Explaining Neural Spike Activity for Simulated Bio-plausible Network through Deep Sequence Learning

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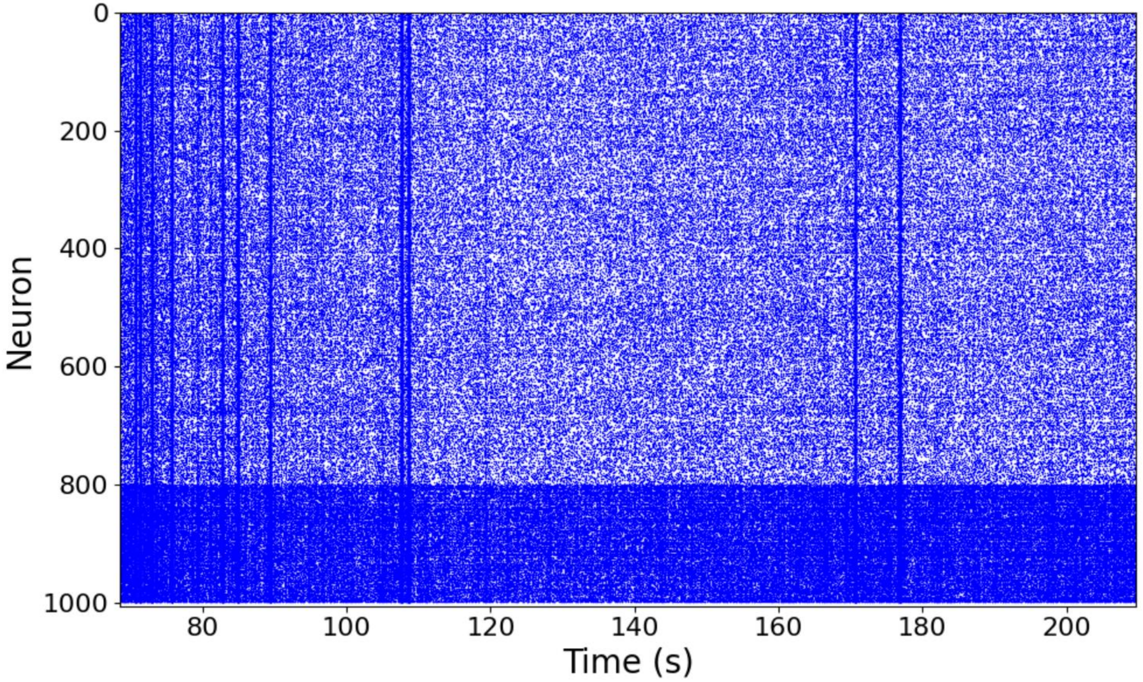
Neuroscience Inspired Neural Network Simulation

- Modeling and Simulation integral for neuroscience research
- Simulations carried out by solving the dynamics of bio-plausible networks of neurons and synapses
- **STACS** – Simulation tool for Asynchronous Cortical Stream enables large scale HPC simulation of neuroscience model
- Analyzing the simulation data - How do we interpret the large-scale results?
  - Employ deep learning models to process temporal data
  - Scalable deep learning models along with neural simulations

- Reservoir network of excitatory and inhibitory neurons (80-20)
- Izhikevich neurons and plastic synapses
- Simulation carried for 180 seconds with spike timing dependent plasticity



- Felix Wang, Simulation Tool for Asynchronous Cortical Streams (STACS): Interfacing with Spiking Neural Networks, Procedia Computer Science, Volume 61, 2015, Pages 322-327.
- F. Wang, et al., "Scaling neural simulations in STACS", IOP Neuromorphic Computing and Engineering, April 2024.

Neural Data Representation

- Reservoir network of E-I spiking neurons
  - 800 excitatory neurons
  - 200 inhibitory neurons
- Simulated by applying random thalamic noise input
  - Output spikes at an average rate of 10 Hz per neuron
- Spike trains for neuron i at times t^f:

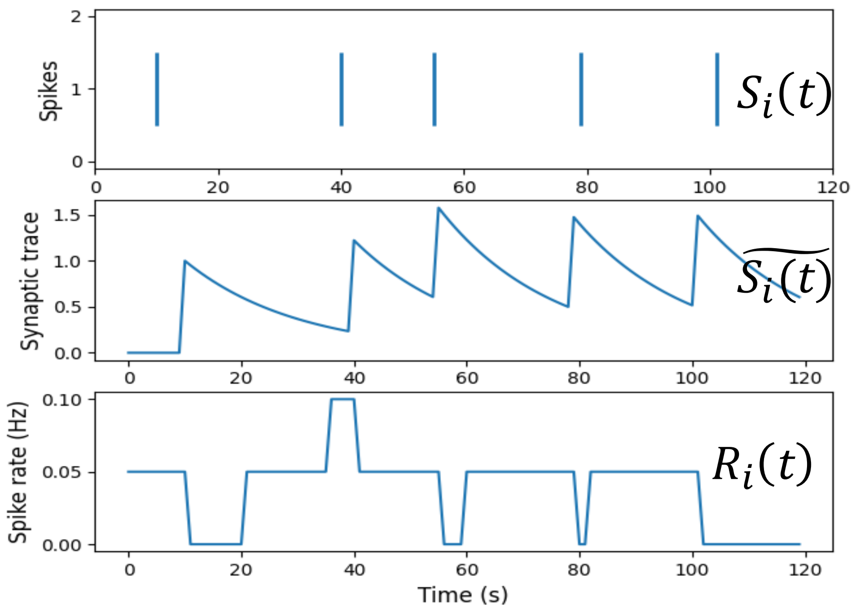
$$S_i(t) = \sum_{t^f} \delta(t - t^f)$$

- Smoothened spike signals using kernel $\alpha(t) = e^{-\frac{t}{\tau}}.\mathrm{H}(t - t^f)$:

$$\widetilde{S_i(t)} = S_i(t) * \alpha(t)$$

- Running average spike rates over T_w:

$$R_i(t) = \sum S_i(t\colon t + \mathrm{T_w})/\mathrm{T_w}$$



- Causal components:
  - Combines underlying structure and network activity
  - Adjacency matrices over a temporal window τ
  - Ω for a spike traveling from neuron i to j*:

$$\Omega_{i,j} = W_{i,j} \times e^{(t_j^f - t_i^f)/\tau} \times H(t_j^f - t_i^f - \delta_{i,j})$$

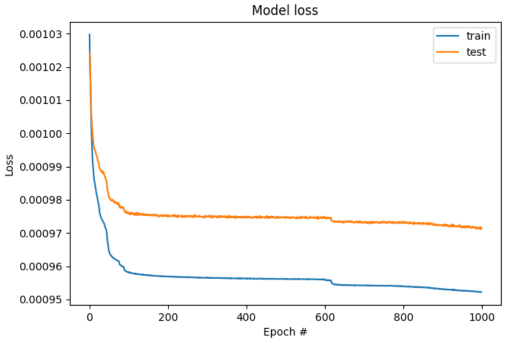
* Theilman, B. H., Wang, F., Rothganger, F., & Aimone, J. B. (2023). Decomposing spiking neural networks with Graphical Neural Activity Threads. *arXiv preprint arXiv:2306.16684*.

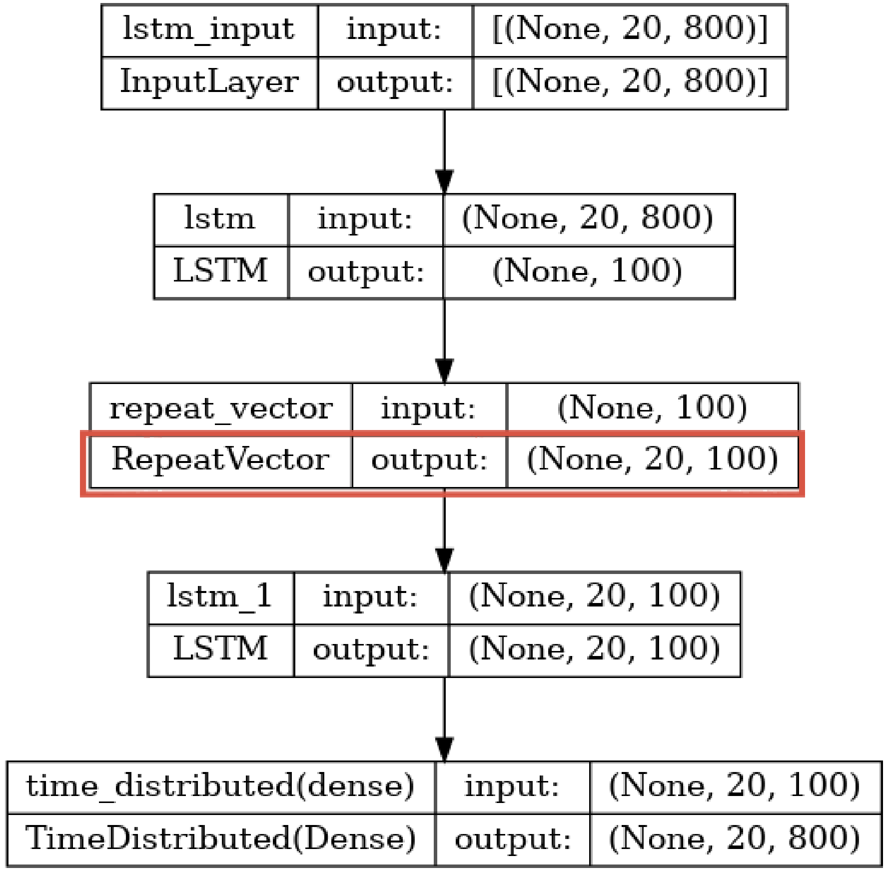
Research goals

- Can deep learning models:
  - be alternative to reduced order representation?
  - Help predict spike sequences in an SNN?
  - Explain the transition of spike activity over time?
- Our approach:
  - Capture a reduced order representation of neuron states
  - Capture attention of each neuron for the SNN spike prediction activity

