Self-assessment activities as factor for driving the learning performance

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Abstract. Machine learning proposes innovative methods for students' learning analysis and new ways for modeling the learning process and its realization. Learning analytics takes advantage of this fact and processes data according to accepted or emerging algorithms that leads to creation of analytical and predictive models. Learning performance is connected to a set of behavioral activities in educational environment concerning improvement of knowledge and skills. It is a very important criterion for students' progress and for the formation of the final students' outcomes. For achieving better learning performance, the activities should lead to the learning optimization in context of time duration, educational tasks organization, content presentation and management. Activities that support learning are oriented to self-dependent and self-regulated learning as well as socially-oriented and group-driven learning. The aim of the paper is to present an exploration focusing on the influence of self-dependent activities in the form of self-assessment on learning performance. An experiment is conducted with students who have had the possibility to direct and organize their self-assessment activities in the learning management system. Self-assessment activities are not graded and they are not included in the formation of the final course mark. The students' behavior is traced during one semester and machine learning algorithms are utilized to analyze the quality and quantity of the taken self-assessment activities. On this base analytical and predictive models regarding learning performance and the achieved academic results are created. The patterns and anomalies are outlined and they are used to point out the directions for learning performance and final outcomes improvement.

INTRODUCTION

Exploration of learning performance, how to be evaluated and improved, is a topic related to the optimization of the students learning process and the improvement of the educator's activities. There is not exact definition of learning performance, but the term is connected to the conducted learning activities that lead to better outcomes, improved learning process and successful course completion. How the learning performance should be measured, what kind of indicators are supposed to be used and what are the main factors that influence it are still among the challenging issues in educational practice. Data collected during the educational process is object of examination and analysis by learning analytics techniques, taking advantage of the recent scientific achievements.

Usually, learning analytics utilizes statistical methods for processing data related to students' behavior, outcomes and created products collected in their portfolios. Nowadays, learning analytics takes benefits from machine learning methods to solve problems like classification and clustering and to predict future facts and events. In this case it is referred to intelligent learning analytics, because data gathered during the educational process could be further utilized for educational activities automation and for development of intelligent tools and systems.

Machine learning algorithms give huge possibilities for solving a wide variety of problems in the area of education with the aim to improve the teaching and learning processes. Machine learning is part of artificial intelligence that takes advantage of the data sets to generate classification and predictive models. The achievement of effective and high quality educational process depends on the teachers' and students behavior and performance. The data received during the students' participation in courses could show patterns and anomalies and they could be explored. The analysis should lead to the appropriate conclusions, decision making and predictions. Among the most utilized machine learning techniques according to the examined literature are: decision trees and naive bayes for students' classification according to their performance and achieved knowledge [1], decision tree, multinomial naive bayes and support vector machines for students' grouping according to the generated content by them [2], artificial neural networks, support vector machines, logistic regression, naïve bayes and decision

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trees for predicting the students' difficulties during a course session [3], random forest and support vector machines for predicting the students' outcomes [4], neural networks and decision trees for predicting the students' performance and final results [5]. These algorithms are developed for "big data" analysis, but also they can also be used for "small data" processing as in the context of this work.

The aim of the paper is to present an exploration of learning performance measured through the quality of the conducted self-dependent students' activities in the form of self-assessment as well as through examination of their quantitative values. Machine learning algorithms are used for development of analytical and predictive models, and the main predictors for evaluation of students' learning performance are identified.

LEARNING PERFORMANCE

This section summarizes and analyzes different points of view regarding learning performance evaluation with the aim to reveal the measurement metrics.

Apple and Ellis connect learning performance to learning-to-learn and examine it from five perspectives which are the base for the theory of performance [6]. These components of learning performance are additionally described by authors and the final set shows thirteen different dimensions related to: learner is capable to learn, learner is responsible for her/his own learning, learner's knowledge is in continuous improvement, learner is aware of her/his learning management process, learner receives knowledge in different forms, learner continuously improves her/his cognitive learning skills, learner elaborates her/his social skills, learner evolves her/his affective skills, learner receives high quality learning-to-learn experience, learner is capable to learn in team tasks, learner performs active learning, learner accepts life challenges and learner makes right choices. These dimensions could be used to measure different aspects of the learning performance.

Chen et al. propose an approach for evaluation of the learning performance according to the students' activities in their portfolios created in a personalized e-learning system and the grade from the final test [7]. The following factors are taken into account: the amount of the read learning materials, learner self-evaluation of difficulty level, learner self-evaluation of the level of understanding, the learner ability for self-evaluation, the time spent on the course pages, the final test grade. This approach delivers feedback that is useful for students to adjust their learning and for teachers who can save time in the assessment process.

