Cross-System Validation of Engagement Prediction from Log Files

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Abstract. Engagement is an important aspect of effective learning. Time spent using an e-Learning system is not quality time if the learner is not engaged. Tracking the student disengagement would give the possibility to intervene for motivating the learner at appropriate time. In previous research we showed the possibility to predict engagement from log files using a web-based e-Learning system. In this paper we present the results obtained from another web-based system and compare them to the previous ones. The similarity of results across systems demonstrates that our approach is system-independent and that engagement can be elicited from basic information logged by most e-Learning systems: number of pages read, time spent reading pages, number of tests/ quizzes and time spent on test/ quizzes.

Keywords: e-Learning, engagement prediction, log files analysis, data mining.

1 Introduction

Engagement is an indicator of student's motivation. It is well know that motivation is essential for learning: lack of motivation is correlated to learning rate decrease [2]. E-Learning systems can motivate students through an attractive design, by using multimedia materials or by including game features that have great potential [8] and have been proved successful in a number of cases (e.g. [4]). Despite these efforts, students are not always focused on learning and even try to game the systems ([21], [22]). Thus, motivation needs to be addressed beyond design issues at individual level and motivational diagnosis is required.

There are several models for eliciting motivational knowledge starting from learner's activity. In this paper we are focused only on one aspect of motivation, engagement, and on validating across two different e-Learning systems, HTML Tutor and iHelp, a previously proposed approach for engagement prediction [7]. The paper is structured as follows. In Section 2 previous work related to engagement prediction is presented. Section 3 includes the analysis of the iHelp data. Section 4 compares the results obtained by the two systems and also relates our outcomes with the previous approaches to engagement prediction. Section 5 discusses the results and concludes the paper.

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2 Previous Research

Several concepts are used in motivational research [16], besides motivation itself: engagement, interest, effort, focus of attention, self-efficacy, confidence etc. For the results presented in this paper the focus of our research on motivation is on engagement. A student is engaged if he/she is focused on the learning activity.

A number of concepts in motivational research such as interest, effort, focus of attention and motivation are related though not identical to engagement (see e.g., [16]): 1) engagement can be influenced by *interest*, as people tend to be more engaged in activities they are interested in; thus, interest is a determinant of engagement; 2) *effort* is closely related to interest in the same way: more effort is invested if the person has interest in the activity; the relation between engagement and effort can be resumed by: engagement can be present with or without effort; if the activity is pleasant (and/or easy), engagement is possible without effort; in the case of more unpleasant (and/or difficult) activities, effort might be required to stay engaged; 3) the difference between engagement and *focus of attention*, as it is used in research is that focus of attention refers to attention through a specific sensorial channel (e.g. visual focus), while engagement refers to the entire mental activity (involving in the same time perception, attention, reasoning, volition and emotions); 4) in relation to *motivation*, engagement is just one aspect indicating that, for a reason or another, the person is motivated to do the activity he/she is engaged in, or the other way, if the person is disengaged, he/she may not motivated to do the activity; in other words, engagement is an indicator of motivation.

Although there are several approaches to motivational issues in e-Learning, we are going to present only some of them, with a focus on those related to engagement prediction.

2.1 Relevant Literature on Motivation and Engagement Prediction

Several approaches for motivation detection from learner's interactions with the e-Learning system have been proposed. A rule-based approach based on ARCS Model [13] has been developed [9] to infer motivational states from the learners' behavior using a ten questions quiz. 85 inference rules were produced by the participants who had access to replays of the learners' interactions with the system and to the learners' motivational traits.

Another approach [17] based on ARCS Model is used to infer three aspects of motivation: confidence, confusion and effort, from the learner's focus of attention and 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 learning plan and the number of questions asking for help.

Engagement tracing [3] is an approach based on Item Response Theory that proposes the estimation of the probability of a correct response given a specific response time for modeling disengagement; two methods of generating responses are assumed: blindly guess when the student is disengaged and an answer with a certain probability of being correct when the student is engaged. The model also takes into account individual differences in reading speed and level of knowledge.

