Mining data from interactions with a motivational-aware tutoring system using data visualization

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Tutoring systems are a common tool for delivering educational content and recent advances in this field include the detection of and reaction to learners' motivation. A data set derived from interactions in a tutoring system and its motivationally-aware variant, provided opportunities to discover patterns of behavior in connection with motivational feedback. The data collected consists of individual log files capturing the behavior of the learner during his/her interaction with the system. To mine this data, techniques was employed to discover patterns of interest when motivational scaffolding was provided by the tutoring system. A graph was constructed to visualize these patterns and to identify significant transitions derived from dyads of actions. This is a first step towards analyzing behaviors when motivational scaffolding is provided in a tutoring system. Work for the future consists of investigating the patterns' impact on learning with the motivation-aware tutoring system.

Key Words: intelligent tutoring systems, motivation, pattern mining, likelihood metric

1. INTRODUCTION

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There is increasing consideration of learner motivation in the design of intelligent tutoring systems. This includes both the automatic recognition of the motivational state of the learner, as well as the development of motivational pedagogy, see for example [Calvo 2011]. The latter requires a better understanding of the relation between motivational pedagogic tactics and their consequential behavioral and learning outcomes. For example, how does the behavior of learners change when scaffolding is introduced that is designed to increase their motivation? The overall method we used to explore this issue was to observe learners working with two variants of an existing tutoring system that differed only in terms of the nature of motivational scaffolding provided. This enabled us to address the following questions: 1) What are the behavioral patterns provoked by each variant of the system? 2) How do these patterns of behavior differ between the variants? And 3) How might these patterns, and their differences, be accounted for theoretically?

To throw light onto these issues, we created and utilized data sets derived from interactions with two tutoring systems: the Ecolab II [Luckin and Hammerton 2002] and its motivational variant the M-Ecolab [Rebolledo-Mendez, du Boulay 2011]. Although both systems share the same scaffolding strategies to provide help at domain level, the M-Ecolab detects and responds to varying levels of the learner's motivation [Rebolledo-Mendez, du Boulay 2006]. Both systems simulate a simple ecological microworld laboratory within which children can learn about the concepts of food chains and food webs. The system poses simple problems about what kind of creature eats what (say) which the learner can find the answers to by exploring the microworld. The system engages learners by providing an interface with different living organisms (both plants and animals) and opportunities to explore their feeding relationships. The child is free to solve the problems suggested or can make his or her own choice of problem to work on. For example, given three organisms in the microworld (vole, snail and rose) the child could suggest a mistaken food chain such as “vole eats rose” to which the system reacts by providing help. The learning objective is to establish correct food chains such as “vole eats snail” that gradually grow into longer chains such as “vole eats snail and snail eats rose”. Later in the curriculum, chains can be developed into webs and these are depicted in the interface using arrows establishing the feeding connections among the organisms provided by the microworld. The system tracks the difficulty of the problems worked on and the degree of help requested by the learner and provides encouragement at the metacognitive level on these issues. The motivational variant additionally scaffolds learner-motivation by displaying on-screen pedagogic agents and by suggesting a number of further activities, as described later.

The objective of this paper is to report on the application of data mining techniques to discover the patterns of behavior associated with the use of motivational scaffolding. To that end, we utilized two approaches: one based on ‘code and count’ [Ohlsson, di Eugenio 2007] and the other based on a probabilistic approach to dyads of actions [D’Mello, Olney 2010].

The paper is organized into five sections. Section Two describes the theoretical foundation of this research and situates the work in the area. It also presents the definition of motivation that underpinned the development of the motivationally-aware variant of the tutoring system. Section Three presents two sets of analyses. The first analysis presents learner patterns of behavior and employed a code and count approach derived from previous evaluations of Ecolab II [Luckin and du Boulay

1999]. The second analysis utilized a probabilistic approach to characterize learner behaviors with both variants. Section Three describes how and why the scaffolding in the motivational variant assisted, and sometimes hindered, the learners and how their behavior differed from those working with the non-motivational variant. Finally, Section Four discusses the results and suggests implications for the design of motivational scaffolding in intelligent tutoring systems, and Section 5 draws conclusions and suggests further work.

