Benchmarking Deep Learning Architectures for Predicting Visual Stimuli Given Single Neuron Spike Patterns

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Introduction

Our study benchmarks various machine learning and deep learning models to predict visual stimuli from single neuron spike trains.

Objectives

- Identify model architectures for predicting function given neuron data at the micro-level.
- Test architectures incorporating spatial, temporal, and attention mechanisms.
- Enhance understanding of neural coding
- Explore applications in neuroprosthetics and brain-computer interfaces.

Experiment Overview

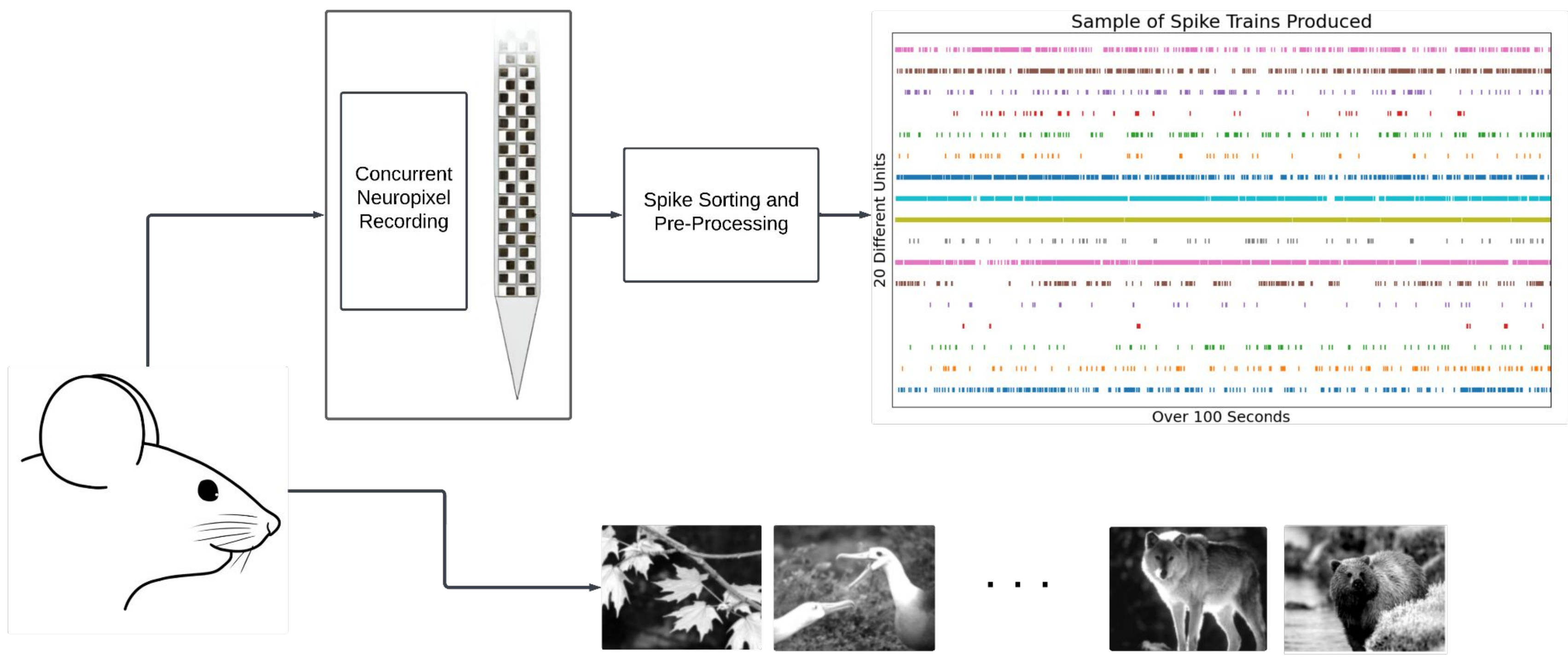

Figure 1: The Allen Institute presented 118 natural scene images to 32 wild-type C57BL6/J mice aged P25-50, while recording single-neuron firing rates using multiple Neuropixel probes. Each image was displayed 50 times for approximately 250 ms. They performed spike sorting and pre-processing to generate the spike trains (1).

