Positive Collaborative Representation for Subspace Clustering

June 10, 2017

Abstract

1 Introduction

2 Motivation

Problem 1: The linear model is restrctive on real applications since many problems exhibit nonlinear properties.

Problem 2: The original model need to process all the data samples, which is not scalable to large datasets.

Problem 3: Block grouping effects of the least square regression is able to group

Problem 4:

Problem 5:

3 RES Model

The proposed robust, efficient, and scalable (RES) subset selection model can be formulated as follows:

$$\min_{\boldsymbol{A}} \|\boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}\|_p^p + \lambda\|\boldsymbol{A}\|_F^2, \tag{1}$$

where $0 \leq p \leq 1$. For analysis simplicity, we just set $p = 1$.

Then the model above can be

$$\min_{\boldsymbol{A}} \|\boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}\|_p^p + \lambda\|\boldsymbol{A}\|_F^2. \tag{2}$$

By introducing auxiliary variables into the optimization program, we can set $\boldsymbol{E} = \boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}$. The program (42) can be transformed into

$$\min_{\boldsymbol{A},\boldsymbol{E}} \|\boldsymbol{E}\|_p^p + \lambda\|\boldsymbol{A}\|_F^2 \text{ s.t. } \boldsymbol{E} = \boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}. \tag{3}$$

By introducing a Lagrangian multiplier $\boldsymbol{\Delta}$, the Lagrangian function of the Eq. (15) can be written as

$$\begin{aligned} \mathcal{L}(\boldsymbol{A}, \boldsymbol{E}, \boldsymbol{\Delta}, \rho) &= \|\boldsymbol{E}\|_p^p + \lambda\|\boldsymbol{A}\|_F^2 \\ &+ \frac{\rho}{2}\|\boldsymbol{E} - \boldsymbol{X} + \boldsymbol{X}\boldsymbol{A} + \rho^{-1}\boldsymbol{\Delta}\|_F^2 \end{aligned} \tag{4}$$

Denote by $(\boldsymbol{A}_k, \boldsymbol{E}_k)$ the optimization variables at iteration k, and by $\boldsymbol{\Delta}$ the Lagrangian multipliers at iteration k. Taking detivatives of $\mathcal{L}$ with respect to the variables and setting the derivatives to be zeros, we can alternatively update the variables as follows:

(1) Obtain $\boldsymbol{A}_{k+1}$ by minimizing $\mathcal{L}$ with respect to $\boldsymbol{A}$, while fixing $(\boldsymbol{E}_k, \boldsymbol{\Delta}_k)$. This is equivalent to solve the following problem:

$$\boldsymbol{A}_{k+1} = \arg\min_{\boldsymbol{A}} \frac{\rho_k}{2}\|\boldsymbol{P}_k - \boldsymbol{X}\boldsymbol{A}\|_F^2 + \lambda\|\boldsymbol{A}\|_F^2 \tag{5}$$

where $\boldsymbol{P}_k = \boldsymbol{X} - \boldsymbol{E}_k - \rho_k^{-1}\boldsymbol{\Delta}_k$. This is a least squares regression problem which has a closed-form solution as

$$\boldsymbol{A}_{k+1} = (\boldsymbol{X}^\top\boldsymbol{X} + 2\lambda\rho_k^{-1}\boldsymbol{I})^{-1}\boldsymbol{X}^\top\boldsymbol{P}_k. \tag{6}$$

