Intelligent Student Profiling for Predicting e-Assessment Outcomes

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***Abstract*—The main objective of this paper is introducing intelligence in the e-Learning and e-Assessment processes. Therefore, we present an existing adaptive e-Learning and e-Assessment strategies, verify them with machine learning (ML) algorithms, build students Profile and eventually, we present our new model that will be able to estimate the final result of the overall students' work during the semester, taking into account all the learning objectives that the students have passed. Thus, our idea is creating an intelligent agent that will simulate the behavior of a real professor as much as possible.**

***Index Terms*—*e-Learning*; *e-Assessment*; *Machine Learning*.**

I. Introduction

Learning can be defined as a process for acquiring knowledge or skills. E-Learning, also known as Computer Assisted Learning, refers to the learning by using sophisticated information and communication technologies, whereas, the e-Assessment, or Computer Assisted Assessment, aims to assess the learner's knowledge.

A comparison of the traditional and online learning and testing has been discussed by many authors [1], [2]. Sun et al. [3] developed an integrated model with six dimensions: learners, instructors, courses, technology, design, and environment to investigate the critical factors affecting learners' satisfaction in e-Learning. The results showed that the critical factors affecting learners' perceived satisfaction are: learners' computer anxiety, instructors' attitude toward e-Learning, e-Learning course flexibility, e-Learning course quality, perceived usefulness, perceived ease of use and diversity in assessments. Another conceptual model for understanding learners' satisfaction, behavioral intention, and effectiveness of using the e-Learning system is discussed by Liaw [4].

The design of online assessment tools has been in the focus recently [5], [6], as well as applying intelligence in e-Learning services. For example, Uday et al. present a system architecture for applying intelligent methodologies to online assessment that adapts to the examinee's ability level and describe how web mining can be applied to improve the learner's performance [7].

Beside the surveys on the students' satisfaction, universities have been given a lot of advices to turn their interests towards cloud computing, since the cloud offers good resource flexibility and scalability, storage, computational requirements, network access, reduced power consumption and lower costs [8], [9], [10]. Ristov et al. [11] propose a SOA architecture of a cloud-hosted e-Assessment system which uses scalability and elasticity in order to achieve sustainable performance. Their solution reduces the overall costs since it uses minimum resources utilized only during the e-Assessment.

The main objective of this paper is introducing intelligence in the e-Learning and e-Assessment processes which will result in producing an intelligent agent (IA) whose decisions will be as similar as possible to the teacher's opinion on the student's outcomes. Therefore, at first, we present the existing adaptive e-Learning and e-Assessment strategies, then we verify them with machine learning (ML) algorithms and eventually, we present our new model.

II. The Problem

In this paper we use the results from an online learning tool that has been implemented at our university since 2002. Recently we have started a new project, based on 10 years of e-Learning and e-Assessment experience to develop a strategy that will be able to provide a proof that the student has achieved all learning objectives (LOs) by providing correct answers for relevant knowledge items during the online learning process.

During the strategy development, we confront several issues. The first is the method of guessing, which actually means randomly clicking on offered answers. Negative scoring is introduced for wrong answers since it does not represent knowledge. The online learning tool acts as an adaptive testing, since further testing depends on the student's achievement during the test.

The goal of the mentioned project is to build a correspondingly good strategy to classify student's knowledge which aims to answer the following questions:

- What is the minimal number of questions the system should ask to get relevant assessment of student's knowledge?
- What number of provided correct answers should classify the student knowledge as a pass?

Since each student has different background and entry level of knowledge, an innovative navigation algorithm is to be developed enabling different learning paths adaptive to the students' achievement. So, the outcome of this project is a system with the following features:

