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RASCH MODEL ANALYSIS WITH THE BICAL
COMPUTER PROGRAM

Benjamin D. Wright and Ronald J. Mead
The University of Chicago

BASIC RESEARCH



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Research Institute for the Behavioral and Social Sciences

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the parameters, is described, with application to military police marksmanship data used as an illustration.

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RASCH MODEL ANALYSIS WITH THE BICAL
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The Definition of Variables is essential for a successful study of human behavior, or for any other scientific investigation. Variables are successful attempts to simplify nature in order to expose recurrent themes and to formulate useful "laws."

The Measurement of a Variable must be achieved before it can be studied in relationship to other variables. This involves inferring the quantity of the unobservable variable possessed by the person or object to be measured from relevant data that can be observed. Not all observations are suitable for inferring variables. Each situation must be specifically structured to meet the requirements of objective measurement.

The Rasch Model is the mathematical formulation of any measurement situation, either physical or psychological, for which the relevant statistic can be expressed in terms of the number of successes (or number of targets hit, items correct or marks exceeded). The model specifies an efficient and reasonable way to make objective inferences from observations to variables.

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Rasch's Philosophy of Measurement emphasizes "specific objectivity" which makes possible the comparison of any two persons (objects) independently of the items (agents) that are used to facilitate the comparison and of all other parameters other than the two in question. This leads to a model for which unweighted scores contain all the information relevant to person ability or item difficulty.

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1. THE NEED FOR OBJECTIVE MEASUREMENT

The Definition of Variables

Work in the behavioral sciences has been hampered by the notion that "measurement" has a different meaning for them than for the physical sciences. But it is fundamental in all scientific investigation to abstract from experience simple ideas which organize the complexity in useful ways. Useful ideas, often called "variables," are drawn from the scientist's careful observations of his experience, but they are necessarily over-simplifications intended to be meaningful for a particular purpose. Another scientist with other purposes may construct a different set of variables to summarize similar experiences. Ideas come to be generally regarded as "true" only when (and so long as) they are useful in predicting outcomes among an interesting class of possible events.

After supposing his variable, the scientist attempts to establish its definition by collecting, validating and calibrating observations that provide information about it. Once the observations with which to measure a variable have been specified and calibrated, the scientist has established an operational definition of that variable. He can then proceed in an orderly way to study the formulation of general principles about the processes involved and to predict the outcomes of other situations involving these processes.

The Measurement of Variables

Even carefully defined observations are of little interest in themselves. They are seldom chosen only for their own sake but rather for the information they contain about

the "variable", which is supposed to lie behind them. In order to extract this information we must attempt to specify explicitly the supposed relationship between observation and variable. It is the specification of this relationship that enables us to make inferences about the amount of the variable that each object possesses and so to make comparisons among objects based on the inferred variable.

The intent of this approach is to become free from the particular observations taken. If the observations are appropriate and the inferences correctly drawn, we want to need nothing else about them. We want to be able to make whatever comparisons we choose, among objects or among different occasions for the same object, regardless of which observations were made in each instance. Even though some observations are necessary to infer the amount of the variable present, once that is done, we want to be no longer bound to them.

These ideas can be illustrated with a simple example. A person entering a room might observe that he looks up to some people standing in the room and down to others. This might lead him to hypothesize the existence of a "height" variable. He might then decide to carry with him a stick with marks at various distances from the end and to observe for each person the number of marks exceeded. This would permit him to make judgements about the amount of height each person possesses that are more precise than "taller than me" or "shorter than me".

If the man developed a means for translating the number of marks passed into the height of the person, i.e. a model, it would be possible for him to compare any person's measure (i.e., the height inferred by the model from the number of marks passed) with any

other measure obtained from any other stick that has been connected to the same variable.

The sticks need not be the same length nor have the same number of marks nor have the marks at the same intervals, so long as each has been properly connected to the variable "height".

In addition to freeing him from the necessity of always using the same (or identical) sticks, the model relating the observation to the variable must also provide him with the means for assessing the validity of the measurement. If a person is measured twice and the two measures are not the same, within statistical limits due to the precision of the instruments, he would conclude that the person has not been properly measured and without additional information would be at a loss to know which of the measures, if either, should be associated with the person.

Because the measurement permits the comparison of every new measure with all previous measures for the person, with a little experience, our observer could come to recognize characteristics of sticks and persons which lead to measures that persist from trial to trial. The measurement model is essential in this process because it provides a framework for recognising when an observation is surprising. If we know a person once passed say, 117 marks on some stick and we now observe that he passes 37 marks on another, we cannot tell if this is a surprising result unless both observations can be connected to the same fundamental variable. By knowing when to be alarmed, an observer can quickly learn, for example, that flexible round-ended sticks often give unpredicted results and that the height of people cannot be measured reliably when they are running or jumping.

Height is so familiar that we feel we can observe it directly. But, in fact, we cannot "observe" the height of an unfamiliar object when it is viewed in complete isolation. Like all other variables, our observation of height involves a series of comparisons of the unknown object with some available calibrated instrument.

The units of measurement for height are equally familiar and arbitrary. Their importance and usefulness is only because they have been defined and the definitions accepted by everyone who measures height. The statement that a person is six feet in height now specifies his height unambiguously with no further information required about how the measure was obtained. This was not the case when the standard of measure was the king's foot.

Psychological measurement is not different in principle from other kinds of measurement but at this point there is little consensus about what variables are important (i.e. useful, in general) and what units are convenient to measure them. The following example should help clarify the parallels between physical and psychological measurement.

An observer of military training might hypothesize the existence of a marksmanship variable, that soldiers vary in the amount of this variable that they possess and that they must possess a certain amount in order to be competent soldiers. (It should be noted that this last hypothesis goes beyond measurement. The consideration of how to determine the amount of the height variable that a person possesses did not involve decisions about how much he should have. Only after obtaining a satisfactory measure of the variable can we begin to investigate the relationship with other variables to establish what amounts of height or marksmanship are required for particular situations.)

One plan for studying marksmanship would be to follow each soldier through his career and observe when his level of marksmanship was adequate and when it was not. While at the end we would know a great deal about those particular soldiers, we would not be able to make comparisons among them, since it is unlikely that we would have comparable data for any two. It would be equally impossible to predict their success in any new situations with any degree of precision.

We would prefer to structure the situation so that observations relevant to marksmanship can be accumulated quickly, efficiently and economically. We might decide that useful observations could be generated from the task of firing at a target on a practice range. While this obviously does not involve all factors that might be considered, it could be argued that it does contain an important element that is common to any situation for which marksmanship would be involved. Knowledge of the variable defined by the observation of firing at a target should enable us to make reasonable predictions about the outcome of more complex situations.

But the number of times the person succeeds in hitting the target is no more the measure of his marksmanship than is the number of marks passed on a stick a measure of his height. The number of hits will depend on the size, distance, etc of the target (i.e., its difficulty) as well as the person's skill. We require a model to remove the effect of target difficulty and to translate the observation into a measurement about the person. With this accomplished we no longer need worry about presenting identical targets to every person any more than we need to measure their height with identical rulers. All we need are calibrated targets.

Selection of the task and the measurement model are crucial. There is no reason to expect that every observation can be converted into the measure of the variable we

want or that every mathematical function that transforms discrete counts into continuous "variables" will be equally useful. In order to understand what is required of these, we need to develop more fully what it is reasonable to require of a "measurement."

The Requirements for Good Measurement

At the very least, a good measurement model should require that a valid test satisfy the following conditions:

1. A more able person always has a better chance of success on an item than does a less able person.
2. Any person has a better chance of success on an easy item than on a difficult one.

It follows from these conditions that the likelihood of a person succeeding on an item is the consequence of the person's position on the variable (his ability) and the item's position on the same variable (its difficulty) and that no other variables influence the outcome. This implies that the difficulty of an item is an inherent property of that item which adheres to it under all relevant circumstances without reference to any particular population of persons to whom the item might be administered.

A major consequence of these conditions is that it is possible to derive an estimator for each parameter that is independent of all other parameters. All information about a person's ability expressed in his responses to a set of items is contained in the simple unweighted count of the number of items which he answered correctly. Raw score is a sufficient statistic for ability. For item difficulty, the sufficient statistic is the number of persons in the sample who responded correctly to that item.

These common sense requirements enable us to formulate an explicit mathematical model and to use this model to assess the appropriateness of the observations for furnishing information about the variable we are seeking. These requirements are also deceptively demanding. Successful measurement depends on achieving sufficient control with respect to the observations taken, so that their variations differ only along a single variable. Even though persons differ in many ways, their measurement becomes possible only when one of these dimensions dominates the behavior prompted by the items administered. Even when items differ on a number of factors, they can be successfully used for measurement if the responses of persons can be dominated by only one of these factors. Thus measurement can succeed despite multidimensionality, when the multidimensionality is controlled so as not to be shared actively by both persons and items. Two examples should help make this clear.

Two types of items: Suppose we wish to measure "general mental ability" and to do this devise an instrument containing both reading comprehension and mathematical computation items. While this instrument is clearly two dimensional, measurement with it could succeed in situations where either

1. there is no person variable which affects the probability of success for the reading items differently than for the math items,
2. math ability and reading ability are so highly correlated in the population that they do not appear different.

In either case we should not care whether measurements were made entirely with reading items, entirely with math items, or any mixture in between, since all items measure the "same" variable. In the first case, there is only one variable (perhaps called "general

mental ability"). In the second, there are two but since they are so highly correlated a person high on one is high on the other. We can measure math ability with reading items and reading ability with math items, if we choose. It does not matter whether we call the resulting measure math, reading or general ability. However, if we try to assert that both types of items are necessary for a "fair" measurement and become involved in setting the correct proportion of each, we have admitted the multidimensionality of the situation and must instead measure the two variables separately with items appropriate to each. (If we are still interested in one number we could then argue about how the two measures could be combined into a single index.)

It is only possible to measure a person, who always has many different abilities, on one variable by carefully constructing an instrument which addresses just that one variable. We may sometimes get by with a multidimensional instrument, since the two alternatives above--one variable versus two highly correlated variables--are not distinguishable in data, but, when we use an instrument of items readily classifiable into two or more types, its (effective) unidimensionality must be corroborated with each new sample.

One type of item with extraneous variables: A contrasting case can be illustrated by considering the measurement of problem solving ability with an instrument composed of word problems. Proficiency on this instrument requires many abilities in addition to problem solving, not the least of which is the ability to read the language in which the problems are written. If the reading ability of every person is well above the readability of the problems, differences among items or persons in this respect will not affect performance on the instrument. However, if any person has difficulty reading

the problems, his measure of problem solving ability will be biased downward by this interfering factor. His probability of success will be influenced by the interaction between his reading ability and the readability of the problem. This can, of course, be eliminated by regulating readability to be well below the reading ability of the target population. Then, although the persons may still vary in their ability to read, variation in their scores on this instrument will be due to their variation in problem solving ability alone.

This case differs from the preceding one in that the items are of one type but each has a "difficulty" on two variables. As long as all persons are sufficiently able readers, the instrument can be used to measure problem solving ability. Theoretically, such an instrument could also be used to measure reading ability among very able problem solvers who were poor readers.

Random guessing on multiple-choice items is another instance of extraneous variation. Persons who are guessing succeed on difficult items more often than their abilities would predict. This makes them appear more able when more difficult items are administered, since their frequency of success does not decrease as difficulty increases. A similar but opposite effect occurs when able persons become careless with easy items, making them appear less able than they are.

Such items "measure" two variables--the ability of interest and the tendency to guess or to become careless. The "guessingness" of the item may or may not be a simple function of the difficulty on the main variable but for the person two different variables are involved. The measure of either variable is threatened by the presence of the other.

These forms of multidimensionality have in common the attribute that different subsets of the items produce non-equivalent estimates of person ability and different subsamples of persons produce different estimates of item difficulties. This contradicts the requirements for good measurement specified in the Rasch model.

Unequal Item Discriminations: No discussion of disturbances in measurement is complete without mention of item "discrimination." Rasch's derivation of what is required in order to achieve objectivity (i.e., measures of person ability that are free of the sets of items administered, and calibrations of items that are free of the samples of persons used) leads to a model which rules out a parameter for item discrimination. If measurement objectivity is to be achieved, the situation must be arranged so that a parameter for discrimination is not necessary.

When the problem is approached from other perspectives, for example, when the observations are considered so valuable that the data are allowed to determine the form of the model, regardless of the effect on measurement, item discrimination is almost always included as a parameter. A model with a discrimination parameter (or any other additional parameter) will recover the observed data more completely than one without, but it is not at all clear when that is done what bearing the resulting "estimates" of discrimination can have on the generalizability and reproducibility of the situation. It remains to be settled whether discrimination "estimates" pertain to stable, meaningful parameters that are useful in characterizing future outcomes of similar situations or whether they are only temporarily useful as descriptive statistics for diagnosing trouble in one set of observations.

In theory, item discrimination is a measure of the amount of information an item contains about the quantity of the variable that a person possesses. In practice, it is better described as an index of the correlation over the sample of the item score with the operationally defined variable. These correlations can be "high" or "low" for the wrong reasons.

With the problem solving example, if the items vary in readability and their readability is near enough to the reading level of the persons so that some persons have difficulty reading some items, then these items will appear to vary in their power to discriminate along the problem solving scale, due to their connection to readability.

If the calibration sample is drawn from one population, items which no one is able to read will have no relationship to problem solving ability and items which everyone reads without difficulty will be the purest instances of the relevant behavior. Hence, the highest "discriminations" will be associated with items dominated by the variable of interest and the lowest will be for items most influenced by other factors.

However, if the calibration group consists of samples from two populations which have identical distributions of problem solving ability but differ in their reading ability, the group with the better readers will tend to score higher on the test. Then the items which are the most effective at separating the high and low scorers will be the items most influenced by readability. Therefore, in this instance, the items with the highest apparent discriminations will not be the ones with the strongest relationship to the variable of interest but rather the ones with the strongest relationship to the dimension along which the populations differ most, namely readability.

Models which include an item discrimination parameter will appear to "explain" data from either of these situations. Both, however, violate the unidimensionality

assumptions employed by these other models, as well as by the Rasch model. Therefore, we are in the unfortunate position of having data which seem to fit the model although they do not comply with the requirements of unidimensionality. The Rasch model avoids this potential danger by uncovering unacceptable variation in discrimination and avoiding discrimination as an item parameter.

A situation for which it is sometimes argued that a discrimination parameter is legitimate is one in which the items vary in the amount of random fluctuation inherent in them. This is analogous to items differing in their factor loadings. But even in this case the requirements for good measurement given previously are not satisfied. Before we sacrifice this, we should consider what it means for items to differ in their inherent error and decide what it is reasonable to do about it.

It is difficult to construct examples of items that vary in information which cannot be explained by the presence of additional factors. One possible case might be an instrument containing both multiple-choice and completion items. They could both reflect the same variable but, since different behaviors are required, they might differ in their relationship to the variable. We might expect a completion item, which requires the person to recall and write in the correct answer, to discriminate more sharply than an item which only requires the person to recognise the answer. Recognition items give the person who does not recall or recognise the correct response the opportunity to eliminate responses he knows to be incorrect, thereby increasing his chances of choosing the correct one. If his success at this is related to his position on the latent variable, not to his "test-wiseness" or any other extraneous factor, intelligent guessing of this sort can provide information about the variable of interest.

But this problematic situation is easily avoidable by simply not mixing items requiring obviously different behaviors on the same elementary instrument. The influence of extraneous factors on the outcome is a problem for all response models. The Rasch model is less susceptible to this source of confusion, since it is not so readily adaptable to mixed influences. Previous research (Panchapakesan, 1969; Wright and Panchapakesan, 1969) indicated that the tests of fit for the Rasch model are sensitive enough to such disturbances to protect measurements from deterioration due to them.

The Rasch Logistic Response Model

George Rasch (1960) provided a rethinking of the measurement problem which overcomes most of the deficiencies of traditional analysis and avoids the theoretical complications of the other latent trait models. Rasch's stochastic response model describes the probability of a successful outcome of a person on an item as a function of only the person's ability and the item's difficulty. Using only the traditional requirement that a measurement be based on a set of homogeneous items monotonically related to the trait to be measured, Rasch derived his measurement model in the form of a simple logistic expression and demonstrated that in this form the item and person parameters are statistically separable. Andersen (1973a) elaborated and refined the mathematical basis for the model. Wright and Panchapakesan (1969) developed practical estimation procedures that made application of the model feasible.

Rasch's model, while based on the same requirement of the sufficiency of total score relied on by traditional methods, offers new and promising opportunities for advancing our understanding of measurement and departures from it. Since the parameters

of the model are separable, it is possible to derive estimators for each parameter independently of the others. The logistic transformation assigns an ability of minus infinity to a score of zero and plus infinity to a score of one hundred percent. This eliminates the bounds on the ability range and puts the standard errors of measurement into a reasonable relationship with the information provided by observed score. The tests of item fit which are the basis for item selection are sensitive to high discriminations as well as to low and so lead to the selection of those items which form a consistent definition of the trait and to the rejection of exceptional items. Finally, the explicitness of the mathematical expression of the model facilitates statistical statements about the significance of individual person-item interactions and so makes both a very general and a very detailed analysis of misfit possible.

The Rasch model provides an explicit framework for comparing observed with expected outcomes. The expected outcome of administering an item to a person is that predicted by the model assuming that the item is appropriate with respect to that person and that the person was adequately motivated to bring his full ability to bear on the item. The model permits us to assess the likelihood of the observed result, and hence, to make statements about the appropriateness of the particular item for the particular person.

Objective measurement eliminates many of the problems that have plagued test users. The Rasch model is both necessary and sufficient for objectivity in measurement. To best utilize the power of this model, we need to develop fully the concepts and mathematics related to it. Chapter II provides this development. The first section reviews the philosophy and concepts presented by Rasch and his students. Section

two derives the estimating equations for the Bernoulli (i.e. one trial per task) form and then generalizes to the Binomial form (several trials per task). Finally, goodness of fit tests are presented for assessing the adequacy of the calibration.

CHAPTER II

DEVELOPMENT OF THE RASCH MODEL

Rasch's development of his approach to measurement places central emphasis on the concept of "specific objectivity". (Rasch, 1960, 1961, 1967, 1968; Wright, 1968.) The problem of measurement is to make comparisons among two or more persons (more generally, "objects") or two or more items ("agents") using the information from the interaction of the objects with the agents. In psychometrics, we often begin by determining the characteristics of items based on an administration to a sample of people but our ultimate aim is to compare the performance of people on a set of items.

By "specific objectivity", Rasch means a comparison of any two persons, derived from a set of person-item interactions, which is independent of all item parameters and of all person parameters other than the two in question. Similarly, a statement about two items is independent of all person parameters and all other item parameters.

While such a property is highly desirable (Loevinger, 1947), it is not a natural consequence of person-item interactions but must be specifically built into the measurement process for every situation. The more natural circumstance is for every person to bring many abilities into every confrontation with an item. Unless the item is carefully constructed to tap only one of these abilities, the process will be governed by any number of person or item characteristics.

Rasch (1960, 1961) based his development of a measurement model on the following assumptions:

- (a) the probability of a correct response to item i by person v is entirely governed by

$$P(X_{vi} = 1 | v, i) = \frac{\theta_{vi}}{1 + \theta_{vi}} \quad \theta_{vi} \geq 0$$

- (b) in which the situational parameter θ_{vi} is the product of two factors

$$\theta_{vi} = \xi_v \epsilon_i$$

where ξ_v pertains to the person and ϵ_i to the item, and

- (c) all answers, given the parameters, are stochastically independent.

It is clear from (a) that θ_{vi} represents the odds of success and from (b) that ξ_v is the ability of person v and ϵ_i is the easiness of item i .

The separability (also called "latent additivity") of the parameters shown in (b) makes possible objectivity in measurement. It follows from this that all information about a person's ability contained in his responses to a set of items is captured by the simple count of correct responses. This permits us to compare the abilities of two persons independently of the items administered.

