Items with the highest discrimination parameter values in a logistic item response theory (IRT) model do not necessarily give maximum information. This paper shows which discrimination parameter values (as a function of the guessing parameter and the distance between person ability and item difficulty) give maximum information for the three-parameter logistic IRT model. The optimal discrimination parameter value is shown to be inversely related to the distance between item difficulty and person ability. An upper bound for the information as a function of these parameters is derived; and this upper bound is used to formulate a fast item selection algorithm for adaptive testing. In a small simulation study this algorithm was one and one half to six times as fast as an algorithm in which the information of all items in an item bank is calculated. (Contains 1 table, 6 figures, and 9 references.)

(Author/SLD)
A Simple and Fast Item Selection Procedure for Adaptive Testing

Wim J.J. Veerkamp
Martijn P.F. Berger

faculty of
EDUCATIONAL SCIENCE
AND TECHNOLOGY

Department of:
Educational Measurement and Data Analysis

University of Twente
A Simple and Fast Item Selection Procedure
for Adaptive Testing

Wim J.J. Veerkamp
Martijn P.F. Berger
A simple and fast item selection procedure for adaptive testing, Wim J.J. Veerkamp & Martijn P.F. Berger - Enschede: University of Twente, Faculty of Educational Science and Technology, December 1994. - 25 pages.
Abstract

Items with the highest discrimination parameter values in a logistic item response theory model do not necessarily give maximum information. In this paper it is derived which discrimination parameter values as a function of the guessing parameter and the distance between person ability and item difficulty, give maximum information for the three-parameter logistic item response theory model. An upperbound for the information as a function of these parameters is derived. This upperbound for the information function is used to formulate a fast item selection algorithm for adaptive testing. In a small simulation study this algorithm was one and a half to six times as fast as an algorithm in which the information of all items in an item bank is calculated.

Key words: adaptive testing, attenuation paradox, item selection, information function, discrimination parameter, logistic IRT model
A Simple and Fast Item Selection Procedure for Adaptive Testing

One of the major features of the information function in item response theory (IRT) is that it can be used for the selection of items from item banks. This can be done sequentially during test administration as is the case in computerized adaptive testing (CAT) (Lord, 1980; Wainer, Dorans, Flaugher, Green, Mislevy, Steinberg, & Thissen, 1990).

Lord (1977) proposed a maximum information selection criterion for adaptive testing. For the two- and three-parameter logistic (2PL and 3PL) IRT models it can be inferred that an increase of the item discrimination parameter $a_i$ will lead to an increase of information. Lord (1980, Eq. 10-6) showed that for the 2PL and 3PL models the maximum obtainable item information is an increasing function of the squared item discrimination parameter as long as item difficulty $b_i$ and person ability $\theta$ are optimally matched. For the 2PL model, maximum information is obtained when item difficulty is equal to person ability. It can also be shown that the area under the item information function for the 2PL model is equal to the discrimination parameter. For the three-parameter model, a similar relation can be found (see Birnbaum, 1968, Eq. 20.4.26).

Figure 1 shows item information functions on a $(\theta-b_i)$-scale for different values of the discrimination parameter $a_i$ for the 2PL model. It can be seen that
increasing the value of the discrimination parameter will lead to a higher but also more peaked information function. This phenomenon shows that the area under the information function is concentrated in a smaller range of ability values, i.e., the width of the information function becomes smaller as the discrimination parameter increases.

Samejima (1994) has shown that the area under the square root of the information function for the 2PL model is equal to \( \pi (\pi = 3.14) \), irrespective of the value of the discrimination parameter. This implies that in the 2PL model the information functions of two items must cross at least once. For reasons of symmetry, the information functions of two items with the same difficulty parameter, but with different discrimination parameters, must cross twice. This fact is shown in Figure 1.

Figure 1 also shows that, when item difficulty is not equal to person ability, an extreme increase of item discrimination may lead to a decrease of item information. This effect has been referred to as the attenuation paradox in IRT by Lord and Novick (1968, p. 368) and Birnbaum (1968, p. 465).

