

Data mining fundamentals




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Data analysis

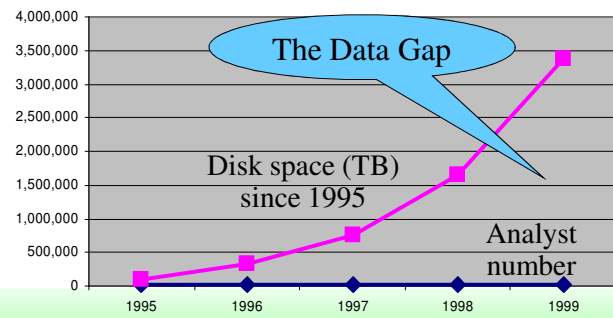
- Most companies own huge databases containing
 - operational data
 - textual documents
 - experiment results
- These databases are a potential source of useful information





Data analysis

- Information is “hidden” in huge datasets
 - not immediately evident
 - human analysts need a large amount of time for the analysis
 - most data *is never analyzed at all*




The Data Gap

Disk space (TB) since 1995


Analyst number

Year	Disk space (TB)	Analyst number
1995	~100,000	~100,000
1996	~300,000	~200,000
1997	~800,000	~300,000
1998	~1,800,000	~400,000
1999	~3,500,000	~500,000



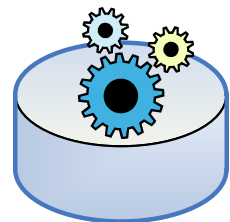
From R. Grossman, C. Kamath, V. Kumar, "Data Mining for Scientific and Engineering Applications"


3




Data mining

- Non trivial extraction of
 - implicit
 - previously unknown
 - potentially useful
 information from available data
- Extraction is automatic
 - performed by appropriate algorithms
- Extracted information is represented by means of abstract models
 - denoted as *pattern*















4



Example: profiling


- Consumer behavior in e-commerce sites
 - Selected products, requested information, ... 
- Search engines and portals  
 - Query keywords, searched topics and objects
- Social network data
 - Facebook, google+ profiles  
 - Dynamic data: posts on blogs, FB, tweets 
- Maps and georeferenced data
 - Localization, interesting locations for users  



5



Example: profiling

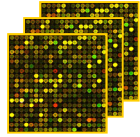
- User/service profiling
 - Recommendation systems
 - Advertisements
- Market basket analysis
 - Correlated objects for cross selling
 - User registration, fidelity cards
- Context-aware data analysis
 - Integration of different dimensions
 - E.g., location, time of the day, user interest
- Text mining
 - Brand reputation, sentiment analysis, topic trends


6






Example: biological data


- Microarray
 - expression level of genes in a cellular tissue
 - various types (mRNA, DNA)
- Patient clinical records
 - personal and demographic data
 - exam results
- Textual data in public collections
 - heterogeneous formats, different objectives
 - scientific literature (PubMed)
 - ontologies (Gene Ontology)



CID	PATIENT ID	sh013: 49A34	sh008: 45A9	sh077: 52A28	sh009: 4A34	sh014: 61A31	sh082: 99A6	sh033: 49A15	sh006: 41A31
IMAGE:74	ISG20 R	-1.02	-2.34	1.44	0.57	-0.13	0.12	0.34	-0.51
IMAGE:76	TNFSF13	-0.52	-4.09	-0.29	0.71	1.03	-0.67	0.22	-0.09
IMAGE:36	LOC3034	-0.25	-4.09	0.06	0.13	0.08	0.09	-0.08	-0.05
IMAGE:22	IG344 R	-1.375	-1.605	0.155	-0.015	0.005	-0.003	0.505	-0.893

