IJESR/January 2013/ Volume-3/Issue-1/Article No-5/7-34 ISSN 2277-2685
International Journal of Engineering & Science Research

DETAILED LITERATURE SURVEY DATA MINING TECHNIQUES IN E-LEARNING

Shakir Khan*[1], Prof. (Dr) Arun Sharma[2]

[1]Researcher at E-Learning and Distance Learning Deanship, King Saud University, Riyadh, Saudi Arabia

[2]Head, Department of Computer Science, Krishna Institute of Engineering and Technology, Ghaziabad-201206, India

ABSTRACT

This paper covers to provide a current snapshot of the existing state of investigate and applications of Data Mining methods in e-learning. Few years ago, the data flow in teaching and learning area was comparatively simple and the function of technology was restricted. However, as we developed into a more incorporated world where technology has turned out to be an essential part of the industry processes, the procedure of transport of data has become more complicated. Today, one of the leading challenges that learning institutions facing is the short-tempered expansion of educational information and to utilize this information to progress the quality of management decisions. Data mining techniques are logical tools that can be utilized to pull out important knowledge from huge data sets. This paper talks to purpose of data mining in educational institutions to take out constructive information from the vast data sets and providing logical tool to view and utilize this information for decision making developments by considering real life paradigms and by applying different data mining technique in E Learning.

Distributed data mining is invented from the requirement of mining over decentralized data sources. Data mining techniques linking in such complex surroundings must come across huge dynamics due to amendment in the system can influence the overall presentation of the system.

Keywords: Data mining technique, E-learning, teaching and learning patterns

1. INTRODUCTION

Within a decade, the Internet has become anenveloping medium that has changed totally, and perhaps forever, the way information and knowledge are transmitted and shared all through the world. The education community has not limited itself to the role of inactive actor in this relating story, but it has been at the frontat most of the changes.

In reality, the Internet and the advance of telecommunication technologies permit us to distribute and manipulate information in almost real time. This reality is shaping the next generation of distance education tools. Distance education came out from traditional education in order to cover up the requirements of remote students and/or help the teaching-learning development, reinforcing or replacing traditional education. The Internet takes this development of delocalization of the educative experience to a new empire, where the lack of presential intercourse is, at least partially, replaced by an increased level of technology-mediated communication. Furthermore, telecommunications permit this interaction to take forms that were not available to traditional presential and distance learning teachers and learners.

This is e -learning (also referred to as web-based education and e-teaching), a new context for education where large amounts of information describing the continuum of the teaching-learning interactions are endlessly generated and ubiquitously available. This could be seen as go-ahead: prosperity of information willingly available just a click away. But it could equally be seen as an exponentially rising terrifying, in which free information blocks the educational system without providing any articulate knowledge to its actors.

Data Mining was born to deal with problems like this. As a field of research, it is almost modern to e-learning. It is, though, rather complicated to define. Not because of its built-in complexity, but because it has most of its roots in the ever-shifting world of business. At its most detailed, it can be understood not just as a collection of data analysis methods, but as a data analysis process that encompasses anything from data understanding, pre-processing and modeling to process evaluation and implementation [16]. It is yet usual to pay special attention to the Data Mining methods themselves. These commonly bridge the fields of traditional statistics, pattern recognition and machine learning to provide analytical solutions to problems in areas as various as medicines, production, and trade, to name just a few. An aspect that perhaps makes Data Mining unique is that it pays special attention to the compatibility of the modeling techniques with new Information Technologies (IT) and database technologies; regularly spotlight on large, heterogeneous and complex databases. E-learning databases frequently fit this depiction.

Therefore, Data Mining can be used to extract knowledge from e-learning systems through the analysis of the information available in the form of data generated by their users. In this case, the main objective becomes finding the patterns of system practice by teachers and students and, possibly most importantly, discovering the students' learning behavior patterns.

This paper aims to provide an as complete as possible review of the many applications of Data Mining to e- learning over the period 1999-2011; that is, a survey of the literature in this area up to date. We must admit that this is not the first time a similar venture has been undertaken: a collection of credentials that cover up most of the significant topics in the field was concurrently presented in [71].

The results of the survey are organized from different points of observation that might in turn contest the different interests of its possible readers: The surveyed research can be seen as being displayed togetherwith two axes: Data Mining troubles, methods, and e-learning applications. Section 2 represents the research along the axis of the Data Mining modeling techniques and methods, while section 3 represents the surveyed content along with the e-learning applications axis. This organization of the surveyed content should permit readers to access the information in a more solid and self-contained way than that in [71].

Most of the information provided in this paper takes the form of tables of publications. I believe it to be the best (or at least the most compact) way to systematize it in a guided approach to findthe main contents.

2. A SURVEY OF DATA MINING IN E-LEARNING FROM THE DATA MINING POINT OF VIEW

As declared in the introduction, my aim to organize the results of the survey in different ways that might match to the various readers' academic or professional backgrounds. In this section, Irepresented the surveyed research according to the Data Mining problems (classification, clustering, etc.), procedures and methods (e.g., Neural Networks, Genetic Algorithms, Decision Trees, or Fuzzy Logic).

In fact, most of the existing research addresses troubles of classification and clustering. For this reason, detailed subsections will be devoted to them. But first, let me try to find a place for Data Mining in the world of e-learning.

2.1. Where does Data Mining fit in e-learning processes?

Some researchers have pointed out the secure relation between the fields of Artificial Intelligence (AI) and Machine Learning (ML) -main sources of Data Mining techniques, methodsand education process [4, 26, 30, 49, 79, and 85].

In [4], the author establishes the research opportunities in AI and education on the basis of three models of learning processes. Models as scientific tool: are used by means of understanding and forecasting some feature of an educational situation. Models as component: matching to some characteristic of the teaching or learning process and used as a component for an educative object; and models as basis for design of educational artifacts: supporting the design of computer tools for education by providing design methodologies and system components, or by constraining the variety of tools that might be accessible to learners.

In [49, 85], studies on how Data Mining techniques could effectively be integrated to e- learning environments and how they could develop the learning tasks were carried out. In [85], data clustering was recommended as a means to encourage group-based collaborative learning and to give incremental student analysis.

A review of the possibilities of the application of Web Mining (Web usage mining and clustering) techniques to gather some of the existing challenges in distance education was presented in [30]. The projected approach could improve the efficiency and effectiveness of distance education in two ways: on the one hand, the discovery of collective and individual paths for students could assist in the growth of effective modified education, providing asign of how to best systematize the educator's organization's courseware. On the other hand, virtual knowledge structure could be recognized through Web Mining methods: The discovery of Association Rules could build it possible for Web-based distance tutors to recognize knowledge patterns and restructure the virtual course based on the pattern exposed.

An analysis on how ML techniques - again, a common source for Data Mining techniques- have been used to computerize the structure and training of student models, as well as the background awareness necessary for student modeling, were presented in [79]. In this report, the difficulty, suitability and possibility of applying ML techniques to student modeling was commented.

2.2. The classification problems in e-learning

In classification problems, we generally plan to model the existing relationships (if any) between a set of multivariate data objects and a certain set of outcomes for each of them in the form of class relationship labels. Although plenty of classification methods that would be healthy in a Data Mining process exist, in what follows, we shall see that only a few techniques (or families of techniques) have been applied to e-learning.

2.2.1. Fuzzy logic methods

Fuzzy logic-based methods have only recently in usefor their first steps in the e-learning field [36, 39, 40, 81, and 89].

In [81], a neuro -fuzzy model for the assessment of students in an intelligent tutoring system (ITS) was presented. Fuzzy theory was used to determine and convert the interaction between the student and the ITS into linguistic terms. Then, Artificial Neural Networks were taught to realize fuzzy relationships operated with the max-min composition. These fuzzy relationships represent the estimation made by human tutors of the degree of alliance between an observed response and a student characteristic.

A fuzzy group-decision approach to help users and domain experts in the assessment of educational web sites were realized in the EWSE system, presented in [39]. In further work by Hwang and colleagues [36, 40], a fuzzy rules-based method for eliciting and integrating system management understanding was proposed and served as the foundation for the design of an intelligent management system for monitoring learning Web servers. This system is competent of predicting and handling feasible failures of educational Web servers, improving their solidity and reliability. It helps students' self-evaluation and provides them with suggestions based on fuzzy reasoning techniques.

