Ipse Dixit, But Not in Science: An Alternative Approach to Implicit Measures

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Predoc Camp @ DiPSCo
University of Trento

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*L'idea che la soluzione venga dall'intuizione del matto genio per natura e non dal lavoro complicato e **collettivo** di centinaia, migliaia di scienziati, questa idea è un'idea falsa e sbagliata, che toglie valore all'Università [...]*

Matteo Bordone, 19 Febbraio 2025

Introduction

According to Greenwald & Banaji (1995), implicit attitudes are defined as:

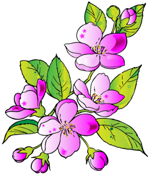
> *Introspectively unidentified – or inaccurately identified – traces of past experience that mediate favorable or unfavorable feelings, thoughts, or actions toward social objects*

IMPLICIT = UNCONSCIOUS

Implicit attitudes are expressed through so-called **automatic associations**

Greenwald, A. G., & Banaji, M. R. (1995) Implicit Social Cognition: Attitudes, Self-Esteem, and Stereotypes. *Psychological Review*, 102-1, doi: 10.1037/0033-295X.102.1.4

Automatic associations

- Not controllable
- Triggered by “triggering” stimuli
- Not accessible through introspection
- Fast and almost immediate

Automatic associations and the unconscious

Studying automatic associations = Studying implicit attitudes

Gaining access to the unconscious and (finally!) being able to study it scientifically

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Fazio & Olson (2003):

> *Being quick in associating snakes with negative adjectives or words does not imply that one is unaware of their negative attitudes toward snakes!*

The only thing one is truly unaware of is that someone is measuring attitudes!
The attitude (the object of measurement) is not implicit, the measurement process itself is.

Implicitly measured constructs Vs. Unconscious constructs

Fazio, R. H., & Olson, M. A. (2003). Implicit measures in social cognition research: Their meaning and use. *Annual Review of Psychology, 54*(1), 297–327. https://doi.org/10.1146/annurev.psych.54.101601.145225

From

Explicit = conscious Vs. Implicit = unconscious/Inconscious
Referring to the nature of constructs

to:

Explicit = direct Vs. Implicit = indirect
Referring to the nature of measurement

Empirical meaning of the term implicit

Banaji & Greenwald (2013):

> ***Theoretical*** *definition of the term implicit as unconscious and unaware*

Greenwald & Banaji (2017), Greenwald & Lai (2020):

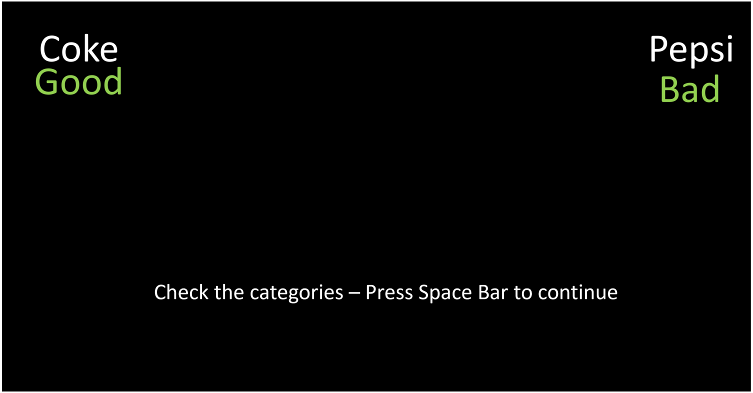
> ***Empirical*** *definition of the term implicit as indirect*

Banaji, M. R., & Greenwald, A. G. (2013). *Blindspot: Hidden biases of good people.* Delacorte Press,
Greenwald, A. G., & Banaji, M. R. (2017). The implicit revolution: Reconceiving the relation between conscious and unconscious. *American Psychologist, 72*(9), 861–871. https://doi.org/10.1037/ amp0000238
Greenwald, A. G., & Lai, C. K. (2020). Implicit social cognition. *Annual Review of Psychology, 71*, 419–445. https://doi.org/10.1146/annurev-psych-010419-050837

Why...?

- Lack of scientific empirical evidence to support access to the unconscious
- Issues related to construct validity → What are we measuring? Are we *sure* we are measuring what we think we are measuring?
- Definition without a supporting theory
- Results cannot be replicated...quite an issue

The Implicit Association Test


Coke
Good
Pepsi
Bad
Check the categories – Press Space Bar to continue

Response key: E

Response key: I

Response key: I

Response key: E

Implicit Association Test

Greenwald et al. (1998):

Block	# Trials	Left Key (E)	Right Key (I)
1	20	Good	Bad
2	20	Coke	Pepsi
3	20	Coke + Good	Pepsi + Bad
4	40	Coke + Good	Pepsi + Bad
5	20	Pepsi	Coke
6	20	Pepsi + Good	Coke + Bad
7	40	Pepsi + Good	Coke + Bad

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Condition Coke-Good/Pepsi-Bad

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Condition Coke-Good/Pepsi-Bad   Condition Pepsi-Bad/Coke-Good

D score

Greenwald et al. (2003)

$$D_{\text{B6,B3}} = \frac{M_{\text{B6}} - M_{\text{B4}}}{sd_{\text{B6,B3}}} \qquad D_{\text{B7,B4}} = \frac{M_{\text{B7}} - M_{\text{B4}}}{sd_{\text{B7,B4}}}$$

$$D = \frac{D_{\text{B6,B3}} + D_{\text{B7,B4}}}{2}$$

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Error responses? Fast responses?

Greenwald, A. G., Nosek, B. A., & Banaji, M. R. (2003). Understanding and using the implicit association test: I. An improved scoring algorithm. *Journal of Personality and Social Psychology, 85*(2), 197– 216. https://doi.org/10.1037/0022-3514.85.2.197

D score	Error responses	Fast responses
D1	Built-in correction	No
D2	Built-in correction	Delete < 400 *ms*
D3	Mean (correct responses) + $2sd$	No
D4	Mean (correct responses) + 600 *ms*	No
D5	Mean (correct responses) + $2sd$	Delete < 400 *ms*
D6	Mean (correct responses) + 600 *ms*	Delete < 400 *ms*

No indications concerning the most appropriate one given different scenarios

Often not reported

The computation is not difficult... yet it is an error prone one

Goodbye replicability

Random Factors

Respondents are random factors

Sampled from a larger population

Need for acknowledging the sampling variability

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

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Stimuli/items are fixed factors

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

Processing speed of positive and negative attributes

There is a <u>universe</u> of **positive attributes** as well as an <u>universe</u> of **negative attributes**

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

Generalizability

Generalizability is bounded to the specific set of stimuli used in the experiment
Results can be generalized <u>if and only if</u> the exact same set of stimuli is used

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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

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Loss of information

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

Every stimulus is assumed to be equally informative

Random Effects for Random Factors

Random effects and random factors

Linear combination of predictors in a Linear Model:

$$\eta = X\beta,$$

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

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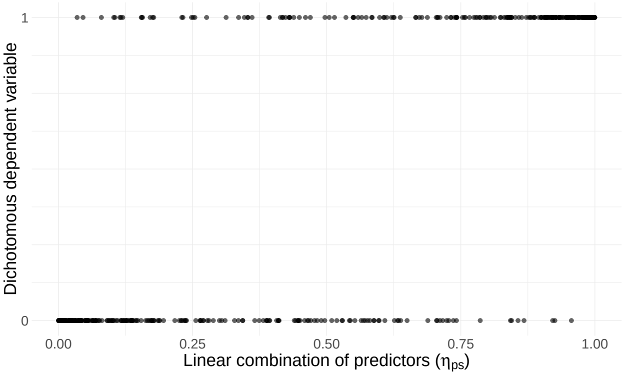
where β indicates the coefficients of the fixed intercept and slope(s), and X is the model-matrix.
Linear combination of predictors in a Linear Mixed-Effects Model (LMM):

