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

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A NEW APPROACH FOR MODELING AND DISCOVERING LEARNING STYLES BY USING HIDDEN MARKOV MODEL

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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). HMM is such a powerful statistical tool that it allows us to predict users' learning styles from observed evidences about them.

I. Introduction

People 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 (so-called *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.

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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:

- Their theoretical importance
- Their wide spread use
- Their influence on other learning style models
- Learning style models are organized within the families such as:
- Constitutionally based learning styles and preferences (Dunn and Dunn)
- The cognitive structure (Witkin, Riding)
- Stable personality type (Myers-Briggs)
- Flexibly learning preferences (Kolb, Honey-Mumford, Felder-Silverman, Pask and Vermunt 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.

II. Learning Style Families

a) Constitutionally based learning styles and preferences

Learning styles in this family are fixed and difficult to change. This family has the famous model "Dunn and Dunn model" developed by authors Rita Dunn and Kenneth Dunn [Dunn, Dunn 2003]. With Dunn and Dunn model, learning style is divided into 5 major strands:

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- 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
- Physiological: surveys perceptual strengths such as visual, auditory, kinesthetic, tactile…
- Psychological: focusing on user's psychological traits namely incorporates the information-processing elements of global versus analytic and impulsive versus reflective behaviors.
- The psychological strand classifies learning styles into modalities such as:
- *Auditory:* Preference to listen to instructional content
- *Visual (Picture):* Preference to perceive materials as pictures
- *Visual (Text):* Preference to perceive materials as text
- *Tactile Kinesthetic:* Preference to interact physically with learning material
- *Internal Kinesthetic:* Preference to make connections to personal and to past learning experiences
- The physiological strand classifies learning styles into modalities such as:
- *Impulsive:* Preference to try out new material immediately
- *Reflective:* Preference to take time to think about a problem
- *Global:* Preference to get the 'big picture' first, details second
- *Analytical:* Preference to process information sequentially: details first, working towards the 'big

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.

i. *Witkin Model*

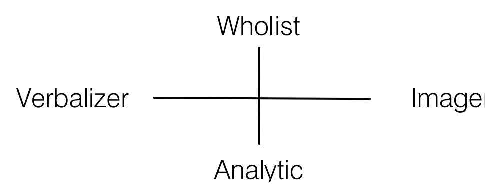
The main aspect in Witkin model [Witkin, Moore, Goodenough, Cox 1997] is the bipolar dimensions of *field-dependence/field-independence* (FD/FI) in which:

- *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.

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.



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.

i. *Myers-Briggs Type Indicator*

This model involves four different pairs of opposite preferences for how person focus and interact with around environment:

- How does a person relate to the world?
  a. *Extravert:* try things out, focus on the world around, like working in teams
  b. *Introvert:* think things through, focus on the inner world of ideas, prefer to work alone
- How does a person absorb/process information?
  a. *Sensor:* concrete, realistic, practical, detail -oriented, focus on events and procedures
  b. *Intuitive:* abstract, imaginative, concept-oriented, focus on meanings and possibilities
- How does a person make decisions?
  a. *Thinker:* skeptical, tend to make decisions based on logic and rules
  b. *Feeler:* appreciative, tend to make decisions based on personal and human considerations
- How does a person manage her/his life?
  a. *Judger:* organized, set and follow agendas, make decisions quickly
  b. *Perceiver:* disorganized, adapt to change environment, gather more information before making a decision.

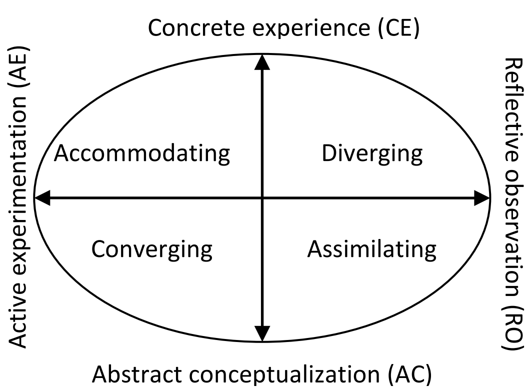
d) Flexible stable learning preference

With models in this family, learning style is not a fixed trait but is a differential preference for learning, which changes slightly from situation to situation. There are three typical models in this family: Kolb's Learning Style Inventory, Honey and Mumford, Felder-Silverman

i. *Kolb Learning Style Inventory*

According to Kolb [Kolb 1999], the author of this model: "learning is the process whereby knowledge is created through the transformation of experience. Knowledge results from the combination of grasping experience and transforming it". The center of Kolb model is the four-stage cycle of learning which contains four stages in learning process: *Concrete Experience* (CE - feeling), *Abstract Conceptualization* (AC - thinking), *Active Experimentation* (AE - doing) and *Reflective Observation* (RO - watching). The four-stage cycle is concretized as below:

