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AUTHOR Lord, Frederic M.
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ABSTRACT

There are currently three main approaches to parameter estimation in item response theory (IRT): (1) joint maximum likelihood, exemplified by LOGIST, yielding maximum likelihood estimates; (2) marginal maximum likelihood, exemplified by BILOG, yielding maximum likelihood estimates of item parameters (ability parameters can be estimated subsequently, using Bayesian procedures); and (3) Bayesian approaches--parameter estimates are usually the mode or mean of the posterior distribution of the parameter estimated. Advantages and disadvantages of these three methods are discussed and compared. (Author/BW)

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MAXIMUM LIKELIHOOD AND BAYESIAN PARAMETER ESTIMATION IN ITEM RESPONSE THEORY

Frederic M. Lord

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Frederic M. Lord, Principal Investigator

Educational Testing Service
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Maximum Likelihood and Bayesian Parameter Estimation in Item Response Theory

Frederic M. Lord

Abstract

Advantages and disadvantages of joint maximum likelihood, marginal maximum likelihood, and Bayesian methods of parameter estimation in item response theory are discussed and compared.

Maximum Likelihood and Bayesian Parameter Estimation in Item Response Theory*

There are currently three main approaches to parameter estimation in item response theory (IRT):

1. Joint maximum likelihood, exemplified by LOGIST, yielding maximum likelihood estimates (Wingersky, 1983).
2. Marginal maximum likelihood, exemplified by BILOG. This approach currently yields maximum likelihood estimates of item parameters. Ability parameters can be estimated subsequently, using Bayesian procedures (Mislevy & Bock, 1981).
3. Bayesian approaches: parameter estimates are usually the mode (or mean) of the posterior distribution of the parameter estimated (Swaminathan & Gifford, in press).

The quantity maximized by each approach is shown below for a test of n items administered to N examinees. $P_i(\theta_a)$ is the probability of success on item i for examinee a at ability level θ_a, $Q_i(\theta_a) = 1 - P_i(\theta_a)$, u_{ia} is the response of examinee a to item i, assumed here to be either 0 or 1, and $g(\ )$ denotes a prior distribution of parameters.

Joint maximum likelihood:

$$\text{Maximize } L(\underset{\sim}{\theta};\underset{\sim}{a},\underset{\sim}{b},\underset{\sim}{c}) = \prod_{a=1}^{N} \prod_{i=1}^{n} [P_i(\theta_a)]^{u_{ia}} [Q_i(\theta_a)]^{1-u_{ia}} \tag{1}$$

$$\text{or } \log L(\underset{\sim}{\theta};\underset{\sim}{a},\underset{\sim}{b},\underset{\sim}{c}) = \sum_{a=1}^{N} \sum_{i=1}^{n} [u_{ia} \log P_i(\theta_a) + (1 - u_{ia}) \log Q_i(\theta_a)] \quad .$$

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Marginal maximum likelihood of <u>item</u> <u>parameters</u>:

$$\text{Maximize} \quad L(\mathbf{a},\mathbf{b},\mathbf{c}) = \prod_{a=1}^{N} \int_{-\infty}^{\infty} g(\theta_a)\, L(\theta_a;\mathbf{a},\mathbf{b},\mathbf{c})\, d\theta_a \quad . \tag{2}$$

Bayesian modal estimation:

$$\text{Maximize} \quad f(\boldsymbol{\theta};\mathbf{a},\mathbf{b},\mathbf{c}) = L(\boldsymbol{\theta};\mathbf{a},\mathbf{b},\mathbf{c})\,g_1(\boldsymbol{\theta})\,g_2(\mathbf{a},\mathbf{b},\mathbf{c}) \tag{3}$$

$$\text{or} \quad \log f(\boldsymbol{\theta};\mathbf{a},\mathbf{b},\mathbf{c}) = \log L(\boldsymbol{\theta};\mathbf{a},\mathbf{b},\mathbf{c}) + \log g_1(\boldsymbol{\theta}) + \log g_2(\mathbf{a},\mathbf{b},\mathbf{c}) \quad .$$

