# PhD projects R3

## Nonnegative Matrix and Tensor Factorizations – Theory and Selected Applications
## Blind Source Separation in Polyphonic Music Recordings

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## Nonnegative Matrix Factorization (NMF)

### Classical NMF Problem

- For a given matrix $\boldsymbol{X} \in \mathbb{R}_{\geq 0}^{N \times T}$, find matrices $\boldsymbol{B} \in \mathbb{R}_{\geq 0}^{N \times K}$ and $\boldsymbol{C} \in \mathbb{R}_{\geq 0}^{K \times T}$ with $K \ll \min\{N, T\}$, s.t. $\boldsymbol{X} \approx \boldsymbol{BC}$.

### Task Areas

- Used e.g. for dimension reduction, data compression, basis learning and source separation.

## Optimization Theory

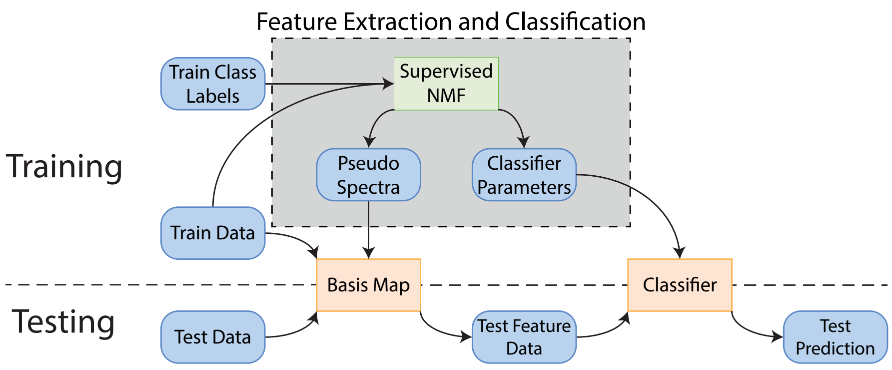
- Review and extension of the *majorize-minimization* principle for generalized NMF models.[1]

$$\min_{\boldsymbol{B},\boldsymbol{C} \geq 0} \mathcal{D}_{\mathrm{NMF}}(\boldsymbol{X}, \boldsymbol{BC}) + \sum_{\ell=1}^{L} \gamma_\ell \mathcal{P}_\ell(\boldsymbol{B}, \boldsymbol{C})$$

## Applications

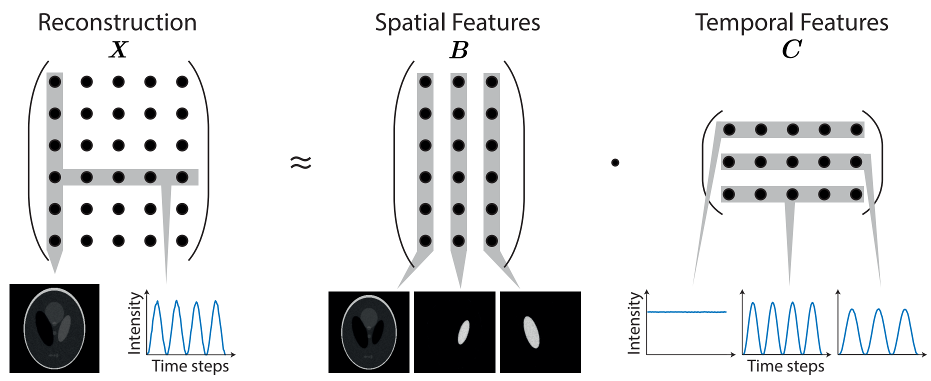
### MALDI Imaging

- Development of supervised NMF models for extracting tumor-specific spectral patterns.[2]




### Dynamic Computerized Tomography

- Reconstruction and low-rank decomposition for dynamic inverse problems via NMF.[3]




### Clustering

- Development of an orthogonal NMF model with total variation regularization to enforce spatial coherence.
- Find connections between regularized orthogonal NMF and generalized K-means models.

## Audio Source Separation

We want to identify and separate the contributions of different instruments in a music recording.


Figure 1: Musical score for a piece by Mozart

This is much easier if the tones from one instrument follow the same pitch-invariant pattern. We developed a pitch-invariant and frequency-uniform time-frequency representation that combines properties from the mel spectrogram and the constant-Q transform.[4] However, in order to improve the resolution, we rely on a *sparse pursuit* method.[5]

## Sparse Pursuit

We use an algorithm to represent a discrete mixture via shifted continuous patterns from a parametric model.

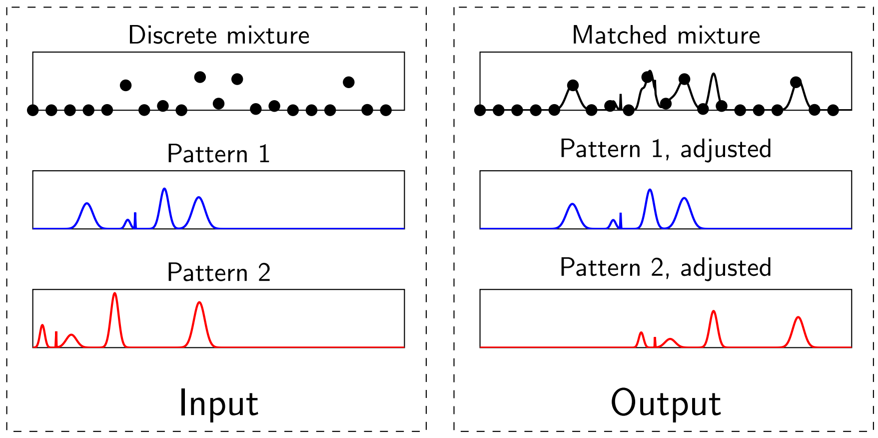



Figure 2: Test example for the sparse pursuit algorithm

With this, we can recover the spectra of the individual instruments.

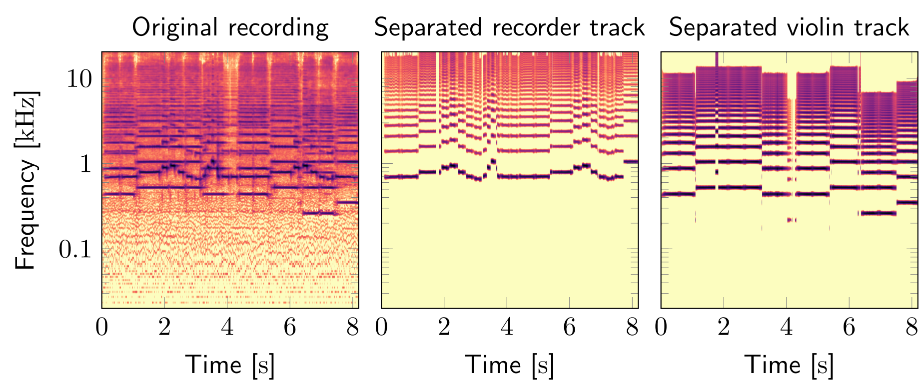



Figure 3: Separation result for the above music piece

In *blind* separation, the sounds of the instruments are not known a-priori, so we train a *dictionary* containing the relative amplitudes of the harmonics.

[1] P. Fernsel, P. Maass: *A survey on surrogate approaches to non-negative matrix factorization*. Vietnam Journal of Mathematics, 46 (2018), pp. 987-1021.
[2] J. Leuschner, M. Schmidt, P. Fernsel, D. Lachmund, T. Boskamp, P. Maass: *Supervised non-negative matrix factorization methods for MALDI imaging applications*. Bioinformatics, 35 (2018), pp. 1940-1947.
[3] S. Arridge, P. Fernsel, A. Hauptmann: *Joint reconstruction and low-rank decomposition for dynamic inverse problems*. arXiv:2005.14042, 2020.
[4] S. Schulze, E. J. King: *A frequency-uniform and pitch-invariant time-frequency representation*. PAMM 2019.
[5] S. Schulze, E. J. King: *Sparse pursuit and dictionary learning for blind source separation in polyphonic music recordings*. Submitted. arXiv:1806.00273, 2020.

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