Following Rasch (1960), the logarithm of the odds of success on item i by person v is:

$$(1) \quad \log \frac{P_{vi}}{1 - P_{vi}} = \log (\xi_v \epsilon_i) = \log \xi_v + \log \epsilon_i.$$

Therefore the abilities of person v and person u when observed on any item i can be compared, in logistic units, by subtraction:

$$(2) \quad \Delta_{vu}^i = \log \xi_v + \log \epsilon_i - \log \xi_u - \log \epsilon_i = \log \xi_v - \log \xi_u$$

which does not involve the item parameter at all. Actually computing a number to estimate this difference requires us to make use of the sufficiency of total score. Since all the information about ability is contained in the number of correct responses, all persons who have the same score must be assigned the same estimated ability. Therefore, by grouping together the responses of all persons who scored r , we can obtain an estimate of P_{vi} for all v with scores or r :

$$(3) \quad P_{ri} \approx \frac{X_{ri}}{N_r} \text{ where } P_{ri} \text{ is the probability of success on item } i$$

by persons with score r ,

X_{ri} is the number of persons with score r who

answered item i correctly, and

N_r is the number of persons with score r .

And so

$$(4) \quad \Delta_{rs}^i \approx \log \left\{ \frac{X_{ri}}{N_r - X_{ri}} \right\} - \log \left\{ \frac{X_{si}}{N_s - X_{si}} \right\}$$

is the difference in ability between a person with score r and a person with score s , estimated with item i . Of course information is usually available from more than one item; statistical techniques which amalgamate the information from all into a single estimate are presented in the next section.

Since all parameters always appear in combination with at least one other parameter, there is an indeterminacy in the system that must be resolved before a particular estimate of a person's ability or an item's difficulty can be calculated. This can be done in many ways; a simple one is to select one item, say item 1, as the reference point and set

log easiness to zero. This arbitrary choice does not affect the comparison of two persons in expression (2) but it makes it possible to compute a particular estimated ability for each person. From expression (1) the estimated ability, $\log \xi_v$ for score r is now equal to the log odds of success on item 1 for persons with score r .

$$(5) \quad \log \xi_v \approx \log \left\{ \frac{X_{r1}}{N_r - X_{r1}} \right\} \quad \text{if } \epsilon_1 \equiv 1$$

Similarly values can be computed for all items other than item 1 by

$$(6) \quad \Delta_{ij}^r = \log \xi_r + \log \epsilon_i - \log \xi_r - \log \epsilon_1 = \log \epsilon_i$$

where Δ_{ij}^r is the difference between the logit for item j in score group r and the logit for item 1 in score group r , or

$$\log \epsilon_i \approx \log \left\{ \frac{X_{ri}}{N_r - X_{ri}} \right\} - \log \left\{ \frac{X_{r1}}{N_r - X_{r1}} \right\}.$$

Once difficulties have been estimated in this fashion, we are able to compare two people, as in (2) above, who did not take the same item.

Andersen (1973a) provides the proof for the other side of specific objectivity. He shows that if raw score is taken as the sufficient statistic for ability, then the underlying model must be the Rasch model. It follows from this that the three assumptions given above are both necessary and sufficient for specific objectivity.

Wright (1968) introduced the terms "sample-free item calibration" and "test-free person measurement." This is not intended to imply that anything can be known about a person's ability without administering some items or that anything can be known about an item's difficulty without giving it to some persons. It does mean, as illustrated above,

that we can obtain estimates of ability that do not depend on the difficulties of the particular set of items we choose to administer. Any other set of appropriate items produce a statistically equivalent estimate for the person.

This avoids some troublesome problems for the test user. It solves the problem of form equating. Once a bank of items has been calibrated (i.e., the difficulty of each item estimated), any form made up of items from that bank has also been calibrated. Its ability estimates are on the common scale of measurement with no further manipulation. This was dramatically illustrated by Rentz and Bashaw (1975) who showed substantial savings in time and money through the use of Rasch techniques over traditional methods of form equating. The logical extension of this property suggests that each person can be administered a test tailored specifically for him and still measures can be obtained that are comparable for all (Wright, 1968, Wright and Douglas, 1975a).

Before presenting a discussion of some of the methods available for obtaining estimates of the model's parameter, we should mention that ability and difficulty will be expressed throughout in "logits" which are arbitrary units of measurement. A person's ability in logits is the natural log odds in favor of his succeeding on an item whose difficulty is at the origin on the scale. In other words, a person with ability 0.0 (i.e., ability equal to the difficulty of an item at the origin) has an even chance (odds 1 to 1) of succeeding on the item since $\log(1) = 0$ or equivalently, from expression (1),

$$(7) \quad 1.0 = \frac{P_{vi}}{1-P_{vi}}$$

or

$$(8) \quad P_{vi} = \frac{1}{2} .$$

Similarly, a person with ability 1.0 has about a three to one chance of success ($\log_e 3$ is approximately equal to 1.0). Logits are used because they are computationally convenient. In connection with this, we will use the notation:

$$\begin{aligned}\beta_v &= \log \xi_v = \text{logit ability for person } v \\ -\delta_i &= \log e_i = \text{logit difficulty for item } i.\end{aligned}$$

Calibration of Item Parameters

Several methods of estimating item parameters, are treated in detail in Douglas (1975) and Wright and Douglas (1975b, 1976, 1977a, 1977b). They are reviewed below.

Conditional Maximum Likelihood Estimation: The mathematically ideal method is the conditional maximum likelihood approach which follows naturally from the separability of parameters. The estimates were derived in detail by Andersen (1973c). An approximation was developed by Wright (1966). Andersen's derivation begins with the Rasch model:

$$(9) \quad P\{X_{vi} | \beta_v, \delta_i\} = \frac{\exp[X_{vi}(\beta_v - \delta_i)]}{1 + \exp[\beta_v - \delta_i]} \quad \begin{aligned} X_{vi} &= 0, 1 \\ i &= 1, L \\ v &= 1, N \end{aligned}$$

If this model fully characterizes the interaction between person v and any item i the likelihood of a particular set of responses to L items, denoted by (X_{vi}) , is

$$(10) \quad P\{(X_{vi}) | \beta_v, \delta_i\} = \prod_i \left\{ \frac{\exp[X_{vi}(\beta_v - \delta_i)]}{1 + \exp(\beta_v - \delta_i)} \right\} = \frac{\exp[r_v \beta_v] \exp\{\sum_i X_{vi} \delta_i\}}{\prod_i [1 + \exp(\beta_v - \delta_i)]}.$$

This probability is seen to be composed of three parts: $\exp(r\sqrt{\beta_v})$ which connects the person's score and his ability; $\exp(-\sum_i X_{vi}\delta_i)$ which connects the data and the item parameters; and the denominator which involves no data.

The probability of observing a given raw score

$$(11) \quad r_v = \sum_i^L X_{vi}$$

is the sum of the probabilities of all possible ways of obtaining the score r . That is,

$$(12) \quad P\left\{\sum_i X_{vi} = r \mid \beta_v, (\delta_i)\right\} = \sum \frac{\exp(\beta_v \sum_i X_{vi}) \exp(-\sum_i X_{vi}\delta_i)}{\prod_i [1 + \exp(\beta_v - \delta_i)]} \quad \text{for all } \sum_i X_{vi} = r$$

or

$$(13) \quad P\{\sum_i X_{vi} = r \mid \beta_v, (\delta_i)\} = \frac{\exp(r\sqrt{\beta_v}) \gamma_r}{\prod_i [1 + \exp(\beta_v - \delta_i)]}$$

where γ_r is an elementary symmetric function of the item difficulties which equals

$$\gamma_r = \sum \left[\exp(-\sum_i X_{vi}\delta_i) \right] \quad \text{for all } \sum_i X_{vi} = r$$

and the summation is over all possible response vectors which sum to r .

The conditional probability of response vector (x_{vi}) given the raw score is found by dividing (10) by (13):

$$(14) \quad P\{(X_{vi}) \mid r_v, (\delta_i)\} = \frac{\exp(-\sum_i X_{vi}\delta_i)}{\gamma_r}$$

which is an expression in the item parameters that is free of the ability distribution of the persons. This result depends on raw score being a sufficient statistic for ability.

The conditional likelihood of the entire data matrix $((X_{vi}))$, consisting of the L responses by each of the N persons, is:

$$(15) \quad \Lambda = P\{(X_{vi}) \mid (r_v), (\delta_i)\} = \prod_v \left[\frac{\exp(-\sum_i X_{vi} \delta_i)}{\gamma_r} \right]$$

since the observations are stochastically independent given the parameters or their sufficient statistics. Letting $s_i = \sum_v X_{vi}$ and $\prod_v \gamma_r = \prod_v \gamma_r^{n_r} = \prod_v \gamma_r^N$ we have for the conditional likelihood:

$$(16) \quad \Lambda = \frac{\exp(-\sum_i s_i \delta_i)}{\prod_v \gamma_r^{n_r}}.$$

Estimators for the (δ_i) are found by maximizing Λ in the usual way. Details of this and the iterative procedures necessary for obtaining estimates are given by Andersen (1972), Douglas (1975) and Wright and Douglas (1975b).

Unconditional maximum likelihood estimation: While formally correct, the conditional estimation techniques have serious practical problems. The computation of the elementary symmetric functions is quite expensive by the methods now used and incurs unacceptably large roundoff errors for tests of length greater than twenty items. Wright developed a less expensive technique using unconditional maximum likelihood which is reported in detail in Wright and Panchapakesan (1969) and Wright and Douglas (1975b). In their development, the unconditional likelihood of the data matrix is the double product of

P_{vi} over all persons and items. Thus,

$$(17) \quad \Lambda = \prod_v \prod_i P[X_{vi} | \beta_v, \delta_i] = \frac{\exp[\sum_i \sum_v X_{vi}(\beta_v - \delta_i)]}{\prod_i \prod_v [1 + \exp(\beta_v - \delta_i)]}$$

or

$$(18) \quad \Lambda = \frac{\exp(\sum_i \sum_v X_{vi} \beta_v) \exp(-\sum_i \sum_v X_{vi} \delta_i)}{\prod_i \prod_v [1 + \exp(\beta_v - \delta_i)]}$$

Again the responses are stochastically independent given the parameters. (The high correlations that are usually observed among a person's responses to a set of items are due entirely to their common relationship to the person's ability, β_v which the items are attempting to measure.)

The algebra for maximizing this likelihood is less complex if we work with the log likelihood:

$$(19) \quad \lambda = \log \Lambda = \sum_v r_v \beta_v - \sum_i s_i \delta_i - \sum_i \sum_v \log [1 + \text{EXP}(\beta_v - \delta_i)] + \varphi \sum_i \delta_i.$$

The final term is included to remove the indeterminacy in the equations that arises because only differences between parameters are estimable.

The φ -term removes the problem here by imposing the restriction that $\sum_i \hat{\delta}_i = 0$. While almost any restriction on the δ_i would do this particular one is convenient for reasons to be discussed later.

The derivatives needed to obtain the maxima of (19) are:

$$(20) \quad \frac{\partial \lambda}{\partial \beta_v} = r_v - \sum_i \frac{\exp(\beta_v - \delta_i)}{1 + \exp(\beta_v - \delta_i)} = r_v - \sum_i P_{vi}$$

$$(21) \quad \frac{\partial \lambda}{\partial \delta_i} = -s_i + \sum_v \frac{\exp(\beta_v - \delta_i)}{1 + \exp(\beta_v - \delta_i)} + \varphi = -s_i + \sum_v P_{vi} + \varphi$$

$$(22) \quad \frac{\partial^2 \lambda}{\partial \beta_v^2} = - \sum_i \frac{\exp(\beta_v - \delta_i)}{[1 + \exp(\beta_v - \delta_i)]^2} = - \sum_i P_{vi}(1 - P_{vi}) < 0$$

$$(23) \quad \frac{\partial^2 \lambda}{\partial \delta_i^2} = - \sum_v \frac{\exp(\beta_v - \delta_i)}{[1 + \exp(\beta_v - \delta_i)]^2} = - \sum_v P_{vi}(1 - P_{vi}) < 0$$

Wright and Douglas (1975b) demonstrated that the cross derivatives are small and can be ignored without harming the resulting estimates.

Since both second derivatives are always negative, there can only be one extreme point and it must represent the maximum likelihood. This point can be determined by setting equations (20) and (21) equal to zero and solving. We first need to evaluate φ . Summing equation (21) over all items,

$$(24) \quad - \sum_i s_i + \sum_i \sum_v \hat{P}_{vi} + \sum_i \hat{\varphi} = 0$$

or

$$(25) \quad - \sum_i \sum_v X_{vi} + \sum_i \sum_v \hat{P}_{vi} + L\hat{\varphi} = 0$$

and since from (20)

$$(26) \quad \sum_i \sum_v X_{vi} = \sum_i \sum_v \hat{P}_{vi} .$$

We must have that $\hat{\phi} = 0$. The estimating equations are simply:

$$(27) \quad s_i = \sum_r n_r \hat{p}_{ri} = \sum_r n_r \left[\frac{\exp(b_r - d_i)}{1 + \exp(b_r - d_i)} \right]$$

and

$$(28) \quad r = \sum_i \hat{p}_{ri} = \sum_i \left[\frac{\exp(b_r - d_i)}{1 + \exp(b_r - d_i)} \right].$$

We are able to substitute an r subscript for the v -subscript in (27) because r is a sufficient statistic for ability so persons who attain the same score are indistinguishable as far as our knowledge of their ability is concerned. It is more efficient to perform the summations from 1 to $L-1$ rather than 1 to N .

Since (27) and (28) can not be solved explicitly for b_r and d_i , we must resort to an iterative solution. The simplified Newton-Raphson approach given by Wright and Panchapakesan (1969) works quite well for this.

$$(29) \quad d_i^{t+1} = d_i^t - \frac{s_i - \sum_r n_r p_{ri}^t}{\sum_r n_r p_{ri}^t (1 - p_{ri}^t)}$$

and

$$(30) \quad b_r^{t+1} = b_r^t + \frac{r - \sum_i p_{ri}^t}{\sum_i p_{ri}^t (1 - p_{ri}^t)}.$$

The meaning of these expressions can be grasped intuitively by noting that the numerator of each correction term (i.e., the right hand terms) are equations (24) and (25). When this term is zero, the equation is solved and we no longer need modify the estimates. If it is not zero, we adjust the estimate by an amount proportional to this

difference. The scaling factor in the denominator is the derivative of the P_{ri} with respect to the parameter, the change in scale from score units to logit units.

Starting values needed to begin the process can be obtained by computing the d_i assuming the b_r are zero and analogously, the b_r assuming the d_i are zero. From (27) we have

$$(31) \quad s_i = \sum_r n_r \left(\frac{\exp(-d_i)}{1 + \exp(-d_i)} \right) = N \left[\frac{\exp(-d_i)}{1 + \exp(-d_i)} \right]$$

or

$$(32) \quad d_i^0 = \log \left(\frac{N - s_i}{s_i} \right).$$

From (28) we obtain

$$(33) \quad b_r^0 = \log \left(\frac{r}{N-r} \right).$$

It is clear from any of the estimation equations that zero or perfect scores for either persons or items can not be used to estimate parameters. In (32) and (33), this would lead to either zero or infinity for which the log function is not defined. In (29) and (30), the process could not converge unless all P_{ri} were zero or one, which can not happen unless the abilities or difficulties are plus or minus infinity.

In light of this, the first step in the estimation process must be the elimination of zero and perfect scores. This process may require more than one cycle since the elimination of an item which every one answered correctly necessitates the elimination of all persons who only answered that one item correctly, and so forth.

A second problem is that the unconditional maximum likelihood estimates are biased (Andersen, 1973b). For the case of a two item test it can be shown that the difficulties are biased by a factor of two. Wright and Douglas (1975b), based on earlier work by Wright (1966), demonstrate that for tests of any length L for which $\sum d_i = 0$ the average bias is $(L/L-1)$ and that correcting all difficulties by this factor results in estimates that are virtually indistinguishable from those given by the more expensive but unbiased conditional estimation procedure.

The corrected unconditional estimation algorithm employed by most Rasch analysis programs (e.g., Wright and Mead, 1975) is

- i) Obtain item scores, (s_i) , and counts of the number of persons at each score, (n_r) .
- ii) Edit these data vectors to remove perfect scores (i.e., $s_i = 0$ or N and $r = 0$ or L) cycling as many times as necessary.
- iii) Define an initial set of (b_r) as

$$b_r^0 = \log \left(\frac{r}{L-r} \right), \quad r = 1, L-1$$

- iv) Define an initial set of (d_i) as

$$d_i^0 = \log \left(\frac{N-s_i}{s_i} \right), \quad i = 1, L$$

Center the item set at zero by subtracting $d_{\cdot} = \sum d_i / L$ from each d_i .

- v) Obtain a revised set of (d_i) by the one dimensional Newton-Raphson algorithm until convergence is achieved.
- vi) Using the tentative set of (d_i) as obtained from (v) above, obtain a revised set of (b_r) once again by Newton Raphson.

- vii) Repeat steps (v) and (vi) as often as necessary to obtain stable values for the (d_i) .
- viii) Correct for bias by multiplying each d_i by $(L-1)/L$.
- ix) Calculate the approximate (b_i) for these unbiased (d_i) .

Cohen's normal approximation: As a final alternative to the problem of estimating item difficulty parameters, Wright and Douglas (1975b) present the details to a very inexpensive procedure that was suggested by Cohen in 1973. This procedure assumes that person abilities are given by an explicit function of total score, and that the function is completely determined except for a single multiplying parameter which can be obtained by maximum likelihood. This implies that the distribution of both person abilities and item difficulties are adequately characterized by the first two moments. If this is true, the resulting estimates are identical to those obtained by the more expensive procedures just discussed.

The procedure is as follows:

- i) Define the initial values of difficulties and abilities and their variances in the sample:

$$d_i^0 = \log \left(\frac{N-s_i}{s_i} \right) - d^0 \text{ where } d^0 = \sum d_i / L$$

$$D = \sum d_i^0^2 / [(L-1)(2.89)]$$

$$b_r^0 = \log \left(\frac{r}{L-r} \right)$$

$$B = \sum n_r (b_r^0 - b^0)^2 / [(N-1)(2.89)] \text{ where } b^0 = \sum n_r b_r^0 / N$$

$$r = 1, L-1$$

ii) Compute the expansion coefficients:

$$X = [(1 + B)/(1 - BD)]^{1/2}$$

$$Y = [(1 + D)/(1 - BD)]^{1/2}$$

iii) Compute the final estimates of the parameters and their standard errors:

$$(34) \quad d_i = X d_i^0$$

$$SE(d_i) = X [N/s_i(N - s_i)]^{1/2}$$

$$b_r = Y b_r^0$$

$$(35) \quad SE(b_r) = Y [L/r(L - r)]^{1/2}.$$

Although there is only modest experience with this form of the algorithm evidence indicates that for moderately long instruments and more or less symmetrical, unimodal score distributions, it yields estimates well within a standard error of the values obtained from the more expensive methods.

Binomial Extension of the Simple Logistic Model

Not all data is scored dichotomously. However, the ideas and equations of the preceding sections can be extended to more complex cases. Consider a situation in which a subject v receives a score of 0, 1, . . . , m_i on an item i . This might be a score on an attitude scale, an aptitude test, or target shooting. If this score is taken to be generated as the result of m_i independent Bernoulli trials, each with probability of success P_{vi} , then the binomial response model

$$(36) \quad P(X_{vi} | P_{vi}, m_i) = \binom{m_i}{X_{vi}} P_{vi}^{X_{vi}} (1 - P_{vi})^{m_i - X_{vi}}$$

describes it (Andrich, 1975). In a given situation we may not be certain that this model (or the specialization we propose) is appropriate, but we can test the fit of the model once the parameters have been estimated.

