Moodle Predicta: A Data Mining Tool for Student Follow Up

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Abstract: Educational data mining (EDM) aims to find useful patterns in large volumes of data from teaching/learning environments, increasing academic results. However, EDM requires previous and deep knowledge of data mining methods and techniques, involving several computing paradigms, preprocessing and results' interpretation. In this paper, Moodle Predicta, an educational data mining desktop tool is presented. This software is developed in Java and enables non-expert data mining users to enjoy benefits from EDM, within the Moodle system. Divided in two modules, Moodle Predicta allows: (i) visualization of Moodle courses data; and (ii) predict students' performance.

1 INTRODUCTION

With the advances in information and communication technologies (ICT), distance learning has grown, allowing people in remote locations to access courses with better educational content, where students can make their own agenda, schedules and define the time spent studying (Zacharis, 2015). Furthermore, distance education has allowed institutions to increase the number of students (García-Saiz and Zorrilla, 2012), (Olama et al., 2014).

In Brazil, distance learning registered 1.2 million enrollments in 2006. By 2015 this number had tripled, presenting more than 3.8 million enrollments, distributed in 25,000 courses, taught semi or totally at a distance *(ABED – Associação Brasileira de Educação a Distância, 2015)*. This is a global movement. According to a 2013 report of the Online Learning Consortium's Survey of Online Learning, in the USA, over 7.1 million students were taking at least one online course, and the number of students taking at least one online course has continued to grow at a rate far in excess of overall enrollments (Allen and Seaman, 2014). These courses range from classes in free programs and from face to face programs, to complete graduation and professionals master degrees (Marquez-Vera et al., 2013).

However, in distance learning there is a huge gap between the number of new students and the number of graduates. In Brazil, in 2014, online courses presented a 25% dropout rate *(ABED – Associação Brasileira de Educação a Distância, 2015)*. Roughly, 950,000 students did not finish the course they started. This generates losses to public and private institutions, because the costs to conduct the course is not reduced with the decrease in the number of participants.

Students have pointed out that the main cause for dropout is the lack of time to study and to participate in activities (Pierrakeas et al., 2004). Considering that students often have a job or do domestic activities, it is hard to keep up their routine of learning. Furthermore, students have justified that dropout is related to the difficulty to adapt to the distance learning methodology and to the tools used, such as the virtual learning environment (VLE) used *(ABED – Associação Brasileira de Educação a Distância, 2015)*, (Pierrakeas et al., 2004).

VLE is a software used in the distribution of online courses available in the internet, offering support to several teaching activities that may go from the delivery of pedagogical content to monitoring students' progress. To do that, VLE has many tools, including: forums, chats, pedagogical resources and quizzes (Romero et al., 2013). Among the available VLEs, there are some that are free and open source software (Moodle and Canvas) and others that are private (Blackboard and Desire2Learn) (EDUCAUSE Center for Analysis and Research, 2014).

While offering support, these VLEs register many

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details of student's behavior inside the platform, for example: activities visualized, answered and their grades. A part of this information is available for analysis inside the virtual environment, through summary statistics and reports of student's participation in: forums, chats and other available resources, allowing the analysis of the cohort or of a given student (Romero and Ventura, 2010).

Activity tracking allows teachers and tutors to follow up and monitor student's performance and eventually detect who is risking dropout, failing the course or has some learning difficulty (Bogarín et al., 2014). However, many cohorts contain a large number of students, so teachers have difficulty in dealing with all the data properly. Although some information is available in several system generated reports, teachers often have difficulty interpreting them. Furthermore, these reports state facts but do not interpret the results, trying to identify students in danger of failure, leaving this analysis to the teachers.

With the goal of analyzing this data automatically, different techniques have been used. A promising approach is the use of data mining (DM) (Danubianu, 2015) (Sharma and Mavani, 2011), (e Ricardo Araujo e Douglas Detoni, 2015), (Moradi et al., 2014). DM allows the abstraction of relevant information stored in databases. By being relieved of the task of analysis and prediction, teachers can focus on the pedagogical aspects of teaching, leaving the identification of at-risk students to data mining.

This paper presents a Java desktop tool for student follow up, called Moodle Predicta. The system connects to Moodle databases, selecting tables according to user requirements, and prepares the data to be analyzed in WEKA data mining software (Hall et al., 2009), that is integrated with the tool. After data preprocessing, Moodle Predicta presents a summary of the results in a visualization module. A second component of the system is used to predict students' final performance. Based on selected data the tool indicates if a student may be at risk of failure or dropout.

