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How can we make use of learner interaction in online learning environments?

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Abstract:

Knowing about learners is one of the key concepts for a successful online instruction. What motivates learners in online learning environments? What did they learn or not from a lecture? These are important questions in order to shape instructional activities. In traditional learning environments teachers are able to watch their students on the fly and respond accordingly. However this opportunity gets lost in online environments because of online learning's very nature. One of the applicable ways is to gather data administrating surveys and questionnaires to students. This approach is questionable and may not reflect students' true nature at all. Monitoring students and interpreting this data in online learning is another method that could prove useful. Learner interaction in e-learning environments gives several clues about learner characteristics. In this paper researchers will be presenting their experiences regarding knowing about learners via learner-environment interaction. Learner interaction was employed in two studies. In first study reporting capabilities of an LMS was used. In second study an innovative LOGO environment was created from scratch and learner interaction was employed to keep track of learners' problem solving practices.

Keywords: e-learning; interaction; problem solving; data mining.

1. Introduction

Conventional teaching environments supply teachers with feedback on student learning experiences via face to face interaction. Teachers couple this data with their pedagogical background and experiences in their decision making process (Romero & Ventura, 2007). However in electronic learning environments this opportunity is lost because of e-learning's very nature. Nevertheless e-learning environments come with their own interaction possibilities which may prove as useful as face to face interactions. Educators can attain required information by evaluating these interactions. In two separate researches authors used records of these interactions in order to gain insight into instruction process. In this paper experiences gained through these applications will be shared and discussed.

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2. Interaction in e-learning

There are several published taxonomies (Moore, 1989; Hillman et al., 1994; Carlson and Repman, 1999; Hannafin, 1989; Northrup, 2001; Bonk and Reynolds, 1997; Harris, 1994; Bonk & King 1998; cited in Hirumi, 2006) which give educators insight into nature and range of interactions that may occur in e-learning. Hirumi (2006) discusses published e-learning interaction taxonomies over four dimensions:

- Communication-based taxonomies specify sender and receiver of the interaction. Among the basic interactions are student-student, student-teacher, student-content, student-interface interactions.
- Purpose-based taxonomies codify interactions based on purpose. These are actions taken by learner like: confirm, pace, inquire, navigate and elaborate.
- Activity-based taxonomies specify the level of type of interactivity experienced by learners. Literature suggests number of activities that may be designed to promote critical thinking, creative thinking and online cooperative learning.
- Tool-based taxonomies focus on the capabilities afforded by various technologies facilitating e-learning. Among these technologies are e-mail, asynchronous messaging, remote access and delayed collaboration tools, real time brainstorming and conversation tools and real time multimedia and hypermedia collaboration tools.

Hirumi (2006) argues these taxonomies to be valuable but away from practice and proposes a framework positing three interrelated levels of interactions.
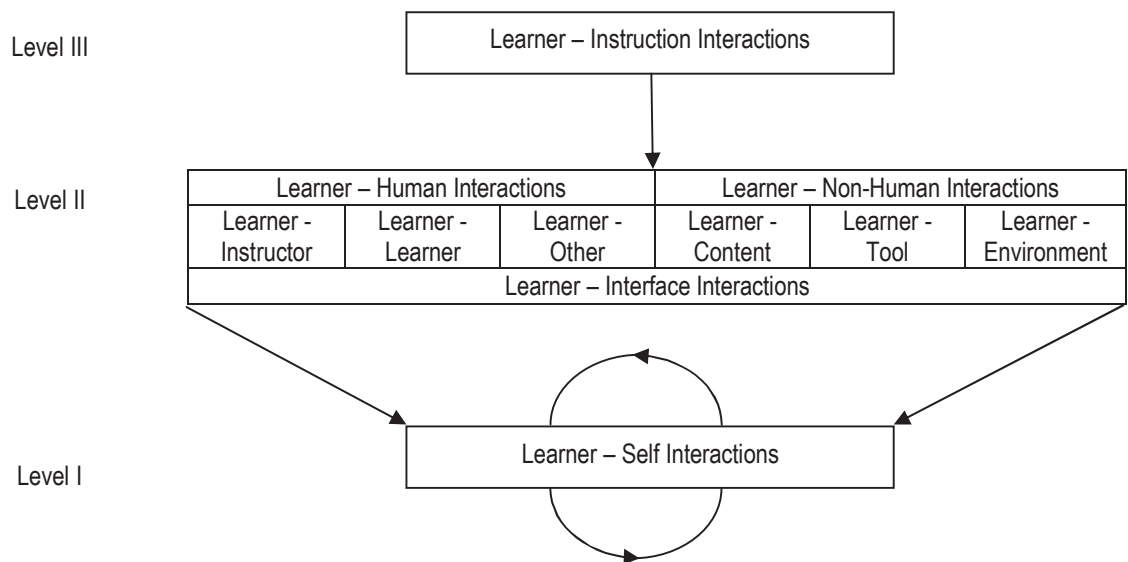

