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

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Taken to be entire population

There is no sampling variability

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

However...

The stimuli can also represent a sample of a larger universe

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So... **there must be a sampling variability!**

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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

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

This contribution

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

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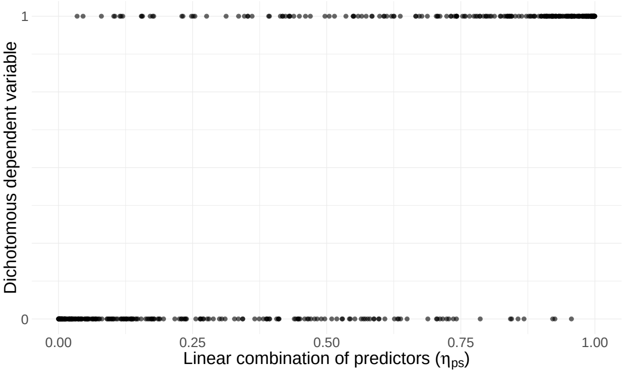
The information at the stimulus level that can be retrieved from the accuracy responses (correct vs. incorrect) from a typical experiment where the response times are usually employed for scoring the data

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

Generalized linear model for dichotomous responses



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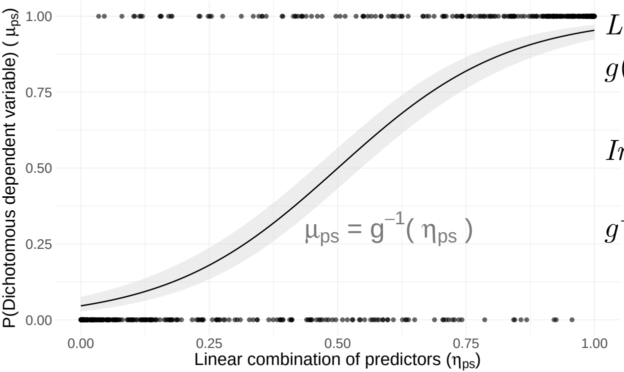

Logit link function g

$$g(\eta_{ps}) = log\left(\frac{\mu_{ps}}{1-\mu_{ps}}\right)$$

Inverse g^{-1}

$$g^{-1} = \frac{\exp(\eta_{ps})}{1+\exp(\eta_{ps})}$$

Random effects and random factors

Linear component in a (G)LM:

$$\eta = \beta X, \tag{1}$$

where β indicates the coefficients of the fixed intercept and slope(s), and X is the model-matrix.
Linear components in a (Generalized) Linear Mixed-Effects Model (GLMM):

$$\eta = \beta X\, Zd, \tag{2}$$

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

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Best Linear Unbiased Predictors

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)

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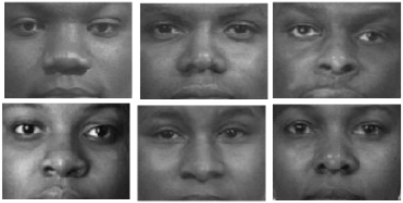
12 Object stimuli

White people faces

Black people faces



16 Attribute stimuli

Positive attributes

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

Negative attributes

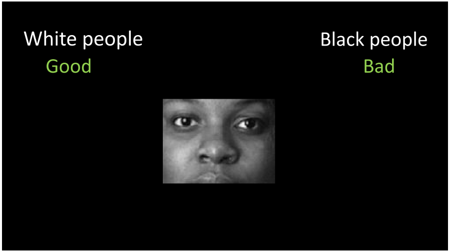
Evil, bad, horrible, terrible, nasty, pain, failure, hate

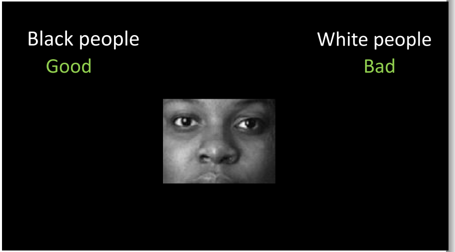
Participants: 62 (F = 48.39%, Age = 24.92 ± 2.11 years)

Two experimental conditions

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

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





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

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

Model 1:

$$y_i = logit^{-1}(\alpha + \beta_c X_c + \alpha_{p[i]} + \alpha_{s[i]} + \varepsilon_i)$$
$$\alpha_p \sim \mathcal{N}(0, \sigma_p^2),$$
$$\alpha_s \sim \mathcal{N}(0, \sigma_s^2).$$

Model 2:

$$y_i = logit^{-1}(\alpha + \beta_c X_c + \alpha_{p[i]} + \beta_{s[i]} c_i + \varepsilon_i)$$
$$\alpha_p \sim \mathcal{N}(0, \sigma_p^2),$$
$$\beta_s \sim \mathcal{MVN}(0, \Sigma_{sc}).$$

Model 3:

$$y_i = logit^{-1}(\alpha + \beta_c X_c + \alpha_{s[i]} + \beta_{p[i]} c_i + \varepsilon_i)$$
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Accuracy: $\epsilon \sim Logistic(0, \sigma^2)$

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Fixed Effects Random structure

Model 2 is the least wrong model

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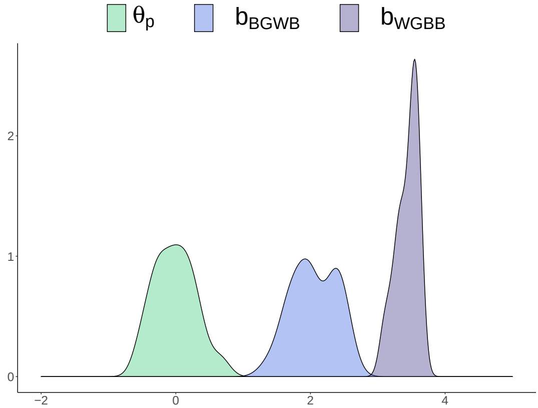
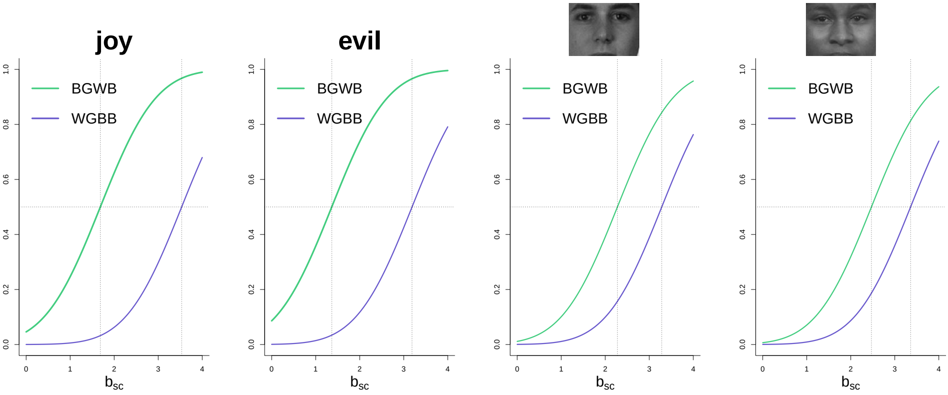


Condition–specific easiness

Highly contributing stimuli

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!

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