Long Short Term Memory (LSTM) Autoencoder

- Use LSTM Autoencoder model for sequence reconstruction
- SNN simulation spikes divided into sequences of 20 timesteps
- Use Spike traces ($\widetilde{S(t)}$) as inputs and targets
- Encoding layer captures a low order encoding with 100 units
- Model presented trained with 6K sequences for 1000 epochs





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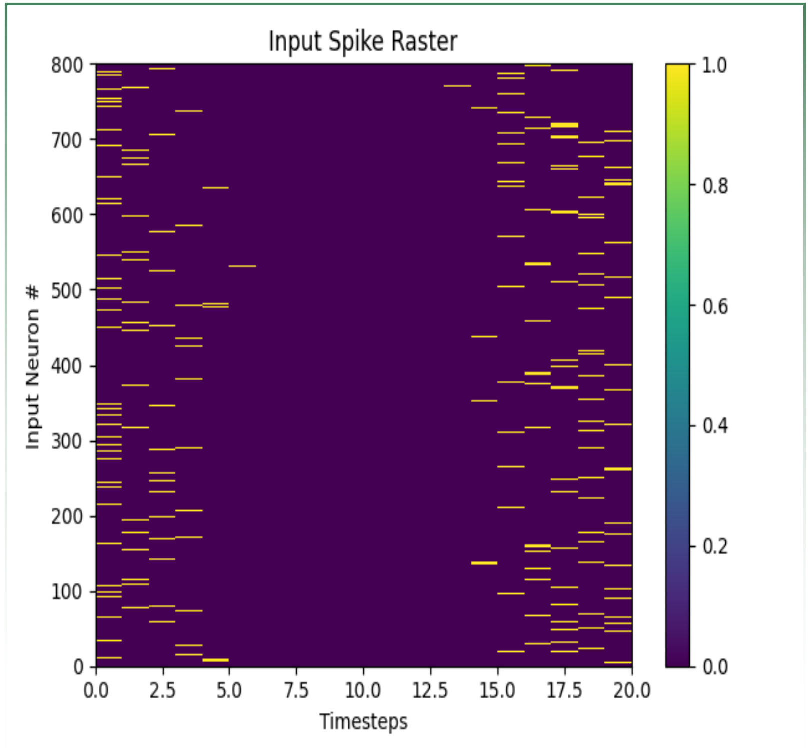
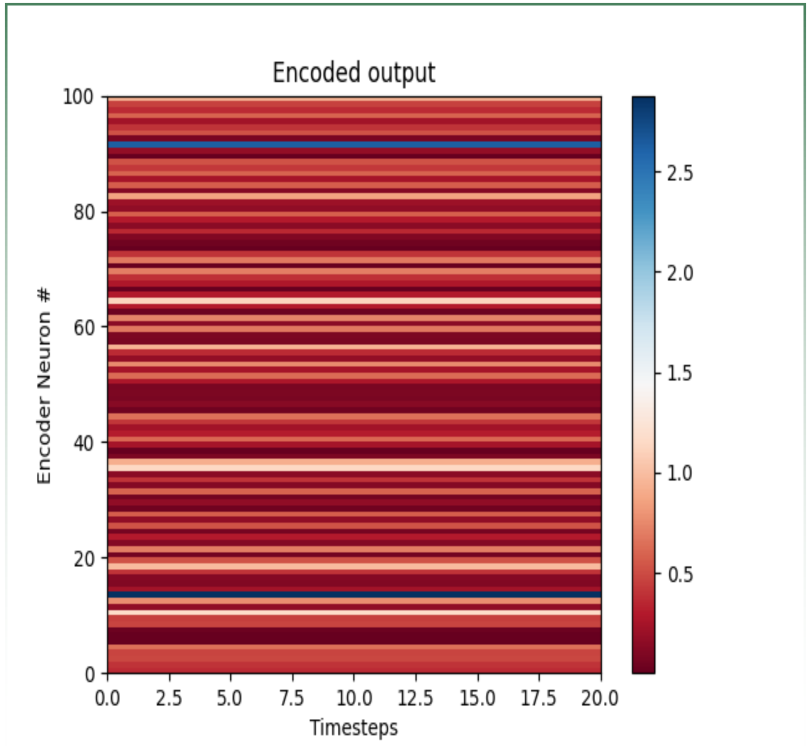
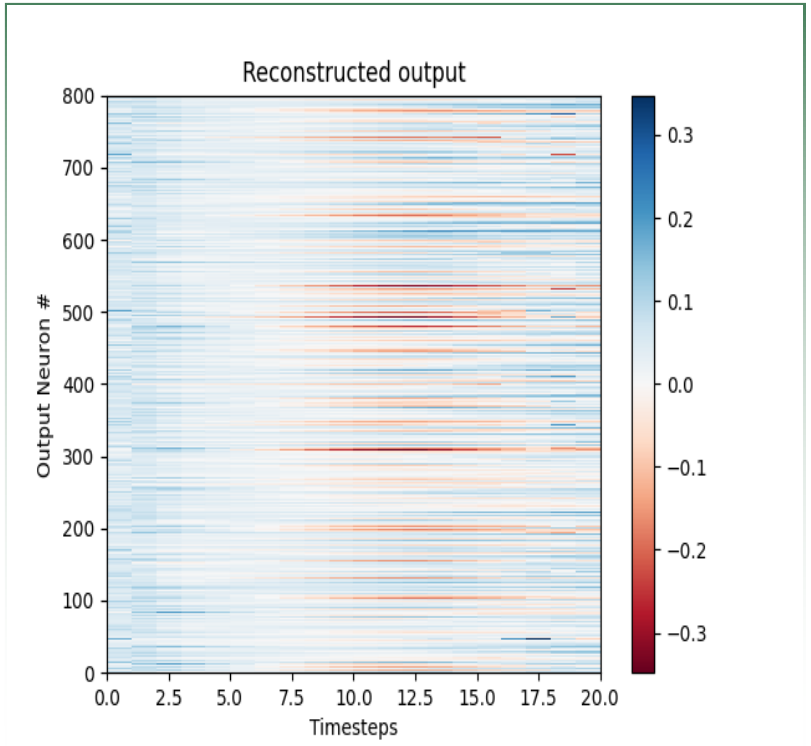
Sample outputs from trained LSTM – AE model