Ugray et al. explore the connection between learning performance and computer-aided tools [8]. The following factors were identified with impact on the learning performance: students' age, the delivery medium of the course content, course topic and the level of the course.

The students' behavior in the learning management system (LMS) has been recorded in databases, stored in a log file and fourteen variables are extracted for learning performance evaluation [9]. Login and logout events in LMS, working with course material, assignments upload and download, forum read and post events are taken into account for preparation of predictive classification models that alert when poor students' learning performance is identified.

Nakayama et al. explore the influence of students' characteristics and note taking activities in a blended-learning course on learning performance [10]. They propose predictive models of learning performance based on students' note taking and prove the effectiveness of note taking supported through instructions as well as the relationship between note taking activities and final students' grade.

The influence of "assessment for learning" (AfL) on learning performance is explored by Oyinloye and Imenda [11]. They show that learners involved in AfL approach are characterized with significantly higher learning performance. The five key strategies for activating the AfL approach that are used for provided experiment are outlined as: clear intention and criteria for successful learning drawn by educators, organization of discussion-based classroom by educators, providing feedback for further learning evolvement by educators, activating peer-to-peer instructional support, activating the students awareness regarding the organization of their own learning.

Stansfield et al. explore several educational and social factors that influence students' learning performance in online and face-to-face classroom. They are: applying strategic studying by experienced learners, clear content with learning goals, flexible access to learning materials, suitable level of control that learners have to possess during their learning and assessment [12].

Table 1 summarizes the discovered findings regarding the factors that are used for learning performance evaluation after scientific literature exploration. It can be said that few authors explore the students' responsibility and awareness to manage their own learning process as measurement factors of learning performance. Also, the topic about the relationship between the students' learning performance and self-assessment activities is not well examined and needs further research.

TABLE 1. Factors for evaluation the students' learning performance according to explored scientific literature

Authors	Factors for evaluation the students' learning performance
Apple and Ellis [6]	• learners' capability to learn • learner's responsibility for his/her own learning • continuous improvement of learner's knowledge • learner's awareness of his/her learning management process • receiving knowledge in different forms • learners' continuously improvement of cognitive skills • elaboration of learners' social skills • receiving high quality learning-to-learn experience • capability to learn in team tasks • acceptance of life challenges and making right choices
Chen et al. [7]	• the amount of the read learning materials • learners' self-evaluation of difficulty level • learner's self-evaluation of the level of understanding • learner's ability for self-evaluation • time spent on the course pages • final test grade
Ugray et al. [8]	• students' age • the delivery medium of the course content • course topic • level of the course
Hu et al. [9]	• login and logout events in LMS • interactivity with course material • assignments upload and download • forum reading and posting
Nakayama et al. [10]	• students' characteristics • note-taking activities
Oyinloye and Imenda [11]	• clear intention and criteria for successful learning drawn by educators • organization of discussion-based classroom by educators • feedback providing for further learning involvement by educators • activating peer-to-peer instructional support by educator • activating the students 'awareness regarding the organization of their own learning
Stansfield et al. [12]	• applying strategic studying by experienced learners • clear content with learning goals • flexible access to learning materials • suitable level of control that learners have to possess during their learning and assessment

RESEARCH METHOD

For undergraduate students involved in the course Applied Computer Graphics are designed self-dependent activities in the form of seven self-assessment quizzes in LMS which outcomes are not included in the formation of the final mark. The aim of these activities is to support students learning and final results through tasks that are performed outside of class. The enrolled in the course students are nineteen, but two of them did not perform their self-assessment activities.

The received results: the number of performed self-assessment quizzes and their scores are taken into account for creating analytical and predictive models regarding the students' learning performance. Self-assessment quizzes are divided in two parts: the first part consists of four quizzes, covering one half of the course material and the second part includes three self-assessment quizzes that test knowledge regarding the rest of the course material. The students had to conduct two summative quizzes which results are included in the formation of the final mark. The first summative quiz covers the first one half of the course content and the second summative quiz tests students' knowledge regarding the second part of the course material. So, the first four self-assessment quizzes are designed in support of learning the first part of course material and to facilitate the first summative quiz. The second three self-assessment quizzes are prepared to assist students during their preparation for the second summative quiz. At the end of the semester, the scores of self-assessment quizzes are compared with the scores of summative assessment tasks. The maximum score of each quiz is 100 points and the threshold for quiz passing is 60 points.

