Ways of Seeing Student Learning & Metacognition with Machine Learning and Learning Models

Mary Loftus
NUI Galway
mary.loftus@nuigalway.ie
Keywords: (Electronic and Computer Engineering; Computer Science and Information Technology; Learning Analytics)

Abstract

The emerging field of learning analytics is showing promise as a light to shine into the dark corners of individual student experience. By making the richness of the learning process more visible, learners and teachers can access deeper insights into their shared experience. Data and models can provide a mirror for self-reflection and metacognition (Koedinger 2009). As Gašević (2015) reminds us, Learning Analytics are about learning. However, too little attention has been paid to the student's role in data-rich learning environments (Kitto 2016).
This research will use probabilistic machine learning techniques in conjunction with other learning model approaches to produce interactive learning models (Millán 2015) that can be integrated in existing learning analytics systems. One such system will be shared with students in a module of a BSc in Computing degree course and a mixed-methods study of their experience conducted – with students having full control of their data.

1. Introduction

As Biesta (2009) notes, central to education's purpose is 'the coming into presence of unique individual beings' and to facilitate this, education spaces must 'open up for uniqueness to come into the world'. He talks about a key part of the education process being the 'individuation' or 'subjectification' of each human being – 'the process of becoming a subject'. Think of Maslow's idea of 'self-actualization', Jung's idea of 'individuation'. This emphasis complements the more usual one in education on 'qualification' and 'socialization'. This is the ontological starting point of this research along with Paulo Freire's (1968) emphasis on the student as an agent of praxis in their learning environment.

A key part of this individual development is the role of metacognition. As students encounter learning challenges, they can greatly increase their agency and personal development by learning about their own learning process and engaging in metacognitive activities (Koedinger 2009). Metacognition, or the ability to learn how we learn, is an important skill for the life-long learner. Brookfield (1995) defines it as follows:

'a self-conscious awareness of how it is they come to know what they know; an awareness of the reasoning, assumptions, evidence and justifications that underlie our beliefs that something is true.'

The questions driving this research include whether we can encourage students in their metacognitive awareness and endeavors and provide data and a system interface to assist in this process. If learners could 'see' their learning and their metacognitive processes through learning data, would they be able to control and develop these faculties more effectively?**.**

2. Goal of the research

Develop and apply machine learning and open learning models to support student metacognition in a pre-existing connected learning analytics systems

This research will seek to bring a number of approaches together to build richer more effective student learning models – while still retaining their accessibility and usability for learners.
It will make clear connections to course learning design and ensure alignment of course learning analytics.
Modelling student learning along with machine learning techniques will be used to make learning more visible to students and facilitate metacognitive reflection on their learning process.
This goal will be achieved through the following objectives:

i. Identify appropriate candidate modelling techniques like Open Learning Modelling (OLM), and similar, to allow students to capture and visualise their metacognitive activities
ii. Classify student learning activity data to build an enhanced model of their learning – particularly in relation to metacognition
iii. Identify, develop and implement appropriate machine learning techniques to use in conjunction with other learning models to allow students to see the nature of their metacognitive activity and to track it over time
iv. Map and visualize these patterns and relations to make them more visible to students
v. Enhance and optimise existing machine learning approaches for future work in student learner modelling

2.1 Ethical framework

These objectives will be grounded in a clear ethical framework for the management and governance of the data involved to ensure the protection of student privacy informed by Prinsloo et al (2013) and Daschler et al (2015).

2.2 Critical analysis of learning analytics approaches

A keystone of this research will be a critical analysis of how we 'do' learning analytics and how that impacts learning environments and learners. Perrotta (2016) notes that learning analytics are not objective and neutral. Embedded in them are societal and political power structures and we need to critically reflect on how our analytics-informed interventions impact learners and teachers at those levels. Learners should not be mere data.

3. Research Questions

The primary questions posed in this research are summarized as follows:
i. Can a Learning Analytics system provide an interface for students to engage in metacognitive activities around their own learning, thereby improving individual learning experience and supporting the student's own development goals?
ii. Can we retool an existing learning analytics system using machine learning modelling and classifiers to provide this metacognitive interface to students?
iii. Can such a system help students visualize, track and reflect on their own learning and development goals and help them to improve performance?

