Developing Self-Regulated Learning through Reflection on Learning Analytics in Online Learning Environments

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This paper describes a conceptual framework for developing self-regulated learning through facilitated dialogue and reflection on learner activity in online learning environments. In particular, the framework focuses on the motivational and contextual aspects of self-regulated learning and how the field of learning analytics can support student metacognitive knowledge in these two areas and distribute instructional support.

Keywords: learning analytics, self-regulated learning, critical pedagogy, inclusion

Introduction

A contemporary challenge of online learning is to create an environment in which a potentially highly diverse cohort of learners can be stimulated to interact with each other and engage in a meaningful learning process in a self-regulated way. This challenge is underlined by two observations: firstly, that growing class size has created a "teacher bandwidth problem" (Wiley & Edwards, 2002) and secondly, that the focus on learner autonomy and self-regulation in online learning may be leaving some learners behind (Beetham & Sharpe, 2013; Fruhmann, Nussbaumer & Albert, 2010). Both researchers and practitioners acknowledge the necessity to extend instructional support and scaffold the learning process in order to face these challenges.

The primary question with which this paper is concerned is: How can students who do not currently possess the necessary skills in self-regulated learning utilise the structures and opportunities of online learning to develop those skills? The field of learning analytics presents new opportunities for "understanding and optimizing learning", through collecting, analysing and reporting upon valuable data about learner activity in online learning environments (SoLAR, 2015). This paper proposes a conceptual framework for online education (referred to as "Uplift") that aims to deal with certain challenges of self-regulated learning by investigating the affordances of learning analytics for building skills in self-regulation.

Affordances of Learning Analytics for Self-regulated Learning

Self-Regulated Learning (SRL) is broadly described as the ability to understand one's own learning processes and manipulate them (Schunk & Zimmerman, 2012). Common components of SRL models include four main areas of regulation (cognition, behaviour, motivation and context) across four broadly cyclic phases of learning (planning, execution, monitoring and evaluation) (Winne *et al*, 2000). For each area and each phase, there are strategies that learners can deploy to understand and control how they learn. Many tools for self-regulated learning are already available to help learners plan, set goals, map their activities and track their progress (Nussbaumer, Dahn, Kroop, Mikroyannidis & Albert, 2013). However, while these tools make it possible to *practice* self-regulated learning, they do not always help learners to *acquire* self-regulated learning skills (Beetham & Sharpe, 2013). Learning Analytics can support this process by providing valuable data to students and teachers that enhance metacognitive gains in certain areas.

Context in Learning

Contextual factors such as educational background, race, class and gender, for example, have been shown to affect the physical classroom experience. Perceived lack of representation can adversely affect motivation (Egalite, Kisida & Winters, 2013) and general participation (White, 2011), while hegemonic classroom dynamics can even entirely exclude learners from non-normative backgrounds (McLaren, 2003). In online learning, learning analytics can help uncover the impact of these factors and others, creating a picture of the learner in context and connecting learner profiles with learner activity and outcomes. This information can then be utilised by learners to help gain metacognitive knowledge about their own learning experience.

Interaction and Motivation in Learning

Interaction is one of the means by which instructors attempt to keep learners engaged and motivated (Dabbagh & Kitsantas, 2012). However, the *quality* of interactions and the types of cognitive and emotional responses they elicit is what dictates the extent to which learning is positively impacted (Picciano, 2002). A quality interaction is one that improves self-knowledge about (meta) cognitive, behavioural, motivational and contextual experiences in learning (Hadwin & Oshige, 2011; Schunk, 1989). Learning analytics can help to identify and understand the nature of quality interactions, which has the potential not only for developing self-regulated learning skills, but also for influencing instructional design.

Facilitation of Learning

Research indicates that instructors play a vital role in facilitating meaningful learning online and in the development of self-regulated learning (Boyer, Maher & Kirkman, 2006). Instructors model strategies, moderate dialogue and track the engagement of students, all of which becomes more difficult as class sizes increase. Learning analytics can already support instructors through collecting baseline activity, identifying at-risk learners and (in some cases) recommending solutions (Arnold & Pistilli, 2012; SoLAR, 2015). Involving students in the process of interpreting learning analytics may provide an avenue for activating motivation and distributing instructional support (Sclater, 2015), as well as sharing the process of self-regulation among students and instructors (Hadwin & Oshige, 2011).

