Student Learning Behavior in an Unsupervised Learning Environment

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Abstract: Learning is commonly associated with knowledge transfer involving guidance from a teacher. However, as people grow older they are expected to know how to learn by themselves. In this research, we analyzed student learning in an unsupervised learning environment, i.e., performing academic research, wherein students have complete control over their learning thus requiring them to manage it. Transition likelihood metrics were used to analyze the interplay between emotion, learning and non-learning related activities while students did research. Several observations were seen from students learning in this environment such as students experiencing cognitive disequilibrium but experiencing disengagement faster. Non-learning related activities were also shown to have the potential of motivating students to resume learning. Lastly, user-specific traits and context seem to affect the interplay between learning and non-learning activities in an unsupervised learning environment. This highlights the need to not only create general models to predict student behavior but also user-specific models to allow future systems to provide appropriate feedback in this environment.

Keywords: unsupervised learning environment, cognitive and affective state transition, likelihood metric

Introduction

Learning is an essential part of human life. It starts from the very beginning of our lives when we start learning simple actions and then eventually moving on to very complex processes. We usually learn through knowledge transfer from a teacher whose role is fulfilled by a parent, a sibling, a peer or a teacher in school. Over time however, we are expected to learn on our own so that we no longer need constant guidance from teachers in acquiring knowledge and applying it to solve the problems we wish to address. In most cases, we become the teachers too and it becomes our turn to share our knowledge to others.

Many computer systems have been created to aid the process of learning so that in cases when a human teacher is unavailable, a computer system can take on that role and provide support for students while learning a particular topic [8]. Although these systems model the students' knowledge of the topic being learned, these do not consider how the student interacts with elements outside of the learning environment and its effects on the learning session.

In this work, we focused on *unsupervised learning environments* which we define as an environment characterized by the absence of supervision from either a human or an automated teacher. As a result, this environment requires students to manage their learning apart from accomplishing their learning goals. Some elements that need to be managed include the goals for the session, the amount of time spent in completing goals, the affective states experienced, the transitions to non-learning related tasks and the avoidance of distractions. Support is important in this kind of environment because students unable to manage learning will most likely perform poorly or fail to complete their requirements.

Our goal for this work was to analyze and model students' learning behavior in an unsupervised learning environment so we can enable future systems to provide appropriate feedback in such an environment.

1. Related Work

Most existing systems designed to support learning provide cognitive and/or affective feedback to students as they solve problems or explore environments generated by the system [1][6]. Tracking both cognitive and affective states have allowed these systems to model students more completely and also provided a better understanding of student learning. This in turn was used as basis for designing and identifying the appropriate feedback for students using these systems for learning.

D'Mello and Graesser [4] developed a model that used both cognitive and affective elements to explain how students' emotions transitioned while learning. This model can be used to predict student behavior and provide appropriate feedback in cases when students engage in activities or experience emotions that are not helping them learn. Students using computer-based learning environments also engage in non-learning related activities and certain cognitive and affective states have been reported to lead to off-task activities like gaming the system and talking to seatmates [2][13]. Although learning environments prevent or discourage students from engaging in non-learning related activities, students learning by themselves can freely do so and are left to deal with them on their own. If they are unable to manage their learning, they may learn less and may need to spend more time to learn [9].

Not much work has been done to investigate the role of non-learning related activities while learning especially when these are not purposely prevented or discouraged. We believe that a better understanding will allow us to design systems that can leverage from its benefits and try to reduce its negative effects.

2. Data Gathering

We gathered data from four students who performed academic research. We considered this an unsupervised learning environment because the students did not receive supervision and they needed to manage their own learning. When students worked on their research, they spent time developing their ideas, performing analysis and making conclusions. They usually consulted or got suggestions and ideas from their supervisor but when they did actual research work, it was their responsibility to identify their goals for the day, which activity to prioritize and how much time to spend on an activity. Research required the students to spend much time working and it was common for them to engage in non-research related activities such as reading an email from their supervisor, exchanging instant messages with a friend and viewing a video aside from others.

The participants consisted of one male undergraduate student, one male master's student and two female doctoral students. All of these students were required to do research as a requirement for their degrees and they commonly did their research with the help of a computer using different applications such as web browsers, word processing software and programming environments. Students were given the freedom to engage in both learning and non-learning related activities either on or our outside of the computer. The annotation software used and the methodology for collecting data are described in the following subsections.

2.1 Sidekick Retrospect Software

The Sidekick Retrospect Software was developed by the authors to help students manage learning and annotate their behavior. It encouraged the use of self-regulation strategies specifically goal setting, self-monitoring and self-reflection [14]. When students began their learning session, they first identified their goals for the session and inputted each one on the interface. While learning, students were allowed to add more goals in case they found the need to. The software also logged the applications used by the students and took screenshots of their desktop and webcam feed throughout the session.

