Chapter XI
Diagnosing Students' Learning Style in an Educational Hypermedia System

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ABSTRACT

Individualizing the learning experience for each student is an important goal for educational systems and accurately modeling the learner is the first step towards attaining this goal. This chapter addresses learner modeling from the point of view of learning styles, an important factor for the efficiency and effectiveness of the learning process. A critical review of existing modeling methods is provided, outlining the specificities and limitations of current learning style based adaptive educational systems (LSAES). The controversy regarding the multitude of partially overlapping learning style models proposed in the literature is addressed, by suggesting the use of a complex of features, each with its own importance and influence (the so called Unified Learning Style Model). An implicit modeling method is introduced, based on analyzing students' behavioral patterns. The approach is validated experimentally and good precision rates are reported.

INTRODUCTION

Accommodating the individual needs of the learner is an important goal of today's e-learning, whether it implies disabilities, a different knowledge level, technical experience, cultural background or learning style. This is also one of the advantages of web-based education versus traditional, face-to-face learning: the increased potential of providing individualized learning experiences.

In order to be able to optimize and facilitate students' interaction with a web-based educational system, one must first decide on the human factors that should be taken into consideration and identify the real needs of the students.

The focus of this chapter is on learning style as the human factor, since it is one of the individual differences that play an important role in learning, according to educational psychologists. Learning style refers to the individual manner in which a person approaches a learning task. For example, some learners prefer graphical representations and remember best what they see, others prefer audio materials and remember best what they hear, while others prefer text and remember best what they read. There are students who like to be presented first with the definitions followed by examples, while others prefer abstract concepts to be first illustrated by a concrete, practical case study. Similarly, some students learn easier when confronted with hands-on experiences, while others prefer traditional lectures and need time to think things through. Some students prefer to work in groups, others learn better alone. These are just a few examples of the many different preferences related to perception modality, processing and organizing information, reasoning, social aspects etc, all of which can be included in the learning style concept.

Research on the integration of learning styles in educational hypermedia began relatively recently and only a few systems that attempt to adapt to learning styles have been developed. Consequently, "it still is unclear which aspects of learning styles are worth modeling and what can be done differently for users with different learning styles" (Paredes & Rodríguez, 2004, pp.211). However scientists agree that taking these student characteristics into account can lead to an increased learning performance, greater enjoyment, enhanced motivation and reduced learning time (Kelly & Tangney, 2006). We therefore believe that accommodating learning styles in adaptive educational hypermedia is a worthwhile endeavor.

The first step towards providing adaptivity is selecting a good taxonomy of learning styles. Most of the educational systems developed so far rely on a single learning style model, such as those proposed by (Felder & Silverman, 1988), (Honey & Mumford, 2000), (Biggs, 1987) or (Witkin, 1962). In this chapter we advocate the use of a unified learning style model (ULSM), which integrates characteristics from several models proposed in the literature.

The second step is suggesting a method for identifying the learning style of the student. The traditional diagnosing approach implies having the students fill in a dedicated psychological questionnaire. What we propose in this chapter is an implicit modeling method, which is based on the analysis and interpretation of student behavior in the educational system.

Furthermore we address questions such as: What learning style characteristics should be diagnosed and adapted to? How can we create a quantitative model of complex psychological constructs? What type of information is needed from students' behavior to identify their learning preferences?

Our approach was applied in a dedicated e-learning platform called WELSA (**W**eb-based **E**ducational system with **L**earning **S**tyle **A**daptation). The analysis of the student behavior, together with the diagnosing rules, are implemented in a built-in "Analysis tool".

We start this chapter by briefly introducing the concept of learning styles. The background section also includes a short review of the methods that have been proposed in the literature for learning style diagnosis: while the majority of the current learning style based adaptive educational systems (LSAES) use dedicated psychological questionnaires for identifying the learning preferences of the students, there are some systems that also use an implicit modeling method, based on analyzing the behavior of the students in the system.

The third section deals with our own approach for implicitly diagnosing student learning preferences included in ULSM. First the ULSM model is succinctly described, next relevant patterns of behavior are associated to each learning preference and finally the learning preferences are identified using a rule-based modeling method.

The approach is validated empirically, with the help of a 71 undergraduate student sample who interacted with our WELSA system. The results of the experiment are evaluated and discussed in section 4.

The last section of this chapter includes some concluding remarks and points towards future research directions.

BACKGROUND

A distinct feature of an adaptive system is the user model it employs, i.e. a representation of information about an individual user. User modeling is the process of creating and maintaining an up-to-date user model, by collecting data from various sources, which may include: i) implicitly observing user interaction and ii) explicitly requesting direct input from the user (Brusilovsky & Millan, 2007). User modeling and adaptation are strongly correlated, in the sense that the amount and nature of the information represented in the user model depend largely on the kind of adaptation effect that the system aims to deliver. Regarding the information contained in the user model, there are identified six features: knowledge, interests, goals, background, individual traits and context of work. In case of adaptive educational hypermedia systems, the learner's knowledge of the subject being taught is the most widely used student feature. More recently, the learning style of the student also started to be taken into account, as being one of the individual traits that play an important role in learning.

Learning style designates everything that is characteristic to an individual when she/he is learning, i.e. a specific manner of approaching a learning task, the learning strategies activated in order to fulfill the task. According to a widely accepted definition given by (Keefe, 1979), learning styles represent a combination of characteristic cognitive, affective and psychological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment.

There has been a great interest in the field over the past 30 years which led to the proliferation of proposed approaches. (Coffield et al., 2004) identified 71 models of learning styles, among which 13 were categorized as major models, according to their theoretical importance, their widespread use and their influence on other learning styles models. Some of these models have started to be used also in a special case of adaptive educational systems, called LSAES, which focus on students' learning preferences as the adaptation criterion. LSAES present several particularities, related to the large variety of learning style models that can be adopted and the inherent difficulty and subjectivity of the categorization. These systems differ in several aspects: underlying learning style model, diagnosing method (implicit or explicit), modeling techniques (rule-based approach, data mining, machine learning techniques), number of modeled student characteristics besides learning preferences (knowledge level, goals) and the type, size and conclusions of the reported experiments.

