Chapter 2.22
An Adaptive Predictive Model for Student Learning

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ABSTRACT

This chapter presents an adaptive predictive model for a student modeling prediction task in the context of an adaptive educational hypermedia system (AEHS). The task, that consists in determining what kind of learning resources are more appropriate to a particular learning style, presents two issues that are critical. The first is related to the uncertainty of the information about the student's learning style acquired by psychometric instruments. The second is related to the changes over time of the student's preferences (concept drift). To approach this task, we propose a probabilistic adaptive predictive model that includes a method to handle concept drift based on statistical quality control. We claim that our approach is able to adapt quickly to changes in the student's preferences and that it should be successfully used in similar user modeling prediction tasks, where uncertainty and concept drift are presented.

INTRODUCTION

In the last decade we have attended to an increased development of adaptive educational hypermedia and Web-based systems (AEHS). An AEHS is able to adapt its contents and presentations to specific characteristics of students. The keys for adaptation are the domain model and the student model. The former represents the knowledge about the subjects to be learned and serves as the base for structuring the hypermedia contents. The latter stores different assumptions about the student (e.g., knowledge, preferences, goals, etc.).

An AHES uses the information stored in both models to implement adaptive algorithms and techniques. An extended discussion of adaptive hypermedia, and in particular, AEHSs can be found in Brusilovsky (2001).

Student modeling involves the construction and updating of the student model. Traditionally, most of student modeling systems have been limited to maintain assumptions related with the student's knowledge, which can be acquired during evaluation activities. However, over the last years there has been an augmented interest in modeling other kind of assumptions about the student, such as the learning style and preferences. An AEHS can make use of this kind of information to decide more effectively how to adapt itself to each student individually.

Usually the students' learning style is acquired using one of existing psychometric instruments. By matching a learning style with some relevant characteristics of the learning resources, these systems can determine which resources are most appropriate for a particular student. As a rule, the acquired assumptions about the students' learning style are no longer updated during their interactions with the system. Moreover, the deterministic rules included in their decision models also never change.

There are some typical issues that are critical concerning a successful implementation of the prediction task, that consists in determining what kind of learning resources are more appropriate to a particular learning style in a real student modeling scenario:

1. Although multiple models to categorize the students according to their learning styles have been developed it is difficult to determine how exactly a person learns. Therefore, the information about the student's learning style acquired by psychometric instruments encloses some grade of uncertainty.
2. During the interactions with the system, the student can change his/her preferences for another kind of learning resource that no longer matches with his/her determined learning style. It is because either the acquired learning style information needs to be adjusted or the student simply changes his/her preferences motivated by other unknown reasons (some hidden contexts). This kind of problem is known as concept drift in the machine learning community.

This chapter aims at presenting a new adaptive machine learning approach for the described prediction task. Our approach is based on an adaptive predictive model capable of fine-tuning its parameters to reflect more accurately the student's preferences. Moreover, this also includes a method to handle concept drift (Castillo, Gama, & Medas, 2003). This method uses a P-Chart (Montgomery, 1997), an attribute Shewhart control chart, to monitor the learner's performance over time. Although this drift-detection method is broadly applicable to a range of domains and learning algorithms, we choose Naïve Bayes classifier (Mitchell, 1997), one of the most used learning algorithms in user modelling, as our predictive model. Furthermore, we propose the use of Adaptive Bayes (Gama & Castillo, 2002), an incremental adaptive version of the Naïve Bayes classifier. This algorithm includes an updating scheme that allows better fitting of the current model to new observations. We argue that the proposed adaptive predictive model can be implemented in any AEHS where we need to adapt the presentation based on the student's learning style and preferences. Finally, we claim that our approach should be successfully used in similar user modeling prediction tasks, where uncertainty and concept drift are presented.

The next section reviews some student modeling approaches based on learning styles. We then cover the use of machine learning in user modeling. This section focuses the concept drift problem in concept learning. We present some adaptive learning approaches to deal with concept