A two-phase fuzzy mining and education algorithm was described in [89]. It integrates an relationship rule mining algorithm, called Apriori, with fuzzy set theory to discover embedded information that could be fed back to instructors for refinement or reorganizing the teaching materials and tests. In a second phase, it uses an inductive learning algorithm of the AQ family: AQR, to find the concept descriptions indicating the missing concepts during students' learning. The results of this phase could also be fed back to teachers for refining or reorganizing the learning path.

2.2.2. Artificial Neural Networks and Evolutionary Computation

A fewresearches on the use of Artificial Neural Networks and Evolutionary Computation models to arrangement with e-learning topics can be found in [53, 55, and 87].

A navigation support system based on an Artificial Neural Network (more precisely, a Multi-Layer Perceptron, or MLP) was put forward in [55] to decide on the right navigation strategies. The Neural Network was used as a navigation strategy decision module in the system. Evaluation has validated the information learned by the Neural Network and the level of efficiency of the navigation strategy.

In [53, 87], evolutionary algorithms were used to assess the students' learning behavior. A combination of multiple classifiers (CMC), for the classification of students and the prediction of their final grades, based on features extracted from logged data in atutoring web-based system, was described in [53]. The classification and prediction correctness are improved through the weighting of the data attribute vectors using a Genetic Algorithm. In [87] we discover a random code generation and mutation process recommended as a method to examine the comprehension facility of students.

2.2.3. Graphs and Trees

Graph and/or tree theory was applied to e-learning in [9, 13, 14, 29, 42, 47, 48, 95, and 97].

An e-learning model for the personalization of courses, based both on the student's needs and capabilities and on the teacher's profile, was described in [9]. Personalized learning paths in the courses were modeled using graph theory. In [47, 48], Decision Trees (DT) as classification models were applied. A debate of the implementation of the Distance Learning Algorithm (DLA), which uses Rough Set theory to find general decision rules, was presented by [47]: A DT was used to agree the original algorithm to distance learning issues. On the basis of the obtained results, the teacher might accept as true the reorganization of the course materials. System architecture for mining learners' online performance patterns was put forward in [13]. A framework for the integration of traditional Web log mining algorithms with pedagogical meanings of Web pages was presented. The approach is based on the definition of an e-learning system concept-hierarchy and the chronological patterns of the pages shown to users.

Also in [48], an automatic tool, based on the students' education performance and communication preferences, for the invention and discovery of simple student models was described, with the ultimate aim of creating a personalized education environment. The approach was based on the PART algorithm, which produces rules from pruned partial DTs. In [97], a tool that can help trace deficiencies in students' understanding was presented. It resorts to a tree abstract data type (ADT), built from the concepts covered in a lab, lecture, or course. Once the tree ADT is created, each node can be associated with different entities such as student performance, class performance, or lab development. Using this tool, a teacher could help students by discovering concepts that needed additional coverage, while students might discover concepts for which they would need to spend additional working time.

A tool to perform a quantitative study based on students' learning act was introduced in [14]. It recommends new courseware diagrams, combining tools given by the theory of conceptual maps [63] and influence diagrams [75]. In [29, 42], modified Web-based learning systems were defined, applying Web usage mining techniques to modified recommendation services. The advance is based on a Web page classification method, which uses attribute-oriented initiation according to related domain awareness shown by a concept hierarchy tree.

2.2.4. Association Rules

Association Rules for classification, applied to e-learning, have been investigated in the areas of learning recommendation systems [18] learning material organization [89], student learning assessments [38, 45, 52, 54, 69, 70], course variation to the students' behavior [19, 35, 50], and estimation of educational web sites [21].

Data Mining techniques such as Association Rule mining, and inter-session and intra-session frequent pattern mining, were applied in [71] to extract useful patterns that might help educators, educational managers, and Web masters to evaluate and interpret on-line course activities. A comparable approach can be found in [54], where contrast rules, defined as sets of conjunctive rules describing patterns of performance inequality between groups of students, were used. A computer-assisted approach to diagnosing student learning problems in science courses and offer students advice was presented in [38], based on the concept effect relationship (CER) model (a specification of the Association Rules technique).

A hypermedia learning environment with a lesson component was described in [19]. It is called Logiocando and objects children of the fourth level of primary school (9-10 years old). It contains a tutor module, based on if- then rules, that follows the teacher by providing suggestions on how and what to study. In [52] we find the description of a learning process evaluation method that resorts to Association Rules, and the well-known ID3 DT learning method. A framework for the use of Web usage mining to support the validation of learning site designs was defined in [21], applying association and sequence techniques [80].

In [50], a framework for personalized e-learning based on aggregate usage profiles and domain ontology were presented, and a combination of Semantic Web and Web mining methods was used. The Apriori algorithm for Association Rules was implemented to arrest relationships among URL references based on the navigational designs of students. A test result feedback (TRF) model that studies the relationships between student learning time and the corresponding test results was presented in [35]. The objective was dual: on the one hand, developing a tool toassist the tutor in reorganizing the course material; on the other, a personalization of the course tailored to the different student needs. The approach was based in Association Rules mining.

A rule-based tool for the adaptive generation of difficulties in IT'S in the context of web-based programming tutors was proposed in [45]. In [18], a web-based course recommendation system, used to offer students with suggestions when having concern in choosing courses, was described. The approach incorporates the Apriori algorithm with graph theory.

2.2.5. Multi-agent systems

Multi Agents Systems (MAS) for classification in e-learning have been proposed in [2, 28]. In [28] this takes the form of an adaptive interaction system created on three MAS: the Interaction MAS captures the user favorites applying some defined usability metrics (affect, efficiency, helpfulness, control and learnability). The Learning MAS shows the contents to the user according to the information collected by the Interaction MAS in the previous step; and the Teaching MAS offers approvals to improve the virtual course. A multi-agent recommendation system, called InLix, was described in [2]; it advises educational resources to students in a mobile learning platform. InLixpools content analysis and the growth of students' virtual clusters. The model includes a procedure of classification and recommendation opinion in which the user agent learns from the student and adjusts itself to the changes in user's interests. This provides the agent with the chance to be more accurate in upcoming classification decisions and recommendation steps. Therefore, the more students use the system, the more agent learns and more accurate its actions become.

2.3. The clustering problem in e-learning

Different in classification problems, in data grouping or clustering we are not involved in modeling a relation between a set of multivariate data items and a certain set of results for each of them (being this in the form of class membership tags). Instead, we generally object to discover the model of groups in which the data items are frequently clustered, according to some item parallel measure.

We discover a first application of clustering methods in [37], where a network-based testing and diagnostic system was applied. It involves a multiple-criteria test-sheet-generating problem and a dynamic programming methodology to create test sheets. The proposed methodology employs fuzzy logic theory to control the difficulty levels of test objects according to the learning status and personal features of each student, and then applies an Artificial Neural Network model: Fuzzy Adaptive Resonance Theory (Fuzzy ART) [10] to group the test items into groups, as well as dynamic programming [22] to test sheet construction.

In [60, 61], an in-depth study telling the usability of Artificial Neural Networks and, more specially, of Kohonen's Self-Organizing Maps (SOM) [43] for the assessment of students in a tutorial supervisor (TS) system, as well as the capability of a fuzzy TS to adapt question trouble in the assessment process, was carried out. An analysis on how Data Mining techniques could be successfully merged to e-learning environments, and how this could progress the learning processes was presented in [85]. Here, data clustering is recommended as a means to promote group-based collaborative learning and to offer incremental student diagnosis.

In [86], user actions associated to students' Web usage were collected and pre-processed as part of a Data Mining process. The Expectation-Maximization (EM) algorithm was then implemented to group the users into groups according to their behaviors. These outcomes could be used by teachers to deliver specialized advice to students belonging to each group. The simplifying hypothesis that students belonging to each group should share web usage behavior makes personalization schemes more accessible. The system administrators could also profit from this developed knowledge by adjusting the e-learning environment they achieve according to it. The EM algorithm was also the technique of choice in [82], where grouping was used to realize user behavior patterns in collaborative activities in e-learning applications.