$$\eta = X\beta + Zd,$$

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

Best Linear Unbiased Predictors

Generalized linear model (GLM) for dichotomous responses



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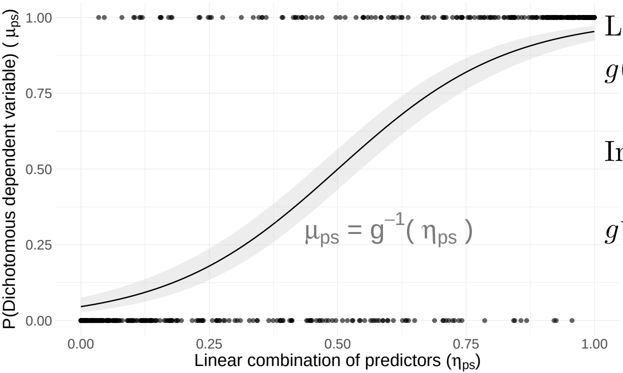

Logit link function g:

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

Inverse g^{-1}

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

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

GLM

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

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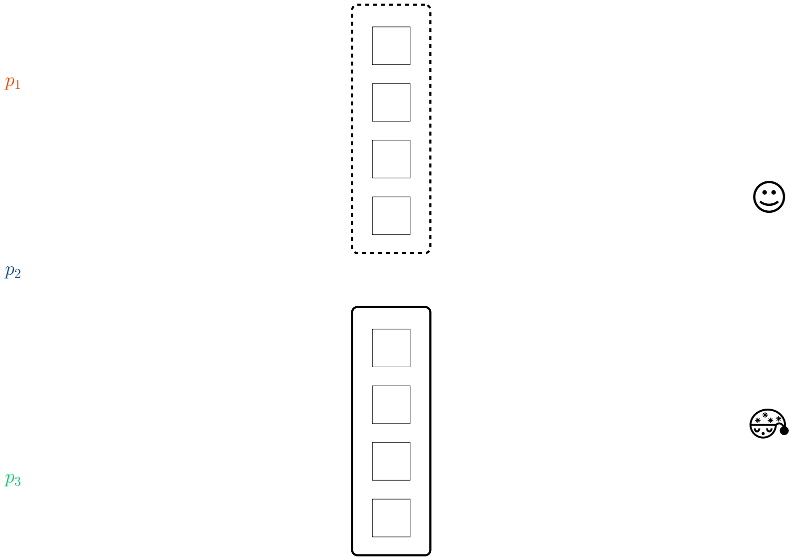
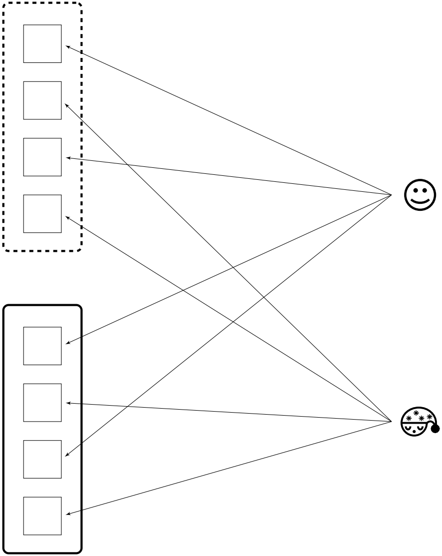
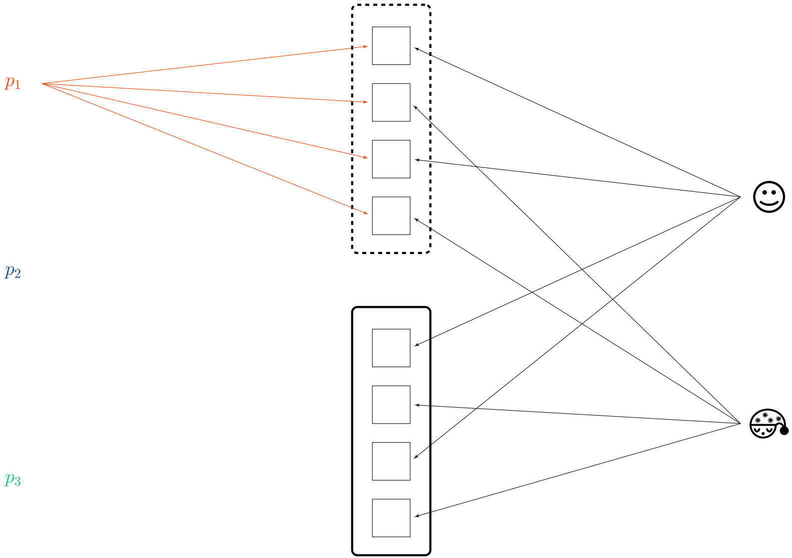