LOGIST finds the ability and item parameter values that maximize the likelihood function of the observations. Bayesian methods typically multiply this likelihood by a prior for each of the parameters, obtaining the joint posterior distribution of the parameters, which are usually assumed to be independently distributed. The Bayesian modal estimates (BME) of all the parameters are the values at the mode of this joint posterior distribution. Marginal maximum likelihood multiplies the original likelihood by a prior on ability, eliminates the ability parameters by integration, and obtains maximum likelihood estimates of the item parameters by maximizing the resulting 'marginal' likelihood function. Supplementary Bayesian procedures may be used to obtain ability parameter estimates. Bayesian priors on item parameters may also be used in MMLE.

When approximately parallel test forms are administered year after year to similar populations of examinees, it becomes possible to deduce appropriate prior distributions for the item and the ability parameters from past results. In such a situation, Bayesian procedures should certainly yield better parameter estimates than maximum likelihood, since Bayesian procedures make use of more information. Even in the absence of data from previous administrations, Bock's BILOG is able to work with a reasonable prior distribution of ability generated directly just from the current data.

Marginal maximum likelihood has an important advantage over joint maximum likelihood, since it can estimate item parameters without having to estimate ability parameters. The advantage is not one of computational speed but rather of theoretical accuracy. When there are one or two thousand examinees and 40 or more items per person, there will be a little difference between the estimates. In cases where there are only 10 or 15 items per person, joint maximum likelihood will obtain biased estimates of ability parameters, especially at low ability levels. This then causes the item parameters to be misestimated, even though the number of examinees per item is large.

Let us turn now to Bayesian procedures. From the mathematical statistician's point of view, one clear virtue of Bayesian methods is that if the posterior mean is used as a parameter estimate, this estimator minimizes the overall mean squared error of estimation, provided the appropriate prior distribution is used. In the case of ability parameters, for example, the quantity minimized is

$$MSE = \mathcal{E}(\hat{\theta}_a - \theta_a)^2 \quad , \tag{4}$$

where $\hat{\theta}$ is an estimate of θ and $\mathcal{E}$ denotes expectation over all examinees. The posterior mean achieves this important result by accepting increased estimation bias in return for reduced MSE. The BME does not minimize this MSE unless the mode of the posterior distribution coincides with its mean, which is not the case in IRT estimation problems. Nevertheless, the BME may be close to the posterior mean.

Why does the posterior mean do better than the maximum likelihood estimate (MLE) in minimizing MSE? When item parameters are known, the MLE of ability assigned to a given response pattern must always be the same. In Bayesian methods, however, the ability estimate assigned to a given response pattern depends on the characteristics of the entire group analyzed. It is this additional flexibility that allows Bayesian methods to obtain a smaller MSE.

Figure 1 shows the bias, estimated by asymptotic formula (7) accurate through terms of order $1/n$, for the BME of θ (dashed curve) based on a normal prior and for the MLE of θ (solid curve), calculated for an 90-item SAT Verbal test that first came to hand, using the three-parameter logistic model. The values shown in the figure assume the item parameters to be known.

The MLE and the BME are biased in opposite directions. The BME is more biased than the MLE. Note that neither bias is linearly related to θ; consequently, the bias cannot be corrected by a simple linear transformation of the estimates.

