Interrogating theoretical models of neural computation with deep inference

Sean R. Bittner[1], Agostina Palmigiano[1], Alex T. Piet[2,3,4], Chunyu A. Duan[5], Carlos D. Brody[2,3,6], Kenneth D. Miller[1], and John P. Cunningham[7].

[1]Department of Neuroscience, Columbia University,

[2]Princeton Neuroscience Institute,

[3]Princeton University,

[4]Allen Institute for Brain Science,

[5]Institute of Neuroscience, Chinese Academy of Sciences,

[6]Howard Hughes Medical Institute,

[7]Department of Statistics, Columbia University

1 Abstract

A cornerstone of theoretical neuroscience is the circuit model: a system of equations that captures a hypothesized neural mechanism. Such models are valuable when they give rise to an experimentally observed phenomenon – whether behavioral or a pattern of neural activity – and thus can offer insights into neural computation. The operation of these mechanistic circuits, like all models, critically depends on the choices of model parameters. A key process in neuroscientific modeling is then to identify the model parameters consistent with observed phenomena: to solve the inverse problem. While statistical inference has proven effective on a broad variety of neuroscientific datasets, we clarify an important incongruity between theoretical approaches to neuroscience and this probabilistic methodology. Theoretical neuroscience is focused on computational properties and how they emerge from biological mechanisms, rather than noisy experimental datasets and their quantified structure. In this work, we present a novel technique to directly infer circuit model parameters producing these computational properties. This method tailors deep inference, the use of deep neural networks for statistical inference, to the nature of theoretical inverse problems, enabling scaling to high dimensions and considerable technical simplifications. With this method, we bring deep inference to bear on important questions in theoretical neuroscience, and demonstrate the broad range of insightful analyses this approach allows. First, we emphasize the general applicability of this approach by inferring channel conductance parameters that produce a distinctive spiking frequency in a biophysical model of the stomatogastric ganglion. Then, in a model of primary visual cortex with multiple neuron-types, where analysis becomes untenable as more

neuron-types are included, we use this technique to discover how noise properties govern excitatory population variability. Next, in a model of superior colliculus, we identify and characterize two distinct regimes of connectivity that facilitate switching between opposite tasks throughout interleaved trials. Finally, we scale inference to 1,000-dimensional parameter spaces of RNN connectivity that exhibit stable, yet amplified responses. These analyses illustrate how we can further leverage the power of deep learning towards solving inverse problems in theoretical neuroscience.

2 Introduction

The fundamental practice of theoretical neuroscience is to use a mathematical model to understand neural computation, whether that computation enables perception, action, or some intermediate processing. A neural circuit is systematized with a set of equations – the model – and these equations are motivated by biophysics, neurophysiology, and other conceptual considerations [1, 2, 3, 4]. The function of this system is governed by the choice of model *parameters*, which when configured in a particular way, give rise to a measurable signature of a computation. The work of analyzing a model then requires solving the inverse problem: given a computation of interest, how can we reason about particular parameter configurations? The inverse problem is crucial for reasoning about likely parameter values, uniquenesses and degeneracies, and predictions made by the model [5, 6].

Consider the idealized practice: one carefully designs a model and analytically derives how computational properties determine model parameters. Seminal examples of this gold standard (which often adopt approaches from statistical physics) include our field's understanding of memory capacity in associative neural networks [7], chaos and autocorrelation timescales in random neural networks [8], the paradoxical effect [9], and decision making [10]. Unfortunately, as circuit models include more biological realism, theory via analytical derivation becomes intractable. Alternatively, we can gain insight into these complex models by identifying the distribution of parameters that produce a specific computational property. By solving the inverse problem in this way, scientific analysis of complex biologically realistic models is made possible [11, 12, 13, 6, 14].

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 [15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29] (see review, [30]). Recent work has used variational autoencoders (VAEs) [33, 34] to interrogate hidden states in models of both cortical population

activity [35, 36, 37, 38] and animal behavior [39, 40, 41], 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 [31, 32], in which reasonable parameters are obtained via simulation and rejection. A flourishing new class of techniques [75, 89, 90] 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.

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 *emergent phenomena* – of our models [7, 8, 9, 10], not noisy observed datasets [30]. 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.

These challenges motivate the development of a novel inference framework called emergent property inference (EPI). As an adaption of variational inference [46], EPI infers parameter distributions that produce an emergent property: not a singular dataset, but a collection of datasets exhibiting some mathematical criteria. EPI fixates on the inverse problem by constraining the predictions of the inferred parameter distribution to produce the emergent property exactly. Conditioning on an emergent property requires a variant of deep probabilistic inference methods, which we have previously introduced [52]. By using deep probability distributions EPI flexibly captures parametric structure in mechanistic models. This technique is designed to identify the full parameter space producing an emergent property and facilitate the seemless structural analysis of the inferred parameter distribution. Thus, EPI provides neuroscientists with an efficient, versatile probabilistic modeling toolkit designed explicitly for theoretical inverse problems.

Equipped with this method, we bring deep inference to bear on theoretical neuroscience to an unprecedented extent. Throughout this work, we showcase the capabilities of EPI on four neural circuit models across ranges of biological realism, neural system function, and network scale. First, we show EPI's ability to capture subtle, nonlinear parametric structure in a stomatogastric ganglion subcircuit model [57]. In a model of primary visual cortex [72], we show how to gain insight from

multiple inferred distributions. Next, we used EPI to idenitfy and structurally characterize multiple parametric regimes of superior colliculus activity in a model of task switching [55]. Finally, we emphasize the superior scalability of EPI compared to other LFI techniques by inferring high-dimensional distributions of RNN connectivities that exhibit amplified, yet stable responses – a hallmark of cortical sensory systems [**?**, 74].

Most importantly of all in this work, we present novel theories of neural computation borne from EPI analysis. We identified an unknown parametric rule of variability with respect to inhibitory neuron type in a V1 model, where analytic techniques became untenable. Furthermore, we identified multiple regimes of SC connectivity which confer rapid task switching, and used the structural analytic tools of EPI to gain a mechanistic understanding of circuit responses. These valuable theoretical insights illustrate the value of deep inference for the interrogation of neural circuit models.

3 Results

3.1 Motivating emergent property inference of theoretical models

Consideration of the typical workflow of theoretical modeling clarifies the need for emergent property inference. First, one designs or chooses an existing model that, it is hypothesized, captures the computation of interest. To ground this process in a well-known example, consider the stomatogastric ganglion (STG) of crustaceans, a small neural circuit which generates multiple rhythmic muscle activation patterns for digestion [56]. Despite full knowledge of STG connectivity and a precise characterization of its rhythmic pattern generation, biophysical models of the STG have complicated relationships between circuit parameters and neural activity [53, 12]. A subcircuit model of the STG [57] is shown schematically in Figure 1A, and note that the behavior of this model will be critically dependent on its parameterization – the choices of conductance parameters $\mathbf{z} = [g_{\text{el}}, g_{\text{synA}}]$. Specifically, the two fast neurons ($f1$ and $f2$) mutually inhibit one another, and oscillate at a faster frequency than the mutually inhibiting slow neurons ($s1$ and $s2$). The hub neuron (hub) couples with either the fast or slow population or both.

Second, once the model is selected, one defines the emergent phenomena of scientific interest. In the STG example, we are concerned with neural spiking frequency, which emerges from the dynamics of the circuit model 1B. An interesting emergent property of this stochastic model is when the hub neuron fires at an intermediate frequency between the intrinsic spiking rates of the fast and slow

populations. This emergent property is shown in Figure 1C at an average frequency of 0.55Hz.

Third, parameter analyses ensue: brute-force parameter sweeps, ABC sampling [32], and sensitivity analyses [96] are all routinely used to reason about what parameter configurations lead to an emergent property. In this last step lies the opportunity for a precise quantification of the emergent property as a statistical feature of the model. Once we have such a methodology, we can infer a probability distribution over parameter configurations that produce this emergent property.

Before presenting technical details (in the following section), let us understand emergent property inference schematically: EPI (Fig. 1D) takes, as input, the model and the specified emergent property, and as its output, produces the parameter distribution EPI (Fig. 1E). This distribution – represented for clarity as samples from the distribution – is then the most random parameter distribution producing the emergent property. In the STG model, this distribution can be specifically queried to reveal the prototypical parameter configuration for intermediate hub frequency (the mode; Figure 1E yellow star), and how it decays based on changes away from the mode. Indeed, samples equidistant from the mode along these EPI-identified dimensions of sensitivity (v_1) and degeneracy (v_2) (Fig. 1E, arrows) agree with error contours (Fig. 1E contours) and have diminished or preserved hub frequency, respectively (Fig. 1F activity traces) (see Section 5.2.1).

3.2 A deep generative modeling approach to emergent property inference

Emergent property inference (EPI) formalizes the three-step procedure of the previous section with deep probability distributions. First, we consider the model as a coupled set of differential equations [57]. In the running STG example, the model activity $\mathbf{x} = [x_{\text{f1}}, x_{\text{f2}}, x_{\text{hub}}, x_{\text{s1}}, x_{\text{s2}}]$ is the membrane potential for each neuron, which evolves according to the biophysical conductance-based equation:

$$C_m \frac{d\mathbf{x}(t)}{dt} = -h(\mathbf{x}(t); \mathbf{z}) + d\mathbf{B} \tag{1}$$

where C_m=1nF, and $\mathbf{h}$ is a sum of the leak, calcium, potassium, hyperpolarization, electrical, and synaptic currents, all of which have their own complicated dependence on $\mathbf{x}$ and $\mathbf{z} = [g_{\text{el}}, g_{\text{synA}}]$, and $d\mathbf{B}$ is white gaussian noise (see Section 5.2.1).

Second, we define the emergent property, which as above is "intermediate hub frequency" (Figure 1C). Quantifying this phenomenon is straightforward: we stipulate that the hub neuron's spiking frequency – denoted $\omega_{\text{hub}}(\mathbf{x})$ is close to a frequency of 0.55Hz. Mathematically, we achieve this

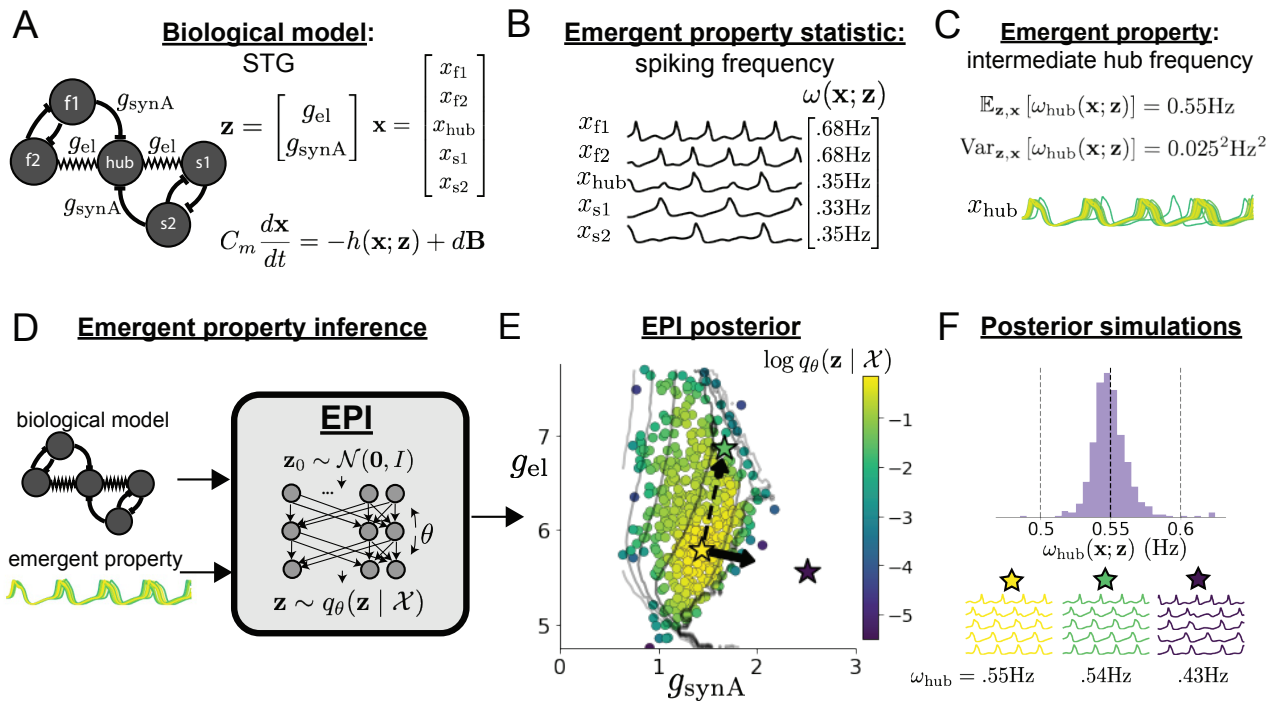

Figure 1: Emergent property inference (EPI) in the stomatogastric ganglion. **A**. Conductance-based biophysical model of the STG subcircuit. In the STG model, jagged connections indicate electrical coupling having electrical conductance g_{el}. Other connections in the diagram are inhibitory synaptic projections having strength g_{synA} onto the hub neuron, and $g_{\text{synB}} = 5\text{nS}$ for mutual inhibitory connections. Parameters are represented by the vector $\mathbf{z}$ and membrane potentials by the vector $\mathbf{x}$. The evolution of this model's activity $\mathbf{x}(t)$ is predicated by differential equations. **B**. Spiking frequency $\omega(\mathbf{x}; \mathbf{z})$ is an emergent property statistic. In this example, spiking frequency is measured from simulated activity of the STG model at parameter choices of $g_{\text{el}} = 4.5\text{nS}$ and $g_{\text{synA}} = 3\text{nS}$. **C**. The emergent property of intermediate hub frequency, in which the hub neuron fires at a rate between the fast and slow frequencies. This emergent property is defined by a mean and variance on the emergent property statistic. Simulated activity traces are colored by log probability density of their generating parameters in the EPI-inferred distribution (Panel E). **D**. For a choice of model and emergent property, emergent property inference (EPI) learns a deep probability distribution of parameters $\mathbf{z}$. Deep probability distributions map a simple random variable $\mathbf{z}_0$ through a deep neural network with weights and biases $\boldsymbol{\theta}$ to parameters $\mathbf{z} = g_{\boldsymbol{\theta}}(\mathbf{z}_0)$. In EPI optimization, stochastic gradient steps in $\boldsymbol{\theta}$ are taken such that entropy is maximized, and the emergent property $\mathcal{X}$ is produced. The EPI posterior distribution is denoted $q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X})$. **E**. The EPI posterior producing intermediate hub frequency. Samples are colored by log probability density. Distribution contours of average hub neuron frequency from mean of .55 Hz are shown at levels of .525, .53, ... .575 Hz (dark to light gray away from mean). Eigenvectors of the Hessian at the mode of the inferred distribution are indicated as $\mathbf{v}_1$ (solid) and $\mathbf{v}_2$ (dashed) with lengths scaled by the square root of the absolute value of their eigenvalues. **F** Simulations from parameters in E. (Top) The predictive distribution of the posterior obeys the emergent property. The black and gray dashed lines show the mean and two standard deviations according the emergent property, respectively. (Bottom) Simulations at the starred parameter values.

with two constraints: by setting the mean hub frequency of model generated activity to 0.55Hz.

$$\mathbb{E}_{\mathbf{z},\mathbf{x}}\left[\omega_{\text{hub}}(\mathbf{x};\mathbf{z})\right] \quad = \quad \left[0.55\right] \tag{2}$$

and requiring that the variance around this mean is small

$$\text{Var}_{\mathbf{z},\mathbf{x}}\left[\omega_{\text{hub}}(\mathbf{x};\mathbf{z})\right] \quad = \quad \left[0.025^2\right]. \tag{3}$$

This level of variance was chosen to be low enough to exclude the fast and slow frequencies of the two populations, but large enough to allow structural examination of the compatible parameter space. In general, an emergent property

$$\mathcal{X}: \quad \mathbb{E}_{\mathbf{z},\mathbf{x}}\left[f(\mathbf{x};\mathbf{z})\right] = \boldsymbol{\mu}, \text{Var}_{\mathbf{z},\mathbf{x}}\left[f(\mathbf{x};\mathbf{z})\right] = \boldsymbol{\sigma}^2 \tag{4}$$

defines a collection of datasets with a statistic $f(\mathbf{x};\mathbf{z})$ (which may be comprised of multiple statistics) and the means $\boldsymbol{\mu}$ and variances $\boldsymbol{\sigma}^2$ of those statistics over the datasets. The choice of $\boldsymbol{\sigma}^2$ predicates the degree of variability in around mean $\boldsymbol{\mu}$ that is consistent with the emergent property.

Third, we perform emergent property inference: we find a distribution over parameter configurations $\mathbf{z}$, and insist that samples from this distribution produce the emergent property; in other words, they obey the constraints introduced in Equation 4. This distribution will be chosen from a family of probability distributions $\mathcal{Q} = \{q_{\boldsymbol{\theta}}(\mathbf{z}) : \boldsymbol{\theta} \in \Theta\}$, defined by a deep generative distribution of the normalizing flow class [47, 50, 51] – neural networks which transform a simple distribution into a suitably complicated distribution (as is needed here). This deep distribution is represented in Figure 1D (see Section 5.1). Many distributions in $\mathcal{Q}$ will respect the emergent property constraints, so we choose a normative selection principle imposing no additional structure beyond the production of the emergent property [58, 59, 52, 60], which is the same normative principle of Bayesian inference (see Section 5.1.6).

The probabilities of the distribution inferred from EPI are the densities of these parameters in the most random distribution producing the emergent property. While existing approaches to probabilistic structural identifiability analysis use the lens of evidence accumulation [96, 75], sensitivity and robustness of parameter space dimensions with respect to emergent phenomena can be directly quantified with EPI. Sensitivity quantifications are measured by the second order derivative of EPI probability along the parameteric dimension of interest: to what extent is the emergent property maintained or diminished along this dimension? Once an EPI distribution has been inferred, this second order derivative requires trivial computation (as long as the correct architecture class is

chosen, see Section 5.1.2). Equipped with this method, we may examine structure in the resulting parameter distributions or make comparisons between distributions conditioned at different levels of the same emergent property statistic. In Sections 3.3 and 3.4, we prove out the value of EPI by using these techniques to investigate and produce novel scientific insight.

3.3 EPI reveals how neuron-type specific noise governs variability in the stochastic stabilized supralinear network

Dynamical models of excitatory (E) and inhibitory (I) populations with supralinear input-output function have succeeded in explaining a host of experimentally documented phenomena. In a regime characterized by inhibitory stabilization of strong recurrent excitation, these models give rise to paradoxical responses [9], selective amplification [61, 62], surround suppression [63] and normalization [64]. Despite their strong predictive power, E-I circuit models rely on the assumption that inhibition can be studied as an indivisible unit. However, experimental evidence shows that inhibition is composed of distinct elements – parvalbumin (P), somatostatin (S), VIP (V) – composing 80% of GABAergic interneurons in V1 [65, 66, 67], and that these inhibitory cell types follow specific connectivity patterns (Fig. 2A) [68]. Recent theoretical advances [54, 69, 70], have only started to address the consequences of this multiplicity in the dynamics of V1, strongly relying on linear theoretical tools. Here, we use EPI to analyze V1 models of greater complexity in order to characterize properties of slow noise governing circuit variability.

We considered the response properties of a nonlinear dynamical V1 circuit model (Fig. 2A) with a state comprised of each neuron-type population's rate $\mathbf{x} = [x_E, x_P, x_S, x_V]^\top$. Each population receives recurrent input $W\mathbf{x}$ from synaptic projections of effective connectivity W and an external input $\mathbf{h}$, which determine the population rate via supralinear nonlinearity $\phi = []_+^2$. The input is also comprised of a slow noise component $\boldsymbol{\epsilon} \sim OU\left(\tau_{\text{noise}}, \boldsymbol{\sigma}\right)$ of time scale $\tau_{\text{noise}} > \tau$ and variance parameters $\boldsymbol{\sigma}$ (see Section 5.2.2)

$$\tau \frac{d\mathbf{x}}{dt} = -\mathbf{x} + \phi(W\mathbf{x} + \mathbf{h} + \boldsymbol{\epsilon}). \tag{5}$$

This model is the stochastic stabilized supralinear network (SSSN) [71] generalized to have inhibitory multiplicity, and introduces stochasticity to previous four neuron-type models of V1 [54]. Stochasticity and inhibitory multiplicity introduce substantial complexity to mathematical derivations (see Section 5.2.3) motivating the treatment of this model with EPI. Here, we consider fixed weights W and input $\mathbf{h}$ according to a fit of the deterministic model to contrast responses [72] (Fig.

