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Adaptive Profiling Tool for Teacher Education

Miikka Miettinen[1], Petri Nokelainen[1], Jaakko Kurhila[2], Tomi Silander[1], Henry Tirri[1]

firstname.lastname@helsinki.fi

[1] Helsinki Institute for Information Technology
Complex Systems Computation Group
P.O. Box 9800, 02015 HUT, Finland
Tel: + 358 9 850 11576, Fax: + 358 9 694 9768

[2] University of Helsinki
Department of Computer Science
P.O. Box 26, 00014 Univ. of Helsinki, Finland
Tel: + 358 9 1911, Fax: + 358 9 191 44441

Abstract: In this paper we introduce EDUFORM, an adaptive questionnaire designed for profiling students in various educational contexts. The idea is to build a probabilistic model from previously gathered data, and use it for profiling other people more efficiently. EDUFORM selects the questions presented to each individual adaptively in order to minimize the number of answers needed for reliable prediction of the profile. Empirical evaluations suggest that 85-90% accuracy can be achieved, while the number of questions is reduced by 30-50%.

Introduction

The information needs involved in organizing effective education are significant. Accurate knowledge of interests, preferences, and motivation aspects is important both for the daily activities of educational institutions and for longer-term research and development efforts. In addition, computer technology enables such information to be used for the immediate benefit of the students. Self-assessment tools can be developed to offer analyses of for example learning styles or metacognitive skills, and adaptive systems to adjust the content or presentation of the material to individual needs. The problem is that nearly all of the interesting and useful information has to be provided explicitly by the students, which easily leads to excessive use of questionnaires. Besides being undesirable in itself, the tedious and sometimes frustrating answering process associated with long questionnaires is likely to reduce the validity of the acquired data.

In order to address this problem, we have developed EDUFORM, an adaptive on-line questionnaire. The idea behind EDUFORM is to build a model from previously gathered data and use it for profiling other students on the basis of a subset of the propositions in the original questionnaire. Furthermore, the propositions and the order in which they are presented are chosen on the basis of the previous answers of a particular individual. Preliminary empirical evaluations suggest that good profiling accuracy can be achieved with a significantly reduced number of propositions.

Modeling approach

The development of EDUFORM was motivated primarily by an observed need to profile students in various educational contexts. Although such profiles can in principle be derived in a theory-driven manner and coded manually, we have adopted a data-driven viewpoint, which means that the profiles are constructed from data gathered previously with similar questionnaires. This leads to the distinction of two phases in the use of EDUFORM: the *Profile creation phase*, where characteristic groups of students are identified, and the *Query phase*, where the constructed profiles are used for predicting the answers of other individuals to the same questionnaire. The design is generic and allows the application of any kind of predictive modules suitable for the task. We have adopted the Bayesian approach (Bernardo and Smith, 2000) and use the language of probability distributions to describe the profiles

If Q denotes the filled-in questionnaire, each group G_i can be described as a mechanism that assigns a probability $P(Q \mid G_i)$ to the questionnaire. The set of groups $G = (G_1, G_2, \ldots, G_K)$, together with their relative sizes $s = (s_1, s_2, \ldots, s_K)$, define a finite mixture (Titterington et al. 1985) that can be treated as a probability model $P(Q \mid G, s) = s_1 P(Q \mid G_1) + s_2 P(Q \mid G_2) + \ldots + s_K P(Q \mid G_K)$.

As the adaptive questionnaire is being completed, the probabilities are updated to reflect the new information gained from the answers. The model is used for calculating the probabilities of possible answers to the yet unanswered questions (Q_U) on the basis of the answered questions (Q_A):

$$P(Q_U \mid Q_A, G, s) \propto P(Q_U, Q_A \mid G, s) = P(Q \mid G, s).$$

We can also keep track of the probability that the person belongs to a particular group G_i. If we denote by g the event that the person belongs to the group G_g,

$$P(g \mid Q_A, G, s) \propto P(g, Q_A \mid G, s) = P(g \mid G, s)\, P(Q_A \mid g, G, s) = s_g\, P(Q_A \mid G_g)$$

The two calculations above let us try to adapt the order of the questions so that we can predict the answers of the unanswered questions confidently enough and/or be confident about the group membership of the student based on as few answered questions as possible. Johnson and Albert (1999, 191) have proposed an alternative approach based on the estimation of item specific model parameters.

Construction of finite mixtures from data is described in (Kontkanen et al. 1996) and (Tirri et al. 1996). The underlying intuitive idea is to describe the data vectors with respect to a set of prototypes, so that the description of an individual vector consists of the index of the closest prototype and a list of differences between the expected and observed values. Alternative definitions of the prototypes can be evaluated on the basis of the amount of information needed to describe the entire data set: the more representative our prototypes are, the fewer differences there are between the data vectors and their associated prototypes. In addition to being of significant interest in itself, the resultant model is suitable for the kind of prediction needed in the *Query phase*.

