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DESIGN OF E-LEARNING ENVIRONMENT TO CAPTURE AND USE LEARNERS' INFORMATION

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Abstract:

Many sophisticated e-learning environments have been developed and are in use around the world. The semantic web technology enables information in machine-processable form to coexist and complement the current web with better enabling computers and people to work in co-operation. In this paper, I focus on enhancing the usability of the web by capturing and reacting to the end-user context. E-learning environments must be truly responsive to the user needs. In this context we need to understand about the users of e-learning environment and their purpose of using it. This paper describes how to design an e-learning system that not only allows us to capture information about the learners' interaction but also allow it to be used in different dimensions to support the teachers and the learners in achieving their goals. This approach involves attaching models of learners to the learning objects they interact with, and then mining these models for patterns that are useful for various purposes. This approach is highly suited and recommended for all e-learning applications

Index Terms: Semantic Web, e-Learning, Data Mining, Learner Modeling & Clustering

1. Introduction:

The concept of e-learning dates back to the 1960's, with the early computer-assisted instruction systems. Subsequent research and development in the field has led to a plethora of computer-based learning paradigms like intelligent tutoring systems, collaborative learning, educational multi-media, situated learning, interactive learning environments, computer assisted learning etc [1]. There are often many debates among proponents of various paradigms listed above, debates that sometimes lead to insights, but more often are self-serving and counterproductive. The debates are often framed by the different backgrounds of subjects of the proponents like education, computer science, engineering, anthropology, sociology, psychology, library science, commerce, etc. It is clear that there are insights to be gained from virtually all perspectives on e-learning, and that to make progress we need to draw on all of these perspectives. In this paper I will make arguments for an approach to the design of e-learning systems, that shows promise to allow information about how learners use a system to be naturally captured and then used in a multitude of ways. In a phrase, the approach involves attaching models of users to the information they interact with, and then mining these models for patterns that are useful for various purposes. The information and the data mining algorithms interact with one another where the relevance and usefulness of information is always being adjusted to suit the changing needs of learners and teachers and to fit changes in the external environment and the system's perceptions. The ideas and techniques are drawn from many theories like Artificial Intelligence into education (AIED) [12], user modeling, collaborative filtering, case-based reasoning, the semantic web [5], data mining, multi-agent systems, information retrieval, recommender systems, learning objects, cognitive science, instructional design, and other social sciences. Particularly important are learning objects in which learning activities and material are encapsulated; the semantic web with its notions of user-centric open access and metadata to expand usability [6]; learner modeling with its focus on individual learners and adaptivity to their needs [4]; collaborative filtering for its concentration on similarities among users; and data mining to make sense of large amounts of unstructured data. The paper is organized as follows. In section 2, the approach to capturing and using information about users that shows great promise particularly in e-learning contexts is outlined. Section 3 focuses on importance of current research which involves exploring several of the issues raised by the approach. Section 4 briefs about the possible implications of the approach advocated here on these disciplines. Finally, section 5 summarizes the advantages of the present approach and the hurdles that must be overcome if the approach is to fulfill its potential.

2. Overview of the Approach:

In most semantic web research and development it is assumed that web content is marked up using standardized metadata. Such metadata is meant to add information that search engines and other Internet technologies can use to more accurately understand the pages and retrieve and/or manipulate them for the user [7]. There has been a considerable international effort to develop metadata standards and tools that allow computation and interoperability on information that adheres to these standards. Once such standards are agreed upon, it is then assumed that content providers will mark up "content" using the standard metadata tags and that anybody wishing to access the content will use the same tags, thus providing additional semantics to the content.

Unfortunately, there are a number of problems with this approach. In particular, there is no way of guaranteeing that the metadata really capture the various domains with the breadth and depth needed. Moreover, the metadata tend to be about the form and the content of the page, even though many other kinds of information could be useful for various purposes. A related problem is that the same page can be used for several purposes, and that the metadata relevant for one purpose may be different from that required for another purpose. There is also no way to guarantee consistency in the application of metadata to content: different content developers, different users, and different applications may interpret the same metadata in different ways. There is also a heavy front-end load in the standard approach, with the requirement for pre-assigning metadata to content to make it usable.