---

Insert Figure 2 about here

---

Figure 2 depicts item information for the 2PL model as a function of item discrimination for different values of the distance between person ability and item difficulty. The well-known fact that an item with a high discrimination parameter is not necessarily the most informative item, and that, therefore, selection of items in an adaptive test should not solely be based on the discrimination parameter, can also be seen in Figure 2.
In this paper, it is shown which discrimination parameter values give maximum information, and how high this maximum information is. Both the optimal discrimination as well as the maximum attainable information are functions of the distance between item difficulty and person ability for logistic IRT models. The results of this paper are implemented in an item selection algorithm for adaptive testing, and a small simulation study will show that this algorithm will improve item selection.

**Derivation of Optimal Item Discrimination Parameter Values**

In this section, it is determined which value of the item discrimination parameter is the most informative one, given certain fixed values of the other item parameters and the person ability parameter for the 3PL IRT model. The corresponding maximum information values will also be given. The 2PL model is a special case of the 3PL model, and the results will therefore also hold for the 2PL model.

The item characteristic curve of the 3PL IRT model is (Lord, 1980, Eq. 4-37):

\[
P_i(\theta) = c_i + (1 - c_i) \frac{e^{L_i}}{1 + e^{L_i}},
\]

where \( L_i = a_i(\theta - b_i) \), and \( a_i \in \mathbb{R}^+ \), \( b_i \in \mathbb{R} \) and \( c_i \in [0,1] \) are the discrimination, difficulty and guessing parameter, respectively, and \( \theta \in \mathbb{R} \) is the ability parameter. \( \mathbb{R} \) and \( \mathbb{R}^+ \) are sets of real and positive real numbers, respectively. In Equation 1, \( P_i(\theta) \) denotes the probability of a correct response to item \( i \) for a person \( \theta \).
ability $\theta$. The corresponding item information function is given by:

$$I_i(\theta) = \frac{a_i^2 (1-c_i)}{(c_i+e^{L_i}) \left(1+e^{-L_i}\right)^2}$$ (2)

(see e.g. Lord, 1980, Eq. 4-43). The value of $a_i$ for which a maximum information function value is reached for fixed values of $c_i$ and $(\theta-b_i)$ is found by setting the derivative of the natural logarithm of the information function with respect to $a_i$ equal to zero, i.e.:

$$\frac{\partial \log[I_i(\theta)]}{\partial a_i} = \frac{2}{a_i} - \frac{e^{L_i}(\theta-b_i)}{c_i+e^{L_i}} + 2 \frac{e^{-L_i}(\theta-b_i)}{1+e^{-L_i}} = 0.$$ (3)

After some elementary operations, this equation can be reduced to:

$$2c_i(1+L_i) + (2c_i+1+L_i)e^{L_i} + (2-L_i)e^{-2L_i} = 0.$$ (4)

It can be shown that solutions of Equation 4 must lie between -6 and 3 (see the appendix for proof). Hence, Equation 4 can be solved iteratively, substituting real numbers for $L_i$ between -6 and 3. This leads to two solutions of $L_i$, namely one for $(\theta-b_i) > 0$ and one for $(\theta-b_i) < 0$. These two optimal values of $L_i$ are
given in Table 1 for \( c_i \)-values ranging from 0.0 to 0.9 with steps 0.1. From these optimal \( L_i \)-values the corresponding optimal \( a_i \)-values can also be derived. If, for example, \( c_i = 0.1 \) and \((\theta - b_i) = -2\), then the optimal \( a_i \)-value will be \(-1.816 / (-2) = 0.908\). This value is depicted as a cross in Figure 3. The optimal \( a_i \)-values for \( c_i = 0 \) and for \( c_i = 0.9 \) are shown as functions of \((\theta - b_i)\) in Figure 3. All lines for \( 0 < c_i < 0.9 \) lie between the line of \( c_i = 0 \) and the line of \( c_i = 0.9 \).

