Title: With great data comes great (theoretical) opportunity

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Abstract: Is there a "critical period" for language? Using a viral online grammar test, Hartshorne, Tenenbaum, and Pinker (2018) collected a new massive dataset on the relationship between age and language learning. Their data highlight both the importance – and the challenges – of creating quantitative theories linking "big data" to cognitive models.

If you learn a language later in life, chances are you will not be mistaken for a native speaker. Your skills with the phonology and morphosyntax of the language are both likely giveaways that you are a later learner [1]. Lower ultimate attainment for later language learners is at the heart of a theoretical debate about the mechanisms of language learning. Is there a critical period – a window of plasticity – for learning some aspects of language [2], or does learning ability decline continuously throughout the lifespan [3]?

A fundamental set of confounds has plagued this research area: later learners start later (by definition), but they also spend less time learning and they learn in different contexts. Data about the competence and learning history of many thousands of individuals are required in order to tease these factors apart. Hartshorne, Tenenbaum, and Pinker [4] (henceforth, HTP) take a creative approach to this issue. They created a viral online language test, recruiting more than 600,000 participants to complete dozens of questions about English morphosyntactic structures. The resulting dataset is an unprecedented resource for understanding the complex interaction of factors in predicting morphosyntactic attainment. Combined with their open sharing of clearly-documented data, these features mean that HTP's work is a great example of what "big data" psychology could look like in the future.

When psychological theories come into contact with larger datasets, they often prove inadequate as the foundation for quantitative analyses [5]. HTP illustrate that this generalization is absolutely true for the critical period debate, showing that very different proposals about age-related change in learning abilities can give rise to nearly identical patterns of ultimate attainment. In particular, discontinuities in learning rate – which have been important in previous theorizing [1] – and more gradual shifts [3] can both have similar effects as they are smoothed out over a lifetime of learning. To address this issue, HTP pose a statistical model to recover the learning rate curve that best fits the measures of grammatical attainment they collected in their test. They find a modest discontinuity in learning rate around age 17, supporting the existence of a critical period – albeit one that closes much later than previously supposed [1, 2].

By formalizing the theoretical issues and bringing data to bear, HTP's work contributes substantially to the critical period debate, but the issue is certainly not yet resolved. First, their model is fit with a maximum-likelihood technique that does not quantify uncertainty in the parameters of the resulting curve; it is hard to rule out other curves with similar shapes but different theoretical import. Further, as with other studies of the critical period [1, 3], HTP's study is correlational. Due to the constraints of their viral format, they could not measure and control for important confounders of age like amount of language exposure or formal language education. Thus, the strongest inference – that age-related changes in learning *cause* declines in morphosyntactic attainment – still remains uncertain.

The introduction of bigger datasets in psychology highlights an important theoretical opportunity to bridge the gap between data-analytic statistical models and cognitive models [6]. Data-analytic models typically make use of generic statistical tools like linear regression for purposes of description and inference; in contrast, cognitive models instantiate hypotheses about particular underlying constructs. Building a bridge between the two requires careful work linking the data that are being collected to the specific constructs instantiated in the cognitive model. Psychometric modeling [7] is one neglected tool that can help connect data to theory by investigating how a specific set of test responses relate to a latent construct (in this case, morphosyntactic knowledge).

To illustrate the potential in this approach, I explored a psychometric model of HTP's data. Modern item response theory (IRT) models participants' latent ability as a parameter that leads to the observed pattern of responses on questions that have varying difficulty and diagnosticity. Figure 1A shows the distribution of latent grammatical ability estimates for test-takers from different language backgrounds, as recovered by a standard four-parameter IRT model [8]. A substantial proportion of every group has the highest latent ability estimated by the model.

