

The Role of Learning Analytic in Education Reform

Ruihong Dai

Wenzhou Polytechnic, Wenzhou, Zhejiang, 325000, China
Email: 424287186@qq.com

Abstract. In year 2009, the nascent research community of Educational Data Mining (EDM) has been found to continually and increasingly grow. Now the education data mining has become popular and deeply studied in all universities. Specially, in United Kingdom, United State, Canada, they held several conferences annually on learning analytic discussion, which is related with Educational Data Mining. Learning analytics refers to the collection of large volume of data about students in an educational setting and to analyze the data to predict the students' future performance, identify risk and provide recommendations for improvement. LA is an increasingly emerging field, it is necessary for higher education stakeholders to become more familiar with the issues related to LA's use in education. Such a paper provides a brief introduction, methods and benefits, and challenges of LA.

Keywords: learning analytic, educational data mining, method and benefits

1 Introduction

The purpose of Learning analytics (LA) represents measurement, collection, analysis and reporting of data about learners and their contexts, then understanding and optimizing learning and the environments in which it occurs (Melanie Booth, 2012). Worsley & Blikstein (2014) argued that it was an advanced tool to solve a human problem which is impossible to resolve in the past years, this is, learning analytic was used to study a complex learning process. The personalization, accessibly and efficiency were supported by learning analytic, which was a powerful and technology-based approach, compared with traditional learning methods (Goldstein, Vieira, Purzer & J. Magana, 2016). As Scheffel et al (2014) mentioned LA is a multi-disciplinary method, which based on data processing, technology-learning enhancement, educational data mining, and visualization. Despite, LA is similar with Educational Data Mining, it pays attention in separated field. Learners were feedback by Educational Data Mining systematically and automatedly, this is, educational data mining focuses on the development of new computational data analysis methods. By contraries, LA prefers to the application of known methods and models to address issues affecting student learning (Bienkowski et al., 2012). This difference lead to a result that, compared with only educational data mining, LA can help learners and educator make constructive decisions and more effectively perform by increasing their awareness in current situation (Scheffel et al., 2014). Although, there are LA researches and studies used in higher education institutions within those several years, LA is still an emerging field of education. As Seheffel et al (2014) said that it is necessary for higher education stakeholders including leaders, administrators, instructors, and course developers to be familiar with LA methods and application.

2 Method and Benefits

2.1 Methods

Before introducing the method and benefits of LA, there is a question that why we need it? Complex and persistent learning process needs a multi-disciplinary solution and directly method. In this process, the learning profession requires measurement, evaluation and analytic which was insufficient in the past years. Analytic, actually, was not only utilized in learning, but also was increasingly used in other sectors. Supermarkets, for example, analytic data on purchasing patterns, effectiveness of marketing campaigns, etc. in order to target spending and manage stock levels. It has also been suggested that analytics helped Germany win the 2014 World Cup. Despite those above instances are irrelevant and

totally different from learning analytic, it indicates that type of analysis process can help to improve original model, identify potential problems, increase efficiency and predict the future result as well as learning analytic. According to those reason, LA is necessary to access to higher educational field. Goldstein, Vieira, Purzer & J. Magana (2016) result research LA method through literature review (synthesizing the literature) which was suggested by Cooper (1988). Firstly, in their research, learning analytic process, which play an important role in LA, is discussed when realizing analytic learning approaches. In educational background, flow of analytical information has been raised which as an important role in process. Considering the complexity and diversity for flow of information, that is, “the flow of analytical information can be traced from the students to the stakeholders within the framework of a hierarchy (Reyes, 2015)” and include indispensable and unwanted information. Thus, the flow of information is necessary to be predigested. At the same time, researchers provided a structured process to collect and analyze data from macroscopic aspects within educational level. Collecting data, reporting the trends and model of data, statistical regression, an intervention to improve learning, and refining the developed model was designed to implement learning analytic (Campbell and Oblinger, 2007). Additionally, based on Campbell and Oblinger (2007)’ experiment design, Clow (2012, 2013) proposed a learning cycle that researchers capture data from learners, make data index-given and interpose learners by index repeatedly as a circulation. This research process offers LA a basic approach to deal with data and reflect them to learners. Secondly, the specific methods supported such as data visualization tools and techniques. Meanwhile, it is popular that other five methods prediction, clustering, relationship mining, discovery with models, and separation of data for use in the process of human judgment are currently used by LA researchers (Baker, 2010; Baker & Yacef, 2009; Romero & Ventura, 2010).