The "Uplift" Framework

"Uplift" is a conceptual framework that describes the affordances of learning analytics to support the development of self-regulated learning skills. Figure 1 illustrates a simple model of self-regulated learning based on Zimmerman (1990), overlaid with types of learning analytics that could be beneficial at each phase. The cycle of self-regulated learning begins at forethought and planning, where "Contextual Learning Analytics" (learner background, previous experiences, demographic data, etc.) can identify certain features that appear to influence learning, so that these can be acknowledged appropriately. The monitoring and control phase of the self-regulated learning cycle can be supported through "Performance and Behavioural Learning Analytics", to help the learner understand the connection between certain strategies and their learning outcomes. In the final phase of evaluation and reflection, learning analytics that support reflection, such as prediction-based analytics, trends and norms, can help learners to identify areas in which they need further support. This knowledge can be brought into the next cycle of self-regulation and also inform the next iteration of collecting, analysing and reporting on learner activities, raising the utility of learning analytics for self-regulated learning over time.

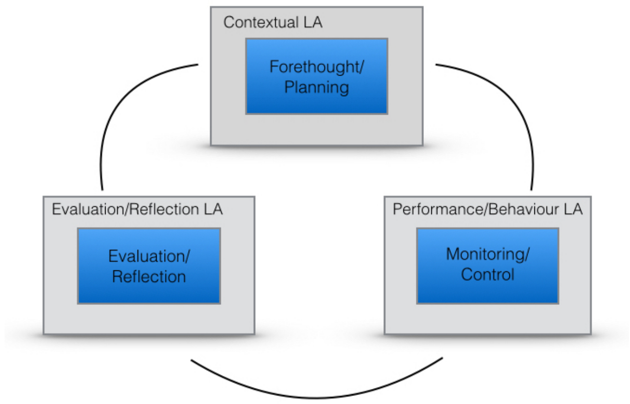

Figure 1 - Learning Analytics Across Phases of Self-Regulation

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Technological Structure

The underlying system of Uplift will be an online learning platform collecting rich profile data on users ("contextual analytics"), married with complex capabilities in analysis of learner activities ("performance analytics", see fig 1). Learner activities will be collected through trace analysis, similarly to the software nStudy, developed at Simon Fraser University (Winne, 2015), as well as manually collected self-assessment of individual and group motivation through emotional proxies and latent variable modelling. On top of these capabilities, a variety of Web 2.0 features will be available to learners to engage with content and with each other, including rating systems, dialogue pages and comments. Finally, some simple, open source tools such as the Python Natural Language Toolkit and the R Text Mining Module will be adapted for use in basic sentiment analysis.

This information will be used to track tendencies in participation, interpersonal relationships, knowledge and cognitive ability, motivation and environment, which can be expressed in the form of classroom learning analytics and used as relevant data for self-regulated learning.

Pedagogical Structure

The pedagogical companion to the system is its most unique aspect, in terms of the state-of-the-art. It involves delivering the data generated by the Uplift system back into the hands of students as a part of the regular classroom structure and learning goals. The data will be examined *with* students through facilitated dialogue based upon reflection protocols adapted from critical pedagogy (McLaren, 2003) and transformative learning (Mezirow, 1990), two educational traditions that place considerable emphasis on empowering students. The aim of the reflection is to illuminate the relationships between students and each other, students and instructors, and students and content, which impact the construction of knowledge and accessibility of education.

Though they are not fool-proof, analytics can provide some general cues for beginning discussions about the contextualized learning experience, which can help target interventions and improve retention strategies.