A dynamic mixture model combining a hidden Markov model with Item Response Theory was proposed in [12]. The dynamic mixture model takes into account: student proficiency, motivation, evidence of motivation, and a student's response to a problem. The motivation variable can have three values: a) motivated, b) unmotivated and exhausting all the hints in order to reach the final one that gives the correct answer: unmotivated-hint and c) unmotivated and quickly guessing answers to find the correct answer: unmotivated-guess.

A Bayesian Network has been developed [1] from log-data in order to infer variable related to learning and attitudes toward the tutor and the system. The log-data registered variables like problem-solving time, mistakes and help requests.

A latent response model [2] was proposed for identifying the students that game the system. Using a pretest–posttest approach, the gaming behavior was classified in two categories: a) with no impact on learning and b) with decrease in learning gain. The variables used in the model were: student's actions and probabilistic information about the student's prior skills.

The same problem of gaming behavior was addressed in [21], an approach that combines classroom observations with logged actions in order to detect gaming behavior manifested by guessing and checking or hint/ help abuse. Prevention strategies have been proposed [22]: two active interventions for the two types of gaming behavior and a passive intervention. When a student was detected to manifest one of the two gaming behaviors, a message was displayed to the student encouraging him/her to try harder, ask the teacher for help or pursue other suitable actions. The passive intervention had no triggering mechanism and consisted in providing visual feedback on student's actions and progress that was continuously displayed on screen and available for viewing by the student and teacher.

2.2 Our Approach to Engagement Prediction

In previous research [7] we proposed a different approach to engagement prediction that would cover both the learning and the testing tasks in an e-Learning system. We analyzed log files from HTML Tutor – a web based interactive learning environment. In a preliminary investigation [6] where we used sessions as basis for analysis, we found that we could predict the level of engagement after 45 minutes of activity. As most of disengaged students would log out before that time leaving no possibility for intervention, we decided to split the sessions in sequences of 10 minutes and thus overcome this problem. Using several data mining techniques we showed that the user's level of engagement can be predicted from logged data mainly related to reading pages and taking tests. Similar results obtained using different techniques and different numbers of attributes showed the consistency of prediction and of the attributes used. The best prediction for all levels of engagement (engaged, disengaged and neutral) was 88%, obtained using Classification via Regression and including two more attributes related to hyperlinks and glossary besides the ones related to reading and tests. The best prediction for disengaged students was 93%, obtained using Bayesian Networks.

Our approach is different from the previous ones in the fact that it envisages prediction of engagement from both main activities encountered in e-Learning systems: reading pages and taking tests. The two models based on IRT presented in Section 2.1 may work very well for quizzes, but they have the disadvantage of considering engagement after the learning activity. Tracking engagement when the student is learning (reading pages) allows intervention at appropriate time and before the evaluation of learning (quizzes), when bad performance could be caused by disengagement in answering the questions, but also by disengagement during learning time.

3 Data Analysis

In order to validate our approach for engagement prediction presented above we analyzed data from iHelp, the University of Saskatchewan web-based system. This system includes two web based applications designed to support both learners and instructors throughout the learning process: the iHelp Discussion system and iHelp Learning Content Management System. The latter is designed to deliver online courses to students working at a distance, providing course content (text and multimedia) and quizzes/surveys. The students' interactions with the system are preserved in a machine readable format.

The same type of data about the interactions was selected from the registered information in order to perform the same type of analysis as the one performed with HTML Tutor data. An HTML course was also chosen in order to prevent differences in results caused by differences in subject matter.

We used logged data from 11 users (from a total of 21 students studying the selected course), meaning a total of 108 sessions and 450 sequences (341 of exactly 10 minutes and 109 less than 10 minutes). So far, we have processed the data from only these 11 students; further work includes an analysis of the data from all 21 learners.

3.1 Attributes Description

In the analysis several attributes mainly related to reading pages and quizzes events were used. These attributes are presented in Table 1. The terms tests and quizzes will be used interchangeably; they refer to the same type of assessment, except that in HTML they are called tests and in iHelp they are named quizzes.

