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Investigating Transitions in Affect and Activities for Online Learning Interventions

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Abstract: In this paper we investigated student online learning and non-learning related activities. The data collected in the research showed that students felt certain affective states when performing particular activity types and performed particular activity types when they felt certain affective states. These transitions were further investigated by generating transition likelihoods between all pairs of activity types and affective states. The transition likelihoods were used to create a model that could predict possible student behavior when they learn online. Certain transitions wherein students may need interventions were identified, so that feedback can be put in place to prevent them from transitioning to activity types and affective states that do not support learning.

Keywords: online, learning, non-learning, affective states, transition likelihood

Introduction

The current generation is quite unique largely because of the available technologies that have enabled them to develop unique characteristics and are often referred to as digital natives, internet generation and generation Y among others. Most if not all of them are tech-competent and perform many of their activities on the internet. Research shows that they have the capability of doing many things in parallel, finding information easily and keeping track of many social connections [13].

The accessibility of the internet and the presence of online services and tools like web portals and search engines allow digital natives to get information about any topic, anytime and anywhere. It has not only been used for entertainment or social interaction, but more importantly also for learning [9]. It is easy for students to look for tutorials or videos to learn more about their lessons in class or about any topic they find interesting.

Students usually use these technologies when they learn on their own because it is the fastest and easiest way to get information without physically going to sources of information such as libraries or personally communicating with a teacher or expert. When students learn under these circumstances they have complete control over how they learn. Apart from *learning* over the internet, it is easy for them to shift into *non-learning* activities since these are equally accessible and no one is present to guide them. In this research we define learning activities to be any activity related to learning including searching for information, viewing video tutorials and listening to podcasts about topics discussed in class. Non-learning activities refer to other activities apart from learning such as browsing unrelated websites or videos, social networking websites and gaming websites among others. Although students may initially have the motivation to learn, non-learning activities have the tendency to disrupt learning. On the other hand, these activities might not be all bad

as these may also help students de-stress. Too much stress has been found to hinder learning [7] so engaging in de-stressing activities may help students to continue more effective learning at a later time. This indicates that affect, i.e., mood or emotion, also plays an important role in learning online [4][10]. This domain now becomes another avenue to support learning. The research reported in this study investigates students' transitions between learning and non-learning activities online together with their affective states so as to identify when support can be given to the student.

1. Related Work

Many research works have highlighted the importance of affect in learning. Apart from identifying affective states, changes in affect during learning are also important. In the context of learning using an intelligent tutoring system (ITS), the affective state and transition from one affective state to another was found to correlate with learning [3]. These states can be used as triggers to provide appropriate support for students. Baker et al. [1] extended the approach and investigated affective transitions together with the activities performed by students. One finding was that gaming the system co-occurred with confusion. Identified affective states can then be used to identify or predict behaviors that are not helpful to learning and provide appropriate interventions.

For the digital natives, however, learning does not occur solely offline but also online. Especially because of the benefits of information availability on the internet, many research works study its impact on learning. These include investigating the relationship between browsing behavior and performance [5][8][11] as well as providing intervention to support student learning [6][10][12].

From the literature studied in the course of this research, most work on using the internet for learning consider student actions only within the learning environment or context. No work, however, seems to consider student activities not related to learning that are performed parallel to these learning environments and contexts. This behavior seems to be innate in browsing the internet and is shown in the data gathered in this research. Thus, this work investigates shifts between student learning and non-learning activities and their affective states. Possible interventions are also identified to support learning.

2. Methodology and Data Gathering

An experiment was conducted to observe online student learning behavior. Twenty-four students (10 male and 14 female) taking an introductory programming course under the Bachelor of Science in Information Systems degree at De La Salle University, Manila, Philippines were asked to participate in the collection of data. This was their first programming course in college and is a major subject for their degree. The programming language used in the course was Java and most of them had no previous knowledge about it. The average age of the respondents is 17, and they were all familiar with the different technologies on the internet such as social networking sites, instant messaging, search engines and multimedia sharing sites.

For this study, we developed a web based system called *Sidekick*, which is composed of two components, namely, the web server and the browser add-on. The add-on was created for the Firefox web browser which collected information about a student's learning behavior. This information was sent over the internet to the web server and stored in a database. A more detailed description of the data collected is discussed later.

