Supplement to 'Common or Distinct Attention Mechanisms for Contrast and Assimilation?'

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# Author note

This document was written in R-Markdown with code for data analysis integrated into the text. The Markdown script is open and freely available at <https://github.com/PerceptionAndCognitionLab/ctx-flanker/tree/public/papers/current>. The data were *born open* (Rouder, 2016) and are freely available at <https://github.com/PerceptionCognitionLab/data1/tree/master/ctxIndDif/flankerMorph4>

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# Abstract

*Keywords:* Inhibition, Selective Attention, Contrast Effects, Assimilation Effects

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# Supplement to 'Common or Distinct Attention Mechanisms for Contrast and Assimilation?'

This document is the supplement to "Common or Distinct Attention Mechanisms for Contrast and Assimilation?". It provides the specification and analysis of a hierarchical Bayesian probit model for assessing the correlation across individuals' abilities to inhibit distractors in assimilation and contrast contexts.

# Model Specification

Let denote whether a response is "A" or "H", respectively. Further, let denote the response for the th participant, , in the th context type ( for word and letter contexts, respectively), for the th context direction (, for contexts that promote "A" and "H" responses, respectively), for the th target, , and for the th replicate, . The context assignments are displayed in the following table:

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | k=1 | k=2 |
|  |  | A-promoting | H-promoting |
| **j=1** | word | C\_T | T\_E |
| **j=2** | letter | H | A |

Observations are dichotomous. To model the effect of covariates in dichotomous observations, we use a probit-regression specification:

Here, , the cumulative distribution function of the standard normal, is the link, and is the combined effect of people, conditions, and the target.

To model individual inhibition effects, we additively decompose into the effect of the target for a particular participant, , the individual's *assimilation* effect when the background context is a word, and the individual's *contrast* effect when the background context is a letter frame, . The decomposition is:

The quantities and are indicators of the context type and direction, as follows:

$$ v\_j=
\begin{dcases}
0 & \quad \text{if} \quad j =2 \text{ (letters)}\\
1 & \quad \text{if} \quad j =1 \text{ (word)}
\end{dcases}
\qquad
x\_k=
\begin{dcases}
\frac{-1}{2} & \quad \text{if} \quad k =1 \text{ (A-promoting)}\\
\frac{1}{2} & \quad \text{if} \quad k =2 \text{ (H-promoting)}
\end{dcases}
$$

Prior distributions are needed for . We start with , the effect of the target for a particular participant. These parameters are not of primary concern, and we use a broad hierarchical prior given by: with hyper priors of and .  
The effects of interest are an individual's assimilation effect, , and an individual's contrast effect, . We follow the development in Rouder et al. (2007) who describe Bayesian analyses in these settings. The joint prior over these parameter is

where is the vector and is a covariance matrix.

Following Rouder et al. (2007), the hyperpriors for and are given by

The hyperprior for is

where . A key property of the above specification is that population covariance in is an explicit parameter given by . Hence, a population correlation is well defined, and subsequent inferences generalize to new data from new participants.

The choices we make above are all reasonable given the expected degree of variability in proportions. The standard normal prior in the probit space on and corresponds to flat priors in the space of proportions, and the shape value of in the Inverse Wishert corresponds to a flat prior on the population-level correlation coefficient. The only substantive choice are the values in the scale of the Inverse Wishert. This small value of precision corresponds to a vaguely informative prior on effects. Additional details are provided in Rouder et al. (2007).

# Analyses and Results

The estimation of probit-transformed parameters follows from Albert and Chib (1995). Accordingly, a new set of latent variables is introduced for each observation, and we denote them . These variables are defined as follows:

$$y\_{ijk\ell m}=
\begin{dcases}
0 & \text{ then } w\_{ijk\ell m} < 0 \\
1 & \text{ then } w\_{ijk\ell m} \geq 0
\end{dcases}
$$

Without loss of generality, the variable is assumed to be distributed as a normal with a variance of one and the mean of . Thus, the parameters of interest at this level are and . It is easy to compute the posterior of given the vector of and, conversely, it is easy to compute the posterior of given the 's. Hence, the marginals of each may be found by Markov chain Monte Carlo (MCMC) sampling. The conditional posterior distribution of is a truncated normal:

$$w\_{ijk\ell m}|y\_{ijk\ell m} \sim
\begin{dcases}
\text{N}\_-(\mu\_{ijk\ell},1) & \text{ if } y\_{ijk\ell m}=0 \\
\text{N}\_+(\mu\_{ijk\ell},1) & \text{ if } y\_{ijk\ell m}=1,
\end{dcases}
$$

where and denote normals distributions truncated at zero from below and above, respectively.

Posterior distributions for remaining parameters may also be sampled with MCMC. In all cases, conditional posterior distributions of parameters may be derived directly from the proportional form of Bayes rule (Jackman, 2009; Rouder & Lu, 2005). Priors were chosen to be conjugate, and consequently, posterior distributions may be sampled from known distributions in Gibbs steps.

Critical parameters are individual estimates of contrast and assimilation, and the population-level correlation of these abilities. Individual estimates are parameters and . Posterior means and posterior standard deviations of these parameters are shown as points and ellipses, respectively, in Figure 4A in the main paper. The most critical parameter is the population correlation. On each iteration of the MCMC chain, we calculated . The prior and posterior distribution of is shown in Figure 4B. A full description of the results may be found in the main paper.

# References

Albert, J. H., & Chib, S. (1995). Bayesian residual analysis for binary response regression models. *Biometrika*, *82*, 747–759.

Jackman, S. (2009). *Bayesian analysis for the social sciences*. Chichester, United Kingdom: John Wiley & Sons.

Rouder, J. N. (2016). The what, why, and how of born-open data. *Behavioral Research Methods*, *48*, 1062–1069. Retrieved from <10.3758/s13428-015-0630-z>

Rouder, J. N., & Lu, J. (2005). An introduction to Bayesian hierarchical models with an application in the theory of signal detection. *Psychonomic Bulletin and Review*, *12*, 573–604.

Rouder, J. N., Lu, J., Sun, D., Speckman, P. L., Morey, R. D., & Naveh-Benjamin, M. (2007). Signal detection models with random participant and item effects. *Psychometrika*, *72*, 621–642.