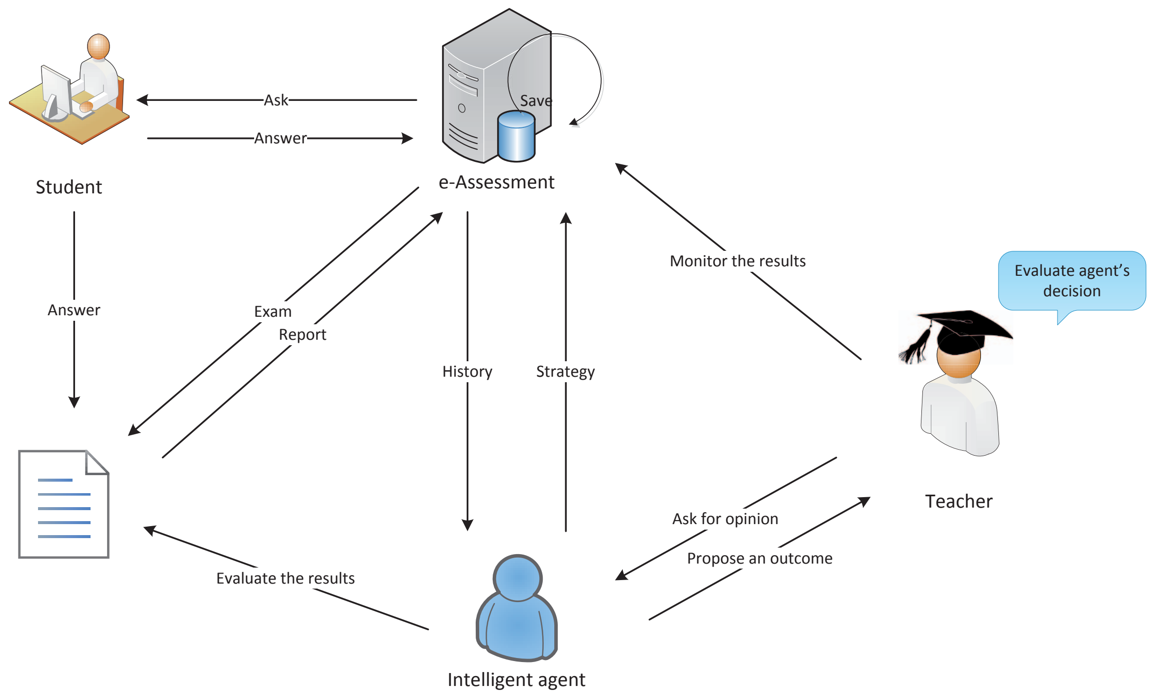

Fig. 1. Interaction between different roles during the e-Assessment process

- *Corrective measure* - whenever the student gives a wrong answer the system suggests corrections.
- *Adaptive learning path* - better students can move faster towards the more complex learning objectives.
- *Clear objectives and goals* - the navigation explains what else has left to be learned.

In order to solve problems identified in the mentioned project, we have analyzed several strategies for a software agent that acts on behalf of the teacher. The obtained results showed that the strategy of moving to upper or lower layers, depending on the answer, is vulnerable to the guessing method and is not appropriate for on-line learning. The least vulnerable strategy that offers satisfactory results is 3R (three correct answers in a row). The probability analysis showed that the probability to randomly choose three consequently correct answers is smaller than the probability to choose any three correct answers from a given set. The overall contribution of this research is that we developed strategy by which the students are asked as minimum questions as 3 and expect 3 correct answers in a row, in order to allow them to continue the online learning process. This strategy somehow confirms the student's knowledge on a particular learning objective.

However, this approach does not estimate the final outcome of the e-Assessments in terms of pass, or, fail, nor evaluates the student efficiency, and this is the motivation to conduct research whose results are reported in this paper.

III. The Challenge

In this paper we propose a model that will be able to estimate the final result of the overall students' work during the semester, taking into account all the learning objectives that the students have passed. Thus, our idea is creating IA that will simulate the behavior of a real professor as much as possible.

This research is an upgrade of already analyzed adaptive strategy, and the focus of this research is to show how the results from the long term e-Learning and e-Assessment of a particular student can be used to build an individual Profile that will represent the previous knowledge, which is essential for automatic ranging of the students' outcome. We believe that this kind of grading that depends on the students' overall work through the whole course will additionally motivate them to work continually during the semester and present their real knowledge during the e-Learning process.

The research reported in this paper consists of two parts. At first we verify the existing strategies for adaptive on-line learning tool using a ML approach. We use the most common Support Vector Machines (SVM) kernels during the training process. We set the hypothesis that the 3R strategy is the best for binary classification of the students in one of the classes, pass, or, fail. All other results that differ from the presented assumptions are correspondingly reported and behind the scientific explanation we make comprehensive conclusions.