It is useful to write this model in odds notation by letting

$$(37) \quad P_{vi} = \lambda_{vi} / (1 + \lambda_{vi})$$

where λ_{vi} is interpreted as the odds of success. Then

$$(38) \quad P(X_{vi} | \lambda_{vi}, m_i) = \binom{m_i}{X_{vi}} \lambda_{vi}^{X_{vi}} / (1 + \lambda_{vi})^{m_i}.$$

By analogy to Rasch's simple logistic model¹ it seems likely that it will be useful to write

$$(39) \quad \lambda_{vi} = \xi_v \epsilon_i.$$

That is, each λ_{vi} will be taken to be the product of a person parameter ξ_v and an item parameter ϵ_i . With this assumption we have

$$(40) \quad P(X_{vi} | \xi_v, \epsilon_i, m_i) = \frac{\binom{m_i}{X_{vi}} (\xi_v \epsilon_i)^{X_{vi}}}{(1 + \xi_v \epsilon_i)^{m_i}}.$$

Note that if $m_i = 1$, then X_{vi} is zero or one and expression (40) reduces to the Bernoulli form of the preceding section.

Conditional Estimation

Let us consider the possibility of estimating the parameters ξ_v and ϵ_i . The model

¹The notation is somewhat less complex if we define: $\xi_v = \exp(\beta_v)$ and $\epsilon_i = \exp(-\delta_i)$.

(40) implies as usual the inevitable assumption of conditional independence of responses over persons and over items, given the parameters of the model. Suppose, then, that a person responds to L items. By our assumption of conditional independence, the probability that his responses will be $X_{v1}, \dots, X_{vL}$ (which we shall write as (x_{vi})), given the parameters, is

$$(41) \quad P\{(X_{vi}) | \xi_v, (\epsilon_i), (m_i)\} = \frac{\prod_i \binom{m_i}{X_{vi}} \xi_v^{\sum_i X_{vi}} \prod_i \epsilon_i^{X_{vi}}}{\prod_i (1 + \xi_v \epsilon_i)^{m_i}}$$

where (ϵ_i) and (m_i) represent $\epsilon_1, \dots, \epsilon_L$ and $m_1, \dots, m_L$ respectively. If we now denote the total score for any person as

$$(42) \quad r_v = X_{v+} = \sum_i X_{vi}$$

then

$$P\{r_v | \xi_v, (\epsilon_i), (m_i)\} = \sum_{r_v} P\{X_{vi} | \xi_v, (\epsilon_i), (m_i)\} = \frac{\prod_i \binom{m_i}{X_{vi}} \xi_v^{r_v} \prod_i \epsilon_i^{X_{vi}}}{\prod_i (1 + \xi_v \epsilon_i)^{m_i}}$$

which can be rewritten as

$$(43) \quad P\{r_v | \xi_v, (\epsilon_i), (m_i)\} = \frac{\xi_v^{r_v}}{\prod_i (1 + \xi_v \epsilon_i)^{m_i}} \prod_i \left[\binom{m_i}{X_{vi}} \epsilon_i^{X_{vi}} \right]$$

where the sum is taken over all collections of responses $(x_{v1}, \dots, x_{vL})$ such that $x_{v1} + \dots + x_{vL} = r_v$.

The conditional probability of a particular set of responses (X_{vi}) can be found by dividing (41) by (43) and, observing that the probability is now independent of δ_v .

$$(44) \quad P\{(X_{vi}) | r_v, (\epsilon_i), (m_i)\} = \frac{\prod_i \binom{m_i}{X_{vi}} \epsilon_i^{X_{vi}}}{\sum \left[\prod_i \binom{m_i}{X_{vi}} \epsilon_i^{X_{vi}} \right]} \quad \text{where the summation in the denominator is over all persons with score } r.$$

Clearly r_v is a sufficient statistic for ξ_v and $s_i = X_{+i}$ is a sufficient statistic for ϵ_i so all the information about a person's ability or an item's difficulty is contained in the appropriate total score. Furthermore, given a group of persons it is now possible in principle to compute the conditional likelihood of their responses and to estimate the item difficulty parameters by conditional maximum likelihood estimation independently of the abilities. Similarly, abilities could be estimated independently of item difficulties.

Details of the conditional maximum likelihood estimation procedure for the simple logistic case (all $m_i = 1$) can be found in Wright and Douglas (1975b). Unfortunately, the conditional maximum likelihood estimation is quite sensitive to round-off errors; even an improved estimation procedure which Wright and Douglas devised failed for moderate numbers of items. There is no reason to believe that conditional estimation would be more practicable in the binomial case.

Unconditional Estimation

Even if the conditional estimation procedure could be made to work, its excessive cost would probably inhibit wide application. Recognizing the cost and instability of

conditional estimation, Wright and Panchapakesan (1969) proposed a method of joint parameter estimation for the simple logistic model. This estimation procedure has been extended to the binomial case.

Let $((X_{vi}))$ be the matrix of responses of persons 1, ..., N to items 1, ..., L, that is,

$$(45) \quad ((X_{vi})) = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1L} \\ X_{21} & X_{22} & \dots & X_{2L} \\ \vdots & \vdots & & \vdots \\ X_{N1} & X_{N2} & \dots & X_{NL} \end{bmatrix}$$

By conditional independence we have the joint probability

$$(46) \quad \Lambda = P \{((X_{vi})) | (\xi_v), (\epsilon_i)\} = \frac{\prod_v \prod_i \binom{m_i}{X_{vi}} (\xi_v \epsilon_i)^{X_{vi}}}{\prod_v \prod_i (1 + \xi_v \epsilon_i)^{m_i}},$$

so

$$\begin{aligned} \lambda = \log \Lambda = & \sum_i \sum_v \log \binom{m_i}{X_{vi}} + \sum_v r_v \log \xi_v + \sum_i s_i \log \epsilon_i \\ & - \sum_i \sum_v m_i \log (1 + \xi_v \epsilon_i). \end{aligned}$$

Writing $\beta_v = \log \xi_v$, $\delta_i = -\log \epsilon_i$ as in the simple logistic case gives

$$(47) \quad L = \sum_i \sum_v \log \binom{m_i}{X_{vi}} + \sum_v r_v \beta_v - \sum_i s_i \delta_i - \sum_i \sum_v m_i \log (1 + \exp(\beta_v - \delta_i)).$$

Thus

$$(48) \quad \frac{\partial \lambda}{\partial \beta_{\mu}} = r_{\mu} - \sum_i m_i P_{\mu i}, \quad \mu = 1, \dots, N,$$

$$(49) \quad \frac{\partial^2 \lambda}{\partial \beta_{\mu}^2} = - \sum_i m_i P_{\mu i} (1 - P_{\mu i}), \quad \mu = 1, \dots, N,$$

$$(50) \quad \frac{\partial \lambda}{\partial \delta_j} = -s_j + \sum_v m_j P_{vj}, \quad j = 1, \dots, L.$$

and

$$(51) \quad \frac{\partial^2 \lambda}{\partial \delta_j^2} = - \sum_v m_j P_{vj} (1 - P_{vj}), \quad j = 1, \dots, L.$$

Recall that all subjects with score r will have the same estimated ability $b_r = \hat{\beta}_{v_r}$ so equations (48) lead to the estimation equations

$$(52) \quad r - \sum_i m_i P_{ri} = 0, \quad r = 1, \dots, M-1$$

where $d_i^0 = \log[(N - S_i)/S_i]$. Observe that (52) has no solutions for zero and perfect scores, so they must be eliminated from the data. Similarly, (50) gives the estimation equations

$$(53) \quad s_j - \sum_r n_r m_j P_{rj} = 0, \quad j = 1, \dots, L$$

where n_r is the number of subjects with score r .

Our experience with the simple logistic model leads us to expect a dependency in these equations, and, indeed, summing (52) over r and (53) over j gives identical sums. We resolve this dependency by setting $\sum_i m_i d_i = 0$. Other constraints might be used,

but this one helps keep down rounding error during estimation; and other linear constraint can be implemented by transforming the parameter estimates obtained using this one.

It is now a simple matter to estimate the β_v and δ_i by the Newton-Raphson method. Details of the estimation process for the simple logistic case can be found in Wright and Douglas (1975b) or Wright and Mead (1975). Their procedure generalizes directly to the binomial case.

Andersen (1973a) has shown that these estimates are biased. However, Wright and Douglas (1975b) show by simulation that most of the bias can be cleared up by multiplying the d_i by $(L-1)/L$ when all $m_i = 1$. Further simulation indicates that $(M-1)/M$ is a suitable unbiasing constant for the binomial case.

Standard Errors

In principle, asymptotic estimates of the standard errors of the parameter estimates are given by

$$SE(\theta) = [-\text{diag} \{(\partial^2 \lambda / \partial \theta^2)^{-1}\}]^{1/2}.$$

Here the matrix of second derivatives is nearly diagonal, so we take

$$\begin{aligned} (54) \quad SE(d_i) &= (-\partial^2 \lambda / \partial \delta_i^2)^{-1/2} \\ &= \left(\sum_{r=1}^{M-1} n_r m_i p_{ri} (1-p_{ri}) \right)^{-1/2} \end{aligned}$$

and

$$(55) \quad SE(b_r) = (\sum m_i P_{ri}(1 - P_{ri}))^{-1/2} .$$

Tests of Fit

A primary benefit from having an explicit mathematical model for a process is the possibility of making rigorous tests of how well the observed data are predicted by the model. In the case of the Rasch model, the most detailed form of the data is an $N \times L$ matrix, denoted by $((X_{vi}))$ consisting of one row for each person and one column for each item. The entry X_{vi} is the score of person v on item i . It has a range of 0 to m_i . For the most familiar Bernoulli form of the model, all m_i are equal to one.

The expected value of X_{vi} is

$$(55) \quad E(X_{vi}) = m_i P_{vi}$$

and its variance is

$$(56) \quad V(X_{vi}) = m_i P_{vi}(1 - P_{vi}).$$

Therefore, the difference between the observed score for the person and the predicted score

$$(57) \quad x_{vi} = X_{vi} - m_i P_{vi}$$

may be standardized by dividing by the estimated standard deviation.

$$(58) \quad Z_{vi} = \frac{X_{vi} - m_i P_{vi}}{(m_i P_{vi}(1 - P_{vi}))^{1/2}} .$$

The sample-free property of the model suggests one strategy for organizing the residuals. Since the estimates of item difficulty should, under the model, be independent of the distribution of person ability, the difficulty estimator should be equally appropriate for all scores. In other words, we should obtain the same estimated difficulty when just the low scores are used as when the high scores are used. If we were to adjust the estimates to fit score r exactly the first adjustment for item i would be proportional to (compare to expression (29))

$$(59) \quad x_{ri} = \sum_{v \in r} X_{vi} - n_r m_i P_{ri}.$$

If we standardize by dividing by the standard deviation and square

$$(60) \quad V_{ri}^2 = \left[\frac{(\sum_{v \in r} X_{vi} - n_r m_i P_{ri})^2}{n_r m_i P_{ri} (1 - P_{ri})} \right] K.$$

We obtain a chi-square statistic with one degree of freedom. The multiplier K is a correction factor, usually near one, to inflate the statistic to the equivalent of one degree of freedom. (Haberman, 1973). If all the n_r are equal and $P_{ri}(1-P_{ri})$ is nearly constant for all r and i , then K can be shown to be:

$$(61) \quad K = \frac{L(M-1)}{(L-1)(M-2)}.$$

The intuitive motivation for this can be grasped easily by noting that since i goes from 1 to L and r from 1 to $M-1$, there are $L(M-1)$ statistics V_{ri}^2 . But, having fit $L-1$ item parameters and $M-1$ person parameters, there are only $(L-1)(M-2)$ degrees of freedom available.

Since it frequently happens that some scores are not observed in a particular sample, or are very rare, the summation may also be done over score groups containing more than one score:

$$(62) \quad V_{ji}^2 = \left[\frac{(\sum_{r \in j} X_{vi} - \sum_{r \in j} n_{ri} p_{ri})^2}{\sum_{r \in j} n_{ri} p_{ri} (1 - p_{ri})} \right] \times K$$

$$K = \frac{Lg}{(L-1)(g-1)}$$

$$i = 1, L$$

$$j = 1, g$$

Collecting over groups, $V_{gi}^2 = \sum_{j \in g} V_{ji}^2$ gives a chi-square statistic with g degrees of freedom.

While V_{gi}^2 specifically asks the question would all score groups give the same estimate of difficulty for item i , it is possible to compute a more general statistic from expression (58). Squaring and summing over all persons gives a test statistic for the fit of item i :

$$(63) \quad NV_i^2 = \sum_v Z_{vi}^2 \left[\frac{NL}{(M-1)(L-1)} \right]$$

which is approximately distributed as a chi-square with N degrees of freedom. V_i^2 will tend to be large when different groups give different estimates of abilities (as will V_{gi}^2) and when persons in the same score group obtain their score in different ways.

A frequently mentioned alternative to the Rasch model is the logistic model containing a second item parameter, item discrimination. While this model lacks the essential measurement properties of the Rasch model, it can help conceptualize misfitting data if an index of discrimination is computed. Such an index can be derived as follows. General expression for the probability of the success of one trial is

$$(64) \quad P(X_{vi} = 1) = \frac{\text{EXP}(\lambda_{vi})}{1 + \text{EXP}(\lambda_{vi})}.$$

One possible parameterization of λ is that employed by the Rasch model; i.e., $\lambda_{vi} = \beta_v - \delta_i$. A possibility for an alternative generator might include a discrimination parameter. Then the probability would be as

$$(65) \quad P(X_{vi} = 1) = \frac{\text{EXP}[\alpha_i(\beta_v - \delta_i)]}{1 + \text{EXP}[\alpha_i(\beta_v - \delta_i)]}.$$

If this is the actual generator, then (64) and (65) are equal and the logits (the exponents in this application) are also equal, statistically, hence,

$$(66) \quad \lambda_{vi} = \alpha_i (\beta_v - \delta_i) + e_{vi}$$

where the residual error e_{vi} is included, because the linear model cannot account for all the variation in λ_{vi} . Since expression (64) provides a unique parameter for each person-item combination, λ_{vi} is the same as the observed logit which in most application would be estimated by:

$$(67) \quad \lambda_{vi} \approx \log \left[\frac{X_{vi}}{m_i - X_{vi}} \right].$$

However, in our case, this cannot be done when X_{vi} is either zero or m_i .

To escape this, let us rewrite (66) in terms of a residual from the Rasch model:

$$(68) \quad \Lambda_{vi} = \lambda_{vi} - (\beta_v - \delta_i) = (\alpha_i - 1)(\beta_v - \delta_i) + e_{vi}.$$

The logistic residual Λ_{vi} can be approximated from (57) by recalling that the rate of exchange between score units and logits is approximately equal to the derivative of P_{vi} with respect to $(\beta_v - \delta_i)$. This derivative is

$$(69) \quad \frac{\partial P_{vi}}{\partial (\beta_v - \delta_i)} = P_{vi} (1 - P_{vi})$$

and therefore,

$$(70) \quad \Lambda_{vi} \approx Y_{vi} = \frac{X_{vi} - P_{vi}}{P_{vi}(1 - P_{vi})}.$$

Rewriting (68) in terms of statistics which we can compute, we have

$$(71) \quad Y_{vi} = a_i(b_r - d_i) + e_{vi}$$

where $a_i = (\alpha_i - 1)$. Since with respect to item i , the difficulty d_i is constant, an index of the item's discriminating power can be computed by regressing Y_{vi} on ability.

Therefore,

$$(72) \quad a_i = \frac{\sum (b_r - b.) Y_{vi}}{\sum (b_r - b.)^2}$$

where $b. = \sum_r n_r b_r / N$

and the associated sum of squares is

$$(73) \quad SS(a_j) = \frac{[\sum_v (b_{rv} - b) Y_{vi}]^2}{\sum_v (b_{rv} - b)^2}$$

All the test of fit statistics presented in this section have the appearance of chi square (or mean square) variates, but recent simulation studies (Mead, 1976) show that this distribution is not exactly correct. Hence, exact probability statements about lack of fit are not possible. The chi-square distribution is a useful background against which to judge these statistics, however.

CHAPTER III

DESCRIPTION OF THE BICAL PROGRAM: ANALYSIS OF MILITARY POLICE PISTOL DATA

BICAL is a FORTRAN program designed to estimate and test the parameters in the Rasch model when written as:

$$(74) \quad P[X_{vi} | \beta_v, \delta_i, m_i] = \binom{m_i}{X_{vi}} \frac{\text{EXP}[X_{vi}(\beta_v - \delta_i)]}{[1 + \text{EXP}(\beta_v - \delta_i)]^{m_i}}, \quad X_{vi} = 1, m_i.$$

The observation X_{vi} represents the numbers of successes by person v in m_i trials at task i . The capacities of the program are listed in Table 1. The number of subjects permitted is restricted only by the availability of auxiliary storage. A description of the required control cards is given in Appendix C. The military police data will be used to illustrate the program's application.

The pistol data was collected to assess the competence of MP candidates. It involved eight target presentations which differed in the distance from the marksman and the position from which he was required to fire. For the first two targets, ten shots were required; for the remaining six, only five shots. The description of the task and number of shots at each are summarized in Table 2. Table 3 shows the control cards used for this analysis.

TABLE 1

BICAL PROGRAM CAPABILITIES

Description	Symbol	Maximum Value
Number of Items	L	150
Trials on one task	m_i	35
Total number of trials	$M = \sum_i m_i$	1000

TABLE 2

DESCRIPTION OF THE MILITARY POLICE PISTOL DATA

Task Number	Meters to Target	Position of Marksman	Task Name	Number of Shots
1	35	Prone	35P	10
2	25	Kneel	25N	10
3	25	Strong Left	25SL	5
4	25	Strong Right	25SR	5
5	15	Kneel	15N	5
6	15	Strong Left	15SL	5
7	15	Strong Right	15SR	5
8	7	Crouch	7C	5

TABLE 3

SAMPLE CONTROL CARDS FOR RUNNING BICAL

Card Number	Card Name	Card Format	Sample from MP data
1	Title Card	(20A4)	Military Police Data-Hits Per Target
2	Input Description	(14I5)	8 25 5 45 12 2 1
3	Item Names	(20A4)	35P 25N 25SL25SR15N 15SL15SR 7C
4	Column Select	(80A1)	AA555555
5	Key	(80A1)	77333333
6	Options Labels	(5A1)	12345
7	(Data Cards)		
7a	End of Data	(A1)	*
10	End of Job	(A4)	****

Card 1, is a title card which supplies identifying information to be printed at the top of each page of output.

Card 2, the data description card, describes how the data is to be presented and handled. The data for this run are described as follows.

First, there are eight tasks, i.e., each person has eight scores to be read, as described in Table 2. Second, the groups used in tests of fit must average at least 25 persons each. This determines the number of groups that will be used. The program format is limited to six groups, but if the total number of persons divided by six is less than twenty-five (as in this case) fewer groups will be used. This value will also halt the estimation of parameters if, after editing, there are fewer than twenty-five persons remaining in the sample. If no value is provided the default value is thirty.

The third and fourth values define the range of scores to be included in the calibration sample. Only persons scoring at least five but not more than forty-five will be included. This is done because extremely high or extremely low scorers frequently behave abnormally. The scores to be excluded need to be thought through for each application, for their choice depends on the way extreme scores might occur. In achievement testing, it is usually desirable to set the lower limit somewhat above the chance level.

Fifth, the value of "12" indicates that only the first twelve columns of each record need be read. Since in this case the data is punched in columns 5 through 12, there is no need to read beyond 12.

Sixth, the "2" selects the second available calibration technique. This is the corrected unconditional method, and is chosen for this problem because of the small sample size and the asymmetrical distribution of scores.

Seventh, the "1" specifies that the data is already scored and the value to be read for each item is the person's number of hits on that target.

All remaining parameters will assume default values. This means that data input is from cards, no output will be produced except on the printer and all standard printed output will be generated.

Card 3, the item name card provides a four character name for each item read. There are eight such fields here and they are coded in the same order as the items occur on the data cards.

Card 4, the column select card serves two functions. First, any character other than blank or zero indicates that the column contains an item included in the item count (8) on the data description card and named on the item name card. An ampersand (&) causes an item to be excluded from the analysis although read and named. This facilitates dropping misfitting items with a minimum of changes to the control cards.

