**Data mining**

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*Not to be confused with analytics, information extraction, or data analysis.*

**Data mining** (the analysis step of the "Knowledge Discovery in Databases" process, or KDD),[1] is a field at the intersection of computer science and statistics,[2][3][4] and is the process that attempts to discover patterns in large data sets. It utilizes methods at the intersection of artificial intelligence, machine learning, statistics, and database systems.[2] The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use.[2] Aside from the raw analysis step, it involves database and data management aspects, data preprocessing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualization, and online updating.[2]

The term is a buzzword, and is frequently misused to mean any form of large-scale data or information processing (collection, extraction, warehousing, analysis, and statistics) but is also generalized to any kind of computer decision support system, including artificial intelligence, machine learning, and business intelligence. In the proper use of the word, the key term is *discovery*, commonly defined as "detecting something new". Even the popular book "Data mining: Practical machine learning tools and techniques with Java"[5] (which covers mostly machine learning material) was originally to be named just "Practical machine learning", and the term "data min­ing" was only added for marketing reasons.[6] Often the more general terms "(large scale) data analysis", or "analytics" – or when referring to actual methods, artificial intelligence and machine learning – are more appropriate.

The actual data mining task is the automatic or semi-automatic analysis of large quanti­ties of data to extract previously unknown interesting patterns such as groups of data records (cluster analysis), unusual records (anomaly detection) and dependen­cies (association rule mining). This usually involves using database tech­niques such as spatial indexes. These patterns can then be seen as a kind of sum­mary of the input data, and may be used in further analysis or, for example, in machine learning and predictive analytics. For example, the data mining step might identify multiple groups in the data, which can then be used to obtain more accurate prediction results by a decision support system. Neither the data collection, data preparation, nor result interpretation and reporting are part of the data mining step, but do belong to the overall KDD process as additional steps.

The related terms *data dredging*, *data fishing*, and *data snooping* refer to the use of data mining methods to sample parts of a larger population data set that are (or may be) too small for reliable statistical inferences to be made about the validity of any patterns discovered. These methods can, however, be used in creating new hypotheses to test against the larger data populations.

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**[edit] Background**

The manual extraction of patterns from data has occurred for centuries. Early methods of identifying patterns in data include Bayes' theorem (1700s) and regression analysis (1800s). The proliferation, ubiquity and increasing power of computer technology has dramatically increased data collection, storage, and manipulation ability. As data sets have grown in size and complexity, direct "hands-on" data analysis has increasingly been augmented with indirect, automated data processing, aided by other discoveries in computer science, such as neural networks, cluster analysis, genetic algorithms (1950s), decision trees (1960s), and support vector machines (1990s). Data mining is the process of applying these methods with the intention of uncovering hidden patterns[7] in large data sets. It bridges the gap from applied statistics and artificial intelligence (which usually provide the mathematical background) to database management by exploiting the way data is stored and indexed in databases to execute the actual learning and discovery algorithms more efficiently, allowing such methods to be applied to ever larger data sets.

**[edit] Research and evolution**

The premier professional body in the field is the Association for Computing Machinery's Special Interest Group on Knowledge Discovery and Data Mining (SIGKDD). Since 1989 they have hosted an annual international conference and published its proceedings,[8] and since 1999 have published a biannual academic journal titled "SIGKDD Explorations".[9]

Computer science conferences on data mining include:

* CIKM Conference – ACM Conference on Information and Knowledge Management
* DMIN Conference – International Conference on Data Mining
* DMKD Conference – Research Issues on Data Mining and Knowledge Discovery
* ECDM Conference – European Conference on Data Mining
* ECML-PKDD Conference – European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases
* EDM Conference – International Conference on Educational Data Mining
* ICDM Conference – IEEE International Conference on Data Mining
* KDD Conference – ACM SIGKDD Conference on Knowledge Discovery and Data Mining
* MLDM Conference – Machine Learning and Data Mining in Pattern Recognition
* PAKDD Conference – The annual Pacific-Asia Conference on Knowledge Discovery and Data Mining
* PAW Event – Predictialytics World
* SDM Conference – SIAM International Conference on Data Mining (SIAM)
* SSTD Symposium – Symposium on Spatial and Temporal Databases

