The dynamic generalized linear mixed effect model: Modeling intensive binary time-series data from the visual-world eye-tracking paradigm with GLMM with crossed random effects

Sarah Brown-Schmidt and Sun-Joo Cho (Vanderbilt University)
sarahbrownschmidt@gmail.com

The visual world paradigm is a popular technique for examining language processing (Tanenhaus et al., 1995) that uses a continuous measure of where a participant is looking as they produce or interpret spoken language. With high sampling rates, this method generates intensive categorical time series data.

Current data analytic practice is varied, and the types of dependent measures used in the literature have varied considerably over the last 20+ years. Repeated measures approaches have been used to examine changes in fixations over time using growth curve models (Mirman, et al., 2008), and other non-linear functions (e.g., McMurray et al., 2010). In contrast, aggregated measures calculate one, or a small number, of measures per person, per condition (or per item and condition), and sometimes include time as a linear covariate across a few time-bins (e.g., Barr, 2008). A disadvantage of these approaches is that they often require aggregation across persons, items, and/or trials, and therefore do not allow simultaneous modeling of all sources of dependencies in the data. Proportion or empirical-logit measures, when calculated for each individual person and trial, typically result in data distributions that are zero-inflated, or bimodal, in the case of difference score calculations (e.g. p(target)-p(competitor)). Using the linear mixed effect model results in biased estimates when it is applied to zero-inflated or bimodal data. Further, repeated measures approaches that do not take into account the temporal autocorrelation in the data (i.e., the fact that adjacent time-points exhibit dependency) may result in underestimated standard errors and biased parameter estimates.

The aim of this research is to present a novel model specification that takes into account change processes (autocorrelation [AR] and trend) in binary time series eye-tracking data, and variability across trials, persons, and items. By 'dynamic' we mean that the model considers change processes in the generalized linear mixed effect model (GLMM). The "dynamic GLMM" is a GLMM with crossed random effects (random person and random item effects). This is an extension of the model specification presented in Cho et al. (2018) in the sense that a trend effect (the change in the mean level per unit time) is considered. This model offers a way to model intensive time-series eye-tracking data in binary form (e.g., fixations to target vs. everything else) in order to test for fixed experimental condition effects and trend (time) effects, while controlling for dependencies in the data including the AR. We apply the model to an empirical study of language processing using the visual world paradigm (Ryskin et al., 2015).

We first describe the model-building steps that the researcher would take when applying the dynamic GLMM to eye-tracking data. We then show how the AR and trend can be characterized descriptively and present how they can be modelled by accounting for the AR and trend effects and variability in the AR effects across persons and items. Next, we describe how to select a model to detect experimental condition effects among candidate models having different random effect structures. We then describe how the model-data fit can be evaluated. Finally, a simulation study was implemented to show the parameter recovery of the specified model using the glmer function in R (Bates et al., 2018). Results of the simulation study showed that parameters were recovered well in the same conditions as the empirical study. The simulation study demonstrated the necessity of modeling the AR for accurate estimates of the fixed effect parameter estimates and their standard errors. We find that ignoring AR effects can lead to biased estimates and underestimated standard errors for the experimental condition effects.

This new GLMM specification is applicable to the analysis of intensive binary time series eye tracking data when researchers are interested in detecting experimental condition effects while controlling for previous responses (i.e. where the eye fixated at the previous time-point), and are interested in modeling nested and crossed random effects for, e.g., trials, persons, and items.

References

Barr, D. J. (2008). Analyzing ‘visual world’ eyetracking data using multilevel logistic regression. *Journal of memory and language*, *59*(4), 457-474.

Bates, D., M ̈achler, M., Bolker, B., Walker, S., Christensen, R. H. B., Singmann, H., . . . Green, P. (2018). Package “lme4”: Linear mixed-effects models using ‘eigen’ and s4. Retrieved from https://cran.r-project.org/web/packages/lme4/lme4.pdf

Cho, S. -J., Brown-Schmidt, S., & Lee, W. -y. (2018). Autoregressive Generalized Linear Mixed Effect Models with Crossed Random Effects: An Application to Intensive Binary Time Series Eye-Tracking Data. *Psychometrika, 83*, 751-771.

McMurray, B., Samelson, V. M., Lee, S. H., & Tomblin, J. B. (2010). Individual differences in online spoken word recognition: Implications for SLI. *Cognitive psychology*, *60*(1), 1-39.

Mirman, D., Dixon, J. A., & Magnuson, J. S. (2008). Statistical and computational models of the visual world paradigm: Growth curves and individual differences. *Journal of memory and language*, *59*(4), 475-494.

Ryskin, R. A., Benjamin, A. S., Tullis, J., & Brown-Schmidt, S. (2015). Perspective-taking in comprehension, production, and memory: An individual differences approach. Journal of Experimental Psychology: General, 144, 898–915.

Tanenhaus, M. K., Spivey-Knowlton, M. J., Eberhard, K. M., & Sedivy, J. C. (1995). Integration of visual and linguistic information in spoken language comprehension. *Science*, *268*(5217), 1632-1634.