4. Current knowledge of the problem

Modelling student learning is an attempt to make visible what goes on in the learning process. It tries to map and model the states and stop-off points as a learner makes their way on their learning journey from start to destination. This process can mirror student activity, provide maps and suggestions for students to guide their metacognitive and other learning processes.
There are many modelling approaches (Chrysafiadi & Virvou 2013) but not all are accessible to the student themselves and not all lend themselves to effective reasoning approaches. Bayesian Networks are simple constructs in some ways but have been proven to be powerful in student modelling (Millán 2010). Bayesian Networks were first described by Judea Pearl (1985) as 'directed acyclic graphs' which can be used to model causal dependencies between variables. The paper was initially presented at a cognitive science conference which may hint at the original motivation behind Bayesian networks. The applications of Bayesian networks are many and varied - they are a widely applicable approach to reasoning using probability.

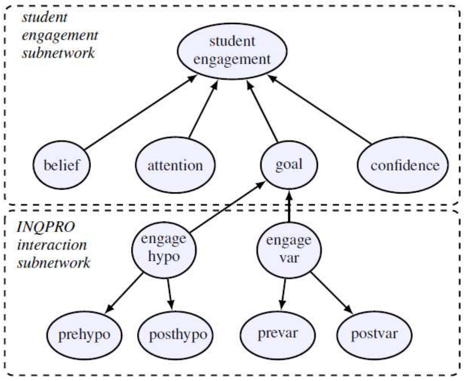

Fig 1. Bayesian Network Model of Student Engagement Ting et al (2013)

In education settings, Bayesian networks have seen a particular application in what was termed Bayesian Knowledge Tracing by Corbett & Anderson (1994). This was an approach where a learner progressing through a given learning path was modelled and this model used to predict whether the learner would successfully negotiate the next step in the learning path. A particular advantage of Bayesian Networks is that they are white-box algorithms and can be relatively easily understood by humans and represented visually to inform – rather than obfuscate (Xing 2015).

5. How is this solution different, new or better than existing approaches?

- Grounded in the Student perspective
- Students as owners of their learning data
- Links learning analytics to learning design
- Emphasis on Connected & Networked learning
- Machine Learning with an emphasis on modelling and visibility as well as prediction
- Data literacy capacity building for students

8. Acknowledgments

The authors acknowledge the support of Ireland's Higher Education Authority through the IT Investment Fund and ComputerDISC in NUI Galway.

8. References

Aleven, V. (2002). An effective metacognitive strategy: learning by doing and explaining with a computer-based Cognitive Tutor. Cognitive Science, 26(2), 147–179. https://doi.org/10.1016/S0364-0213(02)00061-7
Bakharia, A., Corrin, L., de Barba, P., Kennedy, G., Gašević, D., Mulder, R., … Lockyer, L. (2016). A conceptual framework linking learning design with learning analytics (pp. 329–338). ACM Press. https://doi.org/10.1145/2883851.2883944
Biesta, G. (2009). Good education in an age of measurement: on the need to reconnect with the question of purpose in education. Educational Assessment, Evaluation and Accountability (Formerly: Journal of Personnel Evaluation in Education), 21(1), 33–46. https://doi.org/10.1007/s11092-008-9064-9
Boyer, K. E., Ha, E., Wallis, M. D., Phillips, R., Vouk, M. A., & Lester, J. C. (2009). Discovering Tutorial Dialogue Strategies with Hidden Markov Models. In AIED (pp. 141–148).
Brookfield, S. (1995). Adult learning: An overview. International encyclopedia of education, 10, 375-380.
Bull, S., & Kay, J. (2010). Open Learner Models. In R. Nkambou, J. Bourdeau, & R. Mizoguchi (Eds.), Advances in Intelligent Tutoring Systems (Vol. 308, pp. 301–322). Berlin, Heidelberg: Springer Berlin Heidelberg. Retrieved from http://link.springer.com/10.1007/978-3-642-14363-2_15
Bull, S., Ginon, B., Boscolo, C., & Johnson, M. (2016). Introduction of learning visualisations and metacognitive support in a persuadable open learner

model. In Proceedings of the Sixth International Conference on Learning Analytics & Knowledge (pp. 30–39). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=2883853

Chrysafiadi, K., & Virvou, M. (2013). Student modeling approaches: A literature review for the last decade. Expert Systems with Applications, 40(11), 4715–4729. https://doi.org/10.1016/j.eswa.2013.02.007

Corbett, A. T., & Anderson, J. R. (1994). Knowledge tracing: Modeling the acquisition of procedural knowledge. User Modeling and User-Adapted Interaction, 4(4), 253–278.