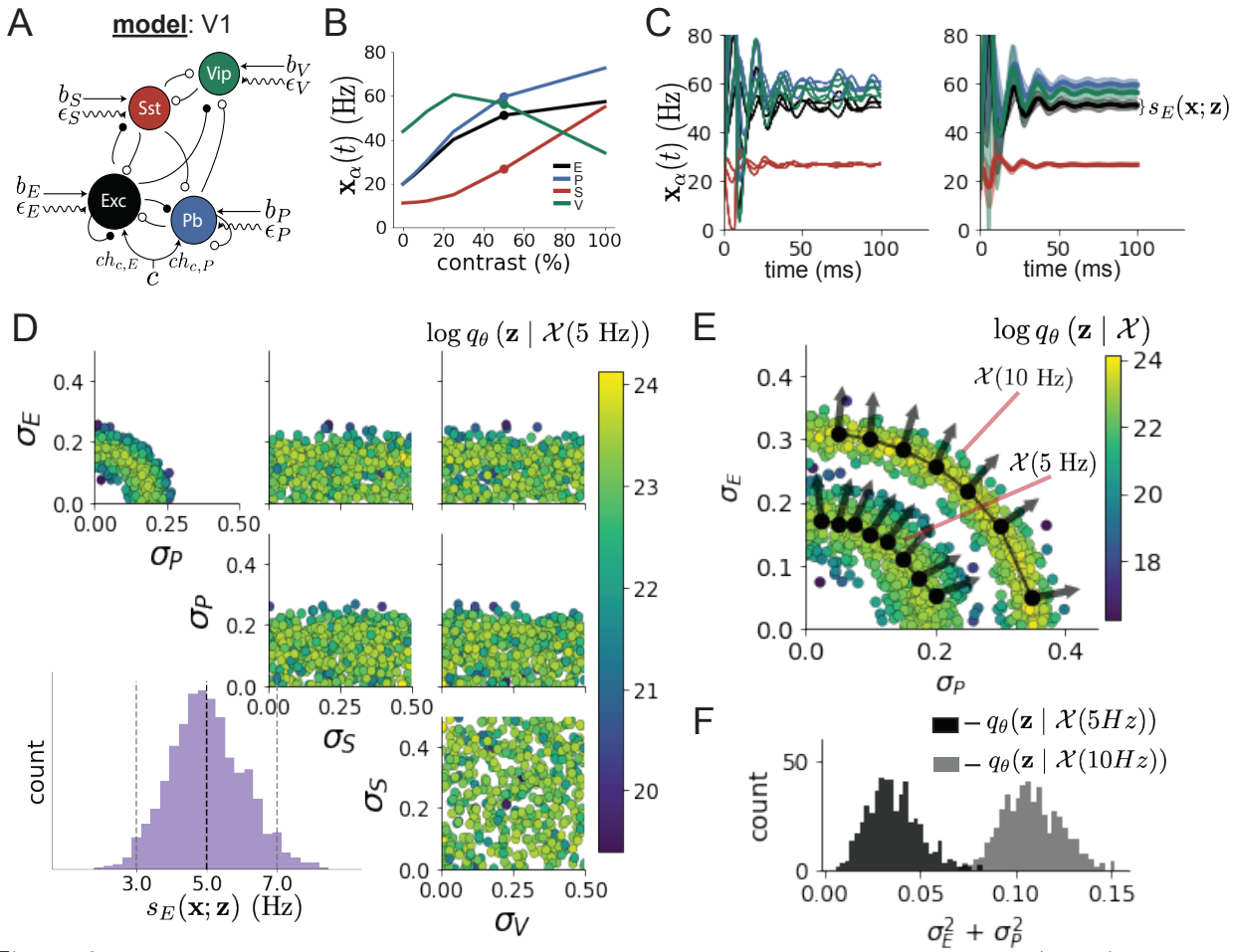

Figure 2: Emergent property inference in the stochastic stabilized supralinear network (SSSN) **A**. Four-population model of primary visual cortex with excitatory (black), parvalbumin (blue), somatostatin (red), and VIP (green) neurons (excitatory and inhibitory projections filled and unfilled, respectively). Some neuron-types largely do not form synaptic projections to others ($|W_{\alpha_1,\alpha_2}| < 0.025$). Each neural population receives a baseline input $\mathbf{h}_b$, and the E- and P-populations also receive a contrast-dependent input $\mathbf{h}_c$. Additionally, each neural population receives a slow noisy input $\boldsymbol{\epsilon}$. **B**. Steady-state responses of the SSN model (deterministic, $\boldsymbol{\sigma} = \mathbf{0}$) to varying contrasts. The response at 50% contrast (dots) is the focus of our analysis. **C**. Transient network responses of the SSSN model at 50 % contrast. (Left) Traces are independent trials with varying initialization $\mathbf{x}(0)$ and noise realization. (Right) Mean (solid line) and standard deviation (shading) of responses. **D**. EPI posterior of noise parameters $\mathbf{z}$ conditioned on E-population variability. The posterior predictive distribution of $s_E(\mathbf{x};\mathbf{z})$ is show on the bottom-left. **E**. (Top) Enlarged visualization of the σ_E-σ_P marginal distribution of the posteriors $q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X}(5 \text{ Hz})$ and $q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X}(10 \text{ Hz})$. Each black dot shows the mode at each σ_P. The arrows show the most sensitive dimensions of the Hessian evaluated at these modes. **F**. The predictive distributions of $\sigma_E^2 + \sigma_P^2$ of each posterior $q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X}(5 \text{ Hz})$ and $q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X}(10 \text{ Hz})$.

2B), and study the effect of noise parameterization $\mathbf{z} = [\sigma_E, \sigma_P, \sigma_S, \sigma_V]^\top$ on fluctuations at 50% contrast.

For this SSSN, we are interested in how noise variability across neural populations governs stochastic fluctuations in the E-population. Here, we quantify different levels y of E-population variability with the emergent property

$$\begin{aligned} \mathcal{X}(y) \quad : \quad \mathbb{E}_{\mathbf{z}}\Big[s_E(\mathbf{x};\mathbf{z})\Big] &= y \\ \mathrm{Var}_{\mathbf{z}}\Big[s_E(\mathbf{x};\mathbf{z})\Big] &= 1\mathrm{Hz}^2, \end{aligned} \tag{6}$$

where $s_E(\mathbf{x};\mathbf{z})$ is the standard deviation of the stochastic E-population response about its steady state (Fig. 2C).

We ran EPI to obtain a posterior distribution $q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X}(5 \text{ Hz})$ producing E-population variability around 5 Hz (Fig. 2D). From the marginal distribution of σ_E and σ_P (Fig. 2D, top-left), we can see that $s_E(\mathbf{x};\mathbf{z})$ is sensitive to various combinations of σ_E and σ_P. Alternatively, both σ_S and σ_V are degenerate with respect to $s_E(\mathbf{x};\mathbf{z})$ evidenced by the high variability in those dimensions of the posterior (Fig. 2D, bottom-right). Together, these observations imply a parametric manifold of degeneracy with respect to $s_E(\mathbf{x};\mathbf{z})$ of 5 Hz, which is indicated by the modes along σ_P in the σ_E-σ_P marginal (Fig. 2E). The dimensions of sensitivity conferred by EPI and this plain visual structure suggest a quadratic relationship in the emergent property statistic $s_E(\mathbf{x};\mathbf{z})$ and parameters $\mathbf{z}$, which is preserved at a greater level of variability $\mathcal{X}(10 \text{ Hz})$ (Fig. 2E). Indeed, the sum of squares of σ_E and σ_P is larger in $q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X}(10 \text{ Hz})$ than $q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X}(5 \text{ Hz})$ (Fig 2F, $p = 0$), while the sum of squares of σ_S and σ_V are not significantly different in the two posteriors (Fig. 11, $p = .402$).

While a quadratic relationship in $s_E(\mathbf{x};\mathbf{z})$ and $\mathbf{z}$ is potentially derivable by extending the derivation in Section 5.2.2 to the case of $\tau \neq \tau_{\text{noise}}$, the coefficients in front of each quadratic term would be unruly, and likely escape comprehensible analysis. This makes EPI an attractive tool for revealing the characteristics of noise governing variability and for answering other questions in this complex model. Intriguingly, this circuit exhibited a paradoxical effect in the P-population, and no other inhibitory types at 50% contrast (Fig. 11) implying that the E-population is P-stabilized. Future work motivated by our analysis here, may uncover a relationship between the neuron-type mediating stability and the factors governing circuit variability.

3.4 EPI identifies multiple regimes of rapid task switching

In a rapid task switching experiment [73], rats were explicitly cued on each trial to either orient towards a visual stimulus in the Pro (P) task or orient away from a visual stimulus in the Anti (A) task (Fig. 3A). Neural recordings in the midbrain superior colliculus (SC) exhibited two populations of neurons that simultaneously represented both task context (Pro or Anti) and motor response (contralateral or ipsilateral to the recorded side): the Pro/Contra and Anti/Ipsi neurons [55]. Duan et al. proposed a model of SC that, like the V1 model analyzed in the previous section, is a four-population dynamical system. We analyzed this model, where the neuron-type populations are functionally-defined as the Pro- and Anti-populations in each hemisphere (left (L) and right (R)), their connectivity is parameterized geometrically (Fig. 3B). The input-output function of this model is chosen such that the population responses $\mathbf{x} = [x_{LP}, x_{LA}, x_{RP}, x_{RA}]^\top$ are bounded from 0 to 1 as a function ϕ of a dynamically evolving internal variable $\mathbf{u}$. The model responds to the side with greater Pro neuron activation; e.g. the response is left if $x_{LP} > x_{RP}$ at the end of the trial. The dynamics evolve with timescale $\tau = 90$ms governed by connectivity weights W

$$\begin{aligned} \tau \frac{d\mathbf{u}}{dt} &= -\mathbf{u} + W\mathbf{x} + \mathbf{h} + d\mathbf{B} \\ \mathbf{x} &= \phi(\mathbf{u}) \end{aligned} \tag{7}$$

with white noise of variance 0.2^2. The input $\mathbf{h}$ is comprised of a cue-dependent input to the Pro or Anti populations, a stimulus orientation input to either the Left or Right populations, and a choice-period input to the entire network (see Section 5.2.4). Here, we use EPI to determine the network connectivity $\mathbf{z} = [sW, vW, dW, hW]^\top$ that produces rapid task switching behavior.

We define rapid task switching behavior as accurate execution of each task. Inferred models should not exhibit fully random responses (50%), or perfect performance (100%), since perfection is never attained by even the best trained rats. We formulate rapid task switching as an emergent property by stipulating that the average accuracy in the Pro task $p_P(\mathbf{x}; \mathbf{z})$ and Anti task $p_A(\mathbf{x}; \mathbf{z})$ be 75% with variance $7.5\%^2$.

$$\begin{aligned} \mathcal{X} \quad : \quad \mathbb{E}_{\mathbf{z}} \begin{bmatrix} p_P(\mathbf{x}; \mathbf{z}) \\ p_A(\mathbf{x}; \mathbf{z}) \end{bmatrix} &= \begin{bmatrix} 75\% \\ 75\% \end{bmatrix} \\ \mathrm{Var}_{\mathbf{z}} \begin{bmatrix} p_P(\mathbf{x}; \mathbf{z}) \\ p_A(\mathbf{x}; \mathbf{z}) \end{bmatrix} &= \begin{bmatrix} 7.5\%^2 \\ 7.5\%^2 \end{bmatrix} \end{aligned} \tag{8}$$

A variance of $7.5\%^2$ in each task will confer a posterior producing performances ranging from about $60\% - 90\%$, allowing us to examine the properties of connectivity that yield better performance in

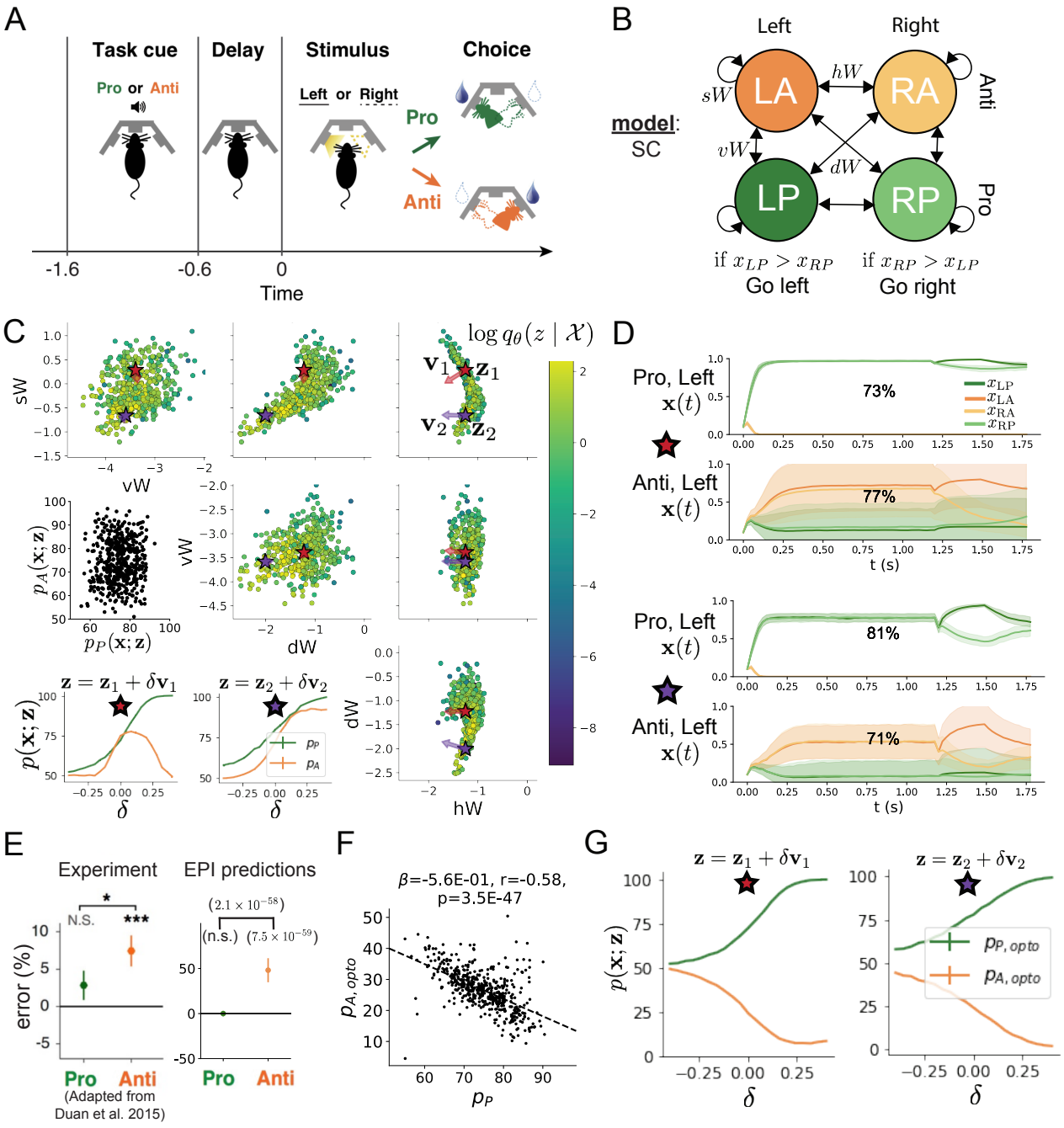

Figure 3: **A**. Rapid task switching behavioral paradigm (see text). **B**. Model of superior colliculus (SC). Neurons: LP - left pro, RP - right pro, LA - left anti, RA - right anti. Parameters: sW - self, hW - horizontal, vW - vertical, dW - diagonal weights. **C**. The EPI posterior distribution of rapid task switching networks. Red and purple stars ($\mathbf{z}_1$ and $\mathbf{z}_2$) indicate different connectivity regimes with different sensitivity vectors $\mathbf{v}_1$ and $\mathbf{v}_2$. (Middle-left) Posterior predictive distribution of task accuracies. (Bottom-left) Task accuracy along dimensions of sensitivity in each connectivity regime. **D**. Means (solid) and standard deviations (shaded) of each population across random simulated trials. Top plots show Pro (top) and Anti (bottom) responses for connectivity $\mathbf{z}_1$. Bottom rows show the same $\mathbf{z}_2$. **E**. The EPI posterior predicts experimental results (left) showing no change in the Pro task, but larger error in the Anti task (right). **F**. Accuracy in the Anti task during delay period optogenetic inactivation $p_{A,\text{opto}}$ is strongly anticorrelated with accuracy in the Pro task. **G**. Accuracy with delay period inactivation along each connectivity regime's dimension of sensitivity.

each task. Notably, this is our first example using EPI to condition on multiple emergent property statistics ($|f(\mathbf{x};\mathbf{z})| = 2$).

The EPI inferred parameters (Fig. 3C) generate a distribution of task accuracies (Fig. 3C, middle-left) according to our mathematical definition of rapid task switching (Equation 8). The nonlinear patterns of connectivity that govern each task accuracy (Fig. 12A-B) are not fully captured by linear prediction (Fig. 12C). For example, the patterns in connectivity increasing Pro accuracy change dramatically after crossing a threshold of sW (Fig. 12A sW-hW marginal). Not only has EPI captured this complex nonlinear posterior, it offers probabilistic tools for understanding the different regimes of model behavior.

To establish these two regimes of connectivity, we took gradient steps along $q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X})$to produce modes $\mathbf{z}_1$ and $\mathbf{z}_2$ (Fig. 3C red and purple stars, Section 5.2.4). Simulations from these two regimes reveal different responses in each task (Fig. 3D). We charcaterized these regimes by identifying the dimensions of connectivity that rapid task switching is most sensitive to. The sensitivity dimensions $\mathbf{v}_1$ and $\mathbf{v}_2$ (Fig. 3C, red and purple arrows) point in different directions, resulting in different changes to task accuracy (Fig. 3D, bottom-left, 13). In regime 1, Anti accuracy diminishes in either direction of sensitivity away from the mode, while in regime 2, Anti accuracy tracks monotonic increases in Pro accuracy. These responses make intuitive sense, recognizing that $\mathbf{v}_1$ (unlike $\mathbf{v}_2$) points strongly in the direction of connectivity eigenvalue λ_{diag}, which is strongly anticorrelated with p_A (Fig. 14, 15, see Section 5.2.4).

In agreement with experimental results from Duan et al., we found optogenetic inactivation during the delay period consistently decreased performance in the Anti task, but had no effect on the Pro task (Fig. 3E)). This difference in resiliency across tasks to delay perturbation is a prediction made by the inferred EPI distribution, rather than an emergent property that was conditioned upon. Similarities across Pro and Anti trials in choice period responses following delay period inactivation (Fig. 17A) suggested that connectivity patterns inducing greater Pro task accuracy increase error in delay period inactivated Anti trials (Fig. 3F). The strong anticorrelation between p_P and $p_{A,opto}$ across posterior connectivities led to the following hypothesis about each connectivity regime: the sensitivity dimension of each regime decreases $p_{A,opto}$ irrespective of its effect on p_A, since both $\mathbf{v}_1$ and $\mathbf{v}_2$ increase p_P. Indeed, in regimes 1 and 2 where sensitivity dimensions elicit different responses in p_A, $p_{A,opto}$ decreases since the connectivity changes enhancing p_P exacerbate Anti trial error (Fig. 3F).

In summary, we used EPI to obtain the full distribution of connectivities that execute rapid task

switching. This posterior revealed multiple regimes of rapid task switching, which we characterized using the probabilistic toolkit EPI seemlessly affords. EPI allowed us to conclude that since *all* parameters of this model producing rapid task switching make an experimentally verified prediction, the model is well-chosen in that regard. Finally, we used our knowledge about how $\mathbf{z}$ governs $p_{A,opto}$ to make accurate predictions about each identified regime of connectivity.

3.5 EPI scales well to high-dimensional parameter spaces

Here, we study the scalability of EPI in number of parameters $|\mathbf{z}|$ by inferring the connectivities of recurrent neural networks (RNNs, Fig. 4A). We consider a rank-2 RNN with N neurons having connectivity

$$W = UV^\top + g\chi \tag{9}$$

and dynamics

$$\tau\dot{\mathbf{x}} = -\mathbf{x} + W\mathbf{x} \tag{10}$$

where $U = \begin{bmatrix}\mathbf{u}_1 & \mathbf{u}_2\end{bmatrix}$, $V = \begin{bmatrix}\mathbf{v}_1 & \mathbf{v}_2\end{bmatrix}$ and $\mathbf{u}_1\mathbf{u}_2, \mathbf{v}_1, \mathbf{v}_2 \in [-1, 1]^N$. The random component has strength $g = 0.01$ and $\chi_{i,j} \sim \mathcal{N}(0, 1)$. We infer connectivity distributions $\mathbf{z} = \left[\mathbf{u}_1^\top, \mathbf{u}_2^\top, \mathbf{v}_1^\top, \mathbf{v}_2^\top\right]^\top$ producing stable amplification. RNN's exhibiting stable amplification amplify responses to input along some dimensions, and are stable across all dimensions. Two conditions are both necessary and sufficient for RNNs to exhibit stable amplification [74]: $\text{real}(\lambda_1) < 1$ and $\lambda_1^s > 1$, where λ_1 is the eigenvalue of W with greatest real part and λ^s is the maximum eigenvalue of $W^s = \frac{W+W\top}{2}$.

