

1 Original Problem

The original problem is :

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

where $\mathbf{X} \in \mathbf{R}^{Dim \times n}$, $\mathbf{A} \in \mathbf{R}^{Dim \times m}$, $\mathbf{Y} \in \mathbf{R}^{k \times n}$. 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 :

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

The problem above is equal to :

$$\begin{aligned} \min_{Y,S,K,Q,J,Z_1,Z_2,Z_3} & \|X - KY\|_F^2 + \alpha \|Y\|_F^2 \\ \text{s.t.} & A \cdot S = K, S = Q, S = J, Q^T Q = I, J \geq 0 \end{aligned} \quad (3)$$

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

3 Solution

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

$$\begin{aligned} \min_{Y,S,K,Q,J,Z_1,Z_2,Z_3} & \|X - KY\|_F^2 + \alpha \|Y\|_F^2 + \langle Z_1, S - Q \rangle \\ & + \langle Z_2, S - J \rangle + \langle Z_3, X \cdot S - K \rangle \\ & + \frac{1}{2}\mu \|S - Q\|_F^2 + \frac{1}{2}\mu \|S - J\|_F^2 \\ & + \frac{1}{2}\mu \|X \cdot S - K\|_F^2 \\ \text{s.t.} & A \cdot S = K, S = Q, S = J, Q^T Q = I, J \geq 0 \end{aligned} \quad (4)$$

where $\mathbf{K} \in \mathbf{R}^{Dim \times k}$, And $\mathbf{S}, \mathbf{Q}, \mathbf{J} \in \mathbf{R}^{m \times k}$.

The ALM can be decomposed into 4 subproblems. All this 4 subproblems have close-formed solutions. So we can do the optimization by 4 steps.

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

$$\min_Y \|X - KY\|_F^2 + \alpha \|Y\|_F^2 \quad (5)$$

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

$$K^T \cdot (KY - X) + \alpha Y = 0$$

$$(K^T K + \alpha I) \cdot Y = K^T \cdot X$$

$$Y = (K^T K + \alpha I)^{-1} K^T X$$

Now we can get Y .

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

$$\min_K \|X - KY\|_F^2 + \langle Z_3, AS - K \rangle + \frac{1}{2}\mu \|AS - K\|_F^2 \quad (6)$$

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

$$2(KY - X)Y^T - Z_3 + \mu(K - AS) = 0$$

$$2K \cdot Y \cdot Y^T + \mu K = 2XY^T + \mu AS + Z_3$$

$$K(2YY^T + \mu I) = 2XY^T + \mu AS + Z_3$$

$$K = (2XY^T + \mu AS + Z_3) \cdot (2YY^T + \mu I)^{-1}$$

Now we can get K .

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

$$\begin{aligned} \min_S & \langle Z_1, S - Q \rangle + \langle Z_2, S - J \rangle + \langle Z_3, AS - K \rangle \\ & + \frac{1}{2}\mu \|S - Q\|_F^2 + \frac{1}{2}\mu \|S - J\|_F^2 + \frac{1}{2}\mu \|AS - K\|_F^2 \end{aligned} \quad (7)$$

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

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

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

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

Now we can get S .

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

$$\begin{aligned} \min_Q & \langle Z_1, S - Q \rangle + \frac{1}{2}\mu \|S - Q\|_F^2 \\ \text{s.t. } & Q^T Q = I \end{aligned} \quad (8)$$

It equals to:

$$\begin{aligned} \min_Q & \langle Z_1, -Q \rangle - \mu \langle S, Q \rangle \\ \text{s.t. } & Q^T Q = I \end{aligned} \quad (9)$$

\Longleftrightarrow

$$\begin{aligned} \max_Q & \langle Q, \mu S + Z_1 \rangle \\ \text{s.t. } & Q^T Q = I \end{aligned} \quad (10)$$

Use the proposition of matrix:

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

$$\|X\|_* := \max_Y \{\langle X, Y \rangle : \|Y\| \leq 1\} \quad (11)$$

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 $\text{Tr}(Y^T \cdot X) = \text{Tr}(V U^T \cdot U \Sigma V^T) = \text{Tr}(\Sigma) = \|X\|_*$. 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 5: Fix $K, Y, S, Q, Z_1, Z_2, Z_3$ to optimize J and ignore the constant items, We can get:

$$\begin{aligned} \min_J & \langle Z_2, S - J \rangle + \frac{1}{2}\mu \|S - J\|_F^2 \\ \text{s.t. } & J \geq 0 \end{aligned} \quad (12)$$

\Longleftrightarrow

$$\begin{aligned} \min_J & \frac{2}{\mu} \langle Z_2, S - J \rangle + \|S - J\|_F^2 + \frac{1}{\mu} \|Z_2\|_F^2 \\ \text{s.t. } & J \geq 0 \end{aligned} \quad (13)$$

\Longleftrightarrow

$$\begin{aligned} \min_J & \| J - (S + \frac{Z_2}{\mu}) \|_F^2 \\ \text{s.t. } & J \geq 0 \end{aligned} \quad (14)$$

\Longleftrightarrow

$$J = \frac{1}{2} \cdot [\text{abs}(S + \frac{Z_2}{\mu}) + (S + \frac{Z_2}{\mu})] \quad (15)$$

Steps 6: Do some updates:

$$\begin{aligned} Z_1 &= Z_1 + \mu \cdot (S - Q) \\ Z_2 &= Z_2 + \mu \cdot (S - J) \\ Z_3 &= Z_3 + \mu(X \cdot S - K) \\ \mu &= \rho \times \mu \end{aligned} \quad (16)$$

where $\rho = 1.1$.

4 Termination Conditions

The algorithm will stop when the conditions are both satisfied:

$$\begin{aligned} \| S - Q \|_\infty &< \varepsilon \\ \| S - J \|_\infty &< \varepsilon \\ \| X \cdot S - K \|_F &< \varepsilon \times \| X \|_F \end{aligned} \quad (17)$$

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