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# Case-Based Reasoning and Knowledge Management to Improve Adaptability of Intelligent Tutoring Systems

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**Abstract.** Educational Adaptive Hypermedia Systems (AHS) and Intelligent Tutoring Systems (ITS) are capable of producing personalized learning courses that are tailored to various learning preferences and characteristics of the learner. In the past ITS traditionally have embedded experts' knowledge in the structure of its content and applied appropriate design models. However, such systems have continually been criticized for believing that this is sufficient for effective learning to occur [Stauffer 96]. For a tutor who develops such a system there may be many permutations of narrative, concepts and content that may be combined to produce the learner courses. However, the more levels of personalization the system can provide the greater likelihood exists that the system may produce an unexpected or undesired effect. As a tutor it can be difficult to monitor the suitability of the personalized course offerings on an individual learner basis. This paper provides a high level overview of a technique for monitoring personalized course suitability and increasing the quality of delivered courses using low latency CBR and filtering techniques.

## 1 Introduction

Research in Knowledge Management (KM) deals with methods, models and strategies to capture, reuse and maintain knowledge. KM is highly relevant for ITS systems and especially later developments of KM where different methods and techniques from artificial intelligence are included, such as case-based reasoning, clustering and collaborative filtering techniques [Ferrario, Smyth 01].

In adaptive education systems such techniques may be used to deliver personalized courses based on the performance of other users (by the system collected and reused experience). By using a collaborative filtering approach, similar users' preferences, successes and failures may be used to better adapt to current users needs and preferences. These approaches, however, traditionally suffer from a training period before the system can produce accurate recommendations. Techniques such as category based filtering [Sollenborn, Funk 02] may be used if learner models, content models, narrative structures and results from different teaching strategies for individual users are sparse. Such systems tend to offer the users recommendations based on the performance of other users on the system, using stereotyping and clustering techniques.

In expert systems [Brusilovsky 98] there are no latency problems as the personalized course is generated based on rules developed by an expert in the knowledge domain. The more complexity that is built into such rules the more likely it is that the system will produce a course that does not fully cater to the learner's needs. The suitability of a personalized can be determined by examining the learner's feedback, explicit and implicit [Kobsa 93], to the learning system. As a tutor, however, it can be difficult to spot the trends in this feedback and correlating it with the personalized course generated.

A case-based reasoning approach is proposed for identifying and correcting potential problems with personalized courses by matching, reusing, validating and storing cases, where cases may be individual learner models, narratives or individual content models. Producing learner stereotypes and similar concepts, using clustering techniques, and comparing the stereotypes can overcome the latency problem. This paper outlines this approach in the context of an existing research Adaptive Hypermedia Service [Conlan et al, 02].

## 2 Multi-model Adaptive Hypermedia Services

Multi-model Adaptive Hypermedia Services combine information about the learner, domain and content to deliver personalized eLearning courses. These three components are characterized as distinct, and separate, models within the AHS (see Figure 1). The domain or narrative model is responsible for describing the possible combinations of learning concepts that may be assembled to fulfill a learner’s personal learning goals. [Conlan et al, 02] proposes a mechanism that enables the personalized course structures to be described in terms of concepts rather than the pieces of learning content that teach those concepts.

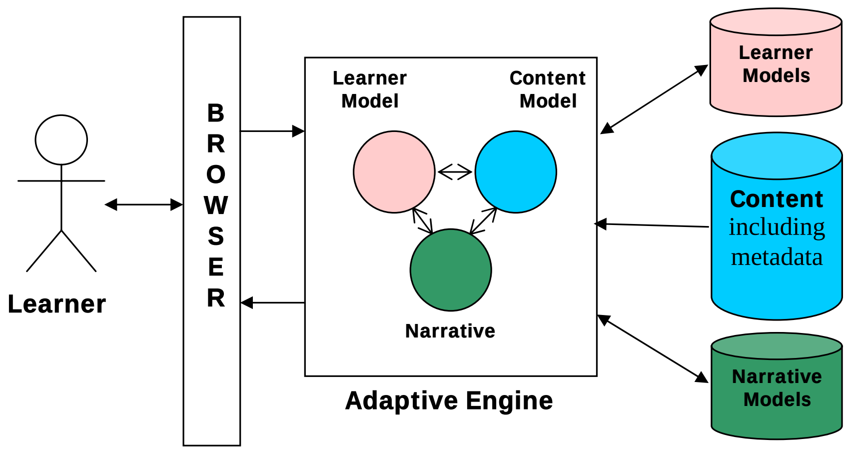


**Fig. 1** Multi-model Adaptive Hypermedia Service

This layer of abstraction (concepts) facilitates the delivery of the most appropriate piece of content to the learner at runtime. For example, if the learner prefers interactive content then a kinesthetic piece of content may be delivered over a non-interactive visual piece of content.