Some researchers [23, 31, 83] proposed the use of clustering techniques to group similar course materials: An ontology-based tool, within a Web Semantics framework, was applied in [83] with the goal of helping e-learning users to discover and organize dispersed courseware resources. An element of this implement was the implementation of the Bisection K-Means algorithm, used for the grouping of similar learning materials. Kohonen's well-known SOM algorithm was used in [23] to devise an intelligent searching tool to cluster similar learning material into courses, based on its semantic similarities. Clustering was proposed in [31] to group similar learning documents based on their subjects and similarities. A Document Index Graph (DIG) for document representation was introduced, and various classical clustering algorithms (Hierarchical

Agglomerative Clustering, Single Pass Clustering and k-NN) were implemented.

Different variants of the Generative Topographic Mapping (GTM) model, a probabilistic alternative to SOM, were used in [11, 12] for the grouping and visualization of multivariate data regarding the behavior of the students of a virtual course. More specially, in a variant of GTM known to behave robustly in the presence of atypical data or outliers was used successfully to identify clusters of students with adistinctive learning behaviors. A different variant of GTM for feature relevance determination was used in [12] to rank the available data structures according to their significance for the definition of student groups.

2.4. Other Data Mining problems in e-learning

As previously statedthat most of the current research compacts with problems of classification and clustering in e-learning environments. However, there are several applications that hold other Data Mining problems such as prediction and visualization, which will be reviewed in this subsection.

2.4.1. Prediction techniques

Prediction is often also an exciting problem in e-learning, although it must be born in mind that it can easily overlap with classification and regression problems. The predicting of students' behavior and performance when using e-learning systems tolerates the potential of simplifying the development of virtual courses as well as e-learning environments in common. Amethodology to develop the performance of developed courses through reworking was presented in [72, 73]. Course log-files warehoused in databases could be mined by teachers using evolutionary algorithms to determine important relationships and patterns, with the goal of discovering relations between students' knowledge levels, e-learning system usage times and students' scores.

A system for the automatic study of user actions in Web- based learning environments, which could be used to make forecasts on future uses of the learning environment, was presented in [59]. It relates a C4.5 DT model for the analysis of the data; (Note that this reference could also have been included in the section reviewing classification methods).

Some studies apply regression methods for forecast [5, 27, and 44]. In [27], a study that expected to find the sources of error in the prediction of students' knowledge behavior was carried out. Stepwise regression was applied to evaluate what metrics help to explain poor prediction of state exam scores. Linear regression was applied in [5] to predict whether the student's next answer would be right, and how long he or she would take to produce that response.

In [44], a set of experiments was conducted in order to forecast the students' performance in e-learning courses, as well as to evaluate the relevance of the attributes involved. In this approach, several Data Mining methods were implemented, including: Naïve Bayes, kNN, MLP Neural Network, C4.5, Logistic Regression and Support Vector Machines. With parallel goals in mind, tests applying the Fuzzy Inductive Reasoning (FIR) methodology to the forecast of the students' final marks in a course taken at a virtual campus were carried out in [62]. The relative relevance of specific features telling course online behavior was also evaluated. This work was extended in

[25] using Artificial Neural Networks for the prediction of the students' final grades. In this work, the predictions made by the network were understood using Orthogonal Search-based Rule Extraction (OSRE) a novel rule extraction algorithm [24]. Rule extraction was also used in [72, 73] with the emphasis on the discovery of interesting prediction rules in student usage information, in order to use them to improve adaptive Web courses.

Graphical models and Bayesian methods have also been used in this context. For instance, an open learning platform for the development of intelligent Web-based educative systems, named MEDEA, was presented in [88]. Systems developed with MEDEA leader students in their learning process, and permit free navigation to better suit their learning needs. A Bayesian Network model lies at the core of MEDEA. In [3] an evaluation of students' attitudes and their connection to students' performance in a tutoring system was implemented. Starting from a association analysis between variables, a Bayesian Network that inferred negative and positive students' attitudes was built. Finally, a Dynamic Bayes Net (DBN) was used in [15], for modeling students' knowledge behavior and predict future performance in an ITS.

In a tool for the automatic detection of atypical behaviors on the students' use of the e-learning system was well-defined. It routes to a Bayesian predictive distribution model to detect irregular learning processes on the basis of the students' answer time. Note that some models for the detection of atypical student behavior were also referenced in the section reviewing clustering applications [11].

2.4.2. Visualization techniques

One of the most important phases of a Data Mining process (and one that is usually neglected) is that of data survey through visualization methods.

Visualization was understood in [68] in the background of Social Network Analysis modified to collaborative distance-learning, where the cohesion of small learning groups was measured. The consistency is computed in several behaviors in order to highlight remote people, active sub-groups and numerous roles of the members in the group communication structure. Note the links between this objective and that of atypical student behavior described in previous sections. The method allows the display of global properties both at individual level and at collection level, as well as to assist efficiently the virtual tutor in following the teamwork patterns within the group.

An educational Data Mining tool is presented in [57, 58] that shows, in a hierarchical and partially ordered fashion, the students' interaction with the e-learning environment and their virtual tutors. The tool provides case analysis and visualizes the results in an event tree, exploiting MySQL databases to obtain tutorial events.

One main limitation to the analysis of high-dimensional multivariate data is the difficulty of representing those data faithfully in an intuitive visual way. Latent methods (of which Principal Component Analysis, or PCA, is perhaps the most widely known) allow such representation. One such latent method was used in [11, 12] to display high-dimensional student behavior data in a 2-dimensional representation. This type of visualization helps detecting the characteristics of the data distributions and their grouping or cluster structure.

2.5. Other Data Mining methods applied in e-learning

Not all Data Mining in e-learning concerns advanced AI or ML methods: traditional statistics are also used in [1, 32, 74, 77], as well as Semantic Web technologies [34], ontologies [46], Case-Based Reasoning [33] and/or theoretical modern didactical approaches [6, 7, 41].

Although it could have been included in the section devoted to classification, Naïve Bayes, the model used in [78, 84], also fits in the description of common statistical method. An approach to automate the classification procedure of Web learning resources was established in [78]. The model arranges and labels learning resources according to a thought hierarchy extracted from the lengthy ontology of the ACM Computing Curricula 2001 for Computer Science. In [84], a method to construct personalized courseware was proposed. It consists of the building of a personalized Web tutor tree using the Naïve algorithm, for mining both the background and the structure of the courseware.

Statistical methods were applied in [8, 56, and 64]. In [64], the objectives were the discovery and extraction of knowledge from an e-learning database to back the analysis of student learning processes, as well as the assessment of the effectiveness and usability of Web-based courses. Three Web Mining-based evaluation criteria were measured: session statistics, session patterns and time series of session data. In the first, basic statistics about sessions, such as average session, length in time or in number of satisfied requests were gathered. In session patterns, the learning processes were mined from navigation and request behavior. Finally, in the time series of session data, the development of session statistics and session patterns over a period of time was studied. All methods were applied to Web log entries. In [8], a personalized learning environment relating different symmetric and asymmetric distance measures between the students' profiles and their interests was offered. In [56], tools for the analysis of student activity were advanced to provide decision makers and course developers with akind of the e-learners needs. Some statistical analyses of the learner's activities were implemented.

An experiment combining a MAS and self-regulation strategies to permit flexible and incremental design, and to provide a more accurate social context for interactions between students and the teachable agent, were presented in [6]. In [41], a model called Learning Response Dynamics that studies learning systems through the concepts of learning dynamics, energy, speed, force, and acceleration, was defined. In [7], the problems of developing multipurpose adaptive and intelligent learning systems that could be used in the context of practical Web-based education were debated. One such system: ELM-ART was developed; it supports learning programming in LISP, and provides adaptive navigation support, course sequencing, individualized diagnosis of student solutions, and example-based problem-solving support.

MAS have also been implemented to e- learning outside classification problems. In [76], one called IDEAL was designed to back student-centered, self-paced, and extremely interactive learning. The analysis was carried out on the students' learning-related profile, which contains learning style and background knowledge in selecting, organizing, and awarding the learning material to back active learning. IDEAL supports personalized interaction between the students and the learning system and enables adaptive course delivery of educational contents. The student learning behavior (student model) is inferred from the performance data using a Bayesian Belief Network model. In [66, 67], a MAS called Cooperative Intelligent Distance Learning Environments (CIDLE) was defined. It abstracts awareness from domain knowledge and students' behavior during a learning discussion. It therefore concludes the learners' behavior and adapts to them the appearance of course material in order to improve their success rate in answering questions. In [51], software agents were planned as an alternative for data extraction from e-learning environments, in order to organize them in intelligent ways. The approach includes pedagogical agents to monitor and assess Web-based learning tools, from the educational point of view.

