Estimation and Adaptation Method for Students' Learning Styles on Web-based Learning Environment

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***Abstract*—Learning Style is an important factor that determines how students acquire knowledge. In this paper, we present our approach for recognition of students learning styles on the web-based learning environment and adaptation features that will help to personalize their learning experience leading to improved learning outcomes.**

Keywords-text; Adaptation; Learning Style; Web-based Learning.

I. INTRODUCTION

With the development of sophisticated e-learning environments, which characterize the huge information, the strong interactivity, the great coverage and no space-time restrictions [1], personalization is becoming an important feature in e-learning systems. The large numbers of students, the main users of such systems have differences in background, goals, capabilities and learning styles [2]. Adapting these differences especially on web-based systems will personalize their learning experience and therefore increase their motivation and learning outcomes especially when they are completely self-directed learners. Learning Styles as one of these individual differences every student possesses can be defined as everything that is characteristic to that particular individual when he/she is learning, i.e., a specific manner of approaching a learning task, the learning strategies activated in order to fulfill the task [3]. Various researches have tried to provide adaptation on the web, based on this important trait, but the main challenges still remain on how to effectively detect and adapt learning styles without destructing student-learning experience. So in this paper, we are outlining different methods especially implicit methods used by related works and then explain our approach and why we think it is effective.

The paper has been arranged as follows: In Section 2, an overview of learning styles estimation methods is given while Section 3 points out the details of implicit methods. Section 4 explains our approach and the last section gives a conclusion and future work to be done.

II. LEARNING STYLES ESTIMATION METHODS

Most of the approaches proposed can be categories into either an explicit or implicit approach. Explicit approaches estimate learning styles by directly gather information using one or more users` query methods while implicit approaches rely on actions and behavior of users observed during their interaction with the system. The latter means the user models are updated by using information that is collected automatically [4].

III. IMPLICIT METHODS

The implicit approaches fall into 2 types, which are literature based approaches and data-driven approaches. In literature-based approaches, behavior and actions of users are monitored and used as hints about their preferences by applying the simple rule method [5] to estimate the match with predefined learning style classes. The advantage of this approach is its ability to deduct learning style without the need of training data since it depends entirely on learning style models [4]. Data-driven approaches depend on real users' data and therefore have a high chance of being accurate but the main challenge is a representative dataset is needed to be available to build an accurate classifier [6][10]. The following are classification methods used by most of the existing data-driven systems.

A. Artificial Neural Networks

Neural Networks are a computational approaches with a model that base on the biological neural structure of the brain. They comprise of input layer, which has neurons that receive signals from the environment, hidden layer transmits signals to other neurons after getting the input from other neurons and output layer that sends output signals to the environment. Feed Forward Neural Network, which is one type of neural network was used by Villaverde et. al [7] to model learning styles from students' actions by identifying ten patterns of behavior to be a network input. The output of this model represents three dimensions of Felder-Silverman learning styles model. The good thing about this method is, it can be updated quickly since it relies on history profiles and therefore, it can distinguish changes in users' behavior.

B. Bayesian Networks

Since a Bayesian Network (BN) is a directed, acyclic graph whose nodes are labeled by random variables [8], it can be used to model the relationship between the learning styles and the factors determining them. Garcia et al [9] used this approach to implicitly detect students learning styles by observing their behavior in SAVER system. The random variables were the different dimensions of Felder-Silverman Learning styles and the factors that determine each of these

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aspects and these factors were extracted from the students' interaction data with the system. The reported reasons to use BN are its natural representation of probabilistic information, its efficiency, and its support to encode uncertain expert knowledge. Fig.1 shows an example of the structure of BN, where leaf nodes represent student's observable behavior and root nodes represent the learning style to infer [9][10].

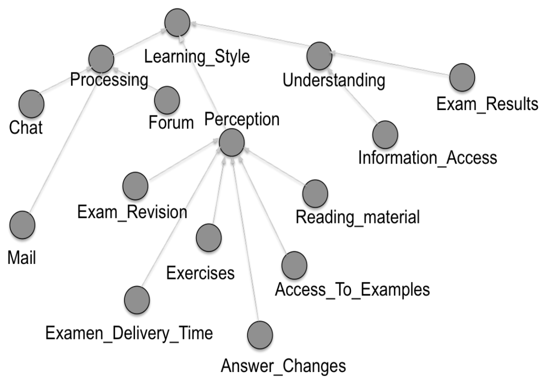

Figure 1. Bayesian Network Modelling Students' Learning Styles.