When a normal prior is used for θ, the asymptotic standard error of the BME and of the MLE for estimated θ are identical to the usual order of approximation ($1/n$). The (familiar) formula for both asymptotic standard

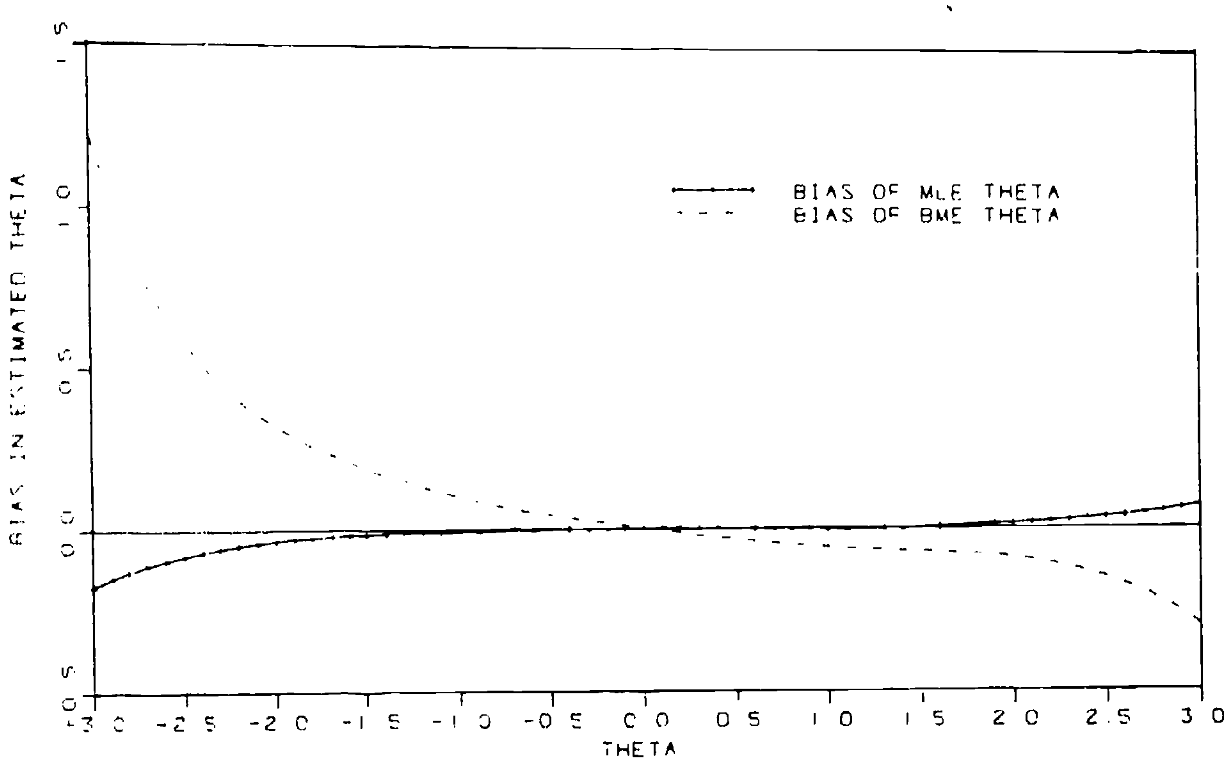

Figure 1. Bias in estimated ability for an 90-item SAT Verbal test.

errors is

$$S.E.(\hat{\theta}) \doteq \left(\sum_{i=1}^{n} \frac{P_i'^2}{P_i Q_i} \right)^{-1/2} , \tag{5}$$

the square root of the reciprocal of the test information function (I). This is also the asymptotic formula for both MSE's. If the S.E. were written out including higher order terms, the Bayesian S.E. would be smaller than the maximum likelihood S.E. by an amount of order $1/n^2$.

The asymptotic bias in the MLE in the three-parameter logistic model is (Lord, 1983)

$$\text{Bias}(\text{MLE}(\theta)) \doteq \frac{D}{I^2} \sum_{i=1}^{n} a_i I_i (\phi_i - \frac{1}{2}) \tag{6}$$

where $D = 1.7$, $I_i \equiv \frac{P_i'^2}{P_i Q_i}$, $P_i' \equiv \frac{\partial P_i}{\partial \theta}$, $\phi_i \equiv \frac{P_i - c_i}{1 - c_i}$,

and a_i and c_i are the discrimination parameter and lower asymptote for item i . The asymptotic bias for the BME is found by the same method to be

$$\text{Bias}(\text{BME}(\theta)) \doteq \text{Bias}(\text{MLE}(\theta)) - \frac{\theta}{I} . \tag{7}$$

Both (6) and (7) are of order $1/n$.