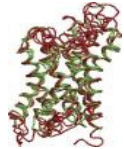






7

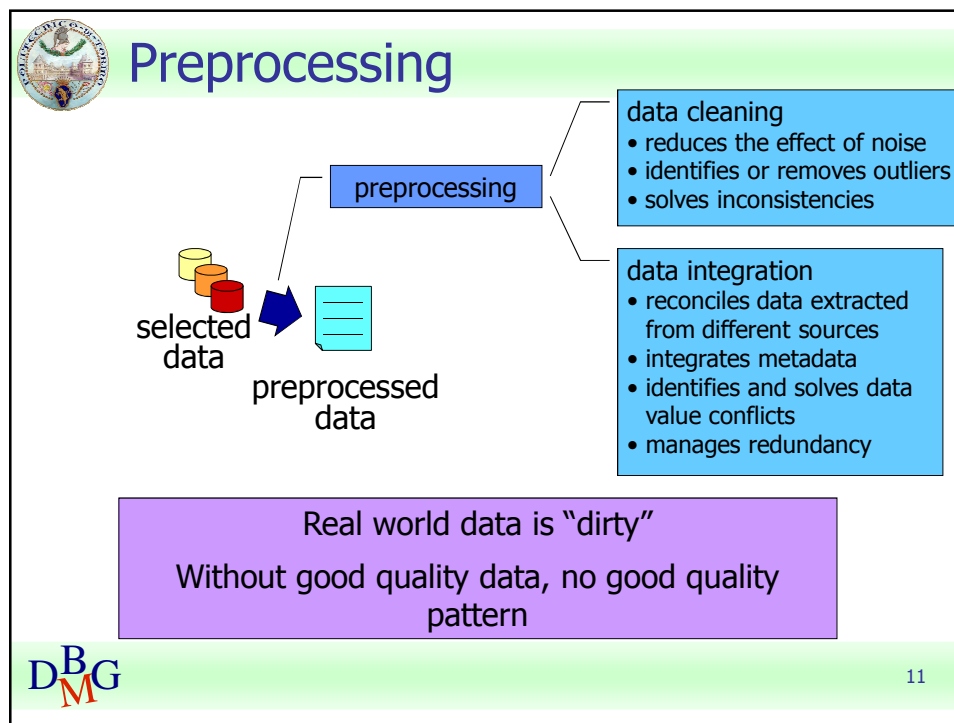
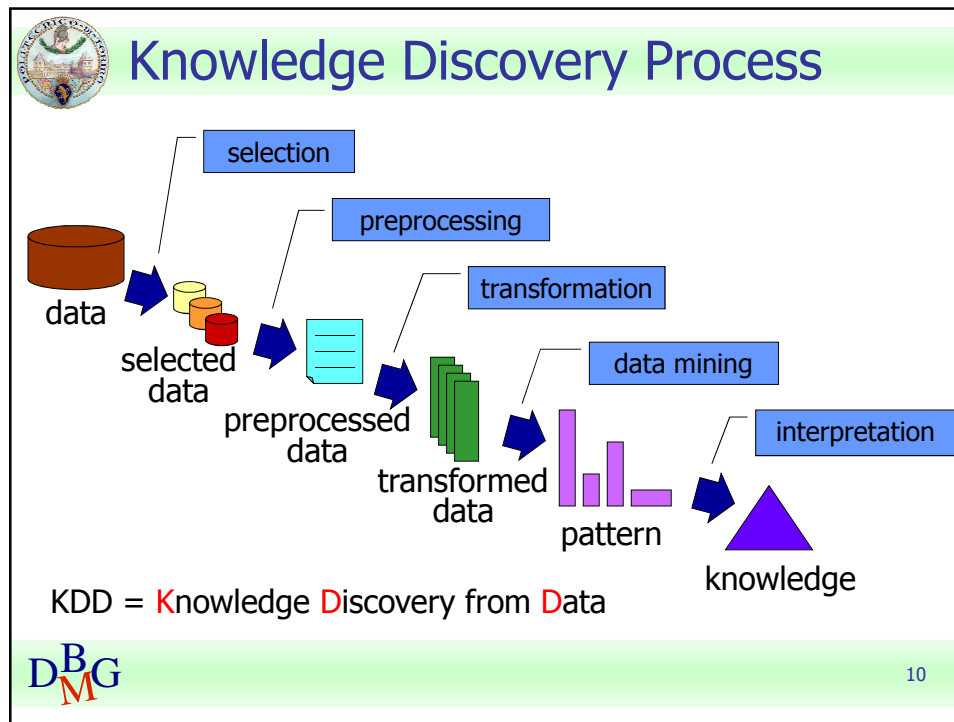



Biological analysis objectives

- Clinical analysis
 - detecting the causes of a pathology
 - monitoring the effect of a therapy
 - ⇒ diagnosis improvement and definition of new specific therapies
- Bio-discovery
 - gene network discovery
 - analysis of multifactorial genetic pathologies
- Pharmacogenesis
 - lab design of new drugs for genic therapies

