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COMPUTER PROGRAMS FOR SCORING TEST DATA WITH ITEM CHARACTERISTI--ETC(U)

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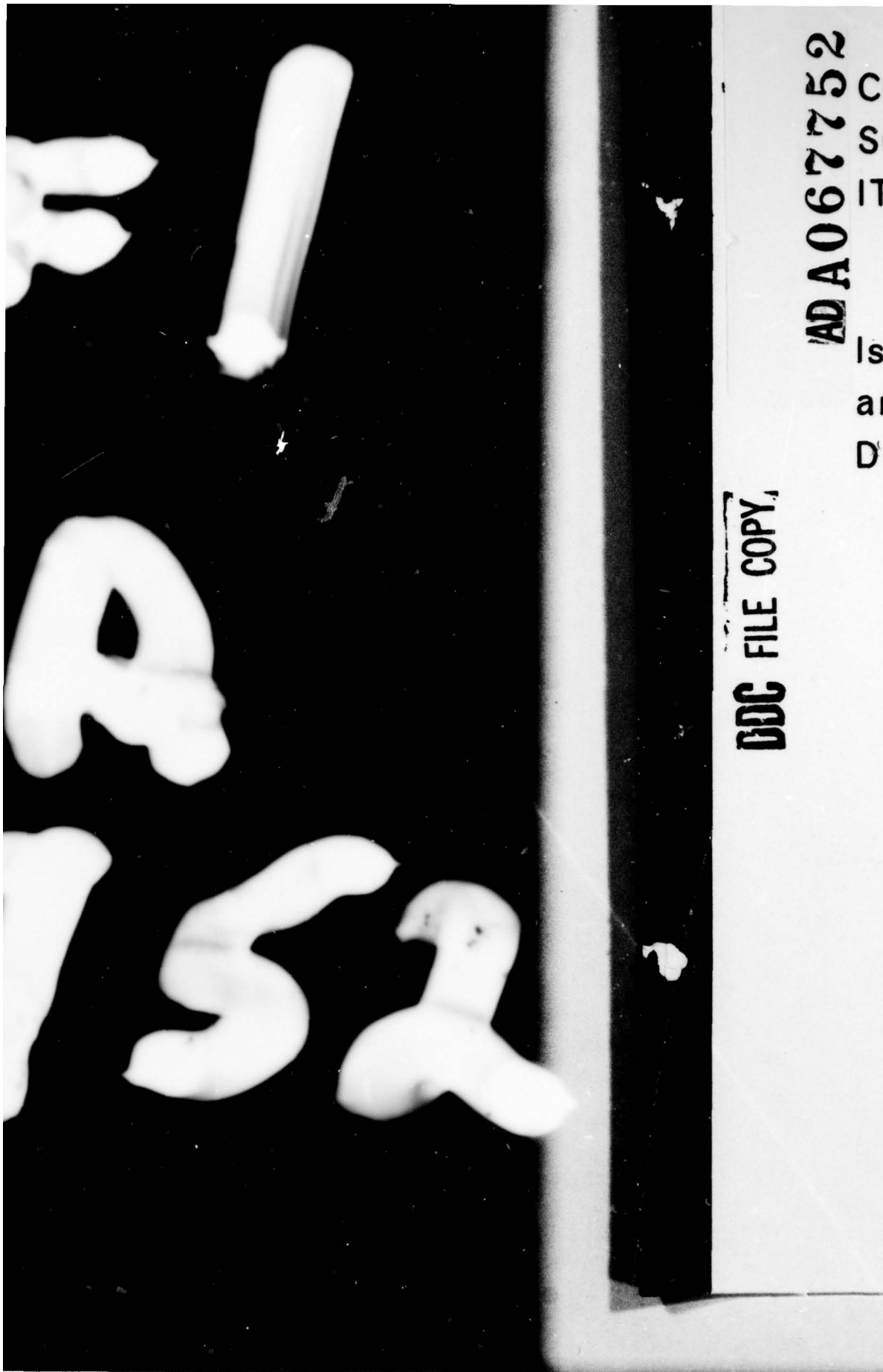
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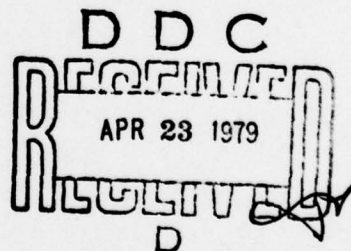
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COMPUTER PROGRAMS FOR
SCORING TEST DATA WITH
ITEM CHARACTERISTIC CURVE MODEL

Isaac I. Bejar
and
David J. Weiss

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PSYCHOMETRIC METHODS PROG
DEPARTMENT OF PSYCHOL
UNIVERSITY OF MINNES
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20. ABSTRACT (Continue on reverse side if necessary and identify by block number) Three computer programs are described for scoring test response data using item characteristic curve (ICC) or latent trait models. The rationale and mathematical basis of both maximum likelihood and Bayesian ICC scoring methods are presented, as well as some data comparing the two methods of scoring. The three computer programs are designed for scoring conventional (linear) test data (LINDSCO) in dichotomous response format, adaptive test dichotomous data (ADADSCO), and conventional (linear) test data scored by polychotomous ICC models (LINPSCO). Options available in these three general		

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purpose programs are described, and examples of the input and output are given for each program. Complete FORTRAN listings of the three programs are included. 

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Disclaimer

While every attempt has been made to insure the accuracy of the computer programs described in this report, the authors assume no responsibility for the accuracy or performance of the programs.

Technical Editor: Barbara Leslie Camm

COMPUTER PROGRAMS FOR SCORING TEST DATA WITH ITEM CHARACTERISTIC CURVE MODELS

Although latent trait test theory, or item characteristic curve (ICC) theory, has been developing since Lawley's (1943) paper more than 30 years ago, applications of the theory have appeared only recently. However, there are indications that latent trait test theory is beginning to reach the practitioner who is concerned with test development and usage in applied settings. This is evidenced, not only by the increasing number of journal articles concerned with latent trait test theory (e.g., the summer 1977 special issue of the Journal of Educational Measurement on applications of latent trait models) and in presentations and training sessions at professional meetings, but also by its application in adaptive (Weiss, 1976) or tailored (Lord, 1970) testing.

A potential disadvantage of latent trait test theory is that its use often involves complex computational procedures. To apply ICC models to the development of tests and their scoring, the psychometrician must be able to estimate the ICC parameters of the items in the test, and then use them in conjunction with the response data of a new group of testees in order to estimate their trait scores (e.g., ability or achievement levels). A number of computer programs are available for estimating ICC item parameters (these are summarized in Appendix Table A). However, there appeared to be no general programs available for scoring test data with ICC models when item parameter estimates were available from previous data sets. This report describes several programs designed to meet this need.

An Introduction to Test Scoring

The problem of test scoring can be conceptualized as the process of summarizing a testee's answers to a set of test questions into a single number in such a way that the score will be indicative of the testee's position on the trait being measured by the test. The most common test scoring strategy is to add the number of correct answers and to transform the score into some type of standard score or percentile to add interpretability. Historically, the number-correct score has been used because it is easy to calculate, and in pre-computer days this was an essential requirement of a test scoring procedure. As a general procedure for scoring tests of ability and achievement, however, the number-correct score has several deficiencies.

Inadequacies of the Number-Correct Score

One major problem with the number-correct score is that it is possible for the same number-correct score to be obtained in several different ways; that is, several response patterns can result in the same number-correct score. If the items in a test are all of equal difficulty and discrimination, and therefore are essentially replicates of each other, this will have little effect on the number-correct score, since different response patterns among

replicate items are of little consequence. But it is a very rare test--and one which would have little general measurement utility--which would have items that are all replicates of each other with regard to difficulty and discrimination.

When test items differ with respect to difficulty or discrimination, they are no longer replicates. Under these circumstances, different patterns of response to the same set of items convey different information with regard to a testee's trait level. The testee who correctly answers only five very difficult items in a test is likely of higher ability than the testee who correctly answers only five very easy items in the same test. Although the total number-correct score is the same for these two testees, their trait level estimates derived from latent trait or ICC theory will differ. An additional unattractive feature of the number-correct score is the fact that the number of possible scores is determined by the number of items in the test. Thus, if a test consists of only 10 items, only 10 unique scores are possible. Although this may be sufficient in some applications, in others it might be desirable to obtain a finer gradation of scores.

The inadequacy of the number-correct score as a general test-scoring procedure is most obvious when considering how to score responses of testees who have been administered different sets of items, as in adaptive or tailored testing. In these kinds of tests, number-correct scores are completely inappropriate, since different testees will receive items of different difficulties and discriminations as well as different numbers of items in an adaptive test. In addition, the proportion of correct responses obtained by all testees will be approximately the same in a well-designed adaptive test (e.g., Weiss, 1975).

ICC-Based Scoring

The scoring programs described in this report use considerably more refined approaches than a mere adding of correct answers and are usable for scoring both conventional and adaptive test data. This refinement is possible because ICC theory makes very explicit specifications about the relationship between performance on a test item and the testee's position on the trait, θ . This relationship is referred to as the *item characteristic curve* (ICC; Lord & Novick, 1968) when the items are scored into two categories (correct or incorrect) or, when there are more than two score categories, as the *operating characteristic function* (Samejima, 1969).

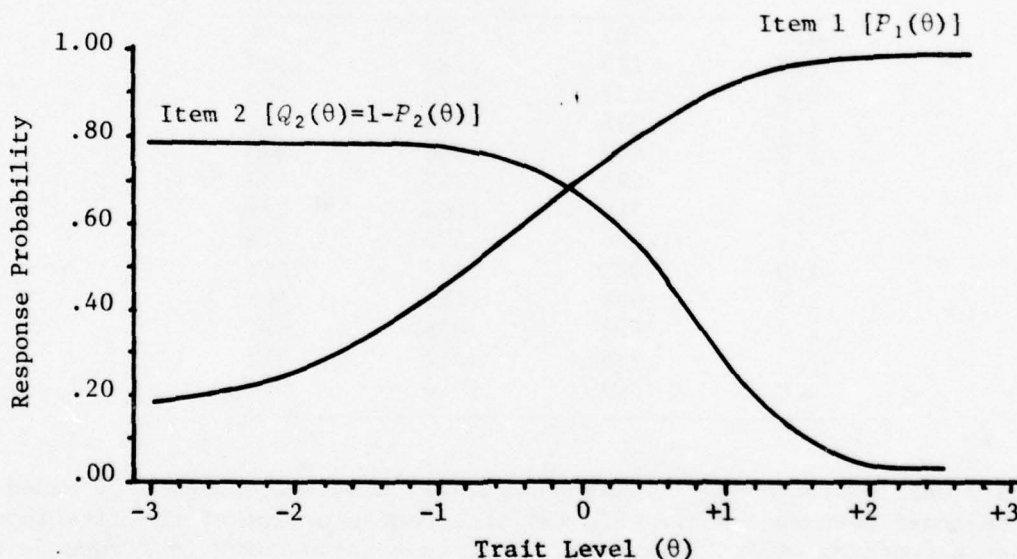
In the context of latent trait test theory, scoring may be conceptualized as finding the value of θ (i.e., the trait being measured) most "compatible," in some sense, with a given pattern of responses to the test items, given the ICC item parameters for each item answered. For maximum likelihood scoring, the score associated with a given response vector is that value of θ for which the likelihood of the response vector is maximum. For Bayesian scoring, the score is usually either the value of θ that minimizes the mean squared difference between the estimated θ and the "true" θ , or the value of θ that is most probable given the observed responses.

Maximum likelihood scoring. The details of the maximum likelihood scoring procedure are presented below. However, a conceptual explanation based on two

dichotomously scored test items will serve to explicate its rationale.

Figure 1 shows response probability curves for two test items--Item 1, which was answered correctly (resulting in an ICC plot of the probability of a correct response), and Item 2, which was answered incorrectly (resulting in a descending plot of the probability of an incorrect response, or 1 minus the ICC). The ICC curves for the two items are described by three parameters: (1) difficulty, b , which is the location of the ICC on the trait (θ) continuum at the point of maximum slope of the ICC ($b=-.5$ for Item 1 and $.75$ for Item 2); (2) their discrimination, a , which is proportional to the slope of the ICC at b ($a=.8$ for Item 1 and 1.4 for Item 2); and (3) "guessing," c , the lower asymptote of the probability of a correct response at $\theta=-\infty$ ($c=.16$ for Item 1 and $1-.78=.22$ for Item 2).

Figure 1
Response Probability Plots for a Correctly Answered Item (Item 1)
and an Incorrectly Answered Item (Item 2)



The first step in maximum likelihood scoring consists of determining the likelihood of the response pattern (correct response to Item 1 and incorrect response to Item 2). Assuming local independence, which means that responses to the test items have nothing in common except their relationship to the underlying trait, θ , the likelihood of a response pattern at any value of θ can be determined by multiplying the separate probabilities of the responses in the response pattern for that value of θ . The value of θ for which the likelihood is maximum is the maximum likelihood estimate of θ .

Conceptually, this can be illustrated with the ICCs in Figure 1 by using discrete values of θ , such as those shown in Table 1. For example, at $\theta=-1.0$, the probability of a correct response to Item 1 (scored as 1) is .442 and the

probability of an incorrect response to Item 2 (scored as 0) is .768; multiplying these values gives the likelihood of the [1,0] response pattern as .340. At $\theta=+1.0$, the probability of a correct response [1] to Item 1 is .903 and the probability of an incorrect response to Item 2 is .277; the likelihood of the [1,0] response pattern is therefore .250. Similarly, at $\theta=0.0$, the probability of a correct response to Item 1 is .718 and the probability of an incorrect response to Item 2 is .668, resulting in a likelihood for the [1,0] response pattern of .479. This process of computing likelihoods for the [1,0] response pattern can be repeated for a large number of values along the θ continuum.

Table 1
Probability of a Correct Response to
Item 1 [$P_1(\theta)$] and Probability of an
Incorrect Response to Item 2 [$Q_2(\theta)$] for
Selected Values of θ (Item 1: $a=.8$,
 $b=-.5$, $c=.16$; Item 2: $a=1.4$, $b=.75$,
 $c=.22$), and Values of the Likelihood
Function [$L(\theta)$]

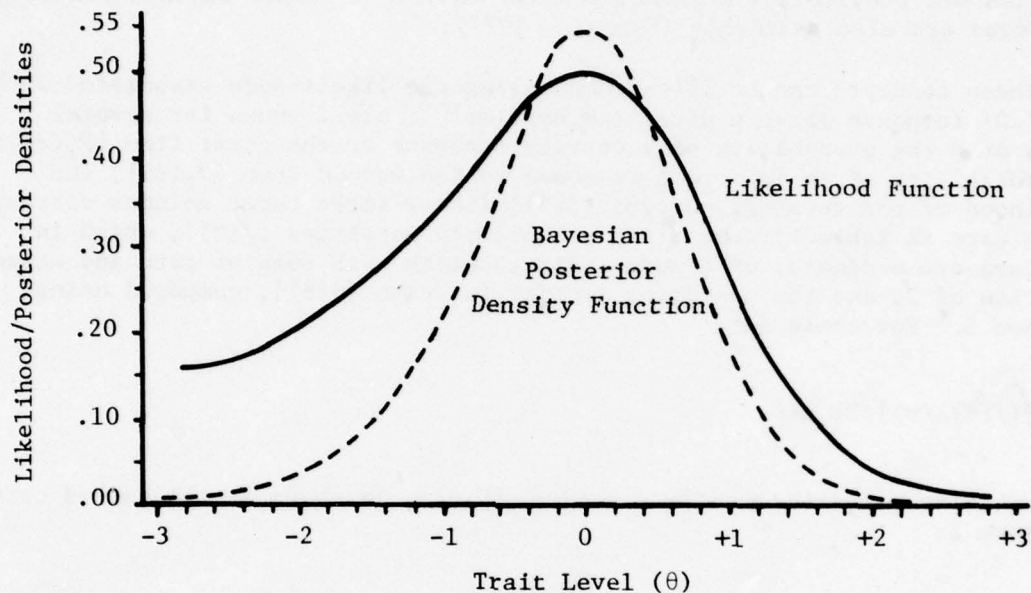
θ	$P_1(\theta)$	$Q_2(\theta)$	$L(\theta)$
-3.0	.187	.780	.146
-2.5	.212	.780	.165
-2.0	.257	.779	.200
-1.5	.332	.776	.257
-1.0	.442	.768	.340
.5	.580	.742	.430
0.0	.718	.668	.479
.5	.828	.503	.416
1.0	.903	.277	.250
1.5	.948	.112	.106
2.0	.973	.038	.037
2.5	.986	.012	.012
3.0	.993	.004	.004

The result of computing likelihoods for all possible values of θ based on the response pattern and the relevant ICCs can be a plot of the likelihood values as a function of θ . This plot, shown as a solid curve in Figure 2, is called a likelihood function. As can be seen, the maximum of the likelihood function in Figure 2 occurs at about $\theta=0.0$ (actually .01). Thus, $\theta=.01$ can be considered the maximum likelihood estimate of θ associated with the [1,0] response pattern, given the parameters of the ICCs for the items generating that response pattern. The maximum likelihood θ estimate is thus the value of θ which maximizes likelihood of the given response pattern for items with the specified ICCs.

The generalization of the scoring method for more than two items is straightforward. For each value of θ , the likelihood would be determined by multiplying the response probabilities for the appropriate ICCs (based on the specified response pattern) across all items that have been answered. Thus, for n items, n probabilities would be multiplied at each value of θ to obtain the likelihoods. The resultant likelihood values for all values of θ

could be plotted; and the maximum of the likelihood function would be used to identify the value of θ that gives the observed response pattern the greatest probability of occurrence.

Figure 2
Likelihood Function and Bayesian Posterior
Function for the [1,0] Response Pattern



Maximum likelihood scores are intuitively appealing; at the same time, they have a number of optimal statistical characteristics, at least asymptotically (i.e., when large numbers of items are administered). Of special relevance is the fact that as the number of items in the response pattern increases, it can be shown (Kendall & Stuart, 1961) that maximum likelihood estimates have minimum variance; and the reciprocal of that variance is known as the information function of θ . As a consequence, different scores (i.e., θ estimates) can have different degrees of accuracy as estimators of θ (Birnbaum, 1968; Samejima, 1969).

Bayesian scoring. Although the numerical details of maximum likelihood and Bayesian scoring are substantially different, the two methods are conceptually very similar. Bayesian scores are based on the likelihood function modified by the prior probability density function of θ . The prior probability density function describes the assumed distribution of θ in the population of individuals to be tested.

To illustrate, call $L(\theta)$ the likelihood of the response pattern for a given θ value. Now call $f(\theta)$ the prior probability density associated with that value of θ . The modified likelihood, which may be called $p(\theta)$ is then

$$p(\theta) = f(\theta)L(\theta) / \int [f(\theta)L(\theta)]d\theta. \quad [1]$$

Equation 1 is called the posterior probability density function. Just as the maximum likelihood score is the value of θ for which $L(\theta)$ is maximum, one kind of Bayesian score is the value of θ for which $p(\theta)$ is maximum. Such scores are called Bayes modal estimates by Samejima (1969) because they are based on the mode of the posterior density function. A different type of Bayesian estimate is based on the mean of the posterior density function. Owen's (1975) Bayesian scoring procedure, which will be described in detail below, is an example of this approach. In his procedure, the prior probability densities are provided by a normal density function. Other Bayesian scoring procedures are also available (Sympson, 1977).

These concepts can be illustrated using the likelihoods associated with the [1,0] response pattern discussed earlier. Table 2 shows for several values of θ the probability of a correct response to the first item [$P_1(\theta)$]; the probability of an incorrect response to the second item [$Q_2(\theta)$]; the likelihood of the response pattern [$L(\theta)$] (these first three columns correspond to the data in Table 1); the prior probability densities [$f(\theta)$], which in this case are ordinates of a normal distribution with mean of zero and standard deviation of 1; and the posterior density function [$p(\theta)$], computed using Equation 1. For these data

$$\int [f(\theta)L(\theta)]d\theta \approx .348. \quad [2]$$

The resulting posterior density function, [$p(\theta)$], is shown as the dashed curve in Figure 2.

Table 2
Response Probabilities [$P_1(\theta)$, $Q_2(\theta)$], Likelihoods [$L(\theta)$],
Weights [$w(\theta)$], and Posterior Density Function [$p(\theta)$] for a
Two-Item Response Pattern

θ	$P_1(\theta)$	$Q_2(\theta)$	$L(\theta)$	$f(\theta)$	$p(\theta)$
-3.0	.187	.780	.146	.004	.002
-2.5	.212	.780	.165	.018	.009
-2.0	.257	.779	.200	.054	.031
-1.5	.332	.776	.257	.130	.096
-1.0	.442	.768	.340	.242	.236
-0.5	.580	.742	.430	.352	.435
0.0	.718	.668	.479	.399	.549
0.5	.828	.503	.416	.352	.421
1.0	.903	.277	.250	.242	.174
1.5	.948	.112	.106	.130	.040
2.0	.973	.038	.037	.054	.006
2.5	.986	.012	.012	.018	.001
3.0	.993	.004	.004	.004	.000

The mode of the posterior density function in Figure 2 is located near $\theta=0$, so the Bayesian modal estimate and the maximum likelihood estimate are about the same for this data. The Bayesian θ estimate based on the mean of the $p(\theta)$ distribution is $-.12$. This θ estimate does not coincide with the maximum likelihood estimate ($\hat{\theta}=.01$); as will be further shown below, estimates of θ obtained from different ICC scoring methods do not generally agree.

Differences Among Scoring Methods

The programs described in this report are capable of scoring test data using most of the ICC response models available. The selection among models should not be arbitrary, especially when individual decisions are to be made on the basis of test scores. Dichotomous data can be scored by means of the one-, two-, and three-parameter ICC models, using either a normal or logistic ogive ICC. Thus, given the decision with regard to the number of parameters that describe the ICC, there still remains the problem of choosing between the normal or logistic ogive response models for scoring purposes. Unfortunately, there are as yet no firm guidelines for choosing between these two response models. Samejima (1969) has shown that the normal and logistic ogive models differ with respect to their scoring "philosophies," but the practical implications of these differences remain to be investigated.

To illustrate the differences among the models and different ICC scoring procedures, all response patterns for a five-item test were scored by maximum likelihood, assuming both normal and logistic ogive ICCs, and by Owen's (1975) Bayesian scoring method. Table 3 gives the item parameters assumed for the hypothetical five-item test. For all items, the c (guessing) parameter was set at 0.0, indicating that a two-parameter ICC model was used. Items varied in difficulty (b) from -2 to $+2$ and had discriminations of 1.00 or 1.50.

Table 3
Item Parameters for Five-Item Test

Item	a	b	c
1	1.00	-2.00	.00
2	1.50	-1.00	.00
3	1.00	0.00	.00
4	1.50	1.00	.00
5	1.00	2.00	.00

In a five-item test in which each item is scored dichotomously, there are $2^5=32$ different response patterns. These response patterns are shown in Table 4 along with the scores associated with them. It is obvious from the data in Table 4 that for a given response pattern, the scores (all of which are on the same metric) differed somewhat. This indicates that the scoring procedures are not interchangeable.

For example, consider the five response patterns which have 20% correct, namely Patterns 2, 3, 5, 9, and 17. Not only do the θ estimates (scores) for a given response pattern differ among the three scoring procedures, but there are some differences in the ordering of the θ estimates derived from these response patterns within each procedure. For maximum likelihood scoring using

a normal ogive ICC, the ordering of the θ estimates derived from the five response patterns was exactly the same as that obtained from the Bayesian scoring procedure, although the numerical values of the θ estimates were uniformly higher for the Bayesian procedure. For both these scoring methods, there was a tendency for higher ability estimates to be obtained when a more difficult item was answered correctly. For example, the lowest θ estimate was obtained by both scoring methods when the easiest item (Item 1) was answered correctly (Response Pattern 17); when only Item 2 was answered correctly (Response Pattern 9), the θ estimates from both the Bayesian and maximum likelihood normal procedures increased. In addition, both scoring methods took into account the discriminations of the items involved. For example, Response

Table 4
Scores Given to Each Response Pattern by Three Scoring Methods

Response Pattern	Maximum Likelihood		Bayesian
	Normal	Logistic	
1. 00000	∞^*	∞^*	-1.72
2. 00001	-.93	-1.60	-.64
3. 00010	-.61	-1.19	-.38
4. 00011	-.13	-.46	.11
5. 00100	-1.42	-1.60	-1.06
6. 00101	-.50	-.84	-.28
7. 00110	-.30	-.46	-.11
8. 00111	.13	.46	.30
9. 01000	-1.24	-1.19	-.89
10. 01001	-.23	-.46	-.15
11. 01010	.03	.00	.00
12. 01011	.50	.84	.41
13. 01100	-.60	-.46	-.42
14. 01101	.23	.46	.17
15. 01110	.39	.84	.28
16. 01111	.93	1.60	.64
17. 10000	-1.63	-1.60	-1.16
18. 10001	-.39	-.84	-.24
19. 10010	-.17	-.46	-.06
20. 10011	.30	.46	.39
21. 10100	-.78	-.84	-.58
22. 10101	.03	.00	.11
23. 10110	.17	.46	.23
24. 10111	.61	1.19	.62
25. 11000	-.42	-.46	-.29
26. 11001	.60	.46	.51
27. 11010	.78	.84	.63
28. 11011	1.42	1.60	1.09
29. 11100	.42	.46	.31
30. 11101	1.24	1.19	.93
31. 11110	1.63	1.60	1.08
32. 11111	∞^*	∞^*	1.55

* For maximum likelihood scoring, it is not possible to score response patterns with all correct or incorrect answers.

Pattern 2 (with a correct response to Item 5, the most difficult item) was assigned higher scores than Pattern 5; but Pattern 2 was assigned lower scores than Pattern 3 (which had a correct response to Item 4, the second most difficult item), since in Response Pattern 3 a correct answer was given to an item (Item 4) with a higher discrimination than that of Pattern 2 (Item 5).

On the other hand, assuming a logistic ogive ICC for the maximum likelihood scoring procedure, estimated values of θ were related to the discriminations of the items answered correctly. Those response patterns for which the discriminations of the items answered correctly were the same were assigned the same score, namely -1.60 for Patterns 2, 5, and 17 and -1.19 for Patterns 3 and 9. For the latter two response patterns, the discriminations of the items answered correctly were 1.50; for the former three response patterns, they were 1.00. Thus, the magnitude of the scores was a function of the item discriminations, and the item difficulties did not affect the θ estimates.

These data indicate that the assumption of different forms of the ICC within the maximum likelihood scoring procedure will, in general, result in different θ estimates. Since the Bayesian θ estimates were different from both the maximum likelihood estimates, these three ICC-based scoring procedures are not interchangeable. However, additional research is required to further delineate the similarities and differences among the θ estimates derived by different ICC-based scoring procedures and, more importantly, to assess the implications of these differences in practical applications.

General Description of the Programs

This report describes three computer programs for scoring test data with ICC models--LINDSCO, ADADSCO, and LINPSCO. Table 5 summarizes the major features of these programs. LINDSCO (LInear Dichotomous SCOring) is designed

Table 5
Summary of Program Capabilities

Model and Scoring Procedure	Dichotomous		Polychotomous (LINPSCO)	
	Linear (LINDSCO)	Adaptive (ADADSCO)	Graded	Nominal
Logistic Ogive				
Bayesian ^a	NO	NO	NO	NO
Maximum Likelihood	YES	YES	YES	YES
Normal Ogive				
Bayesian ^a	YES	YES	NO	NO
Maximum Likelihood	YES	YES	YES	NO

^aThe Bayesian scoring procedure is based on Owen (1975).

to be used for scoring test data for conventional (linear) tests in which all items are administered to each testee. It requires responses to be dichotomous; that is, responses are scored into one of two categories, such as "correct"

and "incorrect." Omissions are permitted, but they are ignored in the computations. The number of omitted items is tallied from the number of items administered and reported as part of the output for each testee. Either the normal or logistic ogive response model can be used with ICCs described by one, two, or three parameters for maximum likelihood scoring. Response patterns may also be scored by Owen's (1975) Bayesian method which assumes a normal ogive ICC. The user can also specify, in addition to a total test score, subscores on as many as 25 subscales.

ADADSCO (ADaptive Dichotomous SCOring) is similar to LINDSCO, but it is designed specifically for scoring item response data derived from adaptive testing. Since in adaptive testing each respondent answers a different set of test items, the program must locate for each testee the item parameter estimates of each attempted item; LINDSCO, in contrast, does the item search only once. ADADSCO also differs from LINDSCO in that it has no subscale scoring capabilities.

LINPSCO (Linear Polychotomous SCOring) is designed to score data from linear (conventional) tests in which each testee is administered all items, and items are scored into more than two categories. Three models are available: the graded normal and logistic ogive models (Samejima, 1969), and the nominal logistic model (Bock, 1972). In LINPSCO only maximum likelihood scoring is available, and subscale scoring is not possible.

All three programs compute both test information and response pattern information values when maximum likelihood scoring is used. Response pattern information (Samejima, 1973) provides an estimate of the precision of measurement for a specified response pattern and can be used to compare the quality of trait estimates derived from specific test administration and/or scoring procedures (e.g., Bejar, Weiss, & Gialluca, 1977).

NUMERICAL PROCEDURES

Dichotomous Data

Maximum Likelihood

The numerical procedure for maximum likelihood scoring of dichotomous data consists of two stages. In the first stage an initial estimate is sought by the bisection method. Once this initial estimate is obtained, it is refined further by the Newton-Raphson method.

The bisection routine begins in the interval ± 5.00 . If the sign of the first derivative of the likelihood function during the first iteration is the same when evaluated at 5.00 and at -5.00, a value of 0.0 is returned as the initial estimate of θ . Otherwise, five additional iterations are performed. After the sixth iteration, the width of the interval has been reduced to $10/(2^6) = 10/64 = .15$. The midpoint of that interval is the initial estimate which is then refined further by Newton-Raphson iterations of the form:

$$\hat{\theta}_{m+1} = \hat{\theta}_m - (f'/f'') \quad , \quad [3]$$

where

$\hat{\theta}_{m+1}$ is the new estimate,

$\hat{\theta}_m$ is the estimate from the last iteration,

f' is the first derivative of the log-likelihood function evaluated at $\hat{\theta}_m$, and

f'' is the second derivative of the log-likelihood function evaluated at $\hat{\theta}_m$.

This iterative process is continued until $|\hat{\theta}_{m+1} - \hat{\theta}_m| < .005$. If that criterion has not been met at the end of 50 iterations, the case is said to be nonconvergent.

Formulas for derivatives. Let $v = \{u_g, g=1, 2, \dots, n\}$ be a response vector such that

$$u_g = \begin{cases} 1 & \text{if the item is answered correctly} \\ 0 & \text{if the item is answered incorrectly.} \end{cases}$$

Note that for scoring purposes, the response vector does not include rejected or omitted items. The probability that $u_g=1$ for a given value of θ and item parameters a_g , b_g , and c_g is given by

$$P_g(\theta) = c_g + (1-c_g)[1 + e^{-1.7a_g(\theta - b_g)}]^{-1} \quad [4]$$

for the logistic ogive model and by

$$\begin{aligned} P_g(\theta) &= c_g + (1-c_g) \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{a_g(\theta - b_g)} e^{-t^2/2} dt \\ &= c_g + (1-c_g) \Phi [a_g(\theta - b_g)] \end{aligned} \quad [5]$$

for the normal ogive model, where Φ stands for the standard cumulative normal distribution.

The log-likelihood function for the response vector is

$$\begin{aligned} L_v(\theta) &= \sum_g \log P_g(\theta)^{u_g} Q_g(\theta)^{1-u_g} \\ &= \sum_g [u_g \log P_g(\theta) + (1-u_g) \log Q_g(\theta)] \end{aligned} \quad [6]$$

where $Q_g(\theta) = 1 - P_g(\theta)$ and $P_g(\theta)$ is given by either Equation 4 or 5.

In general, the first and second derivatives of the log-likelihood function of a response vector are given by

$$\frac{\partial L_v(\theta)}{\partial \theta} = \sum_g \left\{ u_g \left[\left(\frac{1}{P_g(\theta)} \right) \left(\frac{\partial P_g(\theta)}{\partial \theta} \right) \right] + (1-u_g) \left[\left(\frac{1}{Q_g(\theta)} \right) \left(\frac{\partial Q_g(\theta)}{\partial \theta} \right) \right] \right\} \quad [7]$$

and

$$\begin{aligned} \frac{\partial^2 L_v(\theta)}{\partial \theta^2} = \sum_g \left\{ u_g \left[\left(\frac{1}{P_g^2(\theta)} \right) \left(\frac{\partial P_g(\theta)}{\partial \theta} \right)^2 - \left(\frac{1}{P_g(\theta)} \right) \left(\frac{\partial^2 P_g(\theta)}{\partial \theta^2} \right) \right] \right. \\ \left. + (1-u_g) \left[\left(\frac{1}{Q_g^2(\theta)} \right) \left(\frac{\partial Q_g(\theta)}{\partial \theta} \right)^2 + \left(\frac{1}{Q_g(\theta)} \right) \left(\frac{\partial^2 Q_g(\theta)}{\partial \theta^2} \right) \right] \right\} . \end{aligned} \quad [8]$$

For the logistic ogive model, after simplification and letting $x = 1.7a_g(\theta - b_g)$, these expressions are

$$\frac{\partial L_v(\theta)}{\partial \theta} = -1.7 \sum_g \left[\frac{a_g e^x}{1+e^x} \right] + 1.7 \sum_g \left[\frac{u_g a_g e^x}{c_g + e^x} \right] \quad [9]$$

and

$$\frac{\partial^2 L_v(\theta)}{\partial \theta^2} = -2.89 \sum_g \left[\frac{a_g^2 e^x}{(1+e^x)^2} \right] + 2.89 \sum_g \left[\frac{u_g a_g^2 c_g e^x}{(c_g + e^x)^2} \right] . \quad [10]$$

For the normal ogive model, letting $x = -a_g^2(\theta - b_g)^2/2$, the corresponding expressions are

$$\frac{L_v(\theta)}{\partial \theta} = \sum_g \left[\frac{u_g (2\pi)^{-1/2} a_g (1-c_g) e^x}{c_g + (1-c_g) \Phi[a_g(\theta - b_g)]} - \frac{(1-u_g) (2\pi)^{-1/2} (1-c_g) a_g e^x}{1 - \{c_g + (1-c_g) \Phi[a_g(\theta - b_g)]\}} \right] \quad [11]$$

and

$$\begin{aligned} \frac{\partial^2 L_v(\theta)}{\partial \theta^2} = \sum_g \left\{ u_g \left[- \frac{[(2\pi)^{-1/2}(1-c_g)a_g e^x]^2}{\{[c_g - (1-c_g)\Phi[a_g(\theta-b_g)]]\}^2} - \frac{(2\pi)^{-1/2}a_g^3(\theta-b_g)(1-c_g)e^x}{\{c_g - (1-c_g)\Phi[a_g(b_g-\theta)]\}} \right] + \right. \\ \left. \sum_g (1-u_g) \left[- \frac{[(2\pi)^{-1/2}(1-c_g)a_g e^x]^2}{1-\{c_g + (1-c_g)\Phi[a_g(\theta-b_g)]\}^2} + \frac{(2\pi)^{-1/2}a_g^3(\theta-b_g)(1-c_g)e^x}{1-\{c_g + (1-c_g)\Phi[a_g(\theta-b_g)]\}} \right] \right\} \quad [12] \end{aligned}$$

Computation of information. With maximum likelihood scoring, two measures of information are computed for each response pattern. One is response pattern information (Samejima, 1973) denoted by $\hat{I}(\hat{\theta})$; the other is test information (Birnbaum, 1968; Samejima, 1969) denoted by $I(\hat{\theta})$. Test information is defined as the expected value of the second derivative of the log-likelihood function, i.e.,

$$I(\hat{\theta}) = -\sum_g \left[E \left\{ \frac{\partial^2 \log L_v(\theta)}{\partial \theta^2} \right\} \right] \quad [13]$$

Response pattern information, on the other hand, is defined by

$$\hat{I}(\hat{\theta}) = -\sum_g \left[\frac{\partial^2 \log L_v(\theta)}{\partial \theta^2} \right] \quad [14]$$

that is, the "observed," as opposed to expected, value of the second derivative of the log-likelihood function evaluated at $\hat{\theta}$.

These two measures of information will be the same for models in which there is a sufficient statistic for the response vector. In particular, this is true in the one- and two-parameter logistic ogive models. It is also true for the "zero" parameter normal ogive model, i.e., when the items are parallel. The value of $\hat{I}(\hat{\theta})$ for a given response pattern is simply the value of the second derivative of the log-likelihood function at the last iteration, i.e., evaluated at the estimated value of θ .

$I(\hat{\theta})$ is computed by

$$I(\hat{\theta}) = \sum_g \frac{\{P'_g(\hat{\theta})\}^2}{P_g(\hat{\theta})\{1.0 - P_g(\hat{\theta})\}} \quad [15]$$

where $P_g(\theta)$ is given, in general, by Equation 4 for the logistic ogive model and by Equation 5 for the normal ogive model.

For the normal ogive model,

$$P'_g(\hat{\theta}) = \frac{a_g(1-c_g)}{\sqrt{2\pi}} [e^{-a_g^2[\hat{\theta}-b_g]^2/2}] ; \quad [16]$$

and for the logistic ogive model,

$$P'_g(\hat{\theta}) = \frac{1.7a_g(1-c_g)e^{1.7a_g(\hat{\theta}-b_g)}}{[1+e^{1.7a_g(\hat{\theta}-b_g)}]^2} . \quad [17]$$

Standard error. The standard error of measurement associated with $\hat{\theta}$ is computed as $1/\sqrt{I(\hat{\theta})}$, that is, the reciprocal square root of response pattern information evaluated at $\hat{\theta}$.

Bayesian Scoring

The Bayesian scoring procedure used by LINDSCO and ADADSCO is derived from Owen's (1975) sequential adaptive testing strategy. However, since the present application assumes that the test items have already been administered, only the scoring aspect is of interest.

The procedure makes the assumption that the prior distribution of θ is normal, with mean $\mu_0=0.0$ and variance $\sigma_0^2=1.00$, where subscript 0 denotes the fact that no items have yet been administered. After the m^{th} item is administered, the mean and variance of the posterior density function are computed according to the following equations. If the response to the $m+1^{\text{th}}$ item is correct,

$$\mu_{m+1} = E(\theta|1) = \mu_m + (1-c_g) \left(\sqrt{\frac{\sigma_m^2}{\frac{1}{a_g^2} + \sigma_m^2}} \right) \left(\frac{\phi(D)}{c_g + (1-c_g)\phi(-D)} \right) \quad [18]$$

and

$$\sigma_{m+1}^2 = \text{var}(\theta|1) = \sigma_m^2 \left\{ 1 - \left(\frac{1-c_g}{1 + \frac{1}{a_g^2 \sigma_m^2}} \right) \left(\frac{\phi(D)}{A} \right) \left(\frac{(1-c_g)\phi(D)}{A} - D \right) \right\} . \quad [19]$$

Following an incorrect answer,

$$\mu_{m+1} = E(\theta|0) = \mu_m - \left(\frac{\sigma_m^2}{\sqrt{\frac{1}{\alpha_g^2} + \sigma_m^2}} \right) \left(\frac{\phi(D)}{\Phi(D)} \right) \quad [20]$$

and

$$\sigma_{m+1}^2 = \text{var}(\theta|0) = \sigma_m^2 \left\{ 1 - \left(\frac{\phi(D)}{1 + \frac{1}{\alpha_g^2 \sigma_m^2}} \right) \left(\frac{\frac{\phi(D)}{\Phi(D)} + D}{\Phi(D)} \right) \right\}. \quad [21]$$

In Equations 18 through 21 (from Owen, 1975),

$\phi(D)$ is the normal probability density function,
 $\Phi(D)$ is the cumulative normal distribution function,

$$D = \frac{b_g^{-1} \mu_m}{\sqrt{\frac{1}{\alpha_g^2} + \sigma_m^2}}, \text{ and} \quad [22]$$

$$A = c_g + (1 - c_g) \Phi(-D). \quad [23]$$

After the last item has been administered, the posterior mean is the estimated θ and the posterior variance is a measure of the error associated with that estimate. Because the posterior distribution after every item is administered is approximated by a normal distribution in this procedure, there is a certain amount of inaccuracy in the estimate. Moreover, the resulting scores are order dependent (Sympson, 1977), i.e., if a response vector were to be scored after rearranging the items, the resulting θ estimate would be slightly different.

Computation of Expected Proportion of Correct Answers

The expected proportion of correct answers (EXPTOT) is defined as

$$\text{EXPTOT} = \sum_g P_g(\hat{\theta}) / NI, \quad [24]$$

where $P_g(\hat{\theta})$ is computed from Equation 4 for the logistic ogive model and Equation 5 for normal ICCs. NI is the number of items on which the estimate of θ is based. EXPTOT is simply an estimate of the true score associated with $\hat{\theta}$ (Lord & Novick, 1968, p. 387).

Polychotomous Data

LINPSO is capable of scoring polychotomous data when item parameters have been estimated according to a graded model of either normal or logistic ogive form (Samejima, 1969) or according to Bock's (1972) nominal logistic model. For the graded model, the numerical procedure consists of a bisection stage of six iterations followed by Newton-Raphson iterations. For the nominal logistic model, the initial estimate obtained from the bisection stage is refined further by the secant method rather than by Newton-Raphson iterations.

In each case, the bisection phase begins in the interval ± 5.00 . During the first iteration, if the sign of the first derivative of the log-likelihood function is the same when evaluated at 5.00 and at -5.00, a value of 0.0 is returned as the initial estimate. Otherwise, five additional iterations are performed. After six iterations, the width of the interval is reduced to $10/(2^6) = 10/64 = .15$. The midpoint of that interval is taken as the initial estimate.

The Newton-Raphson procedure used with the graded models refines the initial estimate with iterations of the form shown in Equation 3. This iterative procedure is continued until $|\hat{\theta}_{m+1} - \hat{\theta}_m|$ is less than .005 or the number of iterations is greater than 50. The secant procedure is similar to Newton-Raphson iterations, except that f'' in Equation 3 is an approximation to the second derivative of the log-likelihood function given by

$$f'' = \frac{f'(\hat{\theta}_m) - f'(\hat{\theta}_{m-1})}{(\hat{\theta}_m - \hat{\theta}_{m-1})} \quad [25]$$

Graded Models

Let $v = \{x_g, g=1, 2, \dots\}$ be a response vector exclusive of omitted and rejected items such that

$$x_g = \begin{cases} 1 & \text{if the "best" response was given} \\ 2 & \text{if the second "best" response was given} \\ \vdots & \\ m_g - 1 & \text{if the next to worst response was given} \\ m_g & \text{if the worst response was given.} \end{cases}$$

For the graded logistic ogive model, the probability that x_g takes one of the values between 1 and m_g is given in general by

$$P_{x_g}(\theta) = P_{x_g} = [1 + e^{y_{x_g}}]^{-1} - [1 + e^{y_{x_g-1}}]^{-1}, \quad [26]$$

where

$$y_{x_g} = -a_g D(\theta - b_{x_g}) \quad , \quad [27]$$

$$y_{x_g-1} = -a_g D(\theta - b_{x_g-1}) \quad , \quad \text{and} \quad [28]$$

$D = 1.7$ is a scaling factor.

When $x_g = 1$,

$$P_{x_g} = [1 + e^{y_{x_g}}]^{-1} \quad . \quad [29]$$

When $x_g = m_g$,

$$P_{x_g} = 1 - [1 + e^{y_{x_g-1}}]^{-1} \quad . \quad [30]$$

For the graded normal ogive model, the probability that x_g takes one of the values between 1 and m_g is given in general by

$$\begin{aligned} P_{x_g}(\theta) = P_{x_g} &= (2\pi)^{-1/2} \int_{y_{x_g-1}}^{y_{x_g}} e^{t^2/2} dt \\ &= \Phi[y_{x_g}] - \Phi[y_{x_g-1}] \quad , \end{aligned} \quad [31]$$

where

$$y_{x_g} = a_g(\theta - b_{x_g}) \quad [32]$$

and

$$y_{x_g-1} = a_g(\theta - b_{x_g-1}) \quad . \quad [33]$$

When $x_g = 1$,

$$P_{x_g} = (2\pi)^{-1} \int_{-\infty}^{y_{x_g}} e^{t^2/2} dt \quad . \quad [34]$$

When $x_g = m_g$,

$$P_{x_g} = 1 - (2\pi)^{-1} \int_{-\infty}^{y_{x_g}-1} e^{t^2/2} dt \quad [35]$$

The log-likelihood function for a given response vector is given by

$$\begin{aligned} L_v(\theta) &= \log \prod_g P_{x_g}^{r_{x_g}} \\ &= \sum_g r_{x_g} [\log P_{x_g}] , \end{aligned} \quad [36]$$

where

$$r_{x_g} = \begin{cases} 1 & \text{if the } x_g^{\text{th}} \text{ response category is chosen} \\ 0 & \text{otherwise} \end{cases}$$

The general first derivative of the log-likelihood function is

$$\frac{\partial L_v(\theta)}{\partial \theta} = \sum_g \sum_{x_g} r_{x_g} L_{x_g} \quad [37]$$

Samejima (1969) refers to L_{x_g} as the basic function. Since $L_{x_g} = (\partial P_{x_g} / \partial \theta) (P_{x_g})^{-1}$

$$\frac{\partial L_v(\theta)}{\partial \theta} = \sum_g \sum_{x_g} r_{x_g} \frac{\partial P_{x_g} / \partial \theta}{P_{x_g}} \quad [38]$$

The general second derivative of the log-likelihood function is given by

$$\frac{\partial^2 L_v(\theta)}{\partial \theta^2} = \sum_g \sum_{x_g} r_{x_g} \left[-(L_{x_g})^2 + \frac{\partial^2 P_{x_g} / \partial \theta^2}{P_{x_g}} \right] \quad [39]$$

Specifically, for the graded logistic ogive model,

$$\frac{\partial L_v(\theta)}{\partial \theta} = \sum_g \sum_{x_g} a_g 1.7 \{ 1 - P_{x_g}^* - P_{x_g}^{*-1} \} \quad [40]$$

and

$$\frac{\partial^2 L_v(\theta)}{\partial \theta^2} = \sum_g \sum_{x_g} 2.89 a_g^2 \frac{r_{x_g}}{P_{x_g}} \left[- \left\{ (L_{x_g})^2 + (2Q_{x_g-1}^*) (P_{x_g}^* Q_{x_g}^*) - (2Q_{x_g-1}^* - 1) (P_{x_g-1}^* Q_{x_g-1}^*) \right\} \right] , \quad [41]$$

where

$$P_{x_g}^* = [1 + e^{-1.7 a_g (\theta - b_{x_g})}]^{-1} , \quad [42]$$

$$P_{x_g-1}^* = [1 + e^{-1.7 a_g (\theta - b_{x_g-1})}]^{-1} , \quad [43]$$

$$P_o^* = 0 , \quad [44]$$

$$P_m^* = 1 , \quad [45]$$

$$Q_{x_g}^* = 1 - P_{x_g}^* , \text{ and } \quad [46]$$

$$Q_{x_g-1}^* = 1 - P_{x_g-1}^* . \quad [47]$$

For the graded normal ogive model, letting $z_{x_g} = -[a_g^2 (\theta - b_{x_g})^2] / 2$, the corresponding expressions are

$$\frac{\partial L_v(\theta)}{\partial \theta} = \sum_g \left[\sum_{x_g} \left(\frac{r_{x_g} a_g}{\sqrt{2\pi}} [e^{z_{x_g}} - e^{z_{x_g-1}}] \right) / P_{x_g}(\theta) \right] \quad [48]$$

The second derivative is given by

$$\frac{\partial^2 L_v(\theta)}{\partial \theta^2} = \sum_g \left\{ \sum_{x_g} r_{x_g} \left[- (L_{x_g})^2 \right] + \left[\frac{-a_g^3}{\sqrt{2\pi}} \{ (\theta - b_{x_g}) e^{z_{x_g}} - (\theta - b_{x_g-1}) e^{z_{x_g-1}} \} \right] / P_{x_g}(\theta) \right\} \quad [49]$$

When $x_g = 1$, $e^{z_{xg}-1} = 0$, and P_{x_g} is given by Equation 34; when $x_g = m_g$, $e^{z_{xg}} = 0$, and P_{x_g} is given by Equation 35.

Nominal Logistic Model

For the nominal logistic model, the probability of x_g , given θ , is given by

$$P_{x_g}(\theta) = P_{x_g} = \frac{e^{(\alpha_{x_g}\theta + \beta_{x_g})}}{\sum_{s=1}^{m_g} e^{(\alpha_s\theta + \beta_s)}} \quad [50]$$

where α_s and β_s are the slope and intercept parameter for the s^{th} response category.

The secant method requires only the first derivative of the log-likelihood function. That derivative is

$$\frac{\partial L_v(\theta)}{\partial \theta} = \sum_g \frac{\sum_{s=1}^{m_g} r_{x_g} (\alpha_{x_g} - \alpha_s) e^{\alpha_s\theta + \beta_s}}{\sum_{s=1}^{m_g} e^{\alpha_s\theta + \beta_s}} \quad [51]$$

Computation of Information

Response pattern information is computed as the value of the second derivative at the last iteration. For the nominal logistic model, that value is an approximation. Test information is computed from the general formula given by Samejima (1969),

$$I(\hat{\theta}) = \sum_g \sum_{x_g} (\partial P_{x_g} / \partial \theta)^2 P_{x_g} \quad [52]$$

This expression involves only the first derivative of the response model. The appropriate expressions are listed below.

For the graded normal ogive model,

$$\frac{\partial P_{x_g}}{\partial \theta} = \frac{a_g}{\sqrt{2\pi}} \left[e^{z_{xg}} - e^{z_{xg}-1} \right] \quad [53]$$

where $z_{x_g} = -[\alpha_g^2(\theta - b_{x_g})^2] / 2$.

For the graded logistic ogive model,

$$\frac{\partial P_{x_g}}{\partial \theta} = 1.7 \alpha_g [P_{x_g}^* (1 - P_{x_g}^*) - P_{x_g-1}^* (1 - P_{x_g-1}^*)], \quad [54]$$

where $P_{x_g}^* = [1 + e^{-1.7\alpha (\theta - bx_g)}]^{-1}$.

For the nominal logistic model,

$$\frac{\partial P_{x_g}}{\partial \theta} = \frac{[e^{(\alpha_{x_g}\theta + \beta_{x_g})} \sum_{s=1}^{m_g} e^{(\alpha_{s_g}\theta + \beta_{s_g})} (\alpha_{x_g} - \alpha_{s_g})]}{\sum_{s=1}^{m_g} e^{(\alpha_{s_g}\theta + \beta_{s_g})} (\alpha_{s_g})^2} \quad [55]$$

USE OF THE PROGRAMS

Input

For each of the programs, three types of input are required:

1. The *Program Parameters*, which consist of specifications as to the number of items in the pool, the options chosen, the scoring key, and so forth.
2. The *Item Pool*, which contains the item parameter estimates on as many as 600 items for LINDSCO and ADADSCO, and 100 items for LINPSO.
3. The *Test Response Data* consists of testee name and identification number and each testee's item responses. For LINDSCO, item responses need not be dichotomized beforehand; for ADADSCO, they must be dichotomized unless a key is provided as part of the item pool. For ADADSCO, the number of items attempted and the identification number of each item attempted must also be supplied as part of the test response data. For LINPSO, the test response data must be supplied in such a way that the first category corresponds to the "best" response, while the last category corresponds to the "worst" response, based on previously obtained item parameterization data.

Testee response data containing all correct or incorrect answers cannot be scored by maximum likelihood. If such a response pattern is found, a message is printed, and the estimated θ is set to 10.00 if all responses are correct and to -10.00 if all responses are incorrect. The information is set to 0.0 in both cases. Response patterns with all answers correct or incorrect present no problem for Bayesian scoring, and they are processed normally; however, a message is still printed. Appendix B gives examples of the use of each of these programs.

