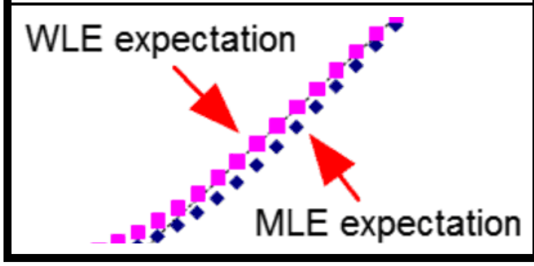
Warm's MLE Bias Correction



RASCH MEASUREMENT

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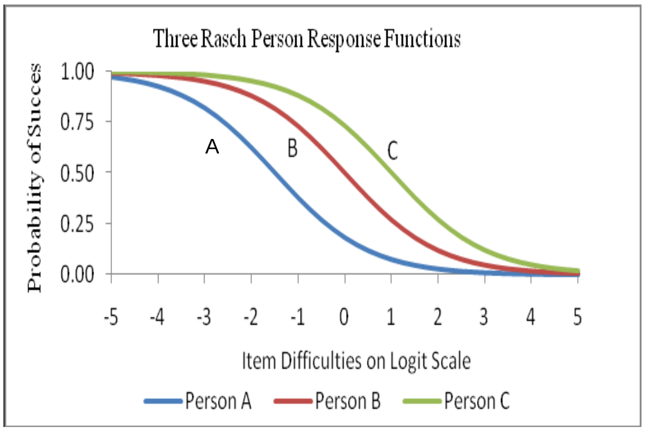
Crossing Person Response Functions

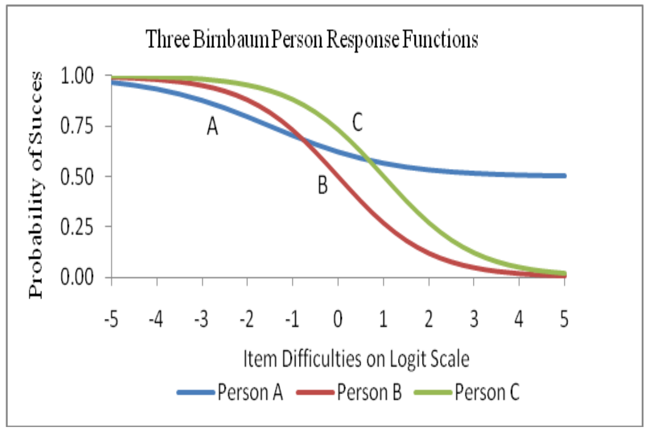
Item Invariant Measurement

Panel A



Item Variant Measurement

Panel B



Panel C

Three persons with **same** order on the latent variable			
Achievement			
High	C	C	C
Medium	B	B	B
Low	A	A	A
	-2	0	+2
Item subsets:	Easy	Medium	Hard

Panel D

Three persons with **different** orders on the latent variable			
Achievement			
High	C	C	A
Medium	B	A	C
Low	A	B	B
	-2	0	+2
Item subsets:	Easy	Medium	Hard

The substantive interpretation of crossing item response functions (IRFs) is fairly well-known. For example, Wright (1997) clearly illustrates how crossing IRFs create a differential ordering of items by difficulty below and above the intersection points. What has not been as clearly realized, despite Wright's valiant efforts in 1992, is that crossing person response functions (PRFs) also cause problems with the substantive interpretation of person performance. The ordering of persons below and above the intersection points varies when PRFs cross. The purpose of this note is to illustrate crossing PRFs, and to show the substantive impact of this situation.

Mosier (1940, 1941) is usually cited as one of the first researchers to discuss PRFs, although graphical displays

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representing PRFs can also be found in the early work of Thorndike, Thurstone, and several other 19th century researchers working in the area of psychophysics. Operating characteristic functions for dichotomous responses have been proposed by Rasch (1960/1980) and Birnbaum (1968). The Rasch Model for dichotomous responses can be written as

$$\phi_{ni} = \frac{\exp(\theta_n - \delta_i)}{1 + \exp(\theta_n - \delta_i)} \qquad [1]$$

and the Birnbaum Model for dichotomous responses as

$$\phi_{ni} = c_i + (1 - c_i)\frac{\exp(\alpha_i(\theta_n - \delta_i))}{1 + \exp(\alpha_i(\theta_n - \delta_i))} \qquad [2]$$

where θ is a parameter specifying the location of person on the latent variable, δ is the difficulty or location of item, a is a discrimination parameter in the Birnbaum model, and c is the lower asymptote of the function in the Birnbaum model. If we select a particular person, such as Person A, then Equations 1 and 2 can be used to define person response functions. The Rasch PRF for Person A is

$$\phi_{Ai} = \frac{\exp(\theta_A - \delta_i)}{1 + \exp(\theta_A - \delta_i)} \qquad [3]$$

while the Birnbaum PRF is:

$$\phi_{Ai} = c_A + (1 - c_A)\frac{\exp(\alpha_A(\theta_A - \delta_i))}{1 + \exp(\alpha_A(\theta_A - \delta_i))} \qquad [4]$$

It should be noted that c_A is conceptually closer to a real "guessing" parameter in the Birnbaum PRFs, and that α_A represents person sensitivity to a particular subset of items.

Engelhard (in progress) describes five requirements of invariant measurement that must be met to yield useful inferences for measurement in the social, behavioral, and health sciences. These five requirements are

1. The measurement of persons must be independent of the particular items that happen to be used for the measuring: Item-invariant measurement of persons.

2. A more able person must always have a better chance of success on an item than a less able person: non-crossing person response functions.

3. The calibration of the items must be independent of the particular persons used for calibration: Person-invariant calibration of test items.

4. Any person must have a better chance of success on an easy item than on a more difficult item: non-crossing item response functions.

5. Items must be measuring a single underlying latent variable: unidimensionality.

Requirements 1 and 2 address issues related to PRFs.

The Figure illustrates the effects of crossing PRFs. Three PRFs were constructed for two situations: Rasch PRFs that do not cross (Panel A) and Birnbaum PRFs that do cross (Panel B). As shown in Panel C, non-crossing PRFs yield comparable person locations over subsets of items centered around easy items (-2 logits) to hard items (+2 logits). If PRFs do not cross, then Persons A, B, and C are ordered in the same way across item subsets. In other words, item-invariant measurement is achieved with the Rasch model.

Crossing PRFs based on the Birnbaum model (Panel D) yield person ordering that varies as a function of the difficulty of the item subsets. For example, Person A is the lowest achieving person with the lowest probability of success on the easy items, while Person A is the highest achieving person on the hard items. Easy item subsets yield persons ordered as A < B < C, while hard item subsets yield persons ordered B < C < A. In other words, the ordering of persons is not invariant over item subsets with the Birnbaum model.

This note calls attention to the idea that model-data fit can be conceptualized in terms of both IRFs and PRFs (Engelhard, in press). Typically IRFs and differential item functioning analyses are explored. Our work suggests that researchers should also begin to think more systematically about differential person functioning. It is important to recognize the items may function differently over different subgroups of persons (differential item functioning), but it is also important to recognize that persons may not function as intended in their interactions with subsets of test items (differential person functioning).

Aminah Perkins & George Engelhard, Jr.
Emory University, Division of Educational Studies

Birnbaum, A. (1968). Some latent trait models and their use in inferring an examinee's ability, Part 5. In F.M. Lord and M.R. Novick (Eds.), *Statistical theories of mental test scores*. Reading, MA: Addison-Wesley Publishing Company, Inc.

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Mosier, C.I. (1940). Psychophysics and mental test theory: Fundamental postulates and elementary theorems. *Psychological Review, 47*, 355-366.

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Wright, B.D. (1997). A history of social science measurement. *Educational Measurement: Issues and Practice*, Winter, 33- 45, 52.

Estimados compañeros:

Nos dirigimos a Uds. Para informarles que se está organizando por el IUDE el IV WORKSHOP sobre **MODELOS DE RASCH EN ADMINISTRACIÓN DE EMPRESAS**, para el **13 de noviembre de 2009**.

Los investigadores que deseen participar pueden enviar sus trabajos, en español o inglés, a la atención de la Comisión Científica del Workshop en iude /at/ ull.es, antes del **15 de septiembre de 2009**, indicando a qué sesión se dirigen.

Las sesiones previstas son: Metodología; Dirección y Estrategias Empresariales; Comercialización e Investigación de Mercados; Sistemas y Tecnologías de la Información; Organización de Empresas, Cultura Estratégica y Recursos Humanos; Sectores y Nuevos Desarrollos.

Los trabajos admitidos está previsto sean publicados en una monografía por la Fundación Canaria para la Formación y el Desarrollo Empresarial (FYDE CajaCanarias) en su colección de E-Books.