When the domain is education, there are a number of special problems with the standard approach. It is important in educational applications to understand the individual needs of each learner, and yet content or form-based metadata have little role for distinguishing one user from another. Ideally, learning objects need to reflect appropriateness to differences among learners' cognitive development, learning styles, motivation and other affective characteristics, [10] etc., in addition to content. They also need to incorporate aspects that allow pedagogical decisions to be made, including information about prerequisites, level of detail, technical level, etc. The standard approach also doesn't allow very well for change [2]. Not only does the content change, learners, by definition, are constantly changing as they gain mastery: their use of a given learning object may differ substantially depending on their stage of learning, the same object fulfilling different roles at different stages. Also, an e-learning system's understanding of learners is constantly changing with more interactions between learners and the system [3].

To overcome these problems, an alternative to the standard approach that essentially is an enhancement of collaborative filtering approaches. In this approach, information about web content is attached to the content as users access that content. The information may include information about the users, including cognitive, affective, and social characteristics of the users and their goals in accessing the content [8]; information about the content itself, including the users' opinions of what the content is and interpretations of the content inferred by text processing algorithms, and pre-specified metadata from a known ontology; information about how the users interacted with the content, including observed metrics such as dwell time, number of user keystrokes, patterns of access, etc., and users' opinions of the effectiveness of the content in meeting their goals; information about the technical context of use, including characteristics of the users' software and hardware environment; information about the social context of use, including access to a particular user's previous experiences with other content and access to other users' experiences with this content. There are many purposes that would be better fulfilled with a deep and broad understanding of content, including recommending relevant content for a particular user with a particular need for it, tailoring the content to a particular user's goals and/or needs, evaluating the effectiveness of the content in meeting the needs of various types of users, deciding whether the content is still relevant or has become obsolete, determining semantic relationships [9].Each such purpose places its own particular constraints on what information is relevant and how it is to be used to help to achieve the purpose. Thus, determining whether to recommend specific content to a particular user may require comparing this user to other users on important characteristics and then looking at how similar users have evaluated the content. On the other hand, determining whether the content is now obsolete may require an examination of all users' evaluations of the content, trying to extract temporal patterns in the evaluations that show how recent users like or dislike the content. Important technologies supporting this kind of purpose-based use of information are data mining and clustering techniques from artificial intelligence [11]. The key point is that it is the purpose that determines what information to use and how it is to be used. The approach can be termed as ecological because over time the system is populated with more and more information, and something like natural selection based on purposes determines what information is useful and what is not.

For some applications, it will be difficult or impossible to have all the relevant knowledge of users or their goals, thus limiting the effectiveness of the proposed approach. However, in educational domains virtually all of this knowledge can be readily available. Traditionally, learners have proven to be more willing to provide information to systems that will help them to learn than they have been to standard application systems, aimed at commercial profit for others, especially if they think that such information will make the e-learning system more effective and responsive to their own needs. They are also more likely to be willing to be monitored and evaluated, including allow diagnosis of their problem solving behaviour (to facilitate intelligent feedback) and the testing of their knowledge [13]. Educational goals can be explicitly known; for example a learner may want to learn about some subject, to find content relevant to a particular issue, to get help to overcome an impasse, etc. Thus, the educational domain is an excellent place to explore the ecological approach, since there is every chance of a very high bandwidth of interaction between the learner and the system. When a learner is accessing a learning object, both parts of the learner model can be used in standard fashion to inform the educational interaction between the learner and the learning object. Once the learner has finished, the learner model in its current state is copied and attached to the learning object as a learner model instance [14]. Of course, this learner model instance does not change once the learner has moved on: even as the learner model itself evolves and changes with the learner as the learner interacts with other learning objects, the learner model instance stays behind as a snapshot of the learner's experiences with this particular learning object at this particular time and in this particular context. When other learners interact with this learning object (or the same learner returns in the future), their learner model instances are also attached. Incrementally, more and more learner model instances accumulate which should allow more and more refined reasoning about the learning object's actual implications for learners. It is an interesting possibility of the ecological approach to allow this pre-assigned metadata to be refined, modified, or even changed based on inferences from end use; that is pre-assigned metadata about content may not agree with what the learners thought the content was, or at least not for every type of learner.

