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A New Approach for Modeling and Discovering Learning Styles by using Hidden Markov Model

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Abstract
Adaptive learning systems are developed rapidly in recent years and the "heart" of such systems is user model. User model is the representation of information about an individual that is essential for an adaptive system to provide the adaptation effect, i.e., to behave differently for different users. There are some main features in user model such as: knowledge, goals, learning styles, interests, background? but knowledge, learning styles and goals are features attracting researchers' attention in adaptive e-learning domain. Learning styles were surveyed in psychological theories but it is slightly difficult to model them in the domain of computer science because learning styles are too unobvious to represent them and there is no solid inference mechanism for discovering users' learning styles now. Moreover, researchers in domain of computer science will get confused by so many psychological theories about learning style when choosing which theory is appropriate to adaptive system.In this paper we give the overview of learning styles for answering the question "what are learning styles?" and then propose the new approach to model and discover students' learning styles by using Hidden Markov model (HMM).

Index terms— learning systems, heart, mechanism for discovering

1 Introduction

eople have different views upon the same situation, the way they perceive and estimate the world is different. So their responses to around environment are also different. For example, look at the way students prefers to study a lesson. Some have a preference for listening to instructional content (socalled auditory learner), some for perceiving materials as picture (visual learner), some for interacting physically with learning material (tactile kinesthetic learner), some for making connections to personal and to past learning experiences (internal kinesthetic learner). Such characteristics about user cognition are called learning styles but learning styles are wider than what we think about them.

Learning styles are defined as the composite 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. Learning style is the important factor in adaptive learning, which is the navigator helping teacher/computer to deliver the best instructions to students.

There are many researches and descriptions about learning style but only minorities of them are valuable and applied widely in adaptive learning. The descriptions of learning style (so-called learning style models) are categorized following criteria: model)

In section 2, we discuses about such learning style families. In general, learning styles are analyzed comprehensively in theory of psychology but there are few of researches on structuring learning styles by mathematical tools to predict/infer users' styles. Former researches often give users questionnaires and then analyze their answers in order to discover their styles but there are so many drawbacks of question-and-answer techniques, i.e., not questions enough, confusing questions, users' wrong answers? that such technique is not a possible solution. It is essential to use another technique that provides more powerful inference mechanism. So, we propose the new approach which uses hidden Markov model to discover and represent users' learning styles in section 4, 5. We should pay attention to some issues of providing adaptation of learning materials to learning styles concerned in section 3. -Constitutionally based learning styles and preferences ??Dunn and Dunn) -The cognitive structure ??Witkin, Riding) -Stable personality type (Myers-Briggs)

2 II.

3 Learning Style Families

-Flexibly learning preferences ??Kolb, Honey-Mumford, Felder-Silverman, Pask and Vermunt model) Environmental: incorporates user preferences for sound, light, temperature? Emotional: considers user motivation, persistence, responsibility? Sociological: discovers user preference for learning alone, in pairs, as member of group

4 b) The Cognitive Structure

In this family, learning styles are considered as structural properties of cognitive system itself. So styles are linked to particular personality features, which implicates that cognitive styles are deeply embedded in personality structure. There are two models in this family: Witkin model and Riding model.

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5 . Witkin Model

The main aspect in Witkin model ??Witkin, Moore, Goodenough, Cox 1997] is the bipolar dimensions of field-dependence/field-independence (FD/FI) in which:

Field-dependence (FD) person process information globally and attend to the most salient cues regardless of their relevance. In general, they see the global picture, ignore details and approach the task more holistically. They often get confused with non-linear learning, so, the require guided navigation in hypermedia space. Field-independency (FI) person are highly analytic, care more inherent cues in the field and are able to extract the relevant cues necessary to complete a task. In general, they focus on details and learn more sequentially. They can set learning path themselves and have no need of guidance.

6 ii. Riding Model

Riding model [Riding, Rayner 1998] identifies learning styles into two dimensions: Wholist-Analytic and Verbalizer-Imager.

Wholist-Analytic dimension expresses how an individual cognitively organize information either into whole or parts. Wholist tends to perceive globally before focusing on details. Otherwise, analytic tends to perceive everything as the collection of parts and focusing on such parts.

Verbalizer-Imager dimension expresses how an individual tends to perceive information, either as text or picture. Verbalizer prefers to text. Imager prefers to picture.

7 c) Stable Personal Type

The models in this family have a common focus upon learning style as one part of the observable expression of a relatively stable personality type. We will glance the famous model in this family: Myers-Briggs Type Indicator. Based on four stages, there are four learning styles: accommodating, assimilating, diverging and converging. Each couple of these stages constitutes a style, for example, CE and AE combine together in order to generate accommodating style. conceptualization and reflective observation. Learners respond to information presented in an organized, logical fashion and benefit if they have time for reflection. A typical question for this style is "What?" conceptualization and active experimentation. Learners respond to having opportunities to work actively on well-defined tasks and to learn by trialand-error in an environment that allows them to fail safely. A typical question for this style is "How?" experience and reflective observation. Learners respond well to explanations of how course material relates to their experience, their interests, and their future careers. A typical question for this style is "Why?"

ii.