La asistencia al Workshop es libre y sin gastos, previa inscripción en iude /at/ ull.es . La información relativa al IV Workshop estará disponible en la página web del IUDE www.iude.ull.es , concretamente a lo relativo a la normativa aplicable a los trabajos, manteniéndose en los mismos términos de la edición anterior.

La Laguna, a 20 de abril de 2009.

Jaime Febles Acosta
Presidente de la Comisión Organizadora
Director del IUDE

Instituto Universitario De La Empresa
Universidad De La Laguna
Avda. 25 De Julio, 9, 1ª Planta
38004 Santa Cruz de Tenerife

AERA Proposal Deadline: July 15, 2009

We hope your summer is going well. As you are scheduling your time, remember that the new deadline for submission of proposals for the 2010 AERA meeting is moved up to **July 15**! The online submission page is up and ready for your submissions at www.aera.net

Also, just a reminder that the number of slots allocated to Special Interest Groups (SIGs) is now a simple formula based on the proportion of the number of proposals submitted. The more proposals we submit, the more slots will be available for faculty and graduate students to present their work.

Sincerely,
Diana Wilmot, Leigh Harrell
Rasch Measurement SIG, Program Chairs

The IEA Bruce H. Choppin Memorial Award

IEA established the Bruce H. Choppin Award as a memorial to Dr. Bruce H. Choppin. The award, which takes the form of a certificate and a prize of €500, is given annually to the author of a master's or doctoral thesis who makes use of data from an IEA study and employs empirical research methods in his or her work. Two awards, one for the best submission at the master's level and one at the doctoral level, are available for each annual competition. In a given year, IEA's Awards Committee may decide that no awards should be made.

Bruce H. Choppin 1940-1983

Bruce H. Choppin studied mathematics at Cambridge University in England before attending the University of Chicago, where he earned his Ph.D. in the area of measurement, evaluation and statistical analysis. He was closely connected with IEA from 1963 until his premature death in 1983. His first work with IEA involved data analysis for the English national report of the First IEA Mathematics Study. Along with Dr. Alan Purves, he later undertook a small-scale exploratory study designed to measure student understanding and appreciation of literary prose and poetry. Dr. Choppin was involved in the conceptualization, instrument construction, and data analysis phases of the IEA Six-Subject Survey. He was International Coordinator for the IEA Item Banking project, Chairman of the IEA Training Committee, and Head of the IEA Data Processing Center in New York from 1969 to 1972.

Dr Choppin was a proponent of the Rasch method of scaling aptitude and achievement test scores (having come under the influence of Benjamin Wright). He was at the center of a debate about Rasch scaling at the time (the 1970s), when this method was still looked upon with skepticism by those in the field of testing. For IEA he wrote a monograph entitled Correction for Guessing and, with Neville Postlethwaite as co-editor, he established the journal Evaluation in Education, which later became the International Journal of Educational Research. In addition to his work with the New York Data Processing Center, Dr. Choppin for several years worked at the National Foundation for Educational Research in England and Wales, the Science Education Centre in Israel, as well as the University of California and Cornell University in the United States.

Bruce Choppin died in Chile, having gone there to help the country's National Research Coordinator for the IEA Study on Written Composition. His ashes are buried in London.

Rules for Entry

For each year's competition, the thesis submitted must have been completed within the three years preceding the entry date (**31 March of that year**).

from www.iea.nl/choppin_award.html

M E S A
PSYCHOMETRIC LABORATORY
University of Chicago, Department of Education
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May 27, 1993

Prof. dr. Eddy Roskam
University of Nijmegen
Institute for Cognition and Information
Department of Mathematical Psychology
P.O. Box 9104
6500 HE Nijmegen
The Netherlands

Dear Eddy,

Thanks for your paper. Great references!!

I must protest, however, against the one or two lines in your paper where you assert nothing happened in America before 1971. On that topic you are seriously misinformed.

Jimmie Savage and I brought Rasch to Chicago in March, 1960, because of our already existing knowledge of and interest in his work. Rasch explained and reported on his work for three months in Chicago. He and I worked daily on the problem of how to analyze the bipolar rating scales used in the semantic differential - a problem to which I had been applying factor analysis with - as you know - ambiguous and sample-dependent results. It was during those three months that Rasch developed the m-dimensional model for rating scales with (m-1) categories which he discussed at the Fourth Berkeley Symposium and published in 1961.

In the next four years we organized a program on Rasch measurement in the MESA Special Field at the University of Chicago, got students working, wrote many FORTRAN programs to implement the least squares/LOG, pairwise/PAIR and conditional/FCON algorithms described in Rasch's 1960 book and tested these programs on real and simulated data to see how they worked. The principals in this were Bruce Choppin, Nargis Panchapakesan and myself.

In the course of these investigations we added the unconditional/UCON (equivalent to what is now called "marginal maximum likelihood") method of estimation. We also attempted a program to estimate an item slope parameter, the infamous item discrimination! No matter what tricks we introduced, some estimates <u>always</u> diverged. There was no unambiguous way to obtain finite values. We consulted our best applied mathematicians to make sure we hadn't missed a trick and, finally did the obvious algebra to prove that, not only in practice, but, more decisive, in principle a second item parameter could NOT be estimated when the observation was a dichotomy.

As you have noticed in the history of American IRT, however, our 1966 result did not deter the foolish adventures by some Americans into two and three item parameter IRT models for dichotomous data. When I showed our results to Fred Lord and Darrell Bock at lunch in December 1967, they merely snickered arrogantly, asserting they would easily, within weeks, have solutions to the problem which I and my students were incompetent to solve. But Lord's three-parameter LOGIST program did not work in 1967 or in 1968 and the lengthy 1989 ETS report on the current functioning of Lord's LOGIST and Bock and Mislevy's BILOG reviews in thorough detail the continuation of the same old problems - failure to recover the generating parameters of data simulated to follow the 3-P model exactly and failure to converge on any data even when the generating values are used to start the iterations.

The 1989 report also explains how LOGIST falls back on a Rasch algorithm every second iteration to keep from exploding and advises would-be users to confine themselves to as few iterations as possible, preferably just four, in order to escape divergence!

Returning to the University of Chicago, our experiences in 1964-1965 with our four ways to obtain Rasch estimates convinced us that, for all practical purposes, it did not matter which method was used. This conclusion and its parts we reported in a well-attended symposium at the September 1965 Annual Meeting of the Midwestern Psychological Association. I still have the program.

Speakers were: my students Bruce Choppin and Nargis Panchapakesan; Washington U. Professor Jane Loevinger (who reviewed Rasch 1960 in 1965); Iowa State U. Professor Paul Blommers, two of his students, Gary Ramsayer and Richard Brooks, who wrote dissertations testing the empirical invariance of Rasch estimates for educational test data; and Chicago Statistics Professor, David Wallace.

The professional attention these activities engendered led to a three year 1965-1968 grant from the National Science Foundation to support Bruce and Nargis and pay for computing to continue our Rasch research.

In 1966 Bruce and I programmed a fully conditional multidimensional pairwise algorithm BIGPAR which estimates an L by (m-1) matrix of item parameters from m category data and expresses this matrix in principal components. I have dated printouts of the FORTRAN coding and a few analyses, if you're interested.

For the Likert rating scale data we analyzed we always got one dominant component specifying a sequence of category values matching the intended direction of the rating scale. We usually also got a minor but distinct second largest component that specified a Guttman 1950 "intensity" effect.

However, as UCON became versatile and we generalized its algorithm from dichotomies to one dimensional rating scales it was easier to enter UCON, first with linear scores like: 1,2,3,4,5,6 for direction, second with quadratic scores like: 3,2,1,1,2,3 for intensity, etc, rather to bother with BIGPAR.

As you might expect, the value and salience of the quadratic form suffered the same fate as Guttman's intensity component - it never mattered enough to bother with.

To finish up, here is a much marked on report I prepared for my Chairman in 1971. The two pages list my Rasch activities during the 1960-1970 period, particularly my explanations and demonstrations of Rasch measurement to the Psychometric Society in June 1967 (Bock, Lord, Tucker, Harris, Angoff and many others were there) and to the enormous audience at the 1967 ETS Invitational Conference on Testing Problems in October 1967.

The list also documents my continuing collaborations with Rasch in 1964, 1965, 1967, 1968-1969 and his participation in the first ever AERA Professional Training Session in February 1969, which was, of all things, on Rasch Measurement.

So you can hardly say with any conviction or a clear conscience that nothing happened in America in the 60's. Indeed almost everything basic had happened in America by the dawn of 1971. What remained were ever widening teaching, training and practice, bigger and better computer programs, Andrich's and Master's filling out and completing the rating scale and partial credit work that Georg and Bruce began and Mike Linacre's derivation and implementation of the many facet measurement model.

I enjoyed being with you in Atlanta. You are a marvelous talker and a fascinating thinker. I believe you and I agree on a great many important principles. I also believe there are several basic things that you could teach me. I hope you will come again to the New World. You are constantly welcome in Chicago.

