Editorial

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1 Introduction

With the general technological advances of the recent years, current learning environments amass an abundance of data. Albeit such data offer the chance of better understand the learning process, stakeholders – learners, teachers and institutions – often need additional support to make sense of it (Dyckhoff et al., 2013; Macfadyen and Dawson, 2012). The acknowledgement of these needs is at the heart of the recent emergence of Learning Analytics (LA), a research area that draws from multiple disciplines such as educational science, information and computer science, sociology, psychology, statistics and educational data mining (Buckingham Shum and Ferguson, 2012). This multidisciplinarity in LA has motivated the work done by Ferguson (2012), which provides a first review of the drivers, development and challenges of this novel and young research area.

Our understanding of *learning analytics* is based on the definition from the Society for Learning Analytics (SoLAR – Society for Learning Analytics[1]) which specifies that "*Learning analytics is 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*".

Since 2011, the Horizon reports list Learning Analytics as a hot topic in higher education and indicate the importance of data for this field (Johnson et al., 2011). Learning analytics are able to provide a fresh view on understanding of teaching and learning by observing patterns of complex data (Johnson et al., 2012). Furthermore, it will influence the evolution of higher education in a great measure. Nowadays, learners have access to a huge amount of online information having themselves the possibility of being content creators and information sharers. Therefore the quantity of available information grows in an exponential way, once that each and every citizen can access and produce information. For these purposes, learners have at their disposal many online resources, including LMSs, VLEs, MOOCs and many other online tools that facilitate the learning process and the development of competences. Taking into account these online learning facilities and therefore the learners' acquisition of knowledge, it is also easier to measure and analyse their experiences by using learning analytics tools. Different online courses and institutions provide dashboards with information about student experiences, flaws and successes. Although the investigation of behavioural-specific data makes learning analytics complex, the time comes to utilise personalised learning environments adapted to students learning paths, skills, previous knowledge, competences and motivation.

2 The research front on learning analytics

Learning analytics is increasingly seen as an important topic in the academic community and many studies have highlighted this development as significant (Kizilcec et al., 2013). For example, the Learning Analytics and Knowledge (LAK) Conference series gathers researchers that enrich the list of learning analytics publications year by year. The relevance of learning analytics in the technology-enhanced learning community has considerably grown over the initial years, both regarding the number of submissions from the initial 38 submissions in 2011 towards 58 in 2013 and 85 in 2014, as well as with respect to the reduction of the acceptance rate from 45% to 28% in only three years.

As part of the Work Programme 2013 (European Commission, 2012), the European Commission highlights the value of learning analytics and educational data mining (Objective ICT-2013.8.2 Technology-enhanced learning), identifying LA as a new emerging research field aiming to reduce the gap between research and practice with reliable analytics tools. These tools and processes for collecting, storing, exploring and reasoning on large-scale educational data should contribute to better understand learners' knowledge, assess their progress and evaluate environments in which they learn. These tools and processes should provide learning and teaching for both students and instructors. The expected impact from the exploitation of learning analytics tools is a more efficient use of ICT for learning and this can only be achieved by using LA tools in real learning scenarios and gaining insights about their real impact. This final work programme for FP7 has also played an important role in preparing for the new approaches proposed to be introduced in Horizon 2020.

As a result, the European Commission through the first work programme 2014–2015 in Horizon 2020 recognises the importance of learning analytics and data analytics, encouraging joint projects with a major focus on "*innovation and technology transfer in multilingual data harvesting and analytics solutions and services*" (European Commission, 2013), and by creating specific calls and programmes to address this issue, not only at R&D level but also in Education, Industry and Entrepreneurship level. Concerning the Education sector in particular, the Horizon 2020 proposes a very specific action named as *ICT 20 – 2015: Technologies for better human learning and teaching* which falls into the attempt of establishing a technological platform in order to provide a framework and a roadmap for all the involved agents, led by industry with a close collaboration of academia. This kind of partnerships will foster the development of certain learning applications based on adaptative solutions, learning analytics, augmented reality and mobile learning.

3 The context and motivation behind learning analytics

The interest on the increasing number of learners' interactions registered by the technological learning environments is not new (Ferguson, 2012). As Romero & Ventura conclude in their state of the art analysis (Romero and Ventura, 2007), there are several research approaches since 1995 dealing with the interpretation of educational data, with the main works, however, starting several years later, especially from 2008, with the advent of first conferences on Educational Data Mining (EDM), the Journal of EDM[2], and the establishment of the EDM Society[3].