In [33], a Case-Based Reasoning system was established to offer navigational guidance to the student. It is based on past user's communication logs and it contains a model describing learning sessions.

A system that evaluates the students' presentation in Web based e-learning was presented in [65]. Its functioning is measured by an expert system using "neurules": a hybrid concept that incorporates symbolic rules and neural computing. Internally, each "neurule" is represented and considered as an Adaline neuron.

Finally, in [17], Social Network Analysis was projected as a method to evaluate the dealings between communication styles, social networks, and learning performance in a computer-supported collaborative learning (CSCL) community. The students' learning performance was measured by their final scores in the second semester of the CSCL course and was designed through a combination of final exam mark, group assignment evaluation, and peer-evaluation.

3. A SURVEY OF DATA MINING IN E-LEARNING FROM THE E-LEARNING POINT OF VIEW

In this section, surveyed research have been presented the according to the e-learning problems to which the Data Mining methods are functional. As mentioned in the introduction, and to avoid unnecessary terminations, we now present in Tables 1 to 5 a survey of the available literature according to the different e-learning topics talked in it. All tables contain, column-wise, the following information: bibliographic reference, Data Mining problem addressed (DM objective), Data Mining technique used (DM technique), e-learning actors involved, and type of publication: Journal (J), International Conference (C), or Book Chapter (B).

Each of these tables summarizes, in turn, the orientations on one of the following e-learning subjects:

1. Applications dealing with the assessment of students' learning presentation.
2. Applications that provide course adaptation and learning references based on the students' learning behavior.
3. Approaches dealing with the assessment of learning material and educational web-based courses.

4. Applications that include feedback to both teachers and students of e-learning courses, based on the students' learning behavior.
5. Developments for the discovery of atypical students' learning behavior.

Table 1 Research works that perform students' learning assessment.

Reference	DM objective	DM approach	e-learning actor	Type of publication
[56]	Statistical analysis	Basic statistical methods	Student and Staff	J
[36]	Classification	Fuzzy reasoning	Student	J
[37]	Clustering	Clustering, dynamic programming and fuzzy logic theory	Student and Teacher	J
[14]	Classification	Conceptual maps	Student and teacher	J
[1]	Statistical analysis	Metadata analysis	Student and Teacher	C
[38]	Classification	Concept effect relationship (CER) model	Teacher	J
[74]	Statistical analysis	Basic statistical methods	Student and Teacher	C
[32]	Statistical analysis	Metadata analysis	Student and Teacher	C
[52]	Classification	ID3	Teacher	C
[31]	Classification and visualization	ADT Tree	Student and Teacher	C
[64]	Classification	Basic statistical methods	Teacher	C
[68]	Visualization and clustering	Social Network Analysis	Teacher	C
[17]	Classification	Social Network Analysis	Teacher	J
[87]	Classification	Code generation and mutation.	Teacher	C
[81]	Classification	Neuro-fuzzy model	Teacher	C
[65]	Classification	Expert systems and Neural computing	Teacher	C
[53]	Classification	Combination of: k-NN, MLP and Decision Tree	Teacher	C

[54]	Classification	Contrast rules	Teacher	C
[69, 70]	Classification	Association Rules	Teacher	C; C
[13]	Classification	Association Rules	Teacher	C
[60, 61]	Clustering	SOM	Teacher	J; C
[35]	Classification	Association Rules	Student and Teacher	C
[45]	Classification	Association Rules	Teacher	C
[77]	Statistical analysis	Basic statistical methods	Student, Teacher and Staff	J
[85]	Clustering	Navigation path clustering ad hoc algorithm	Teacher	C
[48]	Classification	Decision tree-based rule extraction	Teacher	C
[59]	Prediction	Decision tree	Teacher	C
[3]	Prediction	Bayesian Network	Teacher	B
[44]	Classification and Prediction	Naïve Bayes, kNN, MLP-ANN, C4.5, Logistic Regression and SVM	Teacher	J
[5]	Prediction	Linear regression	Teacher	C
[27]	Prediction	Regression	Teacher	C
[57]	Visualization	SQL queries	Teacher	C
[58]	Visualization	SQL queries	Teacher	C
[62]	Prediction	FIR	Teacher	C
[25]	Prediction	FIR and OSRE	Teacher	C
[82]	Clustering	EM algorithm	Teacher	C
[15]	Prediction	Dynamic Bayes Net	Teacher	C

Although an important deal of research effort has been devoted to develop the students' e-learning experience (see Tables 2 and, partially, 4), even more has focused assisting online tutors' tasks, counting the analysis and evaluation of the students' performance and the assessment of course materials (see Tables 1, 3 and 5, as well as, partially, 3.4).

The assessment of students is the e-learning issue most commonly tackled by means of Data Mining methods. This is probably due to the fact that such assessment is closer to the evaluation methods available in the traditional presential education. One of the e-learning topics with the least results obtained in this survey is the analysis of the atypical students' learning behavior. This is probably due to the inherently difficult problem of successfully establishing when the learning behavior of a student is atypical or not.

Table 2. Research works that deal course adaptation based on students' learning behavior.

Reference	DM objective	DM approach	e-learning actor	Type of publication
[29]	Classification	Consistency Queries (CQ) inductive inference machine	Student	C
[42]	Classification	Consistency Queries (CQ) inductive inference machine	Student	C
[13]	Prediction	Software agents	Student	C
[84]	Prediction	Ad hoc naïve algorithm for tutor tree	Student	C
[28]	Classification	Multi-agent systems	Student	C
[9]	Classification	Graph theory	Student	C
[19]	Classification	IF-THEN rules	Student	
[2]	Classification	Multi-agent systems	Student	
[50]	Classification	Apriori algorithm	Student	C
[8]	Classification	Distance measures	Student	C
[15]	Classification	Association Rules	Student	C
[35]	Classification	Association Rules	Student and Teacher	C
[55]	Classification	Neural Network	Student	J
[48]	Classification	Decision Tree-based rule extraction	Teacher	C
[72, 73]	Prediction	Prediction rules	Student	C; J
[33]	Classification	Case-based reasoning	Student	C
[31]	Clustering	HAC, Single-Pass and k-NN	Student	B
[47]	Classification	Rough set theory and decision trees	Student and Teacher	C
[66, 67]	Prediction	Multi-agent systems and ID3	Teacher	C; C
[76]	Prediction	Bayesian Network	Student	J
[88]	Prediction	Bayesian Network	Student	C

Table 3. Data Mining applications providing an assessment of the learning material.

Reference	DM objective	DM approach	e-learning actor	Type of publication
[18, 19]	Classification	Software agents and Association Rules	Student	C; C
[15]	Classification	Association Rules (integrating Apriori algorithm), fuzzy set theory and inductive learning (AQR algorithm)	Teacher	C
[39]	Group Decision methods	Group decision method, grey system and fuzzy theory	Student, Teacher and Staff	J
[40]	Classification and prediction	Fuzzy rules	Student, Teacher and Staff	C
[78]	Classification	Naïve Bayes	Teacher	C
[64]	Classification	Basic statistical methods	Teacher	C
[21]	Classification	Web usage mining: association and sequence	Teacher	C
[77]	Statistical analysis	Basic statistical methods	Student, Teacher and Staff	J
[83]	Clustering and Visualization	Bisection K-Means	Teacher	C
[23]	Clustering	SOM	Teacher	J

Table 4. Data Mining applications providing feedback to e-learning actors (students, tutors andeducational managers).

Reference	DM objective	DM approach	e-learning actor	Type of publication
[18, 19]	Classification	Software agents and Association Rules	Student	C; C
[36]	Classification	Fuzzy reasoning	Student	J
[1]	Statistical analysis	Metadata analysis	Student and Teacher	C
[32]	Statistical analysis	Metadata analysis	Student and Teacher	C
[97]	Classification	ADT Tree	Student and Teacher	C
[35]	Classification	Association Rules	Student and Teacher	C
[18]	Classification	Apriori algorithm	Student	C
[47]	Classification	Rough set theory and decision trees	Student and Teacher	C
[86]	Clustering	EM algorithm	Teacher	C
[3]	Prediction	Bayesian Network	Teacher	B
[5]	Prediction	Linear regression	Teacher	C
[27]	Prediction	Regression	Teacher	C
[25]	Prediction	FIR and OSRE	Teacher	C
[62]	Prediction	FIR	Teacher	C
[11]	Clustering	GTM	Teacher	C
[15]	Prediction	Dynamic Bayes Net	Teacher	C

Table 5. Data Mining applications for the detection of atypical learning behaviors.