Methodology

Initial Testing Phase:

- Select 3 random mice for initial testing.
- Test models for optimal hyperparameters.

Comprehensive Testing Phase:

- Test top scoring models on all 32 mice.

Model Types Tested:

- Models without temporal components, summing firing rates over an image.
- Models with spatial relationships between neurons.
- Models incorporating attention mechanisms.

Benchmark:

- A random guess, which is a test accuracy of 0.85%.

Models with a spatial component were tested with:

- Fully connected graph
- Graph from cross-correlation (25% threshold)
- Graph optimized via back propagation (start fully connected, 25% threshold)

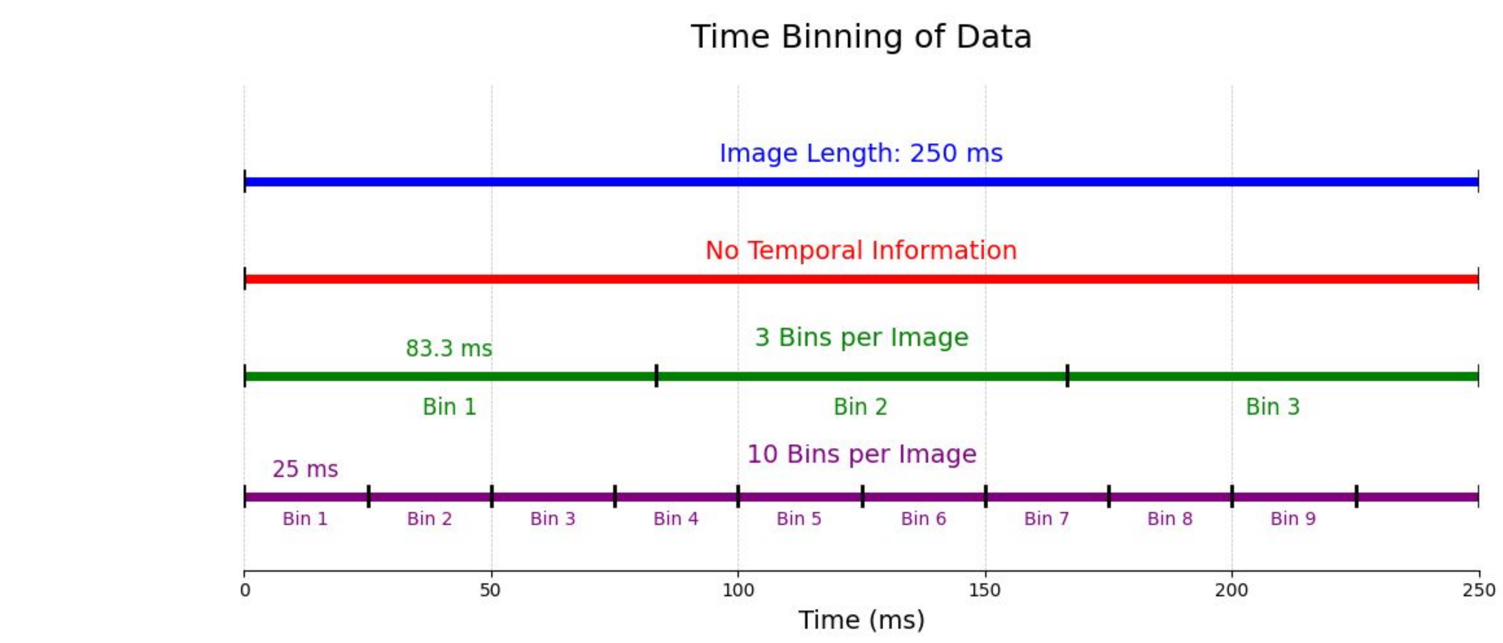

Figure 2: The time binning strategy used for analyzing the effect of different temporal resolutions on model performance. The image length is 250ms and the binning approaches are shown: Red Line: No temporal information considered. Blue Line: 3 bins per image, each 83.3ms long. Purple line: 10 bins per image, each 25ms long. Time bins of size 2, 3, 5, 10, 15, and 20 were tested.