Table 6
Input Program Parameters for LINDSCO, ADADSCO, and LINPSCO: Card Set 1

Columns	LINDSCO	ADADSCO	LINPSCO
1-4 (I4)	INUP, number of items in item pool. 600 is the maximum.	INUP, same as LINDSCO	Number of items in the pool. Maximum is 100.
5-8 (I4)	M, number of items in test. 300 is the maximum	MMAX, maximum number of items administered. 60 is the maximum.	M, number of items in the test. Maximum is 50.
9	blank	blank	blank
10 (II)	OPT1 1 = Punch the item parameter estimates corresponding to the items in the test.	OPT1 1 = Print the item parameter estimates corresponding to the items administered (this is done only for the first 10 testees).	OPT1 1 = Punch the item parameter estimates corresponding to the items in the test.
11 (II)	OPT2 1 = the item pool consists of M items, i.e., there will be no searching of items in the pool.	not used	OPT2 1 = the item pool consists of M items, i.e., there will be no searching of items in the pool.
12 (II)	OPT3 If 1, 2, or 3 item parameters will be edited; see "Editing of item parameters."	OPT3, same as LINDSCO	not used
13 (II)	OPT4, scoring algorithms and response model: 1 = maximum likelihood normal ogive 2 = maximum likelihood logistic 3 = Owen's Bayesian normal ogive	OPT4, same as LINDSCO	OPT4, response model: 1 = graded logistic ogive 2 = graded normal ogive 3 = nominal logistic

14-18 (F5.2)	TS, for Bayesian scoring. This is the prior mean of θ . Not used in maximum likelihood scoring.	TS, same as LINDSCO	D, scaling parameter for graded logistic model. If blank, will be set by default to 1.0; otherwise will usually be set by the user to 1.7.
19-23 (F5.2)	TSS, for Bayesian scoring. This is the prior standard deviation of θ . Not used in maximum likelihood scoring.	TSS, same as LINDSCO	not used
24-28 (F5.2)	AMAX, value of the α parameter. Used in editing. See "Editing of item parameters."	AMAX, same as LINDSCO	not used
29-33 (F5.2)	BMIN, lowest value of the b parameter. Used in editing parameter estimates. See "Editing of item parameters."	BMIN, same as LINDSCO	not used
34-38 (F5.2)	BMAX, highest value of the b parameter. Used in editing parameter estimates. See "Editing of item parameters."	BMAX, same as LINDSCO	not used
39-43 (F5.2)	CMAX, value of the c parameter. Used in editing parameter estimates. See "Editing of item parameters."	CMAX, same as LINDSCO	not used
44-45 (I2)	blank	IFLAG, code for correct response	
46-47 (I2)	IOMIT, code for omitted response.	IOMIT, same as LINDSCO	IOMIT, same as LINDSCO
48-80	blank	blank	blank

Program Parameters

Table 6 describes the input program parameters for all three programs, using Card Set 1 (all numeric information is right justified). After Card Set 1, the program parameter and input for each of the three programs differs, as indicated below.

LINDSCO (Card Set 2-10).

- | | |
|---|--|
| <u>Card Set 2 (8A10).</u> | The variable format for the item pool is punched on this card, using I-fields (see Item Pool below). |
| <u>Card Set 3 (16I5).</u> | Punch in five-column fields the item identification number of the items in the test in the same order in which they appear in the test. Continue on as many cards as necessary. |
| <u>Card Set 4 (80I1).</u> | A "1" in a given column is punched to omit a specified item from all computations, e.g., if the 10th item is to be omitted, punch "1" in column 10; if the 100th item is to be omitted, punch "1" in column 20 of the second card. Continue on as many cards as necessary. |
| <u>Card Set 5 (80I1).</u> | This card contains the scoring key for the test. In general, the n^{th} column contains the key for the n^{th} item, as in Card Set 4. Continue on as many cards as necessary. |
| <u>Card Set 6 (8A10).</u> | Variable format for reading the subject information and test response data (see Test Response Data below for field type specifications). |
| <u>Card Set 7 (8A10).</u> | The description of the run is written on three cards. The three cards must be included even if they are blank. |
| <u>Card 8 (I5).</u> | Punch the number of subscales to be scored in columns 1-5; maximum is 25. If no subscales are to be scored, punch "0" in column 5; in that case, this is the last card set. |
| <u>Card Set 9 (2I5).</u>
(Omit if the number of subscales is 0.) | For each scale, punch the following information:
Columns 1-5: Number of items in subscale (maximum is 60).
Columns 6-10: Scale number. Repeat for each subscale beginning on a new card. |
| <u>Card Set 10 (16I5).</u>
(Omit if the number of subscales is 0.) | Punch in five-column fields the item identification number of the items in the subscales. Continue on as many cards as necessary. Repeat for each subscale, beginning on a new card for each subscale. |

ADADSCO (Card Set 2-5).

Card Set 2 (8A10).

Variable format for item pool, using I-fields. It must be contained on one card (see Item Pool below).

Card Set 3 (16I5).

Columns 1-5: The number of items to be omitted, i.e., excluded from the computations. If none, punch "0" in column 5.
Columns 6-10 and subsequent five-column fields: The item identification numbers of items to be omitted. Continue on as many cards as necessary. If more than one card is necessary, begin punching on the second card in columns 1-5.

Card Set 4 (8A10).

Variable input format for reading subject information and test response data. It must be contained on one card (see Test Response Data below for field type specifications).

Card Set 5 (8A10).

Description of the run is written on three cards. These cards are required, even if they are left blank.

LINPSCO (Card Set 2-7).

Card Set 2 (8A10).

Variable format for the item pool. It must be contained on one card (see Item Pool below for field type specifications).

Card Set 3 (80I1).

Punch in the n^{th} column the number of response categories minus 1 for the n^{th} item. Continue on as many cards as necessary.

Card Set 4 (16I5).

Punch in five-column fields the item identification numbers of the items in the test. The numbers must appear in the same order as the items appear in the test. Continue on as many cards as necessary.

Card Set 5 (80I1).

The information on this card is used to omit specified items from the computations. To omit the n^{th} item, punch a "1" in the n^{th} column of this card; otherwise, punch "0." If no items are to be omitted, punch as many zeros as there are items in the test. Continue on as many cards as necessary.

Card Set 6 (8A10).

Variable format for subject information and test response data. It must be contained on one card (see Test Response Data below for field type specifications).

Card Set 7 (8A10).

Description of the run is written on three cards.

Item Pool

LINDSCO and ADADSCO. To score the response data, a file containing the item pool item parameter estimates must be prepared beforehand and placed in a file called IPOOL. The file consists of a line for each item in the pool with the following information:

1. A unique item number;
2. Estimate of the a parameter;
3. Estimate of the b parameter;
4. Estimate of the c parameter;
5. Correct alternative for this item, i.e., the keyed response.

For LINDSCO, only Items 1 through 4 must be supplied; for ADADSCO, Item 5 must be supplied also, although it could be a "dummy" key (e.g., a blank), since the data may already be scored (see columns 44-45 for Card Set 1).

The exact format of this information is not critical, since it is read with a user-specified variable format. However, the following limitations must be observed: (1) the information must be read in the above order; (2) the item number must be read in integer mode; (3) the item parameter estimates must be read in floating point; and (4) the key, if ADADSCO is being used, must be read in integer mode.

A typical format for LINDSCO could be
(10X,I4,3F10.2) .

For ADADSCO, a typical format might be
(10X,I4,3F10.2,I2) .

All three parameter estimates must be read even if the user is using a one- or two-parameter model. This presents no difficulties, however, since in the case of, say, a two-parameter model, the third parameter is 0 for all items. This may be accomplished by reading blanks or zeros, or by editing item parameter estimates (see below).

The number of items in the pool may range from the number of items in the test, M , to 600. If the item pool for LINDSCO consists of only the items being scored in the test, then OPT2 should be set to 1. This indicates to the program that items do not have to be searched. On the other hand, if the pool consists of items in addition to those used in the present test, then OPT2 should be set to 0. This instructs the program to search for the item and to retrieve the corresponding item parameters. For both LINDSCO and ADADSCO, if at least one of the items being called for is not found in the pool, the program prints a message; and the unavailable item is treated as an omitted item.

Editing of item parameter estimates. LINDSCO and ADADSCO have several options to edit item parameter estimates. If OPT3=1, the program checks that the item parameter estimates are within certain bounds. For the discrimination (a) parameter, the program checks to see if the estimate exceeds AMAX; if it does, it is set to AMAX. For the difficulty (b) parameter, if the estimate is below BMIN, it is set to BMIN; if it is above BMAY, it is set to BMAX. For the "guessing" (c) parameter, the program checks to see if the estimate exceeds CMAX; if it does, it is set to CMAX. If the user wants to edit only one or two parameters, the limits of the other parameters should be chosen so that the editing has no effect.

A more radical form of editing is also possible. If $OPT3=2$, then in addition to the editing caused by $OPT3=1$, the program sets all c parameter estimates to C_{MAX} . If $C_{MAX}=0.0$, this implies that a two-parameter model is in effect. If $OPT3=3$, then in addition to the editing caused by $OPT3=1$ and $OPT3=2$, the program sets all a parameter estimates to A_{MAX} .

LINPSCO. For polychotomous scoring, the item pool consists of the following information for graded normal and logistic ogive models:

1. A *unique* item identification number;
2. The "discrimination" parameter, which is common to all response categories;
3. $m_g - 1$ "difficulty" parameters, where m_g is the number of response categories in the g^{th} item. Since m_g can be at most 10, there would be at most 9 difficulty parameters.

The exact format for reading this information is not crucial, since it is read by a user-supplied format statement. However, the following restrictions must be observed: (1) the identification number is read first, in integer mode; (2) next, the estimated discrimination parameter is read in floating point mode; (3) the $m_g - 1$ "difficulty" parameters are read next, with the difficulty of the best alternative followed by the second best alternative, and so forth.

Since the program allows the number of categories to differ from item to item, the format should be specified so that it can read the information for the item with the most response categories. For example, if in a given test, the maximum number of response categories is seven, then there should be at most six difficulty parameters. The format for such pools might be as follows:

(I4,6X,F5.2/10X,6F5.2) .

In this format the item identification number is read in the I4 field; the discrimination parameter is read next in format F5.2; and the six difficulty values are read from the next card, beginning in column 11.

For the nominal logistic model, the item information is read in the following order:

1. A *unique* item identification number;
2. m_g "slope" parameters; and
3. m_g intercept parameters.

Differing from the graded models, in the nominal model there is a pair of parameters (a slope and an intercept) associated with *each* response category. Since the response categories are not ordered in the nominal model, the order in which the parameters are read is unimportant. However, the ordinal position in which the parameters appear in the pool must correspond with the integer associated with that response category. As in the graded models, the format should be able to read the information for the item with most response categories. For example, if the maximum number of response categories is five, the format

could be

(I4,16X,5F5.2,5X,5F5.2) .

In this format, the item identification number is read in the I4 field; next, the five slope parameters are read in 5F5.2; and finally, the five intercept parameters are read in the last set of 5F5.2 fields.

Test Response Data

Data for all testees must be on a file called DATA. The structure of this file differs slightly for each of the programs. In all cases, however, the last record of DATA must be an end-of-record marker.

LINDSCO. This program requires that for each individual the following information be provided on DATA:

1. Name,
2. Identification number, and
3. Responses to the test items.

The exact format of this information is not critical, since it is read with a user-supplied variable format; but the information must appear in the above order. Two words are used for testee name; thus, name should be read with two alphanumeric words, e.g., 2A10. This allows for up to 20 characters. The testee identification is read with an alphanumeric field of at least 1 column, e.g., A1, A9. Test item responses are read with an integer format, e.g., 2011.

The test data may be raw item responses (i.e., the number of the alternatives chosen) or scored (i.e., 0 for incorrect and 1 for correct). However, in either case, a scoring key must be provided (see Card Set 5 for LINDSCO). The key will contain the number of the correct alternative if raw data are read. If the data are already scored, a "dummy" key full of "1's" must be provided.

Omitted items are indicated by the integer IOMIT (see columns 46 and 47 of Card Set 1 for LINDSCO). For raw data, this will normally be an integer greater than the number of alternatives. Similarly, for scored (0-1) data IOMIT must be an integer greater than 1.

ADADSCO. The program requires that the following information be provided on DATA for each individual:

1. Name,
2. Identification number,
3. Number of items answered by the testee (i.e., number of items attempted),
4. Item identification numbers of items attempted, and
5. Responses to the test items.

This information is read in the above order with a user-supplied variable format; thus, the exact format is not critical. However, the following limitations must be observed. Even though the number of items administered usually varies across individuals in an adaptive test, this program assumes that the data record for each testee is formally the same (i.e., that there is the same number of data

lines per testee and that these lines contain similar information). Thus, if the maximum number of items taken by anyone is MMAX (see Card Set 1 for ADADSCO), but any particular testee takes M items, where $M < \text{MMAX}$, then that testee's record should be "padded" to MMAX items. This can be accomplished by leaving an appropriate number of blank fields. The name is dimensioned for two words so the format should allow for two words, e.g., 2A10. The identification number is read with an alphanumeric format, e.g., A8. The number of items is read in integer mode. The item identification numbers and item responses are also read in integer mode. Note that in reading the item identification numbers and the item responses, the format should read MMAX of each, even if some of these will be blank for a given individual.

As an example assume that MMAX was 25; then the variable format could be (2A10,A10,I2/20I4/5I4/25I1).

In this format, the name, testee identification, and M are read from the first card; the item identification numbers are read from the next two cards; and finally, the item responses are read from the fourth card. Note that for testees attempting 20 items or less, the third card will be blank.

The item responses may be scored or raw data. For scored data, the responses have been reduced to three categories: correct, incorrect, and omitted. In this case, IFLAG should be set to the integer corresponding to the correct code, and IOMIT should be set to the code for omitted responses. Note that if $\text{IFLAG} > 0$, the program ignores the key read as part of the item pool. For raw data, the key will have been read as part of the item pool; IFLAG must therefore be set to 0. IOMIT will still be operational, however; and it must be set to an integer other than the highest numbered response alternative.

LINPSCO. The DATA file is similar to LINDSCO's with the exception that the item responses must include the response category chosen by the testee for a given item. For graded models, the convention that the best response category be coded "1," second best "2," and so forth, must be obeyed. For the nominal logistic model, this convention does not apply; but care must be taken so that a category's response code matches the ordinal position of that category in the IPOOL file. For either graded or nominal data, the code for omitted responses should be an integer greater than the maximum number of response categories.

Output

Four kinds of output are produced by each program: program parameters, item parameters, computational messages, and testee data.

Program Parameters

The output consists of the information in Card Set 1, the description of the run, and the variable formats for reading the item pool and the testee's raw data.

Item Parameters

LINDSCO and LINPSCO. The output consists of item identification number, scoring key, rejection key (i.e., whether or not the item was included in the computations), and the item parameter estimates. If the estimates have been

edited, the edited values will be printed. An option (see column 10 of Card Set 1) permits all of this information to be punched as well. If subscale scoring has been requested, the item identification number of the items in each subscale will be printed.

ADADSCO. The user has the option, but only for the first 10 testees, to print the following: testee's name and identification number; and for each item attempted, the item identification number, the response to that item, and the item parameter estimates.

Computational Messages

The program will print a testee's name and identification number if (1) a response pattern is found with all items correct or incorrect, excluding omitted or rejected items; (2) a zero score has been obtained; or (3) it was not possible to achieve convergence in scoring the testee's responses. For polychotomous data, a perfect or zero vector occurs if the testee responds with the best or worst response categories in all attempted items, exclusive of omitted or rejected items. If an item is not found in the pool or has extreme parameter estimates, an informative message is printed.

The number of testees read and the number of convergence failures are also printed. If Bayesian scoring has been requested, the number of nonconvergent cases will be zero.

Testee Data

LINDSCO. For each testee, the following information is written on a file called TAPE3:

1. Name;
2. Testee identification number;
3. Scale number, or in the case of total score, a "T";
4. Proportion of items answered correctly;
5. Maximum likelihood or Bayesian estimate of θ ;
6. The response pattern information for maximum likelihood scoring or the posterior variance of θ for Bayesian scoring;
7. The number of items used in the estimation of θ , excluding items rejected, omitted, or not found;
8. The test information associated with the estimated θ (for Bayesian scoring, the information is computed using the normal ogive model);
9. The true score corresponding to the estimated θ ;
10. For maximum likelihood scoring,
 - a. The number of Newton-Raphson iterations needed to achieve convergence and
 - b. The standard error of θ .

The format used for writing this information for total scores is
(X,2A10,A9,*T*,F5.2,2F7.2,I4,2F7.2,I4,F7.2) .

The subscale results are written with
(X,2A10,A9,I2,F5.2,2F7.2,I4,2F7.2,I4,F7.2) .

ADADSCO. The same information is written as that for LINDSCO with the exception of the scale number. The format is
(X,2A10,A9,F5.2,2F7.2,I4,2F7.2,I4,F7.2) .

LINPSCO. For LINPSCO, the following information is written:

1. Name;
2. Testee identification number;
3. Proportion of "best" responses;
4. Maximum likelihood estimate of θ ;
5. The response pattern information;
6. The number of items used in the estimation of θ excluding items rejected, omitted, or not found;
7. The number of iterations needed to achieve convergence.
8. The test information associated with the estimated θ ;
9. Estimated standard error of measurement.

AVAILABILITY

FORTRAN source code listings of the three programs are in Appendix C (LINDSCO), Appendix D (ADADSCO), and Appendix E (LINPSCO). Copies of the FORTRAN source code are available on cards or tape at nominal cost from

Psychometric Methods Program
Department of Psychology
University of Minnesota
75 East River Road
Minneapolis, Minnesota 55455

Telephone: 612-376-7378

Potential users of these programs should note that the programs were written for Control Data Corporation CYBER series computers. Because of the large word size of the CYBER computers, accurate computation on other computers may require the use of double-precision arithmetic. Minimal additional modifications required may include (1) modification of A10 fields to smaller sizes used by other computers and (2) modification of FORTRAN statements unique to the CYBER series computers.

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Wright, B. D., & Mean, R. J. CALFIT: Sample free item calibration with a Rasch measurement model (Research Memo No. 18). Chicago: University of Chicago, Department of Education, Statistical Laboratory, 1976.

APPENDICES

Appendix A

Item Parameter Estimation Programs

Program Name	Model	Reference
LOGIST	Three-parameter logistic ogive	Wood, R. L., Wingersky, M. S., & Lord, F. M. LOGIST: A computer program for estimating examinee ability and item characteristic curve parameters (Research Memorandum 76-6). Princeton, NJ: Educational Testing Service, 1976.
NORMOG	Three-parameter normal ogive	Kolakowski, D., Bock, R. A. A FORTRAN IV program for maximum likelihood item analysis and test scoring: Normal ogive model (Research Memo No. 12). Chicago: University of Chicago, Department of Education, Statistics Laboratory, 1970.
ESTEM	Three-parameter logistic or normal ogive	No program documentation available. For a description of the procedure see Urry, V. W., Ancillary estimators for the parameters of mental test models. Washington, DC: U.S. Civil Service Commission, Personnel Research and Development Center, 1974.
BICAL	One-parameter logistic ogive	Wright, B. D., & Mead, R. J. CALFIT: Sample-free item calibration with a Rasch measurement model (Research Memorandum No. 18). Chicago: University of Chicago, Department of Education, Statistical Laboratory, 1976.
LOGOG	Graded normal and logistic ogive, nominal logistic	Kolakowski, D., & Bock, R. D. LOGOG: A FORTRAN IV program for maximum likelihood item analysis and test scoring: Logistic model for multiple response (Research Memorandum No. 13). Chicago: University of Chicago, Department of Education, Statistical Laboratory, 1972.

Appendix B:
Examples of Program Use

The following examples serve to illustrate the use of each of the three programs. These results should also be useful in testing the accuracy of the results of the programs in different installations.

LINDSCO

The IPOOL file for these examples was

1	1.000	-2.000	.25
2	1.500	-1.000	.25
3	1.000	0.000	.25
4	1.500	1.000	.25
5	1.000	2.000	.25

The DATA file is also shown below. The first field contains the names; the second, the subject identification; and the third, the response patterns.

Name	I.D.	Responses
A00	1	00000
A01	2	00001
A02	3	00010
A03	4	00011
A04	5	00100
A05	6	00101
A06	7	00110
A07	8	00111
A08	9	01000
A09	10	01001
A10	11	01010
A11	12	01011
A12	13	01100
A13	14	01101
A14	15	01110
A15	16	01111
A16	17	10000
A17	18	10001
A18	19	10010
A19	20	10011
A20	21	10100
A21	22	10101
A22	23	10110
A23	24	10111
A24	25	11000
A25	26	11001
A26	27	11010
A27	28	11011
A28	29	11100
A29	30	11101
A30	31	11110
A31	32	11111

Example 1. This example illustrates the use of the normal ogive model (OPT4=1) for a five-item test ($m=5$) with a pool containing five items (INUP=5). The example also illustrates the use of parameter editing (OPT3=1) in which BMAX=BMIN=0.0, which in effect sets all b parameter estimates to 0.0. AMAX=2.00, which means that if there were a parameter estimates greater than 2, they would be set to 2.00. CMAX=.10, which means that any c parameter estimates greater than .10 will be edited to .10. This example also illustrates the use of subscales. The program parameter cards for this example were

```

      5      5      111 0.00 1.00 2.00 0.00 0.00  .10  4444
(9X,I1,3F10.3)
      1      2      3      4      5
00000
11111
(2A4,A2,10X,5I1)
RUNS BASED ON ALL POSSIBLE RESPONSE VECTORS FOR A FIVE ITEM TEST

```

```

      1
      3      1
      2      3      5

```

The output corresponding to this example is shown on the following pages.

LINDSCO

LINEAR DICHOTOMUS SCORING WITH THREE PARAMETER MODELS

PSYCHOMETRIC METHODS PROGRAM
DEPARTMENT OF PSYCHOLOGY
UNIVERSITY OF MINNESOTA
MPLS. MINN. 55455

INUP = 5
MMAX = 5
IOMI1 = 4444
OPT1 = -0
OPT2 = 1
OPT3 = 1
OPT4 = 1
TS = 0
TSS = 1.00
AMAX = 2.00
BMAX = 0
BMIN = 0
CMAX = .10
VARIABLE FORMAT FOR POOL=(9X,11,3F10.3)
VARIABLE FORMAT FOR DATA=(2A4,A2,10X,5I1)
RUNS BASED ON ALL POSSIBLE RESPONSE VECTORS FOR A FIVE ITEM TEST

ITEMS IN SUBSCALE NO= 1

2 3 5

ITEM	ID	S	KEYS	REJECTIONS	A	B	C
1	1	0	1.00	0	.10		
2	1	0	1.50	0	.10		
3	1	0	1.00	0	.10		
4	1	0	1.50	0	.10		
5	1	0	1.00	0	.10		

SUBJECT	ID	NO	ANSWERS	CORRECT	IN	TOTAL SCALE
SUBJECT =A00	ID = 1	HAS	NO	ANSWERS	CORRECT	IN TOTAL SCALE 1
SUBJECT =A01	ID = 3	HAS	NO	ANSWERS	CORRECT	IN SUBSCALE 1
SUBJECT =A02	ID = 14	HAS	NO	ANSWERS	CORRECT	IN SUBSCALE 1
SUBJECT =A13	ID = 16	HAS	ALL	ANSWERS	CORRECT	IN SUBSCALE 1
SUBJECT =A15	ID = 17	HAS	ALL	ANSWERS	CORRECT	IN SUBSCALE 1
SUBJECT =A16	ID = 19	HAS	NO	ANSWERS	CORRECT	IN SUBSCALE 1
SUBJECT =A18	ID = 30	HAS	NO	ANSWERS	CORRECT	IN SUBSCALE 1
SUBJECT =A29	ID = 32	HAS	ALL	ANSWERS	CORRECT	IN SUBSCALE 1
SUBJECT =A31	ID = 32	HAS	ALL	ANSWERS	CORRECT	IN TOTAL SCALE 1
SUBJECT =A31	ID = 32	HAS	ALL	ANSWERS	CORRECT	IN SUBSCALE 1

CASES READ= 32 CASES NOT CONVERGED= 0

Contents of TAPE3:

Testee Name	Testee Identification Number	Subscale: T=Total; I=Scale 1	Proportion Correct	Maximum Likelihood Estimate of θ	Response Pattern Information	Number of Items	Test Information Associated with $\hat{\theta}$	Expected Proportion Correct	Number of Iterations	Estimated Standard Error of Measurement
A00	1	T	0	-10.00	0	5	0	0	0	
A00	1	I	0	-10.00	0	5	0	0	0	
A01	2	T	.20	-1.06	1.48	5	1.07	.20	2	.82
A01	2	I	.33	-.65	1.51	3	1.36	.30	3	.81
A02	3	T	.20	-.95	.58	5	1.36	.22	5	1.31
A02	3	I	0	-10.00	0	5	0	0	0	
A03	4	T	.40	-.31	3.35	5	3.40	.42	3	.55
A03	4	I	.33	-.65	1.51	3	1.36	.30	3	.81
A04	5	T	.20	-1.06	1.48	5	1.07	.20	2	.82
A04	5	I	.33	-.65	1.51	3	1.36	.30	3	.81
A05	6	T	.40	-.50	3.08	5	2.84	.35	2	.57
A05	6	I	.67	.05	2.33	3	2.23	.57	2	.66
A06	7	T	.40	-.31	3.35	5	3.40	.42	3	.55
A06	7	I	.33	-.65	1.51	3	1.36	.30	3	.81
A07	8	T	.60	.07	3.98	5	3.94	.58	2	.50
A07	8	I	.67	.05	2.33	3	2.23	.57	2	.66
A08	9	T	.20	-.95	.58	5	1.36	.22	5	1.31
A08	9	I	.33	-.30	1.83	3	1.95	.43	3	.74
A09	10	T	.40	-.31	3.35	5	3.40	.42	3	.55
A09	10	I	.67	.40	2.03	3	2.11	.71	2	.70
A10	11	T	.40	-.12	3.63	5	3.78	.50	2	.52
A10	11	I	.33	-.30	1.83	3	1.95	.43	3	.74
A11	12	T	.60	.27	3.71	5	3.88	.67	2	.52
A11	12	I	.67	.40	2.03	3	2.11	.71	2	.70
A12	13	T	.40	-.31	3.35	5	3.40	.42	3	.55
A12	13	I	.67	.40	2.03	3	2.11	.71	2	.70
A13	14	T	.60	.07	3.98	5	3.94	.58	2	.50
A13	14	I	1.00	10.00	0	5	0	0	0	
A14	15	T	.60	.27	3.71	5	3.88	.67	2	.52
A14	15	I	.67	.40	2.03	3	2.11	.71	2	.70
A15	16	T	.80	.75	2.82	5	2.94	.83	2	.60
A15	16	I	1.00	10.00	0	5	0	0	0	
A16	17	T	.20	-1.06	1.48	5	1.07	.20	2	.82
A16	17	I	0	-10.00	0	5	0	0	0	
A17	18	T	.40	-.50	3.08	5	2.84	.35	2	.57
A17	18	I	.33	-.65	1.51	3	1.36	.30	3	.81
A18	19	T	.40	-.31	3.35	5	3.40	.42	3	.55
A18	19	I	0	-10.00	0	5	0	0	0	
A19	20	T	.60	.07	3.98	5	3.94	.58	2	.50
A19	20	I	.33	-.65	1.51	3	1.36	.30	3	.81
A20	21	T	.40	-.50	3.08	5	2.84	.35	2	.57
A20	21	I	.33	-.65	1.51	3	1.36	.30	3	.81
A21	22	T	.60	-.11	3.94	5	3.79	.50	2	.50
A21	22	I	.67	.05	2.33	3	2.23	.57	2	.66
A22	23	T	.60	.07	3.98	5	3.94	.58	2	.50
A22	23	I	.33	-.65	1.51	3	1.36	.30	3	.81
A23	24	T	.80	.46	3.82	5	3.62	.74	2	.51
A23	24	I	.67	.05	2.33	3	2.23	.57	2	.66
A24	25	T	.40	-.31	3.35	5	3.40	.42	3	.55
A24	25	I	.33	-.30	1.83	3	1.95	.43	3	.74
A25	26	T	.60	.07	3.98	5	3.94	.58	2	.50
A25	26	I	.67	.40	2.03	3	2.11	.71	2	.70
A26	27	T	.60	.27	3.71	5	3.88	.67	2	.52
A26	27	I	.33	-.30	1.83	3	1.95	.43	3	.74
A27	28	T	.80	.75	2.82	5	2.94	.83	2	.60
A27	28	I	.67	.40	2.03	3	2.11	.71	2	.70
A28	29	T	.60	.07	3.98	5	3.94	.58	2	.50
A28	29	I	.67	.40	2.03	3	2.11	.71	2	.70
A29	30	T	.80	.46	3.82	5	3.62	.74	2	.51
A29	30	I	1.00	10.00	0	5	0	0	0	
A30	31	T	.80	.75	2.82	5	2.94	.83	2	.60
A30	31	I	.67	.40	2.03	3	2.11	.71	2	.70
A31	32	T	1.00	10.00	0	5	0	0	0	
A31	32	I	1.00	10.00	0	5	0	0	0	

Example 2. This example is identical to Example 1 except that the Bayesian scoring routine was used (OPT4=3) instead of the maximum likelihood normal ogive. Only the scoring results are shown.