Students were first briefed in class about labeling their activities and affect. They were told that when they visit a website related to discussions in class, they should consider it a learning activity and visiting any other website as a non-learning activity. They were

also asked to identify the affect they felt about visiting the website and select from delight, engagement, neutral, boredom, confusion or frustration. These were based on Craig et al's work [2] which observed these affective states when students used a learning environment. Figure 1 shows a screenshot of the labeling component. Each affective state was discussed so students could easily identify them later. When students experienced more than one affective state, they were asked to consider the most pronounced one. They were then taught how to install and use the Sidekick Firefox extension for labeling the websites. They were instructed to use Sidekick at home when they used the internet for doing their assignments or projects and studying or learning more about the topics discussed in class. Students were given extra credit in the course for participating in the experiment.

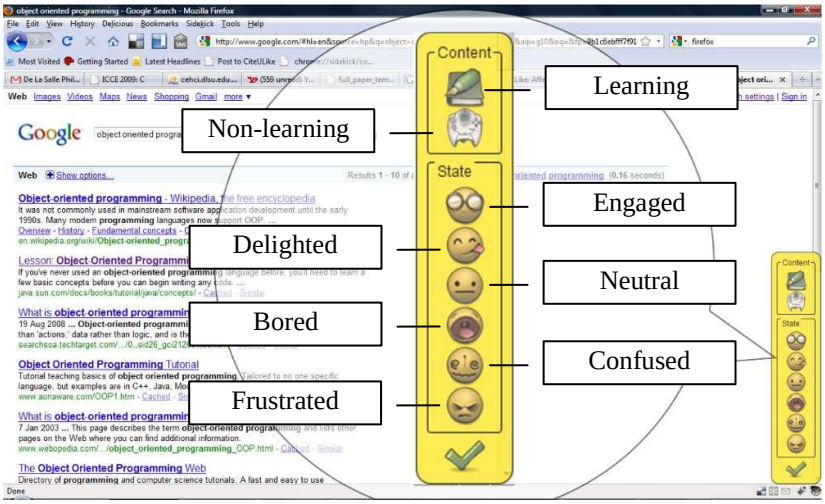

Figure 1. Screenshot of Sidekick's pop-up window for labeling.

At home, students first visited the registration page and created their own accounts. They then downloaded and installed the Sidekick Firefox browser extension which would collect and send data to the Sidekick server. Once the extension was installed, students logged in using their accounts. Every time a new web page was viewed by typing a URL directly on the browser's address bar, following a hyperlink to a different web page or viewing a previously loaded web page in a different tab, a small pop-up window was shown to the student. The student then identified the category of the current web page and the affective state they felt toward it. Icons were used to make it faster for students to identify activity types and affective states. Textual descriptions were also shown when the mouse was hovered over the icons. After labeling, the student ID, timestamp, URL, activity category and identified affective state were sent to the server and stored in a database. Students had total control over the number of times and duration of each learning session when they used Sidekick. Data was gathered within a span of two weeks.

3. Data Characterization and Observation

Students visited 25 web pages and spent two minutes viewing a web page on the average per session. A total of 1,562 data instances were obtained, each consisting of the student ID, timestamp, URL, activity and affect label provided by the student. The data showed that students temporarily shifted to non-learning activities while learning. On average, students spent 47.84% of their time on learning related activities and the rest on non-learning. This can be interpreted according to Vassileva's findings where students who learn online shift tasks in order to temporarily gratify themselves [13]. In this case, viewing videos or chatting may allow them to enjoy or relax when they experience stress while learning. On the other hand, these activities may also serve as distractions that disrupt learning.