The column select also defines the maximum possible score (m_i) for each item. Since the fields are only one column in width, the alphabetical characters (A-Z) are used to designate the values (10-35).¹ A value larger than 35 cannot be accepted by the program as it now stands.

The interpretation of the card given in Table 3 is that no data is wanted from columns 1 to 4 of the input record. Columns five and six contain tasks which have maximum scores of 10. Columns seven through twelve contain tasks, which have maximum scores of five. This accounts for all eight items.

¹Data cards must be coded in the same way.

Card 5, the key card in Table 3 is not referenced in this run since the data is already scored (col. 35 of the data description card) but a key card must be included in the deck.

Card 6, the options label card defines up to five possible data values. The same five values apply to all items. The frequency of occurrence of each of the specified values is accumulated for each item. For this example, a table showing the number of times each target was hit 1, 2, 3, 4 or 5 times will be prepared and printed.

Interpretation of BICAL Output for MP Pistol Data

The analysis offered here is intended to illustrate interpretation of the BICAL output; it is not a definitive analysis of this particular data set. Page 1 of the output shown in Appendix B lists the control cards just discussed. This enables the user to check quickly that the analysis performed is the one intended. In addition, the first input record and the total number of records are shown to verify that the records were read correctly.

Page 2 is the alternative response frequency table that was specified by the Options Label Card 6. The "UNKN" column is the count of the frequency of any character other than the five shown. Since targets 1 and 2 could have scores from zero to ten, these tasks show a large number of unknowns. For the others, the only unknowns are the zero scores.

Page 3 reviews the editing process. For this example there were no persons with zero or fifty hits. If there had been, these persons would have been excluded from all subsequent analyses. There were eight columns selected by the column select card and eight item names were provided.

There were no persons below five and ten above forty-five leaving a total of 126 to be used in the calibration. This table would not include the zero or perfect scores noted earlier.

No items were rejected because of perfect or zero item scores. Therefore, the analysis will be done on eight tasks with 126 persons. Had items and persons been eliminated the minimum and maximum accepted scores would have been suitably adjusted.

Pages 4 and 5 are histograms for person scores and item scores. For persons, the number at each score (i.e., number of hits) is shown. This is scaled to fill the grid with the scale factor shown at the bottom. For items, the figure shows the proportion of success for each item. For instance, there were 764 successes in 1260 trials on item one. The general impression given by these graphs is that the tasks were "relatively easy" for the persons resulting in high item scores, which increase as target distance decreases, and that there is a negatively skewed distribution of person scores.

Page 6 contains the difficulty estimates and the related standard errors of calibration for each item. These are the values needed for any future application of the items. The mean difficulty (weighted by the number of trials for each item) is always zero. As expected from the histogram, the difficulties decrease as target distance decreases. The standard errors are smallest for the most difficult tasks because of the high ability of the sample. These are the tasks with difficulties most like the abilities of the persons tested and hence for which the most information was obtained.

The table also provides some statistics on the estimation process. At the top the difficulty and ability, "scale factors" indicate the amounts by which the initial log odds estimates were inflated by the normal approximation method, "PROX".

The body of the table, in addition to the difficulty estimates and their standard errors, displays the magnitude of the adjustment in the last cycle (an indication of the rate of convergence), the difficulty estimate that was returned by "PROX" and the estimate after one cycle in "UCON". These are displayed to provide experience with how PROX compares to UCON and when the less expensive estimates are good enough. In this instance, there is little difference in the estimates even though the score distribution is skewed.

Page 7 gives the conversion of raw scores to estimated abilities and the standard errors of measurement associated with each score. The test characteristic curve is a picture of the range of ability covered by these eight tasks.

Pages 8 and 9 display a variety of item fit statistics. Unlike estimates of item difficulty, the tests of fit are very much sample dependent. That an item fits for one sample does not guarantee it will fit for another. Useful interpretation of these statistics requires both familiarity with them and a thorough understanding of the tasks and sample that generated them.

The basic statistic is the overall Fit Mean Square which appears on both pages (under the heading "total" on page 8). This is simply the mean squared standard residual $\sum z_{vi}^2$ averaged over persons. It will be large for an item if there are too many high ability persons who failed on the item and/or too many low ability persons who succeeded. What is "too large" depends on the requirements of the particular situa-

tion. The expected values and standard errors of these mean squares are 1 and $(2/f)^{1/2}$ where f is the number of groups. More than three standard errors greater than one seems to be a reasonable rule of thumb for "too large".

Two targets which have little else in common fall into this category. Target 1 is unique in several respects; it is the first in the sequence, it is at the greatest distance and is the only one that involves the prone position. All of these could be contributing to the misfit. Choosing among them would require a clinical investigation of the situation. This mean square says only that performance on this task has the weakest relation to performance on the other seven tasks. The non-significant between group mean square for this item (of 1.90) indicates that statistically equivalent estimates of difficulty would result from using either the low scorers or the high scorers for calibration.

Target 6 is not interesting in its position in the sequence and there were other targets at the same range and same position. This mean square is an index of the disagreement between the variable as defined by the item and the variable as defined by all items. The fit for this target which involved firing from the left could change if the mixture of shots from the right and left were changed. This would imply that an extraneous factor, handedness, has an influence on the outcome.

If we consider the possible effect of handedness on the difficulty of these tasks, the shots from the right side would tend to be easier for right-handed marksmen. Since eighty to ninety per cent of the sample would be right handed, a shot from the right would appear easier than the equivalent shot from the left. However, the effect is reversed for a left-handed marksman and this person would do poorly on the "easy" right handed shots and well on the "difficult" left handed shots. While this would

produce misfit over all person-task combinations, "surprising" results would tend to accumulate on the shots from the left because of the predominance of right-handed marksmen in the data. It might be eliminated by defining the shots as favored and not favored rather than left and right.

The between group mean square tests the agreement between the observed item characteristic curve and the best fitting Rasch characteristic curve as estimated by the groups selected. Five points on the observed curve are shown for each item on the left of page 8. The points shown were chosen by the program to represent groups of increasing ability and approximately equal size such that the average group size is at least 25.

The worst discrepancies between the curves are for targets 4 and 7, both of which involve firing from the right side. In particular, for target 4 score group two was seventy per cent successful while group three was only 62 per cent successful. The model predicted 64 and 73 per cent respectively. The discrepancy in proportion metric is given in the center panel of page 8. Complete understanding of the reasons for this requires greater knowledge of the effect of handedness on marksmanship but one hypothesis is that ability group three contained a preponderance of left-handed persons who do poorer than expected on shots from the right.

The remaining column on page 8 is the within group mean square. It is the misfit remaining after removing the effect of difference in the shape of the characteristic curves. It will be large and the between group effect small if the correct proportion of the group succeeded but the wrong people in the group were the ones who succeeded. It provides no information not contained in the between and the total but is a reorganization that is sometimes convenient.

The discrimination index is also closely related to the between group mean square. It is in fact the linear trend across score groups. Values larger than one indicate that the observed characteristic curve for an item is steeper than the average best fitting logistic curve for all items; values less than one indicate the curve is flatter. In this example there is no reason to suspect that the targets do not all have equal discriminations. In data simulated with exactly equal discriminations the standard deviation of the observed discriminations are frequently as large as 0.20, hence, the value observed here (0.11, from page 9) is quite acceptable.

Page 10 contains a plot of the discrepancies, standardized and squared, between the observed and fitted characteristic curves (center panel, page 8) against the probability of success for that group on that item. In this case, this plot does little to increase our understanding. It is useful with achievement tests where random guessing is a problem. In those situations large values of the z-squares are found near the chance level.

Pages 11, 12 and 13 are two-way plots of the three statistics given for each item on page 9; difficulty, discrimination and total fit mean square. There is no new information in them, but examining the plots is a convenient way to be certain not to miss any interesting results.

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APPENDIX A

BICAL OUTPUT PRODUCED BY THE MP DATA

MILITARY POLICE DATA--HITS PER TARGET

PAGE 3

NUMBER OF PERFECT SCORES 0

NUMBER OF ITEMS SELECTED 0

SUBJECTS BELOW 0
 SUBJECTS ABOVE 40
 SUBJECTS IN CALIB. 120
 TOTAL SUBJECTS 120

REJECTED ITEMS

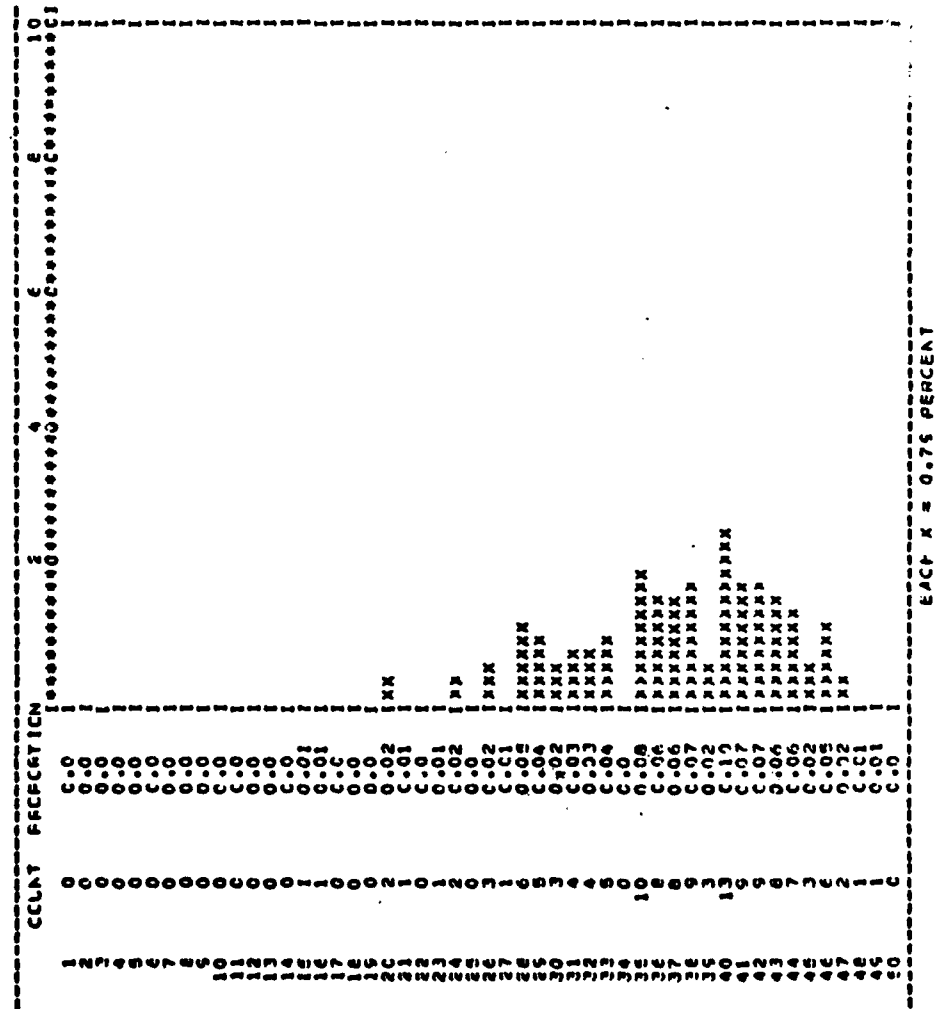
ITEM	ITEM ANSWERED
NUMBER	NAME CORRECTLY
NONE	

SUBJECTS DELETED = 0
 SUBJECTS REMAINING = 120

ITEMS DELETED = 0
 POSSIBLE SCORE = 80

MINIMUM SCORE = 5
 MAXIMUM SCORE = 45

MILITARY POLICE DATA--HITS PER TARGET
SCORE DISTRIBUTION OF ABILITY



MILITARY POLICE DATA--HITS PER TARGET DISTRIBUTION OF EASINESS

PAGE 8

COLMT	PROPORTION	1	2	3	4	5	6	7	8	9	10
1	764	C-01	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX
2	762	C-00	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX
3	356	C-07	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX
4	444	C-70	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX
5	516	C-02	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX
6	510	C-02	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX
7	552	C-52	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX
8	553	C-04	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX	XXXXXXXXXXXXXXXXXXXX

EACT N = 2.00 PERCENT

MILITARY POLICE DATA--HITS PER TARGET PROCECLRE USED LCCN

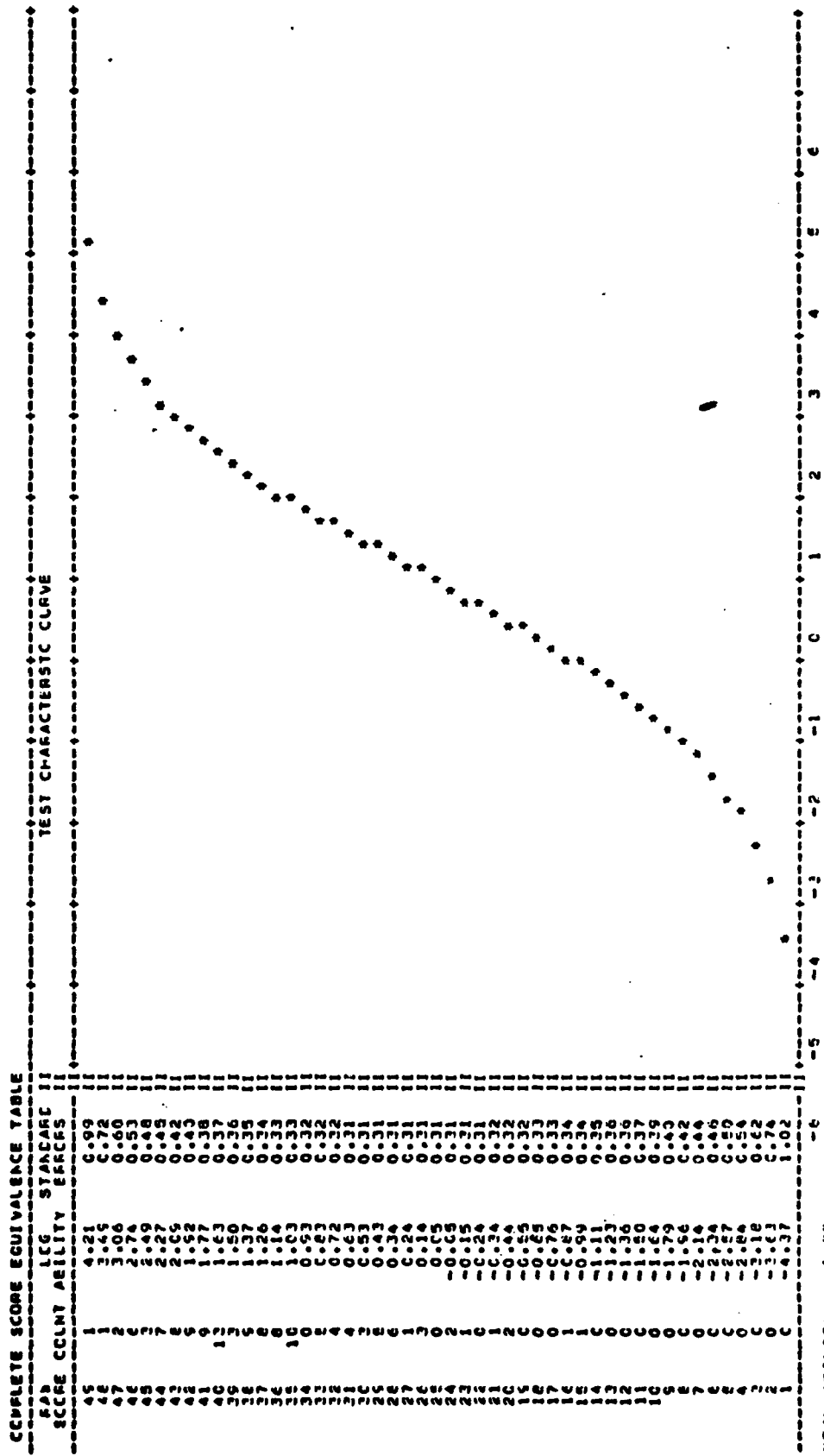
PAGE 8

DIFFICULTY SCALE FACTOR 1.115 ABILITY SCALE FACTOR 1.116
ALDER CP ITERATIONS = 2

SEQUENCE	ITEM	ITEM	DIFFICULTY	STANDARD	LAST DIFF	FROM	FIRST
ALDER	NAME	ITEM	DIFFICULTY	ERROR	CHANGE	DIFF	CYCLE
1	SEP	1	C-78	0.061	-0.001	C-78	0.735
2	SEP	1	C-78	0.061	-0.001	C-78	0.747
3	SEP	1	C-78	0.061	-0.001	C-78	0.528
4	SEP	1	C-78	0.061	-0.001	C-78	0.255
5	SEP	1	C-78	0.061	-0.001	C-78	-0.441
6	SEP	1	C-78	0.061	-0.001	C-78	-0.465
7	SEP	1	C-78	0.061	-0.001	C-78	-1.461
8	SEP	1	C-78	0.061	-0.001	C-78	-1.769

