Approach to Analyses in “Effects of Iconicity in Lexical Decision”

Analyses consisted of mixed effects regression models. Models were computed using the “lme4” package (Bates, Maechler, Bolker, & Walker, 2015) in the statistical software R (R Core Team, 2018). In each model, we took a confirmatory approach, and fit all fixed effects of interest. We developed each model’s random effects structure using the approach suggested by Bates, Kliegl, Vasishth, and Baayen (2015). This was as follows:

1. We began with a model containing all possible random effects for fixed effects of interest. Here and elsewhere, when a model did not converge our first recourse was to refit the model with 100,000 iterations and (in the case of logistic regression) switch to a BOBYQA optimizer. For cases in which this did not converge, we fit a simpler model that omitted correlations among random effects. This was done using the “afex” package in R (Singmann, Bolker, & Westfall, 2015).
2. We then used the “RePsychLing” package in R (Baayen, Bates, Kliegl, & Vasishth, 2015) to perform a principal components analysis on this random effects structure to determine the number of random effects that could be specified (i.e., the number of components explaining > 1% of variance) while achieving model identification. Beginning with the highest order random effect with the least amount of variance, we removed random slope effects until we reached a model that contained the number suggested by the principal components analysis.
3. If correlations among random effects were retained up to this point, we then compared models with and without correlations among random effects using likelihood ratio tests (*LRT*s) to determine if they were warranted.

4. We then tested the inclusion of every remaining random slope effect, beginning with the highest order effect with the least amount of variance, using LRTs.
5. Finally, if there were no correlations among random effects, we tested whether the model could be improved by their inclusion using LRTs.

Note that models always included random subject and item intercepts to deal with non-independence. To generate p-values for fixed effects in all models, we used Satterthwaite degrees of freedom via the “lmerTest” package (Kuznetsova, Brockhoff, & Christensen, 2017). We also used the “prediction” package (Leeper, 2018) to generate predicted values for different levels of our fixed effects. Only real word trials were analyzed.

References

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