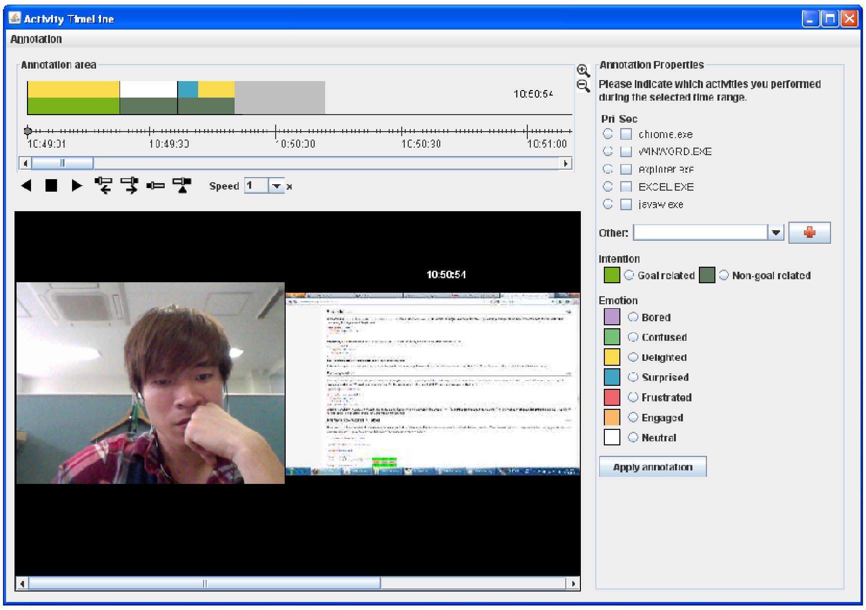

Figure 1. Interface for annotating learning behavior.

When the students ended the session, they were presented with a timeline representing their entire learning session. The corresponding desktop and webcam screenshots were shown whenever the mouse hovered over the timeline to help students recall what activity they did at that moment. Students annotated their behavior by clicking and dragging the mouse to select a time span and then identifying their corresponding intention, activity and emotion label using the interface shown in Figure 1. Intention is the student's purpose for performing an activity which was either goal related or non-goal related. In this work, goal related and non-goal related activities are synonymous to learning and non-learning related activities because the goals defined by the students were for learning. An activity is what students did at a certain point in time such as using the Google Chrome browser to search for information, chatting using Yahoo Messenger, or reading a technical paper. Lastly, emotion is the student's experienced emotion while performing the activity. Two emotion sets were used during annotation. When students performed goal related activities, they selected one emotion from: delight, engagement/flow, confused, frustrated, surprised, afraid and neutral. The list comprised of academic emotions which are commonly observed when students learn [3]. When students performed non-goal related activities, they selected one emotion from Ekman's six basic emotions namely angry, disgusted, sad, delighted, afraid, sad and neutral [7]. A different emotion set was used for learning related activities because academic emotions do not only refer to an affective state but are also indicative of certain cognitive states which are useful for providing feedback. Academic emotions do not have special meaning in non-learning related activities thus Ekman's basic emotions were considered sufficient.

After annotation, students were asked to identify how much of their goals were completed, which activities helped them complete their goals and how productive they felt the learning session was. This helped students self-reflect to identify which activities were helpful to learning or which were not and also for evaluating their performance.

At the end of the entire session, the software generated a log file containing the intention, activity and emotion labels with their corresponding time stamp. Instances in the log file were one second apart.

2.2 Data Gathering Methodology

Before data gathering, each participant was first given a short tutorial on how to use the Sidekick Retrospect software and an explanation of the different annotation elements. They were told that all activities they did which were related to their research goals for that day would be considered goal-related and any other activity would be non-goal related. They were also asked to indicate the different activities they did regardless if it was done on or outside the computer. Lastly, each emotion was explained to them so they would know how to differentiate them. In situations when they experienced more than one emotion, they were asked to identify the most prominent one.

After the tutorial, the software was installed on the participants' computers and they were taught how to start and stop the data gathering module and create annotations in the annotation module. They were then asked to use the software in five separate sessions, wherein each session lasted around two hours. Students had the freedom to choose when, where and which materials to use for learning.

At the end of every session, the students were asked to annotate their learning behavior and then answer a survey. The survey contained questions regarding the students' realizations from their learning behavior. Data was gathered from each student over a period of one week, with five two-hour sessions per day resulting in a total of 40 hours of data from all participants.