The values of \( I_i(\theta)(\theta-b_i)^2 \) in Table 1 can be obtained by substituting the values for \( c_i \) and the optimal values for \( a_i \) and \( L_i \) in equation (2). An upperbound for \( I_i(\theta) \) can be found by dividing \( I_i(\theta)(\theta-b_i)^2 \) by \((\theta-b_i)^2\). As an example, for items with \( c_i = 0.1 \), the information at ability level \( \theta < b_i \) can be at most:

\[
\frac{[-1.816/(\theta - b_i)]^2}{e^{-1.816}(1+e^{1.816})^2} < \frac{0.222}{(\theta - b_i)^2}.
\]

This fact means that the information for items with \( c_i = 0.1 \) and \((\theta - b_i) = -2\) is always less than 0.055. This value is shown as a cross in Figure 4, together with the upperbound information functions, for two different values of \( c_i \), namely \( c_i = 0 \) and \( c_i = 0.6 \). Similar lines can be drawn for \( 0 < c_i < 0.6 \) and these lines all lie between the two previous lines in Figure 4. For \( c_i > 0.6 \), the lines lie below the line of \( c_i = 0.6 \).
The results in Figure 4 and Table 1 show that three factors determine the value of the upperbound information, namely $|\theta - b_i|$ and $c_i$. The second factor denotes whether $(\theta - b_i)$ is greater than or less than 0. Keeping the other factors constant, the maximum information is a decreasing function of both $|\theta - b_i|$ and $c_i$, and it is higher for $(\theta - b_i) > 0$ than for $(\theta - b_i) < 0$.

For example, for items with $c_i > 0.1$ and $(\theta - b_i) < -2$, the maximum information is less than the maximum information for items with $c_i = 0.1$ and $(\theta - b_i) = -2$, which in turn are less informative than items with $c_i = 0.1$ and $(\theta - b_i) = 2$. As a consequence, when we have items with guessing parameter values $c_i \geq 0.1$ which are more difficult than a person's ability by at least two units, i.e. $(\theta - b_i) \leq -2$, then their information $I_i(\theta) \leq 0.055$. For items with the same guessing parameter values, but with $(\theta - b_i) \geq 2$, the information will be $I_i(\theta) \leq 0.392/4 = 0.098$.

Finally, in Figure 5 the upperbound information times the squared distance between person ability $\theta$ and item difficulty $b$ is shown as a function of the guessing parameter. These lines are based on the results given in Table 1.
An Item Selection Algorithm

The upperbounds for the information derived in the previous section can be used to improve item selection for adaptive testing. Suppose that we want to select items from an item bank in an adaptive test with Lord’s (1977) maximum information criterion. This criterion selects the item which has the highest value of the information function at a certain value $\theta_0$ on the ability scale, usually some provisional ability estimate. An heuristic to select the maximum informative item at $\theta_0$ is to calculate the information of all items for this value $\theta_0$. It is not necessary, however, to compute the information of all items in an item bank to determine which one has maximum information.

This can be seen as follows. Let $c_{\min}$ be the smallest guessing parameter value among all items in the itembank. Let $I_{\max,+}(c_{\min})$ and $I_{\max,-}(c_{\min})$ be the upperbounds of $I_i(\theta_0)(\theta_0-b_i)^2$ for positive and negative values of $(\theta_0-b_i)$, respectively. These upperbounds can be found in Table 1 under the heading $I_i(\theta_0)(\theta_0-b_i)^2$ for values of $c_{\min}$ under the heading $c_i$. So, for example, $I_{\max,+}(0.1) = 0.392$ and $I_{\max,-}(0.1) = 0.222$. In the following $I_{\max}$ will either be $I_{\max,+}(c_{\min})$ or $I_{\max,-}(c_{\min})$.