8 Honey and Mumford Model

According to Peter Honey and Alan Mumford [Honey, Mumford 1992] The adaptive strategy (for learning style) is the sequence of adaptive rules which define how adaptation to learning styles is performed. Learning style strategies is classified into three following forms: materials) is presented in various types such as: text, audio, video, graph, picture? Depending on user's learning styles, an appropriate type will be chosen to provide to user. For example, verbalizers are recommended text and imagers are suggested pictures, graphs. This form support adaptation techniques such as: adaptive presentation, altering fragments, stretch text? navigation paths: The order in which learning materials are suggested to users is tuned with learning styles. For active learners, learning materials are presented in the order: activity?example?theory?exercise. For reflective learner, this order is changed such as: example?theory?exercise?activity. This form is corresponding to link adaptation techniques: direct guidance, link sorting, link hiding, link annotation.

Different learning tools are supported to learners according to their learning styles. For example, in Witkin model, FD learners are provided tools such as: concept map, graphic path indicator. Otherwise FI learners are provided with a control option showing a menu from which they can choose in any order (because they have high self-control).

There are two type of strategy: adaptive rules and is in three above forms.

to observe user actions and infer their learning styles. Thus, meta-strategy is applied in order to define strategy.

Our approach is an instructional meta-strategy that apply Markov model to infer users' learning styles. Before discussing about main techniques, it is necessary to glance over hidden Markov model.

9 IV.

10 Hidden Markov Model

There are many real-world phenomena (socalled states) that we would like to model in order to explain our observations. Often, given sequence of observations symbols, there is demand of discovering real states. For example, there are some states of weather: sunny, cloudy, rainy. Based on observations such as: wind speed, atmospheric pressure, humidity, temperature?, it is possible to forecast the weather by using Hidden Markov Model (HMM). Before discussing about HMM, we should glance over the definition of Markov Model (MM). First, MM is the statistical model which is used to model the stochastic process. MM is defined as below: cardinality is n. Let ? be the initial state distribution where ? i ? ? represents the probability that the stochastic process begins in state s i . In other words ? i is the initial probability of state s i , where 1 = ? ?S s i i ? one state from S at all times. The process is denoted as a finite vector P=(x 1 , x 2 ,?, x u) whose element x i is a state ranging in space S. Note that x i ? S is one of states in the finite set S, x i is identical to s i . Moreover, the process must meet fully the Markov property, namely, given the current state x k of process P, the conditional probability of next state x k+1 is only relevant to current state x k , not relevant any past state (x k-1 , x k-2 , x k-3 ,?). In other words, Pr (x k | x 0 , x 1 ,?, x k-1) = Pr(x k | x k-1). Such process is called first-order Markov process. state based upon the transition probability distribution a ij which depends only on the previous state. So a ij is the probability that, the process change the current state s i to next state s j . The probability of transitioning from any given state to some next state is 1:1 , = ? ? ? ?S s ij i j a S s

. All transition probabilities a ij (s) constitute the transition probability matrix A.

Briefly, MM is the triple ? S, A, ? ?. In typical MM, states are observed directly by users and transition probability matrix is the unique parameters. Otherwise, Hidden Markov Model (HMM) is similar to MM except that the underlying states become hidden from observer, they are hidden parameters. HMM adds more output parameters which are called observations. Each state (hidden parameter) has the conditional probability distribution upon such observations. HMM is responsible for discovering hidden parameters (states) from output parameters (observations), given the stochastic process. The HMM have further properties as below:

produces observations correlating hidden states. Suppose there is a finite set of possible observations ?"¨ = {? 1 , ? 2 ,?, ? m } whose cardinality is m.

given observation in each state. Let b i (k) be the probability of observation ? k when the second stochastic process is in state s i . The sum of probabilities of all observations which observed in a certain state is 1, -Instructional strategy is itself, which contains 1) (, = ? ? ? ?? ? k k b S i i . All

11 Uncovering problem and Viterbi algorithm

Given HMM ? and a sequence of observations O = {o 1 ? o 2 ??? o k } where o i ? ?"¨ , how to find the sequence of states U = {u 1 ? u 2 ??? u k } where u ? S so that U is most likely to have produced the observation sequence O . This is the uncovering problem: which sequence of state transitions is most likely to have led to this sequence of observations. It means to maximize the selection of U:)] | [Pr(max arg ? O U .

