Can Log Files Analysis Estimate Learners' Level of Motivation?

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Abstract

The learners' motivation has an impact on the quality of learning, especially in e-Learning environments. Most of these environments store data about the learner's actions in log files. Logging the users' interactions in educational systems gives the possibility to track their actions at a refined level of detail. Data mining and machine learning techniques can "give meaning" to these data and provide valuable information for learning improvement. An area where improvement is absolutely necessary and of great importance is motivation, known to be an essential factor for preventing attrition in e-Learning. In this paper we investigate if the log files data analysis can be used to estimate the motivational level of the learner. A decision tree is build from a limited number of log files from a web-based learning environment. The results suggest that time spent reading is an important factor for predicting motivation; also, performance in tests was found to be a relevant indicator of the motivational level.

1 Introduction

Logging the users' interactions in educational systems gives the possibility to track their actions at a refined level of detail. Log files are easy to record for a large number of users, they can capture a large variety of information and they can even be presented in an understandable form. Thus, these data are a potentially valuable source of information to be analyzed and used in educational settings. Automatic analysis of log data is usually used to detect regularities and deviations in groups of users, to provide more information to tutors about the learners, to offer suggestions for further actions – mostly for the "deviation" cases.

A particularly important type of "deviation" is low motivation behavior usually associated with drop-out [Martinez, 2003]. Thus, identifying the low motivated learners and finding remedial actions would result in lower rates of drop-outs. We are interested in finding regularities in the user's behavior that could indicate their general motivational level. The preliminary investigation presented in this paper is looking at the possibility to predict the engagement / disengagement of learners from common log files data.

The paper is organized as follows. Section 2 discusses previous work related to the use of log files analysis in education, with a particular interest in approaches to motivation. It also includes a brief description of our research approach on motivation. Section 3 describes the information contained in the log files used for analysis and the indicators refined from the basic log data. The actual analysis and possible interpretations are described in Section 4. Section 5 concludes the paper with a summary and implications for further work.

2 Previous work

Automatic analysis of interaction data is used in research areas such as educational systems, data mining and machine learning. Educational systems can benefit from data mining and machine learning techniques by giving meaning to click-through data and associating these data with educational information.

Log files analysis has been used for a variety of purposes: provide information to tutors to facilitate and make more accurate the feedback given to learners [Merceron and Yacef, 2003], monitor group activity [Kay *et al.*, 2006], identify benefits and solve difficulties related to log data analysis [Heiner *et al.*, 2004], use response times to model student disengagement [Beck, 2004], infer attitudes about the system used, attitudes that affect learning [Arroyo *et al.*, 2004], developing tools to facilitated interpretation of log files data [Mostow *et al.*, 2005].

In relation to research on motivation, activity tracking has also been considered as a source of information for assessing users' motivation. Thus, there a number of approaches have been presented trying to infer motivational states from the learners' interactions with the systems: 1) a rule-based approach to infer *relevance*, *confidence*, *satisfaction* (from ARCS model [Keller, 1987]), *effort* and *sensory/ cognitive interest* [de Vicente and Pain, 2003], 2) inferring *confidence, confusion* and *effort* from: the learner's focus of attention, the current task and expected time to perform the task [Qu *et al.*, 2005], 3) inferring *attention* and *confidence* from the learner's actions, using factor analysis to group the actions that indicate the two motivational states [Zhang *et al.*,2003]

The previously presented approaches related to motivation try to infer automatically different motivational states by connecting the learner's actions (reading a page, solving a quiz, etc) and the time to perform them, with performance, which is typical information for educational systems.

Using the same type of information, rather then inferring such well refined motivational states, we are interested in finding a general indicator for motivational level as a starting point for further investigation about the learner's motivation [Cocea, 2006]. Thus, after finding this general indicator of motivation, an assessment of mo-

tivational characteristics will be conducted for the disengaged students, in order to have more detailed and accurate information about their level of motivation and, thus, pursue a more efficient intervention. This approach has the advantage of identifying the low motivated learners and focusing on them for further assessments and interventions because they are the potential drop-out students. Motivated students can also benefit from motivational assessment and intervention, but our main concern is for low motivated students as this is a problem in e-Learning.

We present here the results of the analysis of a limited number of log files from an online-course called HTML-Tutor. The purpose of this analysis is to investigate if commonly logged data can be used for predicting a general level of motivation. If indeed log file analysis can provide information about the motivational level, then potentially a motivational module could be included in educational systems that log the learner's interactions.

