PERSONALIZING DIGITAL LIBRARIES FOR EDUCATION

Floriana Esposito, Oriana Licchelli, Pasquale Lops, Giovanni Semeraro
Dipartimento di Informatica, Università di Bari
Via E. Orabona, 4 – I70126, Bari

Keywords: Digital Library, e-Learning.

Abstract: E-Learning Systems enable students to work with electronic teaching materials, to join online courses, to pass tests, and to communicate with other students or instructors. An important requirement of this systems is the integration of external knowledge management resources into them. The digital libraries are helpful to this purpose because materials of many digital libraries are valuable for learning. The availability of teaching materials provided by an E-Learning Systems can be enlarged by reverting to materials existing in several digital libraries. In this case, it is necessary to find the right document source and to supply the suitable documents basing on the student requirements, also when the student model of the e-learning system is still not available. In this paper, we have focused our attention on the use of user profiles, generated by a personalization system (the Profile Extractor), to improve searching among digital libraries or other generic information sources.

1 INTRODUCTION

Adaptive personalized e-learning systems could accelerate the learning process by revealing the strengths and weaknesses of each student. They could dynamically plan lessons and personalize the comunication technique and the didactic strategy. In this systems, the Learning Management Systems (LMS) consist of several components representing different services to be used within a learning environment. They enable students to work with electronic teaching materials, to join online courses, to pass tests, and to communicate with other students or instructors. The availability of teaching materials provided by a modern Learning Management System (LMS) could be enlarged by reverting to existing materials with the integration of external knowledge management resources into LMS (Rosenberg, 2001). It seems obvious that digital libraries (DL) are predestinated for this purpose because materials of many DL are valuable for learning. For example, the contents of the DL of the Association for Computing Machinery (ACM, http://www.acm.org/dl) and the IEEE Computer Society (http://www.computer.org/publications/dlib) can be used for higher education and scientific research. In this case, it is necessary to find the right document source and to supply the suitable documents basing on the student requirements, also when the student model of the e-learning system is still not available. Then the personalization of the digital libraries access becames an important feature, in fact, the personalization (Resnick and Varian, 1997; Riecken, 2000) involves techniques and mechanisms to reduce the information overload and facilitate the delivery of information that has been customised for the preferences of individual users. Machine Learning techniques have a significant role to play in the personalized services of the Digital Library. For example, many Machine Learning techniques are well suited for transforming user-activity data into useful preference rules as part of a user profile (Jennings and Higuchi, 1993). Similarly, case-based reasoning techniques can be used to implement flexible similarity-based content retrieval strategies (Balabanovic, 1997, Hammond et al., 1996), and recently automated collaborative filtering techniques have been used to transform raw user preference data into sophisticated content filters (Billsus and Pazzani, 1998; Konstan et al., 1997; Perkowitz and Etzioni, 1997).

In this paper, we have focused our attention on a generic LMS and the way to improve searching among digital libraries or other generic information sources, using the user profiles generated by our personalization system (Profile Extractor).

The Profile Extractor system, based on Machine Learning techniques, processes the logs of the user

Esposito F., Licchelli O., Lops P. and Semeraro G. (2004).
PERSONALIZING DIGITAL LIBRARIES FOR EDUCATION.
In *Proceedings of the Sixth International Conference on Enterprise Information Systems*, pages 279-284

accessing the Digital Library and automatically builds the user model.

2 PERSONALIZED E-LEARNING SYSTEMS

In (Lauzon and Moore, 1989) Computer-Assisted Learning is defined as "the delivery of educational materials using computers as the main medium of communication between instructor and student." In the decade that followed, several standards emerged that emphasized the machine delivery of content without an instructor. Thus, most contemporary computer-based instruction emphasizes learner-content interaction or learner-learner interaction.

In Intelligent Tutoring System area (Woolf, 1992), the module devoted to build the student model is one of the major components of the teaching system: namely, the student model module, the pedagogical module, the domain knowledge module, and the communication module. The student model stores information that is specific to each individual learner: it is "how" and "what" the student learns or her/his errors, and the student model plays a main role in planning the instructional path. The pedagogical module provides a model of the teaching process, using the student model in order to decide the instruction method that reflects the differing needs of each student. The domain knowledge module contains information the tutor is teaching, and the communication module creates the interactions with the learner using the information contained in the student model in order to render the communication more effective. The information collected during the interaction can be used to modify the student model.

