The use of an Explainable Artificial Intelligence Tool for Decision-making Support in Virtual Learning Environments

Jose M. Alonso[1] and Gabriella Casalino[2]

[1] Centro Singular de Investigación en Tecnoloxías Intelixentes (CiTIUS), Universidade de Santiago de Compostela, Spain
josemaria.alonso.moral@usc.es
[2] Department of Computer Science, University of Bari Aldo Moro, Italy,
gabriella.casalino@uniba.it

1 Introduction

Distance education history starts almost two centuries ago with postal services [1]. With the advent of Internet, significant changes have occurred, and the use of on-line distance learning (e-Learning in short) platforms has exponentially grown. These virtual learning environments (VLE) eliminate the physical distance between learners and courses, thus facilitating and favouring enrollments. In addition to online teaching material, VLEs provide a set of synchronous and asynchronous study assistance tools, such as chat, video lessons, forums, wikis, messaging systems, emails, etc. In these environments, the students' learning behaviour could be described by their interactions with the platform: the number of times that one student has visited the main page, the number of messages she has exchanged with the professors, the number of extra resources that have been uploaded, and so on. The observation of the students' learning behaviour could be used to suggest adaptive feedback, customized assessment, and more personalized attention [2].

Learning analytics on historic VLE activity data, allow to predict students' failure or success, and they are commonly used to improve student retention [3]. More in general, in educational data mining field, machine learning techniques are used to discover hidden patterns. In literature, several studies have been conducted with different aims: to define the learners' skills [4], to define a big data architecture for supporting learning analytics [5], to visualize the interactions among students [6], to predict students' performance [7–9], to measure students' satisfaction [10] or to manage the big quantity of data coming from student-VLE interactions [11].

Even though current Artificial Intelligence (AI) tools have proved to be ready for finding out valuable knowledge in the context of learning analytics, their effectiveness for decision-making support is still limited by a lack of explanation ability. Getting effective explanations is becoming more and more important in social sciences [12]. In applications such as e-Learning where the interaction between humans and AI systems is a main concern, there is a need of Explainable

AI (XAI in short) systems [13]. Providing students with explanations in relation with their learning activities is expected to be highly appreciated and to contribute to get better students' satisfaction and qualifications. Moreover, XAI systems may help teachers and managers when designing courses and contents.

In this paper, we describe the use of ExpliClas [14], a web service ready to provide users with multimodal (textual + graphical) explanations, in the context of e-Learning. Namely, we study the utility and effectiveness of explanations automatically generated by ExpliClas for teachers or university managers, when considering the Open University Learning Analytics Dataset (OULAD) [15].

The rest of this manuscript is organized as follows. Section 2 introduces some material and methods. Section 3 presents a use case. Section 4 concludes the paper and points out future work.

2 Preliminaries

2.1 The ExpliClas Web Service

ExpliClas [14] is made up of a REST API[3] and a web client[4]. It automatically generates multimodal (textual + graphical) explanations related to Weka classifiers. Actually, four Weka classifiers (J48, RepTree, RandomTree, and FURIA) are available. In addition, several pre-loaded datasets (e.g., iris, wine or glass classification datasets which are known worldwide) let users check the functionality offered by ExpliClas. Moreover, users can upload their own datasets.

2.2 The OULAD Dataset

The Open University (OU)[5] is a public distance learning and research university in the UK. It provides the research community with free open data[6] related to their on-line courses. More precisely, available data are structured in several csv files (courses.csv, assessments.csv, studentInfo.csv, and so on). They contain anonymized information which is taken from the OU database.

In this paper, we have selected a subset of all available information and built a dataset ready to be used by ExpliClas.

3 Case Study

Our dataset is made up of 18 inputs, including students' general information (e.g., gender, region, education level etc.) as well as the number of times the students interacted with different materials (e.g., external quiz, glossary, homepage, subpages, etc.) along the course. Students are classified by their academic results into two classes: 39 *passed*, and 61 *failed* (it is an unbalanced dataset).

[3] ExpliClas API: `https://demos.citius.usc.es/ExpliClasAPI/`
[4] ExpliClas Web Client: `https://demos.citius.usc.es/ExpliClas/`
[5] Open University website: `http://www.open.ac.uk/`
[6] Open Data: `https://analyse.kmi.open.ac.uk/open_dataset#data`

	Fail	Pass
Fail	51	10
Pass	9	30

Table 1. Confusion matrix of the model.

We uploaded this dataset to ExpliClas and built a FURIA classifier which achieves 81% of classification rate (10-fold cross-validation) with 10 fuzzy rules (5 pointing out class=Pass and 5 pointing out class=Fail).

An example of global explanation is as follows: "*There are 2 types of evaluation: Fail and Pass. This classifier is quite confusing because correctly classified instances represent a 81%. There is confusion related to all types of student*". The confusion matrix in table 1 confirms this explanation. Indeed, Fail is confused with Pass in 10 out 61 students who really fail (16.39%). The opposite (Pass is confused with Fail) in 23.09% of students.

