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Adaptive Hypermedia in Learning on the Web

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ABSTRACT: *Today, e-learning demonstrates great opportunities and the variety of existing web-based learning systems and applications underlines this observation. Advanced e-learning applications provide high quality content, efficient structuring, as well as full support for the varied tasks of all the user profiles participating in a typical distance learning scenario. Moreover, such applications have drastically evolved and incorporated methods and techniques from different scientific domains and application areas, such as data mining, web mining, user modelling and profiling, artificial intelligence, agent technologies and knowledge discovery. This paper is about deploying adaptive hypermedia methods and techniques in the domain of web-based educational applications and presents the successive phases of the adaptation process, from constructing learner profiles to producing and delivering adapted output, with emphasis on the close connection of this process to web mining and more especially web usage mining.*

1 INTRODUCTION

The World Wide Web is rapidly evolving and becoming one of the most important means for gathering, sharing, and distributing information and services, and the changes it has already brought (and is expected to bring) to our daily activities are significant. Education is one of the areas that have been greatly affected by the growth of the web. The provision of learning and training over the web has been a strong driving force behind numerous research, as well as commercial efforts in the recent years and the variety of available e-learning applications is a solid indication of the maturity in the area (Fry, 2001), (Wentling et al., 2000). The primary advantage of e-learning is its availability to *anyone*, *anytime*, *anywhere*. However, the current challenge for web-based learning systems is its enhancement by the integration of *adaptive* features that allow for the delivery of *personalized* learning experiences.

These capabilities create a new educational model, which places the user in the centre (user-centric approach) and permits continuous tracking and further analysis of all learning phases including pre-assessment, completed learning modules, practice items, collaboration, communication, testing, etc. The methods and techniques used for the analysis derive from various scientific domains and application areas, such as data mining, web mining and knowledge discovery, user modelling and profiling, artificial intelligence and agent technologies.

Adaptive hypermedia systems “build” a model of the goals, preferences and knowledge of each individual user, and use this model throughout the interaction, in order to adapt to the specific needs of that user (Brusilovsky, 2001). *Adaptive educational hypermedia systems*, comprising a subset of adaptive hypermedia systems, are mainly based on the utilization of users’ knowledge for adaptation, while tracking their browsing behaviour in an effort to determine individual background, experience, knowledge and interests. These systems are a remedy for the problems that arise by the traditional “one-fits-to-all” approach that delivers the same static learning material to everyone, regardless of individual domain knowledge, information needs and preferences, which can be widely different (Brusilovsky, 1998), (De Bra et al., 1999). Adaptations may take up many forms and adjust the content, the presentation (or modality) and the structure of a web-based educational hypermedia system (Kobsa et al., 1999).

Web mining plays a central role in constructing internal user models (profiles), as well as expanding them by inferring additional data (Cooley et al., 1999), (Mobasher et al., 2000). Web mining – a term defined in (Etzioni, 1996) – is the application of data mining techniques on the web in order to discover useful patterns and can be divided into three basic categories: *web content mining*, *web structure mining* and *web usage mining*. The first category includes techniques for assisting users in locating web documents (i.e. pages) that meet certain criteria, while the second relates to discovering information based on the website structure data. The last category focuses on analyzing web access logs and other sources of information regarding user interactions within the website in order to capture, understand and model their behavioural patterns and profiles and thereby improve their experience with the website (Kosala, Blockeel, 2000), (Madria et al., 1999) and has been proposed as the underlying technology for *web personalization* (Mobasher, 2004). The close relation between web mining and web personalization has motivated much research work in the area. Web mining is a complete process and consists of specific primary data mining tasks, namely data collection, data reprocessing, pattern discovery and knowledge post-processing (Pierrakos et al., 2003).

The deployment of web mining in the e-learning domain relates to the analysis of learner behaviour and the production of adequate adaptations. For example, given a specific learner, the presentation of course materials can be tailored to meet individual needs and preferences by providing personal recommendations on topics relative to those already studied. This process is typically based on a solid user model (Mobasher et al., 2002), which holds up-to-date information on dynamically changing learner behaviour. This enables on-the-fly course assembly, addressing exactly what the learner needs to know without wasting time on topics the user is already proficient or not interested in.

