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ABSTRACT

As part of a project formulating optimal rules for decision making in computer assisted instructional systems in which the computer is used as a decision support tool, an approach that simultaneously optimizes classification of students into two treatments, each followed by a mastery decision, is presented using the framework of Bayesian decision theory. The main advantages of handling the three decision points simultaneously compared with separate optimization of such decisions are more efficient use of data and the use of more realistic utility structures. Both optimal weak monotone and strong monotone rules are considered. The results are empirically illustrated using data for 17,259 students for the problem, well-known in The Netherlands, of selecting optimum continuation schools at the end of elementary school on the basis of achievement test scores. (Contains 2 tables, 1 figure, and 6 references.) (SLD)

An Intelligent Tutoring System for Classifying Students into Instructional Treatments with Mastery Scores

Research Report 94-15

Hans J. Vos

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University of Twente

Department of
Educational Measurement and Data Analysis

An Intelligent Tutoring System for Classifying Students
into Instructional Treatments with Mastery Scores

Hans J. Vos

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Abstract

An approach that simultaneously optimizes classification of students into two treatments each followed by a mastery decision is presented using the framework of Bayesian decision theory. The main advantages of handling the three decision points simultaneously compared with separate optimization of such decisions are more efficient use of data and the use of more realistic utility structures. Both optimal weak monotone and strong monotone rules will be considered. The results are empirically illustrated using data of the well-known problem in the Netherlands of selecting optimal continuation schools on the basis of achievement test scores.

Introduction

In the relatively short period of time that instructional programs in computer-aided instruction (CAI) systems have been under development, much has been learned about the construction of instructional materials. Unfortunately, corresponding progress does not seem to have been made on the matter of developing appropriate testing methods and decision procedures for use in such systems. An appropriate set of testing methods and making procedures would facilitate an efficient flow of students through a CAI system.

In a typical individualized program the instruction is divided into comparatively small instructional treatments or modules. In addition, all modules are delimited by means of clear-cut learning objectives. In the case of an adaptive CAI system, at several points of time decisions have to be made about how each individual student should proceed from one module to another. Such decisions mostly depend on the student's results on a few achievement test items administered right after a module as well as his preceding (test) history in the system.

The purpose of this research project is to formulate optimal rules for instructional decision making in CAI systems in which the computer can be used as a decision support tool. The successful implementation of a CAI system depends, in part, upon the availability of appropriate testing and decision making procedures to guide the student through the system. For instance, if a student is not directed to an appropriate module, his motivation may be decreased due to not matching the instruction to his specific learning characteristics. Also, the (expensive) computer time can be considerably reduced by using better instructional decisions in CAI systems.

Instructional networks in CAI systems can be represented as combinations of four elementary test-based decisions, namely selection, mastery, placement, and classification decisions (van der Linden, 1990). To optimize such combinations of decision problems within a Bayesian decision-theoretic framework (e.g., Ferguson, 1967), two major approaches can be distinguished. First, each decision can be optimized separately maximizing the expected utility for the test data exclusively gathered for this individual decision. Second, all decisions can be optimized simultaneously maximizing the expected utility over all possible combinations of decision outcomes (Vos, 1991, 1993, 1994). This paper explores how rules for the simultaneous optimization of combinations of decisions can be found.

As an example, one classification decision with two treatments each followed by a mastery decision are combined into a decision network (see Figure 1). The simple classification-mastery decision problem may be important in classification of students in CAI systems with tracks at different levels followed by a mastery test at the end of each track. Other well-known examples are educational guidance situations where most promising schools must be identified, which will be considered in the empirical example later on.

Insert Figure 1 about here

Compared with separate optimization of decisions, it is expected that two main advantages can be identified for a simultaneous approach. First, it is expected that rules can be found that make more efficient use of the data in the decision network. Second, it is expected that more realistic utility structures can be handled in a simultaneous approach.

