# Application of Non-Negative Matrix factorization for brain electrophysiological data

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## 1 Abstract

Neuronal population data during cognition are noisy high-dimensional data that are difficult to interpret. Improved interpretation of such data could both deepen our understanding of brain functioning and uncover new principles to design neuro-inspired intelligent machines.

Dimensionality reduction is commonly applied to project neural data onto low-dimensional subspaces amenable to geometric analysis and interpretation. There exist a number of dimensionality reduction methods, but, for brain electrophysiological data, Principal Component Analysis (PCA) remains the most commonly employed method to analyze and interpret neuronal population activity.

Over the past years, Non-Negative Matrix Factorization (NMF) [1] [2] [3], a linear-dimensionality reduction technique, has emerged in fields such as image reconstruction, electromyography recordings, oncology [4] to analyze data. A fundamental advantage of this method is its improved interpretability as compared to PCA. Remarkably, NMF has still never been applied to analyze neuronal data. Nevertheless, the non-negativity constraints of the Non-Negative Matrix Factorization method fits naturally with the non-negativity of neural firing rates and could allow easier interpretation of the neuronal population data. As this type of data becomes more and more present, especially in neuro-engineering and deep learning applications, it is important to have a method that can fully exploit its potential. To show the advantages of Non-Negative matrix factorization for neural data analysis and its improved interpretability as compared to other dimensionality reduction techniques, we applied this method to recordings of rhesus monkey neurons from the ventral parietal cortex during a bimodal detection task [5]. We subsequently explored and analyzed the revealed low-dimensional latent dynamics.

The application of this technique showed that, using a relatively small number of basis vectors, the method is able to capture all the key features of the measured neuronal population dynamics during cognition. The projection of the data is able to capture the encoding of the different types of stimulus and their intensity. Acoustic stimulation encoding presents some delay compared to vibrotactile stimulation encoding. The components can also decode the absence of stimuli from any modality throughout the delay. Finally, Non-Negative Matrix Factorization applied on the delay period allowed to separate the different stimulus in the vector basis space. In Comparison to Principal Component Analysis, the method needs less data pre-processing. Furthermore the extracted basis vectors have the direct, biologically meaningful, interpretation of synaptic readout weights to decode cognitive states from the measured population activity, which is not usually the case for PCA. In conclusion, Non-Negative Matrix Factorization shows great potential as a dimensionality reduction technique for easy interpretation of neuronal population data and could be an alternative to Principal Component Analysis in biological, neuromorphic or deep learning data analysis applications.

## References

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