Learning Engagement: What Actions of Learners Could Best Predict It?

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Abstract. One important aspect of motivation is engagement. In order to learn, students need to be engaged in the learning activities. However, that does not always happen due to various factors. This paper investigates the possibility to detect the level of engagement of a learner using an e-Learning system. More specifically, we are looking for actions that could predict it. Using log files analysis we found that these actions are related to reading pages and taking tests, which are common to every e-Learning system. Several experiments showed that predictions based on attributes related to these two actions are as good as those that include a larger number of actions available in an e-Learning system. A comparison between the attributes found relevant in our research and the attributes used in previous research shows the consistency of our findings. The novelty of our approach is that the focus is on the learning time rather that on evaluation through quizzes-type activities.

Introduction

Motivation is a key component for learning success. One aspect of motivation is engagement: if a student is engaged in learning, he/she is motivated to learn; if disengaged, a student will not be efficient in his/her learning. In classroom settings, keeping track of student's level of engagement and acting accordingly is one of teacher's tasks. In e-Learning systems, the "engagement problem" is handled in a different way: through engagement theory [12], that emerged relatively recently from the teaching experience using technology. In fact, engagement became a problem in the context of e-Learning, even if the term existed and was used to designated learner's focus on the activity. Now, in context of e-Learning the term engagement is usually associated with the theory of engagement that offers more than a definition of the term, the actual focus being on how to create activities in order to engage learners.

This paper is structured as follows. Section 1 briefly presents engagement theory, the relation between engagement and motivation, and how engagement concept was used in research. The research question and the methodological approach of our study are discussed in Section 2. The results are presented and discussed in Section 3. Section 4 covers a comparison with previous research results and finally, Section 5 concludes the paper.

1. Learning engagement and motivation

The theory of engagement ([12], [6], [5]) defines engaged learning with reference to two aspects: (1) the activities that involve active cognitive processes and (2) the students that are intrinsically motivated to learn due to the meaningful nature of the learning environment and activities. Thus, engagement is about learning activities and the way they are performed. From the perspective of this theory, motivation would be a result, the focus being on the design of activities in order to increase motivation.

Motivation is also a starting point for learning and could lead to learning engagement. Thus, there is a circular relation between the two. There is also a difference in terms of specificity or generalization: engagement refers to a task/ activity, while motivation is broader. In our approach we use the term engagement to designate the fact that the learner is focused on the activity.

Research that investigates engagement has been done most of the time from a post-hoc perspective and using self-evaluation in classroom context (e.g. [7], [9]) and e-Learning context (e.g. [10], [8]) with the purpose to determine the educational value of a course / institution, or to find methods to improve engagement.

Unlike these approaches, ours is focused on the learning time and is based on external indicators (the actual actions of learners). Thus, we are interesting in monitoring the learners' actions in order to intervene when the student is not engaged in learning. In our research [3] identifying the level of engagement is the first step in eliciting motivation.

2. Study design

A study was conducted using 48 log files that registered the actions of learners using HTML Tutor, a web-based system for learning HTML. A total of 75 sessions (where a session is considered between login and logout) were analysed. Previous results [2] indicated that sequences of ten minutes are more valuable than whole sessions and thus, each session was split into sequences of ten minutes, leading to a database with 1015 entries. This database includes 943 sequences of exactly ten minutes and 72 sequences of less than ten minutes. The 72 entries were eliminated and the analysis was performed only on sequences of exactly ten minutes.

Several actions are possible in an e-Learning system. Following is a list of such possible actions with HTML Tutor: login/logout, setting the goal of using the system, setting preferences, reading pages, taking pre-tests and tests, following hyperlinks, consulting the manual of the system, looking for help, accessing a glossary of terms, communicating with other users or the tutor, search, making remarks, looking at statistics and giving feedback. In log files each action is registered with a time stamp, thus allowing identifying the amount of time spent in doing a certain action.

For each action, the database contains the number of times the action has occurred and the average time spent on that action; for pre-tests and tests two additional parameters are included: number of correct and number of incorrect answers. Thus, the database contained 34 attributes related to the 15 possible actions, plus session and sequence ID. The database also included a parameter referring to the level of engagement, with three values: engaged, disengaged and neutral. The latter was used for situations where it was very difficult to decide for one of the two levels mentioned. The level of engagement was established by analysing the actions of learner for each sequence of ten minutes and based on time frames for HTML Tutor. For example, a learner that spends excessively more time than necessary to read a page, take a test, make a search, etc. or, on the contrary, would spend less time than required to actually perform an action, would be disengaged. The opposite of these situations would indicate engagement. In some cases it was difficult to choose between the two, and thus, another category called neutral was introduced. Thus, by looking at the log files human raters established the level of engagement for each sequence in a similar way to that used by [4].

