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A framework to support educational decision making in mobile learning

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ABSTRACT

Learning Analytics in Mobile Learning is a challenging research topic, due to the distinguishing features of mobile learning. In fact, mobile learning is characterized by the learners' mobility, the possibility of having localized data and information, the large amount of data that can be collected during a learning session, the affordances provided by the technologies and the social dynamics that characterize the context in which learning takes place. As a consequence, Learning Analytics in mobile learning requires original methodological approaches which enrich techniques already tested in different learning contexts (e.g., in Virtual Learning Environments) with specific strategies to deal with the complexity of mobile learning and manage the corresponding datasets. This paper presents a task-interaction framework to support educational decision-making in mobile learning. The framework is based on the relationships between the different types of interactions occurring in a mobile learning activity and the tasks which are pedagogically relevant for the learning activity. A case study has been designed to demonstrate the application of the task-interaction framework to learning scenarios based on the use of mobile devices.

1. Introduction

Learning Analytics is "the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs" (SoLAR, 2012). Learning Analytics developed originally in higher education and academic settings, as a shift from academic analytics and business intelligence towards learning processes.

Although Learning Analytics is considered to be a new research field – the definition reported above dates from 2012, and it is closely linked to a former definition by Siemens in 2010 (Siemens, 2010); the first international conference on Learning Analytics, LAK, was held in 2011 – Ferguson highlights how the origins of Learning Analytics date back to the twentieth century, and how this research area developed during the first decade of the new millennium (Ferguson, 2012). Important contributions to the definition of Learning Analytics have been provided by the field of Educational Data Mining (EDM), a data-driven approach to analyzing logs of student-computer interactions in order to support educators and learners (Zaïane, 2001). However, a determining and distinguishing factor in the construction of the definition of *Learning Analytics* has been the rise of learning-focused perspectives to Learning Analytics: in fact, over the last 10 years, socially and pedagogically driven approaches to analytics have led to educational applications which are strongly grounded in learning theories. The various research fields which have developed around the analysis of the data have therefore concentrated on different aspects: academic analytics has focused more on data analysis to improve administrative processes, while EDM has been more interested in the methodologies to use in analyzing the learning data, and the most recent Learning Analytics research has focused on the interpretation of the results aimed at guiding teachers in intervening to optimize learning processes.

From a pragmatic point of view, interest in Learning Analytics gathered pace with the rapid take-up of Virtual Learning Environments (VLEs) during the early 2000s. As a consequence of the diffusion of VLEs, especially in academic settings, a large amount of data concerning students' learning patterns became available, initially attracting the attention of data mining specialists, and then the research interest of pedagogists, sociologists and educational technologists, thus fostering advancements in Learning Analytics mentioned above.

Central to the concept of Learning Analytics is therefore the possibility of logging and analyzing learner-produced data trails, as a collection of interactions between the learner and the learning context (Long & Siemens, 2011). Considering the development of Learning Analytics described above, it comes as no surprise to find

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that most applications of Learning Analytics have been characterized by well-structured and controlled learning contexts; these applications have focused on the exploitation of learner data stored in academic learning platforms, such as Learning Management Systems and Virtual Learning Environments used by students for fully distance or partially blended learning courses (Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012), and on the different types of interactions occurring in these platforms (Johnson, Hornik, & Salas, 2008; Siemens, 2010; Richards & DeVries, 2011; Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014). Similarly, the learning resources with which the student interacted did not change during the learning experience (this only happened if planned from the beginning). On the one hand, this makes the management of data quite a straightforward process, but, on the other hand, it represents a formal learning situation which does not reflect the complexity of everyday learning.

Mobile and ubiquitous learning, MOOCs, social learning, Open Educational Resources (OER), Semantic Web and Linked Open Data (LOD) technologies are changing the way learning occurs: the number of learners in a MOOC as well as the technologies behind mobile and ubiquitous learning produce abundance of learner-produced data – also referred to as *Big Data* in the McKinsey Global Institute terminology (Manyika, 2011) – that generate *datasets* which are different both in size and type from the ones stored in VLEs (Merino, Valiente, & Kloos, 2013; Ferguson, 2012); learners are increasingly engaged in informal learning settings, and social interactions are central to the participatory online culture which is reshaping the educational landscape (Ferguson and Buckingham Shum (2012)); OER and open data provide learners with dynamic sources of quality information on the Web, and Semantic Web technologies behind LOD support learners with a semantic layer in the interactions with educational context.

