Aiding Digital Natives Learn Positive Learning Behaviors through Reflection

Roberto LEGASPI*, Paul Salvador INVENTADO, Rafael CABREDO & Masayuki NUMAO
The Institute of Scientific and Industrial Research, Osaka University, Japan
*roberto@ai.sanken.osaka-u.ac.jp

Abstract: Commonly attributed to digital natives is the ability to quickly, yet effectively, shift from one task to another. However, several works have debunked this assumption by showing that multitasking even among digital natives led to poor learning performance and productivity. Our aim is to provide a tool to help digital natives be self-aware of desirable, while curbing undesirable, learning behaviors. Our tool is infused with self-annotation and feedback mechanisms that allow students to reflect upon their entire learning history. Our results indicate that the annotation process with the tool helped students understand their learning behaviors better and identify ways in which their behaviors can be improved.

Keywords: Digital natives, learning behaviors, productivity annotation tool, user modeling

Introduction

For a time, the notion that digital natives [17], also called "Gen M" (for multimedia) [19] or "Net Gen" [17,19,22], are capable of switching tasks [8,15,18] prevailed until other researchers started to level this assumption. Digital natives are technology-savvy and carry out many of their activities on the web [18]. They engage with and communicate socially through various multimedia [8,15]. Since the tools they use to study, get entertained and socialize are equally accessible at any time, digital natives tend to switch from learning (e.g., viewing tutorial videos) and non-learning (e.g., engage in game or social network websites) tasks. However, there is evidence to suggest that task-switching behavior can lead to poorer performance and learning outcomes [11] and result to time lost that increases with the complexity of, and unfamiliarity to, the task [20]. It is plausible that productivity deteriorates when alternating tasks.

Our objective is to help the digital native learner become aware of problems resulting from learning and non-learning task-switching and help him/her self-regulate towards increased learning productivity. This paper reports the results we obtained from subjects who experimented with our tool designed to raise self-awareness of effective learning behaviors - to discover routines that lead to productive learning and become cognizant of personal factors that support positive study by constantly aiding reflections on activity choices made that helped achieve (or otherwise) the desired learning outcomes.

1. Productivity Annotation Tool

Being aware of one's own learning behavior is metacognitive and students who are able to step back, reflect in retrospect, and adjust their thinking are able to adapt and monitor their behaviors to know what they need to study and how to do it [10]. We have designed a tool basically to this end. We infused in its design a self-annotation scheme that will allow students to review and reflect on their past learning sessions.

When using our tool, students identify their goals for the current learning session and then start the tool's data collection process to run in the background. Once the session is over, a timeline representing their entire learning session is shown to the students. When the mouse hovers over this timeline, screenshots of the desktop and webcam are shown to help students recall what happened at any point in time. Apart from using their mouse for annotation, an image player can also be used to select time partitions, much like how a video player is used, together with a selection button to indicate when to begin and end the selection. After selecting a time span, students can then provide their annotation.

Students annotate three aspects of their learning session, namely, *intention*, *activity*, and *affective state*. The intention is either goal-related, i.e., the activities relate to reaching any of the defined goals, or nongoal-related. Activities can be labeled as primary or secondary. A primary activity refers to what the student was focused on during the selected time span (e.g., using `chrome.exe`, reading a technical paper, or viewing a tutorial video). Secondary activities are those done together with the primary (e.g., listening to music, drinking coffee and eating, aside from others). The students also input the affective states they experienced as they performed the activities, i.e., delighted, engaged, confused, frustrated, surprised, afraid and neutral for goal-related activities [5], and angry, disgusted, sad, delighted, afraid and neutral [6] for nongoal-related ones.

After annotating the entire session, students assess their learning session in terms of the percentage of goal completion, activities that helped achieve their goals, and their perceived productivity level (in a scale of 1-5). The tool then provides statistics regarding the students' learning sessions in terms of the amount of time they spent in goal- and nongoal-related activities, together with the emotions they felt during each type of activity. The tool then produces a log file that contains timestamps, intentions, activities and affective states for a learning session. The productivity and goal completion ratings will be stored in a separate log file. All these will be used by the software for analysis of student learning patterns.

We designed our tool while taking cues from prior works. Goals enhance self-regulation, self-motivation, self-efficacy, and self-evaluation of progress [4,21]. When goals are defined, there is the tendency for students to do less the other tasks since they are aware of what they are supposed to do. Secondly, when students annotate their activities, they are actually performing self-monitoring. Seeing in retrospect how they spent their time learning, they get an idea of what comprises their study habits [10]. They can identify what behaviors they think are helpful to them as well as those that cause distractions. It will also help them see how their affective states actually influenced their learning process [5,16]. For example, emotions such as boredom and frustration can cause students to engage in non-learning tasks or stop learning altogether [12]. The tool can therefore help students identify and retain good study habits and mitigate unwanted learning behaviors.