3. Analysis

Majority of the students used the software and annotated their learning behavior when they worked at their own table in their respective research laboratories. This was where students commonly did their everyday work wherein other research students were also present in the same room interacting with each other and sometimes with the participant. The students learned in the same setting as they always did and the software did not require them to change their behavior while learning. Although students were asked to annotate their data, this was done after the learning session. We believe that the methodology we used resulted in naturalistic data.

The data showed that students spent about one hour and 30 minutes engaging in learning related activities out of the entire two hour session. The participants set three goals on average throughout the duration of the session. They rarely completed all of the goals they defined but in most cases they completed at least 75% of one of the defined goals. This further indicates that the data gathered from the participants was naturalistic because the students did not avoid non-learning related activities nor favored it. It also shows that they were capable of managing their learning behavior because they were able to identify their goals, perform activities to accomplish their goals, and spend majority of their time in learning related activities. Students experienced engagement, delight, boredom and confusion over prolonged periods of time when learning. On the other hand, students experienced delight and were in the neutral affective state over prolonged periods of time when non-learning.

We further investigated the interplay between learning and non-learning related activities using a transition likelihood metric to identify what caused students to shift between these activity types. D'Mello et al. [5] introduced a metric to measure the likelihood of transitioning from one affective state to another while students used an intelligent tutoring system. However, in our research we did not only consider activities related to learning but also non-learning related activities. We modified the likelihood metric to include the type of activity done by the student which is shown in Eq. 1. The equation measures the likelihood of transitioning from a state pi to state pi+1 where a state consists of the activity intention I, which may either be learning or non-learning and an emotion E, which may either be delight, engagement/flow, confused, frustrated, surprised, afraid and neutral for learning activities and angry, disgusted, sad, delighted, afraid, sad and neutral for non-learning activities. In our analysis, we were only concerned with transitions into a different state since these described instances when certain factors affected the student to move out of the current state. Assuming that a student performs the following transition: State A → State B → State B → State C, the prolonged state is treated as a single state resulting in the following transition: State A → State B → State C. The metric's resulting value ranges from 1 to -∞. When the value is above zero, it indicates a likely transition with increasing likelihood as it approaches 1. A transition likelihood of zero indicates that the transition is equal to chance and values below zero indicate that the transition is less likely to occur compared to the base frequency of the succeeding state.

$$L(p_i, p_{i+1}) = \frac{\Pr(p_{i+1} \mid p_i) - \Pr(p_{i+1})}{(1 - \Pr(p_{i+1}))} \qquad (1)$$
$$\text{where}: p = < I, E >$$

All possible transitions can be generated by combining all possible pairs resulting in a 14x14 matrix. To get a view of the students' learning behavior, we averaged each of the student's transition likelihood values and used a t-test to identify statistical significance. Table 1 shows the resulting matrix of likelihood values containing only the transitions that were more likely than chance (i.e., L>0) with their corresponding p values in parentheses. Likelihood values without p values indicate that there was only one instance of that transition over all sessions from all students. Significant transition likelihood values (i.e., p<0.05) are highlighted. Transitions to the same state were omitted since the data used for the likelihood matrix only contained state changes and not prolonged states.

As many researches have already shown, emotions play an important role in learning which were also observed from the data we gathered. Specifically, there were highly significant and likely transitions from engagement to confusion (L=0.15) which is indicative of cognitive disequilibrium. Cognitive disequilibrium occurs when students encounter errors or anomalies in what they are learning requiring them to either accept new information or to alter their current understanding to return to an equilibrium state [12]. Cognitive disequilibrium is commonly attributed to learning and usually co-occurs with feelings of confusion [10][11]. We also observed that students likely transitioned from a bored learning state to a neutral non-learning state (L=0.40). Boredom is a state where students have already disengaged from the learning activity and it is quite understandable for them to simply shift to a non-learning activity most especially because they are not prevented from doing so. A similar behavior was also seen in the shift from a confused learning state to a neutral non-learning state (L=0.20). Although the transition's p value was p=0.054 it can still be considered statistically significant. This may partially explain why students did not experience hopeless confusion. D'Mello and Graesser [4] described hopeless confusion as a state wherein students in a confused state are unable to resolve the problem and eventually become frustrated. In the case of an unsupervised learning environment, it seemed that when students were not able to resolve the cause of confusion, instead of being frustrated they simply disengaged. On one hand, this is disadvantageous as students would more likely disengage instead of solving the problem. On the other hand, this could have led to lesser frustration, resulting in less stress and allowing them to possibly have more motivation to continue learning at a later time.