The other technologies of importance are data clustering and data mining. Once a sufficient number of learner models has been attached to the various learning objects in a learning object repository, it is possible to use these technologies to find interesting and relevant patterns in the information contained in the learning object instances. What is interesting and relevant, however, is not absolute, but is instead relative to the educational application and the particular purpose that the educational application is trying to achieve. An appropriate clustering algorithm is used to compare this information the same characteristics within learner model instances attached to the learning objects in the repository, to retrieve a set of similar learner model instances [16]. The choice of clustering algorithm and/or data mining algorithm, and the particular constraints put on each such algorithm is highly contextualized. Many other algorithms are also similarly contextualized, such as the experiential summarization algorithms in the recommender system example. Thus, much research is needed into what algorithms work, where, and for what purposes. As in all active approaches, there are many space/time tradeoffs that must be resolved. How much pre-computation can be done to find patterns that can then be retrieved quickly when real time response is needed? How can such pre-computation be done before the various contextual elements are known? How much information can be kept around in learner model instances before there is too much information to deal with? Can this information be compressed or deleted or summarized while still allowing finely tuned performance? There are other serious problems to be resolved too. How can the proposed approach still work in the early stages before there has been much learner interaction with the learning objects in a repository (this is a version of the cold start problem faced by many case-based systems)? Obviously, there is a vigorous research agenda that lies ahead. There is also much research needed into the structure of the learner models, the kinds of information that can be gathered, the kinds of information that are useful. After some experience in applying the ecological approach in a wide variety of applications and a diversity of situations, it will perhaps be possible to devise standard learner model slots and slot fillers, and standard ways of using the information in these slots to achieve particular purposes [15]. This would move the standardization efforts away from defining vocabularies of terms with which to index learning objects, to defining standards for learner models to be attached to learning objects and standards for ecological inference procedures. This would allow interoperability and reuse to be achieved even if an external learning object repository were imported.

3. Importance of the Approach:

Learner model information is obtained in a variety of ways: from the learner (through stated availability and self-assessment of knowledge of different topics); from the short peer evaluations; from a determination of whether or not the learner is currently or frequently online; and from observations of learner participation in both the public and private discussions [18]. The public and private discussions may be used together, or the two components may be used independently. Whichever is used, the obvious educational benefit to learners is that those requiring help receive assistance at the time they need it. Furthermore, peers providing help should also benefit from the reflection necessary to formulate an acceptable explanation. A new learner modeling paradigm called active learner modeling is devised in order to focus on issues to do with computing partial learner models in context, rather than with the representation of a comprehensive single learner model. This paradigm fits the agent-based distributed computational environments that are increasingly prevalent in information technology, including educational environments. In the active paradigm, raw information about learners is slowly gathered over time by a number of agents' most importantly personal agents representing learners [17]. The information about any given learner is thus fragmented among many agents. This raw information is then actively interpreted by particular application agents to achieve some purpose. The purpose defines which information is relevant, where to look for it, how to combine it, and what sense to make of it. Not coincidentally the active learner modeling perspective meshes well with the ecological approach. Here, we have focused on defining purpose hierarchies in particular domains and designing modeling algorithms for each purpose. These algorithms are anytime algorithms, in that computation can be stopped at any point as resources and time permits and there will still be some model computed. The more time and resources there are, the more refined will be the model, of course, but in many real world applications, with real time constraints, these will be in limited supply. This investigation has been carried out in a simulated stock investment domain, but the lessons transfer readily to e-learning environments.