(3) Obtain $\boldsymbol{E}_{k+1}$ by minimizing $\mathcal{L}$ with respect to $\boldsymbol{E}$, while fixing $(\boldsymbol{A}_{k+1}, \boldsymbol{\Delta}_k)$. This is equivalent to solve the following problem:

$$\min_{\boldsymbol{E}} \frac{\rho_k}{2}\|\boldsymbol{Q}_k - \boldsymbol{E}\|_F^2 + \|\boldsymbol{E}\|_p^p, \tag{7}$$

where $\boldsymbol{Q}_k = \boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}_{k+1} - \rho_k^{-1}\boldsymbol{\Delta}_k$. Since this problem is seperable, it can be decoupled into $m \times n$ scalable subproblems which share the following form:

$$\min_{y} = \frac{1}{2}(c - y)^2 + \rho_k^{-1}|y|^p. \tag{8}$$

This problem can be solved by the generalized soft-thresholding algorithm [?] as

$$\hat{y} = \text{sign}(c) * \max(|c| - \tau_p(\rho_k^{-1}), 0) * \mathcal{S}_p(|c|; \rho_k^{-1}), \tag{9}$$

where

$$\tau_p(\rho_k^{-1}) = [2\rho_k^{-1}(1-p)]^{\frac{1}{2-p}} + \rho_k^{-1}p[2\rho_k^{-1}(1-p)]^{\frac{p-1}{2-p}} \tag{10}$$

and $\mathcal{S}_p(|c|;\rho_k^{-1})$ can be obtained by solving the following equation:

$$\mathcal{S}_p(|c|;\rho_k^{-1}) - c + \rho_k^{-1}p(\mathcal{S}_p(|c|;\rho_k^{-1}))^{p-1} = 0. \tag{11}$$

(4) Obtain the Lagrangian multipliers ($\mathbf{\Delta}_{k+1}$) while fixing ($\boldsymbol{A}_{k+1}, \boldsymbol{E}_{k+1}$):

$$\mathbf{\Delta}_{k+1} = \mathbf{\Delta}_k + \tau\rho_k(\boldsymbol{E}_{k+1} - \boldsymbol{X} + \boldsymbol{X}\boldsymbol{A}_{k+1}), \tag{12}$$

where $\tau \in (0, \frac{\sqrt{5}+1}{2})$ is the dual step size and is usually set as $\tau = 1$.

(5) Update the penalty parameter ρ as $\rho_{k+1} = \mu\rho_k$, where $\mu > 1$.

4 RES with Diagonal Constraint

We can also restrict that $\mathrm{diag}(\boldsymbol{A}) = \mathbf{0}$ to avoid the samples to be self-represented. However, I want to mention that the proposed model solved by ADMM algorithm with three variables and does not have convergence results.

Then the model above can be

$$\min_{\boldsymbol{A}} \|\boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}\|_p^p + \lambda\|\boldsymbol{A}\|_F^2 \quad \text{s.t.} \quad \mathrm{diag}(\boldsymbol{A}) = \mathbf{0}. \tag{13}$$

By introducing auxiliary variables into the optimization program, we can set $\boldsymbol{E} = \boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}$ and $\boldsymbol{A} = \mathbf{0}$. The program (42) can be transformed into

$$\begin{aligned} &\min_{\boldsymbol{A},\boldsymbol{E}} \|\boldsymbol{E}\|_p^p + \lambda\|\boldsymbol{A}\|_F^2 \\ &\text{s.t. } \boldsymbol{E} = \boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}, \mathrm{diag}(\boldsymbol{A}) = \mathbf{0}. \end{aligned} \tag{14}$$

Besides, we can further introduce an auxiliary matrix variable $\boldsymbol{C}$ and consider the following program

$$\begin{aligned} &\min_{\boldsymbol{A},\boldsymbol{C},\boldsymbol{E}} \|\boldsymbol{E}\|_p^p + \lambda\|\boldsymbol{A}\|_F^2 \\ &\text{s.t. } \boldsymbol{E} = \boldsymbol{X} - \boldsymbol{X}\boldsymbol{C}, \boldsymbol{C} = \boldsymbol{A} - \mathrm{diag}(\boldsymbol{A}) \end{aligned} \tag{15}$$

whose solution for $(\boldsymbol{A}, \boldsymbol{E})$ coincides with the solution of Eq. (43). By introducing two Lagrangian multipliers $\mathbf{\Delta}, \boldsymbol{\delta}$, the Lagrangian function of the Eq. (15) can be written as

$$\begin{aligned} &\mathcal{L}(\boldsymbol{A},\boldsymbol{C},\boldsymbol{E},\mathbf{\Delta},\boldsymbol{\delta},\rho) = \|\boldsymbol{E}\|_p^p + \lambda\|\boldsymbol{A}\|_F^2 \\ &+ \frac{\rho}{2}\|\boldsymbol{E} - \boldsymbol{X} + \boldsymbol{X}\boldsymbol{C} + \rho^{-1}\mathbf{\Delta}\|_F^2 \\ &+ \frac{\rho}{2}\|\boldsymbol{C} - \boldsymbol{A} + \mathrm{diag}(\boldsymbol{A}) + \rho^{-1}\boldsymbol{\delta}\|_F^2 \end{aligned} \tag{16}$$

Denote by $(\boldsymbol{C}_k, \boldsymbol{A}_k, \boldsymbol{E}_k)$ the optimization variables at iteration k, by $(\mathbf{\Delta}_k, \boldsymbol{\delta}_k)$ the Lagrangian multipliers at iteration k, and by ρ_k the penalty parameter at iteration k. Taking detivatives of $\mathcal{L}$ with respect to the variables and setting the derivatives to be zeros, we can alternatively update the variables as follows:

(1) Obtain $\boldsymbol{A}_{k+1}$ by minimizing $\mathcal{L}$ with respect to $\boldsymbol{A}$, while fixing $(\boldsymbol{C}_k, \boldsymbol{E}_k, \mathbf{\Delta}_k, \boldsymbol{\delta}_k)$. This is equivalent to solve the following problem:

$$\begin{aligned} &\boldsymbol{A}_{k+1} = \boldsymbol{J} - \mathrm{diag}(\boldsymbol{J}), \\ &\boldsymbol{J} = (\rho_k + 2\lambda)^{-1}(\rho_k\boldsymbol{C}_k + \boldsymbol{\delta}_k) \end{aligned} \tag{17}$$

(2) Obtain $\boldsymbol{C}_{k+1}$ by minimizing $\mathcal{L}$ with respect to $\boldsymbol{C}$, while fixing $(\boldsymbol{A}_{k+1}, \boldsymbol{E}_k, \mathbf{\Delta}_k, \boldsymbol{\delta}_k)$. This is equivalent to solve the following problem:

$$\begin{aligned} &\boldsymbol{C}_{k+1} = \arg\min_{\boldsymbol{C}} \frac{\rho_k}{2}\|\boldsymbol{E}_k - \boldsymbol{X} + \boldsymbol{X}\boldsymbol{C} + \rho_k^{-1}\mathbf{\Delta}_k\|_F^2 \\ &+ \frac{\rho_k}{2}\|\boldsymbol{C} - \boldsymbol{A}_{k+1} + \rho_k^{-1}\boldsymbol{\delta}_k\|_F^2 \end{aligned} \tag{18}$$

This is a least squares regression problem which has a closed-form solution as

$$\begin{aligned} &\boldsymbol{C}_{k+1} = \boldsymbol{H} - \mathrm{diag}(\boldsymbol{H}), \\ &(\boldsymbol{X}^\top\boldsymbol{X} + \boldsymbol{I})\boldsymbol{H} = \boldsymbol{X}^\top\boldsymbol{P}_k + \boldsymbol{Q}_k, \end{aligned} \tag{19}$$

where $\boldsymbol{P}_k = \boldsymbol{X} - \boldsymbol{E}_k - \rho_k^{-1}\mathbf{\Delta}_k$ and $\boldsymbol{Q}_k = \boldsymbol{A}_{k+1} - \rho_k^{-1}\boldsymbol{\delta}_k$.

(3) Obtain $\boldsymbol{E}_{k+1}$ by minimizing $\mathcal{L}$ with respect to $\boldsymbol{E}$, while fixing $(\boldsymbol{C}_{k+1}, \boldsymbol{A}_{k+1}, \mathbf{\Delta}_k, \boldsymbol{\delta}_k)$. This is equivalent to solve the following problem:

$$\min_{\boldsymbol{E}} \frac{1}{2}\|(\boldsymbol{X} - \boldsymbol{X}\boldsymbol{C}_{k+1} - \rho_k^{-1}\mathbf{\Delta}_k) - \boldsymbol{E}\|_F^2 + \rho_k^{-1}\|\boldsymbol{E}\|_1. \tag{20}$$

The solution of $\boldsymbol{E}$ can be computed in closed-form as

$$\boldsymbol{E}_{k+1} = \mathcal{S}_{\rho_k^{-1}}(\boldsymbol{X} - \boldsymbol{X}\boldsymbol{C}_{k+1} - \rho_k^{-1}\mathbf{\Delta}_k), \tag{21}$$

where $\mathcal{S}_\tau(x) = \text{sign}(x) * \max(|x| - \tau, 0)$ is the soft-thresholding operator.

(4) Obtain the Lagrangian multipliers $(\boldsymbol{\Delta}_{k+1}, \boldsymbol{\delta}_{k+1})$ while fixing $(\boldsymbol{C}_{k+1}, \boldsymbol{A}_{k+1}, \boldsymbol{E}_{k+1})$:

$$\begin{aligned} \boldsymbol{\Delta}_{k+1} &= \boldsymbol{\Delta}_k + \tau\rho_k(\boldsymbol{E}_{k+1} - \boldsymbol{X} + \boldsymbol{X}\boldsymbol{C}_{k+1}), \\ \boldsymbol{\delta}_{k+1} &= \boldsymbol{\delta}_k + \tau\rho_k(\boldsymbol{C}_{k+1} - \boldsymbol{A}_{k+1}), \end{aligned} \tag{22}$$

where $\tau \in (0, \frac{\sqrt{5}+1}{2})$ is the dual step size and is usually set as $\tau = 1$.

(5) Update the penalty parameter ρ as $\rho_{k+1} = \mu\rho_k$, where $\mu > 1$.

5 Large Scale Subset Selection Via Woodbury Identity

The Woodbury Identity is

$$(\boldsymbol{A}+\boldsymbol{U}\boldsymbol{C}\boldsymbol{V})^{-1} = \boldsymbol{A}^{-1}-\boldsymbol{A}^{-1}\boldsymbol{U}(\boldsymbol{C}^{-1}+\boldsymbol{V}\boldsymbol{A}^{-1}\boldsymbol{U})^{-1}\boldsymbol{V}\boldsymbol{A}^{-1}. \tag{23}$$

We can also restrict that $\text{diag}(\boldsymbol{A}) = \boldsymbol{0}$ to avoid the samples to be self-represented. However, I want to mention that the proposed model solved by ADMM algorithm with three variables and does not have convergence results.

Then the model above can be

$$\min_{\boldsymbol{A}} \|\boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}\|_F^2 + \lambda\|\boldsymbol{A}\|_{p,1}. \tag{24}$$

By introducing an auxiliary variable $\boldsymbol{C}$ into the optimization program, we can get

$$\min_{\boldsymbol{A},\boldsymbol{C}} \|\boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}\|_F^2 + \lambda\|\boldsymbol{C}\|_{p,1} \text{ s.t. } \boldsymbol{C} = \boldsymbol{A}, \tag{25}$$

whose solution for $\boldsymbol{A}$ coincides with the solution of Eq. (43). By introducing two Lagrangian multipliers $\boldsymbol{\Delta}$, the Lagrangian function of the Eq. (43) can be written as

$$\begin{aligned} \mathcal{L}(\boldsymbol{A}, \boldsymbol{C}, \boldsymbol{\Delta}, \rho) &= \|\boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}\|_F^2 + \lambda\|\boldsymbol{C}\|_{p,1} \\ &+ \langle\boldsymbol{\Delta}, \boldsymbol{C} - \boldsymbol{A}\rangle + \frac{\rho}{2}\|\boldsymbol{C} - \boldsymbol{A}\|_F^2 \end{aligned} \tag{26}$$

Denote by $(\boldsymbol{C}_k, \boldsymbol{A}_k)$ the optimization variables at iteration k, by $\boldsymbol{\Delta}_k$ the Lagrangian multipliers at iteration k, and by ρ_k the penalty parameter at iteration k. Taking detivatives of $\mathcal{L}$ with respect to the variables and setting the derivatives to be zeros, we can alternatively update the variables as follows:

(1) Obtain $\boldsymbol{A}_{k+1}$ by minimizing $\mathcal{L}$ with respect to $\boldsymbol{A}$, while fixing $(\boldsymbol{C}_k, \boldsymbol{\Delta}_k)$. This is equivalent to solve the following problem:

$$\min_{\boldsymbol{A}} \|\boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}\|_F^2 + \frac{\rho}{2}\|\boldsymbol{A} - (\boldsymbol{C}_k + \rho_k^{-1}\boldsymbol{\Delta}_k)\|_F^2, \tag{27}$$

which is equalivalently to solve the following problem

$$\boldsymbol{A} = (\boldsymbol{X}^\top\boldsymbol{X} + \frac{\rho_k}{2}\boldsymbol{I})^{-1}(\boldsymbol{X}^\top\boldsymbol{X} + \frac{\rho_k}{2}\boldsymbol{C}_k + \frac{1}{2}\boldsymbol{\Delta}_k) \tag{28}$$

Since the matrices $\boldsymbol{X}^\top\boldsymbol{X}$ is of $N \times N$ dimension. It is computational expensive when N is very large. By employing the Woodburry Identity mentioned above, we can have

$$(\frac{\rho_k}{2}\boldsymbol{I}+\boldsymbol{X}^\top\boldsymbol{X})^{-1} = \frac{2}{\rho_k}\boldsymbol{I}-(\frac{2}{\rho_k})^2\boldsymbol{X}^\top(\boldsymbol{I}+\frac{2}{\rho_k}\boldsymbol{X}\boldsymbol{X}^\top)^{-1}\boldsymbol{X}. \tag{29}$$

and transform this problem as

$$\begin{aligned} \boldsymbol{A} =&(\frac{2}{\rho_k}\boldsymbol{I} - (\frac{2}{\rho_k})^2\boldsymbol{X}^\top(\boldsymbol{I} + \frac{2}{\rho_k}\boldsymbol{X}\boldsymbol{X}^\top)^{-1}\boldsymbol{X}) \\ &* (\boldsymbol{X}^\top\boldsymbol{X} + \frac{\rho_k}{2}\boldsymbol{C}_k + \frac{1}{2}\boldsymbol{\Delta}_k) \end{aligned} \tag{30}$$

which will save a lot of computational costs.

(2) Obtain $\boldsymbol{C}_{k+1}$ by minimizing $\mathcal{L}$ with respect to $\boldsymbol{C}$, while fixing $(\boldsymbol{A}_{k+1}, \boldsymbol{\Delta}_k)$. This is equivalent to solve the following problem:

$$\min_{\boldsymbol{C}} \frac{1}{2}\|(\boldsymbol{A}_{k+1} - \rho_k^{-1}\boldsymbol{\Delta}k) - \boldsymbol{C}\|_F^2 + \frac{\lambda}{\rho_k}\|\boldsymbol{C}\|_{p,1}. \tag{31}$$

Since the $\ell_{p,1}$ norm is separable with respect to each row, we can write the above problem as

$$\min_{\boldsymbol{C}} \sum_{i=1}^{M} \frac{1}{2}\|(\boldsymbol{A}_{k+1})_{i*} - \rho_k^{-1}(\boldsymbol{\Delta}_k)_{i*} - \boldsymbol{C}_{i*}\|_2^2 + \frac{\lambda}{\rho_k}\|\boldsymbol{C}_{i*}\|_p, \tag{32}$$

where $\boldsymbol{F}_{i*}$ is the ith row of the matrix $\boldsymbol{F}$. Since this step is separable w.r.t. each row, we can employ parallel processing resources and reduce its computational time.

(3) Obtain the Lagrangian multipliers $(\boldsymbol{\Delta}_{k+1})$ while fixing $(\boldsymbol{C}_{k+1}, \boldsymbol{A}_{k+1})$:

$$\boldsymbol{\Delta}_{k+1} = \boldsymbol{\Delta}_k + \rho_k(\boldsymbol{C}_{k+1} - \boldsymbol{A}_{k+1}). \tag{33}$$

(5) Update the penalty parameter ρ as $\rho_{k+1} = \mu\rho_k$, where $\mu > 1$.

6 Robust Large Scale Subset Selection via Dissimilarity based Outlier Detection

We can also introduce a dissimiarlity based matrix $\boldsymbol{D}$ to replace the ℓ_p or $\ell_{2,1}$ norms to ensure robustness. This can also remore the additional term $\boldsymbol{Z}$ on modeling the outliers with the restriction of ℓ_1 norm. The matrix $\boldsymbol{D}$ should better be diagonal matrix. How to design the matrix $\boldsymbol{D}$ is another problem need to be solved.

Then the proposed model can be formulated as

$$\min_{\boldsymbol{A}} \|(\boldsymbol{X} - \boldsymbol{X}\boldsymbol{A})\boldsymbol{D}\|_F^2 + \lambda \|\boldsymbol{A}\|_{p,1}. \tag{34}$$

By introducing an auxiliary variable $\boldsymbol{C}$ into the optimization program, we can get

$$\min_{\boldsymbol{A},\boldsymbol{C}} \|(\boldsymbol{X} - \boldsymbol{X}\boldsymbol{A})\boldsymbol{D}\|_F^2 + \lambda \|\boldsymbol{C}\|_{p,1} \text{ s.t. } \boldsymbol{C} = \boldsymbol{A}. \tag{35}$$

By introducing a Lagrangian multiplier $\boldsymbol{\Delta}$, the Lagrangian function of the Eq. (43) can be written as

$$\begin{aligned} &\mathcal{L}(\boldsymbol{A}, \boldsymbol{C}, \boldsymbol{\Delta}, \rho) = \|(\boldsymbol{X} - \boldsymbol{X}\boldsymbol{A})\boldsymbol{D}\|_F^2 + \lambda \|\boldsymbol{C}\|_{p,1} \\ &+ \langle \boldsymbol{\Delta}, \boldsymbol{C} - \boldsymbol{A} \rangle + \frac{\rho}{2} \|\boldsymbol{C} - \boldsymbol{A}\|_F^2 \end{aligned} \tag{36}$$

Denote by $(\boldsymbol{A}_k, \boldsymbol{C}_k)$ the optimization variables at iteration k, by $\boldsymbol{\Delta}_k$ the Lagrangian multiplier at iteration k, and by ρ_k the penalty parameter at iteration k. Taking detivatives of $\mathcal{L}$ with respect to the variables and setting the derivatives to be zeros, we can alternatively update the variables as follows:

(1) Obtain $\boldsymbol{A}_{k+1}$ by minimizing $\mathcal{L}$ with respect to $\boldsymbol{A}$, while fixing $(\boldsymbol{C}_k, \boldsymbol{\Delta}_k)$. This is equivalent to solve the following problem:

$$\min_{\boldsymbol{A}} \|(\boldsymbol{X} - \boldsymbol{X}\boldsymbol{A})\boldsymbol{D}\|_F^2 + \frac{\rho}{2} \|\boldsymbol{A} - (\boldsymbol{C}_k - \rho_k^{-1}\boldsymbol{\Delta}_k)\|_F^2, \tag{37}$$

which is equivalently to solve the following problem

$$\boldsymbol{X}^\top \boldsymbol{X}\boldsymbol{A}\boldsymbol{D}\boldsymbol{D}^\top + \frac{\rho_k}{2}\boldsymbol{A} = \boldsymbol{X}^\top \boldsymbol{X}\boldsymbol{D}\boldsymbol{D}^\top + \frac{\rho_k}{2}(\boldsymbol{C}_k - \rho_k^{-1}\boldsymbol{\Delta}_k) \tag{38}$$

Since the matrices $\boldsymbol{X}^\top\boldsymbol{X}$ and $\boldsymbol{D}^\top\boldsymbol{D}$ are positive semi-definite and positive definite, respectively. The above equation is a standard Sylvester equation which has a unique solution.

(2) Obtain $\boldsymbol{C}_{k+1}$ by minimizing $\mathcal{L}$ with respect to $\boldsymbol{C}$, while fixing $(\boldsymbol{A}_{k+1}, \boldsymbol{\Delta}_k)$. This is equivalent to solve the following problem:

$$\min_{\boldsymbol{C}} \frac{1}{2} \|(\boldsymbol{A}_{k+1} + \rho_k^{-1}\boldsymbol{\Delta}k) - \boldsymbol{C}\|_F^2 + \frac{\lambda}{\rho_k}\|\boldsymbol{C}\|_{p,1}. \tag{39}$$

Since the $\ell_{p,1}$ norm is separable with respect to each row, we can write the above problem as

$$\min_{\boldsymbol{C}} \sum_{i=1}^{M} \frac{1}{2} \|(\boldsymbol{A}_{k+1})_{i*} + \rho_k^{-1}(\boldsymbol{\Delta}_k)_{i*} - \boldsymbol{C}_{i*}\|_2^2 + \frac{\lambda}{\rho_k}\|\boldsymbol{C}_{i*}\|_p, \tag{40}$$

where $\boldsymbol{F}_{i*}$ is the ith row of the matrix $\boldsymbol{F}$. Since this step is separable w.r.t. each row, we can employ parallel processing resources and reduce its computational time.

(3) Obtain the Lagrangian multipliers $(\boldsymbol{\Delta}_{k+1})$ while fixing $(\boldsymbol{C}_{k+1}, \boldsymbol{A}_{k+1})$:

$$\boldsymbol{\Delta}_{k+1} = \boldsymbol{\Delta}_k + \rho_k(\boldsymbol{C}_{k+1} - \boldsymbol{A}_{k+1}). \tag{41}$$

(5) Update the penalty parameter ρ as $\rho_{k+1} = \mu\rho_k$, where $\mu > 1$.

7 Large Scale Subset Selection Via Row-Column Separation

We can also restrict that $\text{diag}(\boldsymbol{A}) = \boldsymbol{0}$ to avoid the samples to be self-represented. However, I want to mention that the proposed model solved by ADMM algorithm with three variables and does not have convergence results.

Then the model above can be

$$\min_{\boldsymbol{A}} \|\boldsymbol{X} - \boldsymbol{X}\boldsymbol{A}\|_F^2 + \lambda\|\boldsymbol{A}\|_{p,1} \quad \text{s.t.} \quad \text{diag}(\boldsymbol{A}) = \boldsymbol{0}. \tag{42}$$

By introducing an auxiliary variable $\boldsymbol{C}$ into the optimization program, we can get

$$\begin{aligned} &\min_{\boldsymbol{A},\boldsymbol{C}} \|\boldsymbol{X} - \boldsymbol{X}\boldsymbol{C}\|_F^2 + \lambda\|\boldsymbol{A}\|_{p,1} \\ &\text{s.t. } \boldsymbol{C} = \boldsymbol{A} - \text{diag}(\boldsymbol{A}), \end{aligned} \tag{43}$$

whose solution for $\boldsymbol{A}$ coincides with the solution of Eq. (43). By introducing two Lagrangian multipliers $\boldsymbol{\Delta}$, the Lagrangian function of the Eq. (43) can be written as

$$\begin{aligned}\mathcal{L}(\boldsymbol{A}, \boldsymbol{C}, \boldsymbol{\Delta}, \rho) &= \|\boldsymbol{X} - \boldsymbol{X}\boldsymbol{C}\|_F^2 + \lambda\|\boldsymbol{A}\|_{p,1} \\ &+ \langle \boldsymbol{\Delta}, \boldsymbol{C} - (\boldsymbol{A} - \mathrm{diag}(\boldsymbol{A})) \rangle + \frac{\rho}{2}\|\boldsymbol{C} - (\boldsymbol{A} - \mathrm{diag}(\boldsymbol{A})\|_F^2\end{aligned} \tag{44}$$

Denote by $(\boldsymbol{C}_k, \boldsymbol{A}_k)$ the optimization variables at iteration k, by $\boldsymbol{\Delta}_k$ the Lagrangian multipliers at iteration k, and by ρ_k the penalty parameter at iteration k. Taking detivatives of $\mathcal{L}$ with respect to the variables and setting the derivatives to be zeros, we can alternatively update the variables as follows:

(1) Obtain $\boldsymbol{A}_{k+1}$ by minimizing $\mathcal{L}$ with respect to $\boldsymbol{A}$, while fixing $(\boldsymbol{C}_k, \boldsymbol{\Delta}_k)$. This is equivalent to solve the following problem:

$$\begin{aligned}&\boldsymbol{A}_{k+1} = \boldsymbol{J} - \mathrm{diag}(\boldsymbol{J}), \\ &\boldsymbol{J} = \arg\min_{\boldsymbol{J}} \frac{1}{2}\|\boldsymbol{C}_k + \rho_k^{-1}\boldsymbol{\Delta}_k - \boldsymbol{J}\|_F^2 + \frac{\lambda}{\rho_k}\|\boldsymbol{J}\|_{p,1}.\end{aligned} \tag{45}$$

(2) Obtain $\boldsymbol{C}_{k+1}$ by minimizing $\mathcal{L}$ with respect to $\boldsymbol{C}$, while fixing $(\boldsymbol{A}_{k+1}, \boldsymbol{\Delta}_k)$. This is equivalent to solve the following problem:

$$\min_{\boldsymbol{C}} \|\boldsymbol{X} - \boldsymbol{X}\boldsymbol{C}\|_F^2 + \frac{\rho_k}{2}\|\boldsymbol{C} - \boldsymbol{A}_{k+1} + \frac{1}{\rho_k}\boldsymbol{\Delta}_k\|_F^2 \tag{46}$$

This is a least squares regression problem which has a closed-form solution as

$$\boldsymbol{C}_{k+1} = (\boldsymbol{X}^\top\boldsymbol{X} + \frac{\rho_k}{2}\boldsymbol{I})^{-1}(\boldsymbol{X}^\top\boldsymbol{X} + \frac{\rho_k}{2}\boldsymbol{A}_{k+1} - \frac{1}{2}\boldsymbol{\Delta}_k). \tag{47}$$

(3) Obtain the Lagrangian multipliers $(\boldsymbol{\Delta}_{k+1})$ while fixing $(\boldsymbol{C}_{k+1}, \boldsymbol{A}_{k+1})$:

$$\boldsymbol{\Delta}_{k+1} = \boldsymbol{\Delta}_k + \rho_k(\boldsymbol{C}_{k+1} - \boldsymbol{A}_{k+1}). \tag{48}$$

(5) Update the penalty parameter ρ as $\rho_{k+1} = \mu\rho_k$, where $\mu > 1$.