2.1. Research question

The research question of our study is: What actions of learners could best predict their engagement? The actual focus is on the disengaged and on the actions or the lack of those actions that would indicate that they are not engaged in learning.

2.2. Methodology

In order to identify the actions that best predict disengagement, we investigated several aspects: (a) the frequency of each possible action; (b) the attribute ranking and (c) the level of engagement prediction results. The frequency of actions would give information about the actions that learners do most frequently; we would expect that the same actions would be reflected in (b) and (c) as well; if that wouldn't happen, like for example, if an action with a low frequency would have a good ranking and a good predictive value, the low frequency would actually indicate that that particular action is not that relevant.

Looking at descriptive statistics for the actions registered in log files, we noticed that two actions were significantly more frequent compared to the rest: reading pages (787 occurrences in 943 sequences) and taking test (415 occurrences in 943 sequences). The following events were: following hyperlinks (226), consulting the glossary (73), setting the learning goal (53), search (26), pre-tests (13), help (9), manual (7), communication (6), statistics (5), preferences (3), remarks (3) and feedback (3).

In order to see which attributes are more important for prediction, we used 3 different single attribute evaluation methods with ranking [13, pp. 424-425] as search method for attribute selection: (a) Chi Squared Attribute evaluation [13, p.302, p.324]: computes the chi-square statistic of each attribute with respect to the class; (b) Information Gain Attribute Evaluation[13, p.99, p.423]: evaluates the attributes based on information gain; (c) OneR Attribute Evaluation [13, pp. 84-85, p.423]: used OneR methodology to evaluate attributes; OneR stands for one-rule and it generates a one-level decision tree expressed in the form of a set of rules that all test one particular attribute.

We present the ranking for the first eight attributes out of 34. The first two methods delivered the same ranking: Average time/ Pages, Number of pages, Tests, Average time/ Tests, Number of correctly answered testes, Number of incorrectly answered testes, Average time/ Hyperlinks, Number of hyperlinks. OneR resulted in the same ranking for the first four attributes, followed by: Number of incorrectly answered testes, Average time/Hyperlinks, Number of correctly answered testes and Number of hyperlinks. Not surprisingly, all eight attributes refer to the three most frequent events registered in log files.

In order to see the prediction and the way it is influenced by the attributes, we used three trials and two experimental conditions. Trial 1 included all actions, Trial 2 comprised only the following actions: reading pages, taking test and following hyperlinks (top three actions found using frequency counting) and Trial 3 included just two actions: reading pages and taking tests. The two experimental conditions are: with attribute selection prior to prediction and without attribute selection. This experimental design is illustrated in Table 1.

Table 1. Experimental design

	Trial 1	**Trial 2**	**Trial 3**
No attribute selection			
Attribute selection			

The results from the three trials in the two experimental conditions are compared in terms of: (a) percentage correct for overall prediction, meaning for all levels of engagement and (b) true positives and false positives rate for disengagement.

3. Results

Waikato Environment for Knowledge Analysis (WEKA) [13] was used for the analysis. Several methods were experimented and similar results were found. We present here only two of them: one that had the best results for overall prediction for all three levels of engagement, classification via regression (CVR), and one that had the best results for the disengagement prediction, Bayesian Networks (BN). The results for these two methods according to the experimental design are presented in Table 2.

Table 2. Predictions of engagement level using Classification via Regression and Bayesian Networks

			Trial 1		Trial 2		Trial 3	
			CVR	**BN**	**CVR**	**BN**	**CVR**	**BN**
No attribute selection		**%correct**	87.64	87.07	88.10	87.00	87.21	86.68
		TP rate	0.92	0.93	0.92	0.93	0.91	0.93
		FP rate	0.20	0.23	0.18	0.22	0.18	0.24
Attribute selection	**Chi-square**	**%correct**	87.75	87.79	88.10	87.47	87.25	86.70
		TP rate	0.93	0.94	0.92	0.93	0.91	0.93
		FP rate	0.21	0.24	0.18	0.22	0.18	0.24
	Info gain	**%correct**	87.70	87.80	88.10	87.44	87.25	86.67
		TP rate	0.93	0.94	0.92	0.93	0.91	0.92
		FP rate	0.21	0.25	0.18	0.22	0.18	0.24
	OneR	**%correct**	87.69	87.55	88.03	87.36	87.20	86.70
		TP rate	0.93	0.93	0.92	0.93	0.91	0.93
		FP rate	0.21	0.24	0.18	0.22	0.18	0.24

The high TP rate and relatively low FP rate indicate a very good level of prediction and a good discrimination (the d-prime values are between 2.11 and 2.32).

