Learning Analytics: Principles and Constraints

Mohammad Khalil
Social Learning, Information Technology Services
Graz University of Technology
Graz, Austria
mohammad.khalil@tugraz.at

Martin Ebner
Social Learning, Information Technology Services
Graz University of Technology
Graz, Austria
martin.ebner@tugraz.at

Abstract: Within the evolution of technology in education, Learning Analytics has reserved its position as a robust technological field that promises to empower instructors and learners in different educational fields. The 2014 horizon report (Johnson et al., 2014), expects it to be adopted by educational institutions in the near future. However, the processes and phases as well as constraints are still not deeply debated. In this research study, the authors talk about the essence, objectives and methodologies of Learning Analytics and propose a first prototype life cycle that describes its entire process. Furthermore, the authors raise substantial questions related to challenges such as security, policy and ethics issues that limit the beneficial appliances of Learning Analytics processes.

Introduction

Within the last years, technology and the availability of the internet have evolved so rapidly that it has changed the world of information. Education has enrolled within this revolution and created a new phenomenon called e-learning (also referred to as web-based education and e-teaching) in which big sets of data exist about learners and the whole educational system (Castro et al., 2007). Learning Analytics is a fast growing area of the research field of online education and Technology Enhanced Learning (TEL). It includes different academic disciplines as an intersection of various fields, e.g. education, psychology, pedagogy, statistics, machine learning and computer science (Dawson et al., 2014). Additionally, Knight, Buckingham and Littleton combined epistemology to the Learning Analytics areas of study (Knight et al., 2013). These social and technical connections have been largely positive to Learning Analytics and with a growing researchers base, we will get the opportunity to influence the development of analytics in education (Siemens, 2012).

Learning is conventionally defined as the process of acquiring competence and understanding (Goodyear & Retalis, 2010). On the other side, analysis techniques that derive information from "big data" such as revealing patterns and applying them to the education stream are named Learning Analytics. In its initial steps of evolving, there has been a plethora of definitions used for Learning Analytics. Siemens defines it as "the use of intelligent data, learner product data and analysis models to discover information and social connections, and to predict and advise on learning" (Siemens, 2010). Elias described it as "an emerging field, in which sophisticated analytic tools are used to improve learning and education" (Elias, 2011). Learners and teachers leave many traces behind them in which Learning Analytics can convert them to be beneficial for the education sector (Duval, 2011). Later, the Society for Learning Analytics Research (SoLAR) defined Learning Analytics as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environment in which it occurs" (SoLAR, 2011). There are several factors driving the emergence expansion of Learning Analytics. These factors are: a) The boundlessness and the proliferation of internet and technology among all educational categories. b) The large abundance of data available from learning environments. c) The availability of tools that can be used to manage and analyze data. d) The increasing demand to understand learners and improve the learning environment and its context.

A key application of Learning Analytics is monitoring and predicting students' learning performance (Johnson et al., 2011). By using Learning Analytics and optimizing it in the learning environment, tutors for example, can predict the student's future performance in courses. Students can improve their grades.

Educational institutions such as decision makers can be involved to enhance the retention percentage of the university's graduates. Course developers would point to the difficulties and weaknesses in the courses' models. However, limited researches have been conducted so far in order to serve Learning Analytics as a standard approach for e-learning environments (Chatti et al., 2012), (Cooper, 2012), (Greller & Drachsler, 2012). Furthermore, and besides the technically focused questions about the related fields between e-learning environment and Learning Analytics, Prinsloo and Slade indicated in their research that higher education institutions' policies may no longer be sufficient to address ethical and privacy issues in the potential of Learning Analytics (Prinsloo & Slade, 2013). Therefore, we raise substantial questions related to the challenges that surround Learning Analytics such as security, privacy, policy and ethics issues.

Research Methodology

In this paper, we will discuss what Learning Analytics is about, and propose an approach that comprises proceeding steps, starting from the learning environment and ending with the appropriate intervention. We conclude a Learning Analytics life cycle after gathering information about Learning Analytics from conference proceedings, workshops results as well as publications in different journals in the last four years. Furthermore, we looked at the current available frameworks and reference models. This motivated us to investigate further to propose an approach that presents a framework as well as a life cycle. We took into account the idea of closing the cycle (Clow, 2012), the current models by (Greller & Drachsler, 2012) and (Chatti et al., 2012) and the information in respect to Learning Analytics in this area to date. Afterwards we modeled our approach and enhanced it by exploring additional related studies about privacy, ethics and security issues.