Opportunities and limitations

Opportunities

The structure of Uplift is intended to provide enough granularity and qualitative insight to consider self-regulated learning as both and event and an aptitude, which helps to forward the state-of-the-art (Winne & Perry, 2000) and combine approaches toward learning analytics from both educational data mining (EDM) and learning analytics & knowledge (LAK) perspectives (Siemens & Baker, 2012). Moreover, the collaborative inquiry aspect of the pedagogical component supports "socially shared regulated learning" (Hadwin & Oshige, 2011), which encourages learners to discuss learning experiences, model successful strategies and develop good practices for self-regulation over time. The dynamic nature of the information that Uplift collects, makes it a continuous source of new knowledge about oneself and others, improving social presence and motivation for participation for all learners, even if they are already skilled (Hadwin & Oshige, 2011). Uplift provides both teachers and students with many more data points to consider not only the efficacy of certain strategies, but also the possible reasons behind successes or failures in learning, addressing the "teacher bandwidth problem" (Wiley & Edwards, 2002), as well as some of the contextual features of education (race, class and gender) that may advantage some students over others. The overall effect of such an approach, richly reflecting with learners on dynamic aspects of their learning experience and highlighting the gaps in their knowledge, is expected to improve self-awareness and self-regulated learning more sustainably.

Limitations

Though the framework provides many opportunities for triggering learner curiosity and motivation to participate, the amount of data could also be over-stimulating for learners (Arnold & Pistilli, 2012) or take attention away from actual domain related content of a learning experience. However, the intention is that, over time, it would be possible to collect data on the types of analytics or facilitated dialogues that produce the most sustained, *quality interactions,* so that learners are not distracted by superficial data. Another significant limitation is that Uplift relies heavily on the strong critical thinking and facilitation skills on part of the instructor to make sense of the vast data that will be possible to collect and analyse. One mechanism that can minimize the effects of this limitation is the distribution of analysis across the whole classroom. As students and instructors are equally encouraged to review and comment on data, it will be possible to uncover more insights (and more diverse insights) from the data.

Conclusion

Online education has made it possible for growing numbers of students from all over the world to participate in learning together. As the diversity and size of the classroom increases, it is necessary to ensure that the quality and accessibility of education are maintained. Uplift, as a framework, aims to leverage the unique qualities of online education, namely that it is possible to track the activities of learners in finer detail and make them transparent, to address those challenges and make learning analytics work more directly on behalf of students. Connecting learning analytics with the cycle of self-regulation can help instructors gain a more intimate picture of the cognitive, emotional and social life of their students. Likewise, delivering learning analytics into the hands of learners in meaningful ways can provoke curiosity, internal motivation and participation by giving learners a sense for the dynamic nature of their own learning process. Moreover, sharing the responsibility for drawing insights from these analytics distributes instructional support, builds rapport and presents a learning opportunity for both instructors and students (Maor, 2008). With more deep, social, contextualized information about all four areas of self-regulated learning in online environments available to students and instructors, the development, not only the practice, of SRL is achievable.

References

Arnold, K. E., & Pistilli, M. D. (2012, April). Course signals at Purdue: using learning analytics to increase student success. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 267-270). ACM. https://doi.org/10.1145/2330601.2330666

Beetham, H., & Sharpe, R. (Eds.). (2013). Rethinking Pedagogy for a Digital Age: Designing for 21st Century Learning. Routledge.

Boyer, N. R., Maher, P. A., & Kirkman, S. (2006). Transformative Learning in Online Settings: The Use of Self-Direction, Metacognition, and Collaborative Learning. *Journal of Transformative Education*, *4*(4), 335-361. https://doi.org/10.1177/1541344606295318

Dabbagh, N., & Kitsantas, A. (2012). Personal Learning Environments, social media, and self-regulated learning: A natural formula for connecting formal and informal learning. *The Internet and higher education*, *15*(1), 3-8. https://doi.org/10.1016/j.iheduc.2011.06.002

Egalite, A. J., Kisida, B., & Winters, M. A. (2013). Representation in the Classroom: The Effect of Own-Race/Ethnicity Teacher Assignment on Student Achievement. *Pridobljeno, 1*(9), 2014.

