

# Matrix Cones and Spectral Operators of Matrices

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- 1 Let  $\mathcal{S}^n$  be set of  $n$  by  $n$  symmetric matrices in  $\mathbb{R}^{m \times n}$  and  $\mathcal{S}_+^n$  be the cone of positive semidefinite matrices in  $\mathcal{S}^n$ .
- 2 Let  $X \in \mathcal{S}^n$  have the following spectral decomposition

$$X = P\Lambda P^{\mathbb{T}} = \sum_{i=1}^n \lambda_i p_i p_i^{\mathbb{T}},$$

where  $\Lambda$  is the diagonal matrix of eigenvalues  $\lambda_1, \dots, \lambda_n$  of  $X$  and  $P$  is a corresponding orthogonal matrix of orthonormal eigenvectors. Then

$$X_+ := \Pi_{\mathcal{S}_+^n}(X) = P\Lambda_+ P^{\mathbb{T}} = \sum_{i=1}^n (\lambda_i)_+ p_i p_i^{\mathbb{T}}.$$

Here  $\Pi_{\mathcal{S}_+^n}(X)$  is the unique optimal solution to

$$\begin{aligned} \min \quad & \frac{1}{2} \|Z - X\|_F^2 \\ \text{s.t.} \quad & Z \in \mathcal{S}_+^n. \end{aligned}$$

- ① Let  $f : \Re \rightarrow \Re$  be a scalar function. The corresponding L\"owner operator  $F : \mathcal{S}^n \rightarrow \mathcal{S}^n$  is defined by<sup>1</sup>

$$F(X) := \sum_{i=1}^n f(\lambda_i) p_i p_i^{\mathbb{T}}, \quad X \in \mathcal{S}^n$$

- ② Let  $g : \Re \rightarrow \Re$  be an odd scalar function satisfying  $g(-t) = -g(t)$  for all  $t \geq 0$  (naturally  $g(0) = 0$ ). One may define L\"owner's operator  $G : \mathbb{R}^{m \times n} \rightarrow \mathbb{R}^{m \times n}$  (assuming  $m \leq n$ ) by

$$G(Z) := \sum_{i=1}^m g(\sigma_i(Z)) u_i v_i^{\mathbb{T}}, \quad Z \in \mathbb{R}^{m \times n},$$

where for any given  $Z \in \mathbb{R}^{m \times n}$ ,  $\sigma_1(Z) \geq \sigma_2(Z) \geq \dots \geq \sigma_m(Z)$  denotes the singular values of  $Z$  (always nonnegative and counting multiplicity) and  $\sigma(Z)$  denotes the vector of the singular values of  $Z$ ;  $\mathbb{O}^{m,n}(Z)$  denotes the set of matrix pairs  $(U, V) \in \mathbb{O}^m \times \mathbb{O}^n$  satisfying the singular value decomposition

$$Z = U [\Sigma(Z) \quad 0] V^{\mathbb{T}},$$

where  $\Sigma(Z)$  is an  $m \times m$  diagonal matrix whose  $i$ -th diagonal entry is  $\sigma_i(Z) \geq 0$ .

<sup>1</sup>L\"owner, K.: *Über monotone matrixfunktionen*. Mathematische Zeitschrift 38 (1934) 177–216.

Let  $X \in \mathbb{R}^{m \times n}$  admit the following singular value decomposition:

$$X = \bar{U} [\Sigma(X) \ 0] \bar{V}^T = \bar{U} [\Sigma(X) \ 0] [\bar{V}_1 \ \bar{V}_2]^T = \bar{U} \Sigma(X) \bar{V}_1^T, \quad (1)$$

where  $\bar{U} \in \mathcal{O}^m$ ,  $\bar{V} \in \mathcal{O}^n$  and  $\bar{V}_1 \in \mathbb{R}^{n \times m}$ ,  $\bar{V}_2 \in \mathbb{R}^{n \times (n-m)}$  and  $\bar{V} = [\bar{V}_1 \ \bar{V}_2]$ . The set of such matrices  $(U, V)$  in the singular value decomposition (1) is denoted by  $\mathcal{O}^{m,n}(X)$ , i.e.,

$$\mathcal{O}^{m,n}(X) := \{(U, V) \in \mathfrak{R}^{m \times m} \times \mathfrak{R}^{n \times n} \mid X = U [\Sigma(X) \ 0] V^T\}.$$

For any positive constant  $\varepsilon > 0$ , denote the closed convex cone  $\mathcal{D}_n^\varepsilon$  by

$$\mathcal{D}_n^\varepsilon := \{(t, x) \in \mathbb{R} \times \mathbb{R}^n \mid \varepsilon^{-1}t \geq x_i, i = 1, \dots, n\}. \quad (2)$$