Don't forget to send me your next draft.

Sincerely,

Benjamin Drake Wright
Professor of Education and Psychology
Director MESA Psychometric Laboratory

cc: George Engelhard

The typeface has been changed from the original Courier.

Prof. Dr. Eddy E.C.I. Roskam of the Katholieke Universiteit of Nijmegen died on May 24th, 1997.

Letter courtesy of George Engelhard, Jr., Emory University.

The Efficacy of Warm's MLE Bias Correction

Thomas Warm (1989) reports that "Lord (1983) found that maximum likelihood estimates of θ [person ability] are biased outward" and then he restates Lord's expression for the size of this bias:

$$\text{Bias (MLE}(\theta)) = -J / 2\,I^2$$

where, for dichotomous Rasch items, I = test information $= \Sigma P_{\theta i}(1-P_{\theta i})$, and $J = \Sigma P_{\theta i}(1-P_{\theta i})(1-2P_{\theta i})$, summed for all items, 1=1,L in the test, where $P_{\theta i}$ is the Rasch-model probability of success of ability θ on item i.

How effective is this bias correction? Warm uses a Monte Carlo study to demonstrate its effectiveness, but an exact algebraic investigation can be conducted.

Dichotomous Items

I posited a test of 25 items, with its item difficulties uniformly spaced 0.2 logits apart. Figure 1 shows the locations (x-axis) of the items on the 25-item test. The item difficulties are centered on 0 logits.

Applying the MLE method of Wright & Douglas (1996) for estimating θ from known item difficulties, a Rasch ability estimate, M(s) is obtained for each possible raw score, s=0-25, on the test of 25 items. Since the estimates corresponding to s=0 and s=25 are infinite, they are substituted by estimates corresponding to s=0.3 and s=24.7 score-points. The MLE ability estimates are shown in Figure 1.

Warm's bias correction is applied to each MLE estimate, M(s), to produce a Weighted Likelihood Estimation (WLE) value, W(s). See Figure 1. WLE estimates are more central than the MLE estimates, except for estimates corresponding to scores of 0.3 and 24.7, where the MLE estimates are used unchanged.

Under Rasch model conditions, each raw score, s, on a given set of items, corresponds to one estimated ability θ(s), but each true (generating) ability corresponds to all possible raw scores. For 25 items, there are 2^25 = 33,554,432 possible different response strings. According to the Rasch model, each of these response strings has a finite probability of being observed for each generating ability.

Probability of response string n for ability θ

$$= P_{n\theta} = \Pi \exp((x_{ni}(\theta - d_i)) / (1 + \exp(\theta - d_i))$$

for i = 1 to 25, where x_{ni} is the scored 0,1 response to item i in response string n, and d*i* is the difficulty of item i.

Response string n has a raw score of $s = \Sigma x_{ni}$ for i = 1 to 25. Score s has an MLE estimate of $M_n = M(s)$ and a WLE estimate of $W_n = W(s)$.

The expected values of the estimates corresponding to each generating value can now be computed:

$$\text{Expectation (MLE}(\theta)) = \Sigma P_{n\theta} M_n \text{ for n = 1 to 2^25}$$

$$\text{Expectation (WLE}(\theta)) = \Sigma P_{n\theta} W_n \text{ for n = 1 to 2^25}$$

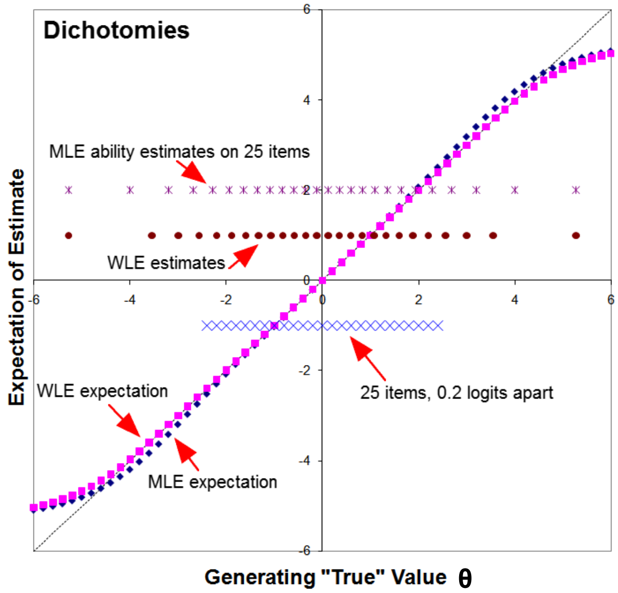

Figure 1. MLE and WLE for 25 dichotomous items.

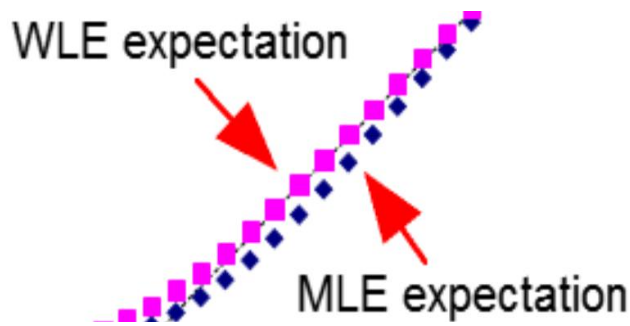

Figure 2. Detail of Figure 1 showing MLE bias.

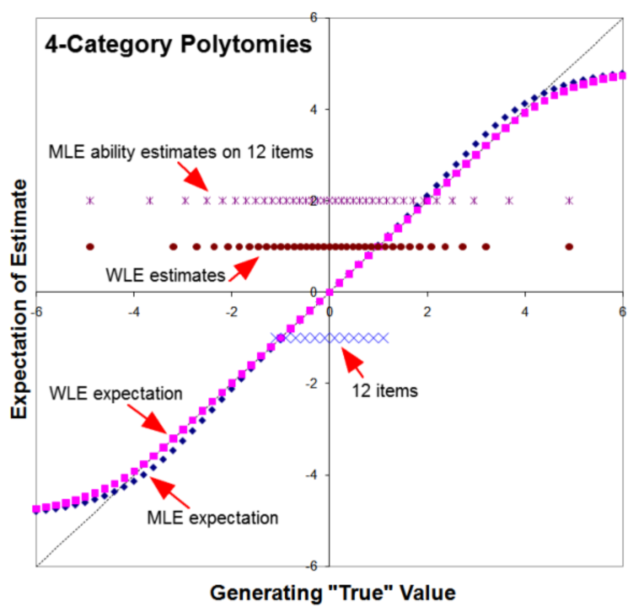

Figure 3. MLE and WLE for 12, 4-category, items.

These values are plotted in Figure 1 for θ in the range -6 logits to +6 logits. The WLE ogive corresponds to the identity line with the generating values for most of its range. The MLE ogive is slightly less central (as predicted by Fred Lord). We can see that the WLE bias correction is effective over the entire range of MLE estimates for non-extreme scores (-4 to +4 logits). The biggest bias correction is 0.23 logits at a generating value of 3.6 logits, as shown in Figure 2. This is less than half the size of the standard error of each estimate. This is close to 0.5 logits for most of the range. We can also see that, for "true" generating abilities within 2 logits of the center of the test, the MLE bias is less than 0.1 logits, and so negligible for practical purposes.

Similar investigations for tests of length 2 to 24 items demonstrated that the WLE bias correction is effective for tests of 7 dichotomous items or more.

Polytomous Items

We can apply the same logic to polytomous items.

$$\text{Bias}(\text{MLE}(\theta)) = -J / 2\, I^2$$

where, $I = \Sigma((\Sigma k^2 P_{\theta ik}) - (\Sigma k P_{\theta ik})^2)$, and
$J = \Sigma((\Sigma k^3 P_{\theta ik}) - 3(\Sigma k^2 P_{\theta ik})(\Sigma k P_{\theta ik}) + 2(\Sigma k P_{\theta ik})^3)$

for i=1, L and the polytomous categories, k=0,m, where $P_{\theta ik}$ is the Rasch-model probability of being observed in category k.

The results of this investigation are shown in Figure 3 with item 0.1 logits apart, and thresholds 1 logit apart. The results are similar to the findings for dichotomous items in Figure 1.

Warm's bias correction is seen to be efficacious for the correction of MLE bias across the useful measurement range of the items, but that MLE bias is also seen to be inconsequential for most practical purposes.

John M. Linacre

Lord, F. M. (1983). Unbiased estimators of ability parameters, of their variance, and of their parallel-forms reliability. Psychometrika, 48, 2, 233-245.

