

# Neural Network Reconstruction via Graph Locality-Driven Machine Learning

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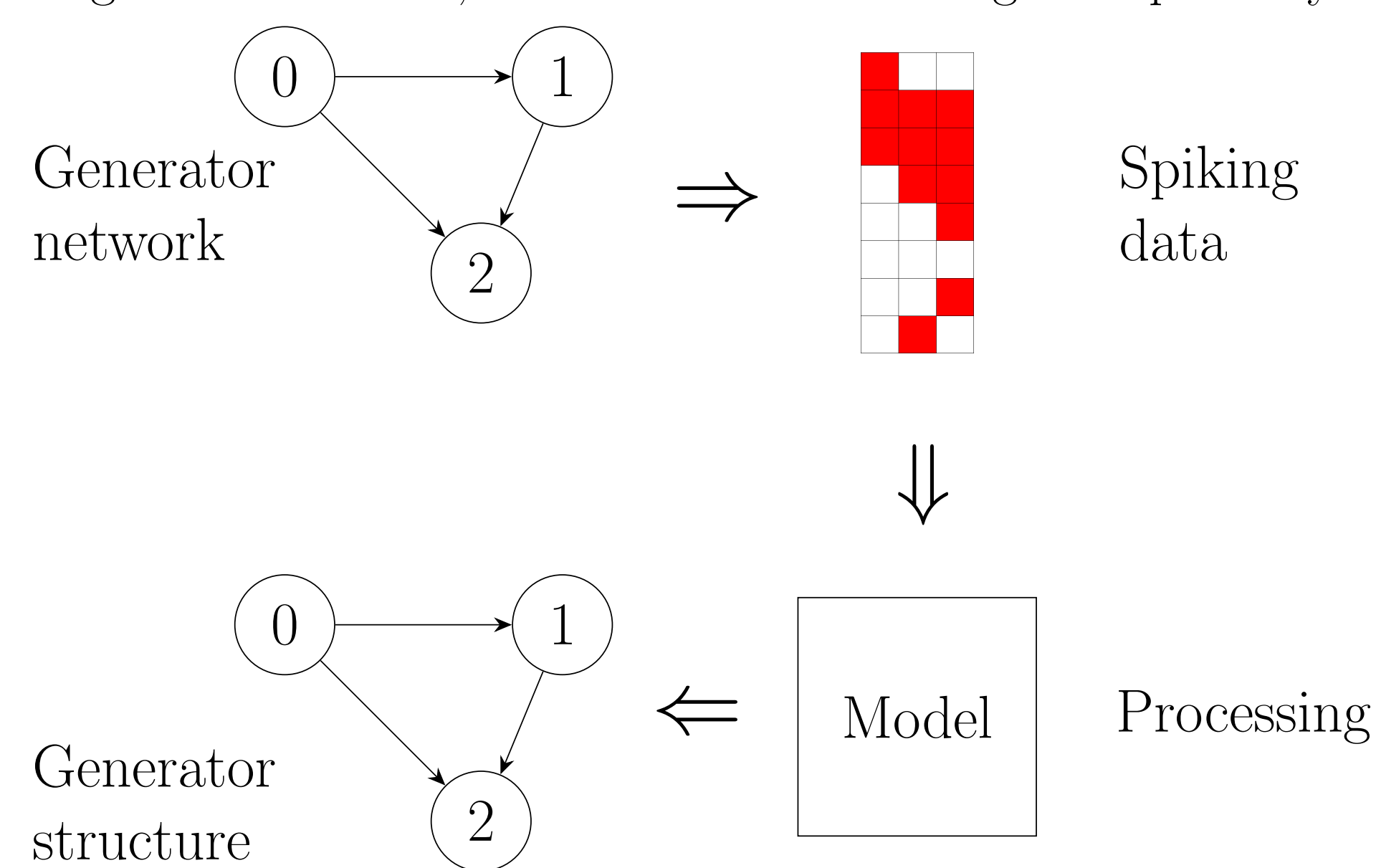
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## Overview

We propose an algorithm inspired by convolutional approaches to image processing, adapted to the graph structure of neural networks, in order to solve the problem of network reconstruction from spiking data. To achieve this, we redefine locality in terms of graph adjacency, and create a scale-independent algorithm facilitated by modern machine learning techniques to incorporate this locality data into individual connection prediction.

