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ENHANCING EDUCATORS' CREDIBILITY IN INTELLIGENT LEARNING ENVIRONMENTS

Mario Mallia Milanes, & Matthew Montebello
Department of Artificial Intelligence, University of Malta (Malta)

Abstract

The deployment and use of Artificially Intelligent tools and techniques has proved to be effective and convenient, rendering them highly popular and desirable within any application. The benefits that such smart services provide are increasingly becoming popular within virtual learning environments as educators and learners continue to revert to such online portals during the academic process of higher education programmes. However, numerous educators have been sceptical of the inferences made by the machine learning techniques that implicitly at the background of the learning environment are monitoring the learner and collecting data to optimize the educational process as well as the learning experience. In an effort to enhance such a credibility we present an intelligent learning environment that justifies its decisions and propositions through an explainable interface that tracks back its conclusions to reasonable and plausible justifications. In this paper we present our research work together with our experiences in developing and deploying such a ground-breaking concept.

Keywords: *Artificial intelligence in education, intelligent learning environment, learning analytics, eXplainable AI.*

1. Introduction

The use of Artificial Intelligence (AI) to the educational domain has been investigated for a number of years (Montebello, 2018a) and a plethora of AI techniques have been employed to add-value to the online learning environment (Montebello, 2014) especially in an effort to personalise the learning experience (Montebello, 2016a), as well as, provide essential learning analytics (Haniya, et al., 2019). The benefits documented (Montebello, 2018b) coupled with the added effectiveness measured (Montebello, 2017a) are clear indications that AI can play an important role in education, supplementing educators while empowering them at the same time. However, numerous educators have been sceptical of the inferences made by the machine learning techniques that implicitly at the background of the learning environment are monitoring the learner process through which the learners can benefit. These same automated systems are programmed to collect masses of learner-generated data while interacting the virtual learning environment (VLE) and processed intentionally to be employed in further optimising the educational process as well as the learning experience. The educators' credibility of an AI-enhanced VLE effects the eventual adoption and deployment of such virtual environments, and thereby it is of utmost important that the educators become the prime advocates who support and take full advantage of the added-value provided by the technology. One way to have educators onboard is to not only provide them with supplementary resources and automated information that assisted them in their task to educate, but to include them as collaborators within the intelligent process as the underlying intelligent learning environment transparently justifies each step of its academic decisions and pedagogical propositions. This can be done through an explainable interface that keeps tracks of every step in the process and presents them back to justify its conclusions to the same educators in a reasonable and plausible manner. Such a technique is referred to as eXplainable AI (XAI) where the intelligent system provides a full trace of how it reached specific inferences thereby demystifying the 'black box' concept of current systems that provide no rational or comprehendible way of how specific educational decision had been reached or how the learning environment provided the additional value to the educational process through the analysis of the data generated by the learners themselves.

The rest of the paper is organised as follows. In the next section the background information related to use of AI within an education context together with the employment of XAI to justify the entire process is provided to assist the reader understand better the rest of the paper. Section 3 presents the proposed intelligent learning environment enriched by the justifications provided by the XAI for educators to better understand and appreciate the additional academic assistance. We close the paper with some future directions and number of conclusions accumulated through our experiences in developing and deploying such a ground-breaking concept.

