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E-Learning by Time Dynamic Model Using Data Mining

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Abstract

The object of this paper is to build up Just in Time Dynamic Learner Models to analyze learners' behaviors and to evaluate learners' performance in online education systems by using rich data collected from e-learning systems. The goal is to create metrics to measure learners' characteristics from usage data. To achieve this goal we need to use data mining methods, especially clustering algorithms, to second patterns from which metrics can be derived from usage data. In this paper, we propose a six layer models(raw data layer, fact data layer, data mining layer, measurement layer, metrics layer and pedagogical application layer) to create a just in time learner model which draws inferences from usage data. In this approach, we collect raw data from online systems, latter fact data from raw data, and then use clustering mining methods to create measurements and metrics.

Index terms— Data mining, E-learning, iHelp.

1 INTRODUCTION

he research in this paper is an investigation on how to apply data mining rules [1,2,4], especially clustering algorithms, to e-learning usage data to dynamically create just in time learner models.

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Make Sense of Usage Data: E-learning systems are used for computerbased education and they have widespread use in many domains. The usage data collected from the forum for each learner includes: Messages posted in the forum, question messages posted in the forum, answering messages posted in the forum, messages accessed by the learner, messages mostly navigated by the learner.

2 Issues of Using Usage Data:

With rich usage data collected from e-learning systems, we try to make sense of this data by applying data mining techniques. There are some challenging issues that need to be navigated: among patterns found from data mining techniques, patterns are useful in an e-learning system, determine that a pattern is useful or not, predict learners' behaviors based on the usage data.

3 OBJECTIVE

In this paper, we did some proof of concept research to study the above issues. We studied the relationships between usage data and learner [6] characteristics and behaviors. This resulted a six layers model to create learner models. This is a dynamic model created by applying clustering techniques on the usage data collected from the real system. We implemented a test system to collect data and to create results. Two experiments have been used to evaluate and compare the results of the test system.

4 III.

PROBLEM DEFINITION Some patterns found from the usage data, also called metrics and measurements to represent learners' characteristics, seem to be clearly useful in building learner models. Other patterns show promise to describe learners' behaviors, but remain unproven. Deferent clustering algorithms produce various results. Selection and determination of data mining algorithms and associated parameters will play an important role in creating learner models. Pre-computation is necessary if anything like just in time modeling is to be achieved, and has been implemented in our test system Global Journal of Computer Science and Technology Volume XI Issue XVII Version I 31 IV.

5 LITERATURE REVIEW

In order to more easily discuss the [1,2] current state of web based e-learning systems, educational data mining and my own research, it is useful to _rest look at the history that has brought educational research and data mining technologies together. It focus on web based educational theories such as adaptive intelligent learning and learner models, data mining algorithms, and educational data mining research.

6 b) Learning Content Management Systems

Developing a course [3]to be taught on the Internet is difficult because it requires the system to do a combination of things: publishing content on web pages, supporting tools for self learning, and providing assessments of learning performance Some good commercial LCMS systems include Blackboard (Web CT), Virtual-U and Top Class, etc. Open source LCMS include iHelp, a Tutor and Model, etc. c) iHelp iHelp is an e-learning system developed[5,7] by the Advanced Research in Intelligent Education Systems (ARIES). iHelp is made up of a number of web based applications designed to support both learners and instructors throughout the learning process1. The main components of iHelp are asynchronous iHelp Discussion forums, synchronous iHelp Chat rooms, the iHelp Learning Content Management Systems (also called iHelp Courses), iHelp Share and iHelp Lecture.

_iHelp Chat: This chat room provides workspaces for learners to have synchronous communication with one another and with their instructors and teaching assistants. _iHelp Courses: This LCMS system provides tools to support full on-line courses and is designed for distance learning. It provides learners with a portal to multimedia course content. _iHelp Share: This is a collaborative learning tool to share information relevant to courses among learners. _iHelp Lectures: This system provides multimedia lectures to learners so that learners can write messages and comments, make notes and tags on video clips, so that all learners can share this information.

Like other LCMS systems, iHelp collects and stores all information, such as personal information, pedagogical results, learners' interaction data, etc. into a database. These data are the source data for our project, as we will discuss in the.

V.

7 RESEARCH CONTRIBUTION AND FUTURE DIRECTION

The goal of this research has been to show that just in time learner models can be created from analyzing learners' online tracking data. This approach consists of clustering raw data, selecting pedagogical applications and applying data mining methods. This has led to measurements and metrics that can be calculated for each individual learner to represent that learner's characteristics and behaviors.

8 a) General Comments on the Two Experiments

From the two experiments' results, some measurements seem to be useful in building just in time learner models; [1] some measurements only show promise to be leading in the right directions; some measurements have not found much support. The expert experiment, in which experts observed and evaluated learners as the third party, shows much more positive results compared to the self evaluation experiment, in which learners evaluated themselves.

(i) A goal of this research has been to compute learner [3] models just in time as we need them instead of keeping static learner models. We do not use the historical learner models in our computations, instead recomposing the metrics and measurement based on the current available fact data and raw data. In this way, any changes in learners will be automatically recognized in the form of new measurements. Through two experiments, we have shown that just in time computations are possible and in some cases they lead to useful measurements.