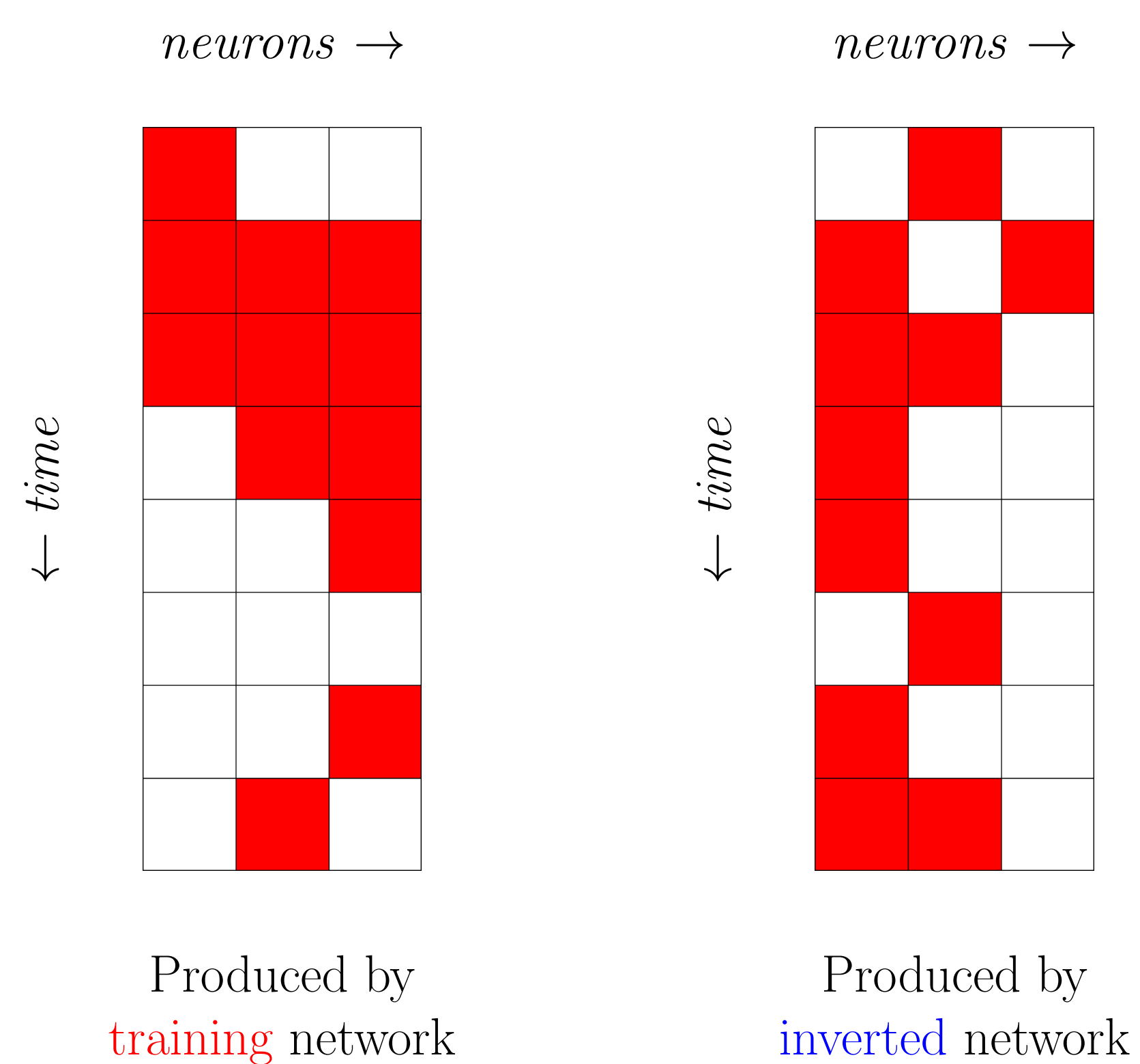
## Process

Our goal was to infer biological neural network connectivity from spiking data. To do so, we created the following data pathway:



## Spike-time Raster Plots

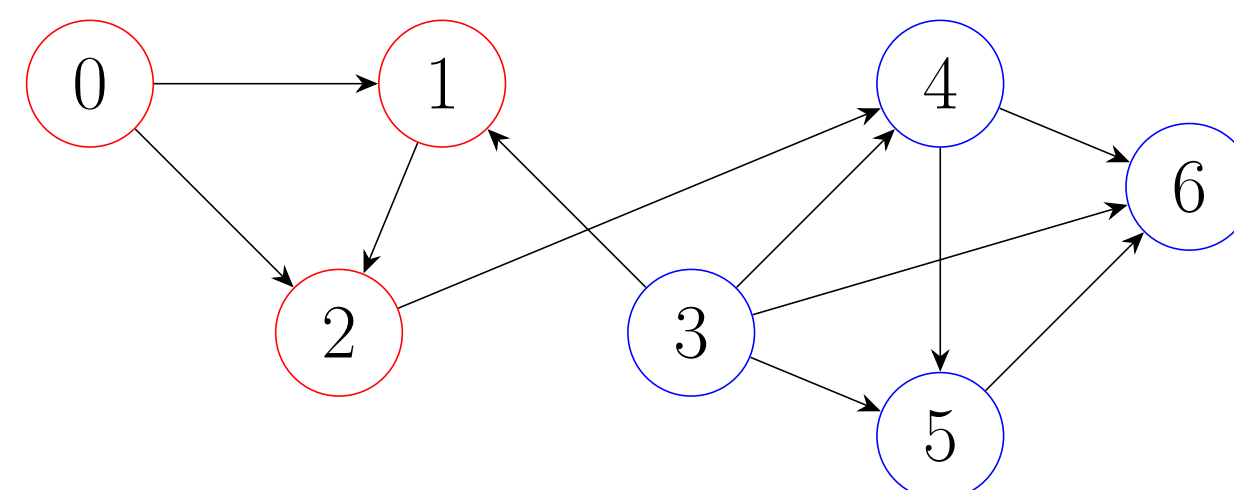
For a three neuron network sampled for eight timesteps, a raster plot might appear as below.



## Biological Networks & Graphs

### Graph Representation of Neural Networks

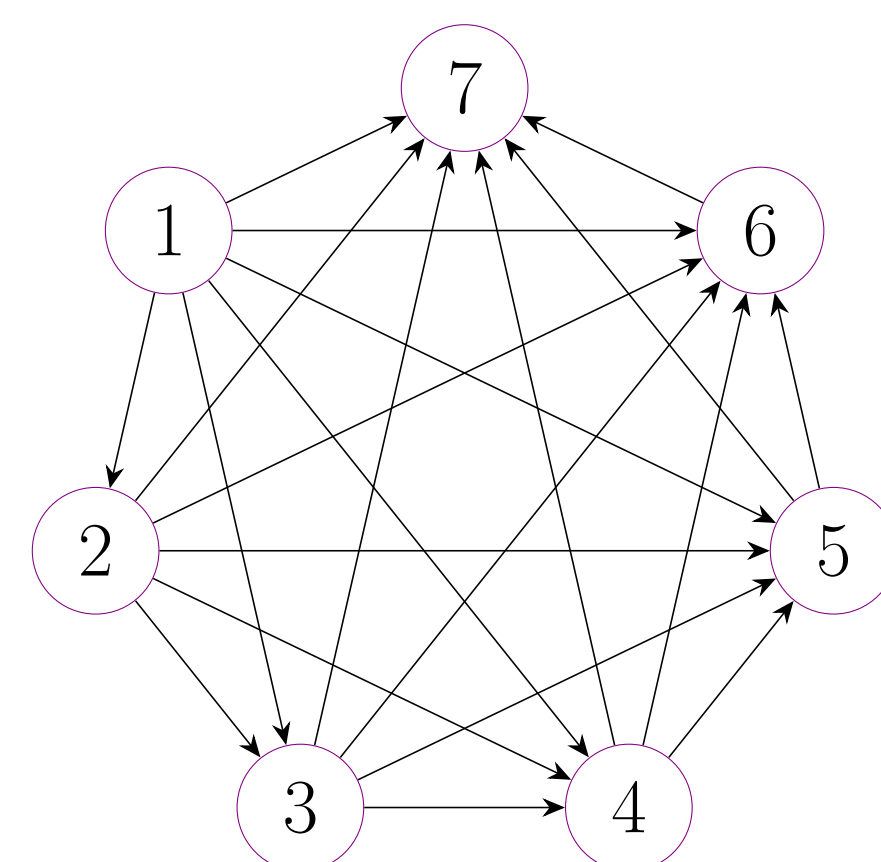
- Biological networks are broadly equivalent to directed graphs (di-Graphs)
- diGraphs consist of nodes and edges, as below
- In neural networks, neurons are nodes and connections are edges
- Probability of connection between two neurons unrelated to physical proximity