In what follows we will focus on the methods used for learner modeling and we classify the systems in two categories: i) those that use questionnaires for identifying the learning style and ii) those that use students' observable behavior.

Explicit Modeling Method

The first adaptive educational systems that dealt with learning styles as adaptation criterion relied on the measuring instruments associated to the learning style models for diagnosing purposes. The main advantage of this method is its simplicity: the teacher / researcher only has to apply a dedicated psychological questionnaire, proposed by the learning style model creators. Based on the students' answers to the questions, a preference towards one or more of the learning style dimensions can be inferred. The main disadvantages of this questionnaire-based approach are:

- some of the measuring instruments used could not demonstrate internal consistency, test–retest reliability or construct and pre-

dictive validity, so they may not be totally reflective of the way a particular student learns (Coffield et al., 2004)
- it implies a supplementary amount of work from the part of the student, who has to fill in questionnaires at the beginning of the course (which sometimes may include over 100 questions, as in case of the Hermmann's Whole Brain Model (Herrmann, 1996))
- it can be easily "cheated" by the students, who may choose to skip questions or give wrong answers on purpose
- there can be non-intentional influences in the way the questions are formulated, which may lead the students to give answers perceived as "more appropriate"
- it is difficult to motivate the students to fill out the questionnaires; especially if they are too long and the students are not aware of the importance or the future uses of the questionnaires, they may tend to choose answers arbitrarily instead of thinking carefully about them
- it is static, so the student model is created at the beginning of the course and stored once and for all, without the possibility to be updated.

A method of improving this approach is to give the student the possibility to modify her/his own profile, if she/he considers that the one inferred from the questionnaire results is not appropriate (does not correspond to the reality). This is called an "open model" (scrutable and modifiable) approach and it is used either in conjunction with the questionnaires or instead of them. This direct access of students to their own learner model has several advantages: it provides an increased learner control, it helps the learners develop their metacognitive skills and it also offers an evaluation of the quality of the model created by the system (Kay, 2001). The main disadvantages of this approach are that it increases the cognitive load of the student and that it must rely on the self-evaluation of a student who might not be aware of her/his learning style.

Examples of systems that use this explicit modeling method are:

- CS383 (Carver et al., 1999) – uses the Index of Learning Styles dedicated questionnaire (Soloman & Felder, 1998) in order to assess 3 constructs of the Felder-Silverman model (FSLSM): sensing/intuitive, visual/verbal, sequential/global (Felder & Silverman, 1988)
- AES-CS (Triantafillou et al., 2003) – uses a Group Embedded Figures Test questionnaire at the beginning of the course, in order to assess the field dependence/field independence characteristic of the learner (Witkin, 1962).
- (Bajraktarevic et al., 2003) – uses the Index of Learning Styles questionnaire in order to assess the sequential/global dimension of the Felder-Silverman learning style model.
- INSPIRE (Papanikolaou et al., 2003) – is based on Honey and Mumford (2000) learning style model. The prevalence of the Activist, Pragmatist, Reflector or Theorist dimension is identified either by applying a dedicated questionnaire or by student's self-diagnosis, since students can directly manipulate and modify the learner model.
- Feijoo.net (Paule et al., 2003) - uses the CHAEA Test (Alonso et al., 2002) for classifying the students in one of the four learning styles it proposes: Active, Reflective, Theoretical, and Pragmatic (inspired by the Honey and Mumford learning style model)
- SACS (Style-based Ant colony system) (Wang et al., 2007) - is based on the VARK style (Flemming, 1995), which is identified by means of a dedicated questionnaire or input by the student.

Implicit Modeling Method

There is also a second category of systems, which use an implicit and/or dynamic modeling method. Three different approaches have been identified in this respect:

- analyze the performance of the students at evaluation tests - a good performance is interpreted as an indication of a style that corresponds to the one currently estimated and employed by the system, while a bad performance is interpreted as a mismatched learning style and triggers a change in the current learner model
- ask the students to provide feedback on the learning process experienced so far and adjust the learner model accordingly
- analyze the interaction of the students with the system (browsing pattern, time spent on various resources, frequency of accessing a particular type of resource etc) and consequently infer a corresponding learning style.

Sometimes, these systems use a mixed modeling approach: they first use the explicit modeling method for the initialization of the learner model and then the implicit modeling method for updating and improving the learner model.

Some examples of systems in this implicit modeling category include:

- Arthur system (Gilbert & Han, 1999) uses Auditory, Visual and Tactile learning preferences (basically a VAK learning style model). It divides the courses in concepts; when the user has finished with the first concept which was presented using a learning style that was chosen at random, the system assesses the student's success, and if this is not higher than 80%, the system changes her/his learning style.
- iWeaver (Wolf, 2002) – is based on the Dunn and Dunn learning style model (1992), including five perceptual (Auditory, Visual – Pictures, Visual – Text, Tactile Kinesthetic, Internal Kinesthetic) and four psychological learner preferences (Impulsive, Reflective, Global, Analytical). When the learner first enters the environment, they fill in the Building Excellence Survey. Then the learner is given an explanation of their assessed learning style and recommendations on a media representation for the first content module and also the option to choose another media representation than the one that was recommended for their style. Also, after each module, the learner is asked for feedback on the media representations they encountered and for a ranked rating, which is used to adjust the learner model.
- TANGOW (Paredes & Rodriguez, 2004) – is based on two dimensions of FSLSM: sensing/intuitive and sequential/global. Learners are asked to fill in the ILS questionnaire when they log into the system for the first time and the student model is initialized correspondingly. Subsequently the student actions are monitored by the system and if they are contrary to the behavior expected for that learning preference, then the model is updated. The student observed behavior is restricted to four patterns, each corresponding to one of the four possible FSLSM preferences.
- Heritage Alive Learning System (Cha et al, 2006) – is based on Felder-Silverman learning style model. Learning preferences are diagnosed implicitly, by analyzing behavior patterns on the interface of the learning system using Decision Tree and Hidden Markov Model approaches.
- EDUCE (Kelly & Tangney, 2006) - is based not on a learning style model but on Gardner's theory of multiple intelligences (MI), using 4 types: logical/mathematical, verbal/

linguistic, visual/spatial, musical/rhythmic (Gardner, 1993). The student diagnosis is done both dynamically (by analyzing the student's interaction with MI differentiated material and using a naïve Bayes classification algorithm) and statically (by applying a Shearer's MI inventory (Shearer, 1996)).

