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Abstract

A numerical procedure is outlined for obtaining an interval estimate of true score. The procedure is applied to several sets of test data.

AN INTERVAL ESTIMATE FOR STATISTICAL INFERENCE ABOUT TRUE SCORES*

We wish to infer the true score of an individual examinee in a group of examinees from his observed score. The distribution of observed scores for a given true score is assumed to be binomial. If the distribution of true scores were known, the usual (Bayes) estimator of true score from observed score would be given by the regression of true score on observed score. If the distribution of true scores is unknown, which is always the case with real data, this regression is not uniquely determined by the observed-score distribution, even in an infinitely large population of examinees (Lord & Novick, 1968, section 23.5).

In practice, the regression function of observed-score on true score is frequently assumed to be linear. This assumption can be correct only if the unconditional observed-score distribution is negative hypergeometric. For any set of real data, then, the question arises--what limits or bounds can be placed on this regression under the binomial error model without making linearity assumptions? This paper presents a technique for computing an interval estimate of the regression function of true score on observed score under the binomial error model. The procedure is not simple. Our main interest here is to demonstrate the range of reasonable estimates of true scores than can be obtained from a set of data.

The same technique is applicable to problems outside of mental test theory whenever there is a set of true values and a set of binomial errors of measurement. This more general empirical Bayes problem, not related to mental test theory, is discussed separately (Lord, 1971).

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The Model

The observed score x is assumed to be an integer $0,1,2,\ldots,n$, where n is the number of items in the test. For each x there is an unobservable true score ζ, $0 \leq \zeta \leq 1$. The difference between x and $n\zeta$ represents error of measurement. For a given ζ, x has the binomial distribution

$$h(x|\zeta) = \binom{n}{x} \zeta^x (1-\zeta)^{n-x} \quad , \qquad x = 0,1,\ldots,n \quad . \tag{1}$$

A sample of N observations on x is drawn at random from some population of pairs (x, ζ). We observe x, but not the corresponding ζ. We wish to estimate the true score ζ corresponding to a particular observed score x.

Let $G(\zeta)$ be the unknown cumulative distribution function of true scores for the population from which the N sample observations were drawn. The relative frequency distribution of observed scores for the population may be written

$$\phi_G(x) = \int_0^1 h(x|\zeta)\, dG(\zeta) \quad , \qquad x = 0,1,\ldots,n \quad . \tag{2}$$

If $G(\zeta)$ were known, the usual Bayes estimate of the true score for a particular observed score would be the regression of true score on observed score,

$$\mu_{\zeta|x} = \frac{1}{\phi_G(x)} \int_0^1 \zeta\, h(x|\zeta)\, dG(\zeta) \quad , \qquad x = 0,1,\ldots,n \quad . \tag{3}$$

If a good estimate $\hat{G}(\zeta)$ of $G(\zeta)$ can be found, then the corresponding estimate $\hat{\mu}_{\zeta|x}$ can be used as the empirical Bayes estimate of ζ for any particular x. A number of techniques are available for constructing reasonable estimates $\hat{\mu}_{\zeta|x}$ from the observed-score distribution (for example, Robbins, 1956; Maritz, 1966; Copas, 1969; Griffin & Krutchkoff, 1971), but they are of unknown accuracy for any given N and n. The technique presented here constructs an interval with lower bound $\underline{\mu}_{\alpha x}$ and upper bound $\bar{\mu}_{\alpha x}$ within which $\mu_{\zeta|x}$ must lie in order to be "reasonably consistent" with the sample of observed scores.