EDUFORM

Even though EDUFORM is an electronic questionnaire on-line, it resembles traditional questionnaires on paper (Fig. 1). A few multiple-choice questions are presented at a time, with the possibility of adding comments. The navigation bar is at the bottom. The arrows on the right allow the user to move to the next or previous set of questions. Clicking the button with the pie chart icon shows the current profile. When the profile of the user is known with sufficient certainty, the user can quit filling in the questionnaire before all questions have been asked by clicking the ‘cross’ button on the navigation bar. On the left, there is a progress indicator showing an estimate of the amount of questions left. Because of the simplicity of the interface, there has been no need for a separate help screen. The meanings of the buttons are shown as tool tips (in Fig. 1, the word “Next” above the mouse pointer).

Adaptation in EDUFORM

In the *Query phase*, we want to find out the profile of the student as efficiently as possible. The profile is represented by a probability distribution over the groups identified in the *Profile creation phase*. As the student answers the questions, some of the groups become much more likely than others, and one of them often reaches almost 100% probability reasonably quickly. EDUFORM takes advantage of this characteristic pattern by optimizing the order in which the questions are presented, and offering the student an opportunity to quit once sufficient certainty about his profile has been achieved.

At any point in time, the most informative set of questions to ask next is the one that changes the profile distribution most. EDUFORM searches for this set by maximizing the expected *Kullback-Leibler distance* (Cover and Thomas 1991) between the current distribution and the distribution that would result if answers to a particular set of additional questions were received. The first questions are the same for everybody, but after that the selection depends on the previous answers of each individual. Therefore, adaptation in EDUFORM is based on continuous assessment of the expected information gain, rather than being limited to a small number of hard-coded paths.

Figure 1: The user interface of EDUFORM.

The purpose of this technique is to minimize the amount of questions needed to find out the student's profile. Additional questions can be omitted entirely once a sufficient degree of certainty has been achieved. In the current experimental version of EDUFORM, the termination criterion is defined by setting a limit, which the most probable group in the profile has to exceed. A limit of 75% to 85% seems to be a suitable range in most cases. It is also possible to specify an additional requirement regarding the stability of the profile. For example, it may be stated that the most probable group has to stay above the limit for two successive sets of answers.

Figure 2 shows the format in which the data is saved. The first column identifies the person. In this particular case, a unique identification string has been created from the questionnaire name ("demo") and a counter. The questions appear in the same order as they were presented to the user. Question numbers are in the second column. The remaining columns contain the probabilities of the alternative answers. If the user has actually answered the question, one of the probabilities is 1 and the rest are 0. Probability distributions for the omitted questions are calculated by the model and saved in the same file. In Figure 2, the first four questions have been answered by the user, and the last two rows are predictions. Additional data include comments, the final profile, and a log of mouse clicks. The main purpose of the log is to record the time used for answering various parts of the questionnaire, but it may also turn out to be helpful in identifying ambiguous questions or making detailed analyses of differences between groups.

```
demo-1  33    0.0    1.0    0.0    0.0    0.0
demo-1  15    0.0    1.0    0.0    0.0    0.0
demo-1  10    0.0    0.0    0.0    1.0    0.0
demo-1  27    0.0    0.0    0.0    1.0    0.0
demo-1  5     0.0149 0.0292 0.1225 0.2392 0.5939
demo-1  11    0.0084 0.0086 0.0422 0.2451 0.6954
```

Figure 2: Format of the saved data.

Empirical results

Perhaps the most important question to ask when judging the value of EDUFORM is whether or not it actually works. The number of answers needed for reliable profiling should be significantly smaller than the total number of propositions in the questionnaire. We would also like the users to benefit from adaptivity and quit when they are offered a chance to do so.

In order to evaluate the predictive performance of EDUFORM, we simulated the operation of the adaptive questionnaire using complete data. The models were constructed from 200 randomly selected cases in each data set, and the remaining test cases were supplied to the models exactly as they would have been received during the course of adaptive questioning. The number of answers given before the fulfillment of the termination criteria was recorded, and the group predicted at that point was compared to the group assigned at the end of the questionnaire. If the predicted group did not match the final group, an error was recorded.

Table 1 shows the main results of the simulation. Two different data sets were available from a questionnaire (Ruohotie 2001) with four sections: “Learning and motivation” (Motiv in Tab. 1), “Study habits” (Habits), “The quality of teaching” (Teaching), and “The effects and outcomes of education” (Effects). Although the sections measure complementary aspects of the same educational setting, they are in the present context best thought of as separate questionnaires. The last data set (Motprof) is from a questionnaire designed for identifying motivational profiles. The second and third columns contain the number of groups defined during model construction and the total number of questions in the questionnaire. The average proportion of questions needed for predicting the group of a test case is in the column labelled “Questions asked”. The next two columns contain the standard deviation of questions asked and the proportion of test cases for which the final group differed from the group predicted upon the fulfilment of the termination criteria.