The classification-mastery decision problem

In classification, the decision problem consists of a choice among several alternative treatments to which students have to be assigned on the basis of their test scores. Prior to the treatments, all students are administered the same classification test and the success of each treatment is measured by its own criterion. Completion of each treatment is followed by a mastery test which the student may pass or fail. Performance on this test is used to decide whether or not the students have profited enough from a treatment to be dismissed and to proceed with a subsequent treatment.

In the following, we shall suppose that the test scores observed prior to the treatments are denoted by a random variable X. Each treatment j is followed by a mastery test, with scores denoted by a random variable Y_j (j=0,1). Let T_j represent the classical test theory true score underlying Y_j. Furthermore, it is assumed that the classification of subjects into j treatments yield a joint distribution $f_j(x,y_j,t_j)$ of X, Y_j, and T_j.

Rescaling of the criterion variables

For technical reasons the observable criterion variables Y_0 en Y_1 will be rescaled such that they both take values on the same domain. As a result, for the realizations y_0 and y_1 of the random variables Y_0 and Y_1, the indices 0 and 1 can be dropped in the remainder of this paper. This is because y_0 and y_1 now represent mathematical variables with the same domain. Of course, this does not mean that a subject does receive the same value for y if (s)he follows different treatments.

On the other hand, the indices 0 and 1 will be maintained for Y_0 and Y_1 because they represent different random variables. Also, the indices 0 and 1 will be maintained in the associate density and cumulative distribution functions.

Similarly, since T is defined as the expectation of Y according to classical test theory, the indices 0 and 1 will be dropped for the realizations t_0 and t_1 of T_0 and T_1 whereas the indices will be maintained again for the random variables T_0 and T_1 as well as their associated density and cumulative distribution functions.

In accordance with the foregoing all functions of y and t to be introduced below will be defined on the new scale.

Weak monotone and strong monotone rules

In the present paper, we restrict the range of all possible decision rules by considering only monotone rules; that is, rules using cutting scores. Let x_c, y_{cj}, and t_{cj} denote the cutting scores on the random variables X, Y_j, and T_j, respectively, where t_{cj} is set in advance by the decision maker. The classification-mastery decision problem now consists of simultaneously setting cutting scores x_c and y_{cj} such that, given the value of t_{cj}, the expected utility is maximized (j=0,1).

In general, the observed scores on the classification test may or may not be explicitly taken into account in setting cutting scores on the mastery test score variable Y_j (j=0,1). For instance, it seems reasonable that students who are assigned to treatment 1 with observed classification scores equal to or just above x_c must compensate their relatively low classification scores with higher scores on the mastery test Y_1. To distinguish between cases where y_{cj} is or is not allowed to depend on x, those rules will be denoted by weak monotone and strong monotone rules, respectively. Thus, for each $x < x_c$ and $x \geq x_c$, the weak cutting scores on the mastery tests Y_0 and Y_1 have to be computed from some functions $y_{c0}(x)$ and $y_{c1}(x)$, respectively.

Let a_{jh} stand for the action either to retain (h=0) or advance (h=1) a student who is classified into treatment j (j=0,1), then for the decision network of Figure 1 the most general form of the decision rule is a weak rule δ defined as:

$$
\begin{aligned}
\{(x,y):\delta(x,y)=a_{00}\} &= A \times B_0(x) \\
\{(x,y):\delta(x,y)=a_{01}\} &= A \times B_0^{c}(x) \\
\{(x,y):\delta(x,y)=a_{10}\} &= A^{c} \times B_1(x) \\
\{(x,y):\delta(x,y)=a_{11}\} &= A^{c} \times B_1^{c}(x),
\end{aligned} \qquad (1)
$$

where A, A_c, $B_j(x)$, and $B_j^{c}(x)$ stand, respectively, for the sets of x and y values for which a student is classified into treatment 0, into treatment 1, retained in treatment j, and advanced in treatment j. Thus, a weak monotone rule δ can be defined for our example as:

$$
\delta(X,Y_j) = \begin{cases} a_{00} & \text{for } X < x_c,\ Y_0 < y_{c0}(x) \\ a_{01} & \text{for } X < x_c,\ Y_0 \geq y_{c0}(x) \\ & \\ a_{10} & \text{for } X \geq x_c,\ Y_1 < y_{c1}(x) \\ a_{11} & \text{for } X \geq x_c,\ Y_1 \geq y_{c1}(x). \end{cases} \qquad (2)
$$

