in vivo, Chapter 3 Basic Parameter Estimation Techniques

I've been working with memory models, and with models in the REM framework in particular, for over 15 years. The framework has core assumptions and many auxiliary assumptions that are combined into a model of a specific situation. I've fit REM models to many data sets and generated even more predictions. I'm going to share a little secret with you. I've never used the parameter estimation techniques described in this chapter (or any advanced approaches) when fitting REM. How can this be? There are three primary reasons.

First, these are complex simulation models. The techniques described here and elsewhere often get "stuck in the mud." Instead, we tend to use a simple grid search of a limited parameter space and a heavy dose of intuition. Good intuitions for a model's behavior take substantial time and are built in the same way that we build relationships with humans or dogs – by spending time playing together. I spent many days (and many nights) in my graduate school career running simulations, fiddling with parameters, and asking myself, "what if" questions that I answered by running yet another set of simulations. Once those intuitions are established, they are invaluable. These intuitions are an informal version of informative priors that might be used with Bayesian approaches covered in later chapters.

Second, the qualitative predictions of REM are heavily constrained by the structure and core assumptions of the model. In many circumstances, varying with a parameter value will change the quantitative outcome (e.g., increase or decrease accuracy) but not the qualitative outcome (e.g., pattern of predicted data in condition A vs condition B).

Third, I tend to focus on qualitative predictions. Evaluating a model based on how closely it fits a specific set of data has merits, no doubt. A common approach is to use parameter estimation techniques to find the best fit for a few competing models and then select the model from that set that has lowest discrepancy function (taking into account model complexity). That approach allows a couple of models to be excluded as the best account for a set of data. In many applications all models fit well, but one fits slightly better. Ruling out a model on this basis is not entirely satisfying because it *does* account for the data (and there is invariably another set of data where the model fits better than the competitors). Imagine instead a scenario where Model A predicts condition X > condition Y and Model B predicts condition Y > condition X. In this situation favoring the model that predicted the observed data is immensely satisfying because boundary conditions have been identified. Assuming the data replicate, the model predicting the opposite pattern simply cannot account for the data without modification.

I've tried to spend most of my research efforts investigating situations like this, where models make different qualitative predictions. Even if this is not possible in your modeling adventures, it is critical to look at how well the best fitting parameters fit the observed data. Sometimes quantitative methods can be misleading and you might find that the model fails to capture the qualitative pattern of data despite satisfying the quantitative criterion. In sum, parameter estimation techniques can be useful for obtaining quantitative fits, but quantitative fits only paint a small part of the picture. They do not show what pattern of data the model is predicting or why the model is making that prediction. You'll need to make use of intuitions and your knowledge about the situation to complete the masterpiece.

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