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Program Chairs: Diana Wilmot and Leigh Harrell
SIG website: www.raschsig.org

Rasch-related Coming Events

July 15, 2009, Proposal Deadline for April 30 - May 4, 2010, Fri.-Tues. AERA Annual Meeting, Denver, CO, USA, www.aera.net

July 20 - Nov. 14, 2009, Mon.-Sat. Introduction to Rasch Measurement of Modern Test Theory online course (D. Andrich, I. Marais, RUMM), www.education.uwa.edu.au/ppl/courses

July 28-30, 2009, Tues.-Thur. PROMS HK 2009 Pacific Rim Objective Measurement Symposium, Hong Kong www.promshk.org

Aug. 21 - Sept. 18, 2009, Fri.-Fri. Rasch - Further Topics online course (M. Linacre, Winsteps), www.statistics.com/ourcourses/raschfurther

Sept. 6-11, 2009, Sun.-Fri. IMEKO XIX World Congress: Fundamental and Applied Metrology, Portugal www.imeko.org

Sept. 8, 2009, Tues. Rasch Refresher workshop
Sept. 9-11, 2009, Wed.-Fri. Introduction to Rasch
Sept. 14-16, 2009, Mon.-Wed. Intermediate Rasch
Sept. 17-18, 2009, Thur.-Fri. Advanced Rasch (A. Tennant, RUMM), Leeds, UK,
www.leeds.ac.uk/medicine/rehabmed/psychometric

Sept. 18 - Oct. 16, 2009, Fri.-Fri. Rasch Applications in Clinical Assessment, Survey Research, and Educational Measurement (W. Fisher, Winsteps), www.statistics.com/ourcourses/raschapps

Oct. 19-20, 2009, Mon.-Tues. Introductory Course on Rasch Measurement: Theory and Application
Oct. 21-22, 2009, Wed.-Thur. Advanced Course on Rasch Measurement: Theory and Application (Andrich, Tognolini, RUMM), Oxford, UK, University of Oxford http://cpd.conted.ox.ac.uk/Rasch/default.asp

Oct. 23 - Nov. 21, 2009, Fri.-Fri. Many-Facet Rasch Measurement online course (M. Linacre, Facets), www.statistics.com/ourcourses/facets

Nov. 13, 2009, Fri. IV Workshop de Modelos de Rasch en Administración de Empresas (Spanish and English proposals by Sept. 15), Canary Islands, www.iude.ull.es

April 30 - May 4, 2010, Fri.-Tues. AERA Annual Meeting, Denver, CO, USA, www.aera.net

June 14-15, 2010, Mon.-Wed. International Conference on Probabilistic Models for Measurement, Copenhagen, Denmark. www.rasch2010.cbs.dk

Bayesian Estimation for the Rasch Model using WinBUGS

In this brief note, we introduce a Bayesian approach to estimating parameters for IRT using a freeware called WinBUGS. We use simple Rasch model below to illustrate such an approach and summarize its benefits at the end, as compared with the use of proprietary software (e.g. WINSTEPS and BILOG).

Simple Dichotomous Rasch Model

A student i will score 1 from answering an item k correctly; 0 otherwise. Let y_{ik} be the score. Using Simple Rasch Model, we have

$$y_{ik} \sim \text{Bernoulli}(p_{ik})$$
$$\text{logit}(p_{ik}) = \theta_i - d_k$$

where θ_i is the ability of student i

d_k is the difficulty of item k.

Formulation of the Rasch Model in WinBUGS

The BUGS (**B**ayesian inference **U**sing **G**ibbs **S**ampling) project is concerned with flexible software for the Bayesian analysis of complex statistical models using Markov chain Monte Carlo (MCMC) methods. WinBUGS is a freeware, which provides graphical interface to access all these modeling utilities.

The first step using WinBUGS is to specify the model concerned and the prior distributions for the unknown parameters. For the simple Rasch model, this is shown in the box below.

The posterior distribution of the unknown parameters can then be obtained by running the model in WinBUGS with the response data.

Bayesian Graphical Modeling of the Rasch Model

In Bayesian graphical modeling, the simple Rasch model is represented in Figure 1.

The known data response[i,j] is represented in rectangular form. The unknown parameters (θ[i], d[j], τ) are represented in circular form. The dependency amongst the data and parameters are shown using directed arrows.

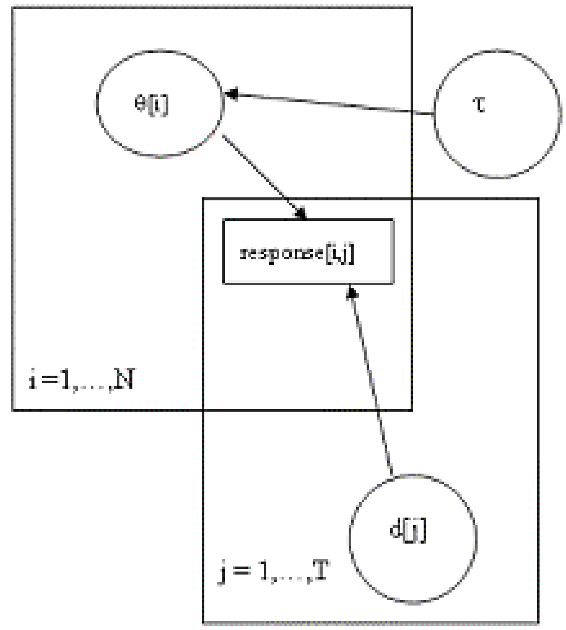

Figure 1. Bayesian Graph of the Rasch Model

Such a graphical illustration can enhance understanding of the model by others; especially for a more complex model.

Empirical Results and Model Checking

We illustrate our approach using the classical example in educational testing - the Law School Admission Test (LSAT) data, which is available in the R package called *ltm* (Latent Trait Model). The data contain responses of 1000 individuals to five items which were designed to

WinBUGS specification of the Rasch dichotomous model

```
model {                                          # Simple Rasch Model in WinBUGS
   for (i in 1 : N) {                            # Total number of students: N
      for (k in 1 : T) {                         # Total number of items: T
         response[i, k] ~ dbern(p[i, k])         # Response follows a Bernoulli distribution
         logit(p[i, k]) <- theta[i] - d[k] }     # The transformed prob. equals to difference between
   }                                             #      student ability and # item difficulty

                                                 # Prior distributions for unknown parameters
   for (i in 1:N) {theta[i] ~ dnorm(0, tau)}     # prior distribution for student abilities
   for (k in 1:T) {d[k] ~ dnorm(0, 0.001)}       # prior distribution for item difficulties
   tau ~ dgamma(0,001, 0.001)                    # prior distribution for precision of student abilities
   sigma<-1/sqrt(tau)                            # calculate the standard derivation from precision
   }
```

measure a single latent ability. Here are the results obtained using WinBUGS. "ltm" are the R statistics as estimates for reference.

Estimates of Item difficulty						
Item	**mean**	**sd**	**2.5%**	**median**	**97.5%**	**ltm**
1	-2.74	0.13	-3.00	-2.74	-2.49	-2.87
2	-1	0.08	-1.15	-1	-0.84	-1.06
3	-0.24	0.07	-0.38	-0.24	-0.1	-0.26
4	-1.31	0.08	-1.47	-1.31	-1.14	-1.39
5	-2.1	0.11	-2.31	-2.1	-1.9	-2.22

We can see that the estimated values from WinBUGS are close to the ones from *ltm* which uses a Marginal Maximum Likelihood (MMLE) approach. As the observed data are discrete, one common method of model checking in Bayesian approach is to draw samples from posterior predictive distribution and compare the simulated frequencies of different possible outcomes with the observed ones. Here are the results of model checking.

	Obs	**Expected Frequency**				
Score	**Freq**	**mean**	**sd**	**2.5%**	**median**	**97.5%**
0	3	2.4	1.6	0	2	6
1	21	20.6	5.1	11	20	31
2	87	88.2	9.7	70	88	107
3	240	228.1	14.5	200	228	256
4	361	366.0	17.1	333	366	399
5	303	294.8	17.6	261	295	330

The model checking statistics are displayed in the graph below. The observed frequencies are shown by a dashed line. The expected frequencies are shown by vertical bars. We can conclude that the observed outcomes are very close to the predicted ones.

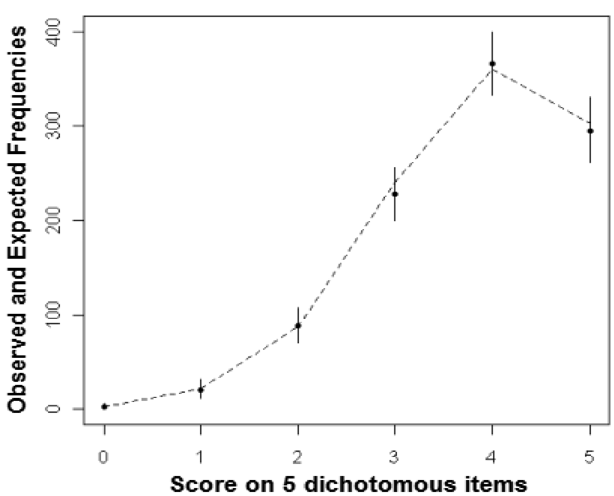

Figure 2. Observed and Expected Frequencies

Flexibility in Enhancing the Model

WinBUGS allows a great flexibility in modeling. For example, we could easily enhance the modeling of student abilities θ_i with other covariates X_{ti}, if such information is available. One of the possible formulations could be:

$$\theta_i \sim N(\mu_i, \sigma_\theta^2)$$

where $\mu_i = \beta_0+\sum_t\beta_t X_{ti}$ and $\sigma_\theta^2 \sim IG(0.001,0.001)$.