Discussions

In this section, we present the Learning Analytics life cycle as shown in (figure 1). It considers four main parts: Learning environment where stakeholders produce data; big data, which consists of massive amounts of datasets; analytics, which comprises different analytical techniques; Act, where objectives are achieved to optimize the learning environment. Later on, eight-dimensional constraints encompass the Learning Analytics holistic cycle will be shown in (figure 3).

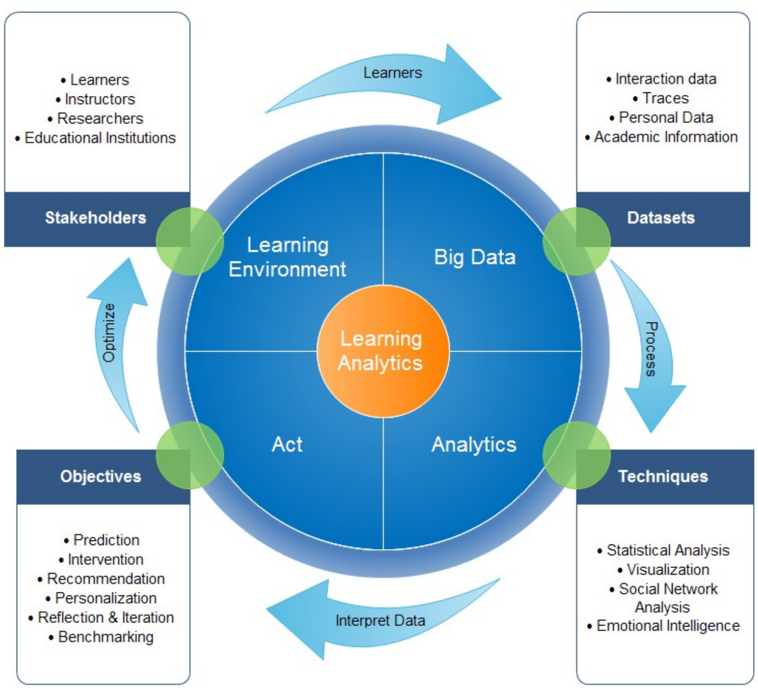

Figure 1: Proposed Learning Analytics Life Cycle

Learning Environment

With the ubiquitous technologies spread among education, there is a large collection of educational and learning environments involved, such as: Personal Learning Environments (PLE), Adaptive Hypermedia educational systems, Interactive Learning Environments (ILE), Learning Management Systems (LMS), Learning Content Management Systems (LCMS), Virtual Learning Environments (VLE), Immersive Learning Simulations (ILS), intelligent tutoring systems and mobile learning. All these learning environments are a gold mine of data that learners leave behind (Romero & Ventura, 2010). For example, logging a mouse click by its x and y coordinates, or the menu items times clicks, or the time a student spent on a question can produce a huge amount of data that can be analyzed to provide information about the students' motor skills (Mostow & Beck, 2006). The learning environment has a lot of aspects and roles, but in this proposed learning analytics cycle, the focus will be on the actors / stakeholders.

Stakeholders

There are different groups who are engaged in Learning Analytics. Each group can get benefits according to their visions and missions. For instance, Learning Analytics is advantageous to support people in clarifying and relating information, peer learners and digital artifacts and to support people in pursuing their learning (Fournier et al., 2011). (Table 1) displays the stakeholders, the objectives and some examples for each group.

Stakeholder	Objectives	Examples
Learners	Enhance their performance. Personalize online learning. Recommend courses.	Students are informed about learning process and compare their performance with others. Starting large assignments earlier and ask questions using applications like Signals (Arnold & Pistilli, 2012).
Instructors	Enhance their teaching methods. Provide real-time feedback to students.	Monitoring learning progress of the students using applications like SNAPP (Bakharia & Dawson, 2011).
Researchers	Evaluate courses. Improve courses models. Discover new methods of delivering educational information.	Through visualizations, course researchers can compare Learning Analytics techniques to be able to recommend the persuasive one.
Educational Institutions	Support decision processes to achieve higher educational goals.	Increase retention rate. Monitor higher educational perspective goal by increasing retention rate, using applications like Signals and C4S (Jackson & Read, 2012).

