DSS-PSP - A decision support software for evaluating students' performance

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Abstract. Prediction, utilizing machine learning and data mining techniques is a significant tool, offering a first step and a helping hand for educators to early recognize those students who are likely to exhibit poor performance. In this work, we introduce a new decision support software for predicting the students' performance at the final examinations. The proposed software is based on a novel 2-level classification technique which achieves better performance than any examined single learning algorithm. Furthermore, significant advantages of the presented tool are its simple and user-friendly interface and that it can be deployed in any platform under any operating system.

Keywords: Educational data mining, machine learning, student evaluation system, decision support software.

1 Introduction

Educational Data Mining (EDM) is an essential process where intelligent methods are applied to extract data patterns from students' databases in order to discover key characteristics and hidden knowledge. This new research field has grown exponentially and gained popularity in the modern educational era because of its potential to improve the quality of the educational institutions and system. The application of EDM is mainly concentrated on improving the learning process by the development of accurate models that predict students' characteristics and performance. The importance of EDM is founded on the fact that it allows educators and researchers to extract useful conclusions from sophisticated and complicated questions such as "*find the students who will exhibit poor performance*" in which traditional database queries cannot be applied [17].

Secondary education in Greece is a two-tied system in which the first three years cover general education followed by another three years of senior secondary education. Therefore, the three years of higher secondary education is an important and decisive factor in the life of any student since it acts like a bridge between school education and higher education, offered by universities and higher technological educational institutes [17]. Thus, the ability to monitor students' academic performance and progression is considered essential since the early identification of possible low performers could lead the academic staff to develop learning strategies (extra learning material, exercises, seminars, training tests) aiming to improve students' performance.

During the last decade, research focused on developing efficient and accurate Decision Support Systems (DSS) for predicting the students' future academic performance [5, 7, 10, 17, 21, 22]. More analytically, an academic DSS is a knowledge-based information system to capture, handle and analyze information which affects or is intended to affect decision making performed by people in the scope of a professional task appointed by a user [4]. The development of an academic DSS is significant to students, educators and educational organizations and it will be more valuable if knowledge mined from the students' performance is available for educational managers in their decision making process.

In this paper, we present DSS-PSP (Decision Support Software for Predicting Students' Performance) which consists of an integrated software application that provides decision support for evaluating students' performance in the final examinations. The presented software incorporates a novel 2-level classifier which achieves better performance than any single learning algorithm. Furthermore, significant advantages of the presented tool are that it employs a simple and user-friendly interface, it is highly expandable due to its modular nature of design and implementation and it can be deployed in any platform under any operating system. Our primary goal is to support the academic task of successfully predicting the students' performance in the final examinations of the school year. Furthermore, decision-makers are able to evaluate various educational strategies and generate forecasts by means of simulating with the input data.

The remainder of this paper is organized as follows: The next section presents a survey of machine learning algorithms that have been used for predicting students' performance. Section 3 presents a description of the educational dataset utilized in our study and our proposed 2-level machine learning classifier. Finally, Section 4 presents the main features of our decision support software and Section 5 presents our conclusions.

2 Related studies

During the last decade, the application of data mining for the development of accurate and efficient decision support systems for monitoring students' performance is becoming very popular in the modern educational era. Baker and Yacef [2], Romero and Ventura [26, 27] and Dutt et al. [9] have provided excellent reviews of how EDM seeks to discover new insights into learning with new tools and techniques, so that those insights impact the activity of practitioners in all levels of education, as well as corporate learning. Furthermore, they described in detail the process of mining learning data, as well as how to apply the data mining techniques, such as statistics, visualization, classification, clustering and association rule mining.

Deniz and Ersan [7] demonstrated the usefulness of an academic decision-support system in evaluating huge amounts of student-course related data. Moreover, they presented the basic concepts used in the analysis and design of a new DSS software package and presented various ways in which student performance data can be analyzed and presented for academic decision making.

Kotsiantis et al. [13, 14] studied the accuracy of six common machine learning algorithms in predicting students that tend to dropout from a distance learning course in Hellenic Open University. Based on previous works, Kotsiantis [12] introduced a prototype decision support system for predicting students' academic progress based on key demographic characteristics, attendance and their marks in written assignments.

Chau and Phung [5] proposed a knowledge-driven DSS for education with a semester credit system by taking advantage of educational data mining. Their proposed educational DSS is helpful for educational managers to make more appropriate and reasonable decisions about students' study and further give support to students for their graduation.