Cronin, C. (2016). Open, networked and connected learning: Bridging the formal/informal learning divide in higher education. Proceedings of the 10th International Conference on Networked Learning 2016. Retrieved from http://networkedlearningconference.org.uk/abstracts/pdf/S3_Paper2.pdf

Dimitrova, V., & Brna, P. (2016). From Interactive Open Learner Modelling to Intelligent Mentoring: STyLE-OLM and Beyond. International Journal of Artificial Intelligence in Education, 26(1), 332–349. https://doi.org/10.1007/s40593-015-0087-3

Drachsler, H., Hoel, T., Scheffel, M., Kismihók, G., Berg, A., Ferguson, R., Manderveld, J. (2015). Ethical and privacy issues in the application of learning analytics (pp. 390–391). ACM Press. https://doi.org/10.1145/2723576.2723642

Ferguson, R., & Buckingham Shum, S. (2012). Social learning analytics: five approaches (pp. 23–33). Presented at the International Conference on Learning Analytics & Knowledge, Canada. Retrieved from http://oro.open.ac.uk/32910/1/LAK2012-RF-SBS.pdf

Ferguson, R., & Shum, S. B. (2012). Social learning analytics: five approaches (p. 23). ACM Press. http://doi.org/10.1145/2330601.2330616

Freire, P. (1968). Pedagogy of the oppressed (revised). New York: Continuum.

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. TechTrends, 59(1), 64–71. https://doi.org/10.1007/s11528-014-0822-x

Glaser, B. G., & Strauss, A. L. (2009). The Discovery of Grounded Theory: Strategies for Qualitative Research. Transaction Publishers.

Kitto, K., Gašević, D., Siemens, G., Lynch, G., Bakharia, A., Lupton, M., Dawson, S. (2016). The connected learning analytics toolkit (pp. 548–549). ACM Press. https://doi.org/10.1145/2883851.2883881

Koedinger, K. R., Aleven, V., Roll, I., & Baker, R. (2009). In vivo experiments on whether supporting metacognition in intelligent tutoring systems yields robust learning. Handbook of Metacognition in Education, 897–964.

Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing Pedagogical Action: Aligning Learning Analytics With Learning Design. American Behavioral Scientist, 2764213479367. https://doi.org/10.1177/0002764213479367

Millán, E., Jiménez, G., Belmonte, M.-V., & Pérez-de-la-Cruz, J.-L. (2015). Learning Bayesian Networks for Student Modeling. In C. Conati, N. Heffernan, A. Mitrovic, & M. F. Verdejo (Eds.), Artificial Intelligence in Education (Vol. 9112, pp. 718–721). Cham: Springer International Publishing. Retrieved from http://link.springer.com/10.1007/978-3-319-19773-9_100

Millán, E., Loboda, T., & Pérez-de-la-Cruz, J. L. (2010). Bayesian networks for student model engineering. Computers & Education, 55(4), 1663–1683. https://doi.org/10.1016/j.compedu.2010.07.010

Mor, Y., Ferguson, R., & Wasson, B. (2015). Editorial: Learning design, teacher inquiry into student learning and learning analytics: A call for action. British Journal of Educational Technology, 46(2), 221–229.

Pearl, J. (1985). Bayesian networks: A model of self-activated memory for evidential reasoning. University of California (Los Angeles). Computer Science Department.

Perrotta, C., & Williamson, B. (2016). The social life of Learning Analytics: cluster analysis and the 'performance' of algorithmic education. Learning, Media and Technology, 0(0), 1–14. https://doi.org/10.1080/17439884.2016.1182927

Rabiner, L., & Juang, B. (1986). An introduction to hidden Markov models. IEEE ASSP Magazine, 3(1), 4–16. https://doi.org/10.1109/MASSP.1986.1165342

Segedy, J. R., Loretz, K. M., & Biswas, G. (2013). Model-driven Assessment of Learners in Open-ended Learning Environments. In Proceedings of the Third International Conference on Learning Analytics and Knowledge (pp. 200–204). New York, NY, USA: ACM. https://doi.org/10.1145/2460296.2460336

Shum, S. B., & Crick, R. D. (2012). Learning dispositions and transferable competencies: pedagogy, modelling and learning analytics (p. 92). ACM Press. http://doi.org/10.1145/2330601.2330629

Slade, S., & Prinsloo, P. (2013). Learning Analytics: Ethical Issues and Dilemmas. American Behavioural Scientist, 57(10), 1510–1529. http://doi.org/10.1177/0002764213479366

Ting, C.-Y., Cheah, W.-N., & Ho, C. C. (2013). Student Engagement Modeling Using Bayesian Networks (pp. 2939–2944). IEEE. https://doi.org/10.1109/SMC.2013.501

Xing, W., Guo, R., Petakovic, E., & Goggins, S. (2015). Participation-based student final performance prediction model through interpretable Genetic Programming: Integrating learning analytics, educational data mining and theory. Computers in Human Behavior, 47, 168–181. https://doi.org/10.1016/j.chb.2014.09.034