Data visualization tools and techniques: Data visualization is the process of displaying data/information in graphical charts, figures and bars. According to the complexity of learning process, data visualization can deduce this complexity through making use of advanced calculating approach and graphic which indicate trends and patterns in data groups, in the other hand, finding the elements in data, variables can be decreased into few (Johnson, Levine, Smith & Stone, 2010).

Prediction: Prediction can be divided into three sectors as classification, regression, and density estimation. For example, Baker (2010) supported decision trees, logistic regression, and support vector machine regression to compare with those three categories respectively.

Clustering: The aim of clustering includes discovery of data points in a naturel data group (Baker, 2010). Additionally, Clustering can help researchers to identify and observe the data whose types are unknown. In logical cluster groups, researchers can evaluate how cluster sets explain the meaning of the data.

Relationship mining: In the larger and complex data, relationship mining can help researchers to distinguish the relation between one variable with other larger amount variables, confirm which variables should be considered in their research depending on the relationship of strength. Baker (2010) described statistical significance and interestingness as necessary elements in relationship mining. Relationship mining get an ability to reduce error in data selection and expend data selectivity.

Discovery with models: In educational field, the rapid growth of students’ interaction data result in the educational data mining and LA model mushrooming (Baker & Yacef, 2009; Romero & Ventura, 2007, 2010; Siemens & Long, 2011). Although, Goldstein et al (2016) didn’t describe much in discovery with models, Hershkovitz et al (2013) argued it was significant to see the potential of discovery with models’ contribution to theory. For instance, carelessness research was sparse according of the complexity in operation. A Better model support research to find the points which give rise to students’ carelessness so that mitigate the negative effect (Hershkovitz et al, 2013), that is, using prediction, clustering or knowledge engineering to develop a model and to predicate and cluster like a cycle (Baker, 2010).

Separation of data for use in the process of human judgment: The purpose of separation of data for use in the process of human judgment are identification and classification in visualization. An example was cited by Baker (2010) that when the visualization data which is easy to recognize but difficult to represent in a public-understanding pattern, distilling data can help to identify and classify the indefinable partly data.

2.2 Benefits

In learning analytic, useful information has been identified which can profit students, teachers, educational institution and researchers in variety ways. For example, learning analytic support a prediction to students for their future opportunity with the large, complexity and potential data in and out of campus. That is, LA can suggest students to select the best choice in a variety possibility, it gets rid of the weak option. Goldstein et al (2016) divided seven parts to brief describe the benefits for LA. In this section, those seven classifications are combined in organization level, curriculum' level, educators' level, students' level and future predication with agreement and argument. Before talking over those benefits, it is necessary and significant to assume that the LA support the correct and careful analysis result to researchers and educational related organization. Otherwise, every benefit can be broken in view of the wrong learning analytic results.

Educational institution area: Educational institution can focus resource to the course which are attracted by students with the data reflect to educational institution from enrollment and feedback. Meanwhile, the resource can also be distributed to the courses which are advanced and accomplished with achievement, which come from visual data graphs and analyses. It assists the historic universities to make more rational use of teaching and research resources and, for newborn universities, plans a further enrollment (Althubaiti & Alkhazim, 2014) and advanced and added major construction. The educational institution can draw up a strategic plan on the basis of learning analytic. It existed an argument that, for example, a course was attracted by huge mount of students on amount of its difficulty, that is, it is more easily to get a high grade in this course. However, actually, this situation cannot be considered because of the hypothesis. Observably, this course data was filtrated in LA as a misdirecting error data to deal with.

Curriculum' area: Teaching method can influence learners' status which reflects as data to learning analytic such as the concentration of attention, comprehension and adaptability. The learning analytic is able to offer suggestion to teachers or educational organization to make a changes and adjustment to improve curriculum. Researchers observe learners' weakness and strength expressed when they are in course. Sequentially, according to the former and later data compared, learning analytic assist to develop curriculum. Goldstein et al (2016) also mentioned that LA can keep the purpose of curriculum to satisfy the requirement of students' motivation and maximize learning ability. There is no doubt that LA can directly see the weakness and strength of a curriculum and end up an improvement loop, which means that curriculum can maximize its advantage and minimize its disadvantage.

