Eliciting Adaptation Knowledge from On-line Tutors to increase Motivation

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Abstract. In the classroom, teachers know how to motivate their students and how to exploit this knowledge to adapt or optimize their instruction when a student shows signs of demotivation. In on-line learning environments it is much more difficult to assess a learner's motivation and to have adaptive intervention strategies and rules of application to help prevent attrition or drop-out. In this paper, we present results from a survey of on-line tutors on how they motivate their learners. These results will inform the development of an adaptation engine by extracting and validating selection rules for strategies to increase motivation depending on the learner's self-efficacy, goal orientation, locus of control and perceived task difficulty in adaptive Intelligent Tutoring Systems.

1 Introduction

On-line learning is a dynamic and potentially enriching forms of learning but attrition remains a serious problem [4]. Motivation to learn is affected by the learner's self-efficacy, goal orientation, locus of control and perceived task difficulty. In the traditional classroom tutors infer learners' levels of motivation from several cues, including speech, behavior, attendance, body language or feedback, and offer interventional strategies aimed at increasing motivation. Intelligent Tutoring Systems (ITS) need to be able to recognize when the learner is becoming demotivated and to intervene with effective motivational strategies. Such an ITS would comprise two main components, an assessment mechanism that infers the learner's level of motivation from observing the learner's behaviour, and an adaptation component that selects the most appropriate intervention strategy to increase motivation. This paper presents the results of a survey of on-line tutors on how they motivate their learners. These results will inform the development of the adaptation component by extracting and validating selection rules for strategies to increase motivation.

The focus of this research is intervention strategies which can be implemented and validated in an Intelligent Tutoring System to increase motivation and reduce attrition. Previous approaches in this field were mainly based on the ARCS model, which is an instructional design model ([3][9][12]). In contrast, the approach being taken in this research is based on Social Cognitive Theory (SCT) [1], particularly on self-efficacy, locus of control, perceived task difficulty and goal orientation. Self-efficacy is the individuals' confidence in their ability to control their thoughts, feelings, and actions, and therefore influence an outcome. Individuals with an external locus of control believe that factors such as luck, task difficulty, or other people's actions, cause success or failure [10]. Individuals with an internal locus of control believe that success is due to their own efforts. Perception of task difficulty will affect the expectancy for success, and it has a strong influence on both instigation of a learning activity as well as persistence. Goals enhance self-regulation through their effects on motivation, learning, self-efficacy and self-evaluations of progress [1]. Individuals with a learning goal orientation strive to master the task and are more likely to engage in self-regulatory activities such as monitoring, planning, and deep-level cognitive strategies. Individuals orientated towards performance approach goals are concerned with positive evaluations of their abilities in comparison to others and focus on how they are judged by parents, teachers or peers. Individuals with performance avoidance goals want to look smart and not appear incompetent and so may avoid challenging tasks, or exhibit low persistence, when encountering difficulties [8]. Individuals may have both mastery and performance goals [7]. Disengaged orientation is displayed by students who "do not really care about doing well in school or learning the material; their goal is simply to get through the activity" [2]. As learners differ widely, intervention strategies must be adapted to suit the individual and the task, thereby focusing the attention on the learner rather than on instructional design.

2 Eliciting intervention strategies from on-line tutors

A learner model was created based on the SCT constructs of Self-Efficacy, Goal Orientation, Locus of Control and Perceived Task Difficulty, as these are the four most important factors contributing to self-regulation. Research has shown that self regulatory behavior can account for academic achievement [8]. The model contained 21 learner profiles which were systematically developed using the above constructs (see Table 1). The profiles were selected from a possible 48 as the most likely to experience demotivation. For example, a person with the profile of Persona 1 is likely to become demotivated when not sufficiently challenged.

Based on the model personas (i.e., short textual descriptions) were then developed, e.g. Persona 1: "Chris is an intelligent student who enjoys learning for its own sake. She is motivated to learn new things and enjoys being challenged *(GO:Mastery)*. She believes she can do very well in her studies as she has a very good understanding of her subject *(SE:High)*. Chris believes hard work will conquer almost any problem and lead to success *(LOC: Internal)*. However, she finds that she becomes bored when she has to work on a concept which she already understands well *(PTD – low)*."

From the literature on motivation and an initial pilot questionnaire, completed by classroom tutors, a list of intervention strategies was compiled (see Table 2). In order to identify rules to determine which intervention strategy is the most appropriate for each learner's persona , on-line tutors were surveyed. If, for example, a learner had low self-efficacy and external locus of control, tutors might indicate that reviewing progress with the student at regular intervals would be a strategy to adopt. In this way the relationship between motivational states and intervention strategies was elicited with the assistance of the on-line tutors.

Participants were randomly assigned to one of six online surveys containing either three or four personas. The same 14 intervention strategies were presented in the same order under each persona. The tutors were asked to select the strategies they would *Highly Recommend*, *Recommend* or considered *Not Applicable* for each persona. They were also asked to suggest any further strategies that they find particularly useful in the case of each persona type. The tutors were required to have at least two years experience teaching on-line. The survey could be completed anonymously or the participants could enter their email address if they wished to get feedback on the results. Sixty participants completed the surveys which resulted in each persona getting a minimum of six and a maximum of fourteen responses.