The WinBUGS code above could be modified easily to incorporate such an enhancement. Parameter estimation in the enhanced model could be automatically taken care by WinBUGS.

Summary

As compared with the proprietary software, the advantages of using the WinBUGS include the following:

(1) the Rasch model can be displayed in a graphical display to facilitate communication and understanding;

(2) testing statistics for model checking could be tailored for the problem at hand; and

(3) a great flexibility in modeling is provided.

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Considerations About Expected a Posteriori Estimation in Adaptive Testing: Adaptive a Priori, Adaptive Correction for Bias, and Adaptive Integration Interval. *Gilles Raîche and Jean-Guy Blais, 138-156*

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Understanding Rasch Measurement: The ISR: Intelligent Student Reports. *Ronald Mead, 208-224*

Richard M. Smith, Editor
JAM web site: www.jampress.org

Mapping Rasch-Based Measurement onto the Argument-Based Validity Framework

This paper integrates the Rasch validity model (Wright & Stone, 1988, 1999) into the argument-based validity framework (Kane, 1992, 2004). The Rasch validity subsumes fit and order validity. Order validity has two subcategories: meaning validity (originated from the calibration of test variables) and utility validity (based on the calibration of persons to implement criterion validity). Fit validity concerns the consistency of response patterns. From 1) analysis of residuals, i.e., the difference between the Rasch model and the responses, 2) analysis of item fit, which can help revising the test, and 3) analysis of person fit, which can help diagnosing the testees whose performance do not fit our expectations, we get response, item function, and person performance validity, respectively.

The evidence-based approach to validity was proposed by Kane (1992). This framework has two phases: interpretive and validity argument. Initially, the interpretive argument (IA) is proposed in the form of statements followed by the validity argument (VA) to investigate the efficacy of the IA. Figure 1 displays a framework to use Rasch-based measurement to build VA's. Observation, generalization, explanation, and extrapolation are four major inferences that help proceeding from one validation stage to the consecutive stage. Warrants comprise any data to back up the postulated inferences. Backings give legitimacy and authority to warrants, e.g., theoretical assumptions behind the posited warrants.

Warrants for the observation inference in a Rasch-based study can include standardization of scoring process, converting raw scores into measured scores and ability. Standardization guarantees the unanimity of the scoring procedure. Converted raw scores to interval or measured scores in the Rasch analysis is essential since the distance between measured scores is real and item difficulty can be directly compared with person ability or trait levels. Rating Scales (Andrich Model) and (Masters') Partial Credit Model help further investigating the efficacy of the measurement scales. To generalize the observed scores into expected scores, person and item reliability, and person and item separation indexes are proposed as warrants and the theories behind them as backings.

The explanation inference bears on the theoretical construct under measurement. Item/person infit and outfit analysis are first warrants. Backings include theoretical concepts of fit validity. Investigating item and person fit provides information about construct-irrelevant factors. The Rasch Principal Component Analysis of Residuals (PCAR) investigates construct irrelevancies in the measure (Linacre, 2005).

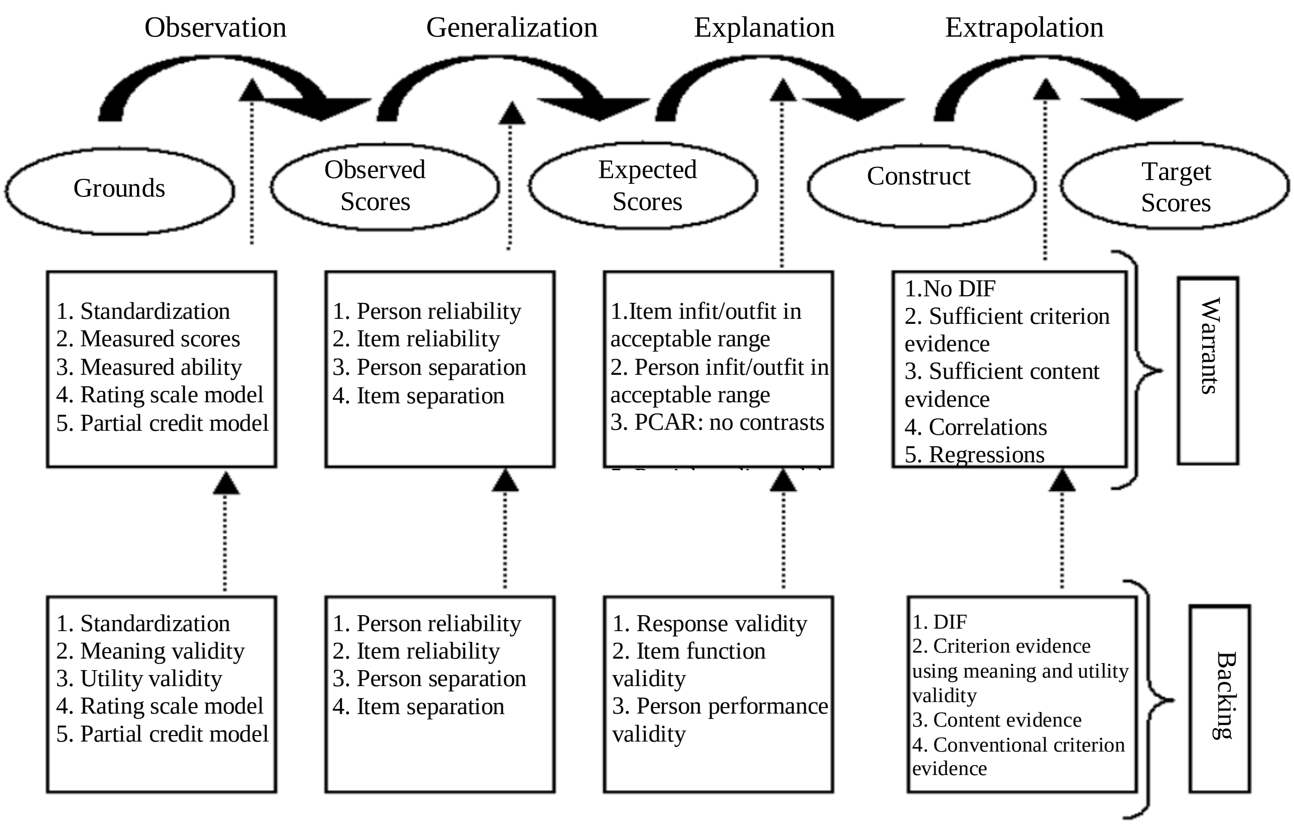

Figure 1. Supporting validity arguments using Rasch analysis.

Then, we can extrapolate the observation to the target scores. The extrapolation inference has an element of subjectivity. Kane, Crooks, and Cohen (1999) indicated that content analysis in the generalization inference can support extrapolation provided that the universe of generalization corresponds to the target domain. Kane (1992, 2004) also proposed the use of criterion-referenced evidence. However, even if this method is used, it may not yield sufficient support for extrapolation. Utility and meaning validity can come to aid again. The confirmed hierarchy of item difficulty is assessed against the *criteria* we have set. Observations which are not in conformity with the theoretical expectations or criteria are possible to be flawed. By the same token, we can anticipate how persons with different characteristics will respond to a particular question. Differential item functioning (DIF) is also useful. DIF occurs when a group of examinees have different probabilities to answer an item due to their background (sex, age, ethnicity, etc.). Background is the major *criterion* because it concerns test takers directly. In this light, background is internal to the assessment.

In the current Rasch-based framework, the Rasch analysis is further supported by the theoretical background of the test. This implies that psychometric models should not disassociate with the psychological and cognitive theories underlying any testing device (Embretson & Gorin, 2001; Wright & Stone, 1999). It is certainly difficult and expensive for academic institutes to carry out many studies in support of the validity arguments of a device (see McNamara, 2003). The Rasch-based validity argument framework can provide reliable and efficient evidence at the lowest expense compared with the accumulation of evidence from different studies.

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Embretson S., & Gorin, J. (2001). Improving construct validity with cognitive psychology principles. *Journal of Educational Measurement, 38*(4), 343-368.

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Kane, M. (2004). Certification testing as an illustration of argument-based validation. *Measurement: Interdisciplinary Research and Perspectives, 2*, 135–170.

Kane, M., Crooks, T., & Cohen, A. (1999). Validating measures of performance. *Educational Measurement: Issues and Practice, 18*(2), 5–17.