Figure 1 Hirumi's (2006) Three levels of planned e-learning interactions

Learner self interactions (Level I) which occur in learner's minds consists of cognitive operations that constitute learning and the metacognitive processes that help individuals monitor and regulate learning. Level II interactions occur between the learner and the other human or non-human resources. Learner – Instruction interactions (Level III) are considered to be a meta-level that transcends and used to guide the design and sequencing of Level II interactions.

Learner – Human Interactions		Learner – Non-Human Interactions	
Learner – Instructor	Communications between learner and instructor before, after and during instruction.	Learner – Content	Accessing audio, video, text and graphic representations
Learner – Learner	Communications between one learner and another learner alone or in group settings.	Learner – Tool	Using telecommunication tools such as e-mail, discussion forum and chat
Learner – Other	Communication of learners with other people who are not part of learning environment in order to acquire, interpret and apply information.	Learner – Environment	Visiting locations or working with resources outside computer environment

Among these three levels only Level II interactions are observable. With respect to aim of the paper Level II interactions need to be elaborated in e-learning context.

Learner – Instructor, Learner – Content, Learner – Learner and Learner – Tool communications are supported by electronic systems in e-learning. Systems supporting these activities are also able to record relevant data. Learning management systems come with recording abilities of such interactions. These interactions are saved into databases by LMSs and stay accessible to instructors, administrators, managers etc.

In two prior studies these interactions have been used to gather data about learners:

2.1. Automatically predicting individual differences

Whether electronic or face to face, all educational systems must meet learner requirements in terms of content and presentation. Learners have different backgrounds, preferences and motivations. In this respect an educational system must probe these individual differences and respond accordingly.

Learning style is one of the commonly studied individual properties. There are many learning style approaches over various dimensions in literature (Coffield, Moseley, Hall & Ecclestone, 2004). Felder – Silverman's Learning Styles Model is one of the widely recognized models (Felder & Silverman, 1988). The model has 4 dimensions which are perception, input, process and understanding. Index of Learning Styles (2010) was created by Felder and Soloman based on Felder&Silverman's Learning Styles Model. It is a 44 item questionnaire with 11 items for each sub dimension. For each dimension subject gets a score ranging from -11 to 11 which reflects his/her tendency in this dimension.

In this research Process sub dimension elaborated. This sub dimension has found to be most observable in LMS records. This sub dimension classifies learners to be active or reflective in learning contexts. Active learners learn by trying things out while reflective learners learn by thinking things through. So in a learning environment active learners are expected to participate in the activities more than reflective learners.

In this study data collected from a mathematics course longing 14 weeks for 27 freshman students with derivative topic. Traditional course sessions were enriched with web support which was implemented with Moodle (http://www.moodle.org) open source LMS system. Among the evaluated interactions are forum usage, content access, quizzes, questionnaires and user profile views. In order to systematically analyze learner behaviors relevant thresholds for each pattern was identified with support from literature. Aim of the study was to compare predicted learning styles with results from Index of Learning Styles. Results of the study showed %79.6 precision.

2.2. Tracking learner's problem solving: hasLOGO

Problem solving is of significant importance in our daily lives. This fact makes problem solving a hot and yet hard to study topic for researchers. Tracking learners' solution developments can make contributions to the field. Recently researchers tried "speak out loud" procedures for this purpose while learners working on a problem. A computerized approach to this problem is possible.

Programmers solve problems using computers via programming languages. Programmers give computers specific instructions to make computers solve problems. Source codes of a software reflects its programmers

problem solving approach. With this in mind a LOGO environment was created from scratch. LOGO environments are best known with turtle graphics which programmers use specific commands to make turtle move or draw lines.