2. BACKGROUND

According to [Lepper and Chabay 1988], tutoring systems should include motivational scaffolding including the recognition, maintenance and improvement of learner motivation. Various designs for motivational scaffolding within Intelligent Tutoring Systems (ITS) have been developed [Rebolledo-Mendez, et al. 2011;du Boulay, Avramides 2010;Boyer, Phillips 2008]. However, one of the problems of designing motivational scaffolding is the definition of the term “motivation” itself. For example, motivation to learn has been understood as expectancy of success [Erez A and Isen 2002;Dweck 1975], as rewards for effort [Deci 1975], based on attributions [Weiner 1984] or in having a mastery or challenge orientation [Ames 1992]. Some examples of motivational scaffolding include the use of focus of attention to detect frustration [Qu and Johnson 2005] and the selection of the next problem depending on an analysis both of the learner’s cognitive and motivational state [del Soldato and du Boulay 1995].

Affect and motivation are intertwined. For example, positive affective states such as confusion or cognitive engagement promote higher states of motivation leading to fulfillment of expectancy [Erez A and Isen 2002] and rewards [Aspinwall 1998] whereas negative affective states such as frustration and boredom hinder motivation to learn. There is increasing use of sensors to detect different affective states with a motivational dimension such as frustration, boredom and cognitive engagement during interactions with a tutoring system [Arroyo, Cooper 2009], and for determining the optimal learner emotional state for effective interaction [Chaffar and Frasson 2004]. One interaction between affect and motivation relates affective states with degrees of motivation.

2.1 Motivation modeling in Ecolab II

Given the different approaches to studying motivation and its various interactions with affect, it was necessary to adopt a working definition of motivation to develop the motivational variant of the Ecolab II tutoring system. Motivation was (and is) understood in terms of the learner's internal desire to learn, externally expressed by his or her degree of willingness to exert effort, to take on challenging activities and work without recourse to the ITS's scaffolding facilities [Rebolledo-Mendez, et al. 2006]. Because the goal was to develop a motivationally-aware variant of Ecolab II, the challenge was to integrate seamlessly new motivational features such as advice, engaging activities and praise with the existing metacognitive scaffolding of Ecolab II [Rebolledo-Mendez, et al. 2011]. We faced both *recognition* and *reaction* problems. The recognition problem was about identifying the learner's degree of motivation *indirectly* by considering interaction traits such as the amount of help requested or the types of activity selected, in accordance with the definition of motivation presented above.

The reaction problem was about deciding which new reactive and interactive elements to implement. Examples of different types of reaction include the use of politeness [Wang and Johnson 2008], empathy [McQuiggan and Lester 2007], reducing frustration [Kapoor, Burleson 2007], narratives for learning [Robertson 2004;McQuiggan, Rowe 2008] and employing animal companions as motivating strategy [Chen, Deng 2005]. The possibilities to react to varying states of motivation or de-motivation constitute an interesting research area. Our approach was to employ on-screen pedagogical agents and to utilize variations in their tones of voice and facial expression to convey the tutoring system's reaction to the learner's changing effort, changing independence of the system's help or changing choice of the degree of challenge in the activities chosen [Rebolledo-Mendez, du Boulay 2006]. We hoped that feedback based on encouraging a positive attitude to learning would lead to positive affective reactions [Rodrigo, Rebolledo-Mendez 2008].