This paper is about deploying adaptive hypermedia methods and techniques in the domain of web-based educational applications, which are among the most popular applications for adaptive hypermedia approaches. After introductory definitions for the domain of adaptive hypermedia and education on the web and the way these notions are connected to each other, we discuss the choices available up-to-date for applying adaptation techniques, as well as the different types and origins of data that can be used to construct the internal model of the learner to base the adaptation decisions upon (section 2). In the same section, we also describe available forms of adaptation addressing the content, the presentation (or modality) and the structure of a web-based educational hypermedia system. Another key issue is the direct connection of web mining (and more especially web usage mining) with constructing the aforementioned internal models, as well as with inferring more data for expanding them. In section 3, we selectively present a number of representative research approaches and commercial applications in the field. Section 4 concludes by discussing dominant concerns and open issues regarding adaptive hypermedia learning on the web including the jeopardy to privacy when recording and modelling the user, the strict speed requirements for online adaptation delivery, and more.

2 ADAPTATION PROCESS

The adaptation process in a typical e-learning system can be decomposed into three successive phases, as depicted in figure 1: *construction of learner profiles*, *application of web mining techniques*, and *adapted output*.

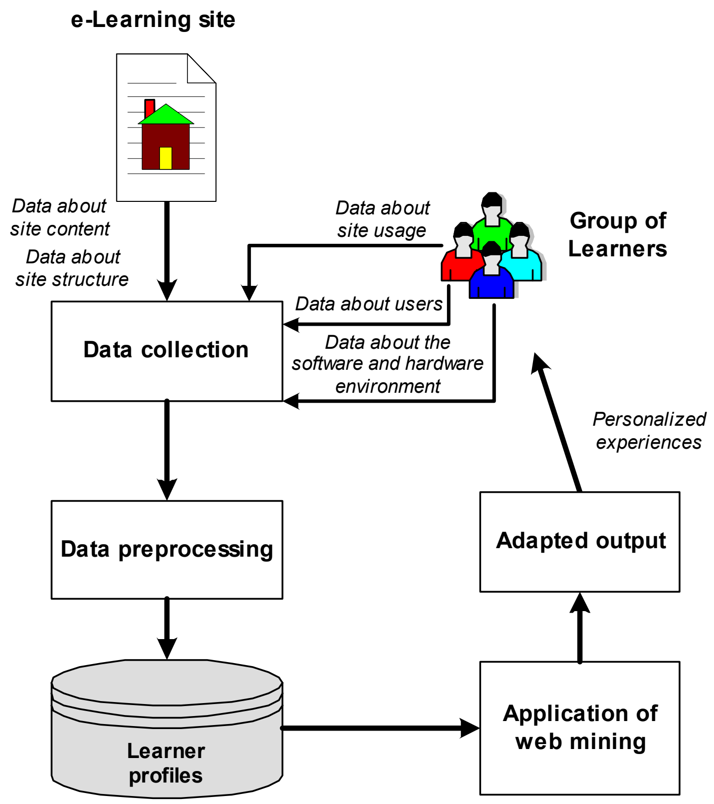

Figure 1 – The adaptation process

2.1 Constructing Learner Profiles

This phase refers to collecting, pre-processing and integrating data from various sources and results in the construction of initial user models, known as *learner profiles*. It is a significant step since the type, volume and internal representation of profile data affect the overall system performance. The construction and maintenance of learner profiles is a data-intensive task and typically uses:

