Detection of learners with a performance inconsistent with their effort

Diego García-Saiz
Department of Software Engineering and Electronics
University of Cantabria
Avda. Los Castros s/n,
Santander, Spain
garciasad@unican.es

Marta Zorrilla
Department of Software Engineering and Electronics
University of Cantabria
Avda. Los Castros s/n,
Santander, Spain
zorrillm@unican.es

ABSTRACT
Motivation is essential to learning and performance in e-learning environments. Designing strategies to intervene in the learning process as soon as possible with the aim of keeping the learner engagement high is thus remarkably important. This paper proposes a method which allows instructors to discover learners with a performance inconsistent with the activity carried out, enabling teachers to send personalised messages to these students.

1. INTRODUCTION
Motivation is essential to carry out any kind of task successfully but, this is even more necessary for activities which require a great cognitive and time effort such as the acquisition and understanding of new knowledge to be applied suitably and rightly to problem solving. This is the case of learning processes supported by e-learning platforms where learners must adopt an active role and guide their self-learning.

To offer support and individualised help to learners, teachers need tools that help them to detect students who require advice. We, in this work, present a method which aims at detecting learners whose effort performed in the e-platform is comparable or higher than that one done by their peers but, unlike them, they do not pass the assessable assignments. These learners require a feedback different from those who are not interested in the course, thus being at risk of dropout. These feedback messages should be automatically generated by the e-learning system in order to provide students with personalized guidance, tailored to their inhomogeneous needs and requirements [1].

To our knowledge, the relationship between effort and performance has never been studied. The closest topic researched is the detection of undesirable student behaviours [3, 2] whose goal is to discover those students who have some type of problem or unusual behavior such as dropping out or academic failure. For instance, Ueno [4] proposed an animated agent which provided adaptive messages to the learners with an irregular learning process and Vellido et al. [5], characterised atypical student behaviors through robust generative relevance analysis.

Next, we describe our method and discuss the results achieved.

2. METHOD AND RESULTS
Our approach aims at detecting students who have carried out a great effort but, however, they have failed. These are thus a subset of the students that a performance classifier would classify wrongly since their activity is very similar to that performed by students who passed. Therefore our method works in two phases: first, a classifier is built in order to detect misclassified instances and next, a clustering technique is applied on the misclassified instances set of ”fail” class with the aim of detecting these learners. The instances from the cluster whose weighted Euclidean distance to ”fail” class prototype is the largest are our target students.

We apply our method on students' activity data from two e-learning courses hosted in Moodle with 43 and 119 learners respectively. In both, the students must carry out four assignments to pass the course. We generated two data sets, one for each course, with the activity data corresponding to the period of the first assignment(named ”d1” and ”d2”). The attributes used were: N# of actions performed by the student (”act”), N# of visits to the content-files (”v-re”), the SCORM resources (”v-sc”), the statistics page (”v-da”), the feedback messages provided by the instructor (”v-fe”) and the html pages (”v-co”); N# of messages read (”v-fo”), posted (”a-di”) and answered (”p-fo”) by the student in the forum and the sum of the attributes ”a-di” and ”p-fo” (”pa-fo”). As class attribute, we used the mark achieved by the learner in the first assignment, pass or fail.

We configured our method for using J48 as classifier and k-means as clustering technique. The accuracy of the classifiers, evaluated with 10-CV, were 69.77% and 85.17%, with 7 and 13 instances misclassified respectively, that means, there were 7 and 13 learners who could have carried out an activity (effort) similar to those who passed the first assignment, but however they failed. To determine if these misclassified students had really a similar activity to those who passed, we performed a clustering process with these

Table 1: Clustering process on "d1"

attr.	relevance	C1	C2	Avg.
act	9	0.1835	0.4639	0.1245
v-re	4	0.093	0.438	0.1270
v-co	1	0.1017	0.3785	0.1239
v-fe	1	0	0.1667	0.0385
v-da	6	0.0435	0.3732	0.0920
a-di	2	1	0.1667	0.0769
p-fo	4	0	0.2	0.0308
pa-fo	1	0.1667	0.1944	0.0385
v-fo	2	0.3061	0.3299	0.0597
v-sc	3	0.075	0.3417	0.0952
N# ins.	-	1	6	-
dist. to avg.	-	2.0183	3.8936	-

Table 2: Clustering process on "d2"

attr.	relevance	C1	C2	C3	C4	Avg.
act	10	0.679	0.049	0.163	0.137	0.07
N# ins.	-	2	5	2	4	-
dist. to avg.	-	0.609	0.021	0,093	0,067	-

instances. Two and four clusters were created for dividing up these students. The number of clusters was manually selected by comparing the different clusters built with k ranges from 2 to 5. Next, we calculated the weighted Euclidean distance from each centroid to the mean of the well-classified instances of class "fail", being the contribution of each attribute weighted according to its relevance. Those instances which belonged to the cluster with a larger distance to the average were marked as outliers. The prototype of each cluster is shown in Tables 1 and 2. These tables also gather the relevance of each attribute ("relevance") calculated with the ClassifierSubSetEval method provided by Weka and the average value ("Avg.") of each attribute corresponding to the well-classified instances of the fail class.

