# Infinite Positive Semidefinite Tensor Factorization for Source Separation of Mixture Signals

Kazuyoshi Yoshii<sup>1)</sup> Ryota Tomioka<sup>2)</sup> Daichi Mochihashi<sup>3)</sup> Masataka Goto<sup>1)</sup>

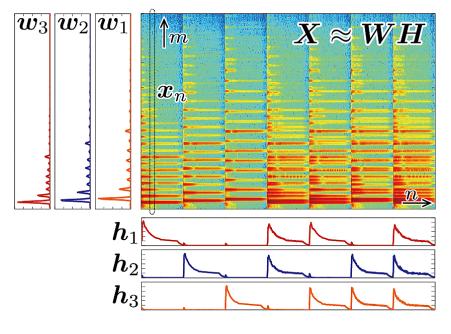
- 1) National Institute of Advanced Industrial Science and Technology (AIST)
- 2) The University of Tokyo 3) The Institute of Statistical Mathematics (ISM)

# **Take-Home Messages**

- We proposed positive semidefinite tensor factorization (PSDTF)
  - Tensor extension of nonnegative matrix factorization (NMF)
    - Nonnegative tensor factorization (NTF) is a naive extension of NMF
  - Bayesian nonparametrics
    - The gamma process is used for Bayesian PSDTF that can deal with an infinite number of bases
- A special case: log-determinant PSDTF (LD-PSDTF)
  - Elegant variational inference
    - Closed-form MU and VB updates were derived
  - Various applications
    - Single-channel audio source separation
    - Multi-channel EEG signal analysis

## **Nonnegative Matrix Factorization**

 Each <u>nonnegative vector</u> is approximated by a convex combination of <u>nonnegative vectors</u> (bases)



## **Observed matrix**

$$oldsymbol{X} = [oldsymbol{x}_1, \cdots, oldsymbol{x}_N] \in \mathbb{R}^{M imes N}$$

## **Basis matrix**

$$oldsymbol{W} = [oldsymbol{w}_1, \cdots, oldsymbol{w}_K] \in \mathbb{R}^{M imes K}$$

#### **Activation matrix**

$$oldsymbol{H} = [oldsymbol{h}_1, \cdots, oldsymbol{h}_K]^T \in \mathbb{R}^{K imes N}$$

## **Vector-wise factorization**

$$oldsymbol{x}_n pprox \sum_{k=1}^K oldsymbol{w}_k h_{kn} \stackrel{ ext{def}}{=} oldsymbol{y}_n$$

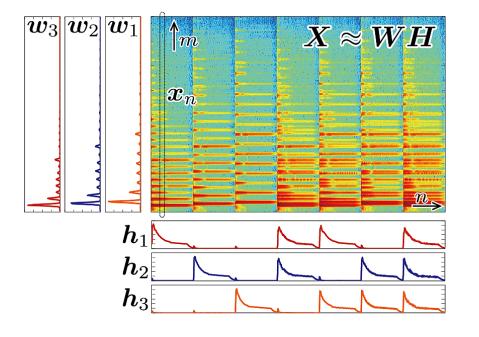
Bregman divergence:  $\mathcal{D}_{\phi}(\boldsymbol{x}_n|\boldsymbol{y}_n) = \phi(\boldsymbol{x}_n) - \phi(\boldsymbol{y}_n) - \phi'(\boldsymbol{y}_n)^T(\boldsymbol{x}_n - \boldsymbol{y}_n) \rightarrow \text{Minimize}$ 

Kullback-Leibler divergence:  $\mathcal{D}_{\text{KL}}(\boldsymbol{x}_n|\boldsymbol{y}_n) = \sum_{m} \left(x_{mn} \log x_{mn} y_{mn}^{-1} - x_{mn} + y_{mn}\right)$ 

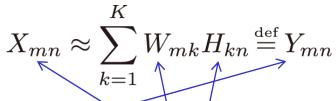
Itakura-Saito divergence:  $\mathcal{D}_{\scriptscriptstyle \mathrm{IS}}(m{x}_n|m{y}_n) = \sum_m \left(-\log x_{mn}y_{mn}^{-1} + x_{mn}y_{mn}^{-1} - 1\right)$ 

# A Major Limitation of NMF

- The elements of each basis vector are assumed to be independent
  - The correlations between those elements are ignored



**Element-wise representation** 



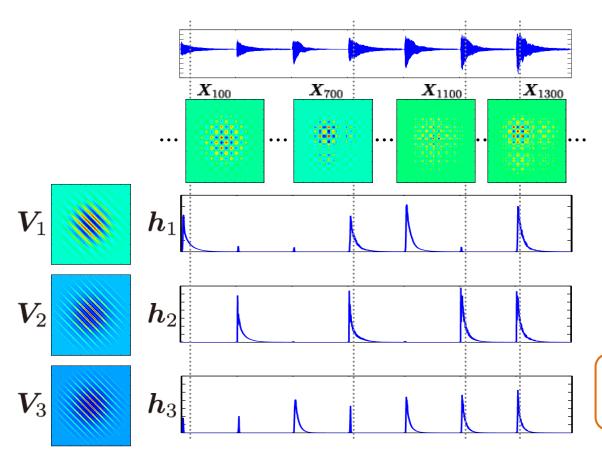
The cost function is defined in an element-wise manner

Gamma priors are placed in an element-wise manner

Problem: STFT cannot completely decorrelate frequency bins because finite windows are used for analyzing non-stationary signals

## **Positive Semidefinite Tensor Factorization**

 Each <u>positive semidefinite matrix</u> is approximated by a convex combination of <u>positive semidefinite matrices</u> (bases)



## **Observed tensor**

$$oldsymbol{X} = [oldsymbol{X}_1, \cdots, oldsymbol{X}_N] \in \mathbb{R}^{M imes M imes N}$$

## Basis tensor

$$oldsymbol{V} = [oldsymbol{V}_1, \cdots, oldsymbol{V}_K] \in \mathbb{R}^{M imes M imes K}$$

#### **Activation matrix**

$$oldsymbol{H} = [oldsymbol{h}_1, \cdots, oldsymbol{h}_K]^T \in \mathbb{R}^{K imes N}$$

## Matrix-wise factorization

$$oldsymbol{X}_n pprox \sum_{k=1}^K oldsymbol{V}_k h_{kn} \stackrel{ ext{def}}{=} oldsymbol{Y}_n$$

Bregman matrix divergence can be used as a cost function

## PSDTF: A Natural Extension of NMF

- Nonnegative Matrix Factorization (NMF)
  - Vector-wise factorization
  - Bregman divergence

$$oldsymbol{x}_n pprox \sum_{k=1}^K oldsymbol{w}_k h_{kn} \stackrel{ ext{def}}{=} oldsymbol{y}_n$$

 Kullback-Leibler (KL) divergence  $\mathcal{D}_{\mathrm{KL}}(\boldsymbol{x}_n|\boldsymbol{y}_n) = \sum_{m} \left( x_{mn} \log x_{mn} y_{mn}^{-1} - x_{mn} + y_{mn} \right)$ 

• Itakura-Saito (IS) divergence  $\mathcal{D}_{\text{IS}}(\boldsymbol{x}_n|\boldsymbol{y}_n) = \sum_{m} \left( -\log x_{mn} y_{mn}^{-1} + x_{mn} y_{mn}^{-1} - 1 \right)$ 

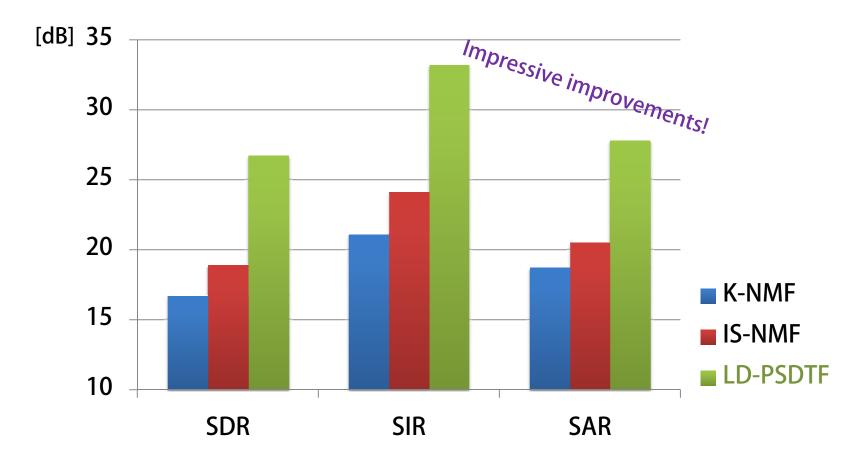
- Positive Semidefinite Tensor Factorization (PSDTF)
  - Matrix-wise factorization

  - Matrix-wise ractorization  $X_n pprox \sum_{k=1}^n V_k h_{kn} \stackrel{ ext{def}}{=} Y_n$ 
    - von Neumann (vN) divergence  $rac{\mathcal{D}_{ ext{vN}}(oldsymbol{X}_n|oldsymbol{Y}_n) = ext{tr}\left(oldsymbol{X}_n \log oldsymbol{X}_n oldsymbol{Y}_n^{-1} - oldsymbol{X}_n + oldsymbol{Y}_n
      ight)}{1$
    - Log-determinant (LD) divergence Log-determinant (LD) divergence  $\mathcal{D}_{\text{LD}}(\boldsymbol{X}_n|\boldsymbol{Y}_n) = -\log\left|\boldsymbol{X}_n\boldsymbol{Y}_n^{-1}\right| + \operatorname{tr}\left(\boldsymbol{X}_n\boldsymbol{Y}_n^{-1}\right) - M$

Nonparametric **Bayesian infinite** extension feasible

# **Single-Channel Audio Source Separation**

- LD-PSDTF outperformed KL-NMF and IS-NMF
  - Tested on a toy mixture signal consisting of three piano sounds



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  - Bayesian nonparametrics
    - The gamma process is used for Bayesian PSDTF that can deal with an infinite number of bases
- A special case: log-determinant PSDTF (LD-PSDTF)
  - Elegant variational inference
    - Closed-form MU and VB updates were derived
- Another special case: von-Neumann PSDTF (vN-PSDTF)
  - This is worth investigating (closed-form solution exists?)