### Common Local Structures

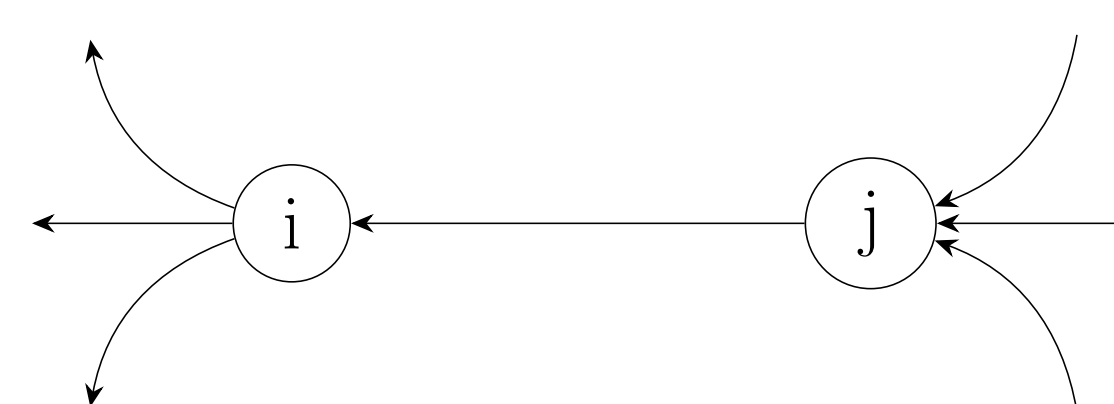
- Motifs, repeating local structures, unusually common in biological networks
- Some motifs, simplices, are structures in which information flows in one direction, from a 'source' node to a 'sink' node

The graph above contains a 2-simplex, in red, and a 3-simplex, in blue. Below, a 6-simplex, in violet.



### Graph Convolution

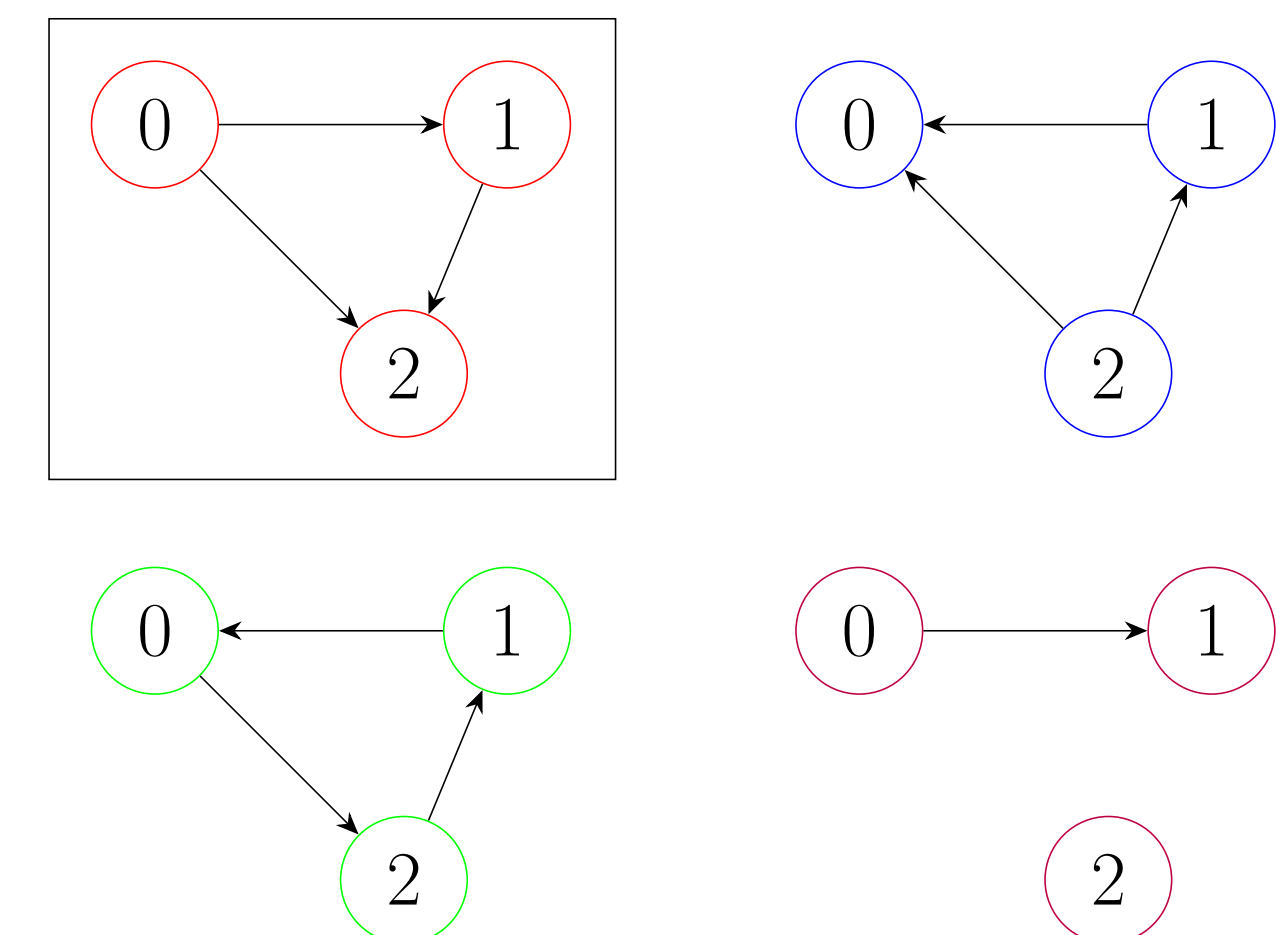
Given that local structure is important to the functioning of biological neural networks, providing locality information to an algorithm performing reconstruction could aid that process.



As such, we designed an algorithm to incorporate information from adjacent nodes in the determination of whether or not a given connection  $ij$  in a network exists.

## Testing

We tested on a variety of  $n$ . For  $n = 3$ , our training and testing data were generated by the following networks. Network key: training, inverted, cyclical, incomplete



## Results

It became clear that our architecture:

1. can reconstruct network structure from spiking data with relative ease for small  $n$
2. can reconstruct networks that it has no training on, as long as the network is similar in nature to the training data
3. learns features of the networks it analyzes: a model trained only on connected graphs will always predict at least one connection at each neuron
4. on small  $n$  ultimately does no better than a simpler model

Preliminary results on much larger networks ( $n > 50$ ) suggest a great leap in efficacy relative to a simple benchmark model; this falls into the future work category.

## Future Work

While our results demonstrate that our algorithm can reconstruct networks, they do not show that the locality operations produce any more useful data than our benchmark model. Based on preliminary results, demonstrating this would require:

1. Testing on a large scale - the small- $n$  networks we used do not present a difficult enough problem to make clear whether or not our model has an advantage over simpler architectures
2. Testing on highly structured vs. random networks - if our model is indeed learning local features to help reconstruction, it should be more effective when used on highly structured networks than on random networks

After completing those benchmarks, and assuming positive results, the next step would be to refine the algorithm and apply it to more realistic data, which is generally more complex and noisy than the data used here.