This work seeks to clarify an important incongruity between theoretical approaches to neuroscience and existing statistical inference methodology.

In theoretical neuroscience, we are concerned with the computational properties -- the \emph{emergent phenomena} -- of our models \cite{hopfield1982neural, sompolinsky1988chaos, tsodyks1997paradoxical, wong2006recurrent}, not noisy observed datasets \cite{paninski2018neural}.

One preferred formalism for parameter identification is statistical inference, which has been used to great success in neuroscience through the stipulation of statistical generative models \cite{kass2001spike, brown1998statistical, paninski2004maximum, truccolo2005point, schneidman2006weak, druckmann2007novel, turner2007maximum, byron2009gaussian, macke2011empirical, park2011bayesian, granot2013stimulus, latimer2015single, lakshminarasimhan2018dynamic, duncker2019learning, ladenbauer2019inferring} (see review, \cite{paninski2018neural}).

Recent work has used variational autoencoders (VAEs) \cite{kingma2013auto, rezende2014stochastic} to interrogate hidden states in models of both cortical population activity \cite{gao2016linear, zhao2017recursive, barello2018sparse, pandarinath2018inferring} and animal behavior \cite{wiltschko2015mapping, johnson2016composing, batty2019behavenet}, thus expanding the domain of neural data sets amenable to statistical modeling.

However, most neural circuit models in theoretical neuroscience are noisy systems of differential equations that can only be sampled or realized through forward simulation; they lack the explicit likelihood necessary for statistical inference.

Therefore, the most popular approaches to theoretical inverse problems have been likelihood-free inference (LFI) methods \cite{sisson2007sequential, liepe2014framework}, in which reasonable parameters are obtained via simulation and rejection.

A flourishing new class of techniques \cite{gonccalves2019training, papamakarios2019sequential, hermans2020likelihood} use deep learning to improve upon traditional LFI approaches.

However, as we detail, all of these approaches require good datasets for the scientific question at hand.

To use the aforementioned inference paradigm, scientists must shoehorn such mathematical criteria into an artificial dataset compatible with existing statistical approaches.

Theorists are therefore barred from using the probabilistic modeling toolkit for science, unless they reformulate their inverse problem to fit an evidence accumulation framework.