Testee Name	Testee Identification Number	Subscale: T=Total; I=Scale 1	Proportion correct	Bayesian estimate of θ	Bayesian Posterior Variance	Number of Items	Test Information Associated with θ	Expected Proportion Correct				
AU0	1	T	0	-1.23	.31	5	.71	.17	0	0	0	0
AU0	1	I	0	-1.04	.39	3	.69	.21	0	0	0	0
AU1	2	T	.20	-.88	.35	5	1.58	.24	0	0	0	0
AU1	2	I	.33	-.55	.44	3	1.55	.34	0	0	0	0
AU2	3	T	.20	-.83	.38	5	1.73	.25	0	0	0	0
AU2	3	I	0	-1.04	.39	3	.69	.21	0	0	0	0
AU3	4	T	.40	-.34	.41	5	3.33	.41	0	0	0	0
AU3	4	I	.33	-.55	.44	3	1.55	.34	0	0	0	0
AU4	5	T	.20	-.89	.30	5	1.56	.23	0	0	0	0
AU4	5	I	.33	-.55	.41	3	1.54	.33	0	0	0	0
AU5	6	T	.40	-.51	.32	5	2.83	.35	0	0	0	0
AU5	6	I	.67	.02	.44	3	2.22	.56	0	0	0	0
AU6	7	T	.40	-.37	.33	5	3.23	.40	0	0	0	0
AU6	7	I	.33	-.55	.41	3	1.54	.33	0	0	0	0
AU7	8	T	.60	.11	.35	5	3.95	.60	0	0	0	0
AU7	8	I	.67	.02	.44	3	2.22	.56	0	0	0	0
AU8	9	T	.20	-.76	.28	5	1.92	.26	0	0	0	0
AU8	9	I	.33	-.56	.39	3	1.87	.41	0	0	0	0
AU9	10	T	.40	-.40	.30	5	3.14	.38	0	0	0	0
AU9	10	I	.67	.23	.43	3	2.22	.65	0	0	0	0
A10	11	T	.40	-.25	.30	5	3.53	.44	0	0	0	0
A10	11	I	.33	-.56	.39	3	1.87	.41	0	0	0	0
A11	12	T	.60	.20	.33	5	3.93	.64	0	0	0	0
A11	12	I	.67	.23	.43	3	2.22	.65	0	0	0	0
A12	13	T	.40	-.40	.27	5	3.15	.38	0	0	0	0
A12	13	I	.67	.22	.42	3	2.22	.64	0	0	0	0
A13	14	T	.60	-.02	.28	5	3.89	.54	0	0	0	0
A13	14	I	1.00	.98	.50	3	1.35	.88	0	0	0	0
A14	15	T	.60	.14	.30	5	3.93	.63	0	0	0	0
A14	15	I	.67	.22	.42	3	2.22	.64	0	0	0	0
A15	16	T	.60	.69	.33	5	3.10	.81	0	0	0	0
A15	16	I	1.00	.96	.50	3	1.35	.88	0	0	0	0
A16	17	T	.20	-.82	.25	5	1.76	.25	0	0	0	0
A16	17	I	0	-1.04	.39	3	.69	.21	0	0	0	0
A17	18	T	.40	-.50	.26	5	2.84	.35	0	0	0	0
A17	18	I	.33	-.55	.44	3	1.55	.34	0	0	0	0
A18	19	T	.40	-.31	.27	5	3.19	.39	0	0	0	0
A18	19	I	0	-1.04	.39	3	.69	.21	0	0	0	0
A19	20	T	.60	.01	.29	5	3.91	.55	0	0	0	0
A19	20	I	.33	-.55	.44	3	1.55	.34	0	0	0	0
A20	21	T	.40	-.50	.24	5	2.84	.35	0	0	0	0
A20	21	I	.33	-.55	.41	3	1.54	.33	0	0	0	0
A21	22	T	.60	-.17	.25	5	3.69	.48	0	0	0	0
A21	22	I	.67	.02	.44	3	2.22	.56	0	0	0	0
A22	23	T	.60	-.01	.26	5	3.90	.55	0	0	0	0
A22	23	I	.33	-.55	.41	3	1.54	.33	0	0	0	0
A23	24	T	.60	.39	.27	5	3.73	.71	0	0	0	0
A23	24	I	.67	.02	.44	3	2.22	.56	0	0	0	0
A24	25	T	.40	-.37	.24	5	3.23	.40	0	0	0	0
A24	25	I	.33	-.56	.39	3	1.87	.41	0	0	0	0
A25	26	T	.60	-.02	.25	5	3.89	.54	0	0	0	0
A25	26	I	.67	.23	.43	3	2.22	.65	0	0	0	0
A26	27	T	.60	.17	.27	5	3.94	.62	0	0	0	0
A26	27	I	.33	-.56	.39	3	1.87	.41	0	0	0	0
A27	28	T	.80	.61	.30	5	3.29	.79	0	0	0	0
A27	28	I	.67	.23	.43	3	2.22	.65	0	0	0	0
A28	29	T	.60	-.03	.24	5	3.88	.54	0	0	0	0
A28	29	I	.67	.22	.42	3	2.22	.64	0	0	0	0
A29	30	T	.80	.34	.26	5	3.80	.69	0	0	0	0
A29	30	I	1.00	.96	.50	3	1.35	.88	0	0	0	0
A30	31	T	.80	.59	.32	5	3.33	.78	0	0	0	0
A30	31	I	.67	.22	.42	3	2.22	.64	0	0	0	0
A31	32	T	1.00	1.20	.37	5	1.72	.92	0	0	0	0
A31	32	I	1.00	.98	.50	3	1.35	.88	0	0	0	0

Example 3. This example illustrates the use of the maximum likelihood logistic scoring routine (e.g., OPT4=2) without subscale scoring. Only the scoring results are shown.

Testee Name	Testee Identification Number	Subscale: T=Total; I=Subscale 1	Proportion Correct	Maximum Likelihood Estimate of θ	Response Pattern Information	Number of Items	Test Information Associated with θ	Expected Proportion Correct	Number of Iterations	Estimated Standard Error of Measurement
AU0	1	T	0	-10.00	0	5	0	0	0	
AU1	2	T	.20	-1.00	1.20	5	.90	.20	2	.91
AU2	3	T	.20	-99.99	-99.99	5	-99.99	-99.99	99	-99.99
AU3	4	T	.40	-.29	3.59	5	3.68	.42	3	.53
AU4	5	T	.20	-1.05	1.20	5	.90	.20	2	.91
AU5	6	T	.40	-.46	3.32	5	2.95	.35	1	.55
AU6	7	T	.40	-.29	3.59	5	3.68	.42	3	.53
AU7	8	T	.60	.07	4.49	5	4.46	.58	2	.47
AU8	9	T	.20	-99.99	-99.99	5	-99.99	-99.99	99	-99.99
AU9	10	T	.40	-.29	3.59	5	3.68	.42	3	.53
A10	11	T	.40	-.11	4.01	5	4.26	.50	2	.50
A11	12	T	.60	.25	4.22	5	4.26	.66	2	.49
A12	13	T	.40	-.29	3.59	5	3.68	.42	3	.53
A13	14	T	.60	.07	4.49	5	4.46	.58	2	.47
A14	15	T	.60	.25	4.22	5	4.26	.66	2	.49
A15	16	T	.80	.71	2.74	5	2.72	.83	2	.60
A16	17	T	.20	-1.05	1.20	5	.90	.20	2	.91
A17	18	T	.40	-.46	3.32	5	2.95	.35	1	.55
A18	19	T	.40	-.29	3.59	5	3.68	.42	3	.53
A19	20	T	.60	.07	4.49	5	4.46	.58	2	.47
A20	21	T	.40	-.46	3.32	5	2.95	.35	1	.55
A21	22	T	.60	-.10	4.53	5	4.28	.50	2	.47
A22	23	T	.60	.07	4.49	5	4.46	.58	2	.47
A23	24	T	.80	.45	3.70	5	3.70	.74	2	.52
A24	25	T	.40	-.29	3.59	5	3.68	.42	3	.53
A25	26	T	.60	.07	4.49	5	4.46	.58	2	.47
A26	27	T	.60	.25	4.22	5	4.26	.66	2	.49
A27	28	T	.80	.71	2.74	5	2.72	.83	2	.60
A28	29	T	.60	.07	4.49	5	4.46	.58	2	.47
A29	30	T	.80	.45	3.70	5	3.70	.74	2	.52
A30	31	T	.80	.71	2.74	5	2.72	.83	2	.60
A31	32	T	1.00	10.00	0	5	0	0	0	

ADADSCO

IPOOL for this example consisted of 10 items:

1	1.00	-2.00	.25 1
2	1.25	-1.50	.25 1
3	1.50	-1.00	.25 1
4	1.75	-0.50	.25 1
5	1.00	0.00	.25 1
6	1.25	0.50	.25 1
7	1.50	1.00	.25 1
8	1.75	1.50	.25 1
9	1.00	2.00	.25 1
10	1.25	2.50	.25 1

The data for the 16 subjects used in the example are shown below:

```

1011101110
1 2 3 4 5 6 7 8 9 10
2 B 4
1010
2 4 6 8
3 C 5
11111
1 2 3 4 5
4 D 5
00000
6 7 8 9 10
5 E 8
11000000
1 2 3 5 6 7 8 9
6 F 2
10
3 7
7 G 6
011111
1 2 4 6 8 9
8 H 9
101010101
1 2 3 4 5 6 7 8 9
9 I 7
1100110
1 3 4 5 6 8 10
10 J 3
110
4 8 9

```



```
11 K      8
10110110
 2 3 4 6 7 8 910
12 L      9
101111111
 1 2 3 4 5 7 8 910
13 M      5
01001
 1 3 5 7 9
14 N      6
000001
 4 5 6 7 8 9
15 P      7
1011110
 1 2 4 5 6 7 8
16 Q      6
011011
 2 4 5 7 810
```

The program control cards for this example were

```
10 10 1012 0.00 1.00 2.00 0.00 0.00 .10 1 3
(8X,12,3F10.2,12)
0
(A2,1X,2A2,12,/10I1,/10I2)
DESCRIPTION
```

In this example the maximum number of items attempted by anyone was 10 (MMAX=10). Although the code for omitted items was 3 (IOMIT=3), IFLAG=1, which means the key to each item was read from IPOOL; however, in this case it was 1 for all items. OPT1=1 means that item information for the first 10 subjects will be printed. Editing of item parameters was requested (OPT3=1). The scoring algorithm was maximum likelihood logistic.

The entire output for this example is shown on the following pages.

ADADSCG
=====

ADAPTIVE DICHOTOMOUS SCORING WITH THREE PARAMETER MODELS

PSYCHOMETRIC METHODS PROGRAM
DEPARTMENT OF PSYCHOLOGY
UNIVERSITY OF MINNESOTA
MPLS. MINN. 55455

INUP = 10
NMAX = 10
IOMIT = 3
IFLAG = 1
OPT1 = 1
OPT2 = 0
OPT3 = 1
OPT4 = 2
IS = 0
TSS = 1.00
AMAX = 2.00
BMAX = 0
BMIN = 0
CMAX = .10
VARIABLE FORMAT FOR POOL=(8X,I2,3F10.2,I2)
VARIABLE FORMAT FOR DATA=(A2,1X,2A2,I2,/,10I1,/,10I2)
DESCRIPTION

Item Identification Number	Scored Answer	Testee Number	Discrimination Parameter (a)	Difficulty Parameter (b)	"Guessing" Parameter (c)
1	1	1	1.00	0	.10
2	0	1	1.25	0	.10
3	1	1	1.50	0	.10
4	1	1	1.75	0	.10
5	1	1	1.00	0	.10
6	0	1	1.25	0	.10
7	1	1	1.50	0	.10
8	1	1	1.75	0	.10
9	1	1	1.00	0	.10
10	0	1	1.25	0	.10
2	1	2	1.25	0	.10
4	0	2	1.75	0	.10
6	1	2	1.25	0	.10
8	0	2	1.75	0	.10
1	1	3	1.00	0	.10
2	1	3	1.25	0	.10
3	1	3	1.50	0	.10
4	1	3	1.75	0	.10
5	1	3	1.00	0	.10
SUBJECT C					
6	0	4	1.25	0	.10
7	0	4	1.50	0	.10
8	0	4	1.75	0	.10
9	0	4	1.00	0	.10
10	0	4	1.25	0	.10

ID= 3 HAS ALL ANSWERS RIGHT

SUBJECT D
E

ID= 4 HAS NO RIGHT ANSWERS

1	1	1.00	0	.10
2	1	1.25	0	.10
3	0	1.50	0	.10
5	0	1.00	0	.10
6	0	1.25	0	.10
7	0	1.50	0	.10
8	0	1.75	0	.10
9	0	1.00	0	.10
F				
3	1	1.50	0	.10
7	0	1.50	0	.10
G				
1	0	1.00	0	.10
2	1	1.25	0	.10
4	1	1.75	0	.10
6	1	1.25	0	.10
8	1	1.75	0	.10
9	1	1.00	0	.10
H				
1	1	1.00	0	.10
2	0	1.25	0	.10
3	1	1.50	0	.10
4	0	1.75	0	.10
5	1	1.00	0	.10
6	0	1.25	0	.10
7	1	1.50	0	.10
8	0	1.75	0	.10
9	1	1.00	0	.10
I				
1	1	1.00	0	.10
3	1	1.50	0	.10
4	0	1.75	0	.10
5	0	1.00	0	.10
6	1	1.25	0	.10
8	1	1.75	0	.10
10	0	1.25	0	.10
J				
4	1	1.75	0	.10
8	1	1.75	0	.10
9	0	1.00	0	.10

CASES READ= 16 CASES NOT CONVERGED= 0

Testee Name	Testee Identification Number	Proportion Correct	Maximum Likelihood Estimate of θ	Response Pattern Information	Number of Items	Test Information Associated with θ	Expected Proportion Correct	Number of Iterations	Estimated Standard Error of Measurement
A	1	.70	.34	9.65	10	9.65	.71	3	.32
B	2	.50	.22	5.06	4	4.66	.43	2	.44
C	3	1.00	10.00	0	5	0	0	0	0
D	4	0	-10.00	0	5	0	0	0	0
E	5	.25	-.78	3.15	8	2.69	.24	1	.56
F	6	.50	-.09	2.57	2	2.57	.50	2	.62
G	7	.83	.79	3.13	6	3.12	.87	2	.57
H	8	.56	-.09	9.85	9	9.55	.50	2	.32
I	9	.57	.05	8.03	7	8.03	.58	2	.35
J	10	.67	.43	3.18	3	3.20	.77	2	.56
K	11	.63	.13	9.62	8	9.62	.62	2	.32
L	12	.89	.89	4.02	9	4.02	.89	3	.50
M	13	.40	-.29	3.59	5	3.68	.42	3	.53
N	14	.17	-1.08	1.40	6	.85	.18	2	.84
P	15	.71	.25	7.55	7	7.52	.68	2	.36
Q	16	.67	.23	7.03	6	7.03	.67	2	.38

LINPSCO

Following are sample runs from LINPSCO using graded models and the nominal logistic model.

Graded models. The IPOOL file for these examples was

1	1.5	3.0	2.0	4.5	5.0
2	1.5	2.0	1.0	3.0	1.5
3	1.5	1.0	0.0	1.5	0.0
4	1.5	0.0	-1.0	0.0	-1.5
5	1.5	-1.0	-2.0	-1.5	-5.0
6	1.5	-2.0	-3.0	-3.0	-4.5

The DATA file, including subject identification and item responses, was as follows. Note that in coding the item responses, a "1" indicated the "best" response and a "3" indicated the "poorest," as specified by the item difficulty parameters in IPOOL.

1	333211
2	332111
3	321212
4	112121
5	112233
6	222222
7	122221
8	322223
9	111333
10	111222
11	333222
12	333111
13	222111
14	211111

The following is an example of the logistic graded model (OPT4=1) with a 1.7 scaling factor. In this example the b parameters for the items were taken from columns 3-4 of the IPOOL file. The option and format cards for this example were

```

      0      0201 1 1.70
(11,1X,F3.1,2(1X,F4.1))
222222
      1      2      3      4      5      6
000000
(2A7,A1,6I1)
EXAMPLE RUN OF THE LOGISTIC GRADED MODEL--USES THE FIRST PAIR OF B
PARAMETERS FROM ITEM POOL

```

The output from this run was as follows:

LINPSCO

LINEAR POLYCHOTOMUS SCORING WITH TWO PARAMETER MODELS

PSYCHOMETRICS METHODS PROGRAM
DEPARTMENT OF PSYCHOLOGY
UNIVERSITY OF MINNESOTA
MPLS. MINN. 55455

INUP = 6
MMAX = 6
IOMIT = 4
OPT1 = 0
OPT2 = 1
OPT4 = 1
MAXCAT = 2
U = 1.7
VARIABLE FORMAT FOR POOL = (I1,1X,F3.1,2(1X,F4.1))
VARIABLE FORMAT FOR DATA = (2A7,A1,6I1)
EXAMPLE RUN OF THE LOGISTIC GRADED MODEL--USES THE FIRST PAIR OF B
PARAMETERS FROM ITEM POOL

ITEM ID = 1 REJECTION = 0
A: 1.50
B: 3.00 2.00

ITEM ID = 2 REJECTION = 0
A: 1.50
B: 2.00 1.00

ITEM ID = 3 REJECTION = 0
A: 1.50
B: 1.00 0

ITEM ID = 4 REJECTION = 0
A: 1.50
B: 0 -1.00

ITEM ID = 5 REJECTION = 0
A: 1.50
B: -1.00 -2.00

ITEM ID = 6 REJECTION = 0
A: 1.50
B: -2.00 -3.00

CASES READ = 14 CASES NOT CONVERGED = 0

Testee Identification	Proportion of "Best" Responses (Coded 1)	Maximum Likelihood Estimate of θ	Response Pattern Information	Number of Items Used to Estimate θ	Number of Iterations	Test Information Associated with $\hat{\theta}$	Estimated Standard Error of Measurement
1	.33	-1.50	4.72	6	2	4.25	.46
2	.50	.50	4.72	6	2	4.25	.46
3	.33	.35	3.69	6	3	4.28	.52
4	.67	1.52	2.63	6	3	4.11	.62
5	.33	-1.00	4.21	6	3	4.41	.49
6	.50	-1.00	5.16	6	2	4.41	.44
7	.50	.51	4.88	6	2	4.25	.45
8	.50	-1.51	4.88	6	2	4.25	.45
9	.50	-1.00	.96	6	3	4.41	1.02
10	.50	.52	2.65	6	2	4.25	.61
11	.50	-1.51	4.86	6	2	4.11	.45
12	.50	-1.00	4.20	6	3	4.41	.49
13	.50	1.51	4.86	6	2	4.11	.45
14	.83	2.69	3.12	6	2	2.67	.57

Following is an example of use of the normal ogive graded model (OPT4=2) using the same DATA and IPOOL as the previous example. In this example the b parameters for the items were taken from columns 5 and 6 of the IPOOL file. Input control cards for this example were

```

      6      0201 2      4
      (11,1X,F3.1,11X,F4.1,1X,F4.1)
      222222
      1      2      3      4      5      6
      000000
      (2A7,A1,6I1)
      EXAMPLE RUN OF THE NORMAL OGIVE GRADED MODEL--USES SECOND PAIR OF B
      PARAMETERS FROM ITEM POOL
  
```


Output was as follows:

LINPSCO

LINEAR POLYCHOTOMUS SCORING WITH TWO PARAMETER MODELS

PSYCHOMETRICS METHODS PROGRAM
DEPARTMENT OF PSYCHOLOGY
UNIVERSITY OF MINNESOTA
MPLS. MINN. 55455

INUP = 6
NMAX = 6
IOMIT = 4
OPT1 = 0
OPT2 = 1
OPT4 = 2
MAXCAT = 2
VARIABLE FORMAT FOR POOL =(I1,1X,F3.1,11X,F4.1,1X,F4.1)
VARIABLE FORMAT FOR DATA=(2A7,A1,6I1)
EXAMPLE RUN OF THE NORMAL OGIVE GRADED MODEL--USES SECOND PAIR OF B
PARAMETERS FROM ITEM POOL

ITEM ID = 1 REJECTION = 0
A: 1.50
B: 4.50 3.00

ITEM ID = 2 REJECTION = 0
A: 1.50
B: 3.00 1.50

ITEM ID = 3 REJECTION = 0
A: 1.50
B: 1.50 0

ITEM ID = 4 REJECTION = 0
A: 1.50
B: 0 -1.50

ITEM ID = 5 REJECTION = 0
A: 1.50
B: -1.50 -3.00

ITEM ID = 6 REJECTION = 0
A: 1.50
B: -3.00 -4.50

CASES READ = 14 CASES NOT CONVERGED = 0

1	.33	-.75	2.97	6	2	3.36	.58
2	.50	.75	2.97	6	2	3.36	.58
3	.33	-.04	8.00	6	2	3.42	.35
4	.67	1.85	8.05	6	2	3.39	.35
5	.33	-.00	11.98	6	2	3.42	.29
6	0	-.00	11.58	6	2	3.42	.29
7	.33	1.09	9.50	6	2	3.39	.32
8	0	-1.09	9.50	6	2	3.39	.32
9	.50	-.00	12.80	6	1	3.42	.28
10	.50	.75	12.29	6	2	3.36	.29
11	0	-2.25	5.18	6	2	3.35	.44
12	.50	-.00	3.19	6	2	3.42	.56
13	.50	2.25	5.13	6	2	3.35	.44
14	.33	3.92	2.05	6	2	2.25	.70

Nominal logistic model. Following is an example of use of the nominal logistic model (OPT4=3). The DATA file was

```

10001 38 9946454134111122442211121114111141111121111111111
10002 38103834541114411414114411111411111411141114111
10003 38 94000542414112111441214121114111144111114111241
10005 381042450424222444424211142442421222421212121222241
10004 38 9954344414144441414444441411144411114114141144411
10005 381045285411144151214551121122111131111155555555551
10004 381055445443511111514111144111511114114111111114111
10008 38 99334942324551432331435241555555555555555555555
10009 3810534444142124152232134413124214124221114321222554
10010 381051509444444111444511141111411414111111111114141
10011 3810529454111111151141111111111111111111111111111
10012 3810584924423231334333114222251313251122144511242151
10013 3810540444414444144111441444111441411441114241511111
10015 38 9524554144512132544411411111111121241134411112141
10014 3810598354211241142144144441211214121141114111154411
10015 3810512954211141112441111411111111111111111111141
10014 381059528524413211314211142512111111411114111131451
10018 3810524844114411141324111414114244431441114114115141
10019 3810528254414411144241112433113442411241121311114114
10020 25104114344444444141441114444441414444141114144144444

```

IPOOL was

3417	0.000000	0.000000	0.000000	0.000000
3422	0.000000	0.000000	0.000000	0.000000
3425	0.870169	0.165509	-1.212113	0.176405
3431	0.840205	0.266821	-2.116617	1.006591
3434	1.030257	0.007821	-1.157598	0.110520
3437	0.900771	-0.711543	-1.432918	1.237689
3440	0.870227	0.313705	-1.132723	-0.059209
3443	0.510097	-0.183194	-1.493435	1.106532
3446	0.840335	-0.056809	-0.936221	0.143745
3449	0.940914	-0.510503	-1.591918	1.154556
3452	0.990644	-0.057006	-1.046348	0.106360
3455	0.220949	-0.511704	-0.842978	1.130754
3458	0.900633	0.452403	-1.315750	-0.040265
3461	1.320394	0.196605	-2.289410	0.768330
3464	0.930577	0.125247	-1.013213	-0.047610
3467	1.750989	-0.277907	-1.862908	0.405916
3470	1.260512	0.165917	-1.188908	-0.244462
3473	0.720900	-0.503602	-1.456565	1.237267
3476	0.400782	0.236527	-0.675647	0.032338
3479	-0.165035	-0.081050	-0.762658	0.968744
3482	0.910800	-0.087146	-0.807633	-0.020027
3485	0.880125	-0.561406	-1.133896	0.019221
3488	0.000000	0.000000	0.000000	0.000000
3491	0.000000	0.000000	0.000000	0.000000
3494	1.210009	-0.160504	-1.049275	-0.005201
3497	0.700199	-0.472306	-1.271001	1.040191
3500	0.940547	0.120504	-1.216024	0.154792
3503	1.010184	-0.227101	-2.405601	1.014638
3506	1.190701	0.289311	-1.692915	0.204903
3509	2.320618	-0.227105	-3.302494	1.207041
3512	1.380173	-0.138215	-1.203993	-0.039965
3515	1.750215	-0.061800	-2.359620	0.960275
3518	1.160829	-0.097002	-1.500254	0.349206
3521	0.150054	-0.506044	-1.636365	1.987376
3524	1.230110	-0.375004	-0.934679	-0.223813
3527	1.110208	0.312128	-1.527765	0.404369
3530	1.020419	0.034101	-0.950948	-0.106622
3533	0.550335	-0.287405	-1.247386	0.981450
3536	1.600121	-0.068501	-1.228285	-0.303305
3539	2.090420	-0.093601	-2.469919	0.460094
3542	1.590045	-0.042903	-1.013761	-0.334310
3545	1.080738	-0.088700	-1.734153	0.139205
3548	1.020427	0.183605	-1.046231	-0.159844
3551	1.570805	-0.443101	-1.656987	0.525223
3554	0.990791	-0.067707	-1.062704	0.135620
3557	1.010407	-0.057804	-1.145208	0.760626
3560	1.240329	0.078503	-1.435152	0.114271
3563	2.360325	-0.059700	-2.638202	1.133657
3566	1.120352	0.184404	-0.962735	-0.343020
3569	1.020360	-0.262202	-1.632686	0.274608
3572	1.350141	0.216103	-1.205470	-0.366864
3575	2.260497	-0.343707	-2.311491	0.389761
3578	0.000197	0.002103	-0.612300	0.007000
3581	0.970607	-0.472700	-1.024609	0.523197
3584	2.040249	0.393202	-1.696127	-0.757373
3587	0.700431	0.132907	-3.787033	-0.054433
3590	1.570801	0.131800	-1.134625	-0.373132
3593	2.120620	0.251702	-2.499505	0.094757
3596	1.540139	0.286402	-2.081177	0.249600
3599	2.040910	0.001304	-3.331305	1.207001
3602	1.560642	-0.007905	-1.296770	-0.257927
3605	2.290293	0.021303	-2.644136	0.326495
3608	1.280965	0.227001	-0.889192	-0.023795
3611	0.010197	-0.447504	-2.181694	-0.339909
3614	1.050257	-0.069409	-0.664305	-0.293623
3617	1.620671	-0.009501	-1.288305	-0.033315
3620	1.450187	0.264101	-1.620217	-0.102162
3623	1.770329	-0.348503	-2.527377	1.184546
3626	1.110323	-0.003904	-0.823243	-0.292120
3629	1.270163	-0.303607	-1.057345	0.061860
3632	1.330099	0.035306	-1.773168	0.406713
3635	2.390180	-0.114603	-3.584809	1.336280
3638	1.480476	-0.073003	-0.823643	-0.589715
3641	2.230098	-0.331406	-1.535212	-0.371390
3644	1.200460	-0.157705	-0.924427	-0.120298
3647	1.770003	-0.425000	-1.844767	0.313329
3650	1.060538	-0.131202	-0.860200	-0.069056
3653	1.630196	-0.343905	-1.242548	0.453307
3656	1.320054	0.287801	-1.959475	0.243501
3659	1.000725	0.560903	-3.220217	0.994529
3662	1.000690	-0.074201	-1.264006	-0.268341
3665	2.070034	-0.045201	-2.330619	0.904840
3668	0.690561	0.155307	-1.158516	0.311618
3671	1.310654	-1.378507	-1.585505	1.053456
3674	1.090246	0.129610	-1.359014	-0.460943
3677	3.620455	-0.533200	-3.131603	0.095448