The use of student models to individualise the interaction in hypermedia and on-line instruction systems has been described by several authors (Bull, 1995; Bull and Smith, 1997; Smith and Jagodzinski, 1995), but the application of the techniques suggested by ITS technology to generate the effective presentation of instructional material has had little practical success. According to Hartley (Hartley, 1998), the main cause is the lack of dialogue between researchers of the different areas, while others think that the intrinsic complexity of student models is at the root of the problem of their application to configure learning for the individual (Cummings, 1998; Ohlsson, 1993; Self, 1990).

The range of student modelling approaches available is surveyed by Ragnemalm (Ragnemalm, 1996), who distinguishes between models that contain student's actual domain knowledge and those that contain student characteristics.

In the 1996 Vassileva (Vassileva, 1996) describes a student model as an example of a general user model, but where a representation of student knowledge, held by the system, is compared with a representation of the domain and a representation of an expert or desired state. The aim of such systems is to compare the student, domain and expert models and to attempt to configure presentation of information based in some way upon differences between them, in order to permit to the student to reach a desirable knowledge level (educational goal).

In the 1996, Brusilovsky (Brusilovsky, 1996) faces the problem to make the adaptive hypermedia systems and states that is necessary to use some features as goals, knowledge, background, experience and preferences.

At present, the main engines of an e-Learning System are the Learning Management System (LMS) and the Learning Content Management System (LCMS).

A Learning Management System is intended to be a content-neutral platform that helps a learner to tailor the delivery of instruction to individual needs. These systems are concerned with the delivery of pre-packaged content. They use the information in the learner profile and learner history to select materials from the content database. In these systems, each instructional module and test in the content database is tied to one or more learning objectives, material selection and sequencing is under the control of the instructional designers who created the original learning modules. Most of these systems will present a pre-test, choose material according to the test results, present the material, then administer post-tests and store those results as well.

The LMS integrates all aspects for managing on-line teaching activities. From an end-user point of view, a LMS provides an effective way to keep track of individual skills and competencies, and provides a means of easily locating and registering for relevant learning activities to further improve the learner's skill levels.

The LCMS (Maish Nichani) offers services that allow for the content management, creation, delivery and reuse. Content is typically maintained in learning objects, each of which satisfies one or more well-defined learning objectives. A LCMS may locate and deliver a learning object to the end-user as an individual unit to satisfy a specific need or may deliver the learning object as part of a larger course, curriculum, or learning activity defined in a LMS. Then the LMS and LCMS both monitor the delivery of content but at different levels of granularity. A LMS concentrates on course-level tracking, on particularly completion status and rolled-up scores. In contrast, an LCMS employs detailed tracking at the learning-object level, not only to trace user performance and interactions at a finer granularity, but also to provide the metrics that help authors analyze the learning object's clarity, relevance, and effectiveness.

Users play a central role in both LMS and LCMS. A typical LMS maintains all information of each user such as organizational affiliations, job role, preferences, competencies, skill levels, participation in past learning activities, and so forth. Adding to this information the capability of monitoring and planning the educational process in order to attain learning objectives means to have an effective student model, with the same philosophy of a traditional computer assisted learning system.

In an e-learning system, users typically use the LMS to manage their current competency status, to analyze their skill gaps, and to register for learning activities that will help them reduce their skill gaps against an aspired career path. An LCMS focuses on delivering a personalized experience to the user providing just enough content to address the person's individual needs, when she/he needs it. An LCMS may also enhance this experience by customizing the content basing on a user's profile or by offering rich collaborative and knowledge-exchange capabilities about the content. The key difference is that the LCMS takes advantage of all the information available about the user to offer a personalized experience when delivering a learning object, while a LMS typically maintains the user information and makes it available to the LCMS to deliver the personalized experience.

The LCMS can use this information also to deliver a customized track of the learning object to the user automatically; it can also analyze trends by correlating the user properties from LMS and can use it to prescribe an appropriate track to future users, based on their profiles. The LCMS may behave as an intelligent system that learns, based on real data, what worked for whom and then uses this information to help future users.