Reference	DM objective	DM approach	e-learning actor	Type of publication
[10, 11]	Outliers detection	Bayesian predictive distribution model	Teacher	C; C
[12]	Outliers detection	GTM	Teacher	C
[14]	Outliers detection	GTM	Teacher	C

4. DISCUSSION AND OPPORTUNITY FOR THE USE OF DATA MINING IN E-LEARNING SYSTEMS

In this section, we analyze in some more detail current state of the research in Data Mining applied to e-learning, importance its future viewpoints and opportunities, as well as its limitations. On the basis of the research papers surveyed in this chapter, we can roughly characterize the above-mentioned opportunities as follows:

4.1. E-learning courseware optimization

The possibility of tracking user behavior in virtual e-learning environments makes possible the mining of the resulting data bases. This opens new possibilities for the educational and instructional designers who create and organize the learning contents.

In order to improve the content and association of the resources of virtual courses, Data Mining methods concerned with the assessment of learning materials, such as those summarized in Table 3, could be used. Classification problems are dominant in this area, although prediction and clustering are also present.

Some of the publications reported in Table 1 could also indirectly be used to expand the course resources. If the students' assessment was unsatisfactory, it could intimate to the fact that the course resources and learning materials are insufficient.

The Data Mining methods applied to evaluate the learning material in an e-learning course, summarized in Table 3, include: Association Rules techniques, Fuzzy theory and clustering techniques, amongst others. We consider that a workable starting point for the development of course material evaluation is the exploration of Web usage models, applying Association Rules to explore the relationships between the usability of the course materials and the students' learning presentation, on the basis of the information gathered from the interaction between the user and the learning environment.

4.2. Students' e-learning experience improvement

One of the most important objectives in e-learning, and one of its major encounters, is the improvement of the e-learning experience of the students enrolled in a virtual course. As seen in Tables 1, 2 and 4, several publications have pointed out like self-evaluation, learning strategies recommendation, users' course alteration based on the student's profile and necessities. Diverse Data Mining models have been applied to these problems, containing Association Rules, Fuzzy Theory, Neural Networks, Decision Trees and traditional statistical analysis.

Applying Data Mining (text Mining or Web Mining) techniques to analyze Web logs, in order to determine useful navigation patterns, or deduce theories that can be used to develop web applications, is the main clue behind Web usage mining. Web usage mining can be used for many different determinations and applications such as user profiling and Web page personalization, server performance enhancement, Web site structure development, etc. [80].

Clustering and visualization methods could also improve the e -learning experience, due to the capacity of the former to group similar actors based on their similarities and the ability of the later to define and explore these groups automatically. If it was possible to group similar student behaviors on the basis of students' interaction with the learning environment, the tutor could provide accessible feedback and learning reference to learners.

Combinations of Data Mining methods have demonstrated their potential in web-based environments, such as the grouping of multiple classifiers and genetic algorithms described in [53] and the neuro-fuzzy models put forward in [81].

4.3. Support tools for e-learning tutors

The provision of a set of automatic, or semiautomatic, tools for virtual tutors that permitted them to get detached feedback from students' learning behavior in order to track their learning process, has been an important line of research on Data Mining for e-learning, as can be deduced from the information summarized in tables 1, 4 and 5. Based on the publications surveyed, the experimental tools developed with this objective in mind could be approximately grouped into:

1. Tools to appraise the students' learning performance (Table 1).
2. Tools that permit performing an evaluation of the learning materials (Table 3).
3. Tools that provide feedback to the tutors based on the students' learning behavior (Tables 4-5).

Diverse Data Mining methods have been applied to assess the students' learning performance, including: Clustering, Decision Trees, Social Network Analysis, Neural Networks, Fuzzy methods and Association Rules. In fact, this is perhaps the e-learning topic with more significant research advances in the field of applications we are surveying.

One of the most difficult and time-consuming activities for teachers in distance education courses is the assessment process, due to the fact that, in this type of course, the review process is better proficient through collaborative resources such as e-mail, discussion forums, chats, etc. As a result, this assessment has generally to be carried out according to a large number of parameters, whose influence in the final mark is not always well defined and/or understood. Therefore, it would be helpful to discover features that are highly relevant for students' evaluation. In this way, it would be possible for teachers to provide feedback to students concerning their learning activities online and in real time. In this sense, GTM [12, 94] with feature significance determination and FIR [25, 62] methodologies have been applied.

From the virtual teacher standpoint, valuable information could be obtain from the e-mail or discussion forum resources; however there is still a lack of automated tools with this purpose, probably due to the difficulty of analyzing the learning behavior from the aforementioned sources. Such tool would entail the use of Text Mining (or Web Mining) techniques. Natural Language Processing (NLP) techniques would be of potential interest to tackle this problem in e-learning, due their ability to extract useful information automatically that would be difficult, or almost not possible to obtain, through other techniques. Unfortunately, NLP techniques have not been applied broadly in e-learning. Some exceptions can be found in [23, 31], where NLP and clustering models were proposed for grouping similar learning materials based on their topics and semantic similarities.

Another almost uncharted research path in Data Mining for e-learningbears a great potential, is that of the application of methods for the explicit analysis of time series. That is despite the fact that much of the evidence that could be gathered from e-learning systems usage takes exactly this form.

5. DATA MINING IN E-LEARNING BEYOND ACADEMIC PUBLICATIONS: SYSTEMS AND RESEARCH PROJECTS

Beyond academic publications, Data Mining methods have been integrated into software platforms applied in real e-learning systems. A general review of these types of systems: WebCT, Blackboard, TopClass, Ingenium Docent, etc. [20, 92], commonly used in universities and higher education, showed two main types of platforms: The first type takes a course as the constructing block, while the second takes the organization as a complete. The former (e.g. WebCT, TopClass) normally does not make a distinction between teacher and author (course-developer). This way, such systems allow the teacher much flexibility but also assume that the teacher will create course materials. The latter (e.g. Ingenium, Docent), have clearly defined and distinct roles. Content can be developed outside the system.

Table 6. E-learning projects in which Data Mining techniques are used.

Project name	**DM techniques applied**	**e-Learning Topic**	**University or institution**	**URL of the project**
LON-CAPA	k-NN, MLP, Decision Trees, Association Rules, Multiple Classifiers, Genetic Algorithms and K-means	Assessment system and feedback to e-learning actor, Feature selection and clustering of students performance	Michigan State University, USA	www.lon-capa.org/
ATutor	Statistical analysis	Assessment system and student behavior tracking	University of Toronto, Canada	www.atutor.ca/
LExIKON	Consistency queries (CQ) inductive inference	Course adaptation to the students' navigational behavior	German Research Center for Artificial Intelligence, Technische Universität Darmstadt, and others, Germany	http://lexikon.dfki.de/

aLFanet	Software Agents, Machine Learning, Association Rules	Course adaptation to the students' navigational behaviour	Universidad Nacional de Educación a Distancia and Open University of the Netherlands. Spain Portugal, Germany and Netherlands	http://alfanet.ia.uned.es/alfanet
AHA!	Prediction Rules	Course adaptation to the students' navigational behaviour	Eindhoven University of Technology and Cordoba University. Netherlands and Spain	http://aha.win.tue.nl
WebCT	Statistical Analysis	Assessment system and student behaviour tracking	WebCT	www.webct.com/
Blackboard	Statistical Analysis	Assessment system and student behaviour tracking	Blackboard	www.blackboard.com/us/index.aspx

All these systems claim to be innovative and stress the importance of content but, unfortunately, they hardly provide any information about which didactical methods and models they implement; it is therefore difficult to evaluate them. As far as adaptation is an essential part of the systems, it would require widecustomization. Most of the surveyed systems do support collaborative learning tasks; however they do not permit the use of any specific scenario. They allow collaboration but merely provide the basic tools for its implementation [12].

Numerousof large research projects have dealt with the integration of Data Mining methods in e -learning (see Table 6). The ALFANET project contains of an e-learning platform that provides individuals with interactive, adaptive and personalized learning through the Internet. ALFANET includes a component to provide support to the understanding and presentation of dynamic adaptive questionnaires and their evaluation at run-time, based on the student preferences and profile. The adaptation component applies ML techniques, Association Rules, and Multi-Agent architectures to provide online real-time recommendations and advice to learners based on previous users' interactions, the course structure, the contents characterization and the questionnaires' results.