Wright, B. D., & Stone, M. H. (1988). *Validity in Rasch measurement*. University of Chicago: Research Memorandum No. 55.

Wright, B. D., & Stone, M. H. (1999). *Measurement essentials*. 2nd ed. Wilmington, Delaware: Wide Range, Inc.

Rasch-related Coming Events

July 15, 2009, Proposal Deadline for April 30 - May 4, 2010, Fri.-Tues. AERA Annual Meeting, Denver, CO, USA, www.aera.net

July 20 - Nov. 14, 2009, Mon.-Sat. Introduction to Rasch Measurement of Modern Test Theory online course (D. Andrich, I. Marais, RUMM), www.education.uwa.edu.au/ppl/courses

July 28-30, 2009, Tues.-Thur. PROMS HK 2009 Pacific Rim Objective Measurement Symposium, Hong Kong www.promshk.org

Aug. 21 - Sept. 18, 2009, Fri.-Fri. Rasch - Further Topics online course (M. Linacre, Winsteps), www.statistics.com/ourcourses/raschfurther

Sept. 6-11, 2009, Sun.-Fri. IMEKO XIX World Congress: Fundamental and Applied Metrology, Portugal www.imeko.org

Sept. 8, 2009, Tues. Rasch Refresher workshop

Sept. 9-11, 2009, Wed.-Fri. Introduction to Rasch

Sept. 14-16, 2009, Mon.-Wed. Intermediate Rasch

Sept. 17-18, 2009, Thur.-Fri. Advanced Rasch (A. Tennant, RUMM), Leeds, UK, www.leeds.ac.uk/medicine/rehabmed/psychometric

Sept. 18 - Oct. 16, 2009, Fri.-Fri. Rasch Applications in Clinical Assessment, Survey Research, and Educational Measurement (W. Fisher, Winsteps), www.statistics.com/ourcourses/raschapps

Oct. 19-20, 2009, Mon.-Tues. Introductory Course on Rasch Measurement: Theory and Application

Oct. 21-22, 2009, Wed.-Thur. Advanced Course on Rasch Measurement: Theory and Application (Andrich, Tognolini, RUMM), Oxford, UK, University of Oxford http://cpd.conted.ox.ac.uk/Rasch/default.asp

Oct. 23 - Nov. 21, 2009, Fri.-Fri. Many-Facet Rasch Measurement online course (M. Linacre, Facets), www.statistics.com/ourcourses/facets

Nov. 13, 2009, Fri. IV Workshop de Modelos de Rasch en Administración de Empresas (Spanish and English proposals by Sept. 15), Canary Islands, www.iude.ull.es

Jan. 8 - Feb. 5, 2010, Fri.-Fri. Rasch - Core Topics online course (M. Linacre, Winsteps), www.statistics.com/ourcourses/rasch1

April 30 - May 4, 2010, Fri.-Tues. AERA Annual Meeting, Denver, CO, USA, www.aera.net

June 14-15, 2010, Mon.-Wed. International Conference on Probabilistic Models for Measurement, Copenhagen, Denmark. www.rasch2010.cbs.dk

Confirmatory factor analysis vs. Rasch approaches: Differences and Measurement Implications

	CFA	Rasch
1 Fundamental and theoretical issues of measurement		
Concept of Measurement	• Based on classical test theory (CTT) • Numbers are *assigned* to respondents' attributes (Stevens 1946, 1951)	• The measure of a magnitude of a quantitative attribute is its ratio to the unit of measurement, the unit of measurement is that magnitude of the attribute whose measure is 1 (Michell 1999, p.13) • Measurement is the process of *discovering* ratios rather than assigning numbers • Rasch Model is in line with axiomatic framework of measurement • Principle of specific objectivity
Model	$x_i=\tau_i + \lambda_{ij}\xi_j + \delta_i$ x_i … manifest item score τ_i … item intercept parameter λ_{ij} ... factor loading of item i at factor j ξ_j... factor score of factor j δ_i… stochastic error term	For dichotomous data: $P(a_{vi}=1)= e^{(\beta v- \delta i)} / [1 + e^{(\beta v- \delta i)}]$ a_{vi} … response of person v to item i β_v … person location parameter δ_i …item location parameter (endorsability)
Relationship of measure and indicators (items)	• Measure is directly and linearly related to the indicators • Hence, the weighted raw score is considered to be a linear measure	• Probability of a response is modeled as a logistic function of two measures, the person parameter β_v and the item location (endorsability) δ_i • Raw score is not considered to be a linear measure, transformation of raw scores into logits (Wright 1996, p.10)
In/dependence of samples and parameters	Parameters are sample dependent, representative samples are important	Item parameters are independent of sample used (subject to model fit and sufficient targeting)
2 Item selection and sampling (scale efficiency) issues		
Item selection	• Items selected to maximize reliability, leads to items that are equivalent in terms of endorsability which plays no explicit role in CTT • Favors items that are similar to each other (see bandwidth-fidelity problem, Singh 2004)	• Items are selected to cover a wide range of the dimension (see 'bandwidth', Singh 2004) • Endorsability of item plays a key role
Item discrimination	• Discrimination varies from item to item but is considered fixed within an item	• Discrimination is equal for all items to retain a common order of all items in terms of endorsability for all respondents • Discrimination varies within an item (concept of information which equals $P(a_{vi}=1) * P(a_{vi}=0)$ in the dichotomous case), it reaches its maximum at $\beta_v = \delta_i$
Targeting	Items that are off-target may even increase reliability and feign a small standard error which can actually be quite large	Items that are off-target provide less information, standard errors will increase and the power of the test of fit will decrease
Standard error of measurement	Based on reliability, assumed to be equal across the whole range	Based on the information the items yield for a specific person

Sample size	The required sample size mirrors recommendations for structural equation modeling (SEM). SEM is not appropriate for sample sizes below 100. As a rule of thumb sample sizes of greater than 200 are suggested (Boomsma 1982; Marsh, Balla, and McDonald 1988). Bentler and Chou (1987) recommend a minimum ratio of 5:1 between sample size and the number of free parameter to be estimated.	In general, the sample sizes used in structural equation modeling are sufficient but insufficient targeting increases the sample size needed. According to Linacre (1994) the minimum sample size ranges from 108 to 243 depending on the targeting with n=150 sufficient for most purposes (for item calibrations stable within ± 0.5 logits and .99 confidence)
Distribution of persons	Commonly assumed to be normal	Irrelevant due to specific objectivity (subject to sufficient targeting)
Missing data	Problematic, missing data has to be imputed, deleting persons may alter the standardizing sample, deleting items may alter the construct, pairwise deletion biases the factors (Wright 1996, p.10)	Estimation of person and item parameters not affected by missing data (except for larger standard errors)
Interpretation of person measures	Usually in reference to sample mean	In reference to the items defining the latent dimension
3 Dimensionality issues		
Multi-dimensionality	Multi-dimensionality easily accounted for	*A priori* multi-dimensional constructs are split up into separate dimensions
Directional factors	Sensitivity to directional factors (Singh 2004) in case of items worded in different directions	Low sensitivity to directional factors (Singh 2004)
4 Investigation of comparability of measures across groups		
Assessment of scale equivalence	• Multi-group analysis • Equivalence statements of parameters estimated across groups	• Differential item functioning analysis (DIF) capitalizing on the principle of specific objectivity • Analysis of residuals in different groups
Incomplete equivalence	Partial invariance (for group specific items separate loadings and/or intercepts are estimated)	Item split due to DIF (for group specific items separate item locations are estimated)
Typical sequence and principal steps of analysis	• Estimation of baseline model (group specific estimates of loadings and item intercepts) • equality constraints imposed on loadings (metric invariance) • equality constraints imposed on intercepts (scalar invariance) • selected constraints lifted if necessary (partial invariance)	• estimation of model across groups • collapsing of categories if necessary • assessment of fit • assessment of DIF • items displaying DIF are split up if necessary
Etic (external) versus emic (internal)	• In principle etic-oriented approach. A common set of invariant items is indispensable. • Concept of partial invariance allows for equal items functioning differently. • Emic items, i.e. items confined to one group, can be considered but technical set-up complicated compared to Rasch analysis	• In principle etic-oriented approach. A common set of invariant items is indispensable. • Accounting for DIF by splitting the item allows for equal items functioning differently. • Emic items, i.e. items confined to one group, can be considered very easily because handling of missing data is unproblematic compared to CFA

Table 1 in *Ewing, Michael T., Thomas Salzberger, and Rudolf R. Sinkovics (2005), "An Alternate Approach to Assessing Cross-Cultural Measurement Equivalence in Advertising Research," Journal of Advertising, 34 (1), 17-36.*

Courtesy of Rudolf Sinkovics, with permission.

Sharing Ideas for Changing Health Care for All Americans

"Share your story and your ideas. We want to hear what you think about health reform. Send us your story, proposals and ideas." -www.healthreform.gov

Bad measurement stymies all health care reform efforts that ignore it. Health care reform will live or die on the quality of measurement.