The second part of the research reported in this paper focuses on building an IA able to estimate the students' final result. As presented on Figure 1, this IA tends to adapt to the student's personality, i.e. it depends on the student's e-Learning knowledge background. Thus, the first step will be

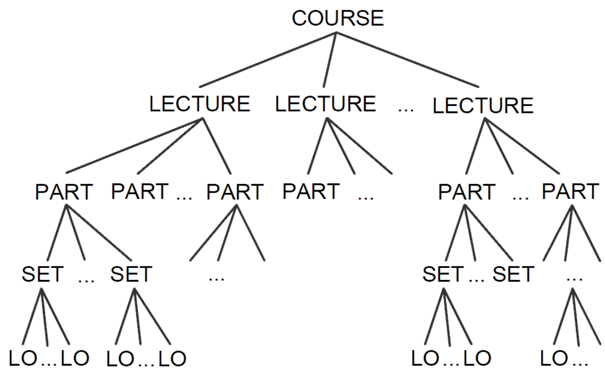

Fig. 2. Knowledge database organization

creating individual students' Profiles, that is, determining the students' manner of passing the learning objectives of the particular lecture. These Profiles will be consequently updated as the students take the e-Assessments during the course. After that, the profiles are used as previous knowledge in the ML methods. At the end of the course, the IA will classify the students' individual Profiles as passed or failed. Since the teacher is allowed to monitor the results and each student's knowledge background, the IA's decision is verified by a human factor. Furthermore, our IA is capable of revealing the students that are classified as failed, but have shown a remarkable improvement on a particular set of learning objectives. This feature is beneficial for both the teachers and the students, since it allows the student to be additionally examined and has an additional chance to successfully pass the course. Hereupon, we propose a system that simulates a real teacher and is able to estimate the real knowledge of its students.

IV. The Methodology

In this section we present the original methodology we developed for deriving an accurate estimation of the student's knowledge based on the e-Learning and e-Assessment results.

A. Knowledge Database Organization

Understanding the knowledge database structure is essential for building our Intelligent Agent. As presented on Figure 2, the knowledge database for each course is organized in a tree-like manner. The decision of representing the knowledge database organization in a hierarchical nested structure is encouraged by Baumgartner and Shankararaman [12]. Hereupon, one course represents the root of the tree. Each course consists of several lectures which are separated in few parts. Then, the basic learning objectives are organized into sets. Eventually, the essential knowledge items to be learned are organized into learning objectives. Each learning objective consists of few questions for which there is one, or, several correct answers. In order to make the 3R strategy applicable for any learning objective, there are at least five questions provided.

We use the tree structure only to present the database organization. Later in the ML approach, we use different structure to represent the knowledge vectors.

B. E-Learning and E-Assessment

In this paper we analyse the online learning process of the *Computer Architecture and Organization* course. During the course teaching, each week the students answer the assigned learning objectives. The course is organized in a manner that there are regularly e-Assessments with different number of questions from different learning objectives passed in the last couple of weeks.

C. Student's Profiling

In order to show how the results from the long term e-Assessment of a particular student can affect the previous e-Learning impression, we must provide each student an individual Profile.

The first step towards students Profiling is extracting their knowledge obtained as a result from the online learning process in a n-dimensional vector, where n is the number of learning objectives. The students knowledge of a particular learning objective is represented as a number of trials to pass the given learning objective and the number of questions answered before the 3R pattern occurred in the passing trial. In order to express the student's efficiency for each learning objective that has been assigned, we propose new metric in (1) to measure the student's *Initial Success*, IS.

In the beginning, the initial success for every student enrolled in the course is a null vector. The dimensionality of the IS vector is the same as the number of all learning objectives in the knowledge database. Therefore, $IS_i = (LO_1, LO_2, ..., LOj)$, where the highest value of i is the total number of students and j is the total number of learning objectives in the database.

Thereafter, each week during the semester, the students are assigned different learning objectives. Hereupon, the IS is calculated as sum of the number of trials (NT) necessary for the student to pass the given LO, and the product of the scalar 0.01 and the number of questions (NQ) in the last trial. We use the value 0.01 in order to scale the number of questions in range $0.03 \leq NQ < 1$, since the maximum number of answered questions per learning objective is a double digit number. Therefore, the lower the IS score is, the more the student has learned the taught lectures.

$$IS_{ij} = NT_{ij} + (0.01 * NQ_{ij}) \tag{1}$$

Using information of the student's initial success from the e-Learning process allows the teacher to conceive preliminary impression on the student's Profile. However, it is not enough to infer the final outcome of the student's work during the course. Hereupon, we propose an intelligent algorithm that revises the student's success every time the student is given an e-Assessment to check the knowledge on a particular set of learning objectives. Therefore, it simulates the behaviour of a real teacher, evaluating the student's activities during the whole course to determine the student's final outcome. The main advantage of our strategy is the elimination of the possibility that the particular student has randomly guessed 3R correct answers to pass the learning objective.