Table 1: Learning Analytics Stakeholders

Learning Analytics consider mining learners' activities. Most of Learning Analytics definitions reference learners as the main actor of the Learning Analytics process. This has been researched in (Siemens, 2010), (Duval, 2011), (Ebner & Schön, 2013), (Taraghi et al., 2014).

Big Data

As mentioned before, learners leave a lot of data behind them while using any learning environment. In the old educational methodologies, the learner is considered as a consumer. She/he has no possibility to be an active actor in the education process. On the other hand, with Learning Analytics, learners are not only consumers, but also become producers of data. In educational environments, there are different types of data to be processed. These data are restricted to the educational area and therefore have an authentic semantic information (Romero & Ventura, 2010). Manyika and his colleagues defined "Big data" as "the reference to datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze." (Manyika et al., 2011). While learners are using the educational platforms, they generate data. This yields to have repositories of datasets. These datasets include, but are not limited to:

1) Interaction data; such as the data that is related to visualizations and forums discussions.
2) Traces; which can be number of logins, mouse clicks, number of accessed resources, number of finished assignments, videos accessed, documents accessed, files downloaded, questions asked, discussions involved, and social network activities; such as tweets, blogs and comments.
3) Personal data: name, date of birth, local address, email address, personal image, ID or any other personal related information.
4) Academic Information; these are courses attended, grades, graduation date, exams taken, certificates… etc.

While big data includes this large amount of educational information, it should be searched, processed, mined and visualized in order to retrieve a meaningful knowledge.

Analytics

There are different methods to analyze data in the atmosphere of education. These analytics methods seek to discover interesting patterns hidden in the educational datasets. Learning Analytics techniques use various types of analytical methodologies. These methodologies fall into two main categories: Quantitative and Qualitative Analysis. In this section, we will summarize the key techniques in both fields.

Quantitative Analysis

Quantitative analysis is all about counting and statistical models. Learning Analytics quantitative methods are:

- *Statistical Analysis*: By applying statistics and mathematical operations, knowledge can be revealed out of data. Statistical analysis is related to traces, in which numeric computations can be executed. We can count the number of visits, analyze mouse clicks and calculate time spent on task. Some of the available statistical analysis tools are: IBM SPSS and MATLAB.
- *Visualizations*: Visualizations are useful for all Learning Analytics stakeholders. Students can display their progress in assignments and classes. Teachers can obtain an overview of their own efforts. Decision makers can make financial decisions upon them. Statistical information can be interpreted into charts, flowcharts, mind mapping, heat maps, 3D plots, scatterplots, evaluation models and diagrams. Learning Analytics lack of clarity in what exactly to measure to get a deeper understanding of learning progress. However, information visualization techniques can connect visualizations not only with meaning or truth, but also with taking actions (Duval, 2011). Dashboards are an adequate and a widely accepted style of Learning Analytics visualizations as seen in Course Signal (Arnold & Pistilli, 2012). Vozniuk and his colleagues offered a portable learning analytics dashboard that provides teachers and learners the ability to view their progress in different scenarios (Vozniuk, 2013). We see that a vast research on development of dashboards is imperative for Learning Analytics as they are easy to understand, render a better visibility and offer an easy insight.
- *Quantitative Social Network Analysis*: Social Network Analysis (SNA) focuses on relationships between entities. The use of SNA allows to carry out detailed investigations on networks composed of actors and the relations between them. These relationships between entities/actors are referred to as strong ties or weak ties (Ferguson, 2012). SNA can employ learning environment data to help instructors understand the atmosphere of his/her class, and to provide help for students when needed. There are several available tools that offer social network analysis enriched by

visualizations such as; SNAPP (Bakharia & Dawson, 2011) and Cytoscape[1]. These tools can help by observing students' contributions in class discussions and propose faculties and decision makers the potentiality to identify students who are isolated (at risk).

Qualitative Analysis

Qualitative analysis is about processing data into more explained description. The study of (Fournier et al., 2011), highlighted that not only quantitative methods should be used with Learning Analytics, but also the qualitative ones; in such cases, the recommendations could be provided to the learners based on their earlier learning activities. Our survey harvests two main qualitative analysis methods:

- *Emotional Intelligence*: Emotional intelligence is based on emotions, which relates to psychology and sociology. A general way of categorizing emotions is dividing them into positive and negative ones. The University of New England for example, has created an early alert engine called Automated Wellness Engine (AWE) in order to improve retention and decrease the dropout rate. The AWE is built on emoticons identification engine that is embedded into the university student portal. Based on various indicators, The AWE sends wellness reports which detail the reasons for withdrawal and wellness ratings within courses (Atif et al., 2013).
- *Qualitative Social Network Analysis*: This can take the form of virtual ethnography by including observations, interviews and surveys (Edwards, 2010). These qualitative data are then analysed by establishing a social network to transform it into a wider contextual findings.