SCCT DEAN SLUPE = 0.002

MEAN ABILITY = 1.115
SC CP ABILITY = 0.000



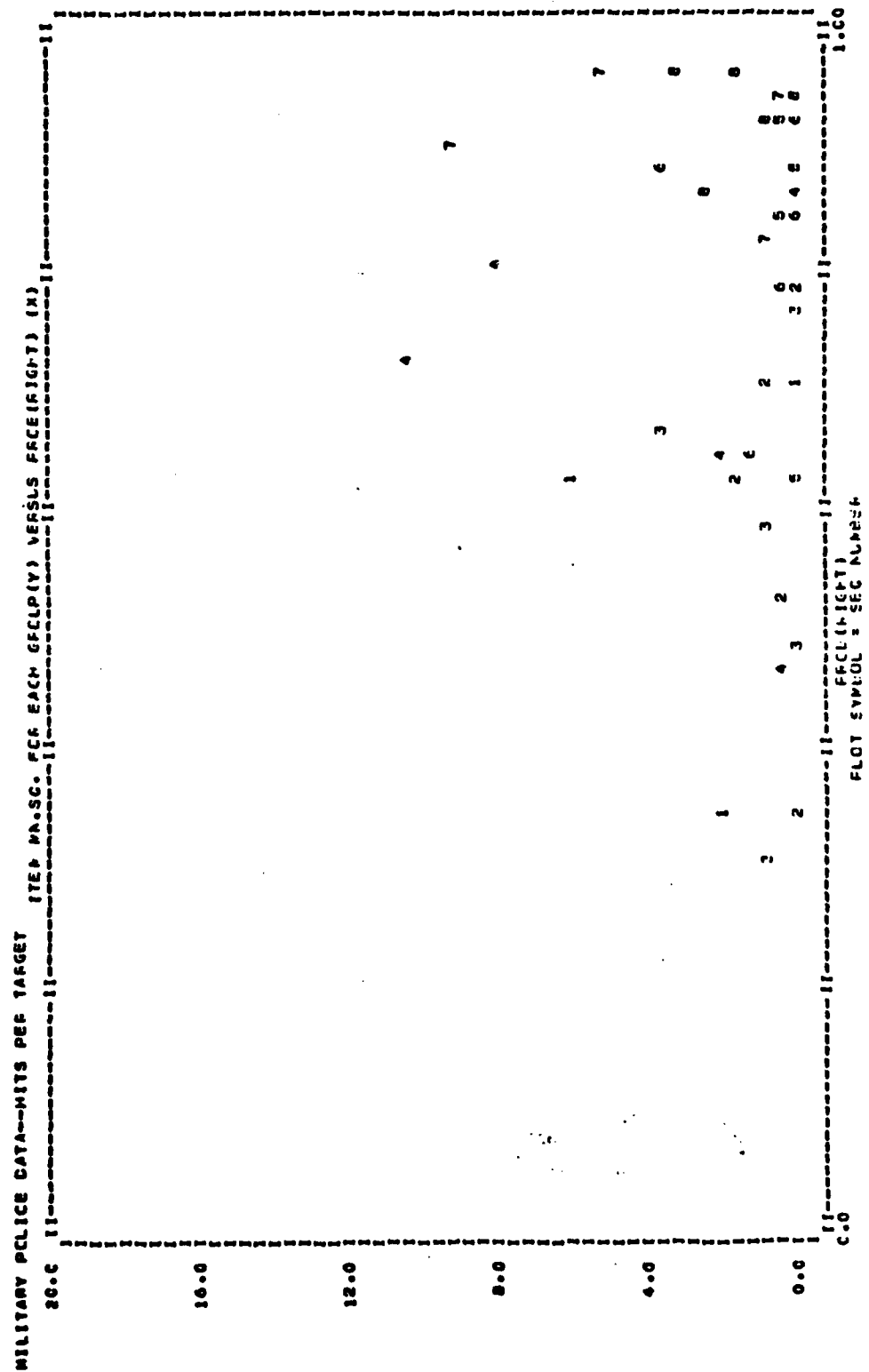
MILITARY POLICE DATA--HITS PER TARGET

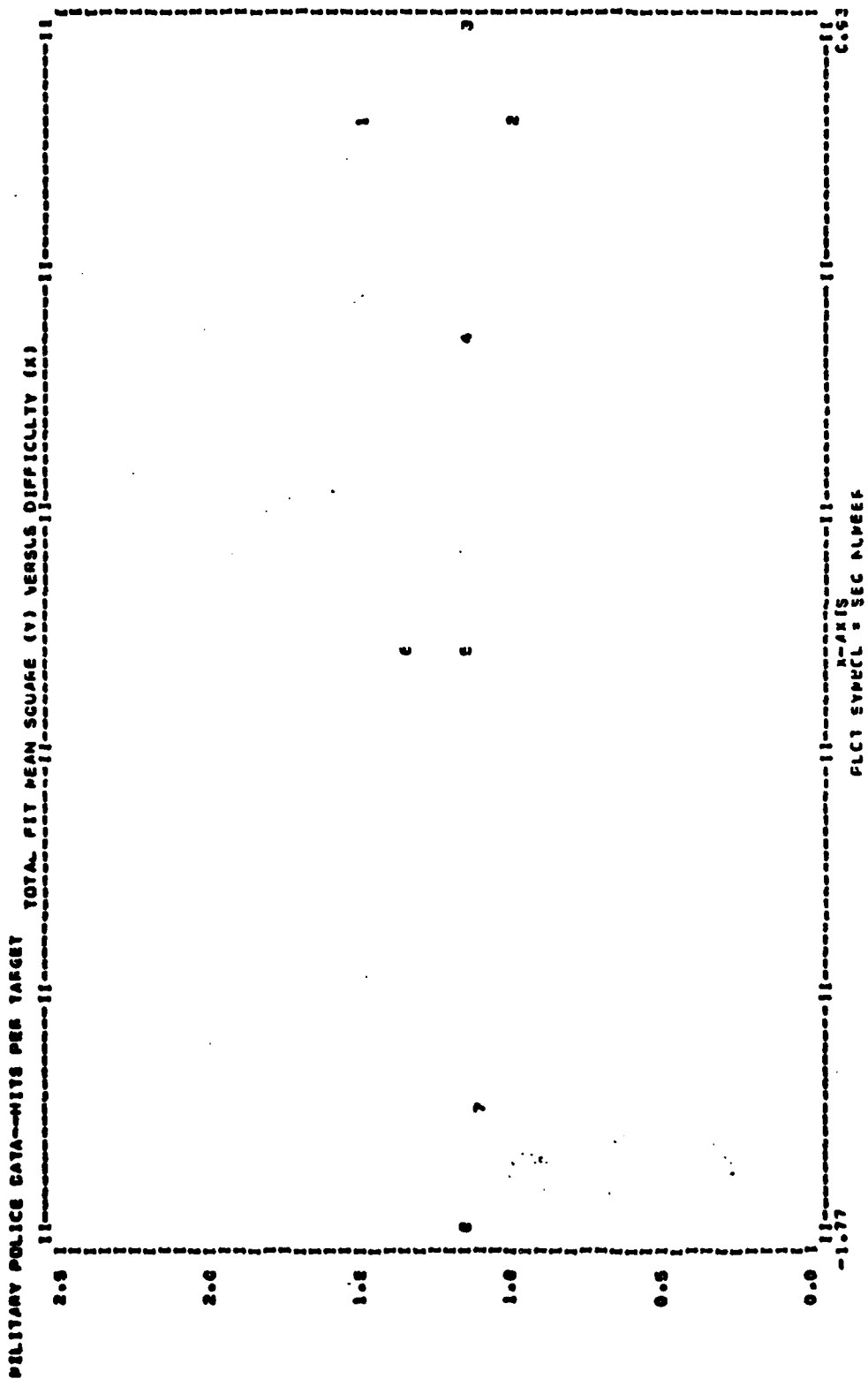
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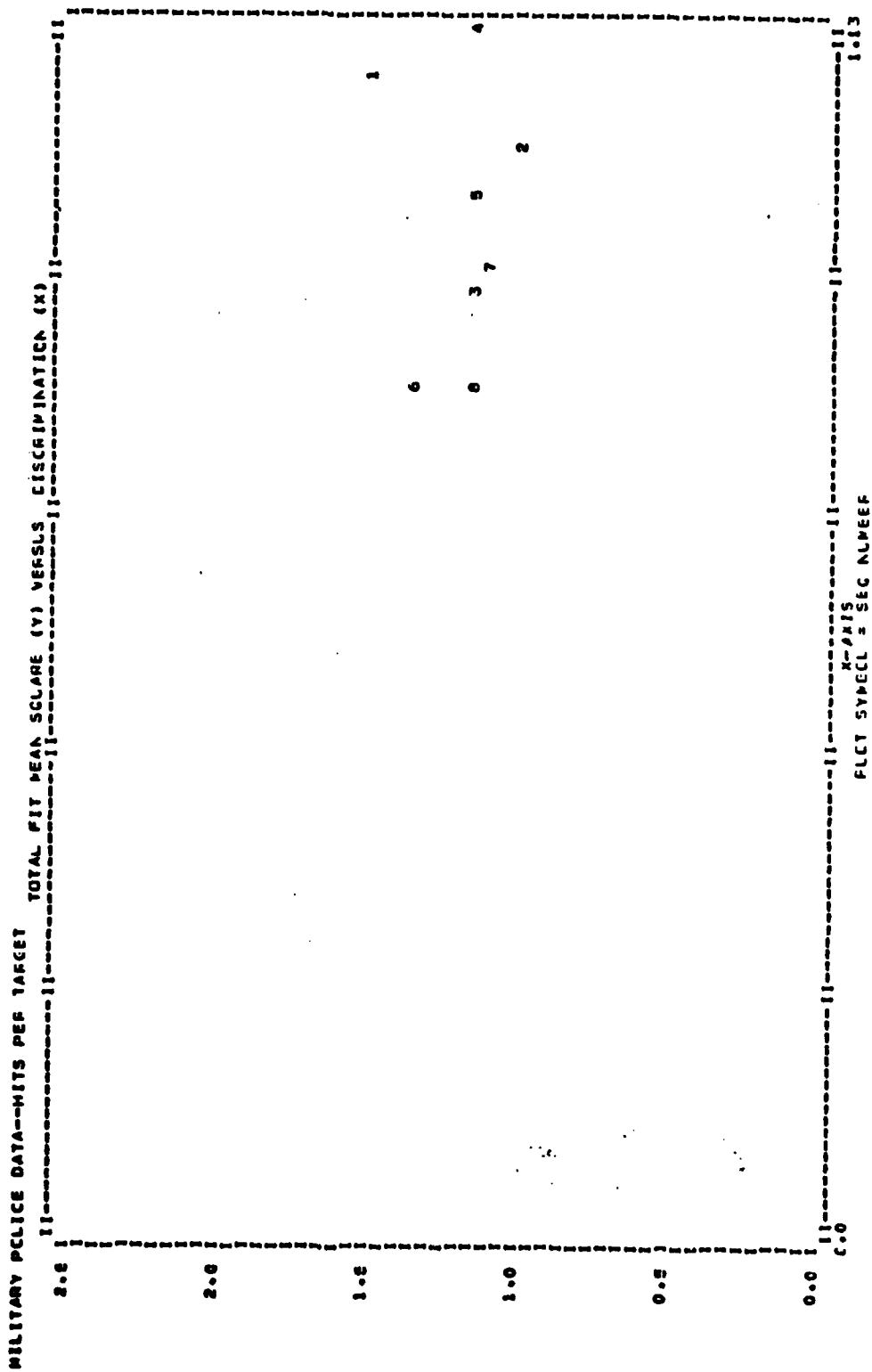
MILITARY POLICE DATA--HITS PER TARGET

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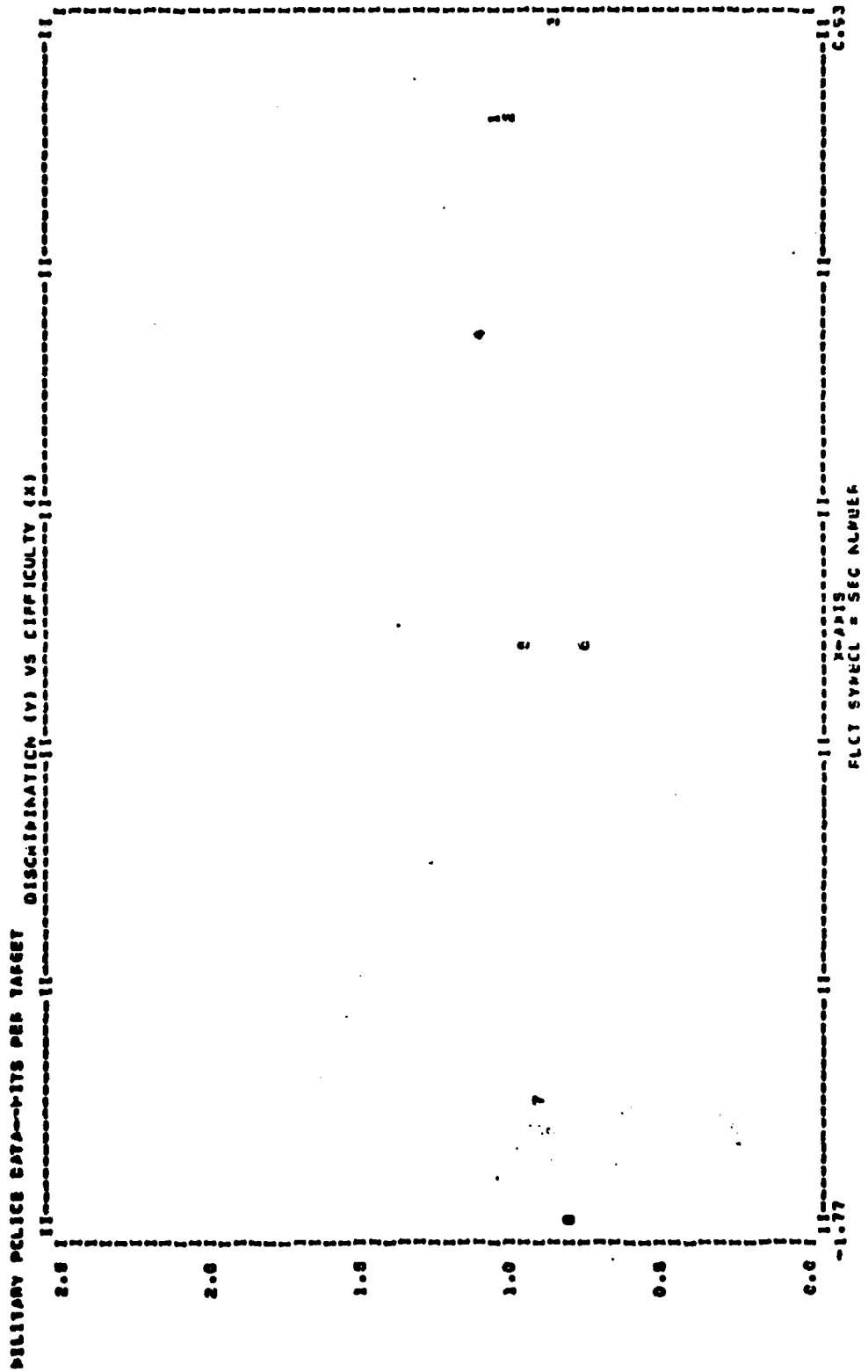
PAGE 9







PAGE 12



APPENDIX B

BICAL SOURCE PROGRAM LISTING

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PCRTAN IV G1  RELEASE 2.0          MAIN          DATE = 76302          CC/16/35

0001 DIMENSION MATX(130J),IB(1000),IS(150),DIFF(450),ABIL(1000)
0002 DIMENSION NSEL(1000),IDATA(150),SNAME(150),C(320),A(320),ID(150)
0003 DIMENSION ISEL(150),Z(150)
0004 CCMCN NITEM,NGRUP,MINSC,MAXSC,LREC,NSUEJ,IC,KCAB,ISN(11)
0005 1,SNAME
0006 1 CALL PAGE(1,1,J)
0007 CALL REDCP(IDATA,1J,IS,ISEL,MATX,A,C,DIFF)
0008 CALL EDITD(IB,15,ISEL,MATX)
0009 CALL PAGE(2,1,J)
0010 WRITE(6,102)
0011 DO 4 I=1,LREC
0012 NSEL(I)=1
0013 IF(IISW(10),NE,1,AND,ISW(10),NE,3)CALL +STGM(IB,LREC ,NSUBJ,0,NSEL)
0014 CALL PAGE(2,1,J)
0015 WRITE(6,103)
0016 CALL NSTGM(IS,NITEM,NSUBJ,1,ISEL)
0017 CALL ESTIM(IS,10,DIFF,ABIL,ISEL,MATX,KCAE)
0018 CALL GFPIV(DIFF,2,IB,ISEL,NSEL,MATX,ICATA,C,IS,ABIL,A,ID)
0019 CALL FITCS(2,C,IB,ISEL,NSEL,DIFF,ABIL,IDATA,MATX,A)
0020 CALL SMFY(DIFF,A ,ICATA,IS,MATX,ISEL,C,IB)
0021 IF(IISW(10),GT,1) GC TC 1
0022 X=10.
0023 CALL FLTR(ABIL,DIFF,IDATA,MATX, C,X)
0024 CALL PAGE(2,1,J)
0025 WRITE(6,100)
0026 X=2.5
0027 CALL FLTR(DIFF,ICATA,IB,X)
0028 CALL PAGE(2,1,J)
0029 WRITE(6,104)
0030 CALL FLTR(A, IDATA,IB,X)
0031 CALL PAGE(2,1,J)
0032 WRITE(6,101)
0033 DO 3 I=1,NITEM
0034 IF(A(I))2.3.3
0035 2 A(I)=0.0
0036 3 MATX(I)=100.0+A(I)
0037 X=2.5
0038 CALL FLTR(DIFF,ICATA,MATX,X)
0039 GC TC 1
0040 100 FORMAT(4X,47HTCTAL FIT MEAN SQUARE (Y) VERSUS DIFFICULTY (X))
0041 101 FORMAT(40X,DISCRIMINATION (Y) VS DIFFICULTY (X),)
0042 102 FORMAT(10X,SCORE,.8X,DISCRIBUTION OF AILITY,)
0043 103 FORMAT(10X,ITEM,.8X,DISTIBUTION OF EASINESS,)
0044 104 FCHMAT(40X,TOTAL FIT MEAN SQUARE (Y) VERSUS DISCRIMINATION (X),)
0045 END

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PCATRAM IV G1  RELEASE 2.0      ABLTV      DATE = 76302      CC/16/35
0001      SUBROUTINE ABLTV (AB,D,SE,IB,ISEL)
0002      DIMENSION AB(1),D(1),SE(1),ISEL(1),IE(1)
0003      COMMON NITEM,NGRCP,MINSC,MAXSC,LREC,NSUEJ,IC,KCAB,ISW(11)
0004      I=NAME(1)
0005      DATA BLK/, ,/.AST/, ,/
0006      LLINE=C
0007      L=NITEM
0008      J=NITEM+LREC
0009      C**CHANGE TO EXPONENTIAL SCALE
0010      210 CONTINUE
0011      LI=LREC-1
0012      C**BEGIN LOOP ON SCORE GROUPS
0013      CC 214 K=1,LI
0014      C**BEGIN ITERATION LOOP
0015      DO 215 I=1,IE
0016      IX=K+L
0017      SE(IX)=0.0
0018      CC=0.0
0019      C**BEGIN LCCF OVER ITEMS
0020      DO 216 I=1,L
0021      IF(ISEL(1))216,216,213
0022      213 P=EXP(AB(K)-D(I))
0023      P=P/(1.0+P)
0024      C**COMPUTE SUM CF P AND HQ
0025      SE(IX)=SE(IX)+P*(1.0-F)*ISEL(I)
0026      CC=CC+P*ISEL(I)
0027      216 CONTINUE
0028      DD=(K-DD)/SE(IX)
0029      AB(K)=AB(K)+DD
0030      C**CHECK CFF CONVERGENCE
0031      IF(ABS(DD)-0.05)214,215,215
0032      215 CONTINUE
0033      214 CONTINUE
0034      C**FINAL ABILITIES AND STANDARD ERRORS
0035      DO 9198 I=1,LI
0036      IX=I+L
0037      SE(IX)=1.0/SORT(SE(IX))
0038      C**CHANGE TO LCG SCALE
0039      DO 9200 I=1,L
0040      IF(ISEL(1))9200,9200,9199
0041      9199 IX=I+L+LREC
0042      SE(IX)=1.0/SORT(SE(IX))
0043      9200 CONTINUE
0044      C**PRINT ABILITY TABLE
0045      WRITE(6,200)
0046      200 FORMAT(0,74(,.,,)/1P, 8MSEQUENCE,4H I ,4PITEM,4P I ,3X
0047      1,ITEM,6X,STANDARD,3X9PLAST DIFF,3X,PROX ,4X,FIRST,5P I I )
0048      WRITE(6,201)
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PCPTRAN: IV G1  RELEASE 2.0  ABLTY  DATE = 76302  00/16/35
0038 201 FCRMAT(1+.7H NUNEEH.5H 1 .4HNAME.4H 1 .10PDIFFICULTY.5HSEHERRCR
1.3X10H CHANGE .3X.DIFF .4X.CYCLE.5H 11/1X.74(.-.))
FCCT=0.0
DC 4 I=1.NITEM
IF(ISEL(1)) 4. 4. 3
XK=XK - XINC
K = XK
IX=K+NITEM
IY = I + NITEM + LMEC
X = SE(IY)
ROOT = ROOT + X*X
IXX = I + NITEM
I22 = IXX + NITEM
Y = C(I22)
WRITE(6.101)I.SNAME(I).D(I).SE(I).X.C(IXX).Y
FORMAT(1+.16.2X4H 1 .44.3H 1 .FB.3.4XF9.3.2X3F9.3.2X3+ 11)
101 4 CCNTINLE
5 ROOT=RCCT/( IC -1)
ROOT=SCGT(ROOT)
INS=0
XTSS2=C.
XTSS=0.
DC 4000 NTS=1.L1
XTSS=XTSS+IB(NTS)*AB(NTS)
XTSS2=XTSS2+IB(NTS)*AB(NTS)*AB(NTS)
INS=INS+IE(NTS)
XTMN=XTSS/INS
XTSD=(XTSS2-(XTSS*XTSS/INS))/(INS-1)
XTSQ=SCRT(XTSD)
WRITE(6.105) ROOT.ATMN.XTSC
105 FCRMAT(1X74(.-.)/25X18HROOT MEAN SQUARE =.F5.3//
127X16HMEAN ABILITY = F6.2/27X.*SD CF ABILITY = .F6.2)
WRITE(6.102)
102 FCRMAT(1 COMPLETE SCGRE EQUIVALENCE TABLE.1X34(.-.1.13(.-.-----+
11/. HAN.10X.LUG STANDARD II.20X.*TEST CHARACTERSTC CURVE.1
23X.*SCORE COUNT ABILITY ERNOKS II/1X31(.-.11+.13(.-.-----+))
K=LREC - 1
L1 = K
DC 10 I=1.L1
N=(AE(K)+6.0)/7.0
IF(N.GT.24)N=24
IX=K+NITEM
WRITE(6.103)K.IB(K).AB(K).SE(IX).(ELK.J=1.N).AST
103 FCRMAT(17.15.2F9.2. 11.25A1)
10 K=K-1
WRITE(6.104)(I.I=1.6).XTMN.XTSD
104 FCRMAT(1X31(.-.11+.13(.-.-----+)))/2EX.16
1 -1 0.617/. MEAN ABILITY =.F5.2/. SD CF ABILITY -3
2=.F5.2)
RETURN
END
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PCRTMAN IV G1 RELEASE 2.0 EDITC DATE = 76302 00/16/35