4. Implications of the Research:

This approach most naturally supports learner-centered constructivist pedagogical philosophies, although any philosophy could be supported. The focus in the this approach is on learners engaged in authentic learning activities being supported by technology to achieve their goals. Personalization and individualization are desirable, but the approach also supports collaboration and interaction. The collaborative filtering in the approach is a generalization makes use of learner models to capture a broad range of learner characteristics and end use experience. Also, it allows purpose-specific data mining and clustering algorithms to carry out appropriate computations on data relevant to that purpose. This provides a high degree of flexibility to the approach, and allows a wide variety of purposes, not just recommending useful learning material, to be carried out. Another major educational influence on this research is the learning objects movement. The approach draws much from investigations into learning objects, including encapsulating learning resources into objects adorned with metadata, collecting learning objects into learning object repositories, and supporting re-use and interoperability. However, this approach makes several transformations to the standard learning object paradigm. First, the metadata are learner models, rather than terms from standard ontologies [19], and the metadata are added automatically as learners interact with the learning objects. This allows the capture of end use data without the need for a human to pre-attach metadata. Second, this metadata is not given any a priori significance, but is instead actively interpreted in the context of the particular purpose and the particular learner(s) involved. This means that the metadata can mean different things depending on the context. The same learning object could be "about" entirely different things, and have entirely different pedagogical implications, for learners with different goals. Meaning is context-dependent and relative to the purpose at hand. This approach also mandates the development of a different array of computational tools, including tools to clean up the learning object repositories of irrelevant or ineffective learning objects, tools to summarize learner behaviour, tools to abstract commonalities among learner models, procedures to mine and cluster learner model data, tools to prune the information in learner models to a manageable level, etc. The focus of the ecological approach on end use context suggests a different way of supporting learning object re-use, a problem for the standard approach to learning objects. Another aspect of re-use is allowing learning objects to negotiate their interrelationships, essentially making them into learning agents. By having learner models of the actual learners attached to the learning objects (agents) to provide the agents with a wide range of end use information to work with, by having a particular learner or learners represented by personal agents also actively involved in the negotiations, and by having an overriding pedagogical purpose for the negotiations, groups of learning objects (agents) have the potential to adjust themselves specifically to a given situation and set of learners. Learning environments are well suited for the approach: the environment can be constrained to a limited set of learning objects; each learner is engaged over a considerable period of time and so more can be known about him or her as time goes on; it is possible to know many characteristics of learners; and learners are likely to be more willing to state their goal (or be provided with one), to be monitored, to take tests, and to undertake activities under direction and receive advice for the greater good of learning a subject. It is unclear whether the fully open web, where it is hard to know much about users, their goals are hugely varied and always changing, and where they are not usually willing to provide much direct feedback to the system. It is surely a very much more complex situation, but the ecological approach, in principle at least, might still work if enough bandwidth of interaction with users can be gathered and maintained over a long enough time.

5. Conclusion:

This paper has argued that e-learning systems could continuously be adapting as the e-learning system's understanding of its external environment changes and as the external environment itself changes. The external environment includes learners, teachers, the subject matter being learned, and the technology that implements the e-learning system. The adaptation includes the possibility of modifications to the objects in the e-learning system, the possible deletion of some objects, and/or the addition of new objects. Over a period of time, the e-learning system slowly evolves, fine tuning itself to its environment and keeping abreast of change in that environment. The approach proposed here has a number of explicit features: it focuses on end-use; it provides a natural way of capturing end-use information; it has a central role for learners and their goals; it is contextual, where context is most importantly a function of purpose and the people (learners and teachers) involved in the learning situation; it is procedural in its emphasis on the process of making sense of information in context; it has need for knowledge of individual learners but uses this to support all learners and to make system level decisions; it naturally supports constructivist learner-centered pedagogical principles; it allows an e-learning system to incrementally evolve and adapt as its environment changes and as it knows more about the environment. The approach scales well as the number of learners grows; in fact, the more learners, the better this approach is likely to perform. This approach draws inspiration from many research communities, including various e-learning paradigms (especially artificial intelligence in education and learning objects), user modelling, the semantic web, collaborative filtering, data mining, and instructional design. It also suggests a number of new research directions including the study of purposes; the exploration of data mining and clustering algorithms that can find patterns in learners' behaviour; efforts aimed at standardizing these algorithms and standardizing the learner model structure; the exploration of a specific notion of context based on purposes and the people involved in the learning situation; the study of intelligent garbage collection; and deep investigations of computational issues such as computational complexity and space-time trade-offs. Many of these issues are very hard, and it is unclear how widely the ecological approach can be applied, even though the approach seems very promising. The final take-away lesson of this paper is that a valuable direction for research is to look at end-use context and thereby transforming investigations of the semantic web into investigations of the pragmatic web.

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