3 Log files description

HTML-Tutor is an interactive learning environment which offers an introduction to HTML and publishing on the Web; it is online and can be accessed freely. We don't have any information about the users except the data from the log files. They could be of any age and using the system for different purposes.

3.1 The logged parameters

The logged information is described in Table 1. Each event is recorded with a timestamp.

Table 1. Information included in HTML-Tutor log files

Event	Properties/Description
Login/logout	User ID
Goal	The purpose of using HTML-Tutor
Preferences	Different options can be changed by the user (e.g. frames/no frames, link annotation/no link annotation etc.)
Page access	PageID
Test	TestID, result: Correct/False
Hyperlink	The Page ID of the triggered page from the link
Manual	Looking for help about the system
Help	Looking for help about the learning content
Glossary	Word looked up
Communication	Access to a discussion lists and if a comment has been made
Search	Terms searched
Remarks	User's Remarks
Statistics	Users can see statistics about their activity, such as: time spent from the last login, percentage covered in a certain chapter, percentage of correctly answered tests etc

3.2 The analysis parameters

From the basic log data presented in Table 1, five indicators/ attributes with higher level of information have been calculated: performance on tests, the time spent reading, the number of accessed pages, the time spent solving tests and level of motivation: engaged / disengaged. A description of these attributes and the way they were calculated is presented in Table 2. These derived indicators are used in the analysis presented in Section 4.

Table 2. Derived attributes to be used in the analysis

Attribute	Description
UserId	A unique identifier per each user
Performance	Percentage of correctly answered tests (calculated as number of correct tests divided by total number of performed tests)
TimeReading	Time spent on pages (calculated as the sum of the time spent on each page accessed) in a session
NoPages	The number of accessed pages
TimeTests	The time spent performing tests (calculated as the sum of time spent on each test)
Motivation	Engaged / Disengaged

The information was aggregated in order to create the database with the same indicators for every user and to give meaning to the click through data. Basically only two events with their average times are considered (reading and taking tests) because none of the other events were registered in the log files considered for analysis.

The time spent reading refers to the total time spent reading in a session. The last attribute in Table 2, motivation, has been inferred from the log-files data using the rules presented in Table 3. The time thresholds mentioned in the table were established on the basis of estimated time required for reading a page or performing a test.

Table 3. Rules for motivational level assignment

Disengagement	Engagement
Click-through pages (consecutive access-page events) with short time per page (less then 20 seconds)	Click-through pages (consecutive access-page events) with an average of at least 60 seconds per page
Very long time spent on a page/ test (above 10 minutes)	Reasonable time spent per page/test (between 1 and 10 minutes)
Automatic logouts from the system due to inactivity (for 30 minutes)	Lack of automatic logouts

We are aware that this way of assigning a motivational level to learners is a limitation for the results of the analysis. An external measure of the engagement or disengagement of the learner would be a more accurate base for prediction. In our further work an experiment will be conducted in order to externally validate the prediction.

There is an overlap between the indicators used for prediction and the indicators used for estimating engagement/ disengagement: time is used in both cases. Given the fact that in the first case the average time for reading and testing is used and that in the second case time thresholds for each page/test are used, the two types of time indicators are almost independent.

4 Analysis

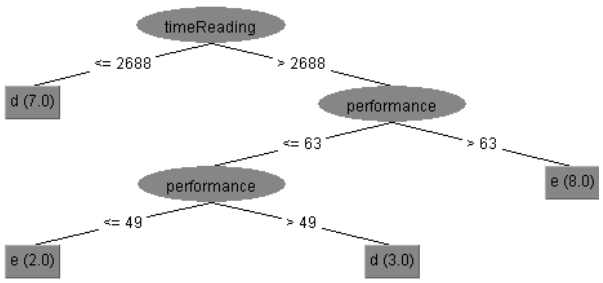
A number of 24 log files were randomly chosen for analysis and four of them were excluded due to very little information contained.

In order to perform the analysis, the Waikato Environment for Knowledge Analysis (WEKA) [Witten *at al.*, 1999] was used. The chosen method was decision trees based on C4.5 algorithm [Quinlan, 1993]. Other methods could be used, such as naïve Bayes classifier or regression. I chose decision trees and C4.5 algorithm because it provides classification and prediction, and also intelligible output in a graphical representation. Thus, the users' motivation can be characterized in terms of the attributes generated from the log files data (classification) and the predictability can be examined in order to see if such log file data can be used for motivation prediction.

In order to use the data for decision tree learning, each user has been assigned a motivational "state": engaged or disengaged. The criteria used for this assignment was described in the Table 3. The distribution of the 20 learners comprised 10 engaged and 10 disengaged.