Educators' area: It accelerate educators force more on their self-improvement. Recently, the interaction of e-learning data exits in educational institution's database. It not only represents learner's experience of learning, but also store educators' positivity, feedback from learner, quality of teaching, teaching method, etc. learning analytic can offer an opportunity to evaluate their qualification to be as an educator by the data be from interaction with students, behavioral comparison and feedback. Xu & Recker (2012) cited a case that learning analytic can determine educators by their online interaction from online libraries or research tools. This crisis awareness caused by LA push educators have to enhance themselves. Meanwhile Hung & Zhang (2012) pointed that instructors, through data analytic, can understand experience of learning from student by technique tools. That is, educator can deeply understand learner's requirement and know their own deficiency to adjust to adapt instruction. But the question is that how to determine the standard. For example, there are two educators that educator A have a high teaching skill, through data compared, educator A can improve itself to offer a better quality of teaching but educator A don't be willing to do it. For Anther educator B, although educator B have enough activity to enhance itself, the limitation exists and cannot catch up with educator A's capacity. For this case, the learning analytic was suffer a shock the standard is different to determine, even if it set up different target for different level educators because it is inequity for everyone. That is, why the higher-level educator assumes a higher responsibility, whereas the lower one enjoys the lower responsibility. This is an argument to educator' level benefits which makes learning analytic more complexity to deal with, analyze and result in human-related problems, despite AlShammari et al (2013) noted that there is positive result in enhancing educator's instruction.

Learner' area: The frequency of student login, interaction within the classroom, total engagement, pace, and grades are regarded as predictors of students' potential success or failure (Goldstein et al 2016). Personalized learning has been supported under the situation with learning analytic, which target

to solve different learning requirement, interests, cultural backgrounds of individual students etc. The original course designed for public ones not consider others who exceeded or fall behind the same learning stage because there is a various course mastery require course before they accept education, the talent is different for everyone (Dietz-Uhler & Hurn, 2013). LA offer an opportunity to succeed personalized learning. According to data collecting from learners, courses and instructors, LA is able to reflect distinct suggestion responsibility to them to adjust to service for different learners in different approach. Learning analytic allows faculty to provide meaningful feedback to student based on predictive models like Course Signal (Arnold, K. E, 2010) but do much better than Course Signal. A question has arisen that whether it is technological determinism. Despite the target of personalized learning is cultivating learners individually, there is no emotion in data analytic. That is, learners accept suggestion and adjustment scheme which LA provide and learners, actually, become better than before in learning process but not the person the learner want to be. The potential target in LA is that to make the leaner better and efficient in all aspects but ignore personal willingness. The noun “good” originate from the analytic, the analytic results originate from the history and designers. It means that LA make learners be the best as they can be, in other hand, LA technique determines what kind of person you should be with data analytic, although it is true.

Future predication area: Because of the huge database, learning analytic supplies detail list of employment opportunity in a various industry for post-graduation, which means it predicts employment, unemployment and uncertain opportunities (Jantawan & Tsai, 2013). In a global learning environment, that predicated information not only may prove useful to organizations as they make hiring and budgeting decisions for college graduates in different disciplines, but also can facilitate better educational and post-education vocational planning, as Goldstein et al (2016) noted. Additionally, LA not only predict employment for post-education, but also can predict the Selection of academic research. LA can supply the prediction of academic research to learners before they graduate, that is leaners are able to make plan for future further research study with the advice be from LA. It assists to predict the suitable research option from a variety of disciplines for under-graduations.

