Guiding students through competence-based educational materials

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ABSTRACT

Student guidance is an always desired characteristic in any educational system, but it represents special difficulty if it has to be deployed in an automated way to fulfil such needs in a computer supported educational tool. In this paper we explore possible avenues relying on machine learning techniques, to be included in a near future -in the form of a tutoring navigational tool- in a teleeducation platform -InterMediActor- currently under development. Since no data from that platform is available yet, the preliminary experiments presented in this paper are built interpreting every subject in the Telecommunications Degree at Universidad Carlos III de Madrid as an aggregated macro-competence (following the methodological considerations in InterMediActor), such that marks achieved by students can be used as data for the models, to be replaced in a near future by real data directly measured inside InterMediActor. We evaluate the predictability of students' qualifications, and we deploy a preventive early detection system -failure alert-, to identify those students more prone to fail a certain subject such that corrective means can be deployed with sufficient anticipation.

1 INTRODUCTION

Automatic student guiding through an electronically supported educational material (Khuwaja et al., 1996) (task also known as curriculum sequencing (CS) or instructional planning) is one of the core technologies in any Intelligent Tutoring System (ITS), following the terminology by Brusilovsky (Brusilovsky, 1999). We will not cover here other ITS tasks such as intelligent analysis of student's solutions or interactive problem solving support, but rather concentrate on the former. The ultimate goal of the preliminary experiments presented here will be the development and deployment of a navigation-aid tool to be integrated into the teleeducation platform under development in our group, known as InterMediActor (Valverde et. al., 2002). The underlying methodology of this platform is that of competences: skill-oriented learning conceptual units, with incorporated evaluation mechanisms (Bousono et al., 1999). Ideally, at any moment, the system should be able to suggest which materials (among those offered in the present course) the student is more prepared to study. The recommending mechanism will rely on prediction models built upon information from past experience of other students, such that the course structure can be adapted or navigation routes suggested accordingly.

2 METHODOLOGY

Unfortunately, the InterMediActor platform has not been deployed yet but, since we wanted to gain insight with respect to these approaches to CS, we have devised a preliminary experiment relying on real data from present and past students of the Telecommunications Engineering Degree at Universidad Carlos III de Madrid. Under this approach we are facing a somewhat rigid educational situation: the structure of every subject is fixed, navigation being dictated by the teacher (we have traditional teaching structure -presential classes and labs plus final exams-). So, the aforementioned scheme is not applicable at this scale. Things make sense, however, if we consider every subject as a competence, which represents a “loose” interpretation of the competences in InterMediActor: every subject in our Telecommunication Engineering Course could be read as a ‘macro-competence’, in each course a set of competences are learnt by the students, and these have been evaluated (aggregatedly) by means of a final exam, such that we have a mark for the global learning task. We use the marks obtained by a population of students in the past as input data for tuning the system, and we build a system that recommends every student which subjects he/she is more prepared to course or, interpreted differently, a system which may serve as a failure alert system, that will tell every student which are his/her knowledge weaknesses and which subjects will be harder for him/her in the next term, so he/she can devote more effort to them and finally succeed in the corresponding exam. Under this scheme, the curriculum sequencing problem reduces to the -navigational- question (Weber et al., 1997) of which are the subjects a particular student should choose next (among all the offered for the next term) or devote special effort, to maximize his/her success rate. Under this formulation, historical data -marks- of the students can effectively be used for the purpose of designing such systems, as we illustrate in the experimental section. Although we have used some “a priori” expert knowledge about the nature of every subject, its relationship with other subjects, and its pre-requisites, we preferred to also carry out an statistical analysis to reinforce all these hypothesis. Therefore both relationship among subjects (pre-requisites), student knowledge state, and the models predicting performance in a certain subject given marks in the pre-requisites are directly estimated from data collected over several years of teaching at our school, procedure that has the advantage that the models are precisely tuned to the expected population of a given educational material.

3 EXPERIMENTAL SET-UP AND RESULTS

We have processed a total number of 10.755 data -marks- belonging to 1.029 students, who studied between the years 1995 and 2001, and we concentrated our analysis in thirteen subjects of the Telecomunication Engineering Degree. We concentrate the study in 4 subjects, we estimate prediction models for them (i.e., which are the most influent previous subjects and in which degree), and finally we develop the preventive alert system.

3.1 BUILDING THE TRAINING DATA

We had to process raw data coming from the university database to build the examples to be used in the training process: given a subject mark for a student, we had to obtain the immediately previous marks obtained in other subjects; simultaneously taught subjects are never used in the same model. This way, causality is preserved. The whole database was processed in this way to obtain the training examples i.e.: marks to be predicted plus qualifications in previously coursed subjects of possible influence, one example per student. Those incomplete records were not considered in the experiments.

