

General Exam Proposal: C. Daniel Greenidge

Committee

- Jonathan Pillow
- Adji Dieng
- Ben Raphael

Abstract

Linear classifiers are a tool used by neuroscientists to quantify the information content of neural population codes and the limits imposed by correlations in neural activity. However, the most commonly used classification methods are prone to overfitting on the high-dimensional, noisy datasets produced by modern neuroimaging technologies. Here, we introduce a novel classifier (also called “decoder” in the neuroscience literature) to overcome these limitations. Our approach, the Gaussian process multi-class decoder (GPMD), is well-suited to decoding a continuous low-dimensional variable from high-dimensional population activity, and provides a platform for assessing the importance of correlations in neural population codes. The GPMD is a multinomial logistic regression model with a Gaussian Process prior over the decoding weights. We provide a spectral variational inference method for fitting the GPMD to data, which scales to datasets with hundreds or thousands of neurons and performs especially well in datasets with more neurons than trials. We apply the GPMD to recordings from primary visual cortex in three different species: monkey, ferret, and mouse. Our classifier achieves state-of-the-art accuracy on all three datasets, and substantially outperforms independent Bayesian decoding, showing that knowledge of the correlation structure is essential for optimal decoding in all three species. We then use our classifier to examine the problems of model mismatch, cortical microcolumn structure, and how neural coding strategies are modulated in the presence of noise.

Reading List

- Bishop, Christopher M. 2006. *Pattern Recognition and Machine Learning*. New York: Springer.

- Blei, David M., Alp Kucukelbir, and Jon D. McAuliffe. 2017. “Variational Inference: A Review for Statisticians.” *Journal of the American Statistical Association* 112 (518): 859–77.
- Cortes, Corinna, and Vladimir Vapnik. 1995. “Support-Vector Networks.” *Machine Learning* 20 (3): 273–97.
- Graf, Arnulf B. A., Adam Kohn, Mehrdad Jazayeri, and J. Anthony Movshon. 2011. “Decoding the Activity of Neuronal Populations in Macaque Primary Visual Cortex.” *Nature Neuroscience* 14 (2): 239–45.
- Kohn, Adam, Ruben Coen-Cagli, Ingmar Kanitscheider, and Alexandre Pouget. 2016. “Correlations and Neuronal Population Information.” *Annual Review of Neuroscience* 39 (1): 237–56.
- Kucukelbir, Alp, Dustin Tran, Rajesh Ranganath, Andrew Gelman, and David M. Blei. 2017. “Automatic Differentiation Variational Inference.” *Journal of Machine Learning Research: JMLR* 18 (14): 1–45.
- MacKay, David J. C. 1992. “Bayesian Interpolation.” *Neural Computation* 4 (3): 415–47.
- Royle, J. Andrew, and Christopher K. Wikle. 2005. “Efficient Statistical Mapping of Avian Count Data.” *Environmental and Ecological Statistics* 12 (2): 225–43.
- Stringer, Carsen, Michalis Michaelos, Dmitri Tsyboulski, Sarah E. Lindo, and Marius Pachitariu. 2021. “High-Precision Coding in Visual Cortex.” *Cell* 184 (10): 2767–78.e15.
- Zou, Hui, and Trevor Hastie. 2005. “Regularization and Variable Selection via the Elastic Net.” *Journal of the Royal Statistical Society. Series B, Statistical Methodology* 67 (2): 301–20.