3 Challenges

The challenges can be brief divided into two major factors: internal and external challenges. As an emerging technology, the learning analytic now and future development require emerging and continuous current and potential technology which may be still in younger stage. The accuracy and efficient are required in data collection, tracking and analytic. Due to the hugeness of data, how to track data efficiently and collect data precisely has become a question to learning analytic. The innovation of emerging technology and more advanced teaching platform assist learning analytic to face obstacle. Since learning analytic is still in a developing stage, competitiveness between different educational and research institution exists. This competitiveness causes the requirement of the learner population who want to engage in this type of learning experience, which is limited and difficult for research. With the passing of time, those type of conference and research has become increasingly. Furthermore, instead of individual study, the educational institution is also willing to share the research achievement to others to collaborate. The most internal severe resistance is data analysis which includes technological aspect and professionals. Erroneous data can skew the researches to lead a misinterpretation and correct data with erroneous analysis can also skew the findings causing a misunderstanding of the overall population. For instance, a learner is provided adjustment by learning analytic which is erroneous as an erroneous analysis process. The learner accepts the advice without any beneficial effect causing dispute to learning analytic or result. Meanwhile, the learner cannot find the reason because there is so much adjustment that cannot identify which one is the bug. What is worse, those bug data flow into the flow of big data all over the world giving rise to the inaccurate findings with who recall this data. Similar, the designer or the researchers must be professionals who possess enough knowledge to face temporary and emergency situation. This type of people is rare or growing. Vahdat et al (2015, p. 299) emphasized that finding an approach to connect “cognition, metacognition, and pedagogy” is an essential capacity.

Besides, the external challenge are ethical and privacy issues. For example, the University of Edinburgh especially set a regulation for protection privacy authority and preventing ethical issues: “...Analytics at the University are exclusively used to understand and increase the success and learning

experience of our students, enhance instruction capabilities of teaching staff, and inform institutional data making. The University takes an active role in national and international initiatives that support the ethical and privacy protective use of learning analytics, and all research activities in this area are carried out in accordance with the UK Research Integrity Office: Code of Practice for Research.” Furthermore, data interpretation, ownership and preservation, sharing data and proper training of members connected with data, which are latent, are concerned. In the other hand, the obvious areas include consent, data accuracy, maintaining anonymity and the potential effects to students (Sclater, 2014b).

4 Conclusion

This study provided an overview of the analytical learning methods, benefits, and challenges regarding the use of big data in education. As an interdisciplinary field, learning analytic utilizes disciplines, methods and analysis technology to reach the target which is improving learners, instructors and educational institutions in the high education area. Complex and persistent learning processes need a multi-disciplinary solution and direct methods. In this process, the learning profession requires measurement, evaluation and analytics which were insufficient in the past years. Besides as a data visualization, learning analytic methods follow prediction, clustering, relationship mining, discovery with models, and separation of data for use in the process of human judgment, which are supported by Baker (2010). As an emerging technique tool in the educational field, the benefits have been described in particular. Though learning analytics appear to demonstrate a comprehensive representation of benefits within education, the arguments and considerations raised in each strength mentioned with approval, query and question. With insufficient experience in the world, learning analytics is too young to face huge and a mass of challenges, which are internal and external. Emerging and advanced technology can support more useful and powerful assistance to learning analytics, in the other hand, there must be enough technique favor. Furthermore, ethical and privacy issues are brought to the forefront as an external challenge. The flow of information, which was utilized as data to analyze, includes learners, educators and organizations' personal information. This type of information flows in the cloud web. Thus, these considerations can include obvious areas of privacy considerations such as consent, maintaining anonymity and the potential effects to students. In fact, the institution sets a connected role before they start learning analytic research.

Reference

1. AlShammari, I. A., Aldhafiri, M. D., & Al-Shammari, Z. (2013). A meta-analysis of educational data mining on improvements in learning outcomes. *College Student Journal*, 47(2), 326-333.
2. Althubaiti, A., & Alkhazim, M. (2014). Medical colleges in Saudi Arabia: Can we predict graduate numbers? *Higher Education Studies*, 4(3), 1-8.
3. Althubaiti, A., & Alkhazim, M. (2014). Medical colleges in Saudi Arabia: Can we predict graduate numbers? *Higher Education Studies*, 4(3), 1-8.
4. Arnold, K. E., (2010). Signals: Applying academic analytics. *EDUCAUSE Quarterly*, 33, 1.
5. Arnon Hershkovitz, Ryan S.J.d. Baker, Janice Gobert, Michael Wixon & Michael Sao Pedro., (2013). Discovery with Models: A Case Study on Carelessness in Computer-based Science Inquiry. *American Behavioral Scientist*.
6. Avella, John T.; Kebritchi, Mansureh; Nunn, Sandra G.; Kanai, Therese., (2016). Learning Analytics Methods, Benefits, and Challenges in Higher Education: A Systematic Literature Review. *Journal of Interactive Online Learning* · June 2016
7. Baker, R. (2010). Data mining for education. *International Encyclopedia of Education*, 7, 112-118.
8. Baker, R., & Yacef, K. (2009). The state of educational data mining in 2009: A review and future visions. *Journal of Educational Data Mining*, 1(1), 3–16.
9. Baker, R., & Yacef, K. (2009). The State of Educational Data Mining in 2009: A Review and Future Visions. *JEDM | Journal of Educational Data Mining*, 1(1), 3-17. Retrieved from <https://jedm.educationdatamining.org/index.php/JEDM/article/view/8>