In our analysis, we seek to condition rank-2 networks of increasing size on a regime of stable amplification. Networks with $\text{real}(\lambda_1) = 0.5 \pm 0.5$ and $\lambda_1^s = 1.5 \pm 0.5$ will yield moderate amplification. EPI can naturally condition on this emergent property

$$\begin{aligned} \mathcal{X} \quad : \quad \mathbb{E}_{\mathbf{z},\mathbf{x}} \begin{bmatrix} \text{real}(\lambda_1) \\ \lambda_1^s \end{bmatrix} &= \begin{bmatrix} 0.5 \\ 1.5 \end{bmatrix} \\ \text{Var}_{\mathbf{z},\mathbf{x}} \begin{bmatrix} \text{real}(\lambda_1) \\ \lambda_1^s \end{bmatrix} &= \begin{bmatrix} 0.25^2 \\ 0.25^2 \end{bmatrix}. \end{aligned} \tag{11}$$

For comparison, we infer rank-2 RNN connectivites with alternative approaches to likelihood free-inference. ABC methods define a tolerance ϵ from observed data x_0 for which we keep sampled parameters. To make this ABC approach as similar as possible to the EPI program defined by

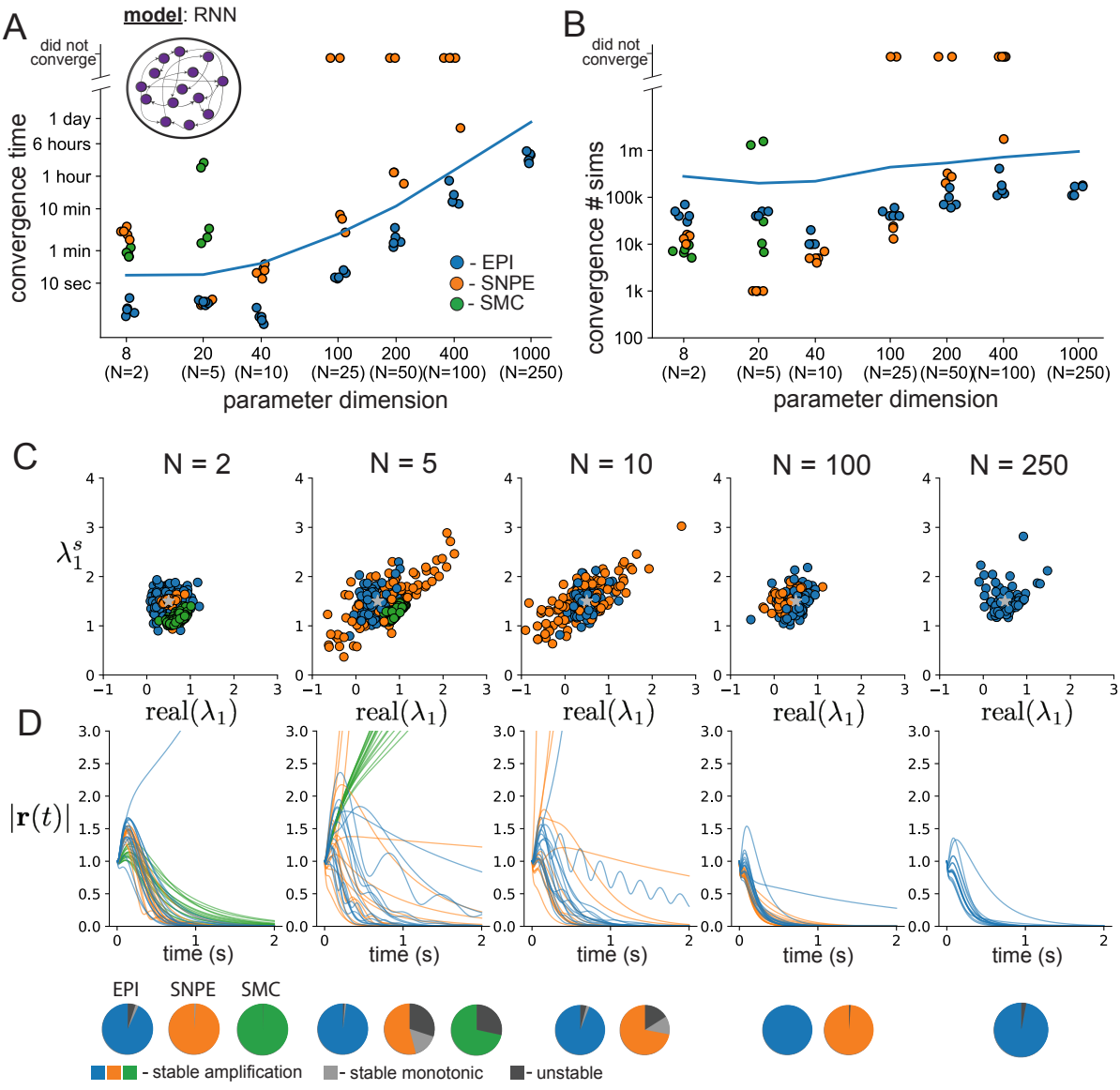

Figure 4: **A**. Recurrent neural network. **B**. EPI scales with z to high dimensions. Convergence definitions: EPI (blue) - satisfies all moment constraints, SNPE (orange)- produces at least $2/n_{\text{train}}$ parameter samples are in the bounds of emergent property (mean +- 0.5), and SMC-ABC (red) - 100 particles with $\epsilon < 0.5$ are produced. **C**. Posterior predictive distributions of EPI (blue), SNPE (orange), and SMC-ABC (red). Gray star indicates emergent property mean, and gray dashed lines indicate two standard deviations corresponding to the variance constraint. For $N <= 6$ where SMC-ABC converges, samples are not diverse (path degeneracies). For $N >= 25$, SNPE does not produce a posterior approximation yielding parameters with simulations near x_0. **D**. Simulations of network parameters resulting from each method ($\tau = 100ms$). Each trace corresponds to simulation of one z. (Below) Ratio of obtained samples producing stable amplification.

Equation 11, we chose $\epsilon = 0.5$, an l-2 distance metric, and

$$x_0 = \begin{bmatrix} \text{real}(\lambda_1) \\ \lambda_1^s \end{bmatrix} = \begin{bmatrix} 0.5 \\ 1.5 \end{bmatrix} \tag{12}$$

located at the mean of our desired emergent property. We use sequential Monte Carlo ABC (SMC-ABC), to compare efficiency, since it is considered the most efficient ABC approach. SNPE [75] is another deep likelihood-free inference method that emerged along with this work. In contrast to EPI, SNPE cannot condition on the variance of the posterior predictive distribution. Also, there is no tolerance parameter for SNPE like ϵ in ABC, so the comparative SNPE approach simply conditions on observation x_0.

As we scale the number of neurons N in the RNN, and thus the dimensionality of the parameter space $\mathbf{z} \in [-1, 1]^{4N}$, we see that EPI has superior scaling properties (Fig. 4B). SMC-ABC and SNPE become intractable around 25 and 90 dimensions respectively, while EPI can infer 1000-dimensional distributions in about 1 day. No matter the number of neurons, EPI always produces connectivity distributions with mean and variance of real(λ_1) and λ_1^s of $\mathcal{X}$(Fig. 4C, blue), and high variation in response profiles 4D, blue). For the dimensionalities in which SMC-ABC is tractable, the inferred parameters always exhibit stable amplification, are less varied 4C, red) and largely produce similar responses 4D, red). When using SNPE the inferred parameters are widely varied 4C, orange), but often produce non-amplified or unstable responses 4D, orange). In conclusion, we found that deep likelihood-free inference techniques are capable of scaling to higher dimensional inference than SMC-ABC. However, only EPI can scale to high dimensions while reproducing the emergent property.

4 Discussion

In neuroscience, machine learning has primarily been used to reveal structure in neural datasets [30]. Such careful inference procedures are developed for these statistical models allowing precise, quantitative reasoning, which clarifies the way data informs beliefs about the model parameters. However, these statistical models lack resemblance to the underlying biology, making it unclear how to go from the structure revealed by these methods, to the neural mechanisms giving rise to it. In contrast, theoretical neuroscience has focused on careful mechanistic modeling and the production of emergent properties of computation. The careful steps of *i.*) model design and *ii.*) emergent property definition, are followed by *iii.*) practical inference methods resulting in an

opaque characterization of the way model parameters govern computation. In this work, we improve upon parameter inference techniques in theoretical neuroscience with emergent property inference, harnessing deep learning towards careful inference in careful models of neural computation (see Section 5.1.1).

Specifically, approximate Bayesian computation [42, 43, 31] has been the standard approach to parameter inference in neural circuit models lacking tractable likelihoods. ABC methods do not confer probabilities on accepted parameters, require an acceptance threshold chosen to trade-off inference quality with tractability, do not scale efficiently to high-dimensional parameter spaces, and require independent techniques to analyze sensitivity for local parameter choices [76]. In contrast, EPI allows probability evaluations at any point in parameter space, conditions posteriors on the natural quantification of emergent properties, scales to high dimensional parameter spaces, and naturally admits sensitivity quantification via fast evaluations of the posterior Hessian.

Technically, EPI is a maximum entropy method, which learns parameter distributions that are as random as possible given that they produce the emergent property. Conceptually, maximally random distributions given some constraints are useful for understanding parametric sensitivity. This is well understood in Bayesian inference, where maximum entropy is the chosen normative principle. This is emphasized by an innovative formalism unifying top-down maximum entropy normative models with bottom-up statistical models [77]. Indeed, EPI is an adaptive variational inference program, and may be considered to have a Bayesian uniform prior (see Section 5.1.6).

Biologically realistic models of neural circuits often prove formidable to analyze for two main reasons. A primary challenge is that the number of parameters scales dramatically with the number of neurons, limiting analysis of its parameter space. We see in Section 3.5 that EPI scales seemlessly to high dimensional parameter spaces of RNN connectivities, while maintaining the production of the specified emergent property. EPI strongly outperforms the standard likelihood-free inference technique (SMC-ABC [31]), and a recently developed deep likelihood-free inference technique (SNPE [75]), most likely because of it's ability to leverage the gradient information of the emergent property statistics and to adapt it's paramter sampling distribution at every step of gradient descent.

A secondary challenge is that the structure of the parametric regimes governing emergent properties is intricate. For example, even in low dimensional circuits, models can support more than one steady state [78] and non-trivial dynamics on strange attractors [79]. With EPI, we use deep probabillity distributions to capture the complex nonlinear parameter distributions governing model behavior.

In Section 3.3, we used EPI to reveal a curved parametric manifolds governing curcuit variability in the stochastic stabilized supralinear network, and used hypothesis testing techniques to validate our findings. In Section 3.4, we identified two regimes of SC connectivity resulting in rapid task switching, and found that the full distribution of rapid task switching networks reproduced an experimental result.

EPI leverages deep learning technology for neuroscientific inquiry in a categorically different way than approaches focused on training neural networks to execute behavioral tasks [80]. These works focus on examining optimized deep neural networks while considering the objective function, learning rule, and architecture used. This endeavor efficiently obtains sets of parameters that can be reasoned about with respect to such considerations, but lacks the careful probabilistic treatment of parameter inference in EPI. All of these approaches can be used complementarily to enhance the practice of theoretical neuroscience.

Acknowledgements:
This work was funded by NSF Graduate Research Fellowship, DGE-1644869, McKnight Endowment Fund, NIH NINDS 5R01NS100066, Simons Foundation 542963, NSF NeuroNex Award, DBI-1707398, The Gatsby Charitable Foundation, Simons Collaboration on the Global Brain Postdoctoral Fellowship, Chinese Postdoctoral Science Foundation, and International Exchange Program Fellowship. Helpful conversations were had with Francesca Mastrogiuseppe, Srdjan Ostojic, James Fitzgerald, Stephen Baccus, Dhruva Raman, Liam Paninski, and Larry Abbott.

Data availability statement:
The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Code availability statement:
All software written for the current study is available at https://github.com/cunningham-lab/epi.

References

[1] Nancy Kopell and G Bard Ermentrout. Coupled oscillators and the design of central pattern generators. *Mathematical biosciences*, 90(1-2):87–109, 1988.

[2] Eve Marder. From biophysics to models of network function. *Annual review of neuroscience*, 21(1):25–45, 1998.

[3] Larry F Abbott. Theoretical neuroscience rising. *Neuron*, 60(3):489–495, 2008.

[4] Xiao-Jing Wang. Neurophysiological and computational principles of cortical rhythms in cognition. *Physiological reviews*, 90(3):1195–1268, 2010.

[5] Ryan N Gutenkunst, Joshua J Waterfall, Fergal P Casey, Kevin S Brown, Christopher R Myers, and James P Sethna. Universally sloppy parameter sensitivities in systems biology models. *PLoS Comput Biol*, 3(10):e189, 2007.

[6] Timothy O'Leary, Alex H Williams, Alessio Franci, and Eve Marder. Cell types, network homeostasis, and pathological compensation from a biologically plausible ion channel expression model. *Neuron*, 82(4):809–821, 2014.

[7] John J Hopfield. Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the national academy of sciences*, 79(8):2554–2558, 1982.

[8] Haim Sompolinsky, Andrea Crisanti, and Hans-Jurgen Sommers. Chaos in random neural networks. *Physical review letters*, 61(3):259, 1988.

[9] Misha V Tsodyks, William E Skaggs, Terrence J Sejnowski, and Bruce L McNaughton. Paradoxical effects of external modulation of inhibitory interneurons. *Journal of neuroscience*, 17(11):4382–4388, 1997.

[10] Kong-Fatt Wong and Xiao-Jing Wang. A recurrent network mechanism of time integration in perceptual decisions. *Journal of Neuroscience*, 26(4):1314–1328, 2006.

[11] WR Foster, LH Ungar, and JS Schwaber. Significance of conductances in hodgkin-huxley models. *Journal of neurophysiology*, 70(6):2502–2518, 1993.

[12] Astrid A Prinz, Dirk Bucher, and Eve Marder. Similar network activity from disparate circuit parameters. *Nature neuroscience*, 7(12):1345–1352, 2004.

[13] Pablo Achard and Erik De Schutter. Complex parameter landscape for a complex neuron model. *PLoS computational biology*, 2(7):e94, 2006.

[14] Leandro M Alonso and Eve Marder. Visualization of currents in neural models with similar behavior and different conductance densities. *Elife*, 8:e42722, 2019.

[15] Robert E Kass and Valérie Ventura. A spike-train probability model. *Neural computation*, 13(8):1713–1720, 2001.

[16] Emery N Brown, Loren M Frank, Dengda Tang, Michael C Quirk, and Matthew A Wilson. A statistical paradigm for neural spike train decoding applied to position prediction from ensemble firing patterns of rat hippocampal place cells. *Journal of Neuroscience*, 18(18):7411–7425, 1998.

[17] Liam Paninski. Maximum likelihood estimation of cascade point-process neural encoding models. *Network: Computation in Neural Systems*, 15(4):243–262, 2004.

[18] Wilson Truccolo, Uri T Eden, Matthew R Fellows, John P Donoghue, and Emery N Brown. A point process framework for relating neural spiking activity to spiking history, neural ensemble, and extrinsic covariate effects. *Journal of neurophysiology*, 93(2):1074–1089, 2005.

[19] Elad Schneidman, Michael J Berry, Ronen Segev, and William Bialek. Weak pairwise correlations imply strongly correlated network states in a neural population. *Nature*, 440(7087):1007–1012, 2006.

[20] Shaul Druckmann, Yoav Banitt, Albert A Gidon, Felix Schürmann, Henry Markram, and Idan Segev. A novel multiple objective optimization framework for constraining conductance-based neuron models by experimental data. *Frontiers in neuroscience*, 1:1, 2007.

[21] Richard Turner and Maneesh Sahani. A maximum-likelihood interpretation for slow feature analysis. *Neural computation*, 19(4):1022–1038, 2007.

[22] M Yu Byron, John P Cunningham, Gopal Santhanam, Stephen I Ryu, Krishna V Shenoy, and Maneesh Sahani. Gaussian-process factor analysis for low-dimensional single-trial analysis of neural population activity. In *Advances in neural information processing systems*, pages 1881–1888, 2009.

[23] Jakob H Macke, Lars Buesing, John P Cunningham, Byron M Yu, Krishna V Shenoy, and Maneesh Sahani. Empirical models of spiking in neural populations. *Advances in neural information processing systems*, 24:1350–1358, 2011.

[24] Il Memming Park and Jonathan W Pillow. Bayesian spike-triggered covariance analysis. In *Advances in neural information processing systems*, pages 1692–1700, 2011.

[25] Einat Granot-Atedgi, Gašper Tkačik, Ronen Segev, and Elad Schneidman. Stimulus-dependent maximum entropy models of neural population codes. *PLoS Comput Biol*, 9(3):e1002922, 2013.

[26] Kenneth W Latimer, Jacob L Yates, Miriam LR Meister, Alexander C Huk, and Jonathan W Pillow. Single-trial spike trains in parietal cortex reveal discrete steps during decision-making. *Science*, 349(6244):184–187, 2015.

[27] Kaushik J Lakshminarasimhan, Marina Petsalis, Hyeshin Park, Gregory C DeAngelis, Xaq Pitkow, and Dora E Angelaki. A dynamic bayesian observer model reveals origins of bias in visual path integration. *Neuron*, 99(1):194–206, 2018.

[28] Lea Duncker, Gergo Bohner, Julien Boussard, and Maneesh Sahani. Learning interpretable continuous-time models of latent stochastic dynamical systems. *Proceedings of the 36th International Conference on Machine Learning*, 2019.

[29] Josef Ladenbauer, Sam McKenzie, Daniel Fine English, Olivier Hagens, and Srdjan Ostojic. Inferring and validating mechanistic models of neural microcircuits based on spike-train data. *Nature Communications*, 10(4933), 2019.

[30] Liam Paninski and John P Cunningham. Neural data science: accelerating the experiment-analysis-theory cycle in large-scale neuroscience. *Current opinion in neurobiology*, 50:232–241, 2018.

[31] Scott A Sisson, Yanan Fan, and Mark M Tanaka. Sequential monte carlo without likelihoods. *Proceedings of the National Academy of Sciences*, 104(6):1760–1765, 2007.

[32] Juliane Liepe, Paul Kirk, Sarah Filippi, Tina Toni, Chris P Barnes, and Michael PH Stumpf. A framework for parameter estimation and model selection from experimental data in systems biology using approximate bayesian computation. *Nature protocols*, 9(2):439–456, 2014.

[33] Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *International Conference on Learning Representations*, 2014.

[34] Danilo Jimenez Rezende, Shakir Mohamed, and Daan Wierstra. Stochastic backpropagation and variational inference in deep latent gaussian models. *International Conference on Machine Learning*, 2014.

[35] Yuanjun Gao, Evan W Archer, Liam Paninski, and John P Cunningham. Linear dynamical neural population models through nonlinear embeddings. In *Advances in neural information processing systems*, pages 163–171, 2016.

[36] Yuan Zhao and Il Memming Park. Recursive variational bayesian dual estimation for non-linear dynamics and non-gaussian observations. *stat*, 1050:27, 2017.

[37] Gabriel Barello, Adam Charles, and Jonathan Pillow. Sparse-coding variational auto-encoders. *bioRxiv*, page 399246, 2018.

[38] Chethan Pandarinath, Daniel J O'Shea, Jasmine Collins, Rafal Jozefowicz, Sergey D Stavisky, Jonathan C Kao, Eric M Trautmann, Matthew T Kaufman, Stephen I Ryu, Leigh R Hochberg, et al. Inferring single-trial neural population dynamics using sequential auto-encoders. *Nature methods*, page 1, 2018.

[39] Alexander B Wiltschko, Matthew J Johnson, Giuliano Iurilli, Ralph E Peterson, Jesse M Katon, Stan L Pashkovski, Victoria E Abraira, Ryan P Adams, and Sandeep Robert Datta. Mapping sub-second structure in mouse behavior. *Neuron*, 88(6):1121–1135, 2015.

[40] Matthew J Johnson, David K Duvenaud, Alex Wiltschko, Ryan P Adams, and Sandeep R Datta. Composing graphical models with neural networks for structured representations and fast inference. In *Advances in neural information processing systems*, pages 2946–2954, 2016.

[41] Eleanor Batty, Matthew Whiteway, Shreya Saxena, Dan Biderman, Taiga Abe, Simon Musall, Winthrop Gillis, Jeffrey Markowitz, Anne Churchland, John Cunningham, et al. Behavenet: nonlinear embedding and bayesian neural decoding of behavioral videos. *Advances in Neural Information Processing Systems*, 2019.

[42] Mark A Beaumont, Wenyang Zhang, and David J Balding. Approximate bayesian computation in population genetics. *Genetics*, 162(4):2025–2035, 2002.

[43] Paul Marjoram, John Molitor, Vincent Plagnol, and Simon Tavaré. Markov chain monte carlo without likelihoods. *Proceedings of the National Academy of Sciences*, 100(26):15324–15328, 2003.

[44] W Keith Hastings. Monte carlo sampling methods using markov chains and their applications. 1970.

[45] Nicholas Metropolis, Arianna W Rosenbluth, Marshall N Rosenbluth, Augusta H Teller, and Edward Teller. Equation of state calculations by fast computing machines. *The journal of chemical physics*, 21(6):1087–1092, 1953.

[46] Lawrence Saul and Michael Jordan. A mean field learning algorithm for unsupervised neural networks. In *Learning in graphical models*, pages 541–554. Springer, 1998.

[47] Danilo Jimenez Rezende and Shakir Mohamed. Variational inference with normalizing flows. *International Conference on Machine Learning*, 2015.

[48] Mark K Transtrum, Benjamin B Machta, Kevin S Brown, Bryan C Daniels, Christopher R Myers, and James P Sethna. Perspective: Sloppiness and emergent theories in physics, biology, and beyond. *The Journal of chemical physics*, 143(1):07B201_1, 2015.

[49] Dustin Tran, Rajesh Ranganath, and David Blei. Hierarchical implicit models and likelihood-free variational inference. In *Advances in Neural Information Processing Systems*, pages 5523–5533, 2017.

[50] Laurent Dinh, Jascha Sohl-Dickstein, and Samy Bengio. Density estimation using real nvp. *Proceedings of the 5th International Conference on Learning Representations*, 2017.

[51] George Papamakarios, Theo Pavlakou, and Iain Murray. Masked autoregressive flow for density estimation. In *Advances in Neural Information Processing Systems*, pages 2338–2347, 2017.

[52] Gabriel Loaiza-Ganem, Yuanjun Gao, and John P Cunningham. Maximum entropy flow networks. *International Conference on Learning Representations*, 2017.

[53] Mark S Goldman, Jorge Golowasch, Eve Marder, and LF Abbott. Global structure, robustness, and modulation of neuronal models. *Journal of Neuroscience*, 21(14):5229–5238, 2001.

[54] Ashok Litwin-Kumar, Robert Rosenbaum, and Brent Doiron. Inhibitory stabilization and visual coding in cortical circuits with multiple interneuron subtypes. *Journal of neurophysiology*, 115(3):1399–1409, 2016.

[55] Chunyu A Duan, Marino Pagan, Alex T Piet, Charles D Kopec, Athena Akrami, Alexander J Riordan, Jeffrey C Erlich, and Carlos D Brody. Collicular circuits for flexible sensorimotor routing. *bioRxiv*, page 245613, 2018.

[56] Eve Marder and Vatsala Thirumalai. Cellular, synaptic and network effects of neuromodulation. *Neural Networks*, 15(4-6):479–493, 2002.

[57] Gabrielle J Gutierrez, Timothy O'Leary, and Eve Marder. Multiple mechanisms switch an electrically coupled, synaptically inhibited neuron between competing rhythmic oscillators. *Neuron*, 77(5):845–858, 2013.

[58] Edwin T Jaynes. Information theory and statistical mechanics. *Physical review*, 106(4):620, 1957.

[59] Gamaleldin F Elsayed and John P Cunningham. Structure in neural population recordings: an expected byproduct of simpler phenomena? *Nature neuroscience*, 20(9):1310, 2017.

[60] Cristina Savin and Gašper Tkačik. Maximum entropy models as a tool for building precise neural controls. *Current opinion in neurobiology*, 46:120–126, 2017.

[61] Mark S Goldman. Memory without feedback in a neural network. *Neuron*, 61(4):621–634, 2009.

[62] Brendan K Murphy and Kenneth D Miller. Balanced amplification: a new mechanism of selective amplification of neural activity patterns. *Neuron*, 61(4):635–648, 2009.

[63] Hirofumi Ozeki, Ian M Finn, Evan S Schaffer, Kenneth D Miller, and David Ferster. Inhibitory stabilization of the cortical network underlies visual surround suppression. *Neuron*, 62(4):578–592, 2009.

[64] Daniel B Rubin, Stephen D Van Hooser, and Kenneth D Miller. The stabilized supralinear network: a unifying circuit motif underlying multi-input integration in sensory cortex. *Neuron*, 85(2):402–417, 2015.

[65] Henry Markram, Maria Toledo-Rodriguez, Yun Wang, Anirudh Gupta, Gilad Silberberg, and Caizhi Wu. Interneurons of the neocortical inhibitory system. *Nature reviews neuroscience*, 5(10):793, 2004.

[66] Bernardo Rudy, Gordon Fishell, SooHyun Lee, and Jens Hjerling-Leffler. Three groups of interneurons account for nearly 100% of neocortical gabaergic neurons. *Developmental neurobiology*, 71(1):45–61, 2011.