Hereupon, the *Revised Success*, RS, is calculated as:

1) *Punishment:*

$$RS_{ij} = IS_{ij} + 1 \tag{2}$$

2) *Reward:*

$$RS_{ij} = IS_{ij} - 1 \tag{3}$$

where i denotes the currently analyzed student and j denotes the particular learning objective.

RS fully depends on the student's result from answering the questions from the e-Assessment. If the student's answer on a question from a particular learning objective is $false$, then the student is punished with adding one more trial on his initial success of the particular learning objective from the e-Learning knowledge background. On the opposite, when the student's answer on a question from a particular learning objective is $true$, the student is rewarded with reducing the number of trials by 1 in the e-Learning history. That is how the student's impression is directly affected by the e-Assessment results during the course.

The Student's Profiling algorithm is presented in Figure 3.

D. Machine Learning Analysis

As we created individual Profiles of each student enrolled in the course, we proceeded to find an appropriate machine learning technique which is capable of distinguishing between the Profiles that failed to earn a final grade to pass the course, and the Profiles that passed the course e-Assessments.

In this research we want to perform two types of analyses:

1) The $first$ analysis refers to the problem of classifying the individuals' Profiles. Since we know the desired outputs of the Profiles classification, we used Support Vector Machines supervised classification technique. To investigate the Profiles separability, we trained the classifier using four types of kernels: linear kernel, quadratic kernel, radial basis function and polynomial kernel. In order to avoid overfitting in the process of training the classifier, we used hold-out cross-validation technique which does not permit overlap between training data and test data, yielding a more accurate estimate for the generalization performance of the algorithm [13].
2) The $second$ problem is determining the Profile that is classified as failed, but has shown remarkable improvement on particular percentage of the learning objectives from the e-Learning process. The expected outcome from this type of analysis is eliminating the possibility of classifying the Profile as failed by mistake and providing the particular student an opportunity to do an additional e-Assessment. The Improvement, I, is calculated as:

$$I_{ij} = RS_{ij} - IS_{ij} \tag{4}$$

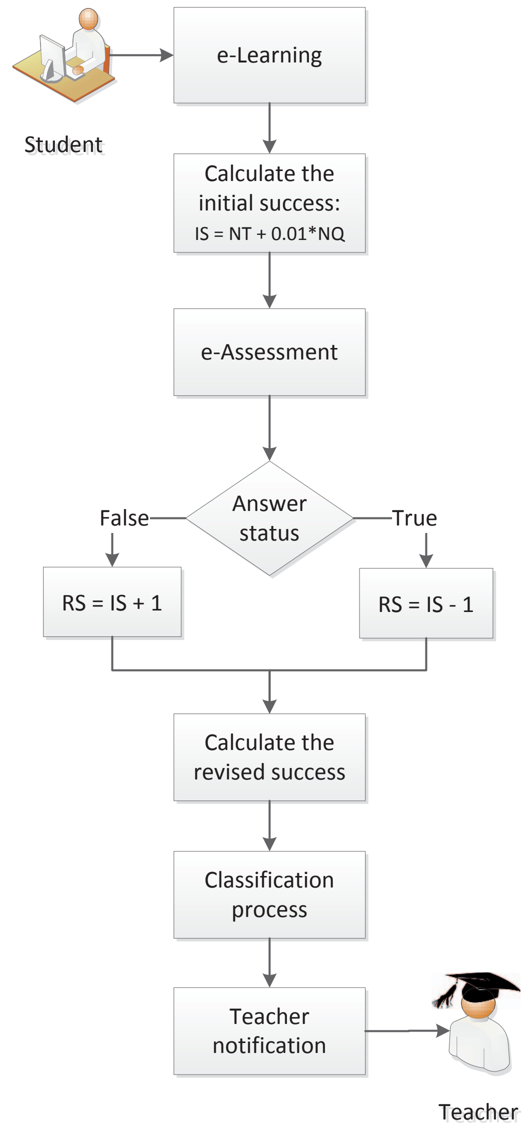

Fig. 3. Student's Profiling algorithm

where i denotes the currently analyzed student and j denotes the particular learning objective.