- The system presented in (Stathacopoulou et al., 2007) - is based on Biggs' surface vs. deep student approach to learning and studying (Biggs, 1987). The student diagnosis is done by means of a neural network implementation for a fuzzy logic-based model. The system learns from a teacher's diagnostic knowledge, which can be available either in the form of rules or examples. The neuro-fuzzy approach successfully manages the inherent uncertainty of the diagnostic process, dealing with both structured and non-structured teachers' knowledge.
- AHA! (version 3.0) (Stash, 2007) – uses the notion of "instructional meta-strategies" (inference or monitoring strategies), which are applied in order to infer the learner's preferences during her/his interaction with the system. A meta-strategy can track student's learning preferences by observing her/his behavior in the system: repetitive patterns such as accessing particular types of information – e.g. textual vs. visual form or navigation patterns such as breadth-first versus depth-first order of browsing through the course. These meta-strategies are defined by the authors, who can therefore choose the learning styles that are to be used as well as the adaptation strategy. However, there is a limitation in the types of strategies that can be defined and consequently in the set of learning preferences that can be used, so these strategies cannot completely replace existing psychological questionnaires.
- (Garcia et al., 2007) – is based on three dimensions of the FSLSM (active/reflective, sensing/intuitive, and sequential/global). The behavior of students in an educational system (called SAVER) is observed and the recorded patterns of behavior are analyzed using Bayesian Networks.
- (Graf, 2007) – is based on the FSLSM. The actions of the students interacting with Moodle learning management system (Moodle, 2008) are recorded and then analyzed using a Bayesian Network approach as well as a rule-based approach. Since the accuracy of the diagnosis was better in the latter case, the rule-based approach was implemented into a dedicated tool called DeLeS, which can be used to identify the learning style of the students in any LMS.
- The system presented in (Sangineto et al., 2008) - is based on Felder-Silverman learning style model, and uses fuzzy values to estimate the preference of the student towards one of the four categories (Sensing-Intuitive, Visual-Verbal, Active-Reflective, Sequential-Global). Initially, the system offers to the learner the possibility to use the Soloman and Felder's psychological test or to directly set the values of the category types, choosing an estimated value for each category (using a slider-based interface). Also, for those people who do not want or are not able to estimate their own learning styles, the system sets the initial values of all the category types to 0.5, which means that the student is initially evaluated as indifferent with respect to any learning style preference. Next the learning style is automatically updated by the system taking into account the results obtained by the students at the multiple-choice tests presented at the end of each learning phase.

AN AUTOMATIC IDENTIFICATION METHOD FOR STUDENTS' LEARNING STYLE

Towards a Different Approach

The novelty of our approach consists in the proposal of a *Unified Learning Style Model (ULSM)*, specifically adapted for e-learning use. This model was conceived to include learner characteristics from various traditional learning styles models, which meet three conditions:

- have a significant influence on the learning process (according to the educational psychology literature)
- can be used for adaptivity purposes in an educational hypermedia system (i.e. the implications they have for pedagogy can be put into practice in a technology enhanced environment)
- can be identified from student observable behavior in an educational hypermedia system: i) navigational indicators (number of hits on educational resources, navigation pattern); ii) temporal indicators (time spent on different types of educational resources proposed); iii) performance indicators (total learner attempts on exercises, assessment tests) (Papanikolaou & Grigoriadou, 2004). Indeed, not all of the characteristics included in a classic learning style model can be identified through an educational hypermedia system, nor can they be used for adaptation.

In this context, our intention is to offer a basis for an integrative learning style model, by gathering characteristics from the main learning styles proposed in the literature. We can thus summarize learning preferences related to:

- perception modality: visual vs. verbal
- processing information (abstract concepts and generalizations vs. concrete, practical examples; serial vs. holistic; active experimentation vs. reflective observation, careful vs. not careful with details)
- field dependence vs. field independence
- reasoning (deductive vs. inductive)
- organizing information (synthesis vs. analysis)
- motivation (intrinsic vs. extrinsic; deep vs. surface vs. strategic vs. resistant approach)
- persistence (high vs. low)
- pacing (concentrate on one task at a time vs. alternate tasks and subjects)
- social aspects (individual work vs. team work; introversion vs. extraversion; competitive vs. collaborative)
- coordinating instance: affectivity vs. thinking

The above learning preferences were included in ULSM based on a systematic examination of the constructs that appear in the main learning style models and their intensional definitions. In case of similar constructs present under various names in different models, we included the concept only once, aiming for independence between the learning preferences and the least possible overlap. A detailed description of this model together with the justification of its use can be found in (Popescu et al., 2007; Popescu, 2008b) and are outside the scope of this chapter.

Of course, learning is so complex that it cannot be completely expressed by any set of learning style dichotomies (Roberts & Newton, 2001). Therefore we do not claim that our model is exhaustive; we argue however that the above set of characteristics is a first step towards building an integrative model and establishing a unified core vocabulary.

Furthermore, the modeling method that we propose based on this integrator model has several advantages:

- it is an implicit modeling method, based on the direct observation and analysis of learner behavior, thus avoiding the psychometric flaws of the measuring instruments
- it is a dynamic modeling method, based on continuous monitoring and analysis of learner behavioral patterns
- it is a feature-based modeling method (at the level of basic learning preferences) rather than a stereotype-based modeling (at the level of traditional learning style models). In turn, this offers the possibility of finer grained and more effective adaptation actions.

