Adaptive elearning system using a dynamic user model

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Abstract

Intelligent elearning platforms try to simulate the pedagogical approaches in a classical educational environment. They collect information about the student's profile and guide the learning process such as to obtain the best fit with the student's behavior. Most such systems focus on a set of fixed learning features. They have the advantage of ensuring the congruence between the way the content is presented, and the way students prefer to receive information. However, a better approach would be to guide the student in adapting his/her learning behavior to approach the ideal style. In this paper we propose a model which considers both static and dynamic features when characterizing the student's profile. The intelligent component, based on a Bayesian network, evaluates the user profile continuously, and adapts the content to improve the student's performance. The novelty of our model consists in the way features are used to better model profiles, such as to approach the ideal one.

Index Terms — elearning, learning styles, user profile, adaptive learning, metacognitive strategies, Bayesian network.

1 INTRODUCTION

The purpose of adaptive elearning systems is to increase the student's performance by adjusting the content and interaction methods to users with different interests, initial knowledge and skills. When confronted with the task of defining the user model, the developers of elearning platforms rely on learning theories from educational psychology and pedagogy. There are some habitual ways of identifying user styles such as: answers to psychological tests and behavioural data observed from user interaction with the elearning platforms.

A general template of an intelligent tutorial system is composed by four components: domain knowledge, student knowledge, tutoring knowledge and communication knowledge [17].

Most of the online training systems are based on curricula segmentation, situation in which the students must go through a predefined structure. It is widely acknowledged that the student should be involved actively in the online learning process and that elearning systems should sustain the student's control and organization upon information [8]. Thus, the online training systems should constrain the user less and should be able to adjust on his characteristic learning style. An essential element is anticipating the students' behaviour and adapting the content (both quantitative and qualitative) according to their needs. Thus, the structure of the courses and the segmentation of their presentation must be personalized according to the type of student.

An intelligent system should adjust the content in order to ensure faster learning and better performance. Moreover, it should help student to develop new, desirable learning abilities.

Section two deals with the implication of using the learning style concept for designing adaptive elearning. Section three describes the development of a generic model for elearning design, based on a fixed factors approach. The final section presents an original approach based on the psychological theory in which the learning styles factors are defined by the interaction between the teaching environment and individual factors.

2 IMPLICATION OF THE LEARNING STYLES CONCEPT FOR ADAPTIVE ELEARNING

This section describes the concept of learning style and its implication in designing adaptive hypermedia. Learning style definition, metrics and usage in the field of education are presented, special attention being given to its use in adaptive elearning systems.

2.1 Defining learning styles

In an extended review of literature concerning learning styles, Coffield et al. [3] identified five families of learning styles and models, containing 71 models: constitutionally based learning styles and preferences,
cognitive structure, stable personality type, ‘flexibly stable’ learning preferences, learning approaches and strategies. The linguistic attribute of style implies a stable component over the time, but different theoreticians submit the conclusion that learning styles may be flexible-stable, meaning that they may change under the influence of previous learning experience, teacher influence and environment factors. For the clarity of argumentation, in this paper we refer to the style concept using a two-way classification: fixed factor approach and dynamical (flexible-stable) approach.

When defining styles, authors fundament their assumption using different epistemological ideas.

Grounded in a positivist epistemology, the advocates of fixed factors approach described styles as stable features, which are specific to each individual, and thus they hardly change over time under the influence of environment. One highly cited model in both traditional education and elearning is Witkin [16] - Field Dependence versus Field Independence conceptualization, measuring the influence of surrounding perceptual or contextual field upon the learner's perception.

On the other hand, there are models based on constructivist epistemology, which define the learning style as a highly dynamical concept, evolving from the interaction between relatively stable learning strategies used by students and environmental features (teacher epistemological view, teaching activities and strategies, sociological and cultural factors). An example of dynamical approach is the Vermunt Learning Styles Model [12]. This model is composed by four elements: two relatively stable, because they change slowly over time (epistemological views and learning orientation), and two highly dynamic, because they continuously change over time, due to the teacher's interventions (modelling and control of teaching content and strategies). The Vermunt Learning Style Inventory provides measures for this model by classifying students in four learning styles: meaning-directed, reproduction-directed, application-directed and undirected.