This paper presents the research associated to the definition of Moodle Predicta and its implementation, and is organized as follows. Section 2 introduces the Moodle virtual environment; section 3 presents related work and the main topics in Educational Data Mining associated to the project; section 4 introduces the Moodle Predicta tool; section 5 represent conclusion and future work.

2 Moodle

Moodle (Modular Object-Oriented Dynamic Learning Environment) has more than 93 million users distributed in 71,000 registered environments in 231 countries (Moodle.org, 2016b). Today it is the most widely used open source virtual learning environment for distance education around the world (EDUCAUSE Center for Analysis and Research, 2014).

Moodle enables educators and institutions to create and manage effective online learning communities, development flexible and comprehensive online courses and experiences. Moodle's modular design makes it easy to create new courses, adding content that will engage learners. Moodle was designed and developed oriented by the social constructionist pedagogical methodology, where new knowledge is constructed when students interact with the content (Moodle.org, 2016a).

Moodle logs record and keep track of what resources students have accessed, modified, created and removed, logging every click that students and teachers make in navigation. However, it offers a limited log viewing module that is built into the system. Logs can be filtered by course, participant, period and resource. If interested, teachers can use these logs to determine who has been active in the course, what they did, and when they did it. For quizzes and activities, the score and elapsed time are available, and a comparative analysis of each student with the others (Bapu et al., 2015).

The Moodle virtual learning environment registers three different user interactions associated to distance learning (Moore, 1989):

- Student-student interactions: are related to the exchanges between the students enrolled in the course. For example: chats and massages in forums or workgroups (Agudo-Peregrina et al., 2012).
- Student-teacher interactions: are related to the participation of teachers in which students perceive a teacher's proximity through online presence. Example: messages from teachers to students answering questions about course topics (Agudo-Peregrina et al., 2012).
- Student-content interactions: these occur when students make use of many of the content resources, such as textbooks, documents, research materials, videos and other learning contents. In Moodle, they are usually associated to browsing and accessing different resources, tasks, etc. (Agudo-Peregrina et al., 2012).

Moodle environment does not store logs as a simple text files. It registers the logs, and all information in a relational database. It is possible to use different management systems, like MySQL, Oracle, Access and others (Moodle.org, 2016b).

Moodle allows teachers to get full reports on the activities of a unique student, or of all students for a specific activity or resource. This is useful to check if everyone has done a certain task or spent time online within some specific resource.

However, all this data is usually raw, without any form of intelligent processing, so users have used different tools for Moodle data analysis. For example (Danubianu, 2015):

- GISMO – tool for data visualization, that uses log data from Moodle, allows its edition and produces graphical information that can be used by teachers to understand social, cognitive and behavioral student interactions;
- MocLog – includes a set of tools, built based on GISMO, that can be used for the analysis and presentation of data within Moodle;
- Analytics and recommendation – plug-in available in a supplement component to be installed within Moodle, that can be used by teachers and students for visualization of students' involvement and to recommend activities.

3 EDUCATIONAL DATA MINING

Educational Data Mining (EDM) is a relatively recent research field, that emerges from two converging trends: the increasing use of VLE in educational institutions, and the application of data mining techniques to business intelligence processes in organizational information (Agudo-Peregrina et al., 2012).

Data mining (DM) represents automated discovery of implicit and interesting patterns from large amount of data. DM is an interdisciplinary scientific area which involves several computing paradigms: rule induction, decision tree, Bayesian learning, Neural networks, etc. Largely used data mining techniques include classification, clustering, association rule mining, visualization and statistics (Avlijaš, 2016). Developed tools that automatize this process help teachers analyze and visualize learning data in order to recognize useful patterns and evaluate the effectiveness of the course and students' participation.

Researches have been conducted with data mining to analyze Moodle data and logs. Some of them are summarized in Table 1, presenting the data mining algorithms and techniques used, as well as the attributes considered for students' prediction.

As in data mining, the educational data mining process in VLE follows four steps (Avlijaš, 2016), (Romero et al., 2008b):

- Data collection: while the students use the system, information is collected and stored in the database. In Moodle, the data is collected in system logs.
- Preprocessing: after data collection, the data is transformed into suitable formats for analysis. Usually software is used for data preprocessing.
- Data mining: with the aim of developing a model and discovering useful patterns, the appropriate data mining algorithms are applied at this stage.
- Results evaluation: in this last step, educators interpret the obtained results and use discovered knowledge to improve the learning and decision making process.