Let  $\Pi_{\mathcal{D}_n^\varepsilon}(\cdot)$  be the metric projector over  $\mathcal{D}_n^\varepsilon$  under the Euclidean inner product in  $\mathbb{R}^n$ . That is, for any  $(t, x) \in \mathbb{R} \times \mathbb{R}^n$ ,  $\Pi_{\mathcal{D}_n^\varepsilon}(t, x)$  is the unique optimal solution to the following convex optimization problem

$$\begin{aligned} \min \quad & \frac{1}{2}((\tau - t)^2 + \|y - x\|^2) \\ \text{s.t.} \quad & \varepsilon^{-1}\tau \geq y_i, i = 1, \dots, n. \end{aligned} \quad (3)$$

For any  $x \in \mathbb{R}^n$ , let  $x^\downarrow$  be the vector of components of  $x$  being arranged in the non-increasing order  $x_1^\downarrow \geq \dots \geq x_n^\downarrow$ . Let  $\text{sgn}(x)$  be the sign vector of  $x$ , i.e.,  $(\text{sgn})_i(x) = 1$  if  $x_i \geq 0$  and  $-1$  otherwise. We use “ $\circ$ ” to denote the Hadamard product operation either for two vectors or two matrices of the same dimensions.

### Proposition

*Assume that  $\varepsilon > 0$  and  $(t, x) \in \mathbb{R} \times \mathbb{R}^n$  are given. Let  $\pi$  be a permutation of  $\{1, \dots, n\}$  such that  $x^\downarrow = x_\pi$ , i.e.,  $x_i^\downarrow = x_{\pi(i)}$ ,  $i = 1, \dots, n$  and  $\pi^{-1}$  the inverse of  $\pi$ . For convenience, write  $x_0^\downarrow = +\infty$  and  $x_{n+1}^\downarrow = -\infty$ . Let  $\bar{k}$  be the smallest integer  $k \in \{0, 1, \dots, n\}$  such that*

$$x_{k+1}^\downarrow \leq \left( \sum_{j=1}^k x_j^\downarrow + \varepsilon t \right) / (k + \varepsilon^2) < x_k^\downarrow. \quad (4)$$

Define  $\bar{y} \in \mathbb{R}^n$  and  $\bar{\tau} \in \mathbb{R}_+$ , respectively, by

$$\bar{y}_i := \begin{cases} \left( \sum_{j=1}^{\bar{k}} x_j^\downarrow + \varepsilon t \right) / (\bar{k} + \varepsilon^2) & \text{if } 1 \leq i \leq \bar{k}, \\ x_i^\downarrow & \text{otherwise} \end{cases}$$

and

$$\bar{\tau} := \varepsilon \bar{y}_1 = \varepsilon \left( \sum_{j=1}^{\bar{k}} x_j^\downarrow + \varepsilon t \right) / (\bar{k} + \varepsilon^2).$$

The metric projection  $\Pi_{\mathcal{D}_n^\varepsilon}(t, x)$  is computed by  $\Pi_{\mathcal{D}_n^\varepsilon}(t, x) = (\bar{\tau}, \bar{y}_{\pi-1})$ .

For any positive constant  $\varepsilon > 0$ , define the matrix cone  $\mathcal{M}_n^\varepsilon$  in  $\mathcal{S}^n$  as the epigraph of the convex function  $\varepsilon\lambda_{\max}(\cdot)$ , i.e.,

$$\mathcal{M}_n^\varepsilon := \{(t, X) \in \mathbb{R} \times \mathcal{S}^n \mid \varepsilon^{-1}t \geq \lambda_{\max}(X)\}. \quad (5)$$

### Proposition

Assume that  $(t, X) \in \mathbb{R} \times \mathcal{S}^n$  is given. Let  $X$  have the eigenvalue decomposition

$$X = \bar{P}\text{diag}(\lambda(X))\bar{P}^T, \quad (6)$$

where  $\bar{P} \in \mathcal{O}^n$ . Let  $\Pi_{\mathcal{M}_n^\varepsilon}(\cdot, \cdot)$  be the metric projector over  $\mathcal{M}_n^\varepsilon$  under Frobenius norm in  $\mathcal{S}^n$ . Then,

$$\Pi_{\mathcal{M}_n^\varepsilon}(t, X) = (\bar{t}, \bar{P}\text{diag}(\bar{y})\bar{P}^T) \quad \forall (t, X) \in \mathbb{R} \times \mathcal{S}^n, \quad (7)$$

where  $(\bar{t}, \bar{y}) = \Pi_{\mathcal{D}_n^\varepsilon}(t, \lambda(X)) \in \mathfrak{R} \times \mathfrak{R}^n$ .