The reason why health care reform efforts have failed has largely to do with the poor quality of measurement. Though everyone recognizes how important measurement is, almost no one shows any awareness of the vitally important features advanced measurement offers. Health care reform will succeed or fail depending on whether we get the measures right.

To live up to the full meaning of the term, measures have to do some very specific things. To keep things simple, all we need to do is consider how we use measures in something as everyday as shopping in the grocery store. The first thing we expect from measures are numbers that stand for something that adds up the way they do. The second thing measures have to do is to stay the same no matter where we go.

Currently popular methods of measurement in health care do not meet either of these expectations. Ratings from surveys and assessments, counts of events, and percentages of the time that something happens are natural and intuitive places from which to begin measurement, but these numbers do not and cannot live up to our expectations as to how measures behave. To look and act like real measures, these kinds of raw data must be evaluated and transformed in specific ways, using widely available and mathematically rigorous methodologies.

None of this is any news to researchers. The scientific literature is full of reports on the theory and practice of advanced measurement. The philosopher, Charles Sanders Peirce, described the mathematics of rigorous measurement 140 years ago. Louis Thurstone, an electrical engineer turned psychologist, took major steps towards a practical science of rigorous measurement in the 1920s. Health care admissions, graduation, and professional licensure and certification examinations have employed advanced measurement since the 1970s. There are a great many advantages that would be gained if the technologies used in health care's own educational measurement systems were applied within health care itself.

Though we rarely stop to think about it, we all know that fair measures are essential to efficient markets. When different instruments measure in different units, market transactions are encumbered by the additional steps that must be taken to determine the value of what is being bought and sold. Health care is now so hobbled by its myriad varieties of measures that common product definitions seem beyond reach.

And we have lately been alerted to the way in which innovation is more often a product of a collective cognitive effort than it is of any one individual's effort. For the wisdom of crowds to reach a critical mass at which creativity and originality take hold, we must have in place a common currency for the exchange of value, i.e., a universal, uniform metric calibrated so as to be traceable to a reference standard shared by all.

Since the publication of a seminal paper by Kenneth Arrow in the early 1960s, many economists have taken it for granted that health care is one industry in which common product definitions are impossible. The success of advanced measurement applications in health care research over the last 30 years contradicts that assumption.

It's already been 14 years since I myself published a paper equating two different instruments for assessing physical functioning in physical medicine and rehabilitation. Two years later I published another paper showing that 10 different published articles reporting calibrations of four different functional assessments all showed the same calibration results for seven or eight similar items included on each instrument.

What many will find surprising about this research is that consensus on the results was obtained across different samples of patients seen by different providers and rated by different clinicians on different brands of instruments. What we have in this research is a basis for a generalized functional assessment metric.

Simply put, in that research, I showed how our two basic grocery store assumptions about measurement could be realized in the context of ratings assigned by clinicians to patients' performances of basic physical activities and mobility skills. With measures that really add up and are as universally available as a measures we take for granted in the grocery store, we could have a system in which health care purchasers and consumers can make more informed decisions about the relationship between price and value. With such a system, quality improvement efforts could be coordinated at the point of care, on the basis of observations expressed in a familiar language.

Some years ago, quality improvement researchers raised the question as to why there are no health care providers who have yet risen to the challenge and redefined the industry relative to quality standards, in the manner that Toyota did for the automobile industry. There have, in fact, been many who tried, both before and since that question was asked.

Health care providers have failed in their efforts to emulate Toyota in large part because the numbers taken for measures in health care are not calibrated and maintained the way the automobile industry's metrics are. It is ironic that something as important as measurement, something that receives so much lip service, should nonetheless be so widely skipped over and taken for granted. What we need is a joint effort on the part of the National Institutes of Health and the National Institute of Standards and Technology focused on the calibration and maintenance of the metrics health care must have to get costs under control.

We need to put our money and resources where our mouths are. We will be very glad we did when we see the kinds of returns on investment (40%-400% and more) that NIST reports for metrological improvement studies in other industries.

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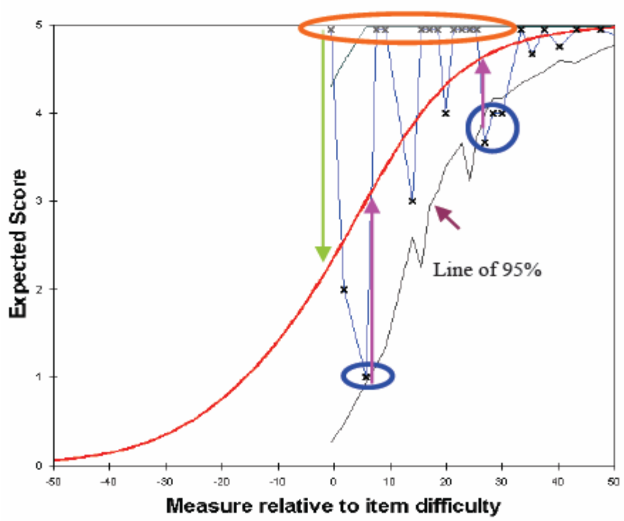
Georg Rasch, Factor Analysis and Scales

[Georg] Rasch was strongly against exploratory factor analysis, for two reasons. Not only because it was based on unrealistic assumptions like linearity and normality, but also because it was exploratory. He therefore always stressed that Rasch analysis is confirmatory. That it does require a theory of the construct and that the purpose of the analysis was both to check the theory and to check the items.

And Rasch never talked about interval scales. To Rasch, the constructs that we measure by Rasch models are constructs on ratio scales with absolute zeros and arbitrary units. Taking the logarithm of a ratio scale measure ["for practical purposes", *Rasch, 1980, p.80]* creates something similar to an interval scale since the arbitrary unit of the ratio scale is transformed into an arbitrary origin of the logit scale. An arbitrary unit on the logit scale corresponds to an arbitrary power transformation on the ratio scale, which is rarely taken to be part of the definition of ratio scales.

Svend Kreiner



Item Characteristic Curves: Model and Empirical. Figure 3 in Rashid et. al (2008) WSEAS Transactions on Advance in Engineering Education, 8, 5, 591-602

Infit Mean-squares: Mean ± 2 S.D.

"There are no hard-and-fast rules for setting upper- and lower-control limits for the infit statistics (i.e., infit mean-square index). In general, as Pollitt and Hutchinson (1987) suggest, any individual infit mean-square value needs to be interpreted against the mean and standard deviation of the set of infit-mean square values for the facet concerned. Using these criteria, a value lower than the mean minus twice the standard deviation would indicate too little variation, lack of independence, or *overfit.* A value greater than the mean plus twice the standard deviation would indicate too much unpredictability, or *misfit.*" (Park, 2004)

Comment: This advice accords with an investigation into "Do the data fit the model usefully". The mean-squares are geometric with a range of 0-1-∞, which suggests that the computation of mean and standard deviation should be done using log(mean-squares). In general, overfit (low mean-square) is generally a much smaller threat to the validity of the measures than excessive unpredictability (high mean-square).

Park, T. (2004) An investigation of an ESL placement test using Many-Facet Rasch Measurement. Teachers College, Columbia University Working Papers in TESOL and Applied Linguistics, 4, 1
http://journals.tc-library.org/index.php/tesol/article/view/41/48

Pollitt, A., & Hutchinson, C. (1987). Calibrated graded assessment: Rasch partial credit analysis of performance in writing. Language Testing, 4, 72-92.

Call for Research Conference Proposals

As announced in the May issue of the *Educational Researcher*, this year AERA has launched a new program of support for conferences in education research. AERA supports conferences intended to break new ground in substantive areas of inquiry, stimulate new lines of study on issues that have been largely unexplored, or develop innovative research methods or techniques that can contribute more generally to education research. Please read the Call and consider bringing forth important conference proposals that can advance the field. Awards may range from $25,000-$50,000 depending upon the scope, duration, and the number of participants anticipated.

For detailed information on the call and guidelines for proposals, see
www.aera.net/uploadedFiles/Conference-Guidelines_ER_Conferences.pdf

The deadline for submission is **September 1, 2009**.

If you have any questions or comments, please contact me at flevine /at/ aera.net.

Felice J. Levine, PhD
Executive Director
American Educational Research Association

Explaining Rasch Measurement in Different Ways

Learning and teaching about Rasch measurement can be exciting and challenging as one needs to help students think about measurement in new ways. As a teacher of measurement to both graduate and undergraduates I try different techniques of presenting Rasch concepts. In the MESA program of the University of Chicago, Ben Wright would explain something and sometimes I would not quite get it. Then someone else would rephrase the issue with different words and I would understand.

In my classes I have found it to be quite helpful to ask students to review the basic technical testing manuals which many U.S. States have produced to document State testing procedures. These manuals discuss Rasch in different ways, using different words, and often the material is organized in a unique way by each State. Often the text is written at a level that is appropriate for an almost non-technical reader!