Table 1: Profile of personas. Self Efficacy (SE) [High (H) / Medium (M) / Low (L)]; Goal Orientation (GO) [Mastery (M) / Performance Avoidance (Pa) / Performance Approach (PA) / Disengagement (D)]; Locus of Control (LOC) [Internal (I) / External (E)]; Perceived Task Difficulty (PTD) [Low (L) / High (H)]

Persona	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**
SE	H	H	M	M	M	M	L	L	M	H	L	L	M	M	M	M	H	L	L	M	M
GO	M	M	M	M	M	M	M	Pa	Pa	Pa	PA	PA	PA	PA	PA	PA	PA	D	D	D	D
LOC	I	E	I	I	E	E	E	E	E	E	I	E	I	E	I	E	I	I	E	E	I
PTD	L	L	L	H	L	H	H	H	H	H	H	H	L	L	H	H	L	H	H	H	H

4 Results

The participants varied widely in the number of years' of experience they had as on-line tutors. The least experienced participants had tutored on-line for two years, and the most experienced had tutored for eighteen years. The average was five years..

For the purpose of this paper, we merged *Highly Recommended* and *Recommended* strategies into one category which is the subject of this paper.

Using the Weka data mining tool set [11], five different algorithms were applied to predict whether a strategy was marked as recommended by the tutors or not. These algorithms included the following classifiers: 1) Bayesian Networks. 2) IBk, an instance-based k-nearest neighbours classifier. 3) J48, generating pruned C4.5 decision trees. 4) PART, a classifier based on partial C4.5 decision trees and rules. 5) Naïve Bayes as a standard baseline. All experiments were run with a 10-fold cross validation. Table 3 provides an overview of the results.

Both, Bayesian Networks and J48 are able to predict the recommendations very well, with correct prediction rates from at least 66% and up to 93%. Strategy 4, *Encourage the student to use on-line quizzes*, seems to be harder to predict. This strategy has also been recommended less often than most other strategies. The fact that results across methods are similar means that the pattern in the data is pretty obvious.

Table 2. Intervention strategies

1	Review progress with student at regular intervals
2	Provide regular positive and specific feedback to student
3	Encourage student to clearly define his/her academic goals
4	Encourage the student to use on-line quizzes
5	Remind student of the student support services
6	Encourage student to use the chat room/discussion forums
7	Help student to develop a study plan/timetable
8	Explain importance of and encourage student to maintain contact with tutor
9	Encourage peer to peer contact
10	Encourage student to base self-evaluation on personal improvement/mastery when possible, rather than grades
11	Encourage the student to reflect on and evaluate his/her learning
12	Explain why learning a particular content is important
13	Provide guidance to extra learning resources
14	No intervention required

5 Discussion

We demonstrated that knowledge about appropriate motivation intervention strategies can be elicited from tutors by prompting them with systematically constructed personas. While the relationship between parameters of the personas and intervention strategies are not obvious and cannot be explained directly by the tutors, we were able to demonstrate that standard machine learning algorithms can learn to predict this relationship well.

Table 3. Correct predictions (%) of the five algorithms separated by the 13 intervention strategies.

	BayNet	**IBk**	**J48**	**PART**	**NaïveBayes**
Strategy 1	**89.86**	**89.86**	**89.86**	**89.86**	**89.86**
Strategy 2	**93.26**	**93.26**	**93.26**	**93.26**	**93.26**
Strategy 3	**84.55**	80.78	**84.55**	82.03	**84.55**
Strategy 4	66.09	58.88	**66.58**	63.11	65.23
Strategy 5	74.04	74.80	**77.31**	77.12	74.33
Strategy 6	**86.50**	85.71	**86.50**	**86.50**	**86.50**
Strategy 7	**70.92**	67.59	68.83	70.23	69.81
Strategy 8	**83.60**	82.64	**83.60**	**83.60**	83.50
Strategy 9	**88.90**	88.22	**88.90**	**88.90**	**88.90**
Strategy 10	**82.64**	80.66	**82.64**	82.25	**82.64**
Strategy 11	**88.90**	**88.90**	**88.90**	**88.90**	**88.90**
Strategy 12	**79.24**	74.86	**79.24**	78.57	78.47
Strategy 13	**80.67**	79.66	**80.67**	**80.67**	**80.67**

An assessment component that creates an accurate model of the motivational states of the learner is currently being developed in a related project being carried out by a fellow researcher and it is planned to use this assessment component in the validation stage of this study. The fact that this automatic assessment component has not yet been developed is currently a limitation for us, but once it exists, appropriate intervention strategies can be inferred. Future work will focus on an empirical validation of the predictions in a real learning environment to see if the intervention strategies adopted actually increase the motivation of the learner.

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