# Non-negative matrix factorization implemented by (anti-)Hebbian neural network 

Eszter<br>Tea talk, 19 November 2015

## Non-negative matrix factorization

$$
\begin{aligned}
& V_{i \mu} \approx(W H)_{i \mu}=\sum_{a=1}^{r} W_{i a} H_{a \mu}
\end{aligned}
$$



Columns of W constrained to be orthonormal



Find $\mathrm{W}, \mathrm{H}$ by minimizing:

$$
F=\sum_{i=1}^{n} \sum_{\mu=1}^{m}\left[V_{i \mu} \log (W H)_{i \mu}-(W H)_{i \mu}\right]
$$



A Hebbian/Anti-Hebbian Network Derived from Online Non-Negative Matrix Factorization Can Cluster and Discover Sparse Features
C. Pehlevan, D.B. Chklovskii, 2015

- Connection between K-means and SNMF
- online SNMF performed by a single layer neuronal network
- Why K-means (therefore SNMF) discovers sparse features
- k-means discovers ICA filters when independent components are sparse

SNMF vs k-means clustering

k-means

$$
\begin{aligned}
& \min _{\{k\}} \sum_{k=1}^{K} \sum_{t \in C_{t}}\left\|x_{t}-\frac{1}{n_{k}} \sum_{s \in C_{k}} x_{s}\right\|_{2}^{2} \\
& \boldsymbol{Y}^{*}=\underset{K \in \Pi}{\arg \min } \frac{1}{2}\left\|\boldsymbol{X}^{\prime} \boldsymbol{X}-\boldsymbol{Y}^{\prime} \boldsymbol{Y}\right\|_{F}^{2} \quad \text { k-means: } Y
\end{aligned}
$$

Online SNMF performed by a single layer neuronal network

$$
\boldsymbol{y}_{T}=\underset{y \geq 00}{\arg \min }\left\|\boldsymbol{X}^{\prime} \boldsymbol{X}-\boldsymbol{Y}^{\prime} \boldsymbol{Y}\right\|_{F}^{2}+\lambda \operatorname{rank}(\boldsymbol{Y})
$$

$$
\begin{aligned}
& \text { ! algebra } \\
& W_{r, i, j}=\frac{\sum_{t=1}^{r-1} y_{l, k} x_{t, j}}{\sum_{t=1}^{T-1} y_{t, i}^{2}} \quad M_{r, k, k+i}=\frac{\sum_{t=1}^{r-1} y_{l, y_{t, k}}}{\sum_{t=1}^{r-1} y_{t, i}^{2}}
\end{aligned}
$$

$$
y_{T, i}=\max \left(\boldsymbol{W}_{T, i} \boldsymbol{x}_{T}-\boldsymbol{M}_{T, i} \boldsymbol{y}_{T}, 0\right)
$$



SNMF network discovers sparse features in natural images