Because of the bias in the BME, which is best described as regression towards the mean, the variance of the BME across examinees is less than the variance of the true θ values. Many people apply a linear transformation to the BME's in an attempt to make the variance (across examinees) of the resulting transformed estimates equal to the variance of the true θ values. This procedure is only a rough approximation, since it is based on an assumption of linear regression of BME on θ, whereas the true regression is curvilinear. From the mathematical statistician's point of view, a linearly transformed BME or posterior mean, or a curvilinearly transformed BME or posterior mean, are nonstandard types of estimators. Such transformed estimators no longer have the property of minimizing MSE.

A further problem arises: Minimizing MSE on the θ scale is not the same as minimizing MSE on the true-score scale, or on some other transformed ability scale. Bayesian estimates of ability will differ in a substantive way depending on the scale chosen for measuring ability. This problem does not arise in maximum likelihood estimation.

Although minimizing MSE on the θ scale seems appropriate to many people, the writer believes it is inappropriate. Large differences in θ's at the extremes of the ability scale are of very much less importance for most practical purposes than smaller differences in the middle of the scale. If the extremes of the scale were important to us, we would be putting more easy items or more hard items in our tests. An average of squared differences, averaged over all parts of the scale, is thus not of real interest. A procedure that attempts to minimize such an average will devote most effort to minimizing the large squared differences found at the extremes of the scale, thus partially neglecting more important differences near the middle of the scale.

In the case of item-parameter estimation, the idea of minimizing the MSE of the item parameter estimates seems inappropriate for a different reason. If the item parameter estimates are to be used for equating, for example, the appropriate quantity to minimize is the squared error in the final equating tables, not the MSE of the item parameters. If the items are to be used for subsequent adaptive testing, the appropriate criterion is a mean squared error of the resulting examinee score the adaptive test.

A thought-provoking circumstance is the following: Suppose the true prior distribution of each item parameter and ability parameter were known. Given repeated testings over a few years, we can actually come close to this. The leading Bayesian IRT practitioners prefer not to use such a 'tight' prior; they prefer to use a more diffuse prior that produces less regression of the estimates towards the mean. This attitude derives from practical considerations rather than from Bayesian logic.

Use of Bayesian priors, even diffuse priors, has several practical advantages that are widely appreciated:

1. Ability estimates ($\hat{\theta}$) on the θ scale are automatically restricted to a reasonable range. Infinite estimates do not occur.
2. Item discrimination parameter estimates never try to become infinite.
3. Estimated lower asymptotes do not come out at implausible values, even in the case of very easy items that provide no relevant data for estimating the asymptotes.

The last two advantages convince the writer that Bayesian priors should probably be used for the discrimination and the lower-asymptote parameters. Regression towards the mean in estimates of these parameters has less serious implications than in the case of the ability and difficulty parameters.

When ability parameter estimates are regressed towards the mean, an examinee's score ($\hat{\theta}$ or some transformation of $\hat{\theta}$) depends not only on the examinee's test performance, but also on the nature of the entire group in which he or she happens to be included. If the group as a whole is a low-ability group, the examinee's score may be regressed downwards; if it is a high-ability group, the examinee's score may be regressed upwards. If the group is heterogeneous, the regression effect may be small; if the group is homogeneous, the regression effect could be large. If the test is long and reliable, the regression of scores may be relatively small; if the test is short and unreliable, the regression effect could be of serious concern.