The "small data" is trained through usage of machine learning algorithms for time series prediction for forecasting the scores of students' future self-assessment activities, for classification and for clustering students in categories regarding their self-directed behavior. For statistical data processing GMDH Shell DC environment is used and Weka software is utilized for obtaining analytical classification and clustering models.

THE EXPERIMENT AND RESULTS

The initial dataset includes data about the number of self-assessment activities conducted by students and the scores from self-assessment quizzes as it is shown on Fig. 1 Every student had the possibility to direct and organize his/her self-assessment activities that means whether and when to conduct them. For example, the first student conducted all quizzes, but the second one only six of them. All students took the first five quizzes, the sixth and seventh quiz are only completed from one part of the students. Quizzes cover all lecture topics and they are a very important assistant for checking the students' knowledge as well as for supporting them in final exam preparation. The number of conducted self-assessment activities and the scores from these quizzes are taken as factors for learning performance measurement.

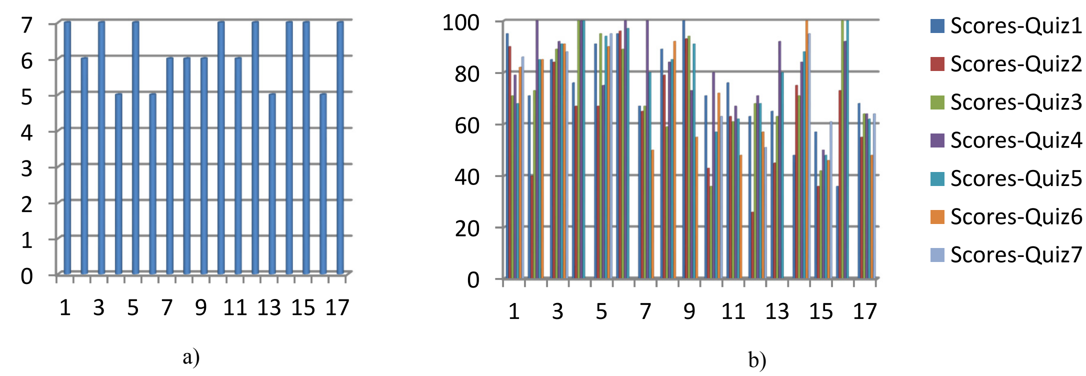

FIGURE 1. Self-assessment activities: a) the number of quizzes, conducted by students; b) the scores from these quizzes

Firstly, the data about non-conducted by students quizzes are generated though applying time series forecasting method with aim to prepare a complete dataset for analysis. Also, time series forecasting method is used to predict the scores of students' future self-assessment activities, presenting a trending direction. This was useful for all course participants, because the advanced students were suggested to keep this learning behavior to the end of the course and the students with worse results to improve their learning behavior. The dataset is prepared in csv format and processed in GMDH Shell DC environment [13]. Figure 2 presents the predicted model for the first student marked with the value x1 and the model points out the increased scores for the future self-assessment activities. The models for the rest students are available under the values from x2 to x17.

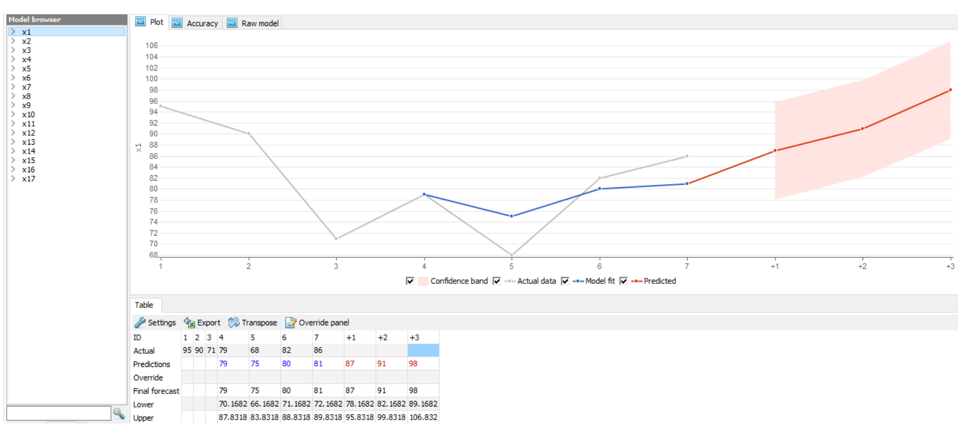

FIGURE 2. Time series prediction method for revealing the trending direction in students' scores

Secondly, an analytical model for learning performance evaluation is constructed and data is trained through a cross-validation method with 6 folds in Weka environment [14]. The model has the following form:

```
@relation lperformance

@attribute numberoftakenquizzes real
@attribute scoresquiz1 {excellent, verygood, good, average, bad, notperformed}
@attribute scoresquiz2 {excellent, verygood, good, average, bad, notperformed}
@attribute scoresquiz3 {excellent, verygood, good, average, bad, notperformed}
@attribute scoresquiz4 {excellent, verygood, good, average, bad, notperformed}
@attribute scoresquiz5 {excellent, verygood, good, average, bad, notperformed}
@attribute scoresquiz6 {excellent, verygood, good, average, bad, notperformed}
@attribute scoresquiz7 {excellent, verygood, good, average, bad, notperformed}

@attribute learnperform {excellentperform, goodperform, badperform}

@data
7, excellent, verygood, good, good, average, verygood, verygood, excellentperform
6, verygood, bad, good, excellent, verygood, verygood, notperformed, goodperform
7, verygood, verygood, verygood, excellent, excellent, excellent, verygood, excellentperform
…
```

The attribute related to the number of taken self-assessment quizzes has numeric value and the rest attributes concerning the scores from quizzes and evaluation of learning performance have nominal values. The first applied algorithm is BayesNet and the result is shown on Fig. 3. The constructed graph presents the factors for evaluation of learning performance: the number of taken self-assessment quizzes and the quizzes scores.

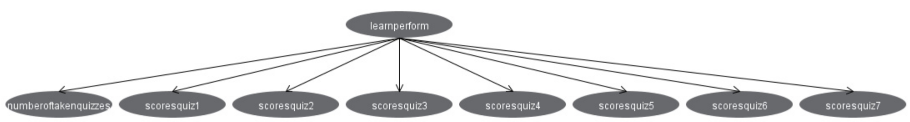

FIGURE 3. Factors for learning performance evaluation and created graph after applying BayesNet method

Then, the J48 algorithm is used for building the pruned classification tree and to extract the main predictor for learning performance evaluation. Another model is created which works with numeric type of attributes: the number of taken quizzes and the scores from quizzes. Only the attribute *learning performance* has nominal value type. It can be seen on Fig. 4 that the built pruned tree consists of one root node, one internal node and three leaves. The root node is the main predictor for the learning performance and it is *the number of the conducted self-assessment quizzes*. The learning performance of the students is evaluated as *excellent* when they have conducted all seven quizzes and the scores from the third quiz are greater than 68 points. The learning performance is evaluated as *bad* when the students are taken all quizzes, but the scores from the third quiz are less than or equal to 68 points.

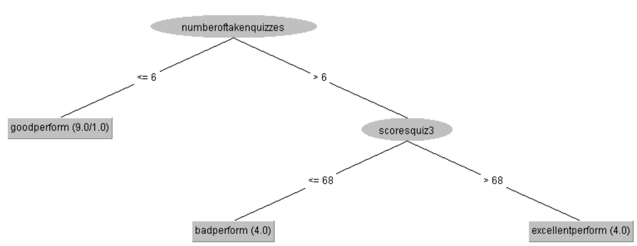

FIGURE 4. The constructed pruned tree through J48 algorithm and obtained main predictor for learning performance evaluation

The constructed full tree through RandomTree algorithm is presented on Fig. 5. The main predictor in the model is the *scores from the seventh quiz* and additional predictors are: the *scores obtained after taking the fourth quiz* and *the number of the taken self-assessment quizzes*. It can be said that the learning performance is *excellent* when all self-assessment quizzes are taken by the students and the scores from the seventh quiz are greater than or equal to 73 points. The *bad* students' performance could be predicted after obtaining the scores from the fourth and seventh quiz in the case when they conducted all seven quizzes.

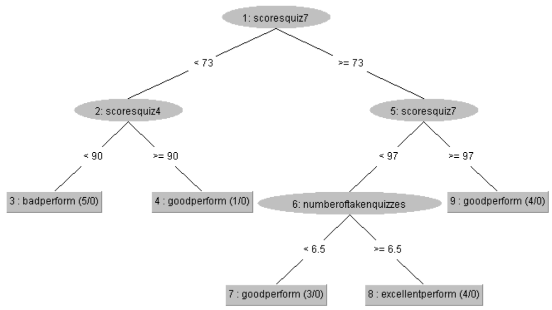

FIGURE 5. The constructed full tree through RandomTree algorithm

In order to group students according to their learning performance two machine learning algorithms are utilized EM (Fig. 6) and HierarchicalClusterer (Fig. 7). According to EM algorithm, the students are grouped into three clusters: (1) students with *bad* learning performance during their self-assessment activities conductance (blue dots on fig. 6.), (2) students with *good* learning performance (green dots) and (3) students with *excellent* learning performance (red dots). X-axis on Fig. 6 depicts the student ID and y-axis shows the evaluated learning performance. The result of the HierarchicalClusterer algorithm (66% split mechanism is applied) is presented in the form of a dendogram on Fig. 7. Two major clusters are formed – the students with excellent and good learning performance. Each cluster consists of branches with elements called leaves. Each branch includes students with similar characteristics. The difference in the elements' height shows differences in the quantitative achievements (points from the quizzes) of the students.

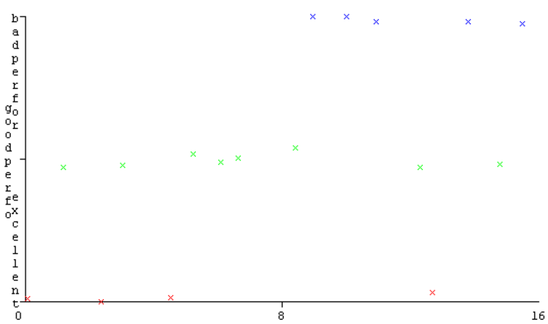

FIGURE 6. EM clustering algorithm

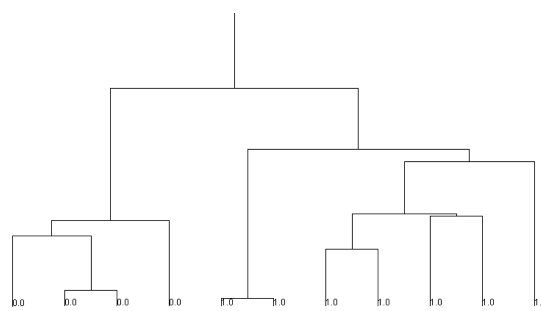

FIGURE 7. HierarchicalClusterer algorithm

Finally, the classification model containing the relationship among the number of taken self-assessment quizzes, the received marks of two summative assessment tasks and the average values of scores regarding the first four self-assessment activities and second three self-assessment activities (the scores are converted into marks) is presented on Fig. 8. It can be seen that the scores of the self-assessment activities and the number of the self-assessment activities play an important role for evaluation the students' learning performance. The core node in the constructed full tree according to the RandomTree algorithm is *selfassessment*1 attribute which is the main predictor for the students with *bad* learning performance. The predictors for students' *excellent* learning performance are the attributes *selfassessment1* (corresponds to the average scores of the first four self-assessment activities) and *numberoftakenquizzes* (corresponds to the number of the taken self-assessment quizzes).

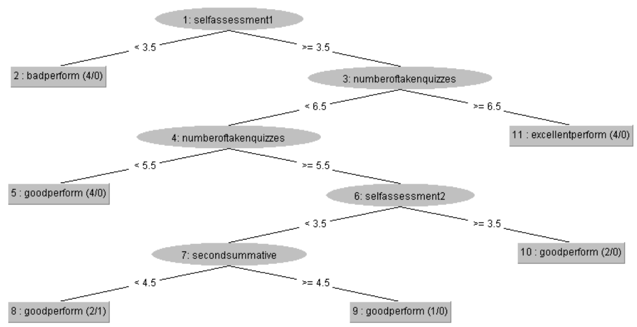

FIGURE 8. Relationship among the number of the taken self-assessment tasks, the outcomes from the self-assessment activities and the results from the summative assessment tasks

CONCLUSIONS

The paper presents a method for evaluating the students' learning performance through machine learning algorithms. The main predictors are proved to be *the number of taken self-assessment quizzes* during the semester and the obtained *scores from these self-assessment quizzes*. The extracted pattern shows that the students with *bad* learning performance could be predicted after the results from the first four self-assessment activities. *Excellent* learning performance is achieved if the students conduct all self-assessment activities and the average mark from the first four self-assessment activities is greater than a given value.

The final classification model points out that 4 of the students are categorized with *excellent* learning performance, other 4 of them as students with *bad* learning performance and the rest 9 students are with *good* learning performance. The anomaly is discovered with one student who is included into the group of the students with *bad* learning performance according to some models and into the group of the students with *good* learning performance according to others.

The results show that the majority of students are responsible for their own learning and they are capable to self-manage their learning process. It is proved with the obtained results after the classification process that the big part of students' are characterized with good and excellent learning performance.

Machine learning algorithms as an approach for learning from data propose powerful tool for learning analytics. Their usage in educational domain contributes to better events and process analysis aiming for different educational tasks to be optimized. Prediction of behavior is a suitable technique that could show the future directions for students' development and could point out measures for learning performance improvement.

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