Total time of a sequence was included as attribute for the trials that took into account the sequences less than 10 minutes, as well as those of exactly 10 minutes. Compared to the analysis of HTML Tutor logs, for iHelp there are fewer attributes related to tests/ quizzes. Thus, information on number of questions attempted and on time spent on them is included, but information about the correctness or incorrectness of answers given by users was not available at the time of the analysis.

Two new attributes were introduced for this analysis, attributes that were not considered for HTML Tutor: the number of pages above and below a certain time threshold, described in the subsequent section.

Table 1. The attributes used for analysis

Codes (as used in analysis)	Attributes
NoPages	Number of pages read
AvgTimeP	Average time spent reading
NoQuestions	Number of questions from quizzes/ surveys
AvgTimeQ	Average time spent on quizzes/surveys
Total time	Total time of a sequence
NoPpP	Number of pages above the threshold established for maximum time required to read a page
NoPM	Number of pages below the threshold established for minimum time to read a page
Eng	Engagement level: e=engaged; d=disengaged

3.2 Level of Engagement

For each 10 minutes sequence, the level of engagement was rated by an expert using the same approach as in our previous research [7], adding two extra rules related to the two additional attributes regarding number of pages that are above or below a threshold, depending on time spent reading.

At first we intended to use the average time spent on each page across all users, as suggested by [18], but analyzing the data, we have seen that some pages are accessed by a very small number of users, sometimes only one, problem encountered in other research as well [10]. Thus, we decided to use the average reading speed known to be in between 200 and 250 words per minute [19, 20]. Looking at the number of words on each page we found that out of 652 pages accessed by the students, 5 pages need between 300 and 400 seconds to be read at average speed, 41 pages need between 200 and 300 seconds, 145 between 100 and 300 seconds and the 291 need less than 100 seconds. Some pages include images and videos. Only 2 of the 11 students attempted to watch videos, one giving up after 3.47 seconds and the other one watching a video (or being on the page with the link to a video) for 162 seconds (almost 3 minutes).

Taking into account the above mentioned information about iHelp pages, we agreed that less than 5 seconds or more that 420 seconds (7 minutes) spent on a page indicates disengagement.

In our previous research with HTML Tutor logs, the level of engagement was established by human experts that looked at the log files and established the level of engagement for sequences of 10 minutes or less, in a similar way to [9]. The same procedure was applied for iHelp, plus the two rules aforementioned.

Accordingly, the level of engagement was determined for each sequence of 10 minutes or less. If in a sequence the learner spent more that 7 minutes on a page, we considered that he/she was disengaged during that sequence. Related to pages accessed less than 5 seconds, we agreed to consider a user disengaged if 2/3 of the total number of pages were below 5 seconds.

With HTML Tutor, three level of engagement were used: engaged, disengaged and neutral. Neutral was used for situations when raters found it hard to decide whether the user was engaged or disengaged. With iHelp, this difficulty was not encountered.

With HTML Tutor, we verified the rating consistency by measuring inter-coding reliability. A sample of 100 sequences (from a total of 1015) was given to a second rater and results indicated high inter-coder reliability: percentage agreement of 92%, Cohen's kappa measurement of agreement of .83 ($p<.01$) and Krippendorff's alpha of .84 [14]. With iHelp only one rater classified the level of engagement for all sequences.

3.3 Analysis and Results

Using the attributes described above, an analysis was conducted in order to investigate engagement prediction with iHelp and compare the results with the ones from HTML Tutor.

Waikato Environment for Knowledge Analysis (WEKA) [23] was used to perform the analysis. The same methods as the ones used in our previous research were experimented and four datasets were used: (i) Dataset 1 including all attributes and all sequences, (ii) Dataset 2 obtained from Dataset 1 by eliminating the two additional attributes (NoPgP, NoPgM), (iii) Dataset 3 including all attributes, but only sequences of 10 minutes and (iv) Dataset 4 obtained from Dataset 3 by eliminating the two additional attributes (NoPgP, NoPgM). Dataset 2 and 4 were used in order to compare the results with the ones from HTML Tutor. Table 2 presents the datasets with the corresponding attributes and sequences.

