Nonnegative Matrix Factorization with Scale-Invariant Binning Features for Spike Data

Goals

We aim to use Nonnegative Matrix Factorization (NMF) or Robust Principal Component Analysis (RPCA) with nonnegativity and sparsity constraints to analyze neural spike data obtained from 132 neurons in inferior temporal cortex (IT). The recordings were made while a monkey viewed 7 different objects that were presented at three different locations.

Specifically, we will try to learn a dictionary directly from the spike data and determine the corresponding physical meanings of the learned dictionary. We will also try to implement a novel scale-invariantl binning methods.

Finally, we could use the learned dictionary to decode neural activities.

Introduction

Matrix factorization methods that exploit nonnegativity and sparsity constraints usually lead to estimation of the hidden components with specific structures and physical interpretations, in contrast to other blind source separation methods. The assumption is that the measurements would consist somewhat "low-rank" or "sparse" (maybe not) component associated to the movement required by the particular task, and some superimposed sparse noise associate to the neuron firings in the background.

Tools

The Neural Decoding Toolbox, Tomaso Poggio’s group
Sparse analysis toolboxs
Spike analysis toolboxs

Deliverables

A conference paper aimed at 2014 IEEE World Congress on Computational Intelligence (IEEE WCCI), which will host three conferences, including International Joint Conference on Neural

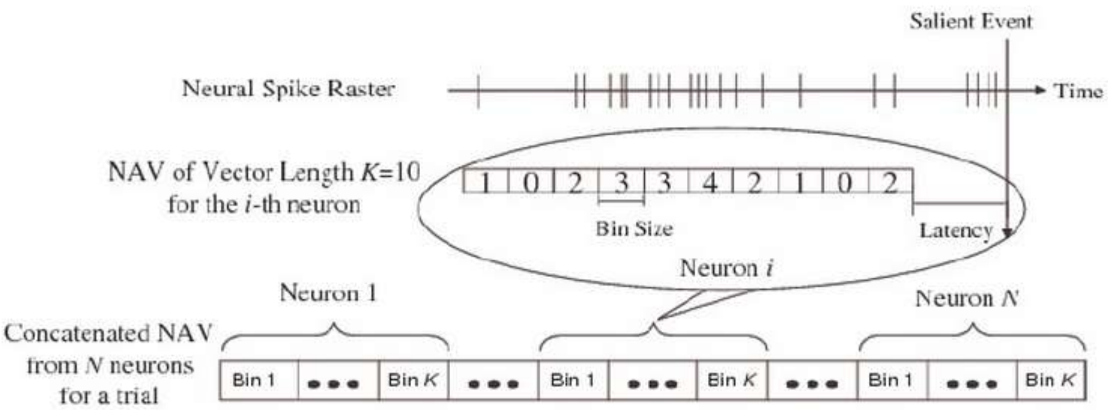
Networks (IJCNN).

Details

Data

We will use [Zhang-Desimone 7 object dataset](). It was collected by Ying Zhang in Bob Desimone's lab in the McGovern Institute at MIT. The data was used in the supplemental figures in the paper [Object decoding with attention in inferior temporal cortex](), PNAS, 2011.

Neural Activity Vector (NAV) consists of firing rates (frequencies) estimated by counting spikes (action potentials) observed in a window of time called a bin offset by a fixed time from some task event. Multiple time windows from multiple neurons are then concatenated into a single vector, as shown below.



Methods

Scale-Invariant Binning Features

NAV captures the spatial and temporal characteristics of a neural representation and serves as input to our component analysis algorithms. We first form high-dimensional scale-invariant feature vectors by stacking NAVs in different binning sizes, and then project them into low-dimensional spaces. This would be the key contribution of our paper.

Non-negativity Matrix Factorization (NMF)

As a model-independent methodology, NMF can identify local spatiotemporal patterns of neural activity in the form of sparse basis vectors. The nonnegativity constraints in NMF result in the unsupervised selection of sparse bases that can be linearly combined (encoded) to reconstruct the original data. The hypothesis is that NMF can similarly yield sparse bases for analyzing neural firing activity, because of the intrinsic nonnegativity of the bin counts and the sparseness of spike trains. The nonnegativity constraint leads to a parts-based representation, since only additive, not subtractive, combinations of the bases are allowed. In contrast, negative basis vectors are allowed in PCA.

The goal of factorizing the neural activity matrix (convert NAV into matrix form) is to determine nonnegative sparse bases for the neural activity, from which we wish to deduce the local spatial structure of the neural population firing activity. These bases also point out common population firing patterns corresponding to the specific behavior.

Robust PCA

Given an observed matrix $M \in \mathbb{R}^{n_1 \times n_2}$ that is formed as a superposition of a low-rank matrix L_0 and a sparse matrix S_0,

$$M = L_0 + S_0$$

RPCA is the problem of recovering the low-rank and sparse components.
The problem of using RPCA is that the basis found by RPCA does not have physical meaning.

Hierarchical or/and Block Sparse NMF

Inspired by *Compressed Sensing for Energy-Efficient Wireless Telemonitoring of Noninvasive Fetal ECG via Block Sparse Bayesian Learning*, I will first try to explore the block sparse properties of spike trains.

In *Hierarchical Convex NMF for Clustering Massive Data*, the authors stacked NMF to form a deep architecture, which is similar to deep neural networks. Though I would not develop the theoretical part of deep learning, I would try to stack the Block Sparse NMF into a deep architecture.

References

Hu, Jing, et al. "Feature detection in motor cortical spikes by principal component analysis." Neural Systems and Rehabilitation Engineering, IEEE Transactions on 13.3 (2005): 256-262.

Kim, Sung-Phil, et al. "Determining patterns in neural activity for reaching movements using nonnegative matrix factorization." *EURASIP Journal on Advances in Signal Processing* 2005.19 (1900): 3113-3121.

Cichocki, Andrzej, et al. Nonnegative matrix and tensor factorizations: applications to exploratory multi-way data analysis and blind source separation. Wiley, 2009.