Data mining topics are also present on many data management/database conferences such as the ICDE Conference, SIGMOD Conference and International Conference on Very Large Data Bases

**[edit] Process**

The **Knowledge Discovery in Databases (KDD) process** is commonly defined with the stages:

(1) Selection…

(2) Pre-processing…

(3) Transformation…

(4) *Data Mining…*

(5) Interpretation/Evaluation.[1]

It exists, however, in many variations on this theme, such as the Cross Industry Standard Process for Data Mining (CRISP-DM) which defines six phases:

(1) Business Understanding…

(2) Data Understanding…

(3) Data Preparation…

(4) Modeling…

(5) Evaluation…

(6) Deployment…

or a simplified process such as (1) pre-processing, (2) data mining, and (3) results validation.

**[edit] Pre-processing**

Before data mining algorithms can be used, a target data set must be assembled. As data mining can only uncover patterns actually present in the data, the target dataset must be large enough to contain these patterns while remaining concise enough to be mined within an acceptable time limit. A common source for data is a data mart or data warehouse. Pre-processing is essential to analyze the multivariate datasets before data mining. The target set is then cleaned. Data cleaning removes the observations containing noise and those with missing data.

**[edit] Data mining**

Data mining involves six common classes of tasks:[1]

* Anomaly detection (Outlier/change/deviation detection) – The identification of unusual data records, that might be interesting or data errors and require further investigation.
* Association rule learning (Dependency modeling) – Searches for relationships between variables. For example a supermarket might gather data on customer purchasing habits. Using association rule learning, the supermarket can determine which products are frequently bought together and use this information for marketing purposes. This is sometimes referred to as market basket analysis.
* Clustering – is the task of discovering groups and structures in the data that are in some way or another "similar", without using known structures in the data.
* Classification – is the task of generalizing known structure to apply to new data. For example, an e-mail program might attempt to classify an e-mail as "legitimate" or as "spam".
* Regression – Attempts to find a function which models the data with the least error.
* Summarization – providing a more compact representation of the data set, including visualization and report generation.

**[edit] Results validation**

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| http://upload.wikimedia.org/wikipedia/en/f/f4/Ambox_content.png | This section **is missing information about non-classification tasks in data mining, it only covers machine learning**. This concern has been noted on the talk page where whether or not to include such information may be discussed. *(September 2011)* |

The final step of knowledge discovery from data is to verify that the patterns produced by the data mining algorithms occur in the wider data set. Not all patterns found by the data mining algorithms are necessarily valid. It is common for the data mining algorithms to find patterns in the training set which are not present in the general data set. This is called overfitting. To overcome this, the evaluation uses a test set of data on which the data mining algorithm was not trained. The learned patterns are applied to this test set and the resulting output is compared to the desired output. For example, a data mining algorithm trying to distinguish "spam" from "legitimate" emails would be trained on a training set of sample e-mails. Once trained, the learned patterns would be applied to the test set of e-mails on which it had *not* been trained. The accuracy of the patterns can then be measured from how many e-mails they correctly classify. A number of statistical methods may be used to evaluate the algorithm, such as ROC curves.

If the learned patterns do not meet the desired standards, then it is necessary to re-evaluate and change the pre-processing and data mining steps. If the learned patterns do meet the desired standards, then the final step is to interpret the learned patterns and turn them into knowledge.

**[edit] Standards**

There have been some efforts to define standards for the data mining process, for example the 1999 European Cross Industry Standard Process for Data Mining (CRISP-DM 1.0) and the 2004 Java Data Mining standard (JDM 1.0). Development on successors to these processes (CRISP-DM 2.0 and JDM 2.0) was active in 2006, but has stalled since. JDM 2.0 was withdrawn without reaching a final draft.