Our research made use of the Ecolab II learning environment [Luckin and Hammerton 2002;Luckin and du Boulay 1999] and its motivational version the M-Ecolab [Rebolledo-Mendez 2003]. Both systems aim at teaching the ecological concepts of food chains and food webs to Year 5 learners (aged 10 years). Both Ecolab II and M-Ecolab employ the metaphor of a Science Laboratory where learners can perform actions with and between organisms added to the environment. The set of actions include moving, eating, eating and be eaten by. The learner can manipulate the environment and study the different outcomes of actions by switching between three different views: World View, Energy View and Web View. The World View presents the chosen organisms as being part of an ecosystem shown in terms of where they belong to in the simulated World. The Energy View presents the organisms in relation to the amount of energy they need to survive, suggesting the amount of food they need, depending on whether the organism is a plant or an animal. The Web View presents the organisms in the environment in relation to the place they belong to in the food chain. These views provide different perspectives for learning about food chains and food webs. The curriculum in the tutoring system consists of 10 learning nodes, organized into 3 different zones. The zones, and the nodes in them, are progressively more complex and go from simple one-to-one feeding relationships (Energy node, Zone 1) to complex food webs containing different food chains (Feeding 3 node, Zone 3). The scaffolding mechanisms at the domain level for both systems are based on a modeling approach in which help is provided depending on the perceived understanding and ability of the learner [Hammerton and Luckin 2001]. For example, less able learners receive more explicit feedback. Motivational scaffolding is based on the same principle, providing more motivational help to less motivated students.

In order to detect and react to varying motivational states, a motivational model capable of underpinning the motivational reactions in M-Ecolab was developed [Rebolledo-Mendez, et al. 2011]. The model detects motivation utilizing interaction traits in terms of our definition of motivation as the *willingness to exert more effort, take on more challenge and having an independent attitude*. In consequence, the learner's motivation is dynamically calculated using three variables: Effort, Independence and Confidence. Effort is the ratio between correct actions and help-seeking behavior. Greater effort corresponds to more correct actions using less help from the system. Independence refers to the quantity (number of instances of help requested) and quality (greater quality corresponds to less explicative feedback) of help. Higher independence is understood as lower quantity and greater quality of help. Confidence corresponds to the degree of challenge the learner is willing to take. A more confident learner is willing to undertake more challenging activities when prompted by the tutoring system. All variables have a value between 0 and 1 and are constantly updated at interaction time. A calculation of the learner's motivation is computed on exit from a learning node by averaging out the values of the variables during that node; the new values are then propagated through the learning curriculum. A learner's motivation is considered low if it has a value between 0 and .5 and high if it has a value between .51 and 1.

2.2 Motivating feedback in M-Ecolab

The value of the learner's motivation determines the reactions of the M-Ecolab including variations in the motivational feedback, tones of voice and facial expressions of the pedagogic agents (see Figure 1) as well as differentiation in the amount and periodicity of the scaffolding provided.

The nature of the spoken feedback depends on the learner's motivation as assessed by the motivation model. If presented, these messages occur after all the activities in the node have been finished (post-activity), immediately before a new action is attempted in a new node (pre-activity) or at both times. The motivational feedback not only conveys praising messages (via changes in the agent's tone of voice and facial expressions, see Table 1) but also may state the objectives for the new learning node or give advice on what to do in the new node. The advice is adjusted according to the cause of any de-motivation detected by the motivation model and can be related to excessive dependence on the system's help or because of a lack of effortful behavior. For example, if the motivation model determines that the motivation is low because the learner lacks independence (excessive help requests) the message provided is: “in the next activities try to ask for less help”. Figure 1 and Table 1 show the type of changes conveyed by the agent when delivering motivational feedback.

