

1 Original Problem

The original problem is :

$$\begin{aligned} \min_{S,Y} & \|X - ASY\|_F^2 \\ \text{s.t.} & S^T S = I, S_{ij} \in \{0,1\}, Y_i \in \Omega \end{aligned} \quad (1)$$

Ω is a set in \mathbf{R}^n , it equals to e_1, e_2, \dots, e_n , where e_i is the i -th column of the identity matrix.

where Y_i is a column of Matrix \mathbf{Y} , $\mathbf{X} \in \mathbf{R}^{Dim \times n}$, $\mathbf{A} \in \mathbf{R}^{Dim \times m}$, $\mathbf{Y} \in \mathbf{R}^{k \times n}$. And \mathbf{S} is the selection matrix, $\mathbf{S} \in \mathbf{R}^{m \times k}, m \geq k$.

2 Relaxed Problem

The original problem is strongly NP-hard and also difficult to solve approximately. It is quite similar to the below one by relax its constraint :

$$\begin{aligned} \min_{S,Y} & \|X - ASY\|_F^2 \\ \text{s.t.} & S^T S = I, S \geq 0, Y_i \in \Omega \end{aligned} \quad (2)$$

The problem above is equal to :

$$\begin{aligned} \min_{Y,S} & \|X - DM\|_F^2 \\ \text{s.t.} & A \cdot S = D, Y = M, S = Q, S = J, Q^T Q = I, J \geq 0, Y_i \in \Omega \end{aligned} \quad (3)$$

where Y_i is a column of Matrix \mathbf{Y} , $\mathbf{X} \in \mathbf{R}^{Dim \times n}$, $\mathbf{A} \in \mathbf{R}^{Dim \times m}$, $\mathbf{Y}, \mathbf{M} \in \mathbf{R}^{k \times n}$. And \mathbf{S} is the selection matrix, $\mathbf{S} \in \mathbf{R}^{m \times k}, m \geq k$.

3 Solution

A popular method for this above problem is the Augmented Lagrange Multiplier Method (ALM). The original problem is transformed below :

$$\begin{aligned} \min_{Y,S,D,Q,J} & \|X - DM\|_F^2 + \langle Z_1, S - Q \rangle + \langle Z_2, S - J \rangle \\ & + \langle Z_3, AS - D \rangle + \langle Z_4, Y - M \rangle \\ & + \frac{1}{2}\mu \|S - Q\|_F^2 + \frac{1}{2}\mu \|S - J\|_F^2 \\ & + \frac{1}{2}\mu \|AS - D\|_F^2 + \frac{1}{2}\mu \|Y - M\|_F^2 \\ \text{s.t.} & Q^T Q = I, J \geq 0, Y_i \in \Omega \end{aligned} \quad (4)$$

where Y_i is a column of Matrix \mathbf{Y} , $\mathbf{D} \in \mathbf{R}^{Dim \times k}$ and $\mathbf{S}, \mathbf{Q}, \mathbf{J} \in \mathbf{R}^{m \times k}$, $\mathbf{M} \in \mathbf{R}^{k \times n}$.

The ALM can be decomposed into 6 subproblems. All this 6 subproblems have close-formed solutions. So we can do the optimization by 6 steps.

Steps 1: Fix $S, D, Q, J, M, Z_1, Z_2, Z_3, Z_4$ to optimize Y and ignore the constant items, We can get:

$$\begin{aligned} \min_Y & \langle Z_4, Y - M \rangle + \frac{1}{2}\mu \|Y - M\|_F^2 \\ s.t. & Y_i \in \Omega \end{aligned} \quad (5)$$

\Rightarrow

$$\begin{aligned} \min_Y & \|Y - (M - \frac{Z_4}{\mu})\|_F^2 \\ s.t. & Y_i \in \Omega \end{aligned} \quad (6)$$

\Rightarrow

$$Y_{ij} = \begin{cases} 1 & j = \mathbf{t} \\ 0 & j \neq \mathbf{t} \end{cases} \quad (7)$$

where \mathbf{t} is the index of max member of the i -th column of matrix $\mathbf{M} - \frac{\mathbf{Z}_4}{\mu}$ and \mathbf{Y}_{ij} is the j -th member of i -th column of matrix \mathbf{Y} .
Now we get Y .

Steps 2: Fix $S, M, Y, Q, J, Z_1, Z_2, Z_3, Z_4$ to optimize D and ignore the constant items, We can get:

$$\min_D \quad \|X - DY\|_F^2 + \langle Z_3, AS - D \rangle + \frac{1}{2}\mu \|AS - D\|_F^2 \quad (8)$$

We can get the first-order differential of this formulation, and let it to be zero:

$$\begin{aligned} 2(DY - X)Y^T - Z_3 + \mu(D - AS) &= 0 \\ 2DY \cdot Y^T + \mu D &= 2XY^T + \mu AS + Z_3 \\ D(2YY^T + \mu I) &= 2XY^T + \mu AS + Z_3 \\ D &= (2XY^T + \mu AS + Z_3) \cdot (2YY^T + \mu I)^{-1} \end{aligned}$$

Now we can get D .

Steps 3: Fix $D, Y, M, Q, J, Z_1, Z_2, Z_3, Z_4$ to optimize S and ignore the constant items, We can get:

$$\begin{aligned} \min_S & \langle Z_1, S - Q \rangle + \langle Z_2, S - J \rangle + \langle Z_3, AS - D \rangle \\ & + \frac{1}{2}\mu \|S - Q\|_F^2 + \frac{1}{2}\mu \|S - J\|_F^2 + \frac{1}{2}\mu \|AS - D\|_F^2 \end{aligned} \quad (9)$$

We can get the first-order differential of this formulation, and let it to be zero:

$$Z_1 + Z_2 + A^T \cdot Z_3 + \mu(S - Q) + \mu(S - J) + \mu A^T(AS - D) = 0$$

$$2\mu \cdot S + \mu \cdot A^T AS = \mu(A^T D + Q + J) - A^T \cdot Z_3 - Z_1 - Z_2$$

$$S = (2I + A^T A)^{-1} \cdot (A^T D + Q + J) - \frac{1}{\mu} \cdot (A^T \cdot Z_3 + Z_1 + Z_2)$$

Now we can get S.

Steps 4: Fix $D, Y, S, Q, J, Z_1, Z_2, Z_3, Z_4$ to optimize M and ignore the constant items, We can get:

$$\min_M \|X - DM\|_F^2 + \langle Z_4, Y - M \rangle + \frac{1}{2}\mu \|Y - M\|_F^2 \quad (10)$$

We can get the first-order differential of this formulation, and let it to be zero:

$$2D^T(DM - X) - Z_4 + \mu(M - Y) = 0$$

$$2D^T D \cdot M + \mu M = Z_4 + \mu Y + 2D^T X$$

$$M = (2D^T D + \mu I)^{-1} \cdot (Z_4 + \mu Y + 2D^T X)$$

Now we can get M.

Steps 5: Fix $D, Y, M, S, J, Z_1, Z_2, Z_3, Z_4$ to optimize Q and ignore the constant items, We can get:

$$\begin{aligned} \min_Q & \langle Z_1, S - Q \rangle + \frac{1}{2}\mu \|S - Q\|_F^2 \\ \text{s.t. } & Q^T Q = I \end{aligned} \quad (11)$$

It equals to:

$$\begin{aligned} \min_Q & \langle Z_1, -Q \rangle - \mu \langle S, Q \rangle \\ \text{s.t. } & Q^T Q = I \end{aligned} \quad (12)$$

\Longleftrightarrow

$$\begin{aligned} \max_Q & \langle Q, \mu S + Z_1 \rangle \\ \text{s.t. } & Q^T Q = I \end{aligned} \quad (13)$$

Use the proposition of matrix:

The dual norm of the operator norm $\|\cdot\|$ in $R^{m \times n}$ is the nuclear norm $\|\cdot\|_*$.

$$\|X\|_* := \max_Y \{ \langle X, Y \rangle : \|Y\| \leq 1 \} \quad (14)$$

Now let $X = U\Sigma V^T$ be a **thin** singular value decomposition of the $m \times n$ matrix X , where U is an $m \times n$ matrix and $U^T \cdot U = I$, but $U \cdot U^T \neq I$. V is an $n \times n$ orthogonal matrix which $V \cdot V^T = I$. Σ is an $n \times n$ matrix. Let $Y := U \cdot V^T$, $\|Y\| = 1$ and $Tr(Y^T \cdot X) = Tr(VU^T \cdot U\Sigma V^T) = Tr(\Sigma) = \|X\|_*$. And can get $Y^T \cdot Y = I$.

So from this derivation, We can also do a **thin** singular value decomposition of $\mu S + Z_1$:

$$\mu S + Z_1 = U\Sigma V^T$$

$$Q = U \cdot V^T$$

Steps 6: Fix $D, Y, S, M, Q, Z_1, Z_2, Z_3, Z_4$ to optimize J and ignore the constant items, We can get:

$$\begin{aligned} \min_J & \langle Z_2, S - J \rangle + \frac{1}{2}\mu \|S - J\|_F^2 \\ \text{s.t. } & J \geq 0 \end{aligned} \quad (15)$$

\Leftrightarrow

$$\begin{aligned} \min_J & \frac{2}{\mu} \langle Z_2, S - J \rangle + \|S - J\|_F^2 + \frac{1}{\mu} \|Z_2\|_F^2 \\ \text{s.t. } & J \geq 0 \end{aligned} \quad (16)$$

\Leftrightarrow

$$\begin{aligned} \min_J & \|J - (S + \frac{Z_2}{\mu})\|_F^2 \\ \text{s.t. } & J \geq 0 \end{aligned} \quad (17)$$

\Leftrightarrow

$$J = \frac{1}{2} \cdot [\text{abs}(S + \frac{Z_2}{\mu}) + (S + \frac{Z_2}{\mu})] \quad (18)$$

Steps 7: Do some updates:

$$Z_1 = Z_1 + \mu \cdot (S - Q)$$

$$Z_2 = Z_2 + \mu \cdot (S - J)$$

$$Z_3 = Z_3 + \mu(AS - D)$$

$$Z_4 = Z_4 + \mu(Y - M) \quad (19)$$

$$\mu = \begin{cases} \rho \times \mu & \mu \leq 10^{-30} \\ 10^{-30} & \text{else} \end{cases}$$

where $\rho = 1.1$.

4 Termination Conditions

The algorithm will stop when the conditions are both satisfied:

$$\begin{aligned} \| S - Q \|_{\infty} &< \varepsilon \\ \| S - J \|_{\infty} &< \varepsilon \\ \| Y - M \|_{\infty} &< \varepsilon \\ \| A \cdot S - D \|_F &< \varepsilon \times \| A \|_F \end{aligned} \tag{20}$$

where $\varepsilon = 10^{-8}$.