Table 2. Datasets used in the experiment

Dataset	Sequences	Attributes
Dataset1	All sequences	NoPages, AvgTimeP, NoQuestions, AvgTimeQ, Total time, NoPpP, NoPM
Dataset2	All sequences	NoPages, AvgTimeP, NoQuestions, AvgTimeQ, Total time
Dataset3	Only 10 minutes sequences	NoPages, AvgTimeP, NoQuestions, AvgTimeQ, Total time, NoPpP, NoPM
Dataset4	Only 10 minutes sequences	NoPages, AvgTimeP, NoQuestions, AvgTimeQ, Total time

The eight methods [15, 23] used for the analysis are: (a) Bayesian Nets with K2 algorithm and maximum 3 parent nodes (BN); (b) Logistic regression (LR); (c) Simple logistic classification (SL); (d) Instance based classification with IBk algorithm (IBk); (e) Attribute Selected Classification using J48 classifier and Best First search (ASC); (f) Bagging using REP (reduced-error pruning) tree classifier (B); (g) Classification via Regression (CvR) and (h) Decision Trees with J48 classifier based on Quilan's C4.5 algorithm [23] (DT). The experiment was done using 10-fold stratified cross validation iterated 10 times.

Results are displayed in Table 3, which comprises the percentage of correctly classified instances, the true positives rate for disengaged class, the precision indicator (true positives/ (true positives (TP) + false positives)) for disengaged class and the mean absolute error. For us, TP rate is more important than precision because TP rate

Table 3. Experiment results summary

		BN	LR	SL	IBk	ASC	B	CvR	DT
Dataset1	**%correct**	89.31	95.22	95.13	95.29	95.44	95.22	95.44	95.31
	TP rate	0.90	0.95	0.95	0.94	0.94	0.94	0.95	0.95
	Precision	0.90	0.95	0.95	0.96	0.97	0.97	0.96	0.96
	Error	0.13	0.07	0.10	0.05	0.08	0.08	0.08	0.07
Dataset2	**%correct**	81.73	83.82	83.58	84.00	84.38	85.11	85.33	84.38
	TP rate	0.78	0.82	0.81	0.79	0.77	0.79	0.80	0.78
	Precision	0.86	0.86	0.86	0.89	0.91	0.91	0.91	0.91
	Error	0.22	0.24	0.26	0.20	0.25	0.23	0.23	0.25
Dataset3	**%correct**	94.65	98.06	97.91	98.59	97.65	97.65	97.76	97.47
	TP rate	0.95	0.97	0.96	0.98	0.96	0.96	0.96	0.96
	Precision	0.94	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	Error	0.07	0.02	0.04	0.02	0.05	0.04	0.03	0.03
Dataset4	**%correct**	84.29	85.82	85.47	84.91	84.97	85.38	85.26	85.24
	TP rate	0.78	0.77	0.76	0.77	0.75	0.76	0.75	0.75
	Precision	0.88	0.92	0.92	0.89	0.92	0.92	0.92	0.92
	Error	0.18	0.22	0.23	0.20	0.25	0.23	0.24	0.24

indicates the correct percentage from actual instances of a class and precision indicates the correct percentage from predicted instances in that class.

The results presented in Table 3 show very good levels of prediction for all methods, with a correct prediction varying between approximately 81% and 98%. There are similar results for the disengaged class, the true positives rate and the precision indicator for disengaged class varying between 75% and 98%. The mean absolute error varies between 0.02 and 0.25. As in the results for HTML Tutor, the very similar results obtained from different methods and trials shows consistency of prediction and of the attributes used for prediction. The results for Dataset 1 and 3 are better that the ones from Dataset 2 and 4, suggesting that the two new attributes bring significant information gain.

Table 4. The confusion matrix for instance based classification with IBk algorithm

		Predicted	
		Engaged	**Disengaged**
Actual	**Engaged**	180	1
	Disengaged	4	155

The highest percentage of correctly predicted instances was obtained using Instance based classification with IBk algorithm on Dataset 3: 98.59%. The confusion matrix is presented in Table 4. Focusing on the disengaged learners we see that the same method performs best on the same dataset: 98%. The distribution of true positives rate is displayed in Fig 1. The vertical axes in the figure are due to fractional true positive rates of the 340 cases, for example 295/340 is approximately 87%. More common results for the true positive rate of a given trial are visible in the density of the color along the line.

