Learning Analytics

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INTRODUCTION

Learning Analytics is considered one of the most promising technologies in the near future of education. It provides tools that help practitioners to reflect on the learning process, to have a better understanding and to achieve more effective educational methods. However, research on the field is at a very initial phase, and more investigation is needed in order to explore its potential. This article formally defines Learning Analytics, covering the complete life-cycle of the process: monitoring, data storage, analysis, and sense-making through visualization techniques. This includes a comprehensive review of the State-of-the-Art, and the main scientific societies and conferences devoted to explore all these topics. The article goes through the most relevant challenges, problems and debates on Learning Analytics research, and concludes with current and future initiatives.

BACKGROUND

Learning analytics is a relatively new field that has drawn techniques widely used in a number of communities. Some of them, as highlighted by Cooper (2012), are Statistics, Bussiness Intelligence, Web analytics or Operational research. The use of Analytics tecniques in the context of the learning process is what the community call Learning Analytics. A widely accepted definition of Learning Analytics, provided at the 2012 *International Conference on Learning Analytics and Knowledge*, describes the field as "the measurement, collection, analysis and reporting of data about learners and their contexts, for [the] purpose of understanding and optimizing learning and the environments in which it occurs" (Siemens, 2012). To discuss such definition, it's necessary to focus on its three main parts, namely: *procedures* (measurement, collection, analysis and reporting), *objects* (data about learners) and *goals* (understand and optimize learning and environments).

Objects: Data About Learners

The rise of Learning Analytics comes from the chance of observing and tracking the learners' activities through log files. Logged data describes who the students are, which activities they carried out and when, and sometimes how and where, they worked. Such intensive data collection produces the so-called Big Data that facilitates the use of data analysis procedures.

Procedures: Measurement, Collection, Analysis and Reporting

Measurement and collection play a relevant role in the existing research. In particular, non-intrusive measurement and collection is difficult to achieve in the learning context. The most popular method is to capture web interactions in a Learning Management System, but the captured data may not be fully representative of the student activity, and other monitoring methods are required (Pardo & Kloos, 2011). Another main focus of these "methods" part relates to analysis and reporting,

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which are the more noticeable part of Learning Analytics because of the immediate usefulness. Methods include social network analysis, collaborative filtering, clustering, neural networks, just to mention some. The reporting methods put emphasis on visualization techniques, so that the sense making process is at the end done by humans judgment,and visual analytics (Keim et al., 2008) plays a relevant role.

Goal: Understand and Optimize Learning and Environments

Learning analytics attempts to discover the factors that affect learning in a certain context, so that instructors and learners and reflect on these factors and improve the teaching/learning experience. Tools can be viewed as decision support systems, where the decision is aimed at driving one's teaching/learning methods.

All in all, Learning Analytics is a research field that investigates methods for collecting data from a learning situation, algorithms to extract hidden information from the collected data, and knowledge representation techniques that have a possitive impact of the learning situation.

Learning Analytics, Educational Data Mining, Academic Analytics. Where is the Difference?

Right in the learning world, there are some other disciplines that apply data mining procedures and techniques to educational data. The most relevant example is educational data mining. Despite there is a strong overlap among these two research areas, there are also some distinction that are important to note. According to Siemens and Baker (2012), one key difference is the role of the human participation in the information discovery process. In other words, educational data mining frequently aims at the development of systems that completely automate the information discovery, and the human participation is a tool to accomplish this goal; on the other hand, the Learning Analytics' goal is the elaboration of systems that leverage human judgment of available information.

Another important difference is the adopted research perspective: educational data mining emphasize on the individual algorithms, techniques and components, analyzing their performance from a individual component perspective. A more holistic approach is taken by the Learning Analytics world, which attempts to understand the systems as a whole, with the goal of understanding their effects on learning scenarios.

Academic analytics (Campbell et al., 2007) is also a related field with some overlapping with Learning Analytics. In both worlds student data is captured and processed in order to extract meaningful information and improve a process. The difference is the scope of the collected data and the overall goal of the analytics. While Learning Analytics aims at improving learning/tutoring strategies from an individual perspective, academic analytics try to improve administrative parameters such as student retention, faculty productivity, and the impact of outreach and engagement. In fact academic analytics is more related to business analytics than to Learning Analytics.