This approach has at least two potential problem areas that the domain expert who designs the narrative may not be able to see –

1. The sequencing of the concepts in the personalized course may not be appropriate for the learner.
2. The piece of content selected to fulfill a concept may not be effective at doing so.

As the narrative models become more complex (or begin incorporating other narrative models) the task of foreseeing and/or diagnosing these problems in the personalized course becomes increasingly difficult for the domain expert. This task is further complicated by the ability to associate multiple base narratives with one course – each narratives produces personalized courses concept sequences that cater to a learning style of the learner.

In these situations it would be desirable to correlate learner feedback (performance on tests, explicit querying, implicit browsing behavior) with the personalized course offerings to determine trends and identify potential problems.

## 3 Improving the Quality of Personalization using CBR

A model is a partially ordered process composed of components (e.g. learning objects) with requirements and results (e.g. required knowledge and learnt knowledge after deployment). Learning objects may have prerequisite requirements (knowledge or competencies the learner is supposed to have) and outcomes (knowledge the learner has acquired after successful completion of the learning object). The full search space may be very large since different parts of the multiple models may be used as input information along with feedback from the learner. CBR systems are able to handle models and processes and are both able to correct problems and reuse parts of models and models in full, se e.g. [Funk 01].

Figure 2, shows an example of how a classical CBR architecture using positive and negative examples from the case library to improve quality of the solution. If the input is an individualized learner model suggested by the system it is compared with other individualized learner model (retrieve in Figure 2). The bad similar cases are analyzed and used to identify where in input model there may be problems. Once these have been identified the good cases are used to modify the input case (reuse experience). The main purpose of the revision is to determine if the proposed solution is good enough, if not, the proposed solution may be given as input to a case-based cycle again until no more improvements are possible. Finally the individualized learner model is stored in the case library when student results are available (to include student's performance). Bad cases may be shown to the tutor who may be able to identify the problem (may be caused by the combination of the current learner and the particular narratives, combination of learner objects, metadata, etc.).

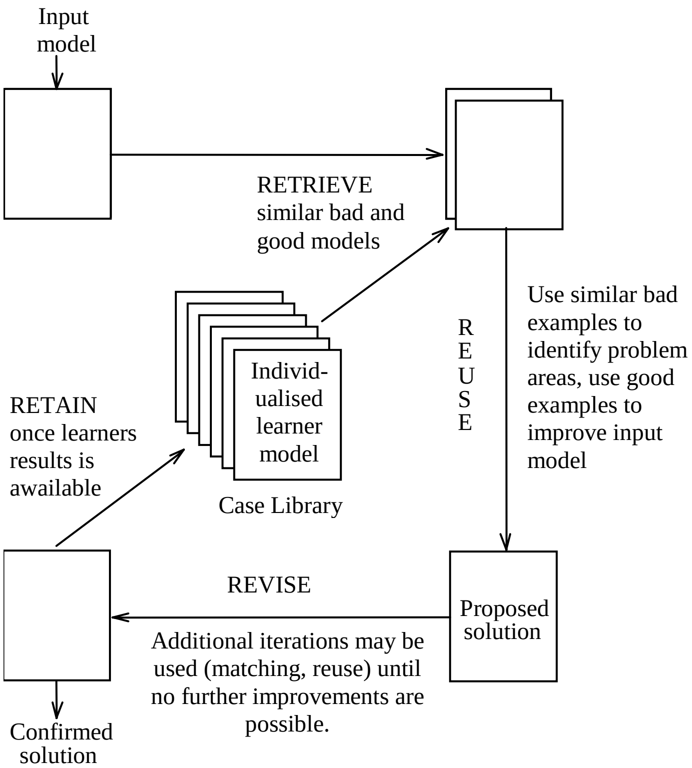


**Fig. 2.** Example of how good and bad cases may be used in improving a solution (modified version of Aamodt and Plazas classical CBR model [Aamodt, Plaza 93]).

If individualized learner models are sparse (few students have completed the course) clustering may be used to create stereotype learners in a similar approach as proposed in [Sollenborn, Funk 02]. This reduces the latency problem and enables reuse of experience at an early stage of a new courses deployment.

## 4 Future Work

The approach described in this paper for improving the effectiveness of adaptive features of ITS/AHS will be implemented by the Department of Computer Science and Engineering, Mälardalen University and the Knowledge and Data Engineering, Trinity College, Dublin. It is hoped that this approach will yield greater and more focused feedback to the author of adaptive courses enabling them to improve the learning experience for the learner.

The proposed implementation will combine the adaptive AHS developed by Trinity College, Dublin [Conlan et al, 02] with the category-based filtering techniques of Mälardalen University, Västerås [Sollenborn, Funk 02] to produce a system that uses the information gathered about learners partaking in personalized courses to produce recommendations to the course author as to how the adaptive features may be better tuned.

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