Since we confine ourselves to monotone rules in this paper, we are to show that there are no nonmonotone rules with larger expected utility, or, equivalently, that the subclass of monotone rules constitutes an essentially complete class (e.g., Ferguson, 1967, p. 55). Conditions under which the subclass of weak monotone rules is essentially complete are given in Vos (1994). If these conditions are met, a weak monotone solution is said to exist.

An additive threshold utility function

A utility function $u_{jh}(t)$ evaluates the consequences of taking action a_{jh} while the true score of the student is t. In the present paper, it is assumed that the utility structure of the combined problem can be represented as an additive function of the following form:

$$
\begin{aligned}
u_{0h}(t) &= w_1 u_{0c}(t) + w_2 u_{0hm}(t) \\
u_{1h}(t) &= w_1 u_{1c}(t) + w_3 u_{1hm}(t)
\end{aligned}
\tag{3}
$$

where $u_{jc}(t)$, $u_{jhm}(t)$ represent the utility functions for the separate classification and mastery decisions under treatment j, respectively, and w_1, w_2, and w_3 represent nonnegative weights. Since utility is measured at least on an interval scale, assuming $w_2 = w_3$ (i.e., the utility functions for both mastery decisions are equally weighted), the weights in (3) can always be rescaled as follows:

$$u_{jh}(t) = wu_{jc}(t) + [(1-w)/2]u_{jhm}(t) \tag{4}$$

where the weight w should obey $0 \leq w \leq 1$.

In the Introduction it was remarked that one of the main advantages of a simultaneous approach was that more realistic utility structures can be handled. This fact is nicely demonstrated by the additive structure of (4), in which utility functions defined on the ultimate criteria variables T_0 and T_1 can also be used in previous decision problems, namely the problem of classifying students into treatment 0 and treatment 1.

In the classification-mastery problem, the following well-known threshold utility functions (e.g., Hambleton & Novick, 1973) are adopted for the separate classification and mastery decisions:

$$u_{jc}(t) = \begin{cases} b_{j0} & \text{for } T_j < t_{cj} \\ b_{j1} & \text{for } T_j \geq t_{cj} \end{cases} \tag{5}$$

$$u_{jhm}(t) = \begin{cases} d_{j00} & \text{for } h = 0,\ T_j < t_{cj} \\ d_{j01} & \text{for } h = 1,\ T_j < t_{cj} \\ d_{j10} & \text{for } h = 0,\ T_j \geq t_{cj} \\ d_{j11} & \text{for } h = 1,\ T_j \geq t_{cj}. \end{cases} \tag{6}$$

The choice of threshold utility functions imply that the 'seriousness' of all possible consequences of the decisions can be summarized by four and eight constants in (5) and (6), one for each of the four and eight possible decision outcomes, respectively. The utility parameters b_{jh}, d_{jh0}, and d_{jh1} (j,h=0,1) can be empirically assessed using lottery methods (e.g., Hambleton & Novick, 1973).

