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Emerging techniques in statistical analysis of neural data

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Global initiatives to study the brain have led to the emergence of new neurotechnologies that probe and manipulate the brain at multiple scales, from neuromodulators to cells to systems, at fine temporal resolution. Availability of these new data has in turn led to the emergence of a new field of computational and data-intensive neuroscience. At the cellular level, the traditional micro-electrode recordings in which the activity of one (or a few) cells at a time are observed are giving space to optogenetics methods that will allow simultaneous recordings from hundreds of task-related cells in an awake behaving animal. Although these data are extremely rich in information, they come with substantial constraints, like missing data (*e.g.* task related neurons that are not included in the observation set) and noisy data (*e.g.* neurons that are observed but not task related).

Traditional statistics used to make inferences and test hypotheses no longer apply, or at the very least need to be adapted to the new paradigms. The neuroscientist today, and even more tomorrow, will require big data science techniques to glean meaningful information from such data. The techniques however must not replace but must enhance the way we model and control neural systems. Mechanistic and statistical models must be developed to understand and explain observed data. Such models can also be used to estimate latent variables (other neural or behavioral signals) that correlate with measured data. For example, state-space models are used to understand how latent variables (states) influence neural and behavioral measurements or to simply explain how and why control systems in the central nervous system operate the way they do.

This special issue includes pioneering studies that describe methods to sift through large amounts of data to identify brain regions and frequency bands of interest (Breault et al. 2018); to construct models from multi-scale neural data ranging from spike trains from individual neurons (Chen et al. 2018, Zhang et al. 2018) to EEG recordings from populations of neurons (Talukdar et al. 2018); and to decode behavior from neural data (Han et al. 2018), with applications to neuroprosthetics and brain-machine interfaces. Network connectivity studies in the contexts of brain state changes (Luckett et al. 2018, Xiao et al. 2018) and language are also presented (Grappe et al. 2018).

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