DSN Journal paper outline

Title: Enhancing theoretical neuroscience with implicit model inversion

Abstract:
Theoretical neuroscientists design and test models of neural computation, assessing a models quality by its recapitulation of experimentally recorded neural activity. In idealized practice of theory, scientists analytically derive the model parameterizations that produce the emergent properties signifying a neural computation. However, the nonlinear dynamical nature of most neural models prohibits such convenient analyses, resulting in the prevalence of simulation analyses in theoretical neuroscience. These mathematical challenges are exacerbated by the trending growth in model complexity as neuroscientists study increasingly complex behaviors. To invert these complex implicit models, which lack an explicit likelihood function, we introduce a novel machine learning methodology, <method> which learns full (maximum entropy) parameter distributions conditioned on theoretician-defined emergent properties. Note SB: I think we should expand on context of <method> in bayesian ML in introduction We demonstrate how <method> facilitates exploratory analyses, scientific hypothesis testing, and experimental design beyond modern practices in models of the stomatogastric ganglion (STG), primary visual cortex (V1), superior colliculus (SC), and recurrent neural networks (RNNs).

Some extra boilerplate:
Idealized theoretical neuroscience entails analytical derivations of how model parameters govern system activity. So naturally, emergent property definition and model design are guided by the interest of analytic convenience. Even so, as theorists work to explain neural computations of increasing complexity, the models become necessarily more complex, and key model properties become analytically intractable with respect to the parameterization. To invert these complex implicit models, which lack an explicit likelihood function, we leverage recent machine learning research enabling likelihood-free inference,

Introduction:
Theory is great and has been useful to neuroscience because of its adoption of technology.

- <2-3 nice statement about the contribution of theory to neuroscience with references to Abbott 2008 and major contributions. >

- Developing a theory for a particular neural computation involves a.) mathematically defining the emergent properties of the neural activity that signify the computation, b.) designing a parameterized model of the brain area(s) executing the computation, and then c.) characterizing the model parameters that produce these emergent properties.

- Talk about workflow of theoretical neuroscience

- Reference historic adoption of tools to improve practice

- Last sentence suggests there are current challenges we can get around with modern ML.

Next para.

- haha