

Matrix Factorization and Mixture Models

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Here we consider a matrix factorization of the form

$$\min_{\mathbf{U}, \mathbf{Z}} \|\mathbf{X} - \mathbf{UZ}\|_2^2 \quad (1)$$

with the constraint $\sum_k z_{k,n} = 1$ and $z_{k,n} \geq 0$. We reformulate it as a problem that consists of two terms: The first term is similar to a Gaussian Mixture Model and the second term is a correction term that is independent of the data \mathbf{X} .

$$\|\mathbf{X} - \mathbf{UZ}\|_2^2 = \sum_{n=1}^N \left\| \mathbf{x}_n - \sum_{k=1}^K \mathbf{u}_k z_{k,n} \right\|_2^2 \quad (2)$$

$$= \sum_{n=1}^N \left(\|\mathbf{x}_n\|_2^2 - 2 \sum_{k=1}^K \mathbf{x}_n^T \mathbf{u}_k z_{k,n} + \sum_{k=1}^K \sum_{k'=1}^K \mathbf{u}_k^T \mathbf{u}_{k'} z_{k,n} z_{k',n} \right) \quad (3)$$

$$= \sum_{n=1}^N \left(\sum_{k=1}^K z_{k,n} \|\mathbf{x}_n\|_2^2 - 2 \sum_{k=1}^K \mathbf{x}_n^T \mathbf{u}_k z_{k,n} + \sum_{k=1}^K z_{k,n} \|\mathbf{u}_k\|_2^2 \right) \quad (4)$$

$$+ \sum_{k=1}^K \sum_{k'=1}^K \mathbf{u}_k^T \mathbf{u}_{k'} z_{k,n} z_{k',n} - \sum_{k=1}^K z_{k,n} \|\mathbf{u}_k\|_2^2 \quad (5)$$

$$= \sum_{n=1}^N \sum_{k=1}^K z_{k,n} (\|\mathbf{x}_n\|_2^2 - 2 \mathbf{x}_n^T \mathbf{u}_k + \|\mathbf{u}_k\|_2^2) \quad (6)$$

$$+ \sum_{n=1}^N \left(\left\| \sum_{k=1}^K \mathbf{u}_k z_{k,n} \right\|_2^2 - \sum_{k=1}^K z_{k,n} \|\mathbf{u}_k\|_2^2 \right) \quad (7)$$

$$= \sum_{n=1}^N \sum_{k=1}^K z_{k,n} \|\mathbf{x}_n - \mathbf{u}_k\|_2^2 - \underbrace{\sum_{n=1}^N \sum_{k=1}^K z_{k,n} \left(\|\mathbf{u}_k\|_2^2 - \left\| \sum_{k'=1}^K z_{k',n} \mathbf{u}_{k'} \right\|_2^2 \right)}_{=: a_n} \quad (8)$$

$$= \sum_{n=1}^N \sum_{k=1}^K z_{k,n} \|\mathbf{x}_n - \mathbf{u}_k\|_2^2 - \sum_{n=1}^N \sum_{k=1}^K z_{k,n} \left\| \mathbf{u}_k - \sum_{k'=1}^K z_{k',n} \mathbf{u}_{k'} \right\|_2^2 \quad (9)$$

In the last step from (8) to (9) we make use of the following equality for a given n :

$$\begin{aligned} a_n &= \sum_{k=1}^K z_{k,n} \left(\|\mathbf{u}_k\|_2^2 - 2 \left\| \sum_{k'=1}^K z_{k',n} \mathbf{u}_{k'} \right\|_2^2 + \left\| \sum_{k'=1}^K z_{k',n} \mathbf{u}_{k'} \right\|_2^2 \right) \\ &= \sum_{k=1}^K z_{k,n} \left\| \mathbf{u}_k - \sum_{k'=1}^K z_{k',n} \mathbf{u}_{k'} \right\|_2^2. \end{aligned}$$

A similar trick that is used to show the relationship $\text{Var}[X] = \mathbb{E}[X - \mathbb{E}[X]]^2 = \mathbb{E}[X^2] - \mathbb{E}[X]^2$.

We observe that the second term in (9) is always negative. Thus, if we consider the minimization problem

$$\min_{\mathbf{U}, \mathbf{Z}} \sum_{n=1}^N \sum_{k=1}^K z_{k,n} \|\mathbf{x}_n - \mathbf{u}_k\|_2^2, \quad (10)$$

we minimize an upper bound of the original problem in (1). The problem in (10) is related to Gaussian Mixture Models as we show below.

In mixture models we assume the $z_{k,n} \in \{0, 1\}$. Consider the full data log-likelihood of the Gaussian Mixture Model, i.e., we assume that both, \mathbf{X} and \mathbf{Z} , are given

$$\ln p(\mathbf{X}, \mathbf{Z} | \boldsymbol{\mu}, \boldsymbol{\Sigma}, \boldsymbol{\pi}) = \sum_{n=1}^N \sum_{k=1}^K z_{k,n} (\ln \pi_k + \ln \mathcal{N}(\mathbf{x}_n | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)).$$

As we do not know the latent variables \mathbf{Z} , we consider the expected value of the complete data log-likelihood. It can be written as

$$\mathbb{E}_{\mathbf{Z}}[\ln p(\mathbf{X}, \mathbf{Z} | \boldsymbol{\mu}, \boldsymbol{\Sigma}, \boldsymbol{\pi})] = \sum_{n=1}^N \sum_{k=1}^K \mathbb{E}[z_{k,n}] (\ln \pi_k + \ln \mathcal{N}(\mathbf{x}_n | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)),$$

due to the linearity of the expectation. $\mathbb{E}[z_{k,n}]$ is the same as the responsibility $\gamma(z_{k,n})$ in the EM algorithm. We now assume that $\boldsymbol{\Sigma}_k = \mathbf{I}$. Rearranging terms and going from a maximization of the log-likelihood to a minimization of the negative log-likelihood we arrive at

$$\min_{\mathbf{U}, \mathbf{Z}} \frac{1}{2} \sum_{n=1}^N \sum_{k=1}^K \gamma(z_{k,n}) \|\mathbf{x}_n - \boldsymbol{\mu}_k\|_2^2 + c(\mathbf{Z}, \boldsymbol{\pi}). \quad (11)$$

Here $c(\mathbf{Z}, \boldsymbol{\pi})$ are (not necessarily only negative) terms that only depend on \mathbf{Z} and $\boldsymbol{\pi}$. Remembering that the $z_{k,n}$ in (10) can be interpreted as probabilities we see the similarities between the minimization problems in (11) and (10).