An example of local explanation is "*Evaluation is Pass because interaction with subpages is medium and highest education is HE qualification*" which verbalizes the information included in the next fired fuzzy rule: "IF subpage in [0.093596, 0.114532, inf, inf] and highestEducation=HEqualification THEN class=Pass (CF=0.91)". This suggests that students who interact properly with sub-pages along the course and have a high grade of education are more likely to succeed.

4 Conclusions and Future Work

We have illustrated the use of the ExpliClas XAI tool with a classification dataset that we built with information extracted from open data, provided online by the Open University. ExpliClas provides us with both global and local explanations related to the given dataset. It is worth noting preliminary results are encouraging. ExpliClas automatically generates multimodal explanations which consist of a mixture of graphs and text. These explanations look like natural, expressive and effective, because they are similar to those explanations expected to be provided by humans. However, no feedback is given to students yet.

As future work, we will set up an online survey to ask human users (including students, teachers and managers) about the goodness of these explanations. Later, we will integrate them in an online XAI decision-support tool.

Acknowledgments

Jose M. Alonso is Ramón y Cajal Researcher (RYC-2016-19802). This research was also funded by the Spanish Ministry of Science, Innovation and Universities (grants RTI2018-099646-B-I00 and TIN2017-90773-REDT) and the Galician Ministry of Education, University and Professional Training (grants ED431F 2018/02, ED431C 2018/29 and "accreditation 2016-2019, ED431G/08").

References

1. Joi L Moore, Camille Dickson-Deane, and Krista Galyen. e-learning, online learning, and distance learning environments: Are they the same? *The Internet and Higher Education*, 14(2):129–135, 2011.
2. Saulius Preidys and Leonidas Sakalauskas. Analysis of students study activities in virtual learning environments using data mining methods. *Technological and economic development of economy*, 16(1):94–108, 2010.
3. Annika Wolff, Zdenek Zdrahal, Andriy Nikolov, and Michal Pantucek. Improving retention: predicting at-risk students by analysing clicking behaviour in a virtual learning environment. In *International Conference on Learning Analytics and Knowledge*, pages 145–149. ACM, 2013.
4. Gabriella Casalino, Ciro Castiello, Nicoletta Del Buono, Flavia Esposito, and Corrado Mencar. Q-matrix extraction from real response data using nonnegative matrix factorizations. In *International Conference on Computational Science and Its Applications*, pages 203–216. Springer, 2017.
5. Thomas Rabelo, Manuel Lama, Ricardo R Amorim, and Juan C Vidal. Smartlak: A big data architecture for supporting learning analytics services. In *Frontiers in Education Conference (FIE)*, pages 1–5. IEEE, 2015.
6. Ángel Hernández-García, Inés González-González, Ana Isabel Jiménez-Zarco, and Julián Chaparro-Peláez. Visualizations of online course interactions for social network learning analytics. *International Journal of Emerging Technologies in Learning (iJET)*, 11(07):6–15, 2016.
7. Ángel F Agudo-Peregrina, Ángel Hernández-García, and Santiago Iglesias-Pradas. Predicting academic performance with learning analytics in virtual learning environments: A comparative study of three interaction classifications. In *International Symposium on Computers in Education (SIIE)*, pages 1–6. IEEE, 2012.
8. Asmaa Elbadrawy, Agoritsa Polyzou, Zhiyun Ren, Mackenzie Sweeney, George Karypis, and Huzefa Rangwala. Predicting student performance using personalized analytics. *Computer*, 49(4):61–69, 2016.
9. Huang Nen-Fu, I Hsu, Lee Chia-An, Chen Hsiang-Chun, Tzeng Jian-Wei, Fang Tung-Te, et al. The clustering analysis system based on students' motivation and learning behavior. In *Learning With MOOCS (LWMOOCS)*, pages 117–119. IEEE, 2018.
10. Jen-Her Wu, Robert D Tennyson, and Tzyh-Lih Hsia. A study of student satisfaction in a blended e-learning system environment. *Computers & Education*, 55(1):155–164, 2010.
11. Xiaoyin Sun, Wei Zhou, Qiyan Xiang, Binyue Cui, and Yi Jin. Research on big data analytics technology of mooc. In *11th International Conference on Computer Science & Education (ICCSE)*, pages 64–68. IEEE, 2016.
12. Tim Miller. Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence*, 267:1–38, 2019.
13. D. Gunning. Explainable Artificial Intelligence (XAI). Technical report, Defense Advanced Research Projects Agency (DARPA), Arlington, USA, 2016. DARPA-BAA-16-53.
14. Jose M. Alonso and A. Bugarín. Expliclas: Automatic generation of explanations in natural language for weka classifiers. In *International Conferences on Fuzzy Systems*, pages 1–6. IEEE, 2019.
15. Jakub Kuzilek, Martin Hlosta, and Zdenek Zdrahal. Open university learning analytics dataset. *Scientific data*, 4:170171, 2017.