hasLOGO is also a web based logo environment with its own programming language constituting four keywords: walk, draw, turn and repeat. A penguin metaphor was used instead of the original turtle. If written code is erroneous hasLOGO warns the programmers about their errors. If no problems caught then hasLOGO will run the code by animating every line of code for a second which is a feedback for the programmer.
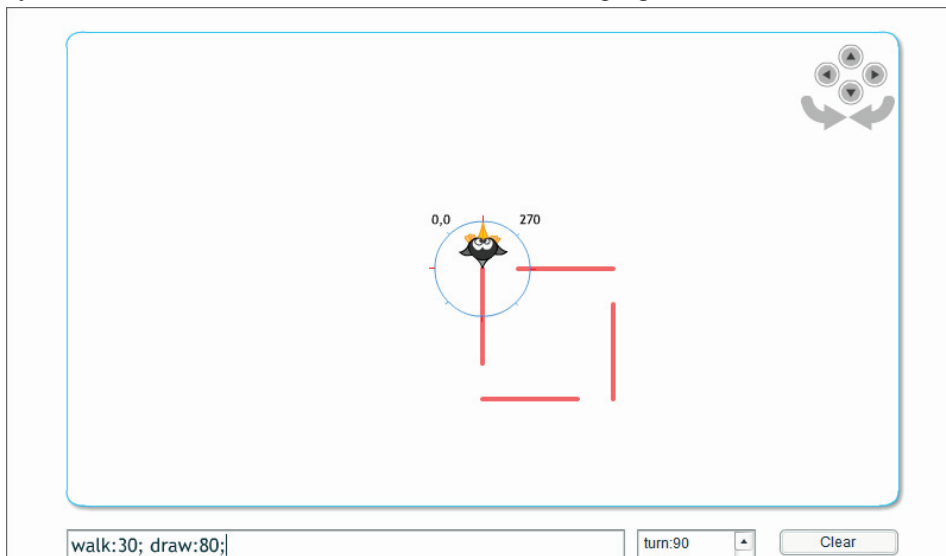

Figure 2 hasLOGO environment overview

hasLOGO is also a data collection tool. It saves written codes in every run attempts which allows researchers to track individual's problem solving developments. In an experiment 45 freshman students were asked to draw a symmetric home figure. After the experimental procedures codes recorded in the database were examined and evaluated. While 24 learners solved the problem flawlessly, 17 had deficiencies in their solutions and 4 could not solve the problem. Researchers were also able to detect syntax error rates and loop usages. Furthermore researchers were able to watch every learner's problem solving progress by running the saved codes. This way, researchers were able to examine the plans learners devised, their solution attempts and fixes they applied to their plans.

Handling data

Collected data can be employed in numerous ways. However a question arises: How much data can we handle? Thanks to automatic data collection abilities of electronic tools, every unique learner interaction can be stored in databases. However this data can easily exceed human comprehension. In such conditions computerized data handling methods are needed.

Data mining or knowledge discovery in databases (KDD) is the automatic extraction of implicit and interesting patterns from large data collections. Data mining is a multidisciplinary area in which several computing paradigms converge: decision tree construction, rule induction, artificial neural networks, instance based learning, Bayesian learning, logic programming, statistical algorithms etc. (Klosgen & Zytkow, 2002; cited in Romero & Ventura, 2007). These techniques are applied to numerous fields including business, medicine, engineering and games (Data mining, 2010). Education is no exception.

Applying KDD to educational system can be viewed as a formative evaluation technique. Formative evaluation is

the judgments of the strengths and weaknesses of instruction in its developing stages, for the purpose of revising the instruction. The major goal of the formative evaluation is to improve the effectiveness and efficiency of the instruction (Triantafillou, Pomportsis, Demetriadis, 2003). Data mining techniques can discover useful information that can be used in formative evaluation to assist educators establish a pedagogical basis for decisions when designing or modifying an environment or teaching approach (Romero & Ventura, 2006). Researchers have used knowledge discovery methods in numerous studies:

Drazdilova, Martinovic, Slaninova and Snasel (2008) used cluster analysis to define relationships among e-learning students in terms of their activities in the Moodle system. Zakrzewska (2008) employed clustering technique to group learners with respect to their individual learning styles and usability preferences. Romero, Ventura and Garcia (2007) presented the application process of data mining techniques in a Moodle case study they went through along with a survey of application of data mining techniques to LMS data. Finally a survey on educational data mining applications from 1995 to 2005 can be found in Romero and Ventura (2007).

3. Conclusion and Suggestions

In two studies learner interaction was captured and evaluated for tracking problem solving and predicting individual properties purposes. Interaction records give researchers valuable insights into learning and learners. However when recorded by automated mechanisms like LMSs, collected data can easily exceed human comprehension. In such condition high order statistical analysis like cluster analysis and data mining can help researcher find valuable information embedded in data.

Beside from learner tool and learner content interactions, learner human interactions may represent valuable information for educators. Furthermore, because these interactions are in linguistic form qualitative analysis may bring much valuable information than counting these interactions.

Coupling qualitative and quantitative methods for analyzing e-learning data may extract information of great value. In such way, researchers will be able to evaluate whole interactions in an e-learning environment.

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