Romero et. al [25] studied how web usage mining can be applied in e-learning systems in order to predict the marks that university students will obtain in the final exam of a course. In addition, they developed a specific mining tool which takes into account the student's active involvement and daily usage in a Moodle forum.

Nagy, Aly and Hegazy [21] proposed a "Student Advisory Framework" that integrates educational data mining and knowledge discovery to build an intelligent system. The system can be used to provide pieces of consultations to a first year university student to pursue a certain education track where he/she will likely succeed in, aiming to decrease the high rate of academic failure among these students. The framework acquires information from the datasets which stores the academic achievements of students before enrolling to higher education together with their first year grade after enrolling in a certain department. After acquiring all the relevant information, the intelligent system utilizes both classification and clustering techniques to provied recommendations for a certain department for a new student. Additionally, they presented a case study to prove the efficiency of the proposed framework. Students' data were collected from Cairo Higher Institute for Engineering, Computer Science and Management during the period from 2000 to 2012.

Mishra et al. [20] focused on the early identification of secondary school students who are at high risk of failure thereby helping the educator to take timely actions to improve the students' performance through extra coaching and counseling. Moreover, they classified the important attributes that influenced students' third semester performance and established the effects of emotional quotient parameters that influenced placement.

In more recent works, Livieris et al. [18] introduced a software tool for predicting the students' performance in the course of "Mathematics" of the first year of Lyceum. The proposed software is based on a neural network classifier which exhibits more consistent behavior and illustrates better accuracy than the other classifiers. Along this line, in [17] the authors presented a user-friendly decision support software for predicting students' performance, together with a case study concerning the final examinations in Mathematics. Their proposed tool is based on a hybrid predicting system which combines four learning algorithms utilizing a simple voting scheme. Their experimental results revealed that the application of data mining can gain significant insights in student progress and performance.

Marquez-Vera et al. [19] studied the serious problem of early prediction of high school dropout. They propose a methodology and a specific classification algorithm to discover comprehensible prediction models of student dropout as soon as possible. Additionally, they presented a case study using data from 419 first year high school Mexican students. They authors illustrated that their proposed method is possible of successfully predicting student dropout within the first 4-6 weeks of the course and trustworthy enough to be used in an early warning system.

3 Methodology

The aim of this study is to develop a decision support tool for predicting students' performance at the final examinations. For this purpose, we have adopted the following methodology that consists of three stages.

The first stage of the proposed methodology concerns data collection and data preparation and in the next stage, we introduce our proposed 2-level classification scheme. In the final stage, we evaluate the classification performance of our proposed 2-level classification algorithm with that the most popular and frequently used algorithms by conducting a series of tests.

3.1 Dataset

For the purpose of this study, we have utilized a dataset concerning the performance of 2206 students in courses of "Algebra" and "Geometry" of the first two years of Lyceum. The data have been collected by the *Microsoft showcase school "Avgoulea-Linardatou"* during the years 2007-2016.

Table 1 reports the set of attributes used in our study which concern information about the students' performance such as oral grades, tests grades, final examination grades and semester grades. The assessment of students during each semester consists of oral examination, two 15-minutes prewarned tests, a 1-hour exam and the overall semester performance of each student. The 15-minutes tests include multiple choice questions and short answer problems while the 1-hour exams include several theory questions and a variety of difficult mathematical problems requiring solving techniques and critical analysis. Finally, the overall semester grade of each student addresses the personal engagement of the student in the lesson and his progress. The students were classified utilizing a four-level classification scheme according to students' performance evaluation in the Greek schools: 0-9 (Fail), 10-14 (Good), 15-17 (Very good) and 18-20 (Excellent).

Attributes	Type	Values
Oral grade of the 1st semester	real	[0,20]
Grade of the 1st test of the 1st semester	real	[0,20]
Grade of the 2nd test of the 1st semester	real	[0,20]
Grade of the 1st semester's final examination	real	[0,20]
Final grade of the 1st semester	real	[0,20]
Oral grade of the 2nd semester	real	[0,20]
Grade of the 1st test of the 2nd semester	real	[0,20]
Grade of the 2nd test of the 2nd semester	real	[0,20]
Grade of the 2nd semester's final examination	real	[0,20]
Final grade of the 2nd semester	real	[0,20]

Table 1. List of features used in our study

Moreover, similar to [17, 18], since it is of great importance for an educator to recognize weak students in the middle of the academic period, two datasets have been created based on the attributes presented in Table 1 and on the class distribution.

- $\mathrm{DATA_A}$: It contains the attributes concerning the students' performance of the 1st semester.
- $\mathrm{DATA_{AB}}$: It contains the attributes concerning the students' performance of the 1st and 2nd semesters.

3.2 2-level classifier

Our major challenge was to develop a new classification scheme which can achieve higher classification accuracy than individual classifiers. For this purpose, we introduce a two-level architecture classification scheme. Two-level classification schemes are heuristic pattern recognition tools that are supposed to yield better classification accuracy than single-level ones at the expense of a certain complication of the classification structure [3, 15, 29].

On the first level of our proposed classification scheme, we utilize a classifier to distinguish the students who are likely to "Pass" or "Fail" in the final examinations. More specifically, this classifier predicts if the student's performance is between 0 and 9 (Fail) or between 10 and 20 (Pass). In the rest of our work, we refer to this classifier as A-Level classifier. In case the verdict (or prediction) of the A-Level classifier is "Pass" in the final examinations, we utilize a second-level classifier in order to conduct a more specialized decision and distinguish between "Good", "Very good" and "Excellent". This classifier is titled as the B-Level classifier. An overview of our proposed 2-level classifier is depicted in Figure 1.

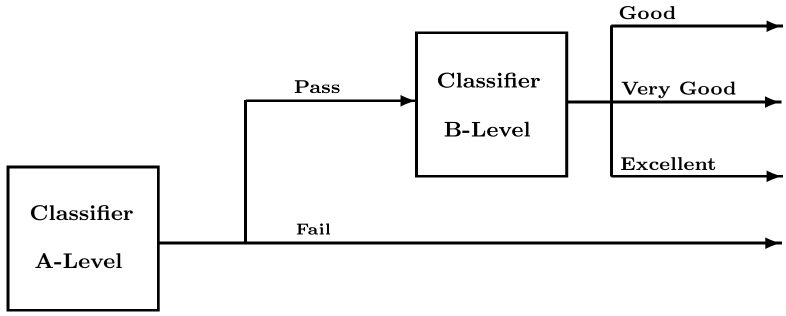

Fig. 1. An overview of the 2-level classifier

It worths noticing that, the decision of the A-Level classifier is more coarse and high level, while the decision of the B-Level is specialized and characterizes the performance of a successful student.

3.3 Experimental Results

In this section, we report a series of tests in order to evaluate the performance of our proposed 2-level classification scheme with that of the most popular and commonly used classification algorithms.

The Back-Propagation (BP) algorithm with momentum [28] was representative of the artificial neural networks which has been established as a well-known learning algorithm for building and training a neural network [16]. From the support vector machines, we have selected the Sequential Minimal Optimization (SMO) algorithm since it is one of the fastest training methods [23] while Naive Bayes (NB) algorithm was the representative of the Bayesian networks [8]. From the decision trees, C4.5 algorithm [24] was the representative in our study and RIPPER (JRip) algorithm [6] was selected as a typical rule-learning technique since it is one of the most usually used methods for producing classification rules. Finally, 3-NN algorithm was selected as instance-based learner [1] with Euclidean distance as distance metric. Moreover, in our experimental results Voting stands for simple voting scheme using RIPPER, 3-NN, BP and SMO as base classifiers presented in [17].

All algorithms have been implemented in WEKA Machine Learning Toolkit [11] and the classification accuracy was evaluated using the stratified 10-fold cross-validation i.e. the data was separated into folds so that each fold had the same distribution of grades as the entire data set.

Table 2 summarizes the accuracy of each individual classifier and the accuracy of the 2-level classification scheme, relative to both datasets. Clearly, our proposed 2-level scheme significantly improved the performance of each individual classifier from 3.8% to 9.5%.

	$DATA_A$		$DATA_{AB}$	
Classifier	Individual	2-level	Individual	2-level
BP	81.1%	89.1%	76.2%	89.1%
SMO	84.1%	89.9%	82.7%	89.9%
NB	75.8%	81.2%	71.7%	79.0%
C4.5	84.2%	89.8%	84.1%	89.8%
JRip	84.7%	90.0%	86.1%	89.6%
3-NN	85.2%	88.1%	78.7%	85.3%
Voting	85.8%	88.2%	84.4%	87.0%

Table 2. Individual classifier and 2-level classifier accuracy (%) for each dataset

Hence, motivated by the previous results we evaluated the proposed 2-level scheme utilizing different classification algorithms at each level. Our aim is to find which of these classifiers is best suited for A-Level and B-Level for producing the highest performance.

Tables 3 and 4 summarize the performance of the proposed 2-level classifier utilizing various A-Level and B-Level classifiers for both datasets, respectively. The best performing technique for each dataset is illustrated in boldface.

		B-Level Classifier					
		BP	SMO	NB	C4.5	JRip	3-NN
A-Level Classifier	BP	89.1%	89.7%	85.9%	89.7%	89.7%	88.0%
	SMO	89.8%	89.9%	85.8%	90.0%	89.9%	88.6%
	NB	84.4%	85.0%	81.2%	84.9%	85.0%	83.1%
	C4.5	89.7%	**90.1**%	86.2%	89.8%	89.8%	88.5%
	JRip	89.8%	90.0%	86.2%	89.9%	90.0%	88.2%
	3-NN	89.1%	89.7%	85.8%	89.7%	89.8%	88.1%

Table 3. 2-level classifier classification accuracy (%) on $DATA_A$

Firstly, we observe that the C4.5 reports the best classification performance as A-Level classifier, slightly outperforming JRip, relative to both datasets. In particular, it exhibits 86.2%-90.1% and 81.8-90.3% classification performance, for $DATA_A$ and $DATA_{AB}$, respectively. Moreover, SMO is best B-Level classifier reporting the best overall performance, followed by C4.5. More specifically,

		B-Level Classifier					
		BP	SMO	NB	C4.5	JRip	3-NN
A-Level Classifier	BP	89.1%	89.6%	81.5%	89.7%	89.4%	86.3%
	SMO	89.7%	89.9%	81.8%	90.0%	89.8%	86.9%
	NB	78.5%	84.9%	79.0%	79.2%	78.9%	76.2%
	C4.5	89.6%	**90.3**%	81.8%	89.8%	89.8%	86.6%
	JRip	89.5%	90.0%	81.6%	89.9%	89.6%	86.7%
	3-NN	88.0%	89.7%	80.5%	88.6%	88.4%	85.3%

Table 4. 2-level classifier classification accuracy (%) on $\mathrm{DATA}_{\mathrm{AB}}$

SMO reported 84.9%-90.3% classification performance, regarding both datasets. Finally, it worths noticing that the best classification performance of the 2-level classifier was presented in case C4.5 was selected as A-Level classifier and SMO as a B-Level one.

4 DSS-PSP: Decision support software

For the purpose of this study, we developed a user-friendly decision support software, which is called DSS-PSP[4] for predicting the performance of an individual student at the final examinations based on its grades on the 1st and/or 2nd semester. The software is based on the WEKA Machine Learning Toolkit and has been developed in JAVA, making it platform independent and easily executed even by non-experienced users. Notice that DSS-PSP consists an updated version of the software presented in [17] with similar functionalities.

Figure 2 illustrates a screenshot of our proposed decision support software DSS-PSP illustrating its main features:

- **Student personal data:** This module is optionally used to import student's name, surname, father's name and remarks.
- **1st Semester's grades:** This module is used to import the student's grades of the first semester.
- **2nd Semester's grades:** This module is used to import the student's grades of the second semester.
- **Messages:** This module is used to print the messages, warnings and outputs of the tool.

Subsequently, we demonstrate a use case in order to illustrate the functionalities of DSS-PSP. Firstly, the user/educator can use our data embedded in the software by clicking on the button "Import data" or he can load his/her data collected from his/her own past courses in XLSX file format.

[4] The tool is available at `http://www.math.upatras.gr/~livieris/DSSPSP.zip`. Notice that Java Virtual Machine (JVM) 1.2 or newer is needed for the execution of the program.

