Learning Analytics as a Metacognitive Tool

Eva Durall[1] and Begoña Gros[2]
[1]*Department of Media, School of Arts, Design and Architecture, Aalto University, Miestentie 3, Espoo, Finland*
[2]*Department of Theory and History of Education, University of Barcelona, Barcelona, Spain*

Keywords: Learning Analytics, Educational Data Mining, Self-directed Learning, Self-Regulated Learning.

Abstract: The use of learning analytics is entering in the field of research in education as a promising way to support learning. However, in many cases data are not transparent for the learner. In this regard, Educational institutions shouldn't escape the need of making transparent for the learners how their personal data is being tracked and used in order to build inferences, as well as how its use is going to affect in their learning. In this contribution, we sustain that learning analytics offers opportunities to the students to reflect about learning and develop metacognitive skills. Student-centered analytics are highlighted as a useful approach for reframing learning analytics as a tool for supporting self-directed and self-regulated learning. The article also provides insights about the design of learning analytics and examples of experiences that challenge traditional implementations of learning analytics.

1 INTRODUCTION

The use of "big data" tools and methods is a growing phenomenon in various fields ranging from computer science, political science, medicine and economics to physics and social sciences. "Big data" analytics refers to the process of examining these large amounts of data to uncover hidden patterns, unknown correlations and other useful information. Its rise coincides with new management and measurement processes in corporations that aim to develop "Business Intelligence" (BI) by transforming raw data into meaningful information that supports more efficient decision-making processes).

In the education sector, analytics are also perceived as reliable tools for decision-making, as well as for achieving greater levels of adaptation and personalization that are evidence-based (Harmelen and Workman, 2012). Beyond BI, analytics in education borrow techniques from different fields, such as Educational Data Mining (EDM), Social Network Analysis, web analytics and Information Visualization in order to come up with tools and methods that facilitate the exploration of data coming from educational contexts. According to Harmelen and Workman, the main potential uses of analytics in education are (p.5):

- "Identify students at risk so as to provide positive interventions designed to improve retention.
- Provide recommendations to students in relation to reading material and learning activities.
- Detect the need for, and measure the results of, pedagogic improvements.
- Tailor course offerings.
- Identify teachers who are performing well, and teachers who need assistance with teaching methods.
- Assist in the student recruitment process".

EDM and Learning Analytics (LA) are two research areas with strong similarities. Both of them seek to improve education by focusing on assessment, the identification of problems and interventions. The main differences can be found in EDM's emphasis on automated discovering and automated adaptation, whereas LA seeks to inform and empower instructors and learners in order to better leverage human judgement (Siemens and Baker, 2012).

LA research has been applied in two close and related areas: learning and academia. Although both of them use educational data, it is important to make a distinction since the underlying motivation of each one varies to great extent. According to the Society for Learning Analytics Research, Learning Analytics can be defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs. Learning analytics are largely concerned

Durall E. and Gros B..
Learning Analytics as a Metacognitive Tool.
DOI: 10.5220/0004933203800384
In *Proceedings of the 6th International Conference on Computer Supported Education* (CSEDU-2014), pages 380-384
ISBN: 978-989-758-020-8

with improving learner success" (SoLAR, 2013, About). On the other hand, academic analytics could be described as more business-oriented, since the main purpose is to improve organizational effectiveness through the use of learner, academic and institutional data.

Lately, the high proportion of computer-mediated interactions in learning has created an interest about how data collected from the interactions can be used to improve teaching and learning. In this regard, the increasing offer of Massive Open Online Courses (MOOCs) can be presented as a case in which institutions take advantage of data generated online in order to achieve a better understanding of how people learn. Despite its positive aims, LA still poses questions about how learners can benefit from the data they are generating in such learning platforms.

2 LEARNING ANALYTICS FOR FOSTERING SELF-DIRECTED AND SELF-REGULATED LEARNING

In the knowledge society, self-directed learning (SDL) and self-regulated learning (SRL) have become particularly important for professional development and lifelong learning.

SDL is an approach in which learners take control of their own learning processes and experiences. Tan et al. (2011) describe the processes of SDL based on a series of requisites or qualities: a) ownership of learning; b) self-management and self-monitoring and c) extension of own learning. The authors argue that providing opportunities to establish and control one's own learning objectives, as well as to direct and monitor the associated educational tasks, helps increase the subject's motivation and commitment to learning.

SRL is a process controlled by learners that may be supported by social and environmental stimuli related to setting objectives, self-monitoring progress, searching for help, feedback, self-directed reflection, time management and planning, etc. According to Zimmerman's (1989) definition, self-regulation is conditioned by students' active involvement in metacognitive, motivational and cognitive areas, in their own learning processes. Self-regulation is very much a metacognitive activity and a useful model to help understand metacognition. According to Pilling-Cormick and Garrison. (2007), metacognition goes to the core of both SDL and SRL and is a link or bridge between reflective inquiry and strategic task control.