And the output from this run was

LINEAR POLYCHOTOMOUS SCORING WITH TWO PARAMETER MODELS

```

INUP      = 43
MMAX      = 22
IOMIT     = 5
OPT1      = 0
OPT2      = 0
OPT4      = 3
MAXCAT    = 3
VARIABLE FORMAT FOR POOL =(I4,4(1X,F9.6),/,4X,4(1X,F9.6))
VARIABLE FORMAT FOR DATA=(2A7,A1,43I1)
EXAMPLE RUN OF THE NOMINAL LOGISTIC MODEL

```

ITEM ID = 0 0 REJECTION = 1
A: 0 0 0 0
B: 0 0 0 0

ITEM ID = 3251 REJECTION = 0
A: 1.04 .01 -1.16 .11
B: .91 -.71 -1.43 1.24

ITEM ID = 3422 REJECTION = 0
A: .85 -.06 -.94 .14
B: .95 -.51 -1.59 1.15

ITEM ID = 3421 REJECTION = 0
A: .90 .45 -1.32 -.04
B: 1.32 .20 -2.29 .77

ITEM ID = 3277 REJECTION = 0
A: .94 .13 -1.01 -.05
B: 1.75 -.28 -1.88 .41

ITEM ID = 3400 REJECTION = 0
A: 1.27 .17 -1.19 -.24
B: .72 -.50 -1.46 1.24

ITEM ID = 0 0 REJECTION = 1
A: 0 0 0 0
B: 0 0 0 0

ITEM ID = 3405 REJECTION = 0
A: 1.22 -.16 -1.05 -.01
B: .70 -.47 -1.27 1.04

ITEM ID = 3213 REJECTION = 0
A: .94 .12 -1.22 .15
B: 1.62 -.23 -2.41 1.01

ITEM ID = 3079 REJECTION = 0
A: 1.38 -.14 -1.20 -.04
B: 1.75 -.66 -2.06 .97

ITEM ID = 3002 REJECTION = 0
A: 1.16 -.01 -1.50 .35
B: .16 -.51 -1.64 1.99

ITEM ID = 3210 REJECTION = 0
A: 1.38 -.04 -1.61 -.33
B: 1.68 -.09 -1.73 .14

ITEM ID = 3404 REJECTION = 0
A: .99 -.07 -1.06 .14
B: 1.02 -.66 -1.15 .79

ITEM ID = 3400 REJECTION = 0
A: 1.24 .08 -1.44 .11
B: 2.36 -.86 -2.64 1.13

ITEM ID = 3021 REJECTION = 0
A: 2.04 .39 -1.70 -.74
B: 3.71 .13 -3.79 -.05

ITEM ID = 3221 REJECTION = 0
A: 1.38 .13 -1.15 -.38
B: 2.12 .28 -2.50 .09

ITEM ID = 3076 REJECTION = 0
A: 1.29 .23 -.69 -.62
B: 3.02 -.45 -2.18 -.39

ITEM ID = 3200 REJECTION = 0
A: 1.20 -.16 -.92 -.12
B: 1.77 -.24 -1.04 .31

ITEM ID = 3029 REJECTION = 0
A: .69 .16 -1.16 .31
B: 1.31 -1.38 -1.59 1.65

ITEM ID = 3078 REJECTION = 0
A: 1.69 .13 -1.36 -.46
B: 3.63 -.59 -3.13 .10

ITEM ID = 3209 REJECTION = 0
A: 1.33 .04 -1.77 .41
B: 2.39 -.11 -3.56 1.31

ITEM ID = 3023 REJECTION = 0
A: 1.48 .07 -.82 -.59
B: 2.24 -.33 -1.54 -.37

CASES READ = 20 CASES NOT CONVERGED = 0

Testee Identification		Proportion of "Best" Responses	Maximum Likelihood Estimate of θ	Response Pattern Information	Number of Items Used to Estimate θ	Number of Iterations	Test Information Associated with θ	Estimated Standard Error of Measurement
8 99484	5	.50	-.63	9.16	20	3	9.12	.33
8103834	5	.65	-.02	6.24	20	3	6.21	.40
8 94000	5	.55	-.33	7.94	20	2	7.60	.35
8104245	0	.15	-1.31	12.19	20	2	12.11	.29
8 99543	4	.35	-1.10	11.43	20	2	11.44	.30
8104528	5	.59	-.47	7.11	17	2	7.11	.37
8105544	5	.71	-.07	5.17	17	3	5.16	.44
8 99334	9	.19	-1.73	9.55	16	2	9.55	.32
8105344	4	.32	-1.40	11.89	19	2	11.89	.29
8105150	9	.47	-.69	9.02	19	3	9.00	.33
8105294	5	.95	3.12	.59	19	3	.59	1.30
8103849	2	.16	-1.90	10.86	19	3	10.85	.30
8105404	4	.45	-.72	9.60	20	3	9.59	.32
8 95245	5	.56	-.51	7.98	18	3	7.97	.35
8105983	5	.40	-1.05	11.34	20	2	11.24	.30
8105129	5	.70	.00	6.17	20	3	6.14	.40
8105952	8	.47	-.85	10.09	19	3	10.09	.31
8105248	4	.55	-.49	8.39	20	3	8.39	.35
8105282	5	.40	-1.03	11.18	20	3	11.18	.30
5104114	3	.30	-.98	10.94	20	3	10.95	.30

APPENDIX C
LINDSCO FORTRAN PROGRAM LISTING

```

1  PROGRAM LINDSCO (INPUT,OUTPUT,DATA,IPOOL,TAPE1=DATA,TAPE2=IPOOL,TA
2  1PE3,PUNCH)
3  DIMENSION ITEM(600), A(600), B(600), C(600), INAD(300), KEY(300),
4  1IREJ(300), IFORM(8), IRAM(300), INADS(300), IRESP(300), ISAD(60,25
5  2), ADM(300), BDM(300), CDM(300), ISADS(300), DESC(24), NAME(2), IF
6  3ORM1(8), NISS(25,2)
7  INTEGER OPT1,OPT2,OPT3,OPT4
8  REAL ITOT
9  N=NC=0
10 *****
11 *
12 *READ OPTIONS AND PROGRAM PARAMETER FROM INPUT FILE DATA IS ON TAPE2
13 *
14 *****
15 IPOOL=2
16 READ 50, INUP,M,OPT1,OPT2,OPT3,OPT4,TS,TSS,AMAX,BMIN,BMAX,CMAX,IOM
17 1IT
18 READ 53, (IFORM1(I),I=1,8)
19 READ (IPOOL,IFORM1) (ITEM(I),A(I),B(I),C(I),I=1,INUP)
20 *****
21 *
22 *
23 *START READING THE SPECIFIC DATA (SPECIFIC FOR THE RUN) FROM THE INPUT
24 *
25 *INAD IS THE ITEM IDS ADMINISTERED
26 *IREJ IS THE REJECTED ITEM ID S
27 *KEY IS THE KEY FOR THE ITEMS IN INAD
28 *NSSC IS THE NUMBER OF SUBSCALES THAT WILL BE GIVEN TO THE PROGRAM
29 *NISS WILL HAVE THE NUMBER OF ITEMS IN EACH SUBSCALE TOGETHER WITH THE
30 *NAME OF THE SUBSCALES
31 *ISAD IS THE ITEM ID S IN EACH SUBSCALE
32 *
33 *****
34 READ 51, (INAD(I),I=1,M)
35 READ 52, (IREJ(I),I=1,M)
36 READ 52, (KEY(I),I=1,M)
37 READ 53, (IFORM1(I),I=1,8)
38 READ 55, DESC
39 PRINT 49
40 PRINT 54, INUP,M,IOMIT,OPT1,OPT2,OPT3,OPT4,TS,TSS,AMAX,BMAX,BMIN,C
41 1MAX,IFORM1,IFORM,DESC
42 C THOSE ITEM ID S THAT ARE IN IREJ ARE SET TO ZERO ZERO ITEM ID S
43 C WILL BE SKIPPED DURING THE COMPUTATIONS
44 DO 1 I=1,M
45 IF (1IREJ(I).EQ.1) INAD(I)=0
46 C READ SUBSCALES
47 READ 48, NSSC
48 IF (NSSC.EQ.0) GO TO 5
49 READ 56, (NISS(I,1),NISS(I,2),I=1,NSSC)
50 C READ SSC INDEX
51 DO 2 JJ=1,60
52 DO 2 II=1,25
53 ISAD(JJ,II)=0
54 DO 3 I=1,NSSC
55 NI=NISS(I,1)
56 READ 51, (ISAD(J,I),J=1,NI)
57 3 CONTINUE
58 DO 4 II=1,NSSC
59 NI=NISS(II,1)
60 PRINT 58, II,(ISAD(JJ,II),JJ=1,NI)
61 4 CONTINUE
62 PRINT 49
63 5 CONTINUE
64 IF (OPT2.EQ.1) GO TO 9
65 *****
66 *

```

```

*
*IN THE NEXT DO LOOP THE ITEM PARAMETERS CORRESPONDING TO THE ITEMS
*IN INAD ARE RETRIEVED FROM A,B,C, AND LOADED INTO ADM,BDM,CDM RESP.
*THE ENTRIES IN THE ADM,BDM,CDM ARE ZEROED FOR THE CASE OF ZERO ITEM
*ID IN THE INAD
*
*****
DO 8 J=1,M
  IF (INAD(J).NE.0) GO TO 6
  ADM(J)=BDM(J)=CDM(J)=0
  GO TO 8
6  CONTINUE
  IFOUND=0
  DO 7 I=1,INUP
    IF (INAD(J).NE.ITEM(I)) GO TO 7
    IFOUND=1
    ADM(J)=A(I)
    BDM(J)=B(I)
    CDM(J)=C(I)
    GO TO 8
7  CONTINUE
  IF (IFOUND.EQ.0) INAD(J)=0
8  CONTINUE
  GO TO 11
C    THE NEXT SECTION IS USED IF OPTION 2 IS ON, IT WILL TAKE THE FI
C    PARAMETERS FROM THE POOL WITHOUT MAKING USE OF INAD
9  DO 10 I=1,M
    ADM(I)=A(I)
    BDM(I)=B(I)
    CDM(I)=C(I)
10  CONTINUE
C    IF OPTION 3 IS ON THE PARAMETERS A,B,C ARE CONSTRAINED WITHIN B
C    OF AMAX,AMIN,BMAX,BMIN,CMAX
11  IF (OPT3.EQ.0) GO TO 13
    DO 12 I=1,M
      IF (INAD(I).EQ.0) GO TO 12
      IF ((ADM(I).GT.AMAX).OR.(OPT3.EQ.3)) ADM(I)=AMAX
      IF (BDM(I).LT.BMIN) BDM(I)=BMIN
      IF (BDM(I).GT.BMAX) BDM(I)=BMAX
      IF ((CDM(I).GT.CMAX).OR.(OPT3.EQ.2)) CDM(I)=CMAX
12  CONTINUE
13  IF (OPT1.NE.1) GO TO 15
    DO 14 I=1,M
      PUNCH 57, INAD(I),KEY(I),IREJ(I),ADM(I),BDM(I),CDM(I)
14  CONTINUE
15  PRINT 57, (INAD(I),KEY(I),IREJ(I),ADM(I),BDM(I),CDM(I),I=1,M)
    PRINT 49
*****
*
*
*READ A SUBJECT FROM TAPE1 CALCULATE THETA, LOOP BACK TO 5 ETC.
*
*****
15  READ (1,IFORM) NAME,ID,(IRAW(I),I=1,M)
    DO 17 JJ=1,M
17  IRESP(JJ)=0
    IO=UNIT(1)
C    CHECK THE END OF FILE ON DATA FILE
    IF (IO.LE.3) GO TO 18
    PRINT 59, IO
18  IF (IO.EQ.0) GO TO 47
    N=N+1
    ITOT=0.0
C    SET THE ITEM ID TO ZERO FOR THE OMISSIONS (THAT IS READ IN FRO

```

```

C
C      AND SET THE RESPONSE VECTOR TO 1 IF THE ANSWER IS CORRECT
C
DO 21 I=1,M
  INADS(I)=INAD(I)
  IF (IRAW(I).EQ.IOMIT) 19,20
19  INADS(I)=0
  GO TO 21
20  IF ((IRAW(I).EQ.KEY(I)).AND.(IREJ(I).EQ.0)) IRESP(I)=1
  ITOT=ITOT+FLOAT(IRESP(I))
21  CONTINUE
  ITINADS=0
  DO 22 KK=1,M
22  IF (INADS(KK).EQ.0) ITINADS=ITINADS+1
  KL=M-ITINADS
  ITOT=ITOT/FLOAT((KL))
  IF (ITOT.EQ.0.) 23,24
23  PRINT 60, NAME, ID
  IF (OPT4.EQ.3) GO TO 26
  T=-10.0
  SFORM=0.0
  TINFO=0.0
  IKL=KL
  ITER=0
  EXPTOT=0.0
  WRITE (3,63) NAME, ID, ITOT, T, SFORM, IKL, TINFO, EXPTOT, ITER
  GO TO 32
24  IF (ITOT.EQ.1.) 25,26
25  PRINT 61, NAME, ID
  IF (OPT4.EQ.3) GO TO 26
  T=10.0
  SFORM=0.0
  TINFO=0.0
  IKL=KL
  ITER=0
  EXPTOT=0.0
  WRITE (3,63) NAME, ID, ITOT, T, SFORM, IKL, TINFO, EXPTOT, ITER
  GO TO 32
*****
*
*
*      NOW THE DATA IS READY TO MAKE THE CALLS TO THE APPROPRIATE ROUTINE
*TO ESTIMATE THE THETA.OPTION 4 WILL DETERMINE THE METHOD BY WHICH
*THE THETA ESTIMATE WILL BE FOUND
*
*****
26  IKL=KL
  IF (OPT4-2) 27,28,29
27  CALL MAXLNO (IRESP, INADS, M, M, ADM, RDM, CDM, 50, .005, T, SFORM, IFAIL, TIN
1FO, EXPTOT, ITER, SEM)
  GO TO 30
28  CALL MAXLK (M, INADS, IRESP, M, ADM, RDM, CDM, 50, .005, IFAIL, SFORM, T, TINF
10, EXPTOT, ITER, SEM)
  GO TO 30
29  T=TS
  SFORM=TS
  SEM=0.0
  CALL HAYES (M, INADS, IRESP, M, ADM, RDM, CDM, T, SFORM, TINFO, EXPTOT, ITER)
  GO TO 31
30  CONTINUE
  IF (IFAIL.EQ.0) GO TO 31
  PRINT 62, NAME, ID
C      SFORM AND T ARE SET TO -99.99 IN MAXLK IF NOT CONV
C
  NC=NC+1
*****

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*
*WRITE THE SUCCESSFUL RESULTS TO THE FILE TAPE3
*
*****
31  WRITE (3,63) NAME,ID,ITOT,T,SFORM,IKL,TINFO,EXPTOT,ITER,SEM
C    IF THERE IS NO SUBSCALE CALCULATIONS LOOP BACK TO READ A SUBJECT
C    OTHERWISE CONTINUE WITH THE COMPUTATIONS FOR SUBSCALES
32  IF (NSSC.EQ.0) GO TO 16
    DO 46 I=1,NSSC
      NI=NISS(I,1)
      ITOT=0.0
      DO 32 J=1,M
        ISADS(J)=INADS(J)
      DO 34 K=1,NI
        IF (ISAD(K,I)-INADS(J)) 34,33,34
33    ITOT=ITOT+FLOAT(IRESP(J))
      GO TO 35
34    CONTINUE
      ISADS(J)=0
35    CONTINUE
      ITISADS=0
      DO 36 KK=1,M
36    IF (ISADS(KK).NE.0) ITISADS=ITISADS+1
      KL=ITISADS
      ITOT=ITOT/FLOAT(KL)
      IF (ITOT.EQ.0.0) 37,38
37    PRINT 66, NAME,ID,NISS(I,2)
      IF (OPT4.EQ.3) GO TO 40
      T=-10.00
      TINFO=EXPTOT=0.0
      ITER=0
      SFORM=0.0
      WRITE (3,64) NAME,ID,NISS(I,2),ITOT,T,SFORM,IKL,TINFO,EXPTOT,ITER
      GO TO 46
38    IF (ITOT.EQ.1.0) 39,40
39    PRINT 67, NAME,ID,NISS(I,2)
      IF (OPT4.EQ.3) GO TO 40
      T=10.0
      TINFO=EXPTOT=0.0
      ITER=0
      SFORM=0.0
      WRITE (3,64) NAME,ID,NISS(I,2),ITOT,T,SFORM,IKL,TINFO,EXPTOT,ITER
      GO TO 46
40    IKL=KL
      IF (OPT4-2) 41,42,43
41    CALL MAXLNQ (IRESP,ISADS,M,M,ADM,BDM,CDM,50,.01,T,SFORM,IFAIL,TINF
10,EXPTOT,ITER,SEM)
      GO TO 44
42    CALL MAXLK (M,ISADS,IRESP,M,ADM,BDM,CDM,50,.01,IFAIL,SFORM,T,TINFO
1,EXPTOT,ITER,SEM)
      GO TO 44
43    T=TS
      SFORM=TSS
      SEM=0.0
      CALL HAYES (M,ISADS,IRESP,M,ADM,BDM,CDM,T,SFORM,TINFO,EXPTOT,ITER)
      GO TO 45
44    IF (IFAIL.EQ.0) GO TO 45
      PRINT 68, NAME,ID,NISS(I,2)
45    WRITE (3,64) NAME,ID,NISS(I,2),ITOT,T,SFORM,IKL,TINFO,EXPTOT,ITER,
1SEM
46    CONTINUE
      GO TO 16
47    PRINT 65, N,NC
      STOP
C
C

