

When randomness opens new possibilities: Acknowledging the stimulus sampling variability in Experimental Psychology

Ottavia M. Epifania^{1,2,3}, Pasquale Anselmi¹, Egidio Robusto¹



¹ University of Padova, (IT)

² Psicostat Group, University of Padova, (IT)

³ Università Cattolica del Sacro Cuore, Milano, (IT)

Computational and Methodological Statistics
16–18 December 2023, University of Applied Sciences,
Berlin, Germany

December, 16th 2023

● ○ ○ ○

○○○

○○○○○

00

Sampled from a larger population

Stimuli are fixed, respondents are random

Respondents are random

Sampled from a larger population

Need for acknowledging the sampling variability

Stimuli are fixed, respondents are random

Respondents are random

Sampled from a larger population

Need for acknowledging the sampling variability

Results can be generalized to other respondents belonging to the same population

Stimuli are fixed, respondents are random

Respondents are random

Sampled from a larger population

Need for acknowledging the sampling variability

Results can be generalized to other respondents belonging to the same population

Stimuli/item are fixed

Taken to be entire population

Results can be generalized to other respondents belonging to the same population

There is no sampling variability

Results can be generalized to other respondents belonging to the same population

There is no need to generalize the results because the stimuli are the population

Stimuli are fixed, respondents are random

However...

The stimuli can also represent a sample of a larger universe

The stimuli can also represent a sample of a larger universe

Processing speed of positive and negative attributes

Stimuli are fixed, respondents are random

However...

The stimuli can also represent a sample of a larger universe

Processing speed of positive and negative attributes

There is a universe of **positive attributes** as well as an universe of **negative attributes**

The stimuli can also represent a sample of a larger universe

There is a universe of **positive attributes** as well as an universe of **negative attributes**

Only samples of **positive attributes** (e.g., good, nice, ...) and **negative attributes** (e.g., bad, evil, ...) are administered

The stimuli can also represent a sample of a larger universe

There is a universe of **positive attributes** as well as an universe of **negative attributes**

Only samples of **positive attributes** (e.g., good, nice, ...) and **negative attributes** (e.g., bad, evil, ...) are administered

So... there must be a sampling variability!

What if the sampling variability is not acknowledged

Generalizability

Generalizability is bounded to the specific set of stimuli used in the experiment

Results can be generalized if and only if the exact same set of stimuli is used

What if the sampling variability is not acknowledged

Generalizability

Generalizability is bounded to the specific set of stimuli used in the experiment

Results can be generalized if and only if the exact same set of stimuli is used

Robustness of the results

Random variability at the stimulus level might inflate the probability of committing Type I errors

Averaging across stimuli to obtain person-level scores results in biased estimates due to the noise in the data

What if the sampling variability is not acknowledged

Generalizability

Generalizability is bounded to the specific set of stimuli used in the experiment

Results can be generalized if and only if the exact same set of stimuli is used

Robustness of the results

Random variability at the stimulus level might inflate the probability of committing Type I errors

Averaging across stimuli to obtain person-level scores results in biased estimates due to the noise in the data

Loss of information

Every stimulus is assumed to be equally informative

All the variability is not considered as well as all the information that can be obtained from it

What if the sampling variability is not acknowledged

This contribution

Focus on the loss of information...the other side of the coin

What if the sampling variability is not acknowledged

This contribution

Focus on the loss of information...the other side of the coin

The information at the stimulus level that can be retrieved from the accuracy responses (correct vs. incorrect) from a typical experiment where the response times are usually employed for scoring the data

What if the sampling variability is not acknowledged

This contribution

Focus on the loss of information...the other side of the coin

The information at the stimulus level that can be retrieved from the accuracy responses (correct vs. incorrect) from a typical experiment where the response times are usually employed for scoring the data

It can actually help in disentangling what is known to be a shortcoming of the score usually employed for analyzing the data of this experiment

Random effects and random factors

Linear combination of predictors in a Linear Model:

$$\eta = X\beta, \quad (1)$$

where β indicates the coefficients of the fixed intercept and slope(s), and X is the model-matrix.