The systems that are closest to our approach among those presented in the previous section are those that identify the learning styles by analyzing the interaction of the students with the educational system, in the form of behavioral patterns, namely (Cha et al., 2006), (Garcia et al., 2007) and (Graf, 2007). The main advantages of our approach versus these related works are:

- All three related systems use the Felder-Silverman learning style model, while we use a combination of learning styles (i.e. ULSM)
- The number of patterns of behavior that are taken into account in our WELSA system is larger (i.e. 11 patterns in (Garcia et al., 2007), 39 in (Graf, 2007) and 58 in (Cha et al., 2006) versus over 100 in WELSA) which should imply a higher precision of the learning style diagnosis (as we will see in section 4). This large number of patterns is due to the fine granularity of the learning objects composing the WELSA courses, which allows for a rich and precise annotation, as detailed in (Popescu et al., 2008).

The methods used for learning style identification are also different: Decision Trees and Hidden Markov Models in case of (Cha et al., 2006), Bayesian networks in case of (Garcia et al., 2007) and a rule-based approach in case of (Graf, 2007). It should be also noted that (Graf, 2007) deals with an existing learning management system (Moodle) that was enhanced with modeling and adaptation capabilities, while our work is based on our own adaptive educational hypermedia system (WELSA), that we have built from scratch.

This implicit modeling method presents a challenge, in that it is difficult to determine what are the learner actions that are indicative for each of the learning preferences included in ULSM. This is why we performed two experimental studies, trying to identify correlations between students' patterns of behavior and their learning preferences. The results were reported in (Popescu, 2008; Popescu et al., 2009).

More specifically, the behavioral patterns that we took into account in our analysis refer to:

- Educational resources (i.e. learning objects - LOs) that compose the course: time spent on each LO, number of accesses to an LO, number of skipped LOs, results obtained to evaluation tests, order of visiting the LOs. For each LO we have access to its metadata file, including information regarding the instructional role (e.g. *'Definition', 'Example', 'Exercise', 'Interactivity', 'Illustration'* etc), the media type (e.g. *'Text', 'Sound', 'Image', 'Video'*), the level of abstractness and formality etc.
- Navigation choices: either linear, by means of the "Next" and "Previous" buttons or non-linear, by means of the course Outline
- Communication tools: a synchronous one (chat) and an asynchronous one (forum) – time, number of visits, number of messages.

Based on the results obtained, as well as similar findings from the literature, we conceived a set of rules for learner modeling and used them to actually diagnose students' ULSM preferences, as detailed in the next subsections.

Definitions and Notations

Please note that in order to illustrate the generality of our approach, we will consider only a subset of ULSM (let's call it ULSM'), in which we included only those learning preferences that could be identified from widely available patterns of behavior (i.e. patterns that can be derived from any educational hypermedia system):

- Visual preference / Verbal preference
- Abstract concepts and generalizations / Concrete, practical examples
- Serial / Holistic
- Active experimentation / Reflective observation
- Careful with details / Not careful with details
- Individual work / Team work

Formally, let *L* be a learner and let *Pref*(*L*) be the set of learning preferences that characterize learner *L*. In the context of our work, *Pref*(*L*) ⊂ *Pref_ULSM'*, where *Pref_ULSM'* is the set of learning preferences included in ULSM'. Specifically, *Pref_ULSM' = {p_visual, p_verbal, p_abstract, p_concrete, p_serial, p_holistic, p_activeExperimentation, p_reflectiveObservation, p_carefulDetails, p_notCarefulDetails, p_individual, p_team}* (meaning of each preference obviously results from its name). It should be noted that the preferences in *Pref_ULSM'* are grouped on several dimensions, each with two opposite axes: *p_visual* ↔ *p_verbal; p_abstract* ↔ *p_concrete* etc. Let *Dim_ULSM' = {p_visual / p_verbal, p_abstract / p_concrete, p_serial / p_holistic, p_activeExperimentation / p_reflectiveObservation, p_carefulDetails / p_notCarefulDetails, p_individual / p_team }*. Thus a student can only exhibit one of the two opposite preferences, e.g. if *p_visual* ∈ *Pref(L)* then *p_verbal* ∉ *Pref(L)*.

Furthermore, the student can have a level of intensity associated to each preference (either mild, moderate or strong preference). Let C be one of the characteristics in ULSM'. Let us denote by $\tilde{C}$ the opposite characteristic in ULSM'. Thus for each dimension $C/\tilde{C}$ ∈ *Dim_ULSM'* we can have $Val_{C/\tilde{C}} \in \{-3, -2, -1, 1, 2, 3\}$, where positive values imply a preference towards the C axis and negative values imply a preference towards the $\tilde{C}$ axis; the greater the absolute value, the more intense the preference (i.e. ±3 represents a strong preference, ± 2 represents a moderate preference and ± 1 represents a mild preference).

The objective of this section is to conceive an implicit method for diagnosing this set of learning preferences as accurately as possible. The first step is to associate relevant behavioral patterns to each of the ULSM' preferences, as detailed in the next subsection.

Associating Relevant Patterns to ULSM' Dimensions

The correspondence between the patterns and the learning preferences that they are indicative of are usually expressed in an informal manner, e.g. "A high amount of time spent on contents with graphics, images, video is an indication of a *Visual* learning preference", "A high performance in questions related to graphics can be associated to a *Visual* preference" etc. On the other hand, the data collected from the system logs are in a precise quantitative form, e.g. *t_Image* = 2350s (the amount of time, in seconds, spent on LOs of type "*Image*") or *t_Image_rel* = 12.5% (the percentage of time spent on images versus the whole study time); *grade_image* = 8.5 (the average grade obtained on questions related to graphics). We therefore encode the values that can be taken by the patterns in three categories: *High (H), Medium (M), Low (L).* Consequently, for each of the patterns we need to establish a mapping from the set of values that can be taken by the pattern to the set *{H, M, L}*. One way to specify this mapping is by means of the thresholds $L \leftrightarrow M$ and $M \leftrightarrow H$. Table 1 includes some common values for these thresholds, based on the recommendations in the literature (Graf, 2007; Garcia et al., 2007; Rovai and Barnum, 2003), as well as our experience.