2. Background

The use of technology within an educational context has always been regarded as a natural combination (Luckin, Holmes, Griffiths, & Forcier, 2016) that both learners and educators benefitted from. Furthermore, the integration of artificially intelligent techniques (Montebello, 2017b) within the educational process provided added-value to supplement the benefits that educators fruitfully deliver on a day-to-day basis. The use of artificial intelligent (AI) techniques to personalise a specific user's experience is an established research domain within the computer science domain (Cawsey, Grasso, & Paris, 2007), whereby various Machine Leaning (ML) techniques are available (Degemmis, 2003) to generate a specific user profile that is used to customise a variety of environments, like information over the World-Wide Web (WWW) while searching (Montebello, 1999), e-Commerce servics (Goy, Andrissono, & Petrone, 2007), healthcare consumers (Cawsey, Grasso, & Paris, 2007), and mobile phone guides (Kruger, 2007). In education this same concept is also possible by generating a student learning profile that is used to customise the entire educational process, as documented by Brusilovsky and Milla (2007). The use of generated digital learner profiles through the use of AI and in particular ML has employed to personalise the learning environment in various scenarios (Montebello, 2014). Numerous notorious learner profile generators are employed to generate a learner profile that can be used to personalise the learning process (Schiaffino & Amandi, 2009). However, one typical concern with automatic profile generators is the inability to produce a profile at the very beginning of the process when no previous information about the learner is available. This problem commonly referred to as the 'cold start' effect (Ortega, Hernando, Bernal, & Bobadilla, 2012) can be easily and quickly addressed by adopting the explicit collection of learner interests and needs at the beginning of the process, and eventually employ automatic profile generation from then onwards. This is possible by the process whereby students trigger off the profile generation by initially providing explicit information during registration whereby they are given the space to declare their specific academic qualities, descriptions or educational characteristics, together with interests and needs that can be employed to generate a much more accurate profile. This initial explicit method generates enough information and momentum for the automatic method to seamlessly take over the process and effectively generates a learner profile that can be productively used to personalise the content, the process, the supplementary educational materials, as well as the learning environment itself (Montebello, 2019). Such a generated profile encapsulates as much as possible the comprehensive learner characteristics that deal with knowledge, interests, and educational needs. In this respect a learner profile is considered a collection of inferences about information concerning a student that one is not able to observe (Zukerman & Albrecht, 2001). The main use of the learner profile is to adapt and personalise the learning process as well as the content and the delivery of the educational material.

Another technology being employed in the proposed system is a technique to justify and explain the artificially intelligent decisions derived from the various ML techniques employed. The demand for more information that is provided to the end user has been documented (Murdoch, Singh, Kumbier, Abbasi-Asl, & Yu, 2019) providing the need and advantage of having a rational explanation of how such conclusions have been reached. The classic closed or black box philosophy of how traditional software operates does not offer any kind of justification that can alleviate and assist the credibility of the user (Gilpin, et al., 2018) especially in circumstances that directly affect their educational future or of those around them. If AI is to be employed ethically and optimally, especially in a support role, the end user, a learner or even an educator, must be kept in the loop and given the facility to follow on conclusions reached. Such a functionality would assist learners and educators alike to gain trust in the back-end system that is assisting them within the virtual learning environment. One of the main inhibitors of progress to explainability is the lack of consistency and measurement metrics (Preece, Harborne, Braines, Tomsett, & Chakraborty, 2018). Currently two eXplainable A.I. methods (XAI) are predominantly being employed to provide additional value to the artificially intelligent services provided. The embedded approach to explainability (Arrieta, et al., 2020) is the first XAI technique being employed, whereby the feature to explain the process forms part of the ML algorithm itself. This means that previously developed ML techniques will need to be adapted and re-coded to accommodate the tracing and reporting of additional information to end users in a way that they will be able to analyse the internal working of the ML algorithm and comprehend the rationale behind the output provided. This output that is provided to add value to the learning experience is required to be padded with human-readable instructions which facilitate understanding (Gilpin, Testart, Fruchter, & Adebayo, 2019). The second XAI technique that is commonly referred to is the post-hoc approach to explainability whereby the rationale behind the AI decisions inferred are applied retroactively. The advantage in this case is that current ML models can still be employed and eventually compile an explanation as a result of applying that specific ML technique. IN this way traditional ML techniques employed within recommender systems are provided with a clear and detailed justification of the decisions the model arrived at. Such an outcome is clear enhancement on previous implementations (Paez, 2019), as XAI managed to convert dry and meaningless responses into significant and informative sources of information providing much needed credibility in the intelligent underlying virtual learning environment.

