Décompositions tensorielles non-négatives du spectrogramme multicanal pour la séparation de sources musicales

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Outline

Generalities about nonnegative matrix factorization (NMF)

Nonnegative tensor decomposition for multichannel audio source separation
- CP decomposition
- Multichannel NMF

Audio results
- SiSEC 2008
- User-guided separation

Nonnegative matrix factorization (NMF)

Given a *nonnegative* matrix $\mathbf{V}$ of dimensions $F \times N$, NMF is the problem of finding a factorization

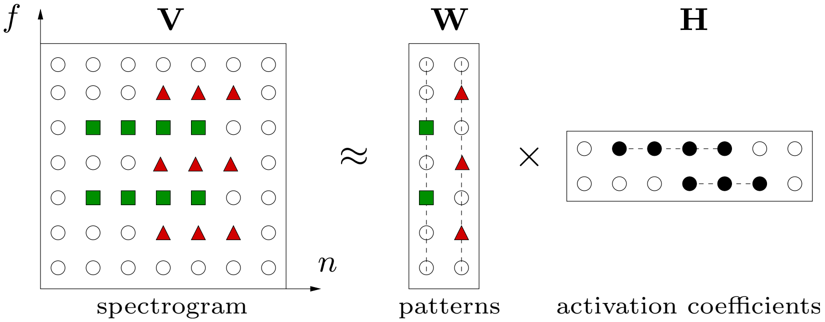
$$\mathbf{V} \approx \mathbf{W}\mathbf{H}$$

where $\mathbf{W}$ and $\mathbf{H}$ are *nonnegative* matrices of dimensions $F \times K$ and $K \times N$, respectively.

Early work by Paatero and Tapper (1994), landmark paper in *Nature* by Lee and Seung (1999).

NMF and music signal processing

NMF applied to the spectrogram, for source separation & transcription (Smaragdis and Brown, 2003)



NMF as a constrained minimization problem

Minimize a measure of fit between data $\mathbf{V}$ and model $\mathbf{WH}$, subject to nonnegativity of $\mathbf{W}$ and $\mathbf{H}$:

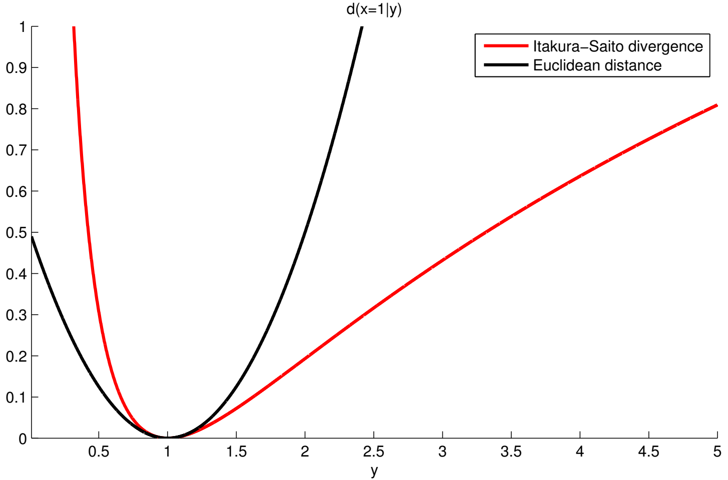
$$\min_{\mathbf{W},\mathbf{H}\geq\mathbf{0}} D(\mathbf{V}|\mathbf{WH}) = \sum_{fn} d([\mathbf{V}]_{fn}|[\mathbf{WH}]_{fn})$$

where $d(x|y)$ is a scalar cost function.

Itakura-Saito NMF

(Févotte, Bertin, and Durrieu, 2009)

Itakura-Saito divergence: $d_{IS}(x|y) = \frac{x}{y} - \log \frac{x}{y} - 1$



Itakura-Saito NMF: inference in a generative model

(Févotte, Bertin, and Durrieu, 2009)

Let $\mathbf{X} = \{x_{fn}\}$ be the (complex-valued) STFT of the signal. Assume

$$x_{fn} = \sum_{k=1}^{K} c_{kfn}$$

$$c_{kfn} \sim \mathcal{N}_c(0, w_{fk} h_{kn})$$

and the components $c_{1fn}, \ldots, c_{Kfn}$ are independent given $\mathbf{W}$ and $\mathbf{H}$.

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and the components $c_{1fn}, \ldots, c_{Kfn}$ are independent given $\mathbf{W}$ and $\mathbf{H}$. Then

$$-\log p(\mathbf{X}|\mathbf{W},\mathbf{H}) = D_{IS}(|\mathbf{X}|^2|\mathbf{WH}) \quad + cst.$$

Additivity assumed in the STFT domain. Phase is preserved in the model, though in a noninformative way (uniform distribution).

Related work by Benaroya et al. (2003); Parry and Essa (2007)

What about multichannel data ?

- NMF is suitable for single-channel data.
- Music is usually available in multichannel (at least stereo).
- Factorizing the channel spectrograms separately is suboptimal.
- The channel spectrograms form the slices of tensor.
- Use adequate tensor decompositions !