4.1 The decision tree

The decision tree generated by WEKA for characterizing motivation is shown in Figure 1. The most important attribute for predicting motivation is, according to this decision tree, the time spent reading (timeReading): the users that spend less then 2688 seconds (approximately 45 minutes) are classified as disengaged; if the time spent reading exceeds 2688 seconds, performance is the second attribute to be used in classifying learners. Thus, if performance ratio is above 63%, users are classified as engaged. Otherwise, the same attribute, performance is used to classify learners as engaged if the ratio does not exceed 49% or as disengaged, otherwise.



e = engaged
d = disengaged

Figure 1.Decision tree for motivation

Summarizing the information from the decision tree, four categories of learners have been identified:

- learners who spend less then approximately 45 minutes reading; they are classified as disengaged;
- learners who spend more them 45 minutes reading and with a performance that exceed 63%; these learners are classified as engaged;
- learners who spend more then 45 minutes reading and with a performance between 49% and 63%; they are classified as disengaged;
- learners who spend more then 45 minutes reading and with a performance below 49%; they are classified as engaged.

4.2 The confusion matrix

The confusion matrix is presented in Table 4. It shows the quality of the decision tree and it has been produced by using fourfold cross-validation.

Table 4. The confusion matrix with fourfold cross-validation

		Predicted	
		Engaged	**Disengaged**
Actual	**Engaged**	8	2
	Disengaged	3	7

The elements in the matrix show the number of test examples for which the actual class is the row and the predicted class is the column. The diagonals of the confusion matrix indicate 75% of correctly classified examples and 25% on examples classified incorrectly. Thus, we can state that the quality of the decision tree is quite good.

Looking at the disengaged learners as they are our main interest, we see a lower rate of correct classification: 70% of the disengaged students are correctly classified.

4.3 Interpretation of results

Since the decision tree was derived only from a small set of examples, the results cannot be generalised in a straightforward manner. Another limitation is the way in which a motivational level, engaged/disengaged, was assigned to each user. It would have been ideal to have an external measure for this.

However, some interesting remarks can be made. The decision tree finds a particularly refined category of disengaged students: learners who spend a considerable time reading (above 45 minutes) and with a performance between 49% and 63%. Trying to give some meaning to these figures, a possible interpretation is the following: the fact that these learners have an average performance gives them a medium level of confidence; they go on reading, as they know they could improve their knowledge and performance, but knowing that they already have a medium or good knowledge level makes them invest less effort in learning. On the other hand, the results outline two categories of engaged learners that spend considerable time reading (over 45 minutes):

- The learners with a performance lower than 49%;
- The learners with a performance greater than 63%.

The engagement in both cases could be explained by the learners' desire to acquire more knowledge or just a better performance. From this perspective, it would be interesting to investigate the type of goal orientation of the learner (mastery / performance).

The results cannot tell anything about the users' level of motivation within the first 45 minutes. According to the decision tree, a user could be qualified as engaged or disengaged only after 45 minutes and, by that time, a demotivated user would have probably already logged out. Thus, it is of no benefit to know this information if there is no possibility to intervene. So, in order to be able to intervene on time, it is required to have information about the level of motivation in less time. This is also supported by the known fact that motivation can fluctuate at short periods of time.

In order to address the above mentioned aspects we intend to: 1) conduct a more detailed analysis using the data from the log files instead of derived indicators and 2) analyze the user's activity for short time periods – 10-15 minutes and extract the level of motivation for those specific times. By this approach information about the level of motivation would be updated at every 10-15 minutes and thus, have the possibility to intervene before the user would log out.

5 Summary and implications

We presented in this paper some results from a log files analysis. This analysis included a limited number of entries (20) and, thus, the results can't be generalised. However, it confirmed that a general indicator of the motivational level could be predicted from very basic data commonly recorded in log files.

This implies that a prediction module could be included in educational systems that record learners' actions. Looking at the two indicators found as predictors in our analysis – time spent reading and performance – the question that needs to be answered is if they depend on the system.

The threshold used for the time spent reading is approximately 45 minutes and the thresholds found for the performance were 49% and 63%. Because of the limited data used, the accuracy of the possible interpretations needs to be investigated in further work.

Another aspect to be investigated that emerged from our analysis is the level of motivation for short periods of time – 10-15 minutes – that would bring benefits in terms of intervention on time (before the user logs out) and taking in consideration the fluctuant nature of motivation.

Further work includes a larger scale and a more refined level of detail in the analysis, including the data from 150 log files. Also, an experiment will be conducted in order to externally validate the predicted motivational level.

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