The Act

In this stage, the analysis outcome is interpreted to achieve the objectives of Learning Analytics. The greatest value of Learning Analytics comes from optimizing the objectives, as interventions that affect the learning environment and its stakeholders (Clow, 2012). In the meanwhile, Learning Analytics aims to:

- *Prediction:* The objective of prediction is to explore an unknown numerical/continuous value such as performance, knowledge, score or grade (Romero & Ventura, 2010). Through prediction, learner activities and future performance can be revealed. Thus, an appropriate intervention would accomplish Learning Analytics goals.
- *Intervention:* A convenient intervention can for example: prevent drop-out, determine which students might be at risk, advise students who may need additional assistance and improve students' success.
- *Recommendation:* Learning Analytics can be mined for recommendations and activities of people (Duval, 2011). The main goal in the context of Learning Analytics is the aptitude to make recommendations to students based on their activities; e.g. recommend a discussion, suggest a course or recommend books related to what previous students consulted.
- *Personalization:* Related to recommendation, in which learners shape their personal learning environment. The objective behind personalization is to support learning for all students, improve educational performance and accelerate educational innovation (Pea et al., 2014). For instance, it can be carried out through personalizing e-learning based on learners' ability, or support students by personalizing learning suggestions.
- *Reflection and Iteration:* Reflection and Iteration are defined as self-evaluating of data clients induced by their own in order to obtain self-knowledge (Greller & Drachsler, 2012). The objective behind reflection is to evaluate the past work to improve future experience and to turn it into learning according to personalization and adaptation. This iteration can optimize all Learning Analytics stakeholders in the design of its life cycle.
- *Benchmarking:* Benchmarking is a learning process, which identifies the best practices that produce superior results. These practices are replicated to enhance performance outcomes (Vorhies & Morgan, 2005). Thus, through learning analytics, we can identify the weak points in the learning

1 www.cytoscape.org; (last access December 2014)

environment as well as educational performance and therefore, suggest and optimize methods in order to enhance learning.

Learning Analytics Constraints

There are constraints that affect Learning Analytics technologies. Ethical and privacy issues emerge while applying Learning Analytics in educational datasets (Greller & Drachsler, 2012). The large-scale of data collection and analysis can lead to questions related to ownership, privacy and ethical issues. In this study, we introduce eight-dimensional constraints that limit the beneficial appliances of learning analytics processes as shown in (figure 2).

Figure 2: Learning Analytics Constraints

Privacy: Conforming to the main objective of Learning Analytics, namely predicting, a professor for instance, can point a student who is at risk in his course. This could lead to the problem of labeling, which a learner is labeled as a "bad/good" student.

The Learning Analytics committee needs to carefully consider the potential privacy issues while analyzing students' data. Data analysis and customization can reveal personal information, attitudes and activities about learners. Therefore, some educators claim that educational institutions are using softwares that collect sensitive data about students without sufficiently considering data privacy and how eventually they are used (Singer, 2014). Datasets may include sensitive information about learners. Thus, anonymization or de-identification may be required to preserve learners' information. The student privacy law of Family Educational Rights and Privacy Act (FERPA)[2] advocates the usage of de-identification in higher education to preserve students' records privacy. There are various cryptographic solutions, anonymization techniques and statistical methods that hide the owner's identity (Fung et al., 2010). The study of (Slade & Prinsloo, 2013) pointed to the requirement of de-identification of data before it becomes available for the institutions use. This would serve the intervention of Learning Analytics based on students' activity and behavior while assuring the anonymity of their information.

Regulations and laws are a good consideration to address the privacy issue. The Open University in England has made the first step to regulate laws, specialized in Learning Analytics and privacy principles (OU, 2014). This is a good example that encourages other institutions to consider privacy as a fundamental element that should not be ignored.