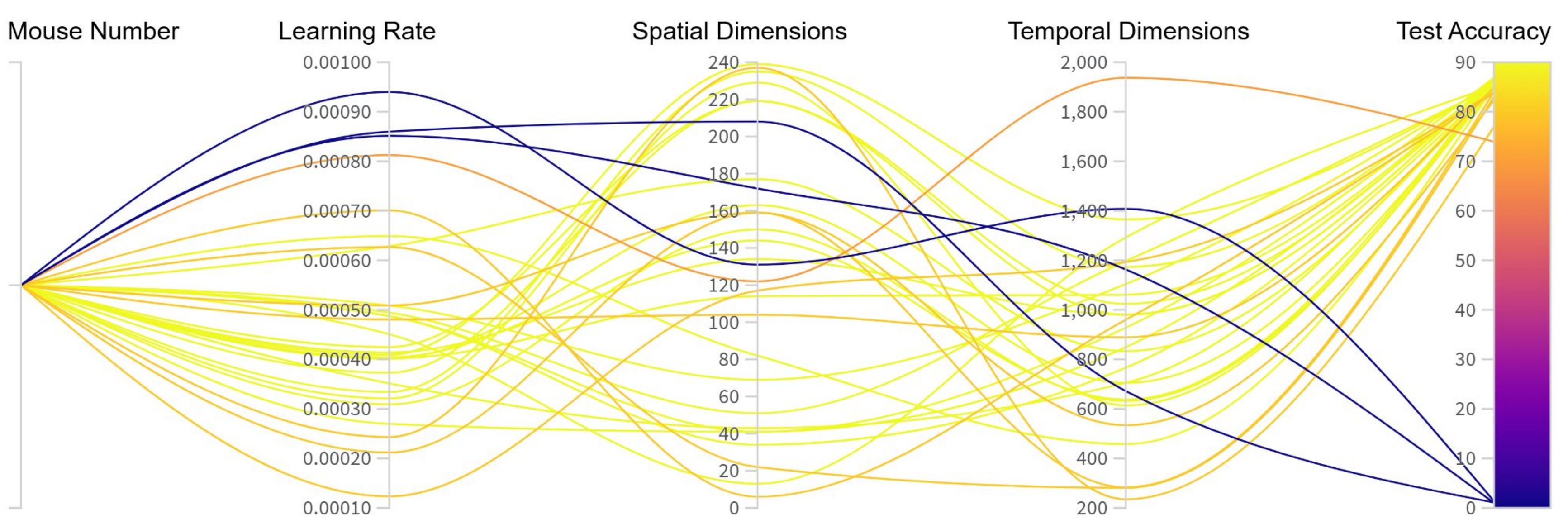

Figure 3: Heteroskedastic Evolutionary Bayesian Optimization (HEBO) for hyper-parameter tuning on the Spatio-Temporal Graph Attention Network over 30 generations. Each line denotes a different run with a unique set of hyper-parameters, with colors indicating test accuracy. Implemented through the Ray Tune package in Python, allowing models to run in parallel (4).

Results

- The LSTM achieved the highest test accuracy of 97.73% across the 3 chosen mice.
- Time bins of 3-5 bins per image shown yielded the highest accuracies for models with spatial components, with no gains from increased bin size.
- All Deep learning models had the most success with a single-hidden layer. Accuracy with additional layers.