3. Intelligent learning environment

An intelligent learning environment that was developed as part of research project (Montebello, 2016a) to provide personalised e-learning services is being upgraded to include XAI functionalities. The supplementary added-value will provide much needed justifications of the customisation provided together with clear rationale of all the decisions and propositions provided by keeping track of the inferences made. The enhanced personal learning environment (Figure 1) is meant not only to tailor the virtual learning environment by providing a personalised learning experience, but also to justify the lateral recommendations and suggestions provided together with simple justifications that the learner can understand and come to terms with what the underlying ML functionality is providing. Over and above these explicit XAI occurrences, the educator who administers the learning environment is provided with an interface to control and oversee the personalisation process both of the content and the academic process. This provides the opportunity for educators to understand the customisation process while strengthening their credibility in the artificially intelligent backend and the holistic learning process provided by the intelligent virtual learning environment.

Figure 1. Upgraded Personal Learning Environment.

4. Future Work

A number of potential avenues will be ensued to further enhance the educators' credibility in the intelligent learning environment as additional XAI functionality is integrated within the proposed backend system. A look-ahead feature to map out a road map of an optimised learning process based on numerous success stories that fall within the same cluster as the specific learner will encourage both the learner and the educator as it provides an explicit rationale based on the individual learner portfolio that has been accumulated and employed to generate both the learner profile and the academic plan. Additionally, the inclusion of an XAI assistant within the virtual learning environment that can seamlessly accompany the learner over multiple devices will enhance the effectiveness and then overall success of the AI added-value while strengthening the output created by the underlying ML techniques that have additional learning data based on the real learning analytics accumulated. The same assistant will interact with the educator's interface to provide additional information to substantiate the inferences performed. Furthermore, the justified integration of social networks and the inclusion of certified crowdsourcing will provide additional content that will deliver a richer learning experience whereby the underlying AI functionality will have even more data to work on and better assist the learner. The XAI component will still provide the proposed functionality with the added-value of applying the smart techniques on richer content that will raise the overall learner experience and educator credibility.

5. Conclusion

In this paper we proposed the integration of eXplainable Artificial Intelligence (XAI) functionality within an intelligent learning environment that was already enriched by Artificial Intelligent (AI) techniques and Machine Learning (ML) technologies to customise and personalise the Virtual Learning Environment (VLE). The rationale at the basis of our enhanced intelligent VLE is aimed at enhancing the learners' and educators' credibility on the functionality provided by the underlying intelligent environment by providing explicit justifications and simple explanations of the decisions and propositions inferred by the ML algorithms that are processing the unique data generated by the individual learners. The XAI interface tracks back its conclusions to generate reasonable and plausible justifications that are communicated back to the end users, learners and educators. We presented our research work, as well as, proposed additional enhancements to the intelligent VLE by taking further advantage and extracting richer benefits that eventually strengthen the use of AI in education in an effort to take e-learning to the next level.

References

Arrieta, A., Díaz-Rodríguez, N., Del-Ser, J., Bennetot, A., Tabik, S., Barbado, A., ... Herrera, F. (2020). *Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI*. Information Fusion, Vol 58, 82-115.

Brusilovsky, P., & Milla, E. (2007). *User Models for Adaptive Hypermedia and Adaptive Educational Systems*. In P. Brusilovsky, A. Kobsa, & W. Nejdl, The Adaptive Web (pp. 3-53). Heidelberg: Springer.

Cawsey, A., Grasso, F., & Paris, C. (2007). *Adaptive Information for Consumers of Healthcare*. In P. Brusilovsky, A. Kobsa, & W. Nejdl, The Adaptive Web. Heidelberg: Springer.

Cawsey, A., Grasso, F., & Paris, C. (2007). *Adaptive Information for Consumers of Healthcare*. In P. Brusilovsky, A. Kobsa, & W. Nejdl, The Adaptive Web. Heidelberg: Springer.

Degemmis, M. (2003). *Extraction of User Profiles by Discovering Preferences through Machine Learning*. In M. A. Kioptek, S. Wierzchon, & K. Trojanowski, Intelligent Information Processing and Web Mining. (pp. 69-78). Zakopane, Poland: Springer.