The following result for two items $i$ and $j$ can be derived:

$$\text{if } (\theta_0 - b_i)^2 > \frac{I_{\max}}{I_j(\theta_0)}, \text{ then } I_i(\theta_0) < I_j(\theta_0).$$

This follows from:
Item Selection

\[(\theta_0 - b_i)^2 > \frac{l_{\text{max}}}{l_j(\theta_0)} \iff l_j(\theta_0) > \frac{l_{\text{max}}}{(\theta_0 - b_i)^2}\] (7)

and

\[l_i(\theta_0) (\theta_0 - b_i)^2 < l_{\text{max}} \iff l_i(\theta_0) < \frac{l_{\text{max}}}{(\theta_0 - b_i)^2}.\] (8)

The left hand side of Equation 8 follows from the definition of \(l_{\text{max}}\) as an upperbound of \(l_i(\theta_0)(\theta_0 - b_i)^2\).

So, as soon as it is determined that a certain item \(j\) has a certain information \(l_j(\theta_0)\), then all items \(i\) with either positive \(\theta_0 - b_i\) and \((\theta_0 - b_i)^2 > l_{\text{max}, +}(c_{\text{min}})/l_j(\theta_0)\), or negative \(\theta_0 - b_i\) and \((\theta_0 - b_i)^2 > l_{\text{max}, -}(c_{\text{min}})/l_j(\theta_0)\) will have less information than item \(j\), no matter what values for \(a_i\) and \(c_i \geq c_{\text{min}}\) are encountered.

The algorithm

The algorithm has the following initialisation steps:

1. Order the \(N\) items in the itembank according to their difficulties:
   \[b_1 < b_2 < \ldots < b_N.\]

2. Determine the smallest guessing parameter value in the itembank: \(c_{\text{min}}\).

3. Compute the constants \(l_{\text{max}, +}(c_{\text{min}})\) and \(l_{\text{max}, -}(c_{\text{min}})\).

   If \(\theta_0\) is an provisional ability estimate after the administration of a set of items in an adaptive test, then the selection of the next item with maximum information on \(\theta_0\) from the set of items in the itembank not already included in the test, consists of the following steps:
Item Selection

Step 1: Search for item $j$ with difficulty value equal to the smallest positive difference $(\theta_0 - b_j)$ among all items.

If $\theta_0 < b_1$ or $\theta_0 > b_N$ item $j$ is the easiest respectively the most difficult item.

Step 2: Search through the itembank for items $i$ in increasing order of $|\theta_0 - b_i|$, for positive values of $(\theta_0 - b_j)$.

If $(\theta_0 - b_j)^2 > I_{max} + (c_{min} - I_j(\theta_0))$, then go to Step 3.

Otherwise, compute $I_i(\theta)$, if $I_i(\theta_0) > I_j(\theta_0)$ set $j=i$, and continue the search.

Step 3: Search through the itembank for items $i$ in increasing order of $|\theta_0 - b_i|$, for negative values of $(\theta_0 - b_j)$.

If $(\theta_0 - b_j)^2 > I_{max} - (c_{min} - I_j(\theta_0))$ then stop searching.

Otherwise, compute $I_i(\theta)$, if $I_i(\theta_0) > I_j(\theta_0)$ set $j=i$, and continue the search.

Step 1 can be sped up somewhat by starting the search for item $j$ with an item that is expected to have a difficulty close to the difficulty of item $j$. Note that in Steps 2 and 3 the index $j$ represents the most informative item which is eventually administered to the test-taker. The answer to this item is scored, and the test-taker's ability is re-estimated. Item $j$ is then removed from the item bank.

In conclusion, this search process only passes through a part of the itembank, i.e. the information is computed only for items with relatively small values of $(\theta_0 - b_j)^2$. This strategy will speed up item selection considerably.
A Simulation Study

To establish the relative speed of this item selection algorithm, a simulation study was performed in which the above described algorithm was compared to the algorithm with straightforward calculation of the information of all items in an item bank. For both algorithms Lord's maximum information criterion was used to select items. This choice means that for each test exactly the same items, in the same order, were selected by the two algorithms. So, the algorithms only differed in their CPU-times. The simulations were performed using a program written in Borland Pascal 7.0, and were run on a 486DX2/66MHz computer.

