An Analysis of Activity Sequence Modeling and Active Clustering for Custom-made E-Learning

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Received May 24, 2017
Accepted June 16, 2017

ABSTRACT

Monitoring and interpretation of sequential activity learning can improve adaptation and customization in the educational environment. We can discover new semantically meaningful information to learners, to model the learner’s problem modeling solution, to use the model at the target, ultimately to automate clustering we present an approach based on. Approach is applicable to different levels to detect resolution of problem of predefined style. To identify the problem of resolution style by analyzing learner’s behavior according to the known dimension of learning, we will establish to discover how semi-automatic learning dimensions and concrete model of problem solving. In this article, the approach itself explains the feasibility of applying to the real world data and address aspects of the approach that can be adjusted to different learning contexts. Finally, we discuss the adaptation cycle to the appropriate intervention in the dialogue process, the incorporation of the proposed approach in the data collection system.

Key words: sequence modeling, clustering, activity model, monitoring, problem solving.

Introduction

Research interest in the field of adaptive systems is steadily increasing over the past 30 years, which is also true for the field of applications that are actively configured to support users. The field of e-Learning is such an area and it has rapidly evolved into a viable alternative to the traditional learning environment, so it has become the focus of research on adaptive systems. Despite attention that adaptive learning has recently received focus (eg, [Brusilovsky et al., 2004]) as a social process, learning is being treated as a process consisting of interconnected activities (For example (see Solar and Lesgold 2007), but not consumption (passive or active) learning content, to an individual or group level. The premise of the line of work reported in this paper is that the monitoring and interpretation of online learning activities can eventually lead to a rich model for learner users, which in turn enables new forms And expanded the adaptive response in the context of e - learning. In this article, we propose a new approach to deal with extraction, analysis and interpretation of information from sequential user activities of this information as the ultimate goal to derive intention knowledge adaptation of natural learning behavior.

As a proposed approach, we use models obtained in combination with other types of monitoring data, especially for modeling and discovering user activity sequences (like Markov model discrete) Integrate into adaptation cycles (Including discovery of new semantics of learner’s behavior) semantically meaningful information of the learner. Discovery is guided in both cases by grouping learning activity sequence patterns. Grouping can be applied at three levels according to the purpose of discovery.

- To detect patterns / behavior defined styles from learners thinking as level I (focusing on patterns), showing their skills, features, knowledge, etc,
- **Level II** (base dimensions), semi-automatically detect settings and may still relate to actions associated with specific learning dimensions that are unknown.

- **Automatically reduces** human intervention in the process of level III (open discovery), to detect potential learning dimensions and specific actions, focuses on assessing the validity and usefulness of the results of the system I am counting on you.

To demonstrate the feasibility of the approach, we applied real-world data to the domain of problem solving. Problem solving is an important part of the learning process in traditional learning environments and e-learning. Learners’ problem solving styles are on different levels but they are explained in the same way as the most well-known learning style, and in most cases (see, for example, [Lefrancois, 2006]) you can see. To solve problems, atoms are applied to problems of different levels of complexity. While analyzing Behavior for problem solving is done using mostly statistical knowledge to study styles based on user activity data, which is almost exactly investigated and can not be modeled without more detailed sequence information when appropriate for the proposed approach.

For the purposes of the work described in this document, we have developed a custom template to capture the sequence of student activities involved in problem solving in a particular intellectual education system (ITS). We set up a resolution sequence student problem that uses these models, depending on the above three levels, then for clustering, (a) Detects the resolution of the style of predefined problem (s). (B) learn a new style of problem solving according to predefined learning dimensions. And (c) finds a potentially interesting learning dimension and associated problem solving style.

### Related Work

The work described here is a wide field of research data mining e-learning (EDM) and data mining [Romero and Ventura, 2006] that combines aspects and questions from various fields (P. Example: E-learning / Distance learning, etc. Machine learning, adaptive system). In [Romero and Ventura 2010], the authors [Srivastava et al., 2000] (a) classify work by searching educational data of statistical and visualization, (b) can search the web Cluster, abnormal value and classification detection, extraction of association rule and sequential extraction pattern, and text timing. The decompression web (use) further integrates classification and place in offline web search, to find models and other information to support education to learn online web and validate models of quest A model discovered can be online [Li and Zaiane, 2004] equipped with "intelligent" systems that can help students of their learning efforts.

Including prediction, regression classification, estimation: Different viewpoints for searching for educational data are established in [Baker and Yacef, 2009] and [Baker 2010] where categories are specified Density, clustering, (association extraction rule extraction Correlation, time series pattern extraction and exploration of causal data) for operating connection, data distillation model and human judgment and discovery.