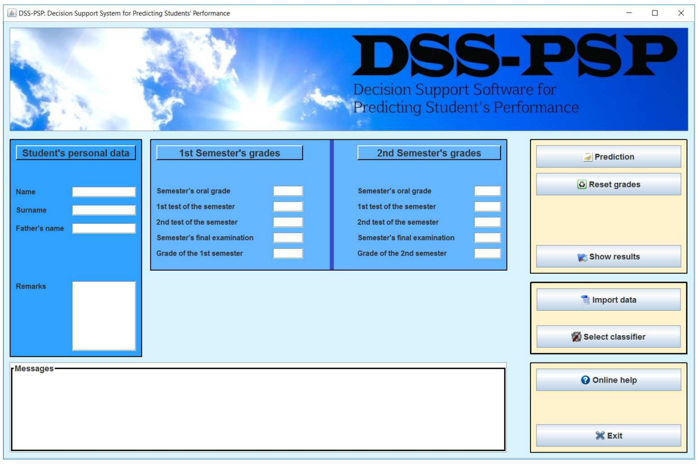

Fig. 2. DSS-PSP interface

Next, by clicking on the "Select classifier" button, DSS-PSP provides the ability to the user to choose between the old classifier based on a voting scheme [17] and the proposed 2-level classification algorithm (Figure 3) which utilizes C4.5 as a A-Level classifier and SMO as B-Level classifier. It worths noticing that the proposed 2-level classification algorithm is more accurate and it can be trained significantly faster than the voting scheme presented in [17].

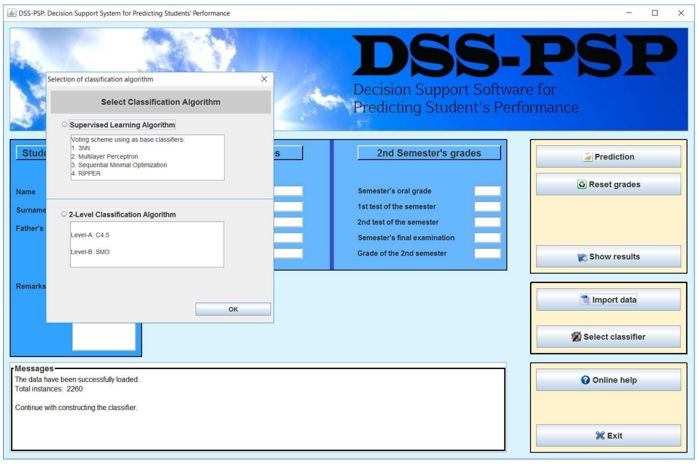

Fig. 3. DSS-PSP: Select classifier

After that, the user can import the new student's grades of the 1st and/or 2nd semester in the corresponding fields. Next, the DSS-PSP is able to predict the student's performance at the final examinations by simply clicking on the button "Prediction" as it is illustrated in Figure 4.

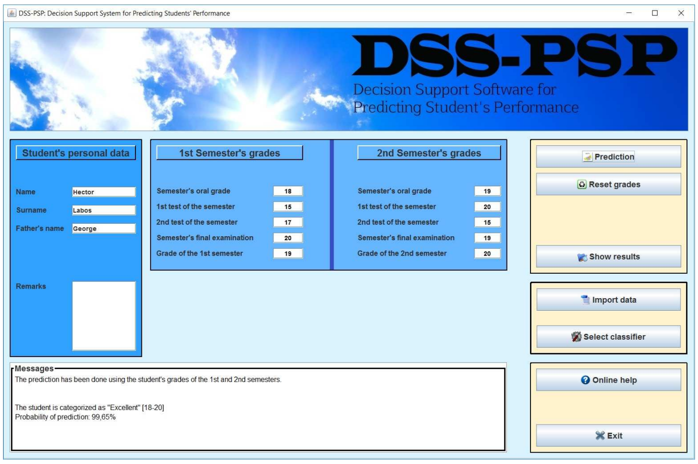

Fig. 4. DSS-PSP: Prediction about the performance of a new student at the final examinations

Moreover, the tool provides on-line help, for novice users and the ability to see all previous predictions by clicking the button "Show results".

5 Conclusions

In this work, we introduced DSS-PSP, a user-friendly decision support system for predicting the students' academic performance at the final examinations which incorporates a novel 2-level machine learning classifier. Our numerical experiments revealed that the proposed scheme significantly improves the accuracy of each individual classification algorithm, illustrating better classification results. Moreover, the software is highly adaptable and expandable due to its modular design and implementation. Additional functionalities can be easily added according to the user needs.

Our objective and expectation is that this work could be used as a reference for decision making in the admission process and strengthen the service system in educational institutions by offering customized assistance according to students' predicted performance.

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