Access: Authentication assures that only legitimate users have the permission to access and view specific data. Data access is relevant to policy regulations where these regulations must adhere to the authentication and authorization modules. The student should be allowed to update his/her information and have the ability to provide additional information when needed. In order to achieve student's privacy, there should be access levels for all Learning Analytics stakeholders. A student has the access level to view and update his information. A teacher is authorized to access students' data without the possibility of viewing sensitive

2 www2.ed.gov/ferpa; (last access December 2014)

information such as ethnic origin or nationality. Decision makers can sustain the data in order to meet the institutional perspective which focuses on preventing the high dropout rate that is considered as a failure of the university system (Grau-Valldosera & Minguillón, 2011). On the other hand, there are still unanswered questions about students, whether they have the right to access results of Learning Analytics, or do researchers have the morality to view and analyze students' data?

Transparency: Disclosing information is a major challenge for information providers. Learning Analytics methods should aim to be transparent and easily described to staff and students. The institution can take the step of assuring transparency by providing information regarding data collection, usage and involvement of third parties in analyzing students' information. Learning Analytics tools use techniques and models that seek to provide assistance to different stakeholders. It would be familiar that students may want to understand the methods of how their performance are being tracked, and based on that, how the evaluation and the interventions are processed. Moreover, students or their parents may ask about their sensitive data, and how much of the information is provided to the instructor.

Transparency in Learning Analytics does not mean that data should be available to the public. Nevertheless, we must bring it to all Learning Analytics involved sectors - educational, psychological and computer science with security experts - to develop the right technical and ethical principles in the whole Learning Analytics life cycle.

Policy: With the adoption of Learning Analytics in the educational fields, institutions are required to adjust their policies with legislative framework. According to the study of (Prinsloo & Slade, 2013), many institutional policies failed to fully reflect the ethical and privacy implications of Learning Analytics. Here, we list some possible regulations that an ethical Learning Analytics policy should describe: a) Collection of personal information, for example: sex, date of birth, address, ethnicity, occupational status, qualifications and study records. b) Describe the usage of this information, if it is for the benefit of the students, such as predicting students' behavior and a series of recommendations and advices based on Learning Analytics, or if it is for research reasons to achieve Learning Analytics objectives. c) Methodology of data collection either by the student's input him/herself or by other services, such as browser cookies. d) Security principles for keeping the data protected. e) A description of the time period of keeping learners' data and a definition of a deletion process. For instance, ClassDoJo, a student tracking company, announced to keep the students statistics for only one school year and to proceed with a deletion policy to remove students' records after their families complained about their children's private data (Singer, 2014).

Security: All Learning Analytics tools should follow expedient security principles in order to keep the analysis results and the students' records safe from any threat. The widely-spread security model known to security experts is the CIA, which stands for Confidentiality, Integrity and Availability (Anciaux et al., 2006). The confidentiality property, guarantees that the data can never be accessed by an unauthorized access. Integrity property guarantees that the data cannot be altered, snooped or changed. The availability property means that the data should be available for authorized parties to access when needed. In the scope of Learning Analytics, students' information and the analysis procedure should be kept safely and only accessible to authorized parties. A key component of protecting learners' information is encrypting their data in order to achieve the confidentiality concept. Encryption guarantees that only authorized people can use the data. Moreover, assuring confidentiality can include: invoking file permissions and granting a secure operating environment, while cryptographic hashing of datasets can assure the integrity property of students' records (Chen & Wang, 2008).

Accuracy: As Learning Analytics is an emerging research topic in the field of Technology Enhanced Learning and a forthcoming trend (Ebner & Schön, 2013), accuracy and validity of information is highly questionable. Mistakes related to picking a wrong dataset, or not recognizing the component relevant to data will negatively affect the accuracy of the outcome (Waterman & Bruening, 2014). Therefore, a wrong selection of educational dataset will lead to inaccurate results. The questions we can ask here are: What if Learning Analytics results were wrong? And what if the predications or the interventions went wrong? Accordingly, Learning Analytics would aim to provide guarantees that it's analyzing, and picking the data, fit quality criteria and produce an agreed level of accuracy.

Restrictions: Data protection and copyright laws are legal restrictions that limit the beneficial use of Learning Analytics. Such legal restrictions are: limitations of keeping the data for longer than a specific period of time, which are regulated differently in each country; the data should be kept secure and safe from internal and external threats; data should be used for specific purposes and the results of any process should be as accurate as possible. The restrictions could be stronger when it relates to personal information. Applying social network analysis as a method of learning analytics causes the adoption of personal information, therefore, these methods should meet the regulations of using individual's information.