Optimal weak monotone and SMMEU rules

For each of the four possible actions, inserting the additive threshold utility function from (3) - (6), the expected utility with respect to $f_j(x,y,t)$ can be calculated. Adding up these expected utilities yields the expected utility for the simultaneous approach, $E[U_{sim}(A^c,B_0^c(x),B_1^c(x))]$. In Vos (1994) it is indicated that an upper bound to $E[U_{sim}(A^c,B_0^c(x),B_1^c(x))]$ is obtained if the sets $B_0^c(x)$, $B_1^c(x)$, and A^c take the form $\{y \mid g(x,y) \geq 0\}$, $\{y \mid h(x,y) \geq 0\}$, and $\{x \mid k(x,B_0^c(x),B_1^c(x)) \geq 0\}$, respectively, with $B_0^c(x)$ and $B_1^c(x)$ appearing as integration regions in the function $k(x,B_0^c(x),B_1^c(x))$.

Optimal weak monotone rules

For weak monotone rules, the sets $B_j^c(x)$ and A^c take the form $[y_{cj}(x),\infty]$ and $[x_c,\infty]$, respectively. Assuming the monotonicity conditions for weak simultaneous rules are satisfied, it then follows that optimal weak monotone rules can be found for those values of $y_{c0}(x)$, $y_{c1}(x)$ and x_c for which $g(x,y_{c0}(x)) = 0$, $h(x,y_{c1}(x)) = 0$, and $k(x_c,y_{c0}(x_c),y_{c1}(x_c)) = 0$, respectively.

Since $g(x,y_{c0}(x)) = 0$ and $h(x,y_{c1}(x)) = 0$ hold for all x, and thus for x_c, the optimal weak cutting score on the classification test can be found by solving $g(x_c,y_{c0}(x_c)) = 0$, $h(x,y_{c1}(x_c)) = 0$, and $k(x_c,y_{c0}(x_c),y_{c1}(x_c)) = 0$ simultaneously for x_c, $y_{c0}(x_c)$, and $y_{c1}(x_c)$. For each $x < x_c$ and $x \geq x_c$, the optimal weak cutting scores on the mastery tests Y_0 and Y_1 can be obtained by solving $g(x,y_{c0}(x)) = 0$ and $h(x,y_{c1}(x)) = 0$ for $y_{c0}(x)$ and $y_{c1}(x)$, respectively.

SMMEU rules

Since in educational testing one is accustomed to using strong cutting scores, optimal rules will also be derived within the subclass of strong monotone rules without bothering about monotonicity conditions. This type of rules will be termed SMMEU (strong monotone rules with maximum expected utility) rules.

The set of SMMEU cutting scores, say x_c^*, y_{c0}^*, and y_{c1}^*, can be obtained by inserting $A^c = [x_c,\infty]$ and $B_j^c(x0 = [y_{cj},\infty]$ into $E[U_{sim}(A^c,B_0^c(x),B_1^c(x)]$, differentiating w.r.t. x_c, y_{c0}, and y_{c1}, setting the resulting expressions equal to zero, and solving simultaneously for x_c, y_{c0}, and y_{c1} (Vos, 1994).

The optimal weak and SMMEU cutting scores can now be computed from the systems of nonlinear equations to be solved. Assuming a trivariate normal distribution for $f_j(x,y,t)$, a computer program called NEWTON, available on request from the author, was written to calculate the cutting scores iteratively (Vos, 1994). For each $x < x_c$ and $x \geq x_c$, the optimal weak cutting scores on the mastery tests under treatment 0 and 1, $y_{c0}(x)$ and $y_{c1}(x)$, were computed iteratively by solving $g(x,y_{c0}(x)) = 0$ and $h(x,y_{c1}(x)) = 0$ for $y_{c0}(x)$ and $y_{c1}(x)$, respectively. These procedures were also implemented in NEWTON. In the program NEWTON only the utility parameters b_{jh}, d_{jh0}, and d_{jh1}, the weight w (i.e., the relative influence of the separate classification decision in %), and the cutting score t_{cj} on the true score scale T_j have to be specified by the decision maker (j,h=0,1).