For any positive constant  $\varepsilon > 0$ , denote the closed convex cone  $\mathcal{C}_n^\varepsilon$  by

$$\mathcal{C}_n^\varepsilon := \{(t, x) \in \mathbb{R} \times \mathbb{R}^n \mid \varepsilon^{-1}t \geq \|x\|_\infty\}. \quad (8)$$

Let  $\Pi_{\mathcal{C}_n^\varepsilon}(\cdot, \cdot)$  be the metric projector over  $\mathcal{C}_n^\varepsilon$  under the Euclidean inner product in  $\mathbb{R}^n$ . That is, for any  $(t, x) \in \mathbb{R} \times \mathbb{R}^n$ ,  $\Pi_{\mathcal{C}_n^\varepsilon}(t, x)$  is the unique optimal solution to the following convex optimization problem

$$\begin{aligned} \min \quad & \frac{1}{2}((\tau - t)^2 + \|y - x\|^2) \\ \text{s.t.} \quad & \varepsilon^{-1}\tau \geq \|y\|_\infty. \end{aligned} \quad (9)$$

In the following discussions, we frequently drop  $n$  from  $\mathcal{C}_n^\varepsilon$  when its size can be found from the context.

Assume that  $\varepsilon > 0$  and  $(t, x) \in \mathbb{R} \times \mathbb{R}^n$  are given. Let  $\pi$  be a permutation of  $\{1, \dots, n\}$  such that  $|x|^\downarrow = |x|_\pi$ , i.e.,  $|x|_i^\downarrow = |x|_{\pi(i)}$ ,  $i = 1, \dots, n$  and  $\pi^{-1}$  be the inverse of  $\pi$ . Let  $|x|_0^\downarrow = +\infty$  and  $|x|_{n+1}^\downarrow = 0$ . Let  $s_0 = 0$  and  $s_k = \sum_{i=1}^k |x|_i^\downarrow$ ,  $k = 1, \dots, n+1$ . Let  $\bar{k}$  be the smallest integer  $k \in \{0, 1, \dots, n\}$  such that

$$|x|_{k+1}^\downarrow \leq (s_k + \varepsilon t)/(k + \varepsilon^2) < |x|_k^\downarrow \quad (10)$$

or  $\bar{k} = n+1$  if such an integer does not exist. Denote

$$\theta^\varepsilon(t, x) := (s_{\bar{k}} + \varepsilon t)/(\bar{k} + \varepsilon^2). \quad (11)$$

Let  $\alpha, \beta$  and  $\gamma$  be the index sets of  $|x|^\downarrow$  as

$$\alpha := \{i \mid |x|_i^\downarrow > \theta^\varepsilon(t, x)\}, \quad \beta := \{i \mid |x|_i^\downarrow = \theta^\varepsilon(t, x)\} \quad (12)$$

and

$$\gamma := \{i \mid |x|_i^\downarrow < \theta^\varepsilon(t, x)\}. \quad (13)$$

Define  $\bar{y} \in \mathbb{R}^n$  and  $\bar{\tau} \in \mathfrak{R}_+$ , respectively, by

$$\bar{y}_i := \begin{cases} \max\{\theta^\varepsilon(t, x), 0\} & \text{if } i \in \alpha, \\ |x|_i^\downarrow & \text{otherwise} \end{cases}$$

and

$$\bar{\tau} := \varepsilon \max\{\theta^\varepsilon(t, x), 0\}.$$

## Proposition

Assume that  $\varepsilon > 0$  and  $(t, x) \in \mathbb{R} \times \mathbb{R}^n$  are given. The metric projection  $\Pi_{\mathcal{C}^\varepsilon}(t, x)$  of  $(t, x)$  onto  $\mathcal{C}^\varepsilon$  can be computed as follows

$$\Pi_{\mathcal{C}^\varepsilon}(t, x) = (\bar{t}, \text{sgn}(x) \circ \bar{y}_{\pi^{-1}}). \quad (14)$$

## Theorem

Assume that  $(t, X) \in \mathbb{R} \times \mathbb{R}^{m \times n}$  is given. Let  $X$  have the singular value decomposition (1). Let  $\Pi_{\mathcal{K}^\varepsilon}(\cdot, \cdot)$  be the metric projector over  $\mathcal{K}^\varepsilon$  under Frobenius norm in  $\mathbb{R}^{m \times n}$ , where

$$\mathcal{K}^\varepsilon := \{(t, X) \in \mathbb{R} \times \mathbb{R}^{m \times n} \mid \varepsilon^{-1}t \geq \|X\|_2\}. \quad (15)$$

For any  $(t, X) \in \mathbb{R} \times \mathbb{R}^{m \times n}$ , we have

$$\Pi_{\mathcal{K}^\varepsilon}(t, X) = \left( \bar{t}, \bar{U} [\text{diag}(\bar{y}) \ 0] \bar{V}^T \right), \quad (16)$$

where

$$(\bar{t}, \bar{y}) = \Pi_{\mathcal{C}^\varepsilon}(t, \sigma(X)) \in \mathfrak{R} \times \mathfrak{R}^m.$$