3.2 SELECTING SUITABLE MODELS

As a preliminary task, we have to obtain a suitable model for every subject under study, i.e., identify which are the marks that most influence the one to be predicted. We select "a priori" a subset of subjects of potential influence, and we apply a step-wise procedure (which incrementally builds a linear Least Squares regression starting with the most relevant inputs to the task to be solved) to adjust a linear model to the data extracted as explained in 3.1. Using a cross-validation technique, we select the model with the optimal (i.e., maximal generalization) number of inputs. In Table 1 below, we illustrate the results, indicating which subjects comprise every model, and corresponding weights. Interpretability of these linear models is straightforward, but we will see in what follows that better models (nonlinear ones) can be constructed, although such direct readability of the results is lost.

Subject's mark to be predicted	Ordered inputs	Weights
Sistemas Lineales	Cálculo II	0.1919
(best model with 3 inputs + offset 1.68)	Cálculo I	0.1502
(654 training patterns)	Sistemas y circuitos	0.1177
Teoría de la Comunicación	Sistemas lineales	0.2773
(best model with 6 inputs – offset 0.18)	Estadística	0.1300
(510 training patterns)	Ampliación de matemáticas	0.0914
	Cálculo II	0.0921
	Cálculo I	0.0511
	Álgebra	0.0446
Lab. Señales y Comunicaciones	Sistemas lineales	0.2191
(best model with 4 inputs + offset 2.6)	Estadística	0.1667
(234 training patterns)	Cálculo I	0.0789
	Sistemas y circuitos	0.0624
Tratamiento Digital de Señales	Sistemas lineales	0.3189
(best model with 3 inputs – offset 0.81)	Estadística..	0.2165
(155 training patterns)	Cálculo II	0.1670

Table 1: Relevant subjects selected by cross-validation, and their weights in the model.

3.3 TRAINING BETTER PERFORMANCE-ESTIMATION MODELS

After some experimentation, we observed that the linear models built following Least Squares fitting and the stepwise procedure were not very powerful, so we decided to keep their form but use a more powerful (nonlinear) modelling technique: the Support Vector Machines (Schölkopf et al., 2002). We have used a general tool for that, the SVMlight package (Joachims, 1999) for conducting a nonlinear regression on the data. In Table 2 below we collect the test estimation errors obtained by selecting the best parameters in every case using cross-validation, and we compare them with the results of the linear model. Normalized Mean Squared Error is shown, where the worst case (a value of 1) means predicting with the mean of the population.

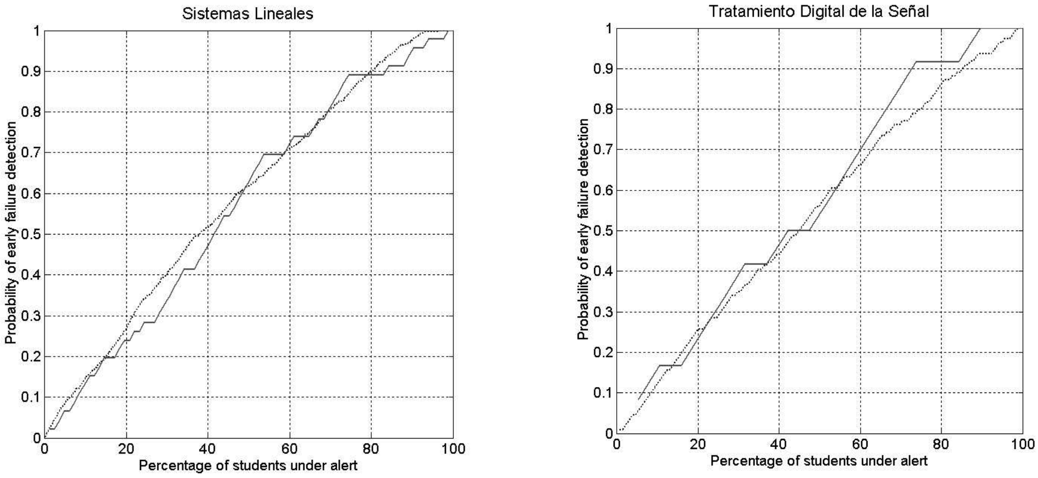
Subject	**Normalized MSE test, linear model**	**Normalized MSE test, SVM regression**
Sistemas Lineales	0.86	0.82
Teoría de la Comunicación	0.89	0.82
Tratamiento Digital de la Señal	0.94	0.91
Lab. Señales y Comunicaciones	0.85	0.79

Table 2: Normalized MSE for the linear and SVM case.