Hereupon, the Improvement Percentage, IP, is derived as:

$$IP_i = \sum(I_{ij}) * 100 / \sum(IS_{ij}) \tag{5}$$

where $i = 1, ..., 100$ and $j = 1, ...1361$, $\forall I_{ij} < 0$ and $\forall IS_{ij} \neq 0$.

V. Experiments and Results

Before we proceed to present the experiments and the results from the students' Profiling and Profiles' classification, we must discuss the first challenge that we presented in

Section III. At the beginning, we set the hypothesis that the 3R strategy is the best for binary classification of the students in one of the classes, pass, or, fail. Even more, we set a second hypothesis that we expect the problem to be linearly separable.

In order to check the hypotheses we performed two different analyses. At first, we collected data from e-Assessments with 10, 25 and 50 questions. After that, we selected the students' knowledge background of the LOs, which were given in the exam. Our idea was to investigate whether there is a correlation between the LOs and the outcomes from the e-Assessment. However, the results showed that the LO outcome can not be estimated as true, or, false, based only on the information of trials and number of questions from the knowledge database.

The second classification trial was performed after we created the students' Profiles. The main idea behind this type of analysis was to show whether the student can be classified as passed or failed taking into account only the knowledge background for all learning objectives passed during the e-Learning process. Once again the classification was not successful and both of the hypotheses defined as a first challenge were rejected.

That is how we derived conclusion that more serious procedure have to be developed and we proposed the methodology presented in Section IV.

A. Profiling Results

In order to model students' individual Profiles, we randomly chose 100 students starting from year 2005 until 2010. All of them were enrolled in the Computer Architecture and Organization course. Each week the students were taught different lectures and were obligated to use the e-Learning system as an online learning tool. The student is considered to have learned the given learning objective and proceeds to another one if the number of correct answers is 3-in-a-row. On the opposite, the student repeatedly answer the questions from the same learning objective which presents the strategy's $corrective\ measure$. The knowledge database consists of over 1000 learning objectives for the Computer Architecture and Organization course. Since the maximum number of learning objectives in the e-Learning history of the students we chose for our analysis is 1361, for each student we create null vector of length 1361, $Student_i = (0, 0, ..., 0)$, $i = 1, ..., 100$.

As soon as the student pass some learning objectives, his vector of initial success is updated using the formula presented in (1). The crucial part in creating the student's individual profile is taking into account the results from the e-Assessments during the course. In this paper we present a well defined methodology that combines both the e-Learning and e-Assessment results to create a realistic estimation of the student's knowledge. That is, we use the e-Assessments results to revise the student's vector of success obtained from the e-Learning process. Therefore, whenever the student takes an exam, the results from the questions of each learning objective affect the student's impression on his knowledge. The revised values of success are calculated according to the formula presented in (2). The student is either rewarded or punished in compliance with the outcomes from the e-Assessment that can be true or false, correspondingly. As we created the Profiles for each of the 100 students analyzed in this paper, we proceeded to test their classification potentiality.

B. Classification Results

After we created each student an individual Profile of his knowledge activities during the course, we took into account all the scores from the e-Assessments over the course duration to calculate the average score achieved by each student. The average score is used to separate the 100 student into two classes, passed and failed. The students whose average score is ≥ 60 are considered as passed, and the students whose average score is < 60 are considered as failed. The results showed that 44 students out of 100 passed the e-Assessments and the other 56 students failed.

As we created the two classes, we used cross-validation technique to choose the training and the testing set. Thus, 50% of the Profiles are chosen for the training process and the other 50% are used to test the trained classifier. The SVM classifier is being trained with the four basic kernels: linear kernel, quadratic kernel, radial basis function and polynomial kernel of order 3. The results are presented in table I, II, III and IV, correspondingly.

TABLE I
LINEAR KERNEL CLASSIFICATION

Performance	Linear kernel
TP	81 %
TN	75 %

TABLE II
QUADRATIC KERNEL CLASSIFICATION

Performance	Quadratic kernel
TP	77 %
TN	78 %

TABLE III
RADIAL BASIS FUNCTION CLASSIFICATION

Performance	RBF
TP	0 %
TN	100 %

TABLE IV
POLYNOMIAL KERNEL CLASSIFICATION

Performance	Polynomial kernel
TP	90 %
TN	75 %

The performance of the classifier is measured in terms of true positive rate, TP, and true negative rate, TN. TP denotes the percentage of correctly classified Profiles that have passed the exams, whereas the TN is the percentage of correctly classified Profiles that have failed the exams. According to the results presented in tables I, II, III and IV, we conclude that the best classification is obtained when using the polynomial kernel during the training process. Both the TP and TN show that the classifier is very accurate when separating the Profiles of students that passed from those that failed the assessments.