- ① Löwner operators are inadequate for applications
- ② For a given unitarily invariant proper closed convex function  $f : \mathcal{X} \rightarrow (-\infty, \infty]$ , in matrix optimization one often considers the proximal mapping of  $f$  at  $X$ :

$$P_f(X) := \operatorname{argmin}_{Y \in \mathcal{X}} \left\{ f(Y) + \frac{1}{2} \|Y - X\|^2 \right\}, \quad X \in \mathcal{X}, \quad (17)$$

where  $\mathcal{X}$  is either the real vector subspace  $\mathbb{S}^m$  of  $m \times m$  real symmetric (or complex) Hermitian matrices, or the real vector subspace  $\mathbb{V}^{m \times n}$  of  $m \times n$

- ③ For example, for  $f(Y) = \|Y\|_2 = \sigma_{\max}(Y)$ , the spectral norm of  $Y$ ,  $P_f(\cdot)$  is no longer the Löwner operator [it is the Löwner operator for  $f(Y) = \|Y\|_* = \sum_{i=1}^m \sigma_i(Y)$ ].
- ④ If  $f(\cdot)$  is the indicator function of a matrix cone, then the proximal mapping  $P_f(\cdot)$  is the metric projector over the corresponding matrix cone.

Let  $s$  be a positive integer and  $0 \leq s_0 \leq s$  be a nonnegative integer. For given positive integers  $m_1, \dots, m_s$  and  $n_{s_0+1}, \dots, n_s$ , define the real vector space  $\mathcal{X}$  by

$$\mathcal{X} := \mathbb{S}^{m_1} \times \dots \times \mathbb{S}^{m_{s_0}} \times \mathbb{V}^{m_{s_0+1} \times n_{s_0+1}} \times \dots \times \mathbb{V}^{m_s \times n_s}. \quad (18)$$

Without loss of generality, we assume that  $m_k \leq n_k$ ,  $k = s_0 + 1, \dots, s$ .

For any  $X = (X_1, \dots, X_s) \in \mathcal{X}$ , we have for  $1 \leq k \leq s_0$ ,  $X_k \in \mathbb{S}^{m_k}$  and  $s_0 + 1 \leq k \leq s$ ,  $X_k \in \mathbb{V}^{m_k \times n_k}$ . Denote

$$\mathcal{Y} := \mathbb{R}^{m_1} \times \dots \times \mathbb{R}^{m_{s_0}} \times \mathbb{R}^{m_{s_0}} \times \dots \times \mathbb{R}^{m_s}. \quad (19)$$

For any  $X \in \mathcal{X}$ , define  $\kappa(X) \in \mathcal{Y}$  by

$$\kappa(X) := (\lambda(X_1), \dots, \lambda(X_{s_0}), \sigma(X_{s_0+1}), \dots, \sigma(X_s)).$$

Define the set  $\mathcal{P}$  by

$$\mathcal{P} := \{(Q_1, \dots, Q_s) \mid Q_k \in \mathbb{P}^{m_k}, 1 \leq k \leq s_0 \text{ and } Q_k \in \pm\mathbb{P}^{m_k}, s_0 + 1 \leq k \leq s\}.$$

Let  $g : \mathcal{Y} \rightarrow \mathcal{Y}$  be a given mapping. For any  $x = (x_1, \dots, x_s) \in \mathcal{Y}$  with  $x_k \in \mathbb{R}^{m_k}$ , we write  $g(x) \in \mathcal{Y}$  in the form  $g(x) = (g_1(x), \dots, g_s(x))$  with  $g_k(x) \in \mathbb{R}^{m_k}$  for  $1 \leq k \leq s$ .

### Definition

The given mapping  $g : \mathcal{Y} \rightarrow \mathcal{Y}$  is said to be *mixed symmetric*, with respect to  $\mathcal{P}$ , at  $x = (x_1, \dots, x_s) \in \mathcal{Y}$  with  $x_k \in \mathbb{R}^{m_k}$ , if

$$g(Q_1 x_1, \dots, Q_s x_s) = (Q_1 g_1(x), \dots, Q_s g_s(x)) \quad \forall (Q_1, \dots, Q_s) \in \mathcal{P}. \quad (20)$$

The mapping  $g$  is said to be *mixed symmetric*, with respect to  $\mathcal{P}$ , over a set  $\mathcal{D} \subseteq \mathcal{Y}$  if (20) holds for every  $x \in \mathcal{D}$ . We call  $g$  a *mixed symmetric mapping*, with respect to  $\mathcal{P}$ , if (20) holds for every  $x \in \mathcal{Y}$ .