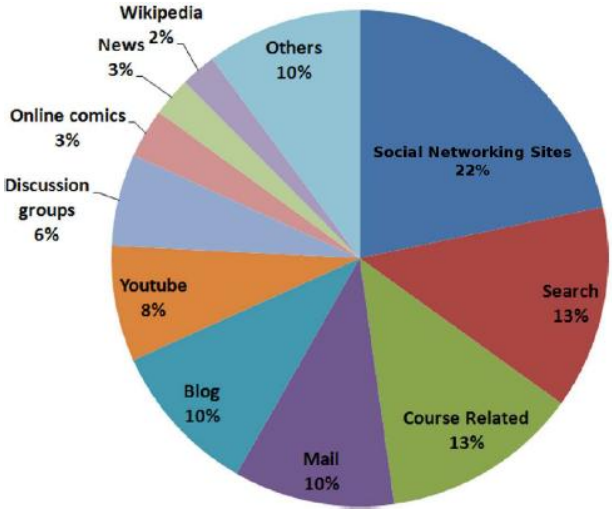

Figure 2. Websites commonly visited by students.

Figure 2 shows websites commonly visited by students. Notably, the most visited websites were social networking sites followed by search engines, course related websites, email hosting sites, blogging websites, multimedia hosting sites, discussion groups, online comics, news sites and wikis. The other sites visited covered special interests like games and personal websites. It was also observed that students seemed to be in either a learning state or relaxed state when performing activities. When in the learning state, they usually searched for a term related to the topic they are learning through a search engine then visited the top results of their search. They would follow the trail of links in cases where information spanned more than a page and repeated the process using different search terms. Many students used search engines as their starting point when learning.

When students shifted to a relaxed state, they usually started from their personal blogs, social networking sites like Facebook or web portals such as YouTube. This also confirms Vassileva's findings where digital natives were described to be particular about their social network and liked to interact with people within it [13]. Students get news about their friends through social networks or blog connections, play multiplayer games over Facebook or watch videos over YouTube which were either linked from Facebook or suggested by a friend.

Interestingly, there were few cases when students shifted from learning to non-learning related activities and vice versa. They usually spent prolonged periods of performing learning related activities then shifted to prolonged periods of non-learning related activities or vice versa. This again confirms Vassileva's findings describing digital natives to be motivated in accomplishing their goal [13]. If the current goal is to learn the student would perform activities that would accomplish this.

Figure 3 shows a general view of the interplay between the student's affective state and activities. Each bar shows the students' affective state while learning or non-learning. The percentages show the ratio of instances when a student experienced a certain affective state relative to all other affective states experienced while either learning or non-learning.

The most common affective state that students felt while non-learning was delight. This is expected because they probably engaged in non-learning activities to relax. Students rarely felt confused or frustrated probably because they refrained from doing activities that were not relaxing. It is also interesting that students experience more boredom while non-learning which may indicate that these activities are not always interesting. Learning may be more challenging so it was considered less boring.

When learning, students reported less feelings of delight and more feelings of engagement since this activity probably required more concentration. This was assumed to occur when the student understood what was being learned. Confusion was experienced

while learning probably when students tried to understand a new or unfamiliar topic. Frustration was experienced probably because of prolonged states of confusion or not understanding the current topic. Students continued to learn despite being confused or frustrated since they needed to overcome them to learn.

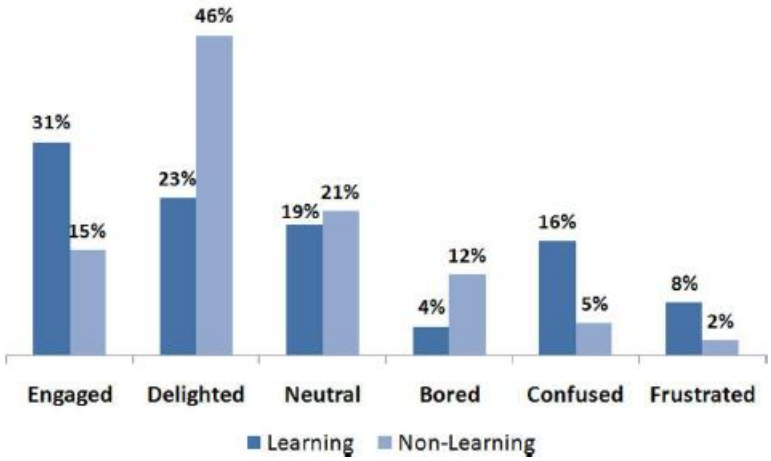

Figure 3. Comparison of affective states during learning and non-learning activities.