- *Data about the user.* This category includes data about the personal characteristics of the user such as: demographics (name, age, sex, education, income, address, phone-number, e-mail address, etc.), specific knowledge and expertise, skills and capabilities, interests and preferences, goals and plans, etc. Data acquisition is done either by explicitly asking the user to provide the data (using questionnaires, fill-in preference dialogs or forms) or by having the system derive *implicitly* such information without initiating any interaction with the user (using acquisition rules, plan recognition, or stereotype reasoning). A good strategy that achieves better results is to use a combination of the two approaches.
- *Data about the e-learning site usage.* Usage data may be either directly observed and recorded, or acquired by analyzing observable data whose amount and detail varies depending on the technologies used during website implementation (i.e. cookies, java applets, etc.). Observable usage data comprise selective actions like clicking on an link, data regarding the temporary viewing behaviour, ratings (using a binary or a limited discrete scale) and other confirmatory or disconfirmatory actions (e-mailing/saving/printing a document, bookmarking a web page and

more). Usage data that derive from analysing observable data regard usage regularities such as the selection frequency of an option/link/service, production of suggestions/recommendations based on situation-action correlations, or variations of this approach, for instance recording action sequences.

- *Data about the software and hardware environment available on the user's side.* In many cases it is important to know details on the software and hardware configuration available at the user's side, in order to incorporate this information in the adaptation process. The different range of hardware and software configurations used on the client's side is wide and includes: browser version and platform, availability of plug-ins, firewalls preventing applets from executing, available bandwidth, processing speed, display and input devices, etc. This knowledge is useful since it may affect website usage. Moreover, geographical information can be used to filter or adapt locale-specific content e.g. language version adjustments.
- *Data about site structure.* This category mostly relates to the hyperlinks that denote the inter-page linkage structure among web pages, as well as the HTML and XML tags within a page that represent the structural semantics of the content (e.g. heading, paragraph, list, etc.).
- *Data about the e-learning site content.* It denotes the objects (or components) comprising the site pages and the relationship among them (static HTML and XML pages, images, scripts, semantic or structural metadata, etc.). This type of data may also refer to other conceptual hierarchies over page contents, like for instance lesson or topic categories.

The process of data collection is continuous, in the sense that after the initial construction, learner profiles must be kept updated by incorporating the newly collected usage data in combination with changes to site structure, content or user and user software/hardware data. After data collection follows data pre-processing, integration and transformation into an internal representation (or *modelling*) that allows for further processing and easier updating. Such internal representation models are used for constructing individual or aggregate (when working with groups of learners) profiles, a process termed *user profiling* in the relative literature. Profiles may be *static* or *dynamic* based on whether and how often they are updated. Static profiles are usually acquired explicitly, while dynamic ones are acquired implicitly by recording and analyzing the navigational behaviour. In both approaches, we have to deal with different but equally serious problems. In the case of explicit profiling, learners are often negative about filling-in questionnaires and revealing personal information online, they comply only when required and even then the data submitted may be false. On the other hand, in implicit profiling, even though our source of information is not biased by the learners' negative attitude, the problems encountered derive once again from the invaded privacy concern and the loss of anonymity, as adaptive systems are striving to identify individual users, record their online behaviour in as much detail as possible and extract needs and preferences in a way they do not notice, understand or control. User profiling affects dramatically the kind of analysis that can be applied after the phase of data acquisition, in order to reach secondary inferences and accomplish more sophisticated adaptations.

2.2 Application of web mining

Web mining techniques are applied for further analysing and expanding learner profiles (Eirinaki & Vazirgiannis, 2003) and aim at discovering "interesting" patterns in recorded navigational behaviour (which in our case are interpreted in online learning patterns). The web mining literature distinguishes two main categories of problems: *prediction* and *knowledge discovery*. Predictive modelling tries to build a model that allows us to predict the value of one variable based on a known set of values of other variables and the most representative technique in this category is *classification* (Hand et al., 2001). Classification requires a set of predefined classes and an initial set of data from the specific domain (known as *training set*) to use it as the *classifier* input. Then the classifier (by observing the class assignment in the training set) learns to assign new data items in one of the classes. It is often the case that clustering is applied before classification to determine the set of classes. Classifiers may be based on a variety of techniques. Decision tree classifiers are a popular approach because they are reasonably accurate and easy to understand and include usually two phases: the building phase and the pruning phase. K-nearest neighbour and

Bayesian classifiers are also used in classification problems. In e-learning the classes can represent different learner profiles and classification is performed by using selected features with high discriminative ability, regardless of the classes that describe each profile.

