Controlling for human response latency with continuous-time deconvolutional regression

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The influence of stimuli in psycholinguistic experiments diffuses across time because the human response to language is not instantaneous. The linear models typically used to analyze psycholinguistic data are unable to account for this phenomenon due to strong temporal independence assumptions, and existing techniques for relaxing these assumptions (e.g. adding spillover regressors) deal poorly with the variable word durations that are typical of real sentence comprehension settings, making it difficult to estimate and control for the effects of latency in the underlying response (see also [1, 2, 6] for discussion of related temporal confounds). Prior work has argued that continuous-time deconvolutional regression (CDR), which uses machine learning to estimate the shape of the response to predictors over time, can address these issues [17] but has not explored the influence on CDR estimates of common real-world challenges (noise, multicollinearity, and impulse response misspecification), hyperparameter settings, and experimental response types (behavioral and fMRI). In this study, we manipulate each of the above variables and empirically assess their impact on CDR model identification, finding that CDR (1) yields consistent estimates across a variety of hyperparameter configurations, (2) faithfully recovers the data-generating model on synthetic data, even under adverse training conditions, and (3) outperforms widely-used statistical approaches when applied to naturalistic reading and fMRI data. Full results are given in [18].

We fitted CDR models to 20-covariate synthetic datasets and found that CDR closely recovered the true model even under highly adverse conditions, including low signal-to-noise ratios in the response (e.g. 0.2), high multicollinearity (e.g. r = 0.95 for each pair of the 20 predictors), and misspecified impulse response kernels (e.g. fitting Gaussian IRFs to data generated by gamma-shaped IRFs). Representative plots are shown in Figure 1. The fact that CDR can identify the underlying model despite these challenges supports its use in psycholinguistic modeling.

We additionally fitted CDR models to naturalistic self-paced reading [10], eye-tracking (go-past) [12], and fMRI [16] data. For the reading data, predictors included *sentence position*, *document position*, *word length*, *unigram surprisal*, and *5-gram surprisal*, as well as (eye-tracking only) *saccade length* and *previous was fixated*. We manipulated the IRF kernel (exponential, Gaussian, shifted gamma, and linear combination of Gaussians), the linking function (linear and log-linear), and the error distribution (normal and sinh-arcsinh). For the fMRI data, predictors included *sound power*, *unigram surprisal*, and *5-gram surprisal*. These (or related variants) are widely used in psycholinguistic modeling [8, 7, 9, 19, 5]. We manipulated the IRF kernel (1, 2, 3, 4, and 5 parameter variants of the canonical hemodynamic response function or *HRF* [4]) and the the error distribution (normal and sinh-arcsinh). All models also included a convolution of the intercept (*rate*). Results are stable across conditions and even corpora, with e.g. positive effects of *word length* [14] and *5-gram surprisal* [7, 9, 19], weak effects of *unigram surprisal* (see e.g. [15]), and response shapes that accord with prior research: reading responses decay to near zero within about two seconds [19], while fMRI responses closely resemble the canonical HRF, peaking around 5s after stimulus onset [4, 13]. Representative plots are shown in Figure 2. Moreover, CDR significantly improved fit to unseen data (1) over linear mixed-effects [3] and generalized additive [20] baselines in the reading domain and (2) over averaging, linear interpolation, Lanczos interpolation [11], and preconvolution with the canonical HRF [4] in the fMRI domain.

This study thus shows that CDR is robust to frequently encountered confounds, finds consistent estimates across datasets, modalities, and model designs in real data, and provides detailed, interpretable descriptions of latent temporal dynamics that are difficult to obtain using other methods. In addition, we offer a documented, open-source Python implementation of the CDR technique (`https://github.com/coryshain/cdr`). We advocate the use of CDR for psycholinguistic analysis, especially in a naturalistic setting where the rate of presentation is not controlled.

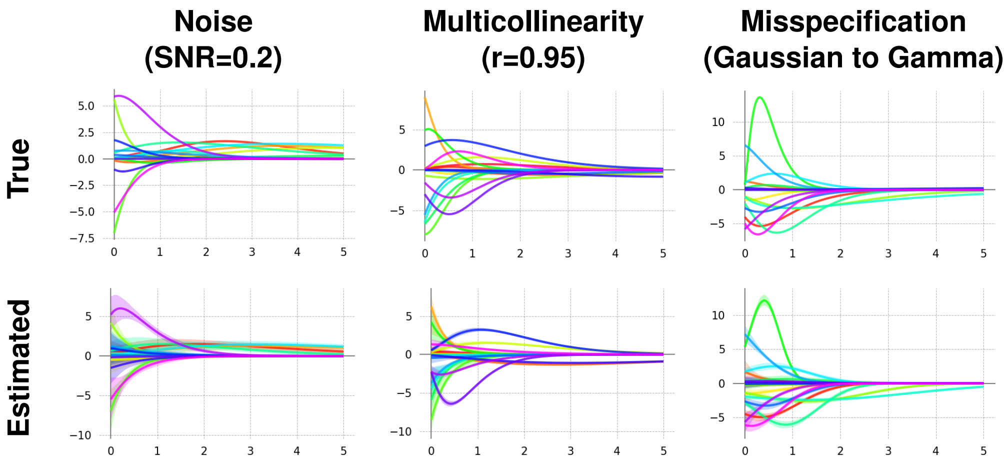

Figure 1: Representative synthetic results

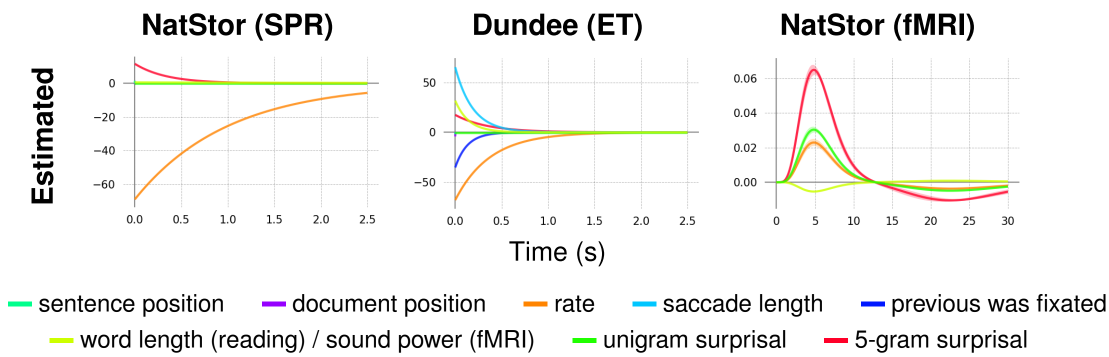

Figure 2: Representative psycholinguistic results. Exponential (reading) and 5-parameter double-gamma HRF (fMRI) kernels. Response (y-axis) is reading time (ms) for reading and BOLD for fMRI.

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