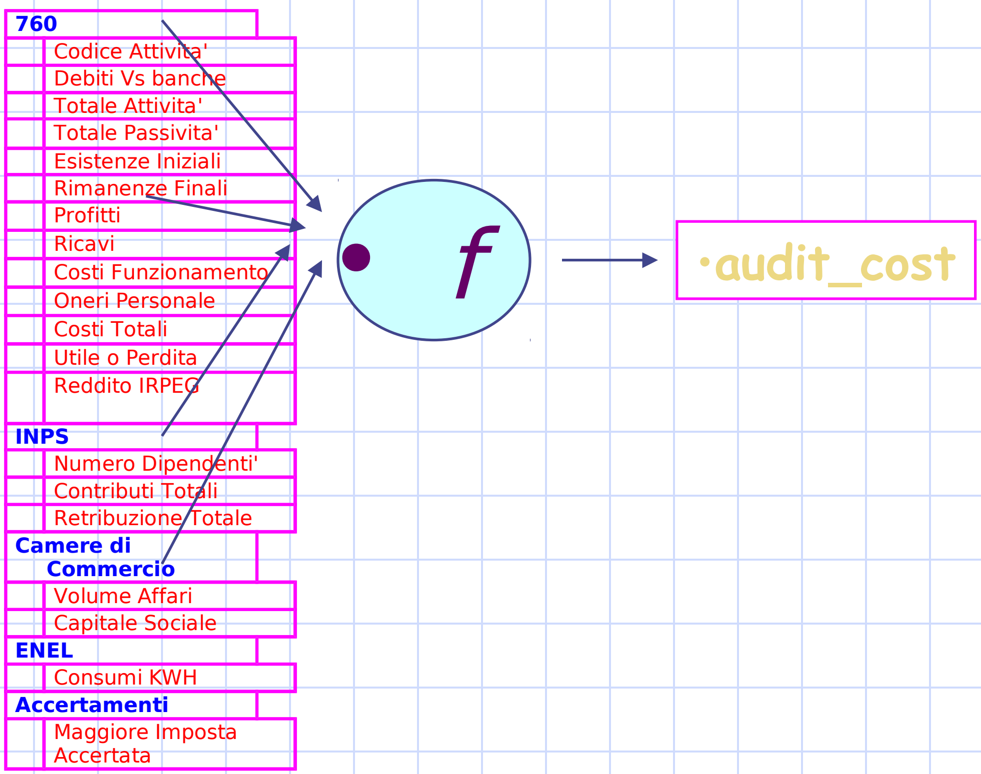
Data preparation



TAX DECLARATION	
	Codice Attivita'
	Debiti Vs banche
	Totale Attivita'
	Totale Passivita'
	Esistenze Iniziali
	Rimanenze Finali
	Profitti
	Ricavi
	Costi Funzioname
	Oneri Personale
	Costi Totali
	Utile o Perdita
	Reddito IRPEG
SOCIAL BENEFITS	
	Numero Dipende
	Contributi Totali
	Retribuzione Tota
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.):

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

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

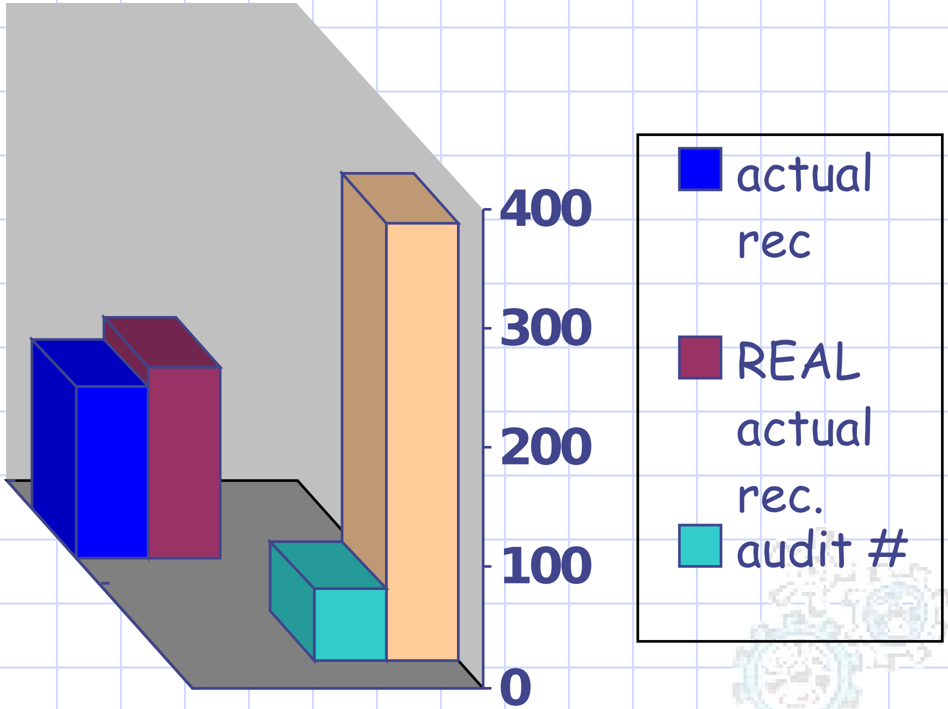
- Classifiers can be compared with the REAL case, consisting of the whole test-set:

- 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