International Journal on Engineering Technologies and informatics

Learning Analytics and Deep Learning in Large Virtual Learning Environments (VLEs)

Short Communication

Volume 3 Issue 1- 2022

Author Details

*Nkesi Wechie, Mike Brayshaw and Neil Gordon**

Department of Computer Science & Technology, University of Hull, UK

*Corresponding author

Neil Gordon, Department of Computer Science & Technology, University of Hull, Cottingham Road, Hull, HU6 7RX, UK

Article History

Received: June 01, 2022 Accepted: June 06, 20222 Published: June 08, 2022

Abstract

In this paper we look at the use of Deep Learning as a technique for Education Data Mining and Learnng Analytics. We discuss existing approaches and how Deep Learning can be used in a complimentary manner in order to provide new and insightful perspectives to existing Learning Analytics Tools and Machine Learning Algorithms. The paper first outlines the context, before considering the use of Big Data. A case study of a Large Virtual Learning Environment (VLE) is introduced. The paper presents a series of Deep Learning Experiments with this Data Set and the new insights this has led to. The paper concludes with a discussion of how this approach compliments other Learning Analytic work in a similar context.

keywords: Learning Analytics, Educational Data Mining, Deep Learning.

Introduction

In this paper we will present Deep Learning as a comparative technique to other existing and tried out Educational Data Mining Techniques and in so doing investigate its comparative strengths and weaknesses. This view is a complimentarist, namely that what you are looking for may be best served by a variety of approaches, depending upon the research question under investigation.

Learning Analytics aim to find extra and new information from the wealth of data that learning interaction produces, to give insights to better inform and personalise the learning experience of the student. The new perspectives that they yield can transform interactive education systems to better cater for an individual's or group's needs and support them on their particular educational journey. Traditional Educational Data Mining (EDM) has used techniques such as visualisation, association nets, decision trees, rule induction, stochastics techniques (e.g. Baysian reasoning or Markov chains), and AI in the form of shallow neural networks. In the work presented here we further expand this repertoire toward a goal of more flexible and personalised learning.

The use of AI in the classroom is a topic that is gaining both momentum and visibility at a great pace in recent years. Machine Learning provides an additional tool to the EDM arsenal. In this paper, we employ Deep Learning to expand and improve the understanding of a learner's state to improve their learning, teaching, and assessment. Deep Learning is a development of neural AI that uses more layers of individual units within the network to provide a more sensitive detection of patterns. It has already been used elsewhere to great effect to provide awareness of hidden knowledge.

In the context of Learning Analytics we here apply Deep Learning to revisit and enhance our perception of key interaction features that can give a better understanding of a user's state and subsequent pedagogical needs and requirements. The approach is therefore one that is much more in tune with learning and interaction considerations, not just on the student outcomes. We here propose, in addition to outcome prediction, a more fine grain analysis that look for a finer detail of student performance and how this might be identified so that we have a more causative model of observed outcome, one that is much more focused on the circumstances of the students themselves. Such states of learning include (with symptomatic signs):

©2022 Wechie, et al. This work is published and licensed by Example Press Limited. The full terms of this license are available at https://skeenapublishers.com/terms-conditions and incorporate the Creative Commons Attribution – Non Commercial (unported, v3.0) License (http://creativecommons.org/licenses/by-nc/3.0/). By accessing the work you hereby accept the Terms. Non-commercial uses of the work are permitted without any further permission from Emample Press, provided the work is properly attributed.

- Engagement indicators - log-ins, how many log-ins, when do this access the coursework/revision notes e.g. all the time vs at the very last minute;
- Spotting drops out – indicators such as Loneliness and Alienation;
- Wheel spinning - characteristics of being stuck – not moving on and unsuccessfully doing the same set of exercises again and again;
- Predicting Outcomes – based on Marks, Extensions, Re-submission, Non-Submission and Failure.

In this paper we apply Deep Learning via the Google engine Tensorflow to a large VLE data set [1,2]). OULEARN has already been extensively mined by existing techniques. The paper presents in details the existing findings and state of the art in order to find a starting point to base our comparisons upon

The approach of this research follows from Hassan et al (2019). The wheel spinning in the research will be used to imitate the interaction patterns of students' correctness to responses in their module course. The research will also explore the relationship between student's dropout, Learning and wheel-spinning using their assessment study profile generated from the OULAD VLE dataset [2]; besides that, the clickstreams learning interactions for each students' daily activities in the course periods across views is also used.