It should be noted that the values of these thresholds depend to a certain extent on the structure and the subject of the course. The values in Table 1 are some general indications that are based on our experience as well as similar research findings. However, the teacher should have the possibility to adjust these values to correspond to the particularities of her/his course. This is why our WELSA Analysis tool has a Configuration option, which allows the teacher to modify the threshold values.

We can now associate the values of the patterns with the ULSM' characteristics that they are indicative of. Since the ULSM' characteristics come in opposite pairs, if an H value for a pattern P can be associated with a characteristic C, then an L value of pattern P can be associated with characteristic $\tilde{C}$ (for all dimensions $C/\tilde{C} \in Dim\_ULSM'$). Therefore in Table 2 we only include the values of the patterns that are characteristic for the left hand side axis of each ULSM' dimension. Furthermore, for each pattern we can associate a weight, indicating the relevance (the level of influence) it has on identifying a learning preference. The weight of each pattern is also included in Table 2, denoted by *hW* (high weight), *mW* (medium weight) and *lW* (low weight).

A few notes should be made regarding Table 2: the number of visits (hits) to an educational resource was found to be less indicative of the student's preference than the time spent on that particular resource (Popescu, 2009); consequently, *t_LO* was assigned a higher weight than *h_LO*. The grades obtained by students were generally allocated lower weights in defining their learning preferences since it can be argued that students' performance depends largely on other factors, such as their motivation; thus a student may obtain a good grade on an item that doesn't correspond to her preferences, in case the student was motivated enough to prepare her for that task. It can also be noted that there are some patterns which are associated to several ULSM' preferences; an example is the level of activity students have in communication channels (chat and forum), which is mainly indicative of a *Team work* preference but could also be associated, to a certain extent, with a *Verbal* preference.

As in the case of thresholds, the above associations and weights are merely general recommendations; the importance of each of the patterns may change with the specificities of the course. For example, in case of a course which contains a very small number of group assignments that the students may choose from, the *n_individualAssignment* pattern is not very relevant anymore and should be assigned a lower weight. Also, some patterns may not be applicable for some courses, in case the course does not include that particular feature. In this case, the teacher should have the possibility to eliminate some of the patterns, which are not relevant for her/his course. Our WELSA Analysis tool has been conceived to accommodate all these requirements, offering the teacher the possibility to adjust the patterns' weights as well as eliminate some patterns.

The values for the patterns are computed from the student actions, as recorded by the system. Obviously, the larger the number of available actions, the more reliable the resulting pattern. Therefore our method (and consequently our Analysis tool) weights the value of each pattern with a reliability coefficient, which is computed from the number of corresponding actions in the system log. Hence a pattern can have a high reliability degree (*hR*), a medium reliability degree (*mR*) or a low reliability degree (*lR*). Thus the particularities of the course are reflected in the patterns' weights, while the particularities of the

Table 1. Description and values for pattern thresholds (note the meaning of prefixes in the pattern names: "n" stands for "number", "t" stands for "time" and "h" stands for "hits")

Pattern	Description	L ↔ M	M ↔ H
t_mediaType *t_instrType*	the relative time spent by the student on LOs of type *mediaType / instructionalType* versus the relative average time spent on LOs of type *mediaType / instructionalType* (the average time is computed based on an average study time indicated by the course creator for each component LO) $t\_mediaType\_rel / (\frac{t\_average\_mediaType}{t\_average\_total\_LO}) * 100$ $t\_instrType\_rel / (\frac{t\_average\_instrType}{t\_average\_total\_LO}) * 100$	<75%	>125%
h_mediaType *h_instrType*	the relative number of visits of LOs of type *mediaType / instructionalType* versus the total relative number of LOs of type *mediaType / instructionalType* available in the course $h\_mediaType\_rel / (\frac{n\_LO\_mediaType}{n\_LO\_total}) * 100$ $h\_instrType\_rel / (\frac{n\_LO\_instrType}{n\_LO\_total}) * 100$	<75%	>125%
grade_X	the grade obtained by the student on items of type *X* versus the total average grade of the student $\frac{grade\_X}{grade\_average} * 100$	<75%	>125%
t_test	the time spent on a test versus the maximum time allowed for that test $\frac{t\_test}{t\_test\_\max} * 100$	<70%	>90%
n_revisions_test	the number of revisions made before submitting a test versus the total number of answers $\frac{n\_revisions\_test}{n\_total\_answers} * 100$	<20%	>50%
sequence_X_before_Y	the number of accesses of LOs in the order *X – Y* versus the number of accesses of LOs in the order *Y – X*. $\frac{sequence\_X\_before\_Y}{sequence\_Y\_before\_X} * 100$	<80%	>120%

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Table 1. Continued

n_nextButton	the number of “Next” button clicks versus the total number of navigation actions $\frac{n\_nextButton}{n\_nextButton + n\_prevButton + n\_jump}*100$	<30%	>70%
n_prevButton	the number of “Previous” button clicks versus the total number of navigation actions $\frac{n\_prevButton}{n\_nextButton + n\_prevButton + n\_jump}*100$	<30%	>70%
n_jump	the number of jump actions versus the total number of navigation actions $\frac{n\_jump}{n\_nextButton + n\_prevButton + n\_jump}*100$	<30%	>70%
n_outline	the number of visits to “Outline” versus the total number of visited LOs $\frac{n\_outline}{n\_LO}*100$	<5%	>15%
t_outline	the time spent on “Outline” versus the total time spent on the course $\frac{t\_outline}{t\_total}*100$	<1%	>5%
n_skippedLO_temp	the number of LOs skipped on a temporary basis versus the total number of visited LOs $\frac{n\_skippedLO\_temp}{n\_LO}*100$	<5%	>15%
n_skippedLO_perm	the number of LOs skipped on a permanent basis versus the total number of visited LOs $\frac{n\_skippedLO\_perm}{n\_LO}*100$	<5%	>15%
n_returns_LO	the number of returns to LOs versus the total number of visited LOs $\frac{n\_returns\_LO}{n\_LO}*100$	<5%	>15%
t_chat	the time spent on chat versus the total time spent on the course $\frac{t\_chat}{t\_total}*100$	<5%	>15%