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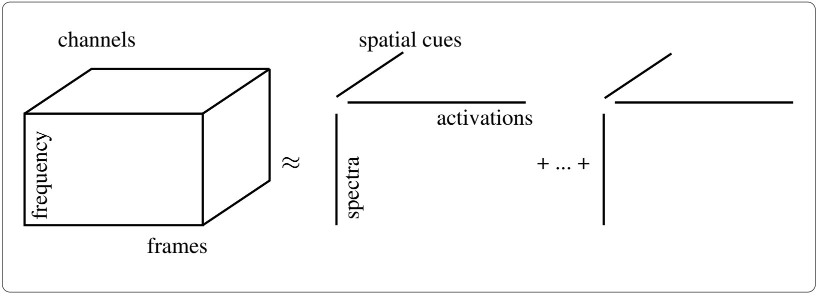
CP decomposition
Principles



Considered for multichannel source separation and/or transcription by (FitzGerald et al., 2005, 2008; Parry and Essa, 2006; Févotte and Ozerov, 2010).

$$\min_{\mathbf{W},\mathbf{H},\mathbf{Q}} \sum_{ifn} d(v_{ifn} | \sum_k q_{ik} w_{fk} h_{nk})$$

CP decomposition

Limitations

- Underlies a linear instantaneous mixing model.
- One source is usually made of several rank-1 components: manual grouping of the spatial cues is required.
- Estimation is statistically not optimal in the standard linear instantaneous mixing model.

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CP IS-NMF

$$x_{ifn} = \sum_{k=1}^{K} \sqrt{q_{ik}}\, c_{kfn}^{(i)} \quad \text{with} \quad c_{kfn}^{(i)} \sim \mathcal{N}_c(0, w_{fk} h_{nk})$$

CP decomposition

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DESIRED

$$x_{ifn} = \sum_{k=1}^{K} \sqrt{q_{ik}}\, c_{kfn} \quad \text{with} \quad c_{kfn} \sim \mathcal{N}_c(0, w_{fk} h_{nk})$$

(point source)

CP decomposition

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DESIRED

$$x_{ifn} \;=\; \sum_{k=1}^{K} \; a_{ik} \; c_{kfn} \quad \text{with} \quad c_{kfn} \sim \mathcal{N}_c(0, w_{fk} h_{nk})$$

(point source + real mixing coefficients)

CP decomposition

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$$x_{ifn} = \sum_{k=1}^{K} a_{ikf}\, c_{kfn} \quad \text{with} \quad c_{kfn} \sim \mathcal{N}_c(0, w_{fk} h_{nk})$$

(point source + real mixing coefficients + convolution)

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(point source + real mixing coefficients + convolution)

+ grouping: $a_{ikf} = a_{ij_kf}$ (J sources)

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DESIRED

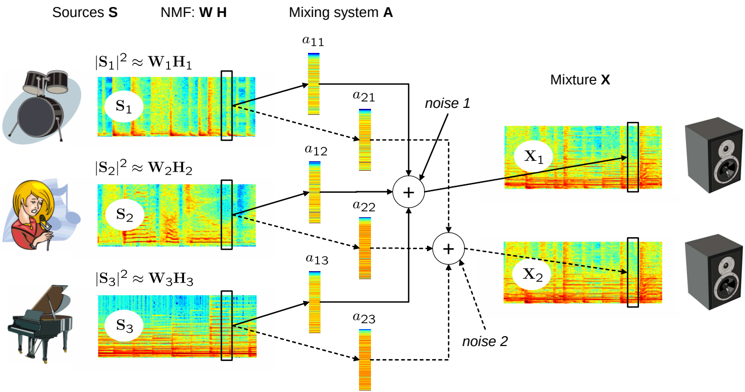
$$x_{ifn} = \sum_{k=1}^{K} {\color{red}a_{ikf}}\, c_{kfn} \quad \text{with} \quad c_{kfn} \sim \mathcal{N}_c(0, w_{fk} h_{nk})$$

(point source + real mixing coefficients + convolution)

+ grouping: $a_{i{\color{red}k}f} = a_{i{\color{red}j_k}f}$ (J sources)

= **MULTICHANNEL NMF**

Multichannel NMF
(Ozerov and Févotte, 2010)



Multichannel NMF problem: Estimate **W**, **H** and **A** from **X**

Multichannel NMF (ctd)
(Ozerov and Févotte, 2010)

Model:

$$x_{ifn} = \sum_j a_{ijf} s_{jfn}$$

$$s_{jfn} \sim \mathcal{N}_c(0, [\mathbf{W}_j \mathbf{H}_j]_{fn})$$

Maximum likelihood estimation:

$$\min_{\mathbf{W},\mathbf{H},\mathbf{A}} -\log p(\mathbf{X}|\mathbf{W}, \mathbf{H}, \mathbf{A})$$

Possible with an EM algorithm that uses the sources $\{s_{jfn}\}$ as latent data.

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SiSEC 2008 results

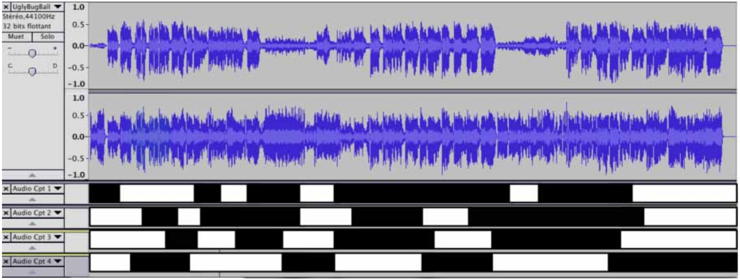
Best scores on task “Under-determined speech and music mixtures” at the 2008 Signal Separation Evaluation Campaign.

http://www.irisa.fr/metiss/SiSEC08/SiSEC_underdetermined/test_eval.html

User-guided multichannel IS-NMF

(Ozerov, Févotte, Blouet, and Durrieu, 2011)

- The decomposition is "guided" by the operator: source activation time-codes are input to the separation system.
- The temporal segmentation is reflected in the form of zeros in **H** when a source is silent.



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