Unsupervised Discovery of Dynamic Neural Circuits

Anonymous Author(s)

Affiliation
Address
email

Abstract

What can we learn about the functional organization of cortical microcircuits from large-scale recordings of neural activity? To obtain an explicit and interpretable model of time-dependent functional connections between neurons and to establish the dynamics of the cortical information flow, we develop 'dynamic neural relational inference' (dNRI). We study both synthetic and real-world neural spiking data and demonstrate that the developed method is able to uncover the dynamic relations between neurons more reliably than existing baselines.

1 Introduction

Extraction of latent temporal dynamics in complex networks is important to understand their functional connectivity and to predict their behavior. Recently, various machine learning methods were used to encode/decode the behavior from recorded activity of large neuronal populations [2, 3]. However, in these mostly 'static' brain models the temporal dynamics of the firing activity as well as interactions between different neurons are often neglected. It is expected, however, that the dynamic interactions in neural networks might be the key to understanding the brain computations. Addressing this, several methods have been proposed to uncover low-dimensional latent representations of neural network activity and its dynamics, including dimensionality reduction-based techniques such as principal components analysis [1] and tensor components analysis [14], pattern extraction techniques based on matrix factorization such as ConvNMF [11] and SeqNMF [7], and autoencoder models such as LFADS [9]. However, temporal correlations between individual neurons in the network are often only modeled implicitly, hindering reconstruction of functional connectivity of the neural circuits.

In contrast to these implicit techniques, here, we develop an extension to Neural Relational Inference [6], which we call Dynamic Neural Relational Inference (dNRI). Specifically, we develop a new model to extract rapid dynamic changes of network activity in the form of a time-dependent adjacency matrix. We aim at extracting rapid (tens of milliseconds) correlations between recorded neurons that capture their functional relations across the network. Moreover, our method enables the tracking of the temporal evolution of this functional connectivity over the span of a trial. This means it can provide an interpretable approach to uncover hidden dynamical structure of brain information flows and to reconstruct the underlying functional brain circuitry. We demonstrate the applicability of our method on both synthetic spiking data and data recorded from the cortex of live and behaving mice.

2 Dynamic Neural Relational Inference (dNRI)

We are interested in recovering the dynamic flow of information between neurons, i.e., we want to estimate whether spiking of one neuron either excites or suppresses spiking of another neuron at various points in time. To address this task, we assume spiking information for a set of neurons to be available. We represent neural spiking information via matrices $x \in \{0, 1\}^{N \times T}$, where $N$ is the number of neurons recorded for $T$ time bins and each entry represents the absence or presence of a spike for a particular neuron $i$ at a given time bin $t$. The goal is to predict binary variables $z_{ij}^{(t)}$ (hereafter called 'edges') for every pair $(i, j)$ of neurons for every timestep $t$ which indicate whether
We demonstrate the efficacy of dNRI using two types of data: the first are three synthetic datasets we then predict spiking activity using the decoder that wants edge predictions to be independent of each other, we use an independent Bernoulli prior to work and sample instead from the concrete distribution \[8, 5\], which approximates discrete sampling. To train the parameters of the predicted spiking probability for every neuron from the current time step, where the process of sampling from their distribution is non-differentiable. Consequently, we follow prior likely interaction patterns which are used by the decoder. Because the latent variables \(z\) are discrete, the choice of the prior \(p(z)\) reduces prediction of spurious edges. On synthetic data, we found that using a value \((\text{i.e., } p_θ(z_i^{(t)} = 0))\) larger than 0.5 reduces prediction of spurious edges. On synthetic data, we found that using a value of 0.8 worked well for our experiments. For the real data, however, we found that using a strong no-edge probability prevented the model from picking up the relatively sparse connections, so we used a uniform prior for the experiments on real-world spiking data reported below.

To train the parameters \(θ\) and \(φ\) of the decoder and encoder, we proceed as follows: for each spike train in the current minibatch, the encoder first predicts the approximate posterior \(q_θ(z|x)\) for each latent variable. We then sample from this distribution as discussed previously. Given these samples \(z\), we then predict spiking activity using the decoder \(p_θ(x|z)\). For training, we use ground-truth spikes as the decoder input; during testing, predictions for each time step are fed as input into the next step.