Accordingly, Learning Analytics approaches have to face these challenges in order to offer important insights to learners and teachers (Agudo-Peregrina et al., 2014; Ferguson, 2012). Important advances of Learning Analytics towards this objective can be found, among others, in the work of Ferguson and Buckingham Shum (2012), who propose the concept of Social Learning Analytics as a subset of Learning Analytics to specifically capture the social interactions underlying social learning processes; similarly, Aljohani and Davis (2012) point out the importance of a Learning Analytics model for mobile and ubiquitous learning environments. The potential cross-benefits of exploiting Linked Data as the data management layer for Learning Analytics are huge, even though the connections between the two research fields are not very well developed yet; thus the need emerges for a closer relationship between the fields of Learning Analytics and Linked Data (d'Aquin et al., 2013). In this perspective d'Aquin and Jay (2013) present an approach that exploits LOD in conjunction with the sequential pattern extraction method for the interpretation of insights resulting from the behavior of learners.

Drawing upon extant literature, this paper focuses on the challenge of using Learning Analytics techniques to support educational decision making in mobile learning settings. A task-interaction framework is presented with the aim of supporting teachers in assessing and evaluating learners during learning experiences based on mobile devices; it is rooted in the task model for mobile learners introduced by Taylor, Sharples, Malley, Vavoula, and Waycott (2006) and Sharples, Taylor, and Vavoula (2007), in the work on classification for mobile learning projects done by Frohberg, Göth, and Schwabe (2009) and in the classification of interactions for Learning Analytics proposed by Agudo-Peregrina et al. (2014). The framework considers three main steps, which are respectively related to: the pedagogical model underlying the mobile learning experience in a real learning context; the analysis of learner-produced data trails; the undertaking of specific actions to rearrange the learning activities according to evidence-based indicators (Fig. 1).

The paper has the following structure: Section 2 provides background about the impact of mobile devices on learning contexts with particular focus on the main factors and challenges related to the evaluation and assessment of mobile learning; furthermore, the potentials of using the Semantic Web to manage data in conjunction with Learning Analytics are introduced. In Section 3, the task-interaction framework is described. Then, a case study is presented in Section 4 in order to show an application of the framework to two learning scenarios. Considerations on the use of the framework are discussed in Section 5, and final remarks conclude the paper.

2. Background

Nowadays, sensors that are always on and mobile devices have been used more and more often to monitor activities in everyday life, collecting huge amounts of data about user behavior (Carmichael & Jordan, 2012; Duval, 2012). This trend also affects learning activities that take place anytime and anywhere. Thus, the challenges of evaluating Mobile Learning, a process which involves a number of independent variables that influence the learning process, are highlighted. Then, the state of the art on using the Semantic Web technologies to handle *Big Data* is introduced; in fact, the Semantic Web enables the management and elaboration of the data produced by the learners in a mobile learning activity.

2.1. The challenge of evaluating mobile learning

In the last few years, mobile learning has been increasingly used to support learning experiences both in formal and informal contexts (Ahmed & Parsons, 2013; Jones, Scanlon, & Clough, 2013). More than 130 million Europeans routinely use their mobile phones to access the Internet (IAB Europe, 2012). Innovative and ever more powerful mobile information communication technologies continue to emerge and become widely available. According to the Educause Center for Applied Research survey on the use of mobile technologies in Higher Education (ECAR, 2012), students want to access academic progress information and course material via their mobile devices (such as smartphones, and tablet computers), and 67% of students surveyed believe mobile devices are important to their academic success and use their devices for academic activities. Likewise, the widespread use of mobile technology, along with the availability of efficient mobile broadband connections, offers a unique opportunity to develop innovative methods of learning as well as to develop policies aimed at participation, given that the use of mobile devices transcends age, social status, economic level, gender and ethnic origins (Arrigo, Kukulska-Hulme, Arnedillo-Sánchez, & Kismihok, 2013). Moreover, in the last decade, numerous studies about the use of mobile and wireless communication technologies in education have been reported (Traxler, 2007). In addition to these studies, we have observed a significant increase in mobile learning penetration rates

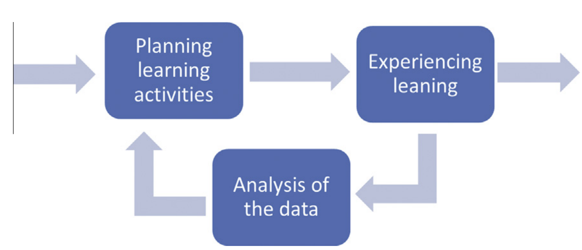

Fig. 1. The Learning Analytics impact on planning learning activities.