For exchanging the extracted models – in particular for use in predictive analytics – the key standard is the Predictive Model Markup Language (PMML), which is an XML-based language developed by the Data Mining Group (DMG) and supported as exchange format by many data mining applications. As the name suggests, it only covers prediction models, a particular data mining task of high importance to business applications. However, extensions to cover (for example) subspace clustering have been proposed independently of the DMG.[10]

**[edit] Notable uses**

*See also category: Applied data mining*

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| [Crystal Clear app kedit.svg](http://en.wikipedia.org/wiki/File:Crystal_Clear_app_kedit.svg) | This section **may need to be rewritten entirely to comply with Wikipedia's quality standards**. You can help. The discussion page may contain suggestions. *(September 2011)* |

**[edit] Games**

Since the early 1960s, with the availability of oracles for certain combinatorial games, also called tablebases (e.g. for 3x3-chess) with any beginning configuration, small-board dots-and-boxes, small-board-hex, and certain endgames in chess, dots-and-boxes, and hex; a new area for data mining has been opened. This is the extraction of human-usable strategies from these oracles. Current pattern recognition approaches do not seem to fully acquire the high level of abstraction required to be applied successfully. Instead, extensive experimentation with the tablebases – combined with an intensive study of tablebase-answers to well designed problems, and with knowledge of prior art (i.e. pre-tablebase knowledge) – is used to yield insightful patterns. Berlekamp (in dots-and-boxes, etc.) and John Nunn (in chess endgames) are notable examples of researchers doing this work, though they were not – and are not – involved in tablebase generation.

**[edit] Business**

Data mining in customer relationship management applications can contribute significantly to the bottom line.[*citation needed*] Rather than randomly contacting a prospect or customer through a call center or sending mail, a company can concentrate its efforts on prospects that are predicted to have a high likelihood of responding to an offer. More sophisticated methods may be used to optimize resources across campaigns so that one may predict to which channel and to which offer an individual is most likely to respond (across all potential offers). Additionally, sophisticated applications could be used to automate mailing. Once the results from data mining (potential prospect/customer and channel/offer) are determined, this "sophisticated application" can either automatically send an e-mail or a regular mail. Finally, in cases where many people will take an action without an offer, "uplift modeling" can be used to determine which people have the greatest increase in response if given an offer. Data clustering can also be used to automatically discover the segments or groups within a customer data set.

Businesses employing data mining may see a return on investment, but also they recognize that the number of predictive models can quickly become very large. Rather than using one model to predict how many customers will churn, a business could build a separate model for each region and customer type. Then, instead of sending an offer to all people that are likely to churn, it may only want to send offers to loyal customers. Finally, the business may want to determine which customers are going to be profitable over a certain window in time, and only send the offers to those that are likely to be profitable. In order to maintain this quantity of models, they need to manage model versions and move on to *automated data mining*.

Data mining can also be helpful to human resources (HR) departments in identifying the characteristics of their most successful employees. Information obtained – such as universities attended by highly successful employees – can help HR focus recruiting efforts accordingly. Additionally, Strategic Enterprise Management applications help a company translate corporate-level goals, such as profit and margin share targets, into operational decisions, such as production plans and workforce levels.[11]

Another example of data mining, often called the market basket analysis, relates to its use in retail sales. If a clothing store records the purchases of customers, a data mining system could identify those customers who favor silk shirts over cotton ones. Although some explanations of relationships may be difficult, taking advantage of it is easier. The example deals with association rules within transaction-based data. Not all data are transaction based and logical, or inexact rules may also be present within a database.

Market basket analysis has also been used to identify the purchase patterns of the Alpha Consumer. Alpha Consumers are people that play a key role in connecting with the concept behind a product, then adopting that product, and finally validating it for the rest of society. Analyzing the data collected on this type of user has allowed companies to predict future buying trends and forecast supply demands.[*citation needed*]

Data mining is a highly effective tool in the catalog marketing industry.[*citation needed*] Catalogers have a rich database of history of their customer transactions for millions of customers dating back a number of years. Data mining tools can identify patterns among customers and help identify the most likely customers to respond to upcoming mailing campaigns.