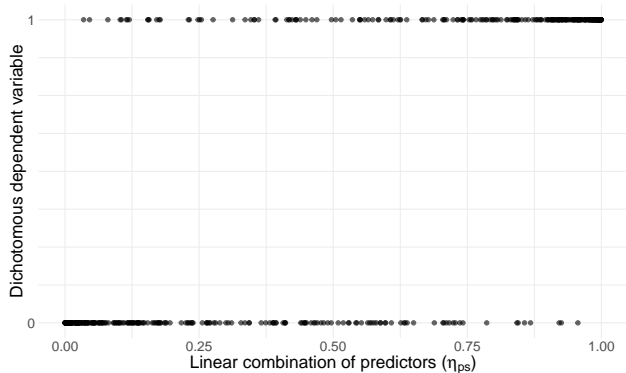
Linear combination of predictors in a Linear Mixed-Effects Model (GLMM):

$$\eta = X\beta + Zd, \quad (2)$$

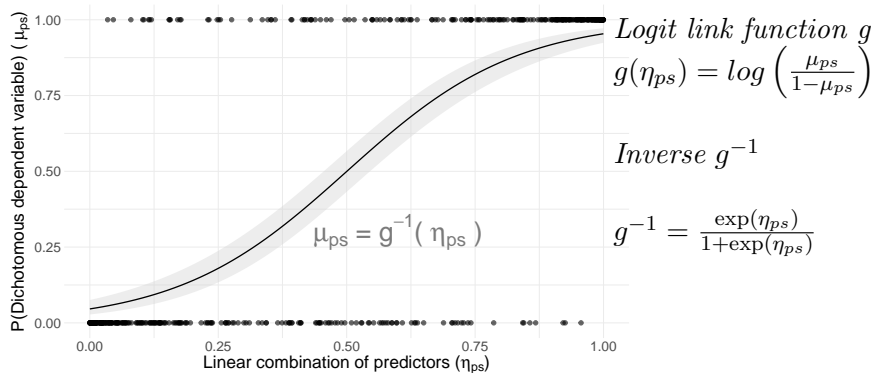
where Z is the matrix and d is the vector of the random effects (not parameters!)

Best Linear Unbiased Predictors

Generalized linear model for dichotomous responses



Generalized linear model for dichotomous responses



The Rasch model

$$P(x_{ps} = 1 | \theta_p, b_s) = \frac{\exp(\theta_p - b_s)}{1 + \exp(\theta_p - b_s)}$$

where:

θ_p : ability of respondent p (i.e., latent trait level of respondent p)

b_s : difficulty of stimulus s (i.e., “challenging” power of stimulus s)

The Rasch model

$$P(x_{ps} = 1 | \theta_p, b_s) = \frac{\exp(\theta_p - b_s)}{1 + \exp(\theta_p - b_s)}$$

where:

θ_p : ability of respondent p (i.e., latent trait level of respondent p)

b_s : difficulty of stimulus s (i.e., “challenging” power of stimulus s)

Standard

$$P(x_{ps} = 1) = \frac{\exp(\theta_p - b_s)}{1 + \exp(\theta_p - b_s)}$$

GLM

$$P(x_{ps} = 1) = \frac{\exp(\theta_p + b_s)}{1 + \exp(\theta_p + b_s)}$$

The Rasch model

$$P(x_{ps} = 1 | \theta_p, b_s) = \frac{\exp(\theta_p - b_s)}{1 + \exp(\theta_p - b_s)}$$

where:

θ_p : ability of respondent p (i.e., latent trait level of respondent p)

b_s : difficulty of stimulus s (i.e., “challenging” power of stimulus s)

Standard

$$P(x_{ps} = 1) = \frac{\exp(\theta_p - b_s)}{1 + \exp(\theta_p - b_s)}$$

GLM

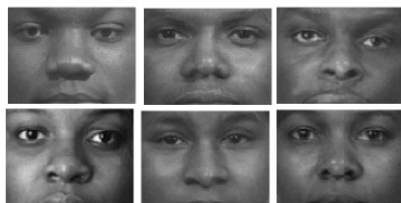
$$P(x_{ps} = 1) = \frac{\exp(\theta_p + b_s)}{1 + \exp(\theta_p + b_s)}$$

12 Object stimuli

White people faces



Black people faces



16 Attribute stimuli

Positive attributes

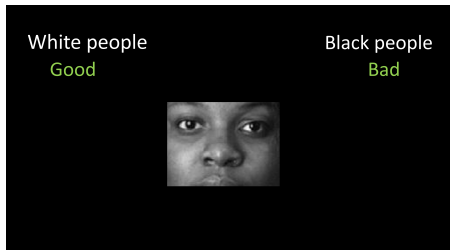
Good, laughter, pleasure, glory, peace,
happy, joy, love

Negative attributes

Evil, bad, horrible, terrible, nasty,
pain, failure, hate

Two experimental conditions

White-Good/Black-Bad
(WGBB): 60 trials



Black-Good/White-Bad
(BGWB): 60 trials



$$D = \frac{M_{\text{BGWB}} - M_{\text{WGBB}}}{s_{\text{BGWB, WGBB}}}$$

Participants: 62 ($F = 48.39\%$, Age = 24.92 ± 2.11 years)