The concepts of SDL and SRL are so similar that on many occasions they have been used as synonyms. Furthermore, the models proposed in both approaches have many elements in common. Loyens, Magda and Rickens (2008) conducted a complete analysis of the similarities and differences between the SDL and SRL models. Both imply learners' active involvement and goal-focused behaviour. In addition, a series of activities can also be identified as implicit in both models: setting goals, analysing tasks, implementing the plan and self-evaluating the learning process. According to Loyens, Magda and Rickens (2008), the difference between SDL and SRL basically relates to the perspective adopted when studying learning processes, depending on whether attention is focused on the personal attributes and actions of the learners and/or on the characteristics of the learning environment. While SDL encompasses both perspectives, SRL focuses more on the personal characteristics and behaviours of the person or people learning, including the cognitive, behavioural and also emotional dimensions. One possible explanation for this difference is the fact that while SRL has been studied above all in an academic context, the origins of the SDL concept lie in studying adult learning in non-formal environments.

In recent years, particular attention has been paid to the use of technology to support processes of SRL and SDL. The design of digital environments to support SDL and SRL processes aims to offer specific help to learners for planning, organizing and directing their research and exploration, as well as for evaluating their own progress. Bartolomé and Steffens (2011) propose a series of criteria that technology-enhanced learning environments should meet in order to support SRL processes: a) encourage learners to plan their own learning activity, including aspects linked to time management (e.g. when to carry out an activity and how long to spend on it), selecting communication channels and ways of representing information and using of the most suitable resources, b) provide feedback on performance in learning activities to aid monitoring and the correct direction of the learning process and, c) provide learners with criteria for evaluating the results of their learning in terms of the objectives that were initially set and the type of competences developed.

In order to successfully self-regulate and self-direct learning it is necessary that students achieve an understanding of their own cognitive process.

Metacognition, understood as the knowledge of one's own thinking, is a central concept in self-regulation and in self-directed learning since it brings together central constructs of motivation, management and monitoring (Pilling-Cormick and Garrison, 2007). In this regard, Learning Analytics can be a tool that offers opportunities to reflect about learning and develop metacognitive skills.

Feedback has been considered as a key tool for helping students improve performance. Traditional feedback usually relates to learners' mechanisms of communication with their teachers and colleagues. The use of technology adds new possibilities for tracking learners' activity and offers them more immediate feedback about their learning performance. However, most efforts to use learning analytics focus on providing information for the instructors in order to refine their pedagogical strategies (Knight et al., 2013). Very rarely are students considered the main receivers of the learning analytics data or given the opportunity to use the information to reflect on their learning activity and self-regulate their learning more efficiently.

Despite LA's potential for improving teaching and learning, scholars have expressed concerns regarding the use of analytics in education. The main criticisms deal with the commercialization of the education sector, the use of outdated performance indicators, simplistic uses of artificial intelligence, as well as the ethics of the datasets and how they are used (Slade and Prinsloo, 2013). Furthermore, some authors warn that learning analytics could actually disempower learners by making them reliant on institutional feedback (Buckingham and Ferguson, 2011). Quoting Kruse and Pongsajapan, learning analytics "perpetuates a culture of students as passive subjects – the targets of a flow of information – rather than as self-reflective learners given the cognitive tools to evaluate their own learning processes" (2012, p.2).

In response to the use of LA as a tool at the service of teachers and the institution, an increasing group of scholars have started to advocate for student-centred analytics (Duval 2012; Clow, 2012, Kruse and Pongsajapan 2012). In line with these authors, we consider that learning analytics can and should be used as a tool for reflection and metacognition to support SDL and SRL. In this regard, identifying the main challenges in the design of learning environments that make use of learning analytics to foster reflection is a key aspect. From our perspective, the most urgent challenges to be faced fall in two directions: data and visualization. What sort of data is most meaningful for learners? What types of visualization can foster reflection most successfully?

3 LEARNING ANALYTICS DESIGN

The demand for analytics that truly recognize users' ownership is connected to a broader need for control of the data that, as online users, we are constantly generating. Considering this, student-centred analytics share many aspects with Human-Data-Interaction since, according to Haddadi et al. (2013) "The term Human-Data-Interaction (HDI) arises from the need, both ethical and practical, to engage users to a much greater degree with the collection, analysis, and trade of their personal data, in addition to providing them with an intuitive feedback mechanism" (p.3). In this regard, and in order to support SDL and SRL, learning analytics should provide mechanisms for learners to interact with these systems explicitly. This requires learners to adopt a questioning attitude and take part in the interpretation of the data generated about them, but they must also be offered the means to access, understand and interact with the datasets.