Despite the existing distinctions among these research communities, the overlapping is strong and some research work may fall into one or another category indistinctly. There is a friendly competition promoted by fluid communication and collaboration, where the approach is "learn from the others" instead of "beat the others."

What Makes Learning Analytics Different?

Analytics techniques have been widely applied in different domains, with particular needs and requirements. Some or these techniques, successfully applied in other domains, can be adapted to the particular needs of the learning process, but some others cannot (Li & Zaiane, 2004). The main difference between Learning Analytics and other Analytics communities is related to the objective to achieve. For example, in e-commerce the goal of analytics is to increase purchases, which is a quite clear objective and also it is easy to measure. However, in Learning Analytics the main goal is to improve the student's learning, which is a much more subjective and difficult to measure objective (Romero & Ventura, 2007).

TECHNIQUES USED THROUGH THE LIFE CYCLE OF ANALYTICS

The formal definition of Learning Analytics includes several actions (measurement, collection, analysis and reporting) that reveal a complete life-cycle composed by clearly differenced steps: data collection, analytics and reporting. This section is devoted to describe these individual steps in the context of Learning Analytics, and how they can influence the learning process.

Data Collection

Data mining and analytics techniques to process big data have been used in different areas such as health or business for many years. For example, the *Association for Computing Machinery's Special Interest Group on Knowledge Discovery and Data Mining* became an official in 1998. However, its impact in the educational field is much recent: the *International Educational Data Mining Society* was founded in July 2011 (EDM, 2013), and the *Society for Learning Analytics Research* (SoLAR, 2013 was also launched at 2011.

One of the reasons for this late impact on education is the lack of data: monitoring classroom activities is difficult to achieve and usually inaccurate. The recent widespread adoption of Learning Management Systems (LMS) by higher education institutions (among others), allows collecting student data so that the required big data is now available.

LMS are the most frequent source of datasets because it is easy to achieve, but it has been criticized because the LMS does only capture a small subset of the learner activities. As an alternatives, some researchers have applied different methods such as the use of virtualization software (Pardo & Kloos, 2011).

A negative impact on the learning activities may result from the deployment of data collection techniques. Firstly, students may perceive privacy issues and refuse to be monitored. Secondly, the data collection method should be as non-intrusive as possible, not distracting the students from their learning activities.

Analytics

A dataset captured from a learning situation contains useful information that describes the scenario at different levels. However, raw datasets are difficult to interpret, and there is a need to separate the wheat from the chaff. More precisely, the goal of the analytics step is the discovery and later communication of meaningful patterns in data. It usually requires two actions: preprocessing, and use of artificial intelligence techniques.

Preprocessing is required in order to transform the collected dataset into a suitable input for the analysis technique in use. Therefore, the steps to follow depend on the data collection method and the technique to apply. Typically, a dataset collected from a LMS requires the following (Koutri et al., 2004; Zorrilla et al., 2005):

- **Data integration:** It is the integration and synchronization of data from heterogeneous sources.
- **Data cleaning:** To remove irrelevant items and log entries that are not needed for the mining process.
- **Session identification:** If we consider that a new session starts when the time interval between two successive user events is longer than a pre-defined threshold (Zorrilla et al., 2005), then user events can be grouped into sessions before main processing.

Once pre-processed, many techniques can be applied. (Romero & Ventura, 2008) identifies the following and provides a comprehensive list of references of their application in the educational world:

- **Statistics:** Descriptive statistics is usually the starting point for the evaluation of a learning system. The techniques range from ranking the learning objects by visits, to correlating these visits with performance.
- **Clustering and classification:** Pursuing automate detection of learning styles, grouping learners by type is one of the most popular data mining techniques used in education. Clustering is frequently the first step of an activity such as collaboratively problem solving, or peer reviewing.
- **Association rule mining:** Algorithms such as Apriori find relationships shaped as "if events A and B occurred, then event C is likely to occur." This technique, widely used in market basket analysis, can be adapted to education for its usage in recommender systems.
- **Sequential pattern mining:** Algorithms for association rule mining discard time and order information. However, the sequential or-

der is important for the achievement of learning objectives. Algorithms like *Generalized Sequential Pattern* algorithm can be used to predict the next actions of the student, and to determine the most useful way to organize learning activities.