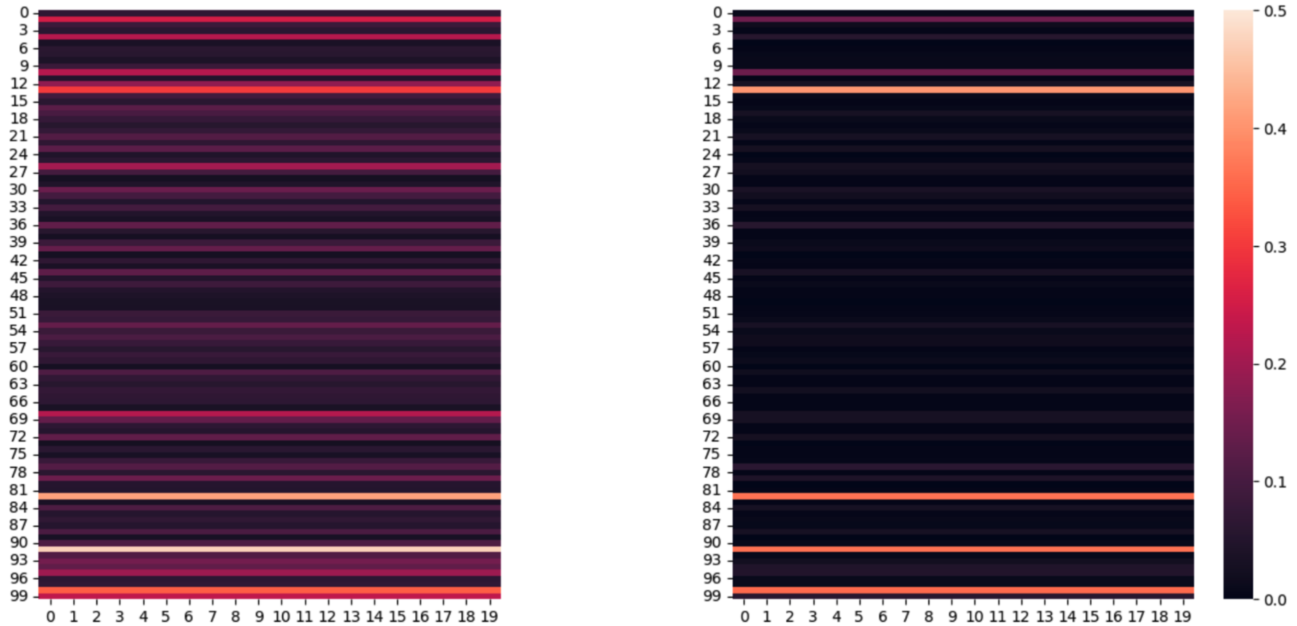


Reconstructed output tracks the temporal regions of high spikes as seen in the input sample.