Discovering knowledge on the other hand, relates to identifying unusual behaviour (hidden patterns) in the context of normal variability. Among the most well-known knowledge discovery techniques are association rules mining, clustering, and sequential patterns discovery:

- *Association rules mining.* It is used for discovering frequent patterns, associations and correlations among different types of information without obvious semantic dependence (Agrawal et al., 1993), (Wang et al., 2002). An association rule has the form A→B and means that when item A is observed, it is likely that item B will also appear. The technique does not consider the order of the items. The challenge here is to find the most important from the produced rules and for this purpose two interestingness measures have been defined: *support* and *confidence*. Support *S* is the number of itemsets which contain A∪B (often expressed as a proportion of the total number of itemsets) and confidence C is the fraction s(A∪B)/s(A) and represents the conditional probability that B appears given that A has already been observed. It is clear that confidence is computed after having computed first the support values for the rule and its antecedent. There are many algorithms for discovering association rules. The Apriori algorithm (Agrawal & Srikant, 1994), which is one of the earliest, performs repeated passes over the database records in order to identify interesting itemsets (satisfying a predefined minimum support value). Its basic idea is that a set A of items is frequent only if all subsets of A are frequent. In the e-learning domain, this method may indicate correlations between pages not directly connected and reveal previously unknown associations between groups of users with specific interests. Such information may prove valuable for the system in order to improve the e-learning experience, for instance by producing recommendations.
- *Clustering.* It is a method used for grouping together items that have similar characteristics (Chakrabarti, 2002), (Hand et al., 2001), (Rasmussen, 1992). Clustering groups data into classes (or clusters) so that objects within a cluster have high similarity in comparison to one another and are dissimilar to objects in other clusters. Cluster analysis aims to discover items that have representative behaviour in the collection. The items may either be users (that demonstrate similar online behaviour) or pages (that are similarly utilized by users). This technique is very suitable for the e-learning domain, since groups of similar students can be treated differently (in terms of recommended topics for instance). As already mentioned, the produced clusters can be used as a basis for applying classification.
- *Sequential patterns discovery.* This technique is an extension to the association rule mining and it is used for revealing patterns of co-occurrence, thus incorporating the notion of time sequence. It relates to data that appear in separate sessions and a pattern in this case, may be a web page or a set of pages accessed immediately after another set of pages.

2.3 Adapted output

The last phase of the adaptation process determines the kind of adaptations the e-learning site will deploy in order to generate variations of itself to better suit individual learners or group of learners. The adaptations may refer to (Markellou et al., 2004):

- *Content.* Typical applications of such adaptations are optional explanations and additional information, personalized recommendations, theory driven presentation, etc., and techniques used for producing them include adaptive selection of web page (or page fragment) variants, fragment colouring, adaptive stretch-text, and adaptive natural language generation.
- *Structure.* It refers to changes in the link structure of hypermedia documents or their presentation. Techniques deployed for producing this kind of adaptations comprise adaptive link sorting, annotation, hiding and unhiding, disabling and enabling, removal and addition. Adaptations of structure are widely used for producing adaptive recommendations for learning modules, exercises, tests, etc., as well as for constructing personalized views and learning spaces.

- *Presentation and media format.* In this type of adapted output the learning content stays the same, but what changes is its format and layout (for example, from images to text, form text to audio, from video to still images). This type of adaptations is widely used for web access through PDAs or mobile phones, or in websites that cater for handicapped people.

In most cases, adaptive e-learning sites deploy hybrid adaptation techniques that combine more than one approach.