We observe that although predictability is improved by using a nonlinear model 8SVM regression, performance is not very good in either case. The number of available patterns is relatively small in most cases, and possibly trying to predict the future marks of a student is not a realistic task at all. In what follows we propose a reformulation of these models to identify those students prone to obtain very low marks.

4 AN EARLY WARNING APPLICATION

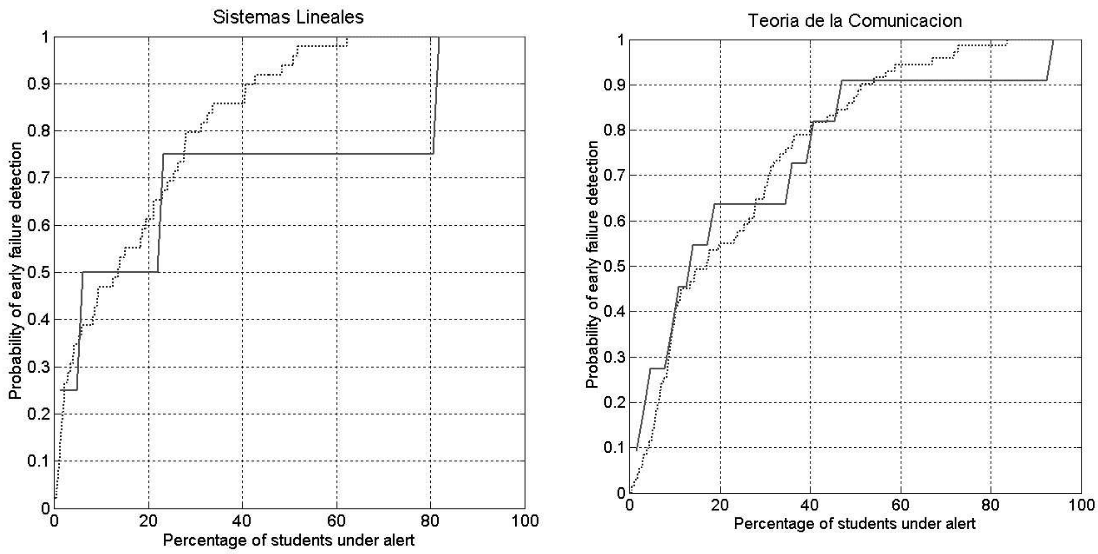
We have reformulated our task into a classification one: identify which students will achieve marks below a certain value. We initially wanted to exactly identify which students were to fail: we run experiments using a value of 5 (in a scale of 0-10) as threshold. We trained a Support Vector Machine using the SVMlight software, and used that model as a classifier. The results are shown in Figure 1, where the probability of detecting such cases is plotted as a function of the percentage of the sorted population for train (dotted) and test (continuous line).



(a) (b)

Figure 1: Results on predicting whose students are prone to fail (dashed for train and continuous line for test). We only illustrate two subjects, the other two yielded similar results.

It can be observed that detection is ill conditioned (roughly, 40% of the population launches the alarm with 0.5 probability, which is almost as bad as random selection), probably because many students lie in the limit and many external factors affect their final marks. Things change a little bit if, instead, we focus on that part of the population with worst predictions: setting up an alert to detect students with very low marks (below 2), leads to the following results:



(a) (b)

Figure 2: Results on predicting whose students are prone to achieve extremely low ratings (dashed for train and continuous line for test)

It can be observed how the situation for two of the subjects (no improvement was obtained in the other) is slightly better: it is possible to identify a 40% of that prone-to-disaster population by selecting only 20% of the population (or an 80% by picking up a 40%), such that, by providing complementary preventive means, large benefit in the students' performance can be expected, and finally they could succeed in the examinations.

5 CONCLUSIONS

We have seen that curriculum sequencing for students coursing several subjects in Telecommunications Engineering Degree at Universidad Carlos III de Madrid is not suitable in its more complete form, since predictability of their marks is not as high as desired, maybe because the learning environment is not uniform enough; we hope that data coming from InterMediActor -a much more controlled environment- will be more suitable for prediction and navigational planning. Still, real-world data has proved useful for the alert application in several subjects, in the sense that it provides automatic means for detecting the population of students more prone to fail a certain subject, such that corrective means can be deployed (tutoring, complementary information, etc.). This and other tools are of paramount importance for an effective improvement in educational quality in both presential and computer based education.

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