C. *Decision Trees and Hidden Markov Model*

Decision trees (DT) are an AI classification algorithm frequently used in estimating learning styles because of its simplicity, the rules of classification are visible and easy to understand, and it is appropriate when many attributes are relevant [10] .Cha et al [11] used this approach with 58 patterns of behavior to automatically deduce the 4 dimensions of Felder-Silverman model [12] of 70 students in a web-based learning course. He used together with Hidden Markov Model (HMM). His DT structure consisted of leaves that represent the learning styles to be inferred, and the nodes that represent the features tracked that lead to those learning styles [10].

IV. Our Approach

A. *Learning Style Estimation*

Since most of the implicit approaches rely on available data, we think at the initial stage when the system does not have enough data about a new log in user, a direct feedback from a user should be used to estimate their preference. This approach helps to solve "cold start" problem. "Cold start" is the problem whereby a new user of the system starts with nothing in his/her profile, and therefore a training period is required to train the profile before it accurately reflects user's preferences [13]. To solve this problem, most systems use collaborative filtering approach in which a prediction is made about a new user based on the similarity between the interest profile of that user and those of other users [14][15][16]. This may be suitable in other domains like e-commerce, but in learning environment may not be effective because no matter how similar users might be, they still have their own unique way of learning. Then, during their learning period, their interaction data should be the one to be used. This means we are using both explicit and implicit approaches with initial and learning process stages respectively.

Initial Stage:

When a new user logs into the system, the Kolb's Learning Style Inventory questionnaire (LSI) will be given. LSI was "designed to measure the degree to which individuals display different learning styles" in accordance with Kolb's learning style model [4][17]. Kolb's model as one of the many learning style models found in the literature is probably the most famous one. This model articulates that people learn from experience so the learning is a continual process, which follows the cycle. Therefore, it is very unlikely that people will always have the same learning style, but changes during the knowledge construction process, which involves the person and the environment they find themselves [18]. It categorizes students into 4 classes of learning styles, which are Accommodators, Assimilators, Convergers, and Divergers. So the system will place a student within one of these four categories based on the response to the questionnaire. We have decided to use this model over others because it base on the idea that people learn through experience so it can accommodate the dynamism of their learning styles with respect to change in time [19]. This means in the next stage where dynamic data about user will be captured, Kolb's model will still act as a better framework that guide the inference of students' categories.

During Learning Process:

Since the learning types of Kolb's are associated with experience and therefore the types of materials users would like to access to accomplish a learning task. We want to estimate their ranking preference of these materials based on the frequency of clicks on a particular material page link at this stage. The idea is based on assumption that frequency and duration of access are two major indicators of a user interest in a page [20][21]. But, we haven't used the duration because in learning environment duration might not necessary give the clear indication of user interest on a page. For example, a slow learner might spend much time on page which he/she don't like but difficult for him/her to comprehend, while a faster learner can still spend much time on the same page because he/she likes the content materials. Also, the size of the page might also affect the duration of access. On the other hand, we think clicking frequency gives a clear indication of learning material preference. This can be seen clearly especially during assessments because users will always go back to revisit the pages of the kind of materials that better give them the understanding to respond to the assessments.

So, the material types and their urls are as follows: Problems solving tasks (url_p), Examples (url_e), Theory (url_t) and Exercises (url_x). Given a session a user initiates we want to determine the preference of Exercises material types with respect to other materials. To do that we take the number of clicks in exercises page (url_x) over the total clicks made in different pages material within a session as shown in (1):

$$Frequency_{urlx} = \frac{\sum Clicks_{urlx}}{\sum Session\ clicks} \quad (1)$$

We are taking the assumption that the higher the frequency of clicks of a given url with respect to other urls within the session, the higher the preference of that kind of material.

B. Adaptation Features

Fragment Sorting:

Fragment Sorting is the technique in which educational resources are presented in a different order considered suitable for each student [19] [22]. This is one of our system's adaptation features. At the "initial stage", different orders of materials to each learning style the Kolb's questionnaire categorizes a user will be given. The orders have the most suitable material at the top to the least one at the bottom. The font size and color of each link to the material is also different with top one larger and bottom one smaller in descending order. This will help users reduce the cognitive effort of deciding which material to access first and therefore help their navigation process. Fig. 3 shows the orders of materials for each student type at the initial stage.

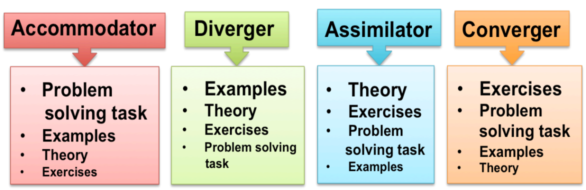

Figure 2. Fragment Sorting for each learning style type.