1. Learner makes acquainted with the concrete situation, accumulates the experience (*CE*- feeling)
2. Learner observes reflectively (*RO* - watching) himself
3. He conceptualizes what he watches (observations) into abstract concepts (*AC* - thinking)
4. He experiments actively such concepts and gets the new experience (*AE* - doing). The cycle repeats again.



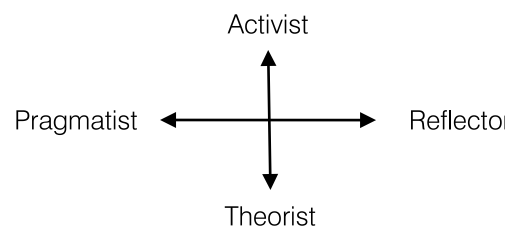
Based on four stages, there are four learning styles: accommodating, assimilating, diverging and converging. Each couple of these stages constitutes a style, for example, CE and AE combine together in order to generate accommodating style.

- *Accommodating* (CE/AE): emphasizes concrete experience and active experimentation. Learners prefer to apply learning material in new situations so that they solve real problems. A typical question for this style is "What if?"
- *Assimilating* (AC/RO): prefers abstract 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?"
- *Converging* (AC/AE): relies primarily on abstract conceptualization and active experimentation. Learners respond to having opportunities to work actively on well-defined tasks and to learn by trial-and-error in an environment that allows them to fail safely. A typical question for this style is "How?"
- *Diverging* (CE/RO): emphasizes concrete 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. *Honey and Mumford Model*

According to Peter Honey and Alan Mumford [Honey, Mumford 1992], the authors of this model, there are four learning styles:

- *Activist:* learners are open-mined and comprehend new information by doing something with it.
- *Reflector:* learners prefer to think about new information first before acting on it.
- *Theorist:* learners think things through in logical steps, assimilate different facts into coherent theory.
- *Pragmatist:* learners have practical mind, prefer to try and test techniques relevant to problems.



iii. *Felder-Silverman Model*

This model developed by Felder and Silverman [Felder, Silverman 1988] involves following dimensions:

- *Active/Reflective*. Active students understand information only if they discussed it, applied it. Reflective students think thoroughly about things before doing any practice.
- *Sensing/Intuitive*. Sensing students learn from concrete tasks related to problems and facts that could be solved by well-behaved methods. They are keen on details. Intuitive students discover alternate possibilities and relationships by themselves, working with abstractions and formula.
- *Verbal/Visual*. Verbal students like learning materials in text form. Otherwise visual student prefer to images, pictures…
- *Sequential/Global*. Sequential students structure their learning process by logically chained steps, each step following from previous one. Global students prefer to learn in random jumps. They can solve complicated problem but don't know clearly how they did it.

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iv. *Pask Model*

Pask model developed by Pask [Pask 1976] states that there are two learning styles:

- Wh*olist:* 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:

- *Meaning-oriented:* Learners prefer to get theory before go to examples (similar to assimilating style of Kolb model)
- *Application-directed.* Learners prefer to know the purpose of information before get theory (similar to accommodating style of Kolb model)
- *Undirected*: similar to FD style of Wikin model
- *Reproduction-oriented:* similar to FI style of Wikin model

