modglm: An R package for testing, interpreting, and displaying interactions in generalized linear
models of discrete data

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Summary

Many researchers hope to examine interaction effects using generalized linear models (GLMs) to predict outcomes on nonlinear scales. For instance, logistic and Poisson GLMs are used to estimate associations between predictors and outcomes in nonlinear probability and count scales, respectively. However, we (McCabe, Halvorson, King, Cao, & Kim, 2020) and others (Ai & Norton, 2003; Mize, 2019; Norton, Wang, & Ai, 2004) have shown that testing and interpreting interaction effects on these scales is not straightforward. GLMs require the application of partial derivatives and/or discrete differences to compute and probe interaction effects appropriately when models are interpreted on their nonlinear scale. Currently available open-source software does not provide methods of computing these interaction effects on probability and count scales, reflecting a central limitation in applying these methods in research practice.

The *modglm* package is an R-based software package that accompanies our manuscript providing recommendations for computing interaction effects in nonlinear probability and count GLMs (C. McCabe et al., 2020). *Modglm* interfaces with well-vetted packages used to estimate GLMs, including the base R package (R Core Team, 2019) for logistic and Poisson models and the *MASS* package for negative binomial models (Ripley et al., 2013). Model objects generated using these packages (e.g., coefficient estimates and variance-covariance matrices of model estimates) are passed into functions in *modglm*, which are used to compute interaction effect estimates using partial derivatives and discrete differences based on conditional predictor values specified by the user.

Functionality and R code for *modglm* extends from the DAMisc package for logit and probit models (Armstrong & Armstrong, 2020), which itself was an adaptation of the *inteff* command in

Stata (Norton, Wang, & Ai, 2004). *Modglm* extends functions from the *DAMisc* package by adding three central features. First, *modglm* provides utilities for computing interaction effects across a range of discrete data models (e.g., Poisson and negative binomial models) in addition to logit models. Second, it provides additional functionality that accommodates several considerations in estimating interactions pragmatically in applied research, described in detail in McCabe et al. (2021). This includes 1.) allowing users to more flexibly estimate interaction effects conditioned on user-specified hypothetical predictor scenarios; 2.) creating a plot that summarizes point estimates of the interaction effect in the observed data; 3.) providing additional output relevant for summarizing results (e.g., the proportion of significant interaction effects in the sample); and 4.) computing the average interaction effect in the observed sample, as well as its standard error, for summary purposes (e.g., Williams, 2012). Third, the function ‘margplot’ provides a means of plotting the marginal effects corresponding with a given interaction. Plots were designed explicitly to mirror conventional approaches used in probing interactions in linear models in psychology (e.g., simple slopes plots; C. J. McCabe, Kim, & King, 2018; Preacher, Curran, & Bauer, 2006). Estimates are generated straightforwardly via producing conditional expected values based on the estimated model. Confidence regions are generated using parametric bootstrapping (i.e., Monte Carlo simulation) following guidelines by King, Tomz, & Wittenberg (2000).

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