We need more practical experience in dealing with these problems in real situations. If our work deals with a single test and a single group of examinees, regressed ability estimates may pose no problem, because the rank order of the examinees' scores will be little affected. If our work deals with comparisons of individuals across groups and across tests, with data analyses made at different times, we may want more experience before we decide exactly how to obtain acceptable results for large-scale testing programs. Bayesian methods may be the ultimate recourse, but we need considerable experience with them before we can be sure how to use them safely.

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Navy

1 Dr. Nick Bond
Office of Naval Research
Liaison Office, Far East
APO San Francisco, CA 96503

1 Lt. Alexander Bory
Applied Psychology
Measurement Division
NAMRL
NAS Pensacola, FL 32508

1 Dr. Robert Breaux
NAVTRAEQUIPCEN
Code N-095R
Orlando, FL 32813

1 Dr. Robert Carroll
NAVOP 115
Washington , DC 20370

1 Dr. Stanley Collyer
Office of Naval Technology
800 N. Quincy Street
Arlington, VA 22217

1 CDR Mike Curran
Office of Naval Research
800 N. Quincy St.
Code 270
Arlington, VA 22217

1 Dr. John Ellis
Navy Personnel R&D Center
San Diego, CA 92252

1 DR. PAT FEDERICO
Code P13
NPRDC
San Diego, CA 92152

1 Mr. Paul Foley
Navy Personnel R&D Center
San Diego, CA 92152

1 Mr. Dick Hoshaw
NAVOP-135
Arlington Annex
Room 2834
Washington , DC 20350

Navy

1 Dr. Norman J. Kerr
Chief of Naval Education and Training
Code 0CA2
Naval Air Station
Pensacola, FL 32508

1 Dr. Leonard Kroeker
Navy Personnel R&D Center
San Diego, CA 92152

1 Daryll Lang
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. William L. Maloy (02)
Chief of Naval Education and Training
Naval Air Station
Pensacola, FL 32508

1 Dr. James McBride
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San Diego, CA 92152

6 Personnel & Training Research Group
Code 442PT
Office of Naval Research
Arlington, VA 22217

1 Dr. Carl Ross
CNET-PDCD
Building 90
Great Lakes NTC, IL 60088

1 Mr. Drew Sands
NPRDC Code 62
San Diego, CA 92152

1 Mary Schratz
Navy Personnel R&D Center
San Diego, CA 92152

Navy

1 Dr. Robert G. Smith
Office of Chief of Naval Operations
OP-987H
Washington, DC 20350

1 Dr. Alfred F. Smode
Senior Scientist
Code 7B
Naval Training Equipment Center
Orlando, FL 32813

1 Dr. Richard Snow
Liaison Scientist
Office of Naval Research
Branch Office, London
Box 39
FPO New York, NY 09510

1 Dr. Richard Sorensen
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Frederick Steinheiser
CNO - OP115
Navy Annex
Arlington, VA 20370

1 Mr. Brad Sympson
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Frank Vicino
Navy Personnel R&D Center
San Diego, CA 92152

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Naval Postgraduate School
Department of Administrative
Sciences
Monterey, CA 93940

1 Dr. Douglas Wetzel
Code 12
Navy Personnel R&D Center
San Diego, CA 92152

1 DR. MARTIN F. WISKOFF
NAVY PERSONNEL R& D CENTER
SAN DIEGO, CA 92152

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Navy Personnel R&D Center
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Navy