III. Providing Adaptation of Learning Materials to Learning Styles

Learning styles are discovered and explored in psychological domain but how they are incorporated into adaptive systems? We must solve the problem of "matching" learning materials with users' learning styles. The teacher must recognize styles of students and then provide individually them teaching methods associated personal learning materials (lesson, exercise, test…). Such teaching method is called learning strategy or instructional strategy or adaptive strategy. Although there are many learning style models but they share some common features, such as: the modality *visual (picture)/visual (text)* in Dunn and Dunn model is similar to *verbalizer /imager* dimension in riding model and *verbal-visual* dimension in Felder-Silverman model. Strategies are supposed according to common features of model because it is too difficult to describe comprehensively all features of model. Features of all models (learning styles) can be categorized into three groups: perception and understanding which are enumerated together with adaptive strategies as below:

Perception group: This group related learners' perception includes:

- The *visual*(*picture*) / *visual*(*text*) modality in Dunn and Dunn model is similar to the *verbalizer/imager* dimension in Riding model and *verbal-visual* dimension in Felder-Silverman model. Instructional strategy is that the teacher should recommend textual materials to verbalizer and pictorial materials to imager.
- The *sensing/intuitive* dimension in Felder-Silverman model is identical to the *sensor/intuitive* dimension in Myer Briggs Type Indicator. Sensing learners are recommended examples before expositions, otherwise, expositions before examples for intuitive learners.
- The *perceptive-judging* dimension in Myer Briggs Type Indicator. Perceptive learners are provided rich media such as the integrative use of pictures, tables and diagram. Otherwise, judging learners are provided lean materials.
- The *impulsive/reflective* modality in Dunn and Dunn model is similar to the *activist/reflector* dimension in Honey and Mumford model, the *active/reflective* dimension in Felder-Silverman model and the *extravert/introvert* of Myers-Briggs Type Indicator. Active (also impulsive, extravert) learners are provided activity-oriented approach: showing content of activity and links to example, theory and exercise. Reflective (also introvert) learners are provided example-oriented approach: showing content of example and links to theory, exercise and activity.
- The *theorist/pragmatist* dimension of Honey and Mumford model. Theorists are provided theory-oriented approach: showing content of theory and links to example, exercise and activity. Pragmatists are provided exercise-oriented approach: showing content of exercise and links to example, theory and activity.
- The *accommodating/assimilating* dimension of Kolb model is similar to *application-directed/ meaning-oriented* dimension of Vermunt model. The adaptive strategy for accommodating style is to provide application-based information to learners. Otherwise, theory-based information for assimilating style.

Understanding group: This group related to the way learners comprehend knowledge includes:

- The *global/analytical* modality in Dunn and Dunn model is similar to *wholist-analytic* dimension in riding model, *global/sequential* dimension in Felder-Silverman model, *wholist-serialist* dimension in Pask model. Global (also wholist) learners are provided breadth-first structure of learning material. Otherwise, analytical (also analytic, sequential, serialist) learners are recommended depth-first structure of learning materials. For the breadth-first structure, after a learner has already known all the topics at the same level, other descendant topics at lower level are recommended to her/him. For the depth-first structure, after a learner has already known a given topic T_1 and all its children (topic) at lower level, the sibling topic of T_1 (namely T_2, at same level with T_1) will be recommended to her/him.
- The *FD/FI* dimension in Wikin model is correlated with *undirected/reproduction-oriented* dimension in Vermunt model. FD learners are provided breadth-first structure of materials, guided navigation, illustration of ideas with visual materials, advance organizer and system control. FI learners are provided depth-first structure of materials or navigational freedom, user control and individual environment.

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:

- Selection of information: Information (learning 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…
- Ordering information or providing different 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.
- Providing learners with navigation support tools: 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:

- *Instructional strategy* is itself, which contains adaptive rules and is in three above forms.
- *Instructional meta-strategy* is strategy which is used 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.

IV. Hidden Markov Model

There are many real-world phenomena (so-called 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:

- Given a finite set of state $S=\{s_1, s_2,…, s_n\}$ whose cardinality is n. Let $\prod$ be the *initial state distribution* where $\pi_i \in \prod$ represents the probability that the stochastic process begins in state s_i. In other words π_i is the initial probability of state s_i, where $\sum_{s_i \in S} \pi_i = 1$
- The stochastic process which is modeled gets only 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 $x_i \in S$ 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, $Pr(x_k \mid x_0, x_1,…, x_{k-1}) = \Pr(x_k \mid x_{k-1})$. Such process is called first-order Markov process.
- At each lock time, the process transitions to the next 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*: $\forall s_i \in S, \sum_{s_j \in S} a_{ij} = 1$. All transition probabilities a_{ij} (s) constitute the *transition probability matrix* A.