3 WEB-BASED SYSTEMS SUPPORTING ADAPTIVE LEARNING

The enhancement of e-learning systems with adaptive features has become the current trend both in the research domain, as well as the commercial applications. Attempting a brief historical overview of the research that led to the development of adaptive hypermedia e-learning systems, we first find the *Intelligent Tutor Systems (ITS)*, which mainly used artificial intelligence to build educational applications. Then, with the appearance of *Hypermedia Systems*, hypertext complicated environments oriented to content were introduced along with high interactivity. With the web offering more and more facilities, new educational systems gained attention, namely *Adaptive Hypermedia Educational Systems*. These systems modelled users and adapted the learning experience to their particular needs and preferences. Early but significant research efforts in this domain comprise the following:

- *ELM-ART* (Weber & Specht, 1997): acronym for Episodic Learner Model – Adaptive Remote Tutor, is one of the first adaptive web-based educational systems for programming in Lisp language. It integrates the features of electronic textbooks, learning environments, and intelligent tutoring systems.
- *InterBook* (Brusilovsky et al., 1998): is a tool for authoring and delivering adaptive electronic textbooks on the web. The system maintains an individual model for each learner and his knowledge and applies this model to provide adaptive guidance, navigation support, and to help focus on link annotation techniques.
- *AHA!* (De Bra & Calvi, 1998): stands for Adaptive Hypermedia Architecture and uses link hiding. It is based on the idea that each learner visits a specific page to update and estimate individual knowledge. The disadvantage is that simply recording learner accesses to content pages, does not indicate that the learner has actually studied and understood the content, and has thus acquired the corresponding knowledge.
- *KBS Hyperbook* (Henze et al., 1999): gives learners the ability to define their own learning goals, proposes next reasonable learning steps to take, supports project-based learning, gives alternative views, and can be extended by documents created by learners.
- *NetCoach* (Weber & Kuhl, 2001): derived from ELM-ART and it is a system designed to enable authors without programming knowledge to develop adaptive learning courses.

Moving on to more recent efforts, representative adaptive web-based learning systems include:

- *AES-CS* (Adaptive Educational System based on Cognitive Styles) (Triantafillou et al., 2002): includes accommodations for cognitive styles in order to improve student interactions and learning outcomes.
- *INSPIRE* (INtelligent System for Personalised Instruction in a Remote Environment) (Papanikolaou et al., 2003): dynamically generates lessons based on the interaction with the learners and leads to the accomplishment of theirlearning goals (lessons are generated according to learners' knowledge level and learning style and follow their progress).
- *WebPersonalizer* (Mobasher et al., 2000): a more general-purpose system used to provide a list of recommended hypertext links to a user while browsing through a website.
- *OOHDM* (Object-Oriented Hypermedia Design Method) (Rossi et al., 2001): is a methodology for designing personalized web applications and managing personalized views.

Finally, there have been a variety of e-learning environments in the market, such as Lotus Learning Space (www.lotus.com), Librarian (www.click2learn.com), Blackboard (www.blackboard.net), WebCT (www.webct.com), TopClass (www.wbtsystems.com), Embanet (www.embanet.com), Intralearn (www.intralearn.com), Ecollege (www.ecollege.com), Eduprise (www.eduprise.com), etc.

4 CONCERNS AND CONCLUSIONS

The upcoming years will certainly bring more exciting research and commercial applications of adaptive educational hypermedia. These systems provide learners with added value by knowing and serving them as individuals and developing personal relationships. However, many issues remain unclear. First of all, determining and delivering personalized learning is a data intensive task and requires the execution of numerous processing steps. This usually causes intolerably *long response times*, which in turn may lead to abandonment. To avoid this obstacle, software designers should consider either having part of the process execution offline or deploying special algorithms, structures and configurations to assure fast online operation. Apart from requiring fast delivery of adaptations, it is equally crucial to assure *accuracy*, in the sense that adaptations that are not successful slow down the learning process by confusing and disorienting users. It is much better not to deliver any adaptations, than deliver a set of useless and annoying ones.

Another area of concern relates to *human aspects*. Adaptive systems and user profiling bring up the invaded *privacy* hazard that remains an unresolved problem. Research in the area of mining web usage data (Sirmakessis, 2004) is accompanied by security preservation methods to increase users' confidence while interacting with an online application. The need for privacy has created a new market dedicated to the design and development of products for private information protection. The future challenges and research in the direction of delivering adaptive web experiences without jeopardising –but in fact protecting– privacy can be summarised as follows (Kobsa, 2001): P3P support, intelligible disclosure of data, disclosure of methods, provision of organizational and technical means for users to modify their user model entries, user model servers that support a number of anonymization methods, and adapting user modelling methods to privacy preferences and legislation.