3.1. Trial 1 versus Trial 2 versus Trial 3

Comparing the results we notice that there is no significant difference between the results obtained using the three different trials. Following the MDL (minimum description length) principle, we should use the trial with the minimum number of attributes, meaning Trial 3.

3.2. No attribute selection versus Attribute selection

The tables shows a better prediction for both percentage correct and true positives rate with attribute selection for the first trial (for both classification methods: CVR and BN); for the second trial there is better prediction with attribute selection for BN, while for CVR is constant for the first two cases and decreases for OneR attribute selection; for the third trial there are both increases and decreases with attribute selection for CVR and BN. However these variations are not statistically significant. From all trials, attribute selection increases most the prediction in Trial 1, which includes 34 attributes. As not all of them are relevant, an increase is to be expected when attribute selection is performed prior to prediction.

3.3. Ranking within "the most valuable attributes"

Using again the three attribute evaluation methods with ranking as search method for attribute selection, we can see the ranking among the 6 attributes from Trial 3, attributes related to reading and taking tests. The ranking is the same as the one obtained when using all attributes, for all three methods. Thus, according to chi-square and information gain ranking the most valuable attribute is average time spent on pages, followed by the number of pages, number of tests, average time spent on tests, number of correctly answered tests and number of incorrectly answered tests. OneR ranking differs only in the position of the last two attributes: number of incorrectly answered tests comes before number of correctly answered tests.

4. Our results and previous research: comparison and implications

Three previous approaches are particularly relevant to our research: (a) a rule-based approach to motivational states [4]; (b) using learner's focus of attention to detect motivation factors [11] and (c) engagement tracing [1]. Each of these approaches has identified aspects from the learners' actions to be used for motivation or engagement estimation or prediction. Each of these are briefly described and compared to our results.

The first mentioned approach identified 61 rules for different motivational states. The input for these rules consisted in four categories of information: performance, teaching materials, motivation model and motivation traits. The aspects related to students' actions are the inputs of performance: quality (correctness of answers), speed (time spent in doing the instructional unit) and give up – whether the student chose to give up the lesson or not. The first two aspects are also reflected in our indicators; about the third, there is no information and it is not something that could be identified and logged as a specific action. This information is due to the fact that the task is very specific and within a limited time.

In the 61 rules there are 21 references to quality, 11 references to quantity and 14 references to speed. The quality corresponds to the number of correctly and incorrectly answered tests from out approach; quantity corresponds to number of tests and speed refers to time spent reading and/or taking tests.

The second approach mentioned uses besides the learner's focus of attention inputs related to learners' actions: time to perform the task, time to read the paragraph related to the task, the time for the learner to decide how to perform the task, the time when the learner starts/ finishes the task, the number of tasks the learner has finished with respect to the current plan (progress), the number of unexpected tasks performed by the learner which are not included in the current plan (the learner's actions are compared to a learning plan) and number of questions asking for help. Compared to our results, we find the time spent reading, the time spent on tests corresponding to time to perform the tasks and number of correctly answered tests corresponding to progress.

The third approach should theoretically be the closest to our research as engagement term is used with the same meaning. It is also similar in terms of information source, both using easily accessible information: in [1] data normally collected by a computer tutor is used and in our approach data normally logged is used. The differences are related to: (a) type of activities: in [1] the only activity is to answer multiple-choice cloze questions, while in our approach the actual study time is also included; (b) [1] starts form item-response theory to estimate (dis)engagement, while we are using data mining methods. The two indicators related to learner's actions used in [1] are responses time and correctness. In our approach they correspond to time spent taking tests and number of correctly and incorrectly answered tests.

The fact that the actions identified in our experiment to be the best predictors of disengagement are found in previous research indicates the consistency of our findings.

5. Conclusion

We presented in this paper a study conducted in order to identify the actions of learners that would best indicate their level of engagement. The results show that these actions are reading pages and taking tests. The attributes related to these actions that were used for level of engagement detection are, in the order of their importance: average time spent reading, number of pages read / accessed, number of tests taken, average time spent on taking tests, number of correctly answered tests and number of incorrectly answered tests.

A comparison with previous approaches indicated that similar indicators were used in detecting/ predicting aspects of motivation or engagement, proving the consistency of the actions identified as most valuable. The difference that adds value to our approach is that we focus on learning time and not only on evaluation / assessment.

The fact that the actions found relevant for engagement are related to common tasks in e-Learning system: reading and taking tests could potentially mean that any e-Learning system could add a module for engagement monitoring. This would be beneficial in terms of keeping track of both motivation and learning outcomes, as disengagement indicated low motivation and ineffective learning.

The next step in our research is to investigate another e-Learning system in order to see if we find similar results: if it is a matter of just changing the timing framework for that system or if a completely different approach is required.

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