[67] Robin Tremblay, Soohyun Lee, and Bernardo Rudy. GABAergic Interneurons in the Neocortex: From Cellular Properties to Circuits. *Neuron*, 91(2):260–292, 2016.

[68] Carsten K Pfeffer, Mingshan Xue, Miao He, Z Josh Huang, and Massimo Scanziani. Inhibition of inhibition in visual cortex: the logic of connections between molecularly distinct interneurons. *Nature Neuroscience*, 16(8):1068, 2013.

[69] Luis Carlos Garcia Del Molino, Guangyu Robert Yang, Jorge F. Mejias, and Xiao Jing Wang. Paradoxical response reversal of top- down modulation in cortical circuits with three interneuron types. *Elife*, 6:1–15, 2017.

[70] Guang Chen, Carl Van Vreeswijk, David Hansel, and David Hansel. Mechanisms underlying the response of mouse cortical networks to optogenetic manipulation. 2019.

[71] Guillaume Hennequin, Yashar Ahmadian, Daniel B Rubin, Máté Lengyel, and Kenneth D Miller. The dynamical regime of sensory cortex: stable dynamics around a single stimulus-tuned attractor account for patterns of noise variability. *Neuron*, 98(4):846–860, 2018.

[72] Agostina Palmigiano, Francesco Fumarola, Daniel P Mossing, Nataliya Kraynyukova, Hillel Adesnik, and Kenneth Miller. Structure and variability of optogenetic responses identify the operating regime of cortex. *bioRxiv*, 2020.

[73] Chunyu A Duan, Jeffrey C Erlich, and Carlos D Brody. Requirement of prefrontal and midbrain regions for rapid executive control of behavior in the rat. *Neuron*, 86(6):1491–1503, 2015.

[74] Giulio Bondanelli and Srdjan Ostojic. Coding with transient trajectories in recurrent neural networks. *PLoS computational biology*, 16(2):e1007655, 2020.

[75] Pedro J Gonçalves, Jan-Matthis Lueckmann, Michael Deistler, Marcel Nonnenmacher, Kaan Öcal, Giacomo Bassetto, Chaitanya Chintaluri, William F Podlaski, Sara A Haddad, Tim P Vogels, et al. Training deep neural density estimators to identify mechanistic models of neural dynamics. *bioRxiv*, page 838383, 2019.

[76] Scott A Sisson, Yanan Fan, and Mark Beaumont. *Handbook of approximate Bayesian computation*. CRC Press, 2018.

[77] Wiktor Młynarski, Michal Hledík, Thomas R Sokolowski, and Gašper Tkačik. Statistical analysis and optimality of neural systems. *bioRxiv*, page 848374, 2020.

[78] Nataliya Kraynyukova and Tatjana Tchumatchenko. Stabilized supralinear network can give rise to bistable, oscillatory, and persistent activity. *Proceedings of the National Academy of Sciences*, 115(13):3464–3469, 2018.

[79] Katherine Morrison, Anda Degeratu, Vladimir Itskov, and Carina Curto. Diversity of emergent dynamics in competitive threshold-linear networks: a preliminary report. *arXiv preprint arXiv:1605.04463*, 2016.

[80] Blake A Richards and et al. A deep learning framework for neuroscience. *Nature Neuroscience*, 2019.

[81] Mark Girolami and Ben Calderhead. Riemann manifold langevin and hamiltonian monte carlo methods. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 73(2):123–214, 2011.

[82] Andrew Golightly and Darren J Wilkinson. Bayesian parameter inference for stochastic biochemical network models using particle markov chain monte carlo. *Interface focus*, 1(6):807–820, 2011.

[83] Kyle Cranmer, Johann Brehmer, and Gilles Louppe. The frontier of simulation-based inference. *Proceedings of the National Academy of Sciences*, 2020.

[84] Sean R Bittner, Agostina Palmigiano, Kenneth D Miller, and John P Cunningham. Degenerate solution networks for theoretical neuroscience. *Computational and Systems Neuroscience Meeting (COSYNE), Lisbon, Portugal*, 2019.

[85] Sean R Bittner, Alex T Piet, Chunyu A Duan, Agostina Palmigiano, Kenneth D Miller, Carlos D Brody, and John P Cunningham. Examining models in theoretical neuroscience with degenerate solution networks. *Bernstein Conference 2019, Berlin, Germany*, 2019.

[86] Marcel Nonnenmacher, Pedro J Goncalves, Giacomo Bassetto, Jan-Matthis Lueckmann, and Jakob H Macke. Robust statistical inference for simulation-based models in neuroscience. In *Bernstein Conference 2018, Berlin, Germany*, 2018.

[87] Deistler Michael, , Pedro J Goncalves, Kaan Oecal, and Jakob H Macke. Statistical inference for analyzing sloppiness in neuroscience models. In *Bernstein Conference 2019, Berlin, Germany*, 2019.

[88] Jan-Matthis Lueckmann, Pedro J Goncalves, Giacomo Bassetto, Kaan Öcal, Marcel Nonnenmacher, and Jakob H Macke. Flexible statistical inference for mechanistic models of neural dynamics. In *Advances in Neural Information Processing Systems*, pages 1289–1299, 2017.

[89] George Papamakarios, David Sterratt, and Iain Murray. Sequential neural likelihood: Fast likelihood-free inference with autoregressive flows. In *The 22nd International Conference on Artificial Intelligence and Statistics*, pages 837–848. PMLR, 2019.

[90] Joeri Hermans, Volodimir Begy, and Gilles Louppe. Likelihood-free mcmc with amortized approximate ratio estimators. In *International Conference on Machine Learning*, pages 4239–4248. PMLR, 2020.

[91] Martin J Wainwright, Michael I Jordan, et al. Graphical models, exponential families, and variational inference. *Foundations and Trends® in Machine Learning*, 1(1–2):1–305, 2008.

[92] Sean R Bittner and John P Cunningham. Approximating exponential family models (not single distributions) with a two-network architecture. *arXiv preprint arXiv:1903.07515*, 2019.

[93] Johan Karlsson, Milena Anguelova, and Mats Jirstrand. An efficient method for structural identifiability analysis of large dynamic systems. *IFAC Proceedings Volumes*, 45(16):941–946, 2012.

[94] Ricky TQ Chen, Yulia Rubanova, Jesse Bettencourt, and David K Duvenaud. Neural ordinary differential equations. In *Advances in neural information processing systems*, pages 6571–6583, 2018.

[95] Xuechen Li, Ting-Kam Leonard Wong, Ricky TQ Chen, and David Duvenaud. Scalable gradients for stochastic differential equations. *arXiv preprint arXiv:2001.01328*, 2020.

[96] Andreas Raue, Clemens Kreutz, Thomas Maiwald, Julie Bachmann, Marcel Schilling, Ursula Klingmüller, and Jens Timmer. Structural and practical identifiability analysis of partially observed dynamical models by exploiting the profile likelihood. *Bioinformatics*, 25(15):1923–1929, 2009.

[97] Dhruva V Raman, James Anderson, and Antonis Papachristodoulou. Delineating parameter unidentifiabilities in complex models. *Physical Review E*, 95(3):032314, 2017.

[98] Maria Pia Saccomani, Stefania Audoly, and Leontina D'Angiò. Parameter identifiability of nonlinear systems: the role of initial conditions. *Automatica*, 39(4):619–632, 2003.

[99] George Papamakarios, Eric Nalisnick, Danilo Jimenez Rezende, Shakir Mohamed, and Balaji Lakshminarayanan. Normalizing flows for probabilistic modeling and inference. *arXiv preprint arXiv:1912.02762*, 2019.

[100] Durk P Kingma and Prafulla Dhariwal. Glow: Generative flow with invertible 1x1 convolutions. In *Advances in neural information processing systems*, pages 10215–10224, 2018.

[101] Durk P Kingma, Tim Salimans, Rafal Jozefowicz, Xi Chen, Ilya Sutskever, and Max Welling. Improved variational inference with inverse autoregressive flow. *Advances in neural information processing systems*, 29:4743–4751, 2016.

[102] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *International Conference on Learning Representations*, 2015.

[103] David M Blei, Alp Kucukelbir, and Jon D McAuliffe. Variational inference: A review for statisticians. *Journal of the American Statistical Association*, 112(518):859–877, 2017.

5 Methods

5.1 Emergent property inference (EPI)

Determining the combinations of model parameters that can produce observed data or a desired output is a key part of scientific practice. Solving inverse problems is especially important in neuroscience, since we require complex models to describe the complex phenomena of neural computations. While much machine learning research has focused on how to find latent structure in large-scale neural datasets, less has focused on inverting theoretical circuit models conditioned upon the emergent phenomena they produce. Here, we introduce a novel method for statistical inference, which finds distributions of parameter solutions that only produce the desired emergent property. This method seamlessly handles neural circuit models with stochastic nonlinear dynamical generative processes, which are predominant in theoretical neuroscience.

Consider model parameterization $\mathbf{z}$, which is a collection of scientifically interesting variables that govern the complex simulation of data $\mathbf{x}$. For example (see Section 3.1), $\mathbf{z}$ may be the electrical conductance parameters of an STG subcircuit, and $\mathbf{x}$ the evolving membrane potentials of the five neurons. In terms of statistical modeling, this circuit model has an intractable likelihood $p(\mathbf{x} \mid \mathbf{z})$, which is predicated by the stochastic differential equations that define the model. Even so, we do not scientifically reason about how $\mathbf{z}$ governs all of $\mathbf{x}$, but rather specific phenomena that are a function of the data $f(\mathbf{x}; \mathbf{z})$. In the STG example, $f(\mathbf{x}; \mathbf{z})$ measures hub neuron frequency from the evolution of $\mathbf{x}$ governed by $\mathbf{z}$. With EPI, we learn distributions of $\mathbf{z}$ that results in an average and variance of $f(\mathbf{x}; \mathbf{z})$, denoted $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}^2$. We refer to the collection of these statistical moments as an emergent property. Such emergent properties $\mathcal{X}$ are defined through choice of $f(\mathbf{x}; \mathbf{z})$ (which may be one or multiple statistics), $\boldsymbol{\mu}$, and $\boldsymbol{\sigma}^2$

$$\mathcal{X} : \mathbb{E}_{\mathbf{z},\mathbf{x}}\left[f(\mathbf{x}; \mathbf{z})\right] = \boldsymbol{\mu}, \mathrm{Var}_{\mathbf{z},\mathbf{x}}\left[f(\mathbf{x}; \mathbf{z})\right] = \boldsymbol{\sigma}^2. \tag{13}$$

Precisely, the emergent property statistics $f(\mathbf{x}; \mathbf{z})$ must have means $\boldsymbol{\mu}$ and variances $\boldsymbol{\sigma}^2$ over the EPI distribution of parameters and stochasticity of the data given the parameters.

In EPI, deep probability distributions are used as posterior approximations $q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X})$. In deep probability distributions, a simple random variable $\mathbf{z}_0 \sim q_0(\mathbf{z}_0)$ is mapped deterministically via a sequence of deep neural network layers $(g_1, \, .. \, g_l)$ parameterized by weights and biases $\boldsymbol{\theta}$ to the support of the distribution of interest:

$$\mathbf{z} = g_{\boldsymbol{\theta}}(\mathbf{z}_0) = g_l(..g_1(\mathbf{z}_0)) \sim q_{\boldsymbol{\theta}}(\mathbf{z}). \tag{14}$$

Such deep probability distributions embed the posterior distribution in a deep network. Once optimized, this deep network representation has remarkably useful properties: immediate posterior sampling, and immediate probability, gradient, and Hessian evaluation at any parameter choice.

Given a choice of model $p(\mathbf{x} \mid \mathbf{z})$ and emergent property of interest $\mathcal{X}$, $q_{\boldsymbol{\theta}}(\mathbf{z})$ is optimized via the neural network parameters $\boldsymbol{\theta}$ to find a maximally entropic distribution $q^*_{\boldsymbol{\theta}}$ within the deep variational family $\mathcal{Q}$ producing the emergent property $\mathcal{X}$:

$$\begin{aligned} q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X}) = q^*_{\boldsymbol{\theta}}(\mathbf{z}) = \underset{q_{\boldsymbol{\theta}} \in Q}{\operatorname{argmax}} \, H(q_{\boldsymbol{\theta}}(\mathbf{z})) \\ \text{s.t. } \mathcal{X} \quad : \quad \mathbb{E}_{\mathbf{z},\mathbf{x}}\left[f(\mathbf{x};\mathbf{z})\right] = \boldsymbol{\mu}, \operatorname{Var}_{\mathbf{z},\mathbf{x}}\left[f(\mathbf{x};\mathbf{z})\right] = \boldsymbol{\sigma}^2. \end{aligned} \tag{15}$$

Entropy is chosen as the normative selection principle, since we want the posterior to only contain structure predicated by the emergent property [58, 59]. This choice of selection principle is also that of standard Bayesian inference, and we derive an exact relation between EPI and variational inference (see Section 5.1.5). However, a key difference is that variational inference and other Bayesian methods do not constrain the predictions of their inferred posteriors. This optimization is executed using the algorithm of Maximum Entropy Flow Networks (MEFNs) [52].

In the remainder of Section 5.1, we will explain the finer details and motivation of the EPI method. First, we explain related approaches and what EPI introduces to this domain (Section 5.1.1). Second, we describe the special class of deep probability distributions used in EPI called normalizing flows (Section 5.1.2). Next, we explain the constrained optimization technique used to solve Equation 15 (Section 5.1.3). Then, we demonstrate the details of this optimization in a toy example (Section 5.1.4). Finally, we establish the known relationship between maximum entropy distributions and exponential families (Section 5.1.5), which is used to explain the relation between EPI and variational inference (Section 5.1.6).

5.1.1 Related approaches

When Bayesian inference problems lack conjugacy, scientists use approximate inference methods like variational inference (VI) [46] and Markov chain Monte Carlo (MCMC) [45, 44]. After optimization, variational methods return a parameterized posterior distribution, which we can analyze. Also, the variational approximating distribution class is often chosen such that it permits fast sampling. In contrast MCMC methods only produce samples from the approximated posterior distribution. No parameterized distribution is estimated, and additional samples are always generated with the same sampling complexity. Inference in models defined by systems of differential has been

demonstrated with MCMC [81], although this approach requires tractable likelihoods. Advancements have leveraged structure in stochastic differential equation models to improve likelihood approximations, thus expanding the domain of applicable models [82].

Likelihood-free (or "simulation-based") inference (LFI) [83] is model parameter inference in the absence of a tractable likelihood function. The most prevalent approach to LFI is approximate Bayesian computation [42], in which satisfactory parameter samples are kept from random prior sampling according to a rejection heuristic. The obtained set of parameters do not have a probabilities, and further insight about the model must be gained from examination of the parameter set and their generated activity. Methodological advances to ABC methods have come through the use of Markov chain Monte Carlo (MCMC-ABC) [43] and sequential Monte Carlo (SMC-ABC) [31] sampling techniques. SMC-ABC is considered state-of-the-art ABC, yet this approach still struggles to scale in dimensionality (cf. Fig. 4). Furthermore, once a parameter set has been obtained by SMC-ABC from a finite set of particles, the SMC-ABC algorithm must be run again with a new population of initialized particles to obtain additional samples.

For scientific model analysis, we seek a posterior distribution exhibiting the properties of a well-chosen variational approximation: a parametric form conferring analytic calculations, and trivial sampling time. For this reason, ABC and MCMC techniques are unattractive, since they only produce a set of parameter samples and have unchanging sampling rate. EPI executes likelihood-free inference using the MEFN [52] algorithm using a deep variational posterior approximation. The deep neural network of EPI defines the parametric form of the posterior approximation. Furthermore, the EPI distribution is constrained to produce an emergent property. In other words, the summary statistics of the posterior predictive distribution are fixed to have certain first and second moments. EPI optimization is enabled using stochastic gradient techniques in the spirit of likelihood-free variational inference [49]. The analytic relationship between EPI and variational inference is explained in Secton 5.1.6.

We note that, during our preparation and early presentation of this work [84, 85], another work has arisen with broadly similar goals: bringing statistical inference to mechanistic models of neural circuits ([86, 87, 75]).We are encouraged by this general problem being recognized by others in the community, and we emphasize that these works offer complementary neuroscientific contributions (different theoretical models of focus) and use different technical methodologies (ours is built on our prior work [52], theirs similarly [88]).

The method EPI differs from SNPE in some key ways. SNPE belongs to a "sequential" class of

recently developed LFI methods in which two neural networks are used for posterior inference. This first neural network is a normalizing flow used to estimate the posterior $p(\mathbf{z} \mid \mathbf{x})$ (SNPE) or the likelihood $p(\mathbf{x} \mid \mathbf{z})$ (sequential neural likelihood (SNL [89])). A recent advance uses an unconstrained neural network to estimate the likelihood ratio (sequential neural ratio estimation (SNRE [90]). In SNL and SNRE, MCMC sampling techniques are used to obtain samples from the approximated posterior. This contrasts with EPI and SNPE, which afford a normalizing flow approximation to the posterior, which facilitates immediate measurements of sample probability, gradient, or Hessian for system analysis. The second neural network in this sequential class of methods is the amortizer. This network maps data $\mathbf{x}$ (or statistics $f(\mathbf{x}; \mathbf{z})$ or model parameters $\mathbf{z}$ to the weights and biases of the first neural network. These methods are optimized on a conditional density (or ratio) estimation objective on a sequentially adapting finite sample-based approximation to the posterior.

The approximating fidelity of the first neural network in sequential approaches is optimized to generalize across the entire distribution it is conditioned upon. This optimization towards generalization of sequential methods can reduce the accuracy at the singular posterior of interest. Whereas in EPI, the entire expressivity of the normalizing flow is dedicated to learning a single distribution as well as possible. While amortization is not possible in EPI parameterized by the mean parameter μ (due to the inverse mapping problem [91]), we have shown this two-network amortization approach to be effective in exponential family distributions defined by their natural parameterization [92].

Structural identifiability analysis involves the measurement of sensitivity and unidentifiabilities in natural models. Around a point, one can measure the Jacobian. One approach that scales well is EAR [93]. A popular efficient approach for systems of ODEs has been neural ODE adjoint [94] and its stochastic adaptation [95]. Casting identifiability as a statistical estimation problem, the profile likelihood can assess via iterated optimization while holding parameters fixed [96]. An exciting recent method is capable of recovering the functional form of such unidentifiabilities away from a point by following degenerate dimensions of the fisher information matrix [97]. Global structural non-identifiabilities can be found for models with polynomial or rational dynamics equations using DAISY [98]. With EPI, we have all the benefits given by a statistical inference method plus the ability to query the gradient or Hessian of the inferred distribution at any chosen parameter value.

5.1.2 Normalizing flows

Deep probability distributions are comprised of multiple layers of fully connected neural networks (Equation). When each neural network layer is restricted to be a bijective function, the sample density can be calculated using the change of variables formula at each layer of the network. For $\mathbf{z}_i = g_i(\mathbf{z_{i-1}})$,

$$p(\mathbf{z}_i) = p(g_i^{-1}(\mathbf{z}_i)) \left| \det \frac{\partial g_i^{-1}(\mathbf{z}_i)}{\partial \mathbf{z}_i} \right| = p(\mathbf{z}_{i-1}) \left| \det \frac{\partial g_i(\mathbf{z}_{i-1})}{\partial \mathbf{z}_{i-1}} \right|^{-1}. \tag{16}$$

However, this computation has cubic complexity in dimensionality for fully connected layers. By restricting our layers to normalizing flows [47, 99] – bijective functions with fast log determinant Jacobian computations, which confer a fast calculation of the sample log probability. Fast log probability calculation confers efficient optimization of the maximum entropy objective (see Section 5.1.3). We use the Real NVP [50] normalizing flow class, because its coupling architecture confers both fast sampling (forward) and fast log probability evaluation (backward). Fast probability evaluation in turn facilitates fast gradient and Hessian evaluation of log probability throughout parameter space. Glow permutations were used in between coupling stages [100]. This is in contrast to autoregressive architectures [51, 101], in which only forward or backward passes are efficient. In this work, normalizing flows are used as flexible posterior approximations $q_{\boldsymbol{\theta}}(\mathbf{z})$ having weights and biases $\boldsymbol{\theta}$. We specify the architecture used in each application by the number of Real-NVP affine coupling stages, and the number of neural network layers and units per layer of the conditioning functions.

5.1.3 Augmented Lagrangian optimization

To optimize $q_{\boldsymbol{\theta}}(\mathbf{z})$ in Equation 15, the constrained maximum entropy optimization is executed using the augmented Lagrangian method. The following objective is minimized:

$$L(\boldsymbol{\theta}; \boldsymbol{\eta}_{\text{opt}}, c) = -H(q_{\boldsymbol{\theta}}) + \boldsymbol{\eta}_{\text{opt}}^{\top} R(\boldsymbol{\theta}) + \frac{c}{2} ||R(\boldsymbol{\theta})||^2 \tag{17}$$

where average constraint violations $R(\boldsymbol{\theta}) = \mathbb{E}_{\mathbf{z}\sim q_{\boldsymbol{\theta}}} \left[\mathbb{E}_{\mathbf{x}\sim p(\mathbf{x}|\mathbf{z})} \left[T(\mathbf{x}; \mathbf{z}) - \boldsymbol{\mu}_{\text{opt}} \right] \right]$, $\boldsymbol{\eta}_{\text{opt}} \in \mathbb{R}^m$ are the Lagrange multipliers where $m = |\boldsymbol{\mu}_{\text{opt}}| = |T(\mathbf{x}; \mathbf{z})| = 2|f(\mathbf{x}; \mathbf{z})|$, and c is the penalty coefficient. The sufficient statistics $T(\mathbf{x}; \mathbf{z})$ and mean parameter $\boldsymbol{\mu}_{\text{opt}}$ are determined by the means $\boldsymbol{\mu}$ and variances $\boldsymbol{\sigma}^2$ of emergent property statistics $f(\mathbf{x}; \mathbf{z})$ defined in Equation 15. Specifically, $T(\mathbf{x}; \mathbf{z})$ is a concatenation of the first and second moments, $\boldsymbol{\mu}_{\text{opt}}$ is a concatenation of $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}^2$ (see section 5.1.5), and the Lagrange multipliers are closely related to the natural parameters $\boldsymbol{\eta}$ of exponential

families (see Section 5.1.6). Weights and biases $\boldsymbol{\theta}$ of the deep probability distribution are optimized according to Equation 17 using the Adam optimizer with learning rate 10^{-3} [102].