During the learning session many references could be cited and, if possible, reproduced. The availability of teaching materials provided by an e-learning system can be enlarged by reverting to materials existing in several digital libraries. In this case, it is necessary to find the right document source and to supply the suitable documents basing on the student requirements, also when the student model of the e-learning system is still not available. The accessibility to the digital library material must be guaranteed and a simple student model which discovers the preferences, needs and interests of users accessing the Digital Library should be sufficient. The preferred searched documents supply an interesting information for the student model too since suggest the user main interest to deepen specific subjects.

3 USER MODELLING FOR ACCESSING DOCUMENT EXTERNAL SOURCES (DL)

In our laboratory, a system has been developed to generate user profiles automatically: the Profile Extractor personalization system which employs supervised learning techniques to automatically discover user/student model through the analysis of past user interaction with the "web" system.

The Profile Extractor is able to analyze data gathered from sources such as data warehouse or interactions (between student and LMS) in order to infer rules describing the user/student behavior.

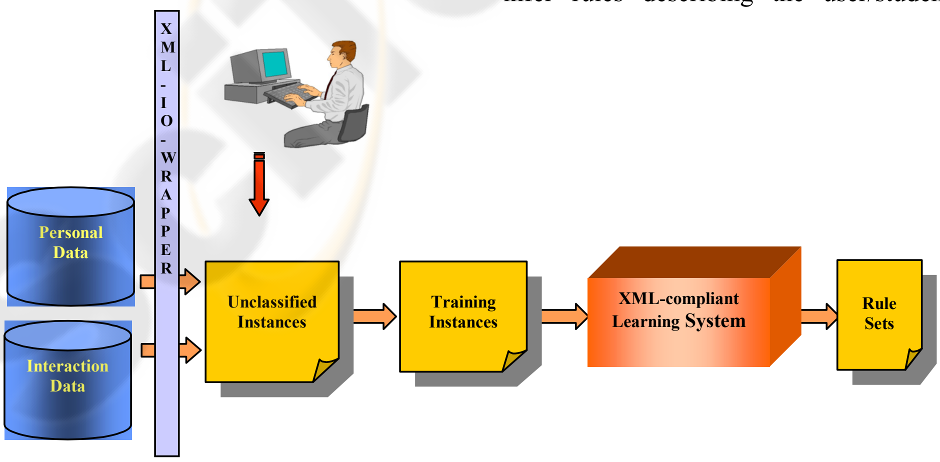


Figure 1: The learning process

Rules are exploited to build profiles containing preferences such as the material categories the user/student is interested into.

Some preliminary work is needed to establish a formal description of the features and attributes that are needed to accomplish the given task; we can use the results to define the representation language of the entire learning framework. From our point of view, the problem of learning user's preferences can be cast to the problem of inducing general concepts from examples labelled as members (or non-members) of the concepts. In this context, given a finite set of categories of interest $C = \{c_1, c_2, \ldots c_n\}$, the task consists in learning the target concept T_i "users interested in the category c_i". In the training phase, each user represents a positive example of users interested in the categories he or she likes and a negative example of users interested in the categories he or she dislikes. We chose an operational description of the target concept T_i, using a collection of rules that match against the features describing a user in order to decide if he or she is a member of T_i.

As depicted in Figure 1, the data about users (an XML file containing personal and interaction data of the user) are arranged into a set of unclassified instances (each instance represents a user). The subset of the instances chosen to train the learning system has to be labeled by a domain expert, that classifies each instance as member or non-member of each category. The training instances are processed by the Profile Extractor, which induces a classification rule set for each category of interest.

More precisely, the architecture of the PE is made up of several sub-modules:

- *XML I/O Wrapper*, which is the layer responsible for the extraction of data required for the learning process.
- *Rules Manager*, which is implemented through one of the WEKA (Frank and Witten, 1998) classifiers. The learning algorithm adopted in the rule induction process is PART (Witten and Frank, 1999), which produces rules from pruned partial decision trees.
- *Profile Manager*, which classifies each user on the ground of the users' transactions and the set of rules induced by the Rules Manager. The classifications, together with the interaction details of users, are gathered to form a user profile.