Vermunt [15] considers that teaching has the purpose of guiding the student in choosing between different learning strategies (memorizing, analyzing information, structuring and relating concepts, critically processing the information, concrete processing of information). Another dynamic component of the model is the regulation strategies, described as methods used by students for controlling the learning process. If we take in consideration the author view on didactic strategies as the mirror reflection of student processing strategies, we observe that the teacher has repertoires of teaching activities and strategies adapted for each learning strategy: for memorizing - the teacher provides a list for the most important concepts to learn, for relating - the teacher explains the relationship between separate parts of theory, for concrete processing - the teacher provides more examples. By choosing a specific teaching strategy, the teacher will influence the ways in which students interact with the educational content, and specifically the learning strategies used by them.

2.2. Strengths and weaknesses of using the learning style concept

The learning style concept has been intensively researched due to the assumption that the information regarding the student learning habits could be exploited to increase the learning performance. The strengths and weaknesses of the learning style concept are strongly related to this claim.

The strengths derive from the main argument that knowing the student learning habits, teachers will adjust their actions to improve the learning outcome. Weaknesses originate in the lack of empirical evidence to sustain this claim. Furnham, Jackson and Miller [4] find a minor influence (8% of variance explained) of the learning style and personality factors on the performance of learners.

Defining learning styles is important for both the student and the teacher. Learning style concept measurements provide means that enable the student to identify his strengths and weaknesses. The teacher uses this concept to elaborate teaching contents adapted to the student's style [3]. Starting from this point, there appears the controversial issue regarding the use of learning styles, namely matching or mismatching the teaching content to the student's style. Matching has stronger advocates between fixed factor researches and implies that prediction of the student's learning outcome can be made using a reliable and valid measurement of a learning type. The supporting evidence for this claim is questionable; Smith, Sekar and Townsend [11] find an equal numbers of studies (9), which demonstrate both efficiencies and inefficiencies of matching. Fixed factor approach is criticized for its potentially harmful consequences (labelling and the idea that type is innate and hard to modify).

There are advocates of the flexible style
approach who propose a deliberate mismatching between teaching and student style. Vermunt [13] defines two basic interaction modes between teacher control and student regulation of learning strategies. Congruence between teaching and learning occurs when students’ learning strategies match the teacher strategies. Friction occurs in case of a mismatch between teaching and learning. In the latter case, the author suggests the terms constructive friction (when mismatching leads to augmenting student learning strategies which are currently underdeveloped) and destructive friction (when the teacher imposes learning strategies which deteriorate the learning outcome and the strategies used by students). The aim is the development of learning styles in order to obtain better performance in the learning process. Teacher actions need to be focused on the progress of the student’s learning style: from an undirected and reproduction directed style to a meaning and application directed style.

Another critique addressing some learning style theories is the high and sometime unrealistic demands imposed to the teacher. If a teacher interacts with a class of students, he/she doesn’t have the opportunity to match every student type (teacher will have to match the content to visual, verbal, concrete, deductive reflective etc.).

The final weakness derives from the measurement made in order to identify learning styles. The subjective student judgments are statistically processed for calculating styles that are error prone.

2.3 Measuring learning styles
The main methods for measuring learning styles are test and inventories, interviews with the students and observing student behaviour during teaching and learning activities.

One of the critiques of fixed factor approach is that it relies too much on scores obtained as an objective test. In traditional education, the teacher can observe student behaviour and correlate the data such as to improve that score.

To overcome the limitation imposed by subjective answers to tests, in the elearning domain there are recent developments that calibrate the user learning type by collecting and analyzing behavioural data recorded during the user navigation in the elearning environment.

2.4. Implication of learning style concept for designing adaptive elearning systems
In traditional education, many of the prescriptions formulated by learning style theories put teacher in a difficult posture when adaptation is required. The intelligent tutors, designed for automatic adaptation of the content to the learning style, overcome this issue because they are able to provide learning material for every particular mode of student perception, representing or transforming information.

In a review made by Papanikolau and Grigoriadou [9] the researchers’ effort to design, adaptive elearning systems are grouped in the following directions: providing adaptive presentation and curriculum sequencing, adaptive navigation support and adaptive collaboration support.

Regarding learning style measurement, there are several strategies for detecting and identifying styles [1], [2], [5]. Based on monitoring user behaviours, the automatic mechanisms use genetic algorithms and data mining techniques to classify and identify students’ learning styles.