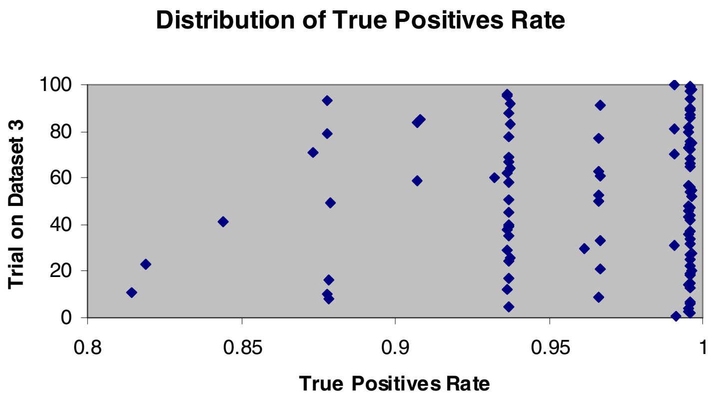

Fig. 1. Distribution of TP rate for disengaged class using instance based classification with IBk algorithm

Looking at the disengaged learners as they are our main interest, the rate of correct classification is similar: 98% of the disengaged students are correctly classified.

Investigating further the information gain brought by the two additional attributes, attribute ranking using information gain ranking filter as attribute evaluator was performed and the following ranking was found: NoPgP, AvgTimeP, NoPages, NoPgM, NoQuestions and AvgTimeQ. Thus the attributes related to an upper and a lower bound for time spent on a page, are more important that the attributes related to quizzes.

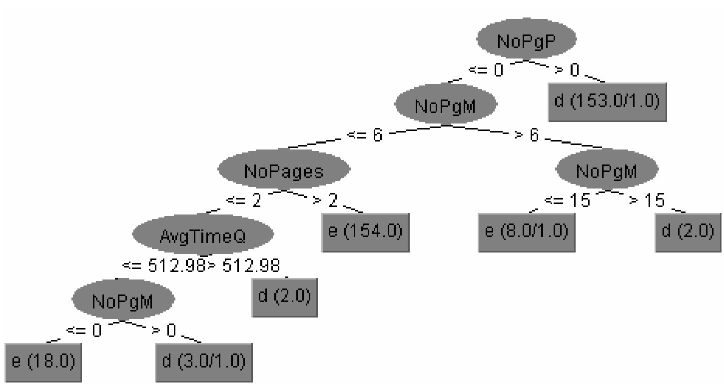

Fig. 2. Decision Tree graph for Dataset 3

The information gain brought by NoPgP is also reflected in the decision tree graph displayed in Fig. 2, where NoPgP is the attribute with the highest information gain, being the root of the tree. Thus one of the rules used for determining the level of engagement is reflected in the results.

4 Results Comparison

Comparing the results of iHelp to HTML Tutor, an improvement for datasets 1 and 3 and a small decrease for datasets 2 and 4 are noticed. For ease of comprehension some of the results from HTML Tutor log file analysis were included. These are only for the dataset with the attributes related to reading and taking tests and they are presented in Table 5.

Table 5. Experiment results summary for HTML Tutor

	BN	LR	SL	IBk	ASC	B	CvR	DT
%correct	87.07	86.52	87.33	85.62	87.24	87.41	87.64	86.58
TP rate	0.93	0.93	0.93	0.92	0.93	0.93	0.92	0.93
Precision	0.91	0.90	0.90	0.91	0.92	0.92	0.92	0.91
Error	0.10	0.12	0.12	0.10	0.10	0.12	0.12	0.11

The decrease observed for Dataset 2 and 4 might be explained by the two missing attributes related to quizzes: number of correct and number of incorrect answers that were available for HTML Tutor. The increase noticed for Datasets 1 and 3 could be accounted by the contribution of the two additional attributes.