Background and Approach

The problem of identifying student academic challenges in order to optimise the academic performance of students has been an area of concern for several decades [3]. Within higher education, there has been a focus on teaching and assessment that will promote students to be independent managers of their own learning experience, especially within virtual learning environments [4]. Digital technology of the virtual learning environment generates more accessible teaching-learning assessments of students' academic learning experiences and can provide interactive engagement activities. These digital environments offer new opportunities for Educational Data Mining and the opportunity to give new learning analytics [5-8]. These identify a range of the learning analytic questions and answers that are can potentially be addressed through differing techniques. The work here aims to compliment the range of these inquiries and explores an alternative way of addressing them. A similar range techniques are also reviewed in Sin et al. [9] in relation to a range of learning analytics question, ustiliding Big Data approaches. They note that the increasing use of Learning Management Tools (LMS – equivalent to the VLEs in this paper) mean that today's students increasingly produce large amount of Big Data in the everyday activities.

Hlosta et al. [1] used a General Unary Hypothesese Automation and Markov Chain-based analysis methods of educational data mining. They looked at course assignment data and whether students had submitted, but not their scores. They found a strong (90%) correlation between failure to submit. Jha et al. [2] used a full set of features, and attempted to find the key features that that show the attributes that indicate these behaviours. Not only did they look at student dropout rates, but also at how to predict student performance. Models based on student interaction were good predictors of both performance and drop out.

In the work outlined here, we look at a student centric and problem solving behaviour rather than just had metric of performance and drop out. In particular the type of pattern of behaviour we investigate are shown in Table 1.

The work that we outline and propose here is to extend the feature analysis presented above. to look specifically in the post-mortem data of the students interactions and identify ones more focused on providing insights into a student thinking and fine-grained problem solving. In providing learning analytics of this type we aim to directly support their problem solving and in doing so get a more personalised basis for subsequent tutor intervention.

Table 1: student behaviours and indicators

Target Behaviour	Typical indicators of our target behaviours
Engagement	Log ins, how many logins, when do this access the coursework/revision notes e.g. all the time vs at the very last minute
Spotting drops out	Last logins, failure to submit work, decreasing patterns of engagement
Wheel Spinning	Characteristics of being stuck – not moving on and unsuccessfully doing the same set of exercises again and again
Outcomes	Marks, Extensions, Re-submission, Failure. Non Submission

To find a validated proven accuracy, a data validation process was used to ensure that the data is clean for quality usage and pre-production. To achieve a potential outcome on this result, we implemented classified data pre-production. To improve prediction accuracy, we measured and calculated filtered data necessary for establishing classified categories tasks, and compared it to other simulation results of data categories. We checked the proportion of each performance of the compared categories, we identified that each categories task had a different percentage size in their performance task:

We compared the overall percentage outcome of Students learning engagement or attendances based on the assumption this would improve retention rates in an institution, and compare it with the prediction performances of students who dropped out, withdrew, or passed. Thus, if a student attends regular classes and does not put more effort to persist in their learning study despite academic stress, that student may not do well even if they have a good attendance record. In such a situation, if the student doesn't have proper support, it may lead to depression and unproductivity i.e. to wheel spinning. Wheel spinning occurs when a student persists in their study but yet cannot take advantage of the learning opportunity despite regularly committing to a course study, regular attendance etc.

Students' performances or engagement can be measured with different forms or methods on their students' academic performances such as clickstream interactive activities, quizzes reading, questionnaires, discussion forums, and observation of group interactions. In the context of this research study, students were measured based on their general categories of evaluation grade-performances, weekly activities, clickstreams in everyday activities and compared with the categories of final_result performances. The established classified result is used to represent each category of dimensional learning or interactive activities [10-17].

Figure 1 represents assessment features that were used to measure the classified task assignment for students' grades and likewise, provide detailed information for each category task that required decisions to provide critical information about student success. To identify the important aspects of students' academic performances and their learning engagement, the featured model was used to illustrate the attributes of different categories of class for each feature. In the experiment study, we consider the information gains weighted by the number of the feature samples split by each feature classified task of the built models. We were able to identify and rank recommended features that are can be used to indicate academic engagement. Using all of the features to build an accurate model, based on the data generated from the OULAD VLE datasets for students' participation, we were able to obtain scores for each students' performances and assisted in identifying students who are at risk of dropout or withdrawing.

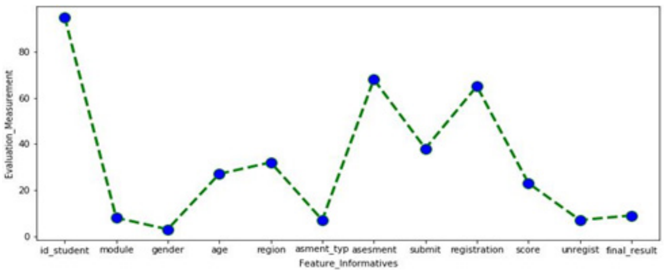

Figure 1: Plotting the recommended features that are informative for each category task performances of data visualisation.