Note that for each  $k \in \{1, \dots, s\}$ , the function value  $g_k(x) \in \mathbb{R}^{m_k}$  is dependent on all  $x_1, \dots, x_s$ . When there is no danger of confusion, in later discussions we often drop the phrase “with respect to  $\mathcal{P}$ ” from Definition 1. Let  $\mathcal{N}$  be a given nonempty set in  $\mathcal{X}$ . Define  $\kappa_{\mathcal{N}} := \{\kappa(X) \in \mathcal{Y} \mid X \in \mathcal{N}\}$ . The following definition of the spectral operator with respect to a mixed symmetric mapping  $g$ .

### Definition

Suppose that  $g : \mathcal{Y} \rightarrow \mathcal{Y}$  is mixed symmetric on  $\kappa_{\mathcal{N}}$ . The spectral operator  $G : \mathcal{N} \rightarrow \mathcal{X}$  with respect to  $g$  is defined as  $G(X) := (G_1(X), \dots, G_s(X))$  for  $X = (X_1, \dots, X_s) \in \mathcal{N}$  such that

$$G_k(X) := \begin{cases} P_k \text{Diag}(g_k(\kappa(X))) P_k^{\mathbb{T}} & \text{if } 1 \leq k \leq s_0, \\ U_k [\text{Diag}(g_k(\kappa(X))) \quad 0] V_k^{\mathbb{T}} & \text{if } s_0 + 1 \leq k \leq s, \end{cases}$$

where  $P_k \in \mathbb{O}^{m_k}(X_k)$ ,  $1 \leq k \leq s_0$ ,  $(U_k, V_k) \in \mathbb{O}^{m_k, n_k}(X_k)$ ,  $s_0 + 1 \leq k \leq s$ .



Next, we will focus on the study of spectral operators for the case that  $\mathcal{X} \equiv \mathbb{V}^{m \times n}$ . The corresponding extensions for the spectral operators defined on the general Cartesian product of several matrix spaces can be considered in a similar fashion.

Let  $\mathcal{N}$  be a given nonempty open set in  $\mathbb{V}^{m \times n}$ . Suppose that  $g : \mathbb{R}^m \rightarrow \mathbb{R}^m$  is mixed symmetric with respect to  $\mathcal{P} \equiv \pm \mathbb{P}^m$  (i.e., absolutely symmetric), on an open set  $\hat{\sigma}_{\mathcal{N}}$  in  $\mathbb{R}^m$  containing  $\sigma_{\mathcal{N}} := \{\sigma(X) \mid X \in \mathcal{N}\}$ . The spectral operator  $G : \mathcal{N} \rightarrow \mathbb{V}^{m \times n}$  with respect to  $g$  then takes the form of

$$G(X) = U [\text{Diag}(g(\sigma(X))) \quad 0] V^{\mathbb{T}}, \quad X \in \mathcal{N},$$

where  $(U, V) \in \mathbb{O}^{m, n}(X)$ . For a given  $\bar{X} \in \mathcal{N}$ , consider the singular value decomposition (SVD) of  $\bar{X}$ , i.e.,

$$\bar{X} = \bar{U} [\Sigma(\bar{X}) \quad 0] \bar{V}^{\mathbb{T}}, \quad (21)$$

where  $\Sigma(\bar{X})$  is an  $m \times m$  diagonal matrix whose  $i$ -th diagonal entry is  $\sigma_i(\bar{X})$ ,  $\bar{U} \in \mathbb{O}^m$  and  $\bar{V} = [\bar{V}_1 \quad \bar{V}_2] \in \mathbb{O}^n$  with  $\bar{V}_1 \in \mathbb{V}^{n \times m}$  and  $\bar{V}_2 \in \mathbb{V}^{n \times (n-m)}$ .

- 1 Let  $\mathcal{X}, \mathcal{Y}$  be two finite-dimensional real Euclidean spaces
- 2  $F : \mathcal{X} \rightarrow \mathcal{Y}$  a locally Lipschitz continuous function.

Since  $F$  is almost everywhere differentiable [Rademacher, 1912], we can define

$$\partial_B F(x) := \{ \lim F'(x^k) : x^k \rightarrow x, x^k \in D_F \}.$$

Here  $D_F$  is the set of points where  $F$  is differentiable. Hence, Clarke's generalized Jacobian of  $F$  at  $x$  is given by

$$\partial F(x) = \text{conv } \partial_B F(x).$$

## Definition

Let  $\mathcal{K} : \mathcal{X} \rightrightarrows \mathcal{L}(\mathcal{X}, \mathcal{Y})$  be a nonempty, compact valued and upper-semicontinuous multifunction. We say that  $F$  is **semismooth**  $x \in \mathcal{X}$  with respect to  $\mathcal{K}$  if (i)  $F$  is directionally differentiable at  $x$ ; and (ii) for any  $\Delta x \in \mathcal{X}$  and  $V \in \mathcal{K}(x + \Delta x)$  with  $\Delta x \rightarrow 0$ ,

$$F(x + \Delta x) - F(x) - V(\Delta x) = o(\|\Delta x\|) \quad (\text{g-semismooth}). \quad (22)$$

Furthermore, if (22) is replaced by

$$F(x + \Delta x) - F(x) - V(\Delta x) = O(\|\Delta x\|^{1+\gamma}), \quad (23)$$

where  $\gamma > 0$  is a constant, then  $F$  is said to be  $\gamma$ -order (strongly if  $\gamma = 1$ ) semismooth at  $x$  with respect to  $\mathcal{K}$ .