Data mining for business applications is a component which needs to be integrated into a complex modeling and decision making process. Reactive business intelligence (RBI) advocates a "holistic" approach that integrates data mining, modeling, and interactive visualization into an end-to-end discovery and continuous innovation process powered by human and automated learning.[12]

In the area of decision making, the RBI approach has been used to mine knowledge that is progressively acquired from the decision maker, and then self-tune the decision method accordingly.[13]

An example of data mining related to an integrated-circuit production line is described in the paper "Mining IC Test Data to Optimize VLSI Testing."[14] In this paper, the application of data mining and decision analysis to the problem of die-level functional testing is described. Experiments mentioned demonstrate the ability to apply a system of mining historical die-test data to create a probabilistic model of patterns of die failure. These patterns are then utilized to decide, in real time, which die to test next and when to stop testing. This system has been shown, based on experiments with historical test data, to have the potential to improve profits on mature IC products.

**[edit] Science and engineering**

In recent years, data mining has been used widely in the areas of science and engineering, such as bioinformatics, genetics, medicine, education and electrical power engineering.

In the study of human genetics, sequence mining helps address the important goal of understanding the mapping relationship between the inter-individual variations in human DNA sequence and the variability in disease susceptibility. In simple terms, it aims to find out how the changes in an individual's DNA sequence affects the risks of developing common diseases such as cancer, which is of great importance to improving methods of diagnosing, preventing, and treating these diseases. The data mining method that is used to perform this task is known as multifactor dimensionality reduction.[15]

In the area of electrical power engineering, data mining methods have been widely used for condition monitoring of high voltage electrical equipment. The purpose of condition monitoring is to obtain valuable information on, for example, the status of the insulation (or other important safety-related parameters). Data clustering techniques – such as the self-organizing map (SOM), have been applied to vibration monitoring and analysis of transformer on-load tap-changers (OLTCS). Using vibration monitoring, it can be observed that each tap change operation generates a signal that contains information about the condition of the tap changer contacts and the drive mechanisms. Obviously, different tap positions will generate different signals. However, there was considerable variability amongst normal condition signals for exactly the same tap position. SOM has been applied to detect abnormal conditions and to hypothesize about the nature of the abnormalities.[16]

Data mining methods have also been applied to dissolved gas analysis (DGA) in power transformers. DGA, as a diagnostics for power transformers, has been available for many years. Methods such as SOM has been applied to analyze generated data and to determine trends which are not obvious to the standard DGA ratio methods (such as Duval Triangle).[16]

Another example of data mining in science and engineering is found in educational research, where data mining has been used to study the factors leading students to choose to engage in behaviors which reduce their learning,[17] and to understand factors influencing university student retention.[18] A similar example of social application of data mining is its use in expertise finding systems, whereby descriptors of human expertise are extracted, normalized, and classified so as to facilitate the finding of experts, particularly in scientific and technical fields. In this way, data mining can facilitate institutional memory.

Other examples of application of data mining methods are biomedical data facilitated by domain ontologies,[19] mining clinical trial data,[20] and traffic analysis using SOM.[21]

In adverse drug reaction surveillance, the Uppsala Monitoring Centre has, since 1998, used data mining methods to routinely screen for reporting patterns indicative of emerging drug safety issues in the WHO global database of 4.6 million suspected adverse drug reaction incidents.[22] Recently, similar methodology has been developed to mine large collections of electronic health records for temporal patterns associating drug prescriptions to medical diagnoses.[23]

**[edit] Human rights**

Data mining of government records – particularly records of the justice system (i.e. courts, prisons) – enables the discovery of systemic human rights violations in connection to generation and publication of invalid or fraudulent legal records by various government agencies.[24][25]

**[edit] Spatial data mining**

Spatial data mining is the application of data mining methods to spatial data. The end objective of spatial data mining is to find patterns in data with respect to geography. So far, data mining and Geographic Information Systems (GIS) have existed as two separate technologies, each with its own methods, traditions, and approaches to visualization and data analysis. Particularly, most contemporary GIS have only very basic spatial analysis functionality. The immense explosion in geographically referenced data occasioned by developments in IT, digital mapping, remote sensing, and the global diffusion of GIS emphasizes the importance of developing data-driven inductive approaches to geographical analysis and modeling.