Let the sample relative observed frequency distribution be $f(x)$, $x = 0,1,\ldots,n$. Consider $\chi^2_{1-\alpha}$ to be the $1 - \alpha$ percentile of the chi-square distribution with n degrees of freedom. A $G(\zeta)$ will be considered reasonably consistent with the data if the chi-square between the corresponding $\phi_G(x)$ defined by (2) and the given $f(x)$ is less than or equal to $\chi^2_{1-\alpha}$:

$$\chi^2_G = \sum_{x=0}^{n} \frac{N[f(x) - \phi_G(x)]^2}{\phi_G(x)} \leq \chi^2_{1-\alpha} \quad . \tag{4}$$

Let Γ_α be the set of all cumulative distribution functions $G(\zeta)$ that satisfy (4). The problem to be solved may then be stated as follows: For each $x = 0,1,\ldots,n$, find $\underline{\mu}_{\alpha x}$, the smallest $\mu_{\zeta|x}$, and $\bar{\mu}_{\alpha x}$, the largest $\mu_{\zeta|x}$ obtainable from (3) under the restriction that $G(\zeta)$ be in Γ_α.

By its construction, the interval $(\underline{\mu}_{\alpha x}, \bar{\mu}_{\alpha x})$ can be considered a confidence interval. With probability at least $1 - \alpha$, it will contain the true value of the regression in the population from which the sample was drawn. This procedure for constructing a confidence interval is not entirely satisfactory, since only a lower bound for the confidence level is known. Until better procedures are developed, however, the interval provides more information about the accuracy of inference about true scores than would otherwise be available.

Constructing the Confidence Interval

Substituting (1) into (2) and expanding gives

$$\phi_G(x) = \binom{n}{x} \sum_{r=0}^{n-x} \binom{n-x}{r} (-1)^r \mu_{x+r} \quad , \qquad x = 0,1,\ldots,n \quad , \tag{5}$$

where μ_k is the k -th moment of $G(\zeta)$ about the origin.

Substituting (1) and (5) in (3) and again expanding gives

$$\mu_{\zeta|x} = \frac{\sum_{r=0}^{n-x} \binom{n-x}{r} (-1)^r \mu_{x+r+1}}{\sum_{r=0}^{n-x} \binom{n-x}{r} (-1)^r \mu_{x+r}} \quad , \qquad x = 0,1,\ldots,n \quad . \tag{6}$$

Using a theorem by Markov (see Possé, 1886, sections V8 and V9; or Karlin & Shapley, 1953) and equation (6) it can be shown (Lord, 1971) that $\underline{\mu}_{\alpha x}$ or $\bar{\mu}_{\alpha x}$ is attained for a given x only when $G(\zeta)$ is a step function. A step function is a cumulative distribution function which arises when discrete probabilities g_v, $v=1,\ldots.V$ are concentrated at points ζ_v, $v=1,\ldots,V$. The theorem also proves that if n , the number of test items, is even, V , the number of different points, will be at most $\frac{n}{2} + 1$. The situation is similar when n is odd, but will not be detailed here. In addition, the theorem by Markov shows that if $(n - x)$ is even, $\underline{\mu}_{\alpha x}$ is attained only when the smallest ζ_v is 0.0, and $\bar{\mu}_{\alpha x}$ is attained only when the largest ζ_v is 1.0. Similarly, if $(n - x)$ is odd, $\underline{\mu}_{\alpha x}$ is attained only when the largest ζ_v is 1.0, and $\bar{\mu}_{\alpha x}$ is attained only when the smallest ζ_v is 0.0.

Thanks to Markov, the problem has now taken on a simpler form. To find $\underline{\mu}_{\alpha x}$ or $\bar{\mu}_{\alpha x}$, only $\frac{n}{2}$ unknown true scores ζ_v need be found. Similarly, since the sum of all probabilities, g_v , must be 1, only $\frac{n}{2}$ unknown probabilities need be found. The problem simplifies further since it can be shown (Lord, 1971) that the solution lies on the boundary defined by $\chi^2_G = \chi^2_{1-\alpha}$, therefore the inequality of equation (4) can be replaced by strict equality.