Embedded output static over the 20 timestep interval

Encoder outputs from LSTM-AE

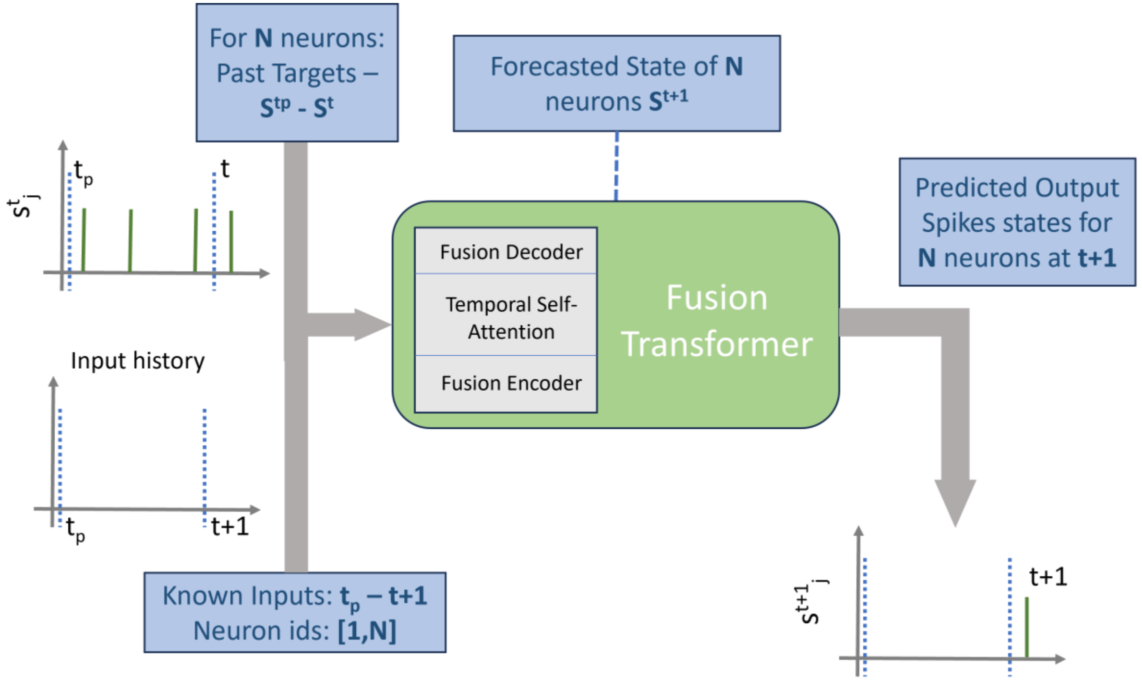
- Mean and variance of the encoded outputs across all test samples
- Overall low variation for a 20 timestep sequence
- LSTM captures the compressed representation of the sparse SNN activity, but not the temporal variations



(a) Mean (b) Variance

Temporal Fusion Transformer (TFT) Model

- TFT - Aggregation of LSTM embedding plus attention mechanism
- Problem to be solved – multi-variate (neuronal spike rates) time series forecasting
- **Input history sequence:**
  - Multi-variate spike rate sequences $R^{t:t+t_m}$
- **Known Inputs:**
  - Time step values t
  - Neuron ids i
- **Target:** Predict spike rates for t_h timesteps in the future
- Analyze attention weights across different neurons



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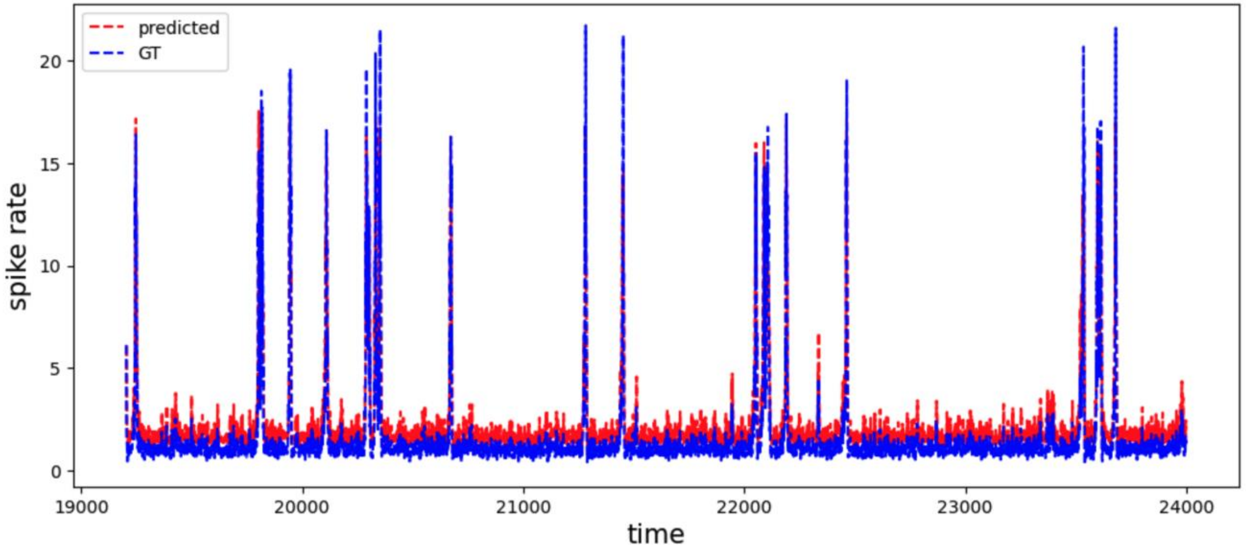
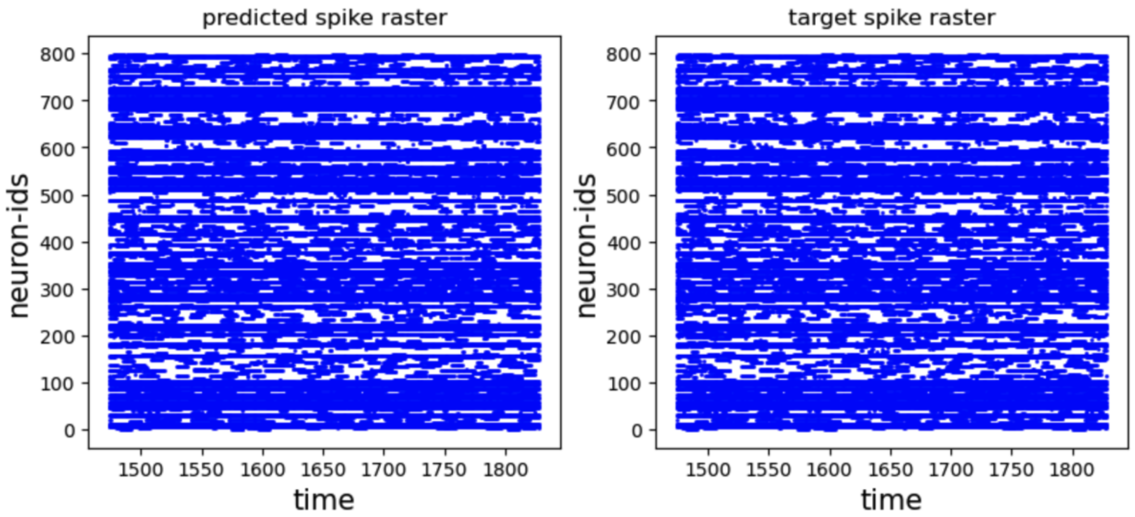
TFT prediction results