p_1
p_2
p_3

p_1

p_2

p_3




p_1
p_2
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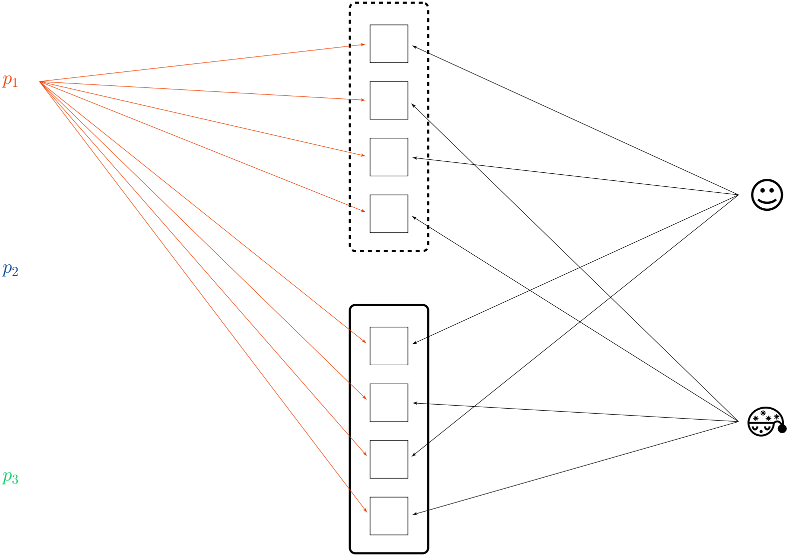
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p_2
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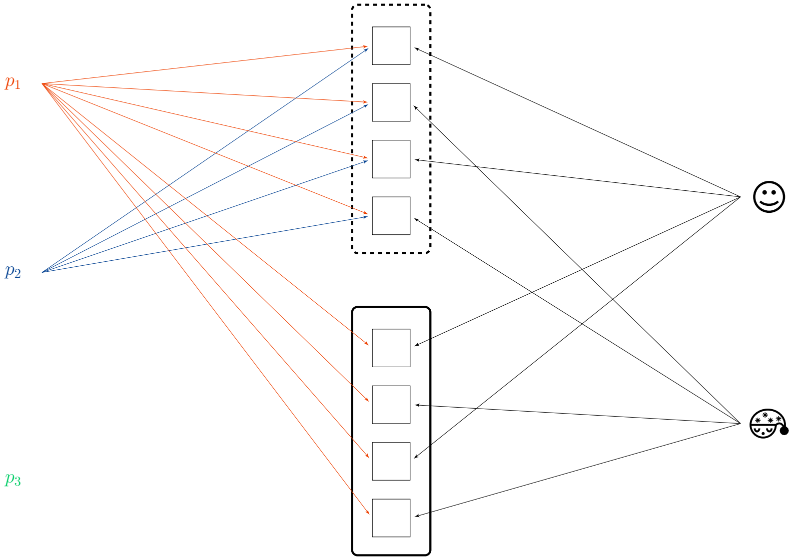
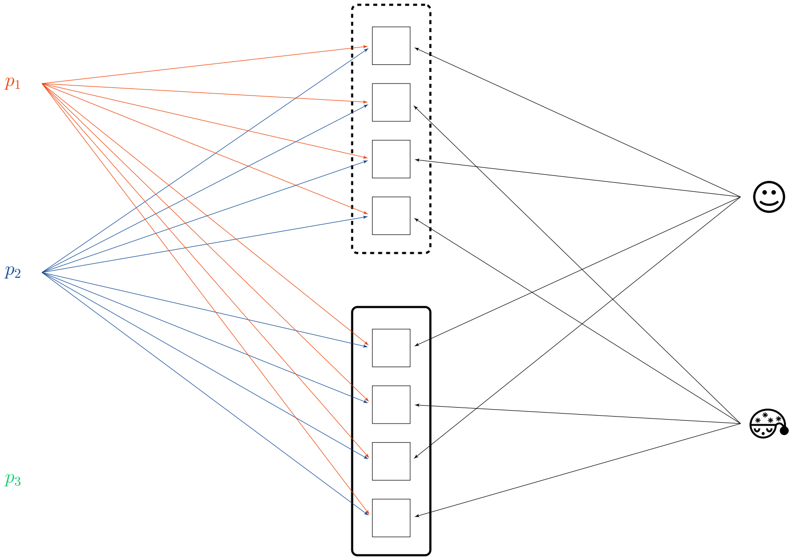