Data set	Groups	Number of questions	Questions asked	Standard dev. of quest. asked	Errors	Number of test cases
Motiv 1	4	28	62%	22%	10%	260
Motiv 2	4	28	65%	22%	15%	357
Habits 1	5	40	62%	22%	15%	260
Habits 2	5	40	48%	21%	13%	357
Teaching 1	5	23	67%	21%	13%	260
Teaching 2	5	23	53%	24%	15%	357
Effects 1	5	25	61%	22%	14%	260
Effects 2	5	25	45%	23%	14%	357
Motprof	6	34	70%	21%	15%	498

Table 1: Predictive performance of EDUFORM.

As can be seen in Table 1, an average of 50-70% of the questions had to be asked to achieve an error rate of 10-15%. Every data set contained a few exceptional cases for which 100% or only 15-30% of the answers were needed, but the standard deviations were consistently within 20-25% of the total number of questions in the questionnaire.

The trade-off between questions and errors can be altered by adjusting the termination criteria. The more uncertainty we accept in the profile, the fewer questions need to be asked. Figure 3 shows the effect of additional answers in the Motprof data set. On the horizontal axis we have the number of answers given, and on the vertical axis the average Kullback-Leibler distance between the predicted and the final profile. By setting the termination criteria to appropriate values, questioning can be stopped approximately at the desired point along the line.

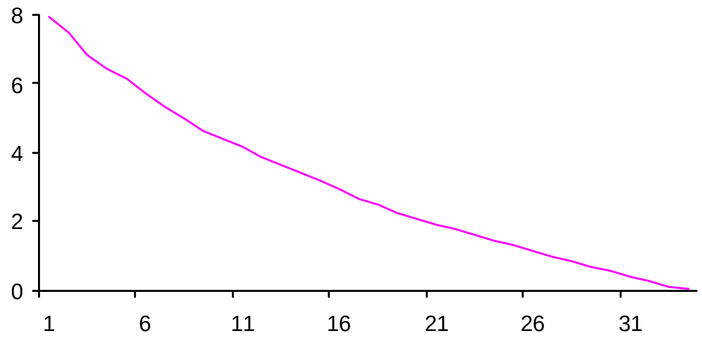

Figure 3: Reduction in the distance between the predicted and the final profile.

At the time of writing, two data sets had been gathered with the adaptive version of EDUFORM. The same sets of questions were used as in the simulation study described above. Of particular interest for the present purpose is the attitude of the users towards prediction. When their predicted profile satisfied the termination criteria, they were asked if they want to quit or refine the profile by answering the remaining questions. They could also quit after answering only some of the additional questions. The decision to quit or continue can be seen as a reflection of the user's opinion about the usefulness of adaptation in EDUFORM.

The results are summarized in Table 2. The first four questionnaires were parts of the same study, and were completed sequentially during one session. The subjects were students from a teacher training programme in the Finnish Polytechnic Institute. In the other study ("Motprof"), motivational characteristics of engineering students from Helsinki University of Technology were examined. The second column contains the proportion of users who quitted before answering all questions. Unfortunately, it seems that adaptivity was not appreciated as much as we thought. The third column shows the number of questions answered by the students who did take advantage of the adaptivity. The second part of the first study ("Habits") was the longest one with 40 propositions. The proportion of answered questions is high because many students gave a few more answers after they had the first chance to quit, but got tired before the end.

Questionnaire	Allowed prediction	Questions answered	Total number of cases
Motiv	11%	64%	66
Habits	35%	82%	66
Teaching	20%	61%	66
Effects	17%	68%	66
Motprof	26%	61%	478

Table 2: The adaptivity of EDUFORM in real use.

Conclusions

EDUFORM is a tool to provide questionnaires with reduced sets of questions. The operation (i.e. the adaptation of the amount of questions) is independent from the questionnaire content. This domainindependence of the adaptation mechanism opens up the possibility to use EDUFORM for more than just a single purpose. For example, EDUFORM can be used in assessing individual differences on-line to support studying in a virtual or traditional campus university. Suitable support material for student self-evaluation could be a questionnaire that provides information of how to study efficiently.

A questionnaire in EDFORM can also be used as a test for students. Testing the students' knowledge on the basis of adaptive questioning is not a novel idea. However, the standard approach is that the system adapts directly to the knowledge of the student. When using EDUFORM as a test, adaptation means the optimization of the length of the test. In other words, the goal is to provide the teacher or evaluator enough information about the students' progress with as few questions as possible.

Because of the particular approach to adaptation, EDUFORM can also be used as a tool for creating user profiles for adaptive educational systems. Sufficient knowledge of the characteristics of the user is a necessary prerequisite for effective adaptation. Some systems are able to accumulate useful data during the course of the interaction, but additional input must almost always be provided explicitly by the user (Brusilovsky 2001). EDUFORM can be employed to gather this information efficiently and create probabilistic user profiles for direct application in the adaptive educational system.

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