To take gradients with respect to the entropy $H(q_{\boldsymbol{\theta}}(\mathbf{z}))$, it can be expressed using the reparameterization trick as an expectation of the negative log density of parameter samples $\mathbf{z}$ over the randomness in the parameterless initial distribution $q_0(\mathbf{z}_0)$:

$$H(q_{\boldsymbol{\theta}}(\mathbf{z})) = \int -q_{\boldsymbol{\theta}}(\mathbf{z}) \log(q_{\boldsymbol{\theta}}(\mathbf{z}))d\mathbf{z} = \mathbb{E}_{\mathbf{z}\sim q_{\boldsymbol{\theta}}}\left[-\log(q_{\boldsymbol{\theta}}(\mathbf{z}))\right] = \mathbb{E}_{\mathbf{z}_0\sim q_0}\left[-\log(q_{\boldsymbol{\theta}}(g_{\boldsymbol{\theta}}(\mathbf{z}_0)))\right]. \tag{18}$$

Thus, the gradient of the entropy of the deep probability distribution can be estimated as an average with respect to the base distribution $\mathbf{z}_0$:

$$\nabla_{\boldsymbol{\theta}} H(q_{\boldsymbol{\theta}}(\mathbf{z})) = \mathbb{E}_{\mathbf{z}_0\sim q_0}\left[-\nabla_{\boldsymbol{\theta}} \log(q_{\boldsymbol{\theta}}(g_{\boldsymbol{\theta}}(\mathbf{z}_0)))\right]. \tag{19}$$

The lagrangian parameters $\boldsymbol{\eta}_{\text{opt}}$ are initialized to zero and adapted following each augmented Lagrangian epoch, which is a period of optimization with fixed ($\boldsymbol{\eta}_{\text{opt}}$, c) for a given number of stochastic optimization iterations. A low value of c is used initially, and conditionally increased after each epoch based on constraint error reduction. The penalty coefficient is updated based on the result of a hypothesis test regarding the reduction in constraint violation. The p-value of $\mathbb{E}[||R(\boldsymbol{\theta}_{k+1})||] > \gamma\mathbb{E}\left[||R(\boldsymbol{\theta}_k)||\right]$ is computed, and c_{k+1} is updated to βc_k with probability $1-p$. The other update rule is $\boldsymbol{\eta}_{\text{opt},k+1} = \boldsymbol{\eta}_{\text{opt},k} + c_k \frac{1}{n}\sum_{i=1}^{n}(T(\mathbf{x}^{(i)}) - \boldsymbol{\mu}_{\text{opt}})$ given a batch size n. Throughout the study, $\gamma = 0.25$, while β was chosen to be either 2 or 4. The batch size of EPI also varied according to application.

The intention is that c and $\boldsymbol{\eta}_{\text{opt}}$ start at values encouraging entropic growth early in optimization. With each training epoch in which the update rule for c is invoked by unsatisfactory constraint error reduction, the constraint satisfaction terms are increasingly weighted, resulting in a decreased entropy. This encourages the discovery of suitable regions of parameter space, and the subsequent refinement of the distribution to produce the emergent property (see example in Section 5.1.4). The momentum parameters of the Adam optimizer are reset at the end of each augmented Lagrangian epoch.

Rather than starting optimization from some $\boldsymbol{\theta}$ drawn from a randomized distribution, we found that initializing $q_{\boldsymbol{\theta}}(\mathbf{z})$ to approximate an isotropic Gaussian distribution conferred more stable, consistent optimization. The parameters of the Gaussian initialization were chosen on an application-specific basis. Throughout the study, we chose isotropic Gaussian initializations with mean $\boldsymbol{\mu}_{\text{init}}$ at the center of the distribution support and some standard deviation $\boldsymbol{\sigma}_{\text{init}}$, except for one case, where an initialization informed by random search was used (see Section 5.2.1).

To assess whether the EPI distribution $q_{\boldsymbol{\theta}}(\mathbf{z})$ produces the emergent property, we assess whether each individual constraint on the means and variances of $f(\mathbf{x};\mathbf{z})$ is satisfied. We consider the EPI to have converged when a null hypothesis test of constraint violations $R(\boldsymbol{\theta})_i$ being zero is accepted for all constraints $i \in \{1, ..., m\}$ at a significance threshold $\alpha = 0.05$. This significance threshold is adjusted through Bonferroni correction according to the number of constraints m. The p-values for each constraint are calculated according to a two-tailed nonparametric test, where 200 estimations of the sample mean $R(\boldsymbol{\theta})^i$ are made using N_{test} samples of $\mathbf{z} \sim q_{\boldsymbol{\theta}}(\mathbf{z})$ at the end of the augmented Lagrangian epoch.

When assessing the suitability of EPI for a particular modeling question, there are some important technical considerations. First and foremost, as in any optimization problem, the defined emergent property should always be appropriately conditioned (constraints should not have wildly different units). Furthermore, if the program is underconstrained (not enough constraints), the distribution grows (in entropy) unstably unless mapped to a finite support. If overconstrained, there is no parameter set producing the emergent property, and EPI optimization will fail (appropriately). Next, one should consider the computational cost of the gradient calculations. In the best circumstance, there is a simple, closed form expression (e.g. Section 5.2.5) for the emergent property statistic given the model parameters. On the other end of the spectrum, many forward simulation iterations may be required before a high quality measurement of the emergent property statistic is available (e.g. Section 5.2.1). In such cases, backpropagating gradients through the SDE evolution will be expensive.

5.1.4 Example: 2D LDS

To gain intuition for EPI, consider a two-dimensional linear dynamical system (2D LDS) model (Fig. S1A):

$$\tau \frac{d\mathbf{x}}{dt} = A\mathbf{x} \tag{20}$$

with

$$A = \begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix}. \tag{21}$$

To run EPI with the dynamics matrix elements as the free parameters $\mathbf{z} = [a_1, a_2, a_3, a_4]$ (fixing $\tau = 1$), the emergent property statistics $T(\mathbf{x})$ were chosen to contain the first and second moments of the oscillatory frequency, $\frac{\text{imag}(\lambda_1)}{2\pi}$, and the growth/decay factor, real(λ_1), of the oscillating system. λ_1 is the eigenvalue of greatest real part when the imaginary component is zero, and

alternatively of positive imaginary component when the eigenvalues are complex conjugate pairs. To learn the distribution of real entries of A that produce a band of oscillating systems around 1Hz, we formalized this emergent property as $\text{real}(\lambda_1)$ having mean zero with variance 0.25^2, and the oscillation frequency $2\pi\text{imag}(\lambda_1)$ having mean $\omega = 1$ Hz with variance $(0.1\text{Hz})^2$:

$$\mathbb{E}\left[T(\mathbf{x})\right] \triangleq \mathbb{E}\begin{bmatrix} \text{real}(\lambda_1) \\ \text{imag}(\lambda_1) \\ (\text{real}(\lambda_1) - 0)^2 \\ (\text{imag}(\lambda_1) - 2\pi\omega)^2 \end{bmatrix} = \begin{bmatrix} 0.0 \\ 2\pi\omega \\ 0.25^2 \\ (2\pi 0.1)^2 \end{bmatrix} \triangleq \boldsymbol{\mu}. \tag{22}$$

Unlike the models we presented in the main text, this model admits an analytical form for the mean emergent property statistics given parameter $\mathbf{z}$, since the eigenvalues can be calculated using the quadratic formula:

$$\lambda = \frac{(\frac{a_1+a_4}{\tau}) \pm \sqrt{(\frac{a_1+a_4}{\tau})^2 + 4(\frac{a_2a_3 - a_1a_4}{\tau})}}{2}. \tag{23}$$

Importantly, even though $\mathbb{E}_{\mathbf{x}\sim p(\mathbf{x}|\mathbf{z})}\left[T(\mathbf{x})\right]$ is calculable directly via a closed form function and does not require simulation, we cannot derive the distribution $q^*_{\boldsymbol{\theta}}$ directly. This fact is due to the formally hard problem of the backward mapping: finding the natural parameters η from the mean parameters $\boldsymbol{\mu}$ of an exponential family distribution [91]. Instead, we used EPI to approximate this distribution (Fig. S1B). We used a real-NVP normalizing flow architecture with four masks, two neural network layers of 15 units per mask, with batch normalization momentum 0.99, mapped onto a support of $z_i \in [-10, 10]$. (see Section 5.1.2).

Even this relatively simple system has nontrivial (though intuitively sensible) structure in the parameter distribution. To validate our method, we analytically derived the contours of the probability density from the emergent property statistics and values. In the a_1-a_4 plane, the black line at $\text{real}(\lambda_1) = \frac{a_1+a_4}{2} = 0$, dotted black line at the standard deviation $\text{real}(\lambda_1) = \frac{a_1+a_4}{2} \pm 0.25$, and the dotted gray line at twice the standard deviation $\text{real}(\lambda_1) = \frac{a_1+a_4}{2} \pm 0.5$ follow the contour of probability density of the samples (Fig. S2A). The distribution precisely reflects the desired statistical constraints and model degeneracy in the sum of a_1 and a_4. Intuitively, the parameters equivalent with respect to emergent property statistic $\text{real}(\lambda_1)$ have similar log densities.

To explain the bimodality of the EPI distribution, we examined the imaginary component of λ_1.

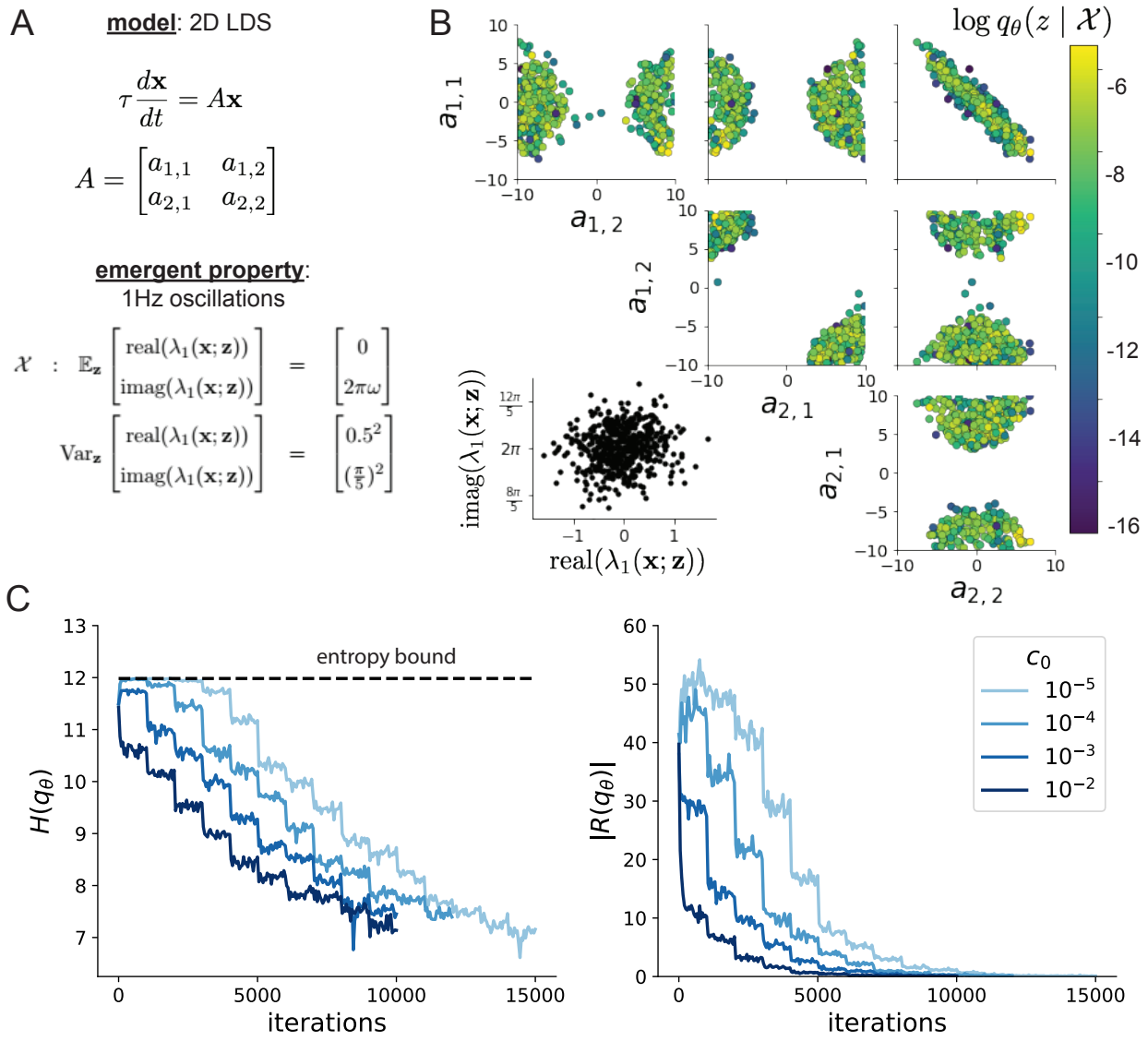

Figure 5: (LDS1): A. Two-dimensional linear dynamical system model, where real entries of the dynamics matrix A are the parameters. B. The EPI distribution for a two-dimensional linear dynamical system with $\tau = 1$ that produces an average of 1Hz oscillations with some small amount of variance. Dashed lines indicate the parameter axes. C. Entropy throughout the optimization. At the beginning of each augmented Lagrangian epoch (2,000 iterations), the entropy dipped due to the shifted optimization manifold where emergent property constraint satisfaction is increasingly weighted. D. Emergent property moments throughout optimization. At the beginning of each augmented Lagrangian epoch, the emergent property moments adjust closer to their constraints.

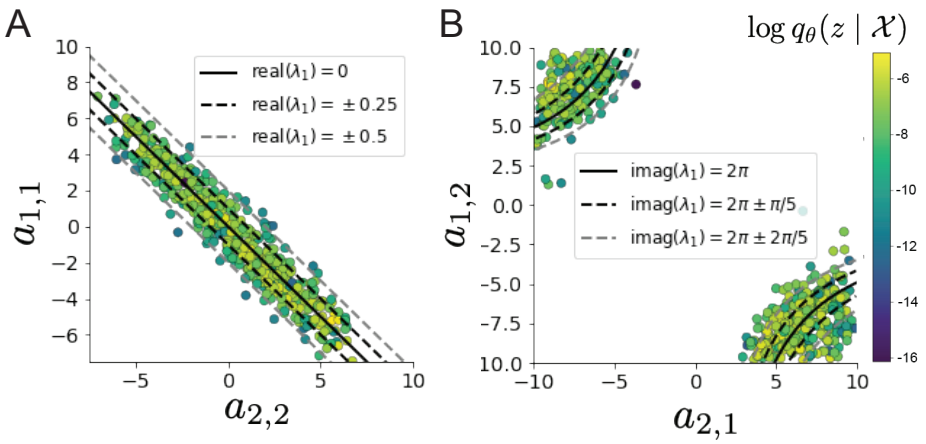

Figure 6: (LDS2): A. Probability contours in the a_1-a_4 plane were derived from the relationship to emergent property statistic of growth/decay factor real(λ_1). B. Probability contours in the a_2-a_3 plane were derived from the emergent property statistic of oscillation frequency 2πimag(λ_1).

When $\text{real}(\lambda_1) = \frac{a_1+a_4}{2} = 0$, we have

$$\text{imag}(\lambda_1) = \begin{cases} \sqrt{\frac{a_1 a_4 - a_2 a_3}{\tau}}, & \text{if } a_1 a_4 < a_2 a_3 \\ 0 & \text{otherwise} \end{cases}. \tag{24}$$

When $\tau = 1$ and $a_1 a_4 > a_2 a_3$ (center of distribution above), we have the following equation for the other two dimensions:

$$\text{imag}(\lambda_1)^2 = a_1 a_4 - a_2 a_3 \tag{25}$$

Since we constrained $\mathbb{E}_{\mathbf{z}\sim q_{\boldsymbol{\theta}}}[\text{imag}(\lambda)] = 2\pi$ (with $\omega = 1$), we can plot contours of the equation $\text{imag}(\lambda_1)^2 = a_1 a_4 - a_2 a_3 = (2\pi)^2$ for various $a_1 a_4$ (Fig. S2B). With $\sigma_{1,4} = \mathbb{E}_{\mathbf{z}\sim q_{\boldsymbol{\theta}}}(|a_1 a_4 - E_{q_{\boldsymbol{\theta}}}[a_1 a_4]|)$, we show the contours as $a_1 a_4 = 0$ (black), $a_1 a_4 = -\sigma_{1,4}$ (black dotted), and $a_1 a_4 = -2\sigma_{1,4}$ (grey dotted). This validates the curved structure of the inferred distribution learned through EPI. We took steps in negative standard deviation of $a_1 a_4$ (dotted and gray lines), since there are few positive values $a_1 a_4$ in the learned distribution. Subtler combinations of model and emergent property will have more complexity, further motivating the use of EPI for understanding these systems. As we expect, the distribution results in samples of two-dimensional linear systems oscillating near 1Hz (Fig. S3).

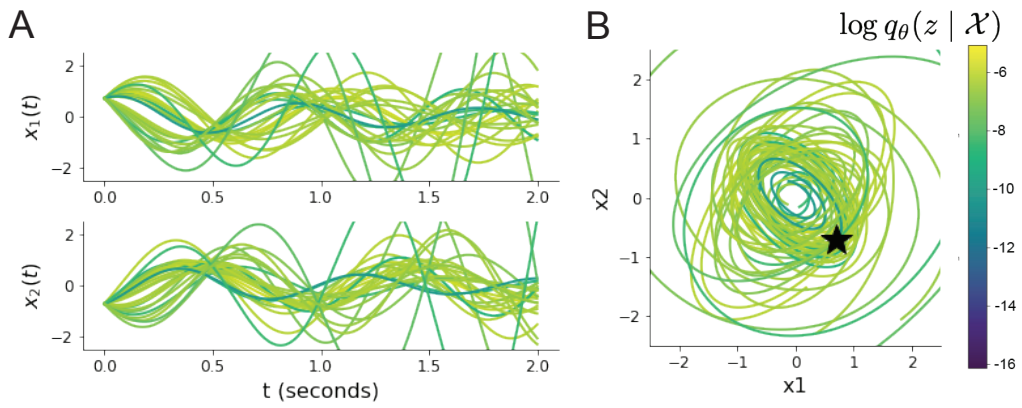

Figure 7: (LDS3): Sampled dynamical systems $\mathbf{z} \sim q_{\boldsymbol{\theta}}(\mathbf{z})$ and their simulated activity from $\mathbf{x}(0) = [\frac{\sqrt{2}}{2}, -\frac{\sqrt{2}}{2}]$ colored by log probability. A. Each dimension of the simulated trajectories throughout time. B The simulated trajectories in phase space.

5.1.5 Maximum entropy distributions and exponential families

Maximum entropy distributions have a fundamental link to exponential family distributions. A maximum entropy distribution of form:

$$\begin{aligned} p^*(\mathbf{z}) &= \underset{p \in \mathcal{P}}{\operatorname{argmax}}\, H(p(\mathbf{z})) \\ &\text{s.t. } \mathbb{E}_{\mathbf{z} \sim p}\left[T(\mathbf{z})\right] = \boldsymbol{\mu}_{\text{opt}}. \end{aligned} \tag{26}$$

will have probability density in the exponential family:

$$p^*(\mathbf{z}) \propto \exp(\boldsymbol{\eta}^\top T(\mathbf{z})). \tag{27}$$

The mappings between the mean parameterization $\boldsymbol{\mu}_{\text{opt}}$ and the natural parameterization $\boldsymbol{\eta}$ are formally hard to identify [91].

In EPI, emergent properties are defined as statistics having a fixed mean and variance as in Equation 4

$$\mathbb{E}_{\mathbf{z},\mathbf{x}}\left[f(\mathbf{x};\mathbf{z})\right] = \boldsymbol{\mu}, \mathrm{Var}_{\mathbf{z},\mathbf{x}}\left[f(\mathbf{x};\mathbf{z})\right] = \boldsymbol{\sigma}^2. \tag{28}$$

The variance constraint is a second moment constraint on $f(\mathbf{x};\mathbf{z})$

$$\mathrm{Var}_{\mathbf{z},\mathbf{x}}\left[f(\mathbf{x};\mathbf{z})\right] = \mathbb{E}_{\mathbf{z},\mathbf{x}}\left[\left(f(\mathbf{x};\mathbf{z}) - \boldsymbol{\mu}\right)^2\right] \tag{29}$$

As a general maximum entropy distribution (Equation 26), the sufficient statistics vector contains

both first and second order moments of $f(\mathbf{x}; \mathbf{z})$

$$T(\mathbf{x}; \mathbf{z}) = \begin{bmatrix} f(\mathbf{x}; \mathbf{z}) \\ (f(\mathbf{x}; \mathbf{z}) - \boldsymbol{\mu})^2 \end{bmatrix}, \tag{30}$$

which are constrained to the chosen means and variances

$$\boldsymbol{\mu}_{\text{opt}} = \begin{bmatrix} \boldsymbol{\mu} \\ \boldsymbol{\sigma}^2 \end{bmatrix}. \tag{31}$$

5.1.6 EPI as variational inference

In Bayesian inference a prior belief about model parameters $\mathbf{z}$ is stated in a prior distribution $p(\mathbf{z})$, and the statistical model capturing the effect of $\mathbf{z}$ on observed data points $\mathbf{x}$ is formalized in the likelihood distribution $p(\mathbf{x} \mid \mathbf{z})$. In Bayesian inference, we obtain a posterior distribution $p(z \mid \mathbf{x})$, which captures how the data inform our knowledge of model parameters using Bayes' rule:

$$p(\mathbf{z} \mid \mathbf{x}) = \frac{p(\mathbf{x} \mid \mathbf{z})p(\mathbf{z})}{p(\mathbf{x})}. \tag{32}$$

The posterior distribution is analytically available when the prior is conjugate with the likelihood. However, conjugacy is rare in practice, and alternative methods, such as variational inference [103], are utilized.