The two missing attributes related to correctness or incorrectness of quizzes answers may improve even more the prediction level. Looking at their role in prediction with HTML Tutor, using three attribute evaluation methods with ranking as search method for attribute selection, these two attributes were found to be the last ones. 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. The attribute ranking using information gain filter for iHelp attributes, shows similar positions for attributes related to reading and tests, meaning that attributes related to reading come before the ones related to tests. This indicated that the two missing attributes with iHelp are not essential, but, if available, they could improve the prediction level. Table 6 summarizes the similarities and dissimilarities between the findings from iHelp and HTML Tutor.

Even with these differences, the fact that a good level of prediction was obtained from similar attributes on datasets from different systems using the same methods indicate that engagement prediction is possible using information related to reading pages and taking test, information logged by most e-Learning system. Thus, our proposed approach for engagement prediction is system independent and can be generalized for any system. A component for detection of engagement level can be built and attached to e-Learning systems to keep track of the learner's engagement status and thus, be able to intervene when appropriate. In our research, disengagement detection is the first step to motivation elicitation. Thus, after detection of disengagement we plan to have a dialog with the learner in order to find out more about his/her motivation [5], information to be used for intervention [11].

Table 6. Similarities and dissimilarities between iHelp and HTML Tutor

Characteristic	iHelp	HTML Tutor
Prediction based on reading and tests attributes	81% to 85% with no information on correctness /incorrectness of quizzes and no additional attributes 85% to 98% with the two additional attributes	86-87%
Attribute ranking	- NoPgP (Number of pages above a threshold) - AvgTimeP (Average time spent reading) - NoPages (Number of pages read/ accessed) - NoPgM (Number of pages below a threshold) - NoQuestions (Number of questions from quizzes) - AvgTimeQ (Average time spent on quizzes)	- average time spent on pages - number of pages - number of tests - average time spent on tests - number of correctly answered tests - number of incorrectly answered tests

5 Discussion and Conclusions

With both iHelp and HTML Tutor some patterns in the disengaged users' behavior were distinguished: a) the disengaged students that click fast through pages without reading them and b) the disengaged students that spend long time on a page, (far) exceeding the needed time for reading that page. Two of the previous approaches mentioned in Section 2.1 also present some patterns, with the difference that those patterns are related only to learners' behavior when answering quizzes. Thus, we find a similarity between blindly guess in [3] or unmotivated-guess in [12], on one hand, and the fast click through pages, on the other hand, as both reflect students' rush and lack of attention. Knowledge about these two patterns would be useful for a more targeted intervention and in further work the possibility to predict them will be investigated.

Engagement or disengagement prediction in previous research was limited to quiz-type activities, while our approach focuses on the learning time. Learning time usually includes some material to read and/ or watch, and a form of self-assessment for the covered topic. Quizzes could be used in such a form, being actually a learning activity, or they could be used to evaluate the student at the end of a course. In HTML Tutor and iHelp, the tests/ quizzes are learning activities.

Gaming is a type of disengagement, as the learner's focus is not on the activity itself, but on how to complete the activity with the least effort. In previous research, like for engagement, gaming detection [2, 21] is addressed only for quiz-type activities and is based on Item Response Theory. For this approach, like for the other ones as well, information on correctness or incorrectness of answers is very important if not essential. For our approach this information has some importance as mentioned previously, but it is not indispensable.

Thus, our approach on disengagement detection is not limited to quizzes and in our research project, detecting the disengaged students is just a first step towards motivation assessment. We are interested in detecting the disengaged in order to intervene before they give up and when it's still time to improve learning outcomes.

To conclude, in this paper we presented results for engagement prediction from iHelp logged data. The analysis showed a good prediction, e.g. 98% using instance based classification with IBk algorithm, for overall prediction and for disengaged class. These results were compared to the ones obtained using log files from HTML Tutor and the similarity of results suggest that our approach on engagement prediction is system independent. Thus, we validated engagement prediction from logged data related to reading pages and taking tests and we can conclude that a prediction module could be added to educational systems, with the great benefit of finding the appropriate time for intervention.

Further work includes 1) the same analysis with all 21 subjects; 2) an attempt to predict the two distinguished patterns of disengagement, as the information may be valuable for effective intervention.

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