LEARNCOM: SUPPORTING COMMUNITIES IN THE LEARNING PROCESS

Marios Katsis, Dip.
Department of Electrical Engineering and Computer Technology
University of Patras, 26500 Patras, Greece
E-mail: makatsis@master.math.upatras.gr

Evaggelia Rigou, Dip.
Department of Physics
University of Patras, 26500 Patras, Greece
E-mail: erigou@master.math.upatras.gr

Maria Rigou, MSc
Research Academic Computer Technology Institute
61 Riga Feraiou Str. 26110 Patras, Greece
E-mail: rigou@cti.gr

Spiros Sirmakessis, PhD
Adjunct Assistant Professor
Research Academic Computer Technology Institute
61 Riga Feraiou Str. 26110 Patras, Greece
Tel: (+302610) 960-420
E-mail: syrma@cti.gr

Athanasios Tsakalidis, Prof.
Department of Computer Engineering and Informatics
University of Patras, 26500 Patras, Greece
Tel: (+302610) 996-936
E-mail: tsak@cti.gr

Abstract

This paper describes the extended version of LearnCom, which allows for explicit and implicit adaptations, as well as easy material updating through a simple web interface. The new version upgrades the system's potential for setting up and maintaining online learning communities that are able to keep growing on their own; new students joining, material added, questions submitted and answered, messages exchanged and more. In LearnCom adaptations are based on the system's ability to gain insight to what may be of value for its users by observing the community behavior and rewards them by adding personalized scent to their online experience.

Introduction

Web-based learning environments revolutionize e-learning by enabling personalized, interactive, just-in-time, current and user-centric learning tools. These systems are able to simulate or coordinate all major stages of the learning process, such as pre-assessment of student knowledge and skills, recording of progress made (referring to successfully completed courses), assessment of acquired skills and conducting of examinations, as well as support for student-teacher cooperation. Depending on the context in which the e-learning system is to be used, self-monitoring of own-progress can also be provided.

e-Learning systems of today, apart from ensuring high quality content, correct and efficient structuring, as well as support for the tasks of all user profiles participating in the learning process, have drastically evolved and incorporated methods and techniques from other domains and application areas, such as: data mining, web content, structure and usage mining (Cooley et al, 1999; Spilioupoulou, 1999), user modeling and profiling, artificial intelligence and agent technologies, and knowledge discovery. More recently, techniques that were initially deployed for the e-commerce domain, in support of activities such as personalization, cross-selling, up-selling, and recommendations (with clustering, similarity indexing, association rules mining, collaborative or content-based filtering as the underlying technology) are transferred and applied to e-learning applications. These techniques aim to tailor and deliver to users an instance (or a "view") of the e-learning environment that best suits their personal needs, preferences and objectives, or the view that best implements the teaching strategy decided by the teacher for the specific students cluster. To this end, researchers try to develop systems that are able to adapt themselves by observing, recording and analyzing user activity (adaptive systems) (Brusilovsky et al, 1998), or to be explicitly "tuned" by the user (adaptable or customizable systems) (Manber et al, 2000).

The issue of upgrading the online learning experience for all participating actors brings up one of the basic ingredients of successful learning: sharing through communication, which develops the feeling of belonging to a group of like-minded people that forms a community. Particularly in the case of online activities that are by nature remote and impersonal the notion of setting up communities of users is of vital importance on the path leading to successful learning. Communities share common problems, needs and goals and can promote solutions and progress if we gain insight into their "accumulated" knowledge. In our context, this knowledge exists in the form of navigation paths recorded in server logs.

In this paper we present the extended version of LearnCom (Christopoulou et al, 2002), an e-learning environment that can be used to set up and support the operation of an online learning community and incorporates adaptation mechanisms for copying with different user profiles. The second section briefly describes the functionalities that were added to the initial version of the system. The third section discusses design and implementation aspects relating to the techniques used for producing adaptations, while the last section presents our future directions and plans.

Extensions to the initial LearnCom version

LearnCom is a distance learning system for supporting online learning communities, populated by all those that need to acquire new skills on a variety of topics that can only be constrained by the availability of the training material itself. Users are distinguished as students, teachers or administrators with different UI views available for each user category. The system incorporates advanced communication utilities that comprise a chat, multiple forums and a mechanism for submitting and answering questions. Individual progress is manually recorded by students and teachers may dynamically upload new material. The newly added features comprise a special purpose authoring tool for creating and uploading new material in the system, an internal mechanism for recording user activity, a rating mechanism for assessing and rewarding student activity level, as well as two types of topic recommendation lists with suggested further reading ("Students that read this topic also read" and "Your teachers suggest that you also read").

The authoring tool follows a sequential scheme; teachers are guided through a form interface to put together the new topic starting by filling-in the top level heading and proceeding with the rest of the structural components (e.g. paragraphs, pictures, other headings, etc). All texts are entered in text entry fields and are consequently formatted according to their type and the internal CSS definitions of the tool. The rest of the new features are described in the next section.

