

Learning Analytics

E**Luis de-la-Fuente-Valentín***Universidad Internacional de La Rioja, Spain***Alberto Corbi***Universidad Internacional de La Rioja, Spain***Rubén González Crespo***Universidad Internacional de La Rioja, Spain***Daniel Burgos***Universidad Internacional de La Rioja, Spain*

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, Business Intelligence, Web analytics or Operational research. The use of Analytics techniques 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,

DOI: 10.4018/978-1-4666-5888-2.ch231

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 positive 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 of 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

7 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:

www.igi-global.com/chapter/learning-analytics/112653

Related Content

Emotion in Interactive Technology-Mediated Decision Taking and Negotiation

Bilyana Martinovski (2015). *Encyclopedia of Information Science and Technology, Third Edition* (pp. 3745-3753).

www.irma-international.org/chapter/emotion-in-interactive-technology-mediated-decision-taking-and-negotiation/112811

Cyberinfrastructure, Cloud Computing, Science Gateways, Visualization, and Cyberinfrastructure Ease of Use

Craig A. Stewart, Richard Knepper, Matthew R. Link, Marlon Pierce, Eric Wernertand Nancy Wilkins-Diehr (2018). *Encyclopedia of Information Science and Technology, Fourth Edition* (pp. 1063-1074).

www.irma-international.org/chapter/cyberinfrastructure-cloud-computing-science-gateways-visualization-and-cyberinfrastructure-ease-of-use/183820

Palmpoint Recognition System Based on Multi-Block Local Line Directional Pattern and Feature Selection

Cherif Taouche, Hacene Belhadefand Zakaria Laboudi (2022). *International Journal of Information Technologies and Systems Approach* (pp. 1-26).

www.irma-international.org/article/palmpoint-recognition-system-based-on-multi-block-local-line-directional-pattern-and-feature-selection/292042

Movie Analytics for Effective Recommendation System using Pig with Hadoop

Arushi Jainand Vishal Bhatnagar (2016). *International Journal of Rough Sets and Data Analysis* (pp. 82-100).

www.irma-international.org/article/movie-analytics-for-effective-recommendation-system-using-pig-with-hadoop/150466

Steel Surface Defect Detection Based on SSAM-YOLO

Tianle Yangand Jinghui Li (2023). *International Journal of Information Technologies and Systems Approach* (pp. 1-13).

www.irma-international.org/article/steel-surface-defect-detection-based-on-ssam-yolo/328091