Table 1. Transition likelihood matrix with corresponding statistical significance

		L						**NL**			
		EN	FR	CO	BO	DE	NE	DI	DE	SU	NE
L	EN			0.15 (0.001)			0.04 (0.390)		0.05 (0.502)	0.05 (0.172)	0.17 (0.037)
	FR										0.74
	CO				0.03 (0.558)		0.03 (0.607)		0.09 (0.303)		0.20 (0.054)
	BO						0.03 (0.691)		0.08 (0.241)		0.40 (0.016)
	DE						0.14 (0.514)		0.50 (0.336)		0.26 (0.610)
	NE	0.41 (0.031)	0.11 (0.351)			0.01 (0.422)					
NL	DI	1.00									
	DE	0.35 (0.013)				0.02 (0.402)	0.13 (0.106)				
	SU			0.43	0.23						0.14
	NE	0.25 (0.024)	0.02 (0.334)	0.06 (0.454)	0.01 (0.895)		0.09 (0.212)	0.02 (0.334)			

Intentions: **L** – Learning; **NL** – Learning; Learning emotions: **EN**gaged, **FR**ustrated, **CO**nfused, **BO**red, **DE**lighted, **NE**utral; Non-learning emotions: **DI**sgusted, **DE**lighted, **SU**rprised, **NE**utral

As mentioned earlier, students were likely to resume learning as shown by the transitions from a delighted and neutral state while non-learning to an engaged learning state (L=0.34 and L=0.26 respectively). This can be interpreted in two ways. It can be that students were capable of fending off distractions in an unsupervised learning environment or, the presence of non-learning related activities reduced stress or helped students maintain a level of motivation which helped them relax more and resume learning at a later time.

Lastly, the likely shift from a neutral learning state to an engaged learning state (L=0.26) also indicated that students were not always engaged. Presumably, they first read and understood content before getting immersed in the activity they were trying to accomplish. Over time, they did become engaged which is the ideal state for learning.

Some students transitioned to and from other states however these were not observed in other students or were only seen in a small number of sessions. This brought up two concerns that needed to be considered when dealing with unsupervised learning environments. First, personality or some other user-specific trait may have an effect on a student's learning behavior that was observed in one student but not others. A more in depth data analysis showed that only one student transitioned to a neutral learning state before experiencing other emotions while learning. Consider the following transitions observed from the student while engaging in a learning activity: EN→NE→CO; EN→NE→BO; EN→NE→EN; CO→NE→EN; BO→NE→EN. The transition to a neutral state indicates that the student might have lost focus first then eventually experienced confusion or boredom. While in the state of confusion or boredom, the student seemed to get back his learning momentum first before transitioning to an engaged state again. Other students transitioned directly between these emotions without passing through a neutral state. Secondly, context may also play a big part in these transitions. For example, when a student had an upcoming deadline, his transitions to a delighted learning state or even to non-learning states were not as frequent as the time when he did not have a deadline.

Both of these concerns indicate that although we were able to get a good idea of how non-learning states interplay with learning states in general, the differences in both context and user-specific traits require a more user-specific and context-dependent analysis. It is also important to observe learning behavior over a longer period of time to gather data on more scenarios that students may encounter.

When the students made annotations using the software, they were also able to reflect about their own learning behavior. The students' answers to the survey reflected the learning behaviors that were uncovered from the data. For example, one student said "I got distracted a lot but I needed it as it helps me get back into focus" showing the value of engaging in non-learning related activities. Another student said "I felt bored before transitioning from a goal related to a non-goal related activity" which explained the high likelihood of transitioning from a bored learning state to performing a non-learning related activity.

4. Conclusion and Future Work

In this research we defined an unsupervised learning environment as a learning environment wherein students do not receive guidance from a human teacher or an automated system and wherein they freely control their activities. Students learning in this environment need to be capable of managing their goals and controlling the attention they give to non-learning related activities.

An analysis of students' learning behavior was conducted which showed the occurrence of cognitive disequilibrium. This indicated that the environment was challenging enough for the students to engage in learning. The accessibility of non-learning related activities also seemed to cause students to disengage faster but also minimized their frustration or stress. Non-learning activities also seemed to help students maintain or regain motivation to continue learning.

The data showed that although students were capable of learning in this environment as well as fend off distractions from non-learning related activities, there were still instances when they needed help in managing them. Students commented that they spent too much time in non-learning related activities and easily gave in to distractions, highlighting the importance of support in such an environment.

The data gathered from the students showed transitions shared among all students and also transitions which were unique only to some students. This indicated that user-specific traits and context may have affected how students transitioned between learning and non-learning activities. This requires not only a general model but also a user-specific model to predict their learning behavior. A general model can be used as a basis for designing feedback which is applicable to all students, while a user-specific model can be used to adapt feedback over time and to provide more appropriate feedback based on their traits and the contexts which they commonly learn in. The creation of such models can lead to the development of systems that can provide support for students learning in unsupervised learning environments. Such a system will also help students become more equipped for learning on their own in the future.

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