Deep Convolutional Neural Networks for Spike Inferrence

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Abstract

We present a convolutional neural network for inferring spikes from calcium imaging that substantially outperforms state-of-the-art models on the same dataset. We also present another model that is simplified to be more interpretable and provide some intuition for why a deep convolutional network provides such substantial performance gains.

Background

- A key idea in neuroscience is that neurons encode information as "spikes" of electrical activity
- *Calcium imaging* is an increasingly popular way to observe population-level spiking activity; when a spike occurs, calcium levels increase. This is detected using calcium indicator dyes
- *Spike inference* is the challenge of predicting spikes from calcium images; the relationship between calcium and spiking is non-linear and noisy

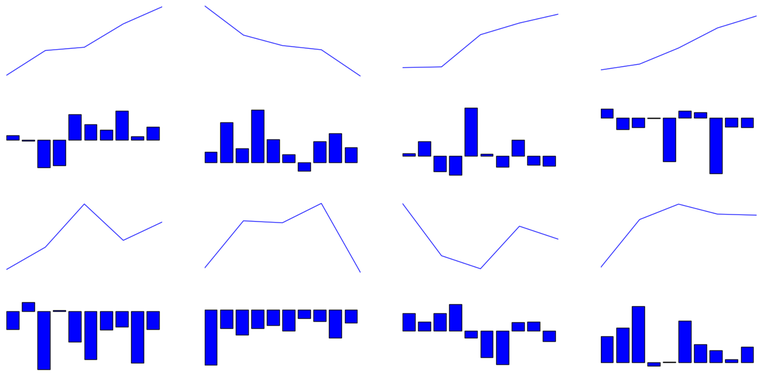
Datasets

- Each dataset consists of approximately 10 minutes of calcium fluorescences paired with spikes, each sampled at 100 Hz
- All the datasets were recorded using mouse V1 cells, except for dataset 4, which was recorded using Retina cells
- OGB-1 dye was used for datasets 1, 2 and 4; GCamp6s dye was used for 3, 5 and 8; GCaMP5k was used for 6; GCaMP6f was used for 7; jRCAMP1a was used for 9; and jRGEC01a was used for 10

Model description

Both the regular and simplified model feature *attended convolution* layers; the activations of each filter are weighted by an embedding for each dataset. Additionally, the first and second order derivatives of the calcium fluorescences are used as additional features, as are their squared values.

The regular model consists of stacked Inception-type cells. The simplified model consists of two convolution layers, followed by a feedforward layer that predicts the spike probability. In both, the first convolutional layer is an attended convolution.

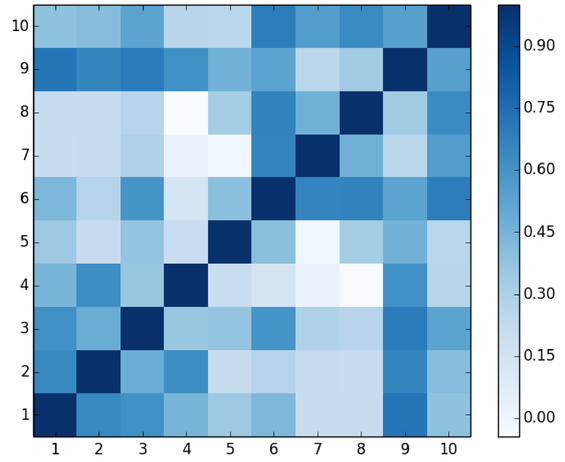


Sample of first-layer convolutions. Each line represents a single filter. The weights below each filter represent the dataset weighting. For example, the bottom right filter is mostly ignored by datasets 4, 5 and 9.

Sample predictions for two different indicator dyes, recorded in the same type of neuron. The model takes as input the calcium fluorescences (green) and outputs spike probabilities (blue). The model clips the predictions from the beginning and end due to dilation of the convolutional filters.

Dataset	1	2	3	4	5	6	7	8	9	10
Model	0.51	0.48	0.53	0.52	0.52	0.73	0.82	0.80	0.60	0.81
Simp. Model	0.40	0.28	0.32	0.02	0.29	0.58	0.68	0.51	0.38	0.22
STM	0.46	0.44	0.44	0.44	0.28	0.52	0.49	0.40	0.41	0.55
OOPSI	0.35	0.34 0	0.38	0.32	0.21	0.60	0.64	0.53	0.34	0.67

Pearson correlation between the model predictions and the actual spikes for the two models described here, as well as STM [Theis et al., 2015] and OOPSI [Vogelstein, 2009].



Cosine similarities between learned embeddings for each dataset. These represent the similarity between how the neuron decodes each dataset's calcium fluorescences. For example, dataset 4 uses different filters from most other datasets, except for 2 and 9.

Discussion

- The high performance of the convolutional model suggests that patterns in calcium fluorescence are hierarchical
- The dataset embeddings surprisingly revealed very little correlation between the filters used for datasets recorded using identical calcium dyes; there is much more variation between recording sessions than between dye types
- Without knowledge of the dataset, the model performed significantly worse; there is a lot of variation between recording sessions
- Future models could combine the convolutional classifier with a physiological model to improve performance

References

[Theis et al., 2015] Theis, L., Berens, P., Froudarakis, E., Reimer, J., Rosón, M. R., Baden, T., Euler, T., Tolias, A., and Bethge, M. (2015). Supervised learning sets benchmark for robust spike detection from calcium imaging signals. *arXiv preprint arXiv:1503.00135*.

[Theis et al., 2016] Theis, L., Berens, P., Froudarakis, E., Reimer, J., Rosón, M. R., Baden, T., Euler, T., Tolias, A. S., and Bethge, M. (2016). Benchmarking spike rate inference in population calcium imaging. *Neuron*, 90(3):471–482.

[Vogelstein, 2009] Vogelstein, J. T. (2009). Oopsi: A family of optimal optical spike inference algorithms for inferring neural connectivity from population calcium imaging. *Ann Arbor*, 1050:48106–1346.