Network Inference from Neural Activation Time Series

A comparative review

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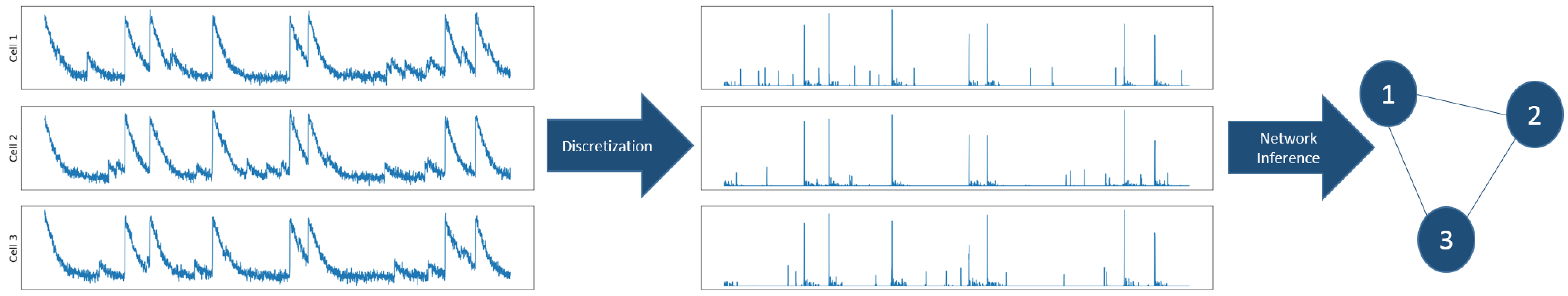
Introduction

Problem: Infer the underlying connectivity of a neural circuit given the time series of neural activations

Motivation: Understand functional connectivity mechanisms in neural populations and study neural circuits without acute neuroimaging experiments



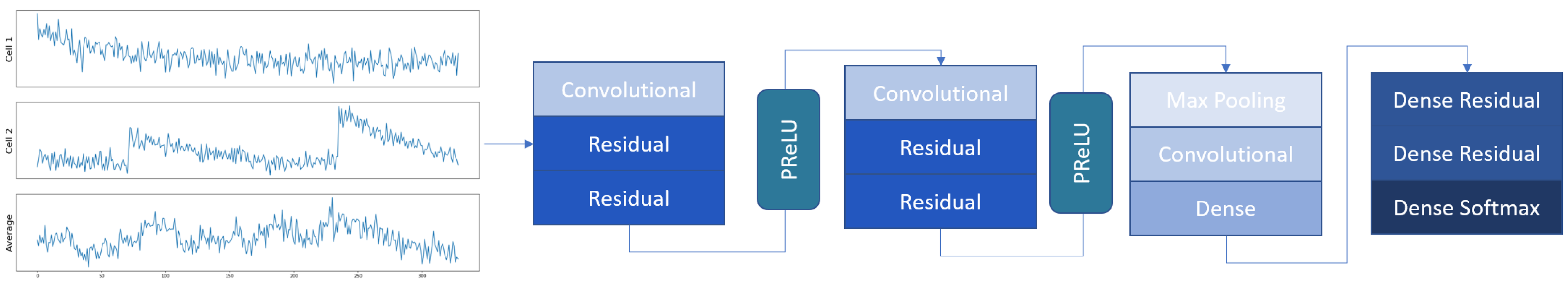
Model-Free Methods

Two neurons are connected if a similarity metric on their spike trains surpasses a threshold.

- Cross Correlation: $\gamma_{xy}(\tau) = \sum_t [(x_t - \overline{x})(y_{t+\tau} - \overline{y})]$
- Partial Correlation using Σ^{-1} with 80% of variance retained.
- Partial Correlation using Graphical Lasso: $\Theta' = argmax_{\Theta \leq 0}(logdet(\Theta) - tr(\Sigma\Theta) - \lambda|\Theta|_1)$
- Transfer Entropy: $\sum_{x_{t+1}, x_t, y_t} p(x_{t+1}, x_t, y_t) log_2 \left(\frac{p(x_{t+1}|x_t, y_t)}{p(x_{t+1}|x_t)} \right)$

Residual Convolutional Neural Network

Fluorescence signals are downsampled to periods with average network activity > 0.02
Then they are standardized and pairs of neurons are chosen to extract training samples from.
Each training sample is a subset with length 320, extracted from a random point in the neural activations of the chosen pair. Connected pairs are sampled more to create a balanced dataset.



The algorithm is tested in one network and trained in the rest.

Hawkes Process

The spike train of neuron k is a series of events s, modeled by a Poisson process with background rate $\lambda_k(s)$. A neuron's spikes induce impulse responses on connected neurons and create new spikes. The set of all spike trains is modeled as a Hawkes process, where the likelihood is:

$$p((s_j, k_j, z_j)|\lambda_k(t), h_{k_t,k}(\Delta t)) = \prod_{k=1} p(s_j, k_j = k, z_j = 0|\lambda_k(t)) \times \prod_{i=1} \prod_{k=1} p(s_i, k_i = k, z_i = j|h_{k_j,k}(t - s_j))$$

for marked events s_j, neuron k_j caused by event at z_j, with $h_{k_j,k}(\Delta t) = A_{k_j,k} W_{k_j,k} g_{\theta_{k_j,k}}(\Delta t)$
The parameters are estimated with stochastic variational inference

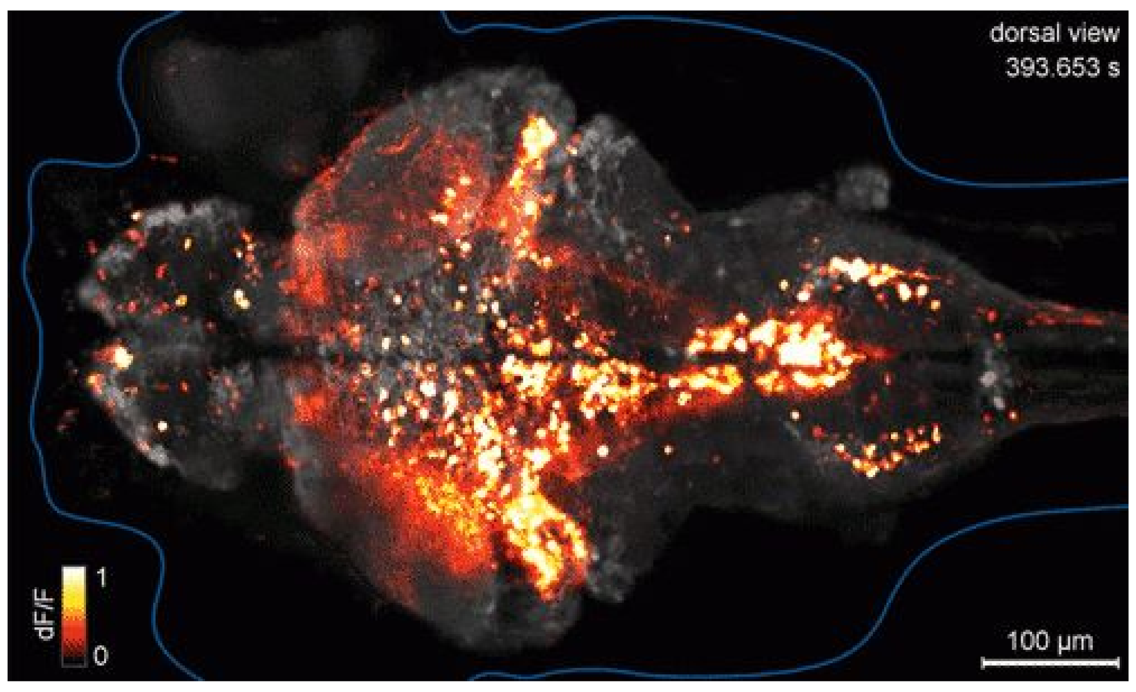
Results

Network Inference	AUC		PRC	
	Filter1	Filter2	Filter1	Filter2
Graphical Lasso	0.7844	0.6992	0.3208	0.2335
Cross Correlation	0.7362	0.6561	0.26453	0.1880
PCA	0.6883	0.6309	0.2150	0.1864
Hawkes	0.6505	0.6511	0.1800	0.1681
RCNN	0.660		0.1849	
Transfer Entropy	0.5436		0.1055	

Data

Chalearn Connectomics Challenge [a]

- Simulated fluorescence signals based on larval zebrafish calcium imaging
- 6 networks of 100 neurons
- One hour of recordings in 50Hz
- Ground truth connections



Light Scattering
Multiply the activity of pairs of neurons with the inverse of radial distance: $D_{i,j} = 0.15 e^{\frac{|p_i - p_j|^2}{2}}$

Discretization

Filter1: First order difference $x_t = x_t - x_{t-1}$ and threshold at 0.12.

Filter2:
Smoothing: $x_t = x_{t-1} + x_t + x_{t+1} + x_{t+2}$ and then $x_t = x_t + x_{t+1} + x_{t+2} + x_{t+3}$
Spike enhancing with first order difference
Threshold at 0.11
Weighing of spikes, based on the overall activity of the network at that time: $x_t = (x_t)^{\left(1 + \frac{1}{\sum_j x_t^j}\right)}$.

[a] https://www.kaggle.com/c/connectomics

Future Work

- Evaluate with the 1000 cells networks
- Bayesian generalized linear model
- Information diffusion in the neural circuit
- Higher order graphical models to analyze pathways of connections in time