Despite EDM provides researchers with relevant insights into the understanding of computer mediated learning (Baker and Yacef, 2009; Romero and Ventura, 2010), organisations and participants keep on asking for information that raises their awareness and helps them to realise what is happening in the learning scenario (Sutherland et al., 2012; Siemens and Baker, 2012). In order to save this gap between research and practice (Siemens, 2012), learning analytics break through in 2010, holding the first conference on Learning Analytics and Knowledge (LAK) and a year later setting up the Society for Learning Analytics (SoLAR).

Learners, teachers/educators, institutions or administrators, parents and government are the main *stakeholders* who can benefit from learning analytics data (Siemens et al., 2011; Drachsler and Greller, 2012). However, not only individual stakeholders may benefit from LA, also the relationship between them can be influenced. As the work of (Drachsler and Greller, 2012) shows, it is the relationships of teachers that are expected to be most widely affected, followed by learners, institutions, and parents at a minimal level.

In every concrete scenario where learning analytics are applied, the *level or object of analysis* performed in the data will also affect the interests of these stakeholders. Learners and educators can benefit from an analysis done at personal level (e.g. data about learning goals and resources) as well as at course-level (e.g. social network analysis or discourse analysis), whereas analysis done at higher level i.e. departmental or institutional may offer more benefits for educators and administrations.

When dealing with learning analytics, the type of data being analysed and the *technological context* where this data comes from play a significant role. During the last few years there have been different technological trends linked to different types of learning. Learning Management Systems (LMS) as well as virtual and Personal Learning Environments (PLE) (e.g. Moodle and ROLE platform) appeared to support teacher and student-centric approaches respectively. In addition, the call for specific functionalities that address users' needs often spreads learning environments over external tools (simulators, social media, forums, etc.). This myriad of VLEs, PLEs and Web 2.0 tools provides to Learning Analytics the opportunity of gaining insight into online and blended learning.

On the other hand, the integration of mobile and pervasive computing devices (e.g. interactive tabletops, whiteboards, tablets and smartphones) offers the possibility of connecting the physical and digital worlds. These technologies give us the chance of analysing ubiquitous learning by capturing learners' location and activity (Long and Siemens, 2011).

Massive Open Online Courses (MOOCs), which occur in decentralised, distributed teaching and learning networks involving large numbers of people, constitute another challenge (Suthers and Road, 2013). In these contexts, there is a clear urgency to uncover the reasons behind the low rates of completion.

Not only the technological aspects are important for learning analytics, but also in which *learning scenarios* they are being used. Especially for this issue, it was also intended to investigate in which real scenarios LA is being successfully applied. These scenarios can range from formal to informal settings, although a clear predominance of formal settings can be identified (both in the LA research community as well as in this special issue). It seems that the jump to informal settings (e.g. workplace settings) that is being currently experienced in the TEL community still has to be transferred to LA. In formal settings, LA approaches are being targeted for learners at any stage, starting from schools and going through higher education until university levels.

Finally, another parameter to categorise learning analytics deals with the nature of the data. A number of research works have addressed the problem of "big data". However, if we go back to the definition of learning analytics, there is no constraint in terms of the data size. Other problems such as the collection and analysis of distributed and heterogeneous data represent a challenge itself regardless of the size of the data sets

(Ferguson, 2012). In addition, as Boy and Crawford discuss in (Boyd and Crawford, 2012), big and small data may provide different and complementary insights into the learning process.

4 Challenges in learning analytics

With the introduction of learning analytics, new challenges related to the capturing and analysis of the data as well as to the learning methodologies have arisen.

As stated by Sutherland et al. (2012), the analysis, visualisation and interpretation of the data provide the opportunity to improve learning and study plans, but *dealing with data* open several issues:

- What real time data do teachers need for monitoring their students? And how can the data be collected and presented in an efficient and useful way?
- How can teachers adapt their teaching in order to improve their students learning after having received real time data?
- How can students themselves benefit from real time data collection? Can students be challenged cognitively or be provided with feedback through representations of real time data?

Learning processes and study methodologies are also affected by the introduction of LA and therefore this adds further challenges which need to be addressed. The connection of LA with pedagogical theory need further work, and a contextual framework that helps teachers interpret the information that analytics provides (Lockyer et al., 2013) is necessary in order to achieve successful results. Ferguson has done a detailed analysis in (Ferguson, 2012) and has identified the following explicit challenges:

- build strong connections with the learning sciences
- develop methods of working with a wide range of datasets in order to optimise learning environments
- focus on the perspectives of learners
- develop and apply a clear set of ethical guidelines

These challenges need further investigation in order to overcome the barriers that LA systems and tools may encounter in any learning scenario.

