Structure from Noise: Mental Errors Yield Abstract Representations of Events

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Our experience of the world is punctuated in time by discrete events, all connected by an architecture of hidden forces and causes. In order to form expectations about the future, one of the brain’s primary functions is to infer the statistical structure underlying past experiences (Hyman, 1953; Sternberg, 1969). In fact, even within the first year of life, infants reliably detect the frequency with which one phoneme follows another in spoken language (Saffran, Aslin, & Newport, 1996). By the time we reach adulthood, uncovering statistical relationships between items and events enables us to perform abstract reasoning (Bousfield, 1953), identify visual patterns (Fiser & Aslin, 2002), produce language (Friederici, 2005), develop social intuition (Gopnik & Wellman, 2012), and segment continuous streams of data into self-similar parcels (Reynolds, Zacks, & Braver, 2007).

Increasingly, the structure of transitions between events is conceptualized as a network (Schapiro, Rogers, Cordova, Turk-Browne, & Botvinick, 2013; Karuza, Kahn, Thompson-Schill, & Bassett, 2017; Kahn, Karuza, Vettel, & Bassett, 2017); and one natural way to interpret a sequence of events is as a random walk along this transition graph (Newman, 2003). It has long been known that people are sensitive to differences in transition probabilities (i.e., differences in the weights on edges in the transition network)—intuitively, people are surprised when they witness a rare transition (Saffran et al., 1996; Fiser & Aslin, 2002). Perhaps more interestingly, mounting evidence suggests that humans are also sensitive to the abstract, higher-order features of transition networks like clusters and communities, even when the transition probabilities are uniform (Schapiro et al., 2013; Karuza et al., 2017; Kahn et al., 2017). But how and why does the brain learn these abstract features? Does the inference of higher-order structures require sophisticated learning algorithms at the expense of precious mental resources? Or instead, does focusing on the coarse-grained architecture of a network allow us to ignore the fine-scale details, thereby conserving mental energy?

To answer these questions, here we propose a single driving hypothesis: that when building models of the world, the brain is finely-tuned to maximize accuracy while simultaneously minimizing the use of computational resources. From this simple assumption, we show that the free energy principle necessarily leads to a maximum entropy description of people’s internal expectations (Shannon, 1948; Friston, Kilner, & Harrison, 2006). As we vary the amount of statistical noise in the model, we find that higher-order features of the transition network organically come into focus while the fine-scale structure fades away, thus providing a concise mechanism explaining an array of previously observed network effects on human expectations (Schapiro et al., 2013; Karuza et al., 2017; Kahn et al., 2017). Importantly, our model admits a concise analytic form that aids intuition and, by learning the model parameters that describe a particular individual, can be used to predict human behavior on a person-by-person basis. Additionally, our model asserts that human expectations should depend critically on the different topological scales in a transition network, a prediction that we subsequently test and validate in a novel experiment.

Generally, our results highlight the important role of mental errors in shaping abstract representations, and directly inspire new physically-motivated models of human behavior. We emphasize that this focus on mental errors stands in stark contrast to the prevailing intuition in reinforcement learning and cognitive science that the human brain is optimized to identify complex patterns (Fiser & Aslin, 2002; Reynolds et al., 2007) and maximize prediction accuracy (Stachenfeld, Botvinick, & Gershman, 2017; Momennejad et al., 2017). More broadly, the surprising role of statistical noise in shaping human expectations highlights the value of simple thermodynamic models for understanding cognition, with real-world applications from learning (Schapiro et al., 2013; Karuza et al., 2017; Kahn et al., 2017) and planning (Stachenfeld et al., 2017; Momennejad et al., 2017) to diagnosing and treating psychiatric disorders (Montague, Hyman, & Cohen, 2004; Maia & Frank, 2011).

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