Assume that  $F(\bar{x}) = 0$ .

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Given  $x^0 \in \mathcal{X}$ . For  $k = 0, 1, \dots$

**Main Step** Choose an arbitrary  $V_k \in \mathcal{K}(x^k)$ . Solve

$$F(x^k) + V_k(x^{k+1} - x^k) = 0$$


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**Rates of Convergence:** Assume that  $\mathcal{K}(\bar{x})$  is nonsingular and that  $x^0$  is sufficiently close to  $\bar{x}$ . If  $F$  is **g-semismooth** at  $\bar{x}$ , then

$$\|x^{k+1} - \bar{x}\| = \underbrace{\|V_k^{-1}\|}_{\text{bounded}} \underbrace{\|F(x^k) - F(\bar{x}) - V_k(x^k - \bar{x})\|}_{\text{g-semismooth}} = \underbrace{o(\|x^k - \bar{x}\|)}_{\text{superlinear}}.$$

It takes  $o(\|x^k - \bar{x}\|^{1+\gamma})$  if  $F$  is  $\gamma$ -order **g-semismooth** at  $\bar{x}$  [the directional differentiability of  $F$  is not needed in the above local convergence analysis]

- 1 The nonsmooth equation approach is popular in the complementarity and variational inequalities (nonsmooth equations) community (Robinson, Pang, ...)
- 2 Josephy (1979) introduced Newton and quasi-Newton methods for generalized equations (in terms of Robinson).
- 3 Kojima and Shindo (1986) investigated Newton's method for piecewise smooth equations.
- 4 Kummer (1988, 1992) gave a sufficient condition (22) to extend Kojima and Shindo's work.
- 5 L. Qi and J. Sun (1993) proved what we know now.
- 6 Since then, many exciting developments, in particular in the **large-scale settings** ...

Why nonsmooth Newton methods important in solving large-scale optimization problems? We illustrate this with an example.

Consider the nearest correlation matrix (NCM) problem:

$$\min \left\{ \frac{1}{2} \|X - G\|_F^2 \mid X \succeq 0, X_{ii} = 1, i = 1, \dots, n \right\}.$$

The dual of the above problem can be written as (in its minimization format)

$$\begin{aligned} \min \quad & \frac{1}{2} \|\Xi\|^2 - \langle b, y \rangle - \frac{1}{2} \|G\|^2 \\ \text{s.t.} \quad & S - \Xi + \mathcal{A}^* y = -G, \quad S \succeq 0 \end{aligned}$$

or via eliminating  $\Xi$  and  $S \succeq 0$ , the following

$$\min \left\{ \varphi(y) := \frac{1}{2} \|\Pi_{\mathcal{S}_+^n}(\mathcal{A}^* y + G)\|^2 - \langle b, y \rangle - \frac{1}{2} \|G\|^2 \right\},$$

which is equivalent to the strongly semismooth system (S. & Sun, 02) of equations

$$\nabla \varphi(y) = \mathcal{A} \Pi_{\mathcal{S}_+^n}(\mathcal{A}^* y + G) - b = 0.$$

Test the second order nonsmooth Newton-CG method [H.-D. Qi & S. 06] ( $[X,y] = \text{CorrelationMatrix}(G,b,\tau,\text{tol})$  in Matlab from Sun's webpage) and two popular first order methods (FOMs) [APG of Nesterov; ADMM of Glowinski (steplength 1.618)] all to the dual forms for the NCM with real financial data:

$G$ : Cor3120,  $n = 3,120$ , obtained from [N. J. Higham & N. Strabić, SIMAX, 2016] [Optimal sol. rank = 3,025, high rank]

$n = 3,120$	Newton-CG	ADMM	APG
Rel. KKT Res.	2.7-8	2.9-7	9.2-7
time (s)	26.8	246.4	459.1
iters	4	58	111
avg-time/iter	6.7	4.3	4.1

Newton's method only takes at most 40% time more than ADMM & APG (or FISTA) per iteration (Newton will take less time on average per iteration if it took more iterations).