1 Dr. Wallace Wulfeck, III
Navy Personnel R&D Center
San Diego, CA 92152

Civilian Agencies

1 Dr. Patricia A. Butler
NIE-BRN Bldg, Stop # 7
1200 19th St., NW
Washington, DC 20208

1 Dr. Vern W. Urry
Personnel R&D Center
Office of Personnel Management
1900 E Street NW
Washington, DC 20415

1 Mr. Thomas A. Warm
U. S. Coast Guard Institute
P. O. Substation 18
Oklahoma City, OK 73169

1 Dr. Joseph L. Young, Director
Memory & Cognitive Processes
National Science Foundation
Washington, DC 20550

Private Sector

1 Dr. Erling B. Andersen
Department of Statistics
Studiestraede 6
1455 Copenhagen
DENMARK

1 Dr. Isaac Bejar
Educational Testing Service
Princeton, NJ 08450

1 Dr. Menucha Birenbaum
School of Education
Tel Aviv University
Tel Aviv, Ramat Aviv 69978
Israel

1 Dr. Werner Birke
Personalstammamt der Bundeswehr
D-5000 Koeln 90
WEST GERMANY

1 Dr. R. Darrell Bock
Department of Education
University of Chicago
Chicago, IL 60637

1 Mr. Arnold Bohrer
Section of Psychological Research
Caserne Petits Chateau
CRS
1000 Brussels
Belgium

1 Dr. Robert Brennan
American College Testing Programs
P. O. Box 168
Iowa City, IA 52243

1 Dr. Glenn Bryan
6208 Poe Road
Bethesda, MD 20817

1 Dr. Ernest R. Cadotte
307 Stokely
University of Tennessee
Knoxville, TN 37916

1 Dr. John B. Carroll
409 Elliott Rd.
Chapel Hill, NC 27514

Private Sector

1 Dr. Norman Cliff
Dept. of Psychology
Univ. of So. California
University Park
Los Angeles, CA 90007

1 Dr. Hans Crombag
Education Research Center
University of Leyden
Boerhaavelaan 2
2334 EN Leyden
The NETHERLANDS

1 Lee Cronbach
16 Laburnum Road
Atherton, CA 94205

1 CTB/McGraw-Hill Library
2500 Garden Road
Monterey, CA 93940

1 Mr. Timothy Davey
University of Illinhois
Department of Educational Psychology
Urbana, IL 61801

1 Dr. Dattpradad Divgi
Syracuse University
Department of Psychology
Syracuse, NE 33210

1 Dr. Emmanuel Donchin
Department of Psychology
University of Illinois
Champaign, IL 61820

1 Dr. Hei-Ki Dong
Ball Foundation
Room 314, Building B
800 Roosevelt Road
Glen Ellyn, IL 60137

1 Dr. Fritz Drasgow
Department of Psychology
University of Illinois
603 E. Daniel St.
Champaign, IL 61820

1 Dr. Stephen Dunbar
Lindquist Center for Measurement
University of Iowa
Iowa City, IA 52242

ivate Sector

1 Dr. John M. Eddins
University of Illinois
252 Engineering Research Laboratory
103 South Mathews Street
Urbana, IL 61801

1 Dr. Susan Embertson
PSYCHOLOGY DEPARTMENT
UNIVERSITY OF KANSAS
Lawrence, KS 66045

1 ERIC Facility-Acquisitions
4833 Rugby Avenue
Bethesda, MD 20014

1 Dr. Benjamin A. Fairbank, Jr.
Performance Metrics, Inc.
5825 Callaghan
Suite 225
San Antonio, TX 78228

1 Dr. Leonard Feldt
Lindquist Center for Measurement
University of Iowa
Iowa City, IA 52242

1 Univ. Prof. Dr. Gerhard Fischer
Liebiggasse 5/3
A 1010 Vienna
AUSTRIA

1 Professor Donald Fitzgerald
University of New England
Armidale, New South Wales 2351
AUSTRALIA

1 Dr. Dexter Fletcher
University of Oregon
Department of Computer Science
Eugene, OR 97403

1 Dr. John R. Frederiksen
Bolt Beranek & Newman
50 Moulton Street
Cambridge, MA 02138

1 Dr. Janice Gifford
University of Massachusetts
School of Education
Amherst, MA 01002

Private Sector

1 Dr. Robert Glaser
Learning Research & Development Center
University of Pittsburgh
3939 O'Hara Street
PITTSBURGH, PA 15260

