## Toward a More Ecological Cognitive Neuroscience

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Human neuroscience has inherited a great deal of its methodology from psychology. We are trained to develop clever laboratory manipulations in hopes of discovering fundamental principles of brain function. In the past decade, however, there has been increasing concern about the "ecological validity" of our neuroscientific models. Tracing the historical development of this term led me to Brunswik's work (e.g., Brunswik, 1955). I'm sure anyone reading this is familiar with the sense of astonishment at finding something written over 60 years ago that's so pertinent to the problem at hand. In an effort to find points of contact between contemporary cognitive neuroscience and Brunswik's ideas, we recently published an opinion piece in the *NeuroImage* special issue on naturalistic neuroimaging (Nastase et al., 2020). In the following, I'll briefly describe the challenge of ecological validity in neuroscience, then highlight two modern parallels of Brunswik's ideas that we believe can provide a way forward.

Our neuroscientific models often grow out of a particular lineage of laboratory tasks designed to decompose a complex phenomenon into manageable subcomponents. There's an implicit assumption in much of our thinking and writing that the resulting models can be recomposed into a satisfying understanding of "real-world" brain function. Although this paradigm has led to a number of fundamental insights, we're left with a veritable zoo of piecemeal models that are difficult to synthesize and, considered individually, account for a disappointing amount of variance under natural conditions. We are trained to clamp or orthogonalize "confounding" variables in the laboratory, but these variables often interact in real-world contexts—and when we remove the experimental constraints, our measurements of neural activity sometimes recoil in unexpected ways. For example, the well-behaved orientation tuning observed in primary visual cortex (V1) during highly-controlled experiments has been shown to shift in response to natural images (David et al., 2004); in a similar vein, seemingly consistent responses to static face images diverge in response to dynamic, naturalistic videos (McMahon et al., 2015). These failures to generalize—due in part to biased stimulus sampling and a tendency toward easily-interpretable models—set off the alarm bells. Olshausen and Field (2005) famously cautioned that "we can rightfully claim to understand only 10% to 20% of how V1 actually operates under normal conditions." The challenge is this: the brain is shaped by evolution and learning to capitalize on the real-world regularities we often try to factor out in our experiments; and any brain variable we measure is contextualized not only by the history and motivation of the organism as well as the state of the environment, but also by countless other brain variables we cannot simultaneously measure.

How should the cognitive neuroscientist negotiate this challenge going forward? Brunswik argued that ecological generalizability demands a "representative sampling of situations" where "situational instances in an ecology are analogous to individuals in a population" (Brunswik, 1955, p. 198) and that the "challenge of further [isolating variables] must be met by after-the-fact, mathematical means" (Brunswik, 1955, pp. 202–203). This resonates with more recent arguments for "late commitment" (Kriegeskorte et al., 2008, p. 19) and "system identification" (Wu et al., 2006) in cognitive neuroscience, where theoretical assumptions are relaxed at the stage of experimental design and data collection, and hypotheses are formalized as quantitative models to be evaluated on naturalistic data. To date, many of our neuroscientific models hinge on small datasets specially manufactured by individual labs to address very particular questions. Advancing the field on this front will require large, naturalistic datasets to serve as public community benchmarks for model development and comparison (Rocca & Yarkoni, 2021). Our first step forward, then, is a pragmatic one: building on Brunswik's notion of representative design, we hope to share rich, naturalistic datasets and promote community-driven model development to cope with the complexity of our data and the multiplicity of models.

The second parallel pertains to the synthetic neuroscience emerging from the machine learning community. In recent years, we've seen a proliferation of neural network models that actually "work" in the real world—that is, end-to-end deep learning models that can reproduce complex human behaviors (such as language comprehension) strikingly well in uncontrolled, real-world contexts. These algorithmic models are a radical departure from the explanatory models traditionally developed in experimental neuroscience (for better or worse, marketability is a stronger "selection pressure" for machine learning models than interpretability). These are "functional" models in the sense that they receive messy, naturalistic inputs (e.g., photographs, text) and must ultimately learn to produce outputs—or "act"—in service of a complex objective (e.g., identifying faces, predicting forthcoming words). We can then interrogate what these models have learned, with variation across architectures, learning rules, and objective functions, and how their internal representations relate to those of the human brain (Richards et al., 2019). Although this new family of models is still in its infancy, we believe that deep learning has important parallels with ecological psychology and will yield unexpected insights into brain and behavior (Hasson et al., 2020).

I hope the reader will forgive our late arrival to Brunswik's work and will take the parallels highlighted here as a good-faith effort to draw inspiration from Brunswik's insights. If this work piques any interest, our published articles provide a more detailed treatment (Hasson et al., 2020; Nastase et al., 2020) and we welcome any feedback. These ideas are reverberating in the neuroscience community right now, and it seems like an opportune time for us to learn from those working in Brunswik's tradition.

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