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0001 SUBROUTINE EDITO(IE,IS,ISEL,MATX)
0002 DIMENSION ID(1),IS(1),ISEL(1)
0003 COMMON NITEM,NGROP,MINSC,MAXSC,LREC,NSUEJ,IC,KCAB,ISW(11)
      1,SNAME(1)
      NLOW=0
      NFIG=0
      ITCK=0
      NCUT=0
      IX=0
      IF(NGRCP.LE.6) NGRUP=30
      L=LREC
      M=L-1
      IF(MAXSC-L)2,1,1
      1 MAXSC=M
      C*COUNT HIGH AND LOW SCORES
      2 CCB8 I=1,MQ
      IF(I-MINSC)4,6,5
      4 NLOW=NLOW+IB(I)
      GC TC 88
      5 IF(I-MAXSC)6,6,7
      6 IX=IX+IB(I)
      GC TC 88
      7 NHIGH=NHIGH+IB(I)
      88 CONTINUE
      WRITE(6,100)MINSC,NLOW,MAXSC,NHIGH,IX,NSLBJ
      NSUEJ=IX
      WRITE(6,202)
      202 FORMAT(1H ,//15H REJECTED ITEMS,/,7H ITEM ,3X4HITEM,3X4HANSWERED/,
      17H NUMBER,3X4HNAME,3X9HCCRECTLY/1X30(,.,.))
      3 IF(NSUEJ-NGRCF)99,99,21
      21 IF(MAXSC-MINSC)99,99,22
      C**BEGIN EDIT LCOP
      22 DC 18 I=1,NITEM
      K=1
      IF(ISEL(1)) 18,18,d
      6 IF(IS(1))15,15,9
      5 IF(IS(1)-NSLBJ*ISEL(1))18 ,1C,10
      C**CPECT FOR PERFECT SCORES
      10 WRITE(6,201)I,SNAME(1),IS(1)
      201 FORMAT(1F ,2X12,5X44,4X14,3X10HHIGH SCORE)
      ITCK=ITCK+1
      C**ADJUST MINSC, MAXSC, AND IB ARRAY FOR REJECTED PEOPLE
      IF(MINSC-ISEL(1))13,13,11
      13 NSUEJ=NSUEJ-IE(1)
      NOUT=NCUT+IB(1)
      MINSC=1 + ISEL(1)
      K=2
      J2=ISEL(1)+1

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PCRTMAN IV G1 RELEASE 2.0          EDITD          DATE = 76302          00/16/35

0043 11 DO 12J=J2.L
0044 J1=J-ISEL(I)
0045 12 IB(J1)=IB(J)
0046 MAXSC=MINSC-ISEL(I)
0047 MAXSC=MAXSC-ISEL(I)
0048 L=L-ISEL(I)
0049 ISEL(I)=0
0050 GU TC (12,3).K
C**CHECK FOR ZERO SCORES
0051 15 WRITE(6,200)I,SNAM(I),IS(I)
0052 200 FORMAT(1H,2X12,5XA4,4X14,3XSHLCN SCORE)
0053 ITCK=1+ITCK
0054 L=L-ISEL(I)
0055 IF(L-MAXSC)17,17,18
0056 CC 171 J=L-MAXSC
0057 NSUBJ=NSUBJ-IB(J)
0058 NOUT=NCUT+IB(J)
0059 NOUT=NCUT+IB(MAXSC)
0060 MAXSC=L-ISEL(I)
0061 ISEL(I)=0
0062 GC TC 3
0063 12 CONTINUE
C**PRINT RESULTS OF DATA EDITING
100 FORMAT(
100VE,5X13,6X14/19H SUBJECTS IN CALIB.114/1H .32(1P--)/
215H TCAL SUBJECTS,12X15)
0065 102 FORMAT(45HC PROBLEM ENDED BECAUSE OF 1 OF THE FOLLOWING/
217H SUBJECTS READ IN 16/18H SUBJECTS IN RANGE 15/14H MAXIMUM SCORE
215/14H MINIMUM SCORE 15)
IF(ITCK)19,19,20
19 WRITE(6,211)
211 FORMAT(1CX,1NCNE)
20 WRITE(6,210)NCUT,NSUBJ,ITCK,L,MINSC,MAXSC
210 FORMAT(1F0,20H SUBJECTS DELETED =.15/21H SUBJECTS REMAINING =.15/
1/6X,1ITEMS DELETED =.15/4X17HPCSSIELE SCORE =.15/6X15HMINIMUM S
2CCRE =.15/6X15HMAXIMUM SCORE =.15)
IC=IC-ITCK
LRECE=L
RETURN
99 WRITE(6,102) IC,NSUBJ,MAXSC,MINSC
STOP
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PCRTAN IV G1  RELEASE 2.0      ESTIM      DATE = 76302      00/16/35

0001  SUBROUTINE ESTIM(15,18,DIFF,ABIL,ISEL,SE,M)
0002  DIMENSION IS(1),IE(1),DIFF(1),AEL(1),ISEL(1),SE(1)
0003  DIMENSION PROC(3)
0004  COMMON NITEM,NGRCF,MINSC,MAXSC,LREC,NSUEJ,IC,KCAB,ISN(11)
0005  1, SNAME(1)
0006  DATA PRCC/'PROX', 'UCCN', 'ERROR'
0007  CALL PAGE(2,1,J)
0008  WRITE(6,155) PRCC(M)
0009  199 FCRMAT(110,15)PRCCURE USED .A4)
0010  C**NGRMAL APPRCXIATION METHCC
0011  CALL PRCC(15,18,DIFF,ABIL,ISEL,SE,M)
0012  GC TC (3,1,1),M
0013  C**CORRECTED UNCONDITIONAL METHCD
0014  1 CALL UCCN(15,18,DIFF,ABIL,ISEL,SE)
0015  3 CCNTINLE
0016  C**COMPUTE FIANT ABILITIES AND PRINT TABLE
0017  CALL AELTY(ABIL,DIFF,SE,18,ISEL)
0018  RETURN
0019  END

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PCSTRAN IV G1 RELEASE 2.0          FITCS          DATE = 76302          GO/16/35

0001 SUBROUTINE FITCS(22,B,IE,ISEL,NSEL,DIFF,ABIL,DATA,MATX,A)
0002 DIMENSION IB(1),ISLL(1),ASEL(1),DIFF(1),AEL(1),ICATA(1),MATX(1)
0003 DIMENSION EXT(6),VAR(6),CBS(6),CCPF(1E),CISC(1E),Z(6),STAT(2)
0004 DIMENSION ESD(4),ZL(1),H(1),IGRCP(1),A(1),TCT(6),SE(6)
0005 COMMON /ITEM,NGROP,MINSC,MAXSC,LREC,NSUEJ,IC,KCAB,ISA(11)
0006 1,SNAP(1)
0007 1,SNAP(1)
0008 CALL PAGE(2,I,J)
0009 C**CLEAR ARRAYS
0010 LLINE=C
0011 CRIT=0.1
0012 DC 157 I=1.6
0013 Z(I)=C.0
0014 CISC(I)=0.0
0015 CBS(I)=0.0
0016 TCT(I)=0.0
0017 SE(I)=0.0
0018 197 IGRDF(I)=0
0019 C**COUNT NUMBER IN EACH SCORE GROUP
0020 CC 158 I=MINSC,MAXSC
0021 J=ASEL(I)
0022 IF(J)158,198,196
0023 196 IGRDF(J)=IGRDF(J)+1E(1)
0024 198 CONTINUE
0025 CC 195 I=1.1E
0026 195 CCMP(I)=C.0
0027 WRITE(6,2C0)
0028 WRITE(6,2C1)
0029 WRITE(6,2C2)
0030 200 FORMAT(1F,18X25HITEM CHARACTERISTIC CURVE11X27HDEPARTURE FROM EXP
0031 1ECTED ICC,18X16HFIT MEAN SCUAHE /1X129(---))
0032 201 FORMAT(1F,12H SEC ITEM 1.2(38H 1ST 2ND 3RD 4TH 5TH 6T
0033 1H I),, WITHN DETW DISC PCINT I.)
0034 202 FCFMAT(1F,12H NUM NAME 1.6(6H GRGUP),2H 1.6(6H GRGUP),2H 1.
0035 1, GROLF GROUP TOTAL INDX BISEF 1./1X129(---))
0036 C**COMPLETE AVERAGE ABILITY FOR EACH SCORE GROUP
0037 X=0.0
0038 DO 181 I=MINSC,MAXSC
0039 J=ASEL(I)
0040 IF(J)181,181,182
0041 182 CCMP(J)=CCMP(J)+1E(1)+ZIL(1)
0042 X=X+IB(I)*ABIL(I)
0043 181 CONTINUE
0044 C**STORE AVERAGE IN LCC SEVEN TO TWELVE AND CENTER LOC ONE TO SIX AT ZER
0045 DO 184 I=1,NGROP
0046 CCMP(I)=CCMP(I)/IGRDF(I)
0047 CCMP(I+6)=CCMP(I)
0048 184 CCMP(I)=CCMP(I)-X

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FCRTRAN IV 61 RELEASE 2.0 FIICS DATE = 76302 00/16/75

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0041      N1=LRFC-1
          C**CHANGE SCALE
          C**BEGIN LOOP THROUGH ITEMS
          CC 9 K=1,NITEM
          L=IDATA(K)
          IF(ISEL(L))9.9,1
          1 LL=L
            LK=L
            X=DIFF(L)
            DC 11 I=1,NGROUP
            EXT(I)=0.0
            11 VAR(I)=0.0
          C**COMPLETE EXPECTED NUMBER NP AND VARIANCE NPQ
          DO 8 I=MINSC,MAXSC
            J=ISEL(I)
            IF(J)8.8,7
            7 P=EXP(AU(L(I))-X)
            P=P/(1.0+P)
            EXT(J)=EXT(J)+IB(I)*P*ISEL(L)
            VAR(J)=VAR(J)+IB(I)*P*(1.-P)*ISEL(L)
            8 CCNTINLE
            P=0.0
            STAT(1)=0.0
            STAT(2)=0.0
          C**BEGIN LOOP THROUGH SCORE GROUPS
          CC 2 I=1,NGROUP
          C**OBSERVED NUMBER CF CORRECT RESPONSES
          ISC=MAX(LL)
          SC=ISC
          VI=SGRT(VAR(I))
          C**CHECK FOR ZERO OR PERFECT SCORES WITHIN A GROUP
          IF(ISC)3.3,4
          4 IF(ISC-IGRCP(I)*ISEL(L))6.3,3
          3 VAR(I)=0.0
          DISC(I)=55.0
          GO TO 12
          6 DD=X
          C**COMPUTE DIFFICULTY ESTIMATE BASED ON THE CNE GROUP
          CALL NEWT(DD,ISEL(L),ABIL,IB,ISC,NSEL,MINSC,MAXSC,I,CRT,6,XX,Y)
          DISC(I)=CC-DIFF(L)
          C**STANDARDIZE THE DEVIATION
          12 Z(I)=(SC-EXT(I))/VI
          C**SCALE TO A SINGLE DEGREE OF FREEDOM
          XX=IC
          XX=XX/(XX-1.0)
          Y=NSUBJ-IGRCP(I)
          XX=XX*NSUBJ/Y
          Z(I)=Z(I)*Z(I)*XX
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PCFTRAN IV G1 RELEASE 2.0 FITS DATE = 76302 00/16/35

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0000      XX=Z(1)
0001      C**STORE Z SQUARE AS AN INTEGER FOR GPLTR
0002      MATX(LL)=100.0*XX
0003      LL=LL+1*ITEM
0004      C**COMPUTE MARGINALS OF FIT TABLE
0005      TCT(1)=TCT(1)+XX
0006      SE(1)=SE(1)+XX*XX
0007      P=P+2(1)
0008      CES(1)= SC/(IGRCP(1)*ISEL(L))
0009      C**COMPUTE DISCRIMINANT INDEX FOR THIS ITEM
0010      XX=CCMF(1)
0011      STAT(1)=STAT(1)+XX*DISC(1)*VAR(1)
0012      DISC(1)=(SC-EXT(1))/(IGRCP(1)*ISEL(L))
0013      2 STAT(2)=(STAT(2)+XX*XX*VAR(1))
0014      STAT(1)=STAT(1)/STAT(2)+1.0
0015      X = 22(LK)*NSUEJ - P
0016      X = X/(NSLWJ-NGRCP)
0017      P = P/NGRCP
0018      C**PRINT LINE OF THE FIT TABLE FOR THIS ITEM
0019      CALL PAGE(4,2,LLINE)
0020      WRITE(6,203)LK,SNAM(LK),CHS,DISC,X,F,22(LK),STAT(1),B(LK)
0021      203 FCFMAT(1H,14,2X,A4,2H 1.6(F6.2),2H 1.6(F6.2),2H 1.
0022      13F7.2,1X,2F7.2,1H 1.
0023      C**STORE DISCRIMINATION INDEX
0024      A(L)=STAT(1)
0025      5 CCNTINLE
0026      CC 5 I=1,NITEM
0027      IF(ISEL(I).LE.0) GL TC 5
0028      IB(1) = 100 + 22(I)
0029      CCNTINLE
0030      C**COMPUTE STANDARD DEVIATION OF Z SQUARES
0031      CC 17 I=1,NGRCP
0032      TCT(1)=TCT(1)/IC
0033      17 SE(1)=SQRT((SE(1)- IC *TCT(1)*TCT(1))/( IC -1))
0034      C**STORE AVERAGE ABILITY FOR GPLTR
0035      CC 10 I=1,NGRCP
0036      J=1+6
0037      10 ABIL(1)=CCMP(J)
0038      DC 12 I=2,12
0039      12 ICATA(1)=0
0040      C**CALCULATE LIMITS OF EACH SCORE GROUP
0041      DO 14 I=1,LREC
0042      J=NSLWJ(I)*2
0043      IF(J)14,14,13
0044      13 ICATA(J)=1
0045      14 CCNTINLE
0046      ICATA(1)=MINSC
0047      J=2*NGRCP

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PCPTRAN IV 61  RELEASE 2.0          FITCS          CA1E = 76302          00/16/35

0119      ICATA(J)=MAXSC
0120      J=J-1
0121      DO 16 I=3,J.2
0122      ICATA(I)=ICATA(I-1)+1
          16  ICATA(I)=ICATA(I-1)+1
C=PRINT DCTICA LINES
0123      ESD(1) = SORT(2.0/(NSUBJ-NGRCP))
0124      ESD(2) = SORT(2.0/NGRCP)
0125      ESD(3) = SORT(2.0/NSUBJ)
0126      ESD(4) = SORT(2.0/1C)
0127      K = NSUBJ - NGRCP
0128      WRITE(6,204)(ICATA(I),I=1,12),(IGRCP(I),I=1,6),K,NGRCP,NSUEJ,
          1(COMP(I),I=7,12),(ESD(I),I=1,3),TOT,SE,(ESD(4),I=1,NGRCP)
          204  PCRMAT(1) = 1291.0/13H MEAN ABILITY.6F6.2.5X. PLUS=TCC MANY FIG
          12X317.0  DEG CF FROM.13H MEAN ABILITY.6F6.2.5X. PLUS=TCC MANY FIG
          24T.58X.
          2  WINUS=TCC MANY WRNG.1IX3F7.2.0  STD ERRCF.0  GRUP MN SQ.6F6.1
          3  .0  SC(MN SQ) .6F6.1.0  EXPC1D SD .6F6.1)
          RETURN
          END
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PCSTRAN IV G1 RELEASE 2.0          FFLTR          DATE = 76302          00/16/35

CC01      SUBROUTINE FFLTR          (DIFF, ICATA, MATX, X2)
CC02      DIMENSION ICAT(11),      DIFF(11), ICATA(11), MATX(11)
CC03      COMMON NITEM, NGRCP, MINSC, MAXSC, LREC, NSUEJ, IC, KCAB, ISM(11)
          1, SNAME(1)
CC04      DATA ICAT/1H1,1H2,1H3,1H4,1H5,1H6,1H7,1H8,1H9,1H0,1H /,1BLK/2H /
CC05      X1=X2
CC06      DMAX=0.0
CC07      DMIN=C.0

          C**FIND LIMITS OF X AXIS
          CC 4 I=1, NITEM
          IF(DIFF(I)-DMIN)1,2,2
          1 GO TO 4
          2 IF(DIFF(I)-DMAX)4,4,3
          3 CMAX=DIFF(I)
          4 CONTINUE

          C**COMPUTE SCALE FACTOR
          DMAX=(CMAX-DMIN)/50.0
          C**SORT INTO ORDER DEFINED BY CONTENTS OF MATX
          CALL SRT(MATX, ICATA)
          NITEM=NITEM

          K=IDATA(NITEM)
          C**COMPUTE SCALE UNIT FOR Y AXIS
          LNIT=MATX(K)/100.
          IF(UNIT-X1)21,21,20
          20 X1=X1+2.0
          21 UNIT=X1

          LNIT=LNIT/50.0
          WRITE(C,102)
          K=2*(NITEM)+102
          KK=2*NITEM+1
          LINE=51

          C**PRINT LABEL FOR Y AXIS
          22 X1=X1+.01
          C**PRINT TEN LINES
          CC 14 I=1,10
          CC 56 J=KK,K
          58 MATX(J)=IELK
          97 99 K=IDATA(NIT)
          C**DCES MATX K GO ON THIS LINE
          IF(X-X1)13,5,5
          5 X=DIFF(K)-DMIN
          X=X/CMAX
          C**FIND CORRECT COLUMN
          J=X
          J=2*(J+NITEM)+1

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00/16/35

DATE = 76302

FFLTR

RELEASE 2.0

PCFTRAN IV G1

CALCULATE SYMBOLS FOR SEQ NUMBER

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CC40 KK=K/1C
CC41 IF(KK)7.7.8
CC42 7 KK=11
CC43 8 MATX(J)=ICHAR(KK)
CC44 IF(KK-10)10.5.9
CC45 5 KK=0
CC46 10 KK=K-KK*10
CC47 IF(KK)11.11.12
CC48 11 KK=10
CC49 12 J=J+1
CC50 MATX(J)=ICHAR(KK)
CC51 NIT=NIT-1
CC52 GC TC 57
CC53 13 X1=X1-LNIT
CC54 KK=2*NITEM+1
CC55 K2=NITEM+102
CC56 C**PRINT LINE WHEN ALL ITEMS HAVE BEEN CHECKED
CC57 IF(1.EC.1) GO TO 23
CC58 WRITE(6,1C1)(MATX(J),J=KK,K)
CC59 GO TO 24
CC60 23 WRITE(6,104)X11,(MATX(J),J=KK,K)
CC61 LINE=LINE-1
CC62 IF(LINE)15.15.14
CC63 14 CONTINUE
CC64 15 CCNT=CCNT+1
CC65 C**PRINT BOTTOM LINES
CC66 DMAX=DMIN+50.C*DMAX
CC67 WRITE(6,102)
CC68 WRITE(6,103) DMIN,DMAX
CC69 101 FORMAT(11,10X)H1,102A1,11I1)
CC70 102 FCRMAT(11,11X,5(.11)-----),11I1)
CC71 103 FCRMAT(10XF5.2,43X, X-AXIS ,42XF5.2/
CC72 151X24+FLCT,SYMBOL = SEQ NUMBER)
CC73 104 FCRMAT(1X,F9.1, I,102A1,1I1)
CC74 RETURN
CC75 END