Design

For seven different ability values, $\theta = -3, -2, -1, 0, 1, 2,$ and $3$, respectively, adaptive tests of 30 items were simulated. These simulations were repeated for three different itembanks. Each itembank consisted of 200 items. In all banks, the distributions of the discrimination parameters and guessing parameters were uniform. The discrimination parameters were uniformly distributed between 0.5 and 2, i.e. $a_i \sim U(0.5,2)$, and the guessing parameters between 0.1 and 0.3, i.e. $c_i \sim U(0.1,0.3)$. The three itembanks differed only in their distributions of the difficulty parameters $b_i$: One bank had a uniform $U(-3,3)$ distribution of item difficulties, and in the other two banks the item difficulties were normally distributed, one with a variance of 1, and the other with a variance of 3. So, the distributions of item difficulties were $U(-3,3)$, $N(0,1)$, and $N(0,3)$, respectively. The number of replications for each condition, i.e., each combination of ability level and itembank, was 100.
Results

In Figure 6, the total amount of CPU-time used to select 30 items in 100 tests is shown as a function of $\theta$ for the two algorithms and the three item banks. The three lines a little above 40 seconds show the CPU-time needed to calculate the information of all items in the bank not already included in the test. The other three lines show the CPU-time needed by the proposed algorithm to select the items.

This algorithm improved item selection speed with a factor between 1.5 and 6. For a uniform distribution of the difficulty parameters the relative speed did not depend much on the ability value of the examinee, but for the item banks with normally distributed difficulties the speed did largely depend on the ability value. For $\theta = 0$ the amount of CPU-time was relatively high, because there were relatively many items with a difficulty parameter in this area. So, in these cases the information had to be computed for relatively many items.

The high CPU-times for extreme negative ability values for the $N(0,1)$-distribution of item difficulties may be explained as follows. The item difficulties are thinly spread around -3. The information of the most informative item $j$ in the search process was usually not very high, because most of the time $(\theta_0 - b_j) < 0$, and $|\theta_0 - b_j|$ is large. So, the range of difficulties of items that can be more informative than item $j$ is rather large. On the other hand, for extreme positive ability values the CPU-times were not that high, because the information for items $j$ with large distances between $\theta_0$ and $b_j$ is higher for $(\theta_0 - b_j) > 0$, than for $(\theta_0 - b_j) < 0$. Note that for the $N(0,3)$-distribution, the $b_j$-values were spread out much more than for the $N(0,1)$-distribution, and that this effect did thus not occur.
Summary and Conclusion

When item difficulty and person ability are not optimally matched, the optimal discrimination parameter value in logistic item response models is not its maximum value. This fact has been referred to as the attenuation paradox in item response theory. In this paper it has been shown that the optimal discrimination parameter value is inversely related to the distance between item difficulty and person ability, and it is derived which discrimination parameter value provides maximum information at certain points on the ability scale. The corresponding maximum information is inversely related to the squared distance between person ability and item difficulty.

The relation between this distance and an upperbound on information can be used in an algorithm for the maximum information item selection criterion for adaptive testing. In a small simulation study this algorithm was 1.5-6 times as fast as a more simple and straightforward algorithm. The difference between these algorithms is that in the simple algorithm the information function values for all items is determined, and in the proposed algorithm information is calculated for a relatively small subset of these items.

It may be argued that this algorithm will not be of much use when so-called info tables (Thissen & Mislevy, 1990, pp. 116-117) are used, where the information of the items is computed in advance, i.e. before the actual testing. This is not entirely true, because the computations needed to set up an info table can also be
sped up by means of the proposed algorithm. Moreover, when itembanks are frequently changed by inclusion of newly calibrated items or exclusion of rejected ones, this algorithm can be used to compute updated info tables.