Briefly, MM is the triple $\langle S, A, \prod \rangle$. 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:

- There is the second stochastic process which produces *observations* correlating hidden states. Suppose there is a finite set of possible observations $\Theta = \{\vartheta_1, \vartheta_2,…, \vartheta_m\}$ whose cardinality is m.
- There is a probability distribution of producing a given observation in each state. Let $b_i(k)$ be the probability of observation ϑ_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*, $\forall i \in S, \sum_{\theta_k \in \theta} b_i(k) = 1$. All

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probabilities of observations $b_i(k)$ constitute the *observation probability matrix B*.

Thus, HMM is the 5-tuple $\Delta = \langle S, \theta, A, B, \prod \rangle$. Back to weather example, suppose you need to predict how whether is tomorrow: *sun* or *cloud* or *rain* since you know only observations about the humidity: *dry, dryish, damp, soggy*. The HMM is represented following:

S = {*sun, cloud, rain*}, θ = {*dry, dryish, damp, soggy*}

sun	cloud	rain
0.5	0.5	0.5

Uniform initial state distribution ∏

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

Transition probability matrix A

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

Observation probability matrix B

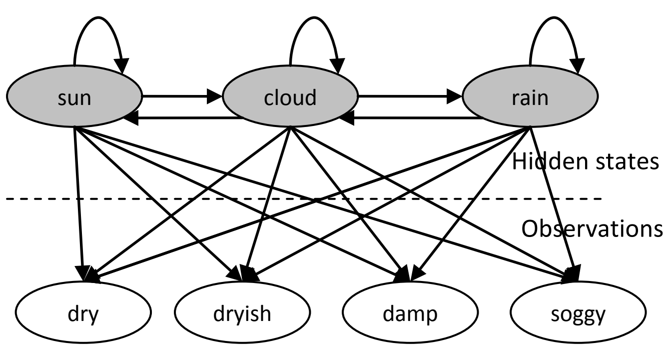

Figure 1 : HMM of weather forecast (hidden states are shaded)

Uncovering problem and Viterbi algorithm

Given HMM Δ and a sequence of observations $O = \{o_1 \rightarrow o_2 \rightarrow \ldots \rightarrow o_k\}$ where $o_i \in \theta$, how to find the sequence of states $U = \{u_1 \rightarrow u_2 \rightarrow \ldots \rightarrow u_k\}$ where $u_i \in S$ 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: $\arg\max_U [\Pr(O \mid \Delta)]$. 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.

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, θ, 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): Δ_1, Δ_2, Δ_3 respectively. For example, in Δ_1, there are two states: *Verbal* and *Visual*; so S_1={*verbal, visual*}. We have:

- $\Delta_1 = \langle S_1, \theta_1, A_1, B_1, \prod_1 \rangle$.
- $\Delta_2 = \langle S_2, \theta_2, A_2, B_2, \prod_2 \rangle$.
- $\Delta_3 = \langle S_3, \theta_3, A_3, B_3, \prod_3 \rangle$.

We are responsible for defining states (S_i), initial state distributions ($\prod_i$), transition probability matrices (A_i), observations (θ_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 $\prod_i$.
   $\prod_1$ = {0.5, 0.5}; it means that *Pr* (*verbal*) = *Pr* (*visual*) = *0.5*
   $\prod_2$ = {0.5, 0.5}; *Pr*(*activist*) = *Pr*(*reflector*) = *0.5*
   $\prod_3$ = {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, $Pr(s_i$=*verbal* | s_{i-1}=*verbal*) = *0.7* is obviously higher than $Pr(s_i$=*verbal* | s_{i-1}=*verbal*) = 0.3.

	verbal	*visual*
erbal	0.7	0.3
visual	0.3	0.7

	Activist	Reflector
Activist	0.7	0.3
Reflector	0.3	0.7

	Theorist	Pragmatist
Theorist	0.7	0.3
Pragmatist	0.3	0.7

Table 1 : Transition probability matrices: A_1, A_2, A_3

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.