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DATE = 76302

GFLTR

PCETRAM IV G1 RELEASE 2.0

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CC43      C**IS THIS THE RIGHT LINE
CC44      IF(KK-ALAE)16.9.16
CC45      9 X=DD-DIFF(I)
CC46      C**COMPUTE PROBABILITY OF SUCCESS
CC47      X=EXP(X)
CC48      X=X/(1.+X)
CC49      X=X/CMAX
          KK=X
          KK=2*KK+1
          C**LOCATE SYMCL FOR SEQ NUMBER
          ISYM=1/10
          IF(ISYM)10.10.11
          10 ISYM=11
          11 LINE(KK)=ICHAR(ISYM)
          12 IF(ISYM-10)13.12.12
          13 ISYM=0
          14 ISYM=1-1SYM#10
          15 IF(ISYM)14.14.15
          16 ISYM=10
          17 KK=KK+1
          18 LINE(KK)=ICHAR(ISYM)
          19 K=K+1
          C**PRINT LINE WHEN FILLED
          WRITE(C,101) LINE
          'F(NLNE)3.3.17
          17 NLNE=NLNE-1
          GC TC 4
          C**COMPUTE ITEM MEAN SQUARE FOR SUMRY AND FFLTR
          3 CC 18 1=1,NITEM
          18 MATX(I)=100.0*B(I)/NRCDF
          DVAX=1.0
          C**PRINT BCTTCM LINES
          WRITE(C,102)
          WRITE(C,103) DMIN,DVAX
          100 FCFMAT(40X,.1ITEM AN-SQ. FOR EACH GROUP(Y) VERSUS PRCB(RIGHT) (X).)
          101 FCFMAT(1H 10X1H1.1J2A1.1F1)
          102 FCFMAT(1F .11X.5(.11-----),.11.)
          103 FCFMAT(1CXF5.2.43X.'PRCB(RIGHT)'.41XF5.2/
          15CX24FFLCT SYMBOL = SEQ NUMBER)
          104 FCFMAT(1F+.F9.1)
          END
CC75      RETURN
CC76      END
CC77

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```

PCSTRAN IV 61  RELEASE 2.0          GRPIM          DATE = 76302          00/16/35
0001 SUBRCUTINE GRPIM(C,2,IB,ISEL,NSEL,MATX,ICATA,B,IS,AB,A,IB)
0002 DIMENSION NSEL(1),IB(1),ISEL(1),MATX(1),ICATA(1),E(1),IS(1),AB(1)
0003 DIMENSION D(1),Z(1),ID(1),A(1)
0004 CCMYCA NITEM,NGRCP,MINSC,MAXSC,LREC,NSUEJ,IC,KCAB,ISM(11)
      1, SNAME(1)
C**DETERMINE NUMBER OF SCORE GROUPS
24 X=NSUBJ/NGRCP
      IF(NGRCP-6)22,22,21
21 NGRCP=6
      X=NSUBJ/NGRCP
      IX=NGRCP+NITEM
      DO 1 I=1,IX
1 MATX(I)=C
      Z(I)=0.0
      A(I)=0.0
25 B(I)=C.0
      SST=0.0
      SRT=0.0
      DO 2 I=1,MINSC
2 NSEL(I)=0
      DO 3 I=MAXSC,LREC
3 NSEL(I)=0
      NSC=0
      IX=X
      L=1
C**DETERMINE GROUPINGS OF SCORES AS EQUAL AS POSSIBLE
      DO 8 I=MINSC,MAXSC
      NSC=NSC+IE(I)
      J=(NSC-IX)*2
      IF(J)7,5,4
4 IF(J-IE(I))5,5,6
5 NSEL(I)=L
      NSC=0
      IF(L-NGRCP)8,29,25
6 L=L+1
      IF(L-NGRCP)20,30,30
20 NSC=IB(I)
7 NSEL(I)=L
8 CCNTINLE
      GO TO 32
29 I=I+1
30 DC 31 L=1,MAXSC
31 NSEL(L)=NGRCP
C**READ AND SCORE SCRATCH FILE
32 ISMT=1
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PCPTRAN IV G1 RELEASE 2.0 GGFIM DATE = 76302 00/16/35

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0045 LLM=ISM(2)
0046 KLIN=ISM(3)
0047 IFILE=ISM(4)
0048 IF(IFILE)16.40.15
0049 IFILE=-IFILE
0050 ISAT=2
0051 GC TC 40
0052 ISAT=3
0053 NSC=0
0054 READ(1,END=12) (ICATA(N),N=1,NITEM),(ID(N),N=LLIM,KLIM)
0055 DO 162 N=1,NITEM
0056 IF(ISEL(N))162.162.161
0057 NSC=NSC+ICATA(N)
0058 CONTINUE
0059 GO TC (17.9.10).15
0060 WRITE(IFILE,100)NSC,AB(NSC),(IC(N),N=LLIM,KLIM)
0061 FORMAT(14,F6.2,70A1/(80A1))
0062 GC TC 17
0063 WRITE(IFILE)NSC,AE(NSC),(IC(N),N=LLIM,KLIM)
0064 SC=NSC
0065 K=ASEL(NSC)-1
0066 IF(K)40.11.11
0067 11 K=NITEM
C**FILL MATX ARRAYS--SCCRE GROUPS BY ITEMS
0068 ABIL = AE(NSC)
0069 DC 14 N=1,NITEM
0070 K=K+1
0071 IF(ISEL(N))14.14.141
0072 MATX(K)=MATX(K)+ICATA(N)
C**CRPUTE FCINT BISERIALS
0073 B(N)=B(N)+SC+IDATA(N)
0074 A(N)=A(N)+IDATA(N)+ICATA(N)
0075 P=EXP(ABIL-D(N))
0076 F=P/(1.+F)
0077 X=IDATA(N)-P*ISEL(N)
0078 Z(N)=Z(N)+X*X/((ISEL(N)-ISEL(N)+P)*F)
0079 14 CCNTIALE
0080 SST=SST+SC
0081 SST=SST+SC*SC
0082 GC TC 40
0083 12 CONTINUE
0084 X=SST+SC/NSUEJ
0085 X=SST-X
0086 DO 13 K=1,NITEM
0087 IF(ISEL(K))13.13.131
0088 XY=IS(K)*SST/NSUBJ
0089 Y=IS(K)*IS(K)/NSUBJ
0090 XV= E(K)-XY
0091 Y= A(K)-Y
0092 B(K)=XY/SCRT(X*Y)
0093 Z(K) = Z(K)/(NSUBJ-1)
C**SET CORDER FOR PRINTING FIT TABLE--IN SEQUENCE
0094 13 IDATA(K)=K
0095 REWIND 1
0096 RETURN
0097 END

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FORTRAN IV G1  RELEASE 2.0      DATE = 76302      00/16/35

0001  SUBROUTINE HSTGM(IS,K,L,IP,ITL)
0002  DIMENSION IS(1),ITL(1)
0003  DATA IX,XI,II/1H1/
0004  M=L
0005  XL=L
0006  C*CHECK METHOD FOR SETTING SCALE FACTOR
0007  IF(IF)11,11,14
0008  11 M=IS(1)
0009  C*FIND LARGEST ENTRY
0010  CC 13 I=2,K
0011  IF(M-IS(1))12,13,13
0012  12 M=IS(1)
0013  13 CCNTINCE
0014  IF(M-LT.50) M= 50
0015  14 XLL=M/XL
0016  C*PRINT HEADING
0017  WRITE(6,102)(J,J=2,10,2),11,11
0018  DC 4 I=1,K
0019  C*CHECK IF LINE IS TO BE INCLUDED
0020  IF(ITL(1))4,4,2
0021  2 XIS=IS(1)
0022  PROP=XIS/(XL*ITL(1))
0023  C*PRINT EDGES OF TABLE
0024  WRITE(6,100)I, IS(1),PROP,11,11
0025  J=(5C.*FRCF)/XLL + .5
0026  IF(J-1) 4,4,3
0027  C*PRINT HISTOGRAM
0028  3 WRITE(6,101) (IX,IJ=1,J)
0029  4 CCNTINCE
0030  C*PRINT BOTTOM LINE
0031  XLL = 2.00 * XLL
0032  WRITE(6,104) XLL
0033  100 FCRMAT(15,16,4X ,F6.2,2X,1,50X,1)
0034  101 FCRMAT(11,12,3X,50A1)
0035  102 FCRMAT(1,1,1H,5(1H+),1H,75(1H-)/1, .6X5+CCUNT,2X,11+PROPORTION ,5110/
0036  123X,1,1H,5(1H+),1H,4(1CH+*****0),A1)
0037  104 FCRMAT(11,12,3X,50A1)
0038  1H,75(1H-)/30X9F EACH X =.F5.2, PERCENT*)
0039  RETURN
0040  END

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0001 SUBROUTINE PAGE(M,K,L)
0002 DIMENSION TITL(20)
0003 COMMON NITEM,NGRCF,MINSC,MAXSC,LREC,NSUEJ,IC,KCAB,ISW(11)
0004 1, SNAME(1)
0005 1, SNAME(1)
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PCBTRAN IV G1 RELEASE 2.0          PRUX          DATE = 763C2          00/16/3E
0001 SUBROUTINE PRUX(IS,IB,DIFF,ABIL,ISEL,SE,M)
0002 DIMENSION IS(1),IB(1),DIFF(1),ABIL(1),ISEL(1),SE(1)
0003 COMMON NITEM,NGROF,MINSC,MAXSC,LREC,NSUBJ,IC,KCAB,ISM(11),
      ISNAME(1)
0004 LI = LREC - 1
0005 DDCT = 0.0
0006 DO 2 I=1,NITEM
0007   DIFF(I)=0.0
0008   IF(ISEL(I))2.2.1
0009     DIFF(I)=NSUBJ+ISEL(I) - IS(I)
0010     DIFF(I) = ALCG(DIFF(I)/IS(I))
0011     DDOT = DDCT + DIFF(I)+ISEL(I)
0012     CCNTINLE
0013     D = 0.0
0014     IX = NITEM + LREC
0015     DDCT = DDCT/LREC
0016     DO 4 I=1,NITEM
0017       IX = IX + 1
0018       IF(ISEL(I))4.4.3
0019         DIFF(I) = DIFF(I) - DDOT
0020         C = C + DIFF(I)+DIFF(I)+ISEL(I)
0021         SE(IX) = DIFF(I)
0022         CCNTINLE
0023         DDCT = 0.0
0024         C = C/(2.89*(LREC-1))
0025         B = 0.0
0026         CC 5 J=1,LI
0027         ABIL(J) = J
0028         ABIL(J) = ALOG(ABIL(J))/(LREC-J))
0029         BCOT = BCCT + ABIL(J)+IB(J)
0030         B = B + ABIL(J)+ABIL(J)+IB(J)
0031         BCCT = BCCT/NSUBJ
0032         B=B-BCCT+BCCT+NSUBJ
0033         B=B/(2.89*(NSUBJ-1))
0034         C = E+C
0035         DDOT = 1.0 - C
0036         X = (1.0+C)/DDCT
0037         Y = (1.0+E)/CCOT
0038         B = SORT(Y)
0039         D = SCRT(X)
0040         WRITE(6,IC1) B,D
0041         FORMAT(0,DIFFICULTY SCALE FACTOR',F6.2,
      1, ABILITY SCALE FACTOR',F6.2)
0042 DO 9 I=1,NITEM
0043   IF(ISEL(I))9.9.8
0044   DIFF(I) = B*DIFF(I)
0045   DIFF(I)+NITEM) = DIFF(I)
0046   Z=B*NSUBJ+ISEL(I)/(IS(I)+(NSUBJ+ISEL(I)-IS(I)))
0047   SE(I) = SCRT(Z)
0048   CCNTINLE
0049   CC 10 J=1,LI
0050   ABIL(J)=C+ABIL(J)
0051   Z = C+LREC/(J*(LREC-J))
0052   SE(I)+NITEM)=SQRT(Z)
0053   RETURN
0054   ENC

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PCRTAM IV G1 RELEASE 2.0      REJOP      DATE = 76302      00/16/36

0001 SUBRCUTINE REDOP( ICATA, IB, IS, ISEL, MATX, IA, ID, DIFF)
0002 DIMENSION IDATA(1), IB(1), IS(1), ISEL(1), MATX(1), IA(1), ID(1), ICPT(5)
0003 DIMENSICN ISM(3), DIFF(1)
0004 CCMPCN NITEM, NGRCF, MINSC, MAXSC, LREC, NSUEJ, IC, KCAB, ISN(11)
      1, SNAME(1)
      DATA IAC/I+/, ISM/.S., I., M./
      ISN=ISM(1)
      IF( ISN1.EQ.0) ISN1=5
      NSUBJ=1
      LLIM=ISM(2)
      KLIM=ISM(3)
      C*REAC COLUMN SELECT CARD
      100 FCFMAT(8C11)
      C*REAC KEY CARD
      READ(5,101) (ID(1), I=1, LREC)
      C*REAC OPTICN LAEL CARD
      READ(5,101) ICPT
      101 FCFMAT(8C11)
      C*PRINT SUMMARY INFORMATION
      WRITE(6,200)
      200 FCFMAT(I+/, //1X16+COLUMNS SELECTED/)
      201 FCFMAT(I+/, 2I10)
      202 FCFMAT(6,202) (IND, N=1, 8), (IND, N=1, 63)
      203 FCFMAT(I+/, 1+1, 8A1, 1+0, 7(9A1, 1+0))
      204 FCFMAT(6,204) (IA(1), I=1, LREC)
      205 FCFMAT(11, 80A1/)
      206 FCFMAT(6,206) (ID(1), I=1, LREC)
      N=1
      NSC=1
      ISN4 = ISN(8)
      CALL TRANS(IA, LREC)
      IF( ISN4.NE.0) CALL TRANS(IC, LREC)
      C*CCUNT ITEMS SELECTED
      DO 22 I=1, LREC
      KK=IA(I)
      IF(KK) 20, 22, 21
      20 NSC=NSC+1
      21 ISEL(N)=IC(I)
      N=N+1
      22 CCNTINLE
      N=NSC
      IC=0
      K=1
      DO 1 I=1, LREC

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PCPTRAN IV G1  RELEASE 2.0      RECOP      DATE = 763G2      00/16/35

0043      JX=IA (1)
0044      IF(JX)19,19,17
0045      IF(1SW4.NE.1)JX=1
0046      DO 12 J=1,JX
0047      IC=IC+1
0048      IB(IC)=0
0049      DO 1 J=1,6
0050      MATX(K)=0
0051      1 K=K+1
0052      1 KLCW=0
0053      AMIGH=C
C**READ AND WRITE FIRST SUBJECT
0054      REAC(15,1,101)(ID(1),I=1,LREC)
0055      WRITE(C,205)(ID(1),I=1,LREC)
0056      205 FORMAT(1F0,12,FIRST SUBJECT/1X80A1/)
0057      ASSIGN SE TO ISIM
0058      DC 51 I=1,3
0059      IF(IC (1).NE.ISM(1)) GO TO 2
0060      51 CCNTINLE 94 TO ISIM
0061      ASSIGN 94 TO ISIM
0062      CALL MESIN(IC,1DATA,CIFF,ISEL,1)
0063      2 DO 12 I=1,NITEM
0064      12 ICATA(I)=0
C**SCRE EACH ITEM
0065      K=1
0066      4 CC66 I=1,LREC
0067      IF(1A(1))65,66,6
0068      6 DC 64 J=1,5
C**CCUNT OPTION SELECTED
0069      IF(IC(1)-ICPT(J))6+.63,64
0070      63 L=6+(K-1)+J
0071      64 CCNTINLE
0072      L=6+K
0073      65 MATX(L)=MATX(L)+1
0074      K=K+1
0075      66 CCNTINLE
0076      CALL SCCRE(1DATA,14,1A,ISEL,ASC,ISW4)
0077      C**DISCARD ZERC OFFERFIT SCORES
0078      5 IF(1NSC) 55,10,7
0079      7 IB(1NSC)=IB(1NSC)+1
0080      IF(1NSC-ICB,11,11
C**WRITE SCRATCH FILE
0081      8 WRITE(11)(ICATA(1),I=1,NITEM),(IC(1),I=LLIM,LLIM),ASC
0082      8 SUBJ=NSLEJ+1
0083      IF(1NSC-1MINSC)55,87,87
0084      IF(1NSC-MAXSC)88,88,55
C**ACCUMULATE MARGINALS FOR CALIBRATION ROUTINES

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PCRTAN IV G1 RELEASE 2.0 REDOP DATE = 76302 00/16/35