Conclusion

Wheel spinning behaviour is an indicator of students who would benefit from intervention.

We identified that Deep Learning algorithms learn from high-level features from data, and learning analytics is suitable for Big Data. The study applied deep neural networks to build models with the use of neural network architectures to automatically learn multiple levels of representation features directly from the collection of learning interaction data. This provided some indicators for student academic grade performances and to identify wheel-spinning before dropout

There are some limitations to this approach, namely that it is dependent upon large amounts of data in order to effectively train the Deep Learning algorithm. In many areas this will not be forthcoming given the size of classes and the limited time window for data gathering. However, with the current trend to using VLEs institution wide and the massive participation in MOOC style delivery, there exists a considerable scope for the application of this approach.

References

1. Jha NI, Ghergulescu I, Moldovan AN, OULAD MOOC Dropout And Result Prediction Using Ensemble Deep Learning And Regression Techniques, In Proceedings of the 11th International Conference on Computer Supported Education (CSEDU 2019); 2019: 154-164, 2019.
2. Hlosta Martin, Herrmannova Drahomira, Vachova Lucie, Kuzilek Jakub, Zdrahal Zdenek, et al. Modelling student online behaviour in a virtual learning environment. In: Machine Learning and Learning Analytics workshop at The 4th International Conference on Learning Analytics and Knowledge (LAK14), 24-28 March 2014. Indianapolis: USA; 2014: 24-28.
3. Yorke M, Longden B (2004) Retention and student success in higher education. McGraw-Hill Education (UK).
4. Lopez-Fernandez O, Rodriguez-Illera JL (2009) Investigating university students' adaptation to a digital learner course portfolio. Computers & Education 52(3): 608-616.
5. Avella JT, Kebritchi M, Nunn SG, Kanai T (2016) Learning analytics methods, benefits, and challenges in higher education: A systematic literature review. Online Learning 20(2): 13-29.
6. Banihashem S, Aliabadi K, Pourroostaei Ardakani S, Delaver A, Nili Ahmadabadi M (2018) Learning Analytics: A Systematic Literature Review. Interdisciplinary Journal of Virtual Learning in Medical Sciences 9(2).
7. Leitner P, Khalil M, Ebner M. Learning Analytics in Higher Education—A Literature Review. In: Peña-Ayala A (eds) Learning Analytics: Fundaments, Applications, and Trends. Studies in Systems, Decision and Control. Springer: USA; 2017.
8. Leitner P, Ebner M, Ebner M. Learning Analytics Challenges to Overcome in Higher Education Institutions. In: Ifenthaler D, Mah DK, et al. (eds) Utilizing Learning Analytics to Support Study Success. Springer; USA: 2017.
9. Sin K, Muthu M (2015) Application Of Big Data In Education Data Mining And Learning Analytics – A Literature Review. Journal On Soft Computing: Special Issue On Soft Computing Models For Big Data 5(4).
10. Agnes Lydia, Sagayaraj Francis F (2019) A survey of Optimization techniques for deep learning networks GPUs. International Journal for Research in Engineering Application & Management.
11. Alshabandar R, Hussain A, Keight R, Laws A, Baker T (2018) The application of Gaussian mixture models for the identification of at-risk learners in massive open online courses. In: 2018 IEEE Congress on Evolutionary Computation (CEC). p. 1-8.
12. Avella JT, Kebritchi M, Nunn SG, Kanai T (2016) Learning Analytics Methods, Benefits, and Challenges in Higher Education. A Systematic Literature Review 20(2).
13. Clark D (2013) MOOCs: Taxonomy of 8 types of MOOC.
14. Jona K, Naidu S (2014) MOOCS: emerging research. Distance Education 35(2): 141-144.
15. Lim Bryan, Arık Sercan Ö, Loeff Nicolas, Pfister Tomas (2021) Temporal Fusion Transformers for interpretable multi-horizon time series forecasting. International Journal of Forecasting 37(4): 1748-1764.
16. https://www.nltk.org/
17. Sharma S, Tyagi V, Vaidya A (2021) Sentiment Analysis in Online Learning Environment: A Systematic Review. In: Singh M, Tyagi V, et al. (eds) Advances in Computing and Data Sciences. ICACDS 2021. Communications in Computer and Information Science: Springe; 2021.

Citation: PWechie N, Brayshaw M, Gordon N. Learning Analytics and Deep Learning in Large Virtual Learning Environments (VLEs). *Int J Eng Tech & Inf.* 2022;3(1):1–3. DOI: 10.51626/ijeti.2022.03.00029