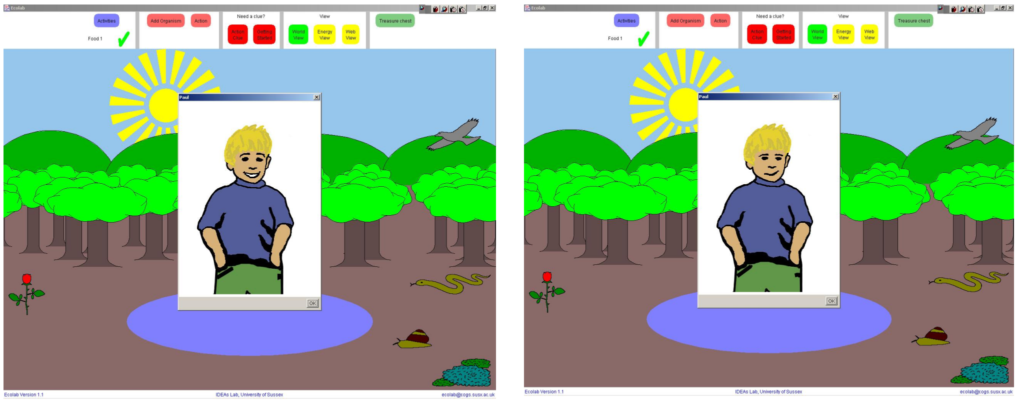

Figure 1 Facial expression variations

Table 1. Variations of agent’s feedback

	Pre-activity feedback		Post-activity feedback	
Motivation	Tone of voice	Facial expression	Tone of voice	Facial expression
Low	Normal	Normal	Worried	Worried
High	Normal	Normal	n/a	n/a

Motivational scaffolding in M-Ecolab also includes a quiz with questions taken from the activities at hand, as well as a button for replaying the agent’s pre-activity feedback [Rebolledo-Mendez, et al. 2011]. The quiz was integrated into the set of motivational strategies with the aim of increasing curiosity about the topic. The use of the quiz was intended as a means to increase Effort, as prompting the learner to answer questions related to the domain could lead to an increased interest to perform actions in relation to the questions of the quiz leading, perhaps, to increased effortful behavior. Although quizzes can be considered a form of cognitive scaffolding, the intention to include a quiz was a motivational mechanism to increase Effort. It might seem strange to add a quiz as a motivating activity, but this was suggested as part of the early design work with children [Rebolledo-Mendez, du Boulay 2011]. Although it might be possible for a child to get the quiz questions themselves wrong, the more light-hearted nature of the quiz compared to the more ‘serious learning work’ in the microworld was expected to mitigate this potential for further demotivation.

Previous analyses of the results of using M-Ecolab have highlighted the benefits of the motivational scaffolding for help-seeking behavior [Rebolledo-Mendez, du Boulay 2005] and for those initially de-motivated learners who followed the suggestions provided by M-Ecolab [Rebolledo-Mendez, et al. 2006] and became more motivated. However these results were not accompanied by improvements in overall learning. This paper provides a further analysis of the data from the evaluation mentioned above.

3. MINING DATA GENERATED BY ECOLAB II AND M-ECOLAB

The context of the evaluation is described first. An experiment was carried out with children (aged about 10) from three parallel Year 5 classes in a school in Horsham, England in May 2005. To assess learning, an isomorphic test was used both before and immediately after the experiment. This test was the same as used in previous evaluations of earlier versions of Ecolab II [Luckin and Hammerton 2002;Luckin and du Boulay 1999]. The participants were 35 learners belonging to the three classes and they were randomly assigned to the two conditions. Scholastic

Achievement Test[2] scores (SATs) were provided for all the participants prior to the experiment. Learners in the control condition (n=16) were asked to interact with Ecolab II whereas learners in the experimental condition (n=19) interacted with the motivational variant, M-Ecolab.

The learners interacted with one or other version of the system for approximately 80 minutes across two sessions with 1 week between sessions. The systems were installed on tablet computers that were used individually by learners during the experiment. The learners had not learnt the topic of food chains and food webs in their normal schooling before the experiment.

The difference in learning gain between the control and experimental conditions was not significant ($t(33)=-1.628$ $p=.113$), see Table 2 for descriptive statistics. During the interactions 70 log files (2 per session per learner) with 28279 lines in total and an average of 807.97 lines per learner were collected. This data is the basis for the data mining analyses presented next. First, a code and count analysis considering typified behaviors is presented followed by a pattern discovery approach.