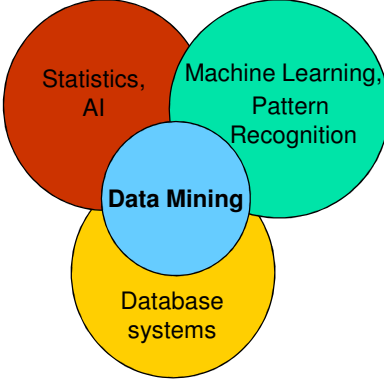

8







Data mining origins

- Draws from
 - statistics, artificial intelligence (AI)
 - pattern recognition, machine learning
 - database systems
- Traditional techniques are not appropriate because of
 - significant data volume
 - large data dimensionality
 - heterogeneous and distributed nature of data




From: P. Tan, M. Steinbach, V. Kumar, "Introduction to Data Mining"



12



Analysis techniques

- Descriptive methods
 - Extract interpretable models describing data
 - Example: client segmentation
- Predictive methods
 - Exploit some known variables to predict unknown or future values of (other) variables
 - Example: "spam" email detection

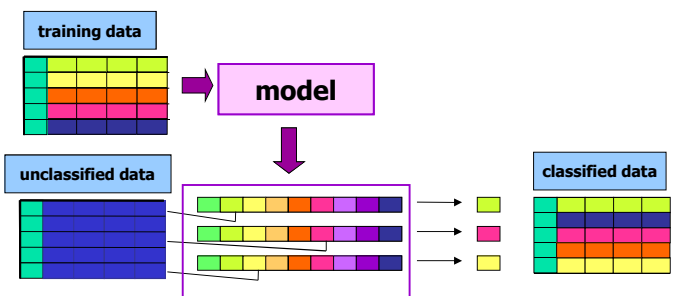

13





Classification

■ Objectives

- prediction of a class label
- definition of an interpretable model of a given phenomenon



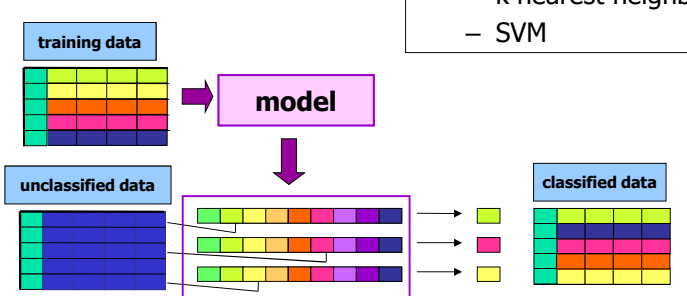

14





Classification

• Approaches

- decision trees
- bayesian classification
- classification rules
- neural networks
- k-nearest neighbours
- SVM

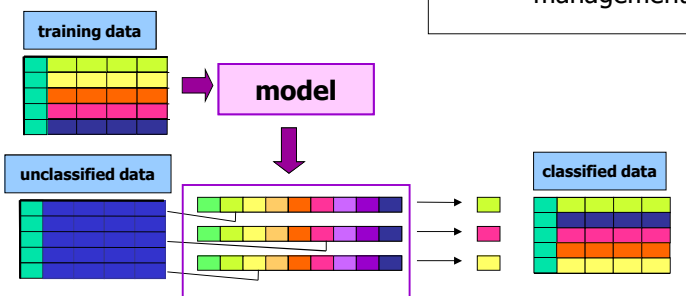



15





Classification

- Requirements
 - accuracy
 - interpretability
 - scalability
 - noise and outlier management



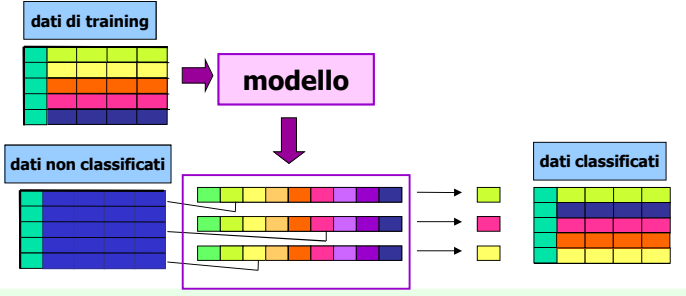
The diagram illustrates the classification workflow. It starts with 'training data' (a 4x4 grid of colored squares) being fed into a 'model' (a pink box). The model is then used to classify 'unclassified data' (a 4x4 grid of blue squares). The output is 'classified data' (a 4x4 grid of colored squares). A detailed view of the classification process shows a single row of unclassified data being processed by the model to produce a row of classified data, with arrows indicating the flow of information.