The expected response y for the observation $i = 1, \dots, I$ for respondent $p = 1, \dots, P$ on stimulus $s = 1, \dots, S$ in condition $c = 1, \dots, C$:

Model 1:

$$y_i = \text{logit}^{-1}(\alpha + \beta_c X_c + \alpha_{p[i]} + \alpha_{s[i]} + \varepsilon_i)$$

$$\alpha_p \sim \mathcal{N}(0, \sigma_p^2),$$

$$\alpha_s \sim \mathcal{N}(0, \sigma_s^2).$$

Model 2:

$$y_i = \text{logit}^{-1}(\alpha + \beta_c X_c + \alpha_{p[i]} + \beta_{s[i]} c_i + \varepsilon_i)$$

$$\alpha_p \sim \mathcal{N}(0, \sigma_p^2),$$

$$\beta_s \sim \mathcal{MVN}(0, \Sigma_{sc}).$$

Model 3:

$$y_i = \text{logit}^{-1}(\alpha + \beta_c X_c + \alpha_{s[i]} + \beta_{p[i]} c_i + \varepsilon_i)$$

$$\alpha_s \sim \mathcal{N}(0, \sigma_s^2),$$

$$\beta_p \sim \mathcal{MVN}(0, \Sigma_{pc}).$$

Accuracy: $\epsilon \sim \text{Logistic}(0, \sigma^2)$

$p = 1, \dots, P$ on stimulus $s = 1, \dots, S$ in condition $c = 1, \dots, C$:

Model 1:

$$\alpha_s \sim \mathcal{N}(0, \sigma_s^2).$$

Model 2:

$$\beta_s \sim \mathcal{MVN}(0, \Sigma_{sc}).$$

Model 3:

$$\beta_p \sim \mathcal{MVN}(0, \Sigma_{pc}).$$

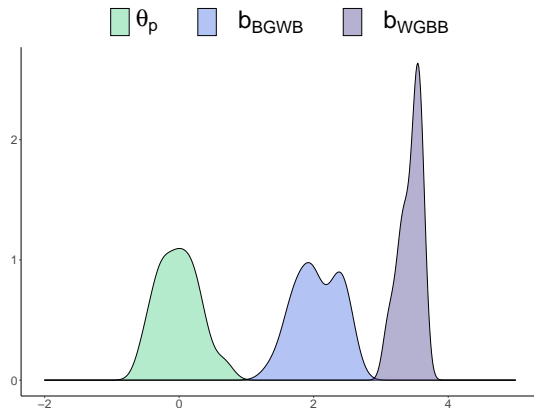
Accuracy: $\epsilon \sim \text{Logistic}(0, \sigma^2)$

Fixed Effects

Random structure

Model 2 is the least wrong model

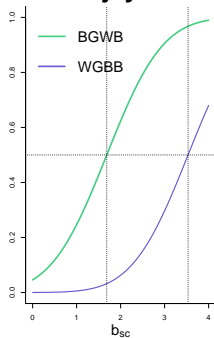
$$y_i = \text{logit}^{-1}(\alpha + \beta_c X_c + \alpha_{p[i]} + \beta_{s[i]} c_i + \varepsilon_i)$$



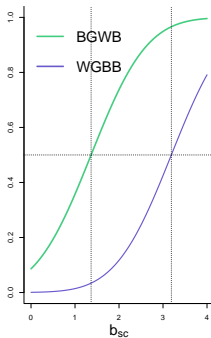
Condition-specific easiness

HIGHLY CONTRIBUTING STIMULI

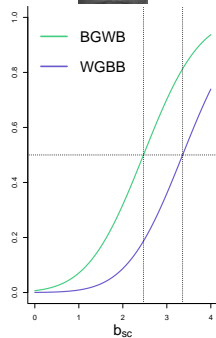
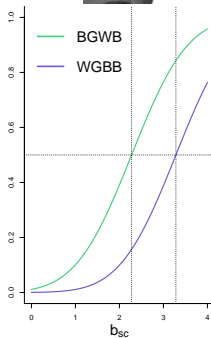
joy



evil



LOWLY CONTRIBUTING STIMULI



- Acknowledge and gather the information at the stimulus level
- Improve generalizability of the results to other sets of stimuli
- Control for random variance in the data
- Allow for obtaining a Rasch-like parametrization of the data
- Possibility of extending the (linear) model to other dependent variables (e.g., response times)

Thank you!

ottavia.epifania@unipd.it