Several surveys give a general overview of EDM research being conducted and DM in VLE is often mentioned. Romero and Ventura (Romero and Ventura, 2007), covers researches published between 1995 and 2005, being extended in 2010 (Romero and Ventura, 2010), Baker and Yacef (Baker and Yacef, 2009), was published in 2009, Jindal and Borah (Jindal and Borah, 2013), covers research published between 1998 and 2012, Peña-Ayala (Peña-Ayala, 2014), papers published between 2010 and 2013, and Thakar (Thakar, 2015) (2002-2014), present a state of the art review in EDM and research trends in this domain. Luan (Luan, 2002) discusses potential applications of EDM in higher education.

(Romero et al., 2008b), gives a broad overview of the use of data mining in the Moodle learning management system. They argue that data mining in virtual learning environments represents an iterative process, that allows improvement of the overall learning and decision making process. In this paper, they apply educational data mining and give suggestions to instructors and e-learning administrators on how to conduct their own research.

(Kotsiantis et al., 2010) proposed a combination of three algorithms: Naive Bayes, the 1-NN and the WINNOW, using the voting methodology. (Avlijaš, 2016), after rigorous data preprocessing and discretization, applies Apriori algorithm to generate association rules to predict student performance outcomes and identify students who require special attention from teachers to increase the overall success ratio. Results present 99% accuracy rate.

In (Yoshida et al., 2013), an algorithm was developed to determine failure of learning, using quiz answers as input. The result is a class used to determine if a student is at risk or not. The algorithm is based

Table 1: Related work.

Research	Data mining tecnhique	Data mining algorithms	Attributes
(Neto and Castro, 2015)	Association	Apriori	Accesses and forum logs, chats and tasks
(Guércio et al., 2014)	Classification	Decision trees (RandomTree and J48)	Interaction logs and forums
(Sisovic et al., 2016)	Clustering	K-Means	Resources logs
(Sorour et al., 2015)	Classification	Support Vector Machine	Students' comments
(Zorrilla and Garcia-Saiz, 2014)	Classification	NearestNeighbours, Jrip, J48 and NaiveBayes	Interaction logs

on statistics analysis, reaching a maximum accuracy of 88.9%. (Romero et al., 2008a) compared different data mining methods and techniques to classify students based on their Moodle usage data and the final marks obtained in their courses.

4 Moodle PREDICTA

Moodle Predicta is a tool developed in Java that allows users to connect into any version of the Moodle database, as well as different management systems, such as MySQL, Oracle, PostgreSQL and others. Moodle Predicta is divided in two parts: visualization and prediction modules.

4.1 Visualization Module

The visualization module allows users to have an overview of student and teacher behavior, interactions, personal data, and academic performance. By means of reports containing relevant information, the module enables teachers to evaluate the course structure, content and its effectiveness.

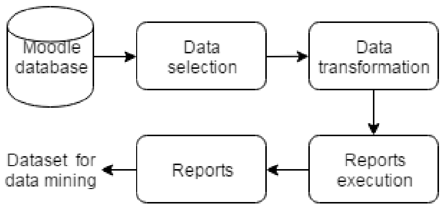


Figure 1: Diagram of visualization module.

To bring the processed data to the user, the visualization module is composed of four main steps, involving data preprocessing, algorithms execution and formatting (Figure 1):

i Data selection – in this step, the data is selected, according to user requirements.

ii Data transformation – after selection, the data is gathered and transformed/discretized.

iii Reports execution – in this stage, the reports are generated.

iv Reports – the reports are presented to the user.

The software was developed for non-expert data mining users. The configuration requires few inputs in an easy to use interface. The options selected by the user are stored in a CSV (Comma Separated Values) local file. This allows the software to load the same configuration in the next execution.