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:

- θ_1 = { *Text, picture, video* }
- θ_2 = { *Theory, example, exercise, puzzle, low* (interaction), *medium* (interaction), *high* (interaction) }
- θ_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:

- $Pr(text \mid verbal) = 0.6$, $Pr(picture \mid verbal) = 0.3$, $Pr(video \mid verbal) = 0.1$
- $Pr(text \mid visual) = 0.2$, $Pr(picture \mid visual) = 0.4$, $Pr(video \mid visual) = 0.4$

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:

- $Pr(puzzle \mid activist) = 0.4$, $Pr(example \mid activist) = 0.3$, $Pr(theory \mid activist) = 0.2$, $Pr(exercise \mid activist) = 0.1$
  $Pr(low \mid activist) = 0$, $Pr(medium \mid activist) = 0$, $Pr(high \mid activist) = 1$.
- $Pr(example \mid reflector) = 0.4$, $Pr(theory \mid reflector) = 0.3$, $Pr(exercise \mid reflector) = 0.2$, $Pr(puzzle \mid reflector) = 0.1$
  $Pr(low \mid reflector) = 1$, $Pr(medium \mid reflector) = 0$, $Pr(high \mid reflector) = 0$.

Because the sum of conditional probabilities of observations on each state is equal *1*, we should normalize above probabilities.

- $Pr(puzzle \mid activist) = 0.4*4/7 = 0.22$, $Pr(example \mid activist) = 0.3*4/7 = 0.17$, $Pr(theory \mid activist) = 0.2*4/7 = 0.11$, $Pr(exercise \mid activist) = 0.1*4/7 = 0.05$
  $Pr(low \mid activist) = 0*3/7 = 0$, $Pr(medium \mid activist) = 0*3/7 = 0$, $Pr(high \mid activist) = 1*3/7 = 0.42$
- $Pr(example \mid reflector) = 0.4*4/7 = 0.22$, $Pr(theory \mid reflector) = 0.3*4/7 = 0.17$, $Pr(exercise \mid reflector) = 0.2*4/7 = 0.11$, $Pr(puzzle \mid reflector) = 0.1*4/7 = 0.05$
  $Pr(low \mid reflector) = 1*3/7 = 0.42$, $Pr(medium \mid reflector) = 0*3/7 = 0$, $Pr(high \mid reflector) = 0*3/7 = 0$.

According to Honey and Mumford model, *theorists* are provided theory-oriented approach: 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.

	Text	Picture	Video
Verbal	0.6	0.3	0.1
Visual	0.2	0.4	0.4

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Table 2 : Observation probability matrices: B_1, B_2, B_3

	Theory	Example	Exercise	Puzzle	Low	Medium	High
Activist	0.11	0.17	0.05	0.22	0	0	0.42
Reflector	0.17	0.22	0.11	0.05	0.42	0	0

	Theory	Example	Exercise	Puzzle	Low	Medium	High
Pragmatist	0.11	0.17	0.22	0.05	0.04	0.08	0.3
Theorist	0.22	0.17	0.11	0.05	0.3	0.08	0.04

Now three HMM (s): Δ_1, Δ_2, Δ_3 corresponding to three dimensions of learning styles: *Verbal/Visual*, *Activist/Reflector*, *Pragmatist/Theorist* are represented respectively in figure 2.