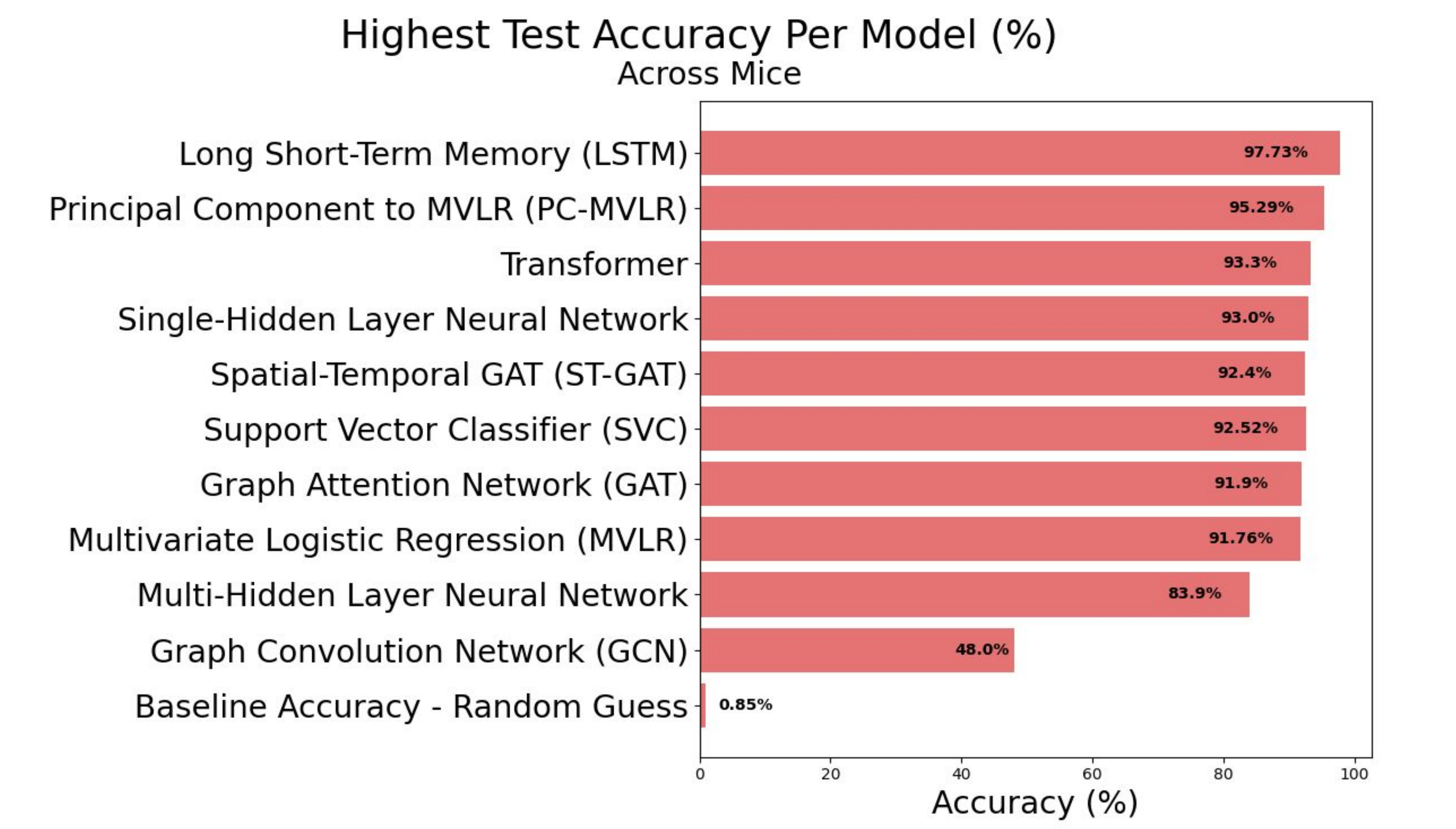

Figure 4: The highest test accuracies achieved by various machine learning and deep learning models when predicting visual stimuli from single neuron spike trains across the three chosen random mice. The models are ranked based on their performance.

