A generative model of EEG data

The core of the linear latent variable representation of EEG data is:

$$\mathbf{x}_{(l,r,p)}(n) = \left[\sum_{j=1}^{J} a^{j}_{(l,p)} \times \mathbf{c}^{j}_{(p)} \times f^{j}\Big(n + \theta^{j}_{(l,p)}\Big)\right] + \mathbf{y}_{(l,r,p)}(n).$$

In this formulation, $\mathbf{x}_{(l,r,p)}(n)$ is a matrix of EEG signal samples. The indices l, r, and p stand for conditions, trials, and participants, respectively, and n is the sampling time.

The most interesting factor for our purposes is the set of functions $f^j(\cdot)$. The function $f^j\left(n + \theta^j_{(l,p)}\right)$ indicates the contribution of the j^{th} ERP component at sampling time n. These ERP components are a set of elementary functional forms that together make up the basic EEG signal (averaged over the trials in condition l for participant p). Figure 1 provides an illustration using (only) three basic components—the N200, the P300, and the Readiness Potential—and Figure 2 illustrates the components with typical data from a representative participant. In the model equation, the shift parameter $\theta^j_{(l,p)}$ captures the latency of the j^{th} component relative to its stereotyped time course – for example, the N200 negative peak is expected to occur around 200ms, so if it in fact occurs at 160ms for participant p in condition l, then $\theta^{\mathrm{N200}}_{(l,p)} = -40$ms, as it is in Figure 1.

Rounding out the neuroelectric model are $\mathbf{c}^j_{(p)}$, the spatial pattern of ERP component j on participant p's scalp; $a^j_{(l,p)}$, the amplitude of ERP component j for condition l and participant p; and the error term $\mathbf{y}_{(l,r,p)}(n)$, which is a white noise series with mean zero and variance $\sigma^2_{(p)}$. The likelihood function of the neuroelectric side of the joint model is therefore a normal distribution whose mean is determined by the linear combination of ERP components. Wu et al. (2014) provide a detailed, efficient estimation method for the parameters of this model, but we will implement it ourselves in the Hamiltonian Monte Carlo engine Stan so that it can be made a component of a larger model.

Finally, to join the parameters of the neuroelectric model together with those of the cognitive model, they will be constrained by a system of linear equations that relies on the same latent variables Φ as do the cognitive parameters, but with their own loadings Λ, so that $\theta^{\mathrm{N200}} = \Phi\Lambda^{\mathrm{N200}}$ and $\theta^{\mathrm{RP}} = \Phi\Lambda^{\mathrm{RP}}$, while $\tau_e = \Phi\Psi^{\tau_e}$ and $\delta = \Phi\Psi^{\delta}$. This approach drastically reduces the number of free parameters in the model. Critically, the equations can be restated such that, if the "global" (i.e., not participant-specific) parameters Λ and Ψ are known, then the ERP components can be predicted from the cognitive model parameters and vice versa. For example, $\theta^{\mathrm{N200}} = \tau_e \left(\Psi^{\tau_e}\right)^{-1} \Lambda^{\mathrm{N200}}$ and $\tau_e = \theta^{\mathrm{N200}} \left(\Lambda^{\mathrm{N200}}\right)^{-1} \Psi^{\tau_e}$.

It is these *global loadings* Λ and Ψ—that represent population-level regularities—that are central to the generalizability tests in the following section. If, for example, the N200 latency does indeed reliably track the visual encoding time on a trial-by-trial basis, then these regularities should have the character of neurocognitive laws, and occur across stimuli, participants, and tasks.

References

Wu, W., Wu, C., Gao, S., Liu, B., Li, Y., & Gao, X. (2014). Bayesian estimation of erp components from multicondition and multichannel EEG. *NeuroImage*, *88*, 319 - 339.

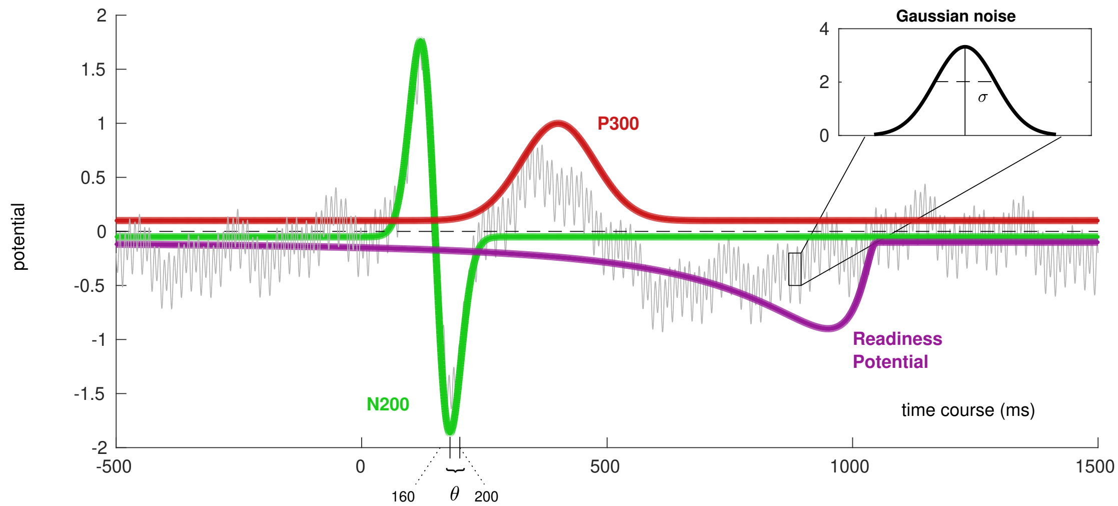

Figure 1. Three stereotypical waveforms (thick lines) and the resulting EEG time course (thinner lines). The latency of the N200 signal is indicated by the time interval θ.

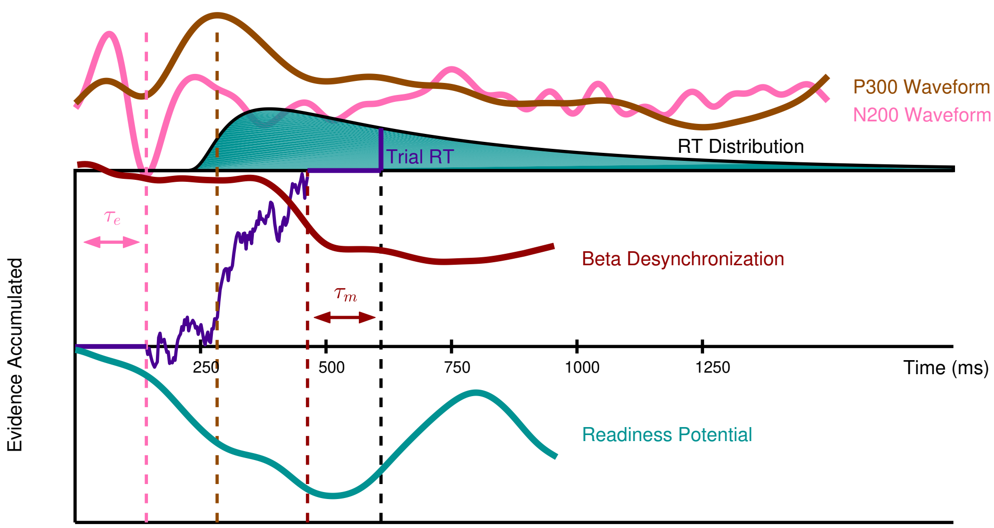

Figure 2. The proposed method of decomposing reaction time into component cognitive processes, using data from one real participant to illustrate the correspondence between the estimated model parameters and the event-related potentials. The data are from a randomly chosen participant and are typical and representative. Response time (RT) is decomposed into non-decision time (t_{em}) and decision time (t_d) from behavior alone. A simulated evidence accumulation time course for one trial is given by the jagged purple line and was generated from real estimates of diffusion model parameters for this participant. The combination of behavior and neural measures allows us to further decompose t_{em} into visual encoding time τ_e, encoded by the N200 peak latency in occipital electrodes (pink lines with the higher frequency noise waveform at the top), and motor response time (τ_m) encoded by the beta (14 -18 Hz) desynchronization in the contralateral motor cortex electrodes (red line in the middle). Similarly, t_d is encoded by the Readiness Potential (RP) in the contralateral motor cortex electrodes (teal lines near the bottom) with contribution by the P300 peak in parietal electrodes (brown lines with the slow waveform at the top) encoding stimulus evidence accumulation.