When $G(\zeta)$ is a step function, (3) can be written as

$$\mu_{\zeta|x} = \frac{\sum_{v=1}^{V} g_v \zeta_v \, h(x|\zeta_v)}{\sum_{v=1}^{V} g_v \, h(x|\zeta_v)} \quad , \tag{7}$$

where $V = \frac{n}{2} + 1$. The problem is to maximize or minimize $\mu_{\zeta|x}$ given by equation (7), subject to the restrictions imposed by (4), by $\sum_{v=1}^{V} g_v = 1.0$ and by the inequalities $0 \le g_v \le 1.0$, $0 \le \zeta_v \le 1.0$. This problem can be solved numerically for any given observed score distribution by mathematical programming algorithms implemented on a computer.

The algorithm used to find the numerical solution to the problem was the sequential unconstrained minimization technique (SUMT) developed by Fiacco and McCormick (1968, Chapter 4) and implemented by M. Hamilton. This algorithm carries out a constrained minimization of a function (equation (7)) by performing a series of unconstrained minimizations. The unconstrained minima converge to the constrained minimum. Each unconstrained minimization minimizes the sum of the function and some penalty function. The penalty function is constructed to be large when a constraint is violated and small when it is not violated. The penalty function used here restricts $G(\zeta)$ to Γ_α . The other restrictions were handled by simpler means. The required minimization of the unconstrained function was accomplished by the Fletcher-Powell-Davidon algorithm (Fletcher & Powell, 1963), programmed by Jöreskog 1967, (section 8) and modified by Hamilton. All computations were performed on an IBM 360/65 in double precision.

Results

This procedure has been applied to a variety of mental test data. The tests presented here were selected for their unusual features. The values of α were chosen for convenience of computation.

Table 1. Observed cumulative frequency distribution and corresponding interval estimates ($\alpha = 0.086$) for the regression of true score on observed score.

x	Cumulative Distribution of x	$\hat{\mu}_{\zeta \mid x}$	Interval Estimate of the Regression
30	1.000	.970	.606-1.000
24	.999	.713	.595-.792
18	.945	.544	.498-.596
12	.741	.371	.342-.395
6	.249	.237	.216-.255
0	.001	.137	.009-.220

Data set 1. One such test consisted of 30 five-choice items administered to 2385 examinees. Table 1, column 2, shows the cumulative observed frequency distribution after random responses have been supplied for omitted items. This test is of particular interest since one-fourth of the examinees had scores at the chance level $(x = 6)$ or below, with one-sixth of the scores below chance.

The presence of so many people at or below the chance level raises a number of questions about the distribution of true scores. Are most or many of the true scores also at or below the chance level? Do some people score systematically lower than if they responded at random? What proportion of examinees can safely be assumed to have true scores above chance level?

The last column shows, for selected values of x, the interval estimates of the regression obtained by the method outlined in this paper for $\alpha = 0.086$. Since the regression function is to be used as giving the estimated true score for a given observed score, one can see the range of estimates that could reasonably be so used. The intervals demonstrate clearly that real differences exist on the dimension tested in spite of all the guessing. One cannot rule out the presence of true scores below the chance level, or of very high true scores.

For observed scores of 12 and 6, the intervals are tolerably short. It is interesting to note that for $x \leq .2n$, the interval estimate lies above x/n; for $x \geq .4n$, the interval estimate lies below x/n. This would seem to be a rather extreme manifestation of regression towards the mean.

It is easily shown that a straight-line regression can fit inside all of the intervals. However, this is not a sensitive test for linearity of regression. Under the binomial error model considered here, linearity necessarily leads to a negative hypergeometric distribution of observed scores (Lord & Novick, 1968, section 23.6). To test for linearity, a negative hypergeometric distribution was fitted to the observed score distribution. The χ^2 obtained for this fit was far beyond the tabled 99.9 percentile. Thus, the hypothesis of a linear regression of true score on observed score cannot be maintained for these data.