The AHA! Project was initially developed to support an on-line course to add adaptation to hypermedia courses at the Eindhoven University of Technology. AHA! is currently in its 3.0

version. One of its most important features is the adaptation of the presentation and navigation system of a course on the center of the level of knowledge of a particular student. AHA! applies specific prediction rules to achieve the adaptation goals.

The Learning Online Network with a Computer Assisted Personalized Approach (LON-CAPA) is an integrated system for online learning and assessment. It consists of a learning content authoring and management system that allows new and existing content to be shared and re-used within and across institutions; a course management system; and an individualized homework and automatic grading system. In LON-CAPA some Data Mining methods, such as k-NN, MLP Neural Networks, Decision Trees, Association Rules, Combinations of Multiple Classifiers, Genetic Algorithms and K-means, are employed to analyze individual access paths though the material interaction behavior.

LExIKON is a research and development project with an innovative approach to knowledge extraction from the Internet. The underlying learning mechanisms invoke inductive inference of text patterns as well as inductive inference of elementary formal systems. A specific inductive inference method called consistency queries (CQ) was designed and applied to this purpose.

ATutor is an Open Source Web-based LCMS designed with convenience and flexibility features. ATutor has also adopted the IMS/SCORM Content Packaging specifications, allowing content developers to create reusable content that can be swapped between different e-learning systems. In ATutor, the tutors can assign partial credit for certain answers and can view grades, by student, and for all students on all tests, even can get reports showing the number of times, the time, date, and the frequency with which each student accessed course content.

WebCT is a commercial e- learning suite providing a Course Management system and an e-learning platform. In WebCT, the tutors can create self-assessments and the system automatically scores multiple choice, matching, calculated, jumbled sentences, fill-in-the-blank, true-false and short answers type questions, and can display instructor-created feedback and links to relevant course material. The tutors can monitor students' activities in the e-learning system and get different reports about the tracking data of their students.

Blackboard is another commercial e-learning suite that allows tutors to create e-learning courses and develop custom learning paths for group or individual students, providing tools that facilitate the interaction, communication and collaboration between all actors. The system provides data analysis for surveys and test item, and the results can be exported for further analysis. The paper includes the number of times and dates on which each student accessed course contents, discussion forums and assignments.

6. CONCLUSIONS

The universality of the Internet has enabled online distance education to become far morenormal than it used to be, and that has happened in a surprisingly short time. E-learning course offerings are now lavish, and many new e-learning platforms and systems have been established and implemented with varying degrees of success. These systems produce an exponentially increasing amount of data, and much of this information has the potential to become new knowledge to develop all examples of e-learning. Data Mining processes should enable the extraction of this knowledge.

It is still early days for the incorporation of Data Mining in e-learning systems and not many real and fully operative implementations are available. Nevertheless, a good deal of academic research in this area has been issued over the last few years. From the point of view of the Data Mining problems dealt with in the surveyed workings, we have seen that these are controlled by research on classification and clustering. This is somehow predictable, given the variety and wide availability of Data Mining methods, techniques and software tools for both of them. From the e -learning problems viewpoint, most work deals with students' learning assessment, learning materials and course evaluation, and course adaptation based on students' learning behavior.

In this chapter we have offered a general and up-to-date survey on Data Mining application in e-learning, as reported in the academic literature. Although we pointed to make it as complete as possible, we may have failed to find and identify some papers, journals and conferences that should have been incorporated. I apologize in advance for any such errors that may have been occurred. I hope that this chapter becomes useful not only for Data Mining practitioners and e-learning system managers and developers, but also even for members and users, teachers and learners, of the e-learning community at huge.

REFERENCES

[1].Abe H, Hasegawa S, Ochimizu K. A Learning Management System with Navigation Supports. In: The International Conference on Computers in Education, ICCE 2003. Hong Kong 2003; 509-513.

[2]. Andronico A, Carbonaro A, Casadei G, Colazzo L, Molinari A, Ronchetti M. Integrating a Multi-agent Recommendation System into a Mobile Learning Management System. In: Workshop on Artificial Intelligence in Mobile System 2003, AIMS 2003. October 12-15, Seattle, USA (2003).

[3]. Arroyo I, Murray T, Woolf B, Beal C. Inferring Unobservable Learning Variables from Students' Help Seeking Behavior. Lecture Notes in Computer Science, Vol. 3220. Springer-Verlag, Berlin Heidelberg New York (2004) 782-784.

[4]. Baker M. The Roles of Models in Artificial Intelligence and Education Research: A Prospective View. International Journal of Artificial Intelligence in Education 2000; 11: 122-143.

[5]. Beck JE, Woolf BP. High-Level Student Modeling with Machine Learning. In: Gauthier G, et al. (eds.): Intelligent Tutoring Systems, ITS 2000. Lecture Notes in Computer Science, Vol. 1839. Springer-Verlag, Berlin Heidelberg New York (2000) 584-593.

[6]. Biswas G, Leelawong K, Belynne K, Viswanath, K. Developing Learning by Teaching Environments that Support Self-Regulated Learning. In: The 7th International Conference on Intelligent Tutoring Systems. Maceió, Brazil (2004).

[7]. Brusilovsky P. Adaptive Hypermedia. User Modelling and User Adapted Interaction, Ten Year Anniversary Issue 2001; 11(1-2): 87-110.

[8]. Carbonaro A. Personalization Mechanisms for Active Learning in a Distance Learning System. In: International Conference on Simulation and Multimedia in Engineering Education, ICSEE'03. Florida, USA, 2003.
[9]. Carchiolo V, Longheu A, Malgeri M, Mangioni G. Courses Personalization in an e-Learning Environment. In: The 3rd IEEE International Conference on Advanced Learning Technologies, ICALT'03. July 9-11, 2003; 252-253.
[10]. Carpenter G, Grossberg S, Rosen DB: Fuzzy ART: Fast Stable Learning and Categorization of Analog Patterns by an Adaptive Resonance System. Neural Networks 4, 1991; 759–771.
[11]. Castro F, Vellido A, Nebot A, Minguillón J. Finding Relevant Features to Characterize Student Behavior on an e-Learning System. In: Hamid, R.A. (ed.): Proceedings of the International Conference on Frontiers in Education: Computer Science and Computer Engineering, FECS'05. Las Vegas, USA, 2005; 210-216.
[12]. Castro F, Vellido A, Nebot A, Minguillón J. Detecting Atypical Student Behaviour on an e-Learning System. In: VI CongresoNacional de InformáticaEducativa, SimposioNacional de Tecnologías de la Información y lasComunicaciones en la Educación, SINTICE'2005. September 14-16, Granada, Spain, 2005; 153-160.
[13]. Chang C, Wang K. Discover Sequential Patterns of Learning Concepts for Behavioral Diagnosis by Interpreting Web Page Contents. In: Kommers, P., Richards, G. (eds.): World Conference on Educational Multimedia, Hypermedia and Telecommunications. Chesapeake, VA, 2001; 251-256.
[14]. Chang FCI, Hung LP, Shih TK. A New Courseware for Quantitative Measurement of Distance Learning Courses. Journal of Information Science and Engineering 2003; 19: 989-1014.
[15]. Chang K, Beck J, Mostow J, Corbett A. A Bayes Net Toolkit for Student Modeling in Intelligent Tutoring Systems. In: Ikeda, M., et al. (eds.): 8th International Conference on Intelligent Tutoring Systems, ITS2006. LNCS Vol. 4053. Springer-Verlag, Berlin Heidelberg New York, 2006, 104-113.
[16]. Chapman P, Clinton J, Kerber R, Khabaza T, Reinartz T, Shearer C, Wirth R. CRIPS-DM 1.0 Step by Step Data Mining Guide. CRISP-DM Consortium, 2000).
[17]. Cho H, Gay G, Davidson B, Ingraffea A. Social Networks, Communication Styles and Learning Performance in a CSCL Community. Computers & Education, In Press, 2006.
[18]. Chu K, Chang M, Hsia Y. Designing a Course Recommendation System on Web based on the Students' Course Selection Records. In: World Conference on Educational Multimedia, Hypermedia and Telecommunications, 2003; 14-21.
[19]. Costabile MF, De A, Roselli A, Lanzilotti R, Plantamura P. Evaluating the Educational Impact of a Tutoring Hypermedia for Children. Information Technology in Childhood Education Annual, 2003; 289-308.