Data mining offers great potential benefits for GIS-based applied decision-making. Recently, the task of integrating these two technologies has become of critical importance, especially as various public and private sector organizations possessing huge databases with thematic and geographically referenced data begin to realize the huge potential of the information contained therein. Among those organizations are:

* offices requiring analysis or dissemination of geo-referenced statistical data
* public health services searching for explanations of disease clustering
* environmental agencies assessing the impact of changing land-use patterns on climate change
* geo-marketing companies doing customer segmentation based on spatial location.

**[edit] Challenges**

Geospatial data repositories tend to be very large. Moreover, existing GIS datasets are often splintered into feature and attribute components that are conventionally archived in hybrid data management systems. Algorithmic requirements differ substantially for relational (attribute) data management and for topological (feature) data management.[26] Related to this is the range and diversity of geographic data formats, which present unique challenges. The digital geographic data revolution is creating new types of data formats beyond the traditional "vector" and "raster" formats. Geographic data repositories increasingly include ill-structured data, such as imagery and geo-referenced multi-media.[27]

There are several critical research challenges in geographic knowledge discovery and data mining. Miller and Han[28] offer the following list of emerging research topics in the field:

* **Developing and supporting geographic data warehouses (GDW's)**: Spatial properties are often reduced to simple aspatial attributes in mainstream data warehouses. Creating an integrated GDW requires solving issues of spatial and temporal data interoperability – including differences in semantics, referencing systems, geometry, accuracy, and position.
* **Better spatio-temporal representations in geographic knowledge discovery**: Current geographic knowledge discovery (GKD) methods generally use very simple representations of geographic objects and spatial relationships. Geographic data mining methods should recognize more complex geographic objects (i.e. lines and polygons) and relationships (i.e. non-Euclidean distances, direction, connectivity, and interaction through attributed geographic space such as terrain). Furthermore, the time dimension needs to be more fully integrated into these geographic representations and relationships.
* **Geographic knowledge discovery using diverse data types**: GKD methods should be developed that can handle diverse data types beyond the traditional raster and vector models, including imagery and geo-referenced multimedia, as well as dynamic data types (video streams, animation).

In four annual surveys of data miners,[29] data mining practitioners consistently identify three key challenges that they face more than any others, specifically (a) dirty data, (b) explaining data mining to others, and (c) unavailability of data/difficult access to data. In the 2010 survey data miners also shared their experiences in overcoming these particular challenges.[30]

**[edit] Sensor data mining**

Wireless sensor networks can be used for facilitating the collection of data for spatial data mining for a variety of applications such as air pollution monitoring.[31] A characteristic of such networks is that nearby sensor nodes monitoring an environmental feature typically register similar values. This kind of data redundancy due to the spatial correlation between sensor observations inspires the techniques for in-network data aggregation and mining. By measuring the spatial correlation between data sampled by different sensors, a wide class of specialized algorithms can be developed to develop more efficient spatial data mining algorithms.[32]

**[edit] Visual data mining**

In the process of turning from analogical into digital, large data sets have been generated, collected, and stored discovering statistical patterns, trends and information which is hidden in data, in order to build predictive patterns. Studies suggest visual data mining is faster and much more intuitive than is traditional data mining.[33][34]

**[edit] Music data mining**

Data mining techniques, and in particular co-occurrence analysis, has been used to discover relevant similarities among music corpora (radio lists, CD databases) for the purpose of classifying music into genres in a more objective manner.[35]

**[edit] Surveillance**

Data mining has been used to stop terrorist programs under the U.S. government, including the Total Information Awareness (TIA) program, Secure Flight (formerly known as Computer-Assisted Passenger Prescreening System (CAPPS II)), Analysis, Dissemination, Visualization, Insight, Semantic Enhancement (ADVISE),[36] and the Multi-state Anti-Terrorism Information Exchange (MATRIX).[37] These programs have been discontinued due to controversy over whether they violate the 4th Amendment to the United States Constitution, although many programs that were formed under them continue to be funded by different organizations or under different names.[38]

In the context of combating terrorism, two particularly plausible methods of data mining are "pattern mining" and "subject-based data mining".

**[edit] Pattern mining**

"Pattern mining" is a data mining method that involves finding existing patterns in data. In this context *patterns* often means association rules. The original motivation for searching association rules came from the desire to analyze supermarket transaction data, that is, to examine customer behavior in terms of the purchased products. For example, an association rule "beer ⇒ potato chips (80%)" states that four out of five customers that bought beer also bought potato chips.