Fruhmann, K., Nussbaumer, A., & Albert, D. (2010, July). A psycho-pedagogical framework for self-regulated learning in a responsive open learning environment. In *Proceedings of the International Conference eLearning Baltics Science* (eLBa Science 2010) (pp. 1-2). Fraunhofer.

Hadwin, A., & Oshige, M. (2011). Self-regulation, coregulation, and socially shared regulation: Exploring perspectives of social in self-regulated learning theory. *Teachers College Record*, *113*(2), 240-264. https://doi.org/10.1177/016146811111300204

Maor, D. (2008). Changing relationship: Who is the learner and who is the teacher in the online educational landscape?. *Australasian Journal of Educational Technology*, *24*(5).

McLaren, P. (2003). Critical pedagogy: A look at the major concepts. *The critical pedagogy reader*, 69-96.

Mezirow, J. (1990). How critical reflection triggers transformative learning. *Fostering critical reflection in adulthood*, 1-20.

Nussbaumer, A., Dahn, I., Kroop, S., Mikroyannidis, A., & Albert, D. (2015). Supporting Self-Regulated Learning. In Responsive Open Learning Environments (pp. 17-48). Springer International Publishing. https://doi.org/10.1007/978-3-319-02399-1_2

Picciano, A. G. (2002). Beyond student perceptions: Issues of interaction, presence, and performance in an online course. *Journal of Asynchronous learning networks*, *6*(1), 21-40.

Society for Learning Analytics Research (SoLAR). (2015). *Society for Learning Analytics Research (SoLAR)*. Retrieved 1 October 2015, from http://solaresearch.org/

Sclater, N. (2015) Student app for learning analytics: functionality and wireframes. Retrieved 15 September 2015, from http://analytics.jiscinvolve.org/wp/2015/08/21/student-app-for-learning-

analytics-functionality-and-wireframes/
Schunk, D. H. (1989). Social cognitive theory and self-regulated learning. *Self-regulated learning and academic achievement* (pp. 83-110). Springer New York.
Schunk, D. H., & Zimmerman, B. J. (Eds.). (2012). Motivation and self-regulated learning: Theory, research, and applications. Routledge.
Siemens, G., & d Baker, R. S. (2012, April). Learning analytics and educational data mining: towards communication and collaboration. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 252-254). ACM. https://doi.org/10.1145/2330601.2330661
Wiley, D., & Edwards, E. (2002). Online self-organizing social systems. *Quarterly Review of Distance Education*, *3*(1), 33.
Winne, P. H., & Perry, N. E. (2000). Measuring self-regulated learning. In *Handbook of Self-Regulation*, M. Boekaerts, P. Pintrich, and M. Zeidner, Eds., pp. 531–566, Academic Press, Orlando, Fla, USA. https://doi.org/10.1016/B978-012109890-2/50045-7
Winne, Philip H. (2015). Leveraging Big Data to Help Each Learner Upgrade Learning and Accelerate Learning Science. Manuscript in preparation.
Winne, Philip H.; Perry, Nancy E.; Boekaerts, Monique (Ed); Pintrich, Paul R. (Ed); Zeidner, Moshe (Ed), (2000). Handbook of self-regulation. (p. 531-566). San Diego, CA, US: Academic Press.
White, J. W. (2011). Resistance to classroom participation: Minority students, academic discourse, cultural conflicts, and issues of representation in whole class discussions. Journal of Language, Identity & Education, 10(4), 250-265. https://doi.org/10.1080/15348458.2011.598128
Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. Educational psychologist, 25(1), 3-17. https://doi.org/10.1207/s15326985ep2501_2

Mikroyannidis, A. & Frey, T.M.F. (2015). Developing Self-Regulated Learning through Reflection on Learning Analytics in Online Learning Environments. In T. Reiners, B.R. von Konsky, D. Gibson, V. Chang, L. Irving, & K. Clarke (Eds.), *Globally connected, digitally enabled*. Proceedings ascilite 2015 in Perth (pp. 507-511). https://doi.org/10.14742/apubs.2015.928

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