In variational inference, a posterior approximation $q^*_{\boldsymbol{\theta}}$ is chosen from within some variational family $\mathcal{Q}$

$$q^*_{\boldsymbol{\theta}}(\mathbf{z}) = \underset{q_{\boldsymbol{\theta}} \in Q}{\operatorname{argmin}} \, KL(q_{\boldsymbol{\theta}}(\mathbf{z}) \mid\mid p(\mathbf{z} \mid \mathbf{x})). \tag{33}$$

The KL divergence can be written in terms of entropy of the variational approximation:

$$KL(q_{\boldsymbol{\theta}}(\mathbf{z}) \mid\mid p(\mathbf{z} \mid \mathbf{x})) = \mathbb{E}_{\mathbf{z} \sim q_{\boldsymbol{\theta}}} \left[\log(q_{\boldsymbol{\theta}}(\mathbf{z}))\right] - \mathbb{E}_{\mathbf{z} \sim q_{\boldsymbol{\theta}}} \left[\log(p(\mathbf{z} \mid \mathbf{x}))\right] \tag{34}$$

$$= -H(q_{\boldsymbol{\theta}}) - \mathbb{E}_{\mathbf{z} \sim q_{\boldsymbol{\theta}}} \left[\log(p(\mathbf{x} \mid \mathbf{z})) + \log(p(\mathbf{z})) - \log(p(\mathbf{x}))\right] \tag{35}$$

Since the marginal distribution of the data $p(\mathbf{x})$ (or "evidence") is independent of $\boldsymbol{\theta}$, variational inference is executed by optimizing the remaining expression. This is usually framed as maximizing the evidence lower bound (ELBO)

$$\underset{q_{\boldsymbol{\theta}} \in Q}{\operatorname{argmin}} \, KL(q_{\boldsymbol{\theta}} \mid\mid p(\mathbf{z} \mid \mathbf{x})) = \underset{q_{\boldsymbol{\theta}} \in Q}{\operatorname{argmax}} \, H(q_{\boldsymbol{\theta}}) + \mathbb{E}_{\mathbf{z} \sim q_{\boldsymbol{\theta}}} \left[\log(p(\mathbf{x} \mid \mathbf{z})) + \log(p(\mathbf{z}))\right]. \tag{36}$$

Now, consider the setting where we have chosen a uniform prior, and stipulate a mean-field gaussian likelihood on a chosen statistic of the data $f(\mathbf{x}; \mathbf{z})$

$$p(\mathbf{x} \mid \mathbf{z}) = \mathcal{N}(f(\mathbf{x}; \mathbf{z}) \mid \boldsymbol{\mu}_f, \Sigma_f), \tag{37}$$

where $\Sigma_f = \text{diag}(\boldsymbol{\sigma}_f^2)$. The log likelihood is then proportional to a dot product of the natural parameter of this mean-field gaussian distribution and the first and second moment statistics.

$$\log p(\mathbf{x} \mid \mathbf{z}) \propto \boldsymbol{\eta}_f^\top T(\mathbf{x}, \mathbf{z}), \tag{38}$$

where

$$\boldsymbol{\eta}_f = \begin{bmatrix} \frac{\boldsymbol{\mu}_f}{\boldsymbol{\sigma}_f^2} \\ \frac{-1}{2\boldsymbol{\sigma}_f^2} \end{bmatrix}, \text{ and} \tag{39}$$

$$T(\mathbf{x}; \mathbf{z}) = \begin{bmatrix} f(\mathbf{x}; \mathbf{z}) \\ (f(\mathbf{x}; \mathbf{z}) - \boldsymbol{\mu}_f)^2 \end{bmatrix}. \tag{40}$$

The variational objective is then

$$\underset{q_{\boldsymbol{\theta}} \in Q}{\text{argmax}}\, H(q_{\boldsymbol{\theta}}) + \boldsymbol{\eta}_f^\top \mathbb{E}_{\mathbf{z} \sim q_{\boldsymbol{\theta}}} \left[T(\mathbf{x}; \mathbf{z}) \right] \tag{41}$$

Comparing this to the Lagrangian objective (without augmentation) of EPI, we see they are the same

$$\begin{aligned} q^*_{\boldsymbol{\theta}}(\mathbf{z}) &= \underset{q_{\boldsymbol{\theta}} \in Q}{\text{argmin}} -H(q_{\boldsymbol{\theta}}) + \boldsymbol{\eta}_{\text{opt}}^\top \left(\mathbb{E}_{\mathbf{z},\mathbf{x}} \left[T(\mathbf{x}; \mathbf{z}) \right] - \boldsymbol{\mu}_{\text{opt}} \right) \\ &= \underset{q_{\boldsymbol{\theta}} \in Q}{\text{argmin}} -H(q_{\boldsymbol{\theta}}) + \boldsymbol{\eta}_{\text{opt}}^\top \mathbb{E}_{\mathbf{z},\mathbf{x}} \left[T(\mathbf{x}; \mathbf{z}) \right]. \end{aligned} \tag{42}$$

where $T(\mathbf{x}; \mathbf{z})$ consists of the first and second moments of the emergent property statistic $f(\mathbf{x}; \mathbf{z})$ (Equation 30). Thus, EPI is implicitly executing variational inference with a uniform prior and a mean-field gaussian likelihood on the emergent property statistics. The data $\mathbf{x}$ used by this implicit variational inference program would be that generated by the adapting variational approximation $\mathbf{x} \sim p(\mathbf{x} \mid \mathbf{z}) q_{\boldsymbol{\theta}}(\mathbf{z})$, and the likelihood parameters $\boldsymbol{\eta}_f$ of EPI optimization epoch k are predicated by $\boldsymbol{\eta}_{\text{opt},k}$. However, in EPI we have not specified a prior distribution, or collected data, which can inform us about model parameters. Instead we have a mathematical specification of an emergent property, which the model must produce, and a maximum entropy selection principle. Accordingly, we replace the notation of $p(\mathbf{z} \mid \mathbf{x})$ with $p(\mathbf{z} \mid \mathcal{X})$ conceptualizing an inferred distribution that obeys emergent property $\mathcal{X}$ (see Section 5.1).

5.2 Theoretical models

In this study, we used emergent property inference to examine several models relevant to theoretical neuroscience. Here, we provide the details of each model and the related analyses.

5.2.1 Stomatogastric ganglion

We analyze how the parameters $\mathbf{z} = [g_{\text{el}}, g_{\text{synA}}]$ govern the emergent phenomena of intermediate hub frequency in a model of the stomatogastric ganglion (STG) [57] shown in Figure 1A with activity $\mathbf{x} = [x_{\text{f1}}, x_{\text{f2}}, x_{\text{hub}}, x_{\text{s1}}, x_{\text{s2}}]$, using the same hyperparameter choices as Gutierrez et al. Each neuron's membrane potential $x_\alpha(t)$ for $\alpha \in \{\text{f1}, \text{f2}, \text{hub}, \text{s1}, \text{s2}\}$ is the solution of the following stochastic differential equation:

$$C_m \frac{dx_\alpha}{dt} = -\left[h_{leak}(\mathbf{x};\mathbf{z}) + h_{Ca}(\mathbf{x};\mathbf{z}) + h_K(\mathbf{x};\mathbf{z}) + h_{hyp}(\mathbf{x};\mathbf{z}) + h_{elec}(\mathbf{x};\mathbf{z}) + h_{syn}(\mathbf{x};\mathbf{z})\right] + dB. \quad (43)$$

The input current of each neuron is the sum of the leak, calcium, potassium, hyperpolarization, electrical and synaptic currents as well as gaussian noise dB. Each current component is a function of all membrane potentials and the conductance parameters $\mathbf{z}$.

The capacitance of the cell membrane was set to $C_m = 1nF$. Specifically, the currents are the difference in the neuron's membrane potential and that current type's reversal potential multiplied by a conductance:

$$h_{leak}(\mathbf{x};\mathbf{z}) = g_{leak}(x_\alpha - V_{leak}) \quad (44)$$

$$h_{elec}(\mathbf{x};\mathbf{z}) = g_{\text{el}}(x_\alpha^{post} - x_\alpha^{pre}) \quad (45)$$

$$h_{syn}(\mathbf{x};\mathbf{z}) = g_{syn} S_\infty^{pre}(x_\alpha^{post} - V_{syn}) \quad (46)$$

$$h_{Ca}(\mathbf{x};\mathbf{z}) = g_{Ca} M_\infty(x_\alpha - V_{Ca}) \quad (47)$$

$$h_K(\mathbf{x};\mathbf{z}) = g_K N(x_\alpha - V_K) \quad (48)$$

$$h_{hyp}(\mathbf{x};\mathbf{z}) = g_h H(x_\alpha - V_{hyp}). \quad (49)$$

The reversal potentials were set to $V_{leak} = -40mV$, $V_{Ca} = 100mV$, $V_K = -80mV$, $V_{hyp} = -20mV$, and $V_{syn} = -75mV$. The other conductance parameters were fixed to $g_{leak} = 1 \times 10^{-4}\mu S$. g_{Ca}, g_K, and g_{hyp} had different values based on fast, intermediate (hub) or slow neuron. The fast conductances had values $g_{Ca} = 1.9\times10^{-2}$, $g_K = 3.9\times10^{-2}$, and $g_{hyp} = 2.5\times10^{-2}$. The intermediate conductances had values $g_{Ca} = 1.7 \times 10^{-2}$, $g_K = 1.9 \times 10^{-2}$, and $g_{hyp} = 8.0 \times 10^{-3}$. Finally, the slow conductances had values $g_{Ca} = 8.5 \times 10^{-3}$, $g_K = 1.5 \times 10^{-2}$, and $g_{hyp} = 1.0 \times 10^{-2}$.

Furthermore, the Calcium, Potassium, and hyperpolarization channels have time-dependent gating dynamics dependent on steady-state gating variables M_∞, N_∞ and H_∞, respectively:

$$M_\infty = 0.5\left(1 + \tanh\left(\frac{x_\alpha - v_1}{v_2}\right)\right) \quad (50)$$

$$\frac{dN}{dt} = \lambda_N(N_\infty - N) \tag{51}$$

$$N_\infty = 0.5\left(1 + \tanh\left(\frac{x_\alpha - v_3}{v_4}\right)\right) \tag{52}$$

$$\lambda_N = \phi_N \cosh\left(\frac{x_\alpha - v_3}{2v_4}\right) \tag{53}$$

$$\frac{dH}{dt} = \frac{(H_\infty - H)}{\tau_h} \tag{54}$$

$$H_\infty = \frac{1}{1 + \exp\left(\frac{x_\alpha + v_5}{v_6}\right)} \tag{55}$$

$$\tau_h = 272 - \left(\frac{-1499}{1 + \exp\left(\frac{-x_\alpha + v_7}{v_8}\right)}\right). \tag{56}$$

where we set $v_1 = 0mV$, $v_2 = 20mV$, $v_3 = 0mV$, $v_4 = 15mV$, $v_5 = 78.3mV$, $v_6 = 10.5mV$, $v_7 = -42.2mV$, $v_8 = 87.3mV$, $v_9 = 5mV$, and $v_{th} = -25mV$.

Finally, there is a synaptic gating variable as well:

$$S_\infty = \frac{1}{1 + \exp\left(\frac{v_{th} - x_\alpha}{v_9}\right)}. \tag{57}$$

When the dynamic gating variables are considered, this is actually a 15-dimensional nonlinear dynamical system. Gaussian noise $d\mathbf{B}$ of variance $(1 \times 10^{-12})^2$ A^2 makes the model stochastic, and introduces variability in frequency at each parameterization $\mathbf{z}$.

In order to measure the frequency of the hub neuron during EPI, the STG model was simulated for $T = 300$ time steps of $dt = 25$ms. The chosen dt and T were the most computationally convenient choices yielding accurate frequency measurement. We used a basis of complex exponentials with frequencies from 0.0-1.0 Hz at 0.01Hz resolution to measure frequency from simulated time series

$$\Phi = [0.0, 0.01, ..., 1.0]^\top .. \tag{58}$$

To measure spiking frequency, we processed simulated membrane potentials with a relu (spike extraction) and low-pass filter with averaging window of size 20, then took the frequency with the maximum absolute value of the complex exponential basis coefficients of the processed time-series. The first 20 temporal samples of the simulation are ignored to account for initial transients.

To differentiate through the maximum frequency identification, we used a soft-argmax Let $X_\alpha \in \mathcal{C}^{|\Phi|}$ be the complex exponential filter bank dot products with the signal $x_\alpha \in \mathbb{R}^N$, where $\alpha \in$

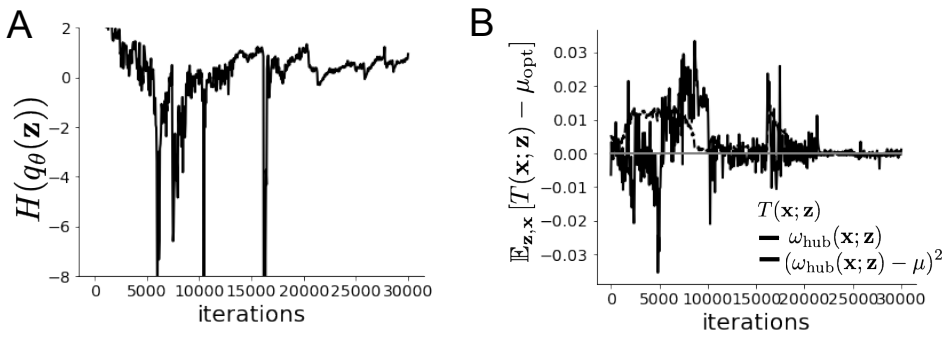

Figure 8: (STG1): EPI optimization of the STG model producing network syncing. A. Entropy throughout optimization. B. The emergent property statistic means and variances converge to their constraints at 25,000 iterations following the fifth augmented Lagrangian epoch.

{f1, f2, hub, s1, s2}. The soft-argmax is then calculated using temperature parameter $\beta = 100$

$$\psi_\alpha = \text{softmax}(\beta |X_\alpha| \odot i), \tag{59}$$

where $i = [0, 1, ..., 100]$. The frequency is then calculated as

$$\omega_\alpha = 0.01 \psi_\alpha \text{Hz}. \tag{60}$$

Intermediate hub frequency, like all other emergent properties in this work, is defined by the mean and variance of the emergent property statistics. In this case, we have one statistic, hub neuron frequency, where the mean was chosen to be 0.55Hz, and variance was chosen to be $(0.025\text{Hz})^2$ to capture variation in frequency between 0.5Hz and 0.6Hz (Equation 4). As a maximum entropy distribution, $T(\mathbf{x}, \mathbf{z})$ is comprised of both these first and second moments of the hub neuron frequency (as in Equations 30 and 31)

$$T(\mathbf{x};\mathbf{z}) = \begin{bmatrix} \omega_{\text{hub}}(\mathbf{x};\mathbf{z}) \\ (\omega_{\text{hub}}(\mathbf{x};\mathbf{z}) - 0.55)^2 \end{bmatrix}, \tag{61}$$

$$\boldsymbol{\mu}_{\text{opt}} = \begin{bmatrix} 0.55 \\ 0.025^2 \end{bmatrix}. \tag{62}$$

Throughout optimization, the augmented Lagrangian parameters η and c, were updated after each epoch of 5,000 iterations(see Section 5.1.3). The optimization converged after five epochs (Fig. S4).

For EPI in Fig 1E, we used a real NVP architecture with three Real NVP coupling layers and two-layer neural networks of 25 units per layer. The normalizing flow architecture mapped $z_0 \sim \mathcal{N}(\mathbf{0}, I)$

to a support of $\mathbf{z} = [g_{\text{el}}, g_{\text{synA}}] \in [4, 8] \times [0.01, 4]$, initialized to a gaussian approximation of samples returned by a preliminary ABC search. We did not include $g_{\text{synA}} < 0.01$, for numerical stability. EPI optimization was run using 5 different random seeds for architecture initialization $\boldsymbol{\theta}$ with an augmented Lagrangian coefficient of $c_0 = 10^5$, a batch size $n = 400$, and $\beta = 2$. The distribution shown is that of the architecture converging with criteria $N_{\text{test}} = 100$ at greatest entropy across random seeds.

We calculated the Hessian at the mode of the inferred EPI distribution. The Hessian of a probability model is the second order gradient of the log probability density $\log q_{\boldsymbol{\theta}}(\mathbf{z})$ with respect to the parameters $\mathbf{z}$: $\frac{\partial^2 \log q_{\boldsymbol{\theta}}(\mathbf{z})}{\partial \mathbf{z} \partial \mathbf{z}^\top}$. With EPI, we can examine the Hessian, which is analytically available throughout distribution, to indicate the dimensions of parameter space that are sensitive (strongly negative eigenvalue), and which are degenerate (low magnitude eigenvalue) with respect to the emergent property produced. In Figure 1D, the eigenvectors of the Hessian v_1 (solid) and v_2 (dashed) are shown evaluated at the mode of the distribution. The length of the arrows is inversely proportional to the square root of absolute value of their eigenvalues $\lambda_1 = -10.7$ and $\lambda_2 = -3.22$. Since the Hessian eigenvectors have sign degeneracy, the visualized directions in 2-D parameter space are chosen arbitrarily.

5.2.2 Primary visual cortex

In the stochastic stabilized supralinear network [71], population rate responses $\mathbf{x}$ to input $\mathbf{h}$, recurrent input $W\mathbf{x}$ and slow noise $\boldsymbol{\epsilon}$ are governed by

$$\tau \frac{d\mathbf{x}}{dt} = -\mathbf{x} + \phi(W\mathbf{x} + \mathbf{h} + \boldsymbol{\epsilon}), \tag{63}$$

where the noise is an Ornstein-Uhlenbeck process $\boldsymbol{\epsilon} \sim OU(\tau_{\text{noise}}, \boldsymbol{\sigma})$

$$\tau_{\text{noise}} d\epsilon_\alpha = -\epsilon_\alpha dt + \sqrt{2\tau_{\text{noise}}} \tilde{\sigma}_\alpha dB \tag{64}$$

with $\tau_{\text{noise}} = 5\text{ms} > \tau = 1\text{ms}$. The noisy process is parameterized as

$$\tilde{\sigma}_\alpha = \sigma_\alpha \sqrt{1 + \frac{\tau}{\tau_{\text{noise}}}}, \tag{65}$$

so that $\boldsymbol{\sigma}$ parameterizes the variance of the noisy input in the abscence of recurrent connectivity ($W = \mathbf{0}$). As contrast increases, input to the E- and P-populations increases relative to a baseline input $\mathbf{h} = \mathbf{h}_b + c\mathbf{h}_c$. Connectivity ($W_{\text{fit}}$) and input ($\mathbf{h}_{b,\text{fit}}$ and $\mathbf{h}_{c,\text{fit}}$) parameters were fit using the deterministic V1 circuit model [72]

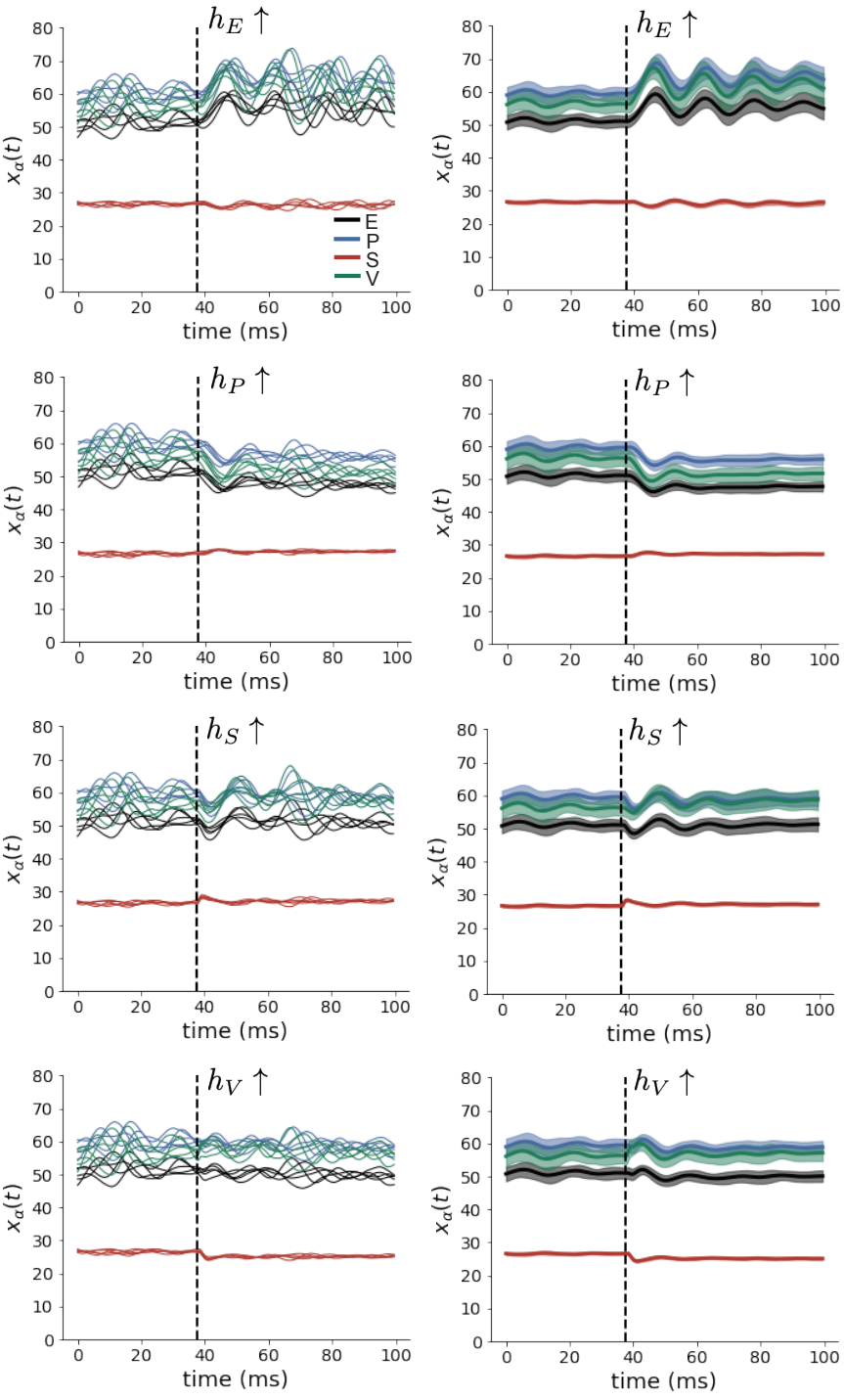

Figure 9: (V1 1) (Left) Simulations for small increases in neuron-type population input. Input magnitudes are chosen so that effect is salient (0.002 for E and P, but 0.02 for S and V). (Right) Average (solid) and standard deviation (shaded) of stochastic fluctuations of responses.