In the context of pattern mining as a tool to identify terrorist activity, the National Research Council provides the following definition: "Pattern-based data mining looks for patterns (including anomalous data patterns) that might be associated with terrorist activity — these patterns might be regarded as small signals in a large ocean of noise."[39][40][41] Pattern Mining includes new areas such a Music Information Retrieval (MIR) where patterns seen both in the temporal and non temporal domains are imported to classical knowledge discovery search methods.

**[edit] Subject-based data mining**

"Subject-based data mining" is a data mining method involving the search for associations between individuals in data. In the context of combating terrorism, the National Research Council provides the following definition: "Subject-based data mining uses an initiating individual or other datum that is considered, based on other information, to be of high interest, and the goal is to determine what other persons or financial transactions or movements, etc., are related to that initiating datum."[40]

**[edit] Knowledge grid**

Knowledge discovery "On the Grid" generally refers to conducting knowledge discovery in an open environment using grid computing concepts, allowing users to integrate data from various online data sources, as well make use of remote resources, for executing their data mining tasks. The earliest example was the Discovery Net,[42][43] developed at Imperial College London, which won the “Most Innovative Data-Intensive Application Award” at the ACM SC02 (Supercomputing 2002) conference and exhibition, based on a demonstration of a fully interactive distributed knowledge discovery application for a bioinformatics application. Other examples include work conducted by researchers at the University of Calabria, who developed a Knowledge Grid architecture for distributed knowledge discovery, based on grid computing.[44][45]

**[edit] Reliability/Validity**

Data mining can be misused, and can also unintentionally produce results which appear significant but which do not actually predict future behavior and cannot be reproduced on a new sample of data. See Data snooping, Data dredging.

**[edit] Privacy concerns and ethics**

Some people believe that data mining itself is ethically neutral.[46] It is important to note that the term "data mining" has no ethical implications, but is often associated with the mining of information in relation to peoples' behavior (ethical and otherwise). To be precise, data mining is a statistical method that is applied to a set of information (i.e. a data set). Associating these data sets with people is an extreme narrowing of the types of data that are available in today's technological society. Examples could range from a set of crash test data for passenger vehicles, to the performance of a group of stocks. These types of data sets make up a great proportion of the information available to be acted on by data mining methods, and rarely have ethical concerns associated with them. However, the ways in which data mining can be used can in some cases and contexts raise questions regarding privacy, legality, and ethics.[47] In particular, data mining government or commercial data sets for national security or law enforcement purposes, such as in the Total Information Awareness Program or in ADVISE, has raised privacy concerns.[48][49]

Data mining requires data preparation which can uncover information or patterns which may compromise confidentiality and privacy obligations. A common way for this to occur is through data aggregation. Data aggregation involves combining data together (possibly from various sources) in a way that facilitates analysis (but that also might make identification of private, individual-level data deducible or otherwise apparent).[50] This is not data mining *per se*, but a result of the preparation of data before – and for the purposes of – the analysis. The threat to an individual's privacy comes into play when the data, once compiled, cause the data miner, or anyone who has access to the newly compiled data set, to be able to identify specific individuals, especially when the data were originally anonymous.

It is recommended that an individual is made aware of the following **before** data are collected[50]:

* the purpose of the data collection and any (known) data mining projects
* how the data will be used
* who will be able to mine the data and use the data and their derivatives
* the status of security surrounding access to the data
* how collected data can be updated.

In America, privacy concerns have been addressed to some extent by the US Congress via the passage of regulatory controls such as the Health Insurance Portability and Accountability Act (HIPAA). The HIPAA requires individuals to give their "informed consent" regarding information they provide and its intended present and future uses. According to an article in *Biotech Business Week', "[i]n practice, HIPAA may not offer any greater protection than the longstanding regulations in the research arena," says the AAHC. More importantly, the rule's goal of protection through informed consent is undermined by the complexity of consent forms that are required of patients and participants, which approach a level of incomprehensibility to average individuals."*[51] *This underscores the necessity for data anonymity in data aggregation and mining practices.*

Data may also be modified so as to *become* anonymous, so that individuals may not readily be identified.[50] However, even "de-identified"/"anonymized" data sets can potentially contain enough information to allow identification of individuals, as occurred when journalists were able to find several individuals based on a set of search histories that were inadvertently released by AOL.[52]

**[edit] Software**

*See also category: Data mining and machine learning software*

**[edit] Free open-source data mining software and applications**

1. Carrot2: Text and search results clustering framework.
2. Chemicalize.org: A chemical structure miner and web search engine.
3. ELKI: A university research project with advanced cluster analysis and outlier detection methods written in the Java language.
4. GATE: a natural language processing and language engineering tool.
5. JHepWork: Java cross-platform data analysis framework developed at Argonne National Laboratory.
6. KNIME: The Konstanz Information Miner, a user friendly and comprehensive data analytics framework.
7. NLTK (Natural Language Toolkit): A suite of libraries and programs for symbolic and statistical natural language processing (NLP) for the Python language.
8. Orange: A component-based data mining and machine learning software suite written in the Python language.
9. R: A programming language and software environment for statistical computing, data mining, and graphics. It is part of the GNU project.
10. RapidMiner: An environment for machine learning and data mining experiments.
11. UIMA: The UIMA (Unstructured Information Management Architecture) is a component framework for analyzing unstructured content such as text, audio and video – originally developed by IBM.
12. Weka: A suite of machine learning software applications written in the Java programming language.
13. ML-Flex: A software package that enables users to integrate with third-party machine-learning packages written in any programming language, execute classification analyses in parallel across multiple computing nodes, and produce HTML reports of classification results.

In 2010, the open source *R* language overtook other tools to become the application used by more data miners (43%) than any other, according to a well-known annual survey.[29]

**[edit] Commercial data-mining software and applications**

* Microsoft Analysis Services: data mining software provided by Microsoft
* SAS: Enterprise Miner – data mining software provided by the SAS Institute.
* STATISTICA: Data Miner – data mining software provided by StatSoft.
* Oracle Data Mining: data mining software by Oracle.
* LIONsolver: an integrated software application for data mining, business intelligence, and modeling that implements the Learning and Intelligent OptimizatioN (LION) approach

According to Rexer's Annual Data Miner Survey in 2010, IBM SPSS Modeler, STATISTICA Data Miner, and the *R* received the strongest satisfaction ratings.[29]

**[edit] Marketplace surveys**

Several researchers and organizations have conducted reviews of data mining tools and surveys of data miners. These identify some of the strengths and weaknesses of the software packages. They also provide an overview of the behaviors, preferences and views of data miners. Some of these reports include:

* Annual Rexer Analytics Data Miner Surveys[29]
* Forrester Research 2010 Predictive Analytics and Data Mining Solutions report[53]
* Gartner 2008 "Magic Quadrant" report[54]
* Haughton et al.'s 2003 Review of Data Mining Software Packages in *The American Statistician*[55]
* Robert A. Nisbet's 2006 Three Part Series of articles "Data Mining Tools: Which One is Best For CRM?"[56]
* 2011 Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery[57]

**[edit] See also**

Methods

* Anomaly/outlier/change detection
* Association rule learning
* Classification
* Cluster analysis
* Decision trees
* Factor analysis
* Neural Networks
* Regression analysis
* Structured data analysis
* Sequence mining
* Text mining

Application domains

* Analytics
* Bioinformatics
* Business intelligence
* Data analysis
* Data warehouse
* Decision support system
* Drug Discovery
* Exploratory data analysis
* Predictive analytics
* Web mining

Application examples

*See also category: Applied data mining*

* Customer analytics
* Data mining in agriculture
* National Security Agency
* Police-enforced ANPR in the UK
* Quantitative structure–activity relationship
* Data mining in meteorology
* Educational data mining
* Surveillance / Mass surveillance (e.g., Stellar wind)

Related topics

Data mining is about *analyzing* data; for information about extracting information out of data, see:

* Information extraction
* Information integration
* Web scraping
* Named-entity recognition
* Data integration
* Data transformation
* Profiling practices

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