We can apply brute-force strategy: "go through all possible such O and pick the one with the maximum" but this strategy is infeasible given a very large numbers f states. In this situation, Viterbi algorithm [Dugad, Desai 1996] is the effective solution. Instead of describing details of Viterbi algorithm, we only use it to predict learner's styles given observations about her/him.

12 V. Applying hidden markov Model Into Modeling and Inferring Users' Learning Styles

For modeling learning style (LS) using HMM we should determine states, observations and the relationship between states and observations in context of learning style. In other words, we must define five components S, ?"¨, A, B, ?. Each learning style is now considered as a state. The essence of state transition in HMM is the change of user's learning style, thus, it is necessary to recognize the learning styles which are most suitable to user. After monitoring users' learning process, we collect observations about them and then discover their styles by using inference mechanism in HMM, namely Viterbi algorithm. Suppose we choose Honey-Mumford model and Felder-Silverman model as principal models which are presented by HMM. We have three dimensions: Verbal/Visual, Activist/ Reflector, Theorist/ Pragmatist which are modeled as three HMM(s): ? 1 , ? 2 , ? 3 respectively. For example, in ? 1 , there are two states: Verbal and Visual; so S 1 ={verbal, visual}. We have:- ? 1 = ? S 1 , ?"¨ 1 , A 1 , B 1 , ? 1 ?. - ? 2 = ? S 2 , ?"¨ 2 , A 2 , B 2 , ? 2 ?. - ? 3 = ? S 3 , ?"¨ 3 , A 3 , B 3 , ? 3 ?.

We are responsible for defining states (S i), initial state distributions (? i), transition probability matrices (A i), observations (?"¨ i), observation probability matrices (B i) through five steps 1. Defining states: each state is corresponding to a leaning style. S 1 = {verbal, visual}, S 2 = {activist, reflector}, S 3 = {theorist, pragmatist}. 2. Defining initial state distributions: we use uniform probability distribution for each ? i . ? 1 = {0.5, 0.5}; it means that Pr (verbal) = Pr (visual) = 0.5 ? 2 = {0.5, 0.5}; Pr(activist) = Pr(reflector) = 0.5 ? 3 = {0.5, 0.5}; Pr (theorist) = Pr (pragmatist) = 0.5 3. Defining transition probability matrices: we suppose that learners tend to keep their styles; so the conditional probability of a current state on previous state is high if both current state and previous state have the same value and otherwise. For example, 4. Defining observations. There is a relationship between learning object learned by users and their learning styles. We assign three attributes to each learning object (such as lecture, example?): ? Format attribute indicating the format of learning object has three values: text, picture, video . ? Type attribute telling the type of learning object has four values: theory, example, exercise, and puzzle . ? Interactive attribute indicates the "interactive" level of learning object. The more interactive learning object is, the more learners interact together in their learning path. This attribute has three values corresponding to three levels: low, medium, high . Whenever a student selects a learning object (LO), it raises observations depending on the attributes of learning object. We must account for the values of the attributes selected. For example, if a student selects a LO which has format attribute being text, type attribute being theory, activity attribute being low, there are considerable observations: text, theory, low (interaction). So, it is possible to infer that she/he is a theorist.Pr(s i =verbal | s i-1 =verbal) = 0.7 is obviously higher than Pr(s i =verbal | s i-1 =verbal) = 0.

The dimension Verbal/Visual is involved in format attribute. The dimensions Activist/ Reflector and Theorist/ Pragmatist relate to both type attribute and interactive attribute. So we have: **??**heory, example, exercise, puzzle, low (interaction), medium (interaction), high (interaction) }? ?"¨ 1 = { Text, picture, video } ? ?"¨ 2 = {
? ?"¨ 3 = { Theory, example, exercise, puzzle, low (interaction), medium (interaction) high (interaction) } 5. Defining observation probability matrices. Different observations (attributes of LO) effect on states (learning styles) in different degrees. Because the "weights" of observation vary according to states, there is a question: "How to specify weights?" If we can specify these "weights", it is easy to determine observation probability matrices.

In the Honey-Mumford model and Felder-Silverman model, verbal students prefer to text material and visual students prefer to pictorial materials. The weights of observations: text, picture, video on state Verbal are in descending order. Otherwise, the weights of observations: text, picture, video on state Visual are in ascending order. Such weights themselves are observation probabilities. We can define these weights as below:? Pr(text | verbal) = 0.6, Pr(picture | verbal) = 0.3, Pr(video | verbal) = 0.1 ? Pr(text | visual) = 0.2, Pr(picture | visual) = 0.4, Pr(video | visual) = 0.4