- **Task: Prediction over the average network spike rate sequence**
- TFT successfully predicts peak spike rates for $(t+1)^{th}$ timestep

- **Task: Predicting individual neuronal spike rates**
- TFT successfully captures the binarized spike rates for each neuron

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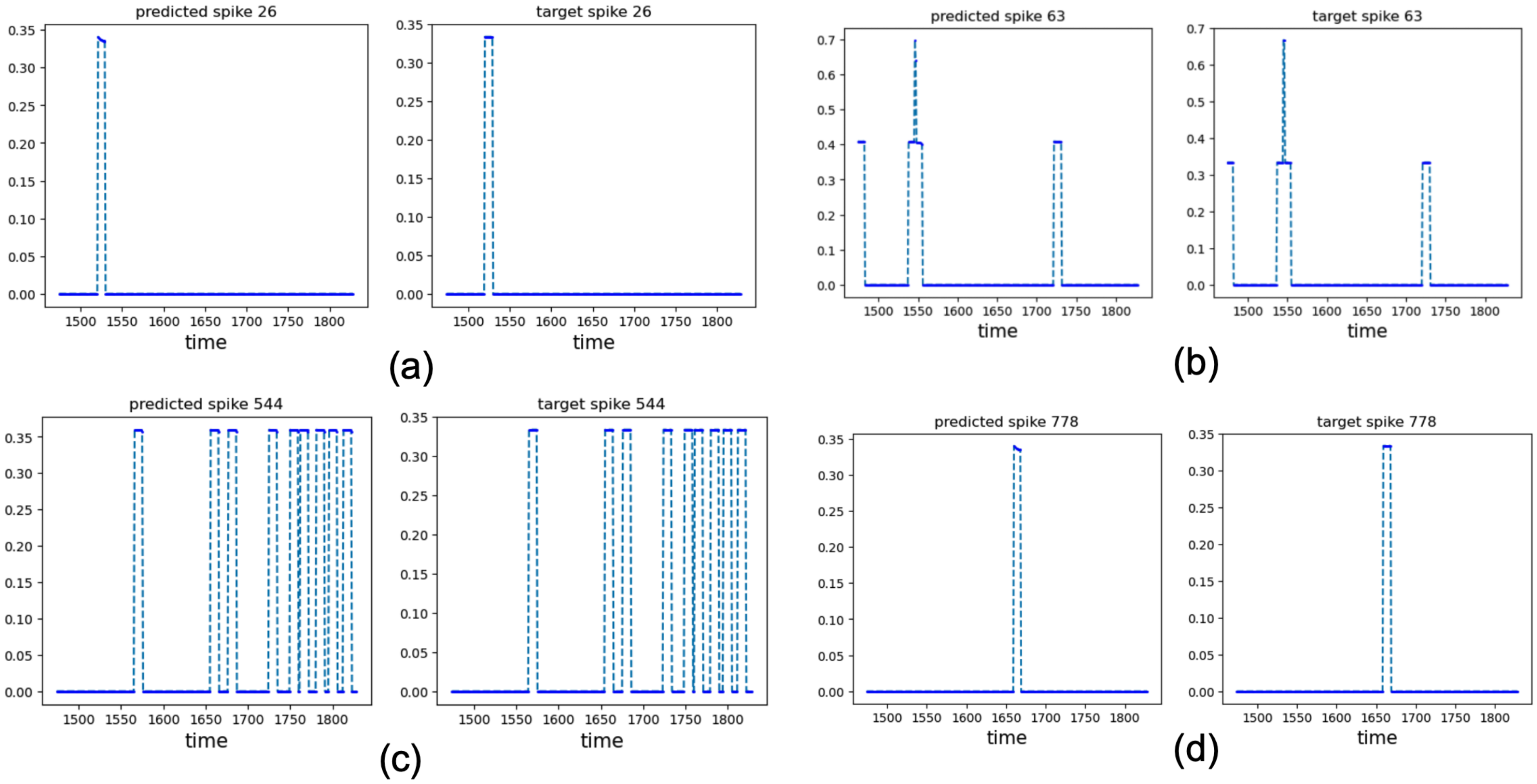
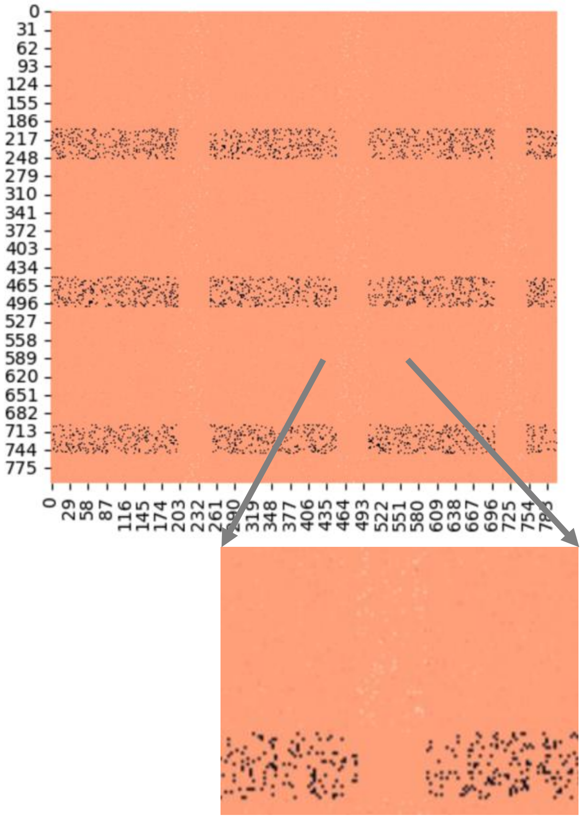
Spike Sequence Prediction with TFT

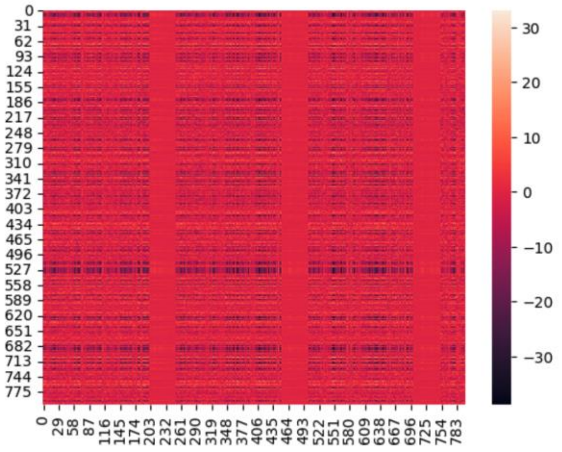


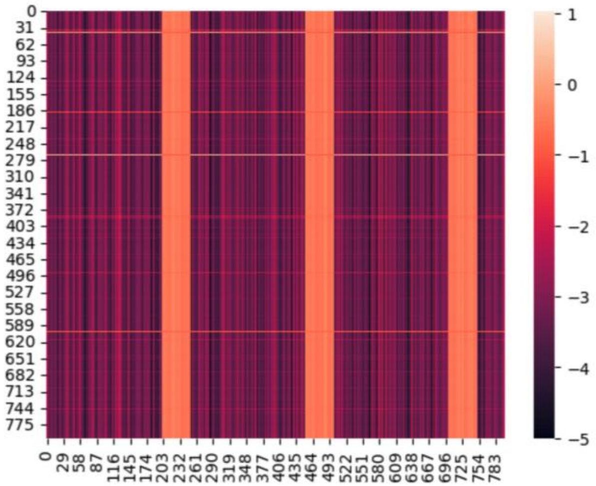
TFT successfully predicts the spike rates for successive timesteps for each neuron