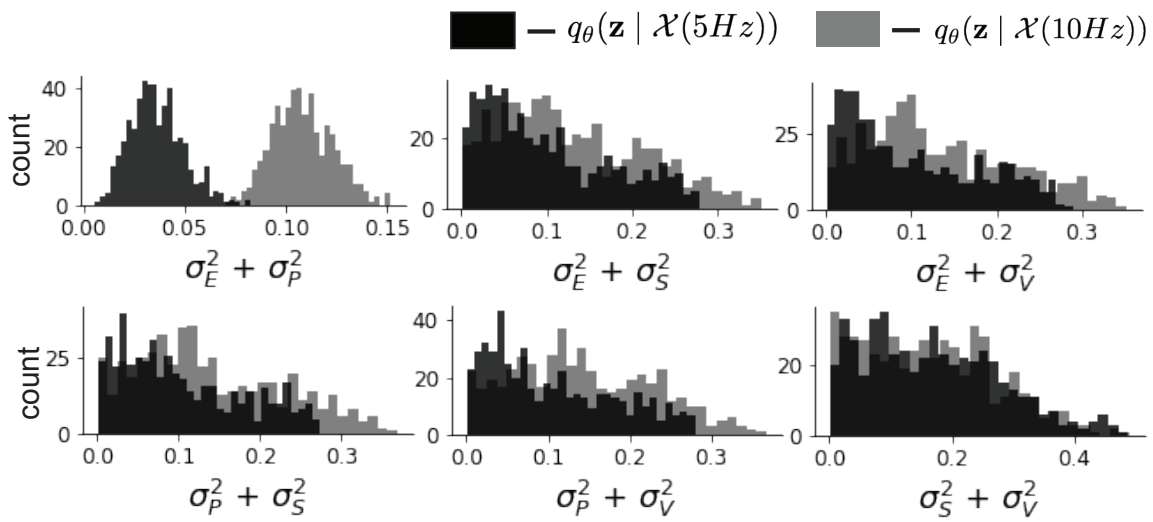

Figure 10: (V1 2) Posterior predictive distributions of the sum of squares of each pair of noise parameters.

$$W_{\text{fit}} = \begin{bmatrix} W_{EE} & W_{EP} & W_{ES} & W_{EV} \\ W_{PE} & W_{PP} & W_{PS} & W_{PV} \\ W_{SE} & W_{SP} & W_{SS} & W_{SV} \\ W_{VE} & W_{VP} & W_{VS} & W_{VV} \end{bmatrix} = \begin{bmatrix} 2.18 & -1.19 & -.594 & -.229 \\ 1.66 & -.651 & -.680 & -.242 \\ .895 & -5.22 \times 10^{-3} & -1.51 \times 10^{-4} & -.761 \\ 3.34 & -2.31 & -.254 & -2.52 \times 10^{-4} \end{bmatrix}, \tag{66}$$

$$\mathbf{h}_{b,\text{fit}} = \begin{bmatrix} .416 \\ .429 \\ .491 \\ .486 \end{bmatrix}, \tag{67}$$

and

$$\mathbf{h}_{c,\text{fit}} = \begin{bmatrix} .359 \\ .403 \\ 0 \\ 0 \end{bmatrix}. \tag{68}$$

To obtain rates on a realistic scale (100-fold greater), we map these fitted parameters to an equivalence class

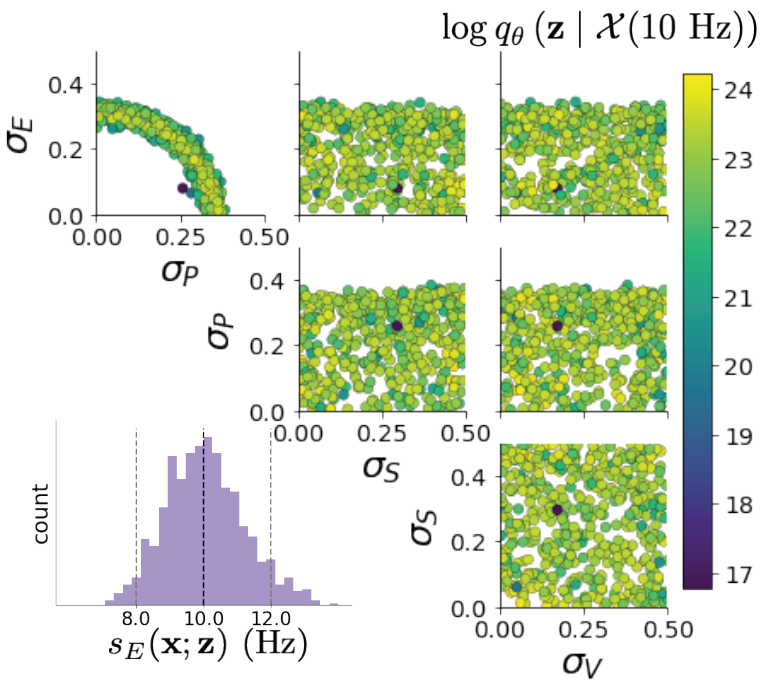

Figure 11: (V1 3) EPI posterior for $\mathcal{X}(10\text{ Hz})$.

$$W = \begin{bmatrix} W_{EE} & W_{EP} & W_{ES} & W_{EV} \\ W_{PE} & W_{PP} & W_{PS} & W_{PV} \\ W_{SE} & W_{SP} & W_{SS} & W_{SV} \\ W_{VE} & W_{VP} & W_{VS} & W_{VV} \end{bmatrix} = \begin{bmatrix} .218 & -.119 & -.0594 & -.0229 \\ .166 & -.0651 & -.068 & -.0242 \\ .0895 & -5.22 \times 10^{-4} & -1.51 \times 10^{-5} & -.0761 \\ .334 & -.231 & -.0254 & -2.52 \times 10^{-5} \end{bmatrix}, \tag{69}$$

$$\mathbf{h}_b = \begin{bmatrix} h_{b,E} \\ h_{b,P} \\ h_{b,S} \\ h_{b,V} \end{bmatrix} = \begin{bmatrix} 4.16 \\ 4.29 \\ 4.91 \\ 4.86 \end{bmatrix}, \tag{70}$$

and

$$\mathbf{h}_c = \begin{bmatrix} h_{c,E} \\ h_{c,P} \\ h_{c,S} \\ h_{c,V} \end{bmatrix} = \begin{bmatrix} 3.59 \\ 4.03 \\ 0 \\ 0 \end{bmatrix}. \tag{71}$$

Circuit responses are simulated using $T = 200$ time steps at $dt = 0.5$ms from an initial condition

drawn from $\mathbf{x}(0) \sim U\left[10 \text{ Hz}, 25 \text{ Hz}\right]$. Standard deviation of the E-population $s_E(\mathbf{x}; \mathbf{z})$ is calculated as the square root of the temporal variance from $t_{ss} = 75$ms to $Tdt = 100$ms averaged over 100 independent trials.

$$s_E(\mathbf{x}; \mathbf{z}) = \mathbb{E}_x \left[\sqrt{\mathbb{E}_{t>t_{ss}} \left[\left(x_E(t) - \mathbb{E}_{t>t_{ss}} \left[x_E(t) \right] \right)^2 \right]} \right] \tag{72}$$

For EPI in Fig 2D-E, we used a real NVP architecture with three Real NVP coupling layers and two-layer neural networks of 50 units per layer. The normalizing flow architecture mapped $z_0 \sim \mathcal{N}(\mathbf{0}, I)$ to a support of $\mathbf{z} = [\sigma_E, \sigma_P, \sigma_S, \sigma_V] \in [0.0, 0.5]^4$. EPI optimization was run using three different random seeds for architecture initialization $\boldsymbol{\theta}$ with an augmented Lagrangian coefficient of $c_0 = 10^{-1}$, a batch size $n = 100$, and $\beta = 2$. The distributions shown are those of the architectures converging with criteria $N_{\text{test}} = 100$ at greatest entropy across random seeds.

In Fig. 2E, we visualize the modes of $q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X})$ throughout the σ_E-σ_P marginal. Specifically, we calculated

$$\begin{aligned} \mathbf{z}^*(\sigma_{P,\text{fixed}}) = &\underset{\mathbf{z}}{\text{argmax}} \log q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X}) \\ &\text{s.t. } \sigma_P = \sigma_{P,\text{fixed}} \end{aligned} \tag{73}$$

At each mode $\mathbf{z}^*$, we calculated the Hessian and visualized the sensitivity dimension in the direction of positive σ_E.

5.2.3 Primary visual cortex: challenges to analysis

TODO Agostina and I are putting this together now.

5.2.4 Superior colliculus

In the model of Duan et al [55], there are four total units: two in each hemisphere corresponding to the Pro/Contra and Anti/Ipsi populations. They are denoted as left Pro (LP), left Anti (LA), right Pro (RP) and right Anti (RA). Each unit has an activity (x_α) and internal variable (u_α) related by

$$x_\alpha = \phi(u_\alpha) = \left(\frac{1}{2} \tanh \left(\frac{u_\alpha - a}{b} \right) + \frac{1}{2} \right) \tag{74}$$

where $\alpha \in \{LP, LA, RA, RP\}$, $a = 0.05$ and $b = 0.5$ control the position and shape of the nonlinearity, respectively. During periods of optogenetic inactivation, activity was decreased proportional to the optogenetic strength γ

$$x_\alpha = (1 - \gamma)\phi(u_\alpha). \tag{75}$$

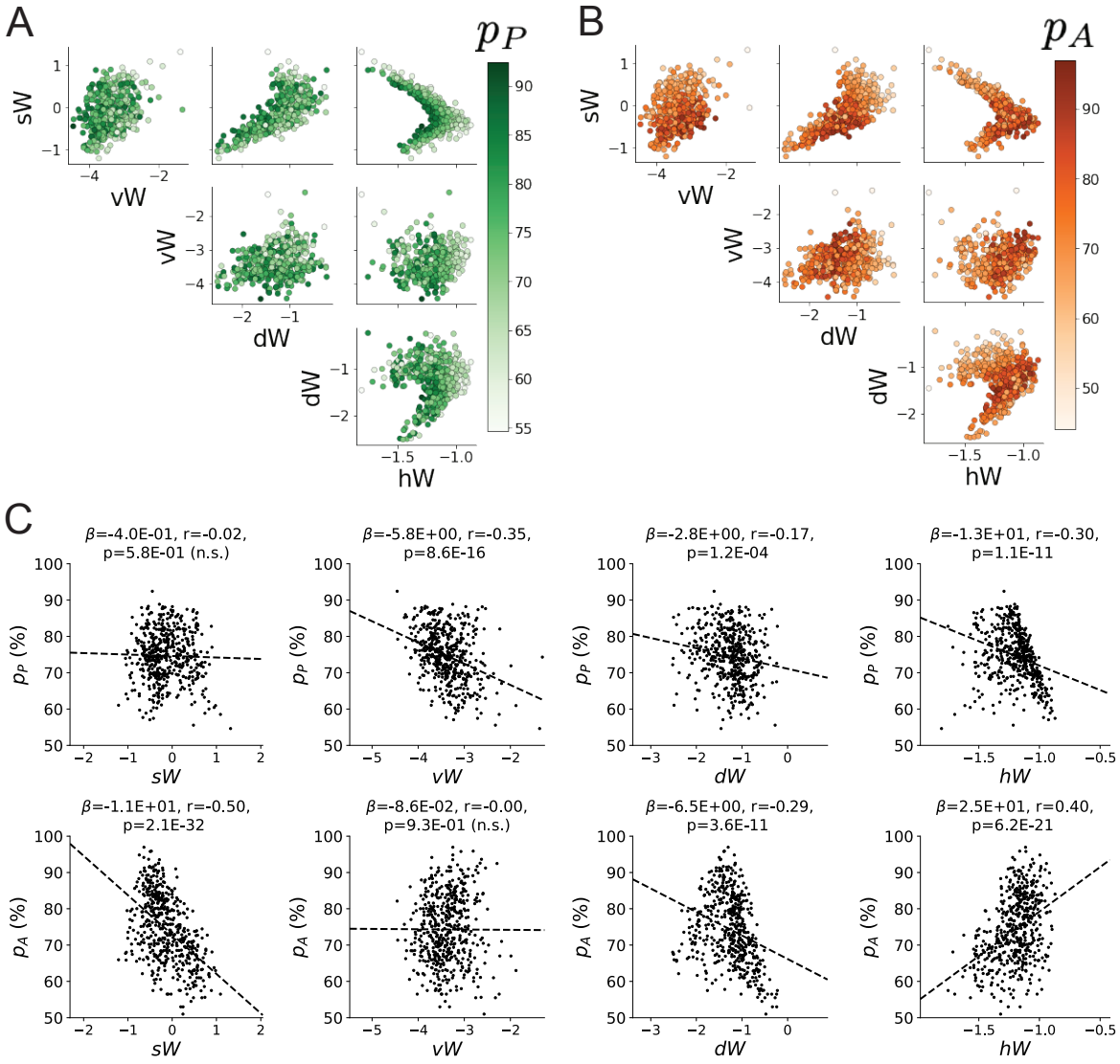

Figure 12: (SC1): **A**. Same pairplot as Fig. 3C colored by Pro task accuracy. **B**. Same as A colored by Anti task accuracy. **C**. Connectivity parameters of EPI distributions versus task accuracies. β is slope coefficient of linear regression, r is correlation, and p is the two-tailed p-value.

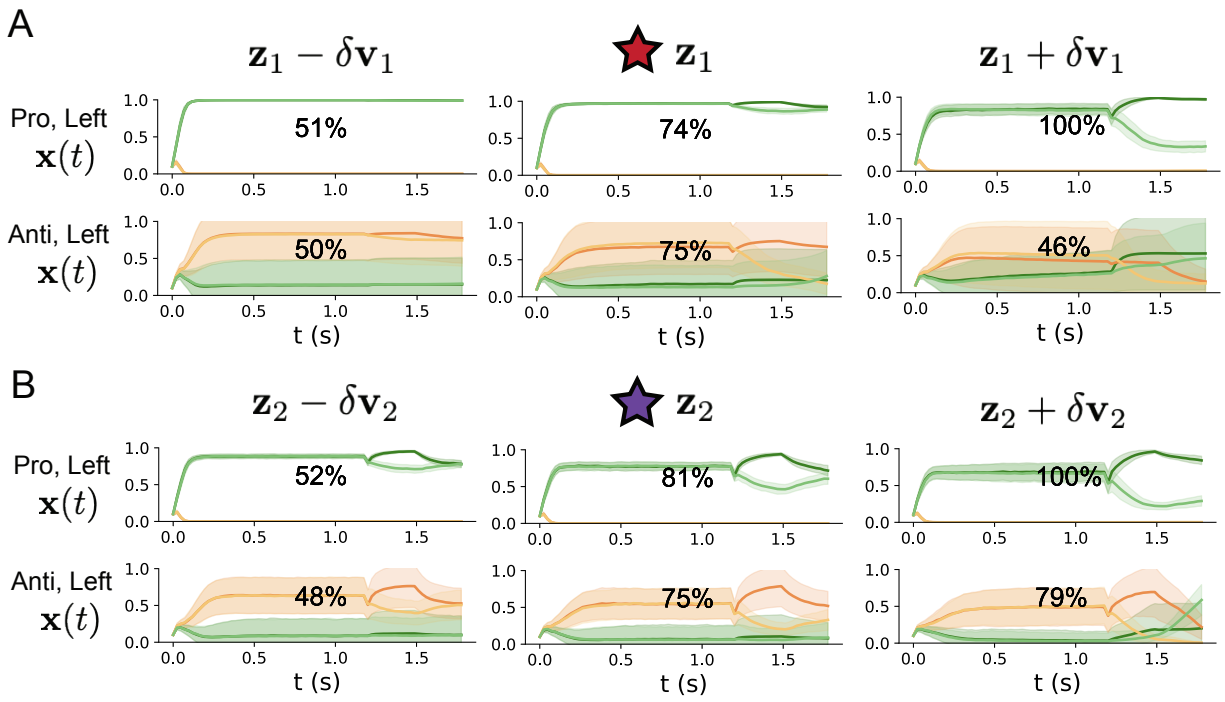

Figure 13: (SC2): **A**. Simulations in network regime $\mathbf{z}_1$ (center) with simulations given connectivity perturbations in the negative direction of the sensitivity vector $\mathbf{v}_1$ (left) and positive direction (right). **B**. Same as A for network regime $\mathbf{z}_2$.

We order the neural populations of x and u in the following manner

$$\mathbf{x} = \begin{bmatrix} x_{LP} \\ x_{LA} \\ x_{RP} \\ x_{RA} \end{bmatrix} \qquad \mathbf{u} = \begin{bmatrix} u_{LP} \\ u_{LA} \\ u_{RP} \\ u_{RA} \end{bmatrix}, \tag{76}$$

which evolve according to

$$\tau \frac{d\mathbf{u}}{dt} = -\mathbf{u} + W\mathbf{x} + \mathbf{h} + d\mathbf{B}. \tag{77}$$

with time constant $\tau = 0.09s$, step size 24ms and Gaussian noise $d\mathbf{B}$ of variance 0.2^2. The weight matrix has 4 parameters sW, vW, hW, and dW:

$$W = \begin{bmatrix} sW & vW & hW & dW \\ vW & sW & dW & hW \\ hW & dW & sW & vW \\ dW & hW & vW & sW \end{bmatrix}. \tag{78}$$

The circuit receives four different inputs throughout each trial, which has a total length of 1.8s.

$$\mathbf{h} = \mathbf{h}_{\text{constant}} + \mathbf{h}_{\text{P,bias}} + \mathbf{h}_{\text{rule}} + \mathbf{h}_{\text{choice-period}} + \mathbf{h}_{\text{light}}. \tag{79}$$

There is a constant input to every population,

$$\mathbf{h}_{\text{constant}} = I_{\text{constant}}[1, 1, 1, 1]\top, \tag{80}$$

a bias to the Pro populations

$$\mathbf{h}_{\text{P,bias}} = I_{\text{P,bias}}[1, 0, 1, 0]\top, \tag{81}$$

rule-based input depending on the condition

$$\mathbf{h}_{\text{P,rule}}(t) = \begin{cases} I_{\text{P,rule}}[1, 0, 1, 0]^\top, & \text{if } t \leq 1.2s \\ 0, & \text{otherwise} \end{cases} \tag{82}$$

$$\mathbf{h}_{\text{A,rule}}(t) = \begin{cases} I_{\text{A,rule}}[0, 1, 0, 1]^\top, & \text{if } t \leq 1.2s \\ 0, & \text{otherwise} \end{cases}, \tag{83}$$

a choice-period input

$$\mathbf{h}_{\text{choice}}(t) = \begin{cases} I_{\text{choice}}[1, 1, 1, 1]^\top, & \text{if } t > 1.2s \\ 0, & \text{otherwise} \end{cases}, \tag{84}$$

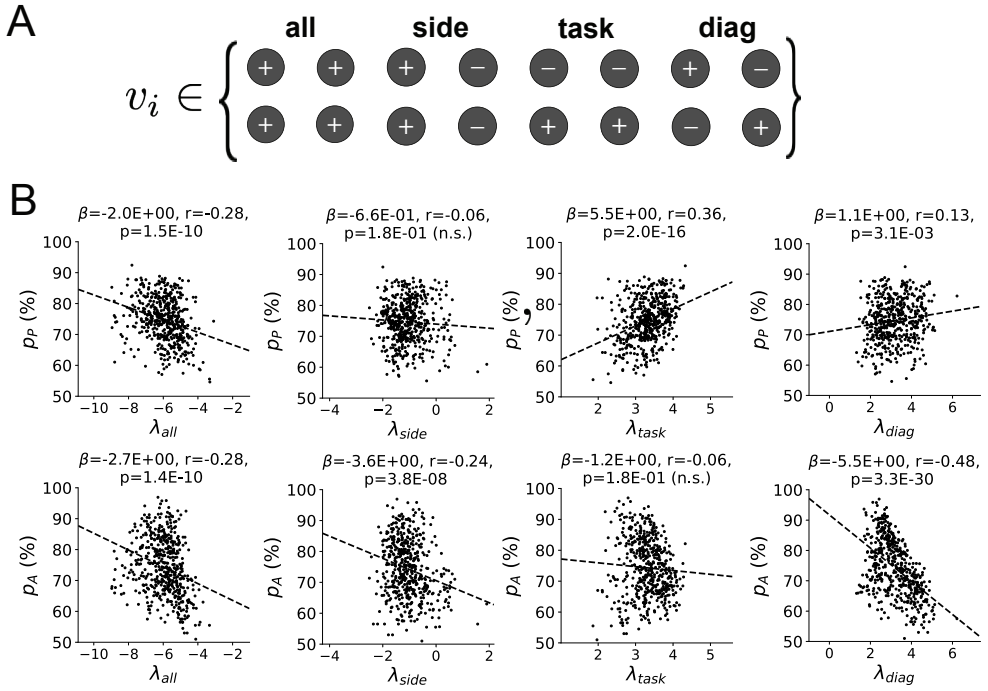

Figure 14: (SC3): **A**. Invariant eigenvectors of connectivity matrix W. **B**. Eigenvalues of connectivities of EPI distribution versus task accuracies.

and an input to the right or left-side depending on where the light stimulus is delivered

$$\mathbf{h}_{\text{light}}(t) = \begin{cases} I_{\text{light}}[1,1,0,0]^\top, & \text{if } 1.2s < t < 1.5s \text{ and Left} \\ I_{\text{light}}[0,0,1,1]^\top, & \text{if } 1.2s < t < 1.5s \text{ and Right} \cdot \\ 0, & \text{otherwise} \end{cases} \tag{85}$$

The input parameterization was fixed to $I_{\text{constant}} = 0.75$, $I_{\text{P,bias}} = 0.5$, $I_{\text{P,rule}} = 0.6$, $I_{\text{A,rule}} = 0.6$, $I_{\text{choice}} = 0.25$, and $I_{\text{light}} = 0.5$.

The accuracies of p_P and p_A are calculated as

$$p_P(\mathbf{x};\mathbf{z}) = \mathbb{E}_{\mathbf{x}\sim p(\mathbf{x}|\mathbf{z})}\left[\Theta[x_{LP}(t=1.8s) - x_{RP}(t=1.8s)]\right] \tag{86}$$

and

$$p_A(\mathbf{x};\mathbf{z}) = \mathbb{E}_{\mathbf{x}\sim p(\mathbf{x}|\mathbf{z})}\left[\Theta[x_{RP}(t=1.8s) - x_{LP}(t=1.8s)]\right] \tag{87}$$

given that the stimulus is on the left side, where Θ is the Heaviside step function, and the accuracy is averaged over 200 independent trials. The Heaviside step function is approximated as

$$\Theta(\mathbf{x}) = \text{sigmoid}(\beta\mathbf{x}), \tag{88}$$

where $\beta = 100$.

