

IS - NMF

* Problem :

We want to solve $\min_{\underline{h}_n \in \mathbb{R}_+^K} C(\underline{h}_n)$ where

$$C(\underline{h}_n) = D_{\text{Is}}(\underline{v}_n \mid \underline{W} \underline{h}_n)$$

$$= \sum_{f=1}^F d_{\text{Is}}([v_n]_f \mid [W \underline{h}_n]_f)$$

$$= \sum_{f=1}^F d_{\text{Is}}(v_{fn} \mid \sum_{k=1}^K w_{fk} h_{kn})$$

$$= \sum_{f=1}^F \left[\frac{v_{fn}}{\sum_k w_{fk} h_{kn}} + \ln \left(\sum_k w_{fk} h_{kn} \right) \right] + \text{cst}$$

$$= \check{C}(\underline{h}_n) + \hat{C}(\underline{h}_n) + \text{cst}$$

where $\check{C}(\underline{h}_n) = \sum_{f=1}^F \check{C}_f(\underline{h}_n)$ and $\hat{C}(\underline{h}_n) = \sum_{f=1}^F \hat{C}_f(\underline{h}_n)$

with $\check{C}_f(\underline{h}_n) = \frac{v_{fn}}{\sum_k w_{fk} h_{kn}}$ and $\hat{C}_f(\underline{h}_n) = \ln \left(\sum_k w_{fk} h_{kn} \right)$

proposition (auxiliary function to $C(\underline{h}_n)$) =

The function $G(\underline{h}_n | \tilde{\underline{h}}_n)$ defined below is an auxiliary function to $C(\underline{h}_n)$:

$$G(\underline{h}_n | \tilde{\underline{h}}_n) = \check{G}(\underline{h}_n | \tilde{\underline{h}}_n) + \hat{G}(\underline{h}_n | \tilde{\underline{h}}_n)$$

with

$$\check{G}(\underline{h}_n | \tilde{\underline{h}}_n) = \sum_{f=1}^F \sum_{k=1}^K \left[\frac{w_{fk} \tilde{h}_{kn}^2}{h_{kn} \left(\sum_{k'=1}^K w_{fk'} \tilde{h}_{k'n} \right)} \right] \sigma_{fn}$$

$$\hat{G}(\underline{h}_n | \tilde{\underline{h}}_n) = \sum_{f=1}^F \left[\ln \left(\sum_{k=1}^K w_{fk} \tilde{h}_{kn} \right) + \frac{\sum_{k=1}^K w_{fk} h_{kn} - \sum_{k=1}^K w_{fk} \tilde{h}_{kn}}{\sum_{k=1}^K w_{fk} \tilde{h}_{kn}} \right]$$

PROOF

Concave part :

→ The condition $\hat{G}(\underline{h}_n, \underline{h}_n) = \hat{C}(\underline{h}_n)$ is trivially met.

→ We will prove that $\hat{C}(\underline{h}_n) \leq G(\underline{h}_n | \tilde{\underline{h}}_n)$

by majorizing each term $\hat{C}_j(\underline{h}_n)$.

As the composition of a concave function ($x \mapsto \ln(x)$) and a linear function, $\hat{C}_j(\underline{h}_n)$ is a concave function, so it can be majorized by its tangent (1st order Taylor expansion) at an arbitrary point $\tilde{\underline{h}}_n \in \mathbb{R}_+^K$:

$$\hat{C}_j(\underline{h}_n) \leq \hat{G}_j(\underline{h}_n | \tilde{\underline{h}}_n) := \hat{C}_j(\tilde{\underline{h}}_n) + \nabla^T \hat{C}_j(\tilde{\underline{h}}_n) (\underline{h}_n - \tilde{\underline{h}}_n),$$

where ∇^T denotes the transpose of the gradient.

Equality iff
 $\underline{h}_n = \tilde{\underline{h}}_n$.

From the definition of $\hat{C}_j(\underline{h}_n)$ we can develop :

$$\hat{G}_j(\underline{h}_n | \tilde{\underline{h}}_n) = \ln \left(\sum_k w_{jk} \tilde{h}_{kn} \right) + \sum_k \left[\frac{w_{jk}}{\sum_{k'} w_{jk'} \tilde{h}_{k'n}} (h_{kn} - \tilde{h}_{kn}) \right]$$

$$\hat{G}_f(\underline{h}_n | \tilde{\underline{h}}_n) = \ln \left(\sum_k w_{fk} \tilde{h}_{kn} \right) + \frac{\sum_k w_{fk} h_{kn} - \sum_k w_{fk} \tilde{h}_{kn}}{\sum_k w_{fk} \tilde{h}_{kn}}$$

Finally,

$$\hat{C}(\underline{h}_n) = \sum_f \hat{C}_f(\underline{h}_n) \leq \sum_f \hat{G}_f(\underline{h}_n | \tilde{\underline{h}}_n) = \hat{G}(\underline{h}_n | \tilde{\underline{h}}_n)$$

which completes the 1st part of the proof.

* Convex part :

→ The condition $\check{G}(\underline{h}_n | \underline{h}_n) = \check{C}(\underline{h}_n)$ is trivially met.

→ We will show that $\check{C}(\underline{h}_n) \leq \check{G}(\underline{h}_n | \tilde{\underline{h}}_n)$ by majorizing each term $\check{C}_f(\underline{h}_n)$.

We introduce the set of variable $\left\{ \tilde{\Phi}_{k,fn} \in \{0,1\} \right\}_{k=1}^K$ defined by

$$\tilde{\Phi}_{k,fn} = \frac{w_{fk} \tilde{h}_{kn}}{\sum_{k'} w_{fk'} \tilde{h}_{k'n}}$$

h that $\sum_k \tilde{\phi}_{k,n} = 1$.

Jensen's inequality: if $x \mapsto \varphi(x)$ is convex on \mathbb{R}_+ ,

we have $\varphi\left(\sum_k x_k\right) \leq \sum_k \tilde{\phi}_k \varphi\left(\frac{x_k}{\tilde{\phi}_k}\right)$ for

$x_1, \dots, x_k \geq 0$ and $\tilde{\phi}_1, \dots, \tilde{\phi}_k \geq 0$ such that $\sum_k \tilde{\phi}_k = 1$.

We have equality iff $\tilde{\phi}_k = \frac{x_k}{\sum_{k'} x_{k'}}$.

As the composition of a convex function ($x \mapsto \frac{1}{x}$ on \mathbb{R}_+) and a linear function, $\check{C}_f(\underline{h}_n)$ is a convex function.

Using Jensen's inequality we have:

$$\check{C}_f(\underline{h}_n) \leq \check{G}_f(\underline{h}_n | \tilde{\underline{h}}_n) := \pi_n \left[\sum_k \tilde{\phi}_{k,n} \cdot \frac{\tilde{\phi}_{k,n}}{w_{fk} h_{kn}} \right] \pi_n \left[\sum_k \frac{\tilde{\phi}_{k,n}^2}{w_{fk} h_{kn}} \right]$$

We can inject in this equation the expression of the auxiliary variables $\{\tilde{\phi}_{k,n}\}_k$ such that:

$$\check{G}_f(\underline{h}_n | \tilde{\underline{h}}_n) = \left[\sum_k \frac{w_{fk}^2 \tilde{h}_{kn}^2}{\left(\sum_{k'} w_{fk'} \tilde{h}_{k'n} \right)^2} \frac{1}{\cancel{w_{fk} h_{kn}}} \right] \sigma_{fn}$$

$$= \left[\sum_k \frac{w_{fk} \tilde{h}_{kn}^2}{h_{kn} \left(\sum_{k'} w_{fk'} \tilde{h}_{k'n} \right)^2} \right] \sigma_{fn}.$$

Then ,

$$\check{C}(\underline{h}_n) = \sum_f \hat{C}_f(\underline{h}_n) \leq \sum_f \check{G}_f(\underline{h}_n | \tilde{\underline{h}}_n) = G(\underline{h}_n | \tilde{\underline{h}}_n)$$

which completes the 2nd part of the proof.

Finally ,

$$C(\underline{h}_n) = \check{C}(\underline{h}_n) + \hat{C}(\underline{h}_n) \leq \check{G}(\underline{h}_n | \tilde{\underline{h}}_n) + \hat{G}(\underline{h}_n | \tilde{\underline{h}}_n) = G(\underline{h}_n | \tilde{\underline{h}}_n)$$

which completes the proof -

TE

$$\frac{\partial G(\underline{h}_n | \tilde{\underline{h}}_n)}{\partial h_{kn}} = \sum_{f=1}^F \left[\frac{w_{fk}}{\sum_{k'=1}^K w_{fk'} \tilde{h}_{k'n}} - \frac{\sigma_{fn}^2}{h_{kn}^2} \times \frac{w_{fk} \tilde{h}_{kn}^2}{\left(\sum_{k'=1}^K w_{fk'} \tilde{h}_{k'n} \right)^2} \right] = 0$$

$$\Leftrightarrow h_{kn}^* = \left[\frac{\sum_{f=1}^F \sigma_{fn}^2 w_{fk} \tilde{h}_{kn} \left(\sum_{k'=1}^K w_{fk'} \tilde{h}_{k'n} \right)^{-2}}{\sum_{f=1}^F w_{fk} \left(\sum_{k'=1}^K w_{fk'} \tilde{h}_{k'n} \right)^{-1}} \right]^{1/2}$$

$$\Leftrightarrow h_{kn}^* = \tilde{h}_{kn} \left[\frac{\sum_{f=1}^F \sigma_{fn}^2 w_{fk} \left(\sum_{k'=1}^K w_{fk'} \tilde{h}_{k'n} \right)^{-2}}{\sum_{f=1}^F w_{fk} \left(\sum_{k'=1}^K w_{fk'} \tilde{h}_{k'n} \right)^{-1}} \right]^{1/2}$$

Using the fact that \tilde{h}_{kn} is equal to the previous value of h_{kn} according to the EM algorithm, we can summarize the update as follows:

$$h_{kn} \leftarrow h_{kn} \left[\frac{\sum_{f=1}^F \sigma_{fn}^2 w_{fk} \left(\underline{\underline{W}} \underline{\underline{H}} \right)_{fn}^{-2}}{\sum_{f=1}^F w_{fk} \left(\underline{\underline{W}} \underline{\underline{H}} \right)_{fn}^{-1}} \right]^{1/2}$$

In matrix form:

$$\underline{\underline{H}} \leftarrow \underline{\underline{H}} \odot \left[\frac{\underline{\underline{W}}^T \left(\underline{\underline{V}} \odot \left(\underline{\underline{W}} \underline{\underline{H}} \right)^{\odot -2} \right)}{\underline{\underline{W}}^T \left(\underline{\underline{W}} \underline{\underline{H}} \right)^{\odot -1}} \right]^{\odot 1/2}$$