Finally, Kingsbury & Zara (1989), and Stocking & Swanson (1993), among others, have described constrained adaptive testing procedures. Their procedures may take much time when a lot of constraints are incorporated in the selection process. So, it may be worthwhile to investigate the possibility of incorporating the algorithm proposed in this paper into constrained adaptive testing.
References


Table 1

Optimal $L_i$-values and Corresponding Maxima for $I_i(\theta)(\theta-b_i)^2$
for Different $c_i$-values Given Fixed $(\theta-b_i)$-Values

<table>
<thead>
<tr>
<th>$c_i$</th>
<th>$(\theta-b_i) &lt; 0$</th>
<th>$(\theta-b_i) &gt; 0$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$L_i$</td>
<td>$I_i(\theta)(\theta-b_i)^2$</td>
</tr>
<tr>
<td>0.0</td>
<td>-2.399</td>
<td>0.440</td>
</tr>
<tr>
<td>0.1</td>
<td>-1.816</td>
<td>0.222</td>
</tr>
<tr>
<td>0.2</td>
<td>-1.669</td>
<td>0.145</td>
</tr>
<tr>
<td>0.3</td>
<td>-1.591</td>
<td>0.101</td>
</tr>
<tr>
<td>0.4</td>
<td>-1.541</td>
<td>0.073</td>
</tr>
<tr>
<td>0.5</td>
<td>-1.505</td>
<td>0.052</td>
</tr>
<tr>
<td>0.6</td>
<td>-1.478</td>
<td>0.037</td>
</tr>
<tr>
<td>0.7</td>
<td>-1.457</td>
<td>0.025</td>
</tr>
<tr>
<td>0.8</td>
<td>-1.440</td>
<td>0.015</td>
</tr>
<tr>
<td>0.9</td>
<td>-1.427</td>
<td>0.007</td>
</tr>
</tbody>
</table>

Note. Values for $I_i(\theta)(\theta-b_i)^2$ were rounded upwards to 3 decimals.
Figure captions

Figure 1. Item information functions.

Figure 2. Item information as functions of the discrimination parameter.

Figure 3. Optimal a-value as a function of (θ-b).

Figure 4. Upperbound information as a function of (θ-b).

Figure 5. Upperbound information times (θ-b)^2 as a function of c.

Figure 6. The total CPU-time for two Maximum Information Item Selec-
   tion Algorithms for 100 30-item Adaptive Tests for three 200-
   item Itembanks.
Figure 1: Information curves for different values of $a$. 

- $a = 2.0$ 
- $a = 1.5$ 
- $a = 1.0$ 
- $a = 0.5$ 

The curves represent the information function on the $(\theta - b)$ scale.
Figure 2

Information

$\theta - b = 0.0$
$\theta - b = 0.5$
$\theta - b = 1.0$
$\theta - b = 1.5$
$\theta - b = 2.0$
Figure 3

(a-Value vs. (θ-b) Scale)

- Two curves are shown:
  - c = 0
  - c = 0.9

Legend:
- c = 0
- c = 0.9
Figure 4
Figure 5

Information(θ - b)

(θ - b) > 0

(θ - b) < 0

c-parameter
CPU-seconds

\( N(0,1) \)

\( U(-3,3) \)

\( N(0,3) \)

\( \theta \) Scale

Figure 6

Item Selection

23
Appendix

Proof that Solutions of Equation 4 Must Lie Between -6 and 3

This proof is split in the following two parts: (1) proof that solutions of Equation 4 cannot be less than -6; and (2) proof that solutions of Equation 4 cannot be greater than 3.

(1) Proof that \( L_i > -6 \)

Equation 4 can be rewritten as:

\[
2c_i(1+L_i) + (2(c_i+1) + \frac{2}{3}L_i)e^{L_i} + [(2-L_i)e^{L_i} \frac{1}{3}L_i]e^{L_i} = 0. \tag{9}
\]

The left part of Equation 9 is negative if \( L_i < -6 \), because it consists of three parts, which are all negative if \( L_i < -6 \):

(a) the first part, \( 2c_i(1+L_i) \), is less than or equal to 0 if \( L_i < -1 \). So it is also less than 0 if \( L_i < -6 \);