Table 2 Learning gains: descriptive statistics

Condition	N	Minimum	Maximum	Mean	Stdev
Control	16	-14	11	2	5.69
Experimental	19	-4	13	4.73	4.24

3.1 Behaviors

A first approach to mine the data obtained in the evaluation followed a similar methodology to that of Luckin and du Boulay [1999] consisting of

[2] A UK national test of achievement scored as a percentage

exploring the behaviors observed during the interaction. Two types of profiles had been defined. Interaction profiles characterize the behavior of the learners during the interaction with the tutoring system and consist of 3 binary distinctions: busyness/quietness, exploration/consolidation and hopping/persistent. Collaboration profiles are more specific and refer to the quantity and quality of help that learners requested during their interactions. These profiles have been found in previous studies [Luckin and du Boulay 1999;Hammerton and Luckin 2001] and represent typical interaction styles with Ecolab II and M-Ecolab.

The profiles were not identified dynamically during the interactions but post hoc, and help us understand the types of action and help-seeking behavior that learners undertook during the interaction. These profiles represent interaction traits and an individual learner may show more than one of these characteristics during the interactions rather than one-to-one correspondence between learners and profiles. To determine the profiles, a code and count approach was used in which instances of particular events were identified for individual learners. Since every profile is understood as having two poles (for example busy *vs.* quiet learners), minimum thresholds on the number of contributing events were established to determine whether learners belonged to one pole or another. The number of events was not proportionalized since we were interested in classifying behaviors following an established methodology and being consistent with previous evaluations of Ecolab II. Correlations between the total number of actions individually performed by the learners and the behaviors described in sections 3.1.1 and 3.1.2 are not significant.

3.1.1 Interaction profiles

The interaction profiles are defined as follows. **Busyness** is "a characteristic of interactions in which the learners completed an average or above average number of actions of any type, such as adding an organism to the environment or making one organism eat another. The opposite of busyness is referred to as **quietness**". **Exploration** is "a characteristic of an interaction if the participant had been involved in some sort of action which allowed his/her to experience more than one level of complexity or more than one level of terminology abstraction". In other words, an explorer was a participant who requested more challenge than was suggested by the system and also experienced more view changes and curriculum zones. The opposite of exploration is referred to as **consolidation**. Finally, a **hopper** is "a participant who switched frequently from one type of interaction to another. For example, from attempting an action to switching a view to accessing a new activity. The participant's interaction contained no or few series of repeated actions of the same type. The participant was particularly prone to frequent changes of view". A hopper was a participant who did more view changing than average, tried more times than average to initiate a new node of the curriculum without finishing the current one and gave-up more times than average with an erroneous activity when challenged. The opposite of a hopper is known as a **persister**.

In the light of the motivational components of M-Ecolab, two new interaction profiles were defined. **Quiz-seekers** used the quiz an above average number of times; the opposite are referred to as **quiz-avoiders**. A **challenge-seeker** is a participant selecting above average levels of challenge. The opposite of challenge-seeker is referred to as **challenge-avoider**. Learners were classified considering the definitions presented above. A correlation table for all the interaction profiles is presented in Table 3.

The correlation table shows that there are highly significant correlations between some of the behaviors. For example, being a busy learner is positively correlated with being an explorer (p=.019) and as consequence negatively correlated with being a consolidator (p=.033). Being an explorer is negatively correlated with being a challenge-seeker (p=.000) and its opposite being an explorer is positively correlated with being a challenge-avoider (p=.000). Finally, being a consolidator is negatively correlated with being a challenge-taker (p=.000) and positively correlated with being a challenge-avoider (p=.001). We were also interested in analyzing learning gains in relation to behaviors in both tutoring systems. To that end, we conducted a series of statistical analyses in order to explore the relation of these behaviors to learning gain in both the experimental and control conditions. However, because of the small cell sizes that resulted from splitting the sample these results should be considered as tendencies only.