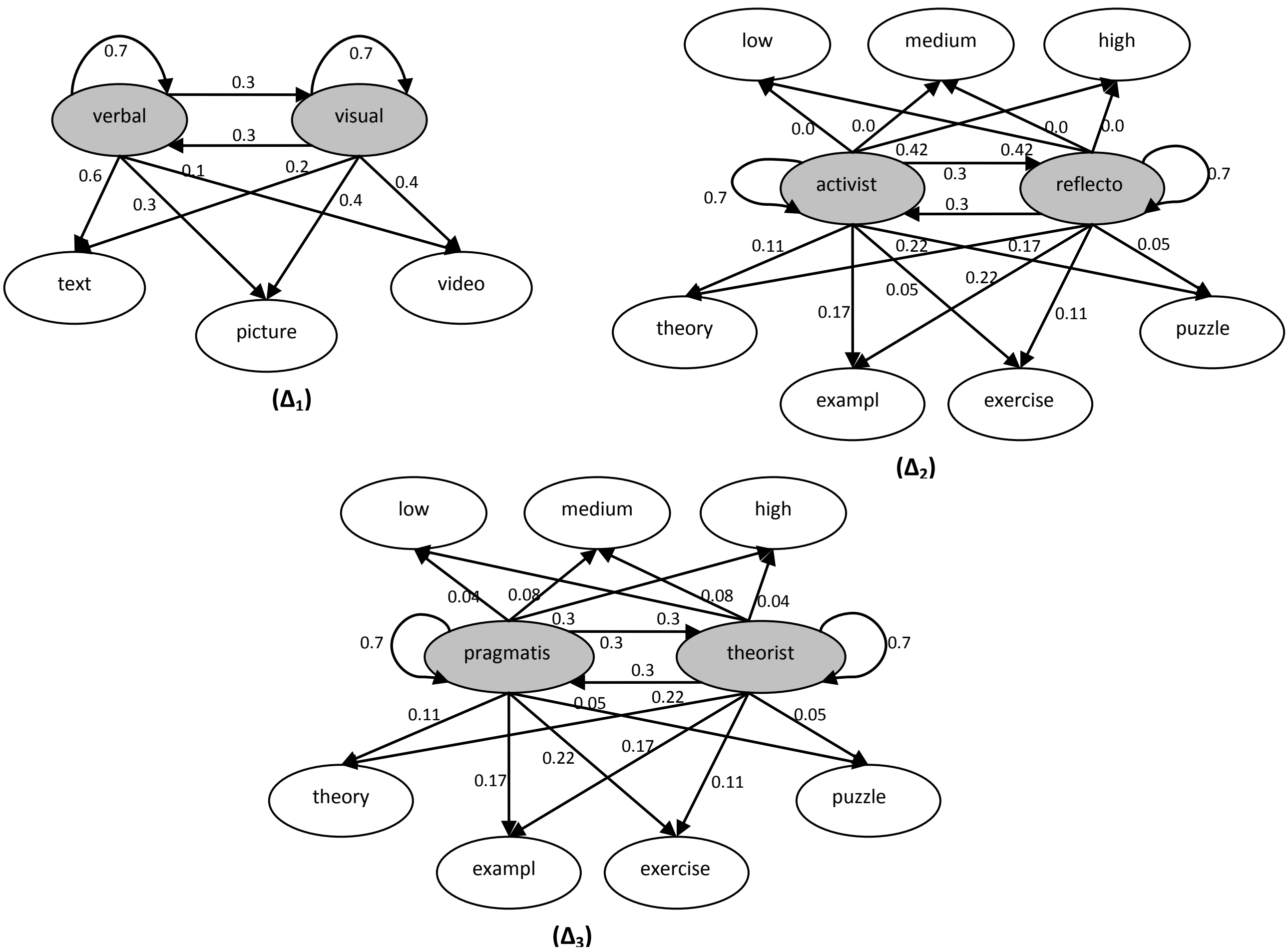

Figure 2 : HMM (s) of learning styles (hidden states are shaded)

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.

Table 3 : Learning objects selected

	Format	Type	Interactive
LO_1	picture	theory	not assigned
LO_2	text	example	not assigned
LO_3	text	not assigned	low

It is easy to recognize the sequence of user observations from the attributes *format, type, interactive.*

Table 4 : Sequence of student observations

Hmm – Dimension	Sequence of Observations
Δ_1: Dimension Verbal/Visual	picture → text → text
Δ_2: Dimension Activist/Reflector	theory → example → low
Δ_1: Dimension Pragmatist/Theorist	theory → example → low

Using Viterbi algorithm for each HMM, it is possible to find corresponding sequence of state transitions that is most suitable to have produced such sequence of observations.

Table 5 : Sequence of state transitions

Hmm - Dimension	Sequence of Observations	Sequence of State Transitions	Student Style
Δ_1	picture → text → text	visual → verbal	verbal
Δ_2	theory → example → low	reflector → reflector → reflector	reflector
Δ_1	theory → example → low	theorist → theorist → theorist	theorist

It is easy to deduce that this student is a verbal, reflective and theoretical person. Since then, adaptive learning systems will provide appropriate instructional strategies to her/him.

VI. 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.

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