10. Bienkowski, M., Feng, M., & Means, B. (2012). Enhancing teaching and learning through educational data mining and learning analytics: An issue brief. U.S. Department of Education, Office of Educational Technology. Washington, D.C. Retrieved from <http://www.ed.gov/technology>.
11. Campbell, J. P., & Oblinger, D. G. (2007). Academic analytics. Educause. Retrieved from <http://net.educause.edu/ir/library/pdf/pub6101.pdf>.
12. Campbell, J. P., De Blois, P. B., & Oblinger, D. G. (2007). Academic analytics: A new tool for a new era. *Educause Review*, 42(4), 40-57. Retrieved from <http://www.educause.edu/ero/article/academic-analytics-new-tool-new-era>
13. Clow, D. (2012). The learning analytics cycle: Closing the loop effectively. Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (pp. 134-138). New York, NY: ACM. doi:10.1145/2330601.2330636
14. Cooper, H. (1988). The structure of knowledge synthesis: A taxonomy of literature
15. Dietz-Uhler, B., & Hurn, J. E. (2013, Spring). Using learning analytics to predict (and improve) student success: A faculty perspective. *Journal of Interactive Online Learning*, 12(1), 17-26.
16. Ganesan Kavitha1, Lawrance Raj: Educational Data Mining and Learning Analytics - Educational Assistance for Teaching and Learning. *International Journal of Computer & Organization Trends (IJCOT) – Volume 41 Number 1- March 2017*
17. Goldstein, Vieira, Purzer & J. Magana (2016): Using Learning Analytics to Characterize Student Experimentation Strategies in Engineering Design. *Journal of Computer Assisted Learning* 3(3):291-317
18. Hung, J., & Zhang, K. (2012). Examining mobile learning trends 2003-2008: A categorical meta-trend analysis using text mining techniques. *Journal of Computing in Higher Education*, 24(1), 1-17. doi: <http://dx.doi.org/10.1007/s12528-011-9044-9>
19. Jantawan, B., & Tsai, C. (2013). The application of data mining to build classification model for predicting graduate employment. *International Journal of Computer Science and Information Security*, 11(10), 1-7.
20. Johnson, L., Levine, A., Smith, R. and Stone, S. (2010): Empirical Analysis of Factors Affecting the E-Book Adoption—Research Agenda. *Open Journal of Social Sciences*, Vol.2 No.5, May 12, 2014
21. Melanie Booth (2012): Learning Analytics: The New Black. <https://er.educause.edu/articles/2012/7/learning-analytics-the-new-black> reviews. *Knowledge in Society*, 1, 104-126.
22. Romero, C., & Ventura, S. (2010). Educational data mining: A review of the state of the art. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, 40(6), 601-618.
23. Scheffel, M., Drachsler, H., Stoyanov S., & Specht, M. (2014). Quality indicators for learning analytics. *Educational Technology & Society*, 17(4), 117–132.
24. Sclater, N. (2014b, November). Code of practice for learning analytics: A literature review of the ethical and legal issues. Retrieved from http://repository.jisc.ac.uk/5661/1/Learning_Analytics_A_Literature_Review.pdf
25. Vahdat, M., Ghio, A., Oneto, L., Anguita, D., Funk, M., & Rauterberg, M. (2015). Advances in learning analytics and educational data mining. Proceedings from 2015 European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, Belgium. Retrieved from <http://www.idemployee.id.tue.nl/g.w.m.rauterberg/publications/ESANN2015paper1.pdf>
26. Worsley, M., & Blikstein, P. (2014). Analyzing engineering design through the lens of computation. *Journal of Learning Analytics*, 1(2), 151–186.
27. Xu, B., & Recker, M. (2012). Teaching analytics: A clustering and triangulation study of digital library user data. *Journal of Educational Technology & Society*, 15(3), 103-115.