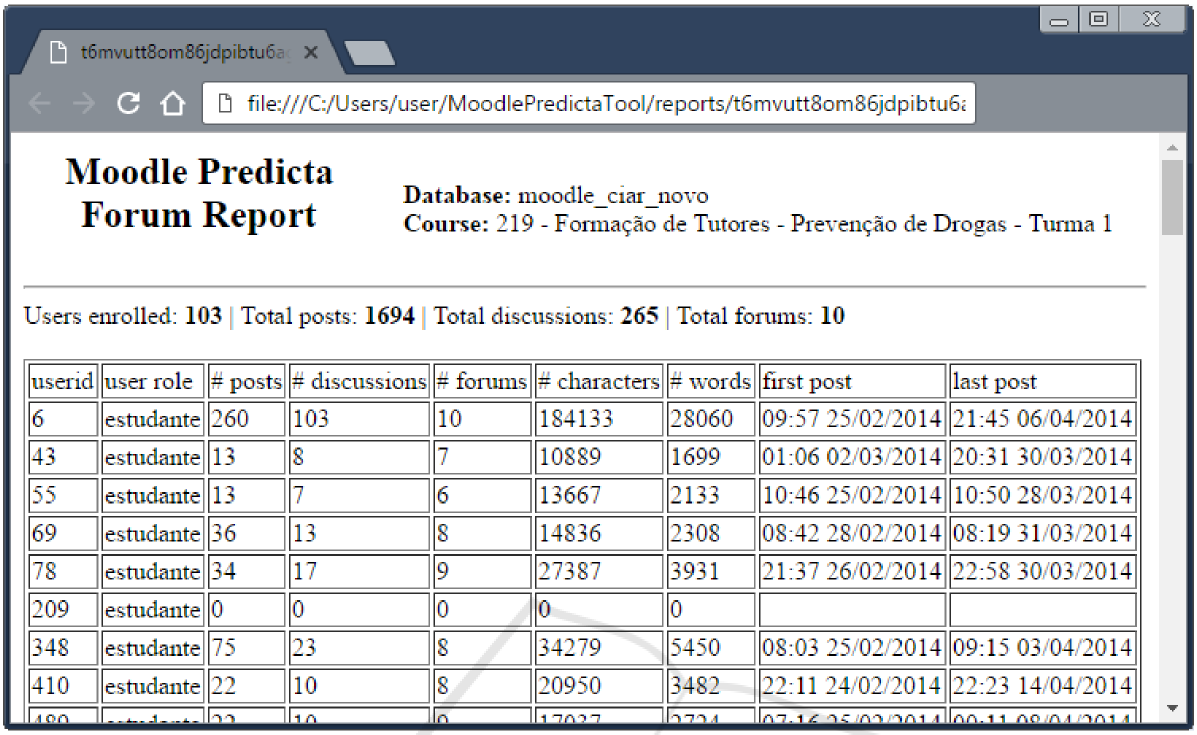
The first step in the visualization module execution is the connection to database. The connection is established into local or remote servers, according to users' requirements. The connection is guided by Java Database Connectivity (JDBC). Therefore, any database that implements JDBC API (Application Programming Interface) should connect successfully.

After the connection is established, all database schemas in the node are listed. This list is constructed by a Java method in the JDBC API. The list is presented to the user, so he can choose the Moodle installation to be analyzed.

Once the user has selected the desired Moodle database, he is asked for a specific course on next screen (Figure 3). To make the selection, Moodle Predicta creates a hierarchical structure of courses, according to categories and subcategories that are stored in the selected Moodle database. This structure is the same presented in the Moodle database schema.

When the course is selected, a new screen is presented to the user, so he can choose the attributes, as seen in Figure 4. The selected attributes will compose the reports, and include: forums, chats, quizzes, logs, grades, and tasks. Once the user makes the selection, Moodle Predicta generates a file as the final result. This file can be in three different formats:

i HTML (HyperText Markup Language) – format indicated for data visualization. The file is generated according to standard characters encode and definitions, and can be opened in any web browser.



userid	user role	# posts	# discussions	# forums	# characters	# words	first post	last post
6	estudante	260	103	10	184133	28060	09:57 25/02/2014	21:45 06/04/2014
43	estudante	13	8	7	10889	1699	01:06 02/03/2014	20:31 30/03/2014
55	estudante	13	7	6	13667	2133	10:46 25/02/2014	10:50 28/03/2014
69	estudante	36	13	8	14836	2308	08:42 28/02/2014	08:19 31/03/2014
78	estudante	34	17	9	27387	3931	21:37 26/02/2014	22:58 30/03/2014
209	estudante	0	0	0	0	0		
348	estudante	75	23	8	34279	5450	08:03 25/02/2014	09:15 03/04/2014
410	estudante	22	10	8	20950	3482	22:11 24/02/2014	22:23 14/04/2014

Figure 2: Forum data analysis report, in HTML format.