This order manually ranked based on Kolb's Experiential Learning cycle shown in Fig. 3:

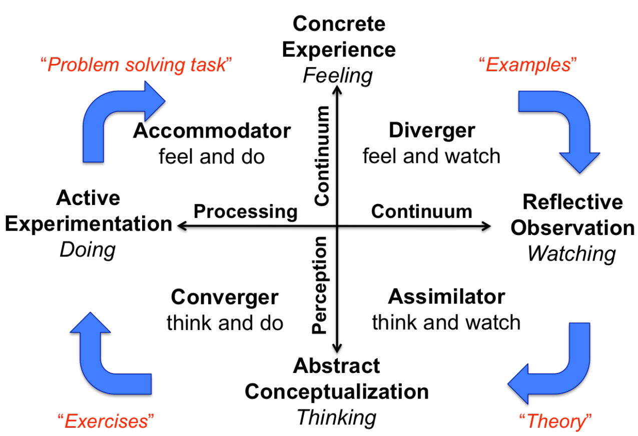

Figure 3. Kolb's Experiental Learning Cycle.

Based on the ranking order in Fig. 2,we want to estimate the value of importance of each material type to a student using reciprocal rank measure [23]. We are calling this importance value as Kolb's Value (KV) and will be calculated using (2) below:

$$KV = \frac{1}{rank_i} \quad (2)$$

where KV refers to the Kolb's value of a particular material type and $rank_i$ refers to its ranking position from the top.

Since our main idea of using Kolb's model at the start, based on our mutual belief with Kolb that users learning style changes with experience and knowledge. We want to provide different fragment sorting each time a user session starts, as we believe his/her preference of learning might change as his/her knowledge of particular topic advances. To do that, we have to estimate and combine the value of importance of each learning material type at the "initial stage" which is Kolb's value and the "learning process" stage, which is the previous active session of the student. The Equation (3) shown below is the combination of (1) and (2), to get the total importance of particular material type based on its url.

$$I_{url} = KV + Frequency_{url} \quad (3)$$

The order now will be changing dynamically in each new session, following the higher the importance value of the material type. For example, If $I_{urlp} > I_{urle} > I_{urlt} > I_{urlx}$ then the order will be Problem Solving Task⇒Examples⇒Theory⇒Exercises.

Adaptive Link Generation

We want to provide navigation support to a user especially during assessments as we believe at this moment is when he/she will revisit materials so as to help him/her to perform assessment tasks. The idea that users always jumps back during assessment is derived from the study conducted on 140,546 students participated in 4 Massive Open Online Courses (MOOCs) by Guo et al [24]. This study found that, despite the linear structure imposed on students-chronological ordering of weeks and learning sequences-learners predominantly navigate through MOOCs in a nonlinear way, on average students skip 22% of learning sequences entirely and perform back jumps, most often from assessments back to early lectures. But because for our case, the situation is different due to the fact that different material types are given for a particular topic. We want a user to be able to easily navigate to the particular material type of his preference when attempting the test.

So after a user opens the test page and attempt all questions, the system then evaluates the results and generates a link based on the previous importance values of urls of different material types for a user. If the score is below 60%, a link to most important material type will be shown. Next links will continue being generated based on the decreasing importance value every time a user re-attempt the exam and get below 60%, otherwise, a user will be allowed to continue to the next learning topic.

V. CONCLUSION AND FUTURE WORK

In this paper, we have presented a method to estimate and adapt student's' learning style, which combines both explicit

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and implicit approaches. The key idea is that our method can leverage the "cold start" problem faced by most data-driven methods, as they don't have enough data at the beginning of student interaction with the system. And also we think in learning environment it is individual actions that are most important, so we have used frequency of clicks information with the expectation that it will give more accurate inference about a user rather than relying on collaborative-filtering approaches used by different existing systems where a user learning style is estimated using data about similar users.

In the future, we would like the system to be updated with more data-driven approaches. This approach will be more suitable as a system continues to build a "rich profile" of the user as he/she continue to learn while interacting with the system. We want to incorporate time spent on materials information in more efficient way by considering the size of pages (materials), and also consider the comparison on duration spent on the same size of material with respect to different learners' performances. We also want to include more users' data about preference of on certain types of system tools like chats, forum, etc. This will help to perform cluster analysis of different type of users and can lead to better recommendation of what types of users should work together in tasks that need collaborative work.