It is important to notice that the weak montone approach actually provides us with some 'artificial intelligence' for setting optimal weak cutting scores. The more test data of each student comes available, the better the optimal weak cutting scores for each student can be set. In fact, the optimal weak cutting scores on the classification test still have to be set for all students at the same point x_c, while the optimal weak cutting scores on the mastery tests, $y_{c0}(x)$ and $y_{c0}(x)$, can be set by taking explicitly into account each student's observed score on the classification test. In other words, the program NEWTON operates as an Intelligent Tutoring System (ITS) in the sense of monitoring the student through the instructional network in such a way that optimal advantage is taken of each student's preceding (test) history in the CAI system.

An application to a real-life decision problem

The numerical example concerns the assignment of pupils to appropriate continuation schools at the end of the elementary school (i.e., at grade 8), a problem that is well-known in the Dutch educational system. The Dutch National Institute of Educational Measurement (CITO) prepares annually an achievement test (*Eindtoets Basisonderwijs*), which is used by most elementary schools for this purpose. In addition, on the basis of a grade-point average, it is decided whether or not a pupil will finish the first year of secondary school j successfully. This means that the problem can be characterized as a classification-mastery decision. Test scores on the CITO achievement test as well as the grade point average range from 0-50.

In the analyses reported here, Lower Vocational Education (LVE) and Lower General Education (LGE) were selected as treatments with 1333 and 15926 pupils assigned to each of them, whereas LVE en LGE could be considered as treatment 0 ('lower') and 1 ('higher'), respectively.

Pupils were considered as having passed the first year of school 0 and 1 successfully if they had mastered at least 52% and 54% of the total subject matter, respectively, at the end of the first year. Therefore, t_{c0} and t_{c1} were fixed at 26 and 27, respectively.

The necessary statistics to compute the optimal weak monotone and SMMEU rules were estimated using maximum likelihood estimates. The results of the computations are shown in Table 1.

Insert Table 1 about here

Results for the simultaneous approach

Using the program NEWTON, the SMMEU and set of weak cutting scores $(x_c, y_{c0}(x_c), y_{c1}(x_c))$ were computed for three different values of the utility parameters as well as for w = 0.3, 0.6, and 0.9. The results are summarized in Table 2.

Insert Table 2 about here

The optimal weak monotone rules are given by x_c, $y_{c0}(x)$ for $x < x_c$, and $y_{c1}(x)$ for $x \geq x_c$. Using the program NEWTON, it appeared that both $y_{c0}(x)$ and $y_{c1}(x)$ were very slowly decreasing in x for $x < x_c$ and $x \geq x_c$, respectively. These patterns were in accordance with our expectations that students with classification scores far above or just below x_c are sooner allowed to proceed with the next treatment than pupils with classification scores just above or far below x_c.

As can be seen from Table 2, and using the decreasing character of

$y_{cj}(x)$, increasing values of w resulted in higher optimal weak cutting scores on the classification test, whereas the optimal weak cutting scores on both mastery tests were hardly influenced by the value of w. This makes sense since one might expect that with increasing weight for $u_{jc}(t)$, classification into the 'higher' treatment becomes less likely.

Optimal separate cutting scores

In Vos (1994) it is indicated that optimal cutting scores for the separate classification and mastery decisions, say $x_{c,sep}$ and $y_{cj,sep}$, can easily be derived imposing certain restrictions on the expected utility for a simultaneous approach. The results are also summarized in Table 2.

As can be seen from Table 2, in particular for low values of w, the optimal cutting scores for the separate classification decision were remarkably higher compared with those in the weak monotone model, implying that students were much sooner assigned to higher types of education in the weak monotone model.

Furthermore, Table 2 shows that $y_{c0}(x_c)$ and $y_{c1}(x_c)$ were somewhat higher compared to $y_{c0,sep}$ and $y_{c1,sep}$, respectively. This makes sense, because if students were sooner assigned to the 'higher' treatment in a weak monotone approach it seems reasonable that those students who were just classified into treatment 0 and 1 had to compensate their relatively low classification scores with higher optimal weak cutting scores on the mastery tests. The decreasing character of $y_{cj}(x)$ in x, however, implies that with increasing classification scores the optimal weak cutting scores on the mastery tests can be slowly decreased again.