## Theorem

*Suppose that  $\bar{X} \in \mathcal{N}$  has the SVD (21). The spectral operator  $G$  is continuous at  $\bar{X}$  if and only if  $g$  is continuous at  $\sigma(\bar{X})$ .*

## Theorem

*Suppose that  $\bar{X}$  has the SVD (21). The spectral operator  $G$  is locally Lipschitz continuous near  $\bar{X}$  if and only if  $g$  is locally Lipschitz continuous near  $\bar{\sigma} = \sigma(\bar{X})$ .*



Let  $\eta(\sigma) \in \mathbb{R}^m$  be the vector defined by ( $i \in \{1, \dots, m\}$ )

$$(\eta(\sigma))_i := \begin{cases} (g'(\sigma))_{ii} - (g'(\sigma))_{ij} & \text{if } \exists j \in \{1, \dots, m\} \text{ and } j \neq i \text{ such that } \sigma_i = \sigma_j, \\ (g'(\sigma))_{ii} & \text{otherwise,} \end{cases} \quad (24)$$

Define the corresponding *divided difference matrix*  $\mathcal{E}_1(\sigma) \in \mathbb{R}^{m \times m}$ , the *divided addition matrix*  $\mathcal{E}_2(\sigma) \in \mathbb{R}^{m \times m}$ , the *division matrix*  $\mathcal{F}(\sigma) \in \mathbb{R}^{m \times (n-m)}$ , respectively, by

$$(\mathcal{E}_1(\sigma))_{ij} := \begin{cases} \frac{g_i(\sigma) - g_j(\sigma)}{\sigma_i - \sigma_j} & \text{if } \sigma_i \neq \sigma_j, \\ (\eta(\sigma))_i & \text{otherwise,} \end{cases} \quad i, j \in \{1, \dots, m\}, \quad (25)$$

$$(\mathcal{E}_2(\sigma))_{ij} := \begin{cases} \frac{g_i(\sigma) + g_j(\sigma)}{\sigma_i + \sigma_j} & \text{if } \sigma_i + \sigma_j \neq 0, \\ (g'(\sigma))_{ii} & \text{otherwise,} \end{cases} \quad i, j \in \{1, \dots, m\}, \quad (26)$$

$$(\mathcal{F}(\sigma))_{ij} := \begin{cases} \frac{g_i(\sigma)}{\sigma_i} & \text{if } \sigma_i \neq 0, \\ (g'(\sigma))_{ii} & \text{otherwise,} \end{cases} \quad i \in \{1, \dots, m\}, \quad j \in \{1, \dots, n-m\}. \quad (27)$$

Define the matrix  $\mathcal{C}(\sigma) \in \mathbb{R}^{m \times m}$  to be the difference between  $g'(\sigma)$  and  $\text{Diag}(\eta(\sigma))$ , i.e.,

$$\mathcal{C}(\sigma) := g'(\sigma) - \text{Diag}(\eta(\sigma)). \quad (28)$$

When the dependence of  $\eta$ ,  $\mathcal{E}_1$ ,  $\mathcal{E}_2$ ,  $\mathcal{F}$  and  $\mathcal{C}$  on  $\sigma$  is clear from the context, we often drop  $\sigma$  from the corresponding notations. Note that the divided difference matrix  $\mathcal{E}_1(\sigma)$  is the same with the commonly defined for the symmetric matrix case. The divided addition matrix  $\mathcal{E}_2(\sigma)$  and the division matrix  $\mathcal{F}(\sigma)$  are particular to general non-Hermitian matrices.

Denote  $\bar{\eta} = \eta(\bar{\sigma}) \in \mathbb{R}^m$  to be the vector defined by (24). Let  $\bar{\mathcal{E}}_1$ ,  $\bar{\mathcal{E}}_2$ ,  $\bar{\mathcal{F}}$  and  $\bar{\mathcal{C}}$  be the real matrices defined in (25)–(28) with respect to  $\bar{\sigma}$ .

## Theorem

Suppose that the given matrix  $\bar{X} \in \mathcal{N}$  has the SVD (21). Then the spectral operator  $G$  is  $F$ -differentiable at  $\bar{X}$  if and only if  $g$  is  $F$ -differentiable at  $\bar{\sigma}$ . In that case, the derivative of  $G$  at  $\bar{X}$  is given by

$$G'(\bar{X})H = \bar{U}[\bar{\mathcal{E}}_1 \circ S(A) + \text{Diag}(\bar{\mathcal{C}}\text{diag}(S(A))) + \bar{\mathcal{E}}_2 \circ T(A) \quad \bar{\mathcal{F}} \circ B] \bar{V}^{\mathbb{T}} \quad \forall H \in \mathbb{V}^{m \times n}, \quad (29)$$

where  $A := \bar{U}^{\mathbb{T}} H \bar{V}_1$ ,  $B := \bar{U}^{\mathbb{T}} H \bar{V}_2$  and for any  $X \in \mathbb{V}^{m \times m}$ ,  $\text{diag}(X)$  denotes the column vector consisting of all the diagonal entries of  $X$  being arranged from the first to the last.