continued on following page

Table 1. Continued

n_chat_msg	the number of messages sent on chat per course session $\frac{n\_chat\_msg}{n\_sessions}$	<10	>30
t_forum	the time spent on forum versus the total time spent on the course $\frac{t\_forum}{t\_total}*100$	<5%	>15%
n_forum_msg	the number of messages posted on forum per course session $\frac{n\_forum\_msg}{n\_sessions}$	<1	>5
n_forum_read	the number of messages read on forum per course session $\frac{n\_forum\_read}{n\_sessions}$	<2	>10
n_askPeerHelp *n_offerPeer-Help*	the number of times a student asks for / offers peer help per course session $\frac{n\_askPeerHelp}{n\_sessions}$ $\frac{n\_offerPeerHelp}{n\_sessions}$	<2	>4
n_individu-alAssignment	the relative number of individual assignments chosen versus the relative number of group assignments chosen $\frac{n\_individualAssignments}{n\_total\_individualAssignments} / \frac{n\_groupAssignments}{n\_total\_groupAssignments}*100$	<80%	>120%

student's interaction with the system are reflected in the patterns' reliability values.

Computing the Learning Preferences

For each characteristic $C \in$ *ULSM'*, we have a set of relevant patterns with values P_1, P_2, ... P_n, each with its weight W_1, W_2, ... W_n, $P_i \in \{H, L\}$, $W_i \in \{hW, mW, lW\}$ (as in Table 2). As already mentioned, if an H value for a pattern P_i can be associated with a characteristic C, then an L value of pattern P_i can be associated with the opposite characteristic $\tilde{C}$.

For each student, we can determine the values corresponding to all the patterns for each of the characteristics in ULSM', together with the reliability levels of these values. Thus for characteristic C and for student j we have: the pattern values P_i^j with the weights W_i (the weights are the same for all students) and the reliability levels R_i^j, with $P_i^j \in \{H, M, L\}$, $W_i \in \{hW, mW, lW\}$, $R_i^j \in \{hR, mR, lR\}$, where the weights and reliability levels are subunitary values (i.e. $hW, mW, lW, hR, mR, lR \in [0,1]$). We can now compute the value of student j's preference for characteristic C with the following formula:

$$V_j(C) = \frac{\sum_{i=1}^{n} p_i^j * R_i^j * W_i}{n}, \text{ where}$$

$$p_i^j = \begin{cases} 1 & if\ P_i^j = P_i \\ 0 & if\ P_i^j = M \\ -1 & otherwise \end{cases}$$

The value obtained for $V_j(C)$ can be interpreted as follows: if $V_j(C) > 0$ then we can say that stu-

Table 2. Relevant patterns for each ULSM' dimension, together with associated weights (L / H – low / high value of the pattern; hW, mW, lW – high / medium / low weight of the pattern)

ULSM' dimension	Patterns
p_visual / p_verbal	*t_Image (H) - hW* *t_Video (H) - hW* *t_Text (L) - hW* *t_Sound (L) - hW* *h_Image (H) - mW* *h_Video (H) - mW* *h_Text (L) - mW* *h_Sound (L) - mW* *grade_Image (H) - mW* *n_chat_msg (L) - lW* *t_chat (L) - lW* *n_forum_msg (L) - lW* *n_forum_reads (L) - lW* *t_forum (L) - lW*
p_abstract / p_concrete	*sequence_fundamental_before_illustration (H) – hW* *sequence_abstract_first (H) – hW* *t_Fundamental (H) - hW* *t_abstract (H) – hW* *t_Illustration (L) – hW* *t_concrete (L) – hW* *h_Fundamental (H) – lW* *h_Illustration (L) - lW* *h_abstract (H) – lW* *h_concrete (L) - lW* *grade_abstract (H) – lW* *grade_concrete (L) - lW*

continued on following page

Table 2. Continued

p_serial / p_holistic	*n_nextButton (H) – hW* *n_prevButton (L) – hW* *n_outline (L) – hW* *t_outline (L) – mW* *n_jump (L) - hW* *t_Introduction (L) – lW* *t_Objectives (L) – lW* *t_AdditionalInfo (L) - lW* *h_Introduction (L) – mW* *h_Objectives (L) – mW* *h_AdditionalInfo (L) – mW* *n_skippedLO_temp (L) – hW* *n_skippedLO_perm (L) – mW* *n_returns_LO (L) - mW* *grade_details (H) – lW* *grade_overview (L) – lW* *grade_connections (L) – lW* *sequence_exercise_last (L) - lW*
p_activeExperimentation / p_reflectiveObservation	*sequence_interactivity _before_fundamental (H) - hW* *sequence_interactivity _before_illustration (H) – hW* *t_Exercise (H) - mW* *t_Exploration (H) - hW* *h_Exercise (H) - lW* *h_Exploration (H) - lW*
p_carefulDetails / p_notCarefulDetails	*t_test (H) - hW* *n_revisions_test (H) - hW* *grade_details (H) - mW* *t_Details (t_Remark + t_Demonstration + t_AdditionalInfo) (H) – mW* *h_Details (h_Remark + h_Demonstration + h_AdditionalInfo) (H) - lW*
p_individual / p_team	*n_chat_msg (L) – hW* *t_chat (L) – hW* *n_forum_msg (L) – hW* *n_forum_reads (L) – hW* *t_forum (L) – hW* *n_individualAssignment (H) – hW* *n_askPeerHelp (L) – mW* *n_offerPeerHelp (L) - mW*

dent *j* has a preference towards characteristic *C*; if $V_j(C) < 0$ then we can say that student *j* has a preference towards the opposite characteristic, $\tilde{C}$. Furthermore, the absolute value of $V_j(C)$ gives an indication on the strength of the preference: a value close to 0 implies a mild preference (a rather balanced learning style), while greater values imply stronger preferences.