In addition to the different classification methods, the data mining process at the educational site can be divided into the following phases [Romero et al. 2007]: data collection, preprocessing of data, data mining application, interpretation of results, evaluation and deployment.

Since the focus is on the utilization of the Internet, especially focusing on integration and sequential extraction patterns in the context of student modeling.
The works presented here cover many of the above categories and analyze the activity data of registered users. On the basis of. The main objective of this research is to facilitate the discovery (semi-automatic) model that happens in an active sequence in the learning context to easily recognize and highlight it. Although the explaining activities described here are being carried out offline, furthermore, the results should be used for online analysis of learning behavior, possibly combined with adaptive intervention. In many cases - another important feature of the proposed approach is that, ultimately, human intervention is only necessary to evaluate the results of the analysis process, but annotate activity data before analysis. As a result, the equivalent purpose and the preconditions of other approaches in literature.

The rest of this section begins with an overview of the relevant research in the field of mining and analysis in the educational system. It focuses on students' modeling based on sequential clustering method on the cluster. Comparison of our approach with those chosen in this section.

The system can process user activities such as individual items (aggregation or event style) [Amershi and Conati, 2009], [Romero and Conati, 2008] or Active Sequence [Solar 2007] [and Solar Lesgold 2007]. Another difference can be made in the way data is being analyzed at a later time. In recent years there is a tendency to use a combination of data mining and machine learning techniques to analyze activity data [Romero and Ventura, 2010], [Romero et al. 2007] [Hamar AINEN et al., 2004], [Amershi and Conati, 2009]. Individually Processing In systems based on individual activities, it is often necessary to predict the success (often, more specifically, grade) [Romero et al., 2008] or behavior and future interest rates [cock, 2009]. Aiming to extract characteristics of users and individual groups [Choi and Kang, 2008].

In [Romero et al. 2007] and [Romero et al., 2008], the authors describe the processing of flight data by expanding to Moodle's Course Management System (CMS) Moodle 2010. Their approach is based on the diary of aggregated data.

**User Activity Data Mining and Analysis in Educational Systems**

Another viewpoint is described in [Lee and Kang, 2008] where learner's activity data identifies inconsistent factors and is monitored and analyzed to promote collaborative learning. The contradictory factors are ultimately discussed as a factor hindering the achievement of the learning objectives. Promotional factors are described as learner's positive or favorable recognition factors for achieving the learning objectives. Here, the authors introduce the approach, compared to the above, based on the semantic information behind the activities of more users. In general, all activities are monitored. Analysis however for example, extracting relevant parts and supporters common to "apprenticeship of action" as "summary of teaching materials", "task bypass", "change material" or "minutes of draft conference."

In [Vialardi et al., 2009], the authors classify a new approach to data mining in the context of the educational system with the aim of predicting the suitability of specific courses to specific students based on prediction. The success of the system for each course will provide personalized recommendations. Unfortunately, the authors do not provide a detailed description of the database records they use. We can, however, conclude that they will work with accumulated data comparable to those stated in Romero et al. (Including, for example, the number of courses the students are enrolled in), their From the rules generated by the classification system. We used it in the work described in this document, 2008].
One approach describes tree-based methods and decision trees of appropriate learning content (objects) provided by conceptual authors, in this issue presented and consolidated in [Sue et al., 2011] Learners Requirements and specific learning / interaction context. This approach is specifically designed to match the "user request" of content elements (also encapsulating hardware features, learning and preferences of network conditions) within the repository of objects Learning Learning.

In [Anaya and Boticario, 2009], the authors explore data mining in the education system with particular emphasis on the collaborative learning process. Their objectives of their approach are as follows. Revealing learner’s collaboration will provide information as soon as the region is independent and after the process is over. This approach is applied with students from Distance Education National University (UNED) in Spain using the learning environment dotLRN [LRN, 2010]. Participating students had access to discussion forums, and other tool analyzes such as FAQs, news, calendars, etc. are limited to statistical interactions in the forum without consideration of semantic information It was. Statistical indicators were used as follows Foundation for extracting information on cooperative behaviors of learners and grouping them accordingly. In this issue, the paper by the same author [Anaya and Boticario, 2011], by characterizing cooperative behavior, by introducing metrics based on statistical indicators with clustering with excellent performance, The approach will present a more complete and comprehensive view Learner.

[Beer et al., 2006], we find approaches to classification of learner engagement based on multiple data sources. We will also explore an integrated approach to acquiring information, including student and teacher’s note self-report motivation profile.

Reference: