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

Eszter Tea talk, 19 November 2015

Non-negative matrix factorization



$$V_{i\mu} \approx (WH)_{i\mu} = \sum_{a=1}^{r} W_{ia} H_{a\mu}$$

Lee & Seung, Nature 1999





Columns of H constrained to be unary



PCA



×

Columns of W constrained to be orthonormal





constraints: W≥0, H≥0









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

$$\min_{\{k\}} \sum_{k=1}^{K} \sum_{t \in C_{k}} \left\| \mathbf{x}'_{t} = \frac{1}{n_{k}} \sum_{s \in C_{k}} \mathbf{x}_{s} \right\|_{2}^{2}$$

$$\mathbf{Y}^{*} = \arg_{\mathbf{Y} \in \Pi} \frac{1}{2} \left\| \mathbf{X}'\mathbf{X} - \mathbf{Y}'\mathbf{Y} \right\|_{F}^{2}$$

$$\mathbf{Y}^{*} = \operatorname{argmin}_{\mathbf{Y} \in \Pi} \frac{1}{2} \left\| \mathbf{X}'\mathbf{X} - \mathbf{Y}'\mathbf{Y} \right\|_{F}^{2}$$

$$\mathbf{SNMF: Y \ge 0}$$

Online SNMF performed by a single layer neuronal network

$$y_{T} = \underset{y_{T} \geq 0}{\operatorname{arg min}} \left\| \left\| \mathbf{X}' \mathbf{X} - \mathbf{Y}' \mathbf{Y} \right\|_{F}^{2} + \lambda \operatorname{rank} \left(\mathbf{Y} \right) \\ \vdots \quad \text{algebra} \\ y_{T,i} \approx \underset{y_{T,j} \geq 0}{\operatorname{arg min}} \left(\left\| \mathbf{W}_{T,i} \mathbf{x}_{T} - \mathbf{M}_{T,i} \mathbf{y}_{T} - \mathbf{y}_{T,i} \right)^{2} \\ W_{T,i,j} = \frac{\sum_{t=1}^{T-1} y_{t,i} \mathbf{x}_{t,j}}{\sum_{t=1}^{T-1} y_{t,i}^{2}} \\ M_{T,i,keri} = \frac{\sum_{t=1}^{T-1} y_{t,i} \mathbf{y}_{t,k}}{\sum_{t=1}^{T-1} y_{t,i}^{2}} \\ y_{T,i} = \max \left(\left(\mathbf{W}_{T,i} \mathbf{x}_{T} - \mathbf{M}_{T,i} \mathbf{y}_{T}, \mathbf{0} \right) \right) \\ \mathbf{W}_{T,i,j} = \max \left(\left(\mathbf{W}_{T,i} \mathbf{x}_{T} - \mathbf{M}_{T,i} \mathbf{y}_{T}, \mathbf{0} \right) \\ \mathbf{W}_{T,i,j} = \max \left(\sum_{t=1}^{T-1} y_{t,j} \mathbf{x}_{T} - \mathbf{M}_{T,i} \mathbf{y}_{T}, \mathbf{0} \right) \\ \mathbf{W}_{T,i,j} = \max \left(\sum_{t=1}^{T-1} y_{t,j} \mathbf{x}_{T} - \mathbf{M}_{T,i} \mathbf{y}_{T}, \mathbf{0} \right) \\ \mathbf{W}_{T,i,j} = \max \left(\sum_{t=1}^{T-1} y_{t,j} \mathbf{x}_{T} - \mathbf{M}_{T,i} \mathbf{y}_{T}, \mathbf{0} \right) \\ \mathbf{W}_{T,i,j} = \max \left(\sum_{t=1}^{T-1} y_{t,j} \mathbf{x}_{T} - \mathbf{M}_{T,i} \mathbf{y}_{T}, \mathbf{0} \right)$$

SNMF network discovers sparse features in natural images

 $\lambda =$





λ