The need for transparency and understandability has also been faced by other areas that are closely related to LA, such as Learner Models (LM). The main difference between LA and LM lies in the type of data monitored and its future use. So, while LA often shows activity data (interaction time in discussion; links in social networks or collaboration tasks; performance data), LM use inferences drawn from interaction in order to create a learner information model that allows the system to be highly personalized and adaptive. The appearance of Open Learner Models (OLM) constitutes an important effort towards making a student's learner model explicit with the aim of fostering self-awareness and enhancing learning and learner autonomy (Bull and Kay, 2008). An interesting case of OLM is MyExperiences (Kump et al., 2012). Here, the model has been designed to show users the inferences about them, as well as the underlying data, through a tree map visualization.

Another area that can provide interesting insights for reframing LA is Personal Informatics (PI). According to Li, Dey and Forlizzi (2010) PI can be defined as a class of systems that allow people to collect and reflect on personal information. In contrast to LA, PI, also known as Quantified Self

(QS), requires the user to take an active role throughout the five stages identified by Li et al. (2010): preparation, collection, integration, reflection and action. PI and QS have supported informal learning in fields linked to sports and health since they offer users opportunities to learn about their progression and undertake new challenges concerning healthy habits. Recently, some scholars have noted that QS approaches can support reflective learning and help people become more aware of their own behaviour, make better decisions, and change behaviour (Rivera-Pelayo et al., 2012; Li et al., 2011; Durall and Toikkanen 2013). One important aspect to note when looking at QS approaches is their voluntary nature. Even if QS is used for monitoring chronic conditions, users who self-track are motivated because they understand the potential benefits that this practice will bring them. In contrast, we cannot say that LA practices rely on the learners' voluntary participation. In this regard, one way of encouraging learners to take an active role in LA would consist of allowing them to choose which data they are going to monitor from a flexible and extendable set of indicators.

Transforming data into knowledge is a cognitive process that can be supported by the way in which data is made available. Information visualization has been recognized as a tool for sense-making (Heer & Agrawala, 2008) since it helps synthesize complex information and facilitates comparisons and inferences (Shneiderman, 1996; Tufte, 1990 and 1997). In the learning field, infovis has already been recognized as a powerful tool for teachers and students, especially through goal-oriented visualizations such as dashboards (Duval, 2011). In this regard, Govaerts (2010) notes that visualizations of the learners' activity has been used to improve collaboration, increase awareness, support self-reflection and find peer learners through social network analysis. Some projects working along these lines are CAMera, a tool for personal monitoring and reporting (Schmitz, 2009) and Moodog , a Moodle plug-in that visualizes data from the activity logs to allow students to compare their progress with others and teachers to visualize the students' activity in the online course (Zhang et al., 2007).

A case study by Santos et al. (2012) using goal-oriented visualizations of activity tracking is an interesting experience of student-centred learning analytics through visualizations. In this case, the overall goal was to enable students to reflect on their activity and compare it with their peers. With this aim, data collected using different tools was displayed in a goal-oriented visualization that allowed students to filter the data by different criteria and to compare it with their learning goals. As the authors state, "linking the visualizations with the learning goals can help students and teachers to assess whether the goal has been achieved" (pp. 143). By enabling learners to filter what they want to visualize, LA can generate metrics that relate to what learners value in their learning process. This way, they will be able to generate their own questions and hypotheses that, later on, can be contrasted through data. Learning analytics can be a great tool for reflection since it offers students the opportunity to revisit past experiences from a different point of view. In order to explain the "new situation", it is necessary that learners recognize their assumptions and change their perspective by building new understandings. However, for reflection to occur, it is important to keep in mind that the situations "observed" must be relevant for learners.

4 CONCLUSIONS

In this article, LA is recognized as a powerful tool for helping students reflect on their learning activity and, therefore, gain knowledge about their learning processes. This is especially important since self-knowledge can be considered as a key metacognitive skill for SDL and SRL. Therefore, in order to truly use analytics to help students become autonomous learners, it is necessary to adopt a student-centred approach.

Nowadays, the value of data requires careful and critical reflection on issues relating to privacy, data analysis, context of use and data ownership. In line with other scholars, we support more transparency and openness in LA (Clow 2012; Kruse and Pongsajapan, 2012) since we are dealing with sensitive information that ultimately belongs to the learners. Therefore, educational institutions cannot ignore the need for transparency and should ensure that learners can see how their personal data is being tracked and used in order to build inferences, and how its use will affect their learning.

LA raises the issue about what is valued in the learning process. Can learning be measured according to, for instance, who logs into the system most often, who engages most in group discussions or uploads the tasks on time? There is a need to rethink how learning indicators are selected and to what extent they contribute to conceiving learning as a process instead of in terms of outcomes (Clow, 2012). In this regard, allowing students to decide what aspects they are going to monitor and analyse could help make LA a tool for reflection on learning processes.

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