In the middle of the semester, when we are toward the end of our discussion concerning the Rasch analysis of testing data, I ask my students to review the web-sites of 5 States (Ohio, Texas, Pennsylvania, California, Illinois). Each of these States use Rasch measurement for their high stakes testing. I ask students to write down what they better understand as the result of these reports. What was it about report phrasing that helped them? I also ask students to tell me what they still do not understand. Finally I require them to write a short summer report of their own in which they explain Rasch and testing to a teacher exploring a State web site.

Here are the URLs of those 5 states. It takes some digging, for as one can imagine, each state has technical reports in different parts of their web-site.

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State of Ohio K-12 Testing. First go here for Ohio
www.ode.state.oh.us/GD/Templates/Pages/ODE/ODEPrimary.aspx?Page=2&TopicID=222&TopicRelationID=285

Then select "Statistical Summaries and Item Analysis Reports". The URL for this part of the site is
www.ode.state.oh.us/GD/Templates/Pages/ODE/ODEDetail.aspx?page=3&TopicRelationID=285&ContentID=9479&Content=60228

Then select a technical report such as "March 2008 OGT Statistical Summary"

State of Texas K-12 Testing. First go here for Texas
www.tea.state.tx.us/index3.aspx?id=3320&menu_id3=793 - t

Then select "Technical Digest" which is this URL
www.tea.state.tx.us/index3.aspx?id=4326&menu_id3=793

Then select a date, for instance, "Technical Digest 2007-2008". Then select a chapter such as 15.
http://ritter.tea.state.tx.us/student.assessment/resources/techdigest/2008/chapter_15.pdf

State of Pennsylvania K-12 Testing. First go here for Pennsylvania
www.pde.state.pa.us/a_and_t/site/default.asp

Then for a sample State of Pennsylvania technical report select "Technical Analysis"
www.pde.state.pa.us/a_and_t/cwp/view.asp?a=108&Q=108328&a_and_tNav=|6395|&a_and_tNav=|

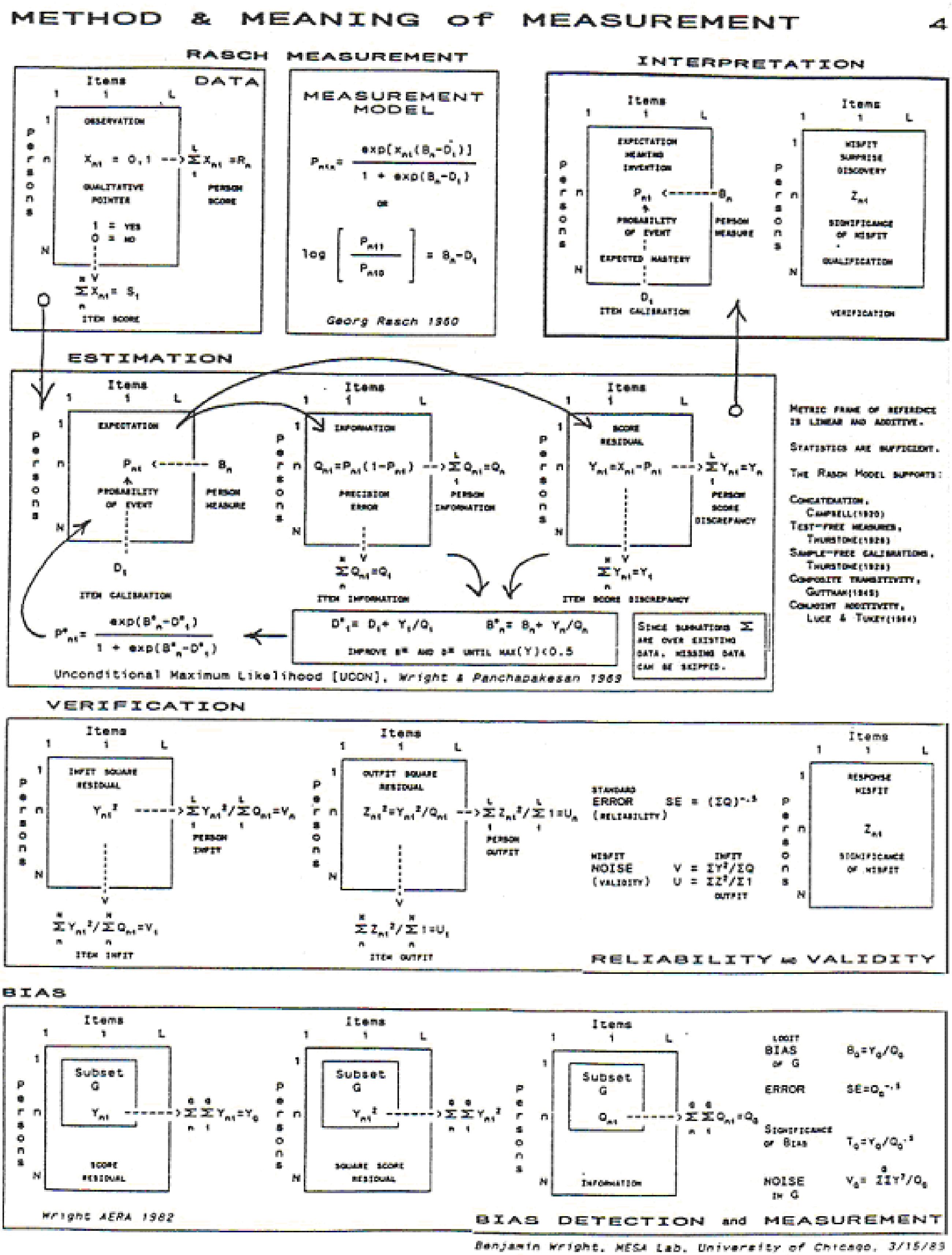
Then select a technical report such as "2008 Reading and Mathematics PSSA Technical Report
www.pde.state.pa.us/a_and_t/lib/a_and_t/2008_Math_and_Reading_Technical_Report.pdf

State of California K-12 Testing. First go here for California
www.cde.ca.gov/ta/tg/sr/technicalrpts.asp

Then go here for a sample State of California technical report select a sample report such as California Standards Tests CSTs Technical Report, Spring 2008 Administration
www.cde.ca.gov/ta/tg/sr/documents/csttechrpt08.pdf

State of Illinois K-12 Testing. First go here in Illinois
www.isbe.state.il.us/assessment/psae.htm - ed

Then you can select a State of Illinois technical report, such as Draft 2006 PSAE Technical Manual
www.isbe.state.il.us/assessment/pdfs/2006_PSAE_tech_manual.pdf



Courtesy of George Engelhard, Jr.

Rasch Benchmarking

When a global 500 company was asked to assess whether they were a "Great Place to Work," they went through a lengthy vendor selection process to find a research organization that could conduct a benchmark study. The winning bid would take six months to complete at a cost of just north of $100,000. Then the economy went south and the project was canceled, but the need for the project persisted so we conducted a stealth benchmark study. Here's what we did.

A *top-down* approach: We put *Business Week, Vault, and Consulting Magazine's* ranking of company prestige into a matrix, converted the rankings into a five-point scale, ran them through Rasched them, and converted them to percentiles.

A *bottom-up* approach: We went to Vault.com, where employees give the inside scoop on the companies they work for and coded who is good to work for and why. For example, "[Company X's] promotion policy is among the best, if not the best in the industry. This is a major draw to X for prospective hires, and is truly one of the best aspects of the firm." This received a 1 under "Career Path," while "The company is certainly the opposite of a meritocracy, with advancement more dependent on who you know rather than what you know" received a 0. We ended up with half a dozen categories that were consistent across all companies: Compensation, Career Path, Culture, Diversity, Work-life Balance, Necessity of Face Time, and Training. As before, we put the data in a matrix, Rasched, and converted into percentiles.

A *both* approach: We then graphed the results (see Figure below) and were surprised to find A) that we stank and B) that a factor that distinguished whether a company was a great place to work was whether they offered tuition reimbursement. The latter (at least) was surprising, surprising because economists consistently argue that companies should *not* offer tuition reimbursement, because it increases employees' portable skills. "Thanks for the degree. Bye." The great companies, however, are not thinking economics. They are thinking game theory. You win the war for talent by outflanking your opponent. "Sure, you can steal my highly-educated people, but I can steal yours and we can all take from those who don't educate their people."

Three interesting things came from this study. First, it became part of a business case for us to create our own legal and accredited graduate program, which puts our competitors in a pickle, because it is too expensive to offer tuition reimbursement and their own degree and once you've offered reimbursement, employees will howl if you take it away. Second, it raises a philosophical issue; all of the data is subjective—prestige ratings and employee comments—but since anybody can replicate the study to get the same result, the study is objective. Third, we completed the study with no non-payroll cost in a week.

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