Personalization: Looking under the hood

This section focuses on selected implementation issues and decisions aiming at upgrading the overall user experience, allocating more power to users and humanizing the feeling of belonging to an electronic community.

Graphical coding of student activity level

This approach was taken on the assumption that the system should foster a rewarding method for those active participants of the learning process, allowing the positive distinction of certain students by displaying a number of stars beside their nickname. The maximum number of stars (corresponding to available scaling levels along with the actual function that allocates students a certain number of stars) can be determined by administrators or teachers. For each student in the system a record is maintained for storing profile and usage data. Usage data collected using cookies and server log analysis are currently used to calculate and deliver the adequate number of stars characterizing the current user, but can also feature as a quite descriptive source of data for assessing the overall user activity on the part of the teacher. Administrators can tune the calculations to match any didactic scenario of students "rewarding" through visual clues in their representation in the system communicational areas. Scenarios may be based on any (weighed or not) combination of metrics such as time connected, material coverage, number of messages posted to the Forum, number of submitted questions, etc. Material coverage $C_{i,j}$ of skill i by user j complies with customary coverage definitions, being:

$$C_{i,j} = \frac{|R_i \cap R'_j|}{|R_i|} \qquad (1)$$

where R_i is the number or all available topics in skill i (e.g. all topics in the MS Word skill) and R'_j is the number of topics in skill i marked as read in the personal progress of student j.

Topics Recommended based on the student community

Students receive recommendations for further study based on association rules mining: topics marked as read in the progress of students that have also read the current topic are recommended under the "People that read this topic also read…" section). Association rules (Agrawal and Srikant, 1994) are used to capture the relationships among topics based on co-occurrence patterns observed in the personal progress during successive student sessions. As Han and Kamber (2001) formally put it, the *support* of an association rule refers to the percentage of the progress records (in our case) for which the rule is true. For association rules of the form "$A \rightarrow B$", where A and B are sets of topics (A is the set of topics in the current student's progress, and B is the set of candidate topics to be recommended to the student), support is defined as:

$$\sup port(A \rightarrow B) = \frac{\#\_progress\mathrm{Re}cords\_containig\_both\_A\_and\_B}{total\_\#\_of\_progress\mathrm{Re}cords} \qquad (2)$$

A certainty measure for association rules of the same form is *confidence*. Given a set of recorded studied topics A (in each student's progress), confidence is defined as:

$$confidence(A \to B) = \frac{\#\_progress\,Records\_containig\_both\_A\_and\_B}{\#\_progress\,Records\_containing\_A} \quad (3)$$

For example, the association rule: $\{topic123, topic34\} \to \{topic15\}$ [support=0.02, confidence=0.68], conveys the relationship that students who read topic123 and topic34 also tend (with a confidence of 68%) to read topic15. The support value represents the fact that the set $\{topic123, topic34, topic15\}$ is observed in 2% of student sessions recorded in all personal progress records. Association rules mining (Wang et al, 2002) typically identifies URI references recorded in server logs on a per-session or per-transaction basis and requires log analysis in order to derive sessions/transactions and then references to URIs of interest, but in our case the personal progress provides a more secure (since we indeed want to recommend topics actually studied by other students and not just accessed) and less demanding option (in terms of required processing). Recommendations returned to the user depend on the minimum support and confidence values set by administrators, as well as the preferences of the current user account (users specify the maximum number of recommended topics or even disable recommendations).

Topics Recommended based on associations defined by teachers

A second set of recommendations is assembled and placed under "Your teachers suggest that you also study…". The teacher that uploaded a new topic creates context links towards topics that relate to the concepts and terms encountered in the new topic. These connections are then used by the system to set up the recommendation list for the students that will study this topic.

Conclusions and Future Work

In this work we discussed selected extensions to the LearnCom system and experimented with various adaptation methods in order to deliver personalized content and better cope with different user profiles, preferences, goals and needs. In the future we plan to proceed with allocating more power and flexibility on the teachers' part, so that different –or even multiple- teaching scenarios can be applied for diverse student profiles. For this purpose, we must incorporate mechanisms for allowing teachers on a per-topic basis to set prerequisite topics and this way provide advanced forms of adaptations (guided navigation support, etc.). Another thought is to work more on the techniques for acquiring recommendations and introduce a ranking procedure that will allow for collaborative filtering and clustering approaches.

Regardless thought, of how many and how intelligent techniques technology offers for delivering online teaching and learning, or how sophisticated, integrated and highly customizable e-learning systems become, the fact remains that the business of e-learning (Ruttenbur et al, 2000) has a fundamental difference from e-business in general; it all comes down to how good the content is, which derives from how skilled the teacher is. Or, as De Bra (2002) more vividly puts it, "…creating "good" content, a sound concept hierarchy, and the right prerequisite relationships still requires (pedagogically) skilled authors and teachers".

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