Gilpin, L., Bau, D., Yuan, B., Bajwa, A., Specter, M., & Kagal, L. (2018). *Explaining explanations: An overview of interpretability of machine learning.* 5th International Conference on Data Science and Advanced Analytics, (pp. 80-89). IEEE.

Gilpin, L., Testart, C., Fruchter, N., & Adebayo, .. (2019). *Explaining Explanations to Society*. ArXiv abs/1901.06560.

Goy, A., Andrissono, L., & Petrone, G. (2007). *Personalization in E-Commerce Applications*. In P. Brusilovsky, A. Kobsa, & W. Nejdl, The Adaptive Web (pp. 485-520). Heisdelberg: Springer.

Haniya, S., Tzirides, O., Georgiadou, K., Montebello, M., Kalantzis, M., & Cope, B. (2019). *Assessment Innovation in Higher Education by Integrating Learning Analytics*. 3rd International Conference on Education and Distance Learning. Barcelona: ICEDL.

Kruger, A. (2007). *Adaptive Mobile Guides*. In P. Brusilovsky, A. Kobsa, & W. Nejdl, The Adaptive Web (pp. 521-549). Heidelberg: Springer.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. (2016). *Intelligence Unleashed - An argument for AI in Education*. London: Pearson.

Montebello, M. (1999). *Personalised Information Retrieval over the WWW*, Ph.D. Thesis. Cardiff: Cardiff University.

Montebello, M. (2014). *Enhancing the Effectiveness of E-Learning through the combination of Personal Learning Portfolios and Social Networks*. 7th International Conference on Education, Research and Innovation (ICERI 2014). Seville, Spain.

Montebello, M. (2016a). *Personalised e-Learning*. Sheffield, UK: Ed.D. Thesis.

Montebello, M. (2016b). *Enhancing e-learning through the merging of e-portfolios, social networks and artificial intelligence*. 10th International Technology, Education and Development Conference (INTED2016). Valencia.

Montebello, M. (2017a). *Measuring E-Learning Effectiveness Using a Three-Way Comparison*. 19th International Conference on e-Education and e-Learning (pp. 921-926). Boston: (ICEEEL), Boston, USA. International Science Index, Educational and Pedagogical Sciences.

Montebello, M. (2017b). *Next Generation e-Learning*. 5th ACM International Conference on Information and Education Technology (pp. 150-154). Tokyo: ICIET.

Montebello, M. (2018a). *AI-Injected e-Learning - The Future of Online Education*. Switzerland: Springer.

Montebello, M. (2018b). *Assisting Education through Real-Time Learner Analytics*. 48th IEEE Annual Frontiers in Education (FIE) Conference (pp. 133-139). San Jose, California, USA: FIE.

Montebello, M. (2019). *Ambient Intelligent Classroom - Beyond the indispensable educator*. Switzerland: Springer.

Murdoch, W., Singh, C., Kumbier, K., Abbasi-Asl, R., & Yu, B. (2019). *Interpretable machine learning: definitions, methods, and applications*. ArXiv, abs/1901.04592.

Ortega, J., Hernando, F., Bernal, A., & Bobadilla, J. (2012). *A collaborative filtering approach to mitigate the new user cold start problem*. Knowledge-Based Systems, 225-238.

Paez, A. (2019). *The Pragmatic Turn in Explainable Arti cial Intelligence (XAI).* Minds and Machines, 29(3), 441-459.

Preece, A., Harborne, D., Braines, D., Tomsett, R., & Chakraborty, S. (2018). *Stakeholders in Explainable AI*. ArXiv abs/1810.00184.

Schiaffino, S., & Amandi, A. (2009). *Intelligent user profiling. Artificial Intelligence*, LNAI 5640.: IFIP, 193-216.

Zukerman, I., & Albrecht, D. (2001). *Predictive statistical models for user modeling*. User Modeling and User-Adapted Interaction, 11(1-2), 5-18.