Another measure that we use to evaluate the classifier's performance is in terms of $Precision$ (6) and $Recall$ (7). The classifier's $Precision$ is a measure of TP among all Profiles classified as positive (pass), the true positives and the false positives. The classifier's $Recall$ is a measure of its ability to select the Profiles that passed the course from all the Profiles in the positive class. The results are presented in Table V.

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

TABLE V
PRECISION AND RECALL

Performance	Precision	Recall
Linear kernel	0.72	0.81
Quadratic kernel	0.73	0.77
RBF	0	0
Polynomial kernel	0.74	0.90

Figure 4 presents the receiver operating characteristic, ROC curve, which illustrates the performance of our binary classifiers as relative tradeoffs between the true positives and the false positives for different thresholds 1 and 0. From ROC analysis we can conclude that the worst classifier is the SVM's radial basis function (blue line) and the best is the SVM's polynomial kernel (black line).

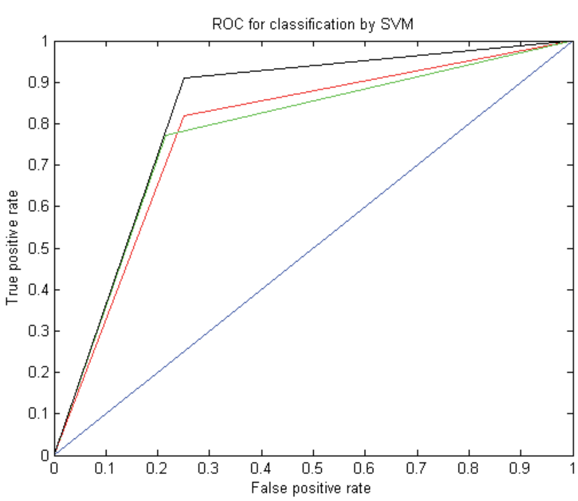

Fig. 4. ROC Analysis

The second part of the analysis refers to determining the percentage of learning objectives, according to the calculation in (5) for which the revised success is improved when compared to the initial success. This kind of analysis is very important for the students that are classified as failed, since it may be an important indicator for the teacher that the student should be given an additional e-Assessment in order to pass the course and earn a grade. In this paper we assume that 35 % improvement is good enough to offer the student that failed one more chance to pass the course. The results showed that only 1 student among the many classified as failed, has showed improvement when learning the LOs.

VI. Conclusion and Future Work

Online learning has been a research challenge of many papers. Recently, most of the researchers were focused on developing strategies for adaptive e-Learning to improve the learners' performance.

In this paper we used results from an online learning tool that has been implemented since 2002. Based on 10 years of e-Learning and e-Assessment experience we developed a strategy that is able to provide a proof that the student has achieved all learning objectives by providing correct answers for relevant knowledge items during the online learning process. The overall contribution of the developed strategy is that we discovered the minimum number of questions (3) the student has to be asked before the system is sure that the student has learned the particular learning objective. Even more, answering the questions must be 3 correct answers in a row, in order for the system to allow them to continue the online learning process. This strategy confirms the student's knowledge on a particular learning objective.

In this paper, we confronted a new challenge, that is, to build an intelligent agent which will be able to behave as a real teacher. That means, the agent will adapt to the student's e-Learning individual Profile and will provide approximation of the reliability of the student's e-Assessment results. This research is an upgrade of 3R strategy, but the focus is to show how the results from the long term e-Learning and e-Assessment of a particular student can be used to build an individual Profile that will represent the previous knowledge, which is essential for automatic ranging of the students outcome. For this purpose we developed an original methodology for creating each student an individual Profile, which when used in a suitable machine learning technique, shows high classification capability.

We believe that this kind of grading that depends on the students' overall work through the whole course will additionally motivate them to work continually during the semester and present their real knowledge during the e-Learning process. Even more, our strategy is less vulnerable to random guessing, since it directly affects the students' final impression on their knowledge.

In our future work, we will aim to develop a different strategy for passing the e-Assessment for each student distinctively.

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