5 In this issue

The aim of this special issue is to move forward in the application of learning analytics in authentic learning scenarios, addressing different learning scenarios, stakeholders, technological contexts, and challenges. In such an emerging field which is evolving from different disciplines, doing a compilation of work done in real learning scenarios contributes to show the success of LA beyond experimental settings.

The table below shows an overview of the articles contained in this special issue and summarises their content following the mentioned criteria.

Title	*Author(s)*	*Learning scenario*	*Technological context*	*Stakeholder*	*Main challenge*
Like diamonds in the sky: how feedback can boost the amount of available data for learning analytics	Mazarakis	Feedback and LA in learning games	Learning games	Learners	Increase motivation of students and get more learning analytics data.
Improving academic outcomes: does participating in online discussion forums payoff?	Carceller, Dawson, Lockyer	LA in LMS and forum participation	Online discussion forum	Learners	Find the difference between students that participate and don't participate in the forums.
Using learning analytics to identify successful learners in a blended learning course	Kotsiantis, Tselios, Filippidi, Komis	Feedback and LA in Moodle – online	Moodle (LMS)	Learners	Predict students' performance.
Towards a script-aware monitoring process of computer-supported collaborative learning scenarios	Rodríguez-Triana, Martínez-Monés, Asensio-Pérez, Dimitriadis	Monitoring and CSCL	Distributed learning environment	Teachers	High efforts for classroom management due to more complex CSCL scenarios, particularly in distributed learning environments.
Effect of visual-assisted pedagogy for teaching and learning properties of relations	Fraij, Al-Dmour	LA in learning mathematics	Visual instruction system	Learners	Improving students' abilities of identifying properties of relations.
Learning analytics and second-language context: a digital instrument for measurement of real-time data regarding second language learners achievement	Figueiredo	LA in learning languages	Second Life®, electronic test battery	Learners	Measurement of learners' achievement in second-language learning in virtual environments.

This issue includes work representing the mentioned diversity of online platforms available for learning analytics, including games, learning management systems and discussion forums. Firstly, *Mazarakis* presents us a short paper with a study that intends to find out how feedback can boost the amount of available data for Learning Analytics. With the presented field study, the role of three different types of feedback is examined (i. right/wrong questions, ii. social ranking, iii. combination of both previous types) with a learning game similar to “Who Wants to Be a Millionaire?”. It is proved that participants in the feedback conditions played longer and were more motivated to play the game, thereby increasing the gathering of data for learning analytics in the game. Secondly, *Carceller, Dawson and Lockyer* investigates the differences between students that participate in online teaching units and those that participate in blended teaching units. They found no difference in performance of students from different groups. Although the participation in online discussions correlates with the performance of students and their final marks both in online and blended learning. The latter proposes the better conditions for the network learning as students have already develop network ties in the physical world. Finally, *Kotsiantis, Tselios, Filippidi and Komis* investigate Moodle usage patterns by using learning analytics in a blended learning environment in order to predict learners’ performance. The authors present a case study involving 337 students over 3 years. Using four complementary LA techniques, they could show that interaction activities together with students’ perceptions towards Moodle can be used as predictor for their performance.

Approaches in learning analytics are not only targeted for learners, but also teachers and instructors play a very important role and can benefit from it. In this issue, *Rodríguez-Triana, Martínez-Monés, Asensio-Pérez and Dimitriadis* give us insights about the influence that pedagogical decisions may have on learning analytics. The authors present a monitoring proposal that takes into account scripting decisions in Computer-Supported Collaborative Learning (CSCL), and illustrate it through the description of an experiment based on a real scenario.

The benefits of learning analytics in very different disciplines like mathematics and languages are also explored in this special issue. *Fraij and Al-Dmour* examine the influence of visual-based instruction in teaching properties and relations. In their selective use case and thorough user study, they demonstrate the positive impact of visual-based instruction on student’s performances. The implications of their work may support the development of new tools that incorporate visual-based metaphors in the learning scenario. Finally, *Figueiredo* presents us the results of a study that intended to develop a reliable electronic instrument in the full sense of learning analytics in order to collect, measure and report data about verbal behaviours, regarding the phonological awareness and specific language skills of second language learners. The author presents the tests battery as an important diagnostic tool applied to educational context in a virtual environment that allows a more complete understanding about the decoding processes and cognitive constraints of language learners.

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Notes

1 http://solaresearch.org/

2 http://www.educationaldatamining.org/JEDM

3 http://www.educationaldatamining.org/