0085 00 DC 9 I=1,NITEM
0086 5 IS(I)=IS(I)+IDATA(I)
0087 GC TC ISIM.(94.95)
0088 54 CALL RESIM(IC,ICATA,CIFF,ISEL,2)
0089 GC TC 56
0090 95 CCNTIAL RECORD
0091 C*READ NEXT RECORD
0092 READ(15,1,101,END=12)(ID(I),I=1,LREC)
0093 C*TEST FOR ENC OF FILE
0094 96 IF( IC(1)-IND)2,12,2
0095 10 ALCH=ALCH+1
0096 GC TC ISIM.(94.95)
0097 11 NHIGH=NHIGH+1
0098 GC TC ISIM.(94.95)
0099 C*WRITE SUMMARY INFORMATION
0100 12 NSUBJ=NSUBJ+1
0101 WRITE(C,107)NITEM,NSUBJ
0102 107 FORMAT(//,ONLBER OF ITEMS'.15/' NLVEEF CF SUBJT'.15)
0103 103 CALL PAGE(2,1,J)
0104 12X'.SEC'.1X'.ITEM'.EXA4.4(1XA4).2X'.LNKN'.3X'.KEY.'/
0105 22X'.ALN'.1X'.NAME'/1X.53(1F-))
0106 104 FORMAT(15.1X.A4.5X.1.615.1.2XA4.16)
0107 L=1
0108 KK=6
0109 C*PRINT OPTION FREQUENCY TABLE
0110 WRITE(C,103) IOPT
0111 I=1
0112 DC 114 M=1,LREC
0113 IF(IA(M))113,114,112
0114 112 WRITE(C,104)I,SHAPE(I),(MATX(K),K=L,KK),ISEL(I)
0115 113 L=KK+1
0116 KK=KK+6
0117 I=I+1
0118 114 CCNTINUE
0119 WRITE(C,105)
0120 NSC=NLGW+NHIGH+NSUBJ
0121 CALL PAGE(2,1,J)
0122 WRITE(C,102) NLGW,NHIGH
0123 102 FORMAT(// 1X21NUMBER OF ZENC SCRES 111/1X24NUMBER CF PERFECT SC
0124 1CRES.1E)
0125 L=0
0126 DO725I=1,LREC
0127 KK=1A(1) 752.725.752
0128 IF(KK)
0129 752 L=L+1
0130 IF(15M4.AE.1)KK=1
0131 ISEL(L)=KK
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FCBTRAN IV G1  RELEASE 2.0  RELOF  DATE = 76302  CG/16/35
0126 72= CONTINLE 1030.
0127 LREC=IC 1031.
0128 NITEN=L 1032.
0129 IC=N 1033.
0130 WRITE(C,106)A,L 1034.
0131 106 FCBMAT(//,ALBBER OF ITE'S SELECTED',14/, NUMBER OF ITEMS NAMED',1 1035.
17//1X,32(0.-)) 1036.
0132 105 FCBMAT(1X,53(1H-)) 1037.
END FILE 1 1038.
0133 REWIND 1 1039.
0134 RETURN 1040.
0135 END 1041.
0136

```

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0001 SUBROUTINE RESIM(IC, IDATA, DIFF, ISEL, N)
0002 DIMENSION IO(1), ICATA(1), DIFF(1), ISEL(1), ICQCE(36), CCM(1)
0003 CCMPCA NITEM, NGRCF, MINSC, MAXSC, LREC, NSUEJ, IC, KCAB, ISN(11)
0004 1. SNAME(1)
0005 1. DATA JC, /, IND, /, /, ICCDE, /, 0, /, 1, /, 2, /, 3, /, 4, /, 5, /, 6, /, 7, /, 8, /,
0006 1. 9, /, A, /, B, /, C, /, D, /, E, /, F, /, G, /, H, /, I, /, J, /, K, /, L, /, M, /, N, /, O, /,
0007 2. P, /, Q, /, R, /, S, /, T, /, U, /, V, /, W, /, X, /, Y, /, Z, /,
0008 GC TC (1,4), N WIDTH, ISLBJ, GMEAN, SC, ISEC
0009 READ(5,101) WIDTH, ISLBJ, GMEAN, SC, ISEC
0010 FCRMAT(F6.0, 15, 2F5.0, 110)
0011 IF(ISEC.GT.0) ISEEC=ISEC
0012 WRITE(6,105) ISLBJ, /, ICTH, GMEAN, SC, ISEEC
0013 FORMAT('OSIMULATION CF', 15, /, 'SUBJECTS', /, /, 'TARGET VALUES ---'
0014 1. 'TEST WIDTH =', F6.3, /, 'ABILITY MEAN =', F6.3, /, 'STANDARC',
0015 2. 'DEVIATION =', F6.3, /, 'SEED FOR RN GENERATCH =', 110, /)
0016 WIDTH= WICTP/(NITEM-1)
0017 AB=0.
0018 P=0.
0019 CC 10 I=1, NITEM
0020 AB=AB+ISEL(I)
0021 P=P-1+ISEL(I)
0022 DIFF(1)=WIDTH*(1.+P/AB)
0023 I=1
0024 WRITE(6,102) I, DIFF(1)
0025 FCRMAT(1, ITEM, NUMBER, 15, /, DIFFICULTY=, F6.3)
0026 DO 2 I=2, NITEM
0027 CUFF(1)=CUFF(1-1)+WICTP
0028 WRITE(6,102) I, DIFF(1)
0029 CUFF(1-1)=EXP(DIFF(1-1))
0030 CUFF(NITEM)=EXP(DIFF(NITEM))
0031 DC 3 I=1, 150
0032 IC(1)=JC
0033 ICNT=0
0034 ABM2=0
0035 IF(ICNT.LT.ISLBJ) GC TC 5
0036 ID(1)=INC
0037 ABM2=SCRT((ABM2-ABM+ABM/ICNT)/(ICNT-1))
0038 ABM=ABM/ICNT
0039 WRITE(6,104) ICNT, ABM, ABM2
0040 FCRMAT(10, 15, /, SUBJECTS SIMULATED, MEAN ABILITY =,
0041 1. F6.3, /, STANDARD DEVIATION =, F6.3)
0042 RETURN
0043 ICNT=ICNT+1
0044 CALL GGLN(ISEED, 1, CCM)
0045 GGLN GENERATES NORMAL VARIATES WITH MEAN 0 AND VARIANCE 1.
0046 C GGLN ISEED IS THE SEED FOR THE GENERATCH WHICH IS READ FROM
0047 C SIMULATION DESCRIPTION CARD.
0048 C

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0040      '1' INDICATES ONLY ONE DEVIATE IS TO BE RETURNED.
0041      CCM IS AN ARRAY IN WHICH THE RANCCA NUMBER IS RETURNED.
0042      ABL=SC+CCM(1)+GMEAN
0043      AEM=AE+ABL
0044      ADM2=ADM2+ABL+ABL
0045      AB=EXF(AEL)
0046      DC 8 I=1,NITEM
0047      IX=ISEL(1)
          IF(IX.EQ.0) GC TO R
          P=EXP(AB-DIFF(1))
          C NEITHER GCM NOR GGU3 ARE INCLUDED IN THE RASCH SOURCE CHECK.
          C THEY ARE PART OF 'SYS2.IMSL' PACKAGE AT THE UNIVERSITY OF CHICAGO.
          P=P/(1.+P)
          NSC=0
          DO 7 J=1,IX
          CALL GGL3(I,SEED,1,CCM)
          C GGU3 GENERATES UNIFORM RANCCM NUMBERS. THE ARGUMENT LIST IS
          C IS IDENTICAL TO 'GGUN.'
          IF(CCM(1)-P)6,6,7
          6   NSC = NSC + 1
          7   CCNTINLE
          IC (1)=ICDCE(NSC+1)
          8   CCNTINLE
          IF(IISH(1),NE.0)WRITE(6,103)ICNT,ABL,(ID(1),I=1,NITEM)
          103  FORMAT(' SUBJECT NUMBER',15,' ABILITY ',F6.3,' RESPONSES ',80A1)
          RETURN
          END
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PCPTRAN	IV	GI	RELEASE	2.0	SCJURE	DATE = 763C2	00/16/3E
0001				SUBROUTINE SCRCR(I,DATA,IC,ISEL,KEY,NSC,M)			1115.
0002				DIMENSION IDATA(1),ID(1),ISEL(1),KEY(1)			1116.
0003				COMMON NITEM,NGRCF,MINSC,MAXSC,LREC,NSUEJ,IC,KCAB,ISW(11)			1117.
				1,ISNAME(1)			1118.
				DATA BLK/,/,AST/,/,			1119.
				MM=MM+1			1120.
				NSC=0			1121.
				J=0			1122.
				GC TC (5,1,14,19,24),MM			1123.
				1 CALL TRANS(ID,LREC)			1124.
				CC 5 I=1,LREC			1125.
				K=ISEL(1)			1126.
				IF(K)4,5,2			1127.
				IF(K-ID(1))6,3,3			1128.
				NSC=NSC+ID(1)			1129.
				J=J+1			1130.
				IDATA(J)=ID(1)			1131.
				CCNTINLE			1132.
				RETURN			1133.
				WRITE(C,101)(ID(K),K=1,LREC)			1134.
				101 WRITE(C,102)(ELK,K=1,1),AST			1135.
				102 FCNMAT(1X,'ILLEGAL CCDE. CASE QUITTED',(1X8011))			1136.
				FORMAT(E1A1)			1137.
				NSC=-1			1138.
				RETURN			1139.
				J=1			1140.
				CC 12 I=1,LREC			1141.
				K=ISEL(1)			1142.
				IF(K)12,13,10			1143.
				IF(IC(1)-KEY(J))12,11,12			1144.
				NSC=NSC+1			1145.
				IDATA(J)=1			1146.
				J=J+1			1147.
				CCNTINLE			1148.
				RETURN			1149.
				CALL TRANS(IC,LREC)			1150.
				J=1			1151.
				CC 18 I=1,LREC			1152.
				K=ISEL(1)			1153.
				IF(K)17,18,15			1154.
				IF(IC(1)-KEY(J))16,16,17			1155.
				NSC=NSC+1			1156.
				IDATA(J)=1			1157.
				J=J+1			1158.
				GC TC 18			1159.
				ICATA(J)=0			1160.
				J=J+1			1161.
				CCNTINLE			1162.

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```

PCATRAM IV 61 RELEASE 2.0          SCORE          DATE = 76302          00/16/35
0248 RETURN
CC45 CALL TRANS(IC,LREC)
0050 J=1
CC51 CC 23 I=1,LREC
0052 K=ISEL(I)
CC53 IF(K)22,23,20
CC54 IF(IC(I)-KEY(J))22,21,21
0055 NSC=ASC+1
CC56 ICATA(J)=1
0057 J=J+1
0058 GC TC 23
CC59 ICATA(J)=0
CC60 J=J+1
CC61 CONTINUE
CC62 RETURN
0063 CENTINLE
CC64 C THIS SPACE RESERVED FOR USED SUPPLIED LCGIC.
CC65 RETURN
END
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 permit fully legible reproduction

PCPTRAM IV 61 RELEASE 2.0 SMRY DATE = 76302 00/16/35

```

0001 SUBECTLINE SMRY(CIFF,A, IDATA,IS,MATX,ISEL,B,IB)
0002 DIMENSION DIFF(1),ISEL(1),IDATA(1),MATX(1),IS(1),A(1),E(1),IE(1)
0003 DIMENSICA XX(3),STAT(6),AVG(3),AABE(3)
0004 CCMACK NITEM,NGFCH,MINSC,MAXSC,LREC,NSUEJ,IC,KCAB,ISW(11)
      1,SNAME(1)
0005 LLLINE=CN
0006 C*CLEAR NECESSARY ARRAYS
0007 DC 97 I=1,NITEM
0008 IF(ISEL(1))97,97,93
0009 SS K=I
0010 SS CCATLINE
0011 DO 98 I=1,3
0012 AVG(I)=0.0
0013 DO 99 I=1,6
0014 STAT(I)=0.0
0015 CALL PAGE(2,I,J)
0016 DC 1 I=1,NITEM
0017 IF(ISEL(1))10,10,1
0018 DIFF(I)=0.0
0019 A(I)=0.0
0020 MATX(I)=0
      1 IS (I)=100.0*CIFF(I)
C*FIND DIFFICULTY AND FIT ORDERS
      CALL SRT(IS ,ICATA)
      CALL SRT(IE,IS)
C*PRINT PEACINGS
      WRITE(C,100)
100 FCRMAT(12X,SERIAL CDEF,.23X,CIFFICULTY CDEF,.21X,FIT CDEF,
1/X115(-.)/2(2X,.3SEQ ITEM,.4X,ITEM,.4X,DISC,.4X,.FIT 1.),
12X,.SEC ITEM,.4X,ITEM,.4X,CISC,.4X,.FIT .3X,PCINT 1.,
2 2(2X,.NLM NAME,.4X,CIFF,.4X,INCH,.4X,MN SQ 1.),
32X,.PUP NAME,.4X,CIFF,.4X,INCH,.4X,MN SQ,.3X,EISER 1./X115(-.)))
C*PRINT TABLE WITH I EG SEQ CDEF, J EG CIFF CDEF AND K EG FIT CDEF
DO22 I=1,NITEM
J=IDATA(I)
K=IS(I)
AAB(1)=16(I)/100.0
AAB(2)=16(J)/100.0
AAB(3)=16(K)/100.0
CALL PAGE(4,3,LLINE)
WRITE(C,101) I,SNAME(1),CIFF(I),A(I),AAB(1),J,SNAME(J),CIFF(J),
1A(J),AAB(2),K,SNAME(K),DIFF(K),A(K),AAB(3),E(K)
101 FCRMAT(2(I5,1X4,3F8.2,2X11),15,1X4,4FE.2,1.)
XX(1)=CIFF(I)
XX(2)=A(I)
XX(3)=AAB(1)
KL=1
IF(ISEL(1))22,22,5

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include identification

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PCFTRAN IV G1  RELEASE 2.0          SMRY          DATE = 76302          00/16/35

0039      5 DC 2 K=1.3
0040      AVG(K)=AVG(K)+XX(K)*ISEL(I)
0041      DO 2 L=1,K
0042      STAT(KL)=STAT(KL)+XX(K)*XX(L)*ISEL(I)
0043      KL=KL+1
0044      IF(1SW(7)) 22,22,21
0045      WRITE(7,103)J,SNAME(I),XX
0046      FORMAT(13,A4,3F7.3)
0047      21
0048      103
0049      22 CCNT INUE
0050      KL=1
0051      X= IC -1
0052      C+CCCMPLTE MEANS, STANDAND DEVIATICNS AND CORRELATIONS
0053      DC 3 I=1.3
0054      AVG(I)=AVG(I)/ LREC
0055      DC 3 J=1,I
0056      STAT(KL)=(STAT(KL)-LREC *AVG(I)*AVG(J))/(LREC-1)
0057      KL=KL+1
0058      3
0059      KL=1
0060      DO 4 I=1.3
0061      K=(1+(I+1))/2
0062      XX(I)=SQRT(STAT(K))
0063      DO 4 J=1,I
0064      STAT(KL)=STAT(KL)/(XX(I)*XX(J) )
0065      KL=KL+1
0066      4
0067      WRITE(6,102) AVG,XX,STAT(2),STAT(4),STAT(5)
0068      102 FCFRMT(1X,119(1H-))/ 6X,MEAN=.3F8.2/ 6X,.S.D.,.3F8.2,6X,.CISC+MNSC=.F6.2,6X,.CISC+MNSC=.F6.2)
0069      10N,.6X,.CISC+MNSC=.F6.2,6X,.CISC+MNSC=.F6.2)
0070      RETURN
0071      END

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LEASE 2.0 UCLN DATE = 76302 00/16/35

```

SUBROUTINE UCON(S,M,D,AB,ISEL,SE)
  INTEGER R(1),S(1),ISEL(1)
  DIMENSION D(1),AB(2),SE(1)
  COMMON NITEM,NGR0P,MINSC,MAXSC,LREC,NSUEJ,IC,KCAB,ISH(11)
  1 SNAPE(1)
  L=NITEM
  LI=LAEC-1
  CX=LFEC
  CX=OX/LI
  GC 155 I=1,L
  IF(ISEL(1).EQ.0) GL TO 159
  D(1) = D(1)+DX
  CCNTINLE
  DO 200 IT=1,10
    NITER = IT
    CRIT=0.0
    CEN=0.0
    DC 201 I=1,L
    IF(ISEL(1)) 201,201,200
  200 CCNTINLE
    CALL MENT(D(1),ISEL(1),AB,F,S(1),NSEL,MINSC,MAXSC,0.05,10,DC,P)
    CEN=CEN+D(1)+ISEL(1)
    SE(1)=F
  201 CCNTINLE
    CEN=CEN/LREC
    CC 212 I=1,L
    D(1)=D(1)-CEN
    IX=I+LI*LFEC
    IF(ISEL(1)) 212,212,211
  211 CRIT=CRIT+ABS(D(1)-SE(IX))
  212 CCNTINLE
    IF(IT.GT.1) GO TC 205
    DO 204 I=1,L
    IF(ISEL(1)) 204,204,202
    D(1)+2*NITEM)=D(1)/DX
  202 CCNTINLE
    IF((CRIT/IC)-0.025) 330,1999,1999
  204 DC 214 K=MINSC,MAXSC
  200 DC 215 ITR=1.5
    IX=K+L
    SE(IX)=0.0
    CC=0.0
    DC 216 I=1,L
    IF(ISEL(1)) 216,216,213
  213 P=EXP((B(K)-C(1)))
    P=P/(1.0+P)
    SE(IX)=SE(IX)+P*(1.0-P)+ISEL(1)
    DC=DD+P*ISEL(1)

```

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```

PCRTAM IV 61  RELEASE 2.0      UCJN      DATE = 76302      C0/16/35
0048      210 CONTINUE
0049      CC=(K-CC)/SE(IX)
0050      AB(K)=AB(K)+CC
0051      IF(ABS(CC)-0.05)214,215,216
0052      216 CONTINUE
0053      214 CONTINUE
0054      IX=L+LREC
0055      DC 2000 I=1,L
0056      IX=IX+1
0057      SE(IX)=D(I)
0058      CCATINLE
0059      IX=L+LREC
0060      CC=LREC-1
0061      DD=DC/LREC
0062      IT=LREC-1
0063      DC 332 I=1,L
0064      IX = IX + 1
0065      SE(IX)=D(I)-SE(IX)
0066      C(I)=D(I)/DX
0067      WRITE(6,100)NITER
0068      FORMAT(' NUMBER OF ITERATIONS = ',I3)
0069      RETURN
0070      END

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APPENDIX C

BICAL CONTROL CARDS

<u>Position</u>	<u>Name</u>	<u>Format and Description</u>
1	Title card	(20A4) Descriptive heading to be printed at the top of each page of output
2	Data Definition	(14I5)
	<u>C C</u>	<u>Label</u>
	1 - 5	NITEM
		Definition
		Total number of items to be read before deletions. This is equal to the number of non-zero entries on the column select card and is the number of item names expected.
	6 - 10	NGROP
		Smallest allowable average group size for testing item fit. This is used to determine the number of score groups. The same value is used to terminate execution before estimation if the total number of subjects is less than NGROP.
	11 - 15	MINSC
		Minimum score to be included in the calibration sample.
	16 - 20	MAXSC
		Maximum score to be included.
	21 - 25	LREC
		Number of columns in the input record to be scanned. It must be large enough to cover all columns containing items and also to skip any extra cards in the subject record.

26 - 30	KCAB	Calibration code 1 = Normal approximation method, should be used with long tests and symmetrical distribution of scores. 2 = Corrected unconditional maximum likelihood estimation. Should be used with shorter tests and skewed distributions.
31 - 35	KSCOR	Scoring code b,0 = score dichotomously according to KEY 1 = data already scored 2 = score dichotomously, correct if $X \leq \text{KEY}$ 3 = score dichotomously, correct if $X \geq \text{KEY}$
36 - 40	INFLE	Alternative input file unit number b,0 = Unit 5.
41 - 45	LLIM	Alternative output file--start of identification field in record
46 - 50	KLIM	Alternative output file--end of identification field in record. If LLIM and KLIM are 1 and LREC the entire record will be copied as the identification.
51 - 55	NUFLE	Alternative output file logical unit number. For each valid input record, a new record will be generated containing raw score, scaled ability in logits and the identification field defined by LLIM and KLIM.
56 - 60	KPRTR	Control switch for optional output b,0 Print all plots 1 Omit score histogram 2 Omit Fit plots 3 Omit both
61 - 65	KSIM	Print simulated persons if > 0

66 - 70	KDIFF	Punch item statistics on unit 7. Output consists of item sequence number, item name, difficulty, discrimination and total fit mean square. Format is (13,A4,3F7.3).
3.	Item Name Card(s)	(20A4) A four character alphanumeric name for each of the "NITEM" items.
4.	Column Selection	(80A1) A record identical in size to each person's record indicating how the data in that position is to be used. For each position - b,0 = skip column 1-9 = include item in corresponding column. Maximum allowable code is 1-9 as given. - A-Z = include item in corresponding column. Maximum allowable code is 10-35 (A=10, etc.) & = delete item in corresponding column after reading names.
5.	Scoring Key	(80A1) Corresponds to perfect input record. It must be included regardless of KSCOR.
6.	Options Label	(5A1) Identifies up to five option labels for which the number of occurrences will be counted for each item.
(7)	Data cards	
(7a)	End of Data	* in col. 1.
(8)	Simulation header	SIMULATE in columns 1-8 causes program to simulate data rather than read. If included it must be followed by

(9) Simulation task description card (F5.0,15,2F5.0,110)

<u>C.C.</u>	<u>Label</u>	<u>Definition</u>
1 - 5	WIDTH	Range of item difficulties to be generated.
6 - 10	ISUBJ	Number of persons to be generated.
11 - 15	GMEAN	Mean ability of population sampled.
16 - 20	SD	Standard deviation of ability.
21 - 25	ISED	Seed for random number generator- should only be coded for first generation in each run.

(10) End of job

**** in columns 1-4
Program will keep recycling looking
for new problems until this card
is encountered. As many jobs as
desired may be stacked.

University of Chicago JCL

```
//iiii JOB (valid UC job card) ,RE=129K
// EXEC PGM=BICAL
//STEPLIB DD DSN=$2DD130.S05.DATA(BICAL) ,DISP=SHR
//FT01F001 DD UNIT=SYSCR,DISP=NEW,SPACE=(TRK,(5,1))
//FTxxF001 DD alternative input file description
//FTyyF001 DD alternative output file description
//FT07F001 DD SYSOUT=B,DCB=(RECFM=FB,BLKSIZE=80)
//FT06F001 DD SYSOUT=A,DCB=(RECFM=FA,BLKSIZE=133)
//FT05F001 DD*
```

The FT05 card is followed by the first job card. Cards FTxx, FTyy and

FT07 are not always required.

Include FTxx if input records are not on cards. The xx should
be replaced by the value of INFLE coded on the data
description card (cc 36-40).

Include FTyy if a new output is to be produced. The yy should
be replaced by the value of NUFLE (cc 51-55).

Include FT07 if item data is to be punched, (cc 66-70).