Comparison of expected utilities

In the Introduction it was remarked that one of the main advantages of a simultaneous approach was the expectation that rules making more efficient use of the data in the decision network could be found. As a consequence, one might expect an increase in expected utility compared with a separate approach. To investigate whether this expectation could be confirmed, the weighted sum of the expected utilities for the optimal separate rules was compared with the expected utilities for a simultaneous approach using a computer program called UTILITY, available on request from the author. The results are also depicted in Table 2.

Table 2 indicates that, although the differences were rather small, the weak monotone approach yielded the largest expected utility for all three approaches for all utility structures. In particular, for a large weight for the utility of the classification decision, hardly any differences could be found. Though this result does not contradict our predictions, we did have stronger expectations.

Concluding remarks

A final remark is appropriate. The models presented in this paper were applied to the problem of assigning students to optimal types of secondary education. However, the procedures advocated in this paper have a larger scope. For instance, in addition to the important application of deriving optimal rules for instructional decision making in CAI systems, the simple classification-mastery decision problem may be useful in the area of psychotherapy in which patients have to be classified into the most appropriate therapy followed by a test, which has to be passed before they can be dismissed from the therapy.

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Table 1

Statistics Classification and Mastery Tests (X and Y_j)

Statistic	X	Y Treatment 0	Y Treatment 1
Mean	34.324	31.551	29.621
Standard Deviation	7.971	3.246	2.208
Reliability		0.812	0.803
Correlation		$\hat{\rho}_0 = 0.129$	$\hat{\rho}_1 = 0.365$

Table [illegible]

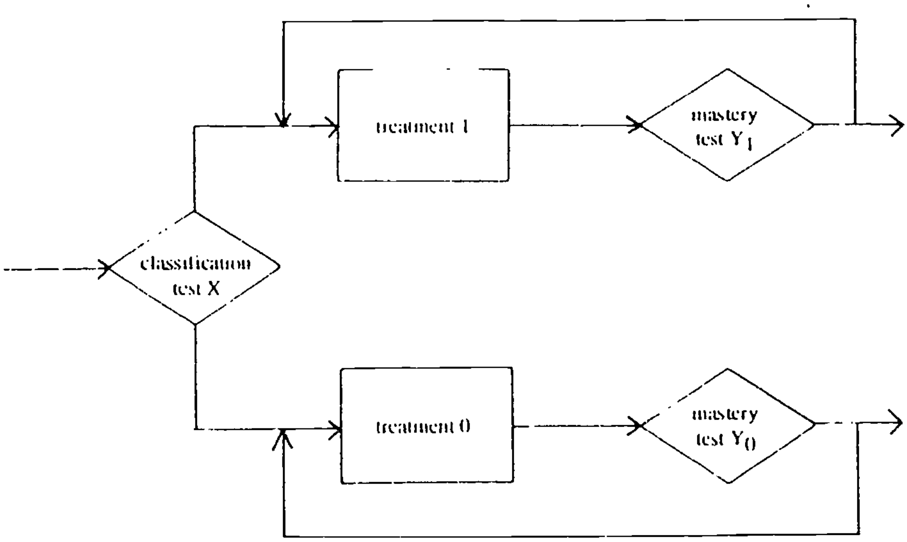
[illegible] and Expected Utilities with Additive Threshold Utility

[illegible]	Optimal Cutting Scores			Expected Utility		
	Simultaneous		Separate	Weak Monotone	CMMEU	Separate
	Weak Monotone	CMMEU				
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	1.11[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	1.244	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

21

Figure Caption

Figure 1 A system of one classification decision with two treatments each followed by a mastery decision.


treatment 1
mastery
test Y_1
classification
test X
treatment 0
mastery
test Y_0

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