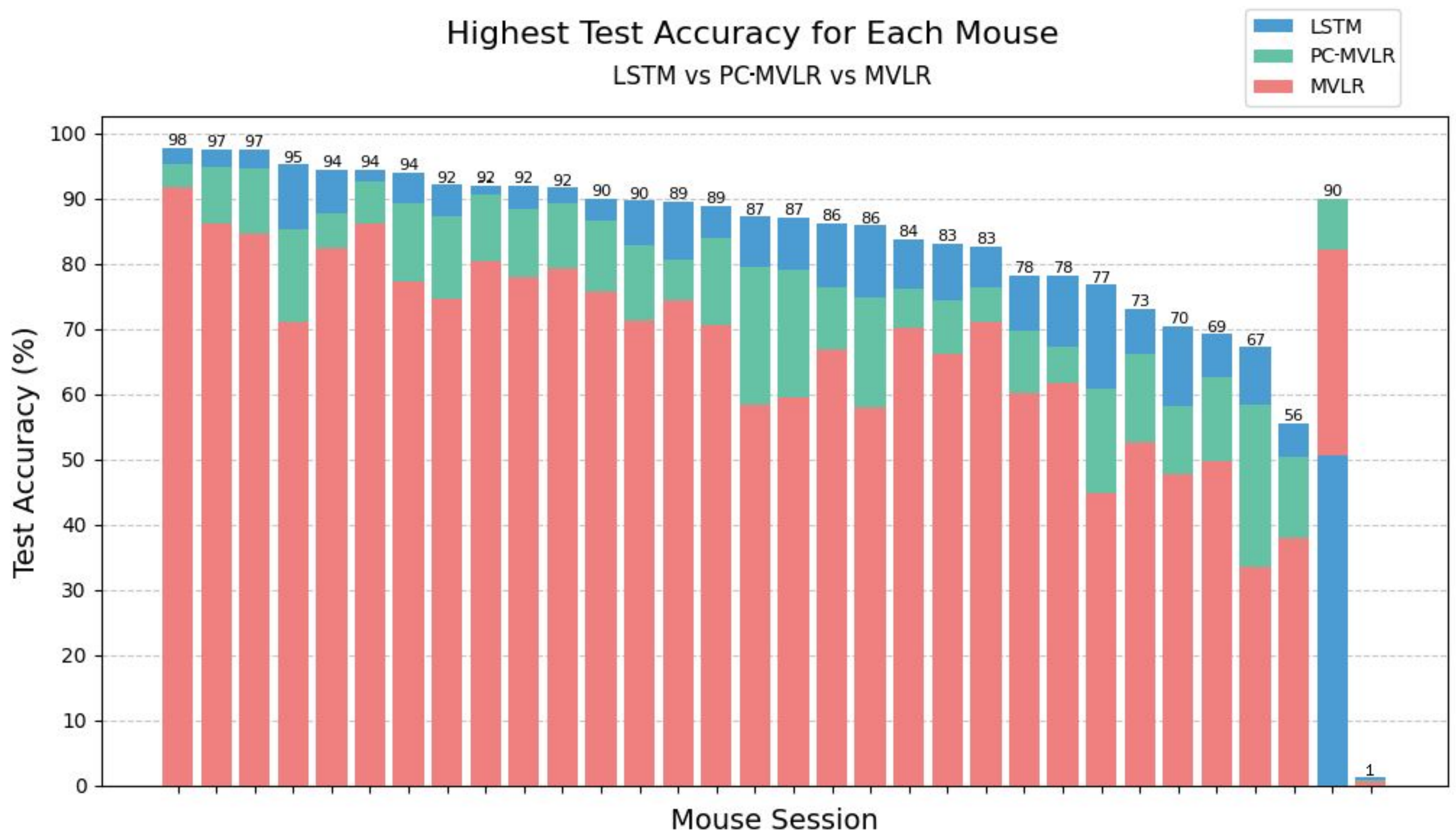

Figure 5: The variation in highest test accuracy across 32 mice for the LSTM, PC-MVLR, and MVLR. The LSTM model consistently outperformed others, with accuracies near or above 90% in most sessions, peaking at 98%. In one case, the PC-MVLR and MVLR outperformed the LSTM.

Conclusions

Our results show models can accurately predict visual stimuli from single neuron spike patterns:

- Demonstrates the effectiveness of deep learning and dimensionality reduction in neural decoding tasks.
- Identifies specific architectures useful for predicting stimuli from spike trains.

Further Exploration

- Extend models to predict other stimuli/functions from neuron firing data.
- Integrate LFP data, general connectivity graph, and neuron locations.
- Benchmark on deconvolved calcium traces and spike trains from voltage imaging.

Contact Information

Code and further benchmarking can be found on GitHub.

Acknowledgments

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Citations

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2. Paulk AC, Kfir Y, Khanna AR et al. Large-scale recording with single neuron resolution using Neuropixels probes in human cortex. Nature Neuroscience, 2022, 25: 252-263.
3. Wein S, Schuller A, Tome AM, et al. Forecasting brain activity based on models of spatiotemporal brain dynamics: A comparison of graph neural network architectures. Network Neuroscience, 2022, 6 (3): 665–701.
4. Ray Tune: Hyperparameter Tuning. https://docs.ray.io/