Mitchel, Chen and Macredie [8] use the field independent (FI) versus field dependent (FD) learning style classification for designing hypermedia interfaces adapted to styles. They conclude that matching the content to style is not necessarily better than mismatching, and that a specific presentation of content may restrict users from doing what they prefer. Using a data mining technique, Lee & co. [2] classify users in FD/FI styles by calibrating the answers from the cognitive styles analysis with user behaviour.

eTeacher [10] is an intelligent agent, which automatically evaluates a learning style profile from the observations of student actions and the analysis of log files. Using Felder’s and Silverman’s conceptualization of learning styles, eTeacher provides specific assistance actions to users with different learning styles. For a sensitive user, the agent recommends that the student should do more exercises or study more examples.

Because there are so many learning styles models, it is difficult to trace the use of every model in the elearning domain. However, the most examined learning style is the Witkin [16] Field Dependence concept. This model belongs to the fixed factor classification presented at the beginning of the chapter.

The majority of elearning researchers adopt the fixed factor approaches to learning styles because of the following advantages: it is easy to determine learning styles; there exist rules for fitting content to particular styles and the promise that if the matching method is used, the student-learning outcome will improve.
This isn’t always the case, even though the fixed factors measured by tests are calibrated by comparing the user interaction with the system.

The advocates of dynamic learning strategies are fewer, because it is difficult to design a user model in which all the parameters are permanently changing over time. However, the advantages of this model are:

- It overcomes the limitation of labelling, and allows the user to develop a better learning style, thus producing better learning outcomes.
- In order to do so, the system might use both matching, if the student has a learning style that improves learning outcomes and mismatching when the important learning strategies are missing from the student profile.

In the following section, we present our approach for an adaptive elearning system, based on a highly dynamical user model. The development of the model is made in two steps. Initially, a generic model for the fixed factors is defined, approach which incorporates many researches made in the field of fixed factor paradigms. Its goal is to better illustrate the improvements proposed by the second model based on highly dynamic models of learning styles (we exemplify using the Vermunt model).

3 ADAPTING ELEARNING ENVIRONMENT BASED ON A RELATIVELY FIXED LEARNING STYLES

In order to elaborate a generic model for designing adaptive elearning systems, we use the classification of intelligent tutor components provided by Woolf [17]: domain knowledge, student knowledge, tutoring knowledge and communication knowledge. To simplify the model we grouped the last two components into a single factor named tutoring knowledge. The model of a fixed factor approach is presented in figure 1.

It consists of four main components: the teacher model, composed by domain knowledge and teaching strategies, the user or student model, the intelligent tutoring model and the evaluation model. The main purpose of the system is to provide adaptive content and interface with the student in order to improve the learning outcome. The teacher model has many parameters such us: content volume, difficulty, number of exercises, the amount of time for presenting content, the balance between theory and example, different ways of representing content [6].

![Figure 1. A generic model for an adaptive elearning system using relatively fixed learning styles](image)

The adaptive property of an intelligent elearning system refers to the behaviour of the user model, based on the input provided by the intelligent component (a Bayesian network in our model). The adjustments depend on the student’s particularities. Different features are collected from an initial psycho-pedagogical pretest, and from the interaction with the system. The former features characterize the stable part of the profile, providing an initial profile, while the later ones form the dynamic component, used during the continuous calibration. This information represents the input for the intelligent module, which outputs the user profile. Consequently, the student’s type changes, and the content is adapted accordingly. The intelligent tutor module (IT) has the following functions: measures the learning styles, monitors the student behaviour, predicts the updated learning styles, adapts content to styles and evaluates student knowledge.

The IT module is responsible for deciding which particular template will be presented to the user, thus controlling the content. The IT also monitors user behaviour and predicts the user type. The main function of the IT is to adapt previously designed content to continuing changing style in order to improve the learning outcome. The main goal of the IT module is the evaluation, which informs the system about the student’s evolution. The user model is informed by three sets of data: learning style data, user behaviour and user knowledge. The first type of data are the most stable one (most of the
researchers in the field of adaptive elearning systems used learning styles concepts to measure fixed factors - personality or cognitive styles. Recent evaluations show that this component has become more dynamic due to the user interaction with the system [5], [10]. This way, initial classification based on the answers provided to specific questions is calibrated with the user behaviour during the user's interaction with the learning activities. This calibration is made using inference rules derived from Bayesian networks, decision trees, neural networks or other data mining techniques.