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REFERENCES

[1] R. Anane, S. Crowther, J. Beadle and G. Theodoropoulos, "eLearning content provision" In Proceedings of the 15th international workshop on database and expert systems applications (DEXA'04) , pp. 420-425, 2004

[2] A. Klasnja-Milicevic,M.Ivanovic and A. Nanopoulos, "Recommender systems in e-learning environment:a survey of the state-of-the-art and possible extensions, " Artificial Intelligence Review, vol. 44, pp. 571-604, Sept. 2015, doi:10.1007/s10462-015-9440-z.

[3] E. Popescu, P. Trigano, and C. Badica, "Toward a unified learning style model in adaptive educational systems," In 7th Proc. IEEE International Conference on Advanced Learning Technology, pp. 804-808, 2007.

[4] A. Al-Azawei and A. Badii, "State of the art of learning styles-based adaptive educational hypermedia systems," International Journal of Computer Science & Information Technology(IJCSIT), vol. 6,No 3, pp. 1-19, June 2014,doi:10.5121/ijcsit.2014.6301.

[5] S. Graf and P. Kinshuk, "An Approach for Detecting Learning Styles in Learning Management Systems," Sixth IEEE Int. Conf. Adv. Learn. Technol., pp. 161–163, 2006.

[6] S. Graf ,"Adaptivity in learning management systems focusing on learning styles," Ph.D. thesis,Vienna University of Technology,9801086 Neulinggasse 22/12A 1030,Vienna, 2007.

[7] J. Villaverde, S. Godoy, and A. Amandi, "Learning styles' recognition in e-learning environments with feed-forward neural networks," J. Comput. Assist. Learn.,vol . 22 no. 3, pp. 197-206,May 2006.

[8] F. Jensen. "An introduction to Bayesian Networks," Springer Verlag,1996.

[9] P. Garcia and A. Amandi, "Using Bayesian networks to detect students' learning styles in a Web-based education system," Proc ASAI, Rosario,no.11,pp. 29-30,2005.

[10] J. Feldman, A. Monteserin, and A.Amandi, "Automatic detection of learning styles:state of the art ," Artificial Intelligence Review, vol. 44, pp. 157-186, May 2014, doi:10.1007/s10462-014-9422-6.

[11] H. Cha, Y. Kim, S. Park, and T.Yoon, "Learning Styles Diagnosis Based on User Interface Behaviors for Customization of Learning Interfaces in an Intelligent G. Eason, B. Noble, and I. N. Sneddon, "On certain integrals of Lipschitz-Hankel type involving products of Bessel functions," Phil. Trans. Roy. Soc. London, vol. A247, pp. 529–551, April 1955.

[12] F.R. Silverman, "Learning and Teaching Styles in Engineering Education," Engineering Education, vol 78(7), pp. 674-681, 1988.

[13] P. Resnick and H. Varian, "Recommender Systems,," Communications of the ACM,40(3):pp. 56-58 ,1997.

[14] D. Billsus and M. J. Pazzani. "Learning collaborative information filters". Papers from The AAAI Workshop on Recommender Systems WS-98-08, AAAI Press, Menlo Park, California, 1998.

[15] D. R. Greening. Collaborative filtering for web marketing efforts. Papers from The AAAI Workshop on Recommender Systems WS-98-08, AAAI Press, Menlo Park, California, 1998.

[16] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl. Grouplens: An open architecture for collaborative filtering of netnews. In Proceedings of the ACM Conference on Computer Supported Cooperative Work, pages 175–186, 1994.

[17] D. Kolb, "Individual learning styles and the learning process," MIT 1971.

[18] E. Brown, "The use of learning style in adaptive hypermedia," Thesis submitted to the university of Nottingham for the degree of doctor of philosophy, 2007.

[19] A. Mbilinyi, S. Hasegawa, and A. Kashihara, "Design for Adaptive User Interface for Modelling Students' Styles," Proc. HCI International 2016, Springer,LNCS 9735,pp. 168-177,Toronto,Canada,July 2016 .

[20] P. Chan, "A non-invasive learning approach to building web user profiles," In Workshop on Web usage analysis and user profiling , Fifth International Conference on Knowledge Discovery and Data Mining,pp. 7–12,1999.

[21] H. Liu, and V. Keselj,. "Combined mining of web server logs and web contents for classifying user navigation patterns and predicting users' future requests". Data and Knowledge Engineering 61(2):pp. 304–330, 2007 .

[22] P. Brusilovsky, "Adaptive Hypermedia," User Model. User-Adap. Interact .11,pp. 87-110, 2001.

[23] Mean reciprocal rank.Available from: https://en.wikipedia.org/wiki/Mean_reciprocal_rank .

[24] P. J. Guo and K. Reinecke, "Demographic differences in how students navigate through MOOCs," In Proceedings of the First ACM Conference on Learning' Scale Conference,pp. 21-30,2014.