1 Dr. Marvin D. Block
217 Stone Hall
Cornell University
Ithaca, NY 14853

1 Dr. Bert Green
Johns Hopkins University
Department of Psychology
Charles & 34th Street
Baltimore, MD 21218

1 DR. JAMES G. GREENO
LRDC
UNIVERSITY OF PITTSBURGH
3939 O'HARA STREET
PITTSBURGH, PA 15213

1 Dipl. Pad. Michael W. Habon
Universitat Dusseldorf
Erziehungswissenschaftliches Inst. II
Universitatsstr. 1
D-4000 Dusseldorf 1
WEST GERMANY

1 Dr. Ron Hambleton
School of Education
University of Massachusetts
Amherst, MA 01002

1 Prof. Lutz F. Hornke
Universitat Dusseldorf
Erziehungswissenschaftliches Inst. II
Universitatsstr. 1
Dusseldorf 1
WEST GERMANY

1 Dr. Paul Horst
677 G Street, #184
Chula Vista, CA 90010

1 Dr. Lloyd Humphreys
Department of Psychology
University of Illinois
603 East Daniel Street
Champaign, IL 61820

Private Sector

1 Dr. Steven Hunka
Department of Education
University of Alberta
Edmonton, Alberta
CANADA

1 Dr. Jack Hunter
2122 Coolidge St.
Lansing, MI 48906

1 Dr. Huynh Huynh
College of Education
University of South Carolina
Columbia, SC 29208

1 Dr. Douglas H. Jones
Advanced Statistical Technologies
Corporation
10 Trafalgar Court
Lawrenceville, NJ 08148

1 Professor John A. Keats
Department of Psychology
The University of Newcastle
N.S.W. 2308
AUSTRALIA

1 Dr. William Koch
University of Texas-Austin
Measurement and Evaluation Center
Austin, TX 78703

1 Dr. Thomas Leonard
c/o Dr. Melvin R. Novick
Lindquist Center for Measurement
University of Iowa
Iowa City, IA 52242

1 Dr. Alan Lesgold
Learning R&D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15260

1 Dr. Michael Levine
Department of Educational Psychology
210 Education Bldg.
University of Illinois
Champaign, IL 61801

Private Sector

1 Dr. Charles Lewis
Faculteit Sociale Wetenschappen
Rijksuniversiteit Groningen
Oude Boteringestraat 23
9712GC Groningen
Netherlands

1 Dr. Robert Linn
College of Education
University of Illinois
Urbana, IL 61801

1 Dr. Robert Lockman
Center for Naval Analysis
200 North Beauregard St.
Alexandria, VA 22311

1 Dr. Frederic M. Lord
Educational Testing Service
Princeton, NJ 08541

1 Dr. James Lumsden
Department of Psychology
University of Western Australia
Nedlands W.A. 6009
AUSTRALIA

1 Dr. Gary Marco
Stop 31-E
Educational Testing Service
Princeton, NJ 08451

1 Mr. Robert McKinley
American College Testing Programs
P.O. Box 168
Iowa City, IA 52243

1 Dr. Barbara Means
Human Resources Research Organization
300 North Washington
Alexandria, VA 22314

1 Dr. Robert Mislevy
711 Illinois Street
Geneva, IL 60134

1 Dr. W. Alan Nicewarder
University of Oklahoma
Department of Psychology
Oklahoma City, OK 73069

Private Sector

1 Dr. Melvin R. Novick
356 Lindquist Center for Measurment
University of Iowa
Iowa City, IA 52242

1 Dr. James Olson
WICAT, Inc.
1875 South State Street
Orem, UT 84057

1 Wayne M. Patience
American Council on Education
GED Testing Service, Suite 20
One Dupont Cirle, NW
Washington, DC 20036