The third column of Table 1 gives the (nonlinear) regression, obtained some years ago by a very different approach (Lord, 1969), for a $\hat{G}(\zeta)$ that produced a good fit to the observed-score distribution (the χ^2 between $\phi_{\hat{G}}(x)$ and $f(x)$ was at the 60th percentile, with 19 degrees of freedom). It is reassuring to find that this regression lies well within the interval estimates shown in the last column.

Data set 2. The technique was applied to another set of data consisting of the responses to 38 five-choice engineering items administered to 717 examinees. The mean number-right score on this subtest was 12. The subtest has spectacularly low reliability: the Kuder-Richardson coefficient KR_{20} is only 0.35. (The reason for such low reliability may be that the questions covered different engineering specialities--such as mechanical, electrical, or chemical engineering--but most examinees were familiar with only one speciality.)

Interval estimates of the regression of true score on observed score were computed for five observed scores, with $\alpha = 0.01$. The results are shown below:

Observed score x :	2	7	12	17	22
Cumulative distribution of x :	.001	.073	.591	.934	.997
Interval estimate of the regression:	.022-.321	.246-.321	.289-.332	.315-.407	.330-.596

All of these intervals contain at least one value in the range 0.32 to 0.33, which leaves open the remote possibility that examinees with observed scores throughout the range $2 \leq x \leq 22$ may all have about the same true score. This lack of discrimination is in agreement with the low test reliability. Zero reliability would imply that all true scores were identical, the variation of observed scores being entirely due to errors of measurement. A direct test of the hypothesis of zero reliability is called for if this hypothesis is of interest.

Data set 3. The effect of large sample size on the width of the interval estimate was investigated by using the scores of 137,052 examinees on a test composed of 50 five-choice math items. Using $\alpha = 0.05$, the interval estimate computed for the median ($x = 25$) of the distribution of number-right scores was found to be 0.496-0.509, a satisfyingly short interval. Calculations for other x values were not done (because of the expense, due to the large n).

Data set 4. In order to check further the efficacy of the interval estimates of regression, a set of hypothetical data was used. The observed relative frequency distribution was constructed by selecting 1000 cases at random from a negative hypergeometric distribution with $n = 24$. Table 2, column 2, shows the cumulative frequency distribution obtained.

The fifth column displays the interval estimates of the regression for seven values of x, with $\alpha = 0.0375$. Since the population distribution from which the sample was drawn was negative hypergeometric, the data are consisistent under the binomial error model with the assumption that the population regression is linear. The actual linear regression for the population was computed and is shown in column 4 of the table. Clearly, the interval estimate in column 5 recovers the information about the population linear regression. In fact, the values of the population linear regression differ from the midpoints of the intervals by a maximum of 0.019.

Data set 5. The third column of this table displays the cumulative frequency distribution of 50 cases that were selected at random from the 1000. Column 6 shows the corresponding interval estimates of the regression. As expected, the intervals are much wider than those for the original 1000 cases, but not $\sqrt{1000}/\sqrt{50} = 4.4$ times as wide. The width of the interval is doubled or tripled.

Table 2. Observed cumulative frequency distribution and interval estimates for hypothetical data, $\alpha = 0.0375$.

x	Cumulative Distribution of x, N=1000	Cumulative Distribution of x, N=50	$\mu_{\zeta \mid x}$	$(\underline{\mu}_{\alpha x}, \bar{\mu}_{\alpha x})$ for N=1000	$(\underline{\mu}_{\alpha x}, \bar{\mu}_{\alpha x})$ for N=50
24	1.000	1.00	.900	.765-.998	.643-1.000
20	.954	.96	.767	.705-.822	.611-.868
16	.795	.72	.633	.575-.675	.532-.742
12	.523	.48	.500	.467-.558	.404-.618
8	.265	.22	.367	.310-.409	.258-.528
4	.072	.06	.233	.185-.297	.093-.454
0	.002	.00	.100	.009-.216	.000-.454

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