```

C		265
48	FORMAT (I5)	266
49	FORMAT (1H1)	267
50	FORMAT (2I4,X,4I1,6F5.2,2X,I2)	268
51	FORMAT (16I5)	269
52	FORMAT (80I1)	270
53	FORMAT (8A10)	271
54	FORMAT (T50,*LINDSCO*,/,T50*====*,////////,T20,*LINEAR DICHOTOMUS	272
	1 SCORING WITH THREE PARAMETER MODELS*,////,T40*PSYCHOMETRIC METHOD	273
	2S PROGRAM*,/,T40*DEPARTMENT OF PSYCHOLOGY*,/,T40*UNIVERSITY OF MIN	274
	3NESOTA*,/,T40*MPLS. MINN. 55455*,/,//,T20*INUP*,T27*==I5,/,T20,*M	275
	4MAX*,T27*==I5,/,T20,*IOMIT*,T27*==I5,/,T20*OPT1*,T27*==I5,/,T20*O	276
	5PT2*,T27*==I5,/,T20*OPT3*,T27*==I5,/,T20*OPT4*,T27*==I5,/,T20*TS*	277
	6,T27*==F5.2,/,T20*TSS*,T27*==F5.2,/,T20*AMAX*,T27*==F5.2,/,T20,*RM	278
	7AX*,T27,*==F5.2,/,T20*BMIN*,T27,*==F5.2,/,T20*CMAX*,T27,*==F5.2,/,	279
	4T20,*VARIABLE FORMAT FOR POOL=*8A10,/,T20,*VARIABLE FORMAT FOR DAT	280
	9A=*8A10,/,T20,8A10,/,T20,8A10,/,T20,8A10,/,)	281
55	FORMAT (8A10)	282
56	FORMAT (2I5)	283
57	FORMAT (*1*,29X,*ITEM ID S*2X,*KEYS*2X,*REJECTIONS*,4X,*A*,9X,*B*,	284
	19X,*C*,/,60(/30X,I5,5X,I3,5X,I3,1X,F10.2,1X,F10.2))	285
58	FORMAT (///,40X,*ITEMS IN SUBSCALE NO=*I3,/,10(20I6,/))	286
59	FORMAT (10X,*PARITY ERROR ON TAPE*,90X,I2)	287
60	FORMAT (10X,*SUBJECT =*,2A10,* ID =*,A9,* HAS NO ANSWERS *,*CORRE	288
	1CT IN TOTAL SCALE*)	289
61	FORMAT (10X,*SUBJECT =*,2A10,* ID =*,A9,* HAS ALL ANSWERS *,*CORRE	290
	1CT IN TOTAL SCALE*)	291
62	FORMAT (10X,*COMPUTATIONAL PROBLEMS WITH SUBJECT =*,2A10,* ID =*,A	292
	19,* IN TOTAL TE*)	293
63	FORMAT (X,2A10,A9,* T*,F5.2,2F7.2,I4,2F7.2,I4,F7.2)	294
64	FORMAT (X,2A10,A9,I2,F5.2,2F7.2,I4,2F7.2,I4,F7.2)	295
65	FORMAT (/10X,*CASES READ=*,I5,* CASES NOT CONVERGED=*,I5)	296
66	FORMAT (10X,*SUBJECT =*,2A10,* ID =*,A9,* HAS NO ANSWERS *,*CORRE	297
	1CT IN SUBSCALE *,I5)	298
67	FORMAT (10X,*SUBJECT =*,2A10,* ID =*,A9,* HAS ALL ANSWERS *,*CORRE	299
	1CT IN SUBSCALE *,I5)	300
68	FORMAT (10X,*MAXIMUM LIKELIHOOD ESTIMATION DOES NOT CONVERGE*,*FOR	301
	1 THE SUBJECT = *,2A10,* ID = *,A9,* ON SUBSCALE *,I5)	302
	END	303
	SUBROUTINE BAYES (M,ITM,RESP,N,A,B,C,BTHET,BVAR,TINFO,EXPTOT,ITER)	1
	INTEGER PESP(M),ITM(M)	2
	REAL A(N),B(N),C(N)	3
	DO 1 I=1,M	4
	IF (ITM(I).EQ.0) GO TO 1	5
	CALL BSCOR (BTHET,BVAR,B(I),A(I),C(I),RESP(I))	6
1	CONTINUE	7
	CALL NOSTAT (M,ITM,A,B,C,BTHET,TINFO,EXPTOT)	8
	ITER=0	9
	RETURN	10
	END	11
	SUBROUTINE BSCOR (BTHET,BVAR,DIF,DIS,GUESP,IRFSP)	1
	D=(DIF-BTHET)/SQRT(2.0*(1.0/DIS**2+BVAR))	2
	ERFD=ERFNP(D)	3
	EDSQ=EXP(D**2)	4
	IF (EDSQ.EQ.0.0) RETURN	5
	EDSQI=1.0/EDSQ	6
	XKINV=0.5*(1.0-ERFD)	7
	XLINV=GUESP*(1.0-GUESP)*XKINV	8
	IF ((XLINV.FQ.0.0).OR.(XKINV.EQ.0.0)) RETURN	9
	XL=1.0/XLINV	10
	IF (IKESP.NE.1) GO TO 1	11
	S=0.398942*(SQRT(BVAR)/SQRT(1.0+(1.0/DIS**2)/BVAR))*(1.0/XKINV)*ED	12
	1SQI	13
	T=1.0-1.772454*D*EDSQ*(1.0-ERFD)	14
	BTHET=BTHET+(1.0-GUESP)*XKINV*XL*S	15
	BVAR=BVAR-(1.0-GUESP)*XKINV*XL*S**2*(T-GUESP*XL)	16

```

1      RETURN
      HTHET=HTHET-0.797395*(BVAR/SQRT(1.0/DIS**2+BVAR))*EDSQI*(1.0/(1.0+
18      1ERFD))
19      PART1=1.128379/(1.0+(1.0/DIS**2)*(1.0/BVAR))
20      PART2=1.0/(EDSQ*(1.0+ERFD))**2
21      PART3=0.564190+0*EDSQ*(1.0+ERFD)
22      BVAR=BVAR*(1.0-PART1*PART2*PART3)
23      RETURN
24      END
25      REAL FUNCTION ERFNP (X)
1      DATA A1/0.254830/
2      DATA A2/-0.284497/
3      DATA A3/1.421414/
4      DATA A4/-1.453152/
5      DATA A5/1.061405/
6      DATA P/0.327591/
7      ERFNP=0.0
8      IF (X.EQ.0.0) RETURN
9      S=SIGN(1.0,X)
10     Y=ABS(X)
11     IF (Y.LT.6.0) GO TO 1
12     ERFNP=ES
13     RETURN
14     Y2=Y*Y
15     T=1.0/(1.0+P*Y)
16     AT=((A1+(A2+(A3+(A4+A5*T)*T)*T)*T)*T)
17     EAT=AT/EXP(Y2)
18     ERFNP=(1.0-EAT)*ES
19     RETURN
20     END
21     SUBROUTINE MAXLK (M,ITM,RESP,N,A,B,C,MAX,EPS,IFAIL,SDRV,THETA,TINF
10,EXPTOT,NUMITS,SEM)
2     EXTERNAL FDDLOG,SDDLOG
3     INTEGER RESP(M)
4     DIMENSION A(N), B(N), C(N), ITM(M)
5     C*** USES MAXIMUM LIKELIHOOD LOGISTIC SCORING ALGORITHM AND RESPONSE
6     C*** MODEL
7     C*** HISSECTION IS USED TO PROVIDE THE INITIAL GUESS FOR THE
8     C*** NEWTON-RAPHSON METHOD
9     CALL BISECT (FDDLOG,RESP,A,B,C,M,ITM,5,GUESS)
10    C
11    CALL NEWTRAP (FDDLOG,SDDLOG,RESP,A,B,C,M,ITM,MAX,EPS,NUMITS,GUESS,
12    1THETA,SDRV,IFAIL)
13    C
14    IF (IFAIL.EQ.1) 1,2
15    C*** NEWTON RAPHSON DID NOT CONVERGE
16    1 CALL NWTRR (THETA,SDRV,SEM,TINFO,EXPTOT)
17    RETURN
18    C
19    2 CALL LGSTAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
20    SEM=1.0/SQRT(ABS(SDRV))
21    RETURN
22    END
23    FUNCTION FDDLOG (RESP,ITM,A,B,C,M,THETA)
1     INTEGER RESP(M),RIGHT
2     DIMENSION A(M), B(M), C(M), ITM(M)
3     DATA XMAX,XMIN/200.0,-200.0/
4     DATA D,RIGHT/1.7,1/
5     C*** CALCULATES FIRST DERIVATIVE OF LOG-LIKELIHOOD FUNCTION OF A
6     C*** RESPONSE VECTOR FOR THE LOGISTIC MODEL
7     SUM=C.0
8     DO 1 I=1,M
9     IF (ITM(I).EQ.0) GO TO 1
10    X=D*A(I)*(THETA-H(I))
11    IF (X.LT.XMIN) X=XMIN
12    IF (X.GT.XMAX) X=XMAX
13

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EXF=EXP(X)
AE=A(I)*EXF
SUM=SUM-AE/(EXF+1.0)
IF (RESP(I).NE.RIGHT) GO TO 1
CE=C(I)+EXF
SUM=SUM+AE/CE
1 CONTINUE
FOOLOG=-1.7*SUM
RETURN
END
FUNCTION SDDLOG (RESP,ITM,A,B,C,M,THETA)
INTEGER RESP(M),RIGHT
DIMENSION ITM(M), A(M), B(M), C(M)
DATA XMAX,XMIN/200.0,-200.0/
DATA D,RIGHT/1.7,1/
C*** CALCULATES SECOND DERIVATIVE OF LOG-LIKELIHOOD FUNCTION
C*** OF A RESPONSE VECTOR FOR THE LOGISTIC MODEL
SUM=0.0
DO 1 I=1,M
IF (ITM(I).EQ.0) GO TO 1
X=0*A(I)*(THETA-B(I))
IF (X.LT.XMIN) X=XMIN
IF (X.GT.XMAX) X=XMAX
EXF=EXP(X)
AE=A(I)*EXF
SUM=SUM-A(I)*AE/((1.0+EXF)*(1.0+EXF))
IF (RESP(I).NE.RIGHT) GO TO 1
CE=C(I)+EXF
SUM=SUM+A(I)*C(I)*AE/(CE*CE)
1 CONTINUE
SDDLOG=-2.89*SUM
RETURN
END
SUBROUTINE BISECT (F1,RESP,A,B,C,M,ITM,NITER,BMID)
INTEGER RESP(M)
DIMENSION A(M), B(M), C(M), ITM(M)
C*** CALCULATES APPROXIMATE ROOT OF F1 BY BISECTION;
C*** BISECTING NITER (NUMBER OF ITERATIONS) TIMES.
C*** BMID IS BEST CURRENT GUESS AT ROOT THETA
C
C*** INITIALIZE LEFT BOUND AND F1(BOUND) AND RIGHT BOUND F1(BOUND)
BL=-5.0
BR=5.0
BMID=0.0
FL=F1(RESP,ITM,A,B,C,M,BL)
FR=F1(RESP,ITM,A,B,C,M,BR)
C*** TEST FOR NO ROOT IN INTERVAL--RETURN IF NO SOLUTION
IF ((TL*TR).GT.0.0) RETURN
C
C*** NOW CALCULATE BISECTIONS NITER TIMES
DO 3 I=1,NITER
TMID=F1(RESP,ITM,A,B,C,M,BMID)
IF ((TMID*TL).GT.0.0) GO TO 1
C*** REPLACE RIGHT BOUND WITH BMID
BR=BMID
GO TO 2
C*** REPLACE LEFT BOUND WITH BMID
1 TL=TMID
BL=BMID
C*** FIND NEW MIDPOINT BMID
2 BMID=(BL+BR)/2.0
3 CONTINUE
RETURN
END
SUBROUTINE NEWTRAP (F1,F2,RESP,A,B,C,M,ITM,NITER,EPS,NUMITS,GUESS,
1 THETA,SORV,IFAIL)
2

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INTEGER RESP(M)
DIMENSION A(M), B(M), C(M), ITM(M)
C*** CALCULATES THE ROOT OF F1 GIVEN ITS FIRST DERIVATIVE F2
C*** AND AN INITIAL GUESS USING NEWTON-RAPHSON METHOD
C*** THETA IS APPR. TO THE ROOT: SDRV IS F2(THETA)
NUMITS=0
THETA=GUESS
C*** LOOP UNTIL ERR<EPS OR NUMBER OF ITERATIONS BECOMES TOO LARGE
1 FDRV=F1(RRESP,ITM,A,B,C,M,THETA)
SDRV=F2(RRESP,ITM,A,B,C,M,THETA)
ERR=FDRV/SDRV
THETA=THETA-ERR
NUMITS=NUMITS+1
C*** EXIT LOOP CRITERION
IF ((NUMITS.LT.NITER).AND.(ABS(ERR).GT.EPS)) GO TO 1
C*** END LOOP. TEST FOR CONVERGENCE AND SET IFAIL
IFAIL=0
IF (ABS(ERR).LT.EPS) RETURN
C
C*** NEWTON RAPHSON METHOD DOES NOT CONVERGE
IFAIL=1
RETURN
END
SUBROUTINE NWTRK (THETA,SFORM,SEM,TINFO,EXPTOT)
C*** SETS ERROR VALUES FOR THE CASE IN WHICH NEWTON RAPHSON FAILS
C*** TO CONVERGE
THETA=-99.99
SFORM=-99.99
SEM=-99.99
TINFO=-99.99
EXPTOT=-99.99
RETURN
END
SUBROUTINE LGSTAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
DIMENSION A(M), B(M), C(M), ITM(M)
DATA XMAX,XMIN/12.0,-12.0/
TINFO=0.0
EXPTOT=0.0
KOUNT=0
C
DO 1 I=1,M
IF (ITM(I).EQ.0) GO TO 1
KOUNT=KOUNT+1
ARGU=-1.7*A(I)*(THETA-B(I))
IF (ARGU.GT.XMAX) ARGU=XMAX
IF (ARGU.LT.XMIN) ARGU=XMIN
P=C(I)+((1.0-C(I))*(1.0/(1.0+EXP(ARGU))))
Q=1.0-P
EARG=EXP(-ARGU)
PPRIME=EARG/((1.0+EARG)*(1.0+EARG))
PPRIME=PPRIME*(1.0-C(I))*A(I)*1.7
TINFO=TINFO+(PPRIME*PPRIME)/(P*Q)
EXPTOT=EXPTOT+P
1 CONTINUE
EXPTOT=EXPTOT/FLOAT(KOUNT)
RETURN
END
SUBROUTINE MAYLNO (RESP,ITM,M,N,A,B,C,MAX,EPS,THETA,SDRV,IFAIL,TIN
1FO,EXPTOT,NUMITS,SEM)
EXTERNAL FDRGV,SDRGV
INTEGER RESP(M)
DIMENSION ITM(N), A(N), B(N), C(N)
C*** USES MAXIMUM LIKELIHOOD NORMAL OGIVE SCORING ALGORITHM AND
C*** RESPONSE VECTOR
C*** BISECTION IS USED TO PROVIDE THE INITIAL GUESS FOR THE
C*** NEWTON RAPHSON METHOD

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C      CALL BISECT (FONOGV,RESP,A,B,C,M,ITM,5,GUESS)
C      CALL NEWTRAP (FONOGV,SDNOGV,RESP,A,B,C,M,ITM,MAX,EPS,NUMITS,GUESS,
1THETA,SDRV,IFAIL)
      IF (IFAIL.EQ.1) 1,2
C***  NEWTON RAPHSON DID NOT CONVERGE
1      CALL MWERR (THETA,SDRV,SEM,TINFO,EXPTOT)
      RETURN
C
2      CALL NOSTAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
      SDRV=ABS(SDRV)
      SEM=1.0/SQRT(SDRV)
      RETURN
END
FUNCTION FONOGV (RESP,ITM,A,B,C,M,THETA)
  INTEGER RESP(M),RIGHT
  DIMENSION A(M), B(M), C(M), ITM(M)
  DATA PI,RIGHT/3.141592,1/
  DATA XMAX,XMIN/7.0,-7.0/
C***  CALCULATES FIRST DERIVATIVE OF LOG-LIKELIHOOD FUNCTION OF
C***  A RESPONSE VECTOR FOR THE NORMAL OGIVE MODEL
C
      SUM=0.0
      ROOTPI=1.0/SQRT(2.0*PI)
      DO 2 I=1,M
      IF (ITM(I).EQ.0) GO TO 2
      TEMP=A(I)*(THETA-B(I))
      IF (TEMP.GT.XMAX) TEMP=XMAX
      IF (TEMP.LT.XMIN) TEMP=XMIN
      X=-(TEMP*TEMP)/2.0
      DENOM1=ROOTPI*A(I)*(1.0-C(I))*EXP(X)
      DENOM=C(I)+(1.0-C(I))*CDFN(TEMP)
      IF (RESP(I).EQ.RIGHT) GO TO 1
      DENOM=- (1.0-DENOM)
1      SUM=SUM+(DENOM1/DENOM)
2      CONTINUE
      FONOGV=SUM
      RETURN
END
FUNCTION SDNOGV (RESP,ITM,A,B,C,M,THETA)
  INTEGER RESP(M),RIGHT
  DIMENSION A(M), B(M), C(M), ITM(M)
  DATA PI,RIGHT/3.141592,1/
  DATA XMAX,XMIN/7.0,-7.0/
C***  CALCULATES SECOND DERIVATIVE OF LOG-LIKELIHOOD FUNCTION
C***  OF A RESPONSE VECTOR FOR THE NORMAL OGIVE MODEL
C
      SUM=0.0
      ROOTPI=1.0/SQRT(2.0*PI)
      DO 2 I=1,M
      IF (ITM(I).EQ.0) GO TO 2
      TEMP1=A(I)*(THETA-B(I))
      IF (TEMP1.GT.XMAX) TEMP1=XMAX
      IF (TEMP1.LT.XMIN) TEMP1=XMIN
      X=-TEMP1*TEMP1/2.0
      TEMP2=ROOTPI*(1.0-C(I))*A(I)*EXP(X)
      FIRNUM=TEMP2*TEMP2
      SECNUM=TEMP2*A(I)*TEMP1
      SDENOM=C(I)+(1.0-C(I))*CDFN(TEMP1)
      FSDENOM=SDENOM*SDENOM
      IF (RESP(I).EQ.RIGHT) GO TO 1
      FSDENOM=(1.0-SDENOM)*(1.0-SDENOM)
      SDENOM=- (1.0-SDENOM)
1      SUM=SUM- (FIRNUM/FSDENOM) - (SECNUM/SDENOM)
2      CONTINUE

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	SNDGV=SUM	27
	RETURN	28
	END	29
	SUBROUTINE NCSTAT (M,ITM,A,H,C,THETA,TINFO,EXPTOT)	1
	DIMENSION A(M), B(M), C(M), ITM(M)	2
	DATA PI/3.1415927	3
	DATA XMAX,XMIN/7.0,-7.0/	4
	TINFO=0.0	5
	EXPTOT=0.0	6
	KOUNT=0	7
		8
	DO 1 I=1,M	9
	IF (ITM(I).EQ.0) GO TO 1	10
	KOUNT=KOUNT+1	11
	TEMP=A(I)*(TH-THETA-2(I))	12
	IF (TEMP.GT.XMAX) TEMP=XMAX	13
	IF (TEMP.LT.XMIN) TEMP=XMIN	14
	P=C(I)+(1.0-C(I))*CDFN(TEMP)	15
	Q=1.0-P	16
	TEMP=-TEMP*TEMP/2.0	17
	PPRIME=(1.0/SQRT(2.0*PI))*(1.0-C(I))*A(I)*EXP(TEMP)	18
	TINFO=TINFO+(PPRIME*PPRIME)/(P*Q)	19
	EXPTOT=EXPTOT+P	20
1	CONTINUE	21
	EXPTOT=EXPTOT/KOUNT	22
	RETURN	23
	END	24

APPENDIX D
ADADSCO FORTRAN PROGRAM LISTING

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PROGRAM ADADSCO (INPUT,OUTPUT,DATA,IPOOL,TAPE1=DATA,TAPE2=IPOOL,TA
1PE3)
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      DIMENSION ITEM(600), A(600), B(600), C(600), KEY(600), IREJ(80), I
      1FORM2(8), IRAN(80), INADS(80), IRESP(80), ADM(80), BDM(80), CDM(80
      2), DESC(24), NAME(2), IFORM1(8)
      INTEGER OPT1,OPT2,OPT3,OPT4
      REAL ITOT
      N=NC=0

C*****
C
C READ OPTIONS AND PROGRAM PARAMETER FROM INPUT FILE, DATA IS ON TAPE 2
C
C*****
      IPOOL=2
      READ 20, INUP,MMAX,OPT1,OPT2,OPT3,OPT4,TS,TSS,AMAX,BMIN,BMAX,CMAX,
      1IFLAG,IOMIT
      READ 22, (IFORM1(I),I=1,8)
C      IFORM1 IS THE VARIABLE FORMAT FOR THE ITEM POOL
      READ (IPOOL,IFORM1) (ITEM(I),A(I),B(I),C(I),KEY(I),I=1,INUP)
C*****
C
C
C START READING THE SPECIFIC DATA (SPECIFIC FOR THE RUN) FROM THE INPUT
C INAD IS THE ITEM IDS ADMINISTERED
C IREJ IS THE REJECTED ITEM IDS
C IRESP IS THE RESPONSE VECTOR
C
C
C*****
      READ 21, MNUM,(IREJ(I),I=1,MNUM)
      READ 22, (IFORM2(I),I=1,8)
C      IFORM2 IS THE VARIABLE FORMAT FOR THE SUBJECT DATA
C
      READ 24, DESC
      PRINT 23, INUP,MMAX,IOMIT,IFLAG,OPT1,OPT2,OPT3,OPT4,TS,TSS,AMAX,BM
      1AX,BMIN,CMAX,IFORM1,IFORM2,DESC
C*****
C
C
C READ A SUBJECT FROM TAPE 1 CALCULATE THETA, LOOP BACK TO 5 ETC.
C
C
C*****
1      READ (1,IFORM2) ID,NAME,M,(IRESP(I),I=1,MMAX),(INADS(I),I=1,MMAX)
      M=MIN0(M,MMAX)
      IO=UNIT(1)
C      CHECK THE END OF FILE ON DATA FILE
C
      IF (IO.LE.0) GO TO 2
      PRINT 25, IO
2      IF (IO.EQ.0) GO TO 19
      N=N+1
      ITOT=0.0
C      SET THE ITEM ID TO ZERO FOR THE OMISSIONS (THAT IS READ IN FRO
C
C      AND SET THE RESPONSE VECTOR TO 1 IF THE ANSWER IS CORRECT
C
      DO 5 I=1,M
      SET THE ITEM IDS IN IREJ TO ZERO
      IF (MNUM.EQ.0) GO TO 4
      DO 3 IJ=1,MNUM
      IF (INADS(I).NE.IREJ(IJ)) GO TO 3
      INADS(I)=0
      GO TO 5
3      CONTINUE
4      CONTINUE
      IF (IRESP(I).EQ.IOMIT) INADS(I)=0

```

```

      IF (INADS(I).EQ.0) GO TO 5
      CALL SEARCH (INUP,INADS(I),ADM(I),BDM(I),COM(I),KKE,ITEM,A,B,C,KEY
1, ID)
C      IF THE FLAG IFLAG IS NOT ZERO IT IS TAKEN TO BE THE DUMMY KEY
C      IF IT IS ZERO THEN KEY IS READ FROM THE POOL AN LEFT IN KKE
      IF (IFLAG.NE.0) KKE=IFLAG
      IRES=0
      IF (IKRESP(I).NE.0,KKE) IRFS=1
      IRESP(I)=IRFS
5      CONTINUE
C*****
C      *
C      *
CIN THE NEXT DO LOOP THE ITEM PARAMETERS CORRESPONDING TO THE ITEMS
CIN INAD ARE RETRIVED FROM A,B,C, AND LOADED INTO ADM,BDM,COM RESP.
CTHE ENTRIES IN THE ADM,BDM,COM ARE ZEROED FOR THE CASE OF ZERO ITEM
CID IN THE INAD
C      *
C      *
C*****
C      IF OPTION 3 IS ON THE PARAMETERS A,B,C ARE CONSTRAINED WITHIN B
C      OF AMAX,AMIN,BMAX,BMIN,CMAX
      IF (OPT3.EQ.0) GO TO 7
      DO 6 I=1,M
      IF (INADS(I).EQ.0) GO TO 6
      IF ((ADM(I).GT.AMAX).OR.(OPT3.EQ.3)) ADM(I)=AMAX
      IF (BDM(I).LT.BMIN) BDM(I)=BMIN
      IF (BDM(I).GT.BMAX) BDM(I)=BMAX
      IF ((COM(I).GT.CMAX).OR.(OPT3.EQ.2)) COM(I)=CMAX
6      CONTINUE
C      OPTION 1 WILL PRINT THE SPECIFIC DATA IF ITS ON
C
7      CONTINUE
      IF ((OPT1.EQ.0).OR.(OPT1.GT.10)) GO TO 8
      OPT1=OPT1+1
      PRINT 26, ID, NAME, (INADS(I), IRESP(I), ADM(I), BDM(I), COM(I), II=
11, M)
8      CONTINUE
      ITINADS=0
      DO 9 KK=1,M
      ITOT=ITOT+IRESP(KK)
9      IF (INADS(KK).EQ.0) ITINADS=ITINADS+1
      KL=M-ITINADS
      ITOT=ITOT/FLOAT((KL))
      IF (ITOT.EQ.0) 10,11
10     PRINT 27, NAME, ID
      IF (OPT4.EQ.3) GO TO 13
      F=-10.0
      SFORM=0.0
      FINFO=0.0
      EXPTOT=0.0
      SEM=0.0
      ITER=0
      IKL=KL
      GO TO 18
11     IF (ITOT.EQ.1.0) 12,13
12     PRINT 31, NAME, ID
      IF (OPT4.EQ.3) GO TO 13
      F=10.0
      SFORM=0.0
      FINFO=0.0
      EXPTOT=0.0
      SEM=0.0
      ITER=0
      IKL=KL
      GO TO 18

```



```

C***** 133
C 134
C 135
C NOW THE DATA IS READY TO MAKE THE CALLS TO THE APPROPRIATE ROUTINE 136
C TO ESTIMATE THE THETA. OPTIN 4 WILL DETERMINE THE METHOD BY WHICH 137
C THE THETA ESTIMATE WILL BE FOUND 138
C 139
C 140
C***** 141
13 IKL=KL 142
   IF (OPT4-2) 14,15,16 143
14 CALL MAXLNO (IRES,INADS,M,M,ADM,BDM,COM,50,.005,T,SFORM,IFAIL,TIN 144
   INFO,EXPTOT,ITER,SEM) 145
   GO TO 17 146
15 CALL MAXLK (M,INADS,IRES,M,ADM,BDM,COM,50,.005,IFAIL,SFORM,T,TINF 147
   INFO,EXPTOT,ITER,SEM) 148
C 149
   GO TO 17 150
16 T=TS 151
   SFORM=TSS 152
   CALL BAYES (M,INADS,IRES,M,ADM,BDM,COM,T,SFORM,TINFO,EXPTOT) 153
   ITER=0 154
   SEM=0.0 155
   GO TO 18 156
17 IF (IFAIL.EQ.0) GO TO 18 157
   PRINT 28, NAME,ID 158
C SFORM AND T ARE SET TO -99.99 IN MAXLK IF NOT CONV 159
   NC=NC+1 160
C***** 161
C 162
CWRITE THE SUCCESSFUL RESULTS TO THE FILE TAPE3 163
C 164
C***** 165
18 WRITE (3,29) NAME,ID,ITOT,T,SFORM,IKL,TINFO,EXPTOT,ITER,SEM 166
   GO TO 1 167
19 PRINT 30, N,NC 168
C 169
   STOP 170
C 171
C 172
20 FORMAT (2I4,X,4I1,6F5.2,I2,I2) 173
21 FORMAT (16I5) 174
22 FORMAT (8A10) 175
23 FORMAT (T50,*ADADSCO*,/,T50*====*,////////,T20,*ADAPTIVE DICHOTOM 176
   IUS SCORING WITH THREE PARAMETER MODELS*,////,T40*PSYCHOMETRIC METH 177
   ODS PROGRAM*,/,T40*DEPARTMENT OF PSYCHOLOGY*,/,T40*UNIVERSITY OF M 178
   INNESOTA*,/,T40*MPLS. MINN. 55455*,/,T20*INUP*,T27*=*I5,/,T20, 179
   4*MMAX*,T27*=*I5,/,T20,*IDMIT*,T27*=*I5,/,T20*IFLAG*,T27*=*I5,/,T 180
   520*OPT1*,T27*=*I5,/,T20*OPT2*,T27*=*I5,/,T20*OPT3*,T27*=*I5,/,T20* 181
   6OPT4*,T27*=*I5,/,T20*IS*,T27*=*F5.2,/,T20*TSS*,T27*=*F5.2,/,T20*A 182
   7MAX*,T27*=*F5.2,/,T20,*RMAX*,T27*=*F5.2,/,T20*PMIN*,T27*=*F5.2, 183
   *,T20*CMAX*,T27*=*F5.2,/,T20,*VARIABLE FORMAT FOR POOL=*8A10,/,T20 184
   9,*VARIABLE FORMAT FOR DATA=*8A10,/,T20,8A10,/,T20,8A10,/,T20,8A10, 185
   F/) 186
24 FORMAT (8A10) 187
25 FORMAT (10X,*PARITY ERROR ON TAPE*,90X,I2) 188
26 FORMAT (10X,A9,2A10,/, (1X,I4,2X,I2,2X,3F10.2)) 189
27 FORMAT (10X,* SUBJECT *,2A10,*ID= *,A9,*HAS NO RIGHT ANSWERS*) 190
28 FORMAT (10X,* MAXIMUM LIKELIHOOD ESTIMATION DOES NOT CONVERGE*,* F 191
   OR THE SUBJECT = *,2A10,* ID= *,A9) 192
29 FORMAT (X,2A10,A9,F5.2,2F7.2,I4,2F7.2,I4,F7.2) 193
30 FORMAT (10X,* CASES READ=*,I5,* CASES NOT CONVERGED=*,I5) 194
31 FORMAT (10X,* SUBJECT *,2A10,*ID= *,A9,*HAS ALL ANSWERS RIGHT*) 195
   END 196
SUBROUTINE SEARCH (INUP,ID,A,B,C,KEY,ITM,AP,BP,CP,KEYP,IDNU4) 1
DIMENSION AP(INUP), BP(INUP), CP(INUP), KEYP(INUP), ITM(INUP) 2