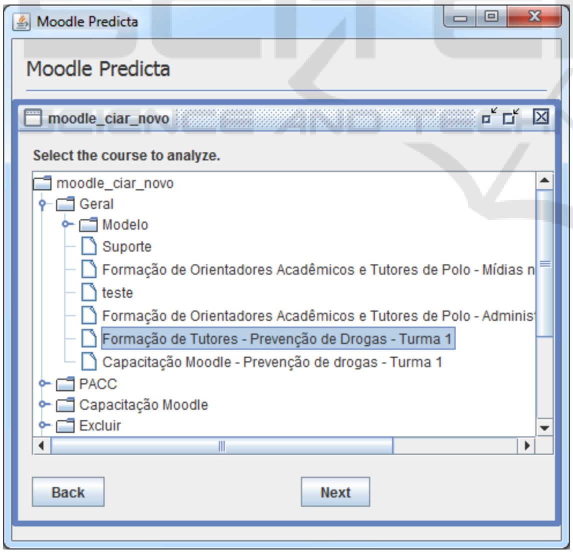


Figure 3: Selection of Moodle course.

ii CSV (Comma Separated Values) – this format is indicated for data import and export, such as spreadsheets and databases.

iii ARFF (Attribute-Relation File Format) – this format is used by WEKA and KEEL, two widely used open source data mining software.

The data is gathered by means of several SQL (Structured Query Language) commands, crossing different tables, joining scattered information, according to the type of report and data to be analyzed. Then, it is processed and presented in the selected format.

For example, when the data to be analyzed are course's forum, eleven different tables are included in the data collection: course, user, forum, user_enrolments, forum_discussions, forum_posts, forum_read, forum_track_prefs, forum_queue, forum_subscriptions, and role.

Joining all these tables and gathering their data, it's possible with the application of data mining preprocessing techniques (cleaning, integration, transformation and reduction), to have a report that can be understandable by non-expert data mining users, as shown in Figure 2.

4.2 Prediction Module

The prediction module allows teachers and tutors to identify students that are not following classes and may abandon the course before the end, making it possible to take some preventive action, and bring the student back into the course. Prediction is based on behavior, interactions, and performance of students inside the Moodle environment.

To undertake the students' prediction perfor-

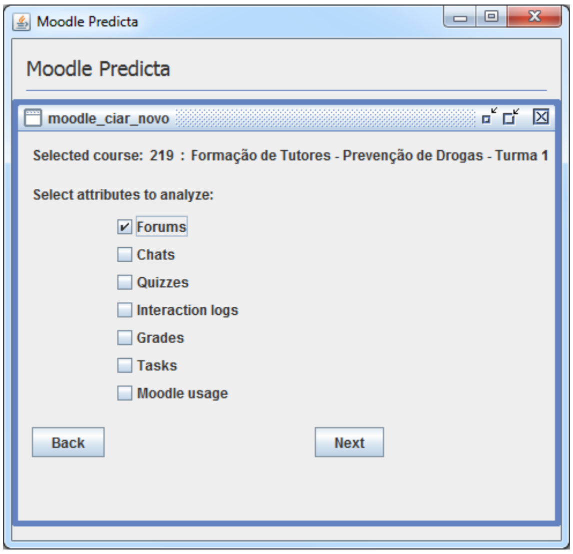


Figure 4: Selection of attributes for analysis.

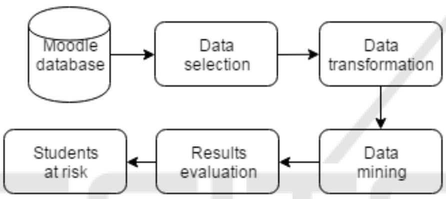


Figure 5: Diagram of prediction module.

mance, the module is composed by five main steps, involving data preprocessing, data mining techniques and formatting (Figure 5):

i Data selection – in this step, the data is selected, from attributes data describe students' behavior, interactions and grades.

ii Data transformation – the data is gathered and transformed/discretized for data mining.

iii Data mining – in this stage, the data is used in decision tree models.

iv Results evaluation – the results presented by data mining are interpreted and evaluated automatically.

v Students at risk – Students at risk are listed to user.

As proposed by (Romero et al., 2008b), and followed by other researches, as (Chayanukro et al., 2014), the relevant attributes from students' behavior for data mining in Moodle and used by Moodle Predicta, are presented in Table 2.