[20]. Croock M, Mofers F, Van VM, Van RP, Brouns F, Boticario J, Barrera C, Santos O, Ayala A, Gaudioso E, Hernández F, Arana C, Trueba I. State-of-the-Art. ALFanet/IST-2001-33288 Deliverable D12, Open Universiteit Nederland (2002). URL: http://learningnetworks.org/

[21]. Dos SML, Becker K. Distance Education: a Web Usage Mining Case Study for the Evaluation of Learning Sites. In: The 3rd IEEE International Conference on Advanced Learning Technologies, ICALT'03. IEEE Computer Society. Athens Greece, 2003; 360-361.

[22]. Dreyfus SE, Law AM. The Art and Theory of Dynamic Programming. Academic Press Inc. New York, 1977.

[23]. Drigas A, Vrettaros J. An Intelligent Tool for Building e-Learning Contend- Material Using Natural Language in Digital Libraries. WSEAS Transactions on Information Science and Applications 2004; 5(1): 1197-1205.

[24]. Etchells TA, Lisboa PJG. Orthogonal Search-based Rule Extraction (OSRE) Method for Trained Neural Networks: A Practical and Efficient Approach. IEEE Transactions on Neural Networks 2006; 17(2): 374-384.

[25]. Etchells TA, Nebot A, Vellido A, Lisboa PJG, Mugica F. Learning What is Important: Feature Selection and Rule Extraction in a Virtual Course. In: The 14th European Symposium on Artificial Neural Networks, ESANN 2006. Bruges, Belgium, 2006; 401-406.

[26]. Fasuga R, Sarmanova J. Usage of Artificial Intelligence in Education Process. In: International Conference for Engineering Education & Research, ICEER2005. Tainan, Taiwan , 2005.

[27]. Feng M, Heffernan N, Koedinger K. Looking for Sources of Error in Predicting Student's Knowledge. In: The Twentieth National Conference on Artificial Intelligence by the American Association for Artificial Intelligence, AAAI'05, and Workshop on Educational Data Mining. July 9-13, Pittsburgh, Pennsylvania, 2005, 54-61.

[28]. Fernández CA, Lopez JV, Montero F, González P. Adaptive Interaction Multi- agent Systems in e-Learning/e-Teaching on the Web. In: Third International Conference on Web Engineering, ICWE 2003. July 14-18, Oviedo, Spain, 2003; 144-153.

[29]. Grieser G, Klaus PJ, Lange S. Consistency Queries in Information Extraction. In: The 13th International Conference on Algorithmic Learning Theory. Lecture Notes in Artificial Intelligence Vol. 2533. Springer-Verlag, Berlin Heidelberg New York, 2002; 173-187.

[30]. Ha SH, Bae SM, Park SC. Web Mining for Distance Education. In: IEEE International Conference on Management of Innovation and Technology, ICMIT'00, 2000; 715-719.

[31]. Hammouda K, Kamel M. Data Mining in e-Learning. In: Pierre, S. (ed.): e-Learning Networked Environments and Architectures: A Knowledge Processing Perspective. Springer-Verlag, Berlin Heidelberg, New York, 2005.

[32]. Hasegawa S, Ochimizu K. A Learning Management System Based on the Life Cycle Management Model of e-Learning Courseware. In: Goodyear, P., et al. (eds.): The Fifth IEEE International Conference on Advanced Learning Technologies, ICALT'05. Los Angeles, CA, 2005; 35-37.

[33]. Heraud J, France L, Mille A. Pixed: an ITS that Guides Students with the Help of Learners' Interaction Log. In: International Conference on Intelligent Tutoring Systems, Workshop Analyzing Student Tutor Interaction Logs to Improve Educational Outcomes. Maceio, Brazil, 2004, 57-64.
[34]. Holohan E, Melia M, McMullen D, Pahl C. Adaptive e-Learning Content Generation Based on Semantic Web Technology. In: Workshop on Applications of Semantic Web Technologies for e-Learning, SW-EL@ AIED'05. July 18, Amsterdam, The Netherlands, 2005.
[35]. Hsu HH, Chen CH, Tai WP. Towards Error-Free and Personalized Web-Based Courses. In: The 17th International Conference on Advanced Information Networking and Applications, AINA'03. March 27-29, Xian, China, 2003; 99-104.
[36]. Hwang GJ. A Knowledge-Based System as an Intelligent Learning Advisor on Computer Networks. J. Systems, Man, and Cybernetics 1999; 2: 153-158.
[37]. Hwang GJ. A Test- Sheet-Generating Algorithm for Multiple Assessment Requirements. IEEE Transactions on Education 2003; 46(3): 329-337.
[38]. Hwang GJ, Hsiao CL, Tseng CR. A Computer-Assisted Approach to Diagnosing Student Learning Problems in Science Courses. Journal of Information Science and Engineering 2003; 19: 229-248.
[39]. Hwang GJ, Huang TCK, Tseng CR. A Group-Decision Approach for Evaluating Educational Web Sites. Computers & Education 2004; 42: 65-86.
[40]. Hwang GJ, Judy CR, Wu CH, Li CM, Hwang GH. Development of an Intelligent Management System for Monitoring Educational Web Servers. In: 10th Pacific Asia Conference on Information Systems, PACIS 2004; 2334-2340
[41]. Hwang-WY, Chang CB, Chen GJ. The Relationship of Learning Traits, Motivation and Performance-Learning Response Dynamics. Computers & Education 2004; 267-287.
[42]. Jantke KP, Grieser G, Lange S. Adaptation to the Learners' Needs and Desires by Induction and Negotiation of Hypotheses. In: Auer ME, Auer U. (eds.): International Conference on Interactive Computer Aided Learning, ICL 2004.
[43]. Kohonen T. Self-Organizing Maps. 3rd edition, Springer-Verlag, Berlin, 2000.
[44]. Kotsiantis SB, Pierrakeas CJ, Pintelas PE. Predicting Students' Performance inDistance Learning Using Machine Learning Techniques. Applied Artificial Intelligence 2004; 18(5): 411-426.
[45]. Kumar A. Rule-Based Adaptive Problem Generation in Programming Tutors and its Evaluation. In: 12th International Conference on Artificial Intelligence in Education. July 18-22, Amsterdam 2005; 36-44.
[46]. Leidig T. L3-Towards an Open Learning Environment. ACM Journal of Educational Resources in Computing, JERIC. ACM Press 2001; 1(1).
[47]. Liang A, Ziarco W, Maguire B. The Application of a Distance Learning Algorithm in Web-Based Course Delivery. In: Ziarko W, Yao Y. (eds.): Second International Conference on Rough Sets and Current Trends in Computing. Lecture Notes in Computer Science. Springer-