A few more comments on this formula are in order. First it should be noted that for $\forall j$:

$$V_j(C) \in [-\frac{\sum_{i=1}^{n} W_i}{n}, \frac{\sum_{i=1}^{n} W_i}{n}] \subseteq [-1,1].$$

The maximum value for $V_j(C)$ is obtained when all the patterns have values indicating towards the characteristic C (i.e. $p_i^j = 1, \forall i = 1..n$) and there is enough data available for student j to reliably compute all the patterns P_i^j (i.e. $R_i^j = 1, \forall i = 1..n$). Similarly, the minimum value for $V_j(C)$ is obtained when all the patterns have values indicating towards the characteristic $\tilde{C}$ (i.e. $p_i^j = -1, \forall i = 1..n$) and there is enough data available for student j to reliably compute all the patterns P_i^j (i.e. $R_i^j = 1, \forall i = 1..n$). When we don't have enough information to compute a reliable value for pattern P_i^j, we want that value to contribute less to the final diagnosis; when we have very few data on a student, most R_i^j will be very small and consequently $V_j(C)$ will be close to 0, indicating a balanced learning style. Indeed, when lacking data to make an informed diagnosis, a balanced preference is the safest assumption one can make.

We can also compute a confidence value associated to each $V_j(C)$, reflecting the degree of trust that we can have in the value of the student j's preference for characteristic C (based on the availability of data for student j):

$$Conf_j(C) = \frac{\sum_{i=1}^{n} R_i^j}{n}$$

It should be noted that $Conf_j(C) \in [0, 1]$. A small value implies a low degree of confidence in the value $V_j(C)$, while a large value implies a high degree of confidence.

EXPERIMENTAL VALIDATION OF THE MODELING METHOD

Experiment Settings

In order to validate the proposed rule-based modeling method, we applied it on the data collected from 71 undergraduate students in the field of Computer Science that participated in our study. As test platform we used WELSA educational system and a course module in the area of Artificial Intelligence. The course module deals with search strategies and solving problems by search and is based on the fourth chapter of Poole, Mackworth and Goebel's AI textbook (Poole et al., 1998). The course consists of 4 sections and 9 subsections, including a total of 46 learning objects (LOs). From the point of view of the media type, the course includes both *'Text'* LOs (35), as well as *'Image', 'Video'* and *'Animation'* LOs (11). From the point of view of the instructional role of the LO, the course consists of 12 *'Fundamental'* LOs (5 *'Definition'* and 7 *'Algorithm'*) and 34 *'Auxiliary'* LOs (4 *'Additional Info'*, 1 *'Demonstration'*, 14 *'Example'*, 5 *'Exercise'*, 3 *'Exploration'*, 5 *'Introduction'*, 1 *'Objectives'* and 1 *'Remark'*). The course also includes access to two communication tools, one synchronous (*chat*) and one asynchronous (*forum*) and offers two navigation choices – either by means of the *Next* and *Previous* buttons, or by means of the *Outline*.

The experiment lasted for 4 hours: 2 hours were reserved for course studying, and 2 hours for discussions and filling-in some questionnaires. For the first part of the experiment, the students accessed WELSA and all of their interactions with the system were recorded. Afterwards, the students were asked to self-diagnose their learning preferences and characterize them as mild, moderate or strong by filling in the ULSM questionnaire. They were also given the chance to comment on their learning preferences, the structure and presentation of the course and their experience in interacting with WELSA.

In order to analyze the data, we first modified some of the default pattern weights (i.e. the values from Table 2), as well as eliminate some of the patterns which were not relevant in the context of our experiment. Thus we excluded the patterns *t_Sound* and *h_Sound*, since the course did not include any audio resources. Furthermore, although WELSA provides a forum, due to the temporal constraints of the experiment, the learners had neither the time nor the incentive to use this forum. We have therefore excluded the patterns related to it from our analysis (*n_forum_msg, n_forum_reads, t_forum*). Moreover, the course did not include any online evaluation tests, so the two related patterns were also left out (*t_test, n_revisions_test*). Finally, there were no group/individual assignments that the students could choose from, so the patterns *n_individualAssignment, n_askPeerHelp*, as well as *n_offerPeerHelp* were excluded from our analysis. The default pattern thresholds from Table 1 were used, since there were no inconsistencies between these values and the course structure.

Next we computed the pattern values and then, based on them, the learning preferences and the associated confidence degrees. All the configurations and computations were done by means of the WELSA Analysis tool.

Evaluation Method

In order to evaluate the quality of our method, we compared the results obtained using the rule-based modeling approach (LP_{Rule}), with the results obtained by student self-diagnosis, using the ULSM questionnaire (LP_{Quest}). We considered three possible values for each dimension $C/\tilde{C} \in$ *Dim_ULSM'*: strong/medium preference towards C (denoted P_C), strong/medium preference towards $\tilde{C}$ (denoted $P_{\tilde{C}}$) or balanced preference (denoted P_B).

In case of the preferences obtained by means of the rule-based method (i.e. $V_j(C)$), values in $[-w, w]$, with $w = \frac{\sum_{i=1}^{n} W_i}{n}$ had to be mapped to the 3-item scale. The range was divided in 3 equal parts: P_C corresponds to the values greater than $\frac{1}{3} * w$, $P_{\tilde{C}}$ corresponds to the values smaller than $-\frac{1}{3} * w$, while P_B corresponds to the values in $[-\frac{1}{3} * w, \ \frac{1}{3} * w]$. The precision of our method can be obtained with the formula in Box 1.

M is the number of students in the sample for which we compute the precision.

The above formula is based on the similarity between the results obtained using our rule-based method and the reference results (obtained by means of the ULSM questionnaire).

Results and Discussion

Table 3 presents the results that we obtained using the rule-based modeling method, for each of the ULSM' dimensions.

As can be seen, we obtained very good results for two ULSM dimensions (*p_abstract / p_concrete* and *p_activeExperimentation / p_reflectiveObservation*), good results for three ULSM dimensions (*p_visual / p_verbal, p_serial / p_holistic, p_carefulDetails / p_notCarefulDetails*) and moderate results for one ULSM dimension (*p_individual / p_team*).