Once the course is selected, as seen in Figure 3, Moodle Predicta prepares the data, in a preprocessing phase (cleaning, integration, transformation and reduction), and generates an ARFF file. After connecting to the WEKA data mining API, the decision

Table 2: Predictors attributes used in Moodle Predicta. Adapted from (Romero et al., 2008b).

Name	Description
course_id	Identification of the course
n_assignment	# of assignments submitted
n_quiz	# of quizzes solved
n_quiz_a	# of quizzes passed
n_quiz_s	# of quizzes failed
n_messages	# of messages sent by chat
n_messages_ap	# of messages sent to the teacher
n_posts	# of messages sent to the forum
n_read	# of messages read on the forum
total_time_assignment	Total time spent in assignment
total_time_quiz	Total time spent on quizzes
total_time_forum	Total time used on forum
mark	Final mark obtained by student in the course

tree algorithms are executed with standard parameters for listing of students at risk of failing, presented in Figure 6.

The WEKA (Waikato Environment for Knowledge Analysis) allows researchers access to updated techniques in machine learning, being recognized as a landmark system in data mining. With an widespread acceptance so in academia and business contexts, has becoming a widely tool for data mining research (Hall et al., 2009).

Integration with WEKA is done through the API library. The decision tree algorithms can be called through specific classes and methods available in the "weka.classifiers.trees" package[1].

Prediction requires that models be built based on prior data. This means that each context will have to build and test their models before prediction is possible. The decision tree models we used were generated using training data from biology undergraduate students from an online course, using predictors attributes presented in Table 2.

The list of students at risk (Figure 6) is defined by the algorithm using the model generated by the training data. Students whose behavior, interactions, and performance, is similar to those students from the

[1] Available at http://weka.sourceforge.net/doc.stable/ Accessed in 12/06/2016.

training dataset that have failed will be difined as “at risk”. Teachers can then follow up on these students to confirm their situation and take some preventive measure to bring back the student to the course.

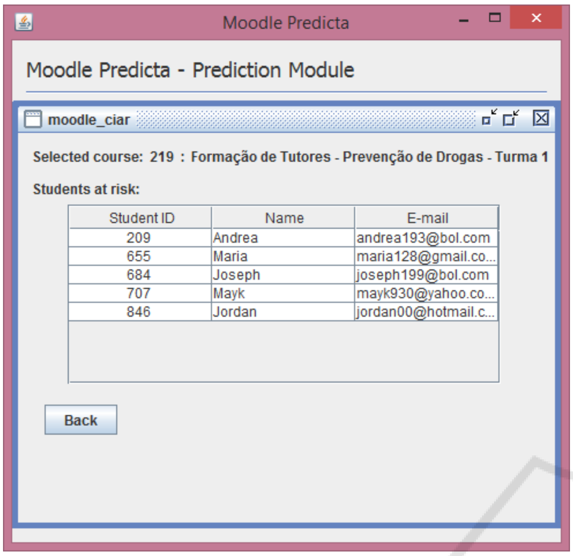


Figure 6: Students at risk (Fictitious personal data for privacy reasons).

5 CONCLUSION AND FUTURE WORK

With the advances of information and communication technologies, new and major challenges are being created, mainly because of the large amounts of data about students’ activities, academic results and users’ interactions being stored. However, this data has can be explored and analyzed by known data mining methods and techniques. These two facts are the basis of the recent area of research, educational data mining, that consists of application of data mining technologies to data collected from educational contexts, with the aim of discover patterns and useful information.

The data mining processes are difficult and need previous knowledge to be applied successfully. Moreover, the data needs to be correctly selected, prepared and the result of process requires evaluation and interpretation. These are barriers that must be overcome so a greater number of users can benefit from educational data mining.

In this paper, Moodle Predicta, an easy-to-use tool was presented. This software enables students follow up, selecting and preparing the Moodle data for two modules: (i) the visualization module, that generates reports for analysis purposes; and (ii) the prediction module, that integrated to WEKA data mining software, uses decision tree models to identify and list students at risk of dropout or failure.

The tool is implemented in Java, connecting to databases by means of JDBC API. The data collection is implemented in SQL queries, taking benefit from the commands offered by database management systems. While the data processing is done inside the tool.

Future work will be undertaken in the direction of using the resulting datasets from the visualization module to build effective models their validation. Moreover, other Moodle tables can be joined in the same reports for more complex analysis.

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