There are some differences in specifying observation probabilities of dimensions Activist/Reflector and Theorist/ Pragmatist. As discussed, active learners are provided activity-oriented approach: showing content of activity (such as puzzle, game?) and links to example, theory and exercise. Reflective learners are provided example-oriented approach: showing content of example and links to theory, exercise and activity (such as puzzle, game?). The weights of observations: puzzle, example, theory, exercise on state Activist are in descending order. The weights of observations: example, theory, exercise, puzzle on state Reflector are in descending order. However, activists tend to learn high interaction materials and reflectors prefer to low interaction materials. So the weight of observations: low (interaction), medium (interaction), high (interaction) on state Activist get values: 0, 0, 1 respectively. Otherwise, the weight of observations: low (interaction), medium (interaction), high (interaction) on state Reflector get values: 1, 0, 0 respectively. We have: showing content of theory and links to example, exercise and puzzle; pragmatists are provided exercise-oriented approach: showing content of exercise and links to example, theory and puzzle. Thus, the conditional probabilities of observations: example, theory, exercise, puzzle, low (interaction), medium (interaction), high (interaction) on states: theorists, pragmatists are specified by the same technique discussed above. ? Pr(puzzle | activist) = 0.4, Pr(example | activist) = 0.3, Pr(theory | activist) = 0.2, Pr(exercise | activist) = 0.1 Pr(low | activist) = 0, Pr(medium | activist) = 0, Pr(high | activist) = 1. ? Pr(example | reflector) = 0.4, Pr(theory | reflector) = 0.3, Pr(exercise | reflector) = 0.2, Pr(puzzle | reflector) = 0.1 Pr(low | reflector) = 1, Pr(medium | reflector) = 0, Pr(high | reflector) = 0.

13 IV Version I

Now three HMM (s): ? 1 , ? 2 , ? 3 corresponding to three dimensions of learning styles: Verbal/Visual, Activist/Reflector, Pragmatist/Theorist are represented respectively in figure **??**.

14 An example for inferring student's learning styles

Suppose the learning objects that a student selects in session 1, 2 and 3 are LO 1 , LO 2 and LO 3 respectively.

15 Format

16 Conclusion

HMM and Viterbi algorithm provide the way to model and predict users' learning styles. We propose five steps to realize and apply HMM into two learning style models: Honey-Mumford and Felder-Silverman, in which styles are considered states and user's selected learning objects are tracked as observations. The sequence of observations becomes the input of Viterbi algorithm for inferring the real style of learner. It is possible to extend our approach into other learning style models such as: Witkin, Riding, Kolb? and there is no need to alter main techniques except that we should specify new states correlating with new learning styles and add more attributes to learning objects. [1] [2]

Figure 1: and-

Pask model developed by Pask [Pask 1976]
states that there are two learning styles:
Wholist: Learners understand problems by building
up a global view
Serialist: Learners prefer to details of activities, facts
and follow a step-by-step learning procedure.
v. Vermunt Model
According to Vermunt [Vermunt 1996], the
author of this model, there are four learning styles:

Concrete experience (CE) Abstract conceptualization (AC) Accommodating Diverging III. Providing Adapta probabilities of observations b i (k) constitute the observation probability matrix B.

S = {sun, cloud, rain}, ?”¨ = {dry, dryish, damp, soggy}

		weather today		
		sun	cloud	rain
	sun	0.5	0.25	0.25
weather yesterday	cloud	0.4	0.2	0.4
	rain	0.1	0.7	0.2

Transition probability matrix A

		humidity			
		dry	dryish	damp	soggy
	sun	0.6	0.2	0.15	0.05
weather	cloud	0.25	0.25	0.25	0.25
	rain	0.05	0.1	0.35	0.5

Observation probability matrix B

Figure 1 : HMM of weather forecast (hidden states are shaded)

-There is the second stochastic process which

-There is a probability distribution of producing a

Figure 3: -

1

	verbal	visual
erbal	0.7	0.3
visual	0.3	0.7

Figure 4: Table 1 :

2

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	Text	Picture	Video
Verbal	0.6	0.3	0.1
Visual	0.2	0.4	0.4

Figure 5: Table 2 :

3

				Hmm -Dimension	Sequence of Observations
				? 1 : Dimension Verbal/Visual	picture ? text ? text
				? 2 : Dimension Activist/Reflector	theory ? example ? low
		Type	Interactive	? 1 : Dimension Pragmatist/Theorist	theory ? example ? low
LO 1	picture	theory	not assigned		
LO 2	text	example	not assigned		
LO 3	text	not assigned	low		

Figure 6: Table 3 :

4

Hmm -Dimension	Sequence of Observations	Sequence of State Transitions	Student Style
? 1	picture ? text ? text	visual ? verbal	verbal
? 2	theory ? example ? low	reflector ? reflector ? reflector	reflector
? 1	theory ? example ? low	theorist ? theorist ? theorist	theorist

Figure 7: Table 4 :

5

VI.

Figure 8: Table 5 :

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