Extensive experimentation of the system proposed for the automatic extraction of the user profile has been carried out in the digital libraries. In particular, the system was tested on the frame of COVAX Digital Library.

The purpose of COVAX (Contemporary Culture Virtual Archives in XML) project (Bordoni, 2002) was to analyse and draw up the technical solutions required to provide access through the Internet to homogeneously-encoded document descriptions of archive, library and museum collections based in the application of XML. The project demonstrated its feasibility through a prototype containing a meaningful sample of all the different types of documents to build a global system for search and retrieval.

In the experiment we considered the four main collections of the COVAX Digital Library (Bibliographic, Museum, Electronic Text, Archive). For each of the 4 classes, the system was trained to infer proper classification rules, on the basis of an instances set representing different digital library users given by an expert acting as a trainer of the system. Figure 2 shows a classification rule set example, that is generated for the "Bibliographic Collection" on the ground of logs containing interaction and user features; those rule sets are expressed as disjunctions of conditions.

The Rules extracted for class COLLECTION_BIB are 3 :

1 .

If

SEARCH_NUM_UOC-BIB-MARC-BUOC > 9.0

Then Class: yes

2 .

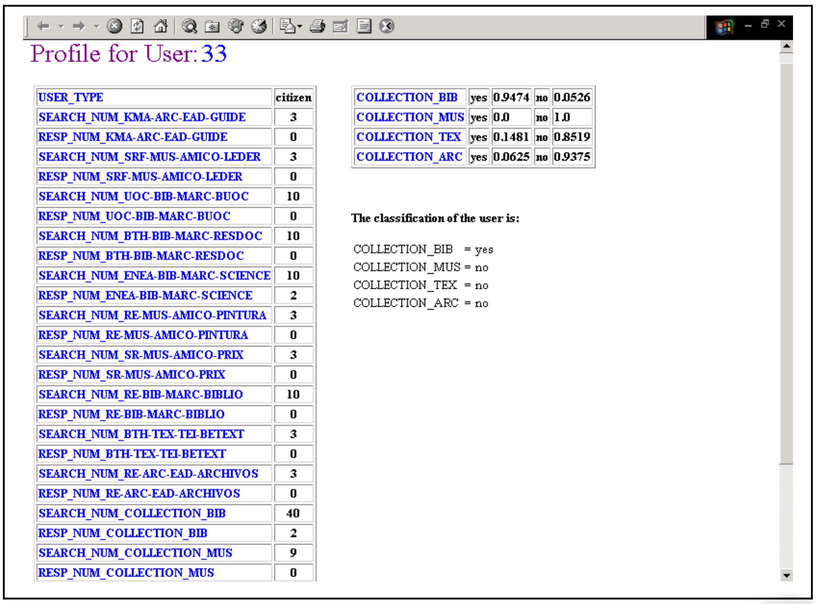
If

RESP_NUM_SRF-MUS-AMICO-LEDER <= 1.0 **And**
RESP_NUM_ENEA-BIB-MARC-SCIENCE <= 177.0

Then Class: no

3 .
Otherwise Class: yes

Figure 2: An example of classification rules for the class "Bibliographic Collection"



Profile for User: 33

USER_TYPE	citizen
SEARCH_NUM_KMA-ARC-EAD-GUIDE	3
RESP_NUM_KMA-ARC-EAD-GUIDE	0
SEARCH_NUM_SRF-MUS-AMICO-LEDER	3
RESP_NUM_SRF-MUS-AMICO-LEDER	0
SEARCH_NUM_UOC-BIB-MARC-BUOC	10
RESP_NUM_UOC-BIB-MARC-BUOC	0
SEARCH_NUM_BTH-BIB-MARC-RESDOC	10
RESP_NUM_BTH-BIB-MARC-RESDOC	0
SEARCH_NUM_ENEA-BIB-MARC-SCIENCE	10
RESP_NUM_ENEA-BIB-MARC-SCIENCE	2
SEARCH_NUM_RE-MUS-AMICO-PINTURA	3
RESP_NUM_RE-MUS-AMICO-PINTURA	0
SEARCH_NUM_SR-MUS-AMICO-PRIX	3
RESP_NUM_SR-MUS-AMICO-PRIX	0
SEARCH_NUM_RE-BIB-MARC-BIBLIO	10
RESP_NUM_RE-BIB-MARC-BIBLIO	0
SEARCH_NUM_BTH-TEX-TEI-BETEXT	3
RESP_NUM_BTH-TEX-TEI-BETEXT	0
SEARCH_NUM_RE-ARC-EAD-ARCHIVOS	3
RESP_NUM_RE-ARC-EAD-ARCHIVOS	0
SEARCH_NUM_COLLECTION_BIB	40
RESP_NUM_COLLECTION_BIB	2
SEARCH_NUM_COLLECTION_MUS	9
RESP_NUM_COLLECTION_MUS	0