As can be observed, in "d1", the cluster C1 only contains one instance which represents the activity of one of the students with the lowest activity in all course and similar to that performed by the students who failed and were well-classified. The centroid of cluster C2 is further from the average of the well-classified instances of the fail class and these, thus, are marked as outliers. In "d2", the only relevant attribute is the N# of total actions, and the instances of the cluster C1 therefore were marked as outliers.

Table 3 collects the most relevant activity performed by the six and the two students misclassified in each course respectively. In "d1", the value of most attributes is larger than the average of their class, being this difference remarkable for the attribute "act". On the one hand, the students labelled as d1s3, d1s4, d1s5 and d1s6 performed a significant activity, but failed the first assignment (q1) with a low qualification, from 0 to 4 out of 10. However, they passed the second assignment (q2) with a good mark, 9 out of 10. That means that the feedback given to them by the instructor was useful and effective, being clearly reflected the importance of giving a good feedback to the students. On the other hand, student named d1s2, even having an appreciable activity, failed the first assignment and dropped out before sending the second task. In this case, the instructor's advice was not successful. If the teacher had known the activity performed at the same time that he assessed the assignment, the message could have been written in a more motivating tone, expressly mentioning the activity already undertaken. Finally, d1s1 was detected by the method but the learner

Table 3: Students' activity

student	act	v-re	v-da	p-fo	v-sc	q1	q2
d1s1	0.23	0.30	0.24	0.00	0.19	0	0(dropout)
d1s2	0.20	0.16	0.15	0.00	0.34	3	0(dropout)
d1s3	0.91	1.00	0.72	0.60	0.63	4	9
d1s4	0.50	0.44	0.20	0.20	0.23	0	9
d1s5	0.58	0.42	0.43	0.40	0.31	3	9
d1s6	0.37	0.30	0.50	0.00	0.36	0	9
d2s1	0.84					3	8
d2s1	0.51					4.5	8.5

did not receive feedback because he did not deliver the assignment. In this case, the teacher missed the opportunity to rescue him. Regarding d2, the N# of actions performed by both students is very high in comparison with the average of the students who failed. Indeed, one of these students had a mark of 4.5 out of 10, being very close to pass. In this scenario, the feedback provided by the instructor was successful since this learner passed the second assignment with a qualification of 8.5 out of 10.

The experimentation carried out shows that our method helps to discover students whose performance do not match with the effort performed. Being able to automatically detect them would allow teachers to act quickly, sending them personalised messages oriented to keep their engagement high and avoid the dropout.

As future work, our aim is to apply this method to other virtual courses and support the teacher during the learning process in order to validate the goodness of our proposal in real online contexts. Another issue which will be addressed shortly is to evaluate the effect of using different classifiers and clustering algorithms in our proposal.

3. ACKNOWLEDGMENTS

This work has been partially financed by the PhD studentship program at University of Cantabria (Spain).

4. REFERENCES

[1] F. Castro, A. Vellido, n. Nebot, and F. Mugica. Applying data mining techniques to e-learning problems. In L. Jain, R. Tedman, and D. Tedman, editors, *Evolution of Teaching and Learning Paradigms in Intelligent Environment*, volume 62 of *Studies in Computational Intelligence*, pages 183–221. Springer Berlin Heidelberg, 2007.

[2] A. Peña Ayala. Review: Educational data mining: A survey and a data mining-based analysis of recent works. *Expert Systems with Applications*, 41(4):1432–1462, Mar. 2014.

[3] C. Romero and S. Ventura. Educational data mining: A review of the state of the art. *IEEE Transactions on Systems, Man, and Cybernetics*, 40(6):601–618, 2010.

[4] M. Ueno. *Data Mining in E-learning*, chapter Online outlier detection of learners' irregular learning processes, pages 261–278. Billerica,MA: WitPress, 2006.

[5] A. Vellido, F. Castro, A. Nebot, and F. Mugica. Characterization of atypical virtual campus usage behavior through robust generative relevance analysis. In *Proceedings of the 5th IASTED International Conference on Web-based Education*, WBE'06, pages 183–188, Anaheim, CA, USA, 2006. ACTA Press.