This ceiling effect raises a fascinating theoretical issue. Does morphosyntactic knowledge continue to accumulate throughout the lifespan or is there a point at which we achieve full mastery of grammar? It is uncontroversial that there is no end to word learning: we keep learning low-frequency, specialized vocabulary like “agapanthus” and “lucubrate” all our life [9]. But perhaps grammar reaches an asymptote, after which we have learned all the rules necessary to become a “native speaker” [10]. HTP’s model is asymptotic and assumes such a fixed ceiling, but models that assume continued growth should also be investigated – and such models could be accompanied by even more sensitive tests of rare grammatical constructions.

One possible source of continued growth in grammar comes from formal education. In HTP’s data, even within the monolingual speakers, a higher level of education was related to faster development and a greater eventual level of latent ability (Figure 1B). Understanding the interactions between morphosyntactic testing and formal education is another important theoretical challenge for future work in this area.

In sum, through creative methodology and major effort, HTP have gathered a dataset that will keep theoreticians and modelers working for years to come. Understanding how these data reflect on the critical period hypothesis will require further formal work to develop models that link observed behavior to theoretical constructs. Psychometric theory may be an useful starting point for this development; other new tools will almost certainly be needed as well. One clear lesson from HTP's work, however, is that bigger data provide the opportunity to construct better theories.

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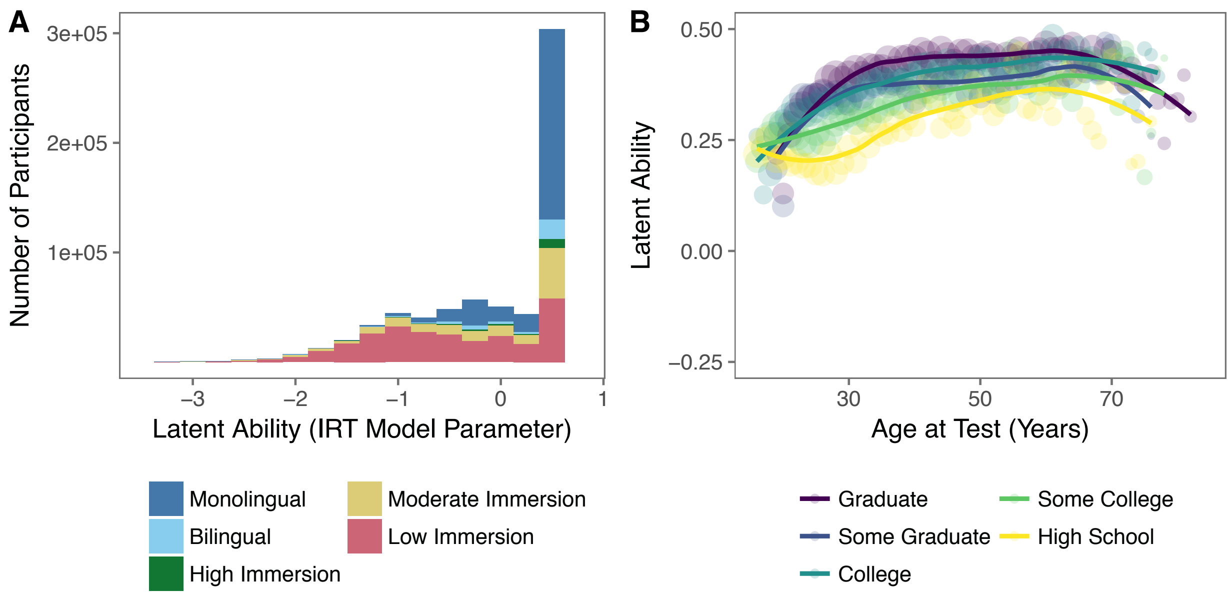

Figure 1. Exploring HTP's rich dataset using item response theory uncovers many rich facets of the data. (A) A histogram of latent-ability scores based on 4-parameter IRT model fits. Color shows participants' language status. (B) Latent ability scores for monolinguals, plotted by participant age and formal educatio. Dot size represents the log of number of observations; curves show loess smoothing functions.