COLLECTION_BIB	yes	0.9474	no	0.0526
COLLECTION_MUS	yes	0.0	no	1.0
COLLECTION_TEX	yes	0.1481	no	0.8519
COLLECTION_ARC	yes	0.0625	no	0.9375

The classification of the user is:

COLLECTION_BIB = yes
COLLECTION_MUS = no
COLLECTION_TEX = no
COLLECTION_ARC = no

Figure 3: An example of a user profile

Using these rule sets, the classifier (Profile Manager) predicts, for each category, whether the user is interested or not. All these classifications, together with the interaction details, are gathered to form a user profile (see Figure 3 as user profile example).

After the training phase, once a user accesses the COVAX Digital Library, his/her dialogue history file is generated or updated by the system. The file is then exploited to produce a new example that the Profile Extractor classifies on the grounds of the rules inferred. In this way, the system is capable of tracking user behaviour evolution and, consequently, the profiles are updated across multiple interactions.

The concepts underlying information retrieval were conceived long before computers and information systems were employed to store library materials. In the digital library domain there is a variety of information retrieval techniques, including metadata searching, full-text document searching, and content searching for several data types.

The success of information retrieval can be measured in terms of the percentage of relevant and extraneous information retrieved, but it is difficult to identify quantitatively the effectiveness of the retrieval process because only an individual user can determine what is truly useful. There are different techniques to improve the retrieval effectiveness by means of the extraction of additional metadata, and recently also by means of the creation and maintenance of user profiles.

A possible way to improve searching in COVAX DL or in another Digital Library is to use the information stored in a user's profile in order to refine the original query issued by the user. For example, the preferred category can be enclosed in the query submitted to COVAX search engine for more precise result identification.

Another possible way to improve the retrieval process (without modifying the original user's request) is to rank the documents in the result set according to the categories and their degree of interest stored in the user's profile.

The preferred searched documents supply an interesting information for the student model too since suggest the user/student main interest to deepen specific subjects.

4 SUMMARY AND OUTLOOK

A key issue when developing personalized applications is constructing accurate and comprehensive customer profiles based on the collected data. User modelling is crucial for improving the interaction between systems and their users. In the e-learning systems, the teaching materials provided by Learning Management System (LMS) could be enlarged by the integration into LMS of external knowledge management resources as the Digital Libraries. Indeed, documents and materials of many DL are valuable for learning and providing intelligent personalized user support in accessing the digital libraries, in finding the right document source and in supplying the suitable documents basing on the student requirements is a main topic.

We have presented the Profile Extractor, a system based on Machine Learning techniques, which processes the logs of the user accessing the

Digital Library and automatically builds the user model. The automatic generation and discovery of the user profile allows to improve searching among extremely large Web repositories, such as Digital Libraries or other generic information sources, by providing them with personal recommendations.

By the e-learning system perspective, this profile constitutes a first student model, based on communication preferences more then on learning performances, useful to create a personalized education environment. The future step is trying to use such information in order to plan a personalized educational path, constantly monitoring the educational process. The student model constructed initially can be refined and/or reviewed on the basis of the new inputs to the system. Once again Machine Learning techniques could be of use in the automatic review of student models, by offering incremental learning methods in order to update the knowledge learned on the basis of new observations.