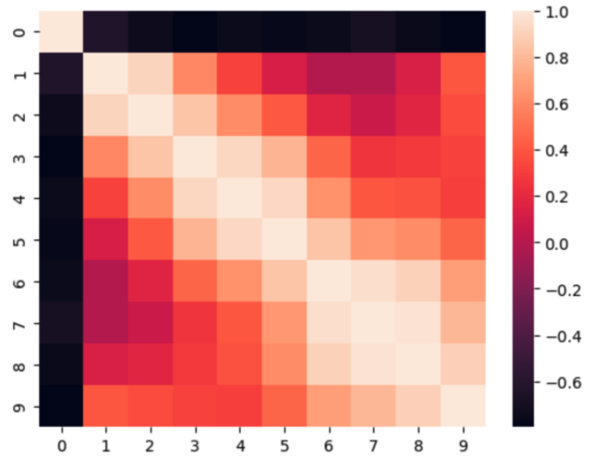
Analyzing attention weights



Ground Truth:
Network adjacency heat-map

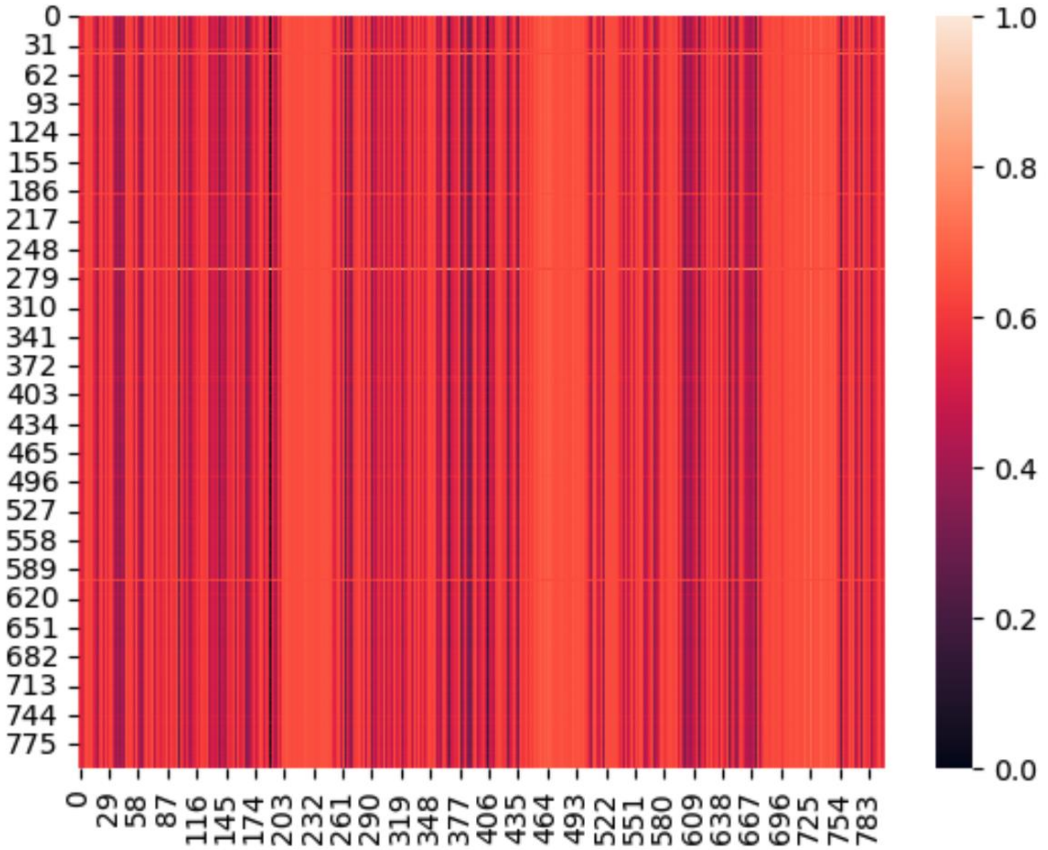






- **Self-attention** weights of TFT of size $N \times k \times m$
- **Correlation** among the mean attention weights for all test samples high for connected neurons in the network
- **TFT Attention Similarity:** High similarity among average connectivity weight and attention weights of all N neurons
- Spike activities among neurons have short-range temporal dependencies.

TFT Attention weights and Causality



- Computed causality adjacency matrices over entire simulation T
  - $N \times N$ sized matrix
- Dot product similarity of mean attention weights (for all test samples) with network's causality components ($\Omega_{i,j}$)
- High similarity for connected neurons

Summary and Conclusion

- Demonstrated two Deep Learning models – LSTM and transformers to analyze sparse neural data
- Application of DL models for performing underlying tasks along with representing the underlying architecture for sparse spike signals
- Models of LSTM and TFT are scalable on HPC, hence, could be applied to very large-scale neural simulation
- Future directions –
  – Developing reduced order cognitive learning models
  – Demonstrate scalability over large-scale simulations
  – Causal representation to interpret relation between different neuronal groups
  – Causal representation for codesigning energy-efficient SNN hardware

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Questions?

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