16





Classification

- Applications
 - detection of customer propensity to leave a company (churn or attrition)
 - fraud detection
 - classification of different pathology types
 - ...



The diagram illustrates the classification workflow. It starts with 'dati di training' (a 4x4 grid of colored squares) being fed into a 'modello' (a pink box). The model is then used to classify 'dati non classificati' (a 4x4 grid of blue squares). The output is 'dati classificati' (a 4x4 grid of colored squares). A detailed view of the classification process shows a single row of unclassified data being processed by the model to produce a row of classified data, with arrows indicating the flow of information.

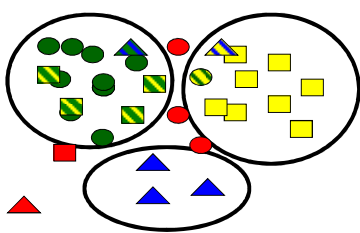

17





Clustering

■ Objectives

- detecting groups of similar data objects
- identifying exceptions and outliers




18



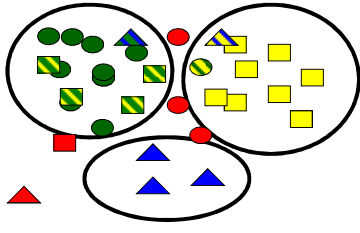
Clustering


• Approaches


- partitional (K-means)
- hierarchical
- density-based (DBSCAN)
- SOM

• Requirements

- scalability
- management of
 - noise and outliers
 - large dimensionality
- interpretability

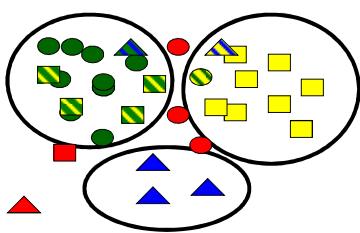




19




Clustering

- Applications
 - customer segmentation
 - clustering of documents containing similar information
 - grouping genes with similar expression pattern
 - ...




20



Association rules

- Objective
 - extraction of frequent correlations or pattern from a transactional database


Tickets at a supermarket counter


TID	Items
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diapers, Milk
4	Beer, Bread, Diapers, Milk
5	Coke, Diapers, Milk
...	...

- Association rule

diapers \Rightarrow beer

 - 2% of transactions contains both items
 - 30% of transactions containing diapers also contain beer


21



Association rules

- Applications
 - market basket analysis
 - cross-selling
 - shop layout or catalogue design


Tickets at a supermarket counter


TID	Items
1	Bread, Coca Cola, Milk
2	Beer, Bread
3	Beer, Coca Cola, Diapers, Milk
4	Beer, Bread, Diapers, Milk
5	Coca Cola, Diapers, Milk
...	...

- Association rule

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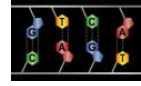

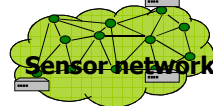
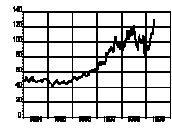
 - 2% of transactions contains both items
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22




Other data mining techniques

- Sequence mining
 - ordering criteria on analyzed data are taken into account
 - example: motif detection in proteins
- Time series and geospatial data
 - temporal and spatial information are considered
 - example: sensor network data
- Regression
 - prediction of a continuous value
 - example: prediction of stock quotes
- Outlier detection
 - example: intrusion detection in network traffic analysis








23

The official seal of Politecnico di Torino, showing a circular emblem with a building and text.

Open issues

- Scalability to *huge* data volumes
- Data dimensionality
- Complex data structures, heterogeneous data formats
- Data quality
- Privacy preservation
- Streaming data

The logo for the Data Mining Group (DBG) at Politecnico di Torino, featuring the letters 'DBG' in blue and red, with a circular emblem to the right.

24