The less accurate results obtained for the *p_individual / p_team* dimension can be explained by the very small number of behavioral patterns used (just two patterns were relevant in the current conditions of the experiment). Furthermore, the students' use of chat was very limited, as resulted from the analysis of available data. When questioned about this aspect, the arguments given by students who declared having a preference towards team work fell in two main categories: some of them prefer "face-to-face" interaction, others said that the course did not necessitate large amount of collaboration since no group assignments existed. Further experiments including team assignments and more sophisticated collaborative tools should be performed in order to obtain better outcomes.

Box 1.

$$\text{Precision} = \frac{\sum_{j=1}^{M} Sim(LP^j_{Rule}, LP^j_{Quest})}{M},$$

where

$$Sim(LP^j_{Rule}, LP^j_{Quest}) = \begin{cases} 1 & if LP^j_{Rule} = LP^j_{Quest} \\ 0.5 & if LP^j_{Rule} \neq LP^j_{Quest} \ and \ (LP^j_{Rule} = P_B \ or \ LP^j_{Quest} = P_B) \\ 0 & otherwise \end{cases}$$

Table 3. Precision of the rule-based modeling method

ULSM' dimension	Precision
p_visual / p_verbal	73.94%
p_abstract / p_concrete	82.39%
p_serial / p_holistic	78.17%
p_activeExperimentation / p_reflectiveObservation	84.51%
p_carefulDetails / p_notCarefulDetails	71.13%
p_individual / p_team	64.08%

The very good results obtained in case of *p_abstract/p_concrete* and *p_activeExperimentation /p_reflectiveObservation* can be attributed to the relatively large number of relevant patterns, as well as to the course composition, which included plenty of related educational resources (*Examples, Exercises, Explorations* etc) and consequently led to the availability of the relevant student data. As expected, the efficiency of our method depends on the amount of data available, which is based both on the amount of time spent by students interacting with the platform and on the nature of the course and the variety of resources it is made up of.

For comparison, we include in Table 4 the results obtained with the approaches used in the papers (Cha et al., 2006), (Garcia et al., 2007) and (Graf, 2007), that we introduced in section 2. It can be observed that our rule-based modeling method yielded above average results.

It should be noted that in the three analyzed papers the learning style model used is Felder-Silverman and the approaches are various, ranging from rule-based modeling to Bayesian networks, Decision trees and Hidden Markov models. The formula used for computing precision in case of (Garcia et al., 2007) and (Graf, 2007) is similar with the one defined above. In case of (Cha et al., 2006), only students with moderate to strong FSLSM preferences (i.e. ILS score >= 5) are considered.

CONCLUSION

Attempting to represent knowledge regarding complex psychological characteristics of the learner is a challenging research goal. In this chapter we tried to address the modeling process of the students' learning style, one of the factors that play an important role in learning. We started

Table 4. Precision of learner modeling methods according to FSLSM model in (Cha et al., 2006), (Garcia et al., 2007) and (Graf, 2007)

FSLSM dimension / Modeling Approach	Active / Reflective	Sensing / Intuitive	Visual / Verbal	Sequential / Global
(Cha et al., 2006) – Decision Trees	66.67%	77.78%	100%	71.43%
(Cha et al., 2006) – Hidden Markov Models	66.67%	77.78%	85.72%	85.72%
(Garcia et al., 2007) – Bayesian Networks	58%	77 %	N/A	63%
(Graf, 2007) - Bayesian Networks	62.50%	65.00%	68.75%	66.25%
(Graf, 2007) – Rule based approach	79.33%	77.33%	76.67%	73.33%

with a critical review of existing approaches, succinctly presenting the educational systems that attempt to model the students' learning style.

However this is a controversial issue, especially due to the multitude of partially overlapping learning style models proposed in the literature. We argue that instead of debating over the most appropriate learning style model, it is better to take the best of each model and use a complex of features, each with its own importance and influence. In this respect, we proposed a Unified Learning Style Model approach and outlined its advantages.

As far as the modeling method is concerned, we introduced an implicit approach, based on analyzing student behavior in the educational system. The rule-based approach was validated through experimental research, obtaining good precision results.

A limitation of our work is represented by the relatively restricted student sample that was used in our experiments – in order to allow for generalization, the modeling method should be tested on a wider scale, with learners of variable age, field of study, background knowledge and technical experience. We therefore plan to repeat the experiment for longer periods of time and with a larger and more diverse student sample.

Modeling is just the first step in the adaptation process – providing a learning experience that is individualized to the particular needs of the learner, as identified in the modeling stage, is the ultimate goal. In this context, an adaptation component was conceived and implemented in our WELSA system, with the aim of adapting the course so as to best suit the ULSM characteristics diagnosed in this chapter.

As future work, the modeling component could also be extended to take into account the perturbations introduced by the adaptation on students' actions. Students' behavior in the adapted version could then be used as a valuable feedback on the effect of adaptation. Furthermore, the modeling method could be improved by automatically fine tuning the behavioral patterns' thresholds and weights to conform to the specificities of each course. In this context, our research can be seen as the basis for a truly dynamic learner modeling approach.

FUTURE TRENDS

The accommodation of individual differences in general and learning styles in particular seems to win ground in current educational hypermedia research. However, most of the existing systems treat learning styles in isolation of the rest of the features in the student profile (knowledge, interests, goals). The ideal would be to integrate all these features in a more comprehensive and representative learner profile. The "context of work" feature should start being taken into consideration also, given the recent advent of mobile and ubiquitous learning. In the same integrative context, implicit modeling methods should be used in conjunction with explicit ones, in order to address the cold start problem and improve the accuracy of the diagnosis.

An important concern of educational systems that record the learning style of the students is to ensure the necessary privacy of their users. In case of an automatic diagnosing method, the learning preferences shouldn't necessarily be revealed to either the student or the teacher, but could only be used by the system for adaptation purposes. This would ensure a complete privacy of the learner and avoid the danger of stereotyping. However, an even better approach would be to educate both the students and the teachers to correctly understand and deal with learning styles. Metacognition and learning style awareness can help students understand their strengths and weaknesses in the learning process and use them to their advantage.

Perhaps the most important desideratum of the LSAES in general is that they surpass their current status of research systems and get to be used in practice, gaining a popularity similar to that of the learning management systems.

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