ACKNOWLEDGEMENT

This work was partially supported by ENEA under grant "An i*nnovative system for the extraction of user profiles"*. The authors would like to thank Luciana Bordoni and Fabrizio Poggi for the dataset used in the Profile Extractor.

REFERENCES

Balabanovic, M. and Shoham, Y., 1997. Fab: Content-Based, Collaborative recommendation. *Communications of ACM*, 40 (3),66-72.

Billsus, D. and Pazzani, M. J., 1998. Learning Collaborative Information Filters. In *Proceedings of the International Conference on Machine Learning*, Wisconsin, USA, 46-54.

Brusilovsky, P., 1996. Methods and techniques in adaptive hypermedia. *User Modelling and User-Adapted Interaction*, 6(2-3), 87-129.

Bordoni, L., 2002. COVAX: A Contemporary Culture Virtual Archive in XML. In *Proceedings of the 6th European Conference ECDL 2002*, Rome, Italy, 661-662.

Bull, S., Brna, P, and Pain, H., 1995. Extending the scope of the student model. *User Modelling and User-Adapted Interaction*, 5(10), 45-65.

Bull, S. and Smith, M., 1997. A pair of student models to encourage collaboration. In Proceedings of the 6th International Conference on User Modeling UM97, Italia, 339-341.

Cummings, G., 1998. Artificial intelligence in education: an exploration. *Journal of Computer Assisted Learning*, 14(4) 252-259.

Hammond, K. J., Burke, R. and Schmitt, K., 1996. A Case-Based Approach to Knowledge Navigation. *Case-Based Reasoning Experiences Lessons and Future Directions*, MIT Press, 125-136.

Hartley, J.R., 1998. Ospite Editoriale: CAL and AI - a time for rapprochement? *Journal of Computer Assisted Learning*, 14(4), 249-250.

Jennings, A. and Higuchi, H., 1993. A user model neural network for a personal news service. *User Modeling and User-Adapted Information*, 3(1), 1-25.

Konstan, J. A., Miller, B. N., Maltz, D., Herlochker, J. L., Gordan, L. R. and Riedl, J., 1997. Grouplens: Applying Collaborative Filtering to Usenet News. *Communications of the ACM*, 40(3), 77-87.

Lauzon, A.C. and Moore, G.A.B., 1989. A fourth generation distance education system: Integrating computer-assisted learning and computer conferencing. *The American Journal of Distance Education*, 3(1), 38-49.

Maish Nichani. *LCMS = LMS + CMS* http://www.elearningpost.com/features/archives/001022.asp

Ohlsson, S., 1993. Impact of cognitive theory on the practice of authoring. *Journal of Computer Assisted Learning*, 9(4) 194-221.

Perkowitz, M. and Etzioni, O., 1997. Adaptive Web Sites: An AI Challenge. In *Proceedings of the 15th International Joint Conference on Artificial Intelligence*, Nagoya, Japan. Morgan Kaufmann, 16-23.

Ragnemalm, E.L., 1996. Student Diagnosis in Practice; Bridging a Gap. *User Modelling and User-Adapted Interaction*, 5, 93-116.

Resnick, P. and Varian, H., 1997. Recommender Systems. *Communications of the ACM*, 40(3), 56-58.

Riecken, D., 2000. Personalized Views of Personalization. *Communications of the ACM,* 43(8), 27-28.

Rosenberg, M.J., 2001. *e-Learning – Strategies for Delivering Knowledge in the Digital Age*. McGraw-Hill.

Self, J.A., 1990. Bypassing the intractable problem of student modelling. *Intelligent tutoring systems: at the crossroads of artificial intelligence and education*. Frasson, C., Gauthier, G. (eds.), Ablex Publishing, Norwood, New Jersey, 107-123.

Smith, C. and Jagodzinski, P., 1995. The implementation of a multimedia learning environment for graduate civil engineers. *Association for Learning Technology Journal*, 3(1) 29-39.

Vassileva, J., 1996. A task-centred approach for user modelling in a hypermedia office documentation system. *User Modelling and User-Adapted Interaction*, 6(2-3) 185-223.

Woolf, B., 1992. *AI in Education. Encyclopedia of Artificial Intelligence*. Shapiro, S. ed., John Wiley & Sons, Inc., New York, 434-444.