A Proximal Point Method for Matrix Least Squares Problem with Nuclear Norm Regularization

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Let $\mathcal{S}^n$ be the set of all real symmetric matrices and $\mathcal{S}^n_+$ be the cone of all positive semidefinite matrices in $\mathcal{S}^n$.

We consider the least squares SDP:

$$\min\left\{\frac{1}{2}\|\mathcal{A}(X)-b\|^2+\rho\langle I,\, X\rangle \;:\; \mathcal{B}(X)=d,\; X\in\mathcal{S}^n_+\right\},$$

where $\mathcal{A}:\mathcal{S}^n\longrightarrow\Re^m$ and $\mathcal{B}:\mathcal{S}^n\longrightarrow\Re^s$ are linear maps and ρ is a given positive scalar.

An example — the regularized kernel estimation (RKE) problem in statistics:

we are given a set of n objects and dissimilarity measures d_{ij} for certain object pairs $(i,j) \in \mathcal{E}$.

The goal is to estimate a positive semidefinite kernel matrix $X \in \mathcal{S}^n_+$ such that the fitted squared distances between objects induced by X satisfy

$$X_{ii} + X_{jj} - 2X_{ij} = \langle A_{ij},\, X \rangle \;\approx\; d_{ij}^2 \quad \forall\, (i,j) \in \mathcal{E},$$

where $A_{ij} = (e_i - e_j)(e_i - e_j)^T$.

One version of the RKE problem is to solve the following SDP:

$$\min\Big\{\sum_{(i,j)\in\mathcal{E}} W_{ij}(\langle A_{ij},\, X\rangle - d_{ij}^2)^2 + \rho\langle I,\, X\rangle \;:\; \langle E,\, X\rangle = 0,\; X \succeq 0\Big\},$$

where $W \in \mathcal{S}^n$ is a given weight matrix with positive entries.

Analogously, we consider the least squares problem with the nuclear norm regularization:

$$\min \left\{ \frac{1}{2}\|\mathcal{A}(X) - b\|^2 + \rho\|X\|_* \,:\, \mathcal{B}(X) = d,\ X \in \Re^{p\times q} \right\},$$

where

$$\|X\|_* = \sum_{i=1}^{k} \sigma_i(X)$$

and $\sigma_i(X)$ are the singular values of X.

The matrix completion example:

$$\min \Big\{ \mathrm{rank}(X) \ : \ X_{ij} \approx M_{ij} \ \ \forall \, (i,j) \in \Omega \Big\},$$

where

$$\Omega \in \{1, \ldots, p\} \times \{1, \ldots, q\} :$$

$$\begin{bmatrix} * & & & & * & \\ & * & & & & * \\ * & & & & * & \\ & & * & * & & \end{bmatrix}$$

get a relaxed convex problem:

$$\min\left\{\|X\|_* \;:\; X_{ij} \approx M_{ij} \;\; \forall\, (i,j) \in \Omega\right\}.$$

Further

$$\min\left\{\frac{1}{2}\sum_{(i,j)\in\Omega}(X_{ij}-M_{ij})^2 + \rho\|X\|_*\right\}.$$

The Netflix Prize problem: the convex relaxation is pretty good.

http://www.netflixprize.com/index

For a random example:

- $p = q = 10^5$, $\text{rank}(X) = 10$, noise level $=0.1$.
- $|\Omega| \approx 1.2 \times 10^7$.
- Proximal point method framework + gradient projection method.
- Need 416 seconds to achieve a relative accuracy 0.0453.

Consider the Moreau-Yosida regularization:

$$
\begin{aligned}
F_\sigma(X) = \ \min \ & \frac{1}{2}\|u\|^2 + \rho\|Y\|_* + \frac{1}{2\sigma}\|Y - X\|^2 \\
\text{s.t.} \ & \mathcal{A}(Y) + u = b \\
& \mathcal{B}(Y) = d \\
& Y \in \Re^{p\times q}, \quad u \in \Re^m.
\end{aligned} \tag{1}
$$

The Lagrangian dual problem of (1) is

$$\max_{y\in\Re^m, z\in\Re^s} \Big\{ \theta_\sigma^\rho(y,z;X) := \inf_{u\in\Re^m, Y\in\Re^{p\times q}} L_\sigma^\rho(Y,u;y,z,X) \\ = -\frac{1}{2}\|y\|^2 + \langle b, y\rangle + \langle d, z\rangle \\ + \frac{1}{2\sigma}\|X\|^2 - \frac{1}{2\sigma}\|D_{\rho\sigma}(W(y,z;X))\|^2 \Big\}, \quad (2)$$

where $W(y,z;X) = X + \sigma(\mathcal{A}^* y + \mathcal{B}^* z)$.

For any $Y \in \Re^{p\times q}$, $D_\rho(Y)$ is the unique optimal solution to the following strongly convex function

$$\min_X \|X\|_* + \frac{1}{2\rho}\|X - Y\|_F^2$$

It is well known that $D_\rho(\cdot)$ is globally Lispchitz continuous with modulus 1.

Let $Y \in \Re^{p\times q}$ admit the following singular value decomposition:

$$Y = U[\Sigma \ 0]V^T,$$

where $U \in \Re^{p\times p}$ and $V \in \Re^{q\times q}$ are orthogonal matrices, $\Sigma = \mathrm{diag}(\sigma_1, \cdots, \sigma_p)$, and $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_p \geq 0$ are singular values of Y. For each $\rho > 0$, the operator D_ρ is given by:

$$D_\rho(Y) = U[\Sigma_\rho \ 0]V^T,$$

where $\Sigma_\rho = \mathrm{diag}((\sigma_1 - \rho)_+, \ldots, (\sigma_p - \rho)_+)$.

Good news is: $\|D_\rho(Y)\|^2$ is continuously differentiable and

$$\nabla\Big(\frac{1}{2}\|D_\rho(Y)\|^2\Big) = D_\rho(Y).$$

So we have a smooth convex optimization problem:

$$\min_{y\in\Re^m, z\in\Re^s} \Big\{ -\theta_\sigma^\rho(y, z; X)\Big\}.$$

Even better: $D_\rho(\cdot)$ is **strongly semismooth** everywhere.

A Lipschitz function $F:\mathcal{X}\to\mathcal{Y}$ is said to be strongly semismooth at $x\in\mathcal{X}$ if

1) it is directionally differentiable at x; and 2)

$$F(x+\Delta x)-F(x)-F'(x+\Delta x)\Delta x=O(\|\Delta x\|^2)$$

for all $x+\Delta x$ such that F is Fréchet differentiable at $x+\Delta x$.

One key issue:

$$\theta_{\sigma}^{\rho}(\cdot,\cdot;X) \notin \mathcal{C}^2.$$

This property allows $\theta_{\sigma}^{\rho}(\cdot,\cdot;X)$ to possess nonsingular (generalized) Hessian, which is vital for an inexact second order method to be efficient.

We apply the **proximal point method** to solve the following unconstrained problem:

$$\min_{X \in \Re^{p\times q}} \ \Phi_\sigma^\rho(X) := \max\{\theta_\sigma^\rho(y, z; X) \, : \, y \in \Re^m, \ z \in \Re^s\}.$$

PPA. Input $X^0 \in \Re^{p\times q}$, $\sigma_0 > 0$, iterate:

1. Compute an approximate maximizer

$$(y^k, z^k) \;\approx\; \text{argmax}\{\theta^{\rho}_{\sigma_k}(y, z; X^k) \,:\, y \in \Re^m,\; z \in \Re^s\},$$

2. $X^{k+1} \;=\; D_{\rho\sigma_k}(W(y^k, z^k; X^k)), \quad Z^{k+1} = \dfrac{1}{\sigma_k}(D_{\rho\sigma_k}(W(y^k, z^k; X^k)) - W(y^k, z^k; X^k)),$

3. If $\|R^k_d := \mathcal{A}^* y^k + \mathcal{B}^* z^k + Z^{k+1}\|_F \leq \varepsilon$; stop; else, update σ_k.

For the inner subproblem, the optimality condition is given by

$$\begin{aligned} \nabla_y \theta^{\rho}_{\sigma_k}(y, z; X^k) &= b - y - \mathcal{A}D_{\rho\sigma}(W(y, z; X^k)) = 0 \\ \nabla_z \theta^{\rho}_{\sigma_k}(y, z; X^k) &= d - \mathcal{B}D_{\rho\sigma}(W(y, z; X^k)) = 0 \end{aligned} \qquad (3)$$

We solve (3) by a **semismooth Newton-CG method.**

The inner problems can be solved by a **(fast) semismooth Newton-CG method**. The outer iteration

$$X^{k+1} \; = \; D_{\rho\sigma_k}(W(y^k, z^k; X^k))$$

only satisfies

$$X^{k+1} = X^k - \sigma_k \nabla \Phi^{\rho}_{\sigma_k}(X^k),$$

a gradient descent step. The good news is that it can also be seen as **an approximate semismooth Newton method**, at least for the least squares SDP case.

Selected examples:

1. For each pair (n, r), we generate a positive semidefinite matrix $M \in \mathcal{S}^n$ of rank r by setting $M = M_1 M_1^T$ where $M_1 \in \Re^{n\times r}$ is a random matrix with i.i.d Gaussian entries. Then we sample a subset Ω of m entries uniformly at random from the upper triangular part of M. The observed data is set to be $\widetilde{M}_\Omega = M_\Omega + \alpha N_\Omega \|M_\Omega\|_F / \|N_\Omega\|_F$, where the random matrix $N_\Omega \in \mathcal{S}^n$ is generated that has sparsity pattern Ω and i.i.d Gaussian entries and α is the noise level.

The minimization problem we solve is given by

$$\min\left\{\frac{1}{2}\|X_\Omega - \widetilde{M}_\Omega\|_F^2 + \rho\langle I,\, X\rangle \;:\; X \succeq 0\;\right\}. \tag{4}$$

Numerical results: $n = 2000$, $r = 100$,

– for $\alpha = 0$, we need 15:00 and 8 (27) iterations; and

– for $\alpha = 0.05$, we need 39:15 and 18(63) iterations

– The relative accuracy is below 10^{-6}.

– The averaged CGs each step ≤ 10.

– $|\Omega| \approx 975,000$.

2. The nonsymmtric problem: similarly generated as in Example 1.

Numerical results: $p = q = 1000$, $r = 50$,

– for $\alpha = 0$, we need **4**:07 and **12** (24) iterations; and

– for $\alpha = 0.05$, we need **16**:01 and **26** (73) iterations.

– The averaged CGs each step ≤ 5.

– The relative accuracy is below 10^{-6}.

– $|\Omega| = 487,500$.