(b) the second part, \( (2(c_i+1) + \frac{2}{3}L_i)e^{L_i} \) is less than 0 if \( L_i < -6 \), because \( 2(c_i+1) + \frac{2}{3}L_i < 0 \iff L_i < -3(c_i+1) \), and \(-3(c_i+1) > -6\), because \( c_i < 1 \); and

(c) the third part, \( [(2-L_i)e^{L_i} \frac{1}{3}L_i]e^{L_i} \) is less than 0 if \( L_i < -6 \), because \( e^{L_i} \) is positive and \( [(2-L_i)e^{L_i} \frac{1}{3}L_i] \) is negative if \( L_i < -6 \); \( [(2-L_i)e^{L_i} \frac{1}{3}L_i] \) is negative because it is an increasing function of \( L_i \) for \( L_i < 1 \), which is negative for \( L_i = -6 \).
(2) Proof that $L_i < 3$

Equation 4 can be rewritten as:

$$L_i e^{2L_i} \left[ \frac{2c_i}{2L_i} + \frac{2c_i}{e^{2L_i}} + \frac{2(c_i + 1)}{L_i} + \frac{1}{e^{L_i}} + \frac{2}{L_i} - 1 \right] = 0. \quad (10)$$

The part between brackets in (10) is a decreasing function of $L_i$ for $L_i > 0$, and it can be found by substitution that for $L_i = 3$ this part is smaller than 0. So, the part between brackets is negative if $L_i > 3$. Combining this result with $L_i e^{2L_i} > 0$ if $L_i > 3$ completes the proof that the left part of Equation 10 is negative if $L_i > 3$. 


Titles of recent Research Reports from the Department of Educational Measurement and Data Analysis.
University of Twente, Enschede, The Netherlands.

RR-94-13 W.J.J. Veerkamp & M.P.F. Berger, A simple and fast item selection procedure for adaptive testing
RR-94-12 R.R. Meijer, Nonparametric and group-based person-fit statistics: A validity study and an empirical example
RR-94-11 M.P.F. Berger, Optimal test designs for polytomously scored items
RR-94-10 W.J. van der Linden & M.A. Zwarte, Robustness of judgments in evaluation research
RR-94-9 L.M.W. Akkermans, Monte Carlo estimation of the conditional Rasch model
RR-94-8 R.R. Meijer & K. Sijtsma, Detection of aberrant item score patterns: A review of recent developments
RR-94-7 W.J. van der Linden & R.M. Luecht, An optimization model for test assembly to match observed-score distributions
RR-94-6 W.J.J. Veerkamp & M.P.F. Berger, Some new item selection criteria for adaptive testing
RR-94-5 R.R. Meijer, K. Sijtsma & I.W. Molenaar, Reliability estimation for single dichotomous items
RR-94-3 W.J. van der Linden, A conceptual analysis of standard setting in large-scale assessments
RR-94-2 W.J. van der Linden & H.J. Vos, A compensatory approach to optimal selection with mastery scores
RR-94-1 R.R. Meijer, The influence of the presence of deviant item score patterns on the power of a person-fit statistic
RR-93-1 P. Westers & H. Kelderman, Generalizations of the Solution-Error Response-Error Model
RR-91-1 H. Kelderman, Computing Maximum Likelihood Estimates of Loglinear Models from Marginal Sums with Special Attention to Loglinear Item Response Theory
RR-90-7 E. Boekkooi-Timminga, A Method for Designing IRT-based Item Banks
RR-90-6 J.J. Adema, The Construction of Weakly Parallel Tests by Mathematical Programming
RR-90-5 J.J. Adema, A Revised Simplex Method for Test Construction Problems
RR-90-4 J.J. Adema, Methods and Models for the Construction of Weakly Parallel Tests
RR-90-2 H. Tobi, Item Response Theory at subject- and group-level
RR-90-1 P. Westers & H. Kelderman, Differential item functioning in multiple choice items

30
Research Reports can be obtained at costs from Bibliotheek, Faculty of Educational Science and Technology, University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands.