

Assessment and Development of new Statistical Methods for the Comparability of Scores

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- New discrete-based equating methods
- Hybrid methods

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- Latent modelling approach

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Importance of Equating

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- Because test scores are used to make important decisions in various settings, it is needed to report scores in a fair and precise way.
- The main idea behind Equating is *to treat scores as if they come from the same test.*

Equating: statistical point of view

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- The scores of these two test forms are defined on score sample spaces \mathcal{X} and \mathcal{Y} respectively.
- In the context of educational measurement these spaces represent the scale of these scores.
- Let X_1, \dots, X_{n_X} and Y_1, \dots, Y_{n_Y} be the scores obtained on the test forms X and Y by n_X and n_Y examinees, respectively.

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Equating: statistical point of view

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- González and Wiberg (2017) give a formal definition of the equating transformation: a mapping between these two score sample spaces i.e.

$$\varphi : \mathcal{X} \rightarrow \mathcal{Y}$$

- Thus, the equating transformation maps the scores on the scale of one test form into the scale of the other.

Some equating transformations

Equipercntile Equating

- The most popular equating transformation was defined by Braun and Holland (1982). It is called the *equipercntile function* defined by:

$$\varphi(x) = F_Y^{-1}(F_X(x))$$

where F_Y and F_X are the CDF functions of Y and X , respectively.

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Equipercntile Equating

- It is important to highlight here that we are interested on equate scores which are usually integer i.e. X and Y are subsets of integer numbers.
- This represent and important drawback of this method: the inverse function F_Y^{-1} is not well defined.
- The continuization step is proposed in order to avoid this problem: linear interpolation, polynomial log-linear models and kernel equating.

Some equating transformations

Linear Equating

- In this method, the equating transformation is defined by:

$$\varphi(x) = \mu_Y + \frac{\sigma_Y}{\sigma_X}(x - \mu_X)$$

where μ_W and σ_W are the expected value and the standard deviation of W .

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- In practice, the parameters involved in this function are estimated as the mean and the standard deviation of each sample.

Goals of this work

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- Propose improved methods based on continuization tools.
- To compare both approaches (discrete-based equating and continuization-based equating).

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- Since the linear equating transformation does not need continuization, we propose to estimate it using both parametric and nonparametric models for the discrete score distributions.

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- We assume

$$X \sim F(x | \theta_X) \quad (1)$$

$$Y \sim F(y | \theta_Y) \quad (2)$$

Discrete-based equating methods

(a) Classical Parametric approach

- For $F(x | \theta_X)$ and $F(y | \theta_Y)$, assume some parametric distributions that have been used to model discrete scores:

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- For $F(x | \theta_X)$ and $F(y | \theta_Y)$, assume some parametric distributions that have been used to model discrete scores:

- 1 Poisson-Binomial
- 2 Negative Binomial

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 - 1 Poisson-Binomial
 - 2 Negative Binomial
- For these models the mean and standard deviation are functions of θ_X and θ_Y .
- By getting estimations(MLE) of θ_X and θ_Y , we can plug them in the linear equating transformation.

Discrete-based equating methods

(b) Bayesian Parametric approach

- Under the same model (1)-(2), assume some of the parametric distribution for discrete scores mentioned before.

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- Let consider a prior distribution for the parameters θ_X and θ_Y as follows:

$$\theta_X \sim p(\theta_X)$$

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- Perform Bayesian inference to obtain estimates of the parameters and then compute the linear equating transformation.

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 - Assume the following model

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$$\begin{aligned} X | F_X &\sim F_X \\ F_X &\sim \mathcal{P} \\ Y | F_Y &\sim F_Y \\ F_Y &\sim \mathcal{P} \end{aligned}$$

where \mathcal{P} is a random probability measure.

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$$F_X \sim \mathcal{P}$$

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$$F_Y \sim \mathcal{P}$$

where \mathcal{P} is a random probability measure.

- Use Bayesian nonparametric inference to estimate the score distributions. Using those estimations, obtain means and standard deviations to be plugged in the linear equating transformation.



Improved continuization methods

- In order to preserve as much as possible the discrete nature of the score data, we propose some statistical tools that take advantages of some results on the continuous framework and relate them with the main characteristic of score data: discreteness.

Improved continuization methods

(a) Latent variable approach

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Improved continuization methods

(a) Latent variable approach

- We assume that the scores are realizations of an underlying continuous latent process.
- Based on a bayesian nonparametric model for the latent process, we can estimate the score distributions and thus the equipercentile equating transformation.
- Since there is a one-to-one relation between the discrete score values and the continuous latent process, we can obtain an equating in the discrete setting.

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where $Lin(x)$ does not need continuization, whereas $R(x)$ does.

- The idea is then look for ways to minimize the use of $R(x)$ and/or to develop measures to decide to what extend is this function important in the estimation of φ .

Ordinal random variables and latent variables

- Let W be an ordinal random variable with C categories named w_1, \dots, w_C .

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- One approach to model this kind of random variables is the latent modelling formulation.
- Let Z be a continuous latent variable with distribution F_Z .

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- The relation between these variables is the following one:

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$$W = \begin{cases} w_1 & \text{if } \gamma_0 < Z \leq \gamma_1 \\ w_2 & \text{if } \gamma_1 < Z \leq \gamma_2 \\ \vdots & \vdots \\ w_C & \text{if } \gamma_{C-1} < Z \leq \gamma_C \end{cases} \quad (3)$$

where $\gamma_1, \dots, \gamma_C$ are called *cutoffs*.

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$$W = w_k \Leftrightarrow W = w_k \mathbb{1}\{Z \in (\gamma_{k-1}, \gamma_k]\} \quad (4)$$

- Then, the probability of W is specified by the probability of Z , for each $k = 1 \dots, C$:

$$P(W = w_k) = P(Z \leq \gamma_k) - P(Z \leq \gamma_{k-1}) \quad (5)$$

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Ordinal random variables and latent variables

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$$W \sim \text{Mult}(1, C, p_{Z,\gamma}) \quad (6)$$

where

$$p_{Z,\gamma} = (p_{Z,\gamma_1}, \dots, p_{Z,\gamma_C}) \quad (7)$$

$$p_{Z,\gamma_k} = P(Z \leq \gamma_k) - P(Z \leq \gamma_{k-1}) \quad k = 1, \dots, C \quad (8)$$

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$$Z_1, \dots, Z_n \mid F_Z \stackrel{iid}{\sim} F_Z \quad (9)$$

$$F_Z \sim G \quad (10)$$

where G is a random probability measure that leads on a continuous density: a DPM model.

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$$X_1, \dots, X_n \mid Z_1, \dots, Z_n \stackrel{ind}{\sim} Mult(1, J, p_{z, \gamma}) \quad (11)$$

$$Z_1, \dots, Z_n \mid \theta_1, \dots, \theta_n \stackrel{ind}{\sim} N(z_i \mid \mu_i, \sigma_i^2) \quad (12)$$

$$\theta_1, \dots, \theta_n \mid G \stackrel{iid}{\sim} G \quad (13)$$

$$G \mid \phi \sim PD(a, b, G_0(\phi)) \quad (14)$$

$$\phi \sim p(\phi) \quad (15)$$

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