p_1
p_2
p_3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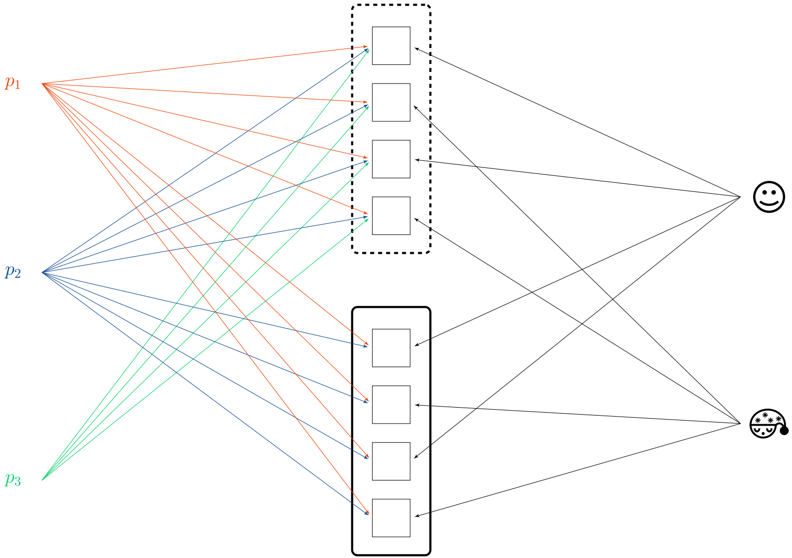
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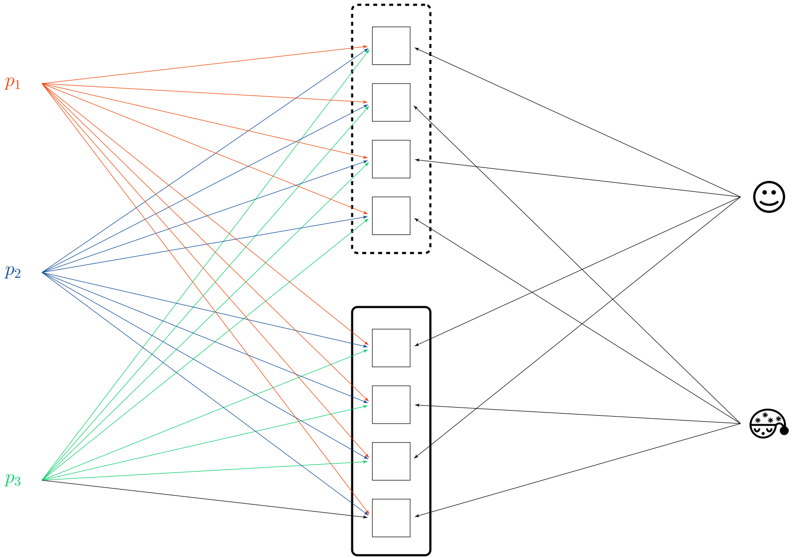
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The expected response y for the observation $i = 1, \dots, I$ for respondent $p = 1, \dots, P$ on stimulus $s = 1, \dots, S$ in condition $c = 1, \dots, C$:

Model 1:

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

Model 2:

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

Model 3:

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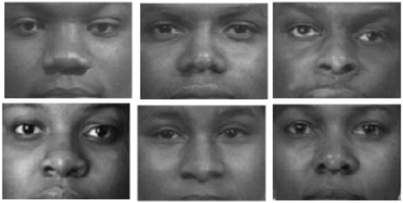
Fixed Effects Random structure

The Implications for the IAT

12 Object stimuli

White people faces

Black people faces



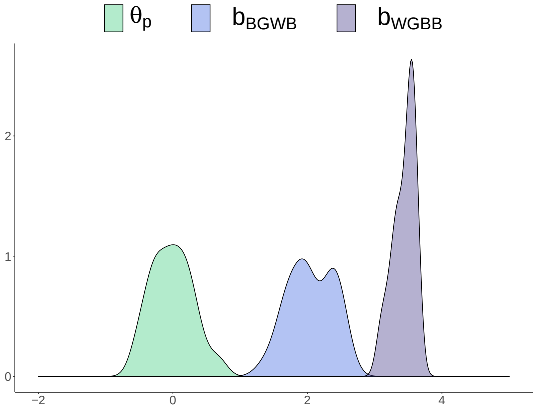
16 Attribute stimuli

Positive attributes	Negative attributes
Good, laughter, pleasure, glory, peace, happy, joy, love	Evil, bad, horrible, terrible, nasty, pain, failure, hate

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

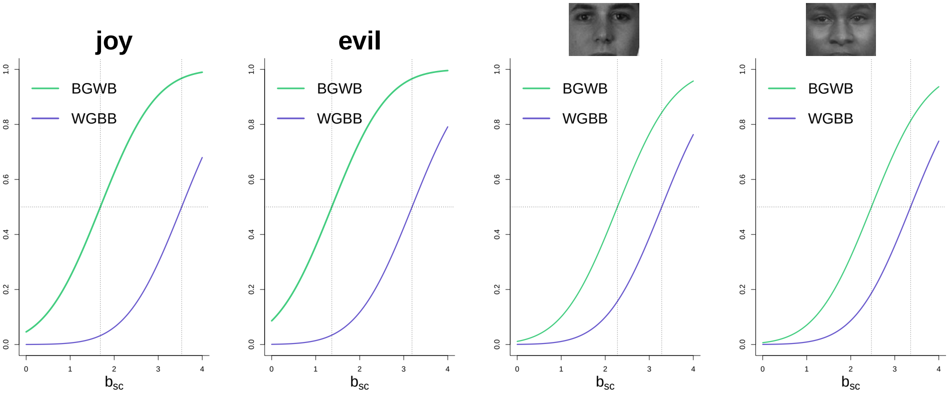
Model 2 is the least wrong model

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



Condition–specific easiness

Highly contributing stimuli   Lowly contributing stimuli



Discussion

- 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, beyond accuracies

Further Information

Epifania, O. M., Anselmi, P., & Robusto, E. (2024). A guided tutorial on linear mixed-effects models for the analysis of accuracies and response times in experiments with fully crossed design. *Psychological Methods*. doi: `https://doi.org/10.1037/met0000708`

Thank you!

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Statistics is Hard