Last but not least, produced adaptations should be delivered in the appropriate way (avoiding learner intrusion and loss of concentration) and should not deprive users control over the learning process.

REFERENCES

AGRAWAL, R., & SRIKANT, R. 1994. *Fast Algorithms for Mining Association Rules*. Proceedings of the 20th VLDB Conference, Santiago, Chile, 487-499.

AGRAWAL, R., IMIELINSKI, & T., SWAMI, A. 1993. *Mining Association Rules Between Sets of Items in Large Databases*. Proceedings of the ACM SIGMOD International Conference on Management of Data, 207-216.

BRUSILOVSKY, P. 1998. *Adaptive Educational Systems on the World-Wide-Web: A Review of Available Technologies*. Proceedings of Workshop WWW-Based Tutoring at Forth International Conference on Intelligent Tutoring Systems (ITS'98), San Antonio, TX.

BRUSILOVSKY, P. 2001. *Adaptive Hypermedia*. User Modeling and User-Adapted Interaction, 11, 87-110.

BRUSILOVSKY, P., EKLUND, J., & SCHWARZ, E. 1998. *Web-based Education for All: a Tool for Developing Adaptive Courseware*. Computer Networks and ISDN Systems, 30, 1-7, 291-300.

CHAKRABARTI, S. 2002. *Mining the Web: Discovering Knowledge from Hypertext Data*. Morgan Kaufmann.

COOLEY, R., MOBASHER, B., & SRIVASTAVA, J. 1999. *Data Preparation for Mining World Wide Web Browsing Patterns*. Journal of Knowledge and Information Systems, 1, 1, 5-32.

DE BRA, P., & CALVI, L. 1998. *AHA! An Open Adaptive Hypermedia Architecture*. The New Review of Hypermedia and Multimedia, 4, 115-139.

DE BRA, P., BRUSILOVSKY, P., & HOUBEN, G.J. 1999. *Adaptive Hypermedia: From Systems to Framework*. ACM Computing Surveys, 31, 4.

EIRINAKI, M., & VAZIRGIANNIS, M. 2003. *Web Mining for Web Personalization*. ACM Transactions on Internet Technology (TOIT), ACM Press New York, 3, 1, 1-27.

ETZIONI, O. 1996. *The World Wide Web: Quagmire or Gold Mine*. Communications of the ACM, 39, 11, 65-88.

FRY, K. 2001. *E-learning Markets and Providers: Some Issues and Prospects*. Education and Training, Emerland, 43, 4, 233-239.

HAND, D., MANNILA, H., & SMYTH, P. 2001. *Principles of Data Mining*. MIT Press.

HENZE, N., NACEUR, K., NEJDL, W., & WOLPERS, M. 1999. *Adaptive Hyperbooks for Constructivist Teaching*. Kunstliche Intelligenz, 26-31.

KOBSA, A. 2001. *Tailoring Privacy to Users' Needs* (Invited Keynote). In M. Bauer, P. J. Gmytrasiewicz and J. Vassileva, eds., User Modeling 2001, 8th International Conference, Berlin – Heidelberg, Springer Verlag, 303-313, online at http://www.ics.uci.edu/~kobsa/papers/2001-UM01-kobsa.pdf (accessed 15.3.2004).

KOBSA, A., KOENEMANN, J., & POHL, W. 1999. *Personalized Hypermedia Presentation Techniques for Improving Online Customer Relationships*. Technical report No. 66 GMD, German National Research Center for Information Technology, St. Augustin, Germany.

KOSALA, R., BLOCKEEL, H. 2000. *Web Mining Research: A Survey*. SIGKDD Explorations, 2, 1, 1-15.

MADRIA, S.K., BHOWMICK, S.S., NG, W.K., LIM, E.P. 1999. *Research Issues in Web Data Mining*. Proceedings of Data Waterhousing and Knowledge Discovery, 1st International Conference, DaWaK '99, 303-312.