1 Dr. James Paulson
Dept. of Psychology
Portland State Unive3rsity
P.O. Box 751
Portland, OR 97207

1 Dr. Mark D. Reckase
ACT
P. O. Box 168
Iowa City, IA 52243

1 Dr. Lawrence Rudner
403 Elm Avenue
Takoma Park, MD 20012

1 Dr. J. Ryan
Department of Education
University of South Carolina
Columbia, SC 29208

1 PROF. FUMIKO SAMEJIMA
DEPT. OF PSYCHOLOGY
UNIVERSITY OF TENNESSEE
KNOXVILLE, TN 37916

1 Frank L. Schmidt
Department of Psychology
Bldg. GG
George Washington University
Washington, DC 20052

1 Lowell Schoer
Psychological & Quantitative
Foundations
College of Education
University of Iowa
Iowa City, IA 52242

Private Sector

1 Dr. Kazuo Shigemasu
7-9-24 Kugenuma-Kaigan
Fujusawa 251
JAPAN

1 Dr. William Sims
Center for Naval Analysis
200 North Beauregard Street
Alexandria, VA 22311

1 Dr. H. Wallace Sinaiko
Program Director
Manpower Research and Advisory Services
Smithsonian Institution
801 North Pitt Street
Alexandria, VA 22314

1 Martha Stocking
Educational Testing Service
Princeton, NJ 08541

1 Dr. Peter Stoloff
Center for Naval Analysis
200 North Beauregard Street
Alexandria, VA 22311

1 Dr. William Stout
University of Illinois
Department of Mathematics
Urbana, IL 61801

1 Dr. Hariharan Swaminathan
Laboratory of Psychometric and
Evaluation Research
School of Education
University of Massachusetts
Amherst, MA 01003

1 Dr. Kikumi Tatsuoka
Computer Based Education Research Lab
252 Engineering Research Laboratory
Urbana, IL 61801

1 Dr. Maurice Tatsuoka
220 Education Bldg
1310 S. Sixth St.
Champaign, IL 61820

1 Dr. David Thissen
Department of Psychology
University of Kansas
Lawrence, KS 66044

Private Sector

1 Mr. Gary Thomasson
University of Illinois
Department of Educational Psychology
Champaign, IL 61820

1 Dr. Robert Tsutakawa
Department of Statistics
University of Missouri
Columbia, MO 65201

1 Dr. Ledyard Tucker
University of Illinois
Department of Psychology
603 E. Daniel Street
Champaign, IL 61820

1 Dr. V. R. R. Uppuluri
Union Carbide Corporation
Nuclear Division
P. O. Box Y
Oak Ridge, TN 37830

1 Dr. David Vale
Assessment Systems Corporation
2233 University Avenue
Suite 310
St. Paul, MN 55114

1 Dr. Howard Wainer
Division of Psychological Studies
Educational Testing Service
Princeton, NJ 08540

1 Dr. Ming-Mei Wang
Lindquist Center for Measurement
University of Iowa
Iowa City , IA 52242

1 Dr. Brian Waters
HumRRO
300 North Washington
Alexandria, VA 22314

1 Dr. David J. Weiss
N660 Elliott Hall
University of Minnesota
75 E. River Road
Minneapolis, MN 55455

1 Dr. Rand R. Wilcox
University of Southern California
Department of Psychology
Los Angeles, CA 90007

Private Sector

1 German Military Representative
ATTN: Wolfgang Wildegrube
Streitkraefteamt
D-5300 Bonn 2
4000 Brandywine Street, NW
Washington , DC 20016

1 Dr. Bruce Williams
Department of Educational Psychology
University of Illinois
Urbana, IL 61801

1 Ms. Marilyn Wingersky
Educational Testing Service
Princeton, NJ 08541

1 Dr. George Wong
Biostatistics Laboratory
Memorial Sloan-Kettering Cancer Center
1275 York Avenue
New York, NY 10021

1 Dr. Wendy Yen
CTB/McGraw Hill
Del Monte Research Park
Monterey, CA 93940