3 Experiments

We demonstrate the efficacy of dNRI using two types of data: the first are three synthetic datasets consisting of 12 simulated neurons with baseline spiking rates each sampled from the interval...
**Tensor Component Analysis (TCA)**

We use the following baselines:

- **GT**
- **dNRI**
- **GLM**
- **TCA**
- **seqNMF**

### Synthetic Data Results

<table>
<thead>
<tr>
<th>Edge Prob.</th>
<th>Method</th>
<th>Edge F1</th>
<th>Reconstruct. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Train</td>
<td>Val</td>
<td>Test</td>
</tr>
<tr>
<td>1</td>
<td>TCA</td>
<td>32.2</td>
<td>32.2</td>
</tr>
<tr>
<td></td>
<td>seqNMF</td>
<td>23.8</td>
<td>26.8</td>
</tr>
<tr>
<td></td>
<td>GLM</td>
<td>43.2</td>
<td>43.6</td>
</tr>
<tr>
<td></td>
<td>Static (d)NRI</td>
<td>43.7</td>
<td>43.7</td>
</tr>
<tr>
<td></td>
<td>Ours (d)NRI</td>
<td><strong>82.5</strong></td>
<td><strong>81.5</strong></td>
</tr>
</tbody>
</table>

| 0.8        | TCA  | 30.8 | 33.1 | 33.7 | 0.479 | 0.449 | 0.465 |
|            | seqNMF | 21.1 | 25.3 | 22.2 | 0.010 | 0.011 | 0.010 |
|            | GLM   | 44.0 | 44.3 | 41.3 | 0.790 | 0.764 | 0.778 |
|            | Static (d)NRI | 43.7 | 43.7 | 43.7 | 1.052 | 0.982 | 1.034 |
|            | Ours (d)NRI | **89.1** | **88.2** | **84.4** | 0.970 | 0.948 | 0.997 |

| 0.6        | TCA  | 29.7 | 32.8 | 32.7 | 0.522 | 0.493 | 0.510 |
|            | seqNMF | 17.4 | 22.2 | 20.1 | 0.008 | 0.008 | 0.008 |
|            | GLM   | 44.4 | 44.3 | 42.4 | 0.824 | 0.799 | 0.813 |
|            | Static (d)NRI | 38.0 | 38.0 | 38.0 | 0.967 | 0.926 | 0.972 |
|            | Ours (d)NRI | **89.7** | **87.6** | **84.9** | 0.918 | 0.901 | 0.931 |

**Mouse Cortical Recording Data Results.**

In analysis of the real-world data, we focus on a choice period between 400ms from the start of the trial, when the animal starts to sense the approaching wall, and 950ms, when the animal is making a decision to change the run direction to avoid the approaching wall. We present the results on this data in Fig. 3 focusing on several frames that correspond to the last stage of sensory information processing when the animal has almost made a choice and is preparing for motor action. Neurons are ordered with respect to their cortical depth and assigned to specific cortical layers. While the overall population spiking activity is relatively dense, significant correlations revealed by dNRI are sparse. This is expected, as we are focusing only on rapid correlations to reveal putative monosynaptic connections. Correlations are also transient, with a
Figure 3: dNRI results for mouse cortex data recorded during animal choice period.

typical lifetime on the order of 90ms. In Fig. 3 we highlight several neuron pairs to exemplify the
power of our representation: dNRI results infer transient information flow from L2/3 to L5B neurons
(red curve) as well as communications within deep L5A and L5B (blue and green curves), as they are
strongest outputs of the somatosensory barrel columns. As expected from the analysis of synthetic
data trials, neither SeqNMF, GLM, nor TCA are able to capture fast transient features revealed by
dNRI.

4 Conclusions

We develop a method to explicitly extract time-dependent functional relations from large-scale neural
spiking data recordings of cortical networks. Using simulated data of spiking activity where ground
truth information is available, we demonstrate that the proposed approach is able to recover the
implanted interactions more accurately than baselines which model relations implicitly.

References