A Dynamic Tree-Based Item Response Model

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Abstract

- This study presents a dynamic tree-based item response (IRTree) model as a novel extension of the autoregressive generalized linear mixed effect model (dynamic GLMM), capable of modeling differentiated processes indicated by intensive polytomous time series eye-tracking data.

- The dynamic IRTree model is a general modeling framework which can model change processes (trend and autocorrelation) and which allows for the decomposition of data into various sources of heterogeneity.

- An experimental study that employed the visual world eye-tracking technique was used to illustrate the dynamic IRTree model.

- The results of a simulation study showed that parameter recovery of the model was satisfactory and that ignoring trend and autoregressive effects resulted in biased estimates and standard errors of experimental condition effects in the same conditions found in the empirical study.

Study Motivation & Purpose

- Literature reviews on existing IRTree models and time series models lead to the conclusion that there is a disconnect between the available analytic methods and a common data structure in studies of real-time cognitive processes using the visual world eye-tracking technique.

- This disconnect can be resolved by combining the IRTree model with the time series model.

- The goal of the novel modeling framework was to allow for:
  - differential processing depending on the response option (based on the tree feature of the model);
  - heterogeneity of the processes (based on the IRT feature of the model);
  - change processes (trend and autoregressive parameter) as in the time series models and in the dynamic GLMM.

- The novelty of the dynamic IRTree model lies in the combination of three features: the tree feature, the IRT feature, and the dynamic feature. All three are important to answer substantive research questions regarding cognitive processes underlying data from a linguistically-inspired eye-tracking study.

Empirical Study: Intensive Polytomous Time Series Data from Eye Trackers

- The data set comes from a study previously published by Ryskin, Benjamin, Tulis, and Brown-Schmidt (2015).

- 152 native English-speaking participants from the University of Illinois at Urbana-Champaign.

- Eye tracking was conducted with Eyelink-1000 eye-trackers.

- Participants took turns instructing each other to click on objects on the computer screen (e.g., "Click on the small elephant!).

- In addition to the target object (e.g., a small elephant), there was a competitor object of a different size (e.g., a large elephant) and unrelated objects (e.g., a banana).

- Each person participated in 288 trials under three experimental conditions (Two Contrasts-Shared: Two Contrasts-Privileged: One Contrast).

- The xy-positions of participants’ eye-fixations were recorded in 5.10 milliseconds intervals. Each of the trials yielded eye-fixation data for 112 equally-spaced time points.

- Each trial featured an “item” which was the object that the participant had to click on (e.g., duck, frog, elephant). There were a total of 96 unique items in the dataset.

- Data had a multilevel structure, with time series eye-fixation data (level 1) nested in 288 trials (level 2) cross-classified by person and items (level 3).

- Two dynamic IRTree models were used to reconcile this missing data, one using two lag covariates indicating whether the person looked at the target or competitor at the previous time point $(x_{ljir}^{t-1})$ and $(x_{ljir}^{t-2})$, and the other using the last preceding observation $(x_{ljir}^{t-1})$.

- The trend effect differed depending on the node. The trend was clearly steeper for the ambiguity resolution process (0.031 at Node 2) than for lexico-semantic processing (0.006 at Node 1).

- The tree approach makes a distinction between processing occurring at the two nodes: Node 1 is for the processing of lexico-semantic information in the initial words in the phrase (e.g., “the small elephant.”). Node 2 refers to the resolution of ambiguity between the target and competitor (e.g., the small and large elephant).

- Random effects were comparable.

- Fixed effects were comparable.

- Person random effects were comparable.

- Second experimental condition (privileged) $\gamma_1$ is positive (0.050) at Node 1, indicating that the lexico-sematic processing of the unfolding target is more important than the competitor.

- Experimental condition effects differed between nodes as well. For example, the Contrast effect was positive (0.013) at Node 1, indicating that the lexico-semantic processing of the unfolding expression activates the target and competitor more in the Two-Contrasts conditions than in the One-Contrast condition. However, the Contrast effect was negative (-0.386) at Node 2.

- Parameter estimation was implemented using the Nelder algorithm in glmm package (R Core Team, 2017) for Laplace approximation and using Stan (Stan Development Team, 2018) for Bayesian analysis. Estimates from Laplace approximation and Bayesian analyses were comparable.

Empirical Study Results

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  - Node 1 is for the processing of lexico-semantic information in the initial words in the phrase (e.g., "the small elephant.").
  - Node 2 refers to the resolution of ambiguity between the target and competitor (e.g., the small and large elephant).

- Model-data fit results and correlations between the two random person intercepts confirmed that each node comes with its own dimension.

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- The trend effect differed depending on the node. The trend was clearly steeper for the ambiguity resolution process (0.031 at Node 2) than for lexico-semantic processing (0.006 at Node 1).