```

```

      INTEGER FLAG
      DO 1 I=1,INUP
      IF (ID.NE.ITM(I)) GO TO 1
      A=AP(I)
      B=BP(I)
      C=CP(I)
      KEY=KEYP(I)
      CALL PCHECK (A,B,C,ID,INUM)
      RETURN
1     CONTINUE
      PRINT 2, ID,INUM
      ID=J
      RETURN
C
C
C
2     FORMAT (10X,* ITEM =*,I4,* IS NOT IN THE POOL FOR SUBJECT ID =*,A9
1)
      END
      SUBROUTINE PCHECK (A,B,C,ID,INUM)
C*** CHECK WHETHER OR NOT ITEM PARAMETERS ARE VALID
C*** IF NOT, ERROR MESSAGE IS PRINTED
C
      IF (A.LE.0.0) PRINT 1, ID,A,INUM
      IF ((-5.0.GT.B).OR.(B.GT.5.0)) PRINT 2, ID,B,INUM
      IF ((0.0.GT.C).OR.(C.GT.1.0)) PRINT 3, ID,C,INUM
      RETURN
C
C
C
1     FORMAT (10X,*ITEM =*,I4,* HAS THE INVALID A PARAMETER OF *,F5.2,*
1     A MUST BE GREATER THAN 0.0*,/10X,*ERROR FOUND *,*FOR THE SUBJECT
2 WITH ID =*,A9)
2     FORMAT (10X,*ITEM =*,I4,* HAS THE EXTREME B PARAMETER OF *,F5.2,5X
1,*ERROR FOUND FOR THE SUBJECT WITH ID =*,A9)
3     FORMAT (10X,*ITEM =*,I4,* HAS THE INVALID C PARAMETER OF *,F5.2,*
1     C MUST BE BETWEEN 0.0 AND 1.0*,/10X,*ERROR FOUND *,*FOR THE SUBJ
2ECT WITH ID =*,A9)
      END
      SUBROUTINE BAYES (M,ITM,RESP,N,A,B,C,BTHET,BVAR,TINFO,EXPTOT)
      INTEGER RESP(M),ITM(M)
      REAL A(N),B(N),C(N)
      DO 1 I=1,M
      IF (ITM(I).EQ.0) GO TO 1
      CALL BSCOR (BTHET,BVAR,I(I),A(I),C(I),RESP(I))
1     CONTINUE
      CALL NOSTAT (M,ITM,A,B,C,BTHET,TINFO,EXPTOT)
      RETURN
      END
      SUBROUTINE BSCOR (BTHET,BVAR,DIF,DIS,GUESP,IRESP)
      D=(DIF-BTHET)/SQRT(2.0*(1.0/DIS**2+BVAR))
      ERFD=ERFNP(D)
      EDSQ=EXP(D**2)
      IF (EDSQ.EQ.0.0) RETURN
      EDSQ=1.0/EDSQ
      XKINV=0.5*(1.0-ERFD)
      XLINV=GUESP+(1.0-GUESP)*XKINV
      IF ((XLINV.EQ.0.0).OR.(XKINV.EQ.0.0)) RETURN
      XL=1.0/XLINV
      IF (IRESP.NE.1) GO TO 1
      S=0.398942*(SQRT(BVAR)/SQRT(1.0+(1.0/DIS**2)/BVAR))*(1.0/XKINV)*ED
1SQI
      T=1.0-1.72454*D*EDSQ*(1.0-ERFD)
      BTHET=BTHET+(1.0-GUESP)*XKINV*XL*S
      BVAR=BVAR-(1.0-GUESP)*XKINV*XL*S**2*(T-GUESP*XL)

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```

1      RETURN
      BTHET=BTHET-0.797885*(BVAR/SQRT(1.0/DIS**2+BVAR))*EDSQI*(1.0/(1.0+
1ERFD))
      PART1=1.128379/(1.0+(1.0/DIS**2)*(1.0/BVAR))
      PART2=1.0/(EDSQ*(1.0+ERFD)**2
      PART3=0.564190+0*EDSQ*(1.0+ERFD)
      BVAR=BVAR*(1.0-PART1*PART2*PART3)
      RETURN
      END
      REAL FUNCTION ERFNP (X)
      DATA A1/0.254830/
      DATA A2/-0.284497/
      DATA A3/1.421414/
      DATA A4/-1.453152/
      DATA A5/1.061405/
      DATA P/0.327591/
      ERFNP=0.0
      IF (X.EQ.0.0) RETURN
      ES=SIGN(1.0,X)
      Y=ABS(X)
      IF (Y.LT.6.0) GO TO 1
      ERFNP=ES
      RETURN
1     Y2=Y*Y
      T=1.0/(1.0+P*Y)
      AT=((A1+(A2+(A3+(A4+A5*T)*T)*T)*T)*T)
      EAT=AT/EXP(Y2)
      ERFNP=(1.0-EAT)*ES
      RETURN
      END
      SUBROUTINE MAXLK (M,ITM,RESP,N,A,B,C,MAX,EPS,IFAIL,SDRV,THETA,TINF
10,EXPTOT,NUMITS,SEM)
      EXTERNAL FODLOG,SODLOG
      INTEGER RESP(M)
      DIMENSION A(N), B(N), C(N), ITM(M)
C***  USES MAXIMUM LIKELIHOOD LOGISTIC SCORING ALGORITHM AND RESPONSE
C***  MODEL
C***  BISECTION IS USED TO PROVIDE THE INITIAL GUESS FOR THE
C***  NEWTON-RAPHSON METHOD
      CALL BISECT (FODLOG,RESP,A,B,C,M,ITM,5,GUESS)
C
      CALL NEWTRAP (FODLOG,SODLOG,RESP,A,B,C,M,ITM,MAX,EPS,NUMITS,GUESS,
1THETA,SDRV,IFAIL)
C
      IF (IFAIL.EQ.1) 1,2
C***  NEWTON RAPHSON DID NOT CONVERGE
1     CALL NWTRP (THETA,SDRV,SEM,TINFO,EXPTOT)
      RETURN
C
2     CALL LGSTAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
      SEM=1.0/SQRT(AHS(SDRV))
      RETURN
      END
      FUNCTION FODLOG (RESP,ITM,A,B,C,M,THETA)
      INTEGER RESP(M),RIGHT
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA XMAX,XMIN/200.0,-200.0/
      DATA D,RIGHT/1.7,1/
C***  CALCULATES FIRST DERIVATIVE OF LOG-LIKELIHOOD FUNCTION OF A
C***  RESPONSE VECTOR FOR THE LOGISTIC MODEL
      SUM=0.0
      DO 1 I=1,M
      IF (ITM(I).EQ.0) GO TO 1
      X=D*A(I)*(THETA-B(I))
      IF (X.LT.XMIN) X=XMIN
      IF (X.GT.XMAX) X=XMAX

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```

      EXF=EXP(X)
      AE=A(I)*EXF
      SUM=SUM-AE/(EXF+1.0)
      IF (RESP(I).NE.RIGHT) GO TO 1
      CE=C(I)+EXF
      SUM=SUM+AE/CE
1     CONTINUE
      SDLOG=-1.7*SUM
      RETURN
END
FUNCTION SDLOG (RESP,ITM,A,B,C,M,THETA)
  INTEGER RESP(M),RIGHT
  DIMENSION ITM(M), A(M), B(M), C(M)
  DATA XMAX,XMIN/200.0,-200.0/
  DATA D,RIGHT/1.7,1/
C*** CALCULATES SECOND DERIVATIVE OF LOG-LIKELIHOOD FUNCTION
C*** OF A RESPONSE VECTOR FOR THE LOGISTIC MODEL
  SUM=0.0
  DO 1 I=1,M
    IF (ITM(I).EQ.0) GO TO 1
    X=D*A(I)*(THETA-B(I))
    IF (X.LT.XMIN) X=XMIN
    IF (X.GT.XMAX) X=XMAX
    EXF=EXP(X)
    AE=A(I)*EXF
    SUM=SUM-A(I)*AE/((1.0+EXF)*(1.0+EXF))
    IF (RESP(I).NE.RIGHT) GO TO 1
    CE=C(I)+EXF
    SUM=SUM+A(I)*C(I)*AE/(CE*CE)
1   CONTINUE
  SDLOG=-2.89*SUM
  RETURN
END
SUBROUTINE BISECT (F1,RESP,A,B,C,M,ITM,NITER,BMID)
  INTEGER RESP(M)
  DIMENSION A(M), B(M), C(M), ITM(M)
C*** CALCULATES APPROXIMATE ROOT OF F1 BY BISECTIONS
C*** BISECTING NITER (NUMBER OF ITERATIONS) TIMES.
C*** BMID IS BEST CURRENT GUESS AT ROOT THETA
  C
C*** INITIALIZE LEFT BOUND AND F1(BOUND) AND RIGHT BOUND F1(BOUND)
  BL=-5.0
  BR=5.0
  BMID=0.0
  FL=F1(RESP,ITM,A,B,C,M,BL)
  FR=F1(RESP,ITM,A,B,C,M,BR)
C*** TEST FOR NO ROOT IN INTERVAL--RETURN IF NO SOLUTION
  IF ((TL*TR).GT.0.0) RETURN
  C
C*** NOW CALCULATE BISECTIONS NITER TIMES
  DO 3 I=1,NITER
    TMID=F1(RESP,ITM,A,B,C,M,BMID)
    IF ((TMID*TL).GT.0.0) GO TO 1
C*** REPLACE RIGHT BOUND WITH BMID
    BR=BMID
    GO TO 2
C*** REPLACE LEFT BOUND WITH BMID
1   TL=TMID
    BL=BMID
C*** FIND NEW MIDPOINT BMID
2   BMID=(BL+BR)/2.0
3   CONTINUE
  RETURN
END
SUBROUTINE NEWTRAP (F1,F2,RESP,A,B,C,M,ITM,NITER,EPS,NUMITS,GUESS,
  1THETA,SDRV,IFAIL)

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```

      INTEGER RESP(M)
      DIMENSION A(M), R(M), C(M), ITM(M)
C*** CALCULATES THE ROOT OF F1 GIVEN ITS FIRST DERIVATIVE F2
C*** AND AN INITIAL GUESS USING NEWTON-RAPHSON METHOD
C*** THETA IS APPR. TO THE ROOT; SORV IS F2(THETA)
      NUMITS=0
      THETA=GUESS
C*** LOOP UNTIL ERR<EPS OR NUMBER OF ITERATIONS BECOMES TOO LARGE
1   FORV=F1(RSP,ITM,A,R,C,M,THETA)
      SORV=F2(RSP,ITM,A,R,C,M,THETA)
      ERR=FORV/SORV
      THETA=THETA-ERR
      NUMITS=NUMITS+1
C*** EXIT LOOP CRITERION
      IF ((NUMITS.LT.NITER).AND.(ABS(ERR).GT.EPS)) GO TO 1
C*** END LOOP. TEST FOR CONVERGENCE AND SET IFAIL
      IFAIL=0
      IF (ABS(ERR).LT.EPS) RETURN
C
C*** NEWTON RAPHSON METHOD DOES NOT CONVERGE
      IFAIL=1
      RETURN
      END
      SUBROUTINE WHERE (THETA,SEDM,SEM,TINFO,EXPTOT)
C*** SET PARAM VALUES FOR THE CASE IN WHICH NEWTON RAPHSON FAILS
C*** TO CONVERGE
      THETA=-99.99
      SEDM=-99.99
      SEM=-99.99
      TINFO=-99.99
      EXPTOT=-99.99
      RETURN
      END
      SUBROUTINE LGSTAT (M,ITM,A,R,C,THETA,TINFO,EXPTOT)
      DIMENSION A(M), R(M), C(M), ITM(M)
      DATA XMAX,XMIN/12.0,-12.0/
      TINFO=0.0
      EXPTOT=0.0
      KOUNT=0
C
      DO 1 I=1,M
        IF (ITM(I).EQ.0) GO TO 1
        KOUNT=KOUNT+1
        ARG=-1.7*A(I)*(THETA-R(I))
        IF (ARGU.GT.XMAX) ARGU=XMAX
        IF (ARGU.LT.XMIN) ARGU=XMIN
        P=C(I)+(1.0-C(I))*(1.0/(1.0+EXP(A-60)))
        Q=1.-P
        FARG=EXP(-ARGU)
        PRIME=FARG/((1.0+FARG)*(1.0+P*Q))
        PRIME=PRIME*(1.0-C(I))*A(I)*1.7
        TINFO=TINFO+(PRIME*PRIME)/(6.*Q)
        EXPTOT=EXPTOT+P
1      CONTINUE
      EXPTOT=EXPTOT/KOUNT
      RETURN
      END
      SUBROUTINE MAXENO (RESP,ITM,M,N,A,R,C,MAX,EPS,THETA,SORV,IFAIL,TIN
      FO,EXPTOT,NUMITS,SEM)
      EXTERNAL F0NOGV,S0NOGV
      INTEGER RESP(M)
      DIMENSION ITM(N), A(N), R(N), C(N)
C*** USES MAXIMUM LIKELIHOOD NORMAL GIVE SCORING ALGORITHM AND
C*** RESPONSE VECTOR
C*** MISERION IS USED TO PROVIDE THE INITIAL GUESS FOR THE
C*** NEWTON RAPHSON METHOD

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```

C      CALL BISECT (FONOGV,RESP,A,B,C,M,ITM,5,GUESS)
C
C      CALL NEWTRAP (FONOGV,SDNOGV,RESP,A,B,C,M,ITM,MAX,FPS,NUMITS,GUESS,
1THETA,SDRV,IFAIL)
      IF (IFAIL.EQ.1) 1,2
C*** NEWTON RAPHSON DID NOT CONVERGE
1      CALL FMTERR (THETA,SDRV,SEM,TINFO,EXPTOT)
      RETURN
C
2      CALL NOSIAT (M,ITM,A,B,C,THETA,TINFO,EXPTOT)
      SDRV=ABS(SDRV)
      SEM=1.0/SQRT(SDRV)
      RETURN
      END
      FUNCTION FONOGV (RESP,ITM,A,B,C,M,THETA)
      INTEGER RESP(M),RIGHT
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA PI,RIGHT/3.141592,1/
      DATA XMAX,XMIN/7.0,-7.0/
C*** CALCULATES FIRST DERIVATIVE OF LOG-LIKELIHOOD FUNCTION OF
C*** A RESPONSE VECTOR FOR THE NORMAL OGIVE MODEL
C
      SUM=0.0
      ROOTPI=1.0/SQRT(2.0*PI)
      DO 2 I=1,M
      IF (ITM(I).EQ.0) GO TO 2
      TEMP=A(I)*(THETA-B(I))
      IF (TEMP.GT.XMAX) TEMP=XMAX
      IF (TEMP.LT.XMIN) TEMP=XMIN
      X=-(TEMP*TEMP)/2.0
      DNMRAT=ROOTPI*A(I)*(1.0-C(I))*EXP(X)
      DENOM=C(I)+(1.0-C(I))*COFN(TEMP)
      IF (RESP(I).EQ.RIGHT) GO TO 1
      DENOM=-(1.0-DENOM)
1      SUM=SUM+(DNMRAT/DENOM)
2      CONTINUE
      FONOGV=SUM
      RETURN
      END
      FUNCTION SDNOGV (RESP,ITM,A,B,C,M,THETA)
      INTEGER RESP(M),RIGHT
      DIMENSION A(M), B(M), C(M), ITM(M)
      DATA PI,RIGHT/3.141592,1/
      DATA XMAX,XMIN/7.0,-7.0/
C*** CALCULATES SECOND DERIVATIVE OF LOG-LIKELIHOOD FUNCTION
C*** OF A RESPONSE VECTOR FOR THE NORMAL OGIVE MODEL
C
      SUM=0.0
      ROOTPI=1.0/SQRT(2.0*PI)
      DO 2 I=1,M
      IF (ITM(I).EQ.0) GO TO 2
      TEMP1=A(I)*(THETA-B(I))
      IF (TEMP1.GT.XMAX) TEMP1=XMAX
      IF (TEMP1.LT.XMIN) TEMP1=XMIN
      X=-TEMP1*TEMP1/2.0
      TEMP2=ROOTPI*(1.0-C(I))*A(I)*EXP(X)
      FIRNUM=TEMP2*TEMP2
      SECNUM=TEMP2*A(I)*TEMP1
      SDENOM=C(I)+(1.0-C(I))*COFN(TEMP1)
      FDENOM=SDENOM*SDENOM
      IF (RESP(I).EQ.RIGHT) GO TO 1
      FDENOM=-(1.0-SDENOM)*(1.0-SDENOM)
      SDENOM=-(1.0-SDENOM)
1      SUM=SUM-(FIRNUM/FDENOM)-(SECNUM/SDENOM)
2      CONTINUE

```


	SND06V=SUM	27
	RETURN	28
	END	29
	SUBROUTINE NOSTAT (M, IIM, A, R, C, THETA, TINFQ, EXPTOT)	1
	DIMENSION A(M), R(M), C(M), IIM(M)	2
	DATA XMAX, XMIN / 7.0, -7.0 /	3
	DATA PI / 3.1415927	4
	TINFQ=0.0	5
	EXPTOT=0.0	6
	KOUNT=0	7
C		8
	DO 1 I=1, M	9
	IF (IIM(I).EQ.0) GO TO 1	10
	KOUNT=KOUNT+1	11
	TEMP=A(I)*(THETA-R(I))	12
	IF (TEMP.GT.XMAX) TEMP=XMAX	13
	IF (TEMP.LT.XMIN) TEMP=XMIN	14
	P=C(I)+(1.0-C(I))*CDFN(TEMP)	15
	Q=1.-P	16
	TEMP=-TEMP*TEMP/2.0	17
	PPRIME=(1.)/SQRT(2.)*PI)*(1.-C(I))*A(I)*EXP(TEMP)	18
	TINFQ=TINFQ+(PPRIME*PPRIME)/(P*Q)	19
	EXPTOT=EXPTOT+P	20
1	CONTINUE	21
	EXPTOT=EXPTOT/KOUNT	22
	RETURN	23
	END	24