2. Related Works

The importance of students setting their own goals, selecting the appropriate strategies, applying these strategies and monitoring their effects in order to modify them when necessary has spawned research in providing support tools for such metacognitive tasks while learning with computer-based learning environments, such as intelligent tutoring systems and hypermedia-based environments (e.g., [2,3,14]). Furthermore, some learning environments keep track of student actions to help maintain the student model (e.g., [1,13]).

However, we see the need to analyze student behavior outside a learning environment and the importance of providing feedback for these instances to support learning. In our previous work, we reported that when students study on their own, they do not only engage in goal-related tasks but also in nongoal-related activities. We reported that the digital natives who participated in our experiments in a span of two weeks spent 47.8% of their time learning and the rest not learning [9]. Furthermore, although most systems track student activities by looking at what they do on the computer, many of their activities are also done without the use of a computer [7].

Our motivation is to provide support to student metacognitive tasks and actions when learning using the computer and without it. Our students may not be constraint to a learning environment or particular domain knowledge. They may use our tool given their chosen topic of study and the tools they will use to study.

3. Experimentation

We are interested in observing learning behaviors in an environment with no guidance from teachers and where students have complete control over their learning tasks, hence, can pose as potential source of distractions. We identified foreign scholars performing their graduate research projects in Japan as good source of data since they are expected to retrieve, process, and analyze information on their own while managing their own time and effort. Since they have full control of their activities, playing games, watching videos, sending SMS and chatting can always pose distractions.

Four subjects participated in our experiments, specifically: two females and two males, who are Filipino, Indonesian, Thai and Vietnamese, respectively, with an average age of 25-years. Everyone fits as digital natives. We aimed for the sessions to be as natural as possible with the subjects deciding when to use the tool, for how many times and for how long. They were taught about the definition of goal and how to provide it to the system. For the annotation, they were taught about the definitions and specifics of intentions, activities and affect. Specific to affect, they were taught to indicate the strongest emotion in cases where they seem to have felt more than one emotion.

At the end of every session, the subjects were asked to fill up a questionnaire to help assess the influence of the tool to their reflections. We wanted to know if they discovered anything interesting about their learning behavior, whether positive or negative, during the annotation process, and based on the statistics provided by the system, whether they see the need to improve their learning behavior.

4. Results and Analyses

4.1 User Feedback on the Tool's Assistance

The subjects agreed that the tool helped point out what is both positive and negative in their learning behaviors. One subject, for example, felt good when after annotating, he realized that he actually got absorbed into work and got distracted less than he thought. He also realized that even though it was very easy for him to fall asleep when confused or frustrated, most of his time was actually spent on goal-related activities. In his last session, after previously having reflected on his past behaviors wherein he spent on the average a third of his time on nongoal-related activities, he still allowed himself to enter into nongoal-related states while making sure he spent still most of the time in learning. Another subject realized that it was a disadvantage for her to switch between tasks - that when she attempted reading three papers simultaneously, none of the goals she set for the session was completed and she gave herself a low productivity score. She also realized that when she got confused, her tendency was to switch to non-goal related tasks rather than stay engaged in learning. Yet another subject realized that he spent more time watching game video streaming and felt bad after. And one reported that standing up every now and then or drinking coffee would help stay focused. Lastly, one subject noticed that the urgency of his goals (i.e., submission deadline) “coerced” him to spend more time learning than usual, and that the lack of urgency or importance of the goal and the lack of desire to accomplish it resulted in less productive learning.

All of the above show positive effects of the tool because the students were able to reflect and monitor themselves through the annotation process. They became more aware of the activities they performed and actively tried to avoid moving away from being goal-engaged thereby learning to improve their learning behavior.

4.2 Self-assessed Productivity

As previously mentioned in the first section, students were asked to assess their learning sessions in terms of how productive they felt they were. It is interesting to note that even though the subjects performed nongoal-related activities only 24% of the time at the average, their average self-assessed productivity is only 71.3%, with the amount of time in goal-related activities not necessarily directly proportional to productivity. Table 1 illustrates this point using snapshots of all the sessions for all subjects, where $\%T_G$, $\%T_{NG}$ and *%Pr* refer to percentage of time spent in goal- and nongoal-related tasks and the percentage of self-productivity, respectively. The norm is that if a subject stayed most of the time in goal-related states, productivity assessment is supposed to be high. However, for the second sessions (S2) of subjects B and D, this did not hold. According to B, she felt that the time she spent in nongoal-related activities in S2 is higher than S1, and on that basis alone, she gave herself a lower productivity score. For D, he could have given a higher productivity score (resulting to %Pr > 80) but he felt that most of his time learning was spent thinking about the problem and not finding the solution. The implication here is that students rate themselves based on the standards they set for themselves and the tasks they set for the sessions. Our aim is that in their process of self-reflection, the students should be able to see the effects of what they impose on themselves in relation to their goals.

Table 1. Self-assessed productivity of each subject per session

	Subject A			Subject B					Subject C					Subject D		
	S1	S2	S3	S1	**S2**	S3	S4	S5	S1	S2	S3	S4	S5	S1	**S2**	S3
$\%T_G$	89	46	84	83	**76**	90	70	89	93	51	64	71	80	90	**83**	64
$\%T_{NG}$	11	54	16	17	**24**	10	30	11	7	49	36	29	20	10	**17**	36
%Pr	80	60	80	60	**40**	80	80	80	80	40	60	60	60	100	**80**	100

5. Conclusion

Although digital natives switch from one task to another as afforded by the advanced digital technologies they grew up with, it does not follow that they can be academically productive in it all the time. The tool we developed allowed our experiment subjects to realize both the positive and negative aspects of their learning behavior.

Our results are clearly preliminary. We aim to find possible generalizations of learning behaviors across learners, which would mean significantly increasing the population of our subjects as well as the amount of time we expose them to our tool. Secondly, we aim to lessen the cognitive load being imposed upon the user by the annotation process. This may mean automating to some effective degree the inference of intention and affective states.

Acknowledgements

This research work is supported in part by the Management Expenses Grants for National Universities Corporations from the Ministry of Education, Culture, Sports, Science and Technology of Japan and by the JSPS KAKENHI Grant Number 23300059.

References

[1] Aleven, V. (2010). Rule-based cognitive modeling for intelligent tutoring systems. *Advances in Intelligent Tutoring Systems*, pp. 33-62.

[2] Azevedo R. & Feyzi-Behnagh R. (2011). Dysregulated learning with advanced learning technologies. *Journal of e-Learning and Knowledge Society*, *English Edition*, *7*(2), 9-18.

[3] Azevedo, R., Johnson, A., Chauncey, A. & Burkett, C. (2010). Self-regulated learning with MetaTutor: Advancing the science of learning with MetaCognitive tools. *New Science of Learning: Computers, Cognition, and Collaboration in Education,* pp. 225–247.

[4] Bandura, A. (1997). *Self-efficacy: The Exercise of Control*. New York: Freeman.

[5] Craig, S. D., Graesser, A. C., Sullins, J., and Gholson, B. (2004). Affect and learning: An exploratory look into the role of affect in learning with AutoTutor. *Journal of Educational Media, 29*(3), 241-250.

[6] Ekman, P. (1999). Basic emotions. *The Handbook of Cognition and Emotion*, 45-60.

[7] Foehr, G. (2006). *Media multitasking among American youth: Prevalence, predictors and pairings*. Kaiser Family Foundation.

[8] Hartman, J., Moskal, P. & Dziuban, C. (2005). Preparing the academy of today for the learner of tomorrow. *Educating the Net Generation*, pp. 6.1-6.15.

[9] Inventado, P.S., Legaspi, R., Suarez, M. & Numao, M. (2011). Investigating transitions in affect and activities for online learning interventions. *Proceedings of 19th ICCE* (pp. 571-578). Chiang Mai, Thailand: Asia-Pacific Society for Computers in Education.

[10] Kerka, S. (2007). Study Skills. *What Works - Evidence-based strategies for youth practitioners*. Learning Work Connection, The Ohio State University.

[11] Kirschner, P.A. & Karpinski, A.C. (2010). Facebook® and academic performance. *Computers in Human Behavior*, *26*(6), 1237-1245.

[12] Luo, M. M., Nahl, D. & Chea, S. (2011). *Uncertainty, Affect, and Information Search*. Los Alamitos, CA, USA. IEEE Computer Society.

[13] Mitrovic, A. (2012). Fifteen years of constraint-based tutors: what we have achieved and where we are going. *User Modeling and User-Adapted Interaction*, *22*, 39-72.

[14] Moos, D.C. (2010). Self-regulated learning with hypermedia: Too much of a good thing? *Journal of Educational Multimedia and Hypermedia*, *19*(1), 59–77.

[15] Oblinger, D. & Oblinger, J. (2005). Is it age or IT: First steps toward understanding the Net Generation. *Educating the Net Generation*, pp. 2.1-2.20.

[16] Picard, R. W., Papert, S., Bender, W., Blumberg, B., Breazeal, C., Cavallo, D., Machover, T., Resnick, M., Roy, D. & Strohecker, C. (2004). Affective learning - A manifesto. *BT Technology Journal*, *22*(4), 253-269.

[17] Prensky, M. (2001). Digital natives, digital immigrants. *On the Horizon*, *9*(5), 1-6.

[18] Roberts, G.R. (2005). Technology and learning expectations of the Net Generation. *Educating the Net Generation*, pp. 3.1-3.7.

[19] Roberts, D.F., Foehr, U.G. & Rideout, V. (2005). *Generation M: Media in the lives of 8-18 year olds*. Kaiser Family Foundation, Menlo Park, CA.

[20] Rubinstein, J.S., Meyer, D.E. & Evans, J.E. (2001). Executive control of cognitive processes in task switching. *Journal of Experimental Psychology*: *Human Perception and Performance*, *27*(4), 736-797.

[21] Schunk, D. H. (1995). Self-efficacy and education and instruction. *Self-efficacy, Adaptation, and Adjustment: Theory, Research, and Application*, 281-303.

[22] Tapscott, D. (2009). *Grown up digital: How the Net Generation is Changing Your World*. McGraw-Hill.