# Automatic relevance determination in nonnegative matrix factorization with the $\beta$ -divergence

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# Nonnegative matrix factorization (NMF)

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

 $V \approx WH$ 

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

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Constrained optimization problem:

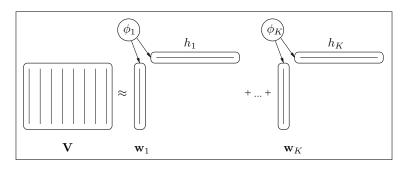
$$\min_{\mathbf{W},\mathbf{H}\geq \mathbf{0}} D(\mathbf{V}|\mathbf{W}\mathbf{H}) = \sum_{fn} d([\mathbf{V}]_{fn}|[\mathbf{W}\mathbf{H}]_{fn})$$

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

Objective of this work is to identify the "right" value of K.

## Automatic relevance determination in NMF

Inspired by Bayesian PCA (Bishop, 1999): each "component" k is assigned a relevance (= variance) parameter  $\phi_k$ .



Half-Gaussian or exponential priors on  $\mathbf{w}_k$  and  $h_k$ .

$$\mathsf{E.g.}, \quad p(\mathbf{w}_k|\phi_k) = \prod_f \phi_k^{-1} \exp{-\phi_k^{-1} w_{\mathit{fk}}}, \quad p(h_k|\phi_k) = \prod_n \phi_k^{-1} \exp{-\phi_k^{-1} h_{\mathit{kn}}}$$

## Automatic relevance determination in NMF

After a few manipulations, we are essentially left with the minimization of

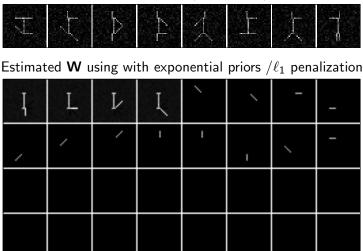
$$C(\mathbf{W}, \mathbf{H}) = D_{\beta}(\mathbf{V}|\mathbf{W}\mathbf{H}) + \rho \sum_{k=1}^{K} \log (\|\mathbf{w}_{k}\| + \|h_{k}\| + \varepsilon)$$

#### where

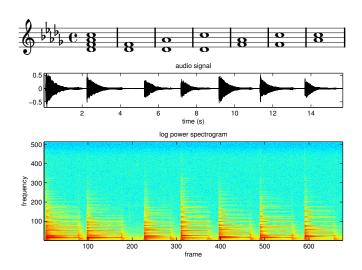
- ▶  $D_{\beta}(V|WH)$  is the measure of fit (in this work,  $\beta$ -divergence)
- ▶  $\|\mathbf{x}\| = \frac{1}{2} \|\mathbf{x}\|_2^2$  (half-Gaussian priors) or  $\|\mathbf{x}\| = \|\mathbf{x}\|_1$  (exponential priors).

## Swimmer decomposition results

8 data samples (among 256)



## Audio decomposition results



## Audio decomposition results

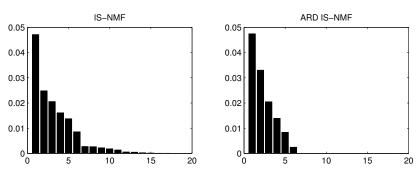


Figure: Histograms of standard deviation values of all K=18 components produced by Itakura-Saito NMF and ARD Itakura-Saito NMF (with  $\ell_2$  penalization). ARD IS-NMF only retains the 6 "right" components.

### Check our full-length technical report available on arxiv.