9 c) Top Down

Top down computation of [2, **??**] measurements promises to allow the calculation of results quite rapidly when compared to computations using a pure bottom up data mining approach. In our approach, the first step is to decide the purpose of the applications such that we can figure out the necessary metrics and measurements to support the Applications. The second step is to find the raw data and retrieve the fact data to support the measurements. The last step is to mine the fact data to find patterns that can be used in creating formula that can later be used to directly calculate the measurements based on the available fact data.

10 VI. FUTURE WORK AND DIRECTION

The main drawback to the two experiments is that the number of evaluators is too low to get statistically significant results. It is easier to have more learners involved in the self evaluation than to get more experts in the expert evaluation. However, we need to improve and design a better self evaluation questionnaire to attract more learners to participate while at the same time get better questions. More involvement of instructors in the design of the questionnaire may be helpful. We have selected four metrics and 15 measurements in the two experiments. Then we need to show how we can use these measurements to build just in time learner models in actual pedagogical applications. Because of the relatively high correlation coefficient results in the two experiments, we can at various time points, apply classification algorithms to predict learner behaviors. A promising direction may be to keep old predictions and combine this information with the latest updated predictions to improve the accuracy of the just in time learner model.

11 VII.

12 Correlation

32

Figure 1: Figure 3 . 2 :

[1] [2] [3]

[1]

[2] E-Learning by Time Dynamic Model Using Data Mining

[3] E-Learning by Time Dynamic Model Using Data Mining

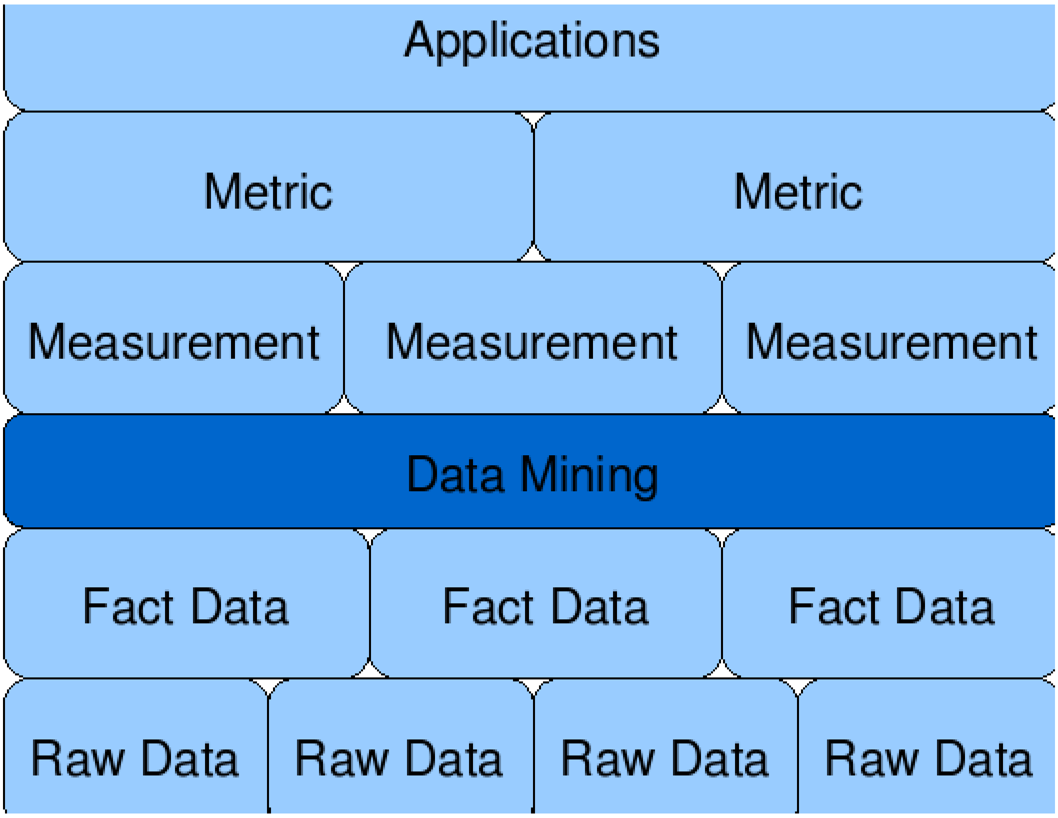

Figure 2:

Table 5.1,5.2 : Summary of expert experiment
b) Just In Time Model
32
experiment clued three measurements from the activity level metric: navigating context, read in discussion forum, chat activity; two measurements from the social tendency metric: presence and social tendency; and one measurement from the knowledge tendency metric: usage instructors to observe and evaluate learners' learning behaviors as in traditional class rooms. The results support that the instructors [5] at least will have a helpful tool to dynamically observe and evaluate learners'

performance in online education

environment. Six measurements had negative results in the expert experiment [4,6], with lower accuracy values or lower correlation coefficient values. Those measurements in the learning style metric especially have lower values in both accuracy and coefficient values.

Figure 3:

Coefficient	Accuracy <0.40	0.4-0.6	>0.6
<0.4	2	1	0
0.4-0.6	1	1	1
0.6-0.8	0	1	1
0.6-0.8	1	4	6

Correlation Coefficient	Accuracy <0.40	0.4-0.6	>0.6
<0.4	3	1	1
0.4-0.6	1	2	0
0.6-0.8	0	1	0
0.6-0.8	0	0	0

2011 October 33

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5.

Figure 4:

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