APPENDIX E

LINPSO FORTRAN PROGRAM LISTING

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PROGRAM LINPSCO (INPUT,OUTPUT,DATA,IPPOOL,TAPE1=DATA,TAPE2=IPPOOL,TA
1PE3,PUNCH)
C*****
C      DEFINITION OF VARIABLES USED IN LINPSCO
C
C      I=THETA: THE ABILITY ESTIMATE
C      ITEM: AN ARRAY OF THE ITEMS IN THE ITEM POOL
C      INUP: THE NUMBER OF ITEMS IN THE ITEM POOL
C      A: AN ARRAY OF THE DISCRIMINATION PARAMETER(S) ASSOCIATED WITH
C      EACH ITEM
C      R: AN ARRAY OF THE DIFFICULTY PARAMETERS ASSOCIATED WITH EACH ITEM
C      MAXCAT: NO. OF RESPONSE CATEGORIES MINUS 1 FOR THE ITEM IN THE
C      ITEM POOL WHICH HAS THE MAXIMUM NO. OF RESPONSE
C      CATEGORIES
C      INAD: AN ARRAY OF THE ITEMS WHICH HAVE BEEN ADMINISTERED TO ALL
C      SUBJECTS
C      M: THE NUMBER OF ITEMS IN THE TEST
C      ADM AND BOM: THE ARRAYS OF PARAMETERS ASSOCIATED WITH THE ITEMS
C      IN INAD
C      INADS: AN ARRAY OF THE ITEMS USED TO CALCULATE THETA FOR A GIVEN
C      SUBJECT (INADS=INAD-(REJECTION AND OMISSIONS) WHERE ID S
C      OF REJECTED OR OMITTED ITEMS ARE SET TO ZERO)
C      IRESP: THE RESPONSE VECTOR OF THE CURRENT SUBJECT
C      NCAT: AN ARRAY OF THE NUMBER OF RESPONSE CATEGORIES MINUS 1 FOR
C      EACH ITEM ADMINISTERED
C      PERCENT: PERCENTAGE OF ITEMS ANSWERED BY A SUBJECT FOR WHICH THE
C      BEST RESPONSE HAS BEEN CHOSEN
C      D: A CONSTANT USED TO CHANGE THE METRIC OF THE LOGISTIC GRADED
C      MODEL. D=1.7 OR 1.0; THE DEFAULT VALUE IS 1.0
C*****
C      COMMON D
C      DIMENSION ITEM(100), A(100,10), R(100,10), INAD(100), IREJ(100), I
C      1RESP(100), ADM(100,10), BOM(100,10), NAME(2), IFORM(8), NCAT(100),
C      2 IFORM1(8), INADS(100), DESC(24)
C      INTEGER OPT1,OPT2,OPT4,ADIM,BDIM
C      N=NC=0
C*****
C      *
C      CREAD OPTIONS AND PROGRAM PARAMETER FROM INPUT FILE DATA IS ON TAPE2 *
C      *
C*****
C      IPPOOL=2
C      READ 30, INUP,M,MAXCAT,OPT1,OPT2,OPT4,D,IOMIT
C      CALL CHKINP (INUP,M,OPT4)
C      IF (D.NE.1.7) D=1.0
C      READ 33, (IFORM1(I),I=1,8)
C      READ 32, (NCAT(I),I=1,M)
C*** INPUT ITEMS AND THEIR PARAMETERS
C      IKI=ADIM(MAXCAT,OPT4)
C      K=BDIM(MAXCAT,OPT4)
C      DO 1 I=1,INUP
C      READ (IPPOOL,IFORM1) ITEM(I),(A(I,JJ),JJ=1,IKI),(R(I,J),J=1,K)
C
C      READ 31, (INAD(I),I=1,M)
C      READ 32, (IREJ(I),I=1,M)
C      READ 33, (IFORM1(I),I=1,8)
C      READ 34, DESC
C      PRINT 35, INUP,M,IOMIT,OPT1,OPT2,OPT4,MAXCAT,D,IFORM1,IFORM,DFSC
C
C*** THOSE ITEM ID S WHICH ARE IN THE REJECTION VECTOR WILL BE SET
C*** TO ZERO. ZERO ITEM ID S WILL BE SKIPPED DURING COMPUTATIONS
C      DO 2 I=1,M
C      IF (IREJ(I).EQ.1) INAD(I)=0
C      IF (OPT2.EQ.1) GO TO 10
C

```

C		67
C***	SEARCH FOR ITEMS ADMINISTERED IN POOL	68
	DO 9 J=1,M	69
	IKI=ADIM(NCAT(J),OPT4)	70
	K=BDIM(NCAT(J),OPT4)	71
	IF (INAD(J).NE.0) GO TO 5	72
C***	BLANK OR REJECTED ITEM ENCOUNTERED	73
	DO 3 L=1,IKI	74
3	ADM(J,L)=0.0	75
	DO 4 L=1,K	76
4	BDM(J,L)=0.0	77
	GO TO 9	78
5	CONTINUE	79
C		80
	DO 4 J=1,INUP	81
	IF (INAD(J).NE.ITEM(I)) GO TO 8	82
	DO 6 L=1,IKI	83
6	ADM(J,L)=A(I,L)	84
	DO 7 L=1,K	85
7	BDM(J,L)=B(I,L)	86
	GO TO 9	87
8	CONTINUE	88
	INAD(J)=0	89
9	CONTINUE	90
	GO TO 13	91
C		92
C***	ALL ITEMS IN POOL HAVE BEEN ADMINISTERED SO POOL DOES NOT	93
C***	NEED TO BE SEARCHED	94
10	DO 10 I=1,M	95
	IKI=ADIM(NCAT(I),OPT4)	96
	K=BDIM(NCAT(I),OPT4)	97
	DO 11 JJ=1,IKI	98
11	ADM(I,JJ)=A(I,JJ)	99
	DO 12 J=1,K	100
	BDM(I,J)=B(I,J)	101
12	CONTINUE	102
C		103
C		104
C***	PUNCH THE ITEM PARAMETERS ESTIMATES CORRESPONDING TO THE ITEMS	105
C***	IN THE TEST	106
13	IF (OPT1.NE.1) GO TO 15	107
	DO 14 I=1,M	108
	IF (INAD(I).EQ.0) GO TO 14	109
	IKI=ADIM(NCAT(I),OPT4)	110
	K=BDIM(NCAT(I),OPT4)	111
	PUNCH 35, INAD(I), IREJ(I), (ADM(I,JJ),JJ=1,IKI)	112
	PUNCH 37, (BDM(I,J),J=1,K)	113
14	CONTINUE	114
C		115
C	PRINT OUT THE ITEMS AND THEIR PARAMETERS	116
15	DO 16 III=1,M	117
	IKI=ADIM(NCAT(III),OPT4)	118
	K=BDIM(NCAT(III),OPT4)	119
	PRINT 39, INAD(III), IREJ(III), (ADM(III,JJ),JJ=1,IKI)	120
16	PRINT 40, (BDM(III,J),J=1,K)	121
	PRINT 43	122
C	*****	123
C***		124
C***	READ SUBJECT FROM TAPE1, CALCULATE THETA, LOOP BACK TO 300 UNTIL*	125
C***	THERE ARE NO MORE SUBJECTS TO SCORE	126
C***		127
C	*****	128
	N=0	129
17	READ (1,IFORM) NAME,IO, (IRESP(I),I=1,M)	130
	IO=UNIT(1)	131
	IF (IO.LE.0) GO TO 18	132

PRINT 38, IO	133
18 IF (IO.EQ.0) GO TO 29	134
C	135
C*** CHECK FOR VALID RESPONSES AND FOR SPECIAL RESPONSE VECTORS	136
CALL CHKRSR (IRES, IOMIT, INAD, NCAT, M, NAME, IO, INADS)	137
C	138
CALL CHKVEC (IRES, INADS, NCAT, M, ICHK, NBEST, NANS)	139
GO TO (19, 20, 21, 23), ICHK	140
C*** ALL ITEMS OMITTED	141
19 PRINT 45, NAME, IO	142
T=-50.00	143
PERCNT=-50.00	144
GO TO 22	145
C*** ALL RESPONSES INCORRECT	146
20 PRINT 46, NAME, IO	147
T=-10.0	148
PERCNT=0.0	149
GO TO 22	150
C*** ALL RESPONSES CORRECT	151
21 PRINT 47, NAME, IO	152
T=10.0	153
PERCNT=1.0	154
C	155
22 SFORM=0.0	156
NUMITS=0	157
TINFO=0.0	158
GO TO 28	159
23 CONTINUE	160
C	161
PERCNT=FLOAT(NBEST)/FLOAT(NANS)	162
C	163
C	164
C*** DETERMINE WHICH MODEL TO USE	165
IF (OPT4-2) 24, 25, 26	166
24 CALL LOGRAD (IRES, ADM, BDM, M, NCAT, INADS, .001, 50, SFORM, IFAIL, T, NUMI	167
ITS, TINFO, SE)	168
GO TO 27	169
25 CALL NOGRAD (IRES, ADM, BDM, M, NCAT, INADS, .001, 50, SFORM, IFAIL, T, NUMI	170
ITS, TINFO, SE)	171
GO TO 27	172
26 CALL NOMLOG (IRES, ADM, BDM, M, NCAT, INADS, .001, 50, SFORM, IFAIL, T, NUMI	173
ITS, TINFO, SE)	174
C	175
C*** OUTPUT RESULTS TO TAPE3	176
27 IF (IFAIL.EQ.0) GO TO 28	177
C*** CONVERGENCE NOT OBTAINED	178
PRINT 41, NAME, IO	179
NC=NC+1	180
C	181
28 WRITE (3, 42) NAME, IO, PERCNT, T, SFORM, NANS, NUMITS, TINFO, SE	182
N=N+1	183
GO TO 17	184
C	185
29 PRINT 44, N, NC	186
STOP	187
C	188
30 FORMAT (2I4, I1, 2I1, 1X, I1, F5.2, 27X, I2)	189
31 FORMAT (16I5)	190
32 FORMAT (80I1)	191
33 FORMAT (8A10)	192
34 FORMAT (8A10)	193
35 FORMAT (T50, *LINPSC0*, /, T50*====*, /, T20, *LINEAR POLYCHOTOMU	194
1S SCORING WITH TWO PARAMETER MODELS*, /, T40*PSYCHOMETRICS METHOD	195
2S PROGRAM*, /, T40*DEPARTMENT OF PSYCHOLOGY*, /, T40*UNIVERSITY OF MIN	196
3NESOTA*, /, T40*MPLS. MINN. 55455*, /, T20, *INUP*, T27, *=*, I4, /, T20	197
4, *MMAX*, T27, *=*I4, /, T20, *IOMIT*, T27, *=*, I4, /, T20*OPT1*, T27*==*I4, /,	198

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51 T20*OPT2*,T27*==*,I4,/,T20*OPT4*,T27*==*,I4,/,T20,*MAXCAT*,T27,*==*,I 199
64, /T20,*U*,T27,*==*,F4.1, /T20,*VARIABLE FORMAT*,* FOR POOL =*,8A10, 200
7 /T20,*VARIABLE FORMAT FOR DATA =*,9A10, /T20,8A10, /T20,9A10, /T20,8 201
9A10) 202
36 FORMAT (15,1X,I2,2X,10F6.2) 203
37 FORMAT (10F6.2) 204
38 FORMAT (*PARITY ERROR ON TAPE*,10JX,I2) 205
39 FORMAT (/10X,*ITEM ID = *,I5,5X,*REJECTION =*,I3, /12X,*A: *,10F6. 206
12) 207
40 FORMAT (12X,*B: *,10F6.2) 208
41 FORMAT (10X,*CONVERGENCE NOT OBTAINED FOR SUBJECT =*,2A10,* ID =*, 209
1A9) 210
42 FORMAT (1X,2A10,A4,F5.2,2F7.2,I4,I4,2F7.2) 211
43 FORMAT (////) 212
44 FORMAT (10X,*CASES READ =*,I5,* CASES NOT CONVERGED =*,I5) 213
45 FORMAT (10X,*ALL ITEMS OMITTED FOR SUBJECT =*,2A10,* ID =*,A9) 214
46 FORMAT (10X,*SUBJECT =*,2A10,* ID =*,A9,* HAS ALL ANSWERS IN*,*COR 215
1RECT*) 216
47 FORMAT (10X,*SUBJECT =*,2A10,* ID =*,A9,* HAS ALL ANSWERS COR*,*RE 217
1CT*) 218
END 219
INTEGER FUNCTION ADIM (NUMCAT,OPT4) 1
INTEGER OPT4 2
C*** DETERMINES THE NUMBER OF A PARAMETERS FOR A GIVEN ITEM 3
ADIM=1 4
IF (OPT4.-2.3) ADIM=NUMCAT+1 5
RETURN 6
END 7
INTEGER FUNCTION BDM (NUMCAT,OPT4) 1
INTEGER OPT4 2
C*** DETERMINES THE NUMBER OF B PARAMETERS FOR A GIVEN ITEM 3
BDM=NUMCAT 4
IF (OPT4.-2.3) BDM=NUMCAT+1 5
RETURN 6
END 7
SUBROUTINE CHKINF (INUP,M,OPT4) 1
INTEGER OPT4 2
C*** CHECKS FOR ERRORS IN THE INPUT DATA 3
C*** IF AN ERROR IS FOUND, A MESSAGE IS PRINTED AND THE PROGRAM 4
C*** HALTS 5
C 6
IERRE=0 7
IF (INUP.LE.100) GO TO 1 8
PRINT *, INUP 9
IERRE=1 10
1 IF (M.LE.INUP) GO TO 2 11
PRINT *, M, INUP 12
IERRE=1 13
2 IF (1.LE.OPT4.AND.OPT4.LE.3) GO TO 3 14
PRINT *, OPT4 15
IERRE=1 16
3 IF (IERRE.EQ.1) STOP 17
RETURN 18
C 19
C 20
4 FORMAT (10X,*INPUT ERROR: NO. OF ITEMS IN ITEM POOL =*,I5, /10X,*N 21
10. MUST BE .LE. 10(*) 22
5 FORMAT (10X,*INPUT ERROR: NO. ITEMS ADMINISTERED =*,I5, /10X,*NO. 23
1 MUST BE .LE. NO. OF ITEMS IN ITEM POOL =*,I5) 24
6 FORMAT (10X,*INPUT ERROR: OPTION 4 =*,I3,* DOES NOT CORRES*,*POND 25
1 TO ANY OF THE AVAILABLE RESPONSE MODELS*) 26
END 27
SUBROUTINE NOGPAD (IRESP,A,P, ITEMS,NCAT, INAD,EPS,MAXIT,SFORM,IFAI 1
1L,THE IA,NUMITS,TINFO,SE) 2
EXTERNAL FORVAD,SORVNO 3
DIMENSION IRESP(100), A(100,10), P(100,10), NCAT(10), INAD(100) 4

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CALL BISECT (FORVNO, IRESP, A, B, NITEMS, NCAT, INAD, S, GUESS)
CALL NEWTAP (FORVNO, SORVNO, IRESP, A, B, NITEMS, NCAT, INAD, MAXIT, EPS, N
1UMITS, GUESS, THETA, SDRV, TFAIL)
SFORM=-SDRV
IF (IFAIL.EQ.1) GO TO 1
CALL NOINFO (A, B, NITEMS, NCAT, INAD, THETA, TINFO)
SE=1.0/SQRT(ABS(SDRV))
RETURN
C
1 TINFO=-99.99
SE=-99.99
RETURN
END
FUNCTION IVALUE (IRESP, NCAT)
C*** CHECKS RESPONSE FOR SPECIAL CASES
C*** IVALUE RETURNS . . . 1 IF IRESP IS BEST RESPONSE
C*** 2 IF IRESP IS WORST RESPONSE
C*** 3 OTHERWISE
C
IVALUE=3
IF (IRESP.EQ.1) IVALUE=1
IF (IRESP.EQ.(NCAT+1)) IVALUE=2
RETURN
END
SUBROUTINE RCAT1 (A, B, THETA, TMINB0, TMINB1, P, ETOZ0, ETOZ1)
C*** COMPUTES VALUES NECESSARY FOR THE CALCULATION OF THE DERIV-
C*** ATIVES OF THE NORMAL OGIVE GRADED MODEL FOR THE SPECIAL CASE
C*** WHEN IRESP IS THE BEST RESPONSE
C
TMINB0=THETA-B
TMINB1=0.0
Y=A*TMINB0
P=CDFN(Y)
ETOZ0=EXP(-Y*Y/2.0)
ETOZ1=0.0
RETURN
END
SUBROUTINE RCATN (A, B, THETA, TMINB0, TMINB1, P, ETOZ0, ETOZ1)
C*** COMPUTES VALUES NECESSARY FOR THE CALCULATION OF THE DERIV-
C*** ATIVES OF THE NORMAL OGIVE GRADED MODEL FOR THE SPECIAL
C*** CASE WHEN IRESP IS THE WORST RESPONSE
C
TMINB0=0.0
TMINB1=THETA-B
Y1=A*TMINB1
P=1.0-CDFN(Y1)
ETOZ0=0.0
ETOZ1=EXP(-Y1*Y1/2.0)
RETURN
END
SUBROUTINE RCATOT (A, B0, B1, THETA, TMINB0, TMINB1, P, ETOZ0, ETOZ1)
C*** COMPUTES VALUES NECESSARY FOR THE CALCULATION OF DERIVATIVES OF
C*** THE NORMAL OGIVE GRADED MODEL FOR ALL OTHER CASES
C
TMINB0=THETA-B0
TMINB1=THETA-B1
Y=A*TMINB0
Y1=A*TMINB1
P=CDFN(Y)-CDFN(Y1)
ETOZ0=EXP(-Y*Y/2.0)
ETOZ1=EXP(-Y1*Y1/2.0)
RETURN
END
FUNCTION FORVNO (IRESP, INAD, NITEMS, NCAT, A, B, THETA)
C*** CALCULATES THE FIRST DERIVATIVE FOR THE NORMAL OGIVE GRADED MODEL
DIMENSION IRESP(100), INAD(100), NCAT(100), A(100,10), B(100,10)

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C
SUM=0.0
DO 5 I=1,NITEMS
IF (INAD(I).EQ.0) GO TO 5
K=I-RESP(I)
J=IVALUE(K,NCAT(I))
GO TO (1,2,3), J
C
C*** IRESP IS BEST RESPONSE
1 CALL FCAT1 (A(I,1),B(I,K),THETA,TMINR0,TMINR1,P,ETOZ0,ETOZ1)
GO TO 4
C
C*** IRESP IS WORST RESPONSE
2 CALL FCATN (A(I,1),B(I,K-1),THETA,TMINR0,TMINR1,P,ETOZ0,ETOZ1)
GO TO 4
C
C*** ALL OTHER RESPONSES
3 CALL FCATOT (A(I,1),B(I,K),B(I,K-1),THETA,TMINR0,TMINR1,P,ETOZ0,ETOZ1)
CONTINUE
4
C
IF (P.EQ.0.0) P=0.0001
SUM=SUM+A(I,1)*(ETOZ0-ETOZ1)/P
CONTINUE
C
SDPVNO=SUM/SDRT(2.0*3.142)
RETURN
END
FUNCTION SDPVNO (IRESP,INAD,NITEMS,NCAT,A,B,THETA)
DIMENSION IRESP(100), INAD(100), NCAT(100), A(100,10), B(100,10)
C*** CALCULATE SECOND DERIVATIVE FOR THE NORMAL OGIVE GRADED MODEL
C
SUM=0.0
ROOTPI=1.0/SDRT(2.0*3.142)
DO 5 I=1,NITEMS
IF (INAD(I).EQ.0) GO TO 5
K=I-RESP(I)
J=IVALUE(K,NCAT(I))
GO TO (1,2,3), J
C
C*** IRESP IS BEST RESPONSE
1 CALL FCAT1 (A(I,1),B(I,K),THETA,TMINR0,TMINR1,P,ETOZ0,ETOZ1)
GO TO 4
C
C*** IRESP IS WORST RESPONSE
2 CALL FCATN (A(I,1),B(I,K-1),THETA,TMINR0,TMINR1,P,ETOZ0,ETOZ1)
GO TO 4
C
C*** ALL OTHER RESPONSES
3 CALL FCATOT (A(I,1),B(I,K),B(I,K-1),THETA,TMINR0,TMINR1,P,ETOZ0,ETOZ1)
CONTINUE
4
C
IF (P.EQ.0.0) P=0.0001
SUM1=A(I,1)*ROOTPI*(ETOZ0-ETOZ1)/P
SUM2=-SUM1*SUM1
SUM3=-(A(I,1)**3)*ROOTPI*((TMINR0*ETOZ0)-(TMINR1*ETOZ1))/P
SUM=SUM+SUM1+SUM2
CONTINUE
C
SDPVNO=SUM
RETURN
END
SUBROUTINE FCINFO (A,B,NITEMS,NCAT,INAD,THETA,TINFO)
DIMENSION A(100,10), B(100,10), NCAT(100), INAD(100)
C*** COMPUTES INFORMATION FOR GRADED NORMAL OGIVE MODEL AT GIVEN

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C*** VALUE OF THETA
C
TINFO=0.0
ROOTPI=1.0/SQRT(2.0*3.142)
C*** LOOP OVER ITEMS
DO 5 I=1,NITEMS
IF (INAD(I).EQ.0) GO TO 5
C
C*** INITIALIZATION--VALUES CALCULATED FOR FIRST CATEGORY OF ITEM I
Y=A(I,1)*(THETA-B(I,1))
P0=CHFN(Y)
P1=0.0
ETOZ0=EXP(-Y*Y/2.0)
ETOZ1=0.0
KATGRY=0
C
C*** LOOP OVER ALL THE CATEGORIES OF ITEM I
1 KATGRY=KATGRY+1
P=P0-P1
IF (P.EQ.0.0) P=0.0001
FDRVP=A(I,1)*ROOTPI*(ETOZ0-ETOZ1)
TINFO=TINFO+(FDRVP*FDRVP)/P
C
ETOZ1=ETOZ0
P1=P0
C
IF (KATGRY-(NCAT(I)+1)) 2,3,4
C*** CURRENT CATEGORY UNDER CONSIDERATION IS NOT ONE OF THE EXTREMES
2 Y=A(I,1)*(THETA-B(I,KATGRY))
P0=CHFN(Y)
ETOZ0=EXP(-Y*Y/2.0)
GO TO 1
C*** LAST CATEGORY OF AN ITEM IS BEING CONSIDERED
3 P0=1.0
ETOZ0=0.0
GO TO 1
C*** ALL CATEGORIES FOR ITEM I HAVE BEEN EXAMINED
4 CONTINUE
C
5 CONTINUE
RETURN
END
SUBROUTINE LOGRAD (IRESP,A,B,NITEMS,NCAT,INAD,EPS,NITER,SFORM,IFAIL,
1L,THETA,NUMITS,TINFO,SE)
EXTERNAL FDRVLL,SORVLL
DIMENSION IRESP(100), A(100,10), B(100,10), NCAT(100), INAD(100)
CALL BISECT (FDRVLL,IRESP,A,B,NITEMS,NCAT,INAD,5,GUESS)
CALL NEWTRAP (FDRVLL,SORVLL,IRESP,A,B,NITEMS,NCAT,INAD,NITER,EPS,N
1UMITS,GUESS,THETA,SORV,IFAIL)
SFORM=-SORV
IF (IFAIL.EQ.1) GO TO 1
CALL LLINFO (A,B,NITEMS,NCAT,INAD,THETA,TINFO)
SE=1.0/SQRT(ARS(SORV))
RETURN
C
1 TINFO=-99.99
SE=-99.99
RETURN
END
SUBROUTINE CALCP (IRESP,INAD,NCAT,A,B,NITEMS,THETA,P)
COMMON D
DIMENSION IRESP(100), INAD(100), NCAT(100), B(100,10), P(100,2), A
1(100,10)
C*** CALCULATES UPPER AND LOWER P FOR EACH ITEM WITH GIVEN ANSWER VECT
DO 4 I=1,NITEMS
IF (INAD(I).EQ.0) GO TO 4

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J=IRESP(I)
IF (J.EQ.1) GO TO 1
P(I,1)=1.0/(1.0+EXP(-D*A(I,1)*(THETA-B(I,J-1))))
GO TO 2
1 P(I,1)=0.0
2 IF (J.EQ.(NCAT(I)+1)) GO TO 3
P(I,2)=1.0/(1.0+EXP(-D*A(I,1)*(THETA-B(I,J))))
GO TO 4
3 P(I,2)=1.0
4 CONTINUE
RETURN
END
FUNCTION FORVLL (IRESP,INAD,NITEMS,NCAT,A,B,THETA)
COMMON D
DIMENSION P(100,2), A(100,10), B(100,10), INAD(100), IRESP(100), N
1 NCAT(100)
C*** CALCULATES FIRST DERIVATIVE OF LOG-LIKE FUNCTION
SUM=0.0
CALL CALCF (IRESP,INAD,NCAT,A,B,NITEMS,THETA,P)
DO 1 I=1,NITEMS
IF (INAD(I).EQ.0) GO TO 1
SUM=SUM+A(I,1)*(1.0-P(I,1)-P(I,2))
1 CONTINUE
FORVLL=SUM*D
RETURN
END
FUNCTION SDPVLL (IRESP,INAD,NITEMS,NCAT,A,B,THETA)
COMMON D
DIMENSION P(100,2), A(100,10), B(100,10), INAD(100), IRESP(100), N
1 NCAT(100)
C*** CALCULATES SECOND DERIVATIVE OF LOGLIKE FUNCTION
SUM=0.0
CALL CALCF (IRESP,INAD,NCAT,A,B,NITEMS,THETA,P)
DO 1 I=1,NITEMS
IF (INAD(I).EQ.0) GO TO 1
Q1=1.0-P(I,1)
Q2=1.0-P(I,2)
P1=P(I,2)-P(I,1)
DIFF1=2.0*Q1-1.0
DIFF2=2.0*Q2-1.0
R1=P(I,1)*Q1
R2=P(I,2)*Q2
SUM=SUM+(A(I,1)**2/P1)*(-DIFF1*R1+DIFF2*R2-((R1-R2)**2)/P1)
1 CONTINUE
SDPVLL=D*D*SUM
RETURN
END
SUBROUTINE PCAT (A,B,THETA,ITEM,NUMCAT,FLOWER,PUPPER)
COMMON D
DIMENSION B(100,10), FLOWER(10), PUPPER(10)
C*** CALCULATES P'S FOR ALL RESPONSE CATEGORIES OF A GIVEN ITEM
C
FLOWER(1)=0.0
DO 1 I=1,NUMCAT
PUPPER(I)=1.0/(1.0+EXP(-D*A*(THETA-B(ITEM,I))))
FLOWER(I+1)=PUPPER(I)
1 CONTINUE
PUPPER(NUMCAT+1)=1.0
RETURN
END
SUBROUTINE LLINFO (A,B,NITEMS,NCAT,INAD,THETA,TINFO)
COMMON D
DIMENSION A(100,10), B(100,10), NCAT(100), INAD(100)
DIMENSION PUPPER(10), FLOWER(10)
C*** COMPUTES INFORMATION FOR THE GRADED LOGISTIC MODEL AT A GIVEN
C*** VALUE OF THETA

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C
  TINFO=0.0
  DO 1 I=1,NITEMS
    IF (INAD(I).EQ.0) GO TO 2
    CALL PCAT (A(I,1),B,THETA,I,NCAT(I),PLOWER,PUPPER)
  1 CONTINUE
  2 CONTINUE
  RETURN
  END
  SUBROUTINE NOMLOG (IRESP,A,B,NITEMS,NCAT,INAD,EPS,MAXIT,SFORM,IFAIL,
  1L,THETA,NUMITS,TINFO,SE)
    EXTERNAL FDRVNL
    DIMENSION IRESP(100), A(100,10), B(100,10), NCAT(100), INAD(100)
    CALL MISECT (FDRVNL,IRESP,A,B,NITEMS,NCAT,INAD,5,GUESHI,GUESLO)
    CALL SECANT (FDRVNL,IRESP,A,B,NITEMS,NCAT,INAD,MAXIT,EPS,GUESHI,GU
    1ESLO,NUMITS,THETA,SDRV,IFAIL)
    SFORM=SDRV
    IF (IFAIL.EQ.1) GO TO 1
    CALL NLINEF (A,B,NITEMS,NCAT,INAD,THETA,TINFO)
    SE=1.0/SQRT(ABS(SDRV))
    RETURN
  1
  TINFO=-99.99
  SE=-99.99
  RETURN
  END
  FUNCTION FDRVNL (IRESP,INAD,NITEMS,NCAT,A,B,THETA)
    DIMENSION IRESP(100), INAD(100), NCAT(100), A(100,10), B(100,10)
    C*** CALCULATES FIRST DERIVATIVE OF NOMINAL LOGISTIC FUNCTION
    C*** NOTE: FOR THIS MODEL, THE A'S ARE THE SLOPE PARAMETERS
    C*** AND THE B'S ARE THE INTERCEPT PARAMETERS
  C
    SUM=0.0
    DO 2 I=1,NITEMS
      IF (INAD(I).EQ.0) GO TO 2
      XNUM=0.0
      DENOM=0.0
      NUMCAT=NCAT(I)+1
      DO 1 J=1,NUMCAT
        CONST=A(I,IRESP(I))-A(I,J)
        ARG=A(I,J)+THETA*B(I,J)
        EZ=EXP(ARG)
        XNUM=XNUM+CONST*EZ
        DENOM=DENOM+EZ
      1 CONTINUE
      SUM=SUM+XNUM/DENOM
    2 CONTINUE
    FDRVNL=SUM
    RETURN
  END
  SUBROUTINE NLINEF (A,B,NITEMS,NCAT,INAD,THETA,TINFO)
    DIMENSION A(100,10), B(100,10), NCAT(100), INAD(100)
    DIMENSION E(10)
    C*** COMPUTES INFORMATION FOR THE NOMINAL LOGISTIC FUNCTION AT A
    C*** GIVEN VALUE OF THETA
  C

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C*** IINFO=0.0
C*** LOOP OVER THE ITEMS
DO 4 I=1,NITEMS
  IF (INAD(I).EQ.0) GO TO 4
  NCATG=NCAT(I)+1
C
C*** COMPUTE THE DENOMINATOR USED TO CALCULATE P AND THE FIRST
C*** DERIVATIVE OF P--IT IS THE SAME VALUE FOR ALL POSSIBLE RE-
C*** SPONSES TO ITEM I
  DENOM=0.0
  DO 1 K=1,NCATEG
    E(K)=EXP(A(I,K)*THETA+B(I,K))
    DENOM=DENOM+E(K)
  1 CONTINUE
C
C*** SUM OVER ALL POSSIBLE RESPONSES
  DO 3 J=1,NCATEG
    P=E(J)/DENOM
C
C*** CALCULATE THE FIRST DERIVATIVE OF P
  DENVNUM=0.0
  DO 2 K=1,NCATEG
    DENVNUM=DENVNUM+E(K)*(A(I,J)-A(I,K))
  2 CONTINUE
  FDRVP=(E(J)*DENVNUM)/(DENOM*DENOM)
C
  IINFO=IINFO+(FDRVP*FDRVP)/P
  3 CONTINUE
  4 CONTINUE
  RETURN
END
SUBROUTINE CHKRSR (IRESP,IOMIT,INAD,NCAT,NITEMS,NAME,IO,INADS)
  DIMENSION IRESP(100), INAD(100), NCAT(100), NAME(2), INADS(100)
C*** DELETES OMITTED ITEMS FOR A SUBJECT FROM LIST OF ITEMS
C*** ADMINISTERED (RESULTS RETURNED IN INADS) AND CHECKS TO SEE
C*** IF ALL RESPONSES ARE VALID. IF NOT AN ERROR MESSAGE IS WRITTEN
C*** AND THE PROGRAM HALTS
C
  DO 2 I=1,NITEMS
    NUMCAT=NCAT(I)+1
    INADS(I)=INAD(I)
    IF (IRESP(I).NE.IOMIT) GO TO 1
    INADS(I)=0
  GO TO 2
C
C*** CHECK FOR INVALID RESPONSE
  1 IF ((1.LE.IRESP(I)).AND.(IRESP(I).LE.NUMCAT)) GO TO 2
  PRINT 3, NAME, IO, IRESP(I), NUMCAT
  STOP
C
  2 CONTINUE
  RETURN
C
C
C
  3 FORMAT (10X,'ERROR IN DATA: SUBJECT = ',2A10,' IO = ',49,' HAS IL-
  LEGAL RESPONSE =',I3,'/10X,'RESPONSES MUST BE',* BETWEEN 1 AND NUMC-
  AT OF CATEGORIES =',I3,' INCLUSIVE')
  END
SUBROUTINE CHKVEC (IRESP,INAD,NCAT,NITEMS,ICLK,NBEST,NANS)
  DIMENSION IRESP(100), INAD(100), NCAT(100)
C
C*** CHKVEC TESTS THE RAW RESPONSE VECTOR TO DETERMINE IF
C IF IT IS ONE OF THE FOLLOWING THREE CASES:
C*** ALL BEST RESPONSES...ICLK SET TO 3
C*** ALL WORST RESPONSES...ICLK SET TO 2
C*** NO RESPONSES.....ICLK SET TO 1
C*** OTHERWISE.....ICLK SET TO 4

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NANS=0
NWORST=0
NREST=0
DO 1 I=1,NITEMS
IF (INAD(I).EQ.0) GO TO 1
NANS=NANS+1
IF (IRESP(I).EQ.1) NREST=NREST+1
IF (IRESP(I).EQ.NCAT(I)+1) NWORST=NWORST+1
1 CONTINUE
C
ICHK=4
IF (NANS.EQ.0) ICHK=1
IF (NWORST.EQ.NANS) ICHK=2
IF (NREST.EQ.NANS) ICHK=3
RETURN
END
SUBROUTINE BISECT (F1,IRESP,A,B,NITEMS,NCAT,INAD,NIL,BMID,BLAST)
DIMENSION IRESP(100), A(100,10), B(100,10), NCAT(100), INAD(100),
1P(100,2)
C*** CALCULATES APPROXIMATE ROOT OF F1 BY BISECTION,BISECTING THE INTER
C*** NIT (NUMBER OF ITERATIONS) TIMES. BMID IS BEST CURRENT GUESS AT T
C*** BLAST IS THE PREVIOUS VALUE OF BMID. IT IS USED AS THE SECOND
C*** INITIAL GUESS FOR THE SECANT METHOD.
C
C INITIALIZE LEFT BOUND AND F1(BOUND), AND RIGHT BOUND,F1(BOUND)
BL=-5.0
BR=5.0
BMID=0.0
TL=F1(IRESP,INAD,NITEMS,NCAT,A,B,BL)
TR=F1(IRESP,INAD,NITEMS,NCAT,A,B,BR)
C TEST FOR NO ROOT IN INTERVAL, AND RETURN IF NOT POSSIBLE
IF ((IL*TR).GT.0.0) RETURN
C NOW CALCULATE BISECTIONS NIT TIMES
DO 3 I=1,NIT
TMID=F1(IRESP,INAD,NITEMS,NCAT,A,B,BMID)
IF ((TMD*TL).GT.0.0) GO TO 1
BR=BMID
GO TO 2
1 TL=TMID
2 BL=BMID
3 BMID=(BL+BR)/2.0
CONTINUE
BLAST=BR
IF (IL.EQ.TMID) BLAST=BL
RETURN
END
SUBROUTINE NEWTRAP (F1,F2,IRESP,A,B,NITEMS,NCAT,INAD,NITER,EPS,NUM
1ITS,GUESS,THETA,SORV,IFAIL)
DIMENSION IRESP(100), A(100,10), B(100,10), NCAT(100), INAD(100)
C*** CALCULATES ROOT OF F1 GIVEN ITS FIRST DERIVATIVE F2 AND AN INITIAL
C*** GUESS. UTILIZES NEWTON-RAPHSONS METHOD
C
C INITIALIZE
NUMITS=0
THETA=GUESS
C*** LOOP UNTIL ERR IS LESS THAN EPS OR NUMBER OF ITERATIONS BECOMES TO
1 SORV=F2(IRESP,INAD,NITEMS,NCAT,A,B,THETA)
FORV=F1(IRESP,INAD,NITEMS,NCAT,A,B,THETA)
ERR=FORV/SORV
THETA=THETA-ERR
NUMITS=NUMITS+1
C EXIT LOOP CRITERION
IF ((NUMITS.LT.NITER).AND.(ABS(ERR).GT.EPS)) GO TO 1
C*** END LOOP, TEST FOR FAILURE AND SET IFAIL
IFAIL=0
IF (ABS(ERR).LT.EPS) RETURN
20

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IFAIL=1
THETA=-99.99
SDRV=99.99
RETURN
END
SUBROUTINE SECANT (F1,IRESP,A,B,NITEMS,NCAT,INAD,MAXIT,EPS,GUESHI,
1 GUESLO,NUMITS,THETA,SLOPE,IFAIL)
2 DIMENSION IRESP(100), A(100,10), B(100,10), NCAT(100), INAD(100)
3
C*** USES THE SECANT METHOD TO CALCULATE THE ROOT, THETA, OF THE
C*** FUNCTION F1
C*** GUESHI AND GUESLO ARE THE TWO INITIAL GUESSES AT THE ROOT
C*** REQUIRED BY THE SECANT METHOD
C
4 NUMITS=0
5 THETA=GUESHI
6 FLAST=GUESLO
7 FLAST=F1(IRESP,INAD,NITEMS,NCAT,A,B,FLAST)
8
C
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13
C*** LOOP UNTIL CONVERGENCE OR NONCONVERGENCE IS ESTABLISHED
14
1 FCUR=F1(IRESP,INAD,NITEMS,NCAT,A,B,THETA)
15
16 IF (FCUR.EQ.FLAST) GO TO 2
17 SLOPE=(THETA-FLAST)/(FCUR-FLAST)
18 CHANGE=FCUR*SLOPE
19 FLAST=THETA
20 FLAST=FCUR
21 THETA=THETA-CHANGE
22 NUMITS=NUMITS+1
23 IF (ABS(CHANGE).GT.EPS.AND.NUMITS.LT.MAXIT) GO TO 1
24
C
25 IFAIL=0
26 SLOPE=1.0/SLOPE
27 IF (ABS(CHANGE).LT.EPS) RETURN
28
C*** SECANT METHOD DOES NOT CONVERGE IN MAXIT ITERATIONS
29 IFAIL=1
30 THETA=-99.99
31 SLOPE=-99.99
32 RETURN
33
C
34
C*** ERROR: SECANT METHOD CANNOT BE USED ON F1
35
2 PRINT 3
36 IFAIL=1
37 THETA=-99.99
38 SLOPE=-99.99
39 RETURN
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