- **Text mining:** Only a small subset of learning activities can be automatically assessed, but students can demonstrate most of their learning with written activities such as compositions that are difficult to analyze without human intervention. Text mining techniques attempt to find similarity between documents, or can identify the main focus in a discussion, which is a step forward in the way to automatic assessment of written activities.
- **Other techniques:** Includes *Social Network Analysis* as a way to identify roles for collaborative learning activities, or to study the influence of relationships in learning acquisition; or *Outlier Analysis* to identify unusual student behaviors and provide personal advice.

Reporting

As described by (Siemens & Baker, 2012), Learning Analytics puts emphasis on leveraging human judgment, instead of automating discovery. Therefore, the analytics techniques extract meaningful information from the captured datasets, but the final sense-making is done by a human. This approach emphasizes the relevance of reporting systems, with special attention to visualization techniques. Assuming that the answer to 'what to report' has been provided in the analytics phase, there are still two remaining questions to solve: "when to report" and "how to report."

When to report? The reporting moment (i.e. the moment in the course life cycle when practitioners get the report) is highly influenced by the goal of the analytics in the particular scenario. In some cases, the goal of Learning Analytics is to understand a learning situation so that models can be created and future replicas of the scenario can be improved. In this case, the reporting usually takes place once the activity has been finished, so that the practitioners and researchers can reflect on the data. In some other cases, the goal of Learning Analytics is to increase the awareness of instructors and learners and therefore the reporting becomes live, taking place during the activity. Also, the technical details of the system architecture have an influence on the reporting moment, because analytics algorithms can be CPU-consuming and might not be suitable for instant reporting or for the provision of details on-demand. In any case, the reporting moment should carefully chosen according to the pedagogical strategy that drives the analytics.

How to report? The most widely adopted method to offer feedback to students and teachers without cognitively overloading them is based on visualization techniques. In fact, information visualization is sometimes used to foster the sense-making of the data and therefore can be understood as the last part of the analytics step, and its refereed as visual analytics (Keim et al., 2008). Learning analytics systems can be oriented to support instructor decisions, or they can be devoted to support the student. In both cases, the results of the analytics step are tipically presented in a visual mode. For example, Santos et al. (2013) and Verpoorten et al. (2011) discuss the concept of 'learning dashboards', and identify its empirical evaluation as a research challenge. Leony et al. (2012) present a framework for the creation of learning dashboards, considering different roles in the learning process and allowing for their integration with third party systems. The state of the art visualization techniques commonly make use of semaphore or gauge based methaphores (e.g. red light means "take care," green light means "go ahead"). The identification of more meaningful visual analytics techniques is one of the existing challenges regarding reporting methods.

SCIENTIFIC FORUMS

Learning Analytics is currently an important research area in the science community. The aims and scope of the main research groups, journals and conferences of this field are working to improve the quality of learning mechanisms and formal methods. Learning Analytics is trying to personalize learning to meet the needs of each student. The most relevant forums are described in the next paragraphs.

The main conference specialized in this topic is the *International Learning Analytics & Knowledge Conference (LAK)*. It is a venue for reporting and advancing research about the rapid expansion of the use of technologies in supporting learning and the unprecedented availability of data that learners generate in the process of accessing learning materials, interacting with educators and peers, and creating new content in these technological settings (LAK, 2013).

Many journals oriented to education, computers and psychology are generating different special issues about Learning Analytics. To this day (2013) the top five journals are listed below:

- Computers and Education (IF: 2.775) ranked in the position 14 of 97 into the computer science, interdisciplinary applications category of the SCI from JCR is an established technically-based, interdisciplinary forum for communication in the use of all forms of computing in this socially and technologically significant area of application. (CE, 2013)
- Journal of Computer Assisted Learning (IF: 1.632) ranked in the position 20 of 216 into the education & educational research category of the SCI from JCR is an international journal which covers empirical research on the uses of information and communication technologies to support learning and knowledge exchange. It aims to facilitate both communication within this research community and mutual understanding between researchers and practitioners. (JCAL, 2013)
- Journal of the Learning Sciences (IF: 3.036) ranked in the position 15 of 139 into the social science, education & educational research category of the SCI from JCR provides a multidisciplinary forum for the presentation of research on learning and education. The journal seeks to foster new ways of thinking about learning that will allow our understanding of cognition and social cognition to have impact in education. (JLS, 2013)
- IEEE Transactions On Learning Technologies (IF: 0.758) ranked in the position 71 of 99 into the computer science, interdisciplinary applications category covers research on such topics as innovative online learning systems, intelligent tutors, educational software applications and games, and simulation systems for education and training. (TLT, 2013)
- International Journal of Human-Computer Studies (IF: 1.415) ranked in the position 10 of 20 into the computer science, cybernetics category publishes original research over the whole spectrum of work relevant to the theory and practice of innovative interactive systems. The journal is inherently interdisciplinary, covering research in computing, artificial intelligence, psychology, linguistics, communication, design, engineering, and social organization, which is relevant to the design, analysis, evaluation and application of innovative interactive systems. (IJHCS, 2013)

Research focusing into online forums which works with this technologies, the *Learning Analytics Google Group* shows several topics such as positional researches, chapter books, special issues on journals or whatever the subscriber wants about Learning Analytics. Also the *Society for Learning Analytics Research* promotes this knowledge area. SoLAR is an inter-disciplinary network of leading international researchers who are exploring the role and impact of analytics on teaching, learning, training and development. SoLAR exists to ensure that there is an expansive, transformative vision for what analytics might mean for the future of learning and to promote a very critical discourse that is non-partisan, and grounded as far as possible in practice-based research. SoLAR is a non-profit organization. Incorporation is currently underway (SoLAR, 2013).

Finally, MOOCs (Massive Open Online Courses) are currently trending on Internet. Coursera, edX, and others offer several courses on Learning Analytics. These online platforms are good data warehouses to understand and learn about this technologies.

FUTURE RESEARCH DIRECTIONS

Learning analytics has emerged in the last decade pushed by the availability of big data in education, and has created big expectations in the educational research (de-la-Fuente et al., 2013). For example, the Horizon Report 2013 (Johnson et al., 2013) expects

Learning Analytics to be adopted in 2-3 years. Despite a lot of successful work has been done in the area, there are a number of challenges to reach in the Learning Analytics research field. Ferguson (2012a) identifies some of them:

- **Consolidate data collection methods and explore the possibilities of new data sources**: Technology enables data collection in a wide range of situations but, in practice, most learning datasets are limited to LMS based scenarios which, according to Dietrichson (2013), do not consider 85% of available data. Constructivist pedagogies require a deeper level of analysis that might require physical sensors, mobile devices, biometric data or contextual data towards the elaboration of more meaningful datasets and will foster the potential of learning analytics (Siemens & Long, 2011).
- **Develop standardized methods for dataset collection, enabling more meaningful datasets and data sharing among researchers and institutions**: Data collection is a costly task, and the validity of datasets is frequently limited to the particular circumstances of a case study. Researchers should work towards a standardized procedure for the collection, storage and share of datasets. As stated by Verbert et al. (2011) this dataset-driven research, this will push cross-validation of analytics models and therefore will bring more generalizable findings.
- **Identify ethical and privacy issues**: Decisions about the ownership and stewardship of the data are usually taken as to accomplish with the local privacy laws, but there are no standard procedures to ensure learners and teachers' rights on the data. A step forward towards this direction is taken by Slade and Prinsloo, (2013), who proposes an ethical framework for learning analytics in higher education, but more research is expected in this direction.
- **Strengthen the relationship with other educational research fields**: While analytics techniques and visualization methods have a great potential by themselves, they will acquire more relevance if they find its basis on existing learning research. As identified by Ferguson (2012b), work focused on cognition, metacognition and pedagogy is under-represented in the current state of the art. A more intense relationship between research fields will result in a better understanding of the learning process, and therefore on a greater impact of the learning analytics tools.
- **Broaden the focus, which is now mainly on higher education and should include formal and informal learning at different levels:** This challenge relates to others above mentioned: with the limitations of the LMS as the most used data capture methods, higher education scenarios are the most feasible ones to investigate. Should we adopt new techniques to achieve datasets, learning analytics will be potentially researched in different scenarios.

CONCLUSION

As explained throughout the article, the term Learning Analytics consists of a set of technologies with a focus on, in a first step, compiling, logging, collecting, and summarising information around students activities. In a second step, this information is data-mined by a variety of statistical and step-wise approaches. The goal of the final third step is to extract valuable conclusions that might lead to prudent student assessment or contribution to the research field widely known as "Technology-enhanced Learning" (TEL).

Given the increasing number of students enrolled in learning management systems, taking part in academic activities and leaving countless trails of their behaviour, both in present and online scenarios, it's becoming more and more necessary to find a way of supporting and helping instructor decisions. This is where Analytics enters the stage. Analytics is not a precise compendium of techniques, recipes, algorithms and software packages, but a wide and open-to-contributions framework for scientists, tutors and educators.

In the name of this openness, Learning Analytics should deepen in the next years in achieving a good mix of automatisms and human judgement. Furthermore, eLearning experts should avoid delegating all conclusions to computer processes. Analytics turns out some sort of smart copilot that inexorably must obey human and docent criteria. At the same time, the community of learners, whose academic success is one of Learning Analytics's most important goals, are entitled to take a more proactive and conscious role.

Openness might also refer to the technical field, where Learning Analytics should embrace, whenever possible, standards for collecting, consolidating and transferring raw and post-processed data (i.e. IMS Global, Tin Can, etcetera).

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KEY TERMS AND DEFINITIONS

Artificial Intelligence: Field of knowledge devoted to provide computers with skills and abilities that are usually attributed to the human being. Some examples include pattern recognition, reasoning, natural language processing, learning, et cetera.

Big Data: An extremely large dataset that cannot be analysed by traditional methods, and require distributed, highly paralelizable computing to extract the information.

Data Collection Method: A technique that observes the users activity and creates written reports of the observations. Methods are usually event-based, that is, each user action is reported as an individual entry shaped as 'observed action, user identifier, timestamp'.

Data Mining: Field of knowledge aimed at the study of techniques to automatically analyse and extract meaningful information from large datasets. There is some overlaping between Data mining and Artificial

Intelligences, and some techniques can be included in both research fields (e.g. cluster identification).

Dataset: A collection of data logged from a certain case of study. The later analysis of the dataset requires some metadata to describe the case of study, such as a description of the context, the existinig event types, the user profiles, et cetera.

Information Visualization: Field of knowledge aimed at the study of techniques to visually represent the information in a meaningful way, so that the representation have an added value over the raw data. For example, infographics are interconnected sequences of facts that have more information than a raw collection of facts.

Visual Analytics: A type of information analytics that relies the last step of the analysis (the sense making process) in the human being. This is achieved by the visual representation of the data that allows humans to easily recognise patterns and make conclusions that are difficult to achieve by computers.

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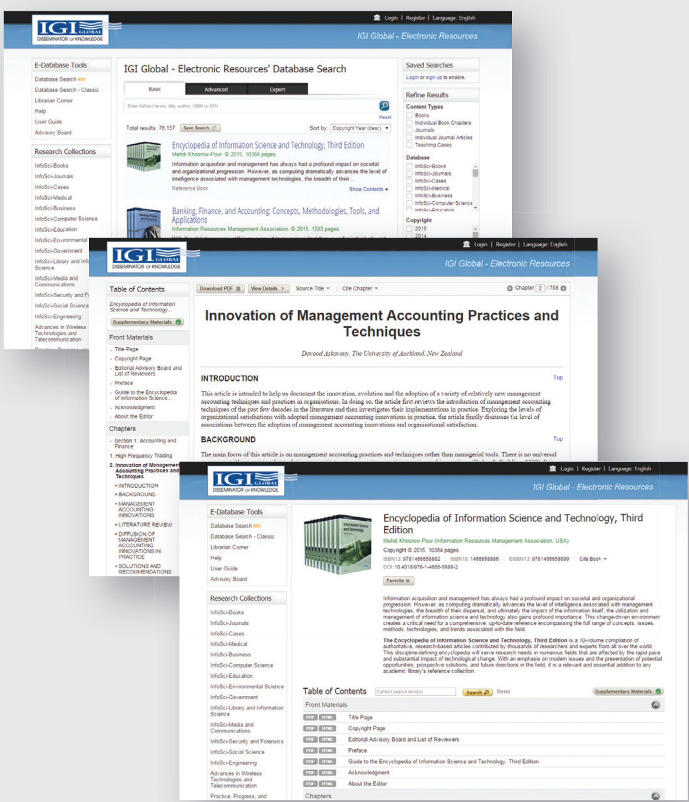

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