Here the two linear matrix operators  $S : \mathbb{V}^{p \times p} \rightarrow \mathbb{S}^p$  and  $T : \mathbb{V}^{p \times p} \rightarrow \mathbb{V}^{p \times p}$  are given by

$$S(Y) := \frac{1}{2}(Y + Y^{\mathbb{T}}), \quad T(Y) := \frac{1}{2}(Y - Y^{\mathbb{T}}), \quad Y \in \mathbb{V}^{p \times p}. \quad (30)$$

Let  $\mathcal{Z}$  be a finite dimensional real Euclidean space equipped with an inner product  $\langle \cdot, \cdot \rangle$  and its induced norm  $\| \cdot \|$ . Let  $\mathcal{O}$  be an open set in  $\mathcal{Z}$  and  $\mathcal{Z}'$  be another finite dimensional real Euclidean space. The function  $F : \mathcal{O} \subseteq \mathcal{Z} \rightarrow \mathcal{Z}'$  is said to be *B(ouligand)-differentiable* at  $z \in \mathcal{O}$  if for any  $h \in \mathcal{Z}$  with  $h \rightarrow 0$ ,

$$F(z + h) - F(z) - F'(z; h) = o(\|h\|).$$

A stronger notion than B-differentiability is  $\rho$ -order B-differentiability with  $\rho > 0$ . The function  $F : \mathcal{O} \subseteq \mathcal{Z} \rightarrow \mathcal{Z}'$  is said to be  $\rho$ -order *B-differentiable* at  $z \in \mathcal{O}$  if for any  $h \in \mathcal{Z}$  with  $h \rightarrow 0$ ,

$$F(z + h) - F(z) - F'(z; h) = O(\|h\|^{1+\rho}).$$

### Theorem

Suppose that  $\bar{X} \in \mathcal{N}$  has the SVD (21). Let  $0 < \rho \leq 1$  be given.

- (i) If  $g$  is locally Lipschitz continuous near  $\sigma(\bar{X})$  and  $\rho$ -order B-differentiable at  $\sigma(\bar{X})$ , then  $G$  is  $\rho$ -order B-differentiable at  $\bar{X}$ .
- (ii) If  $G$  is  $\rho$ -order B-differentiable at  $\bar{X}$ , then  $g$  is  $\rho$ -order B-differentiable at  $\sigma(\bar{X})$ .

## Theorem

*Suppose that  $\bar{X} \in \mathcal{N}$  has the singular value decomposition (21). Let  $0 < \rho \leq 1$  be given.  $G$  is  $\rho$ -order  $g$ -semismooth at  $\bar{X}$  if and only if  $g$  is  $\rho$ -order  $g$ -semismooth at  $\bar{\sigma}$ .*

Assume that  $g$  is locally Lipschitz continuous. Then since the spectral operator  $G$  is locally Lipschitz continuous near  $\bar{X}$ ,  $\Psi = G'(\bar{X}; \cdot)$  is globally Lipschitz continuous if exists. In that case,  $\partial_B \Psi(0)$  and  $\partial \Psi(0)$  are well-defined. Furthermore, we have the following characterization of the B-subdifferential and Clarke's subdifferential of the spectral operator  $G$  at  $\bar{X}$ .

## Theorem

*Suppose that the given  $\bar{X} \in \mathcal{N}$  has the decomposition (21). Suppose that there exists an open neighborhood  $\mathcal{B} \subseteq \mathbb{R}^m$  of  $\bar{\sigma}$  in  $\hat{\sigma}_{\mathcal{N}}$  such that  $g$  is differentiable at  $\sigma \in \mathcal{B}$  if and only if  $g'(\bar{\sigma}; \cdot)$  is differentiable at  $\sigma - \bar{\sigma}$ . Assume further that the function  $d : \mathbb{R}^m \rightarrow \mathbb{R}^m$  defined by*

$$d(h) := g(\bar{\sigma} + h) - g(\bar{\sigma}) - g'(\bar{\sigma}; h), \quad h \in \mathbb{R}^m \quad (31)$$

*is strictly differentiable at zero. Then, we have*

$$\partial_B G(\bar{X}) = \partial_B \Psi(0) \quad \text{and} \quad \partial G(\bar{X}) = \partial \Psi(0).$$

Many more to be developed ...

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- ③ Chao Ding, Defeng Sun, Jie Sun, and Kim-Chuan Toh, “Spectral operators of matrices: semismoothness and characterizations of the generalized Jacobian,” [arXiv:1810.09856](https://arxiv.org/abs/1810.09856), October 2018.