Verlag, Berlin Heidelberg New York 2000; 338-345.
[48]. Licchelli O, Basile TM, Di MN, Esposito F. Machine Learning Approaches for Inducing Student Models. In: 17th International Conference on Innovations in Applied Artificial Intelligence, IEA/AIE 2004. LNAI Vol. 3029. Springer-Verlag, Berlin Heidelberg New York 2004; 935-944.
[49]. Margo H. Data Mining in the e-Learning Domain. Computers & Education 2004; 42(3): 267-287.
[50]. Markellou P, Mousourouli I, Spiros S, Tsakalidis A. Using Semantic Web Mining Technologies for Personalized e-Learning Experiences. In: Uskov, V. (ed.): The Fourth IASTED Conference on Web-based Education, WBE-2005. Grindelwald, Switzerland, 2005.
[51]. Markham S, Ceddia J, Sheard J, Burvill C, Weir J, Field B, et al. Applying Agent Technology to Evaluation Tasks in e-Learning Environments. In: Proceedings of the Exploring Educational Technologies Conference. Monash University, Melbourne, Australia, 2003; 31-37.
[52]. Matsui T, Okamoto T. Knowledge Discovery from Learning History Data and its Effective Use for Learning Process Assessment Under the e-Learning Environment. In: Crawford, C., et al. (eds.): Society for Information Technology and Teacher Education International Conference 2003; 3141-3144.
[53]. Minaei-Bidgoli, B., Punch, W.F.: Using Genetic Algorithms for Data Mining Optimization in an Educational Web-based System. In: Cantu, P.E., et al. (eds.): Genetic and Evolutionary Computation Conference, GECCO 2003. (2003) 2252-2263.
[54]. Minaei-Bidgoli B, Tan PN, Punch WF. Mining Interesting Contrast Rules for a Web-based Educational System. In: The 2004 International Conference on Machine Learning and Applications, ICMLA'04. Louisville, KY,2004.
[55]. Mizue K, Toshio O. N3: Neural Network Navigation Support-Knowledge-Navigation in Hyperspace: The Sub-symbolic Approach. Journal of Educational Multimedia and Hypermedia 2001; 10(1): 85-103.
[56]. Monk D. Using Data Mining for e-Learning Decision Making. The Electronic Journal of e-Learning 2005; 3: 41-54.
[57]. Mostow J, Beck J, Cen H, Cuneo A, Gouvea E, Heiner C. An Educational Data Mining Tool to Browse Tutor- Student Interactions: Time will tell!. In: Proceedings of the Workshop on Educational Data Mining 2005; 15-22.
[58]. Mostow J, Beck J. Some Useful Tactics to Modify, Map and Mine Data from Intelligent Tutors. Natural Language Engineering 2006; 12: 195-208.
[59]. Muehlenbrock M. Automatic Action Analysis in an Interactive Learning Environment. In: 12th International Conference on Artificial Intelligence in Education, AIED 2005. July 18, Amsterdam, The Netherlands 2005: 73-80.
[60]. Mullier D. A Tutorial Supervisor for Automatic Assessment in Educational Systems. International Journal on e-Learning 2003; 2(1): 37-49.
[61]. Mullier D, Moore D, Hobbs D. A Neural -Network System for Automatically Assessing

Students. In: Kommers, P., Richards, G. (eds.): World Conference on Educational Multimedia, Hypermedia and Telecommunications 2001; 1366-1371.

[62]. Nebot A, Castro F, Vellido A, Mugica F. Identification of Fuzzy Models to Predict Students Performance in an e-Learning Environment. In: Uskov, V. (ed.): The Fifth IASTED International Conference on Web-Based Education, WBE 2006. Puerto Vallarta, Mexico 2006; 74-79.

[63]. Novak JD, Gowin BC. Concept Mapping for Meaningful Learning. In: International Conference on Learning. Cambridge University Press 1984; 36-37.

[64]. Pahl C, Donnellan D. Data Mining Technology for the Evaluation of Web-based Teaching and Learning Systems. In: World Conference on e-Learning in Corp, Govt., Health., & Higher Education 2002; 747-752.

[65]. Prentzas J, Hatzilygeroudis I, Garofalakis J. A Web-based Intelligent Tutoring System Using Hybrid Rules as its Representational Basis. In: Cerri, S.A., et al. (eds.): Intelligent Tutoring Systems, ITS 2002. LNCS Vol. 2363. Springer-Verlag, Berlin Heidelberg New York (2002)119-128.

[66]. Razek M, Frasson C, Kaltenbach M. A Confidence Agent: Toward More Effective Intelligent Distance Learning Environments. In: International Conference on Machine Learning and Applications, ICMLA'02. Las Vegas, USA 2002; 187-193.

[67]. Razek M, Frasson C, Kaltenbach M. A Context-Based Information Agent for Supporting Intelligent Distance learning Environments. In: The Twelfth International World Wide Web Conference, WWW 2003. May 20-24, Budapest, Hungary 2003).

[68]. Reffay C, Chanier T. How Social Network Analysis Can Help to Measure Cohesion in Collaborative Distance-Learning. In: International Conference on Computer Supported Collaborative Learning. Kluwer Academic Publishers, Bergen 2003; 343-352.

[69]. Resende SD, Pires VMT. An Ongoing Assessment Model for Distance Learning. In: Hamza, M.H. (ed.): Fifth IASTED International Conference Internet and Multimedia Systems and Applications. Acta Press 2001: 17-21.

[70]. Resende SD, Pires VMT. Using Data Warehouse and Data Mining Resources for Ongoing Assessment of Distance Learning. In: IEEE International Conference on Advanced Learning Technologies, ICALT 2002.

[71]. Romero C, Ventura S. Data Mining in e-Learning. WIT Press 2006.

[72]. Romero C, Ventura S, De BP. Knowledge Discovery with Genetic Programming for Providing Feedback to Courseware. User Modeling and User-Adapted Interaction 2004; 14(5): 425-464.

[73]. Romero C, Ventura S, De BP, De CC. Discovering Prediction Rules in AHA! Courses. In: User Modelling Conference. June 2003, Johnstown, Pennsylvania; 35-44.

[74]. Seki K, Tsukahara W, Okamoto T. System Development and Practice of e-Learning in Graduate School. In: The Fifth IEEE International Conference on Advanced Learning Technologies, ICALT'05. IEEE Computer Society, Los Angeles, CA 2005; 740-744.

[75]. Shachter RD. Evaluating Influence Diagrams. Operating Research 1986; 34: 871 -882.
[76]. Shang Y, Shi H, Chen SS. An Intelligent Distributed Environment for Active Learning. ACM Journal of Educational Resources in Computing 2001; 1(2)..
[77]. Sheard J, Ceddia J, Hurst G. Inferring Student Learning Behaviour from Website Interactions: A Usage Analysis. Education and Information Technologies 2003; 8(3):245-266.
[78]. Singh SP. Hierarchical Classification of Learning Resources Through Supervised Learning. In: World Conference on e-Learning in Corp., Govt., Health., & Higher Education 2004; 178-183.
[79]. Sison R, Shimura M. Student Modelling and Machine Learning. International Journal of Artificial Intelligence in Education 1998; 9: 128-158.
[80]. Srivastava J, Cooley R, Deshpande M, Tan P. Web Usage Mining: Discovery and Applications of Usage Patterns from Web Data. ACM SIGKDD Explorations 2001; 1(2): 12-23.
[81]. Stathacopoulou GD, Grigoriadou M. Neural Network-Based Fuzzy Modeling of the Student in Intelligent Tutoring Systems. In: International Joint Conference on Neural Networks. Washington 1999; 3517-3521.
[82]. Talavera L, Gaudioso E. Mining Student Data to Characterize Similar Behavior Groups in Unstructured Collaboration Spaces. In: Workshop in Artificial Intelligence in Computer Supported Collaborative Learning in conjuntion with 16th European Conference on Artificial Intelligence, ECAI'2003. Valencia, Spain 2004; 17-22.
[83]. Tane J, Schmitz C, Stumme G. Semantic Resource Management for the Web: An e-Learning Application. In: Fieldman S, Uretsky, M. (eds.): The 13th World Wide Web Conference 2004, WWW2004. ACM Press, New York 2004; 1-10.
[84]. Tang C, Lau RW, Li Q, Yin H, Li T, Kilis D. Personalized Courseware Construction Based on Web Data Mining. In: The First international Conference on Web information Systems Engineering, WISE'00. IEEE Computer Society. June 19 - 20, Washington, USA 2000; 204-211.
[85]. Tang TY, McCalla G. Smart Recommendation for an Evolving e-Learning System: Architecture and Experiment. International Journal on e-Learning 2005; 4(1): 105-129.
[86]. Teng C, Lin C, Cheng S, Heh J. Analyzing User Behavior Distribution on e-Learning Platform with Techniques of Clustering. In: Society for Information Technology and Teacher Education International Conference 2004; 3052-3058.
[87]. Traynor D, Gibson JP. Synthesis and Analysis of Automatic Assessment Methods in CS1. In: The 36th SIGCSE Technical Symposium on Computer Science Education 2005, SIGCSE'05. ACM Press. February 23-27, St. Louis Missouri, USA 2005; 495-499.
[88]. Trella, M., Carmona, C., Conejo, R.: MEDEA: an Open Service-Based Learning Platform for Developing Intelligent Educational Systems for the Web. In: 12th International Conference on Artificial Intelligence in Education. July 18-22, Amsterdam (2005) 27-34.
[89]. Tsai CJ, Tseng SS, Lin CY. A Two-Phase Fuzzy Mining and Learning Algorithm for Adaptive Learning Environment. In: Alexandrov VN, et al. (eds.): International Conference on Computational Science, ICCS 2001. LNCS Vol. 2074. Springer-Verlag, Berlin Heidelberg New York 2001; 429-438.