MARKELLOU, P., RIGOU, M., & SIRMAKESSIS, S. 2004. *Mining for Web Personalization*. Chapter in book "Web Mining: Applications and Techniques" (ed. Anthony Scime, State University of New York College, Brockport), Idea Group Publishing Inc. (to be published in 2004).

MOBASHER, B. 2004. *Web Usage Mining and Personalization*. Draft Chapter in Practical Handbook of Internet Computing, Munindar P. Singh (ed.), CRC Press (to be published in 2004), online at http://maya.cs.depaul.edu/~mobasher/papers/IC-Handbook-04.pdf (accessed 15.3.2004).

MOBASHER, B., COOLEY, R., & SRIVASTAVA, J. 2000. *Automatic Personalization Based on Web Usage Mining*. Communications of the ACM, 43, 8, 142-150, online at http://maya.cs.depaul.edu/ ~mobasher/papers/MCS00.pdf (accessed 15.3.2004).

MOBASHER, B., DAI, H., LUO, T., NAKAGAWA M. 2002. *Discovery and Evaluation of Aggregate Usage Profiles for Web Personalization*. Data Mining and Knowledge Discovery, Kluwer Publishing, 6, 1, 61-82, online at http://maya.cs.depaul.edu/~mobasher/papers/dmkd02.pdf (accessed 15.3.2004).

PAPANIKOLAOU, K.A., GRIGORIADOU, M., KORNILAKIS, H., & MAGOULAS, G.D. 2003. *Personalizing the Interaction in a Web-based Educational Hypermedia System: the Case of INSPIRE*. User Modeling and User-Adapted Interaction, 13, 3, 213-267.

PIERRAKOS, D., PALIOURAS, G., PAPATHEODOROU C., & SPYROPOULOS, C.D. 2003. *Web Usage Mining as a Tool for Personalization: a Survey*. User Modeling and User-Adapted Interaction, 13, 4, 311-372, online at http://iit.demokritos.gr/~paliourg/papers/UMUAI2003.pdf (accessed 15.3.2004).

RASMUSSEN, E. 1992. *Clustering Algorithms*. Information Retrieval, W.B. Frakes & R. Baeza-Yates (eds.), Prentice Hall PTR, New Jersey.

ROSSI, G., SCHWABE, D., & GUIMARÃES, R.M. 2001. *Designing Personalized Web Applications*. In the Proceedings of the Tenth International World Wide Web Conference, Hong Kong, 275-284, online at http://www.www10.org/cdrom/papers/pdf/p395.pdf (accessed 15.3.2004).

SIRMAKESSIS, S. (Ed.). 2004. *Text Mining and its Applications*. Studies in Fuzziness and Soft Computing, Springer Verlag.

TRIANTAFILLOU, E., POMPORTSIS, A., & GEORGIADOU, E., 2002. *AES-CS: Adaptive Educational System based on Cognitive Styles*. In the Workshop on Adaptive System for Web-based Education, held in conjunction with AH'2002, Malaga, Spain.

WANG, D., BAO, Y., YU, G., & WANG, G. 2002. *Using Page Classification and Association Rule Mining for Personalized Recommendation in Distance Learning*. Proceedings of the 1st International Conference Advances in Web-Based Learning, Hong Kong, China, 363-374.

WEBER, G., & KUHL, H.C. 2001. *Developing Adaptive Internet Based Courses with the Authoring System*. Online at http://www.weibelzahl.de/literatur/weber-ah2001.pdf (accessed 15.3.2004).

WEBER, G., & SPECHT, M. 1997. *User Modeling and Adaptive Navigation Support in WWW-based Tutoring Systems*. In A. Jameson & C. Tasso (Eds.), User Modeling: Proceedings of the Sixth International Conference, UM97, 289-300.

WENTLING, T., WAIGHT, C., GALLAHER, J., LA FLEUR, J. WANG, C., & KANFER, A. 2000. *E-Learning: a Review Literature*. Knowledge and Learning Systems Group, National Center for Supercomputing Applications, University of Illinois.