4. Points of Intervention

Since we know that affect influences learning, we took a closer look at the transitions between learning and non-learning activities and the affective states associated with them. Although D'Mello's metric [2] can measure the likelihood of transitioning between affective states, we are also interested in activity type transitions. Therefore, we use the same likelihood metric but concatenate the activity type and the affective state to measure the likelihood of transitioning between pairs of activity types and affective states. In Eq. (4.1), $NEXT_{A2,E2}$ refers to the next activity type and affect pair that the $PREV_{A1,E1}$ activity type and affect pair will transition to.

$$L_{A1,E1 \rightarrow A2,E2} = \frac{\Pr(NEXT_{A2,E2} \mid PREV_{A1,E1}) - \Pr(NEXT_{A2,E2})}{(1 - \Pr(NEXT_{A2,E2}))} \quad \textbf{(4.1)}$$

For example, the likelihood $L_{L,D \rightarrow NL,E}$ computes for the likelihood of transitioning from learning while feeling delighted to non-learning and feeling engaged. The likelihood metric will give a value ranging from one and -∞. Values above zero indicate that it is more likely for the transition to happen compared to chance and increases in probability as it approaches one. Zero indicates that the likelihood of transitioning into the state is equal to chance and values below zero indicate that the transition is less likely to happen compared to the base frequency of performing an activity type while feeling a specific affective state toward it. Table 1 shows transition likelihoods that are above zero.

When observing the table of likelihoods, we consider four quadrants. The top left refers to transitions from learning to learning activities and indicate continuous learning. The top right refers to the transitions from learning to non-learning activities. The bottom left refers to the transition from non-learning to learning activities. The bottom right refers to transitions from non-learning to non-learning activities and indicates periods when the student did not engage in learning.

Ideally, we want student transitions to belong to the first quadrant since this is the point where students plausibly learn. As shown in the table, when students transitioned

between learning activities they experienced both positive and negative affect. Although transitioning from positive to negative affect is understandable, continuous transitions to negative affective states need to be kept track of. Particularly, we can see that confusion, boredom and frustration tend to be prolonged as there is a likelihood of transitioning to the same state while learning. This indicates a possible point of intervention either to reduce the student's frustration, e.g., through encouragement, to help sustain learning or advice the student to shift to non-learning activities to de-stress and then return to learning.

Table 1. Transition likelihoods of activities and affect.

	LD	LN	LE	LC	LB	LF	NLD	NLN	NLE	NLC	NLB	NLF
LD	0.01					0.03	0.02					
LN	0.05						0.03					0.04
LE	0.03		0.01	0.04	0.01		0.02					
LC	0.02			0.02								0.04
LB					0.12							
LF						0.07						
NLD							0.06					0.03
NLN								0.02			0.01	0.06
NLE	0.04					0.01	0.05					0.08
NLC					0.01		0.05					0.01
NLB											0.06	
NLF												0.14

L = learning; NL = non-learning; D = delighted; N = neutral; E = engaged; C = confused; B = bored; F = frustrated;

In the second quadrant, we see the transitions from learning to non-learning activities. Transitioning from learning activities to non-learning activities may both be good and bad since it may serve as a reward for successfully learning a certain topic but may also serve as a distraction especially when the student was already engaged in learning. Thus, it is important to help the student maintain self-control. Intervention may be provided by reminding students of their learning goals. It is unfavorable however when students transition from a learning activity to a non-learning activity and experience negative affect because this indicate that it makes the student feel worse and may lead to less motivation and discontinued learning. It is important that at this point, students should be led to more positive non-learning activities. Historical data may be used to identify which non-learning web pages the student visited led to reported positive affective states and suggest them to the student.

The third quadrant is very important because this is when students transition back to learning activities from their non-learning activities. It is beneficial when non-learning activities cause students to transition back to learning with positive affective states since this may indicate more motivation to continue learning. However, returning to learning with negative affective states may indicate that there might be something wrong in the context of what the student is learning rather than the problem being affective in nature. Thus, at this point, intervention should probably provide further explanations regarding what the student is studying or encourage getting help from a tutor or peer.

Lastly, the fourth quadrant indicates the transition between non-learning activities. Sustained positive affective states within these transitions will be beneficial to the student only up to a certain point. Being too engrossed in the non-learning activity minimizes the amount of time the student could have spent to learn. In this case, a balance between relaxation and learning has to be met and students need support to identify when to resume learning. Negative affective states within non-learning activities are also important to track since prolonged negative affective states in non-learning activities may cause the student to stop learning instead of helping the student de-stress.

5. Utilizing Transition Likelihoods for Providing Intervention

The transition table for activities and affective states can be represented as a directed cyclic graph shown in Figure 4 . Each node represents a student's state expressed in terms of the activity category and affect felt towards the activity. The 12 nodes represent the combinations of activity categories and affective states. The connection between a parent node and child node indicates that the student can transition to that state with a corresponding likelihood. Paths can then be traced to predict the student's next state and interventions can be provided depending on the current state and the next probable state.

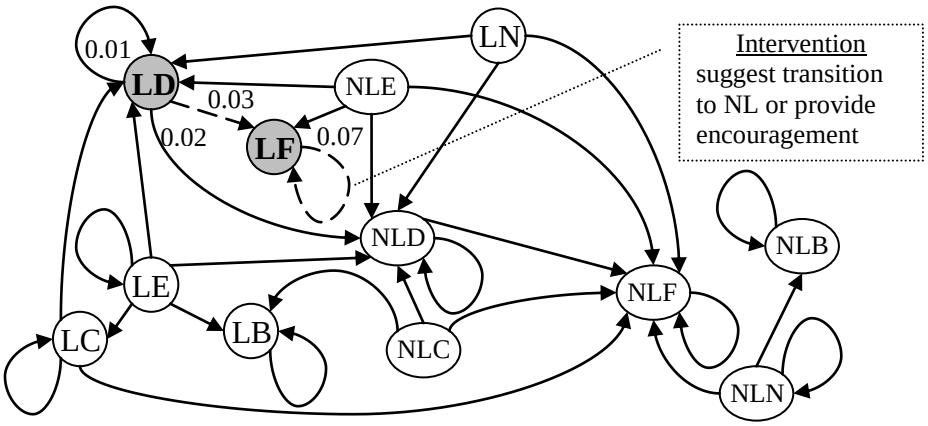

Figure 4. Cylic directed graph of transitions built from the transition likelihoods table.

Given the sample scenario where a student starts in a learning delighted state, the student may either stay in a learning delighted state, transition to a learning frustrated state or a non-learning delighted state. Since transitioning to a learning frustrated state has the highest likelihood, we can assume that the student will transition into this state next. Since the student is currently in a positive affective state and feeling frustration in learning may indicate that the student is still trying to understand the concept, intervention may be reserved at this point. However, assuming that the student continuously transitions to and from the learning frustrated state, it is highly probable that this may continue and intervention needs to be provided such as encouraging the student or suggesting non-learning activities for de-stressing.

The transition likelihoods and transition graph created were based on the data gathered. Because of the limited amount of data, it is possible that some student behavior were not modeled. Given more data, better models of transition may be constructed. The approach can be replicated to build better models with more data and provide more appropriate feedback at the identified points of intervention.

6. Conclusion and Future Work

It was shown that different affective states were felt depending on the activity performed such as feeling confusion while learning. Different affective states may also have influenced students to transition activity types such as frustration causing students to engage in non-learning activities. This was investigated further by viewing the students' transitions between activity types as they experienced certain affective states. Transition likelihoods were used to create a predictive model of activity and affective states that a student can transition to. Based on the current activity type and affective state of the student, interventions can be provided to prevent students from transitioning to undesired states. The approach performed in the research can be replicated to build more accurate models with

more and better data. This model can then be used as basis for providing intervention.

The transition likelihoods used in creating the predictive model were generated from the data set of all students. Each student will most likely behave differently so a personalized model will create a more accurate representation of the student's behavior. Moreover, new data observed from students can be used to update the transition likelihoods and further improve its accuracy.

This preliminary study made use of self-reported data which revealed transitions that were both logical and explainable by commonly perceived and observed student behaviors. However, even if the predictive model can be used for providing intervention, labeling the activity types and affective states were done manually. Automating the identification of activity types and affective states will allow intervention to be given without requiring the subject to perform self-reporting.

Acknowledgements

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