In the time line described in fig 1, user enters the system at t0 and receives a learning style inventory that constitutes an initial categorization: user is style Slsk (k=1..n). At that moment, the system has a predefined template for this type of user, Ctk, which is presented to him. During the navigation, the intelligent module collects the user's behaviour. Based on this information, after a set of lessons, in moment tn the system calibrates the student learning style type (comparing Slsk with Sb1..n) resulting an updated learning styles STupk.

In a simplified causal model, the process of matching the content (Ctk is matched to STupk) is the cause (independent variable) for improving learning outcomes (effect - dependent variable).

Even though the adaptive function is based on a relatively dynamic user model (by performing calibration between learning style tests and user behaviour), the initial categorization is made using a fixed factor. Because of this, psychological theory imposes a constraint to use a simple matching approach (between content and style). The drawback of the matching approach, based on the more stable part of the profile, is that the content is rigid, narrowed by the particular type, thus evolution is limited. They serve only the aim of increasing learning outcomes and do not try to modify (i.e. improve) the user's learning style.

4 Adapting eLearning Environment Based on a Relatively Dynamic Learning Styles

We have developed a generic model for designing adaptive elearning contents, using the learning style concept definition grounded in a dynamical (flexible stable) approach. The intelligent decisions made by such elearning system will be guided by the data collected in a highly dynamic user model that is changing over time in terms of both knowledge and learning styles.

Figure 2 presents a generic model for an adaptive elearning system. Its intelligent agent defines rules based on both matching and mismatching between teaching strategies and learning styles.

By comparing figure 1 with figure 2, it is observed that there are two new elements. The Sd element is part of the student knowledge (student learning styles developed) and the mismatching component is part of the tutoring knowledge.

In a fixed factor approach (figure 1), student style categorization remains the same (even though it is improved by calibration). In a dynamic approach (figure 2), the learning style categorization will be changed by specific actions made by the elearning system. This approach is based on assumptions that the student learning strategies will change according to the decisions made by intelligent agents from the tutoring module.

Mismatching is a method similar to the concept of constructive friction proposed by Vermunt, designed with the purpose of developing student-learning styles (a new function of intelligent tutoring module).

The advantages of such an approach are:

1) it first supplies matching content, for smoothing the learning process, then continues with mismatching, to bring the
student closer to the desired profile. This way, the student will develop skills that proved to be efficient in the learning process.  

2) Considering that the cognitive and metacognitive strategies the student is using depend on teacher's pedagogy, it is necessary that an intelligent tutor provide content, and interaction modes, designed to enhance student's strategies. This helps in developing a dynamic student model: starts with the initial evaluation, and dynamically updates, as the student evolves.

Following Vermunt Scales [9], we present some examples of possible rules:  

(a) if the student isn't able to identify a relation between two theories (scale relating and structuring), then the system will provide those explanations / a case of mismatching between learning type and learning content proposed by the system.  
(b) if a student has a high score on concrete processing of information, meaning that he is able to give personal examples for the theories learned, the system will give him fewer examples when the theory is presented;  
(c) if a student is able of regulating his own learning process – then the system will provide fewer quizzes during the learning of the lesson (matching)  
(d) if a student is externally regulated, then the system will provide a number of clear objectives and quizzes that will decrease after some period. This represents an example of initial matching followed by a mismatching because that student will have to develop his own regulating strategies.  
(e) if a student lacks regulation strategies, the system will take maximal control over the user content presentation and navigation, providing clear instructions, less material, more feedback and more quizzes during the learning cycle.

In the model presented in figure 2, the learning styles represent both the cause for the learning outcomes and the effect of the student's interaction with the adaptive content.

4 Conclusion

We propose a model that considers both static and dynamic features for characterizing the student's profile. The strength of the adaptive elearning model is based on the intelligent agent that defines rules based on both matching and mismatching between teaching strategies and learning styles. It is continuously evaluating the user's profile, and adapts the content to improve the student's performance. The novelty of our model consists in the way features are used to better model profiles, such as to approach the ideal one.

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References

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