Ownership: There are two main perspectives about who own the data: students and institutions. (Jones et al., 2014) concluded that neither the students nor the institutions should win the ownership of the data. They suggested a hybrid module that merges both perspectives. Institutions can invest the students' data in analytics, develop new personalized learning platforms and benchmark their learning management system. While students want to enhance their learning and maintain their performance, they would like to ensure that their information is kept confidential. An uprising question we like to address here is: What if Learning Analytics methods have to modify the students' data for prediction purposes?

Learning Analytics - Principles & Constraints Framework

After the discussion of Learning Analytics cycle and quandaries, we present the final proposed framework that combines the principles and constraints. (Figure 3), illustrates Learning Analytics – Principles & Constraints framework.

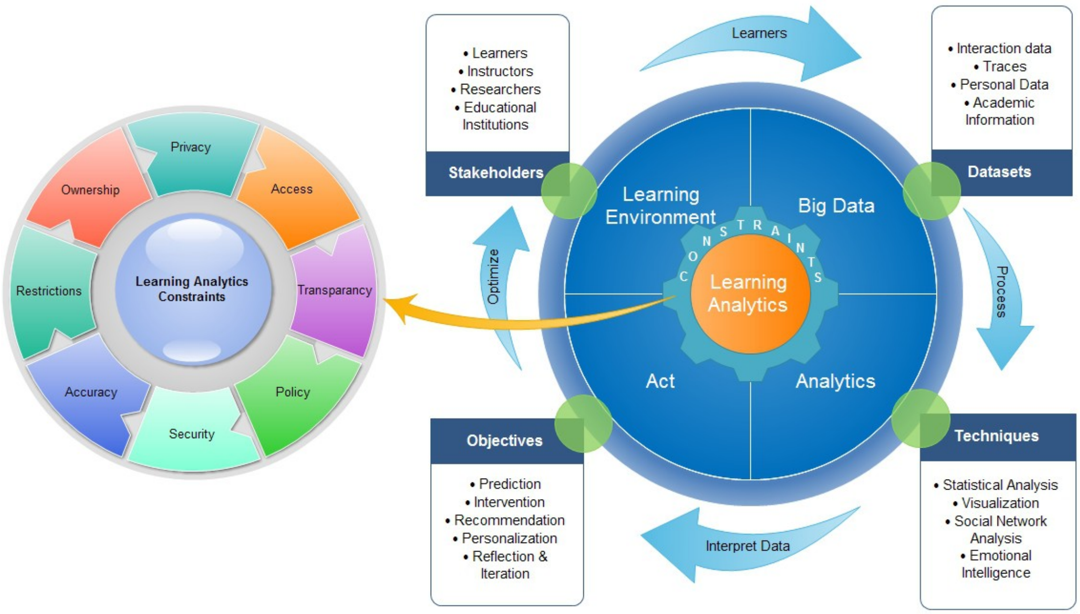

Figure 3: Learning Analytics - Principles & Constraints Framework

The final proposed framework shows Learning Analytics main sections, process flow, methodologies, and objectives, namely as – life cycle, and eight-dimensional constraints encompass the central processes of Learning Analytics. These constraints do not relate to a specific principle, but relate to the entire Learning Analytics proceeding in general.

Conclusion

Learning Analytics is a promising research field, which provides tools and platforms that influence researchers in Technology Enhanced Learning. For instance, there are several institutions that have taken an analytical approach when deciding to update their learning management system (Cooper, 2013). Nonetheless, this emerging new field lacks an approach that delineates a complete overview of its processes. It could be said that learning analytics is advancing quickly, but it is not yet in full bloom. This research study reviewed the definitions of Learning Analytics and the factors that drive its emergence expansion. Then we proposed an approach that portrays a Learning Analytics life cycle. This provides an entire overview consisting of: learning environment, big data, analytics and the interventions which are interpreted to achieve the main goals of Learning Analytics. Based on this approach, we identified the stakeholders, introduced examples of usage, presented methodologies and discussed the objectives. After that, we paved the way of determining the challenges that surround Learning Analytics and shed the light on the privacy, security and ethical issues and anticipated questions that need a further research in near future. In the last section, we presented our vision of a framework that combines both principles and constraints and reflects our vision of the quintessence of Learning Analytics.

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