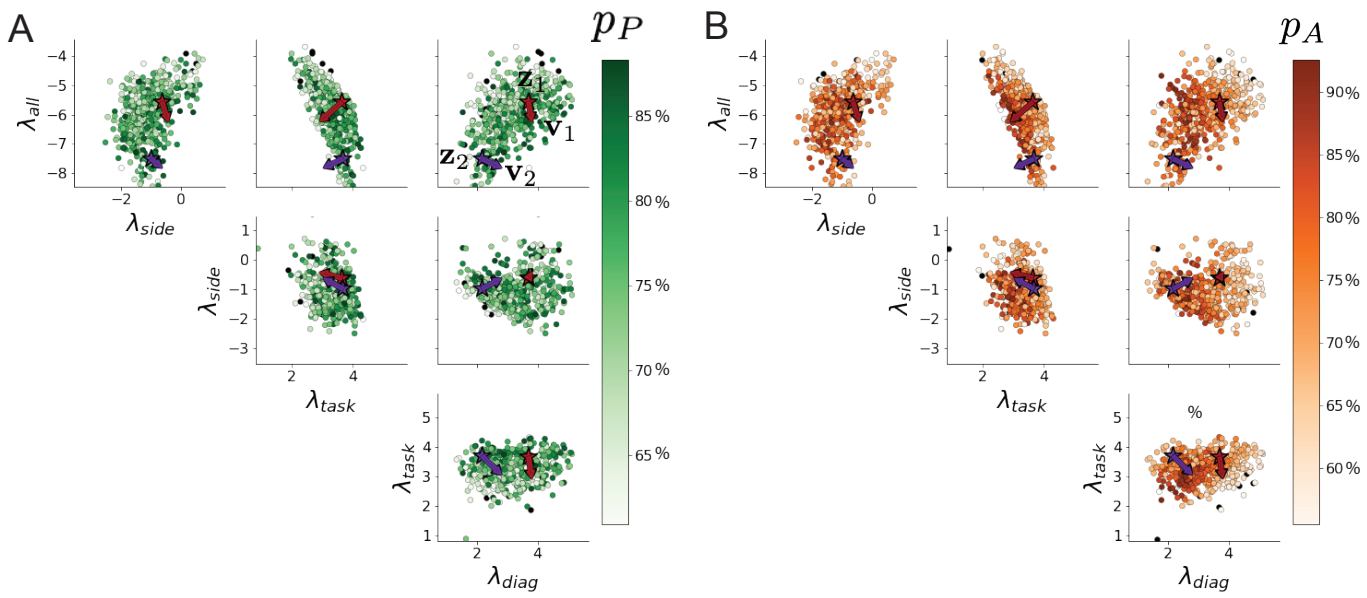

Figure 15: (SC4): **A**. Pairplots of eigenvalues of connectivity matrices in EPI distribution colored by Pro task accuracy. Red and purple stars and arrows correspond to eigenvalues and sensitivity directions $\mathbf{z}_1$, $\mathbf{z}_2$, $\mathbf{v}_1$, and $\mathbf{v}_2$. **B**. Same colored by Anti task accuracy.

Writing the EPI posterior as a maximum entropy distribution, $T(\mathbf{x}, \mathbf{z})$ is comprised of both these first and second moments of the accuracy in each task (as in Equations 30 and 31)

$$T(\mathbf{x};\mathbf{z}) = \begin{bmatrix} p(\mathbf{x};\mathbf{z})_P \\ p(\mathbf{x};\mathbf{z})_A \\ (p(\mathbf{x};\mathbf{z})_P - 75\%)^2 \\ (p(\mathbf{x};\mathbf{z})_A - 75\%)^2 \end{bmatrix}, \tag{89}$$

$$\boldsymbol{\mu}_{\text{opt}} = \begin{bmatrix} 75\% \\ 75\% \\ 7.5\%^2 \\ 7.5\%^2 \end{bmatrix}. \tag{90}$$

Throughout optimization, the augmented Lagrangian parameters η and c, were updated after each epoch of 2,000 iterations(see Section 5.1.3). The optimization converged after six epochs (Fig. 17).

For EPI in Fig. 3C, we used a real NVP architecture with three coupling layers of affine transformations parameterized by two-layer neural networks of 50 units per layer. The initial distribution was a standard isotropic gaussian $z_0 \sim \mathcal{N}(\mathbf{0}, I)$ mapped to a support of $\mathbf{z}_i \in [-5, 5]$. We used an augmented Lagrangian coefficient of $c_0 = 10^2$, a batch size $n = 100$, and $\beta = 2$. The distribution

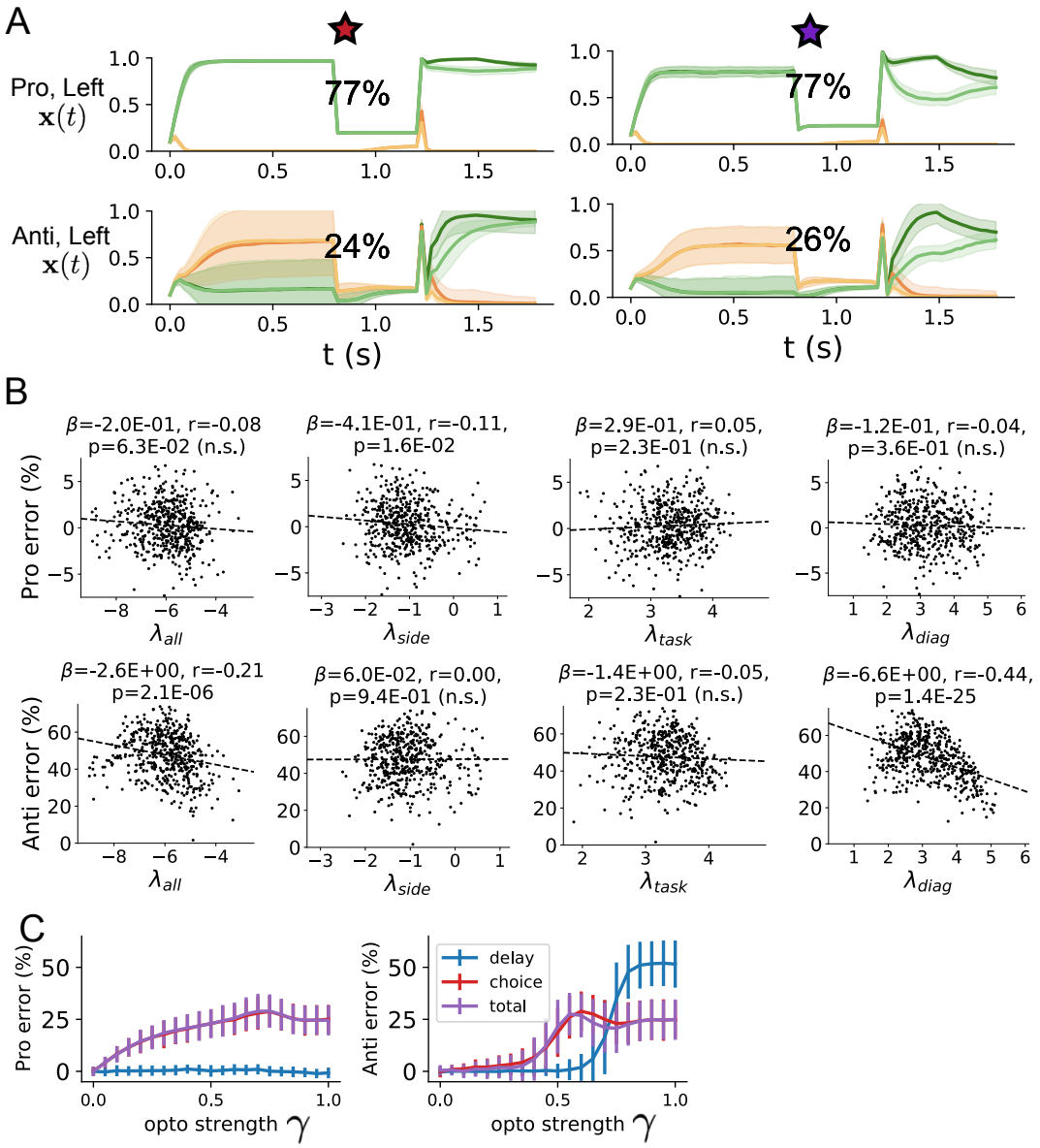

Figure 16: (SC5): **A**. Response of each parameter regime to optogenetic silencing during the delay period. **B**. Connectivity eigenvalues versus the task error induced by delay period inactivation. **C**. Error induced by delay period inactivation with increasing optogenetic strength. Means and standard deviations are calculated across the entire EPI posterior.

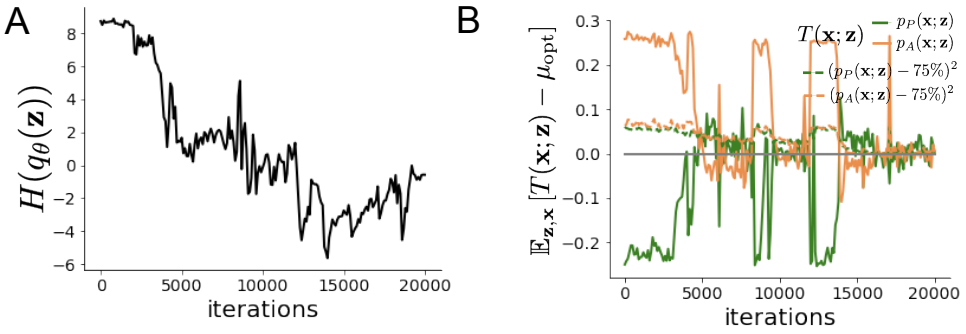

Figure 17: (SC6): A. Entropy throughout optimization. B. The emergent property statistic means and variances converge to their constraints at 20,000 iterations following the tenth augmented Lagrangian epoch.

shown is that of the architecture converging with criteria $N_{\text{test}} = 25$ at greatest entropy across random seeds.

To make sense of this inferred distribution, we identified two modes used to represent the two regimes of connectivity in this posterior:

$$\begin{aligned} \mathbf{z}_1 = &\underset{\mathbf{z}}{\text{argmax}} \log q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X}) \\ &\text{s.t. } hw = -1.25,\ sW > 0 \end{aligned} \tag{91}$$

and

$$\begin{aligned} \mathbf{z}_2 = &\underset{\mathbf{z}}{\text{argmax}} \log q_{\boldsymbol{\theta}}(\mathbf{z} \mid \mathcal{X}) \\ &\text{s.t. } hw = -1.25,\ sW < 0 \end{aligned} \tag{92}$$

To understand the connectivity mechanisms governing task accuracy, we took the eigendecomposition of the symmetric connectivity matrices $W = V\Lambda V^{-1}$, which results in the same basis vectors $\mathbf{v}_i$ for all W parameterized by $\mathbf{z}$ (Fig. 14A). These basis vectors have intuitive roles in processing for this task, and are accordingly named the *all* mode - all neurons co-fluctuate, *side* mode - one side dominates the other, *task* mode - the Pro or Anti populations dominate the other, and *diag* mode - Pro- and Anti-populations of opposite hemispheres dominate the opposite pair. We found significant trends across the EPI posterior connectivities: the eigenvalues λ_{task} and λ_{diag} were correlated with p_P, while λ_{all} was anticorrelated with p_P. λ_{all}, λ_{side}, and λ_{diag} were all significantly anticorrelated with p_A.

Under this decomposition, we can re-visualize the posterior in eigenvalue space (Fig. 15). Furthermore, we can project the dimensions of sensitivity into eigenvalue space as well, giving us a more intuitive sense of how connectivity affects computation in each regime. We see that sensitivity

dimensions $\mathbf{v}_1$ and $\mathbf{v}_2$, which cause p_P to increase and a regime dependent change in p_A, both point in the direction of increasing λ_{side} and decreasing λ_{task}. These eigenvalue changes are evident in the simulations of connectivity perturbations away from the modes (Fig. 13). As the component of connectivity along $\mathbf{v}_1$ and $\mathbf{v}_2$ becomes stronger (left-to-right), there is less separation between Pro an Anti populations (lower λ_{task}) and greater separation between Left and Right populations following stimulus presentation (greater λ_{side}). A key differentiating factor is that $\mathbf{v}_1$ substantially increases λ_{diag}, while $\mathbf{v}_2$ does not.

During optogenetic silencing simulations, activations $x_\alpha(t)$ were set to a fraction of their values $(1-\gamma)$, where γ is the optogenetic perturbation strength. We found that λ_{all} and λ_{diag} were significantly anticorrelated with Anti error during delay period inactivation. Delay period inactivation was from $0.8 < t < 1.2$, choice period inactivation was for $t > 1.2$ and total inactivation was for the entire trial.

5.2.5 Rank-2 RNN

Traditional approaches to likelihood-free inference – approximate Bayesian computation (ABC) methods – randomly sample parameters $\mathbf{z}$ until a suitable set is obtained. State-of-the-art ABC methods leverage sequential Monte Carlo (SMC) sampling techniques to obtain parameter sets more efficiently. To obtain more parameter samples, SMC-ABC must be run from scratch again. ABC methods do not confer log probabilities of samples. Like EPI, sequential neural posterior estimation (SNPE) uses deep learning to produce flexible posterior approximations. Like traditional Bayesian inference methods, SNPE conditions directly on the statistics of data. This differs from EPI, where posteriors are conditioned on emergent properties (moment constraints on the posterior predictive distribution). Peculiarities of SNPE (density estimation approach, two deep networks) make scaling in $\mathbf{z}$ prohibitive.

SMC-ABC has many hyperparameters, of which pyABC selects automatically by running some initial diagnostics upon initialization. In concurrence with the literature, SMC-ABC fails to converge around 25-30 dimensions, since it's proposal samples never get close enough to the target statistics. We searched over many SNPE hyperparameter choices: $n_{\text{train}} \in [2,000, 10,000, 100,000]$ is the number of simulations run per training epoch, and $n_{\text{mades}} \in [2, 3]$ is the number of masked autoregressive density estimators in the deep parameter distribution architecture. The greater n_{train}, the longer each epoch will take, but the more likely SNPE may converge during that epoch. Greater n_{mades} increases the flexibility of the deep parameter distribution of SNPE, but slows optimization.

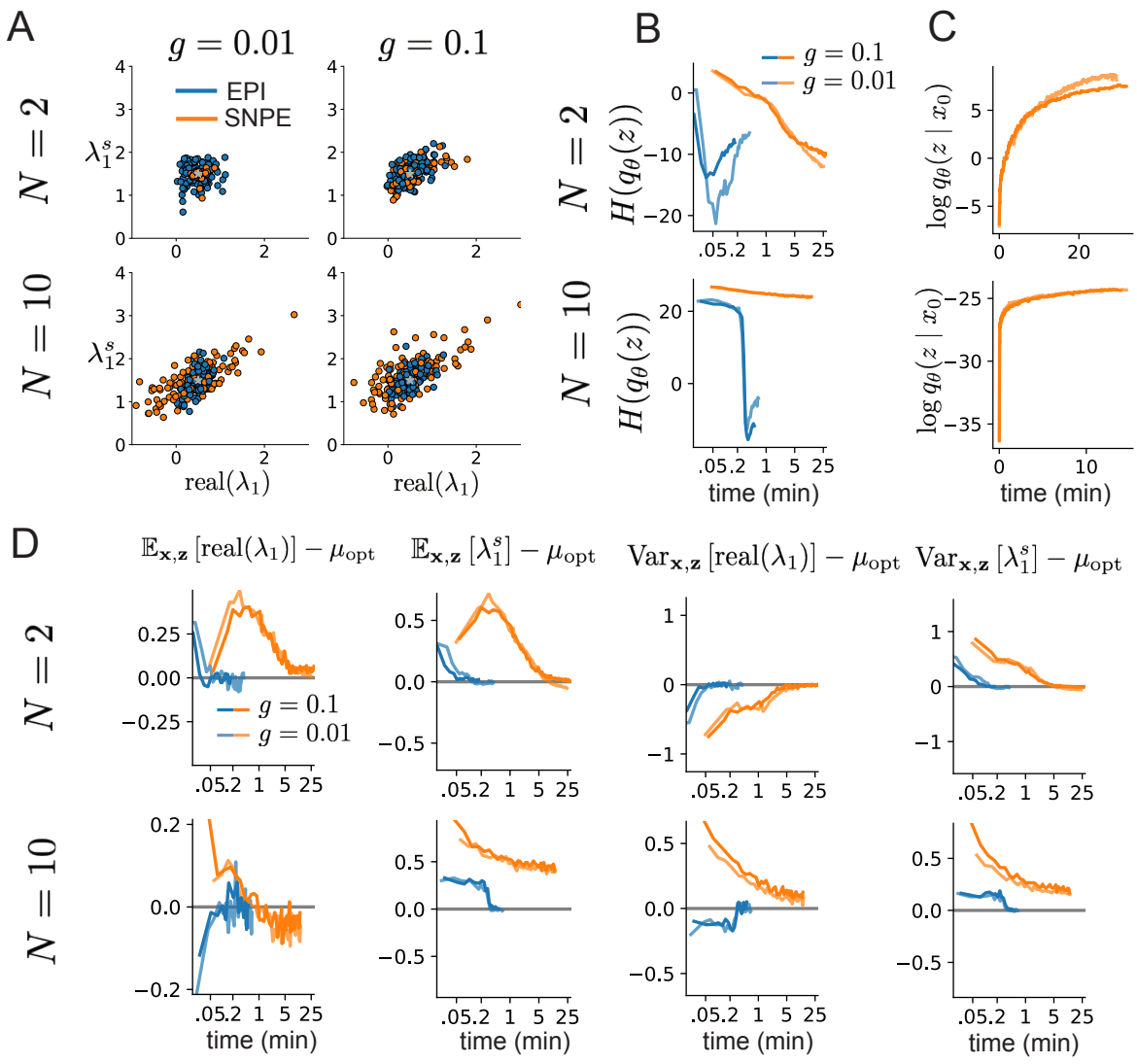

Figure 18: (RNN1): A. cap a B. cap b

For the timing plot, we show the fastest among all of these choices, and for the convergence plot, we show the best convergence among all of these choices. During optimization, we used n_{atom}=100 atomic proposals as is recommended.

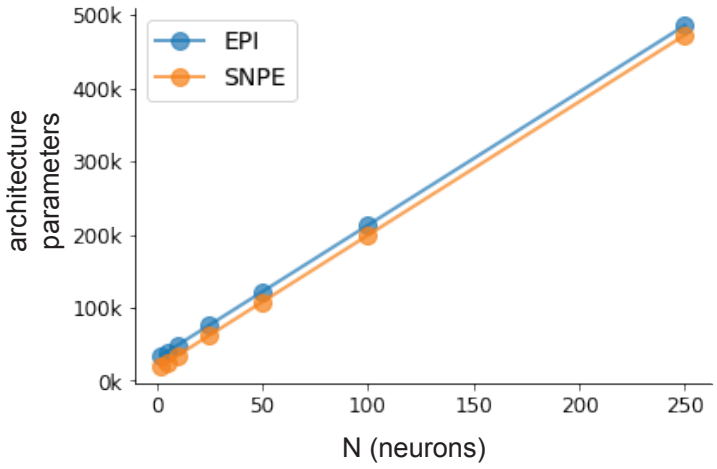

Figure 19: (RNN2): A. cap a B. cap b

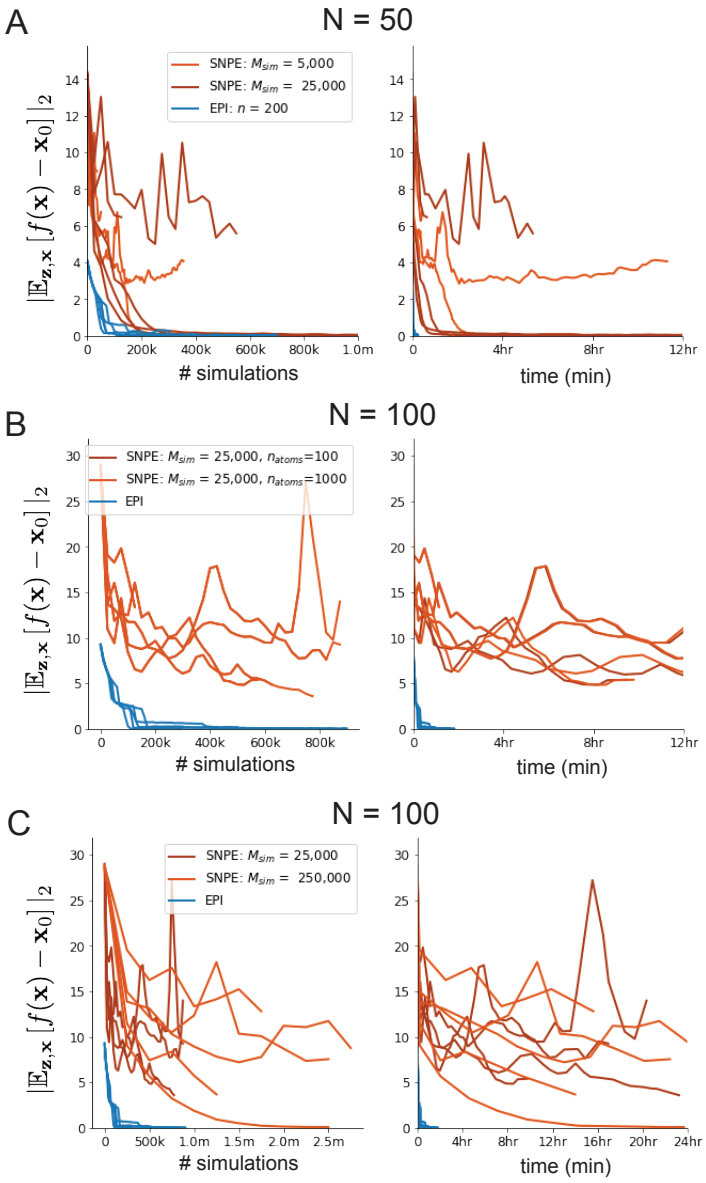

Figure 20: (RNN3): A. cap a B. cap b