

Derive the Block Coordinate Descent Rules for Non Negative Matrix Tri-Factorization (NMTF) with Regularization Terms

Objective

Given input matrix $X \in \mathbb{R}_{\geq 0}^{n \times m}$, find $U \in \mathbb{R}_{\geq 0}^{n \times k_1}$, $S \in \mathbb{R}_{\geq 0}^{k_1 \times k_2}$, and $V \in \mathbb{R}_{\geq 0}^{k_2 \times m}$ that minimize the function

$$0 = \|X - USV^\top\|_F^2 + \alpha_u \sum_{i=1}^n \|U_{i,:}\|_1 + \alpha_v \sum_{i=1}^m \|V_{i,:}\|_1 + \lambda_u \|U^\top U - I_n\|_1 + \lambda_v \|V^\top V - I_m\|_1 \quad (1)$$

subject to the norm of column vectors, u_i and v_i of U and V to be of unit norm.

Note on Normalization of U and V factors

We require that both u_i and v_i have unit norm. Consider the following:

$$X \approx USV^\top \quad (2)$$

$$USV^\top = \sum_{i=1}^{k_1} \sum_{j=1}^{k_2} u_i s_{i,j} v_j^\top \quad (3)$$

$$USV^\top = \sum_{i=1}^{k_1} \sum_{j=1}^{k_2} \frac{u_i}{\|u_i\|_2} (\|u_i\|_2 s_{i,j} \|v_j\|_2) \frac{v_j}{\|v_j\|_2} \quad (4)$$

$$(5)$$

In this way, $s_{i,j}$ can absorb the normalization factors of both u_i and v_j . This step needs to be performed between every iteration of the algorithm.

Optimize v_j

Consider the substitution $P = US \in \mathbb{R}_{\geq 0}^{n \times k_2}$, then the objective function is equivalent to:

$$O = \|X - PV^\top\|_F^2 + \alpha_u \sum_{i=1}^n \|U_{i,:}\|_1 + \alpha_v \sum_{i=1}^m \|V_{i,:}\|_1 + \lambda_u \|U^\top U - I_n\|_1 + \lambda_v \|V^\top V - I_m\|_1 \quad (6)$$

$$= \left\| X - \sum_{j=1}^{k_2} p_j v_j^\top \right\|_F^2 + \alpha_v \sum_{j=1}^{k_2} \|v_j\|_1 + \lambda_v \sum_{j=1}^{k_2} \sum_{h \neq j} v_j^\top v_h + C \quad (7)$$

Where p_j is the j th column of P , v_j is the j th column of V , and C are terms that only contain U . Now 'pull out' terms correspond to the j th column:

$$O = \left\| X - p_j v_j^\top - \sum_{h \neq j} p_h v_h^\top \right\|_F^2 + \alpha_v \|v_j\|_1 + \alpha_v \sum_{h \neq j} \|v_h\|_1 + \lambda_v \sum_{h \neq j} v_j^\top v_h + \lambda_v \sum_{k \neq j} \sum_{h \neq k} v_k^\top v_h + C \quad (8)$$

Substitute $R_j = X - \sum_{h \neq j} p_h v_h^\top$ and let C now represent all terms that do not include v_j .

$$O = \|R_j - p_j v_j^\top\|_F^2 + \alpha_v \|v_j\|_1 + \lambda_v \sum_{h \neq j} v_j^\top v_h + C \quad (9)$$

$$(10)$$

Now expand using the trace.

$$O = \text{Tr}[(R_j - p_j v_j^\top)^\top (R_j - p_j v_j^\top)] + \alpha_v \|v_j\|_1 + \lambda_v \sum_{h \neq j} v_j^\top v_h + C \quad (11)$$

$$= \text{Tr}(R_j^\top R_j) - 2\text{Tr}(R_j^\top p_j v_j^\top) + \text{Tr}(v_j p_j^\top p_j v_j^\top) + \alpha_v \|v_j\|_1 + \lambda_v \sum_{h \neq j} v_j^\top v_h + C \quad (12)$$

$$= \text{Tr}(R_j^\top R_j) - 2(R_j^\top p_j)^\top v_j + p_j^\top p_j v_j^\top v_j + \alpha_v \|v_j\|_1 + \lambda_v \sum_{h \neq j} v_j^\top v_h + C \quad (13)$$

We can expand the 1 norm on v_j with the inner product $I_m^\top * v_j$ due to the non-negativity of V.

$$= \text{Tr}(R_j^\top R_j) - 2(R_j^\top p_j)^\top v_j + p_j^\top p_j v_j^\top v_j + \alpha_v I_m^\top * v_j + \lambda_v \sum_{h \neq j} v_j^\top v_h + C \quad (14)$$

Take the derivative and minimize with respect to v_j

$$\frac{\partial O}{\partial v_j} = 0 - 2R_j^\top p_j + 2p_j^\top p_j v_j + \alpha_v I_m + \lambda_v \sum_{h \neq j} v_j \quad (15)$$

$$0 = -R_j^\top p_j + \|p_j\|_2^2 v_j + \frac{\alpha_v}{2} I_m + \frac{\lambda_v}{2} \sum_{h \neq j} v_j \quad (16)$$

$$v_j = \frac{R_j^\top p_j - \frac{\alpha_v}{2} I_m - \frac{\lambda_v}{2} \sum_{h \neq j} v_j}{\|p_j\|_2^2} \quad (17)$$

Finally we need to constrain v_j to the non-negative constraint

$$v_j = \frac{[R_j^\top p_j - \frac{\alpha_v}{2} I_m - \frac{\lambda_v}{2} \sum_{h \neq j} v_j]_+}{\|p_j\|_2^2} \quad (18)$$

Optimize u_i

The optimization of u_i is similar. Consider the substitution $Q = (SV^\top)^\top = VS^\top \in \mathbb{R}_{\geq 0}^{m \times k_1}$, then the objective function is equivalent to:

$$O = \|X - UQ^\top\|_F^2 + \alpha_u \sum_{i=1}^n \|U_{i,\cdot}\|_1 + \alpha_v \sum_{i=1}^m \|V_{i,\cdot}\|_1 + \lambda_u \|U^\top U - I_n\|_1 + \lambda_v \|V^\top V - I_m\|_1 \quad (19)$$

$$= \left\| X - \sum_{i=1}^{k_1} u_i q_i^\top \right\|_F^2 + \alpha_v \sum_{j=1}^{k_1} \|u_j\|_1 + \lambda_v \sum_{j=1}^{k_1} \sum_{h \neq j} u_j^\top u_h + C \quad (20)$$

Where u_i is the i th column of U, q_i is the i th column of Q, and C are terms that only contain V. Now 'pull out' terms correspond to the i th column:

$$O = \left\| X - u_i q_i^\top - \sum_{h \neq i} u_h q_h^\top \right\|_F^2 + \alpha_u \|u_i\|_1 + \alpha_u \sum_{j \neq i} \|u_j\|_1 + \lambda_u \sum_{j \neq i} u_i^\top u_j + \lambda_u \sum_{h \neq i} \sum_{j \neq h} u_h^\top u_j + C \quad (21)$$

Substitute $R_i = X - \sum_{h \neq i} u_h q_h^\top$ and let C represent all terms that do not contain u_i :

$$O = \|R_i - u_i q_i^\top\|_F^2 + \alpha_u \|u_i\|_1 + \lambda_u \sum_{j \neq i} u_i^\top u_j + C \quad (22)$$

We can now expand using trace:

$$O = \text{Tr}[(R_i - u_i q_i^\top)^\top (R_i - u_i q_i^\top)] + \alpha_u \|u_i\|_1 + \lambda_u \sum_{j \neq i} u_i^\top u_j + C \quad (23)$$

$$= \text{Tr}(R_i^\top R_i) - 2\text{Tr}(R_i^\top u_i q_i^\top) + \text{Tr}(u_i q_i^\top u_i q_i^\top) + \alpha_u \|u_i\|_1 + \lambda_u \sum_{j \neq i} u_i^\top u_j + C \quad (24)$$

$$= \text{Tr}(R_i^\top R_i) - 2u_i^\top R_i q_i + (u_i^\top u_i)(q_i^\top q_i) + \alpha_u \|u_i\|_1 + \lambda_u \sum_{j \neq i} u_i^\top u_j + C \quad (25)$$

We can expand the 1 norm on u_i with the inner product $I_n^\top * u_i$ due to the non-negativity of U:

$$O = \text{Tr}(R_i^\top R_i) - 2u_i^\top R_i q_i + (u_i^\top u_i)(q_i^\top q_i) + \alpha_u I_n^\top * u_i + \lambda_u \sum_{j \neq i} u_i^\top u_j + C \quad (26)$$

Take the derivative and minimize with respect to u_i

$$\frac{\partial O}{\partial u_i} = 0 - 2R_j q_i + 2q_i^\top q_i u_i + \alpha_u I_n + \lambda_u \sum_{j \neq i} u_j \quad (27)$$

$$0 = -R_i q_i + \|q_i\|_2^2 u_i + \frac{\alpha_u}{2} I_n + \frac{\lambda_u}{2} \sum_{j \neq i} u_j \quad (28)$$

$$u_i = \frac{R_i q_i - \frac{\alpha_u}{2} I_n - \frac{\lambda_u}{2} \sum_{j \neq i} u_j}{\|q_i\|_2^2} \quad (29)$$

Finally we need to constrain u_i to the non-negative constraint

$$u_i = \frac{[R_i q_i - \frac{\alpha_u}{2} I_n - \frac{\lambda_u}{2} \sum_{j \neq i} u_j]_+}{\|q_i\|_2^2} \quad (30)$$

Optimize $s_{i,j}$

The optimization of $s_{i,j}$ is unaffected by the additional regularization terms. For this reason I will just ignore those terms and show the derivation for $s_{i,j}$. For the final variable we must expand out in terms of both i and j .

$$O = \|X - USV^\top\|_F^2 \quad (31)$$

$$O = \left\| X - \sum_{i=1}^{k_1} \sum_{j=1}^{k_2} u_i s_{i,j} v_j^\top \right\|_F^2 \quad (32)$$

Now 'pull out' the term that corresponds to a particular i and j .

$$O = \left\| X - u_i s_{i,j} v_j^\top - \sum_{c \neq i} \sum_{d \neq j} u_c s_{c,d} v_d^\top \right\|_F^2 \quad (33)$$

Let $R_{i,j} = X - \sum_{c \neq i} \sum_{d \neq j} u_c s_{c,d} v_d^\top$, then expand using the trace:

$$O = \text{Tr}[(R_{i,j} - u_i s_{i,j} v_j^\top)^\top (R_{i,j} - u_i s_{i,j} v_j^\top)] \quad (34)$$

$$= \text{Tr}(R_{i,j}^\top R_{i,j}) - 2\text{Tr}(R_{i,j}^\top u_i s_{i,j} v_j^\top) + \text{Tr}(s_{i,j}^2 v_j u_i^\top u_i v_j^\top) \quad (35)$$

$$= \text{Tr}(R_{i,j}^\top R_{i,j}) - 2s_{i,j} (R_{i,j}^\top u_i)^\top v_j + s_{i,j}^2 \|u_i\|_2^2 \|v_j\|_2^2 \quad (36)$$

Finally take the derivative with respect to $s_{i,j}$, solve, and apply the positivity constraint.

$$\frac{\partial O}{\partial s_{i,j}} = -2u_i^\top R_{i,j} v_j + 2s_{i,j} \|u_i\|_2^2 \|v_j\|_2^2 \quad (37)$$

$$s_{i,j} = \frac{u_i^\top R_{i,j} v_j}{\|u_i\|_2^2 \|v_j\|_2^2} \quad (